LETTER

Trends in groundwater changes driven by precipitation and anthropogenic activities on the southeast side of the Hu Line

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Abstract

Groundwater resources consumption and management play a crucial role in food-energy-water nexus. However, the trends in groundwater storage variability and its attribution remain unclear because of the combined effects of climatic and anthropogenic terms. Here we use satellites and monitoring well observations to reveal the trends in groundwater storage change (GWSC), which exhibits geographical heterogeneity over the southeast side of the Hu Line in China during 1979–2012. The GWSC in northern China showed a slight decrease from 1979 to 1997, and the declining pattern extended to surrounding regions from 1998 to 2012. A considerable fraction of the GWSC trend can be attributed jointly to precipitation variations and human water usage. The anthropogenic factors that are primarily associated with socioeconomic development contribute to ~31% of the variability in GWSC. Water management policies carried out in recent years reasonably explain the recovery of GWSC across regions with declining groundwater in 2013–2019. A positive trend in GWSC is further projected (2020–2029), though with uncertainties.

1. Introduction

Groundwater resources account for ~20% of freshwater storage on earth (Fan et al. 2013). Approximately 70% of groundwater withdrawals can be attributed to agricultural water usage. Such groundwater depletion has recently increased, especially in developing countries (Famiglietti et al. 2014). The amount of groundwater extraction is growing substantially in China accompanying with the economic development and population growth (Changming et al. 2001, Aeschbach-Hertig and Gleeson 2012). This may result in a series of issues regarding water, food and energy security. Investigating the variations and attributions of groundwater storage is crucial for water management.

Studies have illustrated that climatic variations and anthropogenic factors influence groundwater directly or indirectly (Asoka et al. 2017, Wu et al. 2020). In particular, precipitation variability modifies groundwater recharge and abstraction, thereby impacting groundwater storage dynamics on short- and long-term bases. For instance, decreased precipitation accompanied by increased temperature can result in high evapotranspiration, depleting runoff and soil moisture (Condon et al. 2020, Konapala et al. 2020). This usually causes plentiful irrigation water withdrawals in intensive agricultural regions (Mishra et al. 2020).

China has become the second largest economy over the development of past 40 years, and is considered one of the most severe water consumption regions in the world (Zhou et al. 2020). The demand of anthropogenic water use involving irrigation, industrial and domestic terms has increased. Nevertheless, compound effects of anthropogenic factors and climatic variability on the magnitude of groundwater storage change (GWSC) in the context of high economic growth are poorly quantified for a long timescale. While several studies (Pei et al. 2015,
Lin et al. 2020) have explored such relationship at a basin scale or regional scales, an in-depth assessment at the (semi-) national scale such as in China is lacking. It is challenging to disentangle the natural and anthropogenic contributions to groundwater storage (Cuthbert et al. 2019). This relates to the insufficiency in the available datasets and the corresponding analysis approach, as well as the uncertainty in climatic-hydrological models (Thomas and Famiglietti 2019).

This study provides a semi-nationwide quantification of the spatial patterns of contemporary GWSC from 1979 to 2012 using satellite observations, local well measurements, and economic dataset. We aim to understand how the long-term climatic and socioeconomic drivers contribute to groundwater variability. To achieve this goal, a data-driven, statistical regression-based approach is employed. We specifically focused on the southeast side of the Hu Line (figure 1) where ~90% of China's population resides and more than 95% of the national gross domestic product is produced (Chen et al. 2016). The studied region has witnessed rapid pace of agricultural and economic development, and thus the groundwater storage is hypothesized to be jointly influenced by natural precipitation and anthropogenic interventions.

Although groundwater storage is prone to climate change and anthropogenic drivers, it is also associated with policy interventions. Since 2013, China has begun to transform from an economic priority phase to an ecologic priority phase. A diversity of water-ecology conservancy and restoration measures are being implemented to address the water crisis and protect water resources (Liu et al. 2013). One example is the South-to-North Water Division, which has long transported a large amount of water from southern China (i.e. Hubei and Jiangsu provinces) to northern China (e.g. Beijing, Tianjin and Hebei provinces) since 2013 (Chen et al. 2016). Another point to be noted is that an obvious transition toward large-scale farming has occurred in China (i.e. northeast China and southwest China) in recent years (Wang et al. 2014). Despite the enforcement of water policy management, there is a lack of consensus regarding its impact on groundwater storage variations. Incomplete knowledge of the human-nature interactions that modulate groundwater storage variability further renders the attribution analysis and forecast estimates unreliable. Therefore, another objective of our study is to investigate and project the GWSC trends, from 2013 out to 2029, to provide evidence and guidance for future water management.
2. Dataset

Monthly terrestrial water storage anomalies are obtained from the mean values of two Gravity Recovery and Climate Experiment (GRACE)/GRACE Follow-On mascon-based products: the Center for Space Research and the Jet Propulsion Laboratory. Despite uncertainties existing in the GRACE solutions, these satellite observations can well delineate terrestrial water variations (Feng et al. 2013, Long et al. 2013). We collect the ground water level observations from field wells during 2005–2012 (figure S1 available online at stacks.iop.org/ERL/16/094032/mmedia). These datasets can be accessed from the ‘China Geological Environment Monitoring Groundwater Level Yearbook’ provided by the Ministry of Water Resources of China.

Two types of land–surface hydrological models, i.e. the Global Land Data Assimilation System (GLDAS) (Rodell et al. 2004) and the global hydrological models (GHMs) (Sood and Smakhtin 2015), are used for calculating GWSC. The GLDAS simulates surface status parameters and flux components by assimilating ground and space-based observations into different land surface models. Here, monthly average soil moisture and snow water equivalents are averagely provided by four GLDAS models (i.e. Community Land Model, Variable Infiltration Capacity Model, Mosaic and NOAH). Based on conceptual formations, GHMs model the primary hydrological processes in the water cycle, e.g. those relating to surface water and surface water storage. This study selects three GHMs models, PCR-GLOBWB, SURFEX-TRIP and ORCHIDEE, to provide surface water storage. Monthly GLDAS and GHMs datasets are resampled to the spatial resolution of GRACE.

The monthly precipitation is based on the averaged value of three sets of products from the China Meteorological Administration (CMA), the Climatic Research Unit Time series (CRU TS), and the Global Precipitation Climatology Center. We also use the field precipitation (figure S1) from the National Meteorological Information Center of China to evaluate the trends from gridded datasets. Monthly air temperature, arid index (the ratio of potential evapotranspiration to precipitation), radiation and relative humidity are obtained from the CMA and CRU.

We collect a variety of socioeconomic datasets, including annual irrigation water use, irrigated area, industrial water use, domestic water use, human population, gross value added and livestock population. These data can be obtained from the Statistical Yearbook published by the National Bureaus of Statistics of China or previous studies (Zhou et al. 2020). The digital elevation model (DEM) is obtained from the Shuttle Radar Topography Mission product, while the normalized difference vegetation index (NDVI) and modified normalized difference water index (MNDWI) are obtained from Moderate Resolution Imaging Spectroradiometer product.

We collect groundwater table and surface water storage simulations from 14 members of the Community Earth System Model version 1’s Large Ensemble Project (CESM-LE) (Mankin et al. 2017, Wu et al. 2020). These datasets have a spatial resolution of 0.9° × 1.25°. The CESM-LE simulations cover a period of 1920–2005 with historical forcing and a period from 2006 to 2029 with RCP 8.5 forcing.

3. Method

3.1. GWSC calculation

Based on the water balance principal, the groundwater storage change (GWSC) can be retrieved as:

\[
\text{GWSC} = \Delta \text{TWS} - \Delta \text{SM} - \Delta \text{SWE} - \Delta \text{SW}. \tag{1}
\]

In equation (1), the monthly terrestrial water storage change (\(\Delta \text{TWS}\)) is obtained from GRACE/GRACE Follow-On observations using equation (2). Soil moisture change (\(\Delta \text{SM}\)), snowpack and ice sheet change (\(\Delta \text{SWE}\)) are obtained from GLDAS, and surface water change (\(\Delta \text{SW}\)) can be obtained from GHMs simulations.

\[
\Delta \text{TWS}(t) = \frac{\text{TWSA}(t+1) - \text{TWSA}(t-1)}{2} \tag{2}
\]

where \(\Delta \text{TWS}(t)\) is the terrestrial water storage change at a specific month (t), which can be estimated as the difference between TWS anomalies in the next month \(\text{TWSA}(t+1)\) and the prior month \(\text{TWSA}(t-1)\).

Since GRACE satellite only provides observations after 2003, we have to reconstruct TWS anomaly dataset in 1979–2002 based on other environmental and climatic datasets. This study uses three machine learning approaches, i.e. neural networks, multiple linear regression and random forest, to obtain the reconstructed TWS anomalies, following the strategy of Sun et al. (2020). We treat the GRACE TWS anomalies from 2003 to 2012 as the reference observations and the corresponding precipitation, temperature, and GLDAS-derived TWS anomalies as the explanatory factors. Detailed description can be found in text S1 and figure S2.

3.2. Correlation analysis and contribution analysis

Before analyzing the monthly GWSC and climatic factors, we use seasonal and trend decomposition using loess (STL) to remove seasonal variability. The intra-annual variability in annual human water use is removed using the ensemble empirical mode decomposition (EEMD) method. In this study, the evaluations of GWSC and the related impacting factors are carried out based on the decomposed terms removing the intraseasonal/intraannual signals and remaining
parts. Specifically, we use the Sen’s slope analysis to obtain the trends of monthly and annual datasets. The significance level of the calculated trend is determined by a nonparametric Mann–Kendall (MK) test.

We use the regression subset selection approach (Fu et al 2019) to diagnose the critical factors impacting GWSC. The regression subset selection method assumes that the suppressor variables significantly correlate with each other in multiple regression models, despite that they may be not correlated with the dependent variable separately. The significance percentage is used to measure the probability of the factor impacting GWSC: the higher the significance percentage is, the stronger the ability to impact GWSC. These analyses are conducted using a dataset from 2003 to 2012. We select 15 factors as input parameters, including five monthly climatic factors (i.e. precipitation, radiation, air temperature, arid index, and relative humidity), seven annual economic factors (i.e. irrigation water use, irrigated area, industrial water use, domestic water use, human population, livestock population and gross value added) and three annual surface environmental factors (i.e. NDVI, MNDWI and DEM). Correlations between GWSC and the identified pivotal driving factors are further demonstrated. We implement the general additive model (GAM) to the monthly climatic factors, to reduce the cumulative influences and time delays. The GAM quantifies the nonlinear correlation between the dependent variable and explanatory factors by taking into account the possible nonlinearities with a variety of nonparametric smooth functions (Morton and Henderson 2008).

The relative contribution of anthropogenic factors to the trend of the GWSC is finally calculated using one simple attribution analysis (Xie et al 2019) that is conducted at two stages. In the first stage, the GWSC is regressed with the identified climatic factors. In the second stage, the remaining GWSC obtained from stage one is further regressed using the identified anthropogenic factors. Text S2 in the supplementary material provides detailed descriptions.

3.3. Projected GWSC simulations

Two projected GWSC simulations in 2020–2029 are generated based on the GRACE observations and existing anthropogenic activities. The first simulation is produced using an autoregressive integrated moving average (ARIMA) model (Adamowski and Chan 2011, Li et al 2019b), which is an extensively used model in forecasting time series. The ARIMA mainly includes the modules of the autoregressive model and the moving average model. Specifically, an identified process is implemented based on time series components to produce the best model accurately owning the process-generating mechanism. We apply the seasonal ARIMA models to each seasonal GWSC from 2003 to 2019. Each STL GWSC component and residue in the 2020–2029 period is first simulated using the seasonal ARIMA model. The modeled results of the STL components and residuals are then summed to generate an ensemble simulation for the original GWSC series. Details on the ARIMA model can be found in text S3.

The second simulation is based on the CESM-LE product and assumes that anthropogenic intervention relies on the condition in the prior phase (Wu et al 2020). Since anthropogenic activities are not considered by the CESM-LE, the disparity in the GWSC between the CESM-LE and GRACE-derived products can be mostly attributed to anthropogenic variability. Here we use random forest regressions to calibrate the ensemble mean of CESM-LE simulations. As a machine learning-based method, random forest primarily focuses on the interactions between independent variables while ignoring the distribution of available datasets and the functional form of the regression relationship. Specifically, random forest regression is first established for each month between the ensemble mean of the CESM-LE simulation and GRACE-derived GWSC from 2006 to 2019. The established regression is then applied to the ensemble mean of the CESM-LE simulation from 2020 to 2029. The regression is established and applied at a monthly scale. Note that only CESM-LE groundwater storage is calibrated considering it is the focus of our research. We also compare the surface water storages of CESM-LE with those of GHMs product, and find one rough consistent spatial pattern between two sources. This means CESM-LE simulations is available for further study.

4. Results and analysis

4.1. Trend in GWSC

The monthly GRACE-derived GWSC from 1979 to 2012 is first checked on a global-mean basis. The evaluation of the reconstructed GWSC (i.e. in 1979–2002) is exhibited in the supplementary material (figure S3), indicating that the performance of the proposed model is acceptable. As shown in figure 2(a), a breaking point in GWSC observations, which occurs around 1997, is identified by the MK analysis. This case is captured well in the STL decomposition term, which shows that the trends before and after the breaking point are 0.055 mm yr\(^{-1}\) (\(p < 0.05\)) and −0.024 mm yr\(^{-1}\), respectively. The contrasting pattern around the breaking point coincides with the increased demand for water usage after 1998 due to the ongoing reform of in China’s economic system (Zhao et al 2010).

The trends in the GWSC in the study region vary spatially (figure 2(b)). We divide the study area into six administrative regions, i.e. northeastern China (NEC), northern China (NC), central China (CC), southern China (SC), southeastern China (SEC) and southwestern China (SWC). A negative trend was found in part of NC, SWC and SC in 1979–1997,
Figure 2. The GWSC trend. (a) Global mean monthly GWSC and its STL decomposition term. (b) Spatial distribution of the trend in GWSC for two phases. (c) Regional mean monthly GWSC for six administrative regions, accompanying the STL decomposition terms. (d) Trends of GRACE-derived GWSC and well observations for provinces. The error bars represent the standard deviation. The well observations are collected from 2005 to 2012. The symbols * in (a) and (c) and + in (b) indicate that the significance level is under 95%.

while a positive trend was observed in the remaining regions, especially EC. The decreasing trend accounts for 11% of the total study area. From 1998 to 2012, the negative trend extended to part of NEC and EC, while most of the other regions still exhibited a positive trend. At this phase, the decreasing trend accounts for 37% of the total study area. Note that a considerable fraction of the negative trend in the GWSC is observed in agricultural regions, implying the potential impact of irrigation water usage.

A time series of monthly GWSCs (figure 2(c)) is provided to understand their trends for each region. An increasing trend is observed for all six administrative regions from 1979 to 1997. Nevertheless, the GWSC shows a decreasing trend in NEC and NC when coming to the 1998–2012 period, with trends of $-0.099 \text{ mm yr}^{-1}$ and $-0.193 \text{ mm yr}^{-1}$ at the 95% confidence level, respectively. The quantification of GWSC trends is further divided into provincial regions (figure 2(d)). The trends of GRACE-derived GWSC basically coincide with those from monitoring well observations, with root mean square error (RMSE) and mean absolute error (MAE) values of 0.09 mm yr$^{-1}$ and 0.06 mm yr$^{-1}$, respectively. The trends of GRACE-derived GWSC are found to be slightly larger than those from well observations. The discrepancy in the trend between the two sources is in line with previous studies (Long et al 2016, Liu et al 2020), which is explained in part by uncertainties in the GRACE product, such as coarse resolution and leakage errors, and in part by the uneven distribution of groundwater observation wells. Despite varying magnitudes of GWSC within each region, consistent trends are displayed in individual provinces.
Exceptions are found in Beijing and Tianjin, probably owing to prominent human water usage. Specifically, the trend direction in 1979–1997 converts from positive to negative when coming to the 1998–2012 period for the provinces in NEC and NC (and the surrounding regions, i.e. Henan and Shandong). In particular, the growth rates of the GWSC in several provinces located in EC and SWC obviously slow down.

### 4.2. Precipitation and human water use variability

The correlations between precipitation and groundwater storage have been documented in groundwater studies (Thomas and Famiglietti 2019). The precipitation anomaly trend exhibits an uneven spatial pattern, as illustrated in figure 3(a). From 1979 to 1997, a decreasing trend in the precipitation anomaly was shown in parts of CC, SWC and SC. During 1998–2012, the negative trend further extends to most regions of SWC, SC and EC, but an obvious increasing trend is observed in NC and parts of EC. The precipitation anomaly trend is further investigated at the provincial scale as illustrated in figure 3(b). The trends of grid precipitation anomaly basically coincide with those of site observations, with RMSE and MAE values of 0.95 mm yr⁻¹ and 0.7 mm yr⁻¹, respectively. Note that the observations have good agreement with grid precipitation as compared to the GWSC because of the greater number of field stations and fewer uncertainties in the raw precipitation product (Xu et al 2019). We observe that the GWSC fluctuations at the provincial scale fairly corresponds to the precipitation anomaly variations, with regions of higher GWSC variations being regions of higher precipitation anomaly fluctuations, such as Jiangxi, Fujian, Hunan and Guangdong. Further results in figure 3(c) demonstrate the substantial impacts of precipitation on GWSC. This influence is more pronounced in heavy agricultural regions and exerts greater effect during monsoon seasons.

Human water use is further investigated (figure 4(a)), considering its potential in influencing groundwater storage (Döll et al 2012). From 1979 to 1997, a decreasing trend of irrigation water use existed in parts of NC, EC, CC and SWC. During 1998–2012, most regions showed a decreasing trend in irrigation water use except the EC and SEC regions. Regarding industrial water use, a positive trend is observed in most regions from 1979 to 1997, and high values occur in SEC and SC. From 1998 to 2012, industrial water use noticeably increased for most regions especially the SEC, but its trend in NC and SC slightly decreased, especially in Beijing and its surrounding region. As for the domestic water use, a positive trend is found from 1979 to 1997, and high values occur in Shanghai and Chongqing. Domestic water use is constantly increasing in the period of 1998–2012, but this positive trend is more intensive in large cities and economically developed regions. The exhibited patterns of human water use are further reflected by the annual mean of individual regions and the EEMD compositions (figure 4(b)). Irrigation water use has decreased in most regions since 1997 owing to intense socioeconomic development, but this negative trend can be offset partly by increasing industrial
water use and domestic water use. The human water use trend is further averaged based on the provincial regions (figure 4c). The variations in human water use trends are essentially different for each province due to varying rates of economic development and population growth.

The GWSC of the study region can be interpreted heavily with the conjunct effects of precipitation and anthropogenic factors. China has experienced rapid socioeconomic development during the last 40 years (figure S4), allowing the GWSC to vary spatially. The NC area faced significantly decreased GWSC in 1998–2012, despite the slightly increased precipitation. This is linked to the fact that the NC area is a highly irrigated area, accounting for ~60% of the total water use, with more than 70% of that usage are from groundwater (figures 4 and 5) (Basin 2012). Irrigation water use and industrial water use have

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**Figure 4.** The trend of annual human water use. (a) Spatial distribution of annual human water use trend for two phases. (b) Mean annual human water use for six administrative regions. (c) Trends of annual human water use for provinces. The error bars represent the standard deviation. The symbol + in (a) indicates the significance level is under 95%.
decreased substantially in NC since 1998. However, domestic water use begins to account for a substantial portion of the GWSC. This case is well reflected in Beijing and Tianjin. A consistent pattern is observed in parts of EC (e.g. Shandong and Jiangsu provinces), with a larger contribution from urbanization in addition to agricultural land. In the NEC area, the GWSC shows an insignificant increasing trend in 1979–1997 but then changes to a decreasing trend during 1998–2012. Especially during the later phase, the increasing precipitation is not sufficient to support the decreased GWSC owing to increased evapotranspiration and human water use (figures 4 and S6) (Li et al 2018). Most of the human water use in NEC is probably associated with irrigation since this region has a large fraction of irrigated area. Compared with other regions, the irrigation water use in NEC constantly increases during the study period. In EC and parts of SWC, the slight slowdown of the growth rate in the GWSC trends from 1998 to 2012 can be partly explained by the reduced precipitation. Note that the increased human water use amplifies the magnitude of the GWSC. This means that the GWSC is influenced synthetically by precipitation and human water use. The constant increasing trend in GWSC occurs for parts of SC and SWC (e.g. Guangdong), in which the increase in irrigated areas stagnated over the study period. This case is reasonable since the reduction in irrigation water use can be substantially offset by the increased domestic water use. Note that the GWSC in most regions of CC, SC and SWC is not only impacted by decreased precipitation and increased human water use but also more related to the physical properties, e.g. groundwater depth, soil type and vadose zone porosity, and especially the increased in human institutions leading to the modification in runoff (figure S7) (Shi et al 2007).

4.3. Contribution analysis
One regression subset selection model is used to identify the critical factors explaining the GWSC. As illustrated in figure 5(a), precipitation shows the highest percentage of significant correlation with the GWSC, followed by the arid index and air temperature. We also observe that three human water use
terms exhibit significant correlations with the GWSC, followed by the human population and irrigated area. The associations between eight critical influencing factors and the GWSC are further explored. Given that groundwater generally responds slowly to recharge, the effects of climatic factors on groundwater variations could be nonlinear (e.g. cumulative and lag-time) (Moon et al 2004). This is corroborated by the higher correlation between precipitation and the GWSC (figure 5(b)). The effect of air temperature on the GWSC is obvious in SWC and NC, while the arid index obviously influences the GWSC in the humid region, i.e. SC, CC and EC. The contrast response of the GWSC to climatic factors across different regions can be partly attributed to the inherent regional characteristics under energy-limited (southern China) and water-limited (northern China) conditions (Chang et al 2020, Condon et al 2020). On the other hand, anthropogenic factors show noticeable associations with the GWSC. Figure 5(c) illustrates that irrigation water use, industrial water use and domestic water use contribute significantly to the GWSC, while irrigated area and human population exhibit relatively moderate correlations with the GWSC.

Based on the above analysis, we quantified the relative contributions of five primary anthropogenic factors to the GWSC. Here the precipitation, arid index and air temperature are identified as the explanatory variables in the first regression stage. Figure 5(d) demonstrates that anthropogenic factors account for ~26% and ~35% of the GWSC variations in the 1979–1997 period and the 1998–2012 period, respectively. A higher contribution of human water use has been observed since 1998 owing to the incentivized effects from increased socioeconomic activities. During the whole study period, irrigation water use was the primary anthropogenic factor for the GWSC, especially in intense irrigated regions such as NC, NEC and CC. This is rational since groundwater storage variations in agricultural regions can be controlled by extraction for irrigation, which is mostly influenced by precipitation (Nair and Indu 2021). Since 1998, the relative contributions from industrial water use and domestic water use have amplified, whereas the contributions from irrigation water use are relatively muted for most regions. This case is prominently reflected in two megacities, Beijing and Tianjin. Note that the relative contributions from irrigation water use and irrigated area were proportionally lower from 1998 to 2012. This is partly explained by the fact that the reduction in irrigation water use intensity caused by improved irrigation efficiency can cancel out the positive effects of irrigated area expansion (Blanke et al 2007, Zhou et al 2020).

Note that the variables used for the attribution analysis may not be independent of each other. To examine the contribution of the individual variable to GWSC, we conducted a sensitivity analysis taking the arid index as an example. Figure S8 shows the assessment of the relative contribution of anthropogenic factors to the GWSC after removing the arid index. As is readily apparent, the total contribution and the determination coefficient show a significant drop when the arid index is not considered. In other words, the arid index plays a critical role in depicting the GWSC. This is corroborated by further evidence drawn from the partial linear regression, which is capable of removing spurious effects via fixing the effects of precipitation and temperature while analyzing the effect of arid index (Zhou et al 2021). The divergence in the contribution are relatively small between the two approaches, suggesting that the three contributors used in our study are sufficient in explaining the variance of GWSC.

4.4. Future trend in GWSC

Since 2013, China’s water management have benefited from policies of optimizing water distribution networks and withdrawal by carrying out a variety of artificial aquifer recharge schemes and water diversion projects. Specifically, a first increasing and then decreasing pattern is revealed for China’s water consumption. These anthropogenic interventions have resulted in achievements in water conservation, and are likely to facilitate the groundwater storage recover initiative (Yan et al 2015). Expected results are found in the GRACE-derived observations in 2013–2019 (figure 6(a)), which illustrates a slight increase in GWSC across most regions when compared with those in 1998–2012. The substantial increase of the GWSC in NC (e.g. Beijing) can be partly attributed to the accumulative precipitation increase, effective water-saving policy and the South-to-North Water Diversion projection. Contrasting cases exist in parts of NEC and SWC, probably relating to the increased irrigation water usage. A transition toward large-scale farming has been carried out in NEC and SWC in recent years, which may encourage farmers to expand water intensive crops (i.e. rice) (Wang et al 2014).

We further investigate the projected GWSC from 2020 to 2029. Figure 6(b) shows that the increased GWSC trend in most regions is further enhanced. This is closely related to the continued policy intervention in China’s 14th and 15th Five Year Plans (Li et al 2019a). The reduction in the GWSC in NC and surrounding regions is likely to continually slow over the next decade. In particular, the GWSC conditions in two groundwater deficit provinces, i.e. Hebei and Beijing, seem to be improving. Conversely, decreasing trend in the GWSC is observed in some regions of NEC and SWC, which are susceptible to the implementation of farmland irrigation and water conservancy as well as well dams. For instance, an insignificant increasing trend and decreasing trend in the projected GWSC are found for Heilongjiang regarding the ARIMA-based and CESM-based simulations, respectively.
5. Discussion

Our study provides the first kind of report on the long-term trends of groundwater variability at a semi-nationalwide scale, and its attribution to climatic and anthropogenic causes on the southeast side of the Hu Line in China. The GWSC from satellite-derived observations and well datasets reveals a slightly decreasing trend in northern China from 1979 to 1997, and such declining pattern extends to surrounding regions from 1998 to 2012. Our analysis quantified the compound effects of precipitation variability and anthropogenic factors on the GWSC, which is varied spatially over the study region.

Earlier studies have indicated that human activities could contribute dominantly to stream flow or storage changes on a regional basis (Hu et al 2019, Lin et al 2019, Chao et al 2020). Here we present direct evidence that precipitation variability explains a considerable fraction of the GWSC (~47%). The cumulative effect of precipitation on GWSC is more pronounced in heavy agricultural regions. Combined with other climatic factors (i.e. air temperature and arid index), precipitation explains more than 60% of the groundwater storage variability. Nevertheless, the influence of climatic variability on the GWSC is disturbed by anthropogenic factors, and this interference has been more intense since 1998. The varied response of GWSC to climatic variability is linked to regional characteristics (e.g. vadose zone porosity and groundwater depth) and anthropogenic activities (e.g. dam construction and impervious surfaces). This can be reflected by the geographically divergent trends in the GWSC. Our analysis provides insights into agricultural and urban management especially in regions that experience severe groundwater storage depletion.

We employ a statistical regression approach to assess anthropogenic effects on the GWSC variations, and further provide quantitative evidence showing that anthropogenic factors contribute to ~31% of the GWSC over a long timescale. These contributions are related to the socioeconomic development witnessed in China in the last decade. From 1979 to 2012, increasing industry infrastructure development and human population growth owing to economic liberalization caused a higher industrial and domestic water demand for most study regions. This corresponds to the contribution of anthropogenic factors in decreasing the GWSC trend and the growth rate of the GWSC, especially for regions in NC and EC, which contain the Beijing-Tianjin urban
agglomeration and the Yangtze River Delta economic circle. The presented study is critical for deepening our understanding of how anthropogenic factors affect the sustainability of groundwater storage in regions undergoing increasing water demand. On the other hand, the influences of anthropogenic factors in the CC and SC regions can be muted by intensive precipitation amounts owing to the Asian monsoon and the decreased runoff resulting from anthropogenic construction (Bai et al. 2020). This indicates that the related socioeconomic factors are unlikely to have remarkable effects on the GWSC in parts of southern China (figure 3). The improved knowledge base of provincial patterns provides guidance for strategic implementation of long-distance water diversion project that diverts water from southern China to northern China. Meanwhile, the discrepancy in GWSC attribution across the study region implies a previously unrecognized connection between anthropogenic factors, climatic variability and groundwater storage variations (Hanson et al. 2004, Taylor et al. 2013).

The evaluation of climatic and socioeconomic impacts on groundwater variability is achieved based on administrative boundary that captures the varying development of socioeconomic components, which may be sensitive to the varying population density. An intercomparison between the assessment units is further conducted to ensure a uniform basis. We normalize the GWSC and anthropogenic factors to examine the variation in factor contributions irrespective of the population level. This is realized by estimating the Theil index (text S4 and figure S9). Generally, there is a consistent pattern in the contribution between that using the non-normalized dataset and that using the normalized dataset, though the discrepancy in the contribution of irrigation and domestic is reduced for some provinces. This result suggests the reasonableness to perform the analyses based on administrative boundary. On the other hand, it is challenge to separate the climatic and anthropogenic contribution considering the complex interaction among different impacting factors. For instance, precipitation and temperature inevitably impacts the agricultural evapotranspiration as well its irrigation water use. Our study uses one attribution model that is conducted at two stages to disentangle contribution of human factors. This approach may overestimate climate impacts and underestimate human intervention; nevertheless, it avoids the overestimation of human intervention that is more complex in describing groundwater storage. Meanwhile, partial regression is used since it could allow spurious effects to be controlled by fixing the climatic effects while analyzing the effect of the anthropogenic factors. Partial linear regression-based contributions of climate is smaller as compared to the multiple linear regression-based contributions (not shown). That means the contributions of anthropogenic can be larger. Nevertheless, the divergences in these contributions are relatively smaller between two approaches. This implies the regression models may have limited ability in affecting the variance of GWSC despite the uncertainties in regression approaches.

As water management policies have been implemented in recent years (i.e. 13th Five Year Plan) to regulate human water use, groundwater conditions have been ameliorated in many water deficit regions (e.g. NC and NEC), as illustrated by the GRACE-derived observations in 2013–2019 (figure 6). A weakened declination of the anthropogenic contribution to the GWSC during 2013–2019 (figure S10) backs up the positive role of water management policies. Meanwhile, simulations from the two models manifest the increasing trend in the GWSC from 2020 to 2029 for most regions. This implies that under a constant water management policy, the groundwater supply would potentially be improved in the future considering that the projected precipitation in most of the study region is likely to be increased.

Although some studies, such as Wang et al. (2020), indicate that further population growth in China will pose challenges for water management, our results offer confidence to the government in implementing water management policies for sustaining groundwater storage. However, the uncertainties of future water management associated with anthropogenic interventions should be emphasized, as illustrated in figure 6. For instance, the transition to large-scale agricultural regions may push the adoption of water-intensive crops, thereby offsetting irrigation water use saving due to advanced irrigation efficiency. This case is particularly obvious in the NEC and SWC regions. In addition, the increasing per capita income and household wealth in China, accompanied by the convenient tap water accessibility, will be conducive to a more water-intensive lifestyle and increased domestic water use (Huang et al. 2010). This is likely to occur in EC, which is a priority of economic development for the Chines government. Accordingly, groundwater management and sustainability strategies should adapt hydrological and technical measures to the socioeconomic and environmental conditions of regional settings.

Data availability statement

All data sets used in this research are either publicly available from the cited literature or come from several public data sources.

The data that support the findings of this study are available upon reasonable request from the authors.

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Conflict of interest

The authors declare no competing interests.

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