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Research papers

An enhanced water storage deficit index (EWSDI) for drought detection using GRACE gravity estimates

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ABSTRACT

Accurate detection and monitoring of drought events are important particularly in arid and semi-arid regions of the world. Gravity Recovery and Climate Experiment (GRACE) gravity estimates have been used widely for this purpose and a number of indices have been developed using the GRACE Terrestrial Water Storage Anomalies (TWSA) values. In the current study, a new approach is proposed to enhance the performance of the GRACE-based Water Storage Deficit Index (WSDI). The proposed Enhanced Water Storage Deficit Index (EWSDI) was developed based on the grid-based standardization of the Water Storage Deficit (WSD) values. The decomposed time series of the TWSA were computed in an attempt to evaluate the performance of the approach based on different components of the TWSA time series. Standardized Precipitation Index (SPI) and modelled Soil Moisture Storage (SMS) were also used to validate the functionality of this new GRACE-derived index. The applicability of the EWSDI index was tested in the semi-arid climatic conditions of Turkey and the results showed that the detrended EWSDI better correlated with SPI-09 and annual SPI with correlation coefficient values of 0.70 and 0.76, respectively. The findings also suggested an approximate enhancement of 13% over the existing WSDI when applied on the detrended TWSA. The findings of this study reveal that the proposed approach is effective in improving the performance of the existing WSDI to detect drought events in terms of monthly and annual correlation coefficients achieved.

1. Introduction

Water plays a critical role in the existence and continuation of human and wildlife. The amount of water stored in surface and subsurface water resources demonstrates a highly variable pattern in time and space domains. In particular, climate change and increasing water use have amplified the already existing unequal distribution of water on the planet (Khorrami and Gunduz, 2019a). Droughts are among the consequences of this phenomenon that result in severe implications associated with a net water deficit between the available water and water requirements (Khorrami and Gunduz, 2021). Particularly in arid areas, drought occurrence and water deficit are interconnected such that higher water deficiency can intensify the severity of a drought event and vice versa (Dharpure et al., 2020). Today, it is typically accepted that the losses resulting from drought events overweight those of any other natural disasters in terms of socio-economic and environmental costs (Hagman, 1984; Wilhite, 2000; Sinha et al., 2019; Dharpure et al., 2020). Water scarcity is expected to influence about half the population of the world by 2030 endangering the lives of almost 700 million people (Dharpure et al., 2020). The destructive impacts of droughts are projected to be amplified with the current ascending trends of climate change and population growth (Gerdener et al., 2020). Therefore, accurate drought detection and monitoring are becoming more vital especially in regions with arid and semi-arid climates.

Gravity Recovery and Climate Experiment (GRACE) administrated by the National Aeronautics and Space Administration (NASA) and the German Aerospace Centre (GeoForschungsZentrum) (Wu et al., 2021) is one of the recent achievements in the remote sensing field. The GRACE mission consists of two twin satellites orbiting the Earth with an estimated distance of 270 km to collect the variations in the Earth's gravitational field (Khorrami and Gunduz, 2021). Since the gravity variations

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Nomenclature

Abbreviation	Full name
CLM	The Community Land Model
CLSM	Catchment Land Surface Model
CSR	The Centre for Space Research
EWSDI	Enhanced Water Storage Deficit Index
GLDAS	Global Land Data Assimilation System
GRACE	Gravity Recovery and Climate Experiment
LSM	Land Surface Model
MAD	Mean absolute deviation
MAPE	Mean Absolute Percentage Error
MAP	Mean Annual Precipitation
MAET	Mean Annual Evapotranspiration
MSD	Mean Squared Deviation
SMSA	Soil Moisture Storage Anomalies
SPI	Standardized Precipitation Index
SWEA	Snow Water Equivalent Anomalies
TSMS	Turkish State Meteorological Service
TWSA	Terrestrial Water Storage Anomalies
VIC	Variable Infiltration Capacity
WSDI	Water Storage Deficit Index

are mainly ascribed to the mass movements of water beneath the Earth's surface, GRACE signals are translated into the Terrestrial/Total Water Storage Anomalies (TWSA) (Hu et al., 2019). GRACE is the first remote sensing satellite mission offering the estimations of groundwater storage changes (Frappart and Ramillien, 2018; Tapley et al., 2019; Vishwakarma, 2020) as well as TWSA. GRACE-based TWSA is a composite value of different water cycle compartments including surface water, ice and snow water, soil moisture content, groundwater, and water contained in biomass (Wu et al., 2021) representing all water storage of the planet thus acting as a potent alternative for hydrological information (Rodell and Famiglietti, 2001; Rodell et al., 2009). Therefore, numerous researches report the use of GRACE data for investigating drought events including but not limited to Ramillien et al. (2008), Houborg et al. (2012), Long et al. (2013), Vishwakarma et al. (2013), Thomas et al. (2014), Forootan et al. (2019), Kvas et al. (2019) and Liu et al. (2020).

Several drought indices based on GRACE TWSA estimates have so far been introduced and developed in attempts to evaluate and improve the performance of drought assessments. Yirdaw et al. (2008) proposed a Total Storage Deficit Index (TSDI) using the TWSA values of GRACE by adopting the Palmer Drought Severity Index (PDSI) and Soil Moisture Deficit Index (SMDI). Thomas et al. (2014) developed a Water Storage Deficit (WSD) approach. They defined the WSD as the deviations of GRACE TWSA time series from climatology TWSA values where negative values depict water storage deficits. Sinha et al. (2017) developed Thomas's method into water storage deficit index (WSDI) based on the standardization of the WSD time series. Yi and Wen (2016) suggested a GRACE-based hydrological drought index (GHDI). They used the traditional Palmer Hydrological Drought Index (PHDI) principles for developing a new GRACE-based drought index. Zhao et al. (2017) introduced a GRACE-drought severity index (GDSI) using the regional variability of GRACE TWSA. Hosseini-Moghari et al. (2019) developed a modified total storage deficit index (MTSDI) using residual time series of TWSA to remove the anthropogenic impacts on TWSA variations. Sinha et al. (2019) proposed a new combined climatologic deviation index (CCDI) by integrating the precipitation anomalies into GRACE TWSA.

Being located in one of the arid belts of the world, Turkey has experienced some dramatic drought events especially in its recent history posing critical problems to the country. Taking the geographic location of Turkey as well as its rapid development and the impacts of climate change into account, it is projected that the country will face serious challenges regarding water availability in the future (Harmancioglu and Altinbilek, 2020). Therefore, monitoring and mitigation of drought are of predominant priority for the country.

In general, drought indicators have a very important role in detecting, monitoring and characterizing drought conditions therefore are helpful to determine the best way to take prompt and apt measures in order to mitigate their harsh impacts (Steinemann and Cavalcanti, 2006). Each drought index developed based on GRACE TWSA estimations has its own pros and cons regarding the used approach and consequently their ability in detecting drought events. On the other hand, drought detection is a formidable task, which not only necessitates

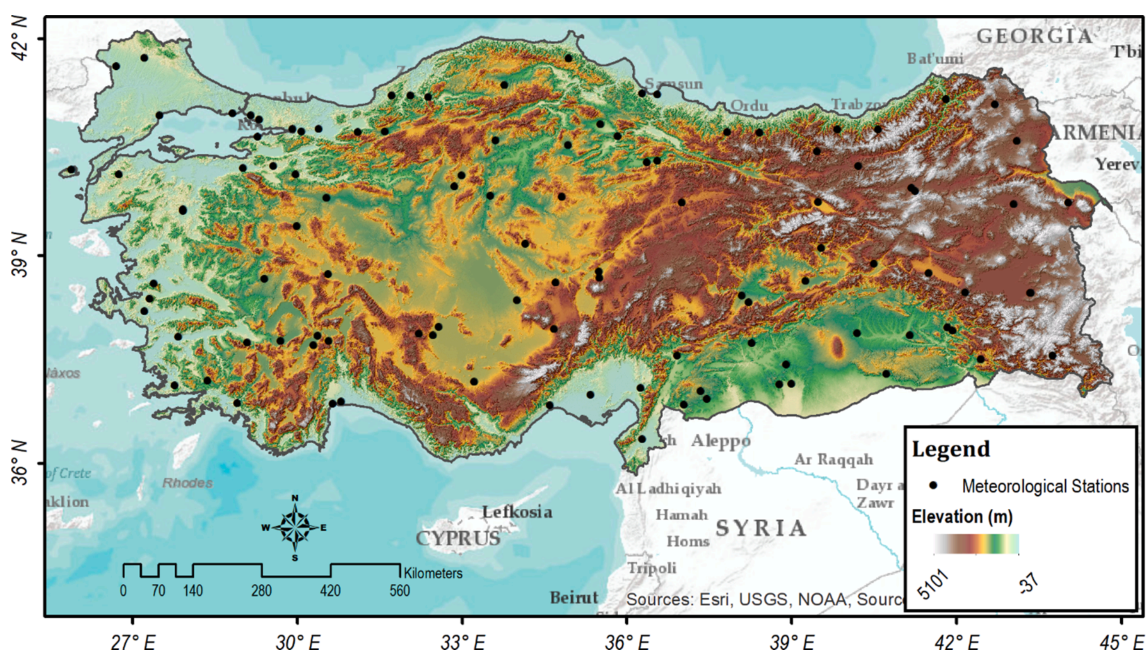

Fig. 1. Geographic location of Turkey and the distribution of the meteorological stations

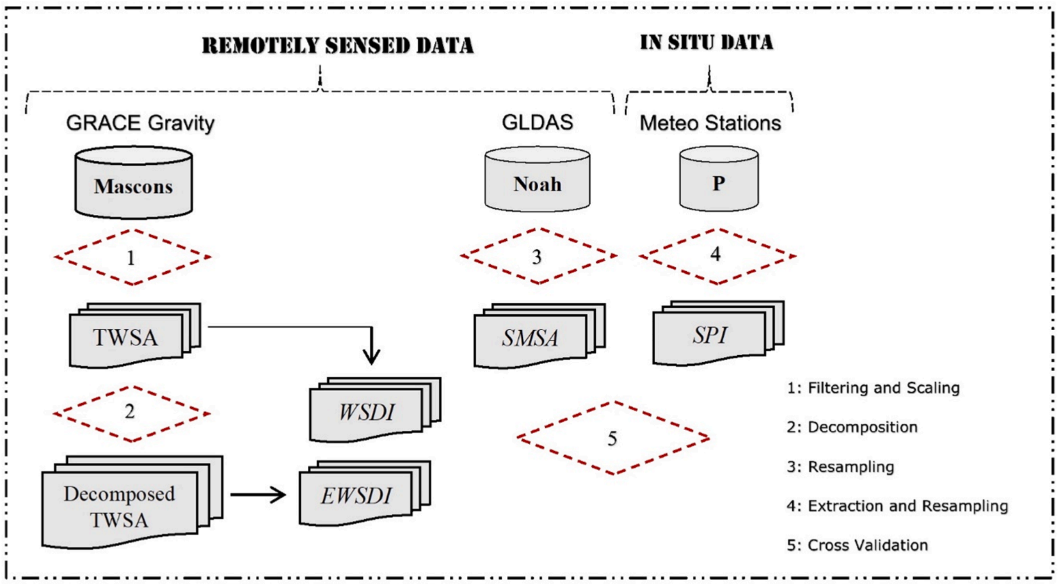

Fig. 2. The schematic flowchart of the study

the development of new indices but also advances on improving the performance of the current indices. Moreover, the decomposition of GRACE TWSA values into individual components can improve GRACE-based drought characterization applications (Andrew et al., 2017). Any enhancement of the spectral indices can provide better characterization and detection of the environmental phenomena, which is deemed important for better monitoring and taking opt measures to manage and mitigate the harsh impacts ascribed to such events. Within the scope of the current study, the authors introduced an enhanced water storage deficit index (EWSDI) for the assessment of the recent droughts over Turkey. The currently available GRACE-based WSDI and the newly proposed EWSDI were investigated together to test the performance and feasibility of the proposed approach. The authors also utilized the decomposed TWSA time series to evaluate the performance of the known WSDI and its enhanced form in drought detection.

2. Methodology

2.1. Data description

2.1.1. GRACE data

GRACE data are processed and offered by three main processing centres: The Centre for Space Research at University of Texas, Austin (CSR), GeoforschungsZentrum Potsdam (GFZ), and the Jet Propulsion Laboratory (JPL) (Jing et al., 2019). GRACE solutions are offered in two forms: the standard Spherical Harmonics (SH) and Mass Concentrations (Masscons). The latter has undergone some post-processing such as filtering and scaling offered by Landerer and Swenson (2012) to diminish the noises by mitigating the signal attenuation and leakage errors and consequently augment the accuracy of the estimations (Xu et al., 2019). Moreover, unlike the SH solutions with a 1-degree resolution, the spatial resolution of Masscons is half a degree. These improvements have led to more demand for Masscons data. In this study, the monthly and the long-term monthly averages (climatology values) of TWSA estimates from the latest release of GRACE TWSA Masscons (2003 to 2016) processed by the JPL centre were received from NASA's webpage (https://earth.gsfc.nasa.gov/geo/data/grace-mascons). There are some missing data in the time series of GRACE TWSA due to repeat-orbit constellations (Jensen et al., 2020), which were reconstructed by the Linear Interpolation (LI) method (Long et al., 2015; Yang et al., 2017).

2.1.2. Soil moisture and precipitation data

To validate the results of the analysis, soil moisture estimates from the remote sensing dataset and field observations of precipitation were used. The Turkish State Meteorological Service (TSMS), the administrative organization of the meteorological network of Turkey, provided this study with the monthly precipitation data observed in 107 meteorological stations distributed almost homogenously over the country (Fig. 1).

Soil moisture deficit seriously influences agriculture and water supply (Wang et al., 2011) so its variations can be used as a drought indicator. Unfortunately, in-situ soil moisture data are not available except for some specific areas of the world (Robock et al. 2000). Moreover, the observed data are limited in space and time, which curtails the application of soil moisture observations in drought analysis. Due to the unavailability of field-based observations of soil moisture over the study area, the authors opted for remotely sensed data and used soil moisture values modelled under Noah Land Surface Model (LSM) offered by the Global Land Data Assimilation System (GLDAS) mission. The observed point-wise precipitation data were used to calculate the Standardized Precipitation Index (SPI) values. The SPI values were then interpolated using the Kriging technique to generate SPI surfaces of the study area. To draw a logical analogy, the soil moisture anomaly and SPI layers were resampled by using the bilinear resampling technique so that they conform to the 0.5-degree resolution of GRACE data. In Fig. 2, the methodological flowchart of the study is given in brief.

2.2. Study area

Turkey is located between the latitudes 36°N and 42°N and longitudes 26 °E and 45°E (Fig. 1). It is one of the countries in the Middle East that face numerous challenges regarding its water resources. Hydro-climatic variables over the country are highly dissimilar (Harmancioglu and Altinbilek, 2020) because of the diversity of the dominant climate in different regions of Turkey posing a potential threat to its water accessibility.

According to Apaydin (2011), Turkey's dominant climate is of semi-arid type. However, the vast diversity in the topography of the country alongside the deep geographic discrepancies among different regions render the climatic situation very disharmonious over the geographic regions of Turkey. Thus, the coastal regions of the country have milder climates while the central parts suffer from hot summer and cold winter conditions (Sensoy et al., 2008). The Mean Annual Precipitation (MAP)

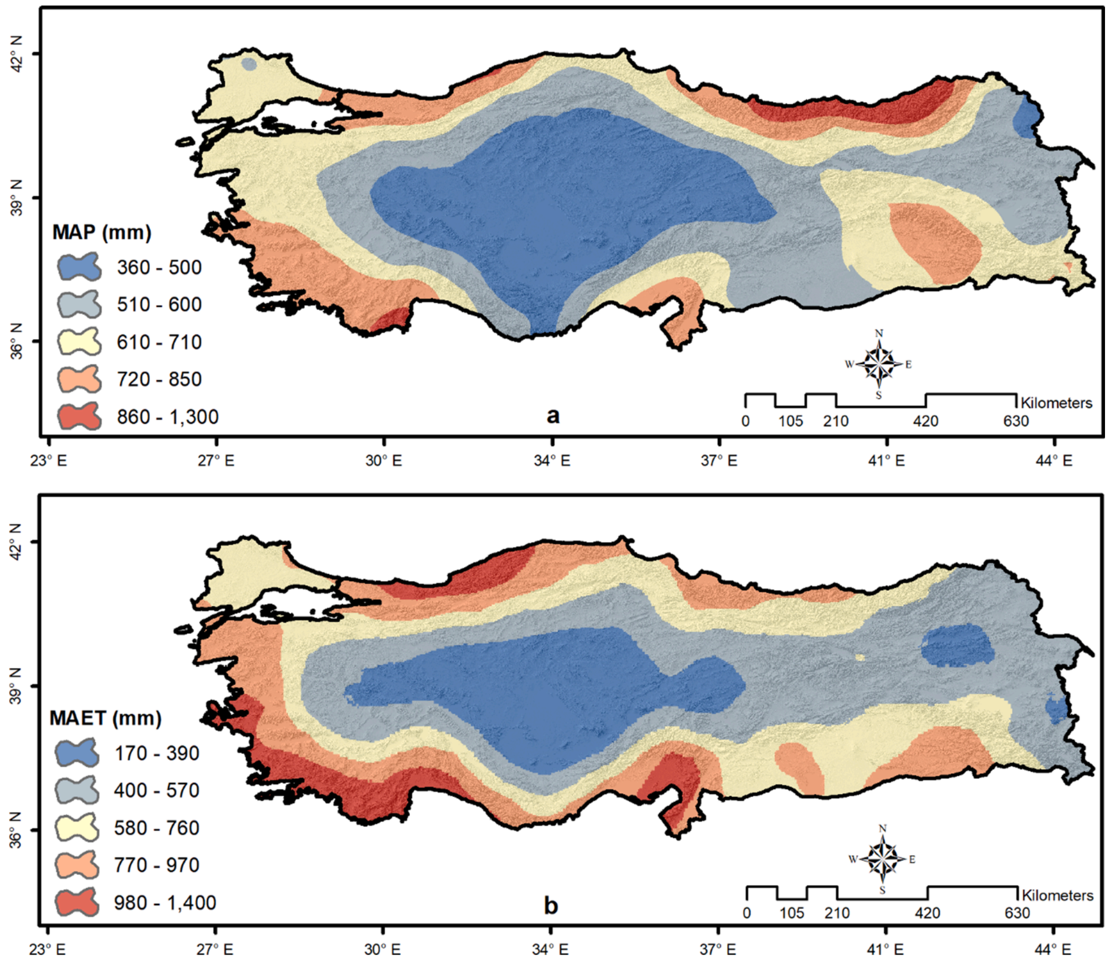

Fig. 3. The spatial distribution of the mean annual precipitation (a) and mean annual evapotranspiration (b) over Turkey.

of Turkey is 391.9 mm (MGM, 2020) where the highest and lowest amounts of precipitation fall in the North-eastern Black Sea and Central Anatolia regions, respectively (Aksoy, 2020). The long-term climatic situation of Turkey regarding the MAP and mean annual evapotranspiration (MAET) is shown in Fig. 3. For the MAET map of the study area, the modelled evapotranspiration values were extracted from the actual evapotranspiration estimations dataset offered by the MODIS mission, which produced the ET values based on the operational Simplified Surface Energy Balance (SSEBop) model (Senay et al., 2013). Precipitation map was generated using the co-kriging interpolation technique (Khorrami and Gunduz, 2019b) where the surface elevation layer was incorporated into the interpolation process as an auxiliary variable to obtain a more realistic portrayal of the spatial distribution of precipitation values over Turkey.

The current climate variability and the outlook of the country's climatic condition introduce a moderate to high climate risk to Turkey (Turkes, 2020). The country has experienced severe drought events over the last four decades between 1971 and 1974, 1983–1984, 1989–1990, 1996–2001, 2007–2008, and in 2014 (Kurnaz, 2014; Okay Ahi and Jin,2019; Khorrami and Gunduz, 2021).

2.3. Temporal decomposition of GRACE signals

The decomposition of GRACE signals is a common practice that has been done for a variety of purposes including disintegrating TWSA components, extracting spatio-temporal patterns of GRACE signals and isolating the time series components (Humphrey et al., 2016). The latter is generally used to infer the relative importance and impact of the time series components on the temporal variability of GRACE TWSA (Barletta et al., 2012; Frappart et al., 2013).

Temporal decomposition of time series into its compartments is a key procedure for the statistical analysis of data, by which trends and seasonal patterns are revealed (Dokumentov and Hyndman, 2020). There are a number of techniques to decompose time series (Dokumentov and Hyndman, 2020), which traditionally fall into two main categories: i) additive and ii) multiplicative decomposition models (Pollock, 1993). Eqs. (1) and (2) define these two models, respectively:

$$Y_t = S_t + T_t + R_t \tag{1}$$

$$Y_t = S_t \times T_t \times R_t \tag{2}$$

where. Y_t represents original time series data and S_t,T_t and R_t denote the seasonal cycle, long-term trend and sub-seasonal residual components of the corresponding time series, respectively (Adenomon and Ojehomon, 2014; Humphrey et al., 2016). Detailed information on time series decomposition can be found in Falk (2006), Kirchgässner and Wolters (2007) and Cryer and Chen (2008).

To make a decision on which model to use, one can apply statistical analysis to evaluate the precision of each model. In this study, the authors utilized Minitab software (https://www.minitab.com) to compare the two available models based on three commonly used accuracy assessment parameters: Mean absolute deviation (MAD), Mean Absolute Percentage Error (MAPE), and Mean Squared Deviation (MSD) (Karmaker et al., 2017). These parameters are defined in Eqs. (3)–(5), respectively.

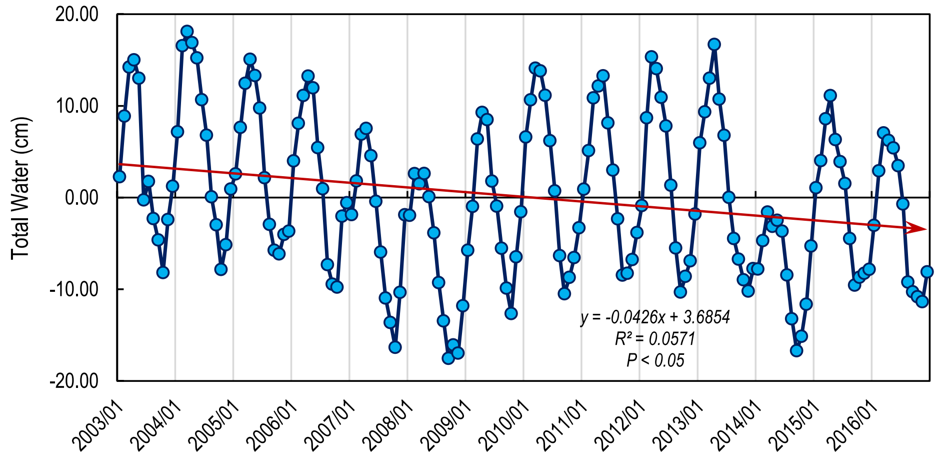

Fig. 4. Temporal fluctuations of the original TWSA over Turkey

Table 1
Accuracy assessment of decomposition models: The accuracy of the used models was tested based on three accuracy metrics: Mean absolute deviation (MAD), Mean Absolute Percentage Error (MAPE), and Mean Squared Deviation (MSD).

Decomposition Model	Accuracy parameter		
	MAPE	MAD	MSD
Additive	378.8	3.25	17.34
Multiplicative	316.8	4.63	3.06

Table 2
The seasonal factors of TWSA derived for each month. Seasonal factor values indicate the seasonal impact on the time series and later are used to de-season the TWSA time series.

Month	Seasonal Factor	Month	Seasonal Factor
Jan	1.54	**Jul**	0.89
Feb	2.57	**Aug**	-1.08
Mar	3.61	**Sep**	-1.36
Apr	3.32	**Oct**	-2.28
May	3.04	**Nov**	-0.65
Jun	2.17	**Dec**	0.30

$$MAD = \frac{\sum_{i=1}^{n} |e_t|}{n} \quad (3)$$

$$MAPE = \frac{\sum_{i=1}^{n} \left|\frac{e_t}{x_t}\right|}{n} \times 100 \quad (4)$$

$$MSD = \frac{\sum_{i=1}^{n} |e_t|^2}{n} \quad (5)$$

where e, x and n represent the deviation of actual from the predicted time series values, actual values and the number of data points, respectively. In general, the lower the parameter, the better the fit of the model (Cooray, 2008).

2.4. Enhanced water Storage Deficit index (EWSDI)

Water Storage Deficit (WSD) expresses the water surplus or deficit in terms of deviations of monthly TWSA values from monthly climatology values (Wang et al., 2020). The standardization of WSD yields WSDI as shown in Eqs. (6) and (7).

$$WSD_{ij} = TWSA_{ij} - \overline{TWSA}_j \quad (6)$$

$$WSDI = \frac{WSD - \mu}{\sigma} \quad (7)$$

where, $TWSA_{ij}$ defines the value of TWSA for the month j of the year i. The climatology value of each month is given by $\overline{TWSA}_j$. μ and σ denote the mean and standard deviation of the WSD time series,

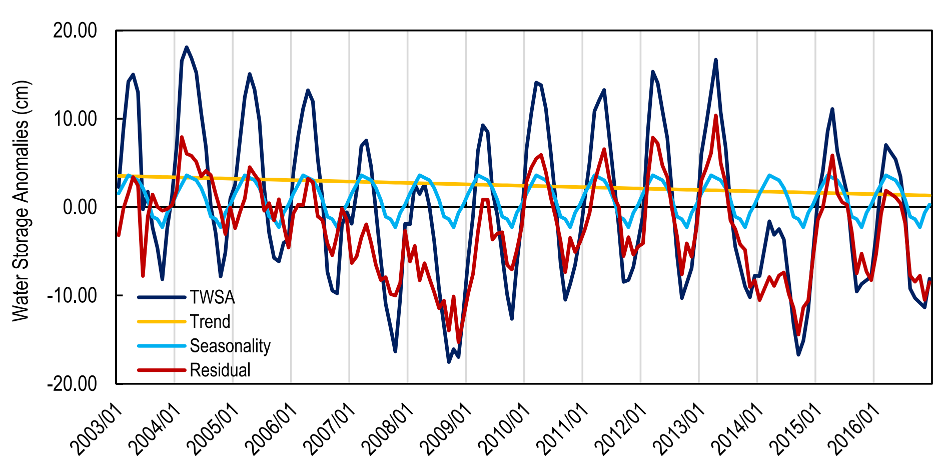

Fig. 5. The decomposed elements of TWSA

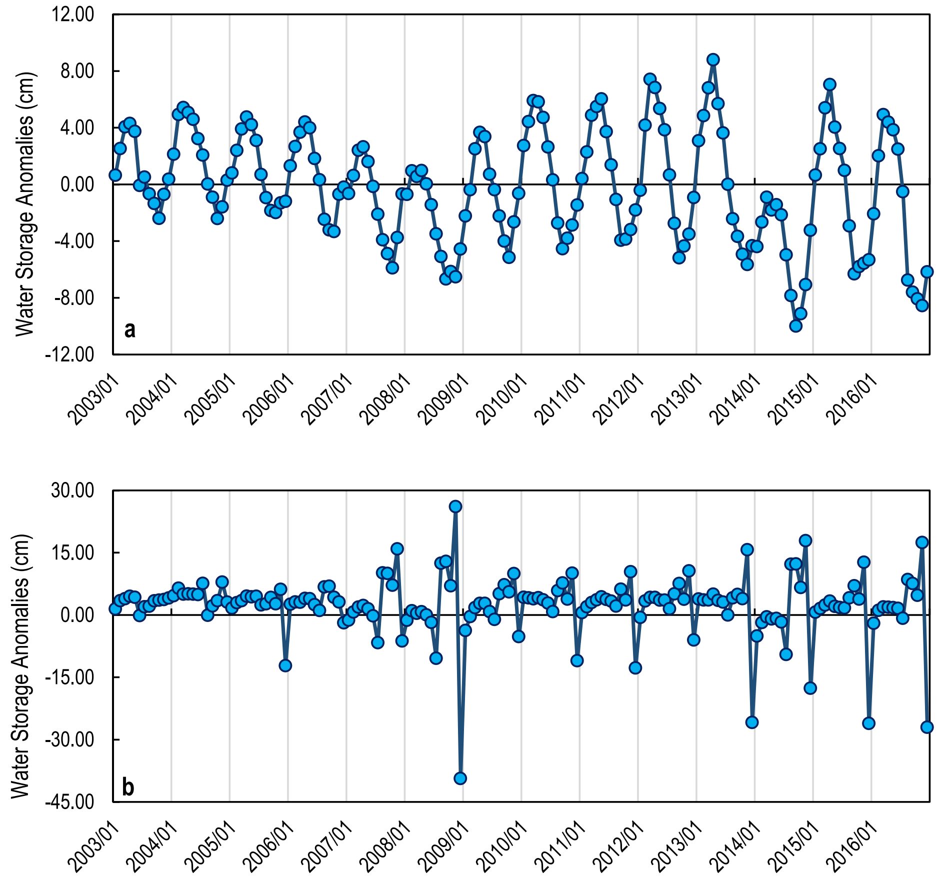

Fig. 6. Time series of decomposed TWSA values: de-trended TWSA (a) and de-seasoned TWSA (b)

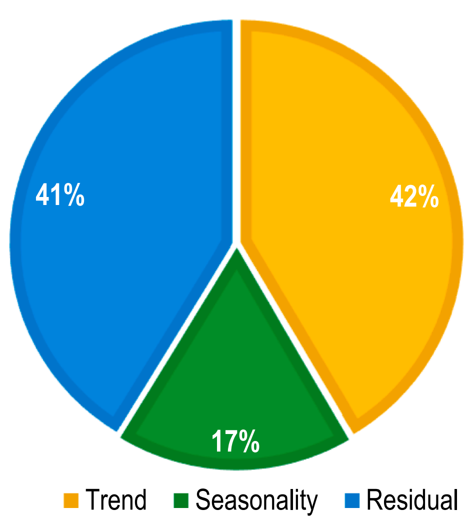

Fig. 7. The contribution of each individual component of the decomposed TWSA to the total variance of the time series

respectively.

As mentioned in Eq. (7), WSDI is computed using the mean and standard deviation of the time series of WSD. In this study, the authors applied a new grid-based approach and used those mean and standard deviation values extracted for each raster layer of each i and j. In this way, the index for each month is generated based on the raster-derived mean and standard deviation. Thus, the proposed Enhanced Water Storage Index (EWSDI) is defined as follow:

$$EWSDI_{ij} = \frac{WSD_{ij} - \left|\overline{X}_{ij}\right|}{\sigma_{ij}} \tag{8}$$

where, $\overline{X}_{ij}$ and σ_{ij} represent the areal average values of the mean and standard deviation of WSD in month j of the year i, respectively.

2.5. Soil moisture Storage (SMS)

Global Land Data Assimilation (GLDAS) system is a large-scale remote sensing-based modelling platform, which generates a variety of hydro-climatic variables integrating remotely sensed and field observations under advanced modelling processes (Ramillien et al., 2008). GLDAS includes several models: The Community Land Model (CLM) Variable Infiltration Capacity (VIC) Model, Noah Model, Mosaic Model and Catchment Land Surface Model (CLSM) (Rahaman et al., 2019). Soil moisture values for the study area were extracted from the Noah model, which simulates soil moisture content in four different soil depths [0–10, 10–40, 40–100 and 100–200 cm]. The layers of each corresponding depth were extracted and assimilated into one layer representing the soil moisture storage of the study area. The anomalies of soil moisture over Turkey were calculated based on the monthly deviations from the mean baseline (2004–2009) similar to that of GRACE.

2.6. Standardized precipitation index (SPI)

Standardized Precipitation Index (SPI) was first developed by McKee et al. (1993). It is one of the well-known and commonly used drought indices, which was also recommended by the "Lincoln declaration on drought indices" (Stagge et al., 2015). SPI is widely used by many hydro-meteorological researchers around the world for drought detection and

Table 3
Assessment of the performance of EWSDI and WSDI compared to SPI and SMS at different time scales. GRACE-derived indices are more correlated with SPI-9 and monthly SMS over Turkey.

Index	SPI time scales*							SMS	
	01	03	06	09	12	24	Annual	Monthly	Annual
WSDI $^{\text{original}}$	0.22	0.32	0.45	0.55	0.54	0.51	0.66	0.65	0.76
EWSDI $^{\text{original}}$	0.20	0.37	0.54	0.67	0.62	0.56	0.71	0.62	0.85
WSDI $^{\text{de-trended}}$	0.25	0.33	0.41	0.50	0.49	0.47	0.66	0.60	0.76
EWSDI $^{\text{de-trended}}$	0.21	0.38	0.56	0.70	0.62	0.58	0.76	0.64	0.87
WSDI $^{\text{de-seasoned}}$	0.12	0.08	0.04	0.06	0.05	0.07	0.37	0.26	0.60
EWSDI $^{\text{de-seasoned}}$	0.25	0.36	0.42	0.40	0.37	0.31	0.70	0.63	0.81
WSDI $^{\text{residual}}$	0.23	0.29	0.41	0.58	0.57	0.56	0.72	0.61	0.79
EWSDI $^{\text{residual}}$	0.21	0.37	0.54	0.65	0.60	0.59	0.75	0.52	0.86

* Time scales represent the response of the water cycle to the variations of precipitation on different time lags

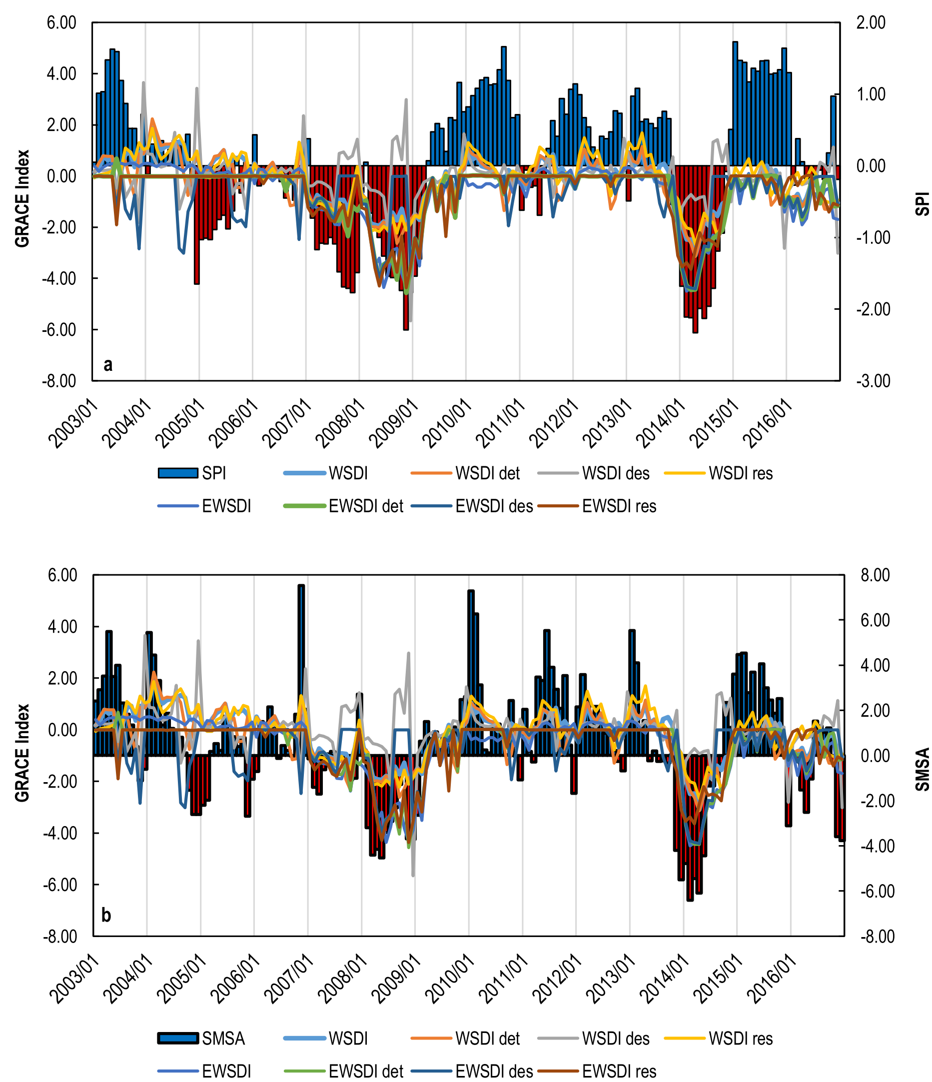

Fig. 8. Temporal interactions of monthly values of GRACE-driven indices with SPI (a) and SMSA (b)

monitoring (Zarei et al., 2021; Hayes et al., 2011). It is generally calculated by fitting a gamma distribution (Hosseini-Moghari et al., 2019) to precipitation data and then transforming probability distributions into the standardized normal distribution (Malik et al., 2021). The SPI is generally computed based on different periods, either shorter or longer time scales, to reflect different lags of water cycle response to precipitation anomalies (Moreira et al., 2008). In this study, to better depict the drought events over Turkey, SPI values at different time scales (01, 03, 06, 09, 12 and 24 months) were calculated using the R studio program. It should be noted that an improved version of SPI is the Standardized Precipitation-Evapotranspiration Index (SPEI), which however, additionally requires accurate evapotranspiration data. As reliable evapotranspiration data is not available for entire Turkey, this analysis was not based on SPEI.

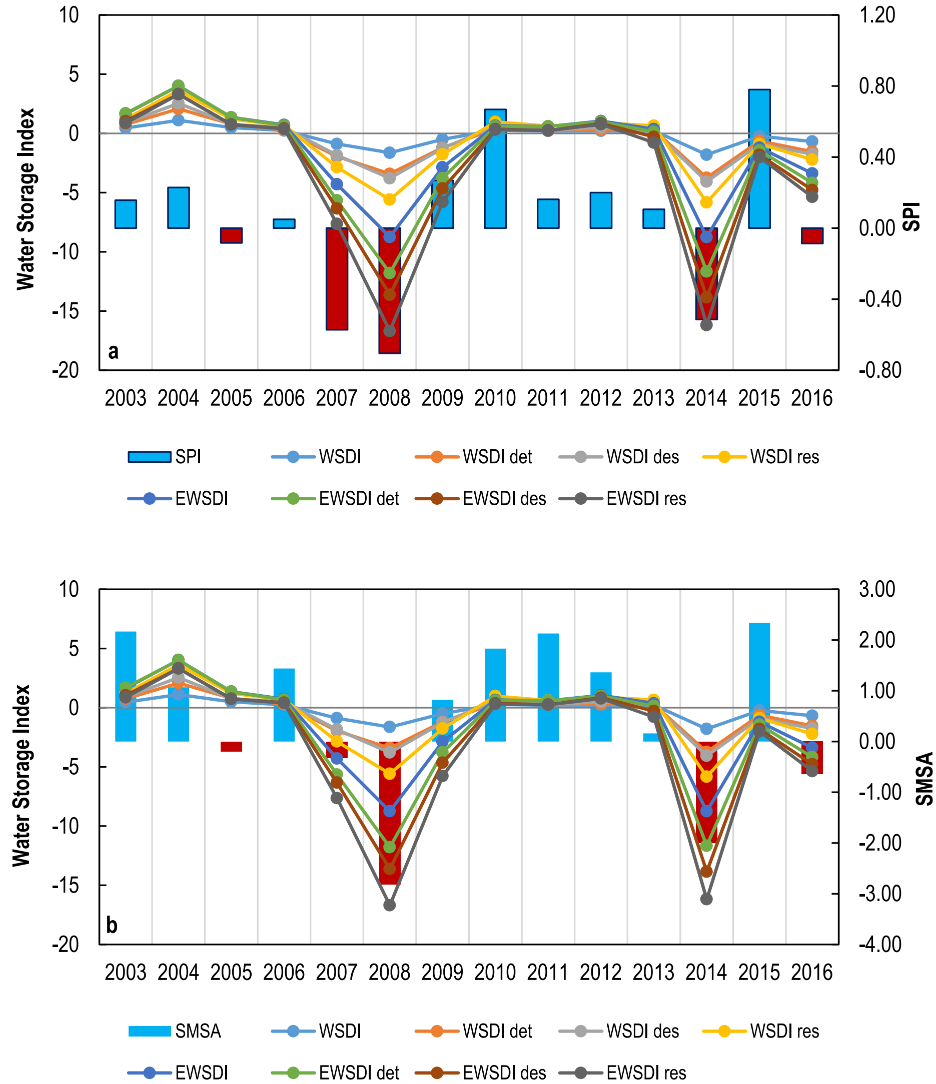

Fig. 9. Temporal interactions of annual values of GRACE-driven indices with SPI (a) and SMSA (b)

3. Results

3.1. Variations of TWSA

The time series of TWSA values over Turkey were extracted from GRACE Masscons grids from 2003 to 2016. The areal mean of each month was then used to graph the temporal fluctuations of TWSA (Fig. 4). The time series of TWSA show a meaningful ($P < 0.05$) descending trend (Khorrami and Gunduz, 2021) with a total water storage loss of 11 cm during the 14 years of this study. The maximum water deficit (19 cm) over Turkey was experienced in September 2008 and 2014. The time series graph also reveals a seasonality for TWSA over Turkey with seasonal fluctuations throughout the study period. The seasonality indicates that the water storage surplus and deficit happen during the months of April-May and September-October, respectively.

3.2. Seasonal and trend decomposition of TWSA time series

To partition the TWSA time series into its components, additive and multiplicative models were used. Then, the accuracy of each model was investigated based on the accuracy parameters of MAPE, MAD and MSD. The results of the accuracy assessment are given in Table 1. The results here indicate that the multiplicative model with lower MSD and MAPE fits better to the TWSA values over the study area. Therefore, the multiplicative model was used for the time series decomposition task.

The monthly values of TWSA (Jan 2003 to Dec 2016) were dismantled into the seasonal, trend and residual components using the multiplicative model. To detrend the TWSA values, the trend component of the time series was first calculated according to the trend equation given in Fig. 4. Later, the trend values were removed from the original TWSA time series to generate the de-trended time series.

The de-seasoned time series of TWSA was calculated based on the seasonal factors obtained from the fitted model (Table 2). For each month, there is a special value indicating the seasonal impact on the time series. The de-seasoned time series of TWSA illustrates the TWSA without the impacts of seasonality. By getting rid of trends and seasonality, residuals are generated. Figs. 5 and 6 give the time series components as well as de-trended and de-seasoned time series of TWSA over Turkey, respectively.

The accumulative decomposed values of each component of the time series estimate the overall variance in the TWSA time series (Shamsudduha and Taylor, 2020). According to the accumulated values of each individual component (Fig. 7), a trend of 42% determines the majority of the TWSA variance over the study area; residual contributes to 41% of the variance and seasonality represents only 17% of the time series' variance.

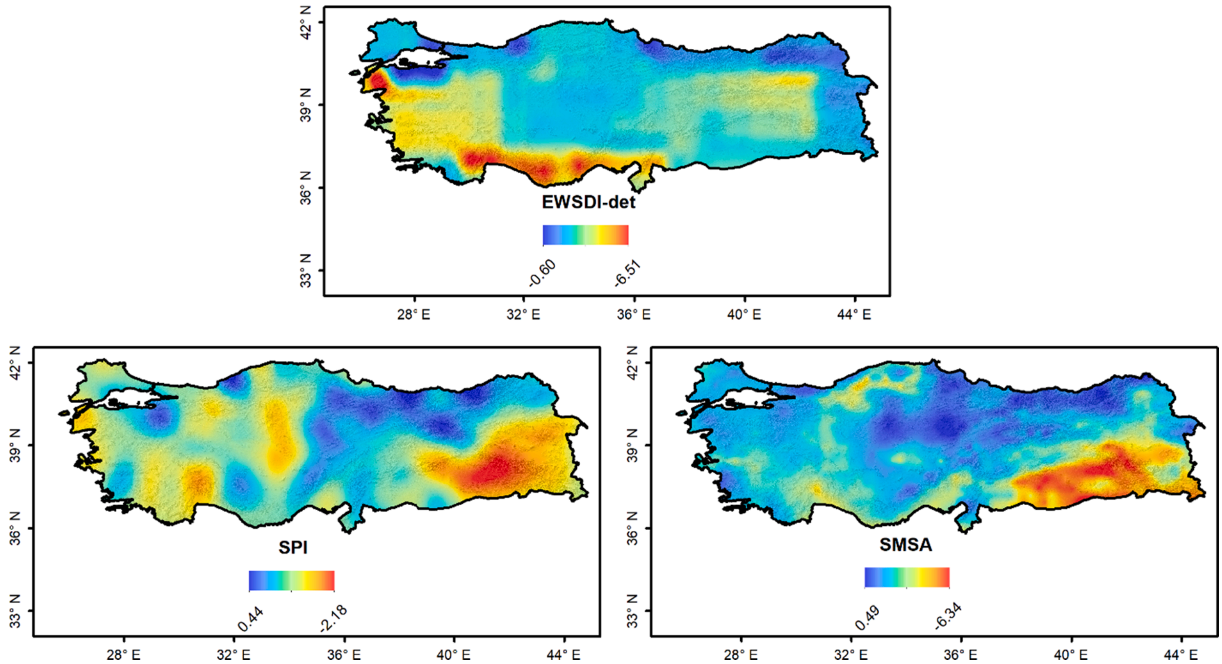

Fig. 10. Spatial illustration of drought event in 2008 over Turkey based on EWSDI, SPI and SMSA.

3.3. Evaluating the performance of WSDI and EWSDI

To investigate the performance of GRACE-derived drought indices (WSDI and EWSDI), drought indices were applied on the decomposed TWSA alongside the original TWSA values separately. The performance of the EWSDI by analogy with WSDI in detecting droughts over Turkey was evaluated based on SPI and Soil Moisture Storage (SMS) values. Table 3 demonstrates the correlation coefficients achieved between each GRACE-based index and SPI and SMS in monthly and annual scales.

The results manifest that while the higher correlation values between SPI and GRACE-derived indices were obtained for SPI-9 and SPI-12, both indices correlate the best with SPI-9 over Turkey. Although among the WSD indices, the residual-based WSDI shows the best performance according to the correlation achieved for SPI-09 (0.58) and annual SPI (0.72), the de-trended EWSDI offers the best agreement with SPI-09 (0.70) and annual SPI (0.76).

The association between monthly and annual values of EWSDI, WSDI and SMS, however, indicates that original WSDI and de-trended EWSDI are more correlated with monthly SMS with correlations of 0.65 and 0.64, respectively. The annual correlations of SMS and indices, on the other hand, suggest that residual WSDI and de-trended EWSDI agree the best with SMS over Turkey with the correlation values of 0.79 and 0.87, respectively. The best performances achieved for residual and detrended TWSA can be ascribed to the fact that the majority of TWSA variations are represented by trend and residual values (Fig. 7). Therefore, the application of these components in spite of the original TWSA values enhances the performance of drought indices. Overall, the results highlight that the enhancement of WSDI proposed in this study, alongside the application of the decomposed GRACE TWSA, outperforms the traditional WSDI in detecting droughts over Turkey.

The monthly and annual time series of GRACE-derived drought indices, SPI and SMS are shown in Figs. 8 and 9, respectively. The figures illustrate the temporal associations between the variants of WSDI and EWSDI with SPI and SMS. Regardless of some disharmonies among GRACE-based indices, they were all able to detect the drought events of 2007–2008 and 2014. Although both monthly and annual graphs show the captured dry periods over Turkey, the associations for annual time series are more clearly depicted and the indices are seen in more harmony fluctuating in lockstep with SPI and SMS.

3.4. Spatial illustration of EWSDI

To investigate the spatial pattern of drought events based on the enhanced WSDI, the most severe drought event (in 2008) was mapped according to the drought index values received from de-trended EWSDI as the best drought indicator for the study area. The SPI and SMS distribution maps were also generated for the same event in order to look over the spatial consistency between the indices visually (Fig. 10). The EWSDI map illustrates the spatial patterns of GRACE-derived drought values where the southern Mediterranean coasts have experienced the most severe drought while the Black Sea coasts have suffered the least from the drought in 2008. It also reveals that the Aegean region in the west and the south-eastern Anatolia region in the east of Turkey have experienced a harsh drought condition at the same time.

The spatial correlation maps (Fig. 11) were then generated using the station-wise correlation values achieved for SPI and SMSA with EWSDI. Fig. 11-a, shows that EWSDI is highly correlated over the eastern regions of the country. It also reveals higher correlation values for the western and some parts of central Turkey. Over the Marmara region and a small proportion of the Black Sea region, EWSDI shows lower correlation with SPI.

The spatial correlation map of EWSDI and SMSA (Fig. 11-b) also suggests almost the same pattern with the higher correlation values over the east and the west of the country. The EWSDI in the central part of Turkey, on the other hand, turns out to be less correlated with SMSA.

4. Discussions

4.1. Decomposition of GRACE TWSA

GRACE reports the variations in the total water storage of the Earth in terms of the varying gravitational pull. The Earth's water storage amount is changed on account of the variations in the different components of the hydrological water cycle resulting from a number of the anthropogenic and natural factors. Therefore, a combination of different elements contributes to the variations of GRACE TWSA. GRACE-based studies need to use the dismantled TWSA values so as to get rid of those contributing factors that bring about changes in the GRACE detected signals.

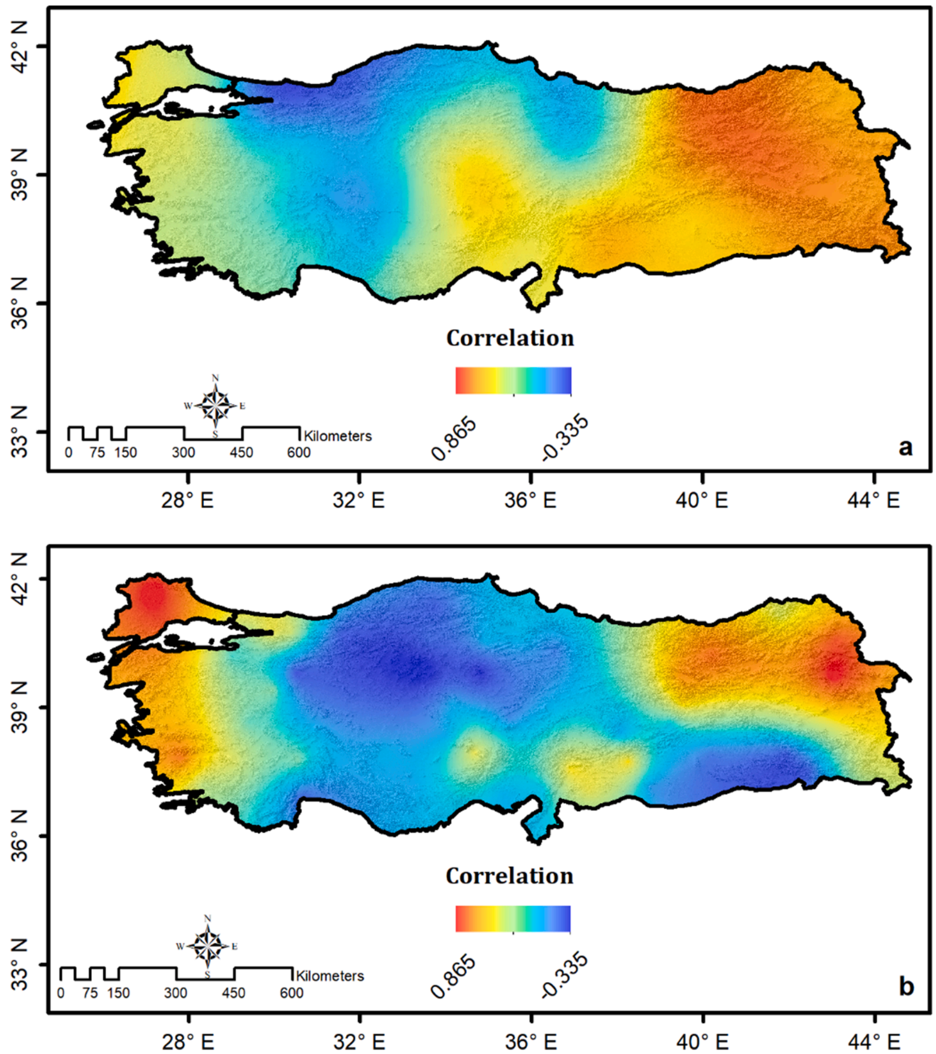

Fig. 11. The spatial illustration of the correlation between EWSDI and SPI (a) and EWSDI and SMSA (b).

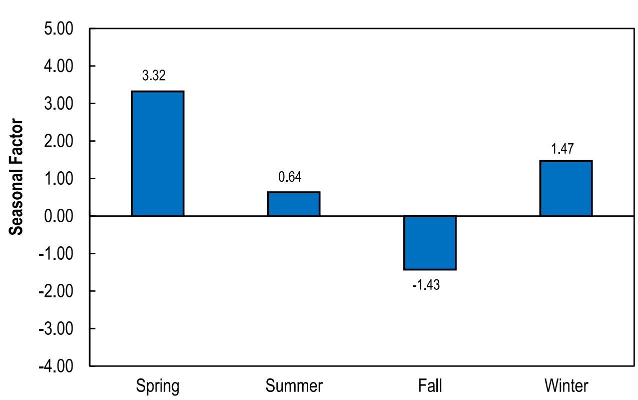

Fig. 12. Seasonal total water storage cycle of Turkey.

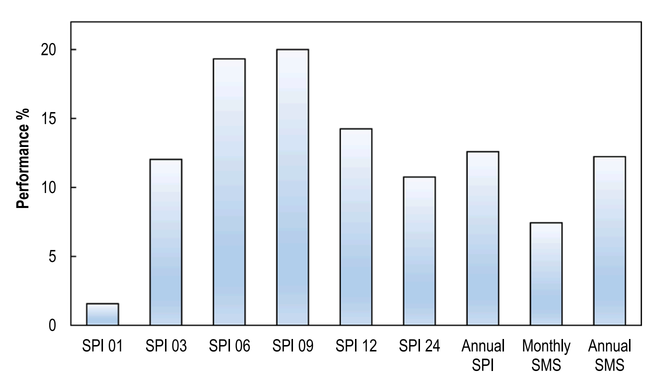

Fig. 13. The average improvement of EWSDI performance over WSDI in detecting drought Time scales represent the response of the water cycle to the variations of precipitation on different time lags

The trend and seasonality of TWSA over Turkey were decomposed using a multiplicative decomposition model. The seasonality of TWSA is described in terms of seasonal factors, which are decomposed TWSA values. They are calculated for each season using the average values of the corresponding months for each season e.g., Mar, Apr and May (Spring), June, Jul and Aug (Summer), Sep, Oct and Nov (Fall) and Dec, Jan and Feb (Winter). The seasonal decomposition of the GRACE time series indicates that the maximum and minimum water storage variations in Turkey happen in spring and fall seasons with 3.32 and −1.43 cm respectively (Fig. 12). The seasonal cycles found for the study area correspond exactly with the findings of Humphrey et al (2016) about the seasonal cycles of TWSA over the temperate regions in the Northern hemisphere.

The decomposition of the GRACE TWSA time series was implemented using the multiplicative model on account of the statistical

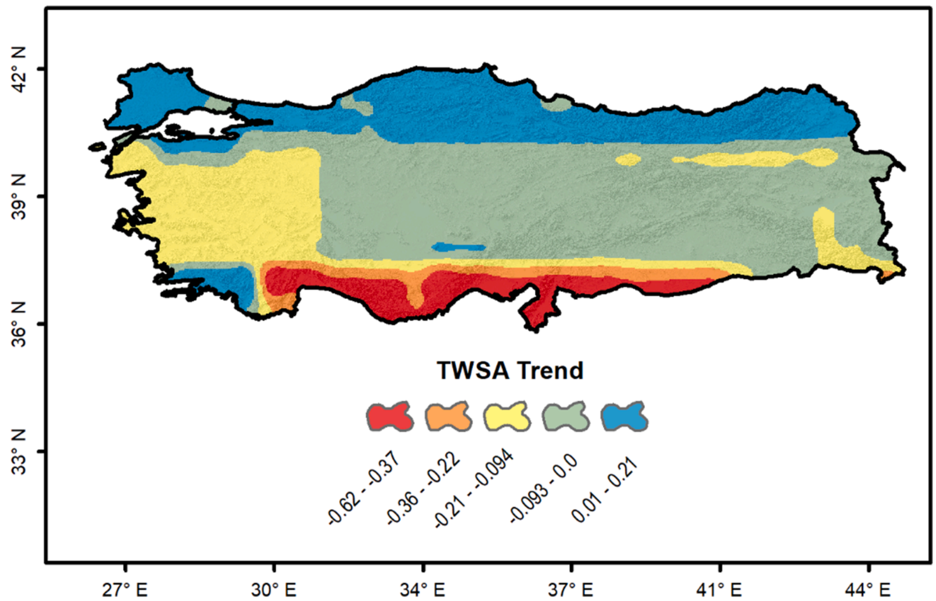

Fig. 14. The trend map of TWSA from 2003 to 2016.

measurements of model accuracy. The best performance achieved for de-trended WSDI among the used indices also highlights the nature of the TWSA variations over Turkey. Since GRACE TWSA values in arid and semi-arid regions are largely affected by anthropogenic water consumption rather than climatic extremes (Singh et al. 2012; Voss et al. 2013; Joodaki et al. 2014; Forootan et al. 2014; Hosseini-Moghari et al., 2019), it can be inferred that the EWSDI is more sensitive to long-term variations of total water storage than WSDI. Therefore, it can be concluded that de-trending TWSA for the study area improves the enhanced index's capability to detect droughts.

Using more sophisticated techniques may improve the outcome of the time series decomposition and result in more accurate inputs for drought index calculation. On the other hand, the time span for this study is limited to 14 years. By extending the study period using GRACE-FO estimations, the background information of GRACE-TWSA time series may be revealed more precisely, which in turn may enhance the overall applicability of the GRACE TWSA time series for analysing the extreme climatic conditions.

4.2. Validation of GRACE-derived drought indices

The SPI variations indicate that there have been three major drought periods (2005, 2007–2008 and 2014) in Turkey during the 2003–2016 period. Among these three events, the drought events of 2007–2008 and 2014 were found to be more severe. These findings agree with the previous studies done by Marım et al. (2008), Türkeş et al. (2009), Kurnaz (2014) and Okay Ahi and Jin (2019). The results of SMS do not fully comply with SPI in terms of temporal fluctuations according to wet and dry months even though it shows the dry periods of 2007–2008 and 2014 clearly. Furthermore, regardless of the uncertainties associated with GLDAS model outputs (Qi et al., 2020), soil moisture derived from the Noah model manifests a stronger association with GRACE-derived indices on an annual scale.

The spatial illustration of the EWSDI-SPI and EWSDI-SMSA correlation maps also suggest an overall good and acceptable harmony between the EWSDI with SPI and SMSA over Turkey. However, there are some discrepancies in the spatial distribution of the correlated values especially in the south-eastern parts of the country, which is believed to be linked to the large-scale analysis of the data where results are highly prone to uncertainties resulting from the differences in the resolution of the datasets. Furthermore, the results are totally based on the areal mean values which, in turn, affects the local scale results and complicates the interpretation of the results. Considering the current resolution and accuracy of the GRACE data, the approach proposed in this study seems to be a viable option for assessing drought via remotely sensed data.

According to the validation results, EWSDI yields more precise results compared to WSDI. Fig. 13 demonstrates the average improvement of EWSDI in detecting drought based on different time scales for SPI and SMS over Turkey. The correlation coefficient achieved for de-trended EWSDI and SPI-9 shows a 20 percent increase in comparison with that of de-trended WSDI. The proposed EWSDI approach turned out to outperform the traditional WSDI by an average improvement of 13 percent, which can reach as high as 19 percent and 20 percent with SPI06 and SPI09. This outcome suggests that the enhancement of WSDI proposed in this study works well in improving the performance of the traditional WSDI.

4.3. Spatiotemporal trend of drought

The analogy among the spatial variability maps of the 2008 drought event over Turkey overall accentuates that GRACE has the potentiality to reveal the spatial patterns of extreme climatic events. The disharmonies seen in some areas indeed stem from the uncertainties associated with GRACE signals resulting from either leakage errors or data processing-induced noises.

In general, the drought trend tends to concentrate on the southern coastline of the country extending towards the Southeast Anatolia region as well as the western territories of the country (Fig. 14). Furthermore, it is found that the GRACE based drought indices emulate the trend of the TWSA time series where the southern coastal areas of the country and the Aegean and eastern regions manifest descending trends in the variations of the total water storage over Turkey, while the coastal Black Sea and Marmara regions have experienced ascending trends at the same period from 2003 to 2016. This can be ascribed to the fact that the trend component dominates the TWSA time series over the study area so that using the de-trended time series instead of the original TWSA values enhances the precision of the index.

5. Conclusions and recommendations

Within the scope of this study, GRACE TWSA values were used to generate drought indices based on the TWSA and its decomposed time series. The authors introduced a new GRACE-based drought index using a different approach for calculating WSDI. The Enhanced WSDI (EWSDI) is computed using the areal means for mean and standard deviation values of monthly WSD grids instead of those of time series, which are generally used for WSDI. SPI and SMS values were then used to check the precision of the indices and draw an analogy between WSDI and EWSDI.

The findings of this study demonstrate the fact that the introduced EWSDI performs better in drought detection and monitoring in comparison with the traditional WSDI. It is found that using de-trended EWSDI over the study area is promising regarding drought detection especially the annual dry periods. The results also indicate that our proposed index is successful in improving the accuracy of the current WSDI compared to SPI and SMS values in different time scales. One specific advantage of using EWSDI instead of WSDI is the ease of computation of the index where just a simple statistical approach is needed to be applied. One of the main obstacles in GRACE-related analysis is the coarse resolution of the data, which seems to omit some detailed signals culminating in some sort of uncertainties. The authors believe that with possible further improvements of GRACE resolution in the near future, the performance of this index would be boosted significantly. On the other hand, the uncertainty analysis of GRACE with different resolutions will provide more details regarding the influence of spatial resolutions of TWSA in the ability of GRACE-driven drought indices to catch dry periods with more precision.

Finally, GRACE-derived drought indices rely on the quality of GRACE data, therefore, more accurate results may be achieved with finer GRACE data. Under such conditions, remote estimation and monitoring of environmental phenomena like droughts would be more accurate both spatially and temporarily.

6. Data availability statement

The data that support the findings of this study are available from the corresponding author, [author initials], upon reasonable request.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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