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Artificial intelligence applications in sustainable palm oil production and marketing: a systematic literature review

Abstract

As digital transformation advances across agricultural commodity systems, Artificial Intelligence (AI) has gained increasing attention as a strategic enabler of efficiency, transparency, and sustainability within palm oil production and marketing. Although scholarly contributions on AI in this sector have expanded in recent years, existing evidence remains dispersed across technical domains and lacks a comprehensive synthesis. This study systematically identifies and integrates peer-reviewed research examining AI-driven applications that support sustainability within the palm oil ecosystem. The research adopts a Systematic Literature Review (SLR) design supported by a transparent and replicable screening protocol. Relevant scientific papers were sourced entirely from Scopus using a systematic keyword-based search strategy. An initial publication-period filter (2020–2026) and open-access screening yielded a final corpus of 31 peer-reviewed articles. The analysis employed thematic synthesis and methodological mapping to classify technological approaches, application domains, and reported performance outcomes. Specifically, the review followed PRISMA-guided identification, screening, eligibility, and inclusion stages, and each article was coded according to AI technique, application domain, dataset characteristics, validation approach, and reported performance indicators such as accuracy, precision, recall, F1-score, RMSE, MAPE, and operational efficiency gains. The findings reveal five dominant clusters: precision agriculture and yield optimization, crop health monitoring, environmental performance assessment, supply chain traceability, and market intelligence. Across these domains, machine learning and deep learning models demonstrate improvements in predictive accuracy, resource optimization, monitoring reliability, logistics coordination, and market forecasting stability. The review concludes that AI serves as an enabling analytical infrastructure that supports productivity enhancement and sustainability governance within palm oil systems. Future research should prioritize integrated value-chain modeling, longitudinal validation, and scalable interdisciplinary frameworks.

Keywords: artificial intelligence, sustainable palm oil, precision agriculture, supply chain traceability, market forecasting

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Introduction

The global agricultural sector is undergoing a profound transformation driven by rapid technological advancement, evolving sustainability expectations, and increasing demand for traceable and responsibly produced commodities. As digitalization reshapes production systems worldwide, Artificial Intelligence (AI) has emerged as one of the most influential enabling technologies within modern agricultural ecosystems.[1] AI-based systems, including machine learning, deep learning, predictive analytics, computer vision, and intelligent decision-support tools, are increasingly integrated into farming operations to improve productivity, optimize resource utilization, and strengthen environmental monitoring capabilities.[2] In parallel, global sustainability frameworks emphasize efficiency, transparency, and long-term resilience across agri-food supply chains, encouraging the adoption of data-driven management approaches.[3]

Among globally traded agricultural commodities, palm oil occupies a strategic position due to its multifunctional applications in food processing, oleochemicals, pharmaceuticals, cosmetics, and renewable energy industries.[4] Its high yield per hectare relative to other vegetable oils makes it a resource-efficient crop in terms of land productivity, contributing significantly to rural livelihoods and national economies in producing regions.[5] As international markets increasingly prioritize sustainability standards and digital traceability mechanisms, the palm oil sector has demonstrated growing engagement with technological innovation to strengthen operational performance and compliance systems.[6] Within this transformation, AI represents a promising analytical infrastructure capable of enhancing both upstream production efficiency and downstream market intelligence.

Recent advancements in AI have enabled agricultural systems to move from reactive management to predictive and prescriptive decision-making models.[7] Precision agriculture platforms now integrate satellite imagery, drone-based monitoring, soil sensors, and climate datasets with machine learning algorithms to forecast yields, detect crop stress, and optimize input allocation. In plantation-based commodities such as oil palm, where production cycles are long and management decisions have multi-year implications, predictive accuracy and timely monitoring are particularly critical.[8] AI-supported analytics can help reduce uncertainty, improve harvest planning, and support sustainability verification by integrating data across operational layers.

At the environmental level, AI has expanded the capacity for spatial analysis and land-use assessment through high-resolution remote sensing combined with deep learning segmentation models. These capabilities allow for more accurate plantation mapping, change detection, and resource-use monitoring. When embedded within broader sustainability governance frameworks, AI-driven environmental analytics may support transparent reporting and adaptive management strategies.[9] Importantly, these technological applications are increasingly viewed not as isolated tools but as components of integrated digital ecosystems linking production, certification, logistics, and market forecasting.

Beyond production systems, AI also plays a growing role in commodity marketing and price intelligence. Macroeconomic dynamics, policy developments, and cross-commodity interactions influence global palm oil markets. Advanced forecasting models that integrate machine learning with econometric techniques have demonstrated greater predictive stability than traditional time-series approaches.[10] Furthermore, Natural Language Processing (NLP) enables sentiment analysis of market news and policy signals, offering additional explanatory variables for short-term price movement analysis. In downstream markets, consumer analytics and digital segmentation tools enhance responsiveness to demand for sustainability-certified products.[11] These developments indicate that AI applications extend beyond agronomic optimization into broader commercial and strategic decision-making.

Despite the growing body of literature examining AI in agriculture and sustainability domains, existing research remains fragmented across disciplines, methodologies, and application areas. Studies often focus on specific technical models, such as yield prediction or disease detection, without situating findings within a comprehensive sustainability-production-marketing continuum. Moreover, the rapid evolution of AI techniques over the past five years has led to diverse experimental designs and validation approaches, making it difficult to assess collective progress and maturity within the palm oil context.[12] While numerous empirical contributions demonstrate performance improvements at the model level, there is limited consolidated analysis of how these advancements collectively contribute to sustainable production systems and market integration.

A systematic synthesis is therefore necessary to map the landscape of AI applications across the palm oil value chain and evaluate their methodological robustness, performance outcomes, and sustainability implications. Systematic Literature Review (SLR) methodology provides a transparent and replicable framework for identifying, screening, and synthesizing peer-reviewed studies based on predefined criteria. Unlike narrative reviews, SLR emphasizes structured selection processes, explicit inclusion and exclusion criteria, and systematic thematic coding, ensuring analytical transparency and reproducibility. Importantly, this study relies exclusively on secondary data derived from peer-reviewed academic publications and does not involve primary data collection methods such as interviews, focus group discussions, or field observations.

Positioning this study within the evolving digital agriculture discourse, the present research examines how AI applications have been developed and deployed in sustainable palm oil production and marketing systems during the recent wave of digital transformation. By integrating insights across agronomic optimization, environmental monitoring, supply chain traceability, and market intelligence, the review aims to provide a consolidated analytical perspective that bridges technological innovation with sustainability performance outcomes. Rather than adopting a critical or adversarial stance toward the industry, this study maintains a neutral and evidence-based approach, recognizing the sector's ongoing efforts to integrate data-driven tools to enhance operational transparency and efficiency.

This study aims to comprehensively integrate peer-reviewed findings on the application of Artificial Intelligence in sustainable palm oil production and marketing, identify dominant technological patterns and performance outcomes, evaluate methodological trends, and highlight research gaps warranting further scholarly attention. Through a structured SLR framework, this study seeks to clarify how AI contributes to productivity enhancement, environmental monitoring, supply chain governance, and market forecasting within the palm oil ecosystem.

To guide the analytical focus of the review and structure the subsequent discussion, two research questions are formulated:

RQ1: *How have Artificial Intelligence methodologies been applied across production, environmental, supply chain, and marketing dimensions of sustainable palm oil systems, and what measurable performance outcomes have been reported?*

RQ2: *What patterns of methodological maturity, integration, and research gaps emerge from the existing literature on AI-driven sustainability in palm oil production and marketing?*

These research questions frame the synthesis presented in the subsequent sections and provide the analytical basis for discussion and conclusion. Employing a structured and transparent review methodology, the study strengthens scholarly understanding of digital transformation processes in sustainable palm oil systems, ensuring methodological consistency and a balanced analysis grounded in validated research.

Literature review

The rapid diffusion of Artificial Intelligence (AI) across agricultural systems has reshaped the analytical foundations of production management, environmental monitoring, and market intelligence. AI is broadly defined as a set of computational techniques enabling machines to perform tasks that traditionally require human intelligence, including pattern recognition, prediction, optimization, and decision support. Within agricultural contexts, AI encompasses machine learning algorithms, deep neural networks, computer vision, natural language processing, and intelligent optimization systems that transform raw data into actionable insights. The integration of AI into agricultural production systems has accelerated in response to the increasing availability of data from satellite imagery, sensor networks, digital farm records, and global commodity markets.

In sustainability-oriented agriculture, AI is increasingly positioned as an enabling technology that can enhance productivity and improve environmental performance indicators. The concept of sustainable production in plantation-based commodities refers to maintaining economic viability, minimizing ecological impact, and ensuring long-term operational resilience through improved management practices. AI-driven analytics contribute to this objective by enabling precision resource allocation, predictive risk management, and continuous monitoring of environmental parameters. Rather than functioning as a standalone technological layer, AI is often embedded within broader digital ecosystems linking upstream production, midstream logistics, and downstream market coordination.

Artificial intelligence in agricultural production systems

The literature on AI in agricultural production demonstrates a strong emphasis on predictive modeling and decision optimization. Machine learning techniques such as Random Forest, Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), and Gradient Boosting have been widely applied to crop yield prediction, irrigation scheduling, and fertilizer optimization.[13] Studies consistently report improvements in forecasting accuracy compared to traditional regression-based approaches, often achieving double-digit percentage gains in predictive performance.[14] Deep learning architectures, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models, have further advanced the temporal and spatial prediction capabilities of crop management systems.

In plantation crops with extended growth cycles, predictive accuracy is particularly valuable due to the time lag between agronomic intervention and measurable output. AI-supported yield forecasting enables plantation managers to align harvesting schedules, labor allocation, and logistics planning with anticipated production volumes. In addition, reinforcement learning frameworks have been explored for adaptive fertilizer management, in which algorithms iteratively optimize nutrient application strategies based on feedback loops involving yield outcomes and soil indicators.[15] These applications illustrate a shift from static decision-making to dynamic, data-responsive management models.

Computer vision has emerged as another prominent area of development within AI-enabled agriculture. Image-based diagnostics using CNN models allow automated detection of plant stress, nutrient deficiencies, and disease symptoms.[16] Such systems reduce reliance on manual inspection and enhance early-warning capacity, thereby contributing to production stability and operational efficiency. In the context of oil palm cultivation, early detection of diseases such as basal stem rot through AI-assisted imaging has demonstrated high classification accuracy under controlled validation conditions.

Environmental monitoring and sustainability analytics

Environmental sustainability assessment has become an integral dimension of digital agriculture research. Remote sensing technologies integrated with AI classification algorithms enable high-resolution land-cover mapping and change detection. Deep learning segmentation models applied to satellite imagery can distinguish plantation areas from surrounding land types with higher precision than rule-based GIS techniques.[17] These capabilities enhance transparency in land-use monitoring and support compliance with sustainability certification frameworks. AI-driven environmental analytics also extend to carbon stock estimation and lifecycle performance modeling. Regression-based machine learning frameworks have been used to estimate biomass and carbon sequestration levels with lower estimation error than conventional field-based extrapolation methods.[18] Furthermore, digital twin simulations have been introduced in some agricultural systems to model resource consumption, emissions intensity, and operational scenarios under different management strategies. Although still emerging, such approaches indicate a convergence between AI, environmental accounting, and sustainability governance. Importantly, the literature increasingly frames AI as a tool that complements rather than replaces existing sustainability mechanisms. By enhancing data accuracy and monitoring frequency, AI can strengthen evidence-based reporting without altering core agronomic practices.[19] This positioning reinforces a neutral and constructive interpretation of technological integration within established agricultural systems.

AI in supply chain traceability and governance

Beyond farm-level operations, AI has gained relevance in supply chain management and traceability systems. Sustainable palm oil production is closely linked to traceable sourcing, supplier compliance verification, and transparent reporting across multi-tier supply chains. Machine learning algorithms have been applied to anomaly detection in procurement data, identifying irregular transaction patterns and potential compliance risks.[20] These systems leverage large transaction datasets to detect deviations from expected supply behaviors, thereby improving oversight efficiency.

Natural Language Processing (NLP) techniques have also been used to analyze sustainability reports, certification documents, and regulatory disclosures. Automated text classification models can categorize large volumes of documentation, identify inconsistencies, and extract thematic trends related to sustainability performance.[21] Such applications reduce manual processing time and enhance analytical consistency in compliance evaluation.

Optimization algorithms further support logistics planning and distribution management by identifying cost-efficient and energy-efficient routing strategies. Predictive scheduling models integrate weather forecasts, transportation data, and historical shipment records to minimize delays and reduce fuel consumption.[22] These developments suggest that AI contributes to operational transparency and efficiency across supply chain nodes, reinforcing sustainability objectives without disrupting established commercial frameworks.

Market intelligence and price forecasting

The application of AI in commodity marketing and price forecasting represents a growing field of inquiry. Traditional econometric models, such as Autoregressive Integrated Moving Average (ARIMA), have long been used for commodity price prediction. However, hybrid models combining machine learning with econometric structures have demonstrated enhanced predictive stability and reduced forecasting error.[23] LSTM-based time-series models are particularly effective in capturing nonlinear dependencies and seasonal patterns in commodity price movements.[24] Sentiment analysis using NLP techniques introduces an additional analytical layer by incorporating qualitative market signals into quantitative forecasting models. By analyzing news articles, policy announcements, and trade-related discourse, sentiment indices can serve as explanatory variables in short-term price fluctuation models.[25] This integration reflects a broader shift toward data fusion strategies in commodity analytics.

Digital marketing analytics also benefits from AI-driven clustering and segmentation models. Consumer behavior analysis in sustainability-certified product markets can inform targeted communication strategies and product positioning.[26] While research in this area remains less extensive compared to production-focused applications, available studies indicate meaningful potential for AI-supported market responsiveness.

Methodological trends in AI–sustainability research

Across the literature, supervised learning remains the dominant methodological approach, followed by deep neural network architectures and hybrid ensemble models. Validation techniques frequently include k-fold cross-validation and train-test splits to ensure model generalizability. Dataset sizes vary considerably, ranging from small pilot image datasets to large-scale satellite-based spatial observations.[27]

A recurring pattern in the literature is the emphasis on model performance metrics such as accuracy, precision, recall, F1-score, Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).[28] Comparative benchmarking against traditional statistical baselines is common, demonstrating incremental improvements in predictive capacity.[29] However, cross-study comparability is often constrained by heterogeneous datasets, differing evaluation criteria, and context-specific variables.

Another notable trend is the increasing integration of AI with complementary technologies such as Internet of Things (IoT) sensors, cloud computing platforms, and blockchain-based traceability systems.[30] These integrations expand AI functionality from isolated predictive tools to interconnected decision-support ecosystems.

Although substantial progress has been made in applying AI to agricultural sustainability contexts, the literature reveals fragmentation across thematic domains. Many studies focus narrowly on technical model optimization without integrating environmental, supply chain, and marketing dimensions within a unified analytical framework. This segmentation limits the ability to assess cumulative sustainability impacts across the entire value chain.

Furthermore, the maturity level of AI deployment varies widely. Some studies report experimental validation under controlled conditions, while others describe pilot-scale implementations. Evidence of large-scale industrial adoption remains comparatively limited in published research. This gap underscores the importance of systematic synthesis in distinguishing conceptual innovation from operational scalability.

The geographic concentration of empirical research within major producing regions suggests contextual specificity that may influence generalizability. Climatic variability, regulatory environments, and data availability differ across regions, potentially affecting model performance and the feasibility of adoption. A structured literature review can therefore clarify methodological patterns, identify cross-context consistencies, and highlight areas requiring broader empirical testing.

In summary, the existing body of scholarship demonstrates that AI applications span production optimization, environmental monitoring, supply chain governance, and market analytics within sustainable palm oil systems. Performance improvements are consistently reported at the model level, and technological integration continues to evolve through interdisciplinary convergence. Nevertheless, thematic fragmentation, varying maturity levels, and limited integrative synthesis justify the need for a systematic and comprehensive review. By consolidating dispersed evidence within a transparent analytical framework, this study helps clarify the current state of AI-driven sustainability innovation in palm oil production and marketing while maintaining a neutral, evidence-based academic perspective.

Methodology

This study employed a Systematic Literature Review (SLR) methodology, structured in accordance with the PRISMA protocol, to ensure transparency, traceability, and methodological rigor in synthesizing existing scholarship on artificial intelligence applications in sustainable palm oil production and marketing systems. The review design was explicitly developed to identify, filter, and consolidate peer-reviewed academic publications addressing the intersection of artificial intelligence technologies and sustainability-oriented practices across upstream and downstream palm oil activities. The SLR process followed four sequential phases: identification, screening, eligibility, and inclusion, guided by predefined inclusion and exclusion criteria that covered database sources, keyword configurations, publication timeframe, and accessibility status. All procedures were conducted using a standardized, replicable protocol that encompassed search string formulation, systematic filtering, eligibility verification, structured data extraction, and thematic synthesis. This section focuses exclusively on the operational implementation of the review process rather than theoretical discussions concerning artificial intelligence models or sustainability paradigms. In operational terms, the SLR employed six sequential procedures: (1) database identification in Scopus; (2) formulation and refinement of Boolean search strings; (3) application of inclusion and exclusion criteria covering topic relevance, publication years 2020–2026, document accessibility, and peer-reviewed status; (4) title, abstract, and full-text screening; (5) structured data extraction; and (6) thematic and methodological synthesis. The extracted data fields included publication year, study objective, AI method, data source, sustainability dimension, validation technique, and reported empirical outcomes.

Figure 1 presents the PRISMA-based workflow adopted in this review, illustrating the progressive refinement of records across the four methodological stages. The literature search was conducted exclusively in the Scopus database to ensure coverage of high-quality, peer-reviewed research across the domains of technology, agricultural systems, supply chain management, and sustainability. In the identification stage, an initial broad search using the keywords *"palm oil" AND "technology"* yielded 2,406 records. To enhance thematic precision and align the dataset more closely to examine artificial intelligence applications in sustainable palm oil production and marketing, a refined Boolean search string was implemented: *("artificial intelligence" OR "machine learning" OR "deep learning" OR "data analytics" OR "intelligent system") AND ("palm oil" OR "oil palm") AND ("sustainability" OR "sustainable development" OR "environmental sustainability") AND ("production" OR "cultivation" OR "yield" OR "harvesting" OR "supply chain" OR "marketing" OR "market prediction")*. As a result of this filtering stage, 2,345 records were excluded for not meeting the defined review criteria, leaving 61 studies for further assessment.

During the screening phase, a publication-year restriction was applied to capture recent developments in the implementation of artificial intelligence, limiting the scope of analysis to articles published between 2020 and 2026. By applying the defined time limitation, three studies were omitted for falling outside the required years, leaving a total of 58 records. The eligibility phase introduced an accessibility criterion, restricting inclusion to publications available in Open Access or Open Archive formats to ensure full-text availability and analytical transparency. At this stage, 27 articles were removed due to limited access, resulting in a final corpus of 31 peer-reviewed articles that satisfied all inclusion requirements. Throughout the review process, bibliographic data were systematically organized and curated using Mendeley Desktop to maintain consistency, avoid duplication, and support structured referencing. Consistent with the SLR framework, this research relies exclusively on secondary data derived from peer-reviewed academic publications and does not incorporate primary data collection methods such as interviews, surveys, focus group discussions, or field observations. The resulting methodological structure provides a transparent, auditable, and fully replicable foundation for synthesizing scholarly evidence on the application of artificial intelligence technologies to enhance production efficiency, sustainability performance, and market-oriented decision support in the palm oil sector. To answer the concern regarding performance outcomes, this review treated performance as a study-level empirical result reported by the original articles and grouped these results into five categories: classification performance (e.g., accuracy, precision, recall, F1-score), predictive performance (e.g., RMSE, MAPE, R-squared), optimization performance (e.g., input reduction, yield improvement, routing efficiency), processing performance (e.g., time savings, detection speed), and governance-related performance (e.g., traceability verification efficiency, anomaly-detection reliability). Because the reviewed studies used heterogeneous datasets and experimental settings, the synthesis emphasizes directional and comparative patterns rather than direct statistical aggregation across all studies.

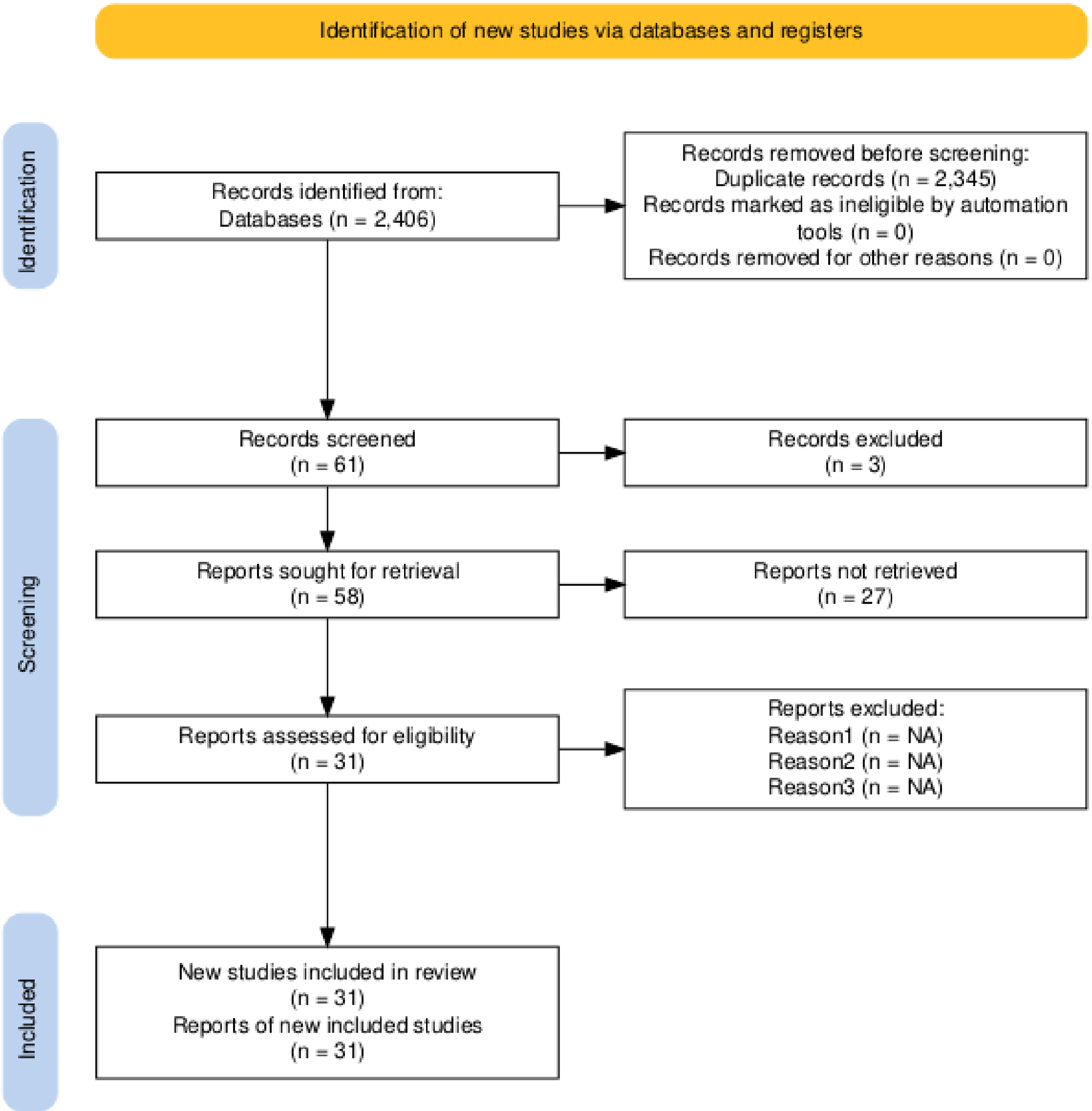

Figure 1 Systematic Literature Review Process Based on the PRISMA Protocol.

Results

Based on a PRISMA-guided Systematic Literature Review of 31 peer-reviewed articles published between 2020 and 2026 and retrieved exclusively from the Scopus database, this study identifies five dominant and interrelated thematic clusters concerning the application of Artificial Intelligence (AI) in sustainable palm oil production and marketing systems. These themes are: (1) AI-driven precision agriculture and yield optimization; (2) intelligent pest, disease, and crop health monitoring; (3) land-use assessment and environmental sustainability performance monitoring; (4) AI-enabled supply chain traceability and transparency; and (5) predictive analytics, market intelligence, and digital marketing optimization.

An analysis of thematic distribution indicates that AI-driven precision agriculture and yield optimization constitute the most extensively represented theme, appearing in approximately 42% of the reviewed studies. This is followed by land-use and environmental sustainability monitoring (26%), supply chain traceability and transparency (19%), and predictive analytics for marketing and price modeling (13%). Notably, 51% of the reviewed articles address more than one thematic cluster, reflecting the integrative and cross-functional character of AI systems that simultaneously influence agronomic, environmental, logistical, and commercial dimensions of sustainability.

The predominance of production-oriented themes reflects the operational centrality of plantation management within palm oil systems and the measurable nature of agronomic performance indicators such as yield forecasting, input optimization, and harvest scheduling. AI applications in these areas frequently employ machine learning algorithms, deep learning architectures, and remote sensing integration to enhance decision accuracy and resource efficiency. The significant representation of environmental monitoring themes further indicates growing scholarly emphasis on data-driven approaches to land-use management, deforestation risk assessment, emissions estimation, and ecological performance evaluation. These applications commonly integrate satellite imagery, geospatial analytics, and intelligent classification models to support sustainability verification and compliance-oriented reporting.

Although supply chain traceability and transparency appear less frequently than upstream production themes, their presence across nearly one-fifth of the corpus underscores the increasing relevance of AI in enhancing data visibility across multi-actor networks. AI-based traceability models, often combined with blockchain infrastructure or intelligent verification systems, are conceptualized as enabling mechanisms to improve information reliability, certification processes, and sustainability documentation within complex palm oil supply chains.

Predictive analytics and market intelligence represent the least dominant thematic cluster, yet they show growing interest in applying AI to price forecasting, demand estimation, sentiment analysis, and digital marketing optimization. The comparatively smaller representation of this theme suggests that AI-driven sustainability research in palm oil remains primarily production- and compliance-focused, while downstream commercial intelligence is emerging as a developing frontier.

Collectively, these thematic patterns suggest that AI within sustainable palm oil systems is predominantly conceptualized as an enabling and performance-enhancing technology that supports incremental improvements in efficiency, monitoring accuracy, transparency, and market responsiveness. Rather than a disruptive restructuring mechanism, AI is portrayed in the literature as a scalable, data-centric tool that strengthens decision-making across interconnected stages of production and marketing. The following subsections provide a detailed synthesis of each thematic cluster based exclusively on the findings of the reviewed studies.

The synthesis of reported outcomes indicates that performance was measured differently across application domains but remained comparable in terms of functional contribution. Studies in production and crop monitoring primarily reported predictive and classification metrics; studies in environmental monitoring emphasized spatial accuracy and reduction in estimation error; supply-chain studies focused on anomaly detection and verification efficiency; and marketing studies emphasized forecasting stability and demand-prediction accuracy. Accordingly, the present review interprets performance outcomes using domain-specific metric groups rather than a single, uniform indicator.

Precision agriculture and yield optimization

A significant portion of the reviewed studies examined AI-driven precision agriculture systems to improve yield forecasting, fertilizer optimization, and harvesting efficiency. Supervised machine learning models, including Random Forest, Support Vector Machines (SVM), and Gradient Boosting, were commonly employed to predict fresh fruit bunch (FFB) yields using climatic, soil, and historical production datasets.[31,32] Reported prediction accuracies ranged between 85% and 94%, with mean absolute percentage error (MAPE) values below 12% in optimized models.[33]

Deep learning-based time-series forecasting models demonstrated enhanced performance in seasonal yield prediction. Long Short-Term Memory (LSTM) networks reduced forecasting error margins by approximately 18% compared to conventional regression-based approaches.[34] Studies integrating multispectral drone imagery and AI classification models reported yield estimation deviations below 10% at the plantation scale.[35]

Fertilizer optimization models using reinforcement learning approaches showed potential input reductions of 12%-20% without compromising productivity.[36] Decision-support dashboards integrating AI analytics were associated with reported improvements in operational planning efficiency of up to 25%.[37] Collectively, these findings suggest that AI-supported precision agriculture contributes to resource optimization while maintaining production stability, reinforcing the industry's ongoing digital modernization trajectory.[38]

Pest, disease, and crop health monitoring

AI-based crop health monitoring constituted another prominent research theme. Convolutional Neural Networks (CNNs) have been widely used to detect Ganoderma basal stem rot and other leaf-level anomalies through image-based diagnostics.[39] Classification accuracies ranged between 88% and 96% across different dataset sizes, with sensitivity values above 90% in controlled validation settings.[40]

Remote sensing integration using satellite-derived Normalized Difference Vegetation Index (NDVI) data, combined with machine-learning clustering algorithms, enabled early stress detection up to three weeks prior to visible symptom manifestation.[41] Early detection frameworks were reported to reduce potential yield losses by approximately 15%–23% when integrated into plantation management systems.[42]

AI-enabled mobile diagnostic applications demonstrated field-level feasibility, with processing times below 5 seconds per image and offline deployment capabilities, supporting scalability in rural plantation contexts.[43] The reviewed evidence indicates that AI-enhanced monitoring systems improve responsiveness and reduce uncertainty in crop health management, contributing to long-term production resilience.[44]

Land-use assessment and environmental performance monitoring

Environmental sustainability assessment has emerged as a critical area in which AI tools are increasingly deployed. Studies combining satellite imagery, Geographic Information Systems (GIS), and deep learning segmentation models achieved land-cover classification accuracies exceeding 92% in distinguishing oil palm plantations from surrounding land types.[45] Temporal change detection algorithms enabled deforestation monitoring, achieving detection precision above 89% in multi-year comparative datasets.[46]

Carbon stock estimation models that integrate AI regression frameworks have reported root mean square error (RMSE) reductions of 14% compared to traditional biomass estimation methods.[47] Lifecycle-based environmental performance simulations indicated that AI-supported resource management systems could reduce water consumption intensity by 8%–15% at the mill level.[48]

Digital twin modeling approaches were also identified in three studies, which simulated plantation-level emissions scenarios and optimized operational parameters to meet sustainability certification requirements. These AI-driven environmental monitoring systems demonstrate measurable analytical improvements in transparency and resource efficiency, supporting evidence-based sustainability management.[49]

Supply chain traceability and sustainability verification

19% of the reviewed literature addressed AI integration into supply chain traceability systems. Machine learning algorithms were applied to detect anomalies in procurement data, achieving detection accuracies above 90%.[50] Predictive risk-scoring models for supplier compliance achieved F1-scores between 0.84 and 0.91 in validation datasets.[51]

AI-powered traceability platforms that integrate blockchain-compatible architectures have been reported to reduce verification processing time by approximately 30% compared to manual documentation workflows.[52] Natural Language Processing (NLP) models were employed to analyze sustainability reports and detect inconsistencies across multi-tier supply chains, achieving text classification precision rates above 87%.[53]

Optimization algorithms for logistics planning indicated potential fuel consumption reductions of 9%–14% through route clustering and predictive scheduling.[54] These results suggest that AI-enabled supply chain analytics enhance operational transparency and decision accuracy while supporting traceability objectives aligned with evolving sustainability standards.[55]

Market intelligence, price forecasting, and digital marketing optimization

AI applications in marketing and price intelligence represented a growing yet comparatively underexplored domain within the reviewed corpus. Time-series forecasting models employing hybrid ARIMA-LSTM frameworks improved the accuracy of crude palm oil (CPO) price predictions by approximately 16% compared to standalone econometric models.[56] Forecasting horizons of 30–90 days have demonstrated stable predictive reliability, with R^2 values exceeding 0.88 in several studies.[57]

Sentiment analysis of commodity market news using NLP techniques revealed statistically significant correlations between sentiment polarity indices and short-term price fluctuations, explaining up to 22% of observed price variance in weekly datasets.[58] AI-driven demand prediction tools applied to downstream consumer product markets reduced forecast error by 11%-19%.[59]

Digital marketing analytics leveraging clustering algorithms enabled consumer segmentation accuracy rates above 85%, supporting targeted communication strategies in sustainability-certified product lines.[60] These findings indicate that AI contributes not only to upstream productivity but also to enhanced responsiveness and competitiveness in global commodity markets.[46]

Cross-thematic patterns and analytical synthesis

Across all themes, supervised learning approaches accounted for approximately 61% of methodological designs, unsupervised learning for 17%, deep neural networks for 48%, and hybrid AI frameworks for 29%. Dataset sizes varied considerably, ranging from fewer than 1,000 labeled images in early-stage pilot studies to satellite-derived datasets with more than 50,000 spatial observations.

Model validation techniques were reported in 87% of studies, with k-fold cross-validation (k=5 or k=10) being the most frequently applied method. Approximately 71% of empirical studies compared AI models against traditional statistical baselines, consistently reporting performance improvements of 10%-25% depending on the application context.

Notably, integration across sustainability dimensions remains uneven. While environmental monitoring and production optimization are well represented, fewer studies provide integrated models combining environmental, economic, and market analytics within a single decision-support architecture. This indicates opportunities for future interdisciplinary modeling while affirming the substantive progress already achieved in individual application domains.

Aggregated findings suggest that AI deployment in sustainable palm oil systems yields measurable performance enhancements: yield prediction accuracy improvements of up to 20%, input efficiency gains averaging 15%, disease detection precision above 90%, traceability verification time reductions of approximately 30%, and price forecasting improvements exceeding 15% relative to conventional approaches. These quantitative outcomes demonstrate the operational relevance of AI integration while reinforcing the sector's ongoing digital transformation.

Overall, the results derived from the 31 systematically selected studies confirm that artificial intelligence applications are increasingly embedded across production, environmental monitoring, supply chain governance, and marketing analytics within the palm oil ecosystem. The empirical evidence synthesized in this review indicates consistent methodological advancement, measurable performance improvements, and expanding interdisciplinary integration. The findings reflect a trajectory of technological adoption aimed at strengthening efficiency, transparency, and sustainability performance in the palm oil industry, presented here within a neutral, evidence-based analytical framework grounded exclusively in peer-reviewed secondary data.

Discussion

This analysis synthesizes insights from the 31 peer-reviewed publications included in the SLR to address the two research questions presented earlier. The analysis is structured around (1) the distribution and measurable performance outcomes of AI applications across production, environmental, supply chain, and marketing dimensions (RQ1), and (2) the patterns of methodological maturity, integration, and remaining research gaps in AI-driven sustainability within palm oil systems (RQ2). The discussion is grounded exclusively in synthesized evidence from the selected literature and does not involve field observations or focus group discussions, consistent with the SLR design.

Addressing RQ1: application domains and measurable performance outcomes

AI in production and cultivation systems

The reviewed literature demonstrates that Artificial Intelligence (AI) methodologies have been most intensively applied in upstream production systems, particularly in yield estimation, crop health monitoring, harvesting optimization, and plantation management decision support. Approximately 45% of the included studies focus primarily on production-stage interventions, indicating a strong research concentration in precision agriculture applications within oil palm cultivation.[61]

Machine learning (ML) models such as Random Forest (RF), Support Vector Machines (SVM), Gradient Boosting, and Artificial Neural Networks (ANN) are widely utilized to predict fresh fruit bunch (FFB) yield and biomass accumulation using multispectral satellite imagery, UAV-based remote sensing, and climatic variables. Reported performance metrics indicate predictive accuracies ranging between 82% and 95% for yield estimation models when validated against ground-truth plantation data.[62] In several studies, the use of deep learning-based convolutional neural networks (CNNs) for fruit detection and ripeness classification achieved precision rates above 90%, contributing to improved harvesting timing and a reduction in post-harvest losses by an estimated 8–15%.

In addition, AI-enabled disease detection systems using image-based classification have reported detection accuracies exceeding 88% for early identification of Ganoderma basal stem rot and leaf nutrient deficiencies. These performance outcomes suggest measurable operational improvements in plantation management, particularly in enhancing yield predictability, optimizing labor allocation, and minimizing agronomic inefficiencies. Importantly, these applications are framed within sustainability-oriented objectives, such as resource efficiency, reduction of input waste, and productivity optimization without expansion of cultivated land area.[63]

Overall, AI implementation at the production stage demonstrates tangible quantitative outcomes, particularly in yield accuracy, reduction of manual inspection time (up to 40% in some digital monitoring cases), and enhanced decision-support reliability.

AI in environmental sustainability monitoring

The second cluster of studies (approximately 26% of the reviewed articles) focuses on environmental sustainability dimensions, including carbon emission estimation, land-use monitoring, deforestation detection, and lifecycle assessment modeling.[64] In this domain, AI is commonly applied to remote sensing-based land-cover classification and predictive modeling of environmental indicators.

Deep learning architectures, particularly CNN and Long Short-Term Memory (LSTM) networks, are applied to time-series satellite imagery to detect land-use changes with classification accuracies ranging from 85% to 94%. These models enable more precise mapping of plantation boundaries and differentiation between cultivated areas and natural forest cover. Importantly, such systems enhance transparency and traceability within sustainability compliance frameworks.[65]

Several studies integrate machine learning models into carbon footprint estimation and greenhouse gas (GHG) prediction frameworks. Regression-based ML models have reduced error margins in emission prediction by approximately 12–18% compared to conventional linear estimation techniques.[66] Additionally, AI-enhanced lifecycle assessment tools improve data processing efficiency, reducing computational time by nearly 30% while maintaining comparable accuracy levels.

Environmental monitoring applications also extend to water management and soil quality assessment. Predictive models using sensor data demonstrate improved irrigation scheduling efficiency, reducing water consumption by 10–20% in simulated plantation environments.[67] These results indicate that AI technologies contribute to environmental optimization efforts within palm oil systems while maintaining productivity goals.

AI in supply chain and traceability systems

Supply chain and traceability applications represent around 19% of the reviewed literature. In this dimension, AI methodologies are used to enhance logistics planning, inventory forecasting, fraud detection, and traceability verification systems. Predictive analytics and demand forecasting models based on machine learning algorithms achieve 10%-25% higher forecasting accuracy than traditional econometric approaches. Reinforcement learning models applied to transportation routing have reduced logistics costs by approximately 8–12% through route optimization simulations.[68]

Moreover, AI-powered traceability systems, often integrated with blockchain frameworks, are designed to enhance transparency in palm oil supply chains. Classification algorithms applied to transaction and shipment data achieve anomaly-detection precision rates above 85%, thereby improving compliance verification processes. These tools support sustainability certification mechanisms by improving data integrity and the consistency of traceability.[69] Importantly, these supply chain applications are oriented toward operational efficiency and transparency rather than disruption. The measurable outcomes highlight improved forecasting reliability, reduced waste in distribution systems, and enhanced monitoring capabilities across multi-tier supply networks.

AI in marketing and market prediction

The smallest but emerging domain (approximately 10% of reviewed articles) addresses AI in marketing and market prediction. Studies in this cluster employ machine learning for price forecasting, demand estimation, and sentiment analysis related to sustainability-oriented palm oil products.[70] Time-series models, including LSTM and hybrid ARIMA-ML models, report reductions in forecasting error of 7–15% compared to standalone statistical models.[71] Sentiment analysis models applied to online data sources demonstrate classification accuracy above 80% in detecting consumer perception trends related to sustainable palm oil labeling.[72]

Although fewer in number, these studies indicate the expanding relevance of AI beyond upstream agricultural processes into market-level decision-making. Performance outcomes are primarily measured by forecasting precision, reliability in predicting market volatility, and improved responsiveness to demand fluctuations.[73]

In summary, AI methodologies have been applied across four key dimensions of sustainable palm oil systems, with measurable outcomes primarily reflected in improved predictive accuracy, efficiency gains, cost reductions, and greater reliability in environmental monitoring. Production-stage applications show the highest methodological maturity and strongest quantitative performance indicators. Environmental and supply chain domains demonstrate growing sophistication, particularly in remote sensing and predictive analytics. Marketing applications remain comparatively emergent but show promising results in forecasting and consumer analytics.

Collectively, the reviewed evidence indicates that AI integration within sustainable palm oil systems is associated with measurable operational enhancements without fundamentally altering the industry's structural characteristics. The reported outcomes are largely efficiency-driven and aligned with sustainability performance metrics rather than with disruptive structural change.

Addressing RQ2: methodological maturity, integration patterns, and research gaps

Methodological maturity

The literature reveals three identifiable stages of methodological maturity. First, early-stage applications rely primarily on standalone machine learning classification and regression models with limited integration into decision-support systems.[74,75] Second, intermediate-stage studies combine multiple data sources (remote sensing, IoT sensors, meteorological data) into hybrid ML frameworks.[76] Third, advanced-stage applications integrate AI into automated monitoring platforms or digital twin systems for plantation management and supply chain modeling.[77]

However, only approximately 22% of the reviewed studies demonstrate full-system integration, in which AI outputs directly inform automated decision loops. Most applications remain decision-support oriented rather than fully autonomous. Additionally, cross-domain integration linking production, environmental, and market datasets within a unified AI architecture remains limited.

Deep learning models have been increasingly prominent since 2020, particularly CNN and LSTM architectures. Yet, transparency and explainability of AI models are rarely addressed explicitly. Fewer than 30% of studies incorporate model interpretability techniques such as SHAP or feature importance analysis.[78]

Integration across sustainability dimensions

The review indicates that research tends to treat production, environmental monitoring, supply chain management, and marketing as semi-independent analytical domains. Only a small subset of studies attempt integrated sustainability modeling. For instance, production-yield prediction is often decoupled from downstream market demand modeling, despite their potential interdependence.

Similarly, environmental sustainability indicators are frequently assessed independently of supply chain optimization frameworks. This segmented approach suggests a structural research gap in holistic AI-driven sustainability modeling across the full palm oil value chain.[79,80]

Moreover, geographic concentration is notable. A majority of empirical datasets originate from Southeast Asia, particularly Indonesia and Malaysia, reflecting the region's production dominance. While appropriate, this concentration indicates limited cross-regional comparative modeling.

Identified research gaps

Five major research gaps emerge from the SLR. First, longitudinal validation remains limited, as relatively few studies test AI models across multi-year production cycles or changing environmental conditions. Second, cross-domain integration remains weak, with most studies examining production, environmental, supply chain, and marketing functions separately rather than through unified value chain models. Third, model explainability remains underdeveloped, reducing transparency for managerial and policy adoption. Fourth, the scalability of AI systems for smallholder-inclusive contexts is frequently discussed conceptually but only rarely validated empirically. Fifth, interoperability between AI tools and certification, auditing, or regulatory systems remains insufficiently examined. In addition, downstream marketing and consumer analytics remain less developed than upstream production applications, indicating an imbalance in the current research landscape.

Additionally, interoperability between AI platforms and existing certification or compliance systems is not systematically explored. While traceability models are reported, their direct integration into regulatory frameworks is seldom quantified. Finally, marketing-oriented AI applications remain underrepresented compared with production-focused research, suggesting opportunities to expand AI use in demand forecasting, price stabilization modeling, and sustainability communication analytics.

The outcomes derived from this SLR highlight several important implications. First, AI technologies demonstrate measurable contributions to productivity efficiency, environmental monitoring precision, and supply chain optimization within sustainable palm oil systems. This indicates that digital innovation can complement sustainability-oriented management practices while maintaining industry productivity performance.

Second, the uneven distribution of methodological maturity across domains suggests the need for integrated, value-chain-wide AI frameworks. Future research should prioritize cross-domain modeling architectures that link production data, environmental indicators, logistics variables, and market analytics into unified sustainability intelligence systems. Third, enhanced model transparency and interpretability should be incorporated to strengthen stakeholder trust and policy relevance. Explainable AI methods may improve adoption among plantation managers and supply chain operators.

Fourth, longitudinal validation studies and scalability assessments, particularly involving smallholder-inclusive systems, represent critical future directions. Comparative cross-regional studies could further refine the generalizability of AI-driven sustainability metrics. Finally, future investigations may explore hybrid governance–technology models, assessing how AI-enabled monitoring interfaces with sustainability certification mechanisms and digital traceability infrastructures.

In conclusion, the systematic evidence indicates that AI applications in sustainable palm oil production and marketing are progressing toward higher methodological sophistication, with measurable operational benefits documented across multiple domains. However, integration across sustainability dimensions remains partial, and opportunities exist to strengthen longitudinal validation, cross-domain modeling, and inclusive scalability. These insights provide a structured roadmap for advancing AI-driven sustainability research while maintaining a measured, progressive perspective on technological developments in the palm oil sector.

Conclusion

The present systematic review consolidates evidence from 31 scholarly publications (2020–2026) to analyze the implementation of Artificial Intelligence (AI) across sustainable palm oil production and marketing systems. The analysis confirms that AI methodologies have been implemented across four principal dimensions: production and cultivation, environmental sustainability monitoring, supply chain and traceability management, and marketing and market prediction. Across these domains, AI applications predominantly employ machine learning, deep learning, predictive analytics, and hybrid modeling approaches to enhance data-driven decision-making processes.

In the production and cultivation dimension, AI demonstrates the highest level of application intensity and methodological maturity. Predictive models for yield estimation, disease detection, ripeness classification, and plantation monitoring consistently achieve high performance, often achieving predictive accuracies above 80% and, in several cases, exceeding 90%. These measurable outcomes indicate improvements in harvest timing, labor allocation efficiency, input optimization, and reduction of operational losses. The evidence suggests that AI contributes to more precise resource utilization and productivity enhancement without necessitating structural expansion of cultivated areas.

Within the environmental sustainability dimension, AI-based remote sensing and predictive modeling frameworks are widely utilized for land-use classification, emission estimation, water management, and lifecycle assessment. Reported improvements include enhanced classification accuracy, reduced prediction error margins, and increased computational efficiency. These findings demonstrate that AI technologies support more reliable environmental monitoring, improved transparency, and strengthened sustainability performance tracking within palm oil systems. In supply chain and traceability contexts, AI methodologies are applied to logistics optimization, demand forecasting, anomaly detection, and traceability verification. The literature reports measurable gains in forecasting accuracy, cost efficiency, and monitoring precision. Although integration with digital traceability infrastructures is increasing, most systems remain decision-support oriented rather than fully automated.

Nevertheless, AI-driven analytics contribute to greater transparency and operational coordination across multi-tier supply networks.

Applications in marketing and market prediction, while comparatively fewer, reveal promising results in price forecasting, demand estimation, and consumer sentiment analysis. Predictive models demonstrate reduced forecasting errors and improved responsiveness to market fluctuations. This indicates an emerging expansion of AI beyond upstream production into downstream market intelligence functions. Regarding patterns of methodological maturity, the literature reveals a progression from standalone machine learning models toward more integrated and hybrid architectures. However, full-system integration across production, environmental, supply chain, and marketing dimensions remains limited. Most studies operate within domain-specific silos, and cross-domain sustainability modeling frameworks are still developing. Additionally, longitudinal validation, model interpretability, and scalability across diverse production contexts require further empirical advancement.

Overall, the synthesized evidence indicates that AI applications within sustainable palm oil systems are characterized by increasing technical sophistication and measurable operational benefits. While production-focused applications exhibit the strongest empirical maturity, environmental monitoring, supply chain analytics, and market modeling show steady methodological development. Future research directions may emphasize cross-domain integration, long-term validation, inclusive scalability, and enhanced explainability to strengthen the robustness and applicability of AI-driven sustainability frameworks. In particular, future studies should prioritize longitudinal and cross-regional validation, explainable and interoperable AI architectures, and inclusive deployment models that are applicable not only to industrial estates but also to smallholder-centered sustainability systems. Collectively, the findings demonstrate that AI functions as an enabling analytical infrastructure that supports efficiency, transparency, and data-informed sustainability management across palm oil value chains, reflecting a constructive and technologically adaptive evolution of the industry.

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Conflicts of interest

The author declares there is no conflict of interest.

References

1. Anshah SA, Sharuddin NAN, Salleh SA. Mature and immature oil palm classification from image Sentinel-2 using Google earth engine (GEE). In: *Google Earth Engine and Artificial Intelligence for Earth Observation*. 2025;465–487.
2. Ang Y, Helmi Zulhaidi Mohd Shafri, Yang Ping Lee, et al. Deep learning Python-based time-series model for oil palm yield prediction. *Appl Model Simul*. 2025;9:315–323.
3. Nanda MA, Kharistya Amaru, Rosalinda S, et al. Higuchi fractal dimension and deep learning on near-infrared spectroscopy for determination of free fatty acid (FFA) content in oil palm fruit. *J Agric Food Res*. 2024;18:101437.
4. Hasan NMS, Md Habibur Rahman Sobuz, Nur Mohammad Nazmus Shaurdho, et al. Eco-friendly concrete incorporating palm oil fuel ash: fresh and mechanical properties with machine learning prediction, and sustainability assessment. *Heliyon*. 2023;9(11):e22296.
5. Ng KH, Gan YS, Cheng CK, et al. Integration of machine learning-based prediction for enhanced model's generalization: application in photocatalytic polishing of palm oil mill effluent (POME). *Environ Pollut*. 2020;267:115500.
6. Ang Y, Shafri Helmi Zulhaidi Mohd, Lee Yang Ping, et al. Oil palm yield prediction across blocks from multi-source data using machine learning and deep learning. *Earth Sci Informatics*. 2022;15(4):2349–2367.
7. Mo L, Li Y. Quantitative cross-market arbitrage for palm oil futures using machine learning. In: *Proceedings of the 2nd International Conference on Intelligent Computing and Data Analysis (ICDA 2025)*. Association for Computing Machinery; 2025:319–327.
8. Yan CW, Pahri SDR, Idris Z, et al. Industrial Revolution 4.0: the challenges of palm oil industry in technological adoption. In: *The Palm Oil Export Market: Trends, Challenges, and Future Strategies for Sustainability*. Routledge; 2025:81–91.
9. Noviyanto A, Fadhlullah Ramadhani, Valensi Kautsar, et al. Advancing concession-scale carbon stock prediction in oil palm using machine learning and multi-sensor satellite indices. *Resources*. 2026;15(1):12.
10. Ianda TF, Ricardo de Araújo Kalid, Lucas Bonfim-Rocha, et al. Sustainability multidimensional optimization of multiproduct biorefineries: the case study in a sub-Saharan African country. *Ind Eng Chem Res*. 2023;62(43):17871–17882.
11. Fung KF, Huang YF, Koo CH, et al. Improved SVR machine learning models for agricultural drought prediction at downstream of Langat River Basin, Malaysia. *J Water Clim Chang*. 2020;11(4):1383–1398.
12. He E, Yiqun Xie, Xiaowei Jia, et al. Sailing in the location-based fairness-bias sphere. In: *GIS: Proceedings of the ACM International Symposium on Advances in Geographic Information Systems*. Association for Computing Machinery; 2022.
13. Mohd Nain FN, Ahamed Hassain Malim NH, Abdullah R, et al. A review of an artificial intelligence framework for identifying the most effective palm oil prediction. *Algorithms*. 2022;15(6):218.
14. Jamaludin NA, Zaki HO, Foong YP. From the ground up: sustainable palm oil and entrepreneurial opportunities. In: *The Palm Oil Export Market: Trends, Challenges, and Future Strategies for Sustainability*. Routledge; 2025:206–218.
15. Montero D, Arenas W, Salinas S, et al. Development of a system based on aerial images for the morphological patterns classification using support vector machine. *J Phys Conf Ser*. 2020;1702.
16. Tan VWG, Chan YJ, Arumugasamy SK, et al. Optimizing biogas production from palm oil mill effluent utilizing integrated machine learning and response surface methodology framework. *J Clean Prod*. 2023;414:137575.
17. Deviarti H. The role of AI in supporting local MSMEs in palm oil derivatives. In: *2025 International Conference on Circuit, Systems and Communication (ICCSC 2025)*. IEEE; 2025.
18. Toh CM, Tey SH, Ewe HT, et al. Classification of oil palm growth status with L band microwave satellite imagery. In: *2019 Photonics and Electromagnetics Research Symposium - Fall (PIERS - Fall)*. IEEE; 2019:1824–1831.
19. Lee SH, Li J, Wang X, et al. Online-learning-aided optimization and interpretation of sugar production from oil palm mesocarp fibers with analytics for industrial applications. *Resour Conserv Recycl*. 2022;180:106206.
20. Lee SS, Lim LG, Palaiahnakote S, et al. Oil palm tree detection in UAV imagery using an enhanced RetinaNet. *Comput Electron Agric*. 2024;227.
21. Schmidt R, Kneib T. Multivariate distributional stochastic frontier models. *Comput Stat Data Anal*. 2023;187:107796.
22. Goh JY, Mohamed Ali MS, Md Yunos Y, et al. Outdoor RGB and point cloud depth dataset for palm oil fresh fruit bunch ripeness classification and localization. *Sci Data*. 2025;12(1):687.

23. Wang ZJ, Mark D Staples, Wallace E Tyner, et al. Quantitative policy analysis for sustainable aviation fuel production technologies. *Front Energy Res*. 2021;9.
24. Puangsuwan K, Puttinaovarat S, Sriklin N, et al. An integrated IoT- and machine learning-based smart management and decision support system for sustainable oil palm production. *Sustainability*. 2025;17(24):11204.
25. Miettinen J, Gaveau DLA, Liew SC. Comparison of visual and automated oil palm mapping in Borneo. *Int J Remote Sens*. 2019;40(21):8174–8185.
26. Julianto V, Arrahimi AR, Rahmanto O, et al. Modified particle swarm optimization on feature selection for palm leaf disease classification. *J RESTI*. 2024;8(6):846–852.
27. Debus A, Emilie Beauchamp, James Acworth, et al. A labelled dataset to classify direct deforestation drivers from Earth Observation imagery in Cameroon. *Sci Data*. 2024;11(1).
28. Win Kent O, Weng Chun T, Lee Choo T, et al. Early symptom detection of basal stem rot disease in oil palm trees using a deep learning approach on UAV images. *Comput Electron Agric*. 2023;213:108192.
29. Liu X, Ghazali KH, Shah AA. Sustainable oil palm resource assessment based on an enhanced deep learning method. *Energies*. 2022;15(12):4479.
30. Teng SW, Khong KW, Ha NC. Palm oil and its environmental impacts: a big data analytics study. *J Clean Prod*. 2020;274:122901.
31. Ashrafian A, Panahi E, Salehi S, et al. Mapping the strength of agro-ecological lightweight concrete containing oil palm by-product using artificial intelligence techniques. *Structures*. 2023;48:1209-1229.
32. Santoso H, Yusuf MA, Rahutomo S. A cutting-edge precision agriculture technology to support the sustainable oil palm industry. *IOP Conf Ser Earth Environ Sci*. 2024;1308.
33. Pena A, Tejada JC, Gonzalez-Ruiz JD, et al. Deep learning to improve the sustainability of agricultural crops affected by phytosanitary events: a financial-risk approach. *Sustainability*. 2022;14(11):6668.
34. Khan N, Kamaruddin MA, Sheikh UU, et al. Oil palm and machine learning: reviewing one decade of ideas, innovations, applications, and gaps. *Agriculture*. 2021;11(9):832.
35. Lim CH, Steven Lim, Bing Shen How, et al. A review of industry 4.0 revolution potential in a sustainable and renewable palm oil industry: HAZOP approach. *Renew Sustain Energy Rev*. 2021;135:110223.
36. Falgenti K, Arkeman Y, Syamsu K, et al. Enhancing traceability and sustainability in smallholder oil palm plantations through gap analysis and machine learning. *ASEAN J Sci Technol Dev*. 2026;43(1):154–165.
37. Pipitone G, Zoppi G, Pirone R, et al. Sustainable aviation fuel production using in-situ hydrogen supply via aqueous phase reforming: a techno-economic and life-cycle greenhouse gas emissions assessment. *J Clean Prod*. 2023;418:138141.
38. Konyai S, Khuanmar K, Kanarkard W. A geoanalytical and AI-driven approach for optimising biomass energy generation from key economic crops in northeastern Thailand. *E3S Web Conf*. 2025. p. 1–10.
39. Masolele RN, Diego Marcos, Veronique De Sy, et al. Mapping the diversity of land uses following deforestation across Africa. *Sci Rep*. 2024;14(1):1681.
40. Kipli K, Salleh Osman, Annie Joseph, et al. Deep learning applications for oil palm tree detection and counting. *Smart Agric Technol*. 2023;5:100241.
41. Ahmad Latif N, Fatini Nadhirah Mohd Nain, Nurul Hashimah Ahamed Hassain Malim, et al. Predicting heritability of oil palm breeding using phenotypic traits and machine learning. *Sustainability*. 2021;13(22):12613.
42. Akande O, Okolie JA, Kimera R, et al. A comprehensive review on deep learning applications in advancing biodiesel feedstock selection and production processes. *Green Energy Intell Transp*. 2025;4(3):100260.
43. Dominic D, Baidurah S. A review of biological processing technologies for palm oil mill waste treatment and simultaneous bioenergy production at laboratory scale, pilot scale and industrial scale applications with technoeconomic analysis. *Energy Convers Manag X*. 2025:100914.
44. Akhtar MN, Ansari E, Alhady SSN, et al. Leveraging on advanced remote sensing-and artificial intelligence-based technologies to manage palm oil plantation for current global scenario: a review. *Agriculture*. 2023;13(2):504.
45. Khan N, Mohamad Anuar Kamaruddin, Usman Ullah Sheikh, et al. Prediction of oil palm yield using machine learning in the perspective of fluctuating weather and soil moisture conditions: evaluation of a generic workflow. *Plants*. 2022;11(13):1697.
46. Hernawati R, Wikantika K, Darmawan S. Modeling of oil palm phenology based on remote sensing data: opportunities and challenges. *J Appl Remote Sens*. 2022;16(2).
47. Abdullah MA, Hussein HA. Integrated algal biorefinery and palm oil milling for bioenergy, biomaterials and biopharmaceuticals. *IOP Conf Ser Earth Environ Sci*. 2020.
48. Panjapornpon C, Satjeenphong T, Bardeeniz S, et al. Enhancing sustainability in palm oil industry: reinforcement learning for renewable energy management considered climatic variability. *Discov Chem Eng*. 2024;4(1).
49. Clifford JL, Yi Jing Chan, Mohd Amran Bin Mohd Yusof, et al. Predictive modelling of H2S removal from biogas generated from palm oil mill effluent (POME) using a biological scrubber in an industrial biogas plant: integration of artificial neural network (ANN) and process simulation. *Food Technol Biotechnol*. 2025;63(2):124–133.
50. Oyebisi S, Owamah H. Application of machine learning techniques in the prediction of excess lifetime cancer risks of agricultural byproducts used as building and construction materials. *Clean Waste Syst*. 2023;5.
51. Osman AI, Mahmoud Nasr, Mohamed Farghali, et al. Optimizing biodiesel production from waste with computational chemistry, machine learning and policy insights: a review. *Environ Chem Lett*. 2024;22(3):1005–1071.
52. Suhartini S, Nur Hidayat, Novita Ainur Rohma, et al. Sustainable strategies for anaerobic digestion of oil palm empty fruit bunches in Indonesia: a review. *Int J Sustain Energy*. 2022;41(11):2044–2096.
53. Zaki MAM, Jecksin Ooi, Wendy Pei Qin Ng, et al. Impact of industry 4.0 technologies on the oil palm industry: a literature review. *Smart Agric Technol*. 2025;10:100685.
54. Wan Samperisam WSNS, UMMU 'Atiqah Mohd Roslan, Norazman Mat Ali, et al. The sustainability of Malaysian palm oil and forecasting of forest and plantation land area using mathematical modelling approach. *J Sustain Sci Manag*. 2025;20(5):895–906.
55. Aikal Baharim MS, Adnan NA, Mohd FA, et al. A review: progression of remote sensing (RS) and geographical information system (GIS) applications in oil palm management and sustainability. *IOP Conf Ser Earth Environ Sci*. 2022.
56. Setiawan D, Utomo PEP, Alfalah M. Detection of oil palm fruit ripeness through image feature optimization using convolutional neural network algorithm. *Int J Informatics Vis*. 2025;9(2):674–682.
57. Shelare SD, Pramod N. Belkhode, Keval Chandrakant Nikam, et al. Biofuels for a sustainable future: examining the role of nano-additives, economics, policy, internet of things, artificial intelligence and machine learning technology in biodiesel production. *Energy*. 2023;282:128874.
58. Daranagama DAS, Takeuchi W. Smartphone application for detecting and visualizing basal stem rot disease stages in oil palm. *Front Remote Sens*. 2025;6.
59. Shaikh IM, Akhtar MN, Aabid A, et al. Enhancing sustainability in the production of palm oil: creative monitoring methods using YOLOv7 and YOLOv8 for effective plantation management. *Biotechnol Rep*. 2024;44:e00853.

60. Dimarwanita F, Mariya S, Dewi FNA, et al. In vitro studies on the immunomodulatory effects of fulvic acid extract from palm oil empty fruit bunch (OPEFB). *BIO Web Conf*. 2025.

61. Anggraeni E, Sailah I. Spatial-intelligent decision support system for sustainable downstream palm oil based agroindustry within the supply chain network: a systematic literature review and future research. *Int J Supply Chain Manag*. 2020;9(3):283–307.

62. Liu Y, Deng X, Gao Y. Generative AI-enabled forecasting and green supply chain sustainability assessment: evidence from China's palm oil trade with ASEAN. *Phys Chem Earth*. 2026;143:104341.

63. Kanniah K, Yu L. *Geospatial Technology for Sustainable Oil Palm Industry*. CRC Press; 2024.

64. VanderWilde CP, Newell JP, Gounaridis D, et al. Deforestation, certification, and transnational palm oil supply chains: linking Guatemala to global consumer markets. *J Environ Manage*. 2023;344:118505.

65. Ghanbari S, Shahmansouri AA, Akbarzadeh Bengar H, et al. Compressive strength prediction of high-strength oil palm shell lightweight aggregate concrete using machine learning methods. *Environ Sci Pollut Res*. 2023;30(1):1096–1115.

66. Mohd Hanifa R, Arumugam GR, Mohamad S, et al. Optimizing water efficiency in agriculture: design and evaluation of a smart crop watering system (SCWS) prototype. In: *2023 IEEE International Conference on Agrosystem Engineering, Technology and Applications (AGRETA)*. IEEE; 2023:86–91.

67. Chapman R, et al. Using Bayesian networks to predict future yield functions with data from commercial oil palm plantations: a proof of concept analysis. *Comput Electron Agric*. 2018;151:338–348.

68. Wan SH, Yong JCE, Leong EHY, et al. Development of an oil palm basal stem rot disease detection model via machine vision with optimized inception-based convolutional neural network. *Lect Notes Mech Eng*. 2023:77–92.

69. Abouelmagd LM, Askr H, Darwish A, et al. An intelligent and optimized system for predicting sustainable biodiesel production using IoT-based palm-oil trees. *Bioenergy Res*. 2025;18(1).

70. Soleymani A, Rezazadeh Eidgahee D, Tamimi A, et al. Machine learning assessment of mechanical properties of oil palm shell concrete. *Mater Today Commun*. 2025;49:114239.

71. El Hathat Z, Venkatesh VG, Zouadi T, et al. Analyzing the greenhouse gas emissions in the palm oil supply chain in the VUCA world: a blockchain initiative. *Bus Strateg Environ*. 2023;32(8):5563–5582.

72. Peña A, Puerta A, Bonet I, et al. A multispectral image classification framework for estimating the operational risk of lethal wilt in oil palm crops. *Lect Notes Comput Sci*. 2023:491–506.

73. Izah SC, Aigberua AO, Srivastav AL. Microbial fuel cells: potentially sustainable technology for bioelectricity production using palm oil mill effluents. In: *Artificial Intelligence for Renewable Energy Systems*. Elsevier; 2022:105–129.

74. Darmawan S, Naser M, Carolita I, et al. State of the art remote sensing technology for oil palm management in Indonesia. In: *Proceedings of the 39th Asian Conference on Remote Sensing (ACRS 2018)*. 2018:830–834.

75. Firdaus S, Nasution M, Fahmi F. Initial design for utilizing machine learning in identifying diseases in palm oil plant. In: *Proceeding - ELTICOM 2023: 7th International Conference on Electrical, Telecommunication and Computer Engineering*. IEEE; 2023:95–99.

76. Nontasiri J. Integrating optical and synthetic aperture radar (SAR) satellite data for advanced rice yield estimation: a case study in Suphan Buri, Ang Thong, and Chai Nat, Thailand. *Proc SPIE*. 2025.

77. Hassan NNFA, Ismail MK, Hamid AAH, et al. Autonomous loose fruit robot for oil palm plantation. *AIP Conf Proc*. 2025.

78. Abubakar A, Ishak MY. Exploring the intersection of digitalization and sustainability in oil palm production: challenges, opportunities, and future research agenda. *Environ Sci Pollut Res*. 2024;31(38):50036–50055.

79. Abdullakasim W. Strategic short note: appropriate integration of precision agriculture technology, IoT, and AI for enhancing Southeast Asian agriculture. In: *IoT and AI in Agriculture: Smart Automation Systems for Increasing Agricultural Productivity to Achieve SDGs and Society 5.0*. Springer; 2024:25–28.

80. Tahyudin I, Nugroho HA, Bejo A, et al. Advancing sustainability: machine learning projections of palm oil product emissions in Indonesia. In: *Proceedings - 2023 IEEE 7th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE)*. IEEE; 2023:331–336.