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Comparison of Sub-Series with Different Lengths Using Şen-Innovative Trend Analysis

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Abstract: Climate change causes trends in hydro-meteorological series. Traditional trend analysis methods such as Mann-Kendall and Spearman Rho are sensitive to correlated series and cannot detect non-parametric trends. Şen-innovative trend analysis method is launched to literature in order to overcome these restrictions. It does not require any restrictive assumptions as serial dependence and normal distribution and examines a main series as equally divided two sub-series. Şen multiple innovative trend analyses methodology is improved to detect partial trends on different sub-series but again equal lengths. Climate change nowadays more effects hydro-meteorological parameters according to last two or three decades and gives asymmetric trend change point on main time series. Due to asymmetric trend change points, it may be necessary to analyze sub-series with different lengths to use all measured data. In this study, Şen innovative trend analyses method is revised for these requirements (ITA_DL). The new approach compared with traditional Mann Kendall (MK) and Şen innovative trend analysis (Şen_ITA) gives successful and consistent results. ITA_DL gives four monotonic trends on Oxford May, July, September and October rainfall series although MK gives three monotonic trends on May, July and December and cannot detect trends on September and October. In the ITA_DL visual inspection, the December rainfall series does not show a trend that is monotonic or non-monotonic. Şen_ITA trend results are consistent with ITA_DL except September, although there are different trend slopes.

Keywords: Trend analyses, innovative trend analyses, trend change point, sub-series

Introduction

With increasing levels of greenhouse gases, the atmosphere warms more or loses its ability to cool sufficiently. There are a lot of studies to investigate increasing or decreasing trends on hydro-meteorological parameters. The most used classical methods are Mann-Kendall (Kendall, 1975; Mann, 1945), Spearman's Rho (Spearman, 1987) and Sen slope estimator (Sen, 1968). These methods have some restrictive assumptions such as Gaussian distribution and serial independence, which leads to type 1 and type 2 errors in trend calculations (Alashan, 2020a; Bayazit and Önöz, 2007; Kulkarni and Storch, 1995; Wang et al., 2015; Yue et al., 2002b, 2002a; Yue and Wang, 2004). Şen, (2012) launched to literature a new trend detection methodology named innovative trend analysis (Şen_ITA) to release these restrictive assumptions. The method has high visualization capability and can identify non-monotonic trends in a given series on low, medium and high values. Although the method is new it is used to determine trends on hydro-meteorological data as temperature (Pandey et al., 2021; Sonali and Nagesh Kumar, 2013); rainfall (Marak et al., 2020; Oruc, 2021; Phuong et al., 2021; Şan et al., 2021; Wang et al., 2020); precipitation (Alifujiang et al., 2020); aerosol optical depth (Kotriake et al., 2021); sea surface temperature (Şişman, 2021); evapotranspiration (Ma et al., 2018); flow (Yilmaz and Tosunoglu, 2019).

Climate change is up to date topic as long two-three decades according to hydro-meteorological data measuring more than one hundred fifty years. Şen_ITA method detects trends on a time series through divided two sub-series with equal lengths. Partial trends on main time series cannot detected by this approach. Also, the method may not show any trend in long series if decreasing and increasing partial trends neutralize each other. Mohorji et al., (2017) prefer to divide a main time series into several sub-series with equal lengths of 5, 10, 20, 30, 40 and 50 years, using Şen_ITA to detect partial trends. Güçlü and friends improved Şen_ITA derivatives as called half-time, double, triple, and triangular to detect partial trends by dividing

a main time series into several sub-series with equal length without detect trend change points (Güçlü, 2020, 2018a, 2018b; Güçlü et al., 2020).

One may want to examine partial trends in sub-series with different lengths according to trend change points. In this study, Şen_ITA method is revised to detect partial trends on sub-series with different lengths (ITA_DL). The method is applied to Oxford annual and monthly rainfall series to detect partial trends on the main series.

Methodology

Mann-Kendall (MK) is most frequently used trend analyses method although some restrictive assumption. It is based on the comparison of the temporal ordered values according to their magnitude. Let Z be a time series as $z_1, z_2, \dots, z_n$ and for $\forall j > i$ if $z_j > z_i$ then $sign(z_j - z_i) = 1$ and if $z_j < z_i$ then $sign(z_j - z_i) = -1$ else $sign(z_j - z_i) = 0$. S is a trend indicator and calculated as $S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n sign(z_j - z_i)$ and its variance is calculated as $Var(S) = n(n-1)(2n+5)/18$. It's variance changes only data number because of Gaussian distribution assumption and tied group number that it is not mentioned in here. Standard normal z values are calculated as if $S > 0$ then $z = (S - 1)/\sqrt{Var(S)}$ else if $S < 0$ then $z = (S + 1)/\sqrt{Var(S)}$. It gives an opinion about trend availability for certain statistical importance level (for example %95, %90 or %80) in a time series. If absolute z values bigger than standard normal z values (1.96, 1.65 or 1.28) for the certain statistical importance level then there is a trend in the time series. The negative (positive) z values give a decreasing (increasing) trend.

Şen_ITA divides a main time series ($Z = z_1, z_2, \dots, z_n$) as two sub-series such as first ($Z_f = z_1, z_2, \dots, z_{n/2}$) and second ($Z_s = z_{n/2+1} + z_{n/2+2} + \dots + z_n$) half series with equal length. Each of the sub-series is ascendingly sorted. First half sub-series ($X = x_1, x_2, \dots, x_{n/2}$) is plotted on x axis and second half series ($Y = y_1 + y_2 + \dots + y_{n/2}$)

on y axis and a 1/1 (45°) line on a graph. Thus, scatter points and the 1/1 (45°) appear on the graph. If the scatter points are above (under) the 1/1 (45°) no trendline then there is an increasing (decreasing) trend. If some of the scatter points are above (under) the 1/1 no trendline and other of the scatter points under (above) this line, then there is a non-monotonic trend. If the scatter points nearly are over the 1/1 no trendline, then there is no trend on the main series. $s = 2(\bar{y} - \bar{x})/n$ gives trend slopes and $\sigma_s = 2\sqrt{2}\sigma\sqrt{(1 - \rho_{\bar{y},\bar{x}})} / (n\sqrt{n})$ standard deviation of the trend slope. In here; $\bar{x}$, $\bar{y}$, n , σ and $\rho_{\bar{y},\bar{x}}$ is first half average, second half average, data length, standard deviation and correlation coefficient between first and second half series. The trend slope deviation formula has the assumption that variations are equality, but this assumption cannot be valid for skew and dependent series (Serinaldi et al., 2020; Wang et al., 2019). Therefore, Alashan, (2020b) put forward a new formulate to calculate trend slope deviations such as $\sigma_s = 2(Var(\bar{x}) + Var(\bar{y}) - 2Cov(\bar{x}\bar{y}))^{1/2}/n$. The formulate gives more successful and robust results according to MK and Şen_ITA also in skew and dependent series. In here; $Var(\bar{x})$, $Var(\bar{y})$ and $Cov(\bar{x}\bar{y})$ is first half variance, second half variance and covariance between first and second halves. z values can be calculated as $z = s/\sigma_s$ to compare with MK.

Şen_ITA detects trends on a main time series with equal sub-series length. In fact, it uses equal data lengths to compare scatter points with equal probabilities. For example, let assume n_1 and n_2 is first and second half series data lengths. If the sub-series data lengths are equal ($n_1 = n_2$), then each of the distribution points has the same probability values between $(1/n_1 = 1/n_2)$ and 1 for the cumulative probability frequency values. To compare sub-series with different data lengths, for $k = n_2/n_1$ and $j = ki$, then equal probability points $(i/n_1 = j/n_2 \text{ to } 1)$. First half series x_i are plotted on horizontal axis and second half series y_j vertical axis same like Şen_ITA. Scatter points locations according to 1/1 no trendline gives monotonic or non-monotonic trends or no trend on sub-series with different lengths (ITA_DLL). ITA_DL converts to Şen_ITA for $k=1$ (Figure 1).

Figure 1. The application of ITA_DL method with increasing and decreasing series.

A random series is produced with one hundred lengths. The last twenty values have increasing and decreasing trends on the random series. ITA_DL method detects trends on sub-

series for various k (n_2/n_1) values in the Figure 1. Trend slope values change with k values. $k=1$ gives Sen_ITA trend slopes and it is between maximum and minimum trend slopes. $k=8/2$ gives trend change point and has maximum (minimum) trend slopes on partial increasing (decreasing) series.

Study Area and Application

Oxford is chosen as the study area because of the long rainfall data measurements. It has an area of approximately 46 km² and an altitude of 60 m from sea level and geographic coordinates of 51° 45' N and 1° 15' W in the southeast of England. The maritime temperate climate prevails in the city (<https://en.wikipedia.org/wiki/Oxford#Geography>). All months are rainy. Annual total rainfall values vary between approximately 379 and 984 mm, with an average of 657 mm (Table 1). The wettest (driest) month is October (February). April has minimum rainfall values. March rainfall values have a maximum skewness coefficient. Standard deviation is maximum in October rainfall values.

Table 1. Statistical parameters of Oxford annual and monthly rainfall series.

Months	Minimum	Mean	Maximum	Standard deviation	Skewness
January	9.90	56.68	146.90	28.10	0.35
February	2.20	43.74	120.30	26.44	0.59
March	1.40	44.94	138.90	27.32	1.01
April	0.50	44.61	143.00	24.72	0.86
May	3.50	52.25	139.10	27.50	0.87
June	1.70	53.25	151.70	30.42	0.60
July	3.10	56.96	155.10	32.95	0.43
August	1.80	59.86	146.20	32.25	0.50
September	2.60	55.02	156.10	34.02	0.83
October	5.00	66.60	192.90	38.09	0.78
November	4.80	62.00	175.50	31.93	0.85
December	7.80	61.56	147.90	32.31	0.52
Annual	379.30	657.48	984.40	112.79	0.13

Mann-Kendall (MK) test is applied for Oxford total annual and monthly rainfall series. MK detects three trends in thirteen series as May, July and December. In May, there are increasing trend on rainfall series. Crucial decreasing trend prevail on July rainfall series. December rainfall series has significant increasing trend.

Table 1. Mann Kendall test results of Oxford annual and monthly rainfall series.

Season	Period	Data length(n)	Trend indicator(S)	Var(S)	MK test statistics(z)	Decision
Annual	1861-2020	160	214	459333	0.31	No trend
January	1861-2020	160	464	459333	0.68	No trend
February	1861-2020	160	90	459333	0.13	No trend
March	1861-2020	160	530	459333	0.78	No trend
April	1861-2020	160	-134	459333	-0.20	No trend
May	1861-2020	160	1098	459333	1.62	Increasing trend
June	1861-2020	160	-648	459333	-0.96	No trend
July	1861-2020	160	-1402	459333	-2.07	Crucial decreasing trend
August	1861-2020	160	194	459333	0.28	No trend
September	1861-2020	160	-636	459333	-0.94	No trend
October	1861-2020	160	-440	459333	-0.65	No trend
November	1861-2020	160	826	459333	1.22	No trend
December	1861-2020	160	1304	459333	1.92	Significant increasing trend

if $|z| \geq 1.96$ then crucial trend, else if $|z| \geq 1.65$ then significant trend, else if $|z| \geq 1.28$ then trend

ITA_DL method gives partial increasing and decreasing trends on Oxford rainfall series. 4 rainfall series out of 13 have increasing or decreasing trends (Table 3). In May, there is a crucial increasing trend for the 1940 change point ($k = 80/80 = 1$ or $\text{\$en_ITA}$) and increasing trend for 1980 ($k=120/40$). July has decreasing trend for the 1940 ($k=80/80$), crucial decreasing trend for the 1980 ($k=120/40$) and significant decreasing trend for the 2010 ($k=150/10$) change point. Crucial decreasing trends are dominant on September rainfall series with $k=120/40$, $k=140/20$ and $k=150/10$ (change points in 1980, 2000 and 2010 years). Its trend slopes are constantly increasing over time. There is a decreasing trend in the October rainfall series with the change point in 1940 ($k=80/80$).

To detect non-monotonic trends on Oxford annual and monthly rainfall series, ITA_DLL graphics are used (Figure 2). There are increasing trend on annual high rainfall

values. In January, low and high rainfall values have increasing trends although there is a decreasing trend on medium values.

Table 3. ITA_DL trend test results of Oxford annual and monthly rainfall series.

Season	1861-1940 & 1941-2020 k=80/80 (Şen_ITA)			1861-1980 & 1981-2020 k=120/40			1861-2000 & 2001-2020 k=140/20			1861-2010 & 2011-2020 k=150/10		
	s	z	Decision	s	z	Decision	s	z	Decision	s	z	Decision
Annual	0.02	0.08	No trend	0.06	0.24	No trend	0.53	0.22	No trend	-1.07	-0.19	No trend
January	0.04	0.84	No trend	0.03	0.40	No trend	0.02	0.07	No trend	0.07	0.08	No trend
February	-0.02	-0.36	No trend	-0.02	-0.48	No trend	0.09	0.24	No trend	-0.11	-0.11	No trend
March	0.04	1.03	No trend	0.04	0.40	No trend	-0.04	-0.10	No trend	-0.65	-0.48	No trend
April	-0.03	-0.36	No trend	0.05	0.22	No trend	-0.38	-0.5	No trend	-1.31	-0.64	No trend
May	0.10	2.15	Crucial increasing trend	0.12	1.31	Increasing trend	0.29	0.37	No trend	-0.21	-0.36	No trend
June	-0.01	-0.2	No trend	-0.11	-0.95	No trend	-0.14	-0.2	No trend	0.02	0.01	No trend
July	-0.15	-1.36	Decreasing trend	-0.32	-2.08	Crucial decreasing trend	-0.12	-0.18	No trend	-1.87	-1.88	Significant decreasing trend
August	0.06	1.08	No trend	-0.11	-0.76	No trend	0.15	0.24	No trend	-0.53	-0.61	No trend
September	-0.01	-0.19	No trend	-0.18	-3.32	Crucial decreasing trend	-1.04	-5.33	Crucial decreasing trend	-2.30	-6.22	Crucial decreasing trend
October	-0.08	-1.45	Decreasing trend	0.09	0.44	No trend	0.16	0.16	No trend	-0.32	-0.12	No trend
November	0.04	0.42	No trend	0.11	1.25	No trend	0.18	0.25	No trend	-0.56	-0.35	No trend
December	0.05	0.49	No trend	0.11	0.74	No trend	0.08	0.62	No trend	0.62	0.63	No trend

February, March, October and November rainfall series only have decreasing trends on high values. There are decreasing trends on low values and increasing trends on high values of April and June rainfall series.

Figure 2. Partial trends on Oxford annual and monthly rainfall series.

148 Figure 2 continues

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155 Figure 2 continues

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157 In May, there are increasing trend on medium values and decreasing trend on high
 158 values. July and September rainfall series have monotonic decreasing trends. There is no non-
 159 monotonic trend on August rainfall series. December rainfall series has increasing trends on
 160 low and medium values and decreasing trend on high values.

161 Results and Discussion

162 Oxford annual and monthly rainfall series from 1861 to 2020 are analyzed to identify
 163 trends with Mann-Kendall (MK), Şen innovative trend analysis (Şen_ITA), and innovative
 164 trend analysis of sub-series with different lengths (ITA_DL). ITA_DL gives results consistent
 165 with MK and turns into Şen_ITA for equal sub-series lengths or $k=1$. MK gives one increasing
 166 trend (May), one crucial increasing trend (July), and a significant increasing trend (December).
 167 ITA_DL trend test results confirm MK except for December. In May, there is a crucial
 168 increasing trend for $k=1$ (1940 trend change point). July has a decreasing trends for $k=80/80=1$,
 169 a crucial decreasing trend for $k=120/40$ (1980 trend change point) and a significant decreasing
 170 trend for $k=150/10$ (2010 trend change point). Crucial decreasing trends are dominant in
 171 September for $k=120/40$, $k=140/20$ (2000 trend change point), and $k=150/10$ values. Neither
 172 MK nor Şen_ITA can detect any trends on September rainfall series. October has a decreasing

trend $k=1$ although MK cannot detect any trend. ITA_DL does not show any trend as monotonic or non-monotonic in December, although MK shows a significant increasing trend.

Rainfall is the main source of clean water and an important part of the hydrological cycle. The monotonic crucial decreasing trend in July and the non-monotonic decreasing trend in low rainfall series in June require designing larger reservoir capacity in dams to provide drinking and irrigation water during summer droughts. Possible floods in Oxford could be more intense, with a monotonic crucial trend in May and non-monotonous increasing trends in high rainfall series in January and April. City planners, hydrologists, and politicians should take into account trends in the Oxford rainfall series to avoid possible damage from droughts and floods.

Conflict of interest

The Author declares that I have no conflict of interest.

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Figures

Figure 1

The application of ITA_DL method with increasing and decreasing series.

Figure 2

Partial trends on Oxford annual and monthly rainfall series.