

SMART FORESTRY: INTEGRATING ARTIFICIAL INTELLIGENCE, REMOTE SENSING AND IOT FOR SUSTAINABLE FOREST MANAGEMENT

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<https://doi.org/10.35410/IJAEB.2026.1074>

Received: 5 August 2026/Published: 17 Sept 2026

ABSTRACT

The convergence of Artificial Intelligence (AI), remote sensing, and the Internet of Things (IoT) is fundamentally transforming conventional forestry practices into smart, data-driven forest management systems. As global forest ecosystems face unprecedented threats from climate change, deforestation, illegal logging, and wildfires, integrating digital technologies has become indispensable for effective and sustainable forest stewardship. This review synthesises current advancements in smart forestry, examining how machine learning (ML), deep learning (DL), satellite remote sensing, unmanned aerial vehicles (UAVs), LiDAR, and IoT sensor networks are being deployed to enhance forest monitoring, wildfire detection, carbon stock estimation, biodiversity assessment, and forest inventory management. Key applications discussed include real-time fire detection using deep learning on drone-captured imagery, above-ground biomass estimation with LiDAR and ML algorithms, deforestation monitoring with Sentinel-2 multispectral data, and continuous ecosystem monitoring via IoT sensor arrays. Challenges, including data interoperability, computational demands, connectivity in remote areas, and ethical concerns regarding data governance, are also critically examined. The review concludes with a forward-looking perspective on digital twins, edge computing, and federated learning as next-generation enablers of precision forestry. Smart forestry technologies, when effectively integrated, offer transformative potential for meeting global sustainable development goals, achieving carbon neutrality targets, and conserving biodiversity.

Keywords: Smart forestry; Artificial intelligence; Remote sensing; Internet of Things; Forest management; Wildfire detection; Carbon sequestration; UAV; LiDAR; Machine learning.

1. INTRODUCTION

Forests represent one of Earth's most vital ecological assets, covering approximately 31% of global land area and providing critical ecosystem services including carbon sequestration, biodiversity habitat, watershed regulation, and climate modulation [1]. However, accelerating anthropogenic pressures, including deforestation, illegal logging, and the escalating frequency of wildfires driven by climate change, have placed unprecedented strain on forest ecosystems

worldwide [2]. Traditional forest management approaches, heavily reliant on ground-based surveys, manual inventories, and periodic aerial photography, are increasingly inadequate for responding to the scale, complexity, and dynamism of contemporary forest threats [3].

The emergence of smart forestry, a paradigm that integrates AI, IoT sensor technologies, and multi-platform remote sensing, offers a transformative shift from reactive to proactive, data-driven forest management [4]. This technological confluence enables continuous, high-resolution monitoring of forest health, structure, carbon stocks, and disturbance dynamics at scales ranging from individual tree canopies to continental landscapes [5]. The exponential growth of satellite constellations, drone technologies, cloud computing, and edge AI has dramatically lowered barriers to deploying sophisticated monitoring systems even in geographically remote and logistically challenging forest environments [6].

Climate-smart forestry (CSF), an evolving management philosophy that integrates adaptation, mitigation, and productivity objectives, increasingly relies on these digital technologies to operationalise data-informed decisions [7]. Machine learning algorithms trained on multi-source remote sensing data now support species classification, disease detection, illegal logging surveillance, and wildfire risk prediction with accuracies that frequently surpass traditional methods [8]. Simultaneously, IoT deployments of low-power, long-range sensor networks are enabling continuous ground-truth data collection on microclimate parameters, soil moisture, tree growth, and carbon fluxes [9].

This review provides a comprehensive synthesis of current smart forestry technologies and their applications across key forest management domains. It critically evaluates methodological advances, discusses operational challenges, and identifies future research priorities to guide the development of next-generation integrated forest management systems. Papers from 2020 to 2025 were prioritised to reflect the most current state of the field.

Remote Sensing Technologies in Smart Forestry

Satellite-Based Forest Monitoring

Satellite remote sensing has undergone profound advances, with the European Space Agency's Sentinel-2 constellation providing freely accessible multispectral imagery at 10–60 m resolution with a revisit time of five days. Deep learning architectures, particularly convolutional neural networks (CNNs), have demonstrated remarkable capability in extracting forest information from Sentinel-2 time series [10]. Applications include forest type classification, tree species mapping, and land cover change detection [10]. The combination of Sentinel-1 SAR and Sentinel-2 optical data further enhances classification robustness, particularly in tropical regions where cloud cover frequently impedes optical-only approaches [11].

NASA's Global Ecosystem Dynamics Investigation (GEDI) space-borne LiDAR has revolutionised large-scale forest structure characterisation, providing high-resolution estimates of canopy height, basal area, and aboveground biomass (AGB) across tropical and temperate forest biomes. Machine learning integration with GEDI footprint data enables wall-to-wall AGB mapping at regional and national scales [12]. Carbon stock monitoring has benefited considerably from combining GEDI observations with Sentinel-2 imagery, enabling 10–30 m resolution biomass maps that support REDD+ accounting frameworks and corporate carbon offset verification [13]. Figure 1 presents the multi-platform remote sensing architecture for smart forest monitoring, showing satellite (Sentinel-1/2, GEDI), UAV, and ground sensor data flows integrated through a cloud AI platform.

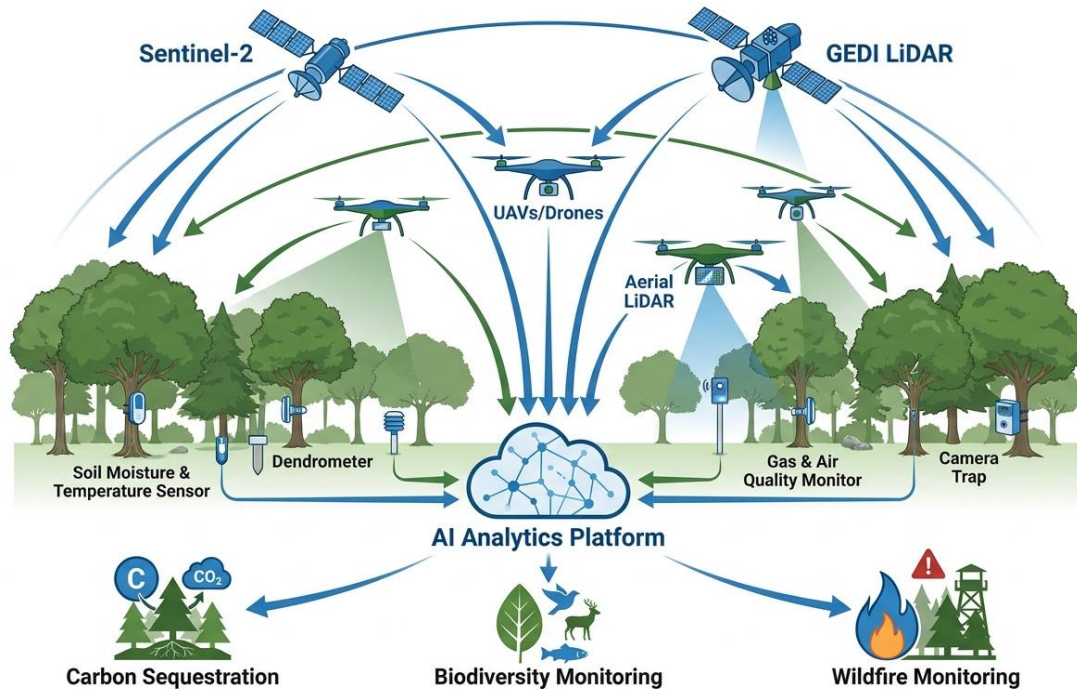


Figure 1: Multi-platform remote sensing architecture for smart forest monitoring, showing satellite (Sentinel-1/2, GEDI), UAV, and ground sensor data flows integrated through a cloud AI platform. Source: Created from references [1, 4, 5, 10, 12].

UAV and Airborne Remote Sensing

Unmanned aerial vehicles have emerged as indispensable tools in smart forestry, bridging the spatial resolution gap between satellite observations and ground-level measurements [3]. UAVs equipped with RGB, multispectral, hyperspectral, and LiDAR sensors provide centimetre-resolution data for individual tree delineation, crown area estimation, and species-level structural characterisation. A growing body of research demonstrates that UAV-LiDAR integration with machine learning algorithms achieves high-accuracy individual tree AGB estimates critical for local-scale carbon accounting [14]. Integration of RGB and LiDAR data has been shown to significantly outperform single-sensor approaches in estimating above-ground biomass of natural secondary forests [14].

For wildfire management, UAVs equipped with infrared and RGB cameras provide real-time smoke and flame detection capability beyond the reach of fixed sensor networks. Deep learning models, particularly variants of the YOLO (You Only Look Once) object detection framework, have been successfully applied to UAV-collected imagery for early smoke detection, achieving detection accuracy competitive with human observers [15]. Chen et al. developed a drone-collected RGB/IR image dataset for wildland fire detection, demonstrating high detection performance and providing a benchmark for further model development [16].

LiDAR for Forest Structural Assessment

LiDAR technology, both airborne and terrestrial, provides three-dimensional point-cloud data that enables precise measurement of forest structural parameters including tree height, crown

volume, canopy gap fraction, and stem density. Random forest, support vector machine, gradient boosting, and deep neural network algorithms have been trained on LiDAR-derived metrics to estimate AGB with root mean square errors substantially lower than those achievable with optical remote sensing alone [17]. Ma et al. demonstrated through cross-validation that LiDAR-derived features combined with ML algorithms achieve high accuracy in total and component forest AGB inversion [17]. Table 1 gives a summary of Remote Sensing Technologies in Smart Forestry.

Table 1: Summary Of Remote Sensing Technologies in Smart Forestry

Technology	Spatial Resolution	Key Application	AI/ML Integration	Key Reference
Sentinel-2	10–60 m	Forest classification, deforestation	CNN, Random Forest, transformer models	[10, 11]
GEDI LiDAR	~25 m footprint	AGB estimation, canopy height	ML regression, deep learning	[12, 13]
Airborne LiDAR	0.1–2 m	Tree biomass, carbon, structure	Random Forest, SVM, gradient boosting	[17, 18]
UAV + RGB/IR	0.01–0.1 m	Fire detection, species mapping	YOLOv5/v8, CNN, transfer learning	[15, 16]
SAR (Sentinel-1)	5–20 m	Forest degradation, biomass	SAR backscatter ML models	[11]
Hyperspectral	1–5 m (airborne)	Species identification, stress detection	SVM, PCA, deep learning	[3, 5]

CNN = Convolutional Neural Network; SVM = Support Vector Machine; AGB = Above-Ground Biomass; SAR = Synthetic Aperture Radar; PCA = Principal Component Analysis

Artificial Intelligence Applications in Forest Management

Wildfire Detection and Prediction

Wildfire represents one of the most devastating and rapidly escalating threats to global forest ecosystems. AI-powered detection systems have demonstrated the capability to drastically reduce the latency between fire ignition and alert generation compared to traditional satellite-based systems. Deep learning models applied to UAV-acquired infrared imagery have achieved smoke detection precision exceeding 90% in controlled environments, though performance in complex, multi-class fire scenarios remain variable [16]. Federated learning approaches, which allow model training across distributed edge nodes without centralising sensitive data, have been explored for fire classification in IoT-equipped forest sensor networks [19].

Convolutional neural network architectures, particularly YOLOv5 and its successor YOLOv8, have been refined for forest fire smoke detection from UAV aerial imagery, with improvements in anchor box clustering and partial convolution reducing model parameters while maintaining detection speed necessary for real-time alerting [15]. Integration with weather data, topographic variables, and fuel moisture indices into multi-modal deep learning architectures has improved temporal wildfire spread prediction, enabling proactive resource pre-positioning [8].

Forest Inventory and Species Classification

AI-driven forest inventory represents a paradigm shift from periodic, plot-based field surveys to continuous, landscape-scale monitoring. Random forest, XGBoost, and neural network classifiers trained on multi-temporal satellite imagery have achieved overall classification accuracies of 85–95% for forest type mapping across diverse biomes [10]. The digital transformation of forestry practices, often termed Forest 4.0, leverages big data analytics, AI, and IoT to optimise timber harvest scheduling, regeneration planning, and biodiversity monitoring [20].

Climate-smart forestry applications increasingly rely on AI algorithms to simultaneously optimise carbon sequestration, adaptation to climate stressors, and biodiversity conservation objectives [7]. Machine learning models trained on multi-year Sentinel-2 time series enable detection of subtle phenological shifts indicative of forest stress, pest outbreaks, or disease spread, enabling timely management interventions [10].

Deforestation and Illegal Logging Detection

Near-real-time deforestation detection represents one of the highest-impact applications of smart forestry technologies. Novel frameworks integrating YOLOv8 object detection with agentic AI systems have been developed for real-time deforestation anomaly detection using satellite and drone imagery, enabling automated alert generation and GIS-driven reporting [21]. Sensor networks that combine acoustic monitoring, using CNNs to detect chainsaw sounds, with GPS positioning provide complementary ground-truth data to satellite observations for combating illegal logging [22].

IoT-enabled UAV systems that autonomously patrol designated forest areas and integrate visual and acoustic AI classification represent an emerging solution for deterring and documenting illegal extraction activities, particularly in biodiversity hotspots where enforcement capacity is limited [22]. The combination of Sentinel-1 SAR data with Google Earth Engine cloud computing facilitates continuous monitoring even in perpetually cloudy tropical forest regions [11]. Figure 2 presents the AI application framework for wildfire detection, deforestation monitoring, and illegal logging prevention in smart forestry systems.

AI-Driven Smart Forestry Monitoring Pipeline – Integrated Multi-Stream Detection and Response System

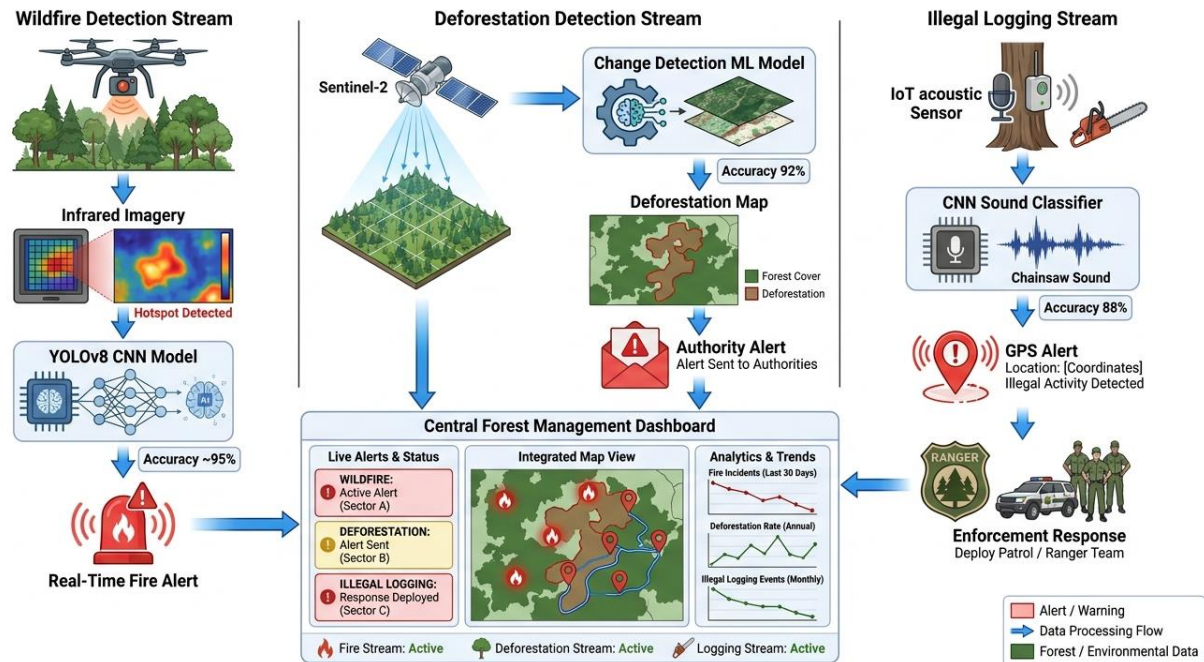


Figure 2: AI Application Framework for Wildfire Detection, Deforestation Monitoring, and Illegal Logging Prevention in Smart Forestry Systems.

Sources: Adapted from references [8, 15, 16, 19, 21, 22].

IoT Sensor Networks for Forest Ecosystem Monitoring Sensor Architecture and Deployment

IoT-based forest monitoring systems typically employ a hierarchical three-layer architecture: a perception layer comprising distributed sensor nodes, a network layer for data transmission, and an application layer for processing and decision support [4]. Wireless sensor nodes measuring temperature, humidity, atmospheric pressure, soil moisture, carbon dioxide concentration, and tree growth are deployed across forest landscapes, transmitting data via low-power wide-area network (LPWAN) protocols including LoRa, NB-IoT, and Sigfox [9]. These technologies offer transmission ranges of up to 15 km with power consumption low enough to support multi-year operation on battery or solar power, making them viable in remote forest locations [22].

The IoT in smart forestry includes applications across forest fire prevention, biodiversity monitoring, carbon accounting, and forest health surveillance [23]. Sensor-collected data streams are increasingly processed at edge computing nodes rather than transmitted in full to central servers, reducing communication bandwidth requirements and enabling faster, locally relevant decision-making [20]. A comprehensive narrative analysis of IoT applications in forestry identified four major implementation axes: fire detection, climate-smart forestry, digital forest inventory, and biodiversity conservation monitoring [23].

Real-Time Carbon and Ecosystem Flux Monitoring

IoT sensor networks co-located with eddy covariance towers enable continuous monitoring of net ecosystem exchange, allowing real-time tracking of forest carbon sink-source dynamics.

Machine learning models trained on sensor-derived microclimate and biometric data increasingly supplement flux tower measurements to extend spatial coverage and fill temporal data gaps [7]. Integration of IoT-collected ground data with spaceborne LiDAR and satellite imagery creates multi-scale, multi-source data fusion pipelines that markedly improve forest carbon stock estimation accuracy [12].

Advancing forest carbon stock mapping through hierarchical machine learning approaches integrating Sentinel-2 imagery with ground-based measurements has demonstrated significantly improved accuracy compared to single-source methods [13]. These advances are particularly relevant for REDD+ implementation, where robust and independently verifiable carbon accounting underpins both mitigation finance flows and governance accountability. Table 2 presents the IoT Sensor Types and Applications in Smart Forestry.

Table 2: IoT Sensor Types and Applications in Smart Forestry

Sensor Type	Parameter Measured	Communication Protocol	Forest Application	Reference
Temperature/humidity	Air temp, RH, dewpoint	LoRa, Zigbee	Fire risk assessment, microclimate monitoring	[4, 9]
Soil moisture	Volumetric water content	NB-IoT, LoRaWAN	Drought stress detection, irrigation planning	[9, 23]
CO ₂ /gas sensors	CO ₂ , CH ₄ , VOC concentration	Sigfox, Wi-Fi	Carbon flux monitoring, fire smoke detection	[7, 22]
Acoustic sensors	Sound spectrogram	LoRa, cellular	Illegal logging detection, biodiversity monitoring	[22, 23]
Dendrometers	Stem diameter growth	Bluetooth, LoRa	Tree growth monitoring, carbon accounting	[4, 20]
GPS tracker nodes	Location, movement	GNSS, cellular	Wildlife tracking, anti-logging patrol	[22]

RH = Relative Humidity; VOC = Volatile Organic Compound; GNSS = Global Navigation Satellite System; LoRa = Long Range radio; NB-IoT = Narrowband IoT

Challenges and Barriers to Implementation

Despite demonstrated technological potential, smart forestry implementation faces substantial challenges that constrain operational deployment at scale. Data interoperability between sensor platforms, satellite missions, and analytical frameworks remains a persistent barrier, as differing data standards, spatial resolutions, temporal frequencies, and coordinate reference systems complicate multi-source data fusion [5]. Establishing standardised data protocols and open data architectures is increasingly recognised as a prerequisite for scaling smart forestry solutions across administrative and national boundaries [20].

Connectivity infrastructure in remote forest regions represents a fundamental constraint on IoT deployment. While LPWAN technologies such as LoRa substantially extend communication range beyond traditional Wi-Fi or cellular networks, significant coverage gaps remain in geographically isolated or mountainous forest landscapes [9]. High-altitude UAV relay nodes and low-Earth orbit satellite internet constellations are being explored as potential solutions, but cost, regulatory complexity, and power consumption introduce additional implementation challenges [6].

Computational demands of deep learning model training, particularly for large-scale, multi-temporal satellite time series, require substantial cloud computing infrastructure that may not be accessible to forest management agencies in lower-income countries [8]. Transfer learning and model compression techniques are being explored to reduce computational requirements and enable edge deployment of inference models on resource-constrained IoT nodes [19]. Ethical concerns including data privacy, community consent in indigenous forest territories, and equitable access to benefits derived from forest data are increasingly foregrounded in discussions of responsible smart forestry deployment [24].

Validation of AI-derived forest attributes against ground truth remains methodologically challenging due to the high cost and logistical complexity of field surveys in remote forest environments [3]. Model generalisation across contrasting forest biomes, phenological stages, and atmospheric conditions remains an active research challenge [18]. Long-term continuity of satellite data streams, contingent on mission lifecycle and funding, introduces additional uncertainty for operational monitoring systems designed for multi-decadal carbon accounting [12]. Table 3 shows the Key Challenges and Proposed Solutions in Smart Forestry

Table 3: Key Challenges and Proposed Solutions in Smart Forestry

Challenge	Impact Domain	Proposed/Emerging Solutions	Reference
Data interoperability	Multi-source data fusion	Open data standards, cloud-native data formats (COG, ZARR), STAC catalogues	[5, 20]
Remote connectivity	IoT sensor deployment	LoRaWAN, satellite IoT (Starlink, Iridium), UAV relay nodes	[9, 23]
Computational cost	Deep learning training	Transfer learning, edge AI, model compression, federated	[8, 19]

		learning	
Model generalisation	Cross-biome accuracy	Domain adaptation, ensemble models, multi-task learning	[10, 18]
Ground truth scarcity	Model validation	Citizen science, lidar-derived reference data, synthetic training data	[3, 14]
Data governance/ethics	Indigenous land rights, privacy	Community consent protocols, data sovereignty frameworks, AI ethics guidelines	[24, 25]
Financial and technical capacity	Developing country adoption	Open-source tools, capacity building, South-South collaboration, international funding	[6, 25]

COG = Cloud-Optimised GeoTIFF; STAC = SpatioTemporal Asset Catalog; IoT = Internet of Things; AI = Artificial Intelligence

Future Directions and Emerging Technologies

The future trajectory of smart forestry will be shaped by several converging technological developments. Forest digital twins, dynamic virtual replicas of forest ecosystems continuously updated by sensor data, satellite observations, and process models, are emerging as a comprehensive platform for simulation-based forest management and scenario planning [20]. Digital twins can integrate structural, physiological, and phenological forest data to simulate responses to management interventions, climate scenarios, and disturbance regimes, providing decision-makers with an unprecedented predictive capability [7].

Federated learning approaches, which train AI models across distributed data nodes without requiring data centralisation, offer a privacy-preserving path to developing large, diverse training datasets by aggregating learning from multiple forest monitoring networks without compromising data sovereignty [19]. Edge AI, the deployment of ML inference directly on sensor nodes and UAV processing units, reduces latency, bandwidth consumption, and cloud dependency while enabling near-real-time response to detected events [9].

Foundation models and large-scale pre-trained geospatial AI systems, analogous to large language models in natural language processing, are beginning to appear in remote sensing applications. These models, pre-trained on petabyte-scale archives of satellite imagery, can be fine-tuned for specific forest monitoring tasks with minimal labelled training data, potentially democratising access to high-accuracy monitoring for organisations with limited data resources [8]. Blockchain-based forest governance systems, integrated with IoT sensor networks, offer transparent and tamper-resistant logging of forest carbon transactions and timber supply chain data, addressing certification trust deficits [20]. Figure 3 illustrates the Future integrated smart forestry ecosystem: digital twins, federated learning, edge AI and blockchain for sustainable forest management.

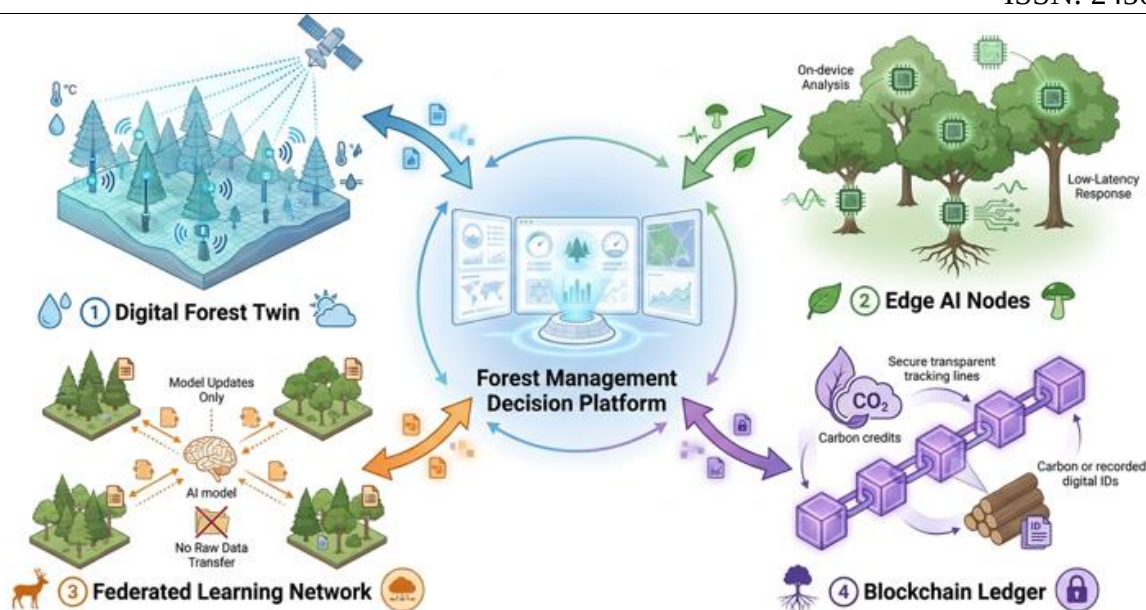


Figure 3: Future integrated smart forestry ecosystem: digital twins, federated learning, edge AI and blockchain for sustainable forest management.

Sources: Adapted from references: [7, 8, 19, 20, 25]

2. CONCLUSION

Smart forestry, enabled by the integration of AI, remote sensing, and IoT, represents a transformative approach to sustainable forest management that addresses the escalating complexity of contemporary forest governance challenges. This review has demonstrated that deep learning applied to multi-platform remote sensing data enables accurate forest type classification, biomass estimation, fire detection, and deforestation monitoring at previously unachievable scales and temporal resolutions. IoT sensor networks provide continuous ground-level ecosystem data that complements satellite observations, while AI algorithms synthesise multi-source data streams into actionable management intelligence.

Critical challenges around connectivity, data standards, model generalisation, computational accessibility, and ethical governance must be systematically addressed for smart forestry technologies to fulfil their transformative potential equitably across global forest regions. Emerging technologies including digital twins, federated learning, edge AI, and blockchain-integrated data governance offer credible pathways to overcoming current limitations.

Looking ahead, realising the full potential of smart forestry will require interdisciplinary collaboration among ecologists, remote sensing scientists, AI researchers, forest managers, policymakers, and local communities. Investment in open data infrastructure, international capacity building, and ethical technology frameworks will be as important as continued technical innovation in ensuring that smart forestry contributes meaningfully to global sustainability goals, including the Paris Agreement carbon targets and the Kunming-Montreal Global Biodiversity Framework.

Declarations

Conflict of Interest:

The authors declare no conflict of interest.

Funding:

This review work received no external funding.

Author Contributions: [Author 1]: Conceptualisation, writing — original draft. [Author 2]: Methodology, data curation. [Author 3]: Review, editing, supervision.

Ethical Approval:

Not applicable.

Data Availability:

Not applicable.

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