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ORIGINAL ARTICLE

Integrating Univariate and Multivariate Trend Detection with Principal Component Analysis

Mohammad Nazeri Tahroudi[a&*], Mohammadjavad Zeynali[b], Omolbani Mohammadrezapour[c]

[a]Department of Water Engineering, Lorestan University, Khorramabad, Iran.

[b]Department of Water Science, Faculty of Agriculture, Torbat Heydarieh University, Torbat Heydarieh, Iran.

[c]Department of Water Engineering, Faculty of Water and Soil, Gorgan University of Agricultural Sciences and Natural Resources, Gorgan, Iran.

[*]Corresponding Author E-mail Address: nazeri.mh@lu.ac.ir

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Abstract

Understanding the intricacies of regional climate change is essential for effective adaptation, yet trend analyses are often constrained by spatial aggregation biases. This study investigates the spatiotemporal evolution of maximum temperature in Lorestan Province, western Iran, over a 20-year period (2001–2020) by integrating conventional univariate trend detection with a novel multivariate approach based on Principal Component Analysis (PCA). Station-scale analysis using the modified Mann-Kendall test revealed a pervasive but largely non-significant positive annual warming trend across all eight stations, with total increases ranging from 0.77 °C to 1.25 °C. Crucially, monthly-scale disaggregation exposed a distinct seasonal asymmetry: significant warming was concentrated in February and the summer months (July–September), while transitional periods exhibited minimal change, demonstrating that annual aggregates conceal critical seasonal extremes. PCA revealed exceptional spatial coherence, with the first principal component explaining 99.9% of the total variance and factor loadings exceeding 0.999 across all stations, indicating a highly synchronized thermal regime governed by regional-scale drivers. However, the multivariate Mann-Kendall test found no significant region-wide trend ($Z = 0.062$, $p = 0.951$), highlighting that locally significant warming signals are diluted when spatially integrated, thereby cautioning against generalized regional policy. These findings underscore the necessity of local-scale trend assessments for climate adaptation, particularly in agriculture and water resources. The pronounced warming in February threatens plant chilling requirements, while intensifying summer heat elevates evapotranspiration and energy demands, necessitating targeted, site-specific management strategies rather than reliance on provincial averages for climate resilience planning in semiarid environments.

Keywords: Climate change, Maximum temperature, Mann-Kendall, Multivariate trend, Principal Component Analysis

1. Introduction

Climate change, and particularly the increasing trend in temperature, has attracted widespread attention from researchers worldwide as one of the most fundamental environmental challenges. Global warming, driven by rising concentrations of greenhouse gases, has significantly altered temperature and precipitation patterns at local, regional, and global scales (Nazeri Tahroudi, 2025). Due to its geographical location within the global arid and semi-arid belt, Iran is recognized as a region highly vulnerable to climate change, and Lorestan Province in western Iran is no exception. Numerous studies have demonstrated that temperature trends in Iran and its various sub-regions exhibit complex spatiotemporal patterns, necessitating the application of advanced statistical methods for accurate identification and analysis. In this regard, univariate methods such as the Mann-Kendall test and multivariate techniques such as Principal Component Analysis (PCA) have proven to be effective tools for detecting trends and patterns in climatic variables.

Several studies in Iran have employed these methods to analyze temperature trends. For instance, Ahmadi et al. (2018) applied the modified Mann-Kendall test and the regional Kendall test to detect significant increasing trends in seasonal and annual temperatures across Iran over the period 1961–2010. Similarly, Asadi et al. (2025) conducted a comprehensive study across 120 synoptic stations in Iran and reported a significant increasing trend in mean annual temperature, with a slope of 0.053 °C per year.

Principal Component Analysis (PCA), initially developed by Pearson (1901) and Hotelling (1933), is a widely used multivariate statistical technique for dimensionality reduction and identification of latent patterns within correlated datasets. In climatological studies, PCA is extensively applied to identify homogeneous temperature patterns and reduce the number of variables without losing essential information. This method transforms correlated variables into a new set of uncorrelated principal components, thereby enabling the identification of the most significant sources of variability. Barbosa et al. (2011) combined PCA with quantile regression to analyze temperature variations in Central Europe, demonstrating the capability of this approach to detect subtle temperature change patterns. In Iran, Khoramabadi et al. (2007) utilized ERA5 reanalysis data and PCA to investigate the spatiotemporal variations of maximum temperature across Iran over the past four decades. Their findings revealed that the first two principal components explained over 78% of spatial variance and 93% of temporal variance, respectively, indicating the existence of coherent and interpretable climatic patterns.

Since station-based changes within any given basin or province cannot fully characterize the overall changes in hydroclimatic variables, the analysis of such variations must be conducted using a multivariate and integrated approach. The Multivariate Mann-Kendall trend test, as a generalization of the univariate Mann-Kendall test, is employed to detect a coherent trend within a set of correlated variables. This method, developed by Hirsch and Slack (1984) and further extended by Libiseller and Grimvall (2002), enables the assessment of whether a single, homogeneous trend exists at the regional scale. In climatological studies, this test is particularly useful when the researcher seeks to identify an overall regional trend across multiple stations and to determine whether all stations are experiencing significant changes in a synchronized manner.

Toros et al. (2025) applied the Mann-Kendall test and observed a sustained increasing trend in maximum, minimum, and mean temperatures across Iran over the period 1980–2017, emphasizing that the spatial variability of these trends is linked to factors such as topography and geographical location. Rousta et al. (2026) examined 30 river basins in Iran over the period 1950–2024 and reported significant increasing temperature trends at rates ranging from 0.015 to 0.045 °C per year. Their findings further revealed that minimum temperatures increased at a faster rate than maximum temperatures, resulting in a narrowing of the diurnal temperature range.

Abdulfattah et al. (2025) analyzed temperature trends in Tunisia (2003–2021) using AIRS data and the Mann-Kendall test. They found significant warming in winter and spring, with central stations warming faster than coastal and desert areas. The highest annual trend (0.070°K year^{-1}) was recorded at Tozeur. Spatial heterogeneity in warming patterns was evident, with southern regions warming faster than northern areas. Dan'azumi et al. (2025) combined Bayesian modeling (BEAST) and Mann-Kendall tests to detect climate change in Kaduna, Nigeria (1901–2022). Results showed significant warming (~0.004°C year^{-1}) and decreasing rainfall (~0.756 mm year^{-1}). Multiple changepoints in temperature were identified. Attribution analysis revealed a weak correlation ($r = 0.27$) between temperature and GHG emissions, with only 7.1% of variability explained ($R^2 = 0.071$), indicating the complexity of regional climate attribution. Aksay et al. (2025) introduced the Normalized Innovative Trend Analysis (N-ITA) method, which enables simultaneous comparison of multiple climatic variables on a single graph through data normalization. Applied to temperature, solar radiation, and sunshine duration data from three Turkish stations, N-ITA demonstrated superior visual interpretability and effectiveness compared to traditional ITA and Mann-Kendall tests, particularly for non-normal data with seasonal fluctuations.

A review of the literature indicates that temperature variations in Iran and Lorestan Province exhibit complex spatiotemporal patterns that necessitate the application of advanced statistical methods for accurate identification and analysis. The modified Mann-Kendall test, Sen's slope estimator, and Principal Component Analysis (PCA) are recognized as effective tools in this context. National and regional studies consistently emphasize an increasing trend in maximum temperatures across most parts of Iran, although the rate and intensity of this increase vary across different regions. Analysis at monthly and seasonal scales reveals that certain months exhibit more significant warming trends, which may be attributed to changes in atmospheric circulation patterns, shifts in the timing of seasonal transitions, or alterations in the frequency and intensity of climatic phenomena affecting the region.

Despite the numerous studies on temperature changes in Iran, the majority of existing research has primarily focused on single-station or univariate analyses, with less attention given to the simultaneous examination of multiple stations using multivariate approaches and the analysis of the internal structure of temperature data. Furthermore, in Lorestan Province—a mountainous and climatically sensitive region in western Iran—comprehensive studies that integrate trend analysis across different temporal scales (monthly and annual), identification of homogeneous spatial patterns, and assessment of regional multivariate trends have rarely been conducted. Therefore, the primary objective of this study is to conduct a comprehensive and integrated analysis of maximum temperature trends in Lorestan Province by combining univariate methods (modified Mann-Kendall test and Sen's slope estimator) and multivariate techniques (Principal Component Analysis and Multivariate Mann-Kendall trend test). This aims to identify latent patterns of temperature variability, disentangle seasonal from annual trends, and evaluate the presence or absence of a homogeneous trend at the regional scale. The novelty of this research lies in the simultaneous application of PCA for dimensionality reduction of the eight correlated stations and identification of the dominant temperature component in the region, coupled with the multivariate trend test to assess the coherence of trends across the province.

2. Materials and Methods

2.1. Study area

This study was conducted in Lorestan Province, western Iran, covering an area of approximately 28,294 km². The region is characterized by a mountainous topography with elevations ranging from 500 to 4,000 meters above sea level. Eight meteorological stations were selected based on data availability and spatial distribution across the province, including Aligudarz, Azna, Borujerd, Dorud, Kohdasht, Nurabad, Poldokhtar, and Khorramabad. Monthly maximum temperature data for a 21-year period (2000–2020) were obtained from the Iran Meteorological Organization (IRIMO). While longer records are desirable for robust trend detection, this period represents the most recent complete dataset and is particularly relevant for near-term climate adaptation planning. However, it is acknowledged that natural climate oscillations such as the El Niño-Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) can influence temperature variability over interannual to decadal timescales. To mitigate the potential confounding effects of such oscillations, the modified Mann-Kendall test was employed to account for serial correlation, and the analysis was disaggregated to monthly and seasonal scales to distinguish long-term trends from natural variability. Table 1 shows the altitude above mean sea level, long-term average meteorological statistics, and climate classification based on the Amberger climatology at 8 synoptic stations in Lorestan province. Figure 1 shows the geographical location of Lorestan province and its synoptic stations.

2.2. Principal Component Analysis (PCA)

To identify the dominant modes of spatio-temporal variability among stations and to reduce data dimensionality, Principal Component Analysis (PCA) was applied to the standardized monthly mean temperature matrix (stations as variables) (Pearson 1901; Hotelling 1933).

Prior to PCA, each variable (station) x_j was standardized to zero mean and unit variance as $z_{ij} = (x_{ij} - \bar{x}_j)/s_j$, where x_{ij} is the value of station j in month i, $\bar{x}_j$ and s_j are the mean and standard deviation of station j, and z_{ij} is the resulting standardized value, so as to remove the influence of differing measurement scales among stations.

Table 1. Geographical and climatic characteristics of synoptic stations in Lorestan province, Iran

Station	Elevation (m)	Annual Precipitation (mm)	Mean Temperature (°C)	Mean Humidity (%)	Mean Annual Tmax (°C)	Sunshine Hours	Amberger Climate Classification
Borujerd	2022	387.3	12.4	40	21.94	2749.7	Semi-arid, cold
Aligudarz	1527	631.7	16.2	40	19.74	3091	Arid, cold
Dorud	1860	467.9	11.9	47.5	22.55	2950.9	Arid, cold
Nurabad	1872	411.6	12.4	50.5	19.87	3088.2	Arid, warm
Azna	1148	500.1	17.2	41	20.48	2959.1	Semi-arid, cold
Khorramabad	713	360.7	22.8	37.2	25.54	3116.1	Humid, cold
Poldokhtar	1198	366.7	15.9	48.7	29.19	3205.2	Semi-arid, cold
Kohdasht	1629	456.6	14.7	42	24.91	3033.4	Semi-arid, cold

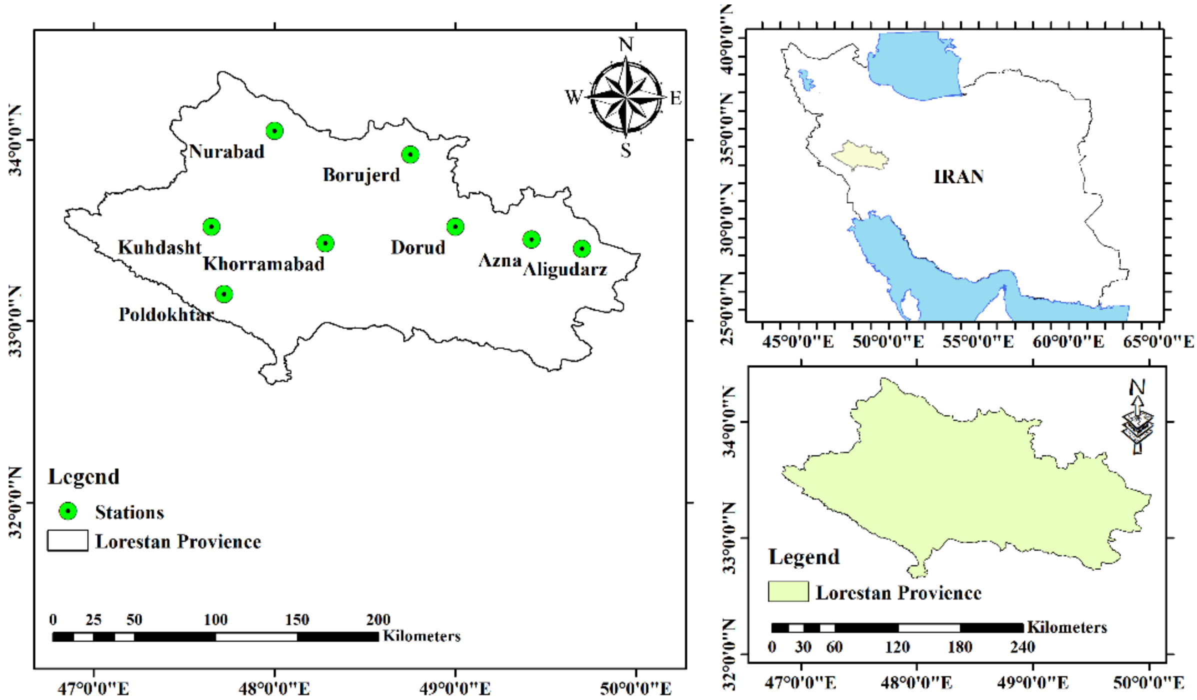

Fig. 1. Geographical location of Lorestan province and its synoptic stations

PCA was then performed by eigenvalue decomposition of the correlation matrix R of the standardized data:

$$R v_k = \lambda_k v_k \quad (1)$$

Where R is the $p \times p$ correlation matrix among the p station variables, λ_k is the k-th eigenvalue of R, and v_k is the corresponding eigenvector, whose elements are the loadings of each station on the k-th principal component (PC_k). Each principal component score for observation i is then obtained as a linear combination of the standardized variables, $PC_{ki} = \Sigma_j \, v_{kj} \, z_{ij}$, and the proportion of total variance explained by component k is given by $\lambda_k / \Sigma_m \lambda_m$. The number of retained components was determined based on this percentage of variance explained by each principal component and a scree-plot inspection (Jolliffe 2002; Cattell 1966).

Variable factor maps (loading plots) were used to visualize the correlation structure between stations and the leading principal components. PC scores (the projected values of each month or year onto the retained components) were subsequently examined for temporal trends using the Mann–Kendall test.

2.3. Trend analysis

Prior to applying the modified Mann-Kendall test, the presence of serial correlation in the monthly temperature series was assessed using the Lag-1 autocorrelation coefficient for each station. The modified test, following the variance correction approach of Yue et al. (2002), was then employed to account for the effect of significant serial correlation on the variance of the test statistic. This correction is essential because positive autocorrelation inflates the variance and may lead to spurious detection of significant trends (Yue et al. 2002).

2.3.1 Mann–Kendall trend test

The non-parametric Mann–Kendall (MK) test was used to detect monotonic trends in the annual and monthly temperature series of each station (Mann 1945; Kendall 1975). The MK test is widely applied in hydro-meteorological trend detection because it does not require the data to follow a specific distribution and is relatively insensitive to outliers (Yue et al. 2002; Noferesti et al. 2021; Lalehpour et al. 2023; Tavasoli et al. 2025; Mohammadi et al., 2024; Rajabi et al. 2026). For a time series of length n, the test statistic S is defined as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}\left(X_j - X_i\right) \tag{2}$$

where x_i and x_j are the sequential data values (annual or monthly station temperature) observed at the earlier time index i and the later time index j (with $j > i$), respectively, n is the total number of observations in the series, and sgn(·) is the sign function, defined as:

$$\begin{aligned} \operatorname{sgn}\left(X_j - X_i\right) &= +1 \;\; if \; \left(X_j - X_i\right) > 0 \\ \operatorname{sgn}\left(X_j - X_i\right) &= 0 \;\; if \; \left(X_j - X_i\right) = 0 \\ \operatorname{sgn}\left(X_j - X_i\right) &= -1 \;\; if \; \left(X_j - X_i\right) < 0 \end{aligned} \tag{2}$$

In other words, each of the x_j values occurring later in the series is compared with every x_i value that precedes it, and S accumulates +1 for each later value that is larger than an earlier one, −1 for each later value that is smaller, and 0 for ties.

A positive S therefore indicates an increasing (upward) trend, while a negative S indicates a decreasing (downward) trend. Under the null hypothesis of no trend, S is approximately normally distributed for large n, with mean E(S) = 0 and variance:

$$Var(S) = \frac{\left[n(n-1)(2n+5) - \sum t_k (t_k - 1)(2t_k + 5)\right]}{18} \tag{3}$$

Where t_k is the number of tied groups of extent k used to correct for tied ranks. The standardized test statistic Z is then computed as

$$\begin{aligned} Z &= \frac{(S-1)}{Var(S)} \quad for \;\; S > 0 \\ Z &= \frac{(S+1)}{Var(S)} \quad for \;\; S < 0 \\ Z &= 0 \qquad\quad for \;\; S = 0 \end{aligned} \tag{4}$$

The associated two-tailed p-value is obtained from the standard normal distribution. Kendall's tau (τ), a normalized, dimensionless measure of the strength of the monotonic association ranging from −1 to +1, was also reported alongside S and Z.

2.3.2 Sen's slope estimator

The magnitude of the monotonic trend detected by the Mann–Kendall test was quantified using Sen's non-parametric slope estimator (Sen 1968), computed as the median of all pairwise slopes between data points:

$$Q_i = \frac{\left(X_j - X_k\right)}{(j-k)} \; for \;\; j > k \tag{5}$$

Here, x_j and x_k denote the observed temperature values at the later time point j and the earlier time point k, respectively, and (j − k) is the time interval (in years) separating the two observations; Q_i is therefore the slope (rate of change) computed between every possible pair of observations in the series in which the later observation (j) follows the earlier one (k). With n observations, N = n(n − 1)/2 such pairwise slopes are computed. The median of all the Q_i values provides a robust estimate of the overall trend magnitude (expressed in °C year^{-1}), which — unlike an ordinary least-squares slope — is insensitive to the influence of extreme values (outliers) or departures from normality in the data (Gilbert 1987). A positive Sen's slope indicates a warming trend, whereas a negative value indicates a cooling trend, consistent in sign with the Mann–Kendall S statistic.

2.3.3 Seasonal (Monthly) Mann–Kendall test

To account for seasonality, the Mann–Kendall test was additionally applied separately to each calendar month across all years, allowing detection of month-specific trends (e.g., stronger warming in summer versus winter months). In addition, the Seasonal Mann–Kendall (SMK) test of Hirsch et al. (1982) was applied to the full monthly time series of each station. The SMK test statistic, S', is computed as the sum of the Mann–Kendall S statistics obtained independently within each of the 12 "seasons" (calendar months):

$$S' = \sum_{m=1}^{12} S_m$$
$$S_m = \sum_{i=1}^{n_m} \sum_{j=i+1}^{n_m} \operatorname{sgn}\left(X_{jm} - X_{im}\right) \tag{6}$$

Where m indexes the calendar month (m = 1, …, 12), S_m is the Mann–Kendall statistic computed using only the observations belonging to month m (i.e., comparing the value of month m in different years), x_{im} and x_{jm} are the temperature values of month m in years i and j (with $j > i$), and n_m is the number of years with data available for month m. If serial correlation exists between months, the variance of S' is adjusted to incorporate the covariances between the S_m of different months (Hirsch and Slack 1984). The standardized statistic and its two-tailed p-value were then obtained in the same manner as for the standard Mann–Kendall test (Section 2.3.1), thereby accounting for seasonal variation while testing for an overall monotonic trend across years, without the need to deseasonalize the data.

2.3.4. Change point detection

To complement the trend analysis and identify potential abrupt shifts in the temperature time series, the Pettitt test (Pettitt 1979) was applied. The Pettitt test is a non-parametric test that detects a single change point in the mean of a time series. The change point year was identified as the point where the test statistic reached its maximum absolute value, and statistical significance was assessed at $\alpha = 0.05$.

2.4. Multivariate (Regional) Mann–Kendall test

To evaluate whether a common, regionally coherent trend existed across all stations simultaneously, a multivariate (regional) extension of the Mann–Kendall test, based on the approach of Hirsch and Slack (1984), was applied to the annual station means. In this framework, the individual Mann–Kendall S statistics of the p stations are summed to obtain a total statistic S_{total}, and the variance of S_{total} is computed by incorporating the Spearman rank cross-correlations among all station pairs to account for spatial (inter-station) dependence, following the covariance-based approach described by Hirsch and Slack (1984) and Douglas et al. (2000). The standardized statistic Z_{total} was then calculated as:

$$Z_{total} = \frac{\left(S_{total} - 1\right)}{Var\left(S_{total}\right)} \quad if \quad S_{total} > 0$$
$$Z_{total} = \frac{\left(S_{total} + 1\right)}{Var\left(S_{total}\right)} \quad if \quad S_{total} < 0 \tag{7}$$
$$Z_{total} = 0 \qquad if \quad S_{total} = 0$$

Where S_{total} is the sum of the individual Mann–Kendall S statistics (as defined in Section 2.3.1, based on the pairwise comparisons of x_i and x_j within each station's annual series) across all p stations, and $Var(S_{total})$ is the total variance of S_{total}, obtained by summing, over every pair of stations i and j (i, j = 1, …, p), the product of the Spearman rank cross-correlation coefficient ρ_{ij} between the two stations' annual series and the individual-series variance term $n(n-1)(2n+5)/18$ (with n the number of years). The associated two-tailed p-value was obtained from the standard normal distribution, providing an overall test for a regionally consistent trend while explicitly accounting for cross-station (spatial) correlation.

3. Results and Discussion

In this study, in addition to investigating the trend of maximum temperature changes in Lorestan Province, western Iran, a multivariate trend method based on Principal Component Analysis (PCA) is also presented. Initially, the station-scale trends of monthly maximum temperature values were analyzed using the modified Mann-Kendall test at both monthly and annual scales.

3.1. Station-scale trend analysis

The results of the station-scale trend analysis of maximum temperature values at the studied stations, at monthly and annual scales, are presented in Fig. 2 and Table 2, respectively.

As shown in Fig. 2, the results of the annual trend analysis indicate that all eight studied stations exhibit a positive (increasing) slope in annual maximum temperature. This signifies that over the 20-year study period, maximum temperature across the entire Lorestan Province has experienced an increasing trend. The Sen's slope values range from 0.0384 °C per year (Khorramabad station) to 0.0625 °C per year (Borujerd station), corresponding to an increase in maximum temperature of between 0.77 and 1.25 °C over the 20-year period.

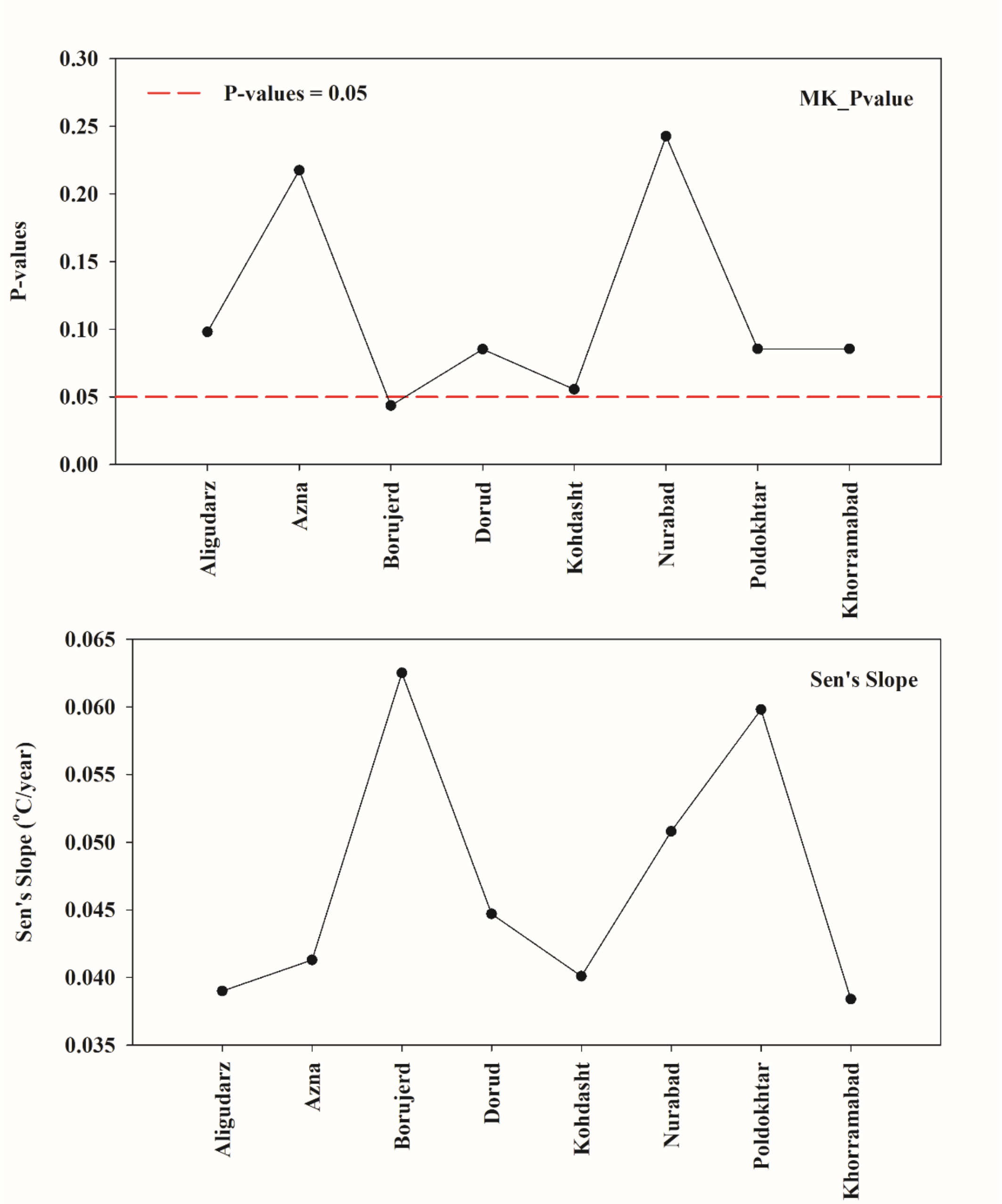

Fig. 2. Results of the annual-scale trend analysis of monthly maximum temperature values at the studied stations.

Table 2. Results of the monthly-scale trend analysis of monthly maximum temperature values at the studied stations.

Month	Aligudarz		Azna		Borujerd		Dorud	
	Tau	P_value	Tau	P_value	Tau	P_value	Tau	P_value
Jan	0.016	0.948	0.198	0.240	0.077	0.669	0.074	0.672
Feb	0.497	0.003	0.415	0.012	0.402	0.017	0.372	0.025
Mar	0.069	0.697	0.000	1.000	0.045	0.817	0.064	0.721
Apr	0.090	0.603	-0.042	0.820	0.051	0.791	-0.080	0.649
May	-0.011	0.974	0.049	0.794	0.000	1.000	-0.070	0.696
Jun	0.027	0.897	0.000	1.000	-0.012	0.973	-0.102	0.558
Jul	0.101	0.558	-0.085	0.626	0.431	0.020	0.306	0.068
Aug	0.194	0.253	0.074	0.673	0.396	0.035	0.245	0.150
Sep	-0.233	0.170	-0.208	0.216	0.254	0.160	0.187	0.269
Oct	-0.228	0.180	-0.011	0.974	-0.053	0.796	-0.005	1.000
Nov	0.074	0.673	0.047	0.795	0.107	0.552	0.159	0.346
Dec	0.085	0.626	0.271	0.104	0.313	0.069	0.245	0.143
Month	Kohdasht		Nurabad		Poldokhtar		Khorramabad	
	Tau	P_value	Tau	P_value	Tau	P_value	Tau	P_value
Jan	0.128	0.455	0.011	0.974	0.175	0.298	0.160	0.346
Feb	0.249	0.135	0.016	0.948	0.340	0.041	0.275	0.098
Mar	0.164	0.330	-0.237	0.153	0.196	0.242	0.128	0.454
Apr	0.063	0.721	-0.063	0.721	0.005	1.000	-0.032	0.871
May	-0.032	0.871	0.048	0.795	0.021	0.922	-0.021	0.922
Jun	-0.138	0.417	-0.085	0.626	-0.016	0.948	-0.021	0.922
Jul	0.422	0.012	0.207	0.217	0.546	0.001	0.497	0.003
Aug	0.321	0.055	0.208	0.216	0.302	0.069	0.400	0.016
Sep	0.338	0.043	0.225	0.182	0.492	0.003	0.253	0.133
Oct	-0.240	0.152	-0.319	0.055	-0.145	0.397	-0.220	0.193
Nov	0.053	0.770	-0.026	0.897	0.032	0.871	0.058	0.745
Dec	0.182	0.282	0.090	0.603	0.138	0.417	0.027	0.896

This temperature increase can be attributed to factors such as the effects of global warming on the region's climate, urban development, changes in vegetation cover, and alterations in atmospheric systems affecting the area. Although all stations exhibit increasing trends, only Borujerd station shows a statistically significant trend at the 95% confidence level (p-value < 0.05). The other stations, while showing positive trends, do not reach statistical significance. This indicates that although a warming trend exists in the region, it has not reached a significant level at most stations.

Examination of the spatial pattern of trend slopes reveals a north-south gradient in the magnitude of temperature increase. Areas with higher slopes (greater temperature increases), such as Borujerd and Poldokhtar, experienced the highest warming, while areas with lower slopes, such as Khorramabad and Aligudarz, experienced the smallest increases.

Analysis of Table 2 reveals that the trend patterns of maximum temperature vary across different months of the year, with clear seasonal variations. In general, the cold months (January, February, November, and December) and the warm months (July, August, and September) exhibit different trend patterns. While the annual analysis indicated increasing trends at all stations, the monthly analysis attributes this increase to specific months and even reveals decreasing trends in some months. This underscores the importance of monthly-scale analysis for a more accurate understanding of climate change, as changes in certain months may be masked by annual averages. February, July, August, and

September exhibited the highest number of significant trends, indicating greater susceptibility of these months to climatic changes. In contrast, May, June, and October showed the fewest significant trends, which may be due to greater natural variability during these months or lower sensitivity to climatic factors. This seasonal pattern may arise from changes in atmospheric circulation patterns, shifts in the timing of seasonal transitions, or alterations in the frequency and intensity of climatic phenomena affecting the region.

February, as the most representative cold month of the year, exhibits a particularly interesting pattern. In this month, all stations except Nurabad show increasing trends, with four stations—Aligudarz, Azna, Borujerd, and Dorud—exhibiting significant trends at the 95% confidence level. The highest trend slope in February belongs to Aligudarz station, with a Tau coefficient of 0.497 and the lowest P-value (0.003), indicating a considerable increase in maximum temperature during this month. This warming trend in February could have significant implications for the agricultural sector, as reduced winter chill may affect the chilling requirements of plants and the timing of flowering.

January exhibits a different pattern, with no station showing a significant trend. Although all stations except Nurabad have positive Tau coefficients, their high P-values indicate the absence of significant trends. This suggests that winter warming is primarily concentrated in February, while January has experienced relatively little change. December shows a similar pattern, with no significant trends observed at any station, although most stations exhibit positive Tau coefficients, indicating a mild temperature increase during this month.

March, like January and December, does not exhibit significant trends. The Tau coefficients for most stations in this month are positive but very small, indicating only minor changes in maximum temperature. Only Nurabad station shows a negative Tau coefficient (-0.237), suggesting a slight temperature decrease, although this decrease is not statistically significant. November exhibits a similar pattern, with no significant trends observed.

July, as the warmest month of the year, reveals a very important pattern. In this month, five stations (Borujerd, Kohdasht, Poldokhtar, Khorramabad, and Aligudarz) exhibit significant increasing trends, indicating a considerable rise in maximum temperature during the hottest month of the year. The highest Tau coefficient belongs to Poldokhtar station (0.546) with a P-value of 0.001, representing the strongest increasing trend among all months and stations. This temperature increase in July could have serious implications for public health, energy consumption, and water resources, highlighting the need for planning to cope with more intense heatwaves.

August exhibits a similar pattern to July, with four stations (Borujerd, Poldokhtar, Khorramabad, and Kohdasht) showing significant increasing trends. The Tau coefficient for Poldokhtar station (0.492) with a P-value of 0.003 is the highest in this month, indicating an increase in maximum temperature at the end of the warm season. Notably, Aligudarz and Azna stations do not show significant trends in August, which may be attributed to their higher elevation and lower susceptibility to warming.

September also shows significant increasing trends at three stations (Kohdasht, Poldokhtar, and Borujerd). Poldokhtar station, with a Tau coefficient of 0.492 and a P-value of 0.003, continues to exhibit the strongest trend. In this month, Aligudarz and Azna stations show negative Tau coefficients (-0.233 and -0.208, respectively), indicating temperature decreases, although these decreases are not statistically significant. This cooling pattern at high-elevation stations may suggest an earlier onset of the cold season in these areas.

June exhibits a different pattern, with no significant trends observed at any station. Most stations have Tau coefficients near zero or negative, indicating no significant changes in early summer maximum temperatures. This suggests that summer warming is primarily concentrated in July and August, while June has experienced relatively little change.

April and May, as transitional months from winter to summer, exhibit a more complex pattern. In April, no significant trends are observed, and Tau coefficients for most stations are near zero. Interestingly, Azna, Dorud, and Khorramabad stations show negative Tau coefficients, indicating slight temperature decreases, although these decreases are not statistically significant. This cooling pattern at some stations may be attributed to changes in precipitation patterns or increased cloudiness during this month.

May, like April, shows no significant trends. Tau coefficients in this month are very small and near zero for most stations. Aligudarz (-0.011), Dorud (-0.070), Kohdasht (-0.032), Poldokhtar (0.021), and Khorramabad (-0.021) stations show negative Tau coefficients, indicating very slight temperature decreases. This decreasing pattern in early summer may suggest a shift in the timing of the warm season onset or increased spring precipitation.

October, as a transitional month from summer to winter, exhibits a decreasing pattern at most stations. Aligudarz (-0.228), Nurabad (-0.319), Kohdasht (-0.240), and Khorramabad (-0.220) stations show negative Tau coefficients, with Nurabad station approaching significance (P-value = 0.055). This decreasing pattern in October indicates cooling in early autumn, which may be attributed to an earlier onset of the cold season or changes in atmospheric circulation patterns.

Examination of the spatial pattern of monthly trends reveals that Borujerd, Poldokhtar, and Khorramabad stations have the highest number of months with significant trends. Borujerd station shows significant trends in February, July, and August, indicating increases in maximum temperature during late winter and late summer. Poldokhtar station exhibits significant trends in February, July, August, and September, demonstrating the strongest trends among all stations. Khorramabad station also shows significant trends in July and August, indicating summer warming.

In contrast, Azna and Nurabad stations have the fewest months with significant trends. Azna station shows a significant trend only in February, with no significant changes observed in other months. Nurabad station exhibits no significant trends in any month, which may be due to its specific geographical location or greater natural variability in this area.

This spatial pattern indicates that stations located in the central and southern parts of the province (Borujerd, Poldokhtar, and Khorramabad) are most susceptible to climate change, while stations in the eastern and northern parts (Azna and Nurabad) have experienced fewer changes. This may be attributed to differences in elevation, geographical location, land use, and local atmospheric circulation patterns.

The increase in maximum temperature during the cold months (particularly February) could have significant implications for the agricultural sector. Reduced winter chill may fail to meet the chilling requirements of certain horticultural crops, leading to reduced yields or altered flowering times. Additionally, winter warming may increase pest and plant disease populations, necessitating integrated pest management strategies.

The increase in maximum temperature during the warm months (July, August, and September) carries even more serious implications. Summer warming can lead to increased energy consumption for cooling, increased heat stress on human and animal populations, increased evapotranspiration, and reduced surface and groundwater resources. Furthermore, summer warming can increase the frequency and intensity of heatwaves, necessitating heat crisis management plans. The decreasing pattern in transitional months (particularly October) indicates shifts in seasons and an earlier onset of the cold season. This can affect the timing of planting and harvesting of agricultural crops, requiring adjustments to the agricultural calendar. Additionally, changes in the timing of the cold season onset can affect precipitation and runoff patterns, posing challenges to water resource management.

3.2. Change point results

To identify abrupt changes (changepoints) in the monthly maximum temperature time series, particularly in February and July where the most significant trends were observed, the non-parametric Pettitt test (Pettitt 1979) was applied. This test is capable of detecting a single change point in the mean of a time series and identifying the exact year of its occurrence. The results of the Pettitt test applied to the annual maximum temperature time series at the studied stations are presented in Table 3. As shown, Borujerd and Dorud stations, with test statistics of 74 and 72 and p-values of 0.04 and 0.0493, respectively, exhibit significant abrupt changes in 2011. Kohdasht station, with a statistic of 71 and a p-value of 0.0546, is at the threshold of significance (α = 0.05), indicating noticeable changes at this station in 2011. In contrast, Azna and Khorramabad stations (in both 2014 and 2016) with p-values above 0.24 do not show significant changes. Notably, Khorramabad station exhibits identical statistics (54) in two different years (2014 and 2016), suggesting similar change patterns in these years. The spatial pattern of changepoints indicates that stations located in the central and southern parts of the province (Borujerd, Dorud, Kohdasht, and Poldokhtar) experienced the most abrupt changes in 2011, while eastern and northern stations (Azna and Nurabad) did not show significant changes. This pattern is fully consistent with the Mann-Kendall trend analysis results, which showed a concentration of significant trends in the central and southern stations.

Table 3. The results of Pettitt test in change point detection of monthly maximum temperature at studied stations

Station	Year	Statistic	P_value
Aligudarz	2010	66	0.0891
Azna	2016	54	0.2491
Borujerd	2011	74	0.04
Dorud	2011	72	0.0493
Kohdasht	2011	71	0.0546
Nurabad	2011	47	0.4128
Poldokhtar	2011	67	0.081
Khorramabad	2014	54	0.2491
Khorramabad	2016	54	0.2491

3.3. PCA results

In this study, monthly maximum temperature data from eight stations in Lorestan Province (Aligudarz, Azna, Borujerd, Dorud, Kohdasht, Nurabad, Poldokhtar, and Khorramabad) over the statistical period 2001–2020 were first subjected to PCA. The results of this analysis are presented in Table 4, including eigenvalues, percentage of variance explained, and cumulative variance for each component.

Principal Component Analysis (PCA) was employed as an efficient multivariate method for analyzing maximum temperature in the study area (Lorestan Province) to reduce the dimensionality of the correlated data from eight stations, identify latent patterns of temperature variability, and simplify the internal structure of the data. Given that temperature data from different stations typically exhibit high spatial autocorrelation, the use of traditional correlation analysis methods generates redundant and repetitive information, complicating the interpretation of results. PCA, by transforming correlated variables into a new set of uncorrelated components, enables the identification of the most significant sources of variability. In doing so, it facilitates the analysis of temperature trends, identification of homogeneous stations, and reduction of the number of variables under investigation without losing essential information. This method also serves as a preprocessing step for subsequent analyses such as multivariate regression, clustering, and climate change modeling. By removing random noise and emphasizing the dominant temperature pattern, PCA significantly enhances the accuracy and efficiency of statistical analyses.

Table 4. Results of principal component analysis of the studied values

PC	Eigenvalue	Variance Percent	Cumulative Variance
1	7.99416	99.92700	99.92700
2	0.00333	0.04164	99.96864
3	0.00157	0.01968	99.98832
4	0.00068	0.00851	99.99683
5	0.00011	0.00135	99.99818
6	0.00010	0.00128	99.99946
7	0.00003	0.00043	99.99989
8	0.00001	0.00011	100.00000

The PCA results clearly demonstrate that the first principal component (PC1), with an eigenvalue of 7.994 and explaining 99.927% of the total variance, alone accounts for nearly all of the temperature variability in the region. This finding is highly remarkable and indicates that all studied stations experience approximately identical temperature variation patterns throughout the year. In other words, although the eight stations are distributed across different parts of Lorestan Province, temperature changes occur in a coordinated and synchronous manner at all of them.

The second principal component (PC2), with an eigenvalue of 0.00333, explains only

0.0416% of the variance, which is negligible compared to PC1. The third through eighth components each explain less than 0.02% of the variance. This indicates that the regional temperature pattern is nearly one-dimensional, and subsequent components primarily contain minor details and random noise.

Considering the cumulative variance, it is observed that the first component alone is capable of explaining more than 99.9% of the total data variability. In conventional PCA applications, components explaining more than 5% of the variance are typically selected as principal components. Here, even the second component explains less than 0.1% of the variance; therefore, only PC1 is considered the main and meaningful component, while PC2 through PC8 can be regarded as noise or negligible information.

This result is further confirmed by the Kaiser criterion (eigenvalues greater than 1), since only PC1 has an eigenvalue above 1 (7.994), while the remaining components have very small eigenvalues. Additionally, based on the scree plot presented in Fig. 3, a steep slope is observed only for PC1, after which the eigenvalues drop sharply.

Overall, the PCA analysis clearly demonstrates that the temperature data from the eight stations in Lorestan Province exhibit very high homogeneity, and a single principal component can explain more than 99% of the temperature variability in the region. This finding represents an effective step toward optimal monitoring network management and integrated analysis of regional climate change. In subsequent analyses, PC1 can be used as the primary temperature indicator for the region, with trend and change analyses concentrated on this component.

In the next step, the factor loadings for each station were examined and are presented in Table 5.

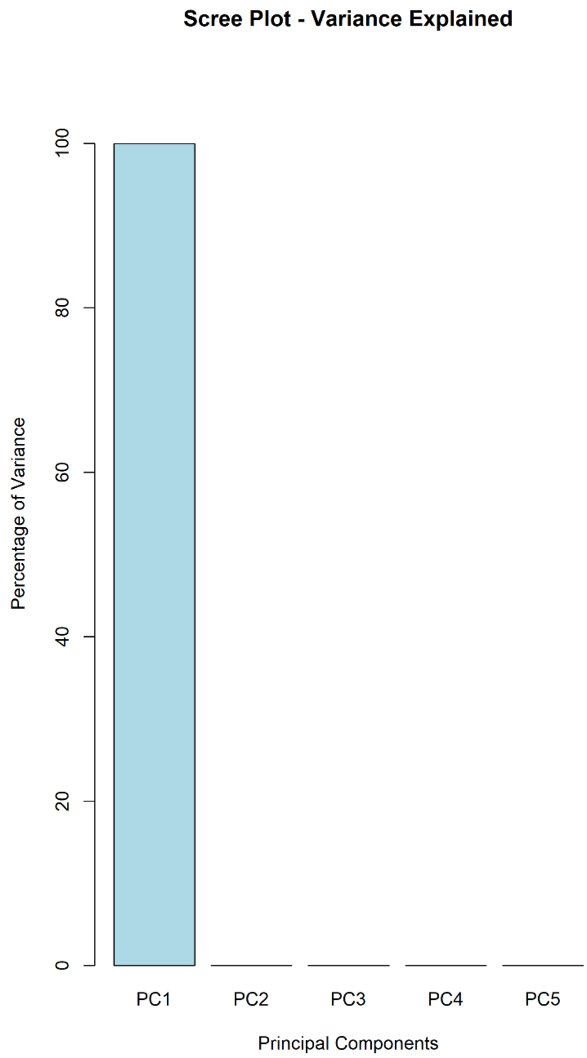

Fig. 3. Scree plot of the studied components in PCA analysis.

Table 5. Factor loadings for each studied station in Lorestan Province

Variable	PC1	PC2	PC3	PC4	PC5
Aligudarz	0.9998	0.0142	-0.0050	0.0023	-0.0078
Azna	0.9991	0.0398	0.0080	0.0057	0.0047
Borujerd	1.0000	0.0052	-0.0009	-0.0044	0.0015
Dorud	0.9998	0.0102	0.0000	-0.0148	-0.0007
Kohdasht	0.9996	-0.0254	-0.0097	0.0020	0.0044
Nurabad	0.9996	-0.0056	-0.0246	0.0108	-0.0005
Poldokhtar	0.9994	-0.0195	0.0276	0.0111	-0.0016
Khorramabad	0.9997	-0.0189	0.0047	-0.0127	-0.0001

Based on Table 5, it can be observed that the first principal component (PC1), with factor loadings very close to unity (ranging from 0.9991 to 1.0000) for all stations, plays a dominant and determining role in explaining the total variance of the data. This high and uniform factor loading across all stations indicates that PC1 represents a common and pervasive pattern across the region, likely influenced by large-scale climatic or environmental factors (such as regional temperature or precipitation variations), with little differentiation between stations in this component. In other words, the first component is capable of explaining more than 99% of the common variability among the variables, and can therefore be considered a general and homogeneous factor at the provincial level, reflecting the climatic integrity of the region.

In contrast, the second through fifth components (PC2 to PC5) have much smaller factor loadings (maximum absolute value of approximately 0.04), indicating their negligible contribution to explaining the total variance. Nevertheless, these small loadings contain valuable information regarding subtle local differences between stations. For instance, in PC2—which has the largest factor loadings after PC1—Azna (0.0398) and Borujerd (0.0052) stations show positive loadings, while Kohdasht (-0.0254), Poldokhtar (-0.0195), and Khorramabad (-0.0189) stations show negative loadings. This bipolar pattern in PC2 may represent a differentiation between northern and eastern stations (with positive loadings) versus southern and western stations (with negative loadings), likely attributable to topographic factors or elevational differences. Furthermore, in PC3, Poldokhtar station (0.0276) and Nurabad station (-0.0246) are positioned on opposite sides, indicating the presence of a specific spatial gradient in this component, although its contribution to the total variance is very small.

Overall, the factor loading analysis reveals that despite the existence of a strong common pattern across the province (represented by PC1), local and subtle differences between stations are detectable in the higher-order components. These differences may arise from factors such as elevation, geographical location, slope orientation, and local wind patterns, which influence the climate of each station at the micro-scale.

3.4. Multivariate trend analysis

Following the univariate trend analysis at each station, the Multivariate Mann-Kendall trend test was employed to assess the presence or absence of a homogeneous and combined trend at the regional level. The results are presented in Table 6.

Table 6. Results of the multivariate trend analysis of maximum temperature values in the study region

Test	Z Statistic	P-Value
Multivariate MK	0.062	0.951

Based on the results presented in Table 6, the Z-statistic was calculated as 0.062 and the p-value as 0.951, clearly indicating that the hypothesis of a multivariate trend is rejected at the 95% confidence level. In other words, when all stations are considered simultaneously, no significant trend is observed in the maximum temperature variations across the region, and the overall regional pattern lacks any coherent upward or downward slope.

This result reveals a notable difference compared to the univariate test results previously calculated for each station. At the station scale, it was found that only one out of eight stations (Borujerd) exhibited a significant increasing trend at the annual scale, while the remaining stations showed no significant trends. However, the multivariate test, by combining all stations, rejects the existence of a single homogeneous trend at the regional level. This apparent contradiction actually indicates spatial heterogeneity of trends across the region. That is, although some stations individually show positive trends, these trends are not consistent in direction and magnitude; when combined, they cancel each other out, resulting in no overall significant trend at the regional level. This inconsistency has led to the absence of a significant trend in the overall regional average.

Therefore, the multivariate test provides an important warning to researchers that trend results from a specific station should not be generalized to the entire region, and any policymaking or resource management should be based on local patterns rather than regional generalizations.

4. Discussion

The station-scale analysis revealed positive annual maximum temperature trends at all eight stations in Lorestan Province (2001–2020), consistent with recent assessments for the wider Zagros region (Attarod et al. 2025) and the broader MENA region, which is warming at 1.5 to 3.5 times the global average (Malik et al. 2024). These findings align with earlier national-scale studies (Shifteh Some'e et al. 2012), confirming that Lorestan is part of a well-documented regional warming pattern.

Despite uniformly positive trends, only Borujerd reached statistical significance at the annual scale. This pattern of "widespread but only partly significant" warming mirrors findings from Shifteh Some'e et al. (2012), where roughly 40% of stations showed significant maximum temperature trends. The limited statistical power is partly attributable to the relatively short 20-year record (Yue et al. 2002).

Monthly analysis revealed significant trends concentrated in February and summer months (July–September), with little change in transitional months. This seasonal asymmetry is consistent with findings from arid regions (Sun et al., 2024). The strong summer signal aligns with amplified MENA summer warming due to land–atmosphere feedbacks in dry conditions (Malik et al. 2024). The February signal is particularly notable, as four stations showed significant positive trends—contrasting with earlier national findings where February showed negative trends suggesting a localized winter-warming signal with agronomic implications for chilling requirements (Attarod et al. 2025).

PCA results revealed exceptional spatial coherence, with PC1 explaining >99.9% of variance and factor loadings >0.999 for all stations—substantially higher than typical continental-scale studies (Vejmelka et al. 2014). This reflects strong regional synchrony in the seasonal temperature cycle, consistent with PCA-based regionalization studies of homogeneous zones (Alinejad et al. 2026).

The multivariate Mann-Kendall test ($Z = 0.062$, $p = 0.951$) showed no significant region-wide trend, contrasting with the significant univariate trend at Borujerd. This outcome is expected in regional trend-detection frameworks (Hirsch and Slack 1984; Douglas et al. 2000), where the regional test down-weights results driven by only a few locally significant stations. This finding reinforces that water-resource and agricultural planning should be based on locally resolved trend information rather than provincial averages, as the latter can mask economically important local warming signals.

5. Conclusion

This study systematically analyzed the spatiotemporal dynamics of maximum temperature across Lorestan Province, western Iran, over the 2001–2020 period, employing both univariate station-scale trend assessments and a novel multivariate framework based on Principal Component Analysis (PCA). The station-scale analysis confirmed a pervasive positive, albeit largely non-significant, warming trend in annual maximum temperatures across all eight stations, with Sen’s slope estimates indicating a total increase ranging from 0.77 °C to 1.25 °C over two decades. However, the monthly-scale analysis revealed a pronounced seasonal asymmetry, demonstrating that the overall annual warming is primarily driven by significant increases during the cold month of February and the peak summer months of July through September. These findings underscore the critical importance of disaggregating climate data to the monthly scale, as annual averages can effectively mask the severity of seasonal extremes that carry profound implications for agriculture, water resource management, and public health.

The application of PCA yielded an exceptionally strong result, with the first principal component alone accounting for more than 99.9% of the total temperature variance and exhibiting near-unity factor loadings across all stations. This extreme spatial coherence confirms that the regional climate system in Lorestan operates under a highly synchronized and homogeneous thermal regime, largely governed by large-scale climatic forcings rather than localized effects. In stark contrast to this spatial uniformity, the multivariate Mann-Kendall test failed to detect a statistically significant regional trend when all stations were considered simultaneously. This apparent contradiction highlights a critical methodological insight: the absence of a coherent region-wide trend does not negate the presence of locally significant warming. Instead, it reflects spatial heterogeneity in the magnitude and timing of temperature changes, where localized signals are effectively diluted when aggregated. Consequently, this study demonstrates that regional-scale policy and resource management strategies must be grounded in locally resolved trend analyses rather than provincial averages. The findings serve as an urgent call for adaptive measures tailored to specific hotspots, particularly in the agricultural sector, where the observed warming in February threatens vernalization requirements, and the intensifying summer heat poses escalating risks to energy security and water availability in this climate-vulnerable region.

6. Conflict of interest

No potential conflict of interest was reported by the authors.

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