

Artificial Intelligence in Forest Plantation Management: A Systematic Literature Review of Operational Applications and Practical Implications

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ABSTRACT

*Artificial intelligence (AI) is increasingly being applied in forest plantation management, yet the literature remains fragmented across technical domains and has rarely been synthesized from an operational management perspective. This study aimed to systematically review how AI has been used in forest plantation management, with particular emphasis on operational applications and practical implications. A systematic literature review approach was adopted using the Dimensions database. The initial search retrieved 627 records from journal articles and conference proceedings published between 2010 and 2026. After removing duplicates, non-English records, and review or conceptual papers, 592 records remained for title–abstract screening. Following the PRISMA-based screening process, 113 full-text reports were assessed for eligibility, and 73 eligible studies were selected for detailed analysis. The reviewed studies were classified into six major themes: growth, yield, and productivity prediction; forest health and protection; plantation establishment, maintenance, and quality monitoring; remote sensing and plantation mapping; plantation inventory and mensuration; and harvesting and operational efficiency. The results show that AI has been most widely used to improve prediction, detection, monitoring, mapping, measurement, and operational control. Across the reviewed studies, the most common practical uses included yield forecasting, biomass estimation, pest and disease detection, fire-related monitoring, planting success assessment, plantation mapping, tree measurement, harvester productivity prediction, and post-harvest timber quantification. The review also indicates that AI is evolving from a technical innovation into a practical support tool for plantation management. However, much of the current literature remains site-specific and weakly connected to routine management workflows. For Indonesia, the findings are especially relevant for peatland plantations dominated by *Acacia crassiparva* and dryland plantations dominated by *Eucalyptus*, where AI has strong potential to support water monitoring, forest health surveillance, growth forecasting, inventory, and harvesting efficiency.*

Keywords: artificial intelligence, forest plantation management, operational applications, practical implications, systematic literature review, industrial forest plantations

1. INTRODUCTION

Forest plantations play an increasingly strategic role in supplying industrial wood, supporting rural economies, and reducing pressure on natural forests. Their management is also becoming more complex because managers must oversee large operational areas, variable site conditions, pest and disease threats, water constraints, productivity fluctuations, and demands for faster and more accurate decisions (Bravo et al., 2024). Recent advances in artificial intelligence (AI), machine learning, deep learning, computer vision, and remote sensing offer new opportunities to improve plantation monitoring, forecasting, measurement, and operational control (Binlajdam et al., 2025; Estrada et al., 2023; Hızıroğlu & Semiz, 2024; Yun et al., 2024).

Previous reviews have examined AI in forestry from broad technological or thematic perspectives. Binlajdam et al. (2025) reviewed AI for sustainable forestry, Estrada et al. (2023)

focused on machine-learning-assisted forest health assessment, Hızıroğlu and Semiz (2024) summarized current and future AI applications in forestry, and Yun et al. (2024) reviewed deep-learning developments in forest studies. These reviews provide important technological overviews, but they do not systematically organize the evidence around the operational functions of forest plantation management. The literature therefore remains fragmented across growth modelling, forest health, remote sensing, machine vision, inventory, and harvesting. Many studies also emphasize algorithm performance rather than the managerial usefulness of their outputs. Consequently, there is still limited synthesis of how AI supports plantation planning, establishment, maintenance, protection, inventory, harvesting, and field efficiency, particularly in large-scale industrial plantation contexts.

Recent empirical studies illustrate the breadth of these applications. AI-assisted deep learning has been used to map planted forests at a regional scale using Sentinel-2 imagery and semantic segmentation models (Mitra et al., 2024; Xi et al., 2022). Object-detection models have been applied to identify young Eucalyptus plants for localized irrigation support (Santana et al., 2024) while machine learning has been used to predict groundwater levels for fire prevention and water-table management in tropical peatland plantations (Li et al., 2022; Yonekura et al., 2025). In harvesting operations, machine learning has also been applied to estimate harvester productivity and improve operational planning (Munis et al., 2022). These developments show that AI is moving beyond experimental forest analytics toward practical plantation-management applications.

Accordingly, this study systematically reviews how AI has been applied in forest plantation management, with particular emphasis on operational applications and practical implications. Its novelty lies in applying an operational-management lens that links AI technologies to six plantation functions: growth and productivity, forest health, establishment and maintenance, mapping, inventory and mensuration, and harvesting efficiency. The study also interprets the evidence for Indonesian plantation systems, particularly peatland *Acacia crassicarpa* and dryland *Eucalyptus* plantations. It addresses three questions: (1) What AI technologies and data sources have been applied across forest plantation management functions? (2) What operational benefits and limitations are reported across the reviewed studies? and (3) What practical implications and research gaps emerge for industrial forest plantation management, particularly in Indonesia?

2. METHODS

2.1. Data Source and Search Strategy

This study used a systematic literature review (SLR) approach to examine the application of artificial intelligence (AI) in forest plantation management, with emphasis on operational applications and practical implications. The literature search was conducted in the Dimensions database because of its broad multidisciplinary coverage of journal articles and conference proceedings. Dimensions was selected because of its broad multidisciplinary coverage and its

inclusion of both journal articles and conference proceedings. Nevertheless, the use of a single primary database is acknowledged as a limitation of this review.

A Boolean search strategy was developed by combining three groups of keywords related to AI technologies, forest plantation contexts, and operational or management functions. The search was applied to the title and abstract fields using the following query: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision" OR "neural network") AND (forestry OR "forest plantation" OR "plantation forestry" OR "industrial forest plantation" OR "precision forestry") AND (monitoring OR prediction OR detection OR inventory OR harvesting OR logistics OR management).

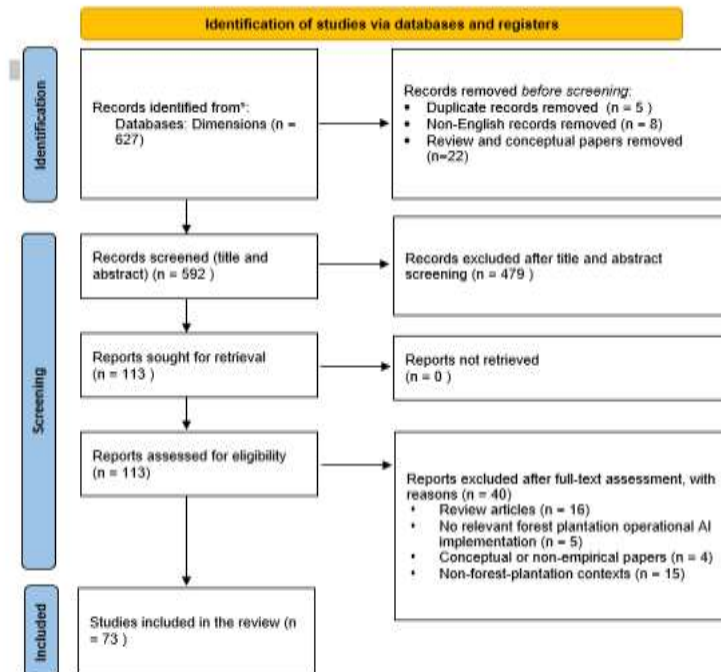
The search was limited to journal articles and conference proceedings published between 2010 and 2026. The initial search yielded 627 records.

2.2. Screening and Eligibility

The study selection process followed the overall logic of the PRISMA 2020 framework. Duplicate records, non-English publications, and records clearly identified as review or conceptual papers were removed before title–abstract screening. The remaining records were screened based on their relevance to artificial intelligence, forest plantation contexts, and operational or management applications.

Studies were included if they: (1) were journal articles or conference proceedings published in English between 2010 and 2026; (2) applied artificial intelligence, machine learning, deep learning, computer vision, or related techniques; (3) focused specifically on forest plantations or plantation forestry; and (4) addressed an operational or management function, including growth prediction, plantation establishment, maintenance, forest health, mapping, inventory, mensuration, harvesting, or operational efficiency.

A total of 113 reports were assessed at the full-text stage. Forty reports were excluded for the following primary reasons: 16 were review articles, five did not provide a clearly identifiable AI implementation relevant to forest plantation operational management, four were conceptual or non-empirical papers, and 15 focused on natural forests, orchards, vineyards, or other non-forest-plantation contexts. Each excluded report was assigned to only one primary exclusion category to avoid double counting. Following the full-text assessment, 73 eligible studies were retained for data extraction and thematic synthesis. The overall selection process is presented in the PRISMA flow diagram (adapted from Page et al., 2021).



Source: Page MJ, et al. BMJ 2021;372:n71. doi: 10.1136/bmj.n71.

Figure 1. PRISMA 2020 flow diagram of the literature selection process

2.3. Data Extraction, Quality Assessment, and Thematic Classification

Relevant information from the 73 eligible studies was extracted into a structured review table. The extracted information included the title, author(s), research objective, study location, data source, research method, AI technology or model used, validation procedure, main findings, operational implications, reported limitations, and conclusion. Each article was then assigned to one of six major themes based on its dominant operational focus: (1) growth, yield, and productivity prediction; (2) forest health and protection; (3) plantation establishment, maintenance, and quality monitoring; (4) remote sensing and plantation mapping; (5) plantation inventory and mensuration; and (6) harvesting and operational efficiency.

A structured narrative quality appraisal was conducted for all eligible studies. Each study was examined in terms of the clarity of its research objective and plantation context, description of the data source, explanation of the AI method, validation procedure, reported model-performance metrics, operational relevance, and acknowledgement of study limitations. The appraisal was used to support a cautious interpretation of the evidence rather than as an additional exclusion criterion. Studies with incomplete methodological reporting or limited validation were retained but interpreted with appropriate caution.

The screening, data extraction, quality appraisal, and thematic classification were conducted by the author. To strengthen procedural consistency, the extracted information and thematic assignments were rechecked against the full texts after the initial classification. Because no independent second reviewer was involved, inter-reviewer agreement could not be assessed. This limitation is acknowledged when interpreting the findings of the review.

Given the substantial heterogeneity of the eligible studies in terms of research design, data sources, AI techniques, validation procedures, and performance metrics, the methodological appraisal was conducted narratively rather than by applying a single numerical risk-of-bias score. The final analysis used a qualitative thematic synthesis approach. Particular attention was given to plantation systems relevant to Indonesia, including peatland (*Acacia crassicarpa*) plantations and dryland (*Eucalyptus*) plantations.

3. RESULTS AND DISCUSSIONS

The 73 eligible studies were grouped into six major themes, as summarized in Table 1. Overall, the literature indicates that AI in forest plantation management is mainly applied to improve prediction, detection, monitoring, mapping, measurement, and operational control.

Table 1. Thematic classification of 73 eligible papers

Theme	n	Dominant AI methods/data	Management value	Common limitation
Growth and productivity	19	ANN, RF, LSTM; inventory and remote sensing	Yield and supply planning	Site-specific validation
Forest health	15	CNN, YOLO, UAV imagery	Early detection and intervention	Weak linkage to treatment thresholds
Establishment and maintenance	14	YOLO, RF, LiDAR, field data	Establishment and water control	Limited company-scale deployment
Mapping	11	Satellite, UAV, LiDAR	Spatial planning and risk mapping	Weak cross-region generalization
Inventory	7	ANN, RF, RGB-D, LiDAR	Automated measurement	Limited workflow integration
Harvesting	7	ML, UAV, computer vision	Productivity and timber control	Machine- and site-specific models

The dominant application areas were “growth and productivity prediction”, “forest health and protection”, and “plantation establishment and maintenance”. Rather than functioning only as a computational tool, AI is increasingly positioned as a practical support system for plantation management.

Overall, the methodological reporting of the reviewed studies was heterogeneous. Most studies clearly described their AI methods and reported model-performance metrics, but fewer provided external validation, cross-site testing, economic evaluation, or evidence of routine operational deployment. Therefore, findings from highly site-specific studies or studies with limited validation were interpreted cautiously, particularly when considering their broader applicability to commercial forest plantation management.

Growth, Yield, and Productivity Prediction

This theme shows that AI has been widely applied to predict tree volume, biomass, stand productivity, DBH, height, evapotranspiration, and gross primary productivity, making it the most developed application area in forest plantation management. Common methods included ANN, Random Forest, SVM, XGBoost, LightGBM, and LSTM, often combined with inventory data, remote sensing, or environmental variables (Rodrigues et al., 2025; Taylor et al., 2023). From a management perspective, the practical value of this theme is clear. These studies show that AI can support yield planning, productivity zoning, inventory efficiency, carbon-related estimation, and resource-use assessment.

However, many studies were still site-specific, based on limited species, restricted age classes, or local environmental conditions (Rodrigues et al., 2025). As a result, strong local accuracy does not always guarantee broad operational transferability.

Forest Health and Protection

The literature in this theme focused mainly on disease detection, pest monitoring, fire danger prediction, smoke detection, and health diagnosis, with a strong dominance of computer vision and deep learning, especially YOLO variants, U-Net, Mask R-CNN, and CNN-based classifiers (Deng et al., 2020; dos Santos et al., 2022; Zheng et al., 2023; Zhi et al., 2024). Pine wilt disease, forestry pests, and fire-related monitoring were among the most common application areas.

From a practical standpoint, these studies indicate that AI can improve early warning, surveillance speed, intervention targeting, and large-area monitoring efficiency, which are essential for plantation protection. Nevertheless, many studies were developed for single threats or local conditions, and fewer linked detection outputs directly to treatment thresholds, intervention prioritization, or long-term protection strategy. Other studies expanded the health domain to pest detection using imagery and transfer learning, fungal spore datasets for diagnosis support, acoustic classification of wood-boring insects, and fire risk or smoke detection using time-series and satellite-based AI models (Zheng et al., 2023).

Plantation Establishment, Maintenance, and Quality Monitoring

This theme demonstrates that AI is increasingly relevant for plantation establishment and routine field management, including planting success assessment, seedling quality classification, thinning support, weed-control monitoring, stand quality evaluation, groundwater prediction, and irrigation-oriented seedling detection (Brandao et al., 2025; Santana et al., 2024; Yonekura et al., 2025). Remote sensing, LiDAR, and machine learning were commonly used to assess plantation condition and support operational decisions. The main practical implication is that AI can strengthen field supervision, maintenance scheduling, thinning selection, and water monitoring and site conditions.

Several studies are particularly important for the early establishment stage. Zhan et al. (2026) developed an interpretable Naive Bayes approach for seedling quality classification, Rathore (2024) predicted plantation survival rate using vegetation indices and Gradient Boosted Trees, and Santana et al. (2024) used YOLOv8 and YOLOv5 for detecting young *Eucalyptus* plants to support localized irrigation management. These studies are operationally relevant because success at the early establishment stage strongly affects future productivity, stocking quality, and maintenance cost. The practical implications of this theme are broad. AI can help managers improve field supervision, planting quality control, maintenance scheduling, stand-condition monitoring, thinning selection, and water or site condition. In

particular, the study on groundwater prediction in tropical peatland plantations is valuable because it links AI directly to canal-gate operation, peat water-table control, and fire prevention (Yonekura et al., 2025). Likewise, ANN-based ecophysiological modelling under different spacing arrangements has practical value for understanding stand development and spacing effects on biomass performance.

Remote Sensing and Plantation Mapping

This theme shows that AI-enhanced remote sensing is becoming a key tool for plantation mapping, species discrimination, crown delineation, site suitability analysis, microsite counting, and spatial risk assessment (Mitra et al., 2024; Pereira Ribeiro Teodoro et al., 2024; Ramalho et al., 2022; Watt et al., 2025). Satellite imagery, UAV multispectral data, hyperspectral sensing, UAV-LiDAR, and GIS-based analysis were widely combined with machine learning and deep learning models. In practical terms, these studies support landscape-level planning, plantation delineation, site assessment, and risk-informed spatial management. However, methods remain highly diverse in scale and output, ranging from pixels to crowns to microsites, and cross-region generalization is still weak, especially under different plantation species and site conditions.

However, this theme also shows strong methodological diversity. Different studies worked at different spatial units—pixels, crowns, plots, tree points, suitability zones, or microsites—which makes synthesis more difficult. In addition, many studies were still limited to one species, one region, or one sensing configuration, which reduces generalizability (Mitra et al., 2024; Pereira Ribeiro Teodoro et al., 2024). Future work should therefore move toward more standardized validation, multimodal sensor integration, and scalable workflows that can bridge broad-area mapping with fine operational needs in plantation management.

Plantation Inventory and Mensuration

The studies in this theme confirm that AI can improve core inventory and mensuration tasks, including DBH prediction, height prognosis, stem profile estimation, taper modelling, stand-age mapping, tree detection, and segmentation quality control (Fernández-Carrillo et al., 2022; Grondin et al., 2023; Ko et al., 2025; Lin et al., 2023; Vieira et al., 2018). Common methods included ANN, ANFIS, Random Forest, XGBoost, LiDAR-based deep learning, and RGB-D vision systems. The practical implication is that AI can support more precise and automated inventory systems, reduce field measurement burden, and improve digital forest records. At the same time, the findings suggest that AI does not always outperform strong conventional forestry models in every case, especially in taper modelling, and more work is needed to integrate these tools into routine operational inventory systems. The practical value of this theme lies in its potential to improve inventory precision, reduce field effort, and support digital forest records.

The main limitations are similar to other themes: many studies were developed under limited geographic conditions, with incomplete reporting in some cases, and only a few explicitly addressed operational integration into routine inventory systems (Vieira et al., 2018). Future research should therefore emphasize cross-site validation, integration of AI with

existing mensuration workflows, and hybrid approaches that combine AI with established forest measurement models.

Harvesting and Operational Efficiency

This theme focused on harvester productivity prediction, post-harvest timber measurement, residue mapping, wheel-rut detection, and log quantification, showing that AI is increasingly relevant to mechanized plantation operations (Bhatnagar et al., 2022; Casas et al., 2024; Leal et al., 2025; Lu et al., 2024; Munis et al., 2022). UAV imagery, computer vision, and machine learning were commonly used to improve post-harvest assessment and operational measurement, while productivity models showed that factors such as tree volume, terrain slope, operator experience, and machine availability strongly affect harvesting performance. The practical implication is that AI can support harvest planning, productivity benchmarking, timber quantification, and environmental monitoring after harvesting. However, most studies remain tied to specific machines, sites, or harvesting systems, limiting their direct generalization to broader plantation conditions.

A major pattern across these studies is the use of UAV imagery, computer vision, and machine learning for post-harvest assessment. Another important cluster concerns harvester productivity modelling. Leal et al. (2025) and Munis et al. (2022) showed that machine learning methods can predict harvester productivity using operational variables such as tree volume, stand density, terrain slope, operator experience, and machine availability.

AI was also used for log measurement and timber quantification. Casas et al. (2024) combined YOLO-based log detection and segmentation with diameter distribution models to estimate stacked timber volume, while Lu et al. (2024) developed a YOLOv3 + DeepLabv3+ system for rapid log diameter measurement.

The key limitation is that most studies were still developed under specific sites, specific machine systems, or single production contexts, which limits generalization across harvesting environments (Leal et al., 2025; Lu et al., 2024; Munis et al., 2022). Future work should therefore focus on more robust field deployment, cross-site validation, and stronger integration with operational forestry management systems, so that AI can move from promising prototypes to routine harvesting tools.

Cross-Theme Practical Implications and Research Gaps

Across all themes, the review indicates that AI offers the greatest practical value when used to support faster monitoring, earlier detection, more objective assessment, and more spatially explicit decision making. For Indonesia, these implications are especially relevant in two major plantation contexts. In peatland plantations, especially in Sumatra and Kalimantan, where *A. crassicarpa* still dominates large operational areas, AI appears particularly valuable for groundwater monitoring, fire prevention, and large-area health surveillance (Yonekura et al., 2025; Zheng et al., 2023). In dryland plantations, which are widely dominated by *Eucalyptus* in Sumatra and Kalimantan, AI shows strong practical value for growth forecasting, establishment monitoring, stand quality control, inventory improvement, and harvesting efficiency (da Silva et al., 2021; Leal et al., 2025; Lee et al., 2025; Miguel et al., 2016).

When the review findings are compared with the practical realities of Indonesian plantation forestry, several gaps become evident. First, although many studies addressed mapping and monitoring, relatively fewer dealt with the broader planning complexity that

Indonesian plantation managers face, including land suitability, peat condition, transport accessibility, social constraints, and operational heterogeneity across very large estates.

Second, the literature still underrepresents several priority operational needs in plantation establishment and maintenance, particularly those relevant to Indonesian *Hutan Tanaman Industri* (HTI; industrial forest plantation) practices. Existing studies already cover planting success, seedling quality, weed-control event monitoring, thinning support, water-level prediction, and localized irrigation support.

Third, the forest health and protection literature is already strong in disease and pest detection, especially for image-based diagnosis and early warning. Nevertheless, from an Indonesian operational perspective, there is still a gap between detecting symptoms and supporting field control decisions. The reviewed studies rarely extend to threshold-based intervention, treatment prioritization, bioagent management, or long-term surveillance of important plantation-specific threats.

Fourth, the review confirms progress in plantation inventory and mensuration, including AI support for DBH, height, taper, stand age, tree detection, and segmentation quality. However, important gaps remain for Indonesia, where plantation management depends heavily on species-specific and site-specific mensuration systems. Future work should therefore prioritize AI-assisted mensuration models tailored to Indonesian plantation species, genotypes/clone diversity, and heterogeneous land conditions.

Finally, the harvesting and operational efficiency theme suggests that AI can improve productivity prediction, residue mapping, timber quantification, and post-harvest control. However, the reviewed studies still provide limited coverage of several major operational concerns that are especially important in Indonesian HTI, such as harvesting and extraction under peat conditions, road and transport planning from compartment to mill or port, log sorting for multiple end uses, and more continuous 24/7 decision support under variable terrain and infrastructure limitations. These are not contradicted by the SLR findings; rather, they emerge as practical priorities that remain insufficiently addressed in the current literature.

Overall, the cross-theme evidence suggests that future AI research in forest plantation management should move beyond isolated, site-specific technical demonstrations and focus more on integrated operational systems that reflect the realities of countries such as Indonesia.

4. CONCLUSION

This systematic literature review shows that artificial intelligence is increasingly being applied across major forest plantation management functions, including growth prediction, health protection, plantation establishment and maintenance, spatial mapping, inventory, and harvesting. Across the 73 reviewed studies, AI was mainly used to improve prediction, detection, monitoring, measurement, and operational efficiency, indicating its growing role as a practical decision-support tool.

For Indonesia, AI is particularly relevant for groundwater monitoring, fire prevention, and health surveillance in peatland plantations, as well as growth forecasting, establishment monitoring, inventory, and harvesting efficiency in dryland plantations. However, the findings should be interpreted considering several limitations, including the use of a single primary database, restriction to English-language publications, the absence of independent dual-reviewer assessment, and substantial methodological heterogeneity among the included studies. Future research should prioritize multi-site validation, integration with routine

management systems, and operational deployment of species- and site-specific AI tools for large and remote plantation estates.

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