



Characterizing and Assessing Forest Density and Productivity of Ulu Muda Forest Reserve Based on Satellite Imageries

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Abstract

The NPP was calculated for 2-m resolution image of Ulu Muda Forest Reserve (UMFR), in Sik, North of Peninsular Malaysia. The GeoEye-1 image was first preprocessed, and land use was classified based on object-based image analysis (OBIA) based on PCI Geomatics Catalyst Professional image processing software. Attributes were segmented by employing three segmentation methods, namely, finer, 50 scale; moderate, 200; and coarse, 350. Based on accuracy assessment, a moderate scale of 200 showed the best kappa with 0.67, whereas for finer and coarse were 0.44 and 0.27, respectively. The moderate segmentation method showed a moderate number of attributes that sufficiently assist in collecting accuracy sampling that resulted in a higher kappa coefficient in the study. Biophysical indices, such as Absorbed Photosynthetically Active Radiation (APAR), Normalized Difference Vegetation Index (NDVI) and the fraction of Photosynthetically Active Radiation (fAPAR), were calculated for the study based on the satellite images. The study showed that the coarse method of NDVI had the highest mean value of 0.709, followed by 0.698 for moderate and 0.966 for finer method. A high NDVI value indicated that the area in UMFR is covered by high-density vegetation dominated by lowland forest. Meanwhile, the

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recorded NPP ranged between $6.7 \text{ g C m}^{-2} \text{ month}^{-1}$ and $300.04 \text{ g C m}^{-2} \text{ month}^{-1}$, with a mean value of $231.85 \text{ g C m}^{-2} \text{ month}^{-1}$ for the study area. Satellite remote sensing allows for the estimation of NPP while also generating land use/land cover and forest density estimates for lowland forests in the peninsular. The findings indicate the presence of intricacies between NDVI, forest density and land cover in explaining NPP variations within this type of forest. The Ulu Muda FR community assessed by the study extracted no major NPP. This type of research can be used in forest management planning in the forestry department to improve forest extraction policy.

Keywords

Remote sensing · NPP · NDVI · Ulu Muda Forest Reserve · Productivity

4.1 Net Primary Productivity

Primary production is the rate of solar energy converted to plant biomass through photosynthesis (Indiarto & Sulistyawati, 2013). Gross Primary Productivity (GPP) is important to measure because it indicates the tree's capability to produce biomass at a specific time; however, understanding the tree's vigour with the given monthly temperature and solar radiation is not possible, certainly not in a short period of time. The GPP calculates the total amount of solar energy converted to biomass (Indiarto & Sulistyawati, 2013). Net primary productivity (NPP), on the other hand, is the net flux of carbon from the atmosphere into green plants per unit of time (Zhang et al., 2017). It is also known as an important index for evaluating the carbon cycling in forest ecosystems (Muhamad, 2010).

The GPP estimation is practical when afforded with a longer period of time, especially when combined with a temporal approach offered by satellite remote sensing. The introduction of MODIS NPP and GPP products in recent years has made the phenological estimation of global terrestrial possible. When employed with the specific model of Biome-BGC carbon cycle, the products showed a promising outcome (Turner et al., 2006). To date, quantification of GPP has been conducted using satellite remote sensing of Sentinel-2 images for a short rotation of forest plantations in Belgium (Maleki et al., 2020).

A comparative study on NPP changes by Shao and Zeng (2017) puts global tropical forests under the spotlight. After that, further studies on tropical forest became sparse, with more studies on NPP for plantation emerging instead of studies on natural forest land. Therefore, this study aims to assess NPP for UMF. To do this, the study employed an NPP equation using satellite remote sensing of GeoEye-1 data of Sungai Teliang, UMF, in Sik, Kedah, Malaysian Peninsula. The forest is one of the tropical evergreen forests in Southeast Asia with a high biodiversity value. In this study, forest density mapping was performed to obtain land cover information for the study area, which was then correlated with the NPP and NDVI values of the study. Three segmentation methods were designated in developing the land cover

maps, namely, finer, medium and coarse. The finer scale is used as reference and validation while the other two scales, i.e. moderate and coarse, as a test method to derive the forest attributes.

NPP has been proven to be very useful carbon cycling assessment of forest ecosystems as demonstrated in a study in rocky areas in southwestern China, which lie in the transition zone of the Qinghai–Tibet Plateau and the Yangtze River valley in the middle and lower reaches (Zhang et al., 2017). Other study showed that NPP is varied between the southern, central and northern sites found in a study in boreal forest, where different climate-driven processes regulate forest growth and C uptake. At the same time, the study found water availability appears to be the critical factor limiting forest NPP on southern site in that tested site (Peng & Apps, 1999). NPP estimation permits knowledge about rainfall amount, maximum temperature, solar radiation and potential evaporation.

4.2 Normalized Difference Vegetation Index (NDVI)

NDVI is an essential indication for estimating productivity, whether it is derived at a higher resolution from image or using products such as MODIS Net Primary Production Yearly L4 Global 1 km (MYD17A3). NDVI is a vegetation index that is used to understand drought and soil nutrient loss and, in general, to identify vegetation stress in the vegetation (Luus & Kelly, 2008). The NPP at the regional level varies depending on the temperature. For instance, the vegetation productivity for a region in a cold area, such as the Pan-Arctic, is lower compared to temperate forests, due to the low temperature that limits plant metabolic activity (Kimball et al., 2006). Many countries are currently estimating NPP for their forests to evaluate carbon cycling in their forest ecosystems. Muhamad (2010), for example, estimated NPP for Kalimantan using MODIS products. Generally, MODIS products can be used to estimate GPP and NPP for various types of forests, namely, evergreen needleleaf forest (EN), evergreen broadleaf forest (EB), deciduous needleleaf forest (DN), deciduous broadleaf forest (DB) and mixed forest (Hashimoto et al., 2012).

Meanwhile numerous researches have demonstrated the applicability of the Normalized Difference Vegetation Index (NDVI) in estimating GPP phenology in short-rotation plantation. For example, the GPP in Changbai Mountain, China, was estimated using MODIS products of land cover and Enhanced Vegetation Index (EVI)/NDVI products (Zhang et al., 2019). In terms of image resolution, it was discovered that using recent and high-resolution images for NPP estimation provided greater benefits to local authorities than using a larger scale.

4.3 Motivation of the Study

As a result, this study estimates NPP for the Ulu Muda FR using OBIA image analysis of remote sensing imagery while also estimating forest density. In addition, the study determined the final NPP value and land use classes for Ulu Muda

FR. Finally, the study connected the NPP to the socio-demographics of the community in districts near Sik, specifically Baling, Kulim and Kuala Muda. The study assumed that the process is part of their socio-economic process that at the same time has interaction on NPP spatial area. It is critical to investigate the relationship between forest density and NPP and to assess its effects on the study area community. In other studies, Razali et al. (2015) assessed the human impact on NPP in the tropical forest in Malaysian Peninsula, while Vu et al. (2014) estimated NPP as a proxy for persistent decline or improvement to reflect previous land degradation in Vietnam.

4.4 Methodology

4.4.1 Study Site

The study was conducted in Sungai Teliang River in UMFR, Sik, Kedah, Malaysian Peninsula. The UMFR is part of the Greater Ulu Muda Forest Complex (UMFC) in north-eastern Kedah (Aik et al., 2017). It consists of about 105,060 ha of forest, which lays on the lowland to hill dipterocarp forest and riverine forest (Sharma et al., 2005). The forest reserve is a protected forest serving as a reservoir for Muda, Pedu and Ah Ning Lake (Fig. 4.1). The forest has a unique grassy environment of Sira Bongor and Sira Keladi that are dynamic habitat patches created and maintained by elephants and other larger herbivores (Chew et al., 2014). Physical observation from the study found that a small herd of elephants was heard walking, feeding, drinking, bathing and actively vocalizing from 22:00 to 02:00 h at Sira Air Hangat on 26–27 February 2014. They were moving in the forest surrounding the salt lick and spent about an hour splashing around the lower stretches of the stream before moving on towards Sungai Muda (Chew et al., 2014). This makes the forest a rich biodiversity habitat for wildlife and a critical water catchment for Kedah, Perak and Penang Island. Meanwhile, the UMFR forms part of a massive water catchment in Kedah, in the north-western part of Peninsular Malaysia, that drains either into the Muda dam or into Sungai Muda downstream from the dam (Miniandi et al., 2021). Annual precipitation recorded for the study area ranged from 1972.2 to 2478.0 mm from 1989 to 1997. The monthly mean averaged 177.43–233.43 mm, indicating an increasing precipitation pattern in Ulu Muda FR. Meanwhile, monthly precipitation ranged from 164.5 to 240.4 mm between 1989 and 2018 (Fig. 4.2).

4.4.2 NPP and Social Demographic Ulu Muda FR Community

Indirect social demographic profile of the Ulu Muda FR community analysis was retrieved and referred from interviewed session conducted by Mei (2020) study that was published in 2020. The study evaluated socio-economic and livelihood status of the inland fisherman around Muda River basin that connected to the forest. A total 46 fisherman respondents were selected randomly from the list provided by the

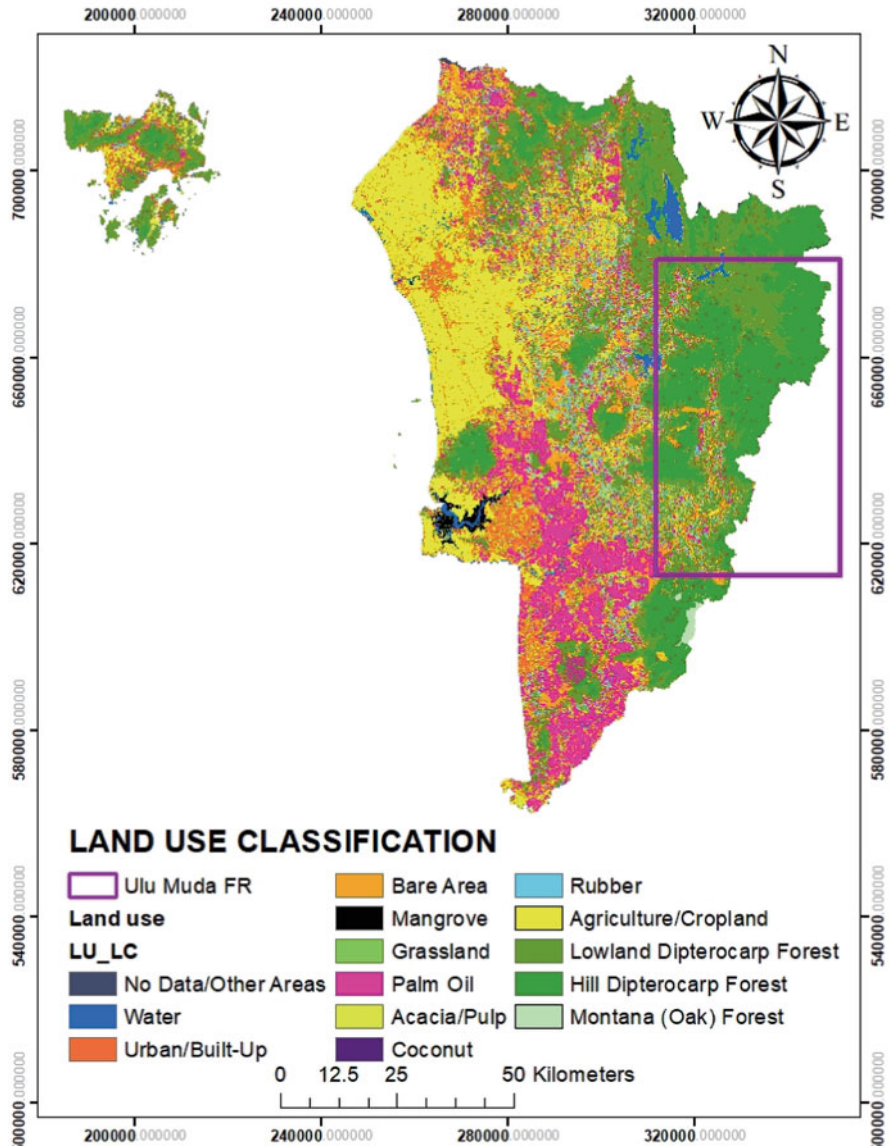


Fig. 4.1 Location of the study area, Ulu Muda Forest Reserve within Kedah map

Department of Fisheries. The article started the data collection in November 2018. The fisherman demographic information was collected and was analysed using Statistical Package for Social Science (SPSS). About 46 fishermen were successfully interviewed from November 2018 until March 2019. Areas that were included in the interviewed were listed below. In general, this interview covered an upstream area which was Kampung Kuala Lesung (Baling district) and mid-stream area of Muda

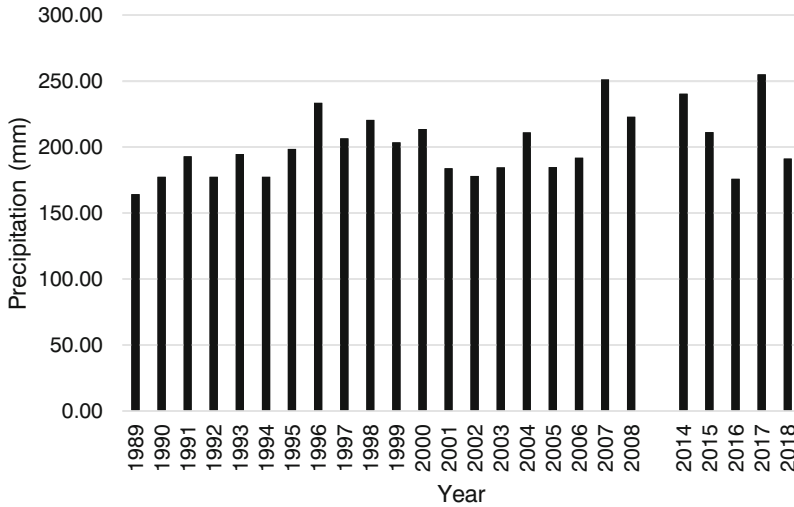


Fig. 4.2 Monthly precipitation for UMFR from 1989 to 2018

River basin that was Muda dam, Gubir (Sik district) and Kampung Ujung Padang (Kulim district). Finally, the study was also included downstream area that was Kampung Titi Merdeka (Kuala Muda district) (please refer Kedah District map in Fig. 4.2).

4.4.3 Satellite Data

The GeoEye-1 data for Sungai Teliang was acquired from image data at 0.46-m panchromatic (black and white), and 1.84-m multispectral bands were used for the NPP estimation, dated 5 April 2018 (Fig. 4.3). The ArcGIS pixel size was approximately 2 m. The GeoEye-1 satellite sensor features the most sophisticated technology ever used in a commercial remote sensing system. It is optimized for large projects, as it can produce over 350,000 km² of pan-sharpened multispectral satellite imagery every day. GeoEye-1 has been flying at an altitude of about 681 km and can produce imagery with a ground sampling distance of 46 cm, meaning it can detect objects of that diameter or greater (Satellite Imaging Corporation, 2017). The satellite image employed in this study consists of four bands, as shown in Table 4.1.

4.4.4 Data Analysis

The study applied ArcGIS version 10.8.2 and PCI Geomatics Catalyst Professional software. The flow data analysis from preprocessing, classification and land use mapping is shown in Fig. 4.4.

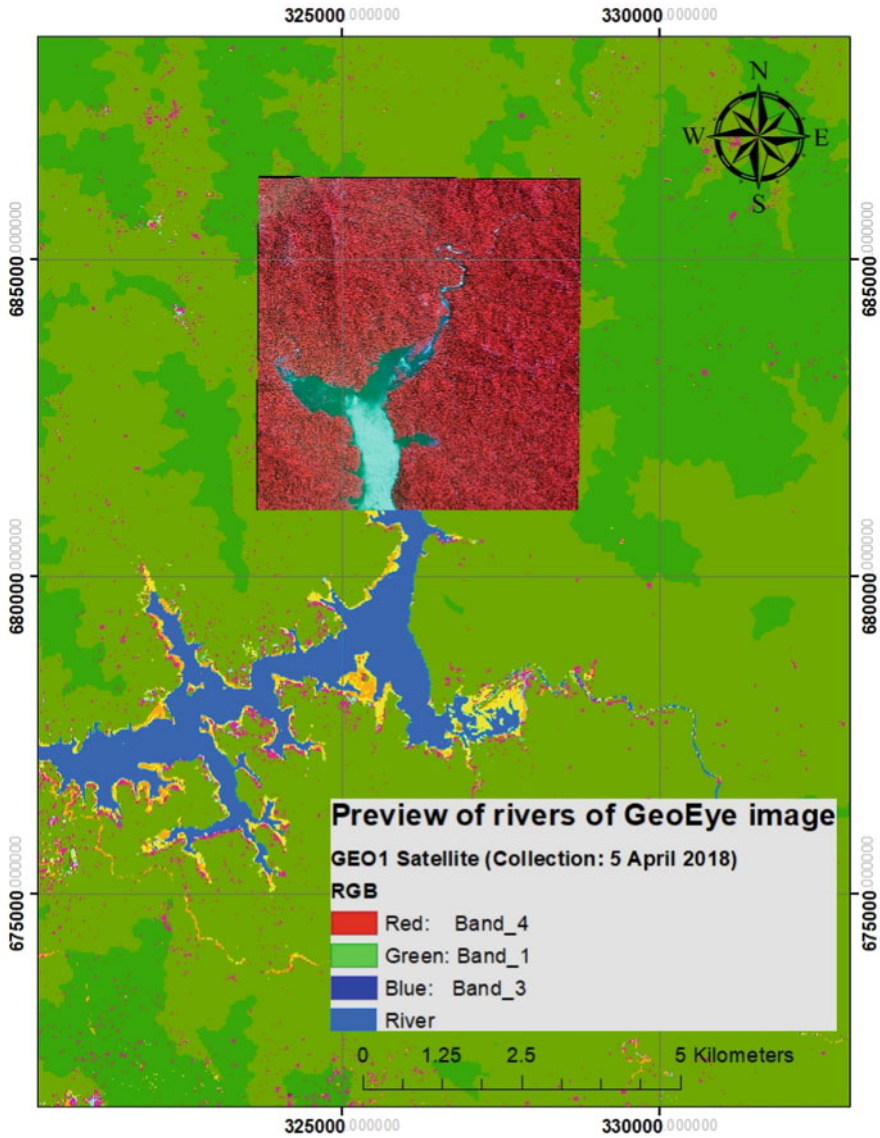


Fig. 4.3 GeoEye-1 preview of Muda Dam and Teliang River dated 5 April 2018

Table 4.1 Spectral range of GeoEye-1 satellite image

Bands	Spectral range (nm)
Blue	450–510
Green	510–580
Red	655–690
Near infrared	780–920

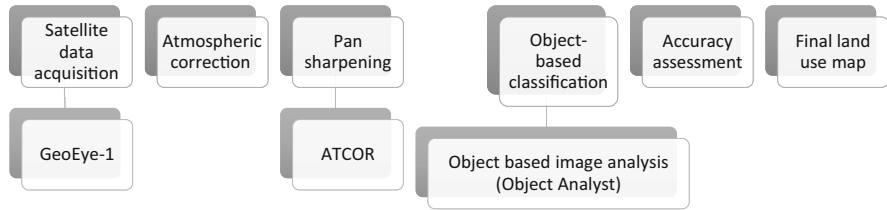
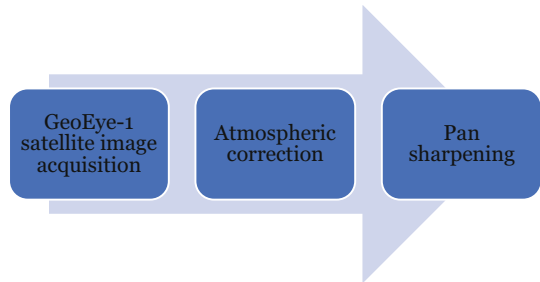


Fig. 4.4 Steps in land use mapping from preprocessing, classification to the final land use map

Fig. 4.5 Image preprocessing using ATCOR of PCI Geomatics Catalyst Professional software



Atmospheric correction tool in PCI Geomatica, which allows users to execute a variety of atmospheric corrections in the simplest and fastest method possible, was employed in the study. The wizard fills in most of the required parameters automatically using image information and walks the user through each key step. The software's focus application was used to prepare the data, and then ATCOR ground reflectance tools were used to analyse atmospheric correction (Fig. 4.5).

4.4.5 Forest Density Mapping

Forest density was assessed by using supervised classification techniques. In this study, the satellite image was classified by using object-based image analysis or OBIA (Fig. 4.6). In this step, segmentation was first performed with a scale of 50, 200 and 350 characterized by a shape of 0.5 and compactness of 0.5. After that, the study calculated the statistical attributes of the segmentation image. Meanwhile, the scale can be modified to fit the land cover types, such as a finer scale for a city with buildings. However, in forest areas with few land cover categories, a greater scale is required for segmentation in order to construct a larger polygon for all the features. The training pixels data were then classified using support vector machine (SVM) classifier; then, accuracy assessment was conducted for all the training and classified images. Accuracy assessment was conducted by assessing overall accuracy and producer's and user's accuracy of the final land use maps based on the three segmentation scales. The maps' confusion matrices and Cohen's Kappa coefficient (Cohen, 1960) were calculated from the error images for each of the three methods

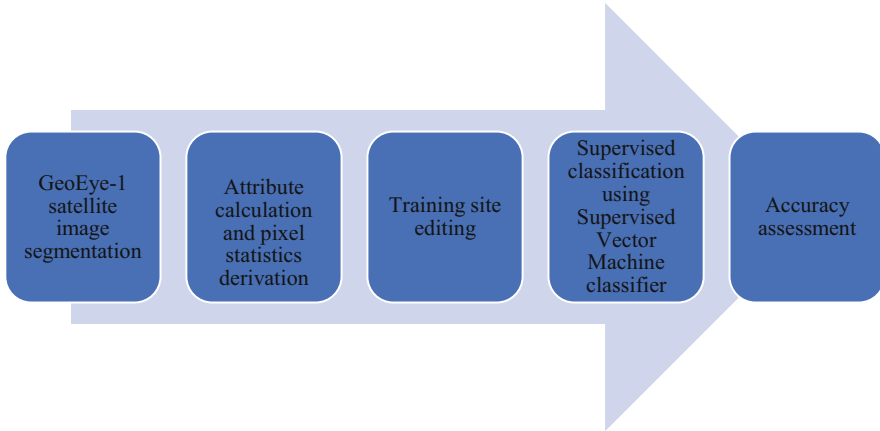


Fig. 4.6 Forest density mapping using OBIA and support vector machine classification

and then reported in an error matrix. After that, the classified polygon was converted into points to calculate the GPP for all the land cover points using ArcGIS software.

4.4.5.1 Forest Density Distribution by Area

Layer properties in ArcGIS software is a tool that uses layer symbology to present quantities of the polygons in the feature layer. Values for fields were chosen, and the colour ramp with suitable range colour was selected. The number of classes chosen was five as the default class due to the medium range of attributes present in the data for all segment scales. Forest density distribution by area was applied to all the segmentation techniques. The study applied graduated colours with Natural Breaks, and five classes were chosen. The chosen colour ramps were red, green and yellowish colour. They are then imported onto all the segmentation for further analysis. The objective of the analysis was to obtain polygon ranges for all the segmentation.

Meanwhile, for further analysis, attributes for more than 1 ha area were extracted by applying select by attributes and added to (area ha > 1) in attributes dialog. The objective of this analysis was to obtain polygon within ranges of more than 1 ha.

4.4.5.2 NPP Equation

Biophysical indices were estimated by using satellite image of GeoEye-1. The indices were included in calculating NPP for the study area. Generally, the NPP can be estimated by reducing the value to 50% of the GPP value. This equation has been employed by many researchers in estimating NPP for tropical forests (Faidi et al., 2010; Girardin et al., 2010; Rasib et al., 2008; Razali et al., 2015). Therefore, in this study, GPP was first quantified using an equation from Xiao et al. (2004). Referring to the study, the GPP is calculated as the following:

$$\text{GPP} = \text{fAPAR} \times \text{PAR} = \varepsilon \times \text{APAR} \quad (4.1)$$

where ε is light use efficiency (ε), which is an important element of the radiation regime for tree growth, incoming photosynthetically active radiation (PAR) ($\text{g MJ}^{-1} \text{m}^{-2}$) and the fraction of PAR intercepted by foliage fAPAR. fAPAR is estimated by remote sensing based on the absorption of a tree canopy between 400 and 700 nm (Luus & Kelly, 2008). This method differs from that used in another study using remote sensing data of MODIS satellite image products such as Pachavo and Murwira (2014). The following equation was used:

$$\text{MODNPP} = 0.5139(\text{MODPRI} \times \text{APAR}) - 1.9818 \quad (4.2)$$

In this study, PAR was estimated from 50% of incoming solar radiation based on the data collected from the meteorological station in the forest reserve. Solar radiation was collected from 1979 until 2014, which is expressed as W m^{-2} . The study derived the value for absorbed fraction of photosynthetically active radiation (APAR) (g MJ^{-1}) by multiplying the two most important elements of radiation, fAPAR and PAR (Coops et al., 2010).

Solar radiation in Malaysia is estimated at around 400–600 MJ m^{-2} , which is higher during the monsoon season of the north-east when the wind direction comes from Central Asia to the South China Sea. After that, the wind goes to Australia between November and March at the final stage (Abdullah et al., 2019). It indicates that Malaysia has high photosynthetic activity in the forests. Daily solar radiation in the forest reserve averaged 18.36 $\text{MJ m}^{-2} \text{day}^{-1}$ between 1978 and 2014. Solar radiation is required for the growth of vegetation on the earth, and many industries used photovoltaic (PV) to convert it into energy for usage. Finally, to calculate the LUE, we referred to a study by Handcock and Csillag (2004):

$$\text{LUE} = 0.8932 + T_{\text{month}} + 0.0015(\text{PRECIP}_{\text{month}}) - 0.002(\text{GDD}) \quad (4.3)$$

where the LUE (g MJ^{-1}) equation was referenced in Band et al. (1999) in which the study had developed based on the data obtained from several sources at the Meteorological Department for the Ulu Muda dam. $\text{PRECIP}_{\text{month}}$ is daily precipitation from 1989 until 2014 that was averaged into monthly precipitation in millimetre (mm) collected from the Ulu Muda weather station derived from the Malaysia Meteorological Department (2018). Meanwhile, the value for T_{month} is the monthly temperature derived for Ulu Muda station, expressed in maximum and minimum temperature for daily readings. Minimum and maximum values can show the variation of temperature over a single day. The data selected for the equation is the maximum value recorded in Celsius ($^{\circ}\text{C}$) calculated from 1979 data until 2014. The air temperature during the north-east monsoon season in Malaysia tends to lower with solar radiation to below 5000 $\text{W m}^{-2} \text{day}^{-1}$ (Muzathik et al., 2010).

The GDD is the average of growing degree days calculated by finding the difference between the mean and minimum temperature values (Sunaryathy et al., 2012), which is also used to evaluate the growth response of the trees. For this study,

the GDD was 9.48 °C. The fAPAR was based on a study by Goward et al. (1994). In this study, the value for fAPAR was derived as:

$$\text{fAPAR} = 1.2 \times \text{NDVI} - 0.04 \quad (4.4)$$

The NDVI was derived by using two bands in the satellite image as shown below, as referenced to a study by Rouse et al. (1973):

$$\text{NDVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{Red}}}{\rho_{\text{NIR}} + \rho_{\text{Red}}} \quad (4.5)$$

where ρ_{NIR} is the reflectance of the WorldView image at 0.77–0.895 nm (near-infrared band, referred to as band 4) and ρ_{Red} is the reflectance of the satellite image at 0.63–0.690 nm (red band referred to as band 3). The NDVI value ranges from -1 and 1 , where -1 represents bare soil and 1 as dense vegetation (Senna, 2005). Using ArcGIS software, Eqs. (4.1)–(4.4) and Eq. (4.6) were employed to calculate the NPP.

After that, the NDVI was calculated using Spatial Analyst map algebra in ArcGIS using the following equation:

$$\text{NDVI ArcGIS} = \text{Float}((B4 - "B3")) / \text{Float}(("B4" + "B3")) \quad (4.6)$$

Equation (4.5) was developed from a similar study conducted in Central Kalimantan, Indonesia, where NDVI is used as an indicator of vegetation health and vigour (Sugiarto & June, 2008) using the following equation:

$$\text{fAPAR} = 1.25 \times \text{NDVI} - 0.025 \quad (4.7)$$

The estimation of fAPAR using the NDVI-derived equation is critical, which is a remote sensing-based approach and is dependent on the availability of satellite data. We chose this equation because it can be used to indicate solar radiation energy that is used in the photosynthetic process, since fAPAR is part of PAR that is absorbed by plant canopy (Sugiarto & June, 2008).

4.5 Results and Discussion

4.5.1 Forest Density Mapping

In the present study, the vegetation density of the forest in Sungai Teliang in UMFR is characterized by various vegetation classes of forest, river and sedimentation percentage by area. The presence of sedimentation was only found in finer and moderate scales. In general, all scales classified water and non-water features were based on the SVM method.

The recorded forest density at the finer scales for forest, river and sedimentation was 97.9%, 1.30% and 0.70%, respectively. At moderate scale, forest, river and sedimentation was 52.8%, 46.6% and 0.70%, respectively. For coarse level at

Table 4.2 Forest density percentage by area for Sg. Teliang, Ulu Muda Forest Reserve

Method	Scale, level	Class	Forest density (%)
1.	50, finer	Forest	97.9
		River	1.30
		Sedimentation	0.70
2.	200, moderate	Forest	52.8
		River	46.6
		Sedimentation	0.70
3.	350, coarse	Forest	21.4
		River	78.6
		Sedimentation	No available

350 scale, forest density for forest and river was 21.4% and 78.6%, while the non-vegetation feature was also identified (Table 4.2).

In this study, the density mapping produced two vegetation classes and a land feature that consists of water and soil characteristics known as sedimentation. During the dry season, the water level in the river is reduced and, hence, exposed the ground river elements. Forest and river recorded good clusters at the finer scale. Meanwhile, forest and river in moderate scale showed clustering balance in discriminating between vegetation and non-vegetated features.

4.5.2 Forest Density Distribution Based on Area

The density distribution throughout the study recorded a range between less than 1 and 8.5 ha in all scales. At the finer scale, more attributes appeared for less than 1–2.5 ha. At moderate scale, more attributes were recorded from 6.0 to 7.5 ha. However, less polygons were recorded for 7.0–8.5 ha (Fig. 4.7). The results also showed that finer scale detected most of the pixel's spectral features identified within similar forest types in the UMFRR.

4.5.3 Forest Density Distribution More than 1 ha

The density distribution was compared to low-scale attributes in areas of larger than 1 ha area with moderate and coarse scale attributes. The result showed that most of the areas were covered with more than 1 ha attributes (Fig. 4.8). The application of finer scale permits more attributes to be developed, resulting in more forest, land and water features being captured. Meanwhile, coarse scale captured less attributes within a larger area, which were mostly attributed to forest class.

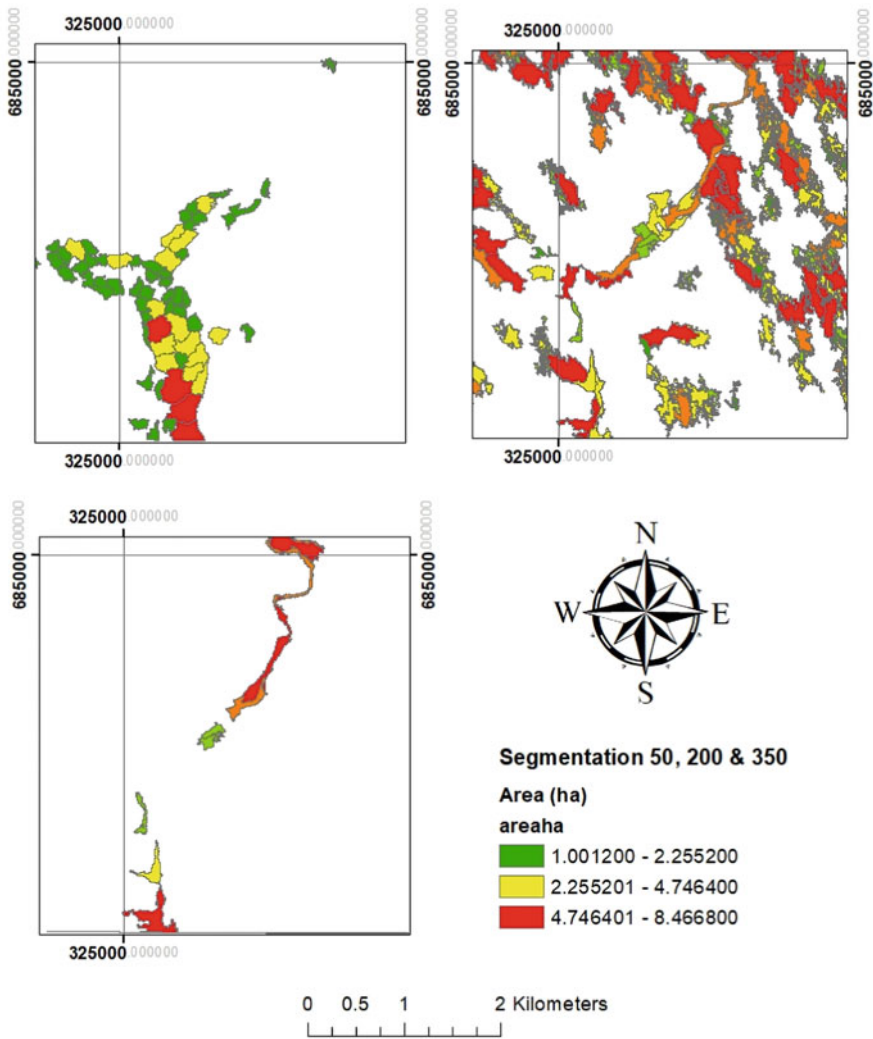


Fig. 4.7 Segmentation for the three methods

4.5.4 Accuracy Assessment

Matrices developed from the accuracy assessment procedures were tabulated as shown below. Because there were more attributes in finer scale, more polygons were selected for accuracy assessment analysis for forest area. As the scale number increases, fewer samples can be collected as accuracy samples (Tables 4.3, 4.4, and 4.5).

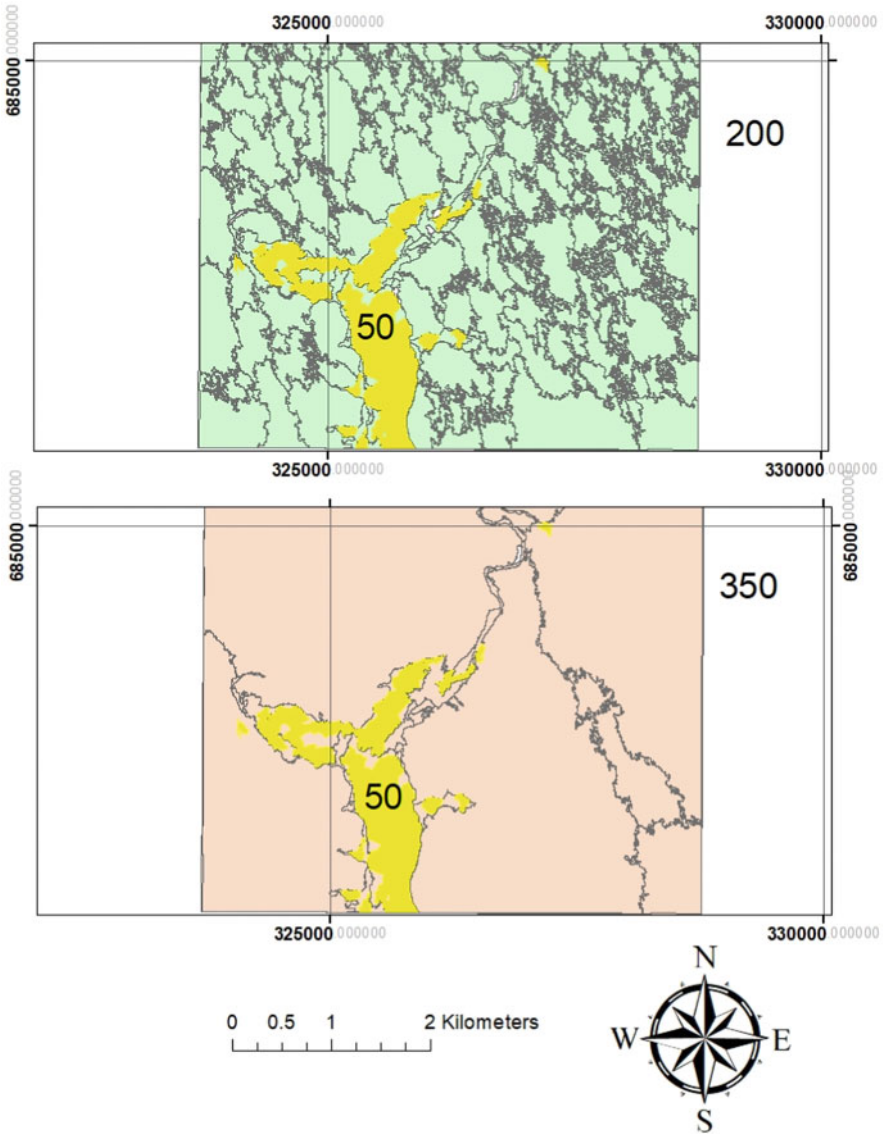


Fig. 4.8 Segmentation attributes for more than 1 ha area

4.5.5 Producer’s and User’s Accuracy

Based on accuracy assessment, the coarse scale showed a low producer’s accuracy, which is 50%, owing to some of the forest being classified as a river. This is because the reflectance of the forest area is closer to sedimentation or elements in the river. However, because the user understood that the attributes should be classified as

Table 4.3 Error matrix for 50 scale

Classified class	Forest	River	Sedimentation	Total (user)
Forest	368	2	6	376
River	0	3	2	5
Sedimentation	0	2	0	2
Unknown	0	0	0	0
Total (producers)	368	7	8	383

Table 4.4 Error matrix for 200 scale

Classified class	Forest1	Sedimentation	River	Total (user)
Forest1	18	0	1	19
Sedimentation	0	0	0	0
River	0	5	9	14
Unknown	0	0	0	0
Total (producers)	18	5	10	33

Table 4.5 Error matrix for 350 scale

Classified class	Forest	River	Sedimentation	Total (user)
Forest	1	0	0	1
River	1	1	1	3
Sedimentation	0	0	0	0
Unknown	0	0	0	0
Total (producers)	2	1	1	4

forest, the user's accuracy was recorded as 100%. Non-forest features were not identified by this scale due to its roughness. The overall kappa for the coarse scale map was 1.0, while the opposite overall kappa was very low with a value of 0.27.

River attributes developed from moderate scale tend to confuse the user, and, in this study, user's accuracy was 94.74%, which is high, while the producer's accuracy was 100%. Producer has better attributes sampling for classifying river than the user, where some of the attributes from the forest were classified as river. However, the misclassification accuracy was higher due to the large number of attributed segments from this scale. Although river sampling collection was more difficult than coarse scale, the classification had a better producer's accuracy of 90% and lower user's accuracy of 64.29%. Kappa for forest was 0.88, while river was 0.49. This makes the overall kappa of 0.67 (Table 4.6).

Finer scale classification produced more attributes that makes it meaningful for sampling collection for the accuracy assessment. The map clearly showed that assigning river and sedimentation sampling is more confusing than in moderate scale, due to the too many attributions in both land covers. Forest provides harder assignments for user in sampling collection than for computer or producer to conduct classification. Therefore, the recorded producer's accuracy was 100%, whereas user's accuracy was 97.87%. Overall kappa for the scale was 0.46, while river's

Table 4.6 Accuracy assessment for final land use^a

Method	Scale	Class	Producer's accuracy	User's accuracy	Overall accuracy (each scale)	Overall kappa	Overall kappa
1	50, finer	Forest	100.00	97.87	96.87	0.46	0.44
		River	42.86	60.00		0.59	
		Sedimentation	0.00	0.00		- 0.02	
2	200, moderate	Forest	100.00	94.74	81.82	0.88	0.67
		River	90.00	64.29		0.49	
		Sedimentation	0.00	0.00		0.00	
3	350, coarse	Forest	50.00	100.00	50.00	1.00	0.27
		River	100.00	33.33		0.11	
		Sedimentation	0.00	0.00		0.00	

^a Note: Shape, compactness = 0.5, 0.5

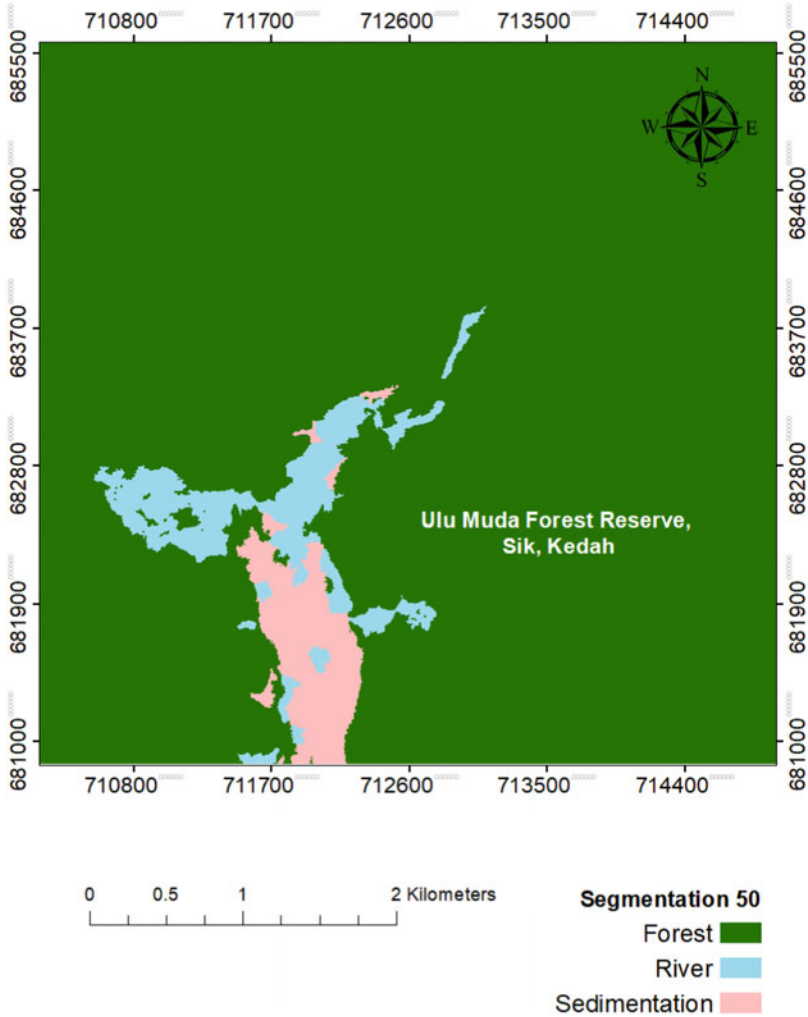


Fig. 4.9 Final land use map for segmentation—50 scale

overall kappa was higher than forest’s 0.59. Moderate scale map showed the best kappa with 0.67 value.

During the dry season, sedimentation occurs as a result of the drying of water in the river. Sedimentation appears in two of the earlier scales but disappears in coarse scale in land use map. The study found that sedimentation class was not counted in the accuracy assessment due to sample inadequacy as determined by the computer algorithm. The final land use map is shown in Figs. 4.9, 4.10 and 4.11.

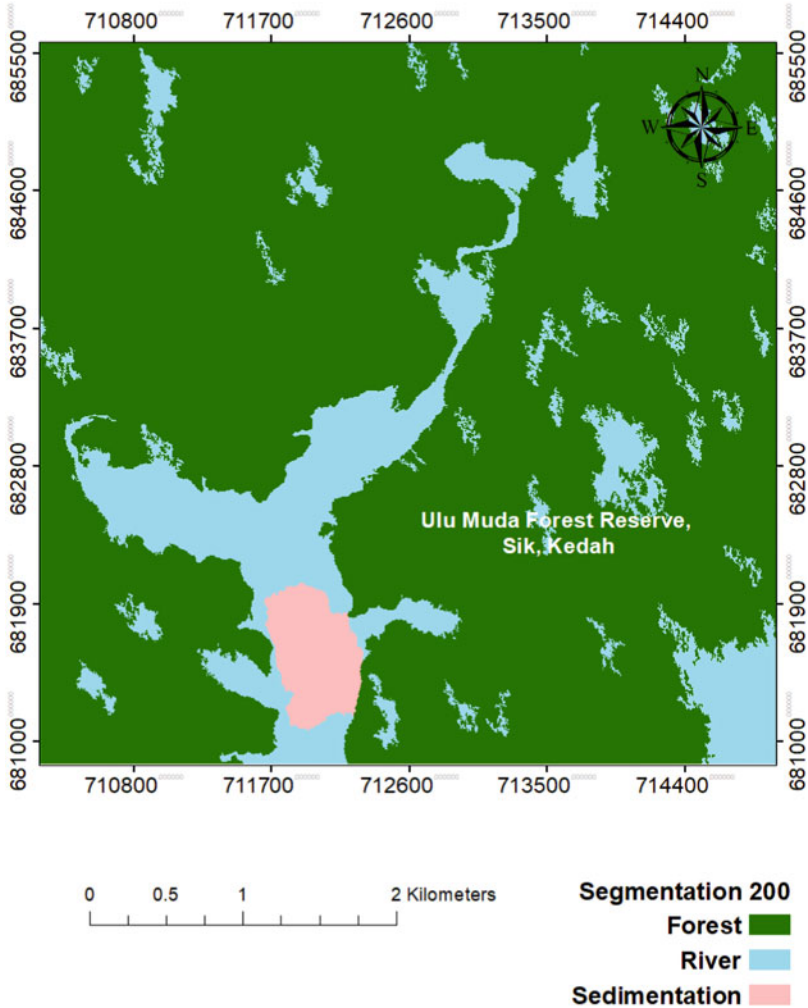


Fig. 4.10 Final land use map for segmentation—200 scale

4.5.6 Biophysical and Vegetation Indices

Understanding the statistics of NDVI is essential for studying vegetation. Here, the study derived NDVI for all the segmentation methods (Fig. 4.12). Generally, the reported NDVI values in other studies vary with different types of land cover types. For example, a study by Gebremichael and Barros (2006) used NDVI maximum and minimum values to derive fractional vegetation cover (f_v).

In this study, the NDVI mean value was derived for all the segmentation methods. Mean NDVI was 0.709, which is the highest for all the methods, whereas the mean for finer and moderate scales was 0.696 and 0.698, respectively. This finding showed

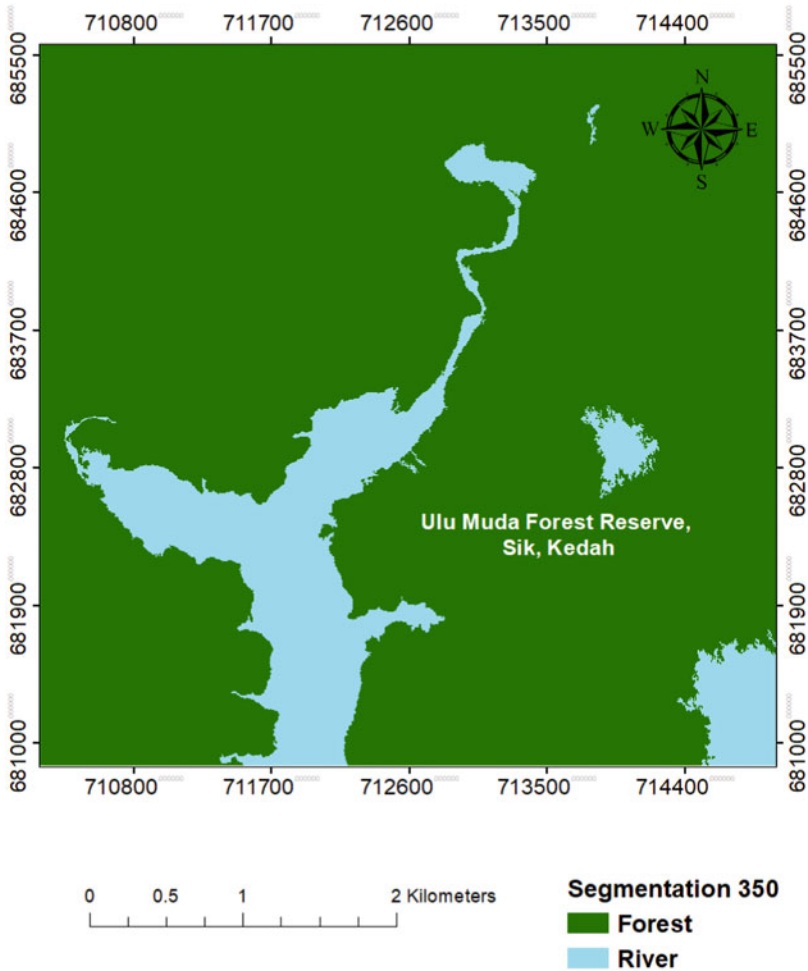


Fig. 4.11 Final land use map for—350 scale

that lower NDVI was caused by the higher spectral reflectance in river in the presence of a large number of forest attributes in the coarse method. This finding can also be associated with higher NDVI as a result of the high biomass area since NDVI is an indicator of biomass level, as demonstrated in the mangrove area in Maubesi Nature Reserve in Indonesia (Pujiono et al., 2013). NDVI is best known as a useful method for distinguishing between vegetation species and assessing the health of vegetation (Luus & Kelly, 2008). In addition, recent study supported that utilization of NDVI as vegetation index (VI) is proven as a good indicator in assessing phenology which is at the meantime a good input for NPP estimation (Maleki et al., 2020).

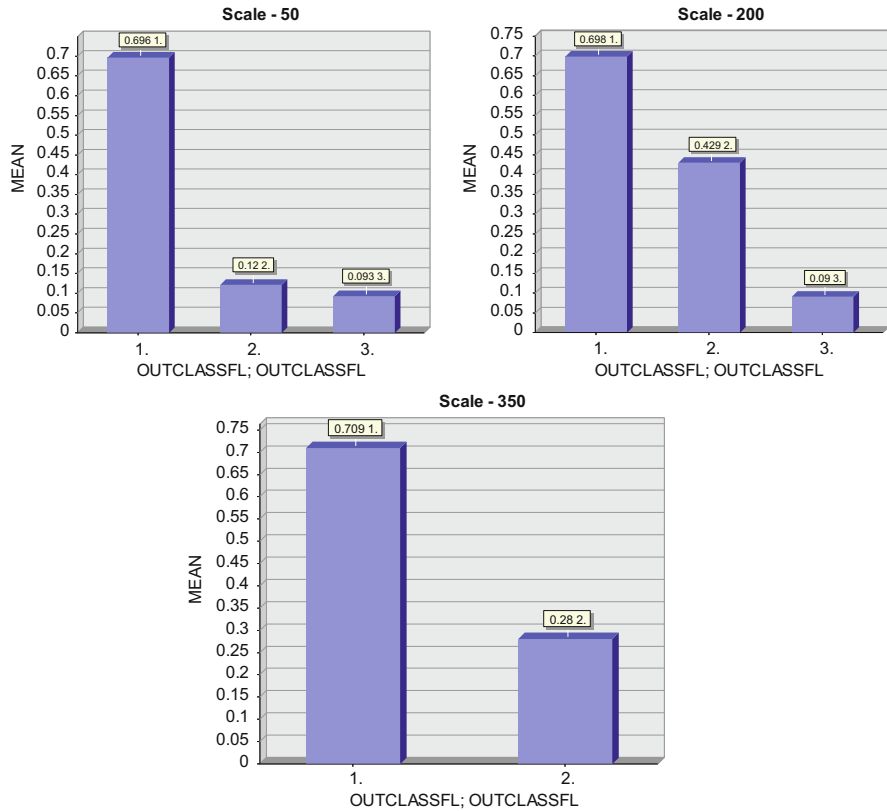


Fig. 4.12 Final land use map for (a) 50 (upper-left), (b) 200 (upper-right) and (c) 350 (lower). (Note: 1, 2 and 3 shown in the graph are forest, river and sedimentation class, respectively)

4.5.7 NPP

The NPP for the study area ranged from $6.7 \text{ g C m}^{-2} \text{ month}^{-1}$ to a maximum value of $300.04 \text{ g C m}^{-2} \text{ month}^{-1}$ (Fig. 4.13). In general, these results show that the UMFR has high forest biomass and that it is an intact forest that has been logged with very good forest management and logging practices.

This is because logging operations have been known to highly influence the environment of tropical forests (Sadeghi et al., 2017). Since 1901, the forest management at UMFR adhered to the Sustainable Forest Management (SFM) on logging operations (MTC, 2020). Through the practice of Selective Management System (SMS) in the area, it has evolved to optimize an economic cut to ensure the sustainability of the forests and the lowest cost for forest development. Therefore, there will be sufficient rehabilitation activities to cover the forest ground and protect it from the effects of forest operations. Another study reported that the NPP in Pasoh

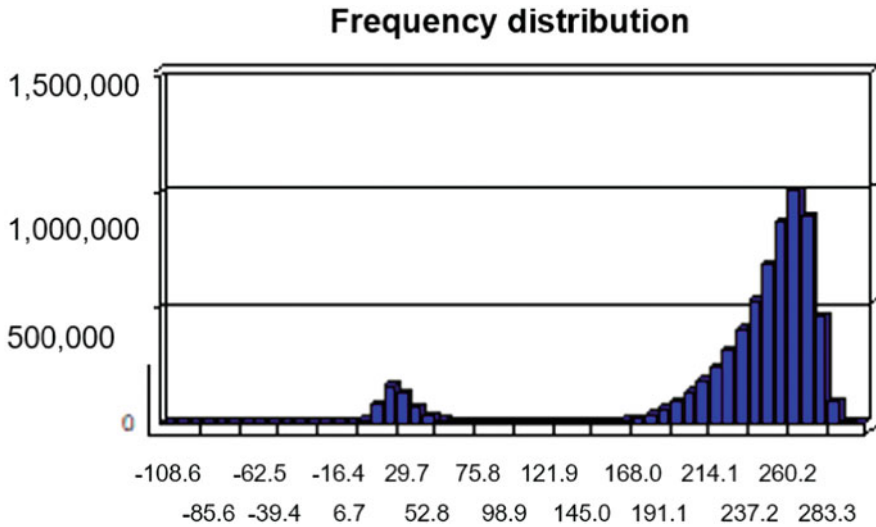


Fig. 4.13 Minimum and maximum value of NPP for the study

Forest Reserve ranges between 202.2 and 133.4 g C m⁻² month⁻¹ (Razali et al., 2015), which corresponds to the same forest features as the current study.

In particular for the case of tropical forest, interannual variation of NPP in the region of tropical rainforest forest of Queensland (Shiba & Apan, 2011) seems to be influenced by rainfall amount, maximum temperature, solar radiation and potential evaporation factors. Hence, the understanding of NPP may enhanced forest management practices for formulation of fertilization regime during dry and wet season. NPP can be indicator to forest fertility because there will be another environmental factor interacting with these factors in the processes of driving NPP in the region. This is because more resources, namely, researchers, tools and specific instruments, are required to assess directly the influence of nutrients, soil pH, cloud cover and soil type (Shiba & Apan, 2011). By deriving NPP values from remote sensing, it showed relation between NPP and climatic condition (Indiarto & Sulistyawati, 2013).

It is important to assess NPP for tropical forest because this forest plays a huge role in slowing down the rate of global warming by about 15% (Malhi, 2010). Early study showed that areas in Malay Peninsula, Sumatra, Borneo, Celebes and north-western of New Guinea showed NPP in declining rate from 2010 to 2013 due to deforestation (Shao & Zeng, 2017); in fact the study also suggests it also could be due to forest degradation. NPP decreases dramatically after natural forest is logged for forest plantation due to the removal of forest cover on the ground. However, as plantations began to cover the land, the respiratory rate in this warm climate induces a low NPP/GPP ratio rate in the tropical region. Simultaneously, fertilizer application during the rainy season caused more nutrient deficiency, which may result in a low NPP value. Therefore, NPP is a good indicator of good and bad forest plantation management practices in a specific area.

4.5.8 NPP and Its Impact on the Ulu Muda FR Community

Full-time fishermen, subsidy recipient and non-subsidy recipient, part-time or seasonal basis, were identified among the respondents interviewed. According to the study, the majority of respondents were between the ages of 41 and 60, with the remainder falling between the ages of 61 and 80. Meanwhile, respondents had varying years of experience as fisherman, which included only about 9 years (17.4%), 11–20 years of experience (23.9%), 21–30 years (26.1%), 31–40 years (23.9%) and more than 40 years of experience (8.7%).

Although the extraction process of fishing uses biomass, which is powered by solar energy, the amount is not calculated in this study NPP analysis. However, the study assumed that the process is part of their socio-economic process, which has an impact on the forest. The NPP value for the study was higher than in other areas with similar forest types. First, the study assumed that their activities were not harmful to the forest and that no major NPP were extracted from the forest in order to carry out their activities. Meanwhile, the following people received subsidies: Kuala Muda (33) recipient, Sik (12), Kulim (9) recipient and Baling (4) recipient. The majority of those polled considered themselves to be subsidy recipients. Subsidies can lower the cost of fishing operations while increasing revenue, making fishing businesses more profitable (Ali et al., 2017).

4.6 Conclusion

Forest density and NPP mapping based on remote sensing satellite image of GeoEye-1 are some of the approaches that can be used to estimate the NDVI as biophysical indices in estimating NPP at UMFR, particularly for Sungai Teliang. Remote sensing based on high-resolution images plays a huge role as potential data that should be used as a reference to other NPP studies in forest evergreen areas, particularly in Malaysian Peninsular. In this study, mapping forest density using OBIA has limited potential, while other techniques should be explored. Nevertheless, OBIA can be used with high-resolution data to produce a more meaningful and accurate assessment. The NPP results from this study support earlier findings that characterize the forest area as having high biomass. Moreover, the study showed NPP value is higher than other area with similar forest types and no major NPP extracted by the Ulu Muda FR fisherman community assessed from the study. The study also showed that forest density can be mapped using remote sensing technology, whereby final land use map is also created from that analysis.

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