Wavelet and Gaussian Approaches for Estimation of Groundwater Variations Using GRACE Data

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Abstract

In this study, a scheme is presented to estimate groundwater storage variations in Iran. The variations are estimated using 11 years of Gravity Recovery and Climate Experiments (GRACE) observations from period of 2003 to April 2014 in combination with the outputs of Global Land Data Assimilation Systems (GLDAS) model including soil moisture, snow water equivalent, and total canopy water storage. To do so, the sums of GLDAS outputs are subtracted from terrestrial water storage variations determined by GRACE observations. Because of stripping errors in the GRACE data, two methodologies based on wavelet analysis and Gaussian filtering are applied to refine the GRACE data. It is shown that the wavelet approach could better localize the desired signal and increase the signal-to-noise ratio and thus results in more accurate estimation of groundwater storage variations. To validate the results of our procedure in estimation of ground water storage variations, they are compared with the measurements of pisometric wells data near the Urmia Lake which shows favorable agreements with our results.

Introduction

From all of the available water in the world, about 97% is distributed in the oceans and seas where the value of salinity is very high and not suitable for specific civilian use. From the 3% of the remaining water, about 2% is frozen in the polar ice sheets, unattainable to most, and only 1% is terrestrial water storage (TWS). TWS is the most important component of the global water cycle comprising the water stored in soil, snow over land, and the so-called groundwater storage (Chen et al. 2014). TWS variations reflect the accumulation of precipitation, evaporation, canopy, and runoff in a region. The estimation of TWS variations is a powerful tool for investigation of forecast flood, natural phenomena such as drought, and the other uses of water supply. Among the aforementioned ingredients in the TWS, groundwater storage is an important parameter in water resource management, land-surface processes, and hydrological cycle.

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TWS variations could be estimated using space-based data, such as remote sensing images or satellite gravimetric measurements, as well as ground-based data such as pisometric wells observations or climatological experiments. The remote sensing images have a good spatial coverage, but their sensing regions reached down to a depth of many centimeters. The data of pisometric wells could provide useful information of groundwater down to a depth of about 100 m and more, but they suffer from drawback of point-wise measurement which does not provide a good spatial resolution. Satellite gravimetric measurements of time variable gravity field are a new data type which is capable of modeling and detecting global mass transfer within the Earth. This subject, in its present form, began with the launch of the GRACE mission (Gravity Recovery and Climate Experiments). The GRACE mission provides a useful apparatus to study the time variation of the gravity field of the Earth. GRACE is able to monitor changes in a TWS from the land surface to the base of the deepest aquifer (surface water, soil moisture, groundwater, and snow) (Tapley et al. 2004b).

Numerous studies have shown that GRACE can offer useful constraints on TWS, including ocean mass change (e.g., Chambers et al. 2004; Lombard et al. 2007), mass balance of the ice sheets (e.g., Lutchke et al. 2006; Ramillien et al. 2006; Velicogna and Wahr 2006), polar ice sheet melting (e.g., Velicogna and Wahr 2006), and groundwater variations (Moiwo et al. 2012; Jin and Feng 2013; Lenk 2013).

GRACE consists of twin satellites which provide a unique opportunity to estimate the groundwater storage and its temporal variations. Because GRACE observations are affected by all sources of TWS, extraction of the groundwater component from GRACE observations requires the estimation of other impacts from auxiliary data sets. The useful data sets that can be used for this purpose are hydrological models such as GLDAS (the Global Land Data Assimilation Systems) or WGHM (WaterGAP Global Hydrology Model) (Rodell et al. 2004). In this study, the GLDAS outputs that are soil moisture, snow water equivalent, and total canopy water storage are used.

Recent outcomes of the GRACE mark a major step forward in assessing groundwater storage variations in our study location. Forootan et al. (2014) derived an estimation of TWS in Iran using combination of GRACE, altimetry, and hydrological data and analyzed a mass decrease with an average linear rate of 15 mm/year and linear trend of groundwater storage for the drought period of 2005 to March 2011. Joodaki et al. (2014) estimated the human contribution to groundwater depletion in the Middle East using GRACE and land surface models and found that the largest groundwater depletion is occurring in Iran, with a mass loss rate of 25 gigatonne (GT)/year and showed that over half of the groundwater loss in Iran may be attributed to human withdrawals. Moreover, Voss et al. (2013) estimated approximately 91 km^3 groundwater depletion in Middle East particularly in Iran using GRACE observations from 2003 to 2009.

In this study, we apply GRACE TWS changes in conjunction with GLDAS outputs to resolve groundwater storage changes in Iran during the period of January 2003 to April 2014. Two different low pass filtering schemes were applied to refine the GRACE spherical harmonic (SH) coefficients, that is, the traditional Gaussian filtering and an innovated wavelet analysis. To show the performance and accuracy of the results, the estimated groundwater changes are compared with groundwater level obtained from in situ measurements of pisometric wells data over the Urmia Lake.

Data and Processing

TWS Variations Using GRACE Coefficients

One of the objectives of the GRACE mission is the Earth's gravity field modeling. Using GRACE observations, the Earth's gravity field could be recovered in the form of SH coefficients up to a degree and order of 120 (Tapley et al. 2004a), which are known as stokes coefficients. In this study, these coefficients which are the latest release of GRACE gravity field coefficients in the period of January 2003 to April 2014 covered by 132 months are used (the release-05 or RL05 from UTCSR, the Center for Space Research at the University of Texas). GRACE can measure TWS variations in form of equivalent water layer thickness by using stokes coefficients variation (Wahr et al. 1998) as follow:

$$\Delta \mathrm{TWS}\,(\phi, \lambda, t) = \frac{a\rho_{\mathrm{ave}}}{3\rho_{\mathrm{w}}} \sum_{n=2}^{60} \sum_{m=0}^{n} \widetilde{P}_{nm}\,(\sin\phi) \frac{2n+1}{1+k_n} (\Delta C_{nm} \cos(m\lambda) + \Delta S_{nm} \sin(m\lambda)) \tag{1}$$

where ρ_{ave} is the mean density of the Earth, ρ_w is the density of fresh water, a is the equatorial radius of the Earth, $\widetilde{P}_{nm}$ is the fully normalized Legendre function of degree n and order m, and k_n is the Love load number of degree n (Wahr et al. 1998). Also, ϕ is latitude, λ is longitude, and C_{nm} and S_{nm} are the so-called stokes coefficients (the symbol Δ denotes the variation)

Atmospheric pressure variations, ocean tides, and barotropic ocean signals have been removed by means of three models, the European Centre for Meteorological Weather Forecasting model, the Finite Element Solution 2004 model (Lyard et al. 2006), and the MOG2D-G barotropic (Carrere and Lyard 2003) model, respectively.

Gaussian Filtering on GRACE Data

Equation 1 is the starting point for using GRACE estimates of ΔC_{nm} and ΔS_{nm} to recover changes in TWS. Because the errors in the GRACE coefficients increase with n (i.e., for short wavelengths), the use of Equation 1, can lead to highly inaccurate results as n increases. Thus, it is necessary to somehow reduce the large n contributions to the Equation 1 in order to obtain more accurate results. This fact involves the insertion of some additional multiplicative factors into Equation 1 that are smaller for large values of n. The problem is to seek a factor that reduces the errors, while keeps the weighting function localized. Jekeli (1981) introduced degree-dependent weighting factors W_n, which subsequently applied into the GRACE observations by Wahr (1998). This averaging function was derived from a spatial Gaussian function. The half-power point of the Gaussian is determined by a parameter referred to the averaging radius, r so that:

$$\Delta \mathrm{TWS}\,(\phi, \lambda, t) = \frac{a\rho_{\mathrm{ave}}}{3\rho_{\mathrm{w}}} \sum_{n=2}^{60} \sum_{m=0}^{n} \widetilde{P}_{nm}\,(\sin\phi) W_n \frac{2n+1}{1+k_n} (\Delta C_{nm} \cos(m\lambda) + \Delta S_{nm} \sin(m\lambda)) \tag{2}$$

where the function W could be determined by a recursion relation as:

$$W_0 = 1, \qquad W_1 = \frac{1+e^{-2b}}{1-e^{-2b}} - \frac{1}{b}$$
$$W_{n+1} = -\frac{2n+1}{b} W_n + W_{n-1}, \qquad b = \frac{\ln(2)}{1-\cos\left(\frac{r}{a}\right)} \tag{3}$$

Figure 1 shows the behavior of Gaussian averaging function for some radiuses:

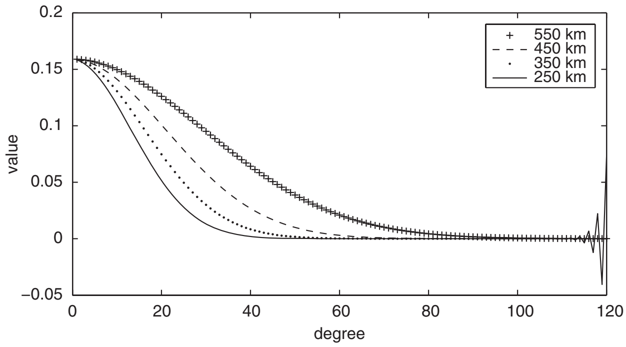

Figure 1. The spectral smoothing coefficients for Gaussian smoothing with different radiuses.

The correlated-error filter introduced by Swenson and Wahr (2006) has also been tested on the results which causes to remove real signals and necessitates the implementation of suitable rescaling method. Moreover, because in the study location of this research there was no north–south stripes, this filtering approach is not considered in the analysis and only the aforementioned Gaussian filtering which does not require rescaling is applied (Chen et al. 2005; Moiwo et al. 2012; Jin and Feng 2013; Lenk 2013).

Filtering and Localization on GRACE Data by Wavelet

Wavelet analysis allows the use of long time intervals, when more precise low frequency information is sought, and shorter regions where high frequency information is needed. One major advantage afforded by wavelets is the ability to perform a local analysis to analyze a localized area of a larger signal (Panet et al. 2007). Also, wavelets are appropriate tools to investigate the regional time variable effects in the gravity field (Kohlhaas 2005; Fengler et al. 2006; Panet et al. 2007). In this study, spherical wavelet modeling of regional and temporal variations of the Earth's gravity field observed by GRACE is applied. Spherical wavelets, introduced by Freeden and Schreiner (1995); Freeden and Windheuser (1996); Freeden et al. (1998), have been used here based on expansions in Legendre polynomials. They form radial basis functions on the sphere whose argument depends only on the spherical distance between the center of the wavelet and its evaluation point.

The families $\left\{\left\{\widehat{\Psi}_J(n)\right\}_{n\in N_0}\right\}_{J\in N_0}$ and $\left\{\left\{\widehat{\widetilde{\Psi}}_J(n)\right\}_{n\in N_0}\right\}_{J\in N_0}$ are said to be the generators of the primal and the dual wavelets, respectively, where in this work, we simply set $\widetilde{\Psi}_J(n) = \Psi_J(n)$, $J \in N_0, n \in N$, hence, the wavelet is computed by:

$$\widehat{\Psi}_J(n) = \sqrt{\left(\widehat{\phi}_{J+1}(n)\right)^2 - \left(\widehat{\phi}_J(n)\right)^2} \tag{4}$$

in which the family $\left\{\left\{\widehat{\phi}_J(n)\right\}_{n\in N_0}\right\}_{J\in N_0}$ is called a generator of a scaling function, if it satisfies the following

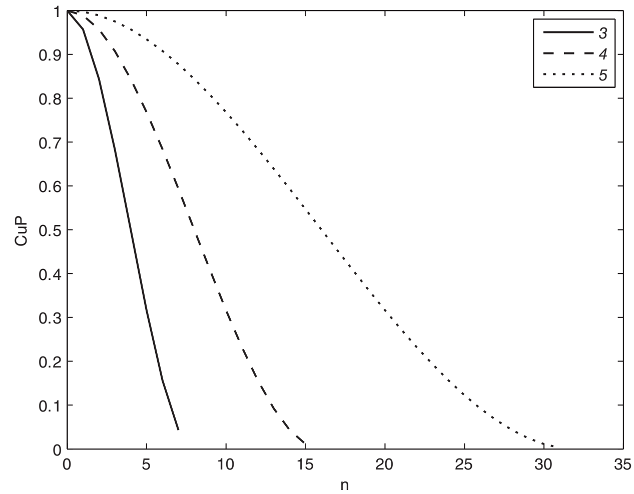

Figure 2. Symbol of the CuP scaling functions ϕ_3, ϕ_4, and ϕ_5.

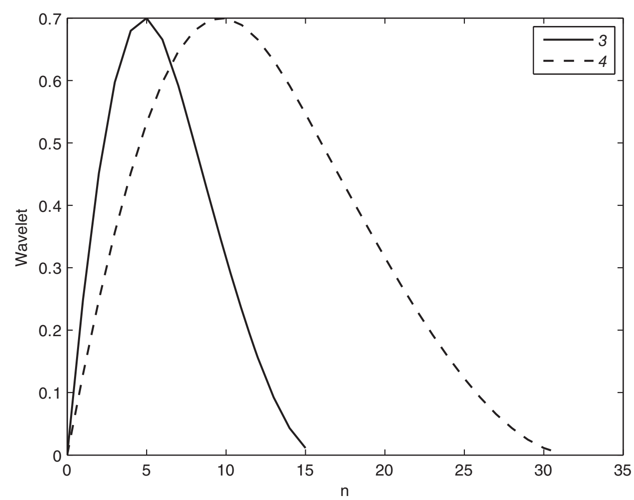

Figure 3. Symbol of the CuP wavelets Ψ_3 and Ψ_4.

requirements (Freeden et al. 1998):

$$\left(\widehat{\phi}_J(0)\right)^2 = 1,\ 0 \le \left(\widehat{\phi}_J(n)\right)^2 \le \left(\widehat{\phi}_{J'}(n)\right)^2, \quad \lim_{J\to\infty}\left(\widehat{\phi}_J(n)\right)^2 = 1 \tag{5}$$

For all $J, J' \in N_0$, with $J \le J'$ and all $n \in N$.

In this study, scaling functions and wavelets, generated by a so-called cubic polynomial (CuP), are considered, so we let:

$$\widehat{\phi}_J(n) = \begin{cases} \left(1-2^{-J}n\right)^2\left(1+2^{-J+1}n\right) & \text{for } n \in \left[0, 2^J\right) \\ 0 & \text{for } n \in \left[2^J, \infty\right) \end{cases} \tag{6}$$

which one can easily verify that all three conditions of a generator (Equation 5) are fulfilled. $j = 2$ is used in this study. The corresponding symbols of the scaling function and the wavelet are shown in Figures 2 and 3.

In a case of GRACE, the following representation provides us with the dimensionless wavelet coefficients (Fengler et al. 2006):

$$\frac{R}{\mathrm{GM}}\left(\Psi_J * \Delta\mathrm{TWS}\right)_{(t,x)} = \sqrt{4\pi}\sum_{n=2}^{60}\sum_{m=-n}^{n} \Delta\mathrm{TWS}\,(t)\,\widehat{\Psi}_J\,(n)\,Y_{n,m} \quad (7)$$

in which GM is the geocentric gravitational constant, R is the radius of the Earth, and $Y_{n,m}$ is surface SH of degree n and order m.

Outputs of GLDAS Model

GLDAS is a joint project between NASA and the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) (Rodell et al. 2004). There are many hydrological models such as GLDAS, Climate Prediction Center model, the NCEP/NCAR, and reanalysis products, but the results have shown that there is accordance between GLDAS model and GRACE coefficients (Jin et al. 2012), so the GLDAS model is used in this research. This land surface model combines data of ground based and space based for producing the optimal field of land surface state (Rodell et al. 2004).

The GLDAS model comprises three land surface models: Mosaic, Noah, and the Community Land Model (Rodell et al. 2004). It has been shown that different selection of Land Surface Models (LSMs) could result in completely different groundwater storage change estimates. Joodaki et al. (2014) showed that the Mosaic model gives the best agreement with the seasonal cycle of GRACE TWS changes. Long et al. (2013, 2014a) indicated that the differences between LSMs can be larger during droughts. Long et al. (2014b) demonstrated that both the frequency and severity of droughts and floods are intensified in selection of different LSMs.

In this study, the Noah model with a resolution of 1° is used from the period of January 2003 to April 2014. We select this model because the soil moisture only in this model was available to columns up to 2 m (in spite of other models that only account for three layers up to 1 m, the data of all four columns of soil moisture are available in this model, see also Chen et al. 2005; Frappart et al. 2011; Moiwo et al. 2012; Lenk 2013; Chen et al. 2014).

TWS variations from the GLDAS model are computed from the sum of soil moisture, snow water equivalent, and total canopy water storage. We have reached the mean annual of outputs data with averaging from the monthly data of GLDAS. A fair comparison with GRACE observations requires that GLDAS fields be also spatially filtered in a consistent way. To accomplish this, GLDAS gridded fields were represented in a SH expansion to a degree and order 60. Finally, GLDAS SH representations were also filtered on a global $1^\circ \times 1^\circ$ grids (Lenk 2013).

Estimation of Groundwater Variations From Combination of GRACE and GLDAS

As was stated, TWS in GRACE consists of groundwater, snow, soil moisture, and total canopy water storage. The GLDAS can model all of these components except groundwater. So, coefficients which are relevant to groundwater can be acquired if we subtract the output parameters of the GLDAS model from the GRACE coefficients which derive TWS in other way, therefore we have (Moiwo et al. 2012; Jin and Feng 2013; Lenk 2013):

$$\Delta\mathrm{GW} = \Delta\mathrm{TWS} - (\Delta\mathrm{SM} + \Delta\mathrm{SWE} + \Delta\mathrm{TCW}) \quad (8)$$

where ΔGW is related to groundwater variations, TWS is related to GRACE, and ΔSM, ΔSWE, ΔTCW are soil moisture, snow water equivalent, and total canopy water related to the GLDAS model.

Data of Pisometric Wells

Urmia Lake is in Northwest of Iran and located between two provinces: East Azerbaijan and West Azerbaijan and between $37^\circ 5'$ to $38^\circ 16'$ north and $45^\circ 01'$ to 46° east. This lake is the largest inner lake in Iran and the second largest salt water lake in the world (Hassanzadeh et al. 2011). It extends as much as 140 km from North to South and is as wide as 85 km East to West during high water periods. In the last decade, the intensive developments of agriculture, over-exploitation of groundwater, and construction of dams have all deprived the lake of one of its main water input resources. In this study, data from pisometric wells distributed around Urmia Lake from 2003 to 2012 are used in order to validate our results. The distribution of 20 groundwater wells near Urmia Lake indicated by a triangle shape is shown in Figure 4.

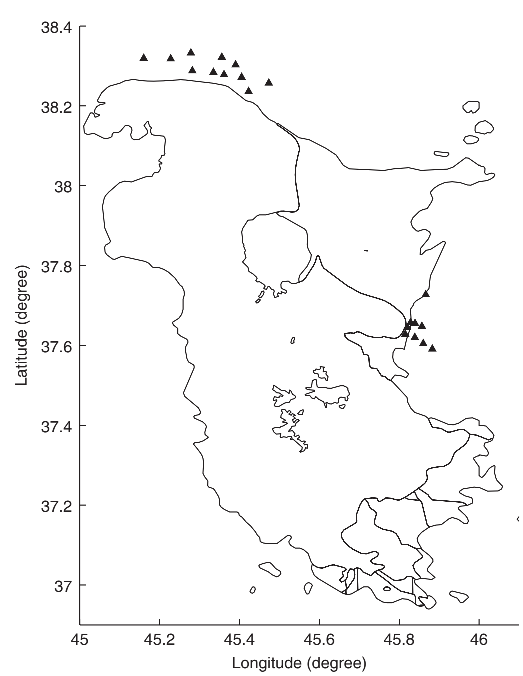

Figure 4. Location of 20 groundwater monitoring wells, indicated by triangle shapes.

Currently, groundwater level data from the wells are not available for all of Urmia Lake. Only limited groundwater level data are available in the east and north of it.

In order to evaluate the groundwater variation using wells data, the monthly and annual water levels are converted to equivalent water layer thickness for every well using a unique yield coefficient that is a ratio between 0 and 1 and indicates the amount of water released due to drainage from lowering the water level in an unconfined aquifer (Johnson 1967). The unique yield for this region was found to be 0.05 (the accurate unique yield was not available for this region). Therefore we have:

$$\Delta \mathrm{GW}^{*} = \Delta H \times S_Y \quad (9)$$

where ΔH is water level variations determined by measurements of well, S_Y is the unique yield, and $\Delta \mathrm{GW}^{*}$ is the groundwater variations determined by wells observations.

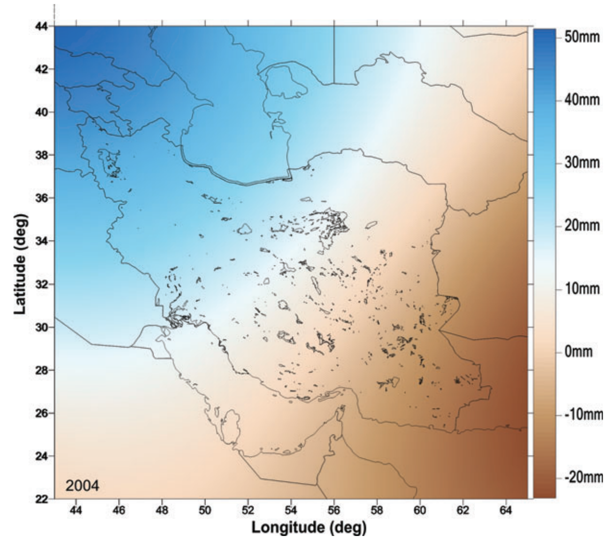

Figure 5. Groundwater storage variations related to Equation 8 based on wavelet in 2004.

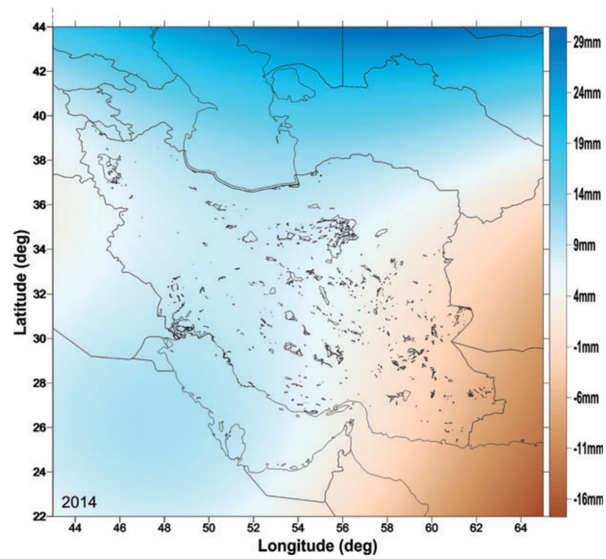

Figure 6. Groundwater storage variations related to Equation 8 based on wavelet in 2014.

Numerical Results

Having discussed the general method for estimation of groundwater storage variations, in this section, as a case study, we evaluate the groundwater storage variations in Iran within the period of 2003 to April 2014. As mentioned in section 1, due to stripping errors in the GRACE data, two methodologies based on wavelet analysis and Gaussian filtering are applied to refine the GRACE data. To select the best scale function for our wavelet analysis, a comparative analysis is conducted in which the mean root mean square error (RMSE) of the groundwater storage variations between wavelet and observation wells is computed at a square grid over all available years for various scales (see Table 1). These values represent that RMSE increases as wavelet scale j becomes larger, and the most precise results are due to $j = 2$, and therefore we select this scale function for wavelet analysis.

Figures 5, 6, 7, and 8 show the point-wise groundwater storage variations in the beginning (between 2003 and 2004) and ending (between 2013 and April 2014) of the selected period calculated by Equation 8. As shown, groundwater storage variations in the selected periods based on wavelet analysis are more homogeneous than the filtering approach. The groundwater variations obtained by wavelet analysis within these yearly time domain (2003–2004 and 2013–2014) decrease from 50 to −20 mm between 2003 and 2004 and 30 to −15 mm between 2013 and 2014. However, with Gaussian filtering approach, the corresponding results are 40 to −20 mm and 35 to −15 mm

Table 1
The Mean RMSE Between Wavelet and Observation Wells for Various Scales

Scale	Mean RMSE (mm)
$J = 2$	6
$J = 3$	9
$J = 4$	11
$J = 5$	13

For a typical measure of yearly groundwater storage variations, the average of total groundwater storage variations throughout Iran for a period of 1 year, starting from January 2003 and ending to April 2014, are computed with wavelet and filtering methods which are shown in Figure 9. As illustrated in this figure, there is an approximate consistency between results of wavelet and filtering in almost all periods (except three of them).

To show the groundwater storage variations of each year with a respect to 2003, the results of this year is compared with the following years up to April 2014.

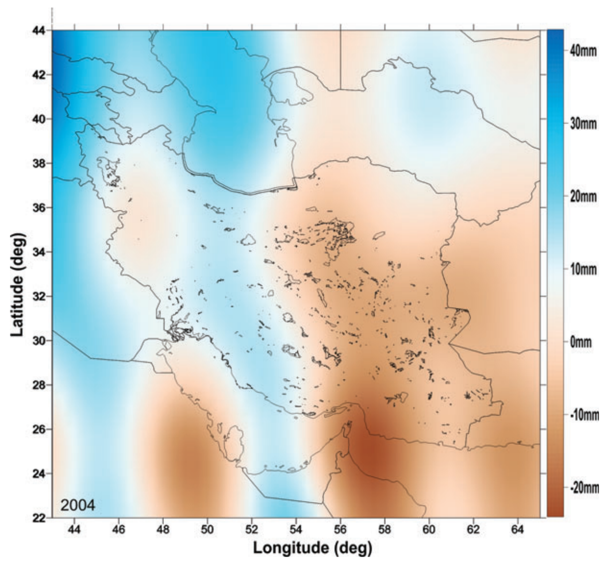

Figure 7. Groundwater storage variations related to Equation 8 based on Gaussian filtering in 2004.

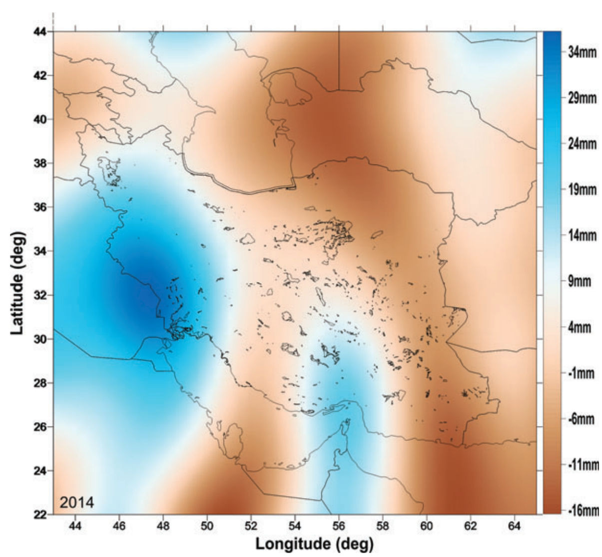

Figure 8. Groundwater storage variations related to Equation 8 based on Gaussian filtering in 2014.

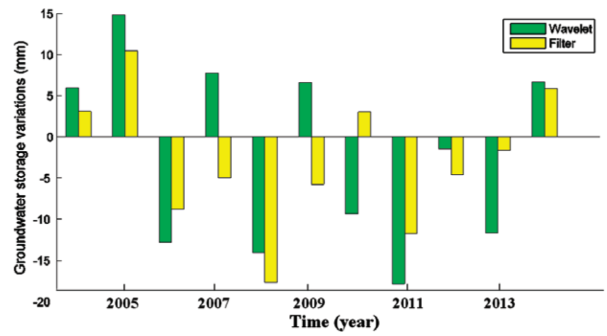

Figure 9. The average of total yearly groundwater variations in whole of Iran.

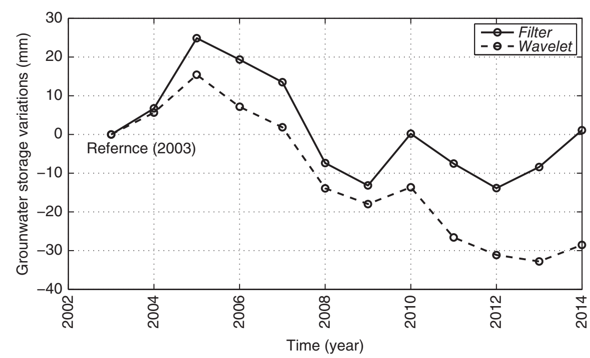

Figure 10. The time histories of groundwater storage variations with a respect to 2003 as a reference year.

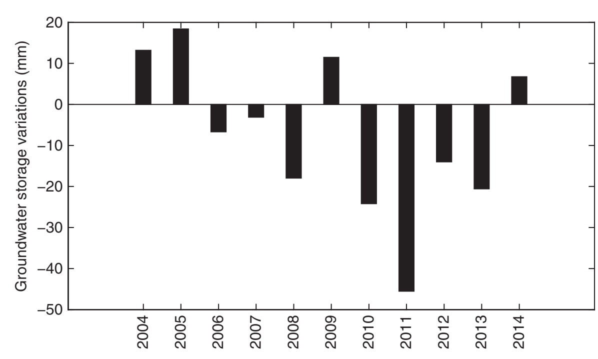

Figure 11. Mean variations amplitude of groundwater by wavelet over Urmia Lake.

The time histories of groundwater storage variations from 2003 to April 2014 are shown in Figure 10. In this figure, the water storage in 2003 is selected as a reference, and the groundwater variations in the other years have been calculated with a respect to this reference. As shown in this figure, variations increase in 2004 to 2007 and decrease in a period of 2007 to present. Moreover, the maximum decreasing amplitude is larger than the maximum increasing amplitude which shows that there is a depletion in groundwater storage variations in these years. This figure also shows the depletion of groundwater storage from 2007 to present which is very crucial problem in the water resources management.

We also compute the mean variations of groundwater over a square grid with the dimensions of 2° in 2° cover the whole of Urmia Lake with the coordinates of 37° to 39° in latitude and 44° to 46° in longitude. There are two reasons for selection of this grid, one is the determination of groundwater storage variations in Urmia Lake as an important water resource of Iran and the other is that this region contains some pisometric wells which can be used for validation of our results as we are doing at the sequel. The groundwater storage variations in this area determined by both wavelet and filtering approaches from 2003 to April 2014 are shown in Figures 11 and 12. By the wavelet approach, the maximum decrease in groundwater variation is -45 mm in 2011 and about -20 mm in 2008, 2010, and 2013. The maximum increase in groundwater variation is about 20 mm in 2005. With the filtering approach,

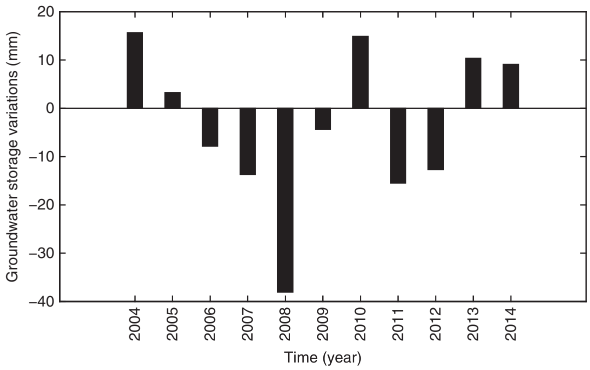

Figure 12. Mean variations amplitude of groundwater by filtering over Urmia Lake.

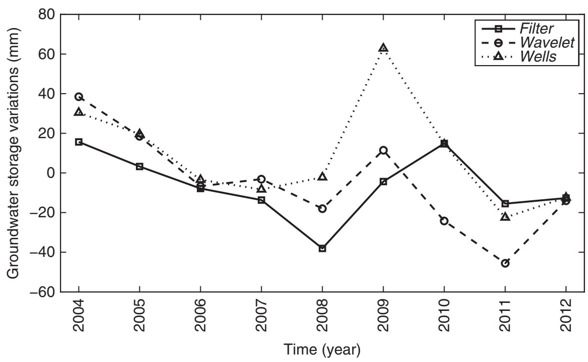

Figure 13. The time series of yearly groundwater storage variations between wavelet, filtering, and pisometric wells.

the maximum decrease in groundwater variation is about −40 mm in 2008 and about 15 mm in 2004 and 2010. The amplitudes of these mean variations of groundwater over Urmia Lake demonstrate that groundwater level in whole of this region have decreased each year and if continue in this way, it may lead to catastrophic environmental problems, such as decreasing in water level, loss of inhabitant species, storm salt build up, the permeation of saltwater into the plains near the lake, wide climate change in the region, reduction of the fertility of agricultural land, and disruption of the qualitative and quantitative interaction in the groundwater of the region.

As we have stated in the preceding argument, in order to validate the results of our analysis, we show the accordance of their time series with pisometric wells measurements located near the Urmia Lake. Figure 13 shows the yearly groundwater storage variations on the selected grid using both GRACE-GLDAS and groundwater wells level data from 2003 to 2012 (Equations 8 and 9). As shown in this Figure 13, there is a consistency between wavelet approach and observation data of wells. Moreover, from 2009 to 2010, well levels have a maximum amplitude of 60 mm which is consistent neither with Gaussian filtering nor with wavelet outputs. The discrepancy observed in these years may be explained by the leakage error in the GRACE observation (Baur et al. 2009; Guo et al. 2010) or by the errors in the groundwater storage variations introduced by the spatial aggregation of point well measurements, as well as the use of an average specific unique yield to calculate groundwater storage changes. The limited amount of well measurements, the limited spatial resolution of GRACE data, and sparse well measurements could be mentioned as the other sources of this discrepancy.

Also for a better check, we show the stochastic correlations of wavelet and Gaussian filtering with pisometric well measurements available nearby the Urmia Lake. In this case, the statistical quantity, namely, a correlation coefficient is computed which shows the degree of compatibility between the results of our analysis and observation data. The computed correlation coefficient between filtering approach and groundwater level data is $R^2 = 0.49$ while this correlation with wavelet approach is $R^2 = 0.70$ which shows that wavelet analysis is more compatible and has more accurate estimation of groundwater storage variations. Also regression analysis as a simple linear regression model used for prediction and forecasting is computed as $y = 0.9x + 16$ and $y = 0.78x + 14$ for wavelet and Gaussian filtering, respectively. The values that obtained in regression model are calculated using the least squares method.

Conclusions

In this study, groundwater storage variations have been computed by a combination of GRACE data and GLDAS model during January 2003 to April 2014. To do so, groundwater storage variations are estimated by subtracting the soil moisture, snow water equivalent, and total canopy water storage which are the outputs of GLDAS model, from TWS variations determined by GRACE observations. Because of stripping errors in the GRACE data, two methodologies based on wavelet analysis and Gaussian filtering are applied to refine the GRACE data. It is shown that the wavelet approach is more consistent with in situ measurements of pisometric wells drilled around the Urmia Lake. In comparison with Gaussian filtering approaches, the wavelet method could better localize the desired signal by increasing the signal-to-noise ratio over the selected region which causes the increase in the accuracy of estimation. Particularly, the correlation analysis leads to correlation coefficient for the wavelet analysis of about $R^2 = 0.70$ and Gaussian filtering of about $R^2 = 0.49$. The results showed that wavelet estimation are in good accordance with the limited available wells groundwater data in the region.

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