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A COMPARISON OF SEVERAL METHODS IN TRACKING SHORT-TERM TRENDS ASSOCIATED WITH THE PRECIPITATION TIME SERIES

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Abstract: Precipitation trends can be linked to large-scale climatic events or cyclic behaviors. However, exploring these patterns in short data records can be problematic. In this study, the monthly precipitation time series recorded across the Bursa district in Turkey were addressed between January 2005 to October 2018. Stations with the minimum data loss and the longest time records in the region were selected for the analysis. Therefore, Osmangazi, Keles, Uludag, Gemlik, Iznik, Karacabey, and Mustafakemalpasa stations were selected. Linear trend (LT), moving average (MA), Mann-Kendall (MK), turn points (TP), Spearman rank-order correlation (SROC), innovative Şen (IS), innovative trend analysis (ITA), changes in distribution (CD), and standardized precipitation index (SPI) methods were used to detect short-term trends in the precipitation time series. Results indicated that the trends, reported by the previous studies could not be reproduced at a monthly scale when using LT, MK, SROC, IS, ITA, and MA. However, the trends observed by the SPI-48 were also tracked down using CD, and SPI methods. It is concluded that the detection of the short-term trends is problematic whilst the outliers deviate results of the analysis. Hence, a combination of CD, ITA, and IS methods is a key in evaluation of the short-term trends within a data run.

Keywords: Precipitation, short term trend, statistical analysis, Bursa

Yağış Zaman Serilerindeki Kısa Dönemli Eğilimlerin İzlenmesinde Çeşitli Yöntemlerin Karşılaştırılması

Öz: Yağıştaki eğilimler, büyük ölçekli iklimsel olaylar veya döngüsel hareketler ile ilişkilidir. Kısa veri kayıtlarında bu davranışın incelenmesi sıkıntılı olabilmektedir. Bu çalışmada, Ocak 2005 - Ekim 2018 tarihleri arasında Bursa ilinde ölçülen aylık yağış zaman serileri kullanılmıştır. Bölgede en uzun zaman kaydına ve en az veri kaybına sahip istasyon verileri analizlerde kullanılmak üzere seçilmiştir. Bu amaca yönelik olarak, Osmangazi, Keleş, Uludağ, Gemlik, İznik, Karacabey ve Mustafakemalpaşa istasyonları seçilmiştir. Seçilen istasyonların yağış zaman serilerindeki kısa dönemli eğilimlerini tespit etmek için doğrusal eğilim (LT), hareketli ortalama (MA), Mann-Kendall (MK), dönüm noktaları (TP), Spearman sıralı korelasyon (SROC), yenilikçi Şen (IS), yenilikçi eğilim analizi (ITA), dağılım fonksiyonundaki değişiklikler (CD) ve standart yağış indis (SPI) yöntemleri kullanılmıştır. Uygulanan analizler neticesinde, önceki çalışmaların ortaya koymuş olduğu eğilimlerin tek başına LT, MK, SROC, IS, ITA ve MA yöntemleriyle tespit edilemediğini göstermektedir. Buna karşın, SPI-48, CD ve SPI yöntemleri ise eğilimleri tek başına belirgin bir şekilde tespit edebilmektedir. Aykırı değerlere sahip olan verilerde kısa dönemli eğilimleri tespit etmek zordur. Aykırı değerler barındıran verilerde kısa dönemli eğilimlerin değerlendirilmesinde CD, ITA ve IS yöntemlerinin birlikte kullanılması önerilmektedir.

Anahtar Kelimeler: Bursa, kısa dönem eğilim, istatistiksel analiz, yağış

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1. INTRODUCTION

Precipitation is the main variable of the hydrological cycle that transfers the evaporated water to the surface of the lands and is a major role player in studying, analyzing, and planning of the water resources. Occasionally, trends associated with precipitation patterns become the major concerns in the planning of the water supplies. These trends are usually linked to large scales hydro-meteorological phenomena like droughts, climate change, and climate variability. For instance, conducted studies of Hurrell (1995; 1996), Pandey et al. (2017), Vaheddoost and Aksoy (2017), Li et al. (2019), Salehi et al. (2019), Verma and Ghosh (2019), Wu et al. (2019) can be mentioned as studies which investigated the trends in the precipitation time series.

Hurrell (1995) analyzed Green Land's ice-cores to evaluate decadal trends of precipitation and temperature. It was concluded that large-scale changes since 1980 can be linked to the recent dry conditions of the southern Europe and the Mediterranean. Zhang et al. (2000) evaluated the trend associated with the precipitation and temperature during the 20th century in Canada. It was concluded that the annual precipitation increased from 5% to 35% in the south while the ratio of snowfall to the total precipitation has been increased due to the increase in winter precipitation. Zhang et al. (2007) also evaluated the human-induced trends in precipitation patterns and extended trend analysis to a new level.

In this respect, several studies reported that evaluation of the precipitation records less than 30-years is problematic since shifts and turns in climate behavior can be defined once in a three-decades. In addition, the effect of greenhouse gases, climate change and/or variability and their particular role in the short- and long-term trends are not clear for the scientists. It is also hard to define the trends associated with the short-recorded precipitation data due to the presence of outliers and undetectable turn points. However, Kwarteng et al. (2009) used to evaluate trends associated with 27-year rainfall records in Oman. Results were found to be reasonable and align with other studies. There are also several studies such as those conducted by Van Beusekom et al. (2015) who concluded that the short-term precipitation patterns can also be reasonable in trend analysis. To this end, most of the previous studies assumed that tracking precipitation trends in short-recorded data is impossible and is a waste of time. However, the rapid shifts in the climate behavior and precipitation patterns recently showed that sometimes, decisions cannot be postponed for the next 30 years. What's more, the changing climate and increase in the sea surface temperature (SST) affects phenomena such as the North Atlantic Oscillation (NAO), El Nino/Southern Oscillation (ENSO), Atlantic Multidecadal Oscillation (AMO), and Pacific Decadal Oscillation (PDO) which in return affects the precipitation patterns around the globe. This urges the need for comprehensive studies that suggest methods in recognition of short-term precipitation trends as well.

Similarly, precipitation patterns at the Bursa district in Turkey have been addressed before. For instance, Turkes et al. (2007) studied the spatial and temporal properties of the precipitations across Turkey. Mann-Kendall rank correlation coefficient test was used and a decreasing trends were observed in the long-term behavior of the precipitation time series of the Bursa. Ozturk (2010), investigated the precipitations in Uludag and its role on the climatology of the Bursa between 1975-2007. It was found that there is an ascending trend in annual precipitations. In addition, Şen (2013) track-down trends in annual and monthly precipitation patterns at Central, and Uludag region of the Bursa district using Şen's method. Gulten and Ataol (2014) investigated the precipitation and temperature trends across Turkey between 1975-2009. Yilmaz (2018) addressed the precipitation trends of Turkey between 1971-2010 while trends in the precipitations were evaluated on a monthly scale. In addition, Sirdas and Şen (2003), Demir et al. (2008), Simisek and Cakmak (2010), Petrie et al. (2014), Tatli (2015), and Katip (2018) evaluated the droughts of the region in advance while the conducted studies of Caliskan et al. (2012), Akkoyunlu et al. (2019), Bacanli and Kargi (2019), and Sezen and Partal (2019) addressed the regional precipitations directly.

Most of these studies have been concluded that there are several ongoing droughts on large scale time spans, mostly on multi-annual scale while, no significant trends on monthly scale could be observed. One of the problems in tracking the precipitation trends at Bursa is the short recorded time series or data loss which deviates the expected results. Another problem is the micro-climates associated with the various geographical features of seashores align with the Sea of Marmara, vast plains in the central parts, and snowy summit of Mount Uludag which makes it hard to come across a decision about the precipitation trends in the region. Thus, the aim of this study is to (*i*) evaluate and update the realization of short-term trends (less than 30 years) associated with the short-recorded monthly precipitation data in the region, and to (*ii*) evaluate the performance of several trend detecting methods in practice. In brief, this study assumes that there is an ongoing large-scale trend in Bursa, regardless of its drivers, and consequently seek evidence of those trends within the short-recorded precipitation time series with less than 30 year data records.

2. STUDY AREA AND DATA

Bursa is the 4th major city, an industrial-, and agricultural-hub of Turkey, located at western Anatolia (40° 11′ N latitude and 29° 03′ E longitude). It is also known with its water surplus, snowy mountains (Mount Uludag, 2543 above mean sea level), and thermal fountains. Based on the Koppen-Geiger climate classification map, it has a warm-temperature climate of steppe together with hot-dry summers (Rubel and Kottek, 2010). However, there is a diverse climatic behavior (temperature and precipitation) between Mount Uludag Summit and the remaining parts of the region.

Data used in this study was provided by Bursa Meteorological Burro in a monthly average format. For the analysis, precipitation records at 16 meteorological stations namely Osmangazi (OSM), Keles (KEL), Uludag (ULU), Inegol (INE), Gemlik (GEM), Gursu (GUR), Iznik (IZN), Karacabey (KAR), Kestel (KES), Mudanya (MUD), Mustafakemalpasa (MUS), Nilufer (NIL), Orhaneli (ORE), Orhangazi (ORG), Yenisehir (YEN), and Yildirim (YIL) were obtained at monthly scale. Properties of monthly precipitations including mean, standard deviation (S. Dev.), kurtosis, skewness, first-lag auto-correlation coefficient (*r*), maximum (Max), and minimum (Min) at these stations are given in Table 1. In addition, to evaluate the similarities between these stations, principle component analysis (PCA) is applied to data using 10 components. Based on the scree-plot analysis of the components (Figure 1), the first and second PCAs could interpret about 80% of the variance disturbance in the data. Therefore, two PCAs were adequate to classify the oscillations of the variance in the precipitation time series of these hydro-meteorological stations.

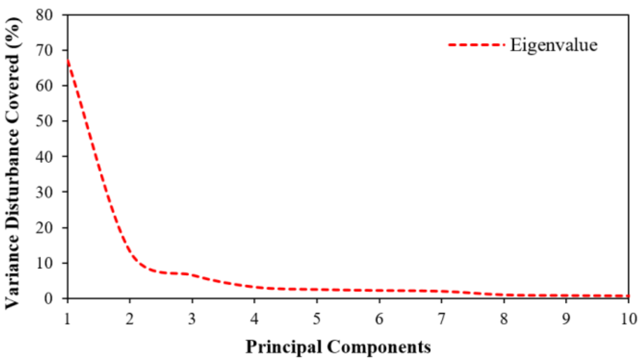

Figure 1:
Scree-plot of the PCA over the precipitation time series

Table 1. Properties of monthly precipitation at stations

Station	Mean (mm)	S. Dev. (mm)	Kurtosis (-)	Skewness (-)	*r* (-)	Max (mm)	Min (mm)	PCA
OSM	59.97	47.98	7.78	1.38	0.23	396.80	0.00	1
KEL	60.98	48.64	3.98	1.06	0.31	254.30	0.00	1
ULU	119.64	101.30	15.25	2.17	0.19	999.50	0.00	1
INE	45.47	35.75	3.78	1.01	-0.15	154.20	0.20	1
GEM	49.45	45.04	11.84	2.03	0.16	335.80	0.00	1
GUR	35.45	28.43	3.62	0.96	0.29	120.20	0.00	1
IZN	40.41	33.45	11.12	1.78	0.13	250.00	0.00	2
KAR	47.64	42.01	6.48	1.46	0.24	257.00	0.00	1
KES	58.27	44.09	3.61	0.76	0.16	200.00	0.00	1
MUD	42.87	36.87	2.49	0.72	0.30	134.40	0.00	1
MUS	51.13	47.71	5.14	1.11	0.30	285.80	0.00	1
NIL	47.25	40.08	2.92	0.77	0.33	157.40	0.00	1
ORE	43.73	33.19	3.72	0.81	0.07	161.50	0.00	1
ORG	52.28	44.87	6.48	1.43	029	238.40	0.00	1
YEN	40.08	38.56	7.10	1.92	0.11	174.70	0.00	2
YIL	45.83	36.34	2.20	0.61	0.31	123.80	0.00	2

Based on the statistics given in Table 1, the highest values are associated with the Uludag (ULU) station, while the *r* (the first-lag auto-correlation coefficient) in all stations is low and indicates weak persistence in the precipitation time series. The PCA analysis also suggests that most of the stations except IZN, YEN, and YIL can be classified under the first PCA. The highest and the lowest skewness respectively are associated with ULU and YIL stations, whilst the ULU station still has the highest values. Since stations had different time records accompanying data losses, a common overlapping time span between January 2005 to October 2018 is used (14 years) at OSM, KEL, ULU, GEM, IZN, KAR, and MUS stations in the subsequent trend analysis (Figure 2). Since 14-year is a short period and could be problematic in trend analysis, results of the previous studies assumed to be right, and several trend detection methods were used to search for the evidence of those large-scale trends in precipitation time series with short-records.

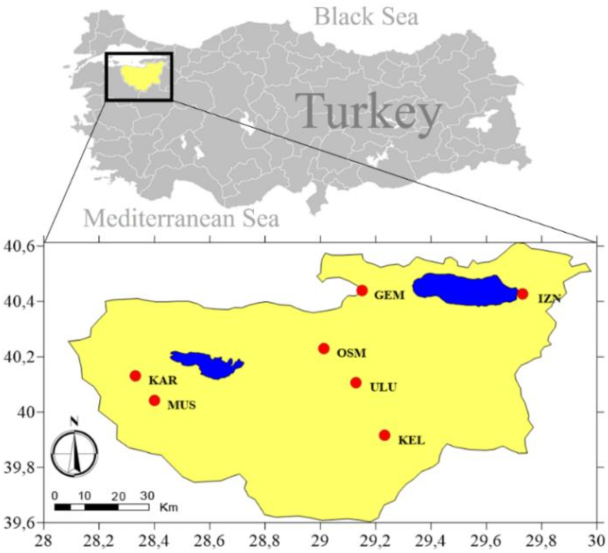

Figure 2:
Bursa map together with the location of the selected stations with highest records available

3. MATERIALS AND METHODS

In this study, several trend analyses methods from the past studies, together with statistical comparison methods are used to evaluate and track down the potential and detectable short-term trends associated with monthly precipitation time series in Bursa. For this aim, precipitation time series at OSM, KEL, ULU, GEM, IZN, KAR, and MUS stations are used, since they have the longest, common time, and no missing data records.

3.1. Linear Trend (LT) Method

Linear regression is a method of which the linear bound between data series is determined using,

$$x_t = \alpha . t + b \tag{1}$$

where coefficient α and intercept β are obtained based on the relationship between two dependent and independent variables, t, and x_t. Then, the statistical significance of coefficient α is tested using a t-value at the desired significance (usually at 0.05 significance). In this respect, the assumption of normal distribution is essential, whilst the results are sensitive to the outliers, and the surrogate values of non-detect.

3.2. Moving Average (MA) Method

A moving average function is a mathematical approach that smooth the values and noise along with the data run in which a large-scale pattern emerges. It is a trend-following or lagging, indicator since the sudden temporal changes are softened or neglected. One of the main benefits of using MA models is to project cyclic trends within the data run (i.e. time series). Depending on the type and the length of the cycles 3-, 6-, 9-, 12-, 24-, and 48-month MA could be used. In this study, 3-, 6-, 12-, 24-, and 48-month MAs were used to investigate the historical trends in the data run. The MA equation is usually used in the form of

$$MA_n = \frac{\sum_{i=1}^{n} x_i}{n} \tag{2}$$

where in this equation, n is the number of periods within the MA component and x is the ith member of the moving average window.

3.3. Mann-Kendall (MK) Method

The Mann-Kendall’s trend test is a nonparametric method that is able to measure the monotonic increase or decrease of the temporal changes within the time series. Although MK is not able to define cyclic trends, it can easily indicate the existing positive or negative trends in the data run. The main idea in this method is to reject the null hypothesis (H_0; is no monotonic trend) or accept the alternative one (H_a; there is a monotonic trend). It can be calculated considering

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(X_j - X_k) \tag{3}$$

while the sign function (i.e. sgn) can be expressed as

$$sgn(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases} \tag{4}$$

In this respect, expected values $E\ [S] = 0$, and the variance would be

$$\sigma^2 = \frac{n(n-1)(2n+5) - \sum_{j=1}^{p} t_j(t_j-1)(2t_j+5)}{18} \tag{5}$$

where p and t_j are respectively the numbers of tied groups in the data set and the number of data points in the jth tied group. Since S is approximately normally distributed, the Z-transformation can be applied; and the obtained Z-value(s) could be evaluated against a critical Z (usually at 0.05 significance). The interested reader may refer to Mann (1945), Kendall (1975), Kendall and Stewart (1976), and Vaheddoost and Akosy (2017) for more details.

3.4. Turn Point (TP) Method

In this method, a time series with length N, is evaluated by the number of turn points (P) in which any of these turns (x_t) are distinguished when the pre- and the post-events are either bigger (i.e. $x_{t-1} < x_t > x_{t+1}$) or less than (i.e. $x_{t-1} > x_t < x_{t+1}$) the turn point, i.e. local extremums. Hence, the expected value of the P, turn point would be

$$E[P] = \frac{2(N-2)}{3} \tag{6}$$

while the variance of P can be obtained as

$$\sigma^2 = \frac{16N-29}{90} \tag{7}$$

Then the Z value can be calculated as

$$Z = \frac{P - E[P]}{\sqrt{\sigma^2}} \tag{8}$$

to be evaluated against a critical Z, similar to those obtained for MK method. The main advantage of this method is to detect non-monotonic trends while all the turn points cannot be recognized as the initiation of future trends. The interested reader may refer to Zuo et al. (2019) for more details.

3.5. Spearman Rank Order Correlation (SROC) Method

Suggested by the World Meteorological Organization (WMO), the SROC is a non-parametric trend test that is able to monitor long term trends in the data run (Adeloye and Montaseri, 2002). The procedure is fully described by McGhee (1985) as,

a) consider time series X_t, $t = 1, 2, \dots n$
b) arrange the values of X_t in descending order and give them ranks (R_{Xt}) such that the first value (i.e. the maximum) gets the first rank and the lowest value (i.e. the minimum) gets the nth rank.
c) calculate the difference between given rank, $R_{x,t}$ and the time step, t of the allocated value as

$$d_t = R_{X,t} - t \tag{9}$$

d) derive the statistic of the trend using,

$$r_s = 1 - \frac{6\sum_{t=1}^{n} d_t^2}{n(n^2-1)} \tag{10}$$

e) by considering the null hypothesis (H_0) as the time series has no trend, the t-value of the data can be calculated as

$$t = r_s\sqrt{\frac{n-2}{1-r_s^2}} \tag{11}$$

which has a Student's t-distribution with n-2 degrees of freedom.

f) obtain the t-critical value using the t-distribution table at α significance level with n-2 degrees of freedom.
g) compare the t-values obtained at step (e) such that the null hypothesis could be rejected if $t > t_{\alpha/2,\, n\text{-}2}$ or $t < -t_{\alpha/2,\, n\text{-}2}$.

The interested reader may also refer to Kendall and Stuart (1976), McGhee (1985), Adeloye and Montaseri (2002), and Vaheddoost and Aksoy (2017) for more details.

3.6. Innovative Şen (IS) Method

This method is based on the graphical interpretation between two halves of a time series. First, the time series is divided into two halves (if the number of the data is odd, the first value of the time series is neglected). Then, each half is ordered ascendingly and a scatter plot is used to project the potential conditions between two halves. Then, arranged data of the first half is projected on the x-axis while the arranged data for the second half is projected on the y-axis. Then, the graphical interpretation of the method can be introduced as no-trend (NT) when the projected data points are located on the perfect fit line (i.e. y=x), monotonic increasing (MI) while data points are located above the perfect fit line, and monotonic decreasing (MD) when the data points are located under the perfect fit line. In addition, the non-monotonic trends also can be introduced under two subclasses as non-monotonic increasing (NMI), and non-monic decreasing (NMD) when the start and end of the data run on the scatter plot are at the opposite side of the perfect fit line. The advantage of this method is to track down non-monotonic, and less significant trends (e.g. short term trends) whilst the degree of significance could not be evaluated easily. The interested reader may refer to Şen (2011), Dabanli et al. (2016), and Şen (2017) for more details.

3.7. Innovative Trend Analysis (ITA) Method

The innovative trend method (ITA) is a revised version of the IS method. Fully described by Wu and Qian (2017), the differences between the two methods are based on introducing the rate of changes in trends, and 0.10 significance band in the analysis. Hence, it can be used in the evaluation of the short term and non-significant trends as well. In this respect, time series with different magnitudes must be normalized and, the rate of the trend can be obtained as,

$$D = \frac{1}{n}\sum\nolimits_{i=1}^{n} \frac{10(y_i - x_i)}{\bar{x}} \tag{12}$$

while D is the acceleration rate of the trend, n is the number of data in the time series. A positive D indicates an increasing rate, whereas a negative D indicates a decreasing rate related to an ascending or descending trend.

3.8. Changes in Distribution (CD) Method

The idea of tracking changes in the properties of the probability distribution is not new. However, recent studies revealed that the changes in the probability distribution function (PDF) between two halves of the time series can be interpreted by means of the moments of the distribution (i.e. mean, variance, skewness, etc.). For instance, whilst the reduction in mean and median can clearly be a sign of descending trend, the reduction in the kurtosis can be interpreted as an ascending trend. The presence of trends, however, can be linked to the extreme values which are problematic in trend detecting procedure. In this respect, outliers can cause major problems in IS and ITA methods which are sensitive to the deviations from the perfect fit line. This method is also used in the trend analysis. The general equation for the moments of the distribution in a time series is given as,

$$\mu^{\circ}_n = \int_{-\infty}^{+\infty} x^n f(x)dx \tag{13}$$

where μ°_n is the *n*th moment of the distribution (1st moment is the sample mean; 2nd moment is the sample variance; 3rd moment is the sample skewness; and 4th moment is the sample kurtosis) allocated for the distribution function, *f(x)*; and *x* is the any independent precipitation within the time series.

3.9. Standardized Precipitation Index (SPI) Method

The concept of standardized precipitation index (SPI) is usually addressed in drought analysis rather than evaluating trends. However, the SPI is the simplest index to evaluate the precipitation time series. It can be used to track a continuous deficit or surplus since it is based on fitting the precipitation time series to a predefined probability distribution such as Gamma distribution using,

$$g(x) = \frac{x^{\alpha-1}e^{-x/\beta}}{\beta^{\alpha}\Gamma(\alpha)} \tag{14}$$

while

$$\alpha = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \tag{15}$$

$$\beta = \frac{\bar{x}}{\alpha} \tag{16}$$

$$A = \ln(\bar{x}) - \frac{\ln(\bar{x})}{n} \tag{17}$$

to be transformed into a standardized Normal distribution. Then, the obtained results can be classified when SPI ≥ 2.0 as extremely wet, 2.0 > SPI ≥ 1.50 as very wet, 1.50 > SPI ≥ 1.00 as moderately wet, 0.99 > SPI ≥ -0.99 as near normal, -1.00 > SPI ≥ -1.49 as moderately dry, -1.50 > SPI ≥ -1.99 as severely dry, and finally SPI ≤ -2.0 as extremely dry conditions.

The interested reader may also refer to WMO (2012) for more details. In this study 1-, 3-, 6-, 9-, 12-, 18-, 24-, and 48-month SPIs are used to evaluate the temporal changes in the monthly precipitation time series.

4. RESULTS

Results of the LT, MK, SROC, IS, and ITA analysis is given in Table 2. Based on LT, MK, and SROC results, no significant trends emerged in the stations; $t_{crtical}$ and $Z_{critical}$ is 1.96 (Figure 3). This was in agreement with the results of the previous studies which could not track down trends at a monthly scale. However, the TP method showed critical descending trends at all of the stations except in ULU, IZN, and KAR. Since the minimization of the false turn points is important, the seasonally adjusted turn points should be used in the analysis as well (Menezes et al., 2006). In this respect, conducted analysis depicts that the ULU station in the Uludag summit and KEL station in the mountain ridge were experiencing non-significant descending trends.

Table 2. Trend analysis for monthly precipitation

Station	LT (*t*)	MK (*z*)	TP (*z*)	SROC (*t*)	IS	ITA
OSM	+1.61	+1.36	-3.56	+1.37	NMI	+1.11
KEL	-0.08	+0.42	-2.02	+0.36	NT	-0.04
ULU	-0.11	-0.48	-1.62	+0.51	NMI	+0.08
GEM	+0.48	+0.28	-2.05	+0.33	NMD	+0.34
IZN	+1.03	+1.15	-1.91	+1.12	NMD	+1.36
KAR	+0.08	+0.00	-1.91	+0.05	NMD	-0.33
MUS	+0.78	+0.91	-3.58	+0.92	NMD	+0.37

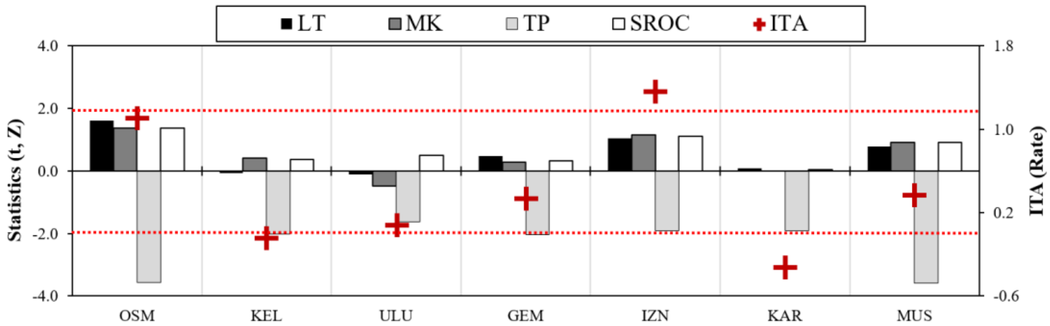

Figure 3:
Results obtained by LT, MK, TP, SROC, and ITA for monthly precipitations in selected stations

In addition, based on the analysis given in Table 2 and Figure 3, in most of the stations, non-monotonic descending trends are available. Yet, in most of the stations except in OSM and IZN the acceleration rate of those trends is decreasing. This means that non-significant trends are accompanied by continuously descending acceleration rates. The IS method, also showed that there are NMD trends in GEM, IZN, KAR, MUS stations; and a NMI trend at OSM and ULU stations (Figure 3). Similarly, the ITA method showed that the rate of these non-monotonic trends is increasing; while in KAR station a decreasing rate of -0.33 was observed (Figure 4 and Table 2). The reported decreasing trend at ULU is obtained as a slightly increasing with an increasing rate of +0.08 based on IS and ITA methods. However, as explained previously, the LT, MK and TP methods detected a non-significant decreasing trend for the same period in ULU. Therefore, it is concluded that the mathematical approach of the trend-detecting method is extremely vital in recognition of the reported trends.

In most of the cases, the last value of the run is deviated from the confidence band and changed the status of the trend from NT to NMI or NMD. It can be linked to the existence of extreme events which can be expressed as outliers of which triggered by the climate variability in the region. To this end, the degree of significance associated with the ITA method showed that the extreme values deviate the trends in such a way that non-significant trends became significant. Since, patterns of the multi-annual scale were somehow different (Vaheddoost, 2019; Katip, 2018), the MA models with 3-, 6-, 12-, 24-, 48-month lags were also used to evaluate the presence of long-term cyclic events and/or changing climate (Figure 5).

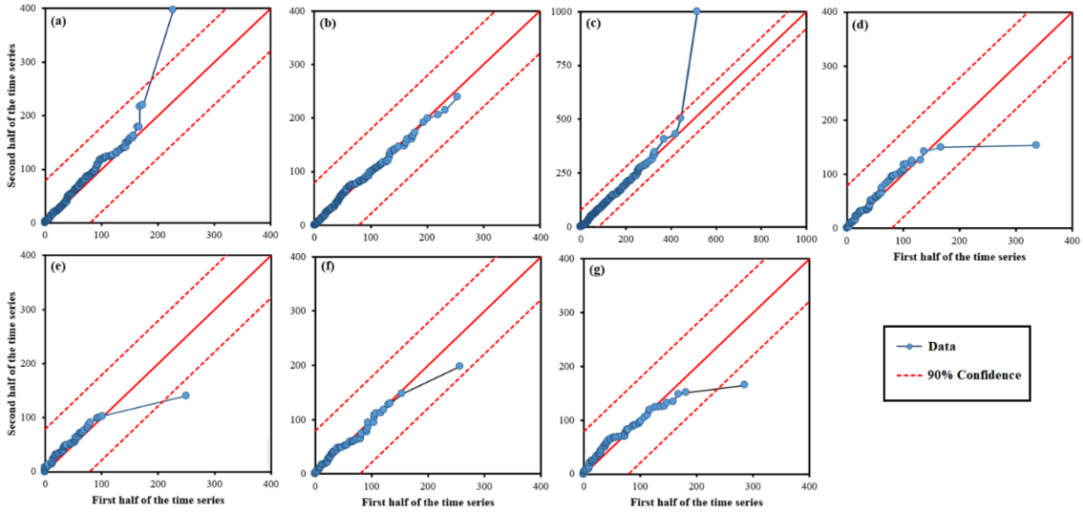

Figure 4:
Trend analysis of monthly precipitation using IS and ITA methods in;
***a.** OSM **b.** KEL **c.** ULU **d.** GEM **e.** IZN **f.** KAR **g.** MUS stations*

Figure 5 shows the results of seasonal smoothing (i.e. MA) at the selected stations. Similarly, no harmonics or significant patterns emerged. However, a slight increase in the precipitation patterns at the ULU and the KEL stations can be compared to the increasing patterns trends at the IZN station. This particularly happened in the MA-48 as the representer of the large-scale cyclic events. Thereby, no significant conclusion could be drawn from the MA and ITA analysis in favor of the existence of the trends at least for those with the short-records. In this respect, the CD method is also applied to investigate the properties of the probability distribution function (PDF) and related outliers. Time series were separated into two halves and PDF of each half together with the Box and Whiskers plot of the allocated half is presented in Figure 6. Based on Figure 6a and Table 3, the second half of the precipitation time series depicts different statistics when compared to the first half of the time series. There are also outliers with higher magnitude and lower frequency (i.e. extreme events, or outliers) which is positively skewed. In Figure 6b and Table 3, no significant changes in the PDF of the KEL stations occurred. In ULU station, which a decreasing trend was reported (Vaheddoost, 2019; Simisek and Cakmak, 2010), different results were obtained by LT, SROC, IS, and ITA methods (Table 2, and Figure 3). In Figure 6c, the second half of the data clearly has a greater median, variance, skewness, and kurtosis. But a slight decrease in the magnitude of the outliers occurred. This particularly means that the extreme events occurred less frequently and in lower magnitudes. Concludingly, the analysis is under the effect of extreme values rather than a lack of information due to the short-time records. This results are also in agreement with the results of MA and CD analysis (in Figures 5 and 6 respectively).

In addition, based on the changes in the kurtosis of the two halves of the precipitation time series, each half showed a different probability of outcomes. This changes for OSM, ULU, and IZN were decreasing and vice versa for the remaining stations. Hence, the recent changes in the 4th moment of the distribution (i.e. kurtosis) can be interpreted as the endeavor of the climate in reaching a new equilibrium. In this regard, the effect of climate born frequency changes is not clear and needs to be investigated in advance.

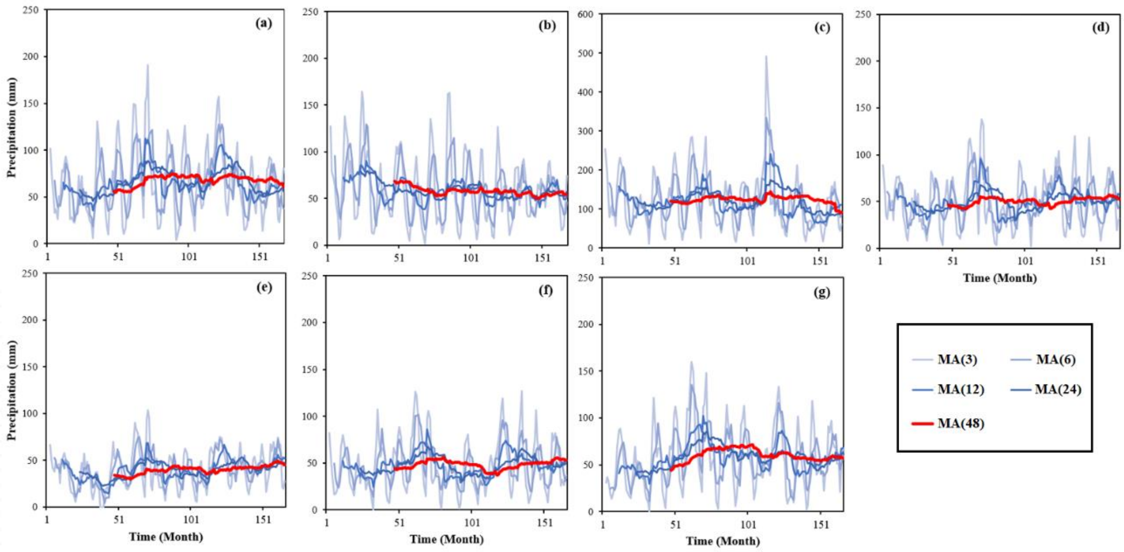

Figure 5:
Trend analysis of monthly precipitation using MA method in;
***a.** OSM **b.** KEL **c.** ULU **d.** GEM **e.** IZN **f.** KAR **g.** MUS stations*

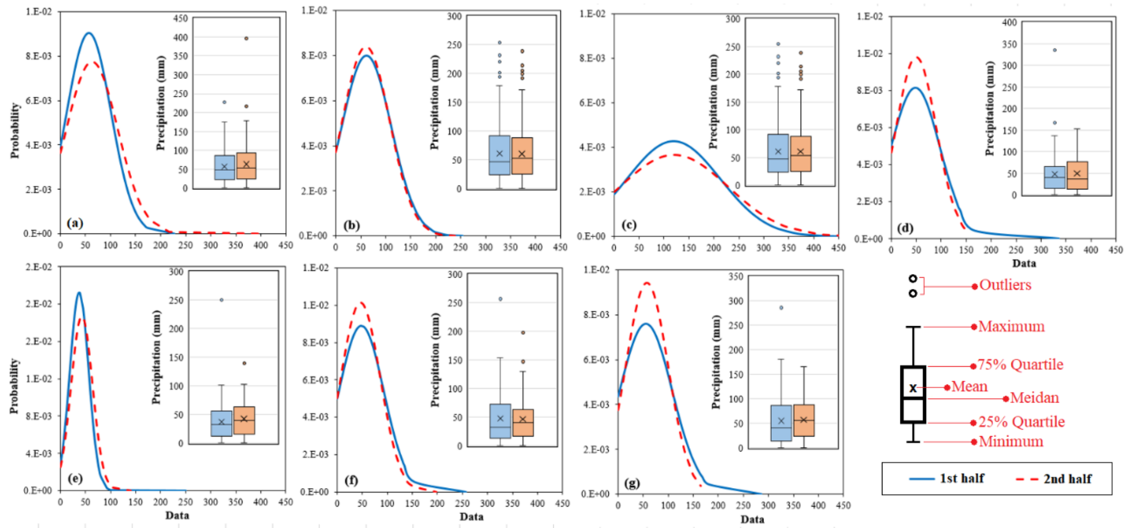

Figure 6:
Trend analysis of monthly precipitation using CD method in;
***a.** OSM **b.** KEL **c.** ULU **d.** GEM **e.** IZN **f.** KAR **g.** MUS stations*

Based on the analysis, several trends emerged in GEM, IZN, MUS and NMD stations (Figure 6d, e, g) while previous studies indicated increasing rates for those time series (Table 2). In the CD method, the GEM and IZN stations have similar patterns, and the second half of the data has higher mean but lower variance, skewness, and kurtosis. This particularly means that the short-term trends are associated with the extreme events of high magnitude with low frequency. Finally, in stations KAR, and MUS respectively an NT and NMD trends with diverse acceleration rate, similar PDFs, and different statistical values are emerged (Figure 4f-g, Table 2-3).

The results of the SPI analysis are also given in Figure 7. Results of the SPI, depicts a recent decrease at SPI-48 (Figure 7c). Hence, the long-term projections may need an update or seasonal adjustment in order to foreseen turn events of the rapid shifts which are emerged at the

CD method. Similar patterns for MUS stations are also observed (Figure 7g). However, the analysis at IZN station was not analogous to other stations (Figure 7e). In other stations, the diverse frequency-magnitude relation was accompanied by similar patterns which are emerged by SPI (Figure 7a, 7d, and 7f) except in the KEL station (Figure 7b).

Table 3. Details of trend analysis using CD method

Station	Half	Mean (mm)	Variance (mm^2)	Skewness (-)	Kurtosis (-)	Outlier
OSM	1st	56.83	1942.48	0.89	3.43	Yes
	2nd	63.11	2642.44	1.65	9.74	Yes
KEL	1st	61.01	2482.72	1.14	4.13	Yes
	2nd	60.74	2264.65	0.96	3.79	Yes
ULU	1st	118.89	8694.89	1.08	4.28	Yes
	2nd	119.86	11843.73	2.83	20.75	Yes
GEM	1st	48.08	2402.67	2.80	16.39	Yes
	2nd	49.69	1659.53	0.75	2.61	No
IZN	1st	37.49	1324.97	5.55	12.56	Yes
	2nd	42.59	915.36	3.59	0.02	Yes
KAR	1st	48.14	2007.37	4.61	4.39	Yes
	2nd	46.57	1547.60	4.21	1.81	Yes
MUS	1st	55.44	2759.36	1.48	6.29	Yes
	2nd	57.49	1795.92	0.47	2.41	No

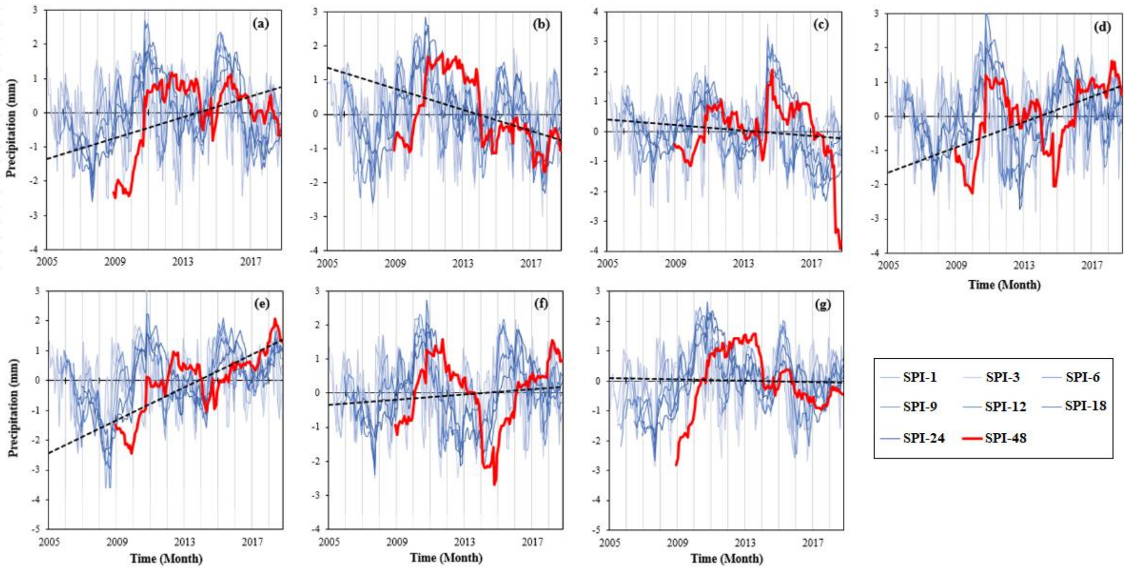

Figure 7:
Trend analysis based on SPI-1, -3, -6, -9, -12, -18, -24, and -48 indices in;
***a.** OSM **b.** KEL **c.** ULU **d.** GEM **e.** IZN **f.** KAR **g.** MUS stations*

Subsequently, the source of most short-term trends in this respect was linked to the magnitude and frequency of the extreme events (i.e. outliers) rather than short-time records or memory loss (i.e. persistent) in the system. Based on the micro-climate of which stations represent, different degrees of change in magnitude and frequency were detected. Yet, it is evident that some changes are taking place in the large-scale phenomena. In addition, each statistical approach has its limitations which may reveal different results in practice. Accordingly, seasonally adjusted estimates were not necessarily reasonable whilst the results of this study are similar to those of Menezes et al. (2006) which indicates to the trade-off between timeliness of detection and false turn points which are affected by the outliers. Regardless of the length of data records, the short-term trends are under the influence of false turn points linked to the outliers, frequency, and magnitude of the precipitation outcomes. In this respect, the obtained results do not necessarily reject the importance of long-term seasonality or climatic drivers, but rather depicts the role of outliers and frequency changes in misleading the short-term trend analysis in advance. These short-term trends, however, thought to be triggered mostly due to the events which take place at the regional- and micro-climates.

It was concluded that the, CD accompanied by IS, and ITA methods are the best package in recognition of non-significant or short-term precipitation trends. It is due to the ability of these methods in recognition of outliers, false-turn points, and magnitude changes in time series. The SPI could also reveal trend patterns in the time series. However, it is not easy to determine if the initiation of the trends is linked to the outliers. Thereby, if the presence of outliers could be tolerated in the analysis, it should be interpreted carefully. Since these outliers can deviate the results of the ITA and IS, they should be removed from the analysis or simply tracked down by outlier resistant methods such as those suggested by non-parametric approaches. It is noteworthy that, a long-record time series with more than 30 years of data, should be preferred in the trend analysis in the first place. However, if there is no option on the table, the outlier resistant methods together with the CD method is the best way in recognition of the non-significant or short-term trends in the time series analysis. Results clearly indicate that short-term trend disturbances are more related to the micro-climate variability while the long-term trends expected to be more sensitive to the large-scale oscillations and climate change.

It is also possible that the changes in the frequency and/or magnitude of the extreme events are linked to climate change which needs to be addressed in future studies. Thereby, the reported descending trends could be reproduced considering the micro-climate of the region and it is clearly indicated that the Bursa slowly but surely is experiencing less extreme precipitation events. Additionally, it is obvious that the climate born events of the short-term trends are more likely to be motivated by climate-variability rather than the clime-change.

5. CONCLUSION

Monthly precipitation trends at Bursa city in Turkey were addressed and several stations are used in order to evaluate these trends between January 2005 to October 2018. The after math of using short-term data records in the evaluation of the trends is investigated in the selected stations. For this aim, LT, MK, TP, MA, SROC, IS, ITA, CD, and SPI methods were used. It is concluded that,

i. The nature of the trend analysis method and its mathematical statement is highly effective in recognition of the evidence of short-term trends in the precipitation.
ii. Nonparametric methods are incapable of detecting short-term trends while no attention is paid to the moments of the distribution.
iii. Methods of which consider cyclic behavior are also incapable of tracking short-term trends due to the absence of long-term repeating patterns in the data run.
iv. CD analysis and the methods in which considers the changes in the moments of distribution and corresponding outliers are strong tools in recognition of the short-term precipitation patters.
v. Micro-climate or climate variability is most probably the main driver of the short-term trends while the long-term trends expected to be triggered by long-term climatic behavior.

Results also indicated that the MA is the less-reliable method between the selected methods whilst the results obtained by the combination of CD together with IS, ITA, and SPI were more realistic and confirmed the results by the previous studies. Particularly, in most of

the cases, especially for ULU station, results were in total agreement with the results of previous studies conducted by Şen (2013), Sirdas and Şen (2003), Simisek and Cakmak (2010), and Vaheddoost (2019) who managed to use longer data records at each of individually selected stations.
Thereby, the magnitude and frequency of the extreme events were linked to the observed long-term trends in the region. Hence, it is obvious that the appropriate determination of turn points especially those which can be affected by the outliers in the data run is vital in future trend analysis studies.

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