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revolutionize the study of basin-scale hydrology, because gravity data reflect mass changes related to ground and surface water redistribution, ice melting, and precipitation accumulation over large scales. However, to use the GRACE data products, de-striping/filtering is required. We applied the multichannel singular spectrum analysis (MSSA) technique to filter GRACE data and separate its principal components (PCs) at different periodicities. Data averaging over the 15 largest river basins of Russia was performed. Spring 2013 can be characterized by the extremely large snow accumulation occurred in Russia. Melting of this snow induced large floods and abrupt increase of river levels. The exceptional maxima are evident from GRACE observations, which can be compared to the hydrological models, such as GLDAS or WGHM, and gauge data. Long-periodic climate-related changes were separated into PC 2. Finally, it was observed that there were mass increases in Siberia and decreases around the Caspian Sea. Overall trend over Russia demonstrates mass increase until 2009, when it had a maximum, followed by the decrease.

| Keywords (separated by “-“) | Earth’s gravity field - GRACE - Hydrological changes - MSSA |
Chapter 3
Gravity Changes over Russian River Basins from GRACE

Leonid V. Zotov, C.K. Shum, and Natalya L. Frolova

Abstract  Gravity Recovery and Climate Experiment (GRACE) twin satellites have been observing the mass transports of the Earth inferred by the monthly gravity field solutions in terms of spherical harmonic coefficients since 2002. In particular, GRACE temporal gravity field observations revolutionize the study of basin-scale hydrology, because gravity data reflect mass changes related to ground and surface water redistribution, ice melting, and precipitation accumulation over large scales. However, to use the GRACE data products, de-striping/filtering is required. We applied the multichannel singular spectrum analysis (MSSA) technique to filter GRACE data and separate its principal components (PCs) at different periodicities. Data averaging over the 15 largest river basins of Russia was performed. Spring 2013 can be characterized by the extremely large snow accumulation occurred in Russia. Melting of this snow induced large floods and abrupt increase of river levels. The exceptional maxima are evident from GRACE observations, which can be compared to the hydrological models, such as GLDAS or WGHM, and gauge data. Long-periodic climate-related changes were separated into PC 2. Finally, it was observed that there were mass increases in Siberia and decreases around the Caspian Sea. Overall trend over Russia demonstrates mass increase until 2009, when it had a maximum, followed by the decrease.

Keywords  Earth’s gravity field • GRACE • Hydrological changes • MSSA
3.1 Introduction

Space-based Earth Observing Systems provided a substantially large amount of information to the scientific community in the recent decades. One of the most important contributions of these data sets is their use to study climate change. Cumulative effects of redistribution of masses in the Earth system can be seen in the changes of the gravity field of the Earth. Gravimetry is a science with a long history. Gravity measurement techniques for land and ocean have been developing all over the twentieth century. But only the space era opened the possibility to study global gravity field and its changes over a planetary scale, including inaccessible distant regions.

Technological achievements of our epoch – the NASA/DLR Gravity Recovery and Climate Experiment (GRACE) twin satellites mission was launched on 17.03.2002 from Plesetsk kosmodrom. It allows the observations of monthly changes in Earth’s gravity field with unprecedented accuracy, working already for 11 years by the time of our study, which is twice more than expected. Though the battery power is ten times less than at a launch time, there is a possibility that the mission period could be extended till 2017, when the GRACE Follow-on Mission is anticipated to be launched.

GRACE satellites fly in a near-polar orbit at ~500 km altitude following one another at a distance of ~220 km. Accelerations of each satellite, occurring during the flight above the Earth’s mass anomalies, influence the range between the two GRACE satellites. Microwave K-band range measurements represent the fundamental observational data, containing information about the gravity field. Data centers located at GFZ (Potsdam), CSR (Austin), and JPL (Pasadena) process these data, taking into account onboard GPS, accelerometers, star cameras, etc, to produce the level one (L1) data products (Case et al. 2004). Then through sophisticated gravity field inversion techniques with regularization (Tikhonov et al. 1998; Wang et al. 2012), correcting the aliasing effects of the atmospheric pressure changes over land and over ocean, applying solid Earth, ocean and pole tides, and other corrections, level 2 (L2) data product (Bettadpur 2007) is obtained, representing monthly gravity field in form of Stokes coefficients (3.1) of spherical decomposition on the surface of Earth’s mean radius (Panteleev 2000; Sagitov 1979).

Modeling of the mean gravitational field is the primary goal of the space gravity missions (Kenyon et al. 2007). Contemporary models incorporate information, obtained from CHAMP, GRACE, and GOCE satellites. But GRACE also provides monthly anomalies (1 month is required to cover the Earth). If the mean model is subtracted from the GRACE monthly Stokes coefficient, it is possible to see month-to-month changes with several microgals accuracy (1 Gal = 0.01 m/s²) and spatial resolution of ~300 km. Monthly L2 files are accessible from GFZ, CSR, and JPL archives, but one needs to mitigate, for example, removing or filtering, the meridional correlated high-frequency noise patterns, called stripes. The source of these noises is the same polar orbit of the satellites, imperfect observability of the gravity signals, etc. Scientific teams are developing various methods of stripe filtering, discussed below.
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GRACE data can be used in geophysical, glaciological, oceanographic, and hydrological studies. Earth rotation research, geodynamics, and climate change studies also benefit from this mission. A wide range of GRACE science and applications have been extensively published in journals or presented in international assemblies.

For the largest country in the world, Russia, not fully covered by meteorological and hydrological observational networks, GRACE data are especially useful. By spring 2013 it became clear that Russia has gone through a very snowy winter. Near Moscow the thickness of snow exceeded up to twice the nominal value and was more than 70 cm. The questions aroused: can it be detected by GRACE?

In this work the study of regional changes of the gravity field from GRACE over Russia will be presented. A novel data processing technique – multichannel singular spectrum analysis (MSSA) – will be applied for the GRACE data filtering toward improved separation of various signal components, related to hydrological, seasonal, and climatological changes. Initial data and method will be presented in the next section, and results of processing will be presented in Sect. 3.3, followed by discussions and conclusion.

### 3.2 Data Processing

#### 3.2.1 Initial Data Preparation

We used JPL Level-2 RL05 GRACE monthly geopotential field data from 01.2003 through 06.2013 with the set of Stokes coefficients complete to degree 60. Release 5 (RL05) of the L2 data product is more accurate than the previous version (RL04) primarily because of GRACE data and model improvement. Six months of data (06.03, 01.11, 06.11, 05.12, 10.12, 03.13) were linearly interpolated (overall, \( N = 126 \) files were used). Absence of some of these monthly solutions in the recent years is caused by the difficulties in battery power maintenance on board.

The spherical harmonic decomposition of the gravity field is given by

\[
V(\varphi, \lambda, r) = \frac{GM}{r} \sum_{n=2}^{\infty} \sum_{m=0}^{n} \left( \frac{a}{r} \right)^n (C_{nm} \cos m\lambda + S_{nm} \sin m\lambda) P_n^m(\sin \varphi),
\]

where \( C_{nm} \), \( S_{nm} \) are normalized Stokes coefficients, representing the exterior geopotential spherical harmonic expansion, \( n \) is the degree, \( m \) is the order of the spherical harmonics, \( P_n^m \) are the fully normalized associated Legendre polynomials, \( a \) is the mean equatorial radius of the Earth, and the arguments \( \varphi, \lambda, r \) are latitude, longitude, and radius, respectively (Panteleev 2000).

The coefficients of zero and first degree are set to zero due to the choice of the coordinate system. GRACE is insensitive to degree-one coefficients (geocenter). Estimates of \( C_{20} \) (oblateness) coefficients from GRACE are not very reliable; they were replaced by SLR-derived solutions. Since we are interested in the monthly
changes, the averaged field over 10 years was subtracted from the GRACE monthly Stokes coefficients. GIA correction was also applied according to Paulson et al. (2007) model. Finally, the results were converted to the surface mass changes in terms of equivalent water height (EWH) level (cm), according to Wahr et al. (1998).

$$\Delta h(\varphi, \lambda, t) = \frac{2 \pi p_{ave}}{3 p_w} \sum_{n=2}^{60} \sum_{m=0}^{n} \frac{2n + 1}{1 + k_n} W_n(\Delta C_{nm}(t)) \cos m\lambda$$

$$+ \Delta S_{nm}(t) \sin m\lambda) P^m_n(\sin \varphi),$$

where $\Delta C_{nm}(t)$, $\Delta S_{nm}(t)$ are normalized Stokes coefficient differences with respect to the mean (model); $p_{ave}$ and $p_w$ are average densities of the Earth and seawater, respectively; $k_n$ is the load Love number of degree $n$; and $W_n$ is a filter coefficient. All spectral filter coefficients in Eq. (3.2) were set to one, so we did not apply any filtering except MSSA.

### 3.2.2 Multichannel Singular Spectrum Analysis Method

Filtering of GRACE data is needed, because they contain meridional error – stripes. Such errors are primarily due to the fact that GRACE satellites are in the same polar orbit and satellite-to-satellite tracking only observes along-track direction, causing the gravity field inversion problem to be near singular.

The orbital and instrument errors are correlated in the resonant orders of the spherical harmonic Stokes coefficients, causing the so-called stripes high-spatial-frequency errors. An unfiltered map, obtained as the difference between January 2003 and January 2013 initial data, is shown in Fig. 3.1.

Different authors use a variety of filtering methods to minimize stripes and reduce noises in the GRACE monthly gravity field solutions. Among them are Gaussian filtering with symmetric and asymmetric Gaussian function (Han et al. 2005), Wiener (Klees et al. 2007) and regularizing (Kusche et al. 2009) filters, whose coefficients depend on degree and order, and de-striping/smoothing (Duan et al. 2009; Guo et al. 2010; Swenson and Wahr 2006) filters, operating to remove the anomalously large values from the resonant orders of the Stokes coefficients.

Filtering methods based on principal component analysis (PCA), empirical orthogonal functions (EOF), singular spectrum analysis (SSA), and independent component analysis (ICA) were also proposed. PCA by the name of EOF analysis was applied to the GRACE data in works by Rangelova et al. (2007), Schrama et al. (2007), and Wouters and Schrama (2007). In Rangelova et al. (2007), SSA was also tested. The rotation of PCA components to increase their meaningfulness.

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1 Glacial isostatic adjustment (GIA), related to the restoration of isostatic equilibrium, is especially large in Canada and Scandinavia due to the release of massive ice sheets located there 20,000 years ago.
Gravity Changes over Russian River Basins from GRACE

Fig. 3.1 Unfiltered GRACE EWH difference between 01.2003 and 01.2013 (2013–2003). Vertical stripes distort the signal

was recommended in Rangelova and Sideris (2008). In Han et al. (2005), non-isotropic filtering was used. It is a kind of nonlinear modification of EOF analysis for nonstationary time series, where PCs are obtained by means of time series envelope calculation and orthogonalization. Good review of EOF-based methods of GRACE data filtering can be found in Boergens et al. (2014). All these methods are quite close to MSSA, but we find that MSSA is more flexible, despite its mathematical complexity, and is thus preferred in this study. For the first time, we applied MSSA for the filtering of GRACE observations in Zotov and Shum (2009). In Rangelova et al. (2010), MSSA was also applied to regional GRACE data, but the length of time series was yet too short to choose parameter \( L \) appropriately. Here we will demonstrate the abilities of MSSA on GRACE data of 11-year extent. Multichannel singular spectrum analysis, also called extended EOF, is a generalization of singular spectrum analysis (SSA) for the multidimensional (multichannel) time series (Ghil et al. 2002; Jollife 2001). SSA, in its turn, is based on PCA, generalized for the time series in such way that instead of the simple correlation matrix, the trajectory matrix is analyzed. It is obtained through the time series embedding into the \( L \)-dimensional space. Parameter \( L \) is called lag or “caterpillar” length. When \( L = 1 \), SSA becomes PCA (trajectory matrix becomes non-lagged signal covariance matrix). SSA algorithm has four stages: (a) formation of trajectory matrix, (b) its singular value decomposition (SVD), (c) singular numbers grouping, and (d) principal components recovering through Hankelization. SSA algorithm is described in details in Golyandina et al. (2001) and Golyandina (2004). MSSA includes similar iterations.

Firstly (a), we select lag parameter \( L \). For every Stokes coefficient, we have time series of length \( N \). The trajectory matrix can be built for one time series component
(channel); let’s say for the Stokes coefficient $C_{ij}(t_k)$, $k = 0, \ldots, N - 1$, as follows:

$$X_{C_{ij}} = \begin{pmatrix}
\Delta C_{ij}(t_0) & \Delta C_{ij}(t_1) & \ldots & \Delta C_{ij}(t_{K-1}) \\
\Delta C_{ij}(t_1) & \Delta C_{ij}(t_2) & \ldots & \Delta C_{ij}(t_K) \\
\vdots & \vdots & \ddots & \vdots \\
\Delta C_{ij}(t_{L-1}) & \Delta C_{ij}(t_L) & \ldots & \Delta C_{ij}(t_{N-1})
\end{pmatrix}. \tag{3.3}$$

here $K = N - L + 1$.

The trajectory matrices $X_{C_{ij}}, X_{S_{ij}}$ for every Stokes coefficient $C_{ij}$ and $S_{ij}$ should be incorporated into large block matrix $X$ as follows:

$$X = [X_{C_{2,0}}, X_{S_{2,0}}, \ldots, X_{C_{ij}}, X_{S_{ij}}, \ldots, X_{C_{60,60}}, X_{S_{60,60}}]^T. \tag{3.4}$$

Thus, in our realization, we put blocks one behind another. This multichannel trajectory matrix, composed of blocks for every channel, can be used to calculate the lagged covariance matrix $A = X^TX$.

At the second stage (b), SVD should be applied to $X$.

$$X = USV^T.$$ 

As a result, a sequence of singular numbers (SNs) $s_i$ standing along the diagonal of matrix $S$ in order of decreasing values (see Fig. 3.2) and the corresponding eigenvectors $v_i$ (left) and $u_i$ (right) are obtained. If to solve the eigenvalue problem for $A = VS^TSV^T$, then the eigenvalues will be squared singular numbers $\lambda_i = s_i^2$ and left eigenvectors $v_i$, included as columns in $V$, form empirical orthogonal functions (EOFs).

The $i$th component corresponds to the matrix

$$X_i' = s_i u_i v_i^T.$$
In MSSA we reconstruct the vectorial PCs from this matrix, knowing its structure, similar to the structure of $X$. It is done through Hankelization (d), allowing to reconstruct every channel of $i$th component from the corresponding blocks of matrix $X^i$, organized as in (3.4). Suppose we need to reconstruct the $C_{lm}$ channel. Then each $k$th count can be obtained from the averaging along the side diagonals of the corresponding matrix block $Y = X^i_{C_{lm}}$. The first and the last $L$ elements are calculated from the fewer number of $Y$ values, so the first and the last points of PCs will be less consistent. It is supposed that elements on the side diagonals of matrix $Y$ are approximately equal and it is almost Hankel. In case when it doesn’t hold strictly, some kind of edge effect appears.

Grouping (c) of components is required, when some of SNs are related to one and the same PC and have similar behavior that could be detected with the use of $\omega$ correlations and other techniques (Golyandina et al. 2001). Then, SNs ($s_i$) should be grouped together and reconstructed as one PC before stage (d). It can be done after Hankelization (d) by simple item-by-item summation of components. Details on grouping and theorems about separability of components can be found in (Golyandina 2004).

As a result, the set of PCs with decreasing amplitudes representing different modes of time series variability are obtained. The main parameter of the algorithm – the time lag $L$, which determines the dimensionality of the time series embedding space, should be chosen heuristically, using recommendations given in Golyandina (2004). It should not be larger than $N/2$, and it is better to choose it as a multiplier of periods, expected in the time series. In earlier works, we used $L = 24$ (Zotov and Shum 2009; Zotov 2012). But with extend of period of observations, we have chosen $L = 36$ months (3 years) that allows to better separate the components. No other filters like Gaussian smoothing were used, though it is possible; see Eq. (3.2).

In Zotov and Shum (2009) and Zotov (2012), we found MSSA more flexible than simple EOF for recognition of trend, modulated oscillations of different periods, and denoising of multidimensional time series. Different channels “help” each other to capture spatiotemporal correlation patterns. Lagged matrix $X$ allows to find them in $L$-dimensional space. The obtained PCs extract correlations, which present in all the channels simultaneously.

### 3.3 Results of Processing

We applied MSSA in the spectral domain to the Stokes coefficients. The distribution of singular numbers is represented in Fig. 3.2. SNs were grouped into several PCs which were converted into spatial maps of EWH. The first two largest SNs were grouped into PC 1 capturing annual cycle, the next two SNs into PC 2, representing trend (slow changes). The sum of MSSA SNs 1–10 represents the largest part of signal variability (energy). Higher-order PCs ($SN > 10$) contain high-frequency components, such as noises related to the stripes and some part of the signal from...
Fig. 3.3 Drainage basins of 15 Russian rivers and the sum of SNs 1–10 over these basins for 06.2013

Table 3.1 Information about 15 Russian river basins used in this study according to STN-30p

<table>
<thead>
<tr>
<th>Basin name</th>
<th>Basin length, km</th>
<th>Basin area, km²</th>
<th>Basin name</th>
<th>Basin length, km</th>
<th>Basin area, km²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rivers of Arctic basin (Asia)</td>
<td></td>
<td></td>
<td>Rivers of Arctic basin (European part)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ob</td>
<td>4,257.41</td>
<td>3,025,923.25</td>
<td>Divina</td>
<td>1,414.96</td>
<td>360,944.03</td>
</tr>
<tr>
<td>Yenisei</td>
<td>4,898.93</td>
<td>2,578,730.25</td>
<td>Pechora</td>
<td>1,491.99</td>
<td>314,291.81</td>
</tr>
<tr>
<td>Lena</td>
<td>4,365.71</td>
<td>2,441,815.75</td>
<td>River of Pacific Ocean basin (Far East)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kolyma</td>
<td>1,971.77</td>
<td>665,648.06</td>
<td>Amur</td>
<td>3,644.61</td>
<td>1,754,681.0</td>
</tr>
<tr>
<td>Khatanga</td>
<td>1,370.25</td>
<td>370,352.91</td>
<td>Rivers of European part</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indigirka</td>
<td>1,451.13</td>
<td>334,126.38</td>
<td>Volga</td>
<td>2,785.36</td>
<td>1,476,411.38</td>
</tr>
<tr>
<td>Anadyr</td>
<td>1,011.96</td>
<td>225,847.92</td>
<td>Dniepr</td>
<td>1,543.60</td>
<td>508,839.19</td>
</tr>
<tr>
<td>Yana</td>
<td>997.73</td>
<td>224,992.69</td>
<td>Don</td>
<td>1,400.51</td>
<td>423,038.44</td>
</tr>
<tr>
<td>Olenek</td>
<td>1,644.33</td>
<td>223,189.27</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

transient events, such as coseismic deformation after earthquakes. Detailed analysis of MSSA PCs for global maps was given in Zotov and Shum (2009).

Simulated Topological Networks (STN-30p, http://www.wsag.unh.edu/Stn-30/stn-30.html) database was used to constrain the region of study to the basins of 15 large Russian rivers (Fig. 3.3, left). Table 3.1 contains information about these basins. The map of the sum of SNs 1–10 for the last month (06.2013) of the data span in the constrained area is represented in Fig. 3.3, right. This map includes contribution from annual PC 1, long periodic PC 2, and other components except the stripes, which are mostly removed (they go to SNs > 10). The animated maps of all the obtained PCs are accessible on the website http://lnfm1.sai.msu.ru/~tempus/GRACE/index.htm.

The signal was averaged over the territory constrained by the basins of 15 large Russian rivers. Results are shown in Fig. 3.4. On top the black curve represents the mean sum of SNs 1–10. The purple curve represents the initial data (sum of all PCs) before MSSA. It is seen that SNs 1–10 sum includes almost all the variability of the initial data. The trend (PC 2) is shown in blue. It has a maximum in 2009, then decreases. This trend is defined mostly by Siberian river basins (Fig. 3.6). The red...
Fig. 3.4 Average mass changes in the basins of 15 large Russian rivers for the sum of SNs 1–10, trend PC 2 (top), and annual PC 1 (bottom), together with a forecast by neural network curve depicts the prediction made in February 2013 by neural network (NN), containing nine neurons in three layers (Zotov 2005). Prediction was made when the data for spring months were not yet available. Later, when they were obtained, we found out that the prediction was inappropriate (NN was too simple). The observed level of mass anomaly sufficiently surpasses the prediction. Unprecedented maxima can be seen in April 2013 that can be attributed to huge snow accumulation over Russia.

Figure 3.4, bottom, depicts the average plot only for the annual oscillation captured by PC 1. Prediction for this annual term worked better. Annual term demonstrates the tendency of amplitude increase since 2009. Some part of spring maxima signal was also assigned to PC 2, probably, as a result of the edge effect.

To see the anomalous snow accumulation, we calculated the differences for the annual PC 1 between monthly (January–June 2013) maps and average maps over 10 previous years (2003–2012) for the corresponding months (monthly anomalies). The maps are shown in Fig. 3.5 for 6 months. All Eurasia is shown; however, this study focuses on Russia. It is seen that snow accumulation was very large over the European part of Russia, West Siberia, Chukotka, and the Far East with respect to the average for the selected months. Positive anomalies start to grow in January, reach maximum in April, and disappear in June.
Weather conditions in the basins of Russian rivers in winter and spring are quite cold, temperatures are below zero, and most of the rivers are frozen. Groundwater mass is not changing during winter. We thus concluded that the increase of mass observed by GRACE can be related mostly to the snow accumulation. According to (Report on Climate 2013), the amount of water stored in snow in winter 2012–2013 was the largest in Russia since 1967. When snow melted in April–June, it caused floods. Fortunately, the ground still had capacity to absorb water. That helped to avoid extreme floods and state of emergency. Still, the occurrence of flood on many rivers was less than 2% (event happens once in 50 years); their water levels increased in spring by several meters, which was detected by the river gauges.

We calculated the average plots for particular rivers of Siberia, European part, Russian North, and the Far East (Fig. 3.6). Our MSSA curves were found to be consistent with CNES RL03-v1 solutions for particular river basins.
Fig. 3.6 Average mass changes captured by the sum of SNs 1–10 and trends (PC 2) for particular river basins

(www.thegraceplotter.com). Curves for all the rivers confirm the height maxima in spring 2013. Different amplitudes of seasonal cycle and different trend behaviors for European and Siberian rivers can be seen. Trends for European rivers (Fig. 3.6, top) are mainly decreasing, while for Siberian rivers (Fig. 3.6, middle), they demonstrate maxima in 2009 like the overall trend (PC 2) in Fig. 3.3, top. Since the Siberian river basins are very large (Table 3.1), they dominate the mass changes within Russia. These river discharges are an important driver for Arctic climate change. If to multiply the basin area from Table 3.1 by average mass change, the total water storage anomaly can be calculated for each river.
The curve for Amur river in the Far East (Fig. 3.6, bottom) is quite different from others. The amplitude of its annual cycle is small, but since 2012, observed mass in the basin of Amur is quickly increasing. In August 2013, huge flood occurred there, caused by heavy precipitation. Recent studies (Reager et al. 2014) have shown that GRACE data incorporation sufficiently improves flood forecast.

Minimum in summer 2010 for Volga river (Fig. 3.6, top) is a footprint of the heat wave that occurred in the European part of Russia, accompanied by fires and aerosol pollution, producing smoke and causing great difficulties for the habitants of Moscow (Barriopedro et al. 2010).

Let us look at the map of a climatologically driven trend, captured by PC 2, in Fig. 3.7. The map of difference for PC 2 between 2003 and 2013 years showing the changes of gravity that occurred since 2003 is much cleaner than the unfiltered map in Fig. 3.1. Himalayas glaciers melting, pattern of Sumatra earthquake coseismic deformation, and changes in China, India, and Africa seen on the map are out of the scope of this study. Mass increase has been observed in some Siberian regions, such as sources of Lena and Irtysh, which may be related to the degradation of permafrost (Frappart et al. 2010; Landerer et al. 2010). Potentially as a result of global warming, melted ground ice is replaced by water, which increases the density, mass, and, consequently, gravity field. Negative anomaly over the Caspian Sea can be related to its level decrease, as reported in Zonn et al. (2010).

**Fig. 3.7** Difference between 2003 and 2013 years (2013–2003) for the trend component (PC 2)
3.4 Discussion

For large territories like Russia, satellite gravity field data represent an important source of hydrologic information. In this study monthly gravity field solutions from GRACE in terms of mass (EWH) changes were processed by MSSA and averaged over the 15 largest Russian river basins. Annual component (PC 1) shows amplitude increase since 2009 (Figs. 3.4 and 3.6). Unprecedented maximum in spring 2013 is caused by the huge snow accumulation over the territory of Russia (Figs. 3.5 and 3.6). Trend component shows increase since 2003, maximum in 2009, followed by the decrease. This behavior is mostly defined by Siberian river basins. Map for the trend (Fig. 3.7) shows mass anomalies increase in Siberia and decrease over the Caspian Sea.

We cannot answer the question why precipitation increased in winter-spring 2013 in Russia, causing unprecedented snow accumulation. It could be related to the anomalies of atmospheric mass transfer from Atlantic, Gulf Stream circulation, El Niño/La Niña, or conditions in the Arctic. There are some evidences in favor of global warming pause (hiatus). Such questions could be answered only after extended interdisciplinary research, involving climatology, meteorology, and other sciences. Some issues and projections for precipitation and anomalous weather conditions into the future could be found in IPCC Fifth Assessment Report (2013) or the report of Hydrometeorological Center of Russia (Report on Climate 2013).

In this work we did not plan to find explanation of the causes of meteorological and hydrological changes over Russia. Our goal was to present observational data, its processing technique, and show its usefulness for hydrological and climatological studies, exploration of our planet.

We used MSSA to filter data and separate meaningful components, founding it a promising method for GRACE data processing. MSSA method has greater flexibility than simple EOF and could be useful in the analysis of other satellite observations, such as altimetry, water vapor, and precipitation data (Zotov 2012).

Exact physical interpretation of the obtained signals requires comparison to hydrological models (GLDAS, WGHM) and ground-based observations. The remaining questions are (i) what is the useful part of the signal in PC 1 and PC 2, (ii) how to reduce boundary effects for the first and the last points of PCs, and (iii) how to better separate secular change from annual and, probably, other periodic signals? As for the last question, fortunately, we already have 11 years of GRACE data, and quite a good separation can be achieved by the appropriate choice of L.

Gravity field can also reveal or constrain the planet’s internal structure. In the recent decades, gravity remote sensing has given impressing results for the Earth (GRACE, GOCE) and for the Moon (GRAIL). Space missions to Mercury, Venus, Saturn, Jupiter, Enceladus, Titan, and Pluto would benefit from dedicated gravimetry or gradiometry sensors in addition to other geodetic instruments to constrain internal structures of terrestrial planets.
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References


Kenyon S et al (2007) Toward the next Earth gravitational model. SEG Annual Meeting


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Reager JT, Thomas BF, Famiglietti JS (2014) River basin flood potential inferred using GRACE gravity observations at several months lead time. Nat Geosci. doi:10.1038/ngeo2203

Sagitov MU (1979) Lunar gravimetry. Nauka, Moscow


AUTHOR QUERIES

AQ1. Please check if updated author name and affiliations are okay.
AQ2. Please expand “GFZ, CSR, JPL, GOCE, GRAIL, CHAMP, GLDAS, and WGHM.”
AQ3. Please check if edit to sentence starting “The purple curve…” is okay.
AQ4. Please check if updated publisher location for “Golyandina et al. (2001), Jollife (2001), Tikhonov et al. (1998), Wang et al. (2012), and Zonn et al. (2010)” are okay.
AQ5. Please provide conference location for “Kenyon et al. (2007)”.
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AQ7. Please check if updated book title, editor name and publisher location for “Rangelova et al. (2010)” is okay.