Estimation of Palm Oil Biomass Carbon from Sentinel-2 Image using the Random Forest Classification Method

Muhammad Ardiansyah[1], Baba Barus[2], Gita Puspita[3], Adi Jaya[4]

Department of Soil Science and Land Resources, Faculty of Agriculture, IPB University, Indonesia | ardysaja@gmail.com[1]
Center for Climate Risk and Opportunity Management in Southeast Asia and Pacific, IPB University, Indonesia | ardysaja@gmail.com[2]
Department of Soil Science and Land Resources, Faculty of Agriculture, IPB University, Indonesia | bababarus@yahoo.com[3]
Department of Soil Science and Land Resources, Faculty of Agriculture, IPB University, Indonesia | gita_puspita@apps.ipb.ac.id[4]
Faculty of Agriculture, University of Palangka Raya, Indonesia | adijaya@agr.upr.ac.id[5*]

Abstract

Oil palm is a carbon absorbing plant that stores it in biomass. To monitor biomass, especially in large areas of oil palm plantations, remote sensing data can be used combined with machine learning algorithms. The aims of this study were to estimate oil palm biomass carbon according to age class using non-destructive methods, as well as analyze the relationship between the reflectance of Sentinel 2 image oil palm and oil palm biomass carbon, and estimate the distribution of oil palm biomass carbon using a learning algorithm random forest (RF) engine. Measurement of biomass at the study site was carried out non-destructively using stratified purposive sampling. The closeness of the relationship between Sentinel 2 image and measured oil palm biomass is assessed from the coefficient of determination of the regression equation. Estimation of the distribution of biomass carbon in all research locations was carried out using the RF method with the Dzetsaka classification tool. The results showed that the highest biomass carbon stock was obtained in oil palm aged 20 years with an average of 59.6 tons C/ha, while the lowest biomass carbon stock was obtained in oil palm aged 17 years with an average of 32.9 tons C/ha. The reflectance value of Sentinel-2 image on the blue, green, red, and near infrared channels has a positive correlation to biomass carbon from oil palm with an R² greater than 0.8. The classification of biomass carbon with the RF approach applied to Sentinel-2 image gives an adequate accuracy value of 76.40% in the combination of the proportion of training and testing data 60% : 40%.

Keywords: *Carbon stock, Dzetsaka classification tool, machine learning*

Introduction

Biomass is an important key in assessing an ecosystem (Chapin et al., 2002). Biomass information is needed to estimate and predict ecosystem productivity, carbon stock, nutrient distribution, and fuel accumulation (Brown, 2002). Carbon stock can usually be estimated from the biomass present in vegetated areas such as forests. In addition to forest land cover, plantations are also vegetated areas that are able to absorb carbon so that they are useful in reducing CO_2 concentrations in the atmosphere due to increased greenhouse gas (GHG) concentrations. One of the plantations that has the potential to contribute quite high carbon stocks is oil palm plantations with a total area of 14.62 million hectares in Indonesia (BPS, 2022). Oil palm during its life cycle captures and stores CO_2 for photosynthetic purposes, and the results are stored as biomass carbon reserves ranging from 53.40 - 80.09 tons C/ha (Maulana, 2010; Sukariawan et al., 2019). Because oil palm is an annual plant that has a long life cycle and accumulates its biomass as a large amount of carbon stock. Thus, oil palm is considered capable of contributing to reducing GHG, especially CO_2 (Tanaka and Makino, 2007).

Measurement of tree standing biomass was carried out both destructively and non-destructively. Measurement using the destructive method is carried out by harvesting all parts of the plant including the roots, drying them and weighing the weight of the biomass (Sutaryo, 2009). The destructive method is also known as the biomass harvesting method and is often used in research on forest ecosystems (Gibs et al., 2007). The non-destructive method is carried out without any damage to the media to be measured by measuring the height or diameter of the tree and using an allometric equation to extrapolate the biomass (Sutaryo, 2009; Purwanto and Kurniasari, 2009).

Pixel clustering algorithms have an important role in producing good classification accuracy and there are many approaches that can be used for mapping and monitoring purposes, and broadly divided into two, namely supervised and unsupervised. Several machine learning (ML) algorithms, such as support vector machine (SVM) and random forest (RF), have been successfully implemented for remote sensing applications (Gislason et al., 2006). The RF and SVM algorithms are considered relatively easy-to-implement methods that can handle learning tasks with a small number of training data sets and produce good accuracy (Sheykhmousa et al., 2020). Research on mapping/monitoring biomass with a combination of remote sensing data and machine learning has been done previously in Usmadi and Pribadi (2021) research using WorldView-2 image and RF classification. The results of this study show a high accuracy value in the RF classification with an R² value of 0.83.

This study used a combination of Sentinel-2 satellite image and the RF classification method to estimate palm biomass carbon in oil palm plantations at PTPN VIII Cimulang, Bogor Regency. The aims of this study were to a) estimate oil palm biomass carbon according to age class using non-destructive methods, b) analyze the relationship between oil palm reflectance derived from Sentinel-2 image and oil palm biomass carbon, and c) estimate the distribution of oil palm biomass carbon using the RF machine learning method.

Literature Review

The development of remote sensing technology can be used to support extensive vegetation monitoring activities. Sensor system technology and digital signal processing algorithms make it easier to retrieve information on the state of the earth faster and more accurately (Sudiana and Diasmara, 2008). Estimation of biomass has been done quite a lot using remote sensing techniques by utilizing multispectral image (Dwinta and Murti, 2016; Astriani et al., 2018; Sukariawan et al., 2019; Golindira, 2022). One of the images whose data can be used to estimate biomass through remote sensing is the Sentinel-2 satellite image. Astriani et al. (2018) utilized the vegetation index derived from Sentinel-2 and Landsat 8 OLI image for monitoring oil palm biomass at PTPN VII Lampung Selatan. In this study, Sentinel-2 image is better at estimating biomass compared to Landsat 8 OLI because Sentinel-2's spatial resolution is higher than Landsat 8 OLI. The accuracy of estimation of oil palm carbon stock using Sentinel-2 image with a vegetation index at this location is low because the number and distribution of samples is limited.

Research Methods

Research sites

Data on the aboveground biomass of oil palm was obtained using non-destructive methods where parameter measurements for the allometric equation were measured directly in the field at PT Perkebunan Nusantara VIII Cikasungka, Afdeling Cimulang, Bogor Regency (Figure 1). Data interpretation and analysis was carried out at the Laboratory of Remote Sensing and Spatial Information Division, Department of Soil Science and Land Resources, Faculty of Agriculture, Bogor Agricultural University. The research location consisted of 11 blocks of oil palm ages with different ages. It namely 5 blocks (B3, B25, B26, B31, B31) with an age of 17 years (planting year 2005), 2 blocks (B19, B30) with an age of 18 years (year planting 2004), 2 blocks (B5, B38) with 19 years old (planting year 2003), and 2 blocks (B1, B2) with 20 years old (planting year 2002).
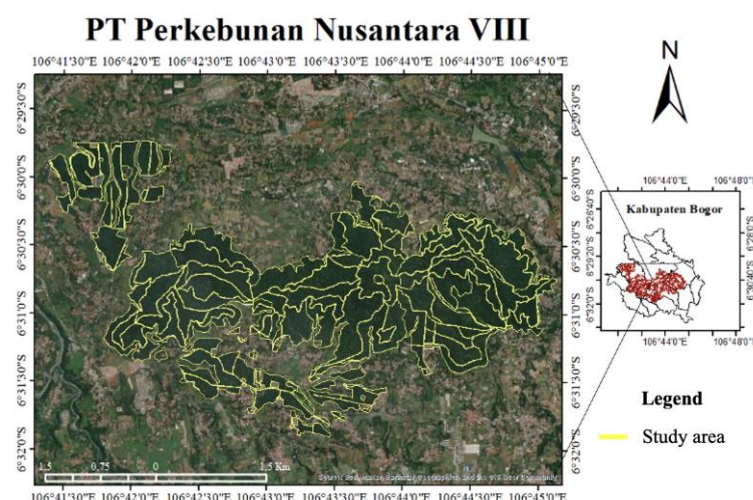

Figure 1. Research Sites

Materials

Tools for collecting data include the Global Positioning System (GPS), rangefinder, measuring tape, field knife, and camera. The tools for data analysis include a set of computers containing Quantum GIS 10.18 software with the Dzetsaka classification tool plugin, and Google Earth. The materials used in this study consisted of Sentinel-2A level 1C multispectral images, national digital elevation model (DEMNAS) data, and plantation block maps.

Biomass Measurement

Measurement of oil palm biomass was carried out in sample plots in 11 plantation blocks with oil palm ages of 17, 18, 19 and 20 years. Each oil palm block has at least three to four category of slope. The sample plots measuring 100 m x 20 m were determined using the stratified purposive sampling method, where the plot locations were stratified according to age class and slope category. In this way there are 39 sample plots with a size of 100 m x 20 m. For each plot of 100 m x 20 m it was further divided into 10 sub-plots measuring 10 m x 20 m and only 3 sub-plots were taken, for a total of 117 sub-plots. Each sub-plot coordinates were determined using a GPS device and its biomass was measured using a non-destructive method. Information regarding plant age, blocks, slope classes, and the number of plots and sub-plots can be seen in Table 1, while the distribution of sample points is presented in Figure 2.

Table 1. Number of plot sample in study area

Age (years)	Block	Slope class (%)	Number of plot 100m x 20m	Number of sub-plot 10m x 20m
17	B3	1 (0-3%)	4	12
		2 (3-8%)		
		3 (8-15%)		
		4 (15-30%)		
	B23	2 (3-8%)	4	9
		3 (8-15%)		
		4 (15-30%)		
	B25	1 (0-3%)	4	12
		2 (3-8%)		
		3 (8-15%)		
		4 (15-30%)		
	B26	1 (0-3%)	4	12
		2 (3-8%)		
		3 (8-15%)		
		4 (15-30%)		
	B31	2 (3-8%)	3	9
		3 (8-15%)		
		4 (15-30%)		
18	B19	2 (3-8%)	3	9
		3 (8-15%)		
		4 (15-30%)		
	B30	2 (3-8%)	3	9
		3 (8-15%)		
		4 (15-30%)		

		2 (3-8%)	3	9
	B5	3 (8-15%)		
		4 (15-30%)		
19		1 (0-3%)		
	B11	2 (3-8%)	4	12
		3 (8-15%)		
		4 (15-30%)		
		1 (0-3%)		
	B1	2 (3-8%)	4	12
		3 (8-15%)		
20		4 (15-30%)		
		1 (0-3%)		
	B2	2 (3-8%)	4	12
		3 (8-15%)		
		4 (15-30%)		

Figure 2. Sample points distribution

Each oil palm tree in the 10m x 20m sample sub-plot was measured at diameter at breast high (DBH) with a measuring tape on the trunk at a height of about 1.3 m from the ground. After measuring the diameter or circumference of the tree trunk, proceed with measuring the height of the oil palm to the top using a rangefinder. Oil palm biomass is estimated using the allometric equation (Lubis, 2011) as follow:

$$B = 0.002382 \times DBH^{2.3385} \times H^{0.9411}$$

Where:

B = Biomass (kg of trees)

D = Diameter of the stem at breast height measured perpendicular to the stem (cm)

H = Height of oil palm until the first oil palm fronds (m)

The value of biomass is converted to carbon biomass (C) using the following equation:

$$C = B \times 0.47$$

Where:

C = Biomass carbon (kg C)

B = Biomass (kg)

Atmospheric Correction of Sentinel-2 Image

Atmospheric conditions affect the pixel values recorded on the satellite sensor in the form of atmospheric disturbances, therefore an atmospheric correction is needed to minimize this influence. Atmospheric correction of Sentinel-2 Image Level 1C was carried out in QGIS software using the DOS 1 (Dark Object Subtraction 1) approach in the Semi-Automatic Classification Plugin (Congedo, 2021).

Correlations between Palm Biomass and Reflectance

In order to study the close relationship between Sentinel 2 image and oil palm biomass as a result of measurements in the field, a linear regression equation was created with reflectance as the independent variable and biomass as the dependent variable. The coefficient of determination (R^2) is used to learn the positive relationship between the two variables, where the reflectance of the blue, green, red, and near-infrared bands is used as the independent variable, while oil palm biomass is the dependent variable. The linear regression equation and the coefficient of determination are as follows:

$$Y = a + bX$$

where:

Y = dependent variable

X = independent variable

a = intercepts

b = regression coefficient

$$R^2 = \frac{\left(\left(n \sum_{i=1}^{n} X_i Y_i - \left(\sum_{i=1}^{n} X_i \right)\left(\sum_{i=1}^{n} Y_i \right) \right) \right)^2}{\sqrt{\left[n \sum_{i=1}^{n} X_i^2 - \left(\sum_{i=1}^{n} X_i \right)^2 \right] \left[n \sum_{i=1}^{n} Y_i^2 - \left(\sum_{i=1}^{n} Y_1 \right)^2 \right]}}$$

where:

R2 = Coefficient of determination

Y = dependent variable

X = independent variable

n = number of data

Estimation of Oil Palm Biomass Distribution

Estimating the distribution of oil palm biomass from Sentinel 2 image at the study site using the RF approach in the QGIS application with the Dzetsaka classification tool plugin (https://github.com/nkarasiak/dzetsaka/#readme). The first step is to run the Train algorithm feature:

- Input Sentinel 2 images with band stacking (bands: blue, green, red and near infrared) on the *Input raster*.
- Input *training sample* on the *Input layer*, which is located the same as the location of the sample sub-plots in the field, which is represented by a polygon measuring 3 pixels × 3 pixels. Next, select the attribute table containing biomass data in the *Field*.
- Select *Random-Forest* on *Select algorithm to train*
- Determine the amount of validation data: 25%, 30% (default), 40% or 50% of *the training sample* on *Pixel (%) to keep for validation*. RF classification is done with 4 combinations comparison of *data training* and *testing (validation)*, namely 75%:25%, 70%:30%, 60%:40% and 50%:50% because the RF results are very sensitive to the size of the training data.
- Save the RF model file in *Output model.*
- Select Run in the *Train algorithm tool* dialog.

If the model accuracy is good enough, then run the classification tool feature:

- Input Sentinel 2 image with *band stacking* (bands: blue, green, red and near infrared) on *Input raster*.
- Input the output training model file from the *Train algorithm tool* on the *model learned*.
- Save the output file in *Output raster*.
- Select Run in the *Classification tool* dialog.

Results and Discussion

Biomass Carbon in Palm Oil

Biomass is the total weight of a living tree above the ground including tree roots and is expressed in tons of dry weight per unit area (Brown, 1997). Based on the measurement, the highest oil palm biomass carbon stock was found at the age of 20 years with an average of 59.6 tons C/ha, while the lowest biomass stock was at the age of 17 years with an average of 32.9 tons C/ha (Table 2). These results indicate that as the age of oil palm increases, the biomass

also increases. At the age of more than 10 years, oil palms experience an optimal growth, therefore an increase in the biomass can occur (PKT, 2018). According to Yulianto (2015), carbon stock will increase with increasing age. Each body part of the tree is a component that stores biomass such as roots, stems, midribs, leaves, and fruit. Furthermore, Catur and Sidiyasa (2006) stated that the biomass in each part of the tree will increase proportionally with increasing tree dimensions. The relationship between plant age and biomass is presented graphically in Figure 3.

Table 2. Oil palm biomass based on plant age

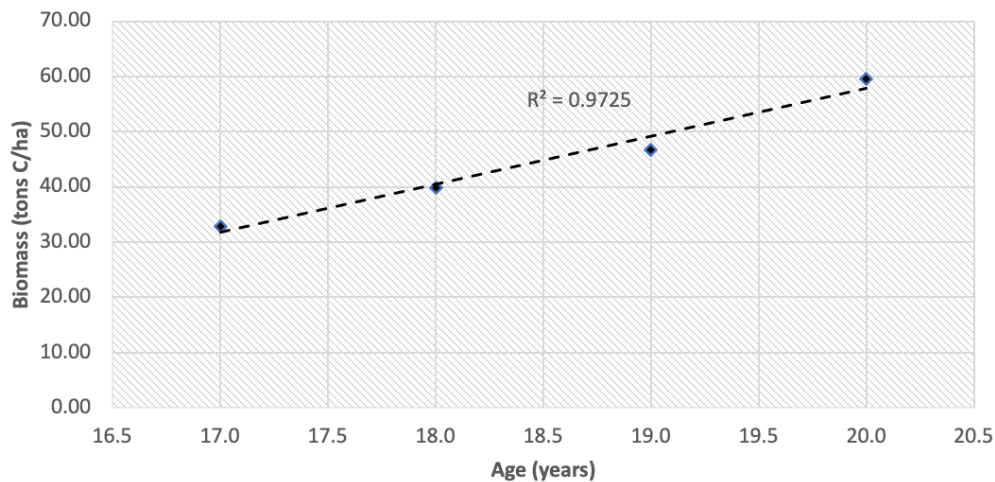| Plant age group (years)	Average plant height (m)	Average plant diameter (cm)	Average biomass (tons C/ha)
17	7.7	51.3	32.9
18	8.5	52.4	39.9
19	8.7	59.0	46.7
20	9.0	60.9	59.6

Figure 3. Relationship between biomass and age of oil palm plants

Relationship between Biomass Stock and Reflectance

Biomass has a strong relationship with plant growth so that the biophysical characteristics of plants will be different for each growth including the spectral response to electromagnetic wavelengths. The results showed that the relationship between biomass stock and reflectance values in the blue, green, red and near infrared bands of Sentinel-2 image had a positive and strong relationship with a coefficient of determination greater than 0.9 (Figure 4). In general, every same object has a different sensitivity in reflecting, absorbing and transmitting electromagnetic energy that comes at different wavelengths. Figure 4, shows that the reflectance of the blue and red bands is slightly higher than the reflectance of the green band, while the reflectance of the near infrared band is much higher than that of the blue, green, and red bands.

Green plants absorb a lot of blue and red wavelengths, while green wavelength is reflected by plants a little more than blue and red wavelengths. According to Amliana et al.

(2016) the blue and red spectrum have a low reflectance value because a lot of energy is absorbed by plants to carry out photosynthesis, but the green spectrum is reflected more so that the reflectance of the green band tends to be greater than that of the blue and red bands.
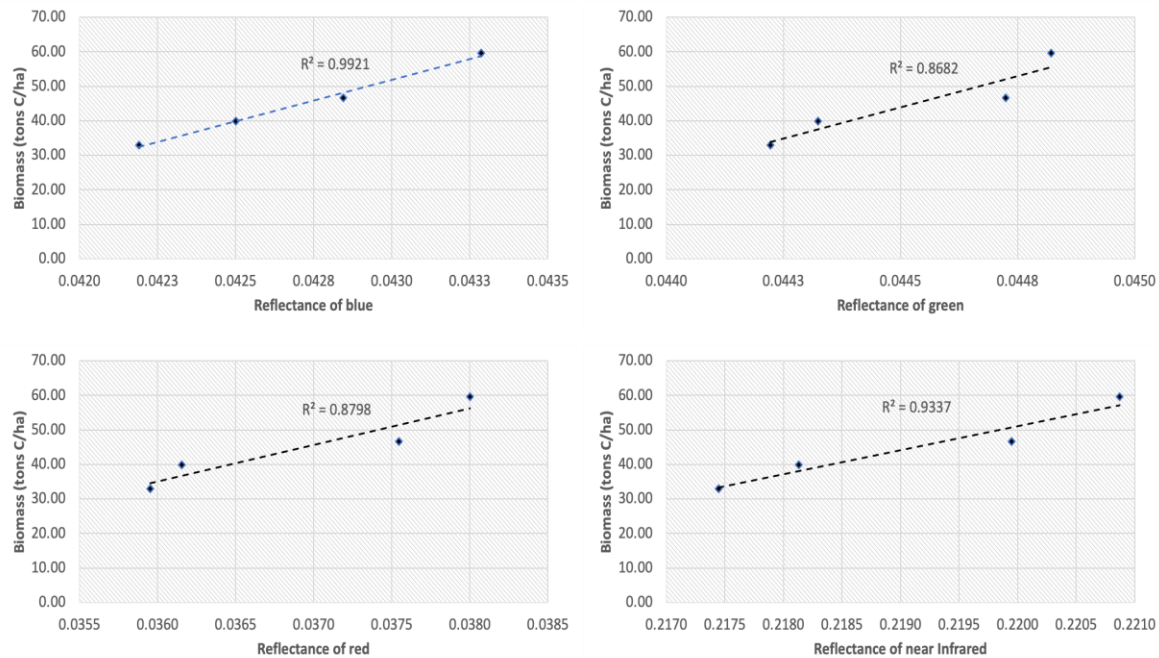

Figure 4. The relationship between oil palm biomass stock and the reflectance of the blue (top left), green (top right), red (bottom left) and near infrared bands (bottom right)

The reflectance of the near infrared band as presented in Figure 4 is much higher than that of the blue, red, and green bands. Plants are very sensitive to the near infrared wavelength and reflect the maximum which causes the reflectance value in this bands to be high. The reflectance of the near infrared band is much higher than that of the visible spectrum due to the internal structure of the leaf, which acts as an excellent reflector of scattering of near infrared wavelength. Therefore, vegetation can be easily identified on this spectrum.

Oil Palm Biomass Distribution

The distribution of biomass is divided into 4 classes according to the results of measurements of sample sub plots in the field based on age class and estimated for the entire study area using the RF approach. The intervals of the 4 classes of oil palm biomass in the PTPN VIII area are 29 – 36, 36 – 43, 43 – 50, and 55 – 63 tons C per ha (Table 3). The accuracy of the RF classification model in grouping pixels into 4 biomass classes using a combination of different amounts of training and testing data shows no difference and the value is greater than 75%, except for the combination of 50% training and 50% testing data. Model accuracy of RF classification with the amount of training and testing data 75% : 25%, 70% : 30%, 60% : 40%, and 50% : 50% respectively are 76.2%, 74.7%, 76 .4%, and 74.4%. In this study, the classification accuracy of greater than 75% was obtained when using training data greater than 60%, while using training data less than 60%, the accuracy of the model obtained was slightly lower than 75%. This shows that the small amount of training data produces weak estimates because the model is limited in learning the grouping or mapping functions on small training

data sets. The limited amount of training data makes it difficult for the model to fully capture the characteristics and variations associated with each class. According to Danoedoro (2015) accuracy results can be affected by the large number and distribution of samples and the selection of representative training samples so that a large number of samples is more reliable than a small one. Furthermore, Millard and Richardson (2015) stated that RF results are very sensitive to the size of the training data set. In addition to as much as possible, the training data used in RF classification must also be randomly distributed or made proportional to the actual classes in the image and must have small spatial autocorrelation.

Table 3. Oil palm biomass class

Biomass class	Age (years)	Biomass range (tons C/ha)
1	17	29 – 36
2	18	36 – 43
3	19	43 – 50
4	20	55 – 63

The distribution of oil palm biomass carbon using the RF approach with different proportions of the amount of training and testing data is presented in Figure 5. In general, the distribution patterns of the 4 classes of biomass carbon in the study area show similarities with slightly different areas (Table 4). In addition, the results of the mapping of biomass carbon are indicated by the presence of disturbances in the appearance of salt and pepper, where 1 pixel appears as one class in most (pixel groups) of biomass carbon classes. This happens because the RF approach in estimating the distribution of biomass in this study is a pixel-based classification. According to Blaschke et al. (2014) pixel-based classification does not treat homogeneous pixels as 1 homogeneous object and does not group these pixels into an image object. Based on this study, biomass carbon was dominated by age class 4 (55 – 63 tons C/ha), followed by class 1 (29 – 36 tons C/ha), class 3 (43 – 50 tons C/ha) and class 2 (36 – 43 tons C/ha). The largest distribution and area of the biomass carbon class of 55 – 63 tons C/ha was obtained from a combination of training and test data 60% : 40% followed by 75% : 25%, 70% : 30%, and 50% : 50%. This sequence actually follows the order of accuracy of the RF model from the highest (60% : 40% combination) to the lowest (50% : 50% combination).

Table 4 Area of the biomass class according to the proportion of training and testing data

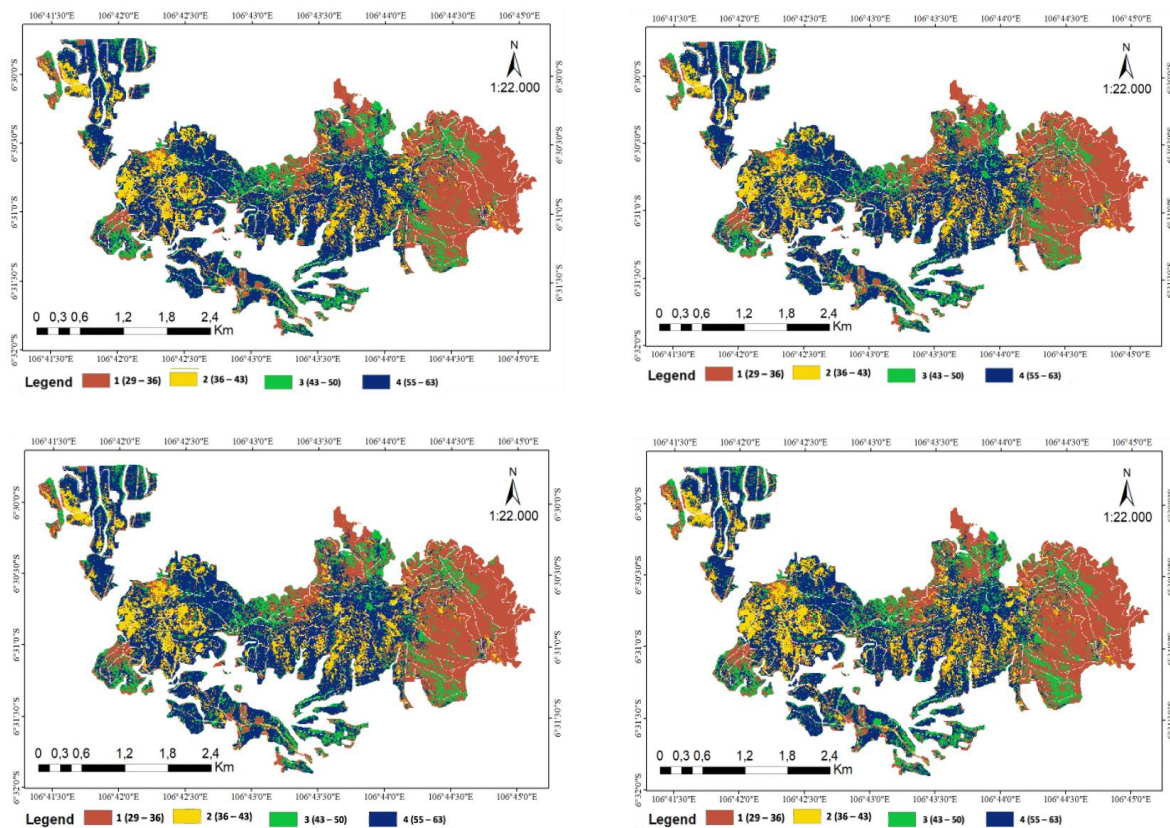| Biomass class (t C/ha)	Area according to the proportion of training and testing data (ha)			
	75% : 25%	70% : 30%	60% : 40%	50% : 50%
1 (29 – 36)	333.90	342.30	337.40	345.00
2 (36 – 43)	112.60	114.60	114.30	127.50
3 (43 – 50)	161.50	155.50	151.10	165.00
4 (55 – 63)	412.50	408.10	417.80	383.20

Figure 5. Distribution of oil palm biomass according to the proportion of training and testing data 75% : 25% (top left), 70% : 30% (top right), 60% : 40% (bottom left), 50% : 50% (bottom right)

Conclusion

Non-destructive measurement results showed that the highest biomass carbon stock was found in 20-year-old oil palm with an average of 59.6 tons C/ha, while the lowest biomass carbon stock was found in 17-year-old oil palm with an average of 32.9 tons C/ha. These results indicate that in the age range of 17-20 years as the age of the oil palm increases, its biomass also increases.

The reflectance of the blue, green, red, and near-infrared bands from Sentinel-2 image has a strong positive relationship with measured oil palm biomass carbon with an R^2 greater than 0.8. This shows that all these bands can be used to estimate and monitor biomass in the oil palm plantation area of PTPN VIII Cimulang, Bogor Regency.

Classification of biomass carbon using the RF method applied to Sentinel-2 image provides sufficient accuracy of 76.40% on the combination of training data and testing 60% : 40%.

Declaration of conflicting interest

The authors declare that there is no conflict of interest in this work.

References

Amliana, D. R., Prasetyo, Y., & Sukmono, A. (2016). Analisis perbandingan nilai NDVI Landsat 7 dan Landsat 8 pada kelas tutupan lahan (Studi kasus: Kota Semarang, Jawa Tengah). *Jurnal Geodesi Undip*, 5(1), 264-274.

Anggraini, S., & Arifin, Y. W. (2021). Analisis Cadangan Karbon Kelapa Sawit Fase Tanaman Menghasilkan (Tm< 20 Tahun) Dilahan Berpirit Kedalaman 40-60 cm. *AGRITEPA. J. Ilmu dan Teknologi Pertanian,* 8 (1): 1-8.

Astriani, H., K.B. Santoso, N. Arifatha, R. Prasetya, SD. Utomo, VC. Juniandari, dan M. Kamal. (2018). Perbandingan Citra Landsat 8 OLI dan Sentinel 2-A untuk Estimasi Stok Karbon Kelapa Sawit (*Elais guineensis Jacq*) di Wilayah PT. Perkebunan Nusantara VIII Unit Rejosari, Natar, Kabupaten Lampung Selatan. *Seminar Nasional Geomatika*. p. 21-28

Blaschke, T., Hay, G. J., Kelly, M., Lang, S., Hofmann, P., Addink, E., ... & Tiede, D. (2014). Geographic object-based image analysis–towards a new paradigm. *ISPRS journal of photogrammetry and remote sensing*, 87, 180-191.

[BPS] Badan Pusat Statistik. (2022). *Statistik Kelapa Sawit Indonesia 2021*. Jakarta: BPS.

Brown, S. (1997). Estimating biomass and biomass change of tropical forests: a primer. *FAO Forestry Paper 134*. FAO, Rome.

Brown, S. (2002). Measuring carbon in forests: current status and future challenges. *Environ Pollut J.*, 1(16): 363–372.

Chapin, F. S., Matson, P. A., Mooney, H. A., & Vitousek, P. M. (2002). Principles of terrestrial ecosystem ecology. 2nd ed. Springer, New York. 511 pp

Catur, W., & K. Sidiyasa. (2006). Model pendugaan biomassa pohon mahoni (*Swietenia macrophylla king*) di atas permukaan tanah. *J. Penelitian Sosial dan Ekonomi Kehutanan*, 3(1): 103-117.

Congedo L. (2021). Semi-Automatic Classification Plugin Documentation Release 7.9.7.1. Sep 07. 2022. https://buildmedia.readthedocs.org/media/pdf/semiautomaticclassificationmanual/latest/semiautomaticclassificationmanual.pdf (accessed on 29 February 2023).

Danoedoro, P. (2015). Pengaruh jumlah dan metode pengambilan titik sampel penguji terhadap tingkat akurasi klasifikasi citra digital penginderaan jauh. *Simposium Nasional Sains Geoinformasi*. p. 161-171.

Dwinta G., & S.H. Murti. (2016). Aplikasi citra penginderaan jauh untuk estimasi produksi kelapa sawit (*Elaies guineensis Jacq*) berbasis Normalized Different Vegetation Index (Perkebunan PT. Mutiara Sawit Seluma, Kabupaten Seluma, Provinsi Bengkulu). *J. Bumi Indonesia*, 1-12.

Gibbs, H. K., Brown, S., Niles, J. O., & Foley, J. A. (2007). Monitoring and estimating tropical forest carbon stocks: making REDD a reality. *Environmental research letters*, *2*(4), 045023.

Gislason, P. O., Benediktsson, J. A., & Sveinsson, J. R. (2006). Random forests for land cover classification. *Pattern recognition letters*, *27*(4), 294-300.

Golindra R. (2022). Estimasi Sebaran Cadangan Karbon Pada Perkebunan Kelapa Sawit [Tesis]. Makassar. UNHAS.

Henson, I.E. (2005). An assessment of changes in biomass carbon stocks in tree crops and forests. *J. of Tropical Forest Science,* 17(2): 279–96

Lubis, A.R. (2011). Pendugaan cadangan karbon kelapa sawit berdasarkan persamaan alometrik di lahan gambut Kebun Meranti Paham, PT Perkebunan Nusantara IV, Kabupaten Labuhan Batu, Sumatera Utara. *Skripsi*. IPB. Bogor.

Millard, K., & Richardson, M. (2015). On the importance of training data sample selection in random forest image classification: A case study in peatland ecosystem mapping. *Remote sensing*, *7*(7), 8489-8515.

Maulana, S.I. (2010). Pendugaan Densitas Karbon Tegakan Hutan Alam Di Kabupaten Jayapura, Papua. *J. Penelitian Sosial dan Ekonomi Kehutanan*, 7 (4): 261-274

[PKT] Plantation Key Technology. (2018). Kapan Sawit Tidak Berbuah Lagi. (Terhubung Berkala). http://sawitnotif.pkt-group.com/2018/02/03/kapansawit-tidak-berbuah-lagi/ [accessed on 23 January 2022].

Purwanto, R.H., D.A. Kurniasari. 2009. Potensi kayu perkakas dan kayu bakar jenis jati (*Tectona grandis*) di hutan rakyat Desa Natah, Gunung Kidul. *J. Ilmu Kehutanan*, 2 (3) : 1-10.

Purwanto, R. H., & Kurniasari, D. A. (2009). Potensi kayu perkakas dan kayu bakar jenis jati (Tectona grandis) di hutan rakyat Desa Natah, Gunung Kidul. *Jurnal Ilmu Kehutanan*, *3*(2), 85-94.

Sheykhmousa, M., Mahdianpari, M., Ghanbari, H., Mohammadimanesh, F., Ghamisi, P., & Homayouni, S. (2020). Support vector machine versus random forest for remote sensing image classification: A meta-analysis and systematic review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 6308-6325.

Sudiana, D. & Diasmara, E. (2008). Analisis indeks vegetasi menggunakan data satelit NOAA/AVHRR dan TERRA/AQUAMODIS. Prosiding Seminar on Intelligent Technology and Its Applications. Universitas Indonesia, p 423 - 428.

Sukariawan, A., Situmorang, H., Juanda, A., & Wahyuni, M. (2019). Estimasi Karbon Tersimpan Tanaman Kelapa Sawit (Elaeis guineensis Jacq) Varietas Socfindo Pada

Kelas Kesesuaian Lahan S3 Di Kebun AEK TOROP PTPN III. *Jurnal Agro Estate*, *3*(2), 73-79.

Sutaryo, D. (2009). Penghitungan Biomassa: Sebuah Pengantar untuk Studi Karbon dan Perdagangan Karbon. *Wetlands International Indonesia Programme* Publ. Bogor. 39 pp.

Tamara, N. (2021). Pemodelan Machine Learning Terhadap Data Citra Satelit Untuk Memprediksi Fase Pertumbuhan Padi. *Tesis*. IPB. Bogor.

Tanaka, A., & Makino, A. (2009). Photosynthetic research in plant science. *Plant and cell physiology*, *50*(4), 681-683.

Usmadi, D., & Pribadi, D. O. (2021). Estimasi biomassa vegetasi Kebun Raya Bogor menggunakan kombinasi citra Worldview-2 dan algoritma pemelajaran mesin. *Buletin Kebun Raya*, *24*(1), 1-12.

Yulianto. (2015). Pendugaan Cadangan Karbon Tersimpan Pada Kelapa Sawit (*Elaeis guineensis Jacq*) dan Analisis Kesuburan Tanah di Perkebunan PT Daria Dharma Pratama Ipuh Bengkulu. *Tesis*. IPB. Bogor.