

COMPARATIVE PERFORMANCE OF SENTINEL-2 VEGETATION INDICES FOR ESTIMATING ABOVEGROUND BIOMASS AND CARBON STOCK IN FOREST AREAS

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ABSTRACT

This study evaluated the performance of Sentinel-2 vegetation indices for estimating aboveground biomass (AGB) and carbon stock in the Maharakham University Forest area, northeastern Thailand. Field data were collected from six 40 × 40 m sample plots, comprising 1,127 trees representing 61 species. AGB was estimated using allometric equations and converted to carbon stock. Six Sentinel-2 vegetation indices—the Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), Modified Soil-Adjusted Vegetation Index 2 (MSAVI2), Ratio Vegetation Index (RVI), Difference Vegetation Index (DVI), and Green Ratio Vegetation Index (GRVI)—were transformed into fractional vegetation cover (FC) and related to field-derived AGB using exponential regression models. A consistent comparative framework was applied to determine how vegetation-index selection affects model fit, prediction error, and agreement with field-derived carbon stock. Among the six indices, MSAVI2 showed the strongest relationship with field-derived AGB ($R^2 = 0.839$) and estimated a total carbon stock of 1,752.866 tC, closest to the field-derived estimate of 1,807.721 tC, with a difference of 3.03%. In contrast, SAVI produced the lowest prediction error (RMSE = 0.901 t ha⁻¹; RMSE% = 1.339%). These results reveal that the best-performing vegetation index depends on the evaluation criterion, as the index with the strongest model fit does not necessarily produce the lowest prediction error. By directly comparing six Sentinel-2 vegetation indices using the same field dataset and modeling framework, this study provides a consistent basis for vegetation-index selection and supports practical applications of Sentinel-2 for forest AGB and carbon stock assessment.

Keywords: Aboveground biomass; Carbon stock; Sentinel-2; Vegetation indices; Fractional vegetation cover; Remote sensing.

1. INTRODUCTION

Forests are a major component of the terrestrial carbon cycle because they store substantial amounts of carbon in vegetation and soils. Changes in forest cover and condition can therefore alter carbon storage and contribute to atmospheric carbon dioxide (CO₂) emissions. Human activities, particularly fossil fuel use, deforestation, and land-use change, have increased greenhouse gas (GHG) concentrations and intensified global warming and climate variability (IPCC, 2014; Angkahad et al., 2024). Reliable assessment of terrestrial carbon stocks is consequently important for climate

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mitigation and carbon accounting. The United Nations Framework Convention on Climate Change (UNFCCC) also encourages developing countries to apply the Intergovernmental Panel on Climate Change (IPCC) framework for estimating emissions associated with land-use change and forest degradation (UNFCCC, 1992; UNFCCC, 2010).

Forest carbon loss occurs not only through deforestation but also through degradation, which can reduce biomass while forest cover remains (Bullock & Woodcock, 2021; Yu et al., 2024). Forest degradation contributes substantially to global greenhouse gas emissions (Grantham Research Institute on Climate Change and the Environment, 2023), with approximately 2.1 billion tonnes of CO₂ emitted annually from degradation in developing countries (Pearson et al., 2017). Globally, around 10 million hectares of forest are cleared each year, while net forest loss during 2010–2020 was approximately 4.7 million hectares annually after accounting for forest gains (Ritchie, 2021). At the regional scale, degradation accounted for approximately 55% of biomass loss in Southern African woodlands (McNicol et al., 2018). These findings emphasize the importance of reliable methods for quantifying forest biomass and associated carbon stocks.

Forest carbon is distributed among aboveground biomass (AGB), belowground biomass, soil organic matter, deadwood, and litter (Uttaruk & Laosuwan, 2020a; Kulmann et al., 2022). AGB is particularly important for evaluating carbon changes associated with forest disturbance (Plybour et al., 2025) and for supporting ecosystem monitoring and forest management (Uttaruk et al., 2024; Wunaphai et al., 2026). Its importance is also recognized within REDD+, which addresses both deforestation and forest degradation (Samek et al., 2014). Reliable AGB estimation is therefore central to forest carbon accounting (Andreoni & Galmarini, 2016; Carpio et al., 2021; Awichin et al., 2025; Laosuwan et al., 2025b). Field inventories and allometric equations are commonly used for this purpose, based on tree attributes such as diameter at breast height (DBH), height, and wood density (Aneseyee et al., 2021; Duangsathaporn et al., 2023; Sun et al., 2024; Uttaruk et al., 2026).

Field inventories provide detailed information but are spatially limited. Satellite remote sensing can extend field-based estimates across larger areas and support spatial mapping of AGB and carbon stocks (Mkuzi et al., 2025; Uttaruk & Laosuwan, 2018; Laosuwan et al., 2025c). Spectral reflectance provides information on vegetation characteristics (Askar et al., 2018; Angkahad et al., 2025), although estimation performance can be affected by image resolution and heterogeneous forest structure (Kulawardhana et al., 2014). Satellite observations nevertheless provide an effective basis for examining spatial biomass patterns (Houghton et al., 2009), and their integration with forest plots has become widely used for spatial biomass modeling (Vicharnakorn et al., 2014; Somprasong, 2024). Satellite sensors differ in spatial, temporal, and spectral characteristics (Samphutthanont et al., 2024), with coarse-resolution observations potentially limiting the representation of heterogeneous vegetation (Mutanga et al., 2012; Vahtmäe et al., 2021). Sentinel-2 provides multispectral observations at spatial resolutions of up to 10 m and has been widely applied to biomass assessment (Haidu et al., 2025). Its spectral information can be transformed into vegetation indices and related to field measurements (Israel et al., 2025), while its free availability supports repeated forest monitoring (Faria et al., 2024; Liu et al., 2024).

Vegetation indices respond differently to vegetation spectral characteristics and may therefore differ in their ability to represent field-derived biomass. Although individual vegetation indices have been widely used for biomass estimation, their relative performance is often difficult to compare across studies because of differences in field data, image processing, study conditions, and modeling approaches. Consequently, it remains unclear whether differences in reported performance are related to the characteristics of the vegetation indices themselves or to differences in the data and analytical procedures used among studies. A direct comparison using the same field data and regression framework is therefore needed to provide a consistent basis for evaluating the relative performance of different vegetation indices. To address this gap, this study compares six Sentinel-2 vegetation indices: the Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), Modified Soil-Adjusted Vegetation Index 2 (MSAVI2), Ratio Vegetation Index (RVI), Difference Vegetation Index (DVI), and Green Ratio Vegetation Index (GRVI). Each index was converted to fractional vegetation cover (FC) and related to field-derived AGB using the same

exponential regression framework. The objectives were to compare the performance of the six indices for estimating AGB and carbon stock, identify the index that most closely represents field observations, and map the spatial distribution of forest carbon across the study area.

2. MATERIALS AND METHODS

2.1. Study Area

The study was conducted in the forest area of Mahasarakham University Farm, Na Si Nuan Subdistrict, Kantharawichai District, Maha Sarakham Province, northeastern Thailand (16.2622° N, 103.2683° E) (Fig. 1). The study area covers approximately 62.9 ha at an elevation of about 153 m above mean sea level. The terrain is generally flat to gently undulating. The region has a tropical monsoon climate with a mean annual temperature of 27.4°C and annual rainfall of approximately 1,000–1,200 mm. The forest is predominantly dry dipterocarp forest with a moderately dense canopy. Dominant tree species include *Shorea siamensis*, *Dipterocarpus obtusifolius*, *Xylia xylocarpa*, *Pterocarpus macrocarpus*, and *Terminalia alata*. The soils are mainly sandy loam to sandy clay loam with good drainage.

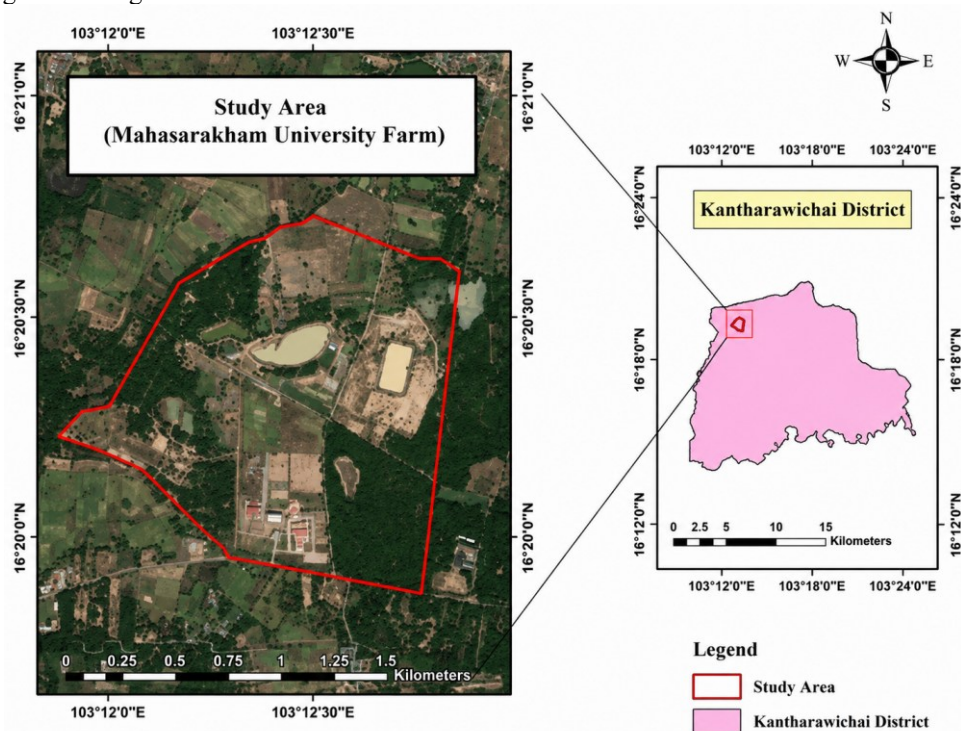


Fig. 1. Study area at Mahasarakham University Farm in Maha Sarakham Province, Thailand.

2.2. Field Data Collection

Field surveys were conducted to characterize tree composition and stand structure within the study area. Six square sampling plots, each measuring 40×40 m, were distributed across the forest to capture spatial variation in canopy conditions. The plot locations were selected during field reconnaissance to represent different levels of canopy cover, ranging from relatively open to denser canopy conditions. This distribution was intended to provide field observations representing the range of vegetation conditions within the study area. The plot size and sampling design followed standard forest inventory procedures, in which approximately 1% of the study area is recommended for plot-based sampling under random sampling conditions (TGO, 2017). Within each plot, all trees with a

diameter at breast height (DBH) greater than 4.5 cm were measured. DBH was recorded using a diameter tape, while total tree height was measured using a laser rangefinder. Aboveground biomass (AGB) was estimated from these field measurements using the allometric equations developed by Ogawa et al. (1965), as expressed in Equations (1)–(4).

$$W_S = 0.0396(D^2 H)^{0.933} \quad (1)$$

$$W_B = 0.00349(D^2 H)^{1.030} \quad (2)$$

$$W_L = \left(\frac{28}{W_S + W_B} + 0.025 \right)^{-1} \quad (3)$$

$$W_T = W_S + W_B + W_L \quad (4)$$

where D represents DBH (cm) and H represents total tree height (m). W_S , W_B , and W_L denote stem, branch, and leaf biomass, respectively, while W_T represents total AGB.

The estimated AGB was subsequently converted to carbon stock using a carbon fraction of 0.47, following the IPCC (2006), as shown in Equation (5):

$$C_j = W_{ic} \times FC \quad (5)$$

where C_j represents the carbon stock of an individual tree, W_T is the estimated aboveground biomass, and FC is the biomass-to-carbon conversion factor (0.47).

2.3. Satellite Data Analysis

Sentinel-2 Level-2A multispectral imagery acquired on 18 January 2026 was used to characterize vegetation conditions across the study area. The Level-2A product provides atmospherically corrected surface reflectance data. To minimize the influence of cloud contamination, an image with cloud cover not exceeding 10% was selected for the analysis. Six vegetation indices were calculated from the spectral bands: the Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), Modified Soil-Adjusted Vegetation Index 2 (MSAVI2), Ratio Vegetation Index (RVI), Difference Vegetation Index (DVI), and Green Ratio Vegetation Index (GRVI). These indices represent different spectral responses of vegetation and were subsequently used to examine their relationships with field-derived aboveground biomass (AGB) and carbon stock. The six vegetation indices were calculated using Equations (6)–(11).

The NDVI was calculated from the near-infrared and red bands, as expressed in Equation (6).

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (6)$$

The SAVI was used to account for the influence of soil background on vegetation reflectance. It was calculated using Equation (7).

$$SAVI = \frac{(NIR - RED) \times (1 + L)}{(NIR + RED + L)} \quad (7)$$

where L is the soil-adjustment factor. A value of 0.5 was applied in this study.

The MSAVI2 further reduces the influence of exposed soil and was calculated using Equation (8).

$$MSAVI2 = (1/2) * (2(NIR + 1) - \sqrt{(2 * NIR + 1)^2 - 8(NIR - Red)}) \quad (8)$$

The RVI represents the ratio between near-infrared and red reflectance and was derived using Equation (9).

$$RVI = \frac{NIR}{RED} \quad (9)$$

The DVI measures the difference between near-infrared and red reflectance and was calculated using Equation (10).

$$DVI = NIR - RED \quad (10)$$

The GRVI was calculated from green and red reflectance using Equation (11).

$$GRVI = \frac{GREEN - RED}{GREEN + RED} \quad (11)$$

To provide a common vegetation-cover measure for subsequent analysis, each vegetation index was transformed into fractional vegetation cover (FC), as expressed in Equation (12).

$$FC = \frac{Index - Index_{soil}}{Index_{forest} - Index_{soil}} \quad (12)$$

where Index represents the vegetation index value of each pixel, Index_{forest} represents the reference value for dense vegetation, and Index_{soil} represents the reference value for bare soil.

For each vegetation index, Index_{forest} and Index_{soil} were determined from the maximum and minimum index values observed within the study area, respectively. These values were used as the vegetation and soil endpoints for calculating fractional vegetation cover (FC).

2.4. Development of the Exponential Regression Model

The relationship between field-derived aboveground biomass (AGB) and fractional vegetation cover (FC) was examined using exponential regression. FC values derived separately from the six Sentinel-2 vegetation indices—NDVI, SAVI, MSAVI2, RVI, DVI, and GRVI—were used as predictor variables, while field-estimated AGB was used as the response variable. An individual regression model was developed for each vegetation index to compare its ability to represent variations in AGB. The exponential relationship was expressed using Equation (13).

$$AGB = a \times b^{e \times FC} \quad (13)$$

where AGB is the estimated aboveground biomass, FC is the fractional vegetation cover derived from each vegetation index, e is the base of the natural logarithm, and a and b are regression coefficients estimated from the field observations.

A separate exponential regression model was fitted for each vegetation index. Model performance was assessed using the coefficient of determination (R^2) and root mean square error (RMSE). The R^2 value was used to describe the strength of the relationship between FC and field-derived AGB, whereas RMSE was used to quantify the difference between estimated and field-observed values. These criteria were then used to compare the performance of the six vegetation indices for AGB estimation.

2.5. Model Error Assessment

Model error was assessed by comparing AGB estimates from each vegetation-index model with field-derived AGB using the root mean square error (RMSE). RMSE was used to quantify the magnitude of differences between model-estimated and field-derived AGB within the dataset used for model development. Lower RMSE values indicate closer agreement between estimated and field-derived values. RMSE was calculated using Equation (14).

$$RMSE = \sqrt{\frac{\sum_{i=1}^n ((P_i - O_i)^2)}{n}} \quad (14)$$

where P_i is the model-estimated AGB, O_i is the field-derived AGB, and (n) is the number of observations.

RMSE was calculated separately for the models derived from NDVI, SAVI, MSAVI2, RVI, DVI, and GRVI to provide a consistent error-based comparison among the six vegetation indices.

3. RESULTS AND DISCUSSION

3.1. Field Inventory, Aboveground Biomass, and Carbon Stock

The field inventory recorded 1,127 trees representing 61 species. *Dipterocarpus obtusifolius* was the most abundant species, with 233 individuals, followed by *Xylia xylocarpa* (120 individuals) and *Rothmannia wittii* (65 individuals). The ten most abundant tree species are presented in **Table 1**.

Table 1.
Ten most abundant tree species recorded in the study area.

Rank	Scientific name	Number of individuals
1	<i>Dipterocarpus obtusifolius</i>	233
2	<i>Xylia xylocarpa</i>	120
3	<i>Rothmannia wittii</i> (Craib) Bremek.	65
4	<i>Hesperethusa crenulata</i> (Roxb.) Roem.	58
5	<i>Memecylon edule</i> Roxb.	55
6	<i>Cratoxylum formosum</i> (Jacq.) Benth. & Hook.f. ex Dyer	54
7	<i>Sindora siamensis</i>	50
8	<i>Cratoxylum formosum</i> subsp. <i>pruniflorum</i> (Kurz) Gogelein	43
9	<i>Ellipanthus tomentosus</i> Kurz	33
10	<i>Catunaregam tomentosa</i> (Blume ex DC.) Tirveng.	32

The total AGB recorded across the sampled plots was 71,915.93 kg (71.916 t). Stem biomass represented the largest component, accounting for 58,034.76 kg (58.035 t), followed by branch biomass at 11,763.19 kg (11.763 t) and leaf biomass at 2,117.99 kg (2.118 t). The predominance of stem biomass indicates that most of the aboveground carbon pool was associated with woody structural components rather than branches and foliage.

AGB and carbon stock were expressed on a per-hectare basis to compare the six sampling plots (**Table 2**). AGB ranged from 42.834 to 137.529 t ha⁻¹, while carbon stock ranged from 20.132 to 64.639 tC ha⁻¹. Plot 4 recorded the highest AGB (137.529 t ha⁻¹) and carbon stock (64.639 tC ha⁻¹), whereas Plot 2 had the lowest values, at 42.834 t ha⁻¹ and 20.132 tC ha⁻¹, respectively. Across all plots, mean AGB was 74.912 ± 35.235 t ha⁻¹ and mean carbon stock was 35.209 ± 16.560 tC ha⁻¹.

The differences among plots indicate considerable spatial variation in biomass within the sampled forest. Because carbon stock was calculated directly from AGB using the same carbon fraction, plots with greater AGB also had proportionally greater carbon stocks. Therefore, this

relationship should not be interpreted as an independent statistical association between biomass and carbon. Rather, the variation in carbon stock reflects the variation in field-derived AGB among plots. The relatively large standard deviations for both AGB and carbon stock further show that biomass was not uniformly distributed across the sampled forest.

Table 2.

Aboveground biomass and carbon stock across the six sampling plots.

Plot	AGB (t ha ⁻¹)	Carbon stock (tC ha ⁻¹)
1	78.187	36.748
2	42.834	20.132
3	48.897	22.982
4	137.529	64.639
5	87.439	41.097
6	54.587	25.656
Sum	449.473	211.252
Mean	74.912	35.209
SD	35.235	16.560

The species composition provides additional context for the field measurements. *D. obtusifolius* accounted for 233 of the 1,127 recorded trees and was substantially more abundant than the other species. However, abundance alone does not determine AGB because biomass estimates also depend on tree dimensions included in the allometric equations. Consequently, the dominance of a species by number of individuals should not be interpreted as evidence that it contributed the largest share of biomass unless species-level biomass is separately quantified.

3.2. Spatial Patterns of Fractional Vegetation Cover

Sentinel-2 imagery was used to derive fractional vegetation cover (FC) from six vegetation indices: NDVI, SAVI, MSAVI2, RVI, DVI, and GRVI. These indices represent different spectral responses and allow comparison of vegetation-cover conditions across the study area. The resulting FC distributions are presented in **Fig. 2**, where panels (a)–(f) represent FC_NDVI, FC_SAVI, FC_MSAVI2, FC_RVI, FC_DVI, and FC_GRVI, respectively.

All six FC products ranged from 0 to 100, although their class boundaries differed among indices (**Fig. 2**). For FC_NDVI and FC_SAVI, values of 0–56.862 represented low or non-vegetated areas, 56.862–79.607 represented intermediate vegetation cover, and 79.607–100 represented dense vegetation. FC_MSAVI2 produced lower class boundaries, with ranges of 0–38.039, 38.039–56.470, and 56.470–100 for low, intermediate, and dense vegetation cover, respectively.

FC_RVI showed corresponding ranges of 0–44.705, 44.705–65.098, and 65.098–100, while FC_DVI produced ranges of 0–50.196, 50.196–66.666, and 66.666–100. FC_GRVI showed ranges of 0–54.901, 54.901–81.960, and 81.960–100. Thus, among the six indices, MSAVI2 had the lowest threshold for the dense vegetation class (56.470), whereas GRVI had the highest (81.960).

Overall, the six FC maps depict a common spatial pattern of vegetation cover but differ in how vegetation density is separated. NDVI and SAVI produced the same class boundaries, whereas MSAVI2, RVI, DVI, and GRVI generated different thresholds. These differences reflect the distinct spectral formulations used by each vegetation index and indicate that the choice of index affects the representation of vegetation cover within the same forest landscape. In particular, the lower dense-vegetation threshold obtained from MSAVI2 shows that its FC transformation responds differently from those based on NDVI, SAVI, RVI, DVI, and GRVI. However, differences in FC class thresholds alone do not establish which index provides the most accurate representation of AGB or carbon stock. This requires direct comparison with the field measurements through the regression and model error analyses presented in the following sections.

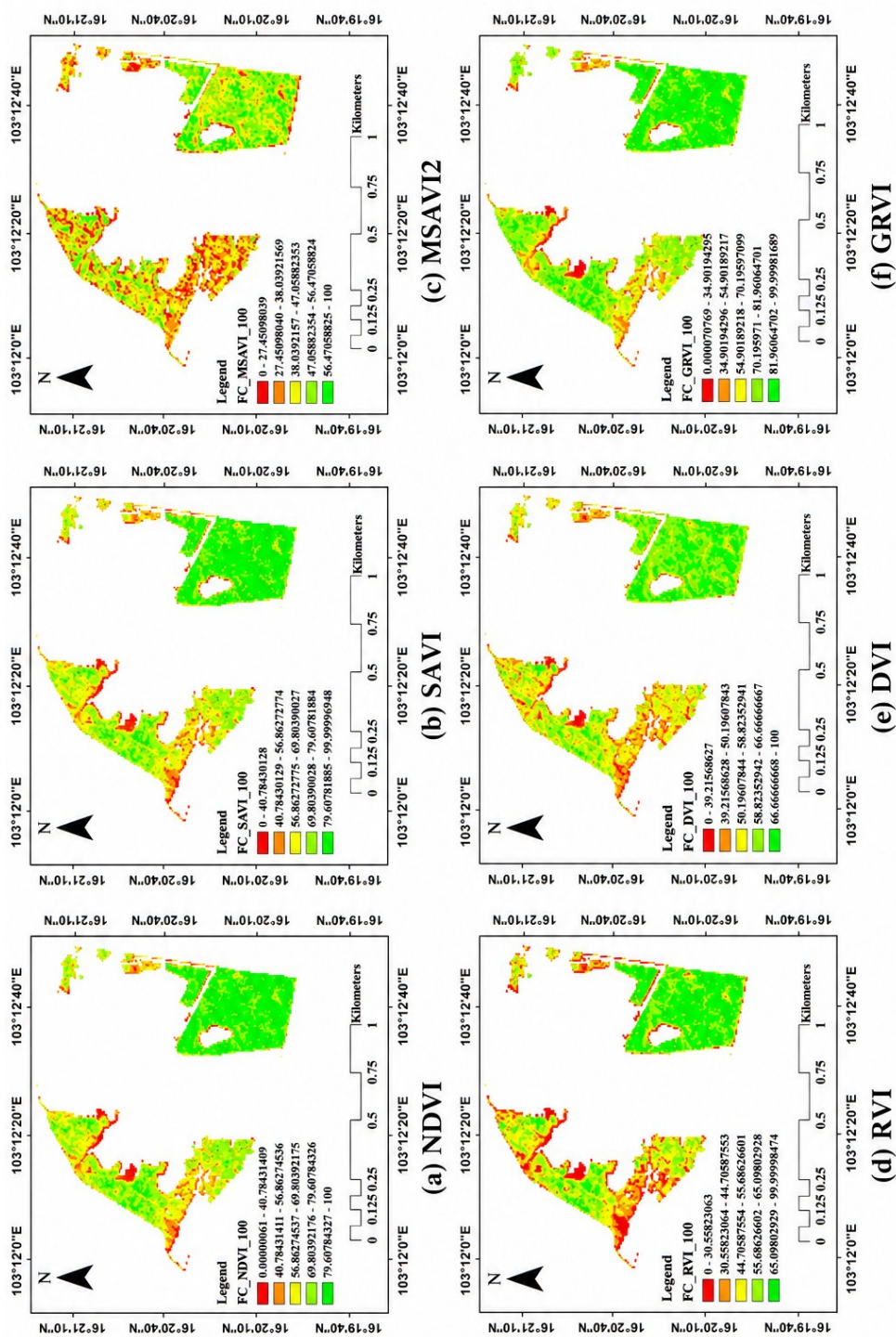


Fig. 2. Spatial distribution of fractional vegetation

3.3. Exponential Regression Model Performance

The relationships between fractional vegetation cover (FC) and field-derived aboveground biomass (AGB) were evaluated using exponential regression models developed separately for NDVI, SAVI, MSAVI2, RVI, DVI, and GRVI. The regression results for the six vegetation indices are presented in **Figure 3(a–f)**.

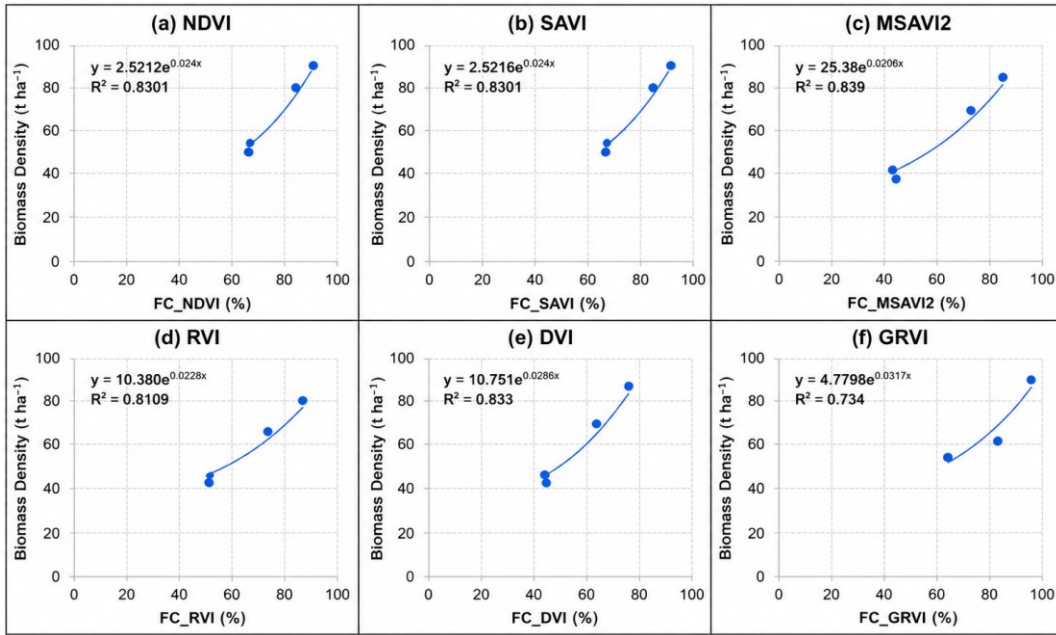


Fig. 3. Relationships between AGB and fractional vegetation cover.

All six models showed positive exponential relationships between FC and field-derived AGB, and the strength of these relationships was evaluated using the coefficient of determination (R^2). MSAVI2 produced the highest R^2 value of 0.839, followed by DVI ($R^2 = 0.833$), NDVI ($R^2 = 0.8301$), SAVI ($R^2 = 0.8301$), RVI ($R^2 = 0.8109$), and GRVI ($R^2 = 0.734$). These results indicate that MSAVI2 had the strongest relationship with field-derived AGB, whereas GRVI showed the weakest performance among the six vegetation indices. The exponential regression equations for each index are summarized in **Table 3**. MSAVI2 was described by $y = 25.38e^{0.0206x}$ ($R^2 = 0.839$), DVI by $y = 10.757e^{0.0286x}$ ($R^2 = 0.833$), and GRVI by $y = 4.7798e^{0.0317x}$ ($R^2 = 0.734$), while the remaining indices followed their respective fitted exponential models as presented in **Table 3**.

The strong performance of MSAVI2 in the present study is consistent with previous Sentinel-2 studies conducted under dry dipterocarp forest conditions. Laosuwan et al. (2025) applied Sentinel-2A imagery, MSAVI2, and fractional vegetation cover (FVC) to estimate aboveground biomass and carbon sequestration in a dry deciduous dipterocarp forest, demonstrating the applicability of MSAVI2 for biomass and carbon estimation under these forest conditions. Similarly, Itsarawisut et al. (2026) compared three Sentinel-2 vegetation indices—NDVI, SAVI, and MSAVI2—for biomass and carbon stock estimation in a tropical dry dipterocarp forest and identified MSAVI2 as the best-performing index among the three indices evaluated. The present study extends this comparison to six vegetation indices by additionally including RVI, DVI, and GRVI under the same field data and regression framework. MSAVI2 remained the strongest index in terms of the coefficient of determination ($R^2 = 0.839$), although SAVI produced the lowest RMSE. These findings provide further support for the usefulness of MSAVI2 in dry dipterocarp forest biomass assessment, while

also showing that the relative performance of vegetation indices depends on the evaluation criterion and the set of indices being compared.

NDVI and SAVI showed nearly identical performance, with the same R^2 value (0.8301) and very similar total carbon stock estimates of 1,464.780 and 1,465.034 tC, respectively. This similarity suggests that the soil-background adjustment incorporated in SAVI had only a limited influence on the biomass–vegetation index relationship under the conditions of this study. Although SAVI produced a lower RMSE than NDVI, their similar R^2 values and carbon stock estimates indicate that both indices responded similarly to the vegetation conditions represented by the field plots.

Although all models were derived from the same field-based biomass dataset, the response of AGB to FC varied among vegetation indices. The relatively close R^2 values obtained for MSAVI2, DVI, NDVI, and SAVI indicate that these indices captured similar proportions of the observed AGB variation. In contrast, the lower R^2 of GRVI indicates a weaker ability to represent biomass variation within the sampled forest. This variation among indices highlights the importance of evaluating multiple spectral metrics rather than selecting an index based solely on its general use in vegetation studies. The regression models were subsequently applied to estimate carbon stock across the study area, and the results are also summarized in **Table 3**. The estimated carbon stocks were 1,464.780 tC for NDVI, 1,465.034 tC for SAVI, 1,752.866 tC for MSAVI2, 1,505.763 tC for RVI, 1,600.873 tC for DVI, and 1,509.777 tC for GRVI, compared with the field-derived carbon stock of 1,807.721 tC. This direct comparison under the same field dataset and modeling framework demonstrates that vegetation-index selection can influence the strength of the relationship with field-derived AGB and the resulting carbon stock estimates. The results therefore provide an empirical basis for selecting spectral indices according to their performance in forest biomass and carbon assessment.

Table 3.
Comparison of regression performance and estimated carbon stock among the six vegetation indices.

Index	(R^2)	Estimated carbon stock (tC)	Difference from field (tC)	Difference (%)
NDVI	0.8301	1,464.780	−342.941	−18.97
SAVI	0.8301	1,465.034	−342.687	−18.96
MSAVI2	0.8390	1,752.866	−54.855	−3.03
RVI	0.8109	1,505.763	−301.958	−16.70
DVI	0.8330	1,600.873	−206.848	−11.44
GRVI	0.7340	1,509.777	−297.944	−16.48
Field data	—	1,807.721	—	—

All six satellite-based models underestimated the field-derived carbon stock, although the magnitude of the difference varied substantially among indices. MSAVI2 produced the closest estimate to the field value, differing by only 54.855 tC, or approximately 3.03%. DVI provided the second-closest estimate, with a difference of 206.848 tC or 11.44%. Larger underestimations were obtained from GRVI, RVI, SAVI, and NDVI. The results therefore indicate that the index with the strongest regression fit also produced the closest estimate of total carbon stock in this study.

The consistent underestimation of carbon stock by all six vegetation-index models may be related to the limited sensitivity of optical vegetation indices to variations in forest structure and biomass, particularly in areas with relatively dense canopy cover. In addition, differences in canopy condition, soil background, and the spatial correspondence between field plots and satellite pixels may have contributed to the lower satellite-derived estimates. These factors were not evaluated separately in this study and should therefore be considered as possible explanations rather than direct findings.

Model accuracy was further examined using RMSE. The RMSE values were 1.042 t ha^{−1} for NDVI, 0.901 t ha^{−1} for SAVI, 1.013 t ha^{−1} for MSAVI2, 1.103 t ha^{−1} for RVI, 1.036 t ha^{−1} for DVI, and 1.319 t ha^{−1} for GRVI. The corresponding RMSE% values were 1.549%, 1.339%, 1.506%,

1.640%, 1.540%, and 1.960%, respectively. SAVI produced the lowest RMSE, whereas GRVI had the highest prediction error.

The combined evaluation of (R^2), RMSE, and total carbon stock shows that model performance depended on the assessment criterion. MSAVI2 provided the strongest overall performance because it had the highest (R^2) and produced the carbon estimate closest to the field-derived value. SAVI, in contrast, achieved the lowest RMSE but substantially underestimated total carbon stock. DVI also performed well, combining a high (R^2) with the second-smallest difference from the field estimate. NDVI and SAVI produced nearly identical (R^2) values and total carbon estimates, while RVI showed slightly lower explanatory performance. GRVI had the lowest (R^2) and the highest RMSE among the six models.

These results demonstrate that no single accuracy statistic is sufficient to evaluate the vegetation indices. A high (R^2) reflects how well variation in FC corresponds to variation in field-derived AGB, whereas RMSE describes the magnitude of prediction error. Agreement in total carbon stock provides an additional measure of how closely the spatial estimate reproduces the field-derived total. Considering these measures together, MSAVI2 was the most suitable index among those evaluated for spatial estimation of AGB and carbon stock in the study area.

3.4. Model Accuracy Assessment

Model accuracy was evaluated using RMSE and RMSE% to quantify the differences between satellite-based and field-derived AGB estimates. The results showed relatively small errors across all six vegetation indices, with RMSE values ranging from 0.901 to 1.319 t ha⁻¹ and RMSE% values ranging from 1.339% to 1.960%. All six models therefore produced RMSE% values below 2%.

SAVI produced the lowest prediction error, with an RMSE of 0.901 t ha⁻¹ and an RMSE% of 1.339%. It was followed by MSAVI2 (1.013 t ha⁻¹; 1.506%), DVI (1.036 t ha⁻¹; 1.540%), NDVI (1.042 t ha⁻¹; 1.549%), and RVI (1.103 t ha⁻¹; 1.640%). GRVI showed the largest error, with an RMSE of 1.319 t ha⁻¹ and an RMSE% of 1.960%. The relatively narrow range among SAVI, MSAVI2, DVI, and NDVI indicates comparable prediction errors, whereas RVI and GRVI showed somewhat larger deviations from the field-derived values.

The different rankings obtained from R^2 , RMSE, and total carbon stock reflect different aspects of model performance. R^2 describes how well variation in field-derived AGB is explained by FC, whereas RMSE measures the magnitude of the differences between estimated and field-derived AGB within the model-development dataset. In contrast, the difference in total carbon stock indicates how closely the spatially aggregated model estimate agrees with the field-derived total. Therefore, an index showing the strongest relationship with AGB does not necessarily produce the lowest prediction error. In this study, MSAVI2 produced the highest R^2 and the closest total carbon estimate, whereas SAVI produced the lowest RMSE and RMSE%. These results indicate that the best-performing vegetation index depends on the evaluation criterion and the intended application.

The RMSE assessment therefore complements the regression and total carbon stock comparisons by providing a direct measure of prediction error. RMSE expresses the magnitude of error in the units of the estimated variable, whereas RMSE% allows relative comparison among the six models. From the error-based evaluation alone, SAVI provided the best performance because it produced the lowest RMSE and RMSE%. These error measures were derived from the model-development dataset and should therefore be interpreted as measures of model fit rather than independent predictive validation.

The performance of vegetation indices may also vary under different environmental and forest conditions. Differences in canopy density and soil exposure can affect the spectral response of vegetation indices, while forest type may influence the relationship between canopy characteristics and biomass. Image-acquisition season may further affect index performance because vegetation and canopy conditions can change throughout the year. Therefore, the relative performance of the six vegetation indices observed in this study should be interpreted in the context of the forest conditions and acquisition date used here, and their performance may differ when applied to other forest types or seasons.

4. CONCLUSIONS

This study evaluated the use of Sentinel-2 imagery and field inventory data for estimating aboveground biomass (AGB) and carbon stock in a dry dipterocarp forest. Six vegetation indices—NDVI, SAVI, MSAVI2, RVI, DVI, and GRVI—were transformed into fractional vegetation cover and evaluated using exponential regression models. The results demonstrated that all six indices were capable of representing variation in field-derived AGB, with R^2 values ranging from 0.734 to 0.839 and RMSE% values below 2%.

Among the six indices, MSAVI2 showed the strongest overall performance. It achieved the highest R^2 (0.839) and estimated a total carbon stock of 1,752.866 tC, which was closest to the field-derived value of 1,807.721 tC, with a difference of 3.03%. DVI also performed comparatively well, with $R^2=0.833$ and an estimated carbon stock of 1,600.873 tC. In contrast, SAVI produced the lowest prediction error (RMSE = 0.901 t ha⁻¹; RMSE% = 1.339%). NDVI, RVI, and GRVI also provided useful estimates, although their performance varied according to the evaluation criterion. These findings emphasize that vegetation-index selection should consider multiple performance measures rather than relying on a single statistic.

Several limitations should be considered when interpreting these results. The field dataset was obtained from a relatively limited number of sampling plots within a single forest area, which restricts the extent to which the developed relationships can be generalized to other forest conditions. In addition, the analysis relied on vegetation indices derived from Sentinel-2 imagery and did not incorporate other potentially informative variables related to forest structure or environmental conditions. The models should therefore be regarded as site-specific relationships that require further evaluation before broader application.

Future studies should increase the number and spatial distribution of field plots and evaluate the models across different forest types and observation periods. Multi-temporal satellite imagery could be incorporated to examine seasonal and interannual variation, while additional remote-sensing information from UAV or LiDAR observations could provide independent information on canopy structure. Machine-learning approaches may also be compared with the exponential models used here, particularly when larger field datasets become available. Such developments would allow the robustness and transferability of biomass estimates to be assessed more thoroughly.

Overall, the results demonstrate the potential of integrating Sentinel-2 vegetation indices with field observations for spatial assessment of AGB and carbon stock. The comparison of six indices provides a practical basis for selecting spectral information according to the intended application, with MSAVI2 providing the strongest overall performance in the present study and SAVI producing the lowest prediction error. With additional field validation and broader spatial and temporal testing, this approach could provide a practical basis for forest carbon monitoring and support forest management and carbon-accounting applications.

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