Accuracy of scaled GRACE terrestrial water storage estimates

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[1] We assess the accuracy of global-gridded terrestrial water storage (TWS) estimates derived from temporal gravity field variations observed by the Gravity Recovery and Climate Experiment (GRACE) satellites. The TWS data set has been corrected for signal modification due to filtering and truncation. Simulations of terrestrial water storage variations from land-hydrology models are used to infer relationships between regional time series representing different spatial scales. These relationships, which are independent of the actual GRACE data, are used to extrapolate the GRACE TWS estimates from their effective spatial resolution (length scales of a few hundred kilometers) to finer spatial scales (∼100 km). Gridded, scaled data like these enable users who lack expertise in processing and filtering the standard GRACE spherical harmonic geopotential coefficients to estimate the time series of TWS over arbitrarily shaped regions. In addition, we provide gridded fields of leakage and GRACE measurement errors that allow users to rigorously estimate the associated regional TWS uncertainties. These fields are available for download from the GRACE project website (available at http://grace.jpl.nasa.gov). Three scaling relationships are examined: a single gain factor based on regionally averaged time series, spatially distributed (i.e., gridded) gain factors based on time series at each grid point, and gridded-gain factors estimated as a function of temporal frequency. While regional gain factors have typically been used in previously published studies, we find that comparable accuracies can be obtained from scaled time series based on gridded gain factors. In regions where different temporal modes of TWS variability have significantly different spatial scales, gain factors based on the first two methods may reduce the accuracy of the scaled time series. In these cases, gain factors estimated separately as a function of frequency may be necessary to achieve accurate results.

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1. Introduction

[2] The Gravity Recovery and Climate Experiment (GRACE) observes temporal variations of Earth's gravitational potential. After atmospheric and oceanic effects are accounted for, the remaining signal on monthly to interannual timescales is mostly related to variations of terrestrial water storage (TWS). Estimates of water storage variations suffer from signal degradation due to measurement errors and noise, which are manifested as both random errors that increase as a function of spherical harmonic spectral degree [*Wahr et al.*, 2006], and systematic errors that are correlated within a particular spectral order [*Swenson and Wahr*, 2006]. Several filtering approaches currently exist to either damp or isolate and remove these errors. In practice, however, filters also modify the true geophysical signal of interest. Filter design focuses on this trade-off, and attempts to minimize signal loss while maximizing noise reduction [*Swenson and Wahr*, 2011].

[3] Because the spatial resolution of filtered GRACE data is typically more coarse than that of other hydrological data sets, it is necessary to reconcile the differences in spatial scale between data sets before an equitable analysis can be performed. When the signal modification resulting from filtering the GRACE data is not accounted for, apparent differences between the TWS estimates will erroneously be attributed to either shortcomings in the observations or model data, when these differences are in fact due to a mismatch in spatial scales [*Tang et al.*, 2010].

[4] A straightforward way to reconcile spatial resolution discrepancies is to filter each data set in the same way. This approach has been used previously when validating satellite-based estimates of winter precipitation [*Swenson*, 2010] and global land-hydrology models [e.g., *Schmidt et al.*, 2006]. An alternate approach is to scale the GRACE data to account for the effect of the filter on the signal. A number of studies [e.g., *Swenson and Wahr*, 2007; *Rodell et al.*, 2004a; *Klees et al.*, 2007; *Landerer et al.*, 2010] have estimated the signal attenuation in basin-averaged time series and applied a gain factor to the GRACE observations. If it is not restored, signal attenuation will reduce the ability

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to close the regional water balance, or when the water budget is used to estimate one component as a residual, signal attenuation becomes an error in the residual. As it is cumbersome for users of GRACE data to estimate the signal degradation via the described route, hydrological research would greatly benefit from gridded-GRACE data that can be used as an independent, stand-alone, and unambiguous data set for hydrology applications without a geodesist's assistance [*Rodell et al.*, 2010]. This would allow users to average gridded-GRACE data over user-defined regions, where the signal attenuation has already been corrected for as part of the GRACE postprocessing, and the errors and uncertainties of a regional average can also be computed from gridded data.

[5] In this paper, we describe the scaling technique used to restore some of the signal loss in regionally averaged time series due to filtering and truncation of GRACE TWS observations, and apply it to regions consisting of $1^\circ \times 1^\circ$ grid cells. The resulting data set is publicly available via the Jet Propulsion Laboratory's TELLUS website (available at http://grace.jpl.nasa.gov). We then compare the accuracy of regional time series scaled using a bulk gain factor to a regional time series computed using the gridded-data set to which distributed gain factors have been applied. Next, we compare the effectiveness of single gain factors relative to frequency-dependent gain factors for a scenario where seasonally varying TWS signals have significantly different spatial patterns than secularly varying TWS signals. We then discuss the limitations of this scaling approach, which should help users of gridded-GRACE TWS data to realize the full potential of this data set while being aware of the uncertainties. The goal of this approach is to simplify the use of GRACE TWS observations for hydrological applications, and to allow for a rigorous quantification of leakage and measurement errors.

2. Gridded-GRACE Data Set

[6] The standard products of the GRACE project are sets of spherical harmonic coefficients describing the monthly variations in Earth's gravity field, which can be inverted to estimate changes in mass at the surface [*Wahr et al.*, 1998]. After filtering to reduce the presence of measurement errors, the data can be gridded, i.e., converted from spectral coordinates to geographical coordinates, in order to create maps of surface mass variations.

[7] The GRACE filter used in this study consists of two parts. The first filter is designed to remove systematic errors that are characterized by correlations between certain spherical harmonic coefficients; these errors are manifested as north-south-oriented "stripes" in maps of GRACE TWS ([*Swenson and Wahr*, 2006], Figure 1). The second filter is a Gaussian averaging filter with a half-width of 300 km that reduces random errors in higher degree spherical harmonic coefficients not removed by "de-striping" [*Wahr et al.*, 1998, 2006]. The Gaussian filter is a smoothing operation and reduces the spatial resolution of GRACE observations by damping the higher degree coefficients.

[8] Another feature of GRACE data is that the gravity field solutions are typically truncated at a spectral degree $l_{\max} \leq 60$. Thus, signals having spatial variability with spatial scales finer than a few hundred kilometers are not resolved by GRACE (e.g., $l_{\max} = 60$ represents a wavelength of $\sim$330 km). This form of signal loss can be thought of as resulting from the application of a spectral low-pass filter.

[9] The errors in the filtered data are estimated following the method described by *Wahr et al.* [2006]. The top panel of Figure 1 shows the root-mean-square (RMS) variability in the filtered GRACE TWS data, gridded at 1° spatial resolution. The bottom panel shows our estimate of the RMS measurement error, which exhibits a zonally banded pattern, with maximum errors of $\sim$36 mm water-equivalent height at lower latitudes; poleward, the error decreases to $<$15 mm.

3. Signal Attenuation From Filtering

[10] All water storage observations from GRACE represent average values, in both space and time. Temporally, GRACE data are approximately monthly averaged quantities. Because of truncation and filtering in the spectral domain, GRACE data are also spatially averaged, with spatially varying weights. This results in a time series that differs from the true, i.e., uniformly weighted, time series; this difference is often referred to as "leakage." The leakage error depends on the filtering process as well as the characteristics of the signal.

[11] The effects of the successive filter operations on the GRACE observations are shown in Figure 2. In the top left panel, the RMS variation of the original GRACE data are shown. Large amplitudes and prominent stripe-like features can be observed. After filtering (Figure 2, bottom left panel; note the different scale), the presence of these features is largely absent, indicating the effectiveness of the filtering process in reducing errors. However, the filters' effects on the actual signal cannot be ascertained from GRACE data alone. Instead, simulations based on realistic TWS models can be used [*Swenson et al.*, 2003; *Seo and Wilson*, 2005].

[12] To obtain quantitative estimates of signal attenuation and leakage error that arise from the application of these GRACE postprocessing filters, we use synthetic monthly TWS anomalies form January 2003 to December 2009 simulated by the NOAH land model, running within the Global Land-Data Assimilation System (GLDAS-NOAH [*Rodell et al.*, 2004b]). GLDAS-NOAH does not explicitly simulate groundwater and surface water, and we exclude TWS variations of glaciers and ice sheets, as these are either not included or unrealistic due to missing model physics. Methods to correct for signal attenuation for Greenland and Antarctica can be found by, e.g., *Velicogna* [2009] and *Chen et al.* [2009]. In order to create a synthetic TWS data set, the model data are first converted to spherical harmonic coefficients, and the two-step GRACE filter is applied. Next, the coefficients are remapped to the original 1×1 latitude/longitude grid [*Wahr et al.*, 1998] to quantify the signal attenuation.

[13] The original GLDAS-NOAH model data (Figure 2, top right panel) at $1 \times 1^\circ$ resolution is taken as the reference, relative to which the filtering effects are evaluated. When applying GRACE filters to the model data (Figure 2, bottom right panel), an implicit filtering step consists of truncating the model data at a spectral degree and order of 60 (or less), since most GRACE observations are only provided at that resolution. This truncation alone effectively reduces the

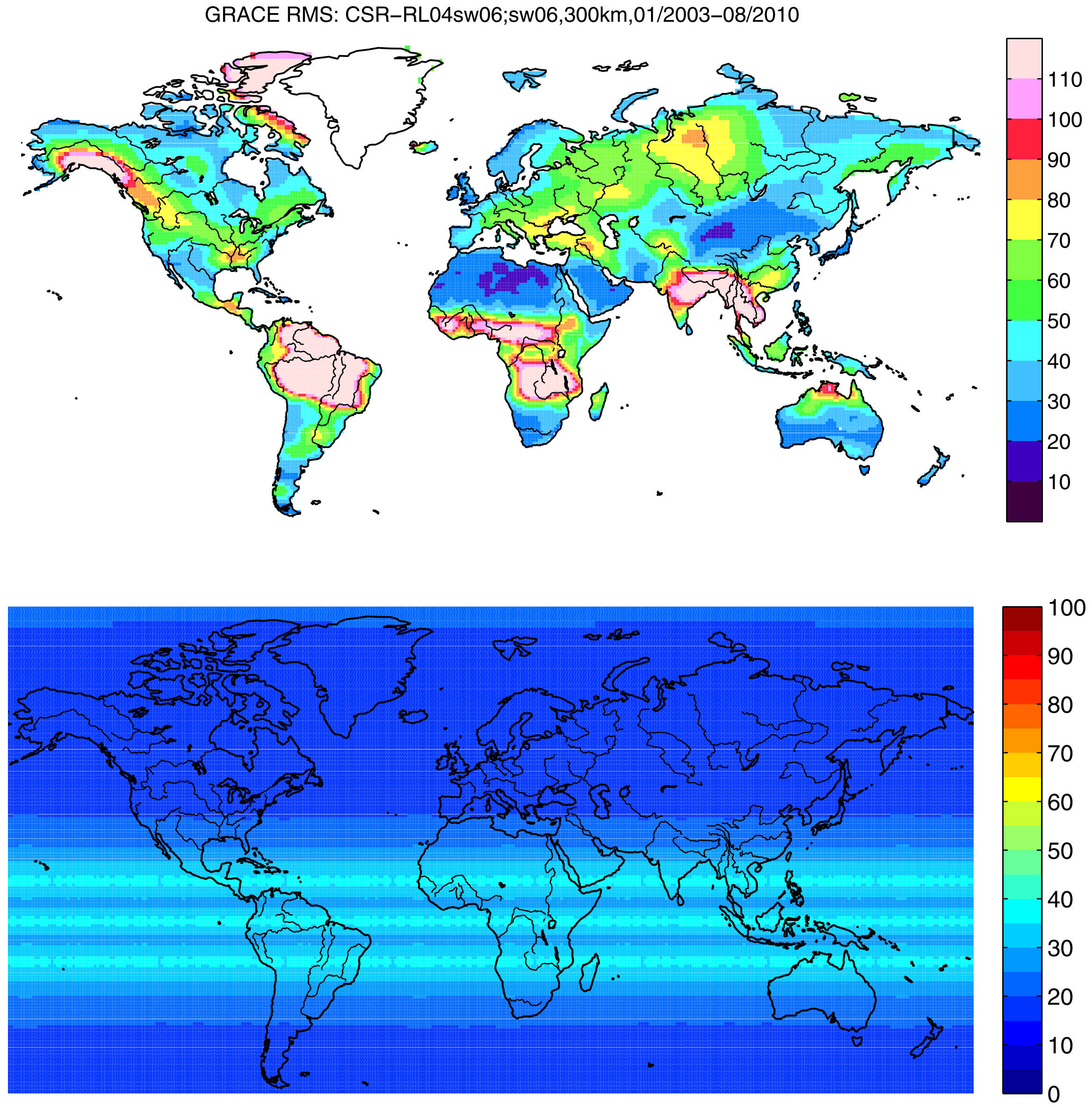

Figure 1. (Top) Root-mean-square variability of filtered GRACE TWS observations (CSR-RL04), and (bottom) corresponding estimates of the measurement error based on *Wahr et al.* [2006]. Note that we have removed longer than annual TWS signal variations to avoid the inflation of the error from these long-period TWS variations. Units: mm-H_2O.

spatial resolution from ~110 km to ~330 km at the equator. Geophysical signals with a prominent north-south orientation are further attenuated by the de-striping filter, and smoothing the truncated, de-striped data with a Gaussian averaging radius of 300 km also reduces signal variance. Signals along coastlines are particularly prone to signal attenuation because the filtering process removes short wavelength features. Therefore, grid points close to the ocean represent averages that include the typically much smaller ocean signals, resulting in strong reductions of TWS signal amplitude (e.g., along the west coast of the United States). Only very few regions exist where the ocean signals are large enough to potentially leak onto land and interfere with terrestrial water storage signals (e.g., Gulf of Carpentaria, north of Australia). Since an ocean model is removed in the GRACE processing, ocean-to-land leakage effects are already significantly reduced.

4. Restoring Signal Attenuation

4.1. Basin-Scale Gain Factors

[14] We quantify leakage error with the root-mean-square difference (RMSD) between the unfiltered and the filtered monthly mean GLDAS-NOAH water storage estimates. In order to reduce this leakage error, we derive a gain factor k by minimizing the misfit between the unfiltered, true (ΔS_T), and filtered (ΔS_f) storage time series through a simple least square regression:

$$M = \sum (\Delta S_T - k\Delta S_F)^2, \qquad (1)$$

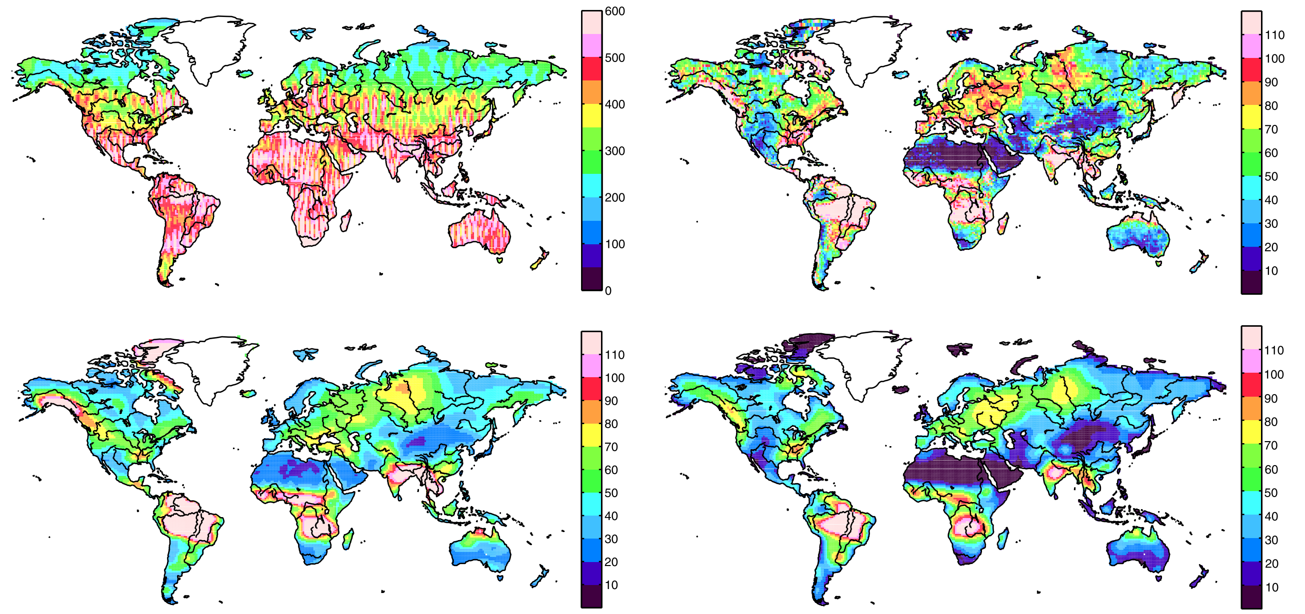

Figure 2. Root-mean-square variability of observed (left column: GRACE CSR-RL04) and simulated (right column: GLDAS-NOAH) terrestrial water storage: (top row) unfiltered GRACE TWS and GLDAS-NOAH TWS at $1 \times 1°$ resolution; (bottom row) spectrally truncated at degree and order 60, de-striped after *Swenson and Wahr* [2006], and smoothed with a Gaussian of 300 km width. Note the different color range for the unfiltered GRACE data. Units: mm-H_2O.

where the summation is over the 84 months of GLDAS-NOAH data used here. Several studies have used this approach to restore TWS signals over hydrological drainage basins [e.g., *Famiglietti et al.*, 2011; *Swenson and Wahr*, 2007; *Klees et al.*, 2007; *Chen et al.*, 2007].

[15] As an illustrative example, we use equation (1) to derive the gain factor for the basin-mean monthly TWS in the Columbia River basin in the northwestern United States (Figure 3). Applying the GRACE filters to GLDAS-NOAH leads to a significant leakage error. A gain factor of 1.44, calculated from equation (1), reduces the variance of the leakage error by nearly 85%. When the gain factor as determined from GLDAS-NOAH is applied to actual GRACE observations, it becomes evident that GLDAS-NOAH underestimates seasonal TWS variations in the Columbia River Basin (Figure 3, bottom panel), likely due to missing groundwater and river-storage components in the present GLDAS-NOAH version (M. Rodell, personal communication, 2011). This example also underscores one important aspect of the scaling approach: it does not seek to match GRACE measurements to synthetic model amplitudes, but uses the synthetic model patterns to determine relative signal attenuation based on the ratio of true and filtered signal amplitudes.

[16] Table 1 summarizes the filter parameter-dependent basin-scale gain factors (k_b, second column) for river basins of various drainage areas and locations. Gain factors for basins having large areas are typically close to 1, while smaller basins have larger gain factors. The third column of Table 1 lists the initial leakage error (E_b^l), while the fourth column shows the residual leakage error (E_{b,k_b}^l) present after the gain factor is applied to the filtered time series. Comparing E_b^l and E_{b,k_b}^l shows that significant reductions in leakage error variance can be obtained after the application of the gain factor.

4.2. Grid-Point Gain Factors

[17] Previous studies [e.g., *Famiglietti et al.*, 2011; *Swenson and Wahr*, 2007; *Klees et al.*, 2007; *Chen et al.*, 2007] have used a scaling approach, computing gain factors for specific regions. To create a global, gridded-data set of GRACE TWS observations that can be averaged over arbitrary regions, we apply the scaling procedure to all land points on a $1 \times 1°$ grid. This results in map of gain factors k_g (Figure 4), that, when applied to the filtered data, restores a significant portion of the signal attenuation. As discussed in more detail below, applying the gain factors first and then averaging leads to regional averages that are comparable to applying a single gain factor to an unscaled regional average (see also Figure 3 for the Columbia River as an example).

[18] The gridded-gain factors shown in Figure 4 are generally close to 1, indicating that signal damping is weak over the majority of interior land points. Along coastlines, gain factors significantly larger than 1 are required due to signal interference with the much weaker ocean signal. Areas of low TWS variability (e.g., Northern Africa) are susceptible to leakage errors from larger signals of surrounding regions. In these locations, gain factors less than 1 are then needed to reduce the signal amplification. As filtering may not only change the amplitude, but also change the shape of the signal through interference with out-of-phase signals from surrounding regions, it is instructive to examine the grid point correlation between the filtered and unfiltered model data (Figure 5). Correlation values close to 1 indicate that the shape (mostly dominated by seasonal variations) is not strongly affected by the filter, whereas lower correlation values indicate that the spatial averaging caused by the GRACE filter has changed the shape of the signal. This typically occurs where strong gradients in the

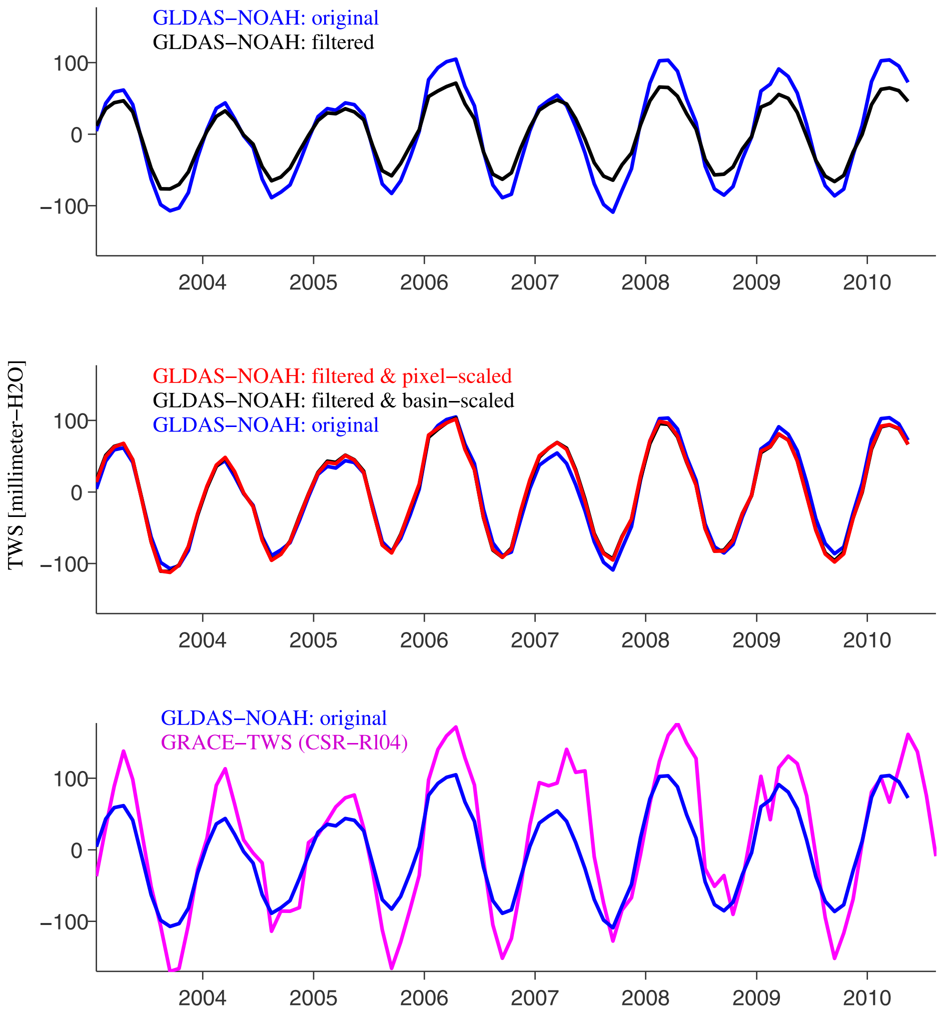

Figure 3. Basin-mean water storage for the Columbia River basin: (top) original and filtered GLDAS-NOAH, (middle) original versus the scaled basin-mean TWS (basin-scaled and pixel-scaled version) GLDAS-NOAH, and (bottom) original GLDAS-NOAH TWS compared to scaled GRACE-TWS (CSR-RL04). Units: mm-H_2O.

phase of the TWS signal exist, such as transitions between mountains and plains. In those areas, the spatial decorrelation length is often much shorter than what GRACE can resolve, and therefore signal leakage and interference are strong. The linear scaling approach (equation (1)) is less effective at restoring the signals in those cases.

4.3. Gridded Uncertainty Estimates

[19] A previously estimated GRACE measurement error [*Wahr et al.*, 2006] did not account for the leakage error from the TWS signals. Figure 6 shows new estimates of the GRACE measurement error (top) and leakage (middle) error for the gridded-GRACE TWS data set. The measurement errors are the result of multiplying the filtered GRACE measurement error map (Figure 1) by the grid point gain factor map (Figure 4).

[20] At each grid point, the leakage error estimate has been multiplied by the ratio of the RMS-variability's of the filtered GRACE and GLDAS-NOAH time series:

$$E_g^l = \mathrm{RMS}(\Delta S_T - k\Delta S_F)\frac{\mathrm{RMS_{GRACE}}}{\mathrm{RMS_{model}}}, \quad (2)$$

with S_T and $k\Delta S_F$ as defined in equation (1). The reason for this is that in some cases there is a significant discrepancy between the amplitudes of the GRACE and modeled TWS signals. The total error at each grid point is then obtained by summing leakage and measurement errors in quadrature.

[21] Globally, the application of the gain factors considerably reduces leakage errors. Figure 7 shows a histogram of the leakage error for the gridded TWS estimates before (blue line) and after (black line) scaling. The total area of grid points having leakage errors greater than $\sim$5 cm is significantly reduced, leading to a more sharply peaked histogram with more areas having leakage errors in the 2–3 cm range. In particular, signals along coastal areas are much better recovered.

[22] The error components shown in Figure 6 reflect the expected uncertainty in the time series of each individual grid point. However, the errors in the gridded data are spatially correlated, so the actual error in a regional average time series cannot be obtained by simply averaging the variances from all points within a given region. To obtain a more accurate uncertainty estimate, we introduce an approximation for the error covariance that is a function of the distance between

Table 1. Gain Factors, Leakage, Measurement, and Combined Errors for Unfiltered and Filtered TWS Variations for Various Drainage Basins[a]

		Error (Leakage)			Error (Measurement)		Error (Combined)		RMS Ratio
Basin	k_b	$(E_b^l)^{b,e}$	$(E_{b,k_b}^l)^{c,e}$	$(E_g^l)^{d,e}$	$(E_b^m)^{f,h}$	$(E_g^m)^{g,h}$	$(E_b^t)^{i}$	$(E_g^t)^{j}$	(GRACE/GLDAS)
Amazon	1.02	7.6	7.1	7.0	9.2	8.8	11.5	11.2	1.8
Zaire	1.14	7.8	4.9	5.5	12.2	11.3	11.8	12.6	1.1
Mississippi	1.00	4.7	4.7	5.1	9.6	6.4	10.7	8.2	1.2
Ob	1.00	2.0	2.0	3.6	9.3	6.1	9.5	7.1	1.1
Parana	1.18	12.3	7.7	6.3	12.6	12.3	13.1	13.8	1.1
Yenisei	1.03	3.8	3.5	5.0	9.6	6.8	9.9	8.4	1.2
Lena	1.10	4.7	2.5	5.3	10.3	7.9	9.6	9.5	1.3
Niger	1.06	5.4	4.1	5.9	11.5	10.5	11.6	12.0	1.4
Tamanrasett	0.62	8.6	6.8	5.0	7.3	6.1	13.6	7.9	3.2
ChangJiang	1.03	7.6	7.5	11.8	10.9	11.8	12.9	16.6	2.1
Missouri	0.78	14.0	8.7	6.9	8.2	6.2	13.6	9.3	1.5
Amur	1.17	5.8	3.2	6.6	12.4	10.1	11.0	12.1	1.1
Mackenzie	0.97	4.6	4.3	7.4	9.8	7.5	11.0	10.5	1.1
Ganges	1.11	13.4	8.5	12.8	12.4	11.5	14.0	17.2	1.5
Volga	1.08	4.8	2.2	3.9	11.3	8.4	10.7	9.2	0.9
Zambezi	1.11	14.1	7.0	7.6	13.3	16.9	13.9	18.5	1.2
Indus	1.26	25.4	23.5	17.2	15.4	12.6	26.5	21.3	2.1
Orinoco	1.23	39.9	27.0	20.7	16.4	18.3	30.1	27.6	2.7
Murray	1.34	18.3	16.5	8.1	16.9	15.3	20.7	17.3	2.4
Yukon	1.23	20.8	12.5	16.4	13.3	11.5	16.6	20.1	1.5
Colorado (Arizona)	1.01	9.3	9.3	6.7	12.6	10.9	15.5	12.8	1.7
Danube	1.15	14.6	11.0	9.1	14.1	11.6	16.5	14.8	1.1
Mekong	1.51	55.9	19.8	18.1	18.9	23.1	23.5	29.4	1.9
Columbia	1.44	31.9	13.5	15.6	17.5	15.5	18.2	21.9	1.6
Okavango	1.10	8.6	6.9	6.9	15.1	18.5	15.4	19.7	0.9
Kolyma	1.15	9.9	7.1	8.5	13.6	12.0	13.8	14.7	1.2
Arkansas	0.99	19.4	19.4	15.3	12.7	12.1	23.3	19.4	1.3
Irrawaddy	1.21	83.5	79.2	39.2	18.4	21.8	80.6	44.8	1.9
Godavari	1.31	36.0	13.9	14.6	19.8	27.8	20.5	31.4	1.3
Huai	1.47	28.8	20.7	17.1	20.8	22.7	25.1	28.4	1.4
Fraser	1.56	53.7	26.3	30.6	20.0	21.1	29.2	37.2	1.6
Anadyr	1.67	39.1	25.0	18.7	21.9	23.8	28.2	30.2	1.6
Chubut	1.98	34.5	22.2	20.5	26.3	28.8	25.9	35.4	1.6
Rufiji	1.23	31.2	23.4	27.6	19.0	26.5	28.1	38.3	1.5
Taz	1.16	17.0	11.1	11.1	14.2	15.3	16.5	19.0	1.1
Sacramento-San Joaquin	2.90	95.2	47.0	27.7	39.6	39.1	48.9	48.0	2.0
Pyasina	1.47	35.8	17.3	13.0	18.9	22.3	21.6	25.8	1.3
Essequibo	1.22	49.8	42.7	36.3	19.5	26.6	45.5	45.0	2.0
Koksoak	1.45	23.9	14.4	9.7	18.6	21.1	19.2	23.2	0.9
Loire	1.44	21.6	10.7	13.5	19.7	21.7	17.4	25.5	0.8
Narmada	1.29	36.1	16.4	16.5	19.2	25.0	22.1	29.9	1.2
Flinders	1.28	28.0	24.1	15.1	21.0	31.9	29.2	35.3	1.2
Cunene	1.37	27.4	20.0	13.9	22.7	34.7	26.0	37.4	0.8
Douro	2.14	46.8	17.0	17.5	30.3	35.7	22.2	39.7	1.0
Barito	2.46	94.4	36.9	33.5	44.0	70.8	41.0	78.4	2.4
Gambia	1.49	45.5	23.4	24.4	24.3	39.7	28.5	46.6	1.3

[a]Basins are ordered by decreasing size. The gain factors k_b are unitless, all errors are in units of mm of eq water height.
[b]Leakage error based on GLDAS.
[c]Basin-mean residual leakage (k_b applied).
[d]Grid-based GLDAS leakage error.
[e]Adjusted for RMS-ratio GRACE/GLDAS.
[f]Basin-mean GRACE measurement error [*Wahr et al.*, 2006].
[g]Grid-based GRACE measurement error.
[h]Adjusted for basin (footnote f) and gridded (footnote g) gain factors.
[i]Total error from basin means (see footnotes c and f).
[j]Total error from basin means (see footnotes d and g).

grid points. A Gaussian window is used, whose half-width is specified by a parameter d_0 representing the distance at which the function has decreased to half its maximum value. The covariance between two points x_i and x_j is then given by

$$\mathrm{Cov}(x_i, x_j) = \sigma_i \, \sigma_j \exp\left(\frac{-d_{ij}^2}{2d_0^2}\right), \quad (3)$$

where σ_i and σ_j are the standard deviations of the uncertainty estimates for grid points i and j, exp(...) is the correlation, d_{ij} is the distance between grid points, and d_0 is a decorrelation-length scale. The error variance of a regional mean TWS estimate then becomes

$$\mathrm{var} = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i \, w_j \, \mathrm{Cov}(x_i, x_j), \quad (4)$$

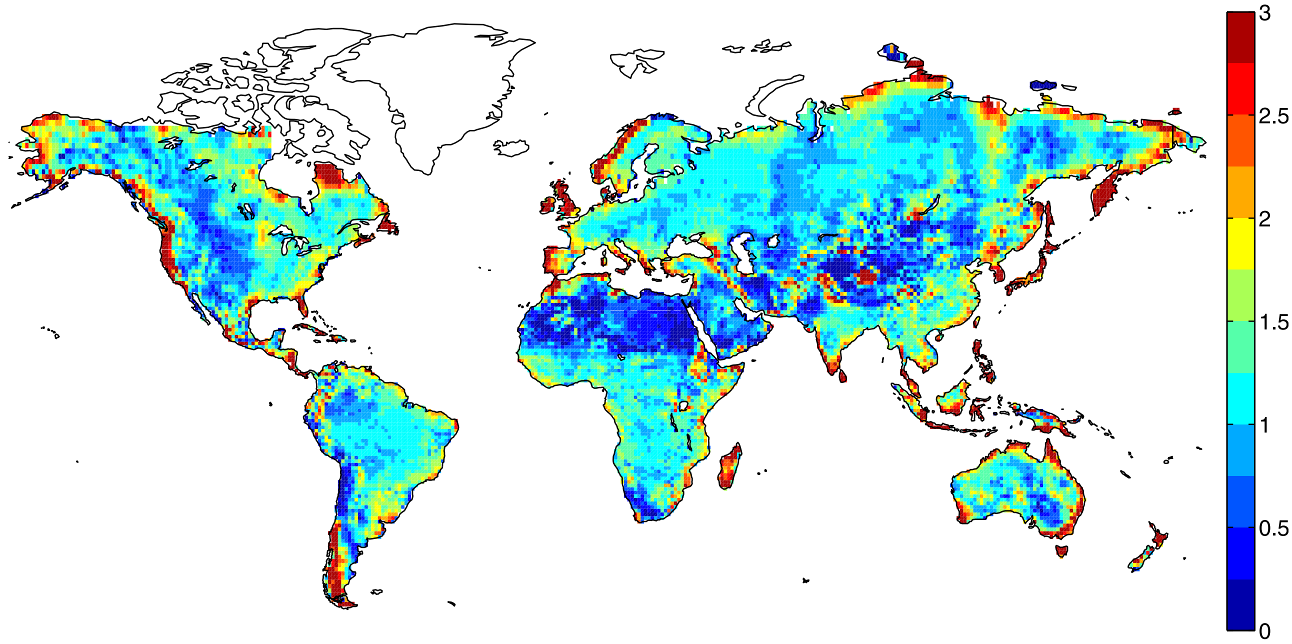

Figure 4. Gain factors for GLDAS-NOAH monthly TWS variations derived by least-square fitting each filtered grid point (at $1 \times 1^\circ$ resolution) time series to the unfiltered time series (see equation (1)).

where w_i is the area weight at each grid point in the basin. The values of d_0 were chosen so that the error budget obtained using the gridded data set matched the budget obtained when computing the regional average TWS time series directly; the area weights w_i simplify to 1/(number of grid points) if one assumes equal contribution from each pixel to the basin mean TWS. For the present choice of filter parameters, we used $d_0^m = 300$ km for the measurement errors, and $d_0^l = 100$ km for the leakage errors. We determined these values by comparing the error budgets based on basin- and grid-point-scaled time series for a large number of river basins.

[23] Column 5 in Table 1 shows the residual leakage error (E_g^l) when basin-averaged time series are computed using the griddedgain factors, applied to the GRACE TWS data set. Using these grid-point gain factors k_g, most basin averages have a similar reduction in RMSD relative to the unscaled estimates as the basin-scale gain factors (column 4),

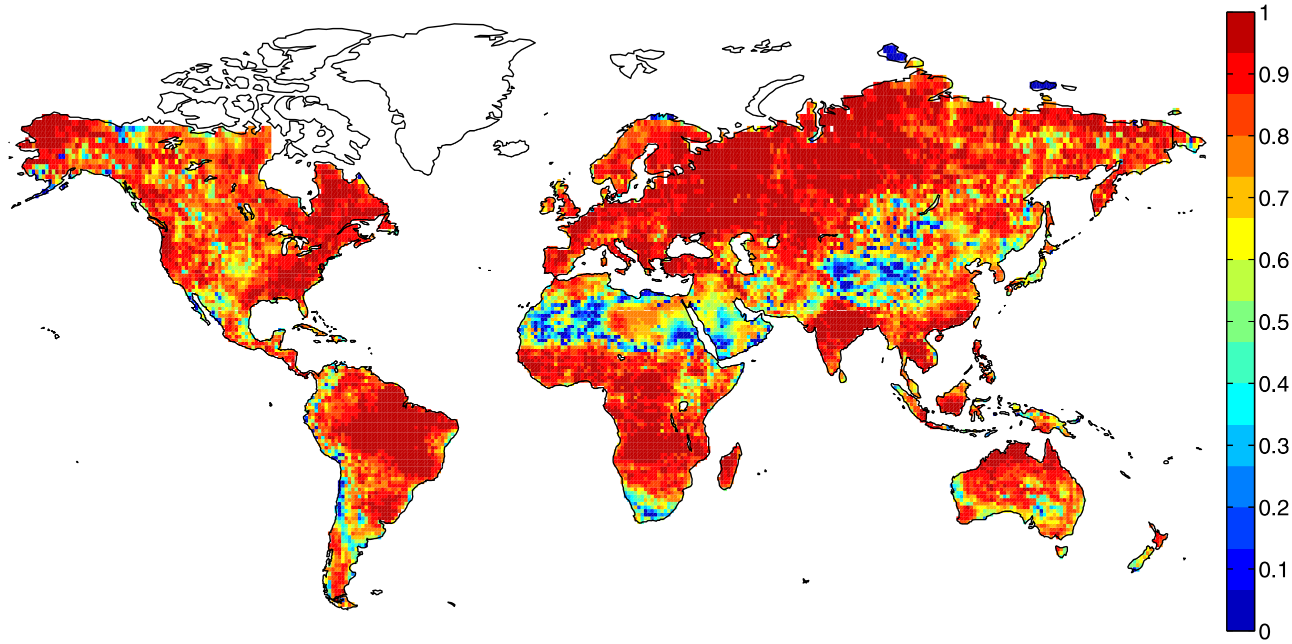

Figure 5. Correlation between filtered and unfiltered time series for monthly TWS variations from GLDAS-NOAH.

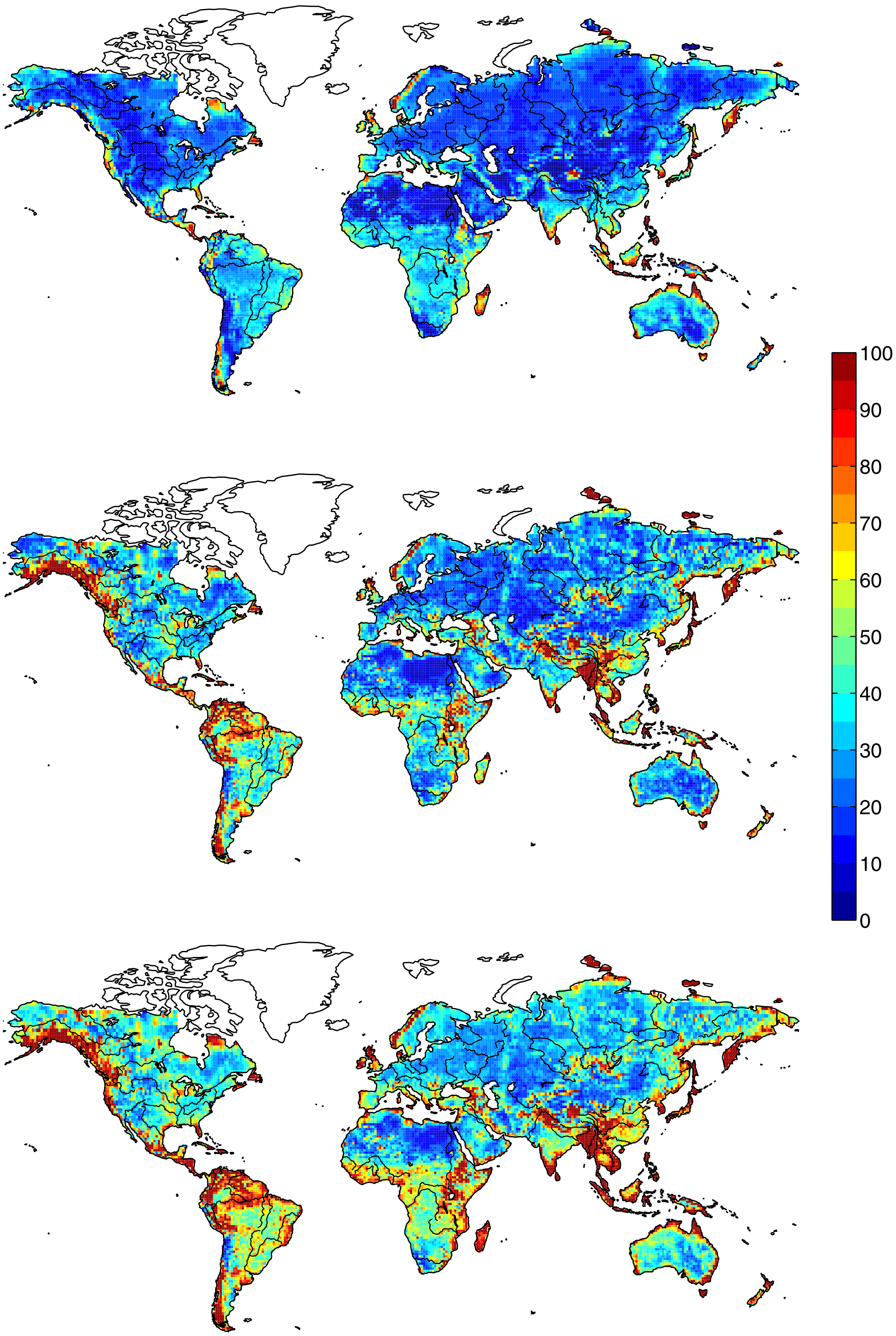

Figure 6.

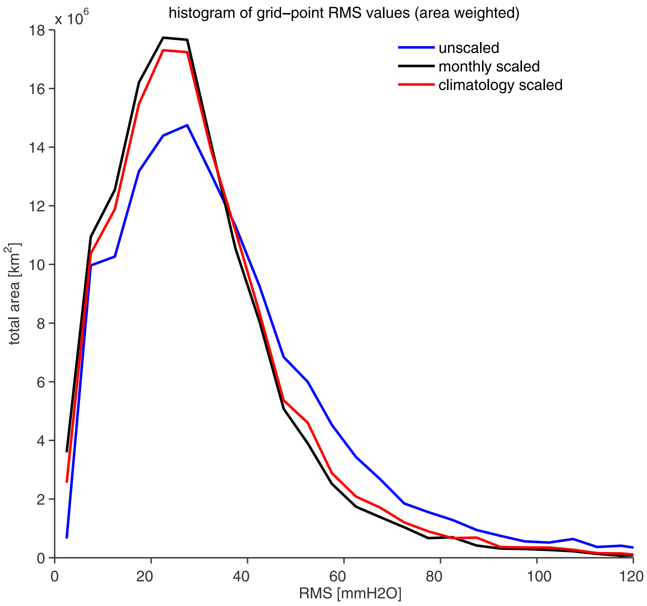

Figure 7. Histogram of RMS differences between unfiltered GLDAS monthly mean TWS and the filtered GLDAS amplitudes (blue line), and the filtered GLDAS amplitudes scaled with a gain factor based on all monthly anomalies (black line), and scaled with a gain factor based on a mean seasonal signal only (red line).

typically agreeing to within 20% or less. This level of agreement can also be seen in the basin-scale- (column 6) and grid-point (column 7)—measurement error estimates. Total error estimates, obtained by summing measurement and leakage errors in quadrature, are shown in columns 8 and 9. Time series for large river basins have RMS uncertainties that are generally <2 cm, while smaller basins have RMS uncertainties ~3–4 cm.

[24] An additional amount of uncertainty may arise from uncertainties of the model-based gain factors themselves. The gain factors shown in Figure 4 are based on GLDAS-NOAH. We evaluated the accuracy of the gain factors by deriving gain factors for the Community Land Model (CLM4) hydrology model [*Oleson et al.*, 2008], and applied the CLM4-based gain factors to the filtered GLDAS-NOAH data. The heterogeneous amplitude reconstructions (e.g., GLDAS-NOAH with CLM4-derived gain factors), yield residual leakage errors that are similar to the homogeneous amplitude reconstruction (e.g., GLDAS-NOAH with GLDAS-NOAH-derived gain factors) when averaged over the basins in Table 1. The differences in the residual leakage errors for different gridded-gain factors are similar to the error differences between basin-scaled and grid-point-scaled basin averages. Out of the 46 basins in Table 1, the residual leakage error for 24 basins agrees to within 10%, and 40 basins have residual leakage errors that agree to within 25%. For very small basins that cover only a few grid points (e.g., in our sample, the Cunene), the residual leakage errors may increase by up to 70%.

[25] As a general rule for the application of gain factors, it must be kept in mind that the estimates of TWS toward the smallest spatial scales can potentially be biased toward the hydrology model on which the gain factors are based. Although a user may use the time series of a single pixel (with its possibly large uncertainty), the motivation for the distributed gain factor data is to allow the user to create time series for arbitrarily shaped regions. As the size of the averaging region increases, the errors generally decrease.

4.4. Modes of Temporal TWS Variability With Different Spatial Scales

[26] The approach in equation (1) to estimate gain factors by minimizing the misfit of the entire time series with a single gain factor lumps together month-to-month variability, seasonal signals, and long-term trends. This issue of different temporal scales concerns both the grid point and the basin-scaling techniques. When the TWS signal contains different modes of temporal variability that have different spatial patterns, a single gain factor may not yield accurate results. *Chen et al.* [2007] found slightly different attenuation effects for annual and semiannual components for several large river basins, but the differences were relatively minor for small smoothing radii as used here (300 km). Moreover, the semiannual TWS amplitudes are generally much smaller than the annual amplitudes (in GLDAS-NOAH and in GRACE), so that the impact of scaling the two components separately was further reduced. Over river basins larger than ~0.6 Mkm^2, we find that gain factors for a mean monthly climatology and fitted semiannual and annual terms agree mostly to within a few percent (not shown), indicating that a single gain factor is applicable for seasonal variations with the present choice of filter parameters. In addition, we tested the performance of a gain factor based on a mean seasonal signal only (multiyear monthly means in the simulated TWS fields), and find that the error reduction is very similar to the case where the gridded-gain factor is based on all monthly TWS anomalies over the 7 yr of model data (Figure 7).

[27] As the GRACE satellites now provide observations of ~9 yr of monthly TWS, interannual variations and trends can be resolved. It is therefore important to assess if the scaling described above is applicable beyond the seasonal timescale. The simulated long-term signals over some regions agree well between GRACE and GLDAS-NOAH (e.g., southeastern United States, La Plata), but this is not the case for many other regions (e.g., northwest India, Amazon). Hydrological models often do not capture the full range of interannual TWS variations due to missing processes and storage parameterizations, such as groundwater storage or water extraction for irrigation. This has been exploited to extract these unmodeled signals by disaggregating the GRACE observations into water storage

Figure 6. GRACE TWS error maps. (Top) GRACE-measurement errors are based on the method of *Wahr et al.* [2006], and are scaled with the grid point gain factors from Figure 4; (middle) the residual leakage error estimate, scaled by the ratio of the RMS variability of GRACE and GLDAS-NOAH; (bottom) total errors from combining leakage and measurement errors in quadrature. Note that although the errors are spatially correlated, averaging over a region will reduce the grid point errors, e.g., for the Amazon basin the total error is ~11.3 mm-H_2O (Table 1). Units: mm-H_2O.

components. However, unmodeled TWS signals limit the use of synthetic data to infer a global map of gain factors that can be applied to actual GRACE observations.

[28] To illustrate this point, we use an example based on *Rodell et al.* [2009], who found significantly different gain factors for the seasonal and secular components of the observed TWS signal in northwest India (Figure 8a). The seasonal signal (TWS^s) was well correlated over a broad region beyond the averaging region, and therefore not significantly attenuated. In contrast, the interannual component was assumed to be originating from the relatively small averaging region only (based on prior knowledge about the spatial extent of the Indus aquifer), and therefore was significantly attenuated in amplitude. In such a case, the leakage error for the long-period signal (TWS^{lp}) must be treated separately from the seasonal variations (TWS^s) by deriving and applying multiple gain factors:

$$\mathrm{TWS} = k^s \mathrm{TWS}^s + k^{lp} \mathrm{TWS}^{lp}. \tag{5}$$

If the spatial extent of the interannual signal TWS^{lp} is known, and if it is only present in GRACE but not in a hydrology model, the gain factor k^{lp} can be estimated by a simple binary distribution of 1 over the a priori assumed region, and zeros outside of that region [*Rodell et al.*, 2009]. For the NW-India aquifer and the present choice of filtering parameters, the basin-scale seasonal gain factor is then $\sim$1, whereas the longer-period signal requires a gain factor of $k^{lp} = 3.2$.

[29] Had the spatially confined trend signal TWS^{lp} actually been present in GLDAS-NOAH, the reconstruction of the true signal would have revealed that the decomposition of the combined TWS signal into seasonal and long-period anomalies is necessary in order to estimate k^s and k^{lp} from the synthetic data. Without this temporal decomposition, the average gain factor is $\sim$1.7, which would overestimate the seasonal variations, but underestimate the trend (Figure 8b). Only with equation (5) can the true signal be accurately reconstructed. Our tests show that this works equally well for the basin-average and grid-point-scaling approach (Figure 8c). The observed TWS changes over the NW-Indus aquifer are rather extreme in amplitude, but this case demonstrates that gain factors based on simulated TWS change patterns in some cases may not be used to infer long-period TWS changes of actual GRACE observations; a case-by-case analysis may still be necessary, in particular for smaller regions, such as aquifers or surface reservoirs.

5. Summary and Discussion

[30] GRACE data processing seeks a balance between accuracy and spatial resolution. The level of noise can be reduced by filtering the data, and a variety of different filters have been developed for this purpose, each modifying the data in a specific and characteristic way. However, along with the error reduction comes some loss of signal. In many cases, measurement noise is substantially reduced leaving signal loss as the dominant term in the error budget of the filtered data. This type of error (leakage) can be estimated by applying the filter to a model, and comparing the original and filtered-model fields. In this paper, we have described one way of using the information supplied by such an experiment, i.e., a multiplicative gain factor that reduces the differences between the original and filtered model time series in a least square sense. It allows users of gridded-GRACE TWS observations to average over arbitrary regions of their choice and compare it to other gridded data (e.g., a hydrology model or groundwater data set), without having to apply the GRACE filtering process to that data in the spherical-harmonic domain. As detailed above, small spatial scales come at the expense of larger errors, in particular from leakage. Therefore, increasing the size of an averaging region generally reduces errors and uncertainties considerably.

[31] The gain factors derived here are based on simulated TWS variations, and are independent of the actual GRACE observations. Their purpose is to extrapolate the GRACE data to finer spatial scales that are not well resolved by the current GRACE satellites. It is important to keep in mind that while these fine scales are not truly measured by GRACE, our gridded-TWS estimates represent these scales to the degree to which a scaling relationship can recover them. This scaling relationship also enables us to quantify leakage and measurement errors based on signal patterns of TWS. The magnitude of the simulated TWS variations is not crucial to the calculation of the gain factors because they aim at restoring relative amplitudes. Thus, the spatial patterns of TWS, which are in part controlled by the

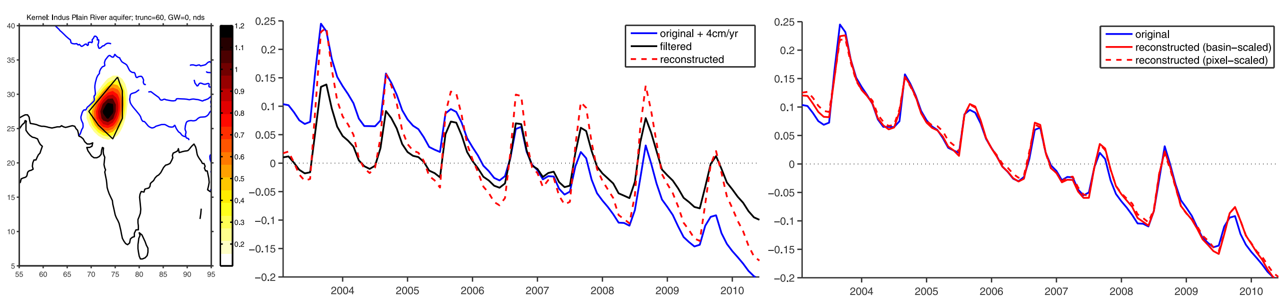

Figure 8. (a) NW-India Indus aquifer averaging region (inside polygon) and averaging kernel after spectral truncation of the exact mask at degree l = 60. (b) Mean TWS over the aquifer based on GLDAS-NOAH plus an added trend (-4 cm yr^{-1}) for the unfiltered, filtered, and reconstructed data using only one gain factor as in equation (1); (c) as (b), but decomposing the signal into seasonal and long-period components and deriving separate gain factors for each using equation (5). See *Rodell et al.* [2009] for a more detailed discussion of TWS in this region.

large-scale climate patterns of the forcing data (e.g., precipitation and radiation), determine the magnitude and spatial variability of the gain factors. In places where important processes are absent from the model, such as melting of ice sheets and glaciers, or human withdrawal of groundwater, the model-derived gain factors will likely not be accurate. In such cases, a more comprehensive analysis is required to estimate and restore the possible signal loss in the data.

[32] Most of the model-simulated TWS changes occur on the subseasonal to seasonal timescales. The derived gain factors therefore are optimized to recover these frequencies, and may not be suitable for interannual or long-term signals. A preliminary comparison of trends in GRACE data and trends in hydrological models indicates that it is not advised at this point to produce a global map of long-period gain factors based on these models. For these types of signals, it is recommended that a user carefully examines the model used to estimate filter effects, and if possible, augment the model [e.g., *Rodell et al.*, 2009].

[33] The presented method of gridded-gain factors and corresponding errors demonstrates that estimating gain factors on a grid point basis is a viable alternative to the basin-scaling approach that has been used previously. This conclusion is drawn by comparing some prominent river basin averages, both large and small. Thus, providing gridded-gain factor and error maps along with gridded-GRACE observations over land should enable users to recover attenuated signals from gridded-GRACE data, and quantify the appropriate uncertainty that takes measurement and leakage errors into account. The differences between the basin- and grid-point-scaling approach generally yield total errors that agree to within 20% over the regions presented here, but we cannot rule out that grid-point gain factors yield worse results than the basin-scaling approach over some user-defined regions. The map of the combined leakage and measurement uncertainty should guide GRACE users in treating regional averages carefully where significant scaling is necessary (Figure 4), or where the combined error is large (Figure 6). Mountainous areas in particular are affected due to the short TWS decorrelation length scales there. Alternative signal-restoring methods are possible and may be more or less suitable for a particular region under investigation. For example, mass loss estimates of the Greenland and Antarctic ice sheets from GRACE can be obtained in an iterative procedure [*Chen et al.*, 2009], or by designing optimized special-averaging kernels [*Swenson and Wahr*, 2002].

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