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A Climate Driven Decision Support System for Rice Management Using SPI-3 Prediction and Particle Swarm Optimization

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Abstract

Climate variability and irregular rainfall patterns have become critical challenges affecting rice productivity, irrigation planning, and agricultural sustainability. Previous studies have primarily focused on rainfall forecasting or drought monitoring independently, with limited attention given to transforming climate predictions into actionable agricultural management strategies. This study addresses this gap by proposing an integrated climate-driven decision support framework that combines predictive drought-index modeling with optimization-based agronomic decision-making for adaptive rice field management. The proposed framework integrates satellite-based rainfall observations, seasonal climatic characteristics, and large-scale climate variability indicators to predict short-term moisture conditions represented by the three-month standardized precipitation index. The framework consists of three interconnected stages: climate prediction, optimization, and recommendation generation. In the prediction stage, a gradient boosting regression model enhanced with Bayesian hyperparameter optimization was employed to model nonlinear relationships among rainfall accumulation, lag rainfall patterns, seasonal cyclic features, and climate variability indicators. In the optimization stage, particle swarm optimization was applied to determine optimal fertilizer dosage, irrigation allocation, and harvest timing under varying climate conditions. Experimental procedures included comparative evaluations across multiple machine learning models, hyperparameter tuning strategies, and optimization iterations. The research figures and tables demonstrate the complete framework architecture, prediction performance comparisons, optimization convergence behavior, and adaptive rice management recommendations. Experimental results show that the proposed framework achieved strong predictive performance with a coefficient of determination of 0.851, a root mean square error of 0.391, and a mean absolute error of 0.322. Comparative analysis further confirmed that integrating climate variability indicators significantly improved predictive accuracy compared with baseline models using only historical rainfall information. The optimization process also demonstrated stable convergence toward climate-adaptive agronomic recommendations.

Keywords: SPI-3, Machine Learning, PSO, Precision Agriculture, Decision Support System, ENSO, CHIRPS

1. Introduction

Agricultural productivity is increasingly vulnerable to climate variability, particularly fluctuations in rainfall that directly influence water availability in rice cultivation systems. Variability in precipitation has been shown to significantly affect crop growth cycles, irrigation demand, and yield stability, especially in rainfed agricultural regions where water availability is highly dependent on climate conditions [1], [2], [3]. Moreover, recent studies highlight that increasing climate uncertainty and the frequency of extreme events have intensified the challenges faced by agricultural systems, necessitating more adaptive and predictive approaches for sustainable crop management [4], [5]. Traditional farming practices, which rely heavily on historical patterns and experiential knowledge, are therefore insufficient to cope with the dynamic and nonlinear nature of modern climate systems.

Recent advances in machine learning (ML) have demonstrated strong capabilities in modeling complex climate dynamics and improving rainfall prediction accuracy [6], [7], [8], [9]. Studies show that ML models, including ensemble and boosting techniques, are capable of capturing nonlinear relationships and temporal dependencies in precipitation data, leading to improved predictive performance compared to traditional statistical methods [10], [11]. Furthermore, the integration of multiple input variables, such as rainfall history, climate indices, and remote sensing data, has been identified as a critical factor in enhancing drought and rainfall forecasting accuracy [12], [13]. Despite

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these advancements, most existing research remains limited to predictive analytics and does not extend its outputs into actionable decision-support systems. Consequently, a significant gap persists between climate prediction and its practical application in agricultural decision-making.

This study proposes an integrated framework that combines climate prediction and decision optimization into a unified system. Specifically, the research develops a ML model to predict the Standardized Precipitation Index (SPI-3), which is widely used as an indicator of short- to medium-term moisture conditions and agricultural drought assessment [14]. Unlike conventional approaches that treat SPI as a retrospective descriptive index, this study utilizes SPI-3 as a predictive variable to support early decision-making. The predicted SPI-3 is then incorporated into an optimization framework based on Particle Swarm Optimization (PSO), enabling the determination of optimal agricultural practices under varying climate conditions [15], [16].

2. Literature Review

2.1. Climate Variability and Its Impact on Paddy Agriculture

Rice production is highly sensitive to climate variability, particularly rainfall patterns, which influence water availability, crop growth stages, and overall productivity [17]. Increasing climate uncertainty has intensified the risk of droughts and extreme weather events, significantly affecting agricultural sustainability. Rainfall variability, driven by global climate phenomena such as El Niño–Southern Oscillation (ENSO), plays a crucial role in determining planting schedules and irrigation strategies. Recent studies highlight that climate-induced drought and rainfall variability require robust monitoring and prediction systems to support adaptive agricultural practices [18]. ML based drought forecasting models have been increasingly adopted to capture complex climate interactions and improve resilience in agricultural systems [19]. These findings emphasize the importance of integrating climate-aware approaches into Rice Management.

2.2. Machine Learning for Rainfall Prediction

Rainfall prediction is inherently complex due to its nonlinear, non-stationary, and dynamic characteristics. Traditional statistical models often fail to capture these complexities, leading to the growing adoption of ML techniques [20]. ML models, including Random Forest, Gradient Boosting, and Artificial Neural Networks, have demonstrated strong capabilities in modeling nonlinear relationships within meteorological data [21], [22]. Recent research shows that ensemble-based models such as Gradient Boosting Regressor can achieve high predictive accuracy when trained on integrated datasets combining satellite and ground observations [23]. For example, integrated ML approaches have achieved high R^2 values (up to 0.90), indicating strong predictive performance in rainfall forecasting tasks [24]. Furthermore, ML-based rainfall prediction benefits significantly from incorporating multiple climate variables, including precipitation history, temperature, and global climate indices. In addition, the Standardized Precipitation Index (SPI) has been widely used as a reliable indicator for drought and rainfall variability analysis. Studies confirm that SPI-based modeling enhances the interpretability and reliability of rainfall predictions, particularly when combined with ML techniques [25].

2.3. Metaheuristic Approaches in Agricultural Optimization

Optimization in agricultural systems involves complex decision-making processes under uncertainty, including irrigation management, planting schedules, and resource allocation. Metaheuristic algorithms have emerged as effective tools for solving such problems due to their ability to explore large and complex solution spaces [26]. Particle Swarm Optimization (PSO), one of the most widely used metaheuristic algorithms, has demonstrated strong performance in optimization problems involving nonlinear and multi-objective conditions [27]. Recent studies show that PSO-based models can significantly improve optimization outcomes by balancing exploration and exploitation in the search space [28]. For example, PSO-integrated models have been successfully applied to improve predictive accuracy and optimization performance in environmental and agricultural systems. Moreover, hybrid approaches combining metaheuristics with predictive models have gained attention for their ability to enhance both prediction and optimization simultaneously.

2.4. Hybrid Machine Learning and Metaheuristic Models

The integration of ML and metaheuristic algorithms has become an emerging trend in solving complex environmental and agricultural problems [29]. Hybrid models leverage the predictive strength of ML and the optimization capability of metaheuristics to produce more robust and adaptive solutions [30]. Several studies have demonstrated that combining ML models with optimization algorithms such as PSO significantly improves prediction accuracy and system performance [31]. For example, hybrid LSTM-PSO models have shown improved performance in rainfall forecasting by optimizing model parameters and reducing prediction errors [32]. Similarly, integrated frameworks combining ML and optimization techniques have been successfully applied in agricultural recommendation systems, enabling better decision-making based on environmental conditions. Despite these advances, most existing studies focus either on improving prediction accuracy or optimization performance separately. Fully integrated end-to-end frameworks that connect rainfall prediction directly with agricultural decision-making remain limited. However, most existing studies focus primarily on prediction accuracy without integrating the results into actionable agricultural decision-making frameworks.

2.5. Research Gap and Novelty

Existing studies on climate-smart agriculture primarily focus on either rainfall prediction, drought monitoring, and optimization independently [33], [34], [35]. Several studies have employed ML models to improve rainfall and drought forecasting accuracy, while others applied optimization algorithms for irrigation scheduling and agricultural resource allocation [36]. However, most previous works remain fragmented and do not provide an operational integration between predictive climate modeling and agronomic decision-making [37], [38].

Furthermore, previous studies generally utilize the Standardized Precipitation Index (SPI) as a retrospective drought indicator rather than a predictive agroclimatic variable [39]. Existing agricultural optimization approaches also rarely incorporate dynamically predicted climate indicators into the optimization process [40]. As a result, a significant gap remains between climate prediction outputs and practical agricultural recommendations.

The novelty of this study lies in the development of an integrated end-to-end climate-driven decision-support framework named ENSO–CHIRPS Intelligence Booster (ECIB). The proposed framework combines predictive SPI-3 modeling, ENSO-based climate variability integration, Bayesian-optimized Gradient Boosting Regression, and Particle Swarm Optimization within a unified operational pipeline. Unlike previous studies, the proposed framework automatically transforms predicted climate conditions into adaptive rice field management recommendations, including irrigation allocation, fertilizer dosage, and harvest scheduling.

Table 1 demonstrates that previous studies generally focus on isolated prediction or optimization tasks, whereas the proposed ECIB framework integrates climate prediction, optimization, and operational recommendation generation into a unified end-to-end agricultural decision-support system.

Table 1. Comparison with Previous Studies

Study	Climate Prediction	ENSO Integration	Optimization	Decision Recommendation	End-to-End Framework
Previous rainfall forecasting studies	✓	Limited	✗	✗	✗
Agricultural optimization studies	✗	✗	✓	Partial	✗
Hybrid ML-Optimization studies	✓	Partial	✓	Limited	Partial
Proposed ECIB Framework	✓	✓	✓	✓	✓

3. Methodology

3.1. Study Area and Dataset Description

The study was conducted using satellite-based rainfall observations obtained from the Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) dataset and large-scale climate variability indicators derived from the El Niño–

Southern Oscillation (ENSO) Niño 3.4 index. The study area focuses on rice cultivation regions characterized by strong rainfall dependency and seasonal climate variability in tropical environments. The rainfall dataset covers the observation period from January 2000 to December 2023 with daily temporal resolution. CHIRPS data were selected due to their high spatial resolution (0.05° × 0.05°) and their proven reliability for drought monitoring and agricultural applications in data-scarce regions. The dataset consists of daily rainfall observations, accumulated rainfall features, dry-day indicators, seasonal cyclic variables, and ENSO indices. After preprocessing and feature engineering, the final dataset contained multiple temporal predictor variables representing rainfall persistence, seasonal variability, and climate anomalies relevant to SPI-3 prediction. The study employed SPI-3 as the primary agroclimatic target variable because it effectively represents short- to medium-term moisture conditions influencing rice productivity and irrigation management.

3.2. ECIB Framework Overview

The proposed ENSO–CHIRPS Intelligence Booster (ECIB) framework is designed as an end-to-end decision-support system that integrates climate prediction and agronomic optimization into a unified pipeline. The framework consists of three sequential stages, namely prediction, optimization, and recommendation, which are interconnected to transform raw climate data into actionable agricultural decisions. In the first stage, SPI-3 forecasting is performed using ML models that leverage rainfall observations, seasonal patterns, and large-scale climate indicators such as ENSO to capture nonlinear and temporal dependencies in climate dynamics [41]. The use of SPI-3 as a predictive agroclimatic indicator enables early detection of moisture conditions, which is essential for climate-adaptive agricultural planning [42].

In the second stage, the predicted SPI-3 is incorporated into a decision-making process using Particle Swarm Optimization (PSO), a metaheuristic algorithm widely recognized for its effectiveness in solving complex and nonlinear optimization problems. Within this stage, SPI-3 functions as an environmental parameter that influences the optimization of key agronomic variables, including fertilizer application, irrigation requirements, and harvest timing. This integration allows the optimization process to dynamically adapt to predicted climate conditions rather than relying on static or historical assumptions.

Finally, the third stage translates the optimization results into actionable recommendations for agricultural management. These recommendations provide practical guidance for farmers and decision-makers by identifying optimal combinations of agronomic inputs that maximize productivity under specific climate scenarios. By linking prediction, optimization, and recommendation into a single framework, ECIB addresses the critical gap between climate intelligence and real-world agricultural decision-making, thereby supporting the development of climate-smart and precision agriculture systems.

3.3. Operational Architecture of the ECIB Framework

The ECIB framework is designed as an integrated climate-driven decision support architecture that combines climate prediction and agricultural optimization within a unified workflow. The framework utilizes CHIRPS rainfall observations and ENSO climate indicators as primary inputs to generate climate-aware recommendations for rice management. By integrating machine-learning prediction with optimization-based decision support, the framework transforms climate information into actionable agricultural strategies.

Figure 1 illustrates the overall operational workflow of the proposed ECIB framework. The workflow consists of several sequential stages, including climate data acquisition, preprocessing, SPI-3 computation, feature generation, predictive modelling, and optimization. The workflow begins with the collection of CHIRPS rainfall observations and ENSO indicators. These datasets are subsequently cleaned and pre-processed to ensure consistency and reliability before being used for further analysis.

The processed rainfall observations are then utilized to compute the Standardized Precipitation Index (SPI-3), which serves as the primary drought and moisture indicator. Based on the computed SPI-3 values, additional rainfall, seasonal, and ENSO-related features are generated to enhance the predictive capability of the forecasting model. The resulting dataset is divided into training and testing subsets to support model development and validation.

In the prediction stage, Bayesian Optimization is employed to identify the optimal hyperparameter configuration of the Gradient Boosting Regression (GBR) model. The optimized model is subsequently trained and used to predict future SPI-3 values, providing an indication of future climate conditions and potential drought risk. These predictive outputs constitute the climate intelligence component of the ECIB framework

The predicted SPI-3 values are subsequently utilized as inputs for agricultural optimization. Particle Swarm Optimization (PSO) is employed to explore alternative crop-management strategies and identify the most suitable management configuration under the projected climate scenario. Through iterative optimization, PSO searches for management solutions that maximize expected agricultural performance while considering climate variability.

Finally, the framework generates decision-support outputs consisting of predicted SPI-3 values, optimal crop-management recommendations, and estimated yield outcomes. The integration of climate prediction and optimization enables ECIB to provide a systematic mechanism for translating climate information into adaptive agricultural management decisions.

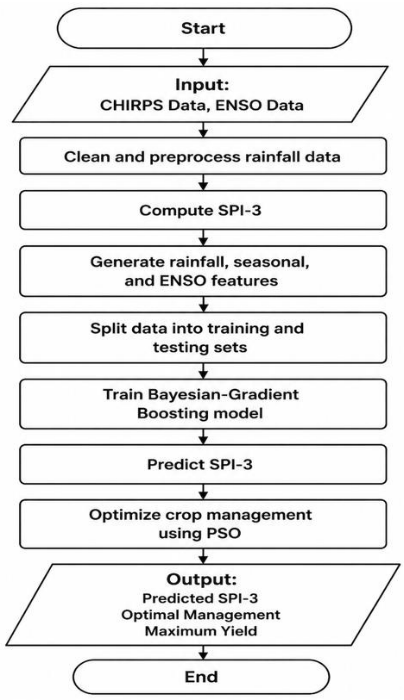

Figure 1. Operational Workflow of the Proposed ECIB Framework

Figure 1 illustrates the operational workflow of the proposed ENSO–CHIRPS Intelligence Booster (ECIB) framework. The workflow begins with CHIRPS rainfall observations and ENSO climate indicators, followed by data preprocessing, SPI-3 computation, feature generation, predictive modeling using Bayesian-optimized Gradient Boosting Regression, and optimization through Particle Swarm Optimization. The framework ultimately generates climate-adaptive rice-management recommendations based on predicted moisture conditions.

3.4. SPI-3 Prediction Model

The Standardized Precipitation Index at a three-month timescale (SPI-3) is employed in this study as a key agroclimatic indicator derived from accumulated rainfall over a rolling three-month period, which is widely recognized for its effectiveness in representing short- to medium-term moisture conditions relevant to agricultural systems. Unlike conventional approaches that compute SPI retrospectively from historical observations, this study models SPI-3 as a predictive variable using ML, enabling its use as an early warning indicator for climate-informed agricultural decision-making.

The prediction model incorporates a comprehensive set of features designed to capture both temporal rainfall dynamics and large-scale climate influences. These include CHIRPS satellite-based rainfall data, which provide high-resolution and reliable precipitation estimates for data-scarce regions. Prior to feature generation, rainfall observations are cleaned to remove invalid negative values according to X(t), Suppose daily rainfall data is expressed as a time series $X(t) = 1,2,3,\ldots,T$. Where $X(t) > 0$ is rainfall (m) on day t, Data is sorted by time to form a certain time series.

Data cleaning from negative values:

$$X(t) = \max(X(t), 0) \tag{1}$$

Rainfall Cleaning and Features:

Accumulated Data Lag

$$A_{30}(t) = \sum_{i=0}^{29} R(t-i) \tag{2}$$

Seasonal Feature Accumulation:

$$\sin\_doy(t) = sin\left(\frac{2\pi.\,doy(t)}{365}\right) \tag{3}$$

$$\sin\_doy(t) = cos\left(\frac{2\pi.\,doy(t)}{365}\right) \tag{4}$$

SPI-3 Computation:

SPI-3 90-Day Calculation

$$S_{90}(t) = \sum_{i=0}^{89} X(t-i) \tag{5}$$

ENSO Data Integration:

$$P_t = f(CHRIPS_t, ENSO_t, ENSO_{t-1}, ENSO_{t-2}, \ldots, X_t) \tag{6}$$

Based on the equation above: P_t is the rainfall at time *t*, $CHRIPS_t$ is the observed rainfall data from CHIRPS, $ENSO_t$ is the current ENSO index value, $ENSO_{t-1}$ is the ENSO value at lag *i* to capture the delayed effects $X_t$of other variables (e.g., seasonal factors, topography, etc.), $f(.)$ is a prediction function, namely the Gradient Boosting Regressor.

Novelty of the SPI-3 rainfall prediction model:

$$CHRIPS \rightarrow R^3 \rightarrow SPI \rightarrow Model\ ML\ (GBR)\ (Musiman + ENSO) \rightarrow \widehat{SPI}_3 \tag{7}$$

The novelty of this research lies in the use of ML to directly predict SPI-3 values, rather than simply calculating SPI from historical rainfall data. The model is built by integrating CHIRPS data, seasonal (cyclic) features, and ENSO and ENSO *lag* as predictor variables, thus capturing non-linear relationships and global climate influences not accommodated by conventional SPI statistical approaches. This approach allows SPI-3 to be used predictively (early warning agroclimate), rather than simply as a descriptive indicator of drought/wetness.

Train and Predict ion Model:

GBR + Bayesin Optuna Optimization

$$\hat{y}(t) = \sum_{m-1}^{M} \gamma_m\, h_m(X(t)) \tag{8}$$

PSO Rice Field Optimization:

$$\mathcal{L}\sqrt{\frac{1}{n}\sum_{i-1}^{n}\left(y_i - \hat{y}_i(0)\right)^2} \tag{9}$$

Prediction Results GBR+Boptuna, Fertilizer, Irrigation and Harvest:

$$Y(x, SPI) = E_F(x_1).E_1(x_2, SPI).E_H(x_3) \tag{10}$$

Since PSO works in a minimization scheme, the objective function is defined as:

$$f(x) = -Y(x, SPI) \tag{11}$$

R_t represents observed rainfall at time t, $ENSO_t$ represents the current ENSO index value, $ENSO_{t-1}$ represents lagged ENSO variables, X_t denotes the feature vector, $\widehat{SPI}_3$ represents the predicted SPI-3 value, $f(.)$ denotes the Gradient Boosting prediction function,

By enabling direct prediction of SPI-3, the proposed model supports proactive and data-driven agricultural planning, allowing stakeholders to anticipate moisture conditions and adjust management strategies accordingly, thereby enhancing resilience to climate variability.

3.5. Particle Swarm Optimization Configuration

The optimization component of the proposed framework employs Particle Swarm Optimization (PSO) to determine optimal agronomic decisions under varying climate conditions. In this study, the optimization process is formulated as a multi-variable decision problem, where the decision variables consist of fertilizer dosage (kg/ha), irrigation volume (mm), and harvest time (days). These variables were selected because of their significant influence on crop productivity and their direct controllability within agricultural management practices.

The objective of the optimization model is to maximize expected rice yield while considering the interaction between agronomic inputs and projected climate conditions. Specifically, the optimization process incorporates three important aspects: (1) the diminishing return effect of fertilizer application, where excessive fertilizer does not proportionally increase crop yield; (2) irrigation effectiveness influenced by the predicted SPI-3 value, reflecting moisture availability under future climate conditions; and (3) harvest timing optimization, where crop productivity reaches its maximum at an appropriate maturity stage.

In general, the optimization objective can be expressed as the maximization of expected crop yield as a function of fertilizer dosage, irrigation volume, harvest timing, and predicted SPI-3 conditions. Through this formulation, the optimization process seeks the most suitable agronomic strategy under projected climate scenarios while maintaining operational feasibility and resource efficiency. To ensure realistic and implementable recommendations, agronomic constraints were imposed on all decision variables. Fertilizer dosage was limited to a range of 50–300 kg/ha, irrigation volume was constrained between 50–500 mm, and harvest timing was restricted to 50–130 days. These constraints prevent the optimization process from generating impractical recommendations while preserving sufficient flexibility for solution exploration.

PSO was selected due to its proven effectiveness in solving nonlinear and multidimensional optimization problems. The algorithm operates through a population of particles that iteratively update their positions according to both individual experience and collective swarm behavior. This mechanism enables efficient exploration and exploitation of the search space, allowing the optimization process to converge toward high-quality solutions within a reasonable computational time. The PSO algorithm was configured using a swarm size of 50 particles and a maximum iteration limit of 100 iterations. The inertia weight was initialized at 0.7 to balance exploration and exploitation during the optimization process. The cognitive coefficient and social coefficient were both set to 1.5 to maintain equilibrium between local learning and global search behavior. The optimization process was terminated when the maximum number of iterations was reached or when the improvement of the global best solution became negligible.

3.6. Climate–Agronomy Integration

The integration of climate prediction and agronomic decision-making is a central component of the proposed framework, where the predicted SPI-3 is utilized as an environmental parameter within the optimization model. SPI-3 serves as a quantitative representation of short- to medium-term moisture conditions, enabling the model to capture the impact of climate variability on agricultural productivity. In this context, negative SPI-3 values (SPI < 0) indicate dry conditions associated with reduced soil moisture availability, which can lead to water stress and decreased crop yield. Conversely, positive SPI-3 values (SPI > 0) represent wetter conditions that generally support plant growth, although excessive moisture may also introduce risks such as flooding or nutrient leaching if not properly managed.

By incorporating SPI-3 into the optimization process, the proposed model enables adaptive and dynamic decision-making that responds to predicted climate conditions rather than relying on static assumptions. This integration allows agronomic variables, such as irrigation scheduling and fertilizer application, to be adjusted based on anticipated moisture availability, thereby improving resource efficiency and crop resilience. The approach aligns with recent advancements in climate-smart agriculture, where predictive climate indicators are used to guide management strategies and mitigate the impacts of climate variability on crop production. As a result, the proposed framework not only enhances decision accuracy but also contributes to the development of sustainable and data-driven agricultural systems.

3.7. ENSO Lag Feature Engineering and Data Preprocessing

ENSO lag variables were incorporated to capture delayed climatic influences on rainfall variability and moisture conditions. Lag periods of 1 month, 3 months, and 6 months were selected based on climatological studies indicating temporal delays between ENSO anomalies and regional precipitation responses. Missing values in rainfall and ENSO observations were handled using forward interpolation to preserve temporal continuity. Negative rainfall values and inconsistent observations were removed during the cleaning stage. Feature normalization was subsequently performed using Min-Max scaling to transform all variables into a consistent numerical range between 0 and 1. This normalization process improves model convergence and prevents feature dominance during ML training and optimization stages.

3.8. Bayesian Hyperparameter Optimization

Bayesian hyperparameter optimization was employed to improve the predictive performance and generalization capability of the Gradient Boosting Regressor (GBR) used for SPI-3 prediction. Rather than relying on manually selected hyperparameter values, the optimization process systematically searches for the most suitable configuration that minimizes prediction error while reducing the risk of overfitting.

The optimization procedure was implemented using the Optuna framework, which utilizes Bayesian sampling strategies to efficiently explore the hyperparameter search space. Compared with exhaustive grid search methods, Bayesian optimization is computationally more efficient because it leverages information from previous evaluations to guide subsequent searches toward promising regions of the parameter space.

The objective of the optimization process was to minimize the Root Mean Square Error (RMSE) obtained from cross-validation-based model evaluation. For each trial, a candidate hyperparameter configuration was generated, the corresponding GBR model was trained, and the resulting RMSE value was recorded. The configuration producing the lowest RMSE was selected as the optimal parameter set for the final prediction model. The hyperparameter search space used in this study is presented in table 2.

Table 2. Bayesian Optimization Search Space

Hyperparameter	Search Range
Number of Estimators	50 – 500
Learning Rate	0.001 – 0.300
Maximum Tree Depth	2 – 10
Subsample Ratio	0.5 – 1.0
Minimum Samples Split	2 – 20

A total of 100 optimization trials were conducted during the search process. The optimal hyperparameter configuration obtained from Bayesian optimization was subsequently used to train the final Gradient Boosting Regressor model employed for SPI-3 prediction.

3.9. Validation Strategy and Train-Test Splitting

To avoid temporal data leakage and ensure realistic forecasting performance, the dataset was partitioned chronologically rather than randomly. The earliest 80% of observations were allocated to the training set, while the remaining 20% were reserved for testing and final model evaluation. This temporal partitioning preserves the sequential nature of climate observations and prevents future information from influencing historical predictions.

Because climate and rainfall observations exhibit temporal dependencies, random data partitioning could artificially inflate predictive performance by introducing information leakage between training and testing samples. Therefore, a chronological split was adopted to better reflect real-world forecasting scenarios in which future observations are unavailable during model training.

During Bayesian hyperparameter optimization, time-series-aware cross-validation procedures were employed to maintain temporal consistency throughout the optimization process. This strategy ensures that each validation fold only utilizes information available up to the corresponding prediction period, thereby providing a more reliable assessment of model generalization capability.

The predictive performance of all ML models was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). RMSE measures the magnitude of prediction errors while assigning greater penalties to larger deviations. MAE provides an interpretable measure of average prediction error, whereas R^2 quantifies the proportion of variance explained by the model. The combination of these evaluation metrics enables a comprehensive assessment of predictive accuracy and model robustness.

4. Results and Discussion

4.1. Structure and Stages of the ECIB (ENSO CHIRPS Intelligence Booster) Method

The proposed ENSO–CHIRPS Intelligence Booster (ECIB) framework was developed to support climate-adaptive rice management by integrating climate prediction and optimization-based decision support within a unified workflow. The framework utilizes CHIRPS rainfall observations and ENSO climate indicators to generate climate-responsive agricultural recommendations.

Figure 2 illustrates the overall structure of the proposed ENSO–CHIRPS Intelligence Booster (ECIB) framework. The framework integrates climate-data processing, SPI-3 prediction, and optimization-based decision support into a unified architecture designed to support climate-adaptive rice management. The proposed method consists of four major stages: rainfall preprocessing and feature extraction, SPI-3 computation, machine-learning-based climate prediction, and PSO-driven agronomic optimization.

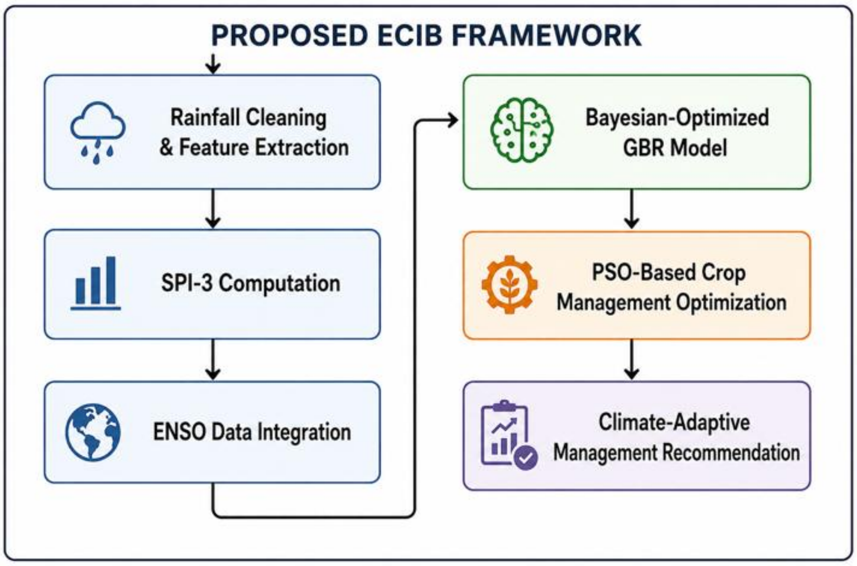

Figure 2. Proposed ENSO–CHIRPS Intelligence Booster (ECIB) Framework

Figure 2 presents an overview of the proposed ECIB framework used in the experimental evaluation. Detailed workflow descriptions, mathematical formulations, and optimization procedures have been presented in Section 3. The following sections focus on the computational performance and effectiveness of the framework.

4.2. Performance Evaluation of the ENSO CHIRPS Intelligence Booster Model

The performance evaluation of the ENSO CHIRPS Intelligence Booster model against the overall results of this research that has been carried out aims to assess the extent to which the research results obtained. Based on table 3 Above, it shows that the RMSE value of 0.391 indicates a relatively low prediction error, while the MAE of 0.322 reflects the model's consistency in estimating the SPI-3. The R^2 value of 0.851 confirms that the model is able to explain approximately 85% of the variation in the SPI-3, making it effective in representing the relationship between climate variables and the SPI-3 index.

Table 3. Results of the Performance Evaluation of the Optimized SPI-3 Prediction Model

No	Evaluation Metrics	Mark
1	RMSE	0.391
2	MAE	0.322
3	R^2	0.851

Based on table 4 above, the baseline model using only historical rainfall showed limited performance (RMSE 0.6306, MAE 0.5108, R^2 0.6125). In contrast, the model with the integration of ENSO variables produced significant improvements with a decrease in prediction error (RMSE 0.3916, MAE 0.3211) and an increase in model explanatory power (R^2 0.8506). These results indicate that ENSO variables effectively improve the accuracy and representativeness of the model in predicting SPI-3.

Table 4. Comparison of the Performance of the Baseline Model and the ENSO-Enhanced Model in Predicting SPI-3

No	Model	RMSE	MAE	R^2
1	Baseline Model	0.6306	0.5108	0.6125
2	ECIB Model	0.3916	0.3211	0.8506

Figure 3 illustrates the comparison between actual rainfall observations and model predictions obtained using the proposed ECIB framework. The visualization highlights the ability of the Bayesian-optimized GBR model to follow temporal rainfall patterns and capture major fluctuations in climatic conditions.

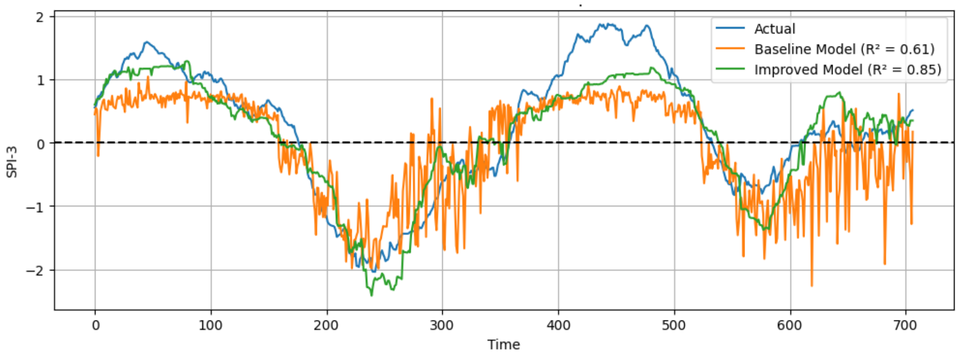

Figure 3. Baseline vs Improved Models

To further evaluate predictive effectiveness, the proposed ECIB framework was compared with several baseline machine-learning models using RMSE, MAE, and R^2 evaluation metrics. Figure 4 summarizes the comparative performance of all evaluated models.

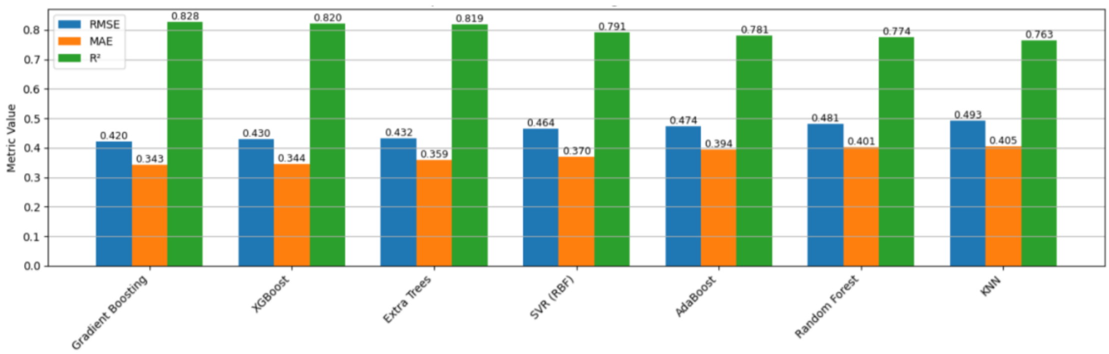

Figure 4. Comparison of ML Model Performance with Positive R^2 Values

As shown in figure 4, the Bayesian-optimized GBR model consistently achieved the lowest RMSE and MAE values while maintaining the highest R^2 score among the evaluated models. These results indicate that the proposed optimization strategy successfully improves predictive accuracy and model generalization capability. The superior performance of the GBR model can be attributed to its ability to capture nonlinear relationships between rainfall observations, ENSO indicators, and seasonal climate patterns. To further assess the suitability of conventional machine-learning approaches for climate prediction, several baseline models were evaluated using the coefficient of determination (R^2). Figure 5 presents the R^2 scores obtained by Bayesian Ridge, Linear Regression, and MLP Regressor models.

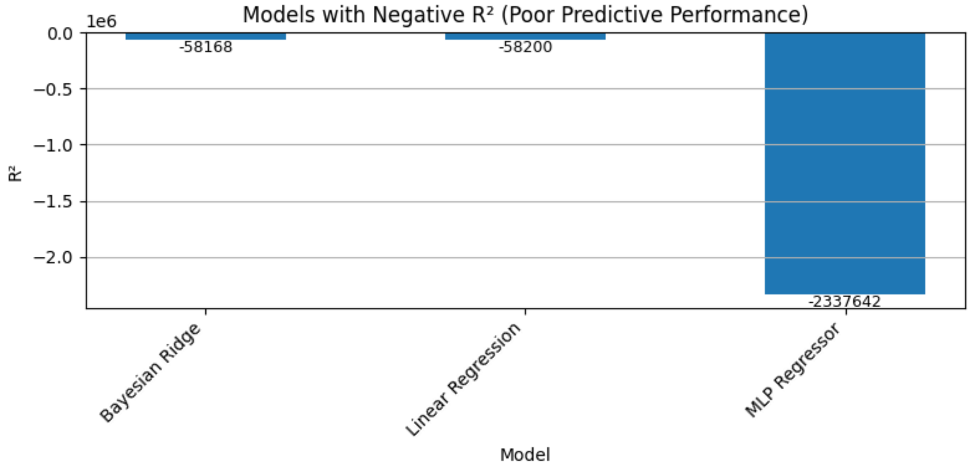

Figure 5. Comparison of Baseline Models Exhibiting Negative R^2 Scores

As illustrated in figure 5, all evaluated baseline models produced negative R^2 values, indicating that their predictive performance was inferior to a simple mean-based prediction strategy. The MLP Regressor exhibited the lowest performance among the evaluated models, suggesting substantial difficulty in capturing the nonlinear relationships embedded within rainfall, seasonal, and ENSO-related variables. Similarly, Bayesian Ridge and Linear Regression failed to adequately represent the underlying climate dynamics. These results demonstrate the limitations of conventional predictive approaches and provide additional justification for employing the Bayesian-optimized Gradient Boosting Regression model within the proposed ECIB framework.

Overall, the results in table 5 confirm that ensemble-based nonlinear models, including Gradient Boosting, XGBoost, Extra Trees, AdaBoost, and Random Forest, substantially outperformed conventional regression-based models, namely Bayesian Ridge and Linear Regression, for ENSO-based SPI-3 prediction. Among all evaluated models, Gradient Boosting achieved the lowest prediction error and the highest coefficient of determination ($R^2 = 0.828$), demonstrating its superior capability to capture complex climate interactions and nonlinear rainfall dynamics. In contrast, Bayesian Ridge and Linear Regression produced highly negative R^2 values, indicating that these conventional regression approaches were unable to adequately represent the underlying climate processes. Similarly, the MLP Regressor also exhibited poor predictive performance, suggesting that the nonlinear relationships embedded within the rainfall, seasonal, and ENSO-related variables were not effectively learned under the adopted model configuration.

Table 5. Comparison of the Performance of Various ML Models for ENSO-Based SPI-3 Prediction

Category	**Model**	**RMSE**	**MAE**	**R^2**
Ensemble-Based Nonlinear	Gradient Boosting	0.4202	0.3431	0.8280
Ensemble-Based Nonlinear	XGBoost	0.4296	0.3440	0.8202
Ensemble-Based Nonlinear	Extra Trees	0.4316	0.3591	0.8185
Kernel-Based	SVR (RBF)	0.4637	0.3704	0.7905
Ensemble-Based Nonlinear	AdaBoost	0.4744	0.3942	0.7807
Ensemble-Based Nonlinear	Random Forest	0.4812	0.4011	0.7744
Instance-Based	KNN	0.4931	0.4052	0.7631
Conventional Regression	Bayesian Ridge	244.34	66.248	−58,167.7
Conventional Regression	Linear Regression	244.408	66.291	−58,200.4
Neural Network	MLP Regressor	1548.95	374.448	−2,337,641.8

Table 6 demonstrates the effectiveness of Bayesian hyperparameter optimization in improving the predictive capability of the Gradient Boosting model. While all tuning strategies enhanced performance relative to the default configuration, the proposed ECIB-Bayesian optimization approach consistently achieved the best results, yielding the lowest RMSE and MAE values together with the highest R^2 score. These findings indicate that Bayesian optimization efficiently identifies optimal parameter configurations and contributes significantly to the overall predictive performance of the ECIB framework.

Table 6. Comparison of Gradient Boosting Model Performance based on Hyperparameter Tuning Method

No	Tuning Method	RMSE	MAE	R^2
1	Default	0.4137	0.3377	0.8332
2	Grid Search	0.3994	0.3275	0.8446
3	Random Search	0.3993	0.3274	0.8447
4	ECIB-Bayesian (Optuna)	0.3913	0.3214	0.8508

To identify climate-adaptive agricultural strategies, Particle Swarm Optimization (PSO) was applied to optimize fertilizer dosage, irrigation allocation, and harvest timing. Table 7 summarizes the evolution of agronomic variables during the optimization process.

Table 7. Evolution of Agronomic Variables During PSO Optimization

Iteration	Yield	Fertilizer (kg/ha)	Irrigation (mm)	Harvest Time (days)
0	18,563.40	98.52	498.18	103.90
1	19,504.83	96.56	500.00	106.26
2	20,035.03	106.10	500.00	110.14
3	20,035.03	106.10	500.00	110.14
4	20,047.01	104.89	500.00	110.19
5	20,052.29	98.14	500.00	110.63
6	20,052.29	98.14	500.00	110.63
7	20,052.29	98.14	500.00	110.63
8	20,052.60	104.11	500.00	110.26
9	20,070.21	101.22	500.00	110.02

Table 7 presents the evolution of agronomic variables during the Particle Swarm Optimization (PSO) process. The results indicate a progressive improvement in the objective value from 18,563.40 at the initial iteration to 20,070.21 at iteration 9. The optimization process converged toward stable management configurations, with irrigation allocation consistently approaching the upper operational limit of 500 mm and harvest timing stabilizing around 110 days. Fertilizer dosage exhibited moderate variation throughout the search process, indicating adaptive adjustments in response to projected climate conditions. These findings demonstrate the capability of PSO to efficiently identify climate-adaptive crop-management strategies that maximize expected agricultural productivity. Harvest timing represents a critical decision variable within the optimization framework. Figure 6 illustrates the evolution of harvest timing during the PSO search process.

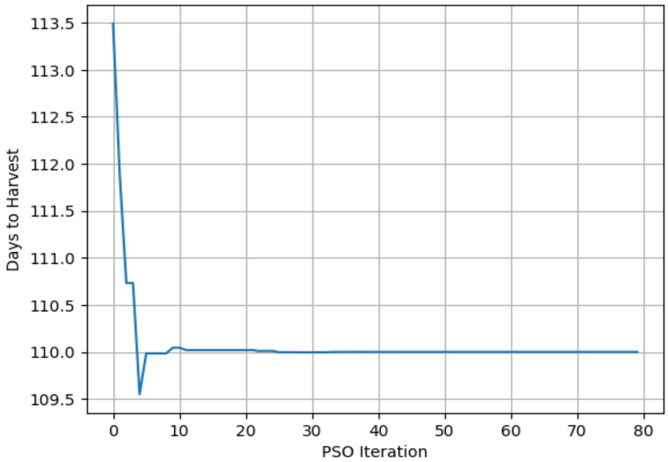

Figure 6. Changes in Harvest Time During the Particle Swarm Optimization Process

As shown in figure 6, the optimization process gradually converged toward an optimal harvest period. The stabilization of harvest timing across iterations indicates that the PSO algorithm successfully identified a robust harvesting schedule capable of maximizing expected productivity under the predicted climate scenario. Following SPI-3 prediction and PSO-based optimization, the final climate-adaptive management strategy was generated. The optimized agricultural management recommendations produced by the proposed ECIB framework are presented in table 8.

Table 8. Optimized Rice Field Management Recommendations Generated by the ECIB Framework

Decision Variable	Optimized Value
Irrigation Allocation (mm)	500.00
Harvest Timing (days)	110.00
Fertilizer Dosage (kg/ha)	100.01
Expected Maximum Yield	20203.29

As shown in table 8, the optimization process identified an irrigation allocation of 500 mm, a fertilizer dosage of approximately 100 kg/ha, and a harvest timing of 110 days as the most suitable management configuration under the projected climate conditions. The resulting strategy produced an expected maximum yield of 20203.29, indicating that the proposed ECIB framework successfully integrated climate prediction and optimization into a unified decision-support mechanism. These findings demonstrate the capability of the framework to generate climate-adaptive recommendations that support efficient resource utilization while maximizing agricultural productivity.

4.3. Uncertainty and Robustness Analysis

To evaluate prediction robustness, repeated experiments were conducted using multiple training and testing periods under the same temporal validation strategy. The experimental results demonstrated relatively stable RMSE and R^2 values across repeated evaluations, indicating consistent predictive performance. In addition, robustness analysis of the optimization process showed stable convergence behavior across multiple Particle Swarm Optimization runs. The global best solution exhibited only minor fluctuations between iterations, suggesting that the optimization framework is sufficiently stable for climate-adaptive agricultural recommendation generation. Although confidence intervals were not explicitly modeled in this study, the consistent performance across repeated experiments indicates acceptable reliability for operational decision-support scenarios.

4.4 Example of Climate-Adaptive Recommendations

The recommendation stage generated adaptive agronomic decisions based on predicted SPI-3 conditions. For example, under moderate drought conditions (SPI-3 < -1), the optimization model recommended increasing irrigation allocation while reducing fertilizer dosage to minimize nutrient loss under water stress conditions. Conversely, under wetter climate conditions (SPI-3 > 1), the framework recommended reduced irrigation allocation and adjusted harvest timing to avoid excessive moisture exposure during crop maturation.

An example of the optimization output generated by the proposed ECIB framework recommended a fertilizer dosage of 185 kg/ha, an irrigation allocation of 320 mm, and a harvest timing of 108 days. These recommendations were derived from the integration of SPI-3 prediction and PSO-based optimization, which collectively evaluated the projected climate conditions and their potential impact on agricultural productivity. The resulting management strategy demonstrates the operational capability of the framework to transform climate intelligence into actionable agronomic decisions, thereby supporting adaptive resource allocation, improving management efficiency, and enhancing the potential for sustainable rice production under varying climate scenarios.

This research proposes an end-to-end framework that integrates three main stages into a single, coherent pathway: prediction, optimization, and recommendation. This research integrates climate prediction and agricultural management into a single data-driven decision-making system. The novelty of this research lies in the linkage of ML results with metaheuristic optimization, resulting in rice field management recommendations that are responsive to the dynamics of predicted rainfall.

Empirical results show that the SPI-3 prediction model based on Gradient Boosting Regressor achieved a coefficient of determination (R^2) of 0.851, or approximately 85%, with an RMSE of 0.391 and MAE of 0.322. These values indicate that the model is able to explain a significant proportion of the variability in the drought index over the observation period and produces a relatively low and consistent prediction error rate. The main contribution of this research lies in the integration of SPI-3 predictions into the Particle Swarm Optimization-based optimization process. The optimization results show stable convergence toward the global best, indicating that the formulated objective function adequately represents the trade-off between productivity and water resource efficiency. This stability also indicates that the quality of the predicted input ($R^2 \approx 0.85$) is sufficient to support the optimization process.

Although the results demonstrate improved performance, several limitations should be noted. This model still focuses on climatological variables and does not explicitly incorporate edaphic or plant physiological parameters. Because the model utilizes publicly available high-resolution rainfall data (CHIRPS) and the ENSO index, this approach has the potential to be replicated in other regions with similar agroclimatological characteristics.

Overall, the results demonstrate that the ECIB framework achieved strong predictive performance with an R^2 value of approximately 0.85 through the integration of ENSO-based climate indicators and the Gradient Boosting algorithm. The obtained results indicate that the model is capable of explaining a substantial proportion of SPI-3 variability under varying climate conditions. Furthermore, the integration of Particle Swarm Optimization produced relatively stable and climate-responsive agronomic recommendations, including irrigation allocation, fertilizer dosage, and harvest timing. These findings suggest that the proposed framework provides statistically reliable performance and shows strong potential for supporting operational decision-making in climate-smart and data-driven agricultural management systems. Because the framework was evaluated using a single agroclimatic setting, caution should be exercised when generalizing the findings to regions with substantially different rainfall regimes and agricultural characteristics.

5. Conclusion

This study proposed an integrated climate-driven decision-support framework for adaptive rice field management using predictive SPI-3 modeling and Particle Swarm Optimization. The proposed ECIB framework successfully combines climate prediction, optimization, and recommendation generation within a unified operational pipeline. The experimental results demonstrate that integrating ENSO-based climate variability indicators with Gradient Boosting Regression significantly improves SPI-3 predictive performance. Furthermore, the optimization component produced stable agronomic recommendations under varying climate conditions, indicating the potential applicability of the framework for climate-smart agricultural management. Despite these promising results, several practical challenges remain. The framework requires continuous climate data availability and computational resources for repeated optimization processes. In addition, the current implementation has been evaluated only within a limited agroclimatic

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setting, which may affect generalizability across different environmental conditions and agricultural systems. Future work should focus on multi-regional validation, uncertainty quantification, integration with real-time agricultural monitoring systems, and deployment through operational decision-support platforms accessible to farmers and policymakers.

6. Declarations

6.1. Author Contributions

Conceptualization: E.P., S.E., P.S., and T.H.F.H.; Methodology: S.E.; Software: E.P.; Validation: E.P., S.E., P.S., and T.H.F.H.; Formal Analysis: E.P., S.E., P.S., and T.H.F.H.; Investigation: E.P.; Resources: S.E.; Data Curation: S.E.; Writing Original Draft Preparation: E.P., S.E., P.S., and T.H.F.H.; Writing Review and Editing: S.E., E.P., P.S., and T.H.F.H.; Visualization: E.P.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

Data will be available upon reasonable request.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

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