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Key Points:

- A water balance and variance analysis approach proposed for terrestrial water storage changes causality analysis
- Precipitation has a greater impact on controlling the variability of terrestrial water storage (TWS) in northern China, but it contributes less to the TWS trend
- Vegetation change is a large contributor to the TWS trends in northern basins

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Dominant Drivers for Terrestrial Water Storage Changes Are Different in Northern and Southern China

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Abstract Subsurface water storage is a key component in the water cycle, and China is facing severe issues with water resource shortage. This study estimates the terrestrial water storage (TWS) changes from 2003 to 2017 using a water balance approach over seven large basins in China. The estimated inter-annual variations and trends in TWS correspond well with those obtained from the Gravity Recovery and Climate Experiment observation. Variance analysis shows that annual precipitation in northern China plays a more important role in controlling annual TWS variability than that in southern China. This increased sensitivity is primarily attributed to the limited availability of water resources and the arid climate conditions prevalent in northern China. Interestingly, actual evapotranspiration is the dominant driver, contributing more than 55% to the declining trend in TWS in two northern basins: Hai River and Yellow River basins, where the leaf area index has strongly increased. Precipitation and evapotranspiration account for over 89% of the TWS trend over basins in northeastern China. Meanwhile, the dominant drivers for TWS in southern China are precipitation (50%–54%) and runoff (33%–41%). Our results suggest that it requires strong ecological conservation actions in order to keep water resources sustainable in northern China.

Plain Language Summary Terrestrial water storage is a vital component of the global hydrological cycle, especially in regions with serious water resource issues, including shortages and disparities in spatiotemporal distribution. This study found that precipitation is the dominant driver of the trends in terrestrial water storage change over southern China. Comparatively, the dominant driver is actual evapotranspiration over northern China, which is caused by the strong increase in the leaf area index in the Hai River and Yellow River basins.

1. Introduction

Terrestrial water storage (TWS) is a vital component of the global hydrological cycle, especially in regions with serious water resource issues, including shortages and disparities in spatiotemporal distribution (Gleeson et al., 2012; Li, Zhang, Shen, Kong, & Zhou, 2020; Li, Zhang, Shen, & Yu, 2020; Mekonnen & Hoekstra, 2016; Zhang et al., 2023). Therefore, accurate accounting of changes in water storage and causality analysis are essential for food security, human health, and water resource management. With increasing water demand for crop irrigation, domestic water, and ecological restoration in China, it is paramount to have a comprehensive and quantitative understanding of the terrestrial water storage changes (TWSC) and its major driving factors. This is a cornerstone for effectively managing current and future water resources (Jia et al., 2017; Rodell et al., 2018; Taylor et al., 2013). An accurate estimation of the trend in water storage change is important not only for an improved understanding of how TWS responds to changing climate, but also for water resources management and restoration.

Rapid urbanization and agricultural intensification in China have resulted in a surge in water demand. Changes in vegetation and hydrological regimes, coupled with the inherent biophysical characteristics of the region, have contributed to notable shifts in water storage. Investigating TWSC and its major drivers is particularly important in China, where anthropogenic and biophysical factors have largely affected water storage (Pang et al., 2020; Zhang et al., 2019a). There are several methods to estimate the TWSC, including in situ observation, hydrological models, remote sensing data, and catchment water balance analysis. The in situ observation directly estimates the TWSC, but can only be carried out at a regional scale. Hydrological models can be used to estimate soil

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Table 1
Summarizing the Studies for Investigating the Terrestrial Water Storage Changes and Dominant Drivers in China

Studies	Region	Method(s)	Main objective	Key conclusion
Chao et al. (2021)	Yangtze River	Lagrange multiplier method	Estimation of component contributions to TWSC	The TWS increased and was dominated by groundwater
Xiong et al. (2021)	China	Machine learning, Mann–Kendall test, and simple linear regression	Continuity of TWS variability and trends across mainland China	The TWS significantly decreased with spatial heterogeneity for the whole of China, especially in north and southwest China (−5∼−15 mm/a)
Yin et al. (2020)	North China Plain	Atmosphere-Biosphere land exchange model, Ensemble Kalman Filter	Improved water storage estimates within the North China Plain	The GRACE data is effective in assimilation toward a reliable estimation of groundwater storage variation in the North China Plain
Lin et al. (2020)	Yellow River	Principal component analysis, stepwise regression, regression subset selection method	Socio-ecological impacts on the change in groundwater	Anthropogenic factors are dominant drivers of groundwater change
Xie et al. (2019)	Globe	Trend analysis, correlation analysis, granger causality test method	Interactions between vegetation greenness and TWSC	The response of normalized difference vegetation index to TWSC is more rapid than that of precipitation
Xu et al. (2019)	China	Water balance, empirical attribution framework	Spatiotemporal TWSC and its possible drivers in China	The decreased TWS in north China is caused by human behaviors, but the increase in south China is caused by precipitation
Meng et al. (2019)	Tibetan Plateau	Water balance, variable infiltration capacity model	Changes in TWS and possible causes	The dominant role on variations of TWS is precipitation in the east Tibetan Plateau and evapotranspiration in the south Tibetan Plateau
Feng et al. (2016)	Loess Plateau, China	Water balance, statistical analysis	Revegetation impacts on water resource limits	Revegetation accelerated the limits of water resources in the Loess Plateau
Long et al. (2015)	Yangtze River	Land surface and global hydrological models, water balance	Deriving scaling factors using a global hydrological model to restore TWS	Marked spatial heterogeneity due to large seasonal and human-induced surface and subsurface variations in water storage
Huang et al. (2015)	Yangtze River	macroscale hydrological modeling, land surface models	Estimation of human-induced change in TWS	The TWS increased in the Yangtze River, which is dominated by anthropogenic modification
This study	Seven major basins in China	Water balance, sensitivity analysis of PML_V2 modeling, variance analysis	Dominant drivers for TWSC in China	The contribution of climate and vegetation change to the TWSC is distinct in different parts of China, and the role of vegetation changes is particularly important in northern China

moisture, runoff and TWSC. However, their applications are limited by the climatic and land coverage conditions of the basin, particularly basins impacted by complex anthropogenic factors. Thirdly, remote sensing data sets, such as the Gravity Recovery and Climate Experiment (GRACE) observation, provide an alternative approach to estimating the TWSC. GRACE data is available from April 2002 onwards, and it observes TWSC across the globe with a coarse resolution of $1 \times 1°$ (Li et al., 2022; Rodell et al., 2018; Voss et al., 2013). This data set is very useful for validating results from other methods but it cannot be directly used for causality analysis. Therefore, we can use GRACE data sets and a water balance approach to analyze the changes and drivers of water storage changes at a catchment or basin scale. The water balance approach uses three variables: precipitation (P), actual evapotranspiration (ET) and streamflow (Q) to estimate TWSC under the assumption that transboundary water movement is negligible. Benefits of using the water balance approach are that the three variables can be used for causality analysis. However, it is also limited to the data available for these three variables (Hu et al., 2021; Thornthwaite, 1955; Wang & Alimohammadi, 2012).

There are some studies that reported the spatiotemporal characteristic changes in TWS and its driving factors at a seasonal or annual scale, which are summarized in Table 1. Previous studies found a larger relative contribution

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of precipitation to TWSC in low-latitude basins (Soni & Syed, 2015; Zhang et al., 2019a). Additionally, the spatial distribution of TWSC more similarly matches to the change in precipitation in southern China than that in northern China (Mo et al., 2016; Zhang et al., 2019a). Other studies found that the water storage change is related to land use, land cover change and other human activities. For instance, vegetation changes have been found to be an important driver for changing water balance components, such as ET and Q (X. M. Feng et al., 2016; Li, Zhang, Shen, Kong, & Zhou, 2020; Li, Zhang, Shen, & Yu, 2020; Lv et al., 2019; Xie et al., 2019). The spatiotemporal changes of TWS in China can be analyzed using land surface models together with GRACE data to investigate the potential driving factors (Xu et al., 2019). These results are helpful in explaining the water storage change and trend analysis over basins in China. Nevertheless, there have been few studies carried out in the last two decades in China for observation-based causality analysis of TWSC, particularly at a large basin scale.

Since TWSC is jointly influenced by climate change and human activities, previous studies have demonstrated the combined impact of climate factors and human activities on TWSC (Du et al., 2020; W. Feng et al., 2013; Tang et al., 2014). It has been found that the growth of CO_2 rates and droughts strongly influence the observed changes in TWS (Humphrey et al., 2018). Furthermore, Zhang et al. (2019b) found that precipitation is a large contributor to river basins of China, while Luan et al. (2022) found that coal mining could drastically drop groundwater levels, and cause a noticeable decrease of river base flow and total streamflow in the dry season. In addition, irrigation, reservoir regulation, water diversion and coal transport can lead to a decrease in streamflow and an increase in ET, affecting the TWSC (Tang et al., 2013). Overall, it is clear that the changes in climate factors and human activities influence ET and Q, and they both drive TWSC. Even though it is very important for understanding the regional water cycle and facilitating water resource management, there are few studies decomposing TWSC systematically into the water balanced components and quantifying the contribution of each TWSC driver (Rodell et al., 2018). The national Ecological Restoration Project—"Grain for Green Project" has been implemented since 1999 to improve vegetation coverage in the region (Wang et al., 2015; Zhang et al., 2016a, 2016b). It is expected that revegetation has a noticeable impact on the TWSC by altering canopy transpiration, rainfall interception and redistribution, and soil water infiltration, as well as changing the energy distribution process (Xie & Cui, 2011). Previous studies investigated the significant interactions between water reserves and vegetation growth (G. A et al., 2015; Geruo A et al., 2017). Vegetation change has a noticeable impact on the TWSC. However, there are few reports that quantify the relative contribution of ET impacted by vegetation change, ET impacted by non-vegetation change, precipitation, and streamflow to TWSC, which is critical to ecological project planning and water resources management.

To address the inquiry regarding how each water balance component influences TWSC, this study aims to investigate inter-annual variability and trends in TWS, and quantify the contributions of precipitation, evapotranspiration and streamflow in seven major river basins in China. The quantification is achieved through the utilization of observed data on precipitation and streamflow, coupled with actual evapotranspiration estimates obtained from diagnostic remote sensing modeling (Figure 1). Additionally, this study also aims to isolate the impact of vegetation changes on TWSC by the two modeling experiments of a water-carbon coupled diagnostic model (PML-V2) with different vegetation inputs but the same climate forcing inputs. Specific objectives include:

1. Comparing annual TWSC estimated by GRACE and the observation-based water balance method in seven major basins in China;
2. Evaluating the variance of TWSC by water balance and its drivers (precipitation, evapotranspiration and streamflow) over basins in China and;
3. Investigating trends in TWSC and the contribution rate of precipitation, streamflow, evapotranspiration by non-vegetation change and evapotranspiration by vegetation change over the large basins in China.

2. Material and Method

2.1. Study Area

The study area covers seven major basins and hydrological stations of China, including Songhua River (Jiamusi station), Liao River (Liujianfang station), Hai River (Yanchi station and Zhangjiafen station), Yellow River (Lijin Station), Huai River (Bengbu station and Linyi station), Yangtze River (Datong station) and Pearl River (Shijia station and Gaoyao station) from north to south. According to the terrain and location, the basins span the humid region, semi-humid region, semi-arid region and arid region, with precipitation decreasing from southeast to northwest.

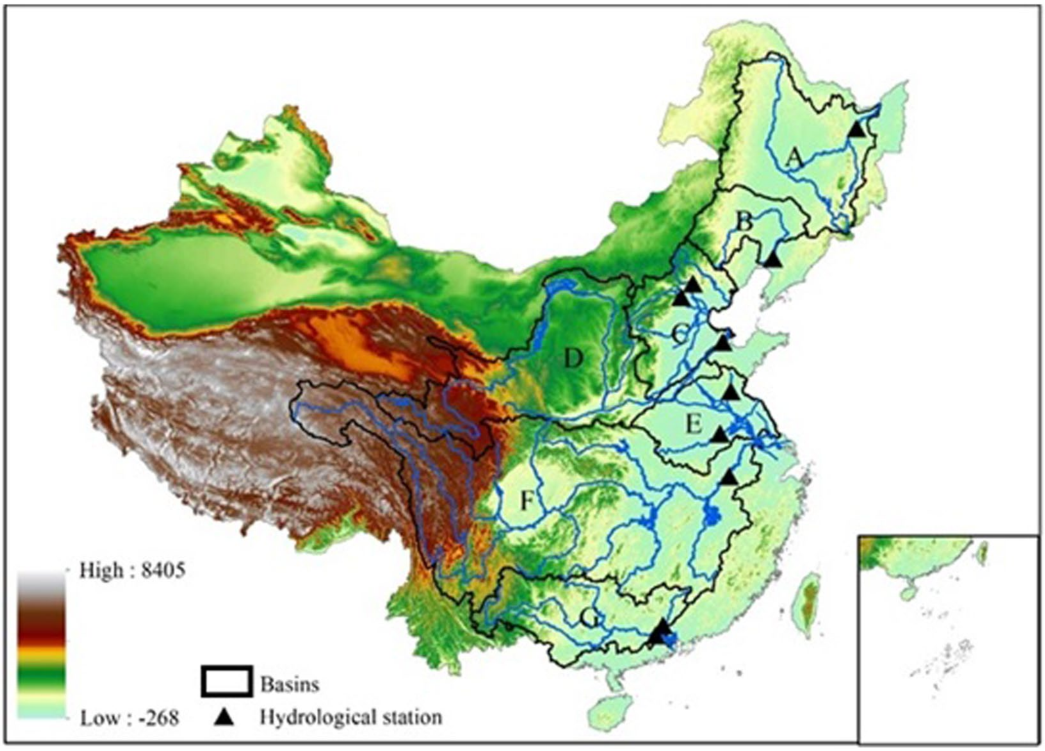

Figure 1. Location of the seven selected river basins and hydrological stations across China. The letters of A, B, C, D, E, F and G represent Songhua River, Liao River, Hai River, Yellow River, Huai River, Yangtze River and Pearl River, respectively. It is noted that the basin area for each river is the contribution area above its most downstream gauge, not the area above its river outlet.

2.2. Data

The precipitation data was obtained from the China Meteorological Forcing Dataset (CMFD), covering a period from 2003 to 2017 with a spatial resolution of $0.1° \times 0.1°$, and a temporal resolution of 1 day, which is the best available forcing data set (J. He et al., 2020). The data was made through a fusion of remote sensing data sets and in-situ observation data from gauges in the China Meteorological Administration. The CMFD forcing data correspond well with ground observations, and are widely used for land surface and hydrological modeling in China (Ma et al., 2019).

GRACE has been a reliable method to estimate the terrestrial water storage anomaly (TWSA) globally since its launch in 2002. This study used the annual TWSC (2003–2016) based on RL06 which used the Mascon approach from 2003 to 2017 (Equation 1). Three GRACE-TWSC data sets with a spatial resolution of $1° \times 1°$ were obtained from NASA Jet Propulsion Laboratory (JPL), German Research Center for Geosciences (GFZ) and Center for Space Research (CSR), respectively (Save et al., 2016; Watkins et al., 2015). The data sets use a-priori constraints in space and time to estimate global TWSA.

This study selected three main-stream remote sensing-based ET products from 2003 to 2017, including Penman-Monteith-Leuning Evapotranspiration V2 (PML_V2) (Zhang et al., 2019), Moderate-resolution Imaging Spectroradiometer data set (MODIS) Evapotranspiration (MODIS-ET) (Mu et al., 2011) and Global Land Evaporation Amsterdam Model data set (GLEAM) (Martens et al., 2017). PML_V2 is a biophysical model coupled to the gross primary production process based on stomatal conductance theory with an 8-day and 500 m resolution. This model uses Global Land Data Assimilation System 2.1 meteorological forcing and MODIS leaf area index (LAI), albedo, and emissivity, to estimate terrestrial evapotranspiration and gross primary production at the corresponding spatial and temporal resolutions. LAI data was obtained from the MCD15A3H.006 product, which has 500 m and 4-day resolutions. Albedo was obtained from the MCD43A3.006 product (Schaaf & Wang, 2015) with 500 m and daily resolutions. Furthermore, surface emissivity data was obtained from MOD11A2.006 (Wan et al., 2015), which has 500 m and 8-day resolutions. The MODIS-ET product (or MOD16A2) has the same spatial and temporal resolutions as the PML-V2 ET product. The GLEAM ET product has daily and 0.25° resolutions. These three ET products were used together with observed precipitation and streamflow to estimate annual TWSC at a basin scale (Equation 2).

The annual Q data for the period of 2003–2017 was obtained from the China Ministry of Water Resources, and it was used to calculate the annual catchment TWSC. To calculate storage change using the basin water balance approach (Equation 2), gridded P, ET and water storage data were aggregated for each basin through the area-weighting averaging approach.

It should be noted that the research period for water balance is 2003–2017 which is one year longer than the research period (2003–2016) of the GRACE TWSC data set since the GRACE data is missing from June 2017 to June 2018.

2.3. Method

2.3.1. Terrestrial Water Storage Change

We conducted a causality investigation on TWSC by calculating trends and variances of TWS over the seven river basins in China: Songhua River, Liao River, Hai River, Yellow River, Huai River, Yangtze River, and Pearl River basins (Figure 1).

The water balance approach to estimate TWSC was validated against the GRACE observations. The P and Q data were obtained from observations. The basin ET was obtained from the estimates of the above-mentioned remote sensing ET products: PML_V2, MOD16A2 and GLEAM. Furthermore, the uncertainty related to the three ET data sets was evaluated, and they were used together with observed precipitation and streamflow to estimate annual TWSC at a basin scale (Shao et al., 2022). Additionally, the impact of human activity on water balance is mostly observed in the changes in ET and Q (Lei et al., 2015; Luan et al., 2022). This study does not consider the contributions from other human activities.

Based on GRACE, the water storage change is calculated by:

$$\Delta S_{\text{grace}} = \text{GRACE}_i - \text{GRACE}_j \tag{1}$$

where GRACE_j is the TWSA value at January of the current year, and GRACE_i is the TWSA value at January of the following year. Missing values were replaced by linear interpolation of adjacent observations.

Based on the water balance equation, the annual water storage change for catchments is defined by:

$$\Delta \text{Swb} = P - \text{ET} - Q \tag{2}$$

where ΔSwb is the annual water storage change, ET is the annual evapotranspiration, and Q is the annual streamflow. Three ET products, including PML_V2, MODIS, and GLEAM, were used to estimate ΔS separately, and their estimates are denoted as ΔSpml, ΔSmodis, and ΔSgleam, respectively.

For further analysis of how annual variance of ΔSwb (Var(ΔSwb)) is influenced by annual P, annual ET and annual Q, this study decomposes the variance of ΔSwb as:

$$\text{Var}(\Delta \text{Swb}) = \text{Var}(P) + \text{Var}(-\text{ET}) + \text{Var}(-Q) + 2\text{Cov}(P, -\text{ET} - Q) + 2\text{Cov}(-\text{ET}, -Q) \tag{3}$$

Evapotranspiration is the main process of water energy exchange between the land, surface and atmosphere. It is a complex process that involves soil evaporation, vegetation transpiration and vegetation rainfall interception. Evapotranspiration is also the primary pathway for water to enter the atmosphere, making it a critical component of the global water cycle and a key driver of both regional and global climates. To further analyze the impact of vegetation changes on evapotranspiration, two modeling experiments were set up for PML-V2 by using different vegetation inputs (land cover and vegetation data) and the same climate inputs (Table 2). The first experiment is "dynamic," and it uses 8-day continuous vegetation dynamics (LAI, albedo and emissivity) and annual land cover types to drive the PML-V2 model (Zhang et al., 2019). The second experiment is "static," and it keeps the same vegetation condition for all the years. This means that we use one year of the vegetation data (2003, 3004, 2005, or 2006, respectively) looping through all the years. Except for this difference, the two experiments share the same climate inputs (precipitation, air temperature, vapor pressure, shortwave downward radiation, longwave

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Table 2
The Description of Modeling Experiments for Isolating Driver Contribution

Inputs	Dynamic	Static
Climate	Time varied	Time varied
Vegetation time series (LAI, albedo and emissivity)	Time varied	One year (2003, 2004, 2005 or 2006) looping through all the years
Land cover and land use	Time varied	One year (2003, 2004, 2005 or 2006) looping through all the years

downward radiation and wind speed). It should be noted that we used 4 years of vegetation data for the static experiment, and took the ensemble mean of the four outputs to compare with the output from the dynamic modeling (Table 2). Therefore, the difference between the two experiments can be used to isolate the impact of climate change or vegetation change on water storage change.

The impact of vegetation change on ET (ET_v) can then be estimated by using the difference between the two experiments. This can be expressed as:

$$ET_v = ET - ET_{nv} \tag{4}$$

where ET is from the dynamic experiment, and ET_{nv} is from the static experiment.

2.3.2. Contribution Rate and Variance Decomposition

Based on water balance, the linear trend of ΔSwb ($T_{\Delta Swb}$) can be decomposed into the trends from P, ET_v (impacted by vegetation), ET_{nv} (impacted by non-vegetation drivers) and Q as follows:

$$T_{\Delta Swb} = T_P - T_{ET_v} - T_{ET_{nv}} - T_Q \tag{5}$$

The contribution ratio (CR) of the four hydrological variables is defined as:

$$CR = \frac{|T(X_i)|}{\sum_{i=1}^{4} |T(x_i)|} \tag{6}$$

where CR is the contribution ratio, and $T(X_i)$ represents the linear trend of P, ET_v, ET_{nv} or Q, respectively.

3. Results

Figure 2 summarizes the annual anomaly and trends of TWSC calculated by the two methods. The water balance TWSC shows a strong correlation with the GRACE TWSC as it compares well and their inter-annual variability is similar. These similarities further validate the effectiveness of the water balance approach in accurately estimating water storage change. In addition, although the trends estimated by water balance TWSC and GRACE TWSC over basins are not significant ($p > 0.05$), the trends calculated by the two remain consistent. The trends both increased in southern China (Yangtze River basin and Pearl River basin) and decreased in northern basins (except for the Songhua River basin) from 2003 to 2017. Furthermore, the trend of TWSC obtained from PML_V2 compares well to that from the GRACE TWSC observation, with a correlation coefficient of 0.85 between the two; it performs similarly to that obtained from GLEAM ($r = 0.84$), and noticeably better than that obtained from MODIS ($r = 0.68$). These results give us confidence that the water balance approach is solid, and reliable for investigating major driving factors influencing TWSC.

Since PML_V2 performs well and can be used for partitioning vegetation and non-vegetation impacts on TWSC, PML_V2 was selected to further investigate the spatial trend and impact of vegetation changes on the TWSC. Figure 3 decomposes the variance of annual TWSC, which is mainly impacted by a change in precipitation. Furthermore, the variance of TWSC in northern China (Songhua River, Liao River, Hai River and Yellow River basins) is more sensitive to a variance of P compared to southern China (Huai River, Yangtze River and Pearl River basins). This increased sensitivity is primarily attributed to the limited availability of water resources and the arid climate conditions prevalent in northern China. The second most important factor impacting the inter-annual variability of TWS is ET in northern China and streamflow in southern China. Therefore, we can see that TWS change in the northern basins is most sensitive to a change in precipitation, followed by ET. Comparatively in the

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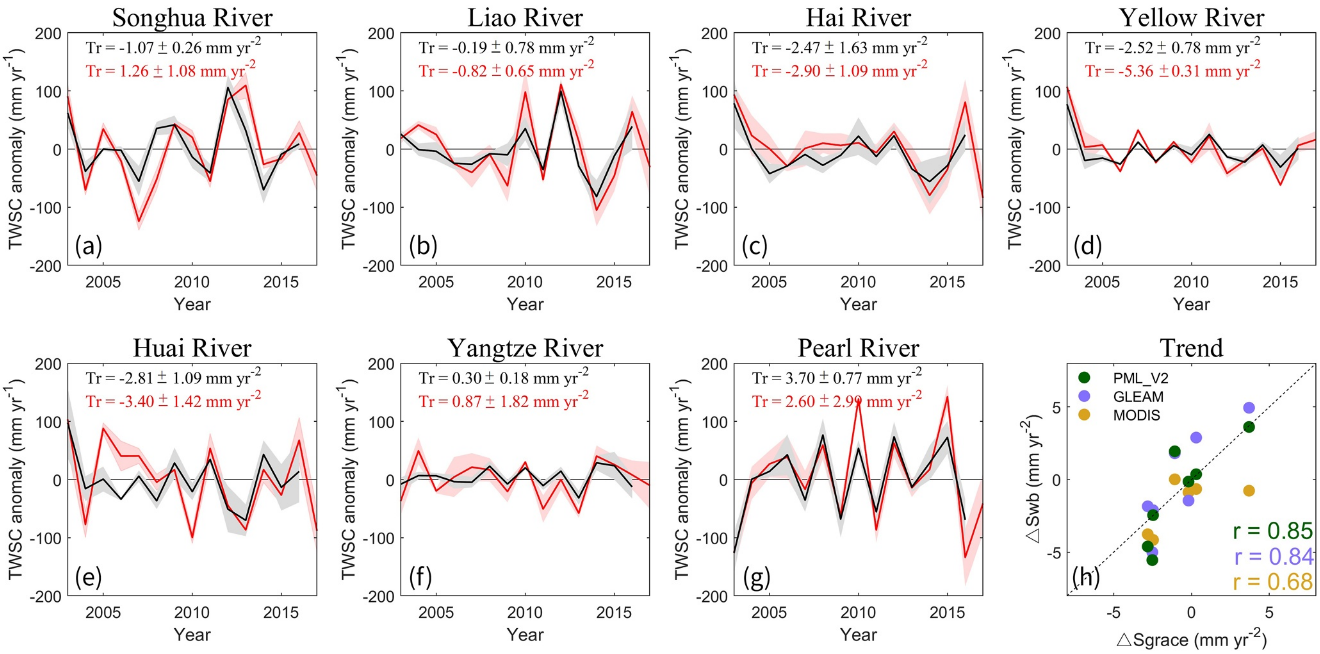

Figure 2. Annual anomaly of water storage changes (based on the average value during 2003–2016) and (h) terrestrial water storage trends obtained from two methods in seven river basins. The black lines show the ensemble mean of Gravity Recovery and Climate Experiment (GRACE) observations from the products Jet Propulsion Laboratory, German Research Center for Geosciences, and Center for Space Research. Meanwhile, the red lines show the ensemble mean from the water balance approach through using three evapotranspiration estimates (PML-V2, Moderate-resolution Imaging Spectroradiometer data set, and Global Land Evaporation Amsterdam Model data set) from 2003 to 2017. The shaded area represents the standard deviation from the multiple estimates. *r* is the correlation between the trends in water balance, which TWSC estimates from the three evapotranspiration products, and trends in GRACE TWSC observation. It is noted that all the trends from the water balances and GRACE data are not significant ($p > 0.05$).

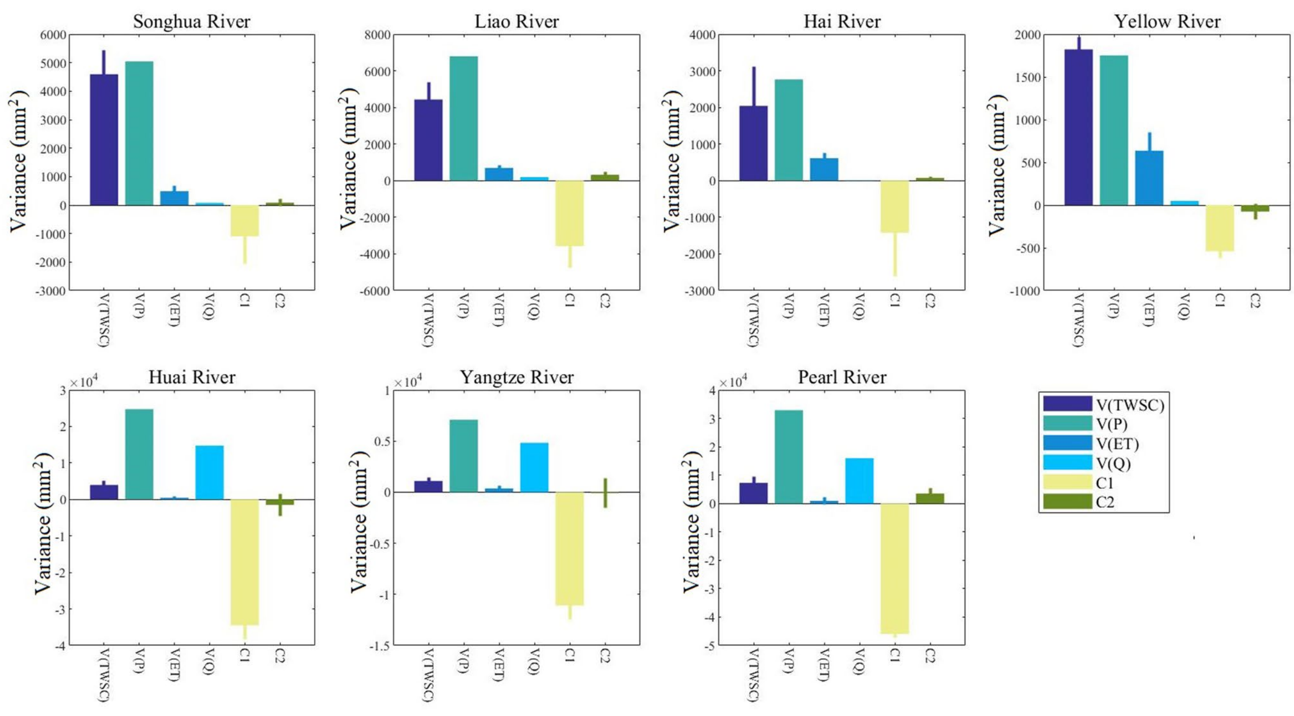

Figure 3. Variance analysis of precipitation (P), actual evapotranspiration (ET), and streamflow (Q) for the terrestrial water storage change (ΔSwb) over seven large river basins. C1 and C2 represent 2Cov(P, -(ET + Q)) and 2Cov(-ET, -Q), respectively (Equation 3). The error bars stand for the standard deviation from the multiple estimates.

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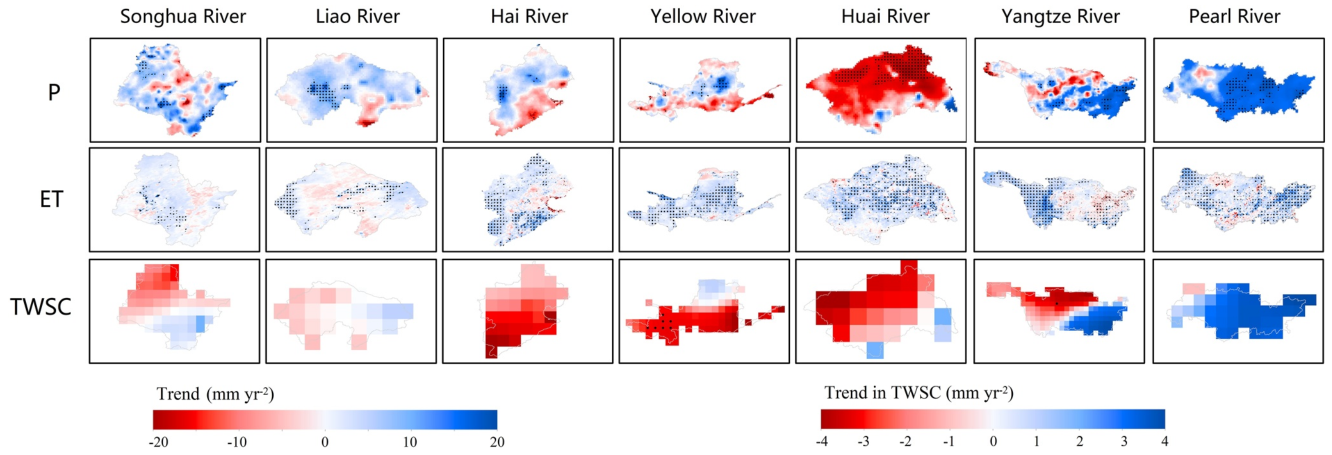

Figure 4. The trends in precipitation (*P*), PML-V2 estimated evapotranspiration (ET) from 2003 to 2017 and terrestrial water storage change (TWSC) obtained from Gravity Recovery and Climate Experiment (mean value of Jet Propulsion Laboratory, German Research Center for Geosciences, and Center for Space Research) over seven basins from 2003 to 2016. Stippling indicates that the trend is significant at $p < 0.05$.

south, it is similarly the most sensitive to changes in precipitation, however, it is then followed by streamflow. This pattern is mainly caused by the precipitation difference between southern China and northern China.

Figure 4 summarizes the spatial pattern of trends in precipitation, PML_V2 estimated ET and the GRACE-observed TWSC over seven basins, respectively. For precipitation, an increasing trend dominated the Songhua River, Liao River, Yangtze River, and Pearl River basins, while a decreasing trend dominated the Huai River basins. Moreover, the trend of precipitation is almost unchanged in the Hai River and Yellow River basins. However, within the two basins there exist contrasting trends, that is, increasing in the middle part and decreasing in the southern part. For ET, the trends are positive in most parts of the seven basins, most noticeably in Hai River, Huai River and Yellow River basins. The trend of spatial pattern of precipitation is largely consistent with that of the TWSC trend in the Hai River, Yangtze River, and Pearl River basins.

Figure 5 further summarizes the contribution ratios of *P*, ET_{nv}, ET_{v} and *Q* to the trends of TWSC calculated by water balances over seven basins. Among the three contributors, the CR of precipitation is less than 25% in the Hai River (21%) and Yellow River (10%), and it is higher than 50% in other five basins. The CR of ET is lower than 20% in the Huai River basin (9%), Yangtze River basin (16%) and Pearl River basin (8%). The CR of ET is about 30% in Songhua River basin (25%) and Liao River basin (36%), while it is higher than 50% in Hai River basin (55%) and Yellow River basin (76%). Overall, the CR of *Q* is above 30% in southern China (Huai River basin, Yangtze River basin and Pearl River basin), but is less than 25% in northern China.

To further investigate how the different components of ET trends influence TWS trends, this study separates the ET trends into two components: trends in ET_{v} (impact by vegetation change) and ET_{nv} (impact by non-vegetation change). It can be found that the contribution rate of ET_{v} is noticeable, especially in the Yellow River basin (42%) and Hai River basin (37%), where the CR of ET is greatly affected by vegetation changes. In summary, precipitation is the major cause of the TWSC over most basins except the Hai River and Yellow River basins. The second major contributor is streamflow in southern basins, but ET in northern basins.

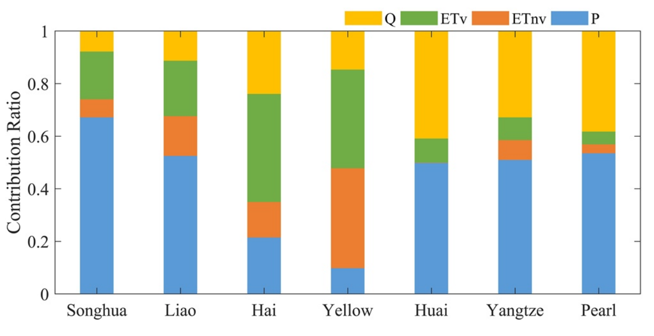

Figure 5. The contribution ratio (CR) of precipitation (*P*), ET_{nv}, ET_{v} and streamflow (*Q*) to TWSC trends over the seven major basins in China. The CR of ET is the sum of ET_{nv} and ET_{v}, obtained from PML-V2.

4. Discussion

4.1. Uncertainty Related to Water Balance Inputs

This study uses observational data (precipitation and streamflow) together with diagnostic remote sensing model estimates (actual evapotranspiration) to quantify TWSC. Our approach is simple and straightforward, and it can be used to analyze the TWSC and its driving factors. It is, however, noted that the accuracy of our study is largely determined by the accuracy of *P*, ET and *Q*. Precipitation is the most critical input variable (Fekete et al., 2004; Tang et al., 2019). The CMFD is the meteorological data set for China which was

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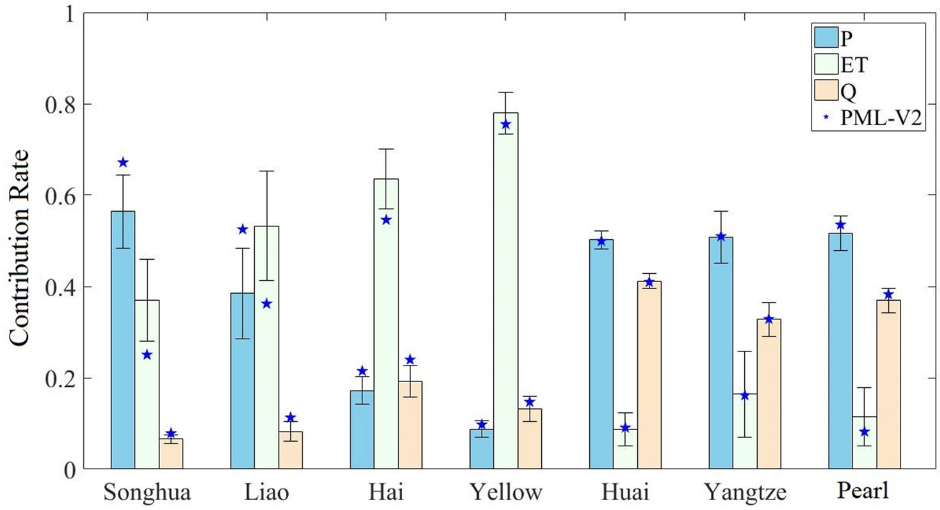

Figure 6. Uncertainty analysis of the contribution rates of precipitation, evapotranspiration (PML_V2, Moderate-resolution Imaging Spectroradiometer data set, and Global Land Evaporation Amsterdam Model data set) and runoff to the trend of terrestrial water storage change (TWSC) obtained from water balance over seven basins from 2003 to 2017. Error bar indicates the standard deviation (±1 std) and star indicates the PML-V2 results.

made through the fusion of remote sensing products, reanalysis data sets and in situ station data (J. He et al., 2020). This product is of high quality, and is the most reliable in China (Luan et al., 2021; Xu et al., 2021). The previous ET study shows that the uncertainty of remote sensing products of ET is 15%–30% due to different sources and methods (Kalma et al., 2008). The accurate ET value is of great significance for understanding the regional hydrological cycle. This study selects three ET products by different approaches to estimate TWSC over China. It is clear that the trends of ET are different. Specifically, ET from MOD16A2 shows faster increased rates than that from PML-V2 and GLEAM (Figure 2). This study further analyses the trend of TWS obtained from GRACE observations, and the estimates from water balance by the three ET products. The results show that TWSC estimated by PML-V2 performs better than the other two (Figure 5). PML_V2 is diagnostic and has a carbon constraint on water flux (Zhang et al., 2019). It should also be noted that we do not validate the three ET products here since they are widely validated in China. This is particularly true for the PML-V2 products. For instance, Li, Zhang, Shen, Kong, and Zhou (2020) and Li, Zhang, Shen, and Yu (2020) investigated the changes in evapotranspiration and gross primary production in northern China by using the PML-V2 products. They were able to validate the PML-V2 ET at four flux sites (one in forest and three in grassland), and they found that the PML-V2 had low errors (root mean square error [RMSE] = 0.43 mm d^{-1}). Ma and Zhang (2022) found that the PML-V2 performed well on the Tibetan Plateau, with the RMSE varying from 0.30 to 0.40 mm d^{-1} at 14 flux sites over six land cover types (Desert steppe, alpine steppe, sparse alpine meadow, dense alpine meadow, alpine wetland and needle-leaved forest). More recently, S. He et al. (2022) tested the PML-V2 across all of China and found that it performs at a good quality for most of plant function types, with the RMSE being 0.39, 0.49, 0.57, 0.70, 0.73, 0.77, 1.00, 0.91, and 1.09 for savannas, mixed forest, open shrublands, grassland, barren sparse vegetation, evergreen broadleaf forest, evergreen needle-leaved forest, cropland and wetlands, respectively. Additionally, the uncertainty of the contribution rates of the water balance components, estimated by the three ET products, is analyzed Figure 6. The results show that the uncertainty is lower over basins in southern China compared to that in northern China. In addition, the uncertainty of the CR of precipitation (or evapotranspiration) over basins in China is lower, indicated by the standard deviation varying from 0.02 (or 0.04) in Yellow River basin to 0.10 (or 0.12) in Liao River basin. In summary, the uncertainty in our results is relatively small, which has limited impacts on the magnitude of TWS variability and trends derived from the water balances. Therefore, the overall conclusions obtained from this study are reliable.

4.2. Strengths and Limitations of This Study

This study used 500 m PML-V2 ET estimates together with the other two main-stream ET products as well as observed P and Q in order to detect variability and trends in TWSC over seven large basins in China. To our knowledge, this is the first attempt of a TWSC study which clearly shows the changes of TWSC and its driving factors at basin and pixel scales. The results show that the variability of TWSC is dominated by precipitation over all the selected basins in China. To reduce the validation uncertainty, this study carefully selected three GRACE products (JPL, GFZ, and CSR) to obtain the "observed" change of water storage change in seven basins. The results show that the difference between the three GRACE products is small, and their average is solid enough for validation.

It is also noted that the PML_V2 biophysical model used in this study is diagnostic and has a carbon constraint on water flux. To explore the impact of vegetation change on water storage change, this study setups two PML_V2 experiments—one being "dynamic," and the other "static." This study considers vegetation impacts on TWSC mainly by changing the land surface variables such as land cover types, LAI, albedo and emissivity. This is the first attempt to clearly isolate the vegetation and non-vegetation contributions to TWSC and to quantify how vegetation changes drive TWSC.

A limitation of this study is that the research period is relatively short due to the limitations of remote sensing data. This study only analyzes the GRACE data set before 2017 since it is not available from May 2017 to June 2018. The GRACE data set is available for the post-2018. The water balance storage analysis for this period has not been conducted since continuous data was used to avoid the uncertainty caused by the data gap.

Notably, this study did not consider the contributions from other human activities, such as transboundary water diversion from southern China to northern China (An et al., 2021; Karesdotter et al., 2022), which could lead to a potential error in the water storage change estimated from water balances. Furthermore, the impact of coal mining was ignored although it may have led to some errors in the TWSC in some basins. Furthermore, this study does consider the impact of local irrigation (such as groundwater pumping) on actual evapotranspiration, since we use a diagnostic evapotranspiration model (PML-V2) to estimate actual evapotranspiration (Zhang et al., 2019). In addition, vegetation can increase transpiration by expanding plant leaf area, and it may contribute to local precipitation recycling. Previous studies showed that precipitation is mainly affected by external atmospheric circulation outside our research regions, and that the impact of precipitation recycling on vegetation change is limited in South and East Asia (Cui et al., 2020; Luan et al., 2021). Therefore, this study does not consider the impacts precipitation recycling has on vegetation change. Furthermore, vegetation changes may lead to changes in some meteorological drivers, such as wind speed and temperature, thus affecting the accuracy of modeled ET. Despite the uncertainty and limitations, this study provides an improved understanding of changes in regional resources and some major driving factors.

4.3. Comparison to Other Studies

Previous studies paid much attention to TWS from spatiotemporal changes by using GRACE data (Chao et al., 2021; Xiong et al., 2021). Nevertheless, our results show that precipitation has more impact on the variance of TWSC in northern basins, while it has a relatively smaller impact on the trend of TWSC in northern China, especially in Yellow River and Hai River basins. The limited water resources and more arid climate conditions in the northern basins result in a higher dependence on precipitation for water replenishment (Wang & Alimohammadi, 2012). Furthermore, vegetation changes and resulting changes in soil structure can raise evapotranspiration rates, which can exacerbate the sensitivity of TWSC to precipitation (An et al., 2021). Moreover, our results illustrate TWS decreasing over basins in northern China but increasing over basins in southern China, which is similar to available research (Li, Zhang, Shen, Kong, & Zhou, 2020; Li, Zhang, Shen, & Yu, 2020; Xiong et al., 2021; Yin et al., 2020). For instance, Xu et al. (2019) investigated the driving factors of TWSC in China by using a water balance approach and data sets generated from land surface models and climate reanalysis. Like our findings, they also obtained the result that precipitation is the dominant driver of TWSC in southern China. However, the direct results from the two studies are different for northern China. Xu et al. (2019) found that human water use contributes the most to water depletion in northern China, whereas we found that evapotranspiration and runoff are the dominant drivers to the TWSC. In essence however, the two results regarding northern China are similar since human water use is a strong contributor to the increase in evapotranspiration and the decrease in runoff. Comparatively, the advantage of our study is that we used remote sensing data and gauge observations data, which further corroborated the results Xu et al. obtained from modeling. More importantly, the water balance analysis we used is based on the observations, which allows us to check contributions from individual water balance components. For instance, we found that streamflow is the second most dominant driver for TWSC over the basins in southern China, but precipitation is the second most dominant driver for TWSC over the basins in northern China.

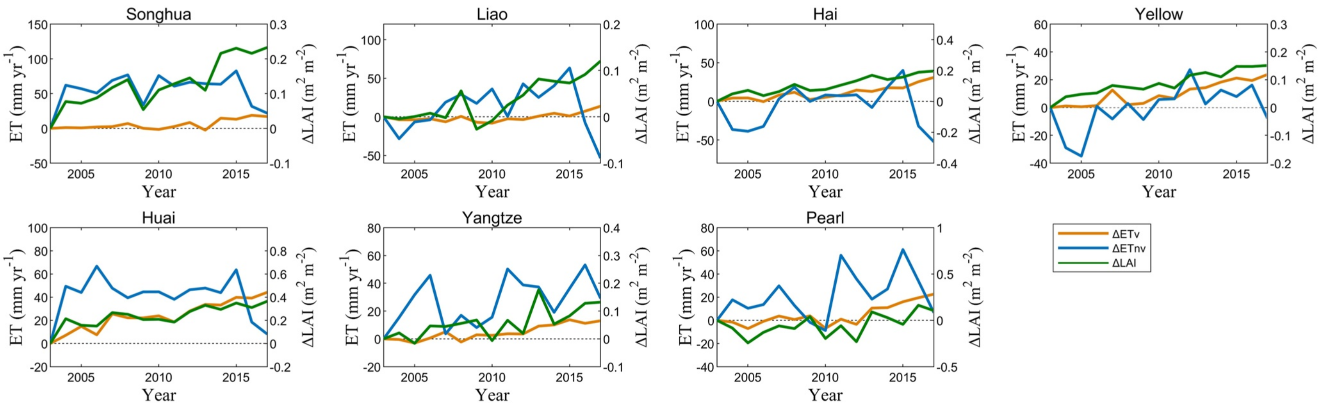

Figure 7. The annual changes in leaf area index (LAI), ET_v and ET_{nv} over seven basins in China based in 2003. The changes are calculated using $\Delta X = X_{year} - X_{2003}$, where X stands for LAI, ET_{nv} or ET_v, respectively.

An interesting finding is that vegetation changes have notably contributed to TWSC over the basins in northern China but have less of an impact in southern China. The contribution rates of evapotranspiration by vegetation changes to TWSC are more than 30% in the Yellow River and Hai River basins where TWS has decreased. On the contrary, the contribution rate of vegetation changes to TWS is less than 10% over the southern basins in China. The major role that ET_v played in northern China can be attributed to the fact that environmental conditions have been largely improved over the last two decades after the implementation of several national policies (Zhang et al., 2016a, 2016b). China accounts for 25% of the global increase in LAI, though it only accounts for 6.6% of the global vegetated area (C. Chen et al., 2019). Vegetation coverage in the Loess Plateau increased from 31.6% in 1999 to 59.6% in 2013, and the production in the North China Plain has shown a rapid upward trend with more irrigation (Y. P. Chen et al., 2015; W. Feng et al., 2013). The "Grain for Green Program" and expanded cropland have overexploited the groundwater resources (Doll et al., 2014). Our results further indicate that ET increases driven by vegetation greening play a major role in controlling the decrease in water storage over basins in northern China. The contribution rate of ET_{nv} in arid northern China is stronger than that in southern China, particularly in the Yellow River basin and Hai River basin. We further analyze the LAI impact on ET over the seven basins in China (Figure 7). The results show that there exists a strong relationship between the changes in LAI and the changes in ET_v, especially in the Hai River, Yellow River and Huai River, where the increasing in LAI leads the ET_v to increase and the TWS to decrease. Comparatively, the relationship is weak in the Pearl River, Yangtze River and Songhua River, indicating that the increase in ET is mainly due to changes in changes in the climate (Zhang et al., 2021).

4.4. Implication of This Study

Surface and subsurface water storage are vital freshwater resources, significantly influencing water resource management. This study investigated the variability and trend of TWS and its dominant drivers over basins in China. Results of this study could be valuable in providing basic scientific support for sustainable water resource development. Additionally, this study quantified the contribution of vegetation changes to TWSC over basins in China. The increase of large-scale vegetation coverage and LAI in northern China has resulted in a strong increase in ET, which is the main contributing factor to TWS change (C. Chen et al., 2019). However, this has resulted in a negative effect on regional water resource management. Our study suggests that it is necessary to constrain the increase of ET in northern China for sustainable water resource management.

5. Conclusions

This study investigates the inter-annual variability and trends in TWS and the dominant drivers of TWS change over seven major river basins in China from 2003 to 2017. We found that TWS change calculated from the water balance approach is consistent with that estimated from GRACE for most river basins. Terrestrial water storage primarily decreased in the Hai River, Yellow River and Huai River basins, while it mainly increased in other the basins which are mostly located in the humid and semi-humid regions. Our results indicate that the decreases in

TWS over the Hai River and Yellow River basins are mainly caused by the human-induced increase of evapotranspiration, which is highly related to the "Grain for Green Program" as well as the intensified cropland regulations (e.g., increased crop yield with more irrigation). However, the trends in TWS change over the other basins are primarily driven by climate changes. Our results suggest that it requires more investigations on balancing ecological and hydrological consequences for sustainable water resource management.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The PML-V2 evapotranspiration data (Zhang et al., 2019) is obtained from National Tibetan Plateau Data Center. The MOD16 evapotranspiration data (Mu et al., 2011) is obtained from USGS. The GLEAM evapotranspiration data (Martens et al., 2017) is obtained from Global Land Evaporation Model. The GRACE data sets (Save et al., 2016; Watkins et al., 2015) are available from Center for Space Research, GeoForschungsZentrum Potsdam and Jet Propulsion Lab. The precipitation data (J. He et al., 2020) is available from National Tibetan Plateau Data Center and streamflow data is available from International Research and training Center on Erosion and Sedimentation. The LAI data (Schaaf & Wang, 2015) used in this study can be accessed from the EarthData.

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