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SEASONAL WILCOXON AND SCATTER DIAGRAM COMBINATION TREND TEST

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ABSTRACT

Climate change, one of the biggest problems of the last century, is of great concern. It is essential and common to examine the impacts of climate change as a holistic trend for different climatic and hydrological parameters with periodicity. However, considering the periodicity character of monthly, weekly, etc., is particularly important for analyzing and understanding seasonal trends. This is because seasonal trends help manage and regulate irrigation and agricultural activities and water resource systems. This study proposes the seasonal Wilcoxon and scatter diagram combination trend test (SWTT) method as an alternative to the seasonal Mann Kendall (SMK) method. This method is based on the combination Wilcoxon test and scatter diagram (CWTSD) trend test which assesses holistic trends. The data utilized for this study came from three sources: flow records from the Danube River, Romania, temperature records from Oxford, UK, and precipitation records from Kobe, Japan, to compare SWTT and SMK methods. The SWTT method shows very similar trends to the SMK, but the SWTT method takes a step forward because it is based on a graphical method providing a visual overview of seasonal trends. The SWTT can also be used as a regional trend test in the same way that the SMK method is used as a regional trend test by using station data instead of seasons The r-codes of the proposed method and the sample dataset are available at the related link.

Keywords: Climate change, Mann-Kendall, Regional trend, Seasonal trend, Wilcoxon test.

1 INTRODUCTION

Human-caused increases in greenhouse gas emissions impact hydrological and climatic variables as part of a decreasing or increasing trend. Climate change's impact increases the frequency of extreme events such as droughts, floods, and heat waves, which are particularly important for water resources management. Therefore, trend analysis studies are taken into account in processes for water resources management, risk assessment, planning, and design [1], [2], [3], [4], [5].

Hydrological or climatological data trends over time can be analyzed in different ways. Mann Kendall (MK) [6], [7] method is frequently used in the literature as a monotonic trend analysis method endorsed by the World Meteorological Organization [8], [9], [10] and is frequently used in the literature compare to other trend methods [11], [12], [13], [14]. However, the MK is affected by serial correlation, data length and distribution type [15], [16], [17]. As an alternative to the MK, different monotonic trend methods have emerged in the last two decades [1], [18], [19], [20]. Partial trends methods have also been proposed recently [18], [21], [22]. The innovative trend analysis (ITA) method [23] which allows visual analysis of low-high value trends, has opened an interesting perspective in the literature. Inspired by the ITA, researchers have introduced or modified different trend methods [1], [24], [25], [26]. The combination of Wilcoxon test and scatter diagram (CWTSD) method [1], like the ITA method, divides the hydro meteorological series into two equal parts. However, unlike the ITA, it determines trend by applying the Wilcoxon rank sign test based on the differences without any sorting within the parts.

Even though monotonic or group trends are essential, hydrometeorological variables include seasonality. Seasonality reduces accuracy of trend analysis by showing serial dependence [27], [28]. Seasonal trends assist farmers in effectively managing agricultural inputs that vary with the seasons, such as water and fertilizer. They enable improved planning for power generation and distribution, help maintain equilibrium between energy supply and demand, and facilitate strategic decision-making regarding water storage and flood control through precise analysis of the long-term impacts of water-level fluctuations [24], [29]. Therefore, the seasonal MK (SMK) method [28] for seasonal trend test is proposed by Hirsch et al. [28]. In contrast to the SMK, the innovative polygon trend analysis (IPTA) graphically showing seasonal trends and trend transitions between seasons was proposed by Şen et al., [24]. However, the limitation of the IPTA is that it lacks statistical significance. As an alternative to SMK, Şan [29] proposed the three combined seasonal trend tests based on the IPTA. Although the proposed three methods examine whether there is a trend in the seasons and the transition behavior between seasons, the behavior from low to high values within the seasons is not observed. However, a similar absence is also present in the SMK. Therefore, this study proposes a new method by applying the CWTSD method to each season, inspired by the SMK, which is based on applying the MK test to each season and is frequently preferred by those evaluating seasonal trends. For this purpose, long-term temperature, flow, and precipitation data are selected from several point around the world. After applying the MK and CWTSD methods to each season, the SMK and SWTT methods are then applied for the seasonal trend to reveal the general behavior.

2 STUDY AREA AND DATA

Three hydrometeorological monthly data from around the world were used to analyze (Fig. 1). Danube River monthly average flow data was used for 1840-2003. Starting in Germany, the Danube River flows through Austria, Slovakia, Hungary, Croatia, Serbia, Romania, Bulgaria, Moldova, and Ukraine. Its total length is about 2850 kilometers, making it the second longest river in Europe after the Volga River [30], [31]. Kobe monthly average precipitation data was used for the period 1897-2022. Kobe has a temperate climate with warm, wet, and no dry seasons [32], [33]. Oxford Radcliffe Meteorological Station's monthly average temperature data was used for 1814-2023. The longest single-site weather records in the United Kingdom are among the longest globally. Seasonal descriptive statistics of the data used in this study are given in Table 1.

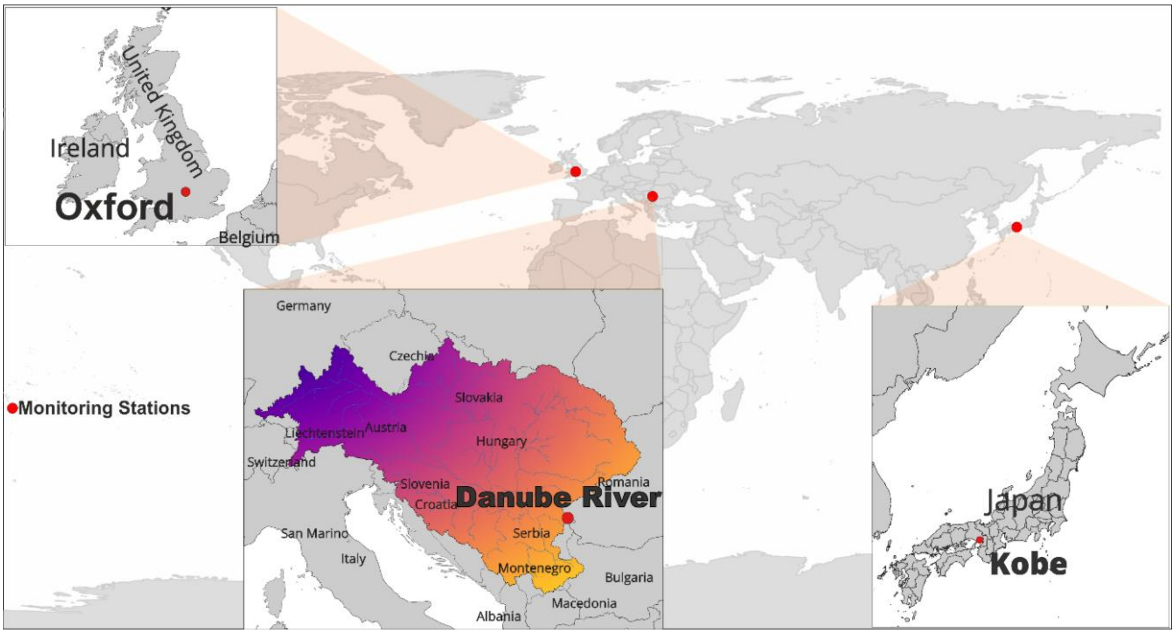

Figure 1. Monitoring station locations of the data used in the study.

Table 1. Seasonal descriptive statistics of the stations.

Station	Season	Min	Max	Mean	Sd	Cv	Cs	Ck
Oxford (°C)	January	−3.01	7.64	3.76	2.16	0.57	−0.71	3.30
	February	−2.22	8.25	4.36	2.10	0.48	−0.65	3.16
	March	2.00	9.89	6.11	1.59	0.26	−0.07	2.50
	April	4.58	13.33	8.72	1.28	0.15	0.06	3.44
	May	8.97	14.44	11.98	1.24	0.10	−0.03	2.29
	June	11.99	18.49	15.18	1.21	0.08	0.10	3.10
	July	14.35	21.14	17.02	1.38	0.08	0.39	2.82
	August	13.54	20.41	16.60	1.31	0.08	0.34	3.04
	September	11.23	17.80	14.15	1.26	0.09	0.11	2.97
	October	7.13	14.06	10.47	1.47	0.14	0.03	2.93
	November	0.85	10.57	6.58	1.56	0.24	−0.25	3.45
	December	−1.99	10.80	4.59	2.01	0.44	−0.41	3.23
Danube (m^3/s)	January	1645	10303	4817	1883	0.39	0.61	2.95
	February	1858	10050	5086	1682	0.33	0.40	2.81
	March	3145	11586	6538	1894	0.29	0.39	2.66
	April	3445	13290	7858	2140	0.27	0.34	2.86
	May	4200	12995	7685	1959	0.25	0.54	2.91
	June	3100	13324	6679	1739	0.26	0.74	4.21
	July	2360	12251	5586	1595	0.29	1.01	4.77
	August	1980	10657	4518	1399	0.31	1.15	5.89
	September	1900	8290	4006	1222	0.30	0.79	3.42
	October	1676	8108	4052	1341	0.33	0.73	3.22
	November	1845	9860	4821	1814	0.38	0.73	2.76
	December	1941	10908	5157	1801	0.35	0.63	3.06
Kobe (mm)	January	1.80	107.60	42.30	24.32	0.57	0.53	2.70
	February	6.50	150.30	54.52	32.62	0.60	1.09	3.58
	March	14.00	204.00	92.71	37.80	0.41	0.46	3.24
	April	22.50	260.60	120.71	46.54	0.39	0.42	3.06
	May	14.60	348.00	131.61	63.91	0.49	0.84	3.39
	June	45.50	584.20	193.52	97.92	0.51	1.05	4.29
	July	14.50	628.00	169.93	124.75	0.73	1.46	5.26
	August	2.80	446.80	114.00	88.34	0.77	1.32	4.74
	September	19.70	558.60	174.50	104.16	0.60	1.28	4.94
	October	28.20	499.30	114.69	68.46	0.60	2.00	10.39
	November	4.00	174.50	69.01	36.83	0.53	0.49	2.70
	December	1.00	108.00	44.38	26.77	0.60	0.47	2.37

Min: Minimum, Max: Maximum, Sd: Standard deviation, Cv: Coefficient of variance, Cs: Coefficient of skewness, Ck: Coefficient of kurtosis

3 METHODS

3.1 Homogeneity test

The homogeneity of data is affected by natural factors, such as climate variability and change, as well as anthropogenic factors, including human-induced alterations in data collection methods or environments[34]. Statistical analysis or modeling conducted with inhomogeneous data may yield calculation results that deviate from expectations, either lower or greater. To determine the homogeneity of the data used in this study, the Pettitt's test [35] was used at a 5% significance level.

In the calculation of the test, the rankings $ra_1, \dots, ra_n$ of the $a_i, \dots, a_n$ variables serving as the basis for the statistic (P):

$$P_y = 2\sum_{i=1}^{y} ra_i - y(n+1) \ ,y = 1, \dots, n \tag{1}$$

The maximum absolute value is the test statistic ($\breve{\mathrm{P}}$):

$$\breve{\mathrm{P}} = \max\left(|Py|\right) \tag{2}$$

The most likely location for change, y, is situated at the intersection of $\breve{\mathrm{P}}$. An approximation of the two-sided test's probability is determined by

$$p \cong 2e^{\left(-6\breve{\mathrm{P}}^2 / n^2(n+1)\right)} \tag{3}$$

So, if p is less than α, the data is not homogeneous at given a significance level α.

3.2 Seasonal Mann Kendall

The SMK test [28] accounts for seasonality by conducting the MK test separately for each season and subsequently integrating the results. The test defines a season as a month, a quarter, or any other period. When the SMK test is used, the first step is to compute the test statistic TS for each season individually, as shown below:

$$TS_i = \sum_{d_i=1}^{N_i-1} \sum_{c_i=d_i+1}^{N_i} sgn(a_{c_i} - a_{d_i}) \tag{4}$$

$$sgn(a_{c_i} - a_{d_i}) = \begin{cases} -1, & if\ (a_{c_i} - a_{d_i}) < 0 \\ 0, & if\ (a_{c_i} - a_{d_i}) = 0 \\ +1, & if\ (a_{c_i} - a_{d_i}) > 0 \end{cases} \tag{5}$$

where N_i represent the data length of season i, when a_c and a_d denote the data values at times c and d, respectively. The computation of the SMK test variance and statistic is performed using the following equations:

$$TS' = \sum_{i=1}^{M} TS_i \tag{6}$$

$$Var(TS') = \sum_{i=1}^{M} \frac{N_i(N_i - 1)(2N_i + 5)}{18} \tag{7}$$

$$Z_{smk} = \begin{cases} \frac{TS' + 1}{\sqrt{Var(TS')}}, & TS' < 0 \\ 0, & TS' = 0 \\ \frac{TS' - 1}{\sqrt{Var(TS')}}, & TS' > 0 \end{cases} \tag{8}$$

where Z_{smk} denotes the standard normal value. If the value of $|Z_{smk}|$ is more than or equal to $z_{\alpha/2}$, then a trend is seen; otherwise, it is not observed [36].

3.3 Seasonal Wilcoxon and scatter diagram trend test (SWTT)

Saplıoğlu and Güçlü [1] proposed the CWTSD method, drawing inspiration from the ITA. The method aims to determine detection of trend by dividing a hydroclimatological series into two equal parts (but not ordered). Subsequently the Wilcoxon signed rank significance test is applied to assess difference of second series from first series. It also places the first unordered series on the horizontal axis and the second unordered series on the vertical axis of the Cartesian coordinate system, as in the ITA. The CWTSD method can also be used to identify seasonal trends, just as the MK is applied separately for each season in the SMK. Thus, the seasonal Wilcoxon and scatter diagram combination trend test (SWTT) method is proposed in this study and computed as follows:

$$W_i = \sum_{j=1}^{N_i/2} \left(sign(x_{second,i,j} - x_{first,i,j}) \times R_{i,j}\right) \tag{9}$$

$$R_{i,j} = rank(|x_{second,i,j} - x_{first,i,j}|) \tag{10}$$

$$W' = \sum_{i=1}^{M} W_i \tag{11}$$

$$Var(W') = \sum_{i=1}^{M} \frac{(N_i/2)((N_i/2)+1)(2(N_i/2)+1)}{6} \tag{12}$$

$$Z_{\mathrm{SWTT}} = \frac{W'}{\sqrt{Var(W')}} = \frac{W'}{\sigma_{W'}} \tag{13}$$

where $x_{first,i,j}$ represent the j^{th} value in the first half of season i^{th}, while $x_{second,i,j}$ denotes the j^{th} value in the second half of season i^{th}. N_i is the length of the hydro climatological series of i^{th} season. $R_{i,j}$ is the rank order of the absolute value of the difference of the j^{th} values in the i^{th} season. The $sign()$ represents the sign function. W_i is the sum of the rank-sign differences in the i^{th} season. M is the total number of seasons. Z_{SWTT} represents the Wilcoxon test statistic utilized for identifying trend conditions, referencing $Z\alpha/_2$ for a two-tailed analysis. A trend is present if $|Z_{\mathrm{SWTT}}| \geq z_{\alpha/2}$ otherwise, it is not [1], [29], [37].

4 RESULTS

Pettit homogeneity test were conducted before the trend analyses. The homogeneity results (Table 2) indicate that Oxford station fails to meet the criteria for homogeneity as determined by the Pettit test. Wijngaard et al. [39] suggested that the inhomogeneity of temperature data may result from an actual climate signal. Although it has not been determined whether the station has experienced unnatural changes, the fact that the Oxford temperature (Appendix 1) shows a similar pattern of increase as in the world average [38] is thought to indicate a climate-induced change. The temperature data from Oxford station was used in this study due to sensitivity of temperature data to homogeneity [39], [40] and the effect of climate signals.

Table 2. Homogeneity test results.

Station (Unit)	Test statistics	p-value	Control
Oxford (°C)	6936	6.745E-14	Non-homogeneous
Danube (m^3/s)	945	5.980E-01	Homogeneous
Kobe (mm)	720	4.276 E-01	Homogeneous

An increasing trend is observed in all seasons for Oxford temperature data (Table 3). In the second season (February), the center of the ordered scatter is slightly above the 1:1 line, and the center of the unordered scatter is slightly above the 1:1 line (Fig. 2), indicating a low confidence significant trend to CWTSD (Table 3). Although there is an increasing trend in the 80% confidence interval in the second season, the seasonal trend results show a significant increase in temperatures at the 95% confidence interval according to the SMK and SWTT methods.

The seasonal trend at Danube and Kobe stations shows a significant decreasing according to the SMK and SWTT methods at 90% and 80% confidence intervals, respectively. The difference is that the magnitudes of the significant decreasing trend in the seasons are higher in the MK method than in the CWTSD method (Table 3). This can also be seen in the collection of ordered and unordered scatter around the 1:1 line in the seasons (Figs. 3 and 4).

Table 3. Trend tests results.

Station	Season	MK			SMK			CWTSD			SWTT		
		TS	Var(TS)	Z_{MK}	TS'	Var(TS')	Z_{SMK}	W	Var(W)	Z_{CWTSD}	W'	Var(W')	Z_{SWTT}
Oxford (°C)	1	5717	1036291.667	**5.62*****				2668	391405	**4.26*****			
	2	3462	1036291.667	**3.40*****				996	391405	**1.59***			
	3	6202	1036291.667	**6.09*****				3100	391405	**4.96*****			
	4	3994	1036291.667	**3.92*****				1998	391405	**3.19*****			
	5	4258	1036291.667	**4.18*****				2126	391405	**3.40*****			
	6	2812	1036291.667	**2.76*****	58948	12435500	**16.72*****	1342	391405	**2.15*****	28570	4696860	**13.18*****
	7	4382	1036291.667	**4.30*****				2077	391405	**3.32*****			
	8	5567	1036291.667	**5.47*****				2565	391405	**4.10*****			
	9	6137	1036291.667	**6.03*****				3257	391405	**5.21*****			
	10	6324	1036291.667	**6.21*****				3263	391405	**5.22*****			
	11	6046	1036291.667	**5.94*****				3129	391405	**5.00*****			
	12	4047	1036291.667	**3.97*****				2049	391405	**3.28*****			
Danube (m3/s)	1	1644	494542	**2.34*****				441	187165	1.02			
	2	1461	494542	**2.08*****				930	187165	**2.15*****			
	3	293	494542	0.42				320	187165	0.74			
	4	319	494542	0.45				58	187165	0.13			
	5	−1196	494542	**−1.70****				−604	187165	**−1.40***			
	6	−1472	494542	**−2.09*****	−4439	5934504	**−1.82****	−802	187165	**−1.85****	−2129	2245980	**−1.42***
	7	−1150	494542	**−1.63***				−773	187165	**−1.79****			
	8	−1488	494542	**−2.11*****				−688	187165	**−1.59***			
	9	−1415	494542	**−2.01*****				−629	187165	**−1.45***			
	10	−901	494542	−1.28				−556	187165	**−1.29***			
	11	−723	494542	−1.03				55	187165	0.13			
	12	189	494542	0.27				119	187165	0.28			
Kobe (mm)	1	−752	224875	**−1.58***				−256	85344	−0.88			
	2	239	224875	0.50				−162	85344	−0.55			
	3	130	224875	0.27				0	85344	0.00			
	4	−651	224875	**−1.37***				−13	85344	−0.04			
	5	629	224875	**1.32***				387	85344	**1.32***			
	6	−340	224875	−0.71	−2999	2698500	**−1.83****	−90	85344	−0.31	−1642	1024128	**−1.62***
	7	385	224875	0.81				203	85344	0.69			
	8	−449	224875	−0.94				−326	85344	−1.12			
	9	−761	224875	**−1.60***				−419	85344	**−1.43***			
	10	−783	224875	**−1.65****				−502	85344	**−1.72****			
	11	−409	224875	−0.86				−259	85344	−0.89			
	12	−237	224875	−0.50				−205	85344	−0.70			

*,** and *** indicate significant trends at 80%, 90% and 95% confidence intervals, respectively. Blue indicates increasing trend and red decreasing trend.

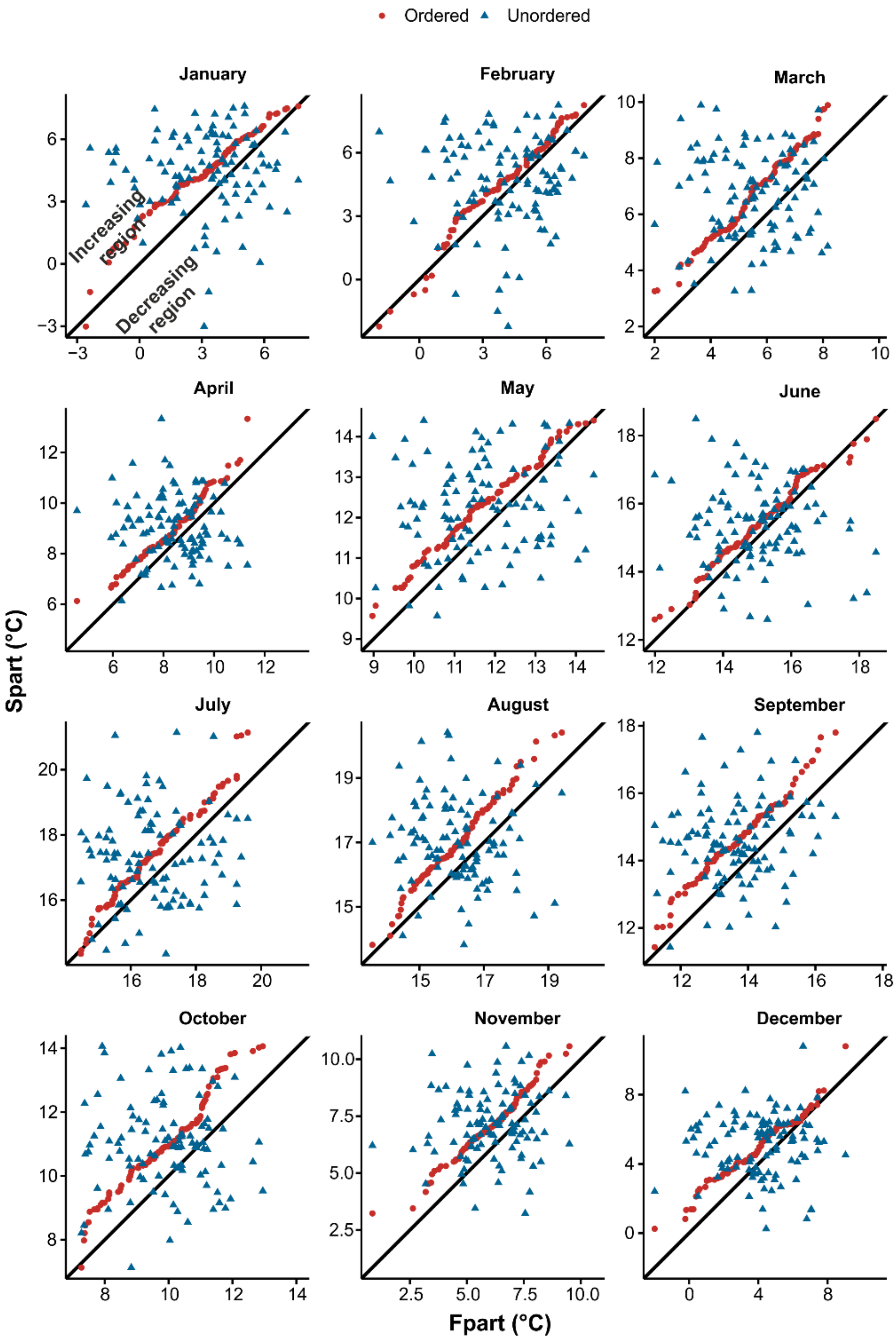

Figure 2. Ordered and non-ordered scatter diagrams of Fpart versus Spart data for seasons at the Oxford station (Temperature).

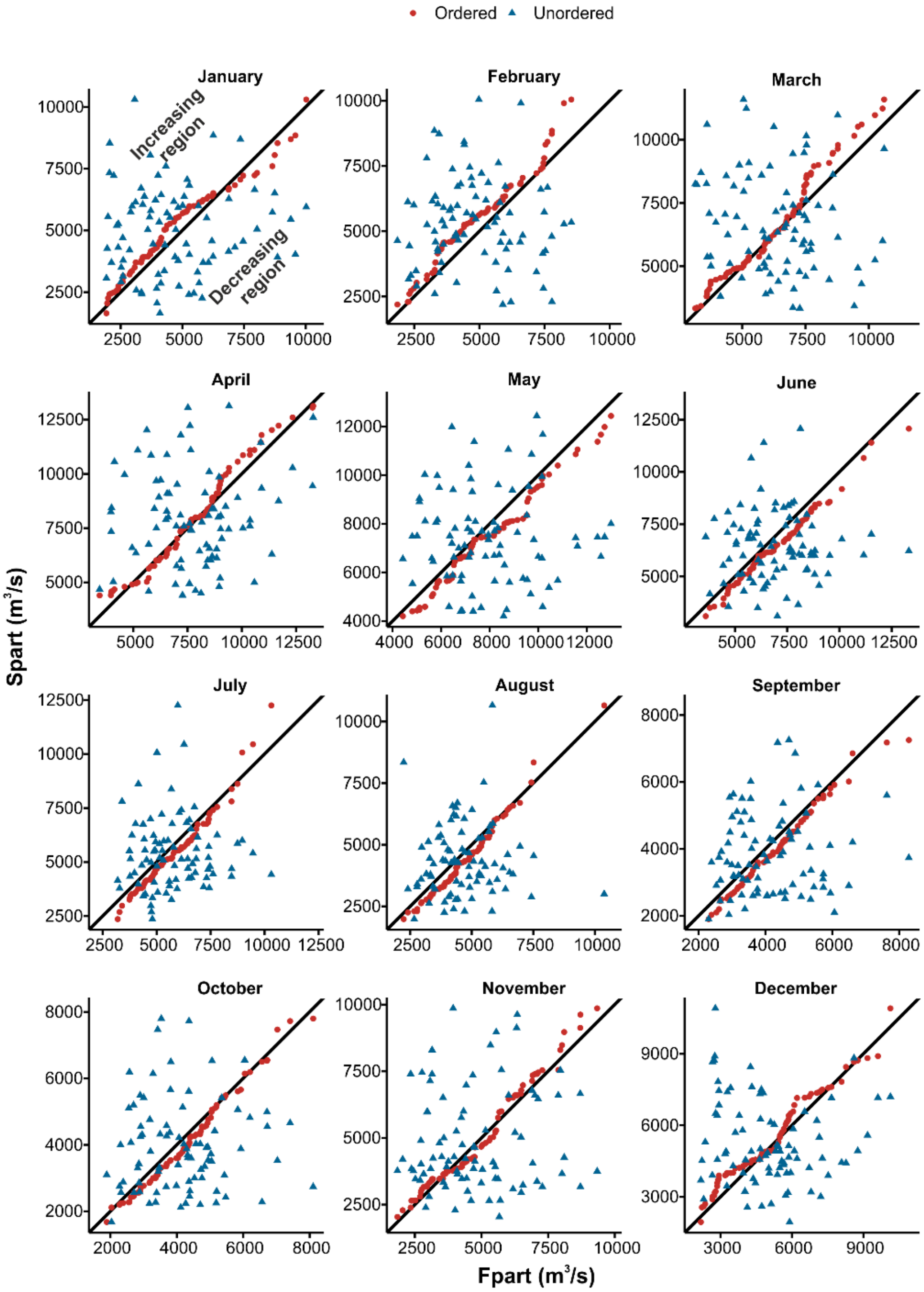

Figure 3. Same as Figure 2 but for the Danube Station (Flow).

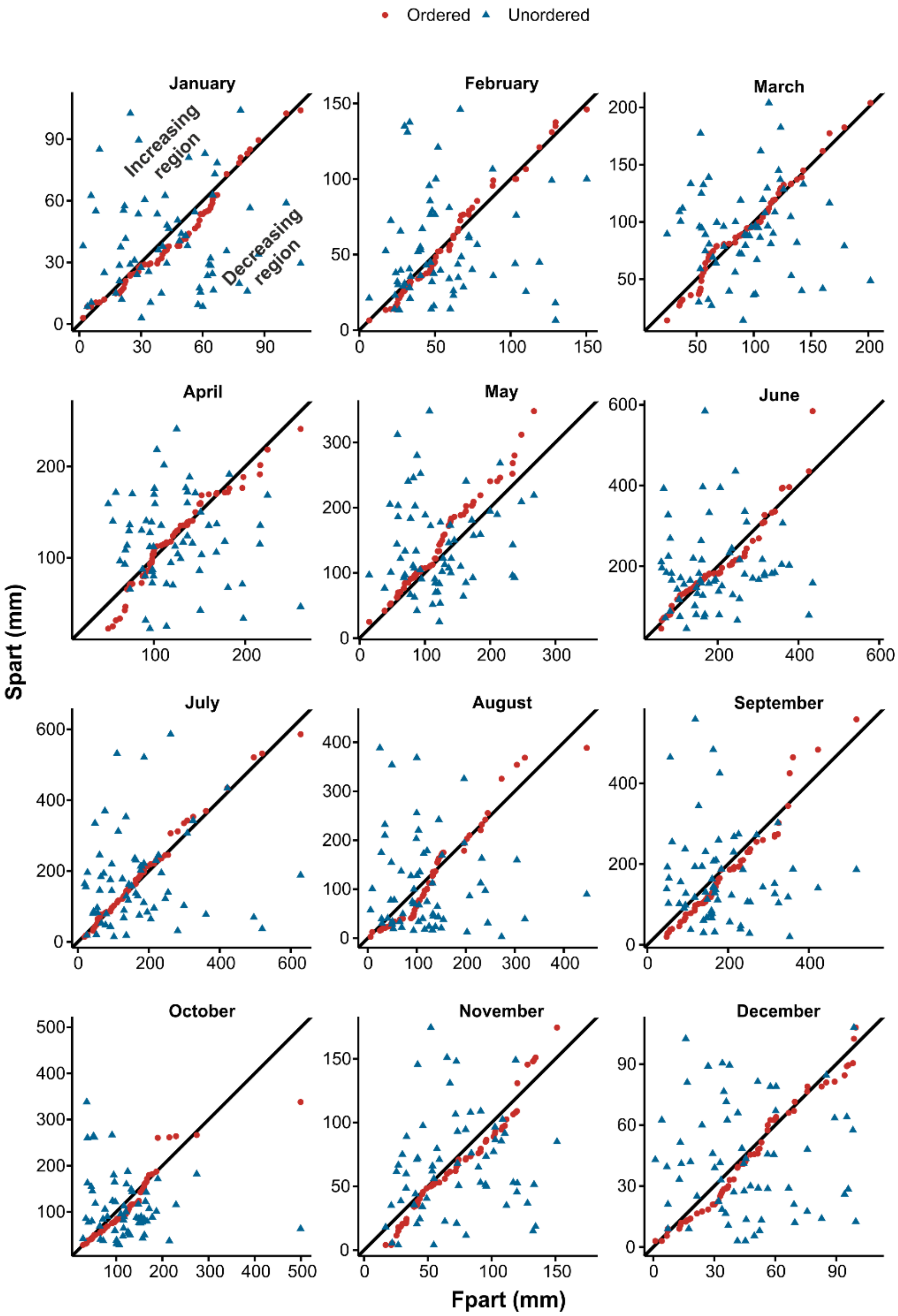

Figure 4. Same as Figure 2 but for the Kobe station (Precipitation)

5 DISCUSSION

The proposed SWTT method shows very similar significant trends to the SMK (Table 3) but stands out by graphically allowing the visualization of trends in seasons (Figs. 2-4). In other words, it is seen from Figs.2-4 that the visual trends of low and high values in-season do not always behave the same way. At Danube station, SMK and SWTT methods show a decreasing trend, but the methods suggested by Şan [29] do not show a trend, which may be due to the fact that they depend on the averages in the seasons. The methods proposed by Şan [29], on the other hand, do not have ability to show intra-seasonal trend behavior in the SWTT, but offer the opportunity to examine inter-seasonal behavior. Another advantage of SWTT is that regional trends can be determined using data from measurement stations instead of seasons.

6 CONCLUSION

This study proposes the seasonal Wilcoxon and scatter diagram combination trend test (SWTT) method based on the combination Wilcoxon test and scatter diagram (CWTSD) method as an alternative to the seasonal Mann Kendall (SMK) method based on Mann Kendall (MK) method. Long-term temperature, flow, and precipitation data from three different regions of the world were used to compare the SMK and SWTT methods. First, the MK and CWTSD methods were applied separately for the interior trend in each season, and then SWTT and SMK methods were used for the seasonal trend. For all data, the SWTT method showed similar trends in the same direction as the SMK method. However, the SWTT method stands out as it is based on the graphical method, which allows us to see the trend and data behavior in seasons. The SWTT method can also be used as a regional trend test using station data instead of seasons, just like the SMK method.

By identifying seasonal trends, the existing and proposed methodology strengthens the scientific basis of decision support systems in applications such as water resources management, flood and drought forecasting. For policy makers, seasonal trend analyses guide the development of climate change adaptation strategies and sustainable policies to reduce disaster risks; for method developers, it enables the development of new graphical non-parametric approaches to examine the extent to which they are valid in data with different distributions and to improve their predictive power in different ways.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

Artificial Intelligence (AI) Contribution Statement

This manuscript was entirely written, edited, analyzed, and prepared without the assistance of any artificial intelligence (AI) tools. All content, including text, data analysis, and figures, was solely generated by the authors.

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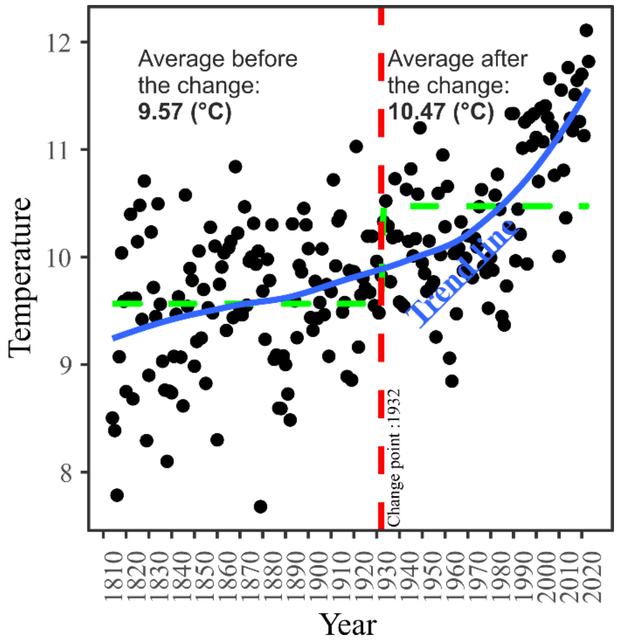
APPENDIX



Appendix 1. Annual temperature for Oxford station