Over-whitening or Pre-whitening in Hydro-climatological Trend Analysis?

Zekai Sen (✉ zsen@medipol.edu.tr)

Istanbul Medipol Universitesi

Research Article

Keywords: Mann-Kendall, over-whitening, pre-bleaching, trend, standard deviation, serial correlation

Posted Date: January 5th, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1183199/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Over-whitening or pre-whitening in hydro-climatological trend analysis?

Zekai Şen

¹Istanbul Medipol University, Engineering and Natural Sciences Faculty, Beykoz, 34815, Istanbul, Turkey. E-mail: zsen@medipol.edu.tr

²Center of Excellence for Climate Change Research / Department of Meteorology, King Abdulaziz University, PO Box 80234, Jeddah 21589, Saudi Arabia. E-mail: zsen@kau.edu.sa

Abstract

To meet the basic assumption of classical Mann-Kendall (MK) trend analysis, which requires serially independent time series, a pre-whitening (PW) procedure is proposed to alleviate the serial correlation structure of a given hydro-meteorological time series records for application. The procedure is simply to take the lagged differences in a given time series in the hope that the new time series will have an independent serial correlation coefficient. The whole idea was originally based on the first-order autoregressive AR (1) process, but such a procedure has been documented to damage the trend component in the original time series. On the other hand, the over-whitening procedure (OW) proposes a white noise process superposition of the same length with zero mean and some standard deviation on the original time series to convert it into serially independent series without any damage to the trend component. The stationary white noise addition does not have any trend components. For trend identification, annual average temperature records in New Jersey and Istanbul are presented to show the difference between PW and OW procedures. It turned out that the OW procedure was superior to the PW procedure, which did not cause a loss in the original trend component.

Keywords: Mann-Kendall, over-whitening, pre-bleaching, trend, standard deviation, serial correlation,

1. Introduction

In the past, hydro-meteorological time series analyzes was based on stationary stochastic processes with periodicity, stochasticity, and independent random variable components. These were the years before 1990, when there was no indication or discussion of global warming and its effects on climate change and variability (IPCC 2007, 2014). Thus, classical methodologies are subject to revision and modification to adapt to current environmental, atmospheric and water resources phenomenon behavior. The basic assumption was that the future is a statistically indistinguishable repetition of the past, but global warming and consequent climate change effects elicited trend component analysis, meaning that stationarity is dead (Kundzewicz, 2004; Milly et al., 2008). Mitigation and adaptation to the impact of climate change have gained unprecedented momentum in recent years (IPCC, 2018; Saint-Lu, et al., 2019). Especially after the 1990s, trend analysis has become a preferred topic among researchers and there are many trend methodology and application studies in the literature recently (Mohorji et al., 2017; Bera, 2017; Preethi et al., 2017; Bisht et al., 2018; Choudhury et al., 2019; Calojero, 2020; Fukushima et al., 2019; Gedefew et al., 2018; Gaponov et al., 2019; Gebrechorkos et al., 2019; Elzopy et al., 2020; Portela et al., 2020; Praveen et al., 2020; Wang et al., 2020; Saini and Sahu, 2021; Skea et al., 2021).

The real question is whether there is a significant trend component in the hydro-meteorology time series records. How can records be detected without any damage on the trend component even if they are serially correlated? Different researchers have reviewed and made recommendations for trend analysis improvements, taking into account reducing the impact of constraining assumptions in various trend analysis methodologies (Helsel and Hirsch, 1992; Kundzewicz and Robson, 2004; Yue et al., 2002a). In many practical studies, especially the Mann-Kendall (MK) trend test is frequently used (Mann 1945; Sen 1968; Kendall 1975). Hamed and Rao (1998) proposed a modified version of the use of the MK trend test to

50 overcome the dependent autocorrelation structure in time series. Next, a pre-whitening (PW)
51 approach is recommended before applying the MK trend test to serially convert the original
52 time-series autocorrelation into independent form (von Storch, 1995; Sheng et al., 2002;
53 Sonali and Kumar, 2013). The serial autocorrelation feature in time series influences MK
54 trending test results (Ahmed et al. 2020b). On the other hand, traditional trend detection
55 methods help to identify holistic and monotonic trend, with serial independence and normality
56 assumptions among the main limitations. In most of the trend analysis application scientific
57 articles, the assumption of serial independence is not taken into account and the method is
58 applied directly. Such application studies reveal biased components as stated by many
59 researchers in the past (Hamed and Rao., 1998; Matalas and Sankarasubramanian, 2003;
60 Hamed, 2009; Önöz and Bayazit, 2012; von Storch, 1995; Wang et al., 2015). Hamed and
61 Rao (1998) tried to eliminate the effect of serial dependence through a series of MK tests
62 statistical variance modification to compensate for the serial dependence effect. There is
63 another aspect to the trend search performed by Zhang and Zwiers (2004), which attempts to
64 estimate the magnitude and statistical significance of trends in serially related hydro-
65 meteorological time series.

66 Very detailed information has been given by Bayazit and Önöz (2004, 2007) about the
67 features, pros and cons of the pre-whitening (PW) procedure. They concluded that the PW
68 procedure is the most commonly used approach to eliminate the serial correlation effect
69 before MK trend analysis. PW effectively eliminates the possibility of finding a significant
70 trend in the MK trend identification test when there is no trend. They also explained that PW
71 has the disadvantage of accepting the high probability no trend hypothesis when there is a
72 trend. Extensive simulation studies have shown that PW only leads to a true power loss when
73 the coefficient of variation is very low, or when the trend slope and sample size exceed certain
74 values when the coefficient of variation is medium or high. Otherwise, although there is a

power reduction due to PW in the MK test, it will not bring the power below the test value in the absence of autocorrelation. All its results depend on the lagged autoregressive AR (1) process both in the simulations and for the PW procedure.

The main purpose of this article is to provide distinguishable performances of over-whitening (OW) procedure over PW procedure through theoretical discussions and real practice studies. It is concluded that the OW procedure is superior to the PW approach without any damage to the original time series trend component. First, simple simulation study results are presented for a simulation-dependent and trend-embedded series, taking into account OW and PW procedural applications, to identify distinctions on a comparative basis. Application of OW and PW procedures is presented for annual temperature series based on annual temperature records from New Jersey, USA and Istanbul, Turkey.

2. Pre-whitening principles and problems

The pre-whitening (PW) procedure was first suggested by von Storch (1995) to avoid the serial correlation structure in a given time series for the application of the MK trend identification test. It has been observed that the presence of serial correlation may lead to the rejection of the neutral trend (no trend) hypothesis. Initial PW application studies were conducted by Douglas et al. (2000) and Zhang et al. (2001). Matalas and Sankarasubramanian (2003) pointed out that the variance of the trend slope estimation increases with the serial autocorrelation dependence. Theoretically, the evaluation of the PW procedure derives from the first-order autoregressive AR (1) process concept, which implies that sequential lagged subtraction over the given time series yields an independent series. This theoretical consideration does not work in practice, because the original time series may have a stochastic nature separate from the AR(1) process, for example, the Autoregressive Integrated Moving Average (ARIMA) type ARIMA (r, p, q) (Box and Jenkins, 1973). Yu et al. (2002a) stated that PW significantly reduces the probability of rejecting the null hypothesis in the MK test.

In addition, Yue et al. (2002b, 2003) proposed the modified PW (MPW) procedure to determine the effects on the size of test errors.

Different researchers have addressed the need for serial independence on various hydro-meteorological time series records (Helsel and Hirsch 2002; (Khaliq et al., 2009; Fan et al., 2013; Zhang and Zwiers, 2004; Imbers et al., 2014; Liebmann et al., 2010; Lettenmaier 1976).

In the literature, a simple subtractive pre-whitening (PW) approach is recommended to avoid the serial correlation structure. The application of the PW method is recommended by Bayazit and Önöz (2007) considering the sample size and the slope is not large, then the power loss is not overly worrying. On the other hand, Hamed (2009) stated that due to the high variance of the slope estimators, these approaches may be insufficient to analyze real data. Wang et al. (2015) noticed that pre-whitening series quenched the series variances, and therefore, aimed to solve these problems by including correction for slope and series variances in the original trend-free PW approach, which is dependent on variance correction. Their approach helped to reduce the impact of serial autocorrelation on the MK test by addressing two important issues that were not given enough attention in other approaches, the inflationary variance of the slope estimator and the deflationary series variance.

The basic idea in the PW procedure is to treat each hydro-meteorology time series record serially as a first-order autoregressive, AR (1) process dependent, which is generally expressed as:

$$X_i = \mu + \rho(X_{i-1} - \mu) + \sigma\sqrt{1 - \rho^2}\epsilon_i \quad (1)$$

where μ , σ and ρ are the arithmetic mean, standard deviation and first-order serial correlation coefficient, respectively. This model has an independent Gaussian (normal) PDF sequence such as ϵ_i with zero mean and unit standard deviation. In practical applications, the statistically standardized expression is often used.

$$X_i = \rho X_i + \epsilon_i \quad (2)$$

It gives the impression that the subsequent lagged subtraction of the values leads to a new series in the form of independent time series as follows.

$$X_i - \rho X_i = \epsilon_i \quad (3)$$

This is the basis for PW application with the expectation that the final product has a serial-independent structure, but meanwhile the trend component may be affected to some extent.

3. Over-whitening principles

The MK trend test, which is valid for serially independent data, rejects the null hypothesis when the data are serially correlated (Von Storch, 1995; Yue & Wang, 2002); there is no trend more often than indicated by the significance level, unless there is variance modification accordingly. Adjusting the standard deviation has already been demonstrated by Şen (2017) as the addition of a zero mean white noise time series with an appropriate variance value. This over-whitening (OW) procedure depends on the superposition of an independent synthetic time series over the original hydro-meteorology record series to reduce the serial correlation coefficient. The main idea of the OW principle is to classically standardize the original hydro-meteorology time series (X_i , $i = 1, 2, \dots, n$) by considering the mean, $\bar{X}$ and standard deviation, σ_X :

$$x_i = \frac{X_i - \bar{X}}{\sigma_X} \quad (4)$$

To reduce the serial correlation effect, it is necessary to overlay this standard time series with an independent synthetic time series (s_i , $i = 1, 2, \dots, n$) with a zero mean, $\bar{s} = 0$, and the standard deviation equal to the original time series standard deviation, and hence the independent time series as the expected series, (z_i , $i = 1, 2, \dots, n$) overlap as,

$$Z_i = x_i + s_i \quad (5)$$

This has zero mean and the standard deviation depending on the OW procedure. The trend component is searched in superimposed time series because none of the above mentioned actions affect the trend component in the original time series. Performing the OW procedure requires the execution of the following steps.

- 1) Definition of real hydro-meteorology time series probability distribution function (PDF),
- 2) Determining the first-order serial correlation coefficient value for the given hydro-meteorology time series,
- 3) Production of an independent synthetic series with the same PDF type and parameters of the same length,
- 4) Conversion of synthetic series to zero means series by subtracting the arithmetic mean value from all values. The new series has a certain standard deviation value,
- 5) Overlaying these synthetic series on the original time series and checking whether the first-order serial correlation coefficient is within the limits of independence according to the Anderson-Darling test (Anderson, 1942; Anderson and Darling, 1952),
- 6) In particular, at small sample sizes, several overlapping procedures transform the original time series into a practical and serial-independent structure, and therefore a series of overlaps with different random time series can be applied,
- 7) It is also possible to superimpose the original hydro-meteorological time series with different synthetic independent sequences each time and calculate the trend slopes, and finally the average of these trend values provides the original time series trend slope,

8) In the case of more than one trend slope calculation in the previous item, the opportunity arises to find the PDF of the slopes and therefore to base the trend slope on a set of risk values.

4. Over-whitening and Pre-whitening comparison

Over-whitening (OW) and pre-whitening (PW) are the two suggested techniques for the application of the classical and frequently used Mann-Kendall (MK) trend identification tests. Both procedures aim at reducing the serial correlation in a given time series to render it into serially independent time series, which is among the major requirements of the MK test possibility. In order to simplify the comparison, an increasing mathematical trend is given in the form of a straight-line as $Y = 5 + 0.5X$ (see Figure 1a). The deterministic trend appears as an increasing straight-line in the same figure. A random white noise of the same length with zero mean and unit variance is generated according to the normal (Gaussian) PDF and then superimposed on the deterministic trend and the result appears as random fluctuations around the same straight-line. Hence, OW procedure preserves the original trend. The application of the PW procedure on the deterministic straight-line with correlation coefficient of 0.5 according to Eq. (3) yields another straight-line in Figure 1a but with lower slope, which is 0.25. Hence, this process indicates that PW causes loss of slope information in the original trend slope significantly. On the other hand, Figure 1b shows PW procedure application on the OW data and the result is in the form of almost complete loss of the original trend component. All these simple explanations prove empirically that the OW operation is superior to PW procedure in trend detection analyses.

Figure 1 Over-whitening and pre-whitening procedures

214 5. Factual applications

215 The representations and performance of the OW and PW procedures can be demonstrated by
 216 considering real time series analyses for possible trend identification research. The OW and
 217 PW procedures comparative application evaluations are presented for actual annual mean
 218 temperature measurements from New Jersey (statewise and southern region) and
 219 Istanbul/Kadıköy (maximum and minimum) time series records. The former (latter) location
 220 has 116 (92) years of records from 1895 (1929) to 2010 (2020). New Jersey State annual
 221 precipitation records are available online (<http://epa.gov/climatechange/index.html>;
 222 <http://climate.rutgers.edu/stateclim>). Although the New Jersey record has changed a lot from
 223 year to year, the normally cool (November-March) and warm (May-September) seasons in
 224 general are now warmer than before. Istanbul records are obtained from the Turkish
 225 Meteorology General Directorate. Figure 2 shows the probability cumulative distribution
 226 function (CDF) for New Jersey statewise and southern districts for a range of risk levels. New
 227 Jersey annual mean temperature CDFs for statewise and southern regional records appear as
 228 logarithmic normal and two-parameter Gamma PDF types with location and scale parameters

229 in the same figure.

236 Figure 2 New Jersey annual mean temperature records CDFs a) statewide, b) southern region

237 Figure 3 shows the same location time series records with the original data and the monotonic
238 trend component. The presence of trend lines is related to slope ($^{\circ}\text{F}/\text{year}$) and intersection ($^{\circ}\text{F}$)
239 values. The existence of trends is obvious even with the naked eye.

247 Figure 3 New Jersey annual mean temperature record trends and intercepts a) statewide, b)
248 southern district

249 Similar calculations and procedural applications are made for the CDFs in Figure 4 and the
250 annual average maximum and minimum temperature records in Istanbul/Kadıköy.
251 Logarithmic normal CDFs are the most suitable representative theoretical PDFs for both
252 temperature types.

253

254

255

256

257

Figure 4 Istanbul/Kadıköy annual mean temperature records CDFs a) maximum, b) minimum

The original time series for the maximum and minimum annual mean temperature records are given in Figure 5 with the monotonic trend component where the slope is °C/year and the intersection is in °C units.

Figure 5 Istanbul/Kadıköy annual mean temperature record trends and intercepts a) maximum, b) minimum

Table 1 presents the various characteristics of all stations covered in this section collectively, including statistical parameters (mean, standard deviation, and serial correlation coefficient), probability characteristics (PDF types and parameters), and monotonic trend slopes with units.

Table 1 various characteristic values for all stations

Records		Statistical parameters			Probability distribution function		
Name	Duration	Mean	St.Dev.	Cor. coef.	Type	Location	Scale
New Jersey (Statewise)	1895-2010	52.25	1.28	0.35	Log- normal	3.956	0.025
New Jersey (Southern)	1895-2010	53.04	1.30	0.39	Gamma	1.670	0.032
Istanbul/Kadıköy (Maximum)	1940-2020	25.62	0.96	0.27	Log-normal	3.242	0.037
Istanbul/Kadıköy (Minimum)	1940-2020	5.52	1.50	0.71	Log-normal	1.672	0.269

After all the explanations, answers to each temperature record trend identification procedure can be sought through the OW and PW procedures as explained in the following sub-sections.

5.1 Over-whitening procedure

The basic principles of OW were given by Şen (2017) in detail, both theoretically and practically. The practical application of the OW procedural approach is given by executing the following steps.

- 1) CDF of original time series records is required to apply the OW procedure. Figures 2 and 4 show two types of CDFs, logarithmic-normal and two-parameter Gamma PDFs,
- 2) Production of record-length synthetic series with the theoretical CDF parameters given in Table 1,
- 3) The synthetic series in the previous step is converted to a zero mean series by subtracting the arithmetic mean from the synthetic series,
- 4) Adding zero means synthetic sequence to the measurement sequence of the same length to get the over-whitened sequence. Adding such an independent and zero

mean sequence on top of the original sequence does not damage the trend component,

- 5) The trend component in this over-whitened series in slope and intersection values is almost identical to the original time series trend,
- 6) The word “almost the same” in the previous step refers to sampling errors that can be reduced as much as possible by adding a set of synthetic sequences as in steps 3 and 4.

Applying these steps to each of the available temperature records according to the theoretical CDF parameters results in the following graphs with nearly indistinguishable slope and intercept values within $\pm 5\%$ error limits compared to the graphs in Figures 3 and 5, respectively.

Figure 6 Annual mean temperature record OW trends and intercepts a) New Jersey statewide, b) New Jersey southern region, c) Istanbul/Kadıköy maximum, d) Istanbul/Kadıköy minimum

Comparing each graph in this figure with the corresponding ones in Figures 3 and 4 shows that the relative error differences are all less than 5%, which is an acceptable range in practical applications.

5.2 Pre-whitening procedure

As already explained by numerous authors, the basic idea in PW is to try and reduce the serial dependency nature of a given time series record by sequential lagged subtraction. It is explained in Section 2 that such a procedure would damage the trend component in the original data series. After applying the necessary steps according to the equation (3) the resulting graphs in each original time series are shown in Figure 7.

345

352 Figure 7 Annual mean temperature record PW trends and intercepts a) New Jersey statewide,
353 b) New Jersey southern region, c) Istanbul/Kadıköy maximum, d) Istanbul/Kadıköy minimum

354 Comparison of these graphs with their counterparts in Figures 3 and 5 clearly shows
355 that the PW procedure is not well suitable for trend identification and the superiority of the
356 OW procedure over the PW procedure emerges.

357 6. Conclusions

358 The effects of global warming and subsequent climate change, with the expectation that it
359 may continue in the near future, have attracted the attention of researchers to search for trend
360 components as a result of temperature increases in the last 30 years. Classical methodologies,

such as the Mann-Kendall (MK) trending tests, require an independent serial correlation structure as a basic assumption, which is not possible in hydro-meteorological time series records. To alleviate this situation, some studies are recommended in which the most frequently applied and discussed in the literature is the pre-whitening (PW) procedure. Its basic mechanism is to subtract the next records from each other, taking into account the first-order autoregressive AR (1) process serial correlation coefficient, which is expected to have a serially independent structure of the new series. However, many researchers noted that such a procedure may cause some loss in the original trend. In this paper, a fairly new over-whitening (OW) procedure methodology is applied that works differently from the PW operation. OW overlays completely independent series on the original time series to reduce the serial dependence on the original time series. Overlap series should have zero mean and trend-free structure at the same data length.

The fundamentals of PW and OW procedures are discussed in detail in a comparative manner and their applications for long temperature records in New Jersey, USA and Kadıköy, Istanbul, Turkey are presented. The OW procedure has been shown to be superior to the PW approach. In future trend studies, it is recommended to apply directly OW procedure rather than the PW operation for robust trend component identification in hydro-meteorological time series recordings.

-Conflict of Interest: There is no conflict of interest

-Funding Statement: There is no funding

-Author's Contribution: Single author and all contribution by him

-Availability of data and material: Data and material will be sent to anyone requests them

-Code availability: The code will be sent to anyone is interested. It is in Matlab form

-Ethics approval: There is no ethical problem in the text

-Consent to participate: I understand that all information I provide for this study will be treated confidentially.

-Consent for publication: I, the, give my consent for the publication of identifiable details.

References

Ahmed, N., Wang, G-X., Oluwafemi, A., et al., (2020). Temperature trends and elevation dependent warming during 1965–2014 in headwaters of Yangtze River, Qinghai Tibetan Plateau Journal of Mountain Science 17:556-571. doi:10.1007/s11629-019-5438-3.

Anderson, T.W., (1942). Distribution of serial correlation coefficient. Annals of Mathematical Statistics, Vol. 13: 1-13.

Anderson TW, Darling DA (1952) Asymptotic theory of certain “goodness-of-fit” criteria based on stochastic processes. Ann Math Stat 23:193–212

Anderson, T.W., and Darling, D.A.,(1952). Asymptotic theory of certain “goodness of fit” criteria based on stochastic processes. Ann. Math. Stat., Vol. 23: 193-212.

Bera, S., (2017). Trend analysis of rainfall in Ganga Basin, India during 1901–2000. Am J Clim Change 06(01):116–131. <https://doi.org/10.4236/ajcc.2017.61007>.

Bisht, D.S., Chatterjee, C., Raghuwanshi, N.S., and Sridhar, V., (2018). Spatiotemporal trends of rainfall across Indian river basins. Theor Appl Clim 132(1–2):419–436. <https://doi.org/10.1007/s00704-017-2095-8>.

Bayazit, M., and Önöz, Ö., (2007) To prewhiten or not to prewhiten in trend analysis?, Hydrological Sciences Journal, Vol. 52(4): 611-624. DOI: 10.1623/hysj.52.4.611

408 Bayazit, M., and Önöz, B., (2004). Comment on Applicability of prewhitening to eliminate
 409 the influence of serial correlation on the Mann-Kendall test by S. Yue & C. V. Wang.
 410 Water Resour. Res. 40(8), W08801.

411 Box, G.E.P., and Jenkins, D.A., (1970). Time Series Analysis, Forecasting and Control, San
 412 Francisco, CA: Holden-Day.

413 Caloiero, T., (2020). Evaluation of rainfall trends in the south island of new zealand through
 414 the innovative trend analysis (ITA). Theor Appl Clima 139(1–2):493–504.
 415 <https://doi.org/10.1007/s00704-019-02988-5>.

416 Choudhury, D., Nath, D., and Chen, W., (2019). Impact of Indian ocean warming on
 417 increasing trend in pre-monsoon rainfall and Hadley circulation over bay of Bengal.
 418 Theor Appl Clim 137(3–4):2595–2606. <https://doi.org/10.1007/s00704-018-02751-2>.

419 Douglas, E.B., Vogel, R.M., and Knoll, C.N., (2000). Trends in floods and low flows in the
 420 United States: impact of serial correlation. J. Hydrol. 240, 90–105.

421 Elzopy, K.A., Chaturvedi, A.K., Chandran, K.M., Gopinath, G.K.N., and Surendran, U.
 422 (2020). Trend analysis of long-term rainfall and temperature data for Ethiopia. South
 423 African Geograph. <https://doi.org/10.1080/03736245.2020.1835699>

424 Fan, H., Hu, J., and He, D., (2013). Trends in precipitation over the low latitude highlands of
 425 Yunnan, China. J. Geog. Sci., 23(6): 1107–1122.

426 Fukushima, A., Kanamori, H., and Matsumoto, J., (2019). Regionality of long-term trends and
 427 inter-annual variation of seasonal precipitation over India. Prog Earth Planet Sci.
 428 <https://doi.org/10.1186/s40645-019-0255-4>

429 Gaponov, V.M., Elizaryev, A.N., Aksenov, S.G., and Longobardi, A., (2019). Analysis of
 430 trends in annual time series of precipitation in the Republic of Bashkortostan, Russian
 431 Federation. IOP Conf Ser Earth Environ Sci 350(012):003.
 432 <https://doi.org/10.1088/1755-1315/350/1/012003>

433 Gebrechorkos, S.H., Hüsmann, S., and Bernhofer, C., (2019). Long-term trends in rainfall and
 434 temperature using high-resolution climate datasets in East Africa. *Sci Rep* 9(1):1–9.
 435 <https://doi.org/10.1038/s41598-019-47933-8>
 436 Gedefaw, M., Yan, D., Wang, H., Qin, T., Girma, A., Abiyu, A., and Batsuren, D., (2018).
 437 Innovative trend analysis of annual and seasonal rainfall variability in amhara regional
 438 state, Ethiopia. *Atmosphere*. <https://doi.org/10.3390/atmos9090326>.
 439 IPCC, (2007) IPCC fourth assessment report 2007, Working Group II Report "Impacts,
 440 Adaptation and Vulnerability"
 441 IPCC (2018) Global warming of 1.5 °C an IPCC special report on the impacts of global
 442 warming of 1.5 °C above pre-industrial levels and related global greenhouse gas
 443 emission pathways, in the context of strengthening the global response to the threat of
 444 climate change, sustainable development, and efforts to eradicate poverty. [Masson-
 445 Delmotte V, Zhai P, Po'trner H-O, Roberts D,
 446 Hamed, K.H., and Rao, A.R., (1998). A modified Mann-Kendall trend test for autocorrelated
 447 data. *J. Hydrol.* 204, 182–196.
 448 Helsel, D.R., and Hirsch, R M., (1992). *Statistical Methods in Water Resources*, Elsevier,
 449 Amsterdam, The Netherlands.
 450 Hamed, K.H., (2009). Enhancing the effectiveness of pre-whitening in trend analysis of
 451 hydrologic data. *J. Hydrol.*, Vol. 368(1–4): 143–155.
 452 Helsel, D.R., and Hirsch, R.M., (2002). *Statistical methods in water resources.*" Techniques of
 453 water-resources investigations, USGS, Washington, DC, 522.
 454 Imbers, J., Lopez, A., Huntingford, C., and Allen, M., (2014). Sensitivity of climate change
 455 detection and attribution to the characterization of internal climate variability. *J. Clim.*,
 456 Vol. 27(10): 3477–3491.
 457 Kendall, M., (1975). *Rank correlation methods* Charles Griffin, London (fourth edition, 1970)

458 Khaliq, M.N., Ouarda, T.B.M.J., Gachon, P., Sushama, L., and St-Hilaire, A., (2009).
 459 Identification of hydrological trends in the presence of serial and cross correlations: A
 460 review of selected methods and their application to annual flow regimes of Canadian
 461 rivers. *J. Hydrol.*, Vol. 368(1–4): 117–130.

462 Kundzewicz, Z.W., (2004). Searching for change in hydrological data. *Hydrol. Sci. J.*, Vol.
 463 49(1): 3–6.

464 Kundzewicz, Z.W., and Robson, A.J., (2004). Change detection in hydrological records—a
 465 review of the methodology. *Hydrol. Sci. J.* 49(1), 7–19.

466 Lettenmaier, D.P., (1976). Detection of trends in water quality data from records with
 467 dependent observations. *Water Resour. Res.*, Vol. 12(5): 1037–1046.

468 Liebmann, B., Dole, R.M., Jones, C., Bladé, I., and Allured, D., (2010). Influence of choice of
 469 time period on global surface temperature trend estimates. *Bull. Am. Meteorol. Soc.*,
 470 Vol. 91(11): 1485–1491.

471 Mann, H.B., (1945). Nonparametric Tests Against Trend *Econometrica* 13:245-259. 600
 472 doi:10.2307/1907187.

473 Matalas, N.C., and Sankarasubramanian, A., (2003). Effect of persistence on trend detection
 474 via regression. *Water Resour. Res.* 39(12), WR002292.

475 Milly, P.C.D., Betancourt, J., Falkenmark, M., Hirsch, R.M., Kundzewicz, Z.W., Lettenmaier,
 476 D.P., and Stouffer, R.J., (2008). Stationarity is dead: Whither water management?
 477 *Science*, Vol. 319(5863): 573–574.

478 Mohorji, A.M., Şen, Z. and Almazroui, M., (2017). Trend Analyses Revision and Global
 479 Monthly Temperature Innovative Multi-Duration Analysis. *Earth Syst Environ*,
 480 Vol. 1, <https://doi.org/10.1007/s41748-017-0014-x>.

481 Önöz, B., and Bayazit, M., (2012). Block bootstrap for Mann-Kendall trend test of serially
 482 dependent data.”*Hydrol. Processes*, Vol. 26(23), 3552–3560.

483 Portela, M.M., Espinosa, L.A., Zelenakova, M., (2020). Long-term rainfall trends and their
 484 variability in mainland Portugal in the last 106 years. *Climate* 8(12):1–18.
 485 <https://doi.org/10.3390/cli8120146>

486 Praveen, B., Talukdar, S., Shahfahad, Mahato, S., Mondal, J., Sharma, P., Islam, A.R.M.T.,
 487 and Rahman, A., (2020). Analysing trend and forecasting of rainfall changes in India
 488 using non-parametrical and machine learning approaches. *Sci Rep* 10(1):1–21.
 489 <https://doi.org/10.1038/s41598-020-67228-7>

490 Preethi, B., Mujumdar, M., Kripalani, R.H., Prabhu, A., and Krishnan, R., (2017). Recent
 491 trends and tele-connections among South and East Asian summer monsoons in a
 492 warming environment. *Clim Dyn* 48(7–8):2489–2505.

493 Saini, A., and Sahu, N., (2021). Decoding trend of Indian summer monsoon rainfall using
 494 multimethod approach(Century long Indian monsoon rainfall trend). *Stochastic*
 495 *Environmental Research and Risk Assessment*. [https://doi.org/10.1007/s00477-021-](https://doi.org/10.1007/s00477-021-02030-z(0123456789().,-volV)(0123456789().,-volV))
 496 [02030-z\(0123456789\(\).,-volV\)\(0123456789\(\).,-volV\)](https://doi.org/10.1007/s00477-021-02030-z(0123456789().,-volV)(0123456789().,-volV))

497 Saint-Lu, M., Chadwick, R., Lambert, F.H., Collins, M., (2019). Surface warming and
 498 atmospheric circulation dominate rainfall changes over tropical rainforests under
 499 global warming. *Geophys Res Lett* 46(22):13410–13419.
 500 <https://doi.org/10.1029/2019GL085295>

501 Sen, P.K., (1968). Estimates of the Regression Coefficient Based on Kendall's Tau *Journal of*
 502 *the American Statistical Association* 63:1379-1389.
 503 [doi:10.1080/01621459.1968.10480934](https://doi.org/10.1080/01621459.1968.10480934) 628.

504 Sheng, Y., Paul, P., and George, C., (2002). Power of the Mann-Kendall and spearman's rho
 505 tests for detecting monotonic trends in hydrological series. *J Hydrol* 259:254–271.
 506 [https://doi.org/10.1016/S0022-1694\(01\)00594-7](https://doi.org/10.1016/S0022-1694(01)00594-7)

Sonali, P., and Kumar, D.N., (2013). Review of trend detection methods and their application to detect temperature changes in India. *J Hydrol* 476:212–227. <https://doi.org/10.1016/j.jhydrol.2012.10.034>.

Şen, Z., (2017). Hydrological trend analysis with innovative and over-whitening procedures. *Hydrological Sciences Journal*, Vol. 62(2).

von Storch, H. (1995) Misuses of statistical analysis in climate research. In: *Analysis of Climate Variability: Applications of Statistical Techniques* (ed. by H. von Storch & A. Navarra), 11–26. Springer-Verlag, Berlin, Germany.

Wang, W., Chen, Y., Becker, S., and Liu, B., (2015). Variance correction pre-whitening method for trend detection in auto-correlated data. *J. Hydrol. Eng*, Vol. 20(12): 04015033

Wang, Y., Xu, Y., Tabari, H., Wang, J., Wang, Q., Song, S., and Hu, Z., (2020). Innovative trend analysis of annual and seasonal rainfall in the Yangtze River delta, eastern China. *Atmos Res* 231:104673. <https://doi.org/10.1016/j.atmosres.2019.104673>

Yue, S., Pilon, P., and Cavadias, G. (2002a). Power of the Mann-Kendall and Spearman's rho tests for detecting monotonic trends in hydrological series. *J. Hydrol.* **259**, 254–271.

Yue, S., Pilon, P., Phinney, B., And Cavadias, G. (2002b). The influence of autocorrelation on the ability to detect trend in hydrological series. *Hydrol. Processes* **16**, 1807–1829.

Yue, S., Pilon, P., and Phinney, B., (2003). Canadian streamflow trend detection: impacts of serial and cross-correlation. *Hydrol. Sci. J.* 48(1), 51–63.

Zhang, X., Harvey, K.D., Hogg, W.D., and Yuzyk, T.R., (2001). Trends in Canadian streamflow. *Water Resour. Res.* 37(4), 987–998.

Zhang, X., and Zwiers, F.W., (2004). Comment on 'Applicability of pre-whitening to eliminate the influence of serial correlation on the Mann-Kendall test' by Sheng Yue and Chun Yuan Wang. *Water Resour. Res.*, Vol. 40(3): 1–5.

532

533

534

535