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# Integration of GRACE mass variations into a global hydrological model

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## Abstract

Time-variable gravity data of the GRACE (Gravity Recovery And Climate Experiment) satellite mission provide global information on temporal variations of continental water storage. In this study, we incorporate GRACE data for the first time directly into the tuning process of a global hydrological model to improve simulations of the continental water cycle. For the WaterGAP Global Hydrology Model (WGHM), we adopt a multi-objective calibration framework to constrain model predictions by both measured river discharge and water storage variations from GRACE and illustrate it on the example of three large river basins: Amazon, Mississippi and Congo. The approach leads to improved simulation results with regard to both objectives. In case of monthly total water storage variations we obtained a RMSE reduction of about 25 mm for the Amazon, 6 mm for the Mississippi and 1 mm for the Congo river basin. The results highlight the valuable nature of GRACE data when merged into large-scale hydrological modeling. Furthermore, they reveal the utility of the multi-objective calibration framework for the integration of remote sensing data into hydrological models.

*Key words:* continental water cycle, total water storage change, GRACE, satellite gravity, time variable gravity, hydrological modeling, model calibration,

## 1 Introduction

2 By mapping time variations of the Earth's gravity field with the Gravity Re-  
3 covery and Climate Experiment satellite mission (GRACE) since its launch in  
4 2002, an unprecedented global data set of mass variations close to the Earth  
5 surface became available (Tapley et al., 2004). After removal of mass variations  
6 due to tides and non-tidal atmospheric and oceanic transport processes, the  
7 time-variable gravity data mainly represent water mass variations in continen-  
8 tal hydrology, i.e., total water storage change (TWSC) on the continents (see  
9 a recent review by Schmidt et al. (2008a)). In specific regions, also mass vari-  
10 ation from post glacial rebound (Tamisiea et al., 2007) and seismic activities  
11 (Chen et al., 2007) could be revealed from the GRACE data.

12 For the field of hydrology, the past six years of GRACE operation contributed  
13 to a significantly improved understanding of the spatio-temporal patterns of  
14 water storage variations on the continents because no comprehensive TWSC  
15 data were available before at large spatial scales due to the absence of ad-  
16 equate monitoring systems (Lettenmaier and Famiglietti, 2006). Thus, the  
17 GRACE TWSC data give new insights into the Earth's water cycle includ-  
18 ing the contribution of TWSC to sea level variations (Ramillien et al., 2008),  
19 the impact of climate variability or extremes on water storage (e.g. Andersen  
20 et al., 2005; Seitz et al., 2008), or melting of glaciers and ice caps (e.g. Chen  
21 et al., 2006; Luthcke et al., 2006). Numerous regional or river basin studies

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22 analyzed GRACE TWS from seasonal to inter-annual time scales (see a re-  
23 cent review by Schmidt et al. (2008a)). Others solved the water balance using  
24 TWS from GRACE for other hydrological components such as evapotranspi-  
25 ration (Rodell et al., 2004; Ramillien et al., 2006) or runoff (Syed et al., 2007),  
26 or separated individual storage compartments such as groundwater (Rodell  
27 et al., 2007; Strassberg et al., 2007) or snow (Frappart et al., 2006; Niu et al.,  
28 2007).

29 Besides observation data, hydrological simulation models are an indispensable  
30 tool to assess the impact of environmental change on the continental water  
31 cycle and the particular processes mentioned above. Thus, in turn, they are a  
32 prerequisite for implementing measures of sustainable management of water-  
33 related issues in future. At continental to global scales, hydrological models  
34 are an integral part of atmospheric circulation models where they represent  
35 the land surface processes for climate and weather prediction simulations, see  
36 Dirmeyer et al. (2006) for an overview on land surface models and their com-  
37 parison. In addition, water balance models are used to represent the full water  
38 cycle in river basins for purposes such as stream flow forecasting and water  
39 resources assessment (for a recent overview on global water balance models see  
40 Widen-Nilsson et al. (2007)). However, these large-scale hydrological models  
41 are known to suffer from uncertainties in terms of model structure, parameter  
42 values and climate forcing data. As a consequence, simulation results for hy-  
43 drological state variables and water fluxes on the continents vary considerably  
44 between models (e.g. Dirmeyer et al., 2006). While river discharge has for a  
45 long time been the only observable to validate and calibrate global water bal-  
46 ance models (Hunger and Döll, 2008), considerable model uncertainties remain  
47 for other components of the water cycle, e.g., water storage, evapotranspira-  
48 tion or groundwater recharge due to the lack of adequate observation data.

49 In this context, GRACE provides a unique data set to evaluate and improve  
50 the simulation of TWSC on large scales and therewith to uncover shortcom-  
51 ings in model designs and parameters. Numerous studies compared GRACE-  
52 derived TWSC data with simulation results of hydrological models and con-  
53 cluded with a recommendation to use GRACE data as a model constraint  
54 (see a recent overview by Güntner (2008)). First attempts have been made  
55 to modify large-scale hydrological models and to evaluate the modifications  
56 with GRACE observations (Niu and Yang, 2006; Ngo-Duc et al., 2007) and  
57 very recently, Zaitchik et al. (2008) assimilated GRACE TWSC into a land  
58 surface model for the Mississippi river basin. A global integration of GRACE  
59 data with hydrological models to improve model performance by calibration  
60 has not been reported so far.

61 This motivated the present study to incorporate for the first time GRACE  
62 data into the tuning process of a global hydrological model (section 2.1). For  
63 this purpose, a multi-objective calibration scheme has been developed (see  
64 section 2.2). Calibration denotes the selection of model parameter values by  
65 evaluating the simulation performance via a model output objective against  
66 observations. In contrary to data assimilation, the system is tuned by deter-  
67 mining model parameter values during a pre-defined time interval, and the  
68 resulting parameter set may be used for subsequent independent model runs.  
69 Multi-objective calibration denotes that more than one model output objec-  
70 tives are taken into consideration. In this study, two different types of measured  
71 data are used to constrain parameter sets (section 2.3). Improvements for the  
72 simulation of TWSC are analyzed (in section 3) and the value of calibration  
73 procedure using GRACE data towards enhanced predictions of the continental  
74 water cycle is outlined (section 4).

## 75 2 Methods and Data

### 76 2.1 Global Hydrological Model

77 The WaterGAP Global Hydrology Model (WGHM) is a conceptual water bal-  
78 ance model which simulates the continental water cycle including the most im-  
79 portant water storage components, i.e., interception, soil water, snow, ground-  
80 water and surface water. The major hydrological processes are simplified by  
81 conceptual formulations. WGHM has a  $0.5^\circ \times 0.5^\circ$  spatial resolution and a daily  
82 computation time step. Information on land surface characteristics such as the  
83 spatial distribution of vegetation, soil types, land use, groundwater and sur-  
84 face water bodies is given in the model from global data sets. For details on  
85 model equations and their parameters see Döll et al. (2003). The model has  
86 widely been used to analyse continental water storage change (Güntner et al.,  
87 2007). In comparisons with GRACE TWSC, a general agreement of seasonal  
88 and other periodic characteristics of TWSC was found at the global scale,  
89 but amplitudes and phases in the model showed significant differences (larger  
90 than GRACE errors) in particular river basins (Ramillien et al., 2005; Schmidt  
91 et al., 2006, 2008b).

92 In this study, WGHM is driven by climate data (temperature, cloudiness and  
93 number of rain days per month) of the European Centre for Medium-Range  
94 Weather Forecast (ECMWF) and monthly precipitation data of the Global  
95 Precipitation Climatology Centre (GPCC). Precipitation is disaggregated to  
96 a daily resolution with the given number of rain days per month. The climate  
97 input data are available from 01/1992 until 12/2007 for this study. Antarctica  
98 and Greenland were excluded from the simulations.

99 We used the most recent WGHM version as described by Hunger and Döll  
100 (2008), who calibrated (i.e. tuned) the model against observed mean annual  
101 river runoff at 1235 discharge stations worldwide, by varying one runoff gen-  
102 eration parameter. This model version is called the original version in the  
103 following. Overall, the model includes 26 process parameters. Their values in  
104 the original model as well as parameter ranges for the calibration are based on  
105 literature and qualitative reasoning (Kaspar, 2004), see Table 2 for the parame-  
106 ters calibrated in this study. Thereof, the parameter root depth is based on the  
107 global land cover distribution and can be calibrated by a multiplicative factor.  
108 The Priestley-Taylor coefficient is used in the corresponding approach to quan-  
109 tify potential evapotranspiration. The radiative fraction of the extraterrestrial  
110 radiation that reaches the Earth’s surface is determined by cloud cover data  
111 and the radiation proportion parameter. The variability of snow melt temper-  
112 ature is due to different elevation and vegetation cover of different regions. A  
113 more detailed description of the model parameters is provided by Döll et al.  
114 (2003).

## 115 *2.2 Calibration Technique*

116 Combining both the present station-based accuracy of WGHM in terms of  
117 river discharge and the integrative nature of the GRACE data with global  
118 coverage, improved simulation results were expected from a multi-objective  
119 calibration approach. Calibration in the sense used here denotes an iterative  
120 method of testing different parameter values and selecting the best parame-  
121 ter sets based on performance criteria that evaluate simulation results against  
122 observation data. Calibration methods differ in their strategies to select pa-  
123 rameter sets for each iteration from the given parameter space. Furthermore,

124 multi-objective calibration denotes the selection of parameter values through  
125 evaluating model performance against more than one objective. In this study,  
126 these objectives are based on two observation data sets: river discharge and  
127 periodic TWSC (see section 2.3); hence, it is a two dimensional problem. In-  
128 stead of a single optimum parameter set, such an approach will lead to a  
129 Pareto set of optimal solutions (Gupta et al., 1998). Each Pareto optimum of  
130 this set is an optimal solution from a multi-objective point of view in the sense  
131 that no other solution exists that provides a better simulation performance  
132 for both model output objectives. Hence, when moving from one Pareto so-  
133 lution to another, simulation performance increases for one objective while  
134 it decreases for the other objective. Without additional information it is not  
135 possible to undertake a ranking among the Pareto solutions. The trade-off (i.e.  
136 the spread) between the Pareto solutions reflects the minimum parameter un-  
137 certainty (Vrugt et al., 2003) caused by errors in the input and the measured  
138 data as well as by model structure.

139 The calibration of a number of model parameters against more than one ob-  
140 jective depicts a highly non-linear optimization problem and requires a global  
141 optimization method. Furthermore, only stochastic methods like a multi-start  
142 simulated annealing or an evolutionary algorithm assure a feasible computing  
143 time for the calibration of the global hydrological model WGHM. Therefore,  
144 to handle the complexity of a multi-objective and multi-parameter calibration  
145 problem as well as the computational demands we select the  $\epsilon$ -Non-dominated-  
146 Sorting-Genetic-Algorithm-II ( $\epsilon$ -NSGAI) (Kollat and Reed, 2006), which ranks  
147 among the most effective and efficient multi-objective optimization methods  
148 (Tang et al., 2006). This global optimization algorithm solves multi-objective  
149 problems using the concept of evolutionary parameter variation (mutation,  
150 crossover and selection). It is an elitist algorithm with a Pareto ranking rou-



151 tine. Furthermore, as an extension of NSGAI (Deb et al., 2000) by the concept  
152 of  $\epsilon$ -dominance, it allows to specify the accuracy to be fulfilled by each ob-  
153 jective. For this study, we parameterize its operators as proposed by Kollat  
154 and Reed (2006). Furthermore, we use a population size of  $N = 8$  and an  
155  $\epsilon$ -resolution of 0.05 for both objectives and stop the optimization after 400  
156 iterations.

157 The calibration of WGHM is exemplarily done for the Amazon, the Mississippi  
158 and the Congo river basins in this study. These basins were selected because  
159 of their large size of over three million km<sup>2</sup>. The period 01/2003-12/2006 was  
160 used for WGHM calibration.

161 Güntner et al. (2007) showed that WGHM parameter sensitivity for TWSC  
162 simulations varies considerably between the river basins. This inter-basin vari-  
163 ability of parameter sensitivity can be explained by differences of the climatic  
164 conditions (represented in the model by the climate input data and param-  
165 eters steering evaporation or snow melt processes, for instance) and of the  
166 land surface properties (represented by, e.g., vegetation or soil parameters)  
167 between the river basins. This results in different water flow and storage char-  
168 acteristics in the basins. In particular, different storage components dominate  
169 the individual river basin response, e.g., snow storage in higher latitude areas  
170 or surface water storage in some tropical areas with large inundation zones.  
171 Thus, also the sensitivity of model parameters used to govern these individ-  
172 ual dominant storage processes varies between the river basins. Consequently,  
173 ahead of the calibration work, a sensitivity study was undertaken by a Latin  
174 Hypercube sampling for 2000 parameter sets and by an analysis scheme going  
175 back to Hornberger and Spear (1981), who selected sensitive parameters based  
176 on their ability to provide behavioural model simulations. For each river basin,

177 we selected the six most sensitive parameters for calibration against TWSC  
178 and river discharge (see row (e) and row (f) of Table 1). Parameter values and  
179 ranges are documented in Table 2.

180 For the Amazon basin, three of these parameters concern the process of surface  
181 water transport, because of the high water volume during an important flood  
182 season. In contrast, evaporation is most important in the tropical Congo river  
183 basin with a distinct dry season. A diverse set of important processes (e.g.  
184 snow, evaporation and surface water) provides the most sensitive parameter of  
185 the Mississippi river basin, due to its location in three different climate regions  
186 (cold in the north, subtropical in the southeast and dry in the southwest).

187 The evaluation of model performance for each iteration is effected by the fol-  
188 lowing four steps: 1) Model simulation of monthly global TWSC fields and  
189 river discharge with the current parameter set. 2) Application of a GRACE-  
190 equivalent filter procedure, which comprises the conversion of WGHM TWSC  
191 fields into the frequency domain, i.e. spherical harmonic coefficients, followed  
192 by Gaussian smoothing (Jekeli, 1981) and the computation of basin aver-  
193 ages of TWSC according to Wahr et al. (1998). 3) Fitting amplitudes and  
194 phases of significant periods which were determined from GRACE data (see  
195 section 2.3.2) to the simulated basin averages of TWSC and reconstruction  
196 of a basin-average time series of TWSC from these periods. 4) Evaluation of  
197 each calibration objective (discharge and TWSC) by computation of the Nash-  
198 Sutcliffe-efficiency coefficient ( $NSC$ ) (Nash and Sutcliffe, 1970) as a criterion  
199 of agreement between modeled and measured time-series.

200  $NSC$  is a simulation performance measure that normalizes the squared differ-  
201 ence of a predicted ( $P$ ) to an observed ( $O$ ) time series by the variance of the

202 observed values with  $n$  time steps:

$$203 \quad NSC = 1 - \frac{\sum_{i=0}^n (O_i - P_i)^2}{\sum_{i=0}^n (O_i - \bar{O})^2}, \quad (1)$$

204 where  $\bar{O}$  is the mean of the observations over the examined period.  $NSC$   
205 evaluates both phase and amplitude agreement between two time series. It  
206 ranges from  $-\infty$  to 1 (optimal fit), with a value of 0 indicating a simulated  
207 time series that performs as well as a model being equal to the mean of the  
208 observable. Therefore Pareto solutions are restricted to  $NSC$  values greater  
209 than 0.

## 210 *2.3 Calibration data*

### 211 *2.3.1 River basin discharge: Objective 1*

212 River discharge data of Amazon, Mississippi and Congo from the most down-  
213 stream gauging station were used (Table 1). We computed monthly mean  
214 values for the calibration period. For the Congo river where no up-to-date  
215 measurements were available, we assigned the monthly mean discharge of ear-  
216 lier observations to the calibration period.

### 217 *2.3.2 GRACE TWSC: Objective 2*

218 Reconstructed significant periodic parts of basin-averaged TWSC resulting  
219 from the investigation presented in Schmidt et al. (2008b) are used as calibra-  
220 tion input for this study. These data are chosen, because errors in the GRACE  
221 original data and the difficulty to separate the errors from real signals mark  
222 the greatest challenge for application of satellite gravity solutions.

223 Schmidt et al. (2008b) developed a technique to extract significant water stor-  
224 age change information from GRACE data by three steps: 1) Identification  
225 of the dominant spatio-temporal patterns in mass variations derived from  
226 GRACE observations through a principal component analysis (applied at the  
227 scale of the river basins to grids previously filtered by a Gaussian smooth-  
228 ing with a 500 km averaging radius), 2) Identification of significant periods  
229 of TWSC contained in the principal components without fixing a priori the  
230 period lengths, and 3) Reconstruction of (error-reduced) basin-average time  
231 series of TWSC from the significant periods.

232 As a basis, monthly GRACE-only time series of global gravity fields generated  
233 as spherical harmonic expansions up to degree and order 120 at the GFZ  
234 German Research Center for Geosciences (GRACE Level-2 products, version  
235 GFZ-RL04, Schmidt et al., 2008a) for the time period from 02/2003 until  
236 12/2006 (excluding unavailable months 06/2003 and 01/2004) were used. The  
237 noise contained in the spherical harmonics increases with the degree of the  
238 expansion terms, and the noise/signal ratio reaches unacceptably high values  
239 in higher-degree terms. In the space domain this noise becomes visible in the  
240 form of the typical meridional-oriented spurious gravity signals (“stripes”)  
241 (e.g. Swenson and Wahr, 2006; Schmidt et al., 2008a). Hence, a spatial filtering  
242 is mandatory when computing water storage variations from GRACE gravity  
243 field models in order to reduce these errors. For the present study a widely  
244 used Gaussian smoothing (Jekeli, 1981) with an averaging radius of 500 km  
245 was applied. Mass variations (TWSC) were derived relative to a mean field  
246 (i.e. in the form of mass anomalies) for the considered data period applying  
247 the procedure presented by Swenson and Wahr (2002).

248 Since the effects of the atmospheric and the oceanic circulations were previ-

249 ously removed in the course of the gravity field recovery from the raw GRACE  
250 data by applying appropriate geophysical models (Flechtner, 2007), the ma-  
251 jor part of the signal contained in the derived grids of mass anomalies can  
252 be attributed to hydrological variations. Due to the rather short time period  
253 covered by the available GRACE data, the long-term trends determined both  
254 from the hydrology model WGHM and from the GRACE gravity fields should  
255 be regarded as less reliable than the periodic components resulting from the  
256 same data. Therefore, as the last preparatory step, the data used in this study  
257 have been de-trended.

258 Subsequently, the three-step strategy for the detection of significant peri-  
259 odic components, depicted at the beginning of this section, was realized, see  
260 (Schmidt et al., 2008b) for more details. It is important to note, that the period  
261 search was not a-priori constrained to seasonal or other postulated variations.  
262 For all three river basins, considered in this study, two periods resulted to be  
263 significant with respect to their signal proportion and an uncertainty study.  
264 Corresponding amplitudes and phases used for the calibration are given in Ta-  
265 ble 1, row (g). TWSC of all three basins exhibit a seasonal period. A second  
266 period of inter-annual scale (about 2.5 years) occurs for the Amazon as well  
267 as the Mississippi and of semi-annual scale for the Congo river basin. The cu-  
268 mulative variability of the reconstructed periodic components dominates the  
269 integral GRACE signal (see Table 1 row (h) for percentage proportion).

270 Error estimations of GRACE data differ between several studies. For example,  
271 using a Gaussian smoothing with an averaging radius of 750 km Wahr et al.  
272 (2006) derived latitude-dependant errors of GRACE mass estimates ranging  
273 from 8 mm near the poles up to 25-27 mm at low latitudes, when expressed  
274 in water column equivalents. This results in a global area-weighted mean of

275 21 mm. Schmidt et al. (2007) gave for a 500 km Gaussian filtering a global error  
276 estimate of 24-30 mm water column. According to Schmidt et al. (2008a) the  
277 accuracy of the GFZ-RL04 used in this study is approximately two times better  
278 than the accuracy of the earlier releases used in both cited studies. However, it  
279 should be taken into account that errors may be higher for particular regions  
280 and months, and are also influenced by leakage errors after forming basin-  
281 average values.

### 282 **3 Results and Discussion**

283 The multi-objective calibration of WGHM with GRACE TWSC and river  
284 discharge led to improved simulation results in all three river basins (Figure 1).  
285 Each Pareto solution (on the red line) is superior to the original model version  
286 (green dot) with regard to both objectives.

287 Best results were obtained for the Amazon basin. *NSC* performances better  
288 than 0.95 with respect to both objectives were achieved for the Pareto solu-  
289 tion closest to the optimum (hereafter referred as the selected Pareto-optimum,  
290 blue dot in Figure 1a). The amplitude of periodic terms of TWSC increased  
291 markedly in the Pareto solutions when compared to the original model (Fig-  
292 ure 2a). Since the narrow uncertainty band given by the Pareto set of solutions  
293 does not include the original model time series, the significance of model im-  
294 provement is substantiated. Although the amplitudes of basin-average TWSC  
295 were slightly overestimated by the selected Pareto solution in 2003 and 2006,  
296 its root mean square error (RMSE) of the complete (but de-trended) TWSC  
297 signal was reduced by 50% compared to the original model version (Table 3).  
298 The reduction of RMSE for discharge was even greater, since a phase shift of

299 discharge seasonality could be corrected by the multi-criteria calibration (see  
300 Figure 3a). A main reason for the model improvements in the Amazon basin  
301 could be attributed to longer residence times of surface water in rivers and  
302 floodplains as expressed by lower values for the flow velocity parameter in the  
303 Pareto solutions.

304 Also in the Mississippi basin a very good fit to observations with *NSC* per-  
305 formances of about 0.9 for both objectives were obtained for the selected  
306 Pareto-optimum (Figure 1b). Although the results for river discharge are more  
307 uncertain than for TWSC, the improvement compared to the original WGHM  
308 is greater for discharge than for TWSC. This is reflected by the reduction  
309 of the RMSE of the monthly mean discharge of about 80%, respectively 13  
310 km<sup>3</sup>/month (Table 3) for the selected Pareto-optimum. The clear improve-  
311 ment of monthly discharge simulations is also due to the fact that the original  
312 model was calibrated for mean annual values and did not take into account  
313 the seasonal distribution of discharge as in the present scheme. Therefore, the  
314 overestimated peaks of monthly discharge during spring in the standard model  
315 version could be corrected for all Pareto solutions (see Figure 3b). The recon-  
316 structed calibrated time series of water storage variations shows a slightly  
317 shifted phase and an amplitude which is closer to the GRACE time series  
318 (Figure 2b). The RMSE of the full de-trended time series of TWSC was im-  
319 proved about 6 mm compared to the original model version (Table 3). This  
320 improvement was most likely caused by changes of two model parameters.  
321 An increased effective root zone increases the soil storage capacity and an in-  
322 creased snow melt temperature smooths the previously overestimated runoff  
323 peaks.

324 Calibration for the Congo basin resulted in a much wider trade-off between

325 both objectives (note the different scaling of both axes in Figure 1c). The  
326 performance of the Pareto solutions varies between 0.0 and 0.8 for discharge  
327 and between 0.7 and 0.9 for TWSC (Figure 1c). This trade-off resulted in  
328 a wider uncertainty band for the calibrated TWSC periods of the Pareto  
329 solutions (Figure 2c). Nevertheless, a small phase shift of TWSC periods was  
330 achieved for all Pareto solutions. The RMSE of the full TWSC signal for  
331 the selected Pareto-optimum was improved by about 1 mm (Table 3). All  
332 other Pareto solutions provide greater RMSE reductions, since they show a  
333 higher simulation performance for the significant periods of TWSC, as the  
334 selected Pareto-optimum. For discharge, there were slight improvements in  
335 the monthly regime (Figure 3c), as indicated by higher peaks during the turns  
336 of the year (from October till January) for the re-calibrated hydrograph of  
337 the selected Pareto-optimum. While the RMSE for discharge could clearly be  
338 decreased by the calibration procedure, the *NSC* value for the selected Pareto-  
339 optimum of 0.76 still indicates only moderate correspondence of simulated  
340 and observed river discharge. Though, the rather discontinuous course of the  
341 Pareto frontier may imply that a higher number of function evaluations would  
342 give better calibration results. These limitations in achieving better discharge  
343 and TWSC simulations as well as the wider uncertainty in the calibration of  
344 the Congo basin are likely due to the lack of river runoff measurements during  
345 the calibration period and complicate the assignment of improved processes  
346 for the Congo basin. The particular characteristics of the rainfall distribution  
347 in each year will cause substantial deviations from the mean hydrograph that  
348 was used for model evaluation in this basin (Figure 3c). This may also point  
349 out errors in the model structure, the model input data, or in the parameter  
350 space allowed for calibration in the Congo basin and is subject to further  
351 studies.



352 Introduction of further observables to the multi-objective calibration scheme  
353 could further reduce the resulting equifinality of parameter sets as expressed  
354 by the dense Pareto-Frontier shown for Amazon and Mississippi. In particular,  
355 parameter values of storage processes that are represented by these additional  
356 observations could be more effectively constrained. For example, surface water  
357 storage derived from satellite altimetry and imagery can provide such data  
358 sets for an individual storage compartment (Papa et al., 2008). Though, the  
359 success will be limited as long as the observables contain high errors (e.g.  
360 groundwater, Döll and Fiedler, 2008) or the approach demands sophisticated  
361 model modifications to make model state variables match the observables (as  
362 for remotely sensed surface soil moisture).

363 A validation of the calibrated model was performed for de-trended GRACE  
364 signals including non-periodic components and errors from January until De-  
365 cember 2007 (see Figure 4). For this year, a simulation run was realized with  
366 WGHM using the parameter values that were calibrated for the period 2003-  
367 2006. For the Amazon and the Mississippi river basins, simulation results were  
368 markedly better for the validation period, when they are compared to the re-  
369 sults of the standard model in terms of amplitude, phase and RMSE values.  
370 This improvement is similar to what was achieved in the calibration period  
371 (see Table 3). This corroborates the model improvement of TWSC that could  
372 be achieved by the multi-criterial calibration for these basins. For the Congo  
373 river basin, however, the RMSE value increased, indicating that the model  
374 performs somewhat worse with the re-calibrated parameter set in the valida-  
375 tion period. This confirms the above results that improvements by calibration  
376 are difficult to achieve with the present model set up and data availability for  
377 this river basin. For further studies it should also be taken into consideration  
378 that it might be justified to reduce the weight assigned to the river discharge

379 data during calibration in the Congo basin due to their high uncertainties.  
380 This may enable the selection of Pareto optima with higher TWSC-simulation  
381 performance (see Figure 1c).

## 382 4 Conclusions

383 The first multi-objective calibration of the global hydrology model WGHM  
384 with TWSC data from GRACE and monthly mean river discharge was suc-  
385 cessfully carried out. By this approach, phase and amplitude differences of  
386 periodic water storage variations between GRACE and WGHM could be sig-  
387 nificantly reduced as compared to earlier versions of WGHM. We could show  
388 that the direct integration of GRACE data into the calibration process of  
389 WGHM leads to a clear improvement of simulated monthly TWSC signals on  
390 a scale of large river basins. At the same time, a better simulation of river  
391 discharge could be achieved. This highlights the particular value of multi-  
392 objective process analyses. If two observables are considered within the cali-  
393 bration approach, the trade-off in model performance of different hydrological  
394 variables is taken into account. Finally, this allows for an improved represen-  
395 tation of the water balance as a whole.

396 It should be pointed out that the calibration approach adopted in this study  
397 followed two principles that can be seen as a prerequisite for the successful  
398 integration of GRACE water storage data into large-scale hydrological models  
399 (Güntner, 2008). First, GRACE and WGHM model data were treated exactly  
400 in the same way before comparison and parameter adjustment, i.e., the same  
401 methods of filtering and basin-averaging were applied to both data sets. This  
402 excludes the risk of poor comparability of the time series if unfiltered model

403 data are compared to filtered GRACE data which may include filter-induced  
404 biases. Secondly, with WGHM a hydrological model was used that represents  
405 all relevant water storage compartments in the analyzed river basins, including  
406 surface water storage. Thus, it is assured that water storage calibrated in the  
407 model is consistent with the observation variable, i.e., the integrative nature  
408 of GRACE-based TWSC.

409 A better process understanding in global hydrology is necessary to provide  
410 more reliable estimates of changes in the continental water cycle, which con-  
411 stitutes an important input for climate studies or water resources management.  
412 In order to get a closer view into the reasons why the model differs from the  
413 real world, more accurate input data and improved calibration settings should  
414 be applied. The former can be achieved by using up-to-date river discharge  
415 data (i.e. for the Congo basin) and better GRACE filter methods. For the  
416 latter, technically more extensive model calibrations in terms of the size of  
417 parameter set population and of function evaluation are necessary to shift the  
418 Pareto frontier towards an even better model performance. Also, the analysis  
419 of a posteriori model states and parameter sets will help to uncover potential  
420 errors in model structure or input data. In this way, an improved understand-  
421 ing of continental water storage processes may finally be achieved by a stepwise  
422 modification of the modelling concept (Fenicia et al., 2008). Especially for re-  
423 gions like the Congo river basin with a very inaccurate or lacking coverage  
424 of terrestrial data, the usage of GRACE data is most proliferous concerning  
425 model improvement. Longer GRACE time series and the continuing error re-  
426 duction within GRACE gravity recovery are likely to reduce the uncertainty  
427 of GRACE TWSC recovery and therefore the data assimilation into global  
428 hydrology modeling in further studies. Additionally, the presented approach  
429 is promising for the integration of alternative data sets from remote sensing,

430 such as soil moisture, snow cover or surface water volumes into hydrological  
431 models. Furthermore, the methods considered here to achieve consistency of  
432 model variables and GRACE observations in terms of, e.g., data filtering and  
433 the selection of dominant signals, may similarly apply to other areas of Earth  
434 system modelling where GRACE data are to be used as a model constraint,  
435 such as for processes of the cryosphere or the Earth’s interior.

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Table 1

(a) Re-calibrated river basins with (b) corresponding area and (c) discharge station. (d) Discharge source and time series for computation of monthly means. (e) Number of WGHM parameters from different processes (S: Soil, SW: Surface water, GW: groundwater, ER: Evaporation and Radiation, SN: Snow, IN: Interception) derived from a sensitivity study against TWSC and river discharge. The underlined process includes the most sensitive parameter. (f) Calibration parameter in corresponding order to row (e) (MCWH: maximum canopy water height, PT: Priestley-Taylor). (g) Significant GRACE derived TWSC periods  $P_n$  of basin averages with associated amplitudes  $A_n$  and phases  $\phi_n$ , with  $t_0 = 01.01.2005$ . (h) Cumulative proportion of the significant periods in the full GRACE signal variability.

(a)	Amazon	Mississippi	Congo
(b)	5.9 Mio $km^2$	3.0 Mio $km^2$	3.6 Mio $km^2$
(c)	Obidos 1.9°S, 55.5°E	Tarbert Landing 31.6°N, 91.5°W	Kinshasa 4.3°S, 15.3°W
(d)	ORE HYBAM 2003-2006	US ACE 2003-2006	GRDC 1903-1983
(e)	3 <u>SW</u> , 1 GW, 1 S, 1 IN	1 <u>SW</u> , 1 S, 2 ER 1 SN, 1 IN	2 <u>ER</u> , 1 S, 1 GW, 2 SW
(f)	runoff coefficients river velocity wetland depth GW baseflow coeff. rooting depth MCWH	runoff coefficient root depth radiation proportion PT coefficient snow melt temperature MCWH	radiation proportion PT coefficient rooting depth GW baseflow coeff. wetland depth SW baseflow coeff.
(g)	$P_1 = 0.9833$ a $A_1 = 146$ mm $\phi_1 = 3.82$ mon $P_2 = 2.5297$ a $A_2 = 22$ mm $\phi_2 = 19.29$ mon	$P_1 = 0.9826$ a $A_1 = 33$ mm $\phi_1 = 2.99$ mon $P_2 = 2.4824$ a $A_2 = 22$ mm $\phi_2 = 29.59$ mon	$P_1 = 0.9881$ a $A_1 = 30$ mm $\phi_1 = 1.82$ mon $P_2 = 0.5022$ a $A_2 = 15$ mm $\phi_2 = 4.75$ mon
(h)	99%	75%	73%

Table 2

Calibration parameter values and their ranges for the calibration work (GW: groundwater, MCWH: maximum canopy water height, PT: Priestley-Taylor, SW: surface water).

Parameter	Standard value and unit	Minimum	Maximum
GW baseflow coefficient	0.01 / day	0.006	0.1
MCWH	0.3 mm	0.1	1.4
PT coefficient	1.26	0.885	1.65
radiation proportion	0.25	0.08	0.54
river velocity	1 m/s	0.05	2.0
root depth mult.	1	0.5	2.0
runoff coefficient mult.	1	0.5	2.0
snow melt temperature	0°C	-3.75	3.75
SW baseflow coefficient	0.01 / day	0.001	0.1
wetland depth	2 m	1.0	5.0

Table 3

RMSE of simulated versus detected hydrological states for the calibration period 01/2003-12/2006: monthly mean river discharge (col. 2-3) and de-trended TWSC signal with non-periodic components (col. 4-5). RMSE is given for the original WGHM (original) and for the selected Pareto solution of the re-calibrated (re-cal.) WGHM version. For the validation period 01/2007-12/2007 RMSE of TWSC is given in col. 6-7.

Basin	Discharge [ $kg3/month$ ]		TWSC [mm]		TWSC [mm] (2007)	
	original	re-cal.	original	re-cal.	original	re-cal.
Amazon	126.6	28.1	49.6	24.7	64.0	34.1
Mississippi	17.2	4.0	21.8	16.1	18.9	13.4
Congo	22.0	13.5	24.7	23.6	25.4	30.5

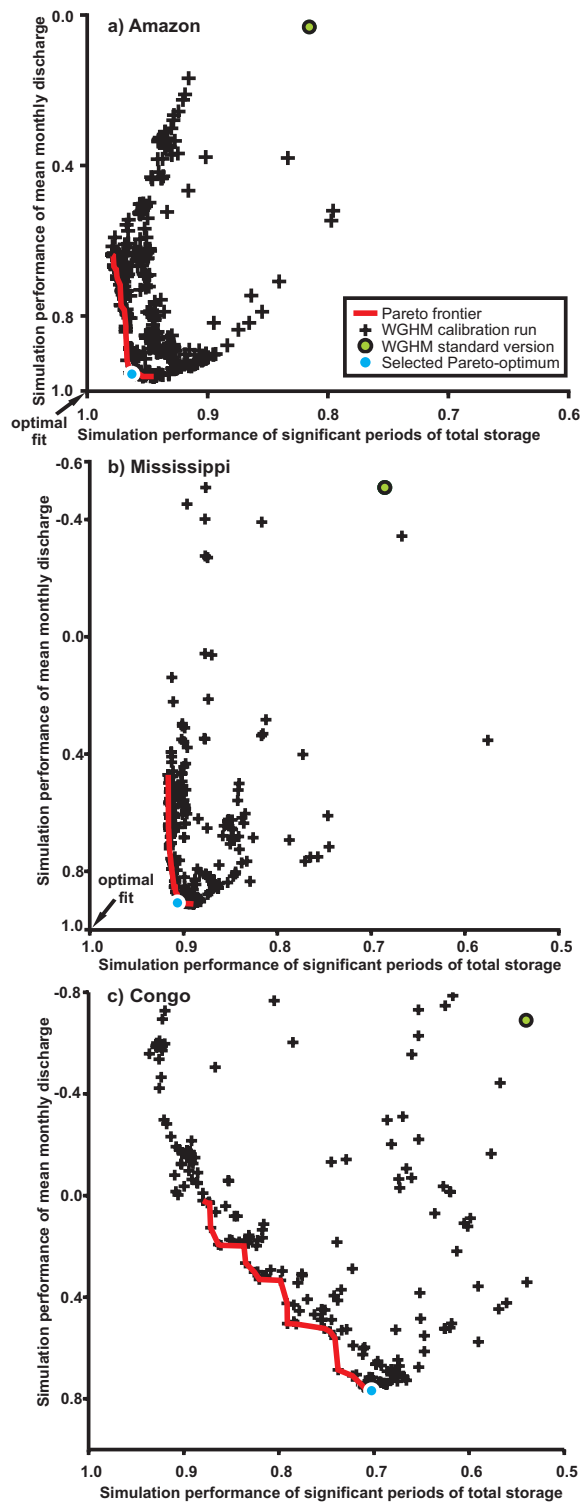


Fig. 1. Calibration results in terms of  $NSC$  indicating the simulation performance for a) the Amazon, b) the Mississippi and c) the Congo river basin.

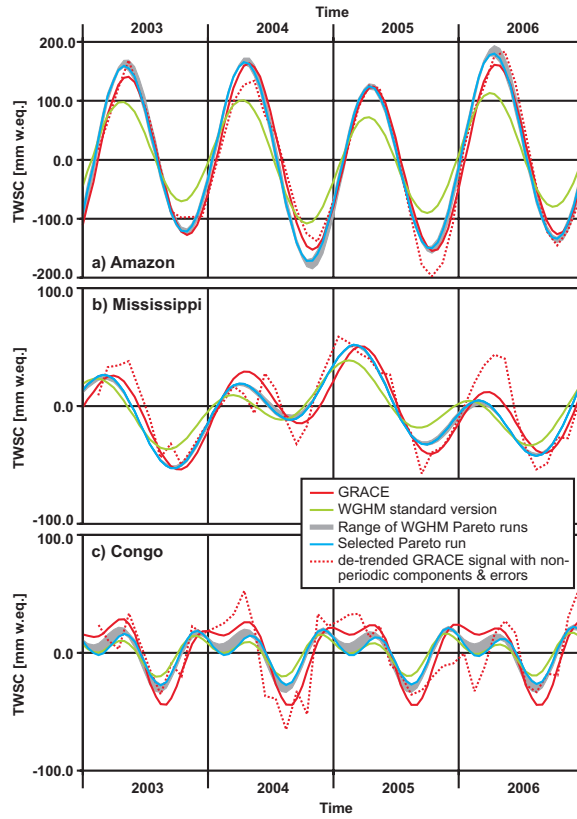


Fig. 2. Calibration results in terms of time series of TWSC from reconstructed periodic terms for a) the Amazon, b) the Mississippi and c) the Congo river basin.

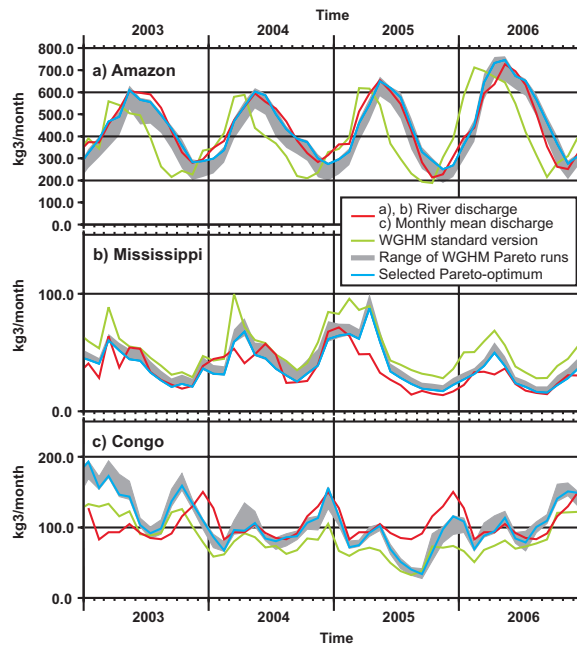


Fig. 3. Calibration results in terms of measured time series of monthly river discharge for a) the Amazon, b) the Mississippi and of mean monthly river discharge for c) the Congo river basin. See Table 1 for detailed sources of discharge measurements.

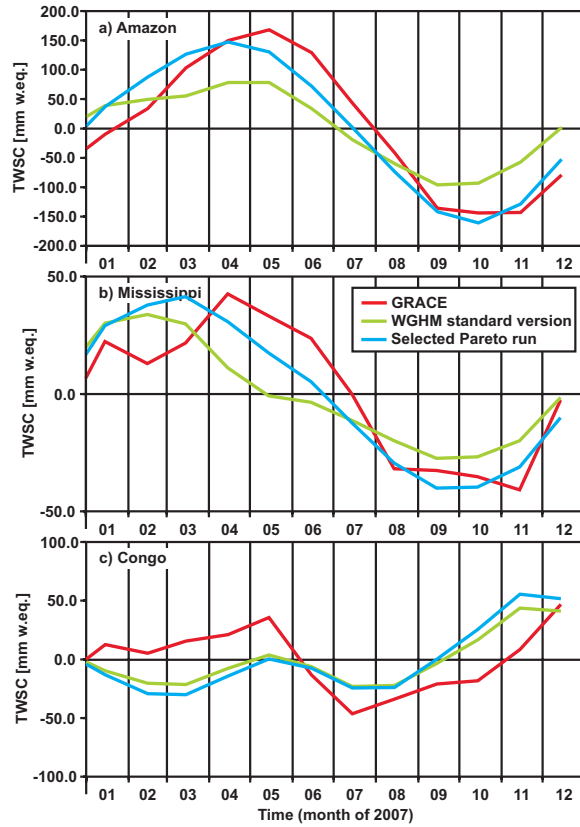


Fig. 4. Validation of de-trended TWSC by model simulations during the period 01-12/2007 (which was not used for calibration) for a) the Amazon, b) the Mississippi and c) the Congo river basins.