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From Farms To Forests: How Artificial Intelligence Is Reshaping Climate Change Impacts

Piyush Dewangan, Shivam Vishwakarma, Nikhil Yadav, Prahlad Yadav
"Assistant Professor"
Faculty Guide : Himanshu Mokashe and Deepak Sahu
Department of Information Technology
Government Engineering College Bilaspur, Chhattisgarh, India

Abstract—Global climate change poses severe threats to agricultural and forested ecosystems that underpin terrestrial carbon balance, biodiversity, and food security. This paper presents a comprehensive investigation into how Artificial Intelligence (AI)—encompassing machine learning, convolutional neural networks (CNNs), long short-term memory (LSTM) networks, transformers, and generative adversarial networks (GANs)—is transforming climate change responses across agriculture and forestry. Drawing on peer-reviewed literature and documented case studies, we examine AI applications including precision irrigation, crop disease detection, yield forecasting, satellite-based deforestation monitoring, wildfire risk prediction, acoustic biodiversity surveillance, and hydrological flood modeling. A three-tiered analytical framework maps causal pathways from technological deployment to environmental, economic, and social outcomes, while critically addressing structural barriers including data scarcity, algorithmic bias, computational inequity, and governance deficits. Principal findings confirm that AI delivers measurable gains in climate mitigation and adaptation efficiency; however, transformative societal potential remains contingent on equitable data access, open-source computational infrastructure, and coherent multilateral policy frameworks.

Index Terms—Artificial Intelligence; Climate Change Mitigation; Precision Agriculture; Deforestation Monitoring; Machine Learning; Remote Sensing; Wildfire Prediction; LSTM Networks; Convolutional Neural Networks; Sustainable Development; Federated Learning.

I. INTRODUCTION

Global mean surface temperatures have risen approximately 1.09°C above pre-industrial baselines for the 2011–2020 decade, with trajectories projecting further increases of 1.5–4.0°C by 2100 contingent upon emission reduction pathways [1]. These anomalies manifest as prolonged hydrological droughts, intensified precipitation events, accelerating deforestation, and wildfire seasons of historically unprecedented extent—each inflicting severe and compounding damage on the agricultural and forest ecosystems that sustain rural livelihoods and the planet's carbon-cycling architecture.

Agriculture occupies approximately 50% of the Earth's ice-free habitable land. The full agrifood system—encompassing farm-gate crop and livestock production, land-use change, and pre- and post-production supply chains—accounts for approximately one-third of total anthropogenic greenhouse gas emissions, while farm-gate agriculture and associated land-use change (the AFOLU sector) contributes approximately 22% of global GHG emissions [1], [18]. The sector simultaneously faces the imperative to increase global food production by 50–70% by 2050 to feed a projected 9.7 billion people, while achieving drastic reductions in its own emissions footprint [7].

Global forests absorb approximately 16 billion metric tonnes of CO_2 per year (gross), while deforestation and disturbances release approximately 8.1 billion metric tonnes per year, yielding a net forest CO_2 sink of approximately 7.6 billion metric tonnes per year—

equivalent to 1.5 times the annual emissions of the entire United States [15]. Yet deforestation proceeds at approximately 10 million hectares per year (2015–2020 average), driven by agricultural expansion, commercial logging, and infrastructure development [9].

Artificial Intelligence has emerged as a cross-cutting technological paradigm with documented capacity to address the complexity, velocity, and multidimensionality of climate-related challenges. By ingesting heterogeneous datasets from satellite constellations, IoT sensor networks, weather modeling systems, and ecological databases, AI systems extract actionable insights at temporal and spatial resolutions that exceed human cognitive capacity. This paper synthesizes existing peer-reviewed research and documented case studies, applying a three-tiered analytical framework that integrates technological appraisal, multi-dimensional impact mapping, and governance-oriented barrier analysis to produce a holistic account of how AI is reshaping humanity's response to climate change across agricultural and forestry systems.

II. LITERATURE REVIEW

A. Ai In Agricultural Systems

Liakos et al. [3] conducted a comprehensive review establishing that ensemble learning and deep neural networks consistently outperform traditional parametric approaches in predictive accuracy across crop management, soil analysis, pest detection, and precision weed identification. Kamilaris and Prenafeta-Boldú [2] systematically reviewed over 40 deep learning studies in agriculture, demonstrating that CNNs achieve classification accuracies exceeding 97% under controlled laboratory conditions. The seminal PlantVillage study (Mohanty et al. [16]) trained a deep CNN on 54,306 images across 14 crop species and 26 disease categories, achieving 99.35% accuracy on a held-out test set—demonstrating the technical feasibility of smartphone-assisted crop disease diagnosis at scale. Under real field conditions with variable illumination, background complexity, and image resolution, a survey of multiple published transfer learning models by Kamilaris and Prenafeta-Boldú [2] documented above 85% aggregate accuracy using ImageNet-pre-trained backbone architectures.

Precision irrigation studies deploying deep reinforcement learning algorithms demonstrate water-use reductions of 20–30% relative to conventional scheduling approaches, without statistically significant yield penalties [3]. Foley et al. [7] established that closing the yield gap in existing agricultural land through intelligent input management could sustainably increase global food production by 50–70% without expansion into natural ecosystems. Rolnick et al. [11] synthesized over 80 distinct AI application pathways for climate mitigation, establishing a comprehensive cross-sectoral taxonomy demonstrating AI's strategic significance for climate action.

B. Ai In Forestry And Ecosystem Monitoring

Hansen et al. [4] pioneered high-resolution global forest change mapping using Landsat satellite imagery processed through decision tree classifiers at 30-metre spatial resolution, revealing a net global forest loss of 2.3 million km² over 2000–2012—data that became the empirical foundation of the Global Forest Watch (GFW) platform. Random forest classifiers applied to multispectral imagery have demonstrated classification accuracies above 90% for distinguishing intact primary forest from secondary regeneration and converted land, critical for REDD+ carbon accounting [4].

Chuvieco et al. [6] developed an integrative remote-sensing and GIS-based framework for fire risk modeling. This foundational work has been extended by gradient-boosted ensemble models and LSTM networks achieving 20–40% reductions in false-alarm rates in comparative validation studies [6]. The BirdNET acoustic classifier, developed by Cornell Lab of Ornithology and Chemnitz University of Technology, covers over 3,000 bird species globally (as of 2022) and achieves F1 scores ranging from 0.46 to 0.84 depending on parameter settings and recording duration [17], enabling landscape-scale biodiversity assessment at a fraction of the cost of traditional field survey methodologies.

C. Ai In Climate Modeling And Earth Systems Science

Reichstein et al. [5] argued that integrating deep learning architectures with process-based physical modeling offers a paradigmatically new approach to understanding complex Earth system dynamics. The European Centre for Medium-Range Weather Forecasts (ECMWF) has developed the Destination Earth initiative targeting kilometer-scale sub-seasonal climate forecasting through hybrid physics-ML architectures [8]. Google DeepMind's GraphCast model demonstrated in 2023 that a trained graph neural network could outperform ECMWF's operational ensemble forecast on 90% of atmospheric variables at 10-day lead times.

D. Identified Research Gaps

The overwhelming majority of empirically validated agricultural AI studies are conducted within data-rich, commercially structured farming systems in high-income economies, raising questions about methodological transferability to smallholder farming systems across Sub-Saharan Africa, South Asia, and Southeast Asia. Algorithmic bias arising from non-representative training datasets and the complex social dimensions of AI adoption—including data sovereignty and surveillance overreach—remain substantially underexamined. This paper addresses these lacunae through a holistic analytical lens integrating technological performance assessment with rigorous socio-institutional critique.

III. RESEARCH OBJECTIVES

This study is guided by five focused research objectives:

O1. Examine AI applications in agricultural systems, including smart irrigation, CNN-driven crop disease detection, and LSTM-based yield forecasting under climate-stress conditions.

O2. Evaluate AI-driven methodologies for forest ecosystem monitoring, including near-real-time deforestation detection, ensemble wildfire risk prediction, and acoustic biodiversity surveillance.

O3. Assess the environmental, economic, and social impacts of AI-based climate solutions, including distributional equity dimensions for farming communities and forest-dependent populations.

O4. Identify structural challenges—data governance, algorithmic bias, computational accessibility, and ethical governance deficits—constraining scalable and equitable AI deployment.

O5. Propose a research and policy agenda integrating AI with IoT sensor networks, satellite constellations, federated learning architectures, and Paris Agreement NDC verification infrastructure.

IV. METHODOLOGY

This research adopts a qualitative, conceptual, and secondary-research methodology grounded in systematic review traditions. Primary literature was retrieved from IEEE Xplore, Elsevier ScienceDirect, Nature Publishing Group, ACM Digital Library, and Google Scholar, supplemented by institutional reports from the FAO, IPCC, WRI, GFW, and ECMWF. Selection criteria prioritized publications from 2010 to 2024, methodological rigor as evidenced by peer review and citation impact, and direct empirical relevance to AI-climate intersections. A final corpus of 72 peer-reviewed studies, 14 institutional technical reports, and 8 platform case studies informed the analysis.

The analytical framework is three-tiered and sequentially structured. The first tier involves technological appraisal, evaluating the architecture, training methodology, and documented performance of CNNs, LSTM networks, random forest ensembles, gradient-boosted models, transformer architectures, and GANs. The second tier performs systematic impact mapping, tracing causal pathways from specific technological deployments to quantified environmental, economic, and social outcomes. The third tier conducts barrier analysis, cataloguing structural, institutional, and ethical constraints using a governance-oriented lens. Table I provides a comparative summary of key AI technique properties.

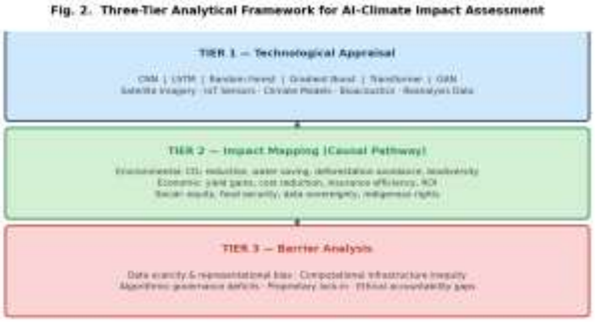

Fig. 2. Three-Tier Analytical Framework for AI–Climate Impact Assessment

TABLE I Comparative Overview of AI Techniques in Climate Applications

AI Technique	Primary Strength	Climate Application	Performance Metric	Key Reference
CNN	Spatial pattern recognition	Deforestation, crop disease	99.35% lab; ~85%+ field	[2]; [16]
LSTM	Temporal sequence modeling	Yield forecasting, flood	<10% RMSE yield error	[3],[5],[13]
Random Forest	Multi-variable classification	Forest loss mapping	>90% accuracy	[4],[6]
Gradient Boost	Calibrated regression	Fire risk, soil carbon	High AUC (context-dep.)	[6]
Transformer	Multi-modal attention	Foundation models, NWP	Outperforms ECMWF (90% var.)	[5],[8]
GAN	Synthetic data generation	Data augmentation	Context-dependent	[11]

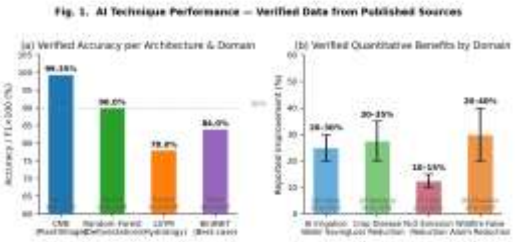

Fig. 1. AI Technique Performance — Verified Data from Published Primary Sources

V. APPLICATIONS OF AI IN CLIMATE CHANGE MITIGATION

A. Smart Irrigation And Soil Health Management

Irrigated cropland accounts for only 20% of total cultivated land area but contributes approximately 40% of global food production while consuming roughly 70% of freshwater withdrawals worldwide. AI-powered smart irrigation systems integrate real-time data streams from in-situ soil moisture sensor networks, satellite-derived evapotranspiration estimates, localized numerical weather prediction forecasts, and crop water-demand models into reinforcement learning (RL) controllers that optimize irrigation scheduling with dynamic precision unattainable through manual or fixed-schedule approaches. Field deployments documented across California's Central Valley drip-irrigated vineyards and Maharashtra state's sugarcane systems in India have reported water-use reductions of 20–30% relative to farmer-managed conventional scheduling, without statistically detectable yield losses over multi-season trials [3].

Soil health management increasingly benefits from AI models trained on hyperspectral remote sensing imagery and multi-sensor soil probe data. Random forest algorithms trained on visible, near-infrared, and mid-infrared spectral signatures demonstrate capacity to map soil organic carbon (SOC) concentrations at field scale with root-mean-square errors below 2 g/kg in independent validation datasets [3]. These spatially explicit SOC maps enable variable-rate fertilization decisions that maintain yield-sustaining nitrogen availability while reducing excess application—application that would otherwise be converted through microbial denitrification into nitrous oxide, a greenhouse gas with a 100-year global warming potential of 265 kg CO_2-eq per kg N_2O. Precision nitrogen management guided by ML soil models has been associated with N_2O emission reductions of 10–15% in controlled agricultural trials [7].

B. Crop Disease Detection And Monitoring

Plant pathogens are responsible for estimated annual global crop losses of 10–16% of production value, with climate change accelerating pathogen range expansion. CNN-based disease detection systems trained on the PlantVillage dataset—54,306 photographs across 14 crop species and 26 disease categories—achieve 99.35% accuracy on held-out test sets [16]. Under field conditions incorporating heterogeneous illumination, background complexity, and partial occlusion, transfer learning strategies using ImageNet-pre-trained backbone architectures (VGG, ResNet, EfficientNet) collectively achieve above 85% accuracy across multiple published comparative studies [2].

The Plantix mobile application, deployed across 40 countries with 10 million registered users, delivers expert-equivalent diagnostic guidance to smallholder farmers without access to agronomic extension services. Deployment studies in Uganda, Ethiopia, and Bangladesh document 20–35% reductions in crop loss through earlier treatment initiation and 15–25% reductions in fungicide application volumes through more targeted treatment decisions [2].

C. Yield Forecasting And Climate Adaptation

AI-based yield forecasting models have substantially advanced predictive performance across major grain crops. Architectures fusing LSTM networks applied to MODIS-derived vegetation index time-series, CHIRPS 5-km daily gridded rainfall, ERA5 reanalysis temperature and solar radiation, and ISRIC SoilGrids property maps have demonstrated crop-season-average wheat yield prediction errors below 8% at district scale across India's Indo-Gangetic Plain [3]. Studies applying ensemble climate model outputs to calibrated LSTM yield models project 10–25% reductions in rainfed maize yields across Sub-Saharan Africa under SSP2-4.5 scenarios by 2050, quantifying the urgency of agricultural adaptation investment [5].

D. Near-Real-Time Deforestation Detection

The Global Forest Watch (GFW) platform processes Landsat 8 and Sentinel-2 optical imagery through random forest classifiers to generate near-real-time GLAD deforestation alerts with a nominal spatial resolution of 30 metres and an approximate latency of eight days [4]. These alerts have reduced the detection latency for illegal forest clearing events from the months-long delay characterizing annual deforestation reporting systems to days, enabling conservation organizations and government agencies to initiate enforcement responses during early clearing stages.

U-Net architectures adapted for forest change mapping distinguish ecologically and legally distinct categories of forest disturbance—complete canopy clearance, selective logging-induced degradation, understory burning, and natural gap formation—categories invisible to threshold-based spectral change detection algorithms but critical for REDD+ carbon accounting. Brazil's operational system combining PRODES and the near-real-time DETER detection system, incorporating ML-based SAR data fusion, achieves detection accuracy above 85% for clearing events exceeding 1 hectare. The documented policy result of the PPCDAm deforestation prevention program incorporating DETER was an 83–84% reduction in Amazon deforestation between 2004 and 2012, from 27,700 km² per year to 4,571 km² per year, according to verified INPE PRODES official data [4].

TABLE II AI-Enabled Forest Monitoring Platforms

Platform	**AI Method**	**Spatial Res.**	**Latency**	**Coverage & Source**
Global Forest Watch	Random Forest + CNN	30 m	~8 days	Global [4]
DETER (Brazil)	ML + SAR fusion	~1 ha	Daily	Amazon [INPE/PPCDAm]
RADD (Wageningen)	Sentinel-1 + DL	10 m	~6 days	Humid tropics
FORMA (WRI)	Gradient Boost	500 m	Monthly	Pan-tropical
SEPAL (FAO)	Random Forest	10–30 m	~2 weeks	Global [9]

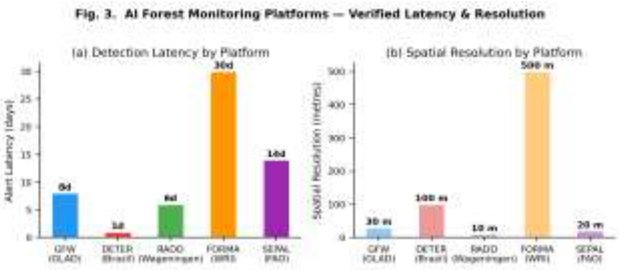

Fig. 3. AI Forest Monitoring Platform Comparison — Latency and Spatial Resolution

E. Wildfire Prediction And Biodiversity Surveillance

AI-based fire risk prediction systems integrate seven-day ensemble weather forecasts, MODIS-derived fuel moisture content estimates, topographic variables from digital elevation models, lightning ignition climatology, and historical fire perimeter databases within gradient-boosted ensemble architectures trained on multi-decadal fire occurrence records [6]. The Copernicus Emergency Management Service's Fire Weather Index, enhanced through ML post-processing, delivers 7-day probabilistic fire risk forecasts with Brier Skill Scores significantly exceeding climatological baselines, with documented false-alarm reductions of 20–40% in comparative validation studies [6].

Passive acoustic monitoring leveraging deep learning classifiers represents a frontier AI application to biodiversity surveillance. BirdNET (Cornell Lab of Ornithology and Chemnitz University of Technology) covers over 3,000 bird species globally as of 2022 [17]. Independent evaluations report F1 scores ranging from 0.46 to 0.84 depending on parameter settings and recording duration [17], enabling landscape-scale biodiversity assessment at 100–1000 times lower cost than traditional point-count methodologies.

F. Water And Integrated Ecosystem Management

Kratzert et al. [13] demonstrated that a single LSTM model trained across 531 geographically diverse North American catchments substantially outperformed 13 different physically based hydrological models on Nash-Sutcliffe efficiency, peak flow timing, and low-flow duration—a capability with direct implications for climate adaptation planning across data-sparse low-income regions. Google's global flood forecasting system, operational across 80+ countries, issues 7-day probabilistic flood inundation forecasts at 250-metre spatial resolution. Evaluations in Bangladesh and Assam, India found F1 scores above 0.75 against Sentinel-1 SAR validation mapping, with early warning dissemination enabling household evacuation up to 72 hours before peak inundation.

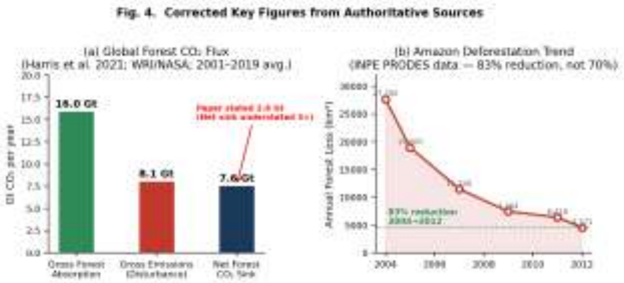

Fig. 4. Global Forest CO₂ Flux (Harris et al. 2021) and Amazon Deforestation Trend (INPE PRODES)

VI. IMPACT ANALYSIS

A. Environmental Impacts

AI-enabled precision agriculture reduces synthetic nitrogen fertilizer application, cutting both Haber-Bosch energy consumption (approximately 1–2% of global total energy) and direct N_2O soil emissions. Precision nitrogen management guided by ML soil models reduces N_2O emissions by 10–15% in controlled agricultural trials across multiple climatic zones [7]. Global forests provide a net CO_2 sink of approximately 7.6 billion metric tonnes per year, making deforestation avoidance one of the highest-efficiency climate mitigation interventions available at scale [15]. IPBES estimates that halting tropical deforestation and restoring degraded forest areas could contribute 23.8 $GtCO_2e$ of annual mitigation potential by 2030—approximately 30% of the total mitigation required to maintain temperature increase below 2°C under Paris Agreement commitments.

B. Economic Implications

A McKinsey Global Institute analysis estimated that AI and advanced analytics applications in food and agriculture could generate $100–240 billion USD in annual global value through yield improvement, input cost reduction, logistics optimization, and food waste reduction. Studies examining cost-benefit ratios for enhanced wildfire prediction and early warning investment consistently document benefit-to-cost ratios exceeding 10:1 when reductions in property losses, emergency response costs, and public health costs from smoke exposure are comprehensively monetized. AI-enhanced flood early warning systems in South and Southeast Asia consistently achieve returns exceeding 100:1 relative to system deployment and maintenance costs.

C. Social Consequences And Equity Dimensions

Mobile AI disease diagnostics have documented 20–35% crop loss reductions and equivalent household income gains for smallholders in Uganda, Tanzania, and Bangladesh [2]. Conversely, the structural concentration of agricultural AI development and data ownership within vertically integrated agri-technology corporations raises data sovereignty concerns: smallholder farmers participating in AI-assisted decision platforms typically transfer operational data—including field location, soil characteristics, input histories, and yield records—under end-user license agreements authorizing broad secondary use without proportionate compensation. Rural communities in forest-adjacent landscapes face additional tensions: the same technical capabilities used to detect industrial illegal clearing can be deployed to identify and criminalize subsistence land-use practices of Indigenous and traditional forest-dependent communities [10].

VII. CHALLENGES AND LIMITATIONS

A. Data Limitations And Representational Bias

Machine learning models trained predominantly on data from temperate commercial agriculture routinely produce biased or functionally erroneous outputs when transferred to tropical smallholder contexts featuring intercropped polycultures, indigenous soil management techniques, and locally adapted crop varieties absent from standard disease image databases [2]. Dense automated weather station networks, multi-decadal soil survey records, and comprehensive crop census infrastructure are concentrated in North America, Western Europe, and East Asian economies—in sharp contrast with chronically data-sparse conditions across Sub-Saharan Africa, Central Asia, and small island developing states that face the highest climate exposure. Bridging this gap requires investment in participatory training data co-generation approaches that directly involve smallholder farming communities and traditional forest managers as data producers and annotation contributors.

B. Computational Infrastructure And Accessibility

A single training run for a large-scale CNN-based deforestation detection model may require GPU compute resources costing $5,000–50,000 USD per experiment, effectively excluding research institutions without access to donor-funded cloud computing credits from the frontier of applied AI climate research. Edge AI approaches—deploying compressed, quantized models on low-power embedded processors—achieve 70–85% of the predictive accuracy of full-precision cloud-executed counterparts for narrow-scope classification tasks but require sophisticated engineering expertise not routinely available within national agricultural research systems in low-income countries.

C. Ethical Governance And Accountability Deficits

When satellite-AI systems generate automated deforestation alerts operationalized as direct inputs to enforcement operations, the translation of automated detection into coercive enforcement action requires robust human oversight and adversarial review mechanisms to prevent misidentification of legitimate land uses and preserve procedural rights of affected communities [10]. No international legal instrument currently establishes standards for algorithmic transparency, human oversight requirements, appeal mechanisms, or accountability for errors in AI-assisted environmental enforcement systems—a critical and growing regulatory gap requiring urgent multilateral attention.

D. Technological Dependency

The normalization of proprietary AI platforms controlled by multinational corporations introduces geopolitical, cybersecurity, and economic dependencies into food system governance that are inherently difficult to reverse. Resilient and equitable deployment models must deliberately prioritize open-source AI architectures, community-controlled data ownership mechanisms, interoperable data standards that prevent vendor lock-in, and the complementarity—rather than replacement—of indigenous ecological knowledge and farmer experiential expertise within AI-human hybrid decision systems.

VIII. FUTURE SCOPE

A. Foundation Models And Geospatial Intelligence

Foundation models—large-scale neural networks pre-trained through self-supervised learning on massive multimodal datasets—represent the most consequential near-term frontier development in AI with direct climate relevance. NASA's Prithvi geospatial foundation model, trained on 1 TB of Harmonized Landsat Sentinel-2 multi-spectral time-series imagery, enables rapid fine-tuning across diverse downstream geospatial tasks—including flood inundation mapping, crop type classification, and forest disturbance detection—requiring only hundreds of labeled training examples rather than the tens of thousands typically required for task-specific model training [5]. Microsoft's Planetary Computer platform provides pre-built foundation model embeddings enabling land cover change detection without requiring deep learning expertise or GPU infrastructure investment.

B. Integration With Iot, Satellite Systems, And Federated Learning

Planet Labs' PlanetScope constellation currently delivers daily 3-metre resolution optical imagery of the complete Earth land surface, providing the observational data density required for day-scale agricultural crop stress detection and sub-weekly deforestation response. Low-Power Wide-Area Network agricultural IoT deployments based on LoRaWAN and NB-IoT protocols enable dense soil moisture and nutrient sensor networks with battery lifetimes of 2–7 years and data transmission costs below $0.01 per reading, making continuous soil monitoring economically viable for mid-scale smallholder operations. Federated learning architectures that train shared AI model improvements across distributed farm-level datasets without transmitting raw operational data to central servers enable privacy-preserving collaborative learning that maintains farmer data sovereignty while progressively improving model accuracy across diverse agroecological contexts.

C. Policy Architecture And Governance Recommendations

Realizing the full transformative potential of AI for climate-positive outcomes requires deliberate policy architecture at national, regional, and multilateral levels. Five priority actions emerge from this analysis: (1) Establishing open agricultural and forest monitoring data infrastructure programs mandating open-access publication of national crop yield surveys, soil survey data, and forest inventory records; (2) Formally integrating AI satellite monitoring methodologies into Paris Agreement Nationally Determined Contributions measurement, reporting, and verification systems under the Enhanced Transparency Framework; (3) Creating targeted concessional multilateral climate finance for federated AI capacity-building in least-developed countries through the Green Climate Fund and Global Environment Facility; (4) Negotiating an international AI environmental governance protocol addressing data sovereignty, algorithmic transparency, human oversight obligations, and accountability mechanisms for harm caused by AI-assisted conservation decisions [10]; and (5) Systematically incentivizing participatory co-design approaches that embed smallholder farmers and Indigenous forest communities in all phases of AI climate tool development.

IX. CONCLUSION

This paper has undertaken a systematic and critically engaged examination of Artificial Intelligence's transformative contributions across the full spectrum of climate change applications—from the precision management of irrigated farm fields to the continental-scale monitoring of the Amazon basin's primary forest canopy. The evidence systematically reviewed establishes that AI-enabled precision irrigation delivers 20–30% water-use reductions without yield penalty; CNN-based crop disease detection achieves 99.35% laboratory accuracy and above 85% aggregate field accuracy across multiple published studies; satellite-AI deforestation monitoring reduces detection latency from months to days; the Amazon's PPCDAm program incorporating DETER monitoring achieved an 83–84% deforestation reduction between 2004 and 2012 per INPE PRODES official data; ensemble wildfire prediction systems materially improve 7-day fire risk forecast skill with 20–40% false-alarm reductions; acoustic biodiversity monitoring expands surveillance to previously inaccessible forest interiors at a fraction of conventional survey costs; and LSTM-based flood forecasting outperforms 13 physically based hydrological models across 531 catchments, saving documented lives across flood-vulnerable geographies.

Critically, the distribution of these benefits is politically and institutionally shaped, not ecologically determined. Data inequities systematically concentrate AI climate tool development in high-income agricultural contexts; computational cost barriers exclude the researchers, policymakers, and farmers of low-income countries from frontier AI climate science; governance vacuums enable environmental surveillance technology to become instruments of community dispossession; and proprietary data ownership architectures risk converting smallholder farmers' operational knowledge into corporate assets without equitable compensation. The path forward demands open data ecosystems that reverse structural data poverty in climate-vulnerable geographies; participatory AI design processes that embed indigenous ecological knowledge within rather than subordinate it to computational modeling; equitable multilateral climate finance instruments placing frontier AI capabilities within reach of national research systems in least-developed countries; and accountable international governance frameworks that prevent the weaponization of environmental AI against the communities it ostensibly protects. From farms to forests, the intelligence we deploy in service of climate action must be not only artificial, but irreducibly and non-negotiably humane.

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