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ESTIMATION OF ABOVE-GROUND CARBON SEQUESTRATION IN THE NATIONAL RESERVED FOREST USING VEGETATION INDICES AND GRADIENT BOOSTING MACHINE LEARNING

W. Vattanavongsiri [1] S. Sangpradid [2] W. Chokkuea [1] T. Laosuwan [1]

1. Department of Physics, Faculty of Science, Mahasarakham University, Kantarawichai, Maha Sarakham, Thailand santino2.vatt@gmail.com, wutthisat.c@msu.ac.th, teerawong@msu.ac.th
2. Department of Geoinformatics, Faculty of Informatics, Mahasarakham University, Kantarawichai, Maha Sarakham, Thailand, satith.s@msu.ac.th

Abstract- The aim of this research is to calculate the amount of above ground carbon (AGC) sequestration in the National Reserved Forest using vegetation indices and gradient-boosting machine learning. Study operation 1 Set 16 sample plots with the size of 40×40 meters, then measure the girth and all trees' height in the plot and calculate the estimation of AGC sequestration using allometric equations, and 2) Analyze the estimation of AGC sequestration using vegetation indices and gradient-boosting machine learning. The result finds that there are 2,186 plants in 33 types. Analysis result for the estimation of AGC sequestration using allometric equations finds that the study area has carbon sequestration of 44.14 tC and the density analysis using Inverse Distance Weight (IDW) finds that the spatial carbon density of 3,180.179 tC. Analysis results for the estimation of AGC sequestration using vegetation indices and gradient-boosting machine learning finds that the sum of carbon in the area is 2,855.18 tC. Statistical analysis of such data finds that the correlation coefficient is 0.964.

Keywords: Remote Sensing, Gradient Boosting, Machine Learning, Above-Ground Carbon Sequestration.

1. INTRODUCTION

Greenhouse gas surrounds the atmosphere which is essential to maintain the stability of global temperature, without greenhouse gas, all creatures are unable to live [1-3]. Excessive greenhouse gases may impact the ecosystem and creatures especially carbon dioxide (CO_2) which has the maximum amount in the atmosphere. CO_2 occurs from human activities such as gas emissions from electricity generation, industrial plants, transportation, agricultural activities, and so on [4-6]. In addition, the increase in CO_2 will impact global temperature change that causes natural disasters continuously [7]. Forest resources are not only essential for human life but also essential for carbon sequestration as the amount of CO_2, an essential greenhouse gas, increases in the atmosphere will impact global climate change [8].

The forest ecosystem plays a crucial role in the exchange of CO_2 in the atmosphere. Trees have the ability to absorb CO_2 through photosynthesis and store it in various forms of biomass, including above ground components like stems, branches, and leaves, as well as below ground components like roots. This stored carbon remains within the trees until they are either burned or cut down, preventing its release back into the atmosphere [9-11]. Deforestation or forest burning for agriculture not only causes carbon emissions but also destroys the essential absorbent source of CO_2 [12].

Currently, the application of Remote Sensing Technology has been developed rapidly with high efficiency such as data from satellites and data from unmanned aerial vehicles [13]. Remote Sensing Technology has a physical basic principle of electromagnetic waves used as a tool to acquire data without directly contacting the object on the earth's surface [14-15]. Moreover, Remote Sensing Technology can explore a wide area at a lower cost than a ground survey, it has been widely applied in various research [16-20]. Application of Remote Sensing Technology in research on the estimation of carbon sequestration in forest areas in Thailand such as research by Boonsang and Arunpraparat [21], research by Uttaruk, et al., [22], and research by Thongmee, et al., [23] and so on. The objective of this study is the estimation of AGC sequestration in the National Reserved Forest using vegetation indices and gradient-boosting machine learning.

2. MATERIAL AND METHOD

2.1. The Study Area

Koke Pak Kood Forest and Pong Daeng Forest (Figure 1) were established by Royal Forest Department as the National Reserved Forest on July 15, 1968, located at Kamphi Sub-district, Non Daeng Sub-district, Borabue District, Khwao Rai Sub-district, Na Chueak District, and Na kha Sub-district, Wapi Patum District, Maha Sarakham Province.

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Plants consist of ironwood, tender wood, Burmese sal, Pluang, and other kinds of wood that have high value, plenty of forest products, and other natural resources. Currently, the remaining area is approximately 1,153 rai (1 rai is 0.16 ha) and surrounding communities have used these forests for their livelihoods such as picking mushrooms, vegetables, herbs, fuel, and so on.

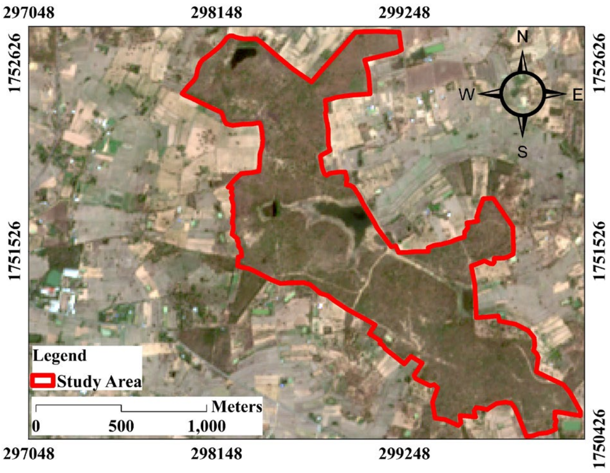

Figure 1. Koke Pak Kood Forest and Pong Daeng Forest

Satellite named Sentinel 2 A is equipped with the Multi Spectral Instrument (MSI) capable of capturing high-resolution images with a wide-angle coverage of approximately 290 km. Image data can be collected every 5 days. The MSI comprises 13 wavelengths ranging from 443 to 2190 nm, each with dissimilar resolutions of 10, 20, and 60 m. Specifically, wavelengths 2, 3, 4, and 8 have a resolution of 10 m, wavelengths 5, 6, 7, and 8A have a resolution of 20 m, and wavelengths 1, 9, and 10 have resolution of 60 m [24].

Table 1. Sentinel 2 A Bands [24]

Sentinel-2 Bands	Central Wavelength	Resolution
1	0.443 μm	60 meters
2	0.490 μm	10 meters
3	0.560 μm	10 meters
4	0.665 μm	10 meters
5	0.705 μm	20 meters
6	0.740 μm	20 meters
7	0.783 μm	20 meters
8	0.842 μm	10 meters
8(A)	0.865 μm	20 meters
9	0.945 μm	60 meters
10	1.375 μm	60 meters
11	1.610 μm	20 meters
12	2.190 μm	20 meters

2.3. Study Operation

2.3.1. Setting Sample Plots

Sixteen sample plots measuring 40×40 m each have been designated to cover the entire area. Trees and poles have been classified based on their girth, with trees having a girth exceeding 30 cm and poles having a girth less than 30 cm but a height greater than 1.30 m. The girth and height of all trees were carefully measured and documented in the data sheet for further analysis. Subsequently, the estimation of AGC sequestration was calculated using specific allometric equations outlined in Equation (1) [25].

$$W_s = 0.0396 D^2 H^{0.932}$$
$$W_b = 0.006003 D^2 H^{1.027} \quad (1)$$
$$W_l = \left(28.0 / W_{tc} + 0.025\right)^{-1}$$

where;
W_s = stem
W_b = branch
W_l = leaf
W_{tc} = stem + branch
D = DBH
H = tree height

2.3.2. Vegetation Indices Analysis

This study analyzes vegetation indices from Sentinel 2 A satellite data in 3 formats: The normalized difference vegetation index or $NDVI$ as shown in Equation (2), the soil adjusted vegetation index or $SAVI$ as shown in Equation (3), and the ratio vegetation index or RVI as shown in Equation (4).

$$NDVI = (NIR - RED) / (NIR + RED) \quad (2)$$

where, the color RED is the segment of the electromagnetic spectrum wavelengths ranging from 0.6 to 0.7 μm, while the near infrared or NIR specifies to the allocation of the electromagnetic spectrum wavelengths ranging between 0.75 to 1.5 μm [17].

$$SAVI = \left(\left(NIR - RED\right) / \left(NIR + RED + L\right)\right) x \left(1 + L\right) \quad (3)$$

where, in areas with moderate green vegetative coverage, the red portion of the electromagnetic spectrum wavelengths (0.6 to 0.7 μm) is represented by the color RED, while the near infrared portion (0.75 to 1.5 μm) is represented by NIR. In areas with very high vegetation coverage, the value of L is 1, and in areas of moderate green vegetation coverage, the amount of L is 0.5 [26].

$$RVI = NIR / RED \quad (4)$$

where, the color RED corresponds to the segment of the electromagnetic spectrum wavelengths ranging from 0.6 to 0.7 μm, while the near infrared or NIR specifies to the allocation of the electromagnetic spectrum wavelengths ranging between 0.75 to 1.5 μm [27].

2.3.3. Using Gradient-Boosting Machine Learning to Analyze Carbon

This study analyzes the estimation of above-ground carbon sequestration using gradient-boosting machine learning and uses the WEKA program with AdaBoostM1 analysis. It uses the result from the decision tree of the classifier random tree which has various instances to put together as a chain and creates a model. Each training will determine the weight value for each classifier instance where the model will use such weight value. If the prediction is wrong the weight value will increase and the classifier instance will obtain a low score if any instance has a correct prediction in a high proportion, it will obtain a high score.

AdaBoostM1 prediction determines *t* as a score weighting with responses of each instance then choose the response from the Class which has the maximum weight. A researcher uses Sentinel 2A satellite data and vegetation indices data in 3 formats: *NDVI*, *SAVI*, and *RVI* for 1845 points to analyze using a regression algorithm. After that, a model of carbon sequestration and vegetation indices was created to design a model map regression result.

3. RESULT

By setting sixteen sample plots and using them to calculate AGC sequestration biomass, the analysis result of the study area of Koke Pak Kood Forest and Pong Daeng Forest found 2,186 plants with 33 kinds. The most common species are Dipterocarpus tuberculous Roxb, Xylia xylocarpa Taub. var, Shorea Obtusa Wall, Cratoxylum cochinchinense (Lour.) Bl, Canarium subulatum Guill, Catunaregam tomentosum (Kurz) Bakh.f, Cratoxylum cochinchinense (Lour.) Bl. and Shorea Siamensis Miq. Such a result is shown in Table 2. After analyzing the density using Inverse Distance Weight (IDW) (Figure 2) finds that the spatial carbon density is 3,180.179 tC.

Table 2. Above Ground Biomass and Carbon Sequestration

Stem biomass	W_s	76,334.47	Kg
Branch biomass	W_b	14,801.79	Kg
Leaf biomass	W_l	27,97.90	Kg
Biomass of Stem + Branch	W_{tc}	91,136.26	Kg
Above Ground Biomass (AGB)	W_S, W_B, W_L	93,934.17	Kg
Carbon Sequestration	(W_S, W_B, W_L) *0.47	44,149.06	Kg
Total Carbon		44.14	tCO_2

3.2. Analysis of Vegetation Indices Using Satellite Data

Analysis result of vegetation indices using Sentinel-2A satellite data in 3 formats: *NDVI*, *SAVI*, and *RVI* (Figures 3-5) can be explained as follows:

1) Analysis result of *NDVI* finds that the lowest is -0.0700483, the highest is 0.372346, and the average value is 0.151148. The red area has very few plants, with most being open areas or water bodies. The most common plants in the plot are Dipterocarpus tuberculous Roxb. And Meselson elude Roxb.

2) Analysis result of *SAVI* finds that the lowest is -0.105057, the highest is 0.558468, and the average value is 0.226705. The red area has very few plants, with most being open areas or water bodies. The most common plants in the plot are Sindora siamensis Miq. and Ellipanthus tomentosus Kuze var. tomentosus.

3) Analysis result of RVI finds that the lowest is 0.457358, the highest is 1.15065, and the average value is 0.804004. The red area has very few plants, with most being open areas or water bodies. The most common plants in the plot are Shorea obtusa Wall, Memecylon edule Roxb. and Xyliaxyloc arpa Taub. Var. Kerrii Nielsen.

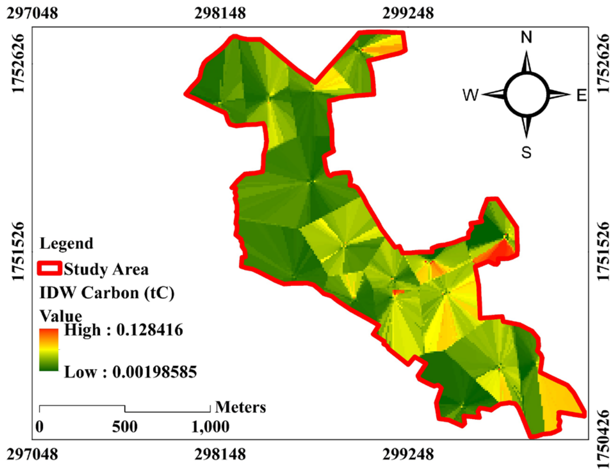

Figure 2. Carbon density with *IDW*

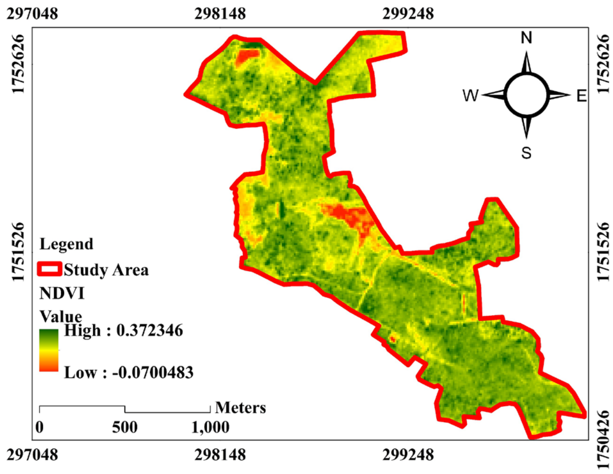

Figure 3. Analysis result of *NDVI*

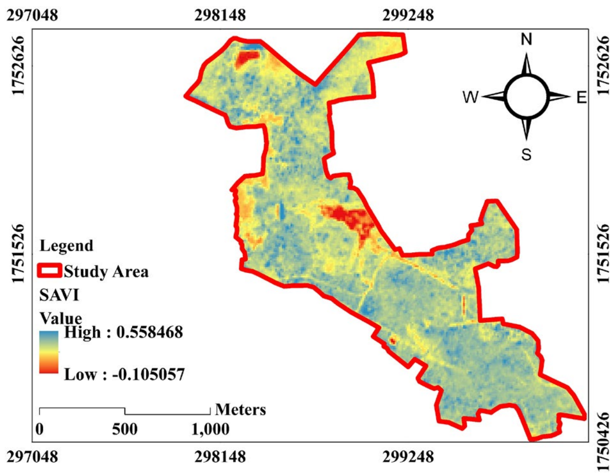

Figure 4. Analysis result of *SAVI*

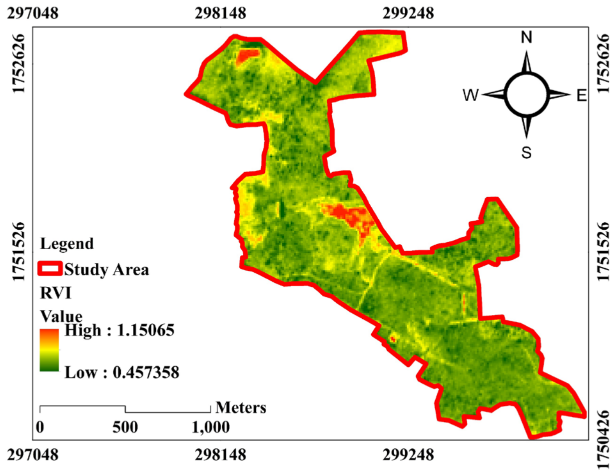

Figure 5. Analysis result of *RVI*

3.3. Analysis Result of Above-Ground Carbon Sequestration Using Gradient-Boosting Machine Learning

The result in gradient-boosting analysis uses AdabootM1 (Random Tree) and 183000 points of data consist of an independent variable which is IDW, and a dependent variable which is *NDVI*, *SAVI*, and *RVI* as shown in Figure 6. The result of the spatial carbon density analysis from the survey found that there was a carbon storage amount of 3,180.179 tC. The result of the gradient-boosting analysis in Figure 6 shows the sum of carbon in the area is 2,855.18 tC. Figure 6 uses color to represent carbon per area: green represents the maximum density of carbon, yellow represents the medium density of carbon, and red represents the minimum density of carbon. When the results were analyzed for relationships with correlation coefficient, it was found that the *R* was equal to 0.943. The statistical analysis result is shown in Table 3.

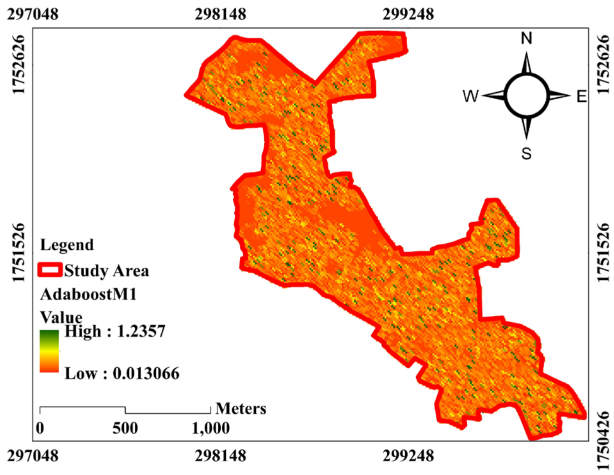

Figure 6. The result of the gradient-boosting analysis

Table 3. Statistical analysis result

Mean absolute error	0.171
Root mean squared error	0.256
Mean Squared Error	0.065

4. CONCLUSIONS

The objective of this study is the estimation of above-ground carbon sequestration in the National Reserved Forest using vegetation indices and gradient-boosting machine learning. For the results of the field survey and calculation, 2186 trees of 33 species were found. The most common tree species were Dipterocarpus tuberculatus Roxb, Xylia xylocarpa Taub. var, Shorea Obtusa Wall, Cratoxylum cochinchinense (Lour.) Bl, Canarium subulatum Guill, Catunaregam tomentosum (Kurz) Bakh.f, Cratoxylum cochinchinense (Lour.) Bl. and Shorea Siamensis Miq. among others. The results of the spatial Carbon density analysis from the survey found that there was a carbon storage amount of 3,180.179 tons of carbon. The results of the spatial Carbon density analysis from Gradient-boosting machine learning found that the amount of carbon stored was 2,855.181 tons of carbon. When the results were analyzed using correlation coefficient, it was found that the *R* was equal to 0.943. This study found that the gradient-boosting machine learning analysis had a relatively high correlation with spatial carbon values. The coefficient is 0.943, and the error is relatively small, accounting for 10.24%, compared to the spatial carbon values.

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BIOGRAPHIES

Name: **Watcharin**
Surname: **Vattanavongsiri**
Birthday: 22.01.1978
Birthplace: Trang, Thailand
Bachelor: Computer Engineering, Department of Computer Engineering, Faculty of Engineering, Prince of Songkla University, Hat Yai, Thailand, 2001
Master: Energy, Department of Physics, Faculty of Science, Mahasarakham University, Maha Sarakham, Thailand, 2021
Research Interests: Remote Sensing, Geographics Information System, Energy Technology, Biomass

Name: **Satith**
Surname: **Sangpradid**
Birthday: 14.11.1976
Birthplace: Khonkaen, Thailand
Bachelor: Management Information System, Faculty of Science, Mahasarakham University, Maha Sarakham, Thailand, 1999
Master: Information Technology, Faculty of Information Technology, King Mongkut's University of Technology, North Bangkok, Thailand, 2003
Doctorate: Geoinformatics, Institute of Science, Suranaree University of Technology, Nakhon Ratchasima, Thailand, 2012
The Last Scientific Position: Assist. Prof., Department of Geoinformatics, Faculty of Informatics, Mahasarakham University, Maha Sarakham, Thailand, Since 2020
Research Interests: Machine Learning and AI, Natural and Environment Science, Geoinformatics, Carbon Sequestration, Information Science
Scientific Publications: 32 Papers

Name: **Wutthisat**
Surname: **Chokkuea**
Birthday: 04.05.1979
Birthplace: Buriram, Thailand
Bachelor: Applied Physics, Faculty of Science, Mahasarakham University, Maha Sarakham, Thailand, 2001
Master: Energy Engineering, Faculty of Engineering, Chiang Mai University, Chiang Mai, Thailand, 2005
Doctorate: Mechanical Engineering, Faculty of Engineering, Mahasarakham University, Maha Sarakham, Thailand, 2015
The Last Scientific Position: Assist. Prof., Department of Physics, Faculty of Science, Mahasarakham University, Maha Sarakham, Thailand, Since 2018
Research Interests: Renewable Energy, Energy Conservation, Energy Modeling
Scientific Publications: 9 Papers

Name: **Teerawong**
Surname: **Laosuwan**
Birthday: 02.10.1971
Birthplace: Songkhla, Thailand
Bachelor: Electronics Engineering, Faculty of Engineering, Southeast Asia University, Bangkok, Thailand, 1994
Master: Remote Sensing, Institute of Science, Suranaree University of Technology, Nakhon Ratchasima, Thailand, 1999
Doctorate: Electrical and Computer Engineering, Faculty of Engineering, Mahasarakham University, Maha Sarakham, Thailand, 2012
The Last Scientific Position: Assoc. Prof, Department of Physics, Faculty of Science, Mahasarakham University, Maha Sarakham, Thailand, Since 2015
Research Interests: Remote Sensing, Geo Informatics, GIS Modeling, Mobile Application Development, Energy Technology and Drone Surveying and Mapping
Scientific Publications: 130 Papers