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Research Paper

Drought assessment in Kabul River basin using machine learnings

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ABSTRACT

Droughts significantly impact water resources and agriculture, leading to economic losses and potential human fatalities. This study aims to predict droughts by analysing changes in the Standardised Precipitation Evapotranspiration Index (SPEI) for the Kabul River basin using data from 1981 to 2022. The research is divided into three phases: calculating SPEI, splitting the dataset into training (80%) and testing (20%) subsets, and evaluating model performance. Various machine learning algorithms, including XGBoost, Decision tree, AdaBoost, and KNN, were employed alongside different climatic variables. The models were assessed using statistical metrics such as R^2, RMSE, MAE, MSE for regression, and confusion matrix, accuracy, precision, recall, F1 score, ROC AUC, and Log loss for classification. Results showed strong performance, with R^2 values of 0.97, 0.86, 0.92, and 0.96 for XGBoost, KNN, Decision tree, and AdaBoost, respectively. SPEI demonstrated significant potential for drought forecasting, and spatial distribution mapping revealed persistent moderate drought occurrences.

Keywords: Drought prediction, Climate change, Machine learning, Standardised Precipitation Evapotranspiration Index (SPEI), Kabul River basin

The extreme weather events and their severe impacts have become increasingly common all over the world. Assessment and monitoring of the condition of the Earth's surface is a key factor in driving global climate change studies. Drought is considered one of the most expensive and damaging but less comprehended natural hazards, particularly from lower reaches of Central Asia to South Asia (Sidiqi *et al.,* 2018). According to the information in the Emergency Events Database, drought is ranked number one among all natural hazards as far as the losses caused worldwide are concerned. Furthermore, climate change is anticipated to increase the frequency and severity of droughts in the future (Khan *et al.,* 2022) but with large uncertainties, in the Kabul River Basin (Afghanistan and Pakistan. The effects of droughts are well-documented, but a universal definition remains elusive. Drought is difficult to define comprehensively due to its spatial variability and context-dependent nature. The duration of drought recovery is also crucial, as experiencing a new drought before fully recovering from a previous one can have more severe ecological consequences (Panda *et al.,* 2023). When a drought ends, the ecosystem needs time to bounce back to how it was before the drought. Having a good understanding of when, why, and how a drought might end can help those in charge make decisions on how to go from a drought to having enough water again. Meteorological drought happens when there's not enough rain. Hydrological drought occurs when there's a shortage of water in lakes, rivers, and underground. Agricultural drought is when there's not enough water in the soil, rain, and groundwater, leading to lower crop yields. With over 150 drought indices recorded in the literature, achieving universal validation is challenging. However, the Standardized Precipitation Evapotranspiration Index (SPEI) developed by Vicente-Serrano *et al.,* (2010) has gained widespread acceptance because it incorporates both rainfall and temperature data. Pandya *et al.,* (2022) used different drought indices like standardized precipitation index (SPI), standardized precipitation evapotranspiration index (SPEI), reconnaissance drought index (RDI), NDVI and NDWI to assess the drought condition and development of composite drought index (CDI).

Responding to this, in recent times, many disciplines have engaged with the use of machine learning strategies to address the aforementioned issues. These fields include, but are

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not limited to, engineering, agriculture, medicine, marketing, earth and environmental sciences (Soh *et al.,* 2018). Sakthipriya and Thangavel (2024) used five machine learning classification techniques viz. K-nearest neighbour (KNN), decision tree (DT), naive bayes (NB), support vector machine (SVM), and logistic regression (LR) and compared for the better predictions of a paddy seed. Another challenge in predicting droughts is choosing and developing an appropriate prediction model. Therefore, the present study was undertaken to address the drought categories of Kabul River Basin using ML models for the SPEI Index using historical values of SPEI and climatic parameters from 1981 to 2022.

MATERIALS AND METHODS

Study area and data

The Kabul River basin, spanning 65-75° E and 32.5-37.5° N, covers 91,297 km² across Afghanistan (upper riparian) and Pakistan (lower riparian) (Fig. 1). Streamflow originates from northern snow-capped mountains, with snowmelt significantly contributing. The basin has a dry, continental climate, with over 1600 mm of annual precipitation in the north, mostly as snow. Elevation ranges from 277 meters in Nowshera to 7,701 meters in Afghanistan, showcasing diverse topography (Sidiqi *et al.,* 2018). The Kabul River Basin (KRB) experiences harsh winters from November to May with significant precipitation, followed by mild, dry summers. Streamflow primarily comes from glacial and snowmelt. Varied altitudes affect precipitation patterns, causing disparities. The river joins the Indus River Basin at Nowshera. (Iqbal *et al.,* 2018)which, together with snow and glacier melt, produce intense floods. The Kabul river basin originates from the Hindukush Mountains and is frequently hit by such floods. We analyses flood frequency and intensity in Kabul basin for a contemporary period (1981–2015. Monthly data for precipitation (PPT), maximum temperature (Tmax), and minimum temperature (Tmin) from 1981 to 2022 was obtained from the Pakistan Meteorological Department Regional Centre Peshawar (PMD) for stations in Chitral, Dir, Peshawar, and Saidu Sharif. Data for Asmar, Kabul, and South Salaang was acquired from the Afghanistan Meteorological Department, Kabul (AMD) for the same period. The average precipitation, maximum temperature and minimum temperature of the river basin is shown in Fig. 2.

Standardized precipitation evapotranspiration index (SPEI)

The Standardized Precipitation Evapotranspiration Index (SPEI) developed by Vicente-Serrano et al., (2010) has gained widespread acceptance because it incorporates both rainfall and temperature data. The general formula of SPEI as expressed in Eq.1 , further explained by Soh et al., (2018), begins with determining the monthly water balance, which is the difference between precipitation (PPT) and potential evapotranspiration (PET). These values are then aggregated over designated timescales.

$$SPEI = W - \frac{c_o + c_1 W + c_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \quad (1)$$

Where W = [−2 ln(P)]0.5 for P ≤ .5; P = 1 − F(x); C0 = 2.515517, C_1 = 0.802853, C_2 = 0.010328; d_1 = 1.432788, d_2 = 0.189269 and d_3 = 0.001308. If the value of P is greater than 0.5, then it is substituted by 1-P and the sign of the final SPEI is reversed. Multi-temporal drought indices viz. three-month (SPEI-3) and six-month (SPEI-6) were analyzed to predict the drought.

The potential evapotranspiration (PET) calculation includes various parameters like temperature, relative humidity, solar radiation, and heat fluxes. Due to the frequent unavailability of

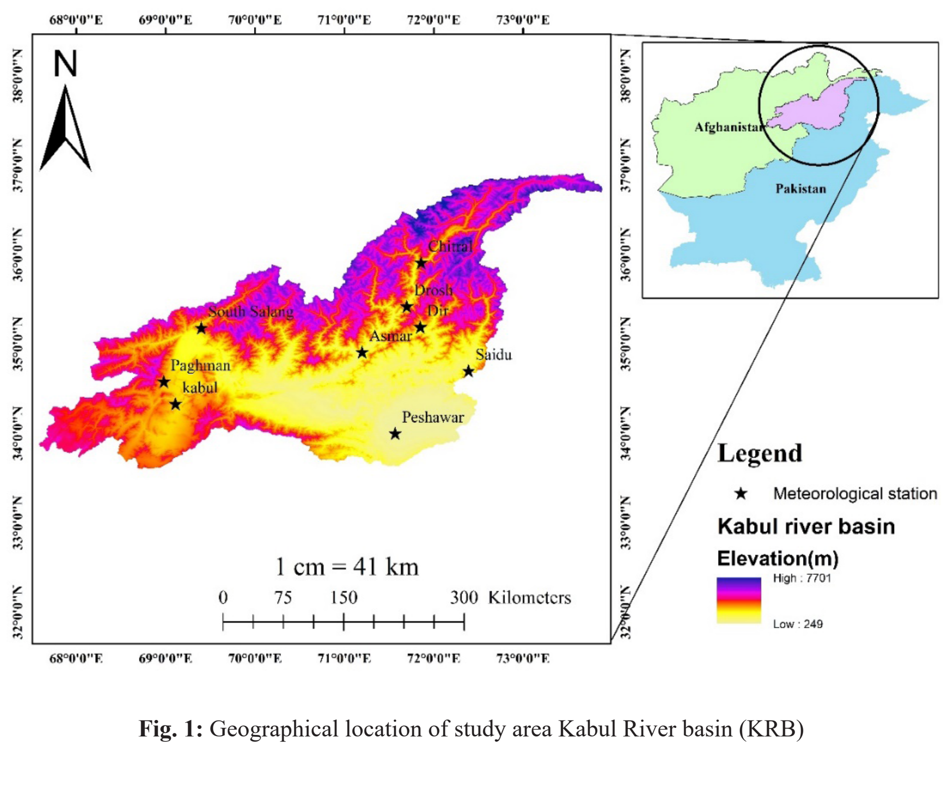

Fig. 1: Geographical location of study area Kabul River basin (KRB)

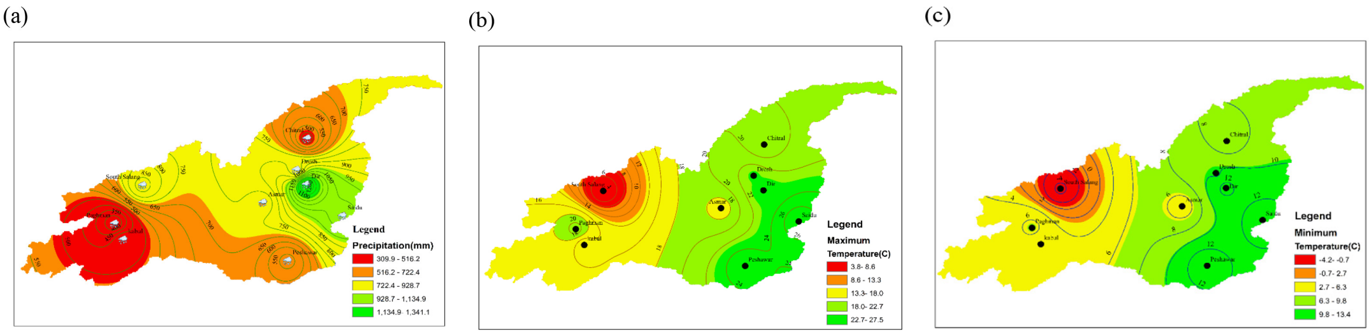

Fig. 2: Spatial distribution of average (a) precipitation (b) maximum temperature and (c) minimum temperature during 1981-2022

Table 1: 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

such detailed meteorological data, methods like Penman-Monteith, Hargreaves, and Thornthwaite are used to estimate PET with available data. In this study, the Hargreaves method (Hargreaves and Allen, 2003) was used which requires only maximum, minimum monthly temperatures and latitude of station as expressed in Eq.2.

$$PET = 0.0023*R_a\,(T_{mean}+17.8)\,(T_{max}-T_{min})^{0.5} \tag{2}$$

Where, PET= reference evapotranspiration (mm day^{-1}); T_{mean}, T_{max} and T_{min}= mean, maximum and minimum temperature (^{0}C) respectively; R_a is the extraterrestrial radiation (MJ m^{-2} day^{-1}), which depends on the latitude and the day of the year. The SPEI and PET calculations were performed using the RStudio package "SPEI version 1.8" SPEI values and their corresponding drought classifications, as defined by the Soh et al., (2018), are detailed in Table 1.

Machine learnings models

Extreme Gradient Boosting (XGBoost): XGBoost is an advanced machine learning algorithm based on the Gradient Boosting Machine (GBM) using regression trees. It employs boosting, iteratively training weak learners to correct errors and create a strong model. XGBoost optimizes GBM to reduce overfitting and underfitting, making it effective for large datasets and complex problems. In our study, we used XGBoost with 4000 trees, a maximum depth of 20, and a learning rate of 0.1. We optimized the model with Optuna for hyperparameter tuning, testing various settings. This fine-tuning adapted XGBoost to our dataset and problem complexity, ensuring optimal performance.

Tree algorithms (Decision tree): Tree-based models segment the input space into regions, assigning predictions to each. In gradient boosting, like XGBoost, trees sequentially correct errors, enhancing predictive performance. These models handle various data types, interactions, outliers, and non-linear relationships, making them suitable for regression and classification. We trained a Decision Tree with 4000 trees and a maximum depth of 25, optimizing with Optuna using different settings for tree count and depth. This thorough tuning ensured the model matched the dataset's characteristics and problem complexity.

Adaptive Boosting (AdaBoost): AdaBoost improves model performance by combining multiple weak learners into a strong one, sequentially training each learner and adjusting weights on misclassified instances to focus on difficult cases. This enhances performance in binary classification and regression and helps prevent overfitting. In our study, we used AdaBoost with a tree base estimator, 6 estimators, the Sammer algorithm for classification, and Sq loss for regression, keeping other parameters at default. This setup leveraged AdaBoost's strengths and tailored the algorithm to our needs, improving model performance.

K-Nearest Neighbors (KNN): KNN is a simple yet effective algorithm for classification and regression, predicting outcomes based on the 'k' nearest data points. It uses the majority class for classification or the average value for regression, often employing the Manhattan distance to determine proximity. In our study, we set KNN with 7 neighbors, used the Manhattan distance metric, and applied distance-based weighting to ensure closer neighbors have a greater influence on predictions, enhancing accuracy by emphasizing local patterns and balancing noise with significant data variations.

Model evaluation

To evaluate predictive models, regression analysis uses R-squared (R^2), RMSE, MAE, and MSE. R-squared measures how well independent variables explain the variance in the dependent variable, with 1 indicating a perfect fit. RMSE and MAE assess the average deviation between predicted and actual values, with lower values indicating better performance; RMSE penalizes larger errors more than MAE. MSE, like RMSE but without the square root, shows the average squared errors. For classification, metrics include the confusion matrix, accuracy, precision, recall, F1 score, ROC AUC, and Log Loss as used by (Sakthipriya and Thangavel, 2024). The confusion matrix breaks down predictions into true positives, true negatives, false positives, and false negatives. Accuracy measures correct predictions' proportion, precision reflects the correctness of positive predictions, recall indicates the model's ability to identify positive instances, and the F1 score balances precision and recall. ROC AUC evaluates the model's ability to distinguish between classes, and Log Loss assesses the accuracy of predicted probabilities. These metrics are essential for evaluating regression and classification models.

RESULTS AND DISCUSSION

The SPEI was computed in RStudio using the SPEI package for 1981-2022, with PET calculated via the Hargreaves formula. Machine learning models were trained and tested on this data, including SPEI-3 and SPEI-6 calculations and predictions for all meteorological stations. However, the detailed information is provided for a representative station Asmar (Afghanistan) for better understanding. The detailed examination of drought episodes using the SPEI-3 and SPEI-6 indices underscores significant temporal variability and severity in drought conditions across the Kabul River Basins (Fig. 3). For the SPEI-3 index, which represents short-term drought conditions, extreme drought was evident from March to June 1981, indicating a rapid onset and severe impact within a relatively brief period. This was followed by multiple severe drought episodes spanning the late 1980s and early 1990s, particularly clustered around the summer months. These patterns suggest a susceptibility to short-term droughts during critical agricultural seasons, potentially exacerbating water stress and impacting crop yields. Notably, the recurrence of severe droughts in the early 1990s and early 2000s reflects a concerning pattern of frequent drought conditions that could strain water resources and agricultural systems.

The SPEI-6 index, reflecting longer-term drought conditions, exhibited a different pattern, with extreme droughts prominently noted in mid-1981 and late 1989 and 1990 (Fig. 3). The persistence of these conditions over extended periods, as seen in the multi-month droughts of 1981 and 1993, indicates prolonged water deficits that could affect groundwater recharge and long-term water availability. The recurrence of severe droughts in the early 1990s, including a notable episode in October 1990, highlights the potential for sustained climatic anomalies impacting the region's hydrology.

The divergence in timing and intensity between the SPEI-3 and SPEI-6 indices underscores the complexity of drought phenomena in the region. While SPEI-3 captures the immediate and acute nature of drought episodes, SPEI-6 reveals the underlying

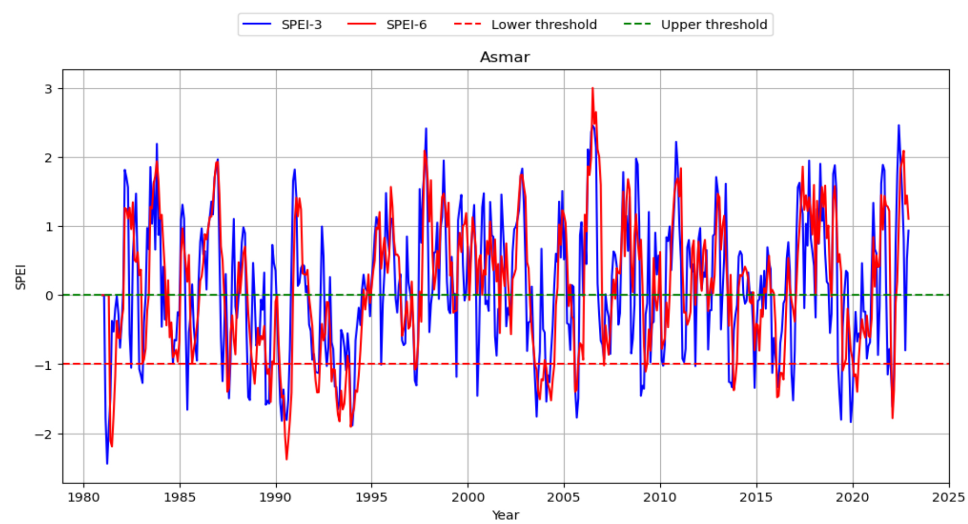

Fig. 3: SPEI-3 and SPEI-6 during study period (1981-2022) at Asmar (Afghanistan)

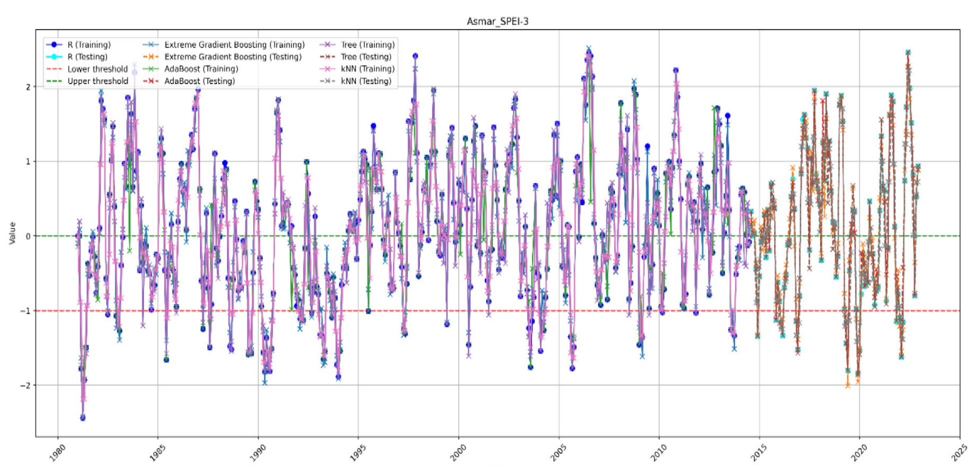

Fig. 4: Training (1981-2013) and testing (2014-2022) of machine learning models at Asmar (Afghanistan)

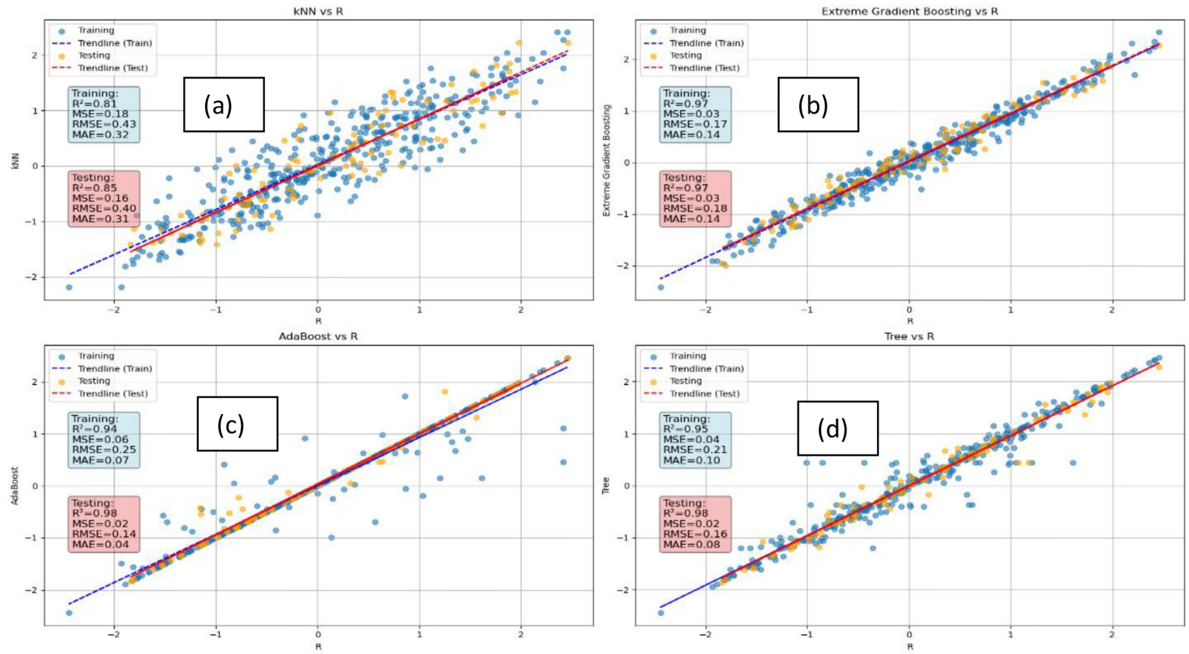

Fig. 5: Performance of machine learning models (a) KNN, (b) XGBoost, (c) AdaBoost and (d) Decision tree during training (1981-2013) and testing (2014-2022) period**.**

prolonged deficits that may not be immediately apparent. This duality suggests that different types of droughts—short-term versus long-term—pose distinct challenges for water resource management, agricultural planning, and mitigation strategies. The findings emphasize the need for a nuanced understanding of drought dynamics, considering both short-term and long-term indicators, to develop comprehensive strategies for managing water resources and mitigating the impacts of droughts. These patterns underscore the need for ongoing monitoring and adaptive management.

Machine learning models were trained on 80% of the data (1981-2013) and tested on 20% (2014-2022), with performance shown in Fig. 4. The evaluation metrics for both the training and testing phases, as shown in Fig. 5, provide a critical comparison of different machine learning models' performance in predicting the SPEI index. Among the models evaluated, XGBoost demonstrated the most robust performance. During the training phase, XGBoost achieved an impressive R^2 value of 0.97 and a Root Mean Squared Error (RMSE) of 0.17, indicating a high degree of fit between the predicted and actual values. Remarkably, the model maintained this high level of accuracy during the testing phase, with an R^2 of 0.97 and a slightly increased RMSE of 0.18. This consistency across both training and testing datasets underscores XGBoost's capacity to generalize well and avoid overfitting, making it a reliable predictive tool for the study.

In contrast, the KNN model showed a notable disparity between training and testing phases, with a significant drop in performance metrics: an R^2 of 0.81 during training versus 0.85 during testing, and a higher RMSE in the testing phase (0.40) compared to training (0.43). Similarly, AdaBoost exhibited reasonable performance during training with an R^2 of 0.94 and RMSE of 0.06, but a reduced performance during testing with an R^2 of 0.88 and RMSE of 0.25, indicating potential overfitting. The Decision tree model also displayed a solid R^2 of 0.98 and RMSE of 0.02 in training, but a noticeable decrease in testing performance metrics, with an R^2 of 0.98 and RMSE of 0.16 (Fig 5).

The comparison highlights that while all models exhibited some degree of predictive power, XGBoost consistently provided the most accurate and reliable predictions, both in training and testing phases. This underscores the model's robustness and effectiveness as a tool for drought prediction in the Kabul River Basins, supporting its selection as the best-performing model among those tested

Machine learning models were evaluated using metrics like confusion matrix, accuracy, precision, recall, F1 Score, ROC AUC, and Log loss. Tables 2 display confusion matrices for KNN models for representative station. The confusion matrix for the KNN model reveals moderate accuracy in classifying drought conditions, with a notable tendency to correctly identify "Near normal" conditions, as evidenced by the 288 correct classifications. However, the model struggles with distinguishing between similar categories, such as "Severely dry" and "Moderately dry," with frequent misclassifications observed. The accuracy, precision, recall, and F1 score all hover around 0.68, indicating balanced but not highly accurate performance (Tables 3). The ROC AUC value of 0.69 suggests moderate discriminative ability, while the high log loss of 11.56 points to frequent misclassifications with high confidence. Overall, the model demonstrates a reasonable starting point for drought classification but requires improvements in feature differentiation and algorithmic sophistication to enhance predictive accuracy and reliability.

CONCLUSION

The study critically assessed the performance of

Table 2: Confusion matrix for KNN model

	Predicted								
	Categories	Extremely dry	Severely dry	Moderately dry	Near normal	Moderately wet	Very wet	Extremely wet	SUM
Actual	Extremely dry	1	0	0	0	0	0	0	1
	Severely dry	1	7	13	7	0	0	0	28
	Moderately dry	0	4	15	21	1	0	0	41
	Near normal	0	2	17	288	24	5	0	336
	Moderately wet	0	0	0	32	14	2	1	49
	Very wet	0	0	1	10	13	12	2	38
	Extremely wet	0	0	0	0	2	3	4	9
	SUM	2	13	46	358	54	22	7	

Table 3: Accuracy, precision, recall, F1 Score, ROC AUC, and Log loss for all models

Model	Accuracy	Precision	Recall	F1 Score	ROC AUC	Log loss
KNN	0.68	0.67	0.68	0.67	0.69	11.56
XGBoost	0.63	0.62	0.63	0.62	0.63	13.41
AdaBoost	0.63	0.62	0.63	0.62	0.64	13.29
Tree	0.61	0.61	0.61	0.61	0.64	14.00

AdaBoost, Decision Tree, XGBoost, and KNN models in predicting SPEI across different time scales in the Kabul River basins. While XGBoost demonstrated the highest overall accuracy and reliability, excelling in capturing drought patterns, it showed some limitations in accurately predicting specific drought classes. The KNN model provided a balanced performance, though it did not surpass XGBoost in overall effectiveness. The findings highlight the importance of selecting appropriate models for different prediction tasks and suggest that further refinement and exploration of ensemble methods could enhance prediction accuracy. Future research should focus on addressing the limitations observed in class prediction and incorporating additional factors to improve the precision of drought forecasting.

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

***Author contributions*: U. Khan:** Conceptualization and design of the study. **A. Khalil:** Methodology and analytical framework. **S. Jan**: Data curation, preparation of tables and figures. All authors contributed to the drafting and revision of the manuscript and approved the final version for publication.

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