Performance Evaluation of a Lightweight and Low-Cost LiDAR Sensor for Mobile Scanning in Forest Plots

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***Abstract*:** *Accurate and rapid forest structure assessment is essential for ecological research, forest management, and environmental monitoring. Terrestrial light detection and ranging (LiDAR) scanning presents a promising approach to acquire detailed forest plot data rapidly. However, its considerable weight and high cost have largely prevented its use in large-scale forest plot surveys. We developed a helmet-mounted mobile LiDAR system (MLS) which incorporated a lightweight, low-cost LiDAR sensor costing approximately $750. The accuracy and efficiency of the system were then evaluated in two forest plots, one coniferous and one deciduous. A comprehensive comparison was also made between the developed MLS and a handheld MLS equipped with a high-end laser scanner. The developed MLS effectively captured forest structure and terrain surface information in two forest plots. The estimated individual tree height (TH) and diameter at breast height (DBH) were highly correlated with field measurements (DBH: R^2 = 0.99, root mean square error (RMSE) = 0.016 m; TH: R^2 = 0.93, RMSE = 1.642 m). The DBH error was smaller for coniferous plots than for deciduous plots, but tree height was the opposite. Overall, the efficiency and accuracy of the developed MLS is comparable to that of the high-end MLS in both plots. Despite its short detection distance and narrow vertical field of view, it is believed that the lightweight and low-cost system developed in this study can alleviate the problems of long field operation time and expensive equipment in most forest inventory applications.*

Keywords: lightweight LiDAR, mobile scanning, low cost, forest inventory

Introduction

Forest sample plot surveys provide important data for forest management, biomass estimation and biodiversity monitoring. Traditional manual inventory methods are costly and time consuming and tree height estimation is not easy (Hyyppä et al., 2020). With the development of close-range remote sensing technology, LiDAR (Tang et al., 2015; Tansey et al., 2009), multi-ocular cameras (Mokroš et al., 2021) and even mobile phones (Wu et al., 2023) can acquire 3D point cloud data of forest sample plots. Terrestrial laser scanning (TLS) is considered to be the most accurate method in close-range remote sensing for acquiring structural data such as DBH and tree height (Liang et al., 2016).

LiDAR is a remote sensing technology that has gained significant traction in the field of forestry by measuring the time it takes for the emitted laser beams to return after reflecting off the surfaces they encounter. Typically the TLS must be mounted on a tripod and utilizes LiDAR technology to acquire detailed 3D information about the forest environment in multiple scans (Stovall et al., 2023). While TLS offers high-resolution data, limitations exist, including high cost, time-intensive data acquisition, and heavy weight. These constraints can hinder extensive forest inventory applications in remote or challenging terrains. MLS represents a significant evolution in the application of LiDAR and simultaneous localization and mapping (SLAM) technology (Bailey & Durrant-Whyte, 2006; Durrant-Whyte & Bailey, 2006), allowing for rapid and extensive data collection over large forested areas (Miettinen et al., 2007). These systems integrate LiDAR sensors with a hand-held or backpack unit enabling dynamic tracking the sensor location and while simultaneously constructing or updating the map of forest environments while in motion (Muhojoki et al., 2024; Stovall et al., 2023; Su et al., 2021).

With the development of Micro-Electro-Mechanical System (MEMS) technology, light and small laser scanners and on-chip inertial measurement units (IMUs) can be integrated into helmet-based laser scanning systems (Lee et al., 2019; Li, Wu, et al., 2023; Sadruddin et al., 2020). Lightweight helmet-mounted systems are more user-friendly in forest environments than backpack and handheld MLS systems (Li, Yang, et al., 2023). Right now, the integration of low-cost sensors into compact helmets and the exploitation of the special characteristics of these sensors to achieve high-precision real-time SLAM is still in the initial research phase. The ranging capability, weight, and noise of low-cost LiDAR sensors worn by humans for extended periods of time are challenging in forest environments.

In this study, we developed a lightweight helmet-mounted MLS that integrates LiDAR and IMU in a single sensor which is priced at $750 to collect point clouds in forest environments. The point clouds obtained for two different tree species plots were processed to estimate the DBH and height of the trees using opensource tools. The results were then compared with those from a high-end MLS and manual surveys. The helmet-mounted MLS is a novel device for effective and accurate forest plot inventory and is essential for the development of the next generation forest inventory method.

Material and Methods

Study area

The study area is located in Chaoyang District, Beijing, China (Figure 1, N40°00′ E116°22′). Two rectangular plots with different tree species and large differences in tree DBH and TH were selected as test plots, which were 30 × 30 m in size with a stem density of 111–244 stems/ha. One sample plot is deciduous species including Chinese scholar tree (*Styphnolobium japonicum* (L.) Schott) and London Planetree (*Platanus acerifolia*), and the other sample plot is coniferous trees such as Chinese red pine (*Pinus tabuliformis Carrière*). The topography of the deciduous sample plot is flat, with grass growing on the ground. The terrain of the coniferous plot is sloping and the ground is covered with grass and shrubs.

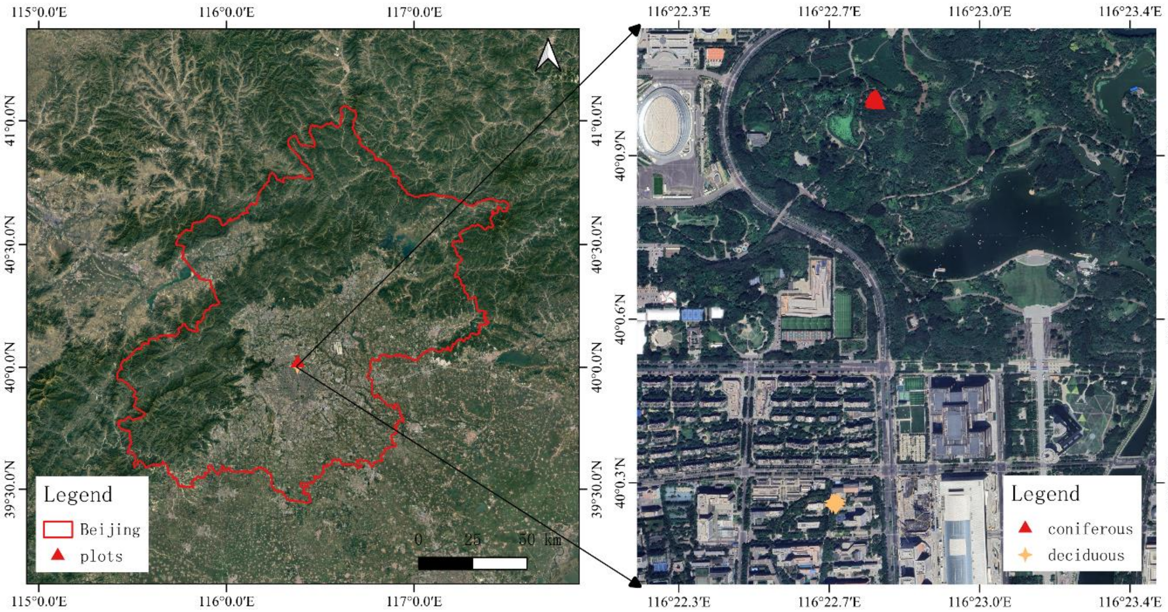


Figure 1: The test plots in Beijing, China (left) and plot samples (right).

Manual measurements

Only stems with a DBH greater than 0.1 m in the sample plot were measured manually and each tree was assigned a unique serial number for identification. In total, the two collaborated to measure the TH, DBH and location of 32 trees and the measurements used as reference values. Reference TH values were obtained using an NTS-332R total station instrument (South Surveying & Mapping Technology Co., Ltd.) and reference DBH values were obtained using a diameter tap (WINTAPE Co., Ltd.). The reference locations were obtained using self-developed RTK equipment.

Mobile laser scanning

The mobile laser scanning systems compared in the study were a GoSLAM RS100 handheld system (Beijing Tianqing Zhizao Aviation Technology CO., LTD.) and a self-developed helmet-mounted system as presented in Table 1. The GoSLAM RS100 system was equipped with a rotating laser scanner for a larger vertical field of view. While scanning, point cloud data can be viewed in real time by connecting to the scanner via a mobile phone app. The helmet-mounted system uses a lightweight MID-360 sensor with tightly integrated LIDAR and IMU (Livox Technologies Co., Ltd.) named AIRCAS HM1. The MID-360 LiDAR has a range of 0.1 to 70m and a range accuracy of 2 cm, both worse than the LiDAR used in the GoSLAM RS100. The total weight of the headset component of the AIRCAS HM1 system is 0.49 kg, which is less than a third of the weight of the handheld component of the GoSLAM RS100 system.

Table 1 Specifications of the GoSLAM RS100 and AIRCAS HM1

Specification	**GoSLAM RS100**	**AIRCAS HM1**
Distance accuracy	1cm	2 cm
Angular accuracy	±0.01°	< 0.15°
Range	120 m (80% albedo), 55 m (10% albedo)	70 m (80% albedo), 40 m (10% albedo)
Field of view	Horizontal: 360°, vertical: 285°	Horizontal: 360°, vertical: 61°
Speed of data acquisition	650 kHz	200 kHz
Mass	1.5 kg (handheld)	0.49 kg (helmet-mounted)

A Graphical User Interface (GUI) software named QTSlam360 has been developed based on the FAST-LIO2 (Xu et al., 2022) SLAM package to facilitate the control of the data acquisition process and the storage of point cloud data in the forest for AIRCAS HM1. The system employs a tightly coupled iterative extended Kalman filter to integrate LiDAR feature points with IMU data for odometry optimization. The raw points are organized by an incremental k-d tree data structure(Cai et al., 2021), and directly registered by the Iterative Closest Point (ICP) algorithm (Sharp et al., 2002; Tagliabue et al., 2021) to achieve real-time mapping while moving in a cluttered forest environment without the assistance of a Global Navigation Satellite System (GNSS). The QTSlam360 software can be utilized by operators on a tablet computer to facilitate the performance of scanning operations and the real-time observation of scanning data.

Figure 2 illustrates the photographic record of scans conducted with both MLSs within a coniferous forest plot. Operators scanned each sample plot from multiple paths using two MLSs independently.. In addition, to account for SLAM and cumulative registration errors in forest conditions, the scan paths were designed to start and end at the same point and in an S-shape. The QTSlam360 software employs a Robotic Operating System (ROS) to record sensor data from the AIRCAS HM1 for the purpose of evaluating the real-time performance of the proposed method. It took approximately 6 minutes to collect data at each sample plot.

Figure 2: Photographs of (a) the handheld MLS (GoSLAM RS100) and (b) the helmet-mounted MLS (AIRCAS HM1) in coniferous plot.

Point cloud processing

The point cloud was preprocessed using CloudCompare (version 2.12.4) software, including plot point cloud cutting and removal of outliers. Separation of point clouds into ground and off-ground points using cloth simulation filtering (Zhang et al., 2016). The point cloud is then normalized using the ground points to remove the effect of ground elevation. Interactive segmentation method based on tree's reference location was used to segment individual trees from the normalized point clouds. Normalized point clouds between 0.3m and 1.3m elevation were selected for trunk detection. Individual tree point clouds were segmented based on the trunk point cloud and reference position, named with the same number as the manual measurement. If there is a scrub point cloud seen around the trunk point cloud, the scrub point cloud needs to be removed manually. Finally, each tree point clouds were imported into R for further tree height and DBH estimation using the TreeLS package (de Conto et al., 2017). The height of each tree was calculated from the normalized height of the highest point of the tree. The point clouds at tree heights of 1.0 to 1.3 m are fitted to a circle with Iterated Reweighted Total Least Squares (IRTLS) algorithm (Mahboub et al., 2013), the diameter of which is DBH. The workflow for processing point cloud as shown in Figure 3.

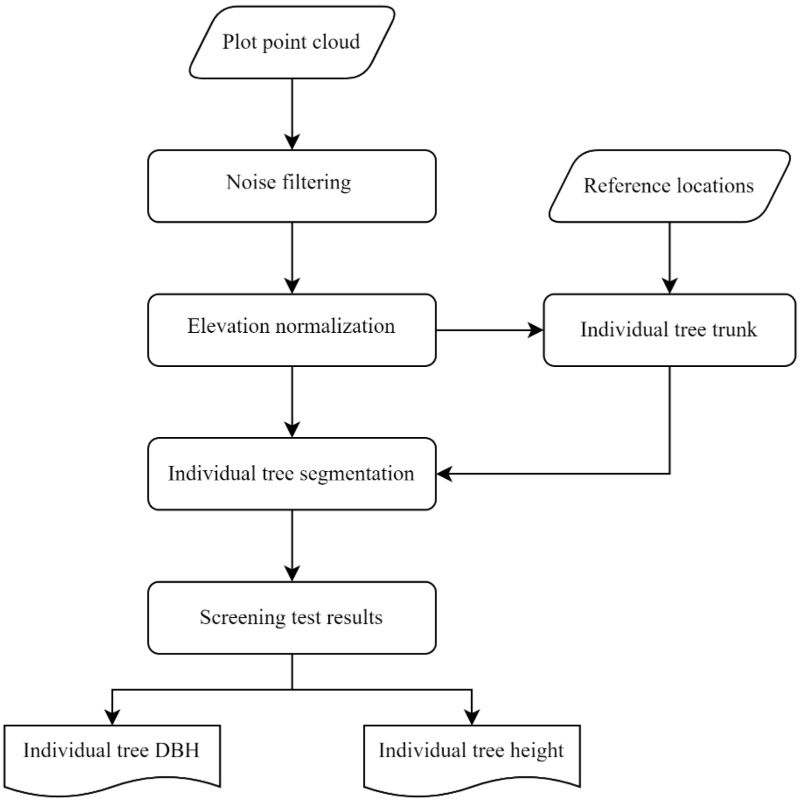


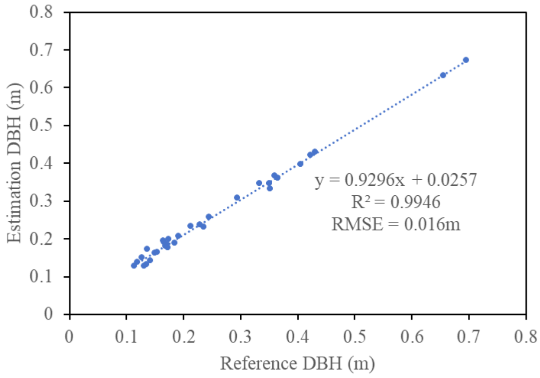
Figure 3: The workflow for processing point cloud.

Results and Discussion

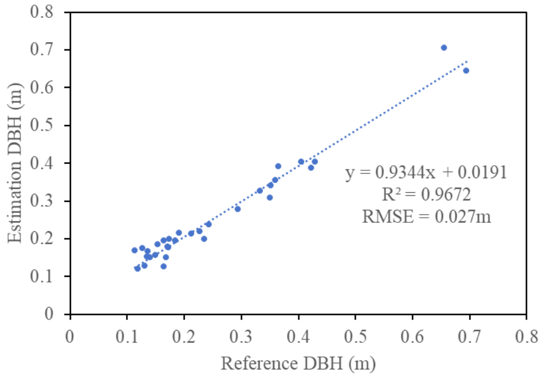
DBH and tree height were estimated from point clouds obtained from different MLS devices using the above method. For evaluation of estimated results, five metrics which include coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), relative Bias (reBias), relative RMSE (reRMSE) are used to verify the precision of our technique (Wu et al., 2023).

DBH comparison

From the regression fitting results in Fig. 4, it was found that the DBH extraction accuracy from the AIRCAS HM1 point cloud was higher, with R^2 and RMSE of 0.99 and 0.016 m, respectively. And the R^2 and RMSE of DBH extraction using the GoSLAM RS100 point cloud were 0.967 and 0.027 cm, respectively. The accuracy of DBH extraction from the AIRCAS HM1 was higher than that of the GoSLAM RS100. The point cloud noise of the GoSLAM RS100 is high near the trunk and the accuracy of the DBH estimation is lower.



(a)



(b)

Figure 4: Results of DBH linear regression (a) DBH estimated from AIRCAS HM1 point cloud vs. diameter tape; (b) DBH estimated from GoSLAM RS100 point cloud vs. diameter tape.

Table 2 presents statistical DBH measurements for tree species named Chinese scholar tree, Plane tree, and Oil pine using AIRCAS HM1 Point Clouds. For Chinese scholar tree, the statistical analysis yielded an RMSE of 0.011 m and an MAE of 0.009 m, indicating the average differences between predicted and actual DBH values. The reBias was estimated at 2.604%, suggesting a slight underestimation in the predictions compared to actual values. Additionally, the reRMSE was calculated as 3.241%. Under the condition of complete point cloud, the RMSE and relative accuracy of the Chinese scholar tree DBH extraction results were better than those of the oil pine DBH extraction results.

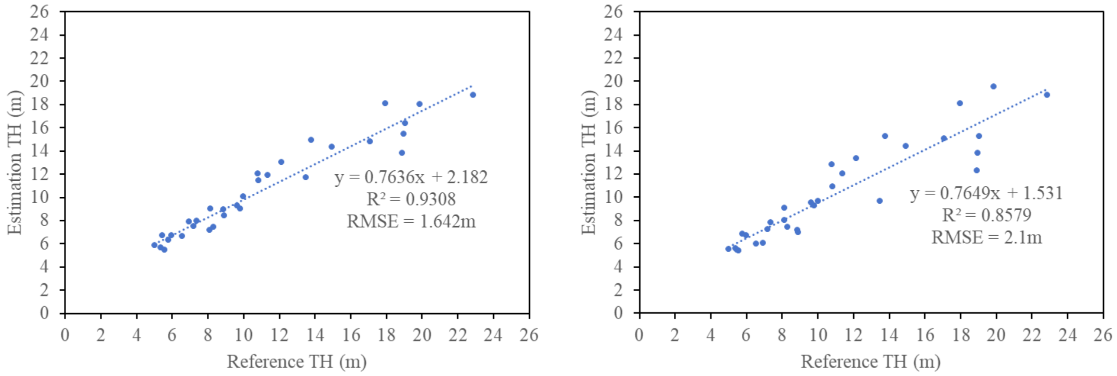
Different tree species bark roughness affects the accuracy of point cloud DBH extraction. In the case of Oil pine, there is a phenomenon of cracked and warped epidermis, and there are some discrete points in the point cloud data caused by the warped epidermis, which affects the DBH extraction accuracy. Compared with Oil pine, the skin of plane tree is relatively smooth, and the proportion of discrete points in the point cloud data of chest diameter slices is significantly lower than that of Pinus.

Table 2 Statistical DBH Estimated from AIRCAS HM1 Point Clouds for Three Tree Species

Tree Species	**RMSE (m)**	**MAE (m)**	**reBias (%)**	**reRMSE (%)**
Chinese scholar tree	0.011	0.009	2.604	3.241
Plane tree	0.016	0.012	3.351	4.311
Oil pine	0.018	0.015	9.317	11.653

Tree height comparison

From the regression fitting results in Fig. 5, it was found that the TH extraction accuracy from the AIRCAS HM1 point cloud was higher, with R^2 and RMSE of 0.9308 and 1.642 m, respectively, and the R^2 and RMSE of TH extraction using the GoSLAM RS100 point cloud were 0.8579 and 2.1 m, respectively. The accuracy of the tree height estimates is relatively low in comparison with the DBH estimates, particularly in plot with dense canopies. Both MLS devices have difficulty in penetrating the canopy to obtain the tree top endpoint cloud, and therefore tree height is underestimated to a greater extent. The one reason is that the wavelength of the LiDARs is 905 nm, which has limited penetrability compared with the TLS with a wavelength of 1550 nm. In particular, dense foliage shading of tall broadleaf trees can seriously affect the quality of canopy data, meanwhile make the manual measurement of reference tree heights using a total station subject to some error. At last, stratification between some of the understory and dominant trees was not evident in sample plot 2, resulting in an overestimation of understory tree heights.



(a) (b)

Figure 5: Results of TH linear regression (a) TH estimated from AIRCAS HM1 point cloud vs. total station; (b) TH estimated from GoSLAM RS100 point cloud vs. total station.

Comparison with existing systems

We compare the proposed MLS system with several existing MLS systems: WHU-Helmet (Li, Yang, et al., 2023), Hand-held MLS (Stovall et al., 2023) , and Backpack MLS (Su et al., 2021). As shown in Table 3, the AIRCAS HM1 system offers excellent portability and lower cost. The RMSE and MAE of DBH estimated from AIRCAS HM1 point clouds is also better than existing helmet-mounted system and Backpack MLS, but worse than Hand-held MLS. This is due to the higher scanning accuracy and distance resolution of the UTM-30LX lidar

used in the handheld MLS compared to the other lidars listed in Table 3. However, its maximum measuring distance of 30 m is not optimal for scanning in dense and tall forests.
In order to fuse laser and IMU data for the purpose of pose estimation, the SLAM framework utilized in both the AIRCAS HM1 and WHU-Helmet is Fast-LIO2. Nevertheless, there are notable discrepancies between the two helmet-mounted systems with regard to the sensors and the algorithms employed for DBH estimation. The MID-360 Lidar used in the AIRCAS HM1 has a larger horizontal field of view than the Avia LiDAR used in the WHU-Helmet, allowing for more precise matching of point clouds scanned at different locations. Although the MID-360 LiDAR has a worse maximum range and angular accuracy than the Avia LiDAR, the MID-360 LiDAR has a near blind spot of only 0.1m, much smaller than the Avia's 1m, making it more suitable for scanning in forests. The IRTLS algorithm for DBH estimation is designed to reduce calculation errors and improve circle fitting accuracy through iterative correction. Our results and previous studies show that DBH estimation with IRTLS algorithm is more robust to outliers in point clouds than RANdom SAmple Consensus (RANSAC) algorithm (de Conto et al., 2017; Zhou et al., 2023). Cylindrical modelling methods perform better in approximating stem features because they can estimate the angle at which the stem segments are inclined from a straight vertical stem, whereas circle-based methods assume that the stem is perfectly vertical and can only estimate the radius of the stem segments in the horizontal plane.

Table 3 A Comparative Analysis of Different Systems for Measuring DBH.

Systems	**Algorithm**	**RMSE (m)**	**MAE (m)**	**Mass (kg)**	**Lidar type**	**Lidar price ($)**
AIRCAS HM1	IRTLS cylinder fit	0.016	0.013	0.49	MID-360	750
WHU-Helmet	RANSAC circle fit	0.038	0.033	1.5	Avia	1,599
Hand-held MLS	LS circle fit	0.013	0.004	0.85	UTM-30LX	4,275
Backpack MLS	LS circle fit	0.02	0.02	8	VLP-16	4,000 × 2

Time requirements

The efficiency of two MLSs were much higher than that of field measurements. In this study, the helmet-mounted MLS enabled the operator to obtain complete point cloud coverage of a sample plot in approximately 4–6 minutes. For comparison, the field measurements of two plots were acquired by two operators in approximately 100 minutes. Nevertheless, the processing time for the point cloud data is longer than that required for the field measurements. The data was processed using the open-source software CloudCompare and the R package TreeLS. Nevertheless, a considerable amount of manual correction work is still required, particularly if the tree is surrounded by dense scrub. The advancement of robust and efficient data processing algorithms has the potential to facilitate the promotion of helmet-mounted MLS in forest inventory applications.

Conclusion and Recommendation

In this study, we extracted the diameter at breast height (DBH) and tree height (TH) of each tree using point cloud data scanned by proposed helmet-mounted MLS in the two sample plots. The AIRCAS HM1 MLS is a system that is both lightweight and highly mobile, with both cost-effective and easy to obtain point cloud data. Furthermore, open-source software is used for the processing of these data. The results of the estimation were compared with those of the manual measurements and show that it enables accurate data collection in coniferous and deciduous plots. Implementation the IRTLS algorithm in DBH estimation ensures the robustness of the process to the presence of outliers in point clouds obtained from the AIRCAS HM1 MLS. The species of tree affects the accuracy of estimating both DBH and TH. DBH estimation accuracy is higher for broadleaved trees within 1–2 cm RMSE, while conifers show better accuracy for TH estimation within 1–2 m RMSE.

Although proposed helmet-mounted MLS has its advantages, it still faces challenges, such as missing tree-top data, data processing complexities, and the need for accurate georeferencing. The deficit of tree-top data can be addressed by enhancing the penetration capability of LiDAR and developing MLS and UAV LiDAR data fusion techniques. Currently, there is still a lack of automated and accurate methods to detect trees in complex forest environments in real time and to extract some important tree attributes, such as tree species and tree height. It is recommended that future research concentrate on integrating these techniques with machine learning or artificial intelligence, with the objective of improving the efficiency of data processing and the accuracy of parameter estimation. This approach would further promote the utility of these techniques in forest inventory applications.

Acknowledgments/funding

This work was supported by the National Key Research & Development Program of China (2022YFF1302100).

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