Integration of Aerial Mapping using UAV and Low-cost Backpack LiDAR for Biomass and Carbon Stock Estimation Calculation

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Abstract

The total forest area in Indonesia reaches 62.97% of Indonesia's land area or approximately 125.76 hectares, requiring effective and accurate inventory methods. Conventional methods have a high level of accuracy but require large costs and labor. The use of UAV (Unmanned Aerial Vehicles) and Backpack LiDAR technology has emerged as an efficient alternative solution for forest inventory. The UAV serves as an aerial image capture platform that generates orthomosaic and canopy height data through the Canopy Height Model (CHM). Meanwhile, Backpack LiDAR can generate detailed point cloud data that enables stem diameter (DBH) measurement and Above-Ground Biomass (AGB) estimation. The analysis showed that the backpack LiDAR had an RMSE error of 0.793 meters and a standard deviation of 0.30332 cm for DBH. Linear regression showed a relationship between DBH and AGB with an R^2 of 0.5591, indicating DBH had a significant effect on AGB. These data were used to calculate carbon stocks, which had small differences between the manual and backpack LiDAR methods. The results show that this technology-based method can improve efficiency and accuracy in forest inventory and support climate change mitigation efforts.

1. Introduction

According to data from the Ministry of Environment and Forestry (2020), the total forest area in Indonesia reaches 62.97% of Indonesia's land area or around 125.76 hectares. Forest inventory information is essential in forest management. In addition, for sustainable forest management, further information is needed, not only for planning future forest management (Koch et al. 2006). Forests need to be managed to ensure their sustainability so that they can be utilized to their full potential. Sustainable forest management requires precise and accurate understanding (Fankhauser et al. 2018) because forests have many important roles for humans and all other living things in the forest (Yilmaz et al. 2017). One of the early stages of forest management is to collect all information related to forest resources through forest inventory activities. Information based on forest inventory results will be very helpful for assessing forest ecosystem services, estimating stand volume, stored carbon and so on (Hematang et al, 2021).

Forest inventorying is still mostly done conventionally by conducting direct field measurements which have a high level of accuracy but require a lot of time, money, and manpower for the implementation in the field to run well. However, along with the times, the technology used for forest inventory has also developed. One of the technologies for capturing field data quickly and precisely is aerial photography technology using UAVs or unmanned vehicles (Hematang et al., 2021) and backpack LiDAR technology.

Unmanned Aerial Vehicles (UAVs) are platforms for taking aerial photographs whose operation is remotely controlled semi-automatically or automatically without a pilot on the platform (Puliti et al, 2017). The advantages of UAVs are that they can be used in high-risk situations without the need to endanger human lives, in inaccessible areas and fly at low altitudes under the clouds so that the resulting photos are free from clouds (Subakti, 2017). On the other hand, Backpack LiDAR technology enables efficient collection of spatial data in the form of point clouds with a high level of detail. Utilized in forest inventory, LiDAR can produce very complete data about tree segmentation. In addition to measuring tree height, LiDAR can also detect the position of each tree in the form of XY coordinates, the number of trees, canopy diameter and so on (Liu et al, 2018)

In contrast to conventional methods, backpack LiDAR offers ease of mobility and time effectiveness, especially in areas that are difficult to reach or have rough terrain. The combination of UAV and backpack LiDAR technology offers a more effective solution for forest inventory activities that require accurate data in a short time and at a lower cost compared to traditional methods. The use of UAVs equipped with high-resolution cameras for aerial mapping enables the acquisition of sharp images of the forest canopy and other areas (Zhang et al., 2019). Meanwhile, backpack LiDAR can provide detailed information on vegetation down to the lower levels of tree trunk and branch structure (Holmgren et al. 2003). The integration of these two technologies can provide more comprehensive data for various forest inventory purposes, such as biomass and carbon stock estimation, which are important indicators in assessing forest health and its potential to store carbon. With these data, sustainable forest management can be

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carried out with a more data-driven approach, to support climate change mitigation efforts and ensure that the potential of forest resources can be utilized while maintaining its sustainability.

2. Methodology

2.1 Research Location

The study area is located in Wonorejo Mangrove with Coordinates -7.312613°E and 112.825161°, Approximately 0.81 hectares of forest were selected for this study, The study area is dominated by vegetation growing close to each other, with the main tree species being *xylocarpus, Avicennia alba,* and *Avicennia Marina.*

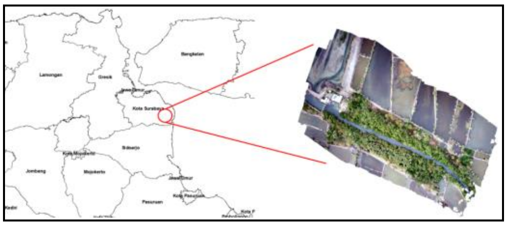

Figure 1. Study Area

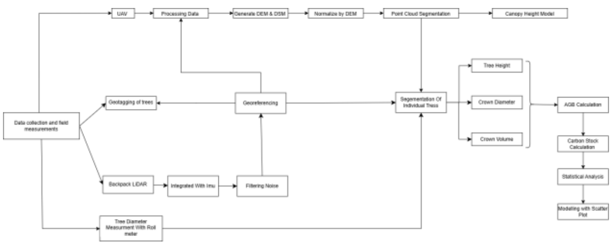

Figure 2. Flow Chart Research

This research aims to detect and segment trees using an approach that integrates aerial imagery and point cloud data. Aerial imagery is captured using a high-resolution drone that provides a detailed view from above the plantation area, while point cloud data is obtained through Backpack LiDAR technology that provides three-dimensional spatial information on topography and vegetation.

2.2 Field Measurements

The data collection process begins with the UAV flying along a predetermined route to obtain aerial imagery of the forest area being studied. Meanwhile, the operator with the LiDAR backpack moves on the ground to map the vegetation structure and topography of the same area. This data was obtained from photogrammetric survey measurements using the DJI Mavic Pro equipped with a camera sensor at a height of 120 m above the ground. Data collection was carried out during the day in clear weather.

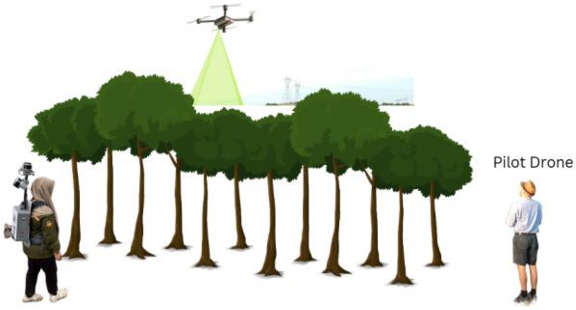

Figure 3. Data Collection Process

Data pre-processing involves aligning and merging aerial imagery to create a comprehensive dataset. Based on the resulting Ortho mosaic, elevation data from the ground surface to the canopy are processed to create a Digital Elevation Model (DEM) and a Digital Surface Model (DSM). DEM represents the elevation of the land without vegetation, while DSM shows the elevation of all elements (Zarco-Tejada et al, 2014). Using DSM and DEM, canopy height can be calculated, an important indicator in estimating biomass. This data is then used to identify vegetation types and canopy densities which form the basis for biomass and carbon stock estimates.

The data generated from the LiDAR backpack is a collection of points (point cloud) with three-dimensional coordinates (x, y, z) that show the position and height of the object (Liu et al, 2018). This data is filtered to remove noise and ensure only relevant points such as tree trunks. The point cloud is segmented to identify different vegetation structures, such as tree trunks and crowns. This segmentation is important for calculating the volume or structure of each tree, which plays a role in calculating biomass.

2.3 Tree Sample

In this study, Tree samples used in this study were taken along the measurement path. All trees were measured for their chest diameter using a roll meter. This DBH data is very important in building a biomass estimation model because it has a close relationship with the volume and biomass of the tree. In addition, the XYZ coordinate position of each tree was also recorded using a GPS device which is a low-cost GPS technology, namely Smart Geo PD ITS. This aims to obtain accurate position data, which will later be used to match trees measured in the field with aerial imagery and point cloud data generated from UAVs and backpack LiDAR. However, because dense tree canopies can block GPS signal reception, which can reduce the accuracy of tree position, position recording is carried out by referring to the direction of the measurement path. This approach is taken so that the position of the tree remains accurate even though there is interference from the canopy that affects the quality of the GPS signal. After the tree position and DBH data are obtained, the next step is to match the measured tree position with aerial imagery data from UAVs and point clouds from LiDAR. This matching process is important to ensure that the position of the tree in the resulting spatial data can be validated with field data, thereby increasing the accuracy of biomass and carbon stock estimates and facilitating better forest management.

2.4 Point Cloud Segmentation Method

Tao et al. (2015) developed a TLS point cloud segmentation method with a bottom-up approach to identify individual trees. This method utilizes TLS data taken from under the canopy, where tree branches are visible and can be used as a reference for segmenting information.

Biomass plays an important role in the carbon cycle, where the amount of biomass in vegetation can be used to estimate carbon stock values. Based on SNI 7724:11, carbon and biomass estimates can be calculated using established formulas. Previous studies used the Allometric formula to calculate biomass in tree branches and leaves, as shown in the following equation:

$$B = \text{V x BJ x BEF} \qquad (1)$$

Description:

- B: Above-ground biomass, in kilograms (kg).

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- V: Volume of wood without branches, in cubic meters (m^3).
- BJ: Wood density, in kilograms per cubic meter (kg/m^3).
- BEF: Biomass expansion factor.

Wood volume is estimated by measurement, usually the tree's height and diameter. The measurement of diameter is taken at a standard height about 1.3 meters from the ground, known as Diameter at Breast Height or DBH, while the height of the tree is measured from the ground to the highest point of the tree. Calculation of wood volume the method used in calculating the volume of wood follows the volume of a cylinder formula as set out by the Indonesian National Standard (SNI), that is, National Standardization Agency 2011. The volume in this method is calculated using the formula below:

$$V = 0,25\ \pi \text{ x } r^2 \text{ x } h \text{ x } F \quad (2)$$

Description:

- **r**: Tree radius (DBH) in meters (m).
- **h**: Tree height in meters (m).
- **F**: Tree shape factor (usually 0.6).

This approach takes into account the differences in tree trunk shape, with a shape factor (F) that corrects for differences between tree and perfect cylinder shapes. Typically, tree trunks are not perfectly straight or perfectly cylindrical; this shape factor accommodates these variations to make the volume calculation closer to reality. The shape factor (F) is calculated by comparing the actual volumes of cylinders with the same diameter and height. A common value for significant tree branches is 0.5, used without a specific shape factor for that category. After calculating biomass, the next step is to estimate carbon stock based on SNI 7724:11 which states that 47% of biomass contains carbon using the following formula:

$$\mathit{Carbon\ Stock} = 0,47 * B \quad (3)$$

Description:

- Carbon Stock: Carbon storage in vegetation (Ca/ha).
- B: Stem biomass (Ca/ha).

The carbon stock in a forest ecosystem is closely related to the biomass stored in trees and other vegetation. The calculated carbon stock is usually expressed in units of Ca per hectare (Ca/ha), illustrating the capacity of carbon stored in a land area. As the amount of biomass in vegetation increases, the amount of carbon stored also increases significantly. Vegetation, especially trees with larger biomass, absorbs carbon dioxide from the atmosphere and stores it in the form of carbon in wood tissue, leaves, and other plant parts. Therefore, forests with large and dense trees tend to store higher amounts of carbon per hectare.

3. Results and Discussion

3.1 Low-cost GNSS Field Data

The Global Navigation Satellite System (GNSS) commonly used for vehicle navigation and positioning, also plays a critical role in geospatial data collection (Cahyadi et al, 2022). In this study, the use of low-cost GNSS type F9R aims to obtain Ground Control Point (GCP) data as a reference point for data from Backpack LiDAR and Aerial Photography. This GNSS data is used for the georeferencing process, which aims for the point cloud to have a global reference system. This georeferencing process only uses translational parameters on the x, y, z axes and rotation on the x, y, and z axes, without using a scale (not enlarging or reducing the data). This approach is taken to avoid errors that can affect the accuracy of LiDAR point cloud data.

No.	Description	Easting (m)	Northing (m)
1	GCP 1	701478.563	9191291.433
2	GCP 2	701476.3379	9191287.387
3	GCP 3	701474.6301	9191283.818
4	GCP 4	701476.1913	9191278.465
5	GCP 5	701467.8404	9191270.683
6	GCP 6	701469.3466	9191269.903

No.	Z (m)	STDV X	STDV Y	STDV Z
1	31.1	0.74	0.15	0.03
2	31.3	0.52	0.11	0.23
3	31	0.81	0.54	0.07
4	31.3	0.37	0.82	0.23
5	30.6	0.98	0.6	0.47
6	31.1	0.47	0.38	0.03

Table 1. Low-cost GNSS Field Data

The data is used to correct the position and orientation of the LiDAR point cloud to match the coordinates of the global reference system, ensuring the accuracy and quality of the data produced. In this table, the columns STDV X, STDV Y, and STDV Z show the standard deviation for each GCP coordinate in the horizontal and vertical directions. These values provide a figure of measurement precision, which serves to assess the reliability of the GNSS data used in the georeferencing process. Data with a smaller standard deviation indicates a higher level of precision at that coordinate.

3.2 LiDAR and UAV Georeferencing with Low-cost GNSS

LiDAR and UAV georeferencing with Low-cost GNSS is conducted as the first step in the 3D modelling process. The use of low-cost GNSS allows the acquisition of GCP data at a lower cost, but still provides accurate accuracy for georeferencing purposes. GNSS data from these GCP points is then used to align LiDAR data and aerial photographs to the same global coordinate system, thus facilitating integration between LiDAR and UAV data.

The georeferencing process begins by adjusting the position and orientation of the LiDAR and aerial photography scanned point cloud data with the GCP references. Translations and rotations on the x, y and z axes were applied to align the data with the actual position on the ground. However, scale transformation was not applied to keep the object dimensions in line with the original size and minimise the risk of data distortion.

The use of F9R type low-cost GNSS data with measurable standard deviations at each GCP point helped to improve the georeferencing accuracy (Cahyadi et al, 2023). A low standard deviation in GCP coordinates is an indicator of measurement accuracy, which plays an important role in maintaining the accuracy of the georeferencing process. Thus, the generation of precise and affordable 3D models that can be utilized for a

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variety of spatial analysis and in-depth field mapping applications is made possible by the combination of inexpensive GNSS data, LiDAR, and aerial photography. Georeferencing is mostly used to convert local LiDAR coordinates to global coordinates. The following outcomes were obtained using the georeferencing procedure.

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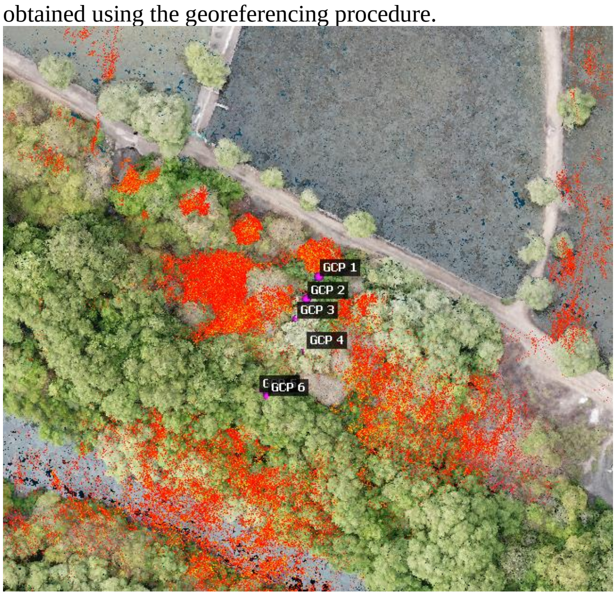


Figure 4. Visualisation of GCP locations in georeferenced data

The Figure 4, The georeferencing process's result displays an RMSE value of 0.793 meters for the point cloud data and 0.667 meters for the UAV aerial photography data. The degree of inaccuracy between the points' locations on the georeferenced point cloud and their real ground positions using the GCP reference is indicated by this RMSE number. While the RMSE of 0.793 meters for the LiDAR data indicates that the LiDAR point cloud accuracy is still within acceptable tolerance limits for large-scale mapping and spatial analysis applications, the RMSE of 0.667 meters for the UAV data indicates that the aerial photography data has a high level of accuracy. The small difference between the RMSE values is due to the difference in resolution and data capture techniques between UAV and LiDAR. Overall, the georeferencing process successfully aligned the LiDAR and UAV data on a global coordinate system with sufficient accuracy, supporting the need for precise 3D modelling.

3.3 Canopy Height Model (CHM)

The UAV data was processed using Agisoft Metashape software to generate an orthomosaic map. This orthomosaic map is made up of many aerial pictures integrated into a single figure. Figure 5 shows how an orthomosaic figure creates a comprehensive and accurate visual representation of the mapped area.


Figure 5. Orthomosaic Results from Aerial Photograph Data

Following the creation of the orthomosaic map, the data is further processed to generate 3D Point Clouds and Mesh, as illustrated in Figure 6. This step seeks to create a Digital Surface Model (DSM) and a Digital Terrain Model. The DSM represents the top surface of all things in the area, including vegetation, buildings, and other structures, whereas the DTM solely represents the ground surface with no items on it.


Figure 6. 3D points clous result from Aerial Photo Data

The following step is to normalize the data by subtracting the DSM from the DTM. This procedure produces the Canopy Height Model (CHM), which represents the height of trees or vegetation in the mapped area, in this case the mangrove forest. Figure 7 depicts the fluctuation in tree canopy height in the mangrove area, as provided by this CHM. This CHM data is extremely important for vegetation study, forest health monitoring, and management of mangrove forest conservation zones.

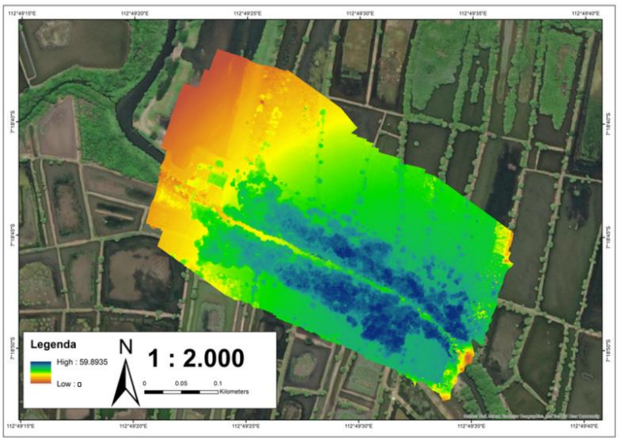
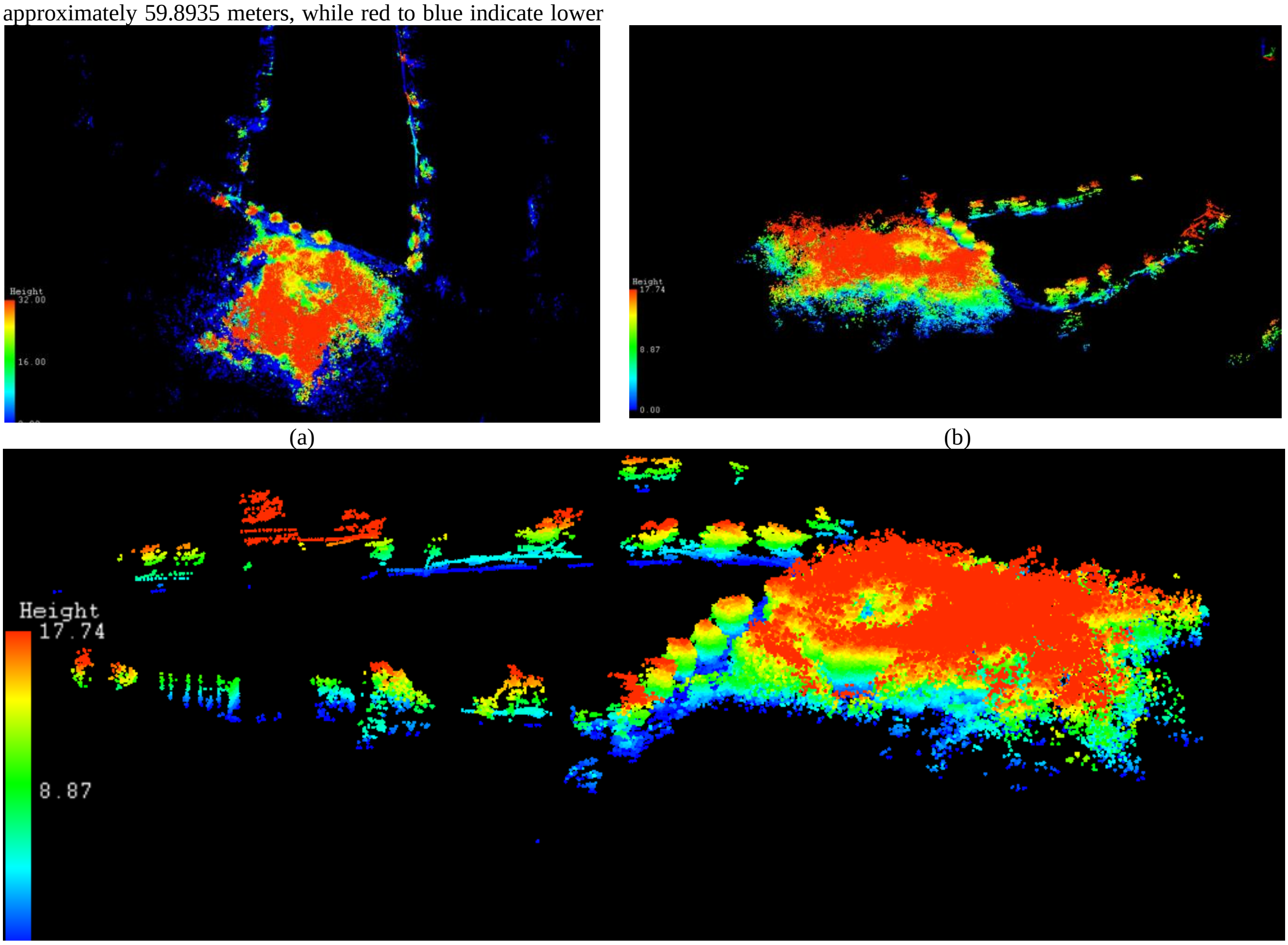


Figure 7. Canopy Height Model

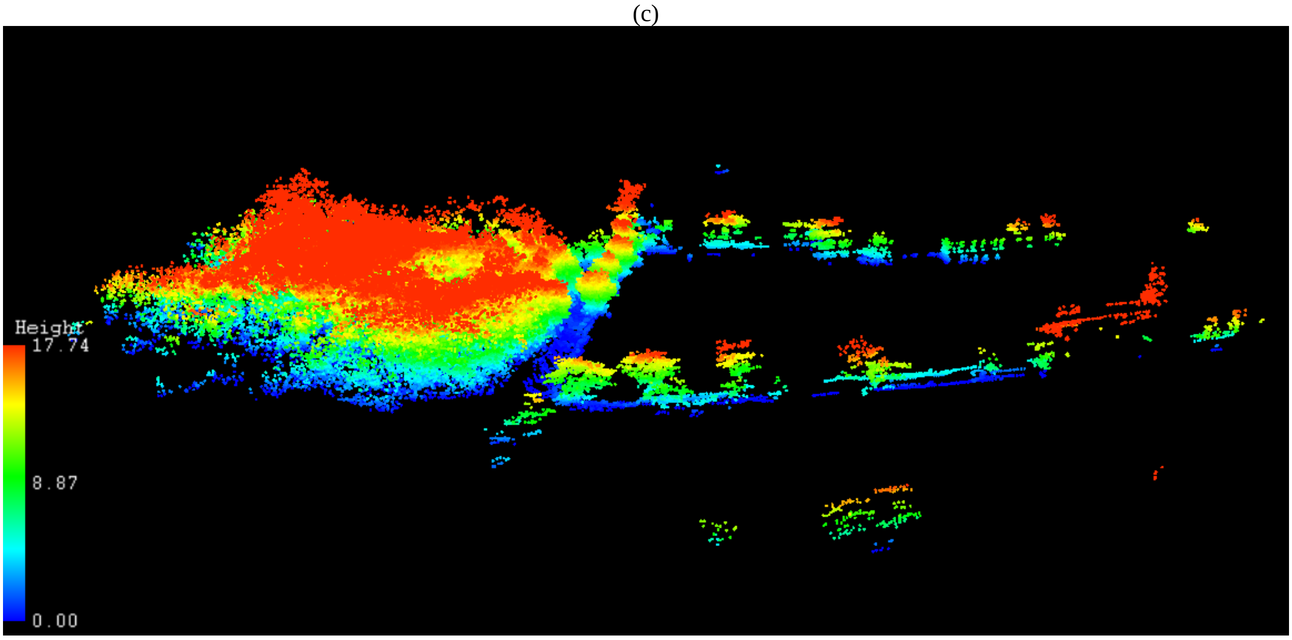
Figure 7 shows the CHM mapping results that represent the variation of canopy height in the mangrove forest area. The model displays color gradations that reflect canopy height, where blue indicates areas with the highest canopy, reaching approximately 59.8935 meters, while red to blue indicate lower heights or even areas with no canopy. This color gradient helps to identify the difference in canopy height, which gives an idea of the vertical structure of the vegetation in the area. The distribution of canopy height in the map shows areas with taller and denser trees (marked in dark blue), as well as areas with lower or open canopy (colored red).

3.4 3D Tree Data Visualization

3D tree data is obtained by utilizing point cloud data scanned using Backpack LiDAR. The process of capturing point cloud data is done through the SLAM process, this method is able to produce point clouds that accurately reflect the spatial structure of the environment, including details of tree shape and density. The tree extraction process is performed by classifying tree objects from the point cloud data based on height and canopy shape. Segmentation filters are applied to distinguish trees from other objects such as land, buildings, or other vegetation elements. The segmentation results are then used to visualize each tree as a separate 3D object, with details of the canopy, trunk, and branches that can be analyzed individually. In the 3D visualization, each tree is represented from the trunk area to the canopy. However, shadows or other obstructing objects can also affect the data density, especially at the top of the tree. The following is the result of 3D visualization of the model using backpack in Figure 8.



(c)



(d)

Figure 8. Backpack Lidar Point Cloud Data Visualization, a). Top View, b) Top View Facing North, c). Left Side View, d) Right Side View

The data visualization of each individual tree is shown in Figure 9 below. The top of the tree (canopy) appears to have a lower density than the trunk area of the tree object

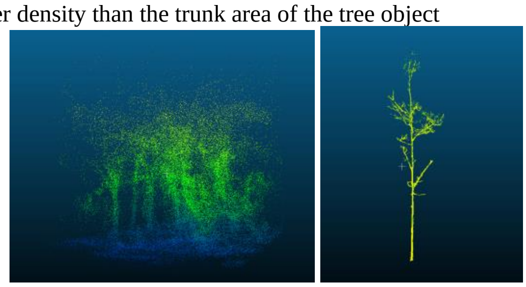


Figure 9. Individual tree data visualization.

3.5 Calculation of DBH and AGB

Comparison of tree diameter between point cloud data and measurements using a tape measure is done by calculating the absolute difference between the two datasets to obtain the discrepancy at each point. Next, the RMSE (Root Mean Square Error) and Standard Deviation values are calculated to assess the accuracy of the data. The results of the difference calculations between the two datasets are shown in Table 2, with visualization in Figure 10. MBP represents the result of subtracting the tape measure data from the backpack LiDAR data.

DBH Roll meter (m)	**DBH BP (m)**	**ID**	**MBP (cm)**	**(MBP) ^2**
1.580	1.587	1	0.700	0.490
0.388	0.396	2	0.800	0.640
0.843	0.849	3	0.600	0.360
1.109	1.113	4	0.400	0.160
1.000	1.003	5	0.300	0.090
0.285	0.287	6	0.200	0.040
3.640	3.632	7	0.800	0.640
1.555	1.558	8	0.300	0.090
0.310	0.312	9	0.200	0.040
1.630	1.636	10	0.600	0.360
1.143	1.145	11	0.200	0.040
1.496	1.497	12	0.100	0.010
2.287	2.299	13	1.200	1.440
0.550	0.549	14	0.100	0.010
0.948	0.955	15	0.700	0.490
1.816	1.822	16	0.600	0.360
4.068	4.071	17	0.300	0.090
2.284	2.286	18	0.200	0.040
0.525	0.534	19	0.900	0.810
1.118	1.126	20	0.800	0.640
			Mean	0.500
			RMSE	0.585
			STDV	0.30332

Tabel 2. Table of comparison DBH

The data of the table can be analysis that the difference in tree diameter between measurement using a roll meter and BP LiDAR shows a significant difference. For example, tree number 2 difference between roll meter and BP LiDAR reach 0.800 cm, while for tree number 12, the difference only 0.100 cm. Overall the average MBP difference between the two measurement methods is 0.500 cm, indicating that although both methods provide similar results, there are still small differences between them.

The value of RMSE is 0.585 cm and indicates an average measurement error that is not too large, but it still suggests a variation in accuracy between the two methods. This could be due to various factors, incl inaccuracies in LiDAR data processing or the influence of external factors in the field, such as objects obstructing the sensor. Meanwhile, the standard deviation is 0.303 cm, which indicates a spread of errors across the various trees measured, although it is not too high. This spread may be caused by factors such as varying BP LiDAR data quality at different points or the impact of field measurements.

In this analysis, it can be concluded with difference between the two methods is not very large, the RMSE and standard deviation values indicate room for improvement in measurement accuracy, especially for trees with more significant diameter differences. In other case, external factors such as object obstructions and field data collection conditions can affect measurement results and serve as additional sources of error.

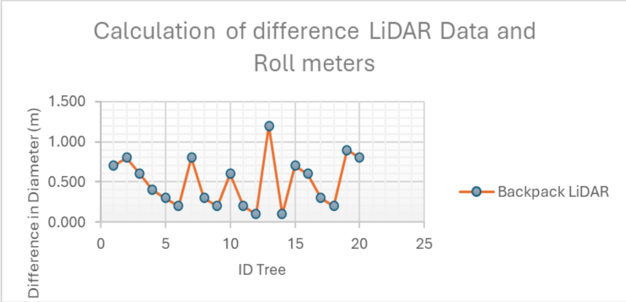


Figure 10. Difference graph between LiDAR Data and Roll meters measured

In Figure 10, it can be seen that most of the MBP data distribution is below 1 m, indicating good horizontal accuracy in the measurements, however there is an outlier for tree number 13, with a value of around 1.2 meters. AGB represents the amount of biomass above the ground in a tree, including the trunk, branches, and leaves. The AGB value is often used as an important indicator in ecology and forestry to assess tree growth and health, as well as its role in carbon storage. Therefore, an AGB value distribution is needed for further processing.

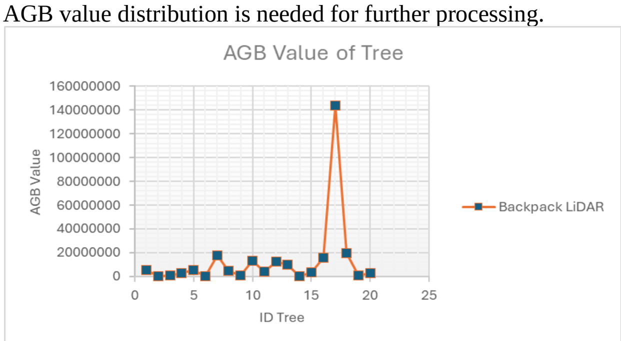


Figure 11. Graph of value AGB each of tree

In figure 11, it can be seen the distribution of AGB values on every tree in the dataset that already analysed. This graphics provide an illustration about the variation of AGB among different trees, also might be seen to us for doing identification to general pattern, such as corelation between the size of the tree by the diameter of the tree trunk or DBH and AGB, also the existence of the outlier or extreme value that can affect the analysis output. DBH calculated the diameter of the tree trunks on 1,3 meters height from the ground. Meanwhile AGB was aimed for the masses of tree biomass on the ground, include the tree trunk, the branch, and the leaves. The following is the relationship between DBH and AGB which can be seen in Figure 13.

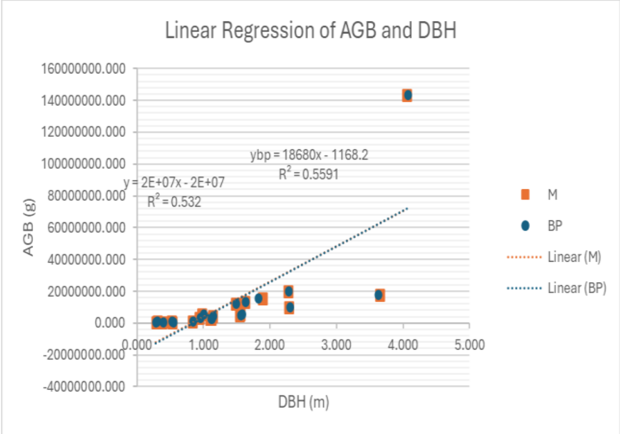


Figure 12. Regression Linear of DBH with AGB

In figure 12, The measurement that already done was using backpack LiDAR with the value of R^2 is equal to 0.5591, that means around 55,91% changes of the DBH value on "BP" data can provide an illustration of how much change has occurred in the AGB (Above-Ground Biomass). This means that DBH has a significant influence in determining the AGB value in the group. However, there is about 44.09% of AGB variation that can't explained only by the changes in DBH, which may be caused by other factors that affect AGB, such as tree species, environmental conditions, or other factors not included in this linear regression model.

Based on the result of the AGB calculation, the carbon stock of each tree was calculated. The estimated of the carbon stock based on SNI 7724:11 states that 47% from biomass content is carbon, so for the estimated of carbon is by multiplied the biomass by 47% of the biomass elements that are thought to be carbon. The visual graph of the carbon stock calculation is shown in Figure 13.

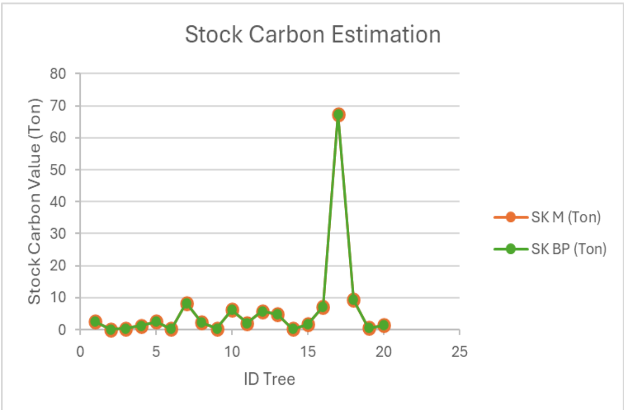


Figure 13. Graph data of Carbon Stock Estimation

In figure 13, the analysis of comparison the Carbon Uptake (CU) that obtained from two measurement methods, the manual method and backpack LiDAR, with the result are similar one to each other, with the very smalls difference. For example, for the first measurement, the value of CU that obtained from the manual method was 2,577,127977 tons, while the BP method is 2,577,121053 tons, with a difference of only about 6 grams. The similar differences are also seen in other measurements, where most of CU values that obtained from both methods are almost identical, with very small differences, for the low and high carbon values. For example, in data with values of 0, 164730167 tons in manual method and 0,164740659 tons in BP method, the differences is about 0,000010492 tons, which is very small. This shows that both of the methods produce estimation of carbon uptake with consistent and accurate. Although the result almost identical, the use of backpack LiDAR have more advantage in efficiency, because it can do measurements on larger area in a short of a time, consider it as the best option for larger area measurements or the location that hard to reach.

4. Conslusion

In light of Indonesia's vast forests, which are essential to the world environment, this study intends to create forest inventory techniques that use technology to improve the accuracy and efficiency of gathering data on forest resources. For efficient forest management and ecosystem health monitoring, which in turn aids in attempts to mitigate climate change, proper inventorying is essential. The study makes use of technologies as Backpack LiDAR to collect detailed spatial data in the form of point clouds and Unmanned Aerial Vehicles (UAVs) for aerial mapping. Furthermore, inexpensive GNSS is used to help with georeferencing, which makes it possible to create precise spatial models in a global reference system.

The research findings indicate that the georeferencing of LiDAR and UAV data resulted in relatively low RMSE values, 0.667 meters for UAV data and 0.793 meters for LiDAR data. These results demonstrate adequate accuracy for 3D modeling, which is essential for various spatial analysis applications. The study also produced a Canopy Height Model (CHM) that visualizes canopy heights in the mangrove forest area, helping to monitor variations in canopy height and identify vegetation structure.

Further analysis included the calculation of Diameter at Breast Height (DBH) and Above-Ground Biomass (AGB), which revealed a significant relationship between tree trunk diameter and biomass. The AGB values obtained from manual measurements ranged from 350,489.716g to 143,424,179.634g, while the values from the Backpack LiDAR measurements ranged from 350,512.040g to 143,424,202.949g. Carbon stock calculations were made based on biomass estimates, showing that the Backpack LiDAR method yielded carbon absorption values very similar to those of manual methods, but with greater efficiency. Overall, the combination of UAV and Backpack LiDAR technologies proved to be effective in providing accurate and efficient forest inventory data. The use of these technologies can save time and costs, especially in large-scale mapping or areas that are difficult to access.

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Reference

Badan Standarisasi Nasional. (2011). Pengukuran dan penghitungan Cadangan karbon Pengukuran lapangan untuk penaksiran cadangan karbon hutan (ground based forest carbon accounting). www.bsn.go.id

Cahyadi, M. N., Asfihani, T., Mardiyanto, R., & Erfianti, R. (2022). Loosely Coupled GNSS and IMU Integration for Accurate i-Boat Horizontal Navigation. *International Journal of Geoinformatics*, *18*(3).

Cahyadi, M. N., Asfihani, T., Mardiyanto, R., & Erfianti, R. (2023). Performance of GPS and IMU sensor fusion using unscented Kalman filter for precise i-Boat navigation in infinite wide waters. *Geodesy and Geodynamics*, *14*(3), 265-274.

Fankhauser, K. E., Strigul, N. S., & Gatziolis, D. (2018). Augmentation of traditional forest inventory and airborne laser scanning with unmanned aerial systems and photogrammetry for forest monitoring. Remote Sensing, 10(10), 1562.

Hematang, F., Murdjoko, A., & Hendri (2021). Model Pendugaan Diameter Pohon Berbasis Citra Unmanned Aerial Vehicle (UAV) Pada Hutan Hujan Tropis Papua: Studi Di Pulau Mansinam Papua Barat. Jurnal Penelitian Kehutanan Faloak, 5(1):16-30. DOI: http://doi.org/10.20886/jpkf.2021.5.1.16-30

Holmgren, J., Nilsson, M., & Olsson, H. (2003). Simulating the effects of lidar scanning angle for estimation of mean tree height and canopy closure. Canadian Journal of Remote Sensing, 29(5), 623-632.

Koch, B., Heyder, U., & Weinacker, H. (2006). Detection of individual tree crowns in airborne LiDAR data. Photogrammetric Engineering and Remote Sensing, 72, pp. 357-63.

Koch, E. W., Barbier, E. B., Silliman, B. R., Reed, D. J., Perillo, G. M. E., Hacker, S. D., Granek, E. F., Primavera, J. H., Muthiga, N., Polasky, S., Halpern, B. S., Kennedy, C. J., Kappel, C. V., & Wolanski, E. (2009). Non-linearity in ecosystem services: Temporal and spatial variability in coastal protection. Frontiers in Ecology and The Environment, 7(1), 29–37.

Lisein, J., Pierrot-Deseilligny, M., Bonnet, S., & Lejeune, P. (2013). A photogrammetric workflow for the creation of a forest canopy height model from small unmanned aerial system imagery. Forests, 4(4), 922-944.

Liu, K., Shen, X., Cao, L., Wang, G., & Cao, F. (2018). Estimating forest structural attributes using UAV-LiDAR data in Ginkgo plantations. ISPRS Journal of Photogrammetry and Remote Sensing, 146, 465-482.

Puliti, S., Ene, L. T., Gobakken, T., & Næsset, E. (2017). Use of partial-coverage UAV data in sampling for large scale forest inventories. Remote Sensing of Environment, 194, 115-126.

Tao, S., Wu, F., Guo, Q., Wang, Y., Li, W., Xue, B., Hu, X., Li, P., Tian, D., Li, C., Yao, H., Li, Y., Xu, G., & Fang, J. (2015). Segmenting tree crowns from terrestrial and mobile LiDAR data by exploring ecological theories. ISPRS Journal of Photogrammetry and Remote Sensing, 110, 66–76. https://doi.org/10.1016/J.ISPRSJPRS.2015.10.007

Yilmaz, V., Levent, T., Cigdem, Y., & Oguz, G. (2017). Determination of tree crown diameters with segmentation of a UAS Based canopy height model. IPSI BgD Transactions on Internet Research, 13(July), 63–67.

Zarco-Tejada, P. J., Diaz-Varela, R., Angileri, V., & Loudjani, P. (2014). Tree height quantification using very high-resolution imagery acquired from an unmanned aerial vehicle (UAV) and automatic 3D photo-reconstruction methods. European Journal of Agronomy, 55, 89-99.

Zhang, Y., Wu, H., & Yang, W. (2019). Forests growth monitoring based on tree canopy 3D reconstruction using UAV aerial photogrammetry. Forests, 10(12), 1–16. https://doi.org/10.3390/f10121052