https://doi.org/10.17221/47/2026-JFS

Forest digital twin via big data integration: Current advances and future perspectives

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Citation: Yang J., Qin C. (2026): Forest digital twin via big data integration: Current advances and future perspectives. J. For. Sci., 72: 383–399.

Abstract: Forest ecosystems face increasing pressures from climate change, biodiversity loss, and human activities, necessitating innovative tools for management and prediction. Forest digital twin is emerging as a transformative tool for monitoring, simulating, and managing forest ecosystems. By integrating multi-source big data – satellite imagery, airborne and terrestrial LiDAR, Internet of Things (IoT) sensors, and process-based ecological models – the forest digital twin can provide dynamic, high-resolution representations of forest structure and function. This review integrates and analyses recent advances reported across 56 scholarly works and finds several gaps in current research, including limited real-time integration of IoT and remote-sensing data, weak interoperability between modelling platforms, and insufficient multi-scale ecological representation. This review addresses these shortcomings by synthesising the technological, ecological, and computational components required for a functional forest digital twin. Overall, the review provides a coherent conceptual framework, identifies critical research priorities, and demonstrates how digital twin technologies can transform forest monitoring and management through adaptive, data-driven decision support.

Keywords: Internet of Things (IoT); forest fire; forest management; remote sensing

The concept of the digital twin originated within engineering disciplines (Sjarov et al. 2020; Agrawal et al. 2022; Ding et al. 2026), particularly aerospace and advanced manufacturing, where virtual replicas of physical assets were developed to enable real-time monitoring, performance optimisation, and predictive maintenance. Over the past decade, this paradigm has broadened to environmental sciences, leading to the emergence of the forest digital twin – a dynamic, data-informed virtual representation of forest ecosystems (Hejtmánek et al. 2022; Lv et al. 2022; Döllner et al. 2023; Tagarakis et al. 2024). Herein, a forest digital twin is defined as a continuously updated, spatially explicit, and computationally executable virtual representation of a forest system that maintains a dynamic linkage with its physical counterpart through data assimilation, process models, and feedback mechanisms, enabling monitoring, simulation, prediction, and scenario testing across multiple spatial

Supported by the National Nature Science Foundation of China (NSFC, Grant No. 42271175).

https://doi.org/10.17221/47/2026-JFS

and temporal scales. Three minimum criteria are essential for this definition: first, the digital representation must be continuously synchronised with the physical forest via observations (e.g. remote sensing, *in situ* sensors). A static map or one-time inventory does not qualify. Second, the twin must encode forest processes (e.g. growth, mortality, disturbance, carbon fluxes, management actions) that can evolve forward in time. Third, information flows from forest to twin (data assimilation) and from twin to decision-making (forecasting, optimisation, risk assessment). Without this feedback loop, the system is better described as a digital model or platform, not a twin (Silva et al. 2023; Tagarakis et al. 2024). A forest digital twin thus should have its capacity for bidirectional information exchange between the physical and virtual systems (Ozel, Petrovic 2023; Wallgrün et al. 2021; Wang et al. 2022). As new observations become available, data assimilation algorithms could update the model's state variables, thereby reducing uncertainty and improving predictive accuracy. Moreover, the digital twin could generate forecasts and scenario simulations, such as future forest growth, forest fuel accumulation, or disturbance spread, which can inform monitoring priorities and management interventions in the physical system. This tight coupling facilitates adaptive management by allowing forest practitioners to explore multiple 'what-if' scenarios and evaluate outcomes before they are implemented on the ground (Ozel, Petrovic 2023; Riaz et al. 2023).

At its core, a forest digital twin integrates heterogeneous big-data sources (Sasaki, Abe 2025; Iwaszczuk et al. 2023; Dao et al. 2025), including remote satellite optical and radar time series, airborne and terrestrial Light Detection and Ranging (LiDAR) derived data, forest inventory datasets, and an expanding suite of *in situ* sensors such as dendrometers, sap flow sensors, soil temperature and moisture probes, and other microclimate loggers. These multimodal datasets are combined within a unified framework to provide spatially explicit, temporally continuous representations of forest conditions (Jo et al. 2025). The integration of such diverse data sources enables the digital twin to characterise forest processes across hierarchical levels, ranging from individual-tree morphology and stand structure to landscape-scale carbon dynamics and disturbance regimes (Huang et al. 2020; Li et al. 2024).

A forest digital twin is typically conceptualised as a cyber-physical system comprising three interconnected layers (Buonocore et al. 2022; Yun et al. 2022; Chen et al. 2025). The physical layer encompasses the real-world forest and its sensing infrastructure. The data integration layer includes pipelines for data ingestion, preprocessing, fusion and storage, often hosted on scalable cloud platforms. The application layer provides user-facing tools, dashboards, and decision-support interfaces that translate model outputs into actionable insights for managers, policymakers, and researchers. This modular architecture not only ensures flexibility and interoperability but also facilitates the incorporation of new sensors, models, and management objectives (Figure 1).

As a result of these capabilities, forest digital twin is increasingly positioned as a transformative approach for sustainable forest management, climate change mitigation, and ecological forecasting (Damaševičius, Maskeliūnas 2024; Li et al. 2022; Huang et al. 2024). They offer great opportunities to monitor forest health, evaluate carbon sequestration potential, assess fire behaviour under variable conditions, and quantify the impacts of pests, pathogens, and extreme weather events (Zhang et al. 2016). Moreover, a forest digital twin reduces operational risks and supports evidence-based decision-making by allowing managers to test intervention strategies, such as alternative harvesting regimes, thinning prescriptions, or fuel-reduction treatments, within the virtual environment before practical implementation (Holm, Schweier 2024; Hejtmánek et al. 2022; Qiu et al. 2023). For example, in simulation experiments using 63 historical North American wildfires in the year 2016 and a structured multi-channel environmental dataset (e.g. climate data, vegetation data), a proposed digital twin's similarity-based hybrid model reduced average prediction error by approximately 50% relative to the physics-based model (Yun et al. 2022). Specifically, this hybrid model combines a physics-based wildfire spread model (FARSITE, Fire Area Simulator – Model Development and Evaluation) with a data-driven correction component and similarity-based training data selection. As global demands intensify for accurate, timely, and scalable forest information, digital twins represent a promising frontier in the integration of big data, ecological modelling, and advanced computation.

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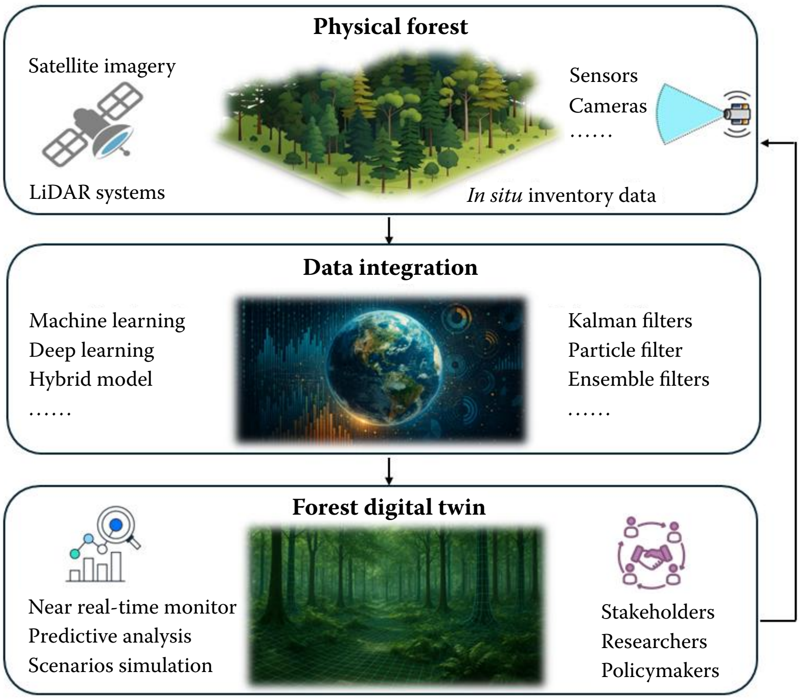

Figure 1. The basic conceptual architecture of a forest digital twin

MATERIAL AND METHODS

We systematically searched Google Scholar using combinations of the terms 'forest digital twin', 'digital twin', and 'forest'. This criterion was used because we focused only on the research progress of forest digital twin, but not on the forest dynamic models, 3D models, machine learning or deep learning-based tree or forest reconstruction and forest ecological workflows. Search strings were restricted to English. The search was extended to scrutinise references in each article for additional studies. This iterative process continued until no further relevant studies were found, from January 10 to February 21, 2025. Subsequently, titles and abstracts of the resulting papers were reviewed, followed by a thorough examination of the full text for relevance. Considering the forest digital twin is a new topic that emerged during the past five years, editorial articles without methods but specifically calling for forest digital twin were included; purely theoretical/conceptual digital twin papers without application were also included. Publications outside relevant forest domains (e.g. purely automotive digital twin) were excluded. We listed all the publications in Table S1 in the Electronic Supplementary Material (ESM). Published papers started in the year 2021, and the number (56 in total) was limited up to now, indicating that the forest digital twin is still in its infancy. Conceptual frameworks/proposals, forest management, forest fire/disturbance case studies, and urban forest studies are the four main branches in this field. A very limited number of forest digital twins were dedicated to the forest industry or operation. Hence, true real-world forest digital twin implementations are still emerging, and many studies are frameworks, prototypes, or experimental systems rather than fully operational or bidirectional systems.

DATA SOURCES FOR THE FOREST DIGITAL TWIN

The forest digital twin is based on multi-scale, multi-source data streams that together represent near-real-time forest conditions and long-term ecological dynamics. Remote satellite technologies are frequently used to gather high-resolution data on forest biodiversity and environmental conditions (Lechner et al. 2020; Radočaj et al. 2020). Those images can capture forest phenology, biomass, disturbances, and other spectral and radiometric properties. Continuous optical or Synthetic Aperture Radar (SAR) data provides temporal dynamics (phenology and disturbance). Sentinel-2, for example, offers high-resolution optical imagery (10 m to 60 m), making

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it great for monitoring forest types and health (Grabska et al. 2019; Lastovicka et al. 2020). Different types of forest damage were identified based on Sentinel-2 satellite images, and tree species classification was also actionable (Molnár, Király 2024). The National Aeronautics and Space Administration (NASA)'s Landsat program is frequently used for large-scale forest monitoring (Woodcock et al. 2001; Banskota et al. 2014). For example, Landsat 7 imagery from 2001 to 2021, collected at annual intervals, was used to predict forest canopy characteristics and tree species (Jiang et al. 2022). Structure-from-Motion photogrammetry also has excellent potential in the future development of the forest digital twin (Sujaswara, Hasegawa 2023).

LiDAR techniques provide a comprehensive representation of forest structures (Yusup et al. 2022; Chen et al. 2024) that can measure tree heights, canopy density, biomass, and even detect forest undergrowth, which helps to create more precise representations of forest ecosystems (Ambarwari et al. 2024). With these advantages, the LiDAR technique has been widely used in forest inventory, biomass estimation, and carbon storage assessment (Hu et al. 2016; Borsah et al. 2023; Coops et al. 2025). The collection of point cloud data can be carried out through various platforms, such as spaceborne LiDAR, Airborne Laser Scanning (ALS), Unmanned Aerial Vehicle-borne Laser Scanning (ULS), Mobile Laser Scanning (MLS), and Terrestrial Laser Scanning (TLS). Studies have demonstrated that a synergy of ICESat-2 (spaceborne LiDAR) with other remote sensing data can make a crucial contribution to spatial-continuous forest canopy height mapping, especially for areas covered by different types of forest (Xi et al. 2022; Gautam et al. 2025). Global Ecosystem Dynamics Investigation (GEDI) is the only full-waveform spaceborne LiDAR system designed specifically to measure the vertical structure of vegetation, and it has the penetration ability in dense vegetation (Potapov et al. 2021; Xu et al. 2024). ALS can provide the landscape-scale structural backbone of a digital twin, delivering wall-to-wall terrain and canopy-height information essential for initialisation, spatial context, and upscaling (Hyyppä et al. 2009; White et al. 2013). ULS complements this by supplying ultra-high-resolution, flexible, and frequently repeatable measurements of crown architecture and fine-scale canopy change, enabling dynamic updates at the tree and stand levels (Panagiotidis et al. 2022). MLS contributes detailed stem and understory information along accessible corridors, efficiently capturing structural elements that are poorly resolved from above and supporting validation of canopy-derived metrics (Mokroš et al. 2021; Stovall et al. 2023). TLS can provide the plot-level reconstructions of stems, branches, and understory vegetation, forming the ground-truth reference needed to calibrate and validate all other platforms and to parameterise biophysically realistic tree models (Newnham et al. 2015). Each platform has advantages and disadvantages; however, a large-scale forest digital twin may require a multiscale laser scanning strategy because no single platform can capture the full range of structural and temporal processes that govern forest dynamics. The geomatic-based approach is also viewed as operationally more efficient than traditional forest field surveys, requiring fewer personnel and less on-site work (Cheng et al. 2025). Nevertheless, the entire workflow of a forest digital twin needs to account for both field measurements and LiDAR scanner data (Niță 2021).

In situ physical sensors placed within forests can monitor parameters like temperature, soil moisture, air quality, and forest health, and feed continuous, near-real-time data. The forest acoustic sensors can monitor tree vibrations (e.g. caused by pests), and thermal sensors can assess plant stress. Integration of Internet of Things (IoT) and sensor networks is central to some forest digital twin frameworks (Aydin, Oktug 2024). For instance, a recent architecture for forest restoration digital twin includes an IoT-enabled physical layer to capture environmental variables as part of its 'real-time' capability (Sasaki, Abe 2025). A multi-ontology network was proposed by combining the semantic sensor network and sensor, observation, sample, and actuator ontologies for sensor and observation data, the GeoSPARQL ontology for geospatial representation, and two domain-specific ontologies for fire prevention and emergency response (Dao et al. 2025). A synthetic dataset containing thousands of forest plots with detailed structural labels was used to produce Boreal3D (Liu et al. 2025). They demonstrated the versatility and effectiveness of synthetic datasets in advancing forest scene analysis by evaluating the multiple platforms (e.g. ALS, MLS, and TLS) and diverse tasks. All the data sources and the associated technologies pave the way for scalable and robust solutions in forest ecological research and management (Table 1).

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Table 1. Basic information for implementing a forest digital twin by the case studies

Case study	Data used	Models/ algorithms	Main outputs	Spatial/temporal scale	Update frequency	Uncertainty handling	Bidirectional feedback
ESA DestinE Forest Digital Twin Component (Forest DTC) – Use cases in Czechia (biotic disturbances), Catalonia (fire fuel/hazard), Finland (management & carbon)	EO Sentinel-2, national forest inventories, flux tower (ICOS) data, weather and climate scenarios; future hyperspectral/ 3D sensing	Hybrid: process-based canopy productivity (e.g. PREBASSO, 3PGmix), stand/ tree growth, soil carbon + AI emulators/data assimilation	Dynamic forest maps, growing stock, yearly fire risk maps, yearly bark beetle maps, 'what-if' climate & management scenarios	Europe focus; daily to annual processes	'Pre-operational' with EO-driven updates; maps stable for a year but refreshed with latest imagery and weather; integration to DestinE platform	Explicit uncertainty estimation modules and parameterisation improvements; aims to reduce model structural/parametric uncertainties via new 3D sensing and data assimilation	Yes – scenario analysis influences management; EO updates feed model states; user-driven processes (disturbances/ management)
Forestry Digital Twin With Machine Learning in Landsat 7 Data (Jiang et al. 2022)	Landsat 7 remote sensing images (historical data over 20 years)	ML (LSTM-based model for spatial-temporal prediction)	Forecasted future forest remote sensing images	Spatial: Study area (forest land); Temporal: 20 years historical, future predictions	Not specified	Not specified	No – one-way prediction from data to model, no actions back into the physical world
Digital Twins in Agriculture and Forestry: A Review (Tagarakis et al. 2024)	Multisource RS (LiDAR, multi-spectral), IoT sensors, drones; inventories	Hybrid (survey): patterns of integration and maturity; common PB & ML blocks	Biomass, fuel loads, growth, hazard maps; decision dashboards	Various (plot → landscape); timescales from near-realtime sensors to annual	Depends on platform; streaming sensor updates	Discusses uncertainty propagation, DA, and maturity levels	Mixed – highlights projects with feedback
A Semantic Digital Twin-Driven Framework for Multi-Source Data Integration in Forest Fire Prediction and Response (Dao et al. 2025)	Multi-source: sensors, geospatial, observation, sample, fire prevention indicators	Semantic + data integration & reasoning (multi-ontology + spatial analytics)	Forest fire risk predictions and emergency response support	Broad fire-management area	Near real-time integration of sensor + spatial data	Likely uncertainty via semantic reasoning layers	Yes (framework) – structured semantic integration enables sensor → model updating and operational support (not fully automated physical control)
Testing Forestry Digital Twinning Workflow Based on Mobile LiDAR Scanner and AI Platform (Niță 2021)	3D point clouds from mobile LiDAR scans	Hybrid (AI-based automatic workflow VirtSilv with LiDAR processing)	Digital twins of individual trees with 95–98% reconstruction accuracy	Spatial: 1-ha sample plots; Temporal: Static snapshot	Not specified	Accuracy metrics (95–98%) for tree reconstruction	Not specified

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Table 1. To be continued

Case study	Data used	Models/ algorithms	Main outputs	Spatial/temporal scale	Update frequency	Uncertainty handling	Bidirectional feedback
Forest Digital Twin as a Relaxation Environment: A Pilot Study (Hejtmánek et al. 2022)	LiDAR scans, spatial audio recordings	Process-based (Unreal Engine with custom scripts for 3D reconstruction)	Virtual reality forest environment for relaxation and meditation	Spatial: Local forest area near Prague; Temporal: Static model	Not specified	Not specified	No
Forest Digital Twin: A New Tool for Forest Management Practices Based on Spatio-Temporal Data, 3D Simulation Engine, and Intelligent Interactive Environment (Qiu et al. 2023)	Remote sensing, forest inventory, Cesium Digital Earth, parametric 3D models; field images	Process-based (3D simulation engine with Cesium Digital Earth)	Tree/stand structural analysis, DBH/H prediction (>90% acc.), interactive thinning experiments; stand spatial structure (*F*-index) improvements	Managed stands in China; plot to stand-level; multi-year growth	Updates through 'twoway interaction' during decision experiments; near-real-time virtual real synchronisation in pilot	Not specified	Yes (conceptual) – human–digital interaction informs thinning decisions; automated control is envisioned but not fully autonomous
Framework of Virtual Plantation Forest Modeling and Data Analysis for Digital Twin (Li et al. 2023)	LiDAR point clouds, forest monitoring data (e.g. diameter at breast height)	Hybrid (LiDAR-based tree modelling AdTree, fitted growth equations), Dijkstra algorithm	Virtual poplar plantation, predicted tree growth trends	Spatial: Experimental plantation stand (2160 trees); Temporal: Growth over time	Not specified	Fitting equations to historical data	Partially – digital twin displays forest models to users, not automated feedback to physical processes; feedback is researcher-mediated
Towards the Digital Twin of Urban Forest: 3D Modeling and Parameterization of Large-Scale Urban Trees from Close-Range Laser Scanning (Chen et al. 2024)	Point clouds from mobile and UAV laser scanning	Hybrid (tree extraction, adaptive modelling, parameterisation)	Parameterised 3D tree models (lightweight representations) with 96% success rate	Spatial: 36,400 m^2 urban area; Temporal: Static snapshot	Not specified	Success rate metrics (96%)	Yes (towards digital twin with implied synchronisation)
A Reinforcement Learning-Based Adaptive Digital Twin Model for Forests (Damaševičius, Maskeliūnas 2024)	IoT sensor data from forest ecosystems	ML (Reinforcement Learning for adaptive modelling)	Adaptive digital twin with improved energy/resource efficiency, spatiotemporal forecasts	Spatial: Forest ecosystems; Temporal: Real-time dynamics	Adaptive (real-time updates via RL)	Handled via RL optimisation	Yes (adaptive feedback loops)

AI – artificial intelligence; IoT – Internet of things; ML – machine learning; RS – remote sensing

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The integration of IoT with advanced forest modelling platforms such as Boreal3D, iLand, and LANDIS-II, enables a multi-scale, data-driven approach to a forest digital twin. IoT provides real-time, ground-based measurements (e.g. microclimate, soil moisture, tree growth sensors). These continuous data streams improve the accuracy of model initialisation, calibration, and validation. Forest dynamic models form the ecological core of a forest digital twin by simulating how forests grow, interact, and respond to environmental change across multiple scales. Models such as iLand capture fine-scale, tree-level physiological processes and competition, while LANDIS-II represents long-term landscape dynamics including succession, disturbances, and management scenarios. When combined with real-time data streams from IoT sensors, these models allow the digital twin to continuously update, forecast future trajectories, and support adaptive forest management with both spatial and ecological realism.

INTEGRATING BIG DATA INTO A DIGITAL TWIN

Bridging the multiple data sources with models or between sensors is thus the core procedure of the forest digital twin. Integrating big data – characterised by high volume, variety, and veracity from sources like satellite images, IoT sensors, and environmental inputs – into the digital twin is essential for enhancing accuracy, reducing noise, handling uncertainties, enabling predictive analytics, and supporting applications.

Data fusion and data assimilation. Data fusion and data assimilation in the forest digital twin need to accommodate the spatial heterogeneity, nonlinear dynamics, and multi-sensor complexity of forest ecosystems. Classical approaches, such as the Kalman Filter, can be adapted to integrate dendrometer data, soil moisture probes, and multispectral or LiDAR observations into growth and carbon-cycle models (Joyce 2002; Lin et al. 2019; Puhm et al. 2020), though their assumptions of near-Gaussian error structures can be limiting in disturbance-prone (e.g. insect outbreaks, windthrow) forests. Ensemble-based methods, particularly the Ensemble Kalman Filter, are considered to be more powerful because they handle nonlinear processes and high-dimensional state vectors (Gao et al. 2011; Rochoux et al. 2015; Chen et al. 2023), enabling assimilation of forest canopy structure, biomass, and phenology from LiDAR, SAR, and optical satellites into models such as iLand and LANDIS-II. The ensemble approaches also support localised filtering, which is essential for forests with fine-scale variability in species composition, canopy structure, and microclimate.

More flexible techniques that do not rely on Gaussian assumptions, such as particle filters (Van Leeuwen 2009), are increasingly used when forest dynamics exhibit threshold behaviour or multimodality, such as regeneration and disturbance recovery. Particle filter is a Monte Carlo–based Bayesian method that builds on the principles of ensemble approaches by representing the posterior distribution of state variables with a set of weighted particles (Li et al. 2019). Particle filters have shown their good ability to predict the propagation of controlled fires and to significantly increase fire simulation accuracy (Silva et al. 2014). A multi-sensor fusion framework should combine spectral (multispectral, hyperspectral), structural (LiDAR), and temporal (e.g. flux towers, dendrometers) data using Bayesian hierarchical models, Gaussian processes, or hybrid machine learning–assimilation systems to improve observation operators and capture competition, phenology, and canopy radiative transfer in heterogeneous stands (Seiler 2025; Reichstein et al. 2019). Hence, all these methods enable near real-time updating of the forest digital twin while acknowledging the latency and uncertainty inherent in ecological sensing.

Machine learning. With the development of technology and computational power, machine learning has been used to train and process big data in forest ecosystems (Raihan 2023; Nie et al. 2022). Growth of forest biomass, tree mortality rates, or the spread of pests and diseases, for example, have been predicted based on historical data and near-real-time environmental data (Rocha et al. 2018; Bayat et al. 2019; Yang et al. 2024). Machine learning algorithms are also powerful in identifying different tree species and other key ecological features (Fisher et al. 2024; Reisi Gahrouei et al. 2024). This is essential for creating an accurate digital twin and sustainable forest management (Yang et al. 2024). Deep learning models are particularly effective for processing unstructured data, like imagery (Wang et al. 2021;

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Seydi et al. 2022). These models are trained to detect subtle patterns in satellite or drone images, such as identifying tree species or assessing forest vitality by quantifying leaf chlorophyll content. An average classification accuracy higher than 93% was found for the tree classification based on the 3D point cloud data (Zou et al. 2017). A novel deep learning model called CNN-BiLSTM for near-real-time wildfire spread prediction was used to capture spatial and temporal patterns (Marjani et al. 2024).

Hybrid model-data systems are foundational to truly 'dynamic' ecological twins (De Koning et al. 2023). Technologies such as Graph Neural Networks (GNNs) and Temporal Convolutional Neural Networks (TCNNs) can effectively model complex spatial relationships together with temporal dynamics in forest ecosystems (Shahriar et al. 2025). GNNs model the spatial structure of forests by representing trees, plots, or stands as nodes connected by ecological relationships such as competition, proximity, or hydrological flow. This allows the twin to capture spatial dependencies in processes like growth, mortality, pest spread, and fuel connectivity. TCNNs can model long-term temporal patterns, such as seasonal phenology, climate responses, and disturbance dynamics, by using time-series data from satellites, sensors, and inventories. GNNs and TCNNs used together can form a spatiotemporal modelling engine that continuously updates the digital twin as new data arrive, enabling realistic forecasting and scenario simulation (Annane et al. 2024; Huang et al. 2024). Semantic digital twin uses ontologies and reasoning to infer fire risks and resource allocations (Dao et al. 2025). This allows not just data fusion but also knowledge inference, enabling richer decision support (alerts, resource suggestions). Such studies advanced forest wildfire risk assessment by combining hybrid models, offering a scalable and robust framework for forest fire forecasting and proactive wildfire management under changing climatic conditions.

Cloud computing. Large-scale data lakes are often used to store data from various sensors, satellite imagery, and other sources. These lakes provide a centralised, scalable storage solution for processing and querying massive amounts of environmental data. Cloud computing, a new high-performance computing paradigm designed to tackle computation-intensive problems, becomes a promising solution technique (Yang et al. 2010; Zhang et al. 2016). Cloud platforms such as Amazon Web Services, Microsoft Azure, and Google Earth Engine (GEE) offer computing power to run the data processing and machine learning models that power the digital twin (Moore, Hansen 2011; Padarian et al. 2015; Yang et al. 2019). These platforms can handle the storage and near-real-time processing of diverse datasets from IoT devices, satellites, and other sources. Based on GEE, a feasible cloud computing method can be used to solve the intensive computational challenges in the analysis of massive remotely sensed data for aboveground biomass estimation (Yang et al. 2019). A generalised approach was introduced for mapping crop yields with satellite data by using GEE (Lobell et al. 2015). Technologies like data integration platforms and Application Programming Interfaces (APIs) are used to ensure that all data is accurately merged and synchronised in near real-time (Domdouzis et al. 2010; Bowie et al. 2014). As forest management often involves multiple stakeholders (governments, companies, conservation organisations), blockchain technology is being explored to ensure data integrity and transparency (Sasaki, Abe 2025). Blockchain can be used to verify and record forest data in an immutable ledger, ensuring that all participants in forest management systems have access to reliable, unaltered information (Buonocore et al. 2022; Varveris et al. 2025). Managers and practitioners interested in using blockchain in the forestry sector, however, should consider the potential risk of data breach and cyberattack (He, Turner 2022).

Visualisation and augmented reality. A digital twin is typically visualised in 3D to better represent the complex structures of a forest. GIS software, 3D modelling tools, and specialised forest simulation tools allow users to explore virtual models of forests and simulate various scenarios (such as LANDIS-II and iLand). Virtual reality and augmented reality are being explored to provide immersive experiences for forestry professionals and decision-makers (Chandler et al. 2022; Murtiyoso et al. 2023; Verstraete et al. 2025). With augmented reality, users could overlay digital information onto near-real-world forests, helping them visualise forest health, tree species, and management interventions directly in the field (Holm, Schweier 2024; Li et al. 2023; Qiu et al. 2023).

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APPLICATIONS OF THE FOREST DIGITAL TWIN

Forest management. The application of digital twin technology in forest management holds significant potential for the forest landscape and industry, offering innovative solutions to enhance monitoring, decision-making, and resource management (Zohdi 2024; Klippel et al. 2021). Forest digital twin developed through remote sensing data and forest inventory information offered valuable insights into the spatial dynamics of individual tree growth and forest structure in managed and protected forest areas (Nie et al. 2022; Murtiyoso et al. 2023). This is particularly relevant for forest management programs that aim to balance resource extraction with the preservation of biodiversity and ecosystem services. A forest digital twin was constructed by using remote sensing data, forest inventory data, and Cesium Digital Earth Engine (Qiu et al. 2023). This study provided a novel pattern for in-depth analysis of forest spatial structure, individual tree dynamic growth and human-digital twin interaction effects. The effects of thinning and pruning were also simulated. Furthermore, advanced models like Reinforcement Learning-based Adaptive Digital Twins could help forest managers understand the dynamic nature of forest ecosystems, providing insights into how forest ecosystems are evolving and how best to manage them using advanced IoT data and spatiotemporal modelling (Damaševičius, Maskeliūnas 2024). A methodology for developing a digital twin of Earth's forests has been proposed (Mõttus et al. 2021), crucial for managing the extensive forest resources and monitoring carbon sequestration across vast areas. A deep learning-based framework that accounts for location, crown area, and height for each individual tree from aerial images at the country level was provided (Li et al. 2022). This study lays the foundation for a global database, where every tree can have its digital twin and is spatially traceable and manageable.

Forest ecology. Forest digital twin can monitor carbon storage and sequestration, simulate the effects of climate scenarios on forest ecosystems, and help governments and organisations strategise forest preservation efforts to mitigate climate change. For instance, the iLand model (Rammer et al. 2024; Thom et al. 2024) has been demonstrated as a tool capable of constructing a digital twin of forest landscapes by simulating multi-decadal dynamics under alternative climate (a climate warming of 1 °C, or of 4.8 °C) and management scenarios (Anja 2024). Prototype forest digital twin uses LANDIS-II as the landscape-level simulation core, integrated with biodiversity models and optimisation workflows to support adaptive management decisions. The outputs from LANDIS-II have been used to generate immersive digital representations of future forest states, illustrating the utility of process-based models within embodied digital twin applications (Wallgrün et al. 2021). These dynamic forest models are needed in forest digital twin frameworks because they bridge the gap between raw data (e.g. from IoT sensors or satellites) and sophisticated simulations, allowing for near-real-time updates, risk mitigation, and decision support systems that go beyond static mapping or simple statistical tools. They embody the digital twin ethos of creating interactive, evolving virtual counterparts to physical forests, aiding in challenges like climate resilience and sustainable management (Buonocore et al. 2022). In short, they are not digital twin by themselves, but they serve as the simulation engine within the twin architecture. Additionally, forest digital twin frameworks like those developed for the Brazilian Amazon (Silva et al. 2023), which study greenhouse gas emissions, carbon sinks, and balance within complex forest ecosystems, could be adapted to the other diverse forest landscapes to enhance the understanding and management of their carbon dynamics.

Forest disturbance. By integrating near-real-time environmental data, a digital twin can simulate forest disturbance behaviour and predict risks, enabling more effective management and prevention strategies. For example, with growing concerns about the spread of pests like the spruce budworm, a digital twin was employed to simulate how these threats might affect forest dynamics and help devise targeted management strategies (Lv et al. 2022). A forest digital model was used to analyse fire behaviour using variables such as the rate of combustion and the time it takes for a species to be wholly burned (Sanchez-Guzman et al. 2022). The proposed digital twin also runs 500 times faster for online predictions than the original JULES-INFERNO model without requiring high-performance computing clusters (Zhong et al. 2023).

Digital twin frameworks, such as the one developed by Duality AI, simulate forest fires to detect them early and assess their severity and spread.

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By creating virtual models of forest environments, these simulations help predict fire behaviour, which is crucial for effective firefighting strategies and minimising environmental damage (Charles 2020). IoT-based systems have revolutionised forest fire detection by providing real-time data from remote areas (Mohanty et al. 2024). Wireless sensor networks, such as those using nRF24L01 modules, monitor environmental parameters like temperature, humidity, and smoke intensity (Anshad et al. 2023). These systems use tree or mesh topologies for data transmission, ensuring reliable and efficient communication. The potential of digital twin technology in wildfire management has been thoroughly reviewed (Li et al. 2024), highlighting its ability to integrate near-real-time environmental data to enhance fire prediction accuracy and inform proactive management strategies. Furthermore, Huang et al. (2024) provided a detailed overview of the technologies necessary for a forestwildfire digital twin, including fire detection, simulation, and prediction, offering a robust and comprehensive model for use in wildfire management. The concept of Forestry 4.0, which applies digital innovations to forest management, has also been explored in the context of forest fire detection, presenting a dynamic mechanism that recommends optimal detection strategies based on real-time IoT applications (Sahal et al. 2021). Furthermore, research into wildfire digital twin frameworks, such as those developed for the Susa Valley in Italy, highlights the potential for automatic extraction of remotely sensed data to enhance wildfire monitoring and response efforts (Zamari 2023).

The other cross-cutting themes. Monitoring changes in habitats and species distribution and modelling the effects of forest management practices on biodiversity can help identify conservation strategies for vulnerable species. The application of digital twin technology and remote sensing in forest biodiversity monitoring and management offers significant opportunities for forestry and conservation efforts. A prototype forest biodiversity dynamics digital twin has been used as a comprehensive platform for stakeholders to navigate complex ecological dynamics and make informed decisions (Afsar et al. 2024). Similarly, the Greece LIFE EL-BIOS project is developing a digital twin for biodiversity analysis (Karolos 2024).

The integration of Forestry 4.0 concepts and emerging technologies (Treeva 2025) is transforming timber harvesting, supply chain optimisation, and offering significant benefits for forestry. A prototype intelligent timber-harvesting system has been developed to create a fully integrated supply chain, from forest owners to timber buyers (Hoppen et al. 2024). However, practical reference experiments are still needed to refine its implementation. Advances in road maintenance monitoring also contribute to forest operations efficiency (Väätäinen et al. 2025); for instance, an automated system using consumer-grade optical sensors and a YOLOv5 model with StrongSORT tracking has been developed to detect and map potholes on forest roads, enabling proactive maintenance scheduling (Hoseini et al. 2023). Similarly, real-time data streaming from yarders (capturing machine movement, productivity, and fuel usage) has been shown to improve yarder design and operational efficiency, benefiting both manufacturers and forestry companies (Matthews 2021).

The broader forest supply chain is also evolving with the advancements of Industry 4.0, as highlighted by a systematic review examining how emerging technologies are reshaping logistics, monitoring, and production processes (He, Turner 2021). One such innovation is AI-powered woody debris detection, which offers a cost-effective alternative to traditional aerial surveys. By using freely available high-resolution imagery and AI-driven analysis, forestry professionals can efficiently monitor woody debris across forests, river catchments, and coastlines, reducing manual labour and operational costs (Katie 2025).

Additionally, the concept of the embodied digital twin has emerged as a transformative tool for forest education, communication, and decision-making. These virtual representations of real-world forest environments allow stakeholders to engage interactively with ecosystems, improving understanding and facilitating data-driven forest management and conservation strategies (Wallgrün et al. 2021). Unlike conventional models or large datasets, digital twins integrates artificial intelligence and domain knowledge, continuously aligning with real-world conditions to provide dynamic, near real-time insights into forest dynamics (de Koning et al. 2023). These interactive platforms could support policymakers, researchers, and forestry professionals in making informed decisions, ensuring sustainable forest management in response to increased challenges and economic demands.

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POTENTIAL CHALLENGES

Despite the current progress and advancements, most forest digital twin implementations remain at the pilot or experimental stage, with operational deployments still relatively rare. Existing applications demonstrate considerable promise, yet they are typically limited in spatial extent, data availability, or temporal continuity. Transitioning these proof-of-concept systems to scalable, landscape-level applications exposes several fundamental technical and methodological constraints.

Data-related issues. A forest digital twin serves as a dynamic virtual replica of forest ecosystems, integrating multi-source data, growth/disturbance simulations, and near-real-time feedback to support applications like sustainable management, biodiversity monitoring, and disturbance recovery prediction. However, it encompasses significant uncertainties across layers: sensor uncertainty, model-parameter uncertainty, structural uncertainty, and methodological uncertainty (Sasaki, Abe 2025; Qiu et al. 2023). Sensor uncertainty stems from noise, bias, and incomplete coverage in remote-sensing and *in situ* measurements, such as LiDAR occlusion, atmospheric effects in optical imagery, or drift in ground sensors, which propagate into estimates of biomass, canopy height, and fuel moisture (Wulder et al. 2008; Zolkos et al. 2013). Model-parameter uncertainty reflects imperfect knowledge of key ecological parameters, including allometric coefficients, species-specific growth rates, and fuel-moisture relationships, all of which vary across space, time, and forest types (Dietze et al. 2014). Structural uncertainty arises because ecological and fire-behaviour models simplify complex processes such as competition, disturbance, regeneration, and radiative transfer, leading to systematic deviations between modelled and real forest dynamics (Fisher et al. 2018). Methodological uncertainty is introduced by the choice of data-fusion or assimilation algorithms (e.g. Kalman filters or particle filters), each of which makes different assumptions about error distributions, nonlinearity, and computational approximations (Evensen 2003; Van Leeuwen 2009). Overall, these uncertainties shape the reliability of the forest digital twin and highlight the need for transparent, adaptive, and well-validated modelling frameworks.

The need for computation. Building and maintaining a forest digital twin at large spatial scales requires substantial computational resources because they must integrate high-resolution remote sensing, continuous sensor streams, and complex ecological models in near-real time (Tagarakis et al. 2024). The challenge becomes greater when spanning diverse forest ecosystems, where heterogeneous tree species compositions, disturbance regimes, and environmental conditions demand customised parameterisation and frequent recalibration. As a result, large-scale forest digital twins often face significant burdens in data processing, model synchronisation, and high-performance computing infrastructure (Aydin, Oktug 2024; Agrawal et al. 2022).

Near-real-time monitoring. Continuous data collection and processing for forest digital twin rely on robust sensors and computational infrastructure, which is often difficult to establish or maintain in remote or expansive forest regions (Buonocore et al. 2022). Limited power supply, unstable network connectivity, and harsh environmental conditions (e.g. heavy snow, storms) can disrupt sensor performance and impede real-time data transmission. These constraints hinder the reliability and completeness of the digital twin, especially in areas where deploying technology is logistically challenging.

Coordination. Unlike industrial or urban digital twins, a forest digital twin faces significant coordination challenges because governance, data sovereignty, and incentives for data sharing are deeply fragmented across public agencies, private companies, and community monitoring groups. Forest Digital Twin Component (part of the European Space Agency Digital Twin Earth program), for example, is developed by a consortium of six partners from Finland, Portugal, Czechia, Germany, and Spain during 2024–2026, illustrating both the promise of integrated forest modelling and the need for robust multi-stakeholder coordination to ensure interoperability, trust, and equitable benefit distribution (Mõttus et al. 2021). Governance is complicated by the absence of a single authority capable of imposing standards, forcing projects to choose between centralised, federated, or consortium models. Data sovereignty adds another layer of complexity: community IoT networks resist extraction without consent, and private actors fear exposing competitive or regulatory-sensitive information, reflecting wider national concerns about digital sovereignty and control over data

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flows (Haraguchi et al. 2024; Joel 2025). Incentive structures are also misaligned, since data sharing imposes costs and risks on contributors while benefits are diffuse; successful initiatives therefore rely on reciprocity, recognition, regulatory alignment, and technical mechanisms such as federated architectures and blockchain-based provenance, which are increasingly emphasised in digital twin research for environmental and forest systems (Sasaki, Abe 2025; Buonocore et al. 2022).

CONCLUSION

A fully developed forest digital twin extends far beyond improving existing management practices. By supplanting static, interval-based planning with a dynamic cycle of observation, simulation, and evidence-driven adjustment, the digital twin establishes a continuously operating feedback system that links near real-time conditions to predictive modelling and operational decision-making. This transition marks a substantive shift toward adaptive governance, in which management strategies are iteratively tested, validated, and recalibrated in response to evolving ecological and climatic signals. In this respect, the digital twin represents not merely a technological enhancement but a structural transformation in the way forest systems are conceptualised, monitored, and stewarded across temporal scales.

Future research will need to address several unresolved challenges to realise this transformative potential. Methodologically, there is a pressing need for robust frameworks that integrate heterogeneous data streams, ranging from high-frequency sensor observations to long-term inventory records, while explicitly quantifying uncertainty across spatial and temporal scales. Advancing data assimilation techniques tailored to forest dynamics, particularly those capable of reconciling asynchronous or incomplete observations, remains a critical frontier. At the modelling level, further work is required to couple process-based, statistical, and machine-learning approaches in ways that preserve ecological interpretability without sacrificing predictive performance. Finally, the governance implications of digital twin adoption warrant sustained examination, including questions of data ownership, institutional capacity, and the co-production of knowledge with practitioners and local communities. Addressing these research directions will be essential for moving from promising prototypes to operational digital twins that can support resilient, evidence-based forest management in an era of rapid environmental change.

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Received: June 5, 2026
Accepted: August 10, 2026
Published online: August 28, 2026