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Article

Longitudinal Drought Patterns and Predictive Analysis in Lalitpur, Uttar Pradesh, India: An Application of SPI and SPEI

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ABSTRACT

Drought is a significant hydrological hazard that leaves a serious footprint on the environment, society and human life. Water resources, agricultural productivity, ecosystems, livelihoods and socio-economic well-beings are negatively impacted by drought. This make a serious footprint on the environment, society and also human lives. Nowadays, many regions of the worlds are experiencing increasing frequent and a severe drought condition. Natural climatic variability and anthropogenic factors combinedly influence the drought patterns and trends. This study investigates the spatial and temporal characteristics and variation of drought patterns in Lalitpur District of Uttar Pradesh State, India. Thirty-five years metrological data collected from the NASA POWER Access Viewer were used to fulfil the research objectives. Two drought indices, Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) were calculated 3, 6, 9 and 12 month timescales. For asses the direction and statistical significance of temporal trends, Spearman's rank correlation method was used. Sen's slope estimator was employed to quantifying magnitude of these trends. The result indicates the occurrence of drought over multiple years and reveals a tendency toward increasing drought severity. Variations in rainfall patterns, overuse of ground water, agricultural transformation and changes in land use pattern may be contribute to the observed of drought trends. As a result, agricultural productivity in this region is also significantly affected. Future projections for 2026–2035 indicated drought occurrence of 11.67%, 8.33%, 1.67%, and 9.17% for SPI-3, SPI-6, SPI-9, and SPI-12, respectively, while SPEI projected 5.83%, 3.33%, 1.67%, and 0.83% at the corresponding time scales. The findings highlight the importance of multi-timescale drought assessment and forecasting for effective drought monitoring, water-resource management, and agricultural planning in Lalitpur District.

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Research Highlights

- A 35-year climate dataset was analysed using SPI and SPEI at 3, 6, 9 and 12 month scales to evaluate drought patterns.
- Spearman's rank correlation and Sen's Slope tests were used to recognize drought trends.
- Holt–Winters forecasting was used to forecast drought circumstances for the next 10 years.
- SPI and SPEI showed strong positive relationships across diverse timescales.

1. Introduction

Drought is a globally occurring hydroclimatic phenomenon characterized by prolonged period of low rainfall, resulting in significant water scarcity relative to normal climatic condition [1]. It generally progressively and may persist for long periods, making its onset and progression distinct from many natural hazards that develop rapidly [2]. Drought can adversely affect multiple sectors, including agriculture, water resources, economics, ecosystem and human well-being [3]. Metrological drought occurs due to insufficient rainfall. This can also lead to soil moisture depletion, water shortages, and reduced streamflow [4]. Furthermore, elevated atmospheric evaporative demand may increase water stress in vegetation and thereby contribute to the development of ecological and agricultural drought [5]. Therefore, systematic analysis of drought characteristics is crucial. These characteristics include severity, timing, duration and spatial distribution. Drought affects different aspects of the climate, agriculture, hydrological system and society [6]; therefore, it is typically classified into several distinct yet interconnected categories. The conventional categorization of drought comprises four categories: Socio economic drought, hydrological drought, meteorological drought and agricultural drought [7]. Each category reflects a different dimension of water scarcity and its consequence. Meteorological drought typically refers to a prolonged efficiency of rainfall relative to the normal conditions of a region [7]. Persistent precipitation deficits can reduce soil moisture content, which can affect agricultural production, leading agricultural drought [8]. Prolonged water deficits can subsequently reduce streamflow, reservoir storage and groundwater resources, contributing to the development of hydrological drought [9]. When water shortages start to disrupt the supply of goods and influence livelihoods and economic activities, they may eventually develop into socio economic drought [10]. Therefore, drought categories are interconnected because, metrological drought may propagate through the hydrological system and subsequently impact agricultural, socio economic and hydrological drought. The intricate progression of drought across the environmental and socio-economic system has increased the need to understand variations in its occurrence, persistence and severity [6]. Fluctuations in precipitation, temperature and atmospheric evaporation demand can influence the development and intensification of drought conditions [11]. In particular, variations in atmospheric Evaporative demand may exacerbate water stress, even when precipitation deficits by themselves do not fully account for the observed drought conditions [5]. The characteristics of drought can differ significantly across different parts and time periods, making the assessment of drought frequency, intensity, duration and severity essential for understanding regional drought risk [12]. A systematic evaluation of drought characteristics can provide valuable information for the agricultural planning, water resource management and proactive drought risk reduction [13]. Because of the varying characteristics of drought conditions, standardised indices are needed to measure their frequency, intensity, duration, and severity [13]. This index provides a systematic assessment and comparison of drought characteristics across spatial and temporal scales. Among the various indices SPI and SPEI are the most important for measuring climatic drought [14]. SPI and SPEI are mainly based on the simple rainfall-based formulas, which make it easy to track dry spell across different timescale [15]. Potential evapotranspiration and precipitation are the two main meteorological factors used in the SPEI [14]. SPEI can also be used to assess drought at different time period considering in variability in atmospheric water demand [15]. By calculating SPI and SPEI at different time scales, we can obtain information about short term and long term drought conditions [16]. Using 3, 6, 9 and 12 months' time [17]. Evaluating changes in drought conditions is important for identifying of Periodically drought occurrence and severity [18]. Information on drought magnitude and trends obtained through statistical trend analysis also helps us gather valuable insights into drought monitoring and regional water resource management [18]. Forecasting can help predict future drought events and their severity by evaluating historical drought occurrence and conditions [19]. These predictions can provide useful information for early warning system, agricultural planning and water resource management [20]. In India, variations in agricultural production and water availability are strongly influenced by the fluctuations of monsoonal rainfall [21]. These fluctuations in rainfall affect agricultural activities, water resources and rural livelihoods, particularly across drought prone area [22]. Lalitpur District in Uttar Pradesh is an important area for drought assessment in India because agriculture and water resources are strongly affected by fluctuation in rainfall [23]. Frequent moisture shortages can adversely

affect water validity and agriculture activities. These adverse effects highlight the importance of systematically studying drought characteristics in Lalitpur District. It is also important to examine how these characterises are vary time to time [23]. The performance of SPI and SPEI for drought assessment may vary across climatic regions and timescales, despite their widespread use**.** Limited research has been conducted on drought using SPI and SPEI indices, particularly regarding drought occurrence, severity, persistence and temporal trends across multiple time scales. This highlights the need to compare both indices systematically to better understand how drought conditions change over time in the district. The present study addressed the research gap by comparing the drought condition of Lalitpur District using SPI and SPEI across 3, 6, 9 and 12 month time scales. The study investigates the drought severity and temporal trends by incorporating multiple drought time scales, trend analysis and forecasting future drought condition. The findings are intended to support improved agricultural planning, water-resource management, and drought-risk reduction in the study area.

2. Study Area

The study examines Lalitpur District, located in the Bundelkhand Plateau region of southern part of the Uttar Pradesh state, India (Figure 1). The district is located between 24°11′–25°14′ N latitude and 78°10′–79°00′ E longitude with an area of 5030 km^2 [24]. The northern part is bounded by Jhansi District, while the eastern, western, and southern boundaries are share with Madhya Pradesh District. The district comprises with total six Blocks: Jakhaura, Mahraoni, Talbehat, Bar, Mandawara, and Birdha. Lalitpur is marked by a subhumid climate, featuring hot, dry summer and comparatively cold winters.

The District receives about 1044.3 mm of rainfall annually, with nearly 91% of the rainfall concentrated during the southwest monsoon season from June to September [25]. Heavy reliance on monsoon rainfall, combined with an extended dry period, results in seasonal water stress, especially during February to June [26]. Major soil types of this district are characterized by black, red and alluvial soils. These soils have different capacities for retaining moisture and holding water [27]. Therefore, agricultural activities are largely influenced by the availability and seasonal distribution of rainfall [28]. Recurrent drought conditions have also been reported in the district [29]. According to the Department of Land Resources Bar, Talbehat, Jakhaura, Birdha, and Mahraoni are among the major blocks affected by drought [24]. The combination of high reliance on monsoon precipitation, seasonal variability, extended dry periods, agricultural dependence and recurrent drought conditions makes Lalitpur a suitable area for examining drought conditions [30]. Accordingly, the present study evaluates drought severity, persistence and temporal variability using the SPI and SPEI across 3, 6, 9 and 12 month time scales.

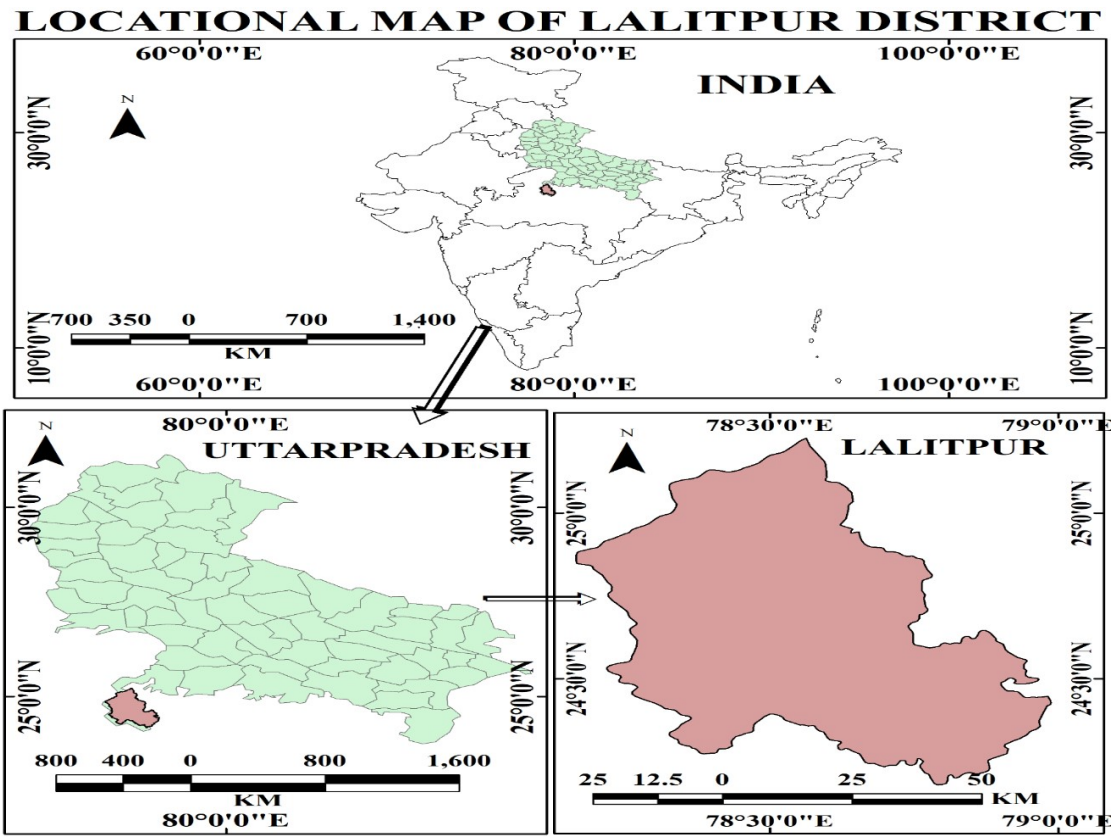


Figure 1. Locational map of Study Area.

3. Meteorological Data and Drought Indices

3.1. Data Availability

This study employed a 35 years climatic dataset spanning from 1990 to 2025 to evaluate drought conditions in Lalitpur District using the SPI and SPEI. Monthly precipitation data covering 1990–2025 were sourced from the NASA POWER Access Viewer (Figure 2).

Temperature data at daily and monthly scales were also retrieved from the same platform. Adequate long term climatic records are necessary for obtaining reliable drought index estimates. While drought-index analysis generally considers a minimum requirement at least 20 years of rainfall data with temperature record extending beyond 30 years are often preferred a more comprehensive representation of climatic variability [31], therefore, the 35-year climatic time series provide an appropriate temporal basis for the calculation and assessment of SPI and SPEI. Earlier research has emphasised the usefulness of long-term climatic records and multiple drought indices for assessing drought variability. Ojha et al. examined the SPI and SPEI at multiple time **scales** to evaluate the metrological drought characteristics [32]. Wable et al. evaluated five drought indices in a semi-arid agricultural river basin of Maharashtra using a 25-year climatic dataset (1985–2009), examining multiple timescales to determine the most appropriate drought index for the region [33]. The findings of these studies support the use of SPI and SPEI at different time scales to characterize drought conditions and provide a methodological basis for evaluating drought severity, persistence, and temporal variability in Lalitpur District. Thus, the 35-year dataset (1990–2025) used in the present study was regarded as appropriate for examining drought characteristics, severity and persistence over time in that district. Multiple SPI and SPEI time scales, namely SPI-3, SPI-6, SPI-9, and SPI-12, and SPEI-3, SPEI-6, SPEI-9, and SPEI-12 were employed to characterize short-, medium-, and long-term variations in precipitation.

3.2. The Standardized Precipitation Index (SPI)

SPI is precipitation-based index that quantify the intensity of drought, frequency of drought and duration of wet and dry conditions across different time scales [34]. McKee et al. proposed SPI as a standardized measure of precipitation anomalies for the assessment of drought conditions [35]. SPI is widely applied indices because of it requires only precipitation data and can be used to evaluation of drought condition at different time scales [36]. SPI was calculated using monthly precipitation data at 3, 6, 9 and 12 month time scales in this study (Figure 3). This scale enabled the evaluation of drought variability over various accumulation periods [37]. Accumulated precipitation at each time scale was fitted to a Gamma probability distribution [38]. The corresponding cumulative probabilities were subsequently transformed into the standard normal distribution to derive SPI values [39].

Gamma probability distribution:

$$gx = 1x\alpha - 1e - x/\beta. \tag{1}$$

where x is the accumulated precipitation, α is the shape parameter, e represents Euler's mathematical constant, and β is the scale parameter [40].

Standardization to obtain SPI:

$$\mathrm{SPI} = -1Gx \tag{2}$$

where Gx is the cumulative probability obtained from the fitted Gamma distribution and -1 is the inverse standard-normal distribution. This transformation produces the standardized SPI value.

3.3. Standardized Precipitation Evapotranspiration Index (SPEI)

SPEI is another important drought indicator which incorporate both climatic data precipitation and as well as the potential Evapotranspiration (PET) to identify the wet and dry condition at different time scale [41]. Vicente-Serrano et al. was proposed the SPEI to consider the role of atmospheric evaporative demand in the assessment of drought conditions [42]. The index is significant because it not only uses precipitation as an indicator, like SPI, but also considers the climatic water balance [14]. Consequently, SPI can capture drought conditions influenced by changes in precipitation [43]. In this study, SPEI was calculated using precipitation and temperature obtained from NASA POWER Access Viewer. The calculation was performed at 3, 6, 9 and 12 month time scales (Figure 4). These time scales were used to evaluate drought variability in different periods. Initially, PET was estimated from the temperature and rainfall data [44]. This climatic water balance then computed as the difference between precipitation and PET [45]. The accumulated climatic water-balance series was used to derive the Standardized Precipitation Evapotranspiration Index (SPEI) through a probability-distribution-based approach. Positive SPEI values indicate wetter-than-normal conditions, whereas negative values indicate drier-than-normal conditions. Positive SPEI values indicate wetter-than-normal conditions, whereas negative values indicate drier-than-normal conditions. R software is used for the calculation of SPEI. The resulting time series were then analysed to examine drought frequency, severity, variability, and temporal trends.

3.3.1. Calculation of Climatic Water Balance

The SPEI is grounded on the climatic water balance, calculated as:

$$D_i = P_i - PET_i \tag{3}$$

where, D_i denotes climatic water balance, P_i represent precipitation, and PET_i signify potential evapotranspiration for month i [42].

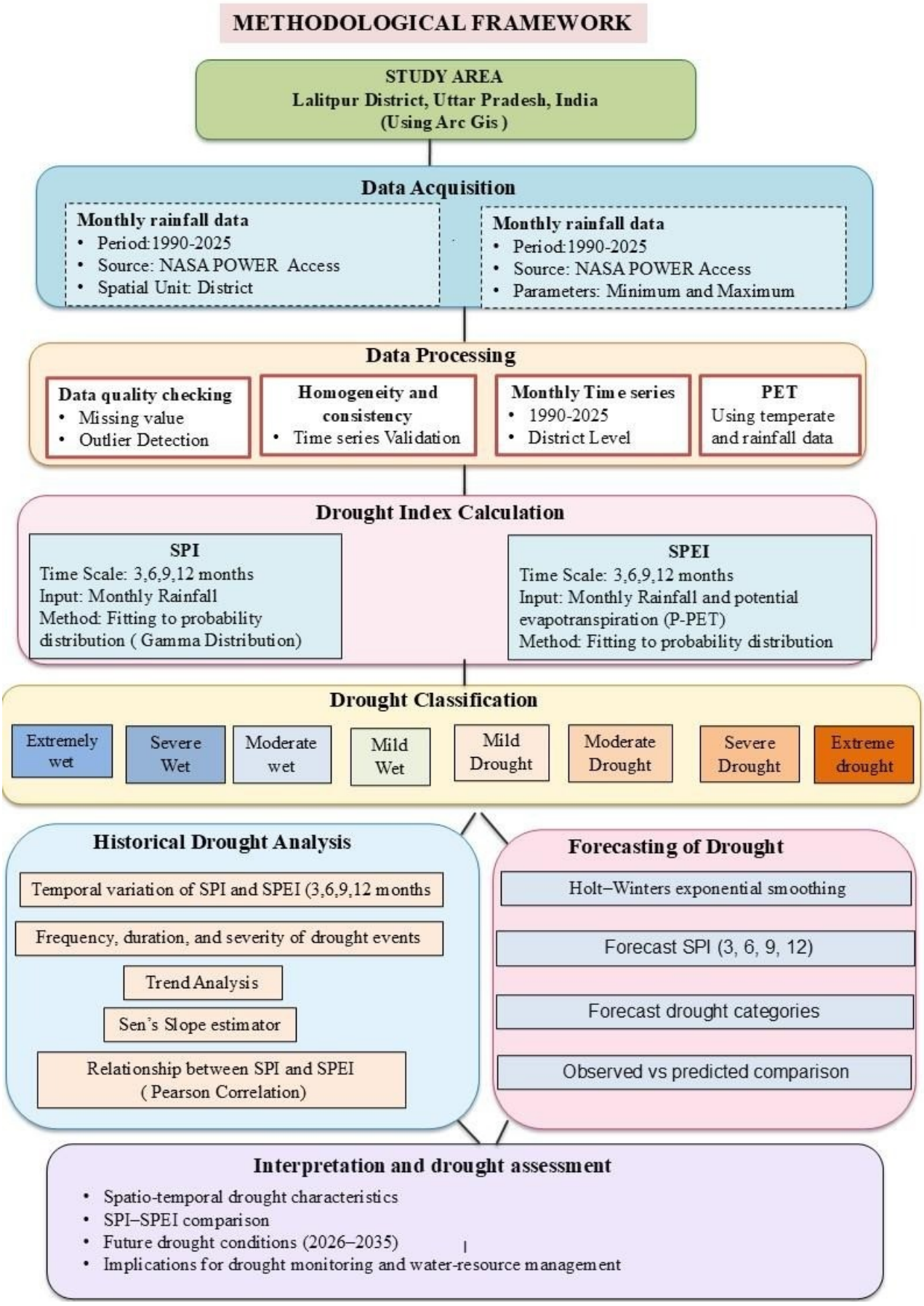


Figure 2. Methodological flow chart.

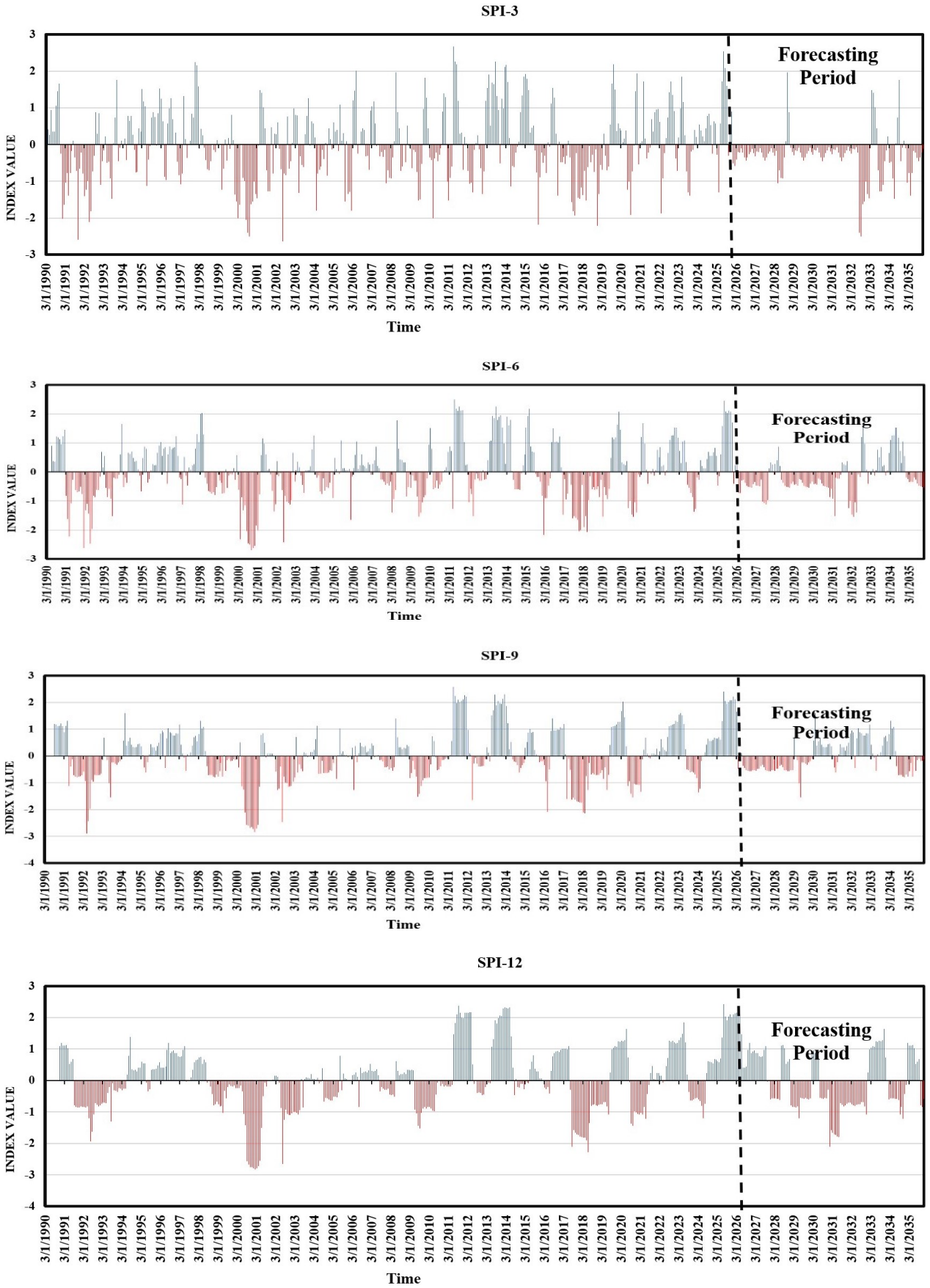


Figure 3. Drought severity was assessed using SPI at 3, 6, 9 and 12 month time scales from 1990–2025, including the projection period of 10 years.

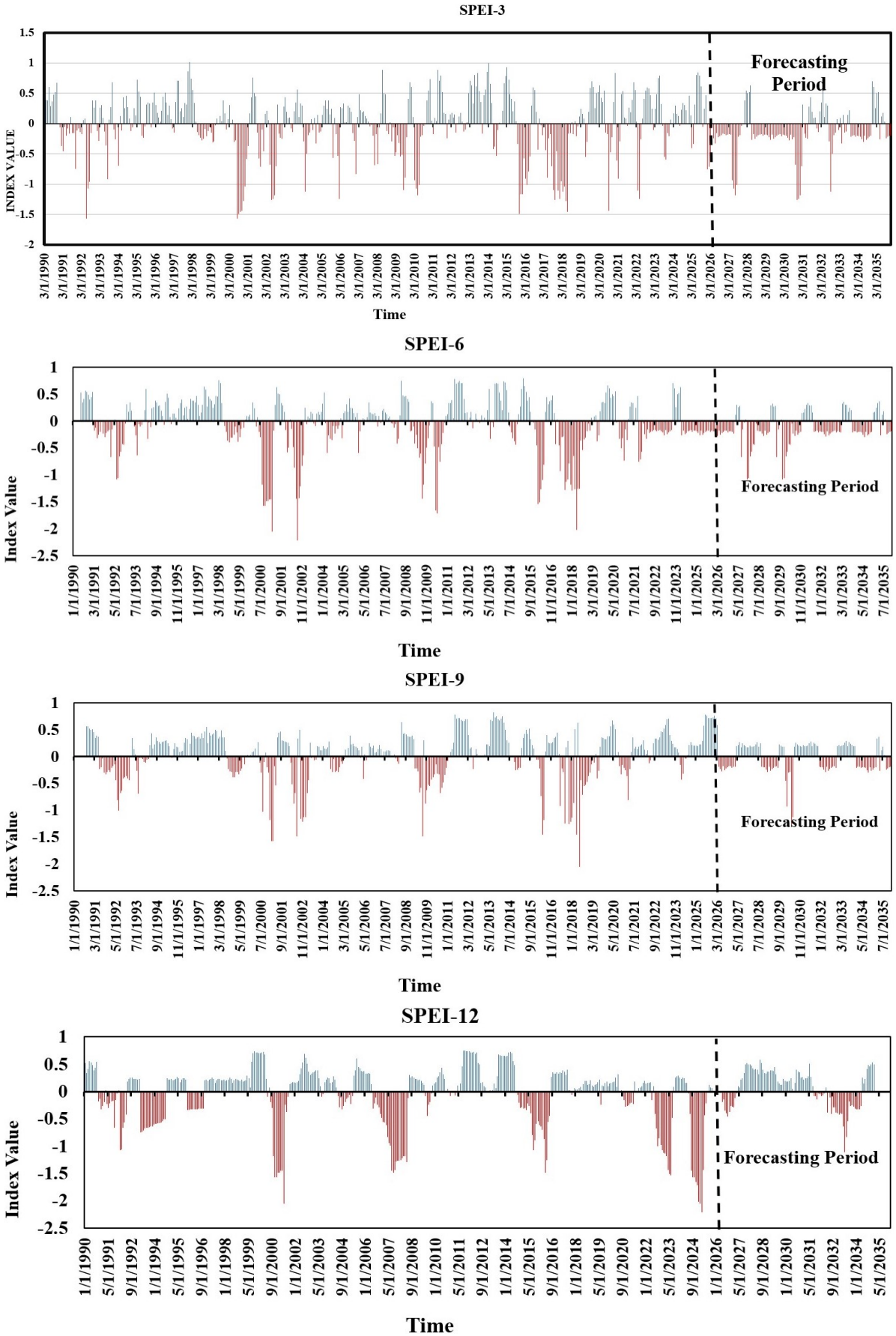


Figure 4. Drought severity assessed using SPI at 3, 6, 9 and 12-month timescales for 1990–2025, including the projection period of 10 years.

3.3.2. Fitting the Probability Distribution

The accumulated water-balance values are fitted to a log-logistic probability distribution, which is commonly used for calculating SPEI:

$$Fx = 1 + x - \gamma - 1 \tag{4}$$

where x is the accumulated water-balance value, β is the scale parameter, α is the shape parameter, and γ is the location parameter [42].

3.3.3. Standardization to Obtain SPEI

The cumulative probability obtained from the fitted log-logistic distribution is transformed into the standard normal distribution:

$$SPEI = -1F_x$$

where F_x is the cumulative probability of the climatic water balance and -1 is the inverse of the standard normal cumulative distribution function. The resulting standardized value represents the SPI [42].

3.4. Evaluation Using Spearman's Rank Correlation and Sen's Slope

Spearman's rank correlation and Sen's slope analysis were employed to identify the direction, magnitude and significance of drought trends [46]. These tests were also applied to assess the relationship and temporal trend of SPI and SPEI values at different time scale [47]. Sen's slope estimator was applied to identify and quantify the rate of magnitude and trend [48]. These non-parametric methods are useful for hydroclimatic dataset because they do not require the assumption of normal distributed data [46]. All statistical analysis were performed in R studio and SPSS.

3.4.1. Spearman's Rank Correlation and Sen's Slope

Spearman's rank correlation coefficient (r_s) is calculated as:

$$r_s = 1 - 6d_i 2nn^2 - 1 \tag{5}$$

where d_i the difference between the ranks of the two variables and n_i the number of observations [49].

The Sen's Slope estimator calculated as:

$$Q_i = x_j - xk_j - k,\ j > k \tag{6}$$

where x_j and x_k are the drought-index values at times j and k, respectively. The median of all calculated slopes represents the Sen's Slope estimate. A positive slope indicates an increasing trend, whereas a negative slope indicates a decreasing trend. These analyses were applied to SPI-3, SPI-6, SPI-9, SPI-12 and the corresponding SPEI timescales [49, 50].

3.5. Evaluation of Drought Patterns and Future Projections

Drought characteristics in the study area were examined using of SPI and SPEI at 3, 6, 9 and 12 month time scales. The severity of drought was categorized into moderately dry, severely dry, and extremely dry categories based on the index value (Table 1). Drought months were calculated and their frequency was estimated for the 35-year period (1990–2025). The Holt–Winters exponential smoothing method was employed to forecast drought conditions for the period up to 2035.

The forecast value Y_{t+h} at h periods in advance was articulated as:

$$Y_{t+h} = L_t + hT_t + S_{t-m+1+h-1}\ m. \tag{7}$$

The Holt–Winters additive model was employed to the observed SPI and SPEI series [51]. In this model, the observed value at time t was represented by Y_t, while L_t, T_t, and S_t signified the level, trend, and seasonal mechanisms, correspondingly [52]. The seasonal period was signified by m, and the smoothing parameters, α, β, and γ ranged from 0 to 1. Here, Y_{t+h} represented the forecasted SPI or SPEI value hperiods ahead [52].

Table 1. Drought category according to SPEI and SPEI index.

SL. No	SPI Index Values	SPEI Index Values	Drought Category
1	≥2.00	≥2.00	Extremely Wet
2	1.50 to 1.99	1.50 to 1.99	Severely Wet
3	1.00 to 1.49	1.00 to 1.49	Moderately Wet
4	>0.00 to 0.99	>0.00 to 0.99	Mildly Wet
5	−0.99 to −0.00	−0.99 to −0.00	Mild Drought
6	−1.49 to −1.00	−1.49 to −1.00	Moderate Drought
7	−1.99 to −1.50	−1.99 to −1.50	Severe Drought
8	≤−2.00	≤−2.00	Extreme Drought

4. Result

In this study, the results are presented in distinct sections focusing on drought severity, drought magnitude, and drought forecasting. These provide a comprehensive understanding of drought characteristics and support the development of appropriate management and planning strategies for future drought conditions.

4.1. Evaluation of Drought Severity

Drought intensity evaluation has been appraised via various statistical methodologies for measuring drought.

4.1.1. Evaluation of Drought Conditions Using SPI for 1990 to 2025

SPI was employed to evaluate the drought conditions at 3, 6, 9 and 12 month time scales from the year 1990 to 2025. Based on the SPI index drought condition was classified into three categories moderately dry (-1.00 to -1.49), very dry (-1.50 to -1.99), and extremely dry (≤ -2.00). For SPI-3 39 moderately dry, 17 very dry and 11 extremely dry months with 67 drought months were identified (Figure 3). SPI-6 recorded 25 moderately dry, 15 very dry, and 16 extremely dry months, resulting in 56 drought months (Figure 3). For SPI-9, moderately dry, 13 very dry, and 15 extremely dry months were recorded, accounting for 54 drought months in total. SPI-12 recorded 28 moderately dry, 13 very dry, and 12 extremely dry months, resulting in 53 drought months. Overall, the results indicate variation in drought occurrence across different accumulation periods, with SPI-3 showing the highest number of drought months and SPI-12 the lowest (Table 2).

4.1.2. Evaluation of Drought Conditions Using SPEI for 1990 to 2025

The SPEI results indicate variations in drought conditions across the 3, 6, 9 and 12 month time scales during 35 years. Most drought events were predominantly concentrated in the moderately dry category (SPEI -1.00 to -1.49), while very dry (-1.50 to -1.99) and extremely dry (≤ -2.00) conditions occurred relatively limited. SPEI-3 recorded 30 moderately dry months and 2 very dry months, while extremely dry conditions were nil. At the SPEI-6 scale, 22 moderately dry, 6 very dry, and 3 extremely dry months were identified (Figure 4). SPEI-9 identified 16 moderately dry, 2 very dry, and 1 extremely dry month. The SPEI-12 results indicated 30 moderately dry, 8 very dry, and 4 extremely dry months. Overall, the highest number of drought months was recorded for SPEI-12 (42), followed by SPEI-3 (32), SPEI-6 (31), and SPEI-9 (19), demonstrating variation in drought occurrence across accumulation periods (Table 3).

Table 2. Drought category and drought months according to the assessment of SPI from 1990–2025.

SPI Time Scale	Moderately Dry (-1.00 to -1.49)	Very Dry (-1.50 to -1.99)	Extremely Dry (≤ -2.00)	Total Drought Months
SPI-3	39	17	11	67
SPI-6	25	15	16	56
SPI-9	26	13	15	54
SPI-12	28	13	12	53
Total	118	58	54	230

Table 3. Drought classification and drought months according to the evaluation of SPEI from 1990–2025.

SPEI Time Scale	Moderately Dry (-1.00 to -1.49)	Very Dry (-1.50 to -1.99)	Extremely Dry (≤ -2.00)	Total Drought Months
SPEI-3	30	2	0	32
SPEI-6	22	6	3	31
SPEI-9	16	2	1	19
SPEI-12	30	8	4	42
Total	98	18	8	124

4.1.3. Trend Analysis of SPI and SPEI through the Spearman's Rank Correlation and Sen's Slope Estimator

The trend analysis assessed the temporal patterns of SPI and SPEI during the 35 years from 1990 to 2025. All four SPI time scales defined positive and statistically significant trends, with Spearman's ρ varying from 0.118 to 0.148 and p-values below 0.05. The Sen's slope estimator values were also showed a positive trend, ranging from 0.01127 to 0.01650 per year, representing a gradual increasing trends in SPI values. Among the SPI time scales, SPI-12 recorded the maximum Sen's slope (0.01650 per year), signifying the greatest rate of increase. The SPEI outcomes indicated relatively various patterns. SPEI-3 revealed a weak positive trend ($\rho = 0.0491$), but the trend was not statistically significant ($p = 0.3100$). SPEI-6 delineate a statistically significant negative trend ($\rho = -0.1369$; $p = 0.0046$), with a Sen's slope of -0.00531 per year, indicating a negative trend in SPEI-6 values. SPEI-9 and SPEI-12 displayed statistically significant positive trends, with Sen's slopes of 0.00428 and 0.00564 per year, correspondingly. Overall, the results demonstrate that drought-related trends vary according to both the drought index and accumulation period (Table 4).

4.2. Prediction of Drought Occurrences

Prediction means the estimation of future trends using historical data of the corresponding parameters. The present study assesses future drought trends in terms their magnitude and frequency and supports drought management strategies through prediction method. The forecasting period extends from 2026 to 2035 covering a period of 10 years. SPI and SPEI indices were used to forecast drought condition at 3, 6, 9 and 12 month time scales. The SPI analysis projected several drought occurrences (Table 5). The SPI-3 forecast indicated 10 moderately dry, 2 very dry, and 2 extremely dry months, resulting in 14 drought months during 2026–2035. The SPI-6 forecast 8 moderately dry and 2 very dry months, giving a total of 10 drought months, while extremely dry conditions were not projected. The SPI-9 forecast indicated 1 moderately dry and 1 very dry month, resulting in a total of 2 drought months. The SPI-12 forecast indicated 4 moderately dry, 6 very dry, and 1 extremely dry month, accounting for 11 drought months during 2026–2035. Similarly, SPEI was used to identify drought conditions by incorporating precipitation and potential evapotranspiration. SPEI-3 indicated 7 moderately dry months in the forecast period, while SPEI-6 projected 4 moderately dry months. SPEI-9 forecast 2 moderately dry months, whereas SPEI-12 indicated only 1 moderately dry month during 2026–2035. The SPEI forecast did not identify extremely dry conditions at any time scale. Therefore, the SPEI projections suggest that the forecast dry conditions are mainly moderate in intensity and become less frequent at longer accumulation period. The forecast results indicate that drought frequency and intensity differ depending on the accumulation periods and drought index used. SPI forecast indicated more dry months, particularly at the 3- and 12-month time scales, whereas the SPEI indices projected fewer drought months void with no occurrence of very dry or extremely dry condition. The comparative distribution of moderately dry, very dry and extremely dry forecast period (2026–2035) is presented in Table 5.

Table 4. The result combines the Spearman Rank Correlation test for trend analysis with Sen's slope to quantify changes, especially in drought trends.

Index	*N*	Spearman's ρ	*p* Value	*t*-Value	*df*	Sen's Slope/Month	Sen's Slope/Year	Sen's Slope/Decade	R^2
SPI-3	430	0.118161	0.014218	2.4618	428	0.000939	0.011267	0.112666	0.01396
SPI-6	427	0.140859	0.003537	2.9331	425	0.001151	0.013809	0.138086	0.01984
SPI-9	424	0.130955	0.00693	2.7135	422	0.001086	0.013027	0.130271	0.01715
SPI-12	421	0.148248	0.002291	3.0685	419	0.001375	0.016497	0.164971	0.02198
SPEI-3	430	0.049068	0.310033	1.0164	428	0.000168	0.002016	0.020162	0.00241
SPEI-6	427	−0.136900	0.004598	−2.8491	425	−0.000443	−0.005311	−0.053112	0.01874
SPEI-9	424	0.112475	0.02053	2.3253	422	0.000357	0.00428	0.042799	0.01265
SPEI-12	421	0.138818	0.004322	2.8693	419	0.00047	0.005642	0.056418	0.01927

4.3. Pearson' Correlation between SPI and SPEI

Pearson' correlation method was applied to evaluate the strength and direction of the relationship between the two drought indices, SPI and SPEI, at different Time scales [53]. It is significant because it determines the degree of linear association between the two drought indices [54]. The correlation analysis indicates that SPI and SPEI exhibit positive relationships across all time scales, with correlation coefficients ranging from 0.32 to 0.72. The strongest relationship was found between SPI-3 (r = 0.72), SPEI-9 and SPI-9 (r = 0.72), and SPEI-12 and SPI-12 (r = 0.72) A comparatively strong positive correlation was observed between the SPEI-6 and SPI-6 (r = 0.61). Multiple descriptive statistical analysis and several indices along with varied time scales have been considered (Tables 6 and 7). The analysis indicates that SPI and SPEI generally represent similar drought variability patterns, while variations between the SPI and SPEI may reflect the additional influence of potential. The prediction performance of SPI and SPEI at various time scales was examined using RMSE and MAE. SPEI-12 indicated the maximum forecasting precession with the lowest RMSE (0.5335) and MAE (0.4565), followed by SPEI-9 (RMSE = 0.5596; MAE = 0.4767). Overall, SPEI displayed lower forecasting errors than SPI (Figure 5).

Table 5. Prediction of drought occurrences from 2026–2035.

Drought Index	Time Scale	Moderately Dry (−1.00 to −1.49)	Very Dry (−1.50 to −1.99)	Extremely Dry (≤−2.00)	Total Drought Months
SPI	SPI-3	10	2	2	14
SPI	SPI-6	8	2	0	10
SPI	SPI-9	1	1	0	2
SPI	SPI-12	4	6	1	11
SPEI	SPEI-3	7	0	0	7
SPEI	SPEI-6	4	0	0	4
SPEI	SPEI-9	2	0	0	2
SPEI	SPEI-12	1	0	0	1

Table 6. Descriptive statistics of SPI and SPEI.

Statistical Analysis	SPI-3	SPI-6	SPI-9	SPI-12	SPEI-3	SPEI-6	SPEI-9	SPEI-12
N	430	427	424	421	430	427	424	421
Mean	−0.003	0	0	0	−0.006	−0.071	0.029	−0.021
Median	−0.039	−0.057	−0.022	−0.024	0.072	−0.006	0.115	0.117
Standard Error	0.048	0.048	0.049	0.049	0.025	0.025	0.022	0.026
SD	1	1.001	1.001	1.001	0.516	0.513	0.453	0.525
Variance	1	1.002	1.002	1.002	0.266	0.263	0.205	0.276
Skewness	0.085	−0.022	−0.079	−0.028	−0.855	−1.259	−1.232	−1.47
Kurtosis	−0.171	0.102	0.416	0.489	0.665	2.231	2.33	2.457
Maximum	2.667	2.491	2.574	2.417	1.015	0.795	0.821	0.754
Minimum	-2.637	−2.701	−2.901	−2.818	−1.569	−2.219	−2.058	−2.219
Range	5.304	5.192	5.475	5.235	2.584	3.014	2.878	2.973

Table 7. Summary statistics for forecasting accuracy across different time scales of SPI and SPEI.

Index	Alpha (α)	Beta (β)	Gamma (γ)	SMAPE (%)	RMSE	MAE	MASE
SPI-3	0.7318	0.0025	0.597	140.442	1.2486	0.9783	0.881
SPI-6	0.5279	0.0065	0.7333	183.068	2.9477	2.7603	2.4293
SPI-9	0.6584	0.0103	0.8097	170.327	2.4788	2.2102	1.879
SPI-12	0.7511	0.008	0.9999	161.501	2.4984	2.2023	1.881
SPEI-3	0.8633	0.0028	0.7641	154.899	0.7001	0.5725	1.0072
SPEI-6	0.913	0.0027	0.9999	156.602	1.4466	1.3731	2.3359
SPEI-9	0.5042	0.0099	0.2115	176.561	0.5596	0.4767	0.9229
SPEI-12	0.8304	0.0074	0.9999	171.724	0.5335	0.4565	0.7486

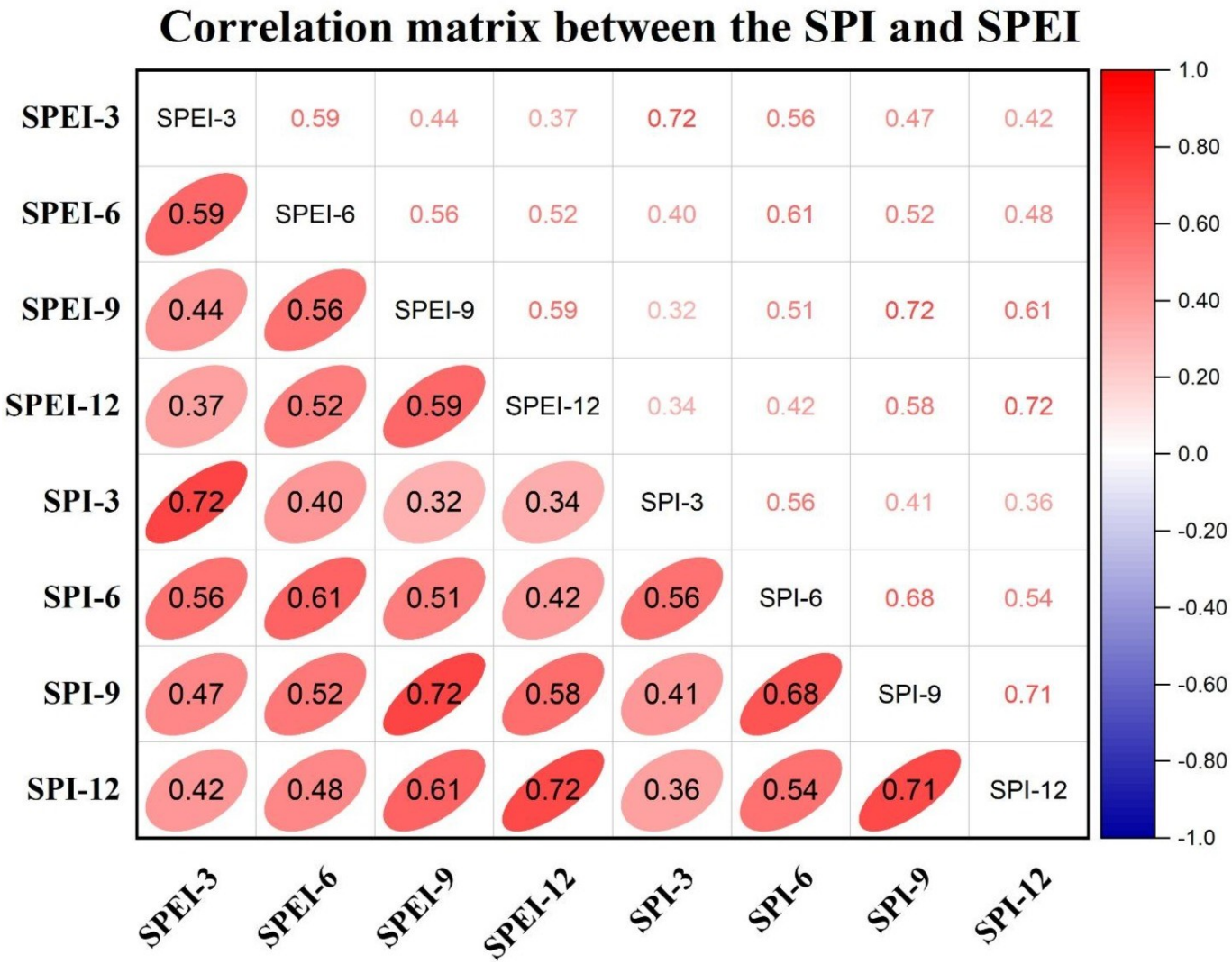


Figure 5. Correlation matrix showing the of correlation between SPI & SPEI in different time scale.

5. Discussion

The multiscalar drought assessment for 1990–2025 demonstrates that drought frequency and severity are strongly influenced by both the choice of drought index and the accumulation period. SPI identified 230 drought months, compared with 124 drought months identified by SPEI. Despite this difference in frequency, the two

indices exhibited positive correlations across the examined timescales ($r = 0.32$–0.72), indicating that they capture a common hydroclimatic signal while responding differently to the variables incorporated in their formulations. SPI is based on precipitation and therefore be understood primarily as a measure of precipitation anomalies at different accumulation periods, whereas SPEI incorporates the climatic water balance through precipitation and PET, thereby accounting for the influence of temperature-related atmospheric water demand [42, 55]. The lesser number of drought months detected by SPEI in the present study should therefore be interpreted as an outcome of the index formulation and the standardization procedure rather than as indication that temperature effects are insignificant. SPEI can respond to changes in evaporative demand, and its values are also influenced by the method used to estimate PET and by the statistical distribution fitted during standardization [42, 55]. Therefore, differences between SPI and SPEI frequencies are expected when precipitation and atmospheric water demand do not vary simultaneously [56]. This distinction is particularly relevant in drought-prone environments where the effect of reduced rainfall may be partly reduced or further aggravated by changes in evaporative demand [57]. The trend analysis indicates a slight increase in rainfall, with slopes ranging from 0.011 to 0.016 per annum. At the 6-month timescales, SPEI shows a negative slope of -0.005 per year. The difference indicates that a slight increase or stable rainfall does not necessarily reduce water stress [58]. A negative SPEI of 6-month interval shows that water loss from heat and evaporation remains a key factor of drought risk. The difference between Rainfall-based drought and drought based on rainfall and water demand indicators highlights the need to consider both rainfall variability and atmospheric water demand. These factors provide a more complete understanding of drought conditions. This approach is also important for assessing future drought risks [59]. The results agree with drought studies in central India and Bundelkhand, which show changes in drought frequency and severity over time. Amrit et al. found considerable variations in meteorological drought across central India in terms of space and time [60]. Similarly, Thomas et al. reported drought variations at different timescales in Bundelkhand using SPI-3, SPI-6, and SPI-12 [61]. Thomas et al. further showed that drought vulnerability in the Bundelkhand region is spatially heterogeneous and is influenced by multiple water-resource indicators [62]. These studies support the interpretation that drought characteristics cannot be sufficiently represented by a single temporal scale or a sole indicator [62]. Trend significance should be interpreted carefully because 3, 6, 9, and 12 month accumulation periods create dependence between successive observations. This dependence can affect the variance of the Mann–Kendall statistic and, in turn, the significance of the detected trends. Hamed and Rao showed that positive autocorrelation can lead to the detection of false trends. They proposed a modified Mann–Kendall test to account for autocorrelation [63]. Therefore, trend conclusions for the multiscalar drought series should preferably be based on an autocorrelation-adjusted test, particularly for longer accumulation periods [64]. The 2000–2001 period emerged as the most severe multi-season drought episode in the study area, with extreme deficits evident in SPI-6, SPI-9 and SPI-12. Severe drought conditions across multiple timescales indicate a long-lasting drought rather than a short-term lack of rainfall [65]. This finding agrees with previous studies showing that droughts in the Bundelkhand region often persist across several seasons and years [62]. The prolonged nature of the 2000–2001 event is particularly important from a water-resource perspective because longer accumulation periods are more closely related to sustained deficits affecting soil moisture, surface-water availability and groundwater recharge [53]. The 2026–2035 forecasts indicate the potential continuation of moderate dry conditions, particularly at shorter accumulation periods. The forecast further shows that SPEI produced lower absolute errors according to RMSE and MAE, whereas MASE indicated superior predictive performance only for SPI-3, SPEI-9 and SPEI-12. Because MASE scales forecast errors relative to a naïve benchmark, it provides a scale-independent basis for comparing predictive performance across drought-index series [66]. The results show that no single index proved to be universally superior. Predictive accuracy varies with the timescale. SPEI-9 and SPEI-12 perform better in identifying long-term water-balance changes, while SPI-3 is useful for predicting short-term rainfall variations. The groundwater vulnerability provides a more robust framework for drought assessment [67]. Lalitpur is characterized predominantly by crystalline and fractured geological formations, in which groundwater storage and movement are strongly controlled by weathered zones and fractures [68]. The available CGWB- based assessment indicates a groundwater development stage of 51.70%, and identifies Bar and Talbehat as semi-critical blocks, indicating that district-level averages can disguise localized groundwater stress. The same assessment also reports substantial long-term fluctuations in groundwater levels, including declining trends at several monitoring sites. These conditions imply that meteorological drought may translate into groundwater stress differently across the district depending on aquifer characteristics, recharge conditions and abstraction pressure. The groundwater findings also highlight the importance of unique climate-driven drought from anthropogenic groundwater depletion [69]. A decline in groundwater levels cannot be attributed exclusively to reduced rainfall where agricultural extraction is heavy [70]. Groundwater drought research has similarly emphasized that groundwater responses are delayed and filtered through aquifer properties and recharge processes, making groundwater drought distinct from meteorological drought [71]. Accordingly, combining SPI and SPEI with groundwater-level observations would provide a more complete assessment of drought propagation from meteorological conditions to groundwater systems [71].

6. Limitations and Recommendations

The study has certain limitations that are being discussed here. First, the use of gridded climate data may smooth localized precipitation and temperature extremes and may therefore underestimate microclimatic drought variability. Second, the analysis does not explicitly incorporate large-scale climate drivers such as the El Niño–Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD), both of which can influence Indian monsoon variability. Third, the forecasting results should be interpreted as scenario-based statistical projections rather than deterministic predictions, particularly because future drought conditions can be affected by changes in rainfall variability, temperature, land use and atmospheric circulation. These limitations indicate the need for future work integrating observed station data, large-scale climate indices and higher-resolution hydroclimatic datasets. Overall, the findings support an integrated drought-management framework for Lalitpur District. SPI and SPEI should be used concurrently because they provide complementary information on precipitation deficits and climatic water-balance stress. The 6- and 12-month accumulation periods are particularly relevant for hydrological early warning because they capture persistent anomalies more effectively than short accumulation periods. At the same time, semi-critical groundwater blocks such as Bar and Talbehat should receive priority for groundwater monitoring, recharge enhancement, irrigation-efficiency measures and demand-side management. The results therefore demonstrate that drought risk in Lalitpur is not spatially or temporally uniform, but instead reflects the interaction of precipitation variability, evaporative demand, drought persistence and groundwater-system characteristics.

7. Conclusions

The analysis identified that the entire Lalitpur district is drought prone region and has experienced several significant drought events in the history. Organized drought evaluation and monitoring are therefore crucial for sustainable water-resource management effective drought preparedness. The outcomes identified that drought occurrence is impacted by the mutual effects of anthropogenic and climatic factors, including reduced precipitation, high evaporation and evapotranspiration rates substantial runoff, and rapid land-use changes. Regular monitoring of rainfall, temperature, evapotranspiration, runoff, soil moisture, plant cover, and groundwater storage is very important for the gathering knowledge of drought dynamics and their long-term changes. The assessment of future drought prediction should be incorporated with advanced statistical and Machine learning methodologies to improve forecasting accuracy and enhance early warning abilities. Drought-vulnerability assessments at the village level are important for identifying communities at risk and formulating appropriate adaptation strategies. Field investigation and socioeconomic information should be integrated with environmental assessments for better evaluation of drought on local populations, especially marginal farmers. This adaptation helps to promote drought- and heat-tolerant crops, improving resilient agricultural practices, and implementing integrated watershed management that enhances water security and reduce drought impacts. The effective administrative policies, public-awareness programmes, and appropriate legal frameworks are also essential to strengthen drought preparedness and resilience. Thus, this study which focuses on regional and local research is essential for developing sustainable strategies to address future drought risks.

Author Contributions

S.K.: Writing—original draft, conceptualization, investigation, methodology; B.B.: Validation, data curation, conceptualization, supervision; S.G.: Review & editing. Each author has read and given their approval to the final version of the manuscript.

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Data Availability Statement

The data used in this study is based on publicly available meteorological records and groundwater data from government sources, which are accessible to researchers upon request. As such, a formal data availability statement is not applicable, as no proprietary or restricted data was used in this research. The codes used for data processing, statistical analysis, and drought index assessment are available from the corresponding author upon reasonable request.

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Conflicts of Interest

The authors declare no conflict of interest, and they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Use of AI and AI-Assisted Technologies

The authors have only used Chat GPT and Grammarly for language improvement.

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