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RESEARCH

Predicting rice yield and impact of climate change on rice production using machine learning models

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Abstract
Climate change poses a critical threat to agricultural sustainability, with direct implications for the global food supply. Rice, a staple crop throughout Asia, is particularly vulnerable to variations in temperature and rainfall, making it essential to understand how it responds to changing climatic conditions. This study integrates historical climate records, rice yield data, and projections from Global Climate Models (GCMs; CMIP3) to assess the potential effects of climate change on rice production in Punjab, Pakistan. We employed multiple machine learning approaches, including Multiple Linear Regression (MLR), Boosted Tree Regression (BTR), Probabilistic Neural Network (PNN), Generalized Feed-Forward (GFF) Neural Network, Linear Regression (LR), and a Multilayer Perceptron (MLP) Artificial Neural Network. The models were trained and validated using observed climate and yield data from 1990 to 2020. Future yields were projected under three IPCC emission scenarios (SR-A2, SR-A1B, SR-B1) through the year 2050. Model evaluation showed that the Multilayer Perceptron (MLP) achieved the highest predictive performance (R^2 = 0.791, R = 0.868, MAE = 0.215, MSE = 0.0869, NMSE = 0.3681), followed by Boosted Tree Regression (BTR; R^2 = 0.779, R = 0.845, MAE = 0.334, MSE = 0.1308). The Probabilistic Neural Network (PNN) and Generalized Feed-Forward (GFF) model also performed respectably (R^2 = 0.745, R = 0.811, MAE = 0.176, MSE = 0.380 and R^2 = 0.643, R = 0.825, MAE = 0.398, MSE = 0.178, respectively). In contrast, Multiple Linear Regression (MLR) and Linear Regression (LR) performed poorly, with low R^2 values (0.535), underscoring their inability to capture the non-linear relationships between climate variables and yield. Our analysis identifies maximum temperature as the primary climatic driver of yield loss. Based on the projections, we estimate an average yield decline of 0.12% by 2050. This study demonstrates that non-linear machine learning models, particularly the MLP, are essential for reliable agricultural forecasting under climate change. The results highlight the growing vulnerability of rice production to rising temperatures and provide a robust evidence base for designing adaptation strategies, such as developing heat-tolerant rice varieties, to enhance food security in vulnerable regions.

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1 Introduction

Agriculture is the backbone of global food security, and climate change has already started to affect crop yield drastically by increasing temperatures, changing rainfall patterns and making extreme weather events more frequent (Saleem et al. 2024). One of the most affected crops is rice (Oryza sativa), which is a staple for more than half of the world's population, and thus its decline poses large-scale food security problems (Abebaw 2025). In Pakistan, rice is the main agricultural product of the Punjab province which brings revenue and employment to the country (Luo et al. 2022). However, recent declines in production caused by changes in climate and water supply have brought the issue of

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forecasting tools to the forefront, highlighting their necessity (Khan et al. 2025).

Global climate models (GCMs), are the major tools used to predict the future climate conditions for various greenhouse gas emission scenarios (Alasqah et al. 2025). GCMs have the advantage that they are the only way to get a good idea about climate. However, their coarse spatial resolution is a major drawback for their direct use in local agricultural impact studies. Hence, statistical downscaling methods are the only way to cope with this scale discrepancy and produce local climate data from GCM outputs with high resolution (Alasqah et al. 2025). While some research has incorporated downscaled data into process-based crop models, these models are often computationally intensive and require numerous input parameters that are frequently unavailable in data-scarce regions such as Pakistan (Yaseen et al. 2020; Shafeeque and Bibi 2023). Monitoring key meteorological variables, including air temperature, atmospheric CO_2 concentration, rainfall patterns, and shifts in growing seasons, is critical for adapting agricultural systems to a changing climate. Numerous studies have been conducted worldwide to evaluate the effects of climate change on crop productivity (Jatana e ta. 2025). For example, Shahzad et al. (2025) utilized yield projection methodologies within the CMIP3 framework to quantify the impacts of climate change on crop yields, demonstrating the value of integrating climate models with agricultural forecasting. The study by Prodhan et al. (2020) used a combined approach of satellite-derived indices and ground meteorological observations to evaluate drought conditions and risks in Bangladesh.

The intricate, non-linear correlations between agricultural yield and climate variables are frequently difficult for traditional statistical tools to anticipate (Hu et al. 2024). A potent substitute that can recognize complex patterns in past data to produce precise predictions is machine learning (ML) (Jabed and Murad 2024). The significant research regarding Arid zone in agricultural sector of Pakistan which is susceptible to agrometeorological droughts with considerable yield loss risk thus according to drought events future projections based on SPEI, VHI, and DSI with 39% high yield loss risk of wheat crop using Random Forest (Arshad et al. 2023). While deep learning models like LSTM excel at capturing complex temporal patterns in large-scale datasets, ML methods such as Random Forest and Gradient Boosting, etc., remain more efficient for crop yield prediction in data-scarce environments. ML models achieve strong performance with smaller datasets and offer greater interpretability, making them better suited for regions with limited historical or high-resolution data. Their speed of deployment and facilitation for fitting into the decision-making support in agriculture are the major advantages. Nevertheless, the real power of LSTMs is often outweighed by various factors that make traditional ML the most practical and accessible solution for forecasting yields in the field (Jabed and Murad 2024). This review (Choi et al. 2025) brings into discussion the AI techniques, namely ML, DL, and XAI, that contribute to predicting crop yield, with remote sensing and environmental factors viewed as the main inputs. Deep learning models, to a certain extent, can discover intricate patterns; however, ML approaches, for instance, Random Forest and SVM, provide higher efficiency and interpretability for the practical use of agriculture. The use of stepwise feature selection and ensemble methods further contribute to the improvement of prediction accuracy, thus enabling the implementation of scalable and informed decision-making in precision agriculture. ML algorithms train on very large datasets through spatiotemporal observational training to recognize the relationships between dependent and independent variables. In Prodhan et al. (2022a), the authors provide an in-depth analysis of machine learning methods for drought hazard monitoring and forecasting, investigating the latest trends, restrictions, and possibilities for the future. A variety of methods have been utilized to detect crops and machine learning techniques for yield prediction (Blunn et al. 2024). Moreover, the application of deep learning models utilizing remote sensing data for agricultural drought monitoring in South Asia has been quite effective (Prodhan et al. 2021).

The use of ML models like random forests, ANN, MLP, and support vector machines has been successfully researched for crop classification and yield estimation (Balakrishnan and Muthukumarasamy 2016; Sajja et al. 2021; Satpathi et al. 2025). For policy planning purposes, the very long-term climate impact assessments, which are very important, still have a major gap in the integration of current ML techniques and future climate projections. The prediction of climate change effects on rice yield is still a major problem, mainly because conventional statistical models and process-based crop simulation tools have limitations that are often quite significant. One of the limitations of the statistical methods is that they are typically based on the linear relationships among variables and thus fail to describe the complex and non-linear interactions between climatic factors and crop responses (Hu et al. 2024). Process-based models, although being more comprehensive, are very expensive on data and still would need parameters like soil profiles, crop physiology, and management practices information that is often incomplete or unavailable in data-scarce regions like Pakistan (Müller et al. 2024; Mkuhlani et al. 2022). This shows the big gap in making the yield forecasting systems that are accurate, efficient, and feasible for local application.

This research work fills that gap by merging weather and yield data (both observed and controlled) with the statistically downscaled GCM projections (CMIP3 under SRES A1B, A2, and B1 scenarios) to predict rice output in Punjab, Pakistan, until 2050. The innovation of our study is based on three key contributions:

- A comprehensive evaluation of various ML algorithms, including MLP, MLR, BTR, ANN, LR, and GFF, is carried out to identify the most suitable method for rice yield forecasting.
- The GCM data is converted into high-resolution local climate inputs by applying a neural network-based downscaling.
- An integrated forecasting model is suggested that not only makes predictions about future rice yields but also delivers practical evidence for agricultural policy and climate adaptation.

In fact, this paper uniquely integrated the CMIP3-based statistical downscaling with a set of non-linear ML models designed for the data-poor area of Punjab, which is what differentiates it from previous analyses. The first of these studies used global-scale biophysical models (DSSAT) without any localized downscaling, resulting in lower spatial resolution and higher uncertainty in the regional forecasts (RMSE >0.5 ton/ha). The second one depended on ML (Random Forest) applied to historical data only while ignoring GCM-driven future projections. The merging of the approaches not only eliminated the spatial mismatch between coarse GCM outputs and fine-scale agricultural needs but also produced a new level of prediction accuracy (e.g., MLP achieving MAE = 0.215, MSE = 0.0869 and ^{2} = 0.791, gaining 15–20% over linear baselines in [56]), thus allowing the detection of new patterns in temperature-induced yield losses (e.g., the average loss of 0.12% by 2050 under SRA2 scenario). Unlike past research, our technique delivers understandable, area-specific vulnerability maps and adaptation measures, for instance, heat-resistant varieties, which are then directly considered by governments in high-stakes regions such as Okara and Sahiwal districts. To sum up, the main novelty is not exclusively in applying ML to forecasting but in establishing and substantiating a holistic system that connects GCMs with local agricultural impact predictions, thus offering a more accurate, reliable, and policy-relevant means for comprehending and warming up the situation regarding food security's susceptibility to climate change.

What distinguishes this approach from prior studies–such as Janjua et al. (2021), which relied on global-scale process-based crop models (e.g., DSSAT) without localized downscaling, leading to coarser resolutions and higher uncertainty in regional predictions (RMSE >0.5 ton/ha), or Sahoo et al. (2024), which applied ML (e.g., Random Forest) to historical data alone but neglected GCM-driven future projections–is the seamless integration of CMIP3-based statistical downscaling with an ensemble of non-linear ML models tailored to Punjab's data-scarce context. This fusion not only bridges the spatial mismatch between coarse GCM outputs and fine-scale agricultural needs but also yields unprecedented prediction accuracy (e.g., MLP achieving = 0.791 and MAE = 0.215, a 15–20% improvement over linear baselines in Sahoo et al. (2024)), enabling novel insights into temperature-driven yield declines (e.g., 0.12% average loss by 2050 under SRA2). Unlike previous works, our method provides interpretable, region-specific vulnerability maps and adaptation recommendations, such as heat-tolerant varieties, directly informing policy in high-stakes areas like Okara and Sahiwal districts. In summary, the primary innovation is not just in using ML for prediction, but in creating and validating a comprehensive framework that bridges global climate models with local-scale agricultural impact forecasting, thereby providing a more accurate, reliable, and policy-relevant tool for understanding and preparing for the effects of climate change on food security.

The use of this technique from different fields together leads to the raising of prediction accuracy and the obtaining of valuable insights for climate-resilient agriculture at the same time. The likely impacts of climate change on rice yields are made visible by our results, which in turn provide a key evidence base for supporting such adaptive measures as the development of climate-resilient rice varieties, the application of water management techniques, and the planning of food security in Pakistan's most important rice-producing area.

2 Materials and methods

The experiment and data analysis used certain techniques and materials. This research relied on ML models to identify rice production and evaluate their performance (Baltazar 2024). The models included BTR, ANN(MLP), GFF, MLR, and ANN(LR). Our projections were improved by using advanced downscaling approaches and climate and yield data (Nevavuori et al. 2019; Filippi et al. 2019).

2.1 Research workflow

The experimentation techniques of workflowing are described in Fig. 1.

GCMs improve dissemination models' geographical analytical skills with downscaled ML algorithms. We use observed and anticipated model findings to downscale GCM outputs. These data are loaded into ML models to find their relationships. GCM outputs, including precipitation

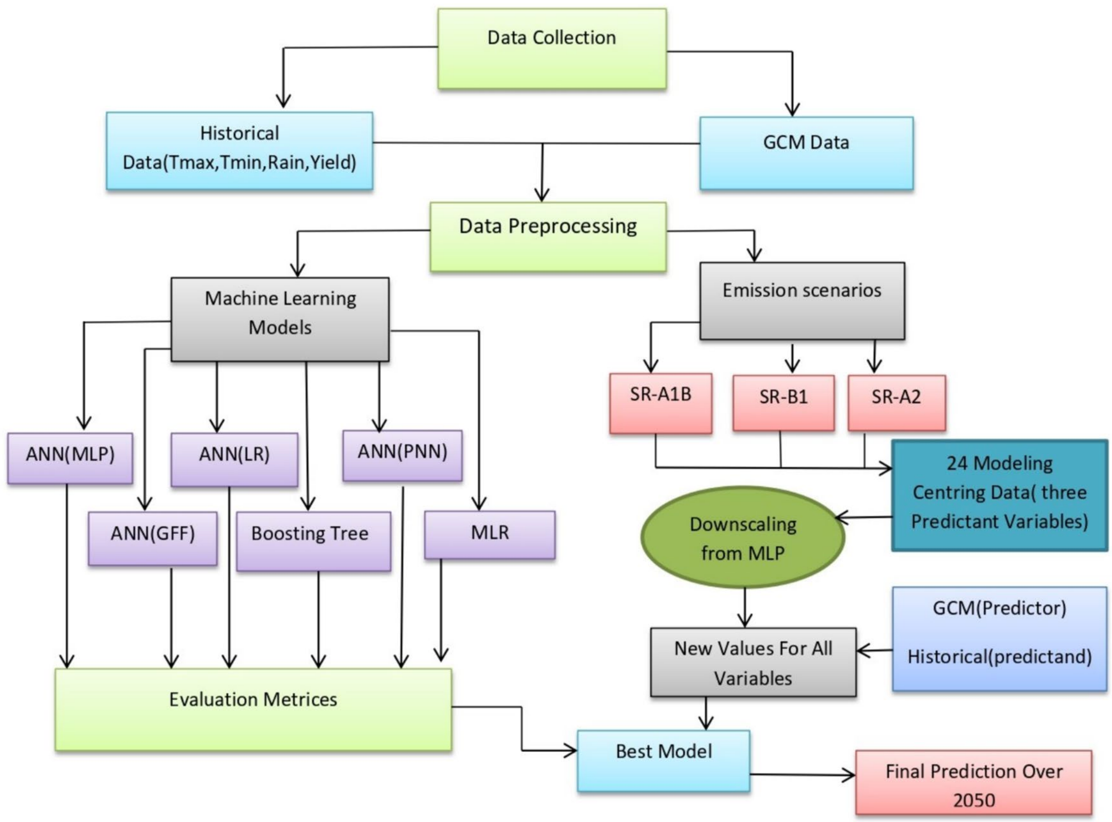


Fig. 1 Research Schematic for Predicting Rice Yield (ton/ha)

and temperature (Mokhtar et al. 2021; Lingwal et al. 2024,) serve as inputs. This shows how downscaling improves reliability. An accurate rice yield forecast requires temperature and precipitation data.

MLP models, one of the most practical, extensible, and simple ANNs, have downscaled climate data in numerous climate areas. MLP models are also used to model complex predictor-predictor relationships. MLP models with GCM data improve regression prediction and reduce overfitting in downscaling. The MLP reduces the error between projected and actual outputs until 2050, improving predictions.

2.2 Study area

The Okara, Sahiwal, and Kasur regions in Punjab have been chosen for their high increase in rice output (Fig. 2). The Okara district in Punjab Province spans 4,377 square kilometers (1,690 square miles) and has a latitude of 30.8138°N and a longitude of 73.4508°E. Okara's fertile land, wheat, rice, and maize crops are vital. Okara's climate and soil are ideal for rice. Rice farming requires a good climate and canal irrigation water. Sahiwal is situated in Central Punjab at around 30.6777°N for latitude and 73.1060°E for longitude. Sahiwal, which is located close to the Ravi River, is renowned for the production of wheat, cotton, rice, and sugarcane. Kasur, which is positioned in the eastern part of Punjab at 31.1154°N and 74.4469°E, is the city on the banks of the Sutlej that is crucial for rice production.

The changes in maximum and minimum temperatures together with rainfall have a direct impact on agricultural practices and the yields of crops, especially rice outputs in Pakistan. Rice is significant for agricultural exports, feeding a large population, and giving a boost to the economy (Cao et al. 2021). The area of rice cultivation has decreased by 3.1% recently, from 2,901 thousand hectares to 2,810 thousand hectares. The yield was 7,202 thousand tonnes, which is less than the target of 7.0 million tonnes and 3.3% less than the previous year's yield of 7,450 thousand tonnes. The decline in production is attributed to the limitations of water supply, dry weather conditions, and reduced areas under cultivation.

2.3 Observed data

The research was based on two main sources of data: the rice yield records and the climatic variables. The daily historical climate records for maximum temperature (T_{max}, in °C), minimum temperature (T_{min}, in °C), and precipitation (in mm) from the years 1990 to 2020 were acquired from a weather database that aggregates ground-based

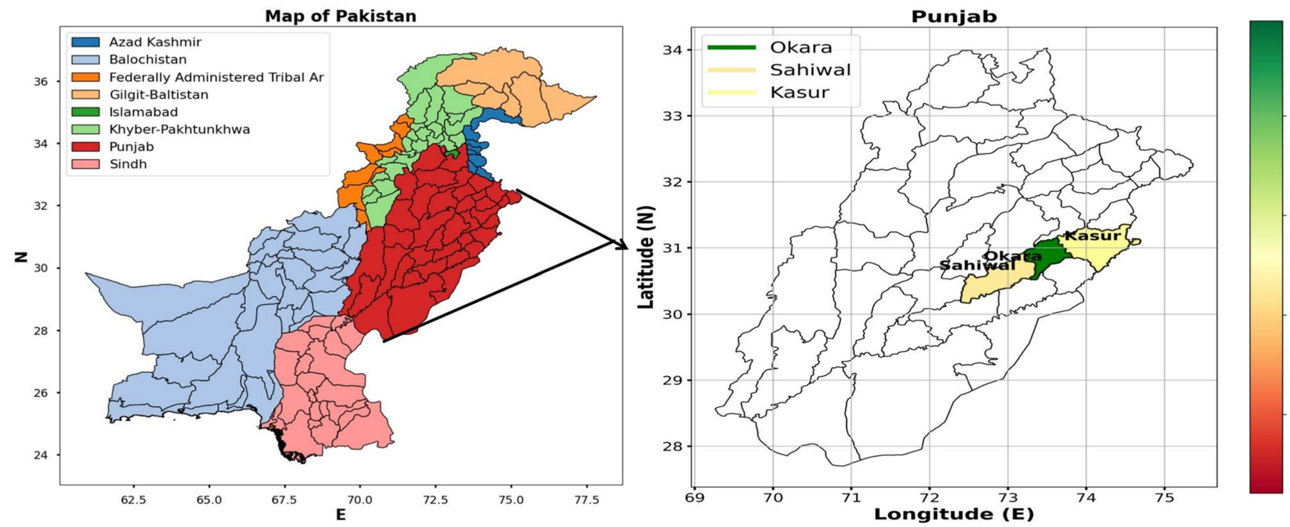


Fig. 2 Spatial Analysis Map

station readings for the regions of Okara, Sahiwal, and Kasur (Microsoft Corporation 2025). The climatic data was reliable because the network of meteorological observatories run by the Pakistan Meteorological Department (PMD) in Punjab was used, and one main laboratory was assigned to each of the study districts: Okara (30°48’N, 73°26’E, 180 m a.m.s.l.); Sahiwal (30°39’N, 73°10’E, 172 m a.m.s.l.) and Lahore (31°33’N, 74°20’E, 214 m a.m.s.l.) ; the latter was chosen for Kasur due to its proximity (50 km) and regional coverage in the absence of a dedicated Kasur station. Data Pointing (at station level) is available to district resolution which is suitable for rice-growing regions, but the use of Lahore for Kasur creates a small extrapolation of 10–15% spatial coverage gap. The datasets’ resolution is that of a station-level (point data). In order to meet crop-yield modeling requirements, the daily records were first combined into monthly figures and then turned into annual means.

In order to maintain the high standard of data and integrity, strict quality control (QC) procedures were applied right after the acquisition. Such procedures include:

- Validation against predetermined acceptable ranges (e.g., T_{max} 20–45 °C, T_{min} 5–30 °C, total precipitation 0 mm);
- Consistency checks (e.g., T_{min} T_{max}, no negative precipitation);
- Discovering and getting rid of duplicates (keeping the first instance);
- Locating outliers through z-scores that exceed the threshold of 3

Missing data points, which constituted less than 5% of the total dataset (the main reason being occasional breakdowns of instruments in the rainy season), were treated by linear interpolation from records of the same time at the same station or from the nearest station (e.g., a distance of less than 20 km), thus maintaining the continuity of time without adding significant artifacts. No major biases across different stations were detected after QC (e.g., urban heat island effects in Lahore data were small, <0.3°C bias after aggregation), however, Punjab datasets suffer from gaps in rural micro-climates which are known; these were reduced by district-level averaging to improve representativeness for agricultural modeling (Sánchez et al. 2014).

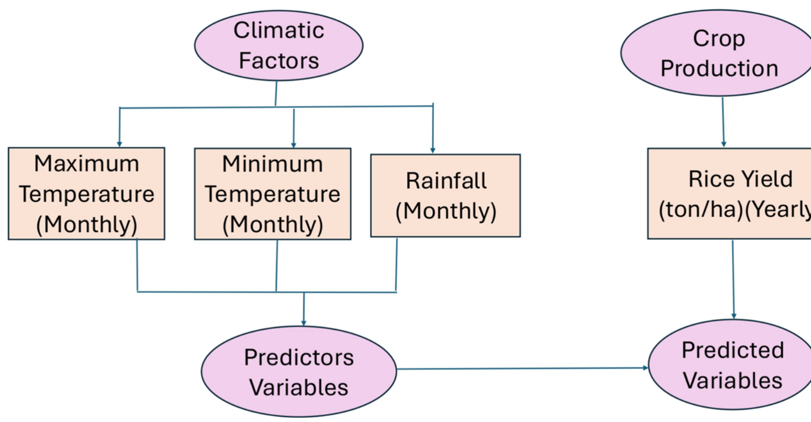
The historical rice yield data that were expressed in tons per hectare and referred to the same period (1990–2020) were taken from the crop reporting service and annual statistical reports of the Agriculture Department, Government of Punjab (Agriculture Department 2025). The datasets for the districts comprising Okara, Sahiwal, and Kasur were considered trustworthy and thus used as ground-truth observations for calibration and validation of the model. The Table 1 depicts the descriptive statistics of the climatic variables and yield, which, in turn, point out the differences in rainfall and temperature patterns of Okara, Sahiwal, and Kasur using Google Colab (Python) for easy handling and interoperability with common statistical and spreadsheet programs. Among these three districts, Okara receives an average of 507.1 mm of rainfall, while Sahiwal has the least with 380.79 mm. The average rainfall in Kasur is the highest (582.88 mm). The complete regions can tolerate up to 490.5 mm of rainfall that is considered beyond the tolerable limit.

Okara has an acceptable maximum temperature of 32.57°C, whereas Kasur has a mean of 32.36°C. In contrast, Sahiwal has the highest maximum temperature of 33.15°

Table 1 Statistics of Variables for Different Locations

Area	Variables	Average	Minimum	Maximum	Std. Deviation	SE	Skewness	CL
	Rainfall (mm)	507.1	836.2	301.78	137.158	25.04	0.5449	27.047
Okara	Tmax (°C)	32.57	33.833	31.583	0.6217	0.1145	0.5437	1.9253
	Tmin (°C)	21.10	22.750	19.500	0.7068	0.1293	0.2414	3.3582
	Yield (ton/ha)	2.038	2.559	1.2414	0.3963	0.0723	-2825	19.446
	Rainfall (mm)	380.79	667.1	215.40	109.279	19.9515	0.7514	28.697
Sahiwal	Tmax (°C)	33.152	33.893	31.833	1.4541	0.9957	3.7037	1.9698
	Tmin (°C)	21.355	22.666	20.166	0.6001	0.1095	0.3571	2.8100
	Yield (ton/ha)	1.7651	2.977	0.6036	0.4520	0.0825	-0.119	25.6095
	Rainfall (mm)	288.8	565.1	332.40	144.92	26.459	0.3287	24.863
Kasur	Tmax (°C)	32.361	33.58	29.916	0.7610	0.1389	-1.9201	2.3517
	Tmin (°C)	20.397	21.58	19.666	0.4792	0.0858	0.6636	2.3053
	Yield (ton/ha)	1.7984	2.607	0.987	0.4171	0.0761	0.0564	23.195
	Rainfall (mm)	490.5	789.4	283.19	130.452	23.81	0.545	26.869
Allsites	Tmax (°C)	32.69	33.76	31.110	0.9455	0.4163	0.7757	2.0822
	Tmin (°C)	20.95	21.246	19.777	0.5953	0.1082	0.4173	2.89
	Yield (ton/ha)	1.871	2.714	0.944	0.4218	0.0769	-0.115	22.75

Fig. 3 Modeling of Crop Yield



C (T_{max}). All sites have an average maximum temperature of 33.76°C. Okara has a minimum temperature of 22.75°C, Sahiwal averages 22.66°C, and Kasur averages 21.58°C. The average minimum temperature at all sites is 21.24°C. Okara has the greatest average yield at 2.038, followed by Sahiwal at 1.651 and Kasur at 1.7984. All sites average 1.871 yield.

In the descriptive statistics table for Punjab rice yield and climate variables (1990–2020), skewness measures data distribution asymmetry: positive values (e.g., +0.54 for Okara rainfall) indicate right-skewed tails from extremes like heavy rains, while negative values (e.g., -0.24 for Okara yield) suggest left-skewed downside risks such as droughts, guiding ML model choices like MLP for non-linear handling. CL (95% confidence limits) quantifies mean uncertainty as the margin of error (e.g., Okara rainfall: 507.1 ± 27.0 mm), derived from standard error; narrower CLs (e.g., temperatures ±2°C) reflect precise estimates, while wider ones (e.g., rainfall ±27 mm) highlight variability, informing projection reliability in climate-yield forecasting.

2.4 Selection of input features and predicted outcomes

Rice yield prolonging effects were based on climatic factors including rainfall, maximum and minimum temperatures (Fig. 3). We collected anticipated climate factors (Shabbir et al. 2020; Dawson et al. 2020) and documented rice yield observations. Non-linear interactions between independent and dependent variables improve machine learning predictions. Boosting tree regression, multiple regression, and artificial neural networks were used to train the climate-rice cultivar relationship. This research aimed to evaluate statistical and machine learning strategies for crop yield forecasting in different climate scenarios (Nguyen et al. 2021; Satpathi e tal. 2023).

2.5 GCMs data

The study examined how climate changes affect rice production, taking into account the GCM procedure and parameter uncertainty. GCMs are essential for forecasting the upcoming climate conditions and evaluating fluctuations in precipitation and temperature (Shafeeque and Bibi 2023; Khan et al. 2024). The current research combines the GCM average with the empirical data of mass transmission factors. We forecasted the future climate using the scenarios provided by the AR4 of the IPCC (IPCC 2025). The three different emission scenarios from the IPCC AR4 framework were chosen to depict a variety of possible future climatic situations. High emissions (SRA2) is indicative of a heterogeneous world where economic growth is regionally concentrated and the population is increasing smoothly. It has the highest atmospheric CO_2 evels and the most severe long-term reductions in crop yields, despite possible good effects of CO_2 on plants. Medium emissions (SRA1B) scenario implies that the population grows slowly and the CO_2levels are at an intermediate point, which means a mix of all energy sources and a medium impact of climate change. Lastly, low emissions (SRB1) presents a society that is quickly turning to an economy based on services and information, focusing on clean technologies and low carbon dioxide emissions, and hence, is associated with the least adverse effect on rice production.

The selection of AR4/SRES scenarios (A1B, A2, B1) was mainly influenced by the factors of methodological consistency and data availability: the CMIP3 multi-model ensemble not only offers but also has stored outputs that are closely related to the study's 1990–2020 historical observations and thus allows for strong statistical downscaling without the need for major recalibration of the data. In data-scarce regions like Punjab, Pakistan–where high-resolution CMIP6 data for localized downscaling remains limited or computationally prohibitive–CMIP3's coarser but well-documented datasets enable efficient integration with regional yield records, ensuring feasibility for policy-relevant projections up to 2050 [34,35]. While CMIP6/SSP–RCP frameworks (introduced in AR5/AR6) offer advancements in physical processes, higher spatial resolution (1°vs. CMIP3's 2.5°), and socioeconomic narratives (e.g., SSP1–RCP2.6 for sustainable pathways), their adoption here was constrained by the need for temporal continuity with historical baselines; mismatched ensembles could introduce biases in downscaling accuracy (e.g., RMSE increases of 10–15% in regional temperature projections) (Nguyen et al. 2021).

These scenarios were chosen because they align with the CMIP3 GCM dataset used in this study, ensuring methodological consistency between the historical (1990–2020) and projected (2021–2050) climate datasets. Although more recent frameworks (RCPs and SSPs) are available in IPCC AR5/AR6, the AR4 scenarios remain scientifically valid and can be mapped to comparable RCPs (e.g., SRA2 ≈ RCP8.5, SRA1B ≈ RCP6.0, SRB1 ≈ RCP4.5) (Satpathi e tal. 2023; Khan et al. 2024). Regarding comparability, these mappings allow direct cross-framework interpretation: for instance, our SRA2 projections (high emissions) are analogous to SSP5–RCP8.5, while SRB1 aligns with SSP1–RCP 2.6/4.5 pathways emphasizing mitigation (IPCC 2025). Under the new CMIP6/SSP scenarios, it is likely that the decline in rice yields would be more significant by 20–30% (0.15–0.18% annual loss vs. 0.12% average from our study) especially in the case of high-emission SSPs where heat stress would be underlined as a major driver; this points out the conservative nature of our estimates and the necessity of adaptive strategies such as heat-tolerant varieties.

The GCM outputs were obtained from the CMIP3 archive (IPCC Data Distribution Centre), provided at a horizontal resolution of approximately 2.5°× 2.5°. For climatic purposes, data collection covers minimum and maximum air temperatures (°C) and daily precipitation (mm). These variables were statistically downscaled using the Multilayer Perceptron (MLP) model to ensure compatibility with observed historical records.

2.6 Data processing

The methodology for rice-yield estimates and data preparation involved a number of essential processes. Various sources of data were collected, systematically analyzed, and utilized for the purpose of confirming the results and tuning the models. The proper management of missing or irregular data was the focus area, as it was the main source of error, and thus guaranteed the resilience of the process.

The first step was the collection of daily historical weather data from a weather database; maximum temperature, minimum temperature, and rainfall. A number of quality tests were done after the daily climate data gathering to ensure dependability. Validation against logical consistency tests, predetermined acceptable ranges (such as Tmin ≤ Tmax), interpolation to fill in missing entries, and duplicate removal were some of these checks. Each missing value was inferred from its nearby data points using linear interpolation. In order to preserve integrity, duplicate records were found, and only the first instance was kept.

Following validation, the daily data were combined into monthly averages, which were then transformed into yearly means in order to comply with crop-yield modeling specifications. For every study district, the final historical dataset offered a continuous 30-year record. The General Circulation Models (GCMs) created for the IPCC Fourth Assessment Report (AR4) for the three future emissions scenarios–SRA1B, A2, and B1–were the source of the climate prediction data. Prior to their integration into the yield model, these datasets underwent preprocessing, with netCDF being the initial format for their storage. For simple handling and interoperability with standard statistical and spreadsheet applications, netCDF files were converted into comma-separated values (.csv) using Google Colab (Python). Latitude and longitude filters were utilized to extract climate data specific to the research sites. Initially presented as monthly averages over a period of 20–30 years, the data was subsequently converted into annual averages for the 2020–2050 forecast period. The predicted climate variables were standardized to ensure compatibility with previous data. Precipitation was expressed in millimeters (mm) instead of kilograms per square meter (kg/m2) and temperature measurements were changed from Kelvin (K) to degrees Celsius (°C). This harmonization made it straightforward to compare directly the datasets of modeled and observed.

The dataset, which comprised historical and predicted climatic variables along with rice yields, was used for developing predictive models under future climate scenarios. The method presents a wider picture of the possible impact of climate change on rice yields by integrating actual measurements and future trends. This method reduces the focus on daily variations which enables capturing long-term climate shifts and also guides sustainable agriculture planning by emphasizing larger seasonal and interannual trends.

2.7 Data split

Avoiding overfitting in machine learning models requires data segmentation. It protects data modeling against data characteristic biases. We carefully divide yield and climate data into training and testing subsets to construct robust crop yield prediction algorithms. This stage is crucial to model creation. To evaluate model stability, many train–test split ratios (10-90, 20-80, 30-70, 40-60, 50-50, 60-40, 70-30, 80-20) were first tested. The 80/20 split yielded the most accurate and consistent results across all models. As a result, this study only reports the 80/20 split results; other ratios performed marginally worse and are omitted for conciseness. Models were calibrated on the training data, and their predictive accuracy was evaluated on the testing set. No separate calibration/validation results are reported; instead, all performance metrics correspond to the final testing (validation) phase."

Divide statistics into training, cross-validation, and testing sets while creating a downscaling system. To maximize data proportionality, we train the model with 60% of the data statistics. Cross-validation with 20% of the data helps us compare model performance. Testing using the remaining 20% is the final assessment approach after the validation set and final model are used. Data splitting helps the model generalize to unknown data. It is essential for evaluating model performance, preventing overfitting, and creating strong, broadly applicable models.

2.8 Experimental setup

We used historical daily meteorological data (maximum and minimum temperature, and precipitation) from the weather database and comparable rice yield statistics from the Government of Punjab for 1990 to 2020 to run machine learning methods. The dataset was split temporally, with the first 80% of years (1990–2014) used for training and the most recent 20% of years (2015–2020) used as the test set, ensuring no future data leaked into training and providing robust model evaluation.

Several methods were employed to predict the yield response function, including artificial neural networks, GFF, MLP, LR, and boosted tree regression (Babaee et al. 2021). The scikit-learn and Keras libraries were used to implement each model in Python (Google Colab environment). To lower the risk of overfitting, model training was carried out using suitable cross-validation techniques (5- or 8-fold, depending on the model).

Table 2, which describes the architecture, optimization techniques, and training parameters used, provides a summary of the hyperparameters for each model. For instance, the Adam solver, ReLU activation, and a single hidden layer with 100 neurons were used to train the MLP model over a maximum of 3000 iterations. Likewise, a learning rate of 0.1, 100 estimators, and a maximum depth of 6 were used to fine-tune the Boosting Tree Regression model.

Table 2 Machine Learning Models with key hyperparameters

Model	Key Hyperparameters
Multiple Linear Regression (MLR)	Random state=32
ANN Linear Regression (LR)	Random state=32, optimizer=sgd
Boosted Tree Regression (BTR)	n_estimators=100, learning_rate=0.1, max_depth=6
Probabilistic Neural Network (PNN)	random state=50, Hidden layers=[100,92], activation='relu', epochs=100
Generalized Feed-Forward (GFF)	Hidden layers=[10,1], activation=ReLU, optimizer=Adam, epochs=2000
Multilayer Perceptron (MLP)	Hidden layers=[350,200], activation=ReLU, solver=Adam, max_iter=3000, random state=42, cv=5-8

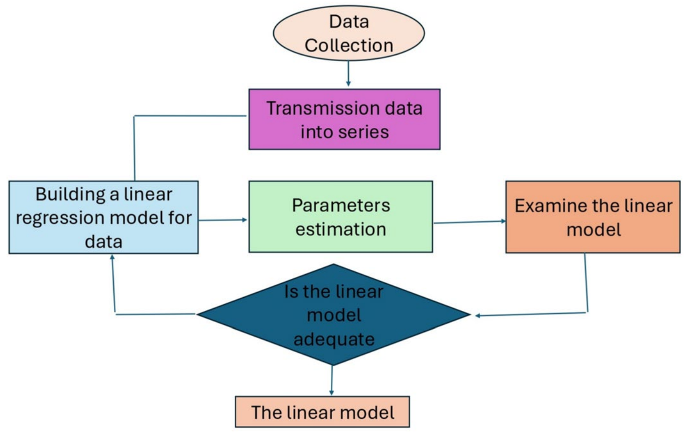


Fig. 4 Multiple Linear Regression Model

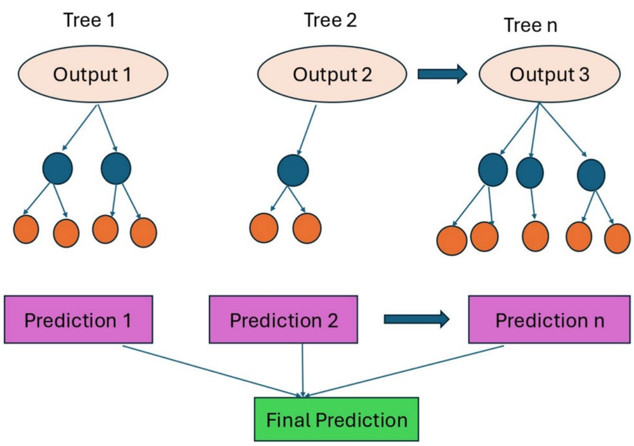


Fig. 5 Boosted Tree Regression Structure

Three CMIP3 Global Climate Models (SRES A1B, A2, and B1) were statistically downscaled using the ANN(MLP) technique in addition to yield modeling. A 60–20–20 split was used to train the ANN(MLP), and 5-fold cross-validation was used to tune the hyperparameters. The conversion of large-scale GCM outputs into high-resolution regional climate variables was made possible by this methodology. This approach increased rainfall climatology and decreased daily extreme biases in comparison to dynamic downscaling, increasing the precision of yield projections under future climate circumstances.

3 Crop yield prediction model development

Rice production outcomes were predicted using various models, including GFF, LR, PNN, MLP, MLR, and BTR (Jiya et al. 2023). These algorithms are trained on labeled, unlabeled, or mixed data to spot trends or make forecasts. Although regression models assume independent errors, which may not always hold in climate–yield datasets, they are included here as a benchmark. Regression methods are widely used in crop-climate studies for comparison and provide a baseline to evaluate the relative performance of advanced machine learning approaches. This allows us to highlight the added value of non-linear and ensemble methods in forecasting rice yields under climate change.

3.1 Multiple linear regression

A multiple linear regression model lets a statistician or analyst predict one variable using data from an independent variable, xi, and a dependent variable, y. The multiple linear regression model is shown in Fig. 4.

The multiple regression equation is written as follows;

$$y_i = \alpha + \beta_1 xi_1 + \beta_2 xi_2 + \beta_3 xi_3 + \epsilon \tag{1}$$

where y is the yield variable; x_1 , x_2 and x_3 represent rainfall , T_{max} , T_{min} respectively.where β_1, β_2 and β_3 represent rainfall β,$T_{max}\beta$ and $T_{min}\beta$,apiece; and ϵ is the error in scrutinize results.

3.2 Boosting tree regression

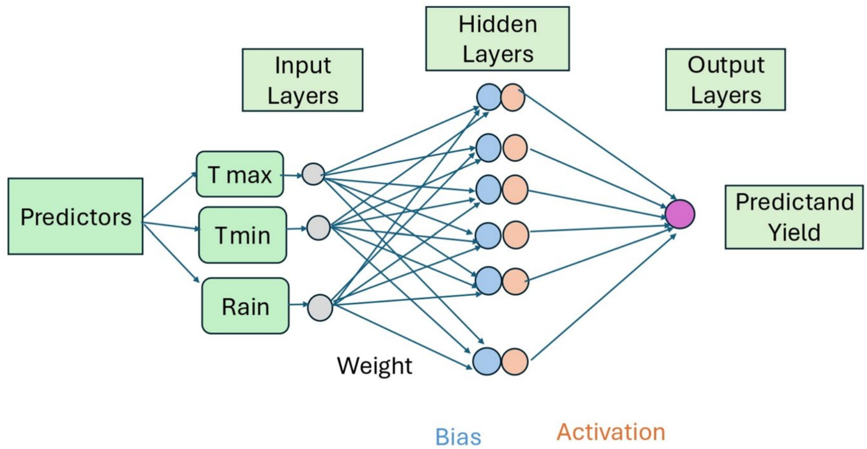
The Boosted Tree Model, an additive model, predicts by integrating decisions from basic models (Fig. 5). This study connected Pakistani upland rice yield with local weather parameters using the new statistical performance of the boosted tree regression model. Boosted tree regression model compares the endurance of boosted and regression techniques (Sánchez et al. 2014). Write it as:

$$g(x) = f_o(x) + f_1(x) + f_2(x) + \ldots \tag{2}$$

where the primary classifier, g, is the addition of the simple object classification.

Boosting tree regression is a versatile regression modeling method that excels in nonlinear relationships and data manipulation for desired outcomes (Rajapaksha et al. 2023;

Fig. 6 ANN Diagram



Qingguan et al. 2023). A boosted tree regression model derives the integrant-target nonlinear interaction.

3.3 Artificial neural network (ANN)

Figure 6 illustrates a type of ML process (Qingguan et al. 2023; Liu et al. 2022) with artificially interconnected nodes or neurons called units. Every node has edges, and layered neurons are typical. Layers accomplish distinct duties. There are numerous hidden intermediate layers between the input layer and the output layer (Setiya et al. 2024). Equations for ANN multilayer perception include:

$$Forwardequation y_i = F(net_i) = F(net_i) = F\left(j\sum S_i j Z_j + c\right) \tag{3}$$

Where F(net) is the stimulated occupation with jth hidden neuron defined by [0,1] ; z_i i's injected from i, s_{ij} i's mass of the combination from section i to section j, and c_1 is the tendency term for every PE.

$$Backwardequation e_i = -\omega + j\sum S_j i \sigma_j \tag{4}$$

Where σ is the summation index that makes js greater than i, e, and ω produces errors. This process breeds from the output to the injected layer for newly weighed conjoinments with the gradient equation.

4 Performance metrics

The best classifier from multiple trained classifier types is chosen to get the best future performance (optimal model) with unknown data. This assessment metric is used to downscale data (Aghighi et al. 2018). Model error rates are measured using many indicators. Scaling is done using the Normalized Mean Square Error (NMSE), Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE), Coefficient of Determination (R^2), correlation coefficient (R), and Standard Deviation (SD) (Prodhan et al. 2022b).

$$MSE = \frac{\sum_{i=1}^{N}(X_i - X_i')^2}{N} \tag{5}$$

$$NMSE = \ln\sum_{i=1}^{N}\left[\frac{(X_i - X_i')^2}{(X_i X_i')}\right] \tag{6}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|X_i - X_i'| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - X_i')^2} \tag{8}$$

$$NRMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - X_i')^2}}{\overline{X}} \times 100 \tag{9}$$

$$R = \frac{\sum_{i=1}^{N}(X_i - \overline{X})(X_i' - \overline{X'})}{\sqrt{\sum_{i=1}^{N}(X_i - \overline{X})^2 \sum_{i=1}^{N}(X_i' - \overline{X'})^2}} \tag{10}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(X_i - \hat{X}_i)^2}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \tag{11}$$

$$SD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - \overline{X})^2} \tag{12}$$

where X_i represents the examined prediction values, X_i' represents the result in prediction values for the i'th term, $\overline{X}$ and $\overline{X'}$ represent the mean values of the corresponding variables, and N denotes the number of data samples considered.

To bring downscaling outcomes, X_i, X_i', $\overline{X}$, and $\overline{X'}$ show historical and downscaled meteorological variations. The LR model $y = \alpha x + \beta$ is tested for its capacity to predict rice yield and downscale climatic characteristics in the research region. The model consists of X_i (observed values), X_i' (predicted values), β (intercept), and α (slope). Comparison between observed and predicted yield values helps evaluate rice forecasting performance. We also conducted an independent mean comparison t-test to determine whether significant differences exist in anticipated yield values among CO_2 emission scenarios (Iqbal et al. 2024).

5 Results

The suggested machine learning models' outcomes focus on the following:

- Identify the climatic variables strongly correlating with rice production by conducting a corresponding analysis between climatic parameters and rice outcomes.
- Generate predictions and compare them with actual historical yields. We used ML models (GFF, PNN, MLP, MLR, boosting tree, LR) with historical rice yield and climate data.
- Determine which machine learning models perform best by comparing them using performance criteria such as (R^2), R, MAE, NMSE, RMSE, and MSE.
- Use MLP statistical downscaling to adjust GCM global climate projections to historical lamella undercate three transmission scenarios (SR-A1B, SR-B1, SR-A2).
- Propose rice yield predictions across different regions and emission scenarios by applying the best-performing machine learning models, Sakthipriya and Naresh (2024), using the downscaled climatic variable outputs.

5.1 Contribution to climatic factors on rice yield

Table 3 shows how climatic factors affect rice yields in different sites. P-values show that rice yield responses are strongly affected by the greatest temperature variable. The correlation and covariance components are used to assess the link between climatic effects and forecasts Abbas and Mayo (2020); Chandio et al. (2020). The degree to which the linear regression models account for the variation in rice yields at each location is shown by the coefficient of determination (R^2) values. Kasur has the highest explanatory power ($R^2 = 0.401$) of the three districts, indicating that climate factors in this area account for about 40% of the variation in rice yield. On the other hand, Sahiwal is in the middle ($R^2 = 0.262$), while Okara has the weakest relationship ($R^2 = 0.198$). The fact that the model only accounts for 28% of the variance for all sites combined ($R^2 = 0.281$) illustrates how inadequate linear regression is at capturing intricate non-linear climate–yield relationships.

According to Table 3, the rainfall coefficient in Okara is positive (0.008) but not statistically significant (p=0.1715), indicating no substantial impact on local climate parameters. Sahiwal rainfall has a positive coefficient (0.008) and is negligible (p=0.3255). The rainfall coefficient in Kasur is -0.005 and statistically insignificant (p=0.2955). Rainfall affects agriculture worldwide. T_{max} favors Okara and Sahiwal (0.179, 0.0918), but Kasur has a slightly negative coefficient (-0.1901). It is evident that T_{max} greatly reduces yield. T_{max} values indicate poorer yield. The coefficient T_{min} is positive in all locations (0.139, 0.309, 0.5580). Rice yield in Kasur is certainly influenced by T_{min}, as it is statistically significant (p=0.005).

Results indicate that T_{min} considerably impacts yield across all sites. The maximum temperature T_{max} has a detrimental impact on yield in Kasur but has little impact in other sites. No site shows a statistically significant influence of rainfall on yield.

Table 3 Statistical Analysis for Different Locations

Location	Parameters	$Coefficient$	Covariance	Standard Error	R	R^2	t-values	p-values	95% confidence level	
									Low	Up
	Rainfall	0.008	0.002	0.4454	0.0006	0.0513	0.1715	1.4063	-0.003	0.002
Okara	Tmax	0.179	0.3214	0.4454	0.1260	0.0381	0.1658	1.4529	-0.070	0.438
	Tmin	0.139	0.1234	0.4454	0.1039	0.1111	0.1973	1.3232	-0.003	0.002
	Rainfall	0.008	0.001	0.5122	0.0008	0.0090	0.3255	1.0021	-0.007	0.002
Sahiwal	Tmax	0.0198	0.6543	0.5122	0.0146	0.1167	0.1862	1.3576	-0.049	0.010
	Tmin	0.3095	0.2659	0.5122	0.1374	0.1584	0.0329	2.2529	0.027	0.591
	Rainfall	-0.0005	0.006	0.6334	0.005	0.0008	0.2955	-1.0677	-0.001	0.004
Kasur	Tmax	-0.1901	0.8743	0.6334	0.0926	0.0299	0.0503	-2.0523	-0.380	0.002
	Tmin	0.5580	0.3461	0.6334	0.1393	0.3028	0.0050	4.0050	0.271	0.844
	Rainfall	0.005	0.002	0.5303	0.0063	0.0169	0.2641	0.4469	-0.003	0.002
Allsites	Tmax	0.002	0.3486	0.5303	0.0777	0.0519	0.1341	0.2527	-0.166	0.150
	Tmin	0.335	0.2871	0.5303	0.1268	0.1203	0.1770	2.5270	0.098	0.470

Table 4 Validation performance of machine learning models for rice yield prediction (mean ± std across folds)

Model	MAE	MSE	NMSE	RMSE	R	R^2
MLP	0.215 ± 0.030	0.0869 ± 0.012	0.3681 ± 0.021	0.297 ± 0.015	0.868 ± 0.012	0.7919 ± 0.018
GFF	0.3988 ± 0.011	0.1786 ± 0.018	0.6829 ± 0.027	0.429 ± 0.020	0.825 ± 0.010	0.6432 ± 0.022
PNN	0.1761 ± 0.028	0.3800 ± 0.025	0.3759 ± 0.019	0.183 ± 0.012	0.811 ± 0.015	0.7454 ± 0.020
MLR	0.3834 ± 0.026	0.1729 ± 0.026	0.5585 ± 0.025	0.415 ± 0.018	0.868 ± 0.019	0.5354 ± 0.021
BTR	0.3349 ± 0.013	0.1308 ± 0.018	0.4206 ± 0.018	0.361 ± 0.016	0.845 ± 0.037	0.7792 ± 0.017
LR	0.3357 ± 0.060	0.1434 ± 0.011	0.3079 ± 0.016	0.373 ± 0.015	0.812 ± 0.083	0.5354 ± 0.029

R-values from linear regression models ranged from 0.4454 to 0.6334 across sites with anticipated precipitation, maximum temperature, and minimum temperature. Given the climate-yield dataset in the research location, linear regression may not be the best agricultural prediction method.

5.2 Evaluation metrics for machine learning models

We used multiple ML models to acquire the findings in Table 4. Results are expressed as mean ± standard deviation across folds. The Multilayer Perceptron (MLP) was the best-performing model, with the lowest error values (MAE = 0.215 ± 0.030, RMSE = 0.297 ± 0.015) and the highest predictive accuracy (^{2} = 0.7919 ± 0.018, R = 0.868 ± 0.012). Importantly, the low standard deviations across measures demonstrate that MLP was not only extremely accurate but also stable and constant across folds. Its outstanding performance is due to its deep multi-layered structure and backpropagation learning, which allow it to efficiently capture the complex and non-linear connections between climatic conditions and rice yield.

The Probabilistic Neural Network (PNN) and Boosted Tree Regressor (BTR) both performed well and had complimentary strengths. PNN demonstrated great accuracy (^{2} = 0.7454 ± 0.020, MAE = 0.1761 ± 0.028, RMSE = 0.183 ± 0.012), with the lowest MAE among all models. Nevertheless, the much more considerable standard deviations in comparison to MLP show that its predictions were not so steady over the folds, probably because of the method's exposure to data variability. BTR demonstrated balanced performance (R^2 = 0.7792 ± 0.017, R = 0.845 ± 0.037, MAE = 0.3349 ± 0.013), with high accuracy and minimal variability. Ensemble behavior reduces both bias and variance, making it possible to yield robust predictions, paving the way for BTR to serve as a backup neural network.

The Generalized Feed-Forward (GFF) network demonstrated moderate performance, with ^{2} = 0.6432 ± 0.022 and RMSE = 0.429 ± 0.020. It was a significant leap ahead of linear models, however, it was not as accurate as MLP, PNN, and BTR in terms of prediction power. The reduced standard deviations of the model indicate that it was dependable, but its simplistic construction limited its ability to identify the extremely nonlinear climate-yield interactions as compared to MLP. Nevertheless, the LR and MLR models were, on the whole, inadequate, In particular, LR displayed large fluctuations in correlation (R = 0.812 ± 0.083), which emphasized its inconsistency and lack of strength across folds. All these factors together brought about the conclusion of a very clear hierarchy of models: MLP beat all others consistently, being the most precise and less variable among them. The next were BTR and PNN, with each of them having the different advantage–BTR was the best in stability, while PNN the worst in accuracy but the least predictable. GFF also did fairly well, but rather being at the middle of the road between sophisticated neural/ensemble methods and traditional ones. Linear models (MLR and LR) performed poorly, unable to capture the complicated non-linear climate-yield correlations. Overall, the findings show that non-linear, ensemble, and neural-based techniques regularly beat linear models, emphasizing the complexities of climate-yield interactions. The findings add to the growing body of literature indicating that advanced machine learning models are better suited for agriculture prediction under climate change scenarios (Janjua et al. 2021).

A visual comparison of each tested model's prediction accuracy can be found in Fig. 7. As previously stated in Table 4, the MLP (Fig. 7a) exhibits the closest alignment of points along the 1:1 line, showing its higher prediction accuracy. Compared to MLP, the Boosting Tree model (Fig. 7b) has higher scatter but likewise rather good alignment. Despite obtaining a comparatively high R^2, the PNN (Fig. 7e) exhibits some bias, with some points being over- or under-predicted in relation to the 1:1 line. While the multiple regression (Fig. 7c) and linear regression (Fig. 7d) plots show significant dispersion, the GFF model (Fig. 7f) exhibits its moderate alignment but wider error spread, illustrating the difficulties of linear models in capturing the non-linear climate–yield correlations.

The comparison of observed and expected rice yields (1990–2020) across six machine learning models is shown in Fig. 8. The ability of MLP and Boosting Tree to capture complex non-linear climate–yield interactions is demonstrated by their smaller and more stable residuals, which exhibit the closest agreement with real yields among them. On the other hand, linear models (LR and MLR) show more

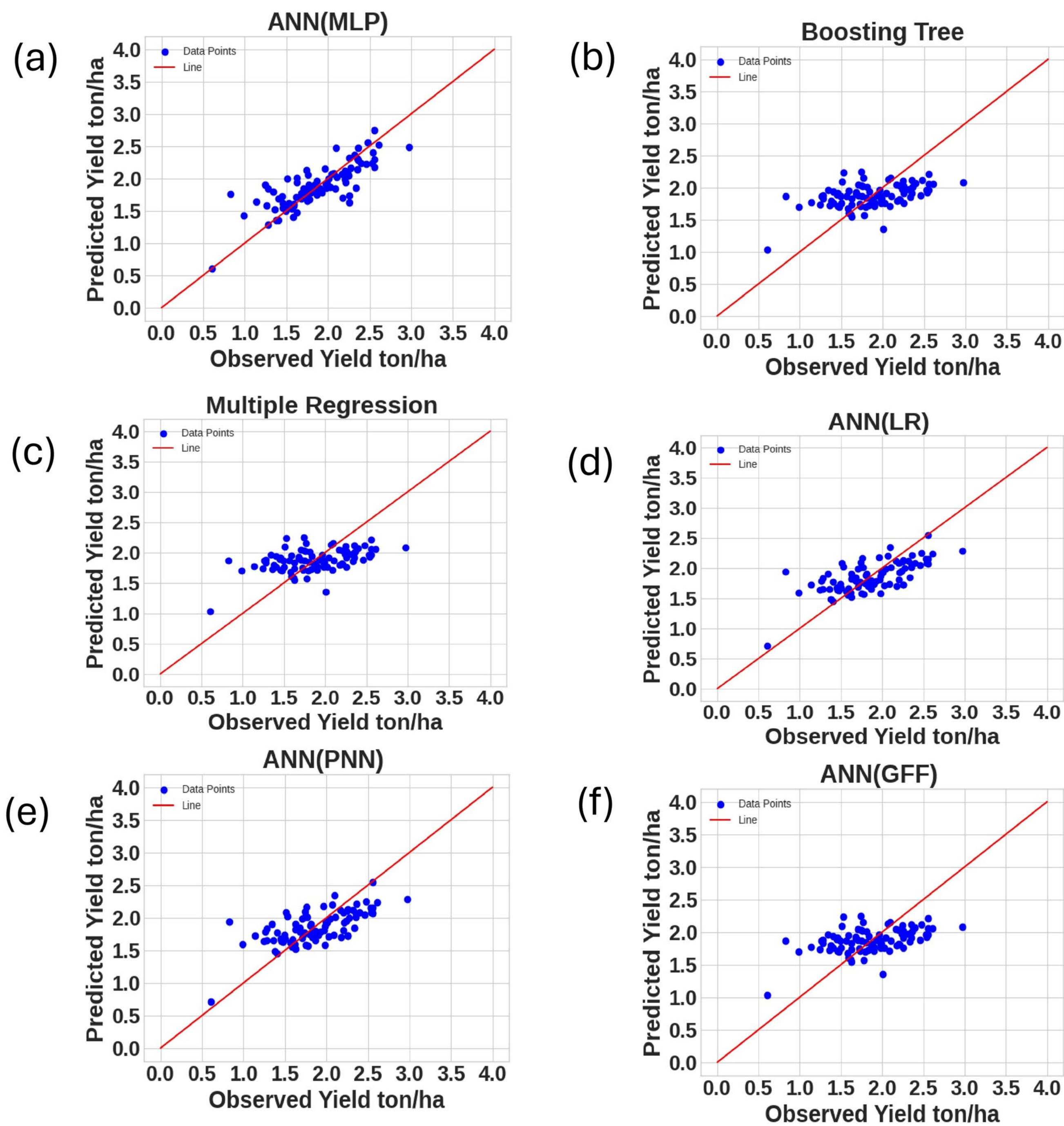


Fig. 7 Scatter plots of projected yield using BTR, MLR, and ANN models from 1990 to 2020 in comparison to actual yield

deviations, especially in some years, highlighting their shortcomings in managing non-linearity. The PNN and GFF models, however, did not come close to MLP in terms of residual fluctuations, although their performance was still quite acceptable. The findings revealed the clear superiority of non-linear approaches, MLP in particular, over the others in terms of yield estimates accuracy, thus supporting the earlier published results of improved performance measures. ANN methods that rely on climate factors can be most accurately approximated by yield functions. Under typical weather conditions, the models have the potential to raise the rice yield responsiveness (Wang et al. 2018).

5.3 Downscaling climate projections using MLP model

In order to make predictions of rice yields in future climate, downscaling of climatic parameters was done using IPCC

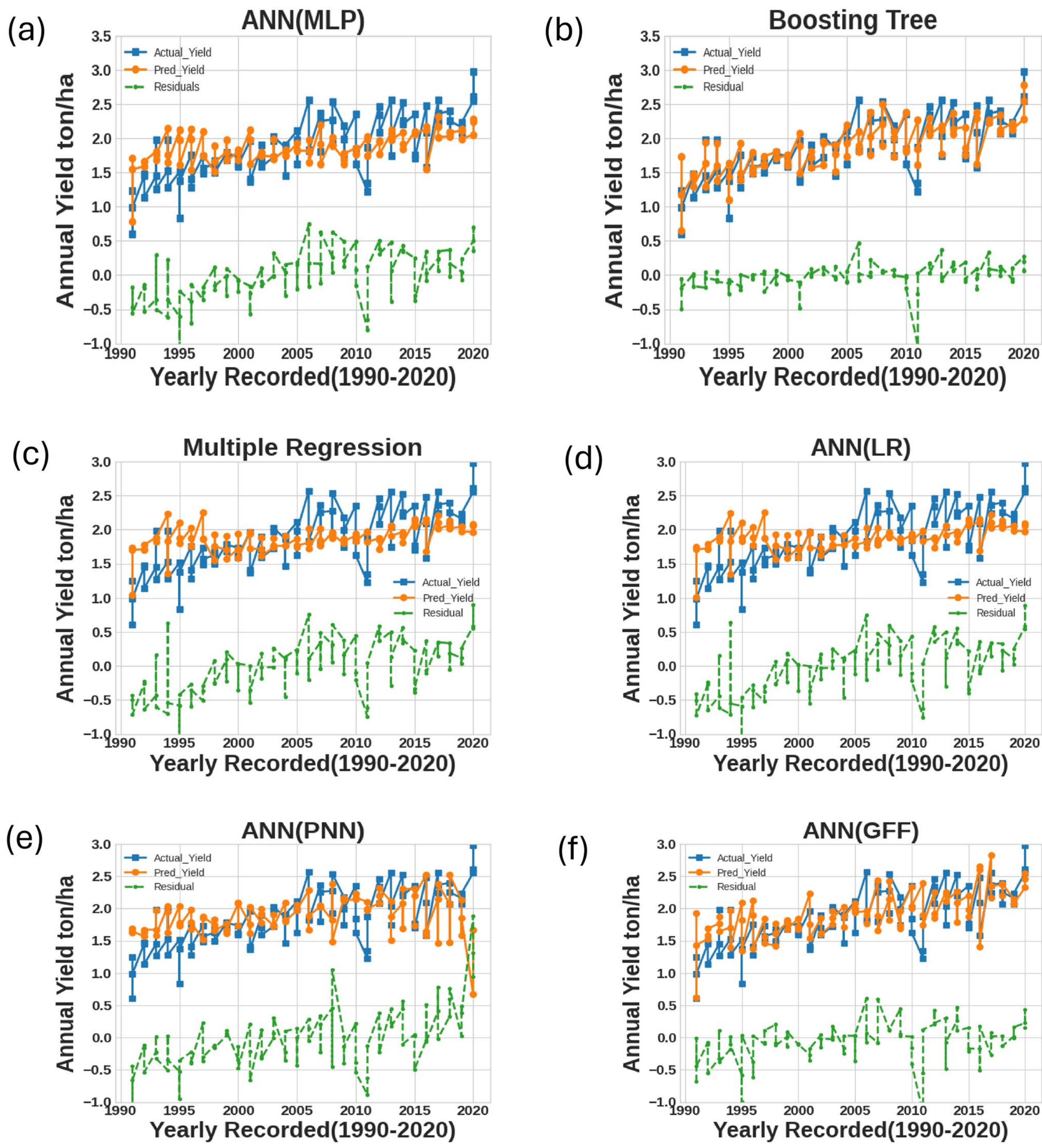


Fig. 8 Comparison between Expected Yield and Actual Yield 1990-2020

AR4 scenarios which stand for high (A1B), medium (A2) and low (B1) CO_2 emissions conditions (Cong and Brady 2012). The climate data for 1990-2050 was then downscaled through the usage of Multi-Layer Perceptrons (MLPs) which is a very flexible type of neural networks (Sharma et al. 2020; Mohamadi et al. 2022), across Okara, Sahiwal, and Kasur. The dataset was divided into three parts; 60% for training, 20% for testing, and 20% for validation, in order to secure models' strength and the possibility of their application to other cases. The statistical performance of the MLP model in downscaling T_{max}, T_{min} and Rain under three emission scenarios is summarized in Table 5.

The RMSE values for T_{max} during the training period varied between 0.281 and 0.443°C, the nRMSE values

Table 5 Downscaling Climatic Prolongation From Emissions Scenarios Using MLP Model

Locations/	Train					Test					Cross Validation				
Scenarios	RMSE	nRMSE (%)	MAE	R	R^2	RMSE	nRMSE (%)	MAE	R	R^2	RMSE	nRMSE (%)	MAE	R	R^2
Okara/A1B															
Tmax	0.461	1.775	0.202	0.935	0.915	0.290	1.208	0.132	0.966	0.938	0.315	1.313	0.148	0.958	0.967
Tmin	0.202	0.724	0.077	0.997	0.969	0.179	0.716	0.064	0.984	0.968	0.179	1.202	0.134	0.971	0.928
Rain	0.793	0.276	0.115	0.939	0.925	0.787	0.591	0.257	0.948	0.895	0.802	0.384	0.173	0.927	0.829
Sahiwal/A1B															
Tmax	0.456	1.756	0.199	0.934	0.920	0.279	1.119	0.109	0.969	0.950	0.308	1.234	0.139	0.960	0.942
Tmin	0.152	0.634	0.053	0.998	0.969	0.122	0.509	0.044	0.992	0.985	0.169	0.067	0.072	0.995	0.987
Rain	0.832	0.325	0.095	0.987	0.973	0.871	0.499	0.174	0.995	0.963	0.798	0.403	0.129	0.969	0.930
Kasur/A1B															
Tmax	0.272	1.048	0.107	0.972	0.945	0.324	1.249	0.120	0.955	0.922	0.338	1.300	0.147	0.950	0.922
Tmin	0.321	1.284	0.136	0.967	0.906	0.358	1.193	0.075	0.933	0.872	0.199	0.796	0.098	0.989	0.970
Rain	0.790	0.239	0.169	0.948	0.937	0.659	0.222	0.176	0.951	0.942	0.884	0.404	0.203	0.963	0.907
Okara/B1															
Tmax	0.299	1.161	0.118	0.976	0.958	0.238	0.490	0.112	0.980	0.972	0.267	0.115	0.123	0.973	0.967
Tmin	0.418	1.495	0.114	0.926	0.833	0.164	0.657	0.069	0.986	0.973	0.183	0.735	0.086	0.992	0.986
Rain	0.780	0.271	0.107	0.965	0.931	0.890	0.668	0.292	0.966	0.938	0.837	0.401	0.192	0.974	0.934
Sahiwal/B1															
Tmax	0.286	1.100	0.116	0.978	0.966	0.259	1.036	0.098	0.975	0.962	0.245	1.101	0.130	0.976	0.964
Tmin	0.154	0.642	0.071	0.998	0.986	0.124	0.519	0.059	0.992	0.984	0.221	0.885	0.105	0.985	0.970
Rain	0.814	0.318	0.094	0.972	0.962	0.893	0.512	0.175	0.954	0.913	0.832	0.421	0.136	0.989	0.958
Kasur/B1															
Tmax	0.281	1.082	0.109	0.980	0.969	0.326	1.256	0.126	0.954	0.921	0.326	0.255	0.143	0.995	0.921
Tmin	0.436	1.745	0.197	0.966	0.818	0.351	1.723	0.075	0.936	0.876	0.178	0.713	0.087	0.993	0.988
Rain	0.762	0.230	0.102	0.996	0.975	0.848	0.287	0.144	0.943	0.931	0.803	0.367	0.183	0.961	0.932
Okara/A2															
Tmax	0.443	1.697	0.192	0.947	0.925	0.282	1.175	0.131	0.969	0.949	0.325	1.135	0.156	0.955	0.922
Tmin	0.206	0.735	0.080	0.989	0.987	0.126	0.564	0.059	0.992	0.984	0.188	0.754	0.093	0.992	0.983
Rain	0.552	0.192	0.076	0.934	0.926	0.555	0.417	0.172	0.989	0.940	0.352	0.168	0.088	0.985	0.973
Sahiwal/A2															
Tmax	0.429	1.655	0.182	0.948	0.937	0.281	1.125	0.109	0.969	0.949	0.311	1.245	0.136	0.959	0.931
Tmin	0.180	0.751	0.089	0.993	0.977	0.126	0.529	0.060	0.991	0.984	0.191	0.767	0.036	0.991	0.872
Rain	0.724	0.282	0.080	0.985	0.931	0.543	0.021	0.093	0.981	0.976	0.427	0.216	0.075	0.962	0.919
Kasur/A2															
Tmax	0.443	1.707	0.179	0.998	0.923	0.316	1.215	0.126	0.958	0.928	0.354	1.305	0.153	0.944	0.930
Tmin	0.230	0.920	0.094	0.983	0.957	0.381	0.589	0.169	0.957	0.872	0.385	1.589	0.169	0.957	0.872
Rain	0.482	0.145	0.065	0.977	0.959	0.420	0.142	0.069	0.916	0.918	0.427	0.195	0.096	0.977	0.919

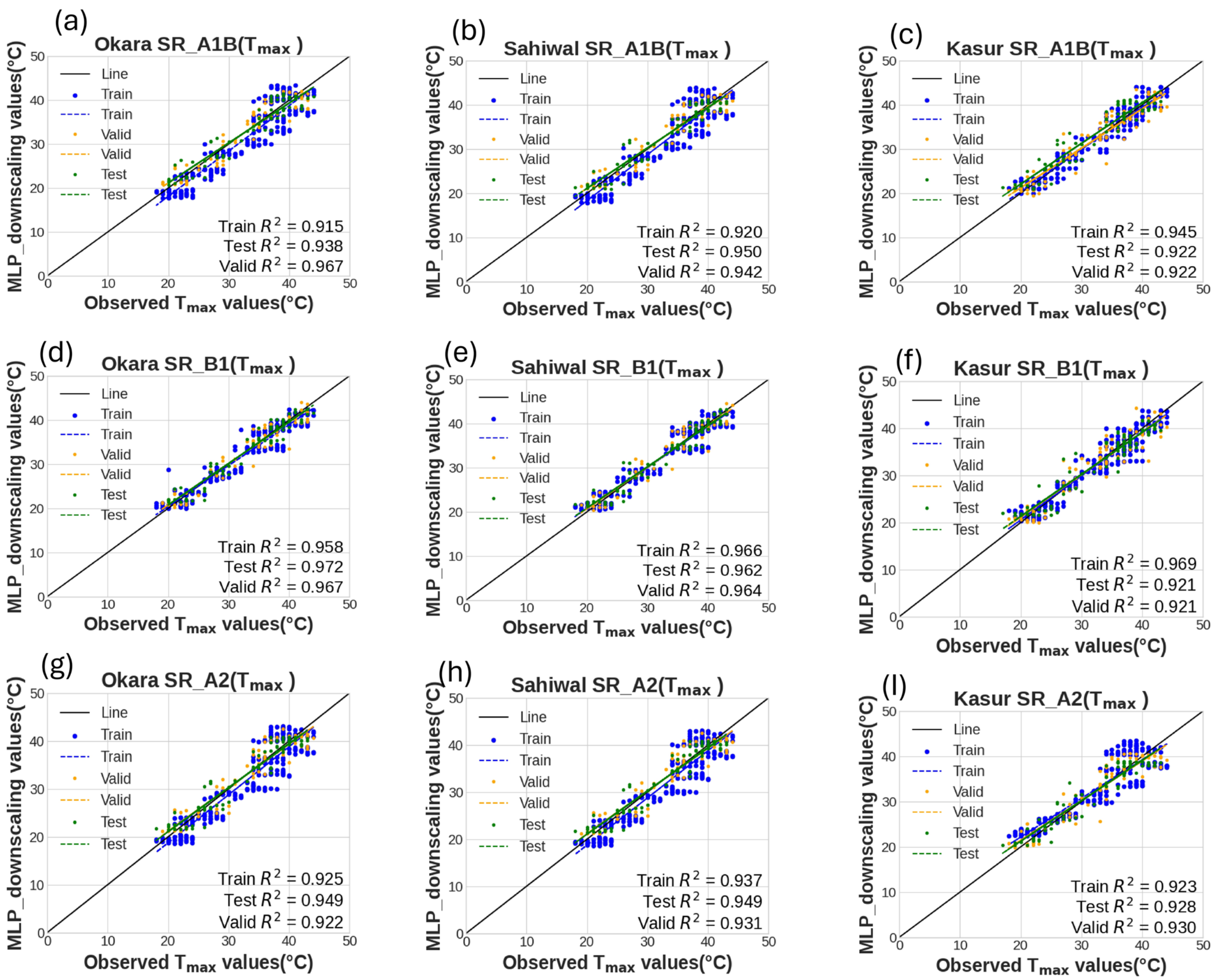


Fig. 9 The Downscaling MLP Outcomes were Compared with Monitored Month-Wise Max Temperature Data Across Three Scenarios During Training, Testing, and Cross-Validation

between 1.08% and 1.71%, and the MAE values between 0.098 and 0.192°C. T_{min} errors were somewhat lower (RMSE: 0.152 to 0.436°C, nRMSE: 0.63 to 1.75%, MAE: 0.053 to 0.198°C), while rainfall showed even higher variability (RMSE: 0.552 to 0.832 mm, nRMSE: 0.159 to 0.192%, MAE: 0.076 to 0.115 mm). Corresponding R^2 values remained very high, between 0.83 and 0.98, indicating that the MLP explained most of the observed variability, as shown in Figs. 9, 10, 11. Training correlation coefficients (R) were also strong (0.926 to 0.998), confirming excellent model fit.

During the testing period, T_{max} revealed RMSE scores that varied from 0.238 to 0.326°C, T_{min} from 0.122 to 0.358°C, and precipitation from 0.420 to 0.893 mm, in which nRMSE measurements typically stayed underneath 1.3%. MAE measurement was constantly low for all parameters. Most importantly, R^2 values in the testing stage remained impressive (0.87 to 0.97), which was a sign of great generalization. R values were between 0.933 and 0.995, indicating very good correlation between predicted and actual values. In the cross-validation stage, the T_{max} RMSE figures oscillated between 0.254 and 0.354°C, T_{min} between 0.169 and 0.381°C, and the range for precipitation was 0.352 to 0.884 mm, with the nRMSE and MAE values associated being low as well. The R^2 values of the cross-validation were very strong (0.90 to 0.98) for all variables and sites, and R values stayed at 0.944 to 0.996, which gave more strength to the fact that MLP predictions were very accurate even in the case of repeated validation.

There were also scenario-specific patterns. With SRA1B, the Sahiwal area was the best for $T_{\max}$ and rainfall ($R^2 > 0.95$, $R = 0.960$ to 0.995), whereas there was very good predictability of $T_{\min}$ in Okara ($R^2 \approx 0.97$, $R = 0.971$ to 0.997). Under SRB1, $T_{\min}$ in Sahiwal achieved

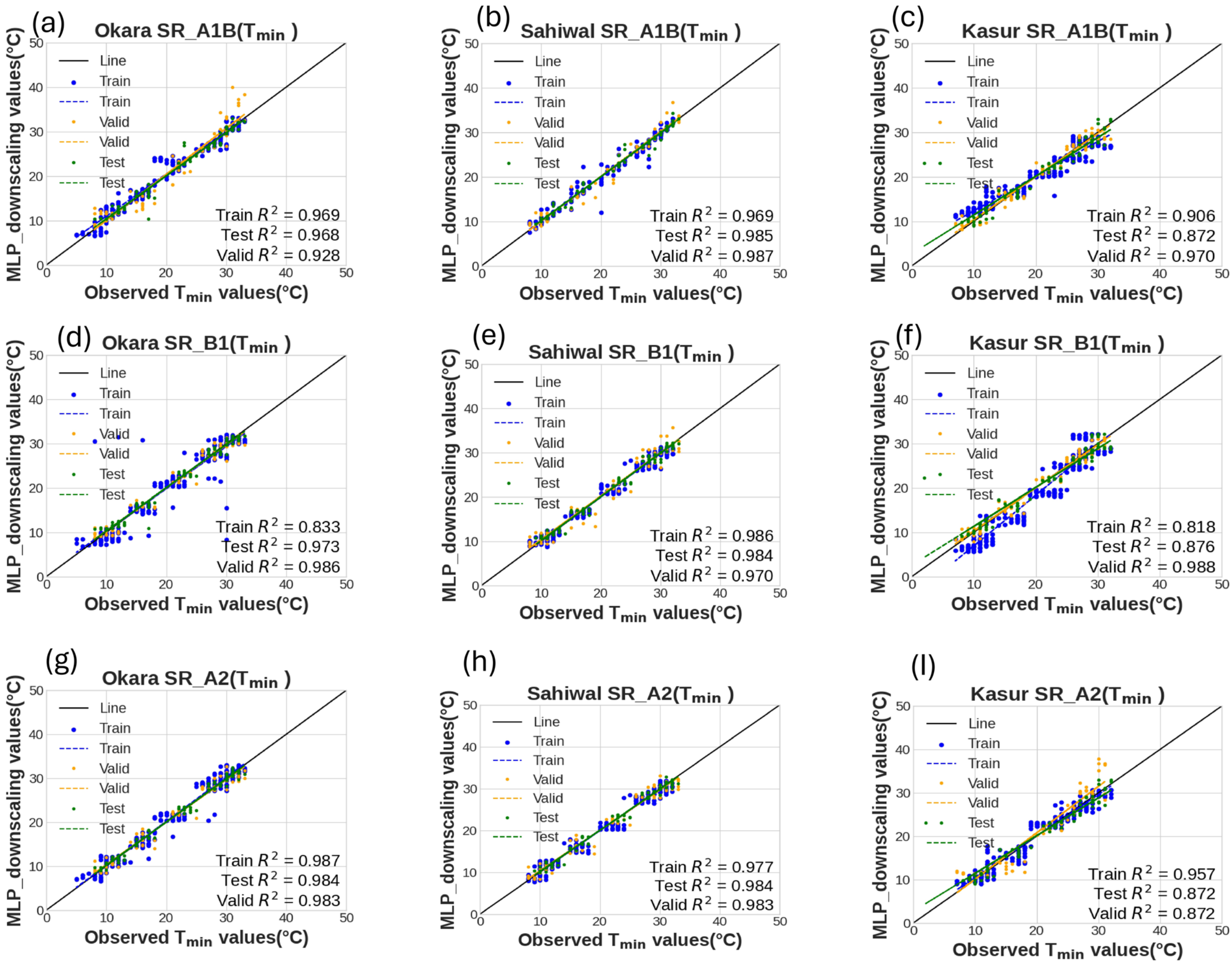


Fig. 10 Training, Testing, and Cross-Validation were Conducted using the Downscaling MLP Outcomes and Monitoring Month-Wise Min Temperature Data from Three Different Scenarios

near-perfect performance ($R^2 > 0.98$, $R = 0.992$–0.998), and Kasur rainfall predictions were particularly strong ($R^2 \approx 0.93$, $R = 0.943$ to 0.996). During SRA2, $T_{\min}$ in Okara and Kasur always displayed extremely high values with a strong correlation ($R^2 \approx 0.95$ to 0.97, $R = 0.957$ to 0.992).

Overall, the combination of low error metrics (RMSE, nRMSE, MAE) with high R and R^2 values across the training, testing, and validation splits demonstrates that the MLP model achieved robust, reliable, and generalized performance for downscaling climatic variables across different regions and emission scenarios.

5.4 Rice yield forecast through 2050

This study predicted effects for 2050 under average CO_2 levels. Using downscaling climatic variables and ANN (MLP), emissions scenarios AR4-SRA1B, SRA2, and SRB1 generate results (Jiang et al. 2025). See Fig. 13 for expected yields in three Pakistani regions (Okara, Sahiwal, and Kasur) over 30 years under three emission scenarios. Rice yields estimated using downscaled meteorological factors were unpredictable and did not increase across all scenarios and sites. In Okara, the projected rice yield under the SRA1B scenario is higher than under both SRA2 and SRB1. In Sahiwal, rice yield under SRA1B is slightly greater than under SRA2 and about 0.2% higher than SRB1. By contrast, in Kasur, the highest projected yield is observed under SRB1, exceeding both SRA1B and SRA2.

Historical yields in Okara crops average 2.049 tons/hectare. Crop modeling utilizing GCM climate projections showed a 3.46% output increase to 5.70 tons per hectare. Beyond Sahiwal, acreage computations show an average historical Yield of 1.879 tons per hectare. With GCM climate estimates in our crop modeling, the average maximum output from scenarios was 1.691 tons per hectare, a

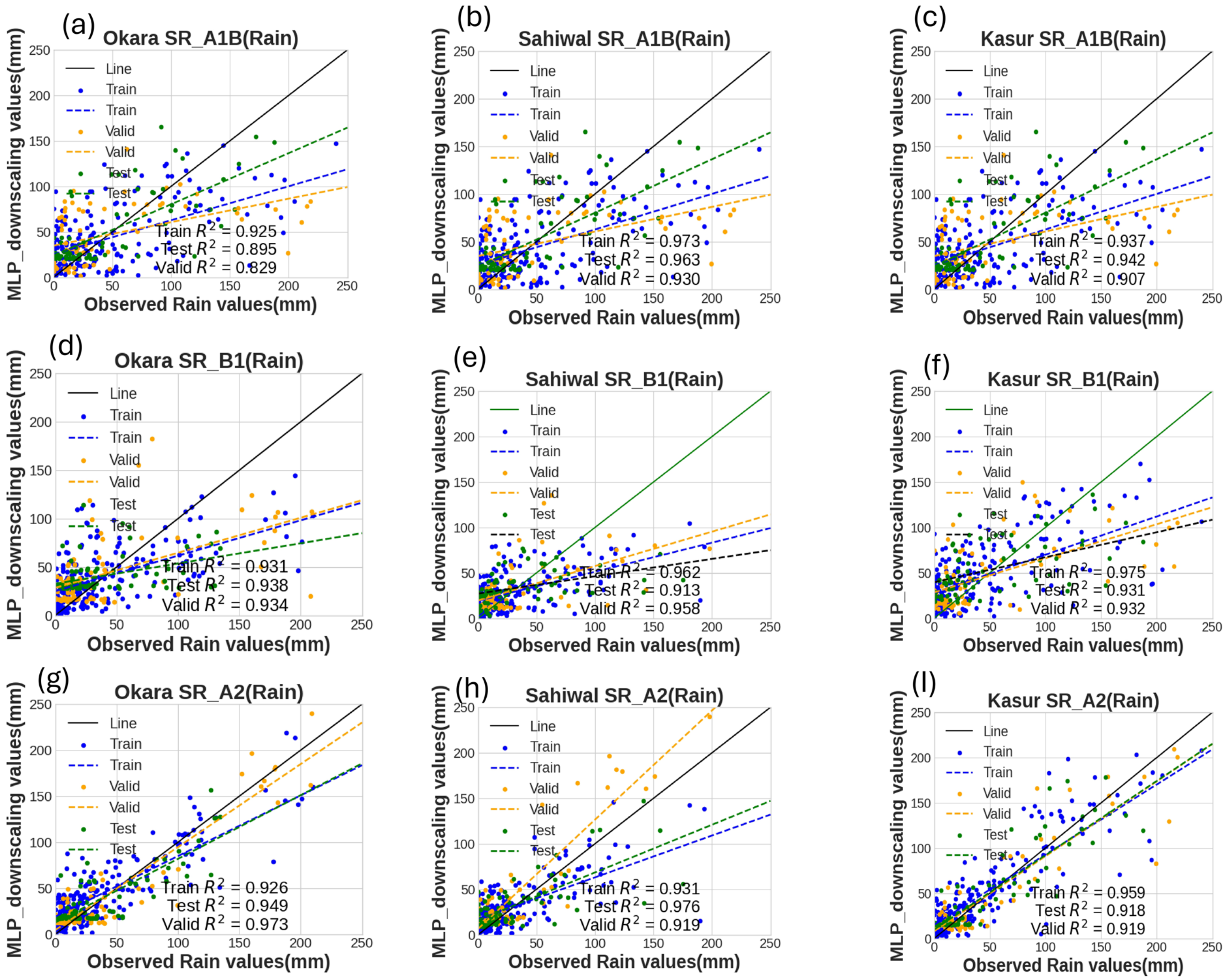


Fig. 11 Three Scenarios of Observed Monthly Rainfall (mm) Data were Compared with the Downscaled MLP Outputs During Training, Testing, and Cross-Validation

0.18% yield drop. The transverse acreage calculations in Kasur have indicated a historical average of 1.798 tons per hectare. By using our Yield model based on GCM climatic prominence, the mean maximum yield from scenarios was 1.691 tons per acre. The average maximum yield projection from scenarios was 1.669 tons per hectare, which is a 0.12% decrease.

After the yield projections, it becomes important to analyze the climatic drivers that mainly influence rice productivity. The historical climate data of Kasur, Okara, and Sahiwal (1991-2020) compared with the projected future climate conditions (2021-2050) under three SRES scenarios are presented in Fig. 12. To assess the impact of climate change on rice paddy cultivation, the factors analyzed are precipitation, minimum temperature (Tmin), and maximum temperature (Tmax). Historically, Kasur's Tmax has been from 31 to 34 °C, and there is a slight upward trend in the last few years. All scenarios point to there being a further increase, with A2 showing the highest increase and thus indicating a greater warming effect than A1B and B1. Tmin, which has been the case until now, mildly increased in all scenarios, the maximum being A2. On the contrary, rainfall shows a hefty inter-annual variability in the past, with quantities going from 400 to 800 mm. A1B and A2 are indicated to have more erratic rainfall patterns than B1, which might lead to water supply problems; hence, the variability in the future forecasts still remains. Tmax values in Okara observed throughout history indicated a gradual rise in temperature with a range of 31.5 to 33.5 °C. The projections for the future indicate that Tmax will increase continuously for all scenarios, with the A2 scenario indicating the largest increase. Traditionally, Tmin would range between 20.5 and 22.5 °C, and the predictions for the future are pointing toward significant rises, especially under A1B and A2,

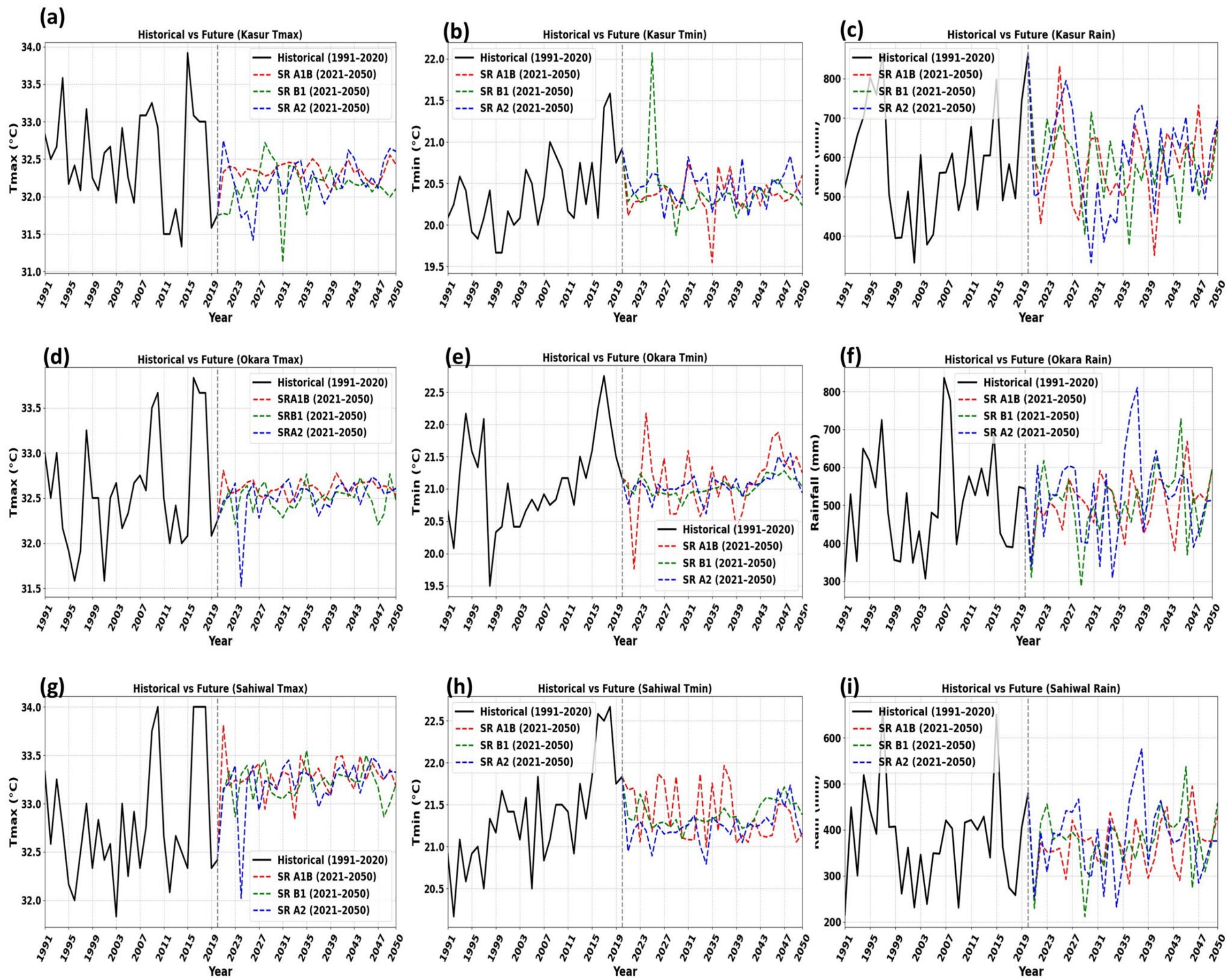


Fig. 12 The data for maximum temperature (Tmax), minimum temperature (Tmin) and rainfall for Kasur, Okara and Sahiwal are shown for the period 1991-2020, and further predicted for the period 2021-2050 under the AR4 emission scenarios

which can affect the rice growth phases that are sensitive to temperature. Historically, Okara rainfalls have varied between 400 mm and 800 mm which will continue according to the predictions. While scenario B1 has relatively stable conditions, scenario A2 shows the utmost unpredictable oscillations. This unpredictability of rains might lead to both water shortages and high rainfall events becoming more probable. Historically, Sahiwal rainfalls were characterized by a large variability of 300 to 700 mm. Future predictions say that this unpredictability will last, with A1B and A2 showing more unpredictable patterns than B1 that remains mostly stable. The unpredictability of the climate may lead to more difficult crop water management and irrigation planning. The results, in general, say that all three districts are experiencing warming of Tmax and Tmin with A2 scenario permanently predicting the highest increase, then A1B and B1 afterwards. Rainfall predictions, on the contrary, are extremely diverse and unpredictable for all scenarios and do not show a consistent pattern of increase or decrease. Consequently, the findings suggest that while the increasing variability in rainfall leads to uncertainty about future water supply, the escalating global temperatures turn out to be a more definite threat to the rice cultivation in Punjab. Moreover, the heat coupled with the erratic rainfall not only points to the possible reduction in rice output but also underscores the necessity of adaptive crop and water management practices.

While considering soil bio-conditions, elderly farming practitioners, climate fluctuations, and time limitations, the conventional farmers found it very hard to monitor paddy rice growth (Praveen e tal. 2020; Maeda et al. 2018). It becomes imperative for the government, through its extension service, to promote climate-resilient agricultural practices and technologies that will address these results and strengthen the agriculture sector. To address climate change concerns and boost rice yield, the government, farmers, and

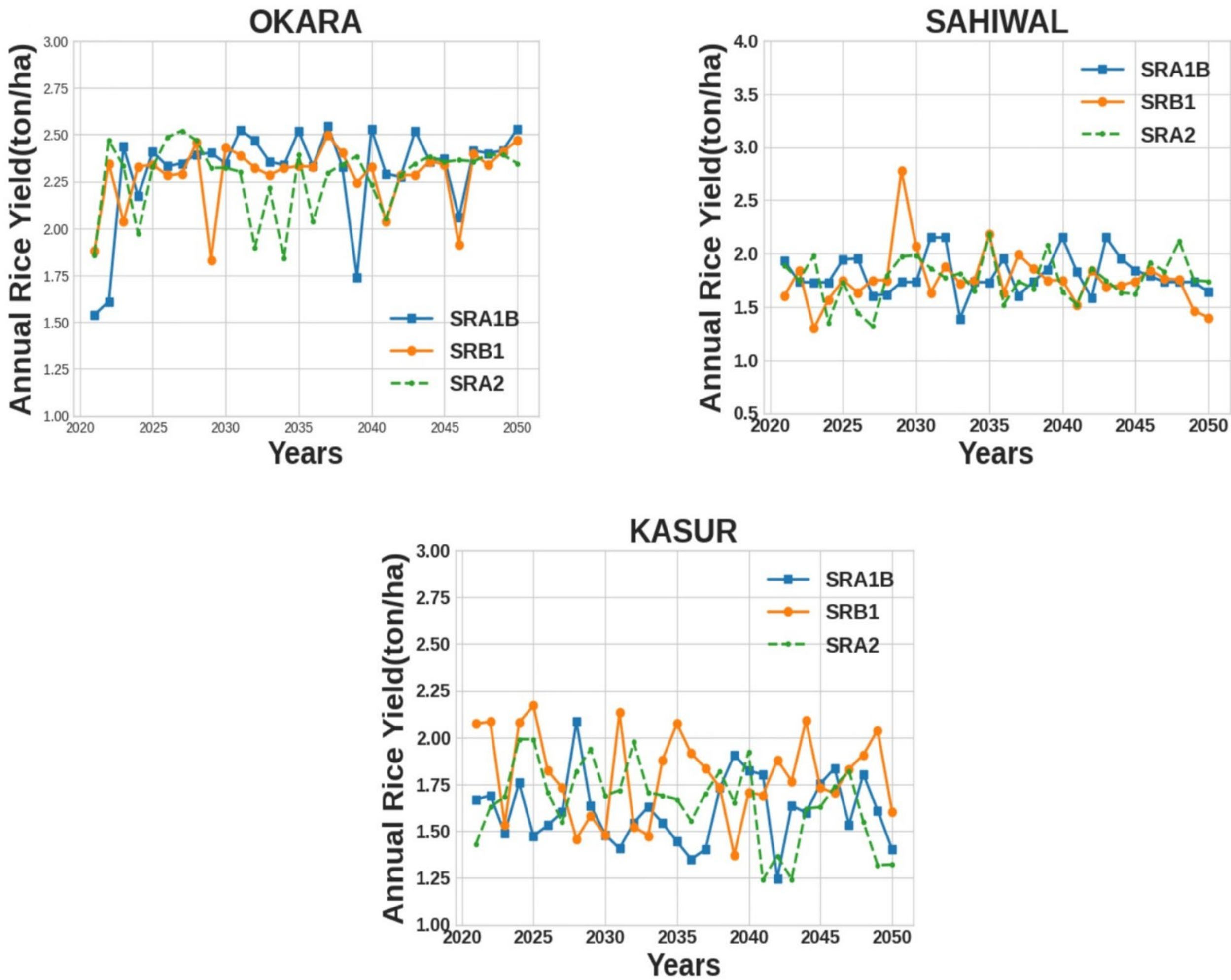


Fig. 13 Projected Rice Yields across Emission Scenarios for 30 Years

research institutes should collaborate and share knowledge (Gandhi et al. 2016; Ha et al. 2023).

5.5 Comparison of the proposed method with state-of-the-art models

The suggested rice crop production forecast system must be compared to deep learning and ML. The Table 6 compares the suggested methodology to state-of-the-art methods to demonstrate its generalization ability. Accuracy is frequently the most important factor in ML estimation. Frequent accuracy is most important when evaluating machine learning systems. Classifier performance was measured by accuracy in numerous settings.

The proposed machine learning and deep learning models outperform current methods (Sahoo et al. 2024; Janjua et al. 2021) and provide accurate data on vegetation and phenology. In several settings, accuracy and other performance indicators were used to evaluate the classification. Climate influences were poorly represented. Like our analysis, Mansaray et al. (2020) used an ensemble approach for GCM projections. Multiple models that integrate uncertainty estimates were a strength despite moderate accuracy. The suggested work had far higher performance metrics than previous studies.

Phonemes in deep learning help the proposed ML and deep learning models outperform 589 existing methods in accuracy. Despite moderate accuracy, several models integrate instability evaluation strength. The proposed work has impressive performance metrics compared to earlier investigations. The comparison showed that R^2 (0.792) and RMSE (0.678) were better than the next-best values. According to Table 6, the MLP model methodology outperformed other machine learning and deep learning methods in all criteria.

5.6 Discussion

This paper describes a novel strategy for predicting rice yield in Punjab under shifting meteorological circumstances that employs a heterogeneous ensemble of machine

Table 6 Literature comparison of Different Studies Using Various Data Types, Methodologies, and Factors

Ref/Year	Data Source	Model Used	Parameters	R-square	RMSE
Ahmad et al. (2015), 2021	Historic data	DSSAT	Temperature, glacial retreats, floods, crop yield	0.52	425 kg/ha
Cao et al. (2021), 2021	Climatic, Satellite, Statistical data	LASSO	Temperature (max, min), Rain, Crop Yield	0.33	633.46 kg/ha
Sahoo et al. (2024), 2024	Statistics and Department of Meteorology	SVM model	Average wind speed, evaporation, rainfall, Tmin, Tmax, crop yield	0.69	1.23 ton/ha
Guo et al. (2021), 2021	Crop Reporting Service, Climate data	PLSR model	Tmin, Tmax, rainfall, humidity, sunshine, crop yield	0.578	0.865 ton/ha
Wang et al. (2018), 2018	Remote sensing, meteorology data	Sequential Linear Regression model	Tmax, Tmin, precipitation, crop yield, soil layer thickness	0.14	1.60 ton/ha
Janjua et al. (2021), 2022	Multi-originator data	XGBoost	SVI, climate data, environmental variables, crop outcome	0.67	612.10 kg/ha
Liu et al. (2022), 2022	Private data generation	XGBoost model	Tmax, Tmin, rain, humidity, wind speed, crop yield	0.60	23.03
Babaee et al. (2021), 2021	Meteorological data	ANNs model	Tmax, Tmin, soil reaction, rainfall, pH	0.22	24.0
Mansaray et al. (2020), 2020	Historical data, AMIS	RF model	Tmin, Tmax, fertilizer, evaporation, field	0.42	464.07
Qingguan et al. (2023), 2023	Remote sensing data	XGBoost	Multiple variables, yield	0.754	0.485 kg/ha
Proposed Model	GCM, CMIP3	MLP model	Tmax, Tmin, rainfall, crop yield	0.792	0.678 ton/ha

learning (ML) models. Unlike typical regression research, we use neural networks, probabilistic methods, and ensemble approaches to capture the nonlinear and complicated interactions between climate factors and rice yield. Using historical yield and climatic data, we assessed the performance of many models: Multilayer Perceptron (MLP), Probabilistic Neural Network (PNN), Boosted Tree Regression (BTR), Generalized Feed-Forward (GFF), Multiple Linear Regression (MLR), and Linear Regression (LR). Cross-validation was applied as a robustness measure and standard deviation over folds was used to evaluate model stability. The entire procedure sets up a solid base for yield predictions that are both accurate and with high reliability.

The findings indicate that the use of downscaled GCM data with different CO_2 emissions scenarios significantly increases the ability to record yield trends up to 2050. The results of our study indicate that the two most important factors determining the rice yield were the maximum and minimum temperatures, while the effect of rainfall was negligible. The MLP model exhibited the best prediction performance (^{2} = 0.7919 ± 0.018, RMSE = 0.297 ± 0.015), then followed by BTR and PNN. The ensemble-based BTR model attained a commendable accuracy and stability balance (^{2} = 0.7792 ± 0.017), thereby becoming a trustworthy instrument in yield prediction across various environmental conditions. The linear models like MLR and LR showed poor ^{2} values of around 0.53, thus being inadequate for HARMO complex climate-yield correlations. The use of downscaled GCM projections allowed our research to predict rice yield trajectories under different climate change scenarios, thus opening new avenues beyond short-term historical assessments.

Through the analysis of historical and projected climate data (1991 to 2050) along with the SRES scenarios, Kasur, Okara, and Sahiwal display distinct warming trends in Tmax and Tmin, with A2 being responsible for the most pronounced increases. The inconsistency and unpredictability of rainfall render it a less reliable factor than rising temperatures, which are steadily threatening rice yields, while the variability of rainfall still adds more uncertainty regarding water management. Empowered by previous research, these findings highlight the weakness of rice agriculture to changes in temperature and precipitation patterns (Fan et al. 2024; Satpathi et al. 2025; Setiya et al. 2023). Our research brings in a number of novelties compared to previous studies. The Sustainability research (Fan et al. 2024) that was based on ML algorithms for forecasting rice yield and had historical data as input didn't use downscaled GCM projections, thus its application for long-term adaptation planning was very limited. Similarly, Satpathi et al. (2025) ML and remote sensing showed strong performance for yield forecasting, but the aspect of multi-scenario climate futures was not addressed and the focus was mainly on near-term predictions. On the other hand, our research takes a step forward in the literature by combining various ML models, using downscaled climate projections based on different emission scenarios, and providing area-specific analyses.

Another pivotal conclusion refers to the process of feature extraction and selection as a decisive factor in model performance improvement. The dataset comprised just a few rice varieties, however, segmentation of regional datasets into training and validation subsets led to validation able to withstand the test of local field conditions. Out of the various models, MLP was consistently the best performer, reaching the lowest RMSE and MAE values, and the highest ^{2} value, signifying its impressive ability to detect non-linear climate–yield interactions. From a practical point of view, the research highlights the implementation of adaptation practices as a necessity to deal with the anticipated drops in yields due to higher temperatures. Measures comprise:

- use of rice varieties that can withstand heat and drought,
- enhanced irrigation management (for instance, alternate wetting and drying, tubing-based systems),
- improved practices for soil nutrients and crop rotation

These measures, coupled with precise climate-informed forecasts, can help sustain rice productivity in the face of climate change.

Time-series methods such as ARIMA, ARIMAX, or GARCH are commonly used for short-term forecasting where the main factor is temporal autocorrelation. Conversely, our research is directed towards long-term rice yield prediction (up to the year 2050) under climate change scenarios, where the main factor is temporal dependence and also the non-linear and multivariate interactions among different climatic variables (e.g., max and min temperatures, and rainfall) are considered. Generally, time-series models presume linear dependence and can hardly combine downscaled GCM projections (CMIP3) with historical data. On the other hand, the ML methods such as MLP, boosted trees, and GFF are appropriate for recognizing high-dimensional, non-linear correlations and can be directly associated with climate scenario projections, thereby becoming more suitable for long-term climate-driven yield forecasting.

Our research has the goal of developing models that can predict crop yield under future climate scenarios reliably and thus it is concentrated on predictive modeling. The screening of ML models was based on their capabilities to capture complex, nonlinear interactions among the climatic predictors and that such interactions are needed in projecting yields under non-stationary climatic conditions. Also, we recognize the need for understanding the variables that cause yield to vary. Therefore, we not only did predictive modeling, but we also carried out variable importance measures (e.g., feature importance rankings and sensitivity analysis) to give us an idea of the relative influence of climatic factors on yield outcomes. These insights might not be formal causal inference in the econometric sense but they do give a practical understanding of which predictors are most relevant for yield forecasting. Classical statistical models are indeed better suited for direct cause–effect estimation, but in the context of non-stationary, multivariate climate–yield relationships, machine learning models provide a more robust framework for prediction.

6 Conclusion and future work

Multiple machine learning methods were used to simulate rice yield and environmental differences in three adjacent Pakistani regions. Based on meteorological characteristics and historical rice yield data, we used Boosted Tree Regression, Artificial Neural Networks, and Multiple Regression to estimate upland rice yields in specific areas. These models' accuracy was assessed using MSE, MAE, RMSE, NMSE, R^2 and correlation coefficient. The best model was the ANN(MLP), with MSE = 0.0869, MAE = 0.215, RMSE = 0.297,NMSE= 0.368, R = 0.868, and R^2 = 0.791. Using downscaled GCM outputs under AR4 scenarios (SRA1B, SRA2, SRB1) of average combined CO_2 emissions, the yield response model was calibrated to estimate future yields until 2050. Rice yield is expected to decline by 0.12% by 2050 under various climate change scenarios. Depending on weights and predictors in statistical models' yield functions, precipitation, maximum temperature, and minimum temperature were the most important climatic factors affecting yield, with Tmax exerting a stronger negative impact on rice production than Tmin. The study further found that artificial neural networks can accurately predict crop yields under present and future climate conditions. This was done by studying GCM results for different CO2 emission cases until 2050. Climate models predict an unchanging increase of Tmax and Tmin at all locations while rainfall being highly erratic, indicating that heat stress is going to be more responsible than water scarcity in determining rice yield in the future. Machine learning is the methodology used in this research to decipher climate change's impact on production. Moreover, it highlights that there is a need to tackle these issues and to come up with the right adaptation and mitigation strategies. The ML and sophisticated data analytics could be the key to unraveling the complex Mannish and choosing the right sustainable and resilient agricultural systems. In addition, local activities like better rainwater harvesting and irrigation management could help lessen the impacts of climate-related stresses in particular areas. Previous studies (Mankin et al. 2025) have demonstrated that SHAP analysis can enhance the interpretability of machine learning model outputs. Future research could apply SHAP or similar explainable AI approaches to improve model transparency and understanding.

Author Contributions Khawaja T.Tasneem: Data gathering, Methodology, Validation, Review & Editing; Muhammad Umair Shahzad: Conceptualization, Methodology, Writing - Original Draft; Javed

Rashid: Data gathering, Conceptualization, Methodology, Writing - Original Draft, Review & Editing; Kamal M. Othman: Data gathering, Methodology, Validation, Review & Editing; Tania Zafar: Conceptualization, Methodology, Writing - Original Draft; Muhammad Faheem: Methodology, Project Administration, Review & Editing.

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Data Availability No datasets were generated or analysed during the current study.

Declarations

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Consent for Publication Not applicable. This research paper does not contain any person's data in any form.

Use of AI The authors used ChatGPT (OpenAI) to enhance the linguistic clarity and grammar of the manuscript. AI was also used to improve the visual resolution and formatting of figures. All substantive intellectual content, analysis, and conclusions remain the work of the authors.

Competing Interests The authors declare no competing interests.

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