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RESEARCH ARTICLE

Enhancing Performance Production Forest Inventory in Java Using LiDAR Technology

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ABSTRACT

Forest inventory (FI) is an essential process for assessing the quality and quantity of forest resources, forming the foundation for strategic planning and sustainable management. Terrestrial methods (sampling / census), remote sensing methods, or a combination of these can be used to obtain this data and information. This study explores the application of LiDAR technology to improve forest inventory practices in plantation forests (teak and pine) in Java, Indonesia. LiDAR sensors, deployed via drones and handheld devices, were tested in several Perum Perhutani Forest Management Unit compartments, which were the locations of proof of concept (PoC). PoC is a testing process to prove the feasibility of a concept or methodology before it is implemented. The results showed that LiDAR-based inventories provide superior accuracy compared to traditional methods, with data showing strong alignment with ground-truth measurements. These results underscore the potential of LiDAR technology to revolutionize FI practices and inform sustainable forest management strategies in Java and beyond. The use of this technology in natural forests where the variety of tree species is more diverse certainly requires further study.

Introduction

Forest inventory (FI) is needed to understand forest resources (FR), plan, and make decisions related to forest management through sampling, census, and remote sensing (RS) methods. This includes highly complex production planning (harvesting, transportation, and standing stock management), which requires a decision support system that combines effective mathematical models [1], carried out at the national, provincial, and management unit levels. Data on forest cover, type, and potential of forest stands, hydrology, and water management can be obtained from inventories at the watershed level [2]. More accurate and less labor-intensive are required to estimate tree dimensions [3–5], so the use of RS based on 3D models is a possible alternative for collecting structural data [3,6,7]. Especially in the current precision forestry paradigm where forest planning uses digital data, detailed procedures, and operational controls. FI data are essential for accurately estimating various dendrometric and forest stand parameters; however, applying them manually is time-consuming, sometimes inaccurate, and expensive [8]. The use of RS is very helpful in obtaining deforestation data in Indonesia, which is estimated to reach ± 840,000 hectares, and Brazil ± 460,000 hectares in 2012 [9] because it is georeferenced, making it easy to integrate with Geographic Information System (GIS) databases.

Visual estimation methods often used in inventory and operations pose a risk of bias, so it is necessary to collect data with multi-source techniques, including terrestrial surveys, satellite imagery analysis, and other georeferenced data. Emerging RS technologies are light detection and ranging (LiDAR), which uses laser pulses to capture images and create 3D models, in addition to aerial photography, satellite imagery, and radio detection and ranging (RADAR) techniques. Aerial photography uses image capture through optical cameras, satellite imagery uses ground electromagnetic radiation sensors, while RADAR, as an active RS, uses radio

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waves to capture images and data according to wave numbers. LiDAR has high resolution and accuracy due to its ability to capture images accurately, aerial photographs can provide high resolution according to camera quality and lens distortion, while satellite imagery has varying resolution depending on the camera and sensor used. RADAR has lower spatial resolution compared to LIDAR and satellite imagery, although it can be used for other applications, such as groundwater mapping or monitoring atmospheric conditions. LiDAR can be affected by rain and fog conditions as well as vegetation density, aerial photographs are influenced by sunlight, and satellite images can be influenced by cloud cover, while RADAR has weaknesses in penetrating solid materials or detecting small objects.

LiDAR technology was developed in 1961, using laser pulses to measure objects and delivering up to 50,000 pulses per second, producing three-dimensional (3D) details, in the future, LiDAR sensors can measure terrain and extract various metrics from point clouds [10]. Unmanned Aerial Vehicles (UAVs) equipped with LiDAR sensors have been developed as an effective tool for land inventory, reducing labor volume and field operational costs [11]. LiDAR technology can be relied on to obtain Digital Surface Model DSM data, which is extracted into Digital Terrain Model (DTM) or Digital Elevation Model (DEM) data with a faster process and relatively low cost [12]. LiDAR data is widely used in inventory and area mapping because it captures metric values in high resolution and 3D to provide appropriate forest variables [13], of which Diameter at Breast Height DBH and agency are very important in FI, but manual surveys are inefficient [14]. LiDAR has significant efficiency and accuracy [15] and can effectively identify structural differences in various tropical forest locations [16]. In Indonesia, the use of LiDAR technology in forest planning is still limited because it relies on satellite imagery and traditional manual methods, while national laser technology in Sweden has been proven to be able to transform forest management planning at a lower cost than field surveys [17].

As one of the world's largest producers of teak, Indonesia relies on two main sources of teak: plantation forests managed by Perum Perhutani, a state-owned enterprise (SOE), and rapidly expanding small-scale private forests, both of which are concentrated on the island of Java [18,19]. Pine is another dominant type of cultivated plant besides teak. The results of processed pine sap tapping contribute around 50% of the income of Perum Perhutani, which manages production and protects forests on the island of Java [20]. Perum Perhutani is a SOE for forestry which was inaugurated by the Indonesian Government in 1972, whose history of forest management began in the Dutch colonial era around 1897. This research will compare the results of measurements using LiDAR technology with those of manual terrestrial sampling measurements in the field. It is hoped that using LiDAR technology will make FI activities more accurate, effective, and efficient in teak and pine production forests on the island of Java. Apart from that, the use of LiDAR technology on the island of Java for inventory forest plantation teak and pine on a large scale has never been carried.

Materials and Methods

Study Area

LiDAR sensors were mounted on UAVs and handheld / backpacks to collect data in Teak (*Tectona grandis*) and Pinus (*Pinus merkusii*) stand areas. Data acquisition in 4 compartments in 3 FMUs, namely in the pine stand area in West Banyumas (18.6 hectares) with airborne laser scanning (ALS) method, pine stand area in Cianjur (7.1 hectares) with ALS and hand-held mobile laser scanning (HMLS) methods, teak stand area in Cianjur (5.9 hectares) with ALS and HMLS methods, and Teak stand area in Purwakarta (12.0 hectares) with ALS and HMLS methods. The implementation time was morning to afternoon in April 2022 in West Banyumas (Central Java Province), August 2022 in Cianjur (West Java Province), and October 2023 in Purwakarta (West Java Province). The location map is shown in Figure 1.

Data Acquisition

The implementation phase begins with initial mapping and UAV flight path creation, where data is then collected via LiDAR sensors mounted on UAVs at 4 locations and handheld / backpacks at 3 locations. The use of LIDAR sensors with UAVs is capable of displaying 3D models, but the data recording position, when taken from above, some parts are not recorded properly [21]. Differences in spatial resolution and acquisition time can affect data accuracy and consistency [22]. Therefore, at 3 locations, data acquisition was carried out using the HMLS method on the same day as ALS, while improving data accuracy was carried out through data analysis and quality control during data extraction.

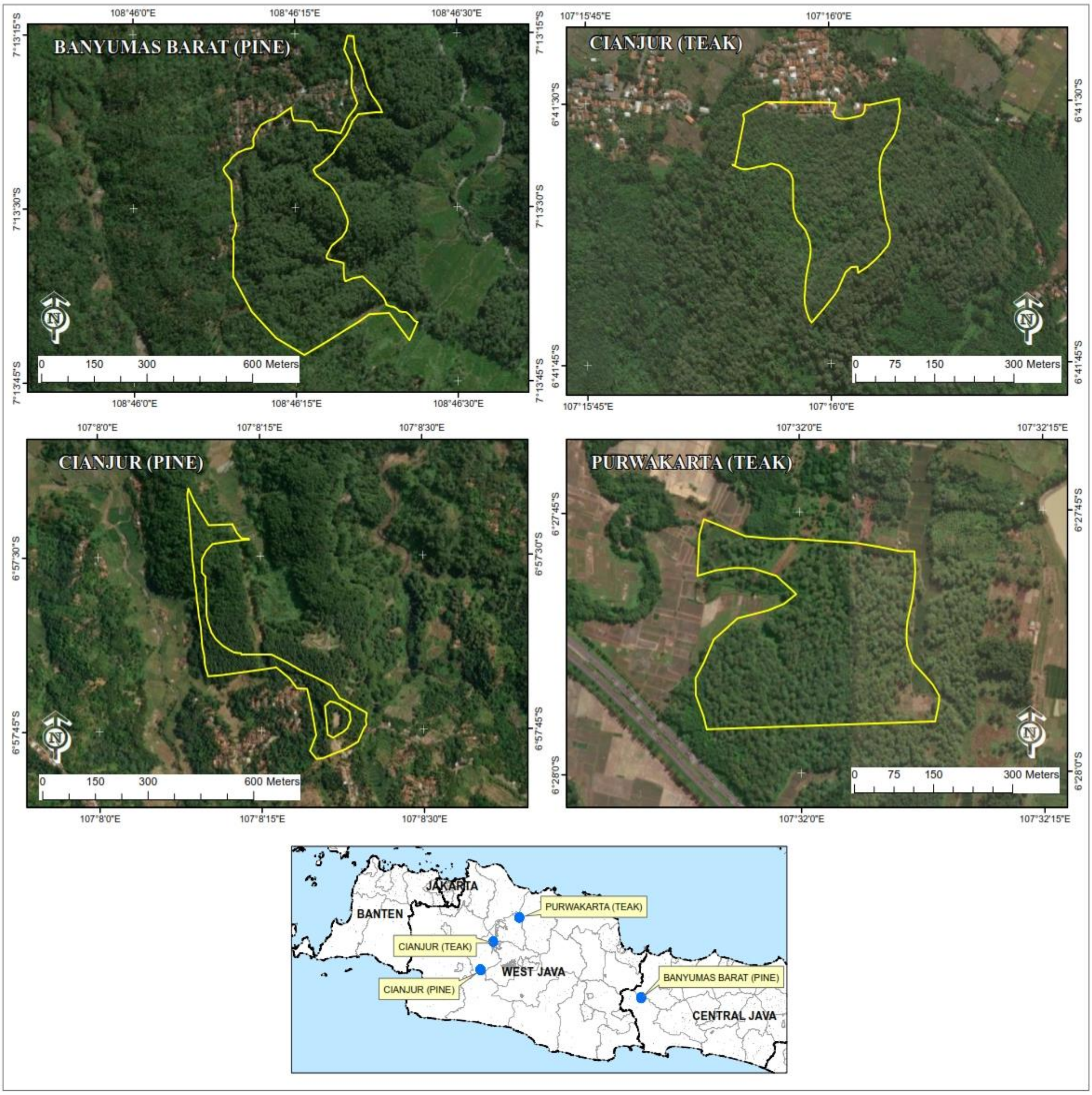

Figure 1. Study location.

Data Processing

Data on the number of trees (N), Diameter Breast (DBH), and tree height are obtained through segmentation per individual tree, with a process flow from data acquisition to data analysis using the ALS and HMLS methods, as shown in Figure 2. Meanwhile, tree plants / forestry stocks are identified through object height. 3D data from point clouds, in addition to analyzing the number of trees, tree height, and DBH, can also be used for contour analysis and mapping (topography). The application of quality control through several stages, including checking the suitability of vegetation characteristic parameters with the results of point cloud segmentation, correcting the position of tree points to the position of tree trunks, and reprocessing the point cloud segmentation according to the corrected tree coordinate positions.

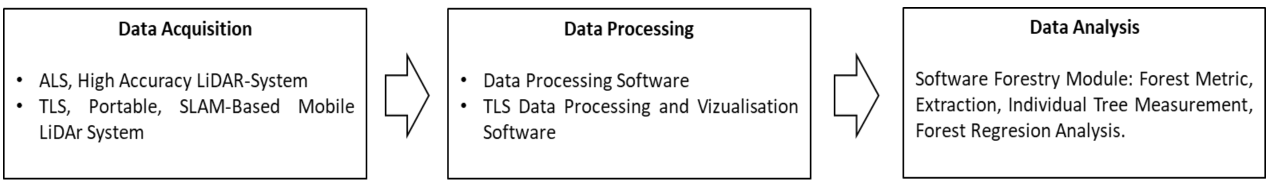

Figure 2. Flowchart of LiDAR process.

Data processing generally occurs after acquisition, including downloading LiDAR and base station data, rendering, and checking data. Point cloud data processing (a collection of points representing the shape of the scanned object's surface and obtaining 3D coordinates (x, y, and z)) is done through the application. The data processed includes GPS and inertial navigation system (INS) data. Combining object-based data (point cloud and imagery) can produce high classification accuracy [23]. Point clouds were analyzed and sorted into 3D models using specialized 3D mapping software. This study used Li-Geoference Software to convert distance measurements and positioning and orientation system (POS) information from ALS or HMLS systems into georeferenced coordinates.

The software generated 3D point clouds in LAS or LiData format. The software maps them to a specific datum (World Geodetic System / WGS 1984) and / or projection system (Universal Transverse Mercator / UTM). The LiDAR360 Software is the foundation for an entire software suite with terabyte-level processing required to effectively interact with and manipulate LiDAR point cloud data. The software functions include data management, automatic strip alignment, and point cloud classification. The output is a detailed 3D model and textual data about the dimensions of the scanned object or area. LiDAR point clouds from ALS can be replicated and scaled to produce high-resolution, spatially clear forest structure maps [24] and obtain 3D tree structures [25].

Data Analysis

In general, the results of data acquisition analysis of LiDAR are in the form of point clouds for further processing into 3D models, tree counting, and cross sections. The data from this process were then analyzed using the application, and a relevant regression model was created. In this study, data from manual terrestrial census techniques in the same area were used to control the accuracy of the output. Census data were collected by manually measuring each tree's DBH and tree height. DBH data were measured using a phiband, and body height was measured with a Haga Hypsometer.

The relative error and ratio between the LiDAR results and manual terrestrial census were calculated as percentage values. The values obtained illustrate the differences between the two techniques. To ensure that there was no statistically significant difference between the manual terrestrial census and LiDAR results, an independent sample t-test was conducted using the SPSS v26 application with the following formula:

$$t = \frac{\overline{x_1} - \overline{x_2}}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \quad (1)$$

Description:

x1: LiDAR sample mean — x2: Terrestrial census sample mean

S1: LiDAR sample standard deviation — S2: Terrestrial census sample standard deviation

n1: LiDAR sample size — n2: Terrestrial census sample size

Decision-making in this independent sample t-test [26], as follows:

1. If the Sig. (2-tailed) > 0.05 then H_0 is accepted and H_a is rejected, because there is no significant difference between the average terrestrial census results and LiDAR results.
2. If the Sig. (2-tailed) < 0.05, H_0 is rejected and H_a is accepted because there is a significant difference between the average terrestrial census results and LiDAR results.

Results

Data Acquisition Results

The range of the LiDAR sensor in the data acquisition process in ALS reaches a distance of ± 450 m, dual return, with an accuracy of ± 3 cm. While in HMLS, it reaches a distance of 25 to 50 meters, a single return, with an accuracy of ± 3 cm. The LiDAR sensor emits laser pulses of ± 300,000 points per second during UAV flight. At the same time, the LiDAR sensor in the HMLS emits laser pulses of ± 320,000 points per second. The laser emitted by the LiDAR drone can penetrate vegetation and reach the ground, although, in *Pinus merkusii* forests, it is sometimes not perfect. The LiDAR and UAV sensors were synchronized with the post-processing kinematic global navigation satellite system (PPK GNSS) from the Base Station for GPS correction for centimeter accuracy. The LiDAR on the HMLS was synchronized with the PPK GNSS to determine the coordinates of the scan path terrestrially.

LiDAR measures the distance to the target using laser light pulses and measures the wave reflections through the sensor. The reconstruction of the original shape is performed automatically using geotagged reflection target points. LiDAR sensors work in forest inventories described in Figure 3. The results of processing tree segmentation data using applications with special 3D mapping software to display individual tree differences through random colors are shown in Figure 4.

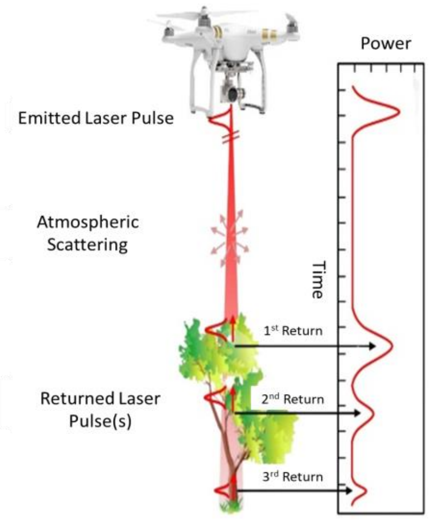

Figure 3. Illustration of laser pulse return signal and measured signal strength (image modified [27]).

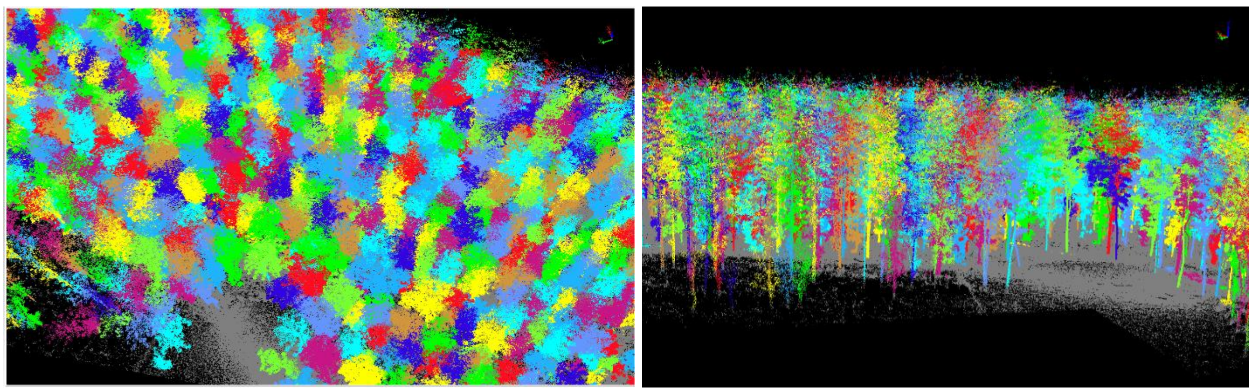

Figure 4. Image 3D individual teak trees as result LiDAR data processing.

Methods Comparison and Accuracy

In general, there is insufficient evidence to show a statistically significant difference between the two methods of measuring the number of trees and volume. In other words, the t-test results show that both methods have almost the same average or no significant difference. This shows that using LiDAR technology in forest inventory is very possible in this study. Volume estimation using only ALS data is still slightly less accurate than combining it with HMLS, as seen in data from West Banyumas. Table 1 compares the results of LiDAR measurements and terrestrial census data. The relative error value (%) shows lower LiDAR measurement results with negative (–) or higher values, which is also seen in the ratio (%) between LiDAR measurement results and terrestrial census as a control.

The result of LiDAR measurement showed the highest difference in tree volume (24.80%) and number of trees (N) (7.28%) in West Banyumas with the *Pinus merkusii*. Data acquisition only used the ALS method in a densely canopied forest (35-year-old *Pinus merkusii*). The relative error and ratio values cannot be statistically concluded to be different with a certain level of confidence. Furthermore, an independent sample t-test with a 95% confidence level on the results of N trees and volume is shown in Table 2. The t-value in Table 2 indicates a negligible difference in the average number of trees (t = 0.109) and tree volume (t = 0.258) between LiDAR measurements and terrestrial census results. The p-values, each exceeding 0.05, statistically demonstrate that the two measurement methods being compared do not differ significantly. Based on the t-test results, no significant difference exists between the two methods; therefore, the null hypothesis (H0) is not rejected.

Table 1. Data analysis LiDAR VS census terrestrial.

FMU	Species	LiDAR		Terrestrial census		Relative error (%)		Ratio (%) (LiDAR: Terrestrial census)	
		N trees	Volume (m^3)	N trees	Volume (m^3)	N trees	Volume (m^3)	N trees	Volume (m^3)
Banyumas Barat	*Pinus merkusii*	1,643	1,151.92	1,772	1,531.73	−7.28	24.80	92.72	75.20
Cianjur	*Tectona grandis*	1,343	571.82	1,328	525.38	1.13	8.84	101.13	108.84
	Pinus merkusii	828	611.26	816	620.56	1.47	−1.50	101.47	98.50
Purwakarta	*Tectona grandis*	1,312	542.16	1,323	495.74	−0.83	9.36	99.17	109.36
Total *Tectona grandis*		2,655	1,113.98	2,651	1,021.12	0.15	9.09	100.15	109.09
Total *Pinus merkusii*		2,471	1,763.18	2,588	2,152.29	−4.52	−18.08	95.48	81.92
Total *Tectona grandis* and *Pinus merkusii*		5,126	2,877.16	5,239	3,173.41	−4.37	−8.98	97.84	90.66

Source: Perum Perhutani.

Table 2. Independent sample T-Test N trees and volume results.

Equal variances assumed	F	Sig	T	Df	Sig.(2-tailed)	Mean Diff.	Std. Error Diff.
N trees	.014	.910	.109	6	.916	28.25000	258.04227
Volume	1.100	.335	.258	6	.805	74.06250	286.85110

Source: Data is processed using SPSS v26.

Technical and Operational Analysis

To determine the type, potential, and distribution of non-timber plants, the shape and dimensions of objects can be separated by analyzing 3D images scanned using LiDAR sensors. The data quality on the number of trees, tree diameter, and microtopography obtained has high accuracy. Sorting data of staple crops, shrubs, crops, and bamboo is faster using this application. In addition to forest inventory, floodplain mapping, hydrology, geomorphology, urban planning, ecology, and landscape can utilize LiDAR and GIS data for the analysis and management, visualization, and distribution of LiDAR data. Operationally, the work performance of teams using LiDAR is higher than that of teams using manual terrestrial methods. Monitoring activities' performance and completion time is easier by collecting automatically recorded and position data.

However, the tool's operation is still weather-dependent because it is not recommended to operate under rainy and lightning conditions. The cost of equipment maintenance and UAV insurance must be considered in addition to the cost of training equipment operators and applications for equipment operation and data processing. Based on the results of this study, some of the advantages of LiDAR technology that can be discussed are that data acquisition can be made faster with a high level of accuracy. Several pieces of information, such as slope and topography for certain analyses, can be obtained at once. The operation can be performed at night, and this technology can be integrated with other data sources.

Discussion

The results of this study indicate that there is no significant difference between the number and volume of trees measured using LiDAR technology with ALS and HMLS devices and terrestrial census in the research location of *Jati* (*Tectona grandis*) and *Pinus* (*Pinus merkusii*) plantations. This finding is consistent with previous studies that also found that both methods provide similar results in estimating tree parameters in relatively homogeneous forests [28]. Moreover, one of the primary advantages of LiDAR lies in its ability to detect all elements of forest composition and structure, from the top of the canopy to the ground surface, allowing for more comprehensive data collection, including tree volume, which is essential information for forest managers [16,28]. The increased resolution and spatial coverage provided by LiDAR technology, particularly through ALS and HMLS devices with high-precision LiDAR sensors, enable more detailed measurements of forest composition and structure. This study supports previous research that shows that LiDAR has great potential to improve the quality of forest inventories and ecological studies [29–32]. However, despite LiDAR's potential, this technology has limitations in terms of cost and operational complexity, particularly for managing large forest areas. Therefore, the application of LiDAR is currently more common in plantations with more structured and homogeneous forests.

Although this study is limited to *Jati* and *Pinus* plantations, it provides valuable insights into the potential capabilities of LiDAR technology in these areas. However, the results cannot be generalized to forests with different tree species or more complex natural forests. The variation in vertical and horizontal forest structure is an important aspect of UAV LiDAR [16], and HMLS [32], and the differences in results become more apparent when applied to forests with higher tree species diversity and more complex forest structures [16]. Therefore, an important question that remains unanswered in this study is how accurate and reliable LiDAR can be when applied to tropical natural forests or restored forests. Furthermore, the high-dimensional data generated by LiDAR, although highly detailed, often poses challenges in statistical analysis and processing. Previous studies have shown that accurate predictive models are difficult to achieve due to the large volume of data that needs to be managed, requiring advanced statistical software and algorithms [16]. The opportunity to reduce the use of traditional methods can certainly save time and costs, but the challenge of processing large datasets must be addressed when implementing LiDAR technology in large areas.

Meanwhile, alternative methods such as satellite imagery or aerial photography, which are currently widely used in Indonesia, have limitations in terms of forest type classification. Remote sensing techniques using these methods are unable to clearly distinguish between different types of restored forests (e.g., between conservation and production forests) [33]. Therefore, the development of machine learning techniques is necessary to address this issue and model forest attributes from remote sensing data more accurately. The implementation of machine learning on remote sensing data can improve the ability to automatically map forest types and reduce dependence on manual interpretation [33]. Further research can expand the use of LiDAR in the context of ALS or HMLS to inventory various other forest species. LiDAR technology, with its ability to provide accurate and detailed spatial information about tree composition and structure, has the potential to improve the accuracy of forest parameter estimation at the individual tree level [34]. However, as also found in several previous studies, the application of LiDAR in very large and dense areas may be limited by spatial and temporal coverage factors [35]. Therefore, one of the questions that needs to be further researched is how to overcome the limitations of spatial and temporal coverage in the use of LiDAR technology for inventorying larger and more diverse forests.

Conclusions

This research shows that LiDAR technology can significantly enhance the accuracy of tree attribute data, including tree number and volume, as confirmed by statistical analysis. Furthermore, the acquisition of spatially explicit data on individual tree characteristics, tree density, volume, canopy volume, and microtopography was accomplished more efficiently than traditional manual methods. Integrating ALS and HMLS techniques in the LiDAR-based forest inventory (FI) further improves the accuracy of the results. Moreover, incorporating artificial intelligence (AI) technology is expected to substantially enhance LiDAR-based data acquisition, processing, and analysis efficiency and effectiveness.

Author Contributions

RPH: Conceptualization, Methodology, Software, Formal Analysis, Validation, Visualization, Writing - Review & Editing; **CK**: Supervision; and **NN**: Supervision.

Conflicts of Interest

There are no conflicts to declare.

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