Predicting staple crop yields under climate variability using multiple regression techniques

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ABSTRACT

Global food systems rely on staple crops—rice, wheat, maize, potato, soybean, and sugarcane, which are vital in Asia, where production is high. However, climate change threatens crop yields, potentially increasing hunger and malnutrition. Yield variability due to climate factors like rainfall and temperature underscores the need for accurate crop yield predictions. This paper analyzed the relationships between staple crop yields, climate variables, and pesticide usage. It aimed to develop a predictive model for crop yields in Asia using multiple regression techniques in Google Colab. The model was evaluated using a hybrid set of metrics like mean absolute error (MAE), root mean squared error (RMSE), and R^2 score. Findings revealed that reliable yield predictions are achievable despite weak linear relationships among variables. The extreme gradient boosting (XGBoost) achieves the highest R^2 score of 0.958367, which indicates superior predictive performance for staple crop yield forecasting due to its lower overall error rates and greater consistency in performance. This highlights the effectiveness of ensemble methods like XGBoost in capturing complex crop yield patterns. Despite newer machine learning (ML) techniques, these models remain recommended for similar tasks due to their robust performance.

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1. INTRODUCTION

Agriculture serves as a foundation for ensuring global food security and driving economic growth, and environmental sustainability. It is essential for feeding the growing global population, providing livelihoods, and supporting various Sustainable Development Goals (SDGs) [1]. The sector supports the global food supply by converting raw agricultural materials into value-added products, such as fruits, vegetables, cereals, and root and tuber crops [2]. Global food systems exhibit a perilous reliance on a limited number of staple crops. Six in particular—rice, wheat, maize, soybean, potato, and sugarcane—contribute to over 75% of global plant-derived energy consumption [3]. These crops are not only staple foods globally but hold particular significance in the Asian regions.

Staple crop production in Asian countries is notably high. Over 90% of rice production and consumption occurs in Asia, where it serves the majority of the population, including approximately 560 million individuals facing hunger in the region [4]. The rice-wheat rotation is predominantly practiced in East and Southeast Asia, supplying a reliable food source for more than 20% of the global population [5].

Furthermore, maize (corn) ranks among the top three cereal crops in Asia. In fact, Asia contributes about one-third to the world's total maize production, with China leading in terms of yield and area [6]–[8]. Moreover, East and Southeast Asia mainly produce and consume soybeans, with Japan, as the largest importing country, exerting considerable influence over the global market [9]. Furthermore, India ranks as the second-largest producer of potatoes after China, with a yield of 51.3 million tonnes cultivated over an area of 2.14 million hectares, representing 11.6% of global production [10].

Overall, Asia has a substantial staple crop production. However, climate change and population growth pose significant threats to crop production, necessitating heightened agricultural productivity. This demand for increased output may adversely impact the yield of staple crops, potentially leading to a dramatic rise in hunger, poverty, and malnutrition [11]. Crop yield variability arising from diverse climate scenarios, including droughts, excessive rainfall, and extreme temperature fluctuations, remains a critical concern for farmers, governments, and markets. This underscores the urgent need for accurate and timely predictions of crop yields in the face of an uncertain climate.

Crop yield prediction is a challenging problem in precision agriculture, and numerous models have been proposed and validated to address it effectively. This highlights that crop yield prediction is a complex task involving multiple intricate steps. While current models can estimate actual yield with reasonable accuracy, improving predictive performance remains an ongoing goal for researchers [12]. Machine learning (ML) approaches have become indispensable tools for predictive modeling not only in agriculture, supporting decision-making processes related to crop selection and management throughout the growing season. Data mining algorithms, including random forest (RF), decision trees (DT), support vector machine (SVM), Gaussian Naive Bayes, and AdaBoost, are among the most commonly used and popular methods for crop yield prediction. These algorithms have demonstrated robust performance, achieving high accuracy and low root mean square error (RMSE) in various studies [12]–[15].

Furthermore, over 50 relevant studies were examined, revealing that the most common methods for crop yield predictions are ML and deep learning methods [12]. Methods like convolutional and recurrent neural networks (CNN-RNN) and artificial neural networks (ANN) are widely utilized and demonstrate strong predictive performance. However, these advancements have limited the exploration of specific linear and non-linear regression algorithms tailored for crop yield prediction [16]–[18]. Additionally, most existing studies are either global in scope or focused on foreign countries, which could lead to overly generalized conclusions.

Overall, research on predicting staple crop yields—such as maize, potato, rice, soybeans, and wheat—under varying climate scenarios specific to Asian countries remains limited. This paper aims to develop a predictive model for staple crop yields in Asia using ensemble methods despite the availability of more advanced ML models. The proposed model is designed to analyze the relationships between crop yields and climate-related variables such as temperature, rainfall, and pesticide usage. Furthermore, this paper seeks to demonstrate that ensemble-based approaches are well-suited for modeling the complex, non-linear relationships inherent in agricultural data, offering accurate and reliable predictions under diverse climate conditions.

2. METHOD

In an attempt to predict crop yield, this paper employs conventional methods, including dataset preparation, which includes data wrangling, exploratory data analysis (EDA), model development and evaluation, and the derivation of insights. To consolidate relevant data, a unified dataset was constructed by integrating information from three distinct sources – Kaggle [19], the Food and Agriculture Organization (FAO) of the United Nations [20], and the World Bank Group [21]. The primary dataset was sourced from Kaggle, containing records from 1990 to 2013, with features such as area (country), year, item (crop), average rainfall (mm), pesticide use (tonnes), average temperature (°C), and yield (hg/ha). The raw data was cleaned, structured, and enriched into the required format through a data wrangling process to facilitate more informed and efficient analysis [22]. This involved several subprocesses, including describing the data based on its general properties and performing data cleaning tasks, such as removing null values, duplicates, and outliers. The initial dataset comprised a global collection encompassing multiple regions worldwide. To focus the study on Asia, only records from Asian countries were included. Given that some Asian countries did not have complete records within the specified year range (1990–2013), the analysis was restricted to Asian countries with complete and continuous data. The selected countries represent diverse regions within Asia. To extend the analysis period, data from two additional sources were integrated, providing information for the years 2014 to 2022. Each record's correctness was verified by cross-checking with the two latter sources to ensure consistency.

To objectively uncover the underlying characteristics of the dataset without any preconceived assumptions [23], an EDA was performed. This process involved data visualizing the distribution of yields using a histogram. Various visualizations, including scatterplots, were employed to describe the dataset and explore relationships between variables.

Given that the dataset contains categorical data, one-hot encoding was applied to convert the categorical variables into a binary format, enabling their effective use in ML models. This method is particularly effective when handling datasets with missing values and incurs lower computational costs [24]. Subsequently, a standard scaler was used to transform the features of the dataset to a comparable scale and to reduce dimensionality, addressing the increase in dimensionality caused by one-hot encoding, particularly in variables with multiple categories. Thereupon, the data was split into training and testing sets, which involved input data (features) and target data (labels or output). Thirty percent of the data was allocated for testing, while the remaining seventy percent was designated for training. The data was shuffled prior to splitting to ensure a well-mixed distribution in both the training and test sets, thereby mitigating any potential ordering bias. The seed for random number generation was set to 40 to ensure reproducibility.

Multiple regression techniques were employed to construct the model using Google Colab. The techniques utilized include gradient boosting regressor, linear regression with stochastic gradient descent (SGD), ridge regression, lasso regression, support vector regression (SVR), ElasticNet, RF regressor, and extreme gradient boosting (XGBoost) regressor some of which have demonstrated effectiveness in similar studies on yield prediction [25].

This study evaluated the performance of the used regressors in predicting crop yields while comparing them to less frequently applied methods to identify strengths and limitations for developing robust predictive models. In evaluating the models, a hybrid set of regression report metrics was used – mean absolute error (MAE), median absolute error, mean squared error (MSE), root mean squared error (RMSE), max error, R2 score, explained variance score (EVS), and mean absolute percentage error (MAPE). These were used along with the implementation of hyperparameter tuning techniques, such as GridSearchCV and RandomizedSearchCV, based on cross-validated performance. The evaluation reports were subsequently visualized to facilitate insights derivation and comparison and improve understanding of the results.

3. RESULTS AND DISCUSSION

By applying the aforementioned methods, the results of this study provide valuable insights into the relationship between climatic variables and the yield of staple crops, highlighting the predictive performance of various regression techniques.

3.1. Dataset for prediction

The initial dataset from Kaggle, consisting of 28,242 rows, was consolidated with other datasets, then cleaned, structured, enriched, and extended for analysis, resulting in a final dataset of 7,043 rows, with its properties detailed in Table 1.

Table 1. Final dataset description

Attribute	Description	Values
area	country name	Armenia, Azerbaijan, Bangladesh, India, Indonesia, Iraq, Japan, Kazakhstan, Lebanon, Malaysia, Nepal, Pakistan, Qatar, Saudi Arabia, Sri Lanka, Tajikistan, Thailand
item	staple crops	maize, potato, rice (paddy), soybean, wheat
year	planting year	1990–2022
average_rain_fall_mm_per_year	average recorded rainfall in millimeters	59–2,875
pesticides_tonnes	average annual use of pesticides in tonnes	0.92–349,797.62
avg_temp	average recorded temperature in celsius	7.44–26.37
hg/ha_yield	Amount of crop yield in hectograms per hectare	50–340,000

3.2. EDA

Since crop yield is primarily the target variable, a histogram was used to see the overall distribution as seen in Figure 1. The distribution is right-skewed, indicating that most fields have lower yields than a smaller number of fields with very high yields. Outliers on the higher end, representing fields with exceptionally high yields, were identified and addressed to prevent overly generalized prediction.

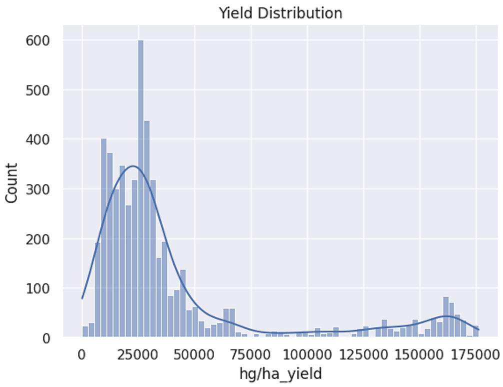
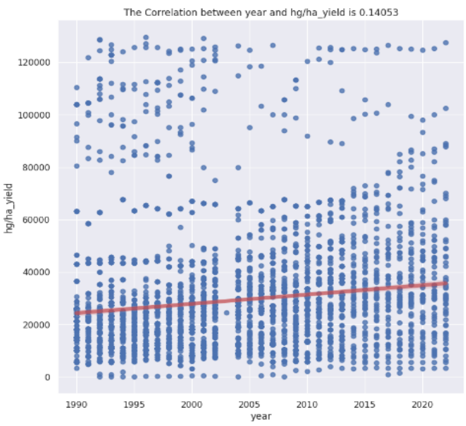


Figure 1. Yield distribution

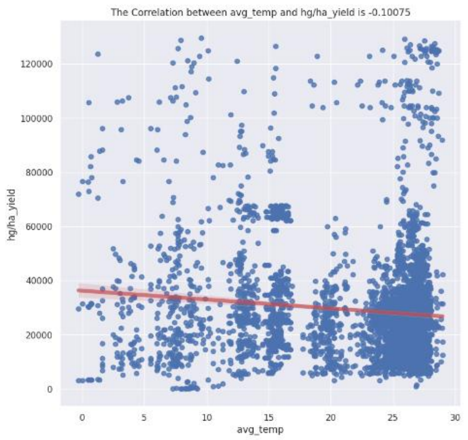
Furthermore, scatterplots were used to reveal the correlations between variables. Figure 2 illustrates the correlation between crop yield (hg/ha) and four key variables: year, average rainfall, pesticide usage, and average temperature. The results show a weak positive correlation of 0.14053 between year and yield, as seen in Figure 2(a), and between rainfall and yield (Figure 2(b)) with 0.01162, suggesting that while yield has slightly increased over the years, the relationship is not strong, and rainfall has a minimal impact on yield. Moreover, increased pesticide usage (Figure 2(c)) and higher temperatures (Figure 2(d)) may slightly decrease yield, but the relationship remains weak.



(a)

(b)

(c)



(d)

Figure 2. Correlation of: (a) yield and year, (b) yield and rainfall, (c) yield and pesticide, and (d) yield and temperature

While a weak positive correlation was observed between variables, the relationship is not statistically significant. This suggests that other factors not considered in this study may play a more significant role in the observed variation. Nevertheless, despite the weak relationships observed, the researcher proceeded with building the model, as the dataset provides factual data, considering that outliers have been addressed.

3.3. Model performance

The features used for the model are pesticides_tonnes, avg_temp, and average_rain_fall_mm_per_year to predict the target variable hg/ha_yield. The performance of each regression model employed for crop yield prediction was evaluated using the aforementioned metrics through cross-validation while implementing GridSearchCV and RandomizedSearchCV hyperparameters. Figure 3 shows that among the ML algorithms evaluated for predicting staple crop yield, the XGBRegressor (in a green-filled bar) achieved the highest performance with an R^2 score of 0.958367. This suggests that the model accounted for about 95.8% of the variation observed in the crop yield data, outperforming all other models tested. XGBoost's ability to handle non-linear relationships, manage missing data effectively, and incorporate regularization likely contributed to its superior accuracy.

Furthermore, XGBR registered one of the lowest RMSE values at 4,253, which further reinforces its strong predictive accuracy and reliability in estimating crop yield outcomes. A lower RMSE indicates that the model's predicted values are, on average, very close to the actual observed values, making the predictions not only statistically accurate but also practically useful in real-world agricultural planning. The RMSE comparison, as visualized in Figure 4, clearly demonstrates the superior performance of both XGBoost and RF regressor, which had notably lower error margins compared to the other models tested. In contrast, models such as ElasticNet, ridge regression, and SGD regressor produced significantly higher RMSE values, indicating less precision and larger deviations in their predictions.

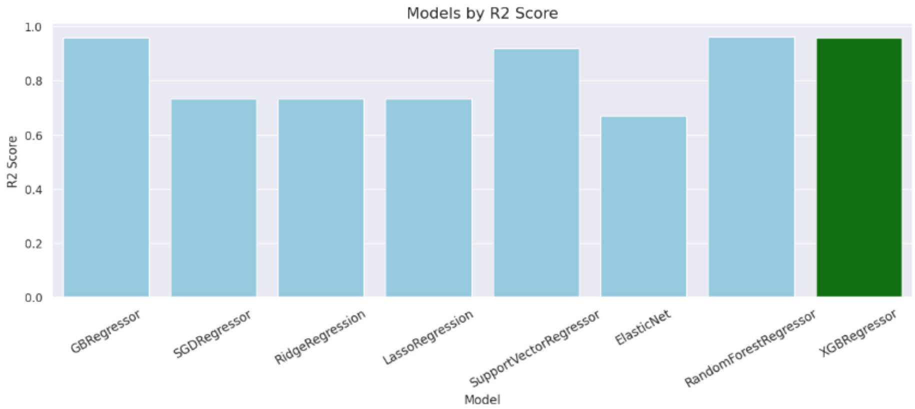


Figure 3. Models by R2 score

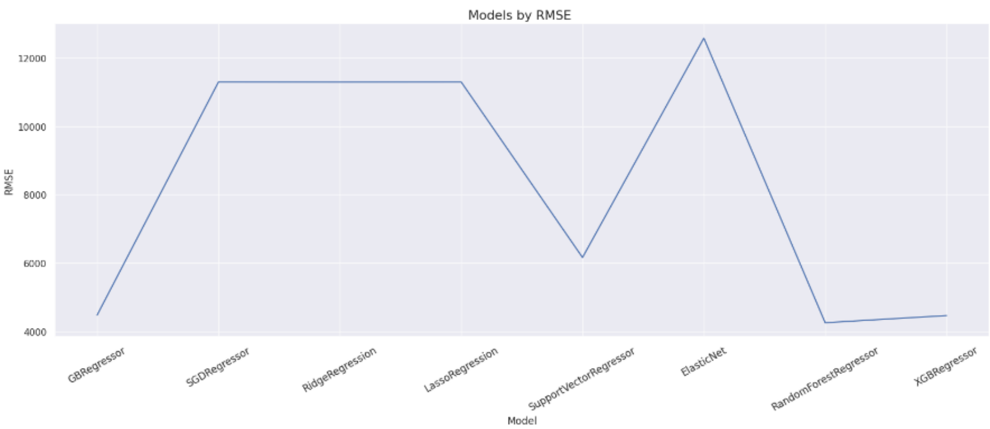


Figure 4. Model performance by RMSE

Moreover, Figure 5 utilizes normalized values for each metric, facilitating a clearer, side-by-side comparison of the regression models. This normalization is particularly important given the considerable variation in raw values. By normalizing the data, no single large value disproportionately influences the visualization, thereby enabling a more balanced assessment of model performance across the various error metrics. Normalized values are indicative of superior predictive performance. Models such as XGBoost (MAE: 1909.11, max error: 62417.16, MAPE: 0.115), RF regressor (MAE: 1845.76, max error: 42377.99, MAPE: 0.143), and gradient boosting regressor (MAE: 1663.13, max error: 77315.79, MAPE: 0.096) consistently exhibit lower normalized values, suggesting they outperform other models across key metrics, including MAE, MEDAE, maximum error, and MAPE.

A noteworthy observation from the graph is the consistent performance of the ensemble models, particularly XGBoost and RF, which maintain relatively low normalized values across all metrics. This consistency is indicative of their robustness in not only minimizing average prediction errors but also in mitigating the occurrence of extreme outliers, as evidenced by their low max error and MAPE values.

In contrast, the linear models, including ElasticNet (MAE: 8001.77, max error: 85168.66, MAPE: 0.684), SGD regressor (MAE: 7314.31, max error: 82864.39, MAPE: 0.571), lasso regression (MAE: 7310.81, max error: 82938.52, MAPE: 0.570), and ridge regression (MAE: 7309.69, max error: 82948.34, MAPE: 0.570), exhibit higher error values across the metrics. The elevated normalized values for these models indicate poor generalization ability and higher variability in prediction accuracy, suggesting that they may not be as reliable for practical applications in agricultural yield prediction.

The SVR (MAE: 2578.87, max error: 77325.95, MAPE: 0.136) demonstrates moderate performance, positioned between the linear models and the ensemble methods. Although its performance exceeds that of the linear models, its error metrics still lag behind those of XGBoost and RF.

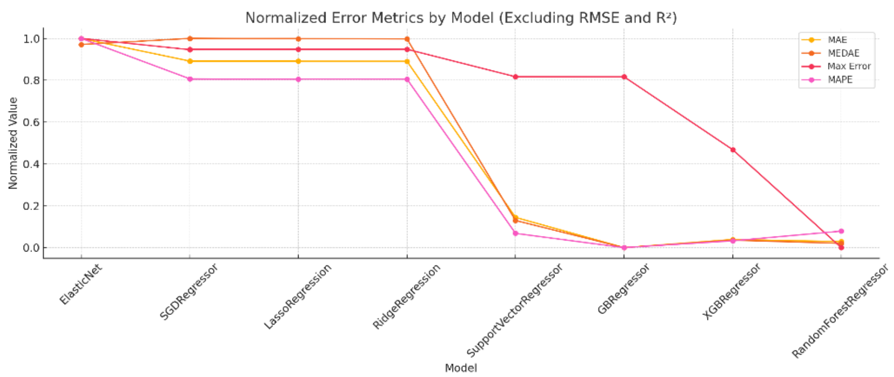


Figure 5. Normalized performance errors (MAE, median, max error, and MAPE)

4. CONCLUSION

Crop yield prediction has gained increasing importance, utilizing advanced statistical and ML techniques to support agricultural planning and food security. In this study, while the EDA revealed relatively weak linear relationships among individual variables, the predictive performance of the evaluated models demonstrated that reliable yield forecasts can still be achieved. The findings underscore the efficacy of ensemble methods, particularly XGBoost, in accurately predicting staple crop yields under varying climate-related conditions in Asia. With XGBoost achieving an impressive R^2 score of 0.958 and maintaining the lowest error margins across key metrics such as RMSE, MAE, and MAPE, the results strongly support the growing scientific consensus that ensemble models are particularly well-suited for modeling complex, non-linear relationships in agricultural data. These findings not only align with existing research on the advantages of tree-based ensemble models but also demonstrate their practical applicability in climate-informed agricultural planning and food security analysis.

Future research can build upon these findings by incorporating a larger dataset and a broader set of features, such as soil quality, irrigation patterns, CO_2 concentration levels, and socioeconomic variables, to further enhance model robustness. Additionally, extending the study to include temporal forecasting (e.g., next-season yield prediction) using time-series methods or hybrid models may yield even deeper insights. Conducting region-specific model training across diverse Asian subregions could also help capture localized agricultural dynamics more effectively. Furthermore, developing a software tool for automatic crop yield prediction could streamline the process, enabling real-time forecasting and facilitating more accessible decision-making for farmers and agricultural stakeholders.

This study highlights that XGBoost provide not only statistical accuracy but also practical reliability for real-world agricultural yield prediction. Its consistent performance across multiple error metrics suggests that it is capable of supporting informed decision-making in climate-resilient agriculture. As climate variability continues to challenge traditional farming systems, adopting such advanced ML approaches could play a critical role in optimizing yield forecasts and ensuring food security in the region.

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AUTHOR CONTRIBUTIONS STATEMENT

Both authors have thoroughly reviewed the content of the manuscript, contributed to its development, and have given their full approval for its submission and eventual publication. They affirm that the manuscript represents an accurate and honest account of the research conducted.

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Thelma D. Palaoag		✓				✓				✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The author declares that there is no conflict of interest associated with this research.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study. However, the data used for the predictive model are available at:

1) https://www.kaggle.com/datasets/patelris/crop-yield-prediction-dataset/data and
2) https://data.apps.fao.org/catalog/dataset/crop-production-yield-harvested-area-and-processed-global-national-annual-faostat.

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