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REVIEW

Applications of Artificial Intelligence in Forest Operations Engineering Research: A Systematic Review

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Abstract

Purpose of Review This systematic review aims to map the current landscape of Artificial Intelligence (AI) applications within forest operations engineering research. It seeks to identify dominant AI techniques, common data sources, key problem domains, demonstrated strengths, persistent challenges, and future research trajectories by analyzing a curated dataset of 173 scholarly papers, providing a comprehensive overview of AI's transformative role in this specific scientific topic.

Recent Findings Current research demonstrates a significant surge in AI adoption in forest operations engineering, particularly since 2017. Machine learning (ML), especially deep learning methods like Convolutional Neural Networks (CNNs), frequently combined with remote sensing data from satellites, drones, and LiDAR, is pivotal. These tools are applied to optimize wood supply chains, assess ergonomic risks, and manage forest infrastructure by accurately extracting and updating road and skid trail networks. Furthermore, tasks such as tree species classification and 3D forest reconstruction are increasingly utilized in operational contexts, specifically to plan extraction trails in single-tree selection harvesting and to feed Decision Support Systems (DSS) for optimal harvesting system selection.

Summary AI enables more accurate and efficient solutions to complex forest engineering challenges. However, practical implementation remains constrained by the "black box" nature of AI, poor model generalizability across diverse ecosystems, and heavy computational demands and large datasets required—which are often incompatible with a typical forest manager's workflows and budget. Future advancements must focus on explainable AI, external validation, benchmarking, and user-friendly, edge-computing systems to transition AI from theoretical research to practical, operational forestry tools. These will further enhance sustainable forest management and engineering practices, guiding impactful future research and application.

Keywords Machine Learning · Deep Learning · Wood Harvesting · Forest Operations · Tree Species Classification · Forest Management · Convolutional Neural Networks · Road Extraction

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Introduction

Forest ecosystems, covering approximately 31% of the global land area, are indispensable for planetary health [1]. They provide critical ecosystem services such as climate regulation, biodiversity conservation, soil and water protection, and yield socio-economic benefits through timber and non-timber forest products [1]. However, these vital resources face unprecedented pressures from climate change-induced disturbances like intensified windthrow and droughts, deforestation driven by agricultural expansion and urbanization, the spread of invasive pests and diseases, and in some cases unsustainable forest management practices [2]. The effective and sustainable management of these complex and dynamic systems is therefore a global imperative. The move toward sustainable management is

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fundamentally executed through forest operations—the physical interface where management objectives meet the ecosystem. Consequently, the engineering of these operations must evolve to handle the increasing data complexity of modern forestry. This necessitates innovative approaches for monitoring, assessment, and decision-making that can address these multifaceted challenges [3]. Traditional approaches within forest operations engineering research and management, while foundational, often encounter limitations in terms of scale, cost-effectiveness, the speed of data acquisition and analysis, and the ability to handle the increasing complexity and volume of data required for holistic ecosystem understanding [4].

Artificial Intelligence (AI) has emerged as a transformative technological paradigm across numerous scientific disciplines [5]. Broadly defined as the capability of a computer system to mimic human cognitive functions such as learning, problem-solving, and pattern recognition [6], AI offers powerful tools to analyze complex data, discern intricate patterns, make accurate predictions, and optimize multifaceted processes [7]. Within this context, forest operations encompass a wide array of forest management activities related to the plantation (or natural regeneration), treatments, restoration, harvesting, and are important for the sustainable utilization of forest ecosystems, aiming to reconcile economic needs with the fundamental objective of reducing waste and emissions while minimizing impacts on the environment's structures and functions [4]. Similarly, forest engineering can be understood as a discipline that applies engineering principles and techniques to the planning, design, construction, operation, and management of forest-related activities, including harvesting, road construction, transportation, and overall resource management, with a focus on efficiency, safety, and environmental sustainability [2]. The integration of AI into forest operations and engineering presents a significant opportunity to revolutionize how data related to these operations, and the broader forest ecosystem is collected, processed, analyzed, and translated into actionable insights, thereby overcoming many traditional limitations. By harnessing a diverse suite of AI techniques—such as machine learning (ML), where systems learn from data without explicit programming [7]; computer vision (CV), which enables computers to "see" and interpret visual information [8, 9]; natural language processing; and optimization algorithms—researchers and practitioners can unlock new levels of understanding from diverse data sources. These sources range from vast archives of high-resolution satellite and drone imagery [9, 10] and LiDAR point clouds [11, 12] to ground-based sensor networks, operational records from increasingly digitized supply chains [13], and even data from worker-operated equipment [14].

The application of AI in forest operations and engineering is not merely a conceptual prospect but an actively advancing field [5], characterized by a rapidly growing body of literature that showcases its practical utility and limitations [5, 6]. AI is being employed to enhance the accuracy and efficiency of forest inventories [15], classify lumber [16], automate the extraction and updating of forest road networks [17], map skid trails for soil disturbance monitoring [18], optimize wood supply chains [19], recognize activity in forest operations [20], and classify tree species with high precision [21]. Conceptual papers within the field have already begun to map out the achievements and future directions for forest operations and engineering in this new era [2] and explore the challenges of integrating information systems into forestry wood supply chains [22]. Understanding the scope, prevalent methods, tangible achievements, and persistent challenges within this dynamic domain is essential for guiding future research, fostering innovation, and promoting the practical implementation of AI for sustainable forest management and operations.

This systematic review aimed to provide a comprehensive analysis of the current state of AI applications strictly focused on forest operations and engineering research. Based on a curated dataset of 175 scholarly articles, the specific objectives were to:

- characterize the reviewed literature in terms of publication trends, geographical focus, and overarching themes;
- identify and categorize the primary operational domains where AI is making significant contributions (e.g., harvest planning, road infrastructure, ergonomics, and supply chain logistics);
- delineate the prevalent AI techniques and input data types used in operational studies;
- synthesize the reported strengths of AI implementations alongside critical operational adoption barriers—such as computational requirements, data availability, and model transferability and;
- outline actionable future research directions to bridge the gap between theoretical AI models and practical implementation by forest engineers.

By synthesizing this diverse body of information, this review can offer valuable insights for researchers developing new AI methods, practitioners seeking to implement AI tools, policymakers shaping forestry and technology strategies, and technologists exploring new frontiers in AI applications in forest operations and engineering research.

Materials and Methods

Literature Search Strategy

This systematic review was based on a dataset comprising 220 scholarly articles related to the methodological approach to systematic review, foundational studies on AI and the application of AI in forest operations and engineering research that were identified from databases and registers. To ensure a comprehensive and reproducible review, a systematic literature search was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [23]. The benchmarking of model performance used a narrative synthesis approach, as the heterogeneity of evaluation metrics across studies precluded a formal statistical meta-analysis. The literature search aimed to identify peer-reviewed original research articles, review articles, and conference proceedings detailing the application of AI techniques within an operational engineering context. A systematic search was performed across several major electronic scientific databases, including Scopus, Web of Science (Core Collection), IEEE Xplore Digital Library, ACM Digital Library, PubMed, and Google Scholar (for an initial broad sweep and to identify grey literature, though primarily focusing on peer-reviewed outputs from other databases). The search covered publications published from January 2002 to March 2026.

Search queries were structured using a combination of Boolean operators to link computational algorithms with specific operational forestry domains. The primary search string employed across the electronic databases was:

(TITLE-ABS-KEY("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Computer Vision" OR "Neural Network" OR "Expert System") AND TITLE-ABS-KEY("Forest Operations" OR "Forest Engineering" OR "Timber Harvesting" OR "Logging" OR "Wood Supply" OR "Silviculture") AND TITLE-ABS-KEY("Remote Sensing" OR "LiDAR" OR "UAV" OR "Routing" OR "Road Extraction" OR "Ergonomics" OR "Decision Support" OR "Supply Chain")).

To strictly align with the engineering scope of this review, NOT operators were subsequently applied to exclude non-operational ecology and pathology subjects: AND NOT ("Wildfire" OR "Smoke" OR "Pest" OR "Disease").

Study Selectionand Data Extraction

The selection process for the studies involved multiple stages [23], summarized in a PRISMA flow diagram (Fig. 1). The first stage was the *duplicate removal and initial data screening*. After compiling results from all relevant databases, duplicate entries were identified and removed. This was accomplished using Zotero reference management software or by conducting manual checks for smaller datasets. The second stage was *title and abstract screening*, where articles were assessed against predefined inclusion and exclusion criteria. The third stage involved *full-text assessment*, where the remaining articles were examined in detail to confirm their eligibility and ensure that they met all methodological and thematic requirements for inclusion in the review.

Inclusion Criteria

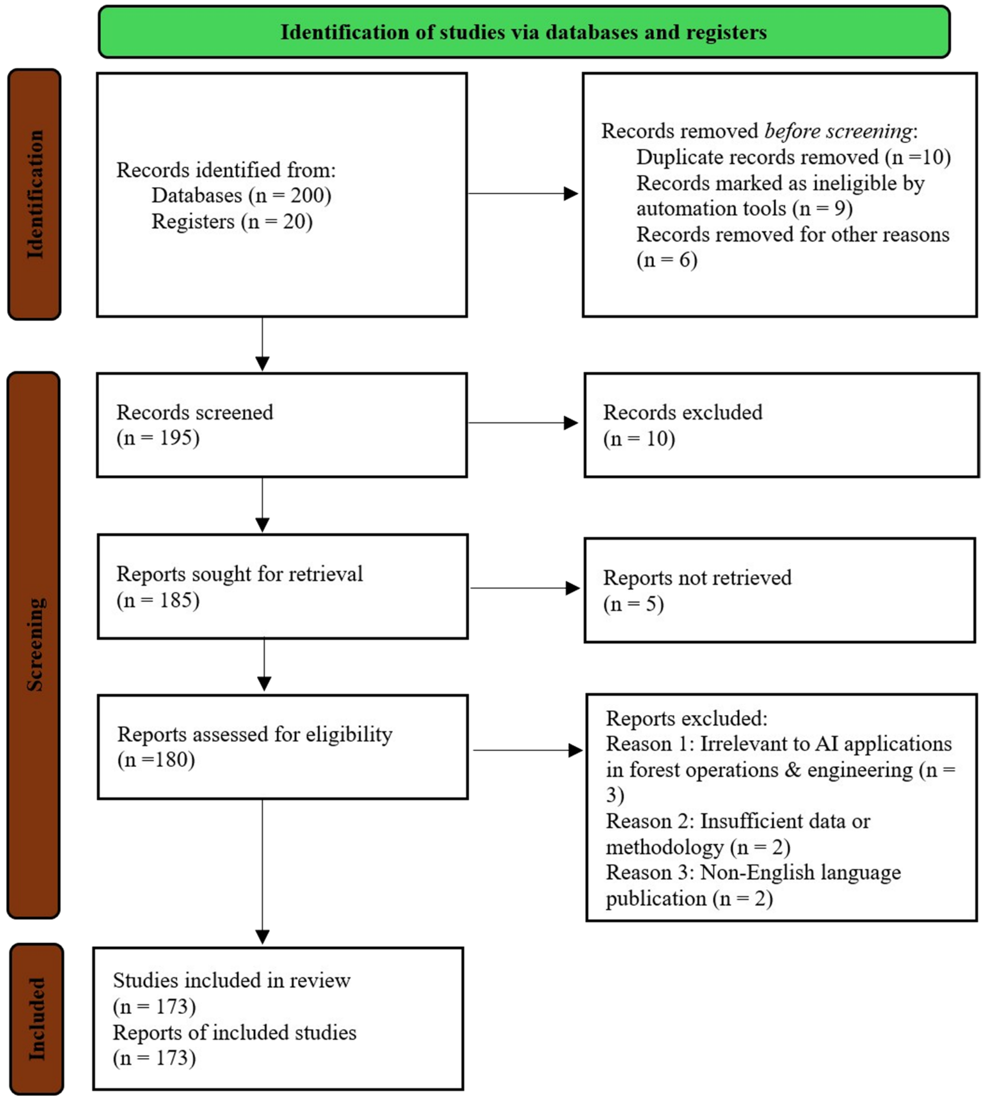
The inclusion criteria specified that studies must: (a) involve the application, development, or conceptual discussion of AI or ML models; (b) address a problem strictly within forest operations and engineering (e.g., harvest planning, road infrastructure, supply chain logistics, and worker safety); and (c) be published in English.

Exclusion Criteria

On the other hand, the exclusion criteria explicitly removed studies where AI was applied to general forest inventory, ecological monitoring, forest pathology (pests and diseases), or wildfire detection, unless the study provided a direct, explicit link to operational decision-making (e.g., using species classification to plan harvesting extraction trails). Editorials, commentaries, book reviews, patents, and non-peer-reviewed grey literature were also removed, unless these sources were specifically targeted and justified. Additionally, studies were excluded if AI was mentioned only peripherally and did not constitute a core component of the methods or findings related to forest operations and engineering. Studies that focused solely on agricultural crops without a significant forestry or agroforestry component were also excluded. Lastly, studies that were not available in full text after a reasonable search effort were not included.

In total, 45 studies were considered ineligible and excluded from the review. For all the 175 articles included in this study, relevant data were systematically extracted and organized into a structured format using an Excel spreadsheet. The data collected for each article included several key elements: the author(s) of the study, the year of publication, the name of the journal, and the title of the paper. Additionally, information regarding the country or countries of study was noted, along with details about the type of task being addressed, the type of input data (e.g., LiDAR, satellite imagery, wearable sensors), and the

Fig. 1 The PRISMA flow diagram showing the stages of literature search and study selection



algorithms employed. The extraction process also included information about the architecture of the models, parameter tuning, and the platform or programming language used for the implementation of the AI techniques. Furthermore, the type of problem each study aimed to address was documented, along with the metrics used for evaluation, including training metrics, validation metrics, and testing metrics. The maturity level of each study was assessed, and explanations and interpretations of the findings were recorded. Additionally, strong points, limitations, and directions for further research were extracted. Lastly, links to both the paper and the abstract were compiled to facilitate easy access to the original sources. This comprehensive data extraction process ensured that all pertinent details were captured to support subsequent analyses and synthesis of the findings.

Thematic Synthesis and Classification

A thematic synthesis and classification approach was employed to identify recurring themes and patterns across the dataset. The main aim of this synthesis was to construct a cohesive narrative that explores how different AI techniques are applied to tackle various problems in forest operations and engineering. This narrative also highlights the different data sources used, along with the outcomes, benefits, and challenges that arise in the application of these technologies in the field. The process began with the initial categorization of research papers, which were broadly grouped based on their primary focus. These categories included conceptual reviews, remote sensing applications, operational optimization, and health monitoring. Following this, common AI methods were identified. This grouping was based on the “type of algorithm” and “model architecture”. The identified methods encompassed a range of techniques, including Convolutional Neural Networks, Support Vector Machines, Random Forests, general Deep Learning, and traditional Machine Learning approaches.

In addition to grouping by methodology, an identification of various forest operations and engineering application domains was conducted. These domains were derived from the “type of task” and “title of the paper” fields and included areas such as species classification, harvesting system selection, defect analysis, supply chain management, and ergonomic assessment. The article classification approach was implemented as follows. Articles were assigned to an AI technique if the use of that technique was explicitly mentioned or implied within the article, such as the application of Convolutional Neural Networks (CNNs) for deep learning-based image analysis. Articles that lacked a clear AI technique, such as those found in general reviews or forestry operations without AI, were noted but excluded from technique-specific rows; however, they were grouped under “Other AI Techniques” if unspecified machine learning or related methods were involved. A tabulation was created to capture these data types, which included satellite imagery, drone imagery, LiDAR, sensor data, and textual data. The synthesis process also involved an analysis of predominant input data types. The insights gathered from “strong points”, “limitations”, and “directions for further research” were synthesized to assess the broader impact, challenges, and future direction of artificial intelligence in forest operations and engineering research.

Data Visualization Software

The processed data were used to generate visualizations using Python (v3.12), implemented in the PyCharm Community Edition 2025 (available online at https://www.jetbrains.com/pycharm/download/?section=windows (accessed on 2 November 2025)).

Results

A total of 175 articles were selected for this study, including 2 foundational papers used in the Introduction and Methodology. Therefore, 173 articles were included in the metadata analysis. The analysis of 173 included articles revealed a vibrant and diverse application of AI in forest operations and engineering research, spanning conceptual frameworks to highly specific technical implementations. The dataset comprises 7 articles focused on “Definitions and Concepts” and 166 articles on “Applications”. The initial 7 papers provided main reviews and outlooks on forest operations and engineering [2, 4], challenges in the field [3], wood supply chain risks [19], forestry ergonomics [14], information systems [22], and the role of AI in sustainable supply chains [13]. These set the stage for the diverse applications that follow.

Publication Trends

The years of publication range from 2002 to 2026 (Fig. 2). A notable surge in publications is observed from 2016 onwards, culminating in a prominent peak in 2020 (25 publications). Following a brief dip, the trend demonstrates sustained high volume through 2022 (20 publications) and concludes with a robust upward trajectory into 2025 (20 publications). This distribution indicates a rapid, accelerating adoption of AI in operational forestry and a strong contemporary research focus in addressing complex logistical and engineering challenges. By the first quarter of 2025, the publication trend indicates a sustained high level of research interest. While the

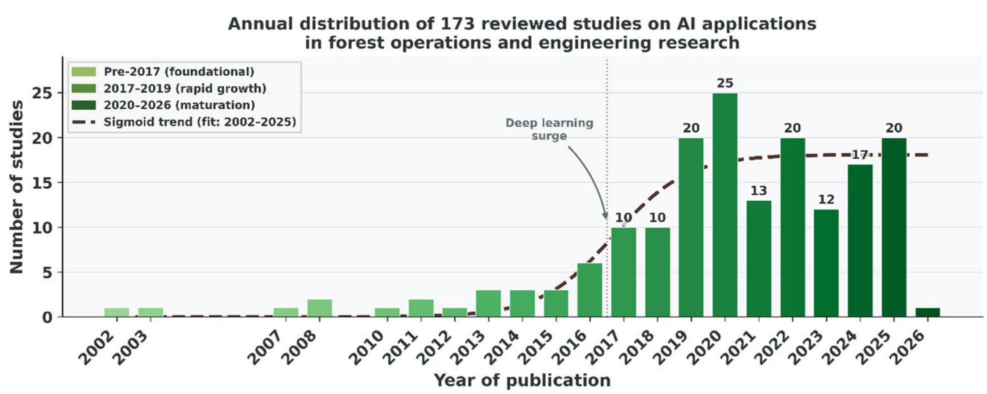


Fig. 2 Annual distribution of the 173 reviewed studies on AI applications in forest operations and engineering research (2002–2026). Bar colors indicate growth phases: light green = foundational period (pre-2017); medium green = rapid-growth phase (2017–2019); dark green = maturation and consolidation phase (2020–2026). The dashed brown curve represents a sigmoid trend line, excluding 2026 (partial year), which better illustrates the saturation and growth phases of AI research in this field. The vertical dotted line at 2017 marks an inflection point coinciding with the widespread adoption of deep learning frameworks and the proliferation of high-resolution UAV and LiDAR platforms

volume showed a slight stabilization after the 2020 peak, the current trajectory suggests an accelerating output as new AI frameworks are adopted. The trajectory continues into 2026, with studies already demonstrating high-accuracy automated postural assessment [24] and operational monitoring in mechanized forest operations [25, 26]. Seventeen other studies indicate that the interest in Forestry 5.0 concepts is increasing, which highlights the significance of AI in addressing engineering and logistical problems of today.

Geographical Focus

The recent surge in publications focusing on the applications of artificial intelligence (AI) in forest operations and engineering indicates a global interest in this field. However, this interest is accompanied by significant concentrations of research activity and focus within specific countries and regions [2, 3, 7, 11, 13, 15, 16, 19, 20, 22, 27–43]. Of the 173 studies analyzed, 147 provided extractable country-level data (comprising 107 single-country and 40 multi-country studies), while 19 lacked unambiguous attribution (primarily conference proceedings). As shown in Fig. 3, the USA (n = 23) and China (n = 22) are the leading contributors to the existing body of research, with Canada notable as a strong third contributor. Moreover, among the single-country studies, the USA and China emerge as the nations where the highest volume of research is being conducted or from which the primary datasets are sourced. This trend suggests that AI applications in forest operations and engineering research are often tailored to meet specific contexts, challenges, or datasets pertinent to individual countries.

The data also revealed key countries that are the focus of research activities in this domain. Moreover, there appears to be a limited number of studies that adopt a broader regional or multi-country focus. Of the reviewed studies, only 40 feature a multi-country collaborative approach, and those with a very broad regional scope, such as studies focusing on the “Northern Hemisphere,” are notably rare, with only one such study identified. When multi-country studies do occur, they often involve collaborations between researchers from China and the USA, highlighting strong ties between these two nations in this research area.

In addition to these leading contributors, several European countries, including Germany, Spain, Finland, and the UK, as well as Asian countries such as South Korea and India, demonstrate a strong presence in the list of top contributors. This indicates that active research communities exist within these nations. Romania has also emerged as a notable contributor, with a growing cluster of studies focused on automated monitoring, ergonomic assessment, and operational performance in forest and wood processing operations [24–26, 44–49]. While it is true that the top countries dominate the publication landscape, the inclusion of nations like Brazil and New Zealand among the prominent contributors underscores a broader, albeit concentrated, global engagement in this specific research area.

Additionally, Europe and Asia emerge as the leading regions in terms of publication contributions. Europe benefits from the combined efforts of several actively publishing countries, while Asia’s prominence is largely influenced by China’s substantial output, along with contributions from India, South Korea, and Japan.

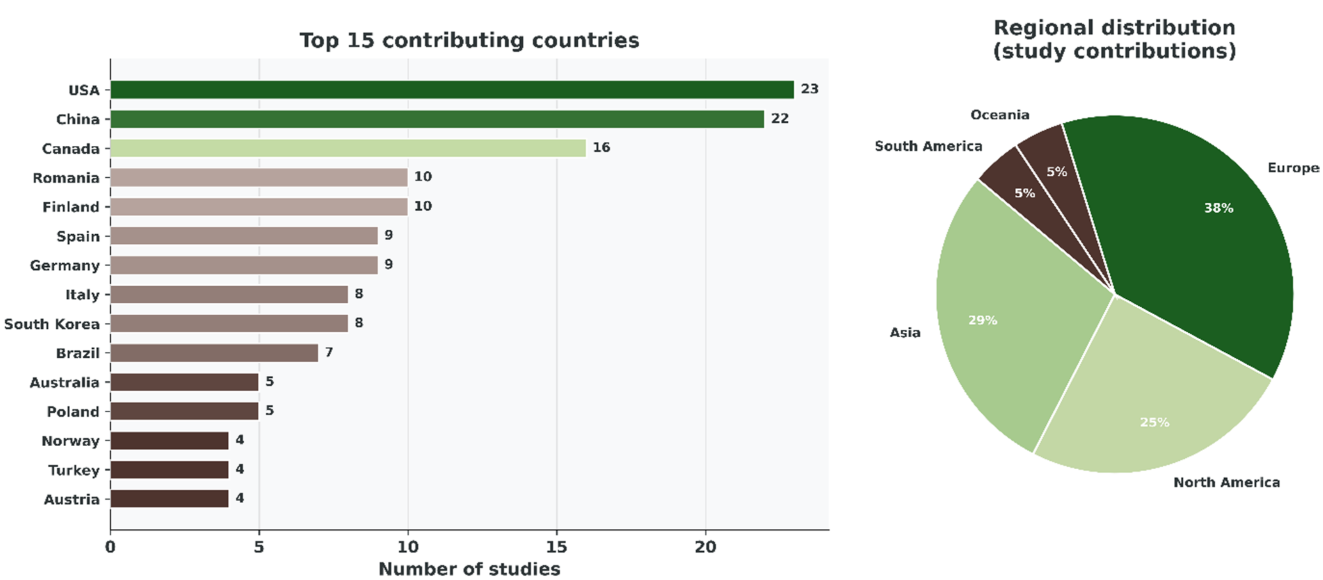


Fig. 3 Global distribution of AI research in forest operations and engineering. (Left) Top 15 contributing countries by number of studies. (Right) Regional proportions of publication output across the full dataset (n=173). The USA (n=23) and China (n=22) emerge as the leading individual contributors, with European countries collectively representing approximately 30% of the reviewed literature

North America, primarily represented by the USA and Canada, is also identified as a significant contributor regionally. Additionally, South America and Oceania are beginning to show moderate levels of contribution, indicating that research activity in these areas is on the rise. In contrast, Africa's representation in the reviewed literature on AI applications in forest operations and engineering is notably minimal. This underrepresentation signifies a gap that could benefit from increased research attention and investment in the future.

Major AI Application Domains in Forest Operations and Engineering Research

The 166 application-focused papers identified in this review address a diverse range of forest operations and engineering problems, which can be broadly categorized into several key domains as illustrated in Fig. 4. Forest Resource Assessment (33%) and Ergonomics/Worker Safety (25%) represent the most mature and voluminous research areas.

Forest Resource Assessment for Harvesting and Operational Planning

Forest resource assessment emerged as a key application area, but in the context of this review, it is strictly linked to operational planning. Numerous studies have focused on identifying tree species using various data sources, including high-resolution imagery and orthophotos [29, 50, 51], multispectral and hyperspectral data [52], LiDAR and 3D point clouds [12, 21, 53–56], and bark images [30, 43, 57]. Common algorithms employed in these studies included Convolutional Neural Networks (CNNs), such as ResNet, AlexNet, and VGG16, as well as Support Vector Machines (SVMs) and Random Forests.

Another area of focus within forest resource assessment is the analysis of forest inventory, density, and structure. Artificial intelligence is used for tasks such as individual tree crown (ITC) delineation and segmentation [11, 53, 58–61], estimating stand height and tree density [33, 62], and conducting 3D forest reconstruction [63]. Primary data sources for these analyses include LiDAR point clouds and high-resolution imagery, which are processed using algorithms such as PointNet++, U-Net, and various segmentation techniques.

Deep learning models have also been employed for automated detection and extraction of forest roads from satellite or aerial imagery [27, 37]. This development aids significantly in accessibility planning and management. Additionally, AI plays an essential role in change detection and mapping, facilitating the monitoring of forest cover changes, deforestation, and land use modifications over time. This aspect is often tackled using time-series satellite data [62].

However, these applications are fundamentally relevant to forest engineering only when the outputs are utilized to make operational decisions. For instance, AI-driven species classification and 3D reconstruction are utilized to identify target trees in single-tree selection harvesting, subsequently using their spatial positions to plan optimal extraction trails and minimize residual stand damage. Furthermore, these metrics serve as critical inputs for Decision Support Systems (DSS) aimed at selecting the most appropriate harvesting systems based on stand density and terrain [64]. The transition from general inventory to AI-driven species identification and 3D reconstruction allows for 'precision harvesting' strategies. By integrating these classification outputs into operational Decision Support Systems (DSS), extraction trails can be mathematically optimized based on

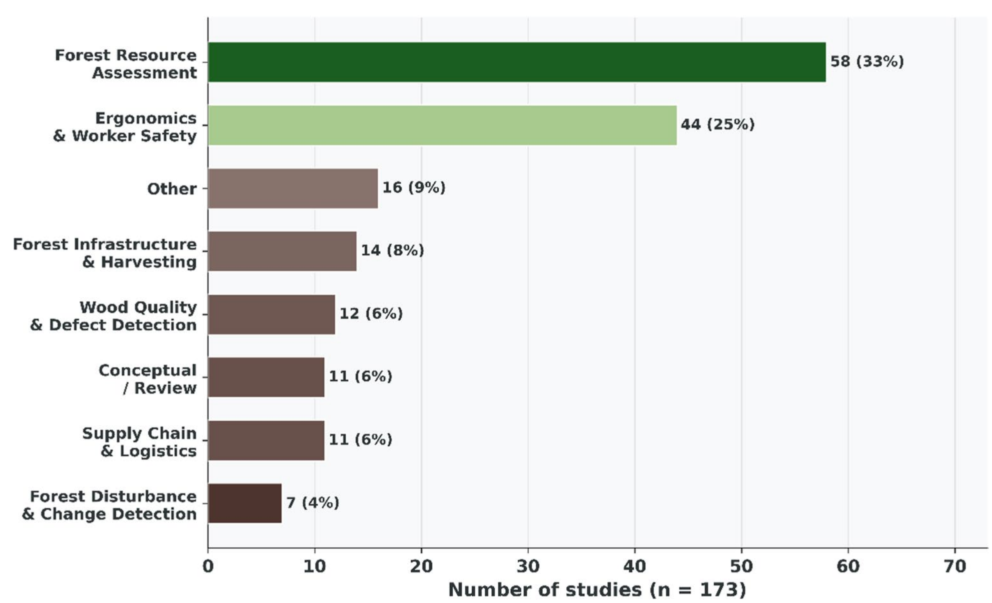


Fig. 4 Distribution of reviewed studies across eight thematic application domains. Percentages represent the proportion of the full dataset ($n = 173$). Forest Resource Assessment dominates the literature (33%), followed by Ergonomics and Worker Safety (25%). Forest Infrastructure, Harvesting, and Disturbance Detection collectively account for 12% of studies, representing the most operationally focused engineering sub-sectors

the exact value and spatial position of target stems, thereby reducing soil compaction and minimizing residual stand damage [54, 64] (see Table 2 for synthesis).

Forest Infrastructure, Harvest Planning, and Logging Impact Monitoring

An important and rapidly expanding domain in forest operations engineering is the use of AI for the automated detection of forest road networks, harvest planning, and monitoring machinery impacts. AI models, particularly CNNs and U-Net architectures applied to LiDAR data, provide a clear link to operational logistics. Recent advancements have successfully utilized hybrid classification to detect forest roads [65] and estimate roadway widths [66, 67]. To overcome manual mapping constraints, deep learning tools like ALSroads [17] and CNN-based methods utilizing LiDAR data [27, 37, 68] have been successfully applied to detect and update forestry road networks.

Beyond infrastructure, AI is revolutionizing harvest planning and monitoring. Machine learning is now used to develop automated operational logging plans that consider multi-criteria optimization [69]. Following extraction, deep learning models applied to UAV-based LiDAR successfully segment skid trails and evaluate machinery-induced soil disturbance [18, 70]. Furthermore, AI and deep learning applied to satellite optical and radar time-series are increasingly relied upon to detect and map selective logging intensities and post-harvest structural degradation, offering forest managers robust tools to monitor operational compliance [71].

Moreover, AI is used in forest operations for damage assessment, such as assessing forest damage from windthrow [10], snow breakage [72], and other abiotic stresses for salvage logging operations. While windthrow [10] and snow breakage [72] represent ecological disturbances, their automated identification via AI is a critical requirement for forest operations engineering. These tools enable managers to rapidly map hazard zones and plan safe, efficient access routes for harvesting machinery, which is essential for the timely execution of salvage logging operations and the mitigation of economic loss in post-disturbance environments [10]. Beyond field operations, AI algorithms (CNNs and SVMs) are also applied to quality control in the timber industry, such as automating wood defect classification (knots, cracks) in lumber or logs [73, 74]. This is particularly relevant for salvage logging, where identifying internal defects early helps optimize the processing of disturbance-affected timber. In the context of salvage logging, the automated identification of structural defects (such as cracks or breaks caused by windthrow or snow) is a critical component of forest engineering, as it facilitates the rapid planning of salvage logging operations and the optimization of harvesting machinery deployment in hazardous post-disturbance environments.

Forest Operations, Logistics, and Ergonomics

AI significantly contributes to enhancing the efficiency and safety of forest operations. For supply chain optimization and logistics, AI models that incorporate discrete event simulations and operational research techniques are utilized for optimizing wood transportation, supply chain planning, and risk mitigation [15, 19, 75]. Machine learning has also been applied to monitor the operational performance of fixed infrastructure in the wood processing sector. For example, a robust model combining artificial neural networks and random forests, trained on triaxial acceleration data from a fixed-post multi-blade vertical sawing machine, achieved overall classification accuracy and F1-scores of 98.7% and 98.4%. This model proved invariant to sampling rates as coarse as 0.05 Hz, enabling cost-effective long-term performance monitoring [48].

Additionally, AI is employed to monitor forestry workers' activities and assess ergonomic risks [14]. By analyzing data from smartphones or wearable sensors, AI can detect unsafe postures or conditions [14, 20, 76]. Pose estimation and activity recognition algorithms play a key role in this aspect. Research also indicates the use of AI in the navigation of autonomous forestry machinery and log recognition for robotic handling [77].

Recent studies have advanced the automation of postural assessment and activity recognition in forest operations through machine learning. Using image embedding with pre-trained CNN models (Inception V3 and SqueezeNet), posture and action classification in motor-manual chainsaw work achieved cross-validation accuracies of 84% and 89%, respectively, demonstrating the feasibility of transfer learning for ergonomic assessment [44]. A direct comparison of machine and human reliability in OWAS assessment found that a ResNet-50 model was 19 to 53 times faster than human raters while achieving comparable agreement (Fleiss' kappa = 0.28–0.49), underscoring the efficiency gains of deep learning in occupational health workflows [45]. Building on this, a ResNet-50 model augmented with computer-generated connected body keypoints achieved an exceptional accuracy and F1-score of 99.8% in OWAS class prediction from forestry images, highlighting that image–skeleton fusion is a highly effective strategy for automated postural classification [24].

Activity recognition in forest operations has also been advanced through multimodal sensor data. A neural network trained on combined accelerometer and noise dosimeter signals from chainsaw work distinguished working events from non-working events with a classification accuracy of up to 99.8%, demonstrating the viability of sensor-driven automated time studies without manual observation [26]. Neural networks applied to GNSS-derived data have been used to classify operational events in cable yarding (carriage moving uphill, downhill, or stopped) with an accuracy exceeding 98% [49], and in mechanized weed control operations using triaxial acceleration coupled with GNSS speed, achieving 91–93% classification accuracy across training and unseen test data [47]. GPS-derived features have also enabled the classification of planting events in willow cultivation machinery operations with neural network models reaching overall accuracy levels above 92% [46]. Collectively, these sensor-fusion approaches highlight the growing role of machine learning in automating operational monitoring across diverse forest and agricultural machinery, substantially reducing reliance on labor-intensive manual time studies [26, 46, 47, 49].

Predominant AI Techniques and Data Sources

AI Techniques

The integration of AI into forest operations and engineering research has notably advanced the field, as evidenced by the comprehensive compilation of 173 articles included in this study. Common AI techniques and their respective input data types are synthesized in Table 1; Fig. 5. CNN-based architectures dominate (38%), correlating with the heavy reliance on LiDAR and point cloud data (27%) for 3D structural analysis. This widespread adoption of CNNs reflects their adaptability to diverse data types, including high-resolution imagery, LiDAR, and video. The versatility of CNNs is particularly evident in the numerous studies centered on ecological and operational tasks, indicating a strong dependence on deep learning for detailed spatial analysis and real-time monitoring.

Support Vector Machines (SVMs) demonstrate a more niche yet consistent application, highlighting their effectiveness in specific classification and recognition tasks, although they are less pervasive compared to CNNs. Random Forest algorithms have emerged as a key method for activity and ergonomic assessments, underscoring a trend towards ensemble learning in human-centric and predictive applications within forestry. The PointNet and PointNet++ frameworks indicate a specialized focus on 3D point cloud processing, highlighting advancements in LiDAR-based forest inventory.

Optimization techniques, including Linear Programming (LP), Dynamic Programming (DP), and Discrete Event Simulation (DES), are steadily applied in logistical and planning domains, aligning with the industry's emphasis on efficiency in supply chain and operational management. Additionally, traditional Artificial Neural Networks (ANNs) continue to be relevant in predictive and biomechanical studies, demonstrating ongoing reliance on classical neural

Table 1 Common AI techniques and their primary application domains in forest operations and engineering research

No.	AI Technique	Primary Application Domains	References
1	CNNs (U-Net, UNet++, DeepLabV3+, LinkNet, MANet, HRNetV2, TransUNet, ResNet, YOLO etc.)	Tree species identification, damage assessment, tree recognition and semantic segmentation, skid trail segmentation and mapping, selective logging mapping, monitoring harvest-related forest disturbance, defect classification, road extraction, crown delineation, object detection, human action recognition, posture detection, deforestation prediction, tree height estimation, tree segmentation, ergonomic risk assessment, posture recognition, human pose estimation, joint detection and grouping	[9–12, 16, 18, 24], 27– [30], 35– [38, 40], 42– [45], 50– [52], 54– [61, 63], 72– [74], 76– [110]
2	SVMs	Forest road detection, species identification, defect classification, posture recognition, forest structural analysis	[68, 111]
3	Random Forest	Species identification, selective logging mapping, human activity recognition, predictive modeling, ergonomic risk assessment, posture recognition	[20, 71], 112– [118]
4	PointNet/PointNet++, Faster-RCNN, 3D-FCN	LiDAR point cloud classification, 3D object segmentation	[21, 32, 53, 119, 120]
5	Optimization (LP, DP, DES, Genetic Algorithms (GA))	Supply chain management, automated harvest planning, operational efficiency, ground plane detection, logging truck routing, harvesting system selection, skid trail mapping, soil disturbance evaluation	[13, 15, 64, 69, 70, 75], 121– [124]
6	ANNs conventional	Predictive modeling, knot classification, biomechanics, posture detection, fall risk prediction	[26, 31], 46– [49, 125, 126]
7	Other AI Techniques (general ML, CV, fuzzy logic, Bayesian networks, k-NN, LLMs, IoT, XAI etc.)	Posture estimation, ergonomic risk assessment, human activity recognition, tree segmentation, wood defect detection, fuzzy logic, macro-postural classification, image processing, automated time study, general operational analysis, forest road detection, updating vectorial maps, selective logging monitoring, deforestation prediction, forest structural analysis, road extraction, fall risk prediction, growth prediction, sustainable management, robotics, designing access solutions	[7, 8, 14, 17, 19, 22, 25, 33, 34, 39, 41, 62], 65– [68, 80], 127– [175]

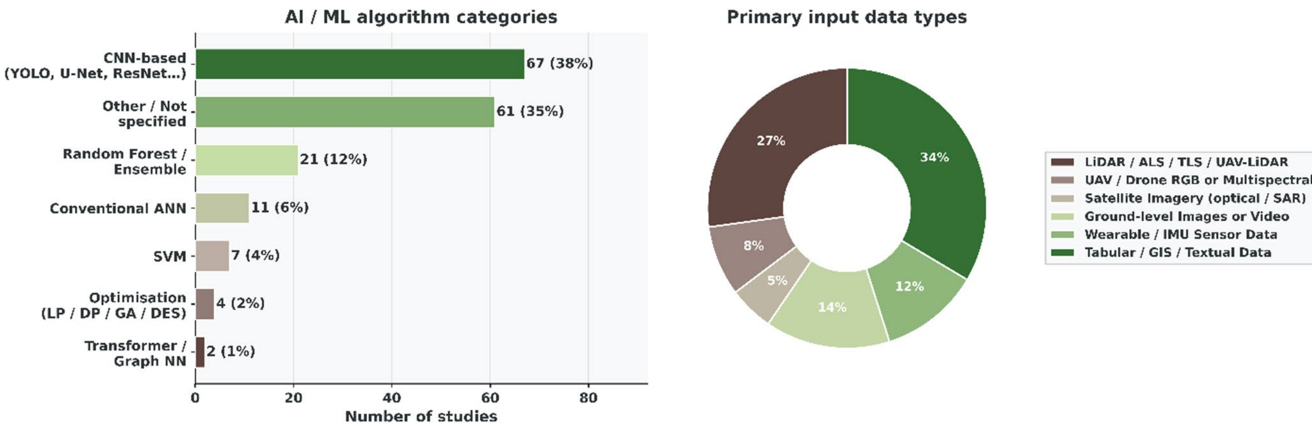


Fig. 5 Synthesis of AI/ML algorithm categories and primary input data types across the 173 reviewed studies. *(Left)* Number of studies per AI/ML algorithm category, showing the dominance of CNN-based architectures (38%). *(Right)* Distribution of primary input data types: Tabular/GIS/Textual Data constitutes the largest share (34%), followed by LiDAR/ALS/TLS/UAV-LiDAR (27%), Ground-level Images or Video (14%), Wearable/IMU Sensor Data (12%), UAV/Drone RGB or Multispectral (8%), and Satellite Imagery optical/SAR (5%)

approaches alongside modern methods. Furthermore, the adoption of automated time study methods for timber harvesting illustrates an emerging trend toward automating workflow analysis, thereby expanding the scope of AI applications in the field.

A diverse range of other AI techniques is also observed, with a significant emphasis on posture estimation and ergonomic risk assessment, indicating a growing concern for worker safety and health in forest operations. Human activity recognition and tree segmentation studies highlight the expansion of AI into both human and environmental monitoring, while wood defect detection underscores quality control efforts. The presence of fuzzy logic, macro-postural classification, and image processing suggests a blend of traditional and innovative approaches to address complex challenges. General AI applications and methodological frameworks provide a foundational layer, supporting the development of specialized techniques, while forestry-specific studies emphasize the contextual challenges driving these technological advancements. Overall, this comprehensive analysis reveals a dynamic evolution in AI applications, with a clear shift toward deep learning and a balanced integration of diverse methods to enhance sustainability, safety, and efficiency in forest operations.

Data Sources

The input data sources used in these studies include high-resolution satellite imagery (from sources like WorldView and Sentinel) [9, 85, 86], drone or UAV-acquired imagery (whether RGB, multispectral, hyperspectral, or thermal) [10, 52, 90], as well as aerial photography. LiDAR data, encompassing both airborne (ALS) [11, 53] and terrestrial (TLS) point clouds [58, 132], is extensively used for three-dimensional structural analysis, Digital Terrain Model (DTM) and Canopy Height Model (CHM) generation, and individual tree segmentation.

Furthermore, ground-level images and video captured via digital cameras [111], smartphone cameras [20, 51], and CCTV are employed for close-range tasks such as wood defect analysis [79], mapping skid trails for soil disturbance monitoring [18], and worker monitoring. Sensor data collected from accelerometers and gyroscopes—often sourced from smartphones [14, 113] or wearable technology—are included for ergonomic studies [81] and automated time studies of harvesting phases. Wearable and machine-mounted sensor data, including accelerometers, GNSS receivers, and noise dosimeters, are additionally used for automated activity recognition in chainsaw operations [26], cable yarding [49], and mechanized weed control and planting operations [46, 47], as well as for monitoring industrial sawmill machine performance [48], and for deep learning-based postural assessment of forest workers using image and body keypoint data [24, 44, 45]. AI and deep learning applied to high-resolution imagery are increasingly relied upon to map forest types and disturbances, which can be utilized by managers to monitor selective logging impacts and plan subsequent silvicultural interventions [91].

Lastly, tabular and Geographic Information System (GIS) data [15, 19], encompassing forest inventory data, climate records, soil data, and supply chain information [22], contribute to predictive modeling and optimization tasks. Textual data is also leveraged in conceptual review papers [2, 13], enhancing the overall understanding of the field's research landscape.

Application Domain Evolution and Operational Readiness

A comparative evaluation across the eight identified application domains reveals clear differences in operational readiness and research maturity. A comprehensive cross-domain synthesis of these applications, including their operational readiness levels, persistent limitations, and priority research gaps, is provided in Table 2. This mapping reveals a clear divide between high-readiness tools like wood defect detection and research-phase prototypes in ergonomics. Wood quality and defect detection and forest infrastructure and harvesting achieve the highest operational readiness scores, with tools such as automated lumber grading systems and the ALSroads pathfinder algorithm approaching or achieving commercial deployment. In contrast, ergonomics and worker safety—despite being the second-largest domain by study count ($n = 44$, 25%)—shows the lowest scores for field validation and operational deployment, confirming that the overwhelming majority of systems remain laboratory or controlled-environment prototypes with no demonstrated field use. However, very recent studies signal progress in this domain: transfer learning-based OWAS systems [44] and ResNet-50 models using skeleton keypoints [24] now demonstrate laboratory-level accuracy exceeding 99%, and a direct reliability comparison shows that a deep learning model outperforms human raters in assessment speed by one to two orders of magnitude [26]. Neural network-based activity recognition from chainsaw accelerometers and noise dosimeters further demonstrates high accuracy in a real operational context [26], suggesting the domain is approaching the threshold from research prototype to field deployment.

Forest resource assessment, the largest domain ($n = 59$, 36%), occupies a middle ground: model maturity is high, but cross-site generalizability remains the dominant bottleneck, as most CNN-based classifiers are trained and validated on single-site datasets that do not transfer across forest types or geographic regions [64]. Supply chain and logistics applications, though relatively few in number ($n = 9$, 5%), exhibit medium-to-high operational readiness because discrete-event simulation and optimization tools have a longer history of operational use than purely data-driven deep learning models.

The longitudinal analysis of research volume from 2014 to 2026 (Fig. 6, **left**) reveals a marked upward trajectory in the number of publications across the identified application domains. While the field was characterized by a low volume of specialized studies in 2014, it experienced a significant surge in activity, reaching a peak of 25 studies in 2020. Forest Resource Assessment has consistently represented the largest share of research effort throughout this period. However, the latter half of the decade shows a clear trend toward thematic diversification; domains such as Wood Quality and Defect Detection and Supply Chain and Logistics have grown from negligible presence to becoming substantial components of the current research landscape. The observed decline toward 2026 likely reflects the limits of the data collection period rather than a decrease in academic interest. The operational readiness heatmap (Fig. 6, **right**) evaluates the practical viability of these technologies using a scoring system from 1 (low) to 5 (high). A cross-domain analysis indicates that the technical foundations of the field are robust, with nearly all domains achieving a score of 4 for Model Maturity. This suggests that the underlying algorithms are well-developed and scientifically sound. Wood Quality and Defect Detection emerges as the most operationally ready domain, maintaining scores of 4 across five of the six criteria, including Data Availability, Model Maturity, and Operational Deployment. This high level of readiness indicates a successful transition from experimental research to commercially available industrial solutions.

Despite high scores in technical maturity, the heatmap reveals significant hurdles regarding the scalability of these applications. The lowest scores across the board are found in Cross-site Generalizability, where several domains—including Forest Resource Assessment and Ergonomics and Worker Safety—score as low as 2. These scores indicate that while models perform well in controlled or specific environments, they often lack the robustness required to maintain accuracy across diverse geographic sites or forest types. Furthermore, while Ergonomics and Worker Safety shows strong model maturity (4), its lower scores (3) in Field Validation and Operational Deployment suggest it remains largely in the research prototype phase, requiring more rigorous testing in real-world environments before achieving widespread operational adoption. Collectively, these patterns suggest that the field must move beyond publication of proof-of-concept results toward standardized benchmarking, multi-site external validation, and the development of lightweight edge-computing tools that can operate within the constraints of field-based forest management workflows.

Discussion

The temporal distribution of the 173 reviewed articles reveals a significant and accelerating interest in AI applications within forest operations and engineering, particularly from 2017 onwards. The rapid increase in publications from 2017 aligns with broader global trends in artificial intelligence research, driven significantly by the proliferation and accessibility of deep learning frameworks (e.g., TensorFlow,

Table 2 Cross-domain synthesis of AI applications in forest operations and engineering. Summary of application domains across the reviewed dataset (n=173), categorizing dominant AI techniques, primary input data, and priority research gaps. Operational readiness is defined as: High=systems validated in real operational contexts or commercially available; Medium=research prototypes validated on real-world datasets; Low=proof-of-concept or laboratory demonstrations only

Application Domain	n (%)	Dominant AI Technique(s)	Primary Data Source(s)	Operational Readiness	Key Limitations Identified	Priority Research Gaps
Forest Resource Assessment (species classification, crown delineation, 3D reconstruction, stand height)	59 (36%)	CNN (ResNet, YOLOv5, U-Net, PointNet++, DenseNet), Random Forest, SVM, k-NN	LiDAR/ALS/TLS, UAV-RGB, hyperspectral and multispectral imagery	**Medium–High**	Poor cross-site generalizability; high LiDAR acquisition cost; model overfitting to training conditions; insufficient external validation	Standardized multi-site benchmark datasets; transfer learning across biomes; direct integration of classification outputs into operational DSS for harvesting planning [121]
Forest Infrastructure & Harvesting (road detection/updating, skid trail mapping, automated logging planning)	14 (8%)	CNN (U-Net, ALSroads pathfinder), hybrid classifiers, multi-criteria optimization (GA, DP, LP)	ALS/single-photon/UAV-LiDAR, CubeSat/satellite imagery, GIS	**High**	Canopy occlusion of road surfaces; dense understory limiting LiDAR penetration; high data volume and processing time	Automated integration with forest GIS platforms; near-real-time road status monitoring; cost-effective UAV-LiDAR acquisition protocols; operational skid trail impact thresholds [65–67, 69, 70, 78, 127]
Forest Disturbance & Change Detection (selective logging, windthrow, snow breakage, post-harvest monitoring)	12 (7%)	CNN (YOLO, U-Net, Mask R-CNN), Random Forest, SAR and optical time-series fusion	Sentinel-1/−2 SAR, Landsat/MODIS, UAV-RGB, aerial LiDAR	**Medium**	Cloud cover limiting optical sensors; temporal resolution gaps; spectral confusion between disturbance types; limited validation in non-tropical biomes	Near-real-time SAR-based operational alerts; fusion of active and passive sensors; standardized disturbance severity metrics compatible with forest management reporting [71, 85, 86]
Wood Quality & Defect Detection (knots, cracks, veneer defects, lumber grading, CT-based scanning)	11 (7%)	CNN (FCN, Faster R-CNN, ResNet), SVM, ANN, LBP-based feature descriptors	High-resolution RGB images, X-ray/CT scans, NIR spectroscopy	**High**	Illumination and surface variability; species-specific training requirements; limited generalization across wood origin and processing states	Robust multi-species, multi-defect models; integration with automated sawmill conveyor lines; open standardized defect taxonomies and annotated datasets [73, 74, 99]
Supply Chain & Logistics (transport optimization, routing, scheduling, risk management)	11 (6%)	Discrete Event Simulation (DES), LP/DP, Genetic Algorithms, ML regression, IoT-RFID	Tabular operational data, GIS, fleet telemetry, RFID supply chain records	**Medium–High**	Data silos across supply chain partners; limited real-time data feeds; complexity of multi-actor systems; scenario-specific models lacking generality	Digital twin integration for real-time optimization; blockchain-based traceability; AI-assisted risk forecasting under climate uncertainty [15, 64, 122–124]
Ergonomics & Worker Safety (pose estimation, activity recognition, WMSD risk, fall detection)	44 (25%)	CNN (OpenPose, HRNet, two-stream), Random Forest, ANN, Bayesian networks, fuzzy logic	Wearable/IMU sensors, depth cameras (Kinect/RealSense), smartphone cameras, video	**Medium**	Occlusion and varying illumination in forest environments; privacy concerns with continuous video monitoring; limited real-forest (vs. laboratory) validation	Edge-computing deployment for real-time in-field use; integration with machinery automation and safety interlock systems; longitudinal prospective field validation [24, 44, 76, 84, 136]
Conceptual, Review & Emerging Tech (definitions, IoT, LLMs, XAI, Forestry 5.0 frameworks)	11 (7%)	N/A (review/conceptual); includes LLMs (ForestGPT), XAI, IoT architectures	Literature synthesis, expert knowledge	**Foundational**	Rapid pace of AI development risks swift obsolescence; limited empirical grounding in some contributions	Domain-specific LLMs for forest operations decision support [173]; XAI dashboards for non-specialist practitioners; Forestry 5.0 conceptual frameworks linking AI adoption to sustainability targets
Other Applications (trunk detection, robotics, plant mapping, AGB estimation)	10 (6%)	CNN, PointNet, traditional ML, structure-from-motion	RGB/thermal images, LiDAR, field measurements	**Low–Medium**	Narrow application scope limiting generalizability; proof-of-concept stage for most robotics applications	Integration into broader operational forest workflows; robustness testing across diverse forest types

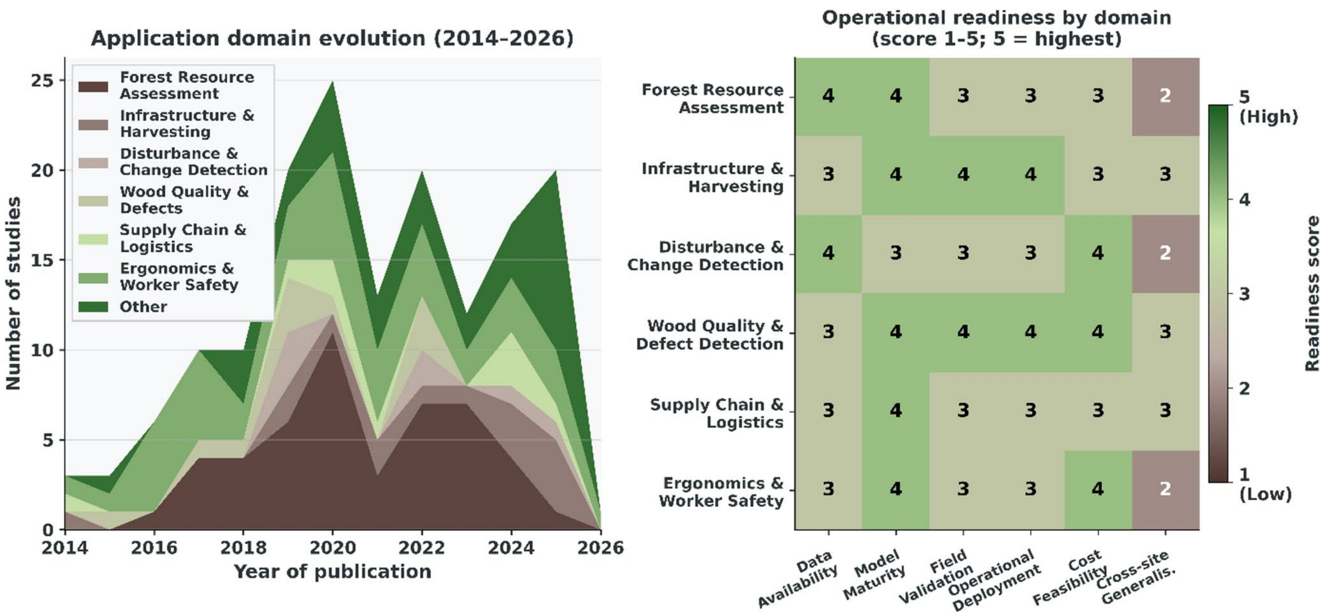


Fig. 6 Domain evolution and operational readiness assessment. (Left) Evolution of research volume across six key application domains (2014–2026). (Right) Heatmap of operational readiness across six criteria (scored 1–5). Wood Quality and Defect Detection achieves the highest overall readiness due to commercial availability, while Ergonomics and Worker Safety remains primarily in the research prototype stage

PyTorch) and enhanced capabilities in acquiring high-resolution datasets, such as those from Unmanned Aerial Vehicles (UAVs), LiDAR, and hyperspectral sensors. For instance, early explorations of Convolutional Neural Networks (CNNs) for tasks like selective logging mapping [71] and joint forest object detection and grouping [82] laid groundwork that gained significant traction in subsequent years. The pronounced peak in publications observed between 2019 and 2022 corresponds with demonstrable advancements in applying AI to specific, complex forestry tasks. Examples include the development of deep learning models for forest road detection [37], skid trail segmentation [18], and automated operational logging planning [69]. These applications often capitalize on the richness of high-resolution imagery and the power of deep learning, reflecting a growing technological maturity and a move towards solving practical field problems. This maturation is further evidenced by the most recent contributions (2022–2026), where sensor-based machine learning systems now achieve near-perfect classification accuracy in diverse operational monitoring tasks, including cable yarding event classification from GNSS data [49], sawmill machine state monitoring from triaxial acceleration data [48], weed control operation event classification from multimodal sensor data [47], and automated postural assessment of forest workers from images combined with body keypoints [24, 44, 45]. These developments confirm that the field is transitioning from proof-of-concept prototypes toward validated, deployable monitoring tools.

Furthermore, the overwhelming thematic focus on applications (as evidenced by 166 studies) compared to definitions and concepts (as evidenced by 7 studies) from 2017 onwards strongly suggests a disciplinary shift. This indicates a transition from foundational theoretical groundwork towards the development and deployment of practical, AI-driven solutions tailored for diverse challenges in forest operations and engineering.

Several interconnected factors likely contributed to the surge in AI research within forest operations and engineering. Firstly, technological advancements have played a pivotal role in this growth. The maturation and widespread adoption of sophisticated deep learning algorithms, such as Convolutional Neural Networks (CNNs) for image-based tasks like road extraction and logging detection [65], have significantly advanced the field. Concurrently, notable improvements in sensor technologies have emerged, including UAV-based high-resolution orthophotos [37] and aerial multispectral remote sensing for mapping skid trails [70]. These advancements provide the high-quality data necessary for training and validating complex models, thereby enabling more accurate and scalable applications in forestry.

The availability of data has also been a crucial factor in this surge. The increased accessibility and creation of specialized datasets have facilitated the research landscape significantly. This includes open-source initiatives, such as the BarkNet 1.0 dataset for tree bark re-identification [43], as well as the broader availability of remote sensing data from platforms like MODIS and WorldView-3 for applications such as forest type mapping [91]. Such resources enable large-scale studies and allow for comparative benchmarking of AI models.

Environmental pressures have likewise played a substantial role in driving this surge. Heightened global concerns related to climate change, deforestation, and the increasing frequency and intensity of other forest disturbances have likely spurred considerable investment and research into AI-based tools designed for improved monitoring. This is exemplified by research addressing the detection of selective logging [71] and the segmentation of machinery-induced soil disturbances [18].

Finally, interdisciplinary collaboration has emerged as a key component in applying AI to forestry. The inherent complexity of this field necessitates collaboration between a diverse range of countries, including China, the USA, Canada, and Finland. The integration of knowledge from various fields—such as computer vision, remote sensing, operational research, and ergonomics—has facilitated innovation and accelerated progress in the development of AI applications in forestry [2, 3].

Across the reviewed literature, several recurring strengths of AI applications in forest operations and engineering research emerged. One of the most notable strengths is enhanced accuracy and precision. AI models, particularly those using deep learning architectures, often demonstrate superior accuracy compared to traditional methods in various tasks, including species classification, object detection (such as trees, road networks, and skid trails), and the monitoring of harvest intensities [16, 65].

Another significant contribution of AI in forest operations and engineering is automation and efficiency. AI enables the automation of labor-intensive and time-consuming tasks, such as manual image interpretation, data collection in the field, wood grading, and continuous monitoring. This automation leads to substantial efficiency gains [76, 81, 89, 165]. AI also stands out for its scalability and capacity for large-area analysis. Its ability to process large quantities of data makes it especially suitable for extensive applications, such as conducting regional or national forest inventories, mapping extensive road networks, or monitoring widespread disturbances [37, 62].

Furthermore, the combination of remote sensing with AI facilitates non-invasive monitoring of forest ecosystems. This integration reduces the need for disruptive field surveys, allowing for more sustainable management practices as indicated in numerous remote sensing studies. Improved decision support is another critical strength of AI-driven models. These models provide quantitative insights and predictions that can significantly enhance informed and timely decision-making in areas such as sustainable forest management, selective logging mapping and monitoring, and operational planning [71, 86, 137, 164].

In addition, AI fosters novel applications and insights that were previously infeasible. For instance, it enables real-time ergonomic risk assessment using smartphone sensors and facilitates the detailed 3D reconstruction of forest structures from point clouds [21, 32, 90]. Lastly, AI's capacity for handling complexity allows it to better capture the intricate dynamics of forest ecosystems than simpler statistical models, particularly those capable of learning non-linear relationships.

Despite the advancements made, several critical barriers hinder the widespread operational adoption of AI by forest engineers. A major challenge is the availability, quality, and cost of data [3, 13, 16]. The requirement for large, high-quality, and accurately labeled datasets—which often require expensive Unmanned Laser Scanning (ULS)/Airborne Laser Scanning (ALS) LiDAR campaigns—is a recurring limitation. Furthermore, a severe lack of external validation and benchmarking makes it difficult to compare models effectively. Data acquisition in remote and diverse forest environments often proves costly and complicated. Common issues include imbalanced datasets, insufficient sample sizes, and the labor-intensive process of manual labeling [3, 13, 16].

Another significant issue is model generalizability and transferability. Models that are trained in one specific geographic region, forest type, or season often struggle to generalize to unseen environments. This lack of robustness restricts broad applicability without costly retraining [76]. A significant divide remains between theoretical 'black box' models and practical, operational forestry tools. As synthesized in the readiness heatmap, wood quality and defect detection achieves the highest operational readiness, supported by commercially available systems validated on production lines. In contrast, domains like ergonomics and worker safety often rely on 'black box' deep learning architectures that, while accurate in laboratory settings, show lower readiness for field deployment due to a lack of transparency in decision-making processes [2, 13, 76].

Many advanced AI models, particularly deep neural networks—such as those used for intricate tasks like 3D forest reconstruction [63], complex image segmentation for species identification [80], or the detection of subtle selective logging [71]—operate in ways that are not easily understood, creating difficulties in ascertaining their decision-making processes. This "black box" nature creates a lack of transparency. This lack of transparency, inherent in many sophisticated architectures, can be especially problematic for critical applications in forest operations and engineering and management where accountability, trust in the model's outputs, and a clear understanding of the factors driving predictions are essential for responsible decision-making [2, 13].

However, there is a gap between the theoretical development of AI and its practical use in everyday forest operations. AI needs powerful hardware such as GPUs, cloud infrastructure, and large training datasets. These computational and latency requirements are usually beyond the reach of a typical forest manager or field practitioner working in remote, resource-limited settings. To gain the confidence of forest engineers for high-stakes decisions—like steep-terrain harvesting or infrastructure planning—explainable AI (XAI) and intuitive software interfaces should be emphasized over purely theoretical algorithmic advances [121].

Moreover, integrating AI into existing workflows and bridging the gap between AI developers and forestry domain experts is absolutely essential. Achieving usability for non-AI specialists within existing forest operations and engineering workflows remains an ongoing challenge. Environmental factors also pose a threat to the performance of AI systems. This is especially true for systems that rely on optical remote sensing or ground imagery, which can be affected by variable illumination, weather conditions, shadows, and occlusions in dense canopies [37]. Finally, while AI can provide long-term benefits, the initial investment in technology, data acquisition, and expertise necessitates careful cost-benefit analysis to ensure practical adoption, particularly in resource-constrained settings. Technical barriers such as illumination variability and sensor occlusion in dense canopies continue to limit the reliability of optical AI systems in the field [37, 65]. Furthermore, organizational 'data silos' across the wood supply chain prevent the seamless exchange of information required for real-time logistics optimization [15, 122]. Addressing these barriers requires a shift from purely algorithmic research toward the development of standardized, multi-site benchmark datasets and edge-computing solutions that can operate in resource-constrained environments.

The articles reviewed indicate several promising future research directions. One area is the exploration of advanced AI architectures and hybrid models. This includes the development of more sophisticated models such as explainable AI (XAI), generative adversarial networks (GANs) for synthetic data generation and augmentation [107], reinforcement learning for adaptive management, and hybrid models that leverage the strengths of different AI techniques. In fact, such directions were already being implemented in research published in 2025, and particular attention has been given to Explainable AI (XAI) to predict tree growth [170] and the introduction of Domain-Specific Large Language Models (LLM) like ForestGPT [173], which is the advent of generative AI into the forestry domain. In the domain of operational monitoring, sensor-fusion approaches using neural networks on multimodal data—including GPS [46, 49], triaxial acceleration [47, 48], and combined accelerometer–noise dosimeter signals [26]—represent a growing body of cost-effective solutions for automated time studies and machine performance monitoring in diverse forest and wood processing operations.

Another future direction involves multimodal data fusion. The integration of data from diverse sources, such as satellite optical, synthetic aperture radar (SAR), LiDAR, thermal imagery, drone imagery, ground sensors, and climate data, could facilitate the creation of more comprehensive and robust models [3, 27]. Real-time processing and edge computing also present exciting opportunities for AI in forest operations and engineering. Developing AI models that can operate in real-time and be deployed on edge devices, such as drones and field sensors, will allow for immediate alerts and decision support in critical applications like steep-terrain routing [64] and worker safety monitoring [24, 76, 151].

Efforts to improve model generalization and domain adaptation are essential. Research should focus on developing techniques that enhance AI models' ability to generalize across different forest types, geographical regions, and sensor characteristics, which is a challenge often highlighted in studies dealing with varied ecological contexts [3, 91]. Approaches like few-shot learning and transfer learning (e.g., as implicitly needed when applying models like those by Urbonas et al. [92] to new defect types) hold potential in this area. There is a clear need for large-scale, standardized datasets. Collaborative efforts aimed at creating and sharing well-annotated, large-scale forestry datasets—perhaps building on initiatives like the BarkNet 1.0 dataset for tree bark [43] or addressing the data scarcity noted in specific applications [16]—would facilitate AI research and establish benchmarks, addressing the data limitations implied in many papers. The integration of decision support systems (DSS) is another avenue for future work, building on the foundational understanding of using operational research for planning [15, 122]. Developing user-friendly DSS that seamlessly integrate AI-driven insights—such as those from advanced classification models [80] or predictive systems [76]—into practical tools for forest management and operational planning can greatly enhance decision-making capabilities. This trend is similarly confirmed by the recent contributions of 2025 that provide new solutions including GIS-based decision support models tailored specifically to harvesting on steep land [64] and genetic algorithms to optimize logging truck routing [124].

Ethical considerations surrounding AI and responsible innovation should also be prioritized. Ongoing research into the ethical implications of AI in forest operations and engineering must focus on aspects of fairness, accountability, transparency, and societal impact. Lastly, specific technical improvements are necessary to enhance the robustness and functionality of AI applications. This includes addressing challenges such as occlusion handling in dense forests [37], improving segmentation of fine tree structures, and enhancing AI's robustness to environmental variability.

While this systematic review provides a comprehensive analysis of the 173 included articles, it is subject to the limitations inherent in qualitative synthesis and the interpretive perspective of the authors. Although every effort was made to remain objective and exhaustive, the process of synthesizing diverse research findings necessarily involves a degree of subjective evaluation. To mitigate this and provide a structured assessment of study quality, the fields of 'Maturity Level,' 'Strong Points,' and 'Limitations' were utilized as standardized proxies to reflect the rigor and operational readiness of the reviewed literature as reported by the original authors and peer reviewers.

Conclusions

The systematic review of 173 scientific papers highlights the profound and expanding impact of artificial intelligence (AI) specifically on modern forest operations and engineering research and practice. The findings illustrate a clear and accelerating trend toward data-intensive approaches, with AI serving as a critical enabler for extracting actionable intelligence from diverse and voluminous datasets relevant to engineering challenges in forestry. AI is demonstrably no longer a niche technology but a diverse toolkit being applied across the spectrum of forest operations and engineering problems—from fundamental resource assessment supporting operational planning and infrastructure development (like road detection) to optimizing supply chains, ensuring worker safety through ergonomic assessments, managing forest health disturbances that impact operations, and contributing to sustainable resource management strategies. Machine learning, particularly the sophisticated deep learning algorithms like CNNs, coupled with the rich data streams from remote sensing platforms (LiDAR, drones, satellites), stands out as a dominant force driving innovation in the field. Conventional artificial neural networks applied to multimodal sensor data—including accelerometers, GNSS receivers, and noise dosimeters—also demonstrate exceptional classification performance in operational monitoring of forest machinery and worker postural assessment, confirming that even non-deep-learning ML architectures remain highly relevant when matched to structured operational data inputs. The significant strengths of AI—enhanced accuracy in tasks like classification and detection, automation of complex and often hazardous tasks, the ability to process vast spatial and temporal datasets, and the generation of novel operational insights—are clearly demonstrated throughout the literature. These capabilities generate more precise forest inventories that are vital for planning, optimizing harvesting systems, detecting soil disturbance affecting site operability earlier, allocating resources and logistics more efficiently, and improving safety conditions for forestry workers. Nevertheless, the path to broad, seamless AI integration into forest operations workflows remains beset with challenges. The high cost of data acquisition, the pressing need for external validation, and the limited generalizability of models across diverse operational settings are major obstacles. An even greater issue is the mismatch between the computational hardware required for AI and the technological realities encountered by field-based forest managers. Addressing these barriers requires moving beyond purely descriptive studies toward rigorous benchmarking, developing lightweight edge-computing tools, and fostering strong interdisciplinary collaboration between AI developers and forestry practitioners, so that Decision Support Systems become accessible, explainable, and operationally viable. The future directions point towards even more sophisticated, integrated, and accessible AI systems tailored for forest operations and engineering needs. The pursuit of real-time monitoring capabilities (e.g., for operational hazards or selective logging mapping), advanced multimodal data fusion techniques, explainable AI (XAI) to build trust, and heightened attention to ethical considerations will shape the next wave of AI applications. AI holds immense promises for advancing sustainable forest management through optimized engineering solutions, enhancing our ability to conserve biodiversity while meeting resource demands, mitigating climate change impacts, and ensuring the long-term health, safety, and productivity associated with global forest resources and operations. The review confirms the role of AI as an essential facilitator of the future of forest operations and engineering science and at the same time shows the need of forestry engineers and technicians who can operate these tools to engage in a more synergistic relationship with the demands of sustainable forest management that are becoming increasingly complex.

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- Giustina S, Spilotro C, Johanna G, Corvello V. The transformative power of artificial intelligence within innovation ecosystems: a review and a conceptual framework. Rev Manag Sci 2024:1–32. doi:https://doi.org/10.1007/s11846-024-00828-z.

◦This article was selected as a key reference since it provides the conceptual framework underpinning the understanding of artificial intelligence as a transformative paradigm within innovation ecosystems but not just as a technical tool. It helps to contextualise the wider discourse of "Forestry 5.0" delivered in our review, connecting the change in technology with the corresponding change in management and strategy.

- Cai C, Xu H, Chen S, Yang L, Weng Y, Huang S, et al. Tree Recognition and Crown Width Extraction Based on Novel Faster-RCNN in a Dense Loblolly Pine Environment. Forests 2023:14:863. doi:https://doi.org/10.3390/f14050863.

  ◦This study was selected as an exemplary case of the most prevalent trend that was found during our systematic review: using deep learning (specifically convolutional neural networks) for precision forestry. It shows the high level of technical maturity that artificial intelligence has reached in automating the complex processes like individual tree segmentation and inventory, which are the focus of modern engineering of forest operations.

- Malladi MVR, Chebrolu N, Scacchetti I, Lobefaro L, Guadagnino T, Casseau B, Oh H, Freißmuth L, Karppinen M, Schweier J, Leutenegger S, Behley J, Stachniss C, Fallon M. Digiforests: a Longitudinal Lidar Dataset for Forestry Robotics. In: 2025 IEEE International Conference on Robotics and Automation (ICRA). IEEE; 2025. p. 1459–66. doi:https://doi.org/10.1109/icra55743.2025.11128697.

  ◦We noted that the lack of a standardized level of benchmarks and data shortage could be considered two major barriers to progress in forest engineering research. The reason why this reference was chosen is that it is directly related to this challenge since it proposes a high-quality, longitudinal dataset specifically focused on forestry robotics and, therefore, allows the interdisciplinary collaboration that we believe is necessary in future forest engineering research.

- Eberhard B, Trailović Z, Magagnotti N, Spinelli R. A Gis-Based Decision Support Model (DSM) for Harvesting System Selection on Steep Terrain: Integrating Operational and Silvicultural Criteria. Preprints 2025:2025011137. doi:https://doi.org/10.20944/preprints202501.1137.v1.

  ◦This recent work was included to represent the "Operational Optimization" domain of our review. It is a good example of the practical transition from theoretical AI models to usable Decision Support Systems (DSS) for complex harvesting operations. It points out that the steep terrain harvesting is one of the high-risk engineering tasks that is being addressed now with the help of AI and GIS integration.

- Sommer F, Eberhard B, Holzinger A. ForestGPT and Beyond: A Trustworthy Domain-Specific Large Language Model Paving the Way to Forestry 5.0. Electronics 2025:14:3583. doi:https://doi.org/10.3390/electronics14183583.

  ◦The reason why we added this very recent paper is that it represents the inception of Generative AI and Large Language Models (LLM) into the forestry field. It speaks to the trends in the future that have been discussed in this study namely the shift toward "Explainable AI" and the availability of human-centric AI applications that would help bridge the gap between complex algorithms and forestry professionals.

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Data Availability No datasets were generated or analysed during the current study.

Declarations

Competing Interests The authors declare no competing interests.

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