

Article

Spatiotemporal Variations in Terrestrial Water Storage and Water Scarcity Assessment Across China Based on TWSA_BTCH

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Highlights

What are the main findings?

- The TWSA across China decreased at a linear rate of -1.65 mm/a during 2000–2023, with the whole country exhibiting moderate overall water scarcity. Both TWSA and water scarcity index show prominent north–south spatial differentiation. This pattern reveals inherent water supply–demand imbalances in arid and semi-arid northern China. Latent terrestrial water storage deficit risks in the southern SWRB cannot be overlooked.
- Distinct decoupling exists between the TWSA-derived water scarcity index and long-term TWSA trends in SRB and SWRB, revealing that water resource risks need joint characterization via hydrological fluxes and storage. The SRB exhibits severe water scarcity. Weak water regulation and thick cohesive aquitards restrict infiltration recharge. Yet increased precipitation sustains its persistent terrestrial water storage surplus. Combined karst leakage, reservoir evaporation and a warm–dry climate trigger latent terrestrial water storage deficit risks in the SWRB.

What are the implications of the main findings?

- Conventional flux-based water scarcity assessments assume stationary terrestrial water storage and neglect annual dynamic fluctuations in groundwater and soil water, making it difficult to simultaneously identify long-term terrestrial water storage depletion risks and the natural buffering endowment of storage-surplus regions. This study constructs an evaluation framework coupling annual hydrological fluxes with annual TWSC, covers water consumption across all sectors, and characterizes long-term storage evolution based on long-term TWSA trends. The framework enables the simultaneous diagnosis of seasonal water scarcity and cumulative terrestrial water storage deficit, and provides support for differentiated zoned water resource management.

Abstract

Clarifying the spatiotemporal variations of terrestrial water storage anomaly (TWSA) and the water scarcity is crucial for maintaining water resources, ecosystem and food security. This study adopts the Bayesian triple collocation method (BTCH) method to fuse three

Academic Editor: Hatim Sharif

Received: 27 May 2026

Revised: 7 July 2026

Accepted: 8 July 2026

Published: 11 July 2026

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GRACE Mascon product datasets to generate the TWSA_BTCH, covering the period from April 2002 to December 2023. The reliability of TWSA_BTCH is further verified using the water balance approach. The spatiotemporal variations of TWSA and the water scarcity index based on terrestrial water storage (WS_{TWS_based}) at the national and primary water resource regional level are then analyzed. The results indicate that: (1) The spatially averaged uncertainty of the TWSA_BTCH over China is 8.13 mm, which is lower than those of TWSA_average (12.51 mm), TWSA_CSR (23.43 mm), TWSA_GSFC (29.79 mm), and TWSA_JPL (31.76 mm). (2) From 2003 to 2023, the TWSA exhibited an overall significant declining trend with an annual depletion rate of 1.65 mm. The national average value of the WS_{TWS_based} index decreased from 0.32 during 2003–2012 to 0.28 over 2013–2023, which indicates that the pressure of nationwide water scarcity has been alleviated to a certain extent, while the whole country still faces a moderate water shortage status. Meanwhile, the mean annual TWSA across China during 2003–2023 was −10.28 mm, indicating a nationwide terrestrial water storage deficit. (3) Regional water resource risks require joint characterization from the dual perspectives of hydrological fluxes and storage. Northern arid and semi-arid regions feature inherent imbalances between water supply and demand. The latent risks of terrestrial water storage depletion within the SWRB cannot be ignored. In addition, insufficient water regulation capacity in the SRB deserves adequate attention.

Keywords: TWSA_BTCH; GRACE; terrestrial water storage; spatiotemporal analysis; water scarcity; China

1. Introduction

Terrestrial water storage encompasses groundwater, soil moisture, surface water, glaciers, and snowfields, playing a critical role in the hydrological cycle and the Earth's climate system. Its variations reflect the overall changes in regional terrestrial water storage, which are essential for maintaining ecological balance [1], supporting agricultural and industrial development [2], and sustaining human survival [3]. Water scarcity, the insufficient availability of freshwater to meet human and ecosystem demands, is a growing global concern [4–6]. Driven by population growth, climate change, and inefficient water management, it poses substantial challenges to human health, economic development, and environmental sustainability [7,8]. Despite China's abundance of rivers and lakes, it exhibits a low per capita water resource availability due to its large population. Moreover, the spatiotemporal distribution of water resources is highly uneven, influenced by meteorological and topographical factors, with certain arid and semi-arid regions within the country contend with water scarcity [9–12]. Accurately characterizing the spatiotemporal distribution of terrestrial water storage in China and identifying the water scarcity are of significant importance for the sustainable utilization of water resources and for maintaining water resource security, ecosystem security and food security.

At present, terrestrial water storage changes are mainly monitored via satellite remote sensing inversion, field observations, and model simulations [1,5,8,13,14]. The effectiveness of field observations and model simulations is limited in many regions due to technical and topographic constraints [15]. The launch of the GRACE gravity satellite in March 2002 provided an effective means for large-scale monitoring of terrestrial water storage changes [7,16]. Numerous domestic and international scholars have conducted extensive studies using GRACE data in global [17], China [18,19], the Tibetan Plateau [20], the Yangtze River Basin [21], the Yellow River Basin [22], the Three-North Region [23], Australia [24], the Indus River Basin [25], and the Amazon Basin [26]. However, most of

these studies were based on a single GRACE data product. Some scholars have employed the Three-Cornered Hat (TCH) method to assess the relative uncertainty of gridded datasets [27–30] to enhance their applicability, while others have utilized the average of multiple GRACE data products [18,31] to reduce the relative uncertainty of TWSA data. Despite this, it remains challenging to obtain a TWSA dataset that minimizes uncertainty to the greatest extent while ensuring consistency across the entire country. To address this issue, this study employs the Bayesian triple collocation method (BTCH) method, which has been previously applied in evapotranspiration [32], soil moisture [33], and global terrestrial water storage [34], to integrate three GRACE Mascon products from CSR, JPL, and GSFC, thereby constructing a fused dataset with minimum uncertainty. In addition, accurately assessing water scarcity is crucial for informed decision-making and risk assessments. It must consider both water availability and water use. Most assessments evaluate the available surface and groundwater (blue water), while rain water stored in soil and used by plants (green water) receives less attention and remains difficult to quantify [35,36]. Few studies have assessed coupled blue and green water scarcity, and existing relevant research underscores the need to incorporate both blue and green water into water availability calculations [37–42]. When calculating water availability, traditional Global Hydrological Models (GHMs) generally only account for available blue water while ignoring green water [43]. Remote sensing observations offer a promising alternative to improve blue green water assessments [44–46]. Therefore, this study employs the water scarcity index proposed by Fitsum T. et al. [43], which is based on terrestrial water storage anomalies inverted from GRACE satellite data, to evaluate water resource risk across China and its primary water resource regions.

This study aims to: (1) fuse the CSR, JPL, and GSFC GRACE Mascon products using the BTCH method to develop a TWSA_BTCH dataset, validated by the water balance approach; (2) analyze the spatiotemporal variations of TWSA in China and its primary water resource regions through statistical methods; and (3) assess the water scarcity in China and its primary water resource regions based on the water scarcity index derived from terrestrial water storage (W_{TWS_based}).

2. Materials and Methods

2.1. Study Area

China, which is located in the eastern part of Asia and along the western coast of the Pacific Ocean, has a vast territory spanning a wide range of latitudes and longitudes. Coupled with its terrain descending stepwise from the high west to the low east, the country exhibits striking regional climatic differentiation. The eastern and southern regions of China are primarily under subtropical monsoon and temperate monsoon climates, where precipitation shows distinct seasonal variations, with higher rainfall in summer and autumn and lower rainfall in spring and winter. In contrast, the western and northern regions are dominated by temperate continental and plateau mountain climates, experiencing relatively low precipitation throughout the year. China comprises 10 primary water resource regions (Figure 1), including the Songhuajiang River water resource region (SRB), Liao River water resource region (LRB), Hai River water resource region (HRB), Yellow River water resource region (YRB), Huai River water resource region (HURB), Yangtze River water resource region (YZRB), Southeast River water resource region (SERB), Pearl River water resource region (PRB), Southwest River water resource region (SWRB), and Northwest River water resource region (NWRB). Among these, the northern subregions include six primary water resource regions: the SRB, LRB, HRB, YRB, HURB, and NWRB; the southern subregions comprise four primary water resource regions: the YZRB, SERB, PRB, and SWRB.

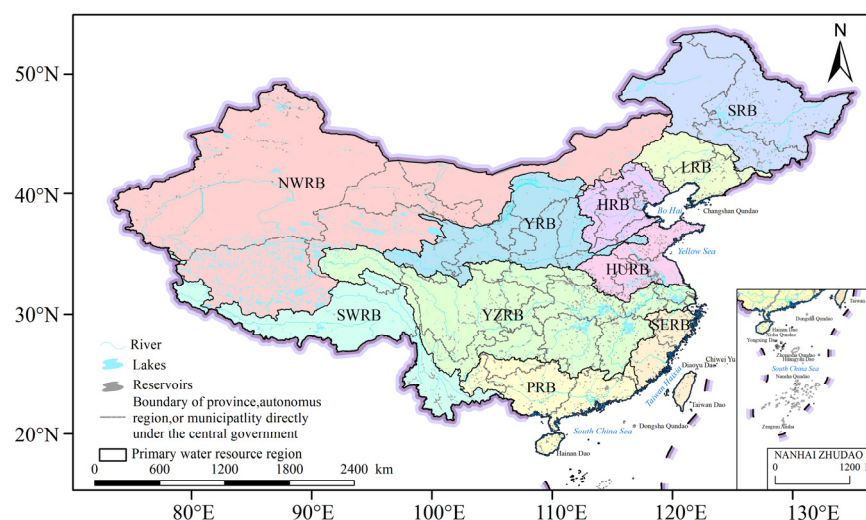


Figure 1. Primary water resource regions map in China. The map is compiled using the standard base map (Approval No. GS(2019)1822).

2.2. Data

(1). GRACE/GRACE-FO data

This study selects three GRACE Mascon solutions from CSR, JPL, and GSFC, covering a time span of 228 monthly data records from April 2002 to December 2023. The spatial resolution of all datasets was resampled to 0.5° (Table 1).

(2). Meteorological, Hydrological, and Water Resource Data

The precipitation data are derived from the CN 05.1 daily gridded dataset [47], which is interpolated from 2416 meteorological stations in China, with a spatial resolution of $0.25^\circ \times 0.25^\circ$. The evapotranspiration data are obtained from the GLEAM dataset [48], known for its high accuracy in China, with a temporal resolution of monthly and a spatial resolution of $0.25^\circ \times 0.25^\circ$. The runoff data are sourced from the China Natural Runoff Gridded Dataset CNRD v1.0, which covers the period from 1961 to 2018 and has a spatial resolution of $0.25^\circ \times 0.25^\circ$. The temporal resolutions of precipitation, evapotranspiration, and runoff data were unified to annual scale, while their spatial resolutions are resampled to $0.5^\circ \times 0.5^\circ$ using bilinear interpolation. The annual water consumption data for China and its primary water resource regions are obtained from the China Water Resources Bulletin published by the Ministry of Water Resources of China (Table 1).

Table 1. The basic information of the dataset used in this study.

Product	Data Name	Spatial Resolution	Temporal Resolution	Study Period	Purpose
GRACE	CSR_Mascon	$0.25^\circ \times 0.25^\circ$	monthly	April 2002–December 2023	Retrieve TWSA time series from three independent Mascon products to support subsequent multi-source data fusion.
	JPL_Mascon	$0.5^\circ \times 0.5^\circ$	monthly	April 2002–December 2023	
	GSFC_Mascon	$0.5^\circ \times 0.5^\circ$	monthly	April 2002–December 2023	
CN05.1	Precipitation	$0.25^\circ \times 0.25^\circ$	monthly	April 2002–December 2023	(1). For calculating Terrestrial Water Storage Change (TWSC);
GLEAM	ET	1 km	monthly	2003–2023	(2). For calculating Net Total Available Water (Q_{net}).
CNRD v1.0	Runoff	$0.25^\circ \times 0.25^\circ$	monthly	2003–2018	For calculating TWSC
China Water Resources Bulletin	Water consumption	-	year	2003–2023	Obtain water consumption data to calculate the WS_{TWS_based} index

2.3. Methods

2.3.1. Production of the TWSA_BTCH Dataset

This study employs the TCH method to calculate the uncertainties of three GRACE Mascon products. The relative uncertainty is determined by calculating the ratio of the uncertainty of each product at grid cells to the average of its absolute values (the average of TWSA absolute values from April 2002 to December 2023 is used in this study). Based on this, the BTCH method is applied to fuse the TWSA_CSR, TWSA_JPL, and TWSA_GSFC products for the Chinese region, resulting in the TWSA_BTCH dataset with a time span of April 2002 to December 2023, a spatial resolution of 0.5° , and a monthly temporal resolution. The Missing Data Dataset for Three GRACE/GRACE-FO Mascon Data Products published by Xie et al. [49] is utilized to fill in the 33 missing data records during April 2002–December 2023. Simultaneously, the average of the three GRACE Mascon products (TWSA_average) is calculated. The uncertainties of the five TWSA products (TWSA_CSR, TWSA_JPL, TWSA_GSFC, TWSA_BTCH, and TWSA_average) are further compared and analyzed via the TCH method. Statistical analysis is subsequently performed using histograms and kernel density estimation.

(1). TCH method

Assuming there are n distinct TWSA datasets, denoted as $\{TWSA_i\}_{i=1,2,\dots,n}$, where i represents different datasets. In this study, i specifically refers to CSR, JPL, and GSFC. Each dataset can be represented as:

$$TWSA_i = TWSA_t + b_i, \forall i = 1, 2, \dots, n \quad (1)$$

In this context, $TWSA_t$ denotes the true value of the dataset, and b_i represents the zero-mean error of the i -th dataset. Since the true value is difficult to obtain, one of the datasets is arbitrarily selected as the so-called “true value,” and the differences between the remaining datasets and this “true value” are calculated to form a difference sequence [50]:

$$Y_{i,ref} = TWSA_i - TWSA_{ref} = b_i - b_{ref}, i = 1, 2, \dots, n - 1 \quad (2)$$

In the equation, $Y_{i,ref}$ denotes the difference between the i -th product and the reference product, where $TWSA_{ref}$ represents an arbitrarily selected reference time series, and b_{ref} corresponds to the zero-mean error of the $TWSA_{ref}$ dataset. This study adopts the CSR solution as the reference time series value.

The covariance of these $n - 1$ difference time series is calculated using the covariance calculation equation and stored in matrix S :

$$S = \begin{bmatrix} s_{11} & s_{12} & \dots & s_{1(n-1)} \\ s_{21} & s_{22} & \dots & s_{2(n-1)} \\ \vdots & \vdots & \vdots & \vdots \\ s_{(n-1)1} & s_{(n-1)2} & \dots & s_{(n-1)(n-1)} \end{bmatrix}, s_{ij} = \text{cov}(Y_{i,ref}, Y_{j,ref}) \quad (3)$$

The element s_{ij} in the matrix denotes the variance estimate of the difference time series when $i = j$, and the covariance estimate between different difference time series when $i \neq j$. Galindo et al. [51] introduced an $n \times n$ symmetric noise covariance matrix R in relation to the covariance matrix S as follows:

$$S = J \cdot R \cdot J^T \quad (4)$$

In this context, J is an $(n - 1) \times n$ matrix:

$$J_{n-1,n} = \begin{bmatrix} 1 & 0 & \dots & 0 & -1 \\ 0 & 1 & \dots & 0 & -1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & -1 \end{bmatrix} \quad (5)$$

Matrix R is defined as:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{12} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{1n} & r_{2n} & \cdots & r_{nn} \end{bmatrix} \quad (6)$$

Based on these equations, $n \times (n - 1)/2$ equations with $n \times (n + 1)/2$ unknown parameters ($r_{11}, \dots, r_{nn}$) can be derived. To determine a unique solution for the remaining parameters, Galindo et al. [52] proposed constraint functions satisfying the Kuhn–Tucher theory:

$$H_{2(r_{1n}, \dots, r_{nn})} = -\frac{H_{1(r_{1n}, \dots, r_{nn})}}{K} < 0 \quad (7)$$

where $K = \sqrt[n-1]{|S|}$, and $H_{1(r_{1n}, \dots, r_{nn})}$ is defined as a constraint:

$$\frac{|R|}{|S|} = r_{nn} - [r_{1n} - r_{nn}, \dots, r_{(n-1)n} - r_{nn}] S^{-1} [r_{1n} - r_{nn}, \dots, r_{(n-1)n} - r_{nn}]^T \quad (8)$$

The specific objective function is defined as:

$$F_{(r_{1n}, \dots, r_{nn})} = \frac{1}{K^2} \sum_{i < j}^n r_{ij}^2 \quad (9)$$

The elements of the symmetric noise covariance matrix R can be obtained by solving the optimal solution of the objective function under constraint functions, where the square roots of the diagonal elements ($r_{11}, r_{22}, \dots, r_{nn}$) of matrix R correspond to the uncertainty of the respective input datasets.

(2). BTCH method

The BTCH method has been applied to integrate various observation time series [27,32,53]. This method represents the observation time series as probability density functions (PDFs) (Equation (10)), and combines the variances derived from the TCH method for each observation time series to obtain the maximum likelihood estimate of the true result (Equation (11)).

$$p(TWSA_i | TWSA_t) = \frac{1}{\sigma_i \sqrt{2\pi}} \exp\left(-\frac{b_i^2}{2\sigma_i^2}\right) = L(TWSA_t | TWSA_i) \quad (10)$$

$$\max L(TWSA_t | TWSA_i, TWSA_j) = p(TWSA_i | TWSA_t) p(TWSA_j | TWSA_t) = \frac{1}{2\pi\sigma_i\sigma_j} \exp\left[-\frac{b_i^2}{2\sigma_i^2} - \frac{b_j^2}{2\sigma_j^2}\right] \quad (11)$$

where $p(TWSA_i | TWSA_t)$ denotes the PDF of the i -th product, and σ_i represents the error variance of $TWSA_i$, and $L(TWSA_t | TWSA_i)$ is the likelihood function.

The maximum likelihood estimate of $TWSA_t$ can be obtained through the linear combination $TWSA_t = \omega_1 TWSA_1 + \dots + \omega_n TWSA_n$. The weights ω_k for each $TWSA$ product can be derived using the following equation:

$$\omega_k = \frac{\prod_{i=1, i \neq k}^n \sigma_i^2}{\sum_{k=1}^n (\prod_{i=1, i \neq k}^n \sigma_i^2)} \quad (12)$$

The error variance (σ_i) of each $TWSA$ product can be derived using the TCH method described previously.

2.3.2. Validation Method for Fused Products

To validate the reliability of the fused GRACE-derived products, this study indirectly validates the fused $TWSA$ products at the regional scale using $TWSC$ data calculated through water balance analysis for YZRB, YRB and SWRB. Furthermore, systematic differences exist between $TWSC$ data derived from the water balance method and GRACE observations [54], such as overestimation of the long-term average $TWSC$ at the regional scale and amplitude deviations. These discrepancies primarily stem from water imbalances in the reanalysis data, errors in evapotranspiration and runoff data, and the neglect of groundwater and human activities. Therefore, the validation process of the fused $TWSA$ data focused solely on the correlation between the two trends.

The core principle of the water balance is the change in terrestrial water storage (TWS) over a specific period should equal the difference between precipitation and the sum of evapotranspiration and runoff, as expressed in the following equation:

$$\text{TWSC} = ds/dt \approx P - R - ET \quad (13)$$

where P represents precipitation, R denotes runoff, and ET is actual evapotranspiration.

To compare the consistency of the monthly trends of TWSC calculated based on the water balance equation and the TWSC calculated top-down based on TWSA, the TWSC calculation formula integrating GRACE product data is as follows:

$$\text{TWSC}(t) = \frac{\text{TWSA_BTCH}(t) - \text{TWSA_BTCH}(t-1)}{\Delta t} \quad (14)$$

where t denotes the number of months in the TWSA time series.

2.3.3. Theil–Sen Trend Analysis and Mann–Kendall Statistical Test

The Theil–Sen trend analysis method is a robust non-parametric statistical approach for trend calculation, primarily used to quantify the rate of TWSA, its components, and precipitation as a driving factor. The calculation formula is as follows:

$$\beta = \text{Median} \left(\frac{x_j - x_i}{j - i} \right), \forall j > i \quad (15)$$

In the equation, β represents the change rate, x denotes Δ_{TWSA} for each time period, i and j indicate the years, and Median refers to the median value. If $\beta > 0$, it indicates an increasing trend in terrestrial water storage; conversely, $\beta < 0$ indicates a decreasing trend.

The Mann–Kendall (MK) test is a non-parametric time series trend test widely used in hydrological and meteorological data analysis, and the test statistic S is defined as:

$$S = \sum_{i=2}^n \sum_{j=1}^{i-1} \text{sign}(x_i - x_j) \quad (16)$$

The trend test is performed using the test statistic Z , and the Z -value is calculated as:

$$Z = \begin{cases} \frac{S-1}{\sqrt{S_{\text{var}}}} & (S > 0) \\ 0 & (S = 0) \\ \frac{S+1}{\sqrt{S_{\text{var}}}} & (S < 0) \end{cases} \quad (17)$$

In the equation, S_{var} denotes the variance of the statistic S . At a significance level $\alpha = 0.05$, when $|Z| \geq 1.96$, the sequence passes the 95% confidence level test, indicating a significant trend in terrestrial water storage changes; conversely, the trend is not significant when $|Z| < 1.96$.

2.3.4. Analysis of Water Resources Scarcity Status

The TWS-based Water Scarcity Index ($WS_{\text{TWS_based}}$) proposed by Fitsume T. et al. [43] is adopted to analyze regional water scarcity. This method incorporates TWSA retrieved from GRACE satellite inversion, enabling a more comprehensive and real-time evaluation of water scarcity. The $WS_{\text{TWS_based}}$ index is defined as total comprehensive water consumption (WC_{total}) divided by net total available water (Q_{net}). We develop the $WS_{\text{TWS_based}}$ index by integrating industrial and domestic water use into agricultural water consumption at the primary water resource region scale. A higher $WS_{\text{TWS_based}}$ value indicates a more severe water scarcity condition. The specific formula is as follows:

$$WS_{\text{TWS_based}} = \frac{WC_{\text{agricultural}} + WC_{\text{industrial}} + WC_{\text{domestic}}}{P - ET - \text{TWSC}} = \frac{WC_{\text{total}}}{Q_{\text{net}}} \quad (18)$$

In the equation, $WC_{\text{agricultural}}$ denotes regional agricultural water consumption; $WC_{\text{industrial}}$ denotes regional industrial water consumption; WC_{domestic} denotes regional

domestic water consumption; P denotes precipitation; ET denotes actual evapotranspiration; and $TWSC$ denotes terrestrial water storage change.

3. Results

3.1. Fused TWSA_BTCH Product Based on the BTCH Method

3.1.1. TWSA Uncertainty Quantification

Absolute uncertainty and relative uncertainty are adopted to quantify data uncertainty. Among them, absolute uncertainty (unit: mm) describes the actual depth amplitude of TWSA estimation error, suitable for comparing raw errors among regions with similar hydrological signal intensity. Relative uncertainty (unit: %) is defined as the ratio between absolute error and regional TWSA magnitude, which eliminates the interference of uneven signal strength across arid and humid zones and enables fair cross-basin comparison. It should be clarified that all uncertainty values derived from TCH are only used for relative ranking across datasets and water resource regions. Correlated errors among homologous GRACE Mascon products violate the independent error assumption of TCH, which systematically underestimates true TWSA error magnitude. Thus these metrics cannot be treated as accurate absolute error quantification. By calculating the area-weighted average of uncertainties and relative uncertainties across the grid cells within the study region, the mean values of uncertainties and relative uncertainties for the three products were derived. The spatial distributions of uncertainties (left column) and relative uncertainties (right column) for the CSR, JPL, and GSFC products are presented in Figure 2. Table 2 summarizes the spatially averaged uncertainty and relative uncertainty of three original GRACE Mascon datasets (CSR, JPL, GSFC) and the TWSA_BTCH product across China and its primary water resource regions.

For the whole of China, the CSR dataset exhibits the lowest TWSA uncertainty at 23.43 mm, followed by GSFC (29.79 mm) and JPL (31.76 mm). In contrast, GSFC yields the smallest relative uncertainty (52.47%), trailed by CSR (56.88%) and JPL (59.47%). The three original GRACE Mascon datasets adopt distinct filtering, error correction, and striping noise reduction algorithms, leading to distinct performance discrepancies across primary water resource regions with varied landforms and coastal-inland geographic settings. Regional statistical results indicate that GSFC delivers prominent nearshore correction advantages in the HRB, a coastal watershed: the spatially averaged uncertainties of CSR and JPL for HRB reach 41.35 mm and 33.49 mm, respectively, whereas GSFC yields merely 25.36 mm. In contrast, for the SERB, a coastal watershed along the southeastern China coastline, GSFC presents an extremely high spatially averaged uncertainty of 57.00 mm, far exceeding CSR (25.64 mm) and JPL (42.29 mm), indicating its poorest nearshore correction performance among the three solutions. The fundamental reason for the polarized performance of the GSFC solution across the above coastal regions lies in the distinct nearshore gravity signal leakage correction algorithms adopted by the three datasets. The HRB borders the Bohai Bay; the fixed buffer filtering employed by CSR and JPL fails to completely eliminate gravitational interference induced by ocean tides. In comparison, GSFC integrates an iterative land–ocean separation module optimized specifically for the Bohai and Yellow Seas. This module can efficiently remove tidal leakage noise in the HRB, where flat terrain and a simple tidal field structure prevail, yielding noticeably better precision than CSR and JPL. In contrast, the SERB abuts open offshore waters, featuring highly winding coastlines and extensive mountainous terrain. The complex tidal waves and drastic topographic variability exceed the applicable scope of the aforementioned module, and over-correction biases tend to emerge during GSFC's correction procedure. Consequently, GSFC exhibits the highest spatially averaged uncertainty among the three datasets within the SERB.

The NWRB corresponds to an inland arid desert region, where JPL exhibits weak striping noise reduction performance with a spatially averaged uncertainty of 26.84 mm; GSFC performs even worse in this region, with a higher uncertainty value of 27.82 mm. The SWRB features fragmented terrain and highly heterogeneous hydrological signals, and the JPL dataset achieves the maximum spatially averaged uncertainty of 60.02 mm across all studied regions. The SRB has gentle terrain and stable hydrological signals, where the correction schemes of all three datasets show good adaptability, resulting in close spatially averaged uncertainty values and negligible inter-dataset differences. By comparison, the LRB displays obvious performance divergence: CSR and JPL maintain comparable precision, while GSFC suffers a sharp rise in spatially averaged uncertainty up to 40.46 mm, substantially inferior to the other two datasets.

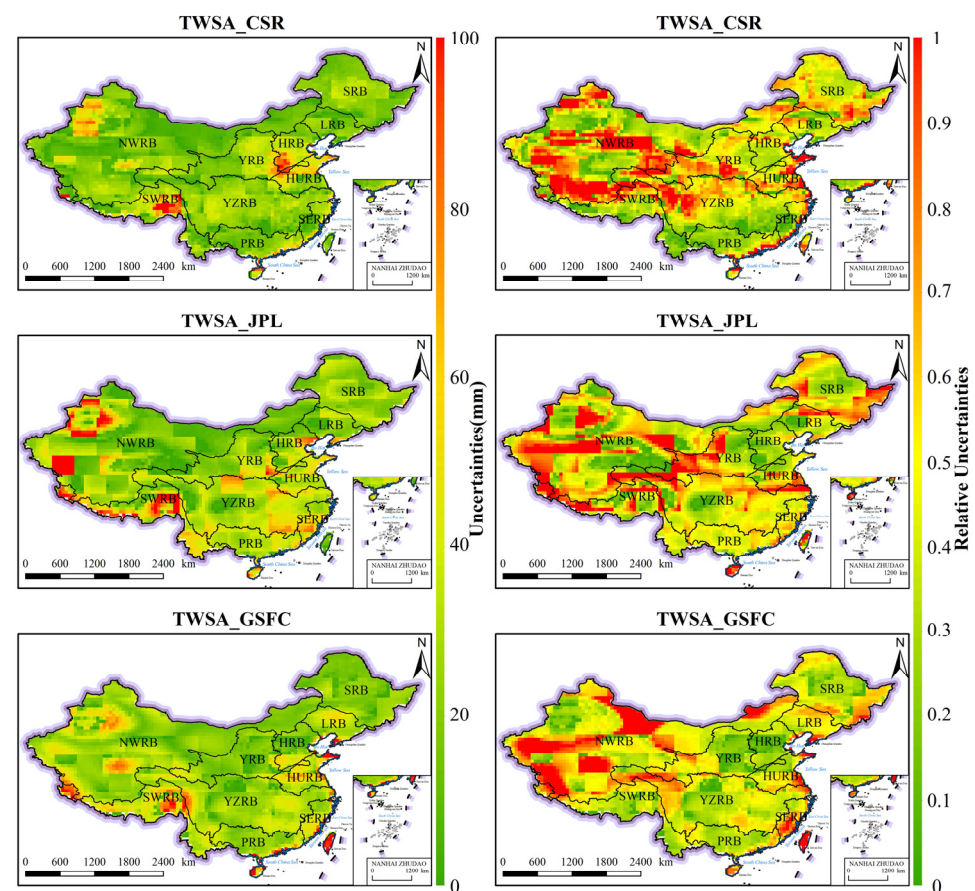


Figure 2. The spatial distribution of uncertainties and relative uncertainties of CSR, JPL and GSFC products based on the TCH method. The map is compiled using the standard base map (Approval No. GS(2019)1822).).

Table 2. The uncertainty and relative uncertainty of the TWSA at China and its primary water resource regions' level.

Regions	Uncertainty (mm)				Relative Uncertainty (%)			
	CSR	JPL	GSFC	BTCH	CSR	JPL	GSFC	BTCH
China	23.43	31.76	29.79	8.13	56.88	59.47	52.47	18.31
SRB	20.42	24.65	19.30	7.01	51.55	53.94	43.13	17.71
LRB	16.82	23.61	40.46	6.84	40.26	43.58	55.81	14.31
HRB	41.35	33.49	25.36	9.31	46.23	28.29	24.10	9.32
YRB	27.37	27.01	20.53	7.33	58.04	60.70	36.91	16.76
HURB	39.84	39.85	49.81	14.05	68.26	53.94	51.63	20.44

YZRB	22.74	35.59	29.07	8.37	50.46	53.43	44.20	16.63
SERB	25.64	42.29	57.00	10.92	53.33	56.76	71.80	20.64
PRB	24.73	36.50	36.18	9.91	40.12	50.62	41.00	14.58
SWRB	36.03	60.02	46.47	12.92	37.40	81.12	39.51	13.49
NWRB	18.94	26.84	27.82	6.80	67.91	61.05	67.28	22.05

3.1.2. Three GRACE Mascon Product Fusion and Validation

(1). Three GRACE Mascon Product Fusion

Consistent with Section 3.1.1, all uncertainty metrics in this subsection are only used for relative performance comparison between original GRACE Mascon datasets and fused products, and cannot be interpreted as absolute TWSA estimation errors.

We adopted the BTCH multi-source fusion framework to integrate the three original GRACE Mascon datasets (CSR, JPL, GSFC). As shown in Figure 3, among the three unfused TWSA products, TWSA_CSR exhibits the lowest uncertainty, with an area-weighted national average uncertainty of approximately 23.43 mm. The uncertainties magnitudes of the other two raw products are comparable, yet TWSA_GSFC features a more concentrated uncertainty distribution. Compared to the three products before fusion, TWSA_average and TWSA_BTCH both yield markedly reduced uncertainty, with national average values of 12.51 mm and 8.13 mm, respectively, alongside much narrower uncertainty ranges. Overall, TWSA_BTCH achieves the optimal performance across China: its average uncertainty is reduced by roughly 65.30% compared with TWSA_CSR and around 35% relative to TWSA_average, accompanied by a tighter uncertainty distribution. While Figure 3 reflects nationwide overall uncertainty characteristics, Table 2 further quantifies the dataset performance across China and its primary water resources region. Consistent with the nationwide results, the TWSA_BTCH dataset developed in this study inherits the merits of the three original GRACE Mascon datasets. Its spatially averaged uncertainty remains below 14 mm in all primary water resource regions, and the maximum relative uncertainty only reaches 22.05%. Collectively, the BTCH fusion product achieves remarkably better observational accuracy than any individual Mascon dataset (CSR, JPL, or GSFC).

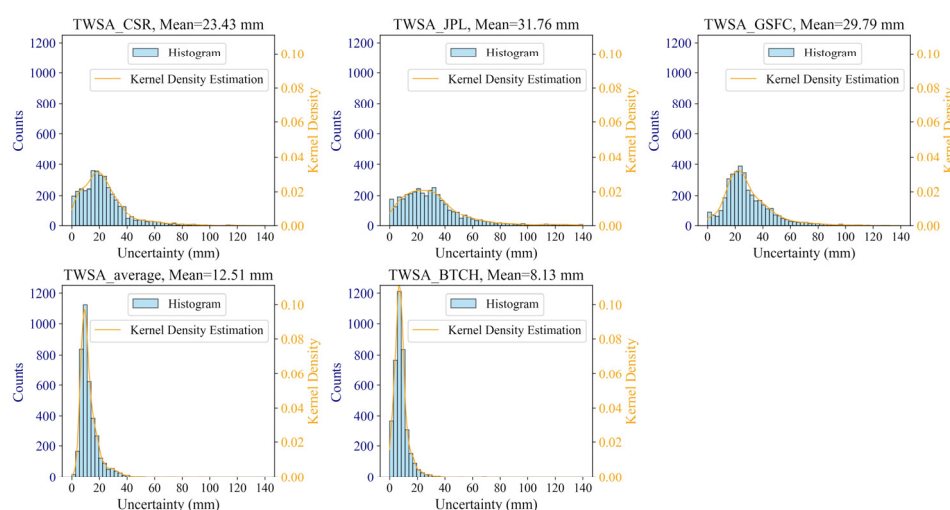


Figure 3. The uncertainty statistical histograms and kernel density estimation of TWSA_CSR, TWSA_JPL, TWSA_GSFC, TWSA_average and TWSA_BTCH.

To explicitly compare the spatial patterns of TWSA derived from different datasets, we computed the temporal mean TWSA spatial distributions over the period April 2002 to December 2023 for the CSR, JPL, and GSFC GRACE Mascon products, their arithmetic

average, and the TWSA_BTCH, as shown in Figure 4. The results indicate that before fusion, the overall spatial distributions and magnitudes of TWSA among the three products are essentially consistent. In contrast, TWSA_average and TWSA_BTCH exhibit a more comprehensive and accurate spatial distribution of TWSA. Notably, the spatial distribution characteristics and magnitudes of TWSA_BTCH are relatively similar to those of TWSA_CSR, which is attributed to the fact that TWSA_CSR holds the highest weight in the fused product compared to the other two products. Nevertheless, TWSA_JPL and TWSA_GSFC still contribute to the fused results to a certain extent.

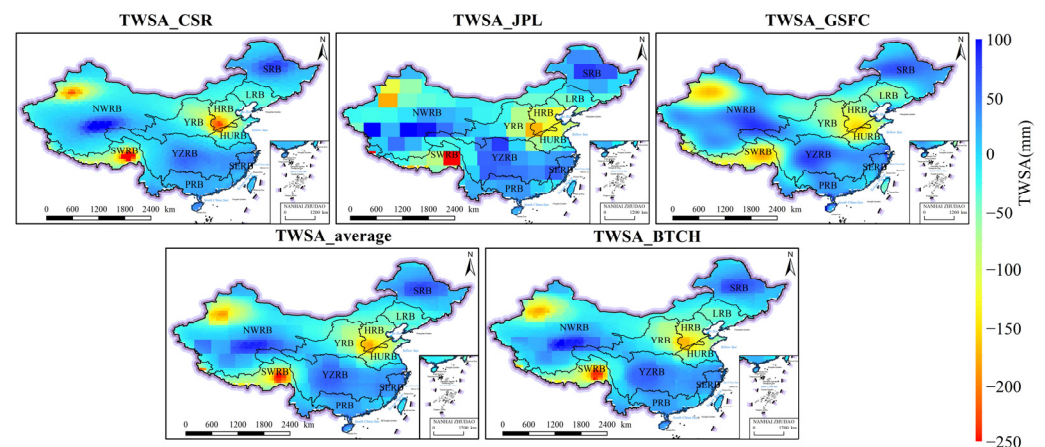


Figure 4. Temporal mean TWSA spatial distributions over China from different datasets (April 2002–December 2023). The map is compiled using the standard base map (Approval No. GS(2019)1822).

(2). Validation of the TWSA_BTCH Product

In this study, three typical regions with the most divergent hydrological seasonal characteristics, namely YZRB, YRB, and SWRB, were selected to conduct cross-validation via the water balance method (Figure 5). The raw monthly series exhibit significant linear relationships, with correlation coefficients of 0.59 (YZRB), 0.57 (YRB), and 0.67 (SWRB). This is consistent with Wang et al. [55] and Ju et al. [56] research. However, these high raw correlations are dominated by synchronous monsoon-driven seasonal oscillations. We further adopted STL seasonal decomposition to remove the annual 12-month seasonal component and recalculated correlations using residual time series free of seasonal interference [57,58]. After deseasonalization, the correlation coefficients decrease to 0.38 (YZRB), 0.38 (YRB), and 0.12 for the weakly seasonal SWRB. After removing seasonal signals, the correlation exhibits a moderate decline, which is consistent with Scanlon et al.'s [59] research. The obvious gap between raw and residual correlation in YZRB/YRB confirms that seasonal periodic signals are the primary contributor to the original strong linear correlation. Moderate residual positive correlations in the two monsoon regions still verify that the fused TWSA_BTCH product can capture interannual terrestrial water storage anomalies consistent with original TWSC. The SWRB exhibits weak natural seasonal fluctuations and a high proportion of random observational noise, resulting in poor consistency of the time series after deseasonalization. Accordingly, when conducting quantitative research on water resource evolution for the SWRB, conclusions drawn solely from this dataset should be interpreted with caution, and cross-validation combined with multi-source hydrological observation data is recommended [60].

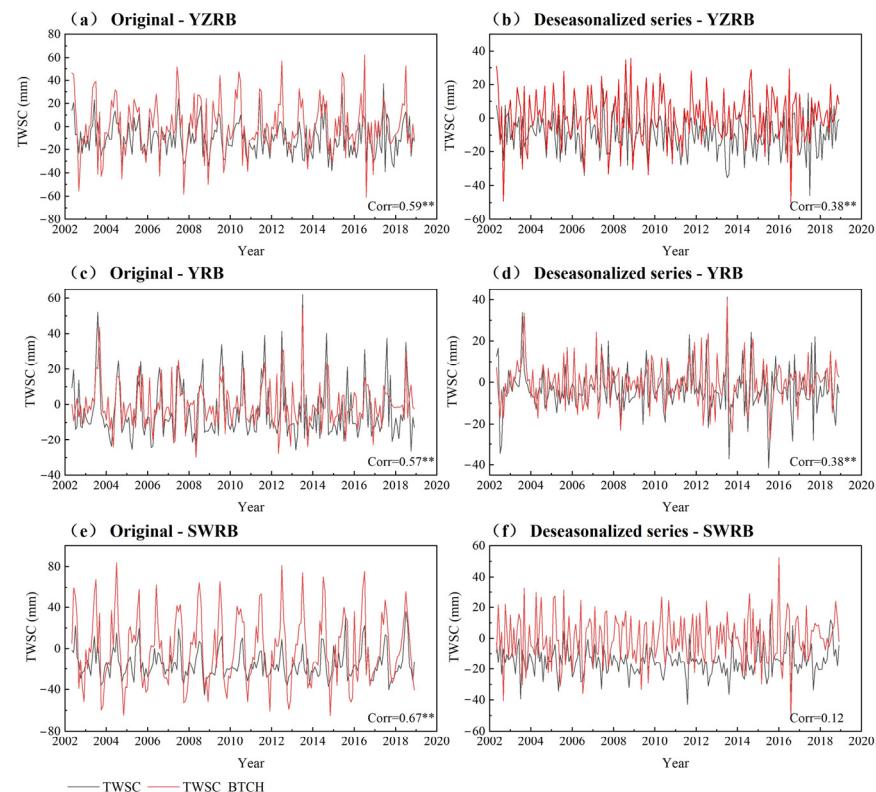


Figure 5. Comparison of original and deseasonalized time series between TWSC_BTCH and TWSC across YZRB; YRB and SWRB (2003–2018). “***” indicates that the test was significant ($p < 0.01$).

3.2. Spatial–Temporal Patterns of TWSA Across China

3.2.1. Analysis of the Temporal Evolution of TWSA

To clarify the temporal variations of terrestrial water storage, this study analyzed the interannual and monthly trends of TWSA in China from 2003 to 2023 based on the TWSA_BTCH dataset (Figures 6 and 7). The interannual TWSA in China exhibited significant fluctuations with an initial value of 5.66 mm in 2003 that rose to a peak of 13.13 mm in 2005 before a continuous decline. Since 2007, TWSA has transitioned from positive to negative values, accompanied by prominent interannual variations, and reached a minimum of −29.52 mm in 2023. It should be noted that the standard deviation of de-seasonalized and de-trended TWSA climatic residuals is 5.53 mm. Under the normal distribution, approximately 68% of interannual climatic disturbances fall within the range of ± 5.53 mm, which represents the typical amplitude of annual terrestrial water storage fluctuations driven by climate. The national average TWSA depletion rate reaches −1.65 mm/a, with a cumulative terrestrial water storage loss of 36.3 mm over the 22-year study period, a magnitude far exceeding that of random climatic fluctuations. This confirms that the nationwide terrestrial water storage deficit constitutes a long-term directional trend jointly dominated by anthropogenic activities and climate change, rather than mere short-term random climatic oscillations. Concurrently, precipitation showed a slight increase, with a negative linear correlation with TWSA trends (Pearson’s $r = -0.39$), indicating that other factors cannot be neglected in driving TWSA (Figure 8). The monthly TWSA trend map (Figure 6a) reveals that TWSA in China declined across all months, with the most significant changes occurring from June to September, which contributed most prominently to the annual TWSA trend. TWSA shows significant deficits during winter and spring, while surpluses are observed in summer and autumn. The most pronounced decline in TWSA occurs in spring, followed by winter, autumn, and the smallest decline in

summer Figure 6b. Although spring precipitation increased, TWSA remained significantly negative, indicating that precipitation was insufficient to meet human water demands such as spring irrigation, necessitating further depletion of groundwater. TWSA lags behind precipitation by approximately 1–2 months (Figure 6c), reflecting the time required for precipitation to be transformed into terrestrial water storage through infiltration, runoff, and evaporation processes and redistributed spatially.

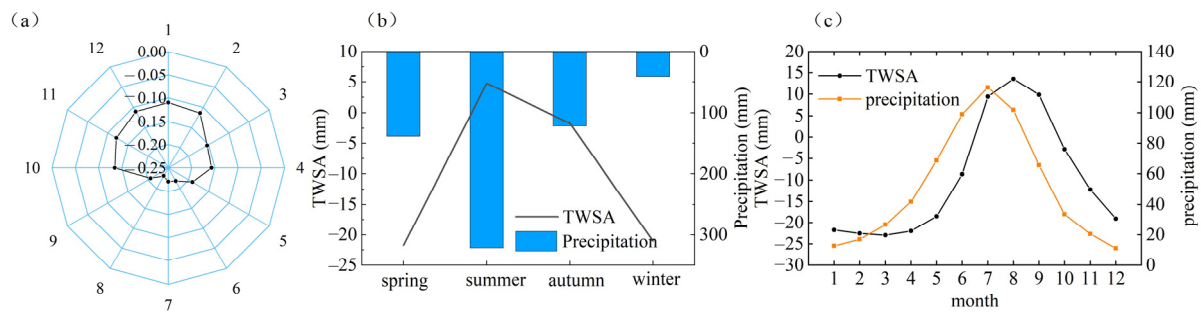


Figure 6. Intra-annual variations of TWSA across China during 2003 to 2023: (a) Monthly variation trend of TWSA (each point represents the trend of an individual month); (b) multi-year mean seasonal variations; (c) multi-year mean monthly variations.

The interannual evolution of TWSA in China and its primary water resources regions during 2003–2023 is shown in Figure 7, which exhibits an evident north–south differentiation pattern consistent with the findings reported by Li and Zhong et al. [61,62]. The HRB located in northern China exhibits the most prominent declining rate of TWSA, at -12.68 mm/a. Before the water delivery of the South-to-North Water Diversion Project (SNWDP) during 2003–2014, the average annual decline rate of TWSA in the HRB reached -14.25 mm/a, indicating sustained severe depletion of terrestrial water storage. After the official water conveyance of the SNWDP in 2015, the rate stood at 2.80 mm/a for the period 2015–2023. From the perspective of full-cycle average values, the overall declining trend was reversed. Nevertheless, the annual precipitation reached 882.8 mm in 2021, 56.3% higher than the multi-year average precipitation of 564.8 mm. The abundant extreme precipitation substantially replenished soil moisture and groundwater, considerably improving the regional water storage conditions. To eliminate the occasional interference induced by extreme precipitation, we recalculated TWSA variations for 2015–2020 after excluding the data of 2021, and the results revealed that the average annual depletion rate still remained as high as -12.92 mm/a. This result indicates that without the substantial recharge from the extremely wet year of 2021, the inter-basin water transfer of the South-to-North Water Diversion Project could only marginally reduce the rate of terrestrial water storage depletion yet fail to halt its persistent decline. Meanwhile, the comprehensive management project for groundwater overexploitation implemented across the North China Plain during the same period provided positive support for local groundwater storage recovery. Nevertheless, the combined effects of the regulation measures still could not fundamentally resolve the inherent contradiction of long-term water resource overconsumption in the HRB, and its underlying declining trend of TWSA has not been thoroughly reversed [63–65]. The decline rate of TWSA in the YRB reaches -5.24 mm/a, which results from the combined effects of droughts triggered by climate anomalies and amplified human activities. Drought events act as the fundamental trigger, and the superposition of repeated droughts and anthropogenic water consumption pressures ultimately drives the long-term continuous decline in terrestrial water storage across the YRB [66]. The TWSA decline rate of the NWRB is -2.03 mm/a. Vegetation water consumption, glacier mass loss, and groundwater extraction jointly aggravate terrestrial water storage depletion. Against

the long-term climate context of warming, human activities act as the dominant driving factor [67,68]. As for SRB, the superposition of multiple favorable conditions, including increased climatic precipitation, low temperature and weak evaporation, natural water retention of permafrost and wetlands, and ecological restoration, ultimately drives the TWSA to maintain an increasing trend [69] with an upward rate of 3.88 mm/a.

The YZRB, SERB and PRB are located in the southeastern monsoon zone with favorable hydrothermal conditions. The correlation coefficients between TWSA and precipitation in these three regions reach 0.80, 0.83 and 0.71, respectively, all passing the extremely significant correlation test at the 0.05 significance level (Figure 8b). Severe droughts occurred in the YZRB in 2011 and 2022, accompanied by obvious declines in TWSA. These phenomena reveal that water resource replenishment in the southeastern monsoon zone is highly dependent on monsoon precipitation. The precipitation recharge is markedly larger than anthropogenic water consumption, which can continuously offset regional water loss and generate stable surplus of water resource replenishment, thereby driving a steady rise in terrestrial water storage across the regions. In contrast, the SWRB suffers from insufficient precipitation induced by the weakening of the South Asian monsoon. Combined with intense evapotranspiration and degradation of glaciers and permafrost caused by climate warming, the surface water supply of the region is inadequate, leading to intensified groundwater extraction by human activities [70,71]. The superposition of multiple processes results in a persistently declining trend of TWSA over the SWRB at a rate of -9.98 mm/a.

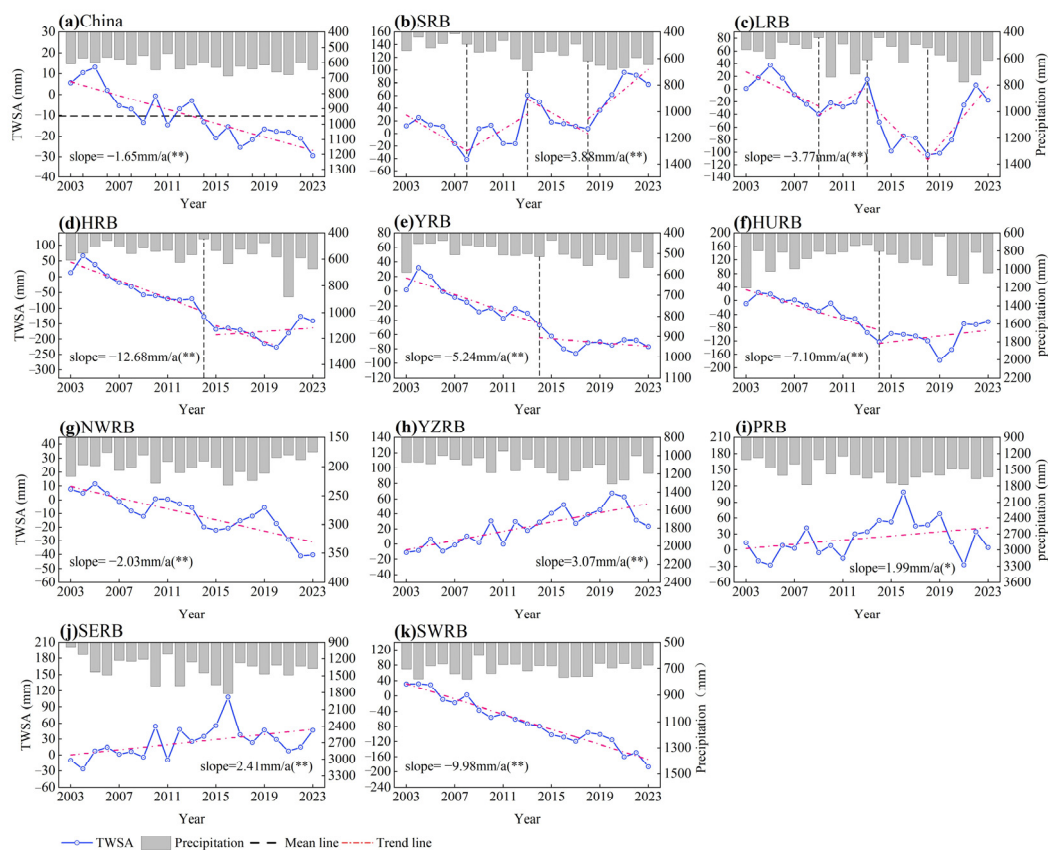


Figure 7. Interannual variations of TWSA and precipitation in China and its primary water resource regions during 2003–2023. (The slopes denote the TWSA trend slopes for 2003–2023, derived via simple linear regression.).

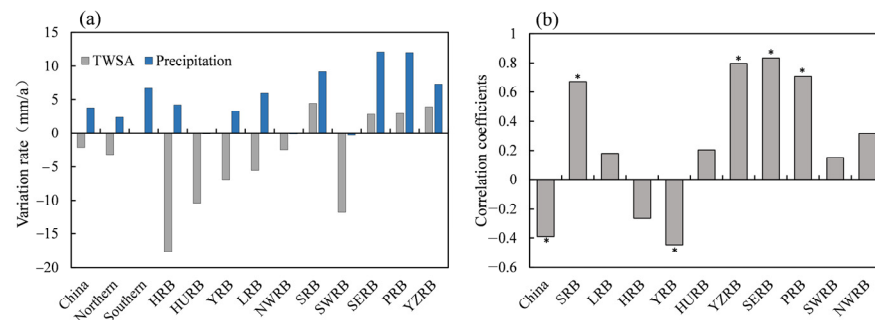


Figure 8. (a) Change rates of TWSA and precipitation in primary water resource regions (Note: The annual change rate of precipitation in the HURB is -0.13 mm/a); (b) Pearson correlation coefficients between TWSA and precipitation across China and its primary water resource regions, 2003–2023. Single asterisks (*) denote significance at $p < 0.05$.

3.2.2. Analysis of the Spatial Variations of TWSA

The mean annual TWSA across China for the 2003–2023 period was -10.28 mm, indicating a nationwide TWS deficit. The northern subregion exhibited an overall TWS deficit of 16.05 mm (mean annual TWSA = -16.05 mm), whereas the southern subregion presented a mild TWS surplus of 1.52 mm. Except for the SRB (mean annual TWSA = 25.12 mm), all other northern subregions exhibited TWS deficits. The HRB recorded the most severe deficit at -95.23 mm, followed by the HURB (-60.95 mm) and the YRB (-38.84 mm). For southern subregions, all zones presented positive TWS anomalies apart from the SWRB (mean annual TWSA = -69.42 mm). The SERB featured the largest TWS surplus at 24.54 mm, followed by the YZRB and the PRB, both exceeding 20 mm (Figure 9a). To quantify the magnitude of long-term TWSA shifts, the cumulative TWSA over 2003–2023 was calculated by subtracting the 2003 TWSA from the 2023 TWSA (Figure 9b). Over the past 20 years, substantial spatial heterogeneity in multi-year TWSA evolution was detected. Zones featuring severe cumulative TWS deficit (cumulative TWSA < -50 mm) are predominantly concentrated across the HRB, HURB, YRB, SWRB; the NWRB is close to this threshold. Notably, the Tianshan Mountainous region and the SWRB experienced a cumulative TWS deficit of over 200 mm (negative anomaly), pointing to persistent terrestrial water storage depletion. Zones with substantial cumulative TWS surplus (cumulative TWSA > 50 mm) are predominantly distributed across the SRB, SERB; the middle reaches of the YRB and parts of the SRB, Qaidam Basin and Qiangtang Plateau show surpluses exceeding 100 mm, indicating net terrestrial water storage gains.

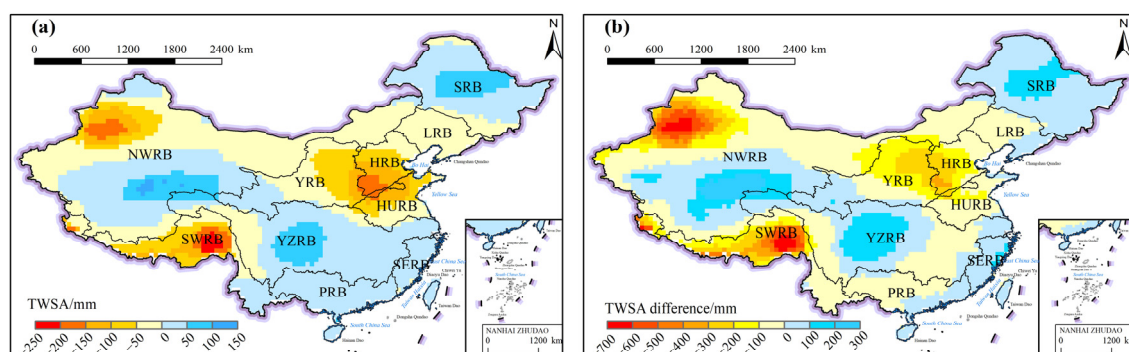


Figure 9. (a) Mean spatial distribution of TWSA across China (2003–2023); (b) spatial distribution of TWSA differences across China (2023–2003). The map is compiled using the standard base map (Approval No. GS(2019)1822).

Based on the Sen–MK trend test, Figure 10a illustrates that 32.82% of China exhibits statistically significant increasing TWSA trends, which are predominantly concentrated in the SRB, YZRB, PRB, and SERB. The upper reaches of the YRB and parts of the Qaidam Basin and Qiangtang Plateau also display significant positive TWSA trends. Such spatial consistency is closely linked to increased precipitation in these regions (Figure 10b). Statistically significant upward precipitation trends are detected within the SRB, YZRB, PRB, and SERB, with zone-averaged precipitation linear change rates reaching 9.15 mm/a, 7.26 mm/a, 11.94 mm/a, and 12.05 mm/a, respectively. Conversely, 43.20% of China features statistically significant decreasing TWSA trends, predominantly concentrated within the LRB, HURB, HRB, and SWRB. Furthermore, statistically significant negative TWSA trends are also observed across the Tianshan Mountainous region, and the middle and lower reaches of the YRB.

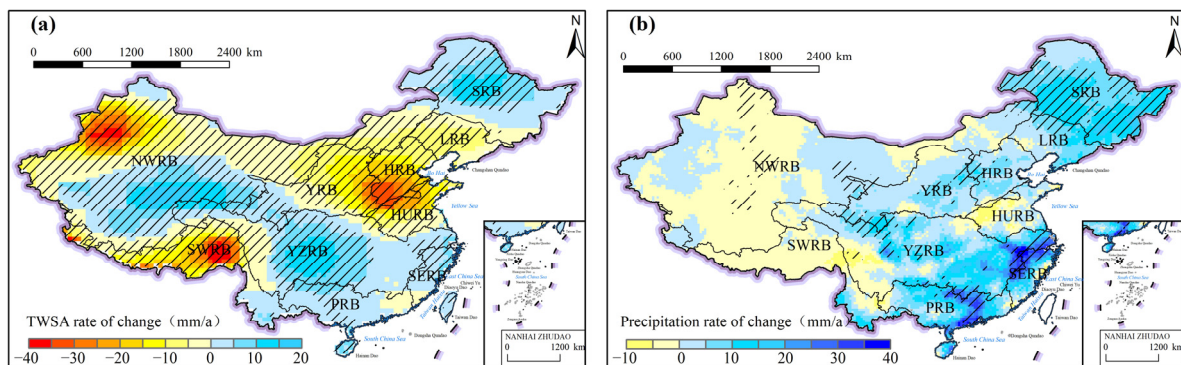


Figure 10. Spatial distribution of change trends for (a) TWSA and (b) precipitation across China during 2003–2023 (shaded areas denote trends significant at the 95% confidence level). The map is compiled using the standard base map (Approval No. GS(2019)1822).

3.3. Regional Water Scarcity Assessment

Referring to the Environmental Flow Requirement (EFR) criteria proposed by Fitsum T. et al. [43], this study classifies water scarcity using the WS_{TWS_based} indicator with four graded intervals anchored to two core critical thresholds (0.2 and 1.0). The threshold of 0.2 serves as the baseline stress threshold, denoting that anthropogenic water consumption accounts for over 20% of ecologically available water resources, wherein 80% of natural runoff is retained to satisfy EFR [72]. The threshold value exceeding 1.0 signify that total water withdrawals outstrip the full volume of sustainable usable water, corresponding to a state of critical water crisis [73]. The four-tier grading criteria are defined as follows: $|WS_{TWS_based}| \leq 0.2$: No water scarcity [72]; $0.2 < |WS_{TWS_based}| \leq 0.4$: Moderate water scarcity [72,74,75]; $0.4 < |WS_{TWS_based}| \leq 1.0$: Severe water scarcity [76,77]; $|WS_{TWS_based}| > 1.0$: Critical water scarcity [73].

The national WS_{TWS_based} index stayed steadily above 0.2 yet below 0.4 across the entire study period, indicating that the whole country was under moderate water scarcity (Table 3, Figure 11). The multi-year average national index was 0.30, with a significant downward trend of -0.003 a^{-1} ($p < 0.05$). The index reached a peak of nearly 0.40 in 2009 and 2011, reflecting relatively severe water scarcity in those two years. In terms of phased variation, the average index was 0.32 during 2003–2012 and declined to 0.28 during 2013–2023. This improvement can be largely attributed to increased monsoon precipitation, the rollout of China’s Strictest Water Resources Management System in 2013, and a suite of initiatives covering inter-basin water transfer, water conservation, and integrated water resources governance. Overall, water resource overexploitation across the country has been effectively alleviated, though the fundamental pattern of water scarcity has not been

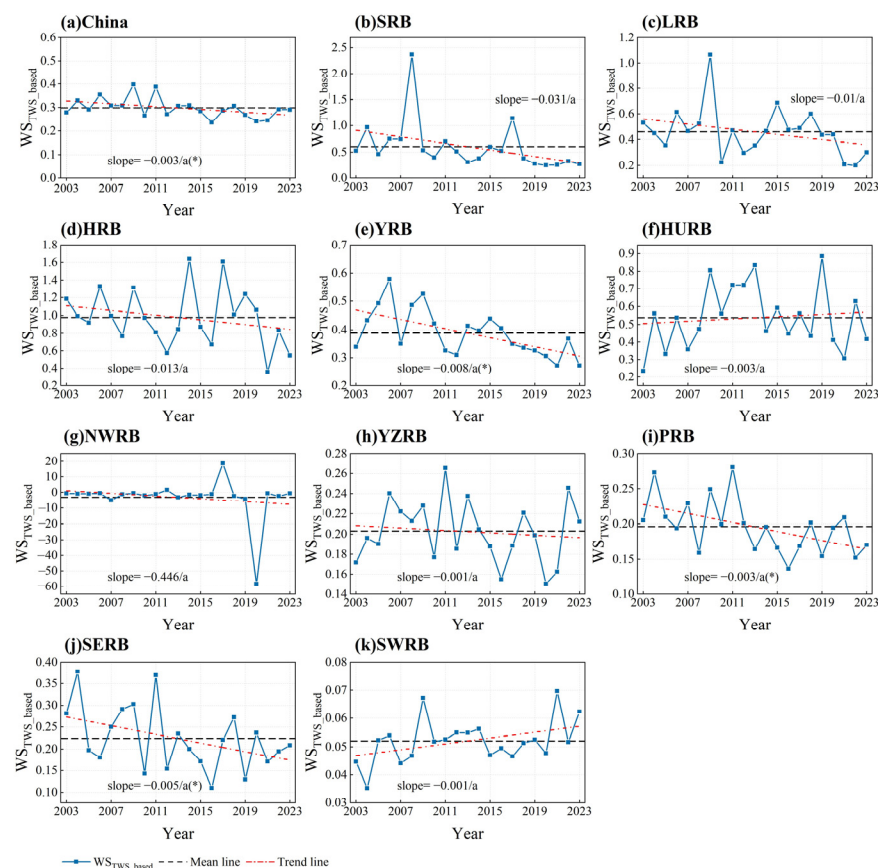
reversed, and most primary water resource regions exhibit stable or significant downward trends over the study period.

From the perspective of primary water resource regions, water scarcity across China exhibits evident spatial heterogeneity and a clear north–south differentiation pattern, with the scarcity level in northern China considerably more severe than that in the southern. All northern water resource regions are plagued by water scarcity of varying degrees. Specifically, the SRB, LRB, HRB and HURB are categorized as severe water scarcity zones, while the YRB falls into the moderate water scarcity class. The NWRB suffers from a critical water crisis (Table 3). Under the superimposed pressures of resource endowment conditions and intensive human activities, the WS_{TWS_based} index of all northern regions remained above the 0.2 water scarcity threshold across the entire study period, even at their minimum levels. The annual peak values for the SRB, LRB and HRB were 2.37, 1.06 and 1.64, respectively, all exceeding the critical threshold of 1.0 indicative of a critical water crisis (Figure 11). Among all northern regions, the HRB records a multi-year average index of 0.98, a value close to the critical threshold of severe water scarcity (1.0). Its high index value is primarily dominated by high total water consumption, especially agricultural water use ($WC_{total} = 108.02$ mm, $WC_{agriculture} = 73.23$ mm), coupled with limited net available water resources ($Q_{net} = 135.21$ mm). More stringent governance strategies for agricultural water saving need to be urgently implemented. A prominent anomaly is observed in the NWRB, which shows a negative WS_{TWS_based} index of -3.24 . This phenomenon is mainly caused by its negative net available water resources ($Q_{net} = -15.86$ mm), indicating that regional water consumption far exceeds precipitation recharge. As mentioned above, the TWSA depletion rate of the NWRB reaches -2.03 mm/a, which reveals the region is in a persistent state of water deficit. Although the WS_{TWS_based} of the NWRB exhibited an insignificant decreasing trend from 2003 to 2023 with a slope of -0.446 , adaptive countermeasures including strict control of groundwater overexploitation, popularization of water-saving irrigation, and guarantee of ecological base flow in river channels still need to be implemented.

By contrast, southern water resource regions are characterized by abundant precipitation. Most bear little water pressure: the YZRB, PRB and SWRB are classified as no-stress areas. The SERB is the only southern zone presenting moderate water scarcity, with a mean index of 0.22 that slightly exceeds the 0.2 scarcity threshold (Table 3). Their WS_{TWS_based} indices fluctuate within the range of 0.035 to 0.38, with the minimum value of 0.035 observed in the SWRB and the maximum value of 0.38 recorded in the SERB. Economically developed regions such as the SERB, PRB and YZRB are witnessing a rapid surge in industrial and domestic water demand. Their WS_{TWS_based} indices are gradually approaching or even exceeding the critical threshold of 0.2, posing new challenges to refined regional water resource allocation. Notably, the SWRB presents the lowest water scarcity level nationwide, with an average index of only 0.05, which benefits from abundant net available water resources ($Q_{net} = 243.15$ mm) and relatively low total water consumption ($WC_{total} = 12.32$ mm). Compared with Fu's research [78], our results reveal comparable spatial patterns of water scarcity risk despite differences in spatial scale and water scarcity classification criteria.

Table 3. Comprehensive summary of water consumption and WS_{TWS_based} in China and its primary water resource regions from 2003 to 2023 (The “*” indicates passing the significance test ($p < 0.05$)).

Region	Water Scarcity Class	Mean Over the Period 2003–2023					WS_{TWS_based}	
		$WC_{agriculture}$ (mm)	$WC_{industry}$ (mm)	$WC_{domestic}$ (mm)	WC_{total} (mm)	Q_{net} (mm)	WS_{TWS_based}	Change Rate (a^{-1})
China	Moderate	38.97	13.36	8.22	60.55	213.04	0.30	−0.003 *
SRB	Severe	37.89	6.07	3.36	47.32	110.06	0.60	−0.031
LRB	Severe	42.46	8.58	9.77	60.81	159.25	0.46	−0.010
HRB	Severe	73.23	15.59	19.20	108.02	135.21	0.98	−0.013
YRB	Moderate	34.17	7.01	5.70	46.88	130.85	0.39	−0.008 *
HURB	Severe	121.43	27.37	25.40	174.21	365.82	0.54	0.003
YZRB	No stress	55.00	38.19	15.93	109.12	559.55	0.20	−0.001
SERB	Moderate	62.67	40.99	24.03	127.70	648.85	0.22	−0.005 *
PRB	No stress	85.05	31.08	26.75	142.87	763.87	0.20	−0.003 *
SWRB	No stress	10.12	0.92	1.28	12.32	243.15	0.05	0.001
NWRB	Critical	17.57	0.54	0.54	18.65	−15.86	−3.24	−0.446

**Figure 11.** Inter-annual changes in WS_{TWS_based} in China and its primary water resources regions during 2003–2023. (The “*” indicates passing the significance test ($p < 0.05$)).

4. Discussion

4.1. Error Characteristics and Robustness Analysis of TWSA_BTCH

The multi-source TWSA fusion framework adopted in this study, namely BTCH, abandons fixed-weight fusion schemes such as simple arithmetic averaging. Taking spatial grids as the basic unit, it dynamically and adaptively assigns fusion weights to each data source based on grid-scale real-time uncertainty derived from three independent

Mascon solutions: CSR, JPL and GSFC. The core advantage of this weighting mechanism lies in its adaptive logic: grids with high uncertainty and severe observational noise are automatically assigned lower weights for the corresponding products, while data sources with stable performance and low uncertainty are given higher contribution ratios. From the perspective of data fusion, this design actively suppresses the interference of high-noise observational signals on the final TWSA time series. In contrast, the simple arithmetic averaging method with globally uniform weights fails to distinguish observational error disparities across different grids and datasets. Noise from high-uncertainty regions is indiscriminately incorporated into fused outputs, artificially amplifying the overall time-series error. The dynamic weighting strategy of BTCH can specifically mitigate random noise in high-error zones including coastal areas with signal leakage and northwest inland regions with low background terrestrial water storage. Compared with arithmetic average products, the BTCH framework systematically reduces the overall uncertainty of nationwide TWSA retrievals, and effectively improves the spatial consistency and data reliability of TWSA.

Given the aforementioned dynamic weighting fusion mechanism, noise interference from high-uncertainty grids can be theoretically suppressed. However, quantitative verification is still required to identify whether high-noise regions would introduce directional systematic biases into the fused time series. Therefore, pixel-stratified statistics are implemented in this study with an uncertainty threshold of 20 mm. The results reveal that for high-noise pixels with uncertainty exceeding 20 mm, the correlation coefficients between the three original single-source datasets (CSR, JPL, GSFC) and TWSA_BTCH are generally low, accompanied by remarkably elevated RMSEs. In contrast, inland stable regions with uncertainty ≤ 20 mm exhibit greatly improved agreement between the raw datasets and TWSA_BTCH, with obvious convergence of monthly error magnitudes. Across both high- and low-uncertainty partitions, the variation trends of errors and consistency metrics for all original datasets perfectly synchronize with those of TWSA_BTCH, without any directional systematic bias (Table 4). This evidence confirms that high-uncertainty zones such as coastal belts and northwest desert areas only amplify the inherent random noise of raw satellite observations, rather than generating directional systematic shifts in the TWSA_BTCH time series. In addition, the BTCH fusion framework developed in this work can effectively reduce estimation biases induced by error coupling among homologous GRACE Mascon datasets. Conventional TCH imposes strict assumptions of independent errors, whereas BTCH incorporates Bayesian prior constraints to reduce the sensitivity of error decomposition to error correlation. Meanwhile, common systematic errors including orbital bias and tidal model errors are uniformly eliminated in the official pre-processing pipeline implemented by each Mascon data provider, which further alleviates error correlation across multi-source datasets.

It should be objectively clarified that all GRACE products systematically underestimate spatially averaged uncertainty due to cross-correlated errors originating from homologous satellite observations. The full ensemble of datasets presents a consistent unidirectional systematic bias relative to true error magnitudes. Nevertheless, this bias exerts an identical degree of influence on the three single-source GRACE Mascon products and two fusion schemes, so the relative accuracy ranking of all datasets remains unchanged, and the cross-comparison conclusions drawn in this study are still credible. Furthermore, when interpreting the temporal evolution trends of TWSA in high-uncertainty regions such as coastal zones and northwest desert areas, the noise amplification effect within these zones should be fully considered to draw regional hydrological conclusions prudently.

Table 4. Correlation (Corr) and RMSE between TWSA_BTCH and three GRACE Mascon TWSA products stratified by pixel uncertainty threshold of 20 mm.

Uncertainty Classification	Pixel Proportion (%)	TWSA_CSR		TWSA_JPL		TWSA_GSFC	
		Corr	RMSE (mm)	Corr	RMSE (mm)	Corr	RMSE (mm)
High uncertainty(>20 mm)	2.6	0.95	10.36	0.9	13.73	0.97	6.34
Low uncertainty($\leq$ 20 mm)	97.4	0.97	2.2	0.92	3.85	0.95	3.08

Note: All pixels are divided into high-uncertainty (>20 mm) and low-uncertainty ($\leq$ 20 mm) groups according to the pixel uncertainty distribution shown in Figure 3.

4.2. Regional Water Resource Risk Need Joint Characterization via Hydrological Fluxes and Storage

Accurately assessing water scarcity is crucial for informed water resource decision-making and risk early warning; nevertheless, such evaluation remains challenging due to data limitations, inherent uncertainties in hydrological simulations, and the subjectivity of indicator selection [74,76,79]. Traditional flux-based water scarcity assessments generally assume stationary terrestrial water storage and neglect interannual dynamics in groundwater and soil moisture, limiting their capacity to simultaneously capture long-term water storage depletion risks and the natural buffering capacity of water-surplus regions. In comparison, the newly developed WS_{TWS_based} index integrates annual water consumption fluxes and annual TWSC. Furthermore, trend analysis is applied to quantify the long-term evolution of terrestrial water storage. By jointly considering hydrological flux balances and water storage evolution, the combination of the WS_{TWS_based} index and trend analysis enables comprehensive two-dimensional identification and quantification of regional water resource risks.

A distinct decoupling relationship exists between the WS_{TWS_based} index and long-term TWSA trends in the SRB and SWRB. This phenomenon reveals that the SRB suffers from weak regulation and storage capacity of hydraulic engineering, which impedes the balanced redistribution of water resources within a year and further induces persistent seasonal water scarcity. Additionally, the widely distributed continuous and thick viscous aquitards in this region substantially reduce the efficiency of precipitation infiltration and groundwater recharge, resulting in inherently limited recharge conditions. Nevertheless, benefiting from a relatively abundant precipitation, the SRB exhibits a long-term cumulative surplus of terrestrial water storage, maintaining superior natural water resource endowments. In contrast, although the overall water supply–demand matching status of the SWRB is better than that of the SRB, driven by the combined effects of severe leakage loss in karst media, intensified evaporation from reservoir water surfaces, and regional climate warming and drying trends, TWSA exhibits a prominent depletion rate of -9.98 mm per year. The NWRB presents a unique negative index value of -3.24 even with a moderate water consumption of 18.65 mm. The essential reason lies in its negative net available water resources ($Q_{net} = -15.86$ mm), indicating that regional water consumption has far exceeded the recharge supplied by precipitation and surface runoff. Furthermore, the region exhibits a persistent TWSA depletion rate of -2.03 mm/a, demonstrating continuous terrestrial water storage loss. In this context, the regional water supply is heavily sustained by unsustainable groundwater exploitation and glacial meltwater retreat. Such long-term hidden water deficit cannot be captured by conventional water consumption statistics alone, which highlights the superiority of the proposed index in identifying latent water resource risks.

The spatial and interannual divergence of the WS_{TWS_based} index is fundamentally governed by differentiated human water consumption patterns across individual water resource regions. Time-series variations of different water use categories during 2003–2023

(Figure 12) further explain the formation mechanism behind such regional disparities. Since 2013, China has successively fully implemented the strictest water resource management system, launched comprehensive groundwater over-extraction control on the North China Plain, and put the South-to-North Water Diversion Project into full operation. Driven by these measures, the national total water consumption reversed its long-term rising trend and entered a steady decline. Agricultural water use, the dominant water-consuming sector, experienced a prominent reduction. During 2013–2023, the growth rate of national total water withdrawal slowed sharply and shifted to an overall downward trend, with an average annual reduction rate of $-2.54 \times 10^9 \text{ m}^3/\text{a}$ (Figure 12). Meanwhile, the national average WS_{TWS_based} index fell from 0.32 (2003–2012) to 0.28 (2013–2023). This phenomenon directly verifies that water management policies have effectively mitigated nationwide water scarcity pressure by curbing anthropogenic water consumption. Differences in water consumption structures between northern and southern water resource regions further account for the spatial divergence of the WS_{TWS_based} index. As illustrated in Figure 12, agricultural water use has been substantially reduced in northern water resource regions including the HRB, YRB and HURB. By contrast, the total water consumption of NWRB rose against the overall trend in the later study period. Sustained intensive agricultural water withdrawal results in negative Q_{net} across the region, which is manifested as distinctive negative value of the WS_{TWS_based} index. In humid southern water resources regions such as SERB, YZRB and PRB, the overall total water withdrawal has declined slightly; nevertheless, continuous urbanization drives a year-on-year rise in domestic water use, gradually pushing the regional WS_{TWS_based} index close to or even exceeding the critical threshold of 0.2. In addition, ecological water consumption presents a slight year-by-year increase across all water resource regions. This trend reflects the routine implementation of ecological water replenishment initiatives, which partially alleviates water scarcity stress. Overall, excessive water withdrawal across the country has been effectively curbed, yet the fundamental spatial pattern of national water scarcity has not been radically transformed.

Spatial patterns of anthropogenic water withdrawal act as the primary driver of spatial heterogeneity in regional water scarcity. However, conventional flux-based water scarcity assessments assume stationary terrestrial water storage and neglect annual dynamic fluctuations in groundwater and soil water. Therefore, reliable identification of water resource risk requires a joint evaluation framework that integrates both hydrological fluxes and terrestrial water storage.

4.3. Limitations and Future Prospects

Firstly, affected by the inherent error and spatial smoothing effect of GRACE satellite data, the constructed TWSA_BTCH dataset still contains non-negligible uncertainty, especially in coastal zones and mountainous areas with complex underlying surfaces. Secondly, this study qualitatively analyzed the driving factors of TWSA variations, but did not quantitatively quantify the individual contribution. Thirdly, China faces eight major water-related risks [80]; the water scarcity assessment in this study solely relied on the WS_{TWS_based} index from the water resource perspective.

Future research can be carried out from the following aspects: (1) Multi-source cross-validation by incorporating land surface hydrological model and in situ groundwater monitoring data can be conducted to verify the reliability of the TWSA_BTCH. Meanwhile, fusion schemes for multi-source data can be explored to optimize the TWSA_BTCH product; (2) to quantitatively separate the impacts of climate and human factors on TWSA variations; (3) construct a multi-index joint evaluation system to assess water resource risks.

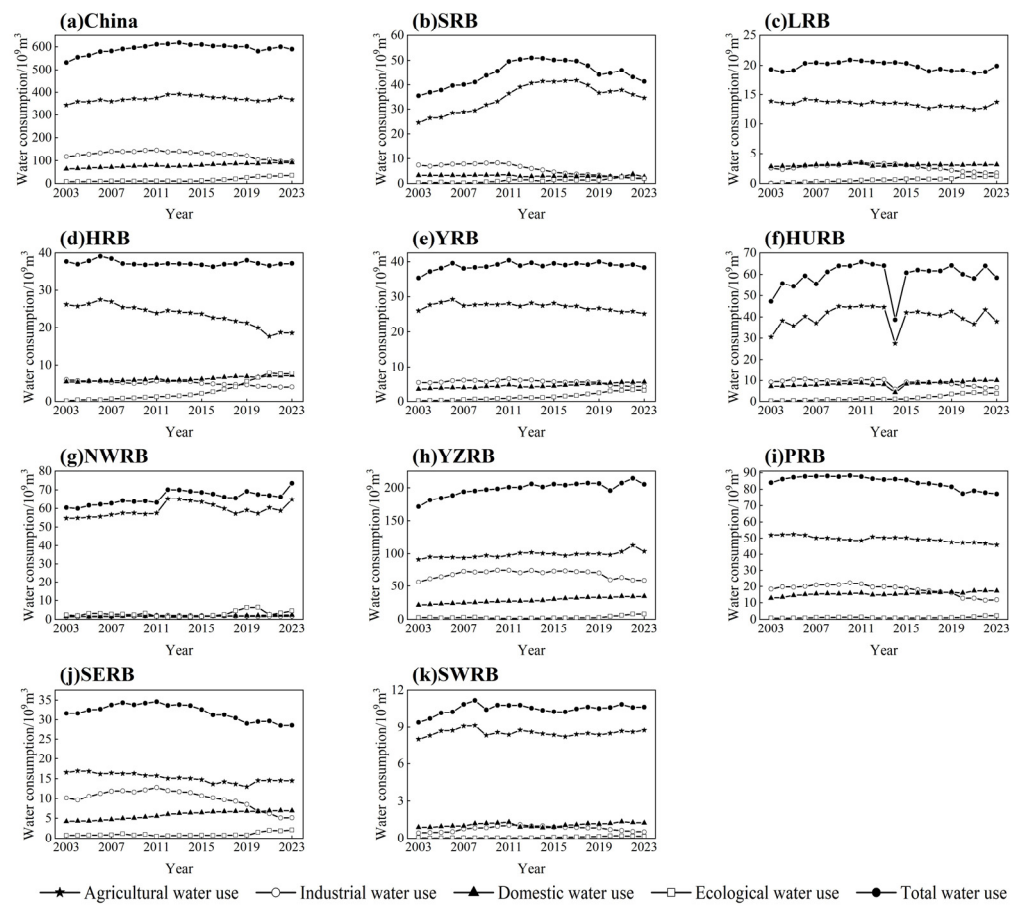


Figure 12. Change rate of water consumption across China and its primary water resource regions (2003–2023).

5. Conclusions

This study integrated three GRACE Mascon products to generate the TWSA_BTCH dataset, analyzed the spatiotemporal variations of TWSA and assessed the water scarcity status. Our work demonstrates that the TWSA_BTCH dataset constructed in this study can systematically reduce the overall uncertainty of regional TWSA results. The WS_{TWS_based} index combined with long-term TWSA evolution enables the characterization of water resource risks from two dimensions: hydrological fluxes and terrestrial water storage, and offers scientific support for differentiated zoned water resources management. This research addresses the critical drawbacks of conventional water scarcity assessments, which neglect annual dynamic fluctuations in groundwater and soil water storage.

The TWSA across China declined at a rate of -1.65 mm/a during 2000–2023, featuring moderate overall water scarcity. Under the combined effects of natural climate variability and anthropogenic regulation, the national water scarcity status has been alleviated overall. But there still exists inherent water supply–demand imbalances in arid and semi-arid northern China. Meanwhile, economically developed southern water resource regions such as SERB are in a moderate water scarcity status, although it slightly exceed the 0.2 scarcity threshold. Distinct decoupling exists between the WS_{TWS_based} index and long-term TWSA trends in SRB and SWRB. The weak water regulation in the SRB and latent terrestrial water storage Adepletion risk in the SWRB should be paid attention to.

Author Contributions: Conceptualization, L.W., Y.M., Z.Z. and W.L.; methodology, L.W., Y.M., and Z.Z.; software, Y.M. and Y.D.; validation, Y.M., L.W., Z.Z., Z.M. and J.Z.; formal analysis, L.W., Y.M.

and Z.Z.; resources, L.W., Z.Z., W.L., Z.M. and Y.Z.; data curation, Y.M., L.W., Z.Z. and J.Z.; writing—original draft preparation, Y.M., L.W. and J.Z.; writing—review and editing, L.W., Z.Z. and W.L.; visualization, Y.M. and L.W.; supervision, L.W., Z.Z. and X.G.; project administration, L.W.; funding acquisition, L.W., Z.Z., Y.Z. and Z.M. All authors have read and agreed to the published version of the manuscript.

Funding: This study is supported by the National Natural Science Foundation of China (Grant No. 42130613, U2244214 and 42375176), Beijing Municipal Science and Technology Commission, Beijing, China (Grant No. Z251100004525001), the China Geological Survey (Grant No. DD2026051015) and the International Partnership Program of the Chinese Academy of Sciences (060GJHZ2022057MI).

Data Availability Statement: The monthly TWSA data are sourced from the Center for Space Research (CSR) (<https://www2.csr.utexas.edu/grace/>, accessed on 8 December 2024), Jet Propulsion Laboratory (JPL) (<https://search.earthdata.nasa.gov/search/>, accessed on 8 December 2024) and Goddard Space Flight Center (GSFC) (<https://earth.gsfc.nasa.gov/geo/data/grace-mascons>, accessed on 8 December 2024). The 33 missing data records for Three GRACE/GRACE-FO Mascon Data Products during April 2002–December 2023 can be obtained at <https://doi.org/10.1016/j.geog.2024.12.004> (accessed on 15 December 2024). The Precipitation dataset CN05.1 published by Jia, W. et al. [47] can be obtained at <https://doi.org/10.6038/cjg20130406> (accessed on 5 March 2025). Monthly evapotranspiration (ET) data were extracted from the Global Land Evaporation Amsterdam Model (GLEAM) database, available at <https://www.gleam.eu/> (accessed 17 June 2025). The runoff dataset CNRD v1.0 published by Chiyuan, M. et al. [81] can be obtained at <https://doi.org/10.11888/Atmos.tpd.272864> (accessed on 5 March 2025). The Water consumption data are sourced from the China Water Resources Bulletin at <http://www.mwr.gov.cn/> (accessed on 16 December 2025). All open-source datasets mentioned above are freely accessible via the listed links, while all self-processed analytical datasets of this study can be acquired from the corresponding author upon reasonable request.

Acknowledgments: We sincerely thank the editors and anonymous reviewers for their valuable comments and suggestions for improving the quality of this paper.

Conflicts of Interest: The authors declare no conflicts of interest.

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