Mangrove Area Delineation using Object-Based Classification on Sentinel-2 Imagery: Tuba Island, Langkawi

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Abstract. Pixel misclassification is a common problem when satellite imagery extracts land-use and land cover classes. Accurate image classification for mangrove areas is essential for management and monitoring to preserve the mangrove ecosystem and expedite the mangrove area delineation process. Therefore, this study aims to i) identify suitable segmentation parameters value to delineate the mangrove area and ii) classify young and mature mangrove trees using the object-based classification (OBIA) approach at Tuba Island, Langkawi, Malaysia. This research applied Support Vector Machine (SVM) based on an object-based method using Sentinel-2A image and segmentation parameters value of scale, compactness, shape, and Gray Level Co-occurrence Matrix (GLCM) mean were tested. Measured tree diameter at breast height (DBH) is used to verify the mangrove tree delineated on the Sentinel-2A image. Segmentation parameters setting of shape (0.2), compactness (0.2), and scale (50) shows minimum errors with mangrove delineation 9.279% as compared to the Global Forest Watch (GFW) data while GLCM mean appropriate to determine the young and mature mangrove tree. The finding of this study will help the Department of Fisheries Malaysia and agritourism to maintain the mangrove ecosystem and enhance the fisheries industry.

Keywords: Mangrove, Geospatial Analysis, Image Segmentation

1. Introduction

Malaysia ranked as the third-largest mangrove forest recorded after Indonesia and Brazil [1]. Mangrove resources significantly contribute to the socio-economy benefits such as timber supply,
shelter for the marine ecosystem and environmental services. Therefore, it is crucial to maintain the mangrove area, and it is difficult using ground-truth observation, especially in an unreachable area. Thus, remote sensing data has been commonly used to delineate mangroves areas [2].

Research in image classification for urban tree analysis and mangrove extent mapping has been carried out in previous work using satellite imageries [3–6]. Many satellite imageries used in mangrove study on species, characteristics, and extent, such as Landsat Thematic Mapper (TM), Enhanced Thematic Mapper (ETM +), Landsat-8 Operational Land Imager (OLI), SPOT and Sentinel imageries [7,8] with 15-60 m spatial resolution. The Landsat satellite imagery is mainly used to estimate volume, aboveground biomass, mangrove land cover because of a large number of scenes and wide coverage for time series analysis [5,9]. Newly satellite images, like Sentinel-2, have better spectral and spatial resolutions and have a huge role in the classification of tree species. The Sentinel-2 and Landsat-8 were suggested by [2] for the detailed composition of mangrove forests’ mapping. It is also capable to discriminate tree species and detect the phenology of mangroves [10]. A study by [11] stated that the Sentinel-2 imagery red-edge band is significant reflectance in mangrove differentiation.

Many classifications such as spectral angle mapper classifiers, linear discriminant analysis, and maximum likelihood. These methods produce a feature classified in the images [12]. However, it is challenging to identify mangroves using moderate spatial resolution such as 30 m satellite data because the spatial and spectral data given by these data may not be adequate for a detailed analysis of mangrove forests and their species composition [13]. Also, monitoring mangroves using satellite imagery is quite challenging due to the cloud shadow and cloud coverage, especially in the pixel-based classification approach [14]. Therefore, multi-scale segmentation for the object-based image analysis (OBIA) has been used to extract an object from satellite imagery to differentiate canopy trees based on their shape, species and map mangrove land cover [3,5,6]. However, studies focused on testing segmentation parameters value suitable to extract mangrove area and characteristics (young and mature) are still limited.

Thus, this study was to identify appropriate segmentation parameters value, which focuses on shape, compactness, and scale for mangrove area delineation and characteristics (young and mature) mangrove three based on the OBIA approach. Therefore, this study improves the existing method for the extraction of mangrove areas and their characteristics.

2. Methodology

2.1. Study Area

Figure 1 shows the Tuba Island, Langkawi, Kedah located at 6° 14’ 18” N, 99° 50’ 24” E in WGS84 coordinate system. The socio-economy activities in Tuba Island are fishing and plantation. It is also the only inhabited islet in the area, aside from Langkawi Island, and it is reachable via boat ride.

2.2. Data Acquisition

Sentinel-2A satellite imagery acquired on 21st April 2020 (https://scihub.copernicus.eu) was used with cloud cover 15% and cloud shadow 0.0014%. Mangrove tree diameter of DBH was measured simultaneously with water quality sampling acquisition on 26th September 2020 to recognize their types. The data from the DBH diameter of the mangrove tree is used for the identification of mangrove tree types.

2.3. Sentinel-2A Image Processing and Segmentation

Sentinel-2A images with 10m and 20m spatial resolution have been processed using SNAP software. Land Surface Reflectance Code (LaSRC) was applied for atmospheric correction [15]. Only selected bands were applied such as band blue (2), green (3), red (4), near-infrared (NIR) (8), vegetation red edge (5, 6, 7) and Narrow NIR (8A) (table 1), which is obtained from Copernicus Open Access Hub. The
reason for the selection of the sensor bands is significant and appropriate mangrove differentiation [2]. Subsequently, these 8 (eight) bands have been stacked and image fusion via High-Pass Filtering (HPF) was applied to improve visual image quality.

The selection of suitable parameters is important to ensure the best segmentation quality of classification [16]. Consequently, the multiresolution segmentation parameter’s value has been determined; scale (50), shape (0.2) and compactness (0.2) (table 2) based on the study by [5,17] to create an image object of mangrove tree and the combination of the parameter’s value is by the trial-and-error method. The mangrove area was classified among other land use land cover using a support vector machine (SVM) algorithm [5,6,17]. Four (4) main settings were tested such as scale parameter, band weights, shape influence, and compactness value. However, only scale in 50, shape 0.2 and compactness 0.2, was applied due to the early finding from the trial-and-error approach on the two (2) other optimisation process settings, which has been identified that scale in 50 much easily handled in terms of processing time.

**Table 1. Multiresolution Segmentation Parameters of Sentinel 2A Imagery**

| Sensor Bands          | Wavelength (nm) | Spatial resolution (m) |
|-----------------------|-----------------|------------------------|
| Band 2 Blue           | 492.4           | 10                     |
| Band 3 Green          | 559.8           | 10                     |
| Band 4 Red            | 664.6           | 10                     |
| Band 5 Vegetation red edge | 704.1       | 20                     |
| Band 6 Vegetation red edge | 740.5       | 20                     |
| Band 7 Vegetation red edge | 782.8       | 20                     |
| Band 8 NIR            | 832.8           | 10                     |
| Band 8A Narrow NIR    | 864.7           | 20                     |

**Table 2. Multiresolution Segmentation Parameters**

| Shape | Compactness | Scale |
|-------|-------------|-------|
| 0.2   | 0.2         | 50    |
| 0.1   | 0.5         | 10    |
| 0.1   | 0.1         | 0.1   |

2.4. Mangrove Area Classification and Verification

This research only focused on two (2) two age groups: young and mature mangrove areas. The other land cover of the study area is not covered for the part of the analysis. The features parameters value such as brightness, compactness, and texture [5,11] were tested to differentiate between young and mature mangrove trees. However, the other segmentation parameters such as color and smoothness were not tested in this study.

For the verification process, there are two stages; i) classified mangrove area map compared to the Global Forest Watch (GFW) and ii) classified mangrove age map to the DBH. The GFW (https://www.globalforestwatch.org) is used to display the mangrove area of Tuba Island, Malaysia and was extracted into shapefile format. The number of samples selected for the classification is 6 for young mangrove age. However, the mature mangrove area verification cannot be accessed due to inaccessible areas. The young mangrove area in the point form was overlayed on the classified mangrove area.
3. Result and Analysis

3.1. Mangrove Area Delineation based on OBIA Segmentation

The Multiresolution Segmentation algorithm is used to extract objects in the framework of Object-Based Image Analysis. The value of segmentation parameters changes the object production. Therefore, several segmentation settings (shape, compactness, and scale) were tested to determine the appropriate combination of the parameter's value to lead to a better mangrove area classification. Table 2 presents the number of objects produced in each land cover class around Tuba Island's mangroves. The result found that the number of LULC objects classes are slightly decreasing when the scale value increases.

The predicted mangrove area obtained from the OBIA segmentation was compared with the observed Global Forest Watch (GFW) data in shapefile format (figure 2). The area with the lowest error percentage represents the suitable segmentation optimisation setting to delineate the mangrove area on Sentinel-2 imagery. The trial-and-error approach showed that shape 0.1 compactness 0.5 produces the highest error with 13.277% at scale 10 and the lowest with 9.683% at scale 30. The segmentation optimisation process with the shape 0.1 compactness 0.2 produce error with 10.306% (highest) at scale 10 and 9.541% (lowest) at scale 30. The setting of 0.2 shape, 0.2 compactness, and scale 50 was the optimum segmentation optimisation process with an error is 9.279% compared to other settings. The
result is produced with different segmentation optimisation settings (shape 0.1, compactness 0.5, and scale 40) used by Rosmasita et al. (2019) due to this parameter's ability to produce less error.

Figure 2. Mangrove from (a) OBIA Classification and (b) Global Forest Watch in 2016

3.2. Differentiate Between Young and Mature Mangrove Tree

Segmentation features such as brightness, compactness, and texture were used in this study to differentiate between young (green colour) and mature mangrove (orange colour) trees. The tree diameter was measured at several points along Tuba River, Langkawi. Figure 3 (a-c) indicates the young and mature mangrove tree using the segmentation optimisation process.

Figures 3a, 3b and 3c show mangrove area, which was extracted using GLCM mean (minimum 105, maximum 167), compactness (minimum 1, maximum 5.9), and brightness (minimum 637, maximum 2125), respectively. According to [18], the diameter of the youngest mangrove was 2.20 ± 0.20 cm, 18-year period (diameter: 9.31 ± 0.91 cm and mature mangroves are in diameter of 12.03 ± 1.81 cm. This study indicates that tree diameter ranges 4-8 cm, representing a young mangrove tree (table 3) and used for verification. The GLCM mean shows the best mangrove area delineation in different characteristics, young and mature tree when overlayed and checked with the measured points obtained along the Tuba River (figure 4). The study only verified the young mangrove trees because the mature mangrove trees are in inaccessible areas.

Table 3. Segmentation Optimisation Testing on Mangrove Object Delineation

| Setting  | Scale | No. of Object | Area (ha) | Error (%) |
|----------|-------|---------------|-----------|-----------|
|          |       |               | Observed  | Predicted |          |
| Shape 0.1| 10    | 28842         | 599.784   | 13.277    |
|          | 20    | 7153          | 622.817   | 9.947     |
|          | 30    | 3111          | 624.647   | 9.683     |
|          | 40    | 1740          | 622.607   | 9.978     |
|          | 50    | 1069          | 617.017   | 10.786    |
|          | 10    | 28798         | 597.934   | 13.545    |
|          | 20    | 7152          | 621.467   | 10.142    |
|          | 30    | 3114          | 625.628   | 9.541     |
|          | 40    | 1742          | 622.577   | 9.982     |
|          | 50    | 1064          | 620.337   | 10.306    |
| Shape 0.2| 20    | 7152          | 621.467   | 10.142    |
|          | 30    | 3114          | 625.628   | 9.541     |
|          | 40    | 1742          | 622.577   | 9.982     |
|          | 50    | 1064          | 620.337   | 10.306    |
| Shape 0.2| 50    | 966           | 627.439   | 9.279     |
| Compactness 0.2| | | | |
Figure 3. Mangrove area Extraction from Segmentation Optimisation Process (a) GLCM mean (b) compactness (c) brightness

Table 4. Verification Points Based on Tree Diameter

| Point | Diameter (cm) | Sentinel-2 | River Zoning |
|-------|---------------|------------|--------------|
| T6    | 8             | Young      | Upstream     |
| T8    | 8             | Young      | Upstream     |
| T13   | 6             | Young      | Middle       |
| T15   | Rock          | Nil        | Middle       |
| T20   | 4             | Young      | Downstream   |
| T22   | 8             | Young      | Downstream   |

Figure 4. Mangrove area Extraction from Segmentation Optimisation Process (GLCM Mean)
4. Conclusion

The research found that the OBIA classification method successfully delineates the mangrove area and differentiates young and mature mangrove trees. The segmentation optimisation process with the setting of 0.2 shape, 0.2 compactness, and scale 50 can extract mangrove objects compared to the Global Forest Watch (GFW) dataset. Furthermore, GLCM mean method indicates an optimum segmentation setting to differentiate the young and mature mangrove trees. Undoubtedly, this study improves the methodology of the classification method for mangrove area and tree delineation. The results from this study will become the input for decision-makers who involve socio-economy activities, marine ecosystems, and environmental services to formulate their strategies for the said area.

Tuba Island offers various approaches of study related to mangroves waiting to be explored. For this study, further investigation will be conducted related to the phytoplankton and how it impacts the economy of the small fishermen in the area.

5. Acknowledgement

This project was funded by Universiti Teknologi MARA (UiTM) Lestari grant (600-RMC/LESTARI SDG-T 5/3 (104/2019)). Many thanks to Mrs Nurulhuda Bt Abd. Kadir@Saad for her assistance in this study.

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