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Machine Learning-Based Assessment of Meteorological Droughts in Chitral and Swat River Basins, Pakistan

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Abstract

The detrimental effects of droughts on water resources and agriculture can lead to significant economic losses and risk to lives. Using key climatic factors to analyze changes in a relevant index, this study aims to forecast droughts. The study is structured into three distinct phases. First, the computation of the Standardized Precipitation Evapotranspiration Index (SPEI) for the Chitral and Swat River basins was carried out using data from 1981 to 2022. This index is designed to predict both short-term and long-term droughts. Second, the dataset was split into training and testing sets, with 80% designated for training and 20% for testing the models, employing algorithms such as XGBoost, Decision Tree, AdaBoost, and Linear Regression, along with various climate variables. Finally, the models were evaluated using statistical metrics like R^2 (Coefficient of Determination), RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and MSE (Mean Squared Error), and future predictions from 2023 to 2045 were made based on the well-trained and tested models. The results demonstrate promising performance, with R^2 values of 0.968, 0.906, 0.901, and 0.287, and RMSE values of 0.265, 0.291, 0.302, and 0.837 for XGBoost, AdaBoost, Decision Tree, and Linear Regression, respectively. The SPEI shows potential as a useful tool for drought prediction, and spatial distribution mapping in ArcMap using the Inverse Distance Weighting method reveals persistent moderate droughts in both basins. Additional research using a larger dataset or combining data from different areas could enhance the applicability of the findings and lead to a deeper understanding.

***Keywords*: Drought prediction, Climate change, Machine learning, Spatio-temporal drought.

1. Introduction

Extreme climatic events have become more frequent and destructive in recent decades, posing serious threats to global ecosystems and economic stability. Monitoring and assessing land changes are essential for understanding and reducing the impacts of these phenomena (Omali, 2022). Among these hazards, drought is known as one of the most economically and environmentally damaging yet poorly understood natural disasters, especially in Central and South Asia (Orimoloye et al., 2022). The Emergency Events Database ranks drought as the top natural hazard in terms of total economic loss and societal disruption, with forecasts suggesting its frequency and severity will rise due to human-induced climate change (Teutschbein et al., 2023). Despite extensive research on drought effects, a universally accepted definition has yet to be established because of its spatial variability and dependence on context (Lloyd-Hughes, 2014). Drought-related disturbances in water and ecological systems can have long-lasting effects, worsening vulnerabilities when multiple droughts happen without sufficient recovery time (Yao et al., 2022). Understanding drought patterns, including their start, length, and end, is key to developing effective mitigation and better water resource management.

Drought recovery is the time taken by an ecosystem to revert to its pre-drought condition. A clearer understanding of the likelihood, timing, and causes of drought termination would greatly assist decision-makers in managing the shift from drought conditions to restored water availability. Drought is typically classified into three broad categories: meteorological, hydrological, and agricultural. Meteorological drought refers to an observable shortfall in rainfall, while hydrological drought involves reduced water levels in surface and underground reservoirs (DeChant and Moradkhani, 2015). Agricultural drought is characterized by inadequate soil moisture, insufficient rainfall, and depleted groundwater levels, ultimately leading to reduced crop yields. While physical and conceptual models play a significant role in analyzing catchment behavior, they are frequently criticized for their complexity, high data demands, and limited forecasting accuracy (Raposo et al., 2023). In response to these challenges, various disciplines have increasingly adopted machine learning techniques in recent years to tackle the identified issues. These include, but are not limited to, engineering, agriculture, medicine, marketing, earth and environmental sciences, and marketing (Benos et al., 2021). Another challenge in drought prediction lies in selecting and developing a suitable forecasting model. A range of models has been employed in the past to estimate drought occurrence and severity, including ARIMA/SARIMA, neural networks, and hybrid approaches. ARIMA, in particular, is a straightforward and widely used technique for predicting droughts in individual locations, relying solely on the time series' internal characteristics without considering the influence of external predictors (Rezaiy and Shabri, 2023). ANN has significantly contributed across various fields by effectively modeling the nonlinear relationships between predictors and target variables. However, they face several limitations, including challenges in handling high-dimensional data, sensitivity to irrelevant features, limited interpretability, and issues related to computational efficiency (Setiono et al., 2002). Specifically, backpropagation NN, a widely used model, is prone to getting trapped in local minima while attempting to solve for the global optimum of complex nonlinear functions, often resulting in unsuccessful training (Duffner and Garcia, 2007).

In recent years, significant efforts have been made toward drought prediction, focusing on the selection and accessibility of forecasting tools. The use of remote sensing products, like the NDVI, has enhanced drought forecasting due to their precise spatial and temporal data at both regional and global levels (Marj and Meijerink, 2011). Furthermore, drought prediction has increasingly incorporated various human activities, which are difficult to quantify. These activities include reservoir operations, irrigation, land use changes, and deforestation. In conditions with limited predictive accuracy, probabilistic drought forecasting is being widely adopted to support decision-making. A strong focus is placed on deriving the probability density function of forecasts and estimating the chances of experiencing different drought categories (Nandgude et al., 2023). In addition to forecasting drought signals using different indicators, some approaches aim to directly predict drought impacts on society and ecosystems. Inventories of drought impacts—ranging from agriculture to water quality—have been developed. Although these initiatives have improved drought forecasting to some extent, it remains a significant challenge for climatologists, hydrologists, and policymakers due to its complex origins and occurrence across varying temporal and spatial scales (Hao et al., 2018; Tramblay et al., 2020).

The Kabul River Basin, especially the Chitral and Swat River Basins, is very vulnerable to repeated droughts, which have become worse in both severity and frequency over the past few decades. This vulnerability is made worse by climate forecasts showing a significant drop in rainfall and a rise in temperature at the same time (Khattak et al., 2017). By 2100, yearly rainfall in the area is expected to fall by 53–65%, while average yearly temperatures are forecast to rise by 1.8°C, 3.5°C, and 4.8°C in the 2020s, 2050s, and 2080s, respectively (Sidiqi et al., 2023). These expected climate changes create serious challenges for water resources, farming, and overall ecosystem health (Ali et al., 2015).

To address this critical issue, this study aims to develop robust predictive models for the SPEI in the Chitral and Swat River Basins using historical climate data spanning from 1981 to 2020. Given the increasing hydrological uncertainties in the region, a comparative analysis of multiple ML models, including XGBoost, Decision Trees, AdaBoost, and Linear Regression, is conducted to forecast SPEI at 3- and 6-month lead times. The rationale for selecting these models lies in their demonstrated efficacy in capturing complex drought patterns while balancing predictive accuracy, computational efficiency, and interpretability. By leveraging ML-driven insights, this research seeks to advance drought early warning systems, inform adaptive water resource management strategies, and enhance regional resilience to climate-induced hydrological stress.

2. Study Area

The Chitral River Basin and Swat River Basin (C&SRB) are geographically located within the latitude range of 34°06'N to 36°50'N and the longitude range of 69°50'E to 72°51'E. They cover an approximate area of 26,382 km² (Fig. 1). Situated in the northwest corner of Pakistan and extending into the eastern part of Afghanistan, this geographical area is characterised by its hilly topography. The basin varies in altitude from 277 metres in Nowshera to 7701 metres in Afghanistan (Syed et al., 2022). C&SRB experiences frigid winters and seven months of heavy rainfall (November–May), which are succeeded by warm summers with little to no rainfall and stream flow, with the exception of rivers and streams nourished by glaciers and snowmelt (Khan et al., 2022). The variation in altitude within the basin causes substantial disparities in precipitation throughout the area (Ali et al., 2018). The basin's climate is characterised by frigid winters (November–May) that receive substantial precipitation, followed by hot summers (June–August) that receive negligible or no precipitation. The majority of streamflow is produced by the thawing of glaciers or snow. Variations in elevation within this river basin contribute significantly to the disparity in precipitation levels. The river ultimately empties into the Indus River Basin at Nowshera (Iqbal et al., 2018).

3. Materials and Methods

3.1 Historical Data

Monthly data on rainfall, maximum and minimum temperature were sourced from the Pakistan Meteorological Department (PMD) for stations located in Chitral, Drosh, Dir, and Saidu Sharif, covering the period from 1981 to 2022 (Table 1). The CMIP6, as outlined by Eyring et al. (2016), the sixth phase of the Coupled Model Intercomparison Project, initiated by the WCRP, includes approximately 100 distinct global climate models developed by 49 modelling groups, and is based on the framework of SSPs (Moss et al., 2010). These SSPs define a range of socioeconomic baseline scenarios. In CMIP6, they are integrated with RCPs to form a comprehensive set of future scenarios (van Vuuren et al., 2014). This study utilizes temperature and precipitation data from five GCMs involved in CMIP6. The models are detailed in Table 2.

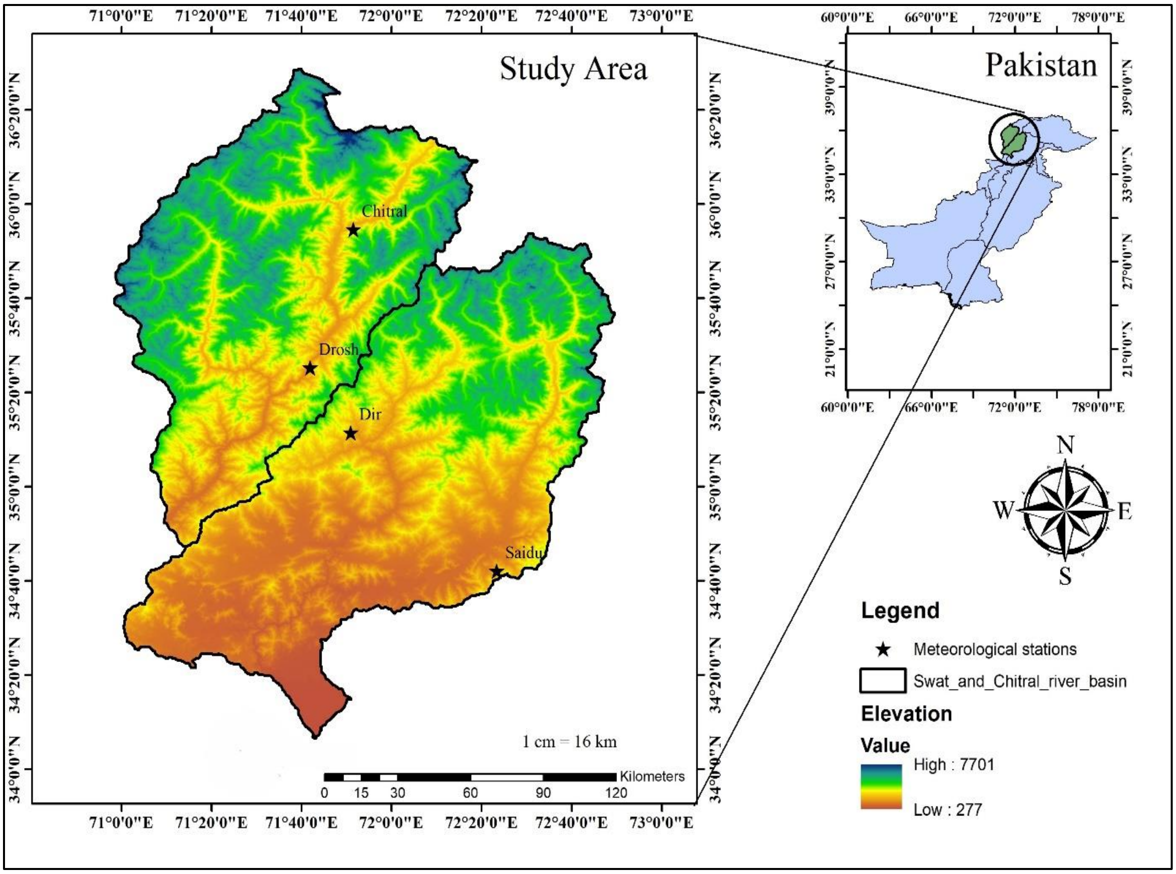

Fig. 1. Geographical location of the study area (Chitral and Swat River Basin (C&SRB)).

Table 1: Geographic and climatic characteristics of met-stations

Station Name	Latitude (N)	Longitude (E)	Elevation (m)	Mean annual rainfall (mm)
Chitral	71˚44’50"	35˚49’34"	2130	477.6
Dir	71˚51’37"	35˚11’33"	1650	1342.1
Drosh	71˚46’46"	35˚26’40"	2230	756.7
Saidu Sharif	72˚21’38"	34˚44’58"	1050	1028.4

Table 2: A list of five global climate models chosen for initial analysis to identify the best-performing models for the study area is provided below.

No.	CMIP6 GCM	Country	Resolution (lon × lat) in degrees
1	ACCESS-ESM1-5	Australia	0.25° × 0.25°
2	GFDL-CM4	USA	0.25° × 0.25°
3	IPSL-CM6A-LR	France	0.25° × 0.25°
4	MPI-ESM1-2-HR	Germany	0.25° × 0.25°
5	NorESM2-MM	Norway	0.25° × 0.25°

Downscaled climate projections from the CMIP6 were incorporated into the NASA NEX-GDDP dataset, from which rainfall and temperature data were extracted for this study. Projections from 21 Global Climate Models (GCMs) under two scenarios—SSP2-4.5 (SSP245) and SSP5-8.5 (SSP585)—were utilized. Specifically, precipitation data for the period 2023–2045 were obtained from the NEX-GDDP dataset using the GCM developed by the CSIRO. CMIP6, initiated by the WCRP, features around 100 unique GCMs developed by 49 modelling teams, integrating RCPs with SSPs.

In order to assure the choice of the most appropriate climate models for each of the scenarios 2 and 5, five models were evaluated according to their proficiency in reproducing current and recently passed climate conditions. The past-performance approach, which is utilised for this selection process, takes into account variables including temperature and precipitation that are considered to be the most pertinent to the objectives of this study's climate change impact assessment. To enhance the correspondence between climate model outputs and observations, bias correction methods were implemented, including distributive mapping and scaling model outputs. This was especially crucial for applications that are susceptible to biases, such as hydrological and land surface modelling. By rectifying biases in the mean and variance of model-simulated fields, these techniques guarantee that the projections more accurately depict extreme values.

Bias correction is performed utilising historical data and the CmHyd utility. The mean outcomes of bias correction for all models, including the optimal model ACCESS-ESM1-5 that utilises observed station data, are displayed in Table 3. The most optimal outcomes are attained via distributive mapping of precipitation and temperature.

Table 3: Results of the best model for future data

Meteorological Data	Before Bias-correction	After Bias-correction
Precipitation	$R^2 = 0.07$ RMSE = 9.11 mm	$R^2 = 0.913$ RMSE = 6.427 mm
Maximum Temperature	$R^2 = 0.58$ RMSE = 11.2 °C	$R^2 = 0.931$ RMSE = 0.271 °C
Minimum Temperature	$R^2 = 0.58$ RMSE = 7.97 °C	$R^2 = 0.929$ RMSE = 0.231 °C

3.2 Standardized Precipitation Evapotranspiration Index (SPEI)

With over 150 drought indices documented in the literature, validating each one and achieving a universal consensus is impractical. However, there is a growing consensus on the use of the SPEI in recent years. This preference is largely due to SPEI's integration of both rainfall and temperature data. The SPEI is computed by initially determining the monthly water balance, which is the difference between monthly rainfall and monthly PET.

These values are then aggregated over the specified timescales of interest. Calculating PET involves several parameters, such as surface temperature, humidity, solar radiation intensity on the earth's surface, and sensible heat fluxes. However, such detailed meteorological data are often unavailable from many meteorological stations worldwide. Therefore, various indirect methods, including the Penman-Monteith, Hargreaves, and Thornthwaite methods, have been suggested to estimate it using available meteorological data. In this study, the Hargreaves method was employed for PET calculation due to data unavailability, which requires maximum and minimum temperatures and the latitude. The SPEI and PET were calculated using the RStudio package "SPEI version 1.8.1". The SPEI values and their corresponding drought categories, as defined by the WMO (2012), are presented in Table 4.

Table 4: Drought and wet categories based on SPEI values

SPEI values	Categories
>02	Extremely wet
1.5 to 1.99	Very Wet
1.0 to 1.49	Moderately Wet
-0.99 to 0.99	Near Normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely drought
< -02	Extremely drought

3.3 Extreme Gradient Boosting (XGBOOST) Model

The XGBoost algorithm, an advanced version of the GBM, is an influential and efficient ML technique based on regression trees. It uses a boosting structure, where several weak learners are successively trained to minimize the errors of their predecessors, resulting in a strong predictive model. XGBoost addresses common machine learning challenges such as overfitting and underfitting through regularization and advanced optimization strategies, making it suitable for complex problems and large datasets. In this study, we applied XGBoost with 4000 trees, a maximum depth of 20, and a learning rate of 0.1, while keeping the remaining hyperparameters at their default settings. To further optimize model performance, we employed Optuna for hyperparameter tuning, running trials at 100, 500, 1000, and 2000 iterations. The tuning process explored various combinations of tree numbers (100 to 4000), maximum depths (1 to 22), and learning rates (0.05, 0.1, and 0.5). This comprehensive approach allowed us to fine-tune the XGBoost model effectively, ensuring it was well-adapted to the specific characteristics of the dataset and the complexity of the drought prediction task.

3.4 Tree Algorithms (DT) Model

The tree-based model, widely used in machine learning, functions by partitioning the input space into smaller regions and conveying prediction values to each, allowing it to effectively capture complex patterns in the data. In gradient boosting frameworks like XGBoost, trees are built sequentially, with each new tree trained to minimize the residuals from the earlier iteration. This iterative refinement enhances the model's predictive accuracy. Tree-based models are highly flexible, capable of handling various data types, capturing non-linear relationships, and demonstrating robustness against outliers. In our study, a Decision Tree model was trained using 4000 trees with a maximum depth of 25. To further optimize model performance, we applied Optuna for hyperparameter tuning, conducting 100, 200, 500, 1000, and 2000 trials. The tuning process explored different configurations of tree counts (ranging from 100 to 4000) and maximum depths (from 1 to 25). This comprehensive tuning strategy allowed us to tailor the Decision Tree model to the unique characteristics of the dataset and the complexity of the drought prediction task.

3.5 Adaptive Boosting (AdaBoost) Model

AdaBoost is a machine learning algorithm that conglomerates several weak learners to form a robust predictive model. It works by training weak learners—typically decision trees—sequentially, where each new learner focuses more on the instances that were misclassified by the previous ones. This adaptive weighting mechanism enables the model to iteratively improve its accuracy by learning from prior errors. AdaBoost is especially effective for binary classification and regression tasks, demonstrating strong performance even on complex datasets. It is also relatively resistant to overfitting, making it a reliable choice in practical applications. In our implementation, we used a decision tree as the base estimator, with six estimators in total. For classification, we employed the "SAMME.R" algorithm, and for regression tasks, we used squared loss. All other hyperparameters were kept at their default settings. This tailored configuration allowed us to harness the strengths of AdaBoost while adapting it to the specific requirements of our dataset, ultimately enhancing the model's predictive capability.

3.6 Linear Regression Model

Linear regression is a vital technique widely used for predictive analysis. It models the connection between a dependent variable and one or more independent variables by an appropriate linear equation that reduces the sum of squared differences between the actual and predicted values. The model attains this by assessing coefficients that best describe the linear association, making it a simple yet powerful tool for tasks such as trend analysis, impact assessment of variables, and forecasting. Its interpretability and ease of implementation make it a foundational model for more advanced techniques. In our study, we also implemented Elastic Net Regression with an α value of 0.0001, an L1:L2 ratio of 0.99:0.01, and the intercept fitting enabled. Elastic Net combines the strengths of both L1 (Lasso) and L2 (Ridge) regularization methods, offering a balanced approach that promotes sparsity while maintaining model stability. This regularization helped improve the model's generalization performance by reducing the risk of overfitting, thereby enhancing its applicability to the drought prediction task.

3.7 Model Evaluation

To evaluate predictive models, several criteria are employed, including R-squared (R^2), RMSE, MAE, and MSE. R-squared signifies the proportion of variance in the dependent variable that is explained by the independent variables, with a value of 1 representing a perfect fit. RMSE and MAE measure the average deviance between predicted and actual values, with lower values portentous better performance. While RMSE gives more weight to larger errors, MAE treats all errors with equal prominence. MSE, similar to RMSE but without taking the square root, reproduces the average of the squared errors. These metrics are decisive for evaluating a model's accuracy, precision, and ability to generalize to new data.

4. Results

The SPEI was calculated in RStudio using the SPEI package for the historical period from 1981 to 2022. Additionally, PET was calculated using the Hargreaves formula. These computations were extended to the future period from 2023 to 2045 for SSP245 and SSP585. SPEI-3 and SPEI-6 calculations and predictions have been implemented for all meteorological stations. The following provides detailed information for a representative station of the study area.

4.1 DIR

The analysis of drought episodes discloses distinct patterns over the years. Notably, in 1989, 2007, 2009, and 2022, the region faced extreme drought conditions, marked by significantly below-average precipitation levels or higher-than-normal temperatures, resulting in prolonged water scarcity and agricultural stress.

Conversely, the period between 1986 and 1987 experienced relatively few drought episodes, suggesting a temporary relief from severe drought conditions, likely due to higher-than-average rainfall. However, this respite was brief, as the region encountered repeated drought episodes in subsequent years, as shown in Figure 2.

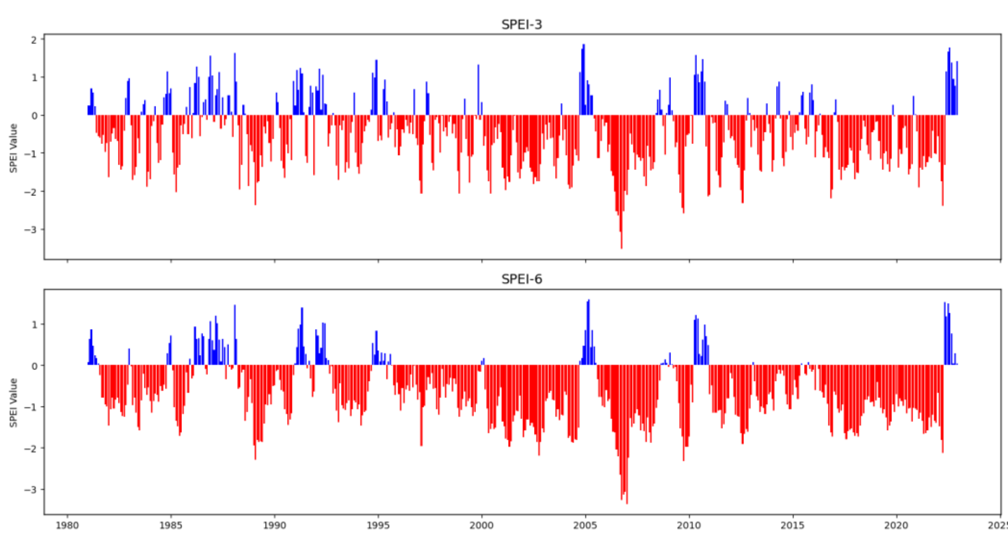

Fig. 2. Historical drought (1981-2022).

The recurring nature of drought episodes highlights the vulnerability of the region to climatic fluctuations. Grasping these patterns is essential for developing effective drought mitigation strategies and enhancing the resilience of communities and ecosystems against future drought events.

In the realm of climate impact assessments, the efficacy of predictive models plays a pivotal role in elucidating future climatic scenarios. For the SSP245 scenario, the Gradient Boosting model demonstrated moderate accuracy, yielding an RMSE of 0.225 and an R2 of 0.926. While these metrics indicate a reasonable alignment between predicted and observed SPEI values, there exists scope for further refinement. On the other hand, the AdaBoost and Tree models exhibited acceptable performance, with RMSE values of 0.218 and 0.343, respectively. Despite providing relatively accurate predictions, they fell short of the precision achieved by the Gradient Boosting model. Conversely, the Linear Regression model displayed poor performance, recording an RMSE of 0.826 and an R^2 close to zero, underscoring its inadequacy in accurately forecasting SPEI values under this scenario. The future time series prediction is shown in Figure 3.

On the contrary, the SSP585 scenario observed that the Gradient Boosting model achieved exceptional accuracy, as evidenced by its RMSE of 0.105 and R^2 of 0.983. The metrics indicate a strong correlation between the model's predictions and the observed SPEI values, which provides further evidence of its reliable predictive capabilities. In a similar vein, the AdaBoost and Tree models performed admirably, as evidenced by their respective RMSE values of 0.150 and 0.123, which validated their ability to provide precise predictions for the SSP585 scenario. However, the Linear Regression model encountered difficulties in accurately predicting SPEI values for this scenario, as evidenced by its RMSE of 0.791 and R^2 of 0.070. In summary, the results of this study emphasise the importance of incorporating sophisticated modelling methods, like Gradient Boosting, into climate impact assessments due to their superior predictive capabilities compared to conventional Linear Regression models. All ML models and their time series prediction is shown in Figure4.

4.2 Spatial Analysis

The Inverse Distance Weighting (IDW) technique was employed to visualize drought conditions across the study region. IDW is an interpolation method that approximates unknown values at locations established on the values of close known points, assuming that nearer points have more influence than those farther away. Specifically, IDW was applied to identify and illustrate the months during which all stations experienced drought conditions, indicated by SPEI values less than 0. These figures exclusively present the SPEI-3 and SPEI-6 values, which reflect short- and medium-term droughts, respectively. The contours displayed on the maps represent interpolated SPEI values with a fixed interval of 0.1, indicating the intensity and spatial spread of drought across the region. The spatial maps offer a clearer representation of meteorological drought intensity under different future climate scenarios. Figure 5(a,b) shows drought months for SSP245, while Figure 6(a,b) shows drought months for SSP585.

4.3 Future drought analysis

Understanding future droughts is crucial for planning effective strategies to minimize their impact on agriculture, the environment, and ecosystems. Knowledge of their intensity and duration allows for informed decision-making to mitigate these adverse effects. Tables 5 and 6 show the three maximum drought durations of all stations for SSP245 and SSP585, respectively.

The drought scenarios under SSP585 are projected to be more prolonged and intense compared to those under SSP245, largely due to rising temperatures. Specifically, at Chitral station, the maximum drought duration is anticipated to be 9 months under SSP245, whereas it extends to 11 months under SSP585. Similarly, the Dir station exhibits a maximum drought duration of 9 months for SSP585, compared to 8 months for SSP245. Interestingly, Drosh and Saidu Sharif stations show a higher drought duration under SSP245 compared to SSP585. Saidu Sharif station is particularly notable, facing the worst drought conditions with a staggering 40 months of drought under SSP585, the longest duration observed across all stations for the entire future period.

These findings highlight significant regional variations in drought intensity and duration under different climate scenarios. The higher temperatures projected in SSP585 contribute to more severe drought conditions, exacerbating water scarcity issues. The extended drought periods at Chitral and Dir stations under SSP585 indicate heightened vulnerability, necessitating targeted water management strategies. Conversely, the unexpectedly higher drought duration at Drosh and Saidu Sharif stations under SSP245 suggests that factors other than temperature, such as precipitation patterns and local climatic conditions, also play crucial roles in drought dynamics.

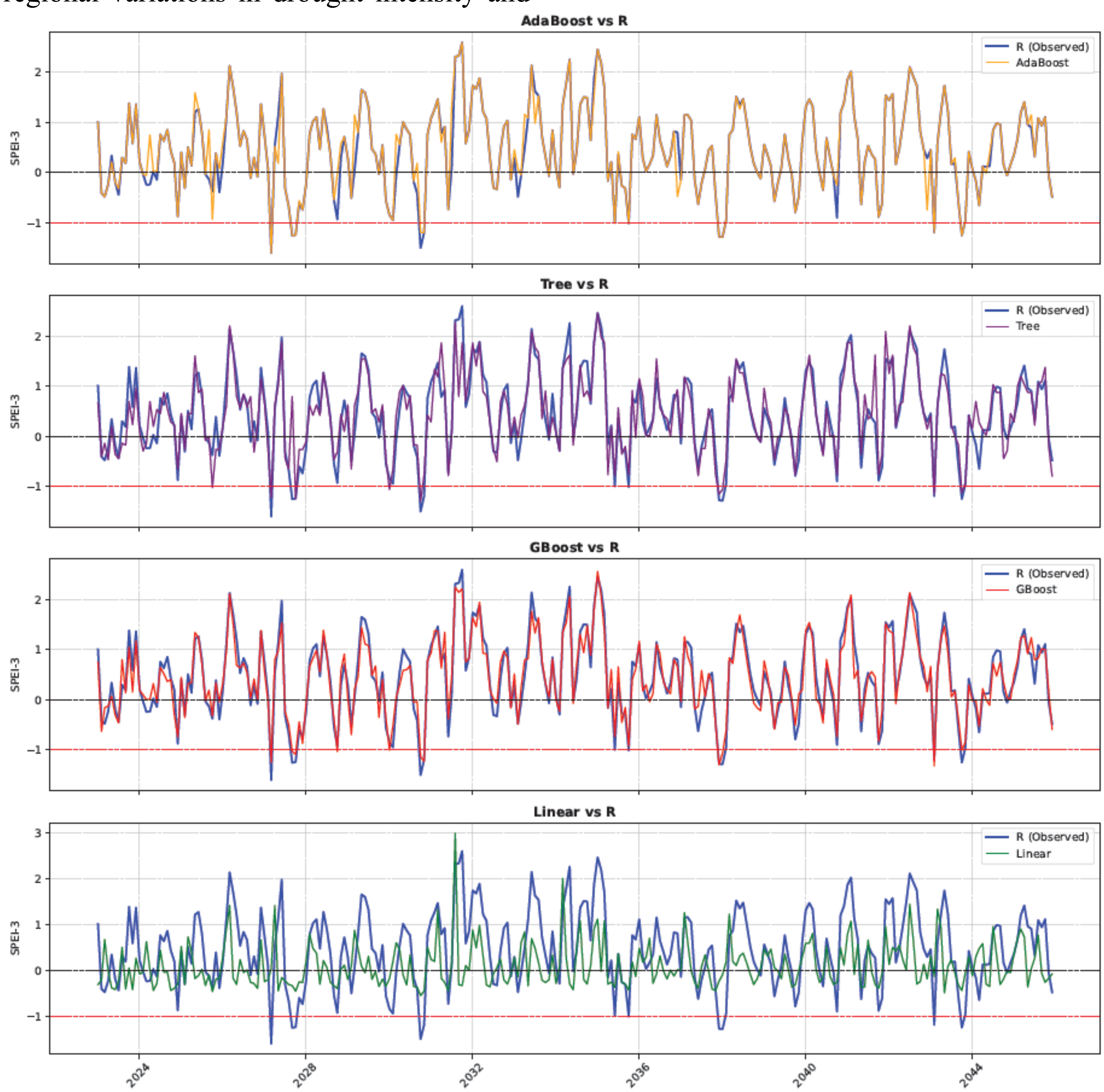

Fig. 3. Future drought prediction of Models for SSP245 (2023-2045).

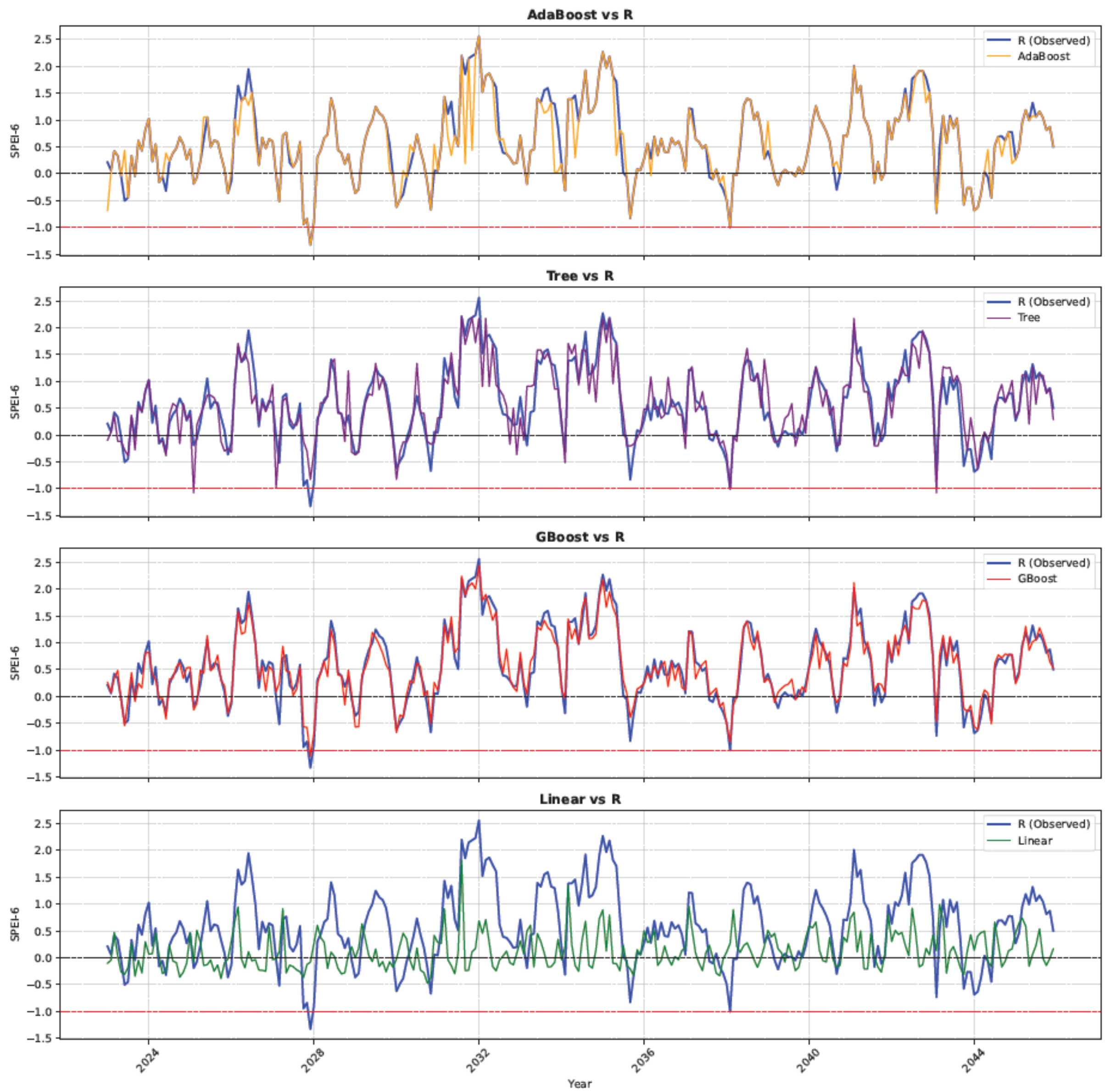

Fig. 3 (continue

5. Discussion

The primary objective of this research was to apply machine learning models—namely AdaBoost, Decision Tree, XGBoost, and Linear Regression—to forecast the SPEI-3 and SPEI-6 for the Chitral and Swat River Basins. While the results indicated that all models delivered reasonable accuracy, a more critical evaluation revealed substantial disparities in model performance, particularly in capturing complex drought dynamics in these high-altitude, data-scarce regions.

The study's comparative analysis, using evaluation parameters such as R^2, RMSE, MAE, and MSE, suggested that although all models performed adequately, the Decision Tree and Linear Regression models underperformed relative to ensemble-based methods. This reinforced the well-documented limitations of standalone tree models in handling non-linear, multi-dimensional relationships typical in climate datasets. AdaBoost demonstrated moderate performance improvements by adaptively focusing on misclassified instances, yet it fell short of the robustness and generalization ability exhibited by XGBoost.

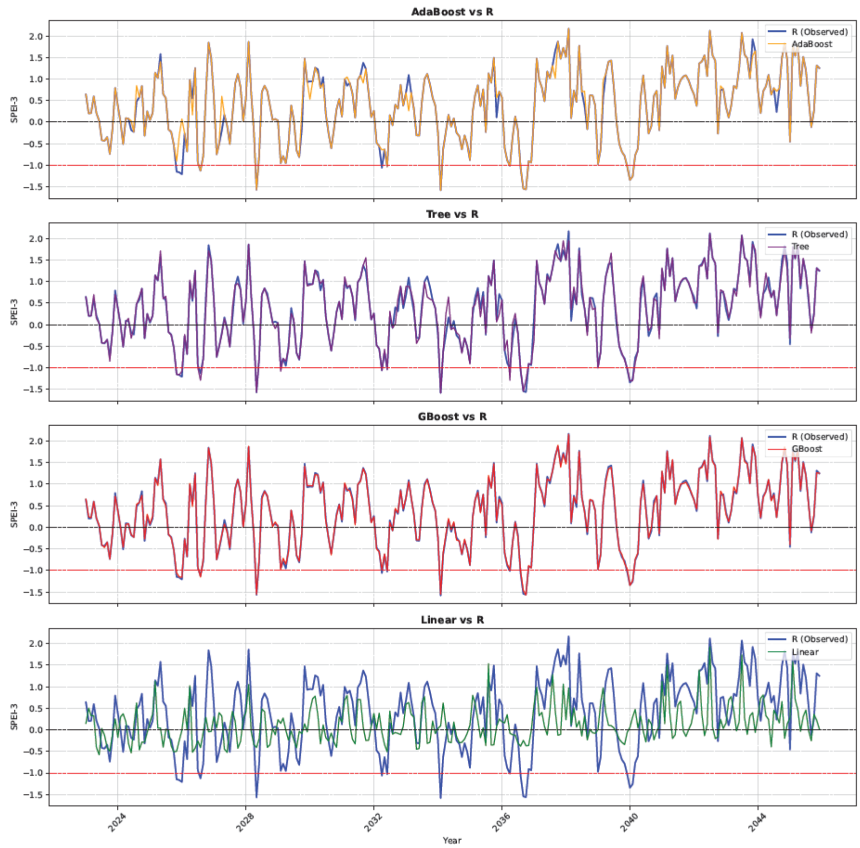

Fig. 4. Future drought prediction of Models for SSP585 (2023-2045).

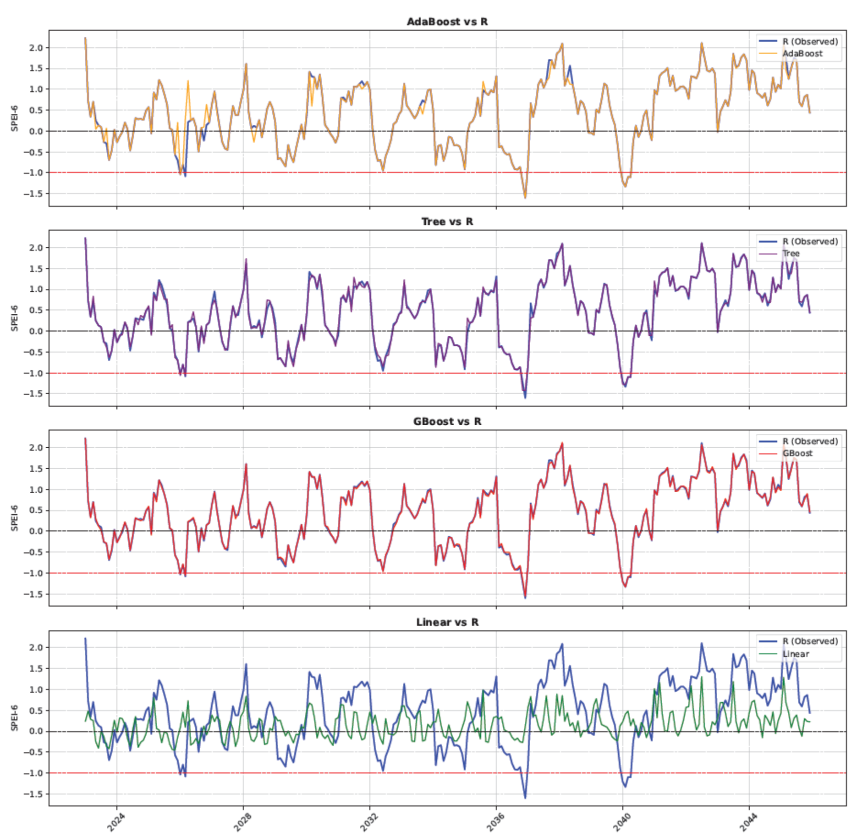

Fig. 4 (continue)

Table 5: Drought duration for SSP245

SPEI	Station	Start	End	Duration	Intensity
SPEI-3	Chitral	May-2037	Feb-2038	9	-1.67
		Jan-2030	Sep-2030	8	-1.56
		Feb-2023	Sep-2023	7	-0.93
	Dir	Jul-2027	Jan-2028	6	-1.25
		Dec-2029	Mar-2030	3	-0.94
		Aug-2030	Nov-2030	3	-1.50
	Drosh	Feb-2023	Jun-2023	4	-0.60
		Nov-2037	Feb-2038	3	-1.30
		Oct-2027	Dec-2027	2	-0.58
	Saidu	Jul-2027	Jan-2028	6	-1.05
	Sharif	Dec-2029	Jun-2030	6	-1.54
		Dec-2038	Jun-2039	6	-0.95
SPEI-6	Chitral	Jan-2024	Mar-2025	14	-1.19
		Oct-2043	Aug-2044	10	-1.01
		Feb-2023	Nov-2023	9	-0.83
	Dir	Nov-2037	Apr-2038	5	-1.00
		Oct-2043	Mar-2044	5	-0.68
		Dec-2029	Apr-2030	4	-0.62
	Drosh	Apr-2023	Jul-2023	3	-0.59
		Dec-2037	Feb-2038	2	-0.69
		Jan-2044	Mar-2044	2	-0.36
	Saidu	Feb-2039	Dec-2039	10	-0.88
	Sharif	Jan-2030	Aug-2030	7	-1.44
		Nov-2037	Apr-2038	5	-1.39

Table 6: Drought duration for SSP585

SPEI	Station	Start	End	Duration	Intensity
SPEI-3	Chitral	Feb-2036	Jan-2037	11	-1.13
		Sep-2030	Jun-2031	9	-0.95
		Jul-2039	Apr-2040	9	-1.15
	Dir	Aug-2039	Apr-2040	8	-1.34
		Aug-2025	Mar-2026	7	-1.21
		Aug-2034	Jan-2035	5	-0.88
	Drosh	Oct-2039	Apr-2040	6	-0.72
		Nov-2025	Mar-2026	4	-1.05
		Aug-2036	Dec-2036	4	-0.63
	Saidu	Apr-2027	Feb-2028	10	-1.41
	Sharif	Oct-2031	May-2032	7	-1.59
		Jun-2023	Dec-2023	6	-1.03
SPEI-6	Chitral	Aug-2039	Aug-2040	12	-1.13
		Nov-2025	Oct-2026	11	-1.52
		Feb-2036	Jan-2037	11	-1.11
	Dir	Feb-2034	Feb-2035	12	-0.92
		Feb-2036	Jan-2037	11	-1.60
		Feb-2029	Oct-2029	8	-0.85
	Drosh	Mar-2036	Dec-2036	9	-0.41
		Apr-2032	Sep-2032	5	-0.36
		Dec-2039	Apr-2040	4	-0.61
	Saidu	May-2025	Sep-2028	40	-1.79
	Sharif	Apr-2040	Apr-2041	12	-1.53
		Sep-2023	Aug-2024	11	-1.09

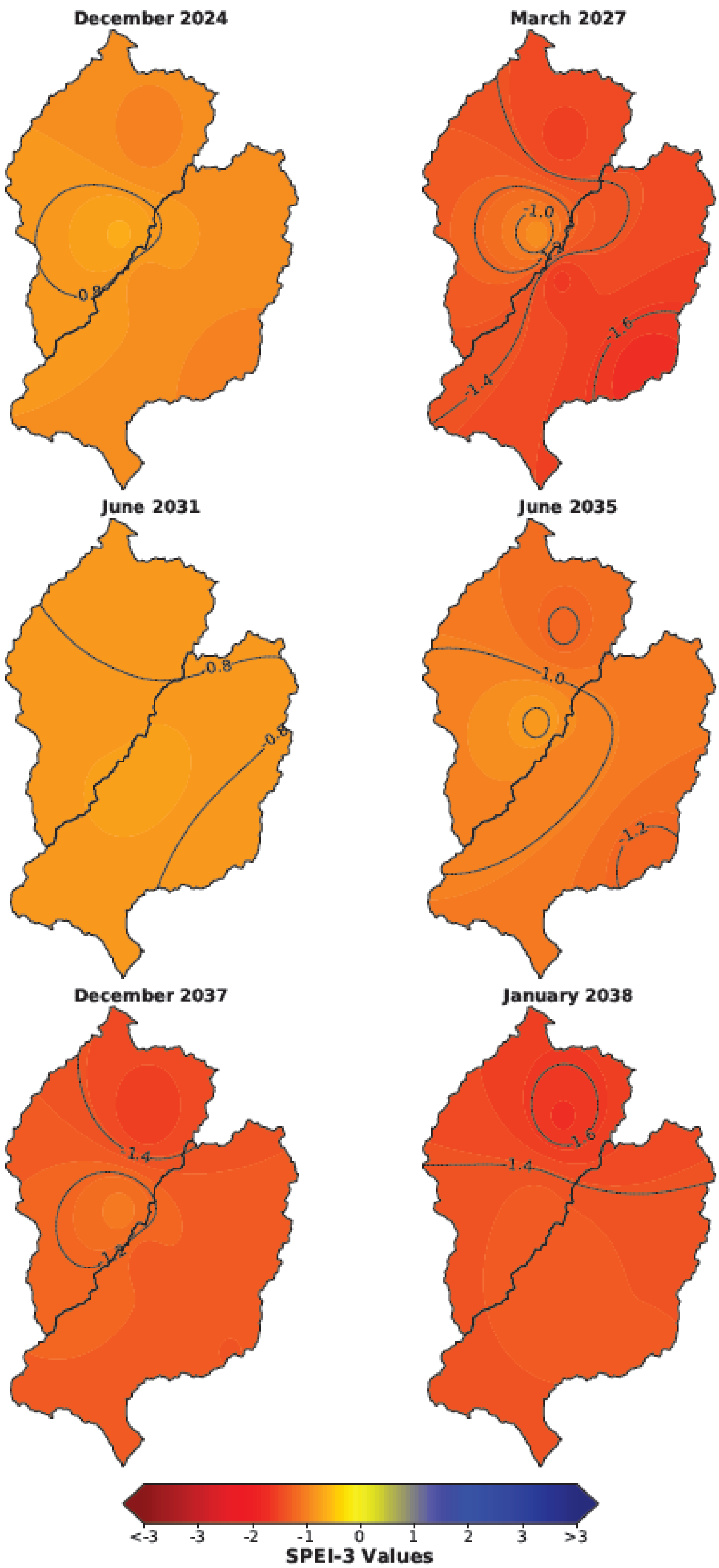

Fig. 5a. SPEI-3 for SSP245

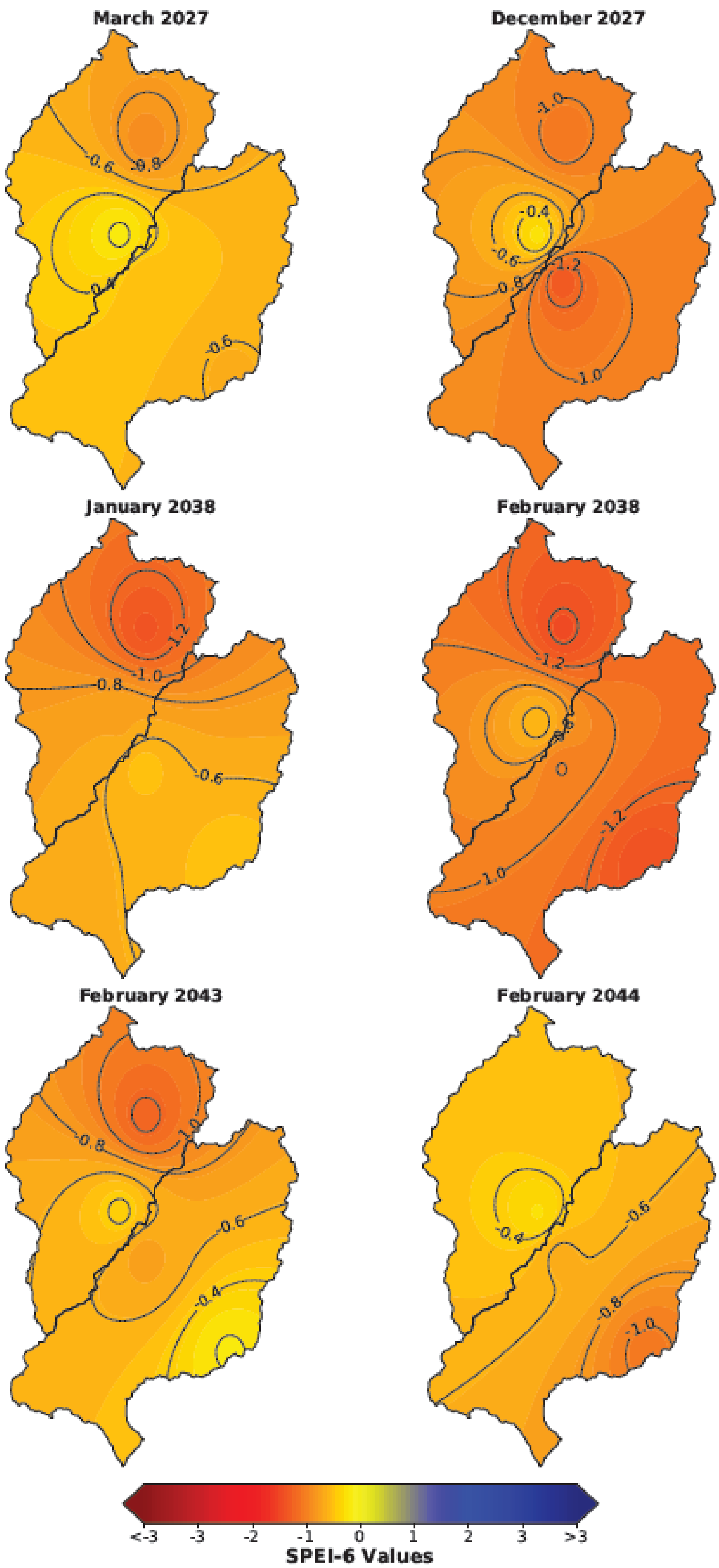

Fig. 5b. SPEI-6 for SSP245

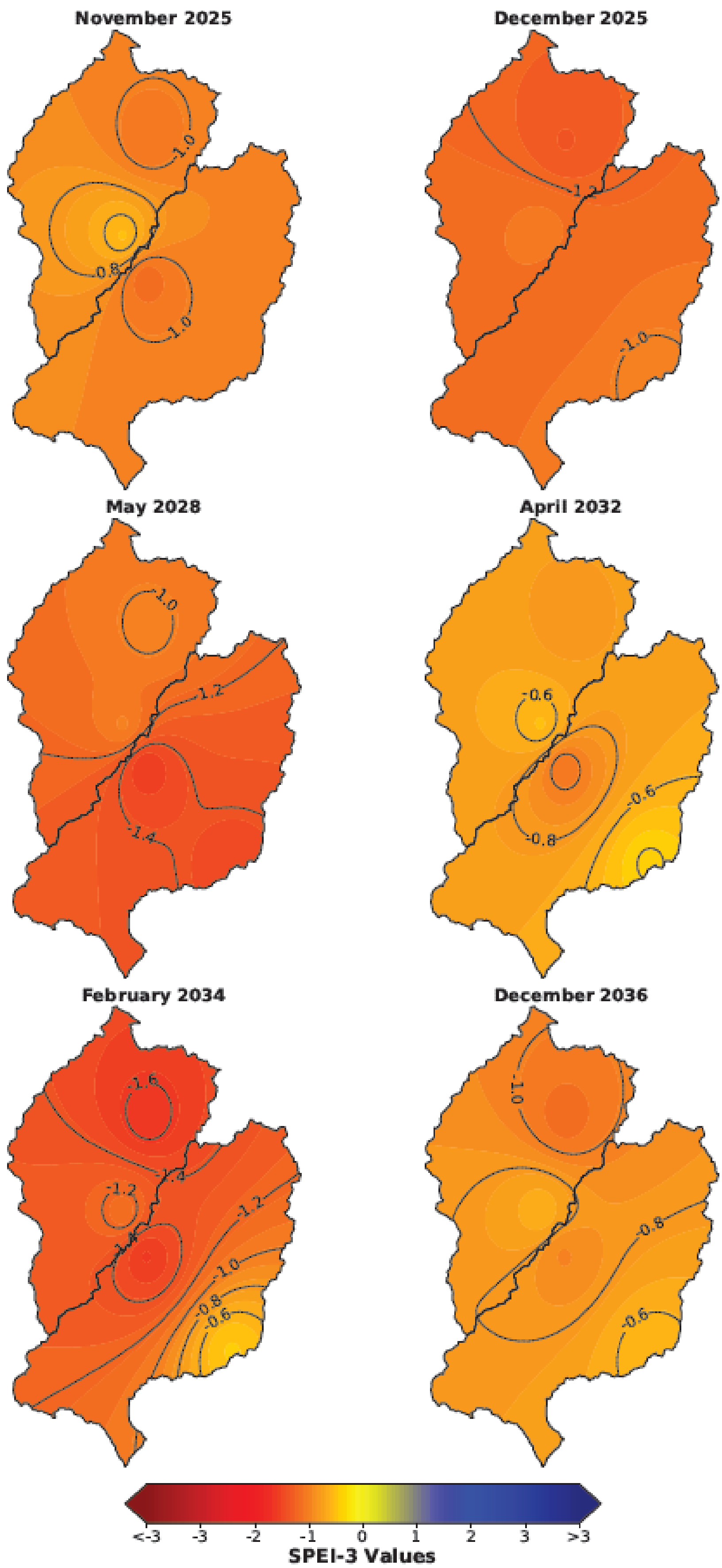

Fig. 6a. SPEI-3 for SSP585

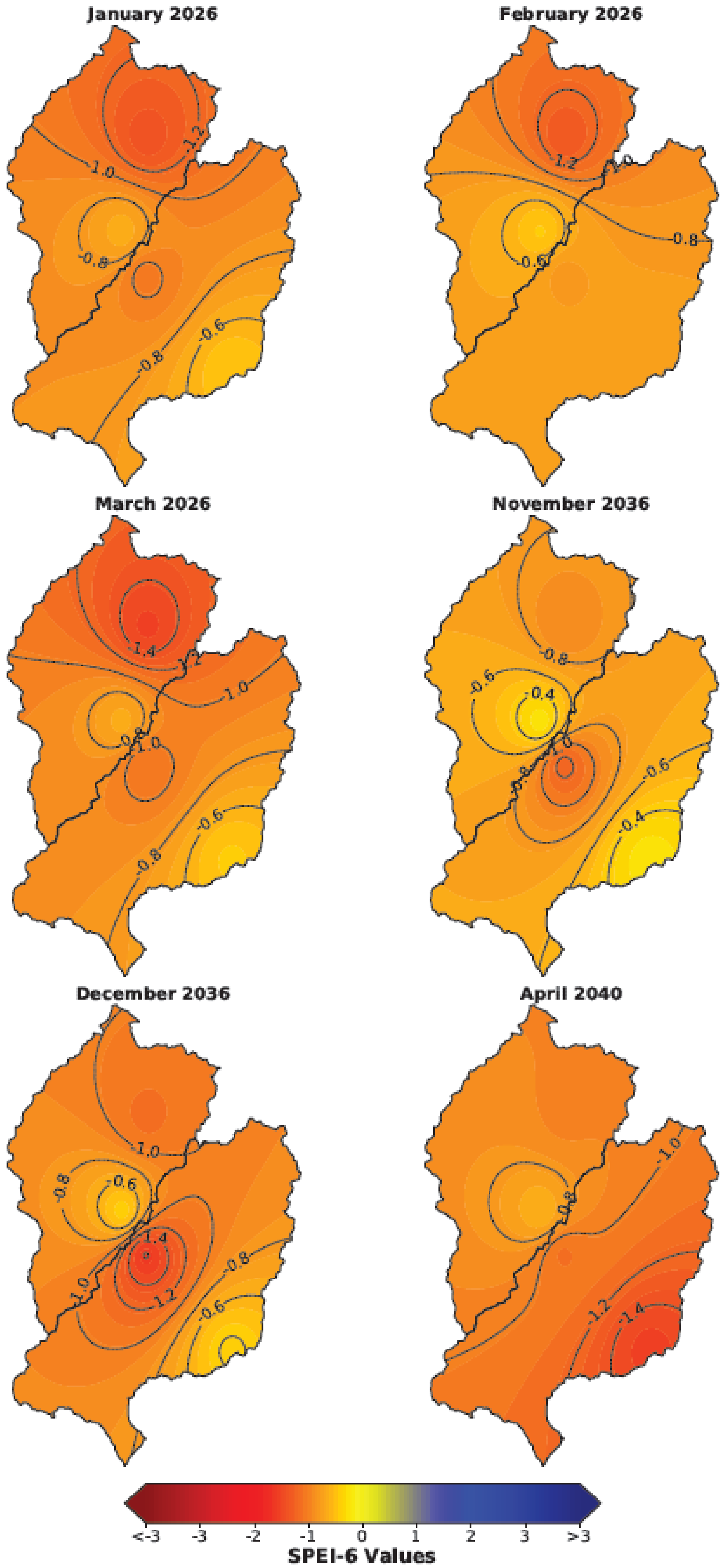

Fig. 6b. SPEI-6 for SSP585

XGBoost emerged as the most reliable model, consistently outperforming others across both short-term (SPEI-3) and mid-term (SPEI-6) drought predictions. Its superior accuracy underscores the advantage of using gradient boosting frameworks that incorporate regularization and advanced optimization techniques to handle noise, overfitting, and data heterogeneity. These findings align with previous work by Khan et al. (2024), who demonstrated that XGBoost achieved the highest predictive accuracy for drought forecasting in the Kabul River Basin. Moreover, XGBoost was successfully employed for inflow prediction into the Tarbela Reservoir by Jan et al. (2024). It delivered exceptional forecasting performance, further validating its efficacy for hydrological modelling in complex terrains.

As an additional point of interest, the findings of the study suggest that, according to the SPEI, the years 2027, 2030, 2035, 2037, 2038, and 2044 will be characterised by mild drought conditions. This highlights the significance of this type of research in terms of understanding and forecasting climatic events for the purpose of improving planning and methodologies for mitigating their effects.

The historical drought patterns identified in this study show strong alignment with previous research, reinforcing the reliability of our findings. For example, Rahman et al. (2021) recounted drought events in 1972, 1988, 2000, 2001, 2002, 2006, and 2017 using the SPEI-12 index in the KPK region, periods that closely correspond to those detected in our analysis. Also, Sidiqi et al. (2023) identified drought in 2019 and 2020 using the SPI and RDI indices, which are consistent with our results across all stations during the same years. Alami et al. (2017) perceived extreme drought in 2001, severe drought in 2000, and moderate drought in 2003–2004, closely identical to our results of extreme drought in 2001 and severe to moderate situations from August to December 2003. Baig et al. (2020) also reported agricultural drought in 2000, 2001, 2002, and 2004 using the SDCI index, years that correspond with our identification of extreme drought in 2001 and moderate droughts in 2000, 2002, and 2004. Furthermore, Taraky et al. (2021) noted moderate hydrological drought in 2001 and 2002 using the SSI index, while our findings suggest more severe drought conditions during those years, which are supported by other researchers as well. These consistent observations across multiple studies underscore the robustness and credibility of our analysis in capturing historical drought events in the region.

The SPI and RDI (Sidiqi et al., 2023) show drought in the years 2026, 2037–2038, and 2043. Likewise, our results show drought during these periods, with moderately dry years in 2024, 2025, 2027–2030, 2035, and 2038–2040. Severe drought events are expected in years including 2030 and 2038.

6. Conclusion

This study assessed the applicability of ML models in forecasting meteorological droughts in the Chitral and Swat River Basins using the SPEI. By integrating long-term climatic data from 1981 to 2022 and employing advanced algorithms—including XGBoost, AdaBoost, Decision Tree, and Linear Regression—the research demonstrated that ensemble-based models, particularly XGBoost, provided superior predictive performance. The results highlighted XGBoost's strong ability to model non-linear climate relationships, with an R^2 of 0.968 and RMSE of 0.265, outperforming other methods significantly. Spatial distribution maps further indicated persistent moderate drought patterns across both basins, emphasizing the importance of localized drought monitoring. The findings underscore the utility of machine learning in drought forecasting and support the integration of such models into early warning systems and regional water resource planning. Future studies incorporating broader datasets and additional geographic regions could further improve the generalizability and accuracy of these predictive tools.

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Author Contributions

The main concept and design of the study were developed by Uzair Khan. Alamgir Khalil provided the methodology and analytical framework. Muhammad Shahid Iqbal completed the data collection. The machine learning model selection, optimization, and prediction were completed by Muhammad Faisal Javed. Shabir Jan and Amjid Ali Khan were responsible for the preparation of tables and figures. All authors contributed to drafting and revising the manuscript and approved the final version for publication.

Conflicts of Interest

The author declares no conflict of interest.

Data Availability Statement

Data will be made available upon request to the corresponding author.

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