C203

Estimating Groundwater Storage Anomalies in Songliao Plain Using GRACE

ODan FENG, Kenji TANAKA, KHUJANAZAROV Temur, Kazuaki YOROZU, Yoshiya TOUGE

1.Introduction

Groundwater, which accounts for 99% of liquid freshwater on Earth, serves as a crucial water source, supplying a quarter of human water consumption. It supplies drinking water for 50% of the population. The utilization of groundwater is divided among agriculture (69%), domestic use (22%), and industry (9%). In the recent 20 years, it has been extensive groundwater exploitation in China, principally driven by population growth and high intensity agriculture. Songliao Plain covers an area of over 256,288 square kilometers which located in Northeast China. It is one of the important crop production areas where Agriculture as the main water user is responsible for 80% of total groundwater pumping.





The objective of this study is to exploring the following questions:

(1) How does groundwater variation for decades?

(2) What are the key features of temporal variability in GWSA?

(3) How do land surface processes correlate with groundwater changes?

GRACE data

We used the Gravity Recovery and Climate Experiment (GRACE) data and GRACE-FO data. Release 06 of terrestrial water storage variations from spherical harmonics solutions. The surface mass change data (terrestrial water storage anomalies -TWSA)are available from March 2002 to June 2017, July 2018 to December 2020. The baseline is Jan 2005 to Dec 2010.

Land surface Models

We used two land surface models: NOAH (version 2.1) and SiBUC model. The time range is from March 2002 to December 2020. The resolution is $1^{\circ} \times 1^{\circ}$. Soil moisture, snow water equivalents, surface runoff and canopy water storage were simulated in the NOAH model. Soil moisture, snow water equivalents, surface storage were simulated in the SiBUC model.

Precipitation data

The Daily Observational Precipitation data is from NOAA. The location of stations are displayed in Figure 1.

3.Methods

The basic approach to deriving groundwater anomalies (GWSA) estimates involves subtracting monthly anomalies of hydrologic water storage components anomalies from TWSA. The GWSA (based on NOAH and SiBUC model) were calculated as follows:

```
\text{GWSA}_{\text{NOAH}} = \text{TWSA}_{\text{GRACE}} - \text{SMSA}_{\text{NOAH}} - \text{SWEA}_{\text{NOAH}} - \text{SRA}_{\text{NOAH}} - \text{CWSA}_{\text{NOAH}} \ (1)
```

 $GWSA_{SIBUC} = TWSA_{GRACE} - SMSA_{SIBUC} - SWEA_{SIBUC} - SSA_{SIBUC}$ (2)

Where TWSA is terrestrial water storage anomalies; GWSA is groundwater storage anomalies;

SSA is surface storage anomalies; SMSA is soil moisture storage anomalies; SWEA is snow water equivalent anomalies; CWSA is canopy water storage anomalies; SSA is surface runoff anomalies.

The uncertainty data in TWSA was from GRACE which depends on latitude and smoothing radius. Uncertainty in the other hydrologic water storage components are taken as the standard deviation, assuming independence between component errors. Uncertainty in GWSA was calculated as follows:

 $\sigma_{\text{NOAH-GWSA}} = \sqrt{\sigma_{\text{TWSA-GRACE}}^2 + \sigma_{\text{NOAH-SMSA}}^2 + \sigma_{\text{NOAH-SWEA}}^2 + \sigma_{\text{NOAH-SRA}}^2 + \sigma_{\text{NOAH-CWSA}}^2}$ (3)

 $\sigma_{\text{SiBUC-GWSA}} = \sqrt{\sigma_{\text{TWSA-GRACE}}^2 + \sigma_{\text{SiBUC-SMSA}}^2 + \sigma_{\text{SiBUC-SWEA}}^2 + \sigma_{\text{SiBUC-SSA}}^2}$ (4)

For exploring the relative importance of key features of temporal variability in GWSA, the time series of storage components can be decomposed using the Seasonal Trend decomposition using Loess (STL)^[1]. This approach is based on decomposing gridded time series of monthly equivalent water height into long-term, seasonal, and subseasonal components. We further decomposed the long-term component into linear trend and inter-annual by Theil-Sen estimator^[2].

 $S_{raw} = S_{linear trend} + S_{Inter-annual} + S_{seasonal} + S_{subseasonal}$ (5) **1 Posults**

4.Results

The GWSA_{SiBUC} and GWSA_{NOAH} all show significant downward trends in the Songliao Plain for decades.Specifically, groundwater depletion estimated from SiBUC and NOAH with -0.045 ± 0.348 cm/year and -0.091 ± 0.360 cm/year.



Fig.2 GWSA based on SiBUC and NOAH models. Uncertainty (grey bands based on the propagated errors from TWS and other water storage errors) (Lower panels) The Annual cumulative precipitation anomaly (CPA).

The GWSA_{SiBUC} and GWSA_{NOAH} have the uncertainty with standard deviation =1.98 to 8.16 cm and 3.40 to 6.42 cm.

GWSA were plummeted in 2011 (La Niña period). The annual cumulative precipitation decreased significantly and the mean temperature was lower in 2011. In the spring of 2012, the Songliao Plain faced a severe drought event. Due to the previous year's less precipitation, the amount of snowmelt was less than normal. The TWSA, GWSA and SMSA showed extremely low values in the beginning of 2012. In the rainy season of 2013, the Songliao Plain experienced elevated precipitation which partial recovery groundwater aquifers. The drought events continued after 2014, groundwater still remained low level. Regarding spatial variations, GWSA has been at low negative values for a long time in Harbin. It could be related to high-intensity agricultural. It was found that dry and paddy lands in Harbin have increased since 2010 due to global warming.

We found that temporal variability in GWSA is dominated by long-term trends in Songliao Plain. The seasonal amplitudes(maximum minus minimum range) are 0.5 cm and 0.6 cm with GWSA_{SiBUC} and GWSA_{NOAH}.

The GWS change is moderately correlated with the TWS change ($R_{NOAH}=0.52$, $R_{SiBUC}=0.37$). The TWS change is moderately correlated with the SMS change ($R_{NOAH}=0.57$, $R_{SiBUC}=0.57$).

5.Conclusion

Generally good agreement between GWSA_{SiBUC} and GWSA_{NOAH} in time series. Both are tracking the dynamics of GWS which increases during wet periods and decreases during drought. Both datasets show long - term declining trends in Songliao Plain. SMS and GWS play important roles in the TWS.

References

[1]Cleveland, R. B., Cleveland, W. S., McRae, J. E., & Terpenning, I. (1990). STL: A seasonal-trend decomposition procedure based on loess. Journal Official Statistics, 6(1), 3–73

[2]Humphrey, Vincent & Gudmundsson, Lukas & Seneviratne, Sonia. (2016). Assessing Global Water Storage Variability from GRACE: Trends, Seasonal Cycle, Subseasonal Anomalies and Extremes. Surveys in Geophysics. 37. 1-39.