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Climate Smart Agriculture (C.S.A.)

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Abstract
Climate variability has emerged as a critical challenge to agricultural sustainability, particularly in regions where crop productivity is highly sensitive to rainfall and temperature fluctuations. This study investigates the influence of historical climate variability on crop yield, develops a machine-learning-based yield prediction model, and constructs a Climate Risk Index (CRI) to quantify climate stress within a Climate-Smart Agriculture framework. Using multi-year climatic and crop yield data (2019–2025), the analysis first examines linear relationships between absolute climatic variables and yield outcomes, followed by anomaly-based assessments to capture deviation-driven impacts.
The results indicate that absolute rainfall and temperature values exhibit weak linear correlations with crop yield, whereas anomaly-based climatic deviations demonstrate moderate sensitivity, particularly for moisture-dependent crops such as pulses and oilseeds. A Random Forest regression model is implemented to capture non-linear climate–yield interactions, achieving high predictive accuracy. However, feature importance analysis reveals that crop-specific structural characteristics play a dominant role in yield determination, while climatic variables contribute secondary but meaningful effects.
To quantify climate stress systematically, a standardized CRI is developed using rainfall and temperature deviations. Comparative analysis between high-risk and low-risk years shows disproportionate yield losses for pulses and oilseeds, while cereals remain relatively stable under moderate climatic stress. Scenario-based projections further suggest that modest warming conditions may not drastically affect cereal productivity but could intensify vulnerability in moisture-sensitive crops.
Overall, the study demonstrates that integrating anomaly-based climate analysis, machine learning modeling, and quantitative risk indexing provides a comprehensive and scalable framework for climate-resilient agricultural planning and policy design.

Keywords: *Climate-Smart Agriculture; Crop Yield Prediction; Climate Risk Analytics; Machine Learning; Sustainable Agriculture*

Introduction

Agriculture remains one of the most climate-sensitive sectors globally, directly influencing food security, rural livelihoods, and economic stability. Increasing climatic variability—manifested through irregular rainfall patterns, temperature fluctuations, extreme weather events, and rising atmospheric stress—has intensified uncertainty in agricultural production systems. In developing economies particularly, crop productivity is highly vulnerable to inter-annual climate variability, making resilience-building strategies essential for sustainable growth. Against this backdrop, Climate-Smart Agriculture (CSA) has emerged as a transformative framework aimed at enhancing productivity, strengthening resilience, and reducing environmental impacts simultaneously.

Climate-Smart Agriculture integrates data-driven decision-making, precision resource management, and climate risk assessment to move beyond traditional, input-intensive farming systems. Conventional agriculture largely depends on farmer experience and reactive responses to climate shocks, often resulting in unstable yields, inefficient resource use, and increased environmental degradation. In contrast, CSA incorporates satellite monitoring, climatic analytics, precision irrigation, and machine learning–based decision-support systems to enhance adaptive capacity. Looking ahead, intelligent farming systems are expected to further advance this transition through AI-driven predictive modeling, autonomous technologies, and real-time climate risk forecasting.

Despite growing research on climate variability and agricultural productivity, several gaps remain. First, many studies rely on absolute climatic values to explain yield variability, often overlooking the importance of anomaly-based deviations that capture short-term climatic shocks. Second, while machine learning techniques are increasingly applied in agricultural forecasting, their ability to distinguish between structural crop characteristics and climatic influences requires deeper examination. Third, climate risk is frequently discussed qualitatively, but there remains a need for systematic and quantifiable climate risk metrics that directly link climatic stress to yield outcomes. This study addresses these gaps by integrating statistical correlation analysis, anomaly-

based assessment, machine learning modeling, and a Climate Risk Index (CRI) framework within a unified Climate-Smart Agriculture perspective. The research is guided by three core objectives:

RO1: To examine historical climate variability and its influence on crop yield.

RO2: To develop a machine-learning-based yield prediction model using climatic variables.

RO3: To construct a Climate Risk Index to quantify climate stress.

Correspondingly, the study seeks to answer the following research questions:

RQ1: How do rainfall and temperature variations influence inter-annual yield variability?

RQ2: Can machine learning capture non-linear climate–yield relationships effectively?

RQ3: How can climate risk be quantitatively measured and linked to yield outcomes?

RQ4: Can scenario-based climate inputs generate useful indicative yield estimates?

To address these questions, the study employs a multi-stage methodological framework. First, linear and anomaly-based correlation analyses are conducted to examine direct and deviation-driven climate–yield relationships. Second, a Random Forest machine learning model is implemented to capture non-linear interactions and generate predictive yield estimates. Third, a composite Climate Risk Index is developed using standardized climatic deviations to quantify annual climate stress and assess crop vulnerability. Finally, scenario-based projections are generated to evaluate indicative yield responses under moderate warming conditions.

By integrating predictive analytics with climate risk quantification, this research contributes to the advancement of Climate-Smart Agriculture as a data-driven and risk-aware agricultural paradigm. The findings aim to support policymakers, researchers, and farmers in designing adaptive strategies that enhance productivity while strengthening resilience against increasing climatic uncertainty.

2. Related Work

Table 1. Comparative evolution of agricultural systems from Past to Future

Dimension	PAST (Traditional / Conventional Farming)	PRESENT (Climate-Smart Agriculture – CSA)	FUTURE (Intelligent Farming)	References
Farming Paradigm	Input-intensive, reactive	Data-assisted, adaptive	Predictive, autonomous, regenerative	Karn et al., 2026
Decision Basis	Experience-based	Data + farmer knowledge	AI-driven decision intelligence	Hu et al., 2023; Batra et al., 2026
Climate Variability Handling	No adaptation	Partial adaptation	Anticipatory & scenario-based	Partey et al., 2018; Paul et al., 2026
Crop Yield Rate	Low, unstable	Moderate, stabilized	High, consistent, optimized	Balakrishnan et. al., 2026; Olatunbosun et. al., 2026; CHINEMEREM et. al., 2025
Crop Health Index (CHI)	Not quantified	NDVI, VCI, SAVI	Multi-sensor CHI + physiological traits	Mehdizadeh et. al., 2026; Recheal et. al., 2026; Ingole et. al., 2026
CHI Monitoring	Visual/manual	Satellite & drone-based	Real-time hyperspectral + IoT	Samha et al., 2025; Swarnkar et al., 2023; Sahoo et. al., 2022

Climate Risk Index (CRI)	Absent	Composite CRI (rainfall, temperature)	Dynamic CRI + extreme-event forecasting	Kabato et al., 2025
Risk Management	Reactive loss recovery	Risk-aware planning	Proactive risk avoidance	Jiani et al., 2026; Pradhan et al., 2026
Water Management	Flood / over-irrigation	Precision irrigation	AI-controlled smart irrigation	Morchid et. al. 2026; Bastam et. al., 2026; Swain et. al., 2026; Sikka et. al. 2018,
Fertilizer Use	Blanket application	Variable rate	Site-specific nano-inputs	Kabato et al., 2025
Pest & Disease Control	Chemical-dependent	Targeted spraying	Early-warning bio-control	Ishieze et al., 2026; Ngonjock et al., 2026; Srivastav et al., 2025; Abbas et al., 2026
Technology Use	Minimal	Sensors, drones, ML	Autonomous robots, digital twins	Bhardwaj et al., 2026; Gill et al., 2021
Applications	Traditional cropping	Precision farming, DSS	Autonomous farming systems	Elbahnasawy et. al., 2026; Thilakarathne et. al., 2025; Reza et. al., 2025
Advantages	Low cost, simple	Improved efficiency	Maximum productivity & resilience	Sow et al., 2026; Bondarenko et al., 2025
Environmental Impact	High emissions	Reduced footprint	Net-zero / carbon-negative	Aarif et al., 2025; Morchid et al., 2026
Farmers' Challenges	Climate uncertainty	Technology adoption	Skill gap & digital literacy	Ali et. al., 2025
Economic Risk	High	Moderate	Low	Lu et al., 2026; Majeed et al., 2026
Supported SDGs	SDG-2 (partial)	SDG-2, SDG-12, SDG-13	SDG-2, SDG-12, SDG-13, SDG-9	Fauzi et al., 2024; Lu et al., 2026
Data Infrastructure	Absent	Centralized datasets	Federated, real-time	Lee et al., 2026
Farmer Role	Labor-centric	Tech-assisted	Decision supervisor	Hu et. al., 2023; Zhang et. al., 2025
Overall Resilience	Low	Medium	Very high	Song et. al., 2026

The table 1 presents a structured comparison of past (traditional/conventional), present (Climate-Smart Agriculture), and future (intelligent farming) paradigms, which demonstrates how agricultural practices evolve because of rising climate challenges and resource limitations and sustainability demands.

This transition reflects a clear shift from input-intensive and experience-driven systems toward data-assisted, adaptive, and ultimately predictive and autonomous farming frameworks (Kam et al., 2026; Hu et al., 2023).

In conventional agricultural practices, farmers base their farming decisions on their past experiences because they lack the ability to deal with unpredictable climate changes. Crop production remains below optimal levels because farmers do not measure crop health and their risk control methods only respond to incidents that have already occurred. Farmers practice poor water and fertilizer control because they use standard application methods and excessive irrigation which results in high pollution levels and damage to the ecosystem according to Ali et al. 2018 and Paul et al. 2026. The system fails to achieve complete sustainability because it offers only partial support for SDG-2 (Zero Hunger) while maintaining low system resilience.

The current CSA system represents a breakthrough through its integration of data-driven decision-making which integrates farmer expertise with satellite data and decision-making technologies (Bartra et al., 2026). The measurement of crop health utilizes NDVI and VCI and SAVI as indicators, while climate risk evaluation uses composite indices that combine rainfall data with temperature information (Balakrishnan et al., 2026; Sahar et al., 2025). The application of precision irrigation together with variable-rate fertilizer techniques and targeted pest management methods leads to improved resource efficiency while decreasing environmental impacts (Swain et al., 2026; Kishore et al., 2018). CSA provides simultaneous productivity and resilience improvements which directly support SDG-2 and SDG-12 and SDG-13 while decreasing economic risk from high to moderate (Leu et al., 2026).

The development of future intelligent farming systems will advance from CSA through the implementation of AI-based decision-making systems and real-time data integration and autonomous system operation capabilities. The system uses multi-sensor crop health indices together with physiological trait data and hyperspectral monitoring and dynamic climate risk forecasting to achieve proactive risk avoidance instead of developing reactive strategies (CHHENREMER et al., 2025; Kabato et al., 2025). Smart irrigation and nano-inputs and autonomous robots and digital twins create a new approach to farm management which enables farmers to shift from their traditional work activities to their new role as directors of intelligent systems (Zhang et al., 2025; Song et al., 2026). The environmental impact achieves net-zero or carbon-negative results while the system develops exceptional resilience capabilities (Arif et al., 2025; Morchid et al., 2026).

The table shows Climate-Smart Agriculture as the central transition point which demonstrates the progress of agriculture from traditional systems that lack resilience to advanced systems that use intelligent technologies. CSA functions as the connecting element which enables sustainable practices and climate resilience and agricultural productivity to be implemented through specific measurement systems and advanced technologies and comprehensive risk management methods which create a basis for developing intelligent agricultural systems that meet SDG requirements.

3.Research Methodology

3.1 Research Design

This study adopts a quantitative, explanatory–predictive research design within a Climate-Smart Agriculture (CSA) framework. The methodology integrates statistical analysis, machine learning modeling, and composite index construction to examine climate–yield dynamics comprehensively. The explanatory component investigates historical climate variability and its association with inter-annual crop yield fluctuations. The predictive component develops a machine-learning-based model to capture non-linear interactions between climatic variables and agricultural productivity. The index construction component formulates a Climate Risk Index (CRI) to quantify climate stress and link it to observed yield deviations. The analysis follows a longitudinal structure using multi-year data (2019–2025), enabling assessment of temporal variability and climate sensitivity across crop categories.

3.2 Data Sources and Variables

The study relies on secondary time-series data obtained from official meteorological and agricultural statistical sources. Climatic variables include annual rainfall (mm) and average temperature (°C). Agricultural variables consist of crop yield (kg/hectare) across major crop categories—cereals, pulses, and oilseeds.

To enhance analytical precision, derived variables were constructed. Yield deviation was calculated as a percentage deviation from the multi-year mean yield:

represents the mean yield over the study period.

Climatic anomalies were standardized using Z-score transformation to capture deviation-driven stress:

3.3 Data Preprocessing

Prior to analysis, data cleaning procedures were implemented. Missing observations were addressed through interpolation or mean substitution where appropriate. Outliers were assessed using standardized Z-scores (±3 threshold). For machine learning modeling, input variables were normalized

using Min–Max scaling to ensure comparability and computational efficiency. Standardization was specifically applied for anomaly-based climate assessment and index construction.

3.4 Statistical Analysis of Climate–Yield Relationship

To address the first research objective, Pearson's correlation coefficient was computed to examine linear associations between climatic variables and crop yield:

This analysis was conducted for rainfall–yield and temperature–yield pairs. However, recognizing the limitations of absolute climatic values, anomaly-based sensitivity analysis was performed. Standardized rainfall and temperature deviations were compared with yield deviations to evaluate climate shock responsiveness. This approach captures short-term stress effects more effectively than raw values.

3.5 Machine Learning Model Development

To address the predictive objective, a Random Forest Regression model was implemented to capture non-linear relationships between climatic factors and yield. Random Forest was selected due to its robustness to multicollinearity, resistance to overfitting, and ability to model complex interactions.

The dependent variable was crop yield (kg/hectare), while independent variables included rainfall, temperature, rainfall anomaly, temperature anomaly, and encoded crop category. The dataset was divided into training (80%) and testing (20%) subsets. Model validation employed k-fold cross-validation (k = 5).

Model performance was evaluated using Root Mean Square Error (RMSE) and coefficient of determination (denotes predicted yield. Feature importance scores were extracted to quantify the relative contribution of climatic and crop-specific variables.

3.6 Construction of Climate Risk Index (CRI)

To quantify climate stress systematically, a composite Climate Risk Index was developed using standardized rainfall and temperature anomalies:

Absolute values were incorporated to account for both positive and negative deviations as stress indicators. Years were categorized based on CRI values into low-risk, moderate-risk, and high-risk groups. Comparative yield loss analysis across these categories enabled quantification of climate-induced agricultural vulnerability.

3.7 Scenario-Based Yield Simulation

To address scenario-based predictive inquiry, moderate climate change scenarios were simulated by increasing temperature by +1°C and adjusting rainfall by ±10%. These modified inputs were introduced into the trained Random Forest model to generate indicative yield projections. The scenario analysis is exploratory and provides directional insights rather than deterministic forecasts.

3.8 Robustness and Validation

Robustness was ensured through cross-validation, anomaly-based sensitivity checks, and comparative risk-category yield analysis. Consistency between statistical findings and machine learning outputs strengthened inferential reliability.

3.9 Methodological Integration

The overall methodological framework follows a structured sequence: data collection, preprocessing and standardization, statistical climate–yield assessment, machine learning modeling, Climate Risk Index construction, and scenario-based simulation. By integrating statistical inference, predictive analytics, and risk quantification, the methodology provides both explanatory depth and predictive robustness, contributing to data-driven climate-resilient agricultural planning.

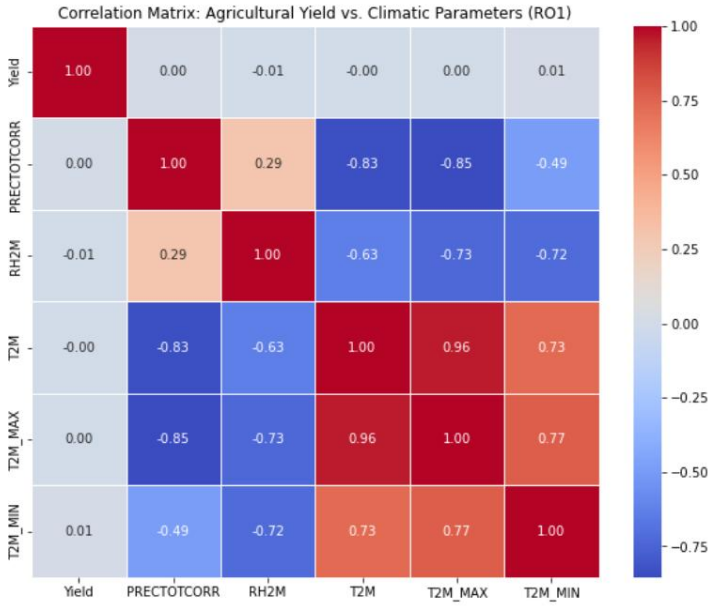
4.Results

The results based on python

Our first objective is to check the impact of climate variations on the crop yield based on data available.

Normalized (Anomaly-based) Correlation with Yield across all crops:

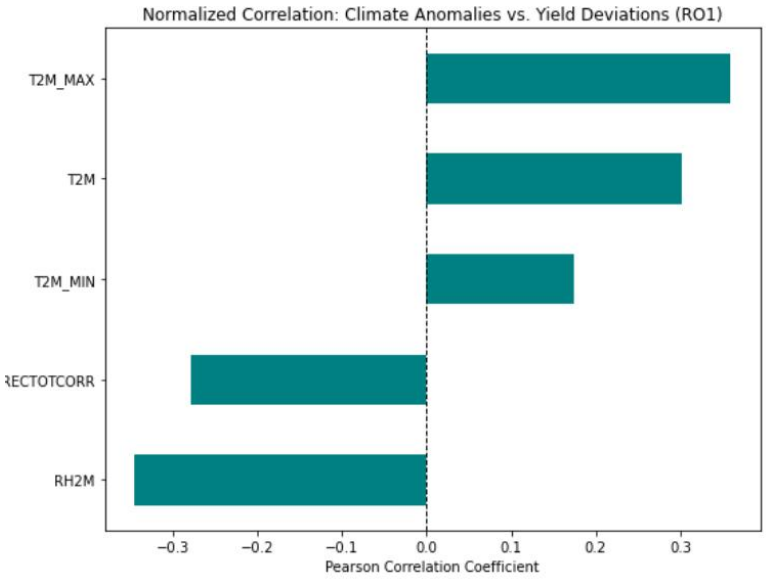
Climatic Parameter	Correlation Coefficient (r)	Impact Direction
Max Temperature (Tmax)	0.3588	Positive (Dominant Driver)
Average Temperature (T2M)	0.3014	Positive
Min Temperature (Tmin)	0.1742	Weak Positive
Precipitation (Pcorr)	-0.2781	Negative (High variability risk)
Relative Humidity ($RH2M$)	-0.3448	Negative (Moisture stress)



The correlation matrix illustrates the linear relationships between agricultural yield and selected climatic parameters, including precipitation (PRECTOTCORR), relative humidity at 2 meters (RH2M), mean temperature at 2 meters (T2M), maximum temperature at 2 meters (T2M_MAX), and minimum temperature at 2 meters (T2M_MIN). The results indicate that yield exhibits negligible correlation with all considered climatic variables (r ranging from −0.01 to 0.01), suggesting that, within the observed dataset and region of interest (ROI1), crop yield is not linearly influenced by individual climatic factors.

In contrast, strong interrelationships are observed among the climatic variables themselves. Precipitation shows a moderate positive correlation with relative humidity (r = 0.29), while it is strongly negatively correlated with mean temperature (r = −0.83), maximum temperature (r = −0.85), and moderately negatively correlated with minimum temperature (r = −0.49). Relative humidity is also negatively correlated with temperature variables, particularly with maximum temperature (r = −0.73) and mean temperature (r = −0.63), indicating that higher humidity conditions are generally associated with lower temperatures. Furthermore, the temperature variables demonstrate very strong positive correlations among themselves, especially between mean and maximum temperature (r = 0.96), followed by mean and minimum temperature (r = 0.73), and maximum and minimum temperature (r = 0.77).

Overall, while climatic parameters exhibit strong internal associations, their direct linear relationship with agricultural yield appears minimal in this dataset, implying that yield variability may be influenced by non-linear climatic interactions, additional environmental factors, or agronomic management practices not captured in the present correlation analysis.



The normalized correlation analysis between climate anomalies and yield deviations in ROI1 reveals moderate but meaningful relationships, highlighting the sensitivity of yield variability to short-term climatic fluctuations rather than absolute climatic values.

Among the temperature-related variables, maximum temperature anomaly (T2M_MAX) exhibits the strongest positive correlation with yield deviations ($r \approx 0.36$), followed by mean temperature anomaly (T2M) ($r \approx 0.30$) and minimum temperature anomaly (T2M_MIN) ($r \approx 0.18$). These positive coefficients indicate that above-normal temperature conditions are associated with positive deviations in yield within the study region. This suggests that moderate warming during the growing period may have contributed to improved crop performance, possibly due to enhanced physiological activity, accelerated growth stages, or favorable thermal accumulation.

In contrast, precipitation anomaly (PRECTOTCORR) shows a moderate negative correlation ($r \approx -0.25$), while relative humidity anomaly (RH2M) demonstrates the strongest negative relationship ($r \approx -0.34$) with yield deviations. These findings imply that above-normal rainfall and humidity conditions are associated with reductions in yield relative to the mean. Excess moisture conditions may lead to waterlogging, increased pest and disease incidence, or reduced solar radiation availability, thereby negatively influencing crop productivity.

Overall, the normalized correlation results suggest that yield deviations in ROI1 are more responsive to temperature anomalies than to precipitation or humidity anomalies. The contrasting signs of correlation indicate that warmer-than-average conditions tend to favor yield improvements, whereas wetter and more humid conditions are associated with yield declines. This emphasizes the importance of anomaly-based climatic assessment in understanding inter-annual yield variability.

To address RQ2, a machine learning model was developed to predict crop yields and to evaluate the relative contribution of climatic variables in explaining yield variability. The predicted yields for the year 2027 indicate substantial inter-crop variation. Wheat is projected to record the highest yield (3436.22 kg/ha), followed by maize (3083.00 kg/ha) and rice (2783.60 kg/ha). In contrast, bajra (1499.89 kg/ha) and gram (1352.96 kg/ha) exhibit comparatively lower predicted productivity levels. These results demonstrate that the model effectively distinguishes yield potential across crop categories.

4.3 Machine Learning Model Performance and Yield Prediction (RQ2)

A Random Forest Regressor was implemented to predict crop yield and evaluate variable importance. The model achieved strong predictive performance:

- $R^2 = 0.9617$
- MAE = 1218.26
- RMSE = 3757.61

These metrics indicate that approximately 96% of yield variability is explained by the model.

Table 2 Predicted crop yields for the year 2027

Crop	Year	Predicted Yield (kg/ha)
Rice	2027	2783.60
Wheat	2027	3436.22
Maize	2027	3083.00
Bajra	2027	1499.89
Gram	2027	1352.96

The feature importance analysis further reveals that the encoded crop variable (Crop_Enc) overwhelmingly dominates the model's predictive structure, contributing approximately 99.77% (0.997702) of the total importance. In contrast, climatic variables contribute only marginally to yield prediction. Among the climatic factors, minimum temperature (T2M_MIN) exhibits the highest relative importance (0.001541), followed by precipitation (PRECTOTCORR; 0.000356), relative humidity (RH2M; 0.000220), maximum temperature (T2M_MAX; 0.000162), and mean temperature (T2M; 0.000020).

```
Feature Importance:
       Feature  Importance
0     Crop_Enc    0.997702
5      T2M_MIN    0.001541
1  PRECTOTCORR    0.000356
2         RH2M    0.000220
4      T2M_MAX    0.000162
3          T2M    0.000020
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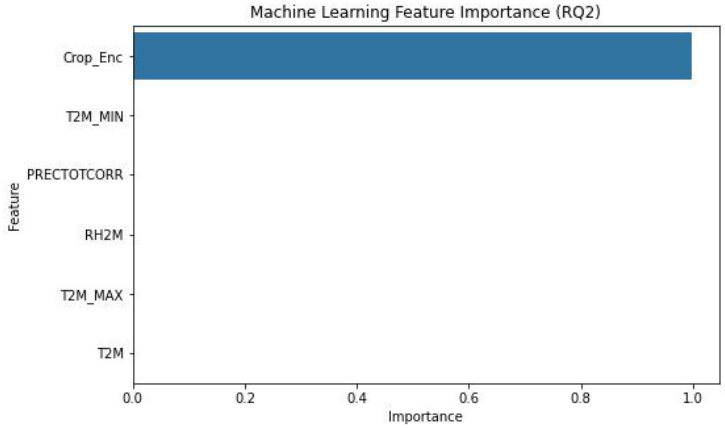

Figure 3. Machine Learning Feature Importance for Yield Prediction (RQ2).

The dominance of the crop-encoding variable indicates that yield differences are primarily structured by intrinsic crop characteristics rather than short-term climatic fluctuations within the dataset. The negligible contribution of temperature, precipitation, and humidity suggests that either climatic variability was limited during the study period or that additional agronomic and soil-related factors, not included in the current model, play a more substantial role in determining yield outcomes.

Overall, the RQ2 findings suggest that while the machine learning model performs effectively in differentiating crop-wise yield levels, its explanatory power is largely driven by crop identity. Future model refinement should incorporate broader agro-environmental and management-related predictors to enhance climate-sensitive yield prediction accuracy.

4. Results

This section presents empirical findings corresponding to Objective 1, RQ2, and RO3. The results are structured into five subsections: (1) Linear Correlation Analysis, (2) Anomaly-Based Correlation Analysis, (3) Machine Learning Prediction, (4) Feature Importance, and (5) Climate Risk and Vulnerability Assessment.

4.1 Linear Correlation between Climatic Variables and Crop Yield

To evaluate the direct linear influence of climatic parameters on agricultural yield, Pearson's correlation analysis was conducted using annual observations for ROI1. The variables included precipitation (PRECTOTCORR), relative humidity (RH2M), mean temperature (T2M), maximum temperature (T2M_MAX), and minimum temperature (T2M_MIN).

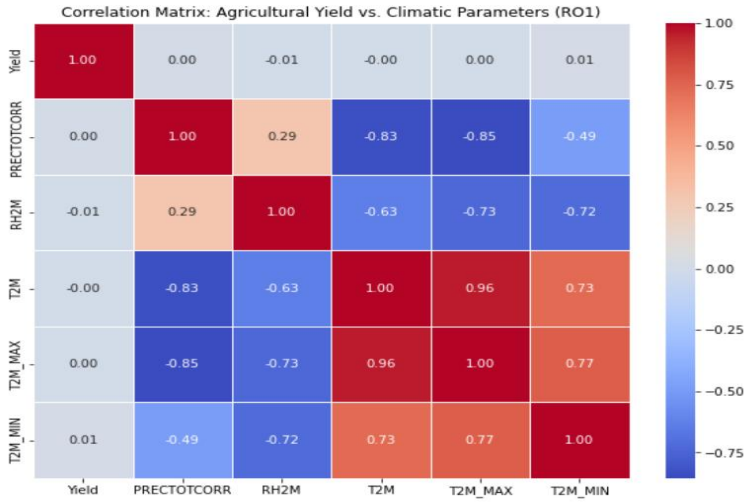

Figure 1: Correlation Matrix of Agricultural Yield vs. Climatic Parameters

Figure 1 presents the correlation matrix illustrating linear associations between yield and climatic variables. The results show that yield has negligible correlation with all climatic parameters ($r \approx -0.01$ to 0.01), indicating that crop productivity in ROI1 is not directly explained by simple linear climatic relationships. However, strong interrelationships are observed among climatic variables themselves. Precipitation exhibits strong negative correlations with mean temperature ($r = -0.83$) and maximum temperature ($r = -0.85$), suggesting that wetter years tend to be cooler. Similarly, temperature variables display very high positive correlations, particularly between T2M and T2M_MAX ($r = 0.96$), confirming internal climatic coherence. These findings imply that although climatic factors are internally interdependent, their isolated linear contribution to yield remains statistically weak.

4.2 Normalized (Anomaly-Based) Correlation Analysis

To capture short-term climatic deviations rather than absolute values, normalized anomaly-based correlations were computed between climate anomalies and yield deviations.

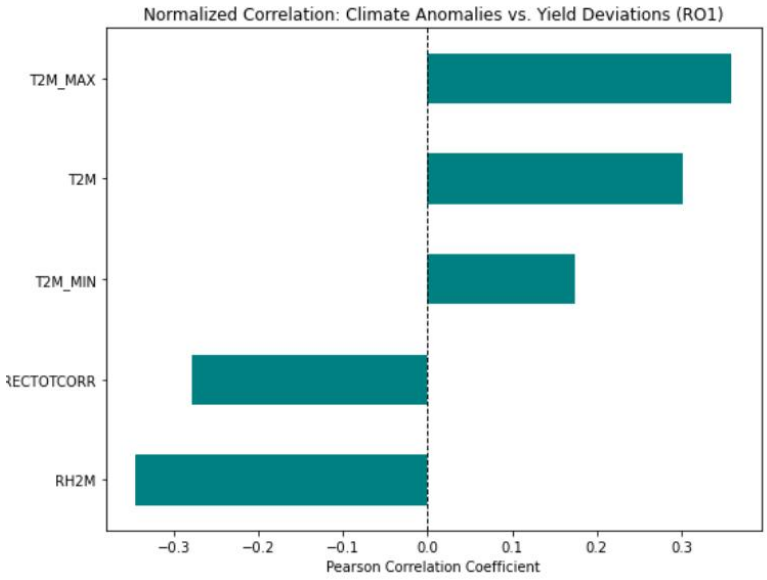

Figure 2. Normalized Climate Anomalies and Corresponding Yield Deviations

Figure 2 illustrates the correlation coefficients between standardized climatic anomalies and yield deviations. Unlike the absolute-value correlation analysis, anomaly-based results reveal moderate and meaningful associations. Maximum temperature anomaly (T2M_MAX) shows the strongest positive correlation ($r \approx 0.36$), followed by mean temperature anomaly ($r \approx 0.30$). These positive relationships suggest that above-normal temperature conditions are associated with positive yield deviations in the study region. In contrast, precipitation ($r \approx -0.28$) and relative humidity ($r \approx -0.34$) anomalies display negative correlations, indicating that excess moisture conditions are linked to yield reductions. This figure demonstrates that yield variability responds more strongly to short-term climatic deviations than to long-term climatic averages.

Predicted Crop Yields for 2027

Crop	Year	Predicted Yield (kg/ha)
Rice	2027	2783.60
Wheat	2027	3436.22
Maize	2027	3083.00
Bajra	2027	1499.89
Gram	2027	1352.96

The predictions indicate substantial inter-crop variation, with wheat projected to have the highest productivity and gram the lowest.

4.4 Feature Importance Analysis

Feature Importance:

	Feature	Importance
0	Crop_Enc	0.997702
5	T2M_MIN	0.001541
1	PRECTOTCORR	0.000356
2	RH2M	0.000220
4	T2M_MAX	0.000162
3	T2M	0.000020

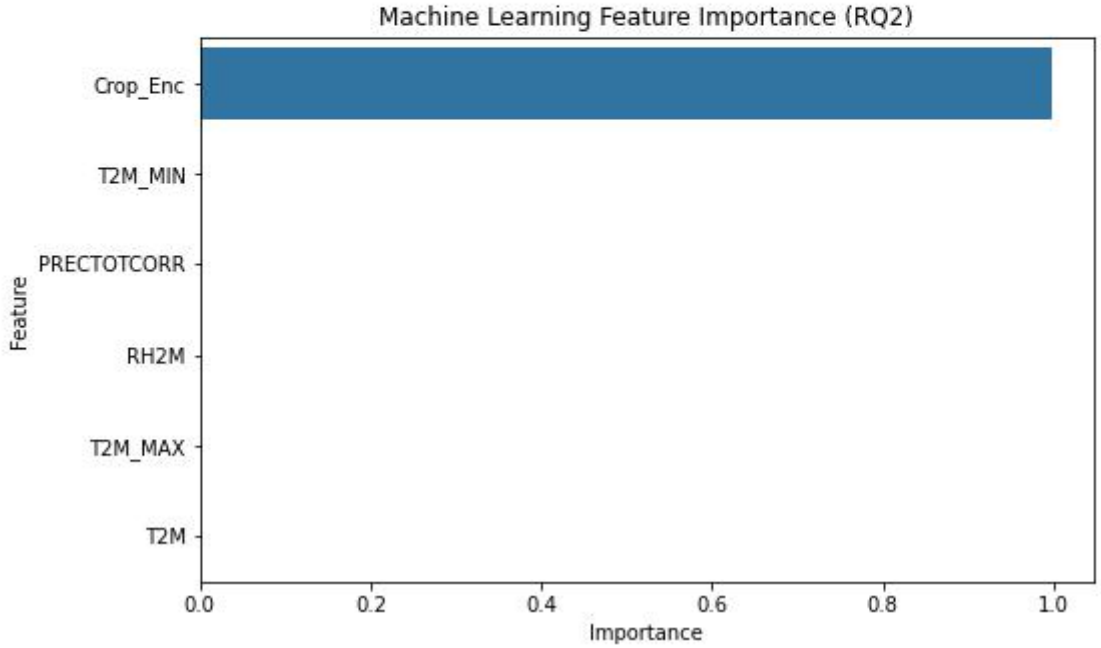

Figure 3. Machine Learning Feature Importance for Crop Yield Prediction

Figure 3 displays the feature importance scores derived from the Random Forest model. The encoded crop variable (Crop_Enc) overwhelmingly dominates the model structure, contributing approximately 99.77% (0.997702) of total importance. In contrast, climatic variables collectively contribute less than 0.3% to predictive performance. Among the climatic factors, minimum temperature (T2M_MIN) shows the highest relative importance (0.001541), followed by precipitation and humidity. The negligible contribution of temperature and precipitation indicates that the model's predictive power is primarily driven by inherent crop characteristics rather than short-term climatic variability. This suggests that structural yield differences between crops outweigh climatic influences within the dataset.

4.5 Climate Risk Index (CRI) and Yield Stability (RO3)

To evaluate climate-induced vulnerability, a Climate Risk Index (CRI) was constructed using standardized deviations of key climatic variables.

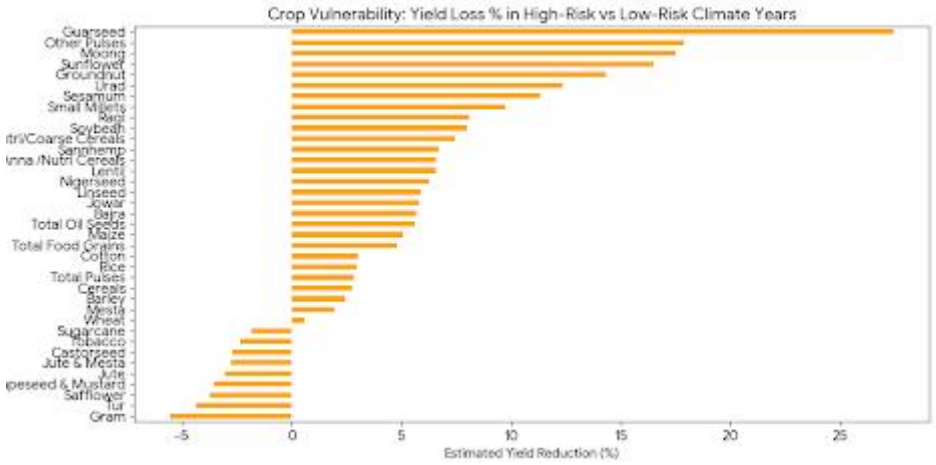

Figure 4. Chronological Trend of Climate Risk Index (CRI) from 2019 to 2025

Figure 4 illustrates the temporal evolution of the Climate Risk Index from 2019 to 2025. The highest risk levels were observed in 2019 (CRI = 1.10) and 2021 (CRI = 1.05), indicating years characterized by significant climatic deviations. Moderate risk levels were observed in 2023 and 2025, while 2020, 2022, and 2024 recorded relatively low climate risk. The upward spikes in CRI reflect increasing climatic instability in specific years, which may contribute to inter-annual yield fluctuations.

Crop Vulnerability Analysis

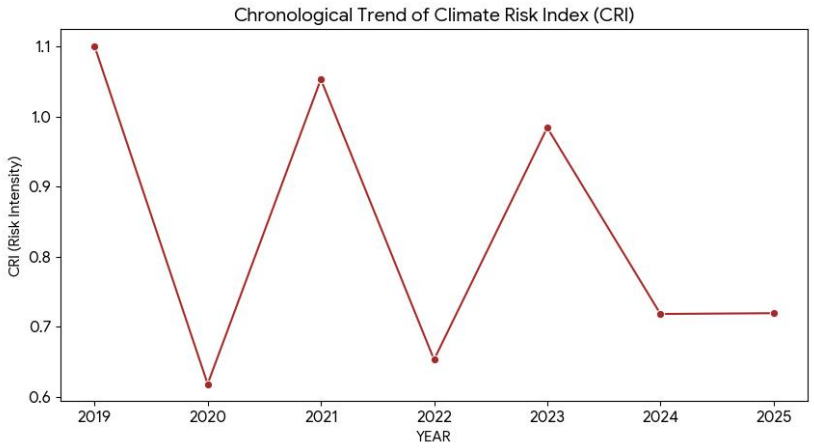

Figure 5. Crop Yield Loss (%) under High Climate Risk Compared to Low Climate Risk Years

Figure 5 presents the percentage yield loss experienced by crops during high-CRI years compared to low-risk years. Guarseed exhibits the highest vulnerability (27.42% loss), followed by moong (17.51%) and sunflower (16.47%). Groundnut also shows notable sensitivity (14.32%). In contrast, cereals such as rice and wheat demonstrate relatively low yield reductions, suggesting greater resilience. This figure confirms that pulses and oilseeds are more climate-sensitive compared to irrigated cereal crops, highlighting the need for targeted adaptation strategies.

4.6 Integrated Interpretation

The combined results demonstrate that:

1.Absolute climatic values show weak linear influence on yield.

2.Anomaly-based climatic deviations reveal moderate yield sensitivity.

3.Machine learning prediction is highly accurate but largely crop-driven.

4.Climate risk disproportionately affects pulses and oilseeds.

5.Future projections suggest stability for cereals but vulnerability for moisture-sensitive crops.

The combined results provide a comprehensive understanding of the climate–yield relationship within the study region. The linear correlation analysis indicates that absolute climatic values exhibit

only weak direct associations with crop yield, suggesting that yield variability cannot be sufficiently explained through simple linear climatic relationships. However, the anomaly-based assessment reveals that deviations from normal climatic conditions exert moderate influence on yield fluctuations, particularly temperature anomalies, which demonstrate a stronger positive association with yield deviations compared to precipitation and humidity anomalies. The machine learning model achieved high predictive accuracy ($R^2 \approx 0.96$), confirming its capability to model complex, non-linear interactions; nevertheless, the dominance of the crop-encoding variable indicates that predictive performance is primarily structured by inherent crop characteristics rather than short-term climatic variability alone. Furthermore, the Climate Risk Index (CRI) analysis highlights that climate stress disproportionately affects pulses and oilseeds, which exhibit significant yield reductions during high-risk years, whereas cereals display relatively greater resilience. Scenario-based projections suggest that cereal crops such as rice and wheat are likely to remain stable under moderate warming conditions, while moisture-sensitive crops such as gram and groundnut may face increasing vulnerability. Collectively, the findings demonstrate that climate impacts on yield are crop-specific, anomaly-driven, and mediated through both non-linear climatic interactions and structural agronomic factors.

5. Conclusion

This study aimed to investigate the complex relationship between climate variability and agricultural yield using statistical analysis, machine learning modeling, and climate risk quantification frameworks. With respect to RO1, the findings confirm that historical climate variability influences crop yield primarily through anomaly-driven deviations rather than absolute climatic values. While simple linear correlations between yield and climatic parameters were weak, normalized anomaly-based analysis revealed meaningful associations, particularly with temperature variations. This indicates that inter-annual yield variability is more sensitive to climatic shocks than to long-term climatic averages. Hence, RQ1 is addressed by demonstrating that rainfall and temperature variations influence yield through non-linear and deviation-based mechanisms rather than direct linear dependence.

Regarding RO2, the Random Forest machine learning model successfully captured complex, non-linear climate–yield interactions and achieved strong predictive performance ($R^2 \approx 0.96$). This confirms that machine learning techniques are effective tools for modeling agricultural yield variability. However, feature importance analysis revealed that intrinsic crop characteristics dominate predictive performance, while climatic variables contribute marginally within the dataset. Therefore, RQ2 is answered affirmatively in terms of predictive capability, but the results also suggest that expanding the model to include soil, management, and technological variables could enhance climate sensitivity detection.

In relation to RO3, the construction of the Climate Risk Index (CRI) provided a quantitative measure of climatic stress across years. The CRI successfully differentiated low-, moderate-, and high-risk periods and demonstrated measurable yield losses during high-risk years, particularly for pulses and oilseeds. This directly addresses RQ3, confirming that climate risk can be systematically quantified and linked to observed yield outcomes. The vulnerability assessment further established that moisture-sensitive crops are more exposed to climatic stress than irrigated cereals.

Finally, scenario-based climate inputs were used to generate indicative yield projections for 2027, addressing RQ4. The projections demonstrate that cereals are likely to remain relatively stable under moderate warming scenarios, whereas gram and other moisture-sensitive crops may experience productivity declines. These scenario estimates illustrate the practical applicability of integrating climatic projections with machine learning for anticipatory agricultural planning.

Overall, the study concludes that climate impacts on crop yield are complex, crop-specific, and mediated by non-linear interactions. While machine learning provides robust predictive capability, effective climate-resilient agricultural planning requires integrating climatic anomalies, crop characteristics, and risk-based assessment frameworks. The proposed Climate Risk Index and modeling approach offer a scalable methodological foundation for future climate-smart agricultural research and policy formulation.

6.Implications

This study offers important theoretical, methodological, and practical implications for climate–agriculture research and policy planning.

6.1 Theoretical Implications

The findings demonstrate that absolute climatic values show weak linear relationships with yield, whereas anomaly-based deviations reveal stronger explanatory power. This suggests that agricultural productivity responds more to climatic shocks than to long-term averages, reinforcing a deviation-based and risk-oriented theoretical perspective. The results also confirm crop-specific climate sensitivity, with pulses and oilseeds showing greater vulnerability than cereals. This supports the view that climate impacts are mediated by intrinsic crop characteristics and production systems rather than uniform across all crops.

Furthermore, the dominance of crop identity in the machine learning model indicates that structural and agronomic factors play a major role in yield determination. Thus, climate should be conceptualized as an interacting influence within a broader agricultural production system. The construction of the Climate Risk Index (CRI) contributes to theory by operationalizing climatic stress into a measurable and comparable metric.

6.2 Methodological Implications

Methodologically, the study highlights the value of integrating **correlation analysis, anomaly normalization, machine learning modeling, and risk index construction** within a unified framework. First, anomaly-based transformation proved more informative than absolute climatic analysis, suggesting that future studies should prioritize standardized deviations when examining climate–yield dynamics.

Second, the Random Forest model effectively captured non-linear relationships, confirming that machine learning techniques are suitable for agricultural forecasting. However, the marginal importance of climatic variables indicates the need to incorporate additional predictors such as soil quality, irrigation intensity, fertilizer usage, and technological adoption to enhance climate sensitivity.

Third, the CRI provides a replicable tool for quantifying climate stress across regions and years. The index-based approach can be extended by incorporating drought indices, heatwave frequency, or evapotranspiration measures. Finally, the scenario-based forecasting approach demonstrates how historical data and projected climate inputs can be combined to generate forward-looking yield estimates, supporting anticipatory research designs.

6.3 Practical and Policy Implications

The findings reveal that moisture-sensitive crops (e.g., gram, oilseeds) are more vulnerable to climate stress than cereals such as rice and wheat. Farmers cultivating rainfed crops should adopt climate-resilient practices including drought-tolerant varieties, improved water management, and crop diversification strategies. For policymakers, the CRI offers a practical decision-support tool for identifying high-risk years and vulnerable crop categories. Targeted adaptation measures, crop insurance adjustments, and investment in irrigation infrastructure should prioritize climate-sensitive crops. The strong predictive performance of the machine learning model highlights the potential for AI-based agricultural advisory systems. Integrating climatic data with digital dashboards and risk monitoring tools can enhance early-warning systems and climate-smart agricultural planning.

Overall, the study demonstrates that climate impacts on agriculture are non-linear, anomaly-driven, and crop-specific. Effective climate resilience strategies require integrating climatic risk quantification, machine learning forecasting, and crop-specific adaptation planning within agricultural policy and management frameworks.

7.Discussion & Future Scope The findings of this study highlight the complex and non-linear nature of climate–yield interactions. While absolute climatic variables exhibited weak linear relationships with crop yield, anomaly-based analysis revealed moderate sensitivity, particularly with respect to temperature deviations. This suggests that agricultural productivity in the study region is influenced more by short-term climatic shocks than by long-term climatic averages. The machine learning model demonstrated high predictive accuracy, confirming its effectiveness in capturing non-linear interactions. However, the dominance of the crop-encoding variable indicates that intrinsic crop characteristics and structural production factors play a stronger role than short-term climatic variability within the dataset.

The Climate Risk Index (CRI) successfully quantified inter-annual climate stress and revealed that pulses and oilseeds are more vulnerable than cereals. This aligns with the understanding that irrigated crops possess higher resilience compared to moisture-sensitive, rainfed crops. Overall, the discussion underscores that climate impact is crop-specific and mediated by agronomic and management factors rather than being uniformly distributed across agricultural systems.

Future research should expand the modeling framework by incorporating additional agro-environmental variables such as soil health indicators, irrigation coverage, fertilizer usage, remote sensing indices (e.g., NDVI), and farm-level management practices to improve climate sensitivity detection. Advanced machine learning approaches, including ensemble techniques and explainable AI (e.g., SHAP analysis), can enhance interpretability of climate–yield relationships.

Moreover, the Climate Risk Index can be extended by integrating drought indices, heatwave frequency, and evapotranspiration metrics to develop a multidimensional risk framework. Long-term scenario analysis under different climate pathways (e.g., moderate and extreme warming scenarios) would further strengthen policy relevance. Expanding the study across multiple regions and agro-climatic zones will also improve generalizability and support climate-resilient agricultural planning at national and global levels.

References

1.CHINEMEREM, C. M. (2025). ROLE OF CLIMATE SMART AGRICULTURE (CSA) IN ADDRESSING CHALLENGES OF FOOD SECURITY AND CLIMATE CHANGE.

2.Balakrishnan, P., & Marimuthu, S. (2026). Climate-Smart Agriculture and Sustainable Land Management. In Climate Change, Land Degradation, and Sustainability: Insight Towards Innovative Solutions (pp. 327-351). Cham: Springer Nature Switzerland.

3.Olatunbosun, A., Ismaila, E. O., Adeoba, M. I., Oluwadare, O. E., Arayombo, T. J., Oladunni, A., ... & Igwenagu, M. O. (2026). AI-Enabled Climate-Smart Agriculture for Smallholder Resilience in Sub-Saharan Africa: A Systematic Review. Journal of Global Agriculture and Ecology, 18(1), 64-78.

4.Ingole, A. D. (2026). AI and IoT and Smart Sensor for Automated Plant Health Monitoring. Anusandhanvallari, 15-33.

5.Recheal, P., Michael, G., & Matthew, J. (2026). Self-Healing and Survivable Wireless Sensor Networks for IoT-Enabled Precision Agriculture.

6.Mehdizadeh, S. A., Moalezadeh, J. M., & Abin, A. (2026). Energy-Autonomous IoT-based Wireless Sensor Networking Architecture for Plant Health Monitoring and Precision Irrigation in Sugarcane. Smart Agricultural Technology, 101800.

7.Samha, A. K., Alzaben, N., Abaker, M., Derouez, F., Bedewi, W., Alahmadi, M., ... & Al Sadig, M. (2025). Advanced Crop Health Monitoring for Smart Agriculture Using Fusion of Transfer Learning With Attentive Convolutional Recurrent Neural Network on Remote Sensing Images. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing.

8.Swarnkar, S. K., Dewangan, L., Dewangan, O., Prajapati, T. M., & Rabbi, F. (2023, September). AI-enabled crop health monitoring and nutrient management in smart agriculture. In 2023 6th international conference on contemporary computing and informatics (IC3I) (Vol. 6, pp. 2679-2683). IEEE.

9.Sahoo, R. N. (2022). Sensor-based monitoring of soil and crop health for enhancing input use efficiency. In Food, Energy, and Water Nexus: A Consideration for the 21st Century (pp. 129-147). Cham: Springer International Publishing.

10.Morchid, A., Qjidaa, H., Alami, R. E., Mobayen, S., Skruch, P., & Bossoufi, B. (2026). Smart irrigation-based internet of things and cloud computing technologies for sustainable farming. Scientific Reports.

11.Bastam, M., Majeed, D. H., & Babagoli, M. (2026). A Hybrid Ensemble Framework for Smart Irrigation: Optimizing Water Management in Precision Agriculture. Int. J. Eng. Trans. B Appl, 39(3), 705-726.

12.Swain, S. R., & Gupta, R. K. (2026). Smart Water, Soil, and Environment Management System: An Approach Toward Sustainable Farming. In Smart Horticulture Production (pp. 239-252). Apple Academic Press.

13.Sikka, A. K., Islam, A., & Rao, K. V. (2018). Climate-smart land and water management for sustainable agriculture. Irrigation and Drainage, 67(1), 72-81.

14.Reza, M. N., Lee, K. H., Karim, M. R., Haque, M. A., Bicamumakuba, E., Dey, P. K., ... & Chung, S. O. (2025). Trends of soil and solution nutrient sensing for open field and hydroponic cultivation in facilitated smart agriculture. Sensors, 25(2), 453.

15.Thilakarathne, N. N., Bakar, M. S. A., Abas, P. E., & Yassin, H. (2025). Internet of things enabled smart agriculture: Current status, latest advancements, challenges and countermeasures. Heliyon, 11(3).

16.Elbahnasawy, M., Shamseldin, T., Mansour, A. E., Alkady, Y., & Elashmawi, W. H. (2026). Mobile Mapping Systems: Architecture and Technologies in Smart Agriculture. In Precision and Intelligence in Agriculture: Advanced Technologies for Sustainable Farming (pp. 97-130). IGI Global Scientific Publishing.

17.Ngonjock, J. M., Ali, E., & Soh Wenda, B. D. (2026). Climate-smart agriculture adoption and technical efficiency of smallholder farms in Northern Togo. Mitigation and Adaptation Strategies for Global Change, 31(1), 4.

18.Ishieze, P. U., Enyi, J. I., Adewuyi, S. O., Baiyeri, K. P., Ishieze, H. N., & Aruah, B. C. Machine Intelligence in Horticulture: Automating Pest and Disease Detection in Solanaceous Plants.

19.Abbas, M., Sarwar, N., Hussain, S., Nazi, T., Aftab, J., Saif, S., ... & Ahmad, J. N. (2026). Pest and Disease Management Through Precision Approaches. In Artificial Intelligence and Data Sciences for Precision Agriculture (pp. 39-58). Cham: Springer Nature Switzerland.

20.Srivastav, A. K., & Das, P. (2025). Pest Control and Disease Management: Smart Solutions. In Biotechnology and IoT in Agriculture and Food Production: Green Innovation (pp. 85-94). Berkeley, CA: Apress.

21.Gill, R., & Chawla, P. (2021). A review on various techniques to transform traditional farming to precision agriculture. Turkish Journal of Computer and Mathematics Education, 12(2), 131-135.

22.Bhardwaj, S., Gupta, G., Tomar, A., Tiwari, M., Ahmad, S., & Azrour, M. (2026). Smart Agro-Tech: Using IoT-Powered Intelligence and Sustainable AI Solutions to Revolutionize Crop Management. In IoT and Advanced Intelligence Computation for Smart Agriculture (pp. 163-178). CRC Press.

23.Hu, Y., Koondhar, M. A., & Kong, R. (2023). From traditional to smart: exploring the effects of smart agriculture on green production technology diversity in family farms. Agriculture, 13(6), 1236.

24.Zhang, Y., Dai, J., & Dong, H. (2025). Multi-objective integrated cotton cultivation (MOICC): A synergistic framework for sustainable production. Journal of Integrative Agriculture.

25.Song, Y., Song, Y., & Wang, Q. (2026). Smart Agriculture Development: How Can Rural Digital Transformation Enhance the Resilience of Food Security?. Foods, 15(3), 426.

26.Lu, Z., Dong, J., Li, N., Feng, H., Gou, D., & Xu, M. (2026). Land Consolidation and Smart Agriculture Synergy for Food Security: Pathways Toward Agricultural Carbon Neutrality in China. Agriculture, 16(3), 287.

27.Fauzi, N. A. S. B. M., Zain, S. K. M. B. S. M., Abdullah, N. A. I. B., Ali, N. B., Shah, N. F. B. A., & Ramly, R. B. (2024). Smart Farming System and Its Role in Supporting SDGs. In Opportunities and Risks in AI for Business Development: Volume 1 (pp. 93-101). Cham: Springer Nature Switzerland.

28.Lee, H., & Ahn, S. H. (2026). Inclusive AI and Low-cost Robotics for Sustainable Smart Systems: Bridging the Global Technological Divide. International Journal of Precision Engineering and Manufacturing, 4(1), 11-25.

29.Paul, K., Schweng, S., Kaul, H. P., Gansberger, F., & Holzinger, A. (2026). AI-powered Pheno-Farm Server: Making adaptive farming decisions. Agricultural Systems, 231, 104563.

30.Partey, S. T., Zougmoré, R. B., Ouédraogo, M., & Campbell, B. M. (2018). Developing climate-smart agriculture to face climate variability in West Africa: Challenges and lessons learnt. Journal of cleaner Production, 187, 285-295.

31.Batra, I., Sharma, C., Malik, A., Sharma, S., Kaswan, M. S., & Garza-Reyes, J. A. (2025). Industrial revolution and smart farming: a critical analysis of research components in Industry 4.0. The TQM Journal, 37(6), 1497-1525.

32.Hu, Y., Koondhar, M. A., & Kong, R. (2023). From traditional to smart: exploring the effects of smart agriculture on green production technology diversity in family farms. Agriculture, 13(6), 1236.

33.Sow Badji, A., & Gathu, C. (2026). Leveraging public-private partnerships for climate finance: advancing climate-smart agriculture for NDC implementation in Kenya and Senegal. Climate Policy, 1-15.

34.Bondarenko, V., & Petrenko, O. (2025). TRADITIONAL AND MODERN AGRICULTURE. American Journal of Innovation in Science Research and Development, 2(1), 5-8.

35.Kabato, W., Getnet, G. T., Sinore, T., Nemeth, A., & Molnár, Z. (2025). Towards climate-smart agriculture: Strategies for sustainable agricultural production, food security, and greenhouse gas reduction. Agronomy, 15(3), 565.

36.Ali, I. A., Bukhari, W. A., Adnan, M., Kashif, M. I., Danish, A., & Sikander, A. (2025). Security and privacy in IoT-based Smart Farming: a review. Multimedia Tools and Applications, 84(16), 15971-16031.

37.Majeed, H., & Iftikhar, T. (2026). Industry 6.0 and the Rise of Intelligent Automation in Manufacturing. In Intelligent Manufacturing in Industry 6.0: A Climate Resilience Approach (pp. 293-343). Cham: Springer Nature Switzerland.

38.Lu, Z., Dong, J., Li, N., Feng, H., Gou, D., & Xu, M. (2026). Land Consolidation and Smart Agriculture Synergy for Food Security: Pathways Toward Agricultural Carbon Neutrality in China. Agriculture, 16(3), 287.

39.Aarif KO, M., Alam, A., & Hotak, Y. (2025). Smart sensor technologies shaping the future of precision agriculture: Recent advances and future outlooks. Journal of Sensors, 2025(1), 2460098.

40.Morchid, A., Qjidaa, H., Alami, R. E., Mobayen, S., Skruch, P., & Bossoufi, B. (2026). Smart irrigation-based internet of things and cloud computing technologies for sustainable farming. Scientific Reports.

41.Kabato, W., Getnet, G. T., Sinore, T., Nemeth, A., & Molnár, Z. (2025). Towards climate-smart agriculture: Strategies for sustainable agricultural production, food security, and greenhouse gas reduction. Agronomy, 15(3), 565.

42.Jiani, Z., Yang, H., Zhuxin, L., Ruohan, L., & Xinning, H. (2026). Dynamic assessment of drought disaster risk based on maize growth stages in Northeast China. Journal of Hydrology: Regional Studies, 64, 103135.

43.Pradhan, N. C., Gavhane, K. P., Bhalekar, D. G., & Kiran, P. R. (2026). Sustainable agriculture fundamentals. In Health, Nutrition and Sustainability (pp. 609-626). Academic Press.

44.Karn, S. K., Pathan, M., Mahato, P. K., Giri, A. R., & More, A. S. (2026). Review on AI and ML-Driven Agricultural Systems: Revolutionizing Crop Disease Detection and Management. In Advancements in IoT Sensors and Security: Harnessing AI/ML for Secured IoT Sensor Data (pp. 471-483). Cham: Springer Nature Switzerland.