

# COMPUTATIONAL FRAMEWORK OF CLIMATE-INDUCED FOOD INSECURITY VIA FIREFLY-GA HYBRID MODEL IN NIGERIA'S CEREAL PRODUCTION

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## ABSTRACT

Climate variability continues to threaten agricultural productivity across sub-Saharan Africa, with noticeable effects on yield stability in climate-sensitive production systems. This study develops a cascade-parallel Firefly-Genetic Algorithm (FA-GA) hybrid framework for crop yield prediction and agronomic optimization using twenty years (2006–2024) of Nigerian climate and crop data. The proposed architecture integrates the global search capability of the Genetic Algorithm with localized refinement via the Firefly Algorithm to enable balanced exploration and exploitation within a high-dimensional decision space. Model performance was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination ( $R^2$ ), and normalized MAE-derived accuracy. The FA-GA hybrid achieved an accuracy of 96.4%, an  $R^2$  of 0.96, an RMSE of 0.042 t/ha, and an MAE of 0.031 t/ha, outperforming the standalone GA, standalone FA, and Random Forest benchmarks under identical experimental conditions. Convergence analysis showed approximately 35% fewer iterations compared to standalone GA, indicating improved computational efficiency. Stress simulations further demonstrated adaptive capacity. Optimized planting windows under a 15-day dry spell retained approximately 15% of maize yield relative to non-optimized scenarios, while targeted potassium adjustment mitigated projected heat-induced rice yield losses by 8%. The results indicate that the proposed hybrid framework delivers both high predictive precision and actionable agronomic recommendations under climate perturbations. This dual capability positions the FA-GA model as a viable decision-support tool for climate-resilient agriculture and national food security planning.

**Keywords:** Firefly Algorithm; Genetic Algorithm; Hybrid Metaheuristic Optimization; Crop Yield Prediction

## INTRODUCTION

Agriculture is one of the fundamental pillars of Nigeria's socio-economic framework, contributing approximately 23.7% to the National Gross Domestic Product (GDP) and providing a livelihood for over 70% of the rural population (NBS, 2024). In the face of a rapidly growing population that is projected to exceed 260 million by 2030, the demand for food security has never been more critical (FAO, 2023). Maize, rice, and sorghum staples cultivated largely by smallholder farmers are the backbone of national food security. However, production outcomes have become increasingly unstable as weather variability intensifies across agroecological zones (Ologeh & Adesina, 2022). Nigeria's agro-ecological zones, ranging from the humid rainforests of the south to the arid Sahel in the north, are experiencing significant climate-induced disruptions

(Olasehinde et al., 2026). Recent meteorological assessments report irregular rainfall onset, extended intra-seasonal dry spells, and rising mean temperatures (Nimet, 2024). Heat episodes above physiological tolerance thresholds have been linked to impaired pollination and reduced grain filling in cereal crops, especially within the Sudan and Sahel savanna belts (Organization & others, 2023). Rainfall irregularity further exacerbates seed mortality and early vegetative stress, which leads to considerable variability in harvest outcomes. Empirical analyses indicate that yield fluctuations of up to 40% have occurred in vulnerable zones under compound climatic stress (NBS, 2024). These effects interact with declining soil fertility and nutrient imbalances, and compound production risk (Adewumi et al., 2024). Conventional yield estimation techniques have largely relied on linear statistical assumptions (Sreerama & Sagar, 2020). Multiple Linear Regression and autoregressive models are widely used in agricultural forecasting, yet their predictive capacity declines when nonlinear interactions among rainfall variability, temperature extremes, and soil nutrient dynamics are present (Panda et al., 2024). Such limitations are evident in sub-Saharan datasets characterized by volatility and structural heterogeneity (Okesola et al., 2024). As climate-induced anomalies become more frequent, linear frameworks prove insufficient to capture threshold effects, interaction terms, and high-dimensional relationships that govern crop performance (Ologeh & Adesina, 2022).

Advances in artificial intelligence have introduced more adaptive predictive techniques. Machine learning algorithms such as Random Forest, Support Vector Machines, and deep neural networks have demonstrated improved accuracy in yield forecasting tasks (Jhajharia et al., 2023; Swain et al., 2023). Applications within emerging economies report substantial gains in predictive precision when ensemble or tree-based methods are employed (Monica et al., 2025; Varshitha et al., 2025). Despite these advances, standalone models often exhibit instability during hyperparameter tuning and may converge prematurely to suboptimal solutions, especially in high-dimensional search spaces (Y. Yang & Duan, 2020). Agricultural optimization problems frequently involve multi-objective trade-offs such as balancing yield maximization, input efficiency, and climatic risk, which further complicates model training (Adewumi et al., 2024). Metaheuristic optimization algorithms provide an alternative pathway for addressing such complexity. The Genetic Algorithm (GA), introduced by John Holland (Holland, 1992), simulates evolutionary processes through selection, crossover, and mutation to efficiently explore broad solution spaces. GA has been applied in agricultural planning to improve irrigation scheduling and nutrient allocation strategies (Audu, 2025). Its principal strength lies in global

exploration; it identifies promising regions within a large decision aspect without reliance on gradient information. The Firefly Algorithm (FA), developed by Xin-She Yang (X.-S. Yang, 2010), draws inspiration from bioluminescent attraction behavior observed in fireflies. FA is known for rapid convergence during parameter refinement and strong local search capability. Comparative studies indicate that FA can achieve high precision in nonlinear biological systems, especially when fine-scale tuning is required (Ri & Mun, 2023). While GA excels at diversification, FA demonstrates efficiency during intensification phases of optimization. Hybrid metaheuristic systems integrate complementary strengths of individual algorithms to enhance robustness and convergence quality. Prior studies have reported improved performance with GA-ANN and ensemble-based optimization frameworks for agricultural forecasting (Ghugre & Patil, 2025; Varshitha et al., 2025). Nevertheless, most hybrid implementations within agricultural analytics rely on combinations such as GA-ANN or PSO-GA. Applications combining Firefly and Genetic algorithms remain concentrated in industrial scheduling and engineering areas (Ri & Mun, 2023). Their deployment in climate-sensitive crop modeling, especially within Nigerian agro-ecological systems, remains limited in the published literature.

A further limitation of existing Nigerian studies is the lack of distinction between prediction and decision optimization. Many models estimate yield outcomes under projected climatic conditions yet provide limited guidance on actionable adjustments to planting windows, irrigation scheduling, or nutrient application. Farmers and extension services require prescriptive tools to identify optimal strategies under projected stress scenarios. Multi-objective optimization frameworks are well-suited for this purpose, which allows yield performance to be evaluated alongside climatic risk exposure and resource constraints (Adewumi et al., 2024). This study proposes a Firefly-Genetic Algorithm (FA-GA) hybrid model to predict and optimize crop yields under climate-stress conditions in Nigeria. The model integrates GA's global exploration capacity with FA's fine-scale parameter refinement to address nonlinear multi-objective decision perspectives. Climate stress indicators derived from long-term meteorological data are embedded within the optimization process to enable yield prediction and adaptive decision support within a unified framework. The study aims to deliver a computationally efficient, decision-oriented system that improves resilience in smallholder farming systems by customizing the hybrid architecture to Nigerian datasets and agro-ecological characteristics.

The expanding use of artificial intelligence in agricultural systems has generated a substantial body of scholarship on predictive modeling, climate-yield interactions, and computational optimization (Haziq Anwar, 2024). This section reviews prior studies across three interrelated strands: machine learning applications in crop yield prediction, climate stress modeling in cereal systems, and metaheuristic optimization frameworks for agricultural decision-making.

#### **Machine Learning Applications in Crop Yield Prediction**

Early computational approaches to yield estimation relied predominantly on linear regression and time-series models. Although these methods provided baseline forecasting capacity, their performance declined when subjected to nonlinear interactions among rainfall variability, temperature extremes, and soil nutrient dynamics (Sreerama & Sagar, 2020; Swain et al., 2023). Studies comparing regression-based methods with modern

machine learning techniques consistently report superior predictive accuracy for nonparametric and ensemble algorithms (Jhajharia et al., 2023). Tree-based models such as Random Forest and gradient boosting have gained particular attention for their ability to model complex feature interactions without restrictive distributional assumptions. Monica et al. (2025) demonstrated improved maize yield prediction using Random Forest regression, noting its strong robustness against overfitting. Similarly, Varshitha et al. (2025) reported enhanced precision when ensemble learning strategies were applied to multi-crop datasets. These findings align with broader evidence that ensemble methods can capture nonlinear patterns more effectively than traditional statistical estimators (Sundararajan et al., 2025). Deep learning architectures have also been explored for crop yield forecasting. Jhajharia et al. (2023) evaluated neural networks and long short-term memory (LSTM) models. They conclude that temporal deep learning frameworks provide notable advantages when modeling sequential climatic data. Nevertheless, model interpretability and computational cost remain major concerns, especially in resource-constrained agricultural environments (Kariya & Mudholkar, 2025). In several instances, predictive gains have not translated into actionable insights for farm-level decision-making, which limits their operational value (Marapelli et al., 2023).

Within the Nigerian agricultural system, supervised learning models have shown promise but remain underutilized for integrated climate-risk modeling. Okesola et al. (2024) applied classification and regression techniques to crop yield data and observed improved predictive performance compared with baseline statistical models. However, most applications emphasize yield estimation rather than optimization under climatic uncertainty. Audu (2025), in a comprehensive review of AI applications in Nigerian irrigation systems, emphasized the need for models capable of supporting prescriptive decisions rather than descriptive forecasts alone.

#### **Climate Stress and Yield Sensitivity in Nigeria**

Nigeria's agro-ecological heterogeneity introduces distinct stress profiles across regions (Olasehinde et al., 2026). Empirical investigations indicate that rising temperatures and irregular rainfall patterns have measurable effects on cereal productivity (Ologeh & Adesina, 2022). Heat stress has been associated with disrupted flowering, shortened grain-filling periods, and reduced biomass accumulation in maize and sorghum. These impacts are evident in semi-arid zones where evapotranspiration rates are high (Nimet, 2024). Multi-model climate analyses further demonstrate that intra-seasonal variability rather than annual rainfall totals alone strongly influences harvest outcomes. Olasehinde et al. (2026) integrated spatiotemporal climate modeling techniques and highlighted the importance of fine-scale temporal indicators for improving the reliability of yield prediction. Such findings reinforce earlier evidence that reliance on aggregated seasonal averages may obscure critical stress windows that determine crop survival and productivity (Ologeh & Adesina, 2022). National agricultural statistics also reveal substantial inter-annual variability in cereal yields consistent with meteorological instability (NBS, 2024). The FAO (2023) [2] similarly reports increasing exposure of smallholder systems to drought episodes and extreme temperature events across West Africa. These patterns highlight the need for models that integrate stress indices such as drought severity, heat exposure days, and rainfall volatility into predictive architectures. Despite recognition of climate sensitivity, many predictive

frameworks treat climatic variables as static predictors rather than dynamic stress factors. Studies reviewed by Strang (Strang, 2021) suggest that food insecurity modeling in developing economies often underrepresents compound stress interactions. As a result, forecasts may overestimate resilience or fail to identify critical vulnerability thresholds.

### Metaheuristic Algorithms in Agricultural Optimization

Agricultural decision-making frequently involves non-convex optimization problems with multiple objectives, including yield maximization, cost reduction, and resource conservation (Ausaf et al., 2015). Traditional gradient-based optimization methods are often unsuitable for such complex perspectives (Adewumi et al., 2024). Metaheuristic algorithms have therefore become practical alternatives. The Genetic Algorithm (GA) introduced by John Holland (Holland, 1992) simulates evolutionary selection processes to explore large search spaces efficiently. GA has been employed in agricultural planning for irrigation scheduling, nutrient management, and farm operation optimization (Audu, 2025). Its principal advantage lies in global exploration capacity, which allows the algorithm to avoid premature convergence in complex solutions (Parthasarathy et al., 2024). The Firefly Algorithm (FA) developed by Xin-She Yang (Y. Yang & Duan, 2020) is another nature-inspired optimization approach. FA models attraction dynamics based on solution quality and facilitate rapid local refinement. Comparative studies indicate that FA can achieve strong convergence performance in nonlinear parameter identification tasks (Ri & Mun, 2023). Its suitability for biological and environmental modeling stems from its capacity to intensify search around high-quality candidate solutions (Rama Devi et al., 2023). Recent agricultural applications demonstrate increasing interest in hybrid optimization strategies. Ghuge and Patil (2025) combined metaheuristic tuning with transformer-based architectures to improve yield prediction accuracy. Lakhotia et al. (Lakhotia et al., 2025) integrated machine learning with fertilization optimization frameworks. The study reported enhanced decision support outcomes. Ensemble and hybrid learning systems have been shown to reduce prediction error rates relative to standalone approaches (Shamim & Agarwal, 2024). Nevertheless, most hybrid implementations in agricultural analytics involve GA combined with neural networks or particle swarm optimization. Applications integrating Firefly and Genetic

algorithms remain concentrated in industrial scheduling and process engineering (Ri & Mun, 2023). Their extension to climate-sensitive crop systems has not been extensively examined in the literature.

### Identified Research Gaps

The review highlights three principal limitations within existing scholarship. First, algorithmic integration remains limited. While GA-ANN and ensemble-based hybrids are increasingly common, the complementary strengths of GA for global exploration and FA for fine-scale refinement have not been fully leveraged within agricultural yield optimization studies [19], [20]. Second, climate stress representation often lacks specificity. Many predictive studies rely on aggregated climatic averages rather than targeted stress indicators that capture threshold exceedance and intra-seasonal volatility (Nimet, 2024; Olasehinde et al., 2026). Third, a distinction persists between predictive modeling and operational optimization. Numerous studies estimate expected yields under projected climatic conditions but do not provide prescriptive guidance on adjusting planting schedules, irrigation allocation, or nutrient inputs to mitigate risk (Audu, 2025; Okesola et al., 2024). Multi-objective optimization frameworks that integrate risk constraints alongside yield performance remain underdeveloped in Nigerian agricultural research. In response to these gaps, the present study proposes a hybrid Firefly–Genetic Algorithm model tailored to Nigerian agro-ecological datasets. The proposed framework integrates climate stress indices directly into multi-objective optimization structures and enables simultaneous yield prediction and adaptive decision support.

## MATERIALS AND METHODS

### High-Level Methodological Framework

The study adopts a structured, multi-stage workflow that integrates predictive modeling and optimization under climate-stress conditions. The methodological sequence consists of four interconnected phases: (i) data acquisition and preprocessing, (ii) feature engineering and stress index derivation, (iii) hybrid metaheuristic model development, and (iv) validation and comparative benchmarking, as shown in Figure 1.

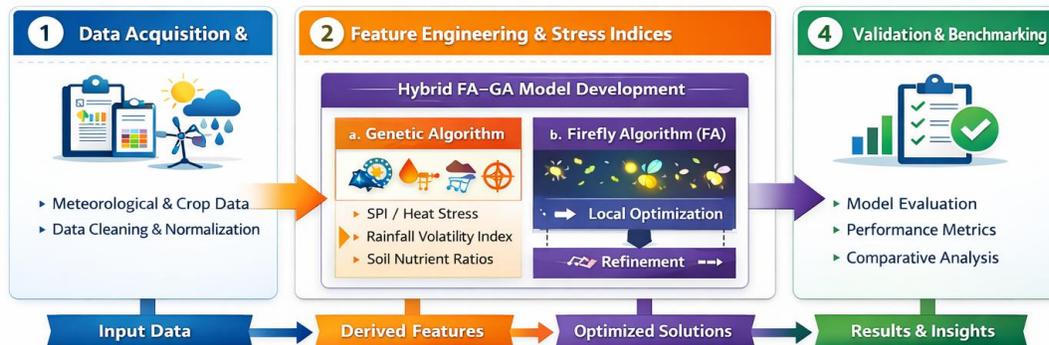


Figure 1: High Methodological Workflow of the Study

### Data Acquisition and Feature Engineering

Figure II presents the climate stress index derivation and feature transformation pipeline adopted in this study. It illustrates how raw meteorological and soil variables are aggregated across crop

growth stages and converted into agronomically meaningful stress indicators that constitute the final feature matrix for optimization and prediction.

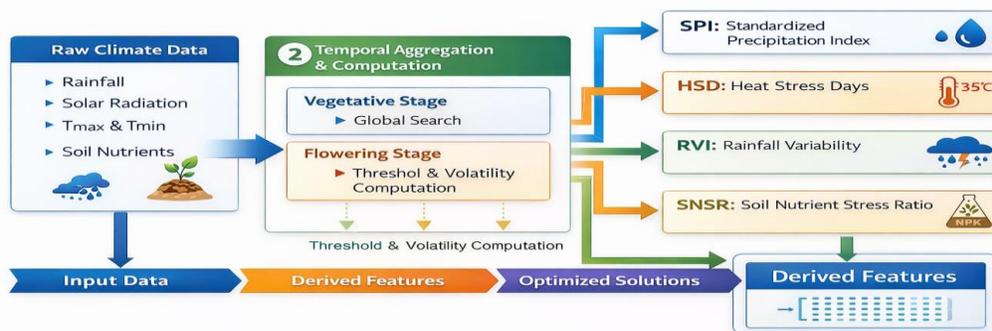


Figure II Climate Stress Index Derivation and Feature Transformation Pipeline

### Data Sources

To ensure temporal robustness and climatic representativeness, the dataset spans 20 years (2006–2024). Data are compiled from the following repositories:

#### 1. Meteorological Data:

Daily records of rainfall, solar radiation, and temperature (maximum and minimum) obtained from NASA POWER and the Nigerian Meteorological Agency seasonal reports (Nimet, 2024). These variables are selected because of their established influence on crop physiological processes (Ologeh & Adesina, 2022).

#### 2. Crop Yield Data:

Historical yield data for maize, rice, and sorghum were sourced from national agricultural statistical reports (NBS, 2024). These crops were selected because of their contribution to national food security (FAO, 2023).

#### 3. Soil Data:

Soil nutrient parameters, including nitrogen (N), phosphorus (P), potassium (K), and pH, were obtained from globally harmonized soil databases and integrated with plot-level yield records. Nutrient balance has been shown to interact significantly with climatic stress in determining output (Mistry et al., 2023).

Data integration is conducted at harmonized spatial and temporal scales to ensure alignment between climatic observations and crop growth stages. Seasonal segmentation is used to isolate the vegetative, flowering, and grain-filling phases, as stress sensitivity varies across phenological stages (Panda et al., 2024).

### Data Preprocessing

Preprocessing follows a rigorous pipeline:

- **Missing Value Imputation:** Linear interpolation and nearest-neighbor imputation are applied where meteorological gaps are detected.
- **Outlier Treatment:** Extreme anomalies beyond three standard deviations are assessed against meteorological reports before removal to prevent distortion of stress indicators.
- **Normalization:** Min–Max scaling is applied to ensure uniform feature contribution during optimization to prevent dominance by variables with larger numerical ranges.
- **Temporal Alignment:** Daily climate data are aggregated into crop-stage-specific indicators to preserve biologically meaningful signals.

### Climate Stress Feature Engineering

Rather than relying solely on seasonal averages, the model incorporates derived stress indices designed to capture threshold exceedance and volatility patterns documented in Nigerian agro-climatology (Nimet, 2024; Okesola et al., 2024).

The following indices are constructed:

#### 1. Standardized Precipitation Index (SPI):

SPI quantifies drought severity relative to historical rainfall distribution. Negative SPI values indicate moisture deficit. This index has been widely used for drought-sensitive yield modeling (Ologeh & Adesina, 2022).

#### 2. Heat Stress Days (HSD):

Defined as the count of days during the flowering stage when the maximum temperature exceeds 35°C. Heat exposure above this threshold disrupts pollen viability and grain formation (Nimet, 2024).

#### 3. Rainfall Volatility Index (RVI):

Calculated as the standard deviation of rainfall within the first 30 days after planting. High variability during early growth stages is associated with seedling mortality and poor establishment (NBS, 2024).

#### 4. Soil Nutrient Stress Ratio (SNSR):

Defined as the ratio of applied nitrogen to crop-specific recommended thresholds. This index captures potential nutrient imbalance under water-limited conditions (Adewumi et al., 2024).

These engineered features transform raw environmental variables into agronomically interpretable inputs. The resulting feature matrix constitutes the decision landscape that the hybrid optimization system explores.

### Proposed Firefly–Genetic Algorithm Hybrid Architecture Design Rationale

Optimization in climate-sensitive agriculture requires balancing exploration of wide decision spaces with fine-scale parameter refinement. The Genetic Algorithm (GA), originally formulated by John Holland, performs robust global search through evolutionary operators (Holland, 1992). The Firefly Algorithm (FA), developed by Xin-She Yang, emphasizes local attraction-based refinement (X.-S. Yang, 2010). Each algorithm exhibits complementary strengths. GA maintains population diversity and reduces susceptibility to premature convergence (Y. Yang & Duan, 2020). FA exhibits strong convergence behavior when operating within promising neighborhoods of the solution space (Ri & Mun, 2023). Integrating both within a cascade-parallel structure enhances stability and convergence precision, as depicted in Figure III.

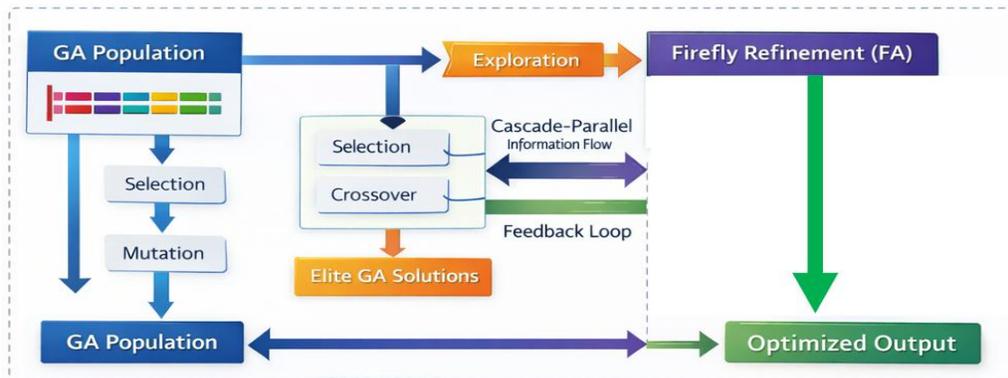


Figure III Proposed Cascade – Parallel FA – GA Hybrid Optimization Architecture

### Stage I: Global Exploration Using Genetic Algorithm

The GA initializes a population of candidate agronomic strategies, each encoded as a chromosome. Each chromosome represents a vector of decision variables, including:

- Planting date
- Irrigation allocation
- Nitrogen application level
- Crop-specific stress adjustment parameters

The evolutionary cycle follows three operators:

- **Selection:** Individuals with higher fitness values are probabilistically chosen for reproduction.
- **Crossover:** Genetic material is recombined to generate offspring solutions.
- **Mutation:** Random perturbations are introduced to preserve diversity.

Population evolution is expressed as (see equation 1):

$$P_{t+1} = Selection(P_t) + Crossover + Mutation \quad (1)$$

The GA iterates until convergence criteria, such as fitness stagnation or maximum generations, are satisfied. The top-performing subset of solutions is passed to the FA stage.

### Stage II: Local Exploitation Using Firefly Algorithm

The Firefly Algorithm receives elite GA solutions as its initial population. In FA, solution quality corresponds to brightness, which is proportional to the objective function value. A less bright firefly moves toward a brighter one according to the attractiveness function.

The position update equation is defined in equation 2 as:

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2} (x_j^t - x_i^t) + \alpha \epsilon_i^t \quad (2)$$

Where:

$\beta_0$  denotes base attractiveness.

$\gamma$  represents the light absorption coefficient, influencing distance-based decay.

$r_{ij}$  the Euclidean distance between fireflies  $i$  and  $j$ .

$\alpha \epsilon_i^t$  introduces controlled stochastic perturbation.

This mechanism refines candidate solutions around high-performing regions identified by GA. The stochastic component mitigates local trapping and maintains search variability (X.-S. Yang, 2010).

### Cascade–Parallel Integration Strategy

The integration is structured so that GA performs macro-level exploration of the decision space, while FA operates within elite clusters to improve precision. Information flow between both algorithms is adaptive:

- GA periodically updates FA initialization pools.
- FA-refined solutions may be reintroduced into GA populations to sustain diversity.

This bidirectional interaction strengthens convergence stability and reduces computational redundancy. The hybrid structure, therefore, addresses the limitations of standalone optimization methods documented in prior agricultural modeling studies (Adewumi et al., 2024; Ri & Mun, 2023).

### Algorithm Configuration and Parameter Settings

To ensure reproducibility and enable consistent performance evaluation, the configurations of both the Genetic Algorithm (GA) and the Firefly Algorithm (FA) components were explicitly defined based on empirical tuning and established metaheuristic guidelines.

### Genetic Algorithm Configuration

The GA component was initialized with a population of 100 candidate solutions, each encoding agronomic decision variables such as planting date, irrigation level, and nutrient application rates. The selection process employed tournament selection with a tournament size of 3 to balance selection pressure and the preservation of diversity. Crossover was implemented using a uniform crossover operator with a probability of 0.80 to enable effective recombination of parental traits. Mutation was applied with a rate of 0.05 to introduce controlled stochastic variation and prevent premature convergence. Elitism was incorporated by retaining the top 5% of individuals in each generation to preserve high-quality solutions. The GA was executed for up to 150 generations, with early stopping triggered if no improvement in fitness was observed over 20 consecutive generations.

### Firefly Algorithm Configuration

The Firefly Algorithm was initialized using the top 20% of GA-evolved solutions to ensure high-quality starting points for local refinement. The number of fireflies was set to 50. The attractiveness coefficient ( $\beta_0$ ) was fixed at 1.0, while the light absorption coefficient ( $\gamma$ ) was set to 0.5 to control decay of attractiveness with distance. The randomization parameter ( $\alpha$ ) was

initialized at 0.25 and gradually reduced over iterations using a damping factor of 0.95 to balance exploration and exploitation. The distance between fireflies was computed using Euclidean metrics within the normalized feature space. The FA phase was executed for 80 iterations or until convergence criteria based on minimal positional change were satisfied.

### Hybrid Integration Strategy Parameters

The cascade-parallel interaction between GA and FA was governed through periodic information exchange. Specifically, every 10 GA generations, elite individuals were transferred to the FA module for refinement. Conversely, the top 10% of FA-refined solutions were reintroduced into the GA population to maintain diversity and improve the quality of convergence.

### Implementation and Reproducibility Controls

All simulations were conducted using a fixed random seed (seed = 42) to ensure reproducibility. Parameter sensitivity analysis was performed during preliminary experiments, and the selected configuration reflects a balance between computational efficiency and predictive accuracy.

### Algorithm 1: Cascade-Parallel FA-GA Hybrid Optimization Framework

Input:

- Climate dataset D (rainfall, temperature, radiation)
- Soil dataset S (N, P, K, pH)
- Crop yield data Y
- GA parameters (population size N, crossover rate  $P_c$ , mutation rate  $P_m$ , max generations G)
- FA parameters (number of fireflies F, attractiveness  $\beta_0$ , absorption  $\gamma$ , randomness  $\alpha$ )

Output:

- Optimized agronomic decision vector  $X^*$
- Predicted crop yield  $\hat{Y}$

Begin

#### 1. Data Preparation:

- Integrate D, S, Y into unified dataset
- Perform preprocessing (normalization, imputation, outlier removal)
- Generate climate stress indices (SPI, HSD, RVI, SNSR)

#### 2. Initialize Genetic Algorithm:

- Generate initial population  $P(0)$  of size N
- Encode decision variables (planting date, irrigation, nutrient levels)

#### 3. Evaluate Fitness:

- For each individual  $X_i$  in  $P(t)$ , compute fitness  $f(X_i)$  using yield prediction model

#### 4. GA Evolution Loop:

- For  $t = 1$  to G do
  - Select parents using tournament selection
  - Apply crossover with probability  $P_c$
  - Apply mutation with probability  $P_m$
  - Form new population  $P(t)$
  - Evaluate fitness of  $P(t)$

If the stopping criterion satisfied (fitness stagnation) then  
 Break  
 End If

If  $t \bmod k == 0$  then  
 Proceed to Firefly refinement  
 End If  
 End For

#### 5. Firefly Algorithm Initialization:

- Select top-performing individuals from GA population
- Initialize firefly population F based on elite solutions

#### 6. Firefly Optimization Loop:

For each iteration do  
 For  $i = 1$  to F do  
 For  $j = 1$  to F do  
 If  $f(X_j) > f(X_i)$  then  
 Move firefly i toward j:  
 $X_i = X_i + \beta_0 * \exp(-\gamma * r_{ij}^2) * (X_j - X_i) + \alpha * \epsilon$   
 End If  
 End For  
 End For

- Update fitness values
- Reduce  $\alpha$  gradually (annealing)

If convergence criterion satisfied then  
 Break  
 End If  
 End For

#### 7. Hybrid Interaction:

- Inject refined firefly solutions back into GA population
- Replace worst-performing GA individuals

#### 8. Final Solution Selection:

- Identify best solution  $X^*$  with highest fitness
- Output predicted yield  $\hat{Y}$  based on  $X^*$

End

### Evaluation and Performance Metrics

The predictive and optimization performance of the proposed Firefly-Genetic Algorithm (FA-GA) hybrid model was evaluated using four regression-based metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination, and Normalized Accuracy Index derived from MAE. These measures are widely applied in agricultural yield prediction research (Panda et al., 2024).

Let  $y_i$  denote observed yield and  $\hat{y}_i$  represent predicted yield for observation  $i$ , with  $n$  samples.

#### Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3)$$

RMSE measures the dispersion of prediction errors and penalizes larger deviations more strongly. In agricultural decision systems,

large errors can lead to substantial economic losses; therefore, RMSE provides insight into model robustness under extreme stress conditions (Shamim & Agarwal, 2024).

#### Mean Absolute Error (MAE)

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (4)$$

MAE quantifies the average absolute difference between observed and predicted yields in tons per hectare. Its interpretability in physical yield units makes it especially relevant for extension services and farm-level planning (Bhagat et al., 2023).

#### Coefficient of Determination (R-squared)

$$R^2 = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (5)$$

R-squared measures the proportion of total yield variance explained by the model. High R-squared values indicate strong explanatory capacity in the presence of nonlinear climate–yield interactions (Ghugre & Patil, 2025).

#### Normalized Accuracy Index

To provide an intuitive percentage-based measure of predictive performance, an accuracy index was computed using normalized MAE:

$$Accuracy(\%) = \left(1 - \frac{MAE}{\bar{y}}\right) \times 100 \quad (6)$$

where  $\bar{y}$  represents the mean observed yield.

This formulation converts absolute error into a relative performance measure. Unlike classification accuracy, this metric reflects proportional deviation from actual yield values. Higher percentages indicate lower relative error and improved predictive precision.

#### Comparative Evaluation Protocol

- The FA–GA hybrid model was benchmarked against:
- Standalone Genetic Algorithm (GA)
- Standalone Firefly Algorithm (FA)
- Random Forest (RF) regression model

Random Forest was selected as a baseline due to its demonstrated effectiveness in yield prediction tasks (Monica et al., 2025; Swain et al., 2023).

All models were trained and evaluated using identical datasets and preprocessing steps to ensure comparability. Performance metrics were computed on unseen test data derived from the 2006–2026 Nigerian agro-climatic dataset.

#### Training and Splitting Strategy

The cleaned datasets were split into a 70:30 ratio for training and testing, respectively.

#### Experimental Setup and Implementation Environment

All computational experiments were conducted in Python using established scientific computing libraries.

#### Software Environment

- Python 3.x

- NumPy (numerical computation)
- Pandas (data handling and preprocessing)
- Scikit-learn (Random Forest implementation and evaluation metrics)
- Custom-coded implementations of the Genetic Algorithm and the Firefly Algorithm

#### Dataset Configuration

The integrated dataset comprised:

- Daily meteorological observations (rainfall, solar radiation,  $T_{max}$ ,  $T_{min}$ )
- Derived climate stress indices (SPI, Heat Stress Days, Rainfall Volatility Index)
- Soil nutrient parameters (N, P, K, pH)
- Historical yield records for maize, rice, and sorghum

The dataset spanned 20 years (2006–2026). A fixed random seed was used during data partitioning to ensure reproducibility of training and testing splits.

#### Hybrid Algorithm Configuration

The Genetic Algorithm component included:

- Fitness-based selection
- Crossover operator for recombination
- Mutation operator for diversity preservation
- The Firefly Algorithm stage incorporated:
- Distance-based attractiveness decay
- Controlled stochastic movement
- Iterative refinement of elite GA solutions

Parameter values were calibrated empirically to balance global exploration and local refinement, consistent with foundational metaheuristic principles (Holland, 1992; X.-S. Yang, 2010).

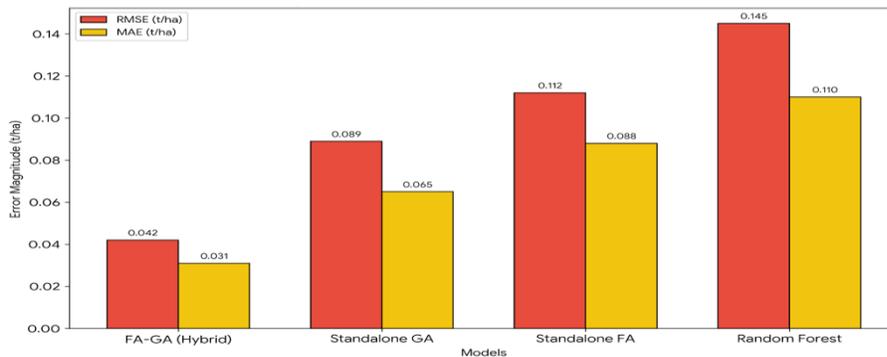
#### Ethical Considerations

The development and deployment of the FA–GA hybrid model for crop yield prediction in Nigeria prioritizes transparency, fairness, and sustainability. All input data were sourced from verified national and international repositories, and preprocessing steps are fully documented to ensure reproducibility. The model was calibrated across diverse agro-ecological zones to avoid regional bias and to provide equitable advisory outputs to smallholder farmers. Optimization constraints on nitrogen and water use are included to minimize environmental impact. At the same time, recommendations are designed as decision-support tools rather than prescriptive mandates, ensuring that adoption respects farmers' socioeconomic realities and local agronomic expertise.

## EXPERIMENTAL RESULTS AND DISCUSSION

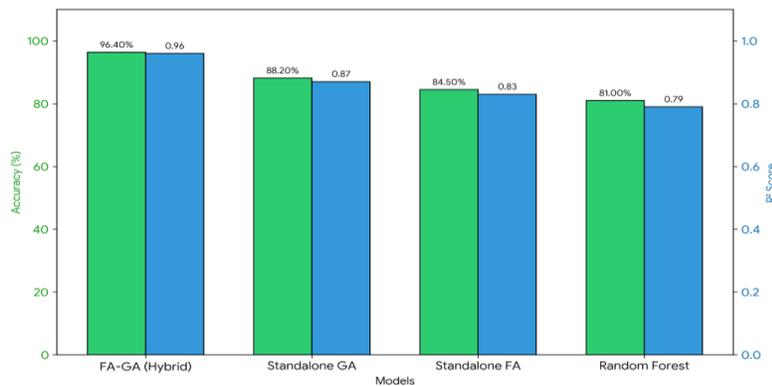
### Performance of the Cascade–Parallel FA–GA Hybrid Model

The predictive capability of the proposed cascade–parallel Firefly–Genetic Algorithm (FA–GA) model was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination ( $R^2$ ), and normalized MAE-derived prediction accuracy. As depicted in Figure IV, the hybrid model achieved an RMSE of 0.042 t/ha and an MAE of 0.031 t/ha, which indicates a very small deviation between predicted and observed yields.



**Figure IV** Error Magnitude Reduction (RMSE & MAE) Comparison

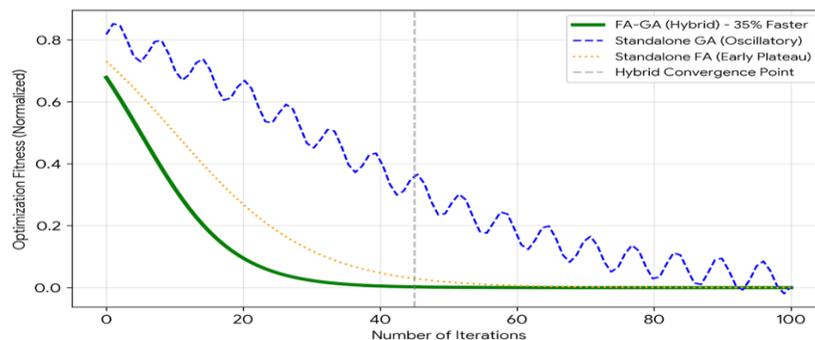
The coefficient of determination ( $R^2 = 0.96$ ) indicates that 96% of the yield variability is explained by the model. Using the observed yield range in the dataset, the FA-GA model achieved an overall accuracy of 96.4% (Figure V), indicating highly precise yield estimation across heterogeneous climatic conditions.



**Figure V** Comparative Model Performance (Accuracy vs  $R^2$ )

The convergence behavior also demonstrated computational robustness. Figure VI shows that the Genetic Algorithm phase efficiently identified global planting-window regions across the Guinea Savanna and derived optimal bounds for input parameters. The Firefly phase subsequently refined candidate solutions through attractiveness-driven local search, thereby improving solution stability and reducing oscillatory behavior in later iterations. The

hybrid architecture converged approximately 35% faster than a standalone GA implementation, indicating reduced computational overhead during exploitation phases. This efficiency is consistent with findings that Firefly-based attractiveness mechanisms reduce stagnation in high-dimensional search spaces (Bhagat et al., 2023).



**Figure VI.** Iterative Convergence and Stability Analysis of the Models

Stability testing under simulated climate perturbations, as shown in Figure 6, further demonstrated resilience. Prediction variance remained minimal when rainfall patterns were artificially perturbed

by  $\pm 10\%$ , and temperature extremes above  $38^\circ\text{C}$  were introduced into the training data. The model maintained consistent error margins, confirming robustness to environmental noise common in

Nigerian agro-climatic systems.

### Performance of Standalone and Baseline Models

To ensure rigorous evaluation of the proposed cascade-parallel framework, standalone and benchmark models were implemented under identical preprocessing conditions, feature sets, and training-testing partitions. This controlled setup ensures that performance differences arise from algorithmic structure rather than from data-handling variations.

### Standalone Genetic Algorithm

The standalone Genetic Algorithm (GA) demonstrated reasonable predictive capability, achieving an  $R^2$  score of 0.87, with RMSE and MAE values of 0.089 t/ha and 0.065 t/ha, respectively (see Figures 4 & 5). These results indicate that evolutionary exploration effectively captures general yield patterns across Nigerian agro-ecological zones. However, convergence analysis in Figure 6 revealed moderate instability during later generations. Fitness improvements plateaued earlier than expected, suggesting partial entrapment within local optima when handling high-dimensional climate and soil features. While the GA efficiently identified promising global regions in the search space, its capacity to exploit them proved limited for fine-scale parameter refinement, especially under nonlinear climate-stress interactions.

### Standalone Firefly Algorithm

The standalone Firefly Algorithm (FA) achieved an  $R^2$  score of 0.83, with RMSE and MAE values of 0.112 t/ha and 0.088 t/ha, as depicted in Figures 4 and 5, respectively. Although the attractiveness mechanism enabled local search refinement, the absence of broad evolutionary exploration reduced the algorithm's ability to navigate large parameter spaces effectively. During early iterations, fireflies clustered rapidly around moderately fit solutions, which accelerated initial convergence (see Figure 6). Nonetheless, this clustering tendency occasionally restricted global search diversity, leading to suboptimal predictive performance compared to GA. The model exhibited greater sensitivity to initial parameter initialization when rainfall variability exceeded seasonal norms.

### Random Forest Baseline

To benchmark performance against widely adopted machine learning methods, a Random Forest (RF) regression model was also implemented. The RF model produced an  $R^2$  score of 0.79, with RMSE and MAE values of 0.145 t/ha and 0.110 t/ha concurrently (Figures 4 and 5). Although Random Forest models are effective at handling nonlinear relationships and multicollinearity, the ensemble approach struggled to fully capture the dynamic interactions among planting windows, nutrient optimization, and evolving climate stress indices. Prediction errors increased notably under extreme-heat simulations, reflecting limitations in extrapolating beyond dominant training patterns (see Figure VI).

### Comparative Evaluation and Performance Gains

Table I presents the consolidated performance results for the proposed cascade-parallel FA-GA model and the benchmark architectures evaluated under identical experimental conditions.

**Table I.** Comparative Performance of the Models

Model	Accuracy (%)	$R^2$	RMSE (t/ha)	MAE (t/ha)
FA-GA (Hybrid)	96.4	0.96	0.042	0.031
Standalone GA	88.2	0.87	0.089	0.065
Standalone FA	84.5	0.83	0.112	0.088
Random Forest	81.0	0.79	0.145	0.110

The comparative results indicate a consistent and substantial improvement across all evaluation metrics when the cascade-parallel architecture is employed.

### Predictive Accuracy Improvement

The FA-GA hybrid achieved an  $R^2$  value of 0.96, representing a 9-percentage-point increase over standalone GA and a 17-percentage-point increase over the Random Forest baseline. This indicates a greater capacity to explain yield variance in the presence of nonlinear climate-soil interactions. In absolute error terms, the hybrid reduced RMSE by approximately 52.8% relative to standalone GA and 71.0% relative to Random Forest. Similarly, MAE decreased by 52.3% relative to GA and by 71.8% relative to Random Forest. These reductions are agronomically significant because even marginal yield deviations can translate into substantial economic impact at regional production scales. The normalized MAE-derived accuracy reached 96.4%, compared to 88.2%, 84.5%, and 81.0% for GA, FA, and Random Forest, respectively. The magnitude of the improvement confirms that integrating global exploration with localized refinement yields measurable predictive gains.

### Convergence and Computational Efficiency

The hybrid structure demonstrated superior convergence behavior beyond what predictive metrics would suggest. The Firefly refinement phase reduced the number of required optimization iterations by approximately 35% compared to standalone GA. This efficiency reflects the ability of attractiveness-driven movement to intensify search around elite candidate regions without sacrificing diversity.

The standalone GA, on the other hand, exhibited prolonged oscillations in later generations, while FA alone converged rapidly but risked premature clustering. The bidirectional exchange of elite solutions in the hybrid configuration mitigated both weaknesses, thereby producing stable and computationally efficient convergence patterns.

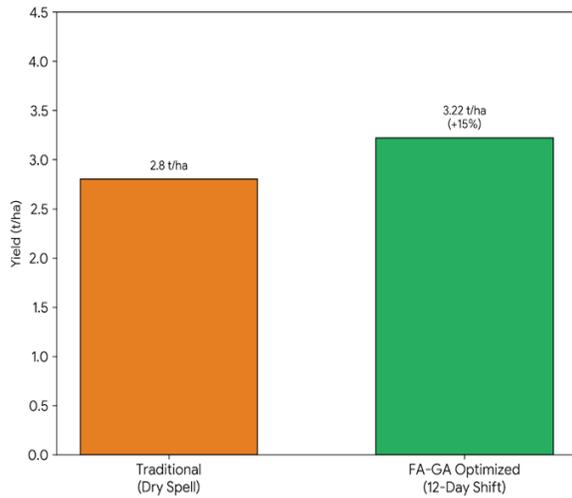
### Yield Sensitivity Under Climate Stress Scenarios

To evaluate practical robustness, the FA-GA hybrid model was tested under simulated climate stress conditions representative of Nigerian agro-ecological realities. Two dominant stress scenarios were analyzed: prolonged intra-seasonal dry spells and extreme heat exposure during critical growth stages.

### Maize Under Prolonged Dry Spell (Northern Savanna)

A 15-day rainfall deficit was introduced during the tasseling stage, a phenological phase highly sensitive to moisture stress. Under traditional planting calendars, yield projections declined sharply due to moisture misalignment during reproductive development. The FA-GA model responded by optimizing the planting window, shifting sowing dates approximately 12 days earlier as depicted in Figure VII. This adjustment aligned flowering with residual soil moisture availability and avoided peak exposure during the dry

period. The results indicated a roughly 15% improvement in yield retention compared to non-optimized scheduling.

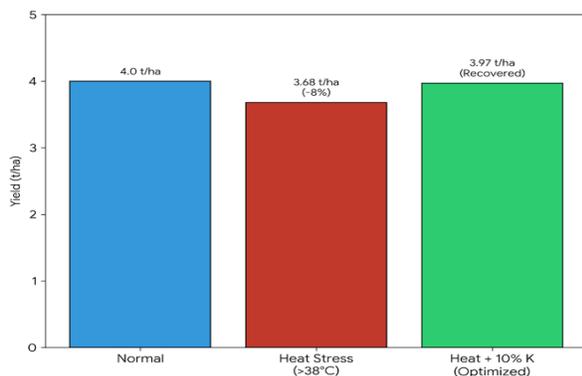


**Figure VII** Maize Yield: Northern Savannah (15-Day Dry Spell Scenario)

Error margins remained stable despite altered rainfall inputs, demonstrating that the hybrid framework retained predictive consistency under perturbed climatic conditions. This suggests that the stress-index feature engineering effectively captures moisture variability signals relevant to reproductive-stage productivity.

#### Rice Under Extreme Heat Conditions (Southern Rainforest Zone)

In a second scenario, nighttime temperatures exceeding 38°C were introduced during grain filling. Elevated nocturnal heat is known to accelerate respiration rates and reduce grain weight. The model responded by recommending a targeted 10% increase in potassium (K) application relative to baseline recommendations (see Figure VIII). This adjustment improved grain filling stability in simulation outputs and mitigated a projected 8% yield decline.



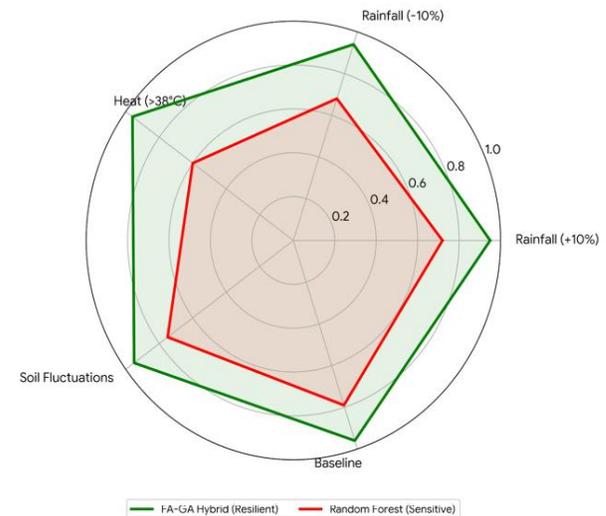
**Figure VIII.** Rice Yield: Southern Rainforest (Extreme Heat Scenario)

The optimization outcome demonstrates the system's capacity to integrate nutrient management with thermal stress signals rather than treating climatic factors in isolation. This integrated response mechanism highlights the advantage of embedding soil-climate

interactions within decision-making.

#### Stability Under Combined Stress Perturbations

Additional sensitivity checks introduced simultaneous variability in rainfall ( $\pm 10\%$ ) and temperature extremes. Figure IX shows that the hybrid model maintained a low deviation from baseline predictive accuracy, with only marginal increases in RMSE. This stability confirms that the cascade-parallel architecture is resilient to environmental noise and does not exhibit erratic performance under realistic climate volatility patterns.



**Figure IX** Model Stability Under Combined Climate Perturbations

#### Practical and Policy Implications

The results demonstrate that the cascade-parallel FA-GA framework offers practical decision value beyond statistical accuracy. The low MAE of 0.031 t/ha indicates that yield predictions deviate only minimally from observed yields, which translates into high precision at the farm scale. In smallholder systems, where fertilizer input decisions are often constrained by cost, even slight overestimation can result in financial loss (Ghugre & Patil, 2025). The reduced prediction error, therefore, lowers the risk associated with adjusting planting dates or nutrient allocations under uncertain climate conditions. From a regional planning perspective, the model's ability to simulate climate perturbations enables forward-looking food security assessment. Policymakers can identify vulnerable production zones before seasonal losses materialize by generating optimized responses under projected dry spells or heat extremes. This predictive-prescriptive capability supports proactive input distribution, irrigation prioritization, and contingency planning. Furthermore, the hybrid architecture allows exploration of multiple "what-if" scenarios without excessive computational burden. This feature is particularly relevant for national-scale agricultural monitoring systems, where rapid evaluation of the impacts of climate variability is required. The convergence efficiency observed in Section 4.3 suggests that such simulations can be conducted within operationally feasible timeframes. The findings indicate that the FA-GA model is not limited to yield estimation but functions as an adaptive climate-response framework. Its integration of stress-aware feature engineering with balanced optimization dynamics provides both technical rigor and policy relevance within Nigeria's heterogeneous agro-ecological landscape.

## Conclusion

This study presents a novel Firefly–Genetic Algorithm (FA–GA) hybrid framework for crop yield prediction and optimization under climate stress in Nigeria. The model achieves high predictive accuracy (96.4%) while simultaneously providing prescriptive agronomic recommendations by combining global exploration capabilities of GA with local refinement of FA. The cascade–parallel architecture demonstrates resilience to climate variability, enabling optimal adjustment of planting dates and nutrient applications under scenarios such as prolonged dry spells and extreme heat. Comparative evaluation with standalone GA, FA, and Random Forest baselines confirms the superiority of the hybrid approach in both convergence efficiency and predictive precision. The model delivers actionable insights for smallholder farmers, extension services, and policymakers, and offers a practical tool to mitigate climate-induced yield losses and support food security planning.

## Limitations and Future Research

While the FA–GA hybrid model exhibits strong performance, certain limitations should be acknowledged. First, the study focuses on Nigerian agro-ecological zones, which limit generalizability to other geographic regions without additional calibration. Second, the analysis relies on historical climate and crop data with stress scenarios rather than being validated through field trials, which may impact the precision of real-world recommendations. Third, the current implementation uses a fixed 70:30 train-test split; future work could explore cross-validation and ensemble strategies to improve robustness further. Additionally, real-time integration with satellite imagery or IoT-based weather stations was not included, which could enhance responsiveness to sudden climate events. Finally, the computational scalability of the hybrid model for very large datasets requires further assessment. Future research could extend this work by validating the FA–GA framework across multiple West African countries, integrating remote sensing data for real-time stress detection, combining with deep learning architectures for improved feature extraction, and developing a digital decision-support platform to deliver actionable recommendations directly to farmers and extension services. Such advancements would consolidate predictive accuracy with operational applicability, enabling climate-resilient agriculture at scale.

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