Under-canopy UAV Solutions for Forest Inventory – Challenges and Opportunities

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Abstract: Forest inventory underpins every facet of ecosystem management and monitoring by providing accurate, spatially explicit data on stand structure, species composition, and site conditions. Yet traditional inventories are frequently constrained by logistical challenges, financial limitations, methodological inconsistencies, and institutional hurdles that undermined the accuracy, completeness, and timeliness of these essential datasets. Over the past two decades, close-range sensing technologies have markedly reduced manual field effort while enhancing the digitization and automation of plot-level measurements. However, these systems remain reliant on human operators for deployment, limiting their ability to fully overcome logistical and technical constraints. Recent advances in under-canopy unmanned aerial vehicles (UAVs) have begun to address these limitations by integrating lightweight, UAV-borne LiDAR and photogrammetric sensors capable of semi-autonomous or autonomous flights beneath dense canopy cover. Such platforms extend the reach of close-range sensing into previously inaccessible forest interiors, enabling rapid, repeatable acquisition of tree- and stand-level metrics without the need for extensive ground crews. In this review, we dissect the technical architectures, sensor configurations, and performance metrics of emerging under-canopy UAV systems for forest inventory. We further identify the principal engineering and operational challenges to guide future research directions and accelerate the adoption of UAV-based forest monitoring solutions.

1. Introduction

Forest in-situ observations have witnessed remarkable progresses over the last two decades. The close-range sensing has been one of the main driven forces of this fast progress, with its capability to capture detailed object information in any contact mode or non-contact target-to-sensor distance up to several hundred meters or even more (Liang et al., 2022).

In forest digitization, Terrestrial Laser Scanning (TLS) represents the most accurate 3D digitization of forest structures at a plot level, which automatically digitizes the objects in its surrounding space using millions to billions of three-dimensional (3D) points. The downside of TLS is its stationary perspective that limits the data coverage and the efficiency of data collection. Mobile Mapping Systems (MMS) speeds up the data acquisition by integrating positioning and data collection sensors on a kinematic platform. Low-altitude aerial systems, such as Unmanned Aerial Vehicles (UAVs) or drones, helicopters, and hybrid airships, provide the aerial observations to compensate the terrestrial perspectives of the stationary and mobile terrestrial systems with an even higher level of mobility. In addition, these systems are flexible and diverse in sizes and payload capacities, and have emerged with great popularity.

However, many obstacles still block close-range sensing from practical field measurements as a reliable supplier of in situ reference information (Wang et al., 2021). Forest environments present formidable challenges for autonomous exploration due to their structural complexity: dense vegetation, heterogeneous architectures, and persistent occlusions degrade the performance of both vision- and LiDAR-based SLAM systems.

Nevertheless, recent advancements in UAV systems have integrated lightweight LiDAR and photogrammetric sensors to enable close-range sub-canopy sensing. While UAV-based Structure-from-Motion (UAV-SfM) systems exhibit operational simplicity and leverage established computer vision pipelines, their efficacy diminishes in environments with limited surface textural variation, resulting in reduced positional accuracy relative to laser scanning (Yao and Liang, 2024). On the other hand, LiDAR systems directly digitize 3D forest structures, yet face the dilemma between high payload requirement and restricted platform size.

This paper summarizes the technological architectures, sensor modalities, and quantitative performances of emerging under-canopy UAV systems applied for forest inventory. We further elucidate core engineering and operational challenges to prioritize critical research trajectories for future developments.

2. Emerging UAV Solutions

Under-canopy UAV operations have caught attentions recently for their potential to efficiently collect complete and reliable data for forest in situ observations.

2.1 Observation perspectives

2.1.1 Under-canopy observation: Under-canopy UAV technology brings benefits to forest management and ecological conservation. Compared to TLS, which is limited by its static observation perspective and time-consuming operation, under-canopy UAVs enable dynamic and multi-angle data acquisition through autonomous flight, thereby greatly improving data collection efficiency. Moreover, under-canopy UAVs exhibit superior manoeuvrability in complex sub-canopy environments, allowing them to penetrate canopy gaps and capture more complete structural information of tree stems. This capability provides more comprehensive data support for forest parameters such as diameter at breast height (DBH) and stem curve (Liang et al., 2024; Muhojoki et al., 2024). Most recent studies focus on the under-canopy fly mode (Chisholm et al., 2013, 2021; Krisanski et al., 2020; Hyyppä et al., 2020a, 2020b, 2021; Liu et al., 2022; Shimabuku et al., 2023; Muhojoki et al., 2024; Trybała et al., 2024; Liang et al., 2024; Yao and Liang, 2024; Zhao et al., 2025).

2.1.2 Integrating above- and under-canopy observations at data level: Integrating above- and under-canopy flies through data fusion is a common way to improve the completeness and the comprehensiveness of the forest representation, and consequently, to enable a comprehensive analysis of individual tree structural parameters at tree-, branch-, and leaf- scales.

Sujaswara and Hasegawa (2023) conducted separate UAV flights above and beneath the forest canopy to capture imagery of the tree crowns, stems, and understory vegetation. SfM was applied independently to each image set, generating two dense point clouds representing the over- and under-canopy structures. By identifying and aligning overlapping regions between two point clouds, the datasets were registered and merged into a unified forest scene. The registration process consisted of two stages: key points were first automatically extracted and matched across images to achieve an initial alignment of the point clouds, and, subsequently, ground control points (GCPs) measured with a total station were used to align the above- and under-canopy point clouds into a unified coordinate system.

2.1.3 Integrating above- and under-canopy observations at trajectory-level : Wang et al. (2021) proposed and validated a novel approach that integrates the above- and under-canopy data collection in one mission via trajectory design. The UAV-LiDAR system performed an above-canopy LiDAR scan at an altitude of 50 meters, and then descended through canopy gaps to a low altitude of 1.5 meters and continued to fly under the canopy along a predefined path. The approach coordinated data collection from both above- and under-canopy perspectives and enabled the acquisition of multi-perspective point cloud data by optimal trajectory design. The flight relied on Global Navigation Satellite System (GNSS) and Inertial Measurement Unit (IMU) for platform positioning and data generation.

2.2 Operation mode

2.2.1 Manual operations

Under-canopy UAV is at an early stage of development. Manual operation is currently popular (Chisholm et al., 2013; Hyyppä et al., 2020b; Kuželka and Surový, 2018; Muhojoki et al., 2024; Shimabuku et al., 2023; Sujaswara and Hasegawa, 2023; Wang et al., 2021). Operators can precisely navigate around small branches or vines and respond swiftly to unexpected events such as startled wildlife or sudden gusts of wind. More importantly, manual operation does not rely on GNSS or vision-based localization systems, which often fail in dense forest conditions.

Some manual operations rely on virtual reality (VR) systems.. Hyyppä et al. (2020) utilized first-person view (FPV) for manual UAV control, and further integrated VR headsets to enable immersive real-time flight path control under the canopy, facilitating obstacle avoidance through intuitive navigation. The built-in anti-collision function was turned off. The operator used manual planning while also disabling the obstacle avoidance function, and controlled the drone to fly at a low speed of 0.5 m/s (Krisanski et al., 2020). Hyyppä et al. (2021) used a FPV system on the UAV to enable more intuitive and effective manual control.

Shimabuku et al. (2023) and Kuželka et al. (2018) conducted manual flight control using the DJI Mini 3 Pro and DJI Phantom 4 Pro combined with DJI Mavic Pro, respectively.

Flight can have complex routes through manual control to achieve full-area coverage beneath the canopy (Hyyppä et al., 2020b, 2021; Krisanski et al., 2020; Muhojoki et al., 2024). Wang et al. (2021) conducted manual flights both above and below the canopy in sequence, completing full-scene data acquisition. Some studies manually operated UAVs to follow grid-like (#-shaped) paths (Kuželka and Surový, 2018; Shimabuku et al., 2023).

2.2.2 Automated operations: Automated operation is currently rare. The objectives of automated flight are also diverse. The study focused on city parks and those focused on natural forests.

Urban park plots are typically characterized by simple terrain, open space, and planted trees, which make UAV flight missions easier to execute. Chisholm et al. (2021) conducted their experiments in an open parkland area in Singapore, where the UAV flew in a straight-line flight pattern, with the start and end points located at the same position, forming a closed-loop trajectory. During the flight, the UAV operated autonomously using a real-time SLAM algorithm for navigation and localization. LiDAR data were collected and was later used for estimating DBH. Zhao et al. (2025) evaluate system performance in a subtropical evergreen broad-leaved city forest in four flights.

In comparison to urban park environments, studies in natural forests involve greater complexity and difficulty. First, natural forests are unmanaged environments characterized by irregular terrain, densely and unevenly distributed vegetation, diverse tree species, and varied growth forms. These conditions greatly complicate UAV obstacle avoidance and trajectory planning. In contrast, urban parks are typically maintained landscapes, where trees are regularly spaced and pruned, the understory is more open, and the terrain is generally flat, making flight operations considerably easier to carry out. Second, natural forests often lack man-made trails or clearings, which means that UAVs cannot rely on predefined routes and must instead perceive their surroundings in real time, perform mapping and obstacle avoidance on the fly, and maintain safe and stable flight while collecting data. In urban parks, by contrast, the vegetation structure is relatively simple, and GNSS signals are generally more stable, which facilitates UAV localization and control (Chisholm et al., 2021; Yao and Liang, 2024).

Fully automated under-canopy system is emerging in recent years. Liang et al. (2024) first developed a fully autonomous UAV flight system to achieve collect data that comprehensively cover entire forest scenes beneath the canopy with dense plot traversal trajectory design, addressing the challenge of automatic data acquisition in the complex forest understory.

2.3 Trajectory design

Trajectory design is often neglected in the studies of under-canopy UAV operations, however, it actually determines the quality, i.e., the completeness and the geometric accuracy of the final data and products. In general, the denser is the traverse trajectory within a forest plot, the better is the data quality. Yet, due to the structural complexity of the forest understory and the high risk of collisions, the trajectory design always needs to be adaptive and adjustable according to on-site conditions.

Flight path strategies can generally be classified into two types: linear trajectory and full-coverage trajectory. To ensure comprehensive data acquisition under the canopy, most operations still favour manual UAV flights over autonomous navigation while using full-coverage trajectory.

2.3.1 Linear flight trajectory: For automated operations, the simplest and safest approach is to carry out a linear flight throughout a forest plot. Trybała et al. (2024) presents a typical case where a UAV conducted a one-way linear flight through a forested area without returning. Chisholm et al. (2013) performed a manually controlled straight-line flight.

A special case of linear flight involves closed-loop trajectories, where the UAV's starting and ending points coincide. Sujaswara et al. (2023) utilized circular flights around individual trees to form closed loops. In addition, some studies conducted field tests using linear flight paths that ultimately formed closed-loop trajectories (Chisholm et al., 2021; Liu et al., 2022; Zhao et al., 2025).

2.3.2 Full-coverage trajectory: The full-coverage trajectory strategy is much more challenging for automated operations. Such strategy involves intricate flight paths back and forth within a single forest plot to capture complete understory data. Liang et al. (2024) employed a zigzag trajectory to scan the entire forest scene in a complex environment. Karjalainen et al. (2024) achieved full forest coverage by designing an “M-shaped” flight path. Yao et al. (2024) investigated the potentials of 3D trajectory verities, aiming at improving the completeness of data collection.

2.4 Source for positioning and data collection

2.4.1 Camera images: Most under-forest canopy UAVs are equipped with cameras to collect spatial information. Camera-equipped UAVs collect photos (Kuželka and Surový, 2018; Krisanski et al., 2020; Sujaswara and Hasegawa, 2023) or videos (Shimabuku et al., 2023) and then recover the 3D point cloud scene under the canopy based on visual SLAM (Trybała et al., 2024; Zhao et al., 2025) or SfM (Kuželka and Surový, 2018; Krisanski et al., 2020; Sujaswara and Hasegawa, 2023) algorithms. The advantage of image-based solutions is that cameras have a low hardware cost and fairly mature UAV equipment.

Kuželka et al. (2018) used two commercial UAVs (DJI Phantom 4 Pro and DJI Mavic Pro) to map forest structures at an 8m flight height. The estimation accuracy from the UAV-SfM-based system was reported to be comparable to that of the terrestrial SfM approaches reported in (Liang et al., 2015; Mokroš et al., 2018). Krisanski et al. (2020). also used commercial UAV (DJI Phantom 4 Pro V2) to obtain under-canopy images located on sloping slopes. Trybała et al. (2024) used stereo camera and visual SLAM algorithms to localize and reconstruct the 3D environment under the forest canopy. Zhao et al. (2025) use depth camera and visual SLAM algorithms to provide support for autonomous navigation.

Dionisio-Ortega et al. (2018) developed an autonomous under-canopy navigation framework for UAVs utilizing an AlexNet-based convolutional neural network (CNN). The CNN model was fine-tuned through transfer learning to output three classes—left, right, and straight operation. During flight, images captured by the onboard camera are fed into the trained network, which outputs a probability distribution over the three classes. The action corresponding to the highest probability is then executed by the UAV as the next movement command. Prakash et al. (2019) proposed an optimization framework for deep neural networks that integrates sparsification with architecture search, aiming to enable high-speed autonomous navigation on low-power edge devices in GNSS-denied environments. The framework starts from a dense, pre-trained model and performs pruning to reduce its size, while exploring structurally superior and more effective sub-networks under the same sparsity constraints.

Trybała et al. (2024) employed UAV-based localization techniques to support wild berry collection under forest canopies. In their experiment, a stereo image sequence and sparse GNSS positions were collected for visual SLAM reconstruction. The forward-looking images were processed using COLMAP-SLAM to generate the UAV flight trajectory and a sparse point cloud, successfully reconstructing scenes with clearly defined tree trunk structures. The visual trajectory was then aligned with the sparse GNSS control points to achieve global coordinate transformation. Finally, berry positions were manually annotated in the downward-looking images and projected onto the orthophoto through coordinate transformation. Karjalainen et al. (2024) developed an autonomous UAV system, combining image collection, planning and control that link the perception to support trajectory adjustments.

2.4.2 LiDAR: A moving camera taking photos with rapidly changing perspectives produces blurred photos. The robustness and accuracy of the system and the produced point cloud data is significantly reduced (Zhao et al., 2025). Compared with camera images, LiDAR can provide direct 3D information about the surrounding environment, making it more popular. LiDAR has the advantage of high robustness. In under-canopy environments with significant lighting variations, visual-based localization has lower accuracy in navigation, especially in turning place (Yao and Liang, 2024).

With manual UAV operations, Chisholm et al. (2013) operated a UAV equipped with a 2D horizontally scanning LiDAR (Hokuyo UTM-30LX) to reconstruct horizontal cross-sectional maps through post-processing algorithms. Later, Chisholm et al. (2021) integrated LiDAR-based SLAM for real-time localization with optimization algorithms, enabling end-to-end stem diameter measurement in a park woodland environment. In (Hyyppä et al., 2020b, 2020a, 2021), UAVs equipped with commercial 3D LiDAR sensors were used to collect under-canopy point clouds. Wang et al. (2021) developed a seamless above- and under-canopy flight method using a UAV equipped with a Riegl miniVUX LiDAR scanner.

With automated UAV operations, Tian et al. (2020) developed a UAV search and rescue system that can operate under forest canopy primarily based on a LiDAR sensor. This system operates in collaboration with a ground station architecture, where the ground station receives submaps uploaded by multiple UAVs, performs map fusion and global optimization, and accomplishes collaborative simultaneous localization and mapping (CSLAM) among the UAVs.

Liu et al. (2022) proposed an autonomous UAV flight under the forest canopy. The system integrates a semantic SLAM module (SLOAM) with the deep learning segmentation model RangeNet++ to perform semantic segmentation of tree trunks and ground from point clouds. Key features are extracted through cylindrical fitting of trunks and ground plane modelling. Subsequently, an optimization algorithm associates the current observations with the historical semantic map to correct the UAV’s pose and update the map content. This method integrates deep learning and machine learning to enable UAV control and planning. Specifically, deep learning is primarily responsible for semantic segmentation of point clouds, while machine learning is applied to process the segmentation results for cylindrical modelling, real-time map construction, and localization.

In addition, some studies also explored similar approaches across forest plots of varying structural complexity. Chisholm et al. (2021) described an end-to-end system, equipped with a horizontally scanning LiDAR. The UAV autonomously navigates beneath the forest canopy, generating a real-time SLAM trajectory. The collected LiDAR point clouds are then used to automatically estimate tree diameters at breast height (DBH).

Most Recently, Yao et al. (2024) and Liu et al. (2022) achieved autonomous under-canopy UAV localization and data collection using 3D LiDAR with complex 2D and 3D trajectory design to satisfy the required data quality for practical forest investigations.

3. Performance

3.1 Camera images

Camera-equipped under-canopy UAVs have been used to reconstruct 3D point clouds from photographs, enabling the estimation of attributes, such as DBH and stem volume.

Kuželka et al. (2018) conducted experiments on two 50 m × 50 m homogeneous plots. These plots were in mature even-aged stands of Norway spruce (Picea abies) and European beech (Fagus sylvatica), lacking understory vegetation. All tree stems were detected, with a DBH bias of –1.17 cm (–3.14%) and RMSE of 3.21 cm (8.2%).

Krisanski et al. (2020) detected the tree stems in two 13 m radius plots located in a native regrowth Eucalyptus Forest. The sites featured slope terrain (mean slope 24°) and understory vegetation. The DBH estimation biases were 1.1 cm and 2.1 cm, respectively. The stem detection rates were 86% and 89%, respectively.

Shimabuku et al. (2023) evaluated two forest plots on Okinawa Island, Japan, reporting RMSEs of DBH measurements ranging from 0.4 to 0.7 cm, while per-tree stem volume RMSEs ranged from 0.0045 to 0.0147 m^3. The first plot, 10 m × 10 m in size, was located in a sparse Bischofia javanica forest. The second plot, with dimensions of 5 m × 5 m, was with a reduced visibility.

Sujaswara et al. (2023) experiment in two plots of irregularly shaped: a sparse Metasequoia glyptostroboides stand covering 634 m^2, and a pine forest covering 370 m^2. The reported DBH RMSEs ranged from 1.52 cm to 1.82 cm, respectively.

3.2 LiDAR

Early work by Chisholm et al. (2013), using a 2D LiDAR scanner, achieved a stem high detection accuracy of 73% for large stems (DBH > 20 cm) within a 3 m sensor range. The RMSE and bias values were 25.1% and –1.2%, respectively. The study was conducted on a flat roadside area, planted mainly with Casuarina equisetifolia and featuring sparse understory vegetation.

Chisholm et al. (2021) later reported DBH RMSE and bias values of 30.6% and 18.4% across all trees within a plot. The survey was conducted in a parkland, featuring scattered trees and palms.

Subsequent research demonstrated that 3D LiDAR achieved superior tree-metric accuracy. Hyyppä et al. (2020) experimented in two single-layer boreal forest, with 32 m × 32 m size. The stem detection rates were 84–93% and DBH RMSEs of 0.60–0.92 cm (2.2–3.1%) using commercial SLAM technology. One site was a sparse, pine-dominated plot with low understory vegetation, while the other was a medium-difficulty site featuring moderate understory and mixed tree species including birches and spruces.

Wang et al. (2021) developed a hybrid above- and under-canopy laser-scanning methodology, achieving relative root mean square errors (RMSEs) of 2.0–4.0 cm for diameter at breast height (DBH), 0.33–1.13m for tree height and 4.0–7.0 cm for stem curvature estimates. The experiment was conducted in a heterogeneous 120 m × 120 m boreal forest plot, dominated by silver birch (Betula pendula), Norway spruce (Picea abies), and Scots pine (Pinus sylvestris).

Liang et al. (2024) conducted experiments in a 50 m × 30 m plot located in a subtropical urban forest. The RMSEs of the DBH and the stem curve estimates were 5.13 cm (22.01%) and 5.18 cm (22.49%), respectively.

4. Applications

Compared with traditional manned operations, under-canopy UAVs are safer and more cost-effective, resulting in substantial improvements in patrol efficiency.

4.1 Forest inventory

under-canopy UAVs provide significant benefits for forest management, ecological conservation, and emergency response. These UAVs enable precise monitoring of tree health, including early detection of pests and diseases and vegetation analysis, as well as efficient resource assessment such as forest inventory, timber volume estimation, and rare species localization. In addition, they support biodiversity studies by facilitating detailed habitat mapping

Liang et al. (2024) collect tree attribute data, aiming to improve the efficiency and automation of in-situ forest observations. Hyyppä et al. (2021) employed LiDAR-based UAVs to measure parameters such as tree height and volume for individual trees. Chisholm et al. (2021) developed an end-to-end system using an autonomously flying UAV under tree canopies, aiming to automatically measure Diameter at Breast Height (DBH). Shimabuku et al. (2023) studied the efficiency of UAV-based 3D reconstruction in forests. Kuželka et al. (2018) tested the performance of consumer-grade UAVs equipped with vision-based localization systems to acquire 3D structural data of forests.

The scope of inventory expanded in recent years. Trybała et al. (2024) demonstrated a UAV-based system for initial berry harvesting under-canopy conditions.

4.2 Search and rescue

under-canopy UAVs equipped with thermal imaging can penetrate dense foliage to locate missing persons, assess disaster sites, and deliver emergency supplies.

They also play a key role in innovative ecological conservation efforts, including precision seed dispersal, illegal logging surveillance, wildlife habitat monitoring and under-canopy resource inventories (Trybała et al., 2024).

Tian et al. (2020) proposed a UAV rescue system under the canopy, based on 3D laser scanning and coordinated with ground infrastructure to enable real-time localization and mapping to support emergency missions.

5. Challenges & Opportunities

Narrow interstitial spaces between trees and low-hanging branches exacerbate flight instability and collision risks. Thus, the mobility of the under-canopy ULS system is expected to decrease as the forest difficulty level increases. The main challenges lie in obstacle avoidance and real-time operation, especially in GNSS signal loss and dense obstacles

5.1 Impact of forest conditions

One main constrain factor for the applying under-canopy ULS system in a dense complex forest stand is the size of the UAV platform, because there is a trade-off between the payload and the mobility. Large UAV platforms can take more payloads that is particular important for LS-based systems as the current LS sensors are often heavier than optical sensors. A large size, however, requires more space for UAV to safely navigate itself through objects, which typically reduces the mobility of the under-canopy UAV system in forests. Nevertheless, because both platform and sensors are rapidly evolving, it can be anticipated that lighter sensors would become available and facilitated smaller system that can manoeuvre in dense and complex forest stands.

In addition, forest plots are often characterized by highly variable terrain conditions, especially in mountainous regions, where steep slopes, dense vegetation, and complex ground structures pose significant challenges to UAV navigation and data acquisition. Therefore, it is necessary to develop under-canopy UAVs with terrain-following capabilities to ensure safe and efficient flight in complex forest environments (Krisanski et al., 2020).

5.2 Impact of trajectory planning

From a methodology point of view, the current route planning methods for autonomous UAV navigation do not meet the forest observation and measurement requirements. The state-of-the-art autonomous exploration strategies typically take the greedy algorithm that makes locally or immediately optimal choices, which often overlook the capability of the platform movement that is not regarded as a constraining factor in controlled, limited, easy, and/or open space conditions.

Forest plots are typically delimited with fixed areas, requiring UAVs to complete data acquisition within a bounded space. Liang et al., (2018) revealed that incomplete data acquisition significantly compromises the accuracy of tree attribute estimation. Owing to the complex understory structure and prevalent occlusions, UAV accessibility to target areas is restricted, rendering complete plot coverage highly challenging. Consequently, a key challenge in trajectory planning is to design a flight path that rigorously adheres to the UAV's manoeuvring constraints while simultaneously ensuring complete and efficient plot coverage.

5.3 Other limitation factors

In practice, autonomous platform endurance depends on battery power, and the energy requirements of a platform are constantly changing along with the flying conditions. To fully explore a space of complicated conditions, e.g., with varying structure and plenty of obstacles and occlusions, an autonomous platform requires more battery power because more redirection and restarting are required. Limited by the capacity of the onboard battery, e.g., typically 10-20 min flying time, the algorithms that prioritize excessive environmental exploration for covering the space do not support the exploration in an unknown challenging environment such as forests.

5.4 Impacts to forest observations

From perspectives of forest observations and inventories, the most concerned issues are the reliability and the richness of the achievable forest and tree attributes, on top of the cost of time, labour, and instruments for data collection and processing. In forest observation, the crucial point is to not only facilitate autonomous under-canopy UAV manoeuvre, but more importantly, to collect reliable data, thus, to meet the forest in situ measurement requirements.

6. Summary

Under-canopy UAV systems are revolutionizing forest investigation through multi-sensor fusion, autonomy, and advanced analytics. While challenges like occlusion and standardization persist, innovations in deep learning, SLAM, and hybrid workflows promise scalable, accurate solutions for sustainable forest management.

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