

The Role of Technological Infrastructure in Forest Engineering and Ecosystem Management: Current Trends and Future Perspectives

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Received:19.10.2025

Accepted:27.10.2025

Published:30.10.2025

<https://doi.org/10.54414/VASL7073>

Abstract

Forest ecosystems are critically important for biodiversity, carbon storage, climate regulation, and socio-economic services. This review examines the transformative role of technological infrastructure in sustainable forest management. Focusing on innovation and methodology, it evaluates the applications of technologies such as remote sensing, GIS, UAVs, IoT, artificial intelligence, and digital twins in forest engineering applications, forest inventory, fire management, biodiversity monitoring, and decision support systems through a systematic literature review. The results reveal that these technologies enable a transition to a data-driven, proactive, and effective management paradigm. However, significant challenges such as cost, the digital divide, human resources, and ethical limitations persist. The article provides strategic recommendations for policymakers, researchers, and forest managers and discusses the contributions of technology-integrated forest engineering and management to socio-economic and ecological sustainability.

Keywords: Forest management, remote sensing, Geographic Information Systems (GIS), UAV, IoT, artificial intelligence, digital twin, sustainable management, ecosystem services, forest policy.

1. Introduction

Forest ecosystems are critical for biodiversity, carbon storage, climate regulation (Bonan, 2008), soil and water cycles, and provide economic and cultural benefits (Lal, 2008). Sustainable forest management requires moving beyond classical timber production-focused approaches to balance ecosystem services and preserve ecological integrity (FAO, 2020). Increasing population, climate change, rapid urbanization, and natural disasters are making the challenges faced by forest engineering and management even more complex (Seidl et al., 2017).

Rapid developments in information technologies have enabled data-driven and real-time decision-making processes in forest ecosystem management. This technological innovation not only increases operational efficiency but also profoundly affects socio-economic dimensions such as the assessment of ecosystem services, rural development, and shaping forest policies. Satellite imagery, UAVs, LiDAR systems, Geographic Information Systems (GIS), sensor networks, Internet of Things (IoT), big data analytics, artificial intelligence and digital twin applications offer revolutionary solutions for monitoring, assessing, and managing forests (Asner, 2013; Pettorelli et al., 2018; Reichstein et al., 2019; Abad-Segura et al., 2020). These technologies enable the collection of high-resolution data over large areas, rapid detection of ecosystem changes, and development of early warning systems for natural disasters (Paneque-Gálvez et al., 2014; Linares & Ni-Meister, 2024).

However, the implementation of technological infrastructure faces challenges such as cost, data standardization, lack of human resources, and legal/ethical limitations (Maxwell et al., 2018; Stone et al.,

2016). Therefore, addressing the opportunities and limitations offered by technological infrastructure with a holistic approach is crucial for shaping future strategies.

The aim of this review is to comprehensively present the current status, application areas, benefits, and limitations of technological infrastructure in forest engineering and ecosystem management; and to provide a guiding assessment of the intersection points of technological progress with forest management policies and sustainable development goals in the context of future trends and policy/application recommendations. This article aims to systematically classify these technological components and detail the synergies and emerging paradigms arising from their integration into forest management practice.

2. Technological Infrastructure Components

Technological infrastructure plays a critical role in monitoring ecosystem dynamics, analyzing, and making sustainable management decisions in forest engineering applications and ecosystem management. This infrastructure has a multidimensional structure encompassing hardware, software, network communication technologies, and information management systems.

2.1. Remote Sensing Technologies

Remote sensing (RS) systems are widely used to monitor large-scale and temporal changes in forest ecosystems. Satellite time series analyses play a critical role in detecting, mapping, and understanding the geographical distribution of forest degradation (logging, fire) (Asner, 2013). High-resolution satellite imagery and LiDAR data provide critical data for estimating forest structure, biomass, and carbon stocks (Pettorelli et al., 2018). Unmanned aerial vehicles (UAVs) enable obtaining detailed data on a smaller scale and are used particularly in assessing young forests, tree diseases, and post-fire areas (Paneque-Gálvez et al., 2014).

2.2. Geographic Information Systems (GIS)

GIS is a fundamental software infrastructure for spatial data management, analysis, and visualization. Numerous applications such as forest road planning, habitat integrity analysis, and erosion risk assessment are GIS-based. Thanks to GIS's powerful data integration capacity, data from different sources (satellite data, meteorological stations, field measurements) can be combined on a single platform and used effectively in decision-making processes in many areas of forest ecosystem management (Kerr & Ostrovsky, 2003).

2.3. Sensors, Monitoring Systems and Internet of Things (IoT)

Ground-based sensors are particularly important for monitoring microclimate, soil moisture, flow dynamics, and biotic-abiotic stress factors, providing foundational data for integrated forest monitoring systems. Long-term ecological research networks in forest ecosystems, such as FLUXNET, supply critical data on carbon cycling and energy flows. These datasets support advanced modeling of forest ecosystem processes (Baldocchi et al., 2001). Sensor-based infrastructures, when integrated with IoT, enable real-time and predictive detection of fire events, pest outbreaks, and drought effects, offering critical applications for forest management (Linares & Ni-Meister, 2024; Ali et al., 2025).

2.4. Big Data and Artificial Intelligence Applications

The increasing volume and complexity of forest-related data in recent years have rendered traditional analysis methods insufficient. Big data analytics and AI-based algorithms have become essential tools for understanding forest dynamics, modeling biodiversity, and predicting complex processes such as fire risk (Reichstein et al., 2019). Machine learning algorithms—such as Random Forest, Support Vector Machines, and Deep Learning—have proven highly successful in land cover classification, fire risk prediction, and habitat modeling (Maxwell et al., 2018).

2.5. Technology Integration and Digital Twins

The real power of technological components comes from their integrated operation. For example, remote sensing data obtained from UAVs and satellites are processed on GIS platforms and analyzed with AI algorithms to transform into meaningful information. The most advanced level of this integration is the 'digital twin' concept. A digital twin is a dynamic virtual model of a physical forest ecosystem, fed with real-time data (Fuller et al., 2020). This model enables managers to predict potential outcomes of events such as fire, disease outbreaks, or different harvesting scenarios and take proactive interventions (Buonocore et al., 2022). The concept of the digital twin, still emerging in forestry, is being explored as a way to replicate and simulate dynamic forest systems. Through big data analytics and AI integration, digital twins can enhance scenario modeling for sustainable forest management.

3. METHODOLOGY

This study is a review based on systematic literature review and thematic analysis approaches (Moher et al., 2009). The study was conducted in three main stages:

3.1. Literature Review

- Databases: Web of Science, Scopus, ScienceDirect, SpringerLink, and Google Scholar were used (Gurevitch et al., 2018).

- Keywords: “forest engineering”, "forest management", "forest ecosystem management", "technological infrastructure", "remote sensing", "GIS", "UAV", "IoT", "artificial intelligence", "big data", "digital twin".

- Time range: Studies published between 2000-2025 were primarily evaluated.

- Language: Peer-reviewed articles, reports, and conference proceedings published in English and Turkish were included in the review (FAO, 2020).

3.2. Selection Criteria

- Inclusion criteria: Being directly related to forest ecosystem management; being technological infrastructure-focused; providing empirical, conceptual, or methodological contribution (Gurevitch et al., 2018).

- Exclusion criteria: Studies not directly related to the topic; those with insufficient methodological description; duplicate content.

3.3. Analysis Process

- The screening process was conducted within the framework of the PRISMA approach (Moher et al., 2009).

- Preliminary screening: 350 studies were identified, reduced to 120 studies through title and abstract review, and after full-text review, 48 studies were analyzed in detail.

- Studies were divided into five main categories using thematic coding method:

Data collection and monitoring technologies (Asner, 2013; Paneque-Gálvez et al., 2014; Ecke et al., 2022)

Data processing and analysis methods (Reichstein et al., 2019; Maxwell et al., 2018)

Application areas (forest inventory, fire risk, biodiversity) (Pettorelli et al., 2018; Kilic et al. 2006; Akçay et al., 2023)

Benefits and contributions (Abad-Segura et al., 2022; Gumus et al. (2008))

Challenges and limitations (Maxwell et al., 2018; Stone et al., 2016; Diktaş-Bulut et al., 2025)

4. CURRENT TRENDS AND APPLICATION AREAS

The use of technological infrastructure in forest ecosystems is increasingly diversifying and intensifying.

4.1. Forest Inventory and Biomass Estimation

Remote sensing and LiDAR data have become cornerstone technologies for forest inventory and the estimation of biomass and carbon stocks (Pettorelli et al., 2018). The deployment of Unmanned Aerial Vehicles (UAVs) and high-resolution satellite imagery has further enhanced the accuracy of monitoring young forest stands and calculating timber volume (Paneque-Gálvez et al., 2014; Ecke et al., 2022). These data integrated with GIS play a critical role in many areas of forest ecosystem management, including spatial distribution analyses. The efficacy of these methodologies is substantiated by a growing body of research in Türkiye, where their application has advanced significantly since the early 2000s. For instance, pioneering work by Kilic et al. (2006) utilized Landsat data to establish a foundation for temporal change detection in Turkish forest ecosystems, a trajectory continued by contemporary studies. Akçay et al. (2023) effectively leveraged multi-temporal Sentinel-2 imagery for precise biomass estimation in Northern Anatolia, demonstrating the enhanced capabilities of recent satellite platforms. Similarly, Vatandaşlar & Zeybek (2020) applied handheld laser scanning technology for detailed inventory purposes in northeastern Turkey. Collectively, these studies underscore the effective integration and evolution of remote sensing, UAV, and GIS technologies for comprehensive forest structural assessment, inventory, and carbon stock modeling.

4.2. Fire and Risk Management

The real-time monitoring of critical environmental variables such as humidity, temperature, soil moisture, wind speed, and precipitation is now enabled by Internet of Things (IoT) networks and sensor systems, forming the backbone of modern fire early warning systems. These measurements are vital for the early detection of fire risk, with their effectiveness well-documented in global research (Jin & Goulden, 2014). The integration of IoT-based sensor networks and real-time data acquisition systems into forest management practices has become increasingly widespread in Türkiye, providing the foundational data for developing sophisticated predictive models (Ali et al., 2025).

The data from these systems feed into big data analytics and artificial intelligence-based algorithms, which are becoming increasingly important for modeling complex processes such as fire risk, propagation, and the preparation of sophisticated risk maps (Reichstein et al., 2019). The considerable potential of AI-based models for early fire detection is well-corroborated. Machine learning and deep learning approaches are now being effectively applied across a spectrum of forestry applications, including forest fire risk mapping and early fire prediction (Yıldırım et al., 2023; Fidanboy et al., 2023). In Türkiye, research in this area is particularly advanced and multidisciplinary. A pertinent example is the work of Baybaş et al. (2024), who applied machine learning algorithms to environmental, terrain, and land cover data to predict forest fire risk in the Mediterranean region, finding that the Random Forest algorithm yielded the most accurate predictions.

This focus on predictive modeling is complemented by post-fire analysis using satellite imagery, as seen in the work of Çolak & Sunar (2018), who monitored fire-affected areas in İzmir using Sentinel-2 and Landsat data. Further contributing to this field, İban & Şekertekin (2022) applied machine learning for wildfire susceptibility mapping in Adana and Mersin.

4.3. Biodiversity and Habitat Monitoring

The precision with which species diversity, tree health, and habitat structure can be monitored has been fundamentally transformed by remote sensing, Unmanned Aerial Vehicles (UAVs), and hyperspectral or multispectral sensors (Turner et al., 2015; Maxwell et al., 2018). The synergy created by combining these technological approaches with artificial intelligence (AI) and Geographic Information Systems (GIS) has proven particularly powerful, significantly enhancing predictive habitat modeling and thereby providing robust support for conservation initiatives and biodiversity protection.

A key development in this domain has been the adoption of UAV-based photogrammetry, which provides a cost-effective and high-resolution alternative to traditional field surveys. The deployment of UAVs equipped with multispectral and thermal sensors has led to their successful application in critical areas such as tree health assessment and detailed habitat mapping (Ecke et al., 2022).

Beyond health and habitat assessments, remote sensing data are extensively used for classification tasks. Machine learning algorithms such as support vector machines and random forest are effectively employed to classify land cover and distinguish between tree species with high accuracy (Kaya & Dengiz, 2024). This capability is crucial for tracking changes in species composition, monitoring ecosystem health, and informing targeted conservation strategies.

4.4. Sustainable Management and Decision Support Systems

Geographic Information Systems (GIS)-based decision support systems are pivotal for sustainable forest management, as they facilitate decision-making by simulating different management scenarios and integrating multi-source data (Diaz-Balteiro & Romero, 2008; Kerr & Ostrovsky, 2003). Furthermore, big data analytics and artificial intelligence (AI) help balance ecosystem services with economic outputs, thereby increasing the accuracy and effectiveness of forest management plans (Reichstein et al., 2019).

In Türkiye, GIS and remote sensing applications in forest engineering have been effectively applied to critical areas such as forest road planning, terrain stability, and environmental impact assessment. The work of Gumus et al. (2008), Hacisalihoğlu et al. (2019) and Gümüş (2021) exemplifies this, integrating GIS with digital terrain models to assess forest road locations, examine the effects of road construction on soil erosion and hydro-physical properties, and highlight the role of spatial analysis in minimizing environmental risks. Complementing this, Akay and colleagues (2008, 2016) utilized LiDAR and GIS for forest structure assessment, fire behavior modeling, and access zone analysis. Collectively, these studies demonstrate the successful integration of spatial modeling and remote sensing into sustainable forest road design and terrain-based risk assessment.

Beyond these applications, recent research is further advancing the digitalization of forest engineering. Studies now emphasize the use of geophysical sensors, such as seismic refraction and electrical resistivity methods, to enhance the precision of subsurface terrain analysis. The integration of this sensor-based data into planning and design processes represents a significant step forward in creating comprehensive, data-driven decision support systems for sustainable forest management (Diktaş-Bulut et al., 2025).

4.5. Ecosystem Services Assessment and Decision Support Systems

Technological advancements are increasingly being harnessed to support the quantitative assessment of ecosystem services, including carbon sequestration, water provision, and recreational value. The use of big data, AI, and GIS facilitates predictive scenario modeling that integrates complex socio-economic and ecological data (Diaz-Balteiro & Romero, 2008). A cutting-edge development in this sphere is the concept of digital twins, which utilize real-time data streams from sensors, UAVs, and satellites to create dynamic virtual replicas of forest ecosystems. These digital twins enable the simulation of management interventions, climate impacts, or fire scenarios, thereby enhancing proactive and evidence-based decision-making (Fuller et al., 2020; Buonocore et al., 2022). Complementing traditional GIS and remote sensing approaches, these studies highlight how big data and AI technologies enhance forest monitoring, inventory, and risk prediction.

4.6. Summary of Current Trends and Application Areas

Technological infrastructure enables proactive, data-driven forest management. Remote sensing and UAVs improve inventory and monitoring; IoT networks allow early detection of threats; GIS and AI enable predictive modeling and scenario analysis; digital twins integrate multiple data streams for strategic decision-making. Challenges include cost, human resources, standardization, and algorithmic transparency (Table 1).

Table 1. Current Trends and Application Areas of Technological Infrastructure in Forest Management

Technology	Application Area	Benefits	Challenges
Remote Sensing (Satellite, LiDAR)	Forest inventory, biomass/carbon estimation	High-resolution, large-scale data; improved accuracy; monitoring of structural changes	Cost; cloud coverage; data processing requirements
UAV / Drones	Young forests, post-fire assessment, species monitoring	Detailed small-scale mapping; rapid deployment; flexible monitoring	Limited flight time; regulatory restrictions; weather dependency
GIS	Spatial planning, erosion risk, habitat analysis, decision support	Integration of multi-source data; spatial analysis; scenario modeling	Data standardization; software training needed
IoT / Sensor Networks	Microclimate, soil moisture, fire/pest detection	Real-time monitoring; early warning systems; ecosystem process tracking	Installation cost; maintenance; network connectivity
Big Data & AI (Machine Learning, Deep Learning)	Fire risk prediction, habitat modeling, vegetation classification	Predictive analytics; pattern recognition; improved decision-making	Algorithm transparency; data quality; model bias
Digital Twin	Simulating scenarios for management, climate, risk	Proactive decision-making; integrated ecosystem modeling; strategic planning	High complexity; real-time data requirement; computational demand

Source: Compiled by the author based on literature review (2024).

5. DISCUSSION

This review demonstrates that technological infrastructure has transformed forest management from a reactive discipline into a proactive, data-driven, and predictive science. The findings are consistent with the existing literature indicating that the integration of remote sensing and AI, in particular, exponentially increases the scale, speed, and accuracy of data collection compared to traditional field studies (Christin et al., 2019; Reichstein et al., 2019; Zulfiqar et al., 2021). Recent research from Türkiye further supports these findings, showing successful applications of UAV-based monitoring (Eker et al., 2021), GIS-integrated risk assessment (Gumus et al. (2008), and IoT-based real-time data acquisition systems (Tagarakis et al., 2024) in forest management contexts.

However, this digitalization process also brings with it a significant paradigm shift. Forest management now requires not only ecological knowledge but also the ability to process big data, understand algorithms, and manage cyber-physical systems. This situation urgently necessitates the revision of forest engineering education curricula (Burleigh & Jönsson 2025).

Furthermore, as dependence on technology increases, 'data quality' and 'algorithmic transparency' become critically important. A machine learning model trained with low-quality data can lead to erroneous management decisions. Similarly, the inability to understand the logic behind decisions made by deep learning models operating as 'black boxes' can undermine managers' trust in these systems (Rudin, 2019). Therefore, explainability in AI applications (explainable AI - XAI) should be one of the focal points of future research (Chinnaraju 2025).

6. CHALLENGES AND LIMITATIONS

Although technological infrastructure transforms forest management, some limitations and challenges exist:

6.1. Cost and Resource Constraints

UAVs, LiDAR, satellite imagery, and sensor networks can require high costs. The applicability of these technologies is limited in small-scale and low-budget projects (Maxwell et al., 2018).

6.2. Data Management and Standardization

Standardizing and harmonizing data from different sources poses a technical challenge; however, planetary-scale platforms like Google Earth Engine largely alleviate this problem (Gorelick et al., 2017).

6.3. Human Resources and Training

Qualified human resources are needed for the effective use of new technologies. Lack of training in GIS, remote sensing, and artificial intelligence applications may limit the use of technological infrastructure (Abad-Segura et al., 2022; Burleigh & Jönsson 2025).

6.4. Legal and Ethical Limitations

The use of drones, data sharing, and personal/environmental privacy are subject to legal regulations. Additionally, ethical standards must be established for the use of technologies (Stone et al., 2016).

6.5. Digital Divide and Algorithmic Bias

Although technological progress is global, access is not equal. Forest management institutions in developing countries risk falling behind these technologies due to high costs and lack of infrastructure. This 'digital divide' could deepen global forest management inequalities. Furthermore, AI models may reflect biases in the data they are trained on. For example, a model trained only on forest types from a specific geography may fail to analyze a different ecosystem (Causevic et al., 2024).

6.6. Policy and Governance Deficiencies

The effective adoption and use of technological infrastructure requires clear policy frameworks and governance mechanisms. There are legislative gaps in areas such as data sharing protocols, privacy regulations, standards for UAV use, and cybersecurity measures. Additionally, collaborative governance models that encourage data and technology sharing among different institutions (forest directorates, environment ministries, research institutes) are needed. Without addressing these deficiencies, the potential return on technological investments cannot be fully realized.

7. CONCLUSION AND FUTURE PERSPECTIVES

Technological infrastructure in forest ecosystem management offers revolutionary opportunities in data collection, analysis, and decision support processes. Remote sensing, UAVs, LiDAR, GIS, sensor networks, IoT, big data analytics, artificial intelligence, and digital twin applications play critical roles in monitoring ecosystem changes, risk management, biodiversity tracking, and sustainable planning.

The review results demonstrate that:

Technological infrastructure enables the collection and analysis of high-resolution data over large areas, increasing the accuracy of management decisions.

GIS and AI-supported decision support systems help balance ecosystem services with economic outputs.

Drone and sensor-based monitoring systems allow early detection of risks such as fire, pest organisms, and climate change.

However, factors such as cost, data standardization, lack of human resources, digital divide, algorithmic bias, and legal/ethical limitations restrict the effective and equitable use of technological infrastructure.

Future Perspectives

- **Digital Twin and Simulation Models:** Digital twin systems fed with real-time data will enable simulation of different management and climate scenarios and strengthen strategic planning (Buonocore et al., 2022; Tagarakis et al., 2024).
- **Integrated Sensor Networks and IoT:** Establishing more widespread sensor networks in forest areas will increase the effectiveness of early warning and automatic monitoring systems (Ali et al., 2025).
- **Big Data, AI and Explainable Artificial Intelligence (XAI):** Big data analytics and deep learning algorithms will help develop more sensitive models of forest dynamics. XAI studies will increase trust by providing transparency in decision-making processes (Chinnaraju, 2025).
- **Policy, Governance and International Cooperation:** For effective implementation of technologies, comprehensive policy frameworks including open data policies, harmonization of standards, and ethical guiding principles should be developed in addition to trained human resources. International cooperation focused on technology transfer and capacity building will play a key role in reducing the digital divide and supporting sustainable forest management at the global scale (FAO, 2020).
- **Citizen Science and Stakeholder Participation:** Data collected by the public through smartphone applications (e.g., tree disease reports) can support professional monitoring networks and democratize data collection processes (Fraisl et al., 2022). This has the potential to strengthen the social acceptability of forest management decisions by increasing public participation in management.

In conclusion, technological infrastructure not only increases operational efficiency in forest management but also contributes to the creation of sustainable and resilient ecosystems. Future research should focus on the integration of existing technologies, cost-effective strategies, XAI applications, policy-governance models, and optimizing decision support processes.

8. ACKNOWLEDGMENTS

The author acknowledges the use of AI assistants in the preparation of this review article, in accordance with ethical AI usage principles. ChatGPT (OpenAI) was employed to support the literature synthesis, conceptual structuring, and initial drafting phases of the manuscript. DeepSeek AI (deepseek.com) was utilized for language refinement, formatting suggestions, DOI verification, and consistency editing. The author retains full responsibility for the final content, interpretations, and conclusions presented in this work.

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