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Precision Forestry-Technological Advancements in Forest Science

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***Abstract*:** Precision forestry integrates advanced technologies to revolutionize forest management, enhancing productivity, sustainability, and environmental stewardship. This review explores recent developments across multiple domains, including forest inventory, tree improvement, timber harvesting, and wood processing. Technological tools such as Terrestrial Laser Scanning (TLS), Synthetic Aperture Radar (SAR), Unmanned Aerial Vehicles (UAVs), and satellite remote sensing have significantly improved forest inventory accuracy, species identification, and real-time pest outbreak monitoring. In tree improvement, Free-Air CO_2 Enrichment (FACE) experiments and mini-plug techniques demonstrate how genetic and environmental responses to elevated CO_2 levels and nursery innovations can optimize seedling quality and forest growth. Mechanized harvesting technologies, such as software-assisted multi-tree handling, improve operational efficiency, while advancements in organosolv and Kraft pulping enhance pulp quality and sustainability. Additionally, deep learning models and X-ray computed tomography are facilitating automated wood quality assessment, offering non-destructive insights into density, moisture, and defect detection. Despite the promise of precision forestry, challenges persist, including high implementation costs, technological integration hurdles, and the need for skilled personnel. Addressing these barriers is crucial for the widespread adoption of precision forestry in sustainable forest management.

***Keywords*:** Free-Air CO_2 Enrichment, Precision forestry, Synthetic Aperture Radar, Terrestrial Laser Scanning and X-ray computed tomography

The growing need for wood production, combined with increasing economic and environmental expectations from forests, necessitates innovative solutions and advanced technologies. Taylor (2002) defines precision forestry as the planning and execution of site-specific forest management activities aimed at improving wood product quality and utilization, reducing waste, increasing profits, and maintaining environmental quality. Ziesak (2006), observed that precision forestry employs advanced sensing and analytical tools to facilitate site-specific, economic, environmental, and sustainable decision-making throughout the forestry value chain—from bare land management to the final consumer purchasing paper or board (Kovacsova and Antalova 2010). The concept of precision farming emerged in the 1990s, recognizing the need to address spatial and temporal variability in crop production through site or soil-specific management practices (Tran and Nguyen 2006). This precision approach was later applied to the forestry sector in the early 2000s in the United States (Becker 2001), where the First International Symposium on Precision Forestry aimed to present advancements in information technologies and analytical tools for supporting site-specific, economic, environmental, and sustainable decision-making (Dyck 2003). Precision forestry integrates information technology and analytical tools to enhance economic, environmental, and sustainable forestry practices (Gallo et al., 2013, Fardusi et al., 2017).

Technological innovation spans multiple disciplines (Lindroos et al., 2017) and, when integrated with sustainable practices, can significantly enhance forestry management (Shah 2020). Smart sensors equipped with predictive analytics can leverage soil and weather data to support conservation and sustainable forest management (Shah 2020). In plant breeding, modern approaches incorporate advanced molecular marker technologies such as gene pyramiding, QTL identification, marker-assisted selection, and transgenic crop development alongside traditional morphology-based selection methods (Panda et al., 2020). Advanced technologies like Remote sensing are important for understanding environmental dynamics and ensuring sustainable management of resources (Wani et al., 2025). Additionally, recent scientific and technological advancements offer new possibilities for improving the efficiency and effectiveness of wildfire management (Zimmerman 2011, Ravivarma et al., 2024). This paper explores the latest developments in precision forestry technologies, with a focus on geospatial information tools that aid in forest management, tree improvement, wood processing, and quality assessment.

Application of Advanced Technologies in Forest Management

Forest inventory: Local forest inventories, traditionally conducted through intensive ground-based sampling, have played a crucial role in strategic planning by offering managers a detailed understanding of timber composition to support tactical decision-making. Enhanced Forest Inventories (EFIs) aim to improve confidence in forest management decisions while maximizing returns on investment throughout the commodity supply chain (White et al., 2013). By integrating traditional inventory data with advanced Laser Scanning technology, EFIs enhance spatial and temporal accuracy. The resulting three-dimensional (3D) representation of the operating area, from tree canopy to ground level, provides managers with precise, customizable, and highly informative insights into forest operations (Bechtold and Patterson 2005, Goodbody et al., 2017).

Terrestrial laser scanning: Terrestrial Laser Scanning (TLS) has been widely applied in various forestry studies, including tree mapping (Pueschel et al., 2013), callipering (Srinivasan et al., 2015), tree height estimation (Olofsson et al., 2014, Srinivasan et al., 2015), and forest biomass calculation (Greaves et al., 2015). Additionally, TLS has been extensively investigated for estimating canopy structural parameters (Cifuentes et al., 2014, Fardusi et al., 2017). Singhal et al. (2021) compared TLS-based tree-level carbon stock estimation with traditional allometric equations in tropical forests of India. Their study found that TLS-based estimates, with a relative RMSE of 26.01%, were more accurate than those derived from local (42.58%-101.88% RMSE) and global allometric equations (38.8%-50.69% RMSE), highlighting TLS as a reliable and non-destructive method for tree biomass estimation, especially for large trees, while allometric equations remain useful when field-measured parameters are available.

Synthetic aperture radar: Synthetic aperture radar (SAR) is an active remote sensing technology known for its ability to estimate biomass and operate in all-weather conditions (Tsui et al., 2013). Wulder et al. (2012) mentioned that SAR provides complementary datasets for forest biomass estimation (Fardusi et al., 2017). Biomass assessment involves volumetric vegetation analysis, leveraging SAR's unique capability to penetrate tree canopies, an advantage not present in optical remote sensing. The accuracy of SAR-based estimation is influenced by wave polarization and frequency, as longer wavelengths exhibit greater penetration capacity, and cross-polarized waves show higher sensitivity to biomass. These characteristics enable SAR to provide more reliable biomass estimates with reduced uncertainties, as microwaves exhibit less saturation at high biomass levels compared to optical electromagnetic waves (Sinha et al., 2015). Gama et al. (2010) utilized interferometric and polarimetric SAR data to estimate biomass and volume in Eucalyptus plantations. By applying X- and P-band SAR images along with multivariate regression analysis, their study identified strong correlations between interferometric height and tree volume, as well as the canopy scattering index (CSI) for biomass estimation. The models developed demonstrated high accuracy, with prediction errors around 10%, underscoring SAR technology's potential for large-scale forest inventory.

Identification of tree species: The use of UAV-based remote sensing for species identification is increasingly gaining attention within the research community (Sothe et al., 2019). Convolutional Neural Networks (CNNs) have been employed for tree species identification using terrestrial datasets, including RGB images of bark (Carpentier et al., 2018), cross-section surfaces of trees (Hafemann et al., 2014), and terrestrial LiDAR data (Mizoguchi et al., 2017). Research has also explored CNN applications for species classification using airborne sensors such as LiDAR and hyperspectral imaging (Trier et al., 2018). Fricker et al., (2019) applied CNN models to airborne hyperspectral imagery labelled with high-precision field training data to identify individual tree species. Their study also compared classification accuracies between the CNN model applied to full hyperspectral imagery and an RGB pseudo true-color subset. CNNs have demonstrated effectiveness in UAV-based tree segmentation and species mapping, whether for individual species, broad vegetation types, or plant cover analysis. Kattenborn et al., (2019) conducted fine-grained mapping of two vegetation species using a CNN-based segmentation approach, with training data derived from UAV-based high-resolution RGB imagery. Similarly, Lobo Torres et al. (2020) evaluated five deep, fully convolutional networks for semantic segmentation of a single tree species using UAV-captured RGB images. Natesan et al. (2020) investigated the application of Dense Convolutional Networks (DenseNet) for identifying individual tree species from high-resolution UAV-based RGB images. Their model achieved high classification accuracy (over 84%) in distinguishing five predominant coniferous species in eastern Canada, despite variations in seasonal, temporal, and illumination conditions. These findings underscore the potential of UAV-integrated deep learning models in automating forest inventory and management, offering a cost-effective alternative to traditional methods.

Real-time monitoring of insect outbreaks: The introduced insects and pathogens pose a significant threat to the health of forested ecosystems, leading to considerable ecological and economic consequences (Lovett et al., 2016). However, identifying changes in forest conditions linked to insect pests over large areas remains a persistent challenge (Senf et al., 2017). The Landsat satellite family is widely used in forest insect disturbance studies due to its moderate spatial resolution and extensive archive of imagery (Senf et al., 2017). The modern Landsat series captures spectral data in visible, near-infrared, and shortwave infrared bands at a 30 m × 30 m pixel resolution, with image acquisitions occurring at least every 16 days. However, because defoliation events are often short-lived, cloud cover remains a significant challenge in leveraging Landsat imagery for operational forest health monitoring (Rullan-Silva et al., 2013, Townsend et al., 2012, Pasquarella et al., 2017). Falanga et al. (2024) introduced a novel method for detecting insect outbreaks in urban trees using high-resolution Planet Scope satellite imagery. By combining remote sensing with field surveys, the study effectively identifies infestations of *Toumeyella parvicornis* in *Pinus pinea* trees across Rome. The research highlights the Renormalized Difference Vegetation Index (RDVI) as a highly accurate indicator of pest damage, achieving an accuracy rate exceeding 99%, underscoring the potential of satellite-based monitoring for proactive pest management and urban forest conservation.

Application of Advanced Technologies in Tree Improvement

Free-Air CO_2 Enrichment (FACE) experiments: The atmospheric CO_2 concentration remained stable at approximately 270 µmol mol^{-1} for at least 1,000 years before the onset of the Industrial Revolution. Since then, CO_2 levels have been rising at an accelerating rate. As a result, both natural and managed ecosystems are now exposed to elevated CO_2 concentrations that terrestrial vegetation has not encountered since the early Miocene (Pearson and Palmer 2000), leading to uncertain future consequences. With advancements in scientific understanding and the identification of underlying mechanisms, the necessity of testing hypotheses under realistic open-air conditions became evident. This led to the development of Free Air Carbon dioxide Enrichment (FACE) technology (Hendrey and Miglietta 2006).

A similar experiment at Aspen FACE, involving North American plantation species such as aspen (*Populus tremuloides*) and birch (*Betula papyrifera*), also demonstrated a lack of photosynthetic acclimation in the initial years. Instead, maximal stimulation was observed (Karnosky et al., 2003, Leakey et al., 2009). Downregulation of photosynthetic capacity in trees in response to Free-Air CO2 Enrichment (FACE) exhibits considerable variability. A significant portion of the data for trees included in this meta-analysis originates from the Duke FACE experiment, which investigated both loblolly pine and understory hardwood species (Rogers and Ellsworth 2002). Findings from the Rhinelander experiment indicate that while elevated CO2 levels enhance leaf area index (LAI) in *Populus tremuloides*, ozone stress diminishes LAI. Consequently, when both CO2 and O3 levels are elevated, there is no net change in LAI (Karnosky et al., 2003, Ainsworth and Long 2005).

Mini-plug technique: The use of low-quality planting stock is often a key factor in reforestation failure (Radoglou and Raftoyannis 2001). Seedling quality, defined by its morphological and physiological characteristics, is the only aspect that can be directly controlled to enhance survival rates after out planting (Kostopoulou et al., 2011). Nursery practices play a crucial role in root development during the nursery phase, which can have lasting effects on seedling establishment (Costa et al., 2004). Among these practices, container type significantly influences both seedling production costs and overall seedling quality (Chirino et al., 2008). A promising innovation in nursery stock production is the use of mini-plugs, where seedlings undergo a short pre-cultivation period under near-optimal environmental conditions (Radoglou et al., 2011). Mini-plug containers, typically smaller than 33 cm³, enable a shorter production cycle compared to standard container-grown seedlings. This approach allows for the development of high-quality seedlings with well-formed fibrous root systems within a single growing season (Kostopoulou et al., 2011).

Kostopoulou et al. (2011) examined the growth of *Picea abies*, *Robinia pseudoacacia*, *Pinus brutia*, and *Pinus nigra* in mini-plug containers of two different depths (37 mm and 60 mm) over a five-week period. Their findings indicated that *P. nigra* and *R. pseudoacacia* benefited from deeper containers, whereas *P. abies* exhibited better growth in shallower ones. Similarly, Kostopoulou et al., (2010) reported that mini-plug transplants outperformed traditional nursery stock, producing seedlings with superior root development, higher quality, and improved field survival. Factors such as seed origin, mini-plug density, and substrate type were found to significantly influence seedling growth. Additionally, pre-cultivation in mini-plugs for five weeks under controlled conditions enhanced seedling survival and transplant success.

Application of advanced technologies in wood processing pulping: Despite advancements in information and communication technology, paper production remains a key indicator of industrialization and educational development worldwide. Pulp and paper production capacity continues to grow (Sridach 2010). Consequently, research and development efforts have focused on minimizing the environmental impact of pulp and paper production through various strategies. These include adopting alternative raw materials, optimizing pulping chemicals, and adjusting pulping conditions such as time, temperature, and pressure, as well as reducing energy consumption.

The organosolv pulping process has gained attention due to its ability to produce high-yield pulp with low residual lignin content, high brightness, and good strength (Yawalata and Pasnez 2004). The advancements in organosolv pulping have led to the development of methods capable of producing pulp with properties comparable to kraft pulp (Sridach 2010). Non-wood fibers are widely used for various paper types, including writing, printing, and packaging papers. Additionally, advances in micro and nanotechnology offer significant benefits to pulp and paper manufacturers, helping the industry achieve its future goals.

Cellulose and lignocellulose have great potential as nanomaterials due to their abundant renewability, non-fibrillar structure, and ability to self-assemble into well-defined architectures while being multifunctional (Mohieldin et al., 2011, Ogunwusi and Ibrahim 2014). Pulping involves chemical, mechanical, and biological methods to break the bonds in woody materials and separate cellulose fibers from lignin (Wang et al., 2014). Improvements in pulping processes have been achieved through lignin genetic modifications, diversification of pulp-based products, the development of extended impregnation and pre-hydrolysis techniques to enhance the Kraft pulping process, and modifications in chemical pulps for nanocellulose production. These modifications improve fibre characteristics, including fiber size, crystallinity, chemical composition, and fibre surface functionality (Jiménez et al., 2008, Rojo et al., 2015, Mboowa 2024). Dissolving pulp production involves pre-hydrolysing wood chips before subjecting them to the standard Kraft and sulphite pulping processes (WangQ et al., 2014, Mboowan 2024). Wei et al. (2020) studied the liquid hot water (LHW) pre-hydrolysis method, using the Combined Severity Factor (CSF) to quantify treatment severity.

Wood quality assessment: Wood defects, including knots, cracks, and discolorations, present a significant challenge for industries that rely on high-quality wood products. The lack of an efficient, automated detection system leads to increased production costs, potential quality issues, and delays. To address these challenges, this study proposes the development of a deep learning model capable of accurately identifying various defect patterns in images of wood surfaces. Recent advancements in deep learning

Table 1. Technological innovations in forest science

Technology	Purpose	Methodology	Conclusion	Reference
Terrestrial Laser Scanning	Carbon stock estimation	12 trees were scanned from at least 4 positions and at most 8 positions	26.01% more accurate than local equations	Singhal et al. (2021)
Synthetic Aperture Radar (SAR)	Biomass and volume estimation	Variables such as interferometric height (Hint), Canopy Scattering Index (CSI), and radar backscatter polarizations (e.g., VV and HH) were analyzed	Models showed a prediction error of around 10% to estimate the biomass and volume.	Gama et al. (2010)
Dense Convolutional Network (DenseNet)	Tree species identification	CNN and DenseNet	84% accuracy	Natesan et al. (2020)
Renormalized Difference Vegetation Index (RDVI)	Real-Time monitoring of Insect Outbreaks	satellite images (PlanetScope) and RDVI Index	99% accuracy	Falanga et al. (2024)
Free-Air CO2 Enrichment (FACE) experiments	To assess effects of elevated CO_2 concentrations	elevated CO_2 treatment (e− CO_2 -550 ppm) and ambient CO_2 (a− CO_2;- 395 ppm)	Elevated CO_2 significantly increased C/N litter biomass flux of N, SS, SP and lipid in to the soil, cellulose, hemicellulose and lignin inputs to soils	Rai et al. 2020).
Mini-plug technique	To improve quality of planting stock	mini-plug containers of two different depths (37 mm and 60 mm) over a five-week period.	*P. nigra* and *R. pseudoacacia* benefited from deeper containers	Kostopoulou et al. (2011)
Multi−tree cut−to−length harvesting	Harvesting	software-based, multi-tree handling (MTH) is used for harvesting	10% higher productivity in comparison with a traditional one	Magagnotti et al. (2020)
Pre hydrolysis Kraft Pulping	Pulping	Reactor was filled with 250 g wood chips and 1.5 L deionized water. The reactions were conducted at a temperature between 100 °C to 200 °C (at 20 °C increments) for 60 min using a stirring speed of 150 rpm and Air-dried hydrolysis wood chips (100 g) were cooked at 165 °C for 90 min	α-cellulose of 92.3%, degree of polymerization (DP) of 1081, brightness of 85.1% ISO, and Kappa number of 0.61.	Wei et al. 2020
X-ray computed tomography (CT)	Wood quality assessment	X-Ray Computed Tomography Technique to determine the Density and Moisture content	R2 , of the models were all higher than 0.97	Wang et al. 2024

frameworks, such as DenseNet (Densely Connected Convolutional Networks), offer a promising solution for automating wood defect detection. DenseNet, a Convolutional Neural Network (CNN) architecture, is particularly effective due to its dense connectivity pattern, which enhances feature reuse and propagation across network layers (Dhanamathi et al., 2024).

Computed tomography (CT) techniques provide a non-destructive and non-invasive means of measuring internal properties of wood specimens (Wang et al., 2020). Wang et al. (2020) specifically utilized X-ray Computed Tomography to determine the density and moisture content of poplar (*Populus xiangchengensis*) and bamboo (*Phyllostachys edulis*). Their findings revealed statistically significant differences in CT-measured values for D and MC between these species. The study established independent D-CT and MC-CT linear models for both species:

Poplar: $D = 0.00098 \times H + 1.02603$, $MC = 0.00309 \times H + 1.89982$

Bamboo: $D = 0.00118 \times H + 0.98684$, $MC = 0.00131 \times H + 0.31488$

where H represents the CT number. The determination coefficients (R^2) for all models exceeded 0.97, demonstrating the feasibility of using X-ray CT technology for accurately determining the density and moisture content of wood and bamboo. Ji et al., (2021) further explored how CT scanning can assess wood quality and predict tree value by analysing knot characteristics in amabilis fir and western hemlock. Their study linked knot features to stand density and sawmilling efficiency, revealing that tree diameter significantly influences knot properties and lumber yield. Additionally, stand density was found to have a greater impact on western hemlock than on amabilis fir. The predictive models developed in this research contribute to preharvest stand valuation and enhanced forest management strategies.

CONCLUSION

The evolution of precision forestry signifies a transformative shift in forest science, integrating cutting-edge technologies to enhance the efficiency, accuracy, and sustainability of forest management. From terrestrial laser scanning and synthetic aperture radar to UAV-based deep learning and X-ray computed tomography, the array of tools now available has revolutionized traditional approaches to inventory, monitoring, tree improvement, harvesting, and wood processing. Advanced techniques like Free-Air CO_2 Enrichment (FACE) and mini-plug cultivation support sustainable silviculture, while sustainable harvesting systems and nanotechnology-driven pulping processes align with modern industrial demands. Despite promising results across diverse applications, the full-scale adoption of precision forestry is hindered by high costs, technical complexities, and a shortage of skilled personnel. Overcoming these challenges will require strategic investment in education, training, and institutional capacity building.

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