Hindawi Journal of Sensors Volume 2018, Article ID 6745629, 11 pages https://doi.org/10.1155/2018/6745629



Research Article

Estimating Aboveground Biomass on Private Forest Using Sentinel-2 Imagery

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Received 15 May 2018; Revised 28 August 2018; Accepted 30 September 2018; Published 16 December 2018

Academic Editor: Franz L. Dickert

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Private forests have a crucial role in maintaining the functioning of the Indonesian forest ecosystem especially because of the continuous degradation of natural forests. Private forests are a part of social forestry which becomes a tool for the Indonesian government to reduce carbon dioxide (CO_2) emission by 26% by 2030. The United Nations Programme on Reducing Emissions from Deforestation and Forest Degradation has encouraged the Indonesian government to establish a forest monitoring system by estimating forest carbon stock using a combination of forest inventory and remote sensing. This study is aimed at assessing the potential of vegetation indices derived from Sentinel-2 for estimating aboveground biomass (AGB) of private forests. We used 45 sample plots and 7 vegetation indices to evaluate the ability of Sentinel-2 in estimating AGB on private forests. Normalised difference index (NDI) 45 exhibited a strong correlation with AGB compared to other indices (r=0.89; R²=0.79). Stepwise linear regression fitted for establishing the model between field AGB and vegetation indices (R²=0.81). We also found that AGB in the study area based on spatial analysis was 72.54 Mg/ha. A root mean square error (RMSE) value from predicted and observed AGB was 27 Mg/ha. The AGB value in the study area is higher than the AGB value from some of forest types, and it indicates that private forests are good for biomass storage. Overall, vegetation indices from Sentinel-2 multispectral imagery can provide a good result in terms of reporting the AGB on private forests.

1. Introduction

The Indonesian tropical forest is home to myriad flora and fauna, including charismatic species such as orangutans (*Pongo pygmaeus*), Sumatran tigers (*Panthera tigris sumatrae*), and rhinos (*Rhinoceros sondaicus*) [1–4]. Unfortunately, the Indonesian tropical forest is under threats due to degradation and deforestation. In a time span of a decade from 2000 to 2010, 14.7 Mha of Indonesian tropical forests has disappeared [5]. Sumatra, during 1990–2010, lost 7.54 Mha of its primary tropical forests [6], and, likewise, Kalimantan between 1996 and 2002 lost nearly 3 Mha of forest cover [7]. Many factors are blamed for triggering deforestation such as inappropriate transmigration policy, mining, and palm oil expansion and the increase in agricultural areas [8].

Deforestation in Indonesia is eventually becoming a global concern. This phenomenon has not only driven Indonesia to lose forest areas but also increased the greenhouse gas (GHG) emission, which in turn can lead to the accumulation of GHG in the atmosphere. Majority of CO_2 emission in Indonesia is from land use, land use change and forestry (LULUCF) sectors [9]. In response to that, the Indonesian government through the 21^{st} of Conference of the Parties (COP) in Paris has committed to reducing CO_2 emission at 29% by 2030 [10]. One of the strategies applied to achieve the goal is through social forestry development [10].

Based on the Ministry of Environment and Forestry regulation, social forestry in Indonesia can be divided into six parts including hutan tanaman rakyat (people's planting

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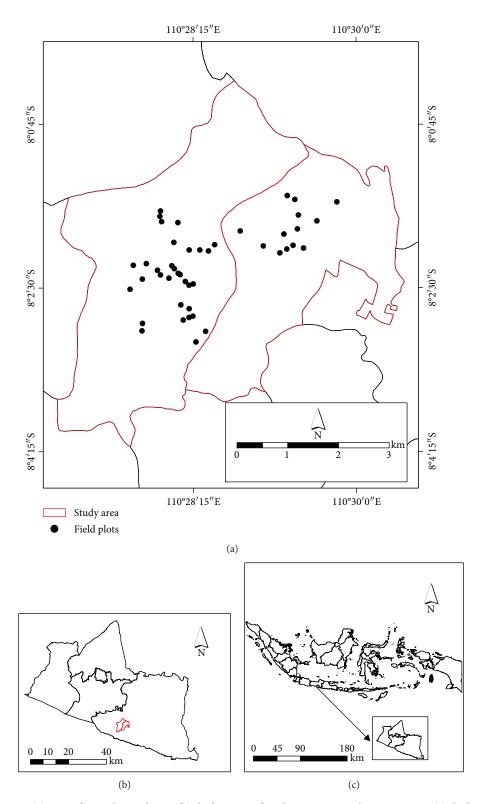


FIGURE 1: The study area: (a) map of Girisekar and Jetis; (b) the location of study area in Yogyakarta Province; (c) the location of Yogyakarta Province in the Indonesian map.

forest), hutan kemasyarakatan (community forest), hutan desa (village forest), kemitraan (partnership), hutan adat (customary forest), and hutan rakyat (private forest) [11]. Private forests are grown by farmers on their own land;

others are facilitated by the government on natural forests. Private forests have a crucial role in the forest ecosystem especially since degradation of natural forests is continuing in Indonesia. Recognition of efforts to reduce greenhouse

gas emission outside the natural forest including the private land (e.g., private forest) originated from the 16th COP held in Mexico in 2010 resulted in a concept of Reducing Emissions from Deforestation and Forest Degradation (REDD) + [12]. A REDD scheme has encouraged United Nations Framework Convention on Climate Change (UNFCCC) members to establish a forest monitoring system by estimating forest carbon stock using a combination of forest inventory and remote sensing [13]. In addition, REDD+ in the private forest community provides a chance to gain international funding as long as they can increase carbon sink.

Considering the important role of the forest monitoring system, understanding the spatial distribution of aboveground biomass (AGB) is crucial [14]. AGB represents a majority of biomass values on the terrestrial ecosystem and is a useful parameter to measure the velocity of forest succession [15-17]. Furthermore, AGB also provides valuable information for forestry strategic planning [18]. AGB accumulation in the earth can be increased through expanding plantation areas such as private forests. Private forests have a potential to store AGB reaching a capacity of up to 300 tons/ha [19]. The number of private forests in Indonesia is likely to increase annually in accordance with the ambition of the government to expand social forestry areas at 12.7 million ha by 2019 [20]. The capabilities of remote sensing for assessing AGB have been tried in some types of forest in Indonesia like tropical forest [21] and mangrove [22]. However, information and methods for estimating AGB in private forests through remote sensing have not been treated in much detail.

Remote sensing based on vegetation indices has been widely used for estimating AGB. The vegetation index is enhanced by strong reflectance of near infrared (NIR) due to leaf internal scattering and high chlorophyll absorption by the red region of wavelength. One of the vegetation indices used to estimate biomass is the normalised difference vegetation index (NDVI) [23–26]. However, there are certain problems associated with the use of NDVI. One of these is that NDVI has a saturation problem particularly for dense vegetation which tends to have a high level of biomass [27, 28]. Utilisation of vegetation indices based on wavelengths located in the red edge is then a method that is proposed to overcome that problem [28].

Sentinel-2 is a new generation of multispectral satellite imagery that has been launched on 23 June 2015 by the European Space Agency (ESA). Sentinel-2 is a continuing image data from Landsat and SPOT, offering 13 spectral bands with 3 spatial resolutions (10 m, 20 m, and 60 m), a wide swath of 290 km, a radiometric resolution of 12 bits, and 5 days of revisit times by two satellites [29]. Utilisation of Sentinel-2 to assess AGB on private forests is interesting since the availability of red edge bands. Sentinel-2 can be applied for mapping and monitoring forest areas and measuring biophysical structures of vegetation like AGB and leaf area index (LAI) [30, 31]. However, there is lack of evidence about the utilisation of Sentinel-2 for predicting AGB on private forests.

Generally, the purpose of this study was to assess the potential of vegetation indices derived from Sentinel-2

Table 1: Allometric equations for calculation AGB in private forest.

| No. | Species | Allometric equation |
|-----|--------------------------------|--|
| 1 | Teak (Tectona grandis) | $AGB = 0.0149 \left(D^2 H \right)^{1.0835}$ |
| 2 | Acacia (Acacia auriculiformis) | $AGB = 0.0775 \left(D^2 H \right)^{0.9018}$ |
| 3 | Mahogany (Swietenia mahagoni) | $AGB = 0.9029 \left(D^2 H\right)^{0.684}$ |
| 4 | Other trees | $AGB = 0.0240 \left(D^2 H \right)^{0.7817}$ |

Remarks: D: stem diameter at breast height; H: total tree height.

imagery for estimating AGB of private forests. Specifically, it is aimed at (1) modelling the relationship between vegetation indices resulted from Sentinel-2 and AGB derived from field measurement from private forests and (2) determining the AGB value on the Girisekar and Jetis private forest management unit. AGB from this study area then was compared with AGB from other forest types to evaluate the ability of private forests on the global carbon cycle and to support the Indonesian government mission for reducing CO₂ emission.

2. Materials and Methods

2.1. Study Area. The study area lies in 8°01′15″N and 110°27′30″ E (Figure 1). The area is located in the Jetis and Girisekar private forest management unit in Gunung Kidul Region, Yogyakarta Province, Indonesia. In terms of topography, Gunung Kidul is dominated by small limestone hills. Soils are shallow and prone to erosion. Annual precipitation is between 1700 and 2500 mm with around 122 rainy days [32].

In the past, massive forest loss, poverty, and soil erosion were common problems experienced by community living in Gunung Kidul [33]. This condition encouraged groups of farmers to start rehabilitation of the barren land through a planting tree program by the central government in 1963 [32]. Therefore, small-scale teak plantations of local farmers were widespread by the mid-1960s and became more attractive to the farmers in 1980 [34]. Nowadays, Gunung Kidul has become the main area of private forests in Indonesia with an annual production around 80,000 to 100,000 m³ [32]. There are several trees commonly planted by farmers such as teak (*Tectona grandis*), mahogany (*Swietenia mahagoni*), and earleaf acacia (*Acacia auriculiformis*).

2.2. Field Data Collection. Field data was taken in September 2017 and the end of November 2017. A total of 45 plots were set up. We used 30 plots for establishing the model and another 15 plots for validation. A stratified random sampling method was applied to select the plots based on accessibility, size, and type of trees. This sampling method was used to ascertain that areas with low and high AGB in community forests would be sampled. Each plot had a dimension of 20×20 m. In each plot, the height and diameter at breast height (DBH) of trees with diameter ≥ 8 cm were measured. Based on the tree DBH and height, field AGB was calculated by applying specific allometric equations developed by Indonesian researchers [35] (Table 1).

| No. | Vegetation indices | Formula | References |
|-----|--------------------|---|------------|
| 1 | NDVI | B7 - B4/B7 + B4 | [40] |
| 2 | EVI | G * B7 - B4/B7 + C1 * B4 - C2 * B2 + L Note: $C1 = 6$; $C2 = 7.5$; $L = 1$; $G = 2.5$ | [41] |
| 3 | MSR | $(B7/B4 - 1)/((B7 + B4)^{1/2} + 1)$ | [42] |
| 4 | SR | <i>B</i> 7/ <i>B</i> 4 | [43] |
| 5 | NDI45 | B5 - B4/B5 + B4 | [44] |
| 6 | S2REP | 705 + 35 * ((((B7 + B4)/2) - B4)/(B6 - B5)) | [30] |
| 7 | GNDVI | B7 - B3/B7 + B3 | [45] |

TABLE 2: Vegetation indices used to establish the AGB model.

2.3. Sentinel-2 Data Acquisition and Preprocessing. Sentinel-2 level 1-C data that covered the study area was acquired on 19 May 2017. The image was freely downloaded through the Copernicus Scientific Data Hub website. It had been scaled to top of atmosphere (TOA) level including orthorectification and spatial registration on a global reference system [29]. Sentinel-2 level 1-C was processed to level 2-A to gain a bottom of atmosphere- (BOA-) corrected reflectance image using the ATCOR algorithm through Sen2Cor plugin in Sentinel Application Platform (SNAP) software [36]. The image was resampled to 20 m spatial resolution using the nearest neighbour method to adjust the size of the sample plots. Finally, subsetting was done for the image to obtain the study area.

2.4. Private Forest Map. All land use patterns in the study area must be selected to classify the image data into land use and land cover categories. The land use pattern was classified into two groups such as private forest and nonprivate forest. Private forests are close to mixed plantation forests which are established by some trees and used for industrial and nonindustrial purposes [37]. These are planted by the farmers, and each farmer has a minimum of 0.25 ha of private forest land [38]. Nonprivate forests include state forest, settlement, agricultural land, water bodies, bare soil, road, and others. Contrary to private forests, state forests in our study area are established by the government and determined as production forests.

The private forest map of the study area was created from the Sentinel-2 image through the classification process. Supervised classification using maximum likelihood classification was employed to distinguish private forest and non-private forest. True colour combination from Sentinel-2 in particular bands 4, 3, and 2 in 10 m resolution was used to classify the image. Accuracy of the classified private forest map was assessed through the confusion matrix.

2.5. Modelling Relationship between Field AGB and Vegetation Indices. In this study, 30 field AGB and 7 vegetation indices were applied to assess the correlation between field AGB and vegetation indices shown in Table 2. Vegetation indices used in this study were divided into two. They were Sentinel-2 vegetation indices and traditional vegetation indices. Sentinel-2 vegetation indices are comprised of normalised difference index (NDI) 45 and Sentinel-2 red edge

position (S2REP) whereas traditional indices involved NDVI, simple ratio (SR), modified simple ratio (MSR), green normalised difference vegetation index (GNDVI), and enhanced vegetation index (EVI). Traditional indices were selected based on simplicity and robustness. NDVI, SR, MSR, and GNDVI work through a simple algorithm, whereas GNDVI uses a green band instead of a red band. GNDVI has sensitivity on variation chlorophyll content. EVI is the robust index and has sensitivity to high biomass regions because it uses a correction factor to eliminate influence of aerosol and canopy background.

Coordinates of each plot were used to extract pixel values of vegetation indices using ArcGis 10.5. Linear regression was employed for exploring the relationship between AGB and vegetation indices. All vegetation indices were evaluated based on Pearson correlation coefficient (r) and coefficient of determination (R^2) . The indices with high r and R^2 were indicated to fit into AGB. Furthermore, AGB equation modelling was conducted by applying a stepwise linear regression method using SPSS version 17 by plotting AGB as a dependent variable and vegetation indices as independent variables. R^2 , root mean square error (RMSE), and multicolinearity of variables, tolerance, and variance inflation factor (VIF) were calculated to confirm the reliability of the model [39].

2.6. Mapping the AGB over the Study Area. AGB stored in the study site could be calculated through an AGB map prediction. The model derived from stepwise linear regression was used to generate the map in ArcGis 10.5. A total of 15 sample plots observing AGB were plotted against 15 predicted AGB to validate the AGB map. R^2 and RMSE were calculated during this process (Figure 2).

The main purpose of community forest development is to meet the necessity of farmers; therefore, harvesting the intensity on the private forest is high. It may lead to unfavorable environmental benefits including a decrease in carbon stocks. Accordingly, AGB stored in our study area was compared to AGB in other types of forest.

3. Results

3.1. Private Forest Composition and Field AGB. The number of trees recorded in 45 (1.8 ha) sample plots was 1451. A total of 8 species of trees were found, namely, *Tectona*

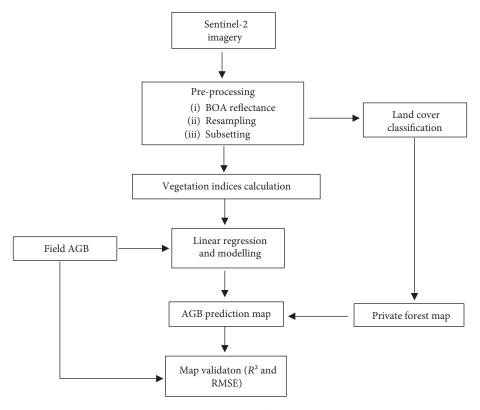


FIGURE 2: Flow chart of this study.

TABLE 3: Important value index for each species found in private forest.

| No. | Species | Count | Density | RD (%) | Frequency | RF (%) | RD1 (%) | IVI |
|-----|-----------------------|-------|---------|--------|-----------|--------|---------|--------|
| 1 | Tectona grandis | 891 | 19.80 | 63.82 | 0.93 | 42.43 | 87.00 | 193.25 |
| 2 | Swietenia mahagoni | 302 | 6.71 | 20.04 | 0.58 | 26.26 | 8.29 | 54.59 |
| 3 | Acacia auriculiformis | 232 | 5.16 | 14.45 | 0.40 | 18.18 | 4.59 | 37.22 |
| 4 | Other trees | 26 | 0.58 | 1.69 | 0.29 | 13.13 | 0.12 | 14.94 |
| | Total | 1451 | 32.24 | 100 | 2.20 | 100 | 100 | 300 |

RD: relative density; RF: relative frequency; RD1: relative dominance. IVI is calculated from RD + RF + RD1 [46].

grandis, Swietenia mahagoni, Acacia auriculiformis, and other trees such as Samanea saman, Gnetum gnemon, Alstonia scholaris, Parkia speciosa, and Tamarindus indica. The dominant species in the Girisekar and Jetis forest management unit was Tectona grandis with a total of trees and important value index (IVI) of 891 and 193.25, respectively (Table 3). The IVI for Swietenia mahagoni and Acacia auriculiformis being the second and third dominant species were 54.59 and 37.22, respectively. Other trees group constituted the lowest in terms of IVI in private forest.

The mean of field AGB was 80 Mg/ha, with minimum and maximum values of 21 Mg/ha and 226 Mg/ha, respectively. Majority of AGB plots were spread evenly, ranging from 50 to 100 Mg/ha. We found 8 sample plots with field AGB < 50 Mg/ha and few sample plots with field AGB > 150 Mg/ha (Figure 3).

3.2. Land Cover Classification Result. As many as 160 ground control sample points were selected for accuracy

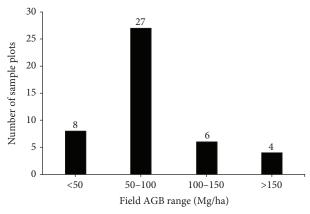


FIGURE 3: Distribution of field AGB within the sample plot.

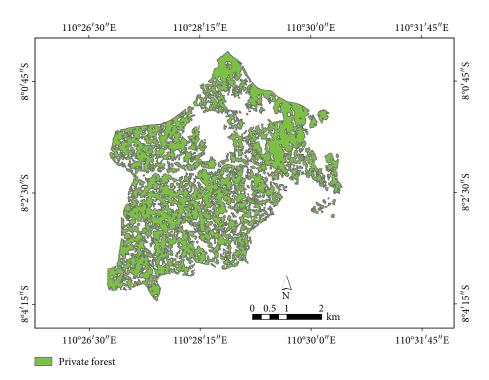


FIGURE 4: Girisekar and Jetis forest management unit map derived from supervised classification.

Table 4: Result of linear regression between vegetation indices and AGB.

| No. | Vegetation indices | r | R^2 |
|-----|--------------------|--------|-------|
| 1 | NDI45 | 0.89** | 0.79 |
| 2 | MSR | 0.86** | 0.75 |
| 3 | SR | 0.85** | 0.73 |
| 4 | NDVI | 0.80** | 0.65 |
| 5 | GNDVI | 0.70** | 0.49 |
| 6 | EVI | 0.48** | 0.23 |
| 7 | S2REP | 0.44** | 0.19 |

^{**} refers to a significant correlation at 0.01 level.

TABLE 5: Statistics of the AGB model.

| Model variable | R^2 | RMSE | p level | Tolerance | VIF |
|----------------|-------|-------|---------|-----------|------|
| (n = 30) | 0.81 | 19.44 | 0.001 | | |
| NDI45 | | | | 0.876 | 1.14 |
| EVI | | | | 0.876 | 1.14 |

assessment of the Girisekar and Jetis private forest management unit map (Figure 4). User's accuracy of the private forest map was 95%, while producer's and overall accuracies were 95% and 94%, respectively. Based on the classification result, the large part of the Girisekar and Jetis private forest management unit was 1427 ha.

3.3. Modelling the Relationship between Vegetation Indices and Field AGB. The results of linear regression analysis between AGB and vegetation indices derived from

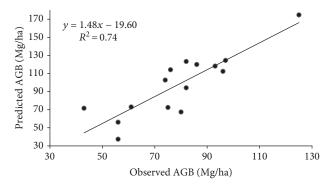


Figure 5: Scatter plot between predictive versus observed AGB.

Sentinel-2 are shown in Table 4. The r value of vegetation indices ranges from 0.44 to 0.89, and R^2 varied between 0.19 and 0.79. All vegetation indices showed a significant and positive correlation with AGB. NDI45 was the best vegetation index which corresponded to AGB (r = 0.89 and $R^2 = 0.79$) followed by MSR, SR, NDVI, GNDVI, EVI, and S2REP. All of the data for modelling is available in Supplementary Materials Section 1.

Based on stepwise linear regression, a model for estimating AGB in this study is expressed as

$$AGB = (537 * NDI45) + (158.42 * EVI) - 353.66.$$
 (1)

A developed model from NDI45 and EVI fitted for estimating AGB ($R^2 = 0.81$, p < 0.05) (Table 5). R^2 81% meant that as much as 81% of AGB variability could be explained by the model. RMSE model was 19.44 Mg/ha,

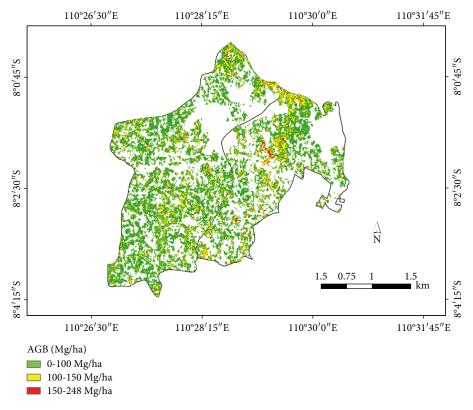


FIGURE 6: The AGB map in Girisekar and Jetis private forest management unit.

and it was not a multicolinearity problem as the tolerance value was more than 0.1 and VIF was less than 10.

3.4. AGB Map Prediction. Simple linear regression was developed to validate the AGB map from 15 plots. The correlation between the predicted and observed AGB gave a strong coefficient of determination, $R^2 = 0.74$. It indicated that approximately 74% of the observed AGB was explained by the predicted AGB according to this model (Figure 5). RMSE of the predicted and observed AGB values was 27 Mg/ha. Data used to validate the AGB map is available in Supplementary Materials Section 2.

Figure 6 illustrates AGB map prediction resulted from the stepwise linear regression model between AGB field and vegetation indices (NDI45 and EVI). The number of AGB predicted for the Girisekar and Jetis private forest management unit from spatial analysis was 72.54 Mg/ha. The AGB values varied from 0 to 248 Mg/ha. Using the 0.5 conversion factor from biomass to carbon [47], the aboveground carbon biomass estimated from the study area was 36.27 Mg/ha.

4. Discussion

Pearson correlation was employed for accessing the relationship between AGB and vegetation indices derived from the Sentinel-2 image. NDI45, MSR, SR, and NDVI had a strong correlation with AGB. NDVI is most widely used to measure biophysical properties of vegetation. Therefore, we compared it with other indices on this research. Once

NDI45 and NDVI were compared, NDI45 was more powerful than NDVI since NDVI had a saturation problem at a higher value of biomass (Figure 7). Saturation resulted from a slight change of the NDVI ratio due to high reflectance of NIR and decreasing red reflectance in an area with close canopy cover, and therefore, it would lead to a weak correlation with biomass [48]. Substitution of NIR to the red edge 1 on NDI45 at the Sentinel-2 image is able to improve the relationship between satellite data and biophysical properties of the vegetation. This is consistent with the result of Frampton et al. [30] where they found that the correlation of NDI45 was higher than NDVI on measuring canopy chlorophyll content (CCC). NDI45 created from Sentinel-2 B4 (665 nm) and red edge 1 B5 (705 nm) is more robust in measuring biophysical parameters of vegetation than other band combination in Sentinel-2 [44].

MSR and SR outperformed NDVI in this study. It might be because the relationship of MSR and SR with biophysical properties of the vegetation was more linear than NDVI [30, 42]. NDVI is much affected by leaf optical and geometry effect from a sun view angle; hence, linearity to parameters of vegetation is lower than MSR [42]. EVI is more reliable than NDVI to measure AGB on dense vegetation because of its ability to reduce the effect of atmosphere and canopy background. However, EVI showed poor correlation to AGB in this research. A possible explanation is that the slope of the plots in the study area varies from flat to slightly inclined (slope range of the sample plots between 0° and 19°). EVI is highly influenced by various terrain conditions [49, 50]. The soil adjustment factor becomes the

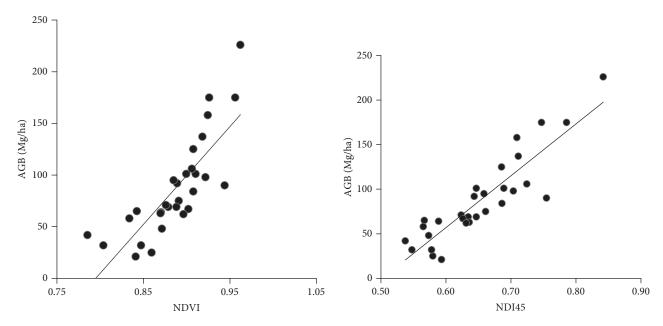


FIGURE 7: Scatter plot comparison between NDVI and NDI45 in estimating AGB.

| 1 | ABLE 6: Comparison | between AGB 1 | from private | forest and other | r forest types; I | Mg/ha = 1 ton/ha. |
|---|--------------------|---------------|--------------|------------------|-------------------|-------------------|
| | | | | | | |

| No. | Type of forest | AGB | Sensor | References |
|-----|------------------------|--------------|--------------------------|------------|
| 1 | Tropical | 382 Mg/ha | Lidar | [51] |
| 2 | Private | 72.54 Mg/ha | Sentinel-2 | This study |
| 3 | Mangrove | 250.53 Mg/ha | GeoEye-1 | [52] |
| 4 | Mediterranean | 38 Ton/ha | QuickBird | [53] |
| 5 | Deciduous | 58 Ton/ha | ALOS PALSAR | [54] |
| 6 | Boreal | 39.5 Mg/ha | Landsat ETM+ | [55] |
| 7 | Conifer and broad leaf | 106.45 Mg/ha | Landsat 8 and Radarsat-2 | [56] |

limitation of EVI because it is very sensitive to topography than indices which are based on the simple ratio algorithm such as SR and NDVI [49].

Private forests are a potential source of AGB, having an important role in climate change mitigation. Therefore, comparing AGB from private forests and other forest types is imperative. AGB predicted in this study area was 72.54 Mg/ha. The estimates of AGB given in the current study are higher than the estimates calculated from deciduous forests in India (58 Mg/ha) [54] (Table 6). It also almost doubles compared to the value from Mediterranean forests in Italy (38 Mg/ha) [53] and the AGB value from boreal forests in Alaska (39.5 Mg/ha) [55]. However, the current AGB is lower than the biomass of mangrove forests in Thailand (250.53 Mg/ha) [52], tropical forests in Borneo (382 Mg/ha) [51], and conifer broadleaf forests in China (106.45 Mg/ha) [54]. The AGB of tropical forests is higher than that of private forests because natural forests store a large amount of biomass on terrestrial ecosystems which accumulates over a long period of time. On the other hand, the sustainability of private forests depends on the success of the silviculture system and harvesting time by the farmers. Yet, AGB on private forests is still higher than AGB from some types of forest, and this is unexpected and suggests that private forests can be an alternative as biomass and carbon reservoir.

This research showed the potential of vegetation indices derived from Sentinel-2 to predict AGB on private forests. A number of researchers have reported AGB in plantation forests with different sensors [56-58]. For instance, Baig et al. [59] utilised ALOS-2 PALSAR to model and map Dalbergia sissoo forest plantation in Pakistan using nonlinear regression between field data and SAR backscatter. Dube and Mutanga [57] demonstrated the ability of WorldView-2 to retrieve AGB on Eucalyptus plantation in South Africa. However, the researchers have used mainly commercial satellite data instead of a cheap data source. This issue is problematic specially for developing countries or forest researchers who have limitation of budget. Therefore, making this methodology used in this research is very vital as it can address the cost issue as it uses free satellite image and is supported by opensource software, SNAP.

Furthermore, the sample plots of this study are limited as a result of accessibility and cost. Nevertheless, the sample plots were successful in establishing a model ($R^2 = 0.81$) and predicted AGB map on the study area. The reason why the model on this research shows good performance can be

attributed to the average of field AGB, which is 80 Mg/ha where only one sample plot had field AGB more than 200 Mg/ha and the others are below 200 Mg/ha. It is too difficult to find areas with high AGB value on private forests because the farmers harvest mature trees. Therefore, it is plausible if majority of the sample plots would be only in low to medium AGB areas. Although NDVI was more saturated than NDI45, saturation data did not significantly influence our work due to limited sample plots in high biomass areas. In the case of Landsat TM, Lu et al. [60] stated that data saturation occurred when biomass reaches 100–150 Mg/ha depending on the complexity of the vegetation structure. There are abundant rooms for further research in evaluating the ability of Sentinel-2 imagery in tropical humid forests which tend to have a high value of biomass.

5. Conclusion

Sentinel-2 multispectral imagery can be utilised to estimate AGB on the Girisekar and Jetis private forest management unit. Vegetation indices were obtained from the Sentinel-2 data image. Normalised difference index (NDI) 45, which is established from red and red-edge 1 bands, had a strong correlation with AGB in comparison with other indices. The study demonstrated that the AGB model derived from stepwise linear regression was robust ($R^2 = 0.81$). R^2 between observed and predicted AGB from the Sentinel-2 private forest model was 0.74 indicating that AGB can be predicted with high accuracy using remote sensing data. The AGB predicted in this research is higher than the AGB from some types of forest like deciduous and Mediterranean. The result suggested that private forests are a reliable source to reducing CO_2 emission.

Data Availability

The data used in this study can be divided by two. They are spatial and field data. Field data was taken from the field via direct measurement, and spatial data was captured from Sentinel-2 satellite image. All of the data then was compared through statistical analysis to achieve the goal of this study. The spatial and field data are included in Supplementary Information files. If there is any doubt about the data, everyone can contact the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

Prince of Songkla University (PSU) has accorded technical support and funding in the accomplishment of this study through Thailand's Education Hub for ASEAN Countries (TEH-AC) program. We thank the Girisekar and Jetis private forest owner for allowing data collection.

Supplementary Materials

The data aforementioned is used to correlate between AGB and the vegetation indices via linear regression. The data is also used to establish the AGB prediction model through multilinear regression. AGB is a field data which is collected through plot measurement in the private forest. Vegetation indices are derived from a Sentinel-2 satellite image through mathematical function. The UTM coordinates are coordinates of each sample plot in the field. The coordinates are used to connect between field data and vegetation index values. The results of this data can be seen in Modelling the Relationship between Vegetation Indices and Field AGB in this manuscript. Section 2: In this section, we provide data for AGB map validation. Output of this research is an AGB map which represents real AGB in the study area. The AGB map was produced from mapping software using the AGB prediction model in Section 1. To ensure the reliability of our map, it has to be validated. For this analysis, the data can be divided into two groups: observed and predicted AGB. Each group has fifteen data. Observed AGB was real AGB and were taken from plot measurement in the private forest while predicted AGB was AGB from the predicted map which had the same coordinate, having observed AGB. The coefficient of determination (R^2) and root mean square error (RMSE) were used to validate the performance of the model. The results of AGB map validation can be seen in AGB Map Prediction in this manuscript. (Supplementary Materials)

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