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LONG-TERM TREND ANALYSIS OF ANNUAL PRECIPITATION FOR SHORT PERIODICITIES

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Abstract

The climate variability analysis is often performed by studying trends in hydro-climatic series. In this study, precipitation series trend analysis was performed by applying the parametric test of linear regression and the non-parametric tests of Mann-Kendall (MK) and Pettitt's. Trend tests were applied on the original precipitation series and the denoised precipitation series via the discrete wavelet transform (DWT). This study aims- to evaluate the classical and new approaches used for analyzing precipitation trends. The paper presents a new approach for analyzing non-significant trends by combining Pettitt's test, linear regression, and discrete wavelet transforms. The most effective periodic component of the time series was determined, and precipitation series were transformed for a short-term periodicity scale (2-years). The trend analysis results obtained from the denoised precipitation series had presented more significant results than those of the original series.

Key words: change point, discrete wavelet transform, precipitation, trend analysis

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1. Introduction

Monitoring the impact of climate change is of vital importance for humankind. The monitoring process is based on developing strategies for climate actions. Planning and management depend on analyzing climate variability. The variability of hydro-climatic data (rainfall, streamflow, temperature…) is often assessed by trend analysis. The commonsense trend test is a simple measure of the time series linear slope for which the data pattern occurs. Besides, other statistical tools are widely used for the study of hydro-climatic series trends. The present paper focuses on assessing precipitation series trends by combining statistical tools, and wavelet transforms. The region in the study is the coastal part of the Black Sea Region. Many studies had been conducted in the Black Sea Region to investigate the different climate variability indicators in the Black Sea Region. Researchers have examined the long-term changes in temperature, humidity, streamflow, and water level (Aleshina et al., 2018; Artamonov et al., 2017; Eris and Agiralioglu, 2012; Kubryakov and Stanichnyi, 2013; Titov and Kuzevanova, 2015). However, few studies focused on precipitation as a metrological indicator. Precipitation is a complicated natural process affected by several climate factors, making modeling a difficult task. However, understanding the general pattern of precipitation in a region may facilitate the analysis of hydrogeological processes under climate change.

The scientific community benefited from statistical methods to adapt to meteorological and hydrological events and understand their long-term changes. Generally, trends are detected by applying non-parametric trend tests such as the Mann-Kendall test (Adarsh and Janga, 2015; Eris and Agiralioglu, 2012; Partal and Kahya, 2015). Regression analysis is also an extensively used method for examining the trends. A study by Yacoub and Tayfur (2019) focused on temperature and precipitation trends in the Taraza Region of Mauritania showed the impact of climate change on water resources. The trend identification

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had been conducted using Mann-Kendall, the Spearman's rho, and the Şen trend tests. The study also included the estimation of time series change points via Pettitt's test and the trend slope magnitude via the Theil-Sen approach. The applied tests had revealed a common change point of temperature trends for the whole study area and had identified the trend magnitude change rate for precipitation and temperature series (Yacoub and Tayfur, 2019).

On the other hand, by the modern technologies that facilitated data processing, new approaches had been suggested for time series analysis and trend detection. For instance, wavelet transforms (WT) had been introduced by Grossmann and Morlet (1984) for signal analysis and image processing. The WT technique has also been deployed in meteorological researches to study trends and periodicities in hydro-climatic time series (De Artigas et al., 2006; Joshi et al., 2016; Mahrt 1991; Sharma and Goyal, 2020). The analysis of time series can be performed either by Discrete Wavelet Transforms (DWT) (Joshi et al., 2016) or by Continuous Wavelet Transforms (CWT) (Nury and Hasan, 2016). Both DWT and CWT are powerful methods for time series periodicity and trend component determination (Pandey et al., 2017; Sang, 2013). The trend analysis of precipitation time series can be performed with various methods. In recent years, the wavelet transform became a popular method for hydrological time series trend analysis (Pandey et al., 2017). However, it is essential to select the mother wavelet that will represent the studied signal. For instance, Priyadarshani et al. (2016) had used wavelet transforms for noise reduction in birdsong recordings. The study aimed to decompose the natural signal using wavelet packet decomposition, band-pass or low-pass filtering, and better record. The conducted approach to birdsong denoising had been based on selecting the most suitable mother wavelet for the decomposition. Priyadarshani et al. (2016) had presented two approaches for choosing the appropriate mother wavelet. The first approach had been visually comparing the shape of the original signal and the mother wavelets. The second approach had been assessing the correlation between the original signal and the denoised signal.

The present paper analyzes precipitation series trends by applying the Mann-Kendall trend test and linear regression to the original and the denoised precipitation series. The Pettitt's test was applied to the precipitation series, and the change point in the original and denoised time series was compared. The discrete wavelet transforms were adopted to obtain a denoised signal in the band of 2 years (2-years periodicity).

The paper is organized as follows. A description of the precipitation data is provided in section 1, and the study area is given in section 2. The applied methodology is presented in section 3. The study results are illustrated in section 4, where the trend and the change point test findings are presented. Section 5 includes a summary of the study and a list of conclusions about the applied approach.

2. Study area and data

The Black Sea is a semi-closed sea connected to the Marmara Sea by the Bosphorus in the southwestern part. The Black Sea's total area is about 413 thousand square kilometers, and it has a coastline of 8,350 kilometers. The considered study area covers about 1,000 km from the west to the east and 200 km from north to south along the Turkish coastlines. The Black Sea has borders with six countries: Bulgaria, Georgia, Romania, Russia, Ukraine, and Turkey.

The prevailing climate in the Black Sea region is mild and humid. The rainfall rate is important during winter, and it decreases gradually towards summer. During winter, the eastern Black Sea Region witnesses the occurrence of snowfall at high altitudes. In coastal regions, the yearly average temperature is about 14°-15° C (Eris and Agiralioglu, 2012). The yearly average humidity rate is about 76 to 77%. The yearly total precipitation varies between 681 mm and 2,276 mm. In this study, a combination of the classical trend analysis methods and the DWT was applied to investigate the annual total precipitation long-term variation from stations located in the coastal Black Sea Region. The precipitation data were obtained from 15 measurement stations located along the Black Sea's southern coast (Fig. 1). The stations are operated by the Turkish State Meteorological Service (MGM). The measured data represents the monthly measured total precipitation.

In the scope of this study, we investigated the annual variability of total precipitation. So, the monthly records were gathered in order to obtain the yearly total precipitation. The timeframe of precipitation data ranges from 36 to 82 years between 1929 and 2010. Although the region's precipitation recording stations are over 40 stations, we only considered the stations having no gaps in the data (Eris and Agiralioglu, 2012). We only considered the stations having records exceeding 30 years since the classical climate period is 30-year as defined by the World Meteorological Organization (Pandy et al., 2017). Table 1 presents features of the stations where the geographical location (Latitude and Longitude), topographic elevation (E), the mean of annual total precipitation values during the recording period (Pmean), and the considered record period are given.

3. Methods

This study investigates the long-term trends in the annual precipitation data. First, a change point detection test was applied to detect changes in the time series trend. The precipitation time series was then subdivided into two periods as before the occurrence of change and after the change. The identification of temporal changes in the precipitation series was performed by the linear regression and the MK test. Linear regression was applied to the subdivided series (according to the change point location), and the MK test was carried out on the series with their original length.

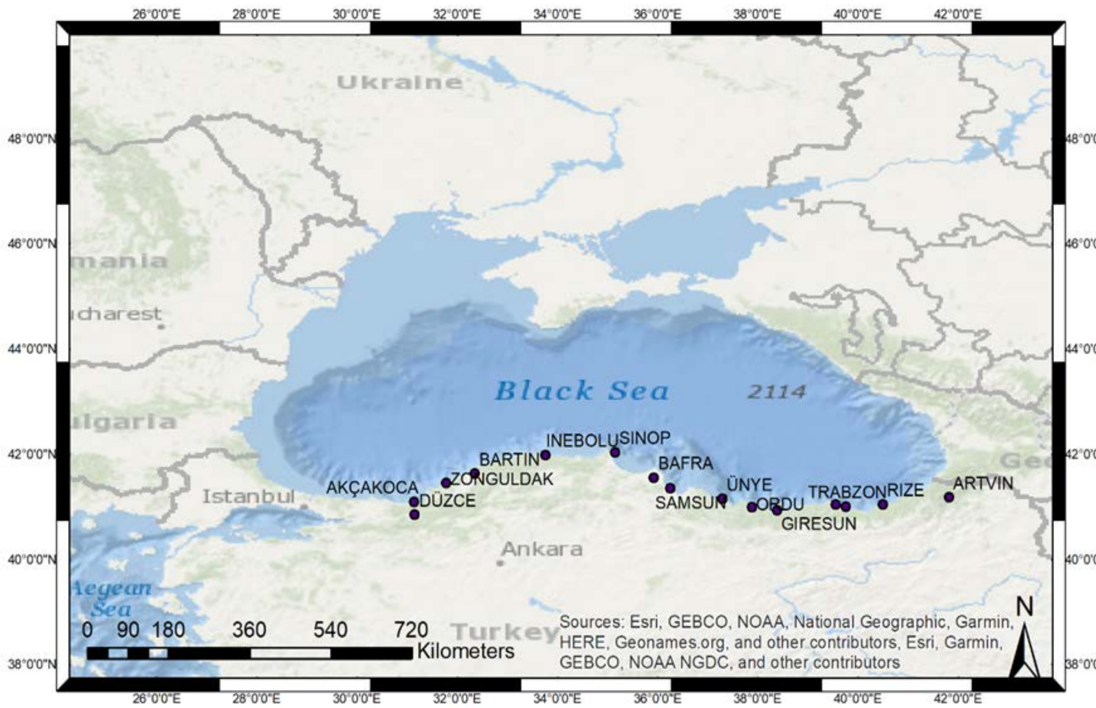

Fig. 1. Locations of the meteorological stations

Table 1. Features of meteorology stations

Station	***Longitude***	***Latitude***	***Elevation (m)***	***Mean precipitation (mm)***	***Record start year***
Artvin	41° 49'	41° 11'	612	703	1947
Rize	40° 31'	41° 02'	8	2276.1	1929
Akçaabat	39° 34'	41° 01'	9	722.9	1964
Trabzon	39° 43'	41° 00'	38	810.8	1937
Giresun	38° 23'	40° 55'	90	1245.9	1929
Ordu	37° 54'	40° 59'	8	1028.2	1929
Ünye	37° 17'	41° 08'	19	1156.4	1955
Samsun	36° 18'	41° 17'	4	700.6	1929
Bafra	35° 56'	41° 35'	107	790.4	1952
Sinop	35° 10'	42° 01'	29	681.1	1929
İnebolu	33° 47'	41° 59'	48	1017.2	1942
Bartın	32° 20'	41° 38'	36	1030	1975
Zonguldak	31° 48'	41° 27'	124	1230.3	1931
Akçakoca	31° 10'	41° 05'	10	1063	1950
Düzce	31° 10'	40° 50'	145	832.9	1948

In the next step, the original time series were denoised by DWT. The decomposition was performed at the first level; in other words, the transformed series represents two years' periodic component. Wavelet transformation can be carried out at different decomposition levels that reflect different periodic components. However, in this study, we are interested only in evaluating the trends for short periodicities. In addition, the transformed series varies according to the mother wavelets. Identifying the most suitable mother wavelet was based on the correlation between the original series and the transformed series. The correlation between the original series and a two years' moving average filtered series was also assessed. The parametric and non-parametric trend tests were applied on the transformed time series after selecting the suitable mother wavelet. The methodology followed in this work is described below:

1. Identification of change points in precipitation series and subdivision of the series in case of change.
2. Application of linear regression test for the precipitation series' subdivisions.
3. Application of the MK trend test to the original precipitation series.
4. Decomposition of the precipitation series via DWT.
5. Selection of the most suitable mother wavelet representing the original series.
6. Application of the change point test (Pettitt's test) and trend test (MK) for the denoised series.
7. Evaluation of the temporal variability of annual precipitation series for short periodicities.

3.1. Pettitt's change point test

Pettitt's test is a non-parametric change point detection test. The test is applied to detect a single change point in time series with continuous data such as hydrological series or climate series (Pettitt, 1979). The change point detection gives an idea about the data homogeneity/non-homogeneity which helps to identify changes in climate pattern. The null hypothesis of the test suggests that no change exists in the time series. The alternative hypothesis states that the change point exists. The test statistics are expressed as given by Eq. (1):

$$K_T = Max\left|U_{t,T}\right| \tag{1}$$

where T represents the variable, K_T represents the change point location, and $U_{t,T}$ is defined by Eq. (2):

$$U_{t,T} = \sum_{t=1}^{t}\sum_{j=t+1}^{T} Sgn\left(X_i - X_j\right) \tag{2}$$

The test statistical significance probability is approximated for p≤0.05, where the p-value is calculated by Eq. (3):

$$p \cong Exp\left(-6K_T^2 / T^2 + T^2\right) \tag{3}$$

3.2. Linear regression

Linear regression is one of the most basic and popular methods used to detect time series linear trends (Adarsh and Janga, 2015; Pandey et al., 2017). Linear regression was applied to precipitation series subdivisions according to the change point location. The linear trend line is drawn and presents the slope of the data sequence. The followed approach reveals the trend slop pattern before and after the change point. The regression line is expressed with a linear relation (Eq. 4):

$$p \cong Exp\left(-6K_T^2 / T^2 + T^2\right) \tag{4}$$

In the regression equation, α represents the regression coefficient and β represents the intercept.

3.3. Mann-Kendall (MK) test

Mann-Kendall trend test, also known as Kendall's tau statistic, is an extensively applied test for trend detection in hydro-meteorological time series. This non-parametric test shows whether a time series contain a trend or not with its null hypotheses. The significance level (p) corresponds to the calculated z test statistic value. The null hypothesis cannot be rejected if it is higher than the critical significance level (α); otherwise, it is rejected. In order to perform the test statistic, the statistic parameters were calculated using the procedure given by Eqs. (5-8):

$$S = \sum_{i=1}^{n\text{-}1}\sum_{j=i+1}^{n} Sgn(X_j - X_i) \tag{5}$$

$$Sgn(X_j - X_i) = \begin{cases} +1\, if\ (X_j - X_i) > 0 \\ 0\ if\ (X_j - X_i) = 0 \\ -1\ if\ (X_j - X_i) < 0 \end{cases} \tag{6}$$

$$\sigma_s = \sqrt{\frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{q} t_p\left(t_p - 1\right)\left(2t_p + 5\right)\right]} \tag{7}$$

$$Z_{MK} = \begin{cases} \dfrac{(S-1)}{\sigma_s}\, if\ S \geq 0 \\ \dfrac{(S+1)}{\sigma_s}\, if\ S \geq 0 \end{cases} \tag{8}$$

The length of the time series is n, t is the extent of a given tie, and σ_s is the standard deviation of the normally distributed S (for n>10). If α is the test significance level, and Z is the standard normal variate, then the null hypothesis (No Trend) is valid for $|Z|<Z(1-0.5\alpha)$. Otherwise, the null hypothesis is rejected, and the presence of a monotonic trend is accepted. In this study, the considered significance level is 95%, and the alternative hypothesis is accepted for the following cases (Eq. 9):

$$Z_{mk} = \{\frac{>1.96\, for\ upward\ trend}{<1.96\, for\ downward\ trend} \tag{9}$$

3.4. Discrete wavelet transform

Wavelet transformations had been first used in quantum mechanics and statistical mechanics. A wavelet transform is a relatively new development in signal processing. This method is a powerful tool that can provide a simultaneous display of time and frequency. Wavelet transformations can decompose the original time series into various periodicities. Low periodicity includes the high-frequency components (fast-changing events), and high periodicity shows the low-frequency components (slow changing events) of the original signal. Wavelet transform has been successfully used to analyze various hydrological and meteorological variables to determine the non-stationary trends and periodicity (Rashid et al., 2015).

The discrete wavelet transforms are orthogonal wavelet functions that use low and high pass filters for signal decomposition. The DWT filters are represented by coefficients that decompose the signal according to a predefined frequency domain. The application of DWT leads to denoising and compressing the signal. The discrete wavelet transform is defined as (Eq. 10):

$$\psi_{m,n}\left(\frac{t-b}{a}\right) = a_0^{-m/2\psi\left(\frac{t-nb_0a_0^m}{a_0^m}\right)} \tag{10}$$

The wavelet dilation and translation depends on the integers m and n, respectively. The location parameter is represented with b_0 where $b_0 > 0$, and a_0 represents a specified fine-scale step where $a_0 > 1$. For practical purposes b_0 and a_0 values can be chosen as 1 and 2, respectively (Pandey et al., 2017).

In order to examine the precipitation series variability for short periodicities, DWT is applied to the original series. The DWT operates with two functions being the high-pass and low-pass filters. When the signal passes through those filters, the time series is then divided into two parts as being the signal approximation (comprising its trend) and the signal detail (comprising the high frequencies and the fast events (Pandey et al., 2017).

The discrete wavelet transform does not have a fixed basis function. As a result, the output signal differs according to the wavelet used in the transform process. It is suggested for hydrological time series to use Daubechies-type wavelets (Pandey et al., 2017). Daubechies wavelets belong to the family of discrete wavelets characterized by compacted support. In other words, this type of orthogonal wavelets requires scaling coefficients with a finite number. The Daubechies wavelet family itself has ten different mother wavelets. The first four Daubechies wavelets (db1, db2, db3, and db4) are not used in the analysis since the mother wavelet shape differs from the analyzed signal. The remaining mother wavelets are used to decompose the signal at the first, second, and third levels, which reflect periodic components of 2-years, 4-years and 8-years, respectively. To select the appropriate mother wavelet and decomposition level, the correlation between the original series and its denoised signal is assessed. The correlation approach is applied for the approximation component (derived from DWT) and for the precipitation series with a moving average filter of 2-years, 4-years, and 8-years periodic structure. Trend analysis is then performed for the denoised series with the highest correlation.

4. Results and discussion

This study combines classical trend analysis methods and discrete wavelet transform to detect precipitation time series variability. The analysis was initiated by detecting the change point in the precipitation series by the Pettitt's test. And then, the precipitation series was subdivided into two parts according to the years of change. MK test was also applied to assess the temporal variability of the precipitation series long term trend. The same process was applied to the precipitation series filtered by DWT and moving average filter. Signal filtering can eliminate the abrupt changes that occur in the precipitation time series (signal denoising) without affecting the long-term changes.

4.1. Change point test results

The obtained results show that the change point detected in the precipitation series varies between 1942 and 1994. The presence of a change point in precipitation data indicates a change in the hydrological cycle. The years of change were divided into four classes according to the standard deviation (Table 2).

Most of the change points had occurred between the years of 1982 and 1994. However, a significant change was detected only at seven stations at a confidence level of 95%. Four stations had exhibited a significant change point between the years of 1982 and 1994 (fourth class), two stations had exhibited a significant change point between the years of 1942 and 1951 (second class), and one station had exhibited a significant change point between the years of 1967 and 1981. The findings show a significant change in the annual precipitation series in the late 1970s (Fig. 2).

4.2. Trend analysis via linear regression

Linear regression was applied to the original precipitation series to detect the linear trend before and after the change point (Fig. 2). For precipitation data, it was found that most stations with change points from the first and second classes have negative linear trends before the occurrence of the change point (Table 4). For the third and fourth classes, most stations located in the western part and middle zone of the Black Sea Region have positive linear trends before the change point.

On the other hand, most stations located in the eastern regions have negative linear trends before the change point. The results obtained from linear regression for the series second subdivision (after change point occurrence) showed that the stations located in the eastern part and middle region of the Black Sea have positive linear trends except Ordu and Trabzon Stations.

Besides, stations located in the western part have negative linear trends except Akçakoca Station. The combination of change point with linear trend analysis can detect the jump in precipitation series (Fig. 3-d) and the temporal modification in the trend slope and magnitude (Fig. 3-a, b, c).

4.3. Trend analysis via MK-test

Annual precipitation series' trend was also examined via MK test. The test was applied for the original time series, and only four stations had a significant trend at a confidence level of 95% (Table 5).

The MK trend directions of series with significant results showed the same results of the linear trend test before and after the change point. For instance, series obtained for Artvin, Ünye, and Akçakoca Stations have a positive trend in both series subdivisions and showed an increasing trend from the MK test. The precipitation series obtained from Ordu Station revealed a significant decreasing trend from the MK test, which is compatible with the change point's linear trend.

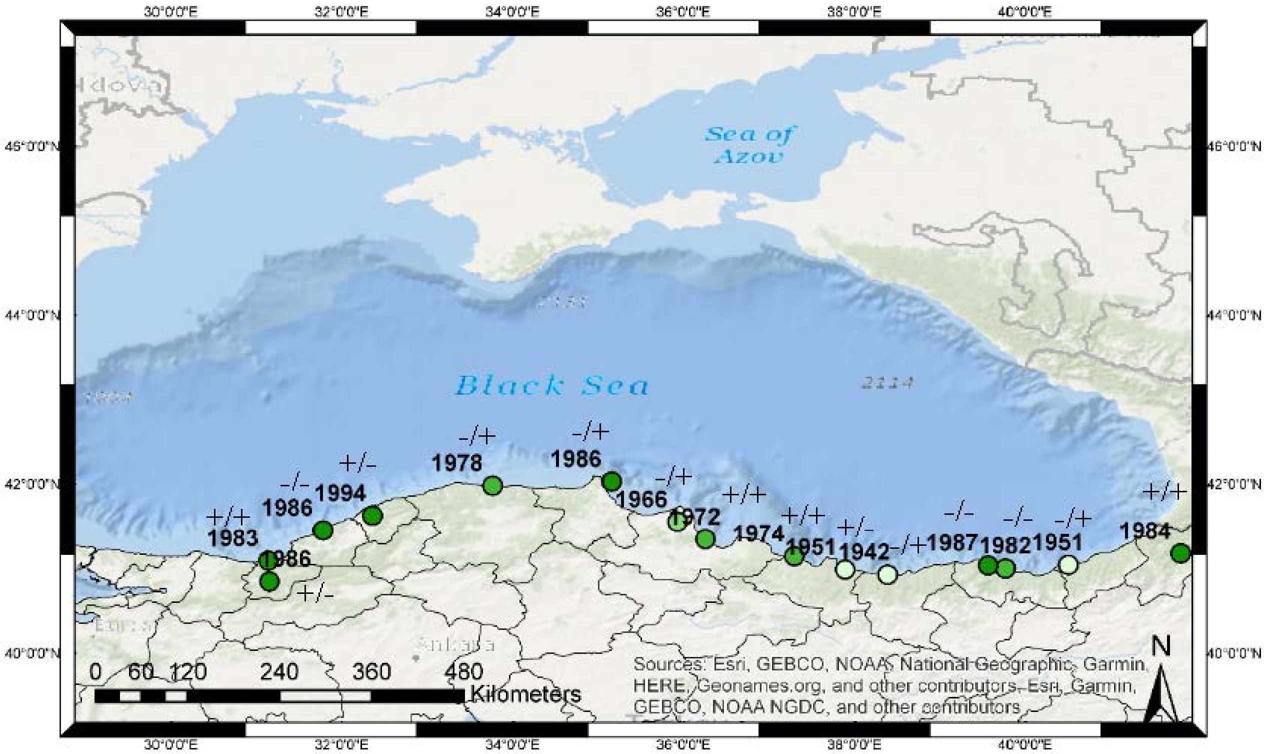

Fig. 2. Spatial distribution of change points and linear trends for the original precipitation series

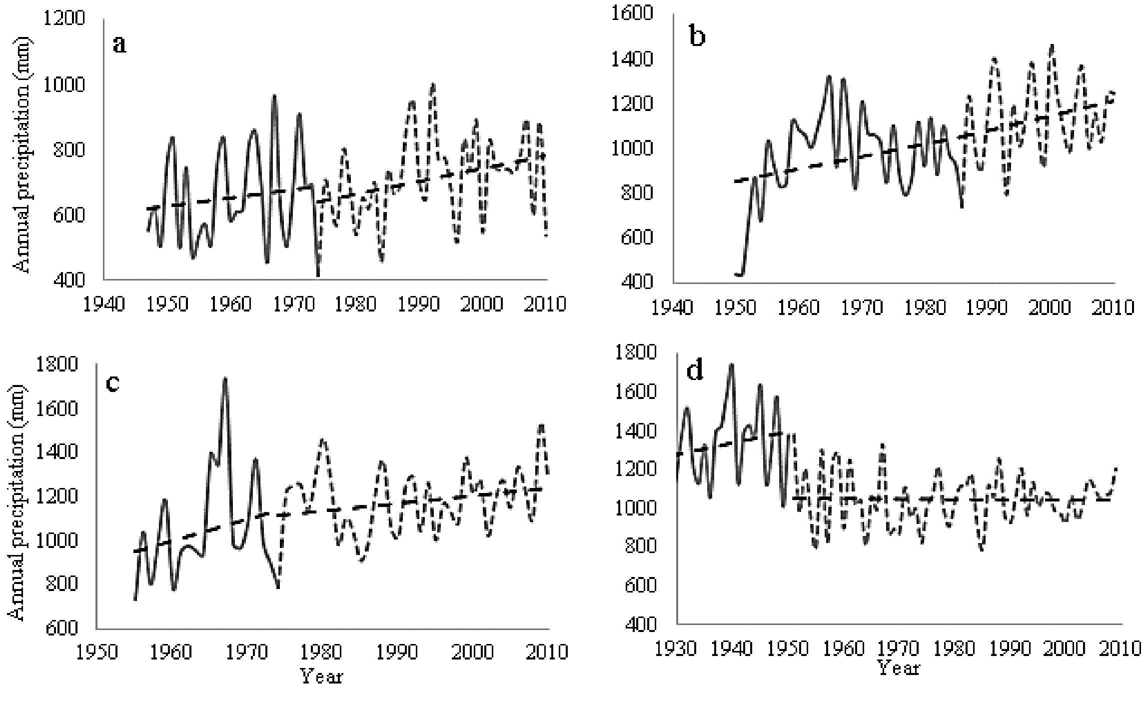

Fig. 3. Linear trends of annual precipitation series (a: Artvin, b: Akçakoca, c: Ünye, d: Ordu).
Continuous and dashed lines refer to the series subdivisions before and after the change point, respectively

Table 2. Features of change point classes (Original series)

Class Number	*Criteria (standard deviation)*	*Range*	*Number of stations*
1	<-1.5	1942-1951	3
2	[-1.5,-0.5[	1952-1966	1
3	[-0.5, 0.5[	1967-1981	4
4	[0.5, 1.3]	1982-1994	8

In the previous study in which Rize and Ordu were used as common stations (Partal and Kahya, 2006), a significant decreasing trend was found in both stations where the ZMK for Rize and Ordu Stations were -2.47 and -2.55, respectively. It is essential to mention that in their study, Partal and Kahya (2006) considered precipitation records between the years 1929-1993. In this study, The ZMK values corresponding to Rize and Ordu were -1.34 and -3.52, respectively, over the recording period of 1929 and 2010.

In another study (Eris and Agiralioglu, 2012), precipitation series from Rize Station had no significant trend over the recording period between 1960 and 2005, matching with the results obtained in this study. It is essential to mention that the recording period and the series length affect the significance and the magnitude of a trend test result.

4.4. DWT coupled with conventional trend analysis methods

The DWT application in this study aimed to obtain a smoother precipitation series reflecting the dominant periodic component. In order to select smoother wavelets and the decomposition level, correlation results between the original series and the approximated series were investigated. The mother wavelet used for decomposition was the Daubechies (db) wavelet, and decomposition was performed for db5, db6, db7, db8, db9, and db10. The db1-db4 was not considered in the correlation test since the mother wavelet shape is different from the treated signal (precipitation series). The highest correlation values were obtained for the first decomposition level (2-years periodicity), and the lowest correlation values were present for the third decomposition level (8-years). This finding clarifies the temporal variability and periodicity of the precipitation events in the Black Sea Region.

The correlation test was also applied for series where an Average Moving Filter (MAF) was applied. The test results showed that series obtained from DWT had higher correlation under different wavelets. The db6 wavelet had shown the highest correlation values for precipitation data. Due to space limitation, only the correlation results of Rize Station are presented (Table 3). In this study, the second decomposition level with the db6 wavelet was applied to obtain a smoother series. The approximation component of the transformed series was then used for trend analysis via linear regression and the MK test.

The change point test and trend analysis tests were performed for the denoised series to eliminate the effect of abrupt changes and involve the series periodic component. The application of Pettitt's test on the approximated series resulted in a significant change point at nine stations at a confidence level of 95%. The years of change were divided into five classes according to the standard deviation (Table 4).

The occurrence of change point had been dominant during the years of 1971-1985, and 1986. However, results with significant change points had mostly occurred in the late 1970s (Table 5). Fig. 4 illustrates the spatial distribution of change points years.

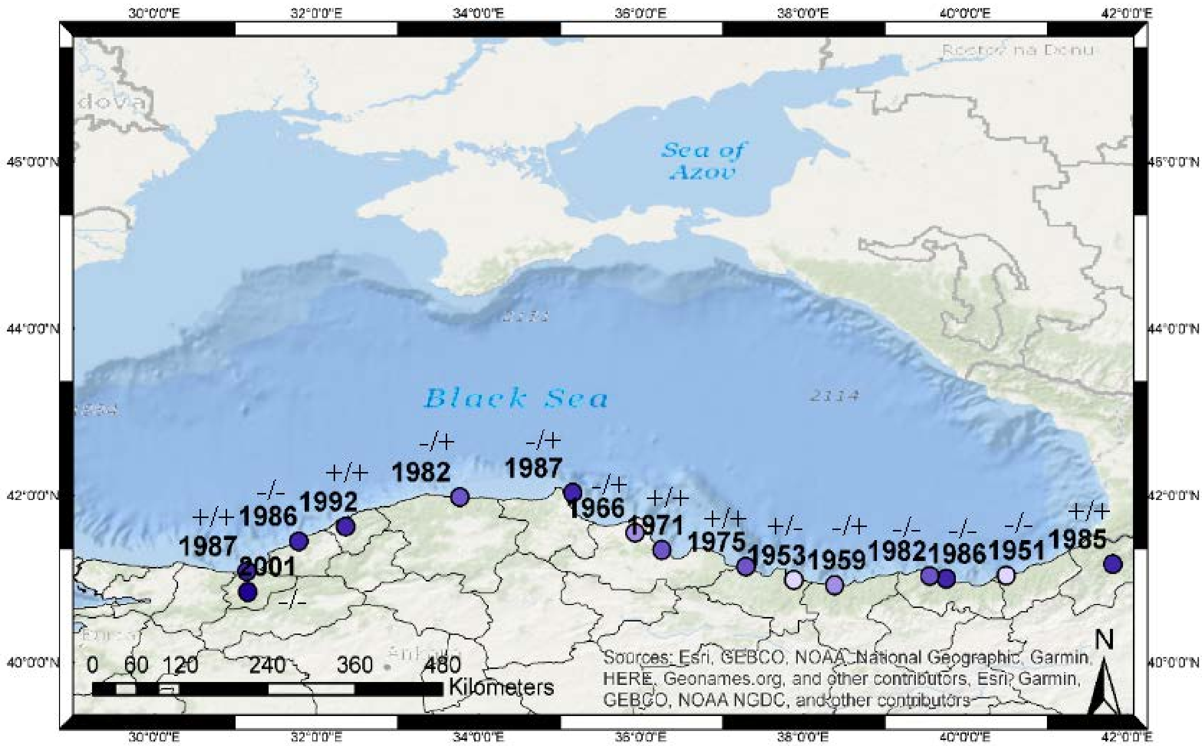

Fig. 4. Spatial distribution of change points and linear trends for the denoised precipitation series

Table 3. Correlation values generated between the original series and denoised series (Rize station)

db5	*db6*	*db7*	*db8*	*db9*	*db10*	*2-MAF*	*4- MAF*	*8- MAF*
0.7504	0.7657	0.7643	0.7565	0.7420	0.7323	0.7180	0.7104	0.7102

Table 4. Features of change point classes (Approximated series)

Class Number	*Criteria (standard deviation)*	*Range*	*Number of stations*
1	<1.5	1951-1956	2
2	[-1.5,-0.5[	1957-1970	2
3	[-0.5, 0.5[	1971-1985	5
4	[0.5, 1.5[	1986-1999	5
5	[1.5, 1.7]	2000-2001	1

Table 5. Trend analysis and change-point test results (values in bold presents statistically significant results)

Station	*Original data*				*Denoised data*			
	Z- MK	*Change point*	*Linear trend*		*Z- MK*	*Change point*	*Linear trend*	
Artvin	**2.682**	**1984**	+	+	**3.748**	**1985**	+	+
Rize	-1.341	**1951**	-	+	-1.53	**1951**	-	-
Akçaabat	0.183	1982	-	-	0.55	1982	-	-
Trabzon	1.148	1987	-	-	1.419	**1986**	-	-
Giresun	0.152	1942	-	+	-0.247	1959	-	+
Ordu	**-3.524**	**1951**	+	-	**-4.693**	**1953**	+	-
Ünye	**3.346**	**1974**	+	+	**4.123**	**1975**	+	+
Samsun	-0.332	1972	+	+	-0.977	1971	+	+
Bafra	1.89	1966	-	+	**2.171**	**1966**	-	+
Sinop	1.386	**1986**	-	+	1.249	**1987**	-	+
Inebolu	0.368	1978	-	+	0.368	1982	-	+
Bartin	1.784	1994	+	-	**2.711**	**1992**	+	+
Zonguldak	0.366	**1986**	-	-	0.295	1986	-	-
Akçakoca	**3.784**	**1986**	+	+	**5.022**	**1987**	+	+
Düzce	-1.423	1983	+	-	**-2.195**	2001	-	-

The linear regression test application on the denoised series revealed a dominant-negative trend in the eastern part of the Black Sea Region and positive trends in both middle zones and western part of the Black Sea Region after the occurrence of the change points (Fig. 4). The MK test was also applied for the approximated series, and six stations showed a significant trend at a confidence level of 95% (Table 5). It is essential to mention that the magnitude of the ZMK had increased for the approximated series. The transformation of precipitation series via DWT gives a better idea of the pattern of precipitation trend.

In this study, the 2-years periodicity component was found influential for determining the precipitation trend in the Black Sea Region. The applied change point and trend analysis tests indicated more significant results for the denoised series. It is essential to mention that the MK test results and linear regression tests were compatible. The MK test outcomes with significant results were the same as the results obtained from the linear regression test after the change point. This finding is valid for both original and denoised series.

5. Conclusions

This study assessed the long-term annual total precipitation trends at fifteen meteorological stations located in the Black Sea Region. The trend analysis by the non-parametric method (MK test) revealed a positive trend in most coastal zones of the study area, but the significance level was rejected for most of the stations. The elimination of abrupt changes in precipitations data via DWT provided a smoother time series and, thus, more significant results. In this study, the original precipitation time series were decomposed according to a periodic structure of 2-years.

This paper proposes a new approach based on Pettitt's test, linear regression, and DWT to investigate the fundamental change of time series by investigating trends before and after the change point. This method was applied for the original time series and for the transformed time series via DWT. The elimination of abrupt changes in precipitations data provided a smoother time series for trend analysis. The MK test and linear trend analysis gave more complementary results for the denoised series than the original series.

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