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Decadal variability analysis of extreme precipitation in Turkey and its relationship with teleconnection patterns

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ABSTRACT

Natural disasters such as droughts and floods originate as a consequence of excessive high or low precipitation amount and/or frequency. Due to the temporal persistence of the latter, the disasters tend to cluster in time. Because global ocean-atmosphere teleconnection patterns with (multi-)decadal oscillations are tightly related with the precipitation variability, it is useful to analyze precipitation variability at the same time-scale to understand any possible connection between them. In this study, decadal oscillations of daily extreme precipitation are investigated using Quantile Perturbation Method (QPM) for 65 stations in Turkey for the period 1955-2014. Arctic Oscillation (AO), North Atlantic Oscillation (NAO), Southern Oscillation Index (SOI) and Western Mediterranean Oscillation (WeMO) teleconnection patterns are examined for their relation with the extreme precipitation variability. The analyses are conducted for 4 climatic

seasons and 7 sub-regions. According to the analysis based on single drivers, NAO is identified as the most effective driver of Turkish extreme precipitation variability in winter, especially over regions influenced by the Mediterranean climate, while AO has a similar effect. When the teleconnection patterns are investigated in pairs, the combination of the NAO and SOI results in the strongest influence on the winter extremes. Though obvious differences are not recorded between the results of linear and non-linear methods for single driver analysis, the non-linear method is superior for the multiple driver analysis.

Keywords: Extreme precipitation, Climate variability, Decadal oscillation, Atmospheric circulations, Linear and non-linear relationship, Multiple correlation.

1 INTRODUCTION

Droughts and floods occur as a consequence of excessive decrease and increase in precipitation amount and/or frequency, respectively. Hence, precipitation is arguably the most significant driver of these events. While drought is a natural event, which results from receiving less precipitation than the long-term average for an extended period of time (Smakhtin, 2001), flood is a rather short duration phenomenon that originates from an extremely high amount of precipitation. Since the occurrence of these natural hazards is closely interconnected with the amount and frequency of extreme precipitation, analysis of trends and variations in extreme precipitation has recently received a great deal of attention (Du, Xia, Zeng, She, & Liu, 2014; Gao & Wang, 2017; Hosseinzadehtalaei, Tabari, & Willems, 2017).

The variability of climate and associated changes in extreme events can be due to internal processes within the climate system itself or to anthropogenic or natural external forcing. These variations lead to the rise of spatially coherent anomalies in large-scale and/or geographically

spatial patterns like sea surface temperature (SST) and sea level pressure (SLP) (Hurrell, 1995). The climate variability that is driven by the anomalies in SST and SLP and consequently in large-scale atmospheric circulations along with anthropogenic activities such as land use vastly influence the distribution of extreme conditions (Taye & Willems, 2012).

Investigation of extreme high precipitation variability is of capital importance for taking precautions for floods. Given the significant ecological and financial consequences of floods, accurate evaluations of the variability of extreme precipitation and related flood recurrence times are very critical for many applications (Engeland, Hisdal, & Frigessi, 2004). With high spatial and temporal variability in its climatic conditions, Turkey frequently experiences floods with varying frequency from region to region. The coastal regions (Black Sea, Mediterranean and Marmara) of Turkey are the most vulnerable areas to flooding, accounting for about 52% of flooding events of the country, while the majority of floods occur in spring, summer and winter months (Özcan, 2006). Therefore, both spatial and temporal assessment of precipitation extremes is essential in coping with floods.

Along with the precipitation analysis for extreme high values, the investigation of the anomaly in the low extremes (i.e., droughts) is also necessary. Given there is continuous increase in urbanization and population density, there is an increased water demand in Turkey (Baltacı, Göktürk, Kındap, Ünal, & Karaca, 2015) particularly during drought periods. The increased water demand and the expected change in the climate make Turkey a drought-prone country; while certain regions located in the central and the western parts of the country already face significant ground water depletion for the past couple decades influencing millions of people dwelling in these regions. Hence, analysis of droughts for a proper water usage term planning is very critical to avoid or minimize the adverse impacts of potential water shortage periods.

The climate and particularly the precipitation variability over Turkey is influenced by large-scale atmospheric teleconnection patterns such as the ones described by the indices Arctic Oscillation (AO), North Atlantic Oscillation (NAO), Southern Oscillation Index (SOI) and Western Mediterranean Oscillation (WeMO) (Corella, Valero-Garcés, Vicente-Serrano, Brauer, & Benito, 2016; Karabörk & Kahya, 2003; Türkeş & Erlat, 2006). Motivated by the need to investigate the relation between the precipitation and the climate variability, the spatial and the temporal variability of droughts have been investigated in several studies (Sönmez, Kömüşçü, Erkan, & Turgu, 2005; Türkeş, 1996a; Türkeş & Tatlı, 2009). A negative relationship between AO and winter precipitation amount has been detected by Givati & Rosenfeld (2013) and Xoplaki, González-Rouco, Luterbacher, & Wanner (2004). Besides, Ünal, Deniz, Toros, & Incecik (2012) have shown that AO is mostly influential for the Mediterranean coast and the western part of the country. The potential influence of NAO on precipitation variability in Turkey has been tested at 78 stations over the country by Türkeş and Erlat (2003). According to their findings, in winter, a significant negative correlation exists for 61 stations at the 5% significance level. Mathbout, López-Bustins, Vide, Rodrigo, and Rustullet (2016) have recently reported a positive correlation between winter precipitation variability and WeMO index, especially for the north-eastern part of the Mediterranean region. Similarly, based on the study of Türkeş (1998), the relationships, although not significant at the 5% level, between SOI and precipitation in most regions in Turkey are mainly positive. In addition to studies that investigate the annual and the seasonal precipitation variabilities, the relationship between extreme precipitation and teleconnection patterns has been examined by a few other studies. Acar and Şenocak (2012) have evaluated NAO as a substantial driver of annual extreme precipitation trends in the Mediterranean hydroclimatic region. Baltacı, Akkoyunlu, and Tayanç (2017) have found that NAO and AO indices show a significant positive relationship at the 5%

level with the number of consecutive dry days for the southern and western parts of the country, whereas these indices have a significant negative relationship with extreme high precipitation across the western part. Krichak, Breitgand, Gualdi, and Feldstein (2014) have identified statistically significant positive correlations at the 5% level between the frequency of extreme high precipitation and SOI over several areas in the eastern Mediterranean region.

According to Tabari and Willems (2016), the investigation of the changes in extreme climatic events is more important than those in mean values, because small changes in mean values can be associated with large changes in the frequency of extremes due to changes in variability (Tabari & Willems, 2016). Accordingly, we investigate the decadal extreme precipitation variability and its relation with the teleconnection patterns using the Quantile Perturbation Method (QPM) approach. This approach aims to extract the changes of quantiles between a reference (*i.e.* baseline) period and a subseries of interest (Tabari & Willems, 2016). On the other hand, some relevant topics still remained unexplored. Previous studies have been limited to a linear relationship analysis between the teleconnection patterns and the precipitation variability, while nonlinear relations have not been investigated so far. Furthermore, the previous studies have examined the influence of the individual circulation pattern on precipitation variability, while several atmospheric circulations can jointly control the variability. Based on the insights and outcomes to be extracted from previous studies and the above-mentioned gaps identified, this study addresses the following fundamental research questions:

- a) Are there significant variabilities in decadal anomalies in extreme precipitation in Turkey?
- Is there any difference between the anomalies in distinct sub-regions (spatial distribution of anomalies)?

b) Is there a relation between teleconnection patterns and extreme precipitation behaviors in Turkey? If a relation exists, then is it linear or non-linear? Which teleconnection patterns are the main drivers of the anomalous behaviors of extreme precipitation?

With the aim of further expanding the argument and responding the research questions above, this study is presented in two parts. In the first part, daily precipitation series are analyzed using QPM to detect whether significant anomalies exist in the high and low extremes. In the second part, relation analyses are carried out between the anomalies of extreme precipitation and global teleconnection patterns in order to have an enhanced understanding on the drivers of extreme precipitation variability. Accordingly, the second chapter introduces the methodology; the third chapter presents the results and the discussions; and the fourth chapter summarizes our conclusions.

2 METHODOLOGY

QPM, developed by Ntegeka and Willems (2008) to investigate variabilities in hydrological extremes, is used to represent decadal extreme precipitation variability. This approach manipulates short-scale (e.g., daily) data to acquire decadal oscillations. In QPM, full-time series of a specific site is taken as baseline. Later, sub-series (block period) are derived from the full-time series, thereafter as block period. The block period of 10 years with a moving step of one year is selected for this study. Using a moving step in the analysis provides the opportunity of testing the extreme values in any period against the baseline period. Afterwards, daily precipitation values are sorted for each block and the return periods of each value in a block are empirically calculated with respect to the ranks. The same steps are also applied for the baseline series. Extreme high precipitation is defined as the values above a threshold, which

can correspond to a specific return period or to a specific exceedance probability. For this study, the precipitation values higher than the 96th percentile are considered as extreme precipitation for each individual station. Then, relative changes are calculated as the ratio that is obtained by dividing the extreme value in a block to the extreme value in the baseline with the same return period. It is worthy to note that the return periods of subseries and baseline are not the same due to having different lengths of data. Hence, extreme values for the same return periods are gained by means of a linear interpolation from values with the closest return periods. Lastly, anomaly is calculated as the average of all relative changes.

For the calculation of anomaly for low extremes, albeit the main procedure is the same as that for high extremes, there is a small difference in the usage of QPM method. The anomaly in low values is calculated by using number of dry days in a year instead of the values over a threshold. In other words, the dry day number is treated as yearly data. Thus, selection of a specific threshold is not needed for the low anomaly calculation. A dry day is defined as a day with precipitation less than 0.3 mm.

Following the anomaly calculation, the significance of the results is tested by Monte Carlo confidence intervals computed for a 5% significance level. These confidence intervals are computed based on the parametric bootstrapping method. See Ntegeka and Willems (2008), Willems (2013) and Tabari and Willems (2016) for details about the QPM.

After determining and testing extreme precipitation anomalies, the relation analyses are carried out between the anomalies of extreme precipitation and climate indices to understand the possible drivers of these extremes. The added utility of the non-linear methods compared to linear methods (Afshar & Yilmaz, 2017) using highly variable hydrological variables such as precipitation has not been explored in detail. Accordingly, both linear and non-linear methods are utilized using single and multiple predictors to test the significance of the relation between

precipitation extremes and climate indices. Here, two linear [Spearman's rank order correlation (SROC) and Multiple Linear Regression (MLR)] and two non-linear [Power Law Regression (PLR) and Multiple Adaptive Regression Splines (MARS)] methods (Table 1) are used to test the dependency between extreme precipitation anomalies and climate indices. The results of the non-parametric linear method, SROC, are compared with the basic non-linear regression model, PLR, to express the relation type of bivariate relationships. The linear relation of multivariate analysis is tested by MLR. Whereas, MARS, a non-parametric regression approach which was first proposed by Friedman (1991), is used to express the nonlinearities between variables. MARS applies adaptive separated linear regressions to sub-regions in order to express the changing relation between dependent and independent variables (Felicísimo, Cuartero, Remondo, & Quirós, 2013). MARS is chosen to carry out relation analyses since it is useful in defining the relations in the extreme cases of randomly generated events.

Leave-one-out cross validation method is used to avoid overfitting and artificial regression skill when forming equations for all regression methods. In this method, one sample is retained for independent validation, while the remaining samples are used for the model parameter estimation. This procedure is applied for each sample separately so that the sample errors are calculated using independent validation data. Since the quality of the model is validated against each sample, leave-one-out cross validation method also increases the generalization ability of the model (Vapnik & Chapelle, 2000). Finally, a mean square error is calculated using sample errors and the correlation coefficient is obtained using the predicted estimates and the independent validation values. For the estimation of the significance of the correlation coefficient, t-test with effective sample size (rather than actual sample size) is used to account for the autocorrelation in the anomaly series due to the use of moving block periods.

Lastly, the correlation coefficients obtained from 65 stations are mapped spatially. The spatial distribution of the relationships of extreme precipitation variability and atmospheric drivers is shown by means of the weighted average of correlations at neighboring points (stations). For this study, inverse distance weighted (IDW) interpolation of the correlation coefficients was considered because sampled points are sufficiently dense and the analyzed variable changes with distance (Gotway, Ferguson, Hergert, & Peterson, 1996). This means that the weights are considered as inversely proportional to the distance between the prediction point and each sampled neighboring point.

3 STUDY AREA AND DATA

3.1 Study area

The study area is selected as Turkey, located between 26° E and 45° E, and between 36° N and 42° N. Three sides of the country have border with sea: the Black Sea is located in the north, the Mediterranean Sea in the south, and the Marmara and the Aegean Sea in the west (connecting the seas in the north and the south). Turkey occupies a large continental extent with an approximate area of 770,000 km². This vast area includes various geographical features such as mountain chains, deep river valleys, major river deltas as well as plains. In general, annual mean precipitation decreases from the coastal regions to the continental regions parts due to the adiabatic process (i.e. orographic). For example, due to the mountain ranges of the northern and southern coasts - the North Anatolian Mountains and the Taurus Mountains - the reaching of coastal effects to Central Anatolia is hindered (Raja, Aydın, Türkoğlu, & Çiçek, 2017). Turkey has different climate types with respect to zones as a result of being affected by different

meteorological factors and climate control elements. By considering these variables, seven different rainfall regions were defined by Türkeş (1996b) as follows:

- i) **Black Sea Region (BLS)**: This region is uniformly rainy and has a temperate climate with the maximum precipitation in autumn.
- ii) **Continental Central Anatolia (CCAN)**: It is a semi-arid region with a cold and rainy winter and a cool and light rainy summer. The region is covered by steppe plants.
- iii) **Continental Eastern Anatolia (CEAN)**: It is a semi-humid region whose topography composes of highlands. It has a quite cold snowy winter and a cool and rainy early summer.
- iv) **Continental Mediterranean (CMED)**: It is a semi-arid region with a hot dry summer and rainy winter.
- v) **Mediterranean (MED)**: It is a semi-humid/humid region which receives very high rainfall during winter, whereas summers are dry and hot. The precipitation behavior of the region dramatically changes from season to season.
- vi) **Mediterranean Transition (MEDT)**: It is mildly rainy in winter and spring while it is lightly rainy in summer.
- vii) **Marmara Transition (MRT)**: It is a region that is uniformly rainy, but warm and lightly rainy in summer.

In this study, regional interpretations are performed with respect to this classification.

3.2 Data

Daily precipitation data between 1926 and 2016 for 417 stations were obtained from Turkish General Directorate of Meteorology (MGM). The length of the available daily datasets

considerably varies for different stations, as only a few stations have datasets dating as early as 1926. Accordingly, a trade-off exists between the length of the datasets and the number of available datasets, while availability of datasets that are both available over as many stations as possible and sufficiently long enough to account for the underlying natural variability (i.e., include both dry and wet years) is required for decadal analysis (Taye & Willems, 2012). In fact, longer time series warrant a better representation of decadal variability. However, considering the tradeoff between the temporal and the spatial coverage, a 60-year long study period (between 1 January 1955 and 31 December 2014) over 65 stations is selected. Afterwards, not available (NA) data at the stations are checked for the specified study period, and it is seen that most of the stations do not have NA data. At the stations with NA data, the fraction at each station do not exceed 4% of the entire data, nor are continuous. The data gaps are not therefore filled as the QPM method on a decadal scale is insensitive to non-continuous missing data. The detailed characteristics of 65 stations are summarized in Table 2 and their locations are illustrated in Figure 1. The average Normalized Difference Vegetation Index (NDVI) data acquired via MODIS satellite (MOD13Q1 product) for the period 2000-2014 is also shown in Figure 1. The variability in the vegetation greenness measured by the NDVI mimics the sharp difference between the climate-regions used in this study. Higher NDVI values indicate greener fields, while lower values indicate relatively less green regions (Bulut & Yilmaz, 2016). In view of this information, Figure 1 shows the greenest area over Turkey in the BLS sub-region.

Four SLP-based climate indices are used in this study. The selection of these indices was based on their influence on Turkish extreme precipitation and the availability of daily data (Tabari & Willems, 2018) for these indices, which are essential for our study. The selected indices are:

- i)** NAO: A large-scale fluctuation in the SLP difference between the Azores high and the Icelandic low pressure (NOAA, 2017a). It has two phases of positive and negative. During the positive phase, Europe, in general, faces wet and warm winter, whereas Turkey faces dry and cold winter. In the negative phase, the reduced SLP gradient causes wet and warm winter in Turkey and dry and cold winter in Europe.
- ii)** AO: A global climatic variability index that is estimated by determining daily SLP anomalies over the region north of 20°N latitude (NOAA, 2017b). Similar to NAO, It has two positive and negative phases. In the positive phase, high pressure forces at the midlatitudes push moist air to the northern part of the world. Consequently, Alaska and Scandinavia encounter wet weather conditions, while the United States and Mediterranean region face dry weather conditions. Turkey, as a country under the effect of Mediterranean climate, also experiences a dry winter. The opposite conditions are expected during the negative phase.
- iii)** SOI: It expresses the oscillations of measured SLP difference between Tahiti and Darwin (NOAA, 2017c). Constitutively, SOI shows its effect over the Pacific region. However, the corresponding temporary perturbations caused by the regional SST change may also affect the precipitation behavior of other regions (Hurrell et al., 2010).
- iv)** WeMO: The climate index resulting from SLP difference between Cadiz-San Fernando (Spain) and Padua (Italy) (UB, 2017). The positive phase of WeMO index corresponds for anticyclones (high pressure zones) in the Gulf of Cadiz and cyclones (low pressure zones) over Central Europe. It is consequential to check its effect on Turkey since the WeMO index is most influential on the countries in the Mediterranean region.

Mean daily data of the NAO and AO indices for the period 1955-2014 were obtained from the NOAA Climate Prediction Center. The daily values of WeMO and SOI developed by Tabari and Willems (2018) are used. Like precipitation data, decadal anomalies of climate indices are also obtained using QPM. The methodology that is followed to obtain extreme high precipitation anomaly is also applied to calculate climate indices anomalies.

4 RESULTS AND DISCUSSION

4.1 Analyses of decadal anomaly in extreme high precipitation

In this section, the oscillations of the decadal extreme high precipitation are analyzed for each region and season separately. Decadal oscillation behavior of the regions is interpreted based on the region anomaly values that are obtained by taking the median of the anomalies of the different stations in the region and also for each station separately.

Decadal anomalies of Turkish extreme precipitation with respect to seasons are represented in Figure 2. As shown in Figure 2, the anomaly of extreme precipitation is more consistent in winter compared to the other seasons, which is attributed to the large-scale nature of winter extreme precipitation. For further investigation of this consistency, the spatial distribution of the anomalies in winter is illustrated for each distinct station in Figure 3. Figure 2 shows that winter anomalies in all sub-regions are positive in the mid-1960s, but the anomalies in MRT and CMED are slightly higher than the baseline. Based on the spatial distribution map (Figure 3), stations intensely show positive anomalies over Turkey. The significant positive anomalies are discovered at 36% of the stations during the 1960s, with the peak anomalies in the BLS, CEAN and MEDT regions. Negative anomalies are widespread in the 1970s in most of the regions. The significant negative anomalies mostly occurred in the northwestern part of Turkey

and both in the center and east of the southern part. Besides, positive anomalies are detected in MEDT and western BLS regions for this time slot. It is difficult to define spatially coherent behavior for the early 1980s since there are both significant positive and negative anomalies during this time period. After the early 1980s and until the mid-1990s, an oscillation low period is dominant, except for CMED and CEAN. There are very low negative anomalies at the remaining 5 regions. For these regions, the anomaly confidence intervals show significant negative anomalies at 51% of the stations between 1985 and 1995. More specifically, 38% of the BLS and 25% of the MRT anomalies are significant for the same time slot. After this oscillation low period, positive anomalies are again commonly prevailing in five of the seven regions during the 2000s. Explicitly in the western part, there are numerous stations indicating significant positive anomalies. However, in the southern and eastern parts, some of the stations demonstrate significant negative anomalies. In summary for the winter season, in the 1960s and 2000s, significant positive anomalies of high precipitation extremes are more widespread over the regions, whereas in the 1970s and early the 1990s significant negative anomalies are observed (Table 3). Although these periodic behaviors are defined for a large part of the country, the results are not coherent all over Turkey. This is due to the different topographic and climatic features of the sub-regions. The total or extreme precipitation behavior in the country strongly differs with respect to regions due to the chain of mountains being located parallel to the southern and northern coastlines (Kadioğlu, 2000). Since there is a gradual increase in the altitude of the mountains towards the eastern parts, their effects are observed to be sharper in the east. For instance, the differences noticed in the two neighboring sub-regions BLS and CEAN are assumed to be attributed to the North Anatolian Mountains, which prevent the moisture of the Black Sea from arriving at CEAN during periods when this leads to higher precipitation over BLS.

For the spring season, the lowest and highest anomalies occur in the 1970s – early 1980s and the late 1990s - early 2000s, respectively. The only exception for low anomalies is the CMED region. About 58% of the stations in the MED region shows a significant negative anomaly in the 1970s, whereas in CMED only 12% of the stations displays a significant negative anomaly.

In autumn, the highest amount of extreme precipitation is observed in the 2000s and the lowest in the 1960s. Approximately 55% and 75% of the stations have significant positive anomalies in CCAN and MEDT in the 2000s, respectively. The significant negative anomalies are caught at 68% of the MED stations and 44% of the MRT stations in the 1960s. For autumn, the fluctuations in the region anomaly are higher than for spring and winter.

During the summer months, Turkey receives low precipitation such that small changes in precipitation quantiles may point towards higher fluctuations. The high level of these fluctuations also makes it difficult to find decadal anomalies for these months. The high fluctuations of summer extreme precipitation are evident from the standard deviation values presented in Table 4. The results indicate the highest standard deviations for summer extremes for all sub-regions except for CCAN where summer shows the second highest extreme precipitation variability. Still, the magnitude of standard deviations differs between regions, with the Mediterranean regions (MED & CMED) having the highest values. The large temporal and spatial variations in summer extreme precipitation anomaly is due to the more local and convective nature of summer precipitation compared with the large-scale winter extremes.

Overall, it can be concluded that in the 1960s, high positive anomalies took place in winter, summer and spring all over Turkey (Figure 2). Likewise, in the 2000s, high positive anomalies are observed in winter, summer and autumn. These two periods are unique in covering three different seasons with such highly positive anomaly values. When the QPM results are compared with the number of occurred flood events (MGM, 2010), it can be seen that the

periods with high positive anomalies largely coincide with the periods with a higher number of flood events (Figure 4). In addition, highly negative anomalies are seen in the early 1990s in winter, which is the season with the highest rain in Turkey. Correspondingly, the MGM records confirm that the number of floods that occurred in the years between 1989 and 1998 is below the long-term yearly average value.

4.2 Analyses of decadal anomaly in extreme low precipitation

The average dry day number in winter in Turkey is about 58 days per year with a standard deviation of 8 days. The remaining 3 seasons, especially autumn and summer, have obviously higher dry day numbers with smaller standard deviations. In parallel, the results (Figure 5 and Table 4) indicate that the highest oscillations in dry day number occur in winter, whereas the lowest are in summer. The significant positive anomalies in winter dry day number may give rise to drought events not only in this season but also during the rest of the year. In respect to this, the decade between 1985 and 1995 is quite dry in winter (74% of MED stations and 78% of MRT stations have significant positive anomalies) and relatively dry in spring, while this dry decade coincides with one of the most significant drought events over the country, particularly between 1990-1994. The impact of this dry period further stretches to years in the 2000s, while majority of the country experienced another significant drought decade, particularly during 2000-2001 and 2004-2008. In the 1960s, 35% of the anomalies are significantly negative across Turkey, and all stations located in CMED, MED, MEDT and MRT encounter significant negative anomalies. In contrast, only 16% of the CEAN stations have significant negative anomaly values. For spring, the driest years are noted for the 2000s when significant positive anomalies are found at 36% of the stations. The period between 1965 and 1975 is the wettest in this season and 26% of the stations shows significant negative anomaly values. For summer

and autumn months, systematic positive and negative values are also noted but are considerably smaller (closer to the baseline value).

The dry day number anomaly oscillations are also comparatively examined with the extreme precipitation anomaly variations. In winter, three different spatially widespread behaviors are detected for extreme high anomaly and discussed in section 4.1:

1. Significant positive anomalies are encountered at 36% of the anomalies during the 1960s.
2. Significant negative anomalies are dominant over the country at the early 1990s (i.e. 1985-1995), where 51% of the stations shows significant negative anomalies.
3. Significant positive anomalies are commonly spotted during the 2000s (at 30% of the stations).

For the first two behaviors, extreme low anomalies are inversely proportional to the extreme high (i.e. when extreme high anomalies show significant positive anomalies, extreme low anomalies show significant negative anomalies or vice versa). However, there is a contradictory situation in the 2000s. Even though significant positive anomalies are extensive in the extreme high anomalies for the 2000s, the significant positive anomalies are also prevalent in the extreme low anomalies. To investigate this situation, the correlation between the extreme high precipitation and extreme low anomalies at the different regions are examined for all seasons with respect to two different time intervals (Table 5). Assuming that the change of the relationship starts after the early 1990s (i.e. after the second spatially widespread behavior), it is decided to choose 1996 as the starting point of the second time interval. In winter, for all of the regions except CMED, the extent of the positive correlation between the anomalies for the period 1996-2009 increases when compared to the correlation in the period of 1959-1996. The most remarkable increment is seen for the winter anomalies in the MEDT region. The

correlation between extreme high precipitation and extreme low anomalies in MEDT is -0.948 between the years 1959 and 1996. However, it becomes 0.235 in the period 1996-2009. In other words, while there is a strong inverse correlation for these two variables between 1959 and 1996, the extreme high precipitation amount increases as the number of dry day increases after 1996. In addition to this, there is no meaningful change in the yearly total precipitation amount of the corresponding regions. This condition reveals that approximately the same amount of precipitation falls in less days than before as both extreme high precipitation amount and dry day number rise. So, both flood and drought related hazards rise. This is confirmed by the climb of occurred flood events towards the end of the 2000s (Figure 4). On the other hand, in all other regions except for BLS, the extent of the negative correlation between spring high and low extremes increases for the period of 1996-2009. However, since Turkey receives the highest precipitation in winter and winter anomalies are more prone to be driven by large-scale climatic components, winter extremes are more profound when evaluating hazards due to climate variability.

4.3 Relationship between the teleconnection patterns and the decadal extreme precipitation variability

The relationships between extreme precipitation anomalies and climate indices anomalies are tested to find out the possible atmospheric and/or oceanographic drivers of extreme precipitation variability. Among the selected climate indices, NAO gives the strongest relationship with extreme high precipitation anomalies. Nevertheless, the influence of NAO is neither spatially nor temporally strong. Even in winter, when NAO has the most distinct effect, only 6 stations show a significant relationship with NAO (Table 6). Although it is dependent on NAO, the impact of AO on extreme precipitation variability is weaker. The relationships with SOI and WeMO at a large number of the stations are more recognizable during the summer

months. According to the results of PLR method, for example, SOI is significantly effective for 4 stations in summer.

The covariations of winter anomaly of extreme precipitation for some selected stations and climate indices are shown in Figure 6. The selected stations have the highest correlation with the climate indices in winter: Akhisar with NAO (-0.82), Ankara with AO (-0.75), Ağrı with SOI (-0.81) and Florya with WeMO (+0.62). The results show a strong correlation between the anomalies of extreme precipitation and WeMO at Florya station and a strong anti-correlations with NAO, AO and SOI at Akhisar, Ankara and Ağrı stations, respectively. For instance, the oscillation high period at Akhisar station during the 1960s obviously corresponds to the negative NAO anomalies, whereas the oscillation low period at the station in the early 1990s coincides with the positive NAO anomalies.

Several authors reported that NAO has a strong influence on Turkish precipitation variability in winter (e.g. Cullen & DeMenocal, 2000; Cullen, Kaplan, & Arkın, 2002; Türkeş & Erat, 2003; Türkeş & Erat, 2005). However, our results show that such a strong influence is not observed for decadal extreme precipitation variability. Still, in parallel with the cited studies above, the decadal behavior of the number of dry days in the winter months is assessed as crucially related to NAO. The SROC coefficients at 28 stations and the PLR coefficients at 22 stations are statistically significant at the 5% level (Table 7). Specifically, NAO appears as one of the essential drivers of the decadal dry day number oscillations in the MED region where 13 of 19 stations show a significant relationship with NAO based on SROC results. The NAO is also influential on the dry day number of the other Mediterranean climatic regions: CMED and MEDT. In CMED, 4 of the 8 stations, and in MEDT, 4 of the 4 stations are significantly correlated to NAO. The positive relationship defined between NAO and the dry day number anomaly in winter is consistent with the findings of Türkeş and Erat (2003). They determined

the impact areas of NAO on winter precipitation in the Aegean part, Marmara and Mediterranean regions, which is compatible with our results.

As it was noted in the study of Krichak et al. (2014), our results also verify that the response to AO is quite analogous to that of NAO. According to the SROC test, the dry day number anomaly shows for 25 stations a significant relationship with AO in winter. Like NAO, AO is also influential in the Mediterranean sub-regions. 19 of 31 stations in CMED, MED and MEDT have a significant correlation with AO. Figure 7 moreover shows that, based on the 5% and 10% significance levels, there are continuous regions with significant correlations with AO and NAO. Baltacı et al. (2017) has reported that both indices are positively influential on the dry day number in winter, particularly for the western and southern parts of the country. Our findings are also consistent with their results (Figure 7). This confirms that the effects of the NAO and AO indices are similar to each other. Hereby, in order to compare the NAO and AO effects, the correlation coefficients at each station are examined. As a result, it is noted that the correlation with NAO is stronger at 62% of the stations.

Mathbout et al. (2016) reported a positive relationship between WeMO and winter precipitation over the northern part of the eastern Mediterranean. The effect of WeMO was also found to be higher than NAO. However, based on our study the effects of SOI and WeMO on the decadal dry day number decadal anomaly oscillations in Turkey are weaker in comparison to AO and NAO. For both climate indices, significant correlations are observed only in summer. Significant relationships are determined at 6 stations for SOI and 3 stations for WeMO. Significant correlations are detected for SOI in the western part of the country, while this is the case for WeMO in the eastern part.

As mentioned in section 4.2, a change in the direction of the relationship between extreme high and extreme low anomalies is detected in winter after 1996. Though significant positive

anomalies are extensive in the extreme high for this time interval, the significant positive anomalies are also prevalent in the extreme low. Accordingly, time series of the anomalies of teleconnection patterns are examined to find the driving force of this behavior change in winter anomalies. Even though a coherent periodic behavior of WeMO anomalies is not defined for the period 1996-2009, the anomalies of NAO and AO show high oscillations starting from the early 1980s and the anomalies of SOI from the mid-1990s. Concurrent oscillation high periods of dry day number, NAO and AO are not surprising, owing to the widespread positive correlation between the corresponding climate indices and the dry day number anomalies. However, the oscillation high behavior of extreme precipitation is unexpected since the negative relationship between extreme high anomalies and climate indices anomalies (AO and NAO) is extensive at the stations. Herein, the relationships between all climate indices and extreme high anomalies are calculated separately for the time period 1996-2009. The result shows prevailing relationships with SOI. Extreme high anomalies of BLS, CCAN, MED and MEDT regions show a significant positive relationship with SOI, while the extreme high anomalies of CMED show a significant negative relationship in that period. The negative relationship also explains the low oscillation of extreme high in CMED. The mentioned correlations are shown in Figure 8.

The collective effect of climate indices on extreme high precipitation is also investigated and the number of the stations having a significant relationship with the corresponding climate indices pair is demonstrated in Table 8. However, the pair of AO and NAO is omitted since their effects are highly correlated to each other. Apart from this, all other climate indices pairs are tested for their combined effects on precipitation extremes. Yet, the results of AO combination with WeMO and SOI are not interpreted because AO has a very similar but weaker influence on extreme precipitation variability when compared to NAO.

It is not reasonable to claim that there is a substantial difference between the results of linear and non-linear methods in the relationship analyses with single drivers. However, the situation is different for the relationship analyses with multiple drivers. MARS defines much stronger relationships between extreme precipitation and the climate indices pairs (Table 8). The NAO-SOI pair is found as the most significant combined driver of the extreme high precipitation in Turkey, particularly for winter. The relationship coefficients of MARS are greater than those of MLR at 97%, 88%, 80% and 69% of the stations for winter, spring, autumn and summer seasons, respectively. Further, the MARS coefficients between decadal extreme high precipitation and the couple of NAO and SOI are propagated over the Turkish map with the help of IDW (Figure 9). By analyzing the significantly correlated regions at the 5% and 10% significance levels, it can be understood that the relationship coefficients are quite high in winter. In addition, the NAO-WeMO and SOI-WeMO pairs show a significant relationship with extreme precipitation anomalies at 19 and 18 stations in summer, respectively.

5 CONCLUSION

In this study, the decadal oscillations of precipitation extremes in Turkey and their relationships with climate indices were investigated. The statistical analyses were performed by means of QPM to discover oscillation high and low periods of decadal anomalies in Turkish daily extreme precipitation over the period 1955-2014. The analyses were carried out at 65 stations spread over seven rainfall regions in Turkey, namely, BLS, CCAN, CEAN, CMED, MED, MDT and MRT. Afterwards, the relationships between the anomalies of extreme precipitation and four SLP-based climate indices (NAO, AO, WeMO and SOI) were investigated. The strength and type of the relationships were assessed with the help of four

statistical methods: linear bivariate, non-linear bivariate, linear multiple and non-linear multiple analyses.

Based on the QPM results, in general, positive extreme precipitation decadal anomalies are dominant during winter in the 2000s. At about 30% of the stations, significant anomalies are detected. Particularly in CCAN and MRT, significant positive anomalies are detected at 45% and 55% of the stations. Such widespread significant positive anomalies have not been observed since the early 1960s. Besides, the lowest winter anomalies are detected in the early 1990s. Winter anomalies are very low in that time period compared to the rest of the study period. The significant negative anomalies are discovered at 42% of stations across Turkey and 75% of the stations in BLS between 1985 and 1995. In spring, oscillation high periods are observed for most of the stations in the 2000s. In contrast to this situation, the spring anomalies are widely negative during the 1970s except for CMED. In autumn, the lowest amount of extreme precipitation anomaly is determined during the 1960s, while the highest is determined in the 2000s. Lastly, summer anomalies are generally highly variable. Still, corresponding to the results, summer extremes are prone to be positive.

In the 2000s, an oscillation high period of both extreme precipitation and dry day number anomaly is detected especially in winter and summer. Correspondingly, the individual precipitation events may generate a higher amount of precipitation when compared to earlier periods. This situation is more obvious in the regions with Mediterranean climate, where the region anomaly reaches values up to 10% higher than the baseline level. SOI is concluded to be the main driver of these events in winter.

According to the relationship analyses with single drivers, NAO is the most influential driver of Turkey's extreme precipitation among the four climate indices tested. Still, it cannot be said that NAO is a very strong driver of decadal extreme precipitation variability as much as it is for

total precipitation and dry day number. It is only partially influential in the interior and western parts of Turkey. Also, AO has a spatially similar effect on extreme precipitation as NAO. Besides, it can be claimed that there is not an explicit difference between the outputs of the linear and non-linear bivariate methods. However, the situation is different for the relationship analysis with multiple drivers. MARS obviously defines higher relationships than MLR. Moreover, in the relationship analysis with multiple drivers, the most effective pair of climate indices is the combination of NAO and SOI. This pair seems to be one of the essential drivers of the winter extremes in Turkey. Even though it is known that summer precipitation commonly originates from convective storms, it can be stated that the SOI-WeMO pair has an important influence on the decadal oscillation of summer extremes.

Compared to extreme precipitation, NAO has a greater impact on the decadal dry day number oscillations of the country. Like the results of the extreme precipitation analysis, the influence of AO on dry day number is quite parallel to NAO. In winter, these two indices are influential drivers of the country's dry day number except for the northeastern and eastern part. The indices are quite operative especially in the western areas. Albeit NAO shows stronger relationships at the stations, AO is superior when analyzing precipitation behavior in some regions. In addition, if the effect of climate indices on the precipitation extremes and the dry day numbers are compared, it can be concluded that climate indices have more effects on the dry day numbers.

To the best of our knowledge, this is the first study that investigates the type of the relationship (linear or non-linear) between decadal extreme precipitation anomalies and the teleconnection patterns and also the combined influence of these patterns. The non-linear relationships identified between the anomalies of precipitation extremes and climate indices give new insights in the drivers of the temporal oscillatory periods with higher and lower

precipitation quantiles. Next to explaining natural variations, the large-scale circulation patterns may also be affected by climate change trends. For instance, the strength of Atlantic Meridional Overturning Circulation (AMOC), which has a key role in the transportation of warm ocean water from the equatorial region to the North Atlantic, is predicted to decrease due to the increase in the CO₂ concentration (Srokosz & Bryden, 2015). Thus, for the future studies, the non-linear multivariate relationship defined in this study can be utilized to predict forthcoming decadal persistence in precipitation by also taking climate change effects into consideration. Indisputably, predicting the possible forthcoming extreme precipitation periods contributes greatly to hazard risk and water management; one of the most important and vital problems of our time.

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REFERENCES

- Acar, R., & Şenocak, S. (2012). Annual extreme precipitation trends for western Turkey in associated with north Atlantic oscillation (NAO) index. *Energy Education Science and Technology Part a-Energy Science and Research*, 29(1), pp. 475-486.
- Afshar, M. H., & Yılmaz, M. T. (2017). The added utility of nonlinear methods compared to linear methods in rescaling soil moisture products. *Remote Sensing of Environment*, 196, pp. 224-237.

- 581 Baltacı, H., Göktürk, O. M., Kındap, T., Ünal, A., & Karaca, M. (2015). Atmospheric
582 circulation types in Marmara Region (NW Turkey) and their influence on
583 precipitation. *International Journal of Climatology*, 35(8), pp. 1810-1820.
- 584 Baltacı, H., Akkoyunlu, B. O., & Tayanç, M. (2017). Relationships between teleconnection
585 patterns and Turkish climatic extremes. *Theoretical and Applied Climatology*. DOI:
586 10.1007/s00704-017-2350-z
- 587 Bulut, B., & Yılmaz, M. T. (2016). Türkiye’ deki 2007 ve 2013 Yılı Kuraklıklarının NOAH
588 Hidrolojik Modeli ile İncelenmesi. *İMO Teknik Dergi*, 463, pp. 7619-7634.
- 589 Corella, J. P., Valero-Garcés, B. L., Vicente-Serrano, S. M., Brauer, A., & Benito, G. (2016).
590 Three millennia of heavy rainfalls in Western Mediterranean: frequency, seasonality and
591 atmospheric drivers. *Scientific Reports*. DOI: 10.1038/srep38206
- 592 Cullen, H. M., & Demenocal, P. B. (2000). North Atlantic influence on Tigris–Euphrates
593 streamflow. *International Journal of Climatology*, 20(8), pp. 853-863.
- 594 Cullen, H. M., Kaplan, A., & Arkin, P. A. (2002). Impact of the North Atlantic Oscillation on
595 Middle Eastern climate and streamflow. *Climatic Change*, 55(3), pp. 315-338.
- 596 Du, H., Xia, J., Zeng, S., She, D., & Liu, J. (2014). Variations and statistical probability
597 characteristic analysis of extreme precipitation events under climate change in Haihe
598 River Basin, China. *Hydrological Processes*, 28(3), pp. 913-925.
- 599 Engeland, K., Hisdal, H., & Frigessi, A. (2004). Practical extreme value modelling of
600 hydrological floods and droughts: a case study. *Extremes*, 7(1), pp. 5-30.
- 601 Felicísimo, Á. M., Cuartero, A., Remondo, J., & Quirós, E. (2013). Mapping landslide
602 susceptibility with logistic regression, multiple adaptive regression splines, classification

and regression trees, and maximum entropy methods: a comparative study. *Landslides*, 10(2), pp. 175-189.

Friedman, J. H. (1991). Multivariate adaptive regression splines. *The Annals of Statistics*, 19(1), pp. 1-67.

Gao, T., & Wang, H. (2017). Trends in precipitation extremes over the Yellow River basin in North China: Changing properties and causes. *Hydrological Processes*, 31(13), pp. 2412-2428.

Givati, A., & Rosenfeld, D. (2013). The Arctic Oscillation, climate change and the effects on precipitation in Israel. *Atmospheric Research*, 132, pp. 114-124

Gotway, C. A., Ferguson, R. B., Hergert, G. W., & Peterson, T. A. (1996). Comparison of Kriging and Inverse-Distance Methods for Mapping Soil Parameters. *Soil Science Society of America Journal*, 60(4), pp. 1237–1247.

Hosseinzadehtalaei, P., Tabari, H., Willems, P. (2017) Uncertainty assessment for climate change impact on intense precipitation: How many model runs do we need? *International Journal of Climatology*, 37(S1), pp. 1105-1117.

Hurrell, J. W. (1995). Decadal trends in the North Atlantic Oscillation: regional temperatures and precipitation. *Science-AAAS-Weekly Paper Edition*, 269(5224), pp. 676-678.

Hurrell, J. W., Delworth, T., Danabasoglu, G., Drange, H., Griffies, S., Holbrook, N., ... & Meehl, G. A. (2010). Decadal climate prediction: Opportunities and challenges. *OceanObs'09: Sustained Ocean Observations and Information for Society*, pp. 521-533. DOI:10.5270/OceanObs09.cwp.45

- 624 Kadioğlu, M. (2000). Regional variability of seasonal precipitation over Turkey. *International*
625 *Journal of Climatology*, 20(14), pp. 1743-1760.
- 626 Karabörk, M. Ç., & Kahya, E. (2003). The teleconnections between the extreme phases of the
627 southern oscillation and precipitation patterns over Turkey. *International Journal of*
628 *Climatology*, 23(13), pp. 1607-1625.
- 629 Krichak, S. O., Breitgand, J., Gualdi S., & Feldstein, S. (2014). Teleconnection–extreme
630 precipitation relationships over the Mediterranean region. *Theoretical and Applied*
631 *Climatology*, 117(3-4), pp. 679-692.
- 632 Mathbout, S., López-Bustins, J. A., Vide, J. M., Rodrigo, F. S., & Rustullet, J. B. (2016). On
633 the Relationship between Atmospheric Circulation Indices and Precipitation in the
634 Eastern Mediterranean. *EGU General Assembly Conference Abstracts*, 18, p. 7224.
- 635 Meteoroloji Genel Müdürlüğü (MGM). (2010). Sel ve Taşkınlar. Available at:
636 <https://www.mgm.gov.tr/arastirma/dogal-afetler.aspx?s=taskinlar>. [Accessed 15 March
637 2017]
- 638 National Oceanic and Atmospheric Administration (NOAA). (2017a). North Atlantic
639 Oscillation (NAO). Available at: <https://www.ncdc.noaa.gov/teleconnections/nao/>.
640 [Accessed 26 December 2017]
- 641 National Oceanic and Atmospheric Administration (NOAA). (2017b). Arctic Oscillation (AO).
642 Available at: <https://www.ncdc.noaa.gov/teleconnections/ao/>. [Accessed 26 December
643 2017].
- 644 National Oceanic and Atmospheric Administration (NOAA). (2017c). Southern Oscillation
645 Index (SOI). Available at:

- 646 <https://www.ncdc.noaa.gov/teleconnections/enso/indicators/soi/>. [Accessed 26
647 December 2017].
- 648 Ntegeka, V., & Willems, P. (2008), Trends and multidecadal oscillations in rainfall extremes,
649 based on a more than 100-year time series of 10 min rainfall intensities at Uccle,
650 Belgium. *Water Resources Research*, 44, W07402. DOI:10.1029/2007WR006471.
- 651 Özcan, E. (2006). Floods and Turkey. *Gazi Eğitim Fakültesi Dergisi*, 26(1), pp. 35–50.
- 652 Raja, N. B., Aydın, O., Türkoğlu, N., & Çiçek, I. (2017). Space-time kriging of precipitation
653 variability in Turkey for the period 1976–2010. *Theoretical and Applied*
654 *Climatology*, 129(1-2), pp. 293-304.
- 655 Smakhtin, V. U. (2001). Low flow hydrology: A review. *Journal of hydrology*, 240(3), pp. 147-
656 186.
- 657 Sönmez, F. K., Kömüşçü, A. Ü., Erkan, A., & Turgu, E. (2005). An analysis of spatial and
658 temporal dimension of drought vulnerability in Turkey using the standardized
659 precipitation index. *Natural Hazards*, 35(2), pp. 243-264.
- 660 Srokosz, M. A., & Bryden, H. L. (2015). Observing the Atlantic Meridional Overturning
661 Circulation yields a decade of inevitable surprises. *Science*, 348(6241). DOI:
662 10.1126/science.1255575.
- 663 Tabari, H., & Willems, P. (2016). Daily precipitation extremes in Iran: Decadal anomalies and
664 possible drivers. *JAWRA Journal of the American Water Resources Association*, 52(2),
665 pp. 541-559.
- 666 Tabari, H., Willems, P. (2018) Lagged influence of Atlantic and Pacific climate patterns on
667 European extreme precipitation. *Scientific Reports*, 8:5748.

- 668 Taye, M. T., & Willems, P. (2012). Temporal variability of hydroclimatic extremes in the Blue
669 Nile basin. *Water Resources Research*, 48, W03513. DOI:10.1029/2011WR011466.
- 670 Türkeş, M. (1996a). Meteorological drought in Turkey: A historical perspective, 1930–
671 1993. *Drought Network News*, 8(3), pp. 17-21.
- 672 Türkeş, M. (1996b). Spatial and temporal analysis of annual rainfall variations in
673 Turkey. *International Journal of Climatology*, 16(9), pp. 1057-1076.
- 674 Türkeş, M. (1998). Influence of geopotential heights, cyclone frequency and Southern
675 Oscillation on rainfall variations in Turkey. *International Journal of Climatology*, 18(6),
676 pp. 649-680.
- 677 Türkeş, M., & Erhat, E. (2003). Precipitation changes and variability in Turkey linked to the
678 North Atlantic Oscillation during the period 1930–2000. *International Journal of*
679 *Climatology*, 23(14), pp. 1771-1796.
- 680 Türkeş, M., & Erhat, E. (2005). Climatological responses of winter precipitation in Turkey to
681 variability of the North Atlantic Oscillation during the period 1930–2001. *Theoretical*
682 *and Applied Climatology*, 81(1), pp. 45-69.
- 683 Türkeş, M., & Erhat, E. (2006). Influences of the North Atlantic Oscillation on precipitation
684 variability and changes in Turkey. *Nuovo Cimento della Societa Italiana di Fisica. C,*
685 *Geophysics and Space Physics*, 29(1), pp. 117-135.
- 686 Türkeş, M., & Tatlı, H. (2009). Use of the standardized precipitation index (SPI) and a modified
687 SPI for shaping the drought probabilities over Turkey. *International Journal of*
688 *Climatology*, 29(15), pp. 2270-2282.

- 689 Universitat de Barcelona (UB). (2017). Western Mediterranean Oscillation (WeMO). Available
690 at: <http://www.ub.edu/gc/en/2016/06/08/wemo/>. [Accessed 26 December 2017].
- 691 Ünal, Y. S., Deniz, A., Toros, H., & Incecik, S. (2012). Temporal and spatial patterns of
692 precipitation variability for annual, wet, and dry seasons in Turkey. *International Journal*
693 *of Climatology*, 32(3), pp. 392-405.
- 694 Vapnik, V., & Chapelle, O. (2000). Bounds on error expectation for support vector
695 machines. *Neural computation*, 12(9), pp. 2013-2036.
- 696 Willems, P. (2013). Multidecadal oscillatory behaviour of rainfall extremes in Europe. *Climatic*
697 *Change*, 120(4), pp. 931-944.
- 698 Xoplaki, E., González-Rouco, J. F., Luterbacher, J. U., & Wanner, H. (2004). Wet season
699 Mediterranean precipitation variability: Influence of large-scale dynamics and trends.
700 *Climate Dynamics*, 23(1), pp. 63-78.
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Table 1 Overview of methods for analyzing the relationships between extreme precipitation and climate driven anomalies

Relation type	Bivariate relationship	Multivariate relationship
Linear	Spearman's Rank-Order	Multiple Linear Regression
	Correlation (SROC)	(MLR)
Non-Linear	Power Law Regression (PLR)	Multiple Adaptive Regression
		Splines (MARS)

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Table 2 Characteristics of the considered Turkish stations

Station ID	Station name	Station region	Longitude	Latitude	Station ID	Station name	Station region	Longitude	Latitude
17070	Bolu	BLS	31.602	40.733	17351	Adana	MED	35.344	37.004
17034	Giresun	BLS	38.388	40.923	17184	Akhisar	MED	27.823	38.912
17024	Inebolu	BLS	33.764	41.979	17310	Alanya	MED	31.98	36.551
17040	Rize	BLS	40.501	41.040	17320	Anamur	MED	32.865	36.069
17069	Sakarya	BLS	30.393	40.768	17372	Antakya	MED	36.151	36.205
17030	Samsun	BLS	36.256	41.344	17300	Antalya	MED	30.799	36.906
17026	Sinop	BLS	35.155	42.030	17234	Aydın	MED	27.838	37.84
17022	Zonguldak	BLS	31.778	41.449	17114	Bandırma	MED	27.997	40.332
17190	Afyon	CCAN	30.560	38.738	17290	Bodrum	MED	27.44	37.033
17130	Ankara	CCAN	32.864	39.973	17112	Çanakkale	MED	26.399	40.141
17080	Çankırı	CCAN	33.610	40.608	17237	Denizli	MED	29.092	37.762
17084	Çorum	CCAN	34.936	40.546	17180	Dikili	MED	26.888	39.074
17074	Kastamonu	CCAN	33.776	41.371	17962	Dört Yol	MED	36.198	36.824
17196	Kayseri	CCAN	35.500	38.687	17296	Fethiye	MED	29.124	36.627
17160	Kırşehir	CCAN	34.156	39.164	17370	İskenderun	MED	36.158	36.592
17244	Konya	CCAN	32.574	37.984	17220	İzmir	MED	27.082	38.395
17250	Niğde	CCAN	34.680	37.959	17186	Manisa	MED	27.405	38.615
17090	Sivas	CCAN	37.002	39.744	17340	Mersin	MED	34.603	36.781
17140	Yozgat	CCAN	34.816	39.824	17292	Muğla	MED	28.367	37.21
17045	Artvin	CEAN	41.819	41.175	17238	Burdur	MEDT	30.294	37.722
17099	Ağrı	CEAN	43.052	39.725	17240	Isparta	MEDT	30.568	37.785
17094	Erzincan	CEAN	39.487	39.752	17155	Kütahya	MEDT	29.989	39.417
17096	Erzurum	CEAN	41.190	39.953	17188	Uşak	MEDT	29.404	38.671
17100	Iğdır	CEAN	44.052	39.923	17120	Bilecik	MRT	29.977	40.141
17172	Van	CEAN	43.346	38.469	17116	Bursa	MRT	29.013	40.231
17968	Ceylanpınar	CMED	40.031	36.841	17050	Edirne	MRT	26.551	41.677
17280	Diyarbakır	CMED	40.203	37.897	17636	Florya	MRT	28.787	40.976
17201	Elazığ	CMED	39.256	38.644	17061	Kireçburnu	MRT	29.050	41.146
17261	Gaziantep	CMED	37.351	37.059	17059	Kumköy	MRT	29.038	41.251
17199	Malatya	CMED	38.217	38.337	17631	Lüleburgaz	MRT	27.311	41.351
17275	Mardin	CMED	40.728	37.310	17610	Şile	MRT	29.601	41.169
17210	Siirt	CMED	41.935	37.932	17056	Tekirdağ	MRT	27.497	40.959
17270	Şanlıurfa	CMED	38.786	37.161	-	-	-	-	-

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Table 3 Percentages of the stations with a significant winter extreme precipitation anomaly in the Turkish sub-regions with respect to sub-periods. Significance of anomalies is tested using Monte Carlo method at the 5% level.

Sub-period	Anomaly Sign	Percentage of the stations having a significant anomaly						
		BLS	CCAN	CEAN	CMED	MED	MEDT	MRT
1959-1969	Positive	63	45	50	13	32	50	11
	Negative	13	27	16	0	11	0	11
1970-1979	Positive	25	27	0	25	11	25	33
	Negative	13	27	33	50	26	0	44
1980-1989	Positive	13	36	50	25	5	25	44
	Negative	50	18	0	25	26	25	44
1990-1999	Positive	0	9	17	25	5	0	22
	Negative	75	54	33	0	37	75	44
2000-2009	Positive	13	45	0	13	37	0	55
	Negative	0	18	67	13	11	25	0

Table 4 Standard deviations of extreme high and extreme low anomalies for each region with respect to seasons. Region anomaly values are obtained by taking the median of the anomalies of the different stations in each of the corresponding region.

Region	Season	Standard Deviation	
		Low Anomaly	High Anomaly
BLS	Spring	0.033	0.088
	Summer	0.026	0.108
	Autumn	0.032	0.077
	Winter	0.038	0.080
CCAN	Spring	0.035	0.087
	Summer	0.015	0.140
	Autumn	0.021	0.162
	Winter	0.042	0.092
CEAN	Spring	0.043	0.064
	Summer	0.017	0.154
	Autumn	0.023	0.115
	Winter	0.029	0.112
CMED	Spring	0.042	0.093
	Summer	0.006	0.259
	Autumn	0.022	0.136
	Winter	0.043	0.076
MED	Spring	0.024	0.108
	Summer	0.007	0.238
	Autumn	0.017	0.182
	Winter	0.065	0.076
MEDT	Spring	0.020	0.102
	Summer	0.010	0.157
	Autumn	0.014	0.136
	Winter	0.063	0.100
MRT	Spring	0.031	0.103
	Summer	0.015	0.132
	Autumn	0.026	0.113
	Winter	0.070	0.088

Table 5 Correlation between the decadal anomalies of extreme high precipitation and dry day number in different sub-periods with respect to sub-regions. Region anomaly values are obtained by taking the median of the anomalies of the different stations in each of the corresponding region.

Spearman's Rank Order Correlation								
Season	Sub-period	BLS	CCAN	CEAN	CMED	MED	MEDT	MRT
Spring	1959-1996	-0.496	0.127	0.425	-0.756	0.589	0.126	-0.023
	1996-2009	0.270	-0.719	-0.424	-0.802	-0.859	-0.878	-0.746
	1959-2009	-0.158	0.201	0.036	-0.804	0.212	-0.036	0.101
Summer	1959-1996	-0.133	0.047	-0.397	0.107	0.133	0.234	0.165
	1996-2009	0.240	-0.736	-0.868	-0.534	0.167	-0.371	-0.086
	1959-2009	0.090	-0.179	-0.438	0.004	0.059	0.007	0.215
Autumn	1959-1996	-0.590	-0.791	0.234	-0.589	0.168	0.614	-0.154
	1996-2009	-0.011	-0.924	0.657	-0.741	-0.152	-0.055	0.569
	1959-2009	-0.550	-0.859	0.322	-0.512	-0.131	0.369	-0.346
Winter	1959-1996	0.127	-0.639	-0.251	0.128	-0.811	-0.948	-0.562
	1996-2009	0.705	-0.525	0.266	-0.226	-0.284	0.235	-0.314
	1959-2009	0.197	-0.530	-0.493	0.153	-0.547	-0.784	-0.378

Table 6 Number of stations having a significant relationship between the anomalies of extreme high precipitation and climate indices with respect to the methods, rainfall regions and seasons, for the single driver scenario. PLR: Power Law Regression, SROC: Spearman's Rank Order Correlation. Significance is tested using t-test at the 5% level.

Climate Indices	Rainfall Region	Total Station Number	Number of stations with a significant relationship							
			Spring		Summer		Autumn		Winter	
			PLR	SROC	PLR	SROC	PLR	SROC	PLR	SROC
AO	BLS	8	0	0	0	0	0	0	0	0
	CCAN	11	0	0	0	0	0	0	2	2
	CEAN	6	0	0	0	0	0	0	0	0
	CMED	8	0	0	0	0	0	0	0	0
	MED	19	1	0	0	0	0	0	0	0
	MEDT	4	0	0	0	0	2	1	0	0
	MRT	9	0	0	0	0	0	0	0	0
	Total	65	1	0	0	0	2	1	2	2
NAO	BLS	8	0	0	1	1	0	0	1	1
	CCAN	11	0	0	0	0	0	0	2	1
	CEAN	6	0	0	0	0	0	0	1	0
	CMED	8	0	0	0	0	0	0	0	0
	MED	19	1	1	0	0	0	0	1	0
	MEDT	4	0	0	0	0	0	0	1	2
	MRT	9	0	0	1	1	0	0	0	0
	Total	65	1	1	2	2	0	0	6	4
SOI	BLS	8	0	1	1	1	0	0	0	0
	CCAN	11	0	0	1	1	0	0	0	0
	CEAN	6	0	0	1	1	0	0	1	1
	CMED	8	0	0	0	0	0	0	0	0
	MED	19	0	0	0	0	0	0	1	1
	MEDT	4	0	0	0	0	0	0	0	0
	MRT	9	0	0	1	0	0	0	0	0
	Total	65	0	1	4	3	0	0	2	2
WeMO	BLS	8	2	1	0	0	0	0	0	0
	CCAN	11	0	0	1	1	0	0	0	0
	CEAN	6	0	0	0	0	1	1	0	0
	CMED	8	0	0	0	0	0	0	0	0
	MED	19	0	0	1	2	0	0	0	0
	MEDT	4	0	1	0	0	0	0	0	0
	MRT	9	0	0	0	0	0	0	0	0
	Total	65	2	2	2	2	1	1	0	0

Table 7 Number of stations having a significant relationship between the anomalies of dry day number and climate indices with respect to the methods, rainfall regions and seasons, for the single driver scenario. PLR: Power Law Regression, SROC: Spearman's Rank Order Correlation. Significance is tested using t-test at the 5% level.

Climate Indices	Rainfall Region	Total Station Number	Number of stations with a significant relationship							
			Spring		Summer		Autumn		Winter	
			PLR	SROC	PLR	SROC	PLR	SROC	PLR	SROC
AO	BLS	8	0	0	0	0	0	0	0	0
	CCAN	11	0	0	0	0	0	0	3	3
	CEAN	6	2	0	0	0	0	0	0	0
	CMED	8	0	0	0	0	0	0	0	2
	MED	19	0	0	1	0	0	0	13	14
	MEDT	4	0	0	0	0	0	0	4	3
	MRT	9	0	0	0	0	0	0	4	3
	Total	65	2	0	1	0	0	1	24	25
NAO	BLS	8	0	0	2	1	0	0	0	0
	CCAN	11	0	0	2	1	0	0	3	3
	CEAN	6	1	0	0	0	0	0	0	0
	CMED	8	2	2	0	0	0	0	3	4
	MED	19	0	1	1	2	0	0	9	13
	MEDT	4	0	0	0	0	0	0	3	4
	MRT	9	0	0	1	1	0	0	4	4
	Total	65	3	2	6	5	0	0	22	28
SOI	BLS	8	0	0	0	1	0	0	0	0
	CCAN	11	0	0	0	1	0	0	0	0
	CEAN	6	0	0	0	1	0	0	1	1
	CMED	8	0	0	0	0	0	0	0	0
	MED	19	0	0	5	5	0	0	0	0
	MEDT	4	0	0	0	0	0	0	0	0
	MRT	9	0	0	0	1	0	0	0	0
	Total	65	0	0	5	6	0	0	1	1
WeMO	BLS	8	0	0	1	1	0	0	0	0
	CCAN	11	0	0	1	0	0	0	0	0
	CEAN	6	0	0	0	1	0	0	0	0
	CMED	8	0	0	0	1	0	0	0	0
	MED	19	0	0	0	0	0	0	0	0
	MEDT	4	0	0	0	0	0	0	0	0
	MRT	9	0	0	0	0	0	0	0	0
	Total	65	0	0	2	3	0	0	0	0

Table 8 Number of stations having a significant relationship between the anomalies of extreme high precipitation and climate indice pairs with respect to the methods, rainfall regions and seasons, for the multiple driver scenario. MARS: Multiple Adaptive Regression Splines, MLR: Multiple Linear Regression. Significance is tested using t-test at the 5% level.

Climate indices pair	Rainfall Region	Total Station Number	Number of stations with a significant relationship							
			Spring		Summer		Autumn		Winter	
			MARS	MLR	MARS	MLR	MARS	MLR	MARS	MLR
AO-SOI	BLS	8	2	2	2	1	0	0	1	0
	CCAN	11	2	1	1	1	1	0	7	2
	CEAN	6	0	0	3	2	0	0	2	1
	CMED	8	3	0	0	0	3	0	3	0
	MED	19	2	1	0	0	2	0	6	0
	MEDT	4	0	0	0	0	1	2	2	0
	MRT	9	0	0	1	1	1	0	1	0
	Total	65	9	4	7	5	8	2	22	3
AO-WeMO	BLS	8	2	2	2	1	0	1	0	0
	CCAN	11	0	0	3	1	3	0	2	2
	CEAN	6	0	0	2	2	1	1	0	0
	CMED	8	0	0	1	0	0	0	1	0
	MED	19	6	1	3	1	1	1	1	0
	MEDT	4	1	0	1	1	2	2	1	0
	MRT	9	2	0	4	0	1	0	0	0
	Total	65	11	3	16	6	8	5	5	2
NAO-SOI	BLS	8	4	2	2	2	0	0	2	2
	CCAN	11	3	1	1	1	0	1	8	2
	CEAN	6	1	0	2	1	0	0	3	3
	CMED	8	5	0	1	0	1	0	4	0
	MED	19	4	1	1	0	1	0	6	1
	MEDT	4	0	1	0	0	0	0	2	1
	MRT	9	2	0	3	2	0	1	1	0
	Total	65	19	5	10	6	2	2	26	9
NAO-WeMO	BLS	8	2	3	3	2	2	1	1	0
	CCAN	11	0	1	3	2	0	0	3	2
	CEAN	6	0	0	3	0	1	1	1	0
	CMED	8	0	0	3	1	0	0	0	0
	MED	19	4	1	1	1	2	0	1	1
	MEDT	4	0	0	1	0	1	1	1	1
	MRT	9	0	0	5	2	0	0	1	0
	Total	65	6	5	19	8	6	3	8	4
SOI-WeMO	BLS	8	4	2	2	2	0	0	0	0
	CCAN	11	2	0	4	1	2	0	2	0
	CEAN	6	0	0	4	2	0	1	1	1
	CMED	8	2	0	1	0	2	0	1	0
	MED	19	1	1	2	1	0	0	2	0
	MEDT	4	1	0	1	0	0	0	0	0
	MRT	9	1	0	4	0	0	0	0	0
	Total	65	11	3	18	6	4	1	6	1

Figure 1 Locations of the selected stations

Figure 2 Comparison of extreme high precipitation anomalies between Turkish sub-regions for different seasons (Median of anomalies in each sub-region is shown)

Figure 3 Spatial distribution of the extreme high anomalies at the study stations over Turkey in winter (The stations over Turkey are delineated with respect to sub-regions. Significance is tested using Monte Carlo method at the 5% level)

Figure 4 The number of floods in Turkey between 1940 and 2010 (Retrieved from <https://www.mgm.gov.tr/arastirma/dogal-afetler.aspx?s=taskinlar>)

Figure 5 Comparison of dry day number anomalies between Turkish sub-regions for different seasons (Median of the anomalies in each sub-region is shown)

Figure 6 Comparison between the anomalies of extreme high precipitation and climate indices for winter season and selected stations

Figure 7 Spatial distribution of the correlation between anomalies of dry day number and the climate indices AO and NAO for winter season. The areas with significant correlations are colored.

Figure 8 Correlation matrix showing the relationships between extreme high anomalies of the regions and SOI for the time period of 1996-2009 in winter

Figure 9 Spatial distribution of the the relationship between extreme high precipitation and the NAO-SOI pair following multivariate adaptive regression splines (MARS) with respect to seasons. The areas with significant correlations are colored.