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GREEN AI FOR SMART AGRICULTURE: ENERGY-EFFICIENT PREDICTIVE MODELS FOR CROP YIELD AND RESOURCE MANAGEMENT

Arockia Nisha S
Assistant Professor
Department of Computer Science
And Engineering
Jayaraj Annapackiam Csi college of engineering.
arockianishajacsi@gmail.com

Nanthini M
PG Student
Department of Computer Science
And Engineering
Jayaraj Annapackiam Csi college of engineering
nanthinibe1004@gmail.com

***Abstract*—Artificial Intelligence (AI) and Machine Learning (ML) have become critical technologies in farming, enabling accurate crop prediction, efficient irrigation, and more effective resource use. However, increasing computational demands of AI systems escalate energy consumption and carbon emissions. This paper presents a Green AI framework for intelligent agriculture, synthesizing six energy-efficient predictive model types—lightweight architectures, model compression, federated learning, edge/fog computing, transfer learning, and green algorithmic innovations—within a layered methodological framework integrating the TOE model, AI-driven precision agriculture, Earth Observation (EO) data integration, AI-IoT-Blockchain systems, human-centered design, and Multi-Criteria Decision-Making. The framework demonstrates that these combined strategies substantially reduce computational energy consumption while maintaining high performance in crop yield forecasting, water management, energy optimization, and nutrient management. Case studies from six global deployments validate practical feasibility. Future directions include integration with IoT, digital twins, explainable AI, and policy-aligned sustainability standards.**

***Keywords*—crop yield forecasting; energy-efficient predictive models; Green AI; smart agriculture; sustainable resource management.**

I. INTRODUCTION

Artificial Intelligence and Machine Learning have transformed diverse sectors by improving prediction, decision-making, and efficiency [1]. Yet this progress carries a significant environmental cost: training GPT-3 alone required approximately 1,287 MWh of electricity and released around 550 tonnes of CO_2, and AI systems could account for more than 30% of total global electricity consumption by 2030 [3][4]. These facts urgently demand a re-orientation of AI development toward sustainability. Green AI offers a key response by prioritizing energy-efficient algorithmic design, hardware optimization, and sustainable deployment [5]. Two complementary orientations exist: green-in AI, reducing models' computational footprint; and green-by AI, which deploys AI to directly address sustainability challenges such as climate prediction, renewable energy management, and eco-friendly agriculture [6][7].

Agriculture is among the sectors most suited to Green AI integration. It accounts for approximately 70% of global freshwater withdrawals and nearly 24% of greenhouse gas emissions when land-use change is included [3]. AI-based interventions have shown significant promise: convolutional neural networks (CNNs) applied to UAV imagery have achieved high-accuracy crop yield prediction, and ML-driven IoT irrigation systems have demonstrated water-use efficiency improvements of 30–40% [8]. However, most of these models carry high computational requirements, raising the question of whether environmental costs negate the agricultural gains. This tension motivates a Green AI approach to smart farming.

This paper makes three main contributions. First, it synthesizes six core methodological frameworks into a layered interaction model that merges technological, organizational, and environmental factors for Green AI in agriculture. Second, it presents an energy-efficient crop yield prediction framework leveraging lightweight algorithms, edge computing, and metaheuristic optimization. Third, it examines how Green AI strategies can achieve measurable improvements in water, energy, and nutrient resource management while preserving predictive accuracy and reducing the carbon footprint of agricultural AI systems.

II. BACKGROUND AND RELATED WORK

A. Key Technologies in Smart Agriculture

Smart agriculture integrates IoT, AI, robotics, and cloud computing across the agricultural value chain, while precision farming applies site-specific crop management decisions at the right place, amount, and time based on real-time analytics [13][14]. The core technology stack includes: IoT sensors for real-time monitoring of soil moisture, temperature, and crop health [17]; AI/ML for predictive yield models, disease detection, and irrigation scheduling [21]–[23]; drones and remote sensing for high-resolution field imagery [56]; GIS/GPS for spatial mapping and precision input guidance [88]; and blockchain with smart contracts for transparent supply chain traceability [91][92].

ML algorithms applied to smart farming span supervised methods (Random Forest, SVM, Decision Trees, KNN), unsupervised approaches (K-means, autoencoders), deep learning architectures (CNNs, RNNs/LSTM, U-Net, YOLO, Transformers), and reinforcement learning for autonomous irrigation and fertilization control [30]–[51]. Despite these advances, high computational requirements motivate a Green AI agenda that balances predictive performance with energy efficiency and environmental sustainability.

B. Green AI: Principles and Concepts

Green AI describes methods for creating and deploying AI with a lower environmental impact and carbon footprint [3][96]. Nine core principles structure Green AI practice: (1) Energy and Resource Efficiency via model pruning, quantization, and knowledge distillation; (2) Carbon Footprint Transparency through public disclosure of training/inference energy costs; (3) Hardware-Conscious Optimization using lightweight architectures (MobileNet, EfficientNet) for edge deployment; (4) Algorithmic Sustainability through early exit and adaptive computation strategies; (5) Reusability via transfer learning and foundation models; (6) Democratization for low-resource environments; (7) Lifecycle Sustainability covering hardware sourcing, energy sources, and e-waste; (8) Regulatory and Ethical Alignment with ESG standards; and (9) Efficiency Benchmarking using metrics such as the Energy-to-Accuracy Ratio (EAR) and Carbon Efficiency Score [96][98]–[110].

III. METHODOLOGICAL FRAMEWORK FOR GREEN AI IN AGRICULTURE

A. Six Core Frameworks

Agricultural systems are inherently complex, involving diverse stakeholders, multi-scalar data sources, and dynamic interactions between natural and socio-economic factors. This study synthesizes six core methodological frameworks that collectively enable Green AI deployment in smart agriculture, organized in a layered interaction model:

1) Technological–Organizational–Environmental (TOE) Framework: Analyzes Green AI adoption across three interdependent dimensions: technological readiness (relative advantage, compatibility, complexity), organizational capacity (leadership commitment, green investment, firm size), and environmental pressures (policy support, regulatory environment, competitive pressure) [111][112]. The TOE framework highlights how energy-efficient algorithms, sustainability-oriented leadership, and policy conditions collectively shape adoption trajectories.

2) AI-Driven Precision Agriculture: Integrates ML-based crop monitoring and yield prediction, computer vision for image-based crop analysis, IoT sensors for soil/water/climate data, and GIS/remote sensing for resource mapping [7][113]–[116]. Energy efficiency is achieved through computationally efficient architectures such as NAS-GBM, model compression frameworks like SUQ-3, IoT systems with adaptive sensor scheduling, and physics-informed neural networks for climate control [130]–[133].

3) AI and Earth Observation (EO) Data Integration: Leverages satellite imagery and EO data for landscape-level soil health monitoring, rangeland management, and resource allocation, supported by ML algorithms aligned with sustainability goals [117]. Energy-efficient practices include generative and energy-based models that reduce computational overhead, data-centric training set optimization, and smart grid-inspired predictive models [134]–[136].

4) Integrated AI–IoT–Blockchain: Combines AI and IoT for real-time sensing and predictive optimization with blockchain for secure, transparent, and verifiable data sharing [7][118][119]. Key applications include real-time irrigation and energy optimization, supply chain traceability of sustainable practices, and AI-driven logistics. Blockchain documentation of sustainability claims ensures accountability across agricultural value chains.

5) Experiential Learning and Human-Centered Design: Addresses socio-technical adoption challenges through participatory co-design, farmer training, and iterative feedback loops [120][121]. Green AI benefits through local adaptation of energy-efficient predictive models, capacity building programs, and continuous refinement cycles, ensuring systems are both technically efficient and socially sustainable.

6) Multi-Criteria Decision-Making (MCDM): Provides structured methods for balancing conflicting objectives such as accuracy, energy efficiency, cost, and sustainability impact using AHP, TOPSIS, and MAUT [122]–[124]. MCDM ensures transparent, evidence-based model selection and deployment decisions, adapting to context from smallholder farms to industrial-scale agriculture [145].

B. Energy-Efficient Predictive Model Types

Energy-efficient predictive models in smart agriculture can be grouped into seven categories, each with distinct strengths and trade-offs. Table I summarizes their evaluation across three dimensions—accuracy, energy consumption, and sustainability—revealing a consistent pattern of high accuracy at low-to-medium energy cost:

TABLE I. Evaluation of Energy-Efficient Predictive Model Types

Model Type	Accuracy	Energy	Sustainability
Lightweight AI [150][151]	High	Low	High
Model Compression [152][153]	High	Low	High
Federated Learning [154]	High	Medium	High
Transfer Learning [155][156]	High	Low	High
Edge/Fog Models [125][131]	High	Low	High
Hybrid Energy-Aware [152][157]	High	Low	High
Green Algorithmic [124][158]	High	Low	High

Lightweight AI models such as MobileNet, SqueezeNet, and TinyML frameworks maintain relatively high accuracy while ensuring minimal computational burden, enabling real-time performance on edge devices including IoT nodes, drones, and soil sensors [150][151]. Model compression techniques—pruning, quantization, and knowledge distillation—reduce model size while retaining accuracy; pruning and distillation have been shown to reduce BERT's energy consumption by approximately 32% [161]. Federated Learning (FL) provides a decentralized approach where farms collaboratively train models without sharing raw data, reducing centralized data transfer energy while preserving privacy [154]. Transfer learning enables re-use of pre-trained models from related domains, significantly reducing training time and energy; a model trained on tomato disease detection can be adapted for rice or potato crops with minimal additional data [155]. Edge/fog models shift computation from cloud servers to local devices, reducing latency, bandwidth, and transmission energy [125][131]. Hybrid energy-aware frameworks combine multiple strategies—pruning, quantization, and FL—to simultaneously balance accuracy, scalability, and energy efficiency [157]. Green algorithmic innovations include Physics-Informed Neural Networks (PINNs), NAS-GBM, and adaptive model scheduling that reserves computationally intensive models for high-priority tasks such as disease detection while using lightweight models for routine monitoring [130][133].

C. Crop Yield Prediction Framework

The energy-efficient crop yield prediction framework integrates three components: diverse input datasets, a portfolio of AI/ML/DL models, and Green AI optimization strategies evaluated on accuracy, energy consumption, and sustainability metrics [167]. Input datasets combine remote sensing imagery (MODIS, NDVI indices), IoT sensor data (soil moisture, temperature, humidity), and historical/environmental records (weather, soil profiles, management practices). Model options span classical SVR, ensemble methods (Random Forest, XGBoost), deep learning (CNN, LSTM, hybrid HRSL and DACO-RNN architectures), and optimization-enhanced recurrent networks [170]–[175]. Green AI optimization strategies include low-power lightweight deployment (avoiding energy-intensive cloud infrastructure), edge computing for local data processing, and metaheuristic algorithms such as Self-Adaptive Whale Optimization (SA-WOA) and Particle Swarm Optimization (PSO) for parameter fine-tuning that balances predictive accuracy with computational efficiency [157][167].

IV. RESOURCE MANAGEMENT THROUGH GREEN AI

A. Water Management

Agriculture consumes approximately 70% of global freshwater resources, making water management a critical sustainability lever [177]. ML algorithms combined with IoT-based soil and weather sensors enable optimal watering schedules, reducing water consumption by up to 30% and increasing crop yield by 15% [184]. Deep learning models outperform conventional rule-based methods by dynamically adapting to changing weather and soil moisture conditions [183], and AI-driven irrigation management reduces greenhouse energy consumption by up to 25% compared to conventional approaches [127]. Federated learning and edge-deployed lightweight models are particularly suited to connectivity-constrained rural areas, enabling real-time inference without continuous cloud dependency. Hybrid AI techniques combining IoT and predictive control show that AI can sustainably balance irrigation requirements even in water-scarce regions [188]. Integration with blockchain ensures transparency in water usage metrics and builds stakeholder trust in sustainability reporting [186].

B. Energy Management

Smart farms increasingly depend on IoT devices, autonomous machinery, and energy-intensive controlled environments, making energy optimization central to Green AI [191]. Integrating AI and IoT with solar and wind energy sources enables autonomous renewable-powered farming; reported implementations achieve up to 80% cost savings and 95% energy efficiency [193]. ML models including support vector regression and artificial neural networks accurately forecast peak energy demand, enabling demand-side management and reduced electricity costs [195]. AI-managed greenhouses reduce energy use by up to 25% while maintaining agricultural output [127]. AIoT and cyber-physical systems enable real-time monitoring of temperature, humidity, light intensity, and soil moisture, automating energy-intensive processes including watering and lighting [197][198]. Robots equipped with LIDAR and electro-optical cameras further reduce the need for manual inspections, lowering overall energy demand [200].

C. Nutrient Resource Management

Nutrient resource management is a cornerstone of precision farming, optimizing fertilizer applications to maximize crop yield while minimizing costs and environmental impacts [29]. AI-driven Fertilizer Recommendation Systems (FRS) integrate soil NPK profiles, pH, moisture, and crop-specific parameters to provide site-specific, real-time recommendations [210]. Integrating ML models with soil data has demonstrated fertilizer use reductions of 18% while maintaining yield levels [212]. IoT-enabled soil sensing combined with hybrid CNN-LSTM models enables accurate macronutrient monitoring [207]. Generative AI integrated with digital twin frameworks allows virtual simulation of fertilizer strategies before field application, enabling farmers to optimize cost, yield, and environmental sustainability [215]. IoT-AI nutrient systems cut fertilizer usage by up to 20% while maintaining crop yield [216], aligning with Green AI principles by reducing computational overheads while delivering sustainable, low-carbon outputs.

V. CASE STUDIES AND GLOBAL APPLICATIONS

Table II presents six real-world AI deployments in agriculture that exemplify Green AI principles including edge computing, model compression, offline capability, and renewable energy independence:

TABLE II. Global Case Studies of Green AI in Agriculture

Case Study	Organization	Technology	Green AI Features
Smart drip irrigation	SunCulture, Kenya	Solar drip kits, on-device AI, weather forecasting	Zero grid dependency; edge AI inference; open firmware
Plant disease detection	Plantix, Germany/India	MobileNet CNN on smartphones	On-device inference; offline capability; model compression
Yield prediction	Microsoft FarmBeats, USA/India	IoT sensors, drones, LightGBM on Azure IoT Edge	Local processing; minimal cloud dependency
Soil health monitoring	Teralytic, UK/US	NPK/pH sensors, rule-based AI on LoRaWAN	Ultra-low-power communication; simple on-device logic
Smart livestock feeding	Cargill, Global	Behavior-sensing cameras, TinyML on edge devices	Local video processing; no cloud video upload
Agroforestry planning	ICRAF, Kenya / Indonesia	Spatial clustering, regression on tablets	Runs offline on low-end devices; no GPU required

These deployments confirm that Green AI principles are achievable across diverse agricultural contexts and resource levels. Projects primarily use edge computing or lightweight models running on smartphones, sensors, or tablets to reduce data transmission and dependency on energy-heavy cloud servers. Notable features include local video processing (Cargill), ultra-low-power LoRaWAN communication (Teralytic), offline capabilities (Plantix, ICRAF), and independence from grid power (SunCulture). These innovations cut carbon footprints and protect data privacy through decentralized management, boosting productivity and resilience while aligning technology use with climate goals.

Across both smallholder and large-scale farms, Green AI demonstrates potential to bridge the digital divide—but only with equitable access, supportive policies, and edge-focused design. Large farms benefit from sophisticated AI-driven supply chain efficiency but primarily rely on energy-intensive cloud systems, while smallholder farms can leverage low-cost offline tools yet face adoption barriers of high costs, inadequate connectivity, and limited digital literacy. Equitable access and edge-first architecture are prerequisites for genuinely sustainable impact.

VI. CHALLENGES AND POTENTIAL MITIGATIONS

Four major challenges impede Green AI realization in agriculture. First, data availability and quality: many agricultural datasets suffer from small sample sizes, inconsistent labels, and missing contextual metadata such as weather, soil moisture, or fertilizer use records, limiting model generalizability across regions, crops, and soil types [236][237]. High-quality, well-labeled, and contextually rich datasets are crucial for creating models that perform reliably beyond initial training conditions.

Second, computational infrastructure: rural and low-resource settings lack reliable Internet connectivity and stable electricity, hampering continuous data collection and cloud-dependent AI inference [239]. Hybrid AI architectures combining IoT sensors, UAVs, satellites, and edge-cloud compute can reduce dependence on constant cloud access, but building this infrastructure requires substantial policy support and investment, particularly in developing countries.

Third, algorithmic bias and fairness: AI systems trained on historically biased datasets can perpetuate inequalities, particularly disadvantaging smallholder farmers whose farming conditions are underrepresented in training data [241][242]. Inclusive data practices, diverse data collection, and adherence to ethical AI frameworks are essential mitigating measures. Fourth, balancing accuracy versus energy efficiency remains an open challenge; AI-driven methods such as the Sustainable Agricultural Optimization Framework (SAOF), combining quantum-inspired adaptive learning with bioinspired energy management, represent promising approaches to maintaining high prediction accuracy while promoting energy efficiency [245].

Proposed mitigations include: edge computing to enable local inference in remote areas; AIoT integration to simplify deployment; open data platforms with standardized metadata and geolocation; bias audits using diverse training data; lifecycle efficiency frameworks that account for full environmental costs from data collection to model disposal; and model pruning and quantization to reduce energy use without sacrificing practical usefulness [244][245].

VII. FUTURE RESEARCH DIRECTIONS

Several high-priority research directions will advance Green AI in agriculture. Integration with digital twins enables virtual simulation of farm scenarios under varied climate conditions, supporting energy-conscious decisions while maintaining yield targets [246]. Federated and collaborative Green AI networks allow privacy-preserving model training across heterogeneous farms through adaptive synchronization; creation of worldwide “Green AI Federations” could democratize AI resources for smallholder farms in developing regions [154]. Explainable AI (XAI) integration within green frameworks will make energy-efficient models interpretable and trustworthy, facilitating regulatory compliance and farmer adoption [158].

Standardized sustainability metrics—Energy-to-Accuracy Ratio (EAR), carbon footprint per prediction, and sustainability indices—are needed to benchmark models beyond accuracy alone [3]. Policy frameworks mandating energy-efficiency standards, supporting open agricultural datasets, and providing incentives for low-carbon computing will be essential, particularly for supporting smallholder farmers in developing countries

[248]. Human-centered design, farmer training, and participatory governance structures will ensure equitable technology transfer and long-term social sustainability of AI in farming ecosystems.

VIII. CONCLUSION

This paper presented a comprehensive Green AI framework for sustainable smart agriculture, integrating six core methodological frameworks—TOE, AI-driven precision agriculture, EO data integration, AI-IoT-Blockchain, human-centered design, and MCDM—into a layered interaction model spanning organizational enablers, operational AI-EO systems, blockchain-based trust infrastructure, and energy-efficient predictive decision support. The framework demonstrates that lightweight architectures, federated learning, model compression, edge computing, transfer learning, and green algorithmic innovations collectively achieve high predictive accuracy in crop yield forecasting while substantially reducing computational energy consumption and CO_2 emissions.

Applications across water, energy, and nutrient management confirm measurable sustainability gains: AI-driven irrigation reduces water consumption by up to 30% and energy use by up to 25% in greenhouse settings; AI-optimized fertilizer systems cut usage by 18–20% while maintaining yields; and renewable-powered AI farms report up to 80% cost savings. Six global case studies validate practical feasibility across diverse contexts from Kenyan smallholder farms to large-scale precision agriculture in the USA.

The layered interaction model proposed here provides a practical roadmap for researchers and policymakers to structure Green AI initiatives. Future efforts should focus on renewable-powered AI infrastructures, global sustainability benchmarking, XAI integration, federated learning networks, and human-centered design frameworks that empower local communities. By aligning AI innovation with environmental stewardship, Green AI offers a viable pathway toward climate-resilient, low-carbon, and resource-optimized agriculture that meaningfully contributes to global food security and the Sustainable Development Goals.

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