Forecasting Climate Extremes-A Data Driven Approach

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Abstract: **Climate extremes such as heavy rainfall, droughts, and heatwaves pose an increased risk to human life, agriculture, buildings, and nature. Currently Pakistan relies on traditional statistical models that are built on limited station-level data, while machine-learning-based forecasts remain underutilized. The objective of this paper is to introduce a provincial-based approach for accurate and precise short-term extreme weather forecasts adapted to the unique climatic conditions of Pakistan. The research uses the Extreme Gradient Boosting algorithm along with 25 years of historical weather data of Pakistan retrieved from Numerical Weather Prediction models, specifically, GFS—Global Forecast System and ICON—Icosahedral Nonhydrostatic Model, in improving the prediction of heatwaves, droughts, and heavy rainfall events. The models showed excellent performance in identifying heatwaves, classifying droughts, and identifying rainfall severity. The results show the potential of refining data from physics-based weather models with machine learning models to significantly improve forecasts of climate extremes, filling a vital gap in Pakistan's weather prediction landscape. This approach would prove beneficial to emergency management agencies in disaster preparedness and response as well as to the general public to make better decisions.**

Keywords: **Climate extremes prediction, Machine Learning, XGBoost, Pakistan Climate, Heatwave prediction, Drought classification, Rainfall prediction.**

I. INTRODUCTION

Rapid climate change has increased the frequency and severity of extreme weather events, such as heavy rainfall, droughts, and heatwaves. These climate extremes are a mounting threat to ecosystems and human life, especially in developing countries like Pakistan. Pakistan is currently vulnerable because its current climate prediction systems lack the spatial and temporal resolution necessary to make timely and highly localized predictions. Consequently, disaster risk reduction efforts are hampered at both regional and national levels.

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Traditional climate models, despite being valuable at larger scales, are not able to capture the spatial detail and deliver early warnings needed for forecasts capable of actual decision-making. This study, "Forecasting Climate Extremes: A Data-Driven Approach", addresses these limitations by exploring the use of Machine Learning (ML) approaches to improve the accuracy, reliability, and responsiveness of climate forecast systems currently used in Pakistan. The main aim of this study is to design an ML-driven prediction system that can predict extreme climate events such as heavy rainfall, droughts, and heatwaves. The study utilizes both real-time and historical weather data from APIs of Open-Meteo [1] and supporting insights from OpenWeather [2], and Pakistan Meteorological Department (PMD) [3], utilizing XGBoost [4] algorithm along with engineered meteorological features to detect intricate patterns and early warnings for risk that conventional models may skip.

The system is evaluated in terms of classification reports, confusion matrices, and F1-scores, considering the detection of rare yet high-impactful events. Fostering more reliable and highly localized forecasting, this study has relevance for disaster risk management, climate resilience-building, and strategic planning in some of the most climate-vulnerable parts of Pakistan. Moreover, the developed model is incorporated into a web-based service, which increases the accessibility and practical usefulness for users such as the government, NGOs, and general public.

II. BACKGROUND RESEARCH

A. Heavy Rainfall Prediction

Heavy rainfall prediction is important for disaster management and agriculture planning. For a long time, traditional statistical methods such as Multiple Linear Regression (MLR) and Auto-Regressive Integrated Moving Average (ARIMA), have been implemented for this purpose. MLR linearizes relation between climatic factors while ARIMA encapsulates temporal dependencies in time-series. However, both models often fail to capture the non-linear and chaotic behavior implicit in meteorological phenomena, especially during extreme events [5].

These traditional models have been gradually replaced by machine learning (ML) methods, including Support Vector Machines (SVM), k-Nearest Neighbors (k-NN) and Decision Trees (DT), because of their capability of modeling non-linear patterns. Studies show that ML models outperformed traditional models when trained on large and complex data [6]. However, a number of these models are still challenged when it comes to scaling for high-dimensional datasets, or extreme rainfall conditions. Deep learning has made recent progress in further improving predictive capabilities. Long Short-Term Memory (LSTM) [7] networks have been successful for time-series prediction task due to the ability to capture long- and short-term dependencies [8]. Convolutional Neural Networks (CNNs), particularly when paired with LSTM layers, have been used to improve spatial-temporal modeling and reduce errors in rainfall forecasts [9].

But these models are generally less flexible to apply in the context of different regional areas. They are often trained for specific geographical areas and have trouble generalizing. Furthermore, difficulties persist in integrating real-time data for events such as flash floods [10]. Our study bridges this gap by introducing a machine learning-based climate prediction system tailored to the diverse climatic regions of Pakistan. We tested LSTM, Random Forest (RF) [11] and XGBoost models, and finally chose XGBoost because it performed best on structured or tabular weather datasets [12]. Unlike most previous work that focus on a single region or city, our system is deployed across all provinces of Pakistan, accounting for local climatic variability.

B. Drought Prediction

Droughts can pose extreme challenges to agriculture, ecosystems, and water supplies. Traditional drought indices like as Standardized Precipitation Index (SPI) and Effective Reconnaissance Drought Index (eRDI) are based on the input of historical precipitation and temperature data [13]. These indices are useful for long-term trend monitoring but lack the resolution for short-term prediction and rapid rise events [14].

ML techniques such as Support Vector Regression (SVR) and RF, have been employed to enhance drought forecasting. RF can especially process a huge amount of data and can capture complex interactions between climatic variables [15, 16]. Hybrid and ensemble models have been developed due to limitations of standalone algorithms. For instance, in the Southern Baluchestan basin located in Iran, hybrid models comprising the Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and SVR with optimization methods including the Marine Predators Algorithm (MPA) have been effectively used [17]. Likewise, ensemble methods, like the Voting Regressors and AdaBoost are shown to achieve better accuracy in areas, including Morocco [18].

A further limitation in existing literature is the region-specific design of models, which hinders generalization. Besides, there is lack of real-time, sensor-based drought forecasting systems as well. In our study, the prediction of drought is considered as a component of integrated approach to predict extreme climate events over Pakistan. By deploying XGBoost models across all provinces and incorporating high-resolution meteorological inputs, our system offers both spatial coverage and temporal adaptability. By using lagged features as well as non-linear associations, more robust early warning signals of drought emergence are obtained.

C. Heatwave Prediction

Heatwaves – prolonged periods of abnormally high temperatures – have become more frequent due to climate change. Traditional forecasting techniques like Autoregressive Moving Average (ARMA) models analyze historical temperature patterns but fail to capture complex antecedents of heatwaves, such as human activities and feedback mechanisms [19].

ML algorithms based on temperature, humidity, and pressure information such as SVM, DT, and Neural Networks have shown some potential but are limited by data quality and the irregularity of heatwave occurrences [20]. The temporal and spatial modeling of heatwave prediction has been facilitated by deep learning models, especially LSTM and CNN. Hybrid approaches like Principal Component Analysis (PCA) combined with ARMA have been also tried in some studies to enhance performance [21].

Existing models often overlook the role of man-made factors, such as urbanization, and there are few specifically developed for developing countries with range of climate regimes such as in Pakistan. Our system predicts heatwave events using engineered features of lagged temperature, humidity, and pressure—factors shown to be influential in our feature importance analysis. The deployment across multiple provinces ensures adaptability to regional microclimates.

III. METHODOLOGY

A. Data Acquisition

To train the selected models, the dataset comprising approximately 4680 grid points was collected for Pakistan across multiple provinces. The dataset consisted of historic hourly and daily weather data from the year 2000 to 2024 using Historical Weather API from Open-Meteo [1], which provides reanalysis outputs based on the ERA5 and ERA5-Land datasets at a resolution of 31 km and 9 km respectively [22]. The parameters were selected based on their relevance, which include variables such as temperature, precipitation, humidity, dew point, rain, wind speed, evapotranspiration, and soil moisture. Similar parameters selection was used in previous studies [23], which confirms the relevance of these features for training the models.

The data collected was stored in separate comma-separated files (CSV) for each grid and later combined into Apache Parquet format. This format optimizes compression and is particularly efficient in large-scale data processing [24].

B. Data Preprocessing

Prior to model training, it is important that the dataset is thoroughly cleaned and validated to ensure quality and credibility, which improves models' accuracy and reliability [25]. With python libraries—pandas, NumPy and Matplotlib, missing values in the data were observed. To ensure accuracy, the mean of the corresponding column was used to replace the missing values as described in [26]. Redundant rows were detected and eliminated. Data types of the columns were adjusted, for the date columns, they were converted to datetime and made sure that the numerical columns were cast accordingly to float64 or int64. Outliers were identified by the Inter-Quartile (IQR) method. A pair-wise correlation analysis was also performed to detect and eliminate highly correlated features with the aim of optimizing model efficiency and eliminating redundancy [27].

C. Feature Engineering and Model Development

Feature engineering is a key part in model development in order to generate reliable predictions. For each of the climate extremes, extensive feature engineering was applied to each of the datasets, enriching it with meaningful temporal and climate-based features that represent seasonality, historical trends and threshold-based classifications. These engineered features were then used to train separate models for heatwave, drought and rainfall prediction, each discussed in the following subsections.

i. Heatwave Prediction

A heatwave event must be clearly defined before developing a model to forecast it. This paper defines a heatwave event as a period when the daily maximum temperature exceeds by the 95th percentile of the maximum temperature of the base year, for at least 5 continuous days. This definition is consistent with that used in [28, 29]. It is important to set the regional threshold percentile in order to provide accurate predictions [26]. Feature engineering played a key role in enabling the model to detect patterns that occur before a heatwave event. To help capture seasonal temperature trends, several time-based features were developed, including year, month, day_of_year, week_of_year, and season. Rolling averages were computed, such as temp_7d_avg and temp_14d_avg, to represent recent climatic behavior. The feature is_heatwave_day was to be used as the binary prediction label while the heatwave_threshold feature stored the regional threshold. These techniques resulted in an information-rich dataset. However, there was a large ratio between heatwave and non-heatwave days leading to an imbalance dataset, which would result in poor predictions. Therefore, the solution was to opt for Synthetic Minority Oversampling Technique (SMOTE) as proposed in [30]. The heatwave prediction task involved training a XGBoost classification model that classifies based on forecasted data of 2 weeks, whether a heatwave will occur in any of those days or not, similar to the approach taken in [31]. XGBoost was chosen due to its high accuracy, stronger generalization and built-in regularization which helps it in preventing overfitting during prediction [32]. A time-aware split was used, where the last 20% of the data was reserved to be used to evaluate the model on unseen future data. Model evaluation metrics included a classification report that provided precision, recall and F1-score for each class and a confusion matrix that helped in the assessment of the model's classification behavior.

ii. Drought Prediction

The definition of drought can vary depending on the focus of a study. This research however is focused on the prediction of meteorological droughts which occur due to the absence of weather-systems that transport moisture and produce heavy precipitation [33]. The drought prediction model aimed to classify drought intensity using a combination of climate indicators and precipitation-based indices like the Standard Precipitation Evapotranspiration Index (SPEI). SPEI is a drought index which standardizes both precipitation and potential evapotranspiration (PET) values, making it particularly useful for the capture of the impacts of temperature-driven water-demand aside from rainfall irregularities [34]. SPEI was used at 1-, 3-, 6-, and 12-month scales to evaluate drought conditions similar to what was proposed in [34, 35].

The dataset was enriched with additional derived features like month, season, day-of-year, rolling precipitation sums, aridity index and cyclical encoding of wind direction. XGBoost multi-class classifier was used along with hyperparameter tuning for which GridSearchCV was used for max_depth, learning_rate, and n_estimators since these parameters are complex and time-consuming [36]. Cross-validation was performed 5-fold to validate results [37]. Evaluation metrics also included a classification report and a confusion matrix.

iii. Rainfall Prediction

Rainfall was divided into five categories: No rain, Weak, Moderate, Heavy, and Severe, following the methodology proposed in [38]. The dataset for rainfall prediction included hourly meteorological variables. The feature engineering pipeline implements Random Forest-based feature importance, mutual information analysis. Key derived features were month, season, day-of-year – capturing seasonal rainfall patterns like monsoon peaks and lag features that included rolling precipitation sums for

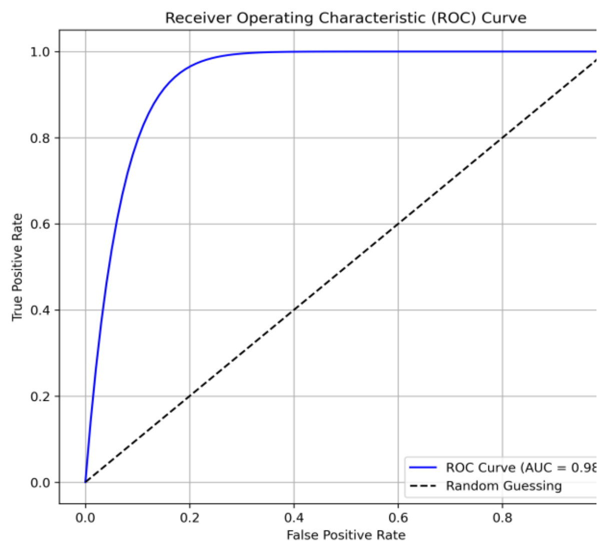

Figure I: Receiver Operating Characteristic (ROC) curve for heatwave classification in Sindh

1, 3, and 6 hours to model short-term rainfall accumulation trends. Key predictive features identified were soil moisture, surface pressure, cloud cover, dew point, relative humidity, and wind gusts. A new target column, rain_class, was created by binning precipitation_sum into five categorical labels based on WMO (World Meteorological Organization) thresholds [39].

A challenge encountered during this phase was an imbalanced dataset, heavily skewed towards the "No rain" category. Ensemble learning techniques are of the potential solution to this challenge [40], however the opted solution was to resample the dataset so each class is evenly represented, as proposed by the study [41]. Specifically, downsampling was used to reduce the dominance of the majority class. The model was trained using XGBoost to classify precipitation into each of the categories. The model overcomes the challenge of predicting rare severe weather events and showed robust performance in a similar study [36]. Evaluation metrics are the same used to assess heatwave and drought prediction.

IV. RESULTS AND DISCUSSION

The classification reports are given in the tables below. A thorough assessment of the models' prediction ability is made possible by the metrics shown in the tables, which provide information on the models' accuracy, precision, recall, and F-1 score [42].

A. Heatwave Prediction Results

Table I shows province-wise evaluation metrics, Punjab and Balochistan show near-perfect classification (Accuracy. Precision, Recall, F1-Score ≥ 0.98) while Khyber Pakhtunkhwa (KPK) performs well (F1-Score: 0.83) with a slightly lower recall (0.80). Sindh has a relatively lower recall (0.78) and low precision (0.68) which suggests that it missed more heatwave days.

Table I: Performance Metrics of Heatwave Prediction Model

Province	Accuracy	Precision	Recall	F1-Score
Sindh	0.82	0.68	0.78	0.73
Punjab	0.99	0.99	0.98	0.99
Balochistan	0.99	0.98	0.98	0.98
KPK	0.95	0.87	0.80	0.83

The Receiver Operating Characteristic (ROC) curve for Sindh, as shown in Figure 1, demonstrates that the model has a strong ability to classify heatwave and non-heatwave events, with an AUC score of 0.9883. However, when evaluated at a fixed-threshold (0.5) model achieved an accuracy of 0.82, precision of 0.68, recall of 0.78 and F1-score of 0.73. This suggests that while the model may be effective at separating the two classes, its performance can be influenced by class imbalance or threshold choice.

B. Drought Prediction Results

Table II: Performance Metrics of Drought Prediction Model

Province	Accuracy	Macro F1	Remarks
Sindh	0.71	0.44	Class imbalance observed
Punjab	0.81	0.71	Class 3 performed best
Balochistan	0.81	0.74	Strong recall for class 3
KPK	0.85	0.79	Balanced performance

Table II shows varying performance across provinces, with KPK achieving the overall highest accuracy (0.85) and macro F1-score (0.79) indicating a balanced classification. Punjab and Balochistan show comparable accuracy (0.81), although Balochistan received a higher macro F1-score likely due to its higher recall for class 3 (Near-Normal), which is the class that represents the Near-Normal drought category. In contrast, Sindh underperforms (Accuracy: 0.71, Macro F1:0.44:) suggesting severe class imbalance effects.

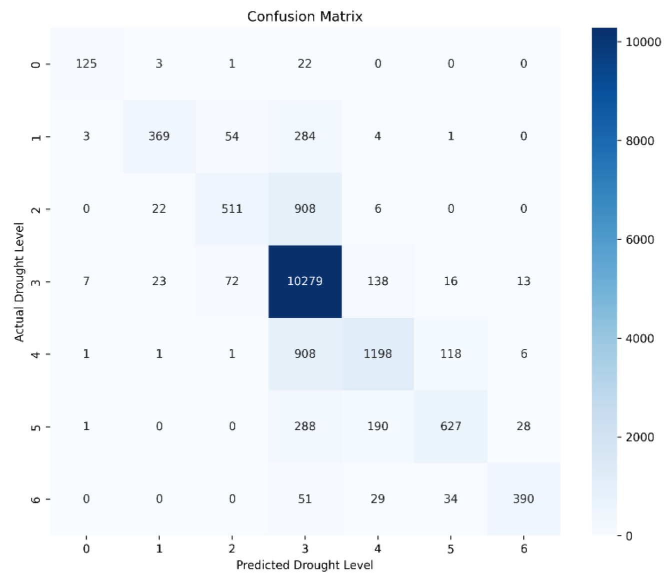

Figure II: Confusion matrix for multiclass drought classification in Punjab.

Multi-class confusion matrix for Punjab's drought classification shown in Figure II, suggests strong predictive performance for the majority class (Level 3), 10,279 correct predictions. However, clear confusion exists between adjacent drought levels, particularly between levels 2-4 and 3-5 which reflects the difficulty of differentiating similar severity levels. Rare drought categories show lower accuracy, likely due to class imbalance.

C. Rainfall Prediction Results

Table III represents the model performance for rainfall prediction in 3 provinces. The model shows high accuracy across all provinces (Sindh: 0.95, Punjab: 0.93, Balochistan: 0.96), however it shows critical weakness in predicting extreme rainfall events as indicated by the lower macro F1-scores (Sindh: 0.55, Punjab: 0.70, Balochistan: 0.64) with particularly poor performance for predicting "Heavy Rain" in Sindh province and "Severe Rain " in Punjab and Balochistan provinces.

Table III Performance Metrics of Rainfall Prediction Model

Province	Accuracy	Macro F1	Weakest Class
Sindh	0.95	0.55	Heavy Rain
Punjab	0.93	0.70	Severe Rain
Balochistan	0.96	0.64	Severe Rain

These metrics suggest that while the model may be good at predicting general weather patterns, its ability to identify extreme rainfall events needs to be significantly improved.

D. Baseline Model Comparison

To assess the effectiveness of the proposed XGBoost models, their results were compared against benchmarks from prior studies that evaluated ML methods for the same climate extremes.

Heatwave: Deep Learning (ANN, CNN, LSTM) was used in prior work [26] for extreme heat prediction, achieving test accuracy of approximately 0.962. Although direct numeric comparison is not possible, the proposed XGBoost models' provincial accuracies are competitive with deep learning performance.

Drought: A recent study on SPEI-based drought forecasting in China [43] compared a basic XGBoost model with enhanced variants using feature selection and particle swarm optimization. The baseline model achieved moderate performance, while the proposed macro F1 scores between 0.71-0.79 across provinces, aligning with or even surpassing the basic model.

Rainfall: The study [44] reported 95% accuracy and F1-Score using hyperparameter-optimized XGBoost on hourly data. Proposed model achieved overall accuracy around 0.94-0.96 with macro F1-scores of 0.55-0.70. These results are comparable given the diverse climatic conditions of Pakistan.

Table IV Comparison of Model Performance with Prior Studies

Climate Extreme	**Baseline Model**	**Reference**	**Proposed Model**	**Performance Comparison**
Heatwave	LSTM (Deep Learning)	[26] (Shafiq et al., 2025)	XGBoost	Similar accuracy (96% vs. 82-99%)
Drought	Basic XGBoost (SPEI-based)	[43](Zeng et al., 2025)	XGBoost	Comparable accuracy (95% baseline vs. 94-96%)
Rainfall	XGBoost (baseline optimized)	[44] (Auriwan et al, 2023)	XGBoost	Better F1 scores (0.71-0.79 vs. 0.70)

Although the proposed models show performance that is similar to prior studies [26, 43, 44], this study presents a broader and more systematic evaluation of ML models for climate extreme prediction in Pakistan as shown in Table IV. Key distinctions include: (1) training on gridded weather datasets across four provinces, (2) developing separate models for heatwaves, drought and rainfall using customized feature engineering and (3) evaluating model performance across different climatic zones. These contributions are a steppingstone towards developing robust, ML-driven solutions.

V. CONCLUSION

This study presented machine-learning based models for the prediction of three major climate extremes, heatwaves, drought and rainfall, across multiple provinces of Pakistan. 25 years of gridded weather data (2000-2024) from NWP models was used and customized feature engineering for each extreme was carried out to train the XGBoost model which showed strong predictive performance across varying regions despite differences in climate and data imbalance.

The results from this study support the use of machine learning in augmenting traditional climate forecasting systems aiding both governmental and non-governmental organizations in fast decision-making against these climate extremes. It is important to address the study's limitations, firstly the model was trained on specific provinces, and their performance may not generalize well to geographically diverse regions. Secondly, the dataset has considerable class imbalance especially for rare events such as extreme drought or heavy rainfall. This has an impact on the model's ability to predict for these categories with high confidence.

Lastly, the study relies on historical data from NWP models, this means that any inaccuracies in that data could be propagated into the predictions. In future studies, deep learning models could be used to better capture the dynamics of climate variables. Furthermore, ensemble learning techniques that combine XGBoost with other ML or neural models could also be utilized for better generalization of varying climate zones. Overall this study contributes to the body of research that validates how data-driven models could be used to predict climate extremes in areas that are vulnerable to climate change.

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