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Drought Prediction in Balochistan: A Comparative Study of Arimax and Machine Learning Models

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ABSTRACT

Background: Drought is harmful to the environment and human life and has a major impact on reducing the quality of life. It's a natural disaster whose negative effects spill into farms, water resources, and ecosystems, causing crop failures and food insecurity. Thus, it is one of the important global issues.
Objective: In this research, we intend to model drought in different regions of Balochistan, Pakistan, using machine learning and traditional methods. The data of monthly precipitation and minimum and maximum temperature from 1951 to 2017 from five stations in Balochistan were used.
Methods: The commonly used method of Autoregressive Integrated Moving Average with independent variables (ARIMAX) was compared with three machine learning methods, namely Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN). The Standardized Precipitation Index (SPI) based on three, six and nine months was chosen as a drought indicator. Four different models using the lagged values of variables were developed. To evaluate the accuracy of these models, three statistical measures, RMSE, MAE, and R^2 were used.
Results: Based on the results of this study, we found that the RF method with the M1 model (with two lagged values of variables) provided satisfactory results of R^2 at each station we studied. Additionally, the RF model showed the best results for the Panjgur station. In this study, we obtained R^2 values 0.825,0.756, 0.584,0.731,0.902 for Dalbandin, Quetta, Sibi, Zhob and Panjgur stations, respectively. These results were average training and testing results for each station. The RMSE, MAE and R^2 values of the Panjgur station were 0.177,0.115,0.974,0.337,0.227,0.902 during the training and testing phases, respectively.
Conclusion: We found that the RF model has a high potential to forecast drought more precisely than other alternative approaches due to its great accuracy and the outcomes of this study will help the researchers accurately predict droughts.

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1. INTRODUCTION

Droughts are complex natural phenomena of great concern to scientists, as they have a serious negative impact on the atmosphere, soil, and plants due to the local phenomenon of lack of rain for an extended

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period. Worsened by climate change, droughts also pose severe threats to agriculture, livestock and human lives in the form of acute water scarcity, dehydration, and malnutrition (Wang et al., 2020). Droughts pose the most significant threat to livestock and crops in almost every part of the world, affecting an estimated 55 million individuals annually. The risk of death due to drought threatens people's livelihoods. 40% of the world's population is currently experiencing a water shortage; by 2030, 700 million individuals may be at risk of being displaced due to drought (WHO, 2018).

The region of Balochistan in Pakistan has been challenging a life-threatening shortage of water assets. Therefore, water is now more valued than land, especially in zones with a lot of planes or underground water. Water scarcity affected people's basic requirements and made it a key factor in determining the land value in the area. The province of Balochistan now recognizes water as a precious resource and its management and maintenance are essential (Ahmed et al., 2016). Like many other parts of the world, Balochistan has experienced a devastating drought that has deeply affected the lives of its citizens. Severe droughts have occurred throughout the region's history; the last one lasted from 1950 to 2017 (Khan et al., 2017).

Various indices have been developed to monitor drought conditions, including Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI), Crop Moisture Index (CMI) and Standardized Water-level Index (SWI). These indices rely on different parameters and probabilities of drought occurrences. Typically, they are utilized to identify drought events across various time scales (Morid et al., 2007). In recent years, the SPI has been commonly used due to its simplicity and requirement of minimal input data. This index solely depends on rainfall data, making it a popular choice among researchers (Rahman & Lateh, 2016). The SPI can be estimated for various scales. A shorter SPI time frame can act as an early warning system for drought and accurately predict drought intensity. It also enables a comparison of locations with varying climates. As it has a probabilistic nature, it has a historical basis that can aid in decision-making (Poornima & Pushpalatha, 2019).

Researchers use both traditional time series techniques and machine learning models to predict droughts. The ARIMA model is a popular uni-variate approach for drought forecasting due to its ability to detect trends and its simplicity compared to other climate models. Many climatology and geophysics experts have utilized ARIMA in their research. ARIMAX model was used by Jariwala and Agnihotri (2024) to assess the drought conditions. Accurate drought predictions for certain Gujarat regions in India were made using an ideal ARIMAX model. The forecasted data were used to create the meteorological drought risk map and drought frequency map. Durdu (2010) developed ARIMA and seasonal ARIMA techniques in Turkey to predict droughts and found that the ARIMA model can predict drought up to two months in advance.

The traditional statistical methods were not able to handle the non-linearity and complexity of real-world problems. On the other hand, machine learning models can deal with complex patterns and multiple variables such as temperature, moisture and windy weather. Therefore, with machine learning techniques, the accuracy of predictions has significantly improved. Machine learning models do not need any special programming practices. In ML techniques, systems can learn and improve their abilities over time by using previous data (N. Khan et al., 2020). The application of ML algorithms has enhanced the accuracy of forecasting droughts by identifying difficult patterns for individuals to detect. Therefore, ML is considered a valuable tool for businesses and organizations (Raja & Gopikrishnan, 2022).

Nikbakht Shahbazi et al. (2012) conducted a study to predict meteorological drought in Tehran. The Support vector machine (SVM) and Artificial Neural Network (ANN) were utilized for SPI-3, SPI-6 and SPI-9. The SVM showed superior performance compared to ANN. Shirmohammadi et al. (2013) performed a study in the Azerbaijan province of Iran to examine meteorological droughts. A combination of wavelet transform was used with machine learning models, including ANN, adaptive neural fuzzy inference system (ANFIS) methods, and two hybrid models. The accuracy of results was increased in the wavelet transform model. The ANN and ANFIS models were found to be inefficient for non-stationary and seasonal actions.

Belayneh et al. (2014) conducted a study in Ethiopia, an East African country, to examine the effectiveness of machine learning models. The three ML algorithms coupled wavelet-ANNs, support vector regression (SVR), and ANNs were utilized and the SPI drought index was used for 1 and 3 months. Among these models, the coupled wavelet neural networks proved to be the most accurate in predicting droughts. In Rajasthan, a study was conducted by Ganguli and Reddy (2014) to predict meteorological drought. The Least Square SVR model and Bivariate Coupla functions were developed to estimate the drought index. The uncertainty of drought forecasting was modelled using the Frank, Clayton, and Plackett families of copulas. The climatic indices were added to the forecasting model to enhance prediction performance for up to three months lead time.

A research study by Jalalkamali et al. (2015) focused on predicting meteorological droughts in the Yazd Province of Iran and used various models, including ANFIS, SVM, MLP, and ARIMAX. The research found that all models were useful for monitoring meteorological droughts, but ARIMAX performed better than the others. Machine Learning Methods were employed to predict long-term hydrological droughts in the Central Valley region of California by Tan and Perkowski (2015). Wavelet transform analysis was used with support vector regression and artificial neural network algorithms, with precipitation, satellite remote sensor, and surface discharge data sets utilized to assess the drought prediction efficiency from January 2011 to May 2014. The study determined that the most effective method for predicting droughts was the wavelet-coupled machine-learning technique, which improved precision when dealing with non-stationary data.

Djerbouai and Souag-Gamane (2016) conducted a study in Algeria's basin to compare the prediction accuracy of the stochastic models, ARIMA and Seasonal ARIMA, against ANNs and Wavelet ANNs models. The SPI was used to estimate drought for intervals of 3, 6, 9, and 12 months. The most effective model found for all SPI series was the Wavelet ANNs. Li et al. (2017) performed a study in China to forecast drought. The input variables precipitation, temperature, and soil moisture were used to develop a Random Forest model. The outcomes of the study indicated the best performance of the Random Forest model. Mokhtarzad et al. (2017) conducted a study that assessed the effectiveness of machine-learning models, including ANN, ANFIS, and SVM, for drought prediction using SPI-3. Although the models produced correct results, SVM outperformed ANN and ANFIS in predicting SPI. Non-parametric inference was also used to verify the accuracy of SVM.

Rehman et al. (2019) conducted a study in the Nushki District of Balochistan attributing lack of rainfall and drying water sources as the crucial indicators of droughts while also assessing the impacts and coping strategies of the locals on droughts. Some of the coping strategies included out-migration, limited crop diversification, as well as reduced consumption of food. Ashraf (2019) examined the drought period from 1998 to 2002 in Balochistan and the adaptive strategies adopted by farmers emphasizing the fact that though they adopted crop diversification and water management, their methods were quite reactive. S. Khan et al. (2020) focused on the Zhob district in the time frame of 1981-2018, analyzing the drought patterns and determining two major drought periods, asserting the need for early warning systems. Dikshit et al. (2020) performed a study in South Australia. This study analyses climate variables like temperature and rainfall by utilizing RF and SPI for three and one month. The RF model outperformed and SPI-3 achieved 84% accuracy and SPI-1 obtained 82% accuracy.

(N. Khan et al., 2020) employed two Machine learning models, SVM and ANN to predict drought characteristics in Pakistan. The SVM model was found to be the most efficient model compared to the ANN. Naz et al. (2020) examined drought trends in Balochistan. The Mann-Kendall test was applied to explore the drought trend in each region. The study showed that Quetta, Zhob, Dalbandin, and Jiwani regions received less rainfall and Barkhan experienced severe drought conditions.

This study aims to evaluate the performance of the traditional approach ARIMAX with machine learning algorithms. The Machine-learning model's predictive skills have increased due to the development of new technology. ML techniques facilitate the optimal selection of methods for more accurate decisions and predictions in many situations. This paper compares three machine-learning approaches with the ARIMAX model for drought forecasting at several stations in Balochistan, Pakistan. This research aims to increase the accuracy of drought predictions by evaluating the performance of these models based on statistical metrics such as root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). This study addresses the problem of developing better methodologies to forecast droughts in Balochistan, Pakistan. This study intends to assess which ML methods provide more accurate predictions than conventional forecasting models such as ARIMAX. Hence, the reason behind this study is to augment drought prediction accuracy, an approach necessary to mitigate the adverse effects of droughts. An ability to make accurate predictions can improve preparedness and response strategies, thus mitigating the impact of such disasters.

2. METHODS

2.1 Research Design

The study analyzes monthly time series data for 66 years ranging from 1951 to 2017.

2.2 Setting of the study

Balochistan is characterized by an arid climate, with an average annual rainfall of less than 250 mm, making it a challenging environment to live in despite the harsh weather conditions. Balochistan province is least developed among all provinces in Pakistan (Panezai, 2012; Panezai, 2017). Balochistan is divided into four distinct zones: higher and lower highlands, plains, and deserts, each with unique climates. The plain zones have hot summers and mild winters, while the upper hill zones experience warm summers and cold winters. The lower plateau zones have hot and dry summers and exceptionally cold winters with freezing temperatures. The deserts are dry, with scorching temperatures (Naz et al., 2020). In this research, we analyzed the monthly precipitation data as well as the maximum and minimum temperature data from multiple stations in Balochistan, including Dalbandin, Panjgur, Quetta, Sibi, and Zhob, between 1951 and 2017.

The study areas are five stations in Balochistan (Figure 1). Each region in Balochistan experiences unique climate conditions, as the Dalbandin region has experienced high temperatures during summers and mild winters. Rainfall occurs during winter, but the climate is generally dry throughout the year. Panjgur station receives less precipitation during the year and experiences hot and roasting summers and mild winters, which collectively contribute to its dry climate. The temperature in the Sibi district is very high during the summer seasons and is considered the scorching spot in Pakistan. In Zhob, summers are very long, and winters are short. During the summer season, the climate is hot, with extreme heat. It receives very little rainfall, which contributes to the dryness of the environment. The Quetta region's climate conditions vary during summer and winter. Quetta has been grappling with water scarcity for a long time.

In Balochistan, the precipitation pattern varies from station to station. Winter precipitation in the Quetta and Zhob regions is mainly attributed to western disturbances. Dalbandin, Sibi, and Panjgur stations get precipitation during the moon soon season. Rabi and Kharif are the two primary farming seasons. Monsoon rainfall determines the Kharif season, whereas winter rainfall determines the Rabi season. Typically, the Rabi season begins in September and lasts until March, whereas the Kharif season begins in April and lasts until August. Quetta and Zhob are categorized as being in the Rabi season, whilst Sibi and Panjgur stations are in the Kharif season. In this study, the SPI for three-, six, and nine-month durations were used. The SPI-3 is commonly used to analyze agricultural droughts due to its ability to reveal short-term precipitation trends. The SPI-6, on the other hand, provides insights into medium-term precipitation trends and seasonal effects on agriculture and water, showing significant long-term trends. We divided three months for Quetta and Zhob from December to February and for Sibi, Panjgur, and Dalbandin from July to September to prepare SPI-3. For Quetta and Zhob, the SPI-6 was measured from October to March. And for Sibi, Panjgur, and Dalbandin from April to September. For SPI-9, we make use of data from April to December for Dalbandin, Sibi, and Panjgur, while for Quetta and Zhob we used the months from October to June. The current research has utilized data from five stations located in Balochistan and analyzed specific parameters. We have only used the SPI for three, six and nine months.

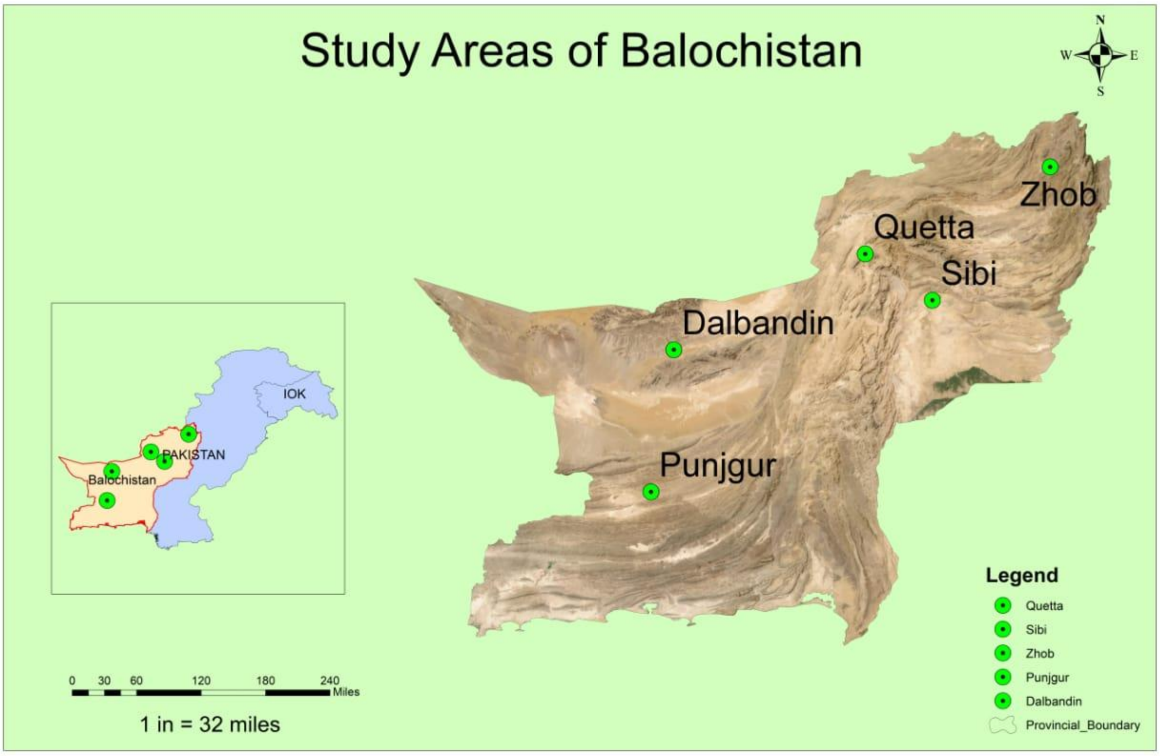

Fig.1 Study areas of Balochistan

2.3 Study variables

The dataset consists of three variables precipitation, maximum and minimum temperature. In this study, four models were developed based on lagged variables. Maximum, minimum temperature and precipitation data were used to create these models with different combinations of lagged variables.

2.4 Data sources

The dataset provided by the Pakistan Meteorological Department (PMD) from 1951 to 2017 of the different stations of Balochistan, Dalbandin, Panjgur, Quetta, Sibi, and Zhob.

2.5 Data analysis methods

The missing observations were handled using the average method. Data were partitioned data into training (80%) and testing (20%) sets. The statistical analysis was carried out with the help of R software. Different R packages are utilized for implementing various ML methods and traditional models.

2.5.1 Statistical and Machine Learning terms

This section explains the drought index and all statistical and machine learning methods used in the study for the analysis.

2.5.2 Standardized Precipitation Index (SPI)

The standardized precipitation index **(**SPI) is a method established by (McKee et al., 1993). Several drought indices have been proposed, but SPI is considered the most suitable index due to its versatility, such as describing drought conditions and comparing droughts with different regions, climates and periods. In the initial stage, it was developed to measure meteorological droughts only, which recognized negative irregularities of precipitation. Still, later, McKee et al. (1993) noted that it could monitor both wet and dry events. To describe a complex event, SPI only uses precipitation data from meteorology. Using the probability density function, rainfall is expressed as a standardized departure from the average. It often uses the gamma function for an aggregate of monthly rainfall. The probability density function is determined by using long-term data on precipitation, and then it is converted into a normal distribution with mean zero and standard deviation one. The SPI index is used to evaluate and compare the precipitation data in particular areas. SPI can be used to categorize both long and short-term drought conditions. For the short term, SPI-3 is suitable; for the long term, SPI-12 and SPI-24 are considered, but SPI-9 is measured for both long and short-term drought conditions. In this study, we found more accurate and reliable results of SPI for nine months, therefore, we mention the results of SPI-9 here only. SPI is used to classify the severity of precipitation or dryness during a specific period and is classified using its value ranges. The several categories into which the SPI readings are separated indicate the level of dryness or rainfall. McKee et al. (1993) and McKee (1995) classify the drought categories (Table. 1). These divisions aid in determining the degree of precipitation and comprehending the possible effects of drought or excessive precipitation in a certain area.

Table 1. The classifications of SPI

SPI	Intensity
3.00 to 2.00	Extremely rainy
1.99 to 1.50	Very rainy
1.49 to 1.00	Moderate rainy
-0.99 to 0.99	Near Regular
-1.00 to -1.49	Adequate dry
-1.50 to -1.99	Severe dry
-2.00 to -3.00	Extremely dry

2.5.3 Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX)

Autoregressive Integrated Moving Average (ARIMA) is a suitable technique for time series analysis. However, it is not useful when there are a large number of explanatory variables. Once exogenous variables influence time series models, use a multivariate ARIMA model that is known as Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX). It is an extension of the ARIMA model. The ARIMAX method is also renowned as Box-Jenkins with exogenous variables. This approach is widely used for forecasting, problem identification, diagnostic checking of the data and handling missing observations of stationarity data. It uses several explanatory variables to predict droughts, such as temperature, monthly and seasonal rainfall, soil moisture, and streamflow. For the computation of ARIMAX, it is important to first ensure that the data is stationary, select the appropriate parameters and check the auto-correction feature, then achieve accurate predictions and future trends. ARIMAX models are considered an effective tool for time series data (Islam & Imteaz, 2021). In this study, the ARIMAX model was fitted using lagged exogenous variables.

2.5.4 Random Forest (RF)

An ensemble method, Random Forest, was proposed by Breiman in 2001 (Breiman, 2001). Random Forest is considered a robust method among data scientists because it handles regression and classification tasks with great accuracy. To create decision trees in large numbers, Random Forest uses randomization. Random Forest is built by utilizing multiple decision trees and these trees were constructed using input samples and training data. The result of each tree is aggregated based on the votes of all trees to obtain a single output. In the last step, decisions were made on the final prediction for regression and classification problems. This method of aggregating results is called bagging or bootstrap. The technique of bagging is an effective tool in Random Forest as it estimates missing observations and maintains the accuracy of the results. It provides more accurate results than any other single tree-based method because it reduces over fitting and uncertainty and handles large datasets. It is used in multiple fields, including agriculture and environmental studies, to predict droughts' severity. It can deal with complex and high-dimensional data; therefore, it is considered a robust method for drought prediction. Random Forests use multiple variables such as soil, moisture level, and vegetation indices.

2.5.5 Support Vector Machine (SVM)

It is a powerful machine-learning technique based on the statistical learning theory known as the Support Vector machine proposed by Cortes & Vapnik in 1995 (Cortes & Vapnik, 1995). It is widely used in classification problems, regression analysis and patterns. It was developed to get the best classification output utilizing limited samples in the training dataset. To create an accurate model for decision-making, it minimizes the risk; therefore, it is a technique of small-sample learning. SVM aims to recognize the data structure. The SVM detects a hyperplane within a space that can have multiple dimensions. The hyperplane attempts to maximize the boundary between the closest points of dissimilar classes. The number of features decides the dimension of the hyperplane. The hyperplane stimulates efficiency and reduces bias. SVM always provides efficient and reliable results in both classification and regression studies. It has multiple characteristics that promote its ability to deal with effective drought predictions and be utilized in a variety of fields such as medicine, finance, and engineering.

2.5.6 K-Nearest Neighbour (KNN)

It is one of the most popular and simplest methods introduced by Fix and Hodges in 1951 (Fix, 1985). It is a non-parametric machine learning Method. This technique is commonly used for statistical pattern recognition and data mining. It attempts to classify an unknown sample by associating it with the known classifications of its neighbours. In KNN, the model is provided for a training set, and to classify objects, it uses this training set and each sample is included in the training data. The KNN is widely used in the case of large datasets. It is used to test different combinations of factors, identify irrelevant factors and eliminate them. This supervised learning technique predicts the value of the target variable; this target variable can be drought severity. It is used for predicting the potential damages caused by dam spillways under various conditions, traffic flow forecasting, and risk intake vortex. KNN is a widely used method due to its effectiveness. It can be used for image identification and recommendation strategies.

2.5.7 Performance evaluation

Three evaluation measures have been developed in this study to assess the performance of ML algorithms and ARIMAX. These measures are mathematically expressed as

1. Root mean square error ($RMSE$):

$$\mathbf{RMSE} = \sum_{i=1}^{n} \sqrt{\frac{(y_i - \hat{y}_i)^2}{n}}$$

2. Mean Absolute error (MAE):

$$\mathbf{MAE} = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n}$$

3. Coefficient of determination (R^2):

$$\mathbf{R^2} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}$$

Here, in the above equations

$\boldsymbol{n}$= Number of data points, $\boldsymbol{y_i}$= observed values, $\hat{\boldsymbol{y}}_i$ = predicted value, $\bar{\boldsymbol{y}}_i$ = the mean value of observed data.

3. REULTS

Four different combinations of input models, namely M1, M2, M3, and M4, were developed for SPI levels. These models are based on lag variables. Lag variables in the regression model represent the explanatory variables. Model structures given in Table 2 represent time series lag variables as SPt-1, one lagged variable, SPt-2, as a two-lag variable and so on. These variables are explanatory. SPt is the dependent variable for each model. These models were compared to obtain the best results. The performance of these four models was evaluated using ARIMAX and various machine learning models such as SVM, RF, and KNN statistical measures such as MAE, RMSE, and R^2. The top model was selected based on the lowest values of MAE and RMSE and the highest value of R^2.

Table 2 Structures of input models

Models	Input variables	Output variables
M1	$SP_{t-1},\ SP_{t-2},\ SP_{t-3}, SP_{t-4},\ P_{t-1},\ P_{t-2}$	SP_t
M2	$SP_{t-1}, SP_{t-2}, SP_{t-3},\ Tmax_{t-1}, Tmax_{t-2}, Tmin_{t-1}, Tmin_{t-2}$	SP_t
M3	$SP_{t-1}, SP_{t-2}, SP_{t-3}, Tmax_{t-1}, Tmax_{t-2},\ Tmax_{t-3}, Tmin_{t-1}, Tmin_{t-2}, Tmin_{t-3}$	SP_t
M4	$SP_{t-1}, SP_{t-2}, SP_{t-3},\ Tmax_{t-1}, Tmax_{t-2}, Tmin_{t-1}, Tmin_{t-2},\ P_{t-1},\ P_{t-2}$	SP_t

Here in Table 2, Tmax denotes Maximum temperature, Tmin represents Minimum temperature, and P signifies precipitation.

The average rainfall plot of each station in (Fig. 2). The average Maximum and minimum temperature of each station is given below in (Fig.3).

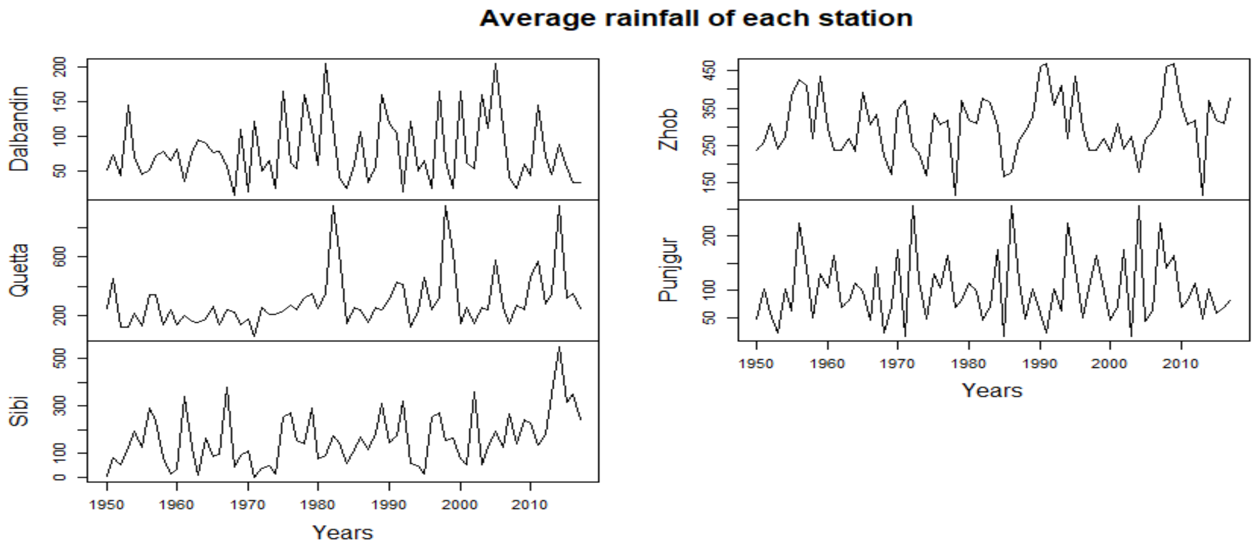

Figure 2 Average rainfall of each station for the years 1951 to 2010

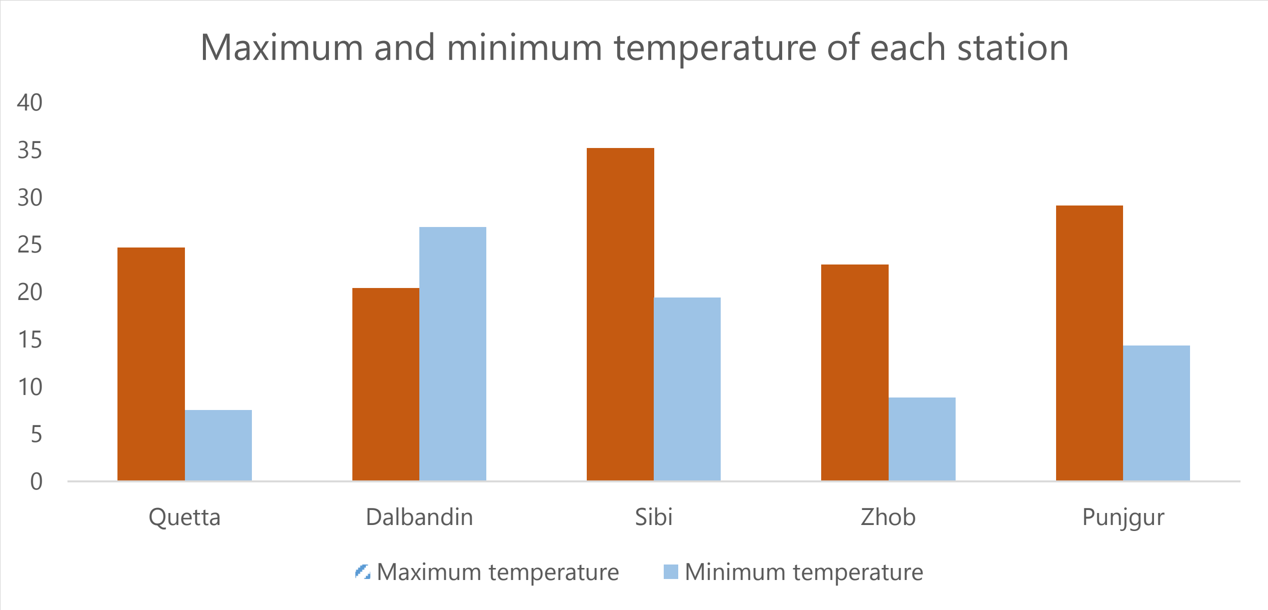

Figure 3 The average maximum and minimum temperature of each station

Table 3 reported the machine learning algorithms and ARIMAX results at the Dalbandin station. The average Training and testing results of each model were mentioned. The table illustrates the performance of various models at three SPI levels (3, 6, and 9) for both training and testing phases. The results obtained from this table showed that the RF model was the most accurate. The RF was found to be the most effective among all of the models analyzed. This was determined through evaluation measures. The values for the RF method were achieved as MAE (0.398), RMSE (0.280), and R^2 (0.825). The SVM model performance was good, especially for SPI-9. The KNN attained the lowest values of R^2 for each SPI. The ARIMAX model performs well in the training phase but not in testing. SPI-3 model showed the best results in the Dalbandin station, as it obtained lower values of MAE, RMSE, and higher values of R^2 mainly for the RF model.

Table 3 Results of a machine learning algorithm and ARIMAX for Dalbandin station

Dalbandin		**Training**			**Testing**		
Model	**SPI-TYPE**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**	**R^2**
	SPI-3	0.453	0.306	0.719	0.495	0.344	0.705
SVM	SPI-6	0.520	0.354	0.684	0.568	0.392	0.689
	SPI-9	0.401	0.251	0.817	0.533	0.386	0.769
	SPI-3	**0.214**	**0.151**	**0.956**	**0.398**	**0.280**	**0.825**
RF	SPI-6	0.242	0.170	0.943	0.454	0.320	0.808
	SPI-9	0.209	0.145	0.952	0.496	0.469	0.792
	SPI-3	0.655	0.528	0.460	0.795	0.610	0.380
KNN	SPI-6	0.721	0.576	0.439	0.871	0.666	0.353
	SPI-9	0.662	0.568	0.458	0.873	0.725	0.345
	SPI-3	0.446	0.331	0.742	1.050	0.822	0.461
ARIMAX	SPI-6	0.511	0.379	0.695	1.143	0.335	0.335
	SPI-9	0.417	0.305	0.792	0.617	0.487	0.758

Note. The bold values represent the values of the best-fitted model.

Table 4 presents an analysis of various models for the Quetta station. As shown in the table, the RF Model achieved the highest value of R^2 at 0.756 for SPI-9. The RF model outperformed other models with the highest R^2 value. The SVM model also performs well for SPI-6 and SPI-9. The performance of KNN demonstrates it is not as effective as SVM and RF. The ARIMAX model had the highest R^2 value and minimal RMSE and MAE values during training, but its performance was not satisfactory during testing data. The ARIMAX produced lower R^2 values of 0.428, 0.398, and 0.453 for SPI-3, SPI-6, and SPI-9 respectively. Overall, RF showed accurate results for SPI-9 in Quetta station.

Table 4. Results of a machine learning algorithm and ARIMAX for Quetta station

Quetta		**Training**			**Testing**		
Model	**SPI-TYPE**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**	**R^2**
	SPI-3	0.463	0.300	0.719	0.495	0.341	0.590
SVM	SPI-6	0.430	0.282	0.827	0.402	0.349	0.625
	SPI-9	0.282	0.217	0.880	0.431	0.338	0.521
	SPI-3	0.213	0.153	0.950	0.458	0.353	0.608
RF	SPI-6	0.202	0.146	0.964	0.431	0.339	0.628
	SPI-9	**0.136**	**0.340**	**0.965**	**0.381**	**0.219**	**0.756**
	SPI-3	0.803	0.595	0.463	0.840	0.680	0.068
KNN	SPI-6	0.756	0.564	0.508	0.806	0.655	0.079
	SPI-9	0.517	0.567	0.502	0.849	0.728	0.118
	SPI-3	0.443	0.310	0.798	0.608	0.478	0.428
ARIMAX	SPI-6	0.350	0.319	0.818	0.616	0.481	0.389
	SPI-9	0.294	0.209	0.863	1.196	0.994	0.453

Note. The bold values represent the values of the best-fitted model.

An analysis was conducted at Sibi station, and the results are shown in Table 5. The RF model was seen to be highly precise after carefully considering the MAE, RMSE, and R^2 values. The RF was moderate at training, and their accuracy slightly declined in the testing phase. KNN showed poor performance at Sibi station as both obtained minimum values of R^2. However, throughout the training and testing stages, the Random Forest approach with SPI-9 seems to be the most accurate predictor for the Sibi station.

Table 5. Results of a machine learning algorithm and ARIMAX for Sibi station

Sibi		**Training**			**Testing**		
Model	**SPI-TYPE**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**	**R^2**
	SPI-3	0.436	0.260	0.780	0.434	0.294	0.577
SVM	SPI-6	0.452	0.272	0.787	0.441	0.304	0.568
	SPI-9	0.291	0.197	0.889	0.517	0.367	0.495
	SPI-3	0.207	0.128	0.813	0.470	0.339	0.523
RF	SPI-6	0.214	0.136	0.957	0.431	0.307	0.602
	SPI-9	**0.165**	**0.122**	**0.966**	**0.419**	**0.298**	**0.584**
	SPI-3	0.548	0.503	0.579	0.475	0.593	0.100
KNN	SPI-6	0.666	0.521	0.566	0.764	0.610	0.309
	SPI-9	0.694	0.566	0.378	0.851	0.763	0.064
	SPI-3	0.413	0.298	0.642	0.818	0.663	0.520
ARIMAX	SPI-6	0.451	0.398	0.787	0.822	0.677	0.501
	SPI-9	0.292	0.219	0.885	0.482	0.409	0.626

Note. The bold values represent the values of the best-fitted model

The result of the Zhob station is reported in Table 6. The value of the R^2 for the KNN model was the minimum, indicating its poor performance. Prediction accuracy is typically a problem for KNN models, particularly when testing. The SVM models perform moderately, with a minor drop in testing accuracy.

Compared to several other models, ARIMAX models exhibit improved consistency across the training and testing stages and perform relatively well. The Random Forest model continuously performs well across various SPI kinds but has outstanding R^2 (0.938, 0.731) values throughout both the training and testing stages for SPI-6. The RF with SPI-6 was proven to be the most optimal model at Zhob station.

Table 6. Results of a machine learning algorithm and ARIMAX for Zhob station

Zhob		**Training**			**Testing**		
Model	**SPI-TYPE**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**	**R^2**
	SPI-3	0.604	0.429	0.720	0.638	0.461	0.623
SVM	SPI-6	0.497	0.416	0.754	0.539	0.404	0.684
	SPI-9	0.393	0.282	0.791	0.673	0.474	0.559
	SPI-3	0.298	0.207	0.933	0.409	0.319	0.693
RF	**SPI-6**	**0.242**	**0.176**	**0.938**	**0.465**	**0.404**	**0.731**
	SPI-9	0.222	0.165	0.951	0.592	0.440	0.671
	SPI-3	0.838	0.649	0.426	0.940	0.747	0.113
KNN	SPI-6	0.803	0.626	0.419	0.730	0.626	0.111
	SPI-9	0.716	0.562	0.285	0.978	0.763	0.079
	SPI-3	0.574	0.414	0.706	0.835	0.777	0.613
ARIMAX	SPI-6	0.511	0.375	0.753	0.889	0.738	0.621
	SPI-9	0.417	0.317	0.754	1.372	1.101	0.612

Note. The bold values represent the values of the best-fitted model

The results for the Panjgur station's machine learning algorithm and ARIMAX are presented in Table 7. The RF model showed high precision, confirming the RF model's effectiveness. The KNN model achieved R^2 as 0.385, 0.420 and 0.327, indicating poor results for this model. The SVM obtained moderate results. The ARIMAX performance was improved than KNN but lower than SVM and RF. However, the RF model achieved the highest R^2 value at (0.974, 0.902) for SPI-6. In general, the performance was best in the Random Forest model using the timescale SPI-6. Training and testing results of each station are given in Figure 4.

Table 7 Results of a machine learning algorithm and ARIMAX for Panjgur station

Panjgur		**Training**			**Testing**		
Model	**SPI-TYPE**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**	**R^2**
	SPI-3	0.525	0.331	0.742	0.575	0.398	0.721
SVM	SPI-6	0.488	0.305	0.773	0.547	0.376	0.349
	SPI-9	0.386	0.252	0.848	0.466	0.443	0.707
	SPI-3	0.195	0.123	0.966	0.353	0.245	0.890
RF	**SPI-6**	**0.177**	**0.115**	**0.974**	**0.337**	**0.227**	**0.902**
	SPI-9	0.177	0.124	0.969	0.428	0.298	0.866
	SPI-3	0.745	0.580	0.570	0.740	0.713	0.385
KNN	SPI-6	0.712	0.556	0.560	0.614	0.682	0.420
	SPI-9	0.683	0.529	0.556	0.922	0.817	0.327
	SPI-3	0.550	0.383	0.713	0.695	0.768	0.615
ARIMAX	SPI-6	0.520	0.361	0.742	0.916	0.729	0.647
	SPI-9	0.402	0.294	0.829	0.674	0.523	0.772

Note. The bold values represent the values of the best-fitted model

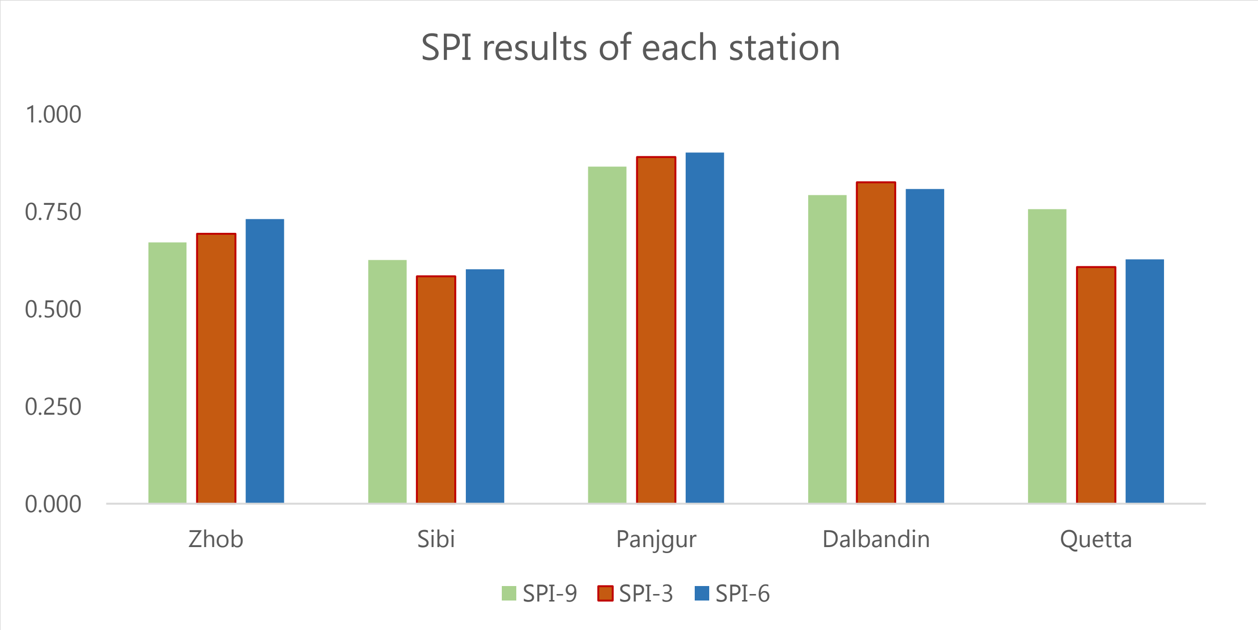

Figure 4 Results of SPI levels for each station

Table 8 consists of different models which provide accurate results. This Table reported the best-developed models and machine learning models for each SPI level. According to Table 8, Random Forest models can accurately predict SPI at different stations and time scales however, performance differs slightly according to the dataset (testing vs. training). Due to possible overfitting or variations in data distribution, the models often perform better on the training sets than on the testing sets. Sibi often has the lowest R^2 values on the testing sets, suggesting worse predictive performance, whereas Panjgur consistently performs the best overall SPI time scales. The most popular model, the RF(M1) model, works well at most stations and time scales.

Table 8 Optimal models for drought prediction

Stations	Model	RMSE	MAE	R^2	RMSE	MAE	R^2
SPI-3							
Panjgur	**RF(M1)**	**0.160**	**0.100**	**0.970**	**0.240**	**0.150**	**0.950**
Dalbandin	RF(M1)	0.220	0.150	0.950	0.350	0.240	0.880
Quetta	RF(M1)	0.220	0.160	0.950	0.460	0.360	0.630
Sibi	RF(M1)	0.210	0.130	0.960	0.410	0.290	0.610
Zhob	RF(M4)	0.296	0.206	0.934	0.408	0.316	0.698
SPI-6							
Panjgur	**RF(M1)**	**0.143**	**0.091**	**0.983**	**0.219**	**0.135**	**0.961**
Dalbandin	RF(M1)	0.251	0.174	0.940	0.398	0.278	0.862
Quetta	RF(M1)	0.204	0.147	0.963	0.430	0.338	0.656
Sibi	RF(M2)	0.210	0.136	0.959	0.434	0.307	0.574
Zhob	RF(M2)	0.218	0.157	0.952	0.465	0.350	0.770
SPI-9							
Panjgur	**RF(M4)**	**0.167**	**0.108**	**0.976**	**0.287**	**0.210**	**0.937**
Dalbandin	RF(M3)	0.186	0.120	0.965	0.386	0.263	0.865
Quetta	RF(M3)	0.103	0.153	0.978	0.341	0.261	0.692
Sibi	RF(M3)	0.140	0.107	0.972	0.496	0.353	0.477

Zhob	RF(M3)	0.213	0.152	0.960	0.459	0.347	0.775

Note. The bold values represent the values of the best-fitted model

4. DISCUSSION

Drought is considered a natural catastrophe with multiple harmful effects on crops, water resources, and the country's economy worldwide. The impacts of drought have been predicted by many researchers in their studies with machine learning and stochastic techniques. The outcomes of this study showed variation across stations and time scales. Random forest performed better than other models. The RF model achieved the lowest values of MAE and RMSE and the highest values of R^2 for training and testing sets. Dalbandin produced R^2 values for RF model as 0.825(SPI-3), 0.808(SPI-6) and 0.792(SPI-9). The SVM model also performed well but was not as effective as RF. The SVM outperformed the KNN and ARIMAX models. The KNN and ARIMAX showed the weakest performance across each station. The ARIMAX training performance was accurate, but its testing results were declined. The KNN achieved lower values of R^2 for example, at Zhob station, R^2 values were recorded as 0.113,0.111, and 0.079, indicating poor prediction. Other stations demonstrate almost the same patterns. In this study, the Panjgur station consistently achieved the highest values of R^2 (0.974,0.904) for training and testing sets. Among the four developed models, M1, M2, M3, and M4, the RF(M1) model performs better across each period. The SPI results were quite different across each station. At Panjgur and Zhob stations (SPI-6), Quetta and Sibi (SPI-9) and Dalbandin (SPI-3) perform well. This result is also presented in Fig.4.The accuracy of Random Forest may be determined by the area being investigated and the dataset. The average rainfall of each station showed that all stations received less amount of precipitation. The maximum temperature was found at the Sibi and Panjgur stations. The minimum temperature was found at Quetta and Zhob stations. However, it was discovered in this study that Random Forest is one of the most reliable techniques for predicting droughts as it shows more precise results than other opposing models at each station of Balochistan.

N. Khan et al. (2020) predicted droughts in Pakistan for the years 1999, 2000, and 2004. The observed values of R^2 for SVM and KNN were reported by N. Khan et al. (2020) as 0.95, 0.91 for 1999, 0.82, 0.74 for 2000, 0.97, and 0.72 for 2004, respectively. These values were higher than the values we achieved in this study. Park et al. (2019) used Random Forests to predict severe drought and reported R^2 ranging from 0.58 to 0.91, which was lower than the values presented in this study. Wahla et al. (2022) monitored climate variability for Cholistan and Punjab, Pakistan, using an RF model and reported R^2 values from 0.80 to 0.87 for SPI-1 and SPI-3 had 0.78 to 0.85, respectively. The values presented in this study were higher than the ones mentioned. Elbeltagi et al. (2023) predicted drought in Jaisalmer, Rajasthan and reported an R^2 of 0.783. On the other hand, Wu and Chen (2017) reported a 73% accuracy rate for Random Forest in predicting drought forecast on Huaihe River. Dikshit et al. (2020) found that the accuracy of SPI-3 results for RF was higher than that of SPI-1, with an R^2 value of 0.76 and 0.73, respectively. Jalalkamali et al. (2015) reported an R-value of 0.900 for the ARIMAX model, which is similar to the value found in the present study at Sibi station. Bazrafshan et al. (2015) reported SARIMA as an accurate model while predicting hydrological drought and found R^2 to be 0.72. The values presented in this study were higher than previously observed.

Lotfirad et al. (2022) found that the R values for predicting drought using a random forest model were 0.94, 0.95, and 0.81 for SPI-3, SPI-12, and SPI-48, respectively in various climates of Iran. Wahla et al. (2022) reported RMSE values of 0.61 and 0.64 for SPI-1 and SPI-3, which were higher than the values we found in the present study. Park et al. (2019) reported RMSE values as 0.052 to 0.382 and MAE values as 0.039 to 0.375. Elbeltagi et al. (2023) reported an RMSE of 0.377 and an MAE of 0.294 for SPI-12. These values were lower than the values we found in the present study. According to Dikshit et al. (2022), the RMSE values for SPI-1 and SPI-3 were 0.50 and 0.53, respectively, higher than the values we found in the current study. The study by Jalalkamali et al. (2015) found the lowest RMSE value of 0.313 forARIMAX. Our study found A similar value for ARIMAX of SPI-9 at the Dalbandin station. Bazrafshan et al. (2015) reported the values of MAE and RMSE as 0.45 and 0.61, which were higher than those we found in this study.

After carefully examining each model of machine learning and stochastic models ARIMAX, we found that modern machine learning models have the potential to improve the accuracy of drought prediction. This study suggested that if we want more reliable and effective drought prediction outcomes, we should increase the parameters and the time frame.

5. CONCLUSION

This study aims to predict droughts in Balochistan by comparing ARIMAX and machine learning models. The ARIMAX model was constructed using lagged explanatory variables. Three machine learning models, SVM, KNN and RF model were utilized. To verify the performance of these models, three evaluation measures MAE, RMSE and R^2 were selected. After examining the performance of the models, the Random Forest model was found to be the most robust in each station studied. On the other hand, the performance of the SVM and ARIMAX models was higher than that of the KNN model. The KNN has shown poor performance at each station. We focused only on three parameters and SPI for three, six and nine months. In this study, the effective method which deals with any climate and region to predict droughts was the Random Forest Method. It can be applied in any environmental condition and any region. This study suggested that if we want more precise predictions, we should improve the different approaches, combining other climate factors and variables and working on other SPI levels and Balochistan stations. It would help us to understand the complex patterns and conditions of drought and predict it more precisely. It would be interesting to use other levels of SPI and stations in Balochistan. However, the present study can be extended using various other statistical and machine learning models.

DECLARATIONS

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