Research papers

Geodetic and hydrological measurements reveal the recent acceleration of groundwater depletion in North China Plain

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As one of the most important agricultural bases in China, the North China Plain (NCP) has experienced serious groundwater depletion. However, estimates of groundwater depletion rates in NCP differ considerably from one another due to different datasets and methods used in the estimation. To get a better estimate of the groundwater depletion and to reveal the recent groundwater changes in NCP, we first merge Gravity Recovery and Climate Experiment (GRACE) mass concentration (mascon) solutions from different organizations and soil moisture from different land surface models to yield unified mascon solutions and soil moisture estimates. We then estimate the groundwater changes by subtracting the unified soil moisture and surface water storages in the major reservoirs in NCP from the unified mascon solutions. Results show that the groundwater storage in NCP depleted at a rate of 1.7 ± 0.1 cm/yr from 2004 to mid-2016 but this depletion accelerated to 3.8 ± 0.1 cm/yr from mid-2013 to mid-2016. Ground-based water table data show a consistent groundwater depletion rate (~3.9 ± 0.3 cm/yr from mid-2013 to mid-2016) with the GRACE results. We also analyze the land subsidence in NCP by using 116 Global Positioning System (GPS) sites and depict the accelerated land subsidence and expanded subsidence funnels since 2013, which is consistent with the groundwater depletion. All these point to a strong acceleration in groundwater depletion in NCP since mid-2013. Land surface model outputs suggest a precipitation decline from 2013 to 2016, which caused a decline in soil moisture content and surface water storage. This drought forced people to exploit more groundwater to compensate the surface water shortage and thereby led to the accelerated groundwater depletion.

1. Introduction

As a vital source of fresh water, groundwater has supplied 50% of drinking water, 40% of industrial consumption, and 20% of agricultural consumption in the globe (Zektser and Lorne, 2004). Overexploitation of groundwater has resulted in serious issues, including groundwater depletion, land subsidence, soil salinization, etc. In the past five decades, groundwater depletion has progressively become a global issue.

The North China Plain (NCP) is the most important political and cultural center as well as an agricultural base in China. In NCP, groundwater accounts for 60% of fresh water consumption. Groundwater overexploitation in the past half-century has led to a tremendous decline in groundwater level and several subsidence funnels (Zhang et al., 2009). The NCP is a hot spot for groundwater depletion as it has become one of the most extensively altered areas by human activities in the world (Tang et al., 2013).

Monitoring networks for groundwater are more limited than those for surface water. Even when monitoring networks are available, data accessibility is often restricted. Alternatively, the groundwater storage (GWS) change and its associated land surface deformation can be remotely monitored by using geodetic methods, such as Gravity Recovery and Climate Experiment (GRACE), Global Positioning System (GPS), Interferometric Synthetic Aperture Radar (InSAR), etc.

GRACE measures the gravity changes that result from mass transport on the Earth, offering us the possibility to monitor large-scale variations of groundwater. Tapley et al. (2004) demonstrated the potential of detecting and monitoring terrestrial water storage change using GRACE. Rodell et al. (2009) estimated the groundwater depletion rates in India using GRACE-derived terrestrial water storage and simulated soil–water. Scanlon et al. (2012) applied a new approach to GRACE observations and estimated the GWS changes in the California Central Valley, USA, which were validated by well data. Using GRACE...
and well data, Feng et al. (2013) estimated the groundwater depletion rates for the period 2003–2010 in NCP. Tang et al. (2013) analyzed the anthropogenic impacts on mass changes in NCP and their influences on estimating GWS changes when using GRACE observations. Huang et al. (2015) explored the capability of GRACE in detecting subregional-scale groundwater depletion in NCP. Gong et al. (2018) studied the long-term GWS changes and land subsidence in NCP. Frappart and Ramillien (2018) reviewed the GRACE satellite mission and its application in monitoring GWS changes. Feng et al. (2018) also reviewed the GWS changes in China derived from satellite gravity.

GPS can be used to infer GWS changes by monitoring the land surface displacements. After removing the contributions from surface loading changes and geophysical effects, GPS-measured land surface displacements correlate with GWS changes. By using GPS, Abidin et al. (2008) revealed the characteristics of the land subsidence in Jakarta between 1997 and 2005 and their correlation with groundwater extraction. Chen et al. (2010) examined the correlation between groundwater level and GPS-measured vertical surface displacements in the Choshuichi Alluvial Fan, Taiwan, and found that groundwater overdraft was the major mechanism for the land subsidence. Ji & Herring (2012) studied the horizontal surface displacements in the San Gabriel Valley, California by using 11 GPS sites, and found a strong correlation between the surface displacements and water table variations. Silverii et al. (2016) found that transient patterns in GPS horizontal time series near large karst aquifers were controlled by seasonal and interannual groundwater recharge and discharge of karst aquifers. Similar to GPS, InSAR provides an alternative to monitor high-accuracy land subsidence due to GWS changes with a millimeter-level accuracy (Bell et al., 2008; Zhang et al., 2013; Castellazzi et al., 2016, 2017; Rahmani & Ahmadi, 2018; Jiang et al., 2018).

Many scientists have investigated the groundwater depletion rate in NCP by using hydrological data, geodetic data, and their combinations. Motowo et al. (2013) estimated the groundwater depletion rate to be 16.8 mm/yr from 2002 to 2009 by using GRACE Release-04 Spherical Harmonic Coefficients (SHC). Feng et al. (2013) estimated a groundwater depletion rate of 2.2 ± 0.3 cm/yr from 2003 to 2010 using GRACE Release-05 SHCs. Tang et al. (2013) calculated the groundwater depletion rate to be 0.8–1.4 cm/yr from 2003 to 2011, considering the influence from reservoir regulation, water diversion, and coal transport. Huang et al. (2015) used the GRACE Release-05 SCH to detect the groundwater depletion in two sub-regions of the NCP and estimated the depletion rates to be 4.65 ± 0.68 cm/yr and 1.69 ± 0.19 cm/yr during 2003–2013. Gong et al. (2018) stated that the GWS in NCP declined at a rate of 1.78 ± 0.01 cm/yr during 1971–2015 by using in-situ groundwater measurements and the GRACE mass concentrations (mascon) data. Wang et al. (2017) deduced that the groundwater depletion rate in NCP was 2.49 ± 0.71 cm/yr from 2003 to 2009 and 2.72 ± 0.25 cm/yr from 2003 to 2012 by using GRACE SHCs data. However, the above studies have some deficiencies. Firstly, the estimates of groundwater depletion rate in NCP are not consistent when using different GRACE solutions and data processing strategies. Secondly, the most recent GWS changes are not studied, especially after 2013 when the project of South-to-North water diversion has been operated. Thirdly, the land surface deformation associated with groundwater depletion in NCP is not well depicted.

The objectives of this study are (1) to merge different mascon solutions to generate a unified solution; (2) to use the unified solution to reveal GWS changes in NCP; and (3) to depict the land surface deformation in NCP by using 116 GPS sites.

2. Research area and data

2.1. Research area

The NCP is surrounded by the Bo Sea to the east, Yanshan Mountains to the north, Taihang Mountains to the west, and Yellow River to the south, having an area of ~140,000 km² (Fig. 1). This area is a large Mesozoic and Cenozoic sedimentary basin, and the quaternary formations are 400–600 m in depth (Zhang et al., 2009). The NCP is one of the world’s largest aquifer systems, which can be divided into one unconfined aquifer (depths of 40–60 m) and three confined aquifers (depths of 120–170 m, 250–350 m, and 400–600 m) (Sakura et al., 2003). All the aquifers consist of sand, gravel, clay, silt, and abundant groundwater (Sakura et al., 2003). Observation data from 27 wells and 116 GPS sites that are located in NCP are accessed. The locations of the sites are shown in Fig. 1.

2.2. Data

2.2.1. GRACE mascon

Different from the GRACE traditional processing approach that is based on spherical harmonics (SH) basis functions, an alternative processing approach based on regional mass concentration (mascon) functions has become operational in the recent years (Luthcke et al., 2013; Watkins et al., 2015; Wiese, 2015; Wiese et al., 2016; Save et al., 2016). Mascon solutions parameterize the gravity field in terms of finite equal-area mascon blocks. The mass within each mascon block is evenly distributed over the larger area encompassed by the bounding quadrilateral in a mass conserving manner. Mascon solutions offer several key advantages over the standard spherical harmonic solutions. With mascons, geophysical constraints are easily implemented to filter out noise from GRACE observations at the Level-2 processing step. And, mascon solutions better handle the mass leakage problem than the SH solutions, which will be beneficial for studies of the regional mass change. Due to these reasons, GRACE mascon solutions from Jet Propulsion Laboratory (JPL) of the National Aeronautics and Space Administration (NASA), Center for Space Research (CSR), University of Texas Austin, and Goddard Space Flight Center (GSFC) of NASA are used. Hereafter, the three mascon solutions are simply called “JPL mascon”, “CSR mascon”, and “GSFC mascon”, respectively. The JPL mascon is the release 5 version 2 with the coastal resolution improvement filter (Wiese, 2015). The CSR mascon is the release 5 version 1.0.
is expressed as:

\[ y = x + e \]

where \( x \) is the true value, \( e \) is the observation error. Given a set of three pairs of observations \((i, j, k)\), the difference between any two sets can be written as:

\[
\begin{align*}
li - lj &= x + ei - (x + ej) = ei - ej \\
lj - lk &= x + ej - (x + ek) = ej - ek \\
lj - lj &= x + ei - (x + ek) = ei - ek
\end{align*}
\]

The corresponding variance relationship can be written as:

\[
\begin{align*}
\sigma_i &= \sigma^2_i + \sigma^2_0 - 2\text{cov}(e_i, e_j) \\
\sigma_j &= \sigma^2_j + \sigma^2_k - 2\text{cov}(e_i, e_j) \\
\sigma_k &= \sigma^2_k + \sigma^2_i - 2\text{cov}(e_i, e_j)
\end{align*}
\]

where \( \sigma_i, \sigma_j, \sigma_k \) are the variance of the differences of the observations, \( \sigma^2_i, \sigma^2_j, \sigma^2_k \) are the variance between the observations, \( \text{cov}(e_i, e_j), \text{cov}(e_i, e_k), \text{cov}(e_j, e_k) \) are the covariances of the observations. The latter 6 are the unknowns to be determined. If the observations from different sets are not correlated, the covariances are zero and the \( \sigma^2_i, \sigma^2_j, \sigma^2_k \) can be easily determined by Eq. (3). Since all the mascon solutions are derived from the GRACE’s inter-satellite ranging observations, the three mascon solutions could be correlated. Therefore, we consider the covariances between different datasets. In this situation, Eq. (3) has 3 knowns and 6 unknowns, and thus is underdetermined. Travella and Premoli (1992) proposed to add mathematical constraints, i.e., the determined variances should be all positive, to solve the problem. This method was further developed by Premoli and Travella (1993) and Travella and Premoli (1994). The detailed methods and equations can be found in Premoli and Travella (1993) and will not be further illustrated here.

### 3. Methods and data processing

#### 3.1. Three-cornered hat method

In this study, the three-cornered hat (TCH) method (Premoli and Travella, 1993; Travella and Premoli, 1994) is used to estimate the relative uncertainties of different datasets. This method has been used in quantifying uncertainties in terrestrial water storage changes from GRACE observations, land surface models, and global hydrological models (Long et al., 2017). This method does not require any a priori knowledge of the actual mass change when at least three different datasets are available. The theory of the TCH method is described below with the assumption that all the observation errors are normally distributed.

A given set of observations \( l_i \) is expressed as:

\[ l_i = x + e_i \]

where \( x \) is the true value, \( e_i \) is the observation error.

### 3.2. Singular spectral analysis

Singular Spectral Analysis (SSA) is an advanced data-adaptive method that can decompose time series into trends, seasonal oscillations, irregular signals, and noise (Ghil et al., 2002). It does not require a priori information on mathematical function or stochastic model, making it suitable for analyzing various kinds of data. Base on these advantages, we use this method to extract the trends from the GWS changes. This method has been proven effective in extracting periodic and non-periodic signals from noisy GPS and GRACE time series (Walder et al., 2016; Zhang et al., 2017, 2018). Details about this method have been well illustrated in Walder et al. (2016) and Zhang et al. (2017) and will not be further illustrated here.
3.3. Deriving groundwater storage changes from mascon solutions

The total water storage (TWS) in NCP can be regarded as the sum of SMS, SWS, and GWS, i.e.,

\[ TWS = SMS + SWS + GWS \]  

(4)

The TWS changes can be estimated by GRACE mascon data, the SMS changes can be simulated by the land surface models, and the SWS changes can be obtained from Haihe River Water Conservancy Commission. The GWS changes can be obtained by two ways, either directly estimated from the ground-based water table observations or indirectly estimated by Eq. (4) using GRACE data and hydrological data. We will estimate the GWS changes in the two ways and compare the results. Here we first introduce how we estimate the GWS changes from GRACE mascon data.

Sakumura et al. (2014) suggested that the ensemble mean (simple arithmetic mean of JPL, CSR, GFZ fields) was most effective in reducing the noise in the gravity field solutions within the available scatter of the solutions. We follow Sakumura et al. (2014) but use different methods to merge the CSR, JPL, and GSFC mascon solutions. Since the reference time have influences on the trend estimates, we need to align these data to the same time reference. Since the CSR mascon and the JPL mascon are relative to 2004.000–2009.999 while the GSFC mascon is relative to 2004.000–2016.000, we remove the 2004.000–2009.999 mean from the GSFC mascon to make it have the same reference with the CSR and JPL mascons.

We first compute the TWS changes in NCP from the CSR, JPL, and GSFC mascon solutions. Then, we apply the TCH method to the three TWS time series to determine their variances and covariances. The results show that the variances for CSR, GSFC, and JPL TWS time series are 6.7 cm², 2.9 cm², and 7.0 cm², and their covariances are very close to zero. Based on these estimated (co)variances, we use a weighted least square method to merge the three mascon solutions and finally generate a unified mascon solution. We use the maximum differences between the unified solution and the other three solutions as the final uncertainties so that it gives a natural confidence interval of 100%. We also interpolate the results into equally-spaced monthly data to be consistent with the SMS data.

We do not apply the TCH method to the SMS time series from the four land surface models (CLM, Mosaic, Noah, and VIC) since the errors in these model data are not normally distributed and there are systematic biases among different time series due to different depths of simulated soil moisture in the four models. We just take an average of the SMS from the four models as the unified SMS and treat the maximum differences between the unified SMS and the other four SMSs as the uncertainties. We remove the 2004.000–2009.999 mean from the unified SMS time series to make it consistent with mascon data.

We also collect data from major reservoirs in or near NCP to account for SWS changes. We also remove the 2004.000–2009.999 mean from the SMS data to ensure the SWS data have the same reference with the TWS data and the SMS data. Fig. 2 shows the retrieved TWS changes from the unified mascon solution, the SMS changes from the unified soil moisture data, and the SWS changes from the Haihe River Water Conservancy Commission. We derive the GWS changes by subtracting the SMS and SWS from the TWS. Then we apply SSA with a window with of 35 months to the GWS time series to separate trends and seasonal oscillations.

3.4. Deriving GPS vertical displacements

Bernese 5.2 software is employed to resolve daily position solutions from the double-differenced carrier phase observations (Dach et al., 2015). The data processing includes all sites from the CMONOC network and 127 globally distributed International Global Navigation Satellite System Service (IGS) sites. The ionosphere-free combination of double-differenced phase observations is used to eliminate the first-order ionosphere delay effects, and the second-order ionosphere delays are estimated by models (Petrie et al., 2010). The VMF1 model (Boehm et al., 2006) and the GPT2 model (Lagler et al., 2013) are used to model the tropospheric delay. The IGS14 absolute phase center model is used to correct the variation of the antenna phase center for both satellites and receivers. The FES2004 model is employed to account for ocean tide corrections. Satellite positions are determined by using IGS final orbit products. On the final adjustment of coordinates, minimal constraints are applied to align daily coordinates to the International Terrestrial Reference Frame 2014 (ITRF2014).

The vertical displacements of these sites are mainly due to surface loading changes while the horizontal displacements are mainly related to plate motions. Therefore, we only use the vertical displacements. We use the National Centers for Environmental Prediction-Department of Energy Reanalysis 2 products to remove the atmospheric loading displacements and the GLDAS data to remove the hydrological loading displacements (van Dam et al., 1994). The residual vertical displacements are mainly due to the GWS changes. All the loading displacements are calculated by convolving the loading mass changes with the Green’s functions (Farrell, 1972) based on the Preliminary Reference Earth Model (PREM) with continuous crust (Dziewonski and Anderson, 1981).

4. Results

4.1. Groundwater storage changes

Fig. 3a shows the GWS changes derived by subtracting the SMS and SWS from the TWS changes. The changes of GWS is characterized by a primary long-term decreasing trend accompanied by seasonal oscillations and interannual variations. Fig. 3b-3c show the trends and seasonal oscillations derived by applying SSA to the GWS time series. We find peaks from the trend curve (Fig. 3b) with minimum peak distance of 2 years and finally detect 3 peaks, which naturally divide the trend curve into 3 sub-periods (excluding the period before 2004.63):
estimate the WT change rates to be $-1.1 \pm 0.1$ m/yr and $-2.3 \pm 0.0$ m/yr for before and after 2013.54. Overall, the WT showed a decreasing trend from 2012 to mid-2016 with a rate of $-1.8 \pm 0.0$ m/yr, accompanied with seasonal variations. It is also evident that the WT accelerated to decline after 2013.54 by declining $0.5$ m/yr more than the average level. Using the same specific yields (0.05–0.07) in Feng et al. (2013), we convert the WT change rates to GWS change rates. The GWS change rate is inferred to be $-3.9 \pm 0.3$ cm/yr for 2013.54–2016.50, which is close to the rate estimated from GRACE data. This further reinforces the finding that the GWS has an accelerated decline from 2013.54.

Feng et al. (2013) estimated the groundwater depletion rate to be 2.0–2.8 cm/yr from 2003 to 2010 using well data. Gong et al. (2018) estimated the groundwater declining rate to be 1.82 cm/yr during 2005–2013 from in-situ observations. Our estimate of GWS decline rate is $\sim 1.7$ cm/yr before 2013.54, which is close to the results in Feng et al. (2013) and Gong et al. (2018). From mid-2013 to mid-2016, our estimate of GWS depletion became $\sim 3.9$ cm/yr, which suggests a strong acceleration in groundwater depletion during that period.

4.3. Land displacements due to groundwater changes

We analyze the vertical displacements at 116 sediment GPS sites. To infer the temporal variation of groundwater depletion from vertical displacements, we perform a linear regression to the time series before and after 2013 to calculate the corresponding displacement rates. Results show that all the 116 sediment GPS sites show similar subsiding trends with average subsidence rates of 15.32 mm/yr and 28.30 mm/yr before and after 2013. These results suggest a strong acceleration in land subsidence after 2013, which agrees well with the accelerated groundwater depletion. Fig. 5 shows the exemplary vertical displacement time series at 6 out of the 116 sites, which visually demonstrates the acceleration of the subsidence. We also present the spatial distribution of the subsidence field (pre- and post- 2013) in Fig. 6, which clearly shows that the subsidence funnels were greatly expanded after 2013.

Zhang et al. (2009) depicted the distribution of subsidence funnels in NCP and pointed out that shallow groundwater funnels spread in the piedmont plain area while deep groundwater funnels were mainly located in the middle and east NCP. The distribution of the subsidence funnels shown in Fig. 6 agrees well with that depicted by Zhang et al. (2009) but the extent has been greatly expanded.

5. Discussions

The acceleration in groundwater depletion after 2013 has been revealed by the unified mascon solution and validated by accelerated WT decline and land subsidence in this study. To find out what caused this acceleration, we analyze water storage change from the perspective of water balance. The natural water storage change ($\Delta S$) is expressed as the result of subtracting runoff ($R$) and evapotranspiration ($E$) from precipitation ($P$):

$$\Delta S = P - R - E$$

The precipitation, runoff, and evapotranspiration from the GLDAS Noah model for period 2004–2016 is used for this analysis. Fig. 7a–d show the accumulated precipitation, accumulated evapotranspiration, accumulated runoff, and the TWS changes derived by Eq. (2) using the Noah model. Fig. 7e–h show the detrended ones.

Fig. 7d shows that the TWS started to decline in 2013 and this decline lasted to 2016, which coincided with our detected GWS changes. Fig. 7e–g show that all the detrended precipitation, evapotranspiration, and runoff started to decline since 2013, but only the decline in precipitation can cause the TWS decline (decline in runoff and evapotranspiration will increase the TWS). It is therefore inferred that precipitation decline is the cause for the TWS decline. However, the TWS
decline does not necessarily cause groundwater decline as it also associates with SWS and SMS. To investigate how the TWS decline influences the groundwater change, we remove the SWS and SMS changes from the TWS changes to derive GWS changes. For clarity, this GWS change is called the Noah-based GWS change to be differentiated from the GRACE-based GWS change. Fig. 8 shows the surface water, soil moisture, and the Noah-based GWS changes.

The surface water (Fig. 8a) showed an increase from 2010 to 2013 followed by a decrease from 2013 to late 2015. The soil moisture (Fig. 8b) also showed a slight increase before late 2013 followed by a sharp decrease from late 2013 to 2016, which is similar to the variations of the Noah-based TWS as shown in Fig. 7d. Both the SWS change and the SMS change suggest a drought occurred in late 2013 and lasted to early 2016. However, the Noah-based GWS change (Fig. 8c) showed a slight decrease from 2011 to late 2013 followed by a slight increase from 2013 to late 2015, which is opposite to the TWS changes. It is not likely that the groundwater increases in NCP when both the SWS and SMS decrease, therefore we attribute this inconsistence to data uncertainties. Overall, the modeled groundwater changes in Fig. 8c do not show any decline during the drought, which is very contradictory with the observations from GRACE, water table, and GPS. It is inferred that human factors which are not included in the model is responsible for this decline in the GWS. Under the condition of less precipitation, drier soil, and deficient surface water during 2013 and 2016, people in NCP had to exploit more groundwater than usual to meet the need of water. Therefore, the drought-induced overexploitation of groundwater is inferred as the cause for the groundwater storage decline from 2013 to 2016.

6. Conclusion

We use the three-cornered hat method and the weighted least square method to merge the different GRACE mascon solutions and generate a unified solution. Based on the unified mascon solution, we estimate the groundwater changes in North China Plain and found an acceleration in groundwater depletion. This acceleration started in mid-2013 and lasted to mid-2016 with an average groundwater depletion rate of $-3.8 \pm 0.1$ cm/yr which doubled the rate before mid-2013. The groundwater depletion rate estimated from the water table data also shows an acceleration during the same period with a rate of

Fig. 6. Vertical displacement rates in NCP derived from GPS data. (a): rates before 2013. (b): rates after 2013.
−3.9 ± 0.3 cm/yr, which is consistent with GRACE results. 116 sediment GPS sites depicted the land subsidence in NCP and revealed the accelerated land subsidence during 2013 and 2016, also in consistence with the groundwater depletion. All these together suggest an acceleration in groundwater depletion from 2013 to 2016.

By analyzing the land surface model, we found that the precipitation decrease from 2013 to 2016 was the reason for the water storage decline. Under the condition of less precipitation, drier soil, and less surface water storage, people had to exploit more groundwater than usual to meet the water need. This led to the accelerated depletion in groundwater storage from 2013 to 2016.

Declaration of Competing Interest

None.

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