Wavelet analysis of GRACE K-band range rate measurements related to Urmia Basin

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Abstract

Space-borne gravity data from Gravity Recovery and Climate Experiment (GRACE), as well as some other in situ and remotely sensed satellite data have been used to determine water storage changes in Lake Urmia Basin (Iran). As usual, the GRACE products are derived from precise inter-satellite range rate measurements converted to different formats such as spherical harmonic coefficients and equivalent water thicknesses of juxtaposed tiles in which the corresponding mass anomalies are estimated, resulting in missing information during these time-consuming processes. In this paper, GRACE level 1B K-band range rates related to Urmia Basin are corrected for non-hydrological processes and the resulting time series are analyzed using wavelet transformation. On the one hand, direct corrected range rates are employed to make an unevenly spaced time series. In addition, the monthly mean measurements of the same type are applied to create a uniform time series. Therefore, a wavelet-based least-squares spectral analysis method is introduced to extract the general behavior of irregularly sampled time series. In addition, the classical wavelet transformation is used to analyze the monthly averaged time series. The results indicate that the extracted coarse parts of the corrected range rates have significantly changed between 2007 and 2008, which are in good agreement with the total water storage (TWS) changes modeled in Urmia Basin, as well as with the similar previous research findings. Besides, the time-frequency behavior of both TWS changes and monthly averaged range rate time series show that the extracted annual constituents, as the main parts of the signals, have mainly weakened after 2007.

Keywords: GRACE, least squares approximation, time series analysis, wavelet transform, Urmia Basin

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1   Introduction

In the late 1990s, Lake Urmia, in the northwest of Iran, was twice as large as Luxembourg and the largest salt-water lake in the Middle East. The lake and its basin have suffered a rapid drying up (by nearly 90%) since the 1970s. Its desiccation will result in increasing the frequency of salt storms and causing the farmers to move away. Poor air, land and water quality will seriously affect the health. Its drying up is destroying one of the world's largest natural habitats for migratory of birds (Mirchi et al., 2015).

Thanks to recent modern space-born approaches, an effective and uniform monitoring of desiccation of the lake or its basin has been reached during the first decade of the 21st century. Especially, the Gravity Recovery and Climate Experiment (GRACE) mission -launched in March 2002 - has globally mapped the temporal variations of the Earth's gravity field that relates to the climate change phenomena (Han et al., 2005). Some investigations have used different types of GRACE data, individually or together with other remote sensing or land surface observations, in order to monitor water storage patterns in the region including Lake Urmia. For example, Fatolazadeh et al. (2016) applied GRACE Total Water Storage (TWS) changes in conjunction with Global Land Data Assimilation System (GLDAS) outputs to resolve groundwater storage changes in Iran during January 2003 to April 2014. They also computed the mean variations of groundwater over a square grid with the dimensions of 2×2 covering the whole Lake Urmia using the GRACE data. Joodaki et al. (2014) studied human contribution to groundwater depletion in the Middle East using the GRACE and land surface models. Tourian et al. (2015) introduced a multi-sensor scheme based on satellite imagery (Moderate Resolution Imaging Spectroradiometer (MODIS) surface reflectance), satellite altimetry (Environmental Satellite (ENVISAT) and CryoSat-2) and satellite gravimetry (GRACE GFZ (GeoForschungsZentrum) Release 05) to extract the water storage behavior in Lake Urmia. Forootan et al. (2014) proposed a statistical approach to separate large scale patterns of water storage changes over the main basins of Iran between 2002 and 2011, using the monthly TWS variations derived from GRACE (GFZ release 04 gravity eld solutions), the surface WS changes from satellite altimetry, the terrestrial WS changes from GLDAS and the in-situ piezometric observations. They reported that the terrestrial WS in most parts of Iran, including Urmia basin, exhibited a mass decrease since 2005. Voss et al. (2013) estimated the groundwater depletion in the Middle East using GRACE observations from 2003 to 2009. Several other studies have used the GRACE gravity products to monitor water storage pattern globally or in other regions (see for example, Awange et al., 2011; Cao et al., 2015; Fatolazadeh et al., 2017; Frappart et al., 2013; Han et al., 2005; Mulder et al., 2015; Rahimi and Raoofian Naeeni, 2017; Ramillien et al., 2012; Rodell et al., 2007; Rowlands et al., 2010; Seoane et al., 2013 and Syed et al., 2008).

In all of the above-mentioned approaches, the desired hydrological signals have been extracted from different GRACE products such as spherical harmonic (Stokes') coefficients and equivalent water thicknesses of juxtaposed tiles, which are mainly estimated using precise inter-satellite K-band range rate measurements, available to the scientific community as Level-1B data, namely the raw satellite products after a low-pass filter and time correction (Chen, 2007), resulting in missing information during the smoothing process. In addition, these procedures are inherently time-consuming. Han et al.

(2009) analyzed differences between four years of actual GRACE range rate observations from 2003 to 2007 (in the form of some different sections of along-track range rates) and the predicted range rate perturbations from various terrestrial water storage models, related to Amazon basin to study the impacts of the total terrestrial water storage components on the relative distance change between the two GRACE satellites over the region. Moradi and Sharifi (2016) employed the range rates directly to extract the spectral behavior of the range rates time series related to Iran's main catchments using Windowed Least-Squares Spectral Analysis (WLSSA) led to the study of time-frequency contents of the monthly averaged range rate time series.

By extracting the range rates related to Urmia basin, which are corrected for non-hydrological processes, such as tide and nongravitational accelerations, an unevenly spaced time series can be created; and simultaneously, a uniform time series can be produced by monthly averaging the corrected measurements. It seems that the resulting signals are more local in nature.

The wavelet transformation is employed as the mathematical tool in this paper to study the trend and extract the time and frequency behavior of the time series. Besides the well-known classical wavelet analysis, restricted to the data sets of equally spaced samples such as monthly averaged range rates, here, a wavelet-based least-squares spectral analysis method is introduced to extract the general behavior of the unequally spaced instantaneous corrected range rates related to the basin.

Finally, the results of the wavelet-based analysis of the monthly range rate time series are compared with those of the monthly modeled Total Water Storage changes related to the basin, which have been extracted from Water - Global Assessment and Prognosis

(WGAP) hydrological model (Döll et al., 2003).

2 Methods

2.1 Introduction to wavelets and wavelet transformation

If a signal or function is expanded to a linear combination of some real-valued functions as the bases for the space containing the signal, then the analysis, representation and processing of that signal will be efficiently possible (Burrus et al., 1997); this is the base of spectral analysis. Accordingly, the wavelet expansion of a function f(t) is written as below (Burrus et al., 1997):

$$f(t) = \sum_{k=-\infty}^{+\infty} \sum_{j=-\infty}^{+\infty} d_{j,k} \psi_{j,k}(t), \qquad (1)$$

where, $d_{j,k}$ is the expansion coefficient at scale j and time translation k, and the wavelets $\psi_{j,k}(t)$, as the base functions, are made by translating and stretching a main producer function, known as the mother wavelet $\psi(t)$ (Burrus et al., 1997):

$$\psi_{j,k}(t) = \psi(2^j t - k). \qquad (2)$$

The expansion coefficients, which can be computed using the inner product of $f(t)$ with $\psi_{j,k}(t)$, are known as the discrete wavelet transform of $f(t)$, and Equation (1), which reconstructs the original signal, is the inverse discrete wavelet transformation.

In the wavelet analysis language, sometimes, another format of using wavelets to represent the signals equivalent to Equation (1) is constructed using some other bases called scaling functions $\varphi_k(t)$, along with wavelets, in order to separate the coarse part of the signal from its details (Burrus et al., 1997). The scaling functions are translated versions of a producer function $\varphi(t)$, sometimes called the father wavelet.

Analogous to expression (1), any given function can be expanded using both scaling and wavelet functions as follows (Burrus et al., 1997):

$$f(t) = \sum_{k=-\infty}^{+\infty} c_k \varphi(t-k) + \sum_{k=-\infty}^{+\infty}\sum_{j=0}^{+\infty} d_{j,k}\psi(2^j t - k). \qquad (3)$$

In the above expression, the first part consists of the coarse information of the function and the details are reflected at the second part so that the larger the index j, the more details are added.

Wavelet transformation maps a function to a set of two dimensional discrete coefficients as a measure of similarity between the function and wavelets. Therefore, this technique analyzes the transformed signal from both time and frequency points of views. Any change in k results in a change in the position of the base function (wavelet) in the time-domain. Similarly, any alteration in j changes the wavelet's width, and consequently the resolution of the extracted information.

2.2   Wavelet-based least-squares spectral analysis

Since unequally spaced wavelets are not defined, the classical wavelet transformation requires equally-spaced data. In addition, it is not suitable to apply this transformation (based on its definition) to unequally weighted time series; on the other hand, the second generation wavelets (Sweldens, 1998), which are able to apply the unevenly data, are not appropriate for analyzing unequally weighted time series. For this reason, a wavelet-based least-squares spectral analysis (WBLSSA) is proposed as an application of Least-Squares Approximation (LSA) (Vaníček and Wells, 1972), analogous to the classical Least-Squares Spectral Analysis (LSSA),

which is closely related to the linear least-squares parametric adjustment (Wells et al., 1985). The proposed wavelet-based method is also capable of estimating the coarse part of the signals, regardless of whether the samples are equally spaced and equally weighted or not.

Given a vector of observations $f = \{f_i\}$, i=1, 2, …, n, sampled at uniform or non-uniform time instants $\{t_i\}$, a parametric model can be set up as follows (Vaníček and Wells, 1972):

$$\mathbf{f}(t) = \sum_i c_i \varphi_i(t) = \mathbf{\Phi c}, \qquad (4)$$

where, $\mathbf{\Phi}$, is a matrix consisting of several column vectors, as base functions, each of which have the same dimension as $\mathbf{f}$, and $\mathbf{c}$ is the vector of unknown coefficients.

In the classical LSSA, the form of the base functions is selected to be trigonometric based on a set of given frequencies ω_j , j=1, 2, …, m, and for each selected frequency, the best fitting approximant $\mathbf{p}$ to $\mathbf{f}$ will be obtained by minimizing the residual vector $\hat{\mathbf{v}} = \mathbf{f} - \mathbf{p}$ in the least-squares sense as follows (Vaníček and Wells, 1972):

$$\mathbf{c} = [c_1\ c_2]^T = (\mathbf{\Phi}^T\mathbf{\Phi})^{-1}(\mathbf{\Phi}^T\mathbf{f})$$
$$\mathbf{p}(\omega_j) = c_1\cos\omega_j t + c_2\sin\omega_j t \qquad (5)$$

Then the corresponding spectral value $s(\omega_j)$, which is equivalent to the fractional content of f represented by $\mathbf{p}(\omega_j)$, can be measured by (Vaníček and Wells, 1972):

$$s(\omega_j) = \frac{\mathbf{f}^T\mathbf{p}(\omega_j)}{\mathbf{f}^T\mathbf{f}}. \qquad (6)$$

Similarly, the wavelet-based least-squares spectral analysis method can be developed by the use of wavelets as the base functions in the parametric model represented by Equation (1). According to Equation (1), at any desired scale and time, the parametric model (4) can be rewritten as:

$$\forall k = K, j = J; \mathbf{f} = \begin{bmatrix} f_1 \\ \\ f_n \end{bmatrix}$$

$$= \begin{bmatrix} \psi(2^J t_1 & K) \\ \\ \psi(2^J t_n & K) \end{bmatrix} d_{J,K} = \mathbf{\Phi c} \qquad (7)$$

Therefore, the least-squares estimation of wavelet coefficient $d_{J,K}$, and consequently, the best fitting approximant $\mathbf{p}(K,J)$ to $\mathbf{f}$ will be computed for each selected scale and translation parameter as below:

$$\mathbf{c} = \hat{d}_{J,K} = (\mathbf{\Phi}^T\mathbf{\Phi})^{-1}(\mathbf{\Phi}^T\mathbf{f})$$

$$\mathbf{p}(K,J) = \begin{bmatrix} \psi(2^J t_1 & K) \\ \\ \psi(2^J t_n & K) \end{bmatrix} \hat{d}_{J,K} \qquad (8)$$

Finally, the spectral value corresponding to the selected scale (pseudo-frequency) and translation parameter is obtained as:

$$s(K,J) = \frac{\mathbf{f}^T\mathbf{p}(K,J)}{\mathbf{f}^T\mathbf{f}} \quad . \qquad (9)$$

The obtained spectrum not only contains the information about the frequency (scale) contents of the signal, but also contains the time of occurrence of these frequencies. This is a valuable feature of the WBLSSA that has not been considered in the classical LSSA.

Similar to the classical wavelet analysis and based on the expression (3), the parametric model (4) can be rewritten by using the scale functions and wavelets:

$$\forall k = K, j = J; \mathbf{f} = \begin{bmatrix} f_1 \\ \\ f_n \end{bmatrix}$$

$$= \begin{bmatrix} \varphi(t_1 & K) \ \psi(2^J t_1 & K) \\ \\ \varphi(t_n & K) \ \psi(2^J t_n & K) \end{bmatrix} \begin{bmatrix} c_K \\ \\ d_{J,K} \end{bmatrix} =$$

$$\mathbf{\Phi c} \qquad (10)$$

And the process will continue like before, with the difference that here it is

preferred to get the Least-Squares estimation of the expansion coefficients instead of the corresponding spectrum. The desired coefficients are estimated as follows:

$$\mathbf{c} = \begin{bmatrix} c_K \\ \\ \hat{d}_{J,K} \end{bmatrix} = (\mathbf{\Phi}^T\mathbf{\Phi})^{-1}(\mathbf{\Phi}^T\mathbf{f}) \qquad (11)$$

where, c_K and $\hat{d}_{J,K}$ are the Least-Squares Estimation of approximation and detail coefficients, respectively.

2.3 Selecting the base functions

One of the specific properties of wavelet analysis is the capability of selecting or designing the base functions applied in the transformation. Besides some characteristics of mother wavelets such as orthogonality, compact support, symmetry and vanishing moments that generally alter the results of transformation, more than one mother wavelet with the same properties often exists. Therefore, various qualitative and quantitative schemes have been developed to choose suitable base functions based on the similarity between the intended signal and mother wavelet (Ngui et al., 2013).

Here, based on previous information, the general behavior of the signals is going to be extracted under investigation similar to what has been illustrated in Figure 1.a. Therefore, in the first step, the similarity between this pattern and various wavelet base functions was examined using the maximum cross correlation coefficient criterion (Jacobs, 2005). The results were almost alike; therefore, suitable bases are chosen by trial and error, which led to the selection of Daubechies 6 base wavelet as the best estimator of the corresponding milestone moments shown in Figure 1.a, as evident in Figure 1.b.
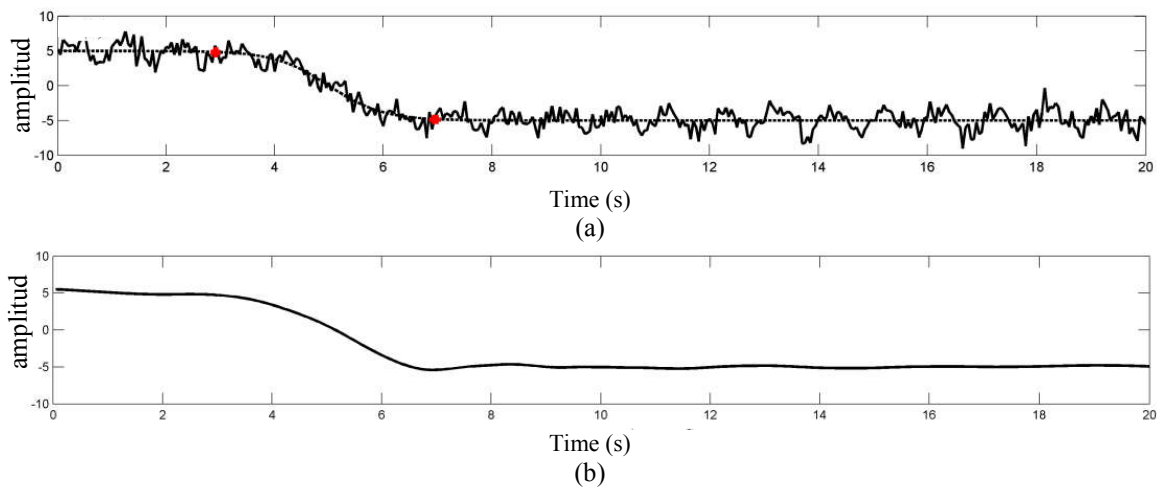
Figure 1. (a) A reference signal, which indicates the expected behavior of the time series under investigation. Red signs show the instants when the signal changes mainly; (b) Extracted coarse part of the time series obtained by the DWT using db6.

In addition, if one is primarily interested in the wavelet power spectra, then the choice of wavelet function is not critical, and one function will give the same qualitative result as another (Torrence and Compo, 1998).

3 Data analysis, results and discussion

Lake Urmia in the North West of Iran is the largest lake in the Middle East and its basin is a closed drainage basin (i.e. no outlet) with an area of about 51876 km^2 with high mountain areas, foothills, and plains.

Among different types of the GRACE data products (Chen, 2007), in this study, the GRACE LEVEL 1B measurements including the inter-satellite K-band range rates (KBRR) with an accuracy of 0.1 μm/s as the main data, the non-gravitational accelerometer measurements (ACC1B), the precise satellite positions (GNVB) and the satellite's absolute orientation with respect to the ICRS provided by the Star Camera Assembly (SCA1B), in the period of January 2003 to December 2012 are used (GRACE LEVEL 1B JPL RELEASE 2.0. Ver. 2. PO.DAAC, CA, USA) (Case et al., 2002). The range rate measurements are corrected for the

effects of non-hydrological processes according to Moradi and Sharifi (2016), then two types of time series are produced using corrected range rate measurements related to Urmia basin, in the following two manners:

- Extracting a uniform time series by monthly averaging of the corrected observations related to the basin (based on the degree of relevance of each observation to the basin, a weight that is proportional to the percentage of the basin area covered by the instantaneous relative position vector between two satellites is assigned to that observation and the monthly quantities are computed as a weighted mean).

- Exploiting an unevenly-spaced time series based on the direct corrected range rates corresponding to every pass of the satellites over the basin.

The classical discrete wavelet transformation and the proposed wavelet-based least-squares spectral analysis are utilized to scrutinize the above-mentioned signals, respectively.

Figure 2 illustrates the monthly averaged range rates as the raw signal along with its coarse parts at scales up to 5 computed using the expression (9), in

which the general trend of the time series can be inferred. Since the aim is to focus on the entire signal, the relevant details have not been displayed. The most significant change in the behavior of the observed signal can be distinguished between 2007 and 2008, indicating the decreased total water storage in the basin in this period, which leads to the increasing of the range rate measurements. Due to the lack of observation in Urmia Basin during September and October 2004, the

monthly range rates have been interpolated for those two months in the mentioned time series.

Because of the relatively long gap in 2004, the second signal is constructed by considering the direct range rates since the beginning of 2005. Applying the wavelet-based least-squares spectral analysis using wavelets and scaling functions, the general behavior of the corrected range rate signal is investigated. The raw signal and its coarse part are depicted in Figure 3.
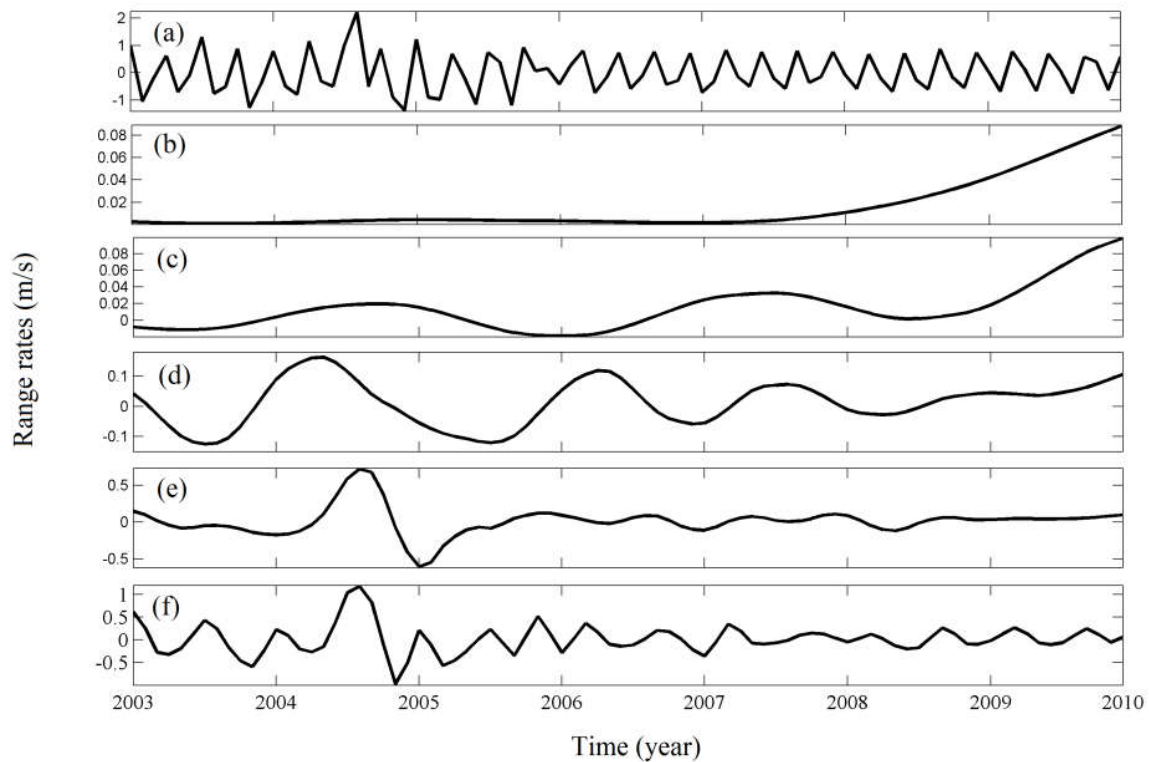

Figure 2. (a) Monthly averaged GRACE K- band range rates related to Urmia basin; (b), (c), (d), (e) and (f) Extracted coarse parts of the time series at scales 5, 4, 3, 2 and 1, respectively, obtained by the DWT.
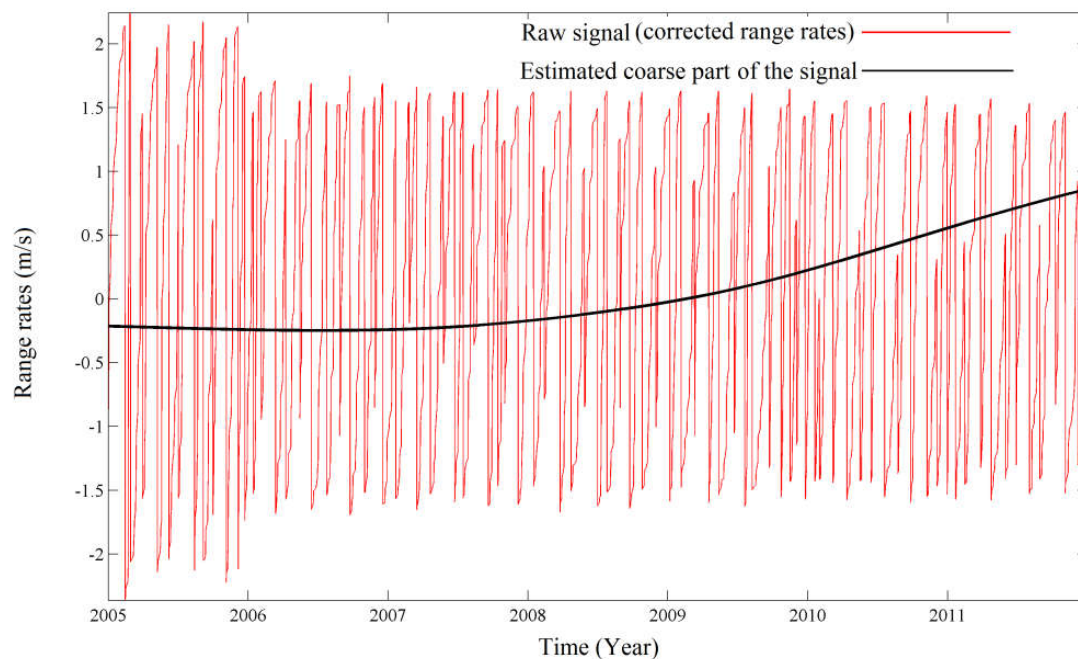
Figure 3. Unevenly spaced corrected range rates related to Urmia basin (red) and the estimated coarse part of the range rates signal based on WBLSSA (black).

Qualitatively, similar to the monthly signal, the moment of principal switching mode in the instantaneous signal that occurred between 2007 and 2008 is evident.

In order to compare the corrected range rate signals and model predictions, the monthly total water storage changes between 2003 and 2010 related to Urmia basin obtained from WGAP hydrological model, which simulates continental water flows and storages as well as human water use for all land areas of the globe excluding Antarctica with a spatial resolution of $0.5° \times 0.5°$ (Döll et al., 2003), have been analyzed using classical discrete wavelet transformation, and the results have been depicted in Figure 4. As expected, the main alterations in the total water storage change signals happened between 2007 and 2008 again, in the opposite direction of the major range rate signal change. At the same time, these results are in line with those of the previous similar researches, which were reviewed earlier in the introduction (Fatolazadeh et al., 2016; Joodaki et al.,

2014; Moradi and Sharifi, 2016; Tourian et al., 2015; and Voss et al., 2013).

As it can be seen in Figures 2 and 4, the extracted coarse parts of the range rates and the modeled total water storage changes at the scales 3 to 5 are more similar to each other than the corresponding coarse parts related to the scale 1 and 2 due to the impact of the finer components of the signals.

In addition to disclosing significant changes and the time of their occurrence, it would be useful to study and compare the frequency contents of the above-mentioned signals using the classical continuous wavelet transformation. Taking into account the sampling rate, the monthly time series are compared. These series are transformed and the results are displayed in Figures 5 and 6. To clarify the significance of a pick in the wavelet power spectrum, the 95% confidence levels for the time series are shown by the thick contours on both figures using the corresponding white-noise spectrum (Torrence and Compo, 1998). According to Torrence and
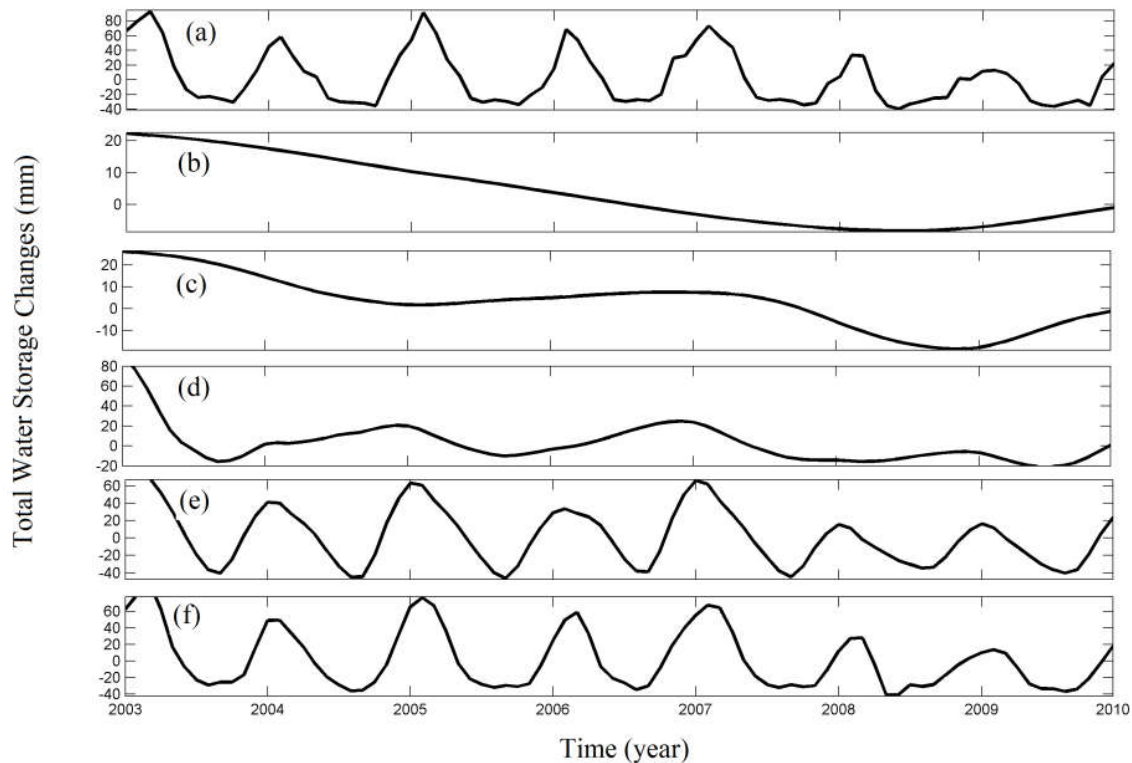
Figure 4. (a) Monthly modelled total water storage changes in Urmia basin; (b), (c), (d), (e) and (f) Extracted coarse parts of the time series at scales 5, 4, 3, 2 and 1, respectively, obtained by the DWT.

Compo (1998), the theoretical white noise wavelet power spectrum is used to establish a null hypothesis for the significance of a peak in the wavelet power spectrum. The null hypothesis is defined based on the assumption that the time series has a known mean power spectrum (see Equation (16) in Torrence and Compo, 1998), such that if a peak in the wavelet power spectrum significantly above this background spectrum, it can be assumed to be a true attribute with a certain confidence.

It is worth noting that some previously known periods in the range rate signal, associated with GRACE orbital configuration (Visser, 2005), are initially filtered and the resulting spectrum is derived from hydrological impacts. The main filtered component has a period of three months (see Figure 2.d) and the remaining part of the monthly range rates corresponds to what it is seen in Figure 2.e.

As it can be seen in the above periodograms, the main constituent with the period of about 12 months exists in both time series corresponding to the main hydrological cycle in the basin rooted in the annual circulation of the atmosphere. These annual components are considerably weakened after 2007, which can be explained as a result of the reported drought in the region (Joodaki et al., 2014, Voss et al., 2013 and Tourian et al., 2015).

The weakening of the annual components of both corrected range rate and TWS change time series can also be clearly seen in Figures 2.d and 4.e. Although, according to Figures 2.a and 4.a, the corrected range rates show a positive trend, contrary to the decreasing trend of TWS resulted from the overall reduction of the water storages in the basin.
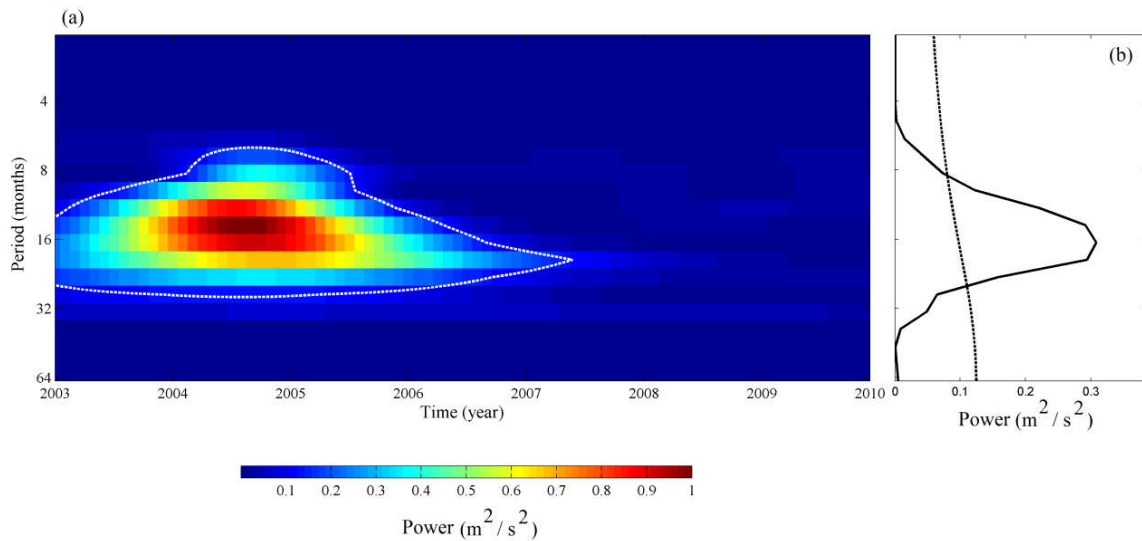
Figure 5. (a) Wavelet power spectrum of the monthly corrected range rates related to Urmia basin (after filtering of the known components associated with GRACE orbital configuration); the dashed contour is the 5% significance level using a white-noise background spectrum; (b) The global wavelet power spectrum (black line). The dashed line is the significance for the global wavelet spectrum assuming the same significance level and background spectrum as in (a).
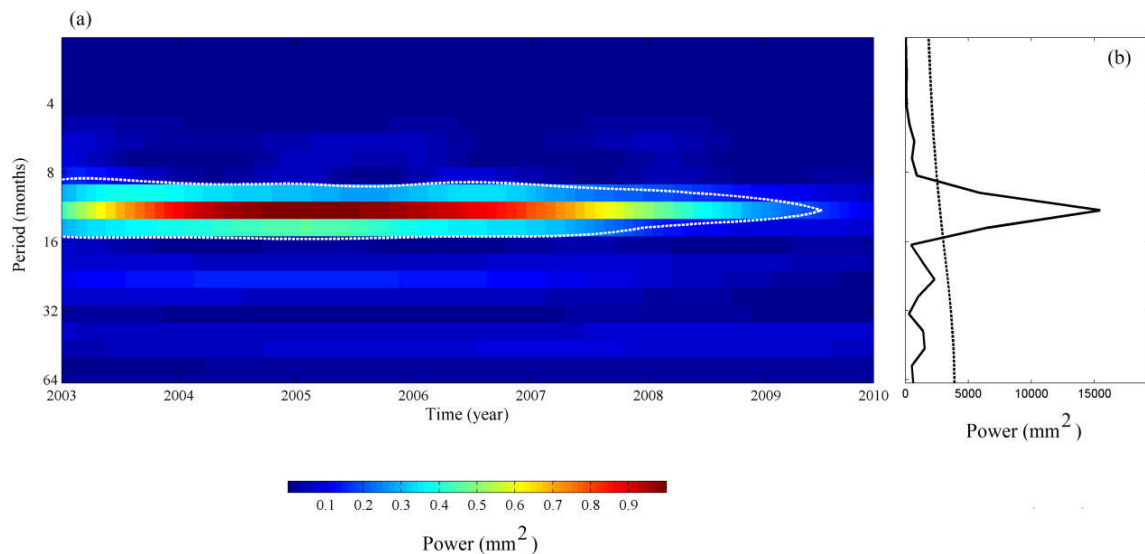

Figure 6. (a) Wavelet power spectrum of the monthly modelled TWS changes related to Urmia basin; the dashed contour is the 5% significance level using a white-noise background spectrum; (b) The global wavelet power spectrum (black line). The dashed line is the significance for the global wavelet spectrum assuming the same significance level and background spectrum as in (a).

4   Conclusions

To sum up the main points of the present paper in a few words, the following statements can be stated:

▪ Typically, GRACE level 1B measurements are used to estimate

other Earth-related quantities such as potential, and then the hydrological information are studied in this way. In this paper, these measurements are directly used to create raw time series mainly affected by hydrological events in a given area (Urmia basin here).

- The main concern of our research was the wavelet analysis of the (instantly and monthly) range rate time series related to Urmia basin to extract the time-frequency behavior of the series as well as their general treatment during the period under study, no need to convert them to gravity products.
- The hydrological constituents of the range rate observations are extracted by reducing the contributions to range rates from tide and non-gravitational accelerations.
- Different time series were analyzed efficiently by using the classical wavelet transformation and our proposed WBLSSA method.
- The results of the wavelet analysis of the GRACE level 1B measurements related to Urmia basin are in good agreement with those of TWS changes and previous researches, which imply the overall reduction of the water storages in the basin, mainly resulted from the reported regional drought started around 2007.
- The comparison between similar results pertaining to other adjacent basins and extracting the probable common behavior can be useful.
- Wavelet-based least-squares spectral analysis can detect the signal behavior, although its effectiveness in extracting different frequency contents of the signals along with the moment of their occurrence should be examined further.
- A regional monitoring system, especially based on geodetic space-born sensors such as GRACE, is required to track the water cycle and monitoring water storage changes in our study area.

Acknowledgements

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