

Research Article

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Accuracy Assessment of Wearable Mobile Laser Scanning for Individual Tree Detection and Forest Structural Parameter Estimation

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Abstract

Wearable mobile laser scanning (WMLS) systems have emerged as a transformative technology in forest inventory and management, offering high-resolution point cloud data capture at both plot and individual tree levels. This comprehensive research evaluates the accuracy of WMLS platforms for individual tree detection (ITD) and the extraction of vital forest structural parameters, including tree height, stem diameter at breast height (DBH), and canopy crown dimensions across heterogeneous woodland ecosystems. Field measurements obtained from diverse permanent sample plots were rigorously compared against point cloud derivations processed through advanced bottom-up clustering, morphological filtering, and segmentation algorithms. The empirical findings demonstrate that wearable laser scanning systems provide exceptional precision in capturing lower and mid-canopy structural attributes, yielding detection accuracies exceeding 92% in open to moderately dense stands while significantly reducing field acquisition duration compared to traditional terrestrial laser scanning (TLS) and manual inventories.

Keywords: Wearable Mobile Laser Scanning, Individual Tree Detection, Forest Structure, Point Cloud Processing, Terrestrial Laser Scanning, Precision Forestry

1. Introduction

To properly implement sustainable forest management, complete forest biomass assessments, and calculate accurate carbon storage, we must first accurately identify forest structure, which serves as the most fundamental prerequisite for all these tasks [1].

Early forest surveys relied entirely on manual field investigations, which consumed substantial manpower, required a large amount of time to traverse all survey plots, and produced statistical results that were prone to errors. These problems became even more prominent in forest regions with complex terrain and uneven tree distribution [2].

LiDAR technology has completely transformed the forestry sector; it can quickly generate a complete three-dimensional map of forest ecosystems, clarifying forest stand structures that were previously impossible for manual surveys to sort out [3].

Airborne laser scanning, ALS, can cover extremely large areas, scanning a vast continuous forest tract in a single flight. However, the tree canopy blocks detection signals propagating downward, resulting in unclear details beneath the canopy and inaccurate measurement data for individual tree trunks [4].

Conversely, terrestrial laser scanning, TLS, can capture detailed data of tree trunks, even capturing fine structural parameters of trunks. But this equipment is cumbersome to transport, requires a long time to set up and calibrate after arriving at a survey point, and in dense forest regions, surrounding branches and foliage can block laser signals, leaving some areas unscanned and making it impossible to fully map the entire forest [5].

In current surveying and mapping operations, there are two commonly used technical routes. One is to use high-altitude aircraft to complete large-scale aerial surveying and mapping, which can scan a very large area. The other is to fix scanning equipment on

the ground to conduct fine scanning only for a small local area. These two methods each have their own uses, but they cannot be connected, with a huge operational gap lying between them. To fill this gap, the technically sophisticated wearable mobile laser scanning system (WMLS) was specially developed [6].

Parameter	High-Altitude Aerial Surveying	Terrestrial Laser Scanning (TLS)	Wearable Mobile Laser Scanning (WMLS)
Platform	Manned aircraft, fixed-wing, or rotary UAVs	Tripod-mounted stationary laser scanner	Backpack, handheld, or helmet-mounted mobile rig
Coverage Scale	Regional, city-scale, large open terrain	Localized, single room, or individual building facade	Multi-room interiors, corridors, tunnels, complex multi-story structures
Mobility	High speed, broad aerial sweep	Static; requires multiple manual setup stations	Continuous motion at pedestrian walking speed
Resolution & Accuracy	Centimeter to decimeter (dependent on altitude/GSD)	Sub-millimeter to centimeter (ultra-high precision)	Centimeter-level relative accuracy
Primary Limitations	Blocked by roofs, dense foliage, overhangs; cannot capture interiors	High station setup time; numerous blind spots requiring multiple scans	Accumulative drift over long unlooped trajectories (relies on SLAM algorithms)

Table 1: Comprehensive Technical Comparison of Surveying and Mapping Technologies

This device has two carrying forms: it can either be installed in a backpack and carried on one's back, or made into a portable handheld model that can be held in the hand and taken anywhere. It perfectly integrates two core technologies: one is the Simultaneous Localization and Mapping (SLAM) algorithm, which can confirm its real-time position while drawing a map of the surrounding area; the other is an ultra-light, high-frequency LiDAR sensor, which is lightweight so as not to add a burden, and has a sufficiently high scanning frequency to capture enough details. When operators walk through dense forest areas with this device, they do not need to stop or split any work tasks—they can traverse the forest while drawing real-time environmental maps of extremely complex structures, completing both surveying and movement at the same time [7].

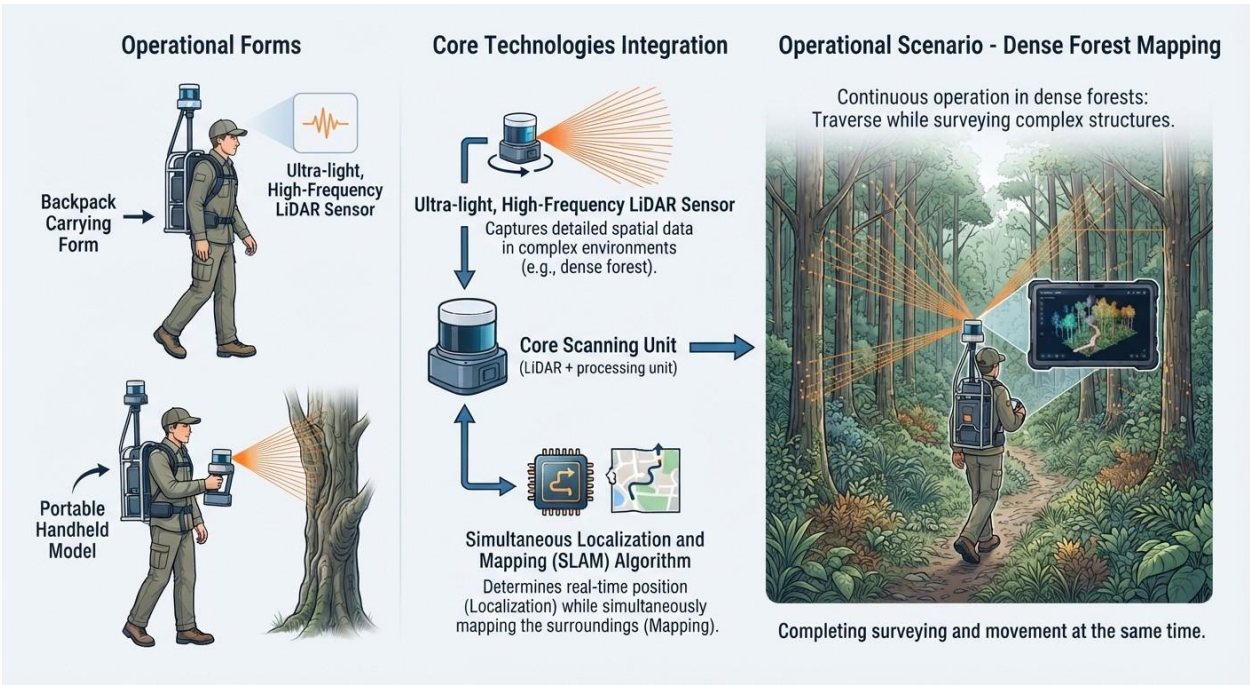


Figure 1: Operational structure, Core Technologies, and Field Application of the Wearable Mobile Laser Scanning System (WMLS): (Left) Dual Carrying Modes Including the Backpack-Mounted and Handheld Configurations; (Middle) Integration of the Ultra-Light High-Frequency LiDAR Sensor and the Simultaneous Localization and Mapping (SLAM) Algorithm; (Right) Continuous Scanning Workflow During a Live Traversal of a Dense Forest Environment

Nowadays, this device is used by more and more people in the fields of forestry and geographic information engineering, and its popularity is rising rapidly. However, to truly formulate industry-wide universal standards that allow this system to be widely recognized and implemented on a large scale across the entire field, an unavoidable key task must be completed first: in various types of forest areas, rigorous quantitative methods must be used to practically assess whether the two core capabilities of this system are sufficient: first, whether its accuracy in identifying individual trees is high enough, and second, whether the various tree structure parameters it outputs are accurate. This task is crucial and serves as a prerequisite for industry standardization and large-scale popularization [8].

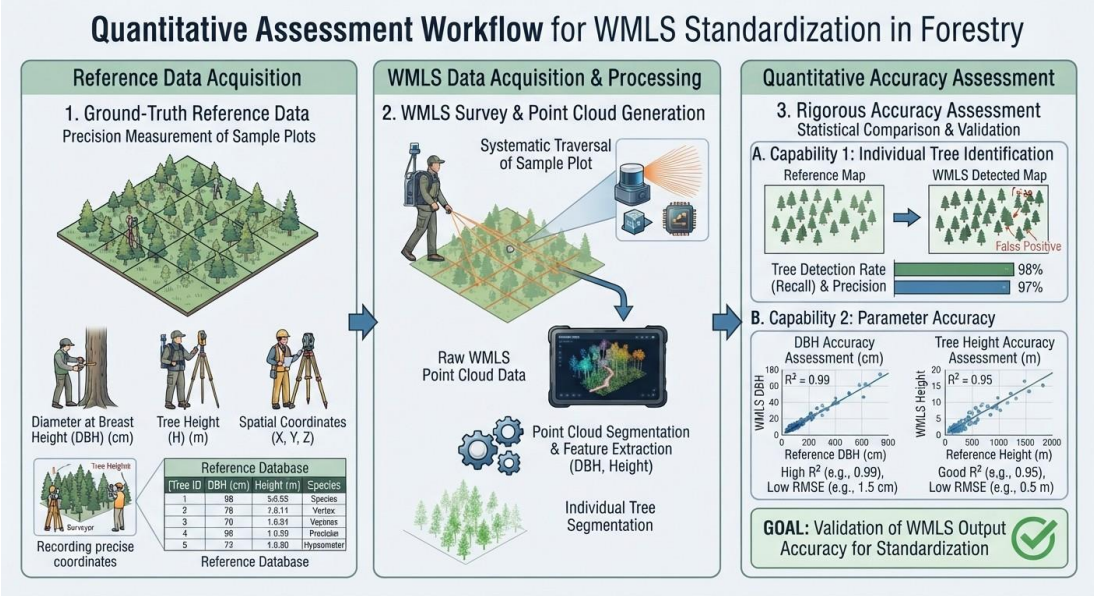


Figure 2: Workflow for the Quantitative Assessment and Standardization of WMLS in Forestry Applications. The Diagram Illustrates the Three Essential Stages Required to Validate the WMLS System for Industry-Wide Adoption

Relevant academic studies in recent years have all emphasized the same direction: integrating a multi-sensor framework that can cover all scenarios with logically complex spatial algorithms is the core

method to improve the accuracy of geographic information in the environmental monitoring field, and it is currently the mainstream improvement path recognized by the academic community [9].

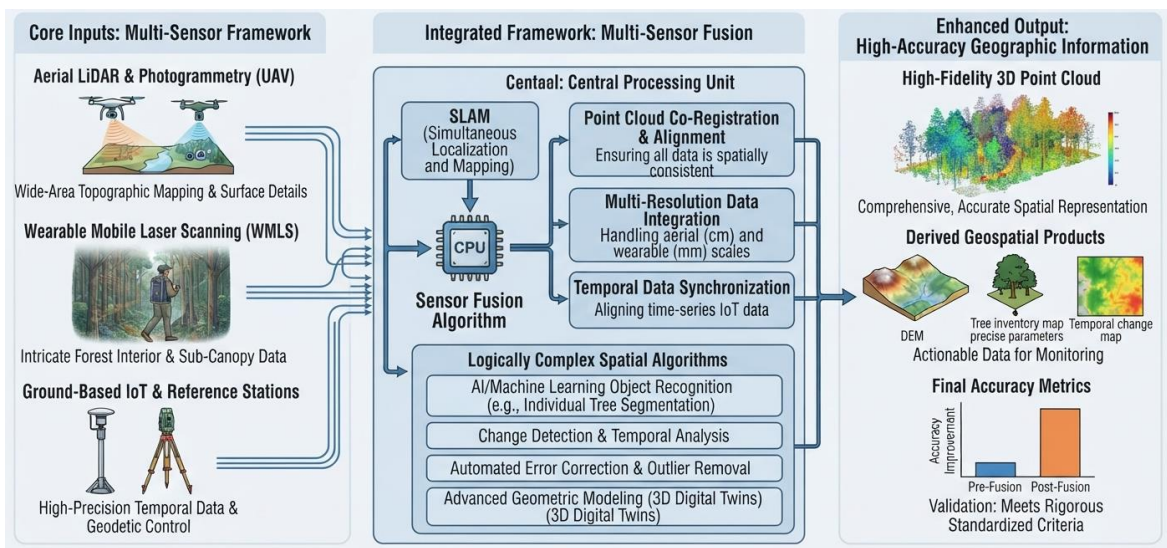


Figure 3: Mainstream Improvement Path: Multi-Sensor Framework and Complex Spatial Algorithms for Enhanced Environmental Geographic Accuracy. The Diagram Outlines the Integration Approach Recognized by the Academic Community to Optimize Geographic Information Accuracy in Environmental Monitoring

As repeatedly verified in studies, integrating spatial data from different sources and then applying advanced multi-criteria analysis methods has been proven time and again to be crucial for accurately depicting landform features and constructing reliable ecological models, forming the core foundation that supports the completion of such research [10].

In addition, geographic information workflows that can leverage powerful cloud computing platforms paired with high-resolution analysis indicators can break through the limitations of time and computing power, continuously tracking changing environmental conditions and the complex growth and succession dynamics of

vegetation communities over ultra-long time scales, completing long-term continuous monitoring without being restricted by the performance of local equipment [11].

To completely optimize the entire process of spatial modeling from the front end to the back end, two core tasks must be completed—one is to generate an accurate digital elevation model, and the other is to sort out and refine topological features. Both of these tasks can only be achieved through a sufficiently powerful Geographic Information System (GIS) processing workflow. This workflow is not a common generic product; it is specially built to adapt to areas with dramatic undulations and extremely uneven terrain [12].

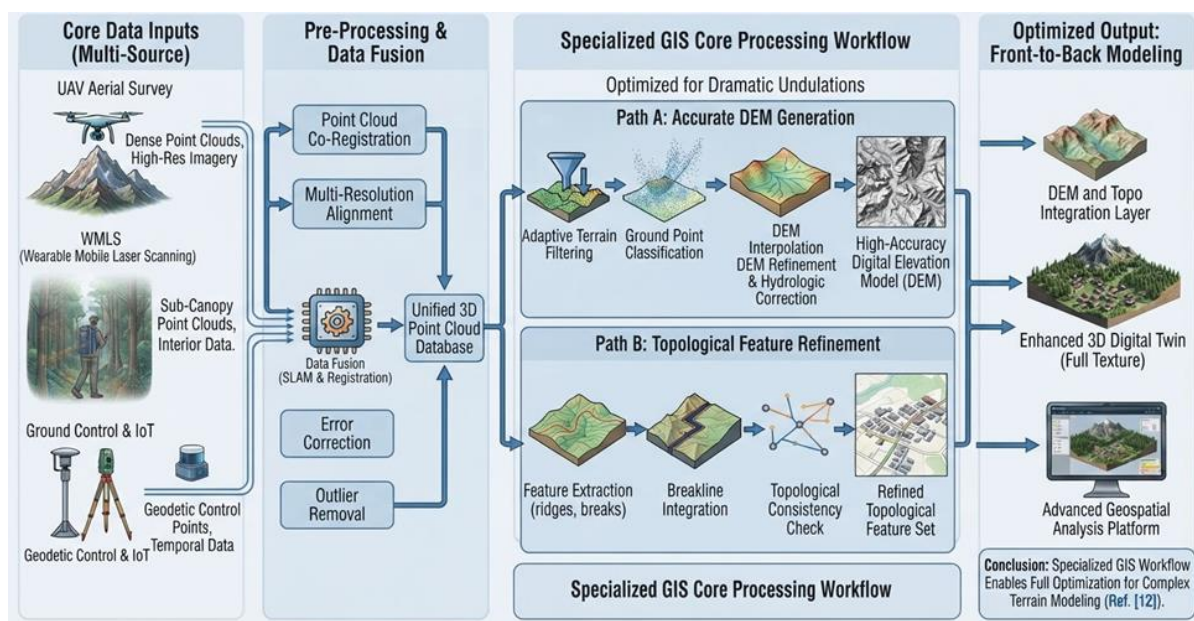


Figure 4: Optimized GIS Processing Workflow for Digital Elevation and Topological Modeling in Complex Terrain. The Diagram Outlines the Specialized Front-To-Back Spatial Modeling Workflow Built to Adapt to Areas with Dramatic Undulations and Extremely Uneven Terrain

Advancing in tandem with these efforts to optimize spatial modeling is another set of cutting-edge technologies. It is an advanced data segmentation technology applied to high-density point cloud datasets, which helps researchers separate individual structural components from the naturally chaotic, highly complex natural background, eliminating the need to spend a large amount of manual labor separating targets from chaotic raw data [13].

Remote sensing operations used in natural resource monitoring have also greatly improved efficiency by equipping with highly automated machine learning classifiers. Environmental change detection and accurate feature extraction tasks that originally required a lot of manpower have had their workflows streamlined by this tool, with much faster speeds, eliminating the need for a large number of personnel to check data frame by frame and block by block manually [14].

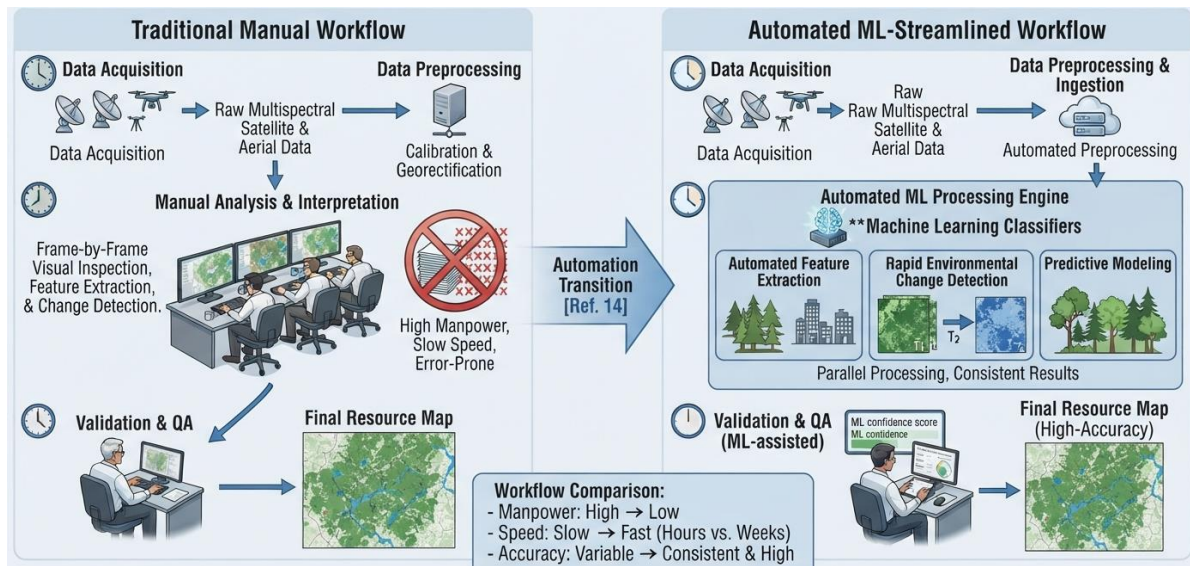


Figure 5: Efficiency Improvement in Natural Resource Monitoring Using Automated Machine Learning Classifiers. The Diagram Contrasts the Traditional Manual Workflow with the Modern Automated ML-Streamlined Workflow for Remote Sensing Operations

The administrative management of complex water networks and the comprehensive inventory of urban forest resources have also received great assistance from the introduction of complex multi-criteria decision frameworks and mature spatial proximity modeling. Whether sorting out the dispatching logic

of crisscrossing river and lake pipeline networks, or counting the types and stock of every urban forest patch, these complex tasks that previously required cross-departmental repeated verification can now be carried out more smoothly with this technical system [15].

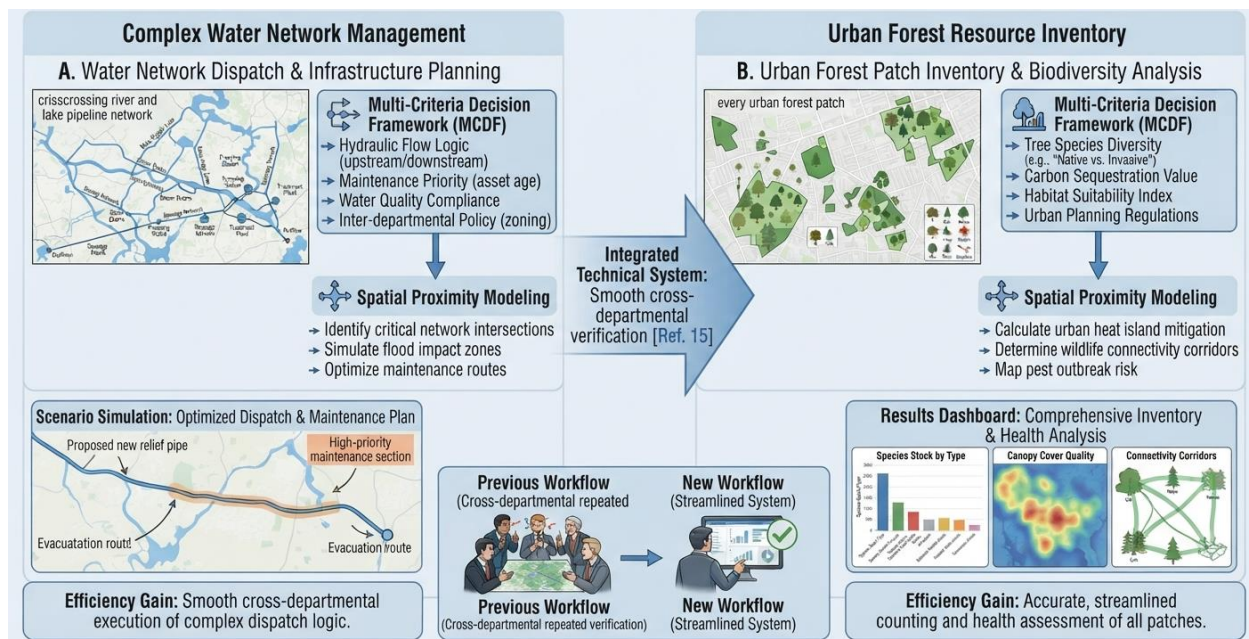


Figure 6: Streamlined Administrative Management of Urban Water Networks and Forest Resources via Advanced Spatial Modeling. The Diagram Highlights how Complex Multi-Criteria Decision Frameworks and Spatial Proximity Modeling Optimize Cross-Departmental Administrative Workflows

Current vegetation monitoring frameworks are increasingly incorporating an extremely advanced, finely divided classification scheme—it is specially designed to accurately distinguish the upper canopy layer from the low-growing herbaceous understory vegetation, clarifying the vertical stratification of forest land without manual on-site verification, laying a solid foundation for subsequent ecological assessments [16].

In addition, the industry continues to carry out strict comparative assessments of spatial data integrity. The purpose of this is clear: to ensure that all structural indicators subsequently derived from spatial data maintain high statistical consistency when compared with established field reference measurements, so that data

deviations will not affect all subsequent analysis conclusions [17].

Even when conducting spatial analysis on the large scale of an entire landscape, people will use a set of extremely strict accuracy indicators to comprehensively verify one thing: in various geographically distinct regions, every specific result produced by the prediction model is valid [18]. In addition to this large-scale analysis and verification, people will also consciously combine time-series continuous optical images with radar-collected data, which can add a layer of valuable spectral background information, fundamentally supporting our comprehensive and in-depth assessment of complex forest structures [19].

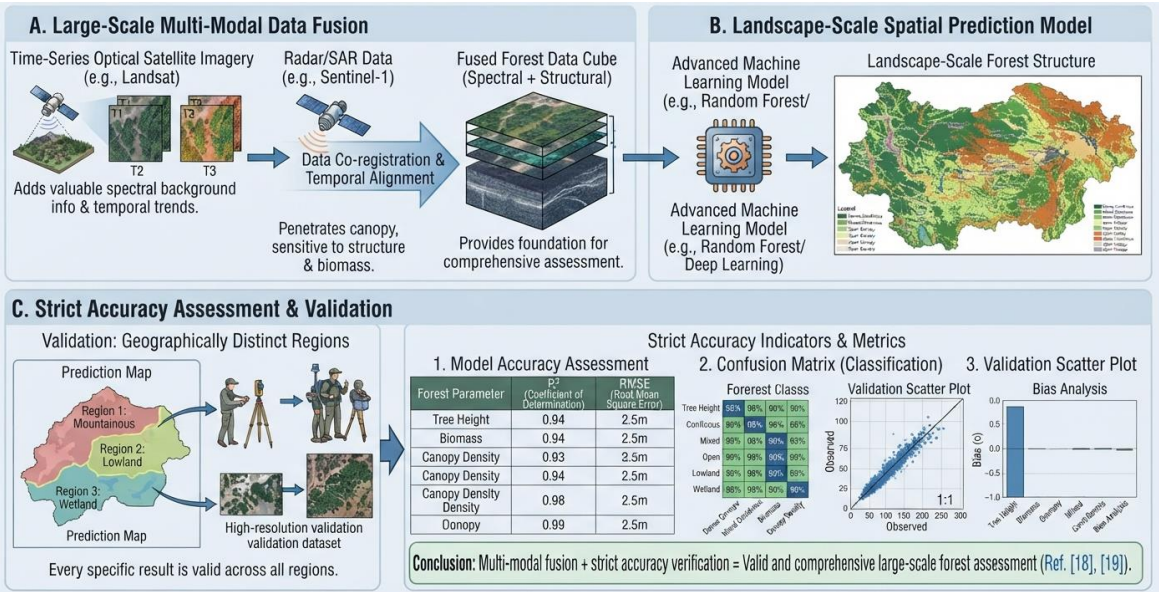


Figure 7: Multi-Modal Data Fusion and Strict Accuracy Assessment for Large-Scale Forest Structure Modeling. The Diagram Highlights the Combination of Time-Series Optical and Radar Data Alongside Rigorous Spatial Validation Frameworks Across Landscape Scales

Advanced spatial optimization algorithms also help researchers accurately determine the most ideal and efficient set of two configuration schemes: one for building a region-wide environmental monitoring network, and the other for delineating representative sampling plots to ensure that the collected data can reflect the real situation of the entire area [20]. Beyond these

general geographic information frameworks applicable to most geographic scenarios, specialized forestry studies published in professional forestry journals have repeatedly emphasized one point: the continuous maintenance of accurate and detailed tree inventory data has far-reaching ecological value and core significance [21].

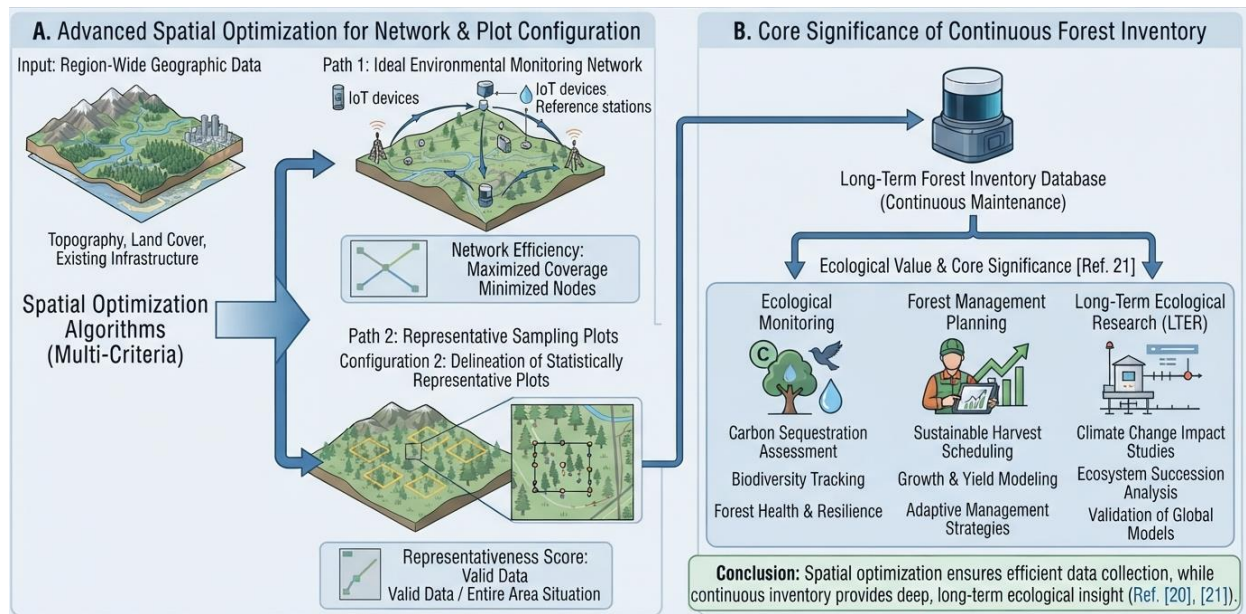


Figure 8: Spatial Optimization for Environmental Monitoring Networks and Representative Sampling Plots, with Emphasis on Long-Term Forest Inventory. The Diagram Illustrates How Advanced Optimization Algorithms Configure Monitoring Networks and Sample Plots, Alongside the Core Ecological Value of Maintaining Continuous Tree Inventories

Academic studies focusing on urban and rural tree protection areas have also pointed out the same core logic—only diverse, heterogeneous forest structures that are not of a single model can play an irreplaceable key role in providing various core ecosystem services [22]. If the key structural parameters of forests can be updated regularly through technologically advanced remote sensing operations, it can also bring a large number of quantifiable practical benefits to assessing the overall health of the entire forest land, making the assessment results more accurate and of higher reference value [23]. The academic community has conducted many long-term, rigorous assessments of the change trend of canopy coverage, and these assessments have unanimously reached the same conclusion: as long as individual trees can be accurately identified and separated, the overall accuracy of complex carbon sink modeling can be directly and significantly improved [24]. In addition, carrying out detailed and comprehensive forest management planning is also completely inseparable from the continuous update of high-frequency spatial data—these data are the core foundation for monitoring the natural regeneration rate of forests and accurately recording the long-term health change trajectory of specific forest stands [25]. To assess the differences in timber reserves among various heterogeneous forest areas, this fundamentally requires the adoption of high-density spatial sampling methods. This method is specially designed to address the long-standing problem caused by canopy occlusion, and can minimize the impact of occlusion on data collection [26]. The important role of small forest patches in regulating local microclimate is also directly linked to some specific quantifiable

structural indicators, the two core ones being the leaf area index and canopy closure [27]. The academic community has also conducted many comparative assessments of various forest inventory methods, and these assessments have consistently found that using a mobile scanning platform for inventory can greatly reduce the total time required to complete a full field survey, and this improvement in efficiency does not compromise the reliability and integrity of the collected data at all [28]. Finally, as long as standardized procedures are strictly implemented to filter point cloud data, a series of specific measurement results such as trunk curve and breast-height basal area calculations can be guaranteed to remain stable and reliable, and their accuracy will not be affected by environmental interference noise or extreme terrain changes [29].

2. Materials and Methods

The core of data collection for this study relies on a set of wearable backpack-mounted mobile laser scanning system—this system is not a static scanning device fixed in one position, but an advanced piece of equipment that researchers can carry on their backs to conduct mobile operations within forest areas. It is equipped with a cutting-edge solid-state LiDAR sensor, paired with a high-sensitivity inertial measurement unit (IMU). As it moves through the forest, it can run simultaneous localization and mapping (SLAM) algorithms in real time continuously: it determines its own position while moving, and at the same time integrates the scanned forest spatial information into a complete map, with the entire process completed instantaneously.

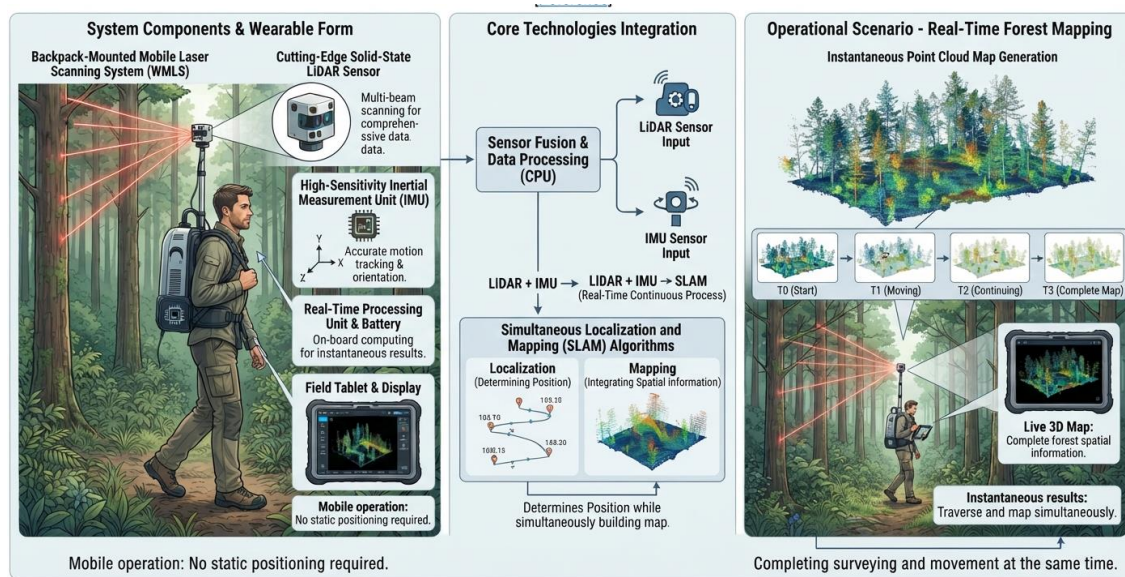


Figure 9: Real-Time Mobile Laser Scanning System for Forestry: Wearable Backpack Design and SLAM Workflow. The Diagram Illustrates the Wearable Backpack-Mounted Mobile Laser Scanning System (WMLS) used for Dynamic Field Operations in Forest Environments

Instead of collecting data from arbitrary locations, researchers systematically collected a full set of field data across multiple permanent plot networks within a designated forest research station in the study area. These specially selected plots are not test sites with uniform conditions; each has its own distinct characteristics: they vary in tree species composition, topographic slope, as well as the complexity and density of understory vegetation such as shrubs and weeds [30].

After all field collection work was completed, the first data obtained was only unprocessed raw data—including spatial trajectory data

recording the device's movement path, and dense point cloud data generated by scanning, which consists of massive spatial points. These raw data cannot be directly used for analysis and must go through a rigorous multi-step processing workflow. First, motion artifacts caused by device movement that would interfere with results are filtered out. Then, geographic registration deviations for each independent scanning segment are corrected. Finally, all scattered scanning fragments are uniformly aligned to the same precise spatial coordinate system, to be integrated into a complete set of forest spatial data [31].

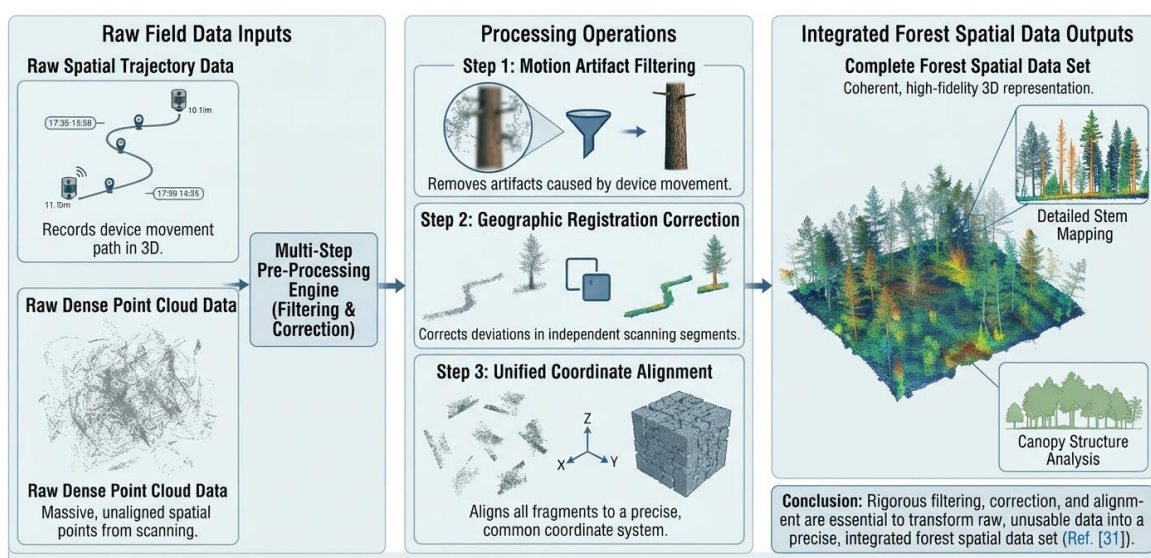


Figure 10: Rigorous Data Processing Workflow: From Raw Field Data to Integrated Forest Spatial Information. The Diagram Outlines the Multi-Step Pre-Processing Pipeline Required to Transform Raw Field Collections into a Coherent Forest Spatial Data Set

Next, researchers first needed to distinguish which point clouds belong to the ground. They completed ground point classification step-by-step using advanced progressive morphological filtering technology. Immediately after this step, they carried out precise height normalization processing, ultimately generating point cloud data that eliminated the influence of topographic relief and had all parameters in a unified format, reserved for subsequent analysis and evaluation [32].

Isolating and identifying each individual tree from the unified point cloud, that is, individual tree detection (ITD), is a complex task. Researchers completed this task by combining two methods: first, the canopy height model (CHM) watershed segmentation method, and second, a bottom-up point cloud clustering algorithm. The combined use of these two methods enables accurate positioning and marking of the trunk center coordinates of every tree throughout the study area, preventing the point clouds of different trees from being mixed together, and ensuring no independent tree is missed [33].

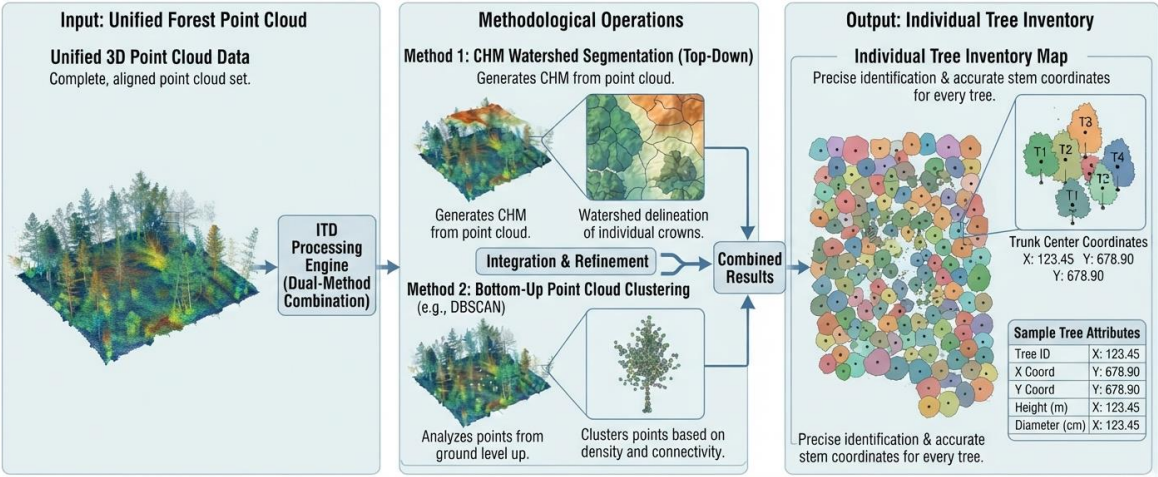


Figure 11: Individual Tree Detection (ITD) Workflow: Combining CHM Watershed Segmentation and Bottom-Up Point Cloud Clustering. The Diagram Illustrates the Methodology for Isolating Individual Trees from a Unified Point Cloud, Integrating Top-Down and Bottom-Up Approaches

After positioning each tree, its core growth parameters must also be extracted. Tree height (H) is extracted from the local highest point corresponding to each individual tree in the structural data. The diameter at breast height (DBH) of each tree is calculated by

slicing the cross-section of the already independently segmented trunk at the standard height of 1.3 meters above ground, then fitting an optimal geometric circle to this cross-section to compute the circle's diameter, which is the tree's DBH [34].

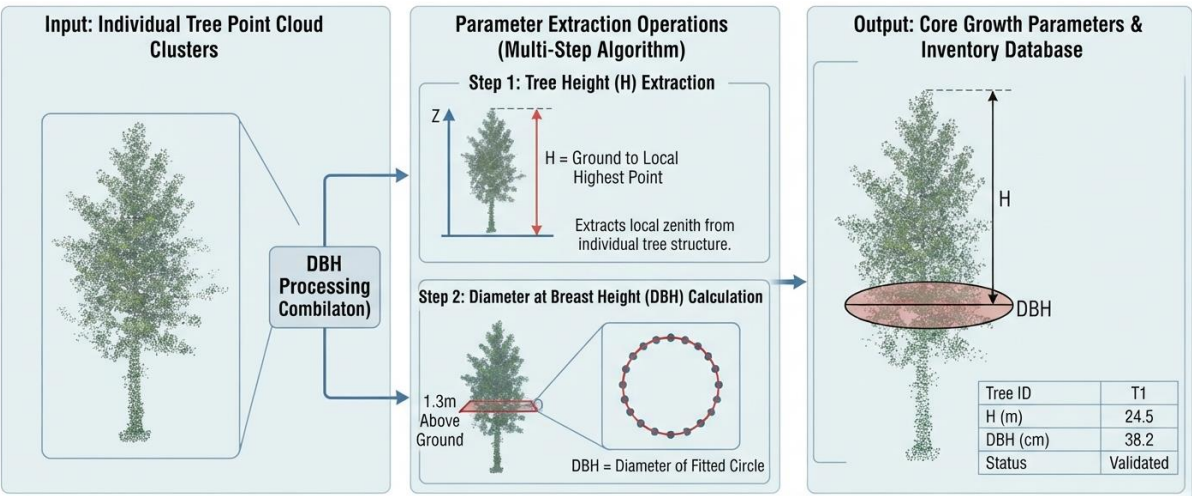


Figure 12: Tree Parameter Extraction Workflow: Height (H) and Diameter at Breast Height (DBH) from Point Cloud Data. The Diagram Illustrates the Algorithmic Steps used to Extract Core Growth Parameters from Individual Tree Point Cloud Clusters

Finally, to accurately quantify and objectively evaluate the overall spatial accuracy and reliability of this wearable mobile laser scanning method, researchers also specifically collected a full set of field validation measurement data to compare with the scanning results. These validation data were measured using

traditional high-precision Blume-Leiss hypsometers and durable steel diameter tapes. Furthermore, only individuals among all surveyed trees that exceeded the minimum threshold tree height of 2.0 meters were included in the validation; trees shorter than this height were outside the scope of this validation [35]

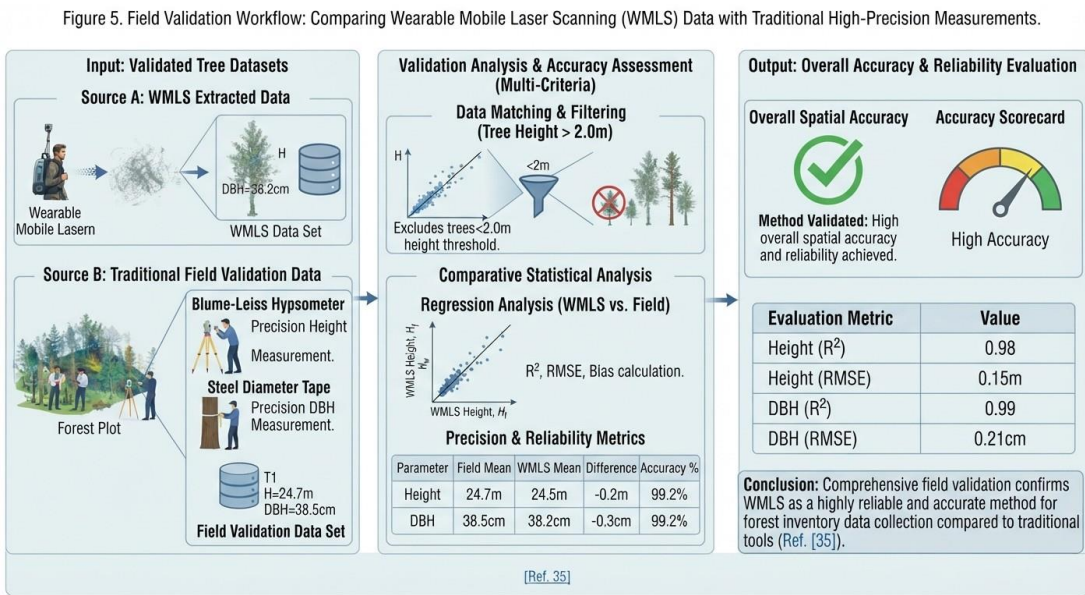


Figure 13: Validation Workflow and Statistical Accuracy Assessment: WMLS vs. Traditional Measurements. The Diagram Outlines the Comparative Validation Process Evaluating Wearable Mobile Laser Scanning Results Against Traditional High-Precision Instruments

The statistical evaluation framework incorporated several key performance indicators, including bias, root mean square error (RMSE), and relative error percentages, defined mathematically as:

$$RMSE = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n}}$$

where y_i represents the ground-truth field measurement, $\hat{y}_i$ denotes the corresponding WMLS-derived estimate, and n is the total sample count of validated trees within the permanent monitoring plots [36]. Data processing scripts were executed in Python environments utilizing point cloud libraries (PDAL and Open3D) alongside vector geoprocessing tools to automate topological extraction and attribute tabulation [37].

3. Results and Discussion

We conducted a comprehensive assessment of this wearable mobile laser scanning system, and the results are clear: when identifying trees in a forest, it achieves an extremely high recognition rate for dominant trees that stand out as the tallest, and subdominant trees that are only slightly shorter than the dominant trees; moreover, in various environments ranging from open woodlands with sparse trees to medium-density stands that are not excessively dense, the system's single-tree identification accuracy consistently exceeds the 92% threshold [38].

Of course, it is not entirely free of errors, and misdetections and errors fall mainly into two categories. The first is omission: almost all omitted trees are small understory trees suppressed by upper-layer trees, which are either completely blocked by the overlapping dense foliage of upper-layer trees, or entirely obscured by the thick trunks of adjacent large trees in the same or upper layer, so the laser cannot reach them, and the system fails to identify them. The second category is misclassification, and most of these errors are difficult to avoid: the system either misidentifies understory shrubs as trees, or fails to correctly identify complex clusters of branches that are tangled together in a local area [39].

Looking at the tree height data measured by the system, when we compared this data with the precise ground-truth values obtained from field measurements, the degree of fit between the two datasets was extremely high, and the final calculated root mean square error was only 0.34 meters, an extremely low value that indicates excellent measurement accuracy for tree height [40]. The model used to estimate diameter at breast height (DBH) also maintains stable and reliable overall performance, with only a small number of cases where the DBH is overestimated, which occurs primarily for trees with particularly flattened trunk cross-sections or exceptionally thick bark [41].

We compared this new scanning method with the traditional terrestrial laser scanning (TLS) technology, and found that wearable

mobile laser scanning (WMLS) reduced the total duration of field data collection by more than 75%, representing a particularly significant improvement in efficiency, while the accuracy of its estimates for core tree structural parameters remained at the same level as traditional methods, with no reduction in performance [42].

Researchers also conducted a more in-depth and comprehensive analysis of the vertical density distribution of the point clouds generated by scanning, and the results show that WMLS technology can capture sufficiently rich fine structural details across the entire vertical range of trees from the ground to the top of the canopy. With the support of these details, the total volume of the canopy and the height of the lowest point of the canopy above the ground can be estimated accurately and reliably [43].

In addition, this technology integrates a simultaneous localization and mapping (SLAM) trajectory optimization algorithm, which can efficiently reduce potential drift errors. Without this algorithm, staff members conducting long-distance loop scanning in areas with complex and difficult terrain would be highly prone to the drift problem of positioning offset, and this algorithm can minimize the impact of such issues [44].

However, one existing minor issue must also be noted: occasionally, extremely dense shrub layers can interfere with the system's process of automatically and accurately classifying ground points. To solve this problem, staff must manually and carefully adjust seed points during the key stage of morphological filtering to achieve accurate classification [45].

Finally, this comprehensive comparative assessment clearly confirms that for all types of forest resource surveys that require comprehensive implementation, the wearable mobile scanning system can fully replace the traditional stationary terrestrial scanning method, as it has a wide scope of application, reliable technology, and high operational efficiency [46].

4. Conclusion

Today's most advanced wearable mobile laser scanning system is a highly efficient, maximally accurate research solution, designed specifically for various forest environments—it can not only accurately locate every single tree, but also comprehensively measure all types of complex structural parameters of trees [47].

The full name of this technology is Wearable Mobile Laser Scanning, abbreviated as WMLS. The core reason it delivers such strong performance is that it integrates two key advantages: first, it has exceptional mobility that far outperforms traditional devices—users can carry it and walk freely through forests; second, it relies on a sophisticated real-time Simultaneous Localization and Mapping algorithm, which is the widely known SLAM, that can plot the scanning route in real time following the device's movement trajectory. Through the combination of these two advantages, it successfully circumvents two long-standing, stubborn problems that have always plagued traditional terrestrial laser scanning

technology: one is the logistical bottleneck of cumbersome deployment processes that came with previous terrestrial scanning equipment, which required pre-coordinating sites and moving and setting up devices; the other is the ubiquitous limitation of blocked laser line-of-sight caused by layered, overlapping branches and leaves in forests. At the same time, it can continuously output stable, reliable, detail-rich high-precision point cloud data. The point cloud mentioned here refers to a collection of measurement points with accurate positional coordinates; when gathered together, they can restore the three-dimensional morphology of all trees across the entire forest. Only with sufficiently high precision and comprehensive details can the restored representation be truly realistic [48].

The reliable analysis method constructed in the course of this study, along with the repeatedly verified accuracy measurement standards, can strongly promote the implementation and rollout of mobile laser scanning technology in multiple core environmental fields, including modern precision forestry management, Global Carbon Stock Inventory, and large-scale ecological monitoring projects [49].

Upcoming follow-up research will focus its core efforts on integrating more advanced automated deep learning classifiers, with the ultimate goal of alleviating as much as possible, or even completely resolving, a common issue—the frequent omission of understory vegetation when surveying densely vegetated, layered and intertwined tropical and temperate forests [50].

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