The Estimation of Forest Stand Above Ground Biomass in the district of Borobudur, Central Java, Indonesia

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ABSTRACT: The vulnerability of the forest stand area in Borobudur District to tourism activities and land cover change causes high greenhouse gas emissions. Forest stand has the potential for higher carbon storage compared to other land covers. The existence of this forest stand area plays a vital role in mitigating the reduction of greenhouse gas emissions. Biomass as an instrument for assessing the level of greenhouse gas emissions can be measured using several approaches, including remote sensing and spatial models. This study aimed to determine the spatial distribution of above-ground biomass with a vegetation index approach and allometric method in Borobudur District. The result shows that ARVI and GEMI have lower standard errors because this study only considers one biophysical aspect, diameter at breast height (DBH). The assumption is that both indices can suppress the influence of the atmosphere well. Other vegetation indices such as NDVI and EVI are more sensitive to vegetation abundance so the biophysical aspects considered are not only DBH but also canopy density. Meanwhile, SAVI also has a SE value that is not too high compared to other indices. This is because some samples show subsurface cover in the form of bare soil or litter so that SAVI can suppress the influence of the background well. EVI, which can suppress the influence of soil and atmospheric background, has a fairly good ability. Its shows that the index's sensitivity to vegetation abundance for biomass mapping cannot depend on one variable alone. This is also caused by vegetation cover factors on the ground surface, such as shrubs and herbs, contributing to the spectral response. The estimation results show that the total biomass of forest in the Borobudur District ranges from 0.002 tons/Ha to 11.89 tons/Ha and is primarily distributed in hilly areas.

1. INTRODUCTION

Forest biomass is an important variable of ecosystem productivity that can be used to measure the role of forests in the carbon cycle, potential energy production, and carbon stock estimates for climate change modeling. The function of forests as carbon sinks, as a result of the accumulation of carbon dioxide (CO2), has long been identified as one of the most important, because forests contain most of the above and below-ground regenerative terrestrial carbon. Forest biomass can generally be divided into Above Ground Biomass (AGB) which includes stems, branches, bark, seeds, and leaves, and Below Ground Biomass which consists of all living roots, and fine and coarse litter associated with the land. AGB estimation of vegetation requires an accurate, fast, effective, and efficient method. Information on AGB potential can be identified through several approaches including terrestrial surveys (West, P. W., 2006) and remote sensing data (Cao, L. et al, 2016). The field survey method produces accurate estimates but is only able to provide local information that tends to be homogeneous and limited in scope, requiring more cost, effort, and time (Karimi et al., 2013).

Remote sensing can provide information about the characteristics and distribution of vegetation at various scales and can be adapted to needs (Kamal et al. 2015). Remote sensing data can be used to derive parameters that are used as inputs for AGB estimation at various spatial and temporal scales. Previous studies have shown that remote sensing can effectively measure and monitor forest AGB on a regional scale; Therefore, various types of remote sensors, using both passive and active sensors, have been used to estimate AGB (Deng, S., et al, 2014, Cao, L. et al, 2016; Shen, W., et al., 2016). Sentinel-2 is one of the remote sensing data that can be used to extract biomass estimation parameters, such as land cover and vegetation index. Various studies related to biomass estimation using allometric methods and remote sensing data on sentinel 2 have been widely used (Zumo, 2021; Adamu, et al, 2021; Muhe and Argaw, 2022). Sentinel 2 has a higher spatial resolution of 10 meters compared to other multispectral images that can be accessed for free, so it is suitable for application in a not-too-large area and minimizes the estimation error value.

2. STUDY AREA

This research was conducted in Borobudur District, Magelang Regency, Central Java Province. Borobudur is a sub-district in Magelang Regency, Central Java, Indonesia with an area of 54.55 Km2. Borobudur District has moderate rainfall with a rainfall value of 1700 mm/year in 2021 with five months without rain (BPS, 2021). The slope conditions of the villages in Borobudur District are mostly sloping < 15 degrees as many as 12 villages and 4 villages are on a moderate slope between 15 degrees to 25 degrees, while the remaining 4 villages are in steep areas > 25 degrees (BPS, 2015).

Borobudur District has a strategic location and has international-scale tourism, namely the Borobudur Temple. The phenomenon of land cover change that commonly occurs in strategic tourist locations is the change in land cover of standing vegetation turning into agricultural land, non-agricultural land, or commercial land (Riswandha and H. Wahyono, 2017). This area is partly covered by the Hutan Rakyat (HTR) with an area of 625 ha, 736 ha of rice fields, and 2,308 ha of agricultural land area (BPS, 2021). The results of this mapping show that there are quite some changes in the use of rural land and productive land into built-up land for commercial purposes (Supandi and Setiawan, 2012).

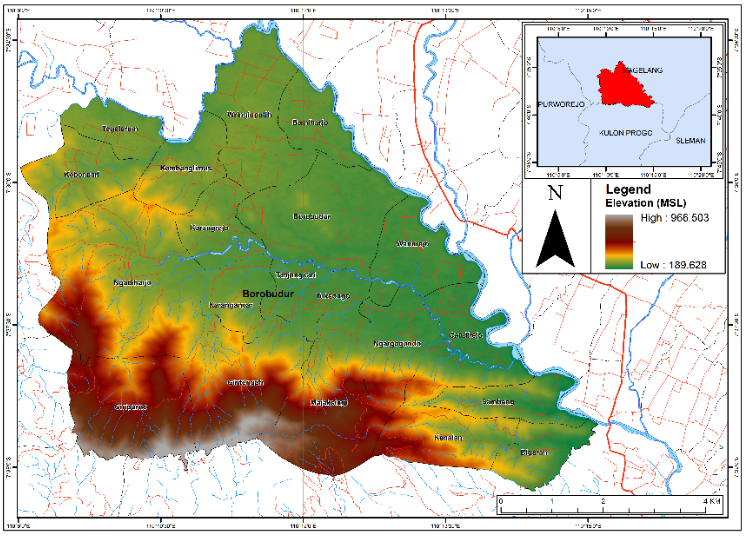


Figure 1. Elevation map of Borobudur District

3. METHODS

The estimation of vegetation biomass was carried out in all study areas. Five vegetation indices were applied to sentinel 2 multispectral level 1C images. Then the sample is made with classification using the Maximum Likelihood Classification with land cover classes into five density classes. After that, the field data collection stage was carried out in the form of tree diameters and other necessary data. Then extracted the transformation of the vegetation index from the Sentinel 2 image which was used for statistical analysis in building a model to estimate the biomass value of the vegetation index. Statistical analysis carried out were normality test, correlation analysis, and regression analysis. Then the data can be tested for accuracy to get the best model. Besides Sentinel 2 image dataset, this study also uses Pleiades images and a 1:25,000 scale RBI topographic map as the basis for assessing field orientation, generalization process, and accuracy.

3.1 Image Pre Processing

We used the Sentinel-2 Level 1C image dataset, which was recorded on May 31, 2022. The image pre-processing was radiometric correction using Semi-Automatic Classification Plugin (SCP) plugin from QGIS. This plugin consists of several tools that include image processing from pre-processing, and classification, to validation tests. The atmospheric correction method adopted by SCP is the DOS1 method developed by (Moran et al., 1992). Then to suppress the influence of topographic variations, we applied the C-Correction method for topographic correction. This method includes non-Lambertian by applying semi-empirical equations by utilizing the illumination pixel value and the sun's angle (Umarhadi & Danoedoro, 2020).

$$\rho H \ = \ \rho T \ (\frac{\cos \theta_Z + c}{I\,L + c}) \qquad (1)$$

(ρH = corrected surface reflection value, ρT = uncorrected surface reflection value, θZ = sun zenith angle, c = C Coefficient, IL = illumination)

3.2 Multispectral Classification

The multispectral classification was carried out in a supervised using maximum likelihood to generate land cover data. This method considers the probability value for each sample that is entered, in contrast to other methods that consider distance (Danoedoro, 2012). Pixels are classified as specific objects based on the shape, size, and orientation of the sample in the feature space. Supervised classification aims to obtain classes between vegetation and non-vegetation. Non-vegetation classes were masked out to focus on vegetation classes, then divided into five density classes for sampling purposes.

3.3 Vegetation Index

Normalized Difference Vegetation Index (NDVI) is a basic vegetation index transformation that involves several channels at once and produces a new image that has a value ranging from -1 to +1 (Danoedoro, 2012). The channels used are red (0.64-0.67 µm) and near-infrared (0.85-0.88 µm) channels. This index has a sensitivity to identify vegetation abundance. The NDVI equation is as follows.

$$\text{NDVI} = \left(\frac{NIR-RED}{NIR+RED}\right) \tag{2}$$

Enhanced Vegetation Index (EVI) is a vegetation index that is applied to minimize the effects of soil reflection and atmospheric disturbance simultaneously (H. Q. Liu and A. Huete, 1995). The EVI equation is as follows.

$$EVI = 2.5 \times \frac{(\rho NIR - \rho Red)}{\rho NIR + C1\rho Red - C2\rho Blue + L} \tag{3}$$

(L = 0.5, C = aerosol coefficient of 6.0 and 7.5 respectively)

The Atmospherically Resistant Vegetation Index (ARVI) is a vegetation index that minimizes atmospheric effects (Kaufman & Tanre, 1992). ARVI is commonly used to eliminate atmospheric effects, but it is necessary to do atmospheric correction before calculating ARVI. The ARVI equation is as follows.

$$\text{ARVI} = \frac{NIR-RedBlue}{NIR + RedBlue} \tag{4}$$

Soil Adjusted Vegetation Index (SAVI) is a vegetation index that suppresses the influence of soil reflectance values by adding a variable L which represents the index of soil surface conditions (Huete, 1988). In this study, we use 0.5 for the L value. The SAVI equation is as follows.

$$SAVI = \frac{((NIR-Red)(1+L))}{(NIR+Red+L)} \tag{5}$$

Global Environmental Monitoring Index (GEMI) is a vegetation index that has a combination of non-linear channels or Simple Ratio. Pinty & Verstraete (1992) proposed this index to minimize the relative influence of atmospheric effects. This index has a fairly large dynamic range and empirically represents surface vegetation cover in a manner comparable to the Simple Ratio or NDVI. The GEMI equation is as follows.

$$\text{GEMI} = \frac{\eta\,(1 - 0.25\ \eta) - (\rho 1 - 0{,}125)}{(1 - \rho 1)} \tag{6}$$

$$\eta = ((2\,(\rho^2{}_2 - \rho^2{}_1)) + 1.5\ \rho_2 + 0.5\ \ \rho_1)\ /\ \ \rho_2 + \ \rho_1\ + 0.5 \tag{7}$$

(ρ_1 and ρ_2 are the measurable reflectances of the Simple Ratio in the visible and Near InfraRed spectral regions)

3.4 Biomass Estimation

The biomass content in this study is above-ground biomass for forest vegetation stands. The method used is a stratified random sampling method without harvesting (non-destructive sampling) by measuring the diameter at breast height (DBH) of vegetation stands. The vegetation of Borobudur district is mainly classified as community forest (legal purpose) and by land cover classification the standing vegetation is mixed gardens with heterogeneous types of vegetation. To calculate the biomass we used an allometric equation from Brown (1997) for heterogeneous vegetation in the category of humid climate of vegetation in medium-to-high density coverage. The allometric equation is as follows.

$$\text{Biomass} = 42.69 - 12.8(\text{DBH}) + 1.242(\text{DBH}^2) \tag{8}$$

Samples taken on the field works include model samples and accuracy test samples. The method of determining the number of samples is stratified random sampling which is determined based on the results of the supervised classification. This research uses a sample that is divided into 60% model sample and 40% accuracy test sample. The sample plot size used was based on Kuchler and Zonneveld (1988) on the composition of the forest structure measuring 20 x 20 meters to be representative in the classification of vegetation types.

3.5 Statistical Analysis

The statistical analysis was used to build a model for the estimation of the biomass value on the vegetation index. Statistical analysis carried out were normality test, correlation analysis, and regression analysis. A Normality test was carried out on the sample data to be used as a model for biomass estimation using the Kolmogorov-Smirnov test. Correlation is calculated using the Pearson correlation by looking at the calculated R-value and R-product. The F-test and T-test based on the ANOVA table were also carried out to test the independent and dependent variables. Making biomass estimation models using several types of regression models, namely simple linear regression, logarithmic, quadratic, and exponential. The independent variable used in this study is the value of the vegetation index and the dependent variable is the value of biomass. The regression equation can be used to see the results of the biomass estimation based on the best vegetation index, considering the value of the correlation coefficient and determination. The regression equation applied for modeling biomass estimation is the highest correlation and determination coefficient value for each type of vegetation index.

3.6 Accuracy Test

Accuracy tests were also carried out on the results of the biomass estimation model based on the vegetation index used. The method used is Standard Error of Estimate (SEE). The accuracy and error of the modeling results are done by calculating the bottom, upper, minimum error (%), and maximum error (%) values based on a 95% confidence level. The SEE equation is as follows.

$$SEE = \sqrt{\frac{\Sigma_i^n (y'-y)^2}{n-2}} \tag{9}$$

(y' = Model Data, y = Field Data, n = number of samples)

4. RESULT AND DISCUSSION

A total of 31 plots of field biomass samples were taken that represent a variety of topographical and understory conditions. The vegetation in Borobudur District is dominated by mixed vegetation consisting of Jati, Sengon, Mahogany, and Klirisidi. There were 35 vegetation species found from 31 sample plots of measurement. This study has a total of 1417 trees with a range of 9 - 114 trees per plot with a DBH range within 2 - 70 cm. The allometric method used by Brown (1997) accommodates variations in tree diameter with a total of 170 trees.

4.1 Vegetation Index in Borobudur District

The use of five vegetation indices at the study site in the Borobudur District shows the range value of GEMI, NDVI, ARVI, and SAVI is within 0 to 0.9, meanwhile, EVI has a range within 0 to 2.04. In general, of the five vegetation indices used, the highest value obtained was occupied by land cover dominated by large trees and dense canopy cover, while the lowest score was found in land covers such as shrubs or vegetation with sparse density and relatively young planting age. Meanwhile, the relatively small value of the vegetation index indicates that the vegetation/plants are relatively young with sparse vegetation and the appearance of the object is dominated by relatively sparse density. For example, in the use of the NDVI vegetation index, theoretically the NDVI value ranges from -1 to +1, but the value of this vegetation index will typically have subdomains between +0.1 to +0.7. A greater value of this domain is associated with a better representation of the health of the vegetation.

4.2 Biomass Modeling

The standing biomass estimation model was calculated based on 18 model samples and tested for accuracy with 13 samples. All samples used for modeling were tested for normality with Kolmogorov-Smirnov to see the distribution of the data. Based on the normality test, a value of 0.169 was obtained, which means it was above 0.05 so that the model sample was normally distributed. Statistical analysis also looks at the strength of the relationship between biomass and vegetation index obtained from topographic corrected images. Based on the value of r product moment in the Pearson correlation test, which is 0.444, the entire vegetation index has a correlation value above the limit value at a significance level of 5%. The highest correlation is EVI with a value of 0.612 and the lowest is GEMI with a value of 0.534. NDVI is the second highest value with 0.601, then SAVI with a value of 0.583, and ARVI with a value of 0.538. The type of regression that can be used in this modeling is determined by the ANOVA value, as shown in Table 1. The highest coefficient of determination (R^2) is ARVI with logarithmic regression which means that the standing biomass in the field can be explained by 53.5% by ARVI and the rest is explained by other variables.

Table 1. Biomass estimation equation in each type regression

Vegetation Index	Regression Type	R^2	Regression	
ARVI	Linear	0.289	Y = 55.647X - 38.942	(10)
	Logarithmic	0.535	Y = 15.032 + 42.445 Ln(X)	(11)
EVI	Linear	0.375	Y = 20.42X - 12.558	(12)
	Logarithmic	0.381	Y = 7.656 + 17.216 Ln(X)	(13)
	Exponential	0.495	ŷ = 0.0641 * 140.4428x	(14)
GEMI	Logarithmic	0.293	Y = 12.609 + 19.047 Ln(X)	(15)
NDVI	Linear	0.361	Y = 55.55X - 40.632	(16)
	Logarithmic	0.358	Y = 13.747 + 44.41 Ln(X)	(17)
SAVI	Logarithmic	0.348	Y = 18.089 + 16.287 Ln(X)	(18)

4.3 Accuracy Assessment

The accuracy assessment was carried out with SEE for all types of vegetation indices and regression. ARVI and GEMI have a lower error (as shown in figure 2) because biomass mapping only considers one biophysical aspect, namely DBH, also hilly and mountainous areas in Indonesia tend to have atmospheric disturbances. The assumption is that both indices have the ability to suppress atmospheric influences well, although only a few biophysical aspects of vegetation are considered. Other vegetation indices such as NDVI are more sensitive to vegetation abundance so the biophysical aspects considered are not only DBH but also canopy density, both vertically and horizontally. However, based on Gamon, et. al. (1995) the sensitivity of NDVI will decrease in vegetation areas with a high leaf area index, such as thick shrubs and very dense standing vegetation. Meanwhile, SAVI also has a SE value that is not too large compared to other indices. This is because some samples show that there is subsurface cover in the form of open soil or dry litter so that SAVI can suppress the background influence well to map the biomass of the vegetation standing above it. EVI which has the ability to suppress the influence of soil and atmospheric background has a fairly good ability. Huete, et. al. (2002) developed the EVI in order to accommodate the index sensitivity to vegetation with high biomass by reducing soil and atmospheric background disturbances. EVI which is also the development of NDVI shows that the sensitivity of the index to vegetation abundance for biomass mapping cannot depend on one variable alone. This is also due to the factor of vegetation cover on the ground surface, such as shrubs and herbs which also contribute to the spectral response.

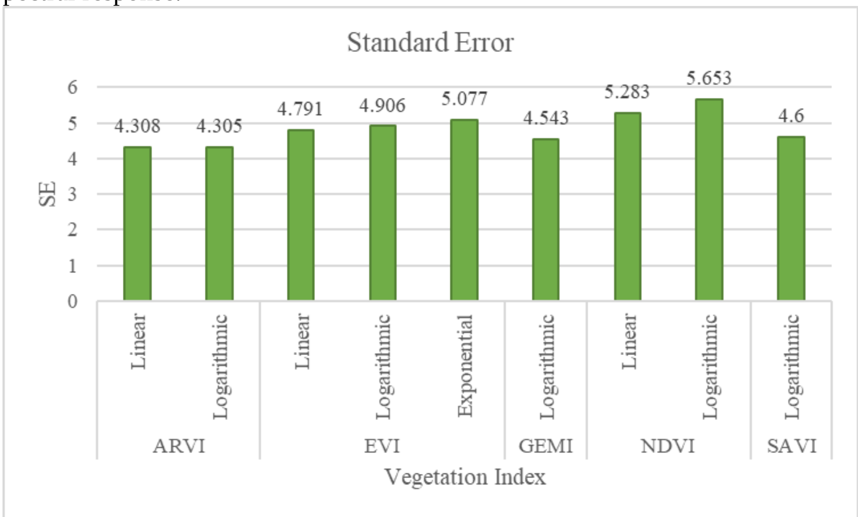
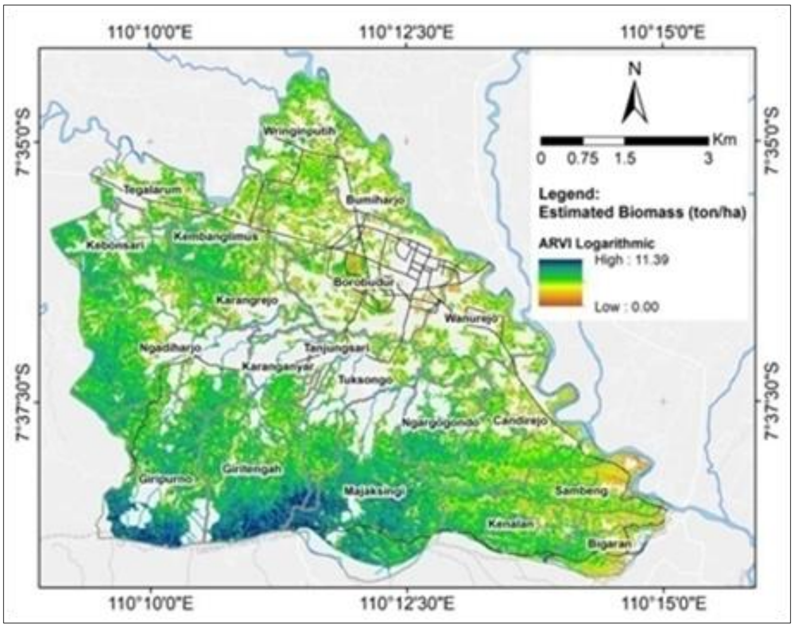


Figure 2. Standard error diagram

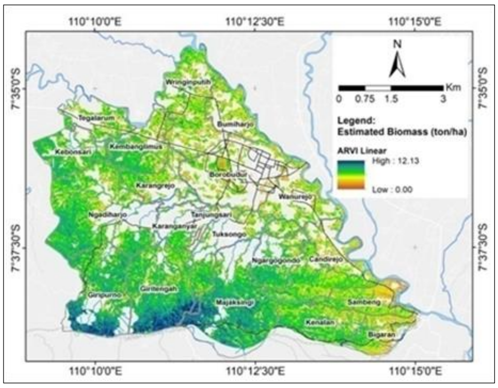
Based on the analysis of topography, homogeneity of vegetation types, and understory conditions, there are several variables that can affect the value of biomass and accuracy. The effect of topographic variations in determining the value of biomass can be seen in the correlation. The correlation is very strong if all samples have a flat topography with a value of r close to 1 and all of the vegetation indices have a strong correlation, which means somewhat steep-to-steep topography can make the not accurate values of biomass. This condition also applies to the homogeneity of vegetation types. There is a strong correlation between biomass values and homogeneous vegetation in each vegetation index because it tends to have a uniform DBH and canopy. In addition, if it is related to the effect of understory (forest floor cover), the biomass has the most influence on forest floor cover which has an understory entirely in the form of soil or dry litter, both on the vegetation index that can suppress the soil background value, such as SAVI has the strong correlation with the value of 0.924, the other four indices also have a strong correlation. EVI and NDVI have a tendency to have a strong correlation or higher than other indices for understory conditions with shrub or herb cover. This shows that EVI and NDVI not only consider the vegetation aspect of the upper canopy cover but also have a relationship with the underlying vegetation cover.

4.4 Biomass Estimation in Borobudur District

The biomass estimation results from each vegetation index show various maximum values. The highest maximum biomass value was obtained from the linear EVI model with a value of 13.74 tons/ha, while the lowest maximum value was obtained from the logarithmic NDVI model with a value of 10.82 tons/ha. If we look at the spatial distribution of biomass estimates in Borobudur District (figure 3), Ngadiharjo Village, Giri Tengah, Majaksingi, Giri Puro, Kenalan, and Wringinputih Village, the biomass content of standing vegetation is high compared to other villages such as Borobudur Village, Tanjung Sari, Tegal Arum, Tuksongo, Karang anyar, Kembanglimus, Bumiharjo and Wanurejo.



(a)



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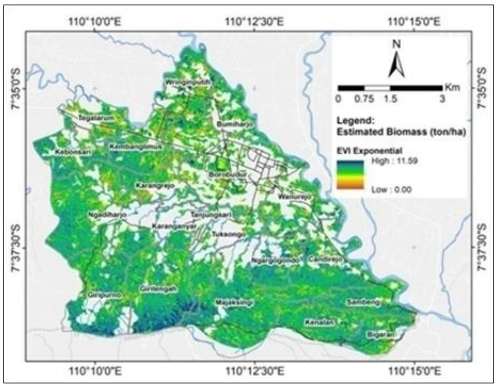

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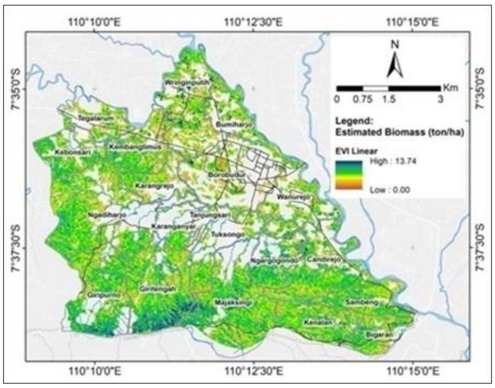

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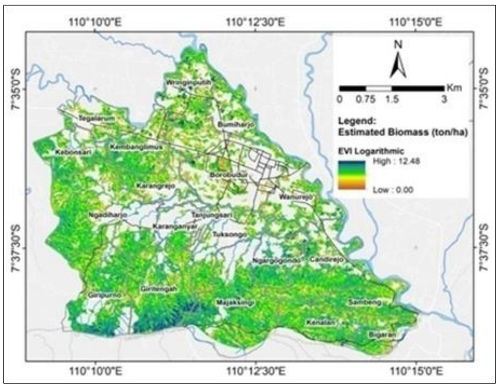

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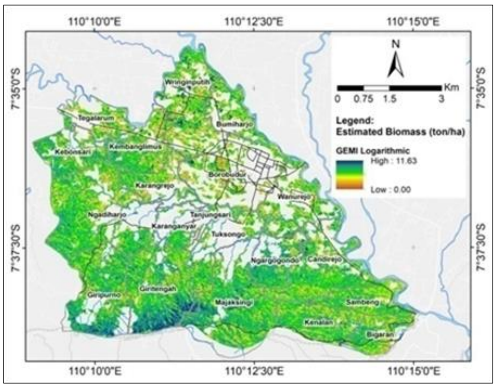

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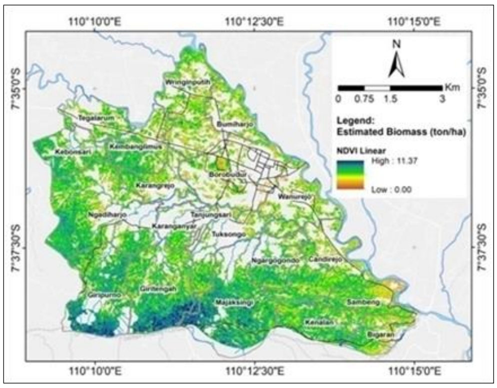

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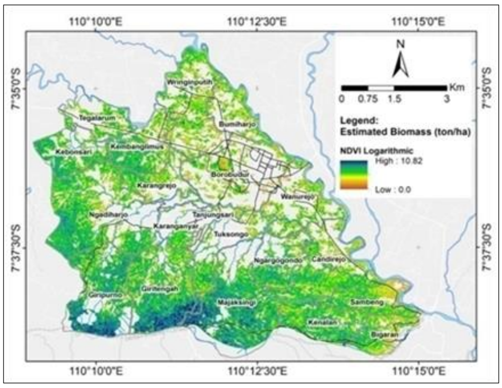

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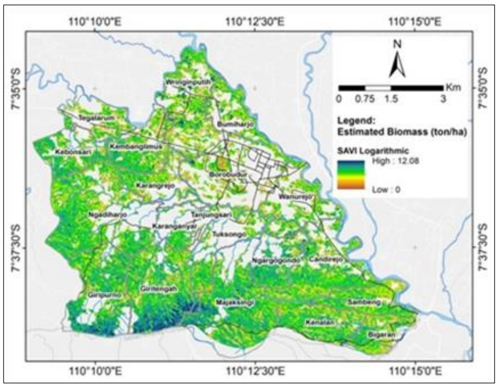

(i)

Figure 3. Estimation of standing vegetation biomass content in Borobudur District is based on the approach of several vegetation indices, (a) Logarithmic ARVI, (b) Linear ARVI, (c) Exponential EVI, (d) Linear EVI, (e) Logarithmic EVI, (f) Logarithmic GEMI, (g) Linear NDVI, (h) Logarithmic NDVI, (i) Logarithmic SAVI

The stand biomass estimation model based on the ARVI vegetation index with logarithmic regression (Figure 3a) analysis was chosen because it has the lowest standard error value. The model was then applied to calculate the biomass in the study area. Based on the selected model, the highest estimated stand biomass was in Ngadiharjo Village at 364,648.13 tons, Giritengah Village at 263,538.17 tons, and Majaksingi Village at 258,813.92 tons. Meanwhile, the lowest estimated stand biomass was in Tanjungsari Village at 13,896.01 tons and Tuksongo Village at 15,621.46 tons. The total estimated stand biomass in Borobudur District is 2,215,335,497 tons spread over 20 villages.

5. CONCLUSION

Measurement of aboveground biomass is influenced by the diameter of the trees measured in the field, the larger the tree size in the plot, the greater the biomass in the plot. The relationship between the vegetation index approach and biomass shows that ARVI and GEMI have lower standard errors because both indices can suppress the influence of the atmosphere well. Other vegetation indices such as NDVI are more sensitive to vegetation abundance so the biophysical aspects considered are not only DBH but also canopy density, both vertically and horizontally. Meanwhile, SAVI also has a SE value that is not too large compared to other indices. This is because some samples show subsurface cover in the form of open soil or dry leaves so that SAVI can suppress the influence of the background well to map the vegetation biomass on it. EVI which can suppress the influence of soil and atmospheric background has a fairly good ability. EVI which is also the development of NDVI shows that the sensitivity of the index to vegetation abundance for biomass mapping cannot depend on one variable alone. This is also caused by vegetation cover factors on the ground surface, such as shrubs and herbs, contributing to the spectral response. The estimation results show that the total biomass of forest in the Borobudur District ranges from 0.002 tons/Ha to 11.89 tons/Ha and is primarily distributed in hilly areas.

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