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Combined parametric and non-parametric assessment of relative humidity trends in a semi-arid river basin

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ABSTRACT

Relative humidity is an essential climatic parameter with direct implications for environmental studies and water resource management. Despite its importance, long-term variability in relative humidity remains less explored in many semi-arid river basins. This study aimed to detect trends in relative humidity in the Darreh Dozdan River Basin, Iran, over the period 1998–2022. To achieve this, four complementary methods were applied at monthly and annual scales, including the Mann–Kendall trend test, Sen's slope estimator, Pearson correlation, and linear regression. The analysis revealed that only two months, January and May, exhibited statistically significant trends. January showed a consistent decline, with relative humidity decreasing by about 0.39% per year (Mann–Kendall $Z = -2.06$; Pearson $r = -0.47$; $p = 0.02$). In contrast, May displayed an increasing trend of approximately 0.51% per year ($Z = 2.18$; Pearson $r = 0.40$; $p = 0.05$). No other months indicated significant changes, and the annual trend analysis confirmed remarkable stability, with no detectable long-term increase or decrease in relative humidity during the 25 years. These findings suggest that while annual humidity has remained stable, seasonal shifts are emerging. Such insights are valuable for climate monitoring and for guiding adaptive water management strategies.

Highlights

- Only January and May showed significant monthly relative humidity trends.
- January showed a significant declining trend of –0.39% per year.
- May revealed a significant increasing trend of +0.51% per year.
- Annual relative humidity remained statistically stable from 1998 to 2022.
- Combined statistical tests ensured robust relative humidity trend analysis.

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1. Introduction

The greenhouse effect is the process by which certain gases, including carbon dioxide, methane, and water vapor trap heat within the atmosphere of the Earth. This trapping of heat causes the temperature at the surface of the Earth to rise (Cassia et al., 2018; Filonchyk et al., 2024). This process is vital for keeping the Earth warm enough to support life. However, human actions such as the burning of fossil fuels and the clearing of forests have greatly increased the amount of these gases, strengthening the greenhouse effect and causing the Earth's temperature to increase (Gharibreza et al., 2018). The temperature rise, known as global warming, results in changes to the climate.

Food security means that all people in a society have access to enough food at all times to live a healthy and active life (Savari et al., 2021). Climate change, one of the greatest challenges of this century, is a serious threat to global food security. Rising temperatures, changing rainfall patterns, and extreme weather events such as droughts, floods, and storms are all directly affecting agricultural production (Vijai et al., 2023). These climate changes are reducing crop yields, increasing plant diseases and pests, and reducing the water resources available for agriculture. As a result, food supplies are reduced, and prices are rising (Amini et al., 2009). This poses serious challenges, especially for developing countries and poor communities, which are more dependent on agriculture and natural resources, jeopardizing their access to food.

Plant evapotranspiration is the combined process of water evaporation from the soil surface and transpiration from plant leaves, playing a crucial role in plant water use and growth (Ahmadpari et al., 2019). This process regulates plant temperature, enables nutrient uptake, and influences crop yield (Sadok et al., 2021; Suliman et al., 2024), directly affecting agricultural productivity and thus food security by determining how efficiently water is used to produce food (Basereh et al., 2024). Managing evapotranspiration helps optimize water resources in agriculture, supporting stable and increased food production to meet global food security challenges.

Studies indicate that relative humidity is among the strongest meteorological factors influencing potential evapotranspiration, alongside solar radiation and precipitation (Amini and Hesami, 2017). Reference evapotranspiration, often estimated via the Penman-Monteith equation, incorporates relative humidity data (typically daily or monthly averages) along with temperature, solar radiation, and wind speed to accurately represent atmospheric evaporative demand (Ahmadpari et al., 2017). Maximum relative humidity, in particular, can significantly improve reference evapotranspiration estimation in humid regions. Changes in relative humidity over land influence evapotranspiration trends and atmospheric drying. Climate model analyses show that underestimations of relative humidity decline relate to biases in simulated evapotranspiration increase, implying that accurate relative humidity representation is essential for correctly modeling evapotranspiration and its effects on the water cycle and drought risks (Kim and Johnson, 2025). Empirical methods for evapotranspiration estimation often incorporate solar radiation and relative humidity as key input parameters, emphasizing relative humidity's substantial contribution to model accuracy (Chatzithomas and Alexandris, 2015). Proper accounting of relative humidity trends is critical in climate studies related to evapotranspiration and water resource management (Kim and Johnson, 2025).

To identify and assess trends in relative humidity time series, researchers utilize a variety of statistical tests. These tests can broadly be classified into two primary categories: parametric and non-parametric methods. Parametric methods, which typically assume that the underlying data follow a specific probability distribution (often normal distribution), include approaches such as linear regression analysis and Pearson's correlation coefficient (Mishra et al., 2019). In contrast, non-parametric methods do not make stringent assumptions about data distribution and are therefore more robust in cases where data deviate from normality or contain outliers; common examples include the Mann-Kendall trend test and Sen's slope estimator (Jiqin et al., 2023).

To date, a substantial body of research has been devoted to the analysis of relative humidity trends using both parametric and non-parametric techniques. Numerous studies conducted across diverse climatic regions worldwide have provided valuable insights into temporal changes and variability in relative humidity. Farooq and Kumar (2021) analyzed relative humidity at Srinagar, Ranichauri, and Leh in the Himalayas. No significant trends were found in Srinagar. Ranichauri showed significant increases of 7.1 to 10.9 percent per decade with an annual rise of 8.5 percent, while Leh showed significant decreases from March to December with an annual decline of 18.1 percent. Asadi and Karami (2022) investigated the maximum and minimum annual trends of relative humidity in Iran, utilizing three statistical methods: the Mann–Kendall test, Sen's slope estimator, and linear regression. Their results indicated that 83.26% of the stations showed a positive trend in maximum and minimum annual humidity, while 17.73% exhibited a negative trend. Rajput et al. (2023) investigated the trend of relative humidity in India, from 1990 to 2020 using the Mann-Kendall test and Sen's slope estimator. The results showed that annual relative humidity exhibited a positive increasing trend. Relative humidity displayed positive trends on annual, monthly, and seasonal bases, except during February, June, July, August, September, and the monsoon season. Kliengchuay et al. (2024) investigated changes in the annual trends of relative humidity Thailand using the Mann–Kendall test and innovative trend analysis methods. The results indicated both upward and downward trends in relative humidity in different areas.

Numerous studies have been conducted on relative humidity trend analysis in Iran. However, a critical review of the existing literature reveals certain limitations and gaps. Many of these studies predominantly utilize either parametric or non-parametric methods independently, which can lead to potential biases or inaccuracies in trend detection. Additionally, some previous research often lacks comprehensive validation or comparative analysis of different statistical approaches, thereby limiting the robustness of their conclusions. In contrast, this study offers significant advancements over these prior efforts. Its primary innovation lies in the simultaneous application and comparison of both parametric (linear regression and Pearson correlation coefficient) and non-parametric (Mann-Kendall test and Sen's slope estimator) methods to analyze average relative humidity trends within the Darreh Dozdan River (DDR) basin, Iran. By evaluating the strengths and weaknesses of each approach, the research aims to provide a more reliable and nuanced understanding of relative humidity fluctuations over time. This dual-method analysis enhances the accuracy of trend detection, helping to identify subtle changes that might be missed if only one method is used. Moreover, this study emphasizes the importance of localized analysis by focusing on the Darreh Dozdan River (DDR) basin, a region that has not been considered in previous studies. Such specificity allows for more tailored insights into the impacts of climate variability on local agriculture, ecosystems, and water resources. The findings are particularly valuable for informing adaptive management strategies aimed at improving agricultural productivity and ensuring regional sustainability. By addressing the methodological shortcomings of earlier studies and providing a comprehensive, validated comparison of trend analysis techniques, this research contributes to advancing scientific understanding in this field. It also offers practical implications for policymakers and stakeholders seeking to develop climate-resilient agricultural practices and sustainable development policies in similar basins across Iran and beyond.

2. Materials and Methods

2.1 Study area

The Darreh Dozdan River (DDR) is a river located in Lorestan Province, Iran. It is part of the second-level watershed known as the Karkheh basin (Ahmadpari and Khaustov, 2025a). In this study, to analyze the trend of relative humidity in the DDR basin, data from the Kuhdasht synoptic station were utilized. The Kuhdasht synoptic station has been established and operated by the Iran Meteorological Organization since 1997. It is situated at longitude 47°38′52″E, latitude 33°31′27″N, and an elevation of 1197 meters above sea level (Ahmadpari and Khaustov, 2025b). Fig. 1 shows 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 Monthly and annual relative humidity trends

In this study, monthly and annual relative humidity data from the Kuhdasht synoptic station, spanning 25 years from 1998 to 2022, were utilized. The trends in monthly and annual relative humidity were analyzed 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. For the Mann-Kendall and Sen's slope estimator tests, the MAKESENS 1.0 Version 1.0 freeware Excel macro, provided by the Finnish Meteorological Institute in 2002, was employed. Mann-Kendall diagrams were produced using an Excel macro, MankenDall, which was developed in 2017 at the Iran Meteorological Organization. Regression analysis and Pearson correlation coefficient calculations were performed using Microsoft Excel 2019 software. A 95% confidence level was used to determine the statistical significance of trends in monthly and annual relative humidity. A significance level below 0.05 indicates a statistically significant relationship unlikely to be due to chance, while a level above 0.05 suggests that the results are not statistically significant (Greenland et al., 2016).

2.2.1 Mann-Kendall test

The Mann-Kendall test is a widely used nonparametric method to detect the presence of a monotonic trend, either increasing or decreasing, in time series data without requiring the data to follow any specific distribution (Amini, 2020). The null hypothesis of the Mann-Kendall test assumes that no trend exists, whereas the alternative hypothesis supports a monotonic trend, either increasing or decreasing, over the study period (Dadashi Roudbari et al., 2016). The Mann-Kendall test is especially useful in environmental and climatological studies, such as analyzing relative humidity time series, due to its robustness to non-normal data distributions and its low sensitivity to abrupt changes or breaks in the data (Agbo et al., 2023). The S statistic of the Mann-Kendall test, indicating the difference between each observation and all subsequent observations, is calculated based on Eq. 1 (Yargholi, 2021).

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

Where, 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 (Yargholi, 2021).

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

The variance of S is determined using Eq. 3 (Ghodoosi et al., 2014).

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

Moreover, the standardized Z statistic is calculated using Eq. 4 (Ghodoosi et al., 2014).

$$Z = \begin{cases} \frac{S-1}{\sqrt{\mathrm{Var}(S)}} & \text{if} \quad S > 0 \\ 0 & \text{if} \quad S = 0 \\ \frac{S+1}{\sqrt{\mathrm{Var}(S)}} & \text{if} \quad S < 0 \end{cases} \tag{4}$$

The null hypothesis is accepted if $|Z| \leq Z_{\alpha/2}$ 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). If the Z value lies between -1.96 and +1.96, the trend in the time series is not statistically significant at the 0.05 confidence level. When the Z value exceeds +1.96, the time series trend is significantly increasing. Conversely, if the Z value is less than -1.96, the trend is significantly decreasing (Coccia and Roshani, 2024). The Mann-Kendall Jump Test, sometimes referred to as the sequential Mann-Kendall test or the Mann-Kendall Change Point Test, is a statistical method designed to detect abrupt changes or jumps in time series data. It is an extension of the general Mann-Kendall trend test, which assesses the overall direction of change, whether increasing or decreasing, in a time series. The purpose of the Jump Test is to identify the specific points in time where a statistically significant change in the trend occurs (Yue and Wang, 2004). 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 Liu and Xu (2016). A potential jump point, also known as a change point, is identified at the intersection of the two lines. For this intersection to be considered a statistically significant jump, it must occur beyond the critical value boundaries, which are set at ±1.96 (Baharvandi et al., 2021). Multiple intersections may occur, indicating the presence of several jump points. When the lines representing U_i and U'_i intersect beyond the critical value boundaries, this indicates a statistically significant change in the trend at that time. The intersection point corresponds to the estimated jump point. The direction of the jump can be deduced by analyzing the behavior of the U_i line before and after the intersection. For instance, if U_i is positive before the intersection and negative afterwards, this signifies a shift from an increasing trend to a decreasing trend, or vice versa. If no intersections occur outside the critical thresholds, then no statistically significant jump points are detected (Hasheminasab and Ataei, 2022).

2.2.2 Sen's Slope Estimator

Sen's Slope Estimator is a non-parametric method used to estimate the true slope of a linear trend in time series data (Abdullahi et al., 2023). This method was first introduced by Theil in 1950 and later developed by Sen in 1968 (Neeti and Eastman, 2011). For N pairs of data points in the time series, the slope between these two points was calculated using Eq. 5 (Dadashi Roudbari et al., 2016).

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

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 $N = n(n-1)/2$, where n is the number of time periods. If there are multiple observations in one or more time periods, then $N < n(n-1)/2$, 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).

$$Q_{med} = \begin{cases} Q_{\left(\frac{N+1}{2}\right)} & \text{if N is odd} \\ \frac{Q_{(N/2)} + Q_{(N+2/2)}}{2}, & \text{if N is even} \end{cases} \tag{6}$$

The sign of Q_{med} indicates the direction of the data trend, while its magnitude represents the steepness of the trend. To determine whether the median slope is statistically significantly different from zero, the confidence interval of Q_{med} should be calculated at a specified confidence level. This confidence interval for the time slope can be computed using Eqs. 7 and 8 (Minh et al., 2025; Da Silva et al., 2015).

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

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

Where, $Z_{(1-\alpha/2)}$ is obtained from the standard normal distribution table. The lower and upper limits of the confidence interval are Q_{min} and Q_{max}. The slope Q_{med} is statistically different than zero if the two limits (Q_{min} and Q_{max}) have similar signs (Da Silva et al., 2015).

2.2.3 Pearson correlation coefficient

The Pearson correlation coefficient, commonly denoted as r, is a statistical measure that quantifies the strength and direction of a linear relationship between two continuous variables. Its value ranges from -1 to 1. The Pearson correlation coefficient is calculated using Eq. 9 (Ahmadpari et al., 2018).

$$\mathrm{Corr}(X, Y) = \frac{\mathrm{Cov}(X,Y)}{\sigma_X \sigma_Y} \tag{9}$$

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

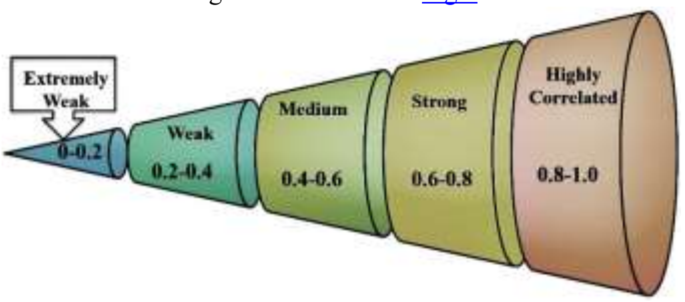


Fig. 2 Classification of Pearson correlation coefficient values by strength (Adapted from Jiang and Sun, 2025)

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 Eq. 10 (Obilor and Amadi, 2018).

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \quad (10)$$

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, where n is the number of observations (Obilor and Amadi, 2018). After calculating the test statistic t and the df, the p-value must be determined. The p-value, or probability value, is a statistical measure that helps researchers assess the significance of their experimental results. It represents the probability of obtaining the observed data, or something more extreme, assuming that the null hypothesis is true. The null hypothesis typically states that there is no effect or no difference within the context of the study. The p-value is calculated using Eq. 11 (Anderson et al., 2020).

$$P_{value} = \text{T. DIST.ZT(ABS(t),df)} \quad (11)$$

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

To assess the temporal trend in relative humidity, a simple linear regression approach was employed. This statistical method evaluates the linear association between a single independent variable (time) and a dependent variable (relative humidity). The model fits a straight line to the observed data, mathematically represented as Eq. 12 (Muhlbauer et al., 2019).

$$Y = a + bX \quad (12)$$

where Y denotes the dependent variable (relative humidity), X is the independent variable (time or year), a is the intercept, and b is the slope, reflecting the rate of change in relative humidity over the study period. The slope parameter b provides insight into the direction and magnitude of the trend. A positive value of b indicates an increasing trend, while a negative value signals a decrease. To determine if the observed trend was statistically significant, the p-value associated with the slope coefficient was checked. A p-value below the standard threshold (typically 0.05) suggests that the trend is unlikely to have occurred by random chance, confirming its significance in the population (Atılgan et al., 2017). All regression analyses were conducted using the Regression feature available in the Analysis ToolPak of Microsoft Excel 2019, which computes all model estimates and significance tests efficiently for large datasets. This methodological framework ensures reproducible and interpretable results when investigating climate trends using linear regression.

3. Results and Discussion

3.1 Monthly and annual relative humidity trends

3.1.1 Mann-Kendall test

The Mann-Kendall trend test was applied to analyze the temporal trends of relative humidity in the DDR basin over the period from 1998 to 2022. The analysis was conducted on a monthly basis as well as annually, using 25 years of data. Fig. 3 displays the results of the Mann–Kendall jump test performed on the monthly relative humidity for the DDR basin from 1998 to 2022.

The test statistics (Z values) for each month indicate varying trends in relative humidity. At the 5% significance level, the critical value for the Mann-Kendall test statistic is approximately ±1.96. Consequently, months with |Z| greater than 1.96 are considered to exhibit statistically significant trends. The results show that January exhibited a statistically significant decreasing trend in relative humidity (Z = -2.06), exceeding the 5% significance threshold (|Z| > 1.96). This suggests that over the 25 years, relative humidity in January has been consistently declining, possibly reflecting changes in winter atmospheric moisture patterns or reduced humidity inflow during this cold season. February showed a slight decreasing trend (Z = -0.37), but this trend is not statistically significant, indicating stability in relative humidity throughout this month. In March, a positive but non-significant trend (Z = 1.00) was identified, suggesting minor upward fluctuations that are insufficient to confirm a meaningful trend. Similarly, April displayed a positive yet insignificant trend (Z = 0.70), indicating no substantial change in relative humidity during the spring onset. May demonstrated a statistically significant increasing trend (Z = 2.18), signifying a steady rise in relative humidity over the study period. This pattern may be linked to spring-summer atmospheric dynamics contributing to enhanced moisture levels. The months of June (Z = 1.31) and August (Z = 0.54) showed positive, but statistically insignificant trends, implying minor increases in relative humidity without robust evidence of a long-term trend. July registered a weak negative trend (Z = -0.23), which is not significant, indicating stable humidity conditions in mid-summer. September and October exhibited decreasing but non-significant trends (Z = -0.79 and -0.91, respectively), indicating slight declines that do not reach statistical significance. Likewise, November (Z = -0.35) and December (Z = -0.49) showed minor negative trends, which remain statistically insignificant. The results of the Mann–Kendall jump test on the annual relative humidity for the DDR basin from 1998 to 2022 are shown in Fig. 4.

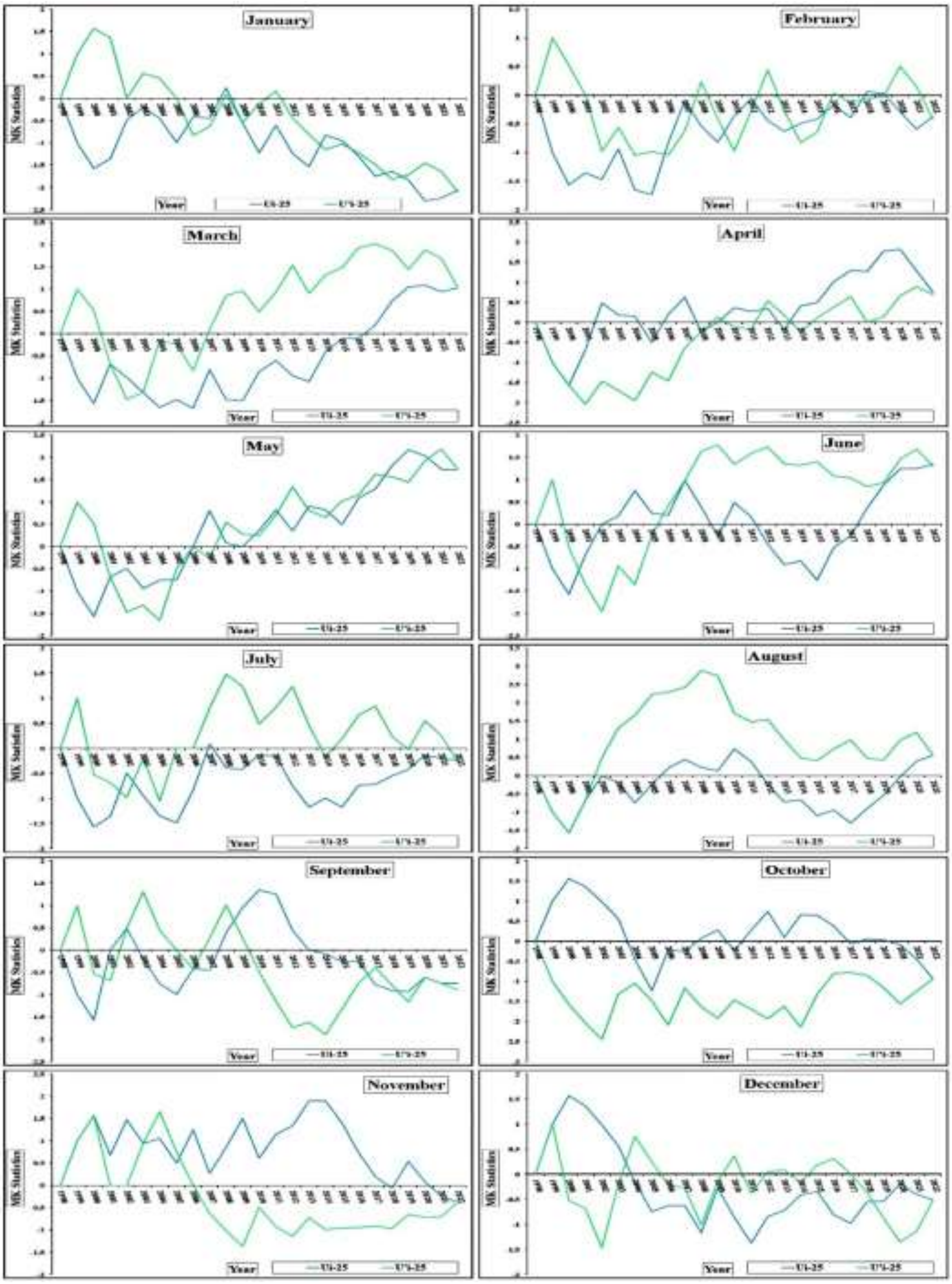


Fig. 3 Mann–Kendall jump test of monthly relative humidity time series data

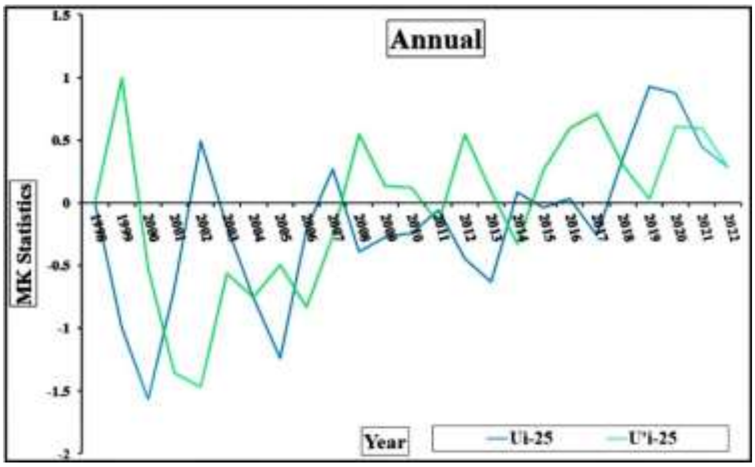


Fig. 4 Mann–Kendall jump test of annual relative humidity time series data

The annual analysis yields a Z value of 0.26, which falls within the nonsignificant range, indicating that the relative humidity remained relatively stable throughout the year, with no significant upward or downward trends. In summary, this trend analysis suggests that while the relative humidity in the DDR basin appears stable on an annual basis, significant seasonal fluctuations occur in January and May. These changes could have important implications for local hydrology, agriculture, and ecosystem dynamics and warrant further investigation, potentially incorporating other climatic variables and modeling approaches for a comprehensive understanding. Numerous investigations have assessed the temporal variability and trends of relative humidity across different climatic regions of Iran. For example, Gharekhani and Ghahreman (2010) applied the Mann-Kendall trend test along with Spearman's rho and regression analyses. Their results revealed significant seasonal trends, especially notable decreases in relative humidity during the winter and summer months. However, the overall annual relative humidity trend remained largely stable or exhibited only slight and statistically non-significant declines in many regions. Similarly, Eblaghian et al. (2019) showed no statistically significant long-term annual trends in relative humidity at most sites, despite the presence of some seasonal variations. These results indicate that relative humidity, as an integrative measure of atmospheric moisture, tends to maintain stability on an annual scale even when seasonal fluctuations occur. The apparent stability of annual relative humidity trends reported in these studies aligns well with the findings of the present study in the DDR basin, where significant trends were limited to January and May, while the overall annual trend remained stable. This consistency suggests that climatic or hydrometeorological factors may induce seasonal shifts in moisture conditions, yet the integrated annual moisture availability remains relatively constant throughout the observational period. Furthermore, similar results have been reported in studies outside Iran, which generally find that annual relative humidity remains broadly stable in most regions. Significant trends, whether increases or decreases, are more commonly observed at seasonal or monthly scales (Dunn et al., 2017; Shin et al., 2021; Jahan, 2024).

3.1.2 Sen's slope estimator

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

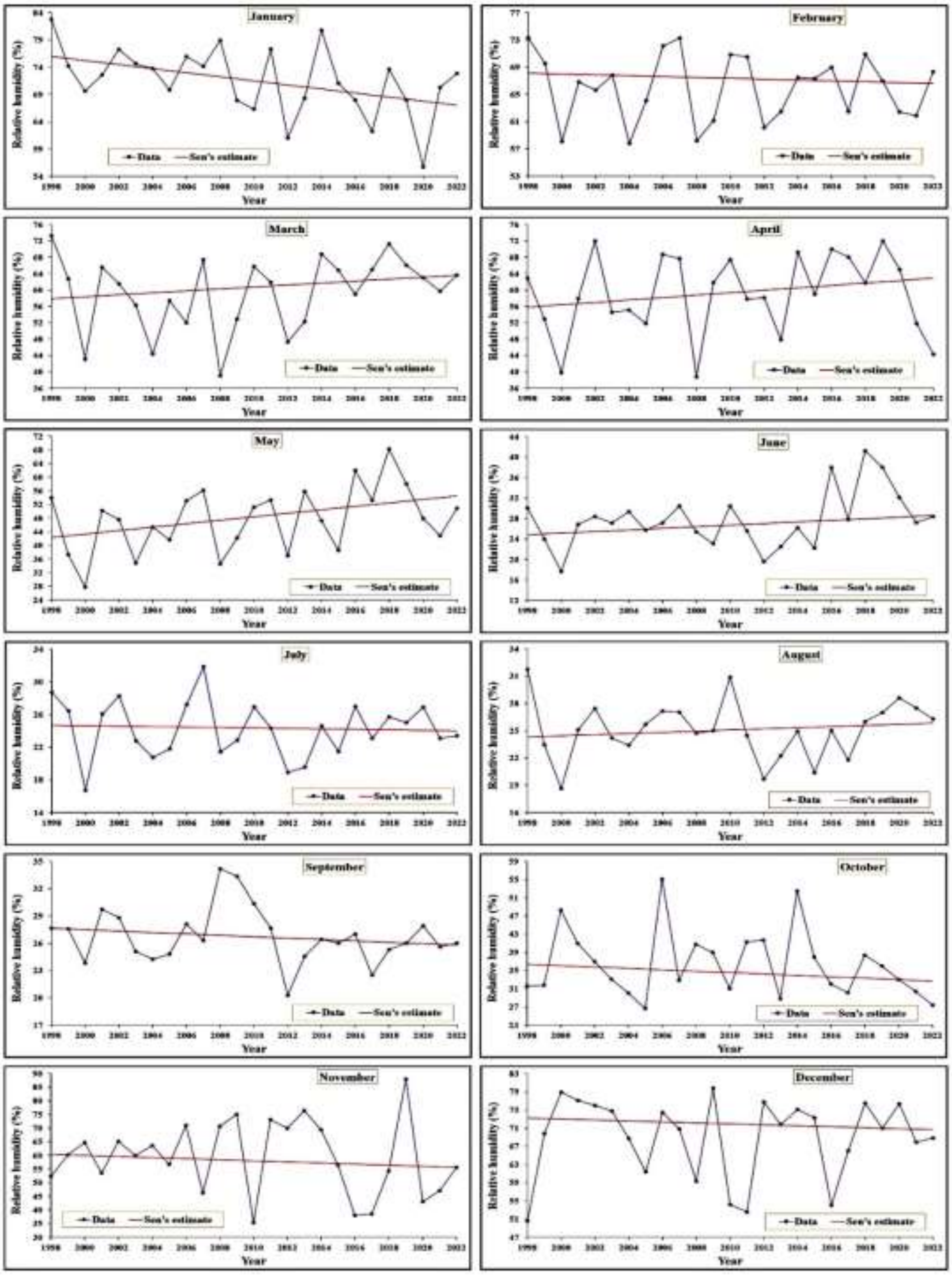
Table 1 Relative humidity trend analysis using the Sen's slope estimator test

Time series	Q_{med}	Q_{min}	Q_{max}	B	B_{min}	B_{max}
January	-0.37	-0.70	-0.02	75.99	72.65	80.06
February	-0.06	-0.34	0.26	68.13	62.89	69.87
March	0.24	-0.28	0.74	57.87	50.94	65.49
April	0.30	-0.40	0.73	55.78	50.90	63.67
May	0.51	0.42	0.60	42.31	34.78	48.83
June	0.16	-0.12	0.58	24.82	21.67	28.12
July	-0.03	-0.23	0.20	24.69	21.46	27.49
August	0.06	-0.17	0.19	24.32	22.95	26.90
September	-0.08	-0.21	0.09	27.64	25.06	29.65
October	-0.15	-0.65	0.18	36.38	32.15	43.63
November	-0.20	-0.99	0.87	60.40	55.44	69.49
December	-0.11	-0.53	0.38	73.21	66.80	78.64
Annual	0.01	-0.20	0.20	46.61	44.32	49.91

Table 1 revealed varying trends over time. A statistically significant increasing trend was observed in May, with a median Sen's slope of 0.51 and tight confidence bounds (0.42 to 0.60), indicating a clear rise in humidity during this month. Conversely, January showed a statistically significant decreasing trend, characterized by a median slope of -0.37 (confidence interval: -0.70 to -0.02). For all other months (February, March, April, June, July, August, September, October, November, and December), the Sen's median slopes, though sometimes positive or negative, were not statistically significant; their confidence intervals consistently encompassed zero. This indicates that despite slight directional tendencies, no conclusive increasing or decreasing trends could be established for these months over the study period. Fig. 5 and Fig. 6 show the fitting of Sen's line to the time series of monthly and annual relative humidity.

On an annual scale, the relative humidity in the DDR basin exhibited remarkable stability over the 25 years (Table 1 and Fig. 6). The calculated annual Sen's median slope was nearly zero (0.01), and its corresponding confidence interval (-0.20 to 0.20) clearly included zero. This result signifies that there is no statistically significant long-term trend in the overall annual relative humidity. The absence of a significant annual trend, coupled with the varied, and mostly non-significant, monthly trends, suggests that while some seasonal shifts in moisture may occur, the basin's climatic moisture regime has remained largely stable from 1998 to 2022. This stability is a key finding for regional climate assessment and informs water resource management strategies. The current study finds complete agreement between the Sen's slope estimator and the Mann-Kendall test results for detecting trends in relative humidity at both monthly and annual scales in the study basin. This consistency supports the robustness and validity of the trend assessments. Such concordance between these two non-parametric methods has been widely reported in climatological research (Sharma et al., 2016; Jiqin et al., 2023).

Fig. 5 Fitting the Sen's line on the monthly relative humidity time series data



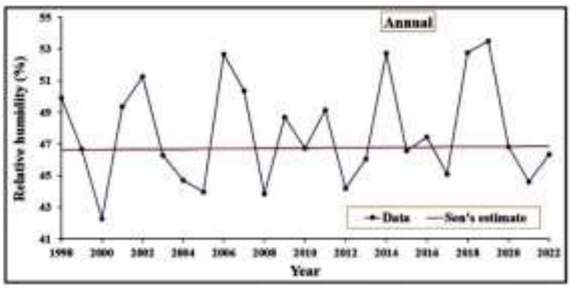


Fig. 6 Fitting the Sen's line on the annual relative humidity time series data

3.1.3 Pearson correlation coefficient

Table 2 presents the results of the relative humidity trend analysis for the DDR basin from 1998 to 2022 (25 years), using the Pearson correlation coefficient, on both monthly and annual scales. The monthly analysis reveals varying patterns of relative humidity trends throughout the year (Table 2). Based on the Pearson correlation coefficients and their statistical significance, January and May stand out as months exhibiting significant trends. In January, the relative humidity demonstrates a medium-strength negative correlation (r = -0.47, p = 0.02), indicating a statistically significant declining trend over the 25 years. This decline suggests potential seasonal climatic variations or changes in atmospheric moisture content during the winter months.

Table 2 Relative humidity trend analysis using the Pearson correlation coefficient

Time series	r	n	t	df	p-value	Significance level
January	-0.47	25	-2.54	23	0.02	Significant
February	-0.06	25	-0.27	23	0.79	Non-significant
March	0.23	25	1.14	23	0.27	Non-significant
April	0.15	25	0.74	23	0.47	Non-significant
May	0.40	25	2.07	23	0.05	Significant
June	0.38	25	1.96	23	0.06	Non-significant
July	-0.07	25	-0.33	23	0.74	Non-significant
August	0.03	25	0.15	23	0.89	Non-significant
September	-0.19	25	-0.94	23	0.36	Non-significant
October	-0.17	25	-0.82	23	0.42	Non-significant
November	-0.14	25	-0.66	23	0.52	Non-significant
December	0.03	25	0.14	23	0.89	Non-significant
Annual	0.07	25	0.33	23	0.74	Non-significant

Conversely, May exhibits a medium-strength positive correlation ($r = 0.40$, $p = 0.05$), signifying a statistically significant increasing trend in relative humidity. This increase during late spring could be attributed to shifts in local meteorological conditions, such as changes in precipitation patterns or evapotranspiration rates. Other months generally show weak or extremely weak correlations with non-significant p-values, implying no substantial temporal trends in relative humidity during those periods. For instance, February, March, April, June, July, August, September, October, November, and December all demonstrate either extremely weak or weak correlations without statistical significance. At the annual scale, the relative humidity trend in the DDR basin over the 25 years appears to be stable, with an extremely weak positive correlation coefficient ($r = 0.07$) that lacks statistical significance ($p = 0.74$). This indicates that, when aggregated over the entire year, relative humidity has not experienced any meaningful upward or downward trend during the study period. The results of this study demonstrate a strong agreement among the Mann–Kendall test, Sen's slope estimator, and Pearson correlation coefficient in analyzing the trends of relative humidity in the DDR basin during 1998–2022. Specifically, all three methods consistently identified statistically significant trends only in January and May, while trends in all other months and on an annual scale were found to be non-significant. This convergence of findings across different analytical techniques reinforces the reliability of the observed temporal patterns in relative humidity.

3.1.4 Regression analysis

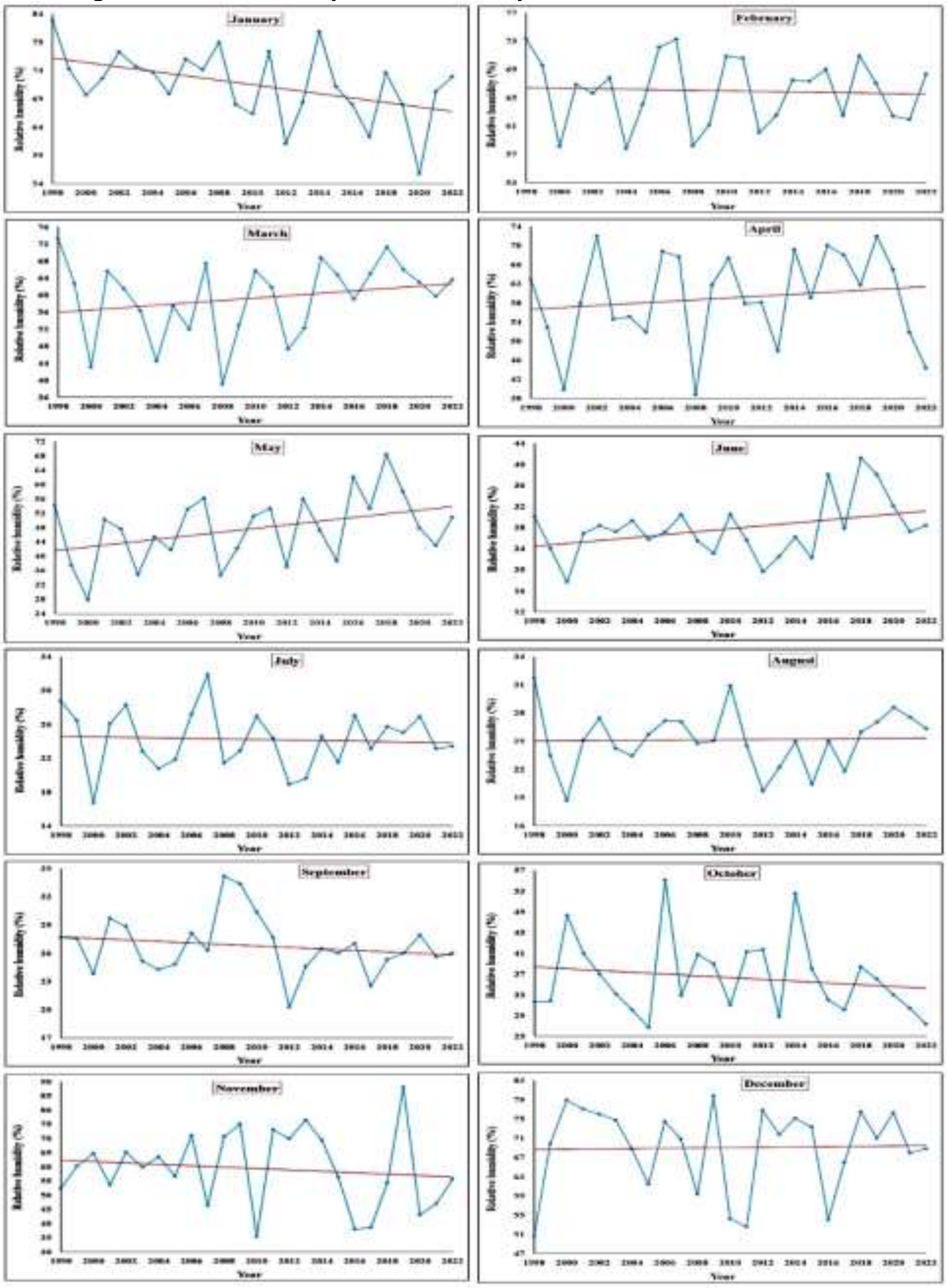
Table 3 presents the results of the relative humidity trend analysis for the DDR basin from 1998 to 2022 (a span of 25 years), using linear regression analysis on both monthly and annual scales.

Table 3 Results of relative humidity trend analysis using the linear regression analysis

Time series	a	b	p-value	Significance level
January	862.63	-0.39	0.02	Significant
February	140.84	-0.04	0.79	Non-significant
March	-505.53	0.28	0.27	Non-significant
April	-342.48	0.20	0.47	Non-significant
May	-981.27	0.51	0.05	Significant
June	-535.94	0.28	0.06	Non-significant
July	89.48	-0.03	0.74	Non-significant
August	-0.79	0.01	0.89	Non-significant
September	186.29	-0.08	0.36	Non-significant
October	380.25	-0.17	0.42	Non-significant
November	556.47	-0.25	0.52	Non-significant
December	1.45	0.03	0.89	Non-significant
Annual	-12.64	0.03	0.74	Non-significant

The linear regression analysis of relative humidity trends in the DDR basin from 1998 to 2022 reveals distinct seasonal behaviors (Table 3). On a monthly scale, the analysis identifies two months with statistically significant trends. January exhibits a significant decreasing trend, with a slope of -0.39 and a p-value of 0.02, indicating that relative humidity in this winter month has declined by approximately 0.39 percentage points annually over the 25-year period. Conversely, May shows a significant increasing trend, with a slope of 0.51 and a p-value of 0.05, reflecting a gradual rise in relative humidity by about 0.51 percentage points per year during late spring. These contrasting seasonal trends highlight changes in atmospheric moisture availability in different parts of the annual cycle. For the remaining months, the slopes fluctuate between -0.25 and 0.28 but lack statistical significance (p-values > 0.05), suggesting stable humidity conditions during most of the year. Fig. 7 and Fig. 8 show the fitting of the linear regression on the time series of monthly and annual relative humidity.

Fig. 7 Fitting the linear regression on the monthly relative humidity time series data



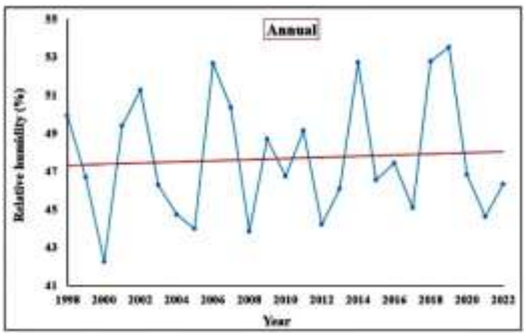


Fig. 8 Fitting the linear regression on the annual relative humidity time series data

The annual scale analysis of relative humidity trends in the DDR basin from 1998 to 2022 reveals no statistically significant change over the 25-year period. This is indicated by a very low slope value of 0.03 and a high p-value of 0.74 (Table 3 and Fig. 8). This suggests that, despite seasonal fluctuations, the overall moisture content aggregated across the year has remained relatively stable. Furthermore, the negligible annual change suggests that factors influencing relative humidity, such as temperature, precipitation, and atmospheric circulation patterns, have not caused consistent year-round shifts over the study timeframe. The remarkable agreement between the parametric linear regression and the non-parametric Sen's slope estimator in quantifying the magnitude and direction of relative humidity trends in the DDR basin significantly strengthens the credibility of the results. Both methods consistently identify significant decreasing and increasing trends in January and May, respectively, while showing negligible and non-significant trends during other months and at the annual scale. This strong concordance indicates that the observed seasonal trends are robust and unlikely to be artifacts of the statistical approach used. Moreover, the alignment between these methods underscores the value of Sen's slope estimator as a complementary tool to linear regression, particularly in environmental data contexts where assumptions of linearity or normality may be violated. Together, these findings enhance confidence in the reliability of the detected relative humidity changes and support their interpretation as genuine climatic signals rather than methodological anomalies. All trend analysis results obtained from the Mann-Kendall test, Sen's slope estimator, Pearson correlation coefficient, and linear regression are fully consistent with each other in assessing relative humidity variations in the DDR basin. This agreement across multiple statistical approaches strengthens the robustness and reliability of the detected trends. Similarly, previous studies in Iran, such as Hosseinzadeh Talaee et al. (2012), have reported close agreement between parametric and non-parametric trend analysis methods in assessing relative humidity. Hosseinzadeh Talaee et al. (2012) applied parametric linear regression and non-parametric Mann–Kendall tests to detect annual and seasonal trends in relative humidity at ten coastal weather stations in Iran during 1966–2005. The results showed that the differences between the parametric and non-parametric tests were small, although the parametric test identified larger significant trends in the relative humidity time series. Furthermore, these differences were not related to the normality of the statistical distribution.

Conclusion

In this study, the trend analysis of monthly and annual relative humidity was performed using the Mann-Kendall test, Sen's slope estimator, Pearson correlation coefficient, and linear regression in the Darreh Dozdan River Basin from 1998 to 2022. The most important results of this study can be stated as follows.

1. The annual trend analysis of relative humidity in the DDR basin from 1998 to 2022, based on the Mann–Kendall test, Sen's slope estimator, linear regression, and Pearson correlation coefficient, indicates no statistically significant change over the study period, demonstrating overall stability in yearly relative humidity levels.

2. January and May exhibited statistically significant trends in relative humidity over the 1998–2022 period in the DDR basin, with January showing a significant decreasing trend and May a significant increasing trend, indicating notable seasonal shifts in atmospheric moisture.

3. All other months displayed no statistically significant trends in relative humidity, suggesting overall stability in the monthly relative humidity regime of the DDR basin throughout the study period.

4. The findings obtained from both parametric methods, including linear regression and Pearson correlation coefficient, and nonparametric methods, such as the Mann–Kendall test and Sen's slope estimator, used to analyze monthly and annual relative humidity trends, exhibit strong consistency.

Although all four methods produced consistent results, the Mann–Kendall test combined with Sen's slope estimator was selected as the most appropriate approach because it reliably detects trends in monthly and annual relative humidity without assuming normality and is less sensitive to outliers, whereas linear regression and Pearson correlation may be biased by non-normal or seasonal data from a single station. One notable limitation of this study is the reliance on data from a single synoptic station within the Darreh Dozdan River Basin which, although providing a valuable 25-year record, limits the spatial representativeness of the analysis. Including additional synoptic stations with longer and more comprehensive datasets would enhance the robustness and spatial coverage of relative humidity trend assessments across the basin. From a practical standpoint, the observed seasonal changes, especially the significant decline in January and the increase in May relative humidity, have implications for water resource management and agriculture. It is recommended that local decision-makers incorporate these seasonal humidity variations into irrigation scheduling, crop selection, and drought preparedness planning. Such considerations can improve agricultural resilience and optimize water use in the basin. Future research should aim to integrate other climatic variables such as temperature, precipitation, and wind patterns to provide a more comprehensive understanding of regional atmospheric dynamics.

Statements and Declarations

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Data availability

The data used (or generated) in this research are provided within the text of the article.

Conflicts of interest

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

Author contribution

H. Ahmadpari: Data Collection, Data Analysis, Investigation, Methodology, Resources, Software, Writing – original draft, Writing – review and editing; V. Khaustov: Conceptualization, Validation, Supervision, Writing – review and editing; A. Amini: Data curation, Investigation, Methodology, Resources, Software, Writing – original draft, Writing – review and editing.

AI Use Declaration

In this study, the Napkin tool from the "https://www.napkin.ai/" website was used to draw Fig. 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://www.perplexity.ai/" 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.

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