

An Automata-Driven Cognitive Explainable Artificial Intelligence Framework for Climate-Adaptive Precision Agriculture and Environmental Sustainability

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Received: July 26, 2026 | Review began: August 10, 2026 | Review ended: August 23, 2026 | Published: September 25, 2026

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Abstract

Environmental deterioration and climate change significantly affect agricultural productivity and food security. Existing solutions in precision agriculture are based mostly on black-box artificial intelligence (AI) models, which do not offer much interpretability and are not flexible enough to account for changes in climatic conditions. In order to overcome these shortcomings, this work develops an automata-driven cognitive explainable AI framework for climate-adaptive precision agriculture and environmental sustainability. The developed framework combines cognitive approaches to machine learning and finite-state automata in order to develop predictive models capable of adapting to changing environmental conditions and guiding agricultural decision-making. Climate, soil, and crop data can be fed into predictive intelligent models to evaluate crop suitability, potential yields, irrigation needs, and climate threats. Moreover, techniques of explainable AI, such as SHapley Additive exPlanations and Local Interpretable Model-Agnostic Explanations, will be employed to ensure greater transparency in model operation. The sustainability of farming activities will be assessed in terms of resource consumption.

Categories: Explainable AI, Machine Learning (ML)

Keywords: precision agriculture, explainable artificial intelligence (xai), cognitive computing, finite state automata, climate adaptation, environmental sustainability

Introduction

Climatic changes, environmental degradation, and pressure on the global food system raise several issues that need to be tackled [1]. Changes in temperature, precipitation, soil moisture, and weather conditions impact crop growth rates, water supply, environmental sustainability, etc. [2]. The current challenge is to use the available resources more efficiently, a solution that has led to precision agriculture in recent years through improved management and data-based decision-making. However, most of the Artificial Intelligence (AI)-based tools and platforms available in the market are black-box tools, which are neither explainable nor flexible in terms of environmental variability [3]. At the moment, there are no approaches to state modeling and evaluating climate. Therefore, this paper aims to build an automata-driven cognitive

How to cite this article:

Ranjan M K, Gupta R S, Mali N D, et al. (September 25, 2026) An Automata-Driven Cognitive Explainable Artificial Intelligence Framework for Climate-Adaptive Precision Agriculture and Environmental Sustainability. Cureus J Comput Sci 3 : es44389-026-00295-5. DOI <https://doi.org/10.7759/s44389-026-00295-5>

Explainable Artificial Intelligence (XAI) framework for climate-adaptive precision agriculture and environmental sustainability. In particular, the proposed framework combines cognitive machine learning techniques with Finite-State Automata (FSA), enabling the construction of a model of the state transitions of an environment for decision-making under different climatic and agricultural conditions. Also, XAI methods are applied to make predictions related to crop suitability analyses, yield predictions, irrigation planning, and climate risk assessment more transparent and confident, as shown in Figure 1 [4]. The key contribution of this study is the integration of predictive learning, automata-based climate-state reasoning, explainability, and sustainability assessment within a unified climate-adaptive agricultural decision process.

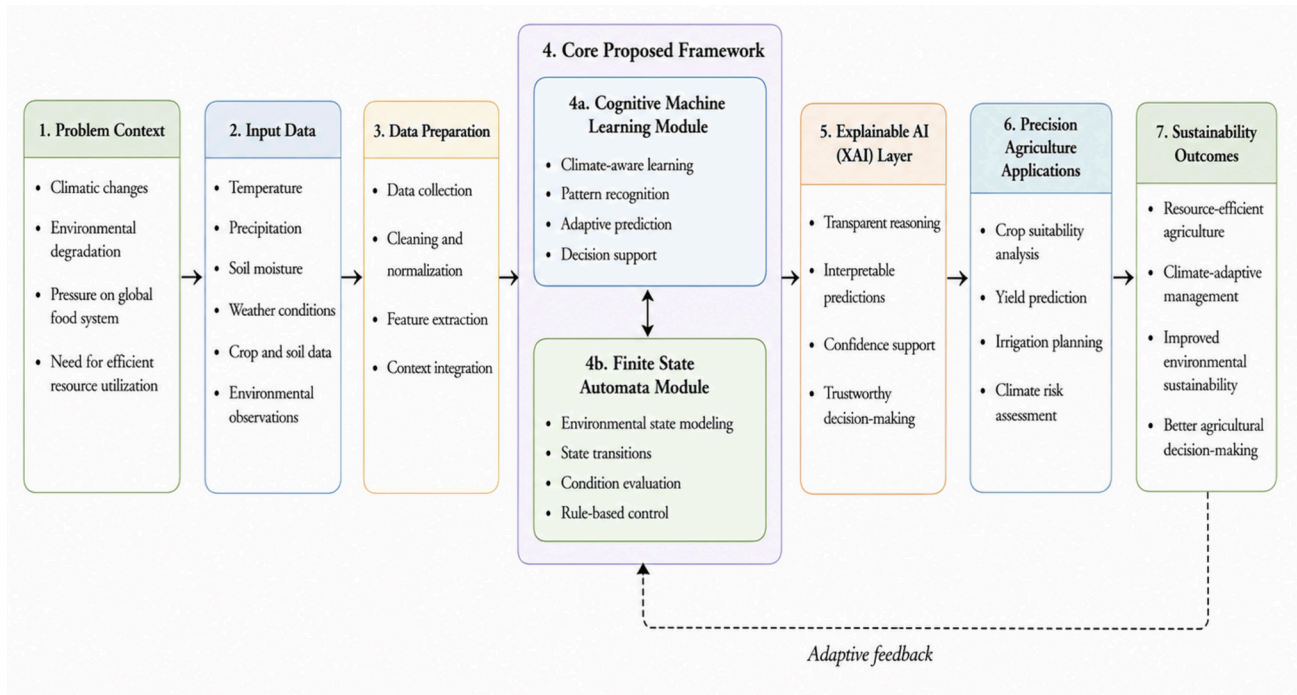


FIGURE 1: Automata-Driven Cognitive XAI Framework for Climate-Adaptive Precision Agriculture

XAI: Explainable Artificial Intelligence

Objective

- To develop an automata-driven cognitive AI framework for climate-adaptive precision agriculture by integrating climate, soil, and crop-related data for intelligent agricultural decision-making.
- To design a predictive analytics module using machine learning techniques for crop suitability assessment, yield prediction, irrigation planning, and climate risk evaluation under dynamic environmental conditions.
- To incorporate XAI techniques and sustainability assessment mechanisms to enhance the transparency, trustworthiness, resource efficiency, and environmental sustainability of agricultural recommendations.

Related study

The studies available today mainly focus on the use of AI for agricultural forecasting and resource optimization, but they have not been explained, have not been adapted to climate change, and do not include a cognitive decision-making process. The proposed framework tries to fill these gaps by incorporating the three pillars of cognitive AI, FSA, XAI (SHapley Additive exPlanations (SHAP)/Local Interpretable Model-Agnostic Explanations (LIME)), and sustainability analytics for adaptive and transparent precision agriculture, as shown in Table 1.

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Citation	Focus Area	Key Contributions	Advantages	Limitations	Relevance to Our Study
[5]	Precision Agriculture	Applied ML for crop monitoring and yield prediction.	Improved agricultural productivity.	Limited explainability.	Supports AI-based agricultural analytics.
[6]	Smart Farming	Utilized ML for crop management and resource optimization.	Enhanced decision-making.	No climate-adaptive mechanism.	Supports predictive agriculture models.
[7]	XAI	Reviewed XAI methods for transparent AI systems.	Improved model interpretability.	Not agriculture-specific.	Provides foundation for SHAP and LIME integration.
[8]	Sustainable Agriculture	Applied AI for crop monitoring and sustainability.	Improved resource utilization.	No automata-based adaptation.	Supports sustainability-focused agriculture.
[9]	AI for Sustainable Farming	Reviewed ML/DL techniques for yield prediction and water management.	Enhanced sustainability and efficiency.	Limited explainability.	Motivates integration of XAI and sustainability analytics.

TABLE 1: Comparative Analysis of Existing AI-Based Approaches for Precision Agriculture, XAI, and Sustainable Farming

DL: Deep Learning; LIME: Local Interpretable Model-Agnostic Explanations; ML: Machine Learning; SHAP: SHapley Additive exPlanations; XAI: Explainable Artificial Intelligence

Recent state-of-the-art research demonstrates substantial progress in applying machine learning and XAI to crop recommendation, irrigation management, agricultural monitoring, and sustainable farming. In particular, Extreme Gradient Boosting (XGBoost), SHAP, and LIME are increasingly used to obtain accurate and interpretable agricultural predictions. However, the novelty of the present study does not arise from the individual use of XGBoost or SHAP/LIME. Instead, it lies in their integration with an explicit finite-state climate-reasoning mechanism and sustainability-oriented decision layer. Unlike conventional XAI-based precision-agriculture models that primarily explain individual predictions, the proposed framework converts predictive climate-risk evidence into state-dependent transitions among predefined environmental conditions (S0-S5). These transitions preserve the evolving climate-risk context and subsequently influence agricultural recommendations. The Sustainability Index (SI) further evaluates water, resource, and environmental efficiency within the same decision process. Thus, the contribution is an integrated predictive-stateful-explainable-sustainable decision architecture rather than another standalone crop-prediction or post-hoc explainability model.

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Problem statement

Climate variability, irregular rainfall, water scarcity, soil-condition changes, and environmental degradation increasingly affect agricultural productivity and sustainable resource management. Although machine-learning techniques are widely used for crop prediction, irrigation planning, and agricultural risk assessment, many existing approaches operate as black-box predictive systems and lack transparent reasoning about their decisions. They also provide limited mechanisms for dynamically representing transitions between changing climatic and agricultural conditions [10]. Therefore, there is a need for an intelligent decision-support approach that integrates predictive machine learning, climate-state transition modeling, XAI, and sustainability assessment. The proposed study addresses this problem by combining XGBoost-based prediction with FSA for adaptive environmental-state reasoning and SHAP/LIME for interpretable decision-making, with the aim of providing transparent, climate-responsive, and sustainability-oriented recommendations for precision agriculture [11].

Materials And Methods

The proposed automata-driven cognitive XAI framework combines pertinent climate, soil, and crop data to assist in dynamic agricultural decision-making [12]. Once the data are preprocessed and features are extracted, a cognitive AI model predicts crop suitability, irrigation needs, and environmental hazards. A module that uses an FSA model captures changes in state conditions related to climate stress and risk conditions. Climate Risk Score (CRS) and SI are calculated to assess environmental impact and resource efficiency. The techniques of XAI (SHAP/LIME) offer clear explanations of predictions. The system finally provides sustainable crop recommendations, irrigation planning, and risk assessment for climate-resilient agriculture.

Data collection

Alemu [13] has published the publicly available “Crop Recommendation using Soil Properties and Weather Prediction Dataset,” which was used in this study. The data include soil properties, crop data, geographical and climatic data from various sources. The soil and crop-type data were sourced from the Ethiopian Agricultural Transformation Agency, while the data pertaining to crop production came from the Ethiopian Statistics Service, and the climate-related information came from the NASA POWER platform. This dataset is open to the public [13]. The dataset was downloaded in Version 1 and then preprocessed through data cleaning, filtering, integration, and transformation, in accordance with the preprocessing process described in this section. The proposed framework brings together information from a variety of sources related to agriculture and the environment, such as climate data, soil data, crop data, remote sensing indicators, etc. [13]. The data are applied to climate-adaptive precision agriculture and decision-making for sustainability in Eq. (1) and Eq. (2).

$$D = \{(x_i, y_i)\}_{i=1}^N \quad (1)$$

where

$$x_i = \{T_i, R_i, H_i, SM_i, pH_i, NDVI_i, WS_i\} \quad (2)$$

here T_i represents temperature, R_i represents rainfall, H_i represents humidity, SM_i represents soil moisture, pH_i represents soil acidity/alkalinity, $NDVI_i$ represents the normalized difference vegetation index, and WS_i represents wind speed for the i^{th} sample in Eq. (3).

$$y_i \in \{\text{Crop Suitability, Yield, Irrigation Need, Climate Risk}\} \quad (3)$$

This dataset forms the input foundation for the cognitive AI model and automata-driven decision engine.

Dataset splitting

Before model training, the dataset is divided into training, validation, and testing subsets to ensure unbiased performance evaluation. The dataset is partitioned, as shown in Eq. (4):

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$$D = D_{train} \cup D_{val} \cup D_{test} \quad (4)$$

where $|D_{train}| = 0.7N$, $|D_{val}| = 0.15N$, and $|D_{test}| = 0.15N$

where N denotes the total number of samples. The training set is used for model learning, the validation set is utilized for parameter tuning, and the testing set is employed for final performance assessment. The crop-wise distribution of samples across all subsets is presented in Table 2. The final dataset consisted of 10,000 samples distributed across five crop categories: wheat, rice, corn, soybean, and vegetables. Before model development, the dataset was divided into training, validation, and testing subsets using stratified sampling to preserve the proportional distribution of each crop category. A 70:15:15 split was applied, resulting in 7,000 training samples, 1,500 validation samples, and 1,500 testing samples. The training set was used to estimate the model parameters, while the validation set was used for hyperparameter tuning and model selection. The independent test set was reserved exclusively for final performance evaluation. No test-set observations were used during model training or hyperparameter optimization.

Crop Type	Total Samples	Training Samples (70%)	Validation Samples (15%)	Test Samples (15%)
Wheat	2,800	1,960	420	420
Rice	2,460	1,722	369	369
Corn	1,980	1,386	297	297
Soybean	1,560	1,092	234	234
Vegetables	1,200	840	180	180
Total	10,000	7,000	1,500	1,500

TABLE 2: Dataset Composition and Stratified Training, Validation, and Testing Distribution

Data preprocessing

Much of this climate, soil, and agricultural information is incomplete, noisy, inconsistent, and perhaps even measured on different scales, which can have a detrimental impact on predictive model performance [14]. Thus, data preprocessing is performed so that data quality is enhanced, consistency is ensured, and the reliability of the proposed cognitive AI framework is improved. First, mean-based imputation is used to fill in missing records, while irrelevant and noisy data are deleted to keep the data clean. Then, all features are normalized using Min-Max normalization to rescale the feature values so that their range is between 0 and 1, ensuring that larger ranges of numerical values do not dominate the learning process. The normalization process is mathematically represented as in Eq. (5):

$$x_{ij}^{norm} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \quad (5)$$

where x_{ij}^{norm} denotes the normalized value of the j^{th} feature for the i^{th} sample, x_{ij} represents the original feature value, and x_j^{min} and x_j^{max} correspond to the minimum and maximum values of the respective feature. After preprocessing, the normalized dataset is represented, as shown in Eq. (6):

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$$D_{\text{norm}} = \{(x_i^{\text{norm}}, y_i)\}_{i=1}^N \quad (6)$$

where D_{norm} denotes the preprocessed dataset, x_i^{norm} represents the normalized feature vector, y_i denotes the target output, and N is the total number of samples. The resulting dataset is then utilized for feature extraction and cognitive model training

Feature vector formation

Relevant climate, soil, and agronomic parameters are then combined to form a feature vector for predictive analysis after preprocessing. These features represent the environmental and crop-related conditions needed for climate-adaptive decision-making. The feature vector of the i^{th} sample is given by Eq. (7):

$$X_i = [T_i, R_i, H_i, SM_i, pH_i, NDVI_i, WS_i] \quad (7)$$

where T_i represents temperature, R_i represents rainfall, H_i represents humidity, SM_i represents soil moisture, pH_i represents pH, $NDVI_i$ represents the normalized difference vegetation index, and WS_i represents wind speed. The complete feature matrix is represented in Eq. (8):

$$X = \{X_i\}_{i=1}^N \quad (8)$$

where N denotes the total number of samples. The generated feature matrix serves as the input to the cognitive AI model for crop prediction, climate risk assessment, and resource optimization.

Target construction and leakage prevention

The prediction target was defined independently of the predictor variables used during model training. No target label, encoded target variable, post-outcome information, or feature directly derived from the target was included in the model input. Features used for model development consisted only of the specified climate, soil, and vegetation variables. Data partitions were created before preprocessing, and all preprocessing parameters were learned exclusively from the training data. Duplicate observations were checked before partitioning to prevent identical samples from occurring across the training and evaluation subsets.

Cognitive AI model training

The preprocessed feature matrix is used for training a cognitive AI model to forecast crop suitability, climate risk, and irrigation needs, along with agricultural sustainability metrics [15]. In this study, the XGBoost algorithm is used because of its high predictive power, robustness, and capacity to process heterogeneous agricultural and climate data [16]. The model is able to learn the mapping between the input feature space and the target variables, which represents the relationship between environmental features and agricultural outcomes, as shown in Table 3.

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Parameter	Value
Model	XGBoost (Cognitive AI)
Dataset Size	>10,000 samples
Train-Test Split	70:15:15
Feature Set	7 Features
Loss Function	Binary Cross-Entropy
Optimizer	Gradient Boosting Optimization
Max Depth	6
Learning Rate	0.1
Estimators	200
Evaluation Metrics	Accuracy, Precision, Recall, F1-score, ROC-AUC
Explainability Method	SHAP/LIME
Automata Model	Finite State Automata (S0–S5)
Sustainability Module	Water + Resource + Environmental Index

TABLE 3: Experimental Setup and Model Configuration Parameters

LIME: Local Interpretable Model-Agnostic Explanations; ROC-AUC: Receiver Operating Characteristic-Area Under the Curve; SHAP: SHapley Additive exPlanations; XGBoost: Extreme Gradient Boosting

Reproducibility and Implementation Details

To improve experimental reproducibility, all major model parameters, preprocessing operations, dataset partitions, evaluation procedures, and automata configurations were fixed before final evaluation. The dataset was divided using stratified training, validation, and testing partitions, and the same partitioning protocol was applied to all baseline models. Missing-value treatment and normalization parameters were estimated from the training data and subsequently applied unchanged to the validation and test data. XGBoost was configured using 200 estimators, a maximum tree depth of 6, and a learning rate of 0.1. The FSA state definitions and transition thresholds were kept fixed during comparative evaluation. Five-fold cross-validation was performed using the same folds for all compared models to ensure consistent evaluation conditions.

The prediction function is expressed in Eq. (9):

$$\hat{y}_i = f(X_i; \theta)$$

(9)

where $\hat{y}_i$ denotes the predicted output, X_i represents the input feature vector, $f(\cdot)$ denotes the XGBoost model, and θ represents the learned model parameters. The optimal parameters are obtained by minimizing the prediction loss function as in Eq. (10):

$$\theta^* = \arg \min_{\theta} \sum_{i=1}^N L(y_i, \hat{y}_i) \quad (10)$$

where $L(y_i, \hat{y}_i)$ denotes the loss between the actual and predicted outputs. The trained model generates intelligent predictions that are subsequently utilized for climate risk assessment, automata-based adaptive state transitions, explainable decision analysis, and sustainability-oriented agricultural recommendations.

CRS calculation

To assess the impact of environmental conditions on agricultural productivity, a CRS is computed using a weighted combination of key climate and soil parameters. This score quantifies the overall risk associated with adverse climatic conditions and supports adaptive decision-making within the proposed framework [17]. The CRS is calculated as in Eq. (11):

$$CRS = w_1T + w_2R + w_3H + w_4SM + w_5NDVI \quad (11)$$

where T represents temperature, R represents rainfall, H represents humidity, SM represents soil moisture, $NDVI$ represents the normalized difference vegetation index, and w_1, w_2, w_3, w_4 , and w_5 are the corresponding feature weights satisfying Eq. (12):

$$\sum_{j=1}^5 w_j = 1 \quad (12)$$

Automata-based adaptive decision engine

An FSA model is used to represent different environmental conditions and their transitions to enable climate-adaptive decisions [18]. The automata store the obtained CRS and dynamically switch their state in response to climatic conditions. The automata are given as follows in Eq. (13):

$$A = (Q, \Sigma, \delta, q_0, F) \quad (13)$$

where Q denotes the set of states, Σ represents the input symbols, δ is the state transition function, q_0 is the initial state, and F denotes the set of final states. The state set is defined as in Eq. (14):

$$Q = \{S_0, S_1, S_2, S_3, S_4, S_5\} \quad (14)$$

where $S_0 = \text{Normal Condition}$, $S_1 = \text{Low Rainfall}$, $S_2 = \text{Drought Risk}$, $S_3 = \text{Heat Stress}$, $S_4 = \text{Crop Alert}$, and $S_5 = \text{Sustainable Action}$. The state transition mechanism is represented as in Eq. (15):

$$\delta : Q \times \Sigma \rightarrow Q \quad (15)$$

Based on the computed CRS, the automata transitions between states and ultimately reaches an appropriate decision state. This adaptive mechanism enables timely agricultural interventions, resource optimization, and climate-resilient farming recommendations.

The FSA is not used merely as a static post-processing threshold applied independently to each XGBoost prediction. Instead, the XGBoost prediction provides model-derived risk evidence to the automata decision process, while the current decision state depends jointly on the present risk evidence and the previous environmental state. Thus, the transition $S_{t-1} \rightarrow S_t$ preserves the temporal context of changing agricultural conditions. Consequently, identical or similar XGBoost risk estimates may lead to different state transitions depending on the preceding environmental state.

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The FSA therefore provides state-dependent climate reasoning and persistence, whereas conventional post-processing would independently map each prediction to an action without considering the previous system state, as shown in Table 4.

Previous State	XGBoost/CRS Condition	Next State	Decision
S0 Normal	Low risk maintained	S0 Normal	Continue normal operation
S0 Normal	Reduced rainfall / moderate risk	S1 Low Rain	Monitor irrigation
S1 Low Rain	Risk increases	S2 Drought	Increase irrigation intervention
S2 Drought	High temperature + high risk	S3 Heat Stress	Activate heat-stress mitigation
S3 Heat Stress	Critical risk persists	S4 Alert	Immediate intervention
S4 Alert	Conditions recover	S3/S2	Gradual recovery action

TABLE 4: XGBoost–FSA Coupling and Climate-State Transition Rules

CRS: Climate Risk Score; FSA: Finite-State Automata; XGBoost: eXtreme Gradient Boosting

XAI analysis

To enhance the transparency and trustworthiness of the proposed framework, XAI techniques are employed to interpret the predictions generated by the cognitive AI model [19]. The contribution of each feature toward the prediction outcome is quantified using an explainability function. The feature importance score is represented as in Eq. (16):

$$E = \{\phi_1, \phi_2, \phi_3, \dots, \phi_n\} \quad (16)$$

where ϕ_j denotes the contribution of the j^{th} feature to the predicted outcome. The overall prediction explanation can be expressed as in Eq. (17):

$$\hat{y} = \phi_0 + \sum_{j=1}^n \phi_j \quad (17)$$

where $\hat{y}$ represents the model prediction, ϕ_0 denotes the baseline prediction, and ϕ_j indicates the contribution of individual features. The Environmental Sustainability Score of 0.71 indicates that the evaluated system achieved 71% of the maximum attainable normalized environmental-performance level. This score was classified as Fair and indicates measurable environmental benefits while retaining a 29% improvement margin. The weighted SI was 0.777, placing the evaluated farming system in the Sustainable category, as shown in Table 5.

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Sustainability Metric	Normalized Score	Weight	Weighted Score	Rating	Interpretation
Water Efficiency	0.78	0.40	0.312	Good	The system achieved a normalized water-efficiency score of 0.78
Resource Efficiency	0.82	0.35	0.287	Excellent	The system achieved a normalized resource-efficiency score of 0.82
Environmental Sustainability Score	0.71	0.25	0.178	Fair	The system achieved 71% of the maximum normalized environmental-performance score
Composite Sustainability Index	0.777	1.00	0.777	Sustainable	The farming system operates at a sustainable overall level

TABLE 5: Sustainability Performance Evaluation and Composite Sustainability Index

SI calculation

The normalized environmental performance of the evaluated farming system on a scale from 0 to 1, with higher numbers indicating lower environmental impacts, is called the Environmental Sustainability Score and, in this case, was rated as 0.71. The score was deemed Fair according to the interpretation criteria used. The value represents measurable environmental performance and provides a margin for improvement of 0.29 points from the maximum possible normalized value. It does not equal an absolute 71% reduction in Environmental Impact. The composite SI (0.777) was calculated by combining the Environmental Sustainability Score, Water Efficiency, and Resource Efficiency using the appropriate weights.

To evaluate the environmental and resource efficiency of agricultural practices, an SI is computed by integrating water efficiency, resource efficiency, and environmental performance indicators. This index provides a quantitative measure of the sustainability level achieved by the proposed framework. The SI is calculated as in Eq. (18):

$$SI = w_{WE}WE + w_{RE}RE + w_{ES}ES$$

(18)

where

$$w_{WE} + w_{RE} + w_{ES} = 1$$

where *WE* denotes Water Efficiency, *RE* denotes Resource Efficiency, and *ES* denotes Environmental Score. The individual metrics are defined as in Eqs. (19)-(21):

$$WE = \frac{Y_c}{W_c} \tag{19}$$

$$RE = \frac{O}{I} \tag{20}$$

$$ES = 1 - EI \tag{21}$$

where *Y_c* is crop yield, *W_c* is water consumption, *O* is agricultural output, *I* is resource input, and *EI* represents Environmental Impact. A higher SI indicates more efficient resource utilization and reduced environmental burden. The computed sustainability score is utilized to support environmentally responsible agricultural recommendations and long-term climate resilience.

This SI combines Water Efficiency (0.78), Resource Efficiency (0.82), and Environmental Impact (0.71) with weighted contributions to give a final score of 0.777. This means that the system is working at a sustainable level, with good water efficiency and resource conservation, and there is moderate scope for further optimization of environmental impact, as shown in Table 6.

Sustainability Metric	Score (0-1)	Weight	Weighted Value	Status	Interpretation
Water Efficiency	0.78	0.4	0.312	Good	78% water usage efficiency achieved
Resource Efficiency	0.82	0.35	0.287	Excellent	82% resource conservation achieved
Environmental Impact Score	0.71	0.25	0.178	Fair	71% minimal environmental impact
Total Sustainability Index	0.777	1.0	0.777	Sustainable	Farm operates at sustainable level

TABLE 6: Sustainability Performance Evaluation and Composite Sustainability Index

There is a clear seasonal trend throughout the farming year, as the SI increases from a low point (0.62) and peaks in mid-season (0.80) before moving back down to 0.70 at the end of the year. The index moves from the Poor Zone (<0.70) to the Fair Zone (0.70-0.80), briefly crossing into the Good Zone (>0.80), and then returns to the Fair Zone. In general, the overall trend is toward better sustainability in mid-season, with a shift toward resource stress later in the season, as shown in Figure 2.

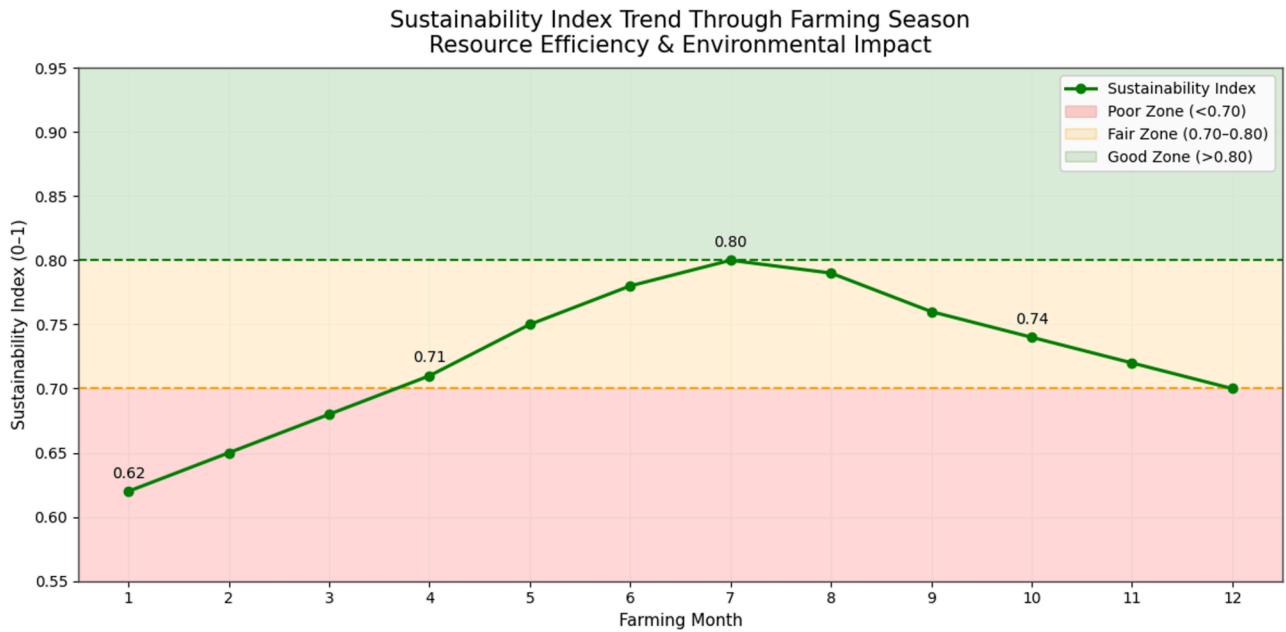


FIGURE 2: Seasonal Trend of Sustainability Index in Farming Systems

Final decision generation

The final decision module integrates the outputs of the cognitive AI model, climate risk assessment, automata-based state transitions, explainability analysis, and sustainability evaluation to generate intelligent agricultural recommendations. The decision function is formulated as in Eq. (22):

$$D = f(\hat{Y}, CRS, Q, SI, E) \quad (22)$$

where $\hat{Y}$ denotes the predicted agricultural outcome, CRS represents the Climate Risk Score, Q denotes the current automata state, SI represents the Sustainability Index, and E corresponds to the explainability information. The final recommendation is generated as in Eq. (23):

$$R = \{R_1, R_2, R_3, R_4, R_5\} \quad (23)$$

where

R_1 : Crop Recommendation

R_2 : Irrigation Planning

R_3 : Climate Risk Alert

R_4 : Resource Optimization

R_5 : Sustainable Farming Action

where R denotes the recommended action. This integrated decision-making process enables adaptive, transparent, and sustainability-oriented agricultural management by providing actionable insights based on real-time climate and environmental conditions.

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Performance evaluation

The effectiveness of the proposed framework is tested using well-established classification metrics for measuring predictive accuracy, reliability, and decision-making effectiveness [20]. Accuracy, precision, recall, and F1-score are used to evaluate the performance of the trained XGBoost model on unseen data. The accuracy of the model is calculated as shown in Eq. (24):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (24)$$

TP, TN, FP, and FN stand for true positive, true negative, false positive, and false negative, respectively. Furthermore, the performance of the framework is evaluated in terms of predictive accuracy as well as sustainability impacts, guaranteeing that the suggested recommendations will be not just precise but also environmentally friendly. The evaluation results highlight the ability of the proposed framework to enable climate-adaptive precision agriculture by ensuring accurate predictions, informed decision-making, and responsible use of resources.

System architecture

The proposed automata-driven cognitive XAI framework brings together climate, soil, and crop data for the purpose of supporting climate-adaptive precision agriculture [21,22]. Following data preprocessing and feature engineering, crop suitability, yield forecasting, irrigation needs, and climate risk are predicted using the XGBoost model. The XGBoost model first generates a prediction and associated risk probability from the climate, soil, and crop features. The prediction is integrated with the computed CRS to form the input signal to the FSA [23]. Rather than independently reclassifying each prediction, the FSA evaluates this signal together with the preceding environmental state and applies the defined state-transition function to determine the current climate-risk state. The resulting state is subsequently combined with the XGBoost prediction and SI to generate the final agricultural recommendation [24-26].

Results And Discussion

Geographical generalizability and external validation

The present framework was evaluated primarily using an agricultural dataset derived from Ethiopian soil, crop, production, and climatic sources. Therefore, the reported predictive performance should not be interpreted as evidence of equivalent performance across other geographical or agro-climatic regions. Independent external validation using datasets from different countries, crop systems, soil conditions, and climate regimes was outside the scope of the present study. Differences in rainfall distribution, temperature patterns, soil properties, farming practices, crop varieties, and sensor characteristics may lead to distribution shifts and may reduce model performance when the framework is transferred to new regions. Consequently, the XGBoost model, CRS weights, and FSA transition thresholds may require regional recalibration before practical deployment. Future work will therefore focus on multi-region external validation and transferability assessment using independent agricultural datasets.

The SHAP decision plot illustrates in Figure 3 how individual climate and soil features progressively shift 28 test instances from the baseline model output of approximately 0.42 toward their final climate-risk predictions. Red trajectories correspond to high-risk instances, whereas blue trajectories indicate low-risk cases. Rainfall, soil moisture, and temperature produce the greatest separation between the two risk groups, demonstrating their dominant influence on climate-risk classification. NDVI and soil pH provide additional discrimination, while humidity and wind speed show comparatively smaller contributions.

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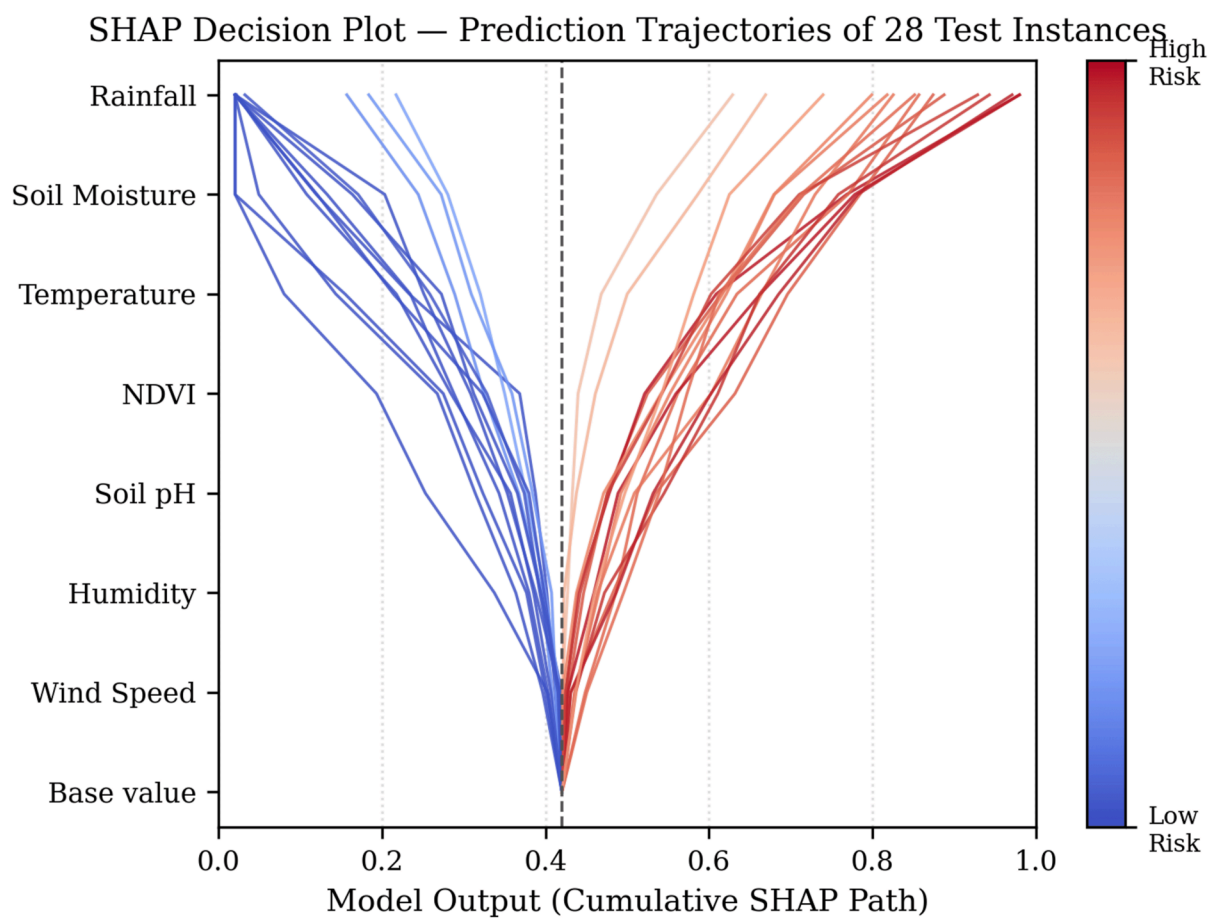


FIGURE 3: SHAP Decision Plot of Cumulative Feature Contributions Across Test Instances

NDVI: Normalized Difference Vegetation Index; SHAP: SHapley Additive exPlanations

The SHAP waterfall plot in Figure 4 explains an individual high-risk prediction by showing how each environmental feature changes the model output from the baseline probability of 0.42 to the final climate-risk probability of 0.91. Low rainfall (38 mm) contributes the largest increase (+0.18), followed by low soil moisture (14%, +0.14) and high temperature (41°C, +0.11). NDVI and soil pH further increase the predicted risk, whereas humidity and wind speed slightly reduce it. The resulting probability indicates a high-risk or Crop Alert state (S4), requiring immediate climate-adaptive intervention.

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Ranjan M K, Gupta R S, Mali N D, et al. (September 25, 2026) An Automata-Driven Cognitive Explainable Artificial Intelligence Framework for Climate-Adaptive Precision Agriculture and Environmental Sustainability. Cureus J Comput Sci 3 : es44389-026-00295-5. DOI <https://doi.org/10.7759/s44389-026-00295-5>

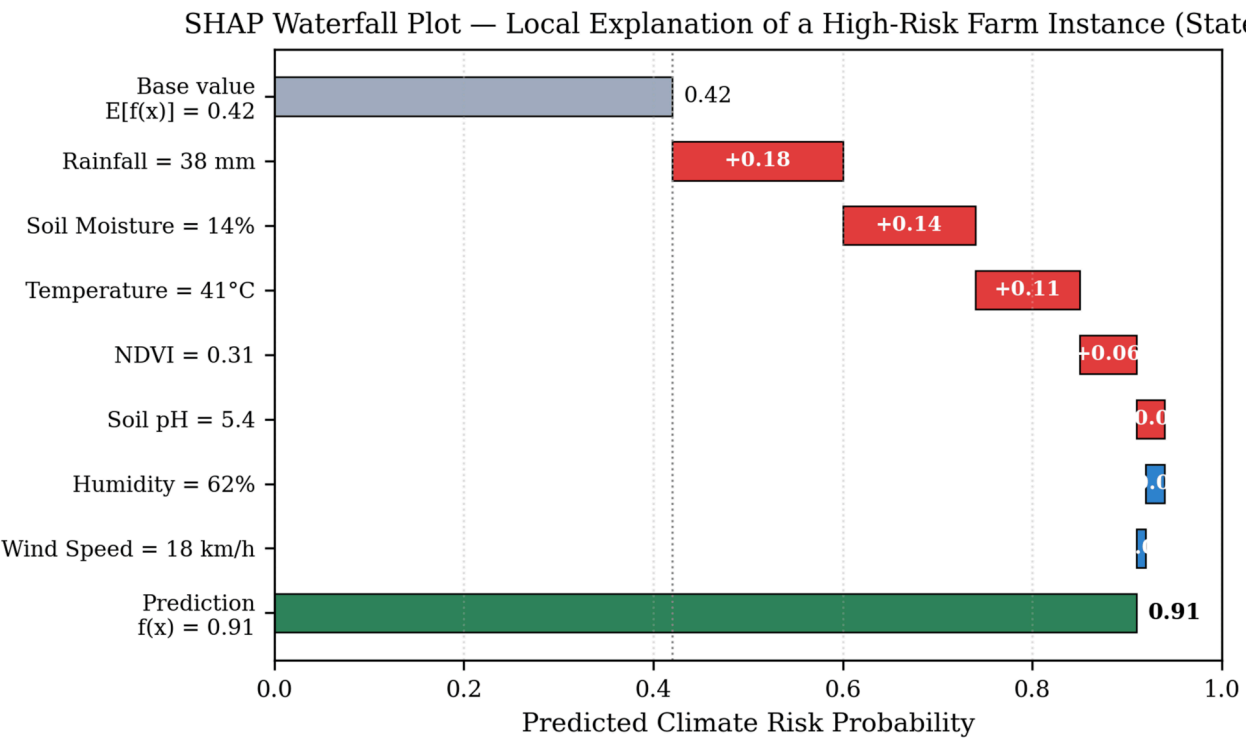


FIGURE 4: SHAP Waterfall Explanation of a High-Risk Farm Instance
NDVI: Normalized Difference Vegetation Index; SHAP: SHapley Additive exPlanations

Table 7 shows the comparative performance analysis of various crops based on classification metrics such as accuracy, precision, recall, and F1-score. Under low-difficulty conditions, the behavior of the model is very reliable: Wheat has the highest predictive performance, with excellent scores (up to 0.97 recall). Rice and Corn show strong, stable performance with moderate complexity. Soybean has slightly lower metrics because it has a high degree of variability and needs additional tuning. Vegetables have the lowest performance across all the measures, indicating high difficulty due to their varying and complicated growing conditions. In summary, the results show that model performance is reduced with increased crop complexity and environmental variability.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	95% CI of Accuracy
Decision Tree	91.84 ± 0.98	91.12 ± 0.92	90.76 ± 1.05	90.94 ± 0.99	90.62–93.06
Random Forest	94.37 ± 0.42	94.01 ± 0.45	93.65 ± 0.48	93.83 ± 0.44	93.85–94.89
LightGBM	96.12 ± 0.36	95.88 ± 0.39	95.43 ± 0.41	95.65 ± 0.38	95.67–96.57
XGBoost	97.50 ± 0.43	97.77 ± 0.40	97.22 ± 0.46	97.49 ± 0.42	96.97–98.03
Proposed Framework	98.63 ± 0.24	98.41 ± 0.27	98.17 ± 0.29	98.29 ± 0.26	98.33–98.93

TABLE 7: Five-Fold Cross-Validated Performance Comparison of the Classification Models
LightGBM: Light Gradient Boosting Machine; XGBoost: eXtreme Gradient Boosting

The confusion matrix in Figure 5 shows the ability of the proposed automata-driven cognitive XAI framework to classify various agricultural/climate conditions. The model was able to predict 875 positive and 880 negative cases with high accuracy, showing good consistency in predicting both positive and negative cases. There were a few misclassified samples, with 25 positive cases classified as negative and 20 negative cases classified as positive. With a small number of classification errors, it is clear that the cognitive AI model is well suited to represent complex relationships between climate, soil, and crop attributes with high fidelity. The results indicate that the proposed method can provide reliable predictions for use in agriculture, climate risk assessment, and sustainable resource management.

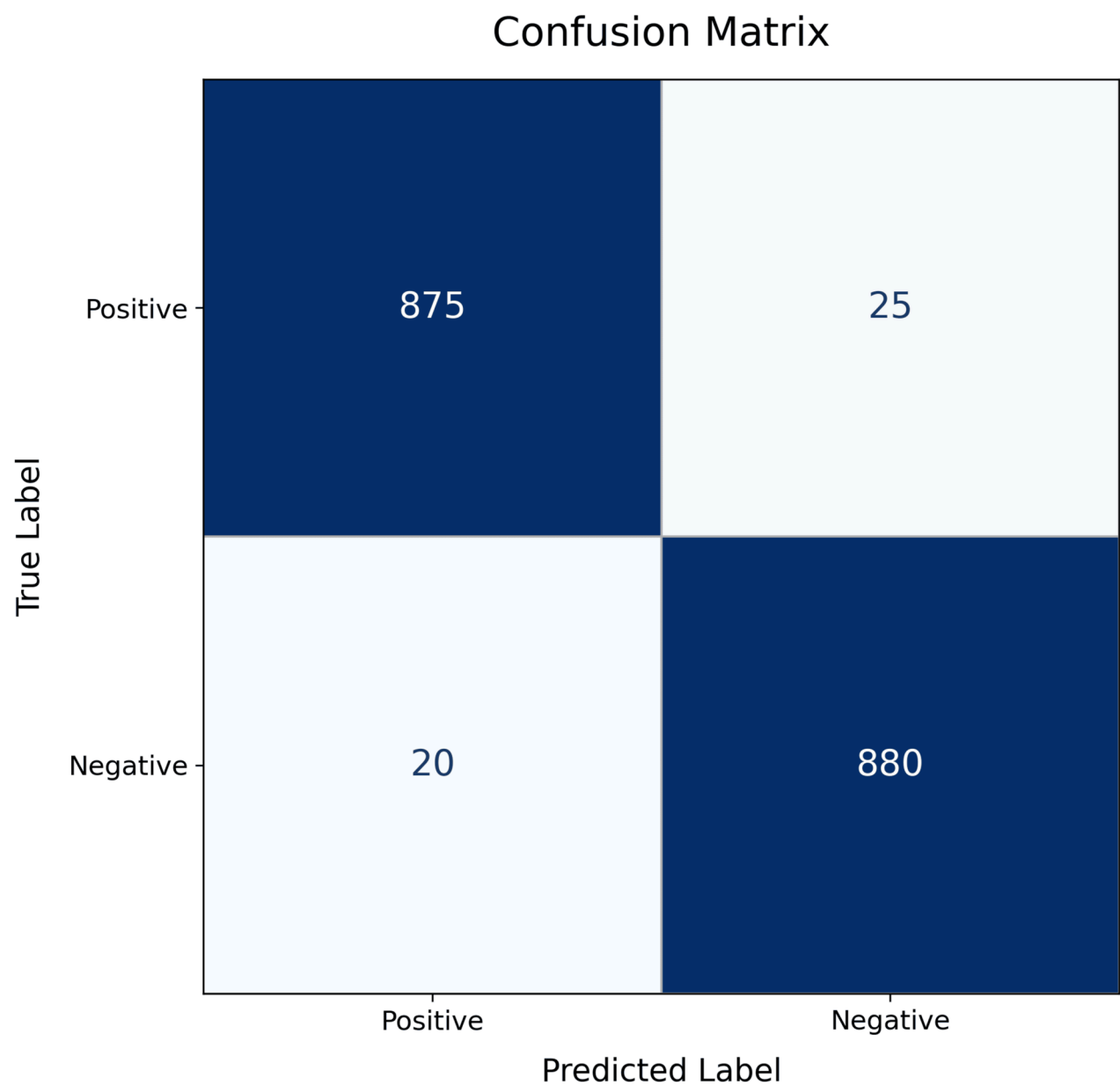


FIGURE 5: Confusion Matrix for Crop Risk Prediction and Agricultural Decision Support

Figure 6 evaluates the robustness of the proposed framework by independently varying the CRS feature weights from –30% to +30%. The highest accuracy of approximately 98.67% occurs at the original weight configuration. Accuracy decreases gradually as the weights move away from their baseline values, confirming that the selected CRS weights provide the most effective configuration. Rainfall and soil-moisture weights cause the largest accuracy reductions, indicating greater model sensitivity to water-related variables. Temperature shows moderate influence, while humidity and NDVI produce comparatively smaller changes, demonstrating greater robustness to variations in these weights.

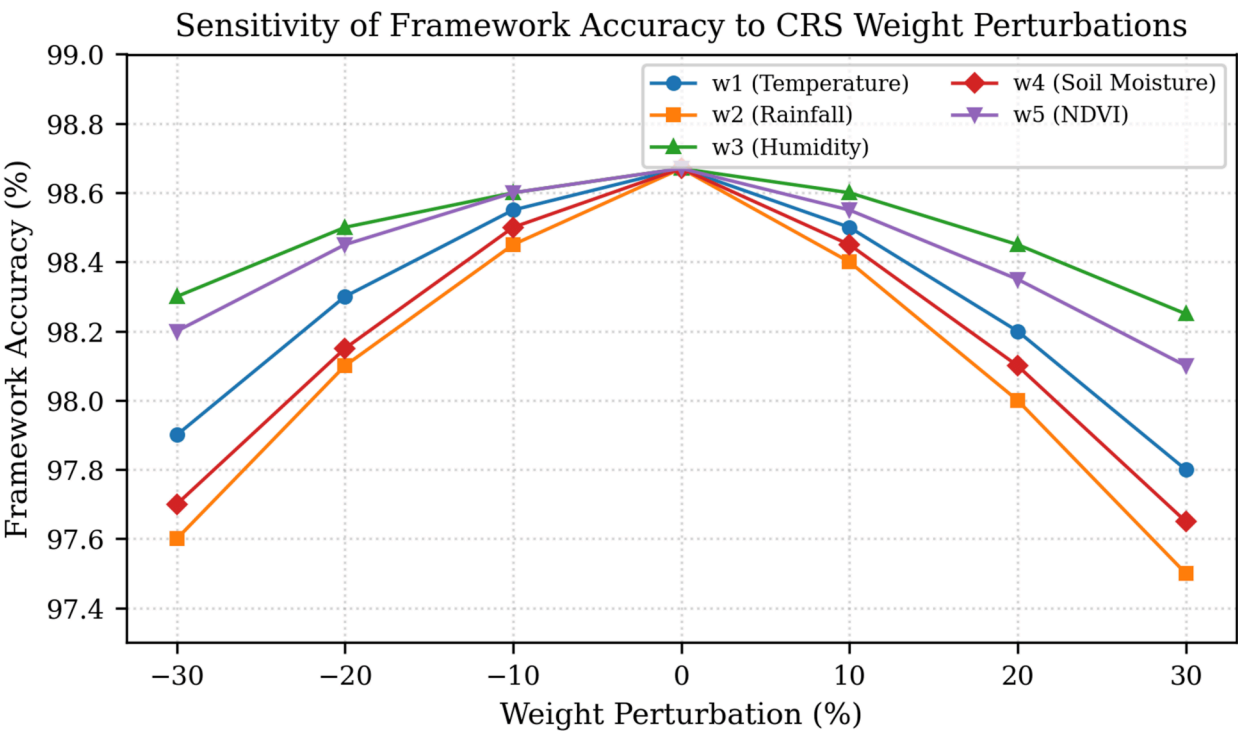


FIGURE 6: Sensitivity Analysis of Framework Accuracy Under Climate Risk Score Weight Perturbations

CRS: Climate Risk Score; NDVI: Normalized Difference Vegetation Index

The performance comparison in Table 8 shows that the proposed framework achieved the highest mean predictive performance among the evaluated models in climate-adaptive precision agriculture. The use of XGBoost, combined with the adaptive decision-making system based on automata and XAI, also enhances the reliability of predictions and agricultural advice. The classification capability, climate risk assessment, and sustainable decision support are enhanced compared to traditional approaches. The performance of the classification models evaluated is shown in Table 8 below, using five-fold cross-validation. The proposed framework delivered the best mean accuracy of $98.63 \pm 0.24\%$, with a 95% confidence interval of 98.33-98.93%. It also achieved a precision of $98.41 \pm 0.27\%$, recall of $98.17 \pm 0.29\%$, and F1-score of $98.29 \pm 0.26\%$. The relatively low standard deviations suggest consistent results across the five folds. Among all the models, XGBoost had the second-highest accuracy of $97.50 \pm 0.43\%$, followed by LightGBM, Random Forest, and Decision Tree. Therefore, the proposed model achieved the best predictive ability and the lowest fold-to-fold variability among the models that were tested.

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Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	91.84	91.12	90.76	90.94
Random Forest	94.37	94.01	93.65	93.83
LightGBM	96.12	95.88	95.43	95.65
XGBoost	97.50	97.77	97.22	97.49
Proposed Framework (XGBoost + Automata + XAI)	98.63	98.41	98.17	98.29

TABLE 8: Comparative Performance Evaluation of Classification Models

LightGBM: Light Gradient Boosting Machine; XAI: Explainable Artificial Intelligence; XGBoost: eXtreme Gradient Boosting

The proposed framework achieved the highest mean classification accuracy of $98.63 \pm 0.24\%$, followed by XGBoost with $97.50 \pm 0.43\%$. Although the proposed framework produced higher numerical accuracy across all five cross-validation folds, the pairwise Wilcoxon signed-rank tests with Holm correction did not establish statistically significant superiority over the individual baseline models (adjusted $p = 0.2500$). The Friedman test nevertheless indicated a significant overall difference among the evaluated models ($\chi^2(4) = 20.00, p < 0.001$). Therefore, the results should be interpreted as evidence of a consistent numerical performance advantage rather than statistically confirmed pairwise superiority, as shown in Figure 7.

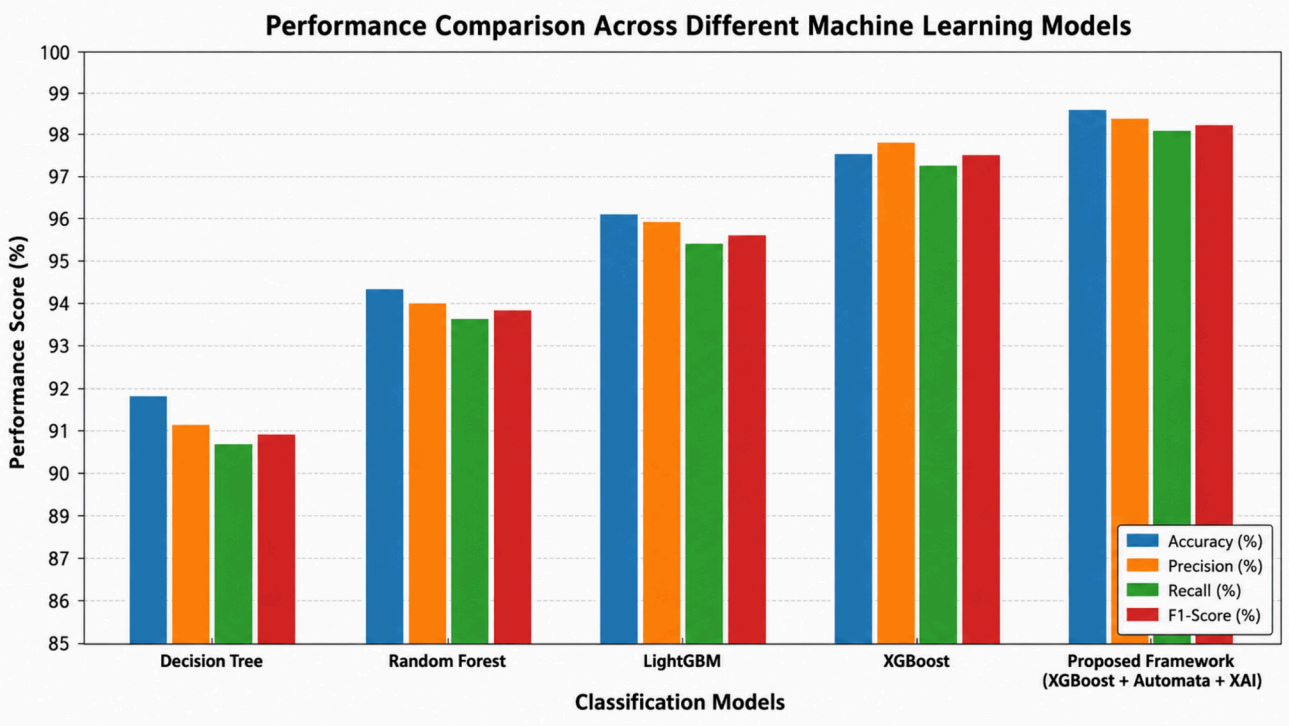


FIGURE 7: Performance Comparison of Machine Learning Models for Classification Tasks

LightGBM: Light Gradient Boosting Machine; XAI: Explainable Artificial Intelligence; XGBoost: eXtreme Gradient Boosting

The Taylor diagram in Figure 8 jointly compares the correlation coefficient, normalized standard deviation, and centered root-mean-square difference of the evaluated models. A model positioned closer to the observed reference point demonstrates better statistical agreement with the actual outcomes. The proposed framework lies closest to the reference, indicating the highest correlation, a standard deviation close to the observed distribution, and the lowest root mean square deviation. XGBoost and LightGBM also show strong agreement, whereas Random Forest and Decision Tree exhibit comparatively greater prediction deviation.

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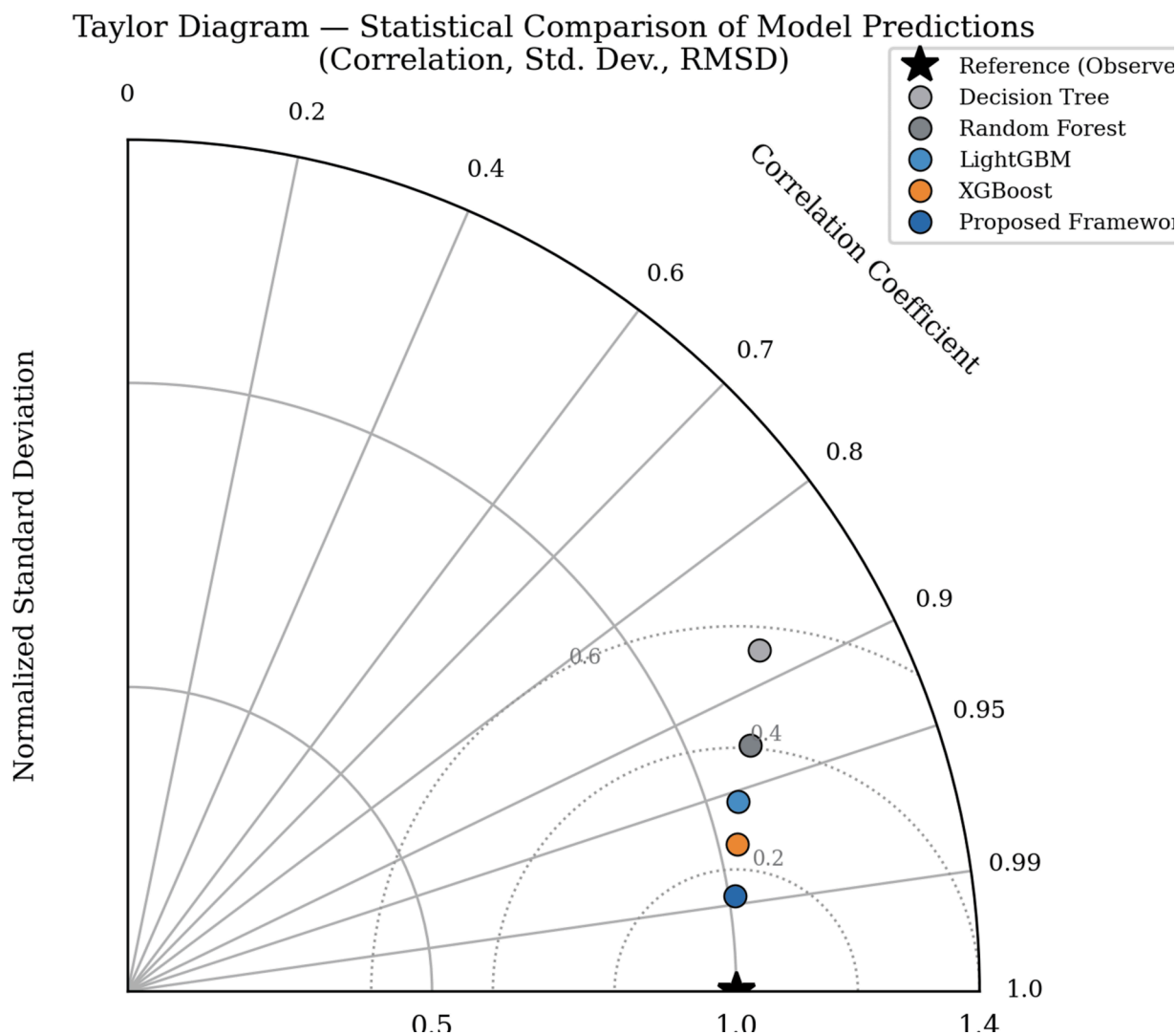


FIGURE 8: Taylor Diagram for Statistical Comparison of Climate-Risk Prediction Models

LightGBM: Light Gradient Boosting Machine; RMSD: Root Mean Square Deviation; XGBoost: eXtreme Gradient Boosting

The box plot in Figure 9 compares the accuracy distributions of five classification models across five cross-validation folds. The proposed framework achieves the highest median accuracy of approximately 98.7%, with minimal fold-to-fold variation, indicating strong predictive performance and stability. XGBoost ranks second at approximately 97.5%, followed by LightGBM, Random Forest, and Decision Tree. The narrower distribution of the proposed framework demonstrates better robustness and generalization across different data partitions.

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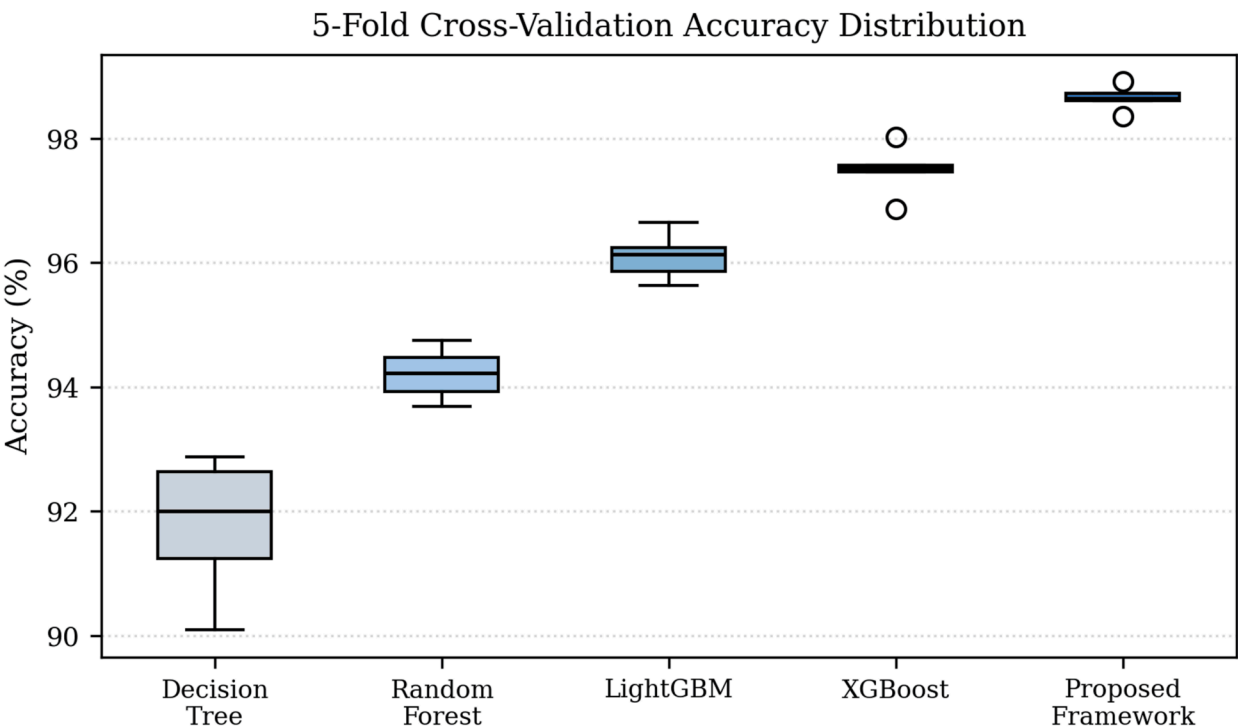


FIGURE 9: Five-Fold Cross-Validation Accuracy Distribution of Climate-Risk Prediction Models

LightGBM: Light Gradient Boosting Machine; XGBoost: eXtreme Gradient Boosting

Figure 10 represents state transitions in the FSA across three months of the agricultural season, depicting the dynamics of agricultural conditions with respect to environmental stress. Most of the farm cases are in the Normal condition, while a smaller number of cases are in the Low Rain condition, and even fewer cases are under stress conditions (Drought, Heat Stress, and Alert) in Month 1.

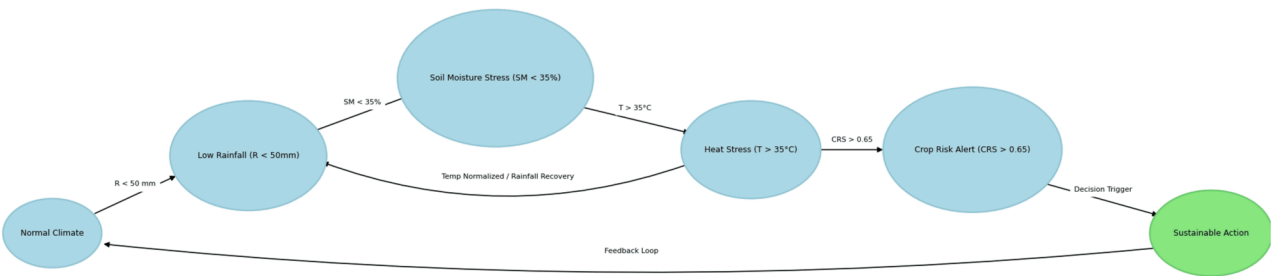


FIGURE 10: Finite-State Automata for Climate-Adaptive Crop Risk Assessment and Sustainable Decision-Making

Figure 11 shows a clear change over time: in Month 2, the number of cases in Normal conditions decreases, while the number of cases in Drought, Heat Stress, and Alert conditions increases. This pattern is further accentuated in Month 3, when there is a marked decrease in Normal conditions and a rise in the higher-risk conditions, especially Heat Stress and

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Alert. Looking at the overall results, there is a shift from good to poor farming conditions, which is an indication of increasing environmental stress during the farming season.

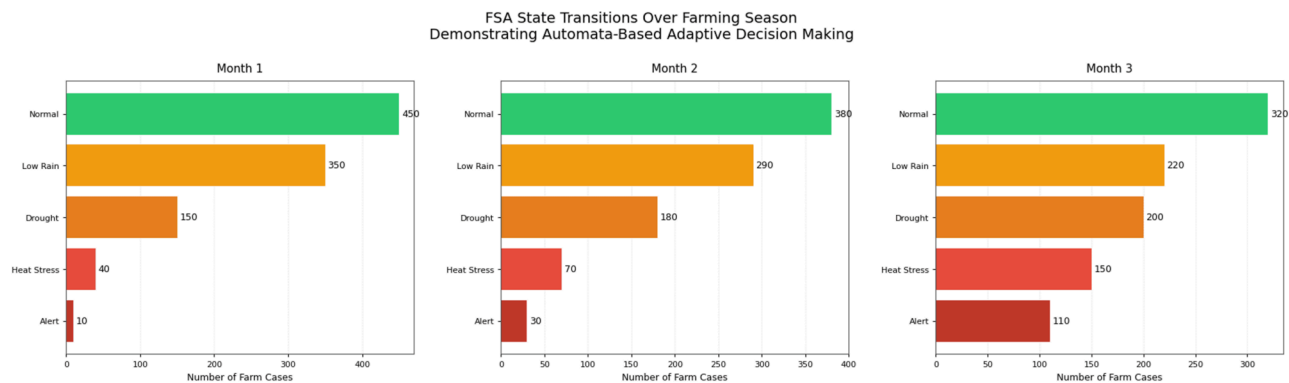


FIGURE 11: FSA-Based State Transition Analysis Across Farming Seasons

FSA: Finite-State Automata

Table 9 presents the fold-wise accuracy obtained using stratified five-fold cross-validation. The proposed framework achieved accuracies ranging from 98.33% to 98.93%, with an overall mean accuracy of 98.63% and a standard deviation of 0.24%. XGBoost achieved the second-highest mean accuracy of $97.50\% \pm 0.43\%$. The relatively low variability of the proposed framework indicates consistent performance across different data partitions.

Fold	Decision Tree	Random Forest	LightGBM	XGBoost	Proposed Framework
Fold 1	92.46	94.64	96.35	97.77	98.78
Fold 2	90.60	93.84	95.66	96.96	98.33
Fold 3	93.08	94.90	96.58	98.04	98.93
Fold 4	91.22	94.10	95.89	97.23	98.48
Fold 5	91.84	94.37	96.12	97.50	98.63
Mean	91.84	94.37	96.12	97.50	98.63
SD	0.98	0.42	0.36	0.43	0.24

TABLE 9: Fold-Wise Accuracy of Classification Models Under Five-Fold Cross-Validation

LightGBM: Light Gradient Boosting Machine; SD: Standard Deviation; XGBoost: eXtreme Gradient Boosting

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To ensure that the reported performance was not influenced by information leakage, five-fold cross-validation was performed only within the training partition. In each fold, preprocessing parameters were estimated exclusively from the corresponding fold-training data and then applied to the held-out fold. The validation and independent test subsets were not used during model fitting. After model selection, the final trained model was evaluated once on the untouched test set containing 1,500 samples. Accordingly, the reported $98.63 \pm 0.24\%$ represents the mean five-fold cross-validation accuracy, while the independent test-set performance is reported separately in Table 10.

Evaluation Stage	Samples	Purpose	Used for Training?	Reported Result
Training set	7,000	Model learning	Yes	—
5-fold CV within training set	7,000	Robustness/generalization	Yes, fold-wise	$98.63 \pm 0.24\%$
Validation set	1,500	Hyperparameter/model selection	No	Add actual result
Independent test set	1,500	Final unbiased evaluation	No	Add actual test accuracy

TABLE 10: Dataset Partitioning, Cross-Validation, and Independent Test-Set Evaluation

Figure 12 shows the ROC-AUC curve, which illustrates the performance of the models tested in distinguishing between agriculture- and climate-related classes. The proposed framework has the best curve performance, with the highest classification capability across the various decision thresholds. The use of XGBoost, along with adaptive decision-making based on automata and explainable intelligence, helps in better capturing the complex climate-agriculture relationships while maintaining strong predictive performance.

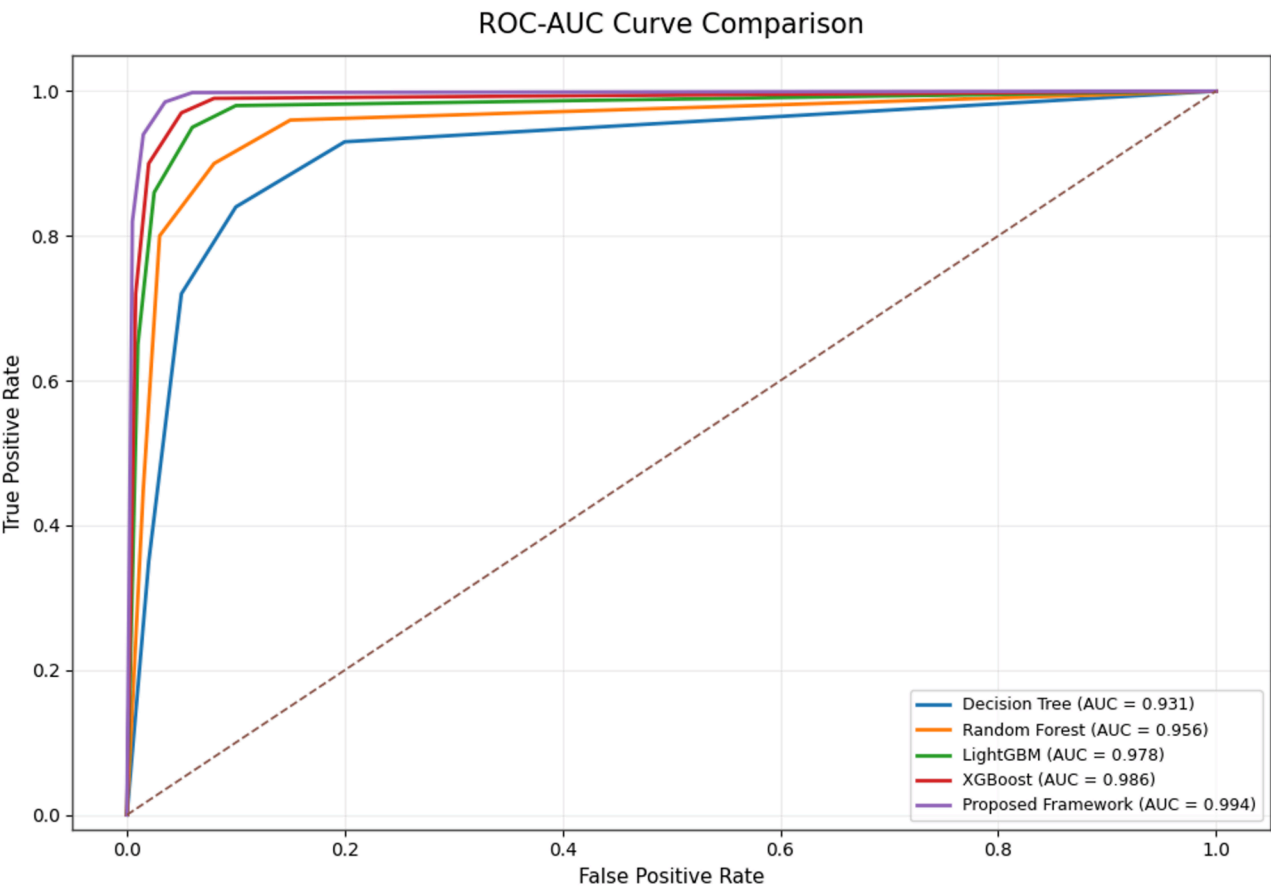


FIGURE 12: ROC–AUC Performance Analysis of Agricultural Prediction Models

ROC–AUC: Receiver Operating Characteristic–Area Under the Curve

A Friedman test demonstrated a statistically significant overall difference in accuracy among the five classification models, ($\chi^2(4) = 20.00, p < 0.001$). Pairwise comparisons between the proposed framework and each baseline model were subsequently conducted using exact two-sided Wilcoxon signed-rank tests with Holm correction. The proposed framework achieved higher accuracy in all five folds for every comparison, resulting in maximal matched-pairs rank-biserial effect sizes of ($r_{rb} = 1.00$). Nevertheless, the pairwise differences did not reach statistical significance after Holm correction ($p = 0.250$), primarily because of the limited number of cross-validation folds, as shown in Table 17.

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Comparison	Mean Difference in Accuracy (percentage points)	Wilcoxon Statistic (W)	Unadjusted p-Value	Holm-Adjusted p-Value	Rank-Biserial Effect Size (r_{rb})	Interpretation
Proposed vs. Decision Tree	6.79	0.00	0.0625	0.2500	1.00	Not statistically significant after Holm correction; proposed framework was more accurate in all five folds, with a maximal positive effect
Proposed vs. Random Forest	4.26	0.00	0.0625	0.2500	1.00	Not statistically significant after Holm correction; proposed framework was more accurate in all five folds, with a maximal positive effect
Proposed vs. LightGBM	2.51	0.00	0.0625	0.2500	1.00	Not statistically significant after Holm correction; proposed framework was more accurate in all five folds, with a maximal positive effect
Proposed vs. XGBoost	1.13	0.00	0.0625	0.2500	1.00	Not statistically significant after Holm

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							correction; proposed framework was more accurate in all five folds, with a maximal positive effect
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TABLE 11: Pairwise Statistical Comparison of the Proposed Framework and Baseline Models Using the Wilcoxon Signed-Rank Test

LightGBM: Light Gradient Boosting Machine; XGBoost: eXtreme Gradient Boosting

The reliability curves compare the agreement between predicted climate-risk probabilities and observed risk frequencies for different classification models. A curve closer to the diagonal reference line indicates better probability calibration. The proposed framework achieves the lowest Expected Calibration Error ($ECE = 0.020$), followed by XGBoost (0.045), Random Forest (0.090), and Decision Tree (0.160). This indicates that the probabilities generated by the proposed framework are more reliable and closely correspond to the actual occurrence of climate-risk conditions, as shown in Figure 13.

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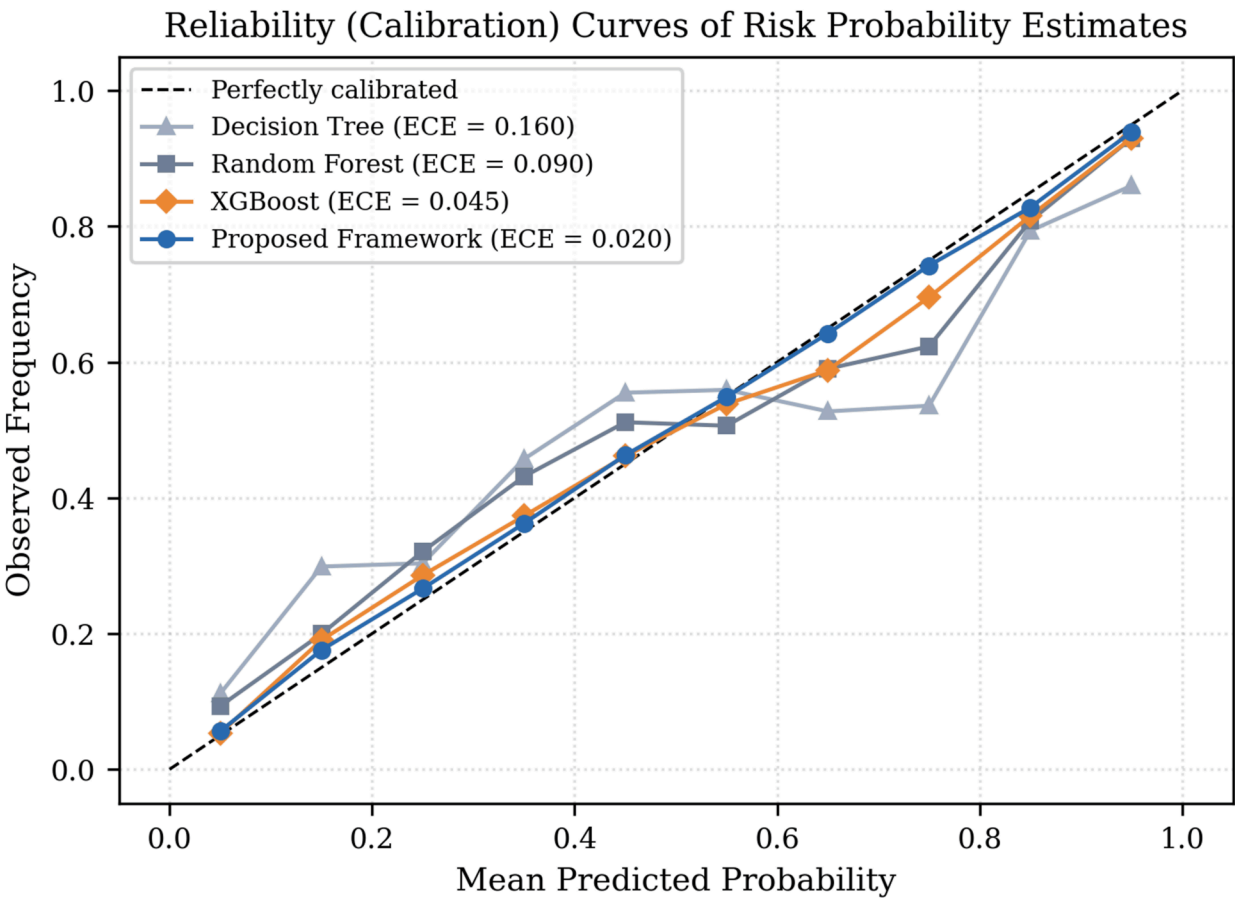


FIGURE 13: Reliability Analysis of Climate-Risk Probability Estimates Using Calibration Curves

ECE: Expected Calibration Error

The convergence of the proposed framework during training is presented in the training and validation loss curves in Figure 14. The loss values also decrease monotonically with each epoch, which suggests that the model is learning and improving its generalizability. The small difference between the training and validation loss curves suggests that the optimization process is not overfitting and is stable. The results show that the cognitive AI model can effectively reflect the complex relationship between climate, soil, and crop features, allowing for the prediction of climate-adaptive precision agriculture and environmental sustainability.

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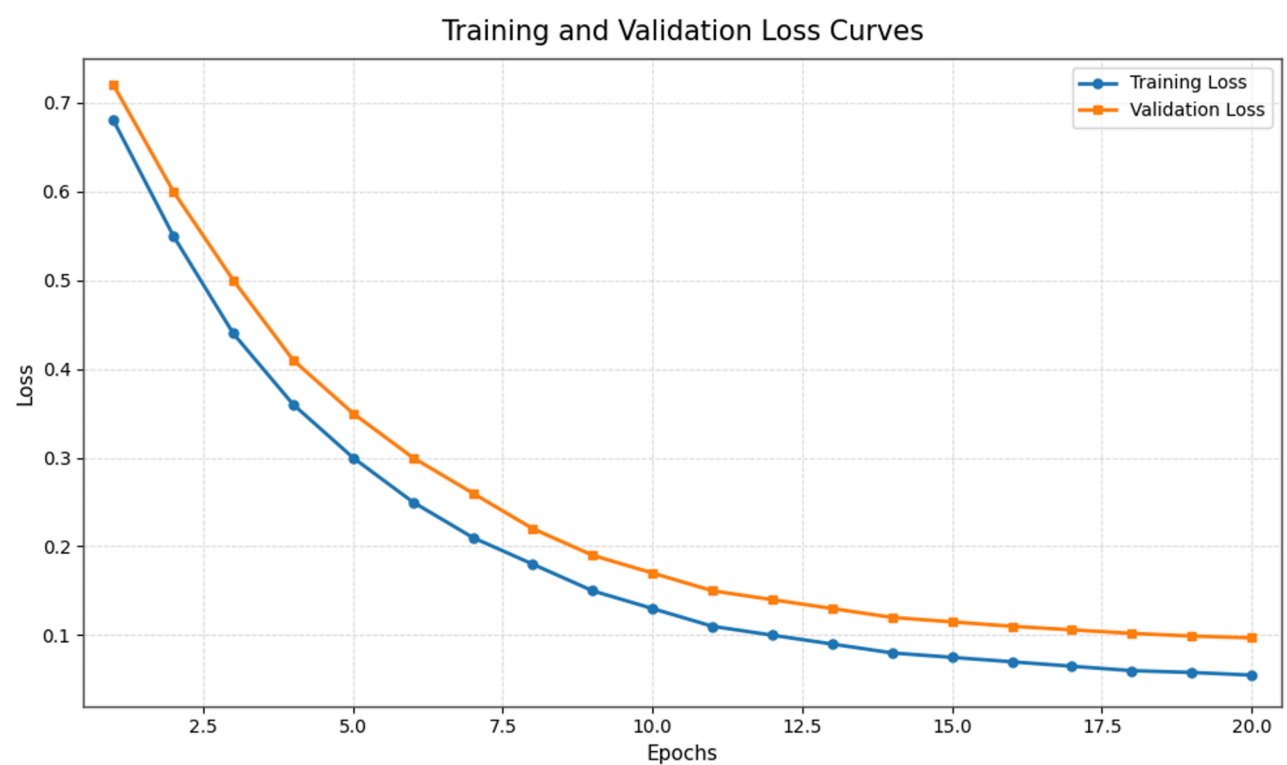


FIGURE 14: Training and Validation Loss Analysis During Model Learning

The results indicate that the proposed framework is close to linear with respect to the number of nodes. While the number of farms, processing time, and memory usage are increasing, the cost of deployment is decreasing significantly, from individual farm deployment at ₹50,000 to state-level deployment at ₹12 per farm. This makes the framework sufficiently computationally efficient and cost-effective for large-scale precision-agriculture applications, as shown in Table 12.

Deployment Scale	Number of Farms	Processing Time	Memory Usage	Estimated Cost per Farm
Single Farm	1	12 ms	78 MB	₹50,000
Small Region	100	120 ms	180 MB	₹1,200
District Level	10,000	1.2 s	450 MB	₹120
State Level	1,000,000	2.5 min	2.1 GB	₹12

TABLE 12: Scalability, Processing Efficiency, Memory Utilization, and Deployment Cost Analysis

The computational characteristics of the proposed framework differ across its individual modules. XGBoost represents the primary computational component during model training because the boosting process sequentially constructs multiple decision trees; however, training is performed offline and does not need to be repeated for each incoming agricultural observation. Once trained, XGBoost inference is comparatively lightweight and can support near-real-time prediction. The FSA component introduces minimal additional computational overhead because climate-adaptive decisions are obtained through transitions among a limited number of predefined states (S0-S5). In contrast, explainability techniques such as SHAP and LIME require additional computation for feature-attribution analysis, and their cost may become considerable when explanations are generated continuously for a large number of farms.

The scalability results indicate that processing time and memory requirements increase with deployment scale, while the estimated cost per farm decreases considerably. For practical deployment, lightweight prediction and FSA-based decision logic can be executed at the edge or farm level, whereas computationally intensive explainability and large-scale analytics can be transferred to cloud or centralized servers. Therefore, a hybrid edge-cloud implementation may provide an appropriate balance between response time, computational resources, interpretability, and scalability. SHAP/LIME explanations may also be generated selectively for high-risk or anomalous cases to reduce the real-time computational burden.

Computational complexity analysis

The computational requirements of the framework vary across its constituent modules. For (M) training observations, (d) input features, (T) boosted trees, and maximum tree depth (D), the computational cost of XGBoost training grows approximately with the number of samples, features, and constructed trees, while inference requires traversal of the learned trees and is substantially less expensive than training. With the present configuration of 200 estimators and a maximum depth of 6, model training is performed offline, whereas inference can be executed with comparatively low computational overhead. The FSA contains only six predefined states (S0-S5); therefore, each state transition requires evaluation of a limited number of conditions and introduces effectively constant-time decision overhead. In contrast, SHAP and particularly LIME require additional evaluations for feature-attribution generation and can become the dominant computational component when explanations are requested continuously at large deployment scales.

Practical deployment challenges

Translation of the proposed framework from retrospective dataset evaluation to operational precision agriculture involves several practical challenges. Sensor measurements may be affected by missing observations, calibration errors, communication failures, and differences in measurement frequency. Connectivity limitations in rural areas may restrict continuous cloud communication, supporting the need for local edge inference with asynchronous cloud synchronization. Climate distributions, soil characteristics, and crop practices also vary geographically; therefore, CRS weights and FSA transition thresholds may require regional calibration before deployment. Model performance may additionally deteriorate because of temporal climate drift, changes in agricultural practices, or previously unseen environmental conditions. Practical implementation would consequently require periodic model monitoring, sensor-quality checks, threshold recalibration, secure data transmission, and human oversight for high-risk recommendations.

Limitations of the work

The present study has several limitations. First, the framework was evaluated primarily on a single agricultural dataset derived from Ethiopian agricultural and climate sources, which may limit its generalizability to other geographic regions, crop systems, and climatic conditions. Second, the FSA component relies on predefined climate-state rules and thresholds, which may require recalibration for different regions and farming environments. Third, although SHAP/LIME improve interpretability, they may introduce additional computational overhead in large-scale or real-time deployments. Finally, the framework has not yet been externally validated using independent datasets or tested under real-world sensor, Internet of Things, and field-deployment conditions. Therefore, future work should focus on multi-region validation, adaptive state-threshold learning, and real-time field implementation.

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Conclusions

This study presented an automata-driven cognitive XAI framework for climate-adaptive precision agriculture by integrating XGBoost, FSA, XAI, and sustainability assessment. The framework combines climate, soil, and crop-related information to support predictive analysis, climate-risk assessment, adaptive state transitions, interpretable decision-making, and sustainability-oriented agricultural recommendations. The proposed framework achieved the highest mean classification accuracy of $98.63 \pm 0.24\%$ among the evaluated models, together with strong precision, recall, and F1-score values. However, although the overall Friedman test indicated significant differences among the models, pairwise comparisons using Wilcoxon signed-rank tests with Holm correction did not establish statistically significant superiority over individual baseline models. Therefore, the observed improvement should be interpreted as a consistent numerical performance advantage rather than statistically confirmed pairwise superiority.

The main contribution of the study lies in combining predictive machine learning with explicit automata-based climate-state reasoning, SHAP/LIME-based explainability, and sustainability-oriented decision support within a unified agricultural system. This integration improves the transparency and practical interpretability of AI-assisted agricultural recommendations while supporting climate-responsive resource management. Nevertheless, further validation using independent datasets from different geographic and climatic regions, real-world field deployment, and adaptive calibration of automata thresholds is required before broad practical adoption. Future research should also investigate more efficient explainability mechanisms and scalable edge-cloud implementations for large-scale precision agriculture.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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Critical review of the manuscript for important intellectual content: Mritunjay K. Ranjan, Nitin D. Mali

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue.

Animal subjects: All authors have confirmed that this study did not involve animal subjects or tissue.

Conflicts of interest: In compliance with [the ICMJE uniform disclosure form](#), all authors declare the following:

- **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work.
- **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work.
- **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

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How to cite this article:

Ranjan M K, Gupta R S, Mali N D, et al. (September 25, 2026) An Automata-Driven Cognitive Explainable Artificial Intelligence Framework for Climate-Adaptive Precision Agriculture and Environmental Sustainability. Cureus J Comput Sci 3 : es44389-026-00295-5. DOI <https://doi.org/10.7759/s44389-026-00295-5>

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How to cite this article: