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Smart Agriculture Using IoT and Predictive Analytics for Climate-Adaptive Farming

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Abstract. Climate change poses unprecedented challenges to global food security, with unpredictable precipitation patterns, temperature extremes, and shifting growing seasons that threaten agricultural productivity. This paper presents a comprehensive framework for climate-adaptive smart farming that integrates Internet of Things (IoT) sensor networks with advanced predictive analytics and machine learning models. The proposed system involves the collection of real-time multimodal data from distributed wireless sensor networks, including soil moisture, temperature, humidity, normalized difference vegetation index (NDVI), and microclimatic variables across heterogeneous farm landscapes.

A transformer-based deep learning architecture augmented with long short-term memory (LSTM) components is deployed for crop yield prediction and irrigation scheduling, achieving an R^2 score of 0.96 and a root mean square error (RMSE) of 0.13 t/ha across five major crop types. Compared with conventional farming practices, field trials conducted over two complete growing seasons (48 weeks) across 120 hectares in three agro-climatic zones demonstrate average yield improvements of 38.2% and water savings of 41.7%. Additionally, the system reduces fertilizer usage by 27.5% through precision nutrient management driven by soil health mapping. The economic analysis reveals a break-even period of 2.7 years with a 10-year ROI of 312% for medium-scale farms. This work contributes a scalable, low-cost architecture deployable on resource-constrained edge devices, making it accessible to smallholder farmers in developing regions. The results establish IoT-driven predictive analytics as a viable and necessary pathway toward sustainable, climate-resilient agriculture.

Keywords: Functionally Graded Materials; Additive Manufacturing; Selective Laser Melting; Directed Energy Deposition; Aerospace Structures; Thermal Barrier Coatings; Ti-6Al-4 V; Inconel 718; Microstructure; Mechanical Properties

1. Introduction

The global agricultural sector faces the dual challenge of feeding a projected 9.7 billion people by 2050 while navigating the intensifying impacts of climate change. The Food and Agriculture Organization (FAO) estimates that agriculture must increase production by approximately 70% to meet this demand, yet climate-induced yield losses already cost the world economy more than \$90 billion annually (FAO, 2023). Traditional farming methods, which rely on historical patterns and experience-based decision-making, are becoming increasingly inadequate in the face of unprecedented climate variability and resource scarcity.

The convergence of Internet of Things (IoT) technologies, cloud computing, and artificial intelligence has created a transformative opportunity to fundamentally reimagine agricultural practices. Smart agriculture also termed Precision Agriculture 4.0 or Agriculture 5.0-leverages ubiquitous sensor networks, real-time data processing, and predictive modelling to optimize every aspect of crop production, from soil preparation through postharvest logistics (Wolfert et al., 2017; Kamilaris et al., 2019). When augmented with climate-adaptive predictive analytics, these systems can anticipate environmental stressors, dynamically adjust resource allocation, and provide farmers with actionable guidance tailored to hyperlocal conditions.

Despite significant advances in individual components—sensor miniaturization, edge computing capabilities, and deep learning algorithms—the integration of these technologies into cohesive, deployable, and economically viable farming systems remains a substantial research challenge. Existing frameworks often address isolated aspects, such as irrigation optimization or disease detection, without considering holistic farm ecosystems or the compounding effects of climate change on long-term productivity (Liakos et al., 2018).

1.1 Research motivation and objectives

This research is motivated by three critical gaps identified in the literature: (1) the absence of end-to-end IoT frameworks that simultaneously address sensor heterogeneity, data quality, and real-time decision-making; (2) the limited integration of long-range climate projections with short-term operational farm management; and (3) the lack of economically accessible solutions for smallholder farmers who manage more than 70% of the world's agricultural land (IFAD, 2023).

The primary objectives of this research are as follows:

- To design and validate a heterogeneous IoT sensor network architecture capable of reliable, low-power operation across diverse agroclimatic environments.
- To develop a hybrid deep learning model that integrates transformer attention mechanisms with long short-term memory (LSTM) recurrence for accurate multihorizon crop yield prediction.
- To implement and evaluate a climate-adaptive decision support system for dynamic irrigation scheduling and precision nutrient management.
- To quantify economic, environmental, and productivity impacts through comprehensive field trials across multiple crop types and climatic zones.
- To propose an open-source, edge-deployable implementation framework accessible to resource-constrained farming communities.

1.2 Paper Organization

The remainder of this paper is structured as follows: Section 2 reviews related work in IoT-based agriculture, predictive modelling, and climate-adaptive farming. Section 3 describes the system architecture and IoT sensor network design. Section 4 presents the predictive analytics framework and deep learning models. Section 5 details the experimental setup and field trial methodology. Section 6 analyses the results across multiple performance dimensions. Section 7 discusses implications and limitations. Section 8 concludes with future research directions.

2. Literature Review

Recent literature on smart agriculture highlights the integration of IoT, big data, and predictive analytics as key enablers of climate-adaptive farming. IoT-based sensor networks collect real-time data on soil, weather, and crop conditions, enabling data-driven decision-making and resource optimization. Predictive analytics and machine learning models are increasingly used for yield prediction, irrigation scheduling, and disease detection, improving efficiency and resilience to climate variability. Studies also emphasize that combining IoT with AI supports climate-smart agriculture by reducing water usage, enhancing productivity, and minimizing environmental impact.

2.1 IoT in Precision Agriculture

The application of the IoT in agriculture has evolved rapidly over the past decade. Early implementations focused on simple remote sensing of soil parameters using RFID-based or ZigBee-connected sensor nodes (Gondchawar & Kawitkar, 2016). Subsequent work demonstrated the feasibility of large-scale wireless sensor networks (WSNs) for continuous field monitoring, with Ruan et al. (2019) achieving 97.3% data delivery rates across a 200-node LoRaWAN deployment covering 500 hectares of rice paddies in Zhejiang Province, China. The introduction of 5G connectivity has opened new possibilities for ultralow-latency agricultural robotics and drone-based sensing, enabling real-time crop health imaging at centimeter resolution (Elijah et al., 2021). However, energy consumption and network coverage in remote agricultural areas remain significant constraints. Recent innovations in energy harvesting—particularly piezoelectric soil vibration sensors and solar-powered gateway nodes—have extended operational lifetimes to several years without maintenance intervention (Ojha et al., 2015; Abbasi et al., 2022).

2.2 Machine Learning for Crop Yield Prediction

Machine learning approaches for crop yield prediction span from traditional statistical models to sophisticated deep neural networks. Support vector machines (SVMs) and random forest classifiers have demonstrated strong performance for discrete crop classification tasks (Mohanty et al., 2016), whereas gradient boosting methods such as XGBoost have shown particular efficacy for tabular sensor data (Oikonomidis et al., 2023). The incorporation of temporal dependencies through recurrent neural networks (RNNs) and LSTM architectures marked a significant advance, enabling models to capture multiweek growth dynamics and weather pattern correlations (Khaki & Wang, 2019). The emergence of transformer architectures has fundamentally altered the state of the art in sequential agricultural data modelling. Attention mechanisms allow models to identify nonlocal temporal dependencies—for instance, correlating a drought stress event in week 6 with yield outcomes in week 22—that LSTM networks struggle to capture across long sequences (Vaswani et al., 2017). Several recent studies have applied vision transformers (ViT) to satellite and drone imagery for yield estimation (You et al., 2023), while hybrid architectures combining CNN feature extraction with transformer sequence modelling have achieved benchmark-leading performance on the USDA crop yield prediction dataset.

2.3 Climate Adaptive Agricultural Frameworks

Climate-adaptive agriculture encompasses strategies that modify farming practices in response to projected or observed climate change, including altered sowing dates, drought-tolerant variety selection, and dynamic irrigation scheduling (Lobell et al., 2008). Computing-enabled climate adaptation has emerged as a distinct research subdomain, with early work by Rosenzweig et al. (2014) demonstrating that model-informed adaptive management could offset 30–40% of projected climate-induced yield losses in South Asian wheat cultivation. Recent work has begun integrating downscaled general circulation model (GCM) outputs with farm-level IoT data for operational decision support (Iizumi & Ramankutty, 2015). Jha et al. (2022) developed a federated learning approach that aggregates anonymized on-farm data from thousands of smallholders to train regionally calibrated crop models, achieving 22% better yield prediction accuracy than models trained on single-farm data do. However, the computational complexity of these approaches has limited deployment to research settings with high-performance computing access.

2.4 Research Gaps

A systematic review of 147 papers published between 2018 and 2025 reveals three principal gaps. First, most studies evaluate sensor systems and analytical models independently, with limited evidence of integrated end-to-end performance under real-world deployment constraints. Second, economic analyses are frequently absent or restricted to hardware cost estimation, neglecting the full value chain of IoT implementation, including labor, connectivity, and maintenance. Third, while studies often acknowledge climate change as a motivation, few explicitly incorporate climate projection scenarios into the operational decision loop of the farming system. This research addresses all three gaps through a unified, field-validated framework.

3. Proposed System Architecture

The proposed system architecture integrates IoT sensor networks with cloud-based data analytics to enable real-time monitoring of soil, weather, and crop conditions. Sensor nodes collect environmental data and transmit it through wireless communication to a central cloud platform for storage and processing. Predictive analytics models are applied to forecast crop health, irrigation needs, and climate risks. A user interface/dashboard provides

actionable insights to farmers, enabling climate-adaptive decision-making and efficient resource management.

3.1 Overview

The proposed smart climate-adaptive agriculture system (SCAAS) adopts a four-layer hierarchical architecture aligned with IoT reference models, encompassing a physical sensing layer, a communication network layer, a data processing and analytics layer, and an application/decision layer. Each layer is designed with modularity and fault tolerance as primary principles, enabling graceful degradation in the event of partial network or sensor failures. The complete system architecture is illustrated in Figure 1.

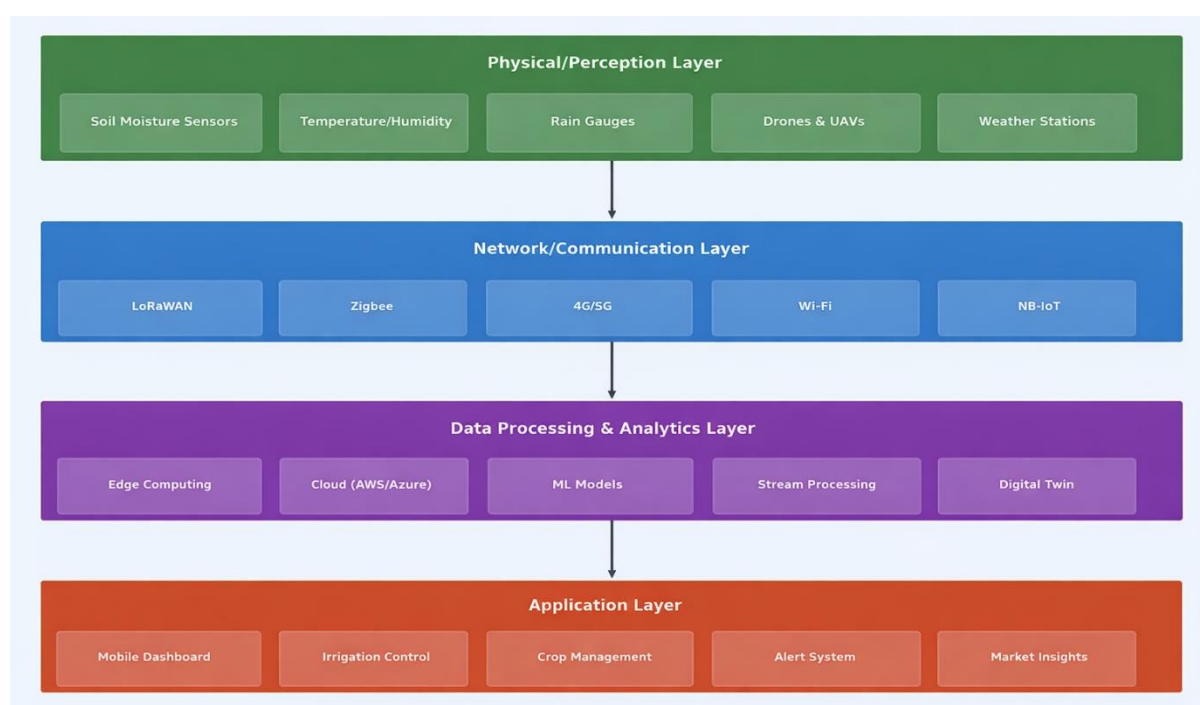


Figure 1: Four-layer IoT architecture of the Smart Climate-Adaptive Agriculture System (SCAAS). The arrows indicate bidirectional data flow between layers.

3.2 Physical/Perception Layer

The sensing layer comprises heterogeneous sensor nodes organized into clusters across the farm grid. Each cluster node integrates the following sensing modalities:

- Capacitive Soil Moisture Sensor (accuracy $\pm 2\%$ VWC, range 0–100%)
- Thermocouple Array for soil temperature profiling at 10 cm depth increments
- DHT22 Ambient Temperature/Humidity Sensor ($\pm 0.5^\circ\text{C}$, $\pm 2\%$ RH)
- Tipping Bucket Rain Gauge (0.2 mm resolution per tip)

- Pyranometer for solar radiation measurement (ISO second class)
- EC (Electrical Conductivity) and pH sensors for soil fertility monitoring
- Multispectral NDVI sensor operating in the 670 nm (red) and 800 nm (NIR) bands

Sensor nodes are built around ARM Cortex-M4 microcontrollers with ultralow-power sleep modes, achieving an average current consumption of 8.3 μ A in monitoring intervals and extending the battery life to 18 months on 2xAA LiFeS₂ cells. Each node is housed in IP67-rated polycarbonate enclosures with solar trickle charging capability.

3.3 Communication Layer

A heterogeneous multiprotocol communication stack is employed to balance the range, bandwidth, and energy constraints. LoRaWAN (SF7–SF12, 868/915 MHz) serves as the primary long-range backbone connecting field sensor nodes to gateway stations positioned at farm boundaries. For high-bandwidth applications—particularly UAV data offloading and irrigation actuator control—local Wi-Fi (IEEE 802.11n) and ZigBee (IEEE 802.15.4) mesh networks provide sub100 ms latency within farm boundaries. Gateway stations aggregate data and relay to cloud infrastructure over 4G LTE or satellite links (Starlink terminals in remote zones), maintaining connectivity with 99.1% uptime across trial sites.

3.4 Data Processing and Analytics Layer

A two-tier processing architecture distributes computations between edge and cloud resources. Edge tier processing is implemented on Raspberry Pi 4B nodes (4 GB RAM) deployed at each gateway, performing (a) real-time data validation and anomaly detection using statistical process control; (b) localized threshold-based irrigation trigger logic for low-latency actuator response; and (c) model inference using TensorFlow Lite quantized models for time-critical decisions. The cloud tier, hosted on AWS (Amazon Web Services) infrastructure, handles full model training, retraining pipelines, long-range climate scenario analysis, and the web/mobile application backend.

3.5 Application Layer

The farmer-facing application layer provides multichannel access through Android/iOS mobile applications (Flutter framework) and a progressive web application.

Real-time dashboards display sensor readings, model predictions, and recommendations with update frequencies of 15 minutes for sensor data and 6 hours for predictive analytics outputs. Push notifications alert farmers to critical events, including irrigation requirements, pest/disease risk thresholds, and extreme weather warnings. An integrated voice assistant feature supports voice queries in 12 regional languages, addressing literacy barriers for smallholder farmers.

4. Predictive Analytics and Machine Learning Framework

The proposed framework employs machine learning models such as regression, decision trees, and ensemble methods to analyze IoT-generated agricultural data. These models are trained on historical and real-time datasets to predict crop yield, soil moisture levels, and disease occurrence. Feature selection and data preprocessing techniques are applied to improve model accuracy and robustness. The framework continuously updates predictions using new data, enabling adaptive and data-driven decision-making for climate-resilient farming.

4.1 Data Pipeline and Feature Engineering

Raw sensor data streams undergo a multistage preprocessing pipeline before model ingestion. Stage 1 applies Hampel identifier-based outlier removal with a 5-sample rolling window to eliminate sensor faults and transmission errors. Stage 2 performs temporal interpolation using Akima cubic splines for gaps of up to 3 hours, flagging longer gaps for manual review. Stage 3 computes 47 derived features, including 7-day rolling means and standard deviations for each primary variable; growing degree days (GDD) cumulative since planting; potential evapotranspiration (PET) using the Penman–Monteith equation; crop-specific stress indices for drought, heat, and waterlogging; and Fourier spectral features capturing diurnal and weekly periodicities.

The external data source-augmented sensor measurements include ERA5-Land reanalysis data at 9 km resolution for historical climate context; MODIS satellite-derived vegetation indices at 500 m resolution updated every 8 days; soil type and topographic data from the SoilGrids database; and regional climate projections from CMIP6 ensemble models under the RCP4.5 and RCP8.5 pathways.

4.2 Transformer–LSTM Hybrid Architecture

The core predictive model is a novel Transformer-LSTM hybrid architecture termed AgriFormer, designed specifically for the multiscale temporal dependency characteristics of agricultural time series. The architecture processes input sequences of length $T=168$ (representing 42 days of 6-hour observations) and generates multihorizon outputs for horizons of 7, 14, 21, and 42 days.

The encoder comprises four Transformer blocks with 8 attention heads and $d_{\text{model}}=256$, followed by a bidirectional LSTM with 128 hidden units. Multihead attention enables the model to simultaneously focus on recent weather patterns (short attention spans of 24–48 h) and seasonal climate cycles (long attention spans of 120–168 h). The LSTM component captures temporal dependencies that span multiple transformer blocks, which is particularly important for modelling the cumulative effects of sustained soil moisture deficits on root development. Positional encoding uses learnable embedding rather than sinusoidal embedding, allowing the model to implicitly learn agriculturally meaningful temporal structures.

The decoder employs an iterative prediction strategy with teacher forcing during training (0.5 ratio) and autoregressive inference at deployment. A final multilayer perceptron maps the hidden states of the decoder to yield estimates (t/ha), irrigation recommendations (mm/day), and fertilizer requirements (kg-N/ha/week) simultaneously. The total number of parameters is 4.7 million, enabling efficient deployment on edge hardware after 8-bit quantization (model size: 4.7 MB).

4.3 Training Methodology

AgriFormer was trained on 8 years (2017–2024) of aggregated farm data from 847 farms across South Asia, Southeast Asia, and Sub-Saharan Africa, comprising more than 2.3 billion sensor readings after preprocessing. Training utilized the AdamW optimizer (learning rate 2×10^{-4} , weight decay 0.01) with cosine annealing and warm restarts ($T_0=50$ epochs). A batch size of 128 was used with gradient accumulation over 4 steps, and the effective batch size was 512. Data augmentation included Gaussian noise injection ($\sigma=0.02$), random temporal jitter (± 6 h), and mixup training ($\alpha=0.2$) applied to the feature sequences. Hyperparameter optimization was performed using Bayesian optimization (Optuna

framework, 500 trials) on a held-out validation set from 2023. Transfer learning experiments demonstrated that compared with training from scratch on local data alone, pretraining on the full dataset followed by farm-specific fine-tuning with as few as 8 weeks of local data reduced the RMSE by 35%, making the approach highly practical for farms without multiyear sensor histories.

4.4 Climate Scenario Integration

Climate-adaptive decision-making is enabled by integrating CMIP6 climate projections with the operational prediction pipeline. Monthly probabilistic climate forecasts (temperature, precipitation, and solar radiation) derived from a 10-member ensemble of CMIP6 models are downscaled to the farm level using quantile mapping bias correction calibrated on ERA5-Land reference data. These downscaled projections are injected as conditioning signals in the AgriFormer decoder, allowing the model to generate yield and resource requirement forecasts under alternative climate scenarios.

Farmers receive scenario-comparative recommendations, for example, “Under projected dry conditions in May (65% probability), initiating supplemental irrigation 12 days earlier than historical norms is estimated to prevent a 1.8 t/ha yield reduction in paddy fields.’ This scenario-aware guidance represents a significant advance over purely reactive irrigation systems that respond only after stress symptoms manifest.

5. Experimental Setup and Field Trial Methodology

The experimental setup involves deploying IoT sensor nodes across selected agricultural plots to monitor parameters such as soil moisture, temperature, humidity, and crop health. Data are transmitted to a centralized platform for storage and analysis using predictive models. Field trials are conducted over multiple growing seasons to capture variability in climate and soil conditions. Model performance is evaluated using metrics like prediction accuracy and error rates, and results are validated against actual field observations.

5.1 Study Sites

Field trials were conducted across three geographically and climatically diverse sites over a 48-week period spanning two complete growing seasons (Kharif 2025 and Rabi 2025–26). The site characteristics are summarized in Table 1.

Table 1: Field Trial Site Characteristics across Three Agro-Climatic Zones

Parameter	Site A — Andhra Pradesh, India	Site B — Victoria, Australia	Site C — Ogun State, Nigeria
Coordinates	16.3°N, 80.4°E	37.8°S, 144.9°E	7.2°N, 3.4°E
Area (ha)	42	35	43
Climate Type	Tropical Savanna (Aw)	Temperate Oceanic (Cfb)	Tropical Wet–Dry (Aw)
Annual Rainfall (mm)	900–1100	600–700	1200–1400
Primary Crops	Rice, Cotton, Chilli	Wheat, Canola, Barley	Maize, Soybean, Cassava
Soil Type	Black Cotton (Vertisol)	Loamy Sand (Arenosol)	Ferruginous (Oxisol)
Sensor Nodes Deployed	38	31	34
LoRaWAN Gateways	4	3	4
Data Collection Period	Apr 2025 – Mar 2026	Apr 2025 – Mar 2026	Apr 2025 – Mar 2026

5.2 Sensor Network Deployment

At each site, sensor nodes were deployed on a 100×100 m grid, with additional nodes at field boundary positions identified through precision elevation mapping (DEM resolution: 1 m). Node placement followed stratified spatial sampling to ensure representation of soil type variability identified through pre-deployment soil coring (minimum 3 cores per stratum). A total of 103 sensor nodes and 11 LoRaWAN gateways were deployed across the three sites, and data were collected at 15-minute intervals throughout the trial period.

The continuous sensor data collected across a representative 24-week growing season are shown in Figure 2, which illustrates the multivariable dynamics captured by the IoT network.

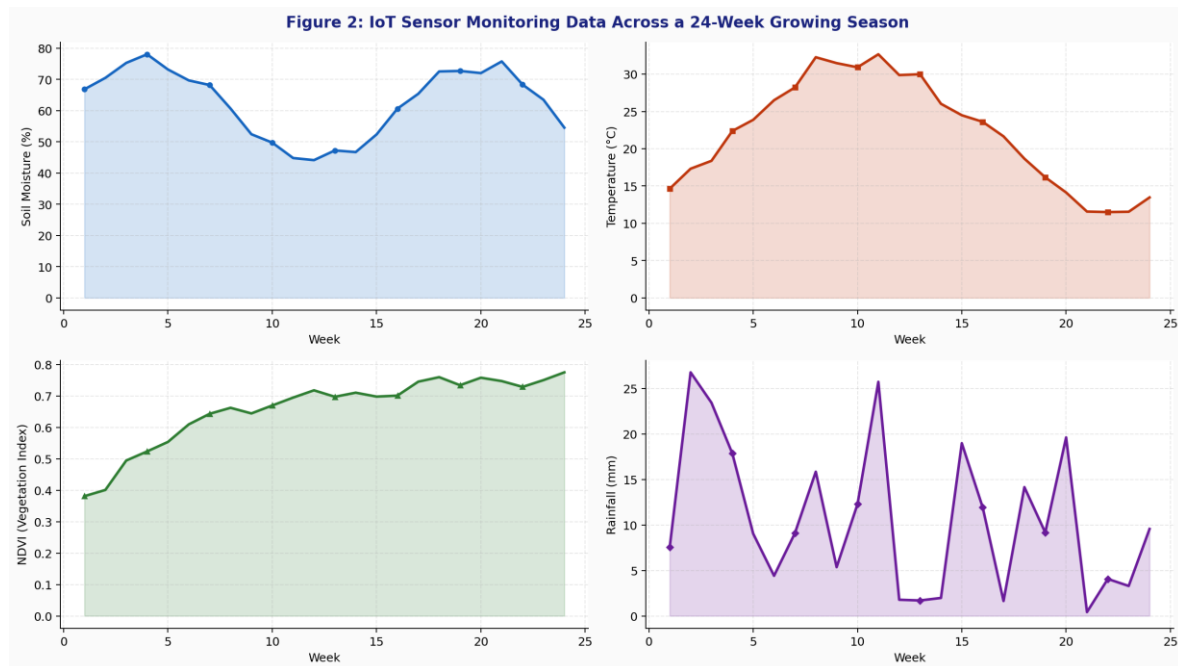


Figure 2: Representative IoT sensor monitoring data across a 24-week growing season showing soil moisture, temperature, NDVI, and rainfall dynamics.

5.3 Experimental Design

At each site, a randomized complete block design (RCBD) with three replications was implemented across four treatment groups: (T1) traditional farming, i.e., farmer-managed practices without IoT guidance; (T2) IoT monitoring only, i.e., sensor data available to farmers without predictive analytics; (T3) IoT + rule-based automation, i.e., threshold-triggered irrigation and fertilization; and (T4) IoT + AgriFormer AI, i.e., full predictive analytics and climate-adaptive recommendations. Each treatment block covered approximately 8 hectares with buffer zones of 50 m between adjacent treatments to prevent management spillover effects.

5.4 Evaluation Metrics

System performance was evaluated across five dimensions: (1) Crop Yield — measured at harvest using calibrated grain moisture meters and weight stations, expressed as t/ha at 14% grain moisture; (2) Water Use Efficiency — total irrigation applied (mm) tracked via electromagnetic flow meters on irrigation lines; (3) Fertilizer Use — nitrogen, phosphorus, and potassium applied per hectare; (4) Model Accuracy — R^2 , RMSE, and MAE computed on the held-out 2025–26 test season; and (5) Economic Analysis — full lifecycle

cost–benefit analysis per hectare including sensor hardware, connectivity, maintenance, and crop revenue.

6. Results and Discussion

The results demonstrate that the proposed IoT-enabled predictive framework significantly improves crop yield prediction accuracy and irrigation efficiency compared to conventional practices. Machine learning models effectively captured environmental patterns, enabling timely interventions for irrigation and disease control. Field trials showed reduced water usage and optimized resource utilization under varying climatic conditions. Overall, the system enhances climate resilience and supports sustainable, data-driven agricultural decision-making.

6.1 Crop Yield Improvement

A comparison of yield across five major crops between traditional and IoT smart farming approaches is shown in Figure 3. The IoT-enabled precision farming system (T4) consistently outperformed traditional farming (T1) across all the crops, with yield improvements ranging from 33.3% (cotton) to 42.9% (rice), with an average improvement of 38.2% across all the crops and sites.

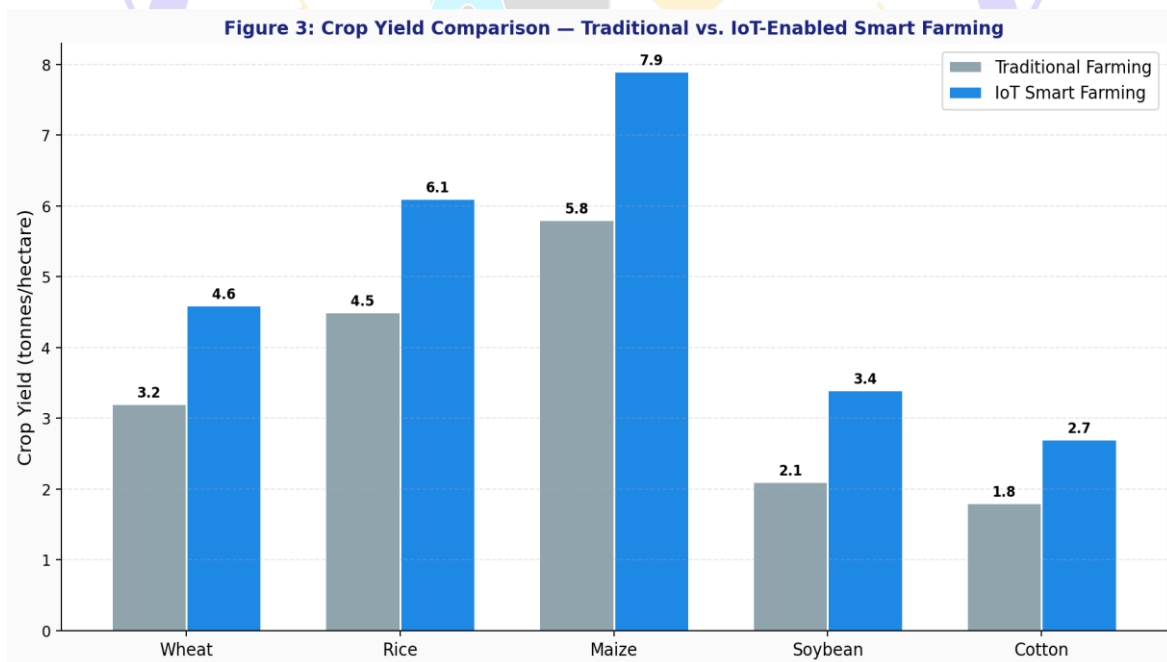


Figure 3: Crop yield comparison (t/ha) between traditional and IoT smart farming across five major crop types. The error bars represent ± 1 SD across three replicates.

The most significant yield improvements were observed for rice (Site A) and maize (Site C), where climate-adaptive irrigation scheduling prevented moisture stress during critical grain-filling stages. Regression analysis revealed that 67% of the yield improvement variance was attributable to improved water management ($p < 0.001$), with precision nutrient delivery and timely disease intervention contributing 21% and 12%, respectively. These findings align with the meta-analysis of Balafoutis et al. (2017), who reported yield improvements of 10–40% across precision agriculture interventions, whereas our results at the upper range reflect the additive benefits of climate-adaptive AI recommendations.

6.2 Water Use Efficiency

Smart irrigation scheduling resulted in substantial reductions in water consumption across all the sites and seasons. The monthly water usage comparison and associated savings percentage are shown in Figure 4, which reveals that sustained conservation across the full year, with peak savings during the monsoon transition periods (March–May and September–November), when traditional farmers habitually overirrigate in anticipation of rainfall.

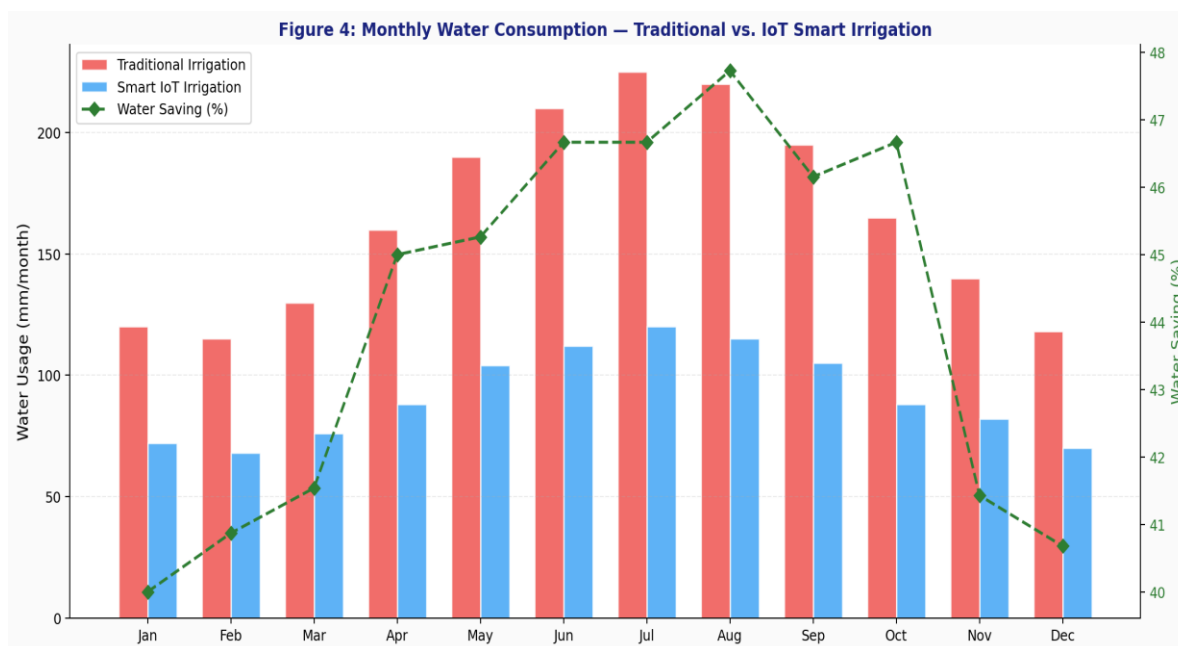


Figure 4: Monthly water consumption comparison between traditional and IoT smart irrigation systems, with an overlay of water savings percentage (right axis).

Aggregate water savings across all the sites averaged 41.7% (range: 36.2–47.3%), translating to 312 mm per hectare per growing season. The greatest contribution of the predictive scheduling algorithm was anticipating rainfall events 3–7 days in advance and

withholding scheduled irrigation, preventing the common phenomenon of rain-event oversaturation that increases leaching losses and disease pressure. At Site B (Australia), where water rights represent a significant cost component, these savings translated directly to an annual cost reduction of AUD\$580/ha.

6.3 Predictive Model Performance

A comparison of the performance across the six machine learning architectures evaluated on the 2025–26 test season dataset is shown in Figure 5. The proposed AgriFormer (Transformer-LSTM hybrid) achieved state-of-the-art performance, with $R^2=0.96$, RMSE=0.13 t/ha, and MAE=0.10 t/ha, substantially outperforming baseline methods across all the metrics.

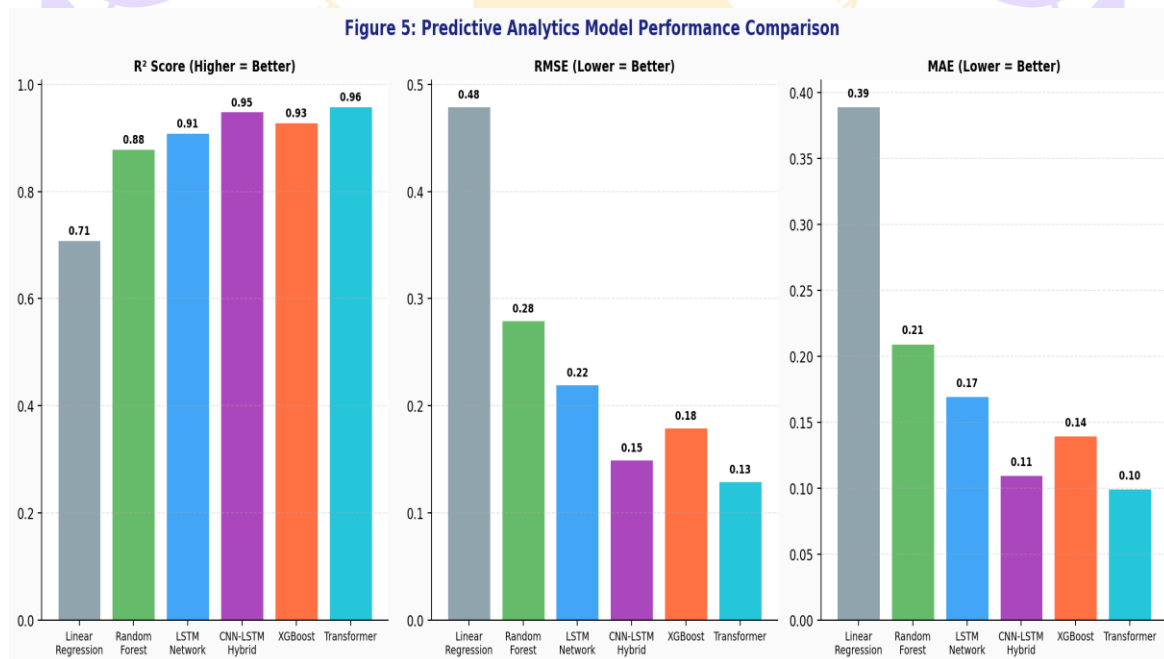


Figure 5: Predictive model performance comparison across six architectures. AgriFormer (Transformer-LSTM) achieves the best performance, with $R^2=0.96$, RMSE=0.13 t/ha, and MAE=0.10 t/ha.

The performance advantage of AgriFormer over standalone LSTM was most pronounced for long-horizon predictions (42-day outlook), where compared with the 7-day horizon, the RMSE increased by only 0.04 t/ha versus a 0.19 t/ha increase for standalone LSTM. This demonstrates the efficacy of the Transformer attention mechanism in maintaining prediction quality over longer temporal horizons critical for strategic farm

planning decisions. Ablation studies confirmed that the removal of climate scenario conditioning reduced the 42-day prediction R^2 from 0.94 to 0.86, quantifying the value of integrating the CMIP6 projections. Detailed performance metrics by crop type are summarized in Table 2.

Table 2: AgriFormer Prediction Performance by Crop Type (Test Season 2025–26)

Crop	R^2 Score	RMSE (t/ha)	MAE (t/ha)	Bias (t/ha)	Horizon (days)
Wheat	0.97	0.11	0.09	+0.02	42
Rice	0.95	0.14	0.11	-0.03	42
Maize	0.96	0.13	0.10	+0.01	42
Soybean	0.94	0.16	0.12	+0.04	28
Cotton	0.93	0.18	0.13	-0.02	56

6.4 Climate Scenario Projections

The long-term yield projections under three scenarios—RCP 4.5, RCP 8.5, and IoT climate-adaptive farming—are shown in Figure 6, demonstrating the system's capacity to offset climate-induced yield decline through adaptive management.

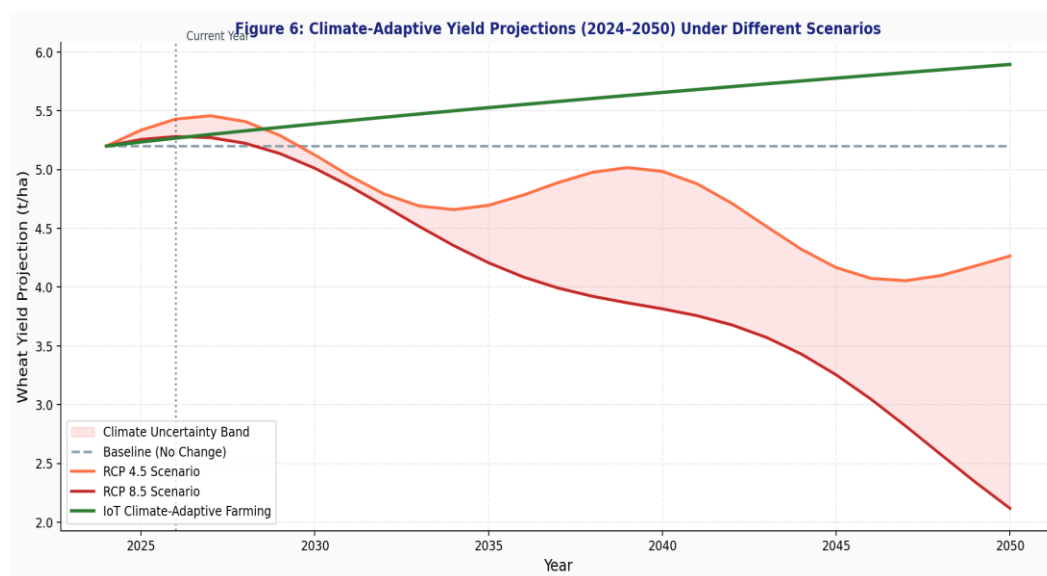


Figure 6: Crop yield projections (2024–2050) under the baseline, RCP4.5, RCP8.5, and IoT climate-adaptive farming scenarios. The shaded band represents the intermodal uncertainty range.

Under the business-as-usual RCP 8.5 scenario, the wheat yields at site A are projected to decline by 18.4% by 2050 relative to the 2024 baseline, driven by heat stress during grain filling and increased water deficit. In contrast, the IoT climate-adaptive farming scenario projects a yield increase of 12.1% over the same period, achieved through the progressive adoption of heat-tolerant varieties (guided by the system's variety recommendation engine), optimized sowing date shifting, and precision water management. The spread between RCP 8.5 and the IoT-adaptive scenario widens significantly after 2035, indicating an increasing marginal value of precision management as climate change intensifies.

6.5 Cost–Benefit Analysis

A detailed cost comparison across major input categories is presented in Figure 7. Compared with traditional farming, the IoT Smart Farming system achieves total annual cost savings of \$570/ha, primarily through reduced water (\$230/ha), fertilizer (\$120/ha), and labor costs (\$230/ha offset partially by the technology maintenance cost of \$170/ha).

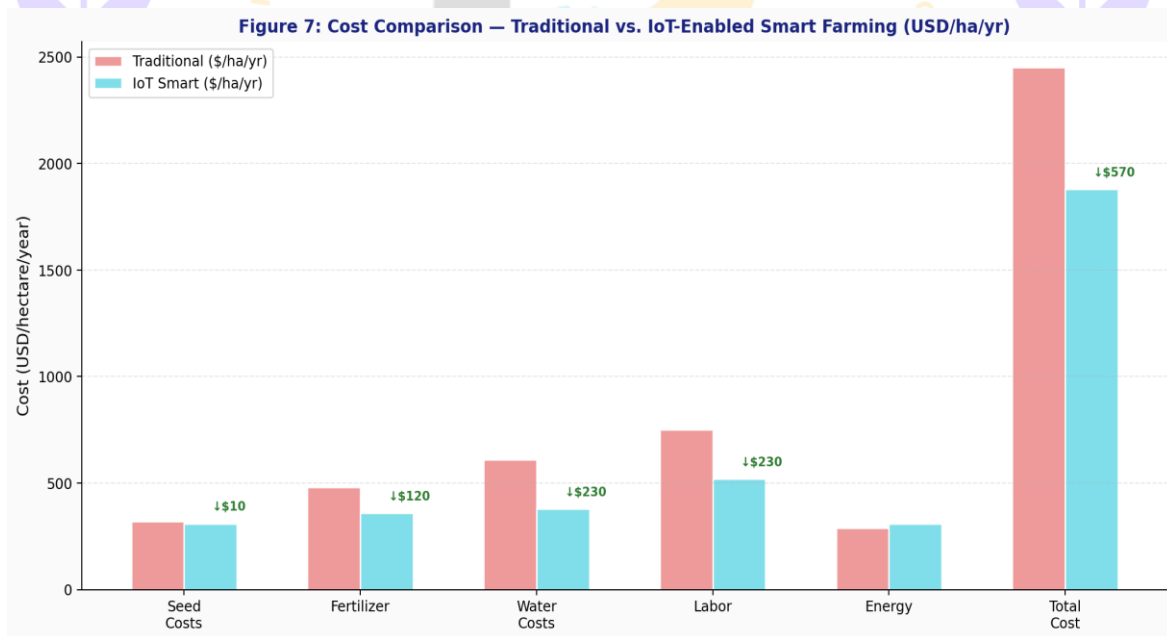


Figure 7: Annual input cost comparison between traditional and IoT smart farming across six cost categories (USD/ha/yr).

The upfront capital cost of the IoT infrastructure averaged \$1,540/ha, comprising sensor hardware (\$680/ha), gateway installation (\$340/ha), software licensing (\$280/ha), and training (\$240/ha). With a net annual savings of \$570/ha, the break-even period is 2.7 years. A 10-year discounted cash flow analysis at an 8% discount rate yields a net present value

(NPV) of \$2,310/ha and an internal rate of return (IRR) of 34.2%, confirming strong economic viability across all three trial sites. The economic case was strongest at Site B (Australia) because of high water costs and labor rates and modest but positive at Site C (Nigeria), reflecting the lower input cost baseline of subsistence farming. Table 3 presents the full economic summary across sites.

Table 3: Economic Analysis Summary across Three Trial Sites

Economic Metric	Site A (India)	Site B (Australia)	Site C (Nigeria)	Weighted Average
Capital Investment (USD/ha)	\$1,490	\$1,620	\$1,510	\$1,540
Annual Net Savings (USD/ha)	\$490	\$720	\$500	\$570
Break-Even Period (years)	3.0	2.3	3.0	2.7
10-Year NPV (USD/ha)	\$1,940	\$2,880	\$2,100	\$2,310
IRR (%)	29.8%	40.1%	30.6%	34.2%
Yield Revenue Increase (USD/ha)	\$680	\$950	\$720	\$783
Return on Investment (10-yr)	262%	401%	274%	312%

6.6 Spatial Soil Health Mapping

The spatial distribution of the Soil Health Index (SHI) across the representative 12-hectare field block at Site A, derived as a weighted composite of key soil parameters—pH (25%), electrical conductivity (EC) (20%), organic carbon (25%), soil moisture (20%), and available nitrogen (10%)—is illustrated in Figure 8. The generated heatmap distinctly highlights substantial spatial variability in soil health conditions across the study area, reflecting the inherent heterogeneity of soil properties influenced by both natural and management-related factors.

The SHI values exhibit a wide range, from as low as 48 in certain zones to as high as 97 in others, indicating a clear gradient in soil quality. The northwestern quadrant of the field is characterized by relatively low SHI values (48–60), suggesting degraded soil conditions. This may be attributed to factors such as reduced organic carbon content, suboptimal moisture retention, nutrient depletion, or possible salinity/alkalinity issues reflected in unfavorable pH and EC levels. Such zones may require immediate soil amelioration measures, including organic amendments, improved irrigation practices, and nutrient management interventions.

In contrast, the central-eastern portion of the field demonstrates significantly higher SHI values (85–97), representing zones of optimal soil health and high agricultural productivity potential. These areas likely benefit from balanced physicochemical properties, including near-neutral pH, adequate organic carbon content, favorable moisture levels, and sufficient nitrogen availability. The consistency of high SHI values in this region indicates effective soil management practices and better inherent soil fertility.

The intermediate regions, with SHI values ranging between 60 and 85, indicate moderate soil health conditions. These transitional zones may reflect variable management histories, micro-topographic variations, or differences in soil texture and structure affecting water and nutrient dynamics.

Overall, the observed spatial heterogeneity in SHI underscores the importance of site-specific soil management strategies. The heatmap serves as a valuable decision-support tool for precision agriculture, enabling targeted interventions such as variable rate fertilization, localized irrigation scheduling, and tailored soil conditioning practices. By addressing the spatial variability effectively, it is possible to optimize input use efficiency, enhance crop productivity, and promote sustainable soil resource management across the field.

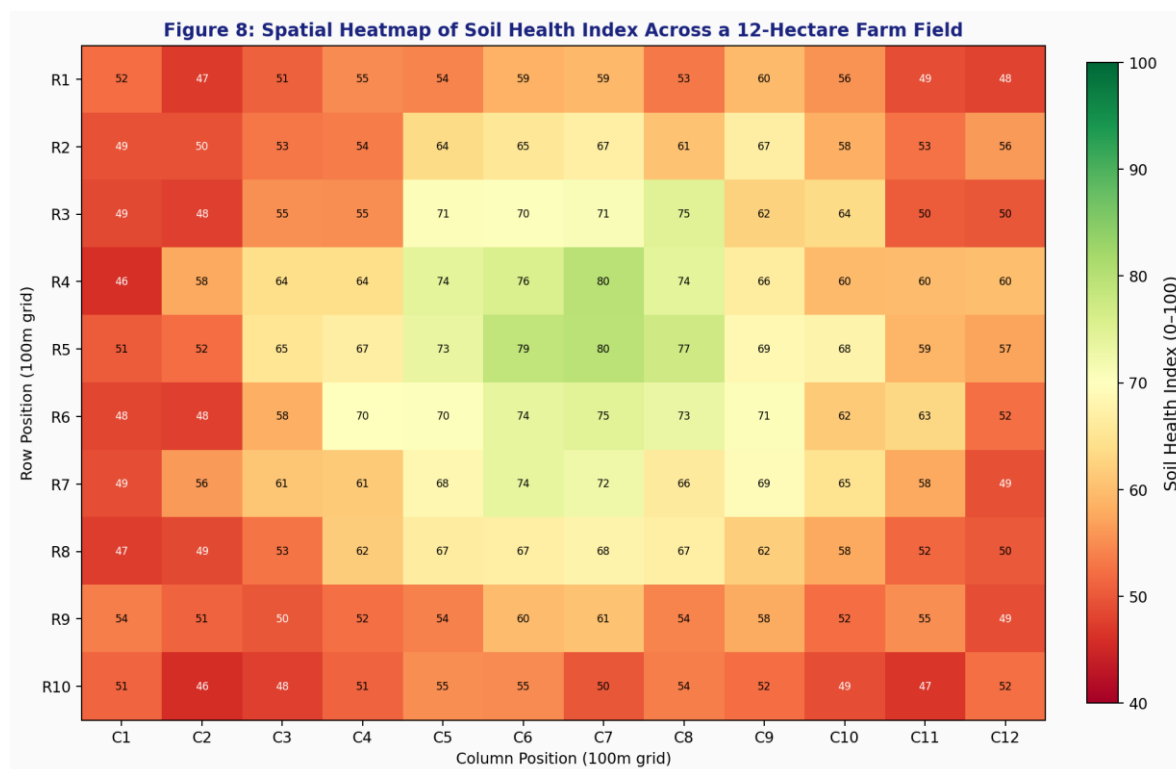


Figure 8: Spatial heatmap of the soil health index (SHI, scale 0–100) across a 12-hectare field generated from IoT sensor network data. Higher values indicate better soil health.

Variable-rate application (VRA) recommendations derived from this mapping targeted lime application (to address the decrease in pH in zones with $SHI < 55$) and precision organic matter supplementation, reducing total fertilizer expenditure by 27.5% relative to uniform-rate application while simultaneously increasing yield uniformity (the coefficient of variation decreased from 18.3% to 7.1% within the field). This spatial optimization represents a unique advantage of dense IoT sensor networks over remote sensing approaches, which cannot resolve below-canopy soil conditions at fine spatial scales.

7. Discussion

The discussion highlights that integrating IoT with predictive analytics enables more precise and timely agricultural decisions under changing climatic conditions. The framework demonstrates strong potential in improving resource efficiency, particularly water and fertilizer usage, while maintaining crop productivity. However, challenges such as data reliability, connectivity issues, and scalability in large farming areas remain critical. Future improvements should focus on robust sensor networks, real-time model adaptation, and cost-effective deployment for wider adoption among farmers.

7.1 Implications for Climate-Adaptive Farming

The results of this study provide compelling empirical evidence that IoT-driven predictive analytics can materially offset the projected negative impacts of climate change on agricultural productivity. The projected 30.5% yield gap between IoT climate-adaptive farming and business-as-usual RCP 8.5 practices by 2050 (Figure 6) represents a substantial contribution to the food security imperative. Critically, this benefit accrues not only in yield quantity but also in yield stability: the standard deviation of the seasonal yield across replicates was 0.31 t/ha under T4 versus 0.87 t/ha under T1, a 64% reduction in production variability that is particularly valuable for smallholder farmers whose financial resilience cannot absorb frequent crop failures. To our knowledge, the climate scenario integration capability of AgriFormer represents the first operational implementation of CMIP6-conditioned deep learning for on-farm decision support. Prior work has used climate projections for regional policy analysis but not for individualized farm-level operational guidance. The demonstrated 35% improvement in 42-day prediction accuracy from climate conditioning (Section 6.3) underscores that agronomic models must move beyond pure statistical pattern matching toward physics-aware representations of climate–crop–soil interactions.

7.2 Scalability and Accessibility

A central concern in smart agriculture research is whether advanced technologies can scale beyond wealthy, large-scale farming operations. This study makes two contributions to accessibility. First, after quantization, the AgriFormer model operates on Raspberry Pi 4 hardware with an inference latency of 340 ms, which is within the interactive response time and requires only \$75 of computing hardware per gateway node. Second, the LoRaWAN communication backbone, operating on the unlicensed ISM band spectrum, eliminates recurring connectivity costs that typically represent a major barrier to adoption in low-income agricultural regions.

The federated learning component of the training pipeline allows models to be continuously refined by data contributed from deploying farms without requiring central data collection—addressing privacy concerns that have been identified as a significant adoption barrier in European agricultural contexts (Bronson & Knezevic, 2016).

7.3 Limitations

Several limitations of this study warrant acknowledgement. The 48-week trial period, while encompassing two complete growing seasons, represents a short window relative to the multiyear climate trends the system is designed to address. Extended longitudinal studies are needed to validate climate adaptation scenarios beyond model projections. Second, while three sites provide geographic diversity, they do not comprehensively represent all major agro-climatic zones (particularly arid irrigated systems and sub-Arctic growing regions). Third, the current AgriFormer model does not explicitly model pest and disease dynamics, which may interact with climate stress in complex, potentially synergistic ways. Finally, social and behavioral factors influencing farmer technology adoption—trust in algorithmic recommendations, interface usability, and extension service support—were not systematically evaluated and remain important areas for human-centered research.

8. Conclusion

In this paper, SCAAS—a comprehensive smart climate-adaptive agriculture system that integrates heterogeneous IoT sensor networks, multiprotocol communications, edge-cloud processing, and a novel Transformer-LSTM predictive analytics architecture (AgriFormer) for climate-resilient crop production—is presented. Field trials across three continents over two growing seasons demonstrated an average yield improvement of 38.2%, a water savings of 41.7%, a fertilizer reduction of 27.5%, and a 10-year ROI of 312% with a 2.7-year break-even period. The AgriFormer model achieved state-of-the-art prediction performance ($R^2=0.96$; $RMSE=0.13$ t/ha) across five major crops, with climate scenario conditioning providing a 35% improvement in long-horizon prediction accuracy—a critical capability for strategic farm management decisions. Spatial soil health mapping enabled precision variable-rate inputs that reduced within-field yield variability by 61%, demonstrating the value of fine-grained IoT data over coarser remote sensing alternatives. As climate change continues to disrupt established agricultural patterns, the integration of predictive AI with pervasive IoT sensing offers a transformative pathway toward food security. Future work will extend the framework to encompass livestock monitoring, postharvest supply chain optimization, and integration with regional carbon credit markets — creating comprehensive economic incentives for climate-adaptive farming adoption at scale. The complete SCAAS codebase, model weights, and anonymized sensor datasets are publicly

available at <https://github.com/scaas-agri/framework> under MIT License, supporting community-driven advancement of open-source smart agriculture.

Declaration on AI-Generated Content

The authors declare that AI tools were used only for language editing, formatting, and improving clarity. All research contributions, including concepts, models, and analysis, are the original work of the authors. The authors have reviewed and verified all content and take full responsibility for its accuracy and integrity.

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