



## Article

# The Drought Events over the Amazon River Basin from 2003 to 2020 Detected by GRACE/GRACE-FO and Swarm Satellites

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**Abstract:** The climate anomaly in the Amazon River basin (ARB) has a very important influence on global climate change and has always been the focus of scientists from all over the world. To fill the 11-month data gap between Gravity Recovery and Climate Experiment (GRACE) and GRACE Follow-On (GRACE-FO) missions, we fused the TWSC results from six GRACE solutions by using the generalized three-cornered hat and the least square method to improve the reliability of TWSC results, and then combined Swarm data to construct an uninterrupted long time series of a TWSC-based drought index (GRACE/Swarm-DSI). The drought index was used to detect and characterize the drought events in the ARB between 2003 and 2020. The results show that GRACE/Swarm-DSI has a strong correlation with Self-Calibrating Palmer Drought Severity Index (SCPDSI) (0.6345), Standardized Precipitation Evapotranspiration Index-3 (SPEI-3) (0.5411), SPEI-6 (0.6377) and SPEI-12 (0.6820), and the Nash–Sutcliffe efficiency between GRACE/Swarm-DSI and the above four drought indices are 0.3348, 0.2786, 0.4044 and 0.4627, respectively. Eleven drought events were identified in the ARB during the study period, and the 2005, 2010 and 2016 droughts are the most severe and the longest. The correlation between GRACE/Swarm-DSI and precipitation (PPT) (the correlation coefficient is 0.55 with a 2-month delay) is higher than that of evapotranspiration (ET) (the correlation coefficient is −0.18 with a 12-month delay). It explains that less PPT is the main cause of drought events in the ARB. The influence of PPT is greater in the plains than the one in the mountains and the response time of GRACE/Swarm-DSI to PPT is 1–2 months in most regions. Our results provide a certain reference for the hydrological application of the Swarm model in filling the gap between GRACE and GRACE-FO missions.

**Keywords:** combined drought index; long time series; Amazon River basin; time variable gravity field model



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## 1. Introduction

Drought is one of the most destructive natural disasters. It has brought huge adverse effects to human social life, industrial and agricultural production and the ecological environment [1]. Global warming and increasing human activities have resulted in the increased number and severity of droughts all over the world year by year [2]. There are four main types of droughts, namely agricultural drought, meteorological drought, socio-economic drought and hydrological drought [3,4], causing a comprehensive effect on the environment and society in the evolution of drought. Therefore, accurate monitoring and prevention of drought is of great significance to the development of human society.

Since 2002, the Gravity Recovery and Climate Experiment (GRACE) and its follow-on (GRACE-FO) missions have been implemented successively. Their main goal is to detect the Earth's time-variable gravity field in the medium and long wavelength parts [5]. The GRACE time-variable gravity field model has played an extremely important role in hydrological applications [6–8]. The basin area and runoff of the Amazon River is the largest in the world. The famous Amazon Rainforest is located in this basin, which covers an area of 5.5 million km<sup>2</sup>, spans eight countries and occupies 1/3 of the world's rainforest area and 20% of the world's forest area [9]. It has a huge influence on regional precipitation (PPT), runoff, evapotranspiration (ET) and even the global climate [10]. The Amazon River basin (ARB) plays an important role in global water vapor exchange [11], and it is also an important composition of the global water cycle and terrestrial ecosystems [12,13]. Extreme climate has caused frequent droughts in the ARB [4]. Therefore, the ARB drought assessment aids the research on regional and global climate change. Many scholars have detected and analyzed the ARB droughts by using GRACE data. For instance, Chen et al. [14] quantified the 2005 extreme drought event in the ARB using GRACE monthly gravity solutions, and the results were verified by PPT data and water level data. Frappart et al. [15] used GRACE satellites to detect the same drought in the ARB, and found that the water storage was 70% lower than the average level in previous years. Nie et al. [16] reproduced the transition process from the 2010 extreme drought to the 2012 flood by comparing GRACE terrestrial water storage change (TWSC) data with PPT data. The GRACE TWSC and PPT data had the same spatial and temporal distribution and variation. Chaudhari et al. [13] investigated the interannual and interdecadal GRACE TWSC from 1980 to 2015. They found that the droughts have occurred frequently since 2010, and their severity was getting worse. Thomas et al. [17] conducted a quantitative assessment of the drought characteristics from 2003 to 2013 based on GRACE-derived water storage deficit, and the results were consistent with meteorological drought data.

However, in the applications of satellite gravimetry data, there is an 11-month data gap between GRACE and GRACE-FO missions, which inevitably caused a discontinuity in drought research of ARB [18,19]. Since the Swarm mission period just covers the above gap, its satellites are equipped with gravity detection equipment, such as accelerometer, Global Navigation Satellite System receiver, etc. [20,21]. Many scholars have discussed the possibility of using the Swarm model to detect time variable gravity signals. The results indicate that the time variable gravity signals of Swarm model are mainly concentrated in the long wave part, and the Swarm model has the possibility of monitoring the regional TWSC [22–25]. Some scholars used the Swarm model to detect TWSC and droughts in the ARB [19,25,26], and the main purpose of their studies is to use the Swarm model to fill the gap between GRACE and GRACE-FO missions. However, to best of our knowledge, there is no literature combining GRACE, GRACE-FO and Swarm models to construct a continuous long observations series to detect and characterize the regional droughts.

Therefore, in our study, we focus on using Swarm model to fill the gap between GRACE and GRACE-FO models to form an uninterrupted TWSC-based drought index series in the ARB to monitor and characterize the regional droughts. We first used the generalized three-cornered hat (GTCH) and the least square method to fuse the TWSC results from six GRACE/GRACE-FO solutions to improve the reliability of TWSC results. Then, the fused TWSC results were used to construct the GRACE/GRACE-FO-based drought index (GRACE/GRACE-FO-DSI), and the Swarm-based drought index (Swarm-DSI) was used to fill the 11-month gap between GRACE-DSI and GRACE-FO-DSI to form an uninterrupted long drought index (GRACE/Swarm-DSI) series in the ARB. Finally, we used GRACE/Swarm-DSI to detect and characterize the drought events in the ARB in the past 18 years. The paper is organized as follows. We briefly introduce the study area, data, and method in Sections 2–4, respectively. Section 5 presents the analysis results of the drought causes and characteristics in the ARB based on GRACE/Swarm-DSI. Sections 6 and 7 are the discussion and conclusions, respectively.

## 2. Study Area

The Amazon River is a river in northern South America that flows from west to east. It originates from the Miami Snow Mountains in the Andes Mountains in Peru and flows into the Atlantic Ocean near the equator in Brazil. The amount of water injected into the Atlantic Ocean every year is about 6.6 trillion  $\text{m}^3$ , which is equivalent to 1/6 of the total amount of water injected into the ocean by the world's rivers. The average annual runoff of the Amazon River is approximately 6591  $\text{km}^3$ . Its drainage area covers 6.915 million  $\text{km}^2$  [19]. The climate of the ARB (Figure 1) is characterized by warm, humid and rainy. Most of ARB has a tropical rain forest climate, and the upper reaches belong to a plateau mountain climate. The annual rainfall in this basin is more than 2000 mm.

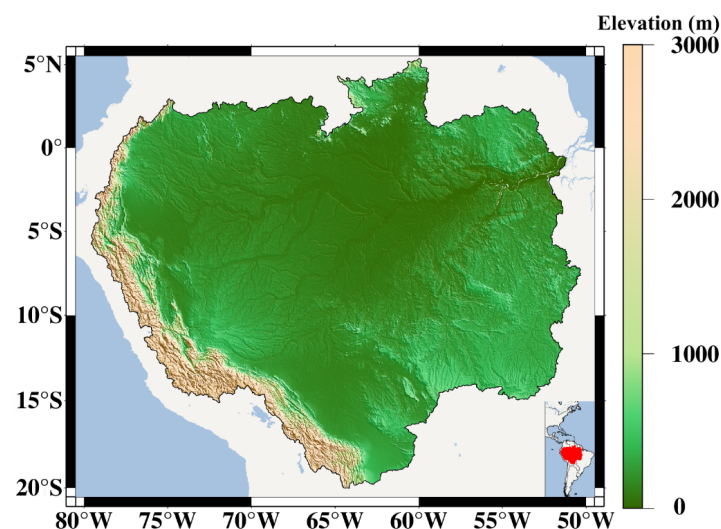


Figure 1. The digital elevation models of the ARB.

## 3. Data

### 3.1. GRACE/GRACE-FO Data

The GRACE/GRACE-FO RL06 spherical harmonic (SH) solutions (truncated to a degree and order 60) were derived from the Center for Space Research at the University of Texas at Austin (CSR), Helmholtz-Centre Potsdam-German Research Centre for Geosciences (GFZ), Jet Propulsion Laboratory (JPL) and Institute of Geodesy at Graz University of Technology (ITSG), respectively. Among them, GRACE SH solutions are from January 2003 to June 2017, and GRACE-FO SH solutions are from June 2018 to December 2020. Before calculating the monthly TWSC gridded data, the SH solutions must be preprocessed. Firstly, we used  $C_{20}$  of satellite laser ranging and the results from Swenson et al. to replace  $C_{20}$  and degree-1 coefficients of SH solutions [27,28]. Then, considering the correlated and high frequency errors, we used 300 km Gaussian filter and P3M6 polynomial filter to process SH coefficients [29]. Finally, the multiple scale factor method (MSF) was used to recover the signal attenuation due to degree truncation and filter process [30], and the further details of scale factors calculation are available in Section 4.2. Except for SH solutions, we can obtain the monthly TWSC gridded data from Mascon solutions. The advantage of Mascon solution is that the monthly TWSC gridded data can be obtained directly without additional data processing. In our study, we used the Mascon solutions derived from CSR and JPL.

Since GRACE and GRACE-FO data are two identical data, GRACE and GRACE-FO were collectively called GRACE in our study. For convenience, the four GRACE SH solutions and two Mascon solutions were termed as CSR-SH, GFZ-SH, JPL-SH, ITSG-SH, CSR-M and JPL-M.

### 3.2. Swarm Data

The Swarm SH solution (truncated to a degree and order 40) was derived from the International Combination Service for Time-variable Gravity, covering the period January 2014 to December 2020. It is a combination model constituted by using variance component estimation, consisting of four Swarm models from the Astronomical Institute at the Czech Academy of Sciences, the University of Bern, the Institute of Geodesy at the Graz University of Technology and Ohio State University [31]. Like GRACE SH solutions, the Swarm SH solutions need to be preprocessed. In addition to the different filtering parameters, the processing flow and methods are basically the same as GRACE data. In our study, 1000 km Fan filter was used to process the Swarm SH solution.

### 3.3. PPT Data

The PPT data came from the Global Precipitation Climatology Centre (GPCC), whose basic data was from quality-controlled data from 7000 stations in the world. The GPCC provided estimates for measuring error of the PPT data. These data were used for global and regional hydrological research and calibration/validation of remote sensing based PPT estimations and numerical models. Its spatial resolution is  $1^\circ \times 1^\circ$  [32]. We extracted PPT gridded data during 2003 and 2020 for this study.

### 3.4. ET Data

The ET gridded data was provided by the Global Land Evaporation Amsterdam Model 3.5a, whose spatial resolution is  $0.25^\circ \times 0.25^\circ$  [33,34]. The model not only estimated the various components of land evaporation: open-water evaporation, bared-soil evaporation, transpiration, interception loss and sublimation, but also calculated potential evaporation, surface and root-zone soil moisture and evaporative stress conditions. The ET gridded data from January 2003 to December 2020 were used in our study.

### 3.5. Standardized Precipitation Evapotranspiration Index (SPEI) Data

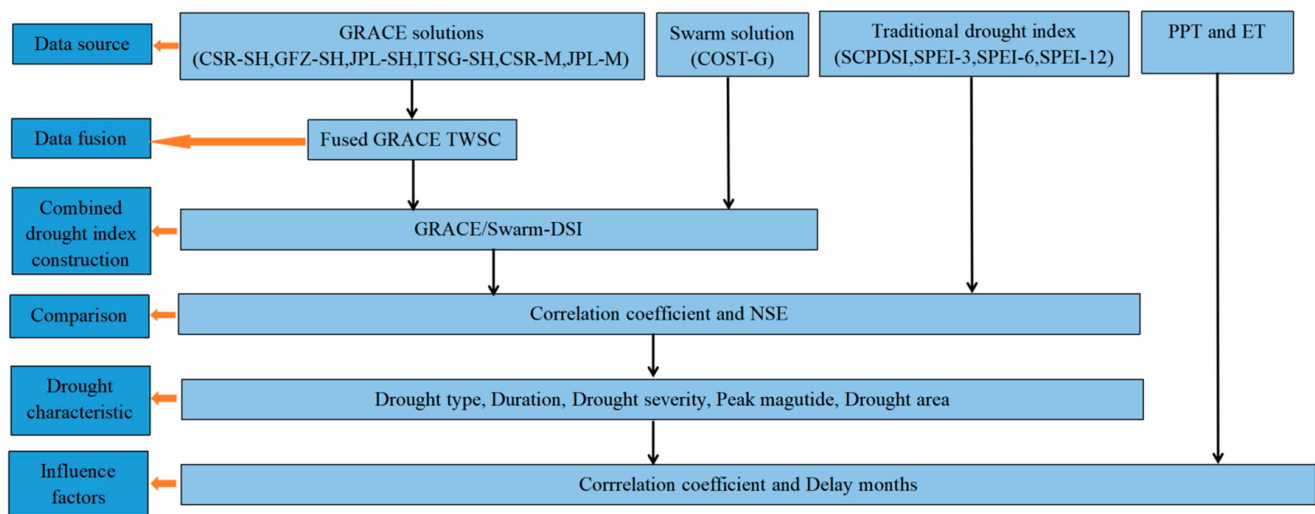
SPEI is estimated according to the cumulative sum of difference between PPT and potential ET on different time scales. Its basic principle is the same as the standardized precipitation index (SPI) [35]. Among them, PPT data were provided by GPCC and the potential ET data were from National Oceanic and Atmospheric Administration. SPEI has three different time scales: 3 months, 6 months and 12 months. The 3-month scale is associated with variations in soil moisture: agricultural drought; the 6-month scale is associated with variations in streamflow: hydrological drought; the 12-month scale is associated with variations in groundwater storage: hydrogeological drought [36]. In our study, SPEI gridded data with the spatial solution  $1^\circ \times 1^\circ$  spanned the period from January 2003 to December 2018.

### 3.6. Self-Calibrating Palmer Drought Severity Index (SCPDSI) Data

SCPDSI is an improved version of PDSI [37], with the aim of making it more suitable for the drought evaluation on a global scale. Similar to PDSI, SCPDSI was calculated from the PPT, temperature and the parameters related to the soil/surface characteristics [38,39]. In our study, the monthly  $0.5^\circ \times 0.5^\circ$  global SCPDSI gridded data were derived from the Climate Research Unit at University of East Anglia, spanning the period from January 2003 to December 2020.

## 4. Method

A schematic illustration of the methodology steps is shown in Figure 2. Our paper mainly has the five parts of work, which are data fusion, combined drought index construction, drought characteristics quantification and influence factors on drought event, respectively. The specific method details were described below.



**Figure 2.** Flowchart of the drought monitoring and characterization.

#### 4.1. Drought Event

##### 4.1.1. GRACE-DSI/Swarm-DSI

We standardized the time series of GRACE TWSC data to obtain GRACE-DSI data, and its specific expression is as follows [13,29]:

$$GRACE-DSI_{i,j} = \frac{TWSC_{i,j} - TWSC_j^{mean}}{\sigma_j} \quad (1)$$

where  $TWSC_{i,j}$  is TWSC in the  $i$  year ( $2003 \leq i \leq 2020$ )  $j$  month ( $January \leq j \leq December$ ).  $TWSC_j^{mean}$  and  $\sigma_j$  are the average and standard deviation of TWSC in  $j$  month, respectively. The missing data in the GRACE TWSC data was filled by using the cubic spline interpolation. The Swarm-DSI was calculated in the same way as GRACE-DSI. According to the size of GRACE-DSI values, the drought events can be classified (Table 1) [8,40].

**Table 1.** GRACE-DSI drought grades classification.

| Type                | GRACE-DSI        | Type             | GRACE-DSI        |
|---------------------|------------------|------------------|------------------|
| Exceptional Drought | $\leq -2.0$      | Moderate Drought | $-1.3 \sim -0.8$ |
| Extreme Drought     | $-2.0 \sim -1.6$ | Light Drought    | $-0.8 \sim -0.5$ |
| Severe Drought      | $-1.6 \sim -1.3$ | No Drought       | $\geq -0.5$      |

##### 4.1.2. Definition of Drought Event

In our study, when the drought area percentage of a region is greater than 20% and the monthly GRACE/Swarm-DSI for three consecutive months is less than or equal to  $-0.1$ , we consider that a drought event occurred in this region. If there is only one month between two drought events and GRACE/Swarm-DSI of this month is less than or equal to  $-0.1$ , the two adjacent drought events are considered the one event; otherwise, there are two independent drought events [8].

##### 4.1.3. Drought Characteristics

The drought characteristics includes drought type, frequency, duration, peak magnitude, severity and drought area. In our study, we focus mainly on the drought duration, peak magnitude, severity and drought area percentage. The drought in our study refers to the hydrological drought; the drought duration is equal to number of months between the start and end month of drought; the peak magnitude represents the maximum of monthly GRACE-DSI during the drought; the drought area percentage indicates the ratio of the

grid area with the GRACE-DSI is less than  $-0.5$  to total area of the study region [8]. The drought severity ( $S$ ) is as follows [17]:

$$S = \overline{M} \times D \quad (2)$$

where  $\overline{M}$  is the monthly average of GRACE-DSI during the drought event and  $D$  is the drought duration both calculated up to the current month.

#### 4.2. MSF Method

Due to degree truncation and filtering processing, the gridded TWSC from the SH solutions inevitably has signal attenuation and leakage [6]. Therefore, it is necessary to modify the TWSC gridded data. Additionally, the scale factor, an effective method, is often used for signal recovery [41,42]. However, since the signal recovery is within the scope of the entire study region, it is unreasonable to only rely on the scale factor obtained from the regional weighted average to recover the signal of the entire region [30]. Additionally, the TWSC time series may be diversity on different scales, so the MSF method was used to recover the Swarm and GRACE TWSC signals in our study. The specific processing flow is as follows:

- (1) The gridded TWSC data were provided by the Global Land Data Assimilation system (GLDAS) the Catchment Land Surface Model (CLSM), which is the sum of soil moisture storage, snow water equivalent storage, plant canopy water and groundwater. Additionally, TWSC time series (denoted as  $TWSC_{original}$ ) in the study region was calculated by spatial averaging.
- (2)  $TWSC_{original}$  was split into the long-term trend items  $S_{original}^{trend}$ , seasonal items  $S_{original}^{seasonal}$  and residual items  $S_{original}^{residual}$ .
- (3) The original TWSC gridded data was expanded into 60-degree (GRACE) or 40-degree (Swarm) SH coefficients, and then it was converted into TWSC gridded data ( $TWSC_{convert}$ ) using the same processing method as GRACE or Swarm data.
- (4) Same as the second step,  $TWSC_{convert}$  was split into the long-term trend items  $S_{convert}^{trend}$ , seasonal items  $S_{convert}^{seasonal}$  and residual items  $S_{convert}^{residual}$ .
- (5) According to the least square method, the scale factors of the above three signal components ( $k^{trend}$ ,  $k^{seasonal}$  and  $k^{residual}$ ) were obtained, respectively.
- (6) The time series of TWSC from GRACE or Swarm data were also split into the long-term trend items  $S_{gravity}^{trend}$ , seasonal items  $S_{gravity}^{seasonal}$  and residual items  $S_{gravity}^{residual}$ .
- (7) The three components obtained by decomposition in step six were multiplied by the three scale factors in step five. The signal modification result  $S^{modified}$  is expressed by the following formula:

$$S^{modified} = k^{trend} S_{gravity}^{trend} + k^{seasonal} S_{gravity}^{seasonal} + k^{residual} S_{gravity}^{residual} \quad (3)$$

The results of scale factors of four GRACE and Swarm SH solutions were shown in Table 2.

**Table 2.** The scale factors of four GRACE SH solutions and one Swarm solution.

| SH Solution | $k^{trend}$ | $k^{seasonal}$ | $k^{residual}$ |
|-------------|-------------|----------------|----------------|
| CSR-GRACE   | 1.171       | 1.171          | 1.000          |
| GFZ-GRACE   | 1.171       | 1.171          | 1.000          |
| JPL-GRACE   | 1.171       | 1.171          | 1.000          |
| ITSG-GRACE  | 1.171       | 1.171          | 1.000          |
| Swarm       | 1.173       | 1.173          | 1.000          |

#### 4.3. Different Datasets Fusion

Due to the discrepancies in the SH solutions from different institutions, it may lead to inconsistent results [43]. To improve the reliability of our results, we used the GTCH method to evaluate the uncertainties of TWSC results from six GRACE solutions. Then, according to the uncertainty results, we fused these six TWSC results by using least square method. The advantage of this method is that it can estimate relative covariances of different datasets without a prior information [44,45]. The technical detail about the GTCH method can be found in Refs. [46,47].

We fused the different observation series by using the least square method, the expression is as follows [48]:

$$Z = \sum_{i=1}^N l_i \bullet Z_i (i = 1, 2, \dots, N) \quad (4)$$

where  $Z_i$  is the  $i$ th dataset and  $l_i$  is the corresponding weight, and  $Z$  is the fused result. The weights were calculated according to the relative variances.

$$l_i = \frac{1/f_{ii}}{\sum_{n=1}^6 1/f_{nn}} \quad (5)$$

where  $f_{ii} (i = 1, 2, \dots, 6)$  is the relative variance of  $i$ th dataset estimate by the GCTH method. We fused the different datasets on each grid point according to the above method.

#### 4.4. The Correlation Coefficient and Delay Months

Suppose the two independent time series are  $z_1$  and  $z_2$ ,  $\tau$  is the delay factor, and the correlation coefficient between  $z_1$  and  $z_2$  is expressed as [49,50]:

$$\rho(\tau) = \frac{\sigma_{12}(\tau)}{\sqrt{\sigma_{11}\sigma_{22}}} \quad (6)$$

where  $\rho(\tau)$  is correlation coefficient,  $\sigma_{11}$  and  $\sigma_{22}$  is the variance of  $z_1$  and  $z_2$ , and  $\sigma_{12}$  is the covariance of  $z_1$  and  $z_2$ . When  $|\rho(\tau)|$  is maximum ( $|\rho(\tau)| \leq 1$ ),  $\tau$  is the maximum delay months ( $|\tau| \leq 12$ ).

#### 4.5. Nash-Sutcliffe Efficiency (NSE)

In the hydrology, the Nash–Sutcliffe coefficient [51] was widely used to evaluate the performance of simulated time series against observations. The formula for calculating this coefficient is as follows [52]:

$$NSE = 1 - \frac{\sum_{i=1}^n (X_i^{obs} - X_i^{sim})^2}{\sum_{i=1}^n (X_i^{obs} - X^{mean})^2} (i = 1, 2, \dots, n) \quad (7)$$

where  $X_i^{obs}$  is the  $i$ th value in the observation series,  $X_i^{sim}$  is the  $i$ th value in the simulated series,  $X^{mean}$  is the mean value of observation series and  $n$  is the number of observations.

$NSE$  ranges between  $-\infty$  and 1.  $NSE = 1$  means the perfect fit.  $0 < NSE \leq 1$  means that the performance of simulated series is acceptable. If  $NSE \geq 0$ , it explains that the simulated series is worse [53]. In our study,  $NSE$  was used as an indicator to compare GRACE/Swarm-DSI (observation series) with the traditional drought indices (simulated series).

#### 4.6. Long-Term Trend Change and Acceleration

The observations series can be decomposed into the long-term trend change term, acceleration term, seasonal change term (annual change and semi-annual change), and residual term. The expression is as follows [43]:

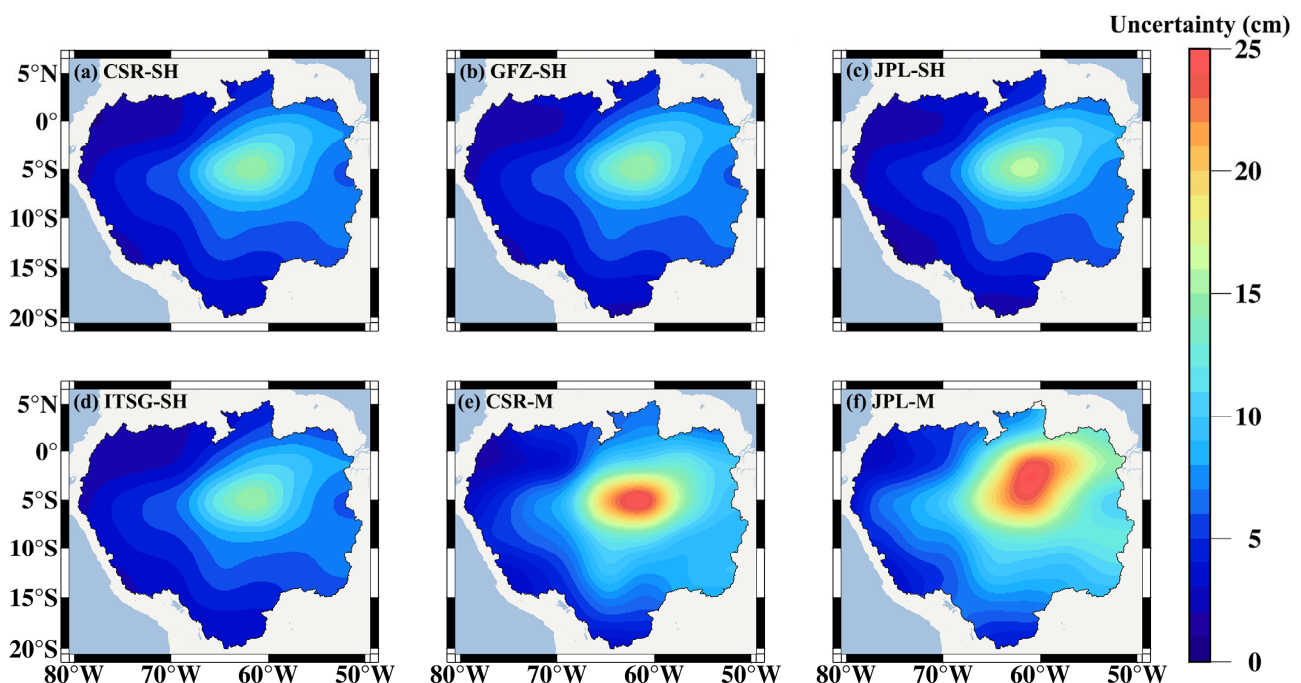
$$Data(t) = A + B(t - t_0) + C(t - t_0)^2 + D_1 \cos(2\pi t) + D_2 \sin(2\pi t) + E_1 \cos(4\pi t) + E_2 \sin(4\pi t) + \varepsilon \quad (8)$$

where  $Data(t)$  is the observation series,  $t$  is the time;  $t_0$  is the midpoint of the entire research period;  $\varepsilon$  is the residual term; and  $A$ ,  $B$ ,  $C$ ,  $D_1$ ,  $D_2$ ,  $E_1$ , and  $E_2$  are the unknown parameters;  $A$  is the constant term;  $B$  is the long-term trend change,  $C$  is the acceleration;  $D_1$  and  $D_2$  are annual terms; and  $E_1$  and  $E_2$  are semi-annual terms.

### 5. Results

#### 5.1. Data Fusion

To assess the accuracy of six TWSC results, we plotted the spatial distribution maps of uncertainties of TWSC results from six GRACE solutions in the ARB (Figure 3). We found that the uncertainties of TWSC results from the four SH solutions are smaller than the ones from the two Mascon solutions. As all the TWSC results from four SH solutions show the uncertainties are greater than 17 cm, while the TWSC results from two Mascon solutions exhibit uncertainties are between 17 cm and 25 cm in the part of ARB. In particular, the uncertainties of TWSC results from JPL-SH are higher than 16 cm in the part of ARB relative to the other three GRACE SH solutions. The red region of Figure 3f (JPL-M) is larger than that of Figure 3e (CSR-M), it explains that the uncertainties of TWSC results from JPL-M are higher than those from CSR-M. Overall, all the TWSC results reveal a similar spatial distribution of uncertainties, that is, the western and southern of ARB show that the uncertainties are smaller and the larger uncertainties are mainly concentrated in the northeast of ARB.



**Figure 3.** The spatial distribution of uncertainties of TWSC results from six GRACE solutions.

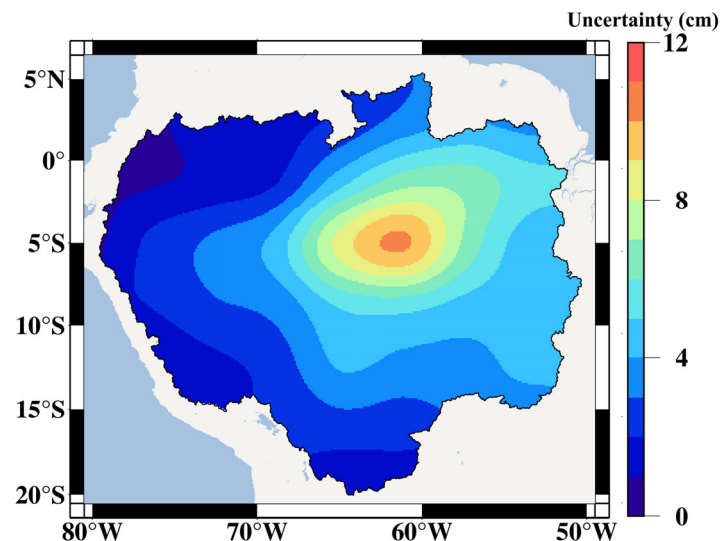
To evaluate the uncertainties of TWSC results from six GRACE solutions, we used the median of all uncertainties gridded values to measure the total uncertainty in the study region (Table 3). From Table 3, we sorted by the uncertainty in ascending order, the arrangement of GRACE solutions is CSR-SH (43.153 mm), ITSG-SH (43.315 mm), GFZ-SH

(43.628 mm), JPL-SH (44.594 mm), CSR-M (10.900 mm) and JPL-M (116.491 mm). It suggests that two Mascon solutions have the greater uncertainties than four SH solutions, and the accuracy level of four SH solutions are not much different.

**Table 3.** Uncertainties of TWSC results from the six GRACE solutions and fused results estimated by the GTCH method.

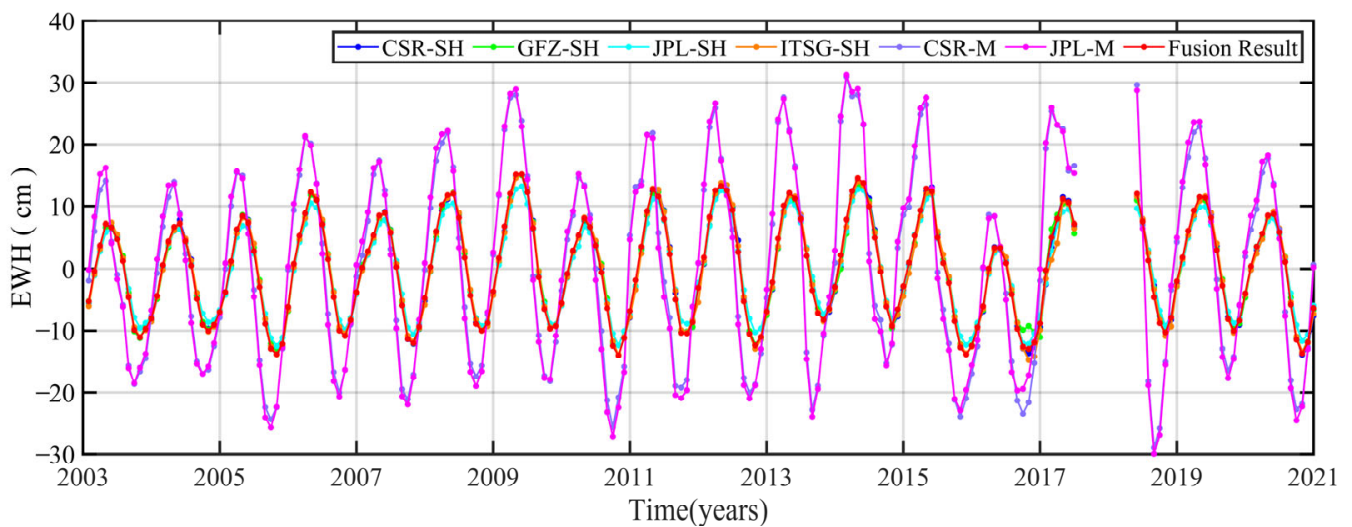
| GRACE Solution | CSR-SH | GFZ-SH | JPL-SH | ITSG-SH | CSR-M   | JPL-M   | Fused Result |
|----------------|--------|--------|--------|---------|---------|---------|--------------|
| Medium (mm)    | 43.153 | 43.628 | 44.594 | 43.315  | 107.900 | 116.491 | 36.577       |

To improve the accuracy of TWSC results from GRACE solutions, we fused six TWSC results from GRACE solutions by the least square method. We plotted the spatial distribution map of uncertainties of fused results (Figure 4). The uncertainties of fused results in the most region of ARB are less than 4 cm, while those in the northeast ARB are greater than 4 cm and the maximum value reaches 12 cm. Comparing Figures 3 and 4, the uncertainties of fused results are significantly smaller than those of any single GRACE solutions. Table 3 shows that the uncertainties of TWSC results from six GRACE solutions are greater than those of fusion results (36.577 mm).



**Figure 4.** The spatial distribution of uncertainties of TWSC from fused results.

We compared the time series of TWSC results from six GRACE solutions and fused result in the ARB during 2003 and 2020 (Figure 5) and calculated the correlation coefficients between fused result and six GRACE TWSC results (Table 4). Figure 5 shows that the change trends of seven time series of TWSC results are basically the same and they all have significant seasonal variation. The TWSC results from two Mascon solutions have the greater magnitudes than those from four SH solutions and fused result, and the magnitudes of fused result and the TWSC results from SH solutions are very close. It is related to the uncertainty results of TWSC results from six GRACE solutions. As the uncertainties of TWSC results from SH solutions are smaller than those of Mascon solutions, the weights of SH solutions are larger than those of Mascon solutions. From Table 4, the fused result has the strongest correlation with CSR-SH (0.9962), followed by JPL-SH (0.9957), GFZ-SH (0.9955), ITSG-SH (0.9950), CSR-M (0.8610) and JPL-M (0.8363). It suggests that the fused result has good consistency with TWSC results from six GRACE solutions. For convenience, we referred to the fused result as GRACE result in the subsequent study. We found that there is an 11-month data gap in these seven TWSC results. Therefore, we used Swarm data to fill this gap in a follow-up study.



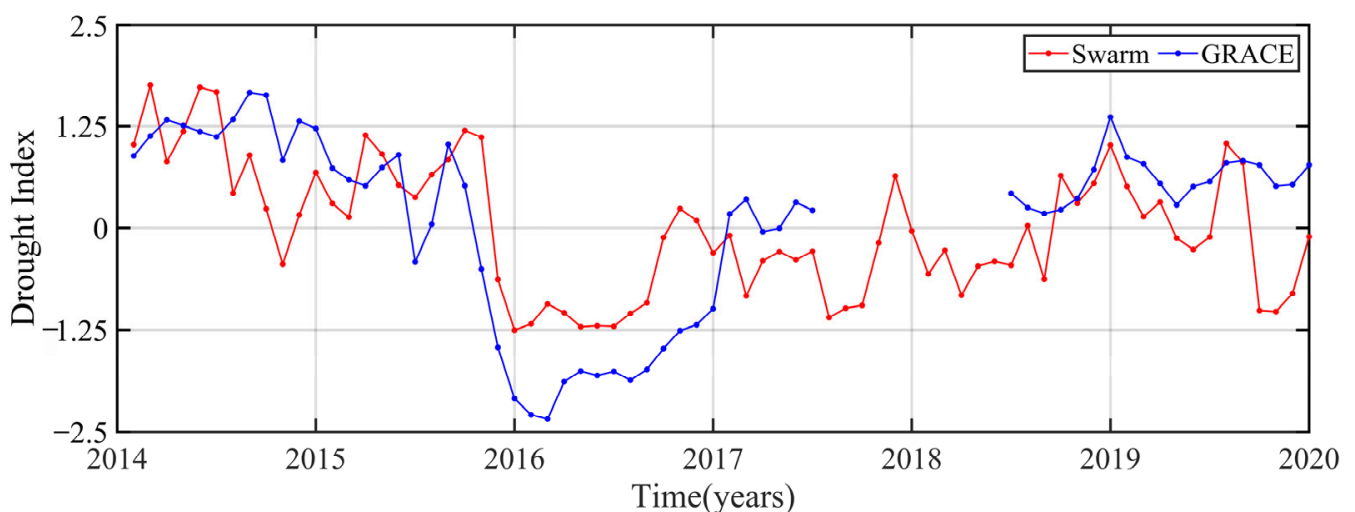
**Figure 5.** The time series of TWSC results from six GRACE solutions and fused result.

**Table 4.** The correlation coefficients between the fused results and TWSC results from six GRACE solutions (These results have passed the 99% confidence level).

| Correlation Coefficient | CSR-SH | GFZ-SH | JPL-SH | ITSG-SH | CSR-M  | JPL-M  |
|-------------------------|--------|--------|--------|---------|--------|--------|
| Fused results           | 0.9962 | 0.9955 | 0.9957 | 0.9950  | 0.8610 | 0.8363 |

### 5.2. Construction of the Combined Drought Index (GRACE/Swarm-DSI)

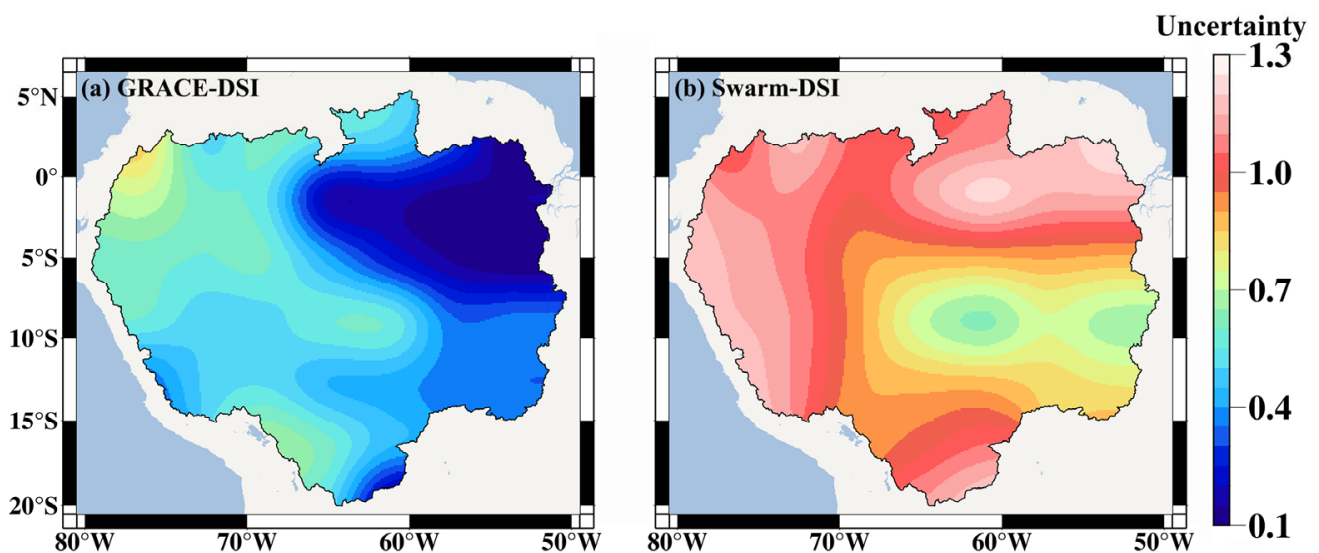
Figure 6 shows the time series of drought indices from GRACE and Swarm models in the ARB from 2014 to 2019. From Figure 6, we found that two drought indices have the similar trend. The correlation coefficient between GRACE-DSI and Swarm-DSI is 0.6711, and the result passed the 99% confidence level. It explains that GRACE-DSI has a strong correlation with Swarm-DSI.



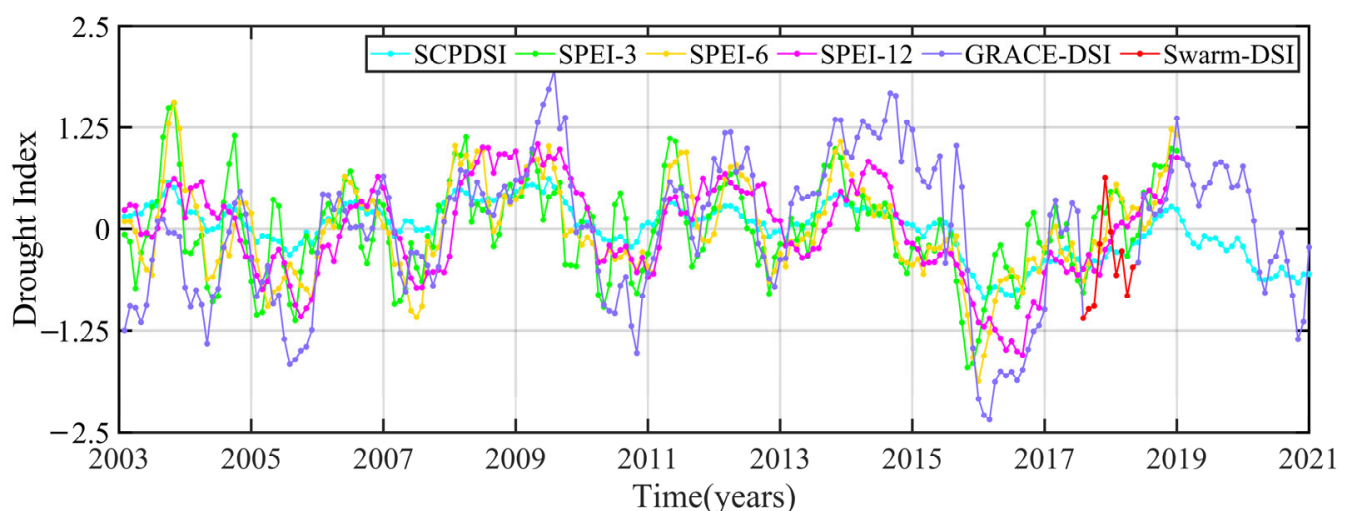
**Figure 6.** The time series of drought indices form GRACE and Swarm models in the ARB from 2014 to 2019.

To further evaluate the Swarm-DSI, we plotted the spatial distribution of the uncertainties of GRACE-DSI and Swarm-DSI in the ARB (Figure 7). From the two figures, we can see that the uncertainties of GRACE-DSI are much smaller than those of Swarm-DSI.

Most of the uncertainties of GRACE-DSI are less than 0.6, while those of Swarm-DSI are larger than 0.8. However, GRACE-DSI has a similar distribution of uncertainties with Swarm-DSI, that is, the larger uncertainties are concentrated in the western and southern ARB. We selected the median of all uncertainties gridded values of GRACE-DSI (0.4299) and Swarm-DSI (0.9880) to represent the accuracy of two drought indices. Subsequently, we used Swarm-DSI to fill the gap in the middle of GRACE-DSI to form a continuous long time series of TWSC-based drought index (GRACE/Swarm-DSI, see Figure 8).



**Figure 7.** The spatial distribution of uncertainties of GRACE-DSI and Swarm-DSI in the ARB.



**Figure 8.** The time-series of GRACE/Swarm-DSI, SCPDSI, SPEI-3, SPEI-6 and SPEI-12 in the ARB during 2003–2020.

### 5.3. The Spatial and Temporal Change of GRACE/Swarm-DSI

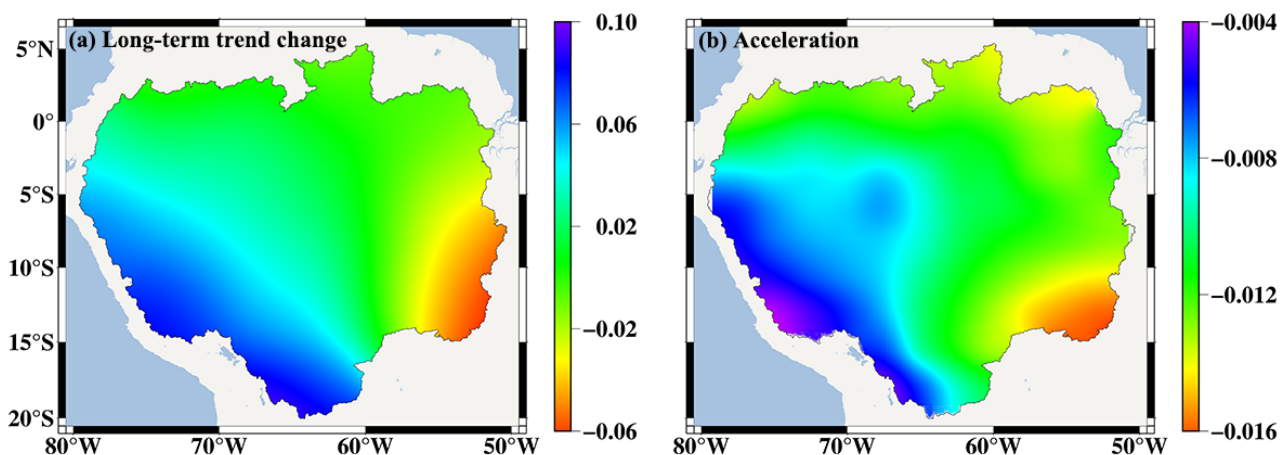
Figure 8 shows the time series of GRACE/Swarm-DSI, SCPDSI, SPEI-3, SPEI-6 and SPEI-12 in the ARB during 2003 and 2020. We found that GRACE/Swarm-DSI and four drought indices have the similar change trend. To quantify the relationship between GRACE/Swarm-DSI and four drought indices, we calculated the correlation coefficients and NSEs between them (Table 5). From Table 5, it suggests that GRACE/Swarm-DSI has the strongest correlation with SPEI-12 (0.6820), followed by SPEI-6 (0.6377), SCPDSI (0.6345) and SPEI-3 (0.5411). It explains that GRACE/Swarm-DSI has a strong correlation with the

four drought indices. The NSEs between GRACE/Swarm-DSI and SCPDSI, SPEI-3, SPEI-6, SPEI-12 are 0.3348, 0.2783, 0.4044 and 0.4627, respectively. It means that GRACE/Swarm-DSI is within the acceptable range. Overall, it's reliable that GRACE/Swarm-DSI can be used to detect the drought events in the ARB.

**Table 5.** The correlation coefficients and NSE between GRACE/Swarm-DSI and four tradition drought indices (The correlation coefficient results have passed the 99% confidence level).

| Variables                   | Correlation Coefficient | NSE    |
|-----------------------------|-------------------------|--------|
| GRACE/Swarm-DSI vs. SCPDSI  | 0.6345                  | 0.3348 |
| GRACE/Swarm-DSI vs. SPEI-3  | 0.5411                  | 0.2783 |
| GRACE/Swarm-DSI vs. SPEI-6  | 0.6377                  | 0.4044 |
| GRACE/Swarm-DSI vs. SPEI-12 | 0.6820                  | 0.4627 |

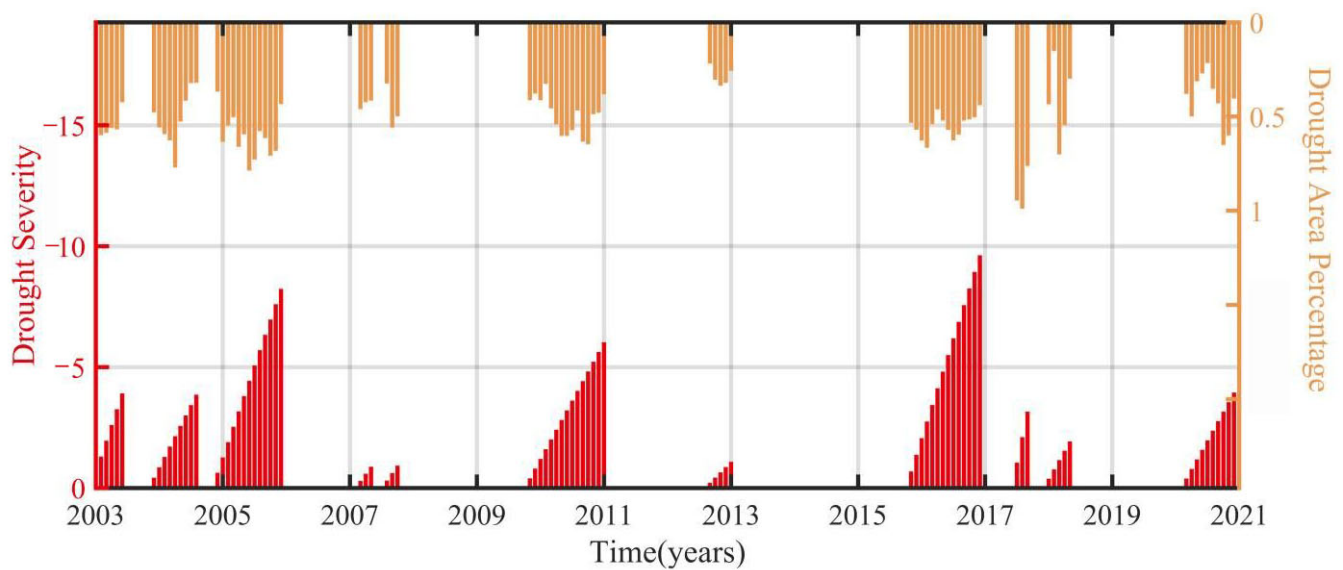
We plotted the spatial distribution maps of long-term trend change and acceleration of GRACE/Swarm-DSI in the ARB during 2003 and 2020 (Figure 9). From Figure 9a, there is an increasing trend in the southwest ARB and the long-term trend changes are between 0.06 and 0.10. A decreasing trend appears in the southeast ARB, and the long-term trend changes in this region are between  $-0.06$  and  $-0.04$ . The long-term trend changes in the other study regions are between  $-0.02$  and  $0.04$ , which are smaller than those in the southwest and southeast ARB. We used the Mann–Kendall trend test [54] to analyze the change trend of GRACE/Swarm-DSI series in the green region in Figure 9a, and the result shows  $|Z_S| < 1.96$ , which means that there is no significant change trend in this region at the 95% significance level [55]. Figure 9b shows the accelerations of GRACE/Swarm-DSI are negative, whose values are very small (between  $-0.016$  and  $-0.004$ ). Among them, the maximum ( $-0.004$ ) occurs in the southwest ARB, while the minimum ( $-0.016$ ) appears in the southeast ARB. Combining Figure 9a,b, we found that the increasing trends in the southwest and the decreasing trends in the southeast ARB have slowed.



**Figure 9.** The long-term trend changes and acceleration of GRACE/Swarm-DSI in the ARB during 2003–2020.

#### 5.4. Drought Event Assessment

We used the method in Section 4.1 to quantitatively analyze the characteristics of drought events in the ARB from 2003 to 2020 (Figure 10 and Table 6). From Figure 10 and Table 6, we can see that there are 11 drought events during the study period. The longest drought event occurred during November 2009 and January 2011, which lasted 15 months. The most severity drought event appeared from November 2015 to December 2016, whose drought severity is  $-9.63$ . The most widespread drought event occurred between July 2017 and September 2017, and 80% of the area was affected by drought event at peak. The previous studies and local news were used to verify our results (Table 6).



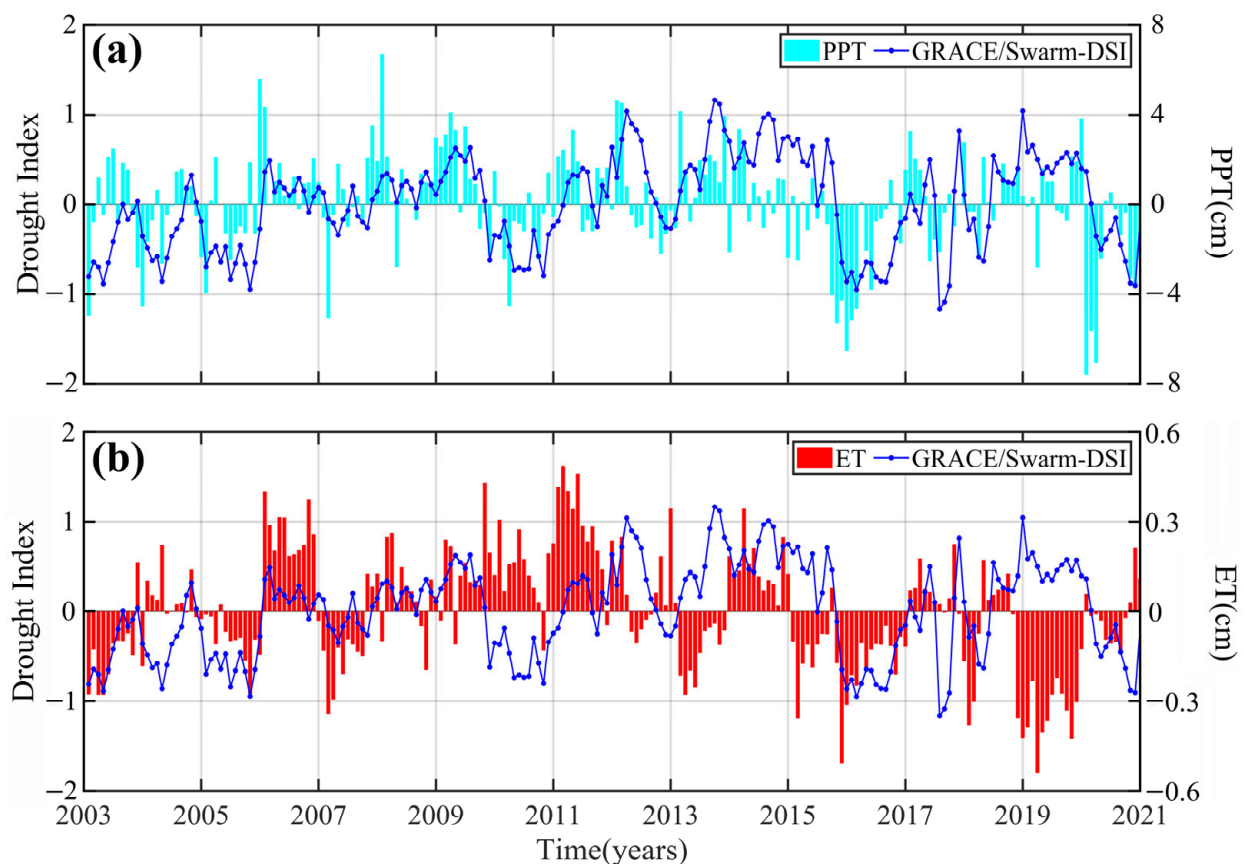
**Figure 10.** The time-series of GRACE/Swarm-DSI in ARB during 2003–2020. The red and orange bars represent the drought severity and drought area percentage for each month during drought event, respectively.

**Table 6.** Summary table of drought events.

| No. of Events | Time Span     | Duration (Months) | GRACE/Swarm-DSI |                   |                  | Drought Area Percentage |                   |                      | Previous Studies Validation (Y/N) |
|---------------|---------------|-------------------|-----------------|-------------------|------------------|-------------------------|-------------------|----------------------|-----------------------------------|
|               |               |                   | Peak Magnitude  | Average Magnitude | Drought Severity | Peak Magnitude          | Average Magnitude | Cumulative Magnitude |                                   |
| 11            | 200301–200306 | 6                 | −0.81           | −0.65             | −3.92            | 66.79%                  | 56.77%            | 340.61%              | Y [19]                            |
|               | 200312–200408 | 9                 | −0.8            | −0.43             | −3.86            | 76.99%                  | 51.22%            | 460.94%              | Y [19]                            |
|               | 200412–200512 | 13                | −0.98           | −0.63             | −8.24            | 78.67%                  | 60.28%            | 783.70%              | Y [15]                            |
|               | 200703–200705 | 3                 | −0.39           | −0.29             | −0.88            | 46.02%                  | 43.31%            | 129.93%              | Y [19]                            |
|               | 200708–200710 | 3                 | −0.38           | −0.31             | −0.93            | 55.89%                  | 46.05%            | 138.15%              | Y [19]                            |
|               | 200911–201101 | 15                | −0.86           | −0.4              | −6.03            | 64.72%                  | 49.35%            | 740.27%              | Y [16,56]                         |
|               | 201209–201301 | 5                 | −0.29           | −0.22             | −1.08            | 33.67%                  | 28.74%            | 143.72%              | Y [19]                            |
|               | 201511–201612 | 14                | −0.95           | −0.69             | −9.63            | 66.56%                  | 54.93%            | 769.06%              | Y [27]                            |
|               | 201707–201709 | 3                 | −1.16           | −1.05             | −3.16            | 98.90%                  | 89.91%            | 269.74%              | Y [57]                            |
|               | 201801–201805 | 5                 | −0.64           | −0.39             | −1.93            | 70.08%                  | 42.64%            | 213.18%              | N                                 |
|               | 202003–202012 | 10                | −0.86           | −0.39             | −3.95            | 65.05%                  | 41.16%            | 411.62%              | Y [58]                            |

### 5.5. The Causes of Drought Events

We compared the time series of GRACE/Swarm-DSI, PPT anomaly and ET anomaly in the ARB during 2003 and 2020 (Figure 11). The PPT and ET anomalies were calculated by subtracting the mean values of the corresponding months from the original time series [29]. Figure 11 shows that PPT anomaly has better consistency with GRACE/Swarm-DSI than ET anomaly. When the PPT anomaly is positive (which means more PPT than normal), GRACE/Swarm-DSI is generally positive, that is, there is no drought. When PPT anomaly is negative (which means less PPT than normal), GRACE/Swarm-DSI is also generally negative, that is, there may be drought (Figure 11a). It explains that GRACE/Swarm-DSI and PPT anomaly have a close connection. However, there is a certain delay in the response of PPT anomaly and GRACE/Swarm-DSI. From Figure 11b, the correlation between GRACE/Swarm-DSI and ET anomaly is not significant. We calculated the correlation coefficients between GRACE/Swarm-DSI and PPT anomaly (0.41), ET anomaly (0.20), respectively, and the above results have passed the 99% confidence level. The results of correlation coefficient verify the conclusion of Figure 11.



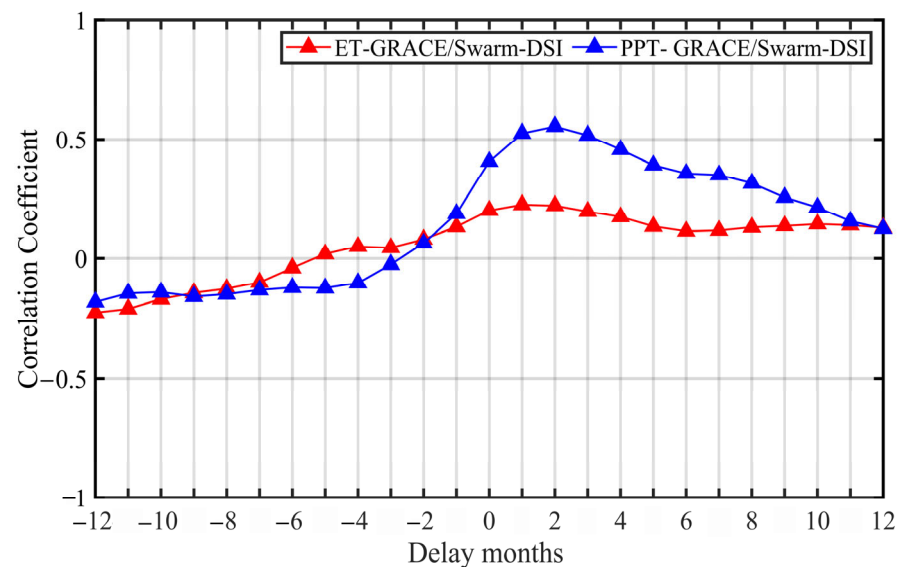
**Figure 11.** The series time of monthly GRACE/Swarm-DSI, PPT anomaly (a) and ET anomaly (b) in ARB during 2003–2020.

To further study the relation between GRACE/Swarm-DSI and PPT anomaly, ET anomaly, we analyzed the performance of PPT and ET anomaly during the drought events. We found that all drought events experienced less PPT than usual, but only four drought events experienced more ET than usual, which occurred from December 2003 to August 2004, from November 2009 to January 2011, from September 2012 to January 2013 and from July 2017 to September 2017. The above results suggest that PPT is an important factor affecting the occurrence of drought events in the ARB, while ET has little effect.

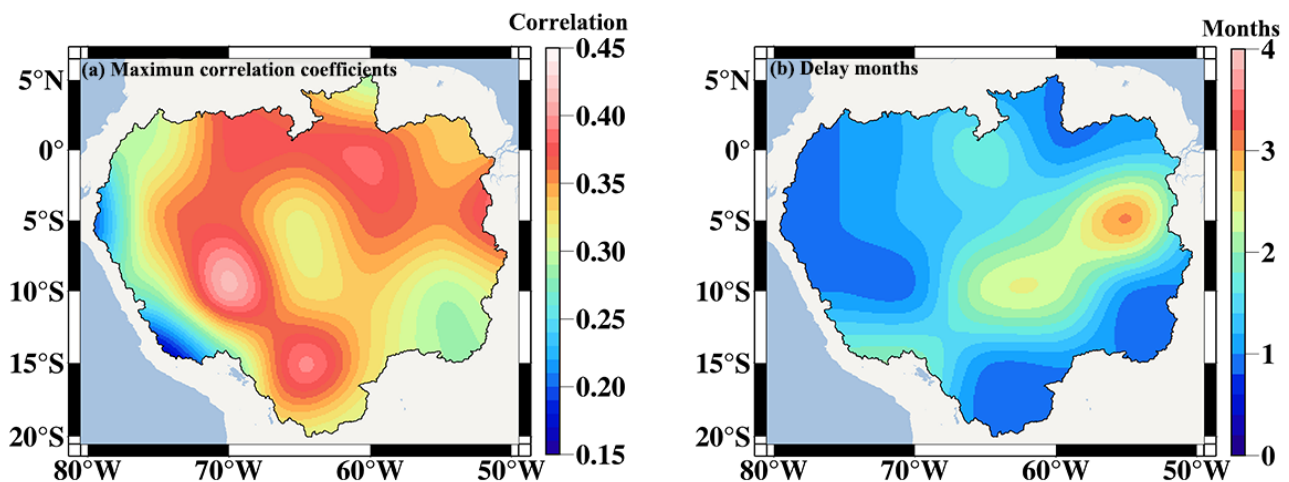
We calculated the maximum correlation coefficients and the delay months between GRACE/Swarm-DSI and PPT anomaly, ET anomaly (Figure 12). Figure 12 shows that the maximum correlation coefficient and the delay months between GRACE/Swarm-DSI and PPT anomaly are 0.55 and 2, respectively, while those of ET anomaly are  $-0.18$  and  $-12$ , respectively. It indicates that PPT anomaly and GRACE/Swarm-DSI have a stronger correlation and there is a 2-month delay in the response of GRACE/Swarm-DSI to PPT. However, the correlation between GRACE/Swarm-DSI and ET anomaly is not strong. The results confirm the analysis of Figure 11.

To further analyze the relationship between GRACE/Swarm-DSI and PPT anomaly in the ARB, we plotted the spatial distribution maps of maximum correlation coefficients (Figure 13a) and delay months (Figure 13b) between GRACE/Swarm-DSI and PPT anomaly. From Figure 13a, GRACE/Swarm-DSI has a positive correlation with PPT anomaly. The correlation coefficients are greater than 0.3 in most of regions. The regions with the larger correlation are mainly concentrated in the Amazon Plain, the lower ARB and the Maldives River basin. The correlation coefficients are smaller in the Andes, the northern and southeastern mountains. It may be related to the fact that the plains receive more PPT than the mountains [59]. From Figure 13b, the delay month is 1–2 months in most of

regions. However, the delay month is greater than 4 months in the lower ARB, and the maximum delay month is 7 months.



**Figure 12.** The correlation coefficients and delay months between GRACE/Swarm-DSI and PPT anomaly, ET anomaly in the ARB (The correlation coefficient results have passed the 95% confidence level).



**Figure 13.** The long-term trend changes and acceleration of GRACE/Swarm-DSI in the ARB during 2003–2020 (The maximum correlation coefficient results in (a) have passed the 95% confidence level).

## 6. Discussion

We used GRACE and Swarm satellites to monitor the droughts in the ARB between 2003 and 2020 and quantified the characteristics of these droughts. However, due to the limitation of Satellite-to-Satellite Tacking in the high-low model, the Swarm model has greater errors than the GRACE model [19]. The uncertainty of TWSC results from the Swarm model in the basin is a hot spot for scientists in the world. Wang et al. [60] computed the long-term trend changes of TWSC in the ARB from December 2013 to June 2017. The results show that the TWSC results from the GRACE and Swarm models have the same change trend, and the long-term change trends of the two models are close. Additionally, there is a strong correlation between TWSC results from GRACE and Swarm models (93.55%). The cycle repetition time and periodic repetition ratio of TWSC from the two models are 3.5 years and 100%, respectively. The results indicate that the Swarm model

is fully suitable for hydrological research in the ARB. Cui et al. [19] also used the GRACE and Swarm models to calculate TWSC results in the ARB from December 2013 to May 2020. They found that the TWSC results from two models have good spatiotemporal consistency. Da Encarnação et al. [25] suggested that the TWSC time series in the ARB from Swarm and GRACE/GRACE-FO are very close, and the correlation between the two series is 0.95. Therefore, it is feasible that GRACE, GRACE-FO and Swarm data were combined to construct a combined drought index to characterize droughts in the ARB.

Regarding the causes of drought in the ARB, Panisset et al. [56] explained that the three severe drought events in the ARB in 2005, 2010 and 2015 were mainly caused by extreme climate. The severely sufficient PPT in most regions of ARB during 2005 and 2015 aggravated the drought severity. It is consistent with our results that PPT is the most important factor affecting drought events. However, although the frequency of droughts in the ARB has increased since 2000, there is a wetter trend in this region [13,61]. Only in the southeast ARB is there a significant negative change trend (Figure 9a), and the trend may be due to the influence of extreme drought in the northeast of Brazil [62,63]. In addition to climate change, human activity also has an influence on the formation of drought in the ARB. Cavalcante et al. [64] indicated that deforestation is an important cause of the runoff change in the ARB. The runoff changes directly affected the soil moisture, and the soil water deficit led to the occurrence of drought [29]. However, it is difficult to assess the human-induced TWSC. Therefore, how to obtain the long-term time series of human-induced TWSC with high temporal resolution is the key to studying the influence of human activity on the drought.

## 7. Conclusions

To obtain the continuous long-term drought index series in the ARB, we combined GRACE, GRACE-FO and Swarm models to construct a set of 18-year uninterrupted TWSC-based drought index series (GRACE/Swarm-DSI). We used the GTCH and least square method to fused the TWSC results from six GRACE solutions to improve the reliability of GRACE TWSC results, and combined fused TWSC results and Swarm data to construct GRACE/Swarm-DSI in our study. Subsequently, we used the correlation coefficients and NSEs between GRACE/Swarm-DSI and four drought indices to measure the reliability of GRACE/Swarm-DSI, and GRACE/Swarm-DSI was used to detect and characterize the drought events in the ARB during 2003 and 2020. The results show that GRACE/Swarm-DSI has the good consistent with SCPDSI, SPEI-3, SPEI-6, SPEI-12, and there are 11 drought events in the ARB during the study period. Among these drought events, the drought event from November 2015 to December 2016 is the most severe, covering 66.56% of the entire basin area and the drought severity is  $-9.63$ . PPT is the main factor affecting drought disasters, while ET only plays an auxiliary role, and the response time of GRACE/Swarm-DSI to PPT is about 1~2 months in most regions of ARB.

Our results indicate that Swarm data have the potential to monitor and characterize the droughts in the ARB. They provide a certain reference for filling the gap between GRACE and GRACE-FO missions in the hydrological research.

**Author Contributions:** Conceptualization, L.C.; methodology, L.C. and X.W.; validation, L.C. and Z.H.; formal analysis, M.Y. and X.L.; investigation, L.C.; resources, C.Y.; data curation, M.Y.; writing—original draft preparation, L.C. and C.Y.; writing—review and editing, X.W. and C.Y.; supervision, M.Y.; funding acquisition, Z.H. All authors have read and agreed to the published version of the manuscript.

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**Data Availability Statement:** GRACE RL06 data from CSR, GFZ, JPL, and ITSG and Swarm data from COST-G: <http://icgem.gfz-potsdam.de/series> (accessed on 10 April 2022); GPCC precipitation data: <https://psl.noaa.gov/thredds/catalog/Datasets/gpcc/catalog.html> (accessed on 10 April 2022); ET gridded data: <sftp://hydras.ugent.be> (accessed on 10 April 2022); SPEI data: (<http://spei.csic.es/>) (accessed on 10 April 2022); SCPDSI data: <https://crudata.uea.ac.uk/cru/data/drought/> (accessed on 10 April 2022).

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**Conflicts of Interest:** The authors declare no conflict of interest.

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