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ORIGINAL ARTICLE

On the postprocessing removal of correlated errors in GRACE temporal gravity field solutions

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Abstract We revisit the empirical moving window filtering method of Swenson and Wahr (Geophys Res Lett 33:L08402, 2006) and its variants, Chambers (Geophys Res Lett 33:L17603, 2006) and Chen et al. (Geophys Res Lett 34: L13302, 2007), for reducing the correlated errors in the Stokes coefficients (SCs) of the spherical harmonic expansion of the GRACE determined monthly geopotential solutions. Based on a comparison of the three published approaches mentioned, we propose a refined approach for choosing parameters of the decorrelation filter. Our approach is based on the error pattern of the SCs in the monthly GRACE geopotential solutions. We keep a portion of the lower degree-order SCs with the smallest errors unchanged, and high-pass filter the rest using a moving window technique, with window width decreasing as the error of the SCs increases. Both the unchanged portion of SCs and the window width conform with the error pattern, and are adjustable with a parameter. Compared to the three published approaches mentioned, our unchanged portion of SCs and window width depend on both degree and order in a more complex way. We have used the trend of mass change to test various parameters toward a preferred choice for a global compromise between the removal of the correlated errors and the minimization of signal distortion.

Keywords GRACE · Geopotential coefficients · Correlation

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1 Introduction

The gravity recovery and climate experiment (GRACE) twin-satellites are designed to determine the changes of the Earth's gravity field. The observations are processed at the Center for Space Research (CSR), University of Texas at Austin, the Geo-Forschungs-Zentrum (GFZ) Potsdam, the Jet Propulsion Laboratory (JPL), California Institute of Technology, and a few other institutions. The final results, known as Level 2 (L2) products, are the monthly geopotential solutions expressed in terms of spherical harmonic expansion, which are widely used to study mass changes at the Earth's surface (e.g., Wahr et al. 1998). However, the GRACE geopotential solutions have systematic errors, resulting in spurious north-south stripes in the geoid and mass changes computed from them. Hence, in practical application, the GRACE results have to be smoothed (e.g., Jekeli 1981; Wahr et al. 1998; Han et al. 2005; Guo et al. 2009).

Swenson and Wahr (2006) found that the Stokes coefficients (SCs) of the spherical harmonics of the GRACE determined geopotential changes (e.g., the difference between two monthly models) are inter-correlated. More specifically, the SCs of the gravity field changes of the same order and the same parity in degrees are correlated with each other.

Let us write each SC in the sum of a signal term, a correlated error term and a random error term. The correlated error can be reduced by high-pass filtering the correlated coefficients as a function of degree. This process is often referred to as decorrelation. It can reduce the stripes significantly (Swenson and Wahr 2006). However, it is also known that the decorrelation may cause signal distortion, as the signal terms are not wholly independent of each other. Hence, different authors have chosen different decorrelation schemes for different purposes based on different compromises between the removal of the correlated errors and the minimization of signal distortion.

We may classify the decorrelation methods developed so far in two categories. One category is empirical that does not use any other information (Swenson and Wahr 2006; Chambers 2006; Chen et al. 2007; Schrama et al. 2007; Wouters and Schrama 2007; Davis et al. 2008). The other category makes use of the error variance-covariance matrix of the SCs, but also requires a priori signal covariance information (Kusche 2007; Klees et al. 2008). This class of filter is based on the minimization of an objective function, thus having a more solid theoretical ground.

Swenson and Wahr (2006) proposed an empirical moving window filtering method to remove the correlation. The idea is to estimate the correlated part of an even/odd degree SC by fitting the even/odd SCs in a predefined window centered by the SC using a quadratic polynomial. Chambers (2006) and Chen et al. (2007) followed the principle of Swenson and Wahr (2006), but chose to fit all the even/odd SCs of the same order to be decorrelated using a polynomial.

Schrama et al. (2007) and Wouters and Schrama (2007) made use of empirical orthogonal functions (EOFs). Their difference is that Schrama et al. (2007) performed the computation in the spatial domain, and Wouters and Schrama (2007) performed the computation in the spherical harmonic domain.

Davis et al. (2008) presented a statistical approach. The idea is to fit each SC using a constant, a trend and an annual term, and then decide whether to include the trend or annual term in the result based on a statistical test. The inputs to the statistical test are positive unit weight residual sums of squares and degree of freedoms of the full mode (all parameters are included in the fit) and of the restricted mode (the parameter tested is set to zero).

Kusche (2007) devised a combined decorrelation-smoothing algorithm, that is similar to a Tikhonov-type regularization of the original normal equation system based on a systematic error covariance matrix computed from the GRACE orbits, and an a priori signal covariance matrix in the spherical harmonic domain. At present, monthly models filtered by this method can be downloaded from the ICGEM website[1] at GFZ.

Klees et al. (2008) addressed the optimal decorrelation filter in a broader scope by minimizing a clearly defined objective function, i.e., the global mean of the mean square difference between the actual (unfiltered) mass change function and the filtered mass change function as inferred from GRACE data. This filter makes use of the full variance-covariance matrix of error in the GRACE solution and signal covariance in the spatial domain. Kusche (2007) turned out to be a simplified case of Klees et al. (2008).

Klees et al. (2008) have compared their optimal filter with a Swenson and Wahr (2006) type empirical filter they defined using the Delft Institute of Earth Observation and Space Systems (DEOS) GRACE solutions, and found the optimal filter outperforms in removing stripes. This is not surprising as the optimal filter uses the actual covariance matrices of the GRACE solutions. However, we believe that the simple Swenson and Wahr (2006) type filter will still be used for its simplicity and providing mass change solutions without biasing the results toward a pre-existing mass change model.

This work follows the empirical approaches of Swenson and Wahr (2006), Chambers (2006) and Chen et al. (2007). Its main difference from the former approaches is the use of the standard deviations (SDs) of the SCs provided by the processing centers as a measure of the quality of the SCs. Generally speaking, if a coefficient's SD is small, its error covariances with other coefficients are also small (though the reverse may not be true). So we choose to filter stronger the coefficients with larger SD. As the SDs of the SCs increase as the degree and order increase, we keep unchanged a portion of lower degree-order SCs with smallest SD, and decorrelate the rest of the SCs using a quadratic polynomial moving window approach as Swenson and Wahr (2006), with window width decreasing as the SD increases. We have tested various choices of the parameters using the trend of mass change computed from the JPL release 4 (RL04) L2 product. Based on a compromise between stripe removal and signal preservation, we suggest a preferred choice of the parameters.

Actually, our choice to follow the SD pattern is in the same spirit as Swenson and Wahr (2006), Chambers (2006) and Chen et al. (2007). They all applied stronger filter to the higher order coefficients which have larger SDs than the lower order coefficients.

We have also compared our approach with those of Swenson and Wahr (2006), Chambers (2006) and Chen et al. (2007) by applying all of them to a synthetic model constructed using the global land data assimilation systems (GLDAS) hydrological model (Rodell et al. 2004), a postglacial rebound (PGR) model (Peltier 2004), the GRACE

[1] http://icgem.gfz-potsdam.de/ICGEM/ICGEM.html.

result over Greenland and the global ocean model for circulation and tides (OMCT) (Thomas 2002; Dobslaw and Thomas 2007).

Following Swenson and Wahr (2006), Chambers (2006) and Chen et al. (2007), the results after decorrelation using our algorithm still need to be smoothed using a Gaussian filter. Chen et al. (2006) discussed the optimal choice of the filter's smoothing radius, i.e., the distance between the two points where the values of the Gaussian function attains maximum and half maximum.

2 Method

We begin by summarizing the approaches of Swenson and Wahr (2006), Chambers (2006) and Chen et al. (2007).

In the approach of Swenson and Wahr (2006), the correlated part to be removed from the coefficient C_l^m (S_l^m is similar) is computed by fitting $C_{l-2\alpha}^m, \ldots, C_{l-2}^m, C_l^m, C_{l+2}^m, \ldots, C_{l+2\alpha}^m$ using a quadratic polynomial. The relation between the window width w (the total number of coefficients fitted) and α is $w = 2\alpha + 1$. The window width used by Swenson and Wahr (2006) is not provided in the paper. Here we cite Swenson and Wahr's unpublished result of window width: Decorrelation is done for the SCs of order $m = 5$ and above, and the window width depends on m in the form of (Swenson and Wahr, personal communication, 2008)

$$w = \max(Ae^{-\frac{m}{K}} + 1, 5), \tag{1}$$

where the function max() takes the larger one of the two arguments. Swenson and Wahr have empirically chosen $A = 30$ and $K = 10$ for the CSR RL01 or RL02 data they used at the time, evidently based on a trial-and-error procedure. Here we round w to an odd integer, that is 19 for $m = 5$, and 5 for $m = 19$ and higher. As the data are fitted using a quadratic polynomial, the window width should be larger than 3 in order that some information is retained after filtering. Hence the minimum window width is set to 5. When $l < m + (w-1)/2$ (near-tesseral) or $l > l_{\max} - (w-1)/2$ (near maximum degree), C_l^m (and S_l^m) can no longer be centered in the window. In these situations, the w coefficients of the same parity as l with lowest or highest degrees are used in the polynomial fit. In this work, we will fix $A = 30$, and allow K to vary for adjusting the window width. The effects of adjusting either A or K are similar. We have chosen to adjust K as the widow width for larger l and m is more sensitive to it.

Chambers (2006) left a lower degree-order portion (7 × 7 in the paper for the CSR RL02 data, and 11 × 11 for the CSR RL04 data provided at the web page[2]) unchanged, and computed the correlated part to be removed by fitting the rest of SCs of the same order using a polynomial (seventh order in the paper for the CSR RL02 data, and fifth order for the CSR RL04 data provided at the web page mentioned), for even and odd degrees separately based on how the SCs are correlated.

Chen et al. (2007) left the SCs of orders 5 and lower unchanged, and computed the correlated part to be removed for orders 6 and above by fitting the SCs of the same order using a third order polynomial, again for even and odd degrees separately.

Although the approaches of Chambers (2006) and Chen et al. (2007) could also be tuned by changing the portion of unfiltered SCs and the order of polynomial, here we follow the approach of Swenson and Wahr (2006) as it allows to filter the SCs of different degree or order with different strength, and is thus more flexible.

The intention of decorrelation is to better balance the preservation of signal detail and the removal of stripes. Certainly, the most straightforward way is to filter more strongly those SCs of worse quality, which is the essence of this work. Here we use the SDs of the SCs provided in the GRACE L2 products as a measure of the quality of the SCs. It is natural that we expect the SCs of geopotential changes to have similar error characteristics to those of the monthly geopotential models of the L2 products. In Fig. 1, we show the SDs of C_l^m as a function of l and m provided by the JPL RL04 L2 product

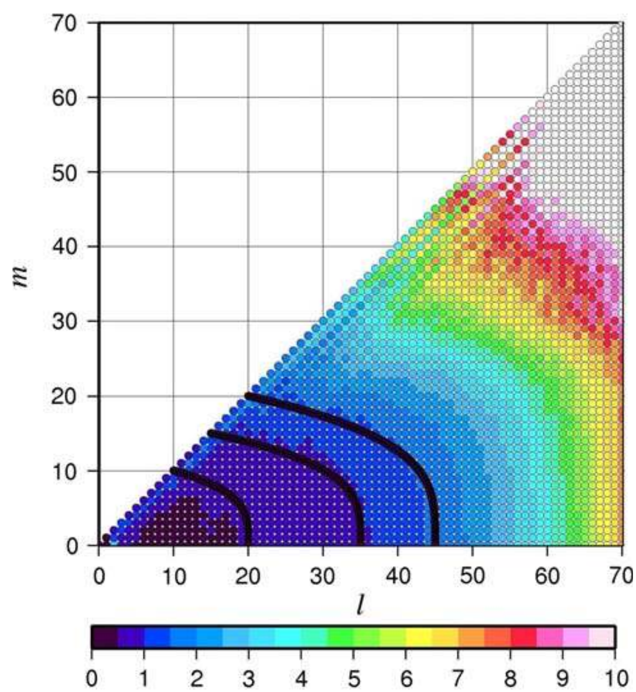

Fig. 1 The error (scaled by $\times 10^{12}$) pattern of C_l^m of a month's JPL GRACE gravity model. The *three dark curves* are used to define the portion kept unchanged in the decorrelation

[2] ftp://podaac.jpl.nasa.gov/pub/tellus/monthly_mass_grids/chambers-destripe/dpc200711/doc/GRACE-dpc200711_RL04.pdf.

of a randomly selected month's (2005.7) geopotential model (the patterns for different months are very similar). It can be seen that the SD strongly depends on both l and m. In general, it increases as l or m increases. This is also observed for the SDs of the CSR coefficients.

However, the SDs of the near-tesseral potential coefficients are apparently larger. In our experiment, we do not particularly apply a stronger filter to these few near-tesseral coefficients than to the adjacent coefficients with much smaller SDs. Instead, we have chosen the filter to be always stronger when l or/and m are larger.

According to the error pattern, we reserve a lower degree-order portion of the SCs with smallest errors unchanged. As shown in Fig. 1 by dark curves, the unchanged portion is defined using the curve

$$l = l_0 + \beta m^r. \quad (2)$$

This curve approximately follows a contour of the error pattern, and allows us to choose the unchanged SCs to be below a common error threshold quasi-independent of both l and m. Based on our computation for a large number of choices, we choose $r = 3.5$ empirically for the trend computed from the JPL RL04 data.

The values of l_0 and β are defined by the coordinates (l, m) of the two ends of the curve, where $m = 0$ at one end, and $l = m$ at the other end. As the curve approximately coincides with a contour of the SDs, the (l, m) end-point pair is practically defined by one parameter (e.g., l_0, which is the value of l at the end point with $m = 0$). In Fig. 1, we show the end-point pairs $(20, 0) \leftrightarrow (10, 10)$, $(35, 0) \leftrightarrow (15, 15)$ and $(45, 0) \leftrightarrow (20, 20)$ for the trend of JPL RL04 data.

In this work we adopt the moving window approach of Swenson and Wahr (2006). We also use a quadratic polynomial, but choose our window width based on the error pattern (another possible choice is to fix the window width and alter the order of the polynomial). The larger the error is, the more strongly the coefficient should be filtered, thus the smaller the window width should be. In our algorithm the window width depends on both l and m, while that of Swenson and Wahr (2006) depends only on m. The formula of the window width is modified from Swenson and Wahr's formula, i.e., Eq. (1):

$$w = \max\left\{A e^{-\frac{[(1-\gamma)m^p + \gamma l^p]^{1/p}}{K}} + 1, 5\right\}, \quad (3)$$

that is then rounded to an odd integer. The parameter A is fixed to 30. The parameters γ and p are empirically chosen so that the pattern of w is similar to the error pattern in Fig. 1. We have also computed the window width using a large number of choices of parameters, and empirically set $\gamma = 0.1$ and $p = 3$ for the trend of JPL RL04 data. After empirically fixing γ and p, the window width is defined by the parameter K alone. A larger K corresponds to larger window widths. We show in Fig. 2 the window width with $K = 10$ and 15 for the trend of JPL RL04 data.

In summary, after empirically fixing the parameters r and p related to the SD pattern, our approach needs to assign two parameters l_0 and K to further fine tune the filter. l_0 specifies the portion of SCs kept unchanged. K specifies the window width.

3 Results

As Swenson and Wahr (2006) pointed out, the decorrelation affects geophysical signals, especially at high latitudes where some short-wavelength features are removed. In this work, we mainly use the trend of mass changes as numerical example, since the trend has ample signal at high latitudes. The trend in geoidal height is obtained by fitting the GRACE monthly SC time series with an offset, a linear term that represents the trend, a yearly term, a half-yearly term and a

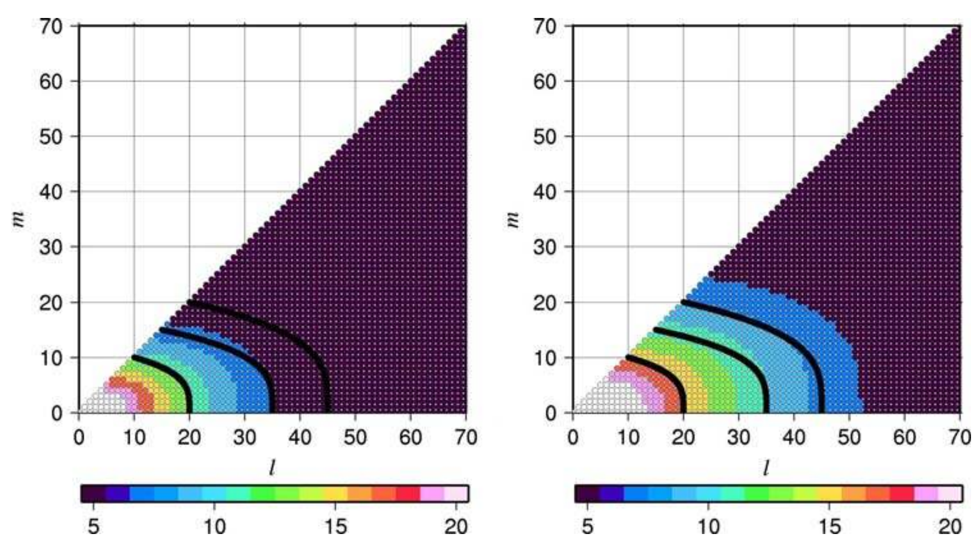

Fig. 2 Window width w as function of l and m used in our decorrelation algorithm computed with $K = 10$ (*Left*) and $K = 15$ (*Right*). The *dark curves* are the same as those in Fig. 1

two-yearly term. The mass changes are computed from the geoidal height changes using the load Love numbers computed by Guo et al. (2004) for each degree by solving the governing ordinary differential equations. As our purpose here is to validate the decorrelation algorithms, a PGR correction is not applied, implying that the PGR gravity variation is hypothetically interpreted as caused by mass changes at the Earth's surface. In this way, the signal at higher latitudes of our illustrative mass change model is amplified. The JPL RL04 data from April 2002 to July 2007 (with some missing months in between: May, June and July, 2002; May, June, 2003) truncated at degree and order 70 are used to compute the trend.

As reference, we first perform the computation using the algorithms of Swenson and Wahr (2006) (for $A = 30$, $K = 10$ and 15), Chambers (2006) (lower 11×11 portion unchanged, fifth order polynomial) and Chen et al. (2007) (orders 5 and lower unchanged, third order polynomial). The results after smoothing using an isotropic Gaussian filter of smoothing radii 300 and 400 km are shown in Fig. 3.

The results of the three previous approaches show differences, particularly at higher latitudes. For example, the two domes in the Hudson Bay area (e.g., Tamisiea et al. 2007) are barely distinguishable in the results using the approaches of Swenson and Wahr (2006) (with $K = 10$) and Chambers (2006). We also observe that the positive dome in the north of Greenland is displaced toward the south and enhanced in the result of Chambers (2006). We also see a dome in the ocean south of Greenland in the original data, that appears in all results, but the amplitude is evidently smaller in the result of Chambers (2006). These features can in fact be expected based on the characteristics of the decorrelation algorithms. The approach of Chambers (2006) is designed to be applied over the ocean. His criterion is to minimize the global variance of the residual between the sea levels determined by GRACE and by steric corrected altimetry. As the signal over ocean is much smaller than that over land, a stronger filter is required to reduce more short wavelength noises. If we use it over land, it may undesirably reduce too much short wavelength signal, as can be seen from the results over Greenland and Antarctica. The approach of Chen et al. (2007) is designed to retrieve the mass changes associated with the coseismic and postseismic deformation from the 2004 Sumatra-Andaman earthquake, and the criterion is that the result obtained after smoothing is closest to that obtained from GPS and seismological data. Hence, this approach preserves more short wavelength details in the equatorial region, and the filter used is weaker. As a result, much of the short wavelength details in other regions are also preserved, but the stripes are less reduced. Swenson and Wahr (2006) did not focus on a particular region. For the case of $K = 10$, apart from the removal of short wavelength signal at higher latitudes that they mentioned, the signal at low-to-mid latitudes is likely well retained, and the stripes are very much reduced. The case of $K = 15$ visually looks quite reasonable. We will compare this case with our decorrelation results later.

We present in Figs. 4 and 5 our decorrelation results for the two choices of window widths computed using $K = 10$ and 15, respectively, as shown in the left and right panel of Fig. 2. Each figure contains the results for the undecorrelated case, and for the three decorrelated cases corresponding to the three choices of the portion of the lower degree-order SCs kept unchanged as shown in Fig. 1. The results are smoothed with radii 300 and 400 km similar to those in Fig. 3.

The characteristics of the results are as we expected. As the results in Fig. 5 are computed with a larger window width than those in Fig. 4, they show a little more short wavelength details, though hard to see in the figures. However, the detail of short wavelength signal preserved is mostly dependent on the amount of lower degree-order SCs kept unchanged in the decorrelation. Here we examine again the signals over the Hudson Bay region and Antarctica. The two domes that appear in the undecorrelated case in the Hudson Bay region are clearly discernable in the bottom row of both Figs. 4 and 5 with roughly the same shape. Their overall shapes also conform with those in the first row. However, they are completely merged together in the second row of Fig. 4. In Fig. 5, it looks like that the two domes are discernable in the second row, but their overall shape is quite different from that in the first row. Thus we believe the seemingly observed distinction of them is only the result of some kind of signal distortion. Over Antarctica, we see that the magnitudes of the signals of the apparent highs and lows are very much reduced in the second row of both Figs. 4 and 5.

The square roots of the variances, i.e., the root mean squares (RMS) values, of the JPL GRACE mass trend after applying the various decorrelation approaches and a Gaussian filtering with a smoothing radius of 300 km are listed in Table 1. We see that different approaches do not lead to significantly different RMS. These are in fact an overall measure of the magnitude of the signal obtained. Very likely, the smaller this RMS value is, the more the unrealistic high magnitude stripes are removed. However, a smaller RMS does not imply a better decorrelation approach, as a too small RMS value may be the result of over decorrelation associated with strong signal distortion.

4 Assessment of signal distortion

Actually, there is no really relevant quantitative criterion to judge the results of different decorrelation processes for GRACE data. Although the variance of the signal indicates to some extent how much the unrealistically high magnitude stripes have been removed, there exists no measure of how well the signal is preserved. Thus we can only expect to get an

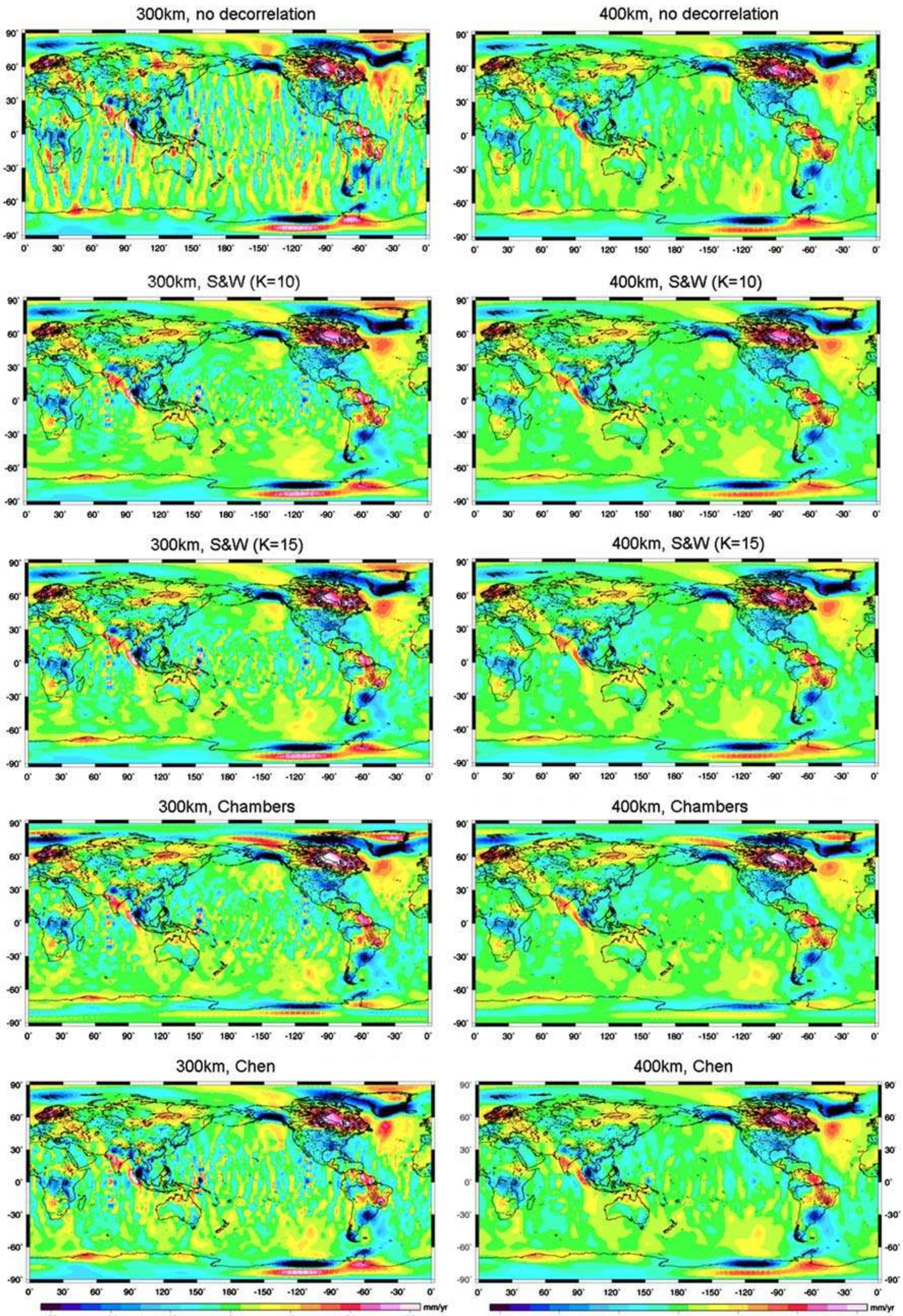

Fig. 3 A comparison between the previous approaches using the trend of mass changes. Isotropic Gaussian filters of radii 300 and 400 km are applied after decorrelation

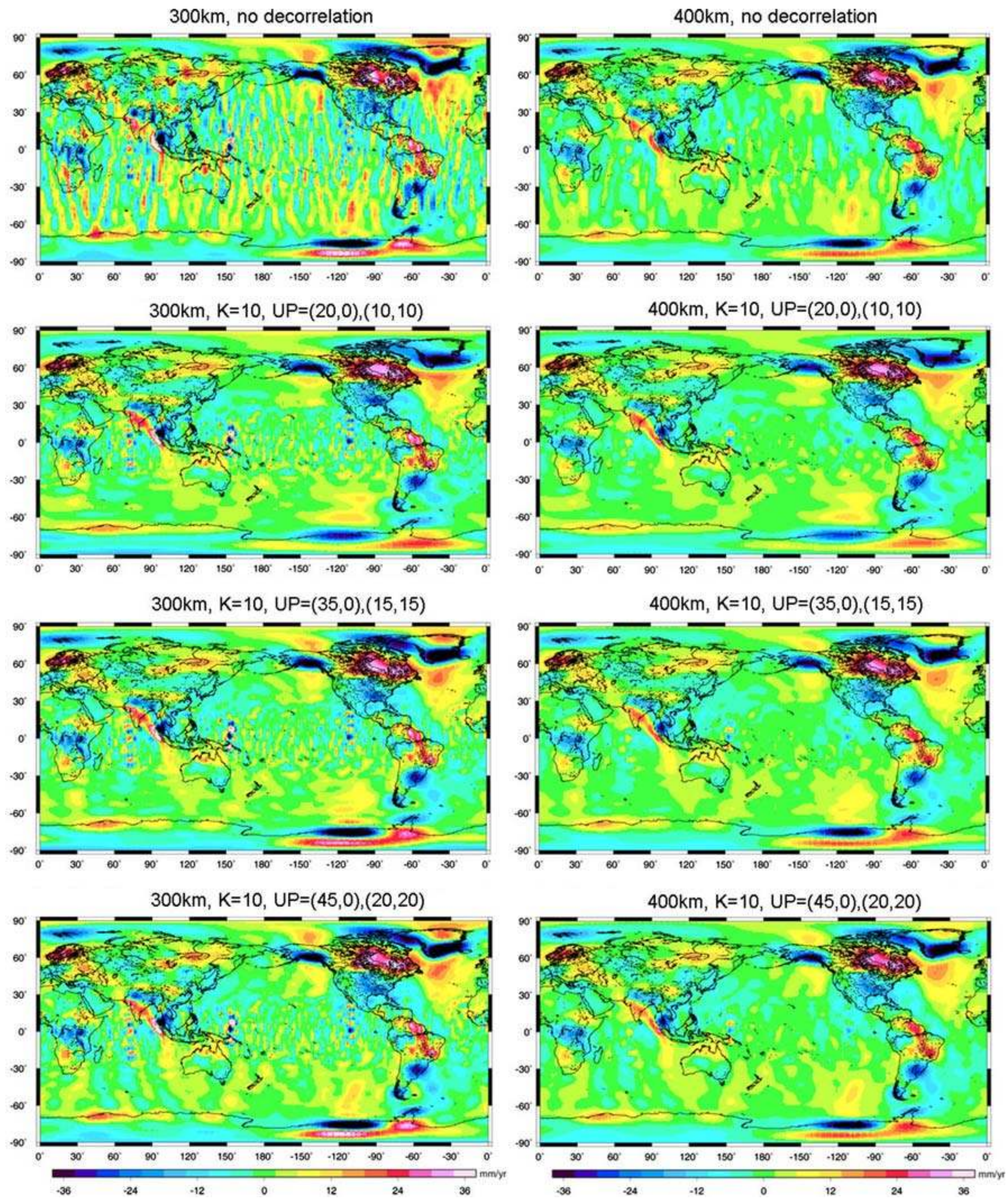

Fig. 4 Results of decorrelation for window width computed using $K = 10$ (Fig. 2, Left) smoothed with radii 300 and 400 km, respectively. As reference, the results without decorrelation are also shown. UP means the end-point pair defining the unchanged portion of SCs

indirect measure of signal preservation by applying the decorrelation algorithm to geophysical data sets like the GLDAS hydrologic model. Here we construct a synthetic model of mass change trend composed of the NOAH GLDAS model (2002.1–2006.4) (Rodell et al. 2004), a surface mass change rate corresponding to the gravity variation of a PGR model based on the ICE-5G ice model (Peltier 2004) with an upper mantle viscosity of 2×10^{20} Pa s and a lower mantle viscosity of 6×10^{21} Pa s, the GRACE result over Greenland and the ocean bottom pressure (OBP) of the OMCT (Dobslaw and Thomas 2007) (see Fig. 6). The addition of the PGR and GRACE data amplifies the signal at higher latitudes, so that the synthetic model becomes comparable to the real GRACE data.

Hence, our judgement on the decorrelation algorithm will be based on (1) the preservation of signal when the filter is

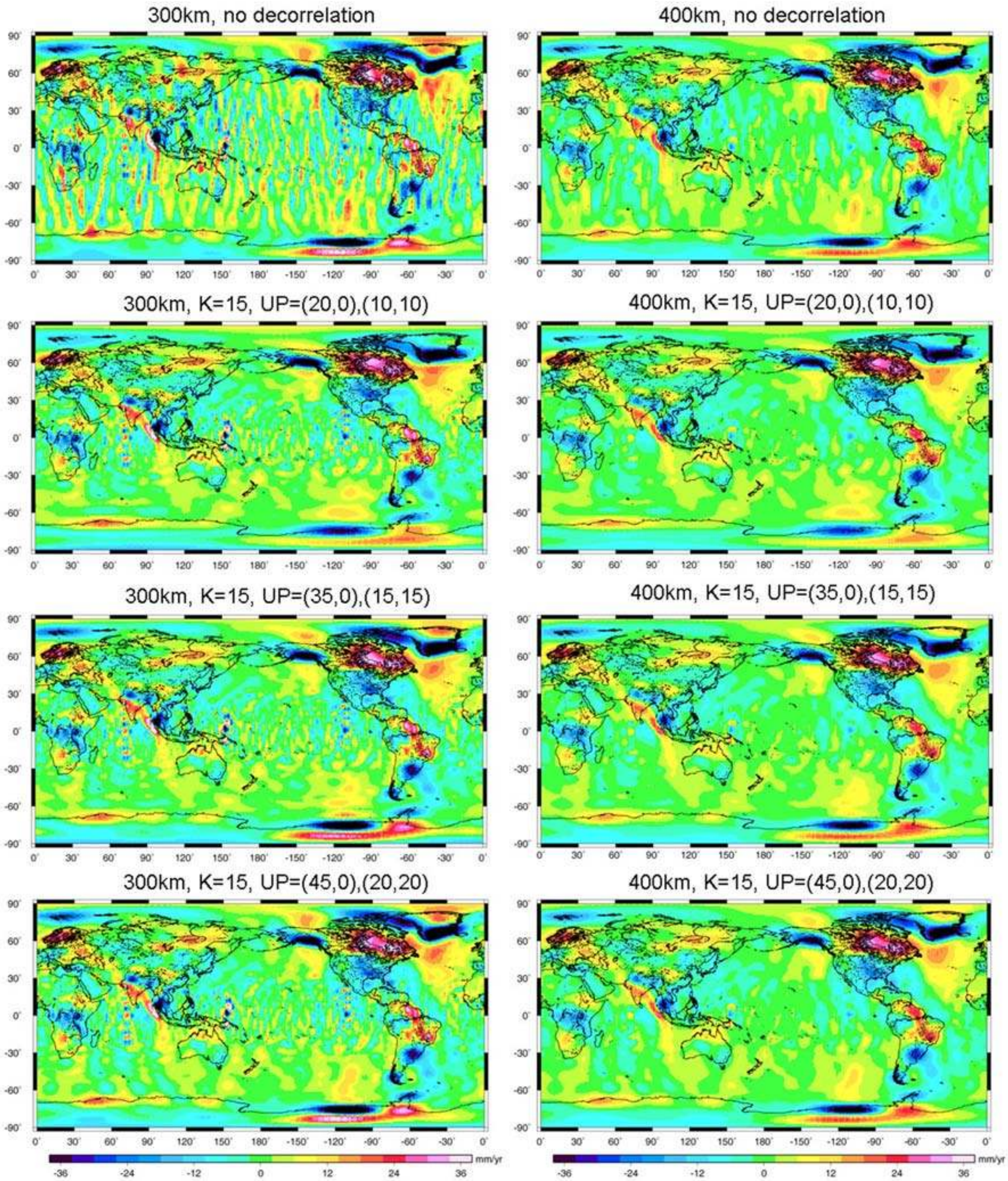

Fig. 5 The same as Fig. 4 for the case of $K = 15$

applied to the synthetic model, (2) the variance of the result when the filter is applied to the GRACE data, and (3) an empirical comparison of the stripes left and the distortion of mass change pattern as compared to the case without decorrelation.

We have applied the destriping approaches of Swenson and Wahr (2006), Chambers (2006) and Chen et al. (2007), as well as ours, together with a Gaussian filter of smoothing radius 300 km, to the synthetic model. To be conform with the postprocessing of GRACE data, we have transformed the mass of the synthetic model to geopotential coefficients, applied the decorrelation algorithms, and then transformed back to mass. We use the RMS values of the differences (DRMS) between the results with and without decorrelation as a measure of the signal distortion caused by the decorrelation. The smaller the DRMS value is, the better the signal is preserved. Certainly, the larger the unchanged portion is, or the wider the window is, the smaller the DRMS.

Table 1 The RMS values (mm) of the trend of JPL GRACE mass changes after applying the various decorrelation algorithms and the Gaussian filtering with a smoothing radius of 300 km (UP: the degree-order pair defining the unchanged portion)

Previous approaches	
Swenson and Wahr (2006) ($K = 10$)	10.09
Swenson and Wahr (2006) ($K = 15$)	10.22
Chambers (2006)	9.63
Chen et al. (2007)	10.81
Our approach with $K = 10$	
$K = 10$, UP = (20, 0), (10, 10)	9.37
$K = 10$, UP = (35, 0), (15, 15)	10.24
$K = 10$, UP = (45, 0), (20, 20)	10.41
Our approach with $K = 15$	
$K = 15$, UP = (20, 0), (10, 10)	9.55
$K = 15$, UP = (35, 0), (15, 15)	10.28
$K = 15$, UP = (45, 0), (20, 20)	10.43

The RMS value after applying only the Gaussian filter with a smoothing radius of 300 km without decorrelation is 12.75 mm

However, this DRMS value does not reveal how well the stripes are removed when the decorrelation process is applied to GRACE data. For our decorrelation approach, we list in Table 2 the cases of $K = 10$ and 15 as shown in Figs. 4 and 5. We see that different approaches lead to quite different DRMS.

As guideline for the choice of parameters, we look for a smaller RMS and DRMS listed in Tables 1 and 2, respectively. Inspection of signal distortion and stripe removal in Figs. 4 and 5 is also necessary. As a compromise, we propose to use our decorrelation results shown in the third row of Fig. 5 for general purpose usage for the case of trend of JPL RL04 data.

The case we have chosen corresponds to the unchanged portion defined by the l, m pairs $(35, 0) \leftrightarrow (15, 15)$, and the window width defined by $K = 15$. This case is likely indistinguishable from the case of Swenson and Wahr (2006) with $K = 15$. However, a comparison between the data provided in Tables 1 and 2 indicates that our choice is more preferable.

As compared to the algorithm of Swenson and Wahr (2006) with $K = 15$, our choice has a smaller DRMS value when applied to the synthetic model (0.64 vs. 1.31), which means our approach better preserves the signal. Our choice has a slightly larger RMS value of the signal obtained (10.28 vs. 10.22), which implies our algorithm may have removed slightly less stripes, or preserved a little more signal. Here we mention once again that a smaller RMS value does not imply better results.

However, all decorrelation methods distort the signal. When we visually compare the third row of Fig. 5 with the first row, we can still find signs of signal distortion. At lower latitudes, we see that the signal of the 2004 Sumatra earthquake is altered significantly. At higher latitudes, the negative signal on the west coast of Greenland is very much reduced.

We remark that the approaches of Swenson and Wahr (2006) and Chambers (2006) are designed for processing monthly data. The trend should have less stripes than the monthly data, as a part of the error may be eliminated in the least squares fit. Hence, when the approaches of Swenson and Wahr (2006) and Chambers (2006) are applied to the trend, they may be too strong, thus removing more stripes and causing more signal distortion.

According to the signal RMS obtained, we can assess that the ability of our and Swenson and Wahr (2006) approaches for removing stripes are about the same (RMS of 10.28 vs. 10.22). We also speculate that the comparison made by Klees et al. (2008) between the optimal filter and a Swenson and Wahr (2006) type filter should also remain principally true for our Swenson and Wahr (2006) type filter. The optimal filter of Klees et al. (2008) is more capable at removing stripes. However, as the optimal filter and the Swenson and Wahr (2006) type empirical method have very different characteristics, such as the way signal is distorted, we believe that the Swenson and Wahr (2006) type methods will still be used in parallel with other methods.

We have also applied our approach to a few cases of mass changes computed using the differences between the monthly gravity models of the CSR GRACE RL04 L2 products (2005.4–2004.4, 2006.4–2005.4 and 2007.4–2006.4). In these cases, the mass change signal is generally much larger than that of the trend. Apart from some differences on the choice of parameters that define the unchanged portion and the window width, the results have similar characteristics. The empirical parameters are $r = 3.5$, $\gamma = 0.1$, $p = 2$. Our results show that the case with the unchanged portion defined by the l, m pairs $(35, 0) \leftrightarrow (10, 10)$, and the window width defined by $K = 15$ is likely the preferred choice.

5 Discussion

We have compared three approaches of the same type of methods (Swenson and Wahr 2006; Chambers 2006; Chen et al. 2007) for removing correlated errors in the SCs of the spherical harmonic expansion of the GRACE gravity changes using the trend. Two of them (Chambers 2006; Chen et al. 2007) are tuned for specific applications. They give significantly different results.

In this work, we have proposed an approach based on the pattern of the SDs of the SCs of the GRACE monthly geopotential models, which should be similar to the error pattern of the gravity changes. We have proposed to keep a portion of the lower degree-order SCs with smallest errors unchanged, and apply a moving window high-pass filter as in Swenson and Wahr (2006) to the rest of SCs. Both the

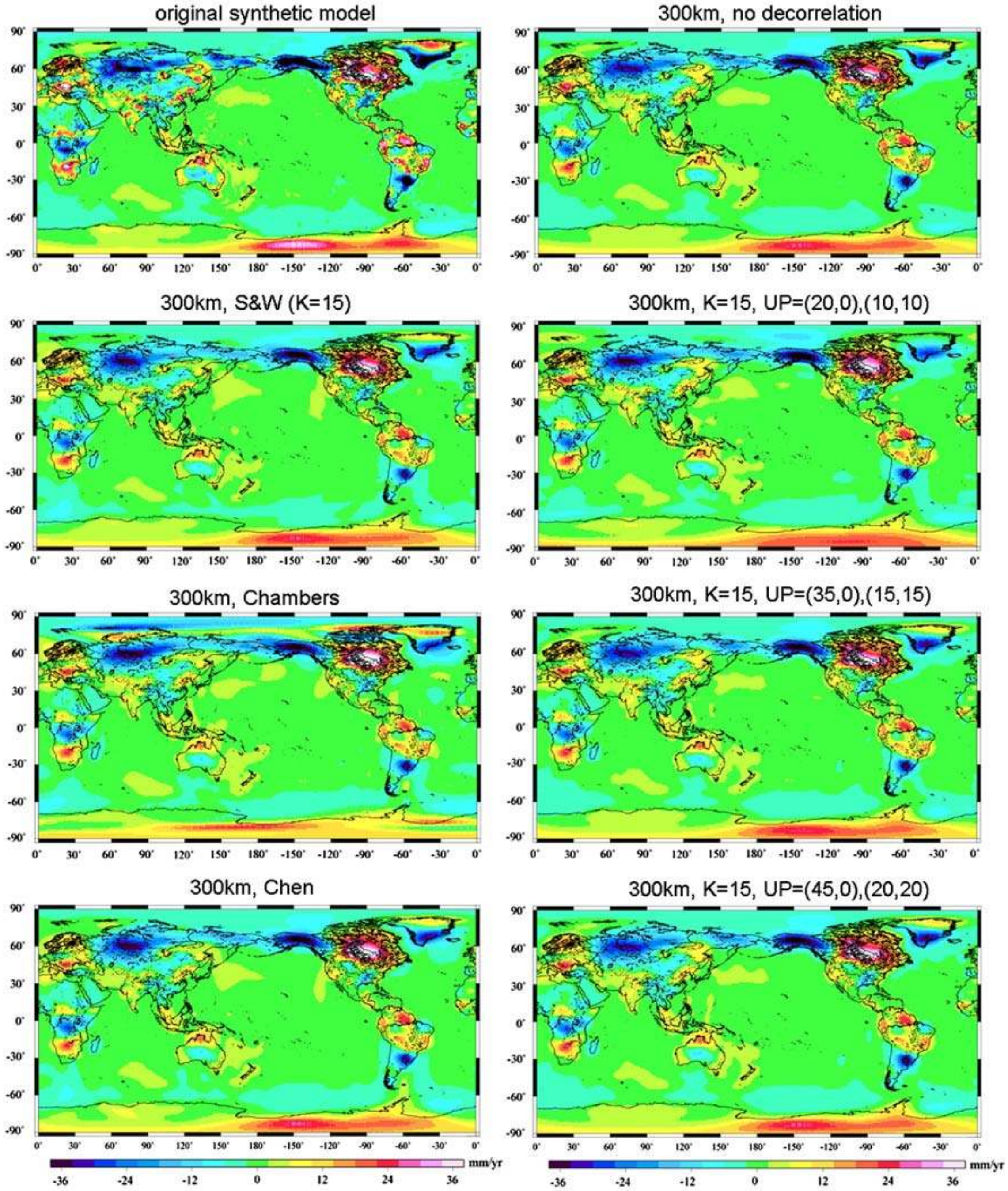

Fig. 6 Results of decorrelation for the synthetic model

unchanged portion and the window width conform with the error pattern of the SCs, and are defined using a single parameter. A smaller window width is chosen for SCs of larger errors, so that SCs of larger errors are filtered more strongly. An apparent difference between our algorithm and that of Swenson and Wahr (2006) is that our unchanged portion and window width depend on both degree and order, while those of Swenson and Wahr (2006) depend only on order.

We have tested our approach using the trend of mass changes obtained from the JPL RL04 data truncated to degree and order 70. As compared to former approaches of the same type of method (Swenson and Wahr 2006; Chambers 2006; Chen et al. 2007), we obtain a better overall global compromise between the removal of stripes and the preservation of signal. It should be mentioned that the former approaches (Swenson and Wahr 2006; Chambers 2006; Chen et al. 2007) may also be tuned to give better balance between

Table 2 The RMS values (mm) of the differences (DRMS) between the results with and without decorrelation of the trend of mass changes computed from the synthetic model (UP: the degree-order pair defining the unchanged portion) smoothed using an isotropic Gaussian filter of radius 300 km

Previous approaches	
Swenson and Wahr (2006) ($K = 10$)	1.41
Swenson and Wahr (2006) ($K = 15$)	1.31
Chambers (2006)	3.68
Chen et al. (2007)	1.16
Our approach with $K = 10$	
$K = 10$, UP $= (20, 0)$, $(10, 10)$	1.63
$K = 10$, UP $= (35, 0)$, $(15, 15)$	0.83
$K = 10$, UP $= (45, 0)$, $(20, 20)$	0.64
Our approach with $K = 15$	
$K = 15$, UP $= (20, 0)$, $(10, 10)$	1.72
$K = 15$, UP $= (35, 0)$, $(15, 15)$	0.64
$K = 15$, UP $= (45, 0)$, $(20, 20)$	0.49

noise removal and signal preservations by changing their unfiltered portion, polynomial order (and window width for the case of Swenson and Wahr (2006)). However, the parameters that we suggest might be a more natural choice, since they are related to the shape of the pattern of the provided standard deviations.

To illustrate our algorithm, we have presented only results of global compromises of the trend for general purpose, for which we suggested a preferred choice of the parameters. Nevertheless, the algorithm is expected to be also applicable for obtaining optimized results at a particular location and for specific geophysical studies. In these cases, the parameters defining the unchanged portion and the window width should be adjusted accordingly. Furthermore, if GRACE L2 data from another Data Center are used, the filter parameters should be chosen accordingly using the SDs of the estimated geopotential coefficients provided by that Data Center.

In summary, our main objective is to show that our method is an alternative to the existing methods for filtering GRACE data. The other point we were trying to make is that the choice of decorrelation filter depends surely on the objectives of various geophysical studies. One simple example is that the same decorrelation parameters for OBP filtering may or may not be appropriate to apply to earthquake co-seismic studies. We also discussed the fact that all filtering methods cause signal distortion, and that there is not an optimal set of filtering parameters to be applied to study all geophysical signals from GRACE.

However, as mentioned by Swenson and Wahr (2006), the decorrelation is a temporary solution for extracting more information from the present GRACE L2 products. The ultimate solution is to identify the source of the correlated errors, and remove or mitigate them during the gravity field inversion process.

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