Journal of the Nivar
Homepage: https://nivar.irimo.ir

Volume 49, Special Issue, Autumn 2025 and Winter 2026, P. 14-33
(Research Article)

Linear Signs and Kendall Lines: Detecting Local Climate Warming through Combined Statistical Approaches

Ahmadpari, H.[1] ✉ | Khaustov, V.[2] | Amini, A.[3]

1. PhD candidate, Hydrology of land, water resources, hydrochemistry, Russian State Hydrometeorological University, Saint Petersburg, Russia.
2. Candidate of Technical Sciences, Associate Professor at the Department of Engineering Hydrology of the RSHU, Saint Petersburg, Russia.
3. Professor, Soil Conservation and Watershed Management Research Department, Kurdistan Agricultural and Natural Resources Research and Education Center, AREEO, Sanandaj, Iran.

Corresponding Author E-mail: h.ahmadpari@gmail.com

(Received: 29 Jul 2025, Revised: 04 Sep 2025, Accepted: 12 Oct 2025, Published online: 23 Sep 2025)

Abstract
Climate variability poses major challenges for semi-arid regions, where rising temperatures directly affect ecosystems, water resources, and human livelihoods. Understanding temperature dynamics is therefore critical for regional climate adaptation and resilience planning. This study aims to detect, quantify, and interpret monthly and annual temperature trends to support climate adaptation in semi-arid regions exposed to increasing climate variability. To achieve this, long-term temperature data recorded at a representative synoptic station from 1998 to 2022 were analyzed using a combined set of statistical tools. The statistical tools used included the Mann–Kendall test for trend detection, Sen's slope estimator to measure the rate of change, Pearson correlation for identifying linear relationships, and linear regression for modeling the trends. The integrated methodology allowed for cross-validation between parametric and nonparametric approaches, ensuring robustness and consistency of the results. Findings revealed statistically significant warming patterns during January, July, August, September, October, November, and in the annual average, with Z-values ranging from 2.39 to 3.55, all exceeding the critical threshold of ±1.96 at the 95% confidence level. No significant trends were observed in March, June, and December, while February, April, and May showed weak negative trends, also statistically non-significant. These results highlighted the uneven nature of warming and confirmed the value of combined statistical methods in detecting subtle climate signals. The approach and findings can be adapted for temperature trend analysis in other semi-arid or data-limited regions, contributing to global climate resilience planning and regional climate diagnostics.

Keywords: Temperature trends, semi-arid climate, Mann Kendall test, climate variability, statistical trend analysis

Cite this article: Ahmadpari,H. , Khaustov,V. and Amini,A. (2025). Linear Signs and Kendall Lines: Detecting Local Climate Warming through Combined Statistical Approaches. Journal of the Nivar, Special Issue, 14-33. DOI: https://doi.org/10.30467/nivar.2025.537834.1347

E-mail: (2) vitaly.khaustov3@mail.ru (3) ata_amini@yahoo.com

Publisher: Iran Meteorological Organization
DOI: https://doi.org/10.30467/nivar.2025.537834.1347

Print ISSN: 1735-0565
Online ISSN: 2645-3347

1. Introduction

Global mean annual temperature, for both surface and ocean air in combination, has increased by 0.65–1.06 °C over the period 1880–2012 (Chattopadhyay and Edwards, 2016). This upward trend in global temperatures clearly indicates ongoing climate change. It is associated with environmental impacts such as melting glaciers, rising sea levels, and more frequent extreme weather events. These temperature increases are primarily driven by human activities, including the emission of greenhouse gases from fossil fuel combustion, deforestation, and industrial processes (Esmaeili et al., 2024; Ahmadpari and Khaustov, 2025). Understanding these temperature trends is crucial for developing effective strategies to mitigate the impacts of climate change and to adapt to the changing environment. The findings of Meshram et al. (2020) highlight that crop production has been declining as a consequence of climate change. This underscores the critical need to analyze temperature trends in order to better understand their impact on agricultural productivity and food security. Temperature strongly affects evaporation, transpiration, and the water demand of all living organisms. Therefore, it plays a major role in determining water requirements and strategies to ensure availability (Chattopadhyay and Edwards, 2016).

To identify trends in temperature time series, different tests are employed, which can be categorized into parametric and non-parametric methods (Legass et al., 2025).

Salameh et al. (2019) conducted a spatio-temporal analysis of 16 extreme temperature indices across 28 stations in the Levant region during 1987 to 2016, using the Mann–Kendall test and Sen’s slope estimator. The results showed a dominant and statistically significant warming trend, particularly in minimum temperatures and summer extremes, with over 90% of stations reflecting increases in indices. Their findings also revealed strong correlations between temperature extremes and large-scale circulation patterns. Sharafi and Mir Karim (2020) investigated trends in the annual mean temperature at 47 synoptic stations across Iran from 1951 to 2017 using linear regression. Their results showed that the trend slope was positive at 42 stations, while the long-term annual average temperatures at 5 stations were negative. Bakhtiari et al. (2021) investigated the annual trend of air temperature changes using the Mann-Kendall test, the Spearman test, and Pearson's correlation coefficient at the synoptic stations in southeastern Iran. The results demonstrated that the mean air temperature exhibited a significant increasing trend on an annual scale at the most stations. Jin et al. (2021) analyzed the trends of annual average temperature and seasonal average temperature time series data over 40 years in South Korea using the Mann-Kendall test and Sen's slope estimator. The results showed that both the Mann-Kendall test and Sen's slope estimator indicated an upward trend in the annual average temperature and seasonal average temperature data in South Korea. Monforte and Ragusa (2022) analyzed temperature trends on a monthly time scale over the period 1925–2015 using the Mann-Kendall test and Sen's slope estimator in Sicily, Italy. The results showed that, in addition to the well-known dry and hot summer season, the island also experienced a winter with rising temperatures and an increased warm spring. The findings indicated the presence of statistically significant increasing trends. Haldar et al. (2023) analyzed the temperature trend in Guwahati city, Assam, India, using tools such as the Mann-Kendall test, Sen's slope estimator, and linear regression, covering the period from 1970 to 2019. The results indicated an upward trend in temperature for both annual and seasonal periods, which was statistically significant at the 95% confidence level. Kliengchuay et al. (2024) analyzed the annual variations in temperature using the Mann-Kendall test for the period from 2001 to 2020 across six regions of Thailand. The results of the Mann-Kendall test indicated that most regions exhibited an upward trend in temperature; however, these trends were not statistically significant at the 5% significance level. Legass et al. (2025) analyzed temperature trends in the Awash River Basin, Ethiopia, using the Mann-Kendall test for historical and projected periods from 1978 to 2098. The results indicated an increasing temperature trend.

In the case of climate change analysis in Iran, Tabari and Hosseinzadeh Talaee (2011) investigated the temporal variability of precipitation in Iran over the period 1966 to 2005. They employed both parametric (linear regression) and non-parametric (Mann–Kendall and Sen’s slope) methods. Their analysis revealed statistically significant decreasing trends in annual precipitation at several stations, particularly in the northwest of Iran. Seasonal analysis also indicated widespread negative trends in winter and spring, while no significant changes were detected during autumn. This study highlights the spatial heterogeneity of climate change signals in semi-arid regions and reinforces the value of integrating multiple trend detection methods for accurate assessment of hydrological variables.

To date, numerous studies have been conducted on temperature trend analysis around the world. Many of these studies predominantly utilize either parametric or non-parametric methods independently, which can lead to potential biases or inaccuracies in trend detection. Many previous studies lack validation or comparison of statistical methods and focus on broad regions, often missing localized climate variations that impact agriculture and ecosystems.

Understanding climate change at the local scale is essential for developing effective adaptation strategies, especially in semi-arid regions where ecosystems, agriculture, and water resources are highly sensitive to temperature fluctuations. While many existing studies focus on broad regional patterns, they often overlook localized variations and rely on a single statistical approach, which can limit the reliability of their findings. This study advances the field by integrating parametric methods such as linear regression and Pearson correlation with non-parametric techniques, including the Mann-Kendall test and Sen's slope estimator. The combined use of these methods enhances the robustness of trend detection and allows for a more precise interpretation of long-term temperature changes. By focusing on a specific semi-arid basin in Iran, the study captures localized climate signals that are critical for informing regional resilience and policy planning. Therefore, the main objectives are to improve the accuracy of temperature trend analysis, compare the strengths of multiple statistical techniques, and emphasize the value of localized assessments in understanding the impacts of climate change.

2. Materials and Methods

2.1. Study area

The Darreh Dozdan River (DDR) is one of the rivers of Lorestan Province, Iran, that flows in the second-level watershed called Karkheh (Ahmadpari and Khaustov, 2025a). The only rain gauge-hydrometric station on the DDR is called Tange Siab. It measures precipitation, flow rate, sediment, and chemical and physical water quality. This station is located in Kuhdasht County, Lorestan Province, Iran (Ahmadpari and Khaustov, 2025a). In this study, the Kuhdasht synoptic station, which is the closest to the Tange Siab station compared to other meteorological stations, was used. Kuhdasht synoptic station has been established and operated since 1997 by the Iran Meteorological Organization. Kuhdasht synoptic station is located at longitude 47°38′52″E and latitude 33°31′27″N and is 1197 m above sea level (Ahmadpari and Khaustov, 2025b). Figure 1 illustrates the geographic location of the research area within Lorestan Province and Iran.

Fig. 1: a) Map of Iran, b) Map of Lorestan Province, c) Digital elevation model map of the study area

2.2 The Data and statistical approaches

In this study, monthly and annual average temperature data from the Kuhdasht synoptic station for the years 1998 to 2022 (25 years) were used. The monthly and annual average temperature trends were carried out using two statistical approaches: parametric methods, including regression analysis and the Pearson correlation coefficient, and nonparametric methods, including the Mann-Kendall test and Sen's slope estimator. To perform Mann-Kendall and Sen's slope estimator tests, the Excel macro (MAKESENS 1.0) Version 1.0 Freeware was used. This macro is provided by the Finnish Meteorological Institute, 2002, as freeware. To draw Mann-Kendall diagrams, an Excel macro created by Dr. Rasoul Hemmati at the Iran Meteorological Organization was used. Regression analysis and Pearson correlation coefficient were performed using Microsoft Excel 2019 software. In this study, a 95% confidence level, i.e., a significance level of 5%, was used to determine the significant trend in monthly and annual average temperatures. A significance level below 0.05 indicates a statistically significant relationship unlikely to be due to chance, while a level above 0.05 suggests the results are not significant (Amini, 2020; Krishnakumar et al., 2025).

2.2.1 Mann-Kendall

The Mann-Kendall trend test is a nonparametric test that is less affected by outliers (Zeleke et al., 2024). The Mann-Kendall test determines whether a time series has a monotonic upward or downward trend in a time series. The test doesn't require data that is randomly distributed and has a low sensitivity to abrupt breaks (Raoufi and Attayee, 2025). The null hypothesis posits that there is no underlying trend in the observed data series. In contrast, the alternative hypothesis suggests the presence of a consistent, either increasing or decreasing, monotonic trend within the data (Gaddikeri et al., 2024). The S statistic of the Mann-Kendall test, indicating the difference between each observation and all subsequent observations, is calculated based on Eq. 1 (Zeleke et al., 2024).

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(x_j - x_i) \qquad (1)$$

In this relation, n is the number of observations in the series; x_j and x_i are the jth and ith data of the series, respectively. The sgn function is calculated with Eq. 2 (Zeleke et al., 2024).

$$\operatorname{sgn}(x) = \begin{bmatrix} +1 & (x_j - x_i) > 0 \\ 0 & (x_j - x_i) = 0 \\ -1 & (x_j - x_i) < 0 \end{bmatrix} \qquad (2)$$

The variance of S is determined using Eq. 3 (Chen et al., 2016).

$$\operatorname{var}(S) = \frac{n(n-1)(2n+5)}{18} \qquad (3)$$

Also, the standardized Z statistic is calculated using Eq. 4 (Chen et al., 2016).

$$Z = \begin{Bmatrix} \frac{S-1}{\sqrt{\operatorname{Var}(S)}} & \text{if} & S > 0 \\ 0 & \text{if} & S = 0 \\ \frac{S+1}{\sqrt{\operatorname{Var}(S)}} & \text{if} & S < 0 \end{Bmatrix} \qquad (4)$$

The null hypothesis is accepted if $|Z| \leq Z_{\frac{\alpha}{2}}$ at the α level of significance in a two-sided test for trend (Chen et al., 2016). If Z is positive, the trend of the data series is considered to be upward, and if it is negative, the trend is considered to be downward (Chen et al., 2016). The Mann-Kendall Jump Test, an extension of the Mann-Kendall trend test, detects abrupt changes (“jumps”) as well as overall trends in a time series. The Mann-Kendall Jump Test involves calculating two series of statistics: a “forward” (U_i) series and a “backward” (U_i') series. The ‘i’ represents the time point in the series. The method of U_i series and U_i' series calculations with all its formulas is described in the study by Amini (2020). A potential “jump point” (or change point) is identified where the U_i and U_i' lines intersect. The intersection must occur outside the critical value lines (outside ±1.96) to be considered a statistically significant jump (Amiri et al., 2015). There can be multiple intersections, suggesting multiple jump points. The direction of the jump can be inferred from the direction of the U_i line before and after the intersection. If U_i is positive before the intersection and negative after, this indicates a shift from an increasing trend to a decreasing trend (or vice versa). If the lines do not intersect outside the critical values, there is no statistically significant jump point detected (Basati et al., 2014).

2.2.2 Sen's Slope

Sen (1968) developed the non-parametric procedure for estimating the slope of trend in the sample of N pairs of data is determined using Eq. 5 (Minh et al., 2025).

$$Q_i = \frac{x_j - x_k}{j - k} \quad \text{for } \mathrm{i} = 1, \ldots, \mathrm{N} \qquad (5)$$

where x_j and x_k are the data values at times j and k ($j > k$), respectively. If there is only one datum in each time period, then $N = \frac{n(n-1)}{2}$, where n is the number of time periods. If there are multiple observations in one or more periods, then $N < \frac{n(n-1)}{2}$, where n is the total number of observations (Gocic and Trajkovic, 2013). The N values of Q_i are ranked from smallest to largest and the median of slope or Sen's slope estimator is computed by Eq. 6 (Gocic and Trajkovic, 2013).

$$\mathrm{Q_{med}} = \begin{cases} \mathrm{Q_{((N+1)/2)}} & \text{if N is odd} \\ \dfrac{\mathrm{Q_{(N/2)}} + \mathrm{Q_{((N+2)/2)}}}{2}, & \text{if N is even} \end{cases} \qquad (6)$$

The Q_{med} sign reflects data trend reflection, while its value indicates the steepness of the trend. To determine whether the median slope is statistically different than zero, one should obtain the confidence interval of Q_{med} at a specific probability. The confidence interval about the time slope can be computed by Eqs. 7 and 8 (Minh et al., 2025).

$$\mathrm{Var\ (s)} = \frac{\mathrm{n(n-1)(2n+5)} - \sum_{\mathrm{i=1}}^{\mathrm{m}} \mathrm{t_i(t_i-1)(2t_i+5)}}{18} \qquad (7)$$

$$\mathrm{C_\alpha} = \mathrm{Z}_{\left(1-\frac{\alpha}{2}\right)} \sqrt{\mathrm{Var\ (S)}} \qquad (8)$$

$Z_{(1-\alpha/2)}$ is obtained from the standard normal distribution table. The lower and upper limits of the confidence interval are Q_{min} and Q_{max}.

2.2.3 Pearson correlation coefficient

The Pearson correlation coefficient, often denoted as r, is a statistical measure that quantifies the strength and direction of a linear relationship between two continuous variables. The Pearson correlation coefficient is calculated using the Eq. 9 (Ahmadpari et al., 2018).

$$\mathrm{Corr(X\,,Y)} = \frac{\mathrm{Cov(X,Y)}}{6_{\mathrm{X}}6_{\mathrm{Y}}} \qquad (9)$$

where, X and Y are the values of two variables, σ_X is standard deviation of variable X, σ_Y is standard deviation of variable Y, Cov (X, Y) is covariance between X and Y. The comparison of the Pearson correlation coefficient and correlation strength can be found in Fig. 2.

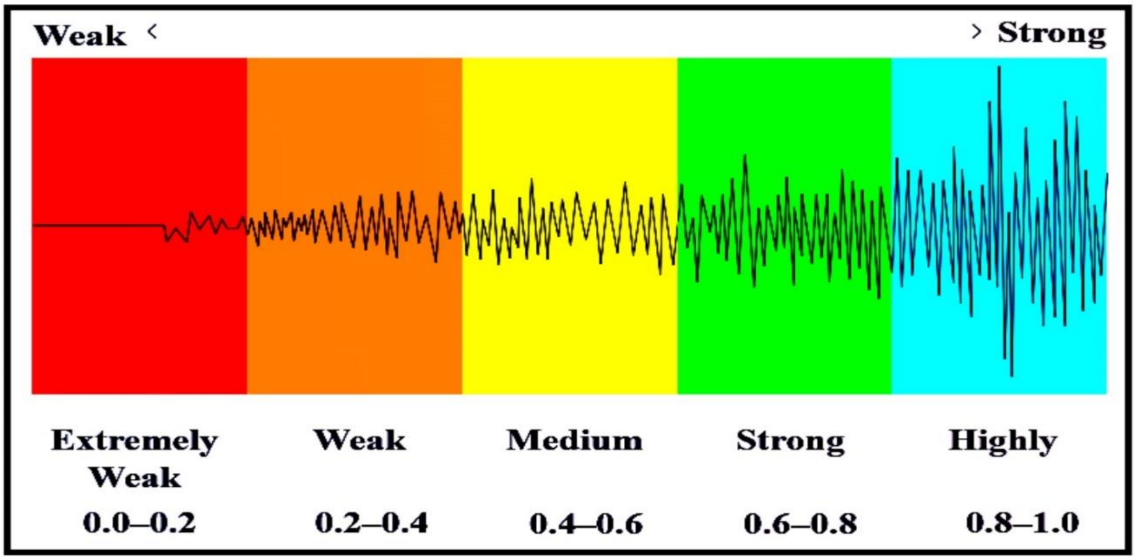

Fig. 2 Classification of Pearson correlation coefficient values by strength (Adapted from Jiang and Sun, 2025)

To test the significance of the Pearson correlation coefficient, a hypothesis test based on the t distribution is usually used. The test statistic (t) is calculated using the Eq. 10 (Obilor and Amadi, 2018).

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \tag{10}$$

where, *t*= *t*-value required for the test of significance of the correlation coefficient *r*, *n*= sample size, *r*= the computed correlation coefficient being tested for significance. The degrees of freedom (df) for this test are equal to *n*-2 (Obilor and Amadi, 2018). The p-value is calculated using the Eq. 11 (Anderson et al., 2020).

$$p_{value} = \mathrm{T.DIST.2T}(\mathrm{ABS}(t), \mathrm{df}) \tag{11}$$

where, *ABS* (t)=$|\ t\ |$, The *ABS* function is used to return the absolute value of a number. The *T.DIST.2T* function returns the two-tailed probability that a t statistic is less than or equal to a specified value, based on the t-distribution. The result of the "T.DIST.2T" function is a value between 0 and 1, representing the probability. A small p-value (typically ≤ 0.05) indicates strong evidence against the null hypothesis, so the null hypothesis would be rejected. A larger p-value (> 0.05) indicates weak evidence against the null hypothesis, so the null hypothesis would fail to be rejected (Anderson et al., 2020).

2.2.4. Regression analysis

Regression analysis is a statistical technique employed to explore the relationship between one or more independent variables (predictors) and a dependent variable (outcome). It is especially valuable for identifying trends, enabling analysts to detect patterns, make forecasts, and comprehend how data behaves over time (Montgomery and Vining, 2021). Simple linear regression is used when there is one independent variable and one dependent variable. The relationship is modeled as a straight line in Eq. 12 (Field, 2013).

$$Y = a + bX \tag{12}$$

where, *Y* is the dependent variable, a is the *Y*-intercept, b is the slope of the line, and *X* is the independent variable. The p-value was used to assess the significance of the trend. In this study, regression analysis was performed with the regression option from the Analysis ToolPak of Microsoft Excel 2019 software.

3. Results and Discussion

3.1. Monthly and annual average temperature trends

3.1.1. Mann-Kendall test

The results of the monthly average temperature trend analysis for the DDR basin from 1998 to 2022 (a 25-year period) are summarized based on the Mann-Kendall test. The Z-values of the Mann-Kendall test for the average temperatures in January, July, August, September, October, and November are 2.39, 2.43, 2.59, 3.55, 2.66, and 3.36, respectively. All Z-values exceed the critical value of ±1.96, which corresponds to a 95% confidence level .This suggests that the observed upward trends are statistically significant. Consequently, there is evidence of a consistent warming pattern during these months over the studied period. Conversely, the Z-values for March, June, and December are 0.44, 0.65, and 1.75, respectively. Although these positive Z-values imply a potential increasing trend in average temperatures for these months, they do not reach statistical significance at the 5% level because they fall within the range of -1.96 to +1.96. Furthermore, the Z-scores obtained from the Mann-Kendall test for February, April, and May are -0.16, -0.79, and -0.54, respectively. These negative values suggest a potential decreasing trend in the mean temperatures during these months. However, since all these Z-values lie within the range of -1.96 to +1.96, they are not statistically significant at the 5% level. This indicates that there is insufficient evidence to confirm a true downward trend in the average temperatures for February, April, and May. In other words, the observed decreases could simply be due to random variability in the data, and we cannot reject the null hypothesis of no trend at the 95% confidence level. Figure 3 displays the results of the Mann–Kendall jump test performed on the monthly average temperatures for the DDR basin from 1998 to 2022.

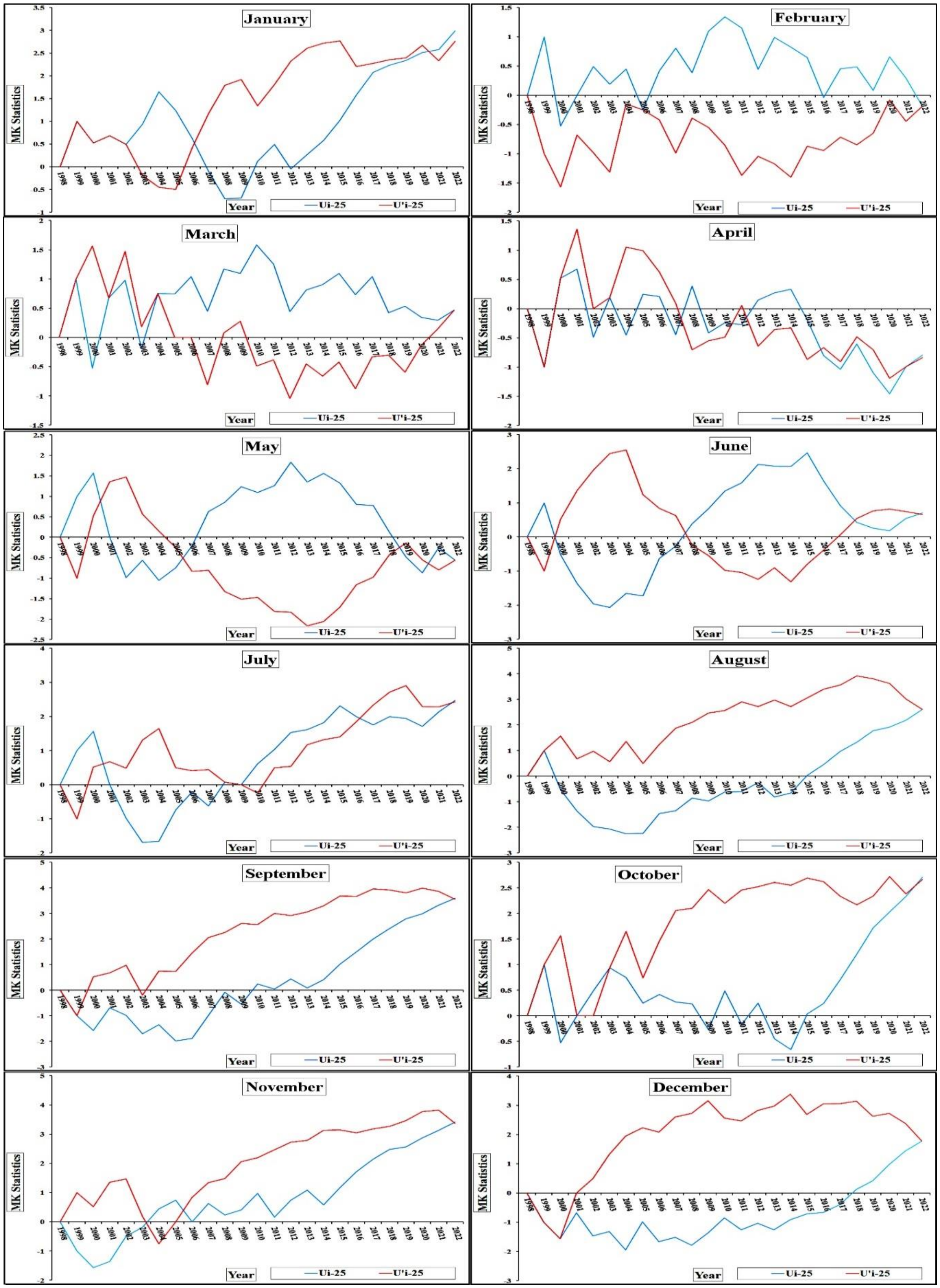

Fig. 3 Mann–Kendall jump test applied to the time series of monthly average temperatures

Figure 3 shows that there is a statistically significant trend in the average temperatures for these months over the analyzed period. Conversely, during February, March, April, May, June, and December, the same statistics do not intersect outside the ±1.96 confidence interval, suggesting that there is no statistically significant trend in the average temperatures for these months throughout the studied timeframe. The results of the Mann–Kendall jump test on the annual average temperature for the DDR basin from 1998 to 2022 are shown in Fig. 4.

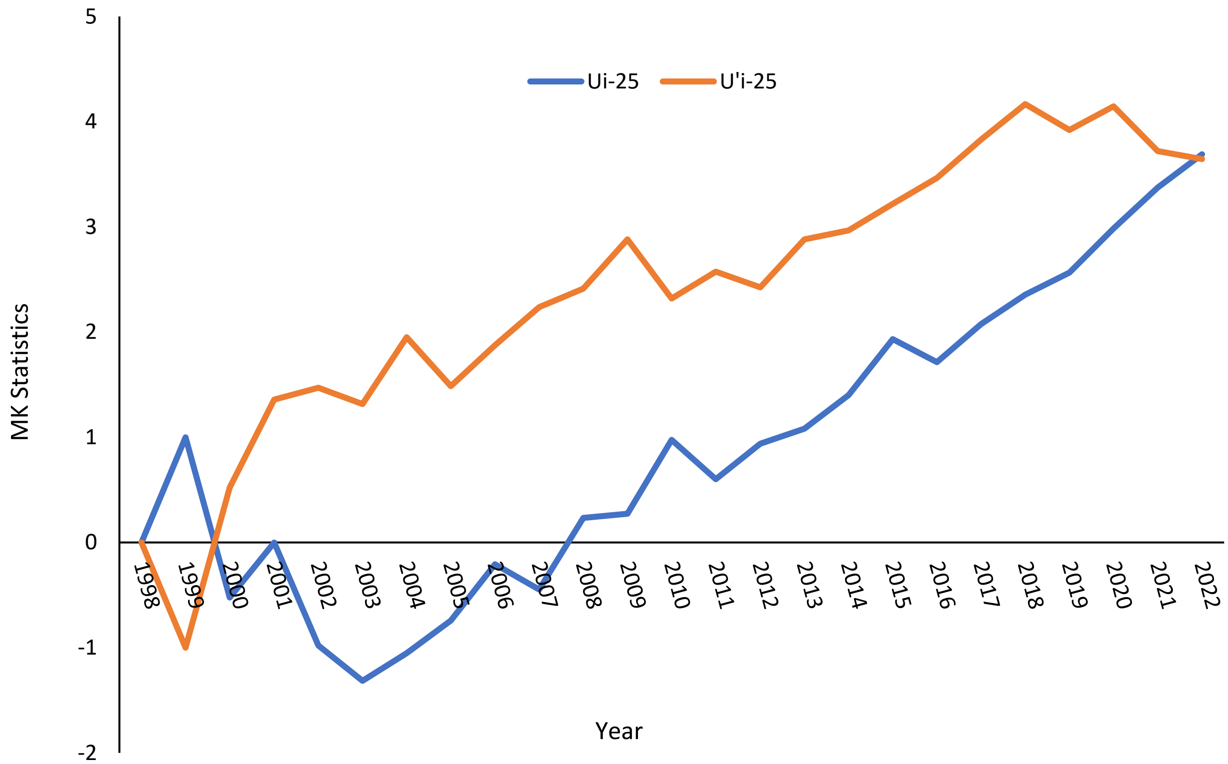

Fig. 4 Mann–Kendall jump test applied to the annual average temperature time series

Figure 4 shows that the Z-value of the Mann-Kendall test for the annual average temperature is 3.64. The positive Z-value indicates an increasing trend in the annual average temperature, and since the Z-value exceeds the critical value of ±1.96 corresponding to a 95% confidence level (significance level of 5 percent) this suggests that the observed upward trend is statistically significant. Figure 4 illustrates that the $\mathrm{U}_{\mathrm{i}-25}$ and $\mathrm{U}'_{\mathrm{i}-25}$ statistics intersect outside the ±1.96 confidence interval within the DDR basin. This intersection outside the confidence bounds confirms the presence of a statistically significant trend in the annual average temperature over the analyzed period.

3.1. 2. Sen's slope estimator test

Table 1 shows the results of the average temperature trend analysis using the Sen's slope estimator test for the DDR basin from 1998 to 2022 (25 years), on both monthly and annual scales.

Table 1 Results of average temperature trend analysis using the Sen's slope estimator test

Time series	Q_{med}	Q_{min}	Q_{max}	**B**	B_{min}	B_{max}
January	0.096	0.016	0.177	3.79	2.37	4.96
February	-0.005	-0.080	0.070	5.81	5.18	6.97
March	0.022	-0.069	0.122	9.30	8.20	10.57
April	-0.028	-0.123	0.030	14.43	13.80	15.12
May	-0.018	-0.101	0.055	19.20	18.32	20.20
June	0.020	-0.057	0.077	24.86	24.00	25.85
July	0.067	0.015	0.110	27.52	26.75	28.00
August	0.111	0.027	0.175	26.64	25.69	27.88
September	0.180	0.098	0.253	21.91	20.86	22.74
October	0.125	0.033	0.204	17.24	16.10	18.01
November	0.177	0.090	0.226	9.53	8.91	10.14
December	0.106	-0.011	0.222	5.68	4.22	7.34
Annual	0.066	0.034	0.096	15.36	15.11	15.72

The positive Q_{med} values for the average temperatures indicate an increasing trend in the average temperatures during these months. Since the Q_{min} and Q_{max} values for these months are also positive (having similar signs), it suggests a significant increasing trend at the 95% confidence level. The Q_{med} values for the average temperatures in March, June, and December are 0.022, 0.020, and 0.106, respectively. These positive Q_{med} values suggest an increasing trend in the average temperatures during these months. However, since the Q_{min} and Q_{max} values for these months have opposite signs, the evidence does not indicate a statistically significant increasing trend at the 95% confidence level. For the average temperatures in February, April, and May negative Q_{med} values indicate a decreasing trend in the average temperatures during these months. Since the Q_{min} and Q_{max} values for these months have opposite signs (positive and negative), this suggests that the decreasing trend is not statistically significant at the 95% confidence level. The Q_{med} value for the annual average temperature is 0.066. The positive Q_{med} values indicate an increasing trend in the annual average temperature. Since the Q_{min} and Q_{max} values for the annual average temperature are also positive (having similar signs), this suggests a significant increasing trend at the 95% confidence level. Figures 5 and 6 show the fitting of Sen's line to the time series of monthly and annual average temperature data for the DDR basin from 1998 to 2022 (25 years).

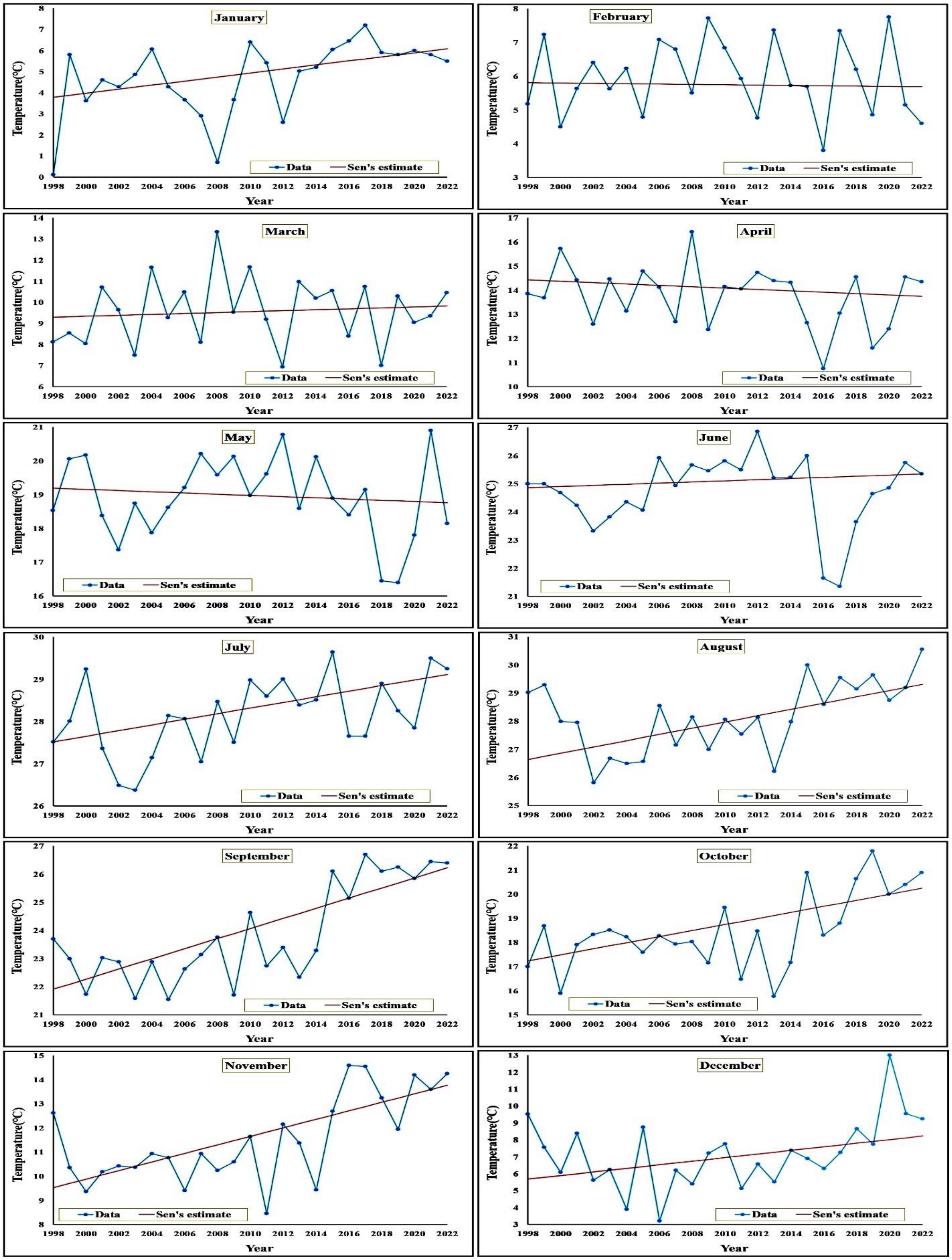

Fig. 5 Fitting the Sen's line on the monthly average temperatures time series data

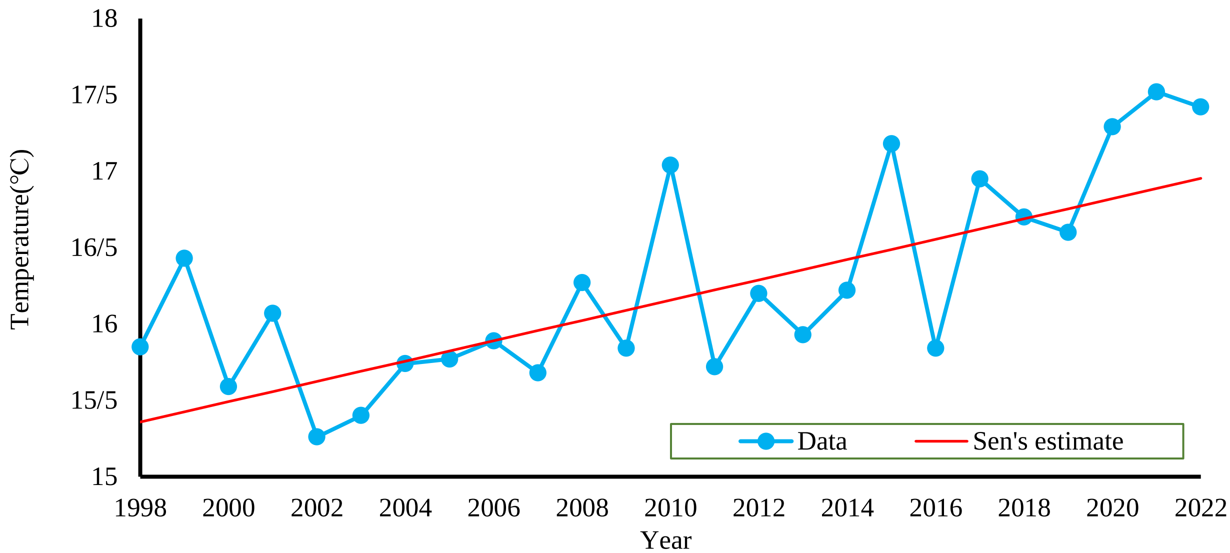

Fig. 6 Fitting the Sen's line on the annual average temperatures time series data

All results of the Sen's slope estimator test confirm all results of the Mann-Kendall test. The results of this study are consistent with the results of Sharma et al. (2016) who analyzed the trend in precipitation and temperature time series using Mann-Kendall and Sen's slope estimator statistical tests in eastern India. The results of their studies showed that the Mann-Kendall and Sen's slope estimator statistical tests demonstrated consistent performance in detecting trends for the precipitation and temperature time series.

3.1.3. Pearson correlation coefficient

Table 2 presents the results of the average temperature trend analysis for the DDR basin from 1998 to 2022 (25 years), using the Pearson correlation coefficient, on both monthly and annual scales.

Table 2 Results of average temperature trend analysis using the Pearson correlation coefficient

Time series	r	n	t	df	p-value	Significance level
January	0.51	25	2.87	23	0.01	Significant
February	-0.06	25	-0.26	23	0.79	Non-significant
March	0.09	25	0.45	23	0.66	Non-significant
April	-0.26	25	-1.30	23	0.21	Non-significant
May	-0.17	25	-0.83	23	0.42	Non-significant
June	-0.01	25	-0.06	23	0.95	Non-significant
July	0.50	25	2.73	23	0.01	Significant
August	0.51	25	2.82	23	0.01	Significant
September	0.78	25	5.97	23	0.00	Significant
October	0.60	25	3.63	23	0.00	Significant
November	0.65	25	4.15	23	0.00	Significant
December	0.37	25	1.91	23	0.07	Non-significant
Annual	0.73	25	5.07	23	0.00	Significant

The positive r values suggest an increasing trend in the average temperatures over these months. The p-values for January, July, August, September, October, and November are less than 0.05, indicating that the observed trends are statistically significant at the 5% significance level. This implies that the increases in average temperature over these months are unlikely due to random variation alone. These r values for February, March, April, May, June, and December, indicate the strength and direction of the linear relationship between time and average temperature during these months. Positive r values, such as those in March and December, suggest a slight increasing trend in average temperatures over time, while negative values in April, May, and June imply a decreasing trend. However, the magnitude of these coefficients is quite small, indicating that the correlations are weak. The absolute values of the coefficients mostly indicate that there is no strong linear relationship between time and temperature in these months. Furthermore, the p-values associated with these correlation coefficients are all greater than 0.05, which exceeds the commonly accepted significance level of 5%. This indicates that the observed correlations are not statistically significant at the 95% confidence level, and therefore, we cannot confidently conclude that there are meaningful increasing or decreasing trends in average temperature over time during these months. The Pearson correlation coefficient for the annual average temperature is 0.73. This positive value indicates a strong increasing trend in the annual average temperature over the studied period. Pearson correlation coefficient between 0.6 and 0.8 signifies a strong correlation between time and annual average temperature. Furthermore, the p-value associated with this correlation is less than 0.05, which indicates that the observed trend is statistically significant at the 95% confidence level. All results of the Pearson correlation coefficient confirm all results of the Mann-Kendall test and Sen's slope estimator. The results of this study are consistent with the results of Panditharathne et al. (2022). These researchers analyzed the trend in rainfall and streamflow using the Mann-Kendall test, Sen’s slope estimator, and the Pearson correlation coefficient in the Nilwala River Basin in Sri Lanka. Their findings indicated that all three methods yield similar results.

3.1.4. Regression analysis

Table 3 presents the results of the average temperature trend analysis for the DDR basin from 1998 to 2022, using linear regression analysis on both monthly and annual scales.

Table 3 Results of average temperature trend analysis using the linear regression analysis

Time series	a	b	p-value	Significance level
January	-238.85	0.12	0.01	Significant
February	22.63	-0.01	0.79	Non-significant
March	-30.31	0.02	0.66	Non-significant
April	104.41	-0.05	0.21	Non-significant
May	74.85	-0.03	0.42	Non-significant
June	29.16	-0.002	0.95	Non-significant
July	-92.55	0.06	0.01	Significant
August	-145.25	0.09	0.01	Significant
September	-345.70	0.18	0.00	Significant
October	-241.99	0.13	0.00	Significant
November	-307.02	0.16	0.00	Significant
December	-198.78	0.10	0.07	Non-significant
Annual	-114.29	0.06	0.00	Significant

Table 3 shows the slope of the regression line (b values) for the average temperatures in January, July, August, September, October, and November. The positive b values suggest an increasing trend in the average temperatures over these months. Furthermore, the p-values for these months are less than 0.05, indicating that the observed trends are statistically significant at the 5% significance level with 95% confidence. This implies that the observed upward trends in temperature are unlikely to be due to random variation alone and may reflect genuine climate changes over the analyzed period. Positive b values, as observed in March and December, indicate a slight increasing trend in average temperatures. In contrast, negative values in April, May, and June suggest a decreasing trend. The p-values associated with these b values are all greater than 0.05 which exceeds the commonly accepted significance level of 5 percent. This implies that the observed trends are not statistically significant at the 95 percent confidence level. Consequently, we cannot confidently assert that there are meaningful increasing or decreasing trends in average temperatures over time during these months. The b value for the annual average temperature is 0.06. This positive value indicates an increasing trend in the annual average temperature over the studied period. Furthermore, the p-value associated with this b value is less than 0.05, suggesting that the observed trend is statistically significant at the 95% confidence level. Figures 7 and 8 show the fitting of the linear regression on the time series of monthly and annual average temperature data for the DDR basin from 1998 to 2022 (25 years). These figures corroborate the findings presented in Table 3.

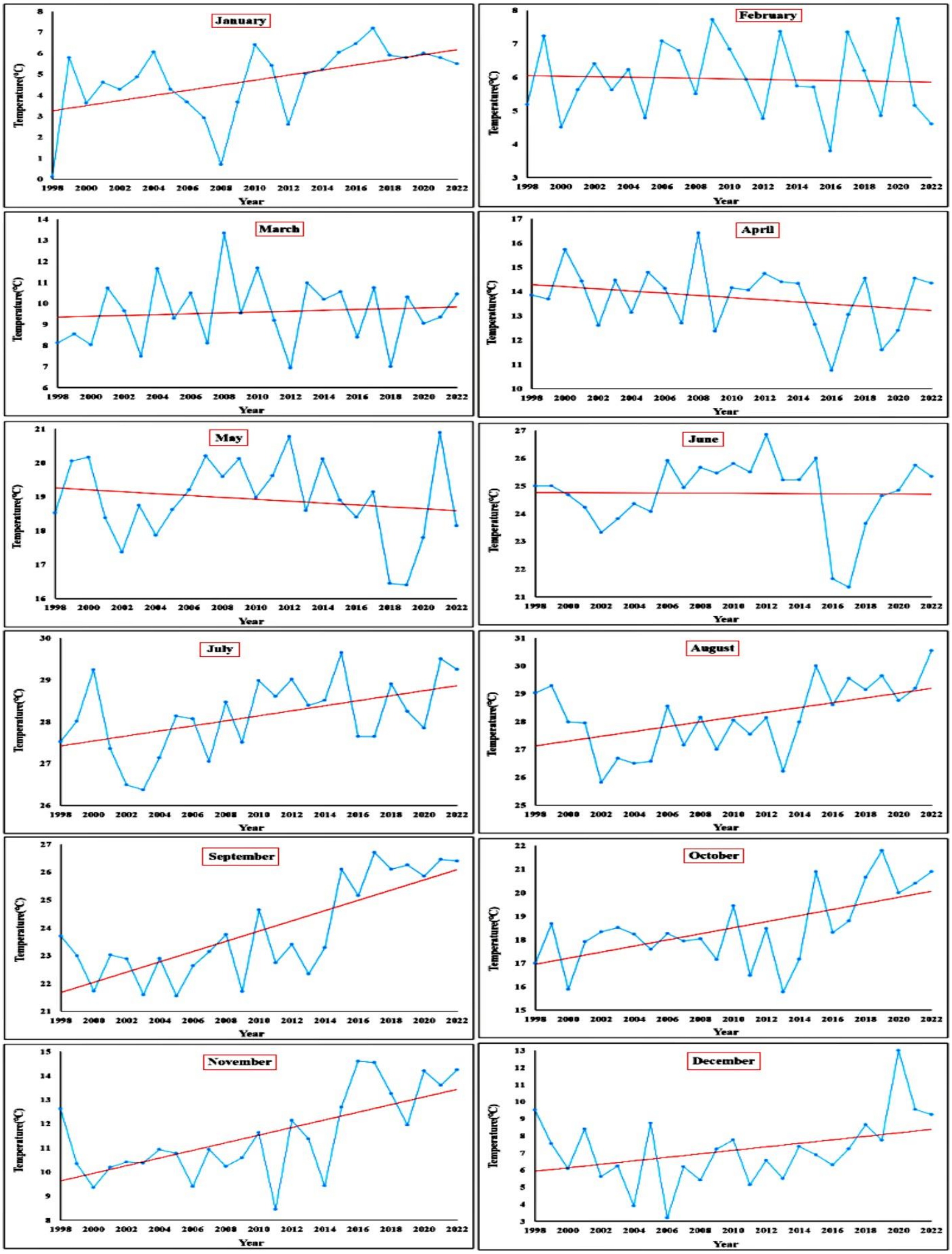

Fig. 7 Fitting the linear regression on the monthly average temperatures time series data

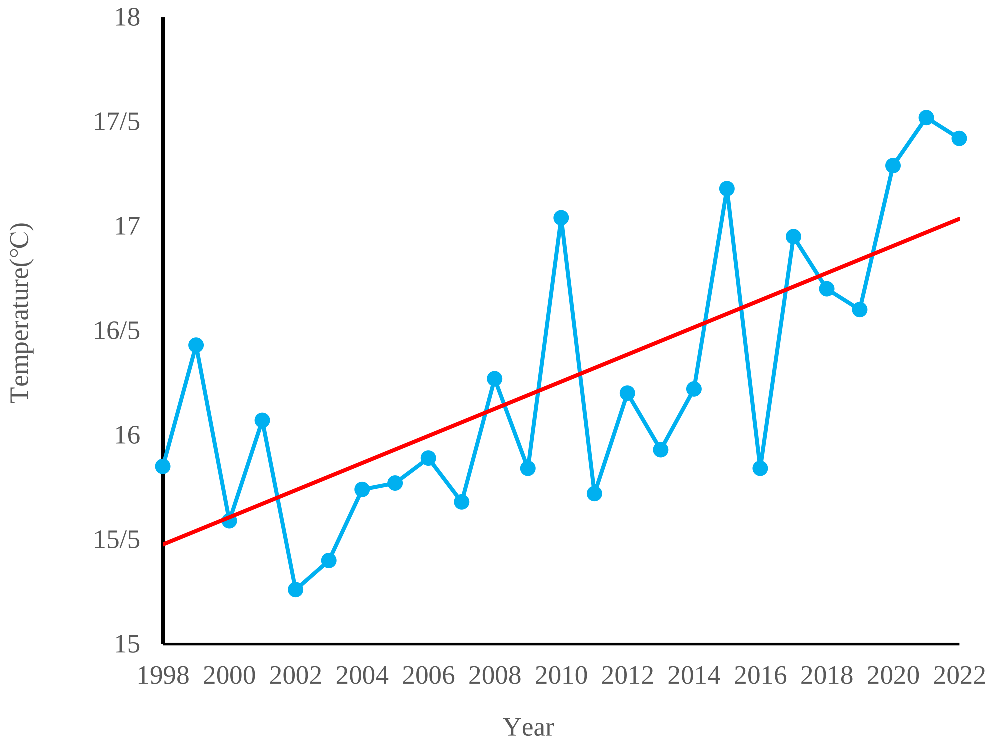

Fig. 8 Fitting the linear regression on the annual average temperatures time series data

Comparing Table 1 and Figures 5 and 6 with Table 3 and Figures 7 and 8 reveals that the values of b and Q_{med}, which represent the slope of the regression line and the slope of Sen's line, respectively, generally have the same direction across all months except June. Moreover, their slope values are very close to each other in all months and annually. Notably, in June the slope values obtained by both methods are very close to each other; however, both slopes are close to zero and point in opposite directions. Since both methods, linear regression and Sen's slope estimator, identified the trend in June as nonsignificant, it can be concluded that these two methods fully corroborate each other. All results of the linear regression confirm all results of the Mann-Kendall test, Pearson correlation coefficient and Sen's slope estimator. The results of this study are consistent with the results of Asadi and Karami (2022). These researchers analyzed the maximum and minimum annual and seasonal trends of relative humidity using the Mann–Kendall statistical test, Sen's slope estimator, and linear regression in 41 synoptic stations in Iran. The results of their studies showed that all three methods depicted similar variations. The results of this study are consistent with the results of Abubakar et al. (2024). These researchers analyzed the trends in land surface temperature and vegetation using Pearson correlation coefficient, Linear Regression, and the Mann-Kendall test at the Kaduna Metropolis, Nigeria. Their findings indicated that all three methods yielded similar results.

4. Conclusion

In this study, trend analysis of monthly and annual average temperatures was conducted using the Mann–Kendall test, Sen's slope estimator, Pearson correlation coefficient, and linear regression for the Darreh Dozdan River Basin over the period from 1998 to 2022. The key findings of the study are as follows:

1. Analysis of the annual average temperature trends using all four statistical methods confirms a statistically significant increasing trend at the 95% confidence level,

highlighting a clear sign of long-term warming in this semi-arid region.

2. Monthly trend analysis shows that the average temperatures in January, July, August, September, October, and November exhibit statistically significant increasing trends based on both parametric and non-parametric tests, indicating noticeable seasonal warming patterns consistent with broader climate change signals.
3. Temperature trends in February, March, April, May, June, and December vary in direction, but none are statistically significant at the 95% confidence level. These fluctuations may still reflect localized climate variability and warrant continued monitoring.
4. The consistency between parametric and non-parametric methods confirms the robustness of the detected trends, strengthening the reliability of the results for understanding climate patterns at the local scale.

A critical aspect of this study is its contribution to identifying localized climate warming signals, which are often masked in large-scale regional assessments. However, the study's reliance on a single synoptic station in the basin poses limitations in terms of spatial coverage. Including additional stations with extended and more detailed datasets would improve the spatial accuracy of the results and offer deeper insights into sub-basin climate variability. Future research should focus on both spatial and temporal trends in maximum and minimum temperatures to further understand localized climate change impacts and support effective climate-resilient planning, particularly in vulnerable semi-arid environments like the Darreh Dozdan River Basin.

Statements and Declarations

Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Data Availability

The data produced in this research are presented in the paper.

Conflict of Interest

The authors of this article declared no conflict of interest regarding the authorship or publication of this article.

Author contributions

Hedieh Ahmadpari: Data Collection, Data Analysis, Investigation, Methodology, Resources, Software, Writing – original draft, Writing – review and editing; Vitaly Khaustov: Conceptualization, Validation, Supervision, Writing – review and editing; Ata Amini: Conceptualization, Validation, Supervision, Writing – review and editing.

Declaration of AI Assistance

In this study, the Napkin tool from the "https://www.napkin.ai/" website was used to draw Figure 2. It is worth noting that this tool did not play a role in producing the textual and numerical content of this figure and was only used to draw the figure. During the preparation of this work, the authors used the "https://talkai.info/chat/" website for editing and language enhancement. The authors have thoroughly reviewed and revised the content as necessary and assume full responsibility for the final manuscript.

References

1. Abbas, S., & Mayo, Z. A. (2021). Impact of temperature and rainfall on rice production in Punjab, Pakistan. Environment, Development and Sustainability, 23(2), 1706-1728. https://doi.org/10.1007/s10668-020-00647-8
2. Abubakar, M. L., Thomas, D., Ahmed, M. S., & Abdussalam, A. F. (2024). Assessment of the relationship between land surface temperature and vegetation using MODIS NDVI and LST timeseries data in Kaduna Metropolis, Nigeria. FUDMA Journal of Sciences, 8(2), 137-148. https://doi.org/10.33003/fjs-2024-0802-2305
3. Ahmadpari, H., & Khaustov, V. (2025) A review of the effects of climate change on watershed runoff in Iran. 8th International Congress of Developing Agriculture, Natural Resources, Environment and Tourism of Iran, Tabriz, Iran.

4. Ahmadpari, H., & Khaustov, V. (2025a). Analyzing meteorological and hydrological droughts in the Darreh Dozdan River Basin through drought indices. Environment and Water Engineering. https://doi.org/10.22034/ewe.2025.506959.2004
5. Ahmadpari, H., & Khaustov, V. (2025b). Agricultural drought monitoring using meteorological indices in Darreh Dozdan Basin, Iran. Advances in Civil Engineering and Environmental Science, 2(2), 72-84. https://doi.org/10.22034/acees.2025.512324.1022
6. Ahmadpari, H., Hashemi Garmdareh, S. E., & Eskafi, M. (2018). Investigating the effect of soil organic matter on gypsum block calibration for measuring soil volumetric moisture content. Journal of Rainwater Catchment Systems, 6 (1), 11-20.
7. Al-Hasani, A. A. J., & Shahid, S. (2022). Spatial distribution of the trends in potential evapotranspiration and its influencing climatic factors in Iraq. Theoretical and Applied Climatology, 150(1), 677-696. https://doi.org/10.1007/s00704-022-04184-4
8. Amini, A. (2020). The role of climate parameters variation in the intensification of dust phenomenon. Natural Hazards, 102(1), 445-468. https://doi.org/10.1007/s11069-020-03933-w
9. Amiri, M. J., Karbasi, A. R., Zoghi, M., & Sadat, M. (2015). Detection of climate changes by mann-kendall analysis and drought indexes (Case study: Agh Gol wetland). Journal of Environmental Studies, 41(3), 545-561. https://doi.org/10.22059/jes.2015.55896
10. Anderson, D. R., Williams, T. A., & Cochran, J. J. (2020). Statistics for business and economics. Cengage Learning.
11. Asadi, M., & Karami, M. (2022). Modeling of relative humidity trends in Iran. Modeling Earth Systems and Environment, 8, 1035–1045. https://doi.org/10.1007/s40808-021-01093-9
12. Bakhtiari, S., Mirahmadi, M., Golestani Kermani, S., & Bakhtiari, B. (2021). Identify the monthly and annual trend of air and soil temperature changes using parametric and non-parametric statistical methods at three synoptic stations in southeast of Iran. Nivar, 45(112-113), 16-28. https://doi.org/10.30467/nivar.2020.239636.1165
13. Basati, S., Yarahmadi, D., & Nasiri, B. (2014). Study of changes in the precipitation forms and clarify the relative humidity and temperature effects on them (Kermanshah station). Nivar, 38(87-86), 63-72.
14. Chattopadhyay, S., & Edwards, D. R. (2016). Long-term trend analysis of precipitation and air temperature for Kentucky, United States. Climate, 4(1), 10. https://doi.org/10.3390/cli4010010
15. Chen, Y., Guan, Y., Shao, G., & Zhang, D. (2016). Investigating trends in streamflow and precipitation in Huangfuchuan Basin with wavelet analysis and the Mann-Kendall test. Water, 8(3), 1-32. https://doi.org/10.3390/w8030077
16. Esmaeili, S., Bahrami, J. and Kamali, B. (2024). The contributions of natural and anthropogenic climate change on water resources reduction in Zarrinehroud basin of Lake Urmia. Advances in Civil Engineering and Environmental Science, 1(1), 1-14. https://doi.org/10.22034/acees.2024.195339
17. Field, A. (2013). Discovering Statistics Using IBM SPSS Statistics. Sage Publications.
18. Gaddikeri, V., Sarangi, A., Singh, D. K., Jatav, M. S., Rajput, J., & Kushwaha, N. L. (2024). Trend and change-point analyses of meteorological variables using Mann–Kendall family tests and innovative trend assessment techniques in New Bhupania command (India). Journal of Water and Climate Change,

15(5), 2033-2058. https://doi.org/10.2166/wcc.2024.462
19. Gocic, M., & Trajkovic, S. (2013). Analysis of changes in meteorological variables using Mann-Kendall and Sen's slope estimator statistical tests in Serbia. Global and planetary change, 100, 172-182. https://doi.org/10.1016/j.gloplacha.2012.10.014
20. Guntukula, R. (2020). Assessing the impact of climate change on Indian agriculture: Evidence from major crop yields. Journal of Public Affairs, 20(1), e2040. https://doi.org/10.1002/pa.2040
21. Haldar, S., Choudhury, M., Choudhury, S., & Samanta, P. (2023). Trend analysis of long-term meteorological data of a growing metropolitan city in the era of global climate change. Total Environment Research Themes, 7, 100056. https://doi.org/10.1016/j.totert.2023.100056
22. Jiang, Y., & Sun, W. (2025). Day-Ahead Electricity Price Prediction and Error Correction Method Based on Feature Construction–Singular Spectrum Analysis–Long Short-Term Memory. Energies, 18(4), 1-22. https://doi.org/10.3390/en18040919
23. Jin, D. H., Jang, S. H., Kim, H. K., & Lee, Y. S. (2021). A trend analysis of seasonal average temperatures over 40 years in South Korea using Mann-Kendall test and Sen's slope. The Korean Journal of Applied Statistics, 34(3), 439-447. https://doi.org/10.5351/KJAS.2021.34.3.439
24. Kliengchuay, W., Mingkhwan, R., Kiangkoo, N., Suwanmanee, S., Sahanavin, N., Kongpran, J., Wai Aung, H., & Tantrakarnapa, K. (2024). Analyzing temperature, humidity, and precipitation trends in six regions of Thailand using innovative trend analysis. Scientific Reports, 14(1), 7800. https://doi.org/10.1038/s41598-024-57980-5
25. Krishnakumar, M., Dachepalli, S., Nair, M., Gutjahr, G., & Sankaran, R. (2025). Statistics for Doctors: Hypothesis Testing and P Values. Amrita Journal of Medicine, 21(1), 43-47. http://dx.doi.org/10.4103/AMJM.AMJM_85_24
26. Legass, A. M., Alamirew, T., Gebrehiwot, S. G., Haro-Monteagudo, D., & Berhanu, D. (2025). Spatiotemporal climate change projection and trend analysis using selected downscaled CMIP6 models for water action over awash River Basin, Ethiopia. Environmental Challenges, 18, 101059. https://doi.org/10.1016/j.envc.2024.101059
27. Liu, L., & Xu, Z. X. (2016). Regionalization of precipitation and the spatiotemporal distribution of extreme precipitation in southwestern China. Natural Hazards, 80, 1195-1211. https://doi.org/10.1007/s11069-015-2018-x
28. Meshram, S. G., Kahya, E., Meshram, C., Ghorbani, M. A., Ambade, B., & Mirabbasi, R. (2020). Long-term temperature trend analysis associated with agriculture crops. Theoretical and Applied Climatology, 140, 1139-1159. https://doi.org/10.1007/s00704-020-03137-z
29. Minh, H. V. T., Meraj, G., Kumar, P., Nam, N. D. G., Lien, B. T. B., Ngan, N. V. C., Thinh, L.V., & Downes, N. K. (2025). Assessment of long-term rainfall trends and variability in the Vietnamese Mekong Delta: implications for water resources management strategies. Discover Environment, 3(1), 1-24. https://doi.org/10.1007/s44274-025-00233-7
30. Monforte, P., & Ragusa, M. A. (2022). Temperature trend analysis and investigation on a case of variability climate. Mathematics, 10(13), 2202. https://doi.org/10.3390/math10132202
31. Montgomery, D. C., Peck, E. A., & Vining, G. G. (2021). Introduction to linear regression analysis. John Wiley & Sons.
32. Obilor, E. I. M., & Amadi, E. C. (2018). Test for Significance of Pearson's Correlation Coefficient. International Journal of

Innovative Mathematics, Statistics & Energy Policies, 6(1), 11-23.

33. Panditharathne, R., Gunathilake, M. B., Chathuranika, I. M., Rathnayake, U., Babel, M. S., & Jha, M. K. (2022). Trends and variabilities in rainfall and streamflow: a case study of the Nilwala River Basin in Sri Lanka. Hydrology, 10(1), 8. https://doi.org/10.3390/hydrology10010008

34. Raoufi, H., & Attayee, S. N. (2025). Assessing Precipitation Trend: a Case Study of Kabul, Afghanistan. Indonesian Journal of Social and Environmental Issues (IJSEI), 6(1), 124-134. https://doi.org/10.47540/ijsei.v6i1.1639

35. Salameh, A. A. M., Gámiz-Fortis, S. R., Castro-Díez, Y., Abu Hammad, A., & Esteban-Parra, M. J. (2019). Spatio-temporal analysis for extreme temperature indices over the Levant region. International Journal of Climatology, 39(15), 5556–5582. https://doi.org/10.1002/joc.6171

36. Sharafi, S., & Mir Karim, N. (2020). Investigating trend changes of annual mean temperature and precipitation in Iran. Arabian Journal of Geosciences, 13, 1-11. https://doi.org/10.1007/s12517-020-05695-y

37. Sharma, C. S., Panda, S. N., Pradhan, R. P., Singh, A., & Kawamura, A. (2016). Precipitation and temperature changes in eastern India by multiple trend detection methods. Atmospheric research, 180, 211-225.https://doi.org/10.1016/j.atmosres.2016.04.019

38. Soureshjani, H. K., Dehkordi, A. G., & Bahador, M. (2019). Temperature effect on yield of winter and spring irrigated crops. Agricultural and Forest Meteorology, 279, 107664. https://doi.org/10.1016/j.agrformet.2019.107664

39. Tabari, H., & Hosseinzadeh Talaee, P. (2011). Temporal variability of precipitation over Iran: 1966–2005. Journal of Hydrology, 396(3–4), 313–320. https://doi.org/10.1016/j.jhydrol.2010.11.034

40. Ullah, A., Nadeem, F., Nawaz, A., Siddique, K. H., & Farooq, M. (2022). Heat stress effects on the reproductive physiology and yield of wheat. Journal of agronomy and crop science, 208(1), 1-17. https://doi.org/10.1111/jac.12572

41. Wang, R., Li, L., Gentine, P., Zhang, Y., Chen, J., Chen, X., ... & Lü, G. (2022). Recent increase in the observation-derived land evapotranspiration due to global warming. Environmental Research Letters, 17(2), 024020. http://dx.doi.org/10.1088/1748-9326/ac4291

42. Zeleke, T. T., Lukwasa, A. Z. W., Beketie, K. T., & Ayal, D. Y. (2024). Analysis of spatio-temporal precipitation and temperature variability and trend over Sudd-Wetland, Republic of South Sudan. Climate Services, 34, 100451. https://doi.org/10.1016/j.cliser.2024.100451