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ORIGINAL ARTICLE

Spatio-temporal evaluation of various global circulation models in terms of projection of different meteorological drought indices

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Abstract

During the coming years, a dramatic increase is expected in the number of drought events mainly due to climate change. In this study, the spatio-temporal variations of duration and intensity of drought events during two 30-year periods in the future (2040–2069 and 2070–2099) together with the reference period (1971–2000) were investigated based on the impacts of climate change. Three drought indices including the Standardized Precipitation Index, the China Z Index, and the Statistical *Z* Score were calculated from the dynamically downscaled precipitation data from the outputs of GFDL-ESM2M, HadGEM2-ES, and MPI-ESM-MR general circulation models (GCMs) under RCP4.5 and RCP8.5 scenarios over the Western Black Sea (WBS) and the Euphrates–Tigris (ET) basins in Turkey. The biases in the GCMs' precipitation were corrected using the linear scaling method. Additionally, the Mann–Kendall trend test was adapted to the values of drought indices to detect the trend. The results of the study showed that there is no meaningful variation between the different drought indices and also the outputs of various GCMs in terms of drought properties. On the other hand, based on the drought indices values calculated from the outputs of all GCMs, it was found that drought duration and intensity will increase during the current century. Additionally, it was concluded that by taking the spatial distribution of drought properties over the basins into the account, there is a slight relationship between the geographical elevation and drought properties over the WBS and the ET basins.

Keywords Climate change · CMIP5 · Drought indices · Turkey

Introduction

According to the Intergovernmental Panel on Climate Change (IPCC), during the last 50 years, there was an increasing trend in the number of drought events globally (IPCC 2013). Today, a large number of countries around the world endeavor with negative effects of drought on the water supply, food production, energy, and social health, etc. Changing climate, increasing water demand for various purposes, and restricted water resources are the main factors that cause frequent drought events in the last decades (Mishra and Singh 2010). The dramatic increase in the duration, frequency, and intensity of drought events make it important to perform adaptive activities and policies based on the understanding of drought in the past and future. A vast number of studies considered changes in the various types of drought indices (meteorological, hydrological and agricultural) based on the historical data, to indicate the quantity and quality of climatic changes (Paulo et al. 2016; Ganguli and Ganguly 2016; Lweendo et al. 2017; Lin et al. 2017; Ayantobo et al. 2017; Zhou et al. 2017; Choi et al. 2016; Deo et al. 2017; Anagnostopoulou 2017; Nguyen et al. 2017; Dabanlı et al. 2017). In a study by Paulo et al. (2016), the monthly precipitation records from 1860 to 2007 were used to calculate a drought index called the Standardized Precipitation Index (SPI) over Portugal. In Turkey, in a study by Dabanlı et al. (2017), the temporal and spatial status of drought over the country was explored based on the 80-year precipitation data measured between 1931 and 2010. They prepared the distribution maps of different characteristics of drought based on the SPI index in different time steps.

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They also concluded that the effects of El Nino and La Nina on the drought severity in Turkey were ignorable. In addition, Vazifehkhah and Kahya (2018) investigated the impacts of North Atlantic Oscillation and Arctic Oscillation on the hydrologic drought in Turkey and showed that there is no strong correlation between those phenomena and drought in Turkey.

Recently, future projections of drought have been established on the calculation of drought indices from the outputs of general circulation models (GCMs) from Coupled Model Intercomparison Project Phase 5 (CMIP5) under new representative concentration pathway (RCP) scenarios (Nkemelang et al. 2018; Venkataraman et al. 2016; Gao et al. 2017; Ahmadalipour et al. 2017; Gizaw and Gan 2017; Chen et al. 2017; Yang and Huntingford 2018; Moon et al. 2018; Mpelasoka et al. 2018; Potopová et al. 2018; Wang et al. 2018; Betts et al. 2018; Ruosteenoja et al. 2018; Um et al. 2017; Carrão et al. 2018; Mitra et al. 2018). In a study by Ahmadalipour et al. (2017), the impacts of climate change over the Willamette River basin (WRB) in the Pacific Northwest U.S. were investigated by looking into projected hydrological and meteorological drought indices during the current century using the downscaled outputs of various GCMs under RCP4.5 and RCP8.5 scenarios. The authors found that despite increasing precipitation, the drought events will be more common during the coming years compared to the last 30 years of prior century as the reference period.

For Turkey, the majority of drought assessment studies have been performed based on the history of the drought to monitor the climate change quantity, rather than the effects of climate change on the properties of drought events in the future (Keskin et al. 2011; Katipoğlu and Can 2018; Tosunoglu and Kisi 2017; Tosunoğlu and Onof 2017; Güner Bacanli 2017; Kutiel and Türkeş 2017; Raja et al. 2017; Aras 2018). Güner Bacanli (2017) investigated the trend in precipitation and drought indices in the Aegean region (Turkey) during the period between 1960 and 2013. In the study, the author concluded that during that period of time the value of drought indices decreased. However, the study did not present a point of view about the future situation of drought. Similarly, in a study by Kutiel and Türkeş (2017), the daily precipitation data of 69 stations which were measured between 1970 and 2011, were used to analyze the spatial and temporal distribution of dryness and drought over Turkey. They found that the dryness in the southern and eastern parts of the country was more intense than in the northern parts.

In this study, the past and future spatio-temporal variation of three drought indices over the Western Black Sea (WBS) and the Euphrates–Tigris (ET) basins in Turkey were evaluated based on the daily precipitation values from observed data during the reference period (1971–2000) and the projected data of three GCMs named GFDL-ESM2M, HadGEM2-ES, and MPI-ESM-MR under RCP4.5 and RCP8.5 scenarios for the future period (2020–2099). On the other hand, the trends in the values of drought indices during the reference and future periods were detected based on the Mann–Kendall trend test. Additionally, the relationships between the terrestrial aspects and drought properties were discussed.

Study area

In this study, the effects of climate change on the drought indices were examined in the WBS and the ET basins in Turkey. The most important properties of these basins are explained in the following subsections.

Western *Black Sea basin*

The WBS basin (Fig. 1) which covers approximately 29,000 km^2 of the northwest part of Turkey is located geographically between 40.56° and 41.45° N, and 30.86° and 35.20° E. Although the climate of the basin is categorized as semi-Mediterranean climate in general, there are some micro-climate regions (TÜBITAK 2013). Figure 2a illustrates the topographic map of the basin, where the highest part of the basin is located in the southern part by approximately 2500 m elevation from the sea surface.

Euphrates–Tigris basin

The ET River basin which is located between Iraq, Turkey, the Islamic Republic of Iran, the Syrian Arab Republic, Saudi Arabia and Jordan [Food and Agriculture Organization United Nations (FAO) 2009] covers a total area of 879,790 km^2 (Fig. 1). The climate of the basin can be classified as the sub-tropical Mediterranean climate with wet winters and dry summers (FAO 2009). This river system has about 50 billion cubic meters per annum discharge and the main source of the rivers' flow is the high mountains of eastern Turkey (FAO 2009) which has been concerned in this study. Figure 2b illustrates the northern part of the ET basin which is located between 36.20° and 45.67° N, and 35.78° and 41.28° E geographical coordinates and contains the whole southwest of Turkey. According to the topographic map of the basin, the northern part is covered by mountains, whereas the southern parts are dominantly low lands.

Data analyses and study approach

Observed and projected data

In this study, to investigate the past and future properties of drought, three meteorological drought indices were calculated from daily precipitation data. For the reference period

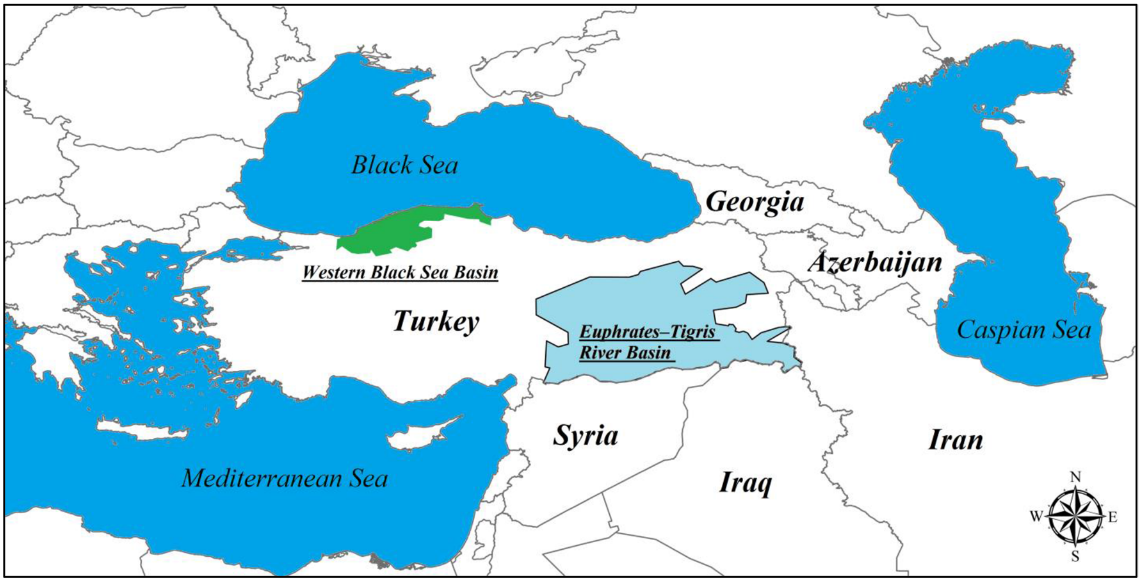

Fig. 1 The position of the Western Black Sea and Euphrates–Tigris basins in Turkey

(1971–2000), the high-resolution precipitation values from high-resolution gridded precipitation data of APHRODITE (https://www.chikyu.ac.jp/precip/) were used in addition to the historical data of GCMs. For the future period, the dynamically downscaled (using a regional climate model named ICTP-RegCM4 [described in Elguindi et al. 2014)] outputs of HadGEM2-ES (Met Office Hadley Center, UK), GFDL-ESM2M (Geophysical Fluid Dynamics Laboratory, USA), and MPI-ESM-MR (Max Planck Meteorology Institution, Germany) GCMs under RCP4.5 and RCP8.5 scenarios were utilized. These data were provided by the Turkish State Meteorological Service with reliable temporal (daily) and spatial (20 km) resolution to use in climate change impact studies for the basin scale for different parts of Turkey. The resolution of projected data was 20 km, while of APHRODITE data was 25 km. To account for the differences in resolution, the APHRODITE data were interpolated into the corresponding data points of GCMs using the Kriging method [originated by Krige (1952) and developed by Matheron (1971)]. The ensemble mean of the three GCMs (the statistical average of three models in the same data points) was also used in the analyses.

Bias correction

Climate models (including GCMs and regional climate models) involve uncertainties that arise from inadequate calibration mainly due to the lack of sufficient observed data, physical, mathematical and computational futures of the models resulted from the complexity of the climate system. In this way, using appropriate bias correction methods to wane the impacts of uncertainties is an obligation in spite of the fact that there are some deficiencies in these methods such as their effects on the consistency between climate variables (Muerth et al. 2012). The other important disadvantage of the bias correction is that the methods do not take physical and geographical aspects of climate into account (Ehret et al. 2012). Between various bias correction methods which can be classified roughly into distribution-based and statistical-based methods, the alpha change, quintile mapping, and the linear scaling method are widely used by researches (Hashino et al. 2007; Hagemann et al. 2011; Teutschbein and Seibert 2012; Ehret et al. 2012; Hawkins et al. 2013; Räty et al. 2014; Prasanna 2018; Maraun 2016; Tschöke et al. 2017; Nuri Balov and Altunkaynak 2019a, b). Among those methods, in this study, the linear scaling method was adapted to daily precipitation data of GCMs and more satisfying and meaningful results were obtained (when other methods were used, in some cases, the calculated values for corrected precipitation values were not physically meaningful where the value of daily precipitation was obtained, for example, as 900 mm). On the other hand, it is better to use distribution-based methods instead of a statistical-based method; however, as the number of zero-precipitation days in the data sets was large, it was very hard to fit the precipitation time series to any distribution.

In the linear scaling method, one can obtain the corrected precipitation data series as (Teutschbein and Seibert 2012):

$$P_{\mathrm{corr.}}(d) = P_{\mathrm{raw}}(d) \times \left[\frac{\mu_{\mathrm{m,obs.,d}}}{\mu_{\mathrm{m,ref.,d}}}\right], \tag{1}$$

where $P_{\mathrm{corr.}}(d)$ is corrected daily precipitation values of the model, which can represent reference and future periods,

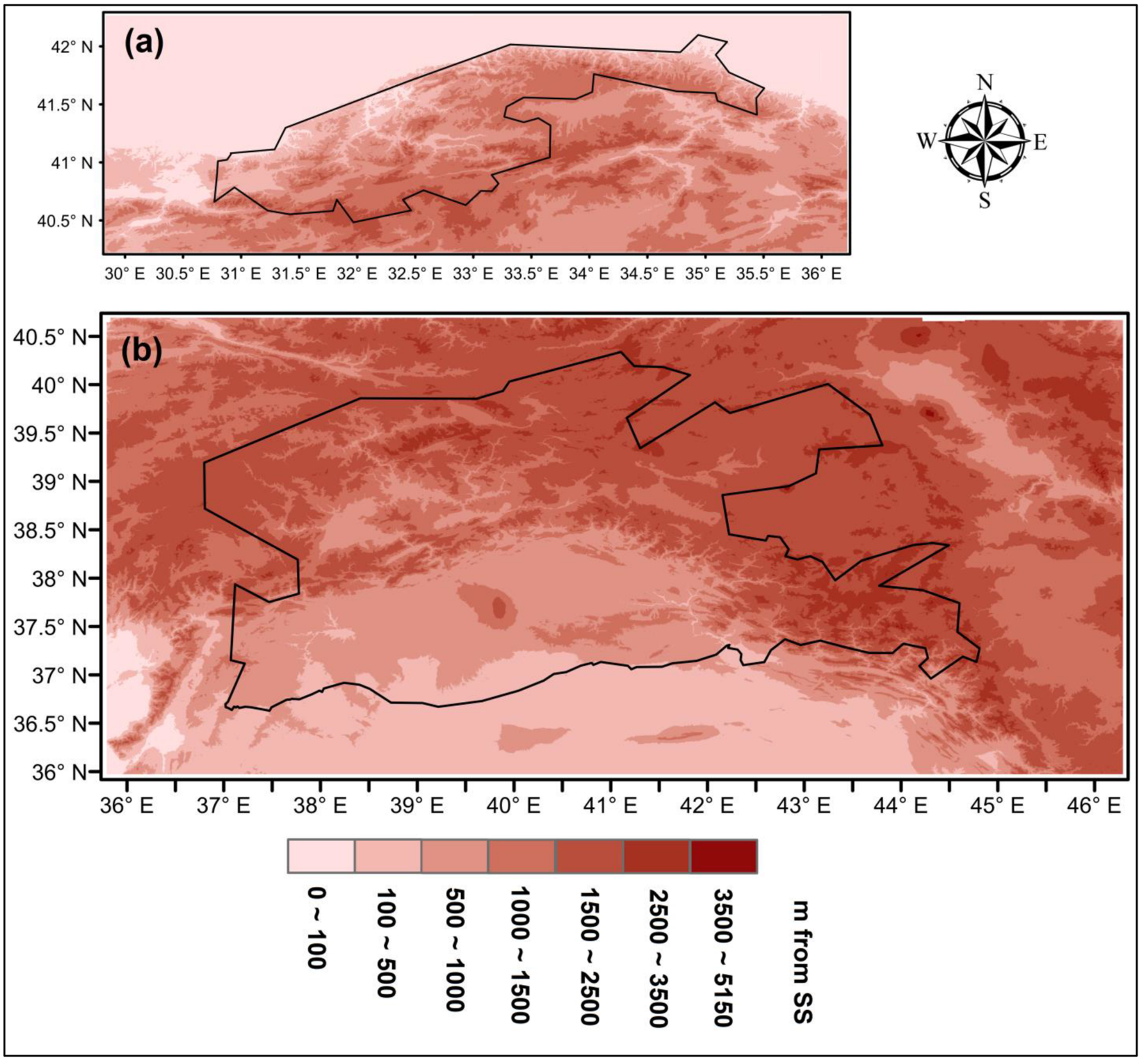

Fig. 2 The topographical map of the Western Black Sea (**a**) and the Euphrates–Tigris (**b**) basins

$P_{\mathrm{raw}}(d)$ is the raw model outputs, $\mu_{\mathrm{m,obs.,d}}$ and $\mu_{\mathrm{m,ref,d}}$ are monthly mean precipitation values obtained from daily observations and GCMs, respectively, for the reference period.

Drought indices

It is difficult to evaluate the drought parameters directly by measuring and it can be useful to use appropriate drought indices (IPCC 2013). These indices represent a key factor of drought which can be useful to evaluate drought parameters (Mishra and Singh 2010). Drought parameters, which also are known as drought characteristics, are (1) duration of drought, (2) frequency of drought, and (3) intensity of drought (Ahmadalipour et al. 2017). Every drought index can represent hydrological, meteorological or agricultural drought. There are various considerations in the selection of appropriate drought index in accordance with the purposes of the study. However, available data and ease of use are usually the most important ones. In this study, three meteorological drought indices were used based on the available data, which are mainly restricted in terms of the future projections of climate. These indices are SPI, China Z Index (CZI), and Statistical *Z* Score (STZS), which are only in need of precipitation data. SPI is the most popular index in drought assessment studies (introduced by McKee et al. 1993). There are two types of SPI in the literature as parametric and non-parametric. The calculation of the parametric SPI is based on the fitness of the data series to an appropriate probability distribution which is usually Gamma distribution (Mishra and Singh 2010). However, there are some important concerns about the implication of SPI. According to Mishra and Singh (2010) before using SPI, it should be checked if the number of data samples is high enough and that the data fit the probability distribution, especially in case of insufficient length of data. On the other hand, Guttman (1999) declared that to reach stability in the center part and tail of precipitation distribution, one has to provide at least 40–60 and 70–80 years of precipitation data, respectively. As known, for some regions, like Turkey, there are shortcomings in the quality and quantity of measurements mainly due to the terrestrial factors (Bozkurt et al. 2012). Additionally, precipitation data rarely can fit any probability distribution satisfyingly. All those concerns make it more appropriate to use non-parametric SPI, which is a ranked-based approach, where it is assumed that the data are fitted to the probability distribution. On the other hand, the differences between parametric and non-parametric SPI should be taken into account, where the difference is more significant in drought severity than drought duration (Soľáková et al. 2014). Nevertheless, there is no evident criterion to determine which approach will be better. A detailed explanation of parametric and non-parametric SPI approaches is presented in Mishra and Singh (2010), and Farahmand and AghaKouchak (2015), respectively.

CZI was identified by the National Climate Center of China (Wu et al. 2001) and nowadays is used widely in drought-assessing studies in the different parts of the world (Wu et al. 2001; Dogan et al. 2012; Jain et al. 2015). In the calculation of this index, it is assumed that the data points are fitted to Pearson Type III distribution (Jain et al. 2015) based on the Wilson–Hilferty cube-root transformation (Kendall and Stuart 1977) as

$$\mathrm{CZI} = \frac{6}{C_{\mathrm{st}}}\left(\frac{C_{\mathrm{st}}}{2} Z\,\mathrm{Score}_t + 1\right)^{1/3} - \frac{6}{C_{\mathrm{st}}} + \frac{C_{\mathrm{st}}}{6}, \tag{2}$$

where C_{st} is the skewness coefficient at t time steps and Z Score is the STZS which is calculated at the same time steps. The time step t can be chosen as 1, 2, 3, …, 9, 12, and 24 months.

Between various drought indices, the STZS is one of the most simple indices in terms of calculation and data (Wu et al. 2001; Morid et al. 2006; Akhtari et al. 2009; Dogan et al. 2012; Jain et al. 2015). For calculation of the index, the following equation can be adapted to the precipitation data:

$$\mathrm{STZS} = \frac{P_i - \overline{P}}{\sigma}, \tag{3}$$

where P_i is the total amount of precipitation in the ith month, $\overline{P}$ is the long-time mean monthly precipitation, and σ is the standard deviation.

Another important part of drought analyses is to determine the appropriate time step in which indices will be calculated. The drought indices can be calculated for 1, 3, 6, 9, 12, and 24 (rarely 36) time steps on the monthly scale. In a study by Jain et al. (2015), the correlation coefficient between various indices and time steps was provided and the authors concluded that in accord with the time pattern of precipitation in the majority of India (monsoon rainfalls) the most effective time step was 9 months. On the other hand, the condition in which the number of months with zero precipitation is more can affect the exactness of the calculated index, and it is better to take a proper time step to avoid this situation. Additionally, in some cases (e.g., Güner Bacanli 2017), the duration and frequency of the drought can be affected by the time steps. Accordingly, in this study, 6-month time step was taken into account, considering the precipitation patterns of both basins and based on the number of consecutive zero-precipitation months. On the other hand, the 30-year monthly average precipitation is depicted in Table 1 for both basins. As can be interpreted from the table, the precipitation amount in the Summer was observed less than other seasons relatively. Additionally, the summer precipitation in this region has occurred in the form of intense short-duration rainfalls.

The Mann–Kendall trend test

The most popular test for the detection of the trend in time series (especially for hydrology and meteorology time series) is the Mann–Kendall (MK) test (Kendall 1957; Mann 1945) which can be defined as a ranked-based non-parametric test (Yue and Wang 2002). In this test for a given time series $P = \{P_1, P_2, \ldots, P_n\}$, the statistics can be defined as:

$$S = \sum_{i<j} \mathrm{sign}(P_j - P_i), \tag{4}$$

in which

$$\mathrm{sign}(P_j - P_i) = \mathrm{sign}(R_j - R_i) = \begin{cases} 1 & \text{for } P_i < P_j \\ 0 & \text{for } P_i = P_j \\ -1 & \text{for } P_i > P_j \end{cases}, \tag{5}$$

where R_i and R_j represent the rank of P_i and P_j observation of the time series in the given order (Hamed 2008). According to Kendall (1957) if it assumed that the data are

Table 1 The 30-year monthly average precipitation in WBS and ET basins in (mm)

Months	January	February	March	April	May	June	July	August	September	October	November	December
ET	51.90	54.20	61.05	65.17	52.67	24.72	8.94	6.73	10.44	38.96	52.54	58.20
WBS	53.99	41.62	44.01	53.67	54.95	46.40	28.02	29.17	29.71	54.83	54.85	63.81

independent and identically distributed, the mean (E) and variance (V) of the S statistic can be calculated as below:

$$E(S) = 0, \tag{5}$$

$$V(S) = \left[n(n-1)(2n+5) - \sum_{p=1}^{g} t_p(t_p-1)(2t_p+5) \right] \frac{1}{18}, \tag{6}$$

where n is the number of data points, g is the number of tied groups—a set of data with the same value—and t_p is the number of data points in the pth group (Hamed 2008). Finally, the significance of the trend in series can be inferred from the comparison of standard normal density of probability, with a given level of significance, and the standardized variable Z which can be obtained as:

$$Z = \begin{cases} (S-1)/\sqrt{V(S)} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ (S+1)/\sqrt{V(S)} & \text{if } S < 0 \end{cases}. \tag{7}$$

The detection of how the trend is increasing or decreasing can be established on the positive or negative values of Z, respectively (Nigussie and Altunkaynak 2018).

Results and discussion

Drought properties

In this study, based on the gridded monthly precipitation values of observations and GCMs, the values of three drought indices (SPI, CZI, and STZS) were calculated. For the evaluation of the drought in a given basin, one has to focus on the properties of the drought, i.e. duration, and intensity of the drought events. First, the calculated values of indices were used for the categorization of the drought, in which the values smaller than − 2 were considered as extremely dry, between − 2 and − 1.50 as severely dry, between − 1.5 and − 1.0 as moderately dry, between − 1.0 and + 1.0 as normal, between 1.0 and 1.50 as moderately wet, between 1.50 and 2.0 as very wet, and more than 2.0 as extremely wet (Jain et al. 2015). In this way, Figs. 3, 4, and 5 present the distribution maps of the number of months during which any type of dryness occurred (the value of the index is less than − 1.0) during the reference (1971–2000) and future periods that were divided into two 30-year periods (2040–2069 and 2070–2099). For the SPI index, the results for all data sets during the reference period were obtained as similar, because the non-parametric approach was used. In the non-parametric SPI, although the calculated index value for every single month was different, the 30-year status of the drought was the same and, for instance, the total number of the months which were extremely dry was equal to 12 in all data series. Accordingly, the results of the SPI index are presented for the future period only.

Figure 3 shows the distribution of the 30-year drought duration based on the values of CZI in the WBS and ET basins. For the reference period, in spite of some biases in the distribution, the total status of the drought duration calculated from the observed and projected data was approximately the same with a maximum of 70–80 months for the WBS basin. The central part of the WBS basin, which is generally covered by urban areas, experienced longer drought periods during the end of the last century. The results of analyses for the future periods are varied from model to model and scenario to scenario. During the mid-time future (2040–2069) it was projected that the duration of drought events will increase from the outputs of GFDL-ESM2M, HadGEM2-ES, and the ensemble mean under RCP4.5 in the same way, whereas of MPI-ESM-MR model will decrease. However, under RCP8.5 in the same period, the duration of the drought will decrease for all GCMs' outputs. On the other hand, for the late future, the increase in the duration of drought will be more evident especially under RCP8.5. This increase will be higher for the outputs of MPI-ESM-MR and the ensemble mean than the others by the end of the century. A similar situation can be interpreted from Figs. 4 and 5 for SPI and STZS indices, respectively. The duration of drought based on the STZS index from the outputs of MPI-ESM-MR for reference period was found to be more than the others; however, as a whole, the other results are very similar to CZI and SPI. In general, in the WBS basin, it is expected that by the end of the twenty-first century there will be longer drought periods over the basin. Additionally, there is no evident relationship between the geographical situation and drought duration in the basin as the highest parts of the basin have an elevation of about 2500 m from the sea surface.

For the ET basin, the distribution of drought duration was found to be more non-uniform in accord with the spatial variations as it is depicted in Figs. 3, 4, and 5 for CZI, SPI, and STZS indices, respectively. Based on the analyses of the observed data, in which non-uniform situation is more significant than of GCMs', in the middle parts of the basin the duration of drought is more sensible than the other parts with high elevation. According to the results obtained for CZI and STZS indices, during the reference period, the drought duration from modeled data was relatively less than of observed data. For the future period, the holistic results seem like the results for the WBS basin, but more intense. Based on the outputs of all GCMs, an increase is expected in the drought duration during the mid-time and late future periods, where the increase will be stronger under the RCP4.5 scenario than under the RCP8.5 scenario. There is only one exception, in which, the outputs of GFDL-ESM2M under RCP4.5 for the

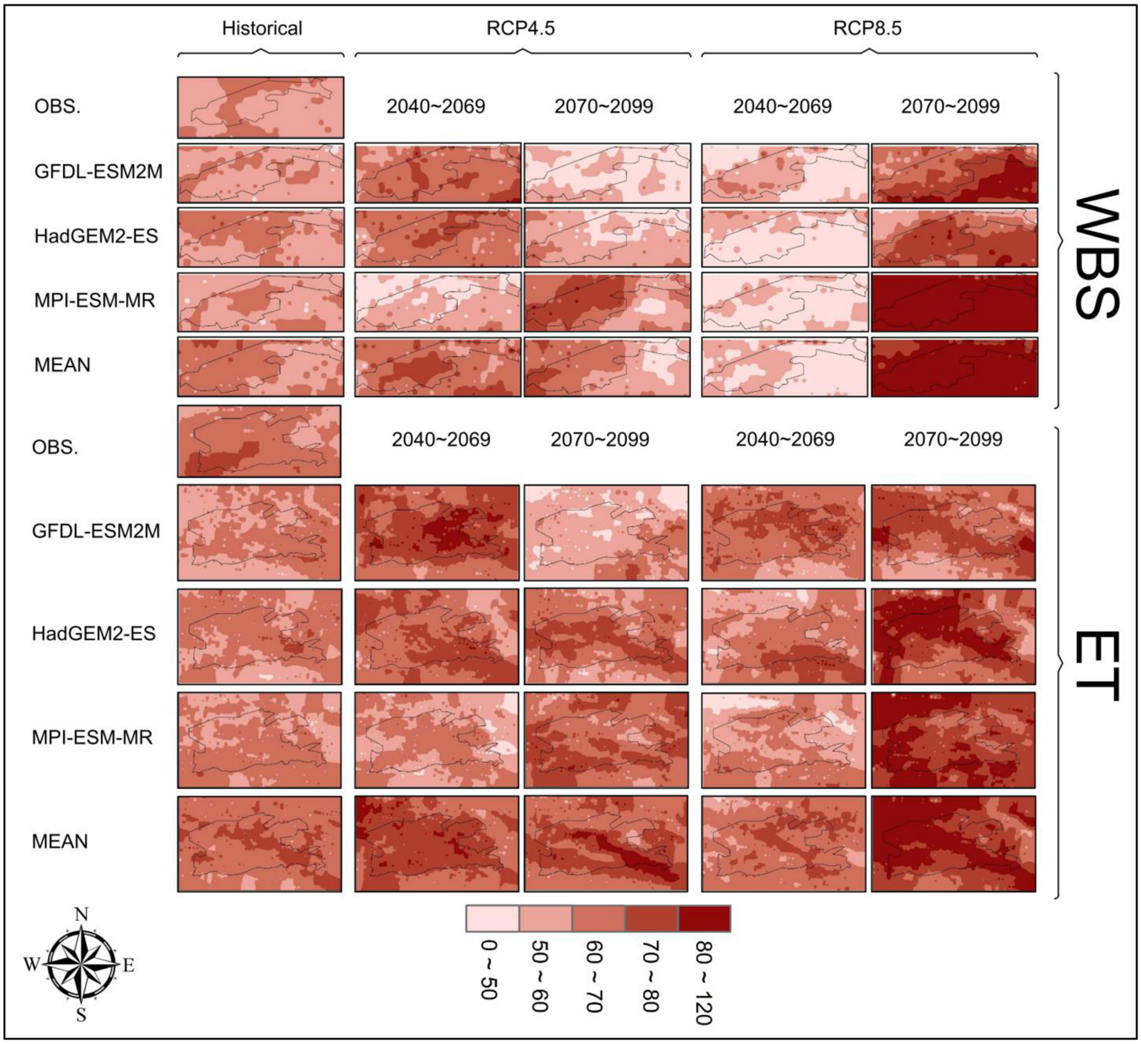

Fig. 3 The distribution maps of drought duration (months) over the WBS and ET basins based on the calculated CZI index from the projected and observed data

late future show a decrease when compared to the reference period.

Table 2 presents the number of months in which any type of dryness occurred (average of the basin) for the reference and future periods during a 30-year period. For CZI and STZS indices which is possible to make a comparison between the results of the models and observations, it can be interpreted that there is no certain relationship between the results of observed data and various GCMs' outputs. However, in general, there is a reliable agreement between them. According to the projected results, especially during the mid-time future, a decline is expected in both basins, while during the late future the values will increase. On average of three indices, for mid-time future, the number of months which was projected to be extremely dry, severely dry, and moderately dry, will be 3.89, 13.15 and 36.34, respectively over the WBS basin. With the same order, those values will be 8.71, 19.10, and 38.97 for the late future which implies that the late future will be drier. For the ET basin, the agreement between projected and observed values is more satisfying than of the WBS basin during the reference period. In this basin, on average, it was projected that the number of extremely dry, severely dry, and moderately dry months will be 3.77, 14.82, and 44.15, respectively, for the mid-time future and 5.76, 16.76 and 45.47 for the late future in the same order. As a whole, the number of dry months considering the SPI index will be more than CZI and STZS indices which have approximately the same values.

Trend detection

Figure 6 presents the spatial variation of trends during the reference and future periods. The trend detection was based on the Mann–Kendall trend test and the obtained values were

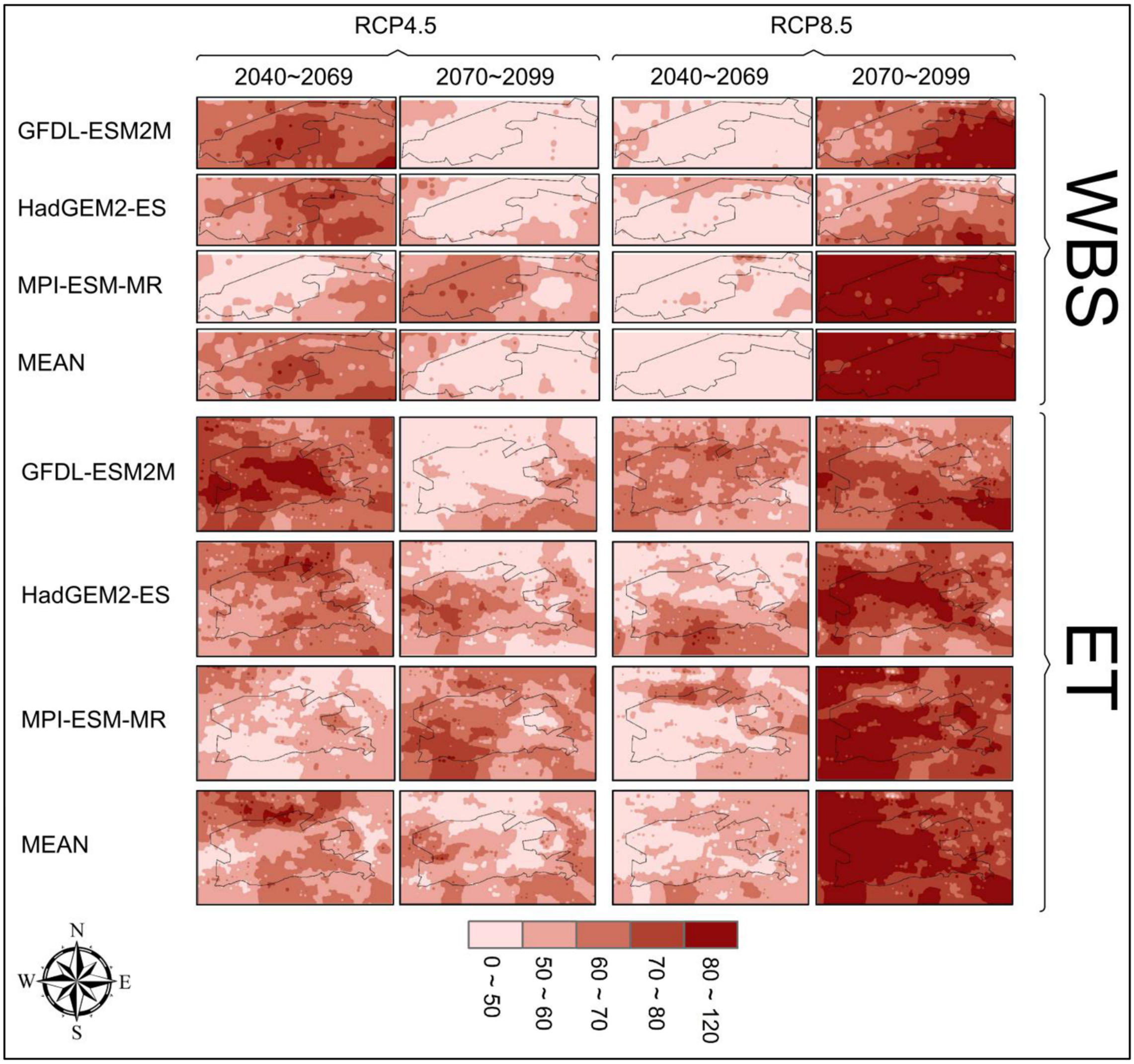

Fig. 4 The distribution maps of drought duration (months) over the WBS and ET basins based on the calculated SPI index from the projected data

divided into four groups by considering the level of significance as 0.05 with the critical value of ± 1.96. Those groups are significant decreasing trend (SDT) for the values less than − 1.96, non-significant decreasing trend (NDT) for the values between − 1.96 and 0.0, non-significant increasing trend (NIT) for values between 0.0 and 1.96, and significant increasing trend (SIT) for the values greater than 1.96. In the figure, the increasing trend means a decrease in drought and vice versa. In the WBS basin during the reference period, the trend was found to be increasing in the majority of the basin, whereas in the ET basin the trend was dominantly decreasing especially in high parts of the basin. In addition, the borderline in the south of the basin experienced a decreasing trend; however, the trend was not significant. For the future period, there is no meaningful variation between the trend patterns of different indices over both basins. Over the WBS basin, the trend was dominantly projected as positive, under the RCP4.5 scenario during the mid-time and late future. However, based on the outputs of MPI-ESM-MR model under the RCP4.5, the trend in lowlands (coastal line) will be negative. On the other hand, under RCP8.5 scenario, there will be a strong negative trend based on the outputs of MPI-ESM-MR and the ensemble mean, over the whole WBS basin, while of HadGEM2-ES and GFDL-ESM2M, the trends were found to be positive dominantly. For the ET basin, there will be a different situation during the coming years in terms of the trend in drought indices. As can be interpreted from Fig. 6, the negative trend is expected for the majority of the basin particularly under the RCP4.5 scenario. Under the RCP4.5, also, except for GFDL-ESM2M model, the other results showed that the negative trend will be preponderance.

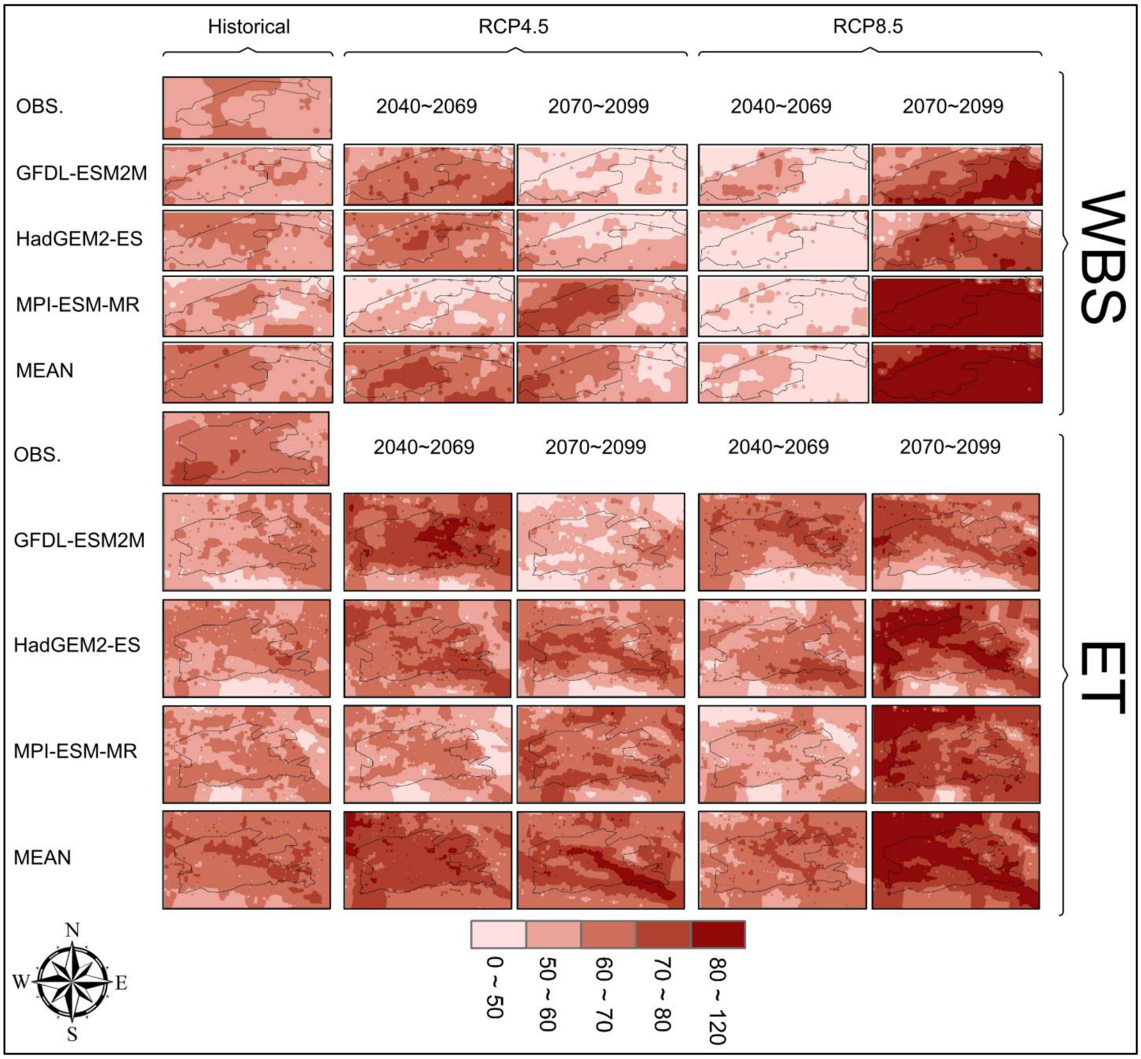

Fig. 5 The distribution maps of drought duration (months) over the WBS and ET basins based on the calculated STZS index from the projected and observed data

In general, the results of the study suggested that the coming years will be drier and this dryness will increase from year to year. Moreover, based on the graphical results, the effects of geographical features on the drought properties can be neglectable and all parts of the basins will experience some types of drought. Additionally, using three drought indices was helpful in the investigation of the performance of the different drought indices. However, as it can be deduced from the results of the study, there is no significant difference between indices in terms of classifying the drought situation. The same status was concluded by Jain et al. (2015), where the authors stated that there was a satisfying correlation between various indices in the same time step.

Summary and conclusion

In this study, the spatio-temporal variations in the future condition of two different types of basins in Turkey in terms of drought properties were investigated using the outputs of three GCMs (GFDL-ESM2M, HadGEM2-ES, MPI-ESM-MR, and ensemble mean of them) under RCP4.5 and RCP8.5 scenarios. The biases in the outputs of the GCMs were corrected using the linear scaling method, with respect to the high-resolution gridded precipitation data of APHRODITE in the reference period. Future analyses of drought were established in two 30-year period as mid-time (2040–2069) and late (2070–2099) future

Table 2 The average number of months with different types of dryness over WBS and ET basins

Dataset	Period	WBS									ET								
		CZI			SPI			STZS			CZI			SPI			STZS		
		ExD	SeD	MoD	ExD	SeD	MoD	ExD	SeD	MoD	ExD	SeD	MoD	ExD	SeD	MoD	ExD	SeD	MoD
APHRODITE	1971–2000	7.27	17.73	33.33	–	–	–	5.47	17.33	35.39	3.40	18.97	42.09	–	–	–	2.09	13.86	47.44
GFDL-ESM2M	1971–2000	7.11	15.67	35.02	–	–	–	3.35	14.15	39.33	2.85	15.64	42.57	–	–	–	1.11	9.18	48.33
HadGEM2-ES	1971–2000	5.25	17.22	38.14	–	–	–	2.44	14.08	43.07	2.60	17.28	42.57	–	–	–	1.09	10.37	48.87
MPI-EMS-MR	1971–2000	7.48	16.39	33.89	–	–	–	2.86	14.31	38.68	3.80	17.87	40.03	–	–	–	1.43	10.82	47.10
Mean	1971–2000	5.16	18.76	38.49	–	–	–	3.14	17.66	41.28	1.47	17.41	48.21	–	–	–	0.64	12.31	53.58
GFDL-ESM2M RCP4.5	2040–2069	6.86	19.72	39.25	9.12	17.27	42.58	2.04	16.31	45.41	2.39	20.63	50.04	10.15	17.07	44.20	0.74	11.61	58.29
	2070–2099	5.21	12.55	30.27	7.21	9.95	24.80	1.92	10.44	34.23	1.94	15.45	38.34	7.96	12.23	28.06	0.44	8.82	44.26
HadGEM2-ES RCP4.5	2040–2069	5.95	20.20	39.11	8.79	16.34	39.19	1.08	16.32	45.79	2.71	21.84	43.51	10.75	15.66	37.11	1.25	14.43	50.78
	2070–2099	6.17	15.19	33.02	10.06	10.61	25.74	1.55	12.96	38.14	2.88	18.81	44.20	8.76	13.04	32.90	1.53	12.31	50.56
MPI-EMS-MR RCP4.5	2040–2069	5.74	14.15	31.99	7.27	12.46	30.98	1.43	10.32	37.53	2.74	17.69	39.21	8.27	12.13	31.26	1.09	10.65	45.95
	2070–2099	9.03	19.12	36.68	10.58	14.55	34.17	2.48	15.86	43.87	4.01	19.82	44.30	10.93	14.84	36.84	1.93	12.00	52.18
Mean-RCP4.5	2040–2069	4.01	19.54	42.80	9.58	15.99	38.35	2.33	17.47	46.24	1.61	21.48	49.54	10.25	14.28	35.68	0.94	17.60	53.81
	2070–2099	5.69	18.83	35.53	7.31	10.93	28.74	3.72	17.47	38.47	2.02	18.20	50.73	8.85	13.54	31.70	1.44	14.89	54.31
GFDL-ESM2M RCP8.5	2040–2069	3.45	12.61	33.29	4.18	8.56	29.47	0.86	10.09	37.23	1.60	20.58	44.76	9.74	15.08	35.26	0.35	10.80	52.33
	2070–2099	12.47	22.86	37.46	14.54	18.70	38.23	5.50	22.32	43.58	2.91	18.92	46.35	12.77	16.81	39.54	1.08	10.77	52.39
HadGEM2-ES RCP8.5	2040–2069	2.54	13.42	32.54	4.04	10.93	30.65	0.44	9.12	37.18	1.39	14.81	47.14	5.74	12.52	36.07	0.19	7.68	53.13
	2070–2099	8.38	21.81	38.44	15.03	14.37	32.03	2.97	18.93	45.13	4.41	23.73	47.12	16.56	18.47	37.61	1.22	15.91	55.97
MPI-EMS-MR RCP8.5	2040–2069	2.17	12.68	32.16	7.18	10.14	25.35	0.33	8.37	36.27	3.12	16.86	38.79	7.57	12.12	31.28	0.88	8.99	46.49
	2070–2099	16.34	33.00	45.76	14.34	21.89	51.83	4.99	32.14	55.72	6.55	23.17	48.85	14.24	19.85	44.53	2.47	14.45	58.44
Mean-RCP8.5	2040–2069	0.64	9.33	36.83	2.93	6.48	23.66	0.34	7.85	38.29	0.56	17.29	48.27	6.23	11.88	33.50	0.24	11.99	53.26
	2070–2099	13.73	30.13	45.51	19.25	24.00	49.48	10.65	29.96	48.41	4.44	25.63	50.32	16.01	19.89	45.71	2.89	20.67	56.06

Exd extremely dry, *SeD* severely dry, *MoD* moderately dry

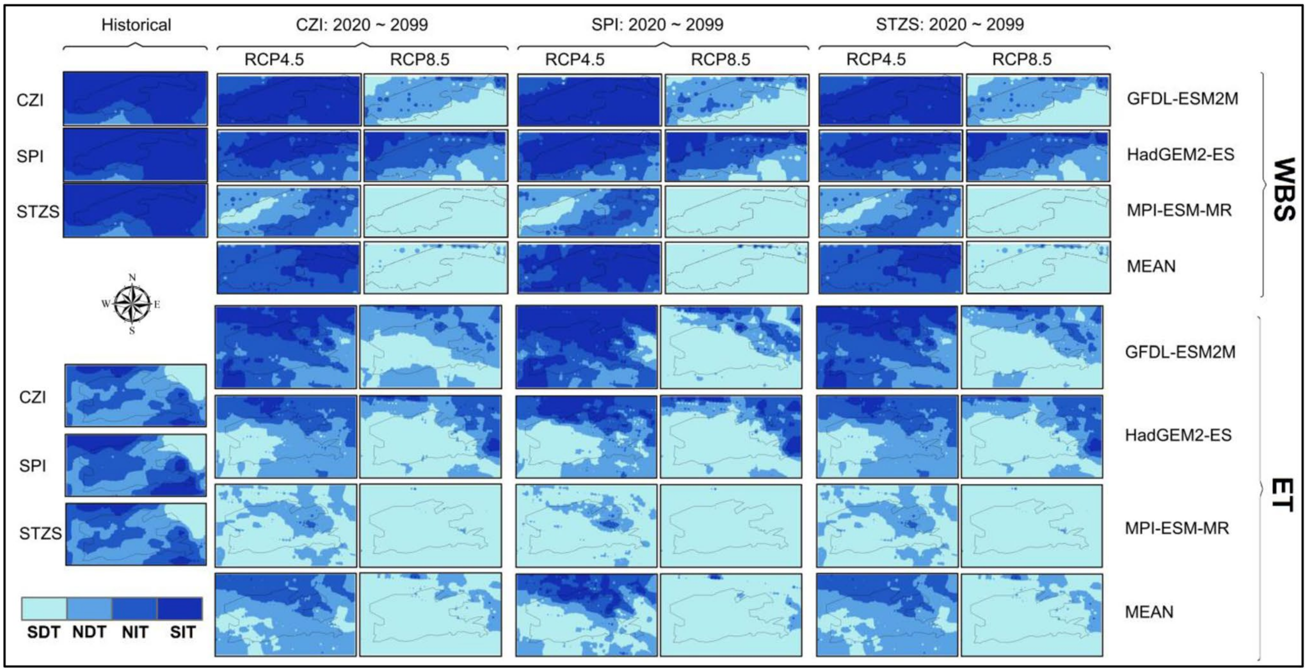

Fig. 6 The distribution maps of trend test in drought indices over the WBS and ET basins. In the maps SDT: significant decreasing trend (for the values less than − 1.96), NDT: non-significant decreasing trend (for the values between − 1.96 and 0.0), NIT: non-significant increasing trend (for values between 0.0 and 1.96), and SIT: significant increasing trend (for values greater than 1.96)

periods. Three drought indices (SPI, CZI, and STZS) were adapted to the precipitation data of the WBS and the ET River basins. The results of the study showed that during the coming years, the duration and intensity of the drought events will increase, and this increase will be more sensible under the RCP8.5 scenario over both basins. On the other hand, the effects of the terrestrial features of the basin on the drought properties were found to be negligible. Furthermore, the trend in the drought indices was evaluated using the Mann–Kendall trend test. Trend test results also showed that in spite of positive trend in the values of drought indices during the reference period, these values will decrease during the coming years and it is excepted that the duration and intensity of the drought will increase by time. Finally, there is no meaningful bias between the results of different drought indices and all three indices figured the same spatial and temporal situation of drought over the basins.

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