Variations in Water Storage in China over Recent Decade from GRACE Observations and GLDAS

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Abstract

We applied GRACE Tellus products in combination with GLDAS simulations and data from reports, to analyze variations in terrestrial water storage (TWS) in China and eight of its basins from 2003 to 2013. Amplitudes of TWS were well restored after scaling, and showed good correlations with those estimated from models at the basin scale. TWS generally followed variations in annual precipitation, it decreased linearly in Huai River basin (-0.56 cm yr^{-1}) and increased with fluctuations in Changjiang River basin (0.35 cm yr^{-1}), Zhujiang basin (0.55 cm yr^{-1}) and Southeast Rivers basin (0.70 cm yr^{-1}).In Hai River basin and Yellow River basin, groundwater exploitation may have altered TWS's response to climate, and TWS kept decreasing until 2012. Changes in soil moisture storage contributed over 50% of variance in TWS in most basins. Precipitation and runoff showed large impact on TWS, with explained variance higher in TWS in the south than in the north. North China and Southwest Rivers region exhibited long-term TWS depletions. TWS increased significantly over the recent decade in the middle and lower reaches of Changjiang, southeastern coastal area, as well as the Hoh Xil, and headstream region of the Yellow River in Tibetan plateau. The findings in this study could be helpful to climate change impact research and disaster mitigation planning.

1 Introduction

Terrestrial water storage (TWS) is a key component of global hydrological cycle and plays a critical role in Earth's climate system (Famiglietti et al., 2004). Despite its importance, there are still much gaps in the existing water storage observation networks at both the global and regional scale (Lettenmaier and Famiglietti, 2006).Although recent advances in satellite imaging and altimetry have strengthened our monitoring capability over vast areas, these technologies primarily provide only variation information for single factor related to TWS, such as precipitation estimates, surface soil moisture, snow cover, and river/lake level. With the progress in satellite gravimetric techniques, direct observation of TWS has become available. The Gravity Recovery and Climate Experiment(GRACE) twin satellites were launched in 2002 as a joint space mission between NASA (US) and DLR (German) to observe variations in Earth's gravity field. Over land, these observations provide information of integrated water storage changes in the vertical profile, including surface water reservoirs, upper layers of soil and underground water reservoirs.

At global, regional and basin scale, GRACE data have been applied to analyze seasonal cycle characteristics of TWS (Schmidt et al., 2006;Syed et al., 2008;Strassberg et al. 2007). Because of its sensitivity to water amount over large area, GRACE data can also be a useful tool for identifying impact caused by extreme climate events like drought and flood, or tracking climate change's influence on local water resource(Andersen et al., 2005; Long et al., 2013; Phillips et al.,2012). Scientist found that inclusion of GRACE-based total water storage information allows to assess the predisposition of a river basin to flooding as much as 5–11 months in advance(Reager et al.,2011). Chen et al.(2009,2010) quantified 2005 extreme drought and 2009 except flood in Amazon river, and found that local interannual TWS changes are closely connected to ENSO events in the tropical Pacific. Because of the lack of direct observations independent to GRACE TWS, TWS estimated from the atmospheric water balance, land water balance and model simulations were used to compare with and verify the GRACE TWS (Yirdaw et al., 2008; Zeng et al., 2008; Syed et al., 2005; Schmidt et al., 2006).These papers have demonstrated that GRACE data are capable of identifying seasonal and long-term variations in TWS and have also made contributions to the development of climate and hydrological models.

GRACE TWS combined with hydrological information from other observations or models could help us further understand and manage variables in the hydrological cycle. Land surface model simulations were used to infer the roles of water components (snow water, canopy water and soil water) in GRACE terrestrial water storage change (TWSC) and to understand the effect of hydrologic fluxes fluctuation on water storage (Syed et al. 2008,Kim et al., 2009). With the help of TRMM data and NOAA's CPC model simulations, Crowley et al. (2008)

found that the source (precipitation) is more important than sink (evapotranspiration and runoff) to the water balance in the Amazon basin. Other papers tried to seperate variations in groundwater storage from GRACE TWS, and their results showed agreement with in situ observations (Rodell et al., 2009; Leblanc et al., 2009, Famiglietti et al., 2011; Jin et al., 2013)

In China, GRACE data have been compared with several model simulations and used to extract TWS's spatial and temporal variation characteristics as well as its responses to droughts (Duan et al., 2007;Zhong et al., 2009;Wang et al., 2013;Hu et al., 2006;Xu et al., 2013;Tang et al., 2013;Tang et al. 2014).The serious TWS depletion in North China has gained much attention in recent years (Su et al., 2011;Moiwo et al., 2012; Feng et al., 2013).Previous researches have mostly focused on characteristics of seasonal cycle in TWS in certain regions, and there has been less further analysis of long-term variations over China. Moreover, early researches were typically limited by the short period of data availability and the obsolete version, and leakage errors in TWS from processed GRACE data could also misguide analyses at the regional scale.

China is one of the countries that is confronted with problems of water scarcity and suffered several regional extreme climate events in recent decade. The knowledge of TWS variations over the recent decade is necessary for understanding the large-scale water storage variation process. In this study, the GRACE Tellus land products and Global Land Data Assimilation System (GLDAS) products, combined with data records from national water resources bulletins, were used to analyze long-term TWS variations in China as well as in its eight major basins. This study could give guidance to water resource management and future research on areas with critical water storage changes in China.

2 Data and Methods

2.1. Data

The monthly grids from GRACE Tellus land data are applied to analyze TWS variations. The product is derived from the latest Release 05 spherical harmonics, which is an improvement over the previous 04 version. Several institutions provide gravity solutions, such as the University of Texas Center for Space Research (CSR),NASA's Jet Propulsion Laboratory (JPL),and Deutsches GeoForschungsZentrum (GFZ).A recent comparison suggested that TWS estimates from GFZ,CSR and JPL solutions were highly correlated with one other， and tiny differences among them were within the margin of solution's error(Sakumura et al., 2014).Among these three products, the one from CSR had the smallest root-mean-square (RMS) of deviations between the ensemble mean and itself in 156 basins around the world. In this study, we chose products derived from CSR's solution for the following analyses. The paper by Swenson et al. (2006) describes the details of the post-processing for the spherical harmonics. The final grid (1 degree in both latitude and longitude) values are presented in the form of changes in equivalent water thickness (unit: centimeter) relative to a time-mean baseline. The data period is from January 2003 to December 2013 and months of absent data are as follows: June 2003, January and June 2011, May and October 2012, March, August and September 2013.Grid scale factors, which correspond to the gridded product, were used to partially correct leakage errors and restore the amplitude-damping caused by the filtering process. Errors and uncertainties in mass variation can be computed from the scaled gridded data (Launderer et al., 2012). In this paper, gridded fields of scale factors and error estimates provided along with the GRACE Tellus products were calculated following Landerer's method based on NCAR's CLM4 model (Oleson et al., 2008). Recently, Long et al. (2015) conducted comprehensive comparisons to assess skills and uncertainties of different approaches for processing GRACE data to restore signal losses caused by spatial filtering.

Monthly flux/state variables (Table 2) from GLDAS (Rodell et al., 2004a) were applied to estimate water storage variations, and these variables were also used to address variations in the components of water storage. GLDAS drives four land surface models: Mosaic(Koster and Suarez,1996),Noah(Chen et al., 1996; Koren et al., 1999, Betts et al., 1997; Ek et al., 2003),Community Land Model (CLM)(Bonan et al., 1998, Dickinson et al., 1993, Dai et al., 1997), and Variable Infiltration Capacity (VIC)(Liang et al. 1994; Liang et al. 1996).Satellite-based and ground-based observations are integrated into these models to generate optimal fields of land surface states and fluxes. The forcings for these models from 2001 to present is a combination of NOAA/GDAS atmospheric analysis fields, spatially and temporally disaggregated NOAA Climate Prediction Center Merged Analysis of Precipitation (CMAP) fields (Xie and Arkin, 1996) and observation-based downward shortwave and long wave radiation fields from the Air Force Weather Agency (AFWA).

Drainage networks are mostly distributed in the monsoon dominated Middle and East China (Fig. 1a), which are also highly populated area with high levels of water consumption. In this study, we specifically focus on eight large basins, Heilongjiang River, the Liao River, Hai River, Huai River, Yellow River, Changjiang, Zhujiang, Southeast Rivers(with abbreviations of HLJ, LR, HaiR, HuaiR, YR, CJ, ZJ and SERs, respectively, in the following tables). Desert is the dominant land cover in northwestern China, while glacier, snow cover and frozen soil are widely distributed across the Tibetan plateau (Fig.1b).Vector data for desert is acquired from the Data Sharing Infrastructure of Earth System Science(http://www.geodata.cn). The Second Glacier Inventory Dataset of China (Version 1.0) is acquired from Science Data Center for Cold and Arid Regions (http://westdc.westgis.ac.cn). Annual Chinese water resources bulletins from 2003 to 2012 are acquired from the Ministry of Water Resources to assist with the analysis. Values for surface water resources, ground water resources and gross water resources provided in the water resources bulletins are the results of existing monitoring and statistical analyses(Fig.5). Surface water resources refer to water storage in rivers, lakes and glaciers, and groundwater resources mainly refer to water storage in underground shallow aquifers.

2.2. Methods

2.2.1. Data pre-processing

Unlike scale factor applied for region-averaged TWS time series in previous researches (Rodel et al., 2004b, Chen et al., 2007, Landerer et al., 2010, Feng et al., 2013), monthly products from GRACE Tellus land data were multiplied by grid scale factors to restore signal attenuation. Next, the average value for each grid from 1/2003 to 12/2013 was subtracted from all other scaled monthly grids. The deviations to time-average TWS were used for the following analyses. At the regional scale, all grids in a basin were averaged with the cosine of latitude as the weight, and missing values for absent months were interpolated from adjacent available months. For regional averaged TWS, total errors were calculated from error fields provided along with the GRACE products (Eq. (1), (2), Table 5). Because of spatial correlation among neighboring grids, covariance was considered in the calculation of regional scale error $\mathrm{Error}_{\mathrm{region}}$ (Landerer et al., 2012; Eq. (1)).The dist in Eq. (1) is the geometric distance between any two grids in the basin (unit: km), n is the number of valid grids in a specific basin, β is the de-correlation length, which is set to 300 for measurement error and 100 for leakage error, number i and j mean the value in the i*th* column and j*th* row of the grid data . And the regional scale total error $\mathrm{Error}_{\mathrm{total}}$ included both regional scale measurement error $\mathrm{Error}_{\mathrm{measure}}$ and regional scale leakage error $\mathrm{Error}_{\mathrm{leakage}}$ (Eq. (2)). Early analysis suggested that the TWS variations could be distinguished from GRACE monthly data over regions larger than 200,000 km^2 ,with an accuracy of 1.5cm equivalent water thickness (Rodell and Famiglietti, 1999),and the larger the spatial scale of the research area was, the better the accuracy the results could acquire (Swenson et al., 2003; Wahr et al., 2004).

$$\mathrm{Error}_{\mathrm{region}} = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} \mathrm{Error}_i * \mathrm{Error}_j * e^{-\left(\mathrm{dist}_{i,j}^2\right)/(2*\beta^2)}} / n \tag{1}$$

$$\mathrm{Error}_{\mathrm{total}} = \sqrt{(\mathrm{Error}_{\mathrm{measure}})^2 + \left(\mathrm{Error}_{\mathrm{leakage}}\right)^2} \tag{2}$$

State variables (snow water equivalent (SWE), canopy water storage (CWS) and total soil moisture storage in all layers(SM)) and flux variables (precipitation (P), evapotranspiration (E) and runoff (Q)) from the four models in GLDAS were presented in the form of equivalent water thickness (unit: cm).The time averages were removed from these variables following the process used for the GRACE data to keep the same time-base for comparison. The ensemble mean (arithmetic average) of the four models’ simulations was also calculated to be used as the representative of model results.

2.2.2. TWS estimates from model simulations

In despite of deficiencies in model simulations, state variables SWE, CWS and SM from GLDAS outputs can be combined to estimate TWS (Eq. (3)).Although the estimates are not able to fully reflect the information in the actual TWS variations, they can still capture the fluctuation and magnitude in land hydrology, which is necessary for assessing and understanding the TWS observation from GRACE (Syed et al., 2004).

$$\mathrm{TWS} = \mathrm{SWE} + \mathrm{CWS} + \mathrm{SM} \tag{3}$$

Pearson correlation coefficients R between TWS from scaled GRACE and model simulations are listed in Table 3.TWS estimates from CLM and VIC have relatively poor correlations with GRACE observations at the national scale. However, all model estimates generally have high correlation coefficients at the regional scale, except in Heilongjiang river basin. The differences between models and regions showed that model simulations have a high degree of uncertainties, and TWS estimates from NOAH and the GLDAS ensemble mean have a good agreement with TWS from scaled GRACE at both the national and regional scale. The differences between the GLDAS simulations and the GRACE observations are mainly the result of missing information on components of of land hydrology, such as groundwater and reservoirs, and poor parameterization (snow cover, frost soil,etc.) in the model mechanism (Syed et al., 2008). These components or processes could be critical to TWS in some parts of the world(Rodell et al., 2001).The RMS of deviations from ensemble mean was calculated as the bias of TWS estimates from the GLDAS simulations(Table 4).

2.2.3. Scaling effect assessment

To understand how much changes scale factors could make to GRACE TWS in China, we compared the spatial distributions of the amplitude of TWS variations from observations and simulations. The RMS of the time series at each grid was taken as a proxy for local TWS amplitude, and then the empirical probability density distributions (PDF) for RMS values over China were calculated for TWS derived from scaled and unscaled GRACE data and the model simulations. To avoid abnormal values, only RMS values between the 5th and 95th quantile over China were considered. For regional averaged TWS, the slopes and coefficients of determination R^2 were calculated with a linear least square fit to assess the damping influence of leakage errors (Eq. (4)).

$$\mathrm{TWS_{scaled}} = \mathrm{a} * \mathrm{TWS_{unscaled}} \tag{4}$$

2.2.4. Analysis of TWS long-term variations

TWSC the integrated changes in the vertical components of TWS, is the difference between current and previous months' TWS (Eq. (5)). This value can also be inferred using the water balance with precipitation, evapotranspiration and runoff data in a specific basin (Hirschi et al. 2006, Eq. (6)).With GLDAS and GRACE products, we applied correlation analysis to find out how much state/flux variables can contribute to TWSC's variance in different basins. After applying a 13-point moving average to remove intra-annual variations in times series, we analyzed annual variations based on the regionally averaged TWS from scaled GRACE and the GLDAS ensemble mean , in combination with annual Chinese water resources bulletins. Annual data from the water resources bulletins were converted from volume (unit: million cubic meters) to equivalent water thickness (unit: centimeter), and the multi-year average was removed. To identify major areas with significant TWS increase or depletion in the recent decade, linear trend of scaled GRACE TWS for each grid was calculated based on linear regression, and the long-term trends of seasonal average TWS were also analyzed. Grids with trends passed the F-test (significant of 95% confidence level) are marked with black dots in Figs. 7 and 8.

$$\mathrm{TWSC_N} = \mathrm{TWS_N} - \mathrm{TWS_{N-1}} \tag{5}$$

$$\mathrm{TWSC} = \mathrm{P} - \mathrm{E} - \mathrm{Q} \tag{6}$$

3 Results and Discussion

3.1. Effect of the scaled factor in China

The effect of the truncation(Order$_{max}$=60) and filtering processes(300km Gaussian filtering) on the GRACE spherical harmonics is equivalent to a low-pass filter, thus the effective resolution of the GRACE TWS product is several hundred kilometers (Tapley et al., 2004). The TWS time series in a 1-degree grid was mixed with TWS signals from surrounding areas, leading to leakage errors. When the outside TWS signal was stronger than the inside, the grid value was exaggerated by leakage errors and vice versa. In addition, the sign of gridded TWS could even be changed in cases where inside and outside TWS signals had opposite phases caused by extreme changes in topography, such as in the Turpan basin in northwestern China. As relationships between TWS series at different spatial scales were inferred from land-hydrology model simulations, grid scale factors calculated base on these information could partially correct GRACE TWS and to some extent recover small-scale information (Landerer et al., 2012); thus, these scale factors can be quite helpful for extracting TWS over arbitrary shaped region.

The RMS value of TWS time series in a specific grid is an indicator for the amplitude of local TWS. And the empirical probability density distribution (empirical PDF) curve for RMS values in research region described the statistical distribution of TWS amplitude within the area. In Fig.2, empirical PDF curves based on TWS data from modeled TWS data (MOSAIC, VIC, CLM, NOAH and GLDAS ensemble mean) and observation TWS data (scaled and unscaled GRACE data) were compared. Empirical PDF curves based on scaled GRACE data and modeled data (except CLM) all showed larger RMS value range in x-axis than that based on unscaled GRACE data. This means the range of TWS amplitude within research area has been stretched after scaling. In addition, empirical PDF curves based on scaled GRACE data and most modeled data showed RMS values concentrated in the relative low numerical zone, with lowest RMS values close to 0 cm. Spatially, areas with low RMS values corresponds to northwest China, which is an arid climate zone with vast deserts (Figs. 1, 3b and c). From the comparison in Fig. 3, we can also see that scaled GRACE TWS has similar distribution of amplitude with that from GLDAS ensemble mean over China, particularly the boundary with RMS of 3cm, separating arid and humid climate zones.TWS is quite stable over some part of the oceans and major deserts around the world, thus a small RMS for TWS in these areas indicates small data noise in GRACE TWS (Sakumura et al., 2014). Both the empirical PDFs and the spatial distribution of the RMS of the TWS suggested that gridded scale factors could correct the amplitude of TWS in space. Previous research has demonstrated that correction for leakage is critical to regional TWS analysis (Chen et al., 2014).

Regionally averaged TWS time series from scaled and unscaled GRACE data are highly correlated, and this means that the fluctuation process in TWS has not been heavily influenced by the scale factors. At the same time, the values of TWS were all amplified to different degrees (Table 5), with the amplitudes in Huai River basin and Zhujiang basin increasing over 50%. However, in the Liao River basin and Yellow River basin only small changes occurred (< 10%). The slopes in Table 5 can be regarded as the basin-specific scale factors for GRACE TWS. Generally, basins with large areas are less affected by leakage errors and have slopes close to 1~~, but geographical location and hydrological cycle characteristics will contribute to this effect, as well~~.

3.2. Annual Variations in Regional TWS time series

In general, fluctuations in annual precipitation could appropriately characterize the inter-annual variability in regionally averaged TWS, but distinct processes also exist in certain basins or over certain periods because of the influence of other factors (Fig. 4, 6). TWS in China was in a relatively high condition before 2006, but then stayed at a continuously low level with a high variability from 2006 to 2012.During this period, severe droughts occurred frequently and caused particularly sharp declines in TWS in 2007, 2009 and 2011. TWS in China did not recover to the same level in 2005 until 2013.This periodic process was partially reflected in the TWS estimates from the GLDAS ensemble mean (mostly soil moisture storage) but not in the residual series or water resources records (Fig. 4, 5). ~~This process may be controlled by changes in some large-scale climate processes, which need to be further analyzed in the future~~.

In Northeast China, TWS observations and simulation estimates in Heilongjiang basin were consistent and showed no long-term trend; the region mainly suffered from two severe regional droughts in 2007 and 2011 and a significant basin flood event in 2013.Annual precipitation in Liao River basin continuously declined from 2005 to 2009 and then increased rapidly in following years;TWS estimates and water resources records both precisely captured this process. Nevertheless, it seemed that the TWS observations failed to respond to heavy precipitation in 2010, with a 9cm increase in TWS estimates and only a 3cm increase in TWS observation. ~~Reservoir regulations may be one of the factors that alter the TWS signal.~~

In North China, annual precipitation in Hai River basin changed following a V- shaped process, with year 2006 as the turning point, which can also be recognized from the TWS estimates and water resources records. After rapid decline from 2004 to 2006(-2.48 cm yr^{-1}), the TWS from the scaled GRACE data in Hai River basin became stable around 2007.Contrary to increasing precipitation, TWS dropped 3cm in 2008 and continued to decline slowly at a rate of -0.22 cm yr^{-1} until it started to recover in 2012.The TWS in Hai River basin generally showed a linear decreasing trend (-1.27 cm yr^{-1}) during 2004-2011. The residual between TWS from scaled GRACE data and the GLDAS ensemble mean could be treated approximately as the sum of surface reservoir and groundwater storage. Moreover, detection depth of GRACE is much deeper than the layers considered in models (1.90m in VIC, 2.00m in NOAH, 3.50m in Mosaic and 3.43m in CLM) and in field monitoring (shallow aquifer).Although the increasing precipitation seemed to have alleviated the depletion trend in these area, we shouldn't ignore the huge gap (~-1.80 cm yr^{-1}) between the trends of the time series of the residuals and summed water resources records (-1.28 cm yr^{-1}, 0.50 cm yr^{-1}) during 2006-2011. The gap between these time series probably suggests that the long-term effect of over exploitation of groundwater still remained, even though water saving management practices had already been carried out in this basin, and water storage would suffer even worse depletion in the future drought years. Similar to Hai River basin , the TWS from scaled GRACE data in Yellow River basin followed a nearly linear decreasing trend (-0.73 cm yr^{-1}) during 2004-2011, and it changed more slowly(0.13cm yr^{-1}) after 2007. The basin averaged TWS, gross water resource and precipitation also showed different processes in the latter half of research period. But Fig.7 revealed that areas with large long term decreasing trends mainly located in midstream of Yellow River basin(Shanxi and Shaanxi Provinces), where is famous for coal mining. To identify the exact causes for decreasing TWS, more local statistical data and groundwater level records should be collected. Over the recent decade, the TWS in Huai River basin showed a long-term descending trend (-0.56 cm yr^{-1}), which is similar to annual precipitation over this basin. The TWS from GLDAS ensemble mean also showed good agreement.

Annual variations in TWS from scaled GRACE data, the GLDAS ensemble mean and water resources records are more similar across basins in South China than they are in North China.

The TWS in the Changjiang River basin, Zhujiang Basin and Southeast Rivers basin all followed an increasing trend from 2003 to 2013, at 0.35 cm yr^{-1},0.55 cm yr^{-1} and 0.70 cm yr^{-1}, respectively. As a result of typhoons and tropical storms, the TWS in these basins also had much stronger fluctuations than in North China.

The TWS variations observed by GRACE are integrated information from different components in the vertical profile. Compared to water storage in surface soil layers, snow cover and canopy water storage are almost negligible in most regions, and analysis results in China suggested that changes in soil moisture contributed significantly to TWSC (Table 6). The percentage of TWSC variance explained by SMC could be as high as 62% at the national scale. In most basins, over half of the TWSC variance could be attributed to SMC, with high percentages in Changjiang basin and Zhujiang basin(64% and 67%). In Heilongjiang River basin, SMC played a less important role in TWSC (38%).Hydrologic fluxes fluctuations over the basin jointly affected water storage. According to correlation analysis based on GRACE TWS and GLDAS fluxes, precipitation, evapotranspiration and runoff each contributed 46%, 41% and 32 %, respectively, of the TWSC variance in China (Table 6).As most basins we focused on are under control of the monsoon climate, precipitation and runoff generally showed higher contributions to the TWSC variance than evapotranspiration did. Overall, precipitation was found to have a much higher impact on TWSC in the south than in the north, with the highest explained variance in Zhujiang basin (60%), followed by that in Changjiang basin (44%).

3.3. Spatial pattern of linear trend analysis

When focusing on differences between large regions, spatial patterns of linear trends calculated from scaled and unscaled GRACE TWS are consistent (Figs. 7a and c). But at local scale, results from scaled GRACE TWS are better corresponding to natural features of the TWS intensity distribution. Areas around river networks usually have large quantity of TWS, thus present big absolute values of trends. From 2003 to 2013, four main regions were identified with intensive and significant long-term trends in TWS. Results also revealed that seasons in a year made different contributions to these trends (Fig. 8).

According to the analysis in previous section, we inferred that human activities rather than climate parameters could be responsible for the significant TWS depletion in North China, as withdrawals usually surpass net recharge in arid and semiarid regions. Severe areas mainly located in the Shanxi Province and south part in the Hebei Province, with decreasing trends less than -0.80 cm yr^{-1}. And offset to loss rate caused by mass gains from reservoir regulation, water diversion and coal transport in this region was estimated to 0.76 cm yr^{-1} (Tang et al., 2013).In the Shanxi Province, the east to midsection of Yellow River, coal mining not only has disturbed normal recharge to the nearby aquifer but has also caused overexploitation of groundwater. The groundwater is a major source to water consumptions in Huang-Huai-Hai plain, agricultural irrigation consumed large amounts of freshwater pumped from deep wells every year(Foster et al., 2004, Kendy et al., 2004). This poor condition deteriorates with seasons and the depletion becomes most severe, impacting the largest area in autumn. Considering irrigation demand concentrated mostly in MMA and high social water consumption comes with JJA, TWS probably needs time to show all this influence in SON. The Southwest rivers region (YarlungZangbo River, Nu River and Lancang River) also showed significant TWS depletion, particularly in the upstream and downstream portions of the YarlungZangbo River. The Areas impacted by significant depletion was the largest in spring, while the depletion also became the most severe in autumn. Climate observation across this region proved that annual precipitation was decreasing over 11 years, with significant droughts in 2006, 2009 and 2012.Moreover, previous research also find ice loss in Himalaya from 2003-2007(Matsuo et al.,2010).

Along with increasing precipitation in Southeast China, there were significant increasing trends in TWS over the middle and lower reaches of the Changjiang and southeastern coastal areas. The main contribution to this significant increase occurred during the summer, when precipitation was the most concentrated of the year. There are two places that showed significant TWS increases in the Tibetan plateau. One of these areas is around the Hoh Xil Mountains and the other is headstream region of the Yellow River; they have maximum increasing trends of 2.59 cm yr^{-1} and 1.77 cm yr^{-1}, respectively. The Hoh Xil Mountains are located at the intersection of the inland lakes in the Qangtang plateau and the north source of the Changjiang River. The headstream region of the Yellow River lies in plateau's two largest freshwater lakes, Eling Lake and Zaling Lake. Previous research applied multi-source satellite data to reconstruct volume changes in the Tibetan plateau’s major lakes, and found that they showed similar spatial distribution to mass variations in GRACE during 2003-2010 (Song et al., 2013). According to satellite images, lakes in Hoh Xil overall showed a trend of expansion during 2000-2011. Further analysis suggested that increasing precipitation and decreasing evaporation were major factors contributing to this trend, and additional water recharge from melting glacier and frozen soil caused by climate warming were minor factors (Yao et al. 2014,Duan et al. 2013).In the headstream region of the Yellow River, precipitation is the main recharge source to runoff ,with a ratio of 63%. Local observations revealed that there was an increasing trend in runoff as this region was becoming warmer and wetter during the period 2000-2012(Lan et al.,2010,Lan et al., 2013, Wang et al., 2014).The Chinese government has launched an ecological protection and construction project in the Three River Sources that started in 2005. According to monitoring data from the Qinghai Provincial Meteorological Bureau, average lake extents during 2005-2012 showed an increase of 34.7 km^2 and 64.4 km^2 compared to those during 2003-2004 for Eling Lake and Zaling Lake, respectively.

In addition to above large areas, there are also some other small regions showing strong TWS changes from 2003 to 2013. Along the northeast country border, there is significant TWS increase(0.34~1.19 cm yr^{-1}), mostly is contributed by winter.The central part in Jilin Province in northeast China shows severe TWS depletion in autumn(-1.10~-2.28 cm yr^{-1}), but those linear trends haven't past significant test(P-value <0.05).In the northwest China, the unscaled GRACE data only shows significant water depletion mainly around Tianshan Mountains, which is also identified with ice loss in previous research(Matsuo et al., 2010). But trends from the scaled GRACE TWS also illustrate significant TWS increase in the Turban basin, while depletion in its surrounding mountains. The Turban basin is the lowest basin in China, and Fig. 3b shows that the basin has much smaller TWS amplitude than that in surrounding mountains. Extreme arid climate and local topography feature in this region could make TWS more sensitive to climate change. Complex terrain in this region leads to more complicated GRACE TWS signal mixture at large spatial scale. Even though scale factors might have separated mixed TWS signals, limitations in factor's production should also be taken care of (Launderer et al., 2012). ~~Thus, more data needs to be added to further quantify and verify the extent of identified TWS change at small scale in the future research.~~

4 Summary and Conclusions

In this study we analyzed annual variations in TWS over 11 years in China and eight of its basins, based on scaled GRACE data in combination with GLDAS simulations and water resources records. Areas with significant long-term trends were also identified and discussed. The major points are summarized as follows:

(1) Gridded scale factors could adequatelly correct leakage errors in the GRACE products and the scaled data gained more spatial details of the TWS intensity distribution. The values of the regionally averaged TWS were amplified after scale factors were applied. These increase percentages reached up to over 50% in Huai River basin (57 %) and Zhujiang basin (54%), but were tiny for basins with larger sizes, such as Liao River basin (10%) and Yellow River basin (8%).

(2)The TWS at the national scale stayed at a relatively low level. These values exhibited high intensity variations from 2006 to 2012, before recovering to their 2003 to 2005 condition. The TWS in the Hai River basin, Huai River basin and Yellow River basin almost decreased linearly while it increased in fluctuations in the Changjiang basin, Zhujiang basin and Southeast Rivers basin. The TWS variations generally followed the variations in annual precipitation at basin scale, but they showed inverse changes in 2007-2013 in both Hai River basin and Yellow River basin.

(3)Changes in soil moisture storage contributed 62% of the TWSC variance at the national scale, and the percentages were generally beyond 50% in all basins with exceptions in Heilongjiang River basin (38%) and Yellow River basin (46%). Under the control of the monsoon climate, precipitation and runoff explained more variance in TWSC than evapotranspiration did, and precipitation's ability to explain TWSC variations was stronger in the south basins than in the north, reaching up to 60% in Zhujiang basin.

(4)From 2003 to 2013, there were significant water storage depletions over the Southwest rivers region and North China, and the areas that exhibited significant depletions were the largest in spring and summer, respectively. The middle and lower reaches of Changjiang and southeastern coastal areas, as well as the Hoh Xil Mountains, and the headstream region of the Yellow River in the Tibetan plateau, all exhibited significant increases in TWS. These identified trends reflected TWS's responses to regional climate changes and human activities.

The current data period of GRACE products is shorter than some existing remote sensing data sets or site records, and the resolution and accuracy of GRACE data also need to be improved. However, TWS from GRACE has proved to be valuable to understanding large-scale hydrological process over land. The results in this study would be helpful for water resources management and climate change impact research. More sources of data will be added to further analyze regions or phenomena addressed in this study. The GRACE Follow On mission has already been scheduled, and will continue to support monitoring and research on TWS in the future.

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Table 1 List for main Acronyms and Variables showed in paper

Acronym/Variable	Full name
GRACE	Gravity Recovery and Climate Experiment
NASA	National Aeronautics and Space Administration
DLR	Deutsches Zentrum für Luft- und Raumfahrt
CSR	University of Texas, Center for Space Research
JPL	Jet Propulsion Laboratory
GFZ	Deutsches GeoForschungsZentrum
CMAP	Climate Prediction Center Merged Analysis of Precipitation
CPC	Climate Prediction Center
CMA	China Meteorological Administration
GLDAS	Global Land Data Assimilation System
CLM	Community Land Model
VIC	Variable Infiltration Capacity model
RMS	Root-mean-square
PDF	Probability Density Distribution
TWS	Terrestrial Water Storage
TWSC	Terrestrial Water Storage Change
SWE	Snow Water Equivalent
CWS	Canopy Water Storage
SM	Soil Moisture
P	Precipitation
E	Evapotranspiration
Q	Runoff

Table 2 Variables used in the GLDAS simulations

GLDAS Variables	Units	Temporal Resolution	Spatial Resolution
Soil moisture	kg/m^2	Monthly	1°* 1°
Snow water equivalent	kg/m^2	Monthly	1°* 1°
Canopy water storage	kg/m^2	Monthly	1°* 1°
Precipitation	kg/m^2/s	Monthly	1°* 1°
Evapotranspiration	kg/m^2/s	Monthly	1°* 1°
Runoff	kg/m^2/s	Monthly	1°* 1°

Table 3 Pearson Correlation coefficients R between regionally averaged TWS from the scaled GRACE data and model simulations in China and eight of its basins.

Region	CLM	VIC	MOSAIC	NOAH	Ensemble mean
HLJ	0.83	0.84	0.74	**0.87**	0.86
LR	**0.71**	0.65	0.54	0.64	0.64
HaiR	0.43	0.54	**0.66**	0.61	0.61
HuaiR	0.68	0.54	0.68	**0.79**	0.72
YR	**0.77**	0.62	0.62	0.70	0.69
CJ	0.61	0.51	0.47	**0.77**	0.60
ZJ	0.70	0.77	0.79	**0.82**	0.81
SERs	0.70	0.69	**0.83**	0.76	0.81
CHN	0.25	0.31	0.53	**0.79**	0.55

Table 4 Error statistics of regionally averaged TWS (unit: cm)

Regions	Areas(km^2)	Measurement Error	Leakage Error	Total Error	Bias for GLDAS
China	9,510,610	0.38	0.31	0.54	0.63
Changjiang	1,815,855	0.90	0.79	1.27	1.47
Heilongjiang	956,832	0.98	0.72	1.39	1.10
Yellow River	860,883	0.78	0.73	1.10	0.72
Zhujiang	463,050	1.86	1.62	2.63	3.35
Hai River	327,096	1.30	1.36	1.84	1.59
Liao river	310,881	1.13	0.98	1.60	1.61
Huai River	288,152	1.74	1.54	2.46	3.51
Southeast Rivers	242,524	1.44	1.29	2.04	3.69

Table 5 Slopes of the fitting for the basin-averaged TWS from the scaled and the unscaled GRACE data

Region	HLJ	LR	HaiR	HuaiR	YR	CJ	ZJ	SERs	CHN
factor	1.26	1.10	1.32	1.57	1.08	1.34	1.54	1.11	1.19
R^2	0.996	0.989	0.988	0.994	0.982	0.992	0.996	0.991	0.982

Table 6 Coefficient of determination R^2 between precipitation (P), evapotranspiration (E), runoff (Q), soil moisture change (SMC) from GLDAS ensemble mean and TWSC from the scaled GRACE data in 2003-2013

	HLJ	LR	HaiR	HuaiR	YR	CJ	ZJ	SERs	CHN
P	0.04	0.20	0.18	0.35	0.41	0.44	0.60	0.23	0.46
E	0.00	0.08	0.10	0.09	0.28	0.25	0.30	0.00	0.32
Q	0.08	0.26	0.291	0.31	0.38	0.47	0.50	0.18	0.41
SMC	0.38	0.52	0.527	0.57	0.46	0.64	0.67	0.51	0.67

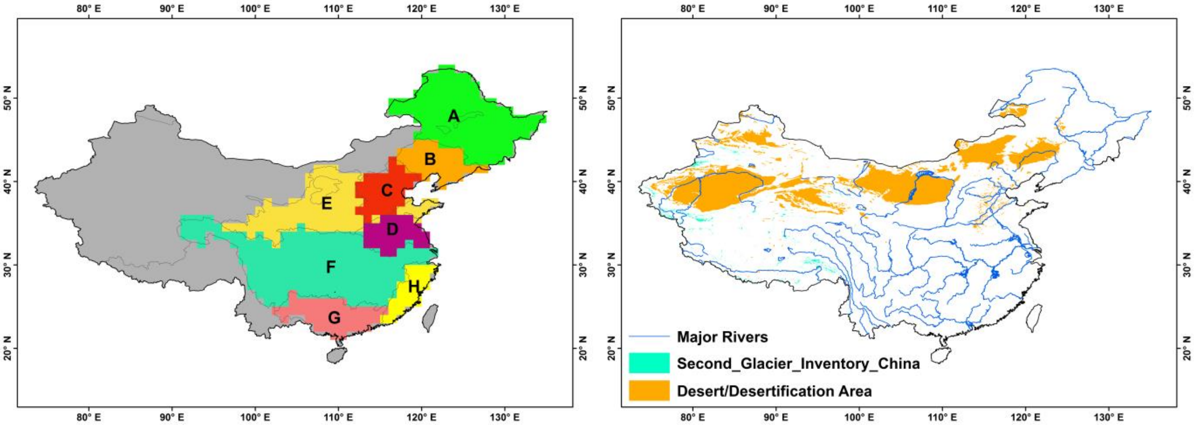

Figure 1 Schematic diagrams of research area (A: Heilongjiang River; B: LiaoRiver; C: HaiRiver; D: HuaiRiver; E: YellowRiver; F: Changjiang; G: Zhujiang; H: Southeast Rivers)

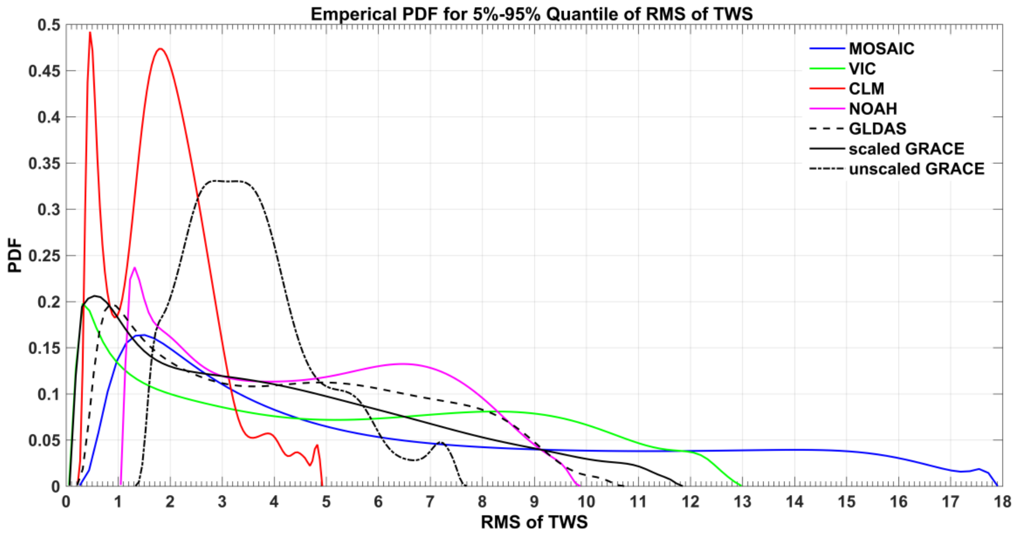

Figure 2 Empirical probability density distributions of root-mean-square of TWS from the scaled GRACE data, the unscaled GRACE data and model simulations (only TWS values between the 5th and 95th quantiles are considered),unit of RMS is cm.

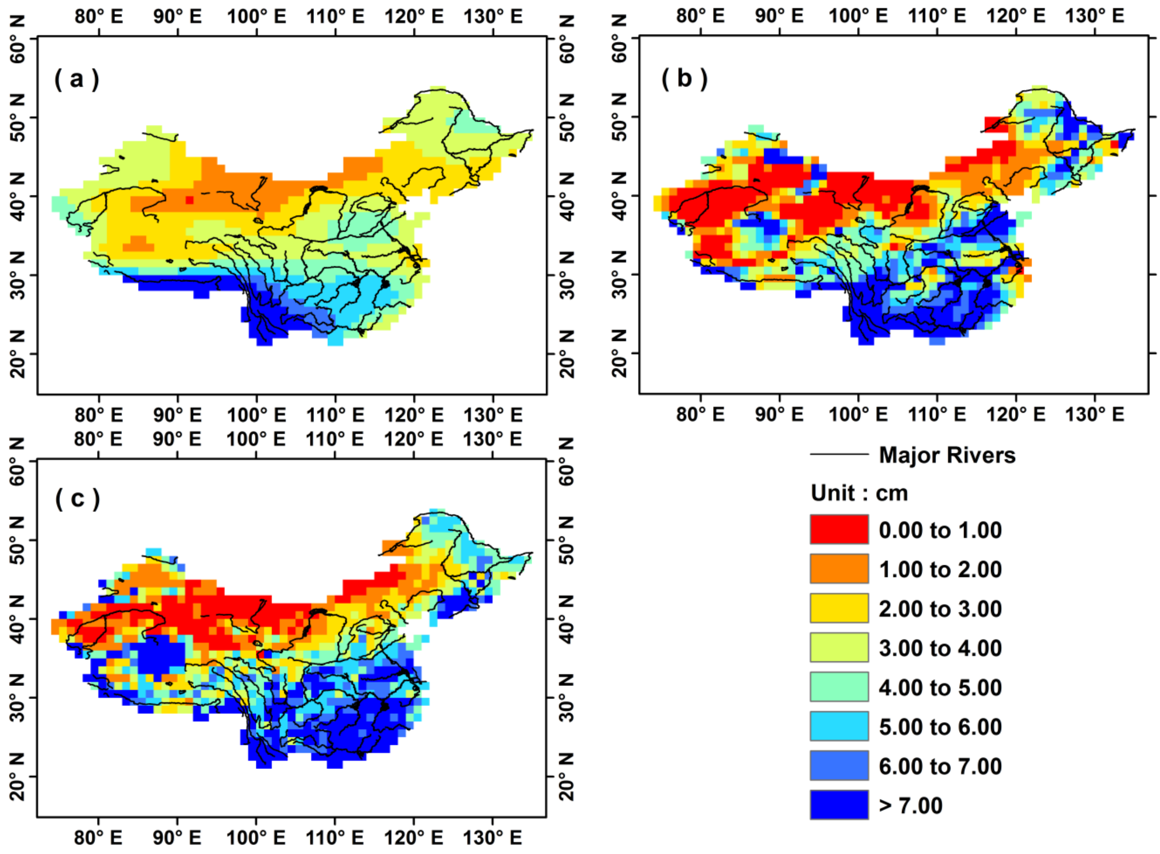

Figure 3 Root-mean-square of TWS from the unscaled GRACE data(a) ,the scaled GRACE data(b) and the GLDAS ensemble mean(c) (unit:cm).

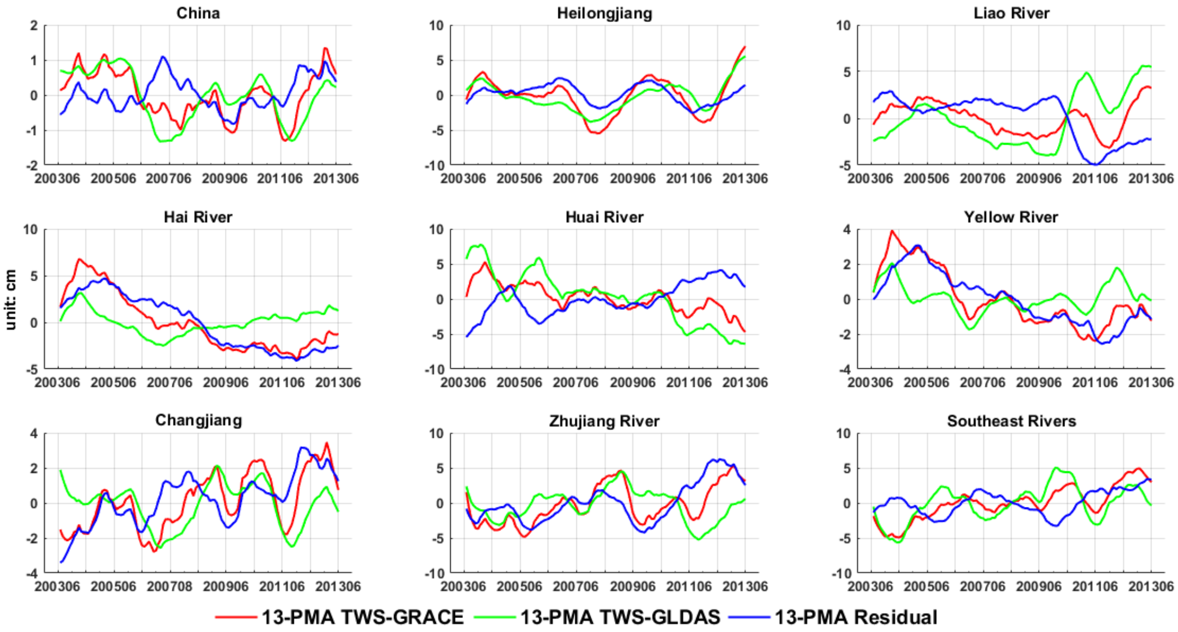

Figure 4 Regionally averaged TWS time series(2003-2013) from the scaled GRACE data and the GLDAS ensemble mean, and their residual time series for China and eight of its basins(all time series have been processed with 13-point moving average; unit: cm)

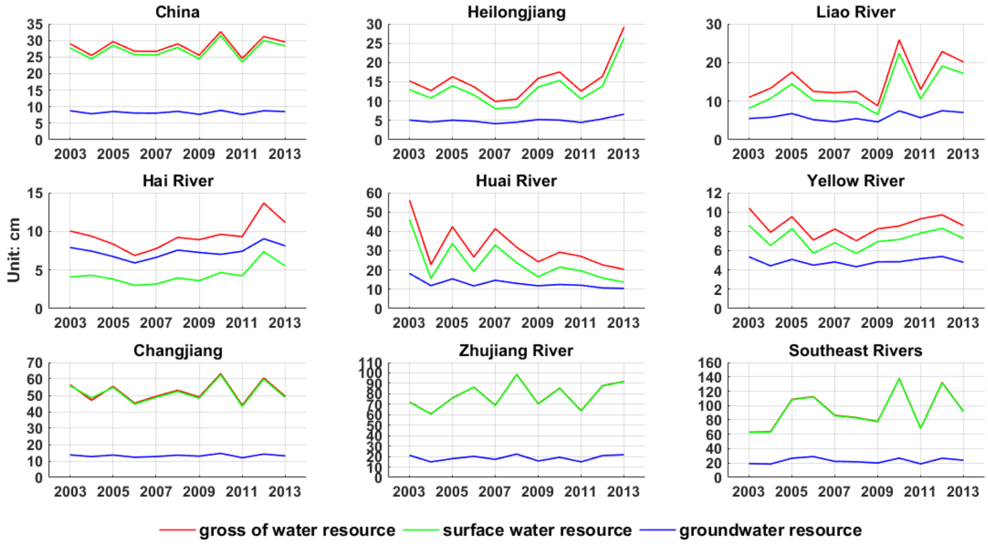

Figure 5 Annual variations of water resources in China and eight of its basins from 2003-2013(unit: cm)

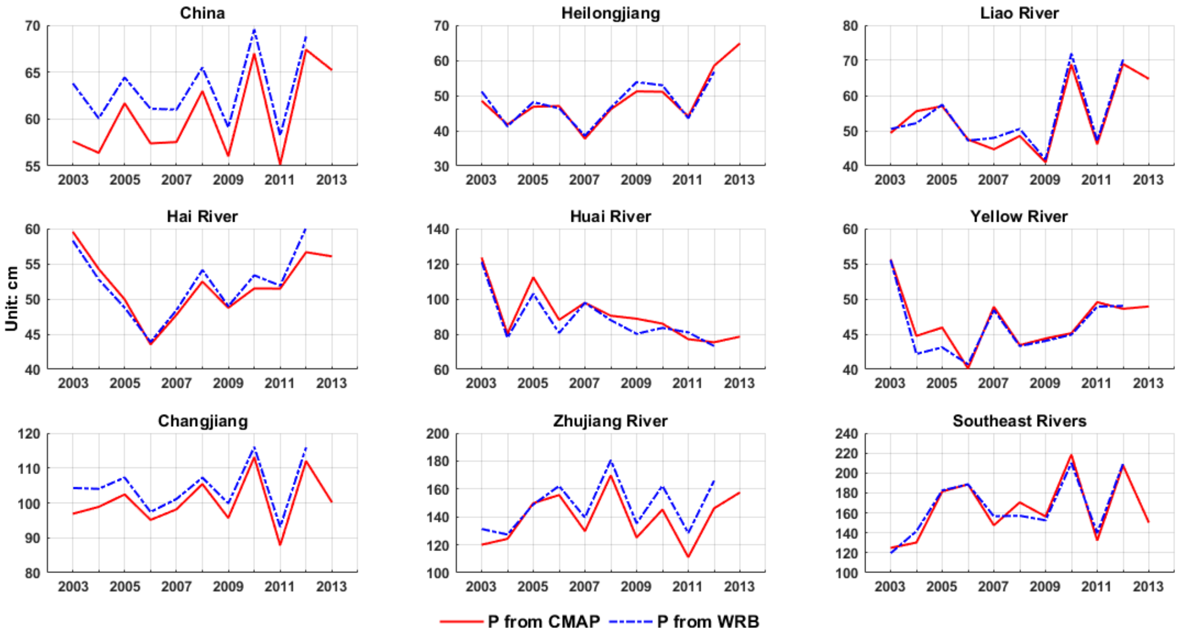

Figure 6 Regionally average annual precipitation for China and eight of its basins from 2003-2013(unit: cm). P-CMAP refers to precipitation grid data from GLDAS forcing ,and P-CMA refers to precipitation grid data from station observation offered by China Meteorological Administration.

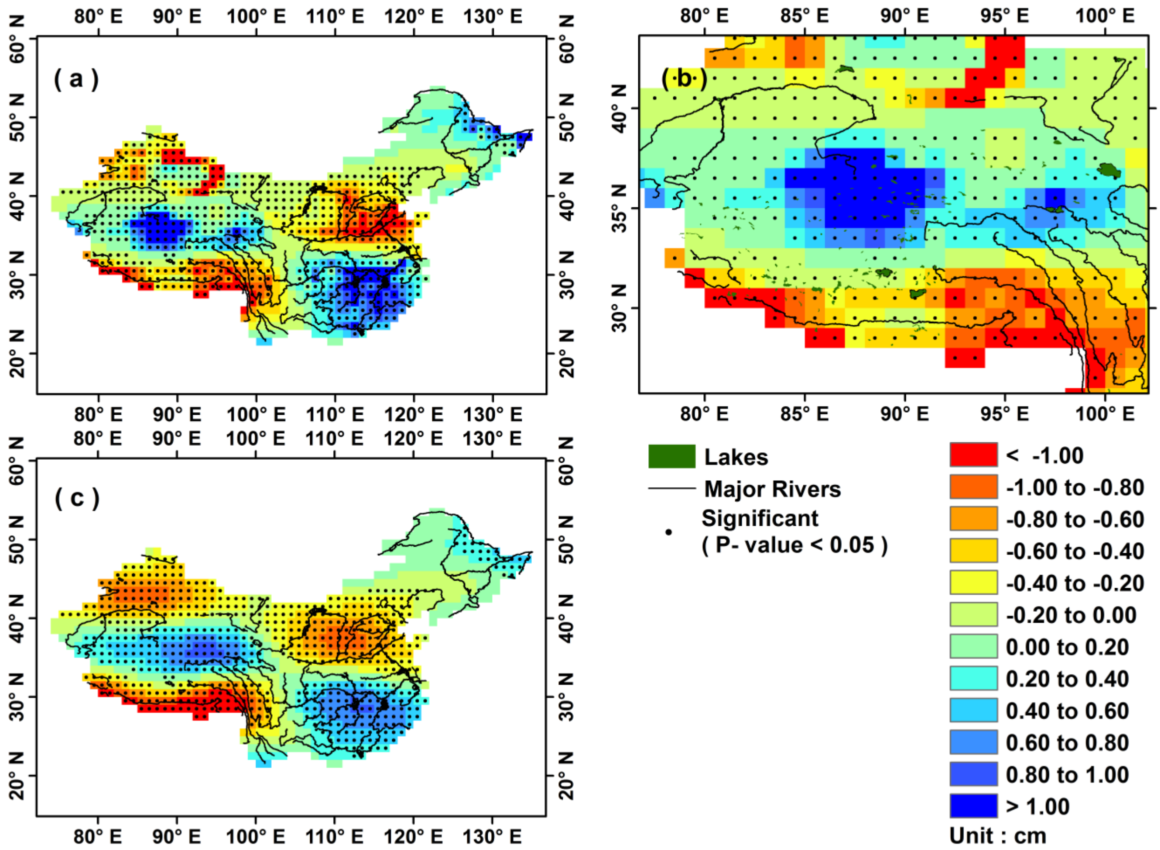

Figure 7 Spatial distribution of linear trends for TWS in 2003-2013(unit: cm yr^{-1}); (a) and (b) are linear trends from the scaled GRACE data and its detailed diagram for west part of China, (c) is linear trend from the unscaled GRACE data. Grids with trends significant at 95% confidence level are marked with black dots.

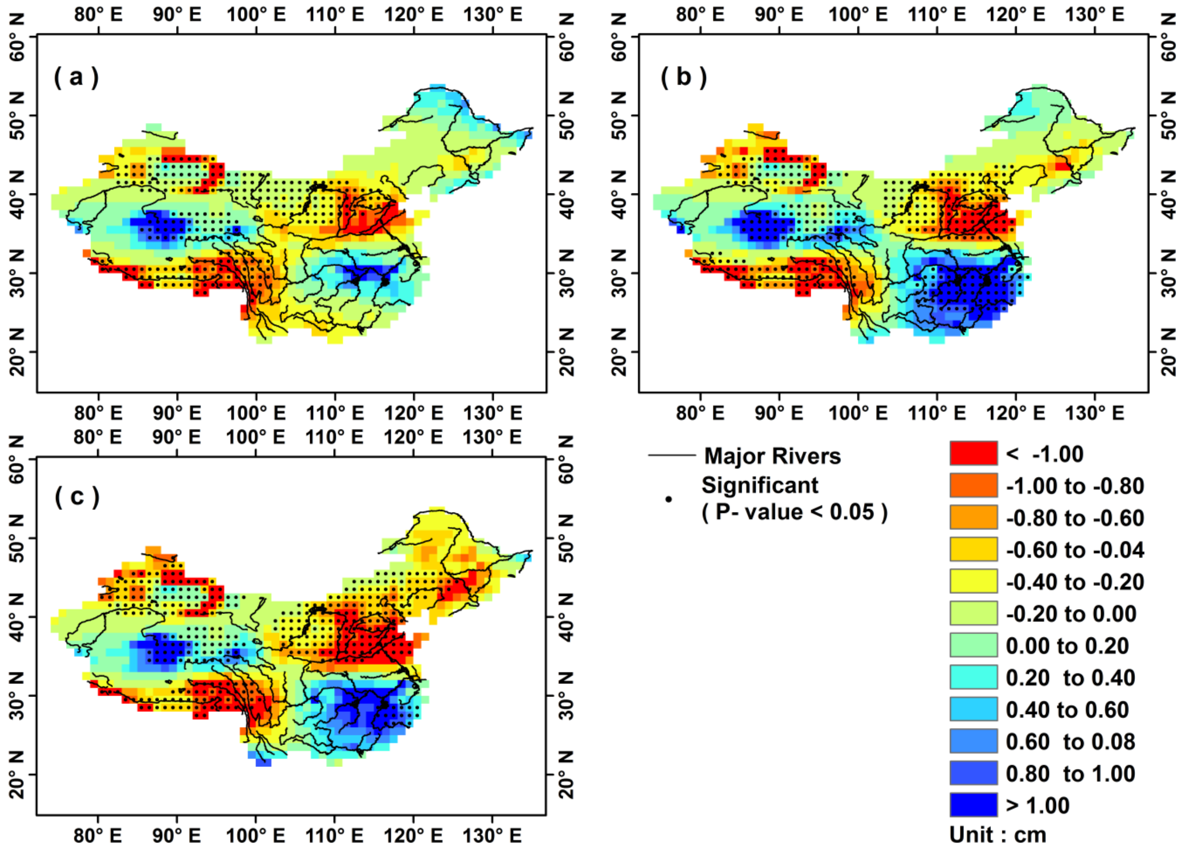

Figure 8 Spatial distribution of linear trends for the seasonal averaged TWS in 2003-2013 from the scaled GRACE data (unit: cm yr^{-1}); (a) spring(March-May); (b) summer(June-August); (c) autumn(September-November). Grids with trends significant at 95% confidence level are marked by black dots.