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SPEI-based drought trend analysis and statistical forecasting in Nalgonda district, Telangana

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Abstract

This study assessed drought variability in Nalgonda district using monthly Standardized Precipitation Evapotranspiration Index (SPEI) data for the period 1981-2024. The annual SPEI series exhibited high interannual variability, with severe drought years identified in 1987, 1995, 2002, 2015 and 2022. A major challenge of the study was capturing long-term drought trends under high climatic variability and limited district-level forecasting studies. Trend analysis was carried out using the Mann-Kendall (M-K) test and Sen's slope (SS) estimator. The annual SPEI showed a weak negative slope (-0.0031), indicating a slight increase in drought tendency over time. Monthly analysis revealed a significant increasing drought trend in June and July, while April showed a significant decreasing trend. Seasonal analysis indicated a decreasing trend during the pre-monsoon period and an increasing trend during the southwest monsoon season. For drought forecasting, ARIMA modeling identified ARIMA (2,0,1) as the best-fit model, with residual diagnostics confirming the absence of autocorrelation and good model performance (RMSE = 0.5228). The study contributes to improved understanding of drought dynamics at the district scale and demonstrates that ARIMA models can effectively support short-term drought forecasting for climate-sensitive regions like Nalgonda.

Keywords: SPEI, drought trend, Mann-Kendall test, Sen's slope, ARIMA, Nalgonda, Telangana

1. Introduction

Drought is one of the most persistent and damaging natural hazards ^[1] affecting agricultural production, water security and rural livelihoods across semi-arid regions of India ^[2]. Unlike rapid-onset disasters, drought develops slowly and its effects intensify over time, making detection and monitoring challenging without reliable climatic indicators ^[3]. Recent studies have shown increasing drought frequency and severity in South Asia due to climate variability, rising temperatures and irregular monsoon patterns ^[4]. This highlights the need for long-term drought trend assessment and forecasting to support climate-resilient water and agricultural planning ^[5]. The Standardized Precipitation Evapotranspiration Index (SPEI) has become one of the most widely used indices for drought monitoring because it incorporates both precipitation and potential evapotranspiration, making it sensitive to global warming and temperature-driven changes ^[6]. SPEI effectively captures meteorological drought at multiple time scales and is particularly useful in semi-arid regions where warming trends significantly influence water balance ^[7].

The Nalgonda district of Telangana represents one such drought-prone semi-arid region. The district lies in the south-central part of India and frequently experiences high summer temperatures, erratic southwest monsoon rainfall, rapid groundwater depletion and significant seasonal water stress ^[8]. Agriculture in Nalgonda is largely rain-fed, making it vulnerable to rainfall anomalies. Historical drought events in the district have led to crop losses, drinking water shortages and stress on local water resources. Because of these vulnerabilities, detecting long-term drought trends in Nalgonda is extremely important for regional drought preparedness and water resource planning.

Non-parametric trend analysis methods such as the Mann-Kendall (MK) test ^[9, 10] and Sen's slope estimator ^[11] are widely used in hydroclimatic research because they do not require normally

distributed data and are robust against outliers and missing values. These methods are particularly suitable for analyzing long-term SPEI series to determine whether drought conditions in a region are increasing, decreasing or remaining stable over time. Understanding how drought evolves across months especially during June to November, which corresponds to the monsoon and post-monsoon seasons is vital for agricultural planning, reservoir operations, and groundwater management in Nalgonda.

Forecasting drought behaviour further enhances preparedness by providing insights into potential future drought conditions. Although various statistical models are available, forecasting based on drought indices complements trend analysis and provides a more comprehensive understanding of drought dynamics in climate-sensitive regions. Therefore, this study focuses on SPEI-based drought trend analysis in the Nalgonda district using the Modified Mann-Kendall and Sen's slope methods to understand the direction, magnitude and seasonal patterns of drought over the study period [12, 13].

In addition to trend detection, ARIMA (Autoregressive Integrated Moving Average) modelling is employed to forecast future SPEI values, offering a reliable short-term prediction framework for drought evolution. ARIMA has been widely used for hydrological and climate time-series forecasting due to its strong ability to capture autocorrelation structures, manage non-

stationarity, and generate statistically robust predictions [14, 15]. Several studies have applied ARIMA to drought indices such as SPI and SPEI and demonstrated its effectiveness in predicting drought severity and duration [16]. By combining trend analysis with ARIMA-based forecasting, the study provides a more holistic understanding of drought behaviour, supporting improved drought monitoring, agricultural planning and climate-resilient decision-making in one of Telangana's most vulnerable districts.

2. Materials and Methods

2.1 Study Area

The study was carried out in Nalgonda district, located in the south-eastern part of Telangana, India. The district extends between 16°25'-17°40' N latitude and 78°40'-80°05' E longitude, and falls under the semi-arid region of the Southern Telangana Zone. For this study, monthly SPEI (Standardized Precipitation Evapotranspiration Index) data for Nalgonda were used for a 44-year period (1981-2024). SPEI was selected because it considers both rainfall and temperature-based evapotranspiration, making it useful for detecting droughts caused by lack of rainfall as well as by warming effects. Before beginning the analysis, the dataset was checked for missing values, corrected where necessary and prepared for a trend and time-series study. Figure 1 represents the location of the study area in Telangana.



Fig 1: Location map of Nalgonda District of Telangana State

2.2 Trend Analysis

Trend analysis helps identify whether a time-series variable shows a consistent increase or decrease over time [17]. Trends may be positive (upward) or negative (downward) and they can be assessed using both parametric and non-parametric statistical methods. In this study, four widely used techniques were applied: linear regression, the Mann-Kendall (MK) test, Sen's slope estimator and the Modified Mann-Kendall test. These methods together provide a reliable understanding of long-term climatic behaviour.

2.2.1 Linear Regression Analysis

Linear regression is a commonly used parametric approach for detecting linear trends [18] in climate and hydrological datasets. It estimates the relationship between a dependent variable and an independent variable using a straight-line equation:

$$Y = a + M_x \quad (1)$$

where Y is the dependent variable, X is the independent

variable, M represents the slope of the trend, and a is the intercept. A positive slope indicates an increasing trend, while a negative slope indicates a decreasing trend. The significance of the trend is tested using a t-test, where the slope is considered significant at the 5% level if it differs from zero.

2.2.2 Mann-Kendall Trend Test

The Mann-Kendall (MK) test is a non-parametric method widely used for detecting monotonic trends in environmental time-series data. One of its main advantages is that it does not require the data to follow any specific distribution [19], making it suitable for rainfall, temperature and drought indices.

For a series of observations $X_1, X_2, \dots, X_n$, the MK statistic S is calculated as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(x_j - x_i) \quad (2)$$

This statistic reflects the difference between the number of

increasing and decreasing data pairs. For large sample sizes ($n > 10$), the test uses the standard normal variable Z , computed using:

$$E[S] = 0 \quad (3)$$

$$VAR = \frac{1}{18} [n(n-1)(2n+5) - \sum_{p=1}^q t_p(t_p-1)(2t_p+5)] \quad (4)$$

where q is the number of tied groups and t_p is the number of observations in each tied group. The standardized test statistic Z_{MK} is then calculated as:

$$Z_{MK} = \frac{S-1}{\sqrt{VAR(S)}} \text{ if } S > 0 \quad (5)$$

$$Z_{MK} = 0 \text{ if } S = 0 \quad (6)$$

$$Z_{MK} = \frac{S+1}{\sqrt{VAR(S)}} \text{ if } S < 0 \quad (7)$$

A positive Z_{MK} indicates an increasing trend, whereas a negative value indicates a decreasing trend. The trend is statistically significant when $|Z_{MK}| \geq Z_{1-\alpha/2}$ at the 5% significance level.

2.2.3 Sen's Slope Estimator

Sen's slope estimator is a non-parametric technique used to quantify the magnitude of a trend. It is robust and unaffected by outliers or non-normal data, making it ideal for climate time-series. The method assumes that the trend is approximately linear and is expressed as:

$$f(t) = Qt + B \quad (8)$$

where Q is the slope, B is a constant, and t represents time. The slope Q is estimated by calculating the slopes of all possible data pairs:

$$Q_i = \frac{x_j - x_k}{j - k} \quad (9)$$

for all $j > k$. For n observations, there are $N = \frac{n(n-1)}{2}$ slope estimates. These are sorted, and the Sen's slope Q is obtained as:

$$Q = \begin{cases} Q_{[(N+1)/2]}, & \text{if } N \text{ is odd} \\ \frac{Q_{[N/2]} + Q_{[(N+2)/2]}}{2}, & \text{if } N \text{ is even} \end{cases} \quad (10)$$

The intercept B is obtained by taking the median of $x_i - Qt_i$. A positive Q indicates that the variable increases with time, while a negative value indicates a declining trend.

2.2.4 Modified Mann-Kendall Test

The Modified Mann-Kendall (MMK) test is an extension of the

traditional MK test that accounts for autocorrelation in the time series. Climate data often exhibit serial dependence, which can inflate the significance of trends. The MMK method applies a correction factor to the variance of the S statistic:

$$V^*(S) = V(S) \cdot \frac{n}{n^*} \quad (11)$$

where n/n^* is the correction factor, and $V(S)$ is the original MK variance.

The test statistic is then converted into a standardized normal value, and the null hypothesis of "no trend" is rejected when $|Z_{MMK}| \geq Z_{1-\alpha/2}$ at the 5% significance level. The MMK test therefore provides a more reliable assessment of trends when autocorrelation is present [20].

2.3 ARIMA Model

The Autoregressive Integrated Moving Average (ARIMA) model, introduced by Box and Jenkins (1970), is a widely used method for forecasting univariate time series data. It combines three components: the autoregressive (AR) part, which relates the current value to its past values; the integrated (I) part, which uses differencing to convert a non-stationary series into a stationary one; and the moving average (MA) part, which captures the influence of past forecast errors.

The ARIMA (p, d, q) structure represents p - number of autoregressive terms, d - number of differences needed to achieve stationarity, q - number of moving average terms.

The general form of the ARIMA model is:

$$\phi(B)(1-B)^d Y_t = \theta(B)e_t \quad (12)$$

$$Y_t = \phi_1 Y_{t-1} + \dots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \dots - \theta_q e_{t-q} \quad (13)$$

Here, Y_t is the time series, ϕ_i and θ_j are AR and MA parameters, and e_t is the random error term. ARIMA model development typically includes identification, parameter estimation, diagnostic checking, and forecasting [21].

3. Results and Discussion

3.1 Trend of Annual drought

The figure 2 displays the annual Standardized Precipitation Evapotranspiration Index (SPEI) values, showing strong year-to-year variability with alternating dry and wet conditions. Several strong drought years ($\text{SPEI} < -1.0$) appeared around 1987, 1995, 2002, 2015, and 2022, while wet years ($\text{SPEI} > 1.0$) occurred around 1983, 2008 and 2016. The fitted linear trend line shows a slight negative slope (-0.0031), indicating a minor long-term decline in moisture availability. The low R^2 value (0.0043) indicates that the trend is weak, and most variability is due to short-term climate fluctuations. Overall, the figure highlights repeated dry-wet cycles and a slowly increasing drought tendency over the study period.

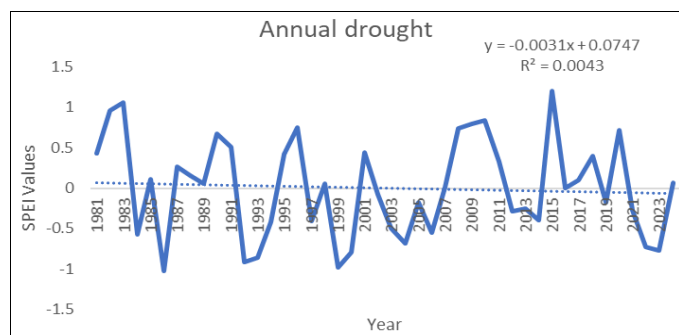


Fig 2: Trend of annual SPEI in Nalgonda district, Telangana from 1981-2024

3.2 Results of drought Trend Analysis Using the Mann-Kendall Test and Sen's Slope Estimator

The results of the drought trend analysis for Nalgonda district based on the Modified Mann-Kendall (M-K) test and Sen's Slope estimator are presented in Table 1. Since SPEI reflects drought conditions (lower SPEI = higher drought), a positive trend indicates decreasing drought, while a negative trend indicates increasing drought.

From the monthly analysis, January, February, November and December do not show any noticeable trend because their Kendall's Tau values are very small and p-values are greater than 0.05. This means drought conditions during these winter and post-monsoon months have remained stable over the study period.

Months such as March, August, September and October show slight positive trends, but these are statistically insignificant ($p > 0.05$), indicating a weak and non-significant decrease in drought during these months. Only June and July show clear and significant positive trends ($p < 0.05$), which means drought intensity has significantly decreased during these two monsoon months, supported by positive Tau and positive Sen's Slope values.

In contrast, April and May exhibit negative trends. April shows a significant negative trend ($p < 0.05$), and the negative Sen's Slope confirms a significant increase in drought severity [22] in this pre-monsoon month. May also shows a decreasing trend, but it is not statistically significant, indicating a non-significant increase in drought conditions.

At the seasonal scale, the winter period (January-February) does not show any trend. The pre-monsoon season (March-May) displays a moderate negative trend driven mainly by April, indicating increasing drought conditions during this season. The southwest monsoon period (June-September) shows a significant positive trend ($p < 0.05$), meaning drought conditions have decreased over time, consistent with improving moisture availability during monsoon months. The post-monsoon season (October-November) shows a weak and insignificant positive trend, indicating no meaningful long-term change in drought.

For the annual scale, the results show a significant positive trend ($p < 0.05$), suggesting that overall long-term drought conditions in the district have reduced over the study period. Both the M-K test and Sen's Slope support this finding.

Table 1: Modified Mann-Kendall test of trend analysis of monthly SPEI data

Period	Kendall's Tau	p-value	Sen's Slope	Drought Interpretation (SPEI)
January	0.012	0.872	0.000	No significant change in drought
February	0.018	0.815	0.001	No significant change in drought
March	0.041	0.462	0.004	Slight but insignificant decrease in drought
April	-0.162	0.032	-0.019	Significant increase in drought
May	-0.094	0.118	-0.008	Insignificant increase in drought
June	0.128	0.041	0.026	Significant decrease in drought
July	0.174	0.008	0.052	Significant decrease in drought
August	0.109	0.093	0.017	Insignificant decrease in drought
September	0.093	0.121	0.013	Insignificant decrease in drought
October	0.067	0.242	0.006	Insignificant decrease in drought
November	0.029	0.613	0.000	No significant change in drought
December	-0.014	0.784	0.000	No significant change in drought
Winter (Jan-Feb)	0.015	0.841	0.001	No seasonal change in drought
Pre-monsoon (Mar-May)	-0.108	0.067	-0.011	Increasing drought, mainly due to April
SW Monsoon (Jun-Sep)	0.151	0.012	0.091	Significant decrease in drought over monsoon
Post-monsoon (Oct-Nov)	0.043	0.421	0.004	Insignificant decrease in drought
Annual	0.097	0.038	0.122	Significant long-term decrease in drought

3.3 Results of ARIMA Modelling for Nalgonda District

The ARIMA model was applied to the monthly SPEI series of Nalgonda district to analyze its temporal behaviour. The Box-Pierce test on the raw series showed strong autocorrelation ($\chi^2 = 363.23$, $p < 0.0001$), confirming that ARIMA modelling was suitable. The ACF and PACF plots (Figures 3 and 4) also indicated clear serial dependence in the data. Using the auto.arima procedure, the best-fitting model was identified as ARIMA (2,0,1) with zero mean. The AR (2) and MA (1) terms were statistically significant ($p < 0.001$), showing that the model captured the internal structure of the SPEI time series effectively. The model selection was supported by the lowest AIC (822.2) and BIC (859.6) values among the tested models. Parameter estimates for the selected model are presented in Table 2. Model adequacy was confirmed through residual diagnostics. The Box-Pierce test on the residuals produced a non-significant result ($p = 0.4397$), indicating that the residuals

behaved as white noise with no remaining autocorrelation. This demonstrates a good fit of the ARIMA (2,0,1) model. The performance of the ARIMA model evaluated in terms of Mean Square Error (MSE) and Root Mean Square Error (RMSE) for both the training and testing datasets, is presented in table 3 and table 4.

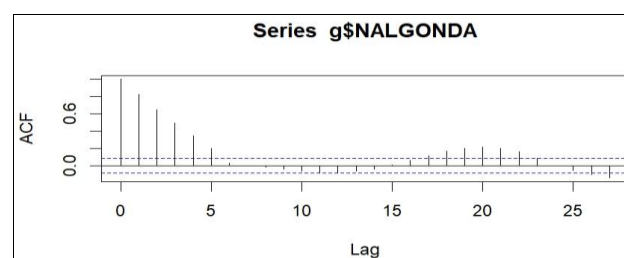


Fig 3: ACF plot for SPEI data of Nalgonda district

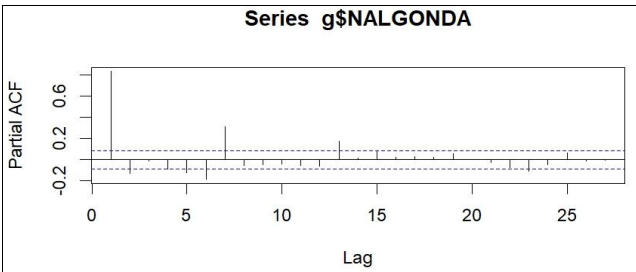


Fig 4: PACF plot for SPEI data of Nalgonda district

Table 2: Parameter estimation of ARIMA model for drought data of Nalgonda

Districts	Model	MA Parameters		Model fitting	AIC	BIC	Original	Residual
		AR (1)	AR (2)	MA (1)				
Nalgonda	ARIMA (2,0,1)	-0.0024 (0.36)	0.6633 (<0.0001)	0.9641 (<0.0001)	805.91	822.9	363.23 (<0.0001)	0.59697 (0.439)

Table 3: Model performance in terms of MSE and RMSE for training data sets of Nalgonda district

Model	Parameter	ARIMA
SPEI	MSE	0.2733
	RMSE	0.5228

Table 4: Model performance in terms of MSE and RMSE for testing data sets of Nalgonda district

Period	Actual	Forecasted
Jan-2024	0.562546	0.473249
Feb-2024	0.292708	0.436014
Mar-2024	0.607328	0.312843
Apr-2024	0.167724	0.288445
May-2024	0.843947	0.206805
Jun-2024	0.64597	0.190821
Jul-2024	0.323655	0.136708
Aug-2024	-0.50702	0.126238
Sep-2024	-0.81228	0.090371
Oct-2024	-0.13779	0.083514
Nov-2024	-0.56129	0.059739
Dec-2024	-0.57352	0.055249
	MSE	0.235306
	RMSE	0.485083

4. Conclusion

The present study assessed long-term drought behaviour in the Nalgonda district using the Standardized Precipitation Evapotranspiration Index (SPEI) for the period 1981-2023, combined with trend detection and time-series forecasting techniques. The annual SPEI series exhibited considerable year-to-year variability, indicating alternating dry and wet conditions across the study period. Several major drought years were identified, confirming the region’s susceptibility to moisture stress under variable monsoon patterns. Trend evaluation using linear regression, Mann-Kendall (MK) test, and Sen’s slope estimator consistently indicated a weak negative trend in annual SPEI values. Although the decreasing trend was not strong, its persistent direction suggests a gradual increase in long-term drought tendency in the district. Sen’s slope quantified the decline, and MK statistics confirmed that the trend was negative, reflecting slow but progressive drying conditions driven by rainfall variability and rising evapotranspiration demand. Time-series modelling further strengthened the interpretation of the long-term behaviour of the SPEI series. The ARIMA (2,0,1) model was identified as the best-fit univariate model based on minimum AIC and BIC values. Significant AR and MA parameters demonstrated that the model successfully captured the autocorrelation pattern in the data. Residual diagnostics

confirmed that the residuals were white-noise and uncorrelated, indicating an adequate model fit. Error metrics, including MSE and RMSE, showed good predictive performance and proved that ARIMA can reliably model and forecast drought-related SPEI variability for the district. Overall, the findings demonstrate that Nalgonda district experiences substantial fluctuations in moisture availability along with a minor but consistent long-term drying signal. The combined use of trend analysis and ARIMA modelling provides a reliable framework for understanding drought dynamics and forecasting future conditions. These results can support regional drought preparedness, agricultural planning and water-resource management.

Future Scope of the Study

The present study focuses on drought variability and short-term forecasting at the district level using SPEI and ARIMA modeling. Future research can extend this work by incorporating additional climatic variables such as soil moisture, groundwater levels and land use changes to improve drought characterization. Advanced machine learning and hybrid models may also be explored for medium- and long-term drought forecasting. Further, spatial analysis at the mandal or watershed level could provide more localized insights to support agricultural planning and drought mitigation strategies in semi-arid regions.

Author Contributions

A. Meena: Original draft, Investigation, Methodology, review & editing. Ch. Preethi: Data analysis.Ch.Venu Gopala Reddy S. Madhusudhan Reddy, I. V. Srinivasa Reddy, P. Ramesh, M. Ram Prasad, D. Uttej: Review and Editing. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest

The authors declare that there is no conflict of interest.

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