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The modified Mann-Kendall test: on the performance of three variance correction approaches

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Abstract

The Mann-Kendall test has been used to detect climate trends in several parts of the Globe. Three variance correction approaches (MKD, MKDD and MKRD) have been proposed to remove the influence of serial correlation on this trend test. Thus, the main goal of this study was to evaluate the probability of occurrence of types I and II errors associated with these three approaches. The results obtained by means of Monte Carlo simulations and from a case of study allowed us to drawn the following conclusions: All approaches are capable of meeting the adopted significant level when they are applied to trend-free uncorrelated series. The approaches are as powerful as the original MK test when they are applied to uncorrelated series. Regarding serially correlated series it was verified that: (i) the performance of the MKDD and MKRD are comparable; (ii) both approaches may not be able to preserve the adopted significance level and (iii) although the MKD is capable of preserving the adopted significance level, it is less powerful than the MKDD and MKRD. Thus, there is a trade-off between the power of the three approaches and their capability of meeting the nominal significance level. Accordingly, we recommend the use of at least two approaches -MKD and MKDD(MKRD)- to evaluate the presence of trends in a given dataset.

Key words: Monte Carlo simulations, serial correlation, climate change.

Teste de Mann-Kendall modificado: desempenho de três abordagens da correção da variância

Resumo

O teste de Mann-Kendall (MK) vem sendo largamente utilizado para detectar tendências climáticas em diversas partes do globo. Três adaptações têm sido propostas (MKD, MKDD e MKRD) para remover a influência da correlação serial sobre o MK. O objetivo deste trabalho foi avaliar a probabilidade de ocorrência dos erros tipos I e II associada a essas três adaptações. Com base em simulações de Monte Carlo e em um estudo de caso, concluiu-se que as três adaptações são capazes de (i) preservar o nível de significância adotado quando aplicadas à séries livres de tendência e autocorrelações e (ii) apresentam a mesma probabilidade de erro tipo II (*power of the test*) do MK quando aplicadas a amostras livres de correlação serial. O MKDD e o MKRD apresentam desempenho equivalente, sendo ambos incapazes de preservar o nível de significância adotado quando aplicados a séries autocorrelacionadas. O MKD sempre preserva a significância nominal. Entretanto, a probabilidade de erro tipo II associada a esse último teste tende a ser mais elevada do que as associadas ao MKDD e ao MKRD. Assim, considerando-se que a adoção da adaptação com menor probabilidade de erro tipo I acarreta em aumento da probabilidade de erro tipo II, recomenda-se o uso simultâneo do MKD e do MKDD (MKRD).

Palavras-chave: simulações de Monte Carlo, correlação serial, mudança climática.

1. INTRODUCTION

The Mann-Kendall test (Kendall and Stuart, 1967; Mann, 1945) has been widely used to detect trends in meteorological, hydrological and agro-meteorological time series. Considering only the years 2010 to 2013, authors such as Back et al. (2012); Blain (2010; 2011a,b,c; 2012a,b; 2013); Blain and Pires (2011); Carvalho et al. (2013); Minuzzi et al. (2011); Sansigolo and Kayano (2010); Streck et al. (2011); Tabari and Talaee (2011) and Weng (2010) used this test to evaluate the presence of significant climate trends in distinct parts of the world.

From a statistical point of view, the non-acceptance of the null hypothesis (H_0) of the original Mann-Kendall test (MK) only implies that the data under analysis cannot be taken as independent and identically distributed (iid; Chandler and Scott, 2011). In practical applications the acceptance of such a H_0 is often taken as an evidence of the presence of no significant trend in a given (agro) meteorological time series. This practical interpretation relies on the fact that in iid datasets no trend is present (Chandler and Scott, 2011). On the other hand, the non-acceptance of such a H_0 is often taken as an evidence of the presence of a significant climate trend in a given location. Accordingly, the type I error associated with the use of this trend test may occur by the rejection of its H_0 due to the presence of temporal dependence in the data. In this view, the presence of a significant positive serial correlation increases the number of false rejections of the above-mentioned H_0 (Hamed and Rao, 1998; Khaliq et al., 2009; Önöz and Bayazit, 2011; von Storch and Navarra, 1995; Yue et al., 2002; Yue and Wang, 2004). Naturally, this drawback associated with the use of the original MK test is of particular interest for (agro/hydro)meteorological studies given that (agro/hydro) meteorological variables frequently exhibit some form of positive serial correlation (Blain and Pires, 2011; Wilks, 2011, among many others).

Several approaches have been carried out to avoid these false trend detections. According to Hamed (2009), in general terms, these approaches can be classified into two different groups. The first group transforms the original serially correlated data into uncorrelated data (Hamed, 2009). The idea behind this transformation is to meet the assumption of no temporal dependence required for applying the original MK test to a given time series. The methods classified into this first group only take into account the magnitude of the lag-1 serial correlation coefficient (Khaliq et al., 2009). Further information regarding the methods classified into this first group, including their advantages and drawbacks, can be found in several studies such as Önöz and Bayazit (2011) and Yue et al. (2002). The methods classified into the second group modify the MK calculation algorithm to account for the presence of serial correlation. The original data remain intact (Hamed, 2009). In addition, these latter methods are capable of incorporating the effect of the serial correlation for other lags besides the lag-1 (Khaliq et al., 2009). At this point, it becomes worth emphasizing that even for a first order serially correlated process, the auto-correlation may extends beyond the lag-1 (Hamed and Rao, 1998).

Regarding the general idea behind the methods classified into this second group, it is worth emphasizing that Hamed and Rao (1998) developed a correction factor ($CF_{rankdetrend}$) that modifies the variance of the MK statistic to compensate for the effect of serial correlation on the data sample (Yue et al., 2002). The Mann-Kendall test calculated by using the $CF_{rankdetrend}$ is referred as to MKRD. The $CF_{rankdetrend}$ is calculated from the auto-correlation coefficients of the ranks of sample data [$r_{rankdetrend(i)}$]. According to authors such as Khaliq et al. (2009); Yue et al. (2002) and Yue and Wang (2004) the MKRD calculation algorithm is similar to another method described in studies such as Khaliq et al. (2009) and Yue and Wang (2004). This latter method also uses a correction factor (CF_{data}) to modify the variance of the MK statistic. However, the CF_{data} is calculated from the auto-correlation coefficients of the original data. This last approach is referred as to MKD.

Based on Monte Carlo experiments, Yue et al. (2002) indicated that the probability of occurrence of a Type I error obtained by using the MKRD tends to be much higher than the adopted significance level. This feature may be linked to the fact that the auto-correlation coefficients of the ranks of sample data may not be capable of representing the true serial correlation of the dataset (Yue and Wang, 2004). Based on sets of Monte Carlo experiments, Yue and Wang (2004) also indicated that when the sample data is free from trends, the MKD is able to properly limit the effect of serial correlation on the trend analysis. However, when a trend is present, it may contaminate the estimate of the auto-correlation coefficients used to calculate the CF_{data}. Therefore, the MKD may not properly assess the significance of a trend. According to Yue and Wang (2004) this problem may be overcome by removing an existing trend (detrending) prior to the estimation of the auto-correlation coefficients. According to Önöz and Bayazit (2011) this detrending procedure should increase the power of the test. The MKD calculated by using this detrending procedure is referred as to MKDD.

In spite of the above-mentioned inferences, neither Önöz and Bayazit (2011) nor Yue and Wang (2004) have performed Monte Carlo experiments to evaluate the probability of occurrence of errors Type I and II associated with the use of MKDD. Moreover, to the author's best knowledge there is no study, based on controlled Monte Carlo simulations, comparing the frequency of occurrence of Types I and II errors obtained from these three variance correction (VC) approaches (MKD, MKDD and MKRD). Thus, the main goal of this descriptive study was to evaluate the probability of occurrence of types I and II errors associated with the use of the MKD, MKDD and MKRD. As a case study, the original MK and its above-mentioned modified forms were also employed to assess the significance of existing trends in monthly values of air temperature data obtained from the weather station of Ribeirão Preto - State of São Paulo, Brazil. It is expected that this study should provide a deeper understanding of the three above-mentioned VC approaches by highlighting some of their strengths and drawbacks.

2. MATERIAL AND METHODS

Minimum (Tmin) and Maximum (Tmax) monthly air temperature data were obtained from the weather station of Ribeirão Preto, São Paulo State, Brazil. This weather station belongs to the Instituto Agronômico (IAC/APTA/SAA-SP).

The length of the records is 68 years (1945-2012). These series do not have missing data, and their consistencies have been previously assessed in Blain (2010; 2011b). It has to be emphasized that the presence of trends in these Tmin and Tmax series has already been evaluated in previous studies, such as Blain (2011b). This last study revealed the presence of significant increasing trends in the Tmin series. Regarding the Tmax series, Blain (2011b) detected a significant decreasing trend only during the months of May. These results are consistent with other studies carried out in several parts of South America (Sansigolo and Kayano, 2010; Vincent et al., 2005). In this study, these Tmin and Tmax series were used to evaluate the performance of the three VC approaches in assessing the significance of trends in real meteorological series. The previous knowledge of the significance of the existing trends was seen as a desirable feature. All hypothesis tests were performed at the 5% significant level.

The Mann-Kendall (trend) test

Consider a dataset consisting of x values with sample size N. The MK calculation begins by estimating the S statistic:

$$S = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \operatorname{sgn}\left(x_j - xi\right) \ldots \text{for } j > I \quad (1)$$

Kendall and Stuart (1967); Mann (1945) states that when N≥8, the distribution of S approaches the Gaussian form with mean E(S) = 0 and variance V(S) given by:

$$V(S) = \frac{N(N-1)(2N+5) - \sum_{m=1}^{SS} ti(m-1)(2m+5)m}{18} \quad (2)$$

Where SS is the number of tied groups and ti is the length of the SS^{th} group.

The statistic S is then standardized (MK), and its significance is estimated from the normal cumulative distribution function.

$$MK = \begin{cases} \dfrac{S-1}{\sqrt{V(s)}} \rightarrow S > 0 \\ 0 \rightarrow S = 0 \\ \dfrac{S+1}{\sqrt{V(s)}} \rightarrow S < 0 \end{cases} \quad (3)$$

Based on sets of Monte Carlo simulations, Yue et al. (2002) have proven that the presence of positive autocorrelation increases the variance of the distribution of S. Accordingly, the three correction factors described in the first section are used to increase the value obtained from equation 2 in the presence of significant positive autocorrelation, i.e.,

$$V^*(S)=CF^*V(S) \quad (4)$$

Where CF may represent $CF_{rankdetrend}$, CF_{data} or $CF_{datadetrend}$ and,

$$CF_{rank\,det\,rend} = 1 + \frac{2}{N(N-1)(N-2)} \sum_{i=1}^{N} (N-i)(N-i-1)(N-i-2) r_{rank\,det\,rend(i)} \quad (5)$$

$$CF_{data} = 1 + 2 * \sum_{i=1}^{N} \left(1 - \frac{i}{N}\right) r_{data(i)} \quad (6)$$

$$CF_{data\,det\,rend} = 1 + 2 * \sum_{i=1}^{N} \left(1 - \frac{i}{N}\right) r_{data\,det\,ernd(i)} \quad (7)$$

Where $r_{datadetrend(i)}$ is the lag-i autocorrelation coefficient estimated from the *detrended* data.

According to Hamed and Rao (1998) $r_{rankdetrend(i)}$ must be estimated only after the removal of a significant trend from the original sample data. This detrend procedure should be based on a robust non parametric trend estimator. Thus, the slope of the trends was estimated by using the Theil-Sen Approach (TSA; Sen, 1968) as recommend by Hamed and Rao (1998) and Yue et al. (2002), among many others.

$$\text{slope} = \text{Median}\left(\frac{X_a - X_b}{a\text{-}b}\right) \forall\, b < a \quad (8)$$

Statistical simulations

The Monte Carlo simulations were based on equation 9.

$$X_t = E(X) + \rho(X_{t-1} - E(X)) + \xi_t + T_t \quad (9)$$

E(X) and ρ are, respectively, the mean and the (true) lag-1 autocorrelation coefficient of the X_t process, ξ_t is a white noise process with zero mean and variance equal to $Var(X)^*(1-\rho^2)$, T is the trend component and t represents the time unit which varies in discrete steps from 1 to N. N is the sample size which was set to 60 and 90. These sample sizes represent series that comprise 2 and 3 climatological normal periods. By following Önöz and Bayazit (2011), the values of ρ were set to 0.0 (an uncorrelated process), 0.2, 0.4 and 0.6. By following Yue and Wang (2004) E(X) was set to 1. The coefficient of variation (CV) of the X_t process was set to 25%, 50%, 75% and 100%. T_t was obtained from Equation 10.

$$T_t = B^*t \text{ for } B=-0.006\ (0.002)\ 0.006 \quad (10)$$

From these adopted B values the mean of the simulated process increases (decreases) by 2, 4 and 6 per 10 time units. At this point, it is worth mentioning that the Monte Carlo simulation carried out in this study can be regarded as pure mathematical evaluations. However, these simulations were carried out concerning meteorological time series. Thus, we assumed that values of T that could lead to a magnitude of change greater than 60%, per 100 time units, would product unrealistic agrometeorological results. The Monte Carlo simulations generated Ns=10000 time series for each ρ, N, and T value. The original MK test and its three VC approaches were applied to each simulated series. Naturally, the probability of occurrence of Type I errors associated with the original MK, MKD, MKDD and MKRD for each ρ and N value was assessed from the simulated series in which B was set to 0. Theoretically, in these cases, we should observe (approximately) 500 false rejections of H_0. In other words, given that the trend analyses were performed at the 5% significance level, it is expected that the rejection rate obtained from the 10000 trend-free series should be close to the adopted significance level for every N and ρ value. By denoting the probability of occurrence of a type II error as β, the quantity 1- β is frequently referred as to "the power of the test". Naturally, the frequency of occurrence of type II errors associated with each approach for each ρ and N value was assessed from the simulated series in which B is greater than or less than 0. In these cases, the power of the tests is simple the ratio between the number of simulations in which H_0 was correctly rejected and the total number of simulations (10000).

3. RESULTS AND DISCUSSION

Type I errors

As expected, when ρ was set to zero the rejection rates obtained from the original MK met the adopted significance level (Figure 1). This result is an empirical evidence that the normal distribution with variance given by Equation 2 and E(S) = 0 is indeed the distribution of S when it is obtained from serially uncorrelated series with no trend. In addition, the rejection rates obtained from each of the three VC approaches were virtually equal to those obtained from the original MK. In other words, for such uncorrelated series, the VC approaches were as good as the original MK test in not rejecting a true H_0. This desirable feature is observed for all CV and N values adopted in this study. A similar result was observed for the MKRD by Hamed and Rao (1998). Thus, the use of the VC approaches in uncorrelated series did not increase the frequency of occurrence of type I errors.

As expected, the results depicted in Figure 1 clearly indicate that the original MK test should not be applied to serially correlated series. As already observed by several authors such as Hamed and Rao (1998); von Storch and Navarra (1995); Yue et al. (2002); Yue and Wang (2004) the rejection rates obtained from the original MK increase as ρ increases. Moreover, the influence of the different ρ values on the type I errors obtained from the original MK seems to overcome the influence of the different CV and N values adopted in this Monte Carlo experiment (Figure 1). This last result is consistent with those found by Yue and Wang (2004). According to these authors the frequency of occurrence of type I errors obtained by applying the original MK to serially correlated series was little affected by the different N values adopted in their study.

The frequency of occurrence of type I errors obtained by using the VC approaches were lower than those obtained by using the original MK test for all ρ>0, N and CV values (Figure 1). Similar to what is observed for the original MK, the rejection rates obtained from the MKD, MKDD and MKRD were also little sensitive to the different CV values adopted in this study. Among the three VC methods, the MKD presented the best performance by bringing the probability of rejecting a true H_0 more close to the adopted significance level. According to Yue and Wang (2004), the MKD is suitable for dealing with the influence of serial correlation on trend-free data samples because it is capable of bringing down the frequency of occurrence of type I errors close to the adopted significance level. In this view, the rejection rates obtained from the MKD (Figure 1) were virtually equal to the adopted 5% significance level. On the other hand, the performance of MKDD and MKRD in not rejecting a true H_0 seems to be a decreasing function of the level of serial correlation of the simulated series (Figure 1).

By considering only the performance of the MKRD, one may state that the results depicted in Figure 1 are consistent with those obtained by Yue et al. (2002) in the sense that this latter approach is not always able to meet the adopted significant level. Among the three approaches, the MKRD presented the highest rates of false detections (Figure 1). However, by way of analogy with this last statement we have to indicate that the MKDD is also not able to properly limit the effect of positive serial correlation on the type I errors. In fact, the rejection rates obtained from this latter VC approach were only slight lower than those obtained from the MKRD. From Figure 1, one may note that when ρ was set to 0.6, the rejection rates obtained from both MKDD and MKRD are more than two times larger than the adopted significance level. Thus, from the results presented in Figure 1 (ρ>0) we may infer that both MKDD and MKRD may not be able to preserve the adopted significance level.

Power of the tests: serially uncorrelated series

Meeting the adopted significance level is perhaps the most important property of a statistical test (Hamed and Rao, 1998; von Storch and Navarra, 1995 among many others). However, according to Hamed and Rao (1998) and Yue et al. (2002) the power of the test is another important property of a given statistical test. Accordingly, it is highly desirable that the power of a trend test increases (rapidly)

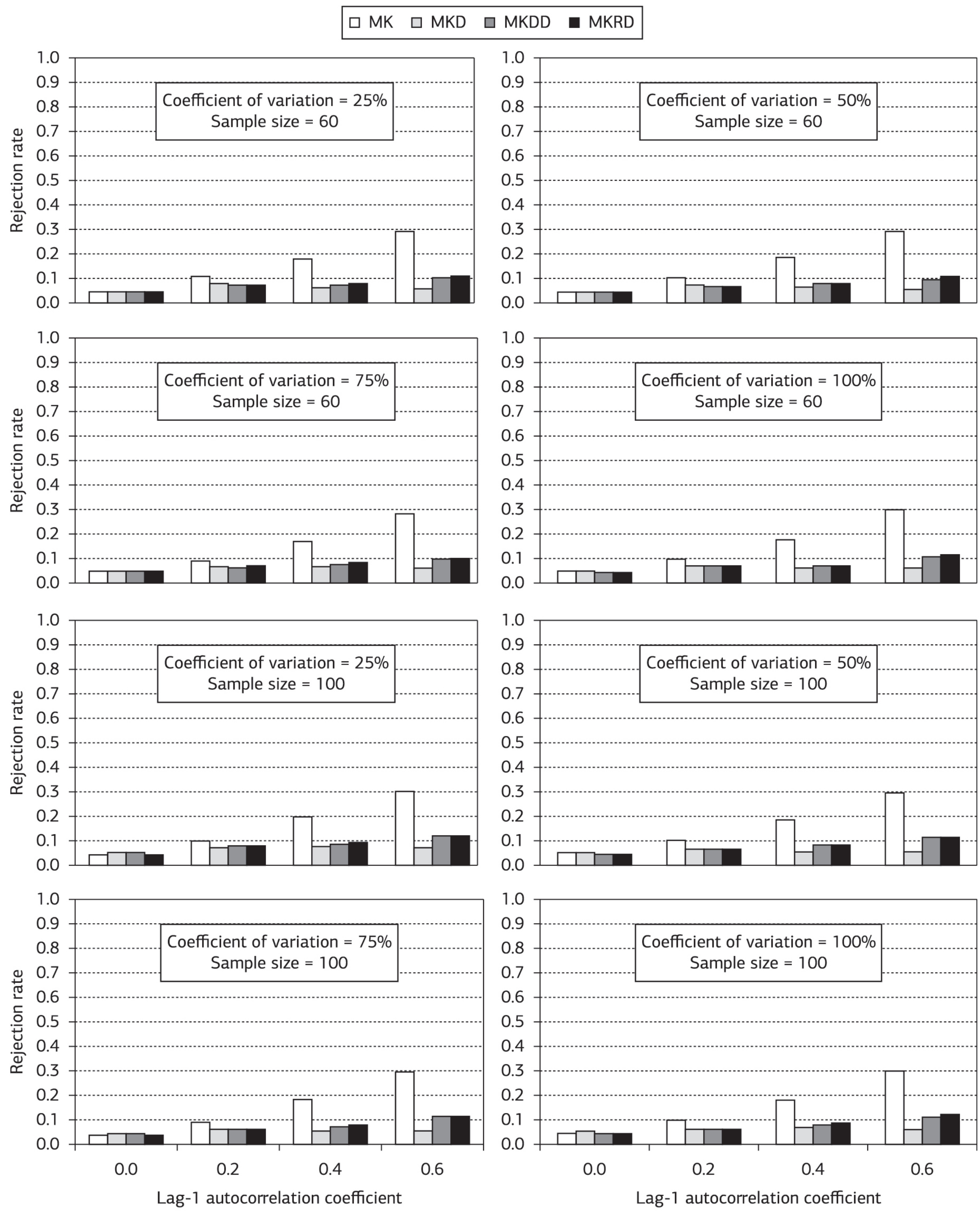

Figure 1. Frequency of occurrence of type I errors obtained from three variance correction approaches as well as the original Mann-Kendall test.

as the slope of the trend departures from zero (Hamed and Rao, 1998). By analyzing the results presented in Table 1, we may indicate that this last desirable feature is only observed for the lowest CV values (25 and 50%). By considering the rejection rates obtained from the series with higher CV values (75 and 100%) one may state that the power of the MK, MKD, MKDD and MKRD were always lower than 50%. Thus, we may indicate that the power of the original MK test as well as the power of the VC approaches is highly affected by the coefficient of variation of the series. As can also be noted, for a given superimposed trend, the power of all trend tests (original MK, MKD, MKDD and MKRD) is also an increasing function of the sample size. These latter results are consistent with the studies of Yue and Pilon (2004)

Table 1. Power of the original Mann-Kendall test (MK) and of three modified forms of calculating this trend test (MKD, MKDD and MKRD) obtained from uncorrelated series with different coefficients of variation (CV) and trends (T)

CV	T	Sample Size = 60				Sample Size = 90			
		MK	MKD	MKDD	MKRD	MK	MKD	MKDD	MKRD
0.25	–0.006	0.88	0.83	0.84	0.84	1.00	1.00	1.00	1.00
0.25	–0.004	0.54	0.49	0.50	0.50	0.97	0.95	0.95	0.96
0.25	–0.002	0.16	0.15	0.15	0.15	0.48	0.44	0.44	0.44
0.25	0.002	0.17	0.15	0.15	0.15	0.48	0.44	0.44	0.44
0.25	0.004	0.54	0.49	0.49	0.50	0.97	0.95	0.95	0.95
0.25	0.006	0.88	0.83	0.83	0.84	1.00	1.00	1.00	1.00
0.50	–0.006	0.33	0.30	0.30	0.31	0.83	0.78	0.78	0.79
0.50	–0.004	0.17	0.15	0.15	0.16	0.48	0.44	0.44	0.45
0.50	–0.002	0.08	0.07	0.07	0.07	0.16	0.15	0.15	0.15
0.50	0.002	0.07	0.07	0.07	0.07	0.16	0.15	0.15	0.15
0.50	0.004	0.17	0.15	0.15	0.15	0.48	0.43	0.43	0.44
0.50	0.006	0.35	0.32	0.32	0.32	0.83	0.77	0.77	0.78
0.75	–0.006	0.17	0.16	0.16	0.16	0.49	0.44	0.44	0.45
0.75	–0.004	0.10	0.09	0.09	0.09	0.24	0.23	0.23	0.23
0.75	–0.002	0.06	0.06	0.06	0.06	0.09	0.09	0.09	0.09
0.75	0.002	0.06	0.06	0.06	0.06	0.09	0.09	0.09	0.08
0.75	0.004	0.11	0.09	0.09	0.10	0.25	0.22	0.22	0.22
0.75	0.006	0.17	0.15	0.15	0.15	0.48	0.43	0.44	0.44
1.00	–0.006	0.11	0.10	0.10	0.10	0.29	0.27	0.27	0.27
1.00	–0.004	0.07	0.06	0.06	0.06	0.15	0.14	0.14	0.14
1.00	–0.002	0.05	0.05	0.05	0.05	0.07	0.07	0.07	0.06
1.00	0.002	0.05	0.05	0.05	0.05	0.08	0.07	0.07	0.07
1.00	0.004	0.07	0.07	0.07	0.07	0.15	0.14	0.14	0.14
1.00	0.006	0.12	0.10	0.11	0.11	0.30	0.28	0.28	0.28

and Önöz and Bayazit (2011). In addition, by analyzing equations 1, 2 and 3, one may state that the signal of the slope of the trend (positive or negative) does not affect the power of the Mann-Kendall test (Yue et al., 2004).

Another important result presented in Table 1 is that the power of the three VC approaches is comparable to the power of the original MK test for every N, CV and B value. Similar results were found for the MKRD and MKD by Hamed and Rao (1998) and Yue and Wang (2004), respectively. Thus, regarding the power of the original MK test, we may indicate that there is no significant loss of power when the VC approaches are applied to uncorrelated series. Thus, in the presence of no significant serial correlation, the outcomes obtained from the original MK test and from the VC approaches tend to be similar to each other (Figure 1; Table 1). By way of analogy with this last statement, we may infer that when the outcomes obtained from the original MK and from the VC approaches do not significantly differ from each other, one may suppose that there is no significant serial correlation affecting the trend analysis. By considering the results found in section 1, we may indicate that this latter statement holds for series with and without trends.

Power of the tests: serially correlated series

Yue and Wang (2004) evaluated the power of the MKD by applying it to simulated series with different levels of serial correlation and trends. The rejection rates obtained by these authors from uncorrelated series were lower than those obtained from serially correlated series. From this result, Yue and Wang (2004) concluded that the MKD overcorrects the influence of serial correlation on the Mann-Kendall test leading to a loss of power. The results presented in Table 2 agree with Yue and Wang (2004) in the sense that the rejection rates obtained by using the MKDD as well as the MKRD are higher than those obtained by using the MKD for every N, CV, ρ and B value. This last result is consistent with the idea that estimating the auto-correlation coefficients and the CF_{data} prior to the removal of the trend overcorrects V(S) and leads to a loss of power (Yue and Wang, 2004). As observed in the previous sections, the rejection rates obtained by using the MKDD and MKRD were similar to each other (although the rejection rates obtained by using the MKRD are slightly higher those obtained by using the MKDD; Table 1 and 2).

Table 2. Power of three modified forms of calculating the Mann–Kendall test (MKD, MKDD and MKRD) obtained from serially correlated series with different coefficients of variation (CV) and trends (T)

DP	T	r	Sample Size = 60			Sample Size = 90		
			MKD	MKDD	MKRD	MKD	MKDD	MKRD
0.25	–0.006 (0.2)	0.2	0.70	0.71	0.73	0.98	0.99	0.99
0.25	–0.006 (0.4)	0.4	0.51	0.58	0.61	0.92	0.97	0.98
0.25	–0.006 (0.6)	0.6	0.36	0.50	0.52	0.74	0.89	0.90
0.25	–0.004 (0.2)	0.2	0.40	0.41	0.43	0.85	0.86	0.88
0.25	–0.004 (0.4)	0.4	0.29	0.33	0.35	0.66	0.75	0.76
0.25	–0.004 (0.6)	0.6	0.18	0.28	0.29	0.44	0.62	0.63
0.25	–0.002 (0.2)	0.2	0.15	0.15	0.16	0.35	0.36	0.37
0.25	–0.002 (0.4)	0.4	0.11	0.12	0.13	0.24	0.30	0.31
0.25	–0.002 (0.6)	0.6	0.10	0.15	0.16	0.16	0.27	0.28
0.25	0.002 (0.2)	0.2	0.16	0.17	0.18	0.35	0.36	0.38
0.25	0.002 (0.4)	0.4	0.12	0.14	0.15	0.24	0.30	0.32
0.25	0.002 (0.6)	0.6	0.09	0.16	0.17	0.16	0.27	0.29
0.25	0.004 (0.2)	0.2	0.41	0.42	0.43	0.84	0.86	0.88
0.25	0.004 (0.4)	0.4	0.29	0.34	0.36	0.66	0.75	0.77
0.25	0.004 (0.6)	0.6	0.19	0.30	0.32	0.44	0.62	0.64
0.25	0.006 (0.2)	0.2	0.70	0.71	0.74	0.98	0.99	0.99
0.25	0.006 (0.4)	0.4	0.51	0.57	0.59	0.92	0.97	0.97
0.25	0.006 (0.6)	0.6	0.33	0.48	0.51	0.74	0.89	0.90
0.5	–0.006 (0.2)	0.2	0.27	0.27	0.28	0.63	0.64	0.66
0.5	–0.006 (0.4)	0.4	0.19	0.22	0.23	0.44	0.53	0.55
0.5	–0.006 (0.6)	0.6	0.13	0.20	0.22	0.27	0.43	0.45
0.5	–0.004 (0.2)	0.2	0.16	0.16	0.17	0.35	0.36	0.37
0.5	–0.004 (0.4)	0.4	0.12	0.14	0.15	0.25	0.30	0.32
0.5	–0.004 (0.6)	0.6	0.09	0.15	0.16	0.15	0.28	0.29
0.5	–0.002 (0.2)	0.2	0.09	0.09	0.09	0.14	0.14	0.15
0.5	–0.002 (0.4)	0.4	0.08	0.09	0.09	0.10	0.14	0.14
0.5	–0.002 (0.6)	0.6	0.07	0.11	0.12	0.08	0.16	0.17
0.5	0.002 (0.2)	0.2	0.08	0.08	0.08	0.14	0.14	0.15
0.5	0.002 (0.4)	0.4	0.08	0.09	0.10	0.10	0.13	0.14
0.5	0.002 (0.6)	0.6	0.06	0.11	0.12	0.09	0.16	0.17
0.5	0.004 (0.2)	0.2	0.15	0.16	0.16	0.35	0.37	0.38
0.5	0.004 (0.4)	0.4	0.12	0.14	0.15	0.24	0.30	0.32
0.5	0.004 (0.6)	0.6	0.09	0.15	0.16	0.16	0.27	0.29
0.5	0.006 (0.2)	0.2	0.27	0.27	0.28	0.64	0.66	0.67
0.5	0.006 (0.4)	0.4	0.19	0.22	0.23	0.45	0.54	0.56
0.5	0.006 (0.6)	0.6	0.13	0.21	0.22	0.29	0.45	0.46
0.75	–0.006 (0.2)	0.2	0.15	0.16	0.16	0.35	0.36	0.37
0.75	–0.006 (0.4)	0.4	0.11	0.13	0.14	0.24	0.30	0.31
0.75	–0.006 (0.6)	0.6	0.08	0.14	0.16	0.16	0.28	0.29
0.75	–0.004 (0.2)	0.2	0.10	0.10	0.10	0.19	0.20	0.21
0.75	–0.004 (0.4)	0.4	0.08	0.10	0.11	0.14	0.17	0.18
0.75	–0.004 (0.6)	0.6	0.07	0.12	0.13	0.10	0.19	0.20
0.75	–0.002 (0.2)	0.2	0.08	0.08	0.08	0.10	0.10	0.10
0.75	–0.002 (0.4)	0.4	0.07	0.08	0.09	0.08	0.10	0.11
0.75	–0.002 (0.6)	0.6	0.07	0.11	0.12	0.07	0.13	0.14
0.75	0.002 (0.2)	0.2	0.08	0.08	0.08	0.09	0.09	0.10
0.75	0.002 (0.4)	0.4	0.07	0.08	0.08	0.07	0.10	0.11
0.75	0.002 (0.6)	0.6	0.05	0.10	0.11	0.07	0.13	0.14
0.75	0.004 (0.2)	0.2	0.10	0.11	0.11	0.20	0.21	0.22
0.75	0.004 (0.4)	0.4	0.08	0.10	0.10	0.14	0.19	0.19
0.75	0.004 (0.6)	0.6	0.07	0.13	0.14	0.10	0.18	0.18
0.75	0.006 (0.2)	0.2	0.16	0.16	0.16	0.34	0.36	0.37
0.75	0.006 (0.4)	0.4	0.11	0.13	0.14	0.25	0.31	0.32

Table 2. Continued...

DP	T	r	Sample Size = 60			Sample Size = 90		
			MKD	MKDD	MKRD	MKD	MKDD	MKRD
0.75	0.006 (0.6)	0.6	0.09	0.16	0.18	0.16	0.27	0.28
1.00	–0.006 (0.2)	0.2	0.11	0.11	0.12	0.22	0.23	0.25
1.00	–0.006 (0.4)	0.4	0.09	0.11	0.12	0.16	0.20	0.21
1.00	–0.006 (0.6)	0.6	0.07	0.13	0.14	0.12	0.21	0.23
1.00	–0.004 (0.2)	0.2	0.09	0.09	0.09	0.13	0.14	0.14
1.00	–0.004 (0.4)	0.4	0.07	0.08	0.09	0.11	0.14	0.14
1.00	–0.004 (0.6)	0.6	0.06	0.12	0.13	0.08	0.15	0.16
1.00	–0.002 (0.2)	0.2	0.07	0.07	0.07	0.08	0.08	0.08
1.00	–0.002 (0.4)	0.4	0.07	0.07	0.08	0.07	0.09	0.10
1.00	–0.002 (0.6)	0.6	0.05	0.10	0.11	0.06	0.12	0.13
1.00	0.002 (0.2)	0.2	0.07	0.07	0.07	0.08	0.09	0.09
1.00	0.002 (0.4)	0.4	0.07	0.08	0.08	0.06	0.09	0.09
1.00	0.002 (0.6)	0.6	0.06	0.10	0.11	0.07	0.14	0.14
1.00	0.004 (0.2)	0.2	0.09	0.09	0.09	0.13	0.13	0.14
1.00	0.004 (0.4)	0.4	0.07	0.08	0.09	0.10	0.13	0.14
1.00	0.004 (0.6)	0.6	0.07	0.11	0.12	0.08	0.15	0.16
1.00	0.006 (0.2)	0.2	0.12	0.12	0.12	0.23	0.24	0.25
1.00	0.006 (0.4)	0.4	0.10	0.11	0.13	0.16	0.20	0.21
1.00	0.006 (0.6)	0.6	0.07	0.13	0.15	0.11	0.20	0.21

Table 3. Outcomes obtained by applying the different approaches evaluated in this study to the monthly air temperature series of Ribeirão Preto, State of São Paulo-Brazil. The lag-1 auto-correlation coefficients were obtained from the original series (r_{data}), from the detrended original series ($r_{datadetrend}$) and from the ranks of the detrended original series ($r_{rankdetrend}$)

Month	Minimum air temperature (°C)						
	r_{data}	$r_{datadetrend}$	$r_{rankdetrend}$	MK	MKD	MKDD	MKRD
January	0.38*	0.11	0.07	4.15*	2.67*	4.15*	4.15*
February	0.38*	0.15	0.21	2.84*	1.89	2.28*	2.36*
March	0.33*	0.12	0.19	4.34*	2.87*	4.34*	3.56*
April	0.37*	–0.15	–0.13	5.75*	3.69*	5.75*	5.75*
May	0.15	0.00	0.03	3.51*	3.51*	3.51*	3.51*
June	0.33*	–0.01	0.08	3.80*	2.96*	3.80*	3.18*
July	0.11	0.11	0.15	3.57*	3.57*	3.57*	3.57*
August	0.18	0.15	0.17	2.23*	2.23*	2.23*	2.23*
September	0.26*	0.21	0.17	2.67*	1.84	2.67*	2.67*
October	0.25*	–0.03	–0.03	3.13*	2.57*	3.13*	3.13*
November	0.16	–0.03	–0.05	3.48*	3.48*	3.48*	3.48*
December	0.38*	0.01	0.02	5.45*	3.52*	5.45*	5.45*
	Maximum air temperature (°C)						
January	0.24	0.24	0.22	–1.71	–1.41	–1.41	–1.71
February	0.03	0.03	0.02	1.21	1.21	1.21	1.21
March	–0.16	–0.16	–0.13	0.49	0.49	0.49	0.49
April	0.09	0.09	0.09	1.43	1.43	1.43	1.43
May	0.23	0.23	0.23	–2.32*	–1.96*	–1.96*	–1.96*
June	0.05	0.05	0.06	–2.18*	–2.18*	–2.18*	–2.18*
July	–0.06	–0.06	–0.06	0.39	0.39	0.39	0.39
August	0.14	0.14	0.13	–1.85	–1.85	–1.85	–1.85
September	0.01	0.01	–0.08	–1.70	–1.70	–1.70	–1.70
October	0.03	0.03	0.03	0.75	0.75	0.75	0.75
November	0.00	0.00	0.00	1.11	1.11	1.11	1.11
December	0.21	0.21	0.25	1.03	1.03	1.03	0.85

*significant at the 5% level.

Case of study and final remarks

Before evaluating the results shown in Table 3, it is worth mentioning that the commonly adopted significance level associated with the use of the Mann-Kendall test is 5%. Accordingly, the results presented in Table 3 are consistent with the assumption that the performance of the MKDD and MKRD are similar to each other. In other words, these two approaches lead to equivalent conclusions regarding the presence of a significant trend in a given data sample. In addition, the results shown in Table 3 for the months of May, July, August and November (Tmin series) and for the months of February, March, April, June, July, August, September and November (Tmax series) agree with the assumption that when the outcomes obtained from the original MK and from the VC approaches do not significantly differ from each other, one may assume the presence of no significant serial correlation affecting the trend analysis. On the other hand, as already observed by Khaliq et al. (2009) the outcomes of the MKD and MKDD(MKRD) tends to differ from each other when the coefficient of autocorrelation obtained from the original series is significant. In this view, the outcomes obtained by using the MK, MKD and MKDD(MKRD) in the months of February and September (Table 3; Tmin series) are different from each other in the sense that they may lead to two different conclusions regarding the presence of significant trends in the Tmin series. The first possible conclusion is that the significant values of the MK and MKD(MKRD) are due to the fact that these three approaches were not able to properly limit the effect of positive serial correlation on the type I errors (as observed in Figure 1). Accordingly, it is recommended to adopt the result obtained by using the MKD and hence assume the presence of no significant trend (at 5% significance level) within these series. The second possible conclusion is that the estimate of the auto-correlation coefficient obtained from these two Tmin series are contaminated by the presence of trends. In such cases, the r_{data} values are artificially high. Therefore, the corresponding CF_{data} becomes artificially high limiting the capability of the MKD to detect real trends. Accordingly, it is recommended to adopt the results of the MK and MKDD(MKRD) that indicate the presence of significant trend within these series.

4. CONCLUSION

The three VC approaches are capable of meeting the adopted significant level when they are applied to trend-free uncorrelated series. The VC approaches are as powerful as the original MK test when they are applied to uncorrelated series. The performance of the MKDD and MKRD are comparable. Both approaches may not be able to preserve the adopted significance level when they are applied to serially correlated series. The MKD is capable of preserving the adopted significance level. However it is less powerful than the MKDD(MKRD). When the outcomes obtained from the MKD and MKDD(MKRD) do not differ from each other it may be supposed that there is no significant serial correlation affecting the trend analysis. There is a trade-off between the power of the three VC approaches and their capability of meeting the nominal significance level. Thus, we recommend the use of the three approaches to evaluate the presence of trends in a given dataset.

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