Machine Learning Driven Predictive Analytics for Climate-Smart Agribusiness Production Systems

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Abstract— Agriculture contributes approximately 14% of global greenhouse gas emissions and is simultaneously the sector most vulnerable to climate variability and change. As extreme weather events intensify and growing seasons shift, agribusiness production systems require robust, forward-looking analytical tools capable of transforming vast multi-source environmental datasets into actionable operational intelligence. Machine learning offers precisely such a capability, enabling predictive modelling of crop yields, climate hazard risks, soil conditions, and supply chain vulnerabilities at unprecedented spatial and temporal resolutions. This paper presents a comprehensive review of machine learning driven predictive analytics frameworks and their applications across the dimensions of climate-smart agribusiness production systems, encompassing crop yield forecasting, climate hazard early warning, soil and water resource management, greenhouse gas emissions prediction, and supply chain optimisation. A systematic narrative review was conducted drawing exclusively on peer-reviewed academic literature from Scopus, Web of Science, PubMed, Nature, Frontiers, Springer, ScienceDirect, and the Consensus academic search repository. Thirty high-quality references spanning agricultural informatics, climate science, remote sensing, and agribusiness were synthesised. Evidence demonstrates that Long Short-Term Memory networks with attention mechanisms explain up to 73% of the spatiotemporal variance in crop yield under climate variability. Random Forest and Gradient Boosting models achieve prediction accuracies of 95.5% to 95.8% in IoT-enabled precision agriculture deployments. Machine learning integration into smart farming platforms reduces water consumption by 15%, boosts yield by 20%, and generates approximately USD 5,000 in annual pesticide savings per farm. Expert-driven explainable AI systems reliably detect multi-hazard agricultural climate risks, enhancing proactive adaptation. Barriers to adoption, particularly for smallholder farmers in developing economies, remain significant. Machine learning driven predictive analytics represents a transformative technological force for climate-smart agribusiness. Its full potential is contingent on addressing data infrastructure deficits, ensuring model explainability, and designing inclusive policy frameworks that prevent smallholder exclusion from the precision agriculture revolution.

Keywords: *machine learning; predictive analytics; climate-smart agriculture; agribusiness; deep learning; crop yield prediction; precision farming; remote sensing; explainable AI; greenhouse gas emissions*

I. INTRODUCTION

Agriculture stands at the crossroads of two of the most consequential global challenges of the twenty-first century: the imperative to feed a global population projected to exceed ten billion by 2050, and the mounting disruptions imposed by anthropogenic climate change. Global average temperatures continue to rise, precipitation patterns are shifting, and extreme weather events including droughts, floods, and heatwaves are increasing in frequency and intensity [1]. These climatic stressors directly threaten crop productivity, livestock systems, and the food supply chains that link producers to consumers worldwide. The Food and Agriculture Organization estimates that abnormal climate-related agricultural losses average USD 123 billion per year, equivalent to approximately five percent of annual global agricultural gross domestic product [2]. Against this backdrop, climate-smart agriculture has emerged as the dominant framework for reconciling food security with environmental sustainability. Climate-smart agriculture encompasses technological, managerial, and policy interventions that simultaneously increase productivity, build adaptive capacity to climate variability and change, and reduce or reverse agricultural greenhouse gas emissions [3]. Realising the full potential of climate-smart agribusiness, however, demands analytical tools commensurate with the complexity of the challenge: systems capable of integrating heterogeneous data streams, modelling non-linear relationships across spatial and temporal scales, and generating predictions that can guide operational decisions in real time.

Machine learning, and its deep learning subfamily, offers exactly such analytical power. By learning statistical patterns from large, complex datasets rather than relying on pre-specified mechanistic equations, machine learning models can capture the intricate interactions among temperature, precipitation, soil properties, crop genetics, and management practices that determine agricultural outcomes under climate variability [4]. The past decade has witnessed a rapid proliferation of machine learning applications across every dimension of the agribusiness value chain, from pre-season input optimisation and in-season crop monitoring to post-harvest supply chain management and emissions accounting.

Despite this proliferation, the literature remains fragmented across disciplinary domains, with crop scientists, climate modellers, agricultural economists, and supply chain researchers each developing partially independent knowledge bases. This paper undertakes a systematic integration of these streams, constructing a unified analytical review of how machine learning driven predictive analytics can serve the full scope of climate-smart agribusiness production systems. Five thematic domains are examined in depth: crop yield prediction under climate variability; multi-hazard climate risk detection and early warning; soil and water resource management; greenhouse gas emissions forecasting; and supply chain optimisation. For each domain, leading algorithmic approaches are characterised, performance benchmarks reviewed, and implementation constraints assessed. A synthesis framework and policy directions conclude the manuscript.

II. METHODOLOGY

A. *Review Design and Search Strategy*

A systematic narrative review methodology was adopted to enable synthesis across a technically diverse body of evidence spanning agricultural informatics, climate science, remote sensing, and agribusiness management. The review protocol followed PRISMA-inspired principles of transparent search design, eligibility screening, and structured thematic synthesis. Academic databases searched included Scopus, Web of Science, PubMed, the Nature and Springer Nature publishing platforms, Frontiers in Science journals, ScienceDirect, and the Consensus AI academic search engine. Boolean search term clusters were constructed across six thematic domains: (a) machine learning AND crop yield prediction AND climate; (b) deep learning AND climate-smart agriculture AND agribusiness; (c) random forest OR gradient boosting OR LSTM AND precision agriculture; (d) remote sensing AND soil moisture AND machine learning AND precision farming; (e) machine learning AND greenhouse gas emissions AND agriculture; and (f) explainable AI AND climate hazard AND agribusiness. Searches were executed in May to June 2026 with no publication date restriction.

B. *Inclusion Criteria and Synthesis*

Studies were included if they: (i) were published in peer-reviewed journals, peer-reviewed conference proceedings, or peer-reviewed book chapters indexed in recognised academic databases; (ii) reported empirical results, systematic reviews, or comprehensive analytical frameworks relevant to machine learning applications in climate-smart agribusiness; and (iii) were written in English. Grey literature and non-peer-reviewed sources were excluded. Thirty references were retained following quality and relevance assessment. Given the technical and disciplinary heterogeneity of included studies, a narrative synthesis approach was employed, organising evidence according to the thematic framework outlined above.

III. MACHINE LEARNING FOR CROP YIELD PREDICTION UNDER CLIMATE VARIABILITY

A. *The Architecture of Climate-Responsive Yield Models*

Accurate crop yield prediction under climate variability is the foundational task around which climate-smart agribusiness analytics are organised. Traditional process-based crop models such as DSSAT and APSIM simulate crop growth mechanistically, but their reliance on calibrated parameters limits spatial scalability and their performance degrades under out-of-sample climate conditions [5]. Machine learning overcomes these limitations by learning directly from observed yield and climate data, achieving superior predictive accuracy particularly in years with unusual meteorological conditions.

A landmark comparative study using maize in the United States Corn Belt trained multiple machine learning architectures against meteorological variables and soil properties using a leaving-one-year-out validation approach. The Long Short-Term Memory network with attention mechanism and shortcut connection, designated LSTMatt, explained 73% of the spatiotemporal variance in observed maize yield, substantially outperforming a widely used regionally calibrated process-based model that explained only 16% of the variance [6]. Crucially, the LSTMatt model maintained predictive accuracy during an extreme drought year when meteorological conditions differed substantially from training data, demonstrating climate robustness that process-based models do not reliably deliver [6].

B. *Ensemble and Comparative Performance*

Ensemble approaches and comparative evaluations confirm the dominance of tree-based and recurrent architectures for crop yield prediction tasks. A comparative study examining multiple algorithms including Recurrent Neural Networks, Convolutional Neural Networks, Random Forest, Decision Trees, and Gradient Boosting Machines found that Random Forest achieved R-squared values of 0.875 for Irish potatoes and 0.817 for maize, while Extreme Gradient Boosting achieved the minimum prediction error of 0.07 for cotton [7]. A novel hybrid SERWI ensemble model integrating LSTM, Support Vector Regression, and XGBoost using an inverse Root Mean Square Error weighting strategy demonstrated superior performance over individual base learners by dynamically assigning higher weights to models with superior validation outcomes, effectively combining temporal and non-linear modelling strengths [8].

Deep learning models integrating genotype data with meteorological variables represent the emerging frontier of yield prediction, enabling the modelling of crop-climate-genome interactions relevant to breeding and adaptation planning [9]. A systematic review of recent trends in machine learning for crop yield evaluation under abnormal climate conditions identified Artificial Neural Networks, Convolutional Neural Networks, and Deep Neural Networks as the most frequently applied architectures, valued for capturing the complex non-linear patterns in high-dimensional satellite, weather, and hyperspectral datasets [2]. Stepwise feature selection was identified as more effective than increasing feature volume for improving model accuracy, a critical insight for data-constrained operational deployments [2].

IV. MULTI-HAZARD CLIMATE RISK DETECTION AND EARLY WARNING

A. *Remote Sensing and Machine Learning for Climate Hazard Mapping*

Climate hazard detection represents one of the highest-value applications of machine learning in agribusiness, enabling proactive risk management rather than reactive loss response. A critical synthesis of machine learning and remote sensing approaches for climate hazard impact on crop yield, applying PRISMA methodology to review 177 hazard studies and 197 remote sensing and machine learning crop yield modelling studies, found that agricultural drought is the most frequently studied hazard and Random Forest is the most widely applied machine learning algorithm at 17% of studies, followed by Support Vector Machines at 11%, Artificial Neural Networks at 8%, and Extreme Gradient Boosting at 5% [4]. Regional variations are significant: Asia leads in adopting advanced architectures including CNN, LSTM, and hybrid models leveraging large remote sensing datasets for spatiotemporal drought monitoring, while Africa tends to employ simpler models such as logistic regression and multinomial Naive Bayes classifiers, reflecting constraints in data infrastructure and computational capacity [4].

B. *Explainable AI for Multi-Hazard Agricultural Early Warning*

Expert-driven explainable AI systems represent a critical advance for multi-hazard early warning in agribusiness contexts. Research published in Communications Earth and Environment demonstrated that expert-driven ensemble-based XAI models reliably detect multiple agricultural climate hazards by combining the knowledge produced by agro-climate analysts with the predictive power of machine learning, generating probabilistic outputs with quantified uncertainty estimates [10]. The ensemble approach reduces the impact of errors from individual models, enabling farmers and agribusiness stakeholders to make more informed decisions about management practices and resource allocation under uncertainty [10].

Three pillars are identified as essential for trustworthy multi-hazard AI systems: explainability and interpretability; probabilistic and uncertainty quantification; and integration of domain expert knowledge [10]. Explainable AI tools, notably SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations), are specifically recommended for agricultural forecasting platforms as mechanisms to address the black-box opacity problem that currently undermines farmer trust in advanced deep learning models [11]. A study of AI and XAI techniques for crop yield prediction under climate stress confirmed that temperature is the most critical single factor influencing crop yields, with notable interactions between rainfall patterns and macronutrient levels, findings that XAI frameworks make accessible to agronomic planners rather than confining them to model internals [12].

ML Algorithm	Best Performance	Primary Application Domain	Key Evidence Source
LSTMatt (attention)	R2 = 0.73 (maize)	Crop yield prediction under extreme drought	[6]
Random Forest	R2 = 0.875 (potato)	Crop yield and climate hazard detection	[4, 7]
Gradient Boosting (XGBoost)	Error = 0.07 (cotton)	CSA practice adoption prediction	[3, 7]
CNN + SVM	Accuracy 97.54%	Crop grading and disease detection	[7]
Random Forest + Gradient Boosting (IoT)	Accuracy 95.8% and 95.5%	Precision crop selection and field monitoring	[13]
SERWI hybrid (LSTM + SVR + XGBoost)	Superior to all base learners	Multi-factor yield prediction	[8]

CNN (ConvLSTM)	Improved over standalone CNN	Soil moisture prediction from SAR imagery	[14]

Table 1: Performance Benchmarks of Key Machine Learning Algorithms in Climate-Smart Agribusiness Applications

V. SOIL AND WATER RESOURCE MANAGEMENT THROUGH PREDICTIVE ANALYTICS

A. *Soil Moisture Monitoring and Irrigation Optimisation*

Precision water resource management is among the highest-return applications of machine learning in climate-smart agribusiness, given that water scarcity is projected to intensify across major agricultural regions under climate change. Convolutional Neural Networks applied to Sentinel-1 synthetic aperture radar observations have been validated for soil moisture prediction in agricultural settings, with integration of advanced modelling techniques and satellite remote sensing products offering a scalable and cost-effective solution for soil moisture monitoring at regional scale [14]. Machine learning retrieval of soil moisture from remote sensing data is shown to produce practical tools for farmers and agricultural planners to optimise irrigation scheduling and enhance water resource management, with direct implications for both productivity and environmental sustainability [14].

A study integrating UAVs, satellite remote sensing, and machine learning in precision agriculture demonstrated that IoT-enabled smart farming systems achieve a simulation accuracy of up to 92% in crop yield predictions alongside a 25.34% reduction in irrigation costs [15]. High-resolution optical imagery reveals robust correlations between vegetation indices, including EVI2 with R-squared of 0.77 and NDVI with R-squared of 0.71, and crop yields, providing actionable signals for irrigation management decisions [15]. At the landscape scale, satellite-based advanced analytics integrating the Water Ratio Index, Normalized Difference Chlorophyll Index, and Cellular Automata Markov modelling can predict future irrigated land dynamics, enabling agribusiness planning horizons that extend a decade or more beyond current observational windows [16].

B. *Soil Health and Nutrient Management*

Beyond irrigation, machine learning is transforming soil nutrient and health management. An IoT-enabled AI system for real-time crop prediction using soil and weather data demonstrated that stacking ensemble techniques with SVC meta-learners achieve a prediction accuracy of 95.9% in crop recommendation, enabling site-specific fertilisation decisions that reduce input costs and environmental contamination [13]. A review of precision agriculture techniques for crop farming monitoring documented that machine learning algorithms processing sensor data detect soil anomalies, forecast disease outbreaks, and recommend precise interventions, reducing dependency on traditional practices that generate resource inefficiencies and elevated emissions [17]. The integration of cloud computing and edge analytics enables real-time monitoring of soil moisture levels, nutrient content, and pest infestations, empowering farmers with timely interventions [17].

VI. GREENHOUSE GAS EMISSIONS PREDICTION AND MITIGATION ANALYTICS

A. *Deep Learning for Emissions Forecasting*

Machine learning is increasingly being deployed to address the emissions accounting and mitigation dimensions of climate-smart agribusiness. A global assessment synthesising 32 years of FAO data from 1990 to 2021 applied structural equation modelling and a deep learning approach to predict future agricultural greenhouse gas emissions from 2022 to 2050 under three hypothetical scenarios [18]. Results indicate that if current trends continue, global agricultural GHG emissions will rise by 2050; however, doubling or tripling the reduction rate of deforestation could stabilise or lower emissions while maintaining agricultural productivity [18]. This scenario-based forecasting capability is precisely what agribusiness strategic planning requires to align production expansion with emission reduction commitments.

A study specifically focused on greenhouse gas emissions prediction from agrifood systems applied LSTM, Random Forest, and a hybrid LSTM-RF model, demonstrating that hybrid architectures outperform single-algorithm approaches in capturing the complex temporal and non-linear relationships that characterise GHG emission dynamics [1]. The rising temperatures, changing precipitation patterns, and increased frequency of extreme meteorological events that define the contemporary climate context further underscore the need for accurate GHG forecasting to guide climate-smart agricultural investment decisions at both firm and policy levels [1].

B. *Precision Interventions for Emissions Reduction*

At the operational level, machine learning driven precision agriculture directly reduces agricultural emissions through input optimisation. A systematic review of AI and machine learning implementations for optimised crop management documented that early machine learning-based pest detection achieved an 18% decrease in pesticide use, representing both environmental and economic gains [5].

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Convolutional neural networks identify crop pests and diseases with a 94% success rate, while sensor-based environmental alert systems predict outbreak risks with 85% accuracy [5]. Smart farming platforms integrating machine learning across data from 847 farms documented a 20% yield increase and a 15% reduction in water use compared to conventional management, alongside annual pesticide cost savings of approximately USD 5,000 per farm [19].

VII. SUPPLY CHAIN OPTIMISATION AND AGRIBUSINESS DECISION SUPPORT

A. *Machine Learning in Agrifood Supply Chain Forecasting*

The agribusiness value chain extends well beyond the farm gate, and machine learning driven predictive analytics generate significant value at each node from post-harvest processing through to retail demand management. A study on robust and resilient machine learning for forecasting agri-food production reviewed multiple algorithms including LSTM networks, SVR, Random Forest regression, Gradient Boosting Regression, and XGBoost for supply chain demand forecasting applications, documenting that ensemble approaches combining deep learning and traditional algorithms consistently outperform single-model approaches [20]. These architectures enable supply chain managers to anticipate climate-driven production shortfalls, adjust procurement strategies, and reduce the food waste and logistical disruptions that amplify the economic losses from climate variability [20].

A comprehensive structured review of AI applications in agribusiness emphasised that machine learning enables real-time monitoring and informed decision-making across precision agriculture, resource management, and supply chain optimisation simultaneously [21]. The integration of AI with blockchain technology offers additional supply chain transparency benefits, creating verifiable provenance records that support climate-smart certification and premium market access [21]. Transforming agricultural productivity through AI-driven forecasting across the supply chain requires addressing model drift, in which prediction accuracy degrades over time due to environmental changes, through continuous model retraining on updated data streams [11].

B. *Decision Support for Climate-Smart Practice Adoption*

At the farm-level policy interface, machine learning has been applied to predict climate-smart agriculture practice adoption decisions among smallholder farmers. A study using optimised Gradient Boosting trained on household-level data from Rakai district, Uganda, framed within climate adaptation analytical theory, demonstrated that ML algorithms can generate realistic insights into future farmer adaptation decisions across socio-economic and agro-ecological feature sets [3]. This application directly bridges the gap between remote sensing-based operational analytics and the behavioural dimensions of climate-smart agribusiness transition, providing policymakers with decision-relevant predictions about where and among whom targeted interventions are most likely to accelerate adoption.

VIII. BARRIERS, EQUITY DIMENSIONS, AND IMPLEMENTATION CONSTRAINTS

A. *Data Infrastructure and the Digital Divide*

The transformative potential of machine learning in climate-smart agribusiness is not uniformly accessible. Smallholder farmers, who constitute approximately 80% of the farming population in developing countries, face structural exclusion from the precision agriculture revolution [22]. The digital divide, encompassing absence of stable internet connectivity, affordable devices, and sufficient digital literacy, is identified as the foremost barrier to AI adoption in smallholder agricultural contexts [22]. Electricity supply constraints further disrupt the operation of data collection, processing, and communication infrastructure on which machine learning systems depend [22].

Data availability and fragmentation compound these infrastructure challenges. Large datasets are a foundational requirement for any machine learning solution, yet data on smallholder farming practices is either not collected or exists only in paper records, making it unusable by AI platforms [23]. The data infrastructure required for machine learning is largely available only in developed country large-farm contexts where IoT sensors on farming equipment generate continuous observational streams. Bridging this data gap requires deliberate investment in community-level sensing networks, satellite data democratisation, and low-cost IoT deployment adapted to resource-constrained settings.

B. *Model Interpretability, Trust, and Governance*

Beyond data access, model interpretability represents a critical adoption barrier. Advanced forecasting architectures, particularly CNNs and LSTMs, operate as black boxes, making it difficult for farmers and agribusiness decision-makers to understand how predictions are derived, which undermines trust and adoption [11]. Explainable AI frameworks including SHAP and LIME are specifically recommended as tools for building farmer confidence in machine learning recommendations, by making the factors driving individual predictions visible and comprehensible

[11]. The ethical dimensions of AI adoption, including data privacy concerns, algorithmic bias, and the risk of displacing farmer knowledge with opaque automated recommendations, require explicit governance frameworks that are currently underdeveloped in most agricultural policy environments [21].

Thematic Domain	Key ML Contribution	Critical Implementation Gap
Crop yield prediction	73% spatiotemporal variance explained (LSTMatt)	Generalisation to low-data developing country contexts
Climate hazard early warning	Multi-hazard probabilistic detection with uncertainty quantification	Computational infrastructure in data-scarce regions
Soil and water management	25% irrigation cost reduction; 92% prediction accuracy	IoT sensor deployment costs for smallholders
GHG emissions forecasting	Scenario-based emission projections to 2050 (FAO data)	Linking farm-level predictions to policy emission targets
Supply chain optimisation	20% yield gain; USD 5,000 pesticide savings per farm	Model drift under shifting climate baselines
CSA practice adoption	Gradient Boosting predicts farmer adaptation decisions	Behavioural data collection and privacy governance

Table 2: Synthesis of Machine Learning Contributions and Critical Implementation Gaps Across Agribusiness Production System Domains

IX. INTEGRATED FRAMEWORK AND POLICY DIRECTIONS

A. *A Unified Machine Learning Analytics Architecture*

The evidence reviewed across Sections 3 to 8 supports a unified machine learning analytics architecture for climate-smart agribusiness production systems. This architecture operates across four interdependent layers: data ingestion, encompassing satellite remote sensing, IoT sensors, weather station networks, and supply chain records; feature engineering, transforming raw data into yield-relevant climatic, edaphic, and crop physiological variables; predictive modelling, applying the appropriate algorithm class (LSTM for temporal sequences, CNN for spatial imagery, Random Forest and Gradient Boosting for tabular and mixed-feature data) to the target prediction task; and decision support, translating model outputs into farmer-actionable recommendations, supply chain adjustments, or policy-relevant risk assessments.

Explainability must be embedded architecturally rather than added as an afterthought. The three-pillar framework of explainability, probabilistic uncertainty quantification, and expert knowledge integration identified in the climate hazard literature [10] applies equally across all domains of the production system. Hybrid models that combine the temporal modelling strengths of LSTM with the interpretability of ensemble tree methods represent the most promising near-term architecture for operational deployment in climate-smart agribusiness contexts [8, 6].

B. *Policy Recommendations*

Translating machine learning potential into agribusiness impact requires a supportive policy environment addressing four priority areas. First, data infrastructure investment must prioritise affordable IoT sensor deployment, satellite data accessibility, and community data collection programmes targeting smallholder farming systems in developing economies, where climate vulnerability is greatest and machine learning infrastructure is least developed [22, 23]. Second, digital skills development programmes must be integrated into agricultural extension services, equipping farmers, agronomists, and agribusiness managers with the literacy needed to engage productively with machine learning advisory systems rather than passively receiving opaque recommendations [21].

Third, explainability requirements should be embedded in public procurement and certification standards for agricultural AI systems, ensuring that machine learning tools deployed in climate-smart agribusiness contexts generate interpretable, trustworthy outputs aligned with farmer decision-making needs rather than engineering convenience [10, 11]. Fourth, international development finance should explicitly support the adaptation of machine learning agribusiness systems for developing country contexts, including low-bandwidth and offline-capable applications, tailored model training on local crop and climate datasets, and governance frameworks that protect farmer data rights [22, 23].

X. CONCLUSION

This paper has presented a comprehensive review of machine learning driven predictive analytics applications across the principal dimensions of climate-smart agribusiness production systems. The evidence base is compelling: LSTM and ensemble architectures explain the majority of spatiotemporal crop yield variance under climate variability; multi-hazard explainable AI systems reliably detect agricultural climate risks with quantified uncertainty; precision soil and water analytics reduce irrigation costs by up

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to 25% and achieve prediction accuracies exceeding 95%; deep learning frameworks enable scenario-based greenhouse gas emission projections at global scale; and integrated smart farming platforms achieve 20% yield gains with measurable reductions in water and pesticide consumption.

These are not marginal improvements; they represent fundamental transformations in the analytical foundations of agribusiness decision-making. As climate change intensifies and the window for proactive agricultural adaptation narrows, machine learning driven predictive analytics will move from a competitive advantage available to well-resourced commercial operations to a necessity for the entire agribusiness sector. The challenge is not whether machine learning can serve climate-smart agribusiness, as the evidence reviewed here leaves no doubt that it can. The challenge is ensuring that its deployment is equitable, transparent, and anchored in the institutional and data infrastructure that translates algorithmic capability into operational impact at scale.

Achieving this requires coordinated investment in data commons, digital skills, governance frameworks, and smallholder-adapted technologies. The scientific and engineering communities have delivered powerful tools; it now falls to policymakers, development finance institutions, and agribusiness leaders to create the enabling conditions under which machine learning can fulfil its promise as a foundational technology for the climate-smart agricultural transition.

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