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Spatial and Temporal Analysis of Drought in Pakistan

[1]Syed Baqar Hussain Shah, MS Statistics, Comsats University Islamabad Lahore Campus, Department of Statistics, [2]Muhammad Furqan Ahmad, BS Statistics, Comsats University Islamabad Lahore Campus, Department of Statistics
Baqarshah97@gmail.com[1]
Ahmadfurqan31@gmail.com[2]

ABSTRACT

In the recent years climate change is the hot topic of research. Climate change can have severe effect on the environment. In this study, the impact of drought in different districts of Punjab, Pakistan was studied using Standardized Precipitation Index (SPI) and Standardized Anomaly Index (SAI). The SPI is applied on the rain data and the SAI was applied on the temperature data. The data was collected from Pakistan Metrological Department. At first, we fit the data on Length Biased Exponential Distribution and then we applied Standardized Precipitation Index on the rain data received from Pakistan Meteorological Department from 1993 to 2022. We also computed SPI using 3-month, 6-month, and 12-month moving average of the original data. We conducted spatial and temporal analysis using SPI and for the visual representation we also plot maps of the past five years for better understanding of the drought. We used temperature to better explain the drought impact in Pakistan. After applying SAI, we find out that temperate of the data is above average which means there is drought impact in different districts of Pakistan. The results show the clear drought pattern in different districts of Pakistan. We ignore the 0 and negative values of rain data before fitting the Length Biased Exponential Distribution as it is undefined for these values and then we compute the results. The graphs show that after taking moving average the drought patterns decrease in districts and also few years does not show any drought pattern.

***Keywords**: Standardized Precipitation Index (SPI), Spatial Analysis, Statistics, Climate Change, Drought.*

I. INTRODUCTION

Our research focuses on conducting a comprehensive study of drought patterns through the application of spatial and temporal analysis techniques. Drought, which refers to the state of drying in a particular land area, can be naturally or affected by human activity. Its impact goes beyond the affected ecosystem and can significantly damage the economy. Meteorological drought is determined by estimating the level of drought or rain deficit, as well as the duration of the dry period. This occurs when dry weather patterns dominate a particular region. In many places around the world drought has been observed using Spatial and Temporal Analysis. In the coming decades the drought intensity has been increased, one of the main reasons is global warming. This technique is widely used to detect unusual wet or drought conditions within a specific time to analyze the climatic records and rain periods. "The Standardized Precipitation Index is a relative new drought index based only on rain. It's an index based on probability of precipitation for any time scale. Some processes are rapidly affected

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by atmospheric behavior, such as dry land agriculture, and the relevant time scale is a month or two. The SPI was designed to show that it is possible to simultaneously experience wet conditions at other time scales.

Consequently, a separate SPI value is calculated for a selection of time scales. Standardized Precipitation Evapotranspiration Index is another method to measure the drought. It is used to give single number by considering the evapotranspiration, rain data and temperature data to differentiate the drought of different regions." Another index used to measure the drought and wet patterns in specific areas named as Aridity Index. "Aridity Index is a numerical Indicator of the degree of dryness of the climate at a given location. "It is different from drought phenomenon due to Aridity is permanent, while Drought is permanent." By measuring both the moisture and dew points and then dividing that value by 100 it can be computed. The drier the area the higher the AI, the wet the area the lower the AI. "Drought intensity is classified according to the deviation of precipitation, stream flow, and soil moisture content from historically established norms." "Temporal statistical analysis enables you to examine and model the behavior of a variable in a data set over time (e.g., to determine whether and how concentrations are changing over time)." To study the drought severity over time we use temporal analysis. For reducing the effect of drought time temporal analysis help in developing strategies. Moving average is one of the best and common techniques in temporal analysis. It helps to underline the long-run patterns and remove the short-run fluctuations that exist in data. Moreover, we can also use this technique for forecasting purposes. "It is a statistic used to capture the average change in data series over time. The Autoregressive Moving Average (ARMA) is a process that combines both Autoregressive and Moving Average. Its observation consists of linear function of the previous observation plus independent random noise minus the fraction of the previous random noise. Principle Component Analysis or PCA is dimensionality reduction method that is often used to reduce the dimensionality of large data sets, by transforming a large set of variables into smaller ones that still contains most of the information in large data sets. "To interpret each principal component, examine the magnitude and direction of the coefficients for the original variables. The larger the absolute value of the coefficient the more important the corresponding variables is in calculating the components. "An orthogonal rotational method that minimizes the number of variables that have high loadings on each factor is known as Varimax rotation. This method simplifies the interpretation of the factors. If you feel that underlying factors are independent or non-orthogonal you should use Varimax rotation. This process generally involves adjusting the coordinates of data that result from a principal component analysis. K means clustering tries to group similar kinds of items in form of clusters. It finds similarity between the items and groups them into the clusters. It is the most used unsupervised machine learning algorithm for partitioning a given data set into a set of k groups (i.e., k clusters), where k represents the number of groups pre-specified by the analyst. They generally provide more information about magnitude of the anomalies because influences of the dispersion have been removed." The unit consists of about 15 research scientists and students and aims to advance our understanding of climate-related phenomena.

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II. Explanation of the Problems

This study investigates a crucial aspect of human-nature interaction against the backdrop of climate change concerns by examining the spatial and temporal dynamics of drought in Pakistan. Given the urgency of climate change as a global concern, it is critical to comprehend its local effects. This article focuses on the effects of the drought in different Punjab, Pakistani districts. This study uses the Standardized Precipitation Index (SPI) and Standardized Anomaly Index (SAI) to try to figure out the complex patterns of drought occurrence. The study applies SPI to rainfall data and SAI to temperature data through an analysis of rain and temperature data from the Pakistan Meteorological Department from 1993 to 2022. Furthermore, using graphical representations in conjunction with spatial and temporal studies helps shed light on how drought patterns change over time and between different places. Specifically, using temperature data improves understanding of the effects of drought by identifying an above-average temperature trend that is suggestive of the incidence of drought in different areas.

III. Research Objectives

The objectives of the study are as follows:

1. To use the Standardized Precipitation Index (SPI) and Standardized Anomaly Index (SAI) to evaluate the temporal and spatial patterns of drought occurrence in several districts of Punjab, Pakistan.

2. To examine how the drought affects the surrounding ecosystem and communities, with an emphasis on comprehending how the severity of the drought varies over time.

3. To assess how well the Length Biased Exponential Distribution model fits rainfall data and whether it can be used to describe patterns of drought.

4. To look into the connection between temperature anomalies and drought events in order to shed light on the meteorological elements that contribute to drought conditions.

5. To use SPI and SAI to create spatial and temporal visualizations of drought patterns, which will help stakeholders and policymakers gain a thorough grasp of the dynamics of drought.

IV. Examining-Test Frame

The Standardized Precipitation Index (SPI) is a widely used drought index that provides a standardized measure of precipitation anomalies. It helps quantify and categorize drought and wet conditions based on historical rainfall data. The transformed rainfall data, previously converted to a standard normal distribution using the equal probability transformation, which serves as the basis for calculating the SPI. These standardized values represent the deviation of precipitation from the average in terms of standard deviations. (Huang, Sun, et al., 2014)[12] Used gamma distribution initially for calculating the SPI values but we used Length Biased Exponential distribution because it uses only one parameter, so we are reducing the cost and it is also a best fit for data. Since the exponential distribution function with length bias F(x) is undefined for x equals to 0 and the precipitation record may contain zero values, the cumulative probability will be”:

$$H(x) = q + (1-q)F(x)$$

Where the probability density function of Length Biased Exponential Distribution is as follow:

$$f(x) = \frac{x}{\beta^2}\, e^{-\frac{x}{\beta}} \qquad x > 0 \quad ,\beta > 0$$

and the cumulative distribution function of Length Biased Exponential Distribution is as follow:

$$F(x) = 1 - \left(1 + \frac{x}{\beta}\right) e^{-\frac{x}{\beta}} \qquad x > 0, \quad \beta > 0$$

Therefore, the cumulative probability becomes:

$$H(x) = q + (1-q)(1 - \left(1 + \frac{x}{\beta}\right) e^{-\frac{x}{\beta}})$$

Where *q* represents the probability of zero precipitation, and *F(x)* is the incomplete Length Biased Exponential Distribution function, representing the cumulative distribution of *f(x)*. The probability *H(x)* is then transformed to the standard normal random variable *Z* according to the following approximation.

$$t = \sqrt{\ln\left(\frac{1}{(H(x))^2}\right)}, \qquad for\ 0 < H(x) \le 0.5$$

$$t = \sqrt{\ln\left(\frac{1}{\left(q + (1-q)\left(1 - \left(1 + \frac{x}{\beta}\right) e^{-\frac{x}{\beta}}\right)\right)^2}\right)}, \qquad for\ 0 < H(x) \le 0.5$$

$$t = \sqrt{\ln\left(\frac{1}{(1-H(x))^2}\right)}, \quad for\ 0.5 < H(x) \leq 1$$

$$t = \sqrt{\ln\left(\frac{1}{\left(1-(q+(1-q)(1-\left(1+\frac{x}{\beta}\right)e^{-\frac{x}{\beta}}))\right)^2}\right)}, \quad for\ 0.5 < H(x) \leq 1$$

$$Z = SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), \quad for\ 0 < H(x) \leq 0.5$$

$$Z = SPI = +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), \quad for\ 0.5 < H(x) \leq 1$$

$c_0 = 2.515517, c_1 = 0.802853, c_2 = 0.010328, d_1 = 1.432788, d_2 = 0.189269, d_3 = 0.001308$

The time scale for the SPI calculation includes 1 month, 3 months, 6 months, and 12 months. Then we assign categories to the calculated SPI values to represent different levels of wetness or drought. The specific thresholds for categorization may vary depending on regional characteristics and previous studies. Common categories include extremely wet, severely wet, moderately wet, near-normal, moderate drought, severe drought, and extreme drought. The intensities of dry and wet events are classified as follow:

Category	**SPI**
Extremely wet	2.00 and above
Severely wet	1.50 to 1.99
Moderately wet	1.00 to 1.49
Near normal	-0.99 to 0.99
Moderate drought	-1.00 to -1.49
Severe drought	-1.50 to -1.99
Extreme drought	-2.00 and less

Another Index for calculating the impact of drought is Standardized Anomaly Index. The formula for calculating Standardized Anomaly Index is as follow:

$$SAI = \frac{X - \mu}{\sigma}$$

Where,

- X = mean temperature per year.
- μ = long-term mean temperature of a district.
- σ = Standard Deviation of temperature of a district.

If the values of SAI are above 0 then we comment that there is drought impact in that area but if there is value below 0 then we comment that that area has wetter condition in that area. This is because we are calculating SAI based on temperature variable.

The data was collected from Pakistan Meteorological Department. They provided us the data of nine stations namely Lahore, Sargodha, Bahawalpur, Bahawalnagar, Multan, Jhang, Jhelum, Faisalabad, and Sialkot from 1993 to 2022. They provide two variables, rain data and temperature data. The data was collected on monthly bases for each location. The data was filtered to remove any negative values. This data set was important for our analysis as the data of rain was useful for conducting the

analysis of Standardized Precipitation Index (SPI) and temperature data was important for conducting the analysis of Standardized Anomaly Index (SAI).
To analyse the distributional characteristics of the rainfall data from Lahore, Bahawalpur, Bahawalnagar, Faisalabad, Jhang, Jhelum, Multan, Sargodha, and Sialkot, the length biased exponential distribution was selected as the fitting model. This distribution is commonly used to model data with positive support and is particularly suited for variables that are influenced by a length bias, such as precipitation. The fitting process was performed using the statistical software R. The estimation of the distribution parameters was carried out using R's maximum likelihood estimation (MLE) method. This method allows us to estimate the parameters that maximize the likelihood of observing the given rainfall data under the length biased exponential distribution. The specific R packages and functions utilized for parameter estimation were “fitdistrplus” package with the “fitdist” function.

V. CONCLUSION

In this study we concluded that after finding the SPI values of simple data, 3 month moving average data, 6-month Moving average data, and 12 month moving average data although the intensity of drought, from moderate drought to extreme drought increase but the drought factor started vanishing as me move toward the 12-month moving average data. There is no drought impact in 2019 and 2022. But overall, we find out that that in some areas the intensity of drought is increasing with time. Moreover, talking about the Standardized Anomaly Index, we clearly see from the bar plots that the SAI is mostly greater than 0 i.e., they are positive which shows the availability of the drought in each district. Although for some districts the SAI is negative that is they are negative for some years of specific districts but mostly for those districts the SAI is positive which shows that the drought is dominant in those districts over the years.

VI. Exchange of Results:

Maximum Likelihood Estimator:

Maximum Likelihood Estimator of Length Biased Exponential Distribution as follow:

$$\beta = \frac{\bar{x}}{2}$$

This is the MLE of the data that is provided by the Pakistan Metrological Department

Maximum Likelihood Estimator (Length Biased Exponential Distribution)	
$\boldsymbol{\beta}$	25.1916(0.3475447)
Loglikelihood	-14456.69
AIC	28915.38
BIC	28921.26

Mean,

$$E(X) = \frac{\Gamma 3}{\beta}$$

Variance,

$$Var(X) = \frac{2}{\beta^2}$$

Table 1: Mean, Variance, Skewness, and Kurtoses for LBE Distribution for several values of parameters.

β	μ	σ^2	$Skewness$	$Kurtoses$
1	2	2	1.414	6
2	1	0.5	1.414	6
3	0.67	0.22	1.414	6
4	0.5	0.125	1.414	6
5	0.4	0.08	1.414	6
25.19161	0.07939	0.00315	1.414	6

Table 1 displays the statistical parameters for Length Biased Exponential Distribution. The variables beta (β), mean (μ), variance (σ^2), skewness, and kurtosis are used to describe in above table. Beta (β) has 1 value with mean and variance of 2 and roughly skewed with the value 1.414, respectively, suggesting increased volatility in comparison to the market. Similarly, beta with value 2 shows mean 1 and variance values of 0.5 and roughly skewed 1.414, respectively, indicating volatility comparable to the market. Beta with value 3 and mean of 0.67 and variance 0.22, respectively, lower than the market, beta 3 and 4 show less volatility. Beta with value 5 is notable for having a mean of 0.4 and a variance of 0.08, indicating strong volatility. Additionally, beta with value 25.1961 shows a kurtosis of 6 and a positive skewness of 1.414.

Figure 1:

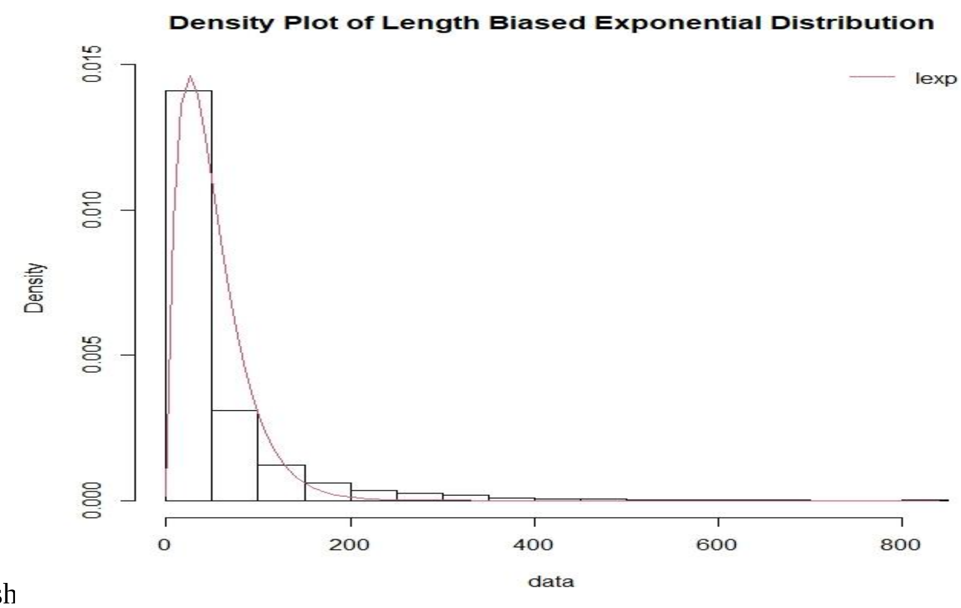

Figure 1 sh

Frequency Tables:

Table 2: Frequency of simple data.

Districts	Moderate drought	Near Normal	Moderately wet	Extremely wet	Severely wet
Bahawalnagar	70	158	12	10	8

Bahawalpur	81	145	5	2	6
Faisalabad	60	187	16	18	14
Jhang	30	124	10	11	11
Jhelum	25	196	28	64	17
Lahore	60	176	16	46	22
Multan	81	166	9	6	4
Sargodha	30	124	13	15	9
Sialkot	35	184	23	66	15

Bahawalnagar, Bahawalpur, Faisalabad, Jhang, Jhelum, Lahore, Multan, Sargodha, and Sialkot are the nine districts whose frequent distribution of drought conditions is shown in Table 2. Bahawalpur and Multan have the highest frequency of moderate drought, with 81 occurrences each, while Jhang and Sargodha have the lowest frequencies, with 30 occurrences apiece. The majority of districts have near normal conditions, with Jhelum having the highest number of occurrences (196), and Jhang and Sargodha having the lowest number of occurrences (124). The number of districts with moderately wet circumstances varies; it ranges from 5 in Bahawalpur to 28 in Jhelum. There is a noticeable prevalence of extremely wet circumstances in Jhelum (64) and Sialkot (66), with lesser occurrences elsewhere. There are comparatively fewer instances of extremely wet conditions elsewhere, with Sialkot (15) and Jhelum (17) having the highest frequency. This distribution provides important insights into local water resource management and agricultural practices by highlighting the spatial heterogeneity in drought situations among the districts.

Table 3: Frequency of 3 month Moving Average data.

Districts	Extreme drought	Severe drought	Moderate drought	Near Normal	Moderately wet	Severely wet	Extremely wet
Bahawalnagar	27	50	45	123	4	8	0
Bahawalpur	31	61	59	82	4	1	0
Faisalabad	16	42	54	149	22	6	5
Jhang	4	27	28	108	12	4	2
Jhelum	8	7	31	169	30	31	54
Lahore	8	34	43	149	19	26	39
Multan	27	52	56	127	2	1	0
Sargodha	7	17	30	107	15	5	9
Sialkot	8	11	30	161	19	19	75

Table 3 shows the frequency distribution of the 3-month moving average data for the nine districts of Bahawalnagar, Bahawalpur, Faisalabad, Jhang, Jhelum, Lahore, Multan, Sargodha, and Sialkot, as well as the various drought classifications. There are four instances of extreme drought in Multan and thirty-one in Bahawalpur; there are seven instances of severe drought in Jhelum and sixty-six in Bahawalpur. Faisalabad (54) has the highest prevalence of moderate drought, while Jhang (28), least, and does. Particularly prevalent are near-normal conditions in Jhelum (169) and Lahore (149). There are 1 occurrence of moderately wet circumstances in Multan and 31 in Jhelum. The frequency of extremely rainy circumstances varies by district, with Sialkot having the highest frequency (75). In Sialkot (75), extremely wet circumstances are common, whereas they are minimal in Bahawalnagar and Bahawalpur.

Table 4: Frequency of 6 month Moving Average data.

Districts	Extreme drought	Severe drought	Moderate drought	Near Normal	Moderately wet	Severely wet	Extremely wet
Bahawalnagar	28	38	54	137	1	0	0
Bahawalpur	37	50	59	93	0	0	0
Faisalabad	10	33	38	199	11	4	0
Jhang	3	18	21	137	6	0	0
Jhelum	3	11	16	178	62	43	17
Lahore	7	20	33	185	46	15	9
Multan	48	41	60	117	0	0	0
Sargodha	0	6	23	142	16	2	0
Sialkot	5	11	28	153	34	54	38

Table 4 shows the frequency distribution of 6-month moving average data for nine districts (Bahawalnagar, Bahawalpur, Faisalabad, Jhang, Jhelum, Lahore, Multan, Sargodha, and Sialkot) for various drought categories. The number of districts experiencing extreme drought varies from 0 to 48 in Multan. Sargodha's score for severe drought ranges from 6 to 50 in Bahawalpur. Frequencies of a moderate drought range from 16 in Jhelum to 60 in Multan. Conditions in Faisalabad (199) and Lahore (185) are largely near-normal. There are zero instances of moderately wet circumstances in certain districts and 62 in Jhelum. There is variation in extremely wet conditions; in Sialkot, the frequency is maximum at 54. Severe precipitation is most common in Sialkot (38), and it is hardly ever seen in other districts.

Table 5: Frequency of 12 month Moving Average data.

Districts	Extreme drought	Severe drought	Moderate drought	Near Normal	Moderately wet	Severely wet
Bahawalnagar	4	22	69	163	0	0
Bahawalpur	2	7	59	171	0	0
Faisalabad	0	0	10	273	12	0
Jhang	1	0	8	173	0	0
Jhelum	1	5	21	280	22	1

Lahore	0	0	0	273	24	13
Multan	25	44	77	120	0	0
Sargodha	0	0	3	156	26	4
Sialkot	0	2	11	258	35	17

Table 5 displays the frequency distribution of data for drought categories during a 12-month period for nine districts: Bahawalnagar, Bahawalpur, Faisalabad, Jhang, Jhelum, Lahore, Multan, Sargodha, and Sialkot. Lahore, Sargodha, Sialkot had zero cases of extreme drought, while Multan has twenty-five cases. From 0 in a few districts to 44 in Multan, there is a severe drought. From 3 in Sargodha to 77 in Multan, there are moderate drought frequencies. Both Faisalabad (273) and Lahore (273), however, are dominated by near-normal conditions. From 0 in numerous areas to 35 in Sialkot, there are variations in the amount of moderate rainfall. At Lahore, the frequency of really wet circumstances is maximum at 24.

Spatial and Temporal Graphs:

Graphical Representation of Drought in Pakistan

The below are the graphs showing the drought pattern in Pakistan from 2018 to 2022. In graphs the off-white colour is showing the area with most drought category and the black colour is showing the less drought area among other districts. In total I have taken the data of 9 districts from Pakistan Metrological Department.

Figure 2:

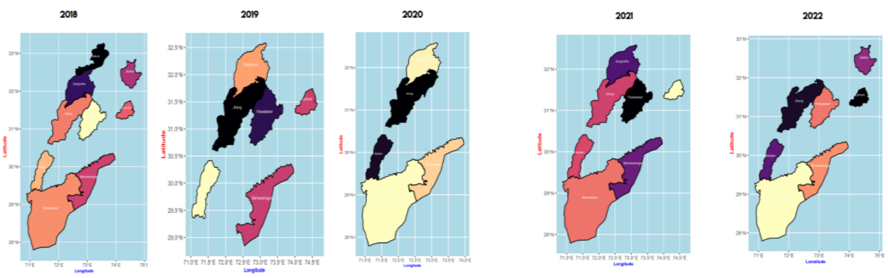

Figure 2 shows drought pattern in Pakistan from 2018 to 2022. In 2018, Faisalabad is showing the most drought pattern among the other districts and Jhelum is showing the least drought pattern among the other districts. In 2019, Multan is showing the most drought pattern among the other districts and Jhang is showing the least drought pattern among the other districts. Moreover, Jhelum, Lahore and Bahawalnagar are not showing any drought pattern in 2019. In 2020, Bahawalpur is showing the most drought pattern among the other districts and Jhang is showing the least drought pattern among the other districts. Moreover, Jhelum, Lahore, Faisalabad, and Sialkot are not showing any drought pattern in 2020. In 2021, Lahore is showing the most drought pattern among the other districts and Faisalabad is showing the least drought pattern among the other districts. Moreover, Jhelum, and Sialkot are not showing any drought pattern in 2021. In 2022, Bahawalpur is showing the most drought pattern among the other districts and Lahore is showing the least drought pattern among the other districts. Moreover, Jhelum, and Sargodha are not showing any drought pattern in 2022.

Graphical representation of Pakistan after taking 3 months moving average:

After taking the 3 months moving average of data provided by Pakistan Meteorological Department. I computed the Standardized Precipitation Index of that data and plot the graphs of 5 years data.

Figure 3:

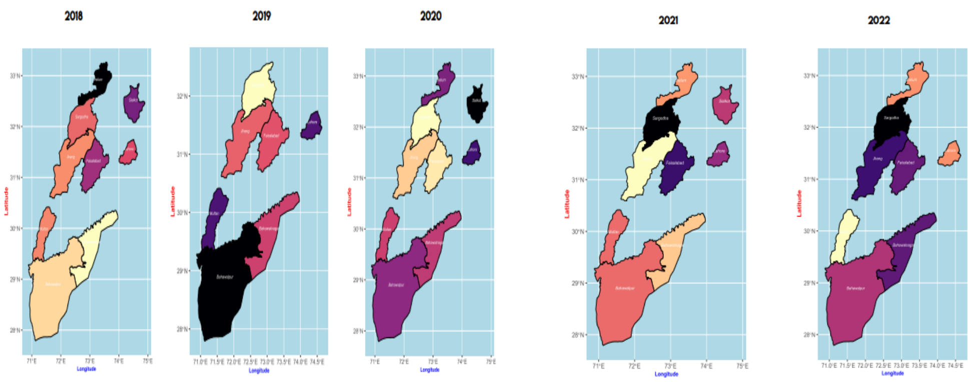

Figure 3 showing Standardized Precipitation Index graphs after taking the 3s months moving average of data provided by Pakistan Meteorological Department. In 2018, Bahawalnagar is showing the most drought pattern among the other districts and Jhelum is showing the least drought pattern among the other districts. In 2019, Sargodha is showing the most drought pattern among the other districts and Bahawalpur is showing the least drought pattern among the other districts. Moreover, Jhelum, and Sialkot are not showing any drought pattern in 2019. In 2020, Sargodha is showing the most drought pattern among the other districts and Sialkot is showing the least drought pattern among the other districts. In 2021, Jhang is showing the most drought pattern among the other districts and Sargodha is showing the least drought pattern among the other districts. In 2022, Multan is showing the most drought pattern among the other districts and Sargodha is showing the least drought pattern among the other districts. Moreover, Sialkot is not showing any drought pattern in 2022.

Graphical representation of Pakistan after taking 6 months moving average:
After taking the 6s months moving average of data provided by Pakistan Meteorological Department. I computed the Standardized Precipitation Index of that data and plot the graphs of 5-years data.

Figure 4:

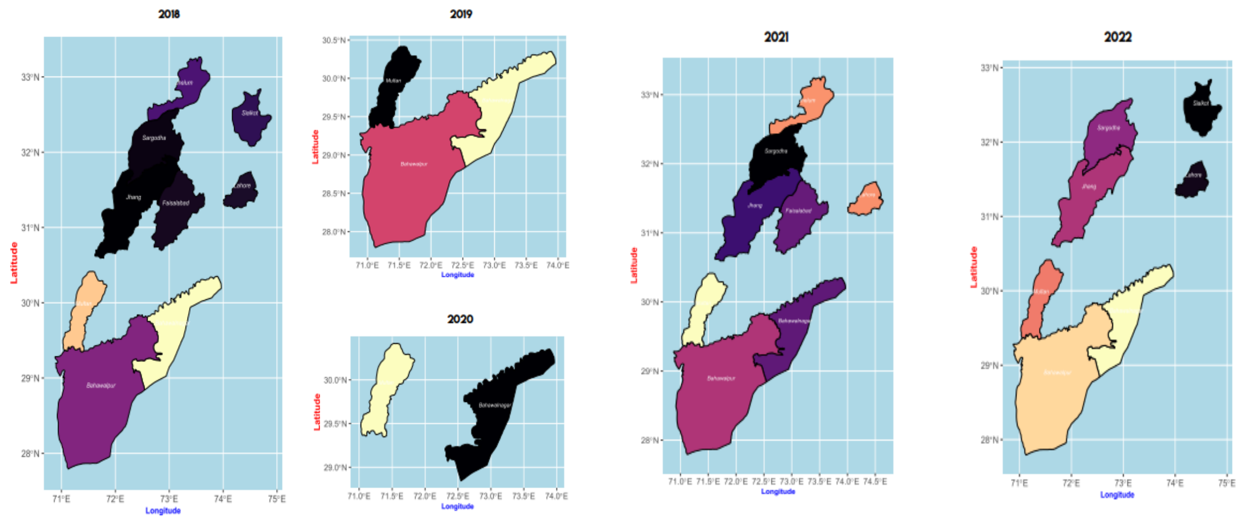

Figure 4 showing Standardized Precipitation Index graphs after taking the 6s months moving average of data provided by Pakistan Meteorological Department. In 2018, Bahawalnagar is showing the most drought pattern among the other districts and Jhang is showing the least drought pattern among the other districts. In 2019, Bahawalnagar is showing the most drought pattern among the other districts and Multan is showing the least drought pattern among the other districts. Moreover, Jhelum, Lahore, Sargodha, Faisalabad, Jhang, and Sialkot are not showing any drought pattern in 2019. In 2020, Multan is showing the most drought pattern among the other districts and Bahawalnagar is showing the least drought pattern among the other districts. Moreover, Bahawalpur, Lahore, Sialkot, Sargodha, Jhelum, Jhang, and Faisalabad are not showing any drought pattern in 2020. In 2021, Bahawalnagar is showing the most drought pattern among the other districts and Sialkot is showing the least drought pattern among the other districts. Moreover, Jhelum, and Faisalabad are not showing any drought pattern in 2021. In 2022, Multan is showing the most drought pattern among the other districts and Sargodha is showing the least drought pattern among the other districts. Moreover, Sialkot is not showing any drought pattern in 2022.

Graphical representation of Pakistan after taking 12 months moving average:
After taking the 12 months moving average of data provided by Pakistan Meteorological Department. I computed the Standardized Precipitation Index of that data and plot the graphs of 5-years data.

Figure 5:

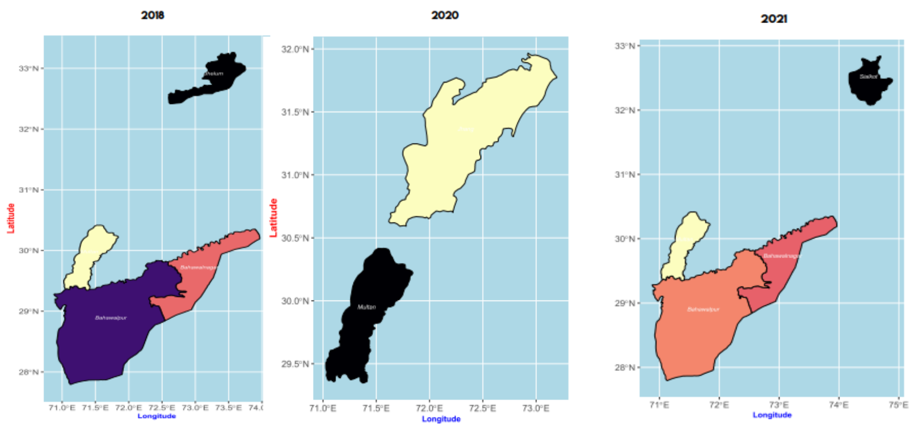

Figure 5 showing Standardized Precipitation Index graphs after taking the 12s months moving average of data provided by Pakistan Meteorological Department. In 2018, Multan is showing the most drought pattern among the other districts and Jhelum is showing the least drought pattern among the other districts. Moreover, Lahore, Sargodha, Faisalabad, Jhang, and Sialkot are not showing any drought pattern in 2019. In 2019, no drought patters are visible on any district. In 2020, Jhang is showing the most drought pattern among the other districts and Multan is showing the least drought pattern among the other districts. Moreover, Bahawalpur, Bahawalnagar, Lahore, Sialkot, Sargodha, Jhelum, and Faisalabad are not showing any drought pattern in 2020. In 2021, Multan is showing the most drought pattern among the other districts and Sialkot is showing the least drought pattern among the other districts. Moreover, Lahore, Sargodha, Jhang, Jhelum, and Faisalabad are not showing any drought pattern in 2021. In 2022, no drought patters are visible on any district.

Standardized Anomaly Index:
In SAI the positive values show the temperature values are above mean indicating drought impact over the years in that area and negative values indicate temperature values below the mean indicating wetter condition over the years in that area.

Figure 6:

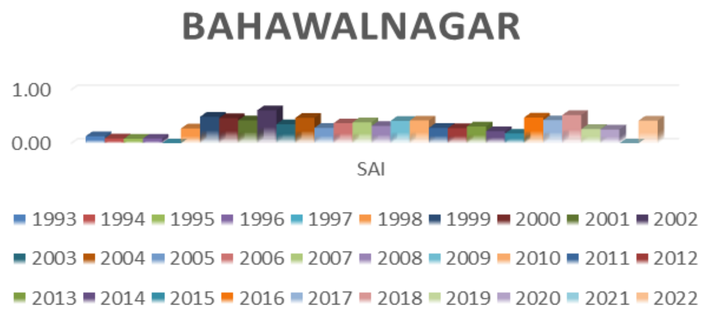

Figure 6 clearly shows that the SAI for 2002 is maximum which shows that the drought pattern in Bahawalnagar were maximum in 2002.

Figure 7:

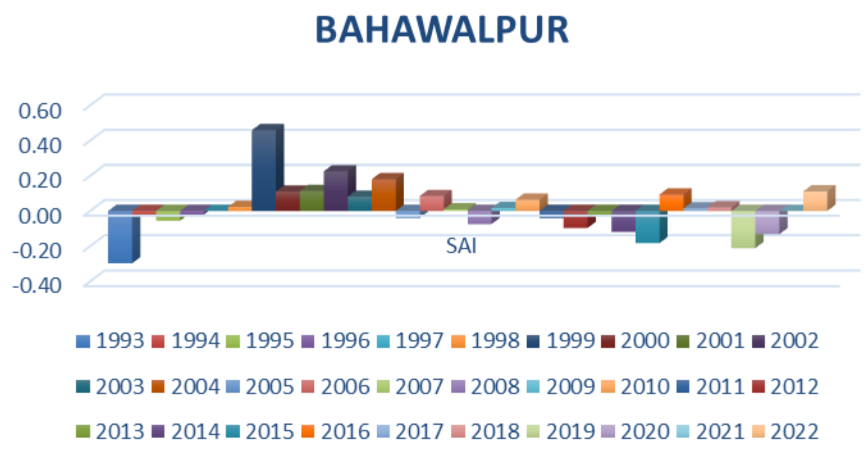

Figure 7 clearly shows that the SAI for 1999 is maximum and minimum in 1993 which shows that the drought patterns in Bahawalpur were maximum in 1999 and wetter pattern were there in 1993.

Figure 8:

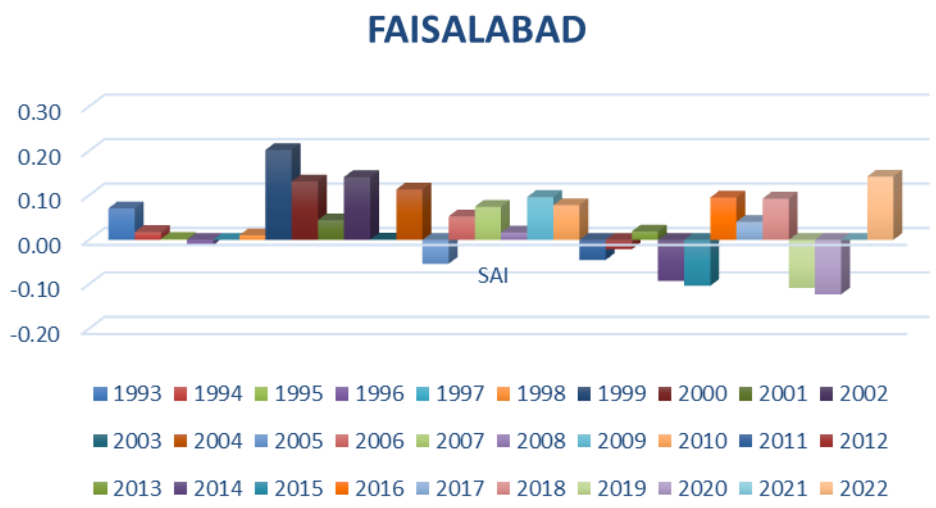

Figure 8 clearly shows that the SAI for 1999 is maximum and minimum in 2020 which shows that the drought patterns in Faisalabad were maximum in 1999 and wetter pattern were there in 2020.

Figure 9:

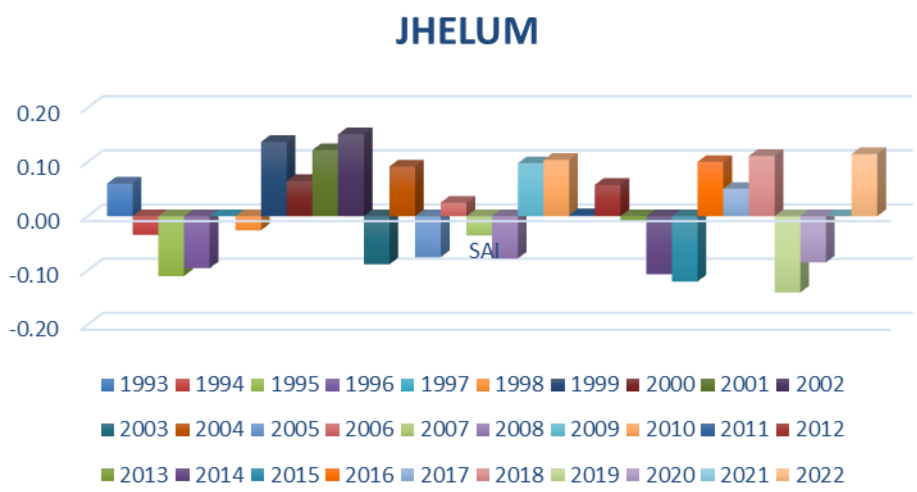

Figure 9 clearly shows that the SAI for 2002 is maximum and minimum in 2019 which shows that the drought patterns in Jhelum were maximum in 2002 and wetter pattern were there in 2019.

Figure 10:

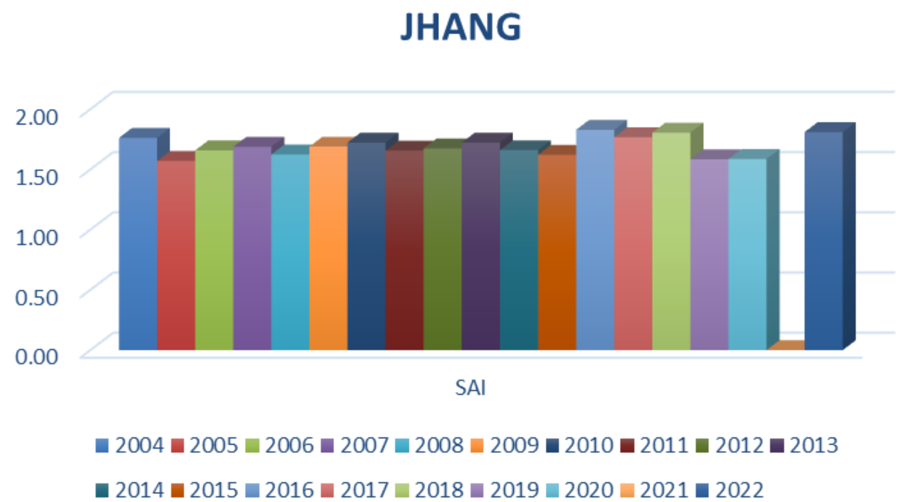

Figure 10 clearly shows that the SAI for 2016 is maximum and minimum in 2021 which shows that the drought patterns in Jhang were maximum in 2016 and no drought pattern were there in 2019.

Figure 11:

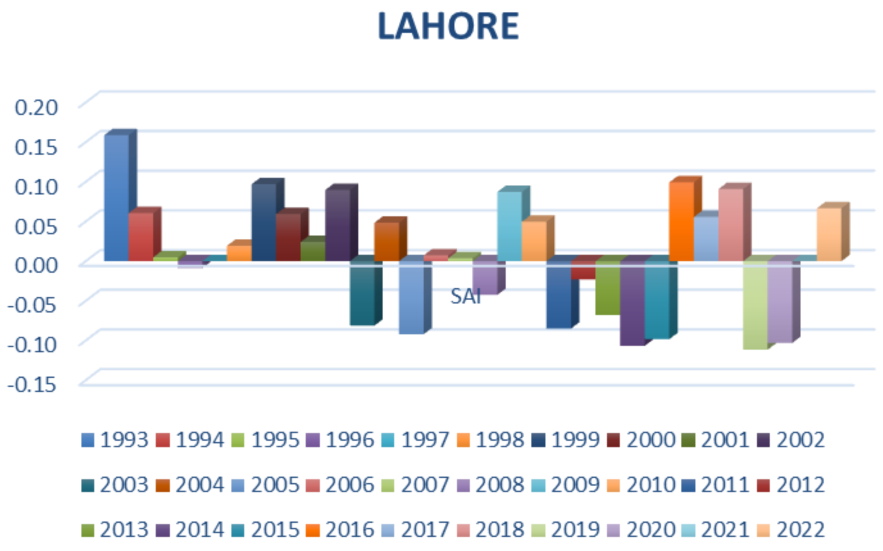

Figure 11 clearly shows that the SAI for 1993 is maximum and minimum in 2014 and 2019 which shows that the drought patterns in Lahore were maximum in 1993 and wetter pattern were there in 2014 and 2019.

Figure 12:

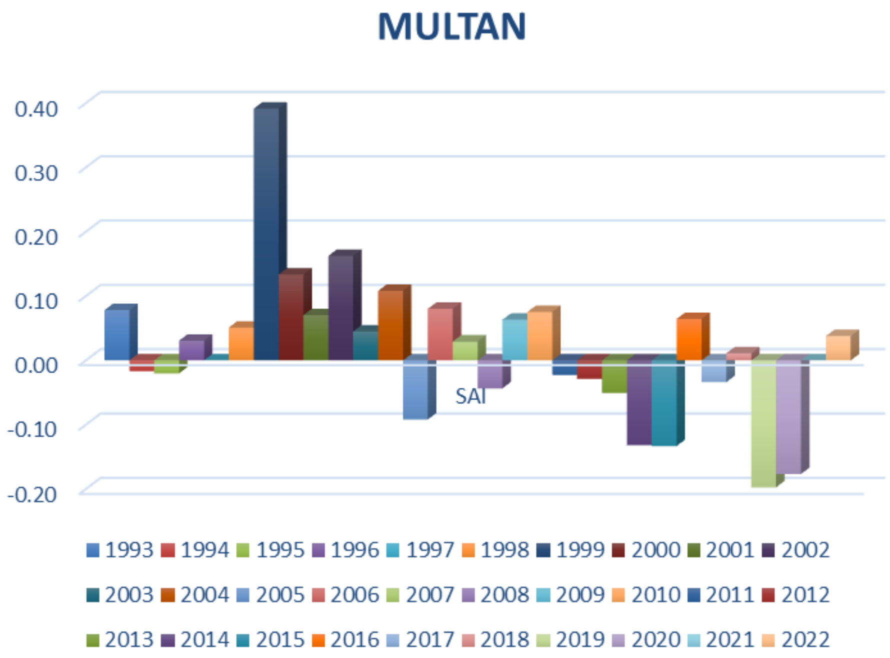

Figure 12 clearly shows that the SAI for 1999 is maximum and minimum in 2019 which shows that the drought patterns in Multan were maximum in 1999 and wetter pattern were there in 2019.

Figure 13:

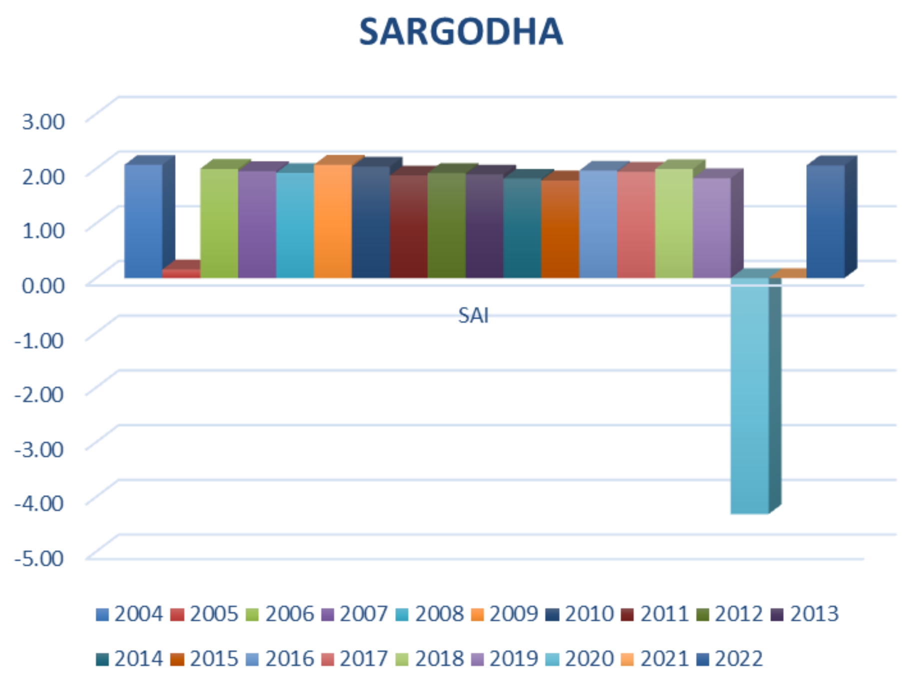

Figure 13 clearly shows that the SAI for 2004 and 2009 is maximum and minimum in 2020 which shows that the drought pattern in Sargodha were maximum in 2004 and 2009 and wetter pattern were there in 2020.

Figure 14:

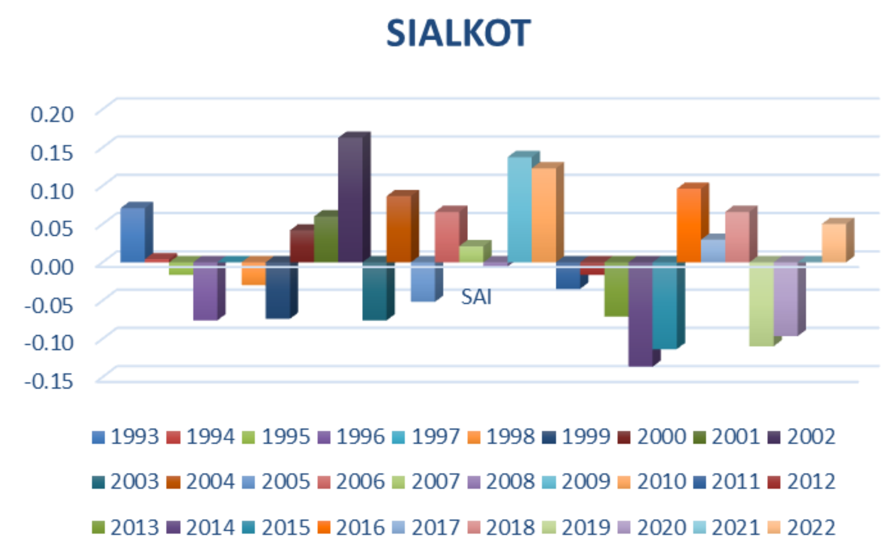

Figure 14 clearly shows that the SAI for 2002 is maximum and minimum in 2014 which shows that the drought patterns in Sialkot were maximum in 2002 and wetter pattern were there in 2014.

REFERENCES

1. An, Q., He, H., Nie, Q., Cui, Y., Gao, J., Wei, C., Xie, X., & You, J. (2020). Spatial and temporal variations of drought in Inner Mongolia, China. Water, 12(6), 1715.
2. Bai, Y., Wu, J., Xing, Q., Pan, Q., Huang, J., Yang, D., & Han, X. (2008). Primary production and rain use efficiency across a precipitation gradient on the Mongolia plateau. Ecology, 89(8), 2140–2153.
3. Baniya, B., Tang, Q., Xu, X., Haile, G. G., & Chhipi-Shrestha, G. (2019). Spatial and temporal variation of drought based on satellite derived vegetation condition index in Nepal from 1982--2015. Sensors, 19(2), 430.
4. Bordi, I., Fraedrich, K., Gerstengarbe, F.-W., Werner, P. C., & Sutera, A. (2004). Potential predictability of dry and wet periods: Sicily and Elbe-Basin (Germany). Theoretical and Applied Climatology, 77(3), 125–138.
5. Bordi, I., Fraedrich, K., Jiang, J.-M., & Sutera, A. (2004). Spatio-temporal variability of dry and wet periods in eastern China. Theoretical and Applied Climatology, 79(1), 81–91.
6. Cindrić, K., Pasarić, Z., & Gajić-Čapka, M. (2010). Spatial and temporal analysis of dry spells in Croatia. Theoretical and Applied Climatology, 102(1), 171–184.
7. Dara, S. T., & Aḥmad, M. (2012). Recent advances in moment distribution and their hazard rates. Lap Lambert Academic Publishing.
8. Di Lena, B., Vergni, L., Antenucci, F., Todisco, F., & Mannocchi, F. (2014). Analysis of drought in the region of Abruzzo (Central Italy) by the Standardized Precipitation Index. Theoretical and Applied Climatology, 115(1), 41–52.
9. Gong, D.-Y., Wang, J.-A., & Han, H. (2005). Trends of summer dry spells in China during the late twentieth century. Meteorology and Atmospheric Physics, 88(3), 203–214.
10. Guo, H., Bao, A., Liu, T., Ndayisaba, F., Jiang, L., Kurban, A., De Maeyer, P., & others. (2018). Spatial and temporal characteristics of droughts in Central Asia during 1966--2015. Science of the Total Environment, 624, 1523–1538.
11. Huang, J., Sun, S., Xue, Y., Li, J., & Zhang, J. (2014). Spatial and temporal variability of precipitation and dryness/wetness during 1961--2008 in Sichuan province, west China. Water Resources Management, 28(6), 1655–1670.
12. Huang, J., Xue, Y., Sun, S., & Zhang, J. (2014). Spatial and temporal variability of drought during 1960e2012 in Inner Mongolia, north China. Quaternary International, 30(1), e11.
13. Huijun, W. (2001). The weakening of the Asian monsoon circulation after the end of 1970's. Advances in Atmospheric Sciences, 18(3), 376–386.
14. Khan, A. A., Zhao, Y., Rahman, G., Rafiq, M., Moazzam, M. F. U., & others. (2021). Spatial and temporal analysis of rainfall and drought condition in Southwest Xinjiang in Northwest China, using various climate indices. Earth Systems and Environment, 5(2), 201–216.
15. Ling, M., Guo, X., Shi, X., & Han, H. (2022). Temporal and spatial evolution of drought in Haihe River Basin from 1960 to 2020. Ecological Indicators, 138, 108809.
16. Liu, F., Chen, S., Dong, P., & Peng, J. (2012). Spatial and temporal variability of water discharge in the Yellow River Basin over the past 60 years. Journal of Geographical Sciences, 22(6), 1013–1033.
17. Mathbout, S., Lopez-Bustins, J. A., Martin-Vide, J., Bech, J., & Rodrigo, F. S. (2018). Spatial and temporal analysis of drought variability at several time scales in Syria during 1961--2012. Atmospheric Research, 200, 153–168.
18. McKee, T. B., Doesken, N. J., Kleist, J., & others. (1993). The relationship of drought frequency and duration to time scales. Proceedings of the 8th Conference on Applied Climatology, 17(22), 179–183.
19. Mekonen, A. A., Berlie, A. B., & Ferede, M. B. (2020). Spatial and temporal drought incidence analysis in the northeastern highlands of Ethiopia. Geoenvironmental Disasters, 7(1), 1–17.
20. Rahman, G., Dawood, M., & others. (2018). Spatial and temporal variation of rainfall and drought in Khyber Pakhtunkhwa Province of Pakistan during 1971--2015. Arabian Journal of Geosciences, 11(3), 1–13.
21. Raziei, T., Saghafian, B., Paulo, A. A., Pereira, L. S., & Bordi, I. (2009). Spatial patterns and

temporal variability of drought in western Iran. Water Resources Management, 23(3), 439–455.

22. Santos, J. F., Pulido-Calvo, I., & Portela, M. M. (2010). Spatial and temporal variability of droughts in Portugal. Water Resources Research, 46(3).
23. Sivrikaya, F., Baskent, E. Z., & Bozali, N. (2013). Spatial dynamics of carbon storage: a case study from Turkey. Environmental Monitoring and Assessment, 185(11), 9403–9412.
24. Tao, J., Qiao, W., Li, H., Qu, X., & Gan, R. (2022). Spatial and temporal evolution characteristics and causes of drought and flood in the Henan section of the Yellow River. Natural Hazards, 1–20.
25. Telesca, L., Vicente-Serrano, S. M., & López-Moreno, J. I. (2013). Power spectral characteristics of drought indices in the Ebro river basin at different temporal scales. Stochastic Environmental Research and Risk Assessment, 27(5), 1155–1170.
26. Qiang Zhang Chong-Yu XuChong-Yu Xu Yongqin David ChenYongqin David Chen Liliang Ren (2011). Comparison of evapotranspiration variations between the Yellow River and Pearl River basin, China. Stochastic Environmental Research 25(2):139-150.
27. Guangju Zhao, Xingmin Mu, Georg Hörmann, Nicola Fohrer, Ming Xiong, Buda Su, Xiucang Li (2012). Spatial patterns and temporal variability of dryness/wetness in the Yangtze River Basin, China. Quaternary International (282):5-13.