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Analysis of Trend and Detection of Change Points in Lake Urmia Level and Climatological Parameters Using R Software

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Abstract
In recent decade, there has been a substantial reduction in the water level of Lake Urmia. Understanding the underlying causes and pivotal moments of these changes, always have importance in environmental and water resources studies. This study aims to analyze the water level fluctuation, the climatic parameters trends and their interrelationship in Lake Urmia Basin. The data were collected from Urmia airport synoptic station and over 50 years, from 1973 to 2022 on a monthly and annual scale. For trend analysis, the Mann-Kendall, seasonal Mann-Kendall, and correlated seasonal Mann-Kendall tests and for change detection, Standard Normal Homogeneity Test (SNHT), Pettitt's test, the Buishand range test, and U Buishand test, were used. The results of study showed that, the maximum and average temperatures time series showing an increasing trend and the minimum relative humidity demonstrating a decreasing trend. Also, a significant decreasing trend was observed in the lake's water level during this period. Change point tests identified the years 1999 to 2001 as the turning point for the lake's water level, and for other parameters, change points were in the 1990s on both annual and seasonal scales. Furthermore, the lake's water level exhibited different behaviors before and after the change points. The results of this study, indicates a major climate change in the Lake Urmia catchment since year 2000, resulting water level decrease and dry up in this lake.
Keywords: Change point test, Precipitation, Relative humidity, Temperature, Water level fluctuation.

1. Introduction

Lakes serve as valuable indicators connecting the atmosphere, biosphere, pedosphere, and hydrosphere, contributing to global/local water cycles and energy exchange (Wang et al., 2024). They provide important insights for examining any changes within their watersheds due to human activities and climatic variations (Adrian et al., 2009). Lake-level changes serve as key indicators of climatic variations and play a crucial role in the lake's biological system, reflecting energy balance and water loss (Tan et al., 2017; Zhang et al., 2019). Water level fluctuations in lakes are influenced by incoming and outgoing runoff, direct precipitation, and changes in groundwater flow, which contribute to maintaining water balance in the lake (Şen et al., 1999; Demir and Keskin, 2020; Demir, 2022). Therefore, understanding and analyzing water level fluctuations and the factors affecting lake level changes, including human activities and climate variations, can lead to a different perspective on water resource management.

Lake Urmia, as an endorheic Salt Lake, is a closed basin with evaporation being its only outflow (UNEP, 2012). In recent decades, natural and human interventions have caused a significant decline in the water level of Lake Urmia. As one of the three largest saltwater lakes in the world, its area has decreased approximately 70 to 88%, causing environmental challenges in the region (Garousi et al., 2013; AghaKouchak et al., 2015). Nearly 65% of the lake's water comes from rivers originating from the southern basins of Lake Urmia. A substantial loss of approximately 30 billion cubic meters of water has led to a significant reduction in the lake's water level (Shirmohammadi et al., 2024). These changes in water body and water area of Lake Urmia, are shown in fig.1.

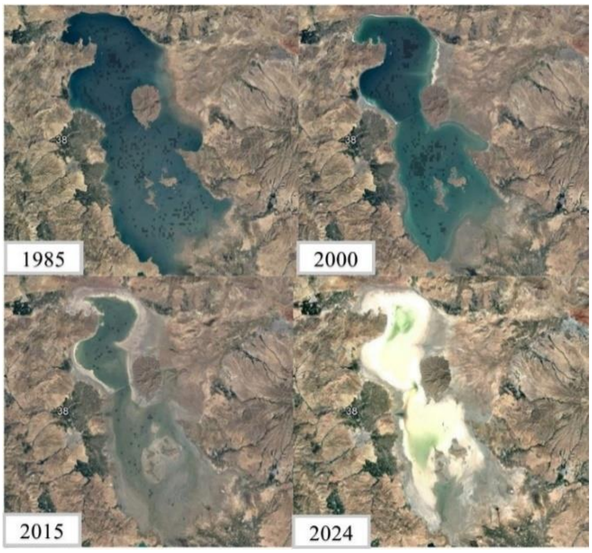

Fig.1. changes of Lake Urmia from 1990 to 2020

Lake Urmia's water level fluctuation has been studied by numerous researchers. According to these studies, the water loss in the lake, began in the mid-1990s and accelerated after 2000 (Eimanifar and Mohebbi, 2007; Kakahaji et al., 2013; Nezammahalleh and Ghadimi, 2015; Soudi et al., 2017; Bashirian et al., 2021). Furthermore, Dastaranj et al. (2018) showed, the lake's water area decreased about one-eighths from 1976 to 2015. Also, the water level and water volume of the lake decreased respectively 4 meters and 9.7 billion cubic meters, from 2002 to 2015, According to Hasanzadeh et al. (2012), the construction of dams, changes in precipitation, and increase in surface water extraction have contributed respectively 25%, 10% and 65% to Lake Urmia's drying up.

An analysis of daily precipitation over 30 years (1981 to 2011) in the Lake Urmia basin revealed significant changes in 1996 and 1999 years, leading to reduced runoff and subsequently decreased water inflow to the lake (Salehi Bavil et al., 2018). Similarly, in Nazeri Tahroudi et al. (2019), a change point was observed in the precipitation time series from 1984 and 2013 between the years 1992 and 1998.

Mehrian et al. (2016) utilized variations in the lake area, monthly precipitation, and average temperatures at synoptic stations in the Lake Urmia basin to demonstrate that extensive agricultural water usage in the basin was the primary factor contributing to the lake's drying trend, rather than precipitation and temperature parameters.

The discharge trend at 26 hydrometric stations in the Lake Urmia basin from 1984 to 2013, analyzed using the modified Mann-Kendall non-parametric test (MMK) by Nazeri Tahroudi et al. (2018a), showed an annual decreasing trend. The change in the decreasing trend was further highlighted using the Pettitt method between 1994 and 1998. In this study, a decreasing trend in the water level of Lake Urmia occurred one year after a decreasing trend in the flow data. Additionally, the study by Fathian et al. (2016) confirms the greater sensitivity of the river flow in the Lake Urmia watershed to temperature changes compared to precipitation.

This study aims to investigate and scrutinize a 50-year time series dataset encompassing the monthly and yearly fluctuations in the water levels of Lake Urmia, alongside the data from the synoptic station located at Urmia airport. Employing two stage methodology for time series analysis, the first stage of inquiry is directed towards detecting prevailing trends within the dataset. Subsequently, the second approach is dedicated to the detection and examination of change points within these time series. The two methods for analyzing seasonal trends, which include the seasonal Sen Slope Estimator and the correlated seasonal Mann-Kendall test, appear to have been applied for the first time in the context of the Urmia Lake watershed in this study.

2. Materials and Methods

2.1. Study area

Lake Urmia is located in northwestern Iran, approximately between 45- and 46-degrees east longitude and 37 to 38 degrees of north latitude. The geographical location of Lake Urmia, based on its water volume in the year 2000, is illustrated in Figure (2) (Nhu et al., 2020). The geographic coordinates of the Urmia airport synoptic station are also listed in table 1.

Table 2 demonstrates the statistical characteristics of the studied climatic parameters. The Lake Urmia's monthly water level fluctuations is showed in figure 3, and the annual changes of the other climatic parameters were indicated in Figure 4.

In this study, the lake level data of Lake Urmia and the synoptic station at Urmia airport for the period of 1973 to 2022 were collected from the West Azerbaijan Water Organization and the West Azerbaijan Meteorological Organization. The data was organized on a monthly scale in Excel software. The non-parametric Mann-Kendall test (MK), seasonal Mann-Kendall (SMK), and Correlated seasonal Mann-Kendall tests (CSMK) were used to analyze the trend. Additionally, change point determination was carried out using the Standard Homogeneity Test (SNHT), Pettitt test, Buishand Range Test (BHR), and Buishand U Test (BHU). All of the analysis was done by the RStudio software and R programming language. In the following sections, the used tests and the statistical methods were provided along with the calculations and methodology.

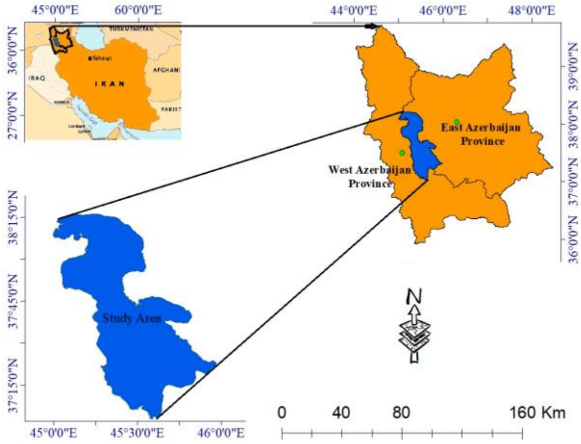

Fig. 2. The position of Lake Urmia based on its water volume in 2000

Table 1. The geographic coordinates of the Urmia Airport station

Elevation of the station	Latitude	Longitude
1335	37 N	45 E

Table 2. The annual statistics of the studied parameters from 1973 to 2022.

Parameter	Mean	Standard Deviation	Skewness	Kurtosis	Max	Min	Variance
Lake Urmia's Water Level (m)	1274.39	2.39	-1.31	-0.39	1277.94	1270.39	5.72
Precipitation (mm)	318.12	90.94	0.36	0.74	562.61	167.24	8269.97
Minimum relative humidity (%)	39.62	3.1	0.7	0.35	49.38	33.41	9.61
Mean temperature (˚C)	11.26	0.94	0.55	-0.43	13.18	8.63	0.88
Max temperature (˚C)	17.91	1.26	0.08	-0.16	20.75	14.79	1.59

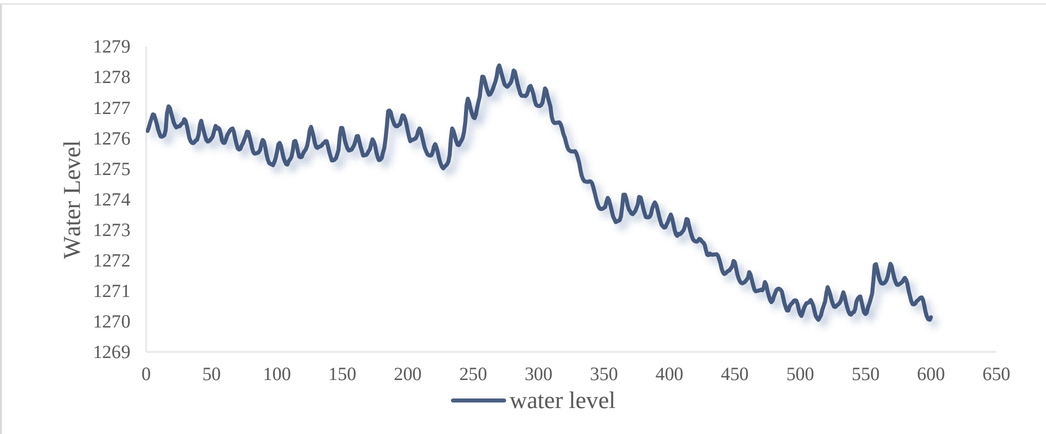

Fig. 3. Chart of water level changes in Lake Urmia from 1973 to 2022 (monthly)

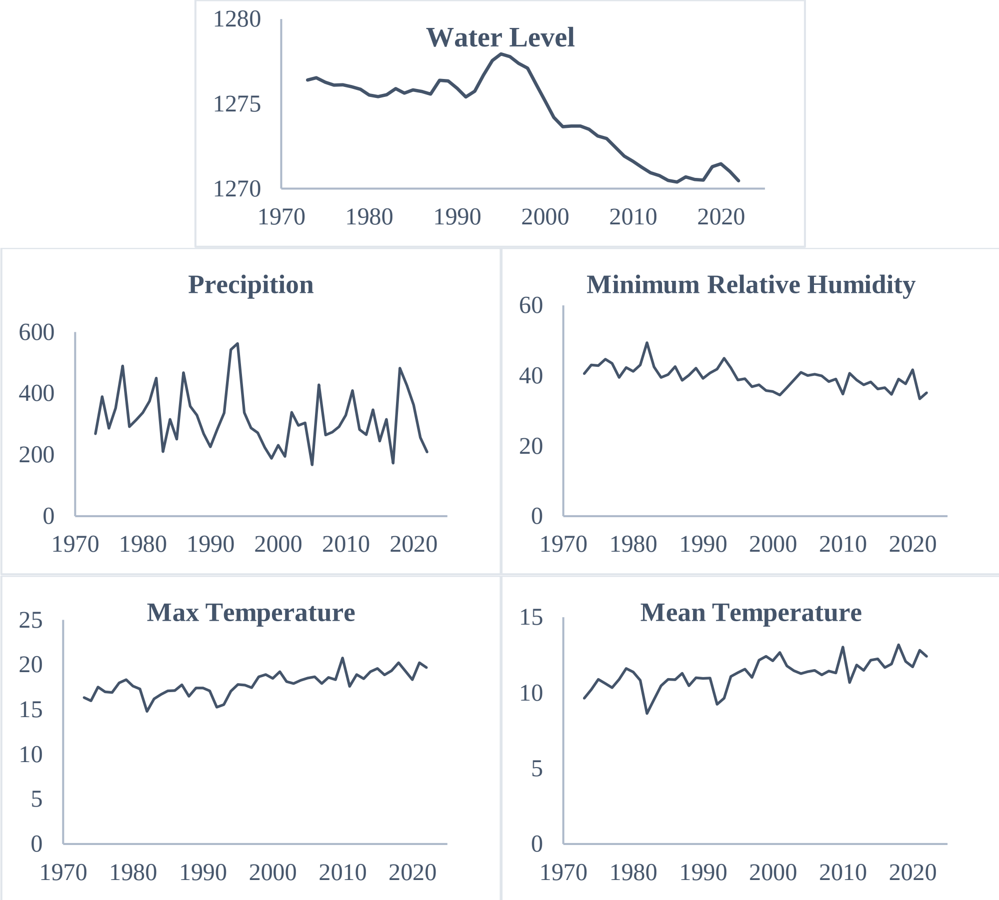

Fig. 4. Long-term changes in the study parameters (annual) over 50 years

2.2. Mann-Kendall test

The Mann-Kendall test is a non-parametric technique (Mann, 1945; Kendall, 1957; Gilbert, 1987) used for trend analysis and is particularly applicable for time series data that do not need to conform to a specific distribution (Halios et al., 2011; Deka, 2021). This test is a specific case of the Kendall test aimed at trend detection, which involves two variables: time and a sequence of observations. This test is based on the rankings of the data. It does not consider the actual values of the data, making it suitable for data with skewness. The null hypothesis of this test assumes randomness in the data (absence of trend) .If $x_1, x_2, \ldots, x_n$ represent the observed data, and x_i and x_k represent the observed data at times j and k, then the Mann-Kendall statistic (S) is calculated using the following equation:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} \mathrm{sng}(x_j - x_k) \tag{1}$$

$$\mathrm{sng}(x_j - x_k) = \begin{Bmatrix} +1 & \text{if} & (x_j - x_k) > 0 \\ 0 & \text{if} & (x_j - x_k) = 0 \\ -1 & \text{if} & (x_j - x_k) < 0 \end{Bmatrix} \tag{2}$$

where $sgn(x)$ is the sign function and n is the number of observations. The variance S is computed by the following equation:

$$\mathrm{VAR}(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{g} t_i(t_i - 1)(2t_i + 5)\right] \tag{3}$$

where n is the number of observations, g is the number of tied groups, and t_p is the number of data in the $p-th$ tied group. The test statistic Z for assessing the significance of the trend is derived as follows:

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

This test is two-tailed. Therefore, if $|Z| < Z\alpha/_2$ the null hypothesis is accepted at the confidence level α; otherwise, the null hypothesis will be rejected, indicating the presence of a trend.

2.3. Seasonal Mann-Kendall test

Data may undergo variations with changing seasons throughout the year. This seasonal component needs to be removed before conducting the test statistic calculation, as otherwise, the power of the Mann-Kendall test to detect the presence of a trend decreases (Abebe, 2016). For time series data with a seasonal pattern, the seasonal Mann-Kendall test is utilized as a non-parametric test (Jaber et al., 2023). This test was extended by Hirsch et al. (1982) to calculate the Mann-Kendall test for each season separately (Si) and ultimately compute the seasonality.

2.4. Correlated seasonal Mann-Kendall test

When there is a dependency structure between the seasons of a time series with a seasonal pattern, the Mann-Kendall test statistics are initially calculated separately for each season. Then, the variance-covariance matrix is computed based on Libiseller and Grimvall (2002), and finally, the value of the Z statistic for the entire time series of interest is obtained as follows:

$$z = \frac{1^{\Gamma} S}{\sqrt{1^{\Gamma} \Gamma 1}} \quad (5)$$

The place where z denotes the quantile normal distributions, 1 is a vector with all elements equal to one, S is a vector of Mann-Kendall values for each season, and Γ represents the variance-covariance matrix.

The general hypothesis of the CSMK test is as follows:

H0: The data are independent and identically distributed in each season.

H1: There is at least one season where a uniform trend exists

2.5. Change point

Change points are sudden alterations in the data of a time series resulting from the presence of shifts that may occur between states. Detecting these points in the modeling and forecasting of time series is useful and is found in various fields such as medical condition monitoring, weather change detection, speech and image analysis, and human activity analysis (Aminikhanghahi and Cook, 2017).

The detection of change points in the water level time series of Lake Urmia and the relevant climatic parameters at the Urmia synoptic airport station is performed for each monthly (and seasonal) series using four change point tests: the Standard Normal Homogeneity Test (SNHT), the Pettitt test, the Buishand Range (BR) test, and the Buishand U (BU) test. A brief explanation of these tests is provided below.

a) Standard Normal Homogeneity Test (SNHT)

A homogenization technique based on the Standard Normal Homogeneity Test (SNHT), developed by Alexandersson (1986), is employed. In this test, the statistic Tk is defined as follows for comparing the mean of the first k years with the last (n-k) years:

$$T(k) = k\bar{z}_1{}^2 + (n-k)z_2{}^2 \quad (6)$$

where:

$$\bar{z}_1 = \frac{1}{k}\frac{\sum_{i=1}^{k}(Y_i - \bar{Y})}{\sigma} \quad (7)$$

$$\bar{z}_2 = \frac{1}{n-k}\frac{\sum_{i=k+1}^{n}(Y_i - \bar{Y})}{\sigma} \quad (8)$$

$\bar{Y}$ is the mean,

σ is the standard deviation,

k is the year where the max value of T is reached and is considered the break year.

$$T_0 = \max(T(k)) \text{ for } 1 \le k \le n \quad (9)$$

If the value of T_k exceeds a certain threshold, depending on the sample size, the null hypothesis is rejected.

b) Pettitt test

The Pettitt test is a non-parametric test developed by Pettitt (1979) for assessing sudden changes and the likelihood of interruption in the time series data of climate parameters. The benefit of this test lies in its sensitivity to detecting changes occurring anywhere within a time series (Jaiswal et al., 2015). It can identify a significant change in the mean of a time series even when the exact time of the change is uncertain (Chakraborty et al., 2017). The test is based on the ranks, r_i, of Y_i and disregards the normality of the series. It identifies a change at year k, where:

$$X_y = 2\sum_{i=1}^{y} r_i - y(n+1), \quad y = 1,2,\dots,n \quad (10)$$

A breakpoint occurs in year k, such that:

$$X_k = max|X_y| \quad for\ 1 \le y \le n \quad (11)$$

The test statistic is then compared with the critical value according to Pettitt (1979)

c) Buishand test

Buishand (1982) developed the Buishand test aiming to detect changes in the mean by studying the cumulative deviations from the mean average. The null hypothesis assumes that the data is homogeneous and normally distributed, while the alternative hypothesis posits the historical existence in the time series where the mean changes (Akadeniz et al., 2016). The partially adjusted sum is defined as:

$$S_0^* = 0;\ S_k^* = \sum_{i=1}^{k} (X_i - \bar{X}),\quad k = 1,2,\dots,N \tag{12}$$

where $\bar{X}$: is the mean of the time series observations.

k: is the number of observations where a break occurs.

The partially adjusted sum is then divided by the sample standard deviation to obtain the adjusted sum:

$$S_k^{**} = \frac{S_k^*}{D_x},\quad k = 1,2,\dots,N \tag{13}$$

$$D_x = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N}} \tag{14}$$

The Buishand test statistics are calculated using the Buishand U Test and the Buishand Range Test:

A) Buishand U test:

$$U = \frac{1}{n(n+1)} \sum_{k=1}^{n-1} \left(\frac{S_k^*}{D_x}\right)^2 \tag{15}$$

B) Buishand range test:

$$R = \frac{(\max S_k^* - \min S_k^*)}{\sigma} \tag{16}$$

3. Results and Discussion

3.1. Trend Analysis

Monthly Time series:

Changes in water level values in Lake Urmia and climatic parameters during the statistical period from 1973 to 2022 are presented in Table 3. According to Table 3, the water level at the monthly scale shows a significant decreasing trend using both the Mann-Kendall test and the Sen Slope Estimator across all months. Based on the Mann-Kendall test, the Kendall's Z statistic for the water level was estimated to be approximately -6.2, while the Sen Slope Estimator indicates a slope of between -0.13 and -0.14 at the monthly scale, meaning that the water level decreases by approximately 0.13 to 0.14 meters each month. For the parameter of minimum relative humidity, both methods indicate a downward trend, except for the month of December, where the Mann-Kendall Z statistic equals 0.73 and the Sen Slope is 0.05, indicating an increase in minimum relative humidity for that month. Additionally, in October and November, the Kendall Z values are -0.83 and -0.51, respectively, suggesting a downward trend that is not statistically significant; the Sen Slope Estimator values for these two months are -0.05 and -0.04, respectively, indicating a decrease.

For the parameters of average temperature and maximum temperature, the overall trend was estimated to be upward by both the Sen Slope Estimator and the Mann-Kendall test, with Kendall Z values exceeding +1.96, indicating a statistically significant upward trend. However, in September, November, and December for maximum temperature, as well as in January, October, November, and December for average temperature, the calculated Kendall Z values were below +1.96 at a 95% confidence level, indicating that the upward trends in these months are not statistically significant.

In the parameter of precipitation, the results from the two methods were inconsistent in certain months. For instance, in May, the Mann-Kendall Z statistic was estimated at -1.67, indicating a downward trend that is not statistically significant (-1.67 > -1.96). However, the slope of the trend line for this month was -0.42, indicating a severe decreasing trend.Annual Time Series:

Comparing the Sen's slope and Z_Kendall statistic in the annual scale showed similar performance for the lake level and minimum relative humidity parameters, while other parameters exhibited different performance for these two methods. Especially in the precipitation parameter on annual scale, where the Z_Kendall value was -1.24 and the Sen's slope value was -1.07, indicating a high Sen's slope value at a 95% confidence level (Table 3).

Seasonal Time Series:

The seasonal Mann-Kendall and seasonal autocorrelated Mann-Kendall tests, along with the seasonal Sen Slope Estimator, were employed for the seasonal time series. The Kendall Z statistic for the water level, without considering the correlation between months, was estimated at -21.53 based on the seasonal Mann-Kendall test. In contrast, when taking this correlation into account, the autocorrelated seasonal Mann-Kendall test yielded a Kendall Z of -6.28, while the seasonal Sen Slope Estimator for the water level was estimated at -0.14, indicating that the water level decreases by -0.14 in each seasonal series present in the time series data. For the precipitation parameter, the Mann-Kendall Z statistic was -1.28 based on the seasonal Mann-Kendall test and -1.08 based on the autocorrelated seasonal Mann-Kendall test, with the seasonal slope being -3.3e-3, showing a downward trend in precipitation that is not statistically significant.

Trends in both maximum and average temperatures were reflected in Mann-Kendall Z values from the seasonal Mann-Kendall test equal to 10.97 and 9.44, respectively, without considering the correlation between months. However, accounting for correlation, the values for the autocorrelated seasonal Mann-Kendall test were 5.5 for maximum temperature and 4.93 for average temperature, with both methods indicating a statistically significant upward trend. Additionally, the seasonal Sen Slope Estimator provided slope values of 0.06 and 0.04 for maximum and average temperatures, respectively, indicating increases in temperature for each season. For the minimum relative humidity parameter, the estimated Kendall Z values for the seasonal Mann-Kendall and autocorrelated seasonal Mann-Kendall tests were -7.88 and -4.62, respectively. According to the Sen Slope Estimator, the seasonal slope for this parameter was estimated at -0.14, indicating a decrease in each season.

Comparison of Seasonal and Annual Time Series:

Comparisons between the annual and seasonal time series using the Mann-Kendall test for the annual series and the seasonal Mann-Kendall test for the seasonal series revealed different trends in terms of the intensity of descending or ascending trends for the studied parameters. However, in the correlated seasonal time series, the Correlated Seasonal Mann-Kendall test, by creating a correlation between the desired seasons, exhibited similar statistical Z_Kendall values to the annual time series in all parameters, with minor differences (Table 3).

The Correlated Seasonal Mann-Kendall test, considering the inter-seasonal structure of the time series, shows a decreasing trend in the data of Lake Urmia's water level and minimum relative humidity, and an increasing trend in the maximum temperature and average temperature, as well as a consistent trend in the precipitation time series. These results indicate the test’s adherence to the trends of each season and demonstrate the overall seasonal trend by linking the seasons to each other. However, the Seasonal Mann-Kendall test combines the results of each season.

3.2. Tau-Kendall results

Given that the Tau-Kendall values for the precipitation parameter are close to zero, it indicates a weak correlation among the data for this parameter. In contrast, the correlation for the water level parameter, with a Tau-Kendall value greater than +0.5, is stronger and exhibits a decreasing trend. For average temperature, maximum temperature, and minimum relative humidity, the Tau values on a seasonal scale range from 0.22 to 0.31, indicating a moderate correlation for these parameters. However, this correlation is stronger at the annual scale.

3.3. Change points

Table 4 provides an overview of the fluctuation in the water level of Lake Urmia, depicting changes both on a monthly and annual basis. The Pettitt method identifies the years 1999 and 2000 as pivotal moments, whereas the SNHT, BHR, and BHU methods pinpoint the years 2000 and 2001 as significant turning points.

Moving onto Table 5, delves into the alterations in precipitation parameters, revealing discrepancies in change occurrences on a monthly scale, yet all four methods unanimously identify the year 1995 as the pivotal year for change on an annual scale.

Tables 6 and 7 highlight the shifts in average temperature and maximum temperature parameters.

These tables showcase varying change timelines on a monthly scale, with all methods concurring on the years 1994 and 1997 as significant points of change on an annual scale, respectively.

Table 8 presents the significant shifts in the minimum relative humidity, a parameter that exerts a notable influence on the evaporation rate. This particular parameter has been observed to undergo variations at different junctures across various years when examined on a monthly scale.

Furthermore, upon evaluating the data on an annual scale, it becomes evident that the year 1994 emerges as the pivotal point signifying a substantive alteration in the minimum relative humidity as it pertains to the evaporation process.

Based on Table 9, seasonal change points on a monthly scale indicate sudden changes in the climate parameters and the water level of Lake Urmia in the years 2000 and 2001. Except for the average temperature, which, using the Standard Homogeneity Test, attributes the change point to the year 1973, other methods have identified the year 1998 as the year of change for this parameter. Furthermore, the beginning of the study period creates greater sensitivity in the SNHT method, whereas the other tests exhibit more accuracy in the middle of the time series.

Table 3. The results of the Mann-Kendall test, seasonal Mann-Kendall test, correlated seasonal Mann-Kendall test, and Sen's slope estimator

Month	Lake Urmia's Water Level			Max temperature			Minimum relative humidity		
	Z-Kendall[1]	Tau-Kendall[2]	Sen's Slope[3]	Z-Kendall	Tau-Kendall	Sen's Slope	Z-Kendall	Tau-Kendall	Sen's Slope
January	-6.12	-0.60	-0.13	2.46	0.24	0.07	-2.66	-0.26	-0.18
February	-6.22	-0.61	-0.13	3.93	0.38	0.11	-3.99	-0.39	-0.29
March	-6.07	-0.59	-0.13	3.63	0.36	0.10	-3.53	-0.35	-0.23
April	-6.21	-0.61	-0.13	3.35	0.33	0.07	-2.55	-0.25	-0.15
May	-6.17	-0.60	-0.14	3.95	0.39	0.07	-2.61	-0.26	-0.17
June	-6.17	-0.60	-0.14	5.08	0.50	0.09	-3.40	-0.33	-0.17
July	-6.22	-0.61	-0.14	3.40	0.33	0.06	-2.09	-0.20	-0.10
August	-6.22	-0.61	-0.14	3.74	0.37	0.06	-3.26	-0.32	-0.15
September	-6.19	-0.60	-0.14	0.57	0.35	0.05	-2.51	-0.25	-0.12
October	-6.26	-0.61	-0.14	3.28	0.32	0.06	-0.83	-0.08	-0.05
November	-6.29	-0.61	-0.14	0.78	0.08	0.01	-0.51	-0.05	-0.04
December	-6.33	-0.62	-0.14	0.75	0.07	0.02	0.73	0.07	0.05
Annual	-6.22	-0.61	-0.14	6.02	0.59	0.06	-5.00	-0.49	-0.14
Seasonal	-21.53[4]	-0.61	-0.14[5]	10.97	0.31	0.06	-7.88	-0.22	-0.14
C.Seasonal[6]	-6.28			5.50			-4.62		

Month	Precipitation			Mean temperature		
	Z- Kendall	Tau-Kendall	Sen's Slope	Z- Kendall	Tau-Kendall	Sen's Slope
January	Z- Kendall	Tau-Kendall	Sen's Slope	Z- Kendall	Tau-Kendall	Sen's Slope
February	-0.18	-0.02	-0.03	1.69	0.17	0.04
March	-0.15	-0.02	-0.04	3.18	0.31	0.08
April	-0.60	-0.06	-0.15	3.66	0.36	0.08
May	0.07	0.01	0.04	2.91	0.28	0.04
June	-1.67	-0.16	-0.42	3.66	0.36	0.05
July	-2.10	-0.21	-0.19	4.95	0.48	0.07
August	-0.27	-0.03	0.00	4.16	0.41	0.05
September	1.28	0.13	0.00	3.51	0.34	0.04
October	-0.76	-0.08	0.00	2.55	0.25	0.03
November	0.49	0.05	0.06	1.46	0.14	0.02
December	-0.05	-0.01	-0.02	0.50	0.05	0.01
Annual	-0.38	-0.04	-0.09	0.40	0.04	0.01
Seasonal	-1.28	-0.04	-3.3E-3	9.44	0.27	0.04
C.Seasonal	-1.08			4.93		

[1] $\propto = 95\% \rightarrow Z = [-1.96, +1.96] \rightarrow z > +1.96$ upward trend and $z < -1.96$ downward trend

[2] The correlation coefficient ranges between +1 and -1 . A value approaching +1 signifies a strong positive correlation, a value approaching -1 indicates a strong negative correlation, and a value of zero reflects the absence of correlation.

[3] The slope of the trend line indicates the rate of changes observed in each season, month, or year.

[4] Seasonal Mann-Kendall

[5] Seasonal Sen's Slope

[6] Correlated Seasonal Mann Kendall

Table 4. The results of determining the change points in Lake Urmia's Level on a monthly and annual scale.

Month	SNHT		Pettitt		Buishand Range Test		Buishand U Test	
	T	Change Year	U*	Change Year	R/sqrt(n)	Change Year	U	Change Year
January	40.74	2001	616	2000	3.1503	2001	3.6744	2001
February	40.792	2001	616	2000	3.1523	2001	3.6854	2001
March	40.816	2001	616	2000	3.1532	2001	3.6991	2001
April	40.796	2001	617	1999	3.1524	2001	3.7236	2001
May	4.338	2001	621	1999	3.1423	2000	3.719	2000
June	40.288	2001	621	1999	3.1462	2000	3.7262	2000
July	40.268	2001	621	1999	3.1483	2000	3.739	2000
August	40.268	2001	621	1999	3.148	2000	3.7395	2000
September	40.263	2001	621	1999	3.1476	2000	3.7398	2000
October	40.279	2001	621	1999	3.1489	2000	3.7545	2000
November	40.302	2000	621	1999	3.1513	2000	3.7544	2000
December	40.552	2000	621	1999	3.161	2000	3.7628	2000
Annual	40.649	2001	621	1999	3.1522	2000	3.7434	2000

Table 5. The results of determining the change points in the precipitation on a monthly and annual scale.

Month	SNHT		Pettitt		Buishand Range Test		Buishand U Test	
	T	Change Year	U*	Change Year	R/sqrt(n)	Change Year	U	Change Year
January	1.89	2015	114	1982	1	1982	0.05	1982
February	5.6	2016	142	2016	1.19	2016	0.08	2016
March	3.18	1974	157	2003	0.9	2003	0.11	2003
April	2.12	2017	107	1991	0.93	1991	0.06	1991
May	6.03	1984	230	1986	1.17	1994	0.4	1994
June	6.65	1995	265	1995	1.29	1995	0.52	1995
July	6.49	1974	115	2008	0.88	2007	0.11	2007
August	3.37	2009	180	2004	0.95	2009	0.1	2009
September	3.49	1975	126	1983	1.03	2012	0.08	1976
October	2.48	2005	131	2005	1.06	2005	0.09	2005
November	2.73	1976	106	1976	1.12	1994	0.08	1994
December	2.04	1993	143	1993	1.29	1993	0.1	1993
Annual	5.07	1995	227	1995	1.35	1995	0.2	1995

Table 6. The results of determining the change points in the mean temperature (monthly and annual scale)

Month	SNHT		Pettitt		Buishand Range Test		Buishand U Test	
	T	Change Year	U*	Change Year	R/sqrt(n)	Change Year	U	Change Year
January	7.55	1993	271	1993	1.41	1993	0.48	1993
February	11.49	1993	354	1998	1.67	1993	1.02	1993
March	17.1	2000	438	2000	2.13	2000	1.4	2000
April	8.64	1997	299	1997	1.47	1997	0.82	1997
May	14.36	1994	383	1994	1.95	1994	1.33	1994
June	22.05	1997	489	1997	2.35	1997	2.27	1997
July	15.64	2009	376	1999	1.83	1999	1.5	1999
August	16.73	1996	433	1996	2.13	1996	1.29	1996
September	8.41	2013	294	1997	1.42	1997	0.67	1997
October	5.99	1996	230	1996	1.46	1996	0.41	1996
November	2.61	1982	86	1978	0.79	1982	0.06	1982
December	2.02	2016	133	1995	0.87	1995	0.07	1995
Annual	24.32	1994	552	1994	2.45	1994	2.25	1994

Table 7. The results of determining the change points in the Max temperature on a monthly and annual scale.

Month	SNHT		Pettitt		Buishand Range Test		Buishand U Test	
	T	Change Year	U*	Change Year	R/sqrt(n)	Change Year	U	Change Year
January	8.27	1993	297	1993	1.45	1993	0.7	1993
February	15.58	1993	408	1998	1.96	1998	1.47	1998
March	19.65	2000	472	1998	2.25	1998	1.59	1998
April	11.74	2007	339	1999	1.67	1999	1.14	1999
May	14.48	1994	392	1994	1.91	1994	1.46	1994
June	21.76	1997	490	1997	2.33	1997	2.34	1997
July	17.65	2009	381	2007	1.87	2007	1.33	2007
August	17.38	1994	435	1995	2.12	1994	1.49	1994
September	13.11	2009	363	2000	1.68	2000	1.13	2000
October	13.08	1996	386	1996	2.03	1996	1.1	1996
November	1.77	1993	116	2006	0.76	1994	0.13	1994
December	2.39	1995	169	1995	1.05	1995	0.14	1995
Annual	28.64	1997	599	1997	2.68	1997	2.79	1997

Table 8. The results of determining the change points in the min relative humidity (monthly and annual scale)

Month	SNHT		Pettitt		Buishand Range Test		Buishand U Test	
	T	Change Year	U*	Change Year	R/sqrt(n)	Change Year	U	Change Year
January	9.18	1985	296	1996	1.34	1985	0.62	1985
February	18.54	1996	447	1996	2.16	1996	1.67	1996
March	16.22	1997	436	1997	2.01	1997	1.34	1997
April	7.34	1996	279	1994	1.35	1996	0.65	1996
May	8.5	1985	260	1986	1.42	1995	0.71	1995
June	17.12	2009	379	2009	1.81	2009	1.31	2009
July	11.84	2009	317	2009	1.79	2009	0.62	2009
August	15.5	1998	410	1998	2.02	1998	1.29	1998
September	9.27	1977	264	1998	1.34	1998	0.7	1998
October	2.79	1974	129	1990	0.97	1989	0.09	1989
November	3.32	1984	162	1984	1.17	1984	0.09	1984
December	5.78	2011	241	2011	1.84	2010	0.2	2010
Annual	23.67	1994	528	1994	2.42	1994	2.08	1994

Table 9. The seasonal change points on a monthly scale for the climatic parameters and the water level of Lake Urmia.

Method	SNHT		Pettitt		Buishand U test		Buishand Range Test	
Parametric	T	Changepoint	U*	Changepoint	U	Changepoint	R/sqrt(n)	Changepoint
Lake Urmia's Water Level	491.51	2001 August	89081	2000 May	46.022	2001 June	10.972	2001 June
Precipitation	5.4452	1995 April	8125	1996 May	0.19398	1996 May	1.3675	1996 May
Max temperature	6.9435	1998 April	11831	1998 April	0.02325	1998 April	1.3758	1998 April
Mean temperature	6.5667	1973 March	9179	1998 April	0.33228	1998 March	1.0721	1998 March
Minimum relative humidity	20.356	1996 April	19238	1996 April	1.6825	1996 April	2.328	1996 April

3.4. Water level trend

Following the identification of the change point, Lake Urmia's water level has been divided into two periods before and after the change point. As shown in Table 10, before the change point, the Kendall statistic has a positive value, and the SNHT and Buishand methods reveal an Almost uniform trend, while the Pettitt method shows an increasing trend in the seasonal data. However, after the change points, the Kendall statistic indicates a considerable decreasing trend in the seasonal data (Table 10).

In the context of analyzing the seasonal trend of Lake Urmia and comparing it with trends before and after the determined change points using a variety of methods, it becomes apparent that the Pettitt method excels in identifying pivotal level changes in the lake. This superiority is evident in the contrast with the SNHT and Buishand methods, where the trend remains consistent before the change point, whereas the Pettitt method displays a discernible upward trend before this critical juncture.

Table 10. Trend analysis in before and after change points in Lake Urmia's Water Level

Method	Before change point	After change point
	Z-Kendall	Z-Kendall
Standard Homogeneity Test	1.24	-15.46
Pettitt Test	3.75	-16.74
Buishand Range and U Test	1.56	-15.64

Furthermore, the Z_Kendall statistic reveals a more prominent downward trend after the change point in the Pettitt method compared to the other two methods, as detailed in Table 3 and Table 10.

Upon scrutinizing the change points of climatic parameters and the water level of Lake Urmia on a seasonal scale, it emerges that climatic parameters exert their influence on the lake with a minimum one-year delay.

The findings of this study can be rationalized by referencing the work of Nazeri Tahroudi et al. (2018a). The investigation into the timing of annual water level trend changes in Lake Urmia, using the Pettitt method, dates back to the year 1999 and has been characterized by a downward trajectory in the lake's level ever since. Moreover, the timing of annual discharge trend changes between the years 1984 and 2013 at the hydrological stations under study predominantly falls within the range of 1994 to 1998, with the effects of the discharge trend on Lake Urmia's level becoming perceptible after one to two years, as reported by Nazeri Tahroudi et al. (2018b). Conversely, in their study on the changes in the water supply of rivers in the Lake Urmia basin, Hessari and Zeinalzadeh (2019) identified the year 1995 as the onset of the lake's drought. This discrepancy in the timing of the lake's drought onset can be attributed to variations in the different parameters studied by different researchers.

Furthermore, the investigations by Ghaleibaf et al. (2017) and Hesarie and Zeinalzadeh (2019) elucidated the impact of reduced surface runoff attributable to decreased precipitation and the containment of surface waters through the construction of large dams on the diminution of Lake Urmia's water level.

The seasonal Mann-Kendall and correlated seasonal Mann-Kendall tests effectively depicted the trend results on a seasonal scale. The correlated seasonal Mann-Kendall test establishes a coherent structure between seasons, representing an advantage of this method. This is attributed to the possibility of interdependence between the seasonal time series of the lake level and climatic parameters across different seasons. However, the seasonal Mann-Kendall test combines the results by calculating the Mann-Kendall test statistic for each season and ultimately integrating the results.

Furthermore, it seems that the change point determination methods were able to effectively demonstrate the break points in the time series of Lake Urmia's water level. This is evident as, before the change points, there was a consistent and rising trend, whereas, after the change points, a noticeable decreasing trend was observed. Hence, there are distinct trends before and after the change points in the lake's water level.

The methodologies employed in this study proved effective in identifying the changing trends and significant points of transformation in the parameters studied. The application of various statistical tests and analyses offered a robust understanding of the complex dynamics influencing Lake Urmia.

The success of the Pettitt method in determining change points and the intensification of the declining trend following the change point underscore its efficacy in capturing critical shifts in the lake's dynamics.

Additionally, the findings align with the broader body of research on Lake Urmia, providing a comprehensive and elaborate understanding of the multifaceted challenges impacting the lake's ecology.

4. Conclusion

The analysis of water level changes in Lake Urmia, coupled with climatic parameters from 1973 to 2022, reveals critical trends and transformations that underscore the lake's ongoing ecological challenges. Employing robust statistical methods, including the Mann-Kendall test, Sen Slope Estimator, and various change point detection techniques, this study provides a comprehensive understanding of the patterns influencing the lake's hydrology and climate.

Significantly, the findings demonstrate a consistent downward trend in the water level of Lake Urmia, marked by a reduction of approximately 0.13 to 0.14 meters monthly. This decline, validated by the Mann-Kendall Z statistic and the Sen Slope Estimator across all months, highlights the urgent issue of water scarcity in the region. Additionally, the analysis revealed an upward trend in average and maximum temperatures, although not all monthly figures reached statistical significance. This warming climate is likely a contributing factor to the diminishing water levels, pointing to the interplay between climatic changes and hydrological dynamics. The seasonal analyses provided further insights, indicating shifts in water level and humidity throughout different periods, with notable change points identified in the years 1999, 2000, and 2001 for water levels and in 1995 for precipitation.

This research aligns with previous studies, reinforcing the notion that anthropogenic factors, including reduced surface runoff and dam constructions, exacerbate the lake's decline. The discrepancies in change point timing across different studies highlight the complex interplay of factors affecting Lake Urmia, necessitating a multi-faceted approach for effective management and restoration efforts.

In conclusion, the various statistical methods utilized here effectively captured the dynamic changes and pivotal moments in Lake Urmia's hydrological history. Through this thorough examination, it becomes evident that immediate and coordinated conservation efforts are crucial to address the alarming decline in the lake's water levels, foster sustainable management, and mitigate the adverse impacts of climate change.

The findings serve as a critical foundation for future research and policymaking aimed at preserving this vital ecosystem. In summary, this study presents a comprehensive analysis of the underlying factors contributing to the declining water levels of Lake Urmia. The findings shed light on the complex interplay of climatic, hydrological, and environmental factors affecting the ecological balance of the lake. Moreover, the study's insights have implications for understanding and potentially mitigating the challenges facing Lake Urmia and other similar water bodies.

The results of this study underscore the importance of preserving and managing water resources in the Lake Urmia basin, as the continuous decline in water levels can have significant impacts on the daily lives of people, the local economy, and regional ecosystems. The reduction in lake water can lead to agricultural losses, decreased drinking water supplies, and negative effects on the tourism industry. These challenges not only threaten the livelihoods of the community but may also result in forced migrations and social unrest, highlighting the urgent need for immediate action and inter-agency cooperation to address this crisis.

5. Disclosure statement

No potential conflict of interest was reported by the authors.

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