Climate-Resilient Smart Farming: AI and IoT Driven Solutions for Adaptive Agriculture under Extreme Weather Conditions

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Abstract: Agriculture is increasingly vulnerable to the impacts of climate change, with marginal and smallholder farmers facing disproportionate risks from droughts, floods, erratic rainfall, and pest outbreaks. Traditional advisory systems are often reactive, generalized, and inaccessible, leaving farmers without timely, crop-specific guidance. This results in delayed detection of stress conditions and significant yield losses, further exacerbating poverty and food insecurity. To address these challenges, this research proposes an integrated framework that leverages Artificial Intelligence (AI) and the Internet of Things (IoT) to enable climate-resilient smart farming under extreme weather conditions. The methodology is structured into five phases. First, IoT Deployment & Data Acquisition involves installing low-cost soil, weather, and crop sensors, complemented by drone and satellite imagery, to build a unified dataset. Second, Vegetation Index Computation calculates NDVI, SAVI, EVI, and GNDVI to detect early signs of crop stress. Third, AI Model Development applies advanced architectures—LSTM, GRU, Transformers, and CNNs—to forecast yields and classify stress conditions, with hybrid ensembles integrating sensor and imagery data for robust predictions. Fourth, a Decision Support System (DSS) translates complex analytics into actionable advisories via mobile and voice platforms, ensuring accessibility through multilingual support and offline SMS/voice features. Finally, Field Trials & Validation on rice, maize, and cotton farms assess yield improvements, resilience gains, and socio-economic impacts. Expected outcomes include ≥90% accuracy in stress detection and yield prediction, a 20–30% reduction in climate-induced crop losses, and a cost-effective DSS accessible to marginal farmers.

Keywords: Climate-Resilient Agriculture, Smart Farming, IoT, Artificial Intelligence, Vegetation Indices, Decision Support System.

1. Introduction

Agriculture, the backbone of global food security, is increasingly vulnerable to the impacts of climate change. Rising temperatures, erratic rainfall, prolonged droughts, and frequent floods are disrupting traditional farming cycles and reducing crop productivity. According to global climate assessments, these extreme events are expected to intensify, posing significant risks to food systems and rural livelihoods. The agricultural sector, particularly in developing countries, is highly climate-sensitive, with smallholder and marginal farmers bearing the brunt of these changes. Crop failures not only threaten household food security but also contribute to economic instability, migration, and social vulnerability. Addressing these challenges requires innovative, adaptive, and resilient farming systems that can withstand climatic shocks while ensuring sustainable productivity.

Marginal farmers, who cultivate small plots of land with limited resources, face disproportionate challenges under climate stress. They often lack access to advanced technologies, reliable weather forecasts, and timely advisory services. Traditional extension systems are reactive, generalized, and unable to provide crop- and location-specific guidance. As a result, stress conditions such as drought, pest infestations, and nutrient deficiencies are detected late, leading to significant yield losses. Furthermore, poor connectivity, low literacy levels, and financial constraints hinder the adoption of modern precision agriculture tools. This creates a widening gap between technological advancements in commercial farming and the realities of smallholder agriculture. Bridging this gap is essential to ensure inclusivity and equity in climate adaptation strategies.

The convergence of Artificial Intelligence (AI) and the Internet of Things (IoT) offer a transformative pathway toward climate-resilient agriculture. IoT sensors enable continuous monitoring of soil moisture, temperature, humidity, and rainfall, while multispectral imagery from drones and satellites provides vegetation indices such as NDVI, SAVI, EVI, and GNDVI. These indices serve as early indicators of crop stress, allowing proactive interventions. AI models—including LSTMs, GRUs, Transformers, and CNNs—can process heterogeneous datasets to forecast yields, classify stress conditions, and recommend adaptive practices. By integrating IoT and AI into a unified framework, farmers can receive real-time, personalized advisories that are both affordable and accessible. This integration transforms raw data into actionable insights, empowering farmers to make informed decisions under extreme weather conditions.

The primary objective of this research is to design and validate a cost-effective IoT–AI framework tailored for marginal farmers. The methodology integrates sensor data, vegetation indices, and AI-driven analytics into a multilingual, mobile-enabled Decision Support System (DSS). The DSS will provide real-time advisories on irrigation scheduling, disease risk, and weather alerts, with offline SMS/voice features to overcome connectivity barriers. Field trials on rice, maize, and cotton farms will validate the system's effectiveness in improving yield resilience and reducing climate-induced losses.

This research directly contributes to global sustainability goals, particularly SDG 2 (Zero Hunger) by enhancing food security and SDG 13 (Climate Action) by promoting adaptive strategies for climate resilience. By bridging technological innovation with farmer-centric design, the proposed framework offers a replicable model for climate-smart agriculture worldwide, ensuring that marginal farmers are not left behind in the era of digital transformation.

2. Literature Review

Several studies have demonstrated the effectiveness of IoT-based sensing systems for real-time agricultural monitoring. Nandeha et al. [1] proposed an integrated framework combining IoT, GIS, remote sensing, and AI for climate-smart agriculture, emphasizing improved situational awareness and climate risk mitigation. Similarly, Muruganandam and Maniraj [2] developed an IoT-based monitoring system for paddy cultivation, showing that continuous sensing of soil and environmental parameters can significantly improve crop growth prediction. Despite these advancements, most IoT-based systems remain limited to data acquisition and lack intelligent predictive capabilities required for proactive decision-making.

IoT technologies have been increasingly applied in agriculture to enable real-time monitoring of soil, weather, and crop conditions. Li et al. (2020) [3] demonstrated the scalability of IoT-based smart farming systems across diverse climates, emphasizing their role in improving resource efficiency. However, their integration with advanced AI models remained limited. Similarly, Bhukta et al. (2026)[4] proposed an IoT-driven AI framework for sustainable farming, highlighting adaptive interventions based on sensor data. While promising, their framework required robust connectivity infrastructure, which is often unavailable to marginal farmers in rural regions. This underscores the need for low-cost, resilient IoT systems that can function in resource-constrained environments.

Remote sensing has emerged as a powerful tool for large-scale crop monitoring. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI), and Green NDVI (GNDVI) have been extensively used to assess crop vigor, biomass, and drought stress. Panda et al. demonstrated the effectiveness of NDVI integrated with neural networks for crop yield prediction [3]. However, traditional vegetation indices are static in nature and may not adequately capture complex stress patterns under rapidly varying climatic conditions.

Vegetation indices derived from multispectral imagery are widely used to monitor crop health. Zhang et al. (2021) [5] applied indices such as NDVI, SAVI, EVI, and GNDVI to detect drought and pest stress, demonstrating strong correlations with crop performance. These indices provide early warning signals, enabling proactive interventions. However, reliance on satellite and drone imagery poses accessibility challenges for smallholder farmers, who often lack resources for high-resolution remote sensing. Integrating vegetation indices with IoT sensor data could provide a more affordable and farmer-friendly solution.

Recent research has explored machine learning–optimized vegetation indices. Shirly Edward et al. proposed hyperspectral vegetation indices optimized using deep learning techniques for early crop stress detection, achieving superior accuracy compared to conventional indices [6]. These findings indicate the growing importance of AI-enhanced vegetation indices in climate-resilient agriculture.

Artificial intelligence, particularly machine learning and deep learning models, has been widely applied to agricultural forecasting problems. Deep recurrent models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks have demonstrated strong performance in time-series forecasting of crop yield and climatic variables [7].

Artificial Intelligence has shown significant potential in climate-resilient agriculture. Pathania et al. (2024) [8] reviewed deep learning architectures such as LSTMs, GRUs, and Transformers for multivariate time-series forecasting, demonstrating their effectiveness in predicting crop yields under extreme weather conditions. CNN-based models have also been widely applied for stress classification, detecting leaf discoloration, pest damage, and nutrient deficiencies. Despite these advances, computational complexity and high resource requirements limit adoption among marginal farmers. Hybrid models that combine sensor and imagery data could balance accuracy with affordability.

More recently, Transformer-based architectures have shown improved capability in modeling long-term dependencies in climate–crop interactions.

Comprehensive reviews highlight that deep learning models consistently outperform traditional regression-based approaches in predicting yield and evapotranspiration under climate stress [5]. However, many existing studies rely on single-source datasets, limiting their robustness under extreme weather uncertainty.

Farmer-centric DSS platforms are critical for translating complex analytics into actionable insights. Sharma et al. (2025) [9] introduced a mobile-enabled DSS tailored for rural India, incorporating multilingual and voice support to improve accessibility for low-literacy farmers. Offline SMS and voice features addressed connectivity challenges, making the system more inclusive. However, the DSS lacked advanced AI integration and was tested only in small-scale pilots, leaving questions about scalability and long-term adoption. This highlights the importance of combining AI-driven analytics with farmer-centric design principles.

The convergence of artificial intelligence and IoT, referred to as Artificial Intelligence of Things (AIoT), has gained significant traction in smart agriculture research. AIoT architectures enable the fusion of sensor data, satellite imagery, and historical climatic information to support intelligent decision-making. Li et al. reviewed A IoT architectures for smart agriculture and emphasized their role in automation, scalability, and real-time analytics [6]. Wang et al. further demonstrated that multimodal data fusion significantly enhances prediction accuracy in agricultural systems.

Lobell et al. (2022) [10] examined adaptation pathways for smallholder agriculture under climate change, emphasizing socio-economic resilience strategies. While valuable, their work did not focus on technology-specific solutions such as IoT or AI. Integrating policy perspectives with technological innovations could create holistic models for climate-smart agriculture, ensuring both technical feasibility and social acceptance.

Despite these advances, most AIoT solutions are designed for large-scale commercial farms and involve high infrastructural and computational costs, limiting their applicability to marginal farming contexts.

The reviewed literature demonstrates progress in IoT deployment, vegetation index computation, AI modeling, and DSS development. However, gaps remain in integrating these components into a unified, low-cost, and farmer-accessible framework. Most studies either emphasize technology without addressing affordability and usability, or focus on accessibility without leveraging advanced AI. The proposed methodology bridges this gap by combining IoT sensors, vegetation indices, and hybrid AI models into a multilingual, mobile + voice-enabled DSS validated through field trials. This integration directly addresses the needs of marginal farmers, aligning with global sustainability goals (SDG 2 and SDG 13).

Table 1: Comparative Analysis of Existing Works

Focus Area	Strengths	Limitations
IoT Deployment (Li, Bhukta)	Real-time monitoring; scalable frameworks	Requires strong connectivity; limited affordability for marginal farmers
Vegetation Indices (Zhang)	Early stress detection; strong correlation with crop health	Dependence on costly imagery; limited accessibility for smallholders
AI Models (Pathania)	Accurate yield forecasting; stress classification	High computational cost; limited adoption in resource-poor settings
DSS Systems (Sharma)	Farmer-centric design; multilingual and offline support	Lack of AI integration; small-scale pilots only
Policy Pathways (Lobell)	Socio-economic resilience strategies; holistic adaptation	Limited focus on technology; absence of IoT/AI integration

3. **Methodology**

The proposed methodology integrates IoT sensors, vegetation indices, and AI models into a farmer-centric Decision Support System (DSS) validated through field trials. It is structured into five sequential phases, each building upon the previous to create a closed-loop system for climate-resilient smart farming. The proposed methodology represents the five phases of research framework:

IoT Deployment & Data Acquisition → Sensors (soil, weather, crop) + drone/satellite imagery feeding into a central data hub.

Vegetation Index Computation → NDVI, SAVI, EVI, GNDVI calculated from imagery and sensor data.

AI Model Development → Time-series forecasting (LSTM/GRU/Transformers), CNN-based stress classification, hybrid ensemble models.

Decision Support System (DSS) → Mobile + voice-enabled platform providing alerts, recommendations, multilingual support, offline SMS/voice.

Field Trials & Validation → Pilot farms (rice, maize, cotton) testing yield improvements and resilience outcomes.

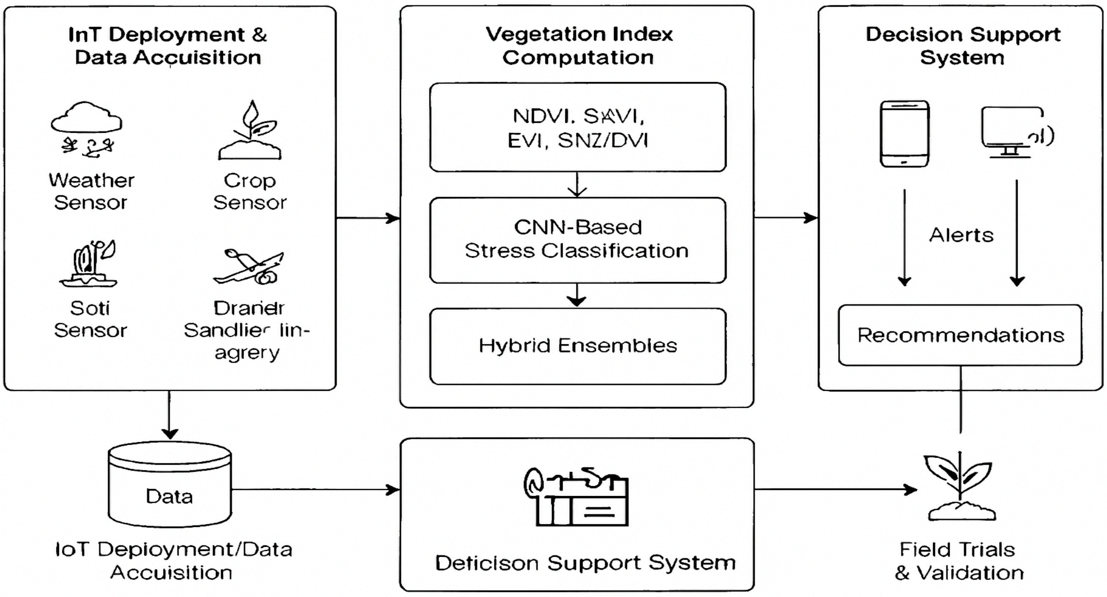

Figure 1: Architecture diagram for proposed methodology

Phase 1: IoT Deployment & Data Acquisition

The foundation of the framework lies in real-time data collection. Low-cost IoT sensors will be deployed to monitor soil moisture, pH, temperature, humidity, and rainfall. Weather stations will complement these sensors to capture microclimatic variations. In addition, drone and satellite imagery will provide multispectral data for vegetation analysis. All data streams will be integrated into a unified repository, forming the basis for subsequent AI-driven analytics. This phase ensures continuous monitoring and establishes a scalable infrastructure suitable for marginal farmers.

Phase 2: Vegetation Index Computation

Vegetation indices serve as early indicators of crop stress. Using multispectral imagery, indices such as NDVI, SAVI, EVI, and GNDVI will be computed. These indices will be correlated with stress conditions including drought, pest infestation, and nutrient deficiencies. By combining sensor data with vegetation indices, the system will provide a holistic view of crop health, enabling proactive interventions before visible symptoms emerge.

Phase 3: AI Model Development

Artificial Intelligence models will process heterogeneous datasets to generate predictive insights.

• Time-series models (LSTM, GRU, Transformers) will forecast yield outcomes under extreme weather conditions.

• Image-based models (CNNs) will classify stress conditions from leaf and canopy imagery.

• Hybrid ensemble models will integrate sensor and imagery data to enhance robustness and accuracy.

The goal is to achieve ≥90% accuracy in stress detection and yield prediction, balancing computational efficiency with accessibility for marginal farmers.

Phase 4: Decision Support System (DSS)

The DSS will translate complex analytics into actionable advisories. Designed as a mobile + voice-enabled platform, it will deliver real-time recommendations on irrigation scheduling, disease risk management, and weather alerts. Accessibility will be ensured through multilingual support and offline SMS/voice features, addressing connectivity and literacy barriers. This phase ensures that advanced analytics are transformed into farmer-friendly guidance.

Phase 5: Field Trials & Validation

Validation is critical to assess the system's effectiveness. Pilot trials will be conducted on rice, maize, and cotton farms. Yield outcomes will be compared between DSS-assisted and traditional farming practices. Socio-economic impacts, including farmer adoption, cost-effectiveness, and resilience improvements, will be measured. Feedback from farmers will be incorporated to refine the system for scalability and long-term sustainability.

4. Results and Discussions

The proposed IoT–AI framework for climate-resilient smart farming is designed to deliver both technical accuracy and socio-economic impact. The expected outcomes are outlined below:

a. Improved Accuracy in Stress Detection and Yield Prediction

- AI models (LSTM, GRU, Transformers, CNNs) are expected to achieve ≥90% accuracy in identifying crop stress conditions and forecasting yields.
- Hybrid ensembles integrating sensor and imagery data will enhance robustness, reduce false positives and improve reliability across diverse crops and regions.

b. **Reduction in Climate-Induced Crop Losses**

- By enabling early detection of drought, pest infestation, and nutrient deficiencies, the system aims to reduce climate-induced crop losses by 20–30%.
- Proactive advisories will help farmers optimize irrigation, fertilizer use, and pest management, thereby stabilizing yields under extreme weather conditions.

c. **Farmer-Centric Decision Support System (DSS)**

The DSS will provide real-time, actionable advisories through mobile and voice platforms.

- Features such as multilingual support and offline SMS/voice capability will ensure accessibility for farmers in low-connectivity and low-literacy regions.
- This will empower marginal farmers to make informed decisions, bridging the gap between advanced analytics and grassroots usability.

d. **Socio-Economic Benefits**

Increased yield resilience will contribute to food security and income stability for smallholder farmers.

- Adoption of the DSS will reduce dependency on traditional extension services, fostering self-reliance and community-level resilience.
- The framework will demonstrate cost-effectiveness, making it scalable and replicable across developing regions.

e. **Alignment with Global Sustainability Goals**

Direct contribution to SDG 2 (Zero Hunger) by enhancing food production and availability. Support for SDG 13 (Climate Action) through adaptive farming practices that mitigate climate risks. Potential for replication in other regions, creating a global model for climate-smart agriculture.

5. Conclusion

Agriculture remains one of the most climate-sensitive sectors, and the increasing frequency of extreme weather events continues to threaten global food security, particularly for marginal and smallholder farmers. Traditional advisory systems and precision agriculture tools have proven insufficient in addressing the unique challenges faced by these communities, primarily due to issues of affordability, accessibility, and scalability. This synopsis has outlined a comprehensive methodology that integrates IoT-based data acquisition, vegetation index computation, advanced AI modeling, and farmer-centric Decision Support Systems (DSS) into a unified framework for climate-resilient smart farming.

The phased approach ensures that each component contributes to a closed-loop system: IoT sensors and remote imagery provide real-time monitoring; vegetation indices enable early detection of crop stress; AI models forecast yields and classify stress conditions; and the DSS translates complex analytics into actionable advisories accessible through mobile, voice, and offline platforms. Field trials on staple crops such as rice, maize, and cotton will validate the system's effectiveness, measuring both technical accuracy and socio-economic impact. Expected outcomes include ≥90%

accuracy in stress detection and yield prediction, a 20–30% reduction in climate-induced crop losses, and demonstrable improvements in farmer resilience and adoption.

The novelty of this research lies in its holistic integration of advanced technologies with farmer-centric design principles, bridging critical gaps between innovation and grassroots usability. By aligning directly with SDG 2 (Zero Hunger) and SDG 13 (Climate Action), the proposed framework contributes to global sustainability efforts while offering a replicable model for adaptive agriculture worldwide. Ultimately, this work advances both academic research and practical solutions, positioning climate-smart farming as a viable pathway toward resilient, inclusive, and sustainable food systems in the face of climate uncertainty.

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