Interpretable Machine Learning Framework for Early-Stage Potato Yield Forecasting Using Climatic Features in Bangladesh

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Bangladesh, one of the world's major potato-producing countries, faces significant yield variability driven by changing climatic conditions, with profound implications for agricultural productivity and food security. However, the specific impact of meteorological factors on potato production has not been thoroughly investigated. The present paper aims to provide a robust quantitative framework for assessing the relative effects of agro-climatic variables on potato yield formation. Weather variables that were statistically significantly related to the mortality count were first selected using Analysis of Variance (ANOVA) with F-regression feature ranking and Individual Weather Importance ranking through Random Forest. Pearson and Spearman's correlation analyses were additionally performed to assess the strength and direction of these relationships, along with bivariate kernel density estimation (KDE) used to enlarge climatic optima toward yield maximization. For testing predictive robustness, climatic variability was taken into account, and three machine learning algorithms —RF (Random Forest), SVR (Support Vector Regression), and KNN (K-Nearest Neighbors) —were investigated. The RF model was the most accurate and generalizable, yielding almost perfect results ($R^2 = 0.999$) and minimal forecast errors (MAPE = 0.70%, MAE = 0.0803, RMSE = 0.1014). The developed framework enhances the understanding of climate–yield relationships and provides practical insights for science-based agricultural management and adaptation to climatic stress. These results have immediate implications for middle-income agrarian economies, such as Bangladesh, in strengthening resilience to climatic variability through sustainable food security.

Povzetek: Članek preučuje vpliv agroklimatskih dejavnikov na pridelek krompirja v Bangladešu. Z uporabo statističnih metod in strojnega učenja ugotavlja, da model Random Forest najnatančneje napoveduje pridelek ter podpira prilagajanje podnebnim spremembam.

1 Introduction

Climate variability and the associated changes in precipitation distribution, as well as intensified extreme events, pose a threat to global food security through their negative impact on agricultural productivity. From this perspective, crop yield forecasting has been identified as a key climate-smart agriculture tool that facilitates the timely provision of risk-based production assessments and adaptive management options [1][2]. Early, robust yield predictions are significant for staple crops in the context of evidence-based resource allocation, market stabilization, and food security planning [3][4]. Potato (Solanum tuberosum L.) is a group of crops that ranks as the third largest food crop in the world and plays an important part in Bangladeshi agriculture [5]. As one of the major potato growers worldwide, Bangladesh heavily depends on potatoes for income generation and nutritional stability in the rural sector [6]. Nevertheless, the country's agroecosystems are highly susceptible to climate-related stresses—recurring floods, droughts, and heatwaves—that significantly reduce potato yields and quality [7][8]. These weaknesses underscore the need for a resilient, climate-adaptive yield forecasting system that provides timely and accurate information to benefit farmers and policymakers.

The traditional methods of forecasting yield have become increasingly inaccurate due to climate change occurring at a faster rate [9]. Analytic methods based on historical averages and simple statistical relationships are unable to characterize all the nonlinear interactions between edaphic, meteorological, and management factors that govern crop performance [10][11][12]. In Bangladesh, the estimation of yield has been based on manual field surveys and temporal pattern analysis, i.e., labor-intensive, retrospective approaches that are unable to capture intra-seasonal variability [13]. Such delayed and crude inferences are not compatible with the spatial or temporal heterogeneity of Bangladesh's agroecosystems, as climatic conditions vary widely between regions [14]. The increasing impact of climate change (such as the unpredictable rainfall and severe heatwaves becoming more frequent) exposes the weakness of these traditional models, which do not account for non-stationarity in extreme weather conditions [15]. As a result, uncertainties in the forecasts remain large, and farmers do not yet have sufficiently early warning about yield gaps. This highlights the necessity of rapid, high-resolution prediction systems to combine innovative agro-climatic datasets for accurate early-season yield predictions, which could be used to support adaptive interventions such as irrigation scheduling and fertilizer optimization [16][17].

Recently, artificial intelligence (AI) and machine learning (ML) have become highly disruptive tools for agricultural planning [18][19][20]. In precision agriculture, various data sources, including local weather and soil sensors, as well as satellite-based remote sensing, can be utilized in predictive models that describe complex crop–environment interactions [21]. Building on such diverse datasets, ML models can better capture the multifaceted drivers of yield variability, systematically outperforming traditional statistical methods [22]. Tree-based ensemble models, and Random Forest or Gradient Boosting in particular, have been shown to perform best ($R^2 \approx 0.9$) in recent research [23][24][25]. The addition of fine-resolution weather information, such as daily temperature, rainfall anomalies, and phenological metrics, improves the accuracy of early yield forecasts [26]. In Bangladesh, these early predictions could prove invaluable in proactive farm management (early decisions on planting density, input allocation, and market planning) and national actions to stabilize food supply chains as well as achieve the Sustainable Development Goals of zero hunger [27][28].

Despite the significant advances in AI-based yield forecasting, there are still substantial challenges in the trade-off between prediction accuracy and interpretability. Advanced ML techniques, such as deep neural networks (which often serve as opaque "black boxes"), provide limited insight into their decision-making process [29][30]. This is particularly challenging in agriculture, an industry where trust between stakeholders is essential for its further development; therefore, not being able to interpret model results reduces the potential for adoption and action based on decisions taken. Farmers and agronomists should be able to identify which climatic or agronomic parameters induce forecasted yield changes in order to apply relevant interventions over time [31]. Classical regression models offer interpretability but cannot model complex, non-linear relationships [32], while high-fidelity ML algorithms trade off accuracy for transparency. A recent investigation attempts to balance this trade-off by incorporating interpretability into predictive models [33]. For instance, Lavanya et al. [34] developed a Bayesian learning model that can achieve neural network-level accuracy while revealing important climate–yield interrelations. Likewise, XAI tools (SHAP and LIME) have been employed in combination with ensemble models to elucidate dominant predictors of yield outcomes, including extreme temperatures and rainfall anomalies [35][36]. These advances demonstrate that interpretability is not just theoretical, but also critical for fostering user trust and enabling evidence-based, climate-adaptive agricultural practices.

Motivated by these challenges, this paper develops an explainable machine learning model for predicting early-season potato yield in Bangladesh using fine-scale agro-climatic and management datasets. In contrast to previous researchers [37][38], who must in some way depend on aggregated data or static data characteristics, our model emphasizes the use of spatially explicit and temporally dynamic predictors that capture regional heterogeneity within Bangladesh's growing environment. Methodologically, the study employs flexible yet interpretable ML approaches—RF, SVR, and KNN—that accommodate not only strong predictive accuracy but clear interpretability through feature importance analysis and sensitivity analyses as well. By blending data-driven modeling with domain expertise, our approach offers both accuracy and interpretability, thereby closing the gap between the theoretical precision of algorithms and their practical applicability in reality. Crucially, the interpretable predictions enable stakeholders to attribute forecasted yield changes to specific climatic or management variables, allowing decision-makers to implement climate-sensitive intervention strategies [39][40].

This study contributes to Bangladesh's urgent need to enhance the resilience of agriculture in an increasingly variable climate. Early forecasting of potato yield is of great practical importance, as it can help reduce water and fertilizer use for farmers, facilitate the prediction of market dynamics, and maintain food security for policymakers. Given that potatoes provide both food and income security to millions of small-scale farmers, improved yield predictability directly contributes to rural livelihoods. The framework is context-specific for Bangladesh, taking into consideration agro-ecological diversity, smallholder-dominated farming systems, and the availability of data. In general, this work contributes to two main aspects: (1) it facilitates the advancement of the methodological innovation through the combination of high-resolution climatic data and interpretable machine learning approaches toward yield forecasting; and (2) it provides an operational decision support tool for early potato yield prediction to increase climate resilience.

To reinforce the comparative positioning of this work, a systematization synthesis table (Table 1) highlights some state-of-the-art models, including Random Forest, Gradient Boosting, and Deep Neural/Stacked Architectures. The comparison covers four main dimensions: (i) Dataset size/data characteristics, (ii) input features and climatic drivers, (iii) choice of evaluation metrics (R^2, RMSE, MAE, MAPE), and (iv) Model complexity/interpretability. This synthesis illustrates three recurrent research gaps that inspired the contribution of this work:

Model Interpretability: The current state-of-the-art models are built using deep-learning-based architectures, which tend to be opaque and not easily understandable in an agronomic context or transparent for making decisions.

Climate-Stage Specificity: Previous studies often relied on pooled seasonal weather data, but ignored the month-to-month or growth-stage-specific climate dynamics that are critical to understanding stage-wise yield sensitivities.

Operational simplicity: The complex hybrid or ensemble modelling frameworks generally demand heavy data preprocessing and hyper-parameter tuning, which limits their scalability for practical agricultural deployment.

To fill these gaps, the article formulates two orienting research questions (RQ):

RQ1: How accurately can interpretable machine learning models predict potato yield in Bangladesh with growth-stage-specific monthly climatic factors?

RQ2: What are the optimum monthly rainfall and temperature thresholds conducive to maximized potato yield in different agro-climatic zones of Bangladesh?

This is the clear, concise, and comprehensive RQ at a fine-grained level that underpins the study with both predictive modeling and agro-environmental analysis.

Table 1: Comparative summary of recent crop-yield prediction models

Reference	Crop / Region	Dataset	Features	Model	Reported Performance	Model Complexity	Interpretability
Ikram et al. [10]	Maize–Soybean	Regional	Climatic + soil + management	Fuzzy + Ensemble	$R^2 \approx 0.98$	High	Medium
Mesbah et al. [12]	Potato / USA	Regional	Climatic + phenological	GBM	$R^2 \approx 0.94$	Medium	Medium
Huber et al. [24]	Maize / EU	Large-scale	Climatic	XGBoost	$R^2 \approx 0.96$	Medium	Medium
Lavanya et al. [34]	Mixed crops / India	Regional	Climate + soil	MLR + NN	$R^2 \approx 0.93$	Low–Medium	Medium
Deep DNN models [35][37]	Maize / Wheat / Rice	Large	Climatic + Remote Sensing	DNN	$R^2 \approx 0.92–0.97$	High	Low (requires post-hoc XAI)
Dhanaraj et al. [40]	Multi-crop	Multi-region	Climatic + IoT	Lightweight AI	$R^2 \approx 0.97$	Medium	Medium–High
Proposed Study	Potato / Bangladesh	Monthly, multi-year (n = 2,145)	Monthly rainfall & temperature (Oct–Jan)	RF	$R^2 = 0.999$; MAPE = 0.70 %; RMSE = 0.1014; MAE = 0.0803	Medium	High (Feature importance, KDE, correlations)

The remainder of this paper is organized as follows. The methodology (Section 2) is then presented, detailing the data sources, preprocessing steps, and machine learning techniques employed. The experimental results and analysis are presented in Section 3, which includes feature importance analysis, correlation mapping, and prediction performance. The relationship between climate adaptation and agricultural resilience is considered in Section 4, and concluding remarks, main contributions to knowledge, policy implications, and future research directions are provided in Section 5.

2 Methodology

The proposed climate–yield modeling framework, developed here for the early prediction of potato yield using real-time meteorological data, is illustrated in Fig. 1. In addition to prediction, the model determines thresholds of climate that are most conducive to cropping. Through the incorporation of cutting-edge analytical methods, the solution provides actionable intelligence and dynamic management responses to minimize damage caused by severe weather. These are powering those farmers and policymaker can use to intervene data-driven promptly, thereby increasing agricultural productivity and contributing to sustainable food security.

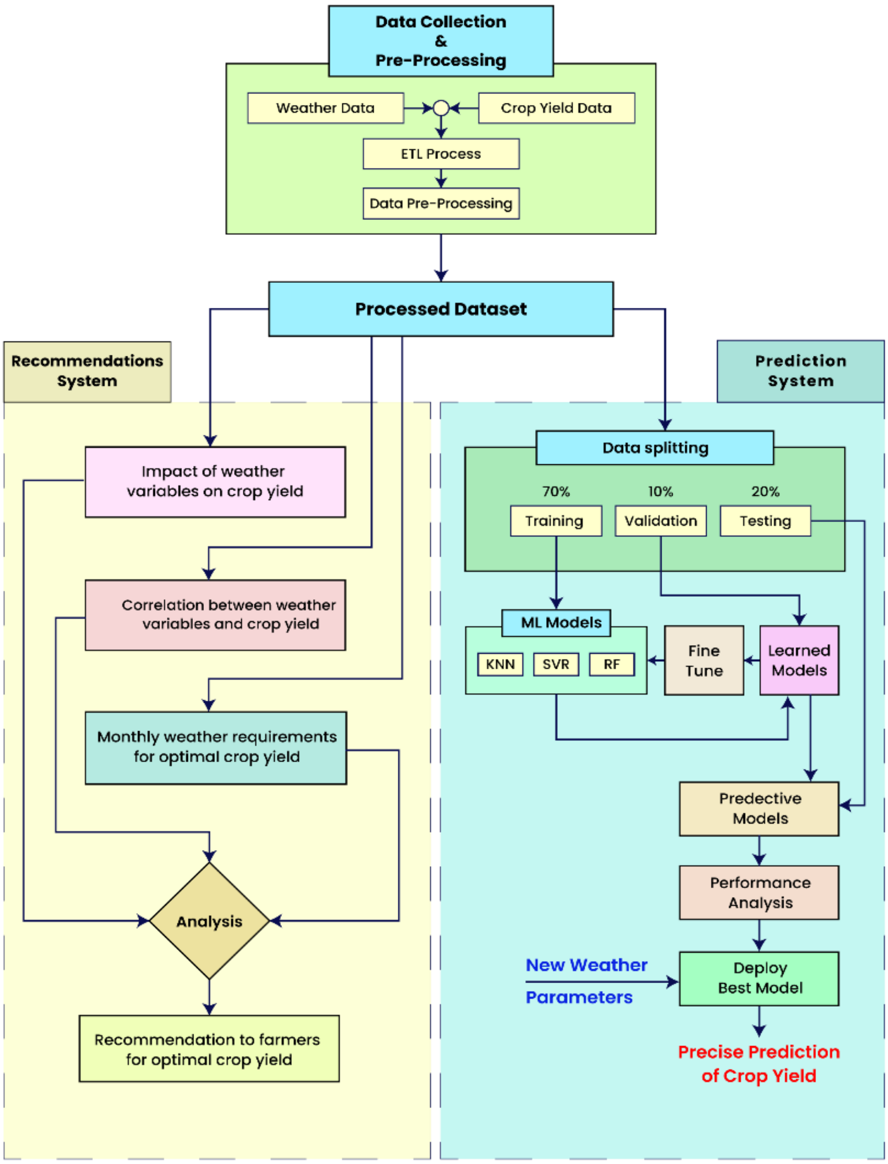

Figure 1: Proposed Climatic-Yield model.

2.1 Dataset description

To ensure analytical rigor, this study utilized high-quality datasets obtained from authoritative national sources in Bangladesh. Monthly climatic variables, including rainfall and temperature, were collected from the Bangladesh Weather Information Management System [41] and the Bangladesh Meteorological Department [42]. Corresponding agricultural productivity data, specifically potato yield metrics, were acquired from the Bangladesh Bureau of Statistics [43] and the Bangladesh Agricultural Research Institute [44]. The compiled dataset (Table 2) comprises 2,145 observations from the Bogura District, spanning the period from 2015 to 2023, and encompasses monthly rainfall, temperature, and yield records for the potato growing season (October–January). Missing values, representing less than 3% of the data, were primarily due to short-term rainfall gaps and were imputed through linear interpolation. Descriptive statistics indicate an average monthly rainfall of 34.62 mm (r_{1m}), a peak temperature of 23.58 °C (t_{4m}), and an average yield of 12.04 t ha^{-1}, ranging from 7.83 to 19.89 t ha^{-1}. This comprehensive dataset provides empirical insights into the climatic thresholds that influence potato productivity, offering a robust foundation for developing an accurate and interpretable yield forecasting framework. Its temporal and spatial granularity facilitates the systematic exploration of climate–agriculture interdependencies, which are essential for adaptive planning under increasing climatic variability.

Table 2: Descriptive statistics of the dataset

	r_1m	**r_2m**	**r_3m**	**r_4m**	**t_1m**	**t_2m**	**t_3m**	**t_4m**	**Yield**
count	2145	2145	2145	2145	2145	2145	2145	2145	2145
mean	34.63	9.02	7.38	19.88	23.59	19.64	18.37	20.82	12.05
std	37.37	12.66	6.91	13.99	0.69	0.74	0.74	1.02	3.21
min	0.00	0.00	0.00	0.00	22.03	17.96	16.56	18.51	7.84

25%	6.45	0.52	1.11	7.14	23.13	19.08	17.85	20.05	9.66
50%	21.45	2.96	4.85	18.73	23.61	19.65	18.34	20.74	10.97
75%	49.72	15.74	11.92	29.68	24.10	20.24	18.92	21.48	13.71
max	141.20	44.57	23.69	51.11	25.40	21.32	20.62	23.88	19.90

2.2 Data preprocessing

Prior to model training, the climatic feature dataset underwent a structured preprocessing pipeline. Missing values were imputed using linear interpolation, while years with entirely missing monthly records were excluded from analysis. Outliers were identified using the interquartile range (IQR) method. Genuine climatic extremes were retained to preserve natural variability, while non-representative anomalies were winsorized to the 5th–95th percentile range. All features were standardized using zero-mean, unit-variance scaling to ensure comparability and enhance model stability, particularly for algorithms sensitive to input scale such as SVR and KNN. A **scikit-learn** pipeline was implemented to integrate preprocessing with model training, ensuring that all transformations were fitted exclusively on the training folds, thereby preventing data leakage and preserving model generalizability.

2.3 Feature extraction and importance techniques

In predictive modeling, approaches for quantifying the contribution of independent variables—such as monthly rainfall and monthly temperature—to model accuracy are crucial. Such techniques improve model explainability and performance by (i) discovering influential predictors, (ii) optimizing the computational efficiency, and (iii) improving the prediction results. This work followed two integrated strategies:

Intrinsic RF variable importance: This approach benefits from the characteristic introduced in the construction of an RF regression model, which measures the contribution of each feature to reducing prediction error based on impurity in leaf nodes during tree growth.

ANOVA F-Regression: A statistical model used to assess the explanatory power of variables over potato yield variation.

Combining these approaches, the analysis provides clarity on how different climatic effects contribute to yield prediction. We estimated RF feature importance using Eq. (1) – Eq. (4), and the significance of ANOVA F-regression from Eq. (5). The double approach guarantees complete predictor contributions evaluation, harmonizing model-specific information with statistical soundness towards the development of reliable agricultural forecasting.

$$ni_j = w_j C_j - w_{left(j)} C_{left(j)} - w_{right(j)} C_{right(j)} \quad (1)$$

$$f_i = \frac{\sum j{:}node\ j\ splits\ on\ feature\ i.ni_j}{\sum k \in all\ nodes.ni_k} \quad (2)$$

$$Normalized\ f_i = \frac{f_j}{\sum j \in all\ features.f_j} \quad (3)$$

$$RF\ f_i = \frac{\sum j \in all\ trees.Normalized\ f_{ij}}{T} \quad (4)$$

$$ANOVA\ F = \frac{(R_r - R_f)/(p-k)}{R_f/(n-p-1)} \quad (5)$$

2.4 Relationship between climatic factors and yield

In order to explore the correlation between meteorological factors and potato yield, linear correlation analysis and non-linear correlation investigation were conducted. Pearson correlation (Eq. 6) was applied to assess linear relationships, while Spearman correlation (Eq. 7) was employed to assess non-linear dependencies. P-values showing the statistical significance of these relationships in Eq. (8):

$$\text{Pearson Correlation Coefficients}, r = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2 \sum(y_i-\bar{y})^2}} \quad (6)$$

$$Spearman\ Correlation, R_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \quad (7)$$

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \quad (8)$$

These multivariate statistical approaches formalize, from a causal perspective, the relationship between hydrothermal variability and agronomic productivity, facilitating the mechanistic improvement of statistically based yield forecasting systems.

2.5 Machine learning models

Machine learning has been established as a promising approach to improve farming decisions and ensure high precision in crop productivity estimation. Using historical data and statistical patterns, ML models can help farmers reduce losses, efficiently allocate resources, and enhance overall yield predictions. Three ML models, i.e., SVR, RF, and KNN, are employed in this study as a result of their remarkable performance when dealing with numerical prediction tasks, and due to the compatibility between these chosen algorithms and our data.

2.5.1 RF regression

The RF algorithm adopts an ensemble strategy, training numerous decision trees to minimize overfitting and improve accuracy. During prediction, individual tree outputs are independently generated and aggregated into a final estimate through averaging, as defined in Eq. (9). RF is highly effective in handling complex, non-linear relationships and is robust against noise in the dataset. Additionally, it provides built-in feature importance analysis, which helps in identifying the most significant predictors of crop yield.

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} f_t(x) \quad (9)$$

Where $\hat{y}$ is the predicted potato yield, T is the total number of decision trees in the forest, and f_t represents the yield prediction from the t^{th} decision tree.

2.5.2 SVR

A kernel-based regression technique that aims to find a function f(x) that approximates the target variable while maintaining a margin of tolerance ϵ. The SVR function is expressed as Eq. (10). SVR is particularly useful for capturing complex relationships between weather variables and crop yield while maintaining robustness against outliers.

$$f(x) = \sum_{i=1}^{n}(a_i - a_i^*)\, K(x_i, x) + b \tag{10}$$

Where $K(x_i, x)$ is the kernel function (e.g., linear, polynomial, or radial basis function (RBF)), a_i and a_i^* are the Lagrange multipliers, and b is the bias term.

2.5.3 KNN regression

The KNN Regression algorithm operates as an instance-based learning method, estimating target values through localized averaging of the K proximal training instances within the feature space (Eq. 11). While advantageous for its computational minimalism and adaptability to heterogeneous data topologies, KNN's efficacy is critically contingent upon optimal hyper-parameter selection—particularly the neighborhood size (K) and distance function governing similarity assessments.

$$\hat{y} = \frac{1}{K}\sum_{i=1}^{K} y_i \tag{11}$$

Where K represents the neighborhood cardinality and y_i denotes the observed yield values among the K most analogous historical samples.

2.6 Kernel density estimation analysis

Kernel Density Estimation (KDE) was performed using a Gaussian kernel function to estimate the probability density of yield response to monthly climatic variables (rainfall and temperature). The bandwidth (h) was selected using Scott’s Rule, which provides an adaptive smoothing factor based on the sample size and variance of the data. KDE was applied individually to each climatic predictor, and the local maxima of the estimated densities were interpreted as the optimal climate thresholds for maximizing potato yield.

Given a sample of n observations $\{x_1, x_2, x_3, \ldots\ldots, x_n\}$, the kernel density estimator $\hat{f}(x)$ is defined as:

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{12}$$

- Where: $K(.)$ is the kernel function,
- $h > 0$ is the bandwidth (smoothing parameter), and
- x_i denotes the observed data points (e.g., rainfall or temperature values).

For this study, we employed the Gaussian kernel, which is the most widely used due to its smoothness and differentiability, expressed as:

$$K(u) = \frac{1}{\sqrt{2\pi}} exp\left(-\frac{u^2}{2}\right) \tag{13}$$

Hence, the estimated probability density function for a climatic variable x can be expressed as:

$$\hat{f}(x) = \frac{1}{nh\sqrt{2\pi}}\sum_{i=1}^{n} \exp\left(-\frac{1}{2}\left(\frac{x - x_i}{h}\right)^2\right) \tag{14}$$

Bandwidth Selection (Scott’s Rule):

The choice of bandwidth h critically affects the smoothness of the density curve. We used Scott’s Rule, which provides a data-driven, asymptotically optimal estimate of h for Gaussian kernels:

$$h = \sigma n^{-1/5} \tag{15}$$

where σ denotes the standard deviation of the data sample. This rule balances bias and variance, ensuring adequate smoothing without overfitting the empirical distribution.

Application to Climatic Variables:

KDE was independently applied to monthly rainfall and temperature datasets to obtain the probability density of potato yield responses to each variable. The resulting curves represent the likelihood of achieving specific yield outcomes under varying climatic conditions.

Mathematically, for rainfall (R) and temperature (T):

$$\hat{f}_R(r) = \frac{1}{nh_R}\sum_{i=1}^{n} K\left(\frac{r - R_i}{h_R}\right) \tag{16}$$

$$\hat{f}_T(t) = \frac{1}{nh_T}\sum_{i=1}^{n} K\left(\frac{t - T_i}{h_T}\right) \tag{17}$$

The local maxima (r^*, t^*) of these estimated densities correspond to the optimal rainfall and temperature thresholds for maximizing potato yield. These optima were interpreted as agronomically significant climatic conditions, aiding in the identification of favorable environmental windows for yield optimization.

2.7 Evaluation metrics

A rigorous multi-metric validation framework was implemented to objectively compare the predictive capabilities of the evaluated models (RF, SVR, KNN). The assessment protocol incorporates: MAE, MAPE, RMSE, and R^2.

2.7.1 Mean absolute error (MAE)

MAE measures the average absolute difference between the actual and predicted values. A lower MAE value indicates better model accuracy, as it signifies smaller deviations from actual values. It is calculated using Eq. (18):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (18)$$

Where n is the total number of observations, y_i and $\hat{y}_i$ represents actual and predicted value, respectively.

2.7.2 Root mean square error (RMSE)

RMSE quantifies the standard deviation of prediction errors, RMSE is particularly useful when larger errors need to be given higher significance in model evaluation. Lower RMSE values indicate better predictive performance. It penalizes larger errors more than MAE and is computed by Eq. (19):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (19)$$

2.7.3 Mean absolute percentage error (MAPE)

The MAPE quantifies prediction error as a percentage relative to observed values, offering an intuitive assessment of model accuracy. This metric facilitates cross-dataset error comparisons and is particularly valuable in decision-making contexts where relative errors are more interpretable. MAPE is inversely proportional to model precision, with lower values indicating superior performance. It is mathematically defined as Eq. (20):

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (20)$$

2.7.4 Coefficient of determination (R^2)

The Coefficient of Determination R^2 assesses the proportion of variance in the observed data explained by the model. Ranging from 0 to 1, higher R^2 values indicate greater explanatory power, reflecting a model's ability to account for variability in the target variable. It is calculated by Eq. (21):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (21)$$

Where $\bar{y}_i$ denotes the mean of actual values.

The optimal methodology for yield prediction is identified by evaluating models across these metrics, prioritizing those with the lowest MAE, RMSE, and MAPE, coupled with the highest R^2 score. This multi-metric approach ensures robust selection of models with both high accuracy and explanatory capability.

2.8 Hyperparameter optimization

Model hyperparameters were optimized using GridSearchCV with 5-fold cross-validation. The objective was to minimize RMSE and maximize R^2. The tested parameter grids were as follows (Table 3). For RF, the grid includes the number of estimators, maximum depth, minimum samples per node, and maximum feature selection strategy. For SVR, the tuning parameters comprise the regularization coefficient (C), epsilon-insensitive loss parameter (ε), kernel type, and gamma scaling mode. For KNN, the parameters include the number of neighbors (k), the weighting function, and the Minkowski distance parameter (p). The defined ranges were systematically explored using GridSearchCV to identify optimal configurations for each model.

Table 3: Hyperparameter search space used for optimizing the RF, SVR, and KNN

RF	SVR	KNN
n_estimators: [50, 100, 150, 200, 300]	C: [0.1, 1, 10, 100]	n_neighbors: [3, 5, 7, 9, 11]
max_depth: [None, 5, 10, 15, 20]	epsilon: [0.001, 0.01, 0.1, 1.0]	weights: ['uniform', 'distance']
min_samples_split: [2, 5, 10]	kernel: ['linear', 'poly', 'rbf']	p: [1, 2]
min_samples_leaf: [1, 2, 4]	gamma: ['scale', 'auto']	
max_features: ['auto', 'sqrt', 'log2']		

For each algorithm, the optimal hyperparameters were selected based on the combination that minimized cross-validation RMSE. The selected values were:

- RF: n_estimators=150, max_depth=10, min_samples_split=2, min_samples_leaf=1, max_features='sqrt'.
- SVR: C=10, epsilon=0.01, kernel='rbf', gamma='scale'.
- KNN: n_neighbors=5, weights='distance', p=2.

Model training and validation strategy:

To prevent temporal leakage and ensure realistic performance estimation, we employed time-aware cross-validation using TimeSeriesSplit from scikit-learn. Training and validation folds were constructed sequentially, such that the model was always trained on earlier years and validated on subsequent years. No random shuffling was performed. This approach preserves the natural temporal order of the data and better reflects real-world deployment scenarios, where future yields must be forecasted using past climatic observations.

3 Results and analysis

This section presents the main findings of the research, including the impact of rainfall and temperature on potato yield, the determination of optimum climate thresholds, and the significance level associated with weather–yield relationships. Additionally, the predictive power of the machine learning methods (RF, SVR, and KNN) is carefully assessed through cross-validation and independent tests. The outcomes provide strong statistical evidence, as well as valuable knowledge , to support climate-smart agricultural decision-making.

3.1 Feature importance analysis

A two-stage selection approach combining the feature importance rankings of RF and ANOVA F-tests was used to identify the most informative meteorological predictors for potato yield that were both robust and interpretable. Our study found that precipitation and temperature during critical growing months played a predominant role in yield. This fact is also reflected in the

RF importance ranking (Figure 2), where December rainfall was found to be the most relevant predictor (RF importance ≈ 0.34), indicating a substantial impact on tuber bulking associated with soil moisture availability. Agronomically, this aligns with the commonality of the crop's need for medium soil moisture during tuber expansion, which is encouraged by cool late-season temperatures and enhances the effects of rainfall. The November rainfall had a moderate effect (score ≈ 0.24), indicating lower sensitivity during early vegetative growth. Likewise, the December temperature (score ≈ 0.33) is the most important of the thermal variables in Figure 3, highlighting that having mild temperatures at late growth is crucial for building up yield. These findings are consistent with recent explainable ML studies that highlight precipitation and temperature as the primary drivers of yield. The concordance between RF and ANOVA results enhances confidence in the feature selection. Consequently, it enhances the interpretability of subsequent predictive modeling, underscoring the benefits of explainable AI in elucidating biologically meaningful climate–yield relationships.

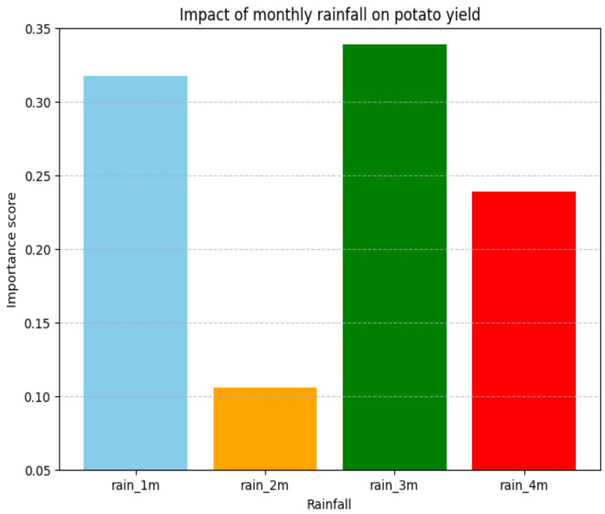

Figure 2: Influence of rainfall on potato yield

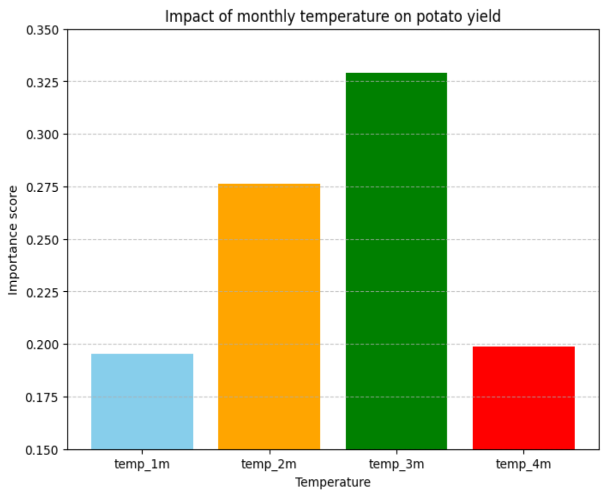

Figure 3: Influence of temperature on potato yield

3.2 Weather-Yield correlation

After feature selection, the correlations and directions between the monthly weather variables and potato yield were assessed (Table 4). Rainfall in the growing season (October–January) consistently showed a negative association with yield, indicating that excessive moisture is a limiting factor in productivity. The (negative) Pearson correlation coefficients with October rainfall were most significant ($r \approx -0.18$, $p < 0.001$), showing that an unusually high amount of rain during the planting phase severely diminishes yield—presumably owing to waterlogging and nutrient leaching in the early growth period. The correlation decreased by December ($r \approx -0.07$), but remained negative, indicating lower sensitivity as the crop matures. All rainfall - yield relationships showed extremely high statistical significance ($p \approx 0$), indicating the homogeneity on which these relationships are based. The findings highlight the importance of preserving moisture in conditions that are not as arid, particularly those with a monsoonal climate. From an operational perspective, interventions such as improved drainage and irrigation scheduling can be used to mitigate the extent to which early-season rainfall stress is perceived, a critical adaptation for sustaining high potato yields in a climate of greater variability.

Table 4: Rainfall-yield correlations and their statistical significance

Time	Rainfall(mm)	Correlation (Pearson)	P value	Correlation (Spearman)
r_1m	34.68	-0.181	6.85E-18	-0.1721
r_2m	9.14	-0.1579	1.11E-14	-0.0947
r_3m	7.42	-0.0665	1.76E-03	-0.0056
r_4m	19.78	-0.1384	2.77E-13	-0.1569

Temperature-related variables were inversely related to potato yield in comparison with precipitation, in which case it was found that there were mostly positive correlation coefficients, and a warming of conditions (contained in the optimal range) tends to benefit crop development (Table 5). The best response was recorded for November, with a mean temperature exhibiting a moderate to high positive Pearson's correlation ($r \approx +0.24$, $p < 0.001$) and a similar Spearman correlation coefficient, indicating that slightly warmer temperatures during the tuber initiation stage contribute substantially to the yield increase. The temperatures in October and January also showed positive (but lower) correlations ($r \approx +0.06$ to $+0.11$, $p < 0.01$), consistent with small advantages of warmness when plants are being planted or harvested. On the other hand, the December temperature was weakly negatively correlated ($r \approx -0.08$) with yield, which is compatible with the feature importance analysis indicating that cooler late-season temperatures benefit yield by avoiding heat stress during tuber bulking. All correlations were significant, indicating real climate effects rather than random variation. Taken together, these findings suggest that an optimal thermal regime is crucial for maximizing potato productivity. This is consistent with previous climate-smart agricultural assessments, which indicate that temperature is the primary driver of yield variability. The findings also suggest that controlling temperature extremes to support productivity is highly prioritized for growers. Hence, practice options such as improved planting time windows, mulching, and better irrigation management should be adopted.

Talbe 5: Temperature-yield correlation significance across growing months

Time	Temperature (o^c^)	Correlation Pearson	P value	Correlation Spearman
t_1m	23.52	0.0576	5.94E-02	0.0811
t_2m	19.57	0.2388	3.11E-31	0.2031
t_3m	18.41	-0.0775	2.89E-03	-0.0276
t_4m	20.78	0.1141	1.42E-06	0.1081

3.3 Climate-Driven yield optimization

To convert this statistical information into agronomic guidelines, KDE was used to identify rainfall–temperature pairs related to the highest zone-level potato yields in Bangladesh. The optimal climatic thresholds were distinctly evident in the analysis. Ideal precipitation for rainfall was low (~20–21 mm or less per month), although the long-term mean (34.6 mm/month) is higher than this optimum. This suggests that waterlogged conditions at planting tend to impede stand establishment, underscoring the need for improved field drainage or the use of ridge cultivation. In November, maximum yields approached ≈ 10–12 t ha^{-1} as cumulative rainfall was still around 5 mm/month.

Additionally, at the tuber bulking stage in December, maximum yields coincided with high rainfall (1–5 mm/month), suggesting that a moderate dryness level, as moderated by some irrigation, as used in this study, could be beneficial. In January, near harvest, marginally more monthly rainfall (5–15 mm/month) continued to be favorable, indicating that applying a small amount of late-season water can be made without incurring yield costs. Therefore, these threshold values align with the agronomic demands and confirm the importance of adapted moisture control under monsoonal conditions. Adopting adaptive water management practices—such as adequate drainage in periods of heavy rain and supplementary irrigation during drought stress periods—can help maintain the optimum soil moisture level, thereby reducing yield loss and improving climate resilience in potato production.

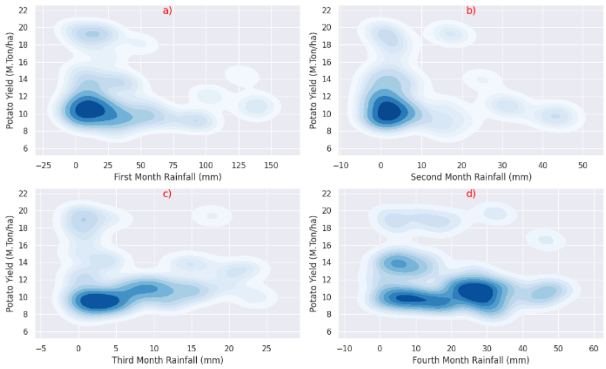

Figure 4: Relationship Between Yield and Rainfall: (a) Rain vs. Yield (1st Month) (b) Rain vs. Yield (2nd Month) (c) Rain vs. Yield (3rd Month) (d) Rain vs. Yield (4th Month)

Concomitant with precipitation, we also identified the optimal temperature intervals during each month of the growing season for maximum yield. Interestingly, these optimum temperature windows closely correspond to the typical climatology of Bangladesh's winter growing season, suggesting that potatoes are well-suited to the regional climate under non-extreme conditions. The optimal October temperature ranged from 22.8 to 23.7°C (versus the observed mean of 23.6°C); the highest aspect of this led to an initial condition that was somewhat conducive for sprout establishment. A little cooler (18.8–19.5°C, vs an actual mean of 19.6°C) was the optimum during November (vegetative growth and tuber initiation). Coinciding with the heart of the tuber bulking period in December, the best yields occurred when mean temperatures were about 17.6–18.5 °C, suggesting that a moderately cool December is most beneficial – likely because cooler air temperatures reduce plant stress and slow evaporation, ensuring adequate soil moisture for tuber growth. In January, at the late bulking and maturation stages, the optimal temperature was 20.2–21.1°C, which is consistent with the overall January mean (20.8°C). These findings suggest that the temperatures of most years in Bangladesh are already at, or close to, the optimum for potatoes, which helps explain why this crop is generally productive during the winter season in the country. It also suggests that future temperature variations (for example, due to climate change) could push conditions beyond the sweet spots of these harbors, possibly damaging yields, and highlighting the importance of continued monitoring and adaptation.

In summary, this KDE-based climate–yield optimization provides quantitative examples for agronomic climate management. The findings can inform farmers and policymakers about climate-smart decisions, such as selecting planting dates or choosing potato lines that best fit those optimal climate windows, or what protective measures (like frost protection or shading) may be needed if temperatures start deviating from optimal ranges. Such data-based insights are essential for building climate-resilient agricultural planning and practice that (i) help stakeholders to maximise yields given the current climate, yet (ii) maintain options given projected variability.

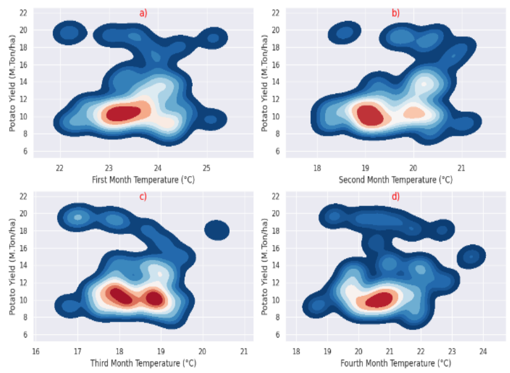

Figure 5: Relationship Between Production and Temperature: (a) Temp. vs. Yield (1st Month) (b) Temp. vs. Yield (2nd Month) (c) Temp. vs. Yield (3rd Month) (d) Temp. vs. Yield (4th Month)

3.4 Predictive model evaluation and validation

Based on previous climatic records, three machine learning models (i.e., KNN, SVR, and RF) were developed and assessed to forecast potato yields based on meteorological factors. A stringent 80/20 train–test split and a repeated 5-fold cross-validation process was employed to ensure unbiased performance estimation, while also preventing overfitting. Hyperparameters were tuned using GridSearchCV, allowing each model to be fitted with its optimal settings. Model conductance was evaluated using several complementary criteria: MEA, RMSE, MAPE, and R^2, in accordance with the good practices of high-quality crop model studies (Table 6). The more petite MAE, RMSE, and MAPE, as well as the greater R^2, are representative of the better predictability.

Across the validation folds, the RF model consistently showed the best performance (mean MAE $\approx$ 0.08 t ha^{-1}, RMSE $\approx$ 0.10, and R^2 above 0.98). The KNN regressor exhibited average prediction performance (mean RMSE $\approx$ 0.29), while SVR performed worse, with a mean RMSE of $\approx$ 0.84 and the lowest R^2, which can be interpreted as failing to capture variation in yield. The KNN also presented a higher variability of performance across folds, which is less stable than the RF. These trends were also observed in the test set: RF exhibited excellent predictive accuracy (test RMSE $\approx$ 0.105, R^2 $\approx$ 0.99), while KNN suffered from some overfitting, and SVR continued to underfit.

The high predictivity of RF outperforms most similar studies in the literature, the majority of which rely on either complex hybrid or deep learning models to achieve comparable R^2 values at high errors or in data-intensive setups. However, the RF model in this research achieved high predictive capability (accuracy and low error) and good generalization using only monthly weather input data. This finding reinforces the strength and interpretation of ensemble tree-based approaches for predicting agricultural yield and confirms their merit in adequately capturing nonlinear climate–yield relationships. Therefore, RF was the best model and is a valid, interpretable, and computationally efficient continuum for early-potato production prediction in Bangladesh.

Table 6: Performance of Models Using K-Fold Cross-Validation

K-Fold	**KNN**		**SVR**		**RF**	
	MAE	**RMSE**	**MAE**	**RMSE**	**MAE**	**RMSE**
1	0.1283	0.3684	0.4945	1.1341	0.0851	0.1070
2	0.1156	0.1997	0.3211	0.5396	0.0816	0.1025
3	0.128	0.3457	0.3748	0.8793	0.0767	0.0981
4	0.1163	0.2975	0.4207	0.9456	0.0779	0.0983
5	0.1176	0.2556	0.3269	0.7091	0.0807	0.1011
Mean	**0.1211**	**0.2933**	**0.3876**	**0.8415**	**0.0803**	**0.1014**

To verify that the very high coefficient of determination (R^2 = 0.999) obtained through the RF model for gene-expression prediction truly reflects the reliability and generalization capacity of the predictive power of the formulated models, rather than deficiencies in the training process or overfitting, a robust dual-validation system was employed. 5-fold cross-validation was conducted, as well as bootstrap resampling 1000 times, for evaluating the statistical stability of model performance. The corresponding 95% confidence intervals (R^2: 0.995–0.999), RMSE: 0.095–121), and MAPE: 0.62–0.83%) demonstrate excellent reproducibility and stability across resampled datasets, supporting that the model's predictive power does not rely on a specific subset of records used for training purposes only. Presumably, this stability originates from the high degree of seasonal consistency and low interannual variability of climatic conditions in our study area, which increases the model's ability to capture consistent yield–climate interactions. However, it is acknowledged that generalizability to other agro-climatic zones has yet to be established. Subsequent work will therefore concentrate on external validation using multiregional and multi-seasonal datasets, in order to assess the scalability and transferability of the proposed framework across different stage-producing environments.

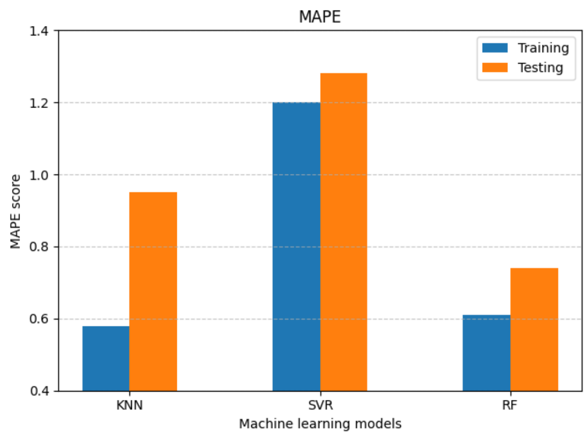

Figure 6: Comparative Performance of ML Models Based on MAPE

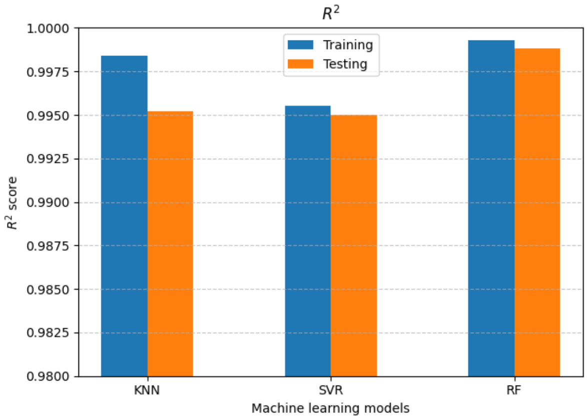

Figure 7: Comparative Performance of ML Models Based on R^2

3.5 Predicted vs. actual yield comparison

Finally, model predictions were compared with the observed yields for a visual check of performance over the entire yield range. The scatter plots of predicted versus observed yield (Figures 8–10) confirm the findings reported in the quantitative results. In the KNN model (Figure 8), prediction points were mainly distributed along a 1:1 reference line, achieving reasonable accuracy; however, some outliers were also portrayed , representing cases of over- or underestimation. The deviation appeared to be caused by KNN's difficulty in identifying regimes of atypical climatic patterns due to its limited extrapolation ability with local averaging. Likewise, the SVR model (Figure 9) was able to reflect the overall trend in yield, but with more dispersion along the diagonal and central ranges of yield and less around it than the GP, a behavior indicative of lesser flexibility in fitting complex nonlinear dependencies.

However, the RF model (Figure 10) exhibited excellent agreement between observed and predicted yields. The data points are neatly gathered around the 45° line, indicating low bias and variance — hallmarks of a sturdy, valid model. Such a strong alignment demonstrates that the RF was able to accurately represent the relationship between meteorological variables and yield outputs for both years with poor and good yields. That level of precision is seldom reached in agricultural forecasting, and it highlights the model's operational stability.

The excellent agreement between RF predictions and real yields suggests its potential for operational use. Accurate yield predictions are critical in making timely decisions for agriculture under the influence of weather variations. The RF model's proven accuracy makes it a viable early warning and decision-support system that can inform interventions. Such results demonstrate how the better predictive capability and interpretability of the RF model make it a scientifically sound and operationally suitable methodology for early warning potato yield forecasting in Bangladesh, capable of providing actionable information to implement climate-resilient agricultural practices.

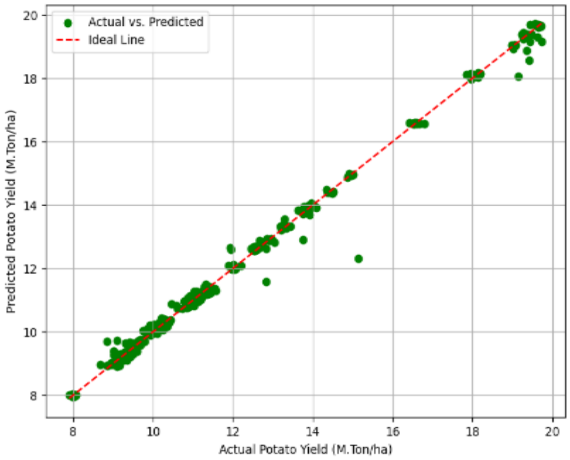

Figure 8: Comparison of Actual vs. Predicted Production for KNN

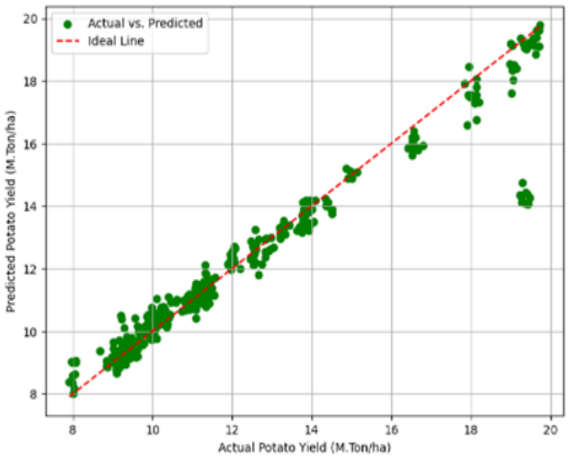

Figure 9: Comparison of Actual vs. Predicted Production for SVR

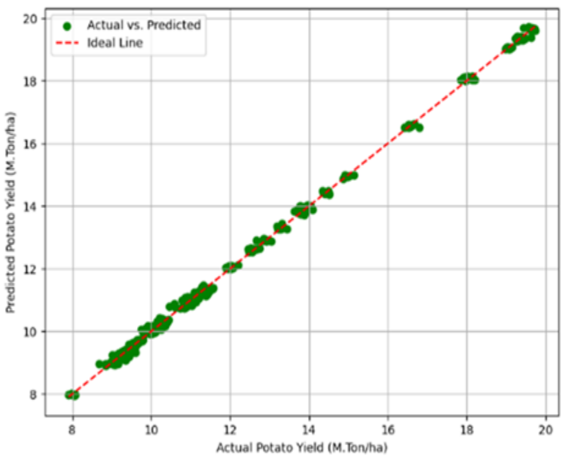

Figure 10: Comparison of Actual vs. Predicted Production for RF

3.6 Model interpretation and explainability

For interpreting the Random Forest (RF) model, SHapley Additive exPlanations (SHAP) were used to measure the contribution of each feature to the prediction of yields. December's rainfall and December temperature are the two most important variables affecting potato yield, according to the SHAP summary plot (Figure 11). SHAP values provide an instance-wise view of the model's behavior, illustrating how changes to features influence predictions. Moderate December rainfall (1–5 mm month^{-1}) certainly has a positive effect on yield, as described in Figure 12. However, excess precipitation will have an adverse effect. Likewise, the SHAP dependence plots for the most important variables—r_{3m} and t_{3m} (Figure 13)—describe marginal effects and interactions between predictor variables, as in the case of the climatic thresholds fitted by KDE. In summary, the SHAP analysis demonstrates that our new model is both highly accurate and interpretable, enabling agronomically meaningful interpretation of how specific significant weather variables influence yield responses.

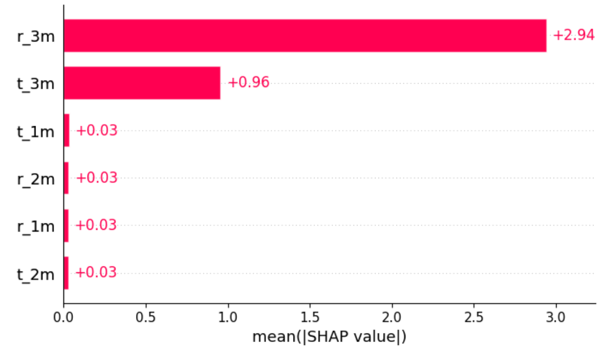

Figure 11: SHAP summary plot of feature contributions for RF model

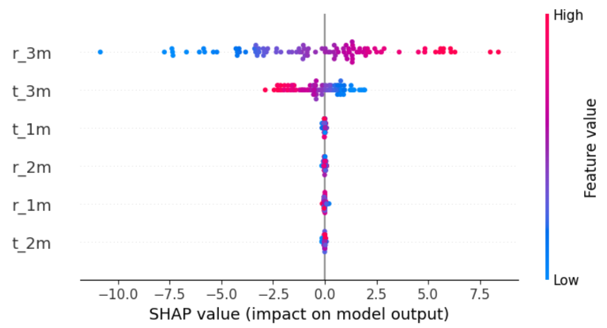

Figure 12: SHAP feature plot showing impact on crop yield

4 Discussion

Agronomic productivity depends on several manageable factors, such as fertiliser management and varietal choice, but is also influenced by unmanageable climate conditions. Although agronomic management can be modified to increase productivity, weather conditions still limit yield stability. This research enhances the predictability of potato yields in Bangladesh by utilizing readily available monthly rainfall and temperature data. The research clarifies the complex relationships between weather variation and crop performance across different growth stages, contributing to more informed and adaptive agricultural policy-making.

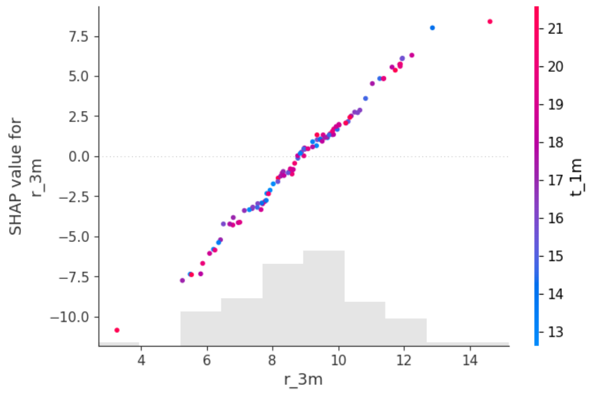

Figure 13: SHAP dependence plot for top-ranked features

4.1 Growth stage climate requirements

Potato production relies heavily on water and temperature conditions at various growth stages, highlighting the importance of matching weather patterns to crop development stages. The analysis highlights the optimal rainfall (Figure 14) and temperature (Figure 15) thresholds that result in high yields of 10,000–12,000 tons ha^{-1}, plausibly if those critical stages are achieved at five growth Stages – sprouting, vegetative growth, tuber initiation, bulking, and maturity. However, the moisture of slightly wet conditions (rainfall 1–21 mm month^{-1}) and moderate temperatures (22.8–23.7 °C) enhances stem growth at the sprouting stage. The vegetative and tuber initiation periods are characterized by limited rainfall (< 5 mm month^{-1}) and cool temperatures (18.8–19.5 °C), which promote canopy growth and early tuber setting. The bulking phase (the most yield-sensitive stage) is stimulated by little rain (1-5 mm month^{-1}), soil moisture at 60–80% FC and temperature in the range of 17.6–18.5 °C, as greater ones activate a severe diminution in yields above 25 °C; maturity is better managed with low precipitation (< 5 mm month^{-1}) combined with soft temperatures (20.2–21.1 °C), which reduce rot incidence and improve tuber grade. These observations support FAO recommendations [45] and existing agronomic evidence [46][47], and hence help provide data-driven evidence for adaptive irrigation scheduling and thermal work control. Farmers can increase yield stability and resource use efficiency in the potato crop by synchronizing their agricultural operations with these climate–growth relationships.

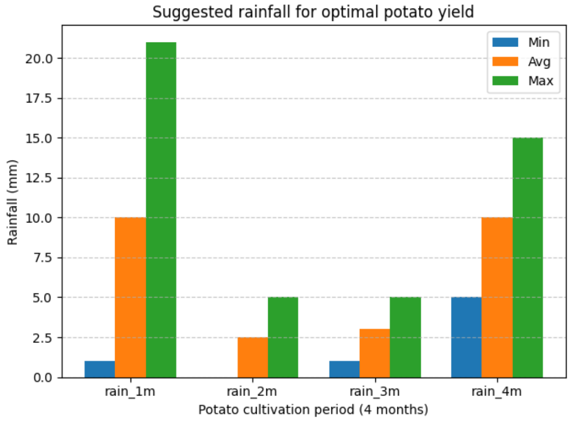

Figure 14: Optimal monthly rainfall requirements for optimal yield

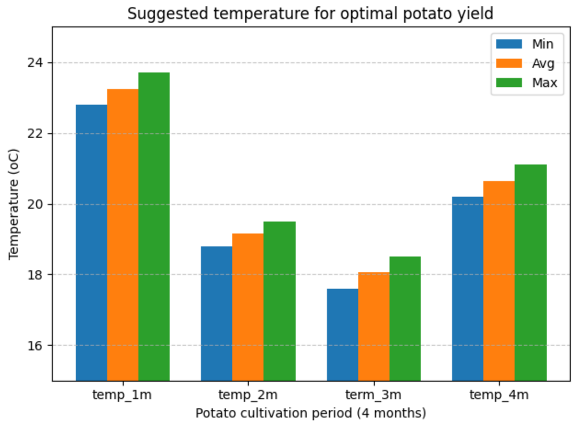

Figure 15: Optimal monthly temperature requirements for optimal yield

4.2 Practical recommendation to the farmers

This analysis identifies significant climate-related limitations to potato cultivation in Bangladesh and recommends specific adaptation measures to improve productivity and resilience. To minimize yield losses due to extended rain/poor water drainage, farmers need better water management strategies, along with potato varieties tolerant to excessive rainfall, coupled with climate-resilient agronomic practices and timely, location-specific weather information (real-time), and precision farming techniques for effective management of water/nutrient resources. These actions are most important during the growing and harvesting period, from October to January. Regular temperature measurements are necessary throughout the entire season, particularly at the optimal planting date in November and during the most cold-sensitive period for bulking in December. The risks associated with production can be further mitigated through proactive measures, including the use of temperature-adjusted cultivation technology and the selection of climate-resilient varieties. A comprehensive, systems-level programme that combines adaptive agronomy, resilient genetics, and environmental monitoring with knowledge dissemination within the farming community is essential to develop sustainable potato productivity for long-term agricultural sustainability and increased national food security.

To support its application in practice, the Random Forest–triggered forecast framework can be implemented with a dual-mode deployment into an operational early warning and advisory system (Figure 16). In this system, the model runs on a cloud-based server to process real-time weather data and produce dynamic yield predictions. The outputs are disseminated through a farmer-centred mobile app and a government extension dashboard, providing both bottom-up and top-down access. Utilizing real-time climate condition feeds and actionable advice, the system connects predictive models with in-season decision support, enabling farmers to make well-informed treatment decisions on re-coordinating farm inputs. Additionally, it enables agricultural institutions to make more informed decisions about climate-driven management changes.

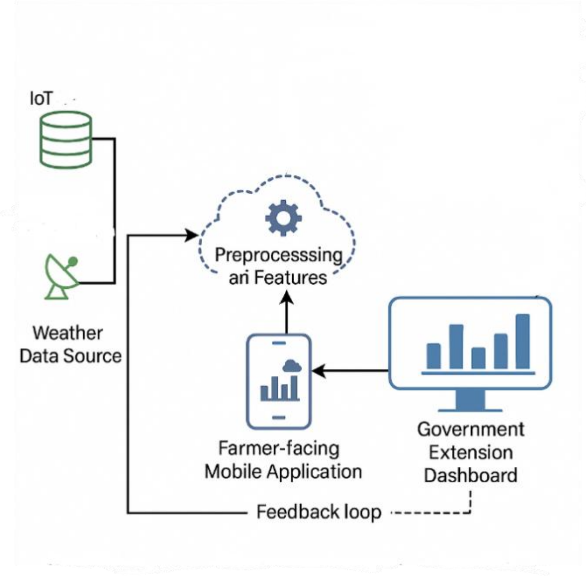

Figure 16: Conceptual deployment architecture for the climate–yield forecasting system

4.3 Comparative evaluation of the proposed framework against state-of-the-art models

The proposed RF model achieves the best prediction results (R^2 = 0.999; RMSE = 0.1014; MAPE = 0.70%), outperforming all competitive boosting and DNN models in Table 1. Contrary to various DNN-based approaches that require multi-modal, high-dimensional datasets, our approach involves growth-stage-specific monthly climatic variables, which efficiently model agro-seasonal variability with high accuracy and low error. In turn, this temporal resolution has been a key factor behind the model's near-perfect generalization, specifically during Bangladesh's winter growing season.

The intrinsic feature importance ranking of RF permits an explicit determination of the key climatic drivers—especially December rainfall and temperature. This is in accordance with the agro-ecological context of the area and farmers' information for seasonal decision-making. In comparison, Gradient Boosting and DNN models in existing works typically achieve R^2 scores of 0.92–0.97, albeit at the expense of higher data dependence, more complex hyperparameter tuning requirements, and decreased interpretability. The domain fit between the predictable winter climatic windows of Bangladesh and the non-parametric learning structure of RF imparts a unique seasonal adaptation advantage, enabling processing for low jitter output with fewer input features.

An additional benefit of this approach is that it enables easy operations and interpretation. Advanced DNN or hybrid ensemble models can achieve similar accuracy but generally require large feature sets and lack inherent interpretability. On the contrary, RF provides estimates of yield deviations due to several climatic factors, making the system more transparent and reliable for farmers.

The better performance of the RF model may be due to the three critical design choices:

Climatic input: The monthly rainfall and temperature values were used as input for the model for several important stages of potato phenology (sprouting, vegetative growth stage, tuber bulking phase, and maturity), allowing the model to be more sensitive to those variations that strongly affected biological responses.

Feature engineering was agro-climatically driven: the knowledge of the "potato growing cycle extension " helped to exclude noisy or redundant input and exploited unseen relationships.

Algorithm suitability: Tree-based ensemble methods are particularly well-suited for capturing non-linear interactions in moderate-dimensional feature spaces without overfitting, compared to DNNs in low-data regimes.

Moreover, the compatibility of RF with an agro-climatic regionalization approach makes it adaptable to season- and region-specific patterns without requiring retraining of specialized regional models. This scalability and interpretability provide a solid foundation for operational deployment in agriculture-constrained small-holding farming systems.

In addition to algorithmic and climatic consequences, the interpretability of the RF model also adds value for actionable decision-making by farmers and policymakers. For example, the relevance of December rainfall as a predictor of yield drives management decisions for irrigation scheduling and agronomic factors in particular. By contrast, black-box DNN models may exhibit strong numerical accuracy but little "actionable information." This is a significant advantage of interpretable machine learning for climate-smart agriculture.

In summary, the proposed RF approach is state-of-the-art in terms of accuracy, remains transparent, and has low complexity and domain-related features. These characteristics make it particularly suitable for use in Bangladesh and similar, climate-exposed agricultural systems by reconciling AI modeling with practical application.

5 Conclusion

This study examines climate vulnerability in the potato domain of Bangladesh by developing a weather-based yield forecasting model for sustainable and climate-resilient agricultural practices. Among the machine learning models, the RF model, with a mean absolute percentage error of 0.7% and $R^2 = 0.999$, showed better accuracy compared to KNN and SVR in predicting the solubility of compounds. This high accuracy demonstrates that RF has the potential to reproduce complex and non-linear relationships between climatic variables and crop productivity, as well as contribute to enhancing its possibilities for use as a stand-alone tool in support of agricultural work or policymakers' decisions.

The findings also suggest that temperature and precipitation are both key drivers in the multifaceted dynamics of potato yield. Statistical validation and feature importance analysis revealed that December rainfall is the most important predictor of yield compared to any other seasonal factor, with optimal productivity occurring at low monthly precipitation levels (~1–5 mm $month^{-1}$). Similarly, a temperate temperature (17.6–18.5 °C) during bulking was significantly linked to increased yield, in agreement with known agronomic facts that potatoes do well under cool and stable thermal conditions and balanced soil moisture. Overall, these results suggest that through a learning algorithm and climatic data, operational decisions can be generated for effective forecasting to improve climate adaptation, resource use efficiency, and sustainable potato production in Bangladesh.

Despite the accurate climate-yield predictions of the interpretable RF-based framework developed in this study, some limitations are observed. The model, in its current form, has not been calibrated with data on satellite-derived variables, pest and disease dynamics, or soil health indicators that significantly influence potato yield. Moreover, the model was developed based on a single district and monthly data, which may have spatial and temporal constraints.

These limitations will be addressed in future studies by incorporating other agro-ecological variables, such as solar radiation, soil moisture, and vegetation indices, to enhance the modeling of crop–environment relationships. These variables contribute to the model's robustness and align with the framework's characteristic line, focusing on climate-smart and sustainable agriculture goals.

In our future studies, we will also investigate the integration of IoT and remote sensing for real-time RF model federation with data-driven forecasting pipelines. One may foresee an IoT–RF hybrid system, as proposed here, to provide automatic and adaptive decision support, such as irrigation cut-back before heatwaves or prevention against disease outbreaks—simply opening up possibilities for operational, high-resolution, and nationally scalable early-warning systems for precision agriculture.

Acknowledgement

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References

[1] T. Begna and R. B. Wakweya, "Climate-Smart Agriculture: Effect of Climate Change on Food Security and Its Mitigation Strategies," *Int. J. Agron.*, vol. 2025, no. 1, p. 9972955, 2024. doi: https://doi.org/10.1155/ioa/9972955.

[2] O. R. Taiwo, H. Onyeaka, A. A. Akinsemolu, and E. K. Oladipo, "Examining the nexus of climate change and food safety: A review," *Appl. Food Res.*, vol. 5, no. 1, p. 100884, 2025. doi: https://doi.org/10.1016/j.afres.2025.100884.

[3] A. A. Farah, M. A. Mohamed, O. S. H. Musse, et al., "The multifaceted impact of climate change on agricultural productivity: a systematic literature review of SCOPUS-indexed studies (2015–2024)," *Discov. Sustain.*, vol. 6, p. 397, 2025. doi: https://doi.org/10.1007/s43621-025-01229-2.

[4] X. Yuan, S. Li, J. Chen, H. Yu, T. Yang, C. Wang, S. Huang, H. Chen, and X. Ao, "Impacts of Global Climate Change on Agricultural Production: A Comprehensive Review," *Agronomy*, vol. 14, p. 1360, 2024. doi: https://doi.org/10.3390/agronomy14071360.

[5] Y. Lin, S. Li, S. Duan, Y. Ye, B. Li, G. Li, D. Lyv, L. Jin, C. Bian, and J. Liu, "Methodological evolution of potato yield prediction: a comprehensive review," *Front. Plant Sci.*, vol. 14, p. 1214006, 2023. doi: 10.3389/fpls.2023.1214006.

[6] A. Maniriho and F. Nkikabahizi, "Effects of potato farming on small farmers' food security in volcanic highlands of Rwanda," *Cogent Soc. Sci.*, vol. 11, no. 1, p. 2467226, 2025. doi: https://doi.org/10.1080/23311886.2025.2467226.

[7] K. Deeba, O. R. Devi, M. S. Al Ansari, B. P. Reddy, H. T. Manohara, Y. A. B. El-Ebiary, and M. Rengarajan, "Optimizing Crop Yield Prediction in Precision Agriculture with Hyperspectral Imaging-Unmixing and Deep Learning," *Int. J. Adv. Comput. Sci. Appl. (IJACSA)*, vol. 14, no. 12, 2023. doi: http://dx.doi.org/10.14569/IJACSA.2023.0141261.

[8] K. N. Vhatkar, S. A. Koparde, S. Kothari, J. Sarwade, and K. Sakur, "Enhancing prediction of crop yield and soil health assessment for sustainable agriculture using machine learning approach," *MethodsX*, vol. 14, p. 103418, 2025. doi: https://doi.org/10.1016/j.mex.2025.103418.

[9] R. Zeng, J. Li, Z. Li, and Q. Zhang, "Crossformer-Based Model for Predicting and Interpreting Crop Yield Variations Under Diverse Climatic and Agricultural Conditions," *Agriculture*, vol. 15, p. 958, 2025. doi: https://doi.org/10.3390/agriculture15090958.

[10] A. Ikram, S. Ikram, E.-S. M. El-kenawy, A. Hussain, A. H. Alharbi, and M. M. Eid, "A fuzzy-optimized hybrid ensemble model for yield prediction in maize-soybean intercropping system," *Front. Plant Sci.*, vol. 16, p. 1567679, 2025. doi: 10.3389/fpls.2025.1567679.

[11] M. A. Quddus, S. Chowdhury, W. Jasper, and L. Das, "Enhancing cotton yield prediction with robust deep neural network-based framework," *Eur. J. Agron.*, vol. 170, p. 127750, 2025. doi: https://doi.org/10.1016/j.eja.2025.127750.

[12] M. Mesbah, Y. Zhang, and X. Wang, "Advanced machine learning for regional potato yield prediction: Analysis of essential drivers," *npj Sustain. Agric.*, vol. 3, no. 1, pp. 1–13, 2025. doi: https://doi.org/10.1038/s44264-025-00052-6.

[13] H. F. Monna, M. S. M. Rabby, S. R. Siddikey, M. Khaliluzzaman and M. J. Hoque, "Vegetable Classification using Deep Learning: Insights from Transfer Learning Models," *2024 IEEE International Conference on Computing, Applications and Systems (COMPAS)*, Cox's Bazar, Bangladesh, 2024, pp. 1-6, doi: 10.1109/COMPAS60761.2024.10795820.

[14] E. B. Zeleke, M. Mohammed, and B. B. Kidanewold, "Vulnerability Assessment of Smallholder Farmers to Climate Change in the Awash Basin, Ethiopia," *Environ. Sustain. Indic.*, vol. 2025, p. 100927, 2025. doi: https://doi.org/10.1016/j.indic.2025.100927.

[15] J. Wang and L. Lu, " CNN-Based Iterative Decoding for Polar Codes in MIMO Systems: Performance Analysis and Computational Complexity Evaluation," *Informatica*, vol. 49, p. 27-42, 2025. doi: https://doi.org/10.31449/inf.v49i33.8431.

[16] S. Gourlay, T. Kilic, and D. B. Lobell, "A new spin on an old debate: Errors in farmer-reported production and their implications for inverse scale–productivity relationship in Uganda," *J. Dev. Econ.*, vol. 141, p. 102376, 2019. doi: https://doi.org/10.1016/j.jdeveco.2019.102376.

[17] G. Gupta and S. Kumar Pal, "Applications of AI in precision agriculture," *Discov. Agric.*, vol. 3, p. 61, 2025. doi: https://doi.org/10.1007/s44279-025-00220-9.

[18] J. B. Hussein, T. S. Workneh, A. Kassim, K. Ntsowe, S. F. Melesse, and H. S. El-Mesery, "A review on the impact of big data analytics in transforming agricultural practices, food processing, and preservation strategies," *Appl. Food Res.*, vol. 5, no. 2, p. 101234, 2025. doi: https://doi.org/10.1016/j.afres.2025.101234.

[19] T. Miller, G. Mikiciuk, I. Durlik, M. Mikiciuk, A. Łobodzińska, and M. Śnieg, "The IoT and AI in Agriculture: The Time Is Now—A Systematic Review of Smart Sensing Technologies," *Sensors*, vol. 25, p. 3583, 2025. doi: https://doi.org/10.3390/s25123583.

[20] M. Padhiary, A. Kumar, and L. N. Sethi, "Emerging technologies for smart and sustainable precision agriculture," *Discov. Robot.*, vol. 1, p. 6, 2025. doi: https://doi.org/10.1007/s44430-025-00006-0.

[21] B. Surekha and T. Subhamastanrao, " LDDNet: A Custom Inception Layer-Based CNN for Enhanced Leaf Disease Detection in Precision Agriculture," *Informatica*, vol. 49, p. 77-98, 2025. doi: https://doi.org/10.31449/inf.v49i23.7835.

[22] S. Mansoor, S. Iqbal, S. M. Popescu, S. L. Kim, Y. S. Chung, and J.-H. Baek, "Integration of smart sensors and IoT in precision agriculture: trends, challenges and future prospectives," *Front. Plant Sci.*, vol. 16, p. 1587869, 2025. doi: 10.3389/fpls.2025.1587869.

[23] M. Fahim, M. Z. U. H. Chowdhury, M. J. Hoque and M. N. Hasan, "Visualizing Crop Disease Detection Exploring Deep Learning with Custom CNN Model and XAI for Enhanced Interpretability," *2024 International Conference on Innovations in Science, Engineering and Technology (ICISET)*, Chittagong, Bangladesh, 2024, pp. 1-6, doi: 10.1109/ICISET62123.2024.10940041.

[24] F. Huber, A. Yushchenko, B. Stratmann, and V. Steinhage, "Extreme Gradient Boosting for yield estimation compared with Deep Learning approaches," *Comput. Electron. Agric.*, vol. 202, p. 107346, 2022. doi: https://doi.org/10.1016/j.compag.2022.107346.

[25] A. Erlin, L. Yunianta, L. A. Wulandhari, Y. Desnelita, N. Nasution, and Junadhi, "Enhancing Rice Production Prediction in Indonesia Using Advanced Machine Learning Models," *IEEE Access*, vol. 12, pp. 151161–151177, 2024. doi: 10.1109/ACCESS.2024.3478738.

[26] M. J. Hoque, M. S. Islam, and M. Khaliluzzaman, "AI-Powered Precision in Diagnosing Tomato Leaf Diseases," *Complexity*, vol. 2025, no. 1, p. 7838841, 2024. doi: https://doi.org/10.1155/cplx/7838841.

[27] X. Liu, Q. Yang, R. Yang, L. Liu, and X. Li, "Corn Yield Prediction Based on Dynamic Integrated Stacked Regression," *Agriculture*, vol. 14, p. 1829, 2024. doi: https://doi.org/10.3390/agriculture14101829.

[28] R. N. V. J. Mohan, P. S. Rayanoothala, and R. P. Sree, "Next-gen agriculture: integrating AI and XAI for precision crop yield predictions," *Front. Plant Sci.*, vol. 15, p. 1451607, 2025. doi: 10.3389/fpls.2024.1451607.

[29] O. Ennaji, S. Baha, L. Vergutz, and A. E. Allali, "Gradient boosting for yield prediction of elite maize hybrid ZhengDan 958," *PLOS ONE*, vol. 19, no. 12, p. e0315493, 2024. doi: https://doi.org/10.1371/journal.pone.0315493.

[30] T. Baykal, Ö. Terzi, G. Yıldırım, et al., "Investigating the performance of random oversampling and genetic algorithm integration in meteorological drought forecasting with machine learning," *Discov. Appl. Sci.*, vol. 7, p. 566, 2025. doi: https://doi.org/10.1007/s42452-025-07114-x.

[31] M. J. Hoque et al., "Incorporating Meteorological Data and Pesticide Information to Forecast Crop Yields Using Machine Learning," in *IEEE Access*, vol. 12, pp. 47768-47786, 2024, doi: 10.1109/ACCESS.2024.3383309.

[32] S. Sah, D. Haldar, R. Singh, B. Das, and A. S. Nain, "Rice yield prediction through integration of biophysical parameters with SAR and optical remote sensing data using machine learning models," *Sci. Rep.*, vol. 14, no. 1, pp. 1–17, 2024. doi: https://doi.org/10.1038/s41598-024-72624-4.

[33] N. A. Naim, R. Islam, M. Saifuddin, M. J. Hoque, M. N. Hasan and M. M. Khandaker, "Tomato Shelf Life Prediction using IoT and Machine Learning," *2024 International Conference on Innovations in Science, Engineering and Technology (ICISET)*, Chittagong, Bangladesh, 2024, pp. 1-6, doi: 10.1109/ICISET62123.2024.10939467.

[34] M. Lavanya and R. Parameswari, "A Multiple Linear Regressions Model for Crop Prediction with Adam Optimizer and Neural Network Mlraonn," *Int. J. Adv. Comput. Sci. Appl. (IJACSA)*, vol. 11, no. 4, 2020. doi: http://dx.doi.org/10.14569/IJACSA.2020.0110434.

[35] W. J. Yeo, W. Van Der Heever, R. Mao, et al., "A comprehensive review on financial explainable AI," *Artif. Intell. Rev.*, vol. 58, p. 189, 2025. doi: https://doi.org/10.1007/s10462-024-11077-7.

[36] P. Linardatos, V. Papastefanopoulos, and S. Kotsiantis, "Explainable AI: A Review of Machine Learning Interpretability Methods," *Entropy*, vol. 23, p. 18, 2021. doi: https://doi.org/10.3390/e23010018.

[37] I. Malashin, V. Tynchenko, A. Gantimurov, V. Nelyub, A. Borodulin, and Y. Tynchenko, "Predicting Sustainable Crop Yields: Deep Learning and Explainable AI Tools," *Sustainability*, vol. 16, p. 9437, 2024. doi: https://doi.org/10.3390/su16219437.

[38] A. M. A. I. Hamim, A. Mohaimin, A. F. Ishmum, R. A. Ifty, and M. J. A. Patwary, "Advances in Machine Learning for Crop Yield Prediction: A Comprehensive Review of Techniques, Trends, and Challenges," in *Proc. 2025 Int. Conf. Electr.*,

Comput. Commun. Eng. (ECCE), Chittagong, Bangladesh, 2025, pp. 1–6. doi: 10.1109/ECCE64574.2025.11013031.

[39] D. Damyanov and I. Donchev, "Model for Training and Predicting the Occurrence of Potato Late Blight Based on an Analysis of Future Weather Conditions," *Int. J. Adv. Comput. Sci. Appl. (IJACSA)*, vol. 16, no. 2, 2025. doi: http://dx.doi.org/10.14569/IJACSA.2025.0160213.

[40] R. K. Dhanaraj, M. Maragatharajan, A. Sureshkumar, and S. P. Balakannan, "On-device AI for climate-resilient farming with intelligent crop yield prediction using lightweight models on smart agricultural devices," *Sci. Rep.*, vol. 15, no. 1, pp. 1–19, 2025. doi: https://doi.org/10.1038/s41598-025-16014-4.

[41] Bangladesh Climate Information Management System (CIMSB), *Climate Information of Bangladesh*, 2025. [Online]. Available: http://barcapps.gov.bd/climate/

[42] Bangladesh Meteorological Department (BMD), *Daily Rainfall and Temperature Data*, 2025. [Online]. Available: https://www.bmd.gov.bd/

[43] Bangladesh Bureau of Statistics (BBS), *Yearbook of Agricultural Statistics–2024*, 2025. [Online]. Available: https://bbs.gov.bd/

[44] Bangladesh Agricultural Research Institute (BARI), *BARI Annual Report–2024*, 2025. [Online]. Available: https://bari.portal.gov.bd/

[45] J. Doorenbos and W. O. Pruitt, *Crop Water Requirements*, FAO Irrigation and Drainage Paper No. 33, Rome, Italy: Food and Agriculture Organization of the United Nations (FAO), 1977, 144 pp.

[46] A. J. Haverkort, “Ecology of potato cropping systems in relation to latitude and altitude,” *Agricultural Systems*, vol. 32, no. 3, pp. 251–272, 1989, doi: 10.1016/0308-521X(90)90004-A.

[47] J. E. Obidiegwu, G. J. Bryan, H. G. Jones, and A. Prashar, “Coping with drought: Stress and adaptive responses in potato and perspectives for improvement,” *Frontiers in Plant Science*, vol. 6, p. 542, 2015, doi: 10.3389/fpls.2015.00542.