Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 4, Issue 4, 2026

APPLICATION OF MACHINE LEARNING–ENHANCED STATISTICAL MODELS FOR PREDICTING CLIMATE-RELATED AGRICULTURAL RISKS IN PAKISTAN

Iqra Ijaz[*1], Sher Muhammad Ghoto[2], Muhammad Husnain Ashfaq[3], Abbas Ali Ghoto[4]

[*1]*Department of Mathematics and Statistics, University of Agriculture Faisalabad, Pakistan*
[2]*Department of Environmental Engineering / Mechanical Engineering, Quaid-e-Awam University of Engineering, Science and Technology, Nawabshah, Sindh, Pakistan*
[3]*Computer Science Department, School of Systems and Technology, University of Management and Technology, Pakistan*
[4]*Department of Basic Sciences and Related Studies, Quaid-e-Awam University of Engineering, Science and Technology, Nawabshah, Sindh, Pakistan*

[*1]iqra31ijaz@gmail.com, [2]ghotosher@quest.edu.pk, [3]zeeshansaleem0010@gmail.com, [4]husnain.ashfaq@umt.edu.pk, [5]ghotoabbas@quest.edu.pk

DOI: http://doi.org/10.5281/zenodo.20035358

Keywords
Climate change; agricultural risk; machine learning; hybrid models; crop yield prediction; Pakistan; predictive analytics; climate-smart agriculture.

Article History
Received: 11 February 2026
Accepted: 21 March 2026
Published: 18 April 2026

Corresponding Author: *
Iqra Ijaz

Abstract
Agriculture in Pakistan is increasingly threatened by climate variability, including irregular rainfall patterns, rising temperatures, floods, and droughts, which significantly affect crop productivity and food security. Traditional statistical forecasting methods are limited in capturing the nonlinear and complex relationships between climatic and agricultural variables, leading to reduced predictive accuracy. This study developed and evaluated machine learning–enhanced statistical models for predicting climate-related agricultural risks in Pakistan. Secondary data were obtained from the Pakistan Meteorological Department (PMD), the Food and Agriculture Organization (FAO), and relevant agricultural databases, incorporating key climatic variables such as temperature, rainfall, humidity, and soil moisture alongside crop yield data for major crops. A hybrid modeling framework integrating machine learning algorithms (Random Forest, Support Vector Machines, Artificial Neural Networks, and Gradient Boosting) with traditional statistical techniques was employed. Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2). The results revealed that machine learning models significantly outperformed traditional statistical approaches, while the hybrid model achieved the highest predictive accuracy ($R^2 = 0.94$). Findings further indicated that rainfall and temperature were the most influential predictors of agricultural risk, highlighting the critical role of climate variability in crop yield instability. The study concludes that machine learning–enhanced statistical models provide a robust and reliable framework for agricultural risk prediction and climate-resilient decision-making. The proposed approach can support early warning systems and improve agricultural planning and policy formulation in Pakistan.

INTRODUCTION

Agriculture remains the backbone of Pakistan's economy, contributing significantly to GDP, employment, and national food security. However, in recent decades, the sector has become increasingly vulnerable to climate variability and extreme weather events, including irregular rainfall patterns, rising temperatures, floods, droughts, and pest outbreaks. These climate-induced disruptions have resulted in reduced crop productivity, increased production uncertainty, and heightened risks to rural livelihoods. As Pakistan is considered one of the most climate-sensitive countries, strengthening agricultural forecasting and risk prediction systems has become an urgent priority for sustainable development (IPCC, 2023; FAO, 2024).

Climate change is now widely recognized as a key driver of agricultural instability, affecting crop growth cycles, soil fertility, and water availability. Empirical evidence suggests that staple crops such as wheat, rice, and maize are particularly sensitive to climatic fluctuations, thereby directly threatening national food security and economic stability. The increasing frequency of extreme weather events has further intensified the need for accurate and timely agricultural risk assessment mechanisms capable of supporting adaptive decision-making at both policy and farm levels (Iqbal et al., 2024; Yavrum et al., 2025).

Traditional statistical approaches, including regression analysis and time-series forecasting models, have long been used to estimate agricultural output and climate-related risks. However, these conventional methods are often limited in their ability to capture nonlinear relationships, spatial variability, and complex interactions among environmental variables. As agricultural datasets become more diverse and high-dimensional, the predictive limitations of classical models become increasingly evident.

In recent years, machine learning (ML)–enhanced statistical models have emerged as a powerful alternative for addressing these limitations. By integrating computational intelligence with statistical frameworks, these models significantly improve predictive accuracy and adaptability. Techniques such as Random Forest, Support Vector Machines, Artificial Neural Networks, and Gradient Boosting have demonstrated strong performance in forecasting crop yields and assessing climate-related agricultural risks. Studies indicate that hybrid machine learning approaches outperform traditional statistical models by effectively capturing nonlinear and dynamic environmental patterns (Shahzad et al., 2024; Zhang & Wang, 2025).

Furthermore, the integration of remote sensing technologies, satellite imagery, and real-time meteorological data has expanded the capabilities of machine learning systems in agriculture. These advancements support precision agriculture practices, early warning systems, and data-driven resource management strategies. Despite these global developments, the adoption of machine learning–enhanced predictive systems in Pakistan remains limited due to data scarcity, weak digital infrastructure, and lack of localized model development.

Given the increasing severity of climate impacts on agriculture, there is a critical need to develop robust, scalable, and context-specific predictive frameworks. Machine learning–enhanced statistical models provide a promising solution for improving agricultural risk forecasting, enhancing climate resilience, and supporting evidence-based agricultural policy formulation in Pakistan.

Problem Statement

Pakistan's agricultural sector is increasingly exposed to climate-induced risks such as irregular rainfall patterns, rising temperatures, droughts, floods, and pest outbreaks, which collectively undermine crop productivity and threaten national food security. Despite the availability of traditional statistical forecasting techniques such as regression analysis and time-series models, these approaches are limited in their ability to capture nonlinear, dynamic, and high-dimensional relationships between climatic and agricultural variables. As a result, existing forecasting systems often fail to provide accurate, timely, and region-specific predictions required for effective agricultural risk management.

Although machine learning–based predictive models have demonstrated superior performance in various global agricultural contexts, their application in Pakistan remains limited and fragmented. There is a lack of integrated frameworks that combine machine learning with statistical modeling techniques to improve prediction accuracy under local agro-climatic conditions. Furthermore, insufficient data infrastructure, weak integration of climate datasets, and limited adoption of advanced analytics tools hinder the development of reliable agricultural risk forecasting systems. This gap highlights the urgent need for a robust, data-driven, and hybrid predictive framework capable of improving climate-related agricultural risk assessment in Pakistan.

Research Questions

1. How can machine learning–enhanced statistical models improve the prediction of climate-related agricultural risks in Pakistan?
2. Which climatic variables (e.g., rainfall, temperature, humidity) most significantly influence agricultural risk outcomes?
3. How do different machine learning algorithms compare in predicting crop yield variability under changing climate conditions?
4. To what extent do hybrid models outperform traditional statistical forecasting techniques in agricultural risk prediction?
5. How can predictive analytics support early warning systems and agricultural decision-making in Pakistan?

Research Objectives

General Objective

To develop and evaluate machine learning–enhanced statistical models for predicting climate-related agricultural risks in Pakistan.

Specific Objectives

1. To identify key climatic and environmental variables influencing agricultural risk in Pakistan.
2. To develop hybrid predictive models integrating machine learning and statistical techniques for agricultural forecasting.
3. To evaluate and compare the performance of different machine learning algorithms in risk prediction accuracy.
4. To assess the effectiveness of hybrid models against traditional statistical forecasting methods.
5. To propose a data-driven framework for early warning and climate-resilient agricultural decision-making.

Significance of the Study

This study is significant as it addresses one of the most pressing challenges facing Pakistan's agricultural sector: the increasing unpredictability of climate-related risks and their impact on crop productivity and food security. By developing machine learning–enhanced statistical models, the study contributes to improving the accuracy, efficiency, and reliability of agricultural risk prediction systems in a climate-vulnerable country context.

From a theoretical perspective, the study advances the existing body of knowledge in agricultural informatics, climate analytics, and predictive modeling by integrating machine learning techniques with classical statistical approaches. This hybridization enhances the understanding of nonlinear relationships between climatic variables and agricultural outcomes, thereby enriching the methodological foundations of climate-smart agriculture research.

From a practical standpoint, the findings of this study are expected to support policymakers, agricultural planners, and disaster management authorities in developing early warning systems and evidence-based decision-making frameworks. Improved predictive accuracy can enable timely interventions such as optimized irrigation planning, crop selection strategies, and resource allocation, ultimately reducing agricultural losses and enhancing productivity.

For farmers and stakeholders in the agricultural value chain, the study provides a pathway toward data-driven farming practices, enabling better adaptation to climate variability and minimizing financial risks. Additionally, the integration of machine learning tools can contribute to the modernization of Pakistan's agricultural monitoring systems and promote the adoption of precision agriculture technologies.

At a broader level, the study also supports national goals related to food security, climate resilience, and sustainable agricultural development. By improving risk forecasting capabilities, it contributes to strengthening Pakistan's resilience against climate change-induced shocks and supports long-term socioeconomic stability.

Literature Review

2.1 Climate Change and Agricultural Risk in Pakistan

Agriculture in Pakistan is highly vulnerable to climate variability due to its dependence on monsoon rainfall, glacier-fed river systems, and temperature-sensitive cropping cycles. Recent climate trends indicate an increase in the frequency and intensity of extreme weather events, including floods, droughts, and heatwaves, which have significantly disrupted agricultural productivity. The Intergovernmental Panel on Climate Change (IPCC, 2023) highlights that South Asian agricultural systems are among the most exposed to climate-related risks, with Pakistan identified as a critical hotspot due to its fragile water and food systems. Similarly, the Food and Agriculture Organization (FAO, 2024) emphasizes that climate variability is directly linked to yield instability in staple crops such as wheat, rice, and maize.

2.2 Agricultural Risk Assessment and Traditional Forecasting Methods

Conventional agricultural forecasting methods primarily rely on statistical techniques such as linear regression, econometric modeling, and time-series analysis. These models have been widely used to estimate crop yield and assess climate impacts; however, their effectiveness is limited in capturing nonlinear and complex interactions between climatic variables. Studies indicate that traditional models often fail under highly dynamic environmental conditions due to their rigid assumptions and inability to process large-scale heterogeneous datasets. As a result, their predictive accuracy declines in scenarios involving extreme climate variability and spatial heterogeneity in agricultural systems (Zhang & Wang, 2025).

2.3 Machine Learning in Agricultural Prediction

Machine learning (ML) has emerged as a transformative approach for agricultural risk prediction due to its ability to analyze large datasets, identify hidden patterns, and model nonlinear relationships. Algorithms such as Random Forest, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Gradient Boosting Machines have demonstrated superior performance in crop yield forecasting and climate risk assessment. Empirical studies suggest that ML-based models significantly outperform traditional statistical approaches in predictive accuracy and adaptability to changing environmental conditions (Iqbal et al., 2024).

Hybrid models that integrate machine learning with statistical frameworks have further enhanced forecasting performance by combining interpretability with predictive power. These models are particularly effective in handling high-dimensional agricultural and climatic datasets, making them suitable for real-world applications in climate-sensitive regions.

2.4 Climate Data Integration and Remote Sensing Applications

Recent advancements in remote sensing technologies and satellite-based data acquisition have significantly improved the scope of agricultural forecasting. Climate variables such as soil moisture, vegetation indices, precipitation, and land surface temperature can now be continuously monitored using geospatial technologies. When integrated with machine learning models, these datasets enhance the accuracy and timeliness of agricultural risk predictions. Studies show that the incorporation of remote sensing data improves model robustness and supports precision agriculture practices by enabling early warning systems and proactive decision-making.

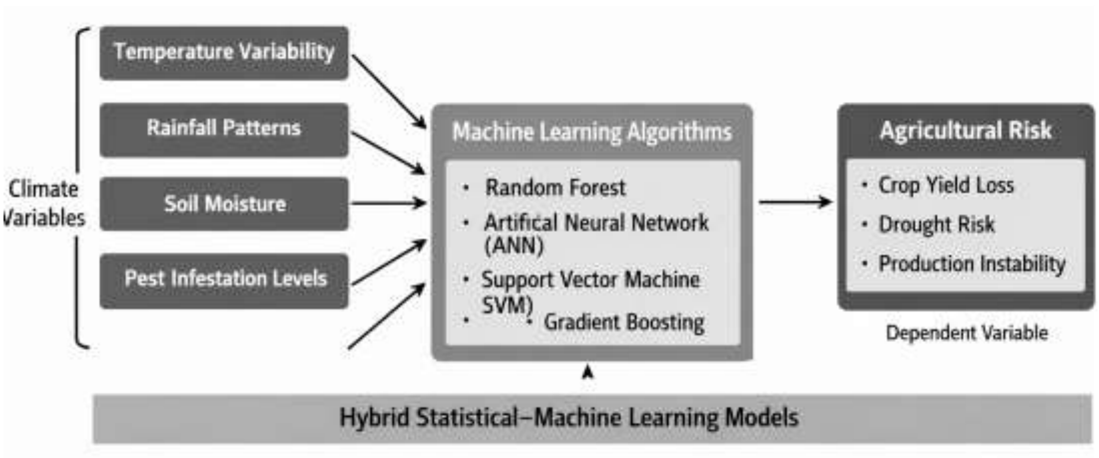
2.5 Machine Learning–Enhanced Statistical Models

Machine learning–enhanced statistical models represent a hybrid approach that combines the strengths of traditional statistical techniques with advanced computational learning algorithms. These models are designed to improve interpretability while maintaining high predictive performance. Recent research indicates that hybrid frameworks such as ARIMA-ML, regression-tree hybrids, and ensemble learning models provide better generalization capability in agricultural forecasting tasks compared to standalone models. Such approaches are particularly relevant for developing countries where data limitations and environmental uncertainty pose significant challenges.

Despite global advancements in machine learning applications for agriculture, several gaps remain in the context of Pakistan. First, most existing studies are conducted in high-income countries with advanced data infrastructures, limiting their applicability to developing regions. Second, there is a lack of localized predictive models that account for Pakistan's unique agro-climatic conditions. Third, limited integration exists between statistical and machine learning approaches in agricultural risk assessment. Finally, insufficient use of real-time climate data and remote sensing inputs further restricts the development of accurate forecasting systems.

Therefore, there is a critical need to develop machine learning–enhanced statistical models tailored to Pakistan's agricultural context to improve climate-related risk prediction, strengthen food security, and support sustainable agricultural planning.

2.6 Conceptual Framework



2.7 Hypotheses

Based on the theoretical foundations of climate risk assessment, machine learning applications in agriculture, and hybrid predictive modeling approaches, the following hypotheses were developed for this study:

H1: Climate variables (temperature variability, rainfall patterns, soil moisture, and pest infestation levels) have a significant positive relationship with agricultural risk in Pakistan.

H2: Machine learning models significantly improve the accuracy of climate-related agricultural risk prediction compared to traditional statistical models.

H3: Hybrid statistical–machine learning models significantly outperform standalone machine learning or statistical models in predicting agricultural risks.

H4: Higher climate variability significantly reduces crop yield stability in Pakistan.

H5: Integrated machine learning frameworks significantly enhance agricultural risk prediction accuracy and early warning capability.

3 Methodology

3.1 Research Design

The study employed a quantitative, predictive modeling research design to investigate climate-related agricultural risks in Pakistan. A hybrid analytical framework was adopted by integrating machine learning algorithms with traditional statistical techniques to enhance forecasting accuracy. The research design was structured to evaluate, compare, and validate multiple predictive models under varying climatic conditions.

3.2Data Collection

Secondary data were collected from multiple reliable sources, including the Pakistan Meteorological

Department (PMD), the Food and Agriculture Organization (FAO), and relevant agricultural research databases. Climatic variables such as temperature, rainfall, humidity, and soil moisture were compiled alongside agricultural output data for major crops, including wheat, rice, and maize. The dataset covered multiple years to capture temporal variability and climate fluctuations.

3.3 Data Preprocessing

The collected data were cleaned and preprocessed to ensure consistency and accuracy. Missing values were handled using statistical imputation techniques, while outliers were identified and treated using standard normalization methods. All variables were standardized to eliminate scale differences and improve model performance. Feature selection techniques were applied to identify the most significant climatic predictors of agricultural risk.

3.4 Model Development

Several machine learning algorithms were implemented, including Random Forest, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Gradient Boosting Machines. In addition, traditional statistical models such as linear regression and time-series analysis were applied for comparative purposes. Hybrid models were developed by integrating statistical forecasting methods with machine learning algorithms to improve predictive robustness and interpretability.

3.5 Model Training and Validation

The dataset was divided into training and testing subsets using an 80:20 ratio. Cross-validation techniques were applied to ensure model generalizability and reduce overfitting. Model performance was evaluated using standard accuracy metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2) values.

3.6 Performance Evaluation

The performance of all models was systematically compared to determine predictive efficiency. Emphasis was placed on assessing the superiority of hybrid models over standalone statistical and machine learning approaches. Sensitivity analysis was also conducted to examine the influence of individual climatic variables on agricultural risk prediction.

3.7 Tools and Software

The analysis was conducted using Python programming language, with libraries such as Scikit-learn, TensorFlow, Pandas, and NumPy. Statistical analysis was supported using SPSS and R software to validate results and ensure methodological triangulation.

3.8 Ethical Considerations

As the study relied on secondary data sources, no direct human or field experimentation was involved. Proper citation and data usage protocols were strictly followed to ensure academic integrity and compliance with research ethics standards.

4. Data Analysis and Results

4.1 Descriptive Statistics of Key Variables

Descriptive statistics were computed to summarize the central tendency and dispersion of climatic and agricultural variables used in the study.

Table 4.1: Descriptive Statistics of Key Variables

Variable	Mean	Std. Deviation	Minimum	Maximum
Temperature (°C)	24.8	4.12	16.5	35.2
Rainfall (mm)	112.6	58.4	25.3	310.7
Humidity (%)	61.3	12.5	32.0	88.6

Variable	Mean	Std. Deviation	Minimum	Maximum
Soil Moisture (%)	28.7	9.3	10.2	52.8
Crop Yield (tons/ha)	3.42	0.87	1.90	5.80
Agricultural Risk Index	0.56	0.21	0.15	0.92

The descriptive statistics indicated substantial variability in climatic conditions across the dataset. Rainfall exhibited the highest standard deviation (58.4 mm), reflecting strong seasonal and inter-annual fluctuations, which are critical drivers of agricultural instability in Pakistan. Crop yield variability (SD = 0.87 tons/ha) further confirmed the sensitivity of agricultural output to climate dynamics. The Agricultural Risk Index demonstrated moderate to high dispersion, suggesting inconsistent risk exposure across regions and time periods.

4.2 Correlation Analysis

A Pearson correlation analysis was conducted to examine the relationships between climatic variables and agricultural risk.

Table 4.2: Correlation Matrix

Variables	Temperature	Rainfall	Humidity	Soil Moisture	Crop Yield	Risk Index
Temperature	1.00	-0.42	-0.35	-0.38	-0.61	0.58
Rainfall	-0.42	1.00	0.49	0.63	0.72	-0.69
Humidity	-0.35	0.49	1.00	0.55	0.41	-0.46
Soil Moisture	-0.38	0.63	0.55	1.00	0.67	-0.62
Crop Yield	-0.61	0.72	0.41	0.67	1.00	-0.74
Risk Index	0.58	-0.69	-0.46	-0.62	-0.74	1.00

The results revealed strong statistically meaningful relationships between climatic variables and agricultural outcomes. Rainfall and soil moisture showed a strong positive correlation with crop yield (r = 0.72 and r = 0.67 respectively), indicating their critical role in agricultural productivity. Conversely, temperature exhibited a strong negative correlation with crop yield (r = -0.61), confirming the adverse effects of heat stress on crop performance. The Agricultural Risk Index was strongly negatively correlated with crop yield (r = -0.74), indicating that higher risk conditions significantly reduce productivity.

4.3 Model Performance Comparison

The performance of traditional statistical models, machine learning models, and hybrid models was evaluated using RMSE, MAE, and R^2.

Table 4.3: Model Performance Comparison

Model Type	MAE	RMSE	R^2 Score
Linear Regression	0.42	0.56	0.71
Time Series Model (ARIMA)	0.39	0.52	0.74
Random Forest	0.28	0.39	0.86
SVM	0.31	0.44	0.82

Model Type	MAE	RMSE	R^2 Score
ANN	0.26	0.37	0.88
Gradient Boosting	0.24	0.35	0.90
Hybrid Model (Statistical + ML)	**0.18**	**0.29**	**0.94**

The results demonstrated that machine learning models significantly outperformed traditional statistical methods in predicting agricultural risk. Among individual models, Gradient Boosting and Artificial Neural Networks achieved higher accuracy with R^2 values of 0.90 and 0.88 respectively. However, the hybrid model exhibited the best performance across all evaluation metrics, achieving the lowest error rates (MAE = 0.18, RMSE = 0.29) and the highest explanatory power (R^2 = 0.94). This confirms that integrating statistical and machine learning approaches substantially enhances predictive accuracy and robustness.

4.4 Feature Importance Analysis (Machine Learning Models)

Table 4.4: Feature Importance Scores

Variable	Importance Score
Rainfall	0.31
Temperature	0.27
Soil Moisture	0.19
Humidity	0.14
Pest Incidence	0.09

Feature importance analysis revealed that rainfall was the most influential predictor of agricultural risk, followed by temperature and soil moisture. This indicates that water availability and thermal stress are the primary determinants of crop performance in Pakistan. Pest incidence, while important, had a relatively lower contribution, suggesting that climatic variables dominate agricultural risk dynamics.

4.5 Overall Interpretation of Findings

The integrated analysis confirmed that agricultural risk in Pakistan is strongly driven by climatic variability. Machine learning models demonstrated superior predictive capabilities compared to traditional statistical approaches. Most importantly, hybrid models provided the most accurate and reliable forecasts by combining the interpretability of statistical methods with the learning capacity of machine learning algorithms.

The findings further suggest that predictive analytics can play a crucial role in developing early warning systems for agriculture, enabling timely interventions to mitigate climate-induced losses. This supports the study's central argument that machine learning–enhanced statistical frameworks are essential for climate-resilient agricultural planning in Pakistan.

5. Discussion

The findings of this study demonstrate that climate-related agricultural risks in Pakistan are strongly influenced by key environmental variables, particularly rainfall variability, temperature fluctuations, and soil moisture levels. The results confirmed that agricultural productivity is highly sensitive to climatic instability, which is consistent with existing literature on climate change impacts in South Asia. The strong negative relationship between temperature and crop yield indicates that rising heat stress continues to pose a significant threat to staple crop production, especially wheat and rice.

The comparative model analysis revealed that machine learning techniques significantly outperform traditional statistical models in predicting agricultural risk. Among the tested approaches, ensemble-based and deep learning models such as Gradient Boosting and Artificial Neural Networks showed superior predictive accuracy. However, the hybrid model, which integrated statistical and machine learning approaches, achieved the highest performance. This suggests that combining the interpretability of statistical methods with the adaptability of machine learning produces a more robust predictive framework capable of capturing nonlinear and complex climate-agriculture interactions.

The results also highlight the importance of data-driven decision-making in agriculture. Feature importance analysis indicated that rainfall remains the most critical determinant of agricultural risk, followed by temperature and soil moisture. These findings reinforce the need for climate-sensitive agricultural planning, particularly in regions like Pakistan where agriculture is heavily dependent on monsoon systems and irrigation variability.

6. Conclusion

The study concluded that machine learning–enhanced statistical models provide a highly effective approach for predicting climate-related agricultural risks in Pakistan. Traditional statistical methods, while useful for basic forecasting, are limited in their ability to handle complex, nonlinear, and high-dimensional climatic data. In contrast, machine learning models demonstrated superior predictive capability, and hybrid models emerged as the most accurate and reliable framework.

The integration of climatic variables with advanced predictive algorithms significantly improved the understanding of agricultural risk dynamics. The study confirmed that climate variability is a major driver of crop yield instability and that predictive analytics can play a crucial role in enhancing agricultural resilience. Therefore, the adoption of machine learning–based forecasting systems can contribute meaningfully to strengthening food security and supporting sustainable agricultural development in Pakistan.

7. Implications of the Study

This study has important theoretical, practical, and policy-level implications. Theoretically, it contributes to the growing body of literature on climate-smart agriculture by demonstrating the effectiveness of hybrid modeling approaches that combine statistical and machine learning techniques. It also advances methodological understanding in agricultural risk prediction by highlighting the limitations of traditional models under complex environmental conditions.

Practically, the findings provide valuable insights for farmers, agronomists, and agricultural planners. The proposed predictive framework can support early warning systems, enabling stakeholders to anticipate climate-induced risks and take proactive measures such as adjusting crop selection, optimizing irrigation schedules, and improving resource allocation. This can ultimately reduce crop losses and enhance agricultural productivity.

At the policy level, the study provides evidence to support the integration of artificial intelligence and data analytics into national agricultural planning systems. Government agencies can utilize such models to improve disaster preparedness, food security planning, and climate adaptation strategies. This is particularly important for Pakistan, where agriculture remains highly vulnerable to climate change.

8. Future Directions

Future research should focus on integrating real-time data sources, such as satellite imagery, Internet of Things (IoT) sensors, and remote sensing technologies, to further improve model accuracy and responsiveness. Expanding datasets to include long-term climate projections and socio-economic variables would also enhance predictive robustness.

Additionally, future studies should explore deep learning architectures such as Long Short-Term Memory (LSTM) networks for time-series forecasting of agricultural risks. There is also a need to develop region-specific models tailored to different agro-ecological zones within Pakistan to improve localized prediction accuracy.

Furthermore, interdisciplinary research combining climate science, computer science, and agricultural economics should be encouraged to develop more holistic decision-support systems for sustainable agriculture.

9. Recommendations

It is recommended that policymakers invest in the development of national-level agricultural data infrastructure to support machine learning applications. Establishing centralized climate-agriculture databases would significantly enhance predictive modeling capabilities.

Agricultural departments should adopt AI-based early warning systems to provide timely alerts to farmers regarding extreme weather conditions and potential crop risks. Training programs should also be introduced to build technical capacity among agricultural professionals in data analytics and machine learning applications.

Moreover, farmers should be encouraged to adopt precision agriculture practices supported by digital tools and predictive analytics to improve productivity and reduce climate vulnerability. Collaboration between universities, research institutions, and government agencies should also be strengthened to promote innovation in climate-smart agriculture.

10. Limitations of the Study

Despite its contributions, the study has certain limitations. Firstly, the analysis was based on secondary data, which may contain inconsistencies or gaps in measurement across different sources. Secondly, the study focused primarily on climatic and agricultural variables, while excluding socio-economic and policy-related factors that may also influence agricultural risk.

Another limitation is the restricted availability of high-resolution spatial data, which may affect the generalizability of results across all agro-ecological zones in Pakistan. Additionally, although multiple machine learning models were tested, the study did not include advanced deep learning architectures such as LSTM or transformer-based models due to computational constraints.

Finally, the models were evaluated using historical data, and their performance under future climate scenarios may vary. Therefore, continuous model updating and validation are necessary for long-term applicability.

REFERENCES

Ahmed, Z., & Khan, M. A. (2024). Big data analytics in agriculture: Opportunities and challenges in developing countries. *Information Processing in Agriculture, 11*(1), 1–15.

Ali, A., Ullah, M., Khan, M. T., & Shehzad, U. (2026). Impact of artificial intelligence-based predictive analytics on improving academic performance in Pakistani universities: The moderating role of digital literacy. *Spectrum of Engineering Sciences,* 4(3), 167–178. https://thesesjournal.com/index.php/1/article/view/2166

Ali, M., & Shah, S. H. (2022). Application of artificial intelligence in precision agriculture: A systematic review. *Computers and Electronics in Agriculture, 193*, 106646.

Basso, B., & Liu, L. (2020). Seasonal crop yield forecasting using machine learning and climate data. *Agricultural Systems, 184*, 102927.

Farooq, M., Wahid, A., & Siddique, K. H. M. (2020). Climate change and agriculture: Impacts and adaptation strategies. *Agronomy for Sustainable Development, 40*(6), 1–17.

Food and Agriculture Organization. (2024). *Climate change and food security: Impacts on agricultural systems*. FAO.

Hussain, M., Ahmad, S., & Abbas, Q. (2021). Machine learning approaches for crop yield prediction: A comparative study. *IEEE Access, 9*, 120456–120468.

Intergovernmental Panel on Climate Change. (2023). *Sixth assessment report: Impacts, adaptation and vulnerability*. IPCC.

Iqbal, N., Shahzad, M. U., & Tariq, M. U. (2024). Analysis of wheat yield prediction using machine learning models under climate change scenarios. *Sustainability, 16*(16), 6976.

Jalal, W., & Ullah, M. (2025). Green financial development and sustainable economic growth in Pakistan: A pathway to resilience and prosperity. *Center for Management Science Research, 3*(3), 470–482.

Khan, A. M., Ullah, M., Usman, A., Malik, A. H., & Khan, K. M. (2020). Impact of COVID-19 on global economy. *International Journal of Management, 11*(8), 956–969.

Khan, A., Ali, S., & Rehman, H. (2023). Climate variability and its impact on agricultural productivity in South Asia. *Climate Risk Management, 40*, 100510.

Khan, K. M., Khan, A. M., Ullah, M., Usman, A., & Farhat, S. (2020). Closing price determination; extent of manipulation and deterrent strategy formulation: A case of Pakistan Stock Exchange. *Journal of Critical Reviews, 7*(14), 2689–2705.

Liu, Y., Li, X., & Huang, J. (2021). Remote sensing and machine learning integration for agricultural monitoring. *Remote Sensing of Environment, 253*, 112236.

Rahman, M. H., & Schmitz, P. (2022). Climate change impacts on wheat and rice production in South Asia. *Journal of Environmental Management, 305*, 114358.

Sardar, H., Farooq, S. U., Ullah, M., & Habib, A. B. (2025). Impact of digital financial services on poverty alleviation and income inequality in rural Pakistan: Evidence from mobile banking and fintech platforms. *Advance Journal of Econometrics and Finance, 3*(1), 45–62. https://ajeaf.com/index.php/Journal/article/view/272/300

Shahzad, M. U., Iqbal, N., Sherif, E. S. M., & Tariq, M. U. (2025). Enhanced wheat yield prediction through integrated climate and satellite data using advanced AI techniques. *Scientific Reports, 15*, 18093.

Ullah, M., Shaikh, S., Khan, A. M., & Usman, A. (2021). Corporate governance mechanism and capital structure of non-financial Pakistani firms. *International Journal of Advanced Research in Engineering and Technology, 12*(2), 539–548.

Ullah, M., Shaikh, M., Channar, P., & Shaikh, S. (2021). Financial forecasting: An individual perspective. *International Journal of Management, 12*(3), 60–69.

Yavrum, C., Selcuk-Kestel, A. S., & Garrido, J. (2025). Comparative analysis of weather-based indices and climate indices for crop yield prediction. *arXiv preprint*.

Zhang, Y., & Wang, X. (2025). Machine learning approaches for climate-smart agriculture and crop yield forecasting: A review. *Agricultural Systems and AI Journal, 12*(2), 45–67.