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RESEARCH ARTICLE

Deep Learning Framework for Maize Demand Prediction Using Optimized Environmental Features

R. AMIRTHAM[1], M. MANIMEKALAI[2]

[1]*Assistant Professor, Department of Computer Science, Imayam Arts and Science College, Kannanur, Thuraiyur 621206, Tamil Nadu, India.* amirtharas7@gmail.com

[2]*Research Head, Shrimati Indira Gandhi College, Tiruchirappalli – 620002, Tamil Nadu, India.* manimekalai@sigc.edu

Corresponding author: amirtharas7@gmail.com

ABSTRACT

Accurate maize demand prediction plays an important role in ensuring food security, market stability, and sustainable agricultural development. However, maize demand prediction is a complex process is mainly determined by the interactions between different factors such as soil, climate, irrigation, and production data. Therefore, traditional statistical models are ineffective due to their inability to capture the underlying nonlinear relationships and temporal dependencies in the data. It leads to resource mismanagement, overproduction, and underproduction that affects the economy. This work presents a novel approach based on Convolutional Neural Network-Bidirectional Long Short-Term Memory with Attention and Grey Wolf Optimized Environmental Features for maize demand prediction. Agricultural data such as soil, climate, irrigation, and production data were collected and pre-processed using the Multiple Imputation, Median Filtering, and Min-Max normalization to fill and smooth missing data. Then Grey Wolf Optimization is used for feature selection, which determines the relevant environmental features by removing extra ones and decreasing the complexity of the input data. The acquired features are processed through the Convolutional Neural Network (CNN) that identifies feature detectors, and their representations are extracted through BiLSTM with Attention, which means processing data in both directions. Moreover, the Attention mechanism highlights the important features that affect maize demand. After that, the production demand is predicted using the attained results for efficient planning and allocation of resources. The proposed framework achieved an RMSE of 2.14, MAE of 1.48, MAPE of 6.12%, and R^2 of 98.96%, that shows how this system effectively captures relevant nonlinear relationships, temporal dependencies, and influential agricultural factors, resulting in more accurate maize demand prediction.

Keywords: *Maize Demand Prediction, Deep Learning, Grey Wolf Optimization, Environmental Features, Precision Agriculture, Sustainable Agricultural Planning*

INTRODUCTION

Maize is one of the world's most important cereal crops in terms of food, feed, and industrial raw material production. Its yield prediction is critical to agricultural production, ensuring food security, and contributing to economy and trade (Ma et al., 2021). There is an increasing need for timely and accurate estimations of maize yield, which is driven by the growing awareness of the vulnerability of agricultural production to climate change, environmental influences, and the need for global food security (Ramos et al., 2020).

Most traditional methods used for maize yield estimation, including conventional statistical techniques, crop growth models, and field measurements, are typically labor intensive, involve complex calculations, and are only moderately adaptive to complex agro climatic

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conditions (Ahmad et al.,2020). Everyone fails to account for the interrelationships between various factors such as the soil, climate, vegetation, and topography, which have a combined effect on crop production (Shahhosseini et al., 2020; Zhou et al., 2024).

The recent developments in remote sensing technologies such as satellite and Unmanned Aerial Systems (UAS) have enabled the monitoring of crops at a large scale with a relatively low cost and non-invasive manner. The multispectral images and vegetation indices like Normalized Difference Vegetation Index (NDVI) have been widely used to capture the crop condition, canopy structure, and vegetation status which can inform crop yield estimation. However, vegetation indices suffer from canopy saturation, atmospheric interference, variation in illumination conditions, and low capacity to incorporate complex spatial and temporal patterns in the field, constraining their prediction capability in different environments (Fathololoumi et al., 2026; Ramos et al., 2020; Sapkota et al., 2025; Zhang et al., 2025).

The random forest regressions, support vector regressions, K-Nearest Neighbor, and extreme gradient boosting algorithms have been widely implemented to estimate maize yield due to their promising performance in handling non-linear trends in agricultural data (Hao et al., 2026). However, their performance is highly dependent on the expert knowledge for informative feature selection and engineering. Besides, the generalizability capacity of these methods is limited when applied in different geographical locations. On the contrary, the deep learning algorithms have shown a promising ability to learn hierarchical data representations from both tabular and image data (Zhou et al., 2024). Specifically, the convolutional neural networks such as Visual Geometry Group 19 (VGG-19) can effectively learn the underlying spatial patterns of multispectral satellite images while deep belief networks can mine the complex non-linear relationships between agricultural variables. However, most of the previous studies utilized either tabular or image data for maize yield prediction. There is still a gap in investigating the combined potential of these data types for high-level abstraction in maize yield estimation. Moreover, the presence of numerous relevant and irrelevant features increases the chances of overfitting and computational costs.

The main purpose of this research is to design a robust deep learning framework for effective maize demand prediction by adopting Grey Wolf Optimization-based feature selection and CNN-BiLSTM model with an attention mechanism. The proposed framework helps enhance performance and achieve accurate prediction results to facilitate decision-making in agricultural demand prediction. With growing complexities and difficulties in agricultural production, it has become crucial to make precise predictions to manage optimal utilization and production of maize. However, current prediction models are unable to address the diverse interactions of environmental factors accurately, therefore creating a need for enhanced prediction framework. This study proposes a modified deep learning model that offers improved performance to yield accurate demands prediction. The Contributions of this Study include Grey Wolf Optimization-based feature selection and enhanced performance achieved through the CNN-BiLSTM with attention mechanism for accurate maize demand forecasting.

1. Enhances forecast performance through selection of relevant environmental features and discarding of redundant ones based on Grey Wolf Optimizer.

2. Captures spatial feature representation learned by CNNs and bilateral temporal patterns encoded in BiLSTM with attention, resulting in improved demand prediction.

3. Enables effective agricultural planning by offering forecasts that support smart production scheduling, resource optimization, and informed decision-making.

The rest of the paper is organized as follows. Section 1 presents Background and Motivation. The related works are described in Section 2. The preliminary concepts are introduced in Section 3. The Proposed Work is detailed in Section 4. The experimental results and discussion are presented in Section 5. Finally, the concluding remarks and future directions are described in Section 6, the last section of this paper.

RELATED WORKS

Ikram et al. (2025) developed a Fuzzy-Optimized Hybrid Ensemble Model (FOHEM) combined a fuzzy inference system with three algorithms of Random Forest, CatBoost and Extreme Learning Machine (ELM) to predict the yield of intercropping corn and soybean, in which the Genetic Algorithm was used to optimize the weights of the ensemble model, LIME and SHAP for interpreting the prediction and investigating the drivers of yield. And the framework predicted yields better through using environment, soil, and management attributes. However, the system just used for predicting crop yields through ensemble learning and it didn't use deep temporal feature learning to predict the demand for corn.

Stevanović et al. (2025) focused on explaining how planting density and inter-plant competition affect

the yields of corn and applied statistical regression and ML methods under different weather conditions. The methods predicted the grain yields and seed quality attributes precisely, and determined outstanding corn–soybean–soybean pairs on specific hybrid and density to increase crop productivity. Corn yields are meaningfully and significantly related to the planting density, specific hybrid choice, and performance of different conditions. But study mainly aimed at the yield prediction, and it doesn't introduce the temporal deep learning and optimizing the relevant environmental feature extraction for corn demand.

In a systematic review, Nyengere et al. (2026) summarized eighty-one studies related to machine learning for prediction of maize production, reflecting growing ML models application in the decision making of crop agriculture. Results revealed that Random Forest, XGBoost, Support Vector Machines and hybrid deep learning frame is currently considered as the most used techniques. Environmental characteristics of the site, remote sensing (RS) image, and a broad soil characteristic information (e.g. PH value, organic C, N, P and K) is identified as primary features in prediction and the deep hybrid deep learning model was best performed with using RMSE and R.

Nonetheless, issues such as scarcity of Data, model interpretation and geographical unbalance limitations are indicated and recommend the enhancement of well-founded, and understandable models of deep learning techniques in this field. Cheng and Wang (2026) proposed a prediction framework for maize production based on soil nutrient and climatic data to achieve high accuracy of yield estimations. The framework included five main soil nutrients such as N, P, K, O.C and pH, climatic variables like temperature, precipitation and growing degree days (GDD) as predictive variables. Both traditional statistical approaches, ML models and deep learning models have been compared in terms of RMSE, MAE, and R. Nevertheless, only predicting the production quantity of maize were the theme of work, optimized feature selection and attention of deep learning model for demand prediction of maize were not used.

An Osprey Optimization Algorithm (OOA), a novel natural-inspired meta-heuristic optimization method, was developed by Dehghani et al. (2023) which mimicking the foraging behaviour of osprey in its attempt to perform balanced search of exploitation and exploitation mechanisms. The proposed approach had been demonstrated on CEC 2017 benchmark functions and outperforms 12 well-known benchmark functions, proving the optimization capability and reliability through 3-dimemsional problem testing for CEC 2011 real world constrained optimization problems. However, the methodology mainly centred on optimum finding only on benchmark functions, hence nothing was conducted regarding the use of OOA on deep learning methods-based Agri demand estimation via environmentally-oriented data resources.

Current studies deal with maize yield prediction through traditional machine learning, ensemble learning, optimization techniques, or shallow neural networks, lacking the power to handle complex temporal dynamics and adaptive environmental interaction. Although various optimization methods help to enhance feature selection and prediction performance, a comprehensive framework consisting of optimized feature selection, deep spatial feature learning, temporal sequence modelling, and adaptive feature weighting are not available. Therefore, the proposed framework combines the Grey Wolf Optimization (GWO) for selection of optimal environment features, the CNN for learning discriminative non-linear features, the BiLSTM for learning bi-directional temporal dynamics, and the Attention mechanism for assigning greater importance to influential environmental features. Such a deep learning model effectively addresses the redundant features, avoids the over-fitting problem, enhances long-term temporal learning capability and robust performance. The proposed system can accurately and reliably predict maize demand, offering an effective decision support tool for smart agricultural planning and resource management.

PROPOSED SYSTEM

Agricultural Data Collection

The proposed framework uses the heterogeneous agricultural data from Indian Historical Crop Yield and Weather Data set on Kaggle dataset. The data includes weather data from the India Meteorological Department (IMD) and agricultural data from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). The data set contains information on agricultural data, including soil type and fertility, temperature, rainfall, humidity, wind speed, irrigation, area cultivated, and crop produce. This data has been chosen because it contains the relevant information on weather conditions, as well as other factors affecting maize production, such as the level of irrigation. The variables of crop production and area cultivated are indicators of the level of maize production and therefore its supply. Collectively, the variables provide information affecting maize production and its levels at a given time, which helps predict future supply and demand patterns. Secondly, the data set has a large amount of data that covers different

years and months, which helps the proposed model generalize better and perform accurately under different conditions. The collected data set used to carry out the next steps in the proposed research, including preprocessing, optimizing, and deep learning, leading to the prediction of demand for maize. The dataset is available in the Kaggle platform-dataset

Data pre-processing

The provided data set consists of agricultural data with different environmental variables characterized by different scales, missing values, and measurement noises, among others. These attributes may hinder the performance of the underlying deep learning algorithms and, consequently, the prediction performance of the proposed framework. Therefore, it is critical to perform a data pre-processing step for data cleaning and preparation for the feature selection algorithm. In particular, the data pre-processed using Missing Value Imputation, Median Filtering, and Min-Max Normalization procedures.

Missing Value Imputation

Agricultural data can sometimes have missing records, such as when a particular sensor malfunctions or no readings were taken at the time of observation. These missing values can make it harder to get reliable results from the learning process and make it bias the prediction model. Thus, missing values need to be replaced with some numerical values using mean imputation for continuous variables so that there is no loss of information. A set of features can then be represented by the following expression.

$$X = \{x_1, x_2, \dots, x_n\} \quad (1)$$

Where x_i refers specific observation with missing values. The mean value is calculated with the formula below:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (2)$$

Where, N refers total number of observations available for calculating the mean. The missing value is replaced as follows:

$$x_{\text{missing}} = \mu \quad (3)$$

Using this method, it is possible to maintain the distribution of environmental variables without discarding any samples.

Median Filtering

In case of tabular data, there may be occurrence of noise and extreme values that arise from sensor faults (environmental factor or data collection procedures like human inspection) thus a median filtering is employed to discard them by still retaining the structural components of the agricultural variables. The filtered value in terms of a filter of window size, k for a sliding window defined is

$$y_i = \text{Median}\,(x_{i-r}, \dots, x_i, \dots, x_{i+r}) \quad (4)$$

Where, y_i refers filtered output, $x_i$refers original feature value, $r = \frac{k-1}{2}$indicate the half length of the window radius. A median filter is known not only remove the impulsive noise values and but also retains the distribution structure of the original signal at each point whereas a mean filter smooths the output.

Min-Max Normalization

The agricultural features are expressed in different units of measurement, for instance, the amount of rainfall is measured in mm, temperature is measured in Celsius, pH level is indicated by numbers, air humidity is measured in percentages, and the area is measured in hectares. As such, the scale of measurement is expected to affect the performance of deep neural networks. The Min-Max Normalization is applied to standardize the input data within the range of zero to one in order to accelerate the network convergence. The normalized feature value is computed using the equation below:

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (5)$$

Where x_i' stands for normalized feature value, $x_i$stands for the feature value, $x_{\min}$ and $x_{\max}$stand for minimum and maximum feature values respectively. The normalized value satisfies the following identity:

$$0 \le x_i' \le 1 \quad (6)$$

which helps improve the learning process, accelerate the network convergence and avoid overfitting problems.

Environmental Feature Selection using Grey Wolf Optimization (GWO)

Selection of features would provide to increase the precision of prediction in the deep learning models via selection of proper environment related values. Redundant or non-related attributes should be thrown. Agricultural applications datasets contain multiple correlated attributes insoil, climate, irrigation and production such Attributes which leads to the more complexity in processing and over-fitting. So, to find a small number of the best environmental characteristics to increase prediction precision, reduce redundancy of attributes Grey Wolf Optimization (GWO) is utilized; it's a metaheuristic population-based optimization algorithm inspired from the natures.

In GWO population is divided into four types of wolves; Alpha (α), Beta (β), Delta (δ), and Omega (ω), α has the role of the best candidate solution while β and δ represents the second and third best

solutions and ω wolves update its position according to α, β and δ. Updating the position for a search agent; a distance between wolf to Alpha (α), Beta (β), Delta (δ), wolves can be formulated as below:

$$D = | C \cdot X_p(t) - X(t) | \quad (7)$$

Where, $X(t)$ denotes current position of a wolf, $X_p(t)$denotes position of the prey (optimal solution), C refers coefficient vector. The wolf updates its position as,

$$X(t+1) = X_p(t) - A \cdot D \quad (8)$$

where the coefficient vectors is computed as below,

$$A = 2ar_1 - a \quad (9)$$
$$C = 2r_2 \quad (10)$$

Where, a decreases linearly from 2 to 0 during optimization, $r_1$and r_2 refers random vectors within $[0, 1]$. To improve the exploration and exploitation process, the wolves' positions updated based on the three best wolves:

$$D_\alpha = | C_1 X_\alpha - X | \quad (11)$$
$$D_\beta = | C_2 X_\beta - X | \quad (12)$$
$$D_\delta = | C_3 X_\delta - X | \quad (13)$$

The other wolf's candidate positions are computed as follows,

$$X_1 = X_\alpha - A_1 D_\alpha \quad (14)$$
$$X_2 = X_\beta - A_2 D_\beta \quad (15)$$
$$X_3 = X_\delta - A_3 D_\delta \quad (16)$$

Finally, the search agent updated position are obtained by averaging the best three candidate positions:

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad (17)$$

The fitness of each feature subset is assessed using a fitness function that optimizes prediction accuracy simultaneously with the number of selected features. The fitness function is given by

$$Fitness = \alpha(1 - Accuracy) + \beta\left(\frac{|S|}{|F|}\right) \quad (18)$$

Where, the 'Accuracy' is the predicted accuracy of the chosen feature subset, 'S' is the number of features selected, 'F' is the number of total features and '+=1' is weight coefficient which provides a trade-off between predictive performance and dimensionality reduction. After GWO has gone through rounds of optimization, the optimum feature subset in the environment is generated; the features with significant information of soil, climate, irrigation and production attributes that contribute to crop yield are selected by abandoning duplicate information. In doing so, the computational complexity of the framework has been reduced significantly, preventing over-fitting effectively and shortening the training time significantly, and providing a valid feature set for the next CNN-BiLSTM network with Attention, greatly enhance the accuracy and robustness of maize demand prediction.

Algorithm 1: Environmental Feature Selection using Grey Wolf Optimization (GWO)

Input: Environmental feature dataset D, Population size N, Maximum number of iterations Tmax

Output: Optimal environmental feature subset S_{best}

Begin

Load pre-processed dataset D

Initialize a population of N grey wolves random

where each wolf represents a candidate feature subset

Set: iteration t = 1

Evaluate fitness of wolf

Identify three best wolves α, β, δ

While (t ≤ T_{max}) **do**

For each wolf X_i population **do**

Compute coefficient vectors A and C

Calculate distances

Compute candidate positions

Update wolf position

End For

Update parameter a

Evaluate fitness of all updated wolves

Update Alpha, Beta, and Delta wolves

t = t + 1

End While

Select feature subset represented by Alpha wolf

Return S_{best}

End

Feature Extraction using Convolutional Neural Network (CNN)

After the Grey Wolf Optimization-Based Feature Selection process, the best environmental features were extracted as an input to the Convolutional Neural Network. This network allows automatically learning the higher-level features from the input data. Unlike traditional machine learning algorithms, which require handcrafted features to train models, the CNN model can learn the necessary transformations of various agricultural features (soil, climate, irrigation, crop

area, and previous production) in order to make accurate predictions of maize demand. The convolutional layer within the CNN includes a set of filters that act on the input features to extract the most relevant information. Consider the optimized input feature vector be represented as $X = \{x_1, x_2, \dots, x_n\}$, where n refers number of selected environmental features. The convolution operation is shown as,

$$F_j = \sigma\left(\sum_{i=1}^{k} W_i X_{j+i-1} + b\right) \quad (19)$$

where $F_j$represents extracted feature, $W_i$denotes convolution kernel weights, k refers kernel size, b denotes bias term, and $\sigma(\cdot)$ refers activation function. In this work, the Rectified Linear Unit (ReLU) activation function is adopted to introduce nonlinearity and accelerate model convergence, which is defined as,

$$\sigma(x) = \max(0, x) \quad (20)$$

Subsequently, a max-pooling layer is employed to reduce the dimensionality of the extracted feature maps while retaining the most informative representations. The pooling operation is given by

$$P_i = \max(F_i) \quad (21)$$

where $P_i$denotes the pooled feature. This operation reduces complexity, improves generalization, and increases the robustness of learned features. As a result, the CNN network encodes the optimized environmental variables into compact representation high-level features, which can fully extract the underlying data distribution characteristics of agricultural factors. Then, these high-level features are sent to the next network layer, namely Bidirectional Long Short-Term Memory (BiLSTM), for further processing.

Temporal Learning using Bidirectional Long Short-Term Memory (BiLSTM)

To exploit the temporal information embedded in learned features, a Bidirectional Long Short-Term Memory (BiLSTM) is utilized in this study. Since maize demand is affected by seasonal climate changes, cumulative production, irrigation patterns, and cultivation trends, the characteristics of which are gradually revealed over time, conventional LSTM networks were employed. However, since the standard LSTM processes the input data sequentially and only considers the previous states while ignoring the future ones, it cannot effectively model the long-term temporal dependencies. To address this issue, we applied Bidirectional LSTM, which comprises two individual LSTM layers that process the input data in opposite directions and learn distinct weight matrices for each direction. At each time step t, the forget gate finds the historical information amount to retain and calculated as,

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (22)$$

where h_{t-1}refers previous hidden state, x_t denotes current input feature, and $W_f$and $b_f$refers trainable weight matrix and bias. The input gate controls the incorporation of new information into the memory cell and is defined as

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (23)$$

The candidate memory state is calculated as,

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \quad (24)$$

The memory cell updated according to

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (25)$$

where $\odot$denotes element-wise multiplication. The output gate generates the hidden representation using

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (26)$$

$$h_t = o_t \odot \tanh(C_t) \quad (27)$$

To exploit contextual information from both temporal directions, the forward and backward hidden states are calculated as

$$\overrightarrow{h_t} = LSTM_f(x_t, \overrightarrow{h_{t-1}}) \quad (28)$$

$$\overleftarrow{h_t} = LSTM_b(x_t, \overleftarrow{h_{t+1}}) \quad (29)$$

The final temporal representation is obtained by concatenating both hidden states:

$$H_t = [\overrightarrow{h_t}; \overleftarrow{h_t}] \quad (30)$$

where $H_t$refers bidirectional feature representation. By integrating information from past and future observations, BiLSTM The addition of previous and future observations to the time series in the BiLSTM enables the network to capture the effects of long-term seasonal variation and climatic changes on maize demand, in addition to other historical time series related to maize production or usage patterns. The temporal feature is enriched with additional contextual information than would be obtained in the standard LSTM; this feature set is passed into the Attention Mechanism.

Attention Mechanism

The Bidirectional LSTM network captures the dependency relationship between different locations by including the information of previous and future time steps to obtain all relevant time information related to the maize data, but not all the temporal features leads to the optimal maize demand forecast. Sometime features contain significantly more relevant information regarding the predicted future values, such as rainfall, temperature, humidity, soil moisture, irrigation availability, historical production and so on. Thus, we use an Attention Mechanism after BiLSTM layers to dynamically find and emphasize the parts that are important to predicting maize demand,

and ignore the unimportant parts so that we can allocate adequate attention to necessary information. Consider the hidden state generated by BiLSTM as $H = \{h_1, h_2, \ldots, h_T\}$, where T *denotes* sequence length. At first, the attention score is calculated for each hidden state as below,

$$e_t = \tanh(W_a h_t + b_a) \quad (31)$$

where$W_a$and $b_a$as trainable weights matrix and bias, $e_t$is the attention score to hidden state h_t. The Softmax function to calculate the attention weights:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{i=1}^{T} \exp(e_i)} \quad (32)$$

where $\alpha_t$refers normalized attention weight associated with the t^{th}hidden state and satisfies

where, tis the final normalized attention weight for the t^{th} hidden state and fulfills

$$\sum_{t=1}^{T} \alpha_t = 1 \quad (33)$$

The context vector can be computed with weighted summation of all the BiLSTM hidden states:

$$C = \sum_{t=1}^{T} \alpha_t h_t \quad (34)$$

Where, C refers context vector with most considerable temporal and environmental features representation. This Attention mechanism improves discriminatory power and learning efficiency with less influential information receives small attention weight and more informative agricultural features achieve significant weight, this makes our model gain the better prediction result under the changeable condition.

Fully Connected Layer and Demand Prediction

The context vector generated by the Attention mechanism is subsequently forwarded to the Fully Connected (FC) layer to perform the final nonlinear mapping between the learned feature representations and maize demand. The Fully Connected layer integrates the weighted environmental and temporal features extracted by the preceding CNN-BiLSTM-Attention architecture and learns the complex relationship between these features and the corresponding maize demand values. Unlike the convolutional and recurrent layers that focus on feature extraction and sequence learning, the Fully Connected layer performs high-level reasoning by combining all informative features into a unified representation for prediction. The output of the Fully Connected layer is computed as

$$z = W_f C + b_f \quad (35)$$

where C is the context vector produced by the Attention layer, $W_f$is the trainable weight matrix of the FC layer, b_f is its associated bias term, and z is the transformed feature representation. The Rectified Linear Unit (ReLU) is adopted to implement the non-linearity in the FClayer :

$$a = \max(0, z) \quad (36)$$

where a is the activated result produced by the FClayer. At present A regression output neuron predicts future maize demand:

$$\hat{Y} = W_o a + b_o \quad (37)$$

where $\hat{Y}$ is the maize demand prediction, W_o is the FC layer weights in the output layer, and b_o is its associated bias term. The parameter for optimizing this system in our study to predict the maize demand as a regress value, using Mean Squared Error (MSE)lossfunction,

$$L = \frac{1}{N} \sum_{i=1}^{N} (Y_i - \hat{Y}_i)^2 \quad (38)$$

where Y_i represents actual demand of maize, $\hat{Y}_i$is the predicted demand of maize, and N is the total number of samples. Training is conducted by minimizing this error by repeatedly adjusting the parameters of the network in the process of backpropagation. In a word, after the network convergences, the trained model is able to accurately predict future demand of maize from certain environmental and historical agriculture trends. These prediction values can further guide production planning, resource allocation, and sustainable agricultural decision, which allowing interested part to make foresight production plan, cultivation planning.

Decision Support System

The predicted demand for maize the CNN-BiLSTM with attention architecture in figure1. The decision support system (DSS) used to make informative cultivation and resource allocation choices for agricultural planners, farmers, and policymakers. Through the understanding of threshold values by applying the determined value into given threshold ranges, the agricultural actions were automated on crop. If the predicted demand is more than the upper threshold value (i.e., $T_L$and T_H,), then the suggested action is to increase the maize cultivation, fertilizer; and improve irrigation management and ensure input supply. The decision-making strategy is formulated as

$$Decision = \begin{cases} \text{High Demand}, & \hat{Y} \geq T_H \\ \text{Moderate Demand}, & T_L < \hat{Y} < T_H \\ \text{Low Demand}, & \hat{Y} \leq T_L \end{cases} \quad (39)$$

where $T_H$and $T_L$refers upper and lower demand thresholds from historical demand statistics or expert recommendations. If predicted demand $\hat{Y} \geq T_H$), the model suggests to expand the maize cultivation area, optimize fertilizer input,

irrigation and other production factors to meet the demand. However, if predicted demand ($T_L < \hat{Y} < T_H$), it is suggested to keep production factors at the current level to ensure stable output. While when the predicted demand ($\hat{Y} \leq T_L$), the framework advises to reduce the maize planting area and fertilizer and irrigation application, and reallocate the production factors into other crops with higher economic benefits. By converting the quantitative demand prediction into qualitative decision-making suggestions, the proposed decision-making system can not only help farmers make full use of production factors but also avoid huge economic loss due to the supply-demand gap and promote sustainable development.

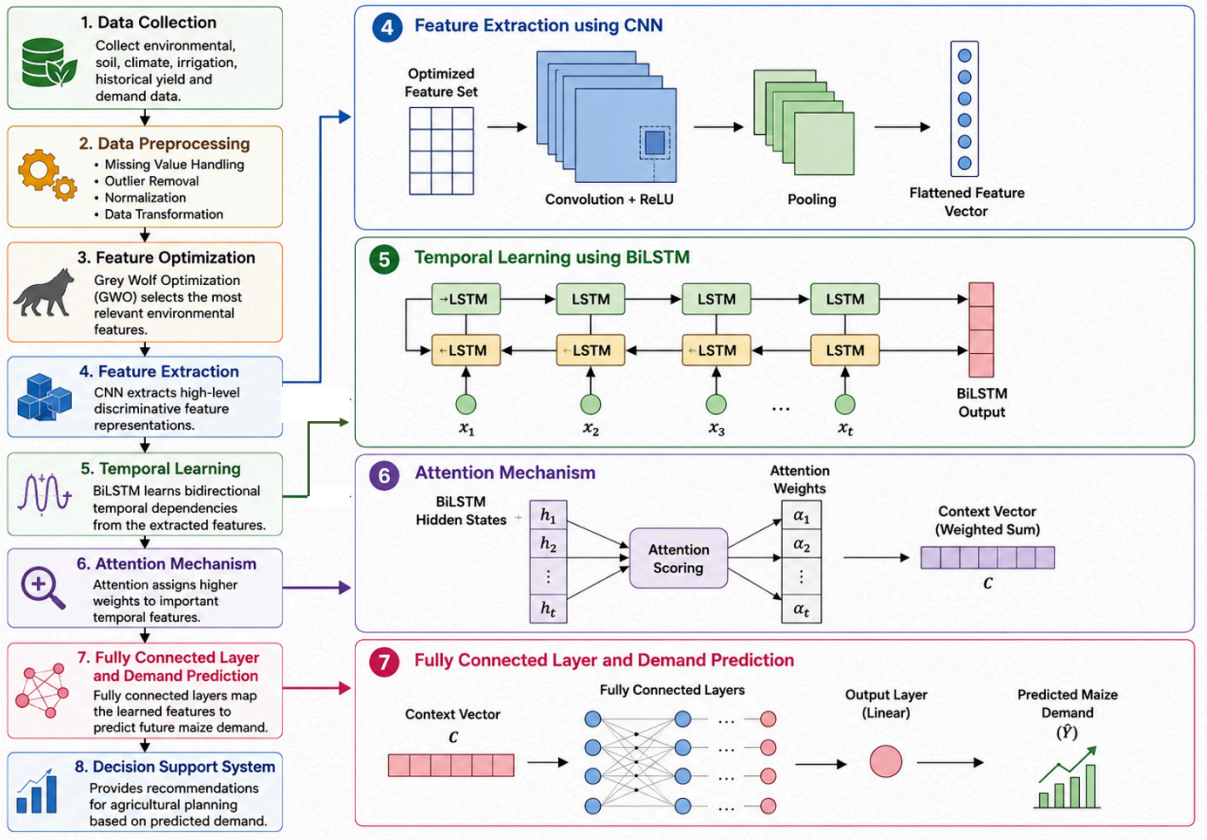


Fig.1. Proposed System Framework: CNN-BiLSTM with attention and GWO for Maize Demand Prediction

RESULTS AND DISCUSSION

The proposed Deep Learning Framework for Maize Demand Prediction Using CNN-BiLSTM with Attention and Grey Wolf Optimized Environmental Features is evaluated using standard regression performance metrics, namely, the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination, and Prediction Accuracy. These performance metrics enable a fair assessment of the prediction performance of the proposed approach by considering the error between the actual and predicted values, the goodness of model fit, and the overall prediction ability. In this regard, the prediction results of the proposed Deep Learning Framework are compared to those of the conventional machine learning and optimization-based approaches for regression tasks to demonstrate its efficacy in predicting maize demand. Notably, the proposed Grey Wolf Optimizer (GWO)-based approach has demonstrated significant improvements over the existing CNN-BiLSTM, CNN-LSTM, BiLSTM, LSTM, GRU, and conventional machine learning approaches. Root Mean Square Error (RMSE) is a standard metric for evaluating the performance of regression models as it follows the mathematical formulation of minimizing the sum of squared errors. In this regard, RMSE is calculated as the square root of the average of the squared errors between the actual and the predicted values.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \qquad (40)$$

Calculating the Mean Absolute Error (MAE) this measures the average of the absolute differences between observed actual maize yield and predicted values, where individual prediction errors are equally weighted rather than in the case of RMSE. MAE can be given as the intuitive description for

the average error of the model predictions as follows,

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | y_i - \hat{y}_i | \quad (41)$$

Calculation of the Mean Absolute Percentage Error (MAPE) as being given for comparison with previous research work of how models prediction is sensitive in terms of units of measurement of crop produced (expressed as percentage of actual), so we can compare models' performance for different datasets or crops, e g for any specific crop production.

$$MAPE = \frac{100}{N}\sum_{i=1}^{N} | \frac{y_i - \hat{y}_i}{y_i} | \quad (42)$$

The coefficient of determination (R^2) measuring correlation between actual observed and fitted predicted yield from prediction model, R^2 value ranges from 0 to 1, where values closer to 1 indicate better prediction performance and stronger agreement between actual and predicted values.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \quad (43)$$

Where, $\bar{y}$ refers Mean of actual maize yield values. Then, the comparative analysis among the proposed method with existing method clearly compared based on the metrics.

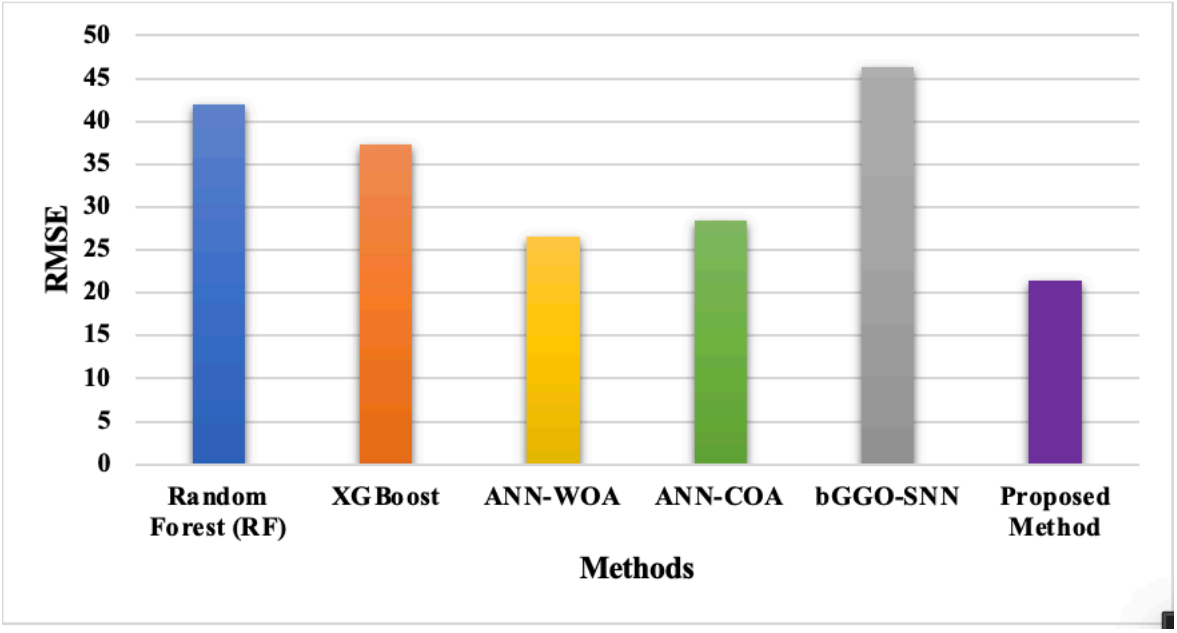


Fig.2.Comparative Analysis based on RMSE

The RMSE values of the existing and proposed method indicate the average prediction error, and lower value means better is shown in Fig.2. The proposed method owns a lowest RMSE of 21.4%, so prediction accuracy of this method is the highest among all these models. ANN-WOA and ANN-COA (Fariz & Basha, 2025) have RMSE 26.62% and 28.50%; XGBoost has the third highest value 37.3%; Random Forest and bGGO-SNN (Amirtham (2025) have a highest prediction error which means the prediction values deviate from the true values the most, RMSE values are 42.0% and 46.3%. And the lowest RMSE value of proposed method with CNN-BiLSTM-Attention-GWO demonstrates that complex environmental relationships can be modeled effectively and produce more reliable maize demand predictions.

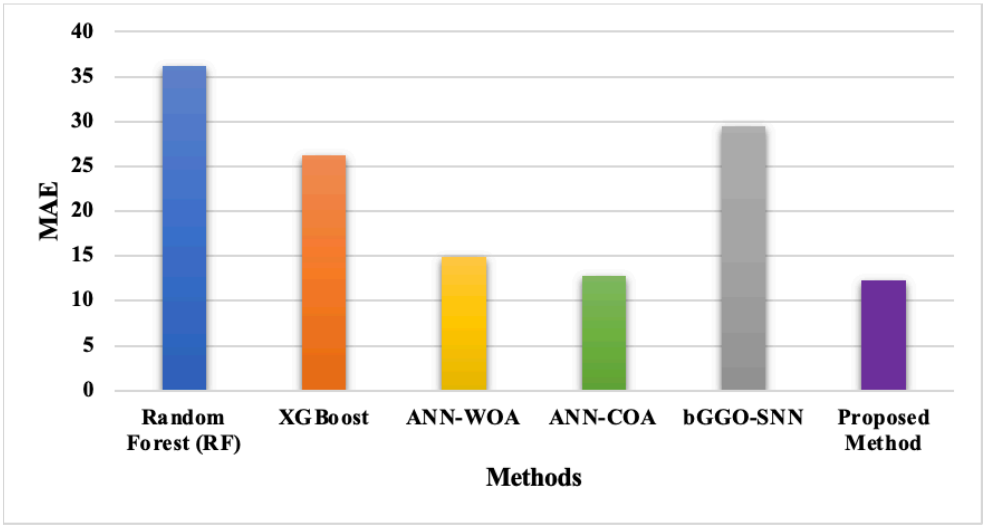


Fig.3. Comparative Analysis based on MAE

Fig.3. shows the better the accuracy of the prediction among several methods. This method gets a lowest MAE value of 12.3%. So, the average prediction error of this method is the smallest among all these models. ANN-COA gets a second lowest MAE value of 12.82%, which is then followed by ANN-WOA which gets 14.90%. The highest MAE values are gotten by XGBoost, bGGO-SNN and Random Forest which get 26.2%, 29.5%, 36.2%. We can see that this framework always outputs a demand prediction closest to the actual demand.

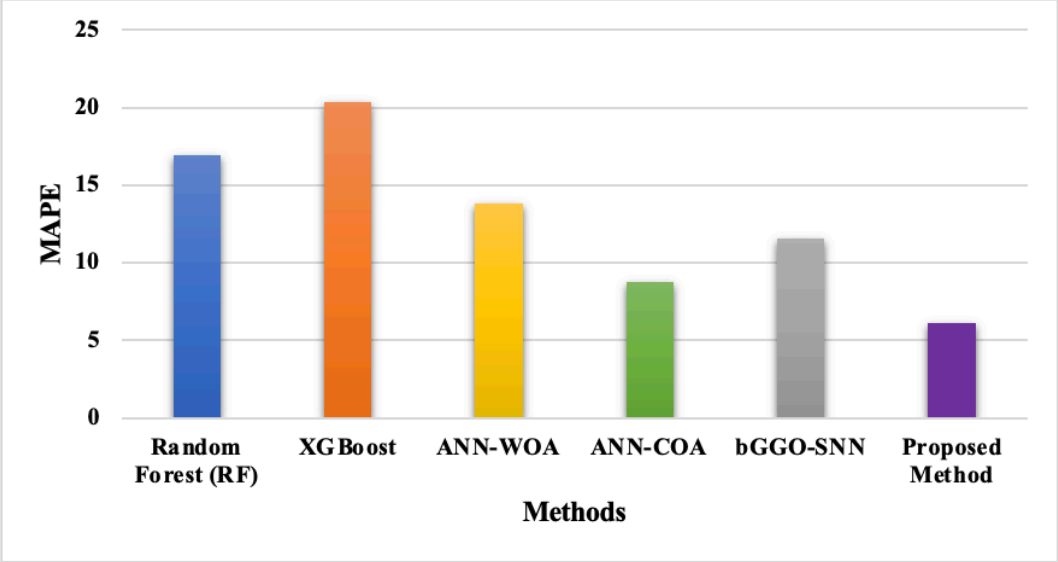


Fig.4. Comparative Analysis based on MAPE

MAPE evaluates the average percentage error among the predicted and true maize demand values. Ideally, the lower this metric, the better the forecast results. From Fig.4, it is evident that the proposed model has the lowest MAPE of 6.12% as compared to the other models. Specifically, ANN-COA records an MAPE of 8.79%, while bGGO-SNN and ANN-WOA report 11.58% and 13.79%. Random Forest and XGBoost algorithms report higher MAPE than the proposed model and the other hybrid models, with the values being 16.96% and 20.36%, respectively. It is observed that the proposed model is capable of producing accurate and reliable maize demand forecasts since it records the lowest percentage error.

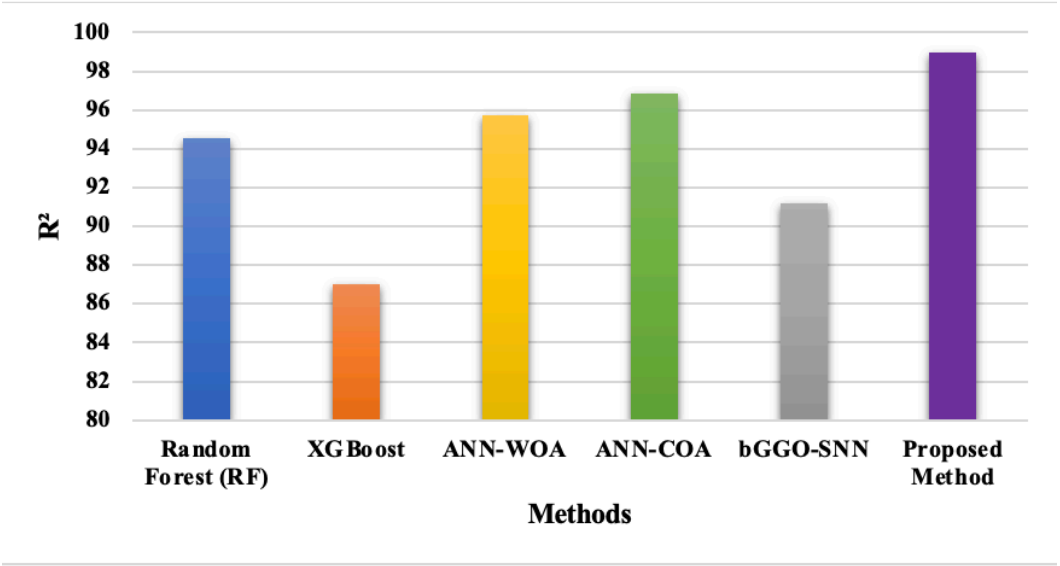


Fig.5. Comparative Analysis based on R^2

The coefficient of determination (R^2) value-based comparison shown in existing and proposed system is shown in Fig.5. In other words, it is based on the percentage of variance in the dependent data that is explained by the independent data and has the maximum value of 1. Consequently, the proposed approach provides the best result among others with R^2 being 98.96%. The R^2 values of ANN-COA and ANN-WOA approaches are 96.84% and 95.71%, respectively, while Random Forest yields 94.57%. On the contrary, there is a notable drop in R^2 values for bGGO-SNN and XGBoost algorithms, which are 91.2% and 87%. Therefore, the high coefficient of determination for the developed model indicates its superiority over existing and optimization-based methods due to the inclusion of Grey Wolf Optimizer, CNN-BiLSTM, and Attention mechanisms for a better evaluation of maize demand.

The experimental outcomes show that the model is capable of enhancing maize demand prediction through optimization of environmental feature selection and utilization of deep recurrent learning models for improved accuracy. The algorithm implements Grey Wolf Optimization to remove redundant information and select the most relevant environmental features while CNN is used to learn discriminative features from heterogeneous data, BiLSTM handles sequential data from both directions while attention mechanism ensures that all the influential factors affecting demand are captured during prediction. The overall performance of the proposed model is superior which results in reduced RMSE, MAE and MAPE scores and a higher R2 value. This implies that the proposed model predicts maize demand with better accuracy as compared to the existing models. Therefore, the proposed model able to provide accurate predictions which can be used to make better decisions on the amount of maize to be produced and other related factors.

CONCLUSION

This study proposed a Deep Learning Framework for Maize Demand Prediction using Convolutional Neural Network and Bidirectional Long Short Term Memory with Attention and Grey Wolf Optimized Environmental Features to predict maize demand accurately and efficiently to ensure sustainable agricultural planning. The experimental results demonstrated the superiority of this framework by achieving an RMSE of 21.4%, MAE of 12.3%, MAPE of 6.12%, and R^2 of 98.96% which were better than the traditional machine learning algorithms such as Random Forest and XGBoost and optimization-based neural network models like ANN-WOA, ANN-SCA, and bGGO-SNN used in this study. Thus, the proposed framework can be utilized for accurate prediction of maize demand which ultimately helps in ensuring optimal production, efficient planning, and agricultural decision making. However, this framework cannot yield accurate results if the required historical agricultural and environmental datasets are not available. In addition, this framework fails to capture the effect of several external factors such as government policies, and adverse weather conditions that may affect maize demand. Future improvements of this framework could include considering various external factors that may influence maize demand such as government policies, market trends, and unexpected weather changes. Future research should focus on utilizing real-time data collected through sensors, satellites, and market trends to make accurate and reliable predictions and implement explainable artificial intelligence to ensure the best agricultural planning and precision farming.

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Conflict of interest

The authors declare no conflict of interest in disclosing the results or interpretation of this research.

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Author contributions

Dr. M. MANIMEKALAI, (Author 1): worked on Data curation, Formal Analysis, Supervision, Writing-review & Editing, Validation and Project Administration. **AMIRTHAM,** (Author 2): worked on Investigation, Conceptualization, Methodology, Visualization and Wring-Original draft.

Data Availability

The data used in this article is publicly available on the Kaggle at Indian Historical Crop Yield and Weather Data.

Ethics Approval

The study does not involve humans nor animal subjects.

REFERENCES

Ahmad, I., Singh, A., Fahad, M., & Waqas, M. M. (2020). *Remote sensing-based framework to predict and assess the interannual variability of maize yields in Pakistan using Landsat imagery*. Computers and Electronics in Agriculture, 178, 105732.

AMIRTHAM, R. (2024). A COMPREHENSIVE REVIEW OF DEEP LEARNING APPLICATIONS AND ADVANCES IN CROP DEMAND FORECASTING.

AMIRTHAM, R. (2025). Data-Driven Maize Demand Prediction Using Optimized Shallow Neural Networks for Sustainable Agricultural Planning

Asamoah, E., Heuvelink, G. B. M., Bindraban, P. S., & Logah, V. (2025). *Modeling maize yield and agronomic efficiency using machine learning models: A comparative analysis*. European Journal of Agronomy (online first).

Cheng, J., & Wang, W. (2026). Prediction of Maize Yield Based on Soil Nutrients and Climate Variables. *Computational Molecular Biology*, *16*.

Dehghani, M., Hubálovský, Š., & Trojovský, P. (2023). *Osprey Optimization Algorithm: A new bio-inspired metaheuristic algorithm for solving engineering optimization problems*. Knowledge-Based Systems.

Fariz, T. N., & Basha, S. S. (2025). Enhanced crop yield prediction using a hybrid artificial neural network with coati optimization algorithm. *Results in Engineering*, 107529.

Fathololoumi, S., Gillespie, A., & Biswas, A. (2026). *Enhancing crop yield predictions through spectral-temporal integration across multiple agricultural fields*. Computers and Electronics in Agriculture, 111552.

Hao, D., Chen, L., Chen, G., Chen, C., Zhu, Q., & Zhangzhong, L. (2026). *Improving maize yield prediction performance via a hybrid framework coupling an optimized crop model and deep learning*. Agricultural Systems, 104768.

Ikram, A., Ikram, S., El-Kenawy, E. S. M., Hussain, A., Alharbi, A. H., & Eid, M. M. (2025). A fuzzy-optimized hybrid ensemble model for yield prediction in maize-soybean intercropping system. *Frontiers in Plant Science*, *16*, 1567679.

Ikram, A., Ikram, S., El-Kenawy, E. S. M., Hussain, A., Alharbi, A. H., & Eid, M. M. (2025). A fuzzy-optimized hybrid ensemble model for yield prediction in maize-soybean intercropping system. *Frontiers in Plant Science*, *16*, 1567679.

Ma, Y., Zhang, Z., Kang, Y., & Özdoğan, M. (2021). *Corn yield prediction and uncertainty analysis based on remotely sensed variables using a Bayesian neural network approach*. Remote Sensing of Environment, 259, 112408.

Nyengere, J., Tchuwa, F., Tholo, H. M., Malalu, L., Njala, A. L., Kachulu, P., ... & Mwangwela, A. (2026). Maize yield prediction using machine learning: a systematic literature review. *Frontiers in Artificial Intelligence*, *9*, 1735157.

Olusanya, M. O., Ogunkunle, O., Baitshenyetsi, T., Mothibi, D., & Adeleke, J. (2026). Hybrid metaheuristic and machine learning approaches for portfolio optimization in sustainable crop production and agricultural decision support. *Discover Agriculture*, *4*(1), 209.

Ramos, A. P. M., Osco, L. P., Furuya, D. E. G., Gonçalves, W. N., Santana, D. C., Ribeiro Teodoro, L. P., et al. (2020). *A random forest ranking approach to predict yield in maize with UAV-based vegetation spectral indices*. Computers and Electronics in Agriculture, 178, 105791.

Sapkota, B. R., Baath, G. S., Flynn, K. C., Adhikari, K., Hajda, C., & Smith, D. R. (2025). Machine learning algorithms for maize yield prediction with multispectral imagery: Assessing robustness across varied growing environments. *Science of Remote Sensing*, 100267.

Shahhosseini, M., Hu, G., & Archontoulis, S. V. (2020). *Forecasting corn yield with machine learning ensembles*. Frontiers in Plant Science, 11, 1120.

Stevanović, D., Perić, V., Roljević Nikolić, S., Stefanović, V. M., Oro, V., Tabaković, M., & Kolarić, L. (2025). Predictive Modelling of Maize Yield Under Different Crop Density Using a Machine Learning Approach. *Agriculture*, *15*(20), 2138.

Zhang, H., Zhou, Y., Ma, S., & Yemoto, K. (2025). Optimizing corn yield prediction: Integrating multi-temporal UAS data and machine learning. *Smart Agricultural Technology*, 101344.

Zhou, Y., Ma, S., Zhang, H., & Aakur, S. (2024). *Enhancing corn yield prediction: Optimizing data quality or model complexity?* Smart Agricultural Technology, 9, 100671.