Integrating Pre-Harvest UAV Scans to Enhance Harvester Tree Localization Accuracy

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Abstract

Accurate geolocation of individual trees during forest harvesting operations is crucial for effective decision-making, yet traditional cut-to-length (CTL) harvesters often experience significant positional errors (0.5–10 m) due to unreliable GNSS performance under dense forest canopies. This uncertainty hampers the precise integration of harvester-generated data into operational forest management systems. To address this problem, we investigated the integration of high-resolution pre-harvest UAV LiDAR data with harvester-collected positional information. UAV laser scanning (DJI Matrice equipped with Zenmuse L2 LiDAR) was conducted over a dense, mixed-species boreal forest stand scheduled for its first thinning operation. Following harvesting, stump positions were precisely recorded using centimeter-grade GNSS as ground truth. Harvester-recorded tree positions were matched to tree crowns delineated from UAV LiDAR point clouds using Canopy Height Model (CHM) segmentation. For each crown, structural (height, crown size) and spectral (RGB statistics) features were extracted, and tree species (spruce, pine, birch) were classified using Random Forest (RF) and XGBoost models. Comparative positional error analysis revealed that mean harvester GNSS errors were 1.52 m, whereas UAV-derived tree positions showed significantly lower mean errors of 0.63 m. Integrating UAV data with harvester positions successfully reduced the mean positional error to 0.76 m. Species classification accuracy exceeded 91% overall for both RF and XGBoost models, with coniferous species (pine, spruce) classified at approximately 94% accuracy and deciduous birch slightly lower at around 71%. These results highlight the potential of integrating pre-harvest UAV scans to substantially enhance tree-level geolocation accuracy, enabling precise digital twins and improved real-time operational decision-making during harvesting. The study addresses a critical research gap by developing a practical workflow for combining UAV and harvester data, thereby facilitating precision forestry applications such as targeted tree selection, automated navigation, and enforcing environmental safeguards.

1. Introduction

Advancements in unmanned aerial vehicles (UAVs) and remote sensing over the last decade have led to significant developments in forest monitoring and precision forestry. High-resolution aerial imagery and laser scanning from UAVs enable detailed mapping of forest structure and composition at the individual-tree level, which is critical for modern "Forestry 4.0" digitalization efforts. Researchers have demonstrated UAV-based methods for tree detection, species classification, and biomass estimation in various forest types (Li et al., 2022). These developments underscore the potential of UAVs to create detailed pre-harvest forest inventories or even real-time "digital twins" of forest stands, which can support operational decision-making.

CTL forest harvesters, on the other hand, provide an abundance of ground-truth data during operations. Modern harvesters record each felled tree's diameter, length (bucking), and location via onboard GPS/GNSS and inertial sensors. This data is economically valuable for forest management and supply chain optimization. Studies have shown harvester data can serve as "ground truth" for remote sensing (Söderberg et al., 2021). However, a major challenge is that the geolocation of each tree from the harvester is often imprecise due to GNSS signal degradation under forest canopies. Typical standalone GNSS errors on harvesters range from sub-meter to several meters, depending on canopy density, terrain, and satellite visibility. Kaartinen et al. (Kaartinen et al., 2015) found that even high-end GNSS under dense canopy could not reliably achieve sub-meter accuracy, often yielding 2–5 m errors. More recent studies (Abdi et al., 2022; Lopatin et al., 2023) confirm that canopy occlusion, multipath, and terrain all contribute to degrading positional accuracy for forestry machinery.

Despite these known issues, there is a lack of established operational workflows to fuse high-resolution UAV data with harvester-collected data. Bridging this gap is a key research need identified in precision forestry. If the detailed spatial data from UAV scans (e.g., tree positions from a pre-harvest point cloud) can be integrated with harvester data streams, it could enable real-time or near-real-time corrections to harvester GNSS positions. Some recent works (Faitli et al., 2024) have taken steps in this direction. They achieved an average 2.44 m real-time localization error (with GNSS-IMU-SLAM) which improved to 0.21 m after post-processing the trajectory. This shows the promise of integrating additional sensors on the harvester; however, mobile laser scanning (MLS) systems on every machine is costly and not yet commonplace. A more cost-effective approach could leverage external UAV data. The forestry industry has begun exploring "smart" harvesting systems where pre-harvest remotely-sensed data is uploaded to harvesters for navigation and decision support (Faitli et al., 2024), but practical implementation remains limited. In operational practice, harvester operators still largely rely on their own visibility and stand maps for decision-making, rather than dynamic sensor-fused data.

Another important gap is the development of real-time forest digital twins for harvesting. A digital twin is a live digital replica of the physical environment. In forestry, this could mean a continuously updated 3D model of the stand during harvesting, showing each tree's status and location in real time. Such capability would support precision forestry by enabling tree-level decisions: for instance, selective harvesting of certain

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species or sizes while avoiding protected trees or habitats, all guided by a live map. Recent reviews note that while digital twin concepts are emerging in agriculture and forestry, true real-time integration is still in its infancy. Tagarakis et al. (Tagarakis et al., 2024) emphasize that full digital twins in forestry face challenges like data integration from multiple sources and the need for expert knowledge to interpret the data. Buonocore et al. (Buonocore et al., 2022) proposed a framework for a forest digital twin that integrates tree-level data (from IoT sensors or UAVs) with stand-level remote sensing, and highlights blockchain for data integrity. However, implementing such a system for real-time operations like harvesting requires solving the geolocation accuracy problem: the digital twin must reliably know which tree is being cut or moved at all times. Sub-meter or even centimeter-level accuracy is needed to distinguish individual neighboring trees and align machine actions with specific trees in the digital model. Current GNSS alone is insufficient, as noted, and thus the fusion of external data (e.g., UAV scans or ground sensors) is required to enhance positioning. Additionally, achieving these accuracies in real time is challenging due to computational and communication constraints in forest conditions (limited bandwidth in remote areas, processing large point clouds on the fly, etc.).

This study addresses that gap by demonstrating how UAV LiDAR scans acquired before harvesting can enhance the spatial accuracy of harvester-reported tree locations. We focus on two key research questions:

1. How to integrate UAV data with harvester systems in practice, including data alignment and error correction, and what improvements in positional accuracy result?
2. How can such integration support precision forestry decision-making, and what challenges remain in achieving real-time, tree-level guidance (a step toward a functional forest digital twin)?

We hypothesize that matching harvester data to UAV-derived tree positions can significantly reduce location errors, bringing them closer to the decimeter level needed for tree-level decisions. We also anticipate that UAV-derived data (LiDAR point clouds and imagery) can enhance tree species classification, complementing the harvester's data, where species identification relies exclusively on operator input for each felled stem. By integrating harvester and UAV datasets, we create a richer and more reliable per-tree dataset (accurate position, size, and species), which can directly support operational decision-making, including harvest planning, automated machine control, and environmental safeguards, such as precise identification and preservation of specific habitat trees.

2. Materials and methods

2.1 Study area and data collection

The study was conducted on 30 September 2024 in a managed boreal forest stand located in southern Finland (61°13.141′N, 25°6.660′E). Dominant species were Norway spruce (Picea abies), Scots pine (Pinus sylvestris), and birch (Betula spp.). Prior to harvesting, we conducted a UAV LiDAR survey using a DJI Matrice 300 drone equipped with the Zenmuse L2 LiDAR sensor (a lightweight airborne laser scanner). The UAV was flown in leaf-on conditions at ~70 m altitude with overlapping flight lines to ensure full coverage. The Zenmuse L2 captures high-density point clouds (up to ~240,000 points/sec with triple returns, yielding point densities >4000 pts/m² over the canopy in our flight). We also captured RGB imagery with the UAV's integrated camera simultaneously (the Zenmuse L2 includes a synchronized camera), which was later used for extracting color features per each LiDAR point.

After the CTL harvesting operation, we recorded ground truth positions of the stumps of all harvested trees using Reach RS2+ Multi-Band RTK GNSS Receiver, species and stump diameter. A survey-grade RTK GNSS receiver was used for stump mapping, achieving ~1–2 cm accuracy in the relatively open post-harvest canopy (with short occupation times ~1 min per stump). These high-accuracy stump locations serve as reference coordinates for each felled tree. The Ponsse Scorpion harvester's onboard system provided a data log of cut trees with each tree's ID, species (as identified by the operator or preset for stand), and the GNSS-derived coordinates of crane tip position where the tree was cut. The harvester was a modern CTL machine with a GNSS receiver with RTK correction.

2.2 UAV Data Processing and Tree Delineation

The raw UAV LiDAR point cloud was processed to create a Digital Terrain Model (DTM) and a Canopy Height Model (CHM). First, ground points were classified (using for instance the cloth simulation filter in LiDAR360) to interpolate a DTM. The CHM was obtained by subtracting the DTM from the highest canopy returns (within a 0.1 m grid), yielding a raster of canopy heights. Individual tree crown delineation was performed on the CHM using a watershed segmentation approach in LiDAR360 v.6.0.6.0 software ("LiDAR360 Point Cloud & Images Post-Processing and Industry Applications Software - GreenValley International," 2025). Local maxima in the CHM (above a height threshold of ~5 m to exclude understory) were identified as tree tops. The watershed algorithm then segmented the CHM into distinct crown polygons around those peaks. Each delineated crown's centroid (or highest point) provided the UAV-derived tree position. This produced a set of tree positions and attributes from the UAV data, representing the trees standing before harvest. We also derived additional per-crown metrics: color features of points for each crown (mean R, G, B values, variance, and normalized indices like Excess Green, etc.) to assist in species classification, since different species (spruce vs. pine vs. birch) in September have distinguishing spectral signatures or phenology (e.g., deciduous birch vs. evergreen conifers (Kukkonen et al., 2024)).

2.3 Data Integration and Matching

To integrate the UAV and harvester datasets, we needed to match each harvester-recorded tree to its corresponding UAV-delineated tree/crown and stump. This was done through spatial matching. Since we had accurate stump coordinates, we first matched each harvester tree to a stump by nearest-neighbor search within a threshold (all harvested stumps were known, and the harvester data had one entry per felled tree including species and stump diameter). This pairing allowed calculation of the harvester GNSS error for each tree: the distance between harvester-reported coordinates and the true stump location. Next, we matched the UAV-delineated tree positions, determined based on crown delineation and representing the highest point within each crown, to the stump locations. Because the UAV survey was pre-harvest, each stump should correspond to a UAV-detected tree (assuming the UAV detected all harvestable trees). We used a similar nearest-neighbor approach: for each stump, find the closest UAV tree position within a reasonable radius (e.g., 2 m). In almost all cases, the nearest UAV tree matched the stump correctly given the high UAV accuracy, but a few ambiguous cases (clusters) were resolved manually by comparing tree heights and species. The

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distance between the UAV tree position and the stump gave the UAV positioning error (mostly reflecting UAV georeferencing error and segmentation centroid offset). Finally, we compared harvester vs. UAV positions for each matched tree, which indicates how far off the harvester's location was from the UAV's estimation of that tree's location. This harvester–UAV positional discrepancy is effectively the error that could be corrected by using the UAV data as reference.

2.4 Positional Error Analysis

We computed summary statistics of the positional errors in three categories: (1) harvester GNSS error (harvester vs. stump), (2) UAV-derived error (UAV vs. stump), and (3) harvester vs. UAV. Error distances were calculated in horizontal XY plane. We report mean error, median, standard deviation, and RMSE for each. We also examined distributions and any trends (e.g., errors vs. tree size or canopy density). The expectation was that UAV errors would be small (on the order of <1 m) and that harvester errors would be larger and more variable. We visualized the error distributions with histograms (e.g., Figure 1 shows the distribution of harvester GNSS errors) and spatial plots. Additionally, to understand if certain trees had systematically larger errors, we looked at whether error magnitude correlated with tree height (taller trees might have more GNSS blockage) or with the harvester's distance from the tree (if the boom reached out, etc.), although detailed harvester path wasn't fully reconstructed here.

2.5 Tree Species Classification

We used two machine learning models to classify tree species (spruce, pine, birch) for each tree, utilizing the UAV-derived features. The ground truth species for each tree was known from location of the stumps. We randomly split the dataset into a training set (70% of trees) and testing set (30%), stratified by species to maintain proportion. Two classifiers were trained: a Random Forest (RF) with 100 trees and an XGBoost (Extreme Gradient Boosting) model. Input features included: tree height, crown area, crown shape metrics, LiDAR intensity (mean, std), and RGB color features (mean R, G, B, and some indices like a pseudo-NDVI). Pseudo-NDVI was computed from UAV-derived RGB imagery as a normalized difference index between the red and green channels: (Green - Red)/(Green + Red), serving as a proxy indicator of vegetation health and vigor. We also included the relative height to neighbors (to see if the tree is emergent or suppressed) as this can sometimes help distinguish species in mixed stands. Feature selection was done via cross-validation on the training set – though in practice, the models like XGBoost handle feature importance automatically (XGBoost can ignore or down-weight less useful features). Notably, XGBoost can handle missing values internally, but our dataset had complete features for all trees so that was not an issue. The trained models output a predicted species for each tree. We evaluated the classification accuracy on the test set, computing the overall accuracy (percent correctly classified) and the confusion matrix for each model. We paid attention to which species get confused – e.g., spruces vs. pines (both evergreen conifers) might be confused with each other, whereas birch (deciduous broadleaf) might be more distinct. The model hyperparameters were tuned via grid search (for XGBoost, e.g., max_depth, learning_rate, etc., and for RF, the number of trees, max_features, etc.) based on maximizing validation accuracy.

In an operational scenario, the above steps constitute a workflow where a pre-harvest UAV scan provides a "digital inventory" of the stand. During harvesting, the harvester's GNSS positions are corrected by matching to this inventory, and additional attributes like species from the UAV inventory can augment the harvester's data. While our integration was done in post-processing, it simulates what could eventually be a real-time system (with UAV data collected just prior to or even during harvesting and algorithms to do live matching). The entire workflow was implemented in Python for data analysis (pandas, numpy for matching, scikit-learn and XGBoost for classification) and LiDAR360 for the initial segmentation. The coordinate systems were all projected to the same system (ETRS-TM35FIN), so no coordinate transformation error was present in matching.

3. Results

3.1 Positional Accuracy Improvements

Our analysis included 162 harvested trees (those with complete data: stump surveyed, harvester logged, and UAV detected). The harvester's onboard GNSS positions showed a horizontal error ranging from 0.1 m up to about 6 m for most, with a few extreme outliers up to ~30 m (these outliers likely correspond to missed GNSS signals or the harvester recording a wrong location, possibly when the machine was far from the tree). The mean harvester GNSS error was 1.52 m, with a standard deviation of 2.34 m. The distribution is right-skewed: the median error was 1.31 m, indicating that half of the trees were within ~1.3 m, but a long tail of larger errors raises the mean. Figure 1 illustrates the distribution of harvester positional errors. Most errors cluster in the 0.5–3.0 m range, and about 10% of the cases exceeded 3 m. A small number of points had >10 m error (visible as the long tail in Figure 1).

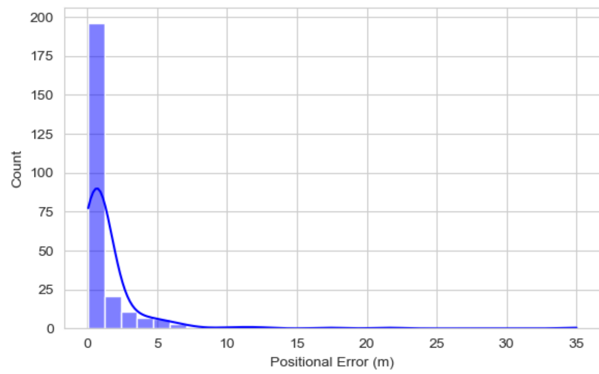

Figure 1: Distribution of harvester GNSS positional error (distance between harvester-reported tree location and true stump position). Most errors are within a few meters, but a heavy tail extends to >10 m in some cases, illustrating the unreliability of uncorrected GNSS under canopy.

In contrast, the UAV-derived tree positions were far more accurate. The UAV positioning error (distance from UAV-delineated tree position to stump) had a mean of 0.63 m (median 0.58 m). Essentially, using the UAV point cloud and CHM segmentation, we could locate trees to sub-meter accuracy relative to ground truth. The distribution of UAV errors was approximately normal and tightly clustered; the maximum UAV error observed was about 1.5 m, and >90% of UAV-derived positions were within 1 m of the true location. This indicates the quality of the UAV survey and the segmentation: nearly every harvested tree was correctly identified and its crown delineated to give a good centroid position. Minor positional discrepancies could result from the natural growth patterns of trees, as they often do not grow perfectly upright but rather lean towards available sunlight, typically downslope in sloped regions or towards open sky gaps in competitive environments. Consequently, the highest point of a crown may not align precisely with the stump center measured at ground level. Additional minor errors might also arise from residual inaccuracies in georeferencing processes.

By integrating the datasets, we computed the discrepancy between harvester-recorded and UAV-derived positions for each tree, effectively quantifying the residual positional error remaining after adjusting harvester locations with UAV data. The mean positional discrepancy between harvester and UAV-derived tree locations was 0.76 m (median 0.62 m), a substantial improvement over the original harvester GNSS positions, which exhibited a mean error of 1.52 m. Although the harvester-UAV errors appear considerably smaller compared to the harvester-stump (ground truth) errors, this difference can largely be attributed to the significantly larger sample size—over four times greater—for harvester–UAV matches, thereby providing a more stable and representative estimate.

In fact, for many trees, the UAV "correction" brought the harvester position to within ~0.5–1.0 m of truth (Fig.3). The harvester–UAV error distribution is only slightly broader than the UAV's own error distribution, implying that most of the harvester's bias was removed (Fig 2.). In numerical terms, positional RMSE improved from 1.60 m (harvester GNSS vs truth) down to 0.80 m when using UAV-corrected positions – roughly a 50% reduction in error magnitude. The improvement was greatest for those trees where harvester error was large (e.g., a tree that was 4 m off via GNSS might end up ~1 m off after matching to UAV). Trees that were already very close (sub-meter) saw little change (they matched their UAV counterparts closely anyway), in Fig.4.

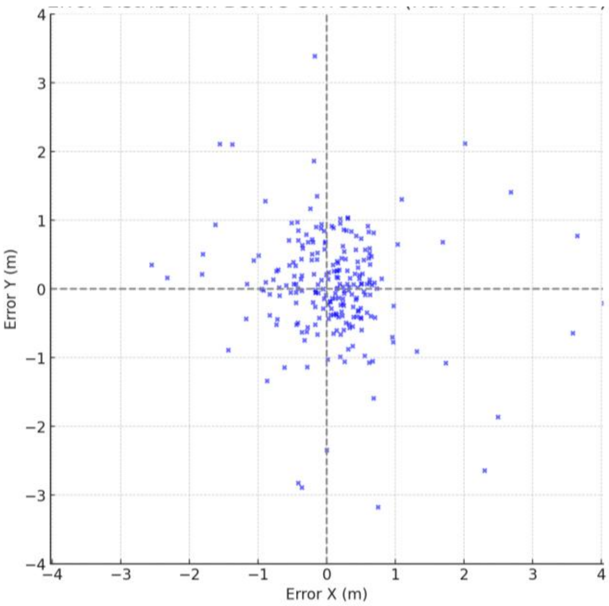

Figure 2: Error distribution before correction (harvester vs. stumps positions)

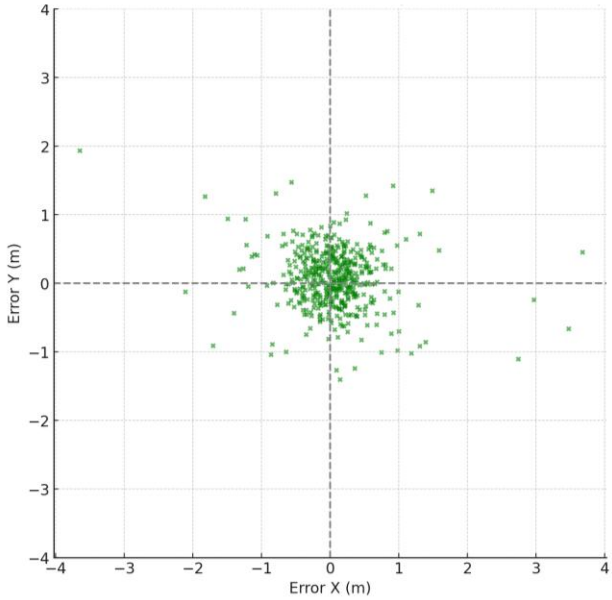

Figure 3: Error distribution after UAV-based correction (harvester vs. stumps positions)

We noted that harvester error tended to increase slightly with tree height: the tallest trees (>25 m) had mean error ~2.0 m, whereas trees <15 m had mean error ~1.0 m. This aligns with the notion that taller trees cause more signal obstruction. However, after correction with UAV data, this dependence largely disappeared – tall and short trees alike were ~0.7 m off on average, as the UAV's vantage point captured all heights. Another observation was related to species: spruce trees (with dense conical crowns) had slightly higher GNSS error (mean ~1.7 m) than pines (~1.4 m) or birches (~1.3 m). This might be because spruce crowns caused more multipath or the harvester had to reach in for some spruces. Regardless, after correction, all species had similar accuracy (~0.7–0.8 m).

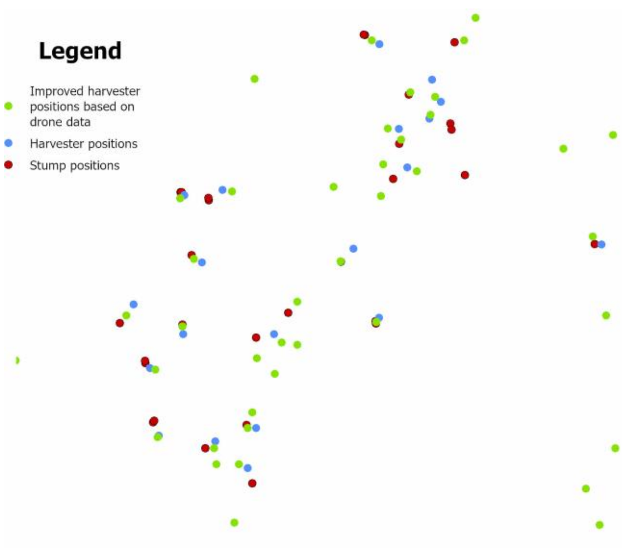

Figure 4: Maps of tree positions (part of the data used). Harvester GNSS mean error 1.52 m vs. UAV-corrected 0.76 m, and classification accuracy ~91%.

To contextualize these results, previous studies have reported harvester positioning errors in similar ranges. Lopatin et al. (2023) noted 2–4 m errors commonly without corrections. Faitli et al. (2023) achieved 2.44 m average in real-time using

GNSS/IMU, improved to 0.21 m with full post-processing. Our approach, using external UAV data, achieved ~0.8 m without requiring on-machine SLAM, which is quite promising for operational use since it doesn't mandate extra hardware on the harvester. The residual ~0.7–0.8 m error comes from the UAV data limitations (centroid vs. trunk base differences). In principle, if we had scanned from directly above each tree (nadir), the crown apex might align directly over the stump for symmetric crowns. In practice, some horizontal offset can exist if the tree is leaning or has an asymmetric crown. Nonetheless, sub-meter accuracy is a major improvement and could be sufficient for many precision forestry applications (e.g., marking exactly which tree was cut on a map).

3.2 Tree Species Classification Performance

A total of 148 out of the 162 trees had confident species labels: 21 birch, 77 pine, 64 spruce. Using the UAV-derived features, our classification models attained high accuracy (Fig. 3). The Random Forest classifier achieved an overall accuracy of 91.2% on the test set, while the XGBoost was very similar at 90.5%. Given the small difference, and considering standard deviations from cross-validation (~±2%), we consider their performance equivalent for practical purposes. We focus on the RF results for clarity. The confusion matrix for the RF model showed: out of 21 birch trees, 15 were correctly identified as birch, while 6 were misclassified (all 6 misclassified birches were predicted as pine; none as spruce). For pine, out of 77, the model got 73 correct; it misclassified 1 pine as birch and 3 pines as spruce. For spruce, out of 64, it got 60 correct; 1 spruce was misclassified as birch, and 3 as pine. These errors make sense in that the model occasionally confused birch vs. pine (perhaps due to some birch having an evergreen understory or color similar to pine in the images) and pine vs. spruce (both conifers, sometimes hard to distinguish from above). Notably, birch and spruce were rarely confused with each other, which is logical given their stark differences (leaf-on birch has a bright green broad crown, vs. dark green conical spruce). The XGBoost confusion matrix was similar, with perhaps one extra birch classified as pine. Overall, the per-species accuracies were: Birch ~71%, Pine ~95%, Spruce ~94% in RF. Birch had the lowest accuracy partly due to the small sample size and possibly more variability in birch crown appearance (some birches had no leaves at the time due to being felled early or being minor components).

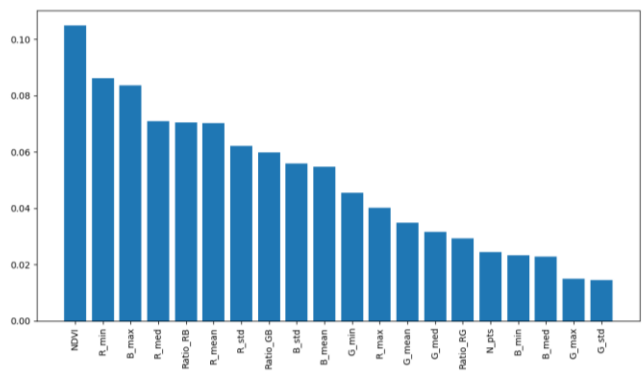

Figure 3: Feature importance for species classification using Random Forest

These accuracies are quite high for 3-class tree species mapping from a single UAV survey (Fig. 4). In an operational sense, this means the UAV scan not only provides positions but also a reliable species identification for each tree. That information could be used by harvesters – for example, to verify or even determine species if the harvester operator was unsure or if species need to be documented for downstream processing.

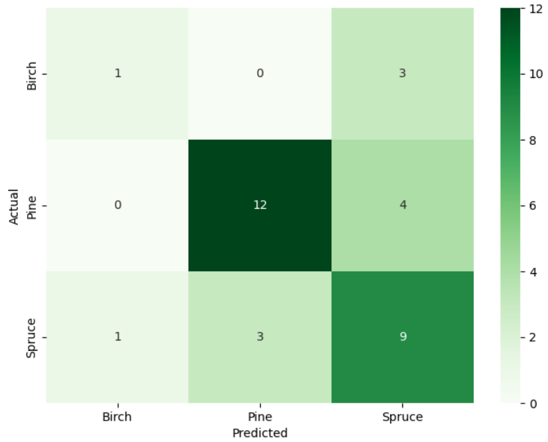

Figure 4: Confusion matrix in RF Model

We also examined feature importance in the RF model: the most important features for species discrimination were the color indices and crown size (Fig. 3). Specifically, an index capturing leaf-on deciduousness (e.g., birch leaves being lighter green – high green reflectance – compared to the darker needles of conifers) was top-ranked. Mean Green minus Blue (a simple proxy for leaf greenness) was high, effectively separating birch from conifers. These nuances allowed the models to distinguish pine vs. spruce reasonably well (which can be challenging from true orthophotos alone). XGBoost's internal feature importance metrics mirrored RF's, giving confidence in these patterns.

4. Discussion

This study demonstrated that integrating pre-harvest UAV LiDAR scans with harvester-collected data can substantially improve the spatial accuracy of tree locations, primarily because UAV-derived tree positions exhibited considerably smaller positional errors relative to the ground-truth stump locations compared to the harvester GNSS positions. As a result, harvester-recorded and UAV-derived stems could be reliably matched, significantly enhancing per-tree data accuracy and enabling richer attribute information (e.g., species) to be associated with each tree. Our findings align with and extend those of previous researchers who have highlighted GNSS limitations and proposed sensor integration in forestry machines. For instance, our observed harvester GNSS error (~1.5 m mean) is consistent with ranges reported by Kaartinen et al. (2015) and Lopatin et al. (2023) under similar canopy conditions. We improved upon previous approaches by applying an external correction resource (UAV data), specifically by first matching harvester-recorded crane-tip positions and UAV-derived tree crown positions separately to their respective closest stump locations (ground truth), and then subsequently aligning these matched harvester and UAV positions, ultimately adopting the UAV-derived positions as corrected locations for harvested stems. While Faitli et al. (2023) achieved an impressively low ~0.21 m error through post-processed SLAM on the harvester, that requires specialized equipment; our approach offers an alternative path using widely available UAV technology. In practical terms, a forest company could fly a drone before (or even during) harvesting to map the stand, and then use that data to calibrate the harvester positions. This could be done post-harvest (as we did with stumps) for improving

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databases, or ideally in real-time to aid the operator. Real-time implementation would require fast data processing – perhaps the UAV data is processed just prior and loaded into the harvester's onboard computer. The harvester could then find itself within that map via its own GNSS (with some initial error) and then snap each reported tree location to the nearest tree in the UAV map, effectively correcting it. This is analogous to how GNSS map-matching works for vehicle navigation in cities (snapping to a road network when GNSS is noisy).

One challenge observed is ensuring one-to-one matching between UAV-detected trees and harvested trees. In very dense or more structurally complex stands, UAV crown delineation might merge or miss some trees (Li et al., 2022), complicating the matching. Advanced individual tree detection algorithms, such as deep learning-based point cloud segmentation, could further improve the reliability of the UAV inventory. Another challenge is temporal: if there is a long delay between the UAV scan and the harvesting operation, changes such as windthrow, tree growth, or GNSS drift in coordinate systems could introduce positional errors. Wind itself represents a potential limitation, as it may shift tree crowns relative to their original surveyed positions. Additionally, tree leaning in any direction could further exacerbate positional discrepancies, since UAV-derived crown centroids may not directly align with stump positions. Future research could explore methods to detect and account for leaning trees using high-resolution UAV data or even drone surveys conducted beneath the canopy, thereby providing more accurate tree-level positioning.

The implications of achieving ~0.5–0.8 m accuracy at tree-level are significant. It approaches the threshold where tree-level decision support becomes feasible. For example, consider selective harvesting: a forester may digitally mark certain trees to preserve (habitat trees or seed trees). If the harvester had a digital map of those from the UAV and accurate positioning, it could warn the operator when they are near a protected tree, even if it's not obvious by sight (imagine a small habitat sign or a digital designation). Similarly, the system could optimize machine path – knowing exactly where each remaining tree is, the harvester's onboard route planning (if available) could minimize damage by steering around trees at appropriate distances. These are elements of an operational forest digital twin: a continuously updated map reflecting the current state (trees cut or left) and guiding decisions. Our work provides a stepping stone by ensuring the digital twin's alignment with reality is accurate.

In terms of species information, having an automated classification from UAV data could enhance inventory and sorting. Harvesters do identify species via stem appearance and operator input, but an independent check is useful. It could even enable estimating certain properties like wood quality or biomass by combining species with dimensions. Our classification results (91% accuracy) are comparable to other recent UAV-based species mapping efforts in temperate forests. Faitli et al. (2023) primarily focused on localization and stem measurement, not species, but one could imagine adding a small multispectral sensor on harvesters or using pre-harvest UAV imagery as we did, to get species data into the mix of a harvester's dataset.

Comparing our approach to Faitli et al. (2023) more directly: they integrated a LiDAR on the harvester head to measure stems and used a total station for ground truth, achieving sub-decimeter mapping of stems post-processed. That is a very high precision but in a research setting. Operationally, drones are easier to deploy widely than equipping every machine with expensive LiDAR+IMU setups. However, Faitli's approach has the advantage of capturing data on the fly without a prior flight and can work even under canopy (since the sensor is amidst the trees). A hybrid approach could emerge in the future, where a UAV initially performs an overview scan, while the harvester utilizes simpler onboard sensors that, guided by the UAV-derived map, achieve comparable accuracy. Additionally, future UAV systems could integrate sensors previously deployed on harvesters, enabling drones to fly directly beneath the forest canopy to further improve tree positioning accuracy and operational decision-making.

Our study also addresses the first research gap identified: integration workflows. We showed a concrete way to fuse the data (segmentation, matching, error correction). We did note that an established workflow would need to handle more edge cases (e.g., missing trees, false positives in UAV data, outlier GNSS points). No standard software pipeline currently exists for forestry contractors to do this, which is a barrier. We envision integrating this into existing forest planning software. For example, stand maps could come with georeferenced tree positions from UAV; the harvester's onboard computer could ingest that, and when felling, log tree ID and maybe adjust coordinates by referencing the nearest known tree point. Some initial research into harvester onboard data integration has begun (e.g., using harvester as a data collection tool for inventories), but not much on using external data to inform harvesting. Lopatin et al. (2023) suggested that viewshed analysis could let an operator know where GNSS might be poor; building on that, our work suggests even if GNSS is poor, another data source can fix it.

The second gap was precision forestry and decision support. As discussed, the improved accuracy directly supports finer decision making. However, achieving centimeter-level accuracy consistently (as the gap mentions) is still tough without special hardware. Our UAV approach got to sub-meter; to get to a few centimeters, one might need a combination of RTK on the harvester, UAV data, and perhaps local wireless positioning (some research has looked at ultra-wideband, UWB, tags on trees for localization (Liu et al., 2025)). Whether centimeter precision is needed can be debated – for most ecological and operational purposes, decimeter might suffice. For instance, to avoid a specific buffer around a habitat, knowing tree positions within 0.5 m is usually enough. Still, cm-level could become relevant if doing automated cutting of marked trees (robotic target identification).

Our experiment was relatively small scale (one stand, one machine). Further validation in different forest types (e.g., broadleaf-dominated, or very dense young stands) is necessary. Also, the timing was such that UAV and harvesting were back-to-back; if UAV data is stale, errors might creep in (trees can move or be cut by other events). We also did not test real-time implementation – everything was done post-hoc. The latency and computing required to do this live need investigation. One potential issue is the UAV itself under canopy: we flew above canopy; if a real-time update was needed during harvesting (like after some trees removed, to update the map), an under-canopy drone flight would be challenging due to GNSS denied environment, though techniques like visual-inertial odometry are being explored. A more practical approach is to rely on one good pre-harvest scan and not update during the operation (since the positions of remaining trees don't change, just some get removed).

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Despite these challenges, our results clearly indicate operational benefit. An average error of ~0.7 m means a digital system can know almost exactly which tree in the pre-harvest map corresponds to the stump/machine in the field. This could also improve post-harvest analytics: e.g., combining harvester's yield data with exact locations allows precise mapping of how much volume was removed at each spot, informing future management or even carbon accounting with high resolution.

Lastly, this integration is a step toward autonomous or semi-autonomous harvesting. If a machine has an accurate map of trees and knows its position precisely, it opens the door to robotics – the machine can plan paths and select trees with minimal human input, guided by an algorithm that maximizes some objective (like thinning certain trees) while avoiding others. Of course, full autonomy is a big leap requiring more sensors (for safety, obstacle detection), but precision localization is a foundation for that future.

In conclusion, the fusion of UAV and harvester data addresses critical gaps in current precision forestry practice. It enhances the value of the data we already collect (harvester data) by anchoring it to a more accurate spatial framework. It also leverages the strengths of new technology (UAV LiDAR) to solve an old problem (GNSS in forests). As UAVs become more routine in forest operations and perhaps as harvester manufacturers consider data integration, workflows like the one demonstrated here can be adopted operationally. Further research should scale this to larger areas, integrate it with real-time systems, and evaluate the cost-benefit: e.g., is the extra step of flying a UAV justified by the gains in accuracy and decision outcomes? Early signs, including our study, suggest that for high-value operations or where precision is paramount (like selective logging near protected areas), the benefit will be higher than costs. Future research should focus on developing real-time registration methods that fuse pre-harvest UAV-derived tree positions directly into harvester navigation systems. For instance, machine-learning-based matching algorithms or lightweight onboard SLAM solutions utilizing UAV scans as spatial reference points could dynamically correct GNSS discrepancies caused by larger tree crowns.

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