Combination of modified Mann-Kendall method and Şen innovative trend analysis

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Abstract
Mann-Kendall (MK) trend test is frequently employed as the most familiar trend detection method. Its application requires serial independence of available hydrometeorological time series records. As suggested in the literature, the serial correlation effect can be removed from the given time series by using prewhitening, variance correction or overwhitening processes such as in the modified Mann-Kendall (MMK) procedure. The PW process may cause some of the current trends to be removed along with the serial correlation. In this study, the MMK method is supported by Şen innovative trend analysis instead of Şen slope estimator (SSE). The MMK method is applied to monthly maximum temperatures of Oxford station in England, for which the data length is large and the moving trend slope values are calculated starting from 1854 for all durations between 1873 and 2017. The MMK_SSE and MMK_ITA methods yield significant increasing trends between 0.0037 and 0.0125 °C/year annual slopes for January, March, May, July, August, September, October, November, December, but for February, there is not any significant trend. While MMK_SSE does not give any significant trend for April that has maximum positive kurtosis and skew, but MMK_ITA reflects an increasing trend of 0.0059 °C per year.

KEYWORDS
climate change, Mann-Kendall, modified Mann-Kendall, Şen innovative trend analysis, trend

1 INTRODUCTION

Greenhouse gas levels in the atmosphere are in steady increase steadily giving rise to global warming, and consequent unbalances in hydrometeorological temporal and spatial occurrences leading to climate change impacts. Temperature increases are the main cause of hydrometeorological disasters such as floods and droughts. In order to appreciate and understand the extent of the impact, trend identification methodological approaches gain play the most significant role. In the literature, there are trend detection methods such as Spearman rho, Şen slope estimator (SSE), wavelet analysis, traditional linear regression, Mann-Kendall, and Şen innovative trend analysis (Şen_ITA). Mann-Kendall (MK) trend test is used for trend detection in hydrometeorological records such as temperature, rainfall, evaporation, evapotranspiration, streamflow, and water quality. In addition, Şen_ITA is used by many researchers, which gives successful results to identify trend component in a given time series such as temperature.
precipitation, water quality and relative humidity, solar radiation, streamflow, water level, evapotranspiration in the literature.

On the other hand, Elnessr et al. used the MK and Sen’s slope estimation methods to investigate the temperature trends for the Kingdom of Saudi Arabia and they identified a warming trend during the 9 months of the year except for the November to January period. Zeng et al. analyzed global grid temperature anomaly dataset and found a warming trend about 0.6°C/100-year in a tropical area over Indian to the western Pacific Oceans and cooling down trend −0.3°C/100-year over the northern Atlantic. Reza et al. used MK, linear regression, Mann Whitney and Spearman’s rho methods to determine trends in air temperature records and calculated an increasing temperature trend in Iran’s Zayandeehrud Basin. Abbam et al. used the MK test to study trends in temperature and decided that the climate in Ghana has turned constantly to dry spell during the last century. Penereiro and Meschiatti applied MK and Pettitt tests to assess the temperature trends in Brazil. For the maximum temperatures, they observed that there are increasing trends of about 35%, decreasing trends in 1%, and no trends in 64%. Basha et al. investigated the vertical trend and obtained warming (cooling) in the lower (upper) troposphere after 1999. Mohorji et al. applied Şen_ITA to global monthly average temperatures between 1881 and 2013 and stated that global warming is about 0.75°C. Alashan, using the Şen_ITA method, investigated trends in July daily temperatures for Diyarbakır (Turkey). In this study, temperature data are divided into minimum, average and maximum groups, and increasing trends are obtained in percentages and magnitudes for each group. Serencam examined annual temperatures anomalies of five stations on the Yeşilirmak basin, Turkey. The author divided the temperature anomaly values into low, medium, and high groups and obtained increasing trends in each group. Machiwa et al. used the MK test for modified MK and Şen_ITA methods to determine trends in annual maximum temperatures at the coastal arid regions of India. In the study, the maximum temperature values of 31 grid points were used, and while increasing trends are obtained in 6 (19%) of the 31 grid points with the MK method, however, no significant trend could be obtained by use of the modified MK methods. The Şen_ITA method yields increasing trends in 23 (79%) of the 31 grid points and it is considered the most sensitive method by these authors.

The main purpose of this article is to support the classical MK trend identification test by means of the Şen_ITA approach leading to more reliable results. The Şen_ITA method is not affected by serial correlation and this strong feature is tried to be added to MK. In the literature, the SSE method is added to reinforce MK, but the SSE method calculates the trend according to the median value, which reduces the contribution of extreme values to the trend component, but the Şen_ITA method is easier to implement than the SSE approach. It is suggested in this article and documented on the basis of annual temperature records from Oxford station that the MK method yields more reliable results with its combination with the Şen_ITA method.

2 ŞEN INNOVATIVE TREND ANALYSIS

This new method is not sensitive to the presence of serial autocorrelation and it is launched by Şen with later mathematical and graphical improvements. The method is based on a comparison of two halves from the parent time series, where each half is sorted in ascending order. The first half of the series is plotted on the horizontal axis and the second half on the vertical axis leading to a graph with a 1:1 (45°) straight-line on it. If scatter points are above (under) the 1:1 line then there is a monotonic increasing (decreasing) trend on the parent time series (Figure 1A). In case the

![Figure 1](A) Monotonic and (B) nonmonotonic trend graphics
scatter points existence exactly or close to the 1:1 line, there is no trend in the parent time series. In many cases frequently the scatter points may not fall on the 1:1 line, which implies either an increasing or decreasing trend component depending on the position of the scatter points as above or below the 1:1 line, respectively. The data range on the horizontal axis can be divided into classes as “low” and “high” in order to identify nonmonotonic trends in different classes (Figure 1B). The trend slope ($s_{ITA}$), is calculated by Equation (1), where $n$ is the data length of the main time series and $\bar{x} (\bar{y})$ is the first (second) half time series average. The trend line can be obtained with Equation (2). The confidence limits (CL) for ITA can be obtained by considering the trend slope, $s_{ITA}$, expectation ($E(s_{ITA}) = 0$) for no trend and SD of two half series ($\sigma_x = \sigma_y = \sigma/\sqrt{n}$) where $\sigma$ is the SD of parent time series. The SD of trend slope, $\sigma_s$ is given by Equation (3), where $\rho_{xy}$ is the crosscorrelation coefficient between first and second halves. The CL, can be obtained using Equation (4). Here, $s_{crit}$ represents the critical SD for standardized timeseries at $±1.96 (1.65)$ for 95% (90%) significance levels ($\alpha$). More information can be found in Reference 35.

$$ s_{ITA} = \frac{2(\bar{x} - \bar{y})}{n}, \quad (1) $$

$$ y = x + s, \quad (2) $$

$$ \sigma_s = \frac{2\sqrt{2}}{n\sqrt{n}} \sigma \sqrt{1 - \rho_{xy}}, \quad (3) $$

$$ \text{CL}_{(1-\alpha)} = 0 \pm s_{crit} \sigma_s, \quad (4) $$

### 3 | MODIFIED MK BY ŞEN_ITA

The MK method is a nonparametric test, which is based on a comparison of a time series, $Z$, in itself, $(z_1, z_2, \ldots, z_n)$. If an examined data is bigger (smaller) than the next then $-1 (+1)$ is added to the MK statistics ($S$) (Equation (5)). Here, variable ($i$) varies from 1 to $n - 1$ and variable ($j$) changes from $i + 1$ to data length $n$. The process is repeated for all data element and the $S$ statistics are calculated and summed (Equation (6)).

$$ \text{sign}(z_j - z_i) = \begin{cases} 
1 & \text{if } z_j > z_i \\
0 & \text{if } z_j = z_i \\
-1 & \text{if } z_j < z_i 
\end{cases}, \quad (5) $$

$$ S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sign}(z_j - z_i). \quad (6) $$

It is assumed that $S$ has a normal PDF with zero mean and a certain variance (Equations (7) and (8)). Moreover, it is assumed that the examined time series does not have any trend at first as a null hypothesis, $H_0$. If $H_0$ is rejected, the alternative hypothesis $H_1$ is valid, meaning that there is a trend in the given time series. The acceptance is made according to the standardized test statistic, $z$, and a certain significance level (Equation (9)). If calculated $z$ value, $z_{cal}$, is bigger than a tabulated normal distribution value, $z_{tab}$, according to significance level $\alpha$ then there is a significant trend in the time series.

$$ E(S) = 0, \quad (7) $$

$$ \text{Var}(S) = \frac{n(n - 1)(2n + 5)}{18}, \quad (8) $$

$$ z = \begin{cases} 
\frac{S - 1}{\text{Var}(S)} & \text{if } S > 0 \\
0 & \text{if } S = 0 \\
\frac{S + 1}{\text{Var}(S)} & \text{if } S < 0 
\end{cases} \quad (9) $$
There may be dependence among hydrometeorological time records and it must be removed from the data before MK method application. The prewhitening method can be applied to the time series to remove autocorrelation effects from the time series. However, the method may remove also a portion of the trend in the time series and this point is critiqued by many researchers.\textsuperscript{38-41} Afterward, modified Mann-Kendall (MMK) is recommended to correct the effects of autocorrelation in a given time series.\textsuperscript{42,43} In this method, first, a trend is calculated by Sen\textsuperscript{2} slope estimator (Equation (10)) and the trend is removed from the time series (Equations (11) and (12)), later lag-1 autocorrelation coefficient is calculated and it is subtracted from the trendless time series (Equation (13)) and the trend is added to the independent time series (Equations (14) and (15)) and the trend in independent time series is calculated by MK method. In this study, \( \hat{\text{Sen}}_{\text{ITA}} \) is used to calculate trend slope instead of SSE (Equations (12) and (15)). Here, \( s_{\text{SSE}} \) and \( s_{\text{ITA}} \) parameters are trend values calculated using SSE and \( \hat{\text{Sen}}_{\text{ITA}} \) methods, respectively. \( Z_{d_{\text{SSE}}} \) and \( Z_{d_{\text{ITA}}} \) parameters show the timeseries without trend. \( Z_{i} \) parameter indicates the independent time series, whose correlation effect is eliminated. The \( Z_{t_{\text{SSE}}} \) and \( Z_{t_{\text{ITA}}} \) parameters represent an independent timeseries, in which the trend values calculated according to the SSE and \( \hat{\text{Sen}}_{\text{ITA}} \) methods are added again.

\[
s_{\text{SSE}} = \text{median} \left( \frac{Z_j - Z_i}{j - i} \right) \text{ for } \forall j > i; i = 1 : n - 1 \text{ and } j = 2 : n, \tag{10}
\]

\[
Z_{d_{\text{SSE}}} = z_k - s_{\text{SSE}} \cdot k; \text{ for } k = 1 : n, \tag{11}
\]

\[
Z_{d_{\text{ITA}}} = z_k - s_{\text{ITA}} \cdot k, \tag{12}
\]

\[
Z_{i} = z_k - \rho_1 z_{k-1}, \tag{13}
\]

\[
Z_{d_{\text{SSE}}} = z_{d_k} + s_{\text{SSE}} \cdot k, \tag{14}
\]

\[
Z_{d_{\text{ITA}}} = z_{d_k} + s_{\text{ITA}} \cdot k. \tag{15}
\]

The data length and variation in a time series may change the \( S \) parameter too much with plus and minus differences. However, climate change is a long process and does not change much from 1 year to the next year. For this reason, moving \( z \) values are calculated in this study. To calculate these values, the final value is subtracted in a time series with the greatest climate change effect due to the increased carbon level. This process is repeated until the series has a minimum data length. Thus, the different series are derived by subtracting the last time values from the main time series (Equation (16)). Here, \( Z \) is the parent time series with elements of \( z_1, z_2, z_3, \ldots, z_n \); and \( Z_{m} \) is the independent moving time series, but has trend and \( m \) is the number of extracted values from the parent time series. Herein, \( m \) varies from 1 to the acceptable minimum data length (\( a \)). It is selected as 20 for statistical requirements. Similarly, moving \( S_{m} \) and \( z_{m} \) values can be calculated using respective Equations (17) to (19).

\[
Z_{m} = z_{1}, z_{2}, z_{3}, \ldots, z_{n-m}, \tag{16}
\]

\[
S_{m} = \sum_{i=1}^{n-m} \sum_{j=i+1}^{n-m+1} \text{sign}(z_{j} - z_{i}). \tag{17}
\]

\[
\text{Var}(S_{m}) = \frac{(n - m)(n - m - 1)(2(n - m) + 5)}{18}, \tag{18}
\]

\[
z_{m} = \begin{cases} \frac{S_{m} - 1}{\text{Var}(S_{m})} & \text{if } S_{m} > 0 \\ 0 & \text{if } S_{m} = 0 \\ \frac{S_{m} + 1}{\text{Var}(S_{m})} & \text{if } S_{m} < 0 \end{cases}, \tag{19}
\]
4 | STUDY AREA AND APPLICATION

Oxford is located on the border of the southern and midland regions of the UK (Figure 2). It is therefore relatively close to the European continent and affected by cold spells in winter and hot and humid weather in summer. Oxford City has a warm and temperate climate. Every season there are rainfall occurrences in the city. The wettest month is October with a monthly average of 66.9 mm, while the driest month is February with 42.6 mm. Monthly average temperatures are above 0°C in all months. The coldest month is January and the hottest month is July. Oxford City is selected as the study area to apply MK, MMK, and Şen_ITA methods. The monthly maximum temperatures are available between 1853 and 2017, inclusive. Data length must be even number for the Şen_ITA method and therefore the data are used from 1854 to 2017. The maximum temperatures vary from −0.2 (February 1947 and January 1963) to 27.1 (July 2006). February (May) has a maximum (minimum) SD and skew coefficients. More detailed statistical information are given in Table 1.

The MK method is sensitive to correlation coefficients in a time series. Positive (negative) correlation coefficients increase (decrease) the possibility of MK to detect a significant trend. The autocorrelation coefficients between the maximum temperatures (blue squares) are calculated from lag-1 to lag-10 to avoid incorrect use of MK for Oxford City and they are shown in Figure 3. Dash lines represent confidence intervals for autocorrelation coefficients, which are calculated as \( \frac{1.96}{\sqrt{n}} \) at the 95% significance level.

There is not a significant autocorrelation coefficient in February, May, June, July, August, September, and December records, but lag-1 autocorrelation in January; lag-9 in March; lag-1, lag-2, and lag-3 in April; lag-1, lag-7, lag-8, and lag-10 in October; lag-8 in November appear effective. After trends are removed from the maximum temperatures, the lag-1 correlation effect is removed from the trendless series with the Monte Carlo simulation application (Equation (13)). The trend removal leads to an equal (parallel) decrease in all correlation coefficients (lag-1 to lag-10). Later, trends are added to the trendless independent series, and hence, independent time series are obtained.

![Figure 2](image-url)  The location of Oxford City in the United Kingdom
The autocorrelation coefficients for the independent series are given in Figure 3 as red circles and do not exceed the CL.

The moving $g$ values at the maximum temperatures are calculated and shown in Figure 4. They are increasing by eliminating the autocorrelation effect in the series in all months except June. Dash lines in this figure represent $g$ values at ±95% (1.96) significance level for important decreasing/increasing trends. The moving $g$ values vary from year to year in all months. There is an important increasing trend ($g \geq 1.96$ and $P < 0.05$) in January, March, May, July, August, September, October, November, and December months. There is an increasing trend ($g \geq 1.65$ and $P < 0.10$) in April according to the MMK ITA method, but there is no trend according to MK and MMK SSE methods. February and June months are without any trend component. Furthermore, there is no difference in correlation coefficients among observed and independent series in these months (Figure 3). If autocorrelation coefficients are removed from the maximum temperatures before a trend removal then the trend is removed instead of autocorrelation coefficients as some researchers have already reported.12,41,44

Finally, the Şen ITA method is applied to the maximum temperatures in Oxford City, UK. In Figure 5, the red dash lines represent the trend slope ($s_{ITA}$), the black line is for the 1/1 trend line and CL1 and CL2 show CL with 90% and 95% significance levels, respectively. According to Şen ITA results, January, March, April, May, July, August, September, October, November, and December months have significantly increasing trends, while in June only an increasing trend exists, and there is no monotonic trend in February. It has a nonmonotonic trend, in which there is a decreasing trend in minimum values and an increasing trend in maximum values. October and November have maximum trend slope values. Trends in the maximum temperatures for Oxford records are given in Table 2.

Trend slope values vary between 0.0015 and 0.0125 (0.003 and 0.0125)°C per year according to Şen ITA (SSE) method (Table 2). Furthermore, in the Şen ITA method, maximum and minimum trend values are observed in October and February, while the SSE method gives the same in March and June. The Şen ITA yields bigger (smaller) trend slopes than the SSE method in April, June, August and October (January, February, March, May, July, September, and December), but the same trend slope on November. January, April, and October have significant lag-1 positive autocorrelation coefficients. In January with a negative skew, the Şen ITA method gives a lower trend value than the SSE method, while in April and October with a positive skew, it indicates higher trend values.

There are significant increasing trends in January, March, May, July, August, September, October, November, and December and no trend in February according to the four methods. In June, while there is an increasing trend according to the Şen ITA method, there is no trend with respect to MK, MMK SSE, and MMK ITA methods. Şen ITA method implies an important increasing trend, but comparatively less increasing trend is yielded by means of MMK ITA method and no trend is found in MK and MMK SSE methods applications. He et al.45 found no warming trend for February, April, May, and June in central England. Their results are consistent with this study in the same months except for May. Prior
FIGURE 3  Autocorrelation coefficients at maximum temperatures in Oxford
FIGURE 4  Moving z values on the maximum temperatures in Oxford City
**FIGURE 5** Innovative trend analysis test results on the maximum temperatures in Oxford City
### TABLE 2  Trend parameters in the maximum temperatures in Oxford City, UK

| Methods     | Months | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   | 11   | 12   |
|-------------|--------|------|------|------|------|------|------|------|------|------|------|------|------|
| Şen _ITA    | First half mean | 6.52 | 7.42 | 9.60 | 12.99| 16.59| 19.78| 21.59| 20.89| 18.26| 13.69| 9.20 | 7.01 |
|             | Second half mean | 6.98 | 7.55 | 10.47| 13.47| 16.89| 20.09| 22.05| 21.67| 18.86| 14.72| 10.22| 7.75 |
|             | z values       | 0.0056| 0.0015| 0.0106| 0.0059| 0.0037| 0.0038| 0.0056| 0.0094| 0.0073| 0.0125| 0.0123| 0.0090|
|             | Significance level | 95% | 90% | 95% | 95% | 95% | 90% | 95% | 95% | 95% | 95% | 95% | 95% |
|             | Critical z value | 0.0049| 0.0045| 0.0047| 0.0045| 0.0037| 0.0034| 0.0052| 0.0047| 0.0041| 0.0037| 0.0037| 0.0051|
|             | Decision        | Yes | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| MK          | Significance level | 95% | 90% | 95% | 90% | 95% | 90% | 95% | 95% | 95% | 95% | 95% | 95% |
|             | Critical z value | 1.96 | 1.65 | 1.96 | 1.65 | 1.96 | 1.65 | 1.96 | 1.96 | 1.96 | 1.96 | 1.96 | 1.96 |
|             | z values        | 3.17 | 1.19 | 3.81 | 1.42 | 2.19 | 1.28 | 2.04 | 2.6 | 3.09 | 5.55 | 5.23 | 3.2 |
|             | Decision        | Yes | No | Yes | No | Yes | No | Yes | Yes | Yes | Yes | Yes | Yes |
| MMK_SSE     | $\delta_{SSE}$ values | 0.0103| 0.0041| 0.0125| 0.0032| 0.0056| 0.003| 0.0068| 0.0074| 0.0078| 0.0112| 0.0123| 0.0100|
|             | Significance level | 95% | 90% | 95% | 90% | 95% | 90% | 95% | 95% | 95% | 95% | 95% | 95% |
|             | Critical z value | 1.96 | 1.65 | 1.96 | 1.65 | 1.96 | 1.65 | 1.96 | 1.96 | 1.96 | 1.96 | 1.96 | 1.96 |
|             | z values        | 3.39 | 1.4 | 4.19 | 1.49 | 2.23 | 1.18 | 2.34 | 2.85 | 3.69 | 5.58 | 5.35 | 3.53 |
|             | Decision        | Yes | No | Yes | No | Yes | No | Yes | Yes | Yes | Yes | Yes | Yes |
| MMK_ITA     | $\delta_{ITA}$ values | 0.0056| 0.0015| 0.0016| 0.0059| 0.0037| 0.0038| 0.0056| 0.0094| 0.0073| 0.0125| 0.0123| 0.0090|
|             | Significance level | 95% | 90% | 95% | 90% | 95% | 90% | 95% | 95% | 95% | 95% | 95% | 95% |
|             | Critical z value | 1.96 | 1.65 | 1.96 | 1.65 | 1.96 | 1.65 | 1.96 | 1.96 | 1.96 | 1.96 | 1.96 | 1.96 |
|             | z values        | 3.2 | 1.39 | 4.21 | 1.72 | 2.17 | 1.19 | 2.33 | 2.86 | 3.7 | 5.61 | 5.35 | 3.51 |
|             | Decision        | Yes | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Abbreviations: MK, Mann-Kendall; MMK, modified Mann-Kendall; Şen _ITA, Şen innovative trend analysis; SSE, Şen slope estimator.
and Perry found significant upward trends in winter and summer in southern England. Although there is an important increasing trend in December and January except for February in winter, however, there is an important increasing trend in all months of summer compared with the Şen_ITA method only. The other three methods show no significant trend in June, but there is an important increasing trend in July and August. Şen_ITA and MMK_ITA methods imply an upward trend in each month of spring, while MK and MMK_SSE show no trend in April. In autumn months, all approaches depict an important upward trend.

5 | RESULTS AND CONCLUSIONS

The MMK method determines trends for time series using the classical MK trend test approach, which is applied to the maximum temperature records in Oxford City, UK. The test results are compared with the Şen_ITA, and various trend detection methods are used by many researchers all over the world. The MK, MMK_SSE, and herein suggested MMK_ITA methods provide consistent results with Şen_ITA. There are significant increasing trends in January, March, May, July, August, September, October, November, and December and no trend in February according to these four methods. Although MK and MMK_SSE methods show no trend, MMK_ITA indicates an increasing trend in April. However, although there is an increasing trend in June on the basis of Şen_ITA, the other three methods (MK, MMK_SSE, and MMK_ITA) yield no trend. The results show that MMK_ITA is more successful than MK and MMK_SSE in trends detection in the April temperature series with the maximum correlation coefficient. The MK and MMK_SSE methods result in the same trend types for the Oxford maximum temperature series. With the combination of the SSE method, the trend results of the MK method do not change for the maximum temperatures for Oxford temperature records. In series with a significant correlation coefficient, the Şen_ITA method yields a smaller (greater) trend value in a negatively (positively) skewed series according to the SSE. Since the SSE method calculates the trend as a median, the contribution of extreme values to the trend may be neglected. Furthermore, this indicates that MMK_ITA is more robust to serial correlation effects than MK and MMK_SSE. MMK_ITA can be used in trend calculations even in the case of a dependent time series better than the classical methods. As a result, accurate trend detection allows authorities to plan future planning projects correctly under the light of the climate change impact.

CONFLICT OF INTEREST

The author declares no potential conflict of interest.

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