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Evaluating the Performance of Machine Learning Models to Predict Climate Zone-Based Crop Yields

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ABSTRACT

In light of the challenges posed by climate change, as highlighted by Wing et al. (2021), which projected a reduction in global crop yields by 3–12% by mid-century and 11–25% by the century's end under severe warming scenarios, six machine learning models have been tested. Leveraging data from the United Nations (UN)’s Food and Agriculture Organization (FAO), this tool integrates parameters such as temperature, rainfall, pesticide usage, and cropland areas for key crops across six climate zones: polar, temperate, arid, tropical, Mediterranean, and mountains. Utilizing advanced machine learning techniques—including Random Forest, XGBoost, Recurrent Neural Network, Artificial Neural Network, Long Short-Term Memory, and K-Nearest Neighbor—the tool evaluates model performances based on $R2$ and RMSE metrics. The ARIMA model demonstrated the highest accuracy for Maize and Soybeans in the Tropical climate zone, while the Random Forest model excelled for Potatoes, Rice (paddy), Sweet Potatoes, and Wheat. In the Dry climate zone, the ARIMA model outperformed others for Maize, Potatoes, Rice (paddy), and Sweet Potatoes, with Random Forest best for Wheat and Soybeans. In the Temperate climate zone, the Long Short-Term Memory model provided the best predictions for Maize, while Random Forest excelled for other crops, and ARIMA was most effective for Rice (paddy). This study underscores the importance of a hybrid machine learning approach, combining the strengths of various models to address climate change complexities. Hybrid models offer more robust and reliable predictions, supporting farmers and decision-makers in adapting to changing conditions and ensuring sustainable agriculture.

Introduction

In the era of climate change, there is a growing necessity for changes in agriculture to accommodate global warming. Crop sustainability is deteriorating further the climate changes due to various associated conditions. These changes could cause economic issues that would reduce food supply, increase prices, and threaten food security in everyday life. With the state of agriculture in modern times, there is a need to use historical data to predict how crops will be affected in the future.

Other researchers have already taken steps to mitigate the effects of climate change on crop production in order to improve the sustainability of crops. For example, investigative methods such as Kazem Javan and Mariam Darestani’s (2024) use of scale and mathematical models and Bijay Subedi et. Al.’s (2023) study into global warming on pest management. A study by Benitez-Alfonzo et. al. (2023) and Mnqobi Zuma et. al. (2023) similarly focuses on how to improve crops in response to climate change with topics such as genetics and crop management. Another study focuses on how to find alternative crops to adapt to the changing environmental conditions.

To ensure that climate change does not further worsen the agricultural industry, predictive information is a requisite for solutions such as adapting current crops for future conditions. The ability to change what crops are grown for optimization in climates is crucial in times of climate change. Having the information of possible futures based on present information can mitigate the effects of global warming on crop production by allowing growers to plan ahead in the crops they grow and how they manage them.

In this study, a machine learning model was developed in order to predict crop productivity in future years. The model would use simple, easily measurable parameters with the goal of machine learning models determining how effective that crop would be in future years. The final purpose of this model is to provide actionable information to those in charge of food production in order to allow them the means of optimizing their crops to produce as much yield as possible.

While global crop sustainability against climate change has been heavily covered by previous researchers, this study is unique in its methodology of hybrid machine learning for predictions of crop yield. This research tested various machine learning models and found the most effective under certain parameters, going beyond a standard, singular machine learning model and enhancing accuracy of predictions. Using various machine learning techniques in hybrid will solidify a high accuracy rate over a wide range that would not be possible if limited by a single model that is not effective across all conditions.

Methods

As shown in Figure 1, the procedural flowchart outlines the step-by-step process used in this study for predicting crop yields across different climate zones. The process begins with the collection of historical climate and crop data from various sources, including the United Nations Food and Agriculture Organization (UN FAO). Key parameters such as temperature, rainfall, pesticide usage, and cropland areas are integrated into the dataset.

Subsequently, the data undergoes preprocessing to ensure quality and consistency, followed by feature selection to identify the most relevant variables for crop yield prediction. The selected features are then input into six advanced machine learning models: Random Forest, XGBoost, Recurrent Neural Network, Artificial Neural Network, Long Short-Term Memory, and K-Nearest Neighbor.

The final output consists of the performance evaluation of these machine learning models across different climate zones, providing insights into their effectiveness and identifying the best-performing models under varying climatic conditions. Depending on the R^2 and RMSE values, the best performing models are selected for each climate zone and each crop. This information will be instrumental in developing forecasting models to assist farmers and decision makers in optimizing agricultural practices and improving crop yield predictions.

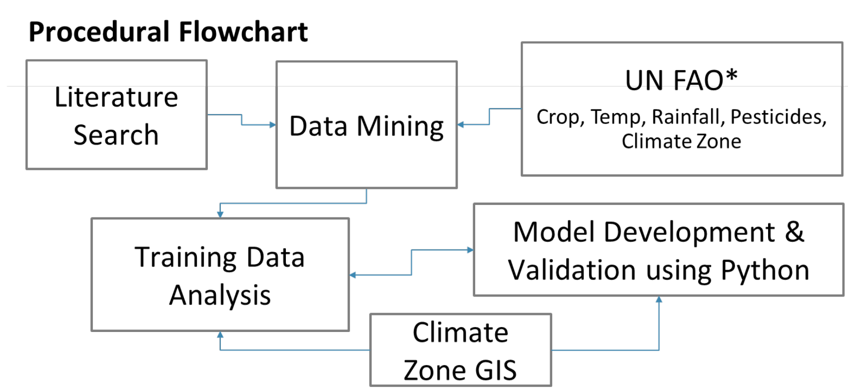
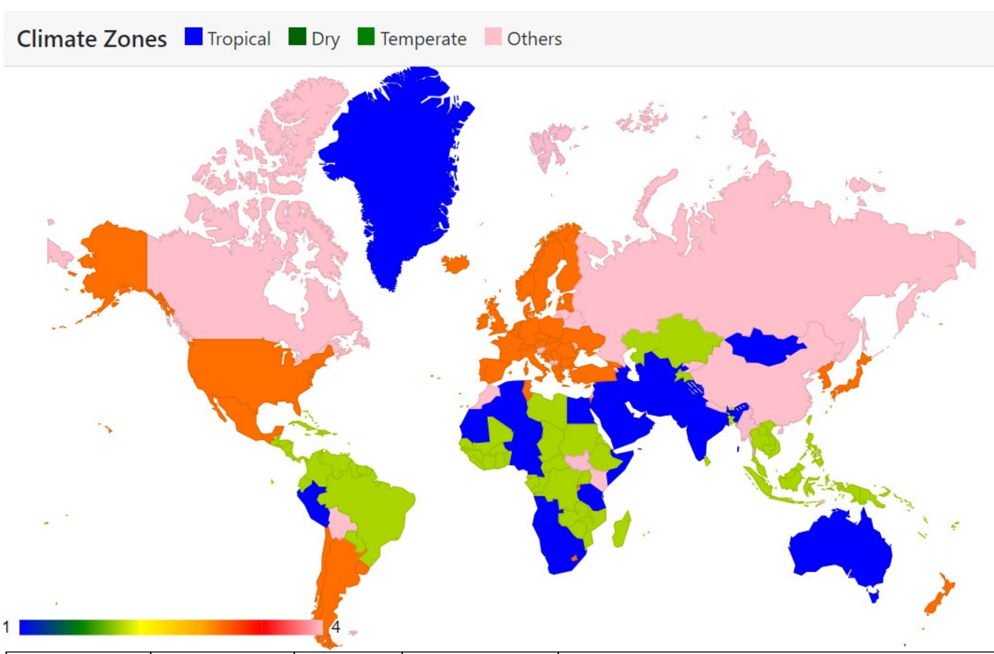


Figure 1. Schematic diagram of study plan to evaluate machine learning approaches in developing hybrid crop sustainability prediction model.

Data Collection

Climate, crop, and pesticide usage data was collected for 1960 to 2018 (Kaggle, 2021), and this data is consistent with the original dataset the Food and Agriculture Organization (FAO) released. This data range is scientifically sound enough to evaluate crop sustainability in the use of this study because 58 years of data provides no significant greater or lesser impact on long-term trends of climate change than if the data reached to 2024. There is no significant difference expected in climate change rate between 64 years (1960 to 2024) and 58 years (1960 to 2018). According to the FAO, linear trends in crop production and livestock were observed for global data over 58 years, which indicates that selection of time window does not make any difference in resulting predictions of future crop yields. In the database, there were 195 countries and their related territories, and those countries were assigned to four climate zones defined by Köppen et. al. (2021). However, the classifications used by Köppen are different from that used in this paper. Koppen's climate zones were reclassified in this study for statistical robustness. For example, Zone 6, characterized as dry-polar, has only two countries which indicates insignificant statistical power. Therefore, in this study, to achieve greater statistical robustness, 4 classes were identified including Tropical, Dry, Temperate, and Others as shown in Figure 2.

This study utilizes a Geographic Information System (GIS) for visualization of crop data on a large-scale map. GIS is typically used in agriculture for the purpose of precision agriculture, which geographic data would be of use. According to the United States Department of Agriculture (USDA), this data is typically used to help farmers in crop planting strategies and monitoring pesticide applications. GIS in terms of this study is the agricultural data represented on a map in order to visualize spatial data.



Climate Zone	Climate Type	Legend	Number of Countries	Note
1	Tropical	Blue	36	Consistently high precipitation and temperature
2	Dry	Green	114	Very little humidity or precipitation
3	Temperate	Orange	56	Mild temperatures ranging from warm to cool
4	Others	Pink	21	Not assigned

Figure 2. Geographical distribution of climate zones and explanation for each zone drawn in Google GeoChart.

Random Forest

Random forest (RF) is a machine learning algorithm based around classification and regression. The algorithm combines multiple decision trees to improve accuracy for classification or regression by averaging their outputs. In this study, included data of rainfall, temperature, pesticide usage, and crops. The four inputs would run through the Random Forest model to predict, based on given parameters, crop yield information in future years. The Python library called RandomForestRegressor was used for this analysis along with a test size of 30% of the training dataset (test_size=0.3), n-estimator of 100 (n_estimator = 100) and random states of 42 (random_state = 42).

Artificial Neural Network

Artificial Neural Network (ANN) is a machine learning technique that utilizes a interconnected group of nodes to form calculations based on a dataset. The concept is inspired by a simplification of neurons in a brain, which also utilizes a network of node-like neurons. Temperature, pesticide usage, and rainfall data is put into the ANN network and run through each layer of nodes. ANN performs ideally under non-linear data conditions. The relevant Python libraries, sklearn… was used for this analysis along with the model configuration parameters of test_size, random_state, batch_size, epochs, and verbose set to 0.3, 42, 10, 100, and 0, respectively.

XGBoosting

XGBoost enhances predictive accuracy by adjusting for residual of earlier models. Each subsequent model targets prior errors, and the output forms precise final predictions. When the model was given the dataset including the variables of temperature, rainfall, pesticide usage, and crop training data, errors in classification, or residuals, continue to create further models to account for inaccuracies in previous models. XGBoost works well with structured, simple datasets. A soybean prediction study (Yuanchao Li et. al.) found that the XGBoost, when coupled with a multidimensional feature engineering, significantly improved their test results and accuracy. XGBoost uses the libraries xgboost, sklearn.model_selection, sklearn.metrics for analysis with the test_size, random_state, colsample_bytree, learning_rate, max_depth, alpha, n_estimator, and n_estimator model configuration parameters being equal to 0.3, 42, 0.3, 0.1, 5, 10, and 100 respectively.

K-Nearest Neighbor

K-Nearest Neighbor (KNN) classifies new data using data that is most similar to the new data. This method takes new data and compares it to older data in order to determine classification. KNN works best when there is a small number of features. When the datapoints of rainfall, temperature, pesticide usage, and crops are input each one is classified into categories through which any new data point is then sorted according to the already classified data. A study by Lontsi Saadio Cedric (Saadio Cedric et. al.) utilized K-Nearest Neighbor as a system similarly to predict crop yield in West African Countries. This model uses sklearn.model_selection, sklearn.metrics, sklearn.neighbors, sklearn.preprocessing, scipy.stats as well as model configurations test_size, random_state, and n_neighbors equal to 0.3, 42, 5 respectively.

ARIMA

ARIMA is a statistical analysis model that combines autoregression, differencing, and moving average components. It utilizes time series data to make forecasts of the future based on the data. Rainfall, temperature, pesticide usage, and crop data would be input and mathematically analyzed based on the time of the data collected, allowing the model to make predictions of data in future years. The ARIMA model uses statsmodels.tsa.stattools, statsmodels.tsa.arima.model, and sklearn.metrics.

Long Short-Term Memory

Long-Short Term Memory (LSTM) is a type of RNN architecture. It is well-suited for handling sequential data with long-term dependencies. Crop, pesticide usage, temperature, and rainfall would be input for LSTM and go through the neural network for calculations with the data. The 4 data groups and the corresponding sequential data is then used for predictions of future years in crop production. Long Short Term Memory is used in a study (Nishu Bali & Anshu Singla) for predictions of wheat production in North India. In the study, LSTM is shown to have an edge over standard RNN. The model utilizes the tensorflow.keras.models, tensorflow.keras.layers, sklearn.preprocessing, and sklearn.metrics in addition to configuration parameters epochs, batch_size, verbose with values of 100, 1, and 2 respectively.The training size for this model is 67% of the data while the test size consists of the remaining 33%.

Results

Impact of Global Warming on Temperature and Rainfall

Analysis of temperature trends shows that there is an overall increase in temperature for the Temperate climate zone from 1901 to 2016. Figure 3 presents the temperature in the Temperate climate zone has increased by approximately 0.85 °C over the span of 115 years, which is consistent with the findings reported by the Intergovernmental Panel on Climate Change (IPCC) in 2021. Additionally, there has been a decrease in rainfall during the same period for the Temperate climate zone, attributed to the release of greenhouse gases and other anthropogenic factors. Rainfall in this zone has decreased by about 0.7% over 115 years. These temperature changes are also evident in other climate zones, with some zones experiencing temperature increases as high as 1.69 °C.

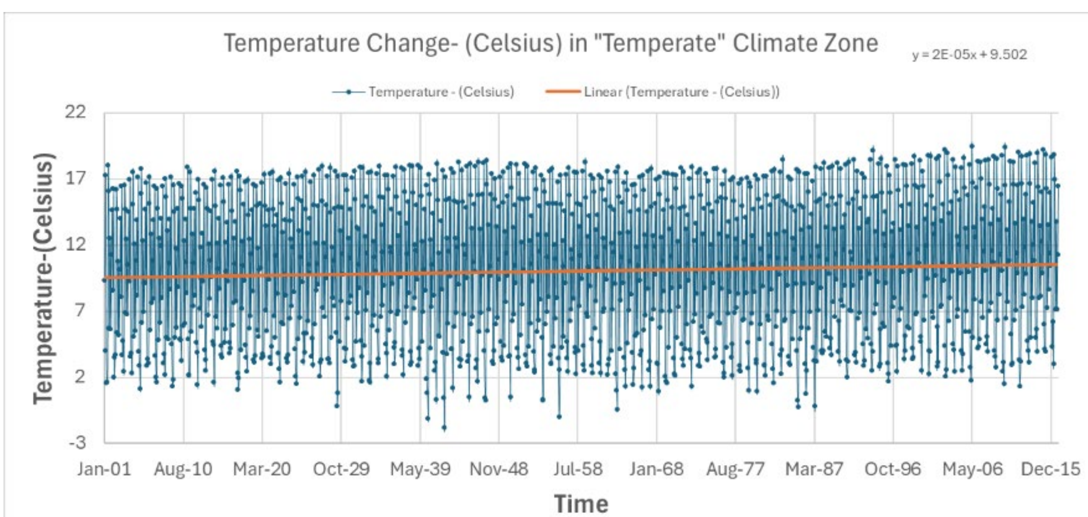


Figure 3. Long-term trend analysis of temperature for 1901 to 2016.

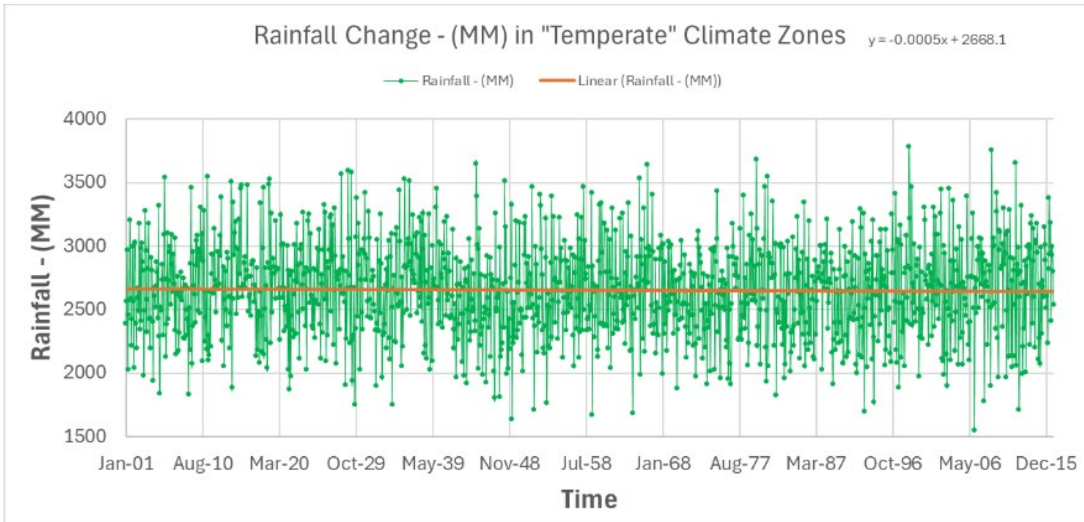


Figure 4. Long-term trend analysis of rainfall for 1901 to 2016.

Long Term Trend Analysis for Crop Yield and Pesticides

The long-term trend analysis indicates an increase in a majority of crop yields in the temperate zone. In the span of 58 years, the rates of change in terms of crop yield is exibited in Figure 5, providing crop yield in hectogram per hectare (hg/ha). Crop yield increased for maize, potatoes, wheat, barley, oats, and rye by 259%, 93%, 159%, 138%, 81%, and 129% respectively. Only Buckwheat showed any decrease in yield by 2.77%. Maize thrived with the largest increase of 259% as it is a common farming crop in temperate zones alongside potatoes which are climate resistant.

As depicted in Figure 6, the long-term analysis of pesticide usage saw many increases in a majority of its crops as well in the temperate zone. In 28 years, the change of pesticide usage ranged from a decrease of 73.8% to an increase of 240.1%. Due to both the pesticide and crop yield graphs showing a majority increase, the increased use of pesticides correlates with increases in crop yield.

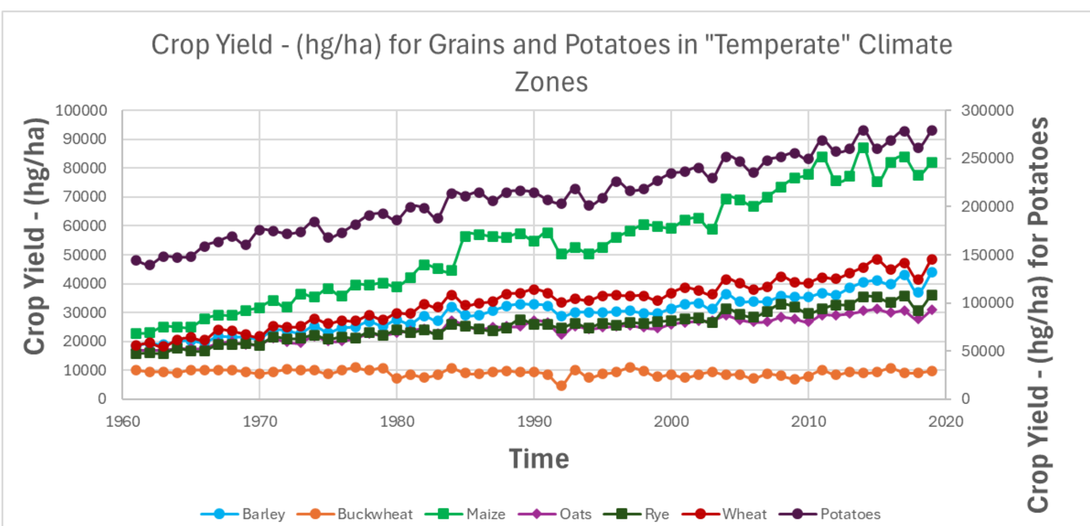


Figure 5. Long-term trend analysis of crop yield from 1961 to 2019.

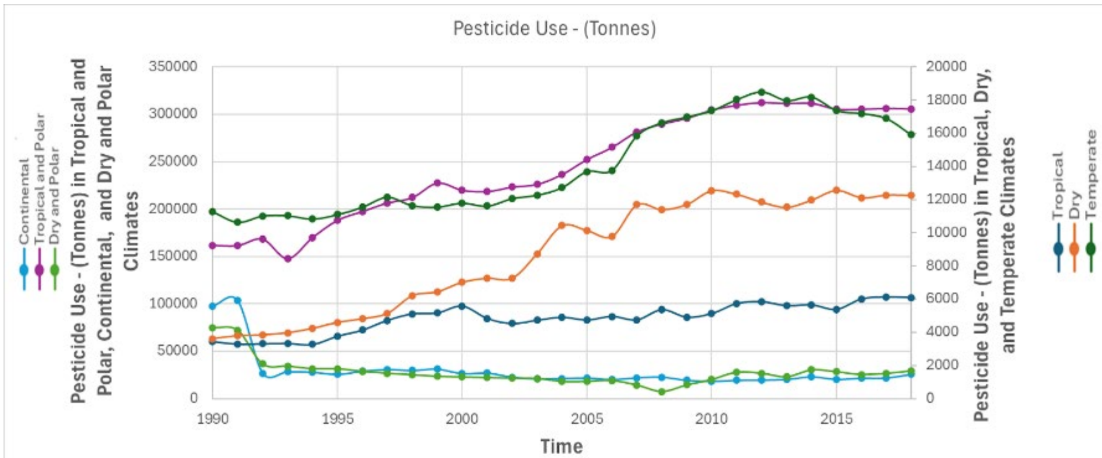


Figure 6. Long-term trend analysis for pesticide usage from 1990 to 2018.

Random Forest

The performance of the Random Forest (RF) model in predicting crop yields across different climate zones is visualized in Figure 7 and summarized in Table 1, which provides the R^2 and RMSE (Root Mean Squared Error) values for six key crops: Maize, Potatoes, Rice (paddy), Sweet Potatoes, Wheat, and Soybeans.

In the Tropical climate zone, the RF model demonstrates high predictive accuracy with R^2 values ranging from 0.91 to 0.96 across all crops. Maize (R^2=0.91), Potatoes (R^2=0.95), and Rice (paddy) (R^2=0.96) exhibit particularly strong correlations between predicted and actual yields. The RMSE values for these crops are relatively low, indicating precise predictions.

For the Dry climate zone, the model's performance varies more, with R^2 values between 0.75 and 0.91. The prediction accuracy is lower for crops like Sweet Potatoes (R^2=0.75), whereas Wheat (R^2=0.90) and Soybeans (R^2=0.91) still maintain high predictive power. The RMSE values in this zone are higher compared to the Tropical zone, suggesting greater variability in yield predictions.

In the Temperate climate zone, the RF model again shows robust performance with R^2 values from 0.84 to 0.94. The model achieves high accuracy for Maize (R^2=0.91), Potatoes (R^2=0.93), and Wheat (R^2=0.94), though Rice (paddy) (R^2=0.85) and Sweet Potatoes (R^2=0.87) are slightly less well predicted. The RMSE values are higher in this zone as well, reflecting the increased complexity in predicting yields under temperate conditions.

Overall, the RF model exhibits strong predictive capabilities, particularly in the Tropical and Temperate climate zones, with generally high R^2 values and relatively low RMSE values.

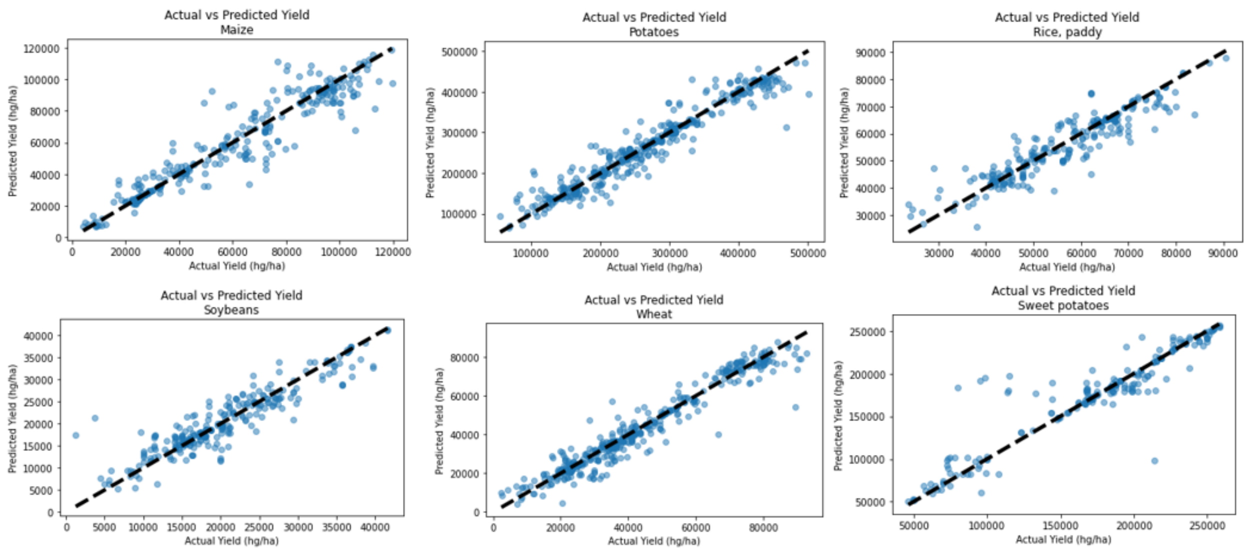


Figure 7. Random Forest model results graph showing actual yield against predicted yield for Temperate climate zone.

Table 1. The R^2 and RMSE value of each crop in every climate zone for the Random Forest model.

Climate Zone	**Models**	**Statistics**	**Maize**	**Potatoes**	**Rice, paddy**	**Sweet potatoes**	**Wheat**	**Soybeans**
Tropical	RF	R^2	0.91	0.95	0.96	0.95	0.95	0.93
		RMSE	5626.68	17831.28	4268.74	11582.52	2607.62	1361.10
Dry		R^2	0.79	0.85	0.82	0.75	0.90	0.91
		RMSE	7643.74	25534.96	5204.23	22704.35	3408.06	1967.49
Temperate		R^2	0.91	0.93	0.85	0.87	0.94	0.84
		RMSE	9174.69	26508.88	5016.94	20921.11	5297.11	3102.11

Artificial Neural Network

The performance of the Artificial Neural Network (ANN) model in predicting crop yields across different climate zones is visualized in Figure 8 and summarized in Table 2, which provides the R^2 and RMSE (Root Mean Squared Error) values for six key crops: Maize, Potatoes, Rice (paddy), Sweet Potatoes, Wheat, and Soybeans.

In the Tropical climate zone, the ANN model shows moderate to low predictive accuracy, with R^2 values ranging from 0.16 for Wheat to 0.58 for Soybeans. The RMSE values are relatively high across all crops, indicating considerable prediction variability.

For the Dry climate zone, the R^2 values vary between 0.09 for Wheat and 0.52 for Soybeans. The RMSE values remain high, suggesting significant prediction variability.

In the Temperate climate zone, the R^2 values range from 0.1 for Rice (paddy) to 0.32 for Maize, Potatoes, and Sweet Potatoes. The RMSE values are notably high in this zone as well, reflecting substantial prediction variability.

Overall, the ANN model demonstrates limited predictive accuracy across all climate zones, with generally low R^2 values and high RMSE values. The scatter plots further illustrate the model's performance, showing significant deviations from the line of perfect prediction for all crops.

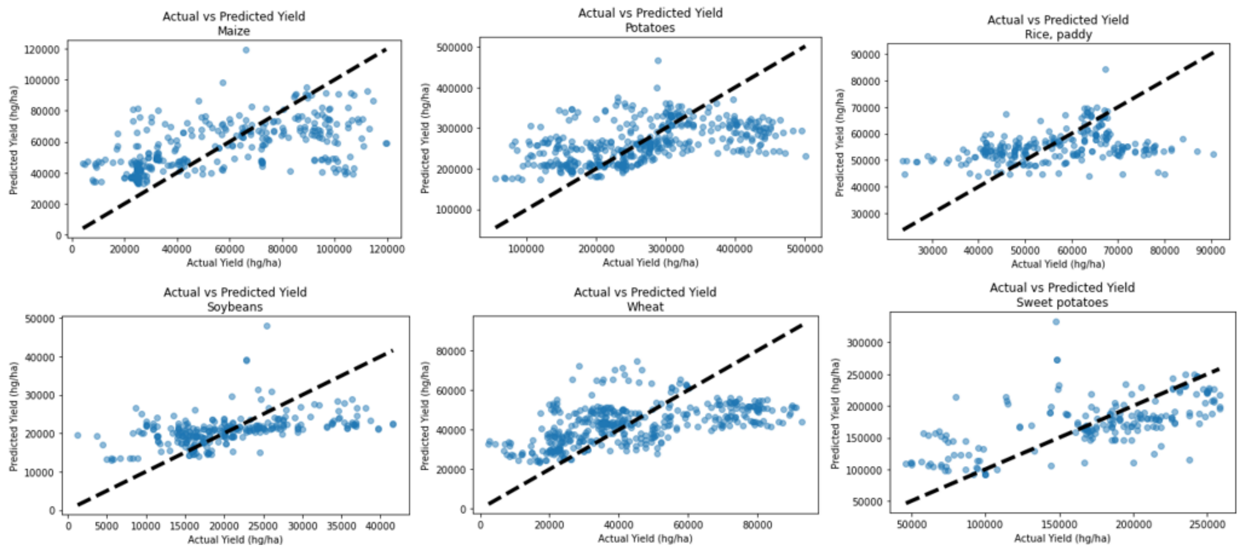


Figure 8. Artificial Neural Network model results graph showing the actual yield against the predicted yield for Temperate climate zone.

Table 2. The R^2 and RMSE value of each crop in every climate zone for the Artificial Neural Network model.

Climate Zone	Models	Statistics	Maize	Potatoes	Rice, paddy	Sweet potatoes	Wheat	Soybeans
Tropical	ANN	R^2	0.25	0.43	0.34	0.36	0.16	0.58
		RMSE	16321.92	58031.09	18279.1	58499.61	10348.86	3288.14
Dry		R^2	0.32	0.31	0.42	0.25	0.09	0.52
		RMSE	13789.21	54182.69	9505.41	39718.77	10523.43	4601.64
Temperate		R^2	0.32	0.24	0.1	0.32	0.24	0.23
		RMSE	25407.53	85444.43	12219.71	48253.05	18389.46	6925.96

XGBoosting

The performance of the XGBoost model in predicting crop yields across different climate zones is visualized in Figure 9 and summarized in Table 3, which provides the R^2 and RMSE (Root Mean Squared Error) values for six key crops: Maize, Potatoes, Rice (paddy), Sweet Potatoes, Wheat, and Soybeans.

In the Tropical climate zone, the XGBoost model demonstrates good predictive accuracy with R^2 values ranging from 0.82 for Maize to 0.93 for Rice (paddy) and Sweet Potatoes. The RMSE values are relatively low, indicating precise predictions, though the RMSE for Sweet Potatoes is notably higher, reflecting some variability.

For the Dry climate zone, the R^2 values indicate moderate performance, with Maize showing an R^2 of 0.64 and Potatoes an R^2 of 0.81. The R^2 values for Wheat and Soybeans are 0.81 and 0.68 respectively, showing relatively good predictive accuracy. However, the RMSE values are higher, indicating considerable prediction variability, especially for Sweet Potatoes.

In the Temperate climate zone, the XGBoost model shows strong performance with R^2 values from 0.73 for Soybeans to 0.89 for Wheat. Maize (R^2=0.84), Potatoes (R^2=0.84), and Sweet Potatoes (R^2=0.83) show high accuracy in predictions. The RMSE values are higher than in the Tropical zone, reflecting increased prediction variations.

The scatter plots in Figure 9 illustrate the model's performance, showing the relationship between actual and predicted yields. The XGBoost model's predictions are closely aligned with the line of perfect prediction for Maize, Potatoes, and Wheat, while showing more scatter for Soybeans and Sweet Potatoes, particularly in the Dry and Temperate zones.

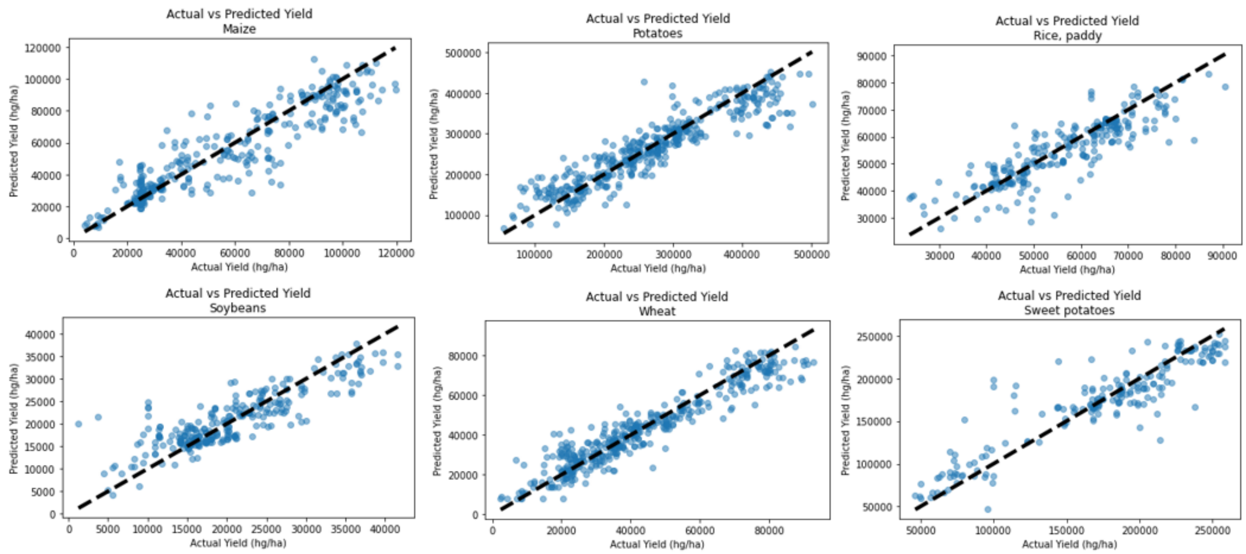


Figure 9. XGBoosting model results graph showing actual yield against predicted yield for Temperate climate zone.

Table 3. The R^2 and RMSE value of each crop in every climate zone for the XGBoost model.

Climate Zone	**Models**	**Statistics**	**Maize**	**Potatoes**	**Rice, paddy**	**Sweet potatoes**	**Wheat**	**Soybeans**
Tropical	XGBoost	R^2	0.82	0.9	0.93	0.93	0.88	0.88
		RMSE	8004.26	24188.87	6141	19325.09	3957.58	1739.11
Dry		R^2	0.64	0.81	0.78	0.56	0.81	0.68
		RMSE	10093.51	28782.03	5823.34	30482.33	4747.90	2449.52
Temperate		R^2	0.84	0.84	0.73	0.83	0.89	0.73
		RMSE	12348.19	38874.75	6732.61	24092.26	6872.23	4102.95

K-Nearest Neighbor

In the Tropical climate zone, as displayed in Figure 10 and Table 4, the KNN model shows moderate predictive accuracy, with R^2 values ranging from 0.44 for Maize to 0.91 for Wheat. Potatoes (R^2=0.90) and Rice (paddy) (R^2=0.85) also display strong correlations between actual and predicted yields. The RMSE values are relatively high, indicating substantial prediction variability.

For the Dry climate zone, the R^2 values indicate varying performance, with Maize showing a moderate R^2 of 0.62 and Sweet Potatoes a lower R^2 of 0.51. Soybeans (R^2=0.86) and Potatoes (R^2=0.84) have higher predictive accuracy. The RMSE values in this zone are high, reflecting considerable prediction variability.

In the Temperate climate zone, the KNN model demonstrates better performance with R^2 values from 0.73 for Soybeans to 0.90 for Wheat. Maize (R^2=0.88), Potatoes (R^2=0.87), and Sweet Potatoes (R^2=0.86) show high accuracy in predictions. The RMSE values, although lower than in other zones, still indicate prediction variability.

The scatter plots in Figure 10 further illustrate the model's performance, showing the relationship between actual and predicted yields. The KNN model's predictions are closely aligned with the line of perfect prediction for Potatoes, Wheat, and Soybeans, while showing more scatter for Maize and Sweet Potatoes, especially in the Tropical and Dry zones.

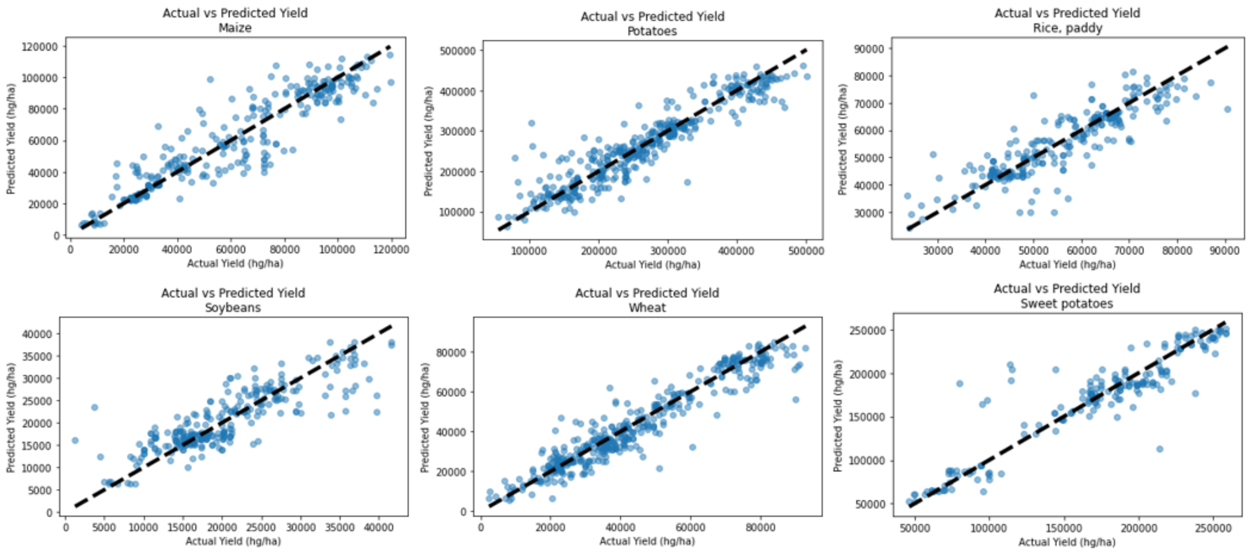


Figure 10. K-Nearest Neighbor model results graph showing actual yield against predicted yield for Temperate climate zone.

Table 4. The R^2 and RMSE value of each crop in every climate zone for the K-Nearest Neighbor model.

Climate Zone	Models	Statistics	Maize	Potatoes	Rice, paddy	Sweet potatoes	Wheat	Soybeans
Tropical	KNN	R^2	0.44	0.90	0.85	0.81	0.91	0.87
		RMSE	14106.64	24782.88	8706.4	31631.52	3445.44	1831.57
Dry		R^2	0.62	0.84	0.83	0.51	0.77	0.86
		RMSE	10368.36	26526.41	5161.93	31924.49	5246.94	2455.36
Temperate		R^2	0.88	0.87	0.75	0.86	0.9	0.73
		RMSE	10684.13	35634.78	6441.59	21787.05	6563.16	4117.48

ARIMA

Figure 11 and Table 5 present that in the Tropical climate zone, the ARIMA model shows high predictive accuracy for Maize (R^2=0.94) and Potatoes (R^2=0.92), with lower RMSE values indicating precise predictions. However, the model performs less effectively for Soybeans (R^2=0.30), with a higher RMSE reflecting greater prediction variability.

For the Dry climate zone, the ARIMA model performs exceptionally well for Maize (R^2=0.97), Potatoes (R^2=0.96), and Rice (paddy) (R^2=0.96), demonstrating strong correlations between actual and predicted yields. The RMSE values are low, indicating accurate predictions. Sweet Potatoes show a high R^2 value of 0.94, though Wheat (R^2=0.39) and Soybeans (R^2=0.67) have lower R^2 values, indicating more variability in predictions.

In the Temperate climate zone, the ARIMA model shows strong performance for Maize (R^2=0.93), Potatoes (R^2=0.85), and Rice (paddy) (R^2=0.91). The RMSE values are higher, particularly for Sweet Potatoes, which show a negative R^2 value, indicating poor predictive performance for this crop. Wheat (R^2=0.71) and Soybeans (R^2=0.18) also exhibit lower predictive accuracy.

The line plots in Figure 11 illustrate the model's performance over time, comparing observed versus predicted yields for each crop. The ARIMA model's predictions closely follow the observed trends for Maize, Potatoes, and Rice (paddy) across all climate zones, while showing more deviations for Soybeans, Wheat, and Sweet Potatoes, particularly in the Temperate and Tropical zones.

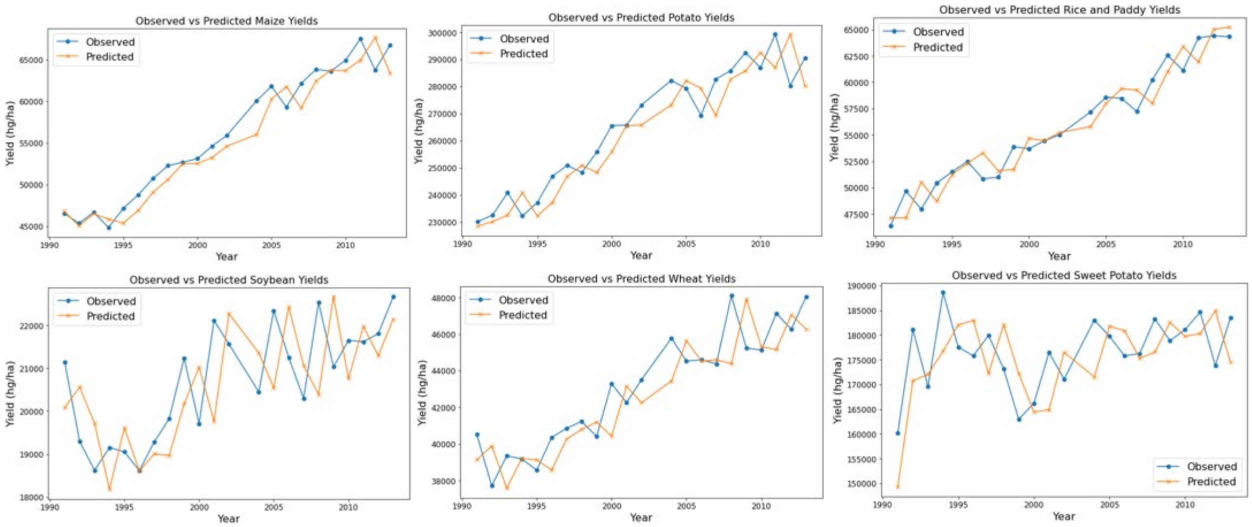


Figure 11. ARIMA model results graph showing actual yield against predicted yield for Temperate climate zone.

Table 5. The R^2 and RMSE value of each crop in every climate zone for the ARIMA model.

Climate Zone	Models	Statistics	Maize	Potatoes	Rice, paddy	Sweet potatoes	Wheat	Soybeans
Tropical	ARIMA	R^2	**0.94**	0.92	0.77	0.74	0.88	0.30
		RMSE	**1394.56**	6402.29	1632.50	6016.1	914.46	798.17
Dry		R^2	0.97	0.96	0.96	0.94	0.39	0.67
		RMSE	1084.1	3959.71	864.227	3239.1	1502.12	727.61
Temperate		R^2	0.93	0.85	0.91	-0.19	0.71	0.18
		RMSE	1992.25	8428.67	1577.10	7637.15	1655.43	1161.84

Long Short-Term Memory

Long Short Term Memory performed well in some instances and worse in others, creating relatively inconsistent predictions accuracies.

As shown in Figure 12 and Table 6, in the Tropical climate zone, the LSTM model shows moderate predictive accuracy, with R^2 values ranging from 0.34 for rice (paddy) and soybeans to 0.85 for Sweet Potatoes. The RMSE values indicate considerable prediction errors, particularly for Potatoes and Sweet Potatoes.

For the Dry climate zone, the LSTM model performs relatively well for Maize (R^2=0.86) and Potatoes (R^2=0.83), demonstrating strong correlations between actual and predicted yields. However, the model shows lower accuracy for Sweet Potatoes (R^2=0.25) and Wheat (R^2=0.02), with high RMSE values reflecting prediction variability.

In the Temperate climate zone, the LSTM model demonstrates good performance for Maize (R^2=0.93) and Potatoes (R^2=0.89), while showing lower accuracy for Wheat (R^2=0.44) and Soybeans (R^2=0.15). The RMSE values for Sweet Potatoes and Wheat are notably high, indicating significant prediction errors.

The line plots in Figure 12 illustrate the model's performance over time, comparing observed versus predicted yields for each crop. The LSTM model's predictions closely follow the observed trends for Maize and Potatoes, while showing more deviations for Soybeans, Wheat, and Sweet Potatoes, particularly in the Tropical and Dry zones.

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Figure 12. Long-Short Term Memory model results graph showing actual yield against predicted yield for Temperate climate zone.

Table 6. The R^2 and RMSE value of each crop in every climate zone for the Long Short-Term Memory model.

Climate Zone	Models	Statistics	Maize	Potatoes	Rice, paddy	Sweet potatoes	Wheat	Soybeans
Tropical	LSTM	R^2	0.67	0.79	0.34	0.85	0.53	0.34
		RMSE	1662.27	6829.69	1411.40	4693.32	1083.86	851.39
Dry		R^2	0.86	0.83	0.64	0.25	0.02	0.57
		RMSE	1173.91	4663.86	1029.26	3824.54	969.86	686.46
Temperate		R^2	0.93	0.89	0.77	0.01	0.44	0.15
		RMSE	1373.84	5613.38	1566.54	7650.76	1690.99	1144.50

Conclusion

Table 7. The best performing models for each climate zone and each crop.

Climate Zone	Statistics	Maize		Potatoes		Rice, paddy		Sweet potatoes		Wheat		Soybeans	
Tropical	R^2	0.94	ARIMA	0.95	RF	0.96	RF	0.95	RF	0.95	RF	0.93	RF
	RMSE	1394		17831		4268		11582		2607		1361	
Dry	R^2	0.97	ARIMA	0.96	ARIMA	0.96	ARIMA	0.94	ARIMA	0.9	RF	0.91	RF
	RMSE	1084		3959		864		3239		3408		1967	
Temperate	R^2	0.93	LSTM	0.93	RF	0.91	ARIMA	0.87	RF	0.94	RF	0.84	RF
	RMSE	1373		26508		1577		20921		5297		3102	

The evaluation of machine learning models across different climate zones for various crops has revealed significant insights into their effectiveness under varying conditions. Based on the performance metrics, the best performing models for each climate zone and crop have been identified as shown in Table 7.

In the Tropical climate zone, the ARIMA model demonstrated the highest accuracy for Maize and Soybeans. The Random Forest (RF) model performed best for Potatoes, Rice (paddy), Sweet Potatoes, and Wheat, achieving strong predictive accuracy. In the Dry climate zone, the ARIMA model outperformed others for Maize, Potatoes, Rice (paddy), and Sweet Potatoes. For Wheat and Soybeans, the RF model showed the best performance. In the Temperate climate zone, the Long Short-Term Memory (LSTM) model provided the best predictions for Maize. The RF model excelled for Potatoes, Sweet Potatoes, Wheat, and Soybeans, while ARIMA was most effective for Rice (paddy).

These findings highlight the varying strengths of different models. The ARIMA model consistently showed strong performance in the Tropical and Dry zones, while the RF model excelled in the Temperate zone. Identifying these best-performing models is crucial for developing accurate forecasting models to aid farmers and decision-makers in optimizing agricultural practices and enhancing food security.

Moreover, the study underscores the importance of adopting a hybrid machine learning approach, which combines the strengths of various models. This approach is particularly valuable in handling the complexities introduced by climate change, offering more robust and reliable predictions to support sustainable agricultural practices.

Despite these insights, the study has limitations, including the use of historical data up to 2016, a focus on limited crops and climate zones, and the inherent limitations of the models. The hybrid approach, while promising, was not fully explored and will be the focus of future research. Additionally, data distribution and the lack of high-resolution, real-time data may limit the models' applicability in providing precise predictions.

Future research should build on these findings to refine hybrid forecasting models, incorporating more climatic and agricultural variables to enhance predictive accuracy and reliability.

Limitations

Despite the valuable insights gained from this study, several limitations should be noted. First, the data used for model training and evaluation was limited to historical records from 1901 to 2016, which may not fully capture recent trends and extreme weather events. Second, the study focused on a limited number of crops and climate zones, which may not represent all agricultural regions and crop types. Third, the models used, including ARIMA, Random Forest, and LSTM, have inherent limitations and assumptions affecting their predictive accuracy. Additionally, the hybrid machine learning approach, while promising, was not fully explored and will be a focus of future research. Furthermore, the data distribution and lack of high-resolution, real-time data may limit the models' applicability in providing timely and precise predictions for farmers and decision-makers.

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