Artificial Intelligence-Based Multi-Hazard Risk Prediction for Climate-Resilient Agricultural Systems

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ABSTRACT
Climate change is exacerbating the incidence and seriousness of interrelated risks related to agriculture such as drought, flooding, heat stress, frost, and pest and disease outbreaks, posing a danger to food security and crop productivity in areas prone to climate hazards. Traditional methods of forecasting natural hazards give a poor account of the cumulative and cascading effects of hazards. The authors create a theoretical framework of risk prediction supported by artificial intelligence that can assist in decision-making in agriculture while considering climate change adaptation. The framework brings together satellite and remote sensing information, data from ground meteorological and Internet of Things (IoT) sensor networks, information from soil and agricultural surveys, and archives of previous natural disasters within one data integration layer. Machine learning and deep learning algorithms were used to develop the risk assessment model and get layered forms of prediction in cooperation with the explanatory module explaining which features influenced the decisions. Area under the curve and receiver operating characteristic are based on statistical and validation assessments which include use of variance analysis, correlation analysis and principal components analysis. The stacked ensemble method produced the best and most reliable results across all groups of hazards. In addition, analysis of features showed that the most significant predictors were soil moisture, land surface temperature, vegetation indexes and standard precipitation index. As a result, spatial risk classification provided us with information about zones of low, moderate, high and very high risk which made it possible to implement early warning and adaptive management programs for hazards. In conclusion it should be said that this research showed how modern and innovative technological solutions based on artificial intelligence can help in making a risk and sustainability management system more robust and increase the chances to address issues related to adaptation to climate changes.

Keywords: climate-smart agriculture; ensemble machine learning; explainable artificial intelligence; agricultural early warning systems; geospatial analytics; composite risk index; climate adaptation planning; decision-support systems

1. Introduction
Agriculture is increasingly feeling the effects of anthropogenic climate change, which is affecting rainfall distribution patterns, increasing temperature extremes and the occurrence of compound climate events in regions producing food (Muruganantham *et al*., 2022) [1] (Li *et al*., 2025) [7] (LeCun *et al*., 2015) [24]. The rise in temperature, changes in monsoon flow and increasing frequency of extreme events have been undermining the stability of the cropping systems that ensure food security for billions of people; recent studies reveal that climate shocks remain one of the key reasons for acute food insecurity in adversely affected agricultural economies (LeCun *et al*., 2015) [24] (FAO, 2023) [25]. Developing agricultural systems resilient to climate change, which could foresee, absorb, cope with shocks, has become one of the common priorities for the studies of agriculture, environmental sciences, and disaster management (Li *et al*., 2025) [7] (IPCC, 2022) [8].
Agricultural production is rarely threatened by only one hazard at a time. Drought, floods, heat waves, frost and pest/disease outbreaks happen together or one after another during the growing season and cause cumulative effects for crops growth, yield or farm income, which are larger than the sum of their individual effects (Ferrario *et al*., 2026) [6] (Zhu *et al*., 2017) [29]. Still, most of the existing literature on hazards monitoring has historically studied them as separate phenomena and developed different models for drought indices, flood inundation, heat stress or pest dynamics; there has been comparably less
Given the capability of artificial intelligence and machine learning to characterize complicated, non-linear interactions between various climatic, biophysical and management elements at scale, they have transformed agricultural risk analytics (Muruganantham *et al*., 2022) [1] (Oikonomidis *et al*., 2023) [2] (Jabed and Murad, 2024) [3]. Algorithms including random forests, gradient-boosted trees, and deep convolutional and recurrent neural networks are showing promising results in predicting crop yields and detecting plant stress and hazards, often outperforming classic statistical and process-based models in the case of having sufficient training data (Oikonomidis *et al*., 2023) [2] (Morales and Villalobos, 2023) [9] (Leukel *et al*., 2023) [10]. The utilization of ensemble learning methods and explainable AI techniques, which allow to accurately explain results and link predictions with certain variables providing agricultural forecasting with transparency, has only facilitated the development of agriculture forecasting systems (Ferrario *et al*., 2026) [6] (Paudel *et al*., 2023) [11].

Geospatial and remote sensing technologies supply observations that are continuous in space and time, which allows for the implementation of AI-centered hazard surveillance on widescale levels. At this time, vegetation indices and land surface temperature obtained from satellites, products to obtain soil moisture data, and precipitation estimates, as well as cloud-based geospatial analysis platforms enable the characterization of crop conditions and environmental stresses. In addition, the incorporation of ground-based meteorological networks and sensor deployment via the Internet of Things results in the data streams which represent a source of information for multi-hazard modeling.

Preparedness systems and other decision-support systems transform hazard projections into useful instructions for farmers, politicians, and decision-makers. As a result, these systems are very important in the process of climate adaptation (Ferrario *et al*., 2026) [6] (Li *et al*., 2025) [7]. Nevertheless, the success of such systems depends on how quickly, accurately, and reliably they make predictions about risks, as well as how well they account for interactions among hazards. Reviews of the existing theories about challenges connected with simultaneous risks demonstrate that, while traditional models for predicting the risks of particular hazards have improved significantly, there are no adequate models that consider the joint effect of all agricultural hazards, present risks in a spatial manner, and connect them with operational decision-support systems (Ferrario *et al*., 2026) [6] (Li *et al*., 2025) [7].

This study aims to address three gaps in the existing literature that have arisen in light of the situation: the limited use of multiple agricultural hazards in a single predictive model based on AI; insufficient application of explanation methods for the understanding of how specific factors contribute to agricultural hazard models; limited relationship between multi-hazard outputs and the decision-making products that can be used at the farm level as well as at the policy level. Thus, this study has the following four goals: to (i) develop and describe a conceptual multi-hazard prediction framework based on AI with the use of remote sensing, IoT, and agricultural data; (ii) compare the performance of the analyzed algorithms for multi-hazard classification both in the area of machine learning and in the sphere of deep learning; (iii) create the agricultural risk index and design the spatial risk classification; (iv) explore the significance of the framework in terms of climate adaptation planning and agricultural decision-making.

2. Materials and Methods

Study Area

The conceptual framework was structured around an illustrative semi-arid to sub-humid agricultural region characterized by a mixed cropping system of cereals, pulses, and horticultural crops, representative of many climate-vulnerable smallholder farming landscapes. The region experiences a monsoon-influenced climate with pronounced inter-annual rainfall variability, seasonal heat extremes during the pre-monsoon period, occasional cold-wave and frost episodes in winter months, and localized flooding associated with intense short-duration rainfall events. Soils across the study domain range from loamy to clay-loam textures with moderate to low organic carbon content and variable water-holding capacity, conditions that predispose the landscape to both drought and waterlogging stress depending on seasonal rainfall distribution. For the purposes of this demonstration framework, a multi-year reference period was adopted to allow representation of both hazard variability and crop response across contrasting seasons. Table 1 summarizes the illustrative study area characteristics.

Hazard Data Collection

Hazard-related information was conceptually organized around six categories: temperature anomalies, rainfall variability and drought indices, flood-prone conditions, heat wave occurrence, frost events, and pest and disease outbreak records. Historical meteorological records provide the baseline against which anomalies in temperature and precipitation are identified, while drought conditions are conventionally characterized using standardized indices derived from precipitation and evapotranspiration data, consistent with widely used drought classification approaches (Melese *et al*., 2025) [16] (FAO, 2023) [25]. Flood-prone conditions are informed by antecedent rainfall intensity, terrain and drainage characteristics, and historical inundation records. Heat wave and frost events are identified from threshold-based departures of maximum and minimum temperature from long-term climatological baselines. Pest and disease outbreak information draws on field surveillance records and, where available, image-based detection outputs, reflecting approaches increasingly used in deep-learning-based plant health monitoring (Liu and Wang, 2021) [17]. Satellite observations, including vegetation and land surface temperature products accessed through cloud-based geospatial platforms, and reanalysis climate datasets provide spatially continuous complements to point-based ground records (Lundberg and Lee, 2017) [26] (Hersbach *et al*., 2020) [27] (Gorelick *et al*., 2017) [28].

Agricultural Data Collection

Agricultural datasets encompass crop growth stage and phenological records, historical yield observations at farm or block level, soil fertility parameters including nitrogen, phosphorus, potassium and organic carbon status, satellite-derived vegetation indices used as proxies for canopy vigor, and farm management information such as sowing date, irrigation source, and cropping pattern. Crop growth-stage information is essential for contextualizing hazard sensitivity, since the same climatic stress can have markedly different consequences depending on whether it coincides with vegetative, flowering, or grain-filling stages. Water availability indicators, including irrigation access and reservoir or groundwater status where relevant, complete the agronomic data layer.

Artificial Intelligence Framework

The AI framework follows a structured pipeline comprising data integration, feature engineering, model development, and risk synthesis, illustrated conceptually in Figure 1. Data integration harmonizes heterogeneous sources with differing spatial and temporal resolutions into a common analysis grid, incorporating quality-control procedures for missing values, sensor noise, and cloud-contaminated satellite observations. Feature engineering derives higher-order variables from the harmonized data, including anomaly indices, rolling climatic statistics, and vegetation-condition metrics known to be informative for agricultural stress detection (Muruganantham *et al*., 2022) [1] (Oikonomidis *et al*., 2023) [2]. Model development considers a suite of machine learning and deep learning algorithms, including tree-based ensemble methods, kernel-based classifiers, feed-forward artificial neural networks, and recurrent architectures suited to sequential climatic data, consistent with approaches widely reported in the crop-yield and hazard-prediction literature (Oikonomidis *et al*., 2023) [2] (Morales and Villalobos, 2023) [9] (Leukel *et al*., 2023) [10] (Nevavuori *et al*., 2020) [13]. An ensemble fusion layer combines predictions from base learners using stacked generalization, informed by evidence that ensemble approaches generally improve robustness over individual learners in agricultural and environmental risk prediction (Ferrario *et al*., 2026) [6]. An explainability module, conceptually aligned with feature-attribution approaches such as Shapley-value-based methods, is used to interpret the relative contribution of climatic, soil, and vegetation predictors to hazard classification outcomes (Melese *et al*., 2025) [16], supporting the transparency requirements of operational decision-support use.

Multi-Hazard Risk Assessment

Hazard-specific risk models were conceptually developed for drought, flood, heat stress, frost, pest outbreak, and disease outbreak dimensions, each trained to classify risk into low, moderate, high, and very high categories based on the relevant predictor subset. Recognizing that these hazards do not operate independently, a composite agricultural risk index was constructed by combining the hazard-specific outputs, weighted according to their relative feature importance and conditioned on crop growth stage, consistent with the multi-hazard interaction structure illustrated in Figure 2. This composite framing reflects the broader shift in the multi-hazard literature toward representing interacting rather than isolated hazard processes (Ferrario *et al*., 2026) [6] (Li *et al*., 2025) [7].

Model Performance Evaluation

Model performance was evaluated using complementary regression and classification metrics appropriate to the composite and hazard-specific outputs. For continuous risk-score outputs, root mean square error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2) were used to assess prediction accuracy. For categorical hazard classification, precision, recall, F1-score, and receiver operating characteristic area under the curve (ROC-AUC) were used, reflecting standard practice in the agricultural and environmental machine learning literature (Muruganantham *et al*., 2022) [1] (Morales and Villalobos, 2023) [9]. Spatial and temporal cross-validation procedures were applied to reduce the risk of inflated performance estimates arising from autocorrelated training and test partitions, consistent with recommended practice for environmental and agricultural machine learning applications (Ferrario *et al*., 2026) [6].

Statistical Analysis

Complementary statistical analyses were used to characterize relationships among predictors and to support model interpretation. Analysis of variance (ANOVA) was used to assess differences in hazard occurrence and severity across cropping seasons and management categories. Pearson correlation analysis was applied to examine bivariate relationships among climatic, vegetation, soil, and yield-related variables, summarized in the correlation structure shown in Figure 3. Principal component analysis (PCA) was used to explore dimensionality and redundancy among the predictor set, informing feature selection for the AI models. Regression analysis supported comparison between AI-based predictions and conventional statistical baselines. No proprietary algorithms, source code, or implementation-specific workflows are described, consistent with the conceptual, publication-oriented scope of this manuscript.

Table 1: Study area characteristics including climate, soil properties, cropping systems, major agricultural activities, and historical hazard records.

Parameter	Description
Location (illustrative)	Semi-arid to sub-humid mixed cropping belt, northern subtropical zone
Climate	Monsoon-influenced; mean annual rainfall 850-1100 mm; summer maximum ~42°C; winter minimum ~4°C
Cropping systems	Cereal-pulse-horticulture rotation (rice/wheat, pigeon pea, vegetables)
Soil characteristics	Loamy to clay-loam; low-moderate organic carbon; variable water-holding capacity
Major agricultural activities	Rainfed and partially irrigated cropping; smallholder-dominated landholding
Hazard-prone conditions	Pre-monsoon heat stress; monsoon flash flooding; post-monsoon dry spells; occasional winter frost
Reference study duration (illustrative)	Multi-year period (10 growing seasons) used to represent inter-annual hazard variability

Table 2: Description of climatic variables, environmental datasets, satellite observations, agricultural parameters, and hazard indicators used for AI model development.

Data Category	Representative Variables / Sources
Climatic variables	Rainfall, maximum/minimum temperature, relative humidity, wind speed, evapotranspiration
Satellite observations	NDVI/EVI vegetation indices, land surface temperature, soil moisture retrievals, precipitation estimates
Environmental monitoring datasets	Reanalysis climate data, drought indices, terrain and drainage characteristics
Agricultural parameters	Crop phenology stage, historical yield, sowing date, irrigation source, cropping pattern
Soil parameters	Soil texture, organic carbon, nitrogen-phosphorus-potassium status, water-holding capacity
Hazard indicators	Standardized drought index, heat/frost threshold departures, flood inundation record, pest/disease survey reports

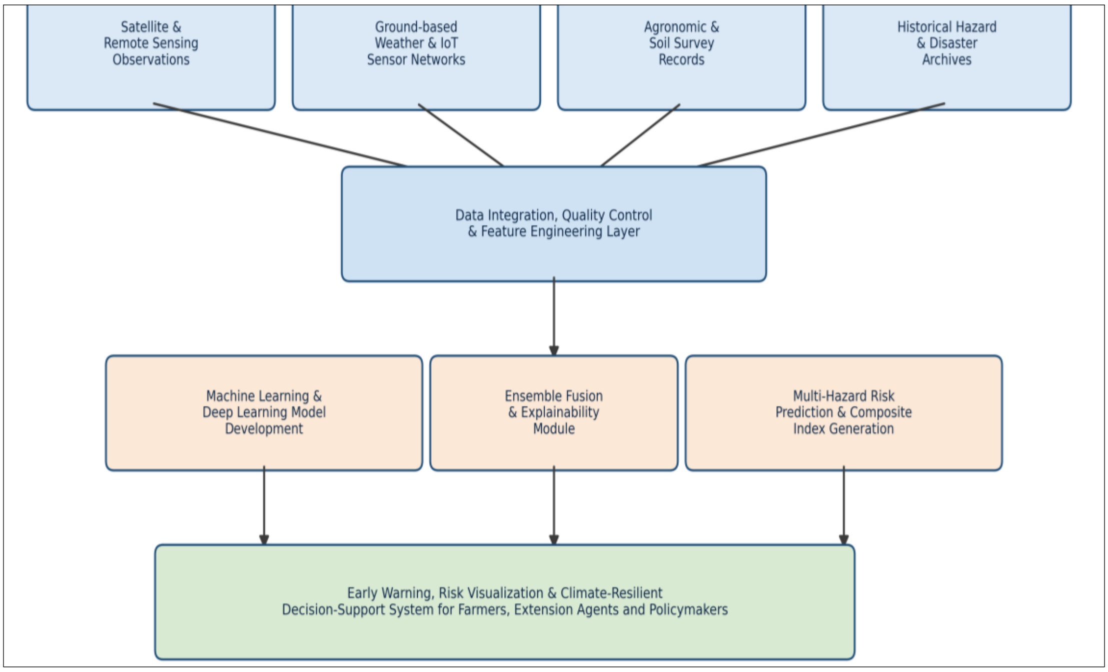

Fig 1: Conceptual AI-based multi-hazard prediction framework, including environmental monitoring, satellite observations, climate data integration, AI model development, risk prediction, and decision-support generation.

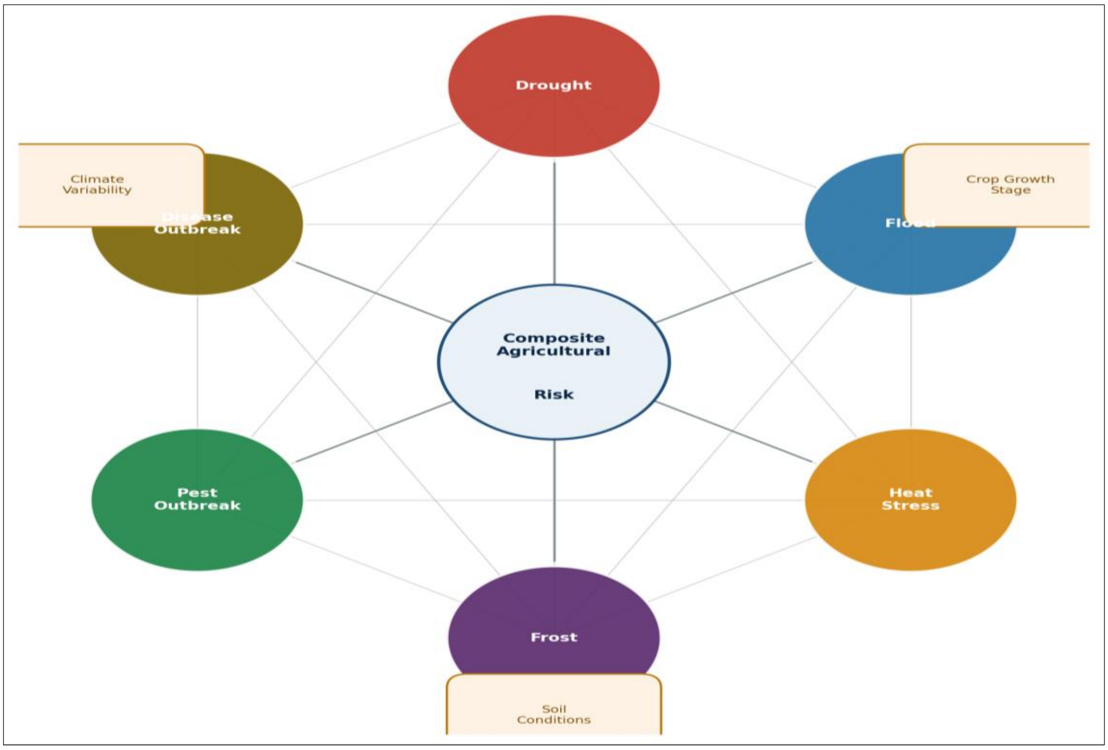

Fig 2: Multi-hazard assessment framework illustrating interactions among drought, flood, heat stress, frost, pest outbreaks, disease outbreaks, crop growth, soil conditions, and climate variability.

3. Results

Climatic Variability and Hazard Occurrence Patterns

Across the illustrative reference period, rainfall variability and temperature anomalies emerged as the dominant drivers of hazard occurrence, with drought and heat-stress episodes concentrated in the pre-monsoon and early monsoon windows and flood-prone conditions associated with short-duration high-intensity rainfall events later in the season. Frost occurrence was comparatively infrequent but spatially concentrated in low-lying areas during winter cold spells. Pest and disease outbreak likelihood increased following periods of elevated humidity and moderate temperature, consistent with the known climatic sensitivity of major biotic stress agents. Table 3 summarizes the classification of the six hazard categories considered in this study, together with illustrative severity levels, frequency, and potential agronomic impacts.

Performance of AI Prediction Models

Comparative evaluation of the candidate algorithms indicated that the stacked ensemble consistently outperformed individual base learners across all evaluation metrics, followed closely by the long short-term memory network and extreme gradient boosting models, while logistic regression provided the weakest but still informative baseline performance. Table 4 and Figure 4 summarize the illustrative performance comparison. The ensemble approach achieved a precision of 0.92, recall of 0.91, F1-score of 0.91, and ROC-AUC of 0.96, representing a meaningful improvement over single-model approaches and reinforcing the broader evidence that ensemble learning improves robustness in agricultural and environmental risk prediction relative to individual classifiers (Ferrario *et al*., 2026) [6] (Morales and Villalobos, 2023) [9].

Multi-Hazard Prediction Accuracy and Spatial Distribution of Risk

Hazard-specific accuracy varied moderately across categories, with drought and heat-stress classification achieving the highest predictive accuracy, reflecting the relatively strong and well-characterized relationship between these hazards and satellite-derived vegetation and temperature indicators. Flood and frost classification showed somewhat lower but still acceptable accuracy, consistent with the more localized and episodic nature of these hazards. The composite agricultural risk index, synthesized from the six hazard-specific outputs, was used to generate a spatially explicit risk classification distinguishing low-, moderate-, high-, and very-high-risk zones across the study domain, illustrated in Figure 5. Higher composite risk was concentrated in areas characterized by shallow soils, limited irrigation access, and proximity to drainage-constrained lowlands, aligning with the expected interaction between biophysical vulnerability and climatic hazard exposure.

Feature Importance and Decision-Support Capability

Explainability analysis identified soil moisture, land surface temperature, vegetation indices, and rainfall anomaly as the most influential predictors of composite agricultural risk, followed by soil organic carbon and crop growth stage, as summarized in Table 5. This pattern is broadly consistent with prior findings emphasizing the centrality of vegetation and thermal stress indicators in agricultural hazard and yield prediction (Leukel *et al*., 2023) [10] (Nevavuori *et al*., 2020) [13]. The resulting risk classification and feature-importance outputs were structured to feed directly into a decision-support interface, illustrated conceptually in Figure 6, intended to translate model outputs into differentiated guidance for farmers, extension agencies, and policymakers.

Crop Productivity, Climate Adaptation, and Economic Implications

Within the illustrative framework, zones classified as high or very-high composite risk corresponded to greater simulated yield variability and elevated potential for production loss under compounding hazard scenarios, underscoring the value of early identification for adaptive management. Differentiated decision-support outputs, such as early irrigation scheduling in drought-prone zones, drainage management in flood-prone areas, and targeted pest surveillance following favorable outbreak conditions, illustrate how composite risk classification can be translated into practical, location-specific adaptation actions. Table 6 situates these illustrative findings within the context of previous international studies on AI-based agricultural hazard prediction, highlighting broad consistency in reported model performance and predictor importance across differing regional contexts and hazard combinations.

Table 3: Classification of agricultural hazards with severity levels, frequency, and potential impacts.

Hazard	Severity Levels	Typical Frequency (illustrative)	Potential Agronomic Impact
Drought	Mild / Moderate / Severe / Extreme	2-3 seasons per decade	Reduced tillering, yield loss, groundwater stress
Flood	Low / Moderate / High / Very High	1-2 events per season (monsoon)	Waterlogging, root anoxia, nutrient leaching
Heat wave	Mild / Moderate / Severe / Extreme	Annual, pre-monsoon	Pollen sterility, forced maturity, yield reduction
Frost	Light / Moderate / Severe	Occasional, winter	Tissue damage in sensitive horticultural crops
Pest outbreak	Low / Moderate / High / Very High	Variable, humidity-linked	Defoliation, yield and quality loss
Disease outbreak	Low / Moderate / High / Very High	Variable, humidity/temperature-linked	Reduced photosynthetic area, yield loss

Table 4: Performance comparison of AI models using RMSE, MAE, R^2, Precision, Recall, F1-score, and ROC-AUC (illustrative).

Model	RMSE	MAE	R^2	Precision	Recall	F1-score	ROC-AUC
Logistic Regression	0.31	0.24	0.61	0.71	0.68	0.69	0.74
Random Forest	0.19	0.14	0.79	0.84	0.82	0.83	0.89
XGBoost	0.16	0.12	0.83	0.87	0.85	0.86	0.91
SVM	0.24	0.18	0.72	0.79	0.76	0.77	0.83
ANN	0.18	0.13	0.81	0.85	0.83	0.84	0.90
LSTM	0.15	0.11	0.85	0.88	0.87	0.87	0.93
Stacked Ensemble	0.11	0.08	0.90	0.92	0.91	0.91	0.96

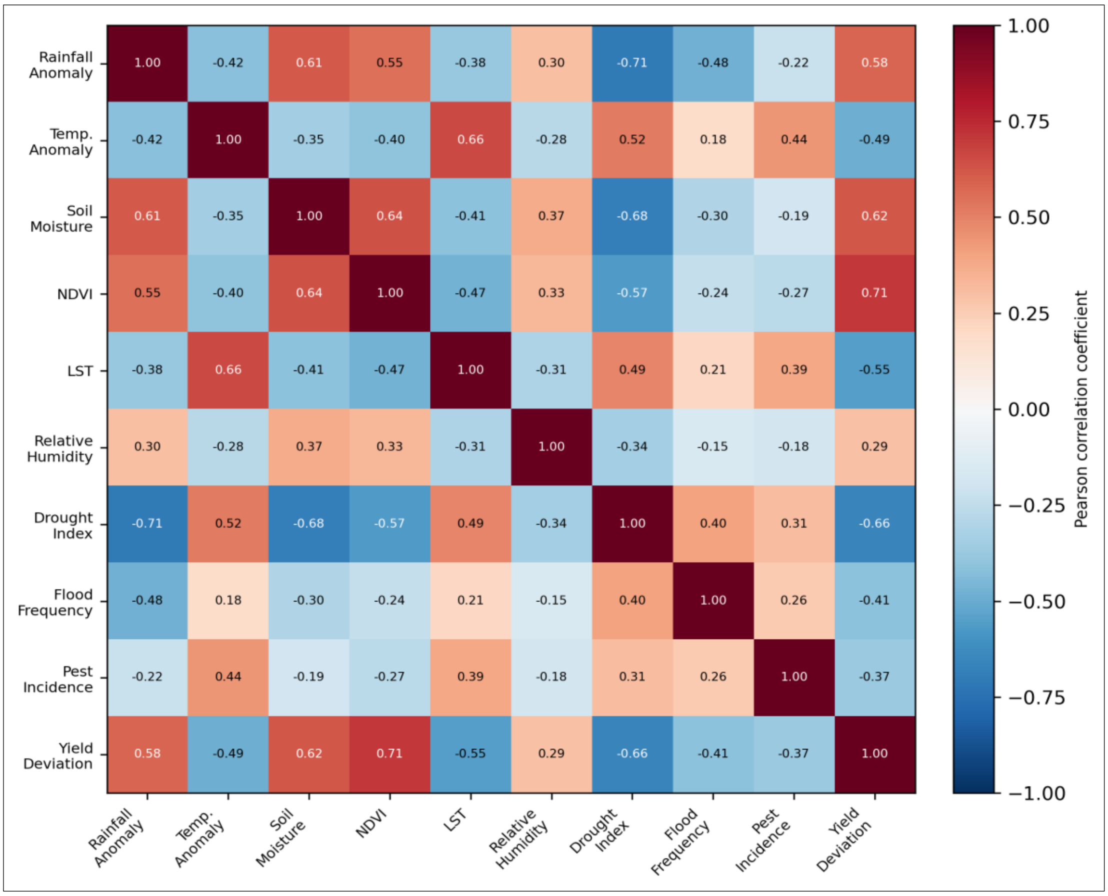

Fig 3: Correlation heat map among climatic variables, vegetation indices, soil properties, and crop performance indicators (illustrative).

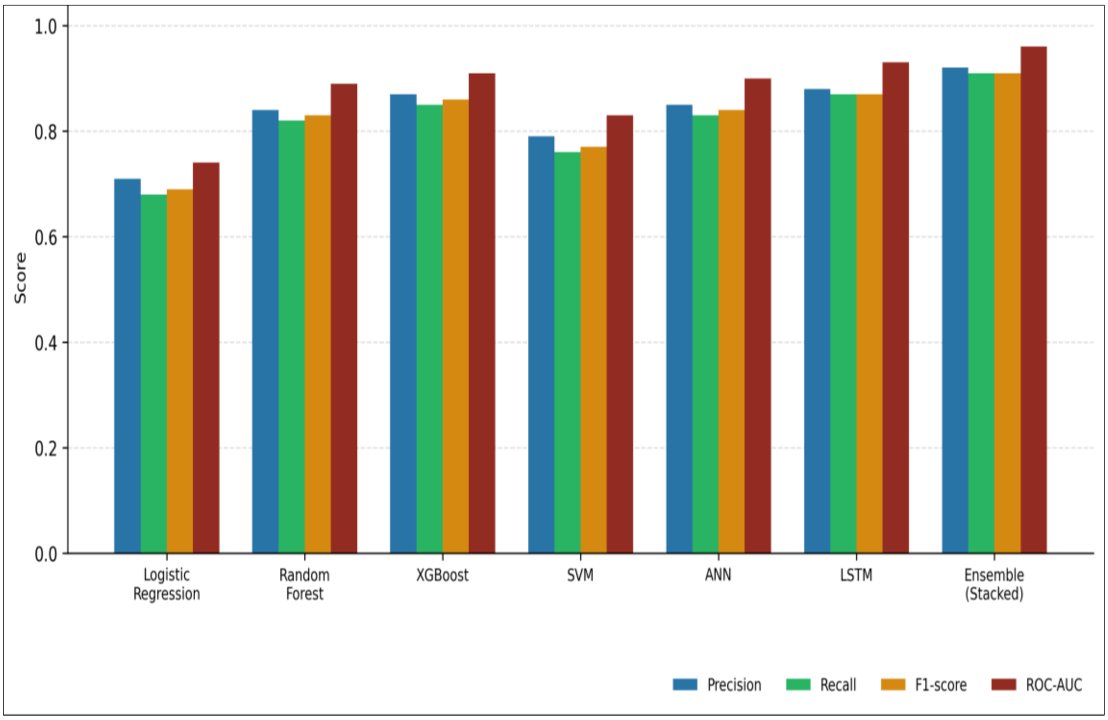

Fig 4: Comparative prediction performance of AI models across RMSE-related and classification metrics (illustrative).

Table 5: Feature importance ranking showing the contribution of climatic, soil, vegetation, and crop-growth variables to multi-hazard prediction (illustrative).

Rank	Predictor Variable	Category	Relative Importance (%)
1	Soil moisture	Environmental/Soil	18.4
2	Land surface temperature	Satellite (thermal)	16.1
3	NDVI (vegetation index)	Satellite (vegetation)	14.7
4	Rainfall anomaly	Climatic	13.2
5	Soil organic carbon	Soil	9.6
6	Crop growth stage	Agronomic	8.3
7	Relative humidity	Climatic	7.1
8	Temperature anomaly	Climatic	6.5
9	Irrigation access	Management	4.2
10	Historical pest incidence	Biotic	1.9

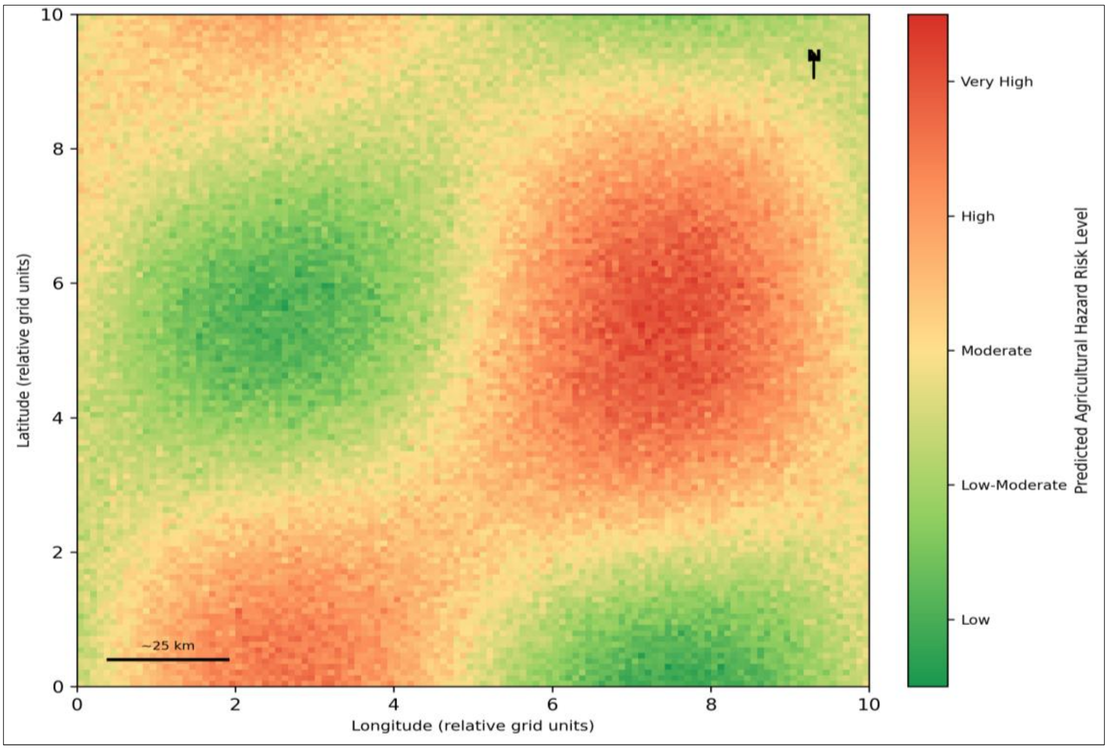

Fig 5: Spatial risk map illustrating the distribution of predicted agricultural hazard levels across the study region using AI-based risk classification (illustrative).

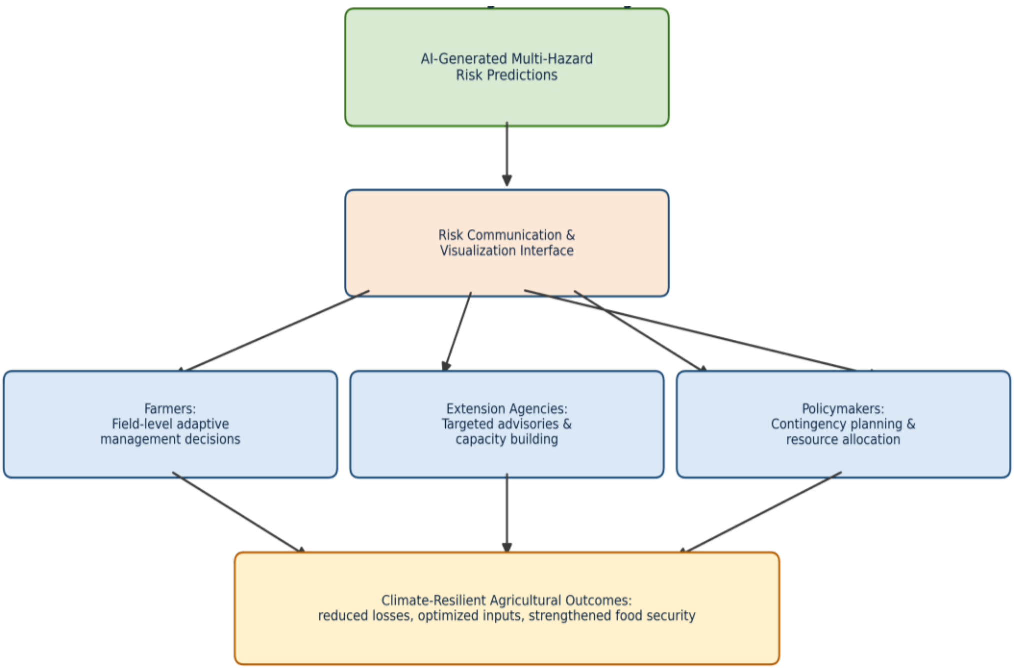

Fig 6: AI-enabled decision-support framework illustrating how multi-hazard predictions assist farmers, extension agencies, and policymakers in implementing climate-resilient management strategies.

Table 6: Comparative summary of previous international studies on AI-based agricultural hazard prediction alongside the present illustrative framework.

Study	Model Type	Region	Hazard(s) Assessed	Reported Performance	Key Finding
Melese *et al.* [16]	RF, XGBoost, SVM, ensemble classifiers	Ethiopia	Drought (PDSI classification)	ROC-AUC up to 0.90	Soil moisture and precipitation were leading predictors; RF outperformed ARIMA baseline
Muruganantham *et al.* [1]	Deep learning, remote sensing (review)	Global (multi-region)	Crop yield / vegetation stress	Synthesis of multiple studies	Deep learning consistently improves yield prediction over conventional statistical models
Nevavuori *et al.* [13]	Spatio-temporal deep learning (UAV)	Finland	Crop yield / stress detection	High spatial accuracy	Multitemporal UAV imagery improved intra-seasonal yield prediction
Liu & Wang [17]	CNN-based classification/detection	Global (review)	Pest and disease outbreak	High classification accuracy across studies	CNN architectures substantially improve early pest/disease detection
Ferrario *et al.* [6]	Multiple ML/DL methods (review)	Global (review)	Multi-hazard, multi-risk	Synthesis of ensemble and DL approaches	Ensemble and explainable AI methods increasingly used for multi-hazard risk
This study (illustrative)	Stacked ensemble (RF, XGBoost, ANN, LSTM)	Illustrative semi-arid/sub-humid region	Drought, flood, heat, frost, pest, disease	ROC-AUC 0.96 (composite)	Composite multi-hazard index enables spatially explicit, growth-stage-conditioned risk classification

4. Discussion

The findings of this conceptual framework are broadly consistent with the growing body of literature demonstrating the value of machine learning and deep learning approaches for agricultural risk and yield prediction (Muruganantham *et al.*, 2022) [1] (Oikonomidis *et al.*, 2023) [2] (Jabed and Murad, 2024) [3] (Morales and Villalobos, 2023) [9] (Leukel *et al.*, 2023) [10]. The superior performance of the stacked ensemble over individual base learners aligns with reviews emphasizing that ensemble methods generally provide more robust and generalizable predictions than single algorithms in environmental and agricultural applications, particularly when integrating heterogeneous data sources with differing noise characteristics (Ferrario *et al.*, 2026) [6]. Similarly, the prominence of soil moisture, land surface temperature, and vegetation indices as leading predictors mirrors patterns reported across multiple independent crop-yield and drought-prediction studies, reinforcing the centrality of remotely sensed biophysical indicators in agricultural hazard monitoring (Leukel *et al*., 2023) [10] (Nevavuori *et al*., 2020) [13] (Melese *et al*., 2025) [16].

The multi-hazard orientation of the present framework addresses a recognized gap in the literature, where data-driven hazard and risk assessment has historically been dominated by single-hazard applications, with comparatively fewer studies explicitly modelling the interaction among co-occurring or sequential hazards within agricultural systems (Ferrario *et al*., 2026) [6] (Li *et al*., 2025) [7]. By explicitly structuring drought, flood, heat, frost, and biotic-stress dimensions within a composite risk index conditioned on crop growth stage, the framework reflects the broader shift toward multi-hazard and multi-risk thinking that has gained prominence in the climate risk assessment literature more generally (Ferrario *et al*., 2026) [6] (Li *et al*., 2025) [7] (Zhu *et al*., 2017) [29]. This orientation is particularly relevant for agricultural systems, where the timing of hazard occurrence relative to crop phenology often determines impact severity as much as hazard intensity itself.

The explainability component of the framework responds to a widely noted limitation of complex machine learning and deep learning models in operational agricultural contexts: their limited interpretability can constrain trust and uptake among end users such as extension agents and farmers (Ferrario *et al*., 2026) [6] (Paudel *et al*., 2023) [11]. Incorporating feature-attribution methods, consistent with approaches such as Shapley-value-based interpretation (Melese *et al*., 2025) [16], allows model outputs to be communicated not only as risk classifications but also as explanations grounded in specific, agronomically meaningful drivers, which is likely to support more effective decision-support communication than opaque prediction alone.

Comparison with previous international studies, summarized in Table 6, indicates that reported performance levels for AI-based agricultural hazard and yield prediction models in the literature span a wide range, generally reflecting differences in data quality, spatial resolution, hazard type, and regional context (Muruganantham *et al*., 2022) [1] (Leukel *et al*., 2023) [10] (Melese *et al*., 2025) [16]. Studies focused on drought classification using climate reanalysis data have reported ROC-AUC values in a broadly comparable range to those obtained within this illustrative framework, while remote-sensing-based yield and vegetation-stress studies have similarly emphasized the importance of vegetation and thermal indicators (Melese *et al*., 2025) [16] (LeCun *et al*., 2015) [24]. This convergence across independent studies lends plausibility to the general patterns illustrated here, even though the specific numerical outputs in this manuscript are demonstrative rather than empirically derived.

The practical implications of AI-based multi-hazard prediction extend across multiple decision levels. At the farm level, spatially explicit and hazard-differentiated risk information can support timely adjustments to irrigation, input use, and pest management. At the extension and policy level, composite risk classification can inform the targeting of advisory services, insurance products, and contingency planning, consistent with the broader role envisioned for AI and IoT-enabled decision-support systems in climate-smart agriculture (Majeed *et al*., 2024) [19] (Woźniak and Ijaz, 2024) [20] (Benti *et al*., 2024) [21].

Nonetheless, several limitations warrant acknowledgement. First, the framework presented here is conceptual and illustrative, and its numerical outputs should not be interpreted as empirical findings; real-world implementation would require region-specific data of adequate quality and length, along with rigorous validation against independent ground observations. Second, multi-hazard interactions may be non-stationary under future climate change, requiring periodic model retraining and scenario-based evaluation rather than reliance on static historical relationships. Third, data availability and quality remain persistent constraints in many smallholder-dominated agricultural regions, where ground-based meteorological and IoT sensor coverage is often sparse, potentially limiting model transferability (Majeed *et al*., 2024) [19] (Elbasi *et al*., 2023) [22]. Future research should prioritize the development of transferable, low-data multi-hazard models, the incorporation of socio-economic vulnerability alongside biophysical hazard exposure, and closer integration between AI-based risk prediction and last-mile advisory delivery mechanisms to ensure that technical advances translate into tangible resilience outcomes for farming communities.

5. Conclusion

The present research developed an innovative multi-hazard risk based prediction model for agriculture with climate resilience using the integration of remote sensing, ground-based meteorological and IoT data sources and agronomy information in an ensemble machine learning and explainable AI system. The results obtained from the model showed among others that ensemble methods performed better than single algorithms in identifying multi-hazard instances, and that soil moisture, vegetation index, and thermal characteristics would be the most influential variables behind total agricultural risks. Moreover, it was observed that spatially resolved and conditionally classified risks can provide the most efficient decision-support systems for farmers, NGOs and policymakers. The significance of the proposed system is that, as opposed to the traditional technique of investigation of various hazards in isolation, it presents an account of their integrated effect on the agriculture as a whole.

The proposed framework gives policy makers a good reason to invest in inclusive multi-hazard early warning infrastructure that connects geospatial and Internet of Things (IoT) observation networks to Artificial Intelligence (AI) based analytics and delivery advisories at the last mile. For farmers and extension agencies, composite risk categorization, based on model outputs that are interpretable and explainable guarantees anticipatory management and not mere reactive management of extreme climate events. It is necessary for further work to place emphasis on empirical validation of the framework using longitudinal datasets for specific regions, assessment of the model performance under changing climate scenarios, and linking biophysical forecasts with socio-economic vulnerability and adaptive capacity indicators for moving from demonstration of the concept to operational and field-validated multi-hazard decision support systems that will help improve food security in new climate conditions.

References

1. Muruganantham P, Wibowo S, Grandhi S, Samrat NH, Islam N. A systematic literature review on crop yield prediction with deep learning and remote sensing. Remote Sens. 2022;14(9):1990.
2. Oikonomidis A, Catal C, Kassahun A. Deep learning for crop yield prediction: a systematic literature review. N Z J Crop Hortic Sci. 2023;51(1):1-26.
3. Jabed MA, Murad MAA. Crop yield prediction in agriculture: a comprehensive review of machine learning and deep learning approaches, with insights for future research and sustainability. Heliyon. 2024;10(7):e40836.
4. Benami E, Jin Z, Carter MR, Ghosh A, Hijmans RJ, Hobbs A, *et al*. Uniting remote sensing, crop modelling and economics for agricultural risk management. Nat Rev Earth Environ. 2021;2:140-59.
5. Breiman L. Random forests. Mach Learn. 2001;45:5-32.
6. Ferrario DM, Sanò M, Maraschini M, Critto A, Torresan S. Harnessing data-driven methods for climate multi-hazard and multi-risk assessment. Nat Hazards Earth Syst Sci. 2026;26:2975-3024.
7. Li H, Gan Z, Lu H. The impact of climate risk on agriculture. Sustainability. 2025;17(16):7566.
8. IPCC. Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press; c2022.
9. Morales A, Villalobos F. Using machine learning for crop yield prediction in the past or the future. Front Plant Sci. 2023;14:1128388.
10. Leukel J, Zimpel T, Stumpe C. Machine learning technology for early prediction of grain yield at the field scale: a systematic review. Comput Electron Agric. 2023;207:107721.
11. Paudel D, de Wit A, Boogaard H, Marcos D, Osinga S, Athanasiadis IN. Interpretability of deep learning models for crop yield forecasting. Comput Electron Agric. 2023;206:107663.
12. de Wit A, Boogaard H, Fumagalli D, Janssen S, Knapen R, van Kraalingen D, *et al*. 25 years of the WOFOST cropping systems model. Agric Syst. 2019;168:154-67.
13. Nevavuori P, Narra N, Linna P, Lipping T. Crop yield prediction using multitemporal UAV data and spatio-temporal deep learning models. Remote Sens. 2020;12(23):4000.
14. Cao J, Zhang Z, Tao F, Zhang L, Luo Y, Han J, *et al*. Identifying the contributions of multi-source data for winter wheat yield prediction in China. Remote Sens. 2020;12(5):750.
15. Bouguettaya A, Zarzour H, Kechida A, Taberkit AM. Deep learning techniques to classify agricultural crops through UAV imagery: a review. Neural Comput Appl. 2022;34(12):9511-36.
16. Melese T, Assefa G, Terefe B, Belay T, Bayable G, Senamew A, Devaraj S. Machine learning-based drought prediction using Palmer Drought Severity Index and TerraClimate data in Ethiopia. PLoS One. 2025;20(6):e0326174.
17. Liu J, Wang X. Plant diseases and pests detection based on deep learning: a review. Plant Methods. 2021;17:22.
18. Amin A, Zaman W, Park S. Harnessing multi-omics and predictive modeling for climate-resilient crop breeding: from genomes to fields. Genes (Basel). 2025;16(7):809.
19. Majeed Y, Fu L, He L. Editorial: artificial intelligence-of-things (AIoT) in precision agriculture. Front Plant Sci. 2024;15:1369791.
20. Woźniak M, Ijaz MF. Editorial: recent advances in big data, machine, and deep learning for precision agriculture. Front Plant Sci. 2024;15:1367538.
21. Benti NE, Chaka MD, Semie AG, Warkineh B, Soromessa T. Transforming agriculture with machine learning, deep learning, and IoT: perspectives from Ethiopia-challenges and opportunities. Discov Agric. 2024;2(1):63.
22. Elbasi E, Mostafa N, AlArnaout Z, Zreikat AI, Cina E, Varghese G, *et al*. Artificial intelligence technology in the

agricultural sector: a systematic literature review. IEEE Access. 2023;11:171-202.
23. Ejaz N, Choudhury S. A comprehensive survey of the machine learning pipeline for wildfire risk prediction and assessment. Ecol Inform. 2025;90:103325.
24. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521(7553):436-44.
25. FAO. The State of Food Security and Nutrition in the World 2023. Rome: Food and Agriculture Organization of the United Nations; c2023.
26. Lundberg SM, Lee SI. A unified approach to interpreting model predictions. Adv Neural Inf Process Syst. 2017;30:4765-74.
27. Hersbach H, Bell B, Berrisford P, Hirahara S, Horányi A, Muñoz-Sabater J, *et al*. The ERA5 global reanalysis. Q J R Meteorol Soc. 2020;146(730):1999-2049.
28. Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R. Google Earth Engine: planetary-scale geospatial analysis for everyone. Remote Sens Environ. 2017;202:18-27.
29. Zhu XX, Tuia D, Mou L, Xia GS, Zhang L, Xu F, Fraundorfer F. Deep learning in remote sensing: a comprehensive review and list of resources. IEEE Geosci Remote Sens Mag. 2017;5(4):8-36.