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ESTIMATION OF ABOVE-GROUND BIOMASS USING HYBRID MACHINE LEARNING BASED ON SATELLITE IMAGERY

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Abstract- This paper assesses the performance of different machine learning algorithms, specifically decision tree, support vector machines, k-nearest neighbors, and a hybrid model that integrates these techniques in estimating above-ground biomass (AGB) using remote sensing and field data. Vegetation indices derived from Sentinel-2A satellite imagery, such as NDVI, RVI, SAVI, and TNDVI, were analyzed for their correlation with AGB. The results indicated that while these indices provide valuable insights into vegetation health, their correlation with AGB is relatively weak. The hybrid model, which combines DT, SVM, and kNN, outperformed individual models, achieving the lowest RMSE (0.389), highest R^2 (0.803), and lowest MAE (0.287), thus providing the most accurate and reliable predictions of AGB. The geographic spread of AGB estimates indicated that the hybrid model produced more consistent and constrained estimates, emphasizing its robustness. These findings highlight the hybrid machine learning approach as a promising tool for improving the precision and reliability of AGB estimates, which is crucial for forest carbon storage assessment and ecological health monitoring. Future research should focus on incorporating data from other remote sensing platforms and exploring advanced machine learning algorithms to further enhance predictive performance.

Keywords: Remote Sensing, Vegetation Indices, Forest Carbon Storage, Decision Tree, Support Vector Machines, k-Nearest Neighbors, Hybrid Models.

1. INTRODUCTION

Forests are essential to the global carbon cycle and are integral to efforts aimed at mitigating climate change [1]. Carbon sequestration in forests refers to the process by which atmospheric carbon dioxide (CO_2) is absorbed by trees, plants, and soil, transforming it into biomass through photosynthesis and storing it in the form of carbon [2,3]. This natural process serves to reduce atmospheric CO_2 concentrations while also supporting biodiversity, water regulation, and soil fertility [4,5]. Forests significantly impact global warming by: 1) absorbing CO_2 and stabilizing Earth's temperature, 2) releasing vapor and increasing atmospheric moisture, and 3) providing land cover that reduces surface heat by blocking sunlight [6].

In recent decades, the importance of forests in carbon sequestration has gained significant attention due to the increasing levels of greenhouse gases and the urgent need to combat global warming [7]. Forests act as carbon sinks, capturing more carbon than they release, thus offsetting a portion of human-induced carbon emissions [8]. Sustainable forest management practices, including reforestation and afforestation, are essential strategies in enhancing the carbon sequestration capacity of forests [9].

One of the critical aspects of understanding and enhancing forest carbon sequestration is accurate measurement of carbon stored in trees. This involves various methods to estimate both above-ground and below-ground biomass. Above-ground biomass, which encompasses the carbon stored in trunks, branches, and leaves, is often measured using allometric equations. These equations correlate tree dimensions like diameter at breast height (DBH) and height to biomass [10,11]. These equations are developed from extensive field data and can vary depending on species, region, and forest type.

Remote sensing technologies, especially satellite imagery, has become a valuable tool in monitoring the environment [12,13] and assessing the biodiversity of forests on a larger scale. It facilitates mapping and monitoring carbon quantities in forests with detailed spatial resolution and high accuracy [14]. Vegetation indices derived from satellite data, including the normalized difference vegetation index (NDVI) that quantifies vegetation health and density, and the enhanced vegetation index (EVI) which assesses vegetation greenness, offer insights into forest health and productivity, directly linked to carbon sequestration potential [15]. Additionally, other vegetation indices serve specific purposes: soil-adjusted vegetation index (SAVI) corrects for soil brightness effects in low vegetation areas in NDVI. Ratio vegetation index (RVI) highlights healthy vegetation, while transformed normalized difference vegetation index (TNDVI) correlates with the quantity of green biomass.

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These indices have been developed to enhance precision in vegetation monitoring and biomass estimation. Traditionally, carbon stock estimation has relied heavily on regression-based models that use linear or non-linear regression techniques to correlate field-measured biomass with vegetation indices. For example, simple linear regression might correlate NDVI values with biomass measurements, while more complex approaches could include multiple regression models incorporating various indices and environmental variables. While effective, these regression models can be limited by their assumptions of linearity and the need for extensive field data for calibration [16].

In recent years, machine learning techniques have emerged as robust alternatives for carbon estimation. These methods process extensive datasets and capturing intricate, non-linear connection between remote sensing variables and biomass. Various machine learning algorithms have shown significant promise in enhancing the accuracy of biomass and carbon stock predictions. For instance, random forests and support vector machine (SVM) can model intricate patterns in the data without the strict assumptions required by traditional regression methods, thus providing more robust and flexible tools for carbon estimation [17]. Moreover, hybrid approaches that combine multiple machine learning methods have been developed to further enhance prediction accuracy. By leveraging the strengths of different algorithms, these hybrid models can better generalize across various forest types and conditions, offering more reliable estimates of carbon sequestration potential [18].

To advance the estimation of above-ground biomass (AGB) sequestration in forests, the objective of this paper aims to employ hybrid machine learning techniques. Through the integration of multiple machine learning algorithms, to enhance the reliability of carbon stock estimates derived from remote sensing data. Specifically, will investigate the combined application of decision tree (DT), SVM, and k-nearest neighbors (kNN) for analyzing vegetation indices like NDVI, SAVI, RVI, and TNDVI.

2. MATERIAL AND METHOD

2.1. Study Area

Phu Faek Forest Park, located in Kalasin Province, Thailand, serves as the study area for this research. This forest park is renowned for its rich biodiversity and complex ecosystem, encompassing a range of topographical features from lowland areas to rolling hills. The park's landscape is characterized by its diverse flora, which includes various species of trees, shrubs, and ground vegetation [19] that contribute significantly to its ecological value and carbon sequestration potential. The region is characterized by a tropical climate featuring distinct wet and dry seasons, which significantly influence the growth patterns and health of the forest. The wet season, typically from May to October, is marked by heavy rainfall, fostering lush vegetation growth. In contrast, the dry season, from November to April, brings lower humidity and reduced precipitation, affecting the forest's water retention and biomass productivity. Phu Faek Forest Park covers an area of approximately 6.5 square kilometers, and it plays a crucial role in regional environmental conservation efforts. The park is part of the larger forest network in the northeastern region of Thailand, contributing to the area's ecological stability and biodiversity conservation.

2.2. Data Collection

The data collection methodology for this study incorporated both field measurements and remote sensing data to estimate AGB sequestration in Phu Faek Forest Park. To obtain accurate field data, the sampling plot was designed using the stratified random sampling method, ensuring that different strata or layers of the forest are represented for comprehensive analysis. Primary sample plots of size 40×40 meters were established across the study area, distributed randomly within various strata to capture variability in vegetation types and densities. Within each 40×40 meters plot, four subplots of 20×20 meters were delineated systematically to ensure thorough coverage and facilitate detailed measurements.

All trees within the primary and subplots were measured and recorded. Each tree's height was assessed at 1.30 meters above the ground, a standard practice known as diameter at breast height (DBH). Each tree was documented with the following details: species identification (botanical name), DBH, and tree height. This meticulous approach to data collection ensures that the dataset is comprehensive and representative of the forest's structural diversity, which is crucial for accurate carbon estimation.

2.3. Data Set for Satellite Analysis

This paper, satellite imagery from the Sentinel-2 satellite was utilized to analyze various vegetation indices crucial for estimating above-ground carbon sequestration. Sentinel-2 provides high-resolution optical imagery that is particularly suitable for environmental monitoring and agricultural applications [20]. The data were acquired for the Phu Faek Forest Park area, focusing on the spectral bands necessary for the calculation of the following vegetation indices: NDVI, SAVI, RVI, and TNDVI. Vegetation indices are advantageous as they can indicate the health of the forest through remote sensing imagery. In this study, higher values of these indices represent good forest health and dense vegetation, while lower or negative values indicate poor health or lack of vegetation [21]. NDVI is derived from the near-infrared (NIR) and red (RED) bands of the Sentinel-2 imagery:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \tag{1}$$

SAVI is specifically designed to reduce impact of soil brightness in regions where vegetation cover is sparse [22]:

$$SAVI = \frac{(1+L) \times NIR - RED}{NIR + RED} \tag{2}$$

RVI uses NIR and RED bands to assess vegetation [23]:

$$RVI = \frac{NIR}{RED} \tag{3}$$

TNDVI is a transformation of the NDVI to enhance vegetation monitoring [24]:

$$TNDVI = \sqrt{\frac{NIR - RED}{NIR + RED}} + 0.5 \quad (4)$$

2.4. Methodology

The methodology of this research was structured as follows. The field data collection process was meticulously planned to ensure comprehensive sampling and accurate measurements. Initial plot locations were precisely determined using GPS receivers or compasses, along with measuring tapes to accurately mark coordinates on the map. Primary sampling plots were laid out with dimensions of 40 meters by 40 meters, strategically positioned within the study area. Within each primary plot, the area was further subdivided into four subplots, each measuring 20 meters by 20 meters. These subplots were systematically positioned to cover the primary plot thoroughly and facilitate detailed measurements of vegetation and trees. Data recorded for each tree included species identification, DBH measured with a diameter tape, and total height measured using a clinometer or hypsometer. Estimating above-ground carbon sequestration from allometric equations involves using mathematical equations based on the DBH and tree height measurements.

The analysis of AGB sequestration utilized satellite imagery from Sentinel-2, which provided high-resolution spectral bands essential for calculating vegetation indices: NDVI, SAVI, RVI, and TNDVI. To establish relationships between vegetation indices and AGB sequestration, several machine learning models were employed. These included DT, kNN, SVM, and Hybrid models. The models were trained and evaluated using both field-measured data and remote sensing indices to predict carbon sequestration potential across the study area. Performance evaluation of each machine.

2.4.1. Estimating Above-Ground Biomass

Okawa's method for estimating above-ground biomass relies on specific allometric equations that relate DBH and tree height to biomass [25]. These equations are essential in forest ecology and carbon accounting studies, providing a quantitative approach to assess tree biomass using easily measurable variables. The allometric equations used in Okawa's method are derived from field measurements and statistical analyses across various tree species and forest types [26]. The equations include:

$$Ws = 0.0396 D^2 H^{0.9326} \quad (5)$$

$$Wb = 0.003489 D^2 H^{1.0270} \quad (6)$$

$$Wl = (28.0 / Wtc + 0.025)^{-1} \quad (7)$$

where, D is the DBH, H is the height, Ws is the stem, Wb is the branch, and Wl is the above-ground biomass.

2.4.2. Above-Ground Carbon Sequestration with Hybrid Machine Learning

Machine learning is pivotal in estimating above-ground carbon sequestration due to its capability to manage complex, multi-dimensional data and uncover patterns effectively. Machine learning has led to the development of various algorithms for geospatial predictive modelling, significantly advancing environmental research [27]. Hybrid machine learning leverages the strengths of multiple algorithms, combining their individual capabilities to achieve higher predictive accuracy and robustness in solving complex problems. This paper specifically employs DT, SVM, and kNN in our hybrid approach.

DT are versatile supervised machine learning algorithms utilized for classification as well as regression tasks. These algorithms partition the data recursively into subsets at each decision node based on the most informative features [28]. This process creates a hierarchical tree structure where each internal node signifies a feature or attribute, and each branch represents a decision rule, culminating in final predictions or classifications at the leaf nodes. The SVM algorithm is highly regarded for its effectiveness in classification tasks. It achieves this by identifying a hyperplane that maximizes the margin, or distance, between the support vectors (data points) of different classes [29]. This approach aims to create a clear separation between classes, enhancing the algorithm's ability to accurately classify new data points. SVM offers advantages such as avoiding majority voting through the transformation of training variables into new, non-probabilistic binary linear classes, superior performance with limited datasets, effectiveness even without prior dataset information, precise evaluation with minimal training samples, and reduced susceptibility to overfitting and high-dimensional data [30]. kNN is a simple yet robust algorithm that predicts outcomes based on data point similarities. It computes distances from a new data point to all training points to identify its k nearest neighbors. In classification tasks, kNN determine the predominant class among these neighbors. For regression tasks, it calculates a weighted average based on the target values from the k neighbors, giving greater weight to closer neighbors in the feature space.

Hybrid machine learning refers to integrating multiple techniques or models to enhance predictive performance and tackle specific challenges in data analysis. This approach leverages the strengths of different algorithms or methodologies. In the context of estimating above ground biomass, a hybrid approach combining DT, SVM, and kNN capitalizes on each algorithm's unique strengths to improve accuracy and robustness. This hybrid model combines multiple individual classifiers to achieve more accurate and reliable predictions compared to using any single model alone [30].

2.4.3. Accuracy Assessment

Accuracy assessment in machine learning involves evaluating how well a model predicts outcomes compared to actual observations. Three commonly used metrics for this assessment are root mean squared error (RMSE), coefficient of determination (R^2), and mean absolute error (MAE). These metrics quantify the discrepancy between predicted and observed values, providing insights into the model's predictive performance and reliability.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_{is} - y_{it})^2}{N}} \quad (8)$$

$$MAE = \frac{\sum_{i=1}^{N}|y_{is} - y_{it}|}{N} \quad (9)$$

$$R^2 = 1 - \sum_{i=1}^{N}(y_{is} - y_{it})^2 / \sum_{i=1}^{N}(y_{is} - \overline{y}_{is})^2 \quad (10)$$

where, y_{is} is AGB predicted, y_{it} is AGB observed, $\overline{y}_{is}$ is the average predicted of AGB, and N represents sample size.

3. RESULTS

3.1. Relationships between AGB and Vegetation Indices

The data collection from 50 sample plots, each measuring 40 meters by 40 meters, recorded a total of 4,602 trees. The estimation of AGB using allometric equations yielded the following results: stem biomass (Ws) was 3,157,246.62 kg, branch biomass (Wb) was 784,801.01 kg, and leaf biomass (Wl) was 64,093.83 kg. The total above-ground biomass (AGB) was calculated to be 4,006,141.48 kg. The corresponding carbon density was estimated to be 1,882.88 tCO_2. The analysis of vegetation indices derived from Sentinel-2A satellite imagery revealed the following results across the study area: NDVI were 0.056 to 0.428, RVI were 0.832 to 1.187, SAVI were 0.786 to 0.321, and TNDVI were 0.310 to 0.863. These indices provide valuable insights into the health, density, and greenness of the vegetation within the study area. NDVI, with its range of 0.056 to 0.428, indicates varying levels of vegetation health and productivity. RVI, ranging from 0.832 to 1.187, highlights the relative density of the vegetation cover. SAVI, with values between 0.786 and 0.321, adjusts for soil brightness, providing a clearer assessment of vegetation health in less dense areas. Lastly, TNDVI, ranging from 0.310 to 0.863, offers a transformed perspective on vegetation greenness, enhancing the contrast between healthy and stressed vegetation.

The relationships between AGB and vegetation indices were analyzed using a statistical model of correlation coefficients (r). The results showed that AGB had a weak positive correlation with NDVI ($r = 0.14$), RVI ($r = -0.14$), SAVI ($r = 0.14$), and TNDVI ($r = 0.13$). These correlations indicate that, although there is some degree of association between AGB and the vegetation indices, it is relatively low. The scatter plots illustrating these relationships are shown in Figure 1.

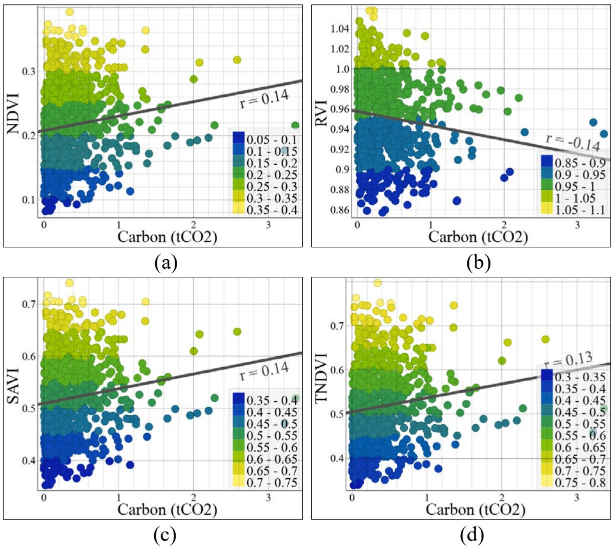

Figure 1. Scatter plots depicting the AGB and vegetation indices: (a) NDVI, (b) RVI, (c) SAVI, and (d) TNDVI.

3.2. Comparison of Machine Learning Model for Estimated AGB

Learning models is crucial for precise evaluation of above-ground biomass (AGB). This section evaluates the predictive performance of prominent machine learning algorithms DT, SVM, and kNN alongside a hybrid approach combining DT, SVM, and kNN. These models are assessed based on their capability to predict AGB using a combination of remote sensing data and field measurements. Key metrics used for this assessment include $RMSE$, R^2, and MAE, which are presented in Table 1.

Table 1. Accuracy assessment of machine learning model for estimated AGB

Model	$RMSE$	R^2	MAE
DT	0.305	0.782	0.205
SVM	0.453	0.693	0.298
kNN	0.342	0.63	0.240
Hybrid (DT+SVM+kNN)	0.285	0.803	0.172

Table 1 demonstrates that the hybrid model (combining DT, SVM, and kNN) exhibits superior overall performance compared to the individual models. It achieves the lowest RMSE, highest R-squared, and lowest MAE, indicating more accurate and reliable predictions of AGB. The results of the estimated AGB spatial data model from machine learning indicate a range of values for each method. The estimates of AGB using DT range from 0.011 to 1.820 tCO_2, SVM estimates range from 0.055 to 0.550 tCO_2, kNN estimates range from 0.036 to 1.434 tCO_2, and the hybrid machine learning model estimates range from 0.326 to 0.423 tCO_2, as shown in Figures 2, 3, 4 and 5, respectively. In these figures, the green indicates low carbon sequestration, signifies high carbon values as predicted by the model. Furthermore, the estimated total carbon sequestration for the machine learning models DT, SVM, kNN, and Hybrid are provided in Table 2. These totals reflect the cumulative AGB predictions for the study area, highlighting the differences in carbon sequestration estimates among the models.

4. CONCLUSIONS

This paper evaluated the effectiveness of different machine learning models DT, SVM, kNN, and a hybrid approach combining these algorithms in estimating AGB using remote sensing and field data. The main findings can be summarized as follows: The analysis of vegetation indices derived from Sentinel-2A satellite imagery showed that indices such as NDVI, RVI, SAVI, and TNDVI provide valuable insights into vegetation health, density, and greenness.

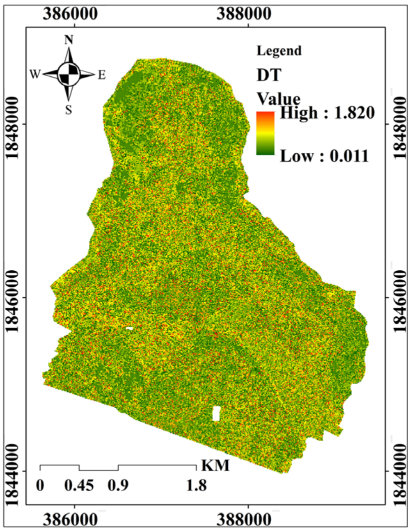

Figure 2. The estimated AGB using Decision Tree analysis

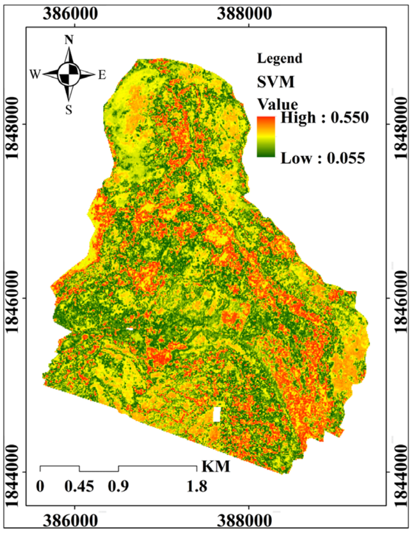

Figure 3. The estimated AGB using Support Vector Machine analysis

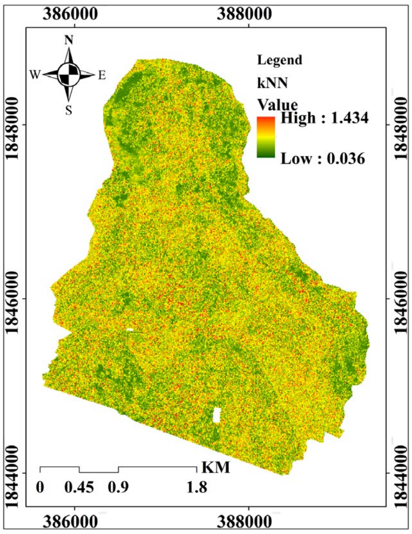

Figure 4. The estimated AGB using k-Nearest Neighbors analysis

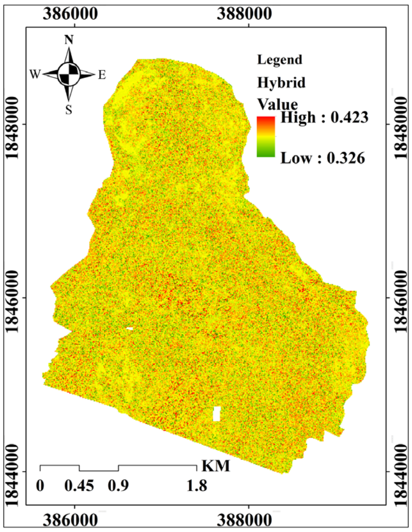

Figure 5. The estimated AGB using Hybrid analysis

Table 2. Comparison of Total Above-Ground Biomass (AGB) Carbon

Model	AGB carbon (tCO_2)
DT	25,723.66
SVM	17,777.21
kNN	24,906.59
Hybrid (DT+SVM+kNN)	24,841.29

However, the correlation between these indices and AGB was relatively weak, indicating that while useful, vegetation indices alone may not fully capture the complexity of AGB estimation. The comparison of machine learning models undicated that the hybrid model, which combines DT, SVM, and kNN, demonstrated superior performance in predicting AGB. The hybrid model achieved the lowest RMSE of 0.389, the highest R^2 of 0.803, and the lowest MAE of 0.287, suggesting it provides the most accurate and reliable predictions of AGB compared to individual models.

The spatial distribution of AGB estimates varied across the different models. DT estimates ranged from 0.011 to 1.820 tCO2, SVM estimates ranged from 0.055 to 0.550 tCO2, kNN estimates ranged from 0.036 to 1.434 tCO2, and the hybrid model estimates ranged from 0.326 to 0.423 tCO2. The hybrid model provided more consistent and constrained estimates, highlighting its robustness in AGB prediction. Accurate estimation of AGB is crucial for assessing forest carbon storage and ecological health. The hybrid machine learning approach, leveraging the strengths of DT, SVM, and kNN, offers a promising tool for improving the precision and reliability of AGB estimates. This has significant implications for environmental monitoring, carbon accounting, and the development of effective forest management and conservation strategies. Future work should consider incorporating data from other remote sensing platforms (e.g., LiDAR, hyperspectral imagery) to improve the accuracy and resolution of AGB estimates and Exploring techniques such as deep learning, which may provide further improvements in predictive performance.

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