VOL. 21, NO. 11, JUNE 2026 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences
©2006-2026 Asian Research Publishing Network (ARPN). All rights reserved.
www.arpnjournals.com

SPATIAL MODELING OF ABOVEGROUND BIOMASS AND CARBON STOCK THROUGH VEGETATION INDICES AND EXPONENTIAL REGRESSION

Jumpol Itsarawisut[1,2], Teerawong Laosuwan[1,2], Tanutdech Rotjanakusol[1,2], Natcha Laosuwan[1], Phaisarn Jeefoo[3], Maharaja Singharaj[3], Kongkiet Lucknuch[4] and Somwung Srimoongkoon[4]
[1]Department of Physics, Faculty of Science, Mahasarakham University, Maha Sarakham, Thailand
[2]Space Technology and Geoinformatics Research Unit, Faculty of Science, Mahasarakham University, Mahasarakham, Thailand
[3]Geographic Information Science, School of Information and Communication Technology, University of Phayao, Phayao, Thailand
[4]Merchant Marine Training Center, Marine Department Bang Duan, Mueang Samut Prakan, Samut Prakan, Thailand
E-Mail: teerawong@msu.ac.th

ABSTRACT

The rapid accumulation of atmospheric CO_2 is a leading cause of global warming that has profound implications for ecosystem functioning and human welfare. Objective The purpose of this study was to develop a reliable method for estimating aboveground biomass (AGB) and potential carbon sequestration capacities in trees by using remote sensing data as well as field-based measurements. The initial analysis was based on the Sentinel-2 vegetation indices (SAVI, MSAVI2 and GNDVI). Field data were next measured in systematically selected sample plots, the AGB and carbon content were estimated using allometric equations. The association between AGB and VIs was modelled by an exponential relationship to produce spatially explicit estimates of biomass. It was observed that GNDVI produced the best estimation for both the total above ground biomass and total carbon stock, estimated at 2,798.23 tons and 1,315.17 tons, respectively. These results demonstrate the important role that remote sensing and ground observations play in obtaining reliable biomass and carbon estimates to support sustainable management of natural resources, planning of urban green spaces, and strategies for mitigating climate change.

Keywords: remote sensing, aboveground biomass, carbon sequestration, vegetation indices, climate change.

Manuscript Received 2 April 2026; Revised 11 May 2026; Published 10 August 2026

INTRODUCTION

Climate change and the increase in the emission of greenhouse gases (GHGs) have become challenging problems for human beings around the globe [1]. Deterioration of air quality is mainly attributed to global warming, and the accumulating quantity of released carbon dioxide (CO_2) into the environment serves as one reason [2]. Such emissions are mainly due to fossil fuel burning in industry, transport and everyday energy utilization [3, 4]. The resulting increase in average temperature across the globe has caused major climatic alterations with devastating effects on biodiversity [5]. Many plant and animal species are undergoing modifications of their habitats, some even at risk of extinction resulting from their limited capacity to adapt to faster environmental changes [6]. In addition to the biodiversity loss, climate change disturbs ecosystem stability, negating the life-sustaining system of nature [7]. Farming, too, has suffered, as hotter temperatures and uncertain weather lead to decreased productivity. Arable lands which used to be fertile are increasingly battling seasonal rains, out-of-season downpours, or recurring droughts, forcing farmers to redefine appropriate climate-resilient crops and planting calendars [8]. Concurrently, human health is suffering from increasing challenges, such as increased prevalence of heat-related illnesses and diseases associated with air pollution [9].

Urban tree cover provides a tangible approach to climate change adaptation by exploiting ecosystem services. Trees are important in the sequestration of atmospheric carbon, mitigation of urban heat effects, provision for biodiversity, as well as enhancing air and water quality [10]. In addition to their ecological function, urban trees play a role in increasing livability by mitigating psychological stress and reinforcing the mental health of city residents [11]. To optimize these benefits, planning and managing urban green spaces in a systematic way are required; therefore, urban tree planting forms a key part of climate change actions and adaptation [12].

Plant biomass is one of the nature's best resources for capturing C from free atmosphere in nature which stored as organic carbon into plant tissue [13]. The quantification of AGB and carbon sequestered in AGB across various landscapes enhances knowledge on the vegetation role for carbon storage and contributes to sustainable natural resources management [14]. Higher AGB also contributes to mitigating urban heat islands and improving the quality of life in cities [15]. Carbon stored in the trees is strongly correlated to their biomass- the total mass of stems, branches, leaves, and roots [16]. Therefore, tree morphological or structural characteristics - like height, stem diameter, and crown width - are normally employed to estimate the stored carbon by means of allometric equations with aboveground versus belowground biomass relationships for trees [17].

©2006-2026 Asian Research Publishing Network (ARPN). All rights reserved.

Recent advances in geospatial science-especially in remote sensing-have offered powerful solutions to address the labor-intensive and time-consuming limitations of conventional field surveys [18-20]. Satellite imagery and aerial photographs enable large-scale, precise, and rapid assessments of biomass and carbon sequestration, significantly improving survey efficiency and reducing costs [21, 22]. Remote sensing further facilitates long-term monitoring of biomass dynamics, offering accurate and timely insights into the impacts of management interventions and policy measures. Against this backdrop, this study focuses on estimating the aboveground biomass and carbon stock of urban forests by integrating Sentinel-2 imagery with field measurements. The findings provide valuable insights into the application of vegetation indices for urban biomass modeling and deliver policy-relevant recommendations for green space planning and carbon credit assessment.

Recent developments in geospatial science, notably remote sensing, provide effective methods to overcome the labour-intensive and time-consuming character of traditional field investigations [18-20]. The visualization of satellite and aerial images for biomass and carbon estimation by rapid mapping can provide large scale accurate results, which reduces survey time and cost [21, 22]. Remote sensing also provides long-term monitoring of biomass dynamics, which results in an accurate and timely assessment of the effects of management interventions and policy measures. In this context, we aim to estimate the AGB and carbon stock of urban forests by the use of Sentinel-2 imagery combined at field measurements. These results contribute significantly to the use of vegetative indices in urban biomass modelling and generate a series of policy implications for green space planning and carbon credit estimation.

MATERIALS AND METHODS

Study Area

The research was carried out in the residual area of Mahasarakham University, which could be used as a model for an urban site to estimate carbon stocks of urban trees (Figure-1). It is located at coordinates 3164.71.52 E and 1791741.78 N in Talat Sub-district, Mueang Mahasarakham District, Mahasarakham Province of the northeastern region of Thailand. The province is an area of level to gently undulating terrain with elevation between 130 -230 meters above sea level. Climate the climate of the locality is designated as Tropical Monsoon, with well-marked wet and dry seasons resulting from the southwesterly monsoon wind regime from the Indian Ocean. Average temperature is 27.4 °C, with mean minimum and maximum temperatures of 22.4 °C and 33.7 °C respectively. April is usually the warmest and buggiest month of the year, taking into account annual weather patterns that mark this place's climate.

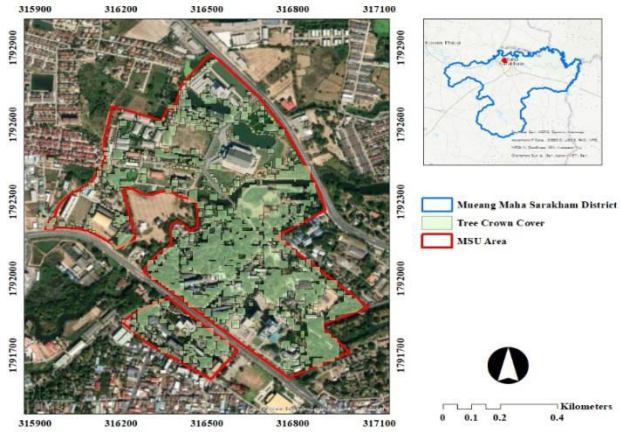


Figure-1. Study area.

Field Data Collection

Field data collection was conducted by first identifying tree species and measuring the dimensions of all trees with a diameter at breast height (DBH) greater than 4.5 cm, taken at 1.30 m above ground level. Thirty sample plots, each measuring 20 × 20 m, were systematically established across the study area to represent site variability. DBH was measured using a diameter tape, while tree height (H) was determined with a laser rangefinder to ensure measurement accuracy.

Tree growth assessment focused on DBH and height, as these parameters are key indicators of tree development and form the basis for biomass estimation. After field measurements were obtained, aboveground biomass (AGB) was calculated using established allometric equations (Equation 1) [23], which convert growth measurements into biomass values. These biomass estimates were then used to calculate carbon stock by applying Equation 2. For this conversion, the IPCC default wood carbon fraction of 0.47 was applied, indicating that 47% of the dry mass of aboveground tree components consists of carbon [24].

$$W_S = 0.0396(D^2H)^{0.933}$$
$$W_B = 0.00349(D^2H)^{1.030}$$
$$W_L = \left(\frac{28}{W_S + W_B} + 0.025\right)^{-1}$$
$$W_T = W_S + W_B + W_L \quad (1)$$

In this study, D represents the diameter at breast height (cm), H indicates the total tree height (m), while WS, WB, and WL correspond to the biomass of stems, branches, and leaves, respectively, expressed in tons per hectare (t/ha).

$$C_j = W_{tc} \times FC \quad (2)$$

In this equation, Cj refers to the carbon storage potential of an individual tree (kg), Wtc indicates its

©2006-2026 Asian Research Publishing Network (ARPN). All rights reserved.

aboveground biomass (kg), and *FC* represents the carbon fraction of the biomass, which is assumed to be 0.47.

Satellite Image Processing

In this study, Sentinel-2 satellite imagery was employed as the primary data source to evaluate vegetation conditions within the study area. Vegetation characteristics were assessed using three widely recognized vegetation indices: the Soil-Adjusted Vegetation Index (SAVI) [25], the Modified Soil-Adjusted Vegetation Index (MSAVI) [26], and the Green Normalized Difference Vegetation Index (GNDVI) [27]. Each index was calculated using Equations 3 through 5, respectively. Once the index values were derived, they were subsequently used to compute the Fractional Green Vegetation Cover (FC) through Equation 6. This transformation converts vegetation index data into a form that explicitly represents the proportion of surface area covered by green vegetation.

$$SAVI = \frac{(NIR - RED) \times (1 + L)}{(NIR + RED + L)} \quad (3)$$

In this context, NIR refers to the near-infrared reflectance, Red corresponds to the reflectance in the red spectral band, and L is the soil brightness correction factor used to minimize the effect of soil background on vegetation signals. The value of L typically ranges from 0, representing areas with very dense vegetation, to 1 for bare soil, with 0.5 frequently adopted for sites with moderate vegetation cover.

$$MSAVI = (1/2) * (2(NIR + 1) - sqrt((2 * NIR + 1)^2 - 8(NIR - Red))) \quad (4)$$

In this equation, NIR refers to the near-infrared spectral band, while Red corresponds to the red band. The MSAVI2 index was developed to minimize the impact of exposed soil on vegetation measurements, making it particularly suitable for regions with low or patchy vegetation cover.

$$GNDVI = \frac{NIR - GREEN}{NIR + GREEN} \quad (5)$$

In this equation, GREEN refers to reflectance within the green portion of the spectrum, while RED indicates reflectance in the visible red band. Unlike the conventional NDVI, this index substitutes the near-infrared (NIR) band with the green band, allowing for a slightly different sensitivity to vegetation characteristics

Relationship Analysis using an Exponential Regression

To estimate aboveground biomass (AGB) from Sentinel-2 satellite imagery, analyzing the relationship between Fractional Green Vegetation Cover (FC) and AGB is a crucial step for predicting biomass across larger spatial scales. In this study, the relationship was modeled using an exponential regression approach. The results of the model demonstrated a clear and consistent trend: AGB increases at an accelerating rate as FC values rise. This pattern reflects the capacity of vegetation within the study area to accumulate biomass in proportion to the greenness levels detected from satellite imagery. The use of exponential regression proved to be an effective method for translating remotely sensed vegetation information into practical biomass estimates. This approach enhances the reliability of spatial biomass mapping and provides a robust foundation for subsequent carbon stock assessment and management applications.

Model Accuracy Assessment

Evaluating the precision of the model employed to estimate aboveground biomass (AGB) requires a comparison between predicted values and actual field measurements. In this study, model performance was quantified using the Root Mean Square Error (RMSE). The RMSE is derived by calculating the difference between observed and predicted values, squaring these differences, averaging the squared residuals, and finally taking the square root of the mean. This statistic provides a direct measure of the prediction error, with smaller RMSE values signifying a closer agreement between model outputs and observed data, thereby indicating higher model reliability. Within the context of this study—where satellite imagery and vegetation indices were applied for AGB estimation-RMSE served as a key indicator for validating the robustness of the developed model. Beyond assessing accuracy, the RMSE results highlight potential areas where model adjustments may be required to enhance predictive performance. Its inclusion in the analytical workflow ensures that the biomass estimation process remains statistically sound and that the outputs are suitable for decision-making and practical resource management.

RESULTS

Physical Tree Data and Aboveground Biomass

Field measurements were conducted in October 2024, at the end of the rainy season, when weather conditions were favorable for efficient data collection. Within each of the 30 sample plots, two key tree parameters-diameter at breast height (DBH) and total height (H)-were measured. Plot coordinates were recorded with a GPS device to ensure accurate spatial referencing. The DBH and height data were used to calculate aboveground biomass (AGB) by applying species-appropriate allometric equations. Table-1 summarizes the results, presenting mean DBH, mean height, and the summed biomass of branches, stems, and leaves for each plot, as well as the total AGB expressed in kilograms, tons per 400 m², and tons per hectare.

©2006-2026 Asian Research Publishing Network (ARPN). All rights reserved.

Table-1. Aboveground biomass of trees in 30 sample plots.

Plot	Mean DBH (cm)	Mean H (m)	Branch Biomass (kg)	Stem Biomass (kg)	Leaf Biomass (kg)	Total AGB (kg)	Total AGB (ton/400 m²)	Total AGB (ton/ha)
01	21.23	7.23	235.08	1,156.81	49.72	1,441.61	1.44	36.04
02	21.69	5.43	1,079.90	3,949.66	179.64	5,209.20	5.21	130.23
03	22.36	8.23	271.52	1,338.01	57.49	1,667.02	1.67	41.68
04	19.78	7.94	310.43	1,501.53	64.73	1,876.69	1.88	46.92
05	38.48	12.00	1,439.85	5,754.56	256.95	7,451.36	7.45	186.28
06	35.65	10.67	476.37	2,043.86	90.01	2,610.25	2.61	65.26
07	37.40	14.13	1,104.23	4,421.06	197.34	5,722.63	5.72	143.07
08	28.46	10.60	489.38	2,206.36	96.29	2,792.02	2.79	69.80
09	67.48	21.75	2,032.66	7,474.00	339.53	9,846.19	9.85	246.15
10	65.49	17.50	2,023.25	7,208.00	329.69	9,560.95	9.56	239.02
11	58.09	19.50	2,958.65	11,109.71	502.45	14,570.81	14.57	364.27
12	31.19	10.14	600.32	2,424.50	108.04	3,132.86	3.13	78.32
13	7.79	5.74	48.15	271.45	11.43	331.03	0.33	8.28
14	22.18	8.89	456.61	1,939.73	85.59	2,481.94	2.48	62.05
15	35.57	10.25	870.19	3,120.51	142.53	4,133.22	4.13	103.33
16	30.74	13.00	1,181.44	5,036.95	222.10	6,440.48	6.44	161.01
17	14.26	7.21	291.33	1,356.14	58.86	1,706.33	1.71	42.66
18	29.33	10.43	1,116.56	4,031.71	183.87	5,332.14	5.33	133.30
19	27.25	12.13	2,817.58	9,878.23	453.44	13,149.25	13.15	328.73
20	28.03	10.50	905.27	3,824.41	168.93	4,898.61	4.90	122.47
21	87.54	21.00	1,842.89	6,350.37	292.62	8,485.88	8.49	212.15
22	17.54	6.91	113.09	595.72	25.32	734.13	0.73	18.35
23	16.64	7.00	104.51	554.43	23.54	682.49	0.68	17.06
24	54.37	13.20	1,442.02	5,300.96	240.83	6,983.80	6.98	174.60
25	32.20	11.50	700.38	2,761.89	123.66	3,585.93	3.59	89.65
26	43.99	9.80	587.15	2,422.83	107.50	3,117.48	3.12	77.94
27	127.32	15.00	1,231.16	4,195.18	193.80	5,620.14	5.62	140.50
28	25.46	9.77	876.49	3,972.19	173.19	5,021.87	5.02	125.55
29	32.07	8.13	359.79	1,643.35	71.55	2,074.69	2.07	51.87
30	20.51	7.29	213.80	1,085.46	46.41	1,345.68	1.35	33.64

Note: Bold values indicate the highest (Plot 11) and lowest (Plot 13) biomass density per hectare.

Across all plots, the total aboveground biomass (AGB) was 4,650.75 tons, representing a carbon stock of approximately 2,185.85 tons. Plots with greater mean DBH and height generally stored more biomass, with Plot 11 showing the highest density (364.27 ton/ha) and Plot 13 the lowest (8.28 ton/ha). These differences likely reflect variations in tree species composition, stand density, and micro-site conditions within the study area.

Satellite Image Processing Results

Satellite imagery from Sentinel-2 was utilized to assess vegetation conditions across Mahasarakham

©2006-2026 Asian Research Publishing Network (ARPN). All rights reserved.

University. Three key vegetation indices were analyzed: Soil-Adjusted Vegetation Index (SAVI), Modified Soil-Adjusted Vegetation Index (MSAVI), and Green Normalized Difference Vegetation Index (GNDVI). The outputs of these indices were further processed using the Fractional Cover technique to provide a comprehensive representation of vegetation cover. The summarized results are presented in Table-2.

Table-2. Fractional vegetation cover (%) calculated from SAVI, MSAVI, and GNDVI across 30 sample plots.

Plot	Fractional Cover (SAVI)	Fractional Cover (MSAVI)	Fractional Cover (GNDVI)
1	61.15	69.94	48.62
2	69.17	76.75	58.15
3	75.91	82.33	65.02
4	73.43	80.25	64.29
5	67.17	74.94	55.91
6	75.20	81.78	66.05
7	64.97	73.02	51.54
8	57.75	65.92	45.84
9	77.00	83.19	69.48
10	73.56	80.42	64.39
11	58.19	67.29	46.17
12	72.68	79.44	63.83
13	84.75	89.17	77.76
14	75.59	82.02	68.10
15	76.37	82.68	67.60
16	41.81	50.33	32.78
17	82.74	87.67	74.08
18	79.07	84.82	71.33
19	83.27	88.04	76.89
20	80.99	86.32	73.68
21	42.53	51.48	32.93
22	84.96	89.32	74.92
23	87.21	90.99	83.20
24	66.64	74.68	56.92
25	45.91	55.56	37.92
26	69.82	77.38	61.19
27	82.61	87.54	72.73
28	74.54	81.13	67.04
29	63.15	71.48	49.50
30	74.28	81.00	67.07
Min	41.81	50.33	32.78
Max	87.21	90.99	83.20
Mean	70.75	77.56	61.50
SD	12.13	10.72	13.25

©2006-2026 Asian Research Publishing Network (ARPN). All rights reserved.

Table-2 Presents the fractional vegetation cover (%) derived from SAVI, MSAVI, and GNDVI across 30 systematically established sample plots. The results reveal clear spatial variation in vegetation density within the study area. Fractional cover values derived from SAVI ranged from 41.81% to 87.21%, with a mean of 70.75% and a standard deviation (SD) of 12.13%. MSAVI, which incorporates a soil-adjustment factor optimized for heterogeneous conditions, exhibited a slightly higher range (50.33-90.99%) and the highest mean (77.56%), suggesting that this index is particularly sensitive to areas with moderate-to-dense vegetation cover. GNDVI showed the lowest overall values (32.78-83.20%) and a mean of 61.50%, accompanied by the largest SD (13.25%), indicating its ability to capture greater variability in canopy greenness across the plots.

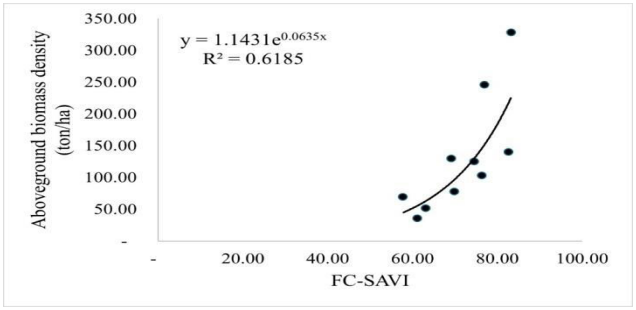
Notably, plots 16, 21, and 25 reported the lowest fractional cover across all indices, consistent with areas characterized by sparse vegetation or open spaces, while plot 23 consistently recorded the highest values, indicating dense and well-developed canopy cover. The observed differences between indices highlight the importance of index selection in biomass modeling: MSAVI appears to reduce soil background effects and enhance vegetation signal, whereas GNDVI provides stronger sensitivity to chlorophyll content, making it a valuable indicator for differentiating plots with varying vegetation vigor. Together, these metrics provide complementary insights into the spatial distribution of vegetation, offering a robust basis for subsequent aboveground biomass estimation and carbon stock assessment.

Correlation Analysis

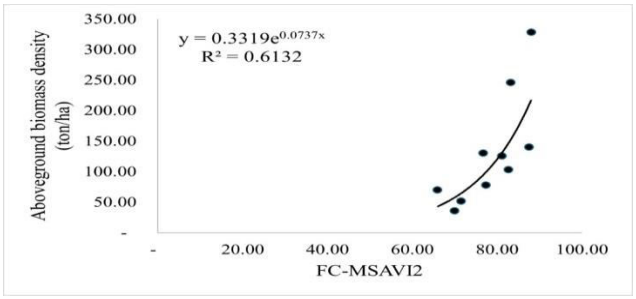
The relationship between Fractional Cover (FC) and aboveground biomass (AGB) was examined using exponential regression, and the results are illustrated in Figure-2. The analysis revealed that the coefficients of determination (R^2) for SAVI**,** MSAVI**,** and GNDVI were 0.6185, 0.6132, and 0.7201, respectively. Among the three indices, GNDVI demonstrated the strongest correlation with AGB, achieving the highest R^2 value of 0.7201. The derived regression equation for this relationship was $\mathbf{y = 3.9972e^{0.0533x}}$, indicating that a substantial proportion of the variability in AGB can be explained by FC derived from GNDVI. This result highlights the reliability of GNDVI-based FC as a predictive metric for AGB estimation within the study area.

The findings clearly show that GNDVI is the most effective indicator for explaining biomass variation in the study area. This is likely because the index relies on the green spectral band, which is particularly sensitive to vegetation vigor and canopy greenness-two characteristics closely tied to biomass accumulation. In the case of Mahasarakham University's mixed landscape, where tree cover, shrubs, and open spaces coexist, GNDVI was better able to capture subtle differences in canopy density than SAVI or MSAVI, both of which focus on minimizing soil background effects.

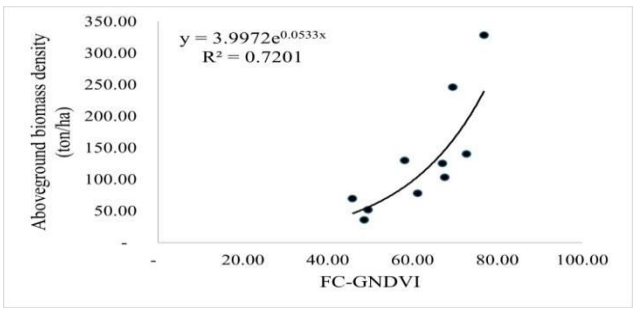
Although SAVI and MSAVI also showed moderate correlations, their slightly lower R^2 values suggest that they may be more influenced by soil reflectance and sparse cover conditions. By contrast, GNDVI-based FC provided a clearer signal that corresponded well with field-measured AGB. These results emphasize the suitability of GNDVI as a primary input for biomass modeling and carbon estimation in heterogeneous campus ecosystems, offering a practical approach for long-term vegetation monitoring and sustainable land management planning.



(a)



(b)



(c)

Figure-2. Exponential Regression-Based Relationship of Fractional Cover to Aboveground Biomass, (a) SAVI, (b) MSAVI2, and (c) GNDVI.

Statistical Accuracy Assessment

The accuracy of biomass density estimates derived from satellite imagery was evaluated against field measurements using Root Mean Square Error (RMSE) and its percentage equivalent (RMSE%). The results showed that SAVI produced an RMSE of 2.15 ton ha^{-1}, indicating an average deviation of approximately 2.15 ton ha^{-1} from the observed field data, with an RMSE% of 41.11%.

©2006-2026 Asian Research Publishing Network (ARPN). All rights reserved.

MSAVI yielded an RMSE of 2.19 ton ha^{-1} and an RMSE% of 41.76%, reflecting a level of accuracy comparable to SAVI. In contrast, GNDVI achieved superior performance with an RMSE of only 1.90 ton ha^{-1} and the lowest RMSE% at 36.21%, demonstrating the highest agreement between satellite-derived estimates and field observations among the indices tested.

CONCLUSIONS

This study successfully integrated field-based measurements and Sentinel-2 satellite imagery to quantify aboveground biomass (AGB) and carbon stock within Mahasarakham University. Systematic field sampling across 30 plots provided robust data on tree dimensions, enabling precise AGB estimation through species-specific allometric equations. The use of three vegetation indices-SAVI, MSAVI, and GNDVI-allowed for a comprehensive assessment of vegetation conditions, while the calculation of Fractional Cover (FC) transformed spectral data into spatially explicit indicators of canopy density.

Among the indices analyzed, GNDVI consistently outperformed SAVI and MSAVI, exhibiting the highest coefficient of determination ($R^2 = 0.7201$) and the lowest prediction error (RMSE = 1.90 ton ha^{-1}, RMSE% = 36.21%). These findings underscore the strong predictive capacity of GNDVI for modeling AGB in heterogeneous landscapes. The exponential regression model linking FC to AGB proved effective for scaling field measurements to the landscape level, producing reliable biomass and carbon stock estimates (total AGB = 4,650.75 tons; carbon stock ≈ 2,185.85 tons).

Overall, the results highlight the value of integrating remote sensing techniques with ground data to support evidence-based urban green space management. The methodological framework presented here can be applied to monitor biomass dynamics, inform carbon credit assessments, and guide decision-makers in enhancing ecosystem services. Future research should explore the integration of higher-resolution imagery, machine learning algorithms, and temporal monitoring to further improve biomass prediction accuracy and to capture seasonal vegetation changes.

ACKNOWLEDGEMENTS

This research project is financially supported by Mahasarakham University.

REFERENCES

[1] Uttaruk Y. and Laosuwan T. 2020. Comparison of carbon storage measurement methods on agroforestry systems in Sakon Nakhon Province, Northeast Thailand. Scientific Journal of King Faisal University. 21, 95-99.

[2] Uttaruk Y. and Laosuwan T. 2020. Methods of estimation for aboveground carbon stock in Nongbua-Nonmee Community Forest, Maha Sarakham Province, Thailand. Agriculture and Forestry, 66(3): 183-195. https://doi.org/10.17707/AgricultForest.66.3.15

[3] Rahim, N. H., Abdul Razak, S., Chang, X., Saun, F. C., Nauman Khan, M., Hamzah, S. N., Rohman, F., Ali, B., Kaplan, A., Iqbal, M., Bozhuyuk, M. R. and Ercisli, S. 2024. Ecosystem services by urban forest (UF) towards climate change adaptation: A review. Polish Journal of Environmental Studies, 33(4): 3503-3513. https://doi.org/10.15244/pjoes/177147

[4] Vattanavongsiri W., Sangpradid S., Chokkuea W. and Laosuwan T. 2023. Estimation of above-ground carbon sequestration in the national reserved forest using vegetation indices and gradient boosting machine learning. International Journal on Technical and Physical Problems of Engineering, 16(3): 361-366.

[5] Uttaruk Y., Laosuwan T., Sangpradid S., Butthep C., Rotjanakusol T., Sittiwong W. and Nilrit S. 2024. Thailand's urban forestry programs are assisted by calculations of their ecological properties and economic values. Land, 13(9): 1440. https://doi.org/10.3390/land13091440

[6] United Nations. (n.d.). Biodiversity - our strongest natural defense against climate change. Retrieved May 2, 2025, from https://www.un.org/en/climatechange/science/climate-issues/biodiversity

[7] U.S. Environmental Protection Agency. (n.d.). Climate change impacts on ecosystems. Retrieved May 3, 2025, from https://www.epa.gov/climateimpacts/climate-change-impacts-ecosystems

[8] Yuan X., Li S., Chen J., Yu H., Yang T., Wang C., Huang S., Chen H. and Ao X. 2024. Impacts of global climate change on agricultural production: A comprehensive review. Agronomy. 14(7): 1360.

[9] Ragettli M. S., Saucy A., Flückiger B., Vienneau D., De Hoogh K., Vicedo-Cabrera A. M., Schindler C. and Röösli M. 2023. Explorative assessment of the temperature-mortality association to support health-based heat-warning thresholds: A national case-crossover study in Switzerland. International Journal of Environmental Research and Public Health. 20(6): 4958.

©2006-2026 Asian Research Publishing Network (ARPN). All rights reserved.

[10] Heidt V. and Neef M. 2008. Benefits of urban green space for improving urban climate. In M. M. Carreiro, Y. C. Song, & J. Wu (Eds.), Ecology, planning, and management of urban forests (pp. 84-96). Springer.

[11] Woodward A., Hinwood A., Bennett D., Grear B., Vardoulakis S., Lalchandani N., Lyne K., and Williams. C. 2023. Trees, climate change, and health: An urban planning, greening and implementation perspective. International Journal of Environmental Research and Public Health. 20(18): 6798.

[12] Bayulken B., Huisingh D. and Fisher P. M. 2021. How are nature-based solutions helping in the greening of cities in the context of crises such as climate change and pandemics? A comprehensive review. Journal of Cleaner Production, 288, 125569. https://doi.org/10.1016/j.jclepro.2020.125569

[13] Plybour C., Laosuwan T., Uttaruk Y., Awichin P., Rotjanakusol T., Itsarawisut J. and Singharath M. 2025. An investigation of plant species diversity, above-ground biomass, and carbon stock: Insights from a dry dipterocarp forest case study. Diversity, 17(6): 428. https://doi.org/10.3390/d17060428

[14] Aisyah N. S., Norashikin M. F., Ibrahim B. and Rhushalshafira R. 2016. Estimating aboveground biomass in hill dipterocarp forest, Kelantan, Malaysia using Landsat 8 OLI. ARPN Journal of Engineering and Applied Sciences. 11(15): 9481-9486.

[15] Rahman, M. M., and Hasan, J. (2024). Evaluating the impact of green spaces on urban heat reduction in Rajshahi. Bangladesh using the InVEST model. Land. 13(8): 1284.

[16] Laosuwan T., Uttaruk Y., Nakapan S., Itsarawisut J. and Plybour C. 2025. Evaluation of tree biomass and carbon sequestration through remote sensing and field methods. Geographia Technica. 20(1): 33-43.

[17] Saengpradit P., Sangpradid S. and Laosuwan T. 2024. Estimation of aboveground biomass using hybrid machine learning based on satellite imagery. International Journal on Technical and Physical Problems of Engineering. 16(4): 7-13.

[18] Pradabmook P. and Laosuwan T. 2021. Estimation of PM_{10} using spatial interpolation techniques. International Journal on Technical and Physical Problems of Engineering. 13(4): 33-39.

[19] Laosuwan T. 2012. Online web GIS-based services for spatial data and sharing of leptospirosis epidemiology information: Development of a pilot project in Mahasarakham Province, Thailand. International Journal of Geomatics and Geosciences. 3(1): 121-133.

[20] Laosuwan T., Chunpang P. and Sukkasena S. 2011. Development of robotic aerial remote sensing system for field educational purposes. International Journal of Geoinformatics. 17(4): 21-27.

[21] Angkahad T., Chokkuea W., Sangpradid S., Uttaruk Y., Viriyasatr K. and Laosuwan T. 2025a. The assessment of above ground biomass and carbon sequestration in community forests using UAV technology. Defense Technology Academy Journal. 7(15): R11-R28.

[22] Angkahad T., Laosuwan T., Sangpradid S., Prasertsri N., Uttaruk Y., Phoophathong T. and Nuchthapho J. 2025b. Developing drone-based machine learning for spatial modeling and analysis of biomass and carbon sequestration in forest ecosystems. Engineered Science, 35, 1508. https://doi.org/10.30919/es8d1568

[23] Ogawa H., Yoda K., Ogino K. and Kira T. 1965. Comparative ecological studies on three main types of forest vegetation in Thailand II. Plant biomass. Natural and Life in Southeast Asia. 4, 49-80.

[24] Intergovernmental Panel on Climate Change. 2006. 2006 IPCC guidelines for national greenhouse gas inventories. IGES.

[25] Huete A. R. 1988. A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment, 25(3): 295-309. https://doi.org/10.1016/0034-4257(88)90106-X

[26] Qi J., Chehbouni A., Huete A. R., Kerr Y. H. and Sorooshian S. 1994. A modified soil-adjusted vegetation index. Remote Sensing of Environment, 48(2): 119-126. https://doi.org/10.1016/0034-4257(94)90134-1

[27] Gitelson A. A., Kaufman Y. J. and Merzlyak M. N. 1996. Use of a green channel in remote sensing of global vegetation from EOS-MODIS. Remote Sensing of Environment, 58, 289-298. https://doi.org/10.1016/S0034-4257(96)00072-7