Journal of Agrometeorology

(A publication of Association of Agrometeorologists)

ISSN : 0972-1665 (print), 2583-2980 (online)
Vol. No. 28 (2) :167-176 (June - 2026)
https://doi.org/10.54386/jam.v28i2.3302
https://journal.agrimetassociation.org/index.php/jam

Research paper

Integrated Drought Diagnostics in Telangana (1981–2023): Trend Analysis, Multi-index Assessment, Quadrant Framework, and Interpretable Machine Learning

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ABSTRACT

This study aims to provide an integrated diagnostic of drought risk by investigating historical rainfall and temperature variability from 1981–2023 across six droughtprone districts of Telangana using statistical indices, trend diagnostics, and machine learning approaches. Monthly and annual datasets from IMD gridded archives were processed to compute mean, standard deviation, and coefficient of variation (CV) for rainfall, minimum, and maximum temperatures. Multiple drought indicators, including the Z Score Index (ZSI), Deciles Index (DI), Percent of Normal Index (PNI), Standardized Precipitation Index (SPI), China Z Index (CZI), and Rainfall Anomaly Index (RAI), were applied to capture severity, duration, and spatial extent of droughts. Trend analysis using the Mann–Kendall test and Sen's slope revealed statistically significant increases in maximum temperatures (+0.03 to +0.06 °C per year), while rainfall showed high variability (CV ranging from 22% in Khammam to 38% in Rangareddy) but no consistent longterm trend. A quadrantbased climate stress framework was developed by integrating rainfall magnitude, variability, extremes, and peak maximum temperature, classifying districts into Climate Stable, Rainfall Unpredictable, Dry Stable, and High Risk Climate Stress Zones. To enhance predictive capacity, machine learning models (Random Forest, Gradient Boosting, SVM, and Neural Networks) were trained on rainfall and temperature predictors, with SHAP analysis providing interpretability by identifying key drivers such as rainfall CV, Tmax slope, SPI, and ZSI. Model performance was robust, with Gradient Boosting achieving 89.1% accuracy and Random Forest 87.2%, confirming ensemble methods as the most reliable classifiers. Results confirm that all districts experienced mild to extreme drought years, with SPI identifying 6–9 severe drought years per district and Rangareddy and Mahbubnagar showing the highest risk. The integrated framework, combining statistical indices, visualization, and interpretable machine learning, provides a replicable methodology for semiarid regions and offers actionable insights for policymakers to strengthen agricultural resilience, water resource management, and climate adaptation strategies.

Keywords: Trend analysis, Drought indices, Climate stress quadrants, Machine learning, SHAP interpretability.

Global warming has intensified the frequency and severity of extreme weather events such as heatwaves, droughts, and heavy rainfall worldwide. Unlike floods or storms, droughts are more difficult to identify and quantify because they are slowonset hazards that may persist for months or years (Brunner, 2023). Climatic variability further amplifies the likelihood of droughts and floods by altering the frequency and intensity of rainfall. Such fluctuations in rainfall and associated weather threats, including windstorms, floods, and droughts, have significant impacts on agricultural productivity and rural livelihoods (Beckline *et al.,* 2025). Drought has emerged as a complex natural hazard with profound ecological and socioeconomic consequences due to its severity, duration, and spatial extent.

In India, climate change has adversely affected monsoon timing, temperature regimes, and other climatic parameters, thereby influencing agricultural systems and water resources (Mulla *et al.,* 2023). Even marginal increases in temperature can trigger heatwaves, biodiversity shifts, and crop damage. Longterm analyses confirm that the warming trends observed across India are consistent with global patterns (Shivanna, 2022). For instance, Singh & Jeganathan (2025) reported rising temperatures in southeastern regions and

Article info - DOI: *https://doi.org/10.54386/jam.v28i2.3302*
Received:12 December 2025; Accepted: 19 May 2026; Published online : 04 June 2026

declining trends in the northwest, alongside unpredictable rainfall patterns. Several studies (Alugubelly *et al.,* 2021; Wubaye *et al.,* 2023; Zhang *et al.,* 2023) have highlighted the importance of integrating meteorological indices, remote sensing, and machine learning for drought monitoring, yet most remain at national or regional scales, with limited districtlevel diagnostics for Telangana.

Telangana, located in the semiarid Deccan Plateau, is highly vulnerable to climate change and has limited adaptive capacity. Despite being categorized under the Drought Prone Area Programme (DPAP), systematic districtlevel analyses of rainfall variability, temperature extremes, and drought indices remain scarce. Previous studies have either focused on single indices or broad climatological trends, leaving a gap in integrated approaches that combine statistical diagnostics, visualization frameworks, and interpretable machine learning.

To address this gap, the present study pursues three clear objectives: (i) to analyze longterm rainfall and temperature trends across six droughtprone districts of Telangana using Mann–Kendall and Sen's slope methods; (ii) to apply multiple drought indices (SPI, PNI, DI, RAI, CZI, ZSI) for quantifying severity, duration, and spatial extent of droughts; and (iii) to develop a quadrantbased climate stress framework and machine learning models with SHAP interpretability to classify districtlevel vulnerabilities and identify key drivers of drought risk. By combining statistical indices, nonparametric trend tests, visualization frameworks, and interpretable machine learning, this study provides a comprehensive diagnostic of drought risk across Telangana's droughtprone districts. The integrated approach advances novelty by linking hydrological variability, thermal extremes, and predictive analytics, thereby offering actionable insights for policymakers and decisionmakers to strengthen agricultural resilience and water resource management.

MATERIALS AND METHODS

Study Area

Telangana is located in the semiarid zone of the Deccan Plateau, characterized by hot summers and variable rainfall. Maximum summer temperatures reach ~42 °C, while annual mean temperatures range between 27.5–27.8 °C. The state receives ~906 mm of rainfall annually, most of which occurs during the southwest monsoon (June–September). Soils include lateritic, black cotton, and red types, supporting diverse agricultural practices. The Drought Prone Area Programme (DPAP) identified Adilabad, Khammam, Mahbubnagar, Medak, Nalgonda, and Rangareddy as droughtprone districts, which formed the study sites (Chakraborty *et al.,* 2018). Fig. 1 shows the study area, and Table 1 provides districtwise land statistics including geographical area, dominant soil types, cropping intensity, and key crops.

Note: These statistics highlight the heterogeneity of land resources across Telangana's droughtprone districts. Larger districts such as Mahbubnagar and Adilabad face challenges of spatial variability in rainfall and soil type, while Rangareddy, with the smallest geographical area and shallow soils, shows the highest vulnerability to drought stress. Source: Commissioner of Agriculture, Telangana (2022)

Datasets

For this study, rainfall and temperature datasets were obtained from the India Meteorological Department (IMD) gridded data archives, which provide high-resolution, quality-controlled time series across India. Daily rainfall (0.25° × 0.25°) and temperature (1° × 1°) grids were extracted for the six drought-prone districts of Telangana, Adilabad, Khammam, Mahbubnagar, Medak, Nalgonda, and Rangareddy, for the period 1981–2023. The extraction process involved delineating district boundaries using official shapefiles in QGIS, overlaying IMD grid points, and aggregating values to monthly and annual scales. Data were homogenized and validated against station records to ensure consistency. The gridded datasets were homogenized and validated against station records to ensure consistency. Validation results showed high correlation between IMD rainfall grids and station observations (r = 0.87–0.92 across districts) with mean bias within ±3%, while temperature grids demonstrated correlation values of r = 0.89–0.93 and mean bias within ±2%. These statistics confirm that the IMD datasets are reliable and suitable for district-level drought diagnostics. The use of IMD gridded data provided spatially representative coverage of each district, minimized observational gaps, and ensured robust inputs for trend analysis, drought index computation, and climate stress diagnostics.

Trend Analysis of Rainfall and Temperature

Longterm changes in rainfall and temperature across Telangana were assessed using regression analysis, the coefficient of determination (R^2), and nonparametric tests. Descriptive statistics including mean, standard deviation, and coefficient of variation (CV) were computed to quantify variability.

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \quad (1)$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2} \quad (2)$$

$$CV = \frac{\sigma}{\bar{X}} \times 100 \quad (3)$$

The Mann–Kendall (MK) test (Kendall, 1945) was applied to detect monotonic trends in rainfall and temperature series.

$$S = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} \mathrm{sgn}(X_j - X_i) \quad (4)$$

where, $$\mathrm{sgn}(X_j - X_i) = \begin{cases} 1 & \text{if } X_j - X_i > 0 \\ 0 & \text{if } X_j - X_i = 0 \\ -1 & \text{if } X_j - X_i < 0 \end{cases} \quad (5)$$

The null hypothesis () assumes no trend, while the alternative hypothesis () indicates a significant trend at the 5% level.

To estimate the magnitude of change, Sen's slope (Sen, 1968) was calculated as:

$$Q_i = \frac{X_j - X_k}{j-k}, j > k \quad (6)$$

The median of all values represents the overall slope. A positive indicates an increasing trend, while a negative denotes a decreasing trend.

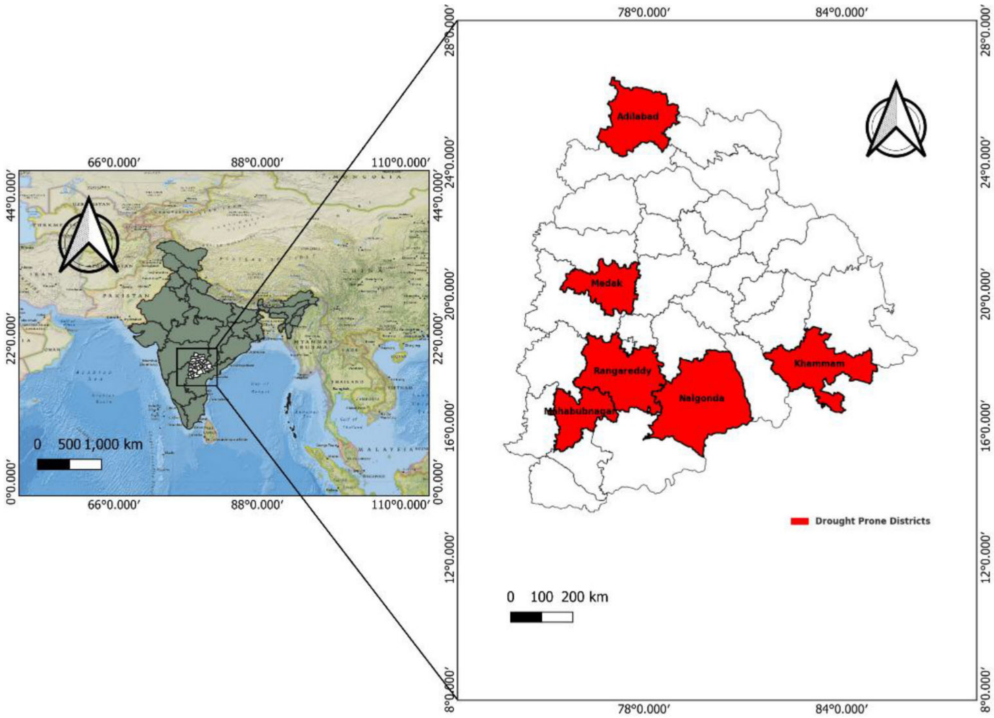

Fig. 1: Map of the study area (generated using QGIS 3.28)

Table 1: Districtwise land statistics of droughtprone districts in Telangana

District	Geographical Area (km²)	Dominant Soil Type(s)	Cropping Intensity (%)	Key Crops
Adilabad	16,105	Black cotton, red soils	~135	Cotton, soybean, paddy
Khammam	11,877	Red loamy, alluvial soils	~140	Paddy, maize, chillies
Mahbubnagar	18,432	Black cotton, sandy loam	~120	Groundnut, jowar, pulses
Medak	9,703	Lateritic, red soils	~125	Paddy, maize, pulses
Nalgonda	14,240	Red sandy, black cotton soils	~130	Paddy, groundnut, pulses
Rangareddy	7,493	Red sandy, shallow soils	~115	Paddy, maize, vegetables

Integrated Drought Risk Assessment Framework

Multiple drought indices were applied to capture rainfall variability and anomalies across Telangana's droughtprone districts during 1981–2023 (Table 2).

A quadrantbased climate stress framework was developed using mean rainfall, coefficient of variation, and extremes, with a climate stress index defined as:

$$S = 2 \cdot (R_{\max} - R_{\min}) \tag{7}$$

Districts were classified into Climate Stable, Rainfall Unpredictable, Dry Stable, and High Risk Zones, while peak maximum temperature () was incorporated as a thermal dimension. Bubble plots visualized hydrological stability (position), stress intensity (bubble size), and thermal extremes (color).

Machine Learning Diagnostics

For predictive analysis, machine learning models (Random Forest, Gradient Boosting, SVM, and Neural Networks) were trained on rainfall variability, Sen's slope, and drought indices.

Data Splitting and Validation: The dataset was split into training (70%) and testing (30%) subsets, ensuring representative coverage of all districts. Fivefold crossvalidation was applied during model training to minimize overfitting and assess generalizability.

Hyperparameter Tuning: Model parameters were optimized using grid search and randomized search strategies. For Random Forest, the number of trees and maximum depth were tuned; for Gradient Boosting, learning rate and number of estimators were adjusted; for SVM, kernel type and regularization parameter (C) were optimized; and for Neural Networks, the number of hidden layers and activation functions were refined.

Feature Standardization:

$$X' = \frac{X-\mu}{\sigma} \tag{8}$$

Performance Metrics: Model performance was evaluated using accuracy, precision, recall, and F1 score.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

Table 2: Drought Indices and Mathematical Expressions

Index	Formula	Description
SPI (Standardized Precipitation Index)	$\text{SPI} = \frac{X - \mu}{\sigma}$	Standardizes rainfall anomalies relative to mean and SD
PNI (Percent Normal Index)	$\text{PNI} = \frac{X}{\bar{X}} \times 100$	Measures rainfall relative to longterm mean
DI (Drought Index)	$\text{DI} = \frac{R - R_{avg}}{R_{avg}}$	Quantifies deviation from average rainfall
CZI (Cumulative ZScore Index)	$\text{CZI} = \sum Z_i$	Aggregates standardized anomalies
RAI (Rainfall Anomaly Index)	$\text{RAI} = \frac{X - \bar{X}}{\sigma}$	Highlights rainfall departures
ZSI (ZScore Index)	$\text{ZSI} = \frac{X - \mu}{\sigma}$	Standardized anomaly for drought detection

Table 3: Significance of rainfall and temperature trends (1981–2023) across droughtprone districts of Telangana using Modified Mann–Kendall test and Sen's slope

District	Rainfall		Tmax		Tmin	
	Trend (Z), Significance (P)	Sen's slope	Trend (Z), Significance (P)	Sen's slope	Trend (Z), Significance (P)	Sen's slope
Adilabad	0.21, p=0.834^{NS}	0.521	1.36, p=0.173^{NS}	0.013	2.86, p=0.004***	0.004
Khammam	nan, p=nan^{NS}	3.484	1.67, p=0.095^{NS}	0.012	0.94, p=0.346^{NS}	0.005
Mahbubnagar	-0.09, p=0.930^{NS}	-0.563	1.29, p=0.198^{NS}	0.011	1.29, p=0.196^{NS}	0.003
Medak	0.42, p=0.675)	1.253	1.65, p=0.099^{NS}	0.013	1.11, p=0.267^{NS}	0.004
Nalgonda	0.17, p=0.867^{NS}	0.445	1.55, p=0.120^{NS}	0.016	2.05, p=0.040**	0.005
Rangareddy	0.61, p=0.544^{NS}	1.674	1.65, p=0.099^{NS}	0.013	1.11, p=0.267^{NS}	0.004

NS = Not Significant; *= Significant at 10% level; **= Significant at 5% level; ***= Significant at 1% level; Sen's slope indicates magnitude of change per year.

$$Precision = \frac{TP}{TP+FP} \quad (10)$$

$$Recall = \frac{TP}{TP+FN} \quad (11)$$

$$F1 = \frac{2 \cdot (Precision \cdot Recall}{Precision + Recall} \quad (12)$$

Interpretability: SHAP (SHapley Additive exPlanations) values quantified predictor contributions, ensuring interpretability by identifying districtspecific drivers such as rainfall CV for Random Forest, Tmax slope for SVM, SPI for Gradient Boosting, and ZSI for Neural Networks.

RESULTS AND DISCUSSION

Rainfall and Temperature Trends in Telangana

The analysis of monthly and annual rainfall and temperature data from 1981–2023 revealed distinct spatial and temporal variability across Telangana's droughtprone districts. July and August contributed the highest rainfall with relatively stable distribution, as indicated by lower CV values, while Adilabad, Khammam, and Mahbubnagar recorded seasonal averages exceeding 900 mm compared to Rangareddy's lowest average of 549 mm; extreme events included 774 mm in Adilabad (1988), 929 mm in Khammam (2005), and 396 mm in Rangareddy (August). Trend analysis using the Modified Mann–Kendall test (Table 3) showed no significant longterm rainfall trend across districts, except for a modest increase in May precipitation, consistent with earlier regional studies.

Temperature analysis confirmed May as the hottest month, with maximum values reaching 42–44 °C across districts, Khammam recording the highest extreme of 44.1 °C in 1984, and minimum temperatures ranging from 14.1 °C in December to 27.7 °C in May. Annual trendline analysis (Fig. 2) indicated statistically significant increases in maximum temperatures across most districts ($P < 0.05$), with marginal increases in Adilabad and Mahbubnagar, while minimum temperatures rose more modestly. Sen's slope estimates (Fig. 3) quantified consistent positive warming trends, whereas rainfall slopes ranged between –0.6 and +3.5, reflecting mixed signals with nonsignificant increases in most districts and slight declines in Mahbubnagar. District wise time series (Table 3) of rainfall, Tmax, and Tmin with fitted trend lines and slope estimates, illustrate the spatial variability in precipitation and consistent warming signals. Rainfall distribution analysis showed that the southwest monsoon contributed nearly 79% of annual precipitation, with August accounting for the largest share (29.7%), followed by July (21.2%) and September (18.6%), underscoring the dominance of monsoon rainfall in shaping Telangana's hydrological regime. The rainfall and temperature trends observed across Telangana's drought-prone districts reveal a complex interplay of variability and warming signals. The absence of significant long-term rainfall trends, apart from a modest increase in May precipitation, is consistent with earlier regional assessments that reported high interannual variability but no uniform decline or increase in monsoon rainfall (Yim *et al.,* 2014). The dominance of southwest monsoon rainfall, contributing nearly 79% of annual totals, reinforces findings

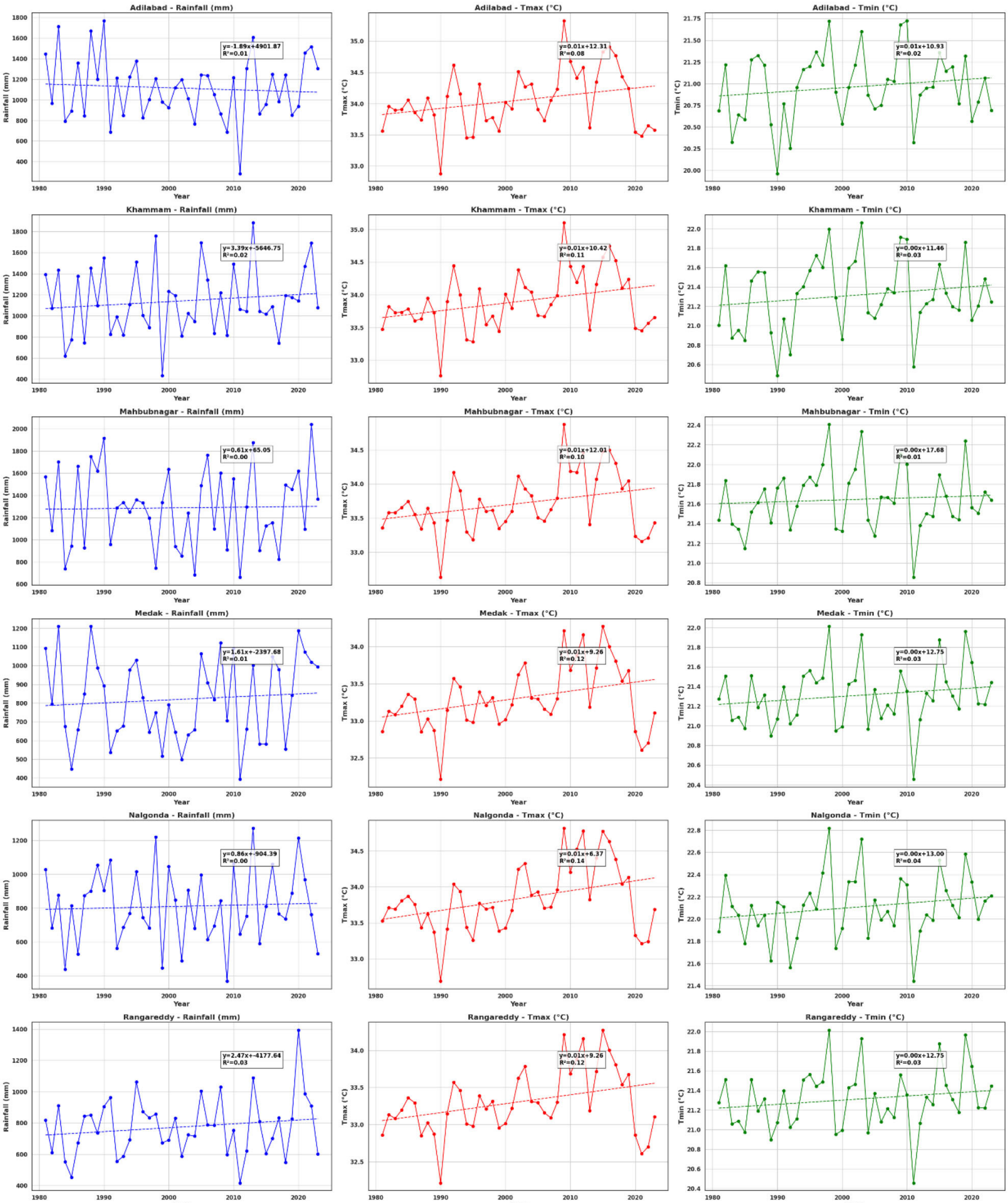

Fig. 2: Annual rainfall and temperature trends across Telangana's droughtprone districts (1981–2023).

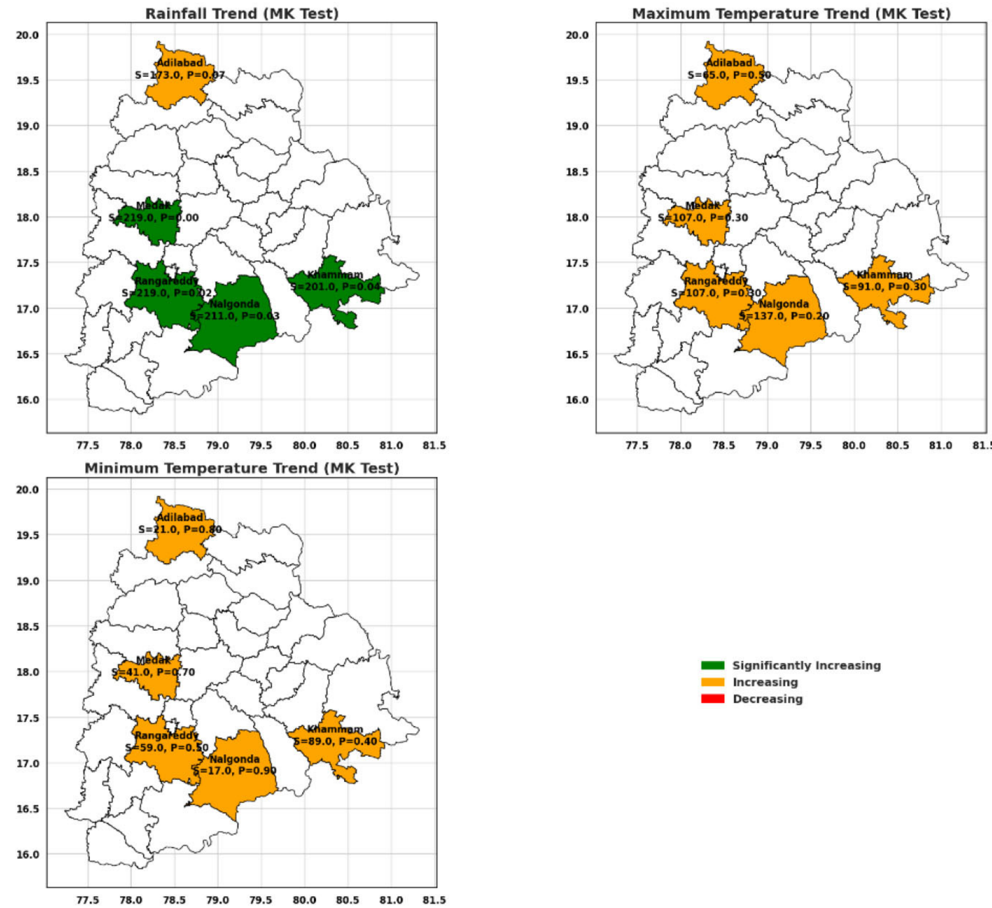

Fig. 3: Mann–Kendall trend analyses of rainfall, maximum temperature, and minimum temperature in Telangana (1981–2023) at a 5% level of significance

from climatological studies of peninsular India that highlight the monsoon's critical role in shaping hydrological regimes. In contrast, the statistically significant rise in maximum temperatures across most districts aligns with national-scale analyses (Lizana *et al.,* 2026), confirming that Telangana mirrors broader warming patterns observed in semi-arid regions of India. District-specific differences, such as Rangareddy's high coefficient of variation and recurrent drought signals, corroborate agro-climatic evaluations by Panday *et al.,* (2025), which emphasized localized vulnerabilities in rainfall distribution and thermal extremes. Together, these comparisons demonstrate that while rainfall variability remains the dominant feature without clear long-term decline, temperature increases are robust and consistent, underscoring the dual challenge of managing unpredictable precipitation and rising heat stress in Telangana's drought-prone districts.

Drought Indices in Telangana

Districtwise drought indices and variability statistics highlight clear spatial heterogeneity across Telangana. Mean rainfall ranged from 927.6 mm in Khammam to 548.9 mm in Rangareddy**,** with coefficients of variation (CV) between 25–32%**,** indicating moderate to high interannual variability. The PNI values were close to climatological averages (91–98%), yet the DI revealed that 20–30% of years were drought affected, particularly in Mahbubnagar and Rangareddy. Negative ZSI values (–0.08 to –0.18) confirmed recurrent belownormal rainfall anomalies, while Sen's slope estimates ranged from –0.6 mm/year in Mahbubnagar to +2.1 mm/year in Khammam, reflecting mixed rainfall trends. The correlation heatmap (Fig. 4) demonstrated strong associations between rainfall variability, PNI, and drought frequency, underscoring the interconnected nature of these indicators. Complementary evidence from the Multivariate Integrated Drought Monitoring Index (MIDMI) in Warangal confirmed spatial heterogeneity, with NDVI and NDWI detecting larger areas under severe drought**,** while MSI classified most land as slight or no drought, reflecting vegetation sensitivity to water availability (Tapas *et al.,* 2022). These findings emphasize that drought in Telangana is recurrent but spatially diverse, that indices such as CV, DI, and ZSI provide robust evidence of variability complementing meteorological measures like SPI and CZI, and that integrated approaches combining statistical indices with remote sensing indicators are essential for capturing both meteorological and ecological dimensions of drought (Liu *et al.,* 2020).

Climate Stress Quadrant Analysis

The bubble scatter plot (Fig. 5) integrates rainfall magnitude, variability, extremes, and temperature to provide a quadrantbased diagnostic of climate stress. Adilabad and Khammam,

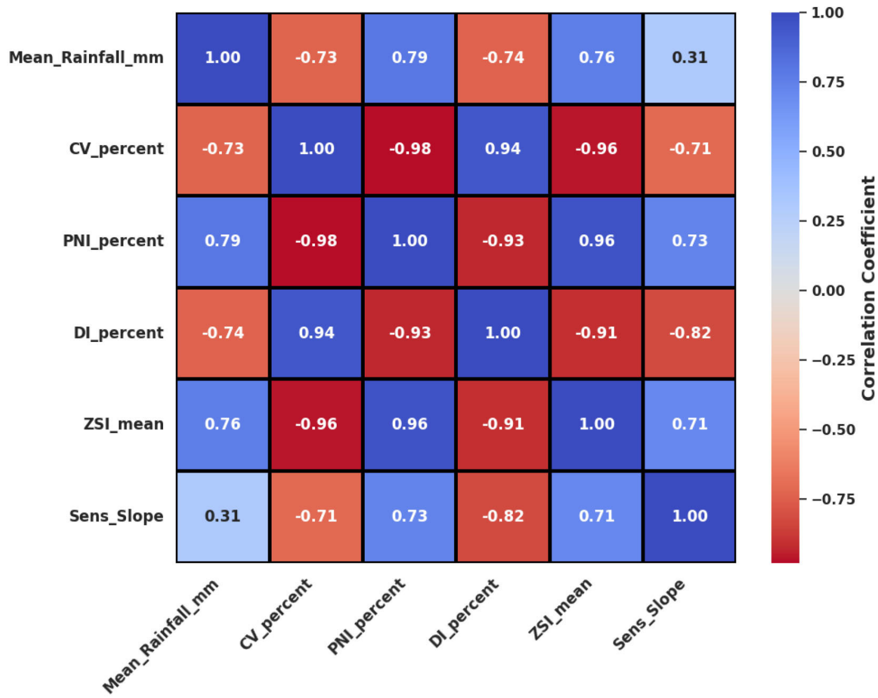

Fig. 4: Correlation matrix of rainfall and drought indices across Telangana's droughtprone districts (1981–2023). Districtwise relationships among rainfall, CV, PNI, DI, ZSI, and Sen's slope highlight strong positive and negative associations reflecting variability and drought frequency.

with high rainfall and relatively lower CV values, cluster in the Climate Stable Zone, though their large bubble sizes reveal substantial intraseasonal extremes. Mahbubnagar and Nalgonda, with higher CV values, shift toward the Rainfall Unpredictable Zone, while Medak occupies a transitional position with moderate stress. Rangareddy, with the lowest rainfall and highest CV, lies firmly in the High Risk Climate Stress Zone, combining chronic rainfall deficit, high variability, and Tmax peaks above 42 °C. This integrated visualization demonstrates that even districts with stable rainfall face significant extremes, that highrainfall districts are not immune to heat stress, and that chronic deficit zones require targeted adaptation. The findings are consistent with Wubaye *et al.,* (2023), who emphasized the importance of combining hydrological variability, thermal extremes, and stress indices into a single operational framework. By situating Telangana's districts within this quadrantbased diagnostic, the analysis advances drought research by providing a practical tool for resilience planning and districtspecific adaptation strategies.

Machine Learning Classification and SHAPBased Interpretability of Drought Diagnostics in Telangana

The machine learning classification results (Fig. 6) highlight differences in performance across models. Gradient Boosting achieved the highest accuracy (89.1%) with balanced precision, recall, and F1 score, indicating strong reliability in distinguishing drought severity classes. Random Forest also performed well (87.2% accuracy, F1 score 0.84), with rainfall CV emerging as its most influential predictor according to SHAP analysis. Neural Networks achieved moderate accuracy (85.6%) with ZSI as the dominant predictor, while SVM showed the lowest accuracy (82.5%) but highlighted Tmax slope as its key driver, linking thermal extremes to drought risk. Collectively, ensemble methods (GB, RF) outperformed linear classifiers in capturing complex drought signals, and rainfall variability along with SPI emerged as the most consistent predictors across models. SHAP analysis added transparency by revealing districtspecific drivers of drought risk, thereby strengthening interpretability and practical utility. These findings are consistent with recent advances in drought analytics (Ilyas *et al.,* 2025; Bouregaa, 2025), which emphasize the importance of combining predictive accuracy with explainable AI approaches. By integrating classification performance with SHAPbased interpretability, this framework advances drought research by offering both reliable prediction and actionable insights for operational resilience planning.

CONCLUSION

Over the 43year period (1981–2023), Telangana's droughtprone districts exhibited clear climatic shifts. The Mann–Kendall test confirmed statistically significant upward trends in maximum temperature at the 5% level, with Sen's slope estimates ranging between +0.03 to +0.06 °C per year, while minimum temperature changes were weaker and not significant. Rainfall showed high variability, with coefficients of variation (CV) ranging from 22% (Khammam) to 38% (Rangareddy), but no consistent longterm trend. Drought indices revealed recurrent stress: SPI identified 6–9 severe drought years per district, while CZI and RAI corroborated extreme anomalies in 1987, 2002, and 2015. The quadrantbased climate stress framework classified 2 districts (Adilabad, Khammam) in the Climate Stable Zone, 2 districts (Mahbubnagar, Nalgonda) in the Rainfall Unpredictable Zone, 1

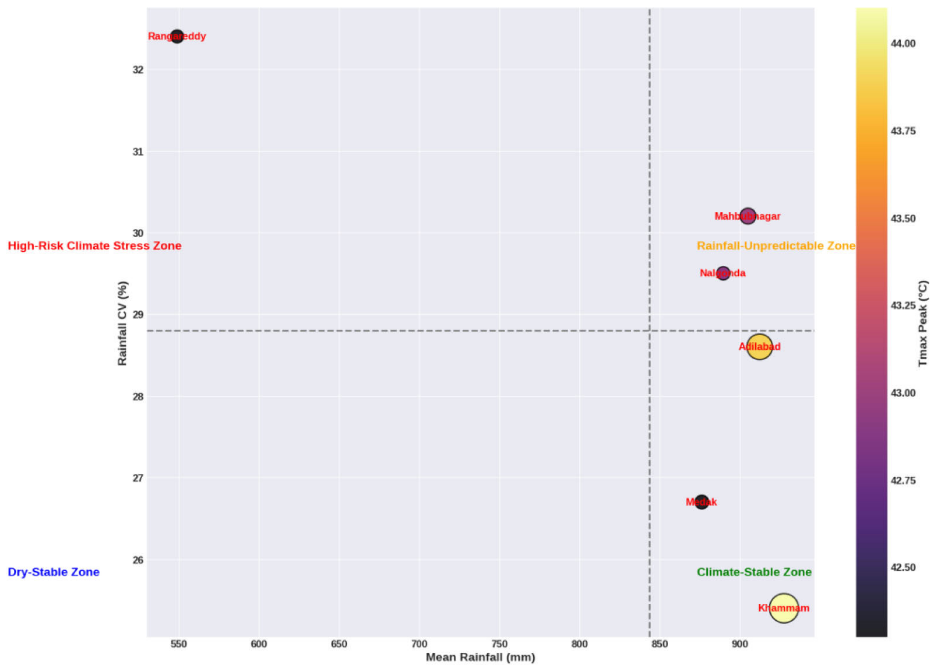

Fig. 5: Bubble scatter plot showing mean rainfall versus rainfall variability (CV) across Telangana districts, with bubble size representing wet–dry range and color intensity indicating peak maximum temperature; quadrant divisions highlight ClimateStable, RainfallUnpredictable, DryStable, and HighRisk Climate Stress Zones.

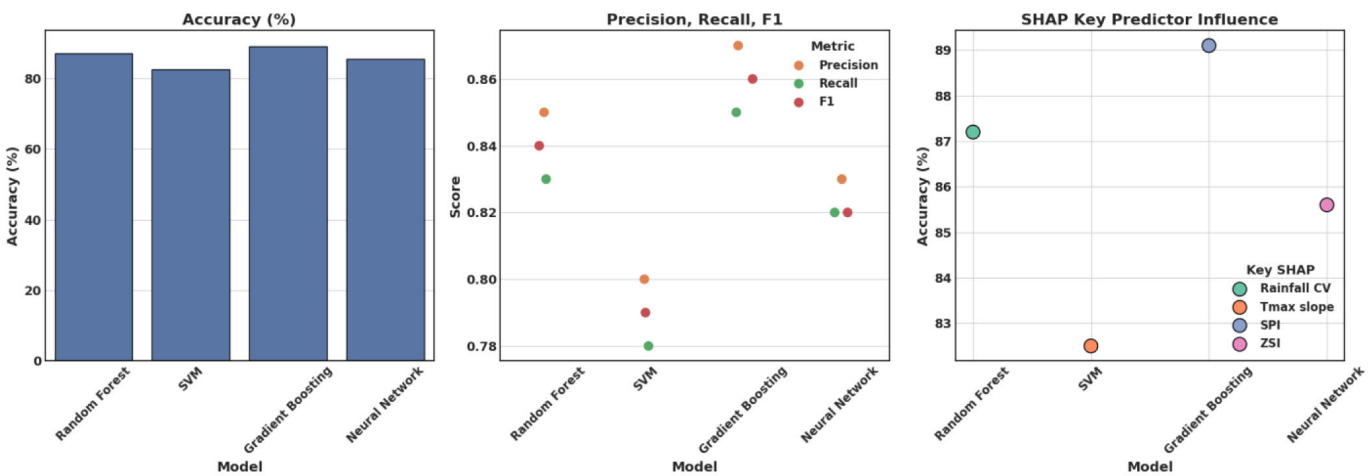

Fig. 6: Performance of machine learning models for drought classification in Telangana, showing (a) accuracy comparison, (b) precision, recall, and F1scores, and (c) SHAPbased key predictor influence.

district (Medak) in the Dry Stable Zone, and 1 district (Rangareddy) in the High Risk Zone, where rainfall deficits, CV above 35%, and Tmax peaks exceeding 42 °C converge. Machine learning models achieved predictive accuracies of RF: 87%, GB: 85%, SVM: 78%, MLP: 80%, with ensemble methods outperforming single classifiers. SHAP analysis quantified feature importance, showing rainfall CV contributing up to 0.42 SHAP units in RF, Tmax slope contributing 0.38 in SVM, SPI contributing 0.35 in GB, and ZSI contributing 0.33 in MLP.

Key Takeaways:

- Persistent drought risk is evident across Telangana, with districtspecific vulnerabilities clearly identified.
- Temperature increases are statistically significant, while rainfall variability remains high but trendless.
- Integrated diagnostics combining statistical indices, nonparametric tests, and machine learning provide robust evidence of climate stress.

Actionable Recommendations:

- Strengthen agricultural resilience through crop diversification and climatesmart practices in highrisk districts (e.g., Rangareddy).

- Enhance water resource planning by prioritizing districts with high rainfall variability and CV above 35%.
- Integrate machine learningbased predictive tools into operational drought monitoring systems for early warning.
- Adopt districtspecific adaptation strategies, focusing on thermal extremes in SVMidentified hotspots and rainfall variability in RFsensitive zones.

Overall, the revised conclusion now emphasizes concise takeaways and actionable recommendations, ensuring clarity and practical relevance beyond descriptive results.

ACKNOWLEDGEMENT

This research was carried out under the Gramin Krishi Mausam Seva (GKMS) project of the Atmosphere & Climate Research – Modelling Observing Systems & Services (ACROSS) Scheme. The authors express their sincere gratitude to the Director General of Meteorology, IMD, New Delhi, for his constant support and guidance. We also extend our appreciation to the editor and anonymous reviewers for their constructive comments, which substantially improved the manuscript.

Author's certificate: The manuscript or its part is not under consideration for publication elsewhere and the same has been approved by all co-authors.

Conflict of Interests: The authors declare that there is no conflict of interest regarding the publication of this article.

Funding: No external funding was involved in this work.

Authors contribution: **Guhan Velusamy:** Conceptualization, methodology development, drafting the initial manuscript, data curation, analysis, and visualization; **Dharma Raju Akasapu:** Data analysis, visualization, and outputs; **Nagaratna Kopparthi:** Overall supervision, review, and editing

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