Forecasting the agriculture yield in Nepal using machine learning techniques

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Abstract

Accurate prediction of agricultural yield is extremely important to ensure food security and to cope with the challenges created by climate change and natural disasters. Forecasting agricultural yield is a challenging task due to the complex nature of variables (fertiliser, rainfall, temperature and others) that affect agricultural production. This study employs six supervised machine learning algorithms: Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), and Convolutional Neural Network (CNN) to build a predictive model using 49 years of historical data (1973-2021) on paddy, wheat, and maize. Model performance was evaluated using Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (rMSE). Results show that DT and RF models are the most precise with MSE 1% to 5%, MAE of 8% to 21%, followed by SVM and CNN. Key predictors of crop yield include area cultivated, capital expenditure, banking expansion, rainfall, temperature, and fertilizers, while irrigation and road network were less significant. The study recommends that farmers prioritize commercial farming, agricultural equipment, and timely available of fertilizer application. The Government of Nepal (GoN) should redirect subsidies towards agricultural mechanization, ensure timely supply fertilizer, and expand banking services in agricultural areas.

Keyword: Agricultural yield, Machine learning, Support vector machine, Random forest, Decision tree, Multilayer perceptron

JEL Classification: C61, C63, Q19

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INTRODUCTION

Agricultural yield prediction is becoming a more profound issue because of the growing concern of people regarding global food security (OECD, 2013). Even though precise output forecasting is complex and challenging, it is vital for sustainable farming and efficient use of natural resources.(Paudel et al., 2021). Accurate estimation of agricultural yield has gained significant importance as it enables policymakers, farmers, agronomists, commodity traders and other stakeholders to make informed decisions and plan strategies to enhance productivity and address potential food shortages. The production of food crops is influenced by a myriad of factors, including crop-specific characteristics, environmental conditions and management decisions (Fischer, 2015). Understanding the interplay between these factors is crucial for developing effective strategies to maximise agricultural yield (Pretty et al., 2006). To address this challenge, researchers have stepped in for advanced technological solutions, particularly machine learning models. Many developed economies have benefited from it. However, countries like Nepal have not been able to take advantage of advanced modelling tools.

The agriculture sector of Nepal, which once dominated the entire economy, is now in decline. The sector contributed 69% to the GDP in 1975, but by 2013/14, this figure dropped to 30.3%, and to 24.1% in 2022/23 (MoF, 2023; World Bank, 2023). The sector grapples with challenges such as inadequate irrigation infrastructure, delayed availability of seeds and fertilizers, subsistence farming, and slow adoption of improved seeds. Moreover, the absence of rural planning exacerbates issues, leading to unused arable land due to significant youth migration for foreign employment. Over the last decade, the nation observed a modest growth rate of 2.9% in the agriculture sector (MoF, 2023). The labour force dependent on agriculture decreased from 60.4% in 2018 to 50.4% in 2021 (CBS, 2018; MoF, 2023). Nepal has transitioned into a net importer of major crops, with import values of NRS 47.6, NRS 19.6, and NRS 6.32 for paddy, maize, and wheat, respectively, in the fiscal year 2021/22 (MoF, 2023).

Over the past few decades, policymakers introduced various initiatives to support farmers, including the Institutional Development Program, Community Ground Water Irrigation Sector Project, Small Farmer Development Program, and Small Irrigation Project. Recent efforts involve minimum support prices, an 80% subsidy on insurance premiums, digital soil mapping, and an agriculture mechanization project (MoF, 2023). Monetary initiatives, such as priority sector lending, concessional loans, and setting a threshold for agricultural credit as a proportion of total credit, underscore the sector's priority. As of July 2023, total loans disbursed to the agricultural sector amounted to NRS 414.6 billion, constituting 8.5% of the total loan portfolio (NRB, 2023). These interventions underscore the paramount importance of the agricultural sector for policymakers. Given the substantial financial investment by the government, allocating significant resources to bolster this sector, a model for yield prediction becomes not only justifiable but imperative.

Field surveys, crop growth models, remote sensing, statistical models, and various combinations are frequently employed to predict crop yield. With the increasing availability of reliable models and less than adequate precision of existing econometric models, a comprehensive study that objectively assesses the suitability of machine learning models for agricultural yield prediction seems appropriate. The effectiveness of ML in predicting agricultural yield is still unknown for low-income countries whose agricultural ecosystems are not well developed. To the best of the knowledge of the researcher, no published research in Nepal has used ML to predict agricultural yield. The study is the first of its kind on many counts. First, it is the first study to use machine learning models to predict Nepalese agricultural yield. Nepal is contextually unique in different aspects such as geography, climate, access to technology and scale of farming. Second, this study incorporates several explanatory variables (such as Inflation, Bank Branches and Capital Expenditure) that affect agricultural production but have not been considered in most earlier research. Identification of a suitable forecasting model also benefits all stakeholders. Such studies are valuable to the farmers and stakeholders such as traders, researchers, agronomists and policymakers.

The remaining portion of this paper has been presented in the following five sections. Section two presents the review of relevant literature. The research methodology is presented in the third section; the results and discussion of the study are presented in the fourth section, and the study ends with the discussion and conclusion section.

LITERATURE REVIEW

A larger number of studies have investigated the relationship between agricultural yield and its determinants using different econometric models. Time series and panel data models are the most widely used models (Blanc & Schlenker, 2017; S. R. Singh, 2007). Nguyen et al. (2019) used regression discontinuity to assess the impact of credit policy on rice production in Myanmar. Similarly, Abu and Haruna (2017) and Houensou et al. (2021) used endogenous switching regressions to investigate the impact of access to finance on agricultural commercialization and farm productivity. Weber et al. (2015) used 2SLS for examining crop price impact on agricultural revenue. On the other hand, Headey et al. (2010) and Rada et al. (2011) used data envelopment analysis for assessing agricultural productivity. Studies of D'Agostino and Schlenker (2016), McArthur and McCord (2017), and Schlenker and Roberts (2009) used a fixed effect estimator and, Nguyen Chau and Scrimgeour (2022) and Yitayew et al. (2022) used propensity score matching. Lio and Liu (2006) used Cobb-Douglas production function and, Butler and Cornaggia (2011) used DID estimation. Time series and panel data models have a significant contribution to agricultural economic research, but they still possess a limitation, especially in their capacity to precisely predict (Hill et al., 2020; Huang et al., 1998).

With the advancement in statistical computation and estimation methods, several new models based on machine and deep learning methods have emerged (Muruganantham et al., 2022). In the last couple of years, machine learning models can be seen in substantial research in developed economies (Liakos et al., 2018). The concept of machine learning emerged during the 1950s (Samuel, 1959). However, its use as a tool for the estimation of economic variables started quite later. The use of machine learning models for predicting bankruptcy, stock performance, financial distress forecasting and bond rating became quite frequent (Wong & Selvi, 1998) in the 1990s. The utility of the machine learning model in agricultural economics was not common though its use in agriculture can be traced back to Yost et al. (1988). In recent years, research studies have started using machine learning models for agricultural output prediction (Abbaszadeh et al., 2022; Bijanzadeh et al., 2010; Crane-Droesch, 2018; Everingham et al., 2016; M. D. Johnson et al., 2016; Kaul et al., 2005; Koirala et al., 2019; Liu et al., 2001; Pantazi et al., 2016; Wang et al., 2020). More specifically, Stas et al. (2016) used boosted tree regression and SVM, Liang et al. (2015) used ANN and RF, and Kaul et al. (2005) used ANN and Multiple Linear Regression (MLR). Most of the studies on agricultural yield or yield estimation are based on data from developed economies, especially the US (Ball et al., 2016; Butler & Cornaggia, 2011; Hutchins, 2022; Kukal & Irmak, 2020; Schlenker & Roberts, 2009; Troy et al., 2015; Weber et al., 2015) and other developed economies such as UK, France, Germany, Italy, Japan and South Korea (Chavas et al., 2019; Corrales et al., 2022; Horie et al., 1992; Landau et al., 1998; Ruß & Brenning, 2010; Yoo et al., 2012).

Extant literature has examined how various factors affect agricultural productivity. However, the application of machine learning models to estimate agricultural yield is still in its early stages. Furthermore, the use of these models in low-income countries like Nepal is uncommon. The capacity of machine learning models to process highly complex data and provide superior fit has made it popular in forecasting agricultural yield. Studies such as Kaul et al. (2005) and Koirala et al. (2019); and Pant et al. (2021) noted a mean error of below 10% when predicting yield using machine learning models. Van Klompenburg et al. (2020) noted SVM, DT, RF, and MLP as the most preferred models; therefore, this research has adopted the same to predict the yield of the major crops.

RESEARCH METHODOLOGY

Data Collection and Pre-processing

This study tried to incorporate all possible data; however, the data before 1973 was not available for some of the variables. Therefore, the study used data from the period 1973 to 2021. The study selected only the principal crops (Paddy, Wheat and Maize) for two reasons: first, they occupy a major chunk of the total agricultural production, and second, a complete data set is available for only major crops. The major data sources were Food and Agriculture Organisation (FAO) statistics, Nepal Rastra Bank, the Central Bureau of Statistics of Nepal and the World Bank. The study has altogether used 13 independent variables and three dependent variables. The missing data problem for variables like population, tractors and road network was encountered. Since the census is conducted once a decade there are only 6 data points from 1971 to 2021. Similarly, road network data collected from economic surveys from 2002 to 2022 was available for only 14 data points, with a gap of just a year between two data points to a gap of up to 7 years. The variable number of tractors was constructed by taking data from the Department of Transport Management (DOTM) and the FAO. The cumulative number of tractors imported up to the year 2004 was obtained from FAO, and the remaining data was obtained from the DOTM. Linear interpolation and extrapolation methods were used to generate the data for the 49 data points for population, road network and number of tractors. The data was normalised using a standard scalar to scale features to a mean of zero and a standard deviation of one. It ensures that all features contribute equally, speeds up convergence in gradient-based optimization, prevents bias towards features with larger scales, and stabilizes numerical computations. This pre-processing step enhances the accuracy and robustness of the models.

Exploratory Data Analysis (EDA) and Feature Engineering

The study utilized line plots to understand the data patterns. An increasing trend was observed in most of the variables, including crop yield, population, road network, financial deepening, farm size, fertilizer use, irrigation, exchange rate, bank branches, capital expenditure, and PCI. Unit root was observed for the majority of the variables, so data was transformed to the first difference. Even after the first difference, per capita income and population were not found stationary, and they were dropped. Similarly, all the variables used for estimation were scaled and normalized to ensure effective learning by the machine. Additionally, during the EDA, the study presented only the mean and standard deviation to describe the data, as the primary focus of this study was on forecasting.

Model Tuning and Validation

The study employed GridSearchCV for tuning SVM, DT, RF, and MLP models, while RandomizedSearchCV was used for RNN and CNN models. Fivefold cross-validation was conducted for SVM, DT, RF, and MLP, with parameter estimates averaged for accuracy. For CNN and RNN, validation was performed using various train-test splits, ultimately maintaining a 75:25 ratio for final evaluation.

Model Training

The study tried different training test splits and finally used 75:25, realizing its performance as compared to other compositions. This change is now reflected in the methodology section, and the results section discusses its positive impact on model accuracy and reliability. The study utilized machine learning libraries including scikit-learn (version 0.24) and Keras (version 2.4) with TensorFlow backend (version 2.5). The training procedures were executed on a workstation with an Intel i5 processor, 16 GB RAM, and an NVIDIA GeForce 820M GPU to accelerate the training of deep learning models. The training durations varied: traditional machine learning models like SVR, DT, and RF completed training in a few seconds, while more complex models like RNN and CNN required double time because of their iterative training processes. Standard scaling for features and reshaped input data to fit the requirements of the neural network architectures have been used. These configurations ensured efficient training processes and optimized model performance.

Explanation of variables

The explanatory variables used in this study are farm size, fertilizer, temperature, rainfall, exchange rate, inflation, bank branches, capital expenditure, population and per capita income.

Farm size: Farm size is the size of land in which the crop is cultivated. Farm size is directly proportional to agricultural yield, as large farm sizes benefit from economies of scale, operational efficiency and market power. Studies such as Auffhammer and Carleton (2018) and Cornia (1985) have found positive and significant effects of farm size on agricultural yield, thus motivating us to keep farm size as a predictor variable. In this study, a farm size area is in a million hectares.

Fertilizer: Fertilizers such as nitrogen, phosphorous, and potassium play a crucial role growth and development of plants. Fertilizers promote healthy growth by supplying necessary nutrition and by replenishing nutritional deficiencies in the soil. Fertilizers also help to improve pest and disease resistance and it also improves soil fertility and sustainability. Studies such as Madzokere et al. (2021), McArthur and McCord (2017), and Wei et al. (2018) have noted positive and significant effects of fertilizer on crop yield. In this study, the aggregate fertilizer data in thousands of tons.

Temperature and Rainfall: Temperature, precipitation and rainfall have a significant impact on crop productivity. Different crops have specific temperature and rainfall requirements for quality and quantity of yield. Extreme temperatures such as frost and heat waves can damage crops and reduce yield. Similarly, excessive rainfall and soil erosion can impair root health and nutrition availability. Studies such as Auffhammer and Carleton (2018), Chavas et al. (2019), Chen et al. (2022), and D'Agostino and Schlenker (2016) have used temperature and rainfall as predictor variables for agricultural yield.

Irrigation: Efficient irrigation ensures a consistent water supply, promoting optimal crop growth and minimizing water wastage. This contributes to increased agricultural yield and resilience against drought. The study has used land areas equipped with irrigation as a proxy for irrigation.

Agricultural Mechanization: Modern machinery streamlines farming tasks, reducing labour and cultivation time. This enhances efficiency, boosts productivity, and improves crop yield and quality. Since data regarding other tools and machinery were unavailable, the number of agricultural tractors has been used as their proxy.

Financial Deepening: Improved financial access enables farmers to invest in advanced technologies and inputs, fostering sustainable practices and resilience against economic uncertainties. Timely credit empowers strategic decision-making for increased agricultural yield. The Private Credit to GDP ratio has been used as the proxy for financial deepening.

Road Network: A well-connected road network facilitates the efficient transportation of agricultural produce, reducing post-harvest losses and ensuring timely delivery to markets. This contributes to increased profitability and market integration for farmers. The total road network in kilometres has been used as its proxy.

Inflation: Price level affects input cost, production cost and investment and expansion of the farm. Inflation also affects the purchasing power of consumers, leading to a slash in demand for certain crops and shifting towards lower-cost options. Reduction in demand demotivates producers to produce, thus affecting the overall production volume. Studies such as Alston et al. (2009), Auffhammer and Carleton (2018), and D. G. Johnson (1980) found a significant impact of price level on agricultural yield.

Population: Population is directly interrelated with food demand, production and agricultural labour supply. A large population creates market opportunities for producers. A large consumer base incentivizes farmers to increase food production to meet the demand. Excessive rise in population may also create challenges for the agricultural sector by increasing pressure on land and by increasing pollution. Studies such as Auffhammer and Carleton (2018), Baffes and Haniotis (2016), and Schneider et al. (2011) have also considered population as a predictor of agricultural yield and price. In this study, the population is in a million number.

Exchange rate: The exchange rate affects the overall export competitiveness of the country. A low value of domestic currency makes items cheaper for foreign buyers and helps in an increase in demand. Similarly, an exchange rate also influences the cost of imported inputs such as seeds, fertilizer, machinery and other input items. Obayelu and Salau (2010) and Carter et al. (1990) have found a consequential impact of the exchange rate on agricultural yield. Since the major trading currency for international trade in Nepal is USD, ergo, this study has adopted NPR/USD as an explanatory variable.

Bank Branches: Sharpe's rise in commercial and microfinance branches can be seen in Nepal in the last two decades. The number of bank branches has reached 11569 (NRB, 2023) across 77 districts of Nepal. Similarly, the loan disbursed by banks to the agricultural sector is NRs 370 billion (NRB, 2023). Bank branches help in agricultural production by providing financial excess to the farmers and by supplying them with credit required for the necessary investment in irrigation systems, purchasing farming equipment, improved seeds and fertilizers etc. Binswanger et al. (1993) and Khandker and Koolwal (2016) has observed a positive effect of banking expansion on agricultural yield.

Capital expenditure: Government capital expenditure in the form of road, irrigation, canal, input subsidies, and research and development has a direct effect on the agricultural supply chain and overall productivity. Nepal's government spends around USD 2 billion per annum for infrastructural development which is approximately 12 percent of the country's total expenditure. Studies such as Diakosavvas (1990) and, Matthew and Mordecai (2016) have noted a sizeable effect of government capital spending on agriculture.

Per Capita Income: Per capita income can have an impact on demand for agricultural products and farmers' access to agricultural inputs. Nepal is a low-income country but its average income per head is increasing trend, CBS (2022) reported an increment from USD 260 (FY 2000/01) to USD 1246 (FY 2020/21). Lusigi et al. (1998) and Schultz (1956) have also considered per capita income as a probable predictor variable for agricultural yield.

Modelling approach

The general architecture for the prediction of crop yield is presented in the following Figure 1

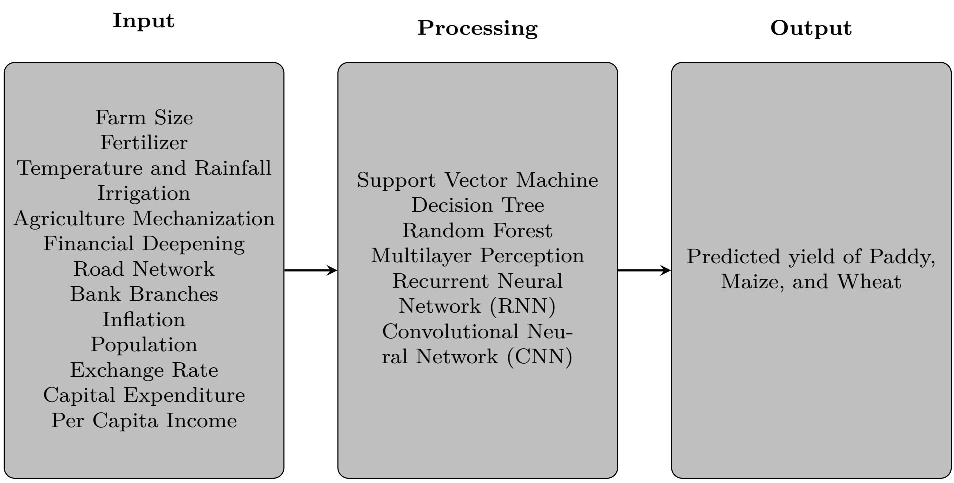

Figure 1: General architecture for crops yield prediction

In the study, four different machine learning models were used in order to predict and back-test the production volume of three major crops. The machine learning data period is segregated from the training and testing period. A certain portion of historical data is used to train the machine and predict the testing period. But in this study, instead of testing for a certain fraction of time, this study has made the prediction for the entire period (both training and testing) so that the accuracy of prediction for both the training and testing period is visible in graphs. Since there is no fixed rule for splitting the data into training and testing sets, we tried different ratios and found the highest precision with a 75:25 split and reported the same in the data analysis section.

Support Vector Machine (SVM): SVM is a supervised machine learning tool used for the prediction and analysis of complex data using high dimensional space Vapnik (1963). Ruß and Kruse (2010) noted SVM as a common machine learning model for predicting crop yield whereas Pant et al. (2021) have used SVMs for predicting agricultural yield. The goal of SVM is to obtain a function that minimizes the gap between actual and predicted values. The nonlinear model that has been extensively used for modelling non-stationary time series variables and generated useful results is a support vector. SVR builds linear regression functions as shown below:

$$\hat{y} = w^T x + b \tag{1}$$

Eq. 2 shows Vapnik's linear e-Insensitivity loss function.

$$|y - \hat{y}|_\epsilon = \{0 \qquad if|y - \hat{y} \leq \epsilon|y - f(x_i, w)| - \epsilon, otherwise\} \tag{2}$$

In the Eq. (1 and 2) $\hat{y}$ represent dependent variables that are paddy, wheat and maize production volume for a given input vector x. The linear regression $\hat{y}$ is estimated by simultaneously minimizing and the sum of the linear e-Insensitivity losses as shown in eq. (iv). The constant c controls a trade-off between an approximation error and the weight vector.

$$R = \frac{1}{2}||w||^2 + c\left(\sum_t^m |y - \hat{y}|_\epsilon\right) \tag{3}$$

Minimizing the risk R is equivalent to minimizing the risk shown in Eq. 4 under the constraints depicted in Eq. 5 - 6. Here, ζ_i and ζ_i^* are surplus variables, one for exceeding the target value by more than ϵ and the other for being more than ϵ below the target.

$$R = \frac{1}{2}||w||^2 + c\left(\sum_t^m |y - \zeta_i + \zeta^*|\right) \tag{4}$$

$$\left(w^T X_i + b\right) - y_i \leq \epsilon + \zeta_i \tag{5}$$

$$y_i - \left(w^T X_i + b\right) \leq \epsilon + \zeta_i^* \tag{6}$$

$$\zeta_i \quad and \quad \zeta_i^* \geq 0, i = 1, 2, 3...., m \tag{7}$$

Decision Tree (DT): It is a supervised machine learning algorithm used to classify and predict using the non-parametric model. Unlike other estimation tools, a DT does not have a formula. Instead, it builds a tree such as the model of input and its possible consequences. Studies such as Kumar et al. (2020), Pant et al. (2021), and Rajeswari and Suthendran (2019) have used a DT regression model in predicting crop yield.

$$\hat{y} = \sum_i \left(W_i * f_i\left(X_i\right)\right) \tag{8}$$

Where, $\hat{y}$ represents the expected value of the dependent variable $'y'$ for a given input vector X. $\sum_i$ signifies the summation of all the individual nodes. W_i represents the weight assigned to the prediction of the i^{th} node in the tree. And $f_i\ (X_i)$ represents the decision rule or function associated with the i^{th} node or leaf in the DT. It takes the input features X_i as input and produces a yield.

Random Forest (RF): RF is an ensemble machine learning tool that uses multiple DTs to predict the targeted variable. Sometimes the single tree is not accurate in predicting the actual value of the dependent variable because of confusion with noise and pattern. Therefore, the creation of n tresses increases the chances of accurate prediction where each tree makes an independent prediction, and the final prediction is obtained by assigning weights and averaging them. Studies such as Dang et al. (2021), Everingham et al. (2016), and Jeong et al. (2016) have used a rRF regression model in predicting crop yield.
The formula for the RF regression can be expressed as;

$$\hat{y} = \frac{1}{T} * \sum_i \left(W_i * f_i\left(X_i\right)\right) \tag{9}$$

Where $\hat{y}$ represents the expected value (or mean) of the dependent variable y for a given input vector X. T denotes the total number of trees in the RF ensemble. $\sum_i$ signifies the summation of all the individual trees in the RF. W_i represents the weight assigned to the prediction of the ith DT in the RF. And $f_i(X)$ represents the non-linear prediction function of the ith DT in the RF for the input vector X.

Multilayer perceptron (MLP) regressor : MLP is a type of artificial neural network algorithm that can learn complex relationships between input and yield variables. It has an input, hidden and yield layer. The layer is composed of interconnected neurons flowing from the input to the hidden and yield layers. Studies such as Gonzalez-Sanchez et al. (2014), Piekutowska et al. (2021), and Ruß and Kruse (2010) have used MLP regressor to predict crop yield. The equation of an MLP regressor can be represented mathematically as follows:

$$\hat{y} = f\left(W_2 * f\left(W_1 * X_i + b_1\right) + b_2\right) \tag{10}$$

Where, $\hat{y}$ represent dependent variables that are paddy, wheat and maize production volume. X_i represents independent variables that are area cultivated, average temperature, rainfall, fertilizer, and BFIs etc. W_1 and W_2 are the weight matrices that contain the weights for the connections between the input layer and the hidden layer, and between the hidden layer and the yield layer, respectively. b_1 and b_2 are the bias vectors associated with the hidden layer and the yield layer. The $'f'$ represents the activation function applied element-wise to the yield of each neuron in the network. During training, the weights (W_1 and W_2) and biases (b_1 and b_2) are adjusted through an optimization algorithm, such as back-propagation, to minimize the difference between the predicted values ($\hat{y}$) and the actual values of the dependent variable. The activation function $'f'$ introduces non-linearity to the model, allowing it to learn complex relationships between the inputs and the target variable. The architecture for MLP regressor is,

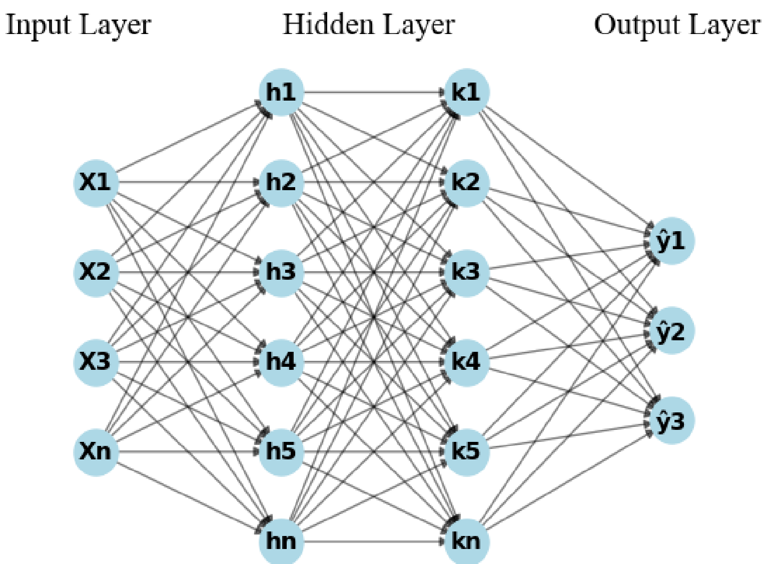

Figure 2: MLP architecture for multivariate time series prediction

In the architecture presented in Figure 2, $X1$, $X2$, $X3$ .... Xn are input nodes. They represent independent variables that are farm size, fertilizer, rainfall, temperature, bank branches, inflation, exchange rate, inflation, capital expenditure, population and per capita income. And $\hat{y_1}$, $\hat{y_2}$, and $\hat{y_3}$ represent predicted variables that are Paddy, Maize and Wheat. The remaining two are hidden layers.

Recurrent Neural Network (RNN): Lets denote the number of hidden layers as L, where $L = 1, 2, ...L$. The equation for input to the first hidden layer is:

$$h_t^1 = Activation\left(W_{ih}^1 * x_t + b_{ih}^1 + W_{hh}^1 * h_{t-1}^1 + b_{hh}^1\right) \tag{11}$$

Now, forward pass equation from layer l to hidden Layer $l+1$ would be;

$$h_t^{1+l} = Activation\left(W_{ih}^{1+l} * x_t + b_{ih}^{1+l} + W_{hh}^{1+l} * h_{t-1}^{1+l} + b_{hh}^{1+l}\right) \tag{12}$$

And the equation from hidden to yield layer would be;

$$O_t = W_{ho} * h_t^l + b_{ho} \tag{13}$$

Where, h_t^1 is the hidden state of layer l at time t. W_{ih}^l and W_{hh}^l are the weight matrices for the input-to-hidden and hidden-to-hidden connections for layer l, respectively. b_{ih}^l and b_{ih}^l are the bias vectors for the input-to-hidden and hidden-to-hidden connections for layer . W_{ho} is the weight matrix for the hidden-to-yield connection. b_{ho} is the bias vector for the hidden-to-yield connection.

Convolutional Neural Network (CNN): The regression equation for the convolutional neural network is;

$$Y_t = Activation(W_y * f(h_t) + b_y) \tag{14}$$

Where, Y_t is the predicted yield at time t, h_t is the yield from the convolutional layers, $f(h_t)$ is the operation that flattens or reshapes the yield h_t as needed, W_y is the weight matrix for the regression layer and b_y is the bias vector for the regression layer.

Evaluation Measures

The study conducted by Van Klompenburg et al. (2020) highlighted Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), relative Root Mean Squared Error (rRMSE), Mean Squared Error (MSE) and Coefficient of Determination (R^2) as the most preferred performance metrics for the evaluation of machine learning models. Formulas of these evaluation measures are shown in the following equations.

$$MAPE = \frac{1}{n}\sum_{t-1}^{n}\frac{|y_t - \hat{y}_t|}{|y_t|} * 100 \tag{15}$$

$$MAE = \frac{1}{n}\sum_{t-1}^{n}\frac{|y_t - \hat{y}_t|}{|y_t|} \tag{16}$$

$$rRMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\frac{y_t - \hat{y}_t}{y_t}\right)^2} \tag{17}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2 \tag{18}$$

$$R^2 = 1 - \frac{SSR}{TSS} \tag{19}$$

Where y_t is actual and $\hat{y}_t$ are the forecasted value.

RESULTS

The result of the study is presented in this section. Table 1 depicts major crop yield, input factors and other variables. The average paddy yield is 2.54 tons per hectare, with a standard deviation of 0.59, indicating a moderate level of variability. Similarly, Maize and Wheat yields have mean values of 1.91 and 1.76 tons per hectare, with standard deviations of 0.44 and 0.57, respectively. The average land area equipped for irrigation is 0.97 million hectares, with a standard deviation of 0.37, highlighting the extent and variability of irrigated land. The average number of tractors is 3.2 thousand units, but the higher standard deviation of 4.6 suggests significant variability in tractors across time. The table also presents information on rainfall, temperature, bank branches, exchange rate, inflation, capital expenditure, population and per capita income.

Table 1: Descriptive Statistics

Variables	**Mean**	**Std. Dev.**
Paddy Yield (Tons/Hectare)	2.54	0.59
Maize Yield (Tons/Hectare)	1.91	0.44
Wheat Yield (Tons/Hectare)	1.76	0.57
Paddy (Million Hectare)	1.43	0.11
Maize (Million Hectare)	0.74	0.17
Wheat (Million Hectare)	0.59	0.15
Land area equipped for irrigation (Million Hectare)	0.97	0.37
Tractors (Thousand units)	3.2	4.6
Road network (Km)	18.6	6.9
Fertilizer (1000 tons)	70.14	57.32
Average Temperature (Degree Celsius)	13.99	0.45
Rainfall (mm)	1293.43	147.72
Financial Deepening (Credit/GDP ratio)	30.16	25.05
New Bank Branches	227.08	441.14
Exchange Rate (NRS/USD)	55.03	34.93
Food and Beverage Inflation (%)	8.79	6.13
Capital Expenditure (% of GDP)	7.82	3.35
Population (Million)	21.28	5.22
Per Capita Income (USD)	420.62	367.29

Predictive Performance of Machine Learning Models

Fig. 3, 4 and 5 illustrate the predictive performance of six machine learning models for yield over time. The graph depicts the actual and predicted crop yield across the time frame of 1973 to 2021. In the figures, the train represents the training period, and the test represents the testing period.

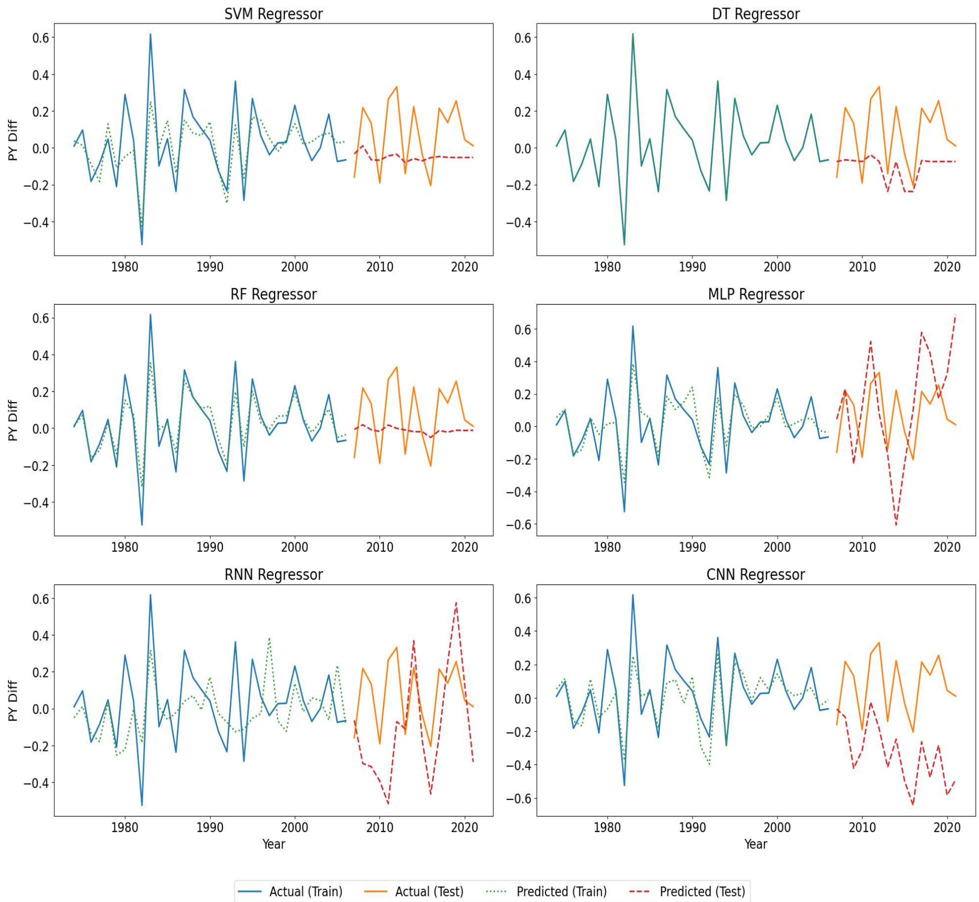

Figure 3: Prediction results for paddy yield

The Figure 3, shows predictions of the first difference in paddy yield. During the training period, all models (SVM, DT, RF, MLP, RNN, CNN) performed well, closely following the actual values. However, in the testing period, the models' performance varies. The SVM shows reasonable predictions with some deviations. The DT struggles significantly, while the RF and MLP exhibit noticeable divergences. The RNN also shows reduced accuracy, and the CNN, though better than others, still has periods of deviation. Overall, these models face challenges in maintaining accuracy during the testing period, highlighting potential overfitting or limitations in capturing yield patterns.

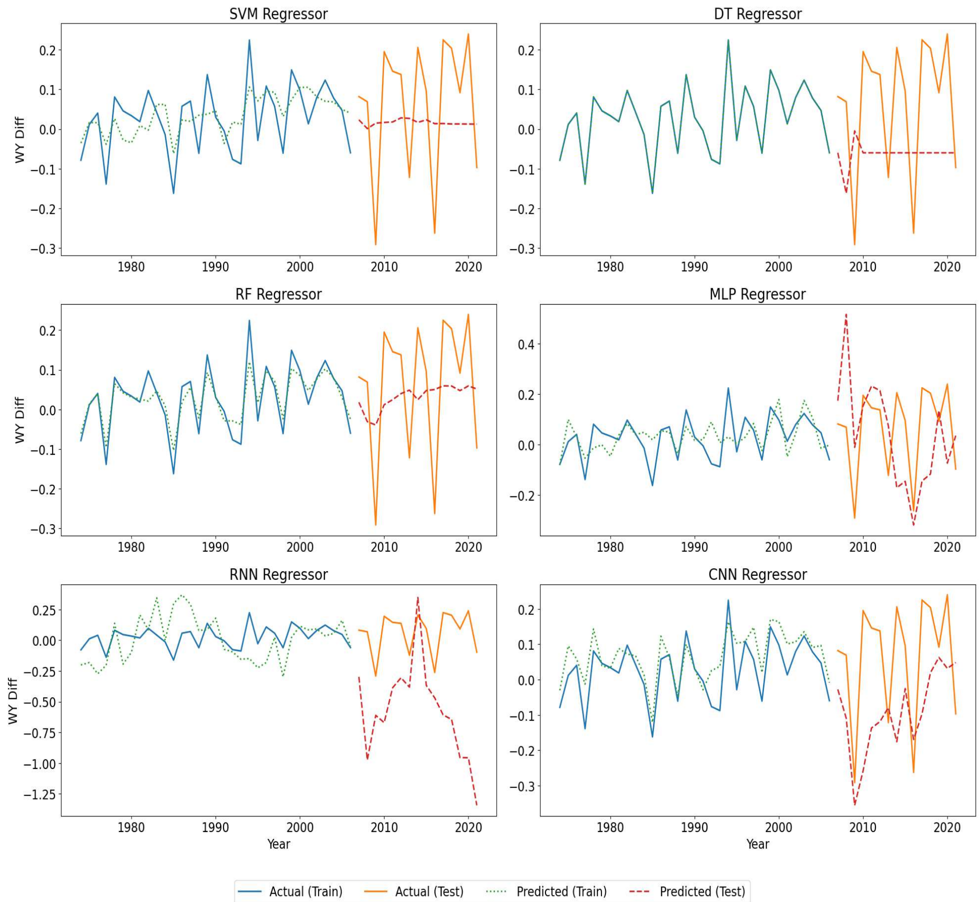

Figure 4: Prediction results for wheat yield

In Figure 4, the DT and RF models show good performance during training but perform poorly during testing. Similarly, the SVM and MLP models exhibit accurate predictions in the training phase but lack predictive power in the testing phase. The RNN model displays significant fluctuations and inaccuracies, particularly in the testing period. Conversely, the CNN model consistently delivers satisfactory performance across both the training and testing periods, despite some errors in the test phase.

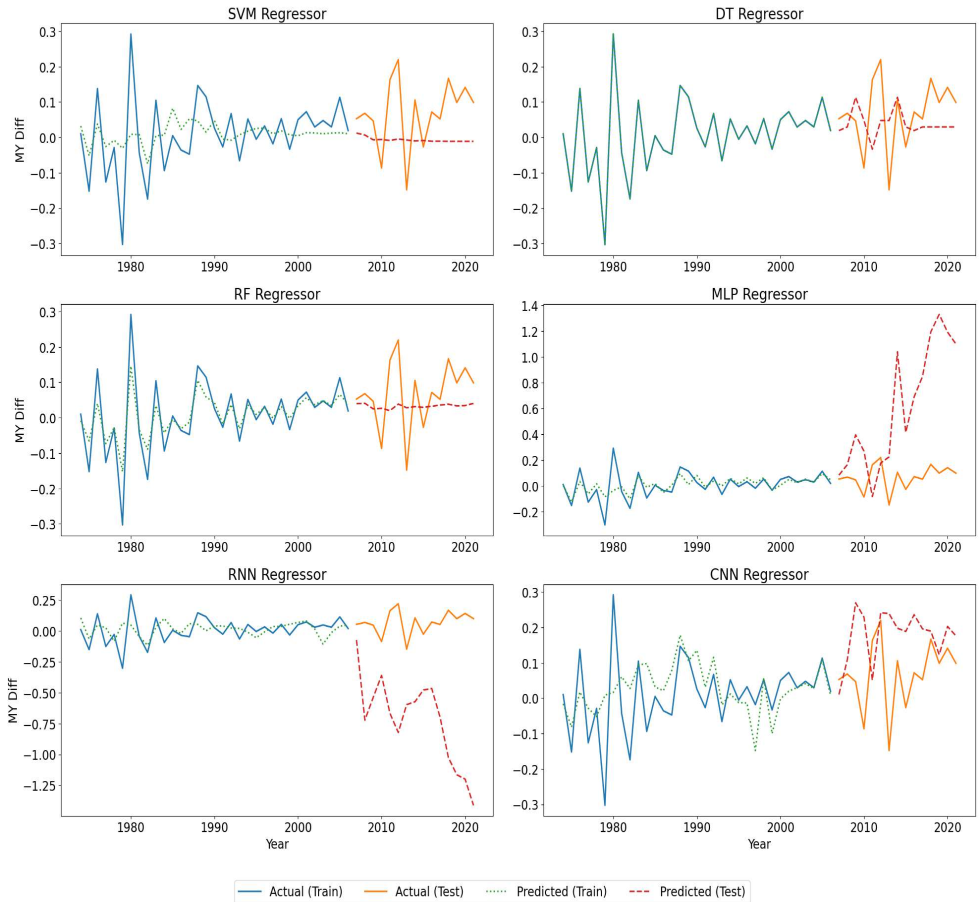

Figure 5: Prediction results for maize yield

In Figure 5, the SVM model provides decent predictions in the training phase but loses accuracy in the testing phase. The MLP model displays significant errors during the testing period, indicating poor generalization. The RNN model exhibits considerable fluctuations and inaccuracies, especially in the testing period. The CNN model, despite some errors in the test phase, demonstrates relatively consistent performance across both the training and testing periods. DT and RF perform relatively better in the testing period as compared to other models.

Table 2: Performance Metrices

Product	Model	MAE		MSE		RMSE		MAPE	
		Train	Test	Train	Test	Train	Test	Train	Test
Paddy	SVM	0.10	0.19	0.02	0.04	0.13	0.21	3243.6	144.5
	DT	0.00	0.21	0.00	0.05	0.00	0.23	0.0	193.4
	RF	0.07	0.17	0.01	0.03	0.09	0.19	414.1	103.1
	MLP	0.08	0.85	0.01	0.91	0.11	0.95	2428.2	1518.2
	RNN	0.17	0.23	0.05	0.08	0.23	0.28	6182.0	346.1
	CNN	0.10	0.43	0.02	0.25	0.15	0.50	827.2	731.3
Wheat	SVM	0.06	0.16	0.00	0.03	0.07	0.17	134.4	94.0
	DT	0.00	0.21	0.00	0.05	0.00	0.23	0.0	137.5
	RF	0.03	0.15	0.00	0.03	0.04	0.17	60.2	96.4
	MLP	0.05	0.65	0.00	0.58	0.06	0.76	134.1	411.6
	RNN	0.07	1.35	0.01	2.63	0.09	1.62	136.4	915.9
	CNN	0.05	0.18	0.00	0.05	0.06	0.22	156.2	114.4
Maize	SVM	0.07	0.11	0.01	0.01	0.09	0.12	154.2	101.9
	DT	0.00	0.10	0.00	0.01	0.00	0.11	0.0	94.1
	RF	0.04	0.08	0.00	0.01	0.05	0.10	54.4	78.1
	MLP	0.05	0.17	0.01	0.05	0.08	0.23	103.4	199.4
	RNN	0.15	0.47	0.04	0.32	0.19	0.56	474.8	575.7
	CNN	0.06	0.16	0.01	0.04	0.09	0.19	130.0	159.0

The Table 2 shows performance metrics of different machine learning models (SVM, DT, RF, MLP, RNN, CNN) for predicting Paddy, Wheat, and Maize yields. For Paddy, the RF performs best with a Test MAE of 0.17 and Test MAPE of 103.1, while SVM and CNN show moderate errors, and MLP and RNN struggle with higher errors. For Wheat, RF again excels with a Test MAE of 0.15 and Test MAPE of 96.4, whereas SVM and CNN perform moderately, and MLP and RNN have significant challenges. For Maize, RF and DT are most effective, with RF showing the lowest Test MAE of 0.08 and Test MAPE of 78.1. SVM also performs well, while MLP and RNN exhibit higher errors. Tree-based models likely perform well due to their ability to handle non-linear relationships and interactions within the data, making them well-suited for agricultural yield prediction. In contrast, RNN and MLP models may struggle with capturing the complex temporal and spatial dependencies inherent in crop yield data. Overall, RF is the most promising model across all crops, while RNN and MLP struggle and CNN shows variable performance depending on the crop, suggesting it may be better suited for specific patterns or dependencies.

Feature Importance

Since a superior fit was found only for RF and DT during the testing period, feature importance was calculated using these two models. For each dependent variable, the data was split into training and testing sets after scaling, and feature importances were extracted.

Table 3: Feature Importance

Features	Paddy		Maize		Wheat	
	RF	DT	RF	DT	RF	DT
Capital Expenditure	0.381	0.182	0.156	0.120	0.156	0.080
Banking Expansion	0.183	0.077	0.159	0.077	0.09	0.09
Area Cultivated	0.111	0.148	0.21	0.256	0.13	0.14
Food and Beverage Inflation	0.04	0.11	0.19	0.0665	0.174	0.189
Agricultural Mechanization	0.07	0.09	0.068	0.113	0.14	0.130
Temperature	0.04	0.075	0.06	0.054	0.064	0.12
Rainfall	0.11	0.185	0.054	0.183	0.140	0.098
Fertilizers	0.05	0.087	0.04	0.085	0.044	0.13

Table 3 indicates the significance of each variable in predicting agricultural productivity using both RF and DT models. For Paddy, Capital Expenditure emerges as the most crucial factor in the RF model with a high importance value of 0.381, followed by Banking Expansion and Area Cultivated. The DT model also places importance on Capital Expenditure (0.182) but highlights Area Cultivated (0.148) as more significant. For Maize, the Area Cultivated is the most influential variable in both RF (0.21) and DT (0.256) models, with Capital Expenditure and Banking Expansion also showing significant importance. In the case of Wheat, Food and Beverage Inflation stands out as the most important feature in both RF (0.174) and DT (0.189) models. Capital Expenditure and Agricultural Mechanization are also critical factors in the RF model, while the DT model assigns considerable importance to Area Cultivated and Agricultural Mechanization. Interestingly, variables like Temperature and Fertilizers have lower importance across both models for all crops, indicating a lesser impact on productivity predictions.

DISCUSSION AND CONCLUSION

Predicting crop yield is challenging because of several factors both directly and indirectly affecting their productivity. This study builds a predictive model using three major crops and fourteen key indicators driving their productivity. Six supervised machine learning algorithms, SVM, DT, RF MLP, RNN and CNN, were used. Experiments were conducted using 49 years of historical data from 1973 to 2021 on three principal crops — paddy, wheat, and maize; and the model performance was measured using MSE, MAE, MAPE, and rMSE. DT and RF have been found to be the most precise, followed by SVM and CNN. The outcomes are robust across crop types. Additionally, variables such as area cultivated, capital expenditure, banking expansion, rainfall, temperature and fertilizers have been found to be the most important features for predicting crop yield. Surprisingly, feature importance did not show irrigation, road network and financial deepening as key drivers of yield. The DT observed a MAE of 21%, for paddy and wheat and 10% for maize. Similarly, RF found an MAE of 17% for paddy, 15% for wheat and 8% for maize. Similarly, MSE is lowest for DT and RF for all crop types. Different from our findings Kung et al. (2016) observed the error of only 1.3% on the general and it identified agricultural, meteorological and harvest data as key features. Similarly, Pantazi et al. (2016) obtained an accuracy of 81.6% while estimating the wheat yield within field variation. Su et al. (2017) modelled for predicting rice yield and found significantly low rMSE and found soil quality and surface weather as major features. Amaratunga et al. (2020) observed the mean square error of 2% to as high as 38% in ANN. P. K. Singh et al. (2022) observed relatively low MAPE and MSE when applied SVM. Kang et al. (2020) XGBoost algorithm outperforms other algorithms both in accuracy and stability, while deep neural networks such as LSTM and CNN are not advantageous. As per Grinsztajn et al. (2022) tree based model like RF and DT performs better due to their ability to handle non-linear relationships and robustness to outliers.

Research indicates that the area cultivated, the use of fertilizers, and agricultural mechanization are key drivers of crop yield. To improve yields, farmers should prioritize allocating more resources towards commercial farming practices, investing in essential agricultural equipment such as tractors, and ensuring the timely and adequate application of fertilizers. Additionally, the GoN has been investing billions of rupees in agricultural subsidies. To further boost crop yields, it is recommended that GoN redirect subsidies towards the acquisition of agricultural machinery, guarantee the timely and sufficient supply of fertilizers to farmers, and establish more bank branches in agricultural areas to facilitate easier access to financial services and support. By focusing on these areas, both farmers and the government can work together to directly and indirectly enhance crop yields, leading to increased agricultural productivity and food security. Regarding the limitations, this study could not incorporate key indicators like agricultural tools, fertilizer type, and policy variables, and the study used yearly data for only 49 years due to the unavailability of data. Future research in this field could incorporate variables like irrigation, agricultural tools, fertilizer type, and other socio-economic and policy variables for improved prediction capacity. Future research can also utilize district-wise panel data as both temporal and spatial data would provide sizeable data for the model to train itself and provide a superior fit. Based on the findings of this study, diverting resources to increasing cultivation area, capital expenditure, banking expansion, climatic conditions, and fertilizers is likely to help increase yield. Similarly, instead of applying only a linear prediction model, it is recommended to use a tree-based model like DT and RF for a superior fit.

For future research, one of the most challenging aspects will be obtaining crop-specific data. The reliability of predictions will significantly improve with detailed crop-wise input data such as irrigation availability, fertilizer use, seed quality, labour, and average farm size. Variables like rainfall, temperature, and prices, which affect yield, are inherently random and exhibit stochastic properties. Integrating stochastic models like Vasicek, Heston, or Stochastic Block Allocation Regression (SBAR) alongside crop-specific variables presents both opportunities and challenges for future research.

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