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Abstract: Tree height is an important variable to use for calculating biomass sequestration. This study aims to compare the level of the tree height measurement method in different family forest plots. Using canopy height models in comparison with the results from the field surveys, it was found that in both experimental plots, the RMSE was 2.740 and 2.863 meters. The MAE was 2.654 and 2.666 meters. The comparison of both methods using the correlation, resulting in an R-value of 0.758 for Experimental Plot 1 and 0.993 for Experimental Plot 2. This suggestion is useful for measuring tree height in large plots.

Keywords: Carbon Sequestration; Tree Height Measurement; Family Forest; UAVs; Field Surveys

1. Introduction

The global environment is grappling with substantial obstacles stemming from climate change, giving rise to phenomena such as El Niño, La Niña, and Global Warming. These occurrences, which encompass droughts, floods, hurricanes, and agricultural issues, impact the livelihoods of the Earth's inhabitants[1)], particularly in the Southeast Asian region, where communities heavily depend on agriculture[2-3)]. This dependency eventually contributes to global food shortages[4-5)]. Acknowledging these issues, the United Nations has recognized and prioritized sustainable solutions, delineating Sustainable Development Goals[6)] to tackle these challenges, such as Goal 13 focusing on Climate Action and Goal 15 addressing Life on Land[7)]. In response to this concern, numerous nations are increasingly emphasising the significance of forested areas and green spaces within their territories.

Thailand is a country where economic activities predominantly rely on agriculture. This dependence is observable nationwide, notably pronounced in its northeastern region[8)]. The agricultural endeavors encompass rice cultivation, crop plantations, horticulture, and notably, integrated farming in both residential and agricultural domains[9)]. Presently, Thailand has incorporated environmental conservation as a cornerstone of its national strategies, with a specific emphasis on forest restoration and the establishment of community green spaces to promote environmental harmony. This commitment has led to the creation of community forests and family forests, serving as biodiversity hubs and facilitating carbon credit trading[10)]. Family forests are usually found on ancestral lands, conserved by families who desire to preserve natural ecosystems[11)], or on developed lands transformed into diverse, nature-resembling forests, particularly evident in peri-urban agricultural areas[12)].

Nevertheless, assessing the health and growth of trees within family forest areas poses challenges, as it often requires a considerable amount of time and effort. Current methods for measuring tree height span from traditional approaches such as tape measurement to mathematical techniques. Advancements in mobile phone technology have revolutionized tree height analysis, enabling efficient measurements through various applications[13)], notably those employing hypsometers[14)]. Furthermore, Borges de Lima et al. (2021) have studied height-diameter allometry for the tropical forests in northern Amazonia to compare allometric models parameterized at different scales. The result of their study, the Weibull model was the best local model.[15)]

In recent years, developments in remote sensing technology have played a significant role in forestry studies[16] and agricultural research[17-18], particularly with the increased utilization of unmanned aerial vehicles (UAVs)[19] for assessing forest health and tree growth[20]. This is because UAVs allow for flexible surveying based on surveyors' needs, and their imagery quality surpasses satellite imagery[21]. Moreover, Nasiri et al. (2021) studied the use of canopy height models to analyze tree canopies and tree canopy diameters in the Hyrcanian mixed forest area. This study used UAVs for analysis CHM to estimate tree heights. The study found that estimating tree height and diameter using UAVs can be accepted according to statistical principles and is also beneficial for estimating tree height[22]. Thus, this technique is also employed to survey tree height within plantation plots[23]. In addition, Corte et al. (2020). used a method to measure the circumference and height of trees using a lidar sensor by unmanned aerial vehicle. The study found that the above techniques and methods can be used together to measure the circumference and height of trees within plots. The advantage of measuring is a wide area instead of measuring in a real area and can also reduce the time of operation[24].

Therefore, this study employs tree height measurement methods to compare biodiversity levels across various family forest plots, designated as green spaces for family-oriented recreational activities. The techniques encompass the use of unmanned aerial vehicles (UAVs) and hypsometer applications on mobile devices. The research settings included oil palm plantations, representing both agricultural areas and family forests surrounding residential zones. The findings from this study are significant for future researchers interested in monitoring agricultural and woodland growth. This research contributes to potential applications in tracking other types of agricultural and forest landscapes. Lastly, this approach serves as a blueprint for global green space development, offering a pathway to address the pressing issue of climate change worldwide.

2. Methodology

2.1 Study Area

Mukdahan is a province located in the upper northeastern region of Thailand. It is characterized by its landscape of alternating hills and high plains covered with forests. In this study, the experimental area was the Nichawan Farm, situated at latitude 16° 24' 18" N. and longitude 104° 36' 19" E. in Nong Kha Village, Nikhom Kham Soi District, Mukdahan Province. This agricultural area was divided into two parts: the first part consisted of oil palm plantations covering an area of approximately 1.92 hectares, primarily cultivated for oil palm production. The second part comprised fruit orchards utilizing integrated farming, covering an area of approximately 2.08 hectares. As shown in Fig. 1

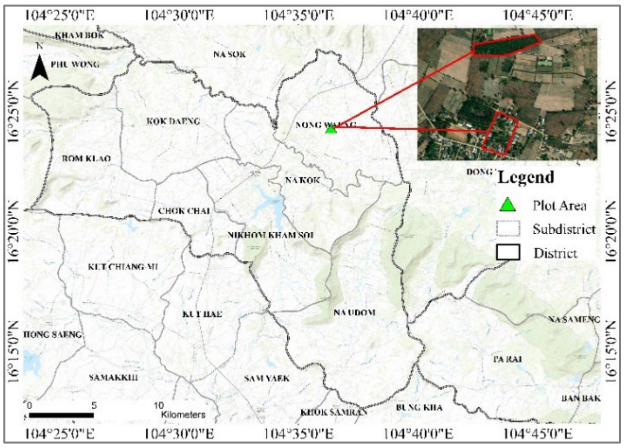

Fig. 1: Study area of the study in Nong Kha Village, Nikhom Kham Soi District, Mukdahan Province.

2.2 Data Collection

In this study, data were collected from experimental plots, each covering an area of 0.12 hectares. Within each oil palm plantation, there was a sub-plot measuring 32 x 32 meters. This sub-plot contained 15 oil palm trees selected as research samples. Additionally, another group of 15 trees was purposively selected from the surrounding areas, representing products of integrated farming. The data collection process employed two methods as follows. First, field surveys utilized an Android 9 software EMUI version 9.1.0.330, equipped with a 16MP camera (4608× 3456-pixel resolution) to measure tree height using a 3D accelerometer. This sensor detects changes in screen tilt automatically, enabling precise measurements based on trigonometric principles[25].

Second, surveys were conducted using an unmanned aerial vehicle (UAVs), specifically a 4-propeller DJI Phantom 4 Pro V 2.0 model. This UAVs features camera boasts a 1-inch CMOS sensor (12.80 x 9.60 millimeters) with a static image resolution of 20 megapixels (MP), an 84-degree field of view, and an aperture ranging from f/2.8 to f/11, with a focus distance of 1 meter or more. Additionally, the UAVs includes three-axis stabilization: Pitch, Roll, and Pan, and supports ground satellite positioning systems using GPS and GLONASS.

The aerial photography method utilized a double grid flight pattern, flying at a height of 90 meters and maintaining a 70% side lap and an 80% overlap between images to achieve a ground sample distance of 2.5 centimeters per pixel. Ground control points were set at the corners and edges of the plots, totaling eight positions for the aerial survey.

2.3 Tree Height Measurement Methods

To measure tree height, the mobile phone was held at eye level and the distance between the observer and the tree was set at 15 or 20 meters. Then, the observer's eye-level height (in meters) was set in the application. Subsequently, the positions of the tree base and tree top were marked to measure the tree height using Equation 1, as illustrated in Fig. 2.

$$CE = AE \; x \; SIN \; \alpha$$
$$BC = AB \; x \; SIN \; \beta$$
$$H = CE + BC \qquad (1)$$

When AC = Distance from the observer to the tree along the horizontal plane, AE = Distance from the observer's line of sight to the base of the tree, and AB = Distance from the observer's line of sight to the top of the tree.

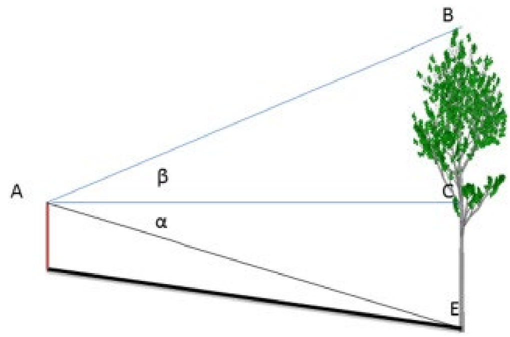

Fig. 2: Tree Height Measurement Principle

For the analysis aimed at determining tree height within the study area, we utilized photogrammetry, employing orthorectification techniques with the Pix4D Mapper software. This process rectifies positional inaccuracies resulting from relief displacement and camera tilt displacement during image capture, adjusting based on terrain elevation data and referencing the Universal Transverse Mercator (UTM) grid system. The output includes ortho-rectified color imagery, digital terrain models (DTM), and digital surface models (DSM)[26]. Then, these results were utilized to calculate tree height using canopy height models (CHM) with geographic information system (GIS) software as described in Equation 2.

$$CHM = DSM - DTM \qquad (2)$$

When CHM = Canopy Height Model, DSM = Digital Surface Model, DTM = Digital Terrain Model.

Next, the accuracy of the height models was verified by comparing the tree height measurements obtained from different methods: 1) field surveys and 2) aerial measurements by UAVs, a commonly used method for assessing tree height. Then, these values were evaluated for accuracy using the root mean square error (RMSE) [27] as shown in Equation 3, and the mean absolute error (MAE) [28] as presented in Equation 4.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - X_i)^2} \qquad (3)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - X_i| \qquad (4)$$

When

Yi = Tree height value from the model.
Xi = Tree height value from field survey data.
n = Number of data points used in modelling.

Once the tree height values had been obtained from both methods, they were then analyzed to estimate the carbon sequestration from the tree biomass using the allometric equation[29], which analyzed tree biomass composed of above ground biomass (AGB) [30-31]. The calculation details are illustrated in Equations 5 and 6. To calculate the quantity of carbon sequestration from belowground biomass (BLG), it is necessary to estimate the biomass of the belowground portion of trees using the dry weight ratio of roots per tree for each tree species [32]. This calculation can be performed using Equations 7 and 8.

$$C_{ABG} = \sum_{i=1}^{n} C_{ABG,i} \qquad (5)$$

$$C_{ABG,i} = \left(\sum_{j=1}^{n} M_j \times CF \times \frac{44}{12}\right) \times \frac{A}{a} \qquad (6)$$

When

C_{ABG} = Total above-ground carbon sequestration of the area (tons of carbon dioxide equivalent)
$C_{ABG,i}$ = Above-ground carbon sequestration of stratum *i* (tons of carbon dioxide equivalent)
M = Above-ground biomass of trees in the sample plot calculated from the allometric equation (ton dry weight per hectare)
i = Stratum 1, 2, 3,...n
j = Tree species 1, 2, 3,...n
A = Total area in that stratum (rai)
a = Area of the sample plot in that stratum (rai)
CF = Carbon fraction ratio in the wood

To calculate the quantity of carbon sequestration from belowground biomass (BLG), it is necessary to estimate the biomass of the belowground portion of trees using the dry weight ratio of roots per tree for each tree species [33]. This calculation can be performed using Equations 7 and 8.

$$C_{BLG} = \sum_{i=1}^{n} C_{BLG,i} \qquad (7)$$

$$C_{BLG,i} = C_{ABG,i} \times R \qquad (8)$$

When

C_{BLG} = Total below-ground carbon sequestration of all trees in the area (tons of carbon dioxide equivalent per year)
$C_{BLG,i}$ = Below-ground carbon sequestration of stratum *i* (ton of carbon dioxide equivalent per year)
$C_{ABG,i}$ = Above-ground carbon sequestration of stratum *i* (tons of carbon dioxide equivalent per year)
R = Dry weight ratio of roots per tree
i = Stratum 1, 2, 3,... n

After calculating the amount of carbon sequestration both above and below ground, the total carbon sequestration of trees in the area was determined using Equation 9.

$$C_{TT} = C_{ABG} + C_{BLG} \tag{9}$$

When C_{TT} = Total carbon sequestration of trees in the area (tons of carbon dioxide equivalent)
C_{ABG} = Above-ground carbon sequestration of trees (tons of carbon dioxide equivalent)
C_{BLG} = Below-ground carbon sequestration of trees (tons of carbon dioxide equivalent)

Once the biomass accumulation results had been acquired, based on the height data from both sources—unmanned aerial vehicles and field surveys—the obtained results were then analyzed to determine the relationship using Pearson correlation, as shown in Equation 10. r_{xy} = Pearson correlation coefficient, N = Total number of data, X = Biomass accumulation data obtained from ground surveys, Y = Biomass accumulation data obtained from unmanned aerial vehicles.

$$r_{xy} = \frac{N\sum XY-(\sum X)(\sum Y)}{\sqrt{[N\sum X^2-(\sum X)^2][N\sum Y^2-(\sum Y)^2}} \tag{10}$$

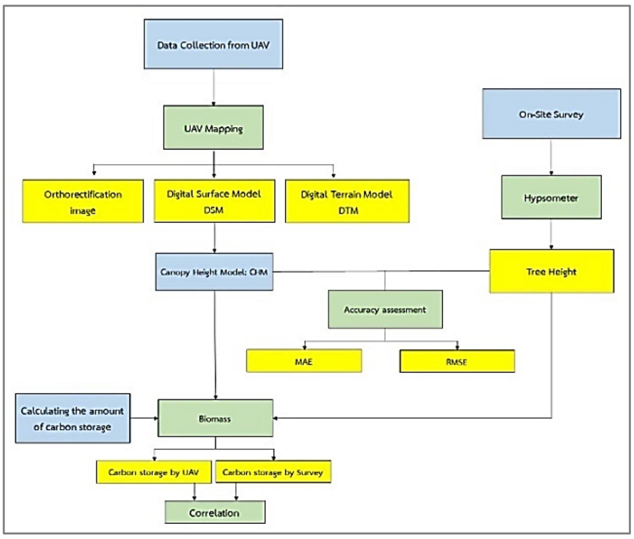

Fig. 3: Conceptual Framework showed the step by step of the methods in this research.

3. Result and Discussion

3.1 Results

3.1.1 Tree Height Measurement Using Unmanned Aerial Vehicles with Canopy Height Model and Field Surveys.

In this study, tree height measurement using a mobile phone application in comparison with the tree height measurement performed by unmanned aerial vehicles (UAVs). The study involved two experimental plots. The first plot consisted of single-species plantations, comprising 15 oil palm trees, all of the same age (15 years). The UAV-based method employed the canopy height model (CHM), which utilized the principle of differencing between digital terrain models (DTM) and digital surface models (DSM). The analysis of the efficiency of both methods was conducted using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). For the tree height within Experimental Plot 1, the RMSE was 2.740, and the MAE was 2.654, as shown in Table 1 and Fig. 4.

Table 1 Tree Heights in Experimental Plot 1 Measured by UAVs and Field Surveys.

No	Sampling group	Easting (m)	Northing (m.)	Height from survey (m.)	Height from UAV (m.)	Ages (yrs.)
1	Oil palm 1	457949	1814249	14	11	15
2	Oil palm 2	457950	1814258	13.5	10.5	15
3	Oil palm 3	457950	1814267	15	12	15
4	Oil palm 4	457949	1814276	12	10	15
5	Oil palm 5	457958	1814275	11	10.5	15
6	Oil palm 6	457959	1814266	14	11	15
7	Oil palm 7	457957	1814259	14	11	15
8	Oil palm 8	457965	1814252	14	11	15
9	Oil palm 9	457964	1814262	14.5	11.5	15
10	Oil palm 10	457966	1814270	13.5	10.5	15
11	Oil palm 11	457967	1814275	14.5	11.5	15
12	Oil palm 12	457972	1814276	13	11	15
13	Oil palm 13	457972	1814269	13	10.68	15
14	Oil palm 14	457971	1814261	14	11	15
15	Oil palm 15	457972	1814252	13	10	15

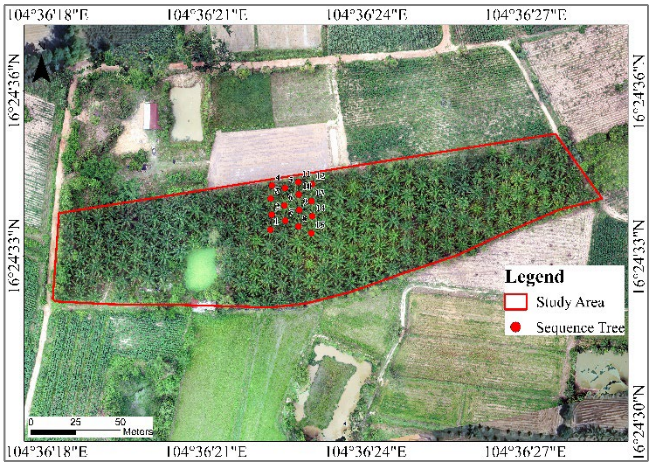

Fig. 4: Experimental Plot 1

For Experimental Plot 2, which encompassed both an integrated farming area and the owner's family forest, there were 13 sample trees consisting of various tree species and bamboo. These trees ranged in age from 7 to 15 years. UAVs were used to measure tree height using the canopy height model, which relies on disparities between the digital terrain model and the digital surface model. The analysis of the effectiveness of both methods using RMSE and MAE for tree height measurement within Experimental Plot 2 yielded an RMSE of 2.863 and an MAE of 2.666, respectively, as depicted in Fig. 5 and Table 2.

Table 2 Tree Heights in Experimental Plot 2 Measured by UAVs and Field Surveys

No	Sampling group	Easting (m)	Northing (m.)	Height from survey (m.)	Height from UAV (m.)	Ages (yrs.)
1	Teak	457949	1813851	18	16	15
2	Coconut 1	457959	1813832	14	12	10
3	Iron Wood	457957	1813891	18	13.75	15
4	Hedge bamboo 1	457926	1813839	15	14	15
5	Santol	457965	1813853	18	14	10
6	Mango 1	457967	1813864	16	11	10
7	Mango 2	457962	1813842	12	10	10
8	Mango 3	457941	1813829	10	7	10
9	Coconut 2	457916	1813830	10	10	10
10	Coconut 3	457917	1813819	16	13	10
11	Coconut 4	457930	1813889	6	5	10
12	Antidesma 1	457946	1813824	10	7	7
13	Antidesma 2	457938	1813829	14	11	7

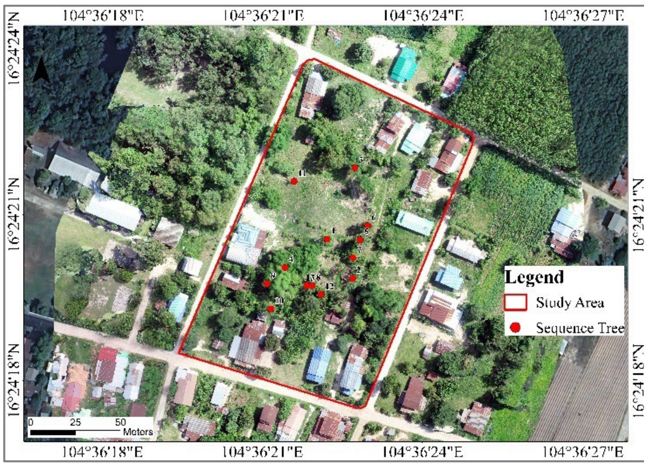

Fig. 5: Experimental Plot 2

3.1.2 Correlation between the Biomass Sequestration obtained from Tree Height Measurements Using UAVs and Field Surveys.

According to the tree height measurement from UAVs and field surveys, the biomass sequestration of trees in both experimental plots was examined using the allometry equation, a method for analyzing carbon sequestration from tree biomass. In general, each tree species has a different index of wood types, depending on the botanical species of the tree. In this study, the trees were grouped into three categories: general tree species [34], palm group [35], and bamboo group [36], each with distinct characteristics.

Experimental Plot 1 was an oil palm plantation area, so the wood type index of the palm tree group was primarily used for calculations. Figure 6 shows the comparison of the carbon sequestration in Experimental Plot 1 determined by the two methods explained above. The statistical analysis of the correlation between the results from both methods using the Pearson correlation coefficient revealed a significant correlation at the 0.01 level, indicating a highly consistent relationship between the results obtained from both methods, with an R-value of 0.758.

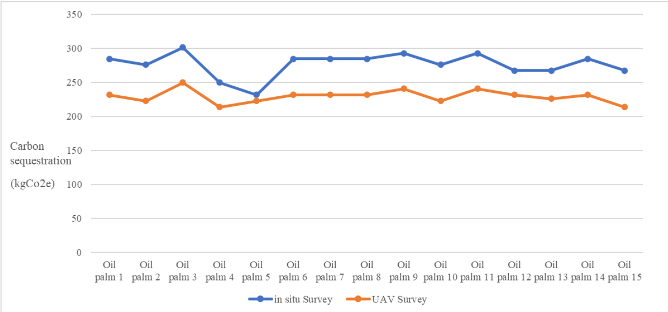

Fig. 6: Comparison of carbon sequestration obtained from tree height measurements in experimental Plot 1

However, Experimental Plot 2, which served as the Nichawan Farm owner's family forest, was an integrated farming area. Various types of plants were cultivated here, including valuable trees such as teak, red sandalwood, and fruit trees like mango, pomelo, custard apple, and coconut. In addition, there were numerous bamboo trees in this area. Diverse tree species were intentionally selected to create a distinct contrast from Experimental Plot 1. Nevertheless, assessing bamboo biomass sequestration varied by the number of stems and their diameters. Therefore, height-based calculations were not applicable for bamboo, and only tree species relying on height for calculations were considered in this study. After comparing the carbon sequestration quantities using both survey methods, the results are illustrated in Fig. 7. Further statistical analysis using the Pearson correlation coefficient revealed a significant correlation at the 0.01 level, indicating a highly consistent relationship between the results obtained from both methods, with an R-value of 0.993.

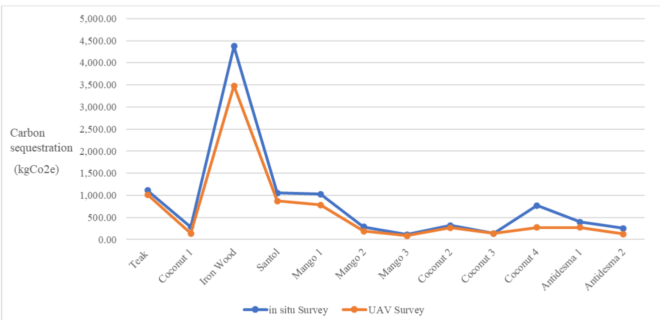

Fig.7 Comparison of carbon sequestration obtained from tree height measurements in experimental plot 2

3.2 Discussion

Currently, there is a growing interest in the study of biomass, accompanied by rapid technological advancements, particularly in geospatial technology, which plays a crucial role in biomass assessment [37-38]. Unmanned aerial vehicles (UAVs) have been widely employed to verify above-ground carbon sequestration, as evidenced by the findings of Rinnaman et al. (2020), who estimated above-ground biomass using teak plantations (Tectona Grandis) in Thailand[39], agrees with the results of this study that general plant allometry equations can be applied to tree groups inside the plot.

Correspondingly, the results of this study demonstrated the feasibility of utilizing UAVs, especially in analyzing tree height, a critical factor in calculating carbon sequestration. UAVs offered the advantage of operating over large plot areas and providing more coverage than field surveys, which required the establishment of sample plots that could represent the area, potentially leading to inaccuracy. Furthermore, UAVs provided high-resolution imagery with Ground Sampling Distance (GSD) ranging from 2 to 3 centimeters, consistent with the findings of Thanh et al. (2023)[23]. Moreover, Corte et al.'s recommendations have been shown to save time and money on tree surveys within plantations [24]. The results of both studies were in the same direction as the results of this work, which can UAVs be used to replace the measurement of trees within the experimental plots.

Additionally, LiDAR-based UAVs were more accurate [40-41] compared to UAVs using RGB and Multispectral cameras, but they came with significantly higher costs[42]. Therefore, for surveys accessible to everyone, including farmers or plantation plot owners themselves, UAVs with RGB and Multispectral cameras are still viable alternatives.

Although UAVs assisted in height measurements, they still posed limitations in assessing carbon sequestration of bamboo plants due to their unique evaluation methods. Bamboo required a different assessment approach compared to other plant species, as it did not rely solely on height but involved counting the number of stems and measuring their diameters[43]. Future studies should analyze various variables affecting biomass production and carbon sequestration to improve prediction accuracy and increasing of biomass [44-46]. In addition, a variety of models such as machine learning and deep learning must be examined for the study for future implementation[47-48]. For forest management, UAVs can help track the growth and monitor the health of trees within the plot.

4. Conclusion

In this study, it was observed that evaluating biodiversity conservation from two distinct sample areas, differing in land use patterns, allowed for a comparison between agricultural and family forest areas which were the unique land use patterns found in rural Thailand, characterized by the combination of food-producing plants like fruits and plants used for livelihood such as bamboo, teak, and redwood. Given the significant presence of such landscapes in Thailand, both types of areas were examined. The results indicated that the method of measuring tree height using a canopy height model with UAVs could effectively replace traditional field surveys. This was validated through testing the models using RMSE and MAE methods, yielding RMSE values of 2.740 meters and 2.654 meters for Plot 1, and 2.863 meters and 2.666 meters for Plot 2, respectively. Subsequently, biodiversity conservation was assessed using an allometric equation, with different variables identified in the two measurement methods. The correlation between the results of carbon sequestration from both methods was then compared using Pearson Correlation statistics. The results revealed that Plot 1 and Plot 2 had correlation coefficient (r) values of 0.758 and 0.993, respectively. Although measuring the height of trees in the field is an easy way to collect data in the field, it is not possible to collect data for a limited of time throughout the entire plot. Therefore, using unmanned aerial vehicles to help collect data is a method that can help save time. In addition, the use of unmanned aerial vehicles can improve the accuracy of the instrument using digital photogrammetry by specifying ground control points, resulting in accurate values, which is different from measuring height by in-situ survey**.** This is especially when using phone applications, which are more prone to errors by both tools and humans**.**

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