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A Comparison of the Rank-based and Slope-based Nonparametric Tests for Trend Detection in Climate Time Series

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ABSTRACT

Trend detection in climate time series data is crucial for understanding climate change, predicting future climate patterns, assessing impacts, managing resources, and formulating policies. Several trend detection methods have been introduced in the literature, including parametric and non-parametric approaches. Nonparametric trend detection methods are often considered more preferable than parametric methods in certain situations due to their flexibility and robustness. Comparing various nonparametric methods of trend detection is vital in data analysis because different techniques can yield divergent results based on the same dataset. In this study, three nonparametric trend tests which were the Mann-Kendall (MK), Sen's Innovative Trend Analysis (ITA) and Modified Mann-Kendall by Sen's Innovative Trend Analysis (MMK_ITA) were compared based on their power. The MK test is a rank-based test and the ITA is a slope-based test. Meanwhile, the combination of rank-based and slope-based methods is known as the MMK_ITA test. The power analysis was conducted through Monte Carlo simulation on normal, non-normal and autocorrelated time series. The simulation results indicated that test power relied on magnitude of linear trend slope, sample sizes, distribution type and variation in time series. These tests were then applied to monthly maximum temperature from 2002 until 2021 for Selangor, Malaysia. This study found that the slope-based test performed better compared to the rank-based test and their combined methods from the simulation studies and real data application based on the calculated power.

Keywords: Trend detection, Climate change, Power of a test, Mann-Kendall, Sen's Innovative Trend Analysis, Modified Mann-Kendall by Sen's Innovative Trend Analysis

1 INTRODUCTION

Global warming scenario leads to drastic changes in climate variables including temperature, precipitation, relative humidity, wind speed and sea level. Climate change has become one of the major concerns globally as this phenomenon can be seen as detrimental to living things. For assessing the significance of the monotonic trends in climatological time series data, there are a wide variety of parametric and nonparametric methods that have been proposed and employed over the years. Nonparametric methods, either rank-based or slope-based, are more preferred over parametric methods by the researchers because hydrometeorological time series data often fail to fulfil the assumption of normality [1]. Comparing various nonparametric methods of trend detection is vital in data analysis because different techniques can yield divergent results based on the same dataset. This comparison allows analysts to assess the accuracy, reliability, and robustness of each method, ensuring the trends identified are consistent and trustworthy across different approaches.

One of the rank-based nonparametric statistical tests is the Mann-Kendall (MK) test which used to identify monotonic trends (either upward or downward) in time series data by comparing the ranks of data points, making it suitable for datasets with unknown or non-normal distributions [2, 3]. This test is a widely used test to detect monotonic trends in climatological data, hydrological data or environmental data and it is often accompanied by the Sen's slope estimator (SSE) to quantify the trend magnitudes [4–8]. However, this method is inaccurate for time series data with autocorrelation and less sensitive to outliers. This drawback has led to the introduction of modified methods by other researchers, such as prewhitening, block-bootstrap, and others [9, 10].

On the other hand, Şen suggested a slope-based method named Sen's Innovative Trend Analysis (ITA), which was further improved in the papers published in 2014 and 2017 [11–13]. ITA is a nonparametric graphical technique used for trend analysis, capable of identifying and visualizing both monotonic and non-monotonic trends within a given data series. This method is not restricted to any sample sizes, distribution types, valid for autocorrelated data and also provides graphical illustration of trends. This method has been applied in many studies to discover trends in climate variables, mostly along with the MK test for comparison purpose [14–19].

Another trend detection method is known as modified Mann-Kendall supported by Sen's Innovative Trend Analysis (MMK_ITA) which was proposed by Alashan [20]. This test can be considered as the combination of rank-based and slope-based methods. The MMK_ITA tests uses the ITA method to calculate the trend slope instead of the SSE method (MMK_SSE) as the ITA method includes the contribution of extreme values to the trend component. Alashan concluded that MMK_ITA was better than other MK methods as it was more robust in the influence of serial correlation after applying the ITA, MK, MMK_SSE and MMK_ITA methods to monthly maximum temperature records in Oxford station, England [20].

Currently, studies regarding the power of tests for trend detection are very limited. Lettenmaier compared a parametric and a nonparametric trend detection tests, the *t*-test and the Spearman's rho (SR) test, respectively, in terms of their powers to detect a linear trend in normally distributed series. The results showed that the *t*-test had a slightly higher power compared to the SR test [21]. Similarly, Yue and Pilon compared the power of slope-based tests, *t*-test and bootstrap-based slope test with the power of rank-based tests, MK and bootstrap-based MK tests. Based on the Monte Carlo simulation results, the power of slope-based and rank-based tests varied for different types of time series distribution and slightly sensitive to the shape of trend but have similar power among themselves [1]. From the results, it is clear that parametric trend detection methods such as the *t*-test, are undoubtedly better for normally distributed time series. Other than that, Yue et al. investigated the influence of various pre-assigned significance levels, sample sizes, trend magnitudes and sample variations on the power of rank-based methods, which were the MK and the SR tests [22]. Contrary to the popular belief that nonparametric methods are more robust to distribution type, the power of both methods were discovered to rely on the time series distribution type and skewness. Although various trend detection methods have been developed until now, not many researchers truly evaluate the capabilities of their proposed methods. Instead of investigating the power of the tests, they only compared the results obtained by the newly proposed method with another established methods such as the MK test and the SR test.

The main objective of this study is to compare the performance of the rank-based and slope-based nonparametric tests for detecting linear monotonic trends in normal, non-normal and autocorrelated time series by Monte Carlo simulation based on the power of these tests. In addition, the three tests are also applied to assess the significance of trends in a 20-year monthly maximum temperature data from Selangor, Malaysia.

2 MATERIAL AND METHODS

The simulation and real data application results were generated and illustrated by using R software.

2.1 Mann-Kendall Test

The MK test is a rank-based test because it considers the order and correlation between the ranks in a time series. The null hypothesis of this test assumes that there is no trend in the data and the data are independent and identically distributed. The alternative hypothesis indicates that the data have a significant monotonic trend. The MK test statistic (S) for a time series $(x_1, x_2, ..., x_n)$ is calculated by using Equation (1).

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(X_j - X_i) \quad (1)$$

where

$$sign(X_j - X_i) = \begin{cases} 1 & \text{if } x_i > x_j \\ 0 & \text{if } x_i = x_j \\ -1 & \text{if } x_i < x_j. \end{cases} \quad (2)$$

The mean and variance of S under the assumption that the data are independent and identically distributed are given by Equation (3) and (4) [3].

$$E[S] = 0 \quad (3)$$

$$Var(S) = \sigma^2 = \frac{1}{18}[n(n-1)(2n+5)] \quad (4)$$

where n is the number of observations. For the data with tied observations, the variance will be reduced into Equation (5).

$$Var(S) = \sigma^2 = \frac{1}{18}[n(n-1)(2n+5) - \sum_{j=1}^{p} t_j(t_j - 1)(2t_j + 5)] \quad (5)$$

where p is the number of tied groups and t_j is the number of tied observations in the jth tied group.

As the number of observations becomes large, the S statistic tends to follow a normal distribution. The decision can be made by comparing the standardised test statistic, z, that can be obtained from Equation (6) to the tabulated normal distribution value, z_{tab} at desired significance level, α. If the z value is greater than z_{tab}, the null hypothesis will be rejected indicating that there is a significant trend in the time series data and vice versa [3]. Alternatively, the decision for this test can be made based on the probability value or p-value. Suppose that the p-value $\leq \alpha$ at significance level of α, then the trend in time series is said to be statistically significant [22].

$$z = \begin{cases} \frac{S-1}{\sigma} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sigma} & \text{if } S < 0. \end{cases} \tag{6}$$

In the presence of autocorrelation, a correction is needed if the lag-1 ($k = 1$) correlation, ρ_k coefficient in Equation (7) does not satisfy the condition in Equation (8) before applying the MK test.

$$\rho_k = \frac{\frac{1}{n-k}\sum_{i=1}^{n-k}(X_i - \bar{X})(X_{i+k} - \bar{X})}{\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2} \tag{7}$$

$$\frac{-1 - f(c)\sqrt{n-2}}{n-1} \leq \rho_k \leq \frac{-1 + f(c)\sqrt{n-2}}{n-1} \tag{8}$$

where $f(c)$ is the function of confidence probability, usually 1.96 at 5% significance level. The VCPW by Wang et al. will be employed to replace the classical MK test due to its ability to maintain low type I error and high power of the test when compared to other prewhitening methods [9].

2.2 Sen's Innovative Trend Analysis

In this method, the time series data are divided into two halves and sorted in ascending order. The first sub-series is plotted on the horizontal axis while the second sub-series is plotted on the vertical axis. Both sub-series are plotted against each other based on the Cartesian coordinate system with a 1:1 (45°) straight line. If the data fall on the 1:1 straight line, the data can be considered as trendless. If the data are plotted above and below the 1:1 straight line, then there is a monotonic increasing and decreasing trend exists in the time series, respectively.

The first step is done by calculating the average of each sub-series denoted as $\bar{Y}_1$ and $\bar{Y}_2$. Next, the slope or magnitude of the trend can be obtained from Equation (9) as follows:

$$s_{ITA} = \frac{2(\bar{Y}_2 - \bar{Y}_1)}{n} \tag{9}$$

Moreover, type of slope can also be interpreted from its sign, s_{ITA}, where positive slope indicates increasing trend and vice versa.

To determine whether the null hypothesis, which refers to no statistically significant trend exists in the time series can be rejected or not, the conclusion can be made by comparing s_{ITA} value with the confidence limits (CL). The CL is constructed by considering the slope, expected value for no trend, $E[s_{ITA}] = 0$ and the variance equality for both half series ($\sigma_{y_2} = \sigma_{y_1}$) as follows:

$$CL_{(1-\alpha)} = 0 \pm s_{cri}\sigma_s \tag{10}$$

where s_{cri} represents the critical standard deviation for standardised time series for different significance levels, α, which is 1.96 at 5% significance level and σ_s can be determined by using Equation (11).

$$\sigma_s = \frac{2\sqrt{2}}{n\sqrt{n}}\sigma\sqrt{1 - \rho_{\bar{y_2}\bar{y_1}}} \tag{11}$$

where σ is the standard deviation of original time series and $\rho_{\bar{y_2}\bar{y_1}}$ is the cross correlation coefficient between the mean of the first and second sub-series and can be calculated using Equation (12).

$$\rho_{\bar{y_2}\bar{y_1}} = \frac{E(\bar{y_2}\bar{y_1}) - E(\bar{y_2})E(\bar{y_1})}{\sigma_{\bar{y_2}}\sigma_{\bar{y_1}}} \tag{12}$$

If the s_{ITA} value falls outside the CL, the trend is said to be statistically significant. Alternatively, the null hypothesis is valid when the slope falls within the CL Şen [13].

2.3 Modified Mann-Kendall by Sen's Innovative Trend Analysis

The MMK_ITA method is proposed as an alternative way to correct the effect of autocorrelation in time series. In opposition to the modified MK with Trend-Free Prewhitening (TFPW) method [23, 24] where the trend slope is calculated using SSE procedure, this method uses ITA formula as stated previously in Equation (9). Subsequently, the trend is removed from the time series $(z_1, z_2, ..., z_n)$ by using Equation (13).

$$Z^d = z_k - s_{ITA}k;\ for\ k = 1, 2, ..., n \tag{13}$$

After that, the lag-1 correlation coefficient, ρ_1 that can be computed using Equation (7), is subtracted from detrended time series, Z^d as follows:

$$Z^i = z_k^d - \rho_1 z_{k-1}^d \tag{14}$$

The previous computed trend is added back into the independent series, Z^i in Equation (15).

$$Z^t = z_k^i + s_{ITA}k \tag{15}$$

Lastly, the same procedure for MK test from Section 2.1 will be applied to the blended series, Z^t that is no longer affected by autocorrelation problem.

2.4 Comparisons of the Power of the Tests

The power of a test can be defined as the probability of correctly rejecting the null hypothesis when it is actually false. The null hypothesis (H_0) implies that there is no significant linear monotonic trend in the time series while the alternative hypothesis (H_1) indicates that there is significant linear monotonic trend exists in the time series. When the power is high, then that test is assumed to be efficient. The power analysis can be performed by the Monte Carlo simulation and be calculated using Equation (16) [22]:

$$Power = \frac{N_{rej}}{N} \tag{16}$$

where N is the total number of simulation experiments and N_{rej} is the number of rejections from the simulation.

2.5 Monte Carlo Simulation

This simulation study considers two types of time series, which are independent time series and autocorrelated time series. A linear trend, T_t, with slope, $b = -0.01$ (0.002) 0.01 will be superimposed onto each of the generated series. All three trend detection methods will be applied to these time series and their power will be computed using Equation (16) after the process is repeated for 2000 times.

2.5.1 Independent Time Series

The experiment generates 2000 time series for each sample size, $n = 20$ (20) 100 for several types of distribution with different pre-assigned parameters values. Next, each of the generated series are superimposed with some selected linear trend scenarios, $T_t = bt$ with b ranging from -0.01 to 0.01 with an increment of 0.002 and $t = 0, 1, 2, ..., n$ as given by this below equation:

$$X_t = Z_t + T_t \tag{17}$$

where Z_t is the generated time series and X_t is the generated time series with superimposed linear trend, T_t.

The selected distribution types are the normal distribution, Gumbel distribution, Generalized Extreme Value distribution (GEV), Weibull distribution and Log-Normal distribution. These distributions are found to be the best fitted distributions for modelling climate variables such as temperature [25], streamflow [26] and rainfall [27]. The probability density function (PDF) formulae that are used to generate series for these distribution types can be referred in a paper by Stedinger [28].

2.5.2 Autocorrelated Time Series

To investigate the performance of these tests in the presence of autocorrelation, a total of 2000 time series which consisted of linear trends and lag-1 autoregressive (AR(1)) process with noise will be generated [24, 29, 30]. Fixed mean value of 1.0 and coefficient of variation of 0.5 are assigned for AR(1) processes time series generation for $n = 20$ (20) 100 with different given $\rho_1 = \pm 0.1$ (± 0.2) $\pm$ 0.9.

The AR(1) process is given by this following equation:

$$A_t = \mu_A + \rho_1(A_{t-1} - \mu_A) + \epsilon_t \tag{18}$$

where μ_A is the mean of A_t, ρ_1 is the AR(1) coefficient and ϵ_t is the white noise.

The generated time series with autocorrelation is given by:

$$X_t = T_t + A_t \tag{19}$$

where T_t is the linear trend and A_t is the AR(1) process.

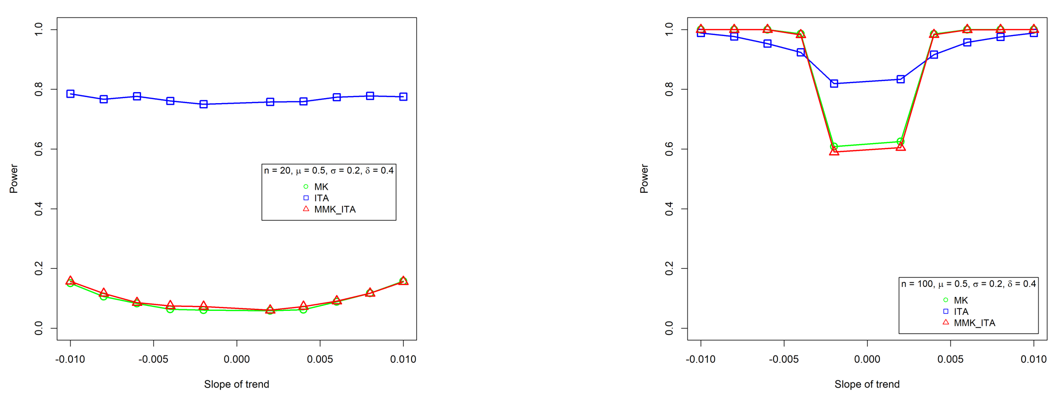
Lastly, the power of the tests will be computed using Equation (16) and their performances will be assessed.

3 RESULTS AND DISCUSSION

The performance of the MK, ITA and MMK_ITA tests were compared in terms of their power through a simulation study. The power of the tests was calculated by using Equation (16) at significance level of 0.05. A test that has a greater power indicates high probability of detecting the presence of linear trend. This paper only includes the significant results for the sake of brevity.

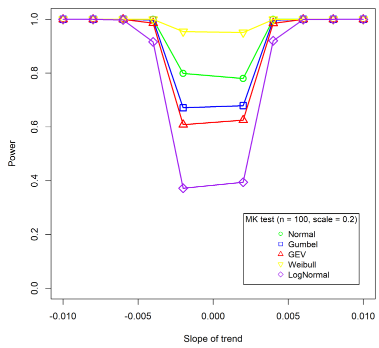
3.1 Power of the Tests for Independent Time Series

From the simulation study, the power of these tests was found to rely on the magnitudes of the trend slope. Regardless of the distributions, sample sizes, and parameter values, the higher the magnitude of the slope, the greater the test power, indicating that the method has a high ability to detect the trend. There was also a significant relationship between the statistical power and the sample size. As the sample size increased, the test power also increased for both normal and non-normal distributions. It can be seen in the Figure 1 for the GEV distribution when sample size increased from 20 to 100. The results were in agreement with findings from Yue et al., where they concluded that the tests became more powerful if the absolute magnitude of trend and sample size values were high [22].

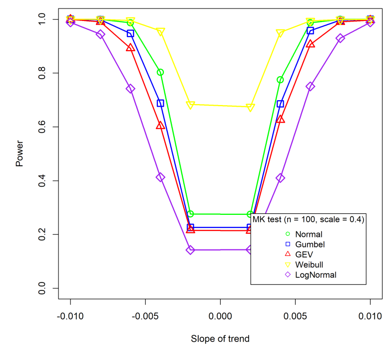


(a) $n = 20$ (b) $n = 100$

Figure 1 : Power of the test for data generated from the GEV distribution at different sample sizes with location value, $\mu = 0.5$, shape value, $\delta = 0.4$, and scale value, $\sigma = 0.2$

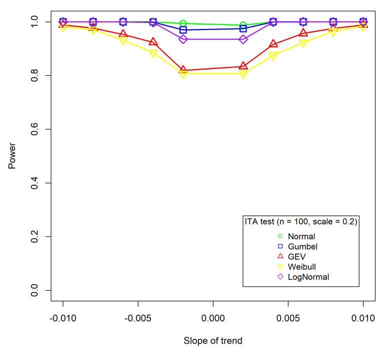


(a) Scale parameter = 0.2

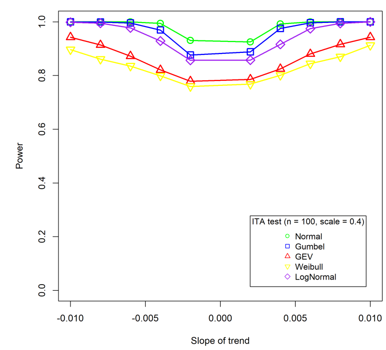


(b) Scale parameter = 0.4

Figure 2 : Power of the test for data generated at $n = 100$ using MK test at different scale values, location value, $\mu = 0.5$, shape value, $\delta = 0.4$

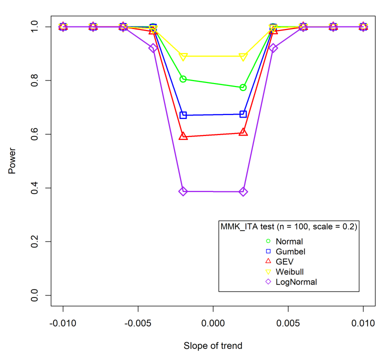


(a) Scale parameter = 0.2

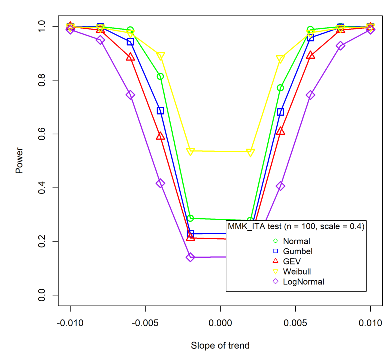


(b) Scale parameter = 0.4

Figure 3 : Power of the test for data generated at $n = 100$ using ITA test at different scale values, location value, $\mu = 0.5$, shape value, $\delta = 0.4$



(a) Scale parameter = 0.2



(b) Scale parameter = 0.4

Figure 4 : Power of the test for data generated at $n = 100$ using MMK_ITA test at different scale values, location value, $\mu = 0.5$, shape value, $\delta = 0.4$

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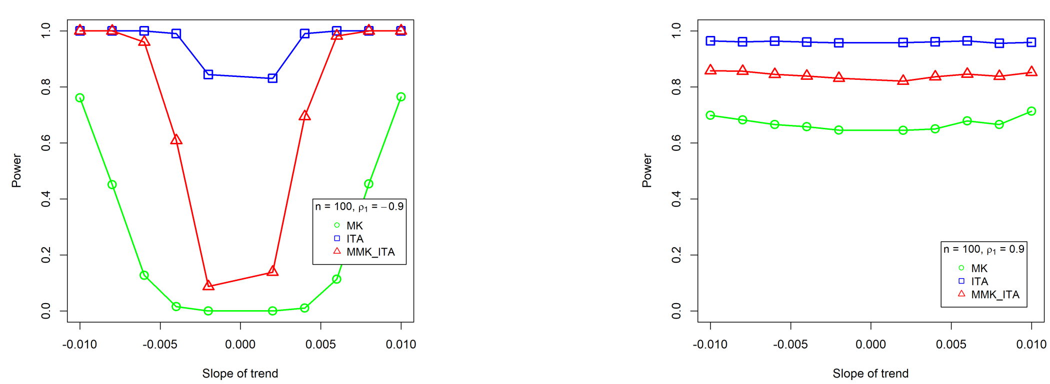
In addition, the power of the tests was influenced by the scale parameter values of the distributions. The scale parameter values were chosen arbitrarily for normal and non-normal distributions, which were 0.2 and 0.4. The results for three tests were depicted in Figure 2, 3 and 4.

In a study conducted by Yue and Pilon, they found that the power of the rank-based tests was higher than the power of the slope-based tests for non-normal distributions [1]. Contrary to that findings, in this study, the ITA test recorded the highest power among these trend detection methods for each distribution except for the GEV and Weibull distributions.

Overall, it could be observed that the ITA test, which was one of the slope-based tests dominated both normal and non-normal distributions in terms of its power. Meanwhile, the power for both MK and MMK_ITA methods were almost identical to each other.

3.2 Power of the Tests for Autocorrelated Time Series

For this study, the MK test was applied to the autocorrelated time series without any prewhitening procedure to verify the effect of the autocorrelation on its power as mentioned in the previous studies by Yue and Wang and Wang et al. [9, 30]. The ITA test recorded the highest power among these trend detection methods, followed by MMK_ITA and lastly the MK, as illustrated in Figure 5. The findings were consistent with several studies that have been conducted before such as Nguyen et al. who found that the ITA result was still accurate even in the presence of autocorrelation [31]. The results for the MK test power concurred with findings from Wang et al. which stated that the presence of autocorrelation misinterpreted the power of MK test [9] . Alashan also discovered that the MMK_ITA was more robust to serial correlation than the classical MK test [20].



(a) $\rho_1 = -0.9$ (b) $\rho_1 = 0.9$

Figure 5 : Power of the test for data generated at $n = 100$ test at different autocorrelation coefficients

Similar to the power of the tests for independent time series, the statistical power for time series with autocorrelation was also affected by sample sizes and slope magnitudes regardless of the methods. However, there was a slight difference in the power since this analysis was done by considering both negative and positive autocorrelation coefficients. For these tests, their power increased when negative ρ_1 values increased and approaching zero. To put it simply, the test powers were increasing from strong negatively correlated to weak negatively correlated series. The power of these three tests continued to increase when the positive ρ_1 values increased. In short, test power for time series with positive ρ_1 was higher when compared to time series with negative ρ_1 values. These findings were significant as Yue et al. have found in their study that the positive autocorrelation was often displayed in hydrological series compared to negative autocorrelation [24].

3.3 Real Data Application

This section applies all tests to assess the significance of trend in monthly maximum temperature for Selangor from 2002 to 2021. The 20-year historical data was extracted from secondary data provided by the Weather Underground from https://www.wunderground.com/weather/my/subang-jaya/WMSA. The data for each month was plotted in Figure 6. From the line plots, increasing trends were observed in March, April and September. It can be further confirmed by statistical tests since result from the line plots is very subjective. Table 1 shows the descriptive statistics of the data. The maximum temperatures varied from 33.0 ℃ to 39.0 ℃. Maximum and minimum standard deviation and skewness can be observed in November and December, respectively.

Table 1 : Descriptive statistics of monthly maximum temperature (2002-2021) for Selangor

Month	**Minimum (℃)**	**Maximum (℃)**	**Mean**	**Standard Deviation**	**Skewness**	**Kurtosis**
January	34.00	36.00	34.65	0.6708	0.5071	2.2939
February	34.00	36.00	35.20	0.6156	-0.1111	2.5556
March	34.00	38.00	35.60	0.9947	0.5399	3.1227
April	34.00	37.00	35.40	0.6806	0.3700	2.9917
May	34.00	36.00	35.35	0.7452	-0.6441	2.1301
June	33.00	36.00	35.05	0.8256	-0.6665	3.1239
July	34.00	36.00	34.65	0.6708	0.5071	2.2939
August	34.00	36.00	34.85	0.7452	0.2369	1.9145
September	33.00	36.00	34.60	0.7539	0.0302	2.6584
October	34.00	36.00	34.55	0.6048	0.5382	2.3620
November	33.00	39.00	34.40	1.3139	2.0798	8.6300
December	33.00	35.00	34.00	0.5620	0	3.3333

In order to produce accurate and reliable results from the MK test, it was essential to check whether the autocorrelation coefficients for each month satisfy Equation (7) or not. The data must be free from autocorrelation before conducting the trend analysis using MK test, unlike the other two methods. Results indicated that all of the months were uncorrelated except for three months, which were May, June and September. Therefore, the VCPW procedure was applied on these three months to reduce the effect of autocorrelation on the MK test.

The decision to reject the null hypothesis was made based on the p-values for both MK and MMK_ITA tests, while the decision for ITA was made based on s_{ITA} values. Based on Table 2, the null hypotheses for all months were failed to be rejected since the p-values for the MK test in every month were greater than the significance level of 0.05. Next, the MMK_ITA analysis found that only null hypothesis for February can be rejected as its p-value was less than the significance level of 0.05, whereas there were no significant trends detected in other months. In the ITA method, the s_{ITA} values were compared with the confidence limits (CL). The results indicated that there were no significant trends detected in July, October and November because their s_{ITA} values fell outside of the CL.

The results showed that the MK test did not to detect any significant trends in each month from this time series. According to the MMK_ITA test, there was significantly increasing trend in only February while no trends were observed in the other months. In contrast, the ITA method suggested that almost all months have increasing trends except for July, October and November. From early inspection in Figure 6, only March, April and September displayed distinct increasing trends in the monthly maximum temperature. The results from the trend detection tests showed that only the ITA test detected trends in these three months.

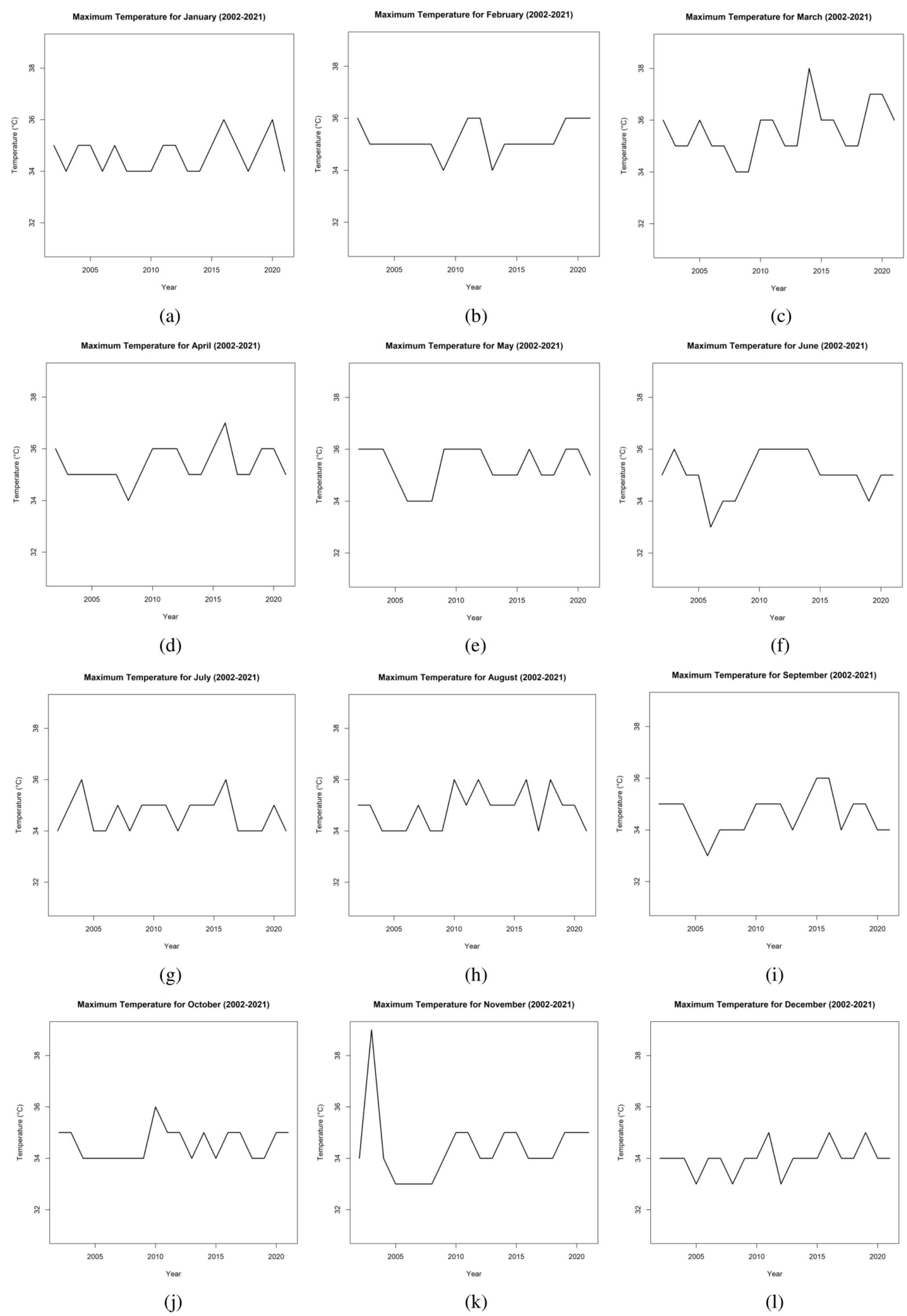


Figure 6 : Line plot of monthly maximum temperature (2002-2021) for Selangor from (a) January to (l) December

Table 2 : Trend analysis of monthly maximum temperature (2002-2021) for Selangor using MK, ITA and MMK_ITA methods

Methods		Months											
		1	2	3	4	5	6	7	8	9	10	11	12
MK	Significance level	95%	95%	95%	95%	95%	95%	95%	95%	95%	95%	95%	95%
	Critical z value	1.96	1.96	1.96	1.96	1.96	1.96	1.96	1.96	1.96	1.96	1.96	1.96
	z value	0.5785	1.0899	1.5197	1.0656	-0.166	-1.0541	-0.2892	0.9164	-0.1317	0.5910	1.7338	1.3778
	p-value	0.5629	0.2758	0.1286	0.2866	0.9207	0.3231	0.7724	0.3595	0.9475	0.5545	0.0830	0.1683
	Decision	No	No	No	No	No	No	No	No	No	No	No	No
ITA	First half mean	34.5	35.1	35.2	35.2	35.3	34.9	34.7	34.6	34.4	34.5	34.3	33.9
	Second half mean	34.8	35.3	36	35.6	35.4	35.2	34.6	35.1	34.8	34.6	34.5	34.1
	s_{ITA} value	0.03	0.02	0.08	0.04	0.01	0.03	-0.01	0.05	0.04	0.01	0.02	0.02
	Significance level	95%	95%	95%	95%	95%	95%	95%	95%	95%	95%	95%	95%
	Confidence limits (CL)	±0.0185	±0.0178	±0.0274	±0.0230	±0.0279	±0.0146	±0.0135	±0.0239	±0.0226	±0.0235	±0.0493	±0.0183
	Decision	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes
MMK_ITA	s_{ITA} value	0.03	0.02	0.08	0.04	0.01	0.03	-0.01	0.05	0.04	0.01	0.02	0.02
	Significance level	95%	95%	95%	95%	95%	95%	95%	95%	95%	95%	95%	95%
	Critical z value	1.96	1.96	1.96	1.96	1.96	1.96	1.96	1.96	1.96	1.96	1.96	1.96
	z value	0.1622	2.3684	1.3951	1.2000	0.6813	-0.1622	0.8111	1.2653	0.4867	1.2004	0.1273	1.3302
	p-value	0.8711	0.0179	0.1630	0.2300	0.4957	0.9225	0.4173	0.2058	0.6265	0.2300	1.5249	0.1834
	Decision	No	Yes	No	No	No	No	No	No	No	No	No	No

4 CONCLUSION

In summary, the power of the tests considered in this study depended on the magnitude of the linear trend slope and sample sizes. Additionally, the power of these tests was influenced by the distribution types and their scale parameter values. Furthermore, the power of the MK test was significantly affected by the presence of autocorrelation in a time series, as observed in the simulation study, which aligns with earlier research. In the presence of autocorrelation, the MK test may be less powerful because it does not correct for the correlation structure in the data. Autocorrelation can lead to inflated variability in the test statistic under the null hypothesis, making it more challenging to detect a true trend. The ITA test, a slope-based method that accounts for autocorrelation in the error terms, demonstrated higher power compared to the MK test. This is because it provides a more accurate representation of the underlying trend in the presence of correlated observations. In other words, the ITA test can more easily detect the presence of a linear trend in time series than the other two methods. In conclusion, the slope-based test outperforms the rank-based test and the combination of both in terms of statistical power. However, the combination of the slope-based and rank-based tests is still slightly better than the rank-based test alone, as it exhibits higher power, indicating its enhanced ability to detect trends.

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