

Using water storage variations derived from GRACE to calibrate a global hydrology model

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Background

Calibration of the global hydrological model WGHM

Water balance of a river basin:

$$\textcircled{P} = E + \textcircled{R} + \Delta S$$

Model input

Calibration variable

P: Precipitation

E: Evapotranspiration

R: Runoff (**measured time series of river discharge**)

ΔS : Water storage change

Objectives

Multi-criterial calibration of the global hydrological model WGHM

Water balance of a river basin :

$$\textcircled{P} = E + \textcircled{R + \Delta S}$$

Model input

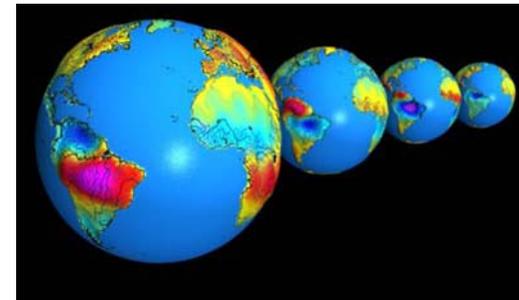
Calibration variables

P: Precipitation

E: Evapotranspiration

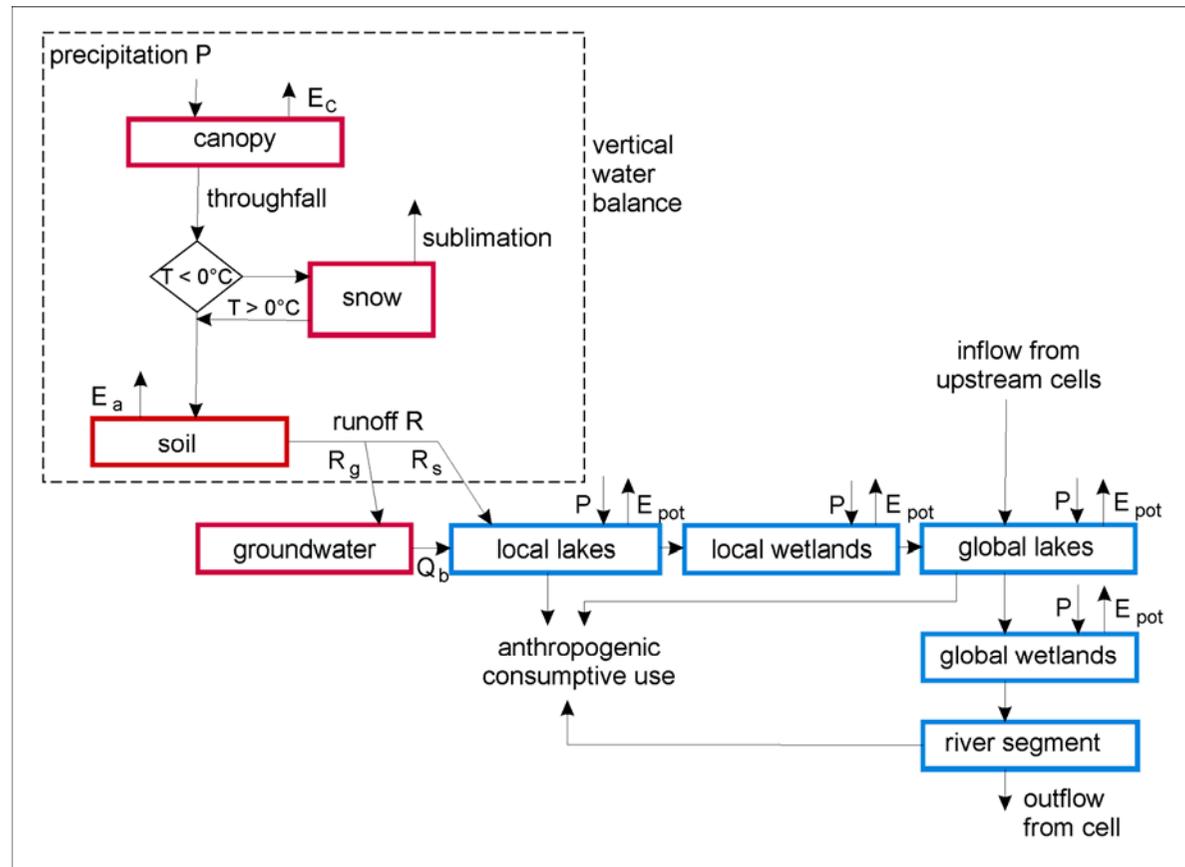
R: Runoff (**measured time series of river discharge**)

ΔS : Water storage change (**basin-average values from GRACE**)



The WaterGAP Global Hydrology Model (WGHM)

- Conceptual water balance model
- 0.5° spatial resolution
- Daily time-step
- Human water use accounted for
- Climate forcing data from CRU, GPCC, ECMWF
- Calibration for river discharge at 1200 stations worldwide



Total continental storage change:

$$\Delta S = \Delta S_{\text{canopy}} + \Delta S_{\text{snow}} + \Delta S_{\text{soil}} + \Delta S_{\text{gw}} + \Delta S_{\text{lakes}} + \Delta S_{\text{wetl}} + \Delta S_{\text{river}}$$

Work steps

1) Analyse model properties with respect to storage change

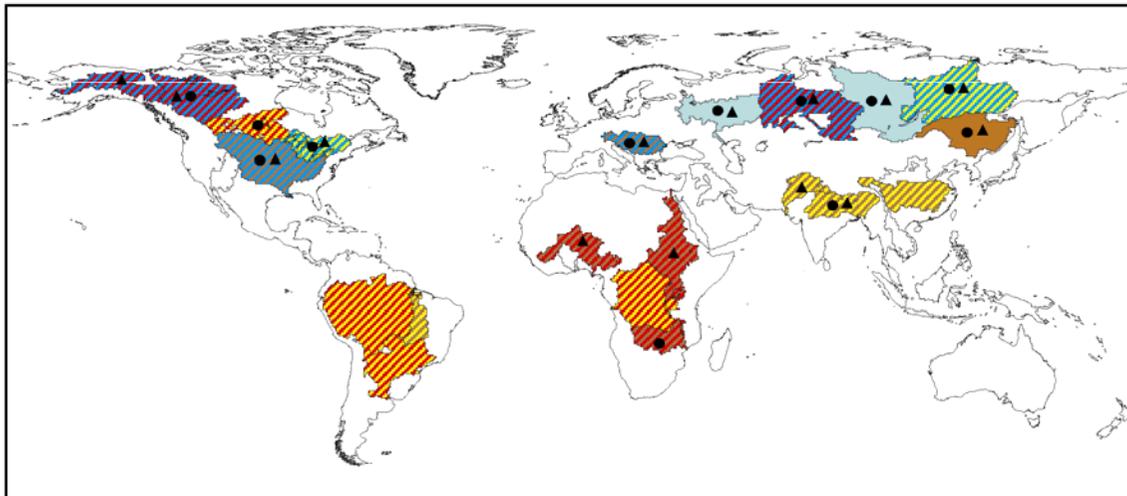
- Identify sensitive model parameters
- Uncertainty assessment

2) Select adequate GRACE data and filter tools

3) Perform multi-objective model calibration

Step 1.1) Selection of calibration parameters

Parameter sensitivity for seasonal storage change, WGHM model



Most sensitive parameters govern processes in the field of

 evapotranspiration / radiation

 soil water

 snow accumulation / melt

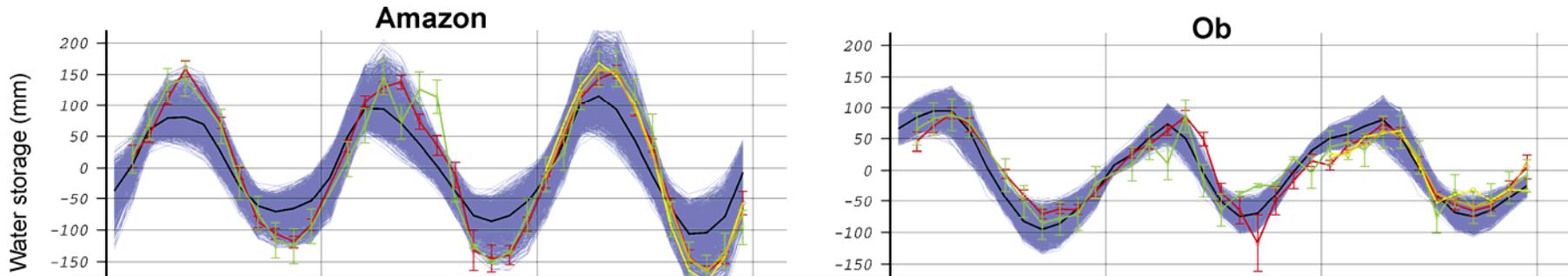
 surface water transport (rivers, lakes, wetlands)

● original calibration parameter (for runoff) is highly sensitive

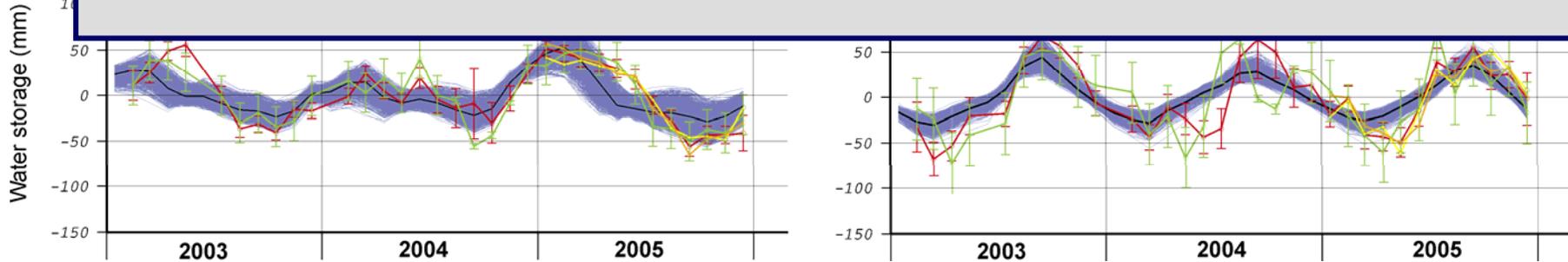
▲ precipitation input uncertainties are very sensitive

➔ Parameter sensitivity varies regionally with the dominant water storage processes / components

Step 1.2) Model uncertainty analysis



→ Structural model errors may exist if model uncertainty range does not enclose GRACE data



GRACE	— GFZ_RL03	— CSR_RL01	WGHM	— single Monte Carlo run
	— GFZ_RL04	— CSR_RL04		— Monte Carlo mean

Work steps

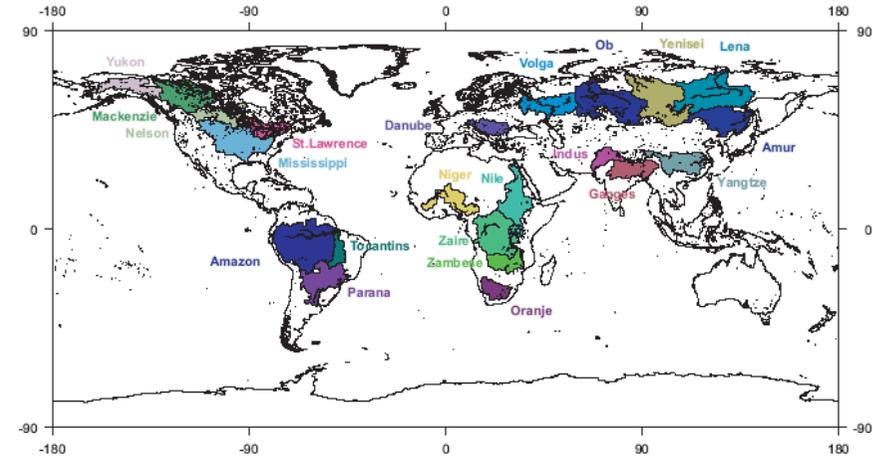
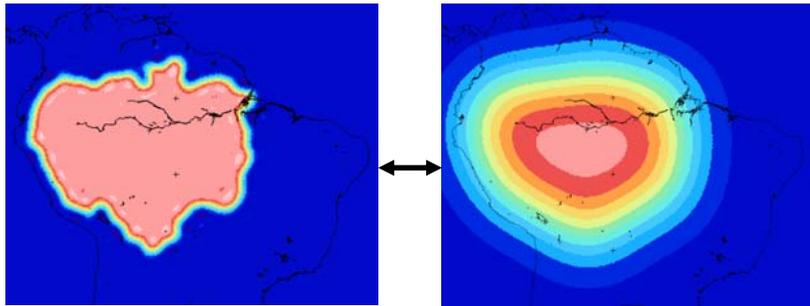
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- Identify sensitive model parameters
- Uncertainty assessment

2) Select adequate GRACE data and filter tools

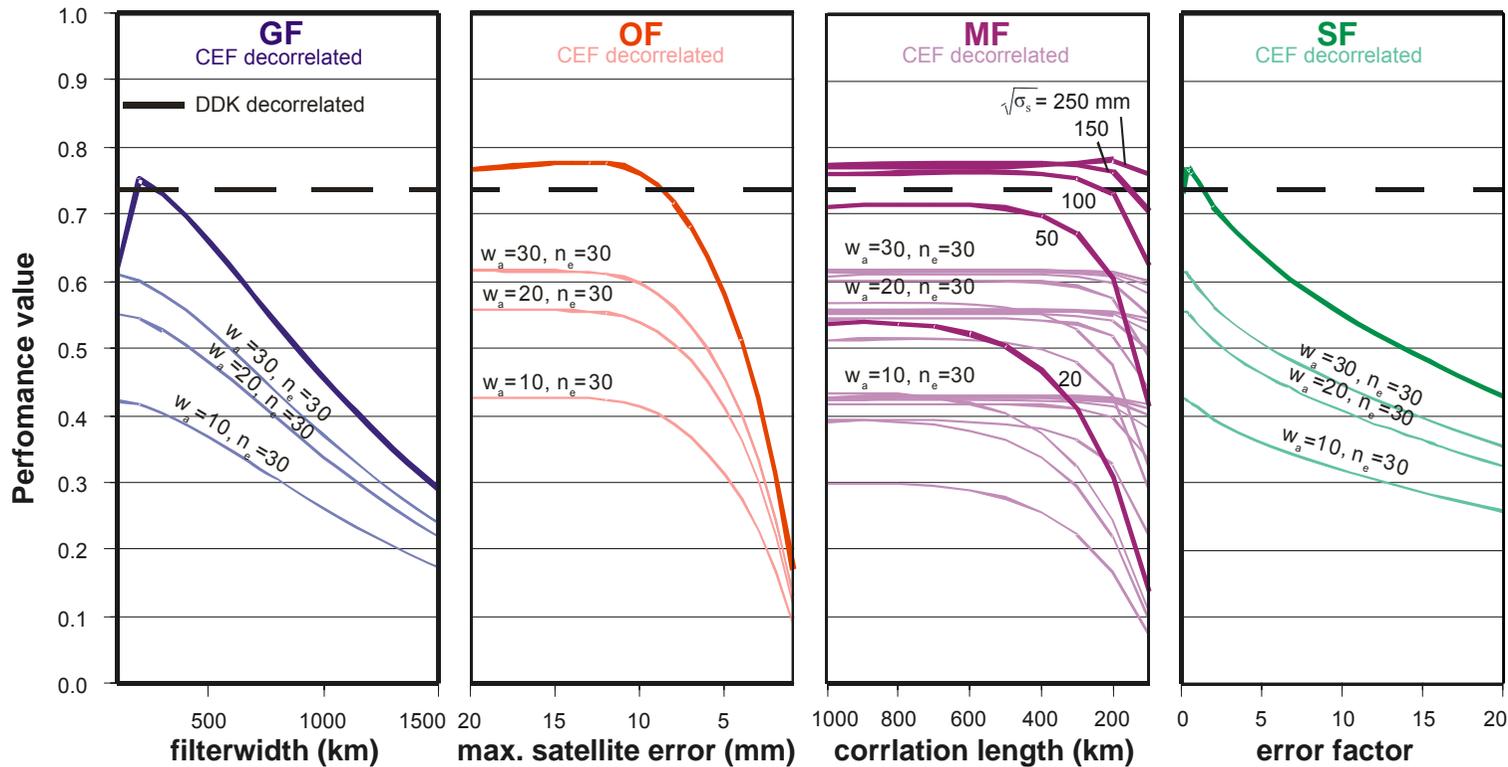
3) Perform multi-objective model calibration

Step 2) Selection of adequate GRACE filter tools to derive basin-average water mass variations



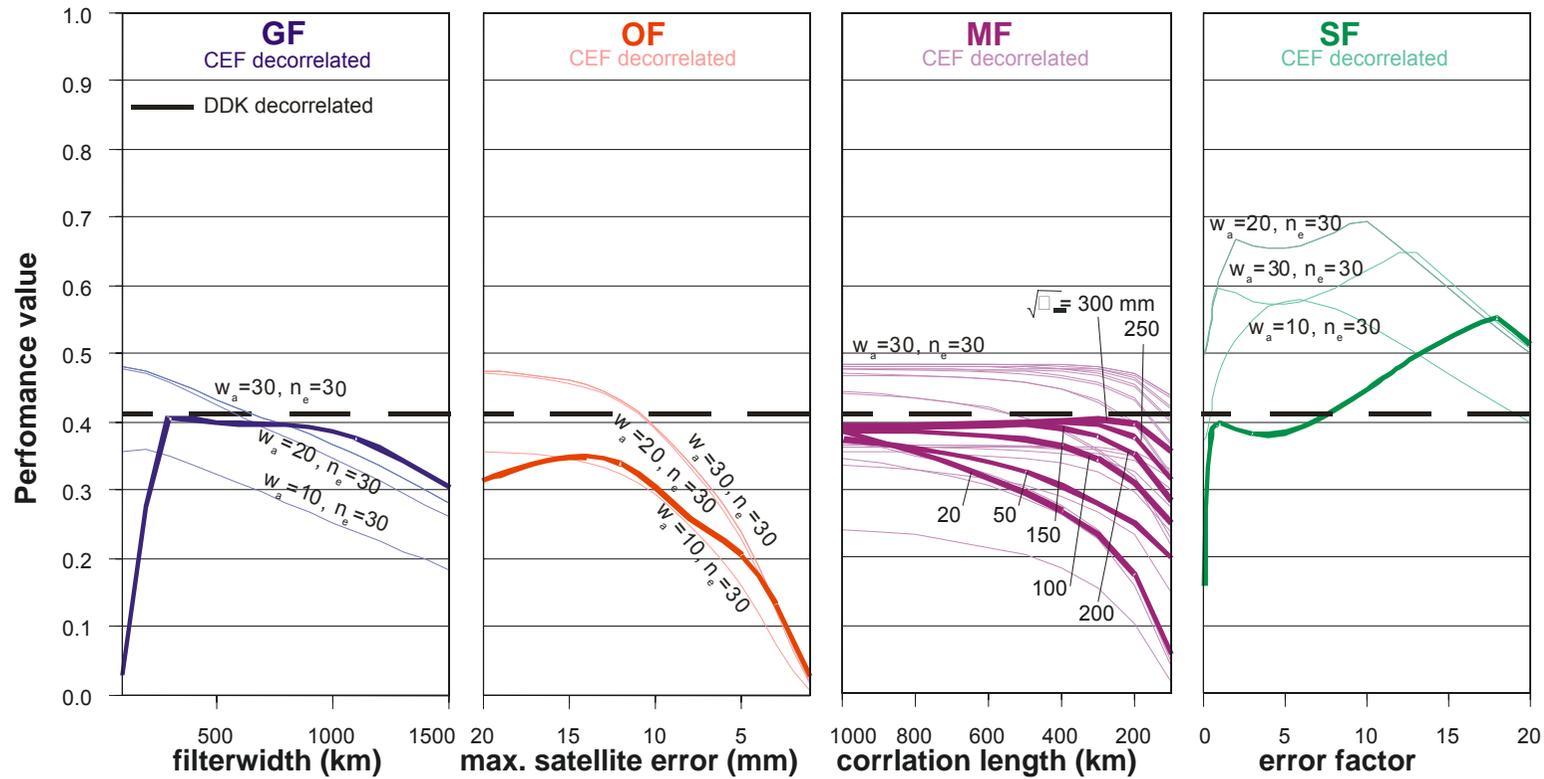
Filter type	Parameter for filter intensity	Source
Gaussian filter (GF)	filter width	Jekeli, 1981
Filter optimized for basin shape (OF)	max. satellite error	Swenson and Wahr, 2002
Filter optimized for exp. signal model (MF)	correlation length, signal variance	Swenson and Wahr, 2002
GRACE signal-noise-ratio optimized (SF)	factor of formal errors	Seo et al, 2005
Correlation Error Filter (CEF)	filter window properties	Swenson and Wahr, 2006
Decorrelation Filter (DDK)	covariance matrix parameter	Kusche, 2007

Step 2) Selection of adequate GRACE filter tools: Amazon basin



- Gaussian filter (GF)
- Filter optimized for basin shape (OF)
- Filter optimized for exp. signal model (MF)
- GRACE signal-noise-ratio optimized (SF)
- Correlation Error Filter (CEF)
- Decorrelation Filter (DDK)

Step 2) Selection of adequate GRACE filter tools: Lena basin



- Gaussian filter (GF)
- Filter optimized for basin shape (OF)
- Filter optimized for exp. signal model (MF)
- GRACE signal-noise-ratio optimized (SF)
- Correlation Error Filter (CEF)
- Decorrelation Filter (DDK)

Step 2) Selection of adequate GRACE filter tools

Example: Amazon basin

Filter	Parameter	Parameter Value	Performance value
Gaussian filter (GF)	r_g [km]	200	0.75
Filter optimized for basin shape (OF)	ϵ_{max} [mm]	13	0.78
Filter optimized for exp. signal model (MF)	error factor	0.4	0.77
GRACE signal-noise-ratio optimized (SF)	σ_s [mm], c_1 [km]	250, 200	0.78
Correlation Error Filter (CEF)	w_a, w_e, n_a, n_e	30, 3, 2, 30	0.63
Decorrelation Filter (DDK)	a, p	$10^{14}, 4$	0.74

Optimal filter for 5 example river basins and two global hydrological models

Basin	WGHM	GLDAS
Amazon	OF, MF	OF, MF
Ganges	MF	MF
Mississippi	GF	DDK
Volga	SF	SF
Yukon	CEF ^{MF}	MF

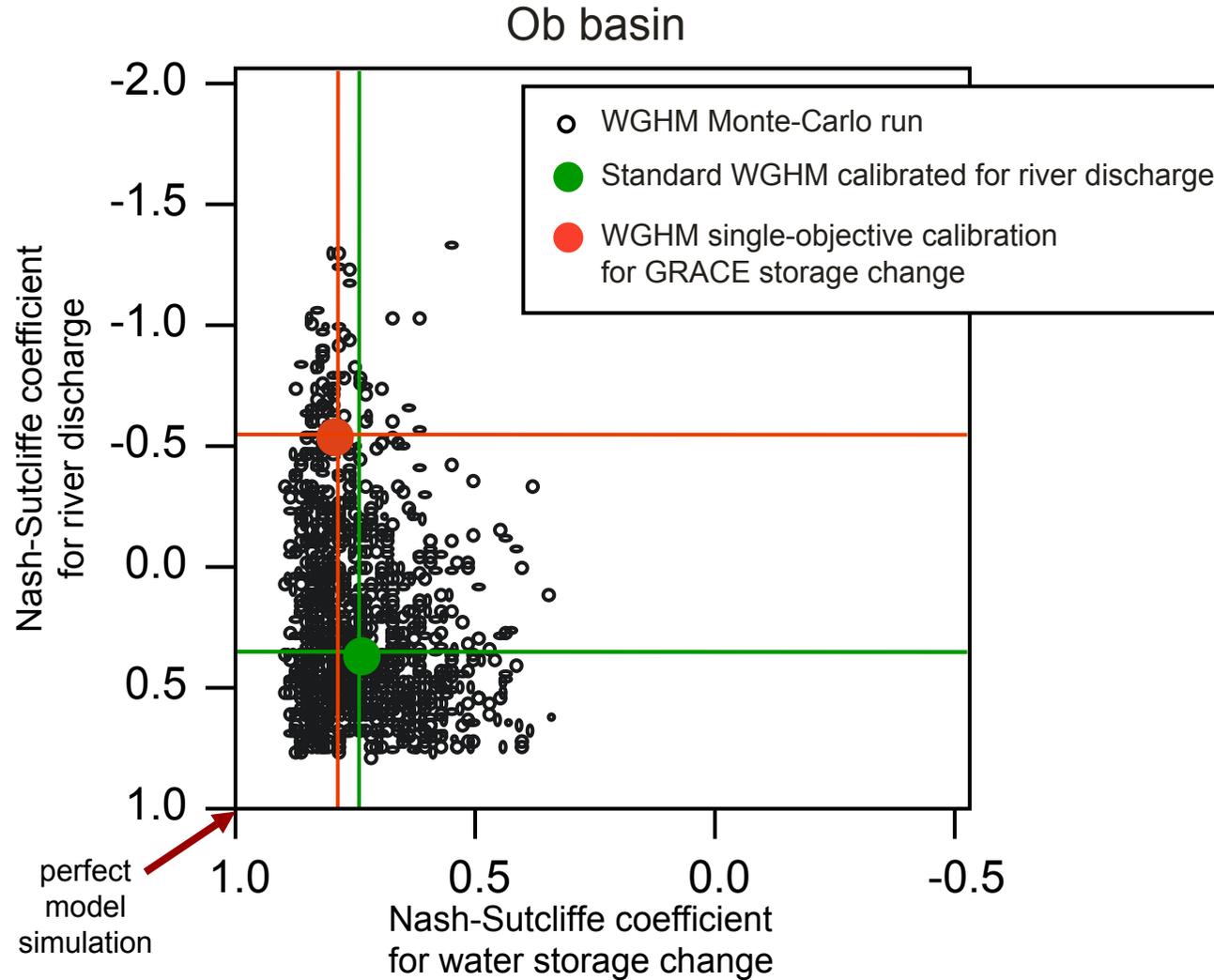
Work steps

- 1) Analyse model properties with respect to storage change
 - Identify sensitive model parameters
 - Uncertainty assessment

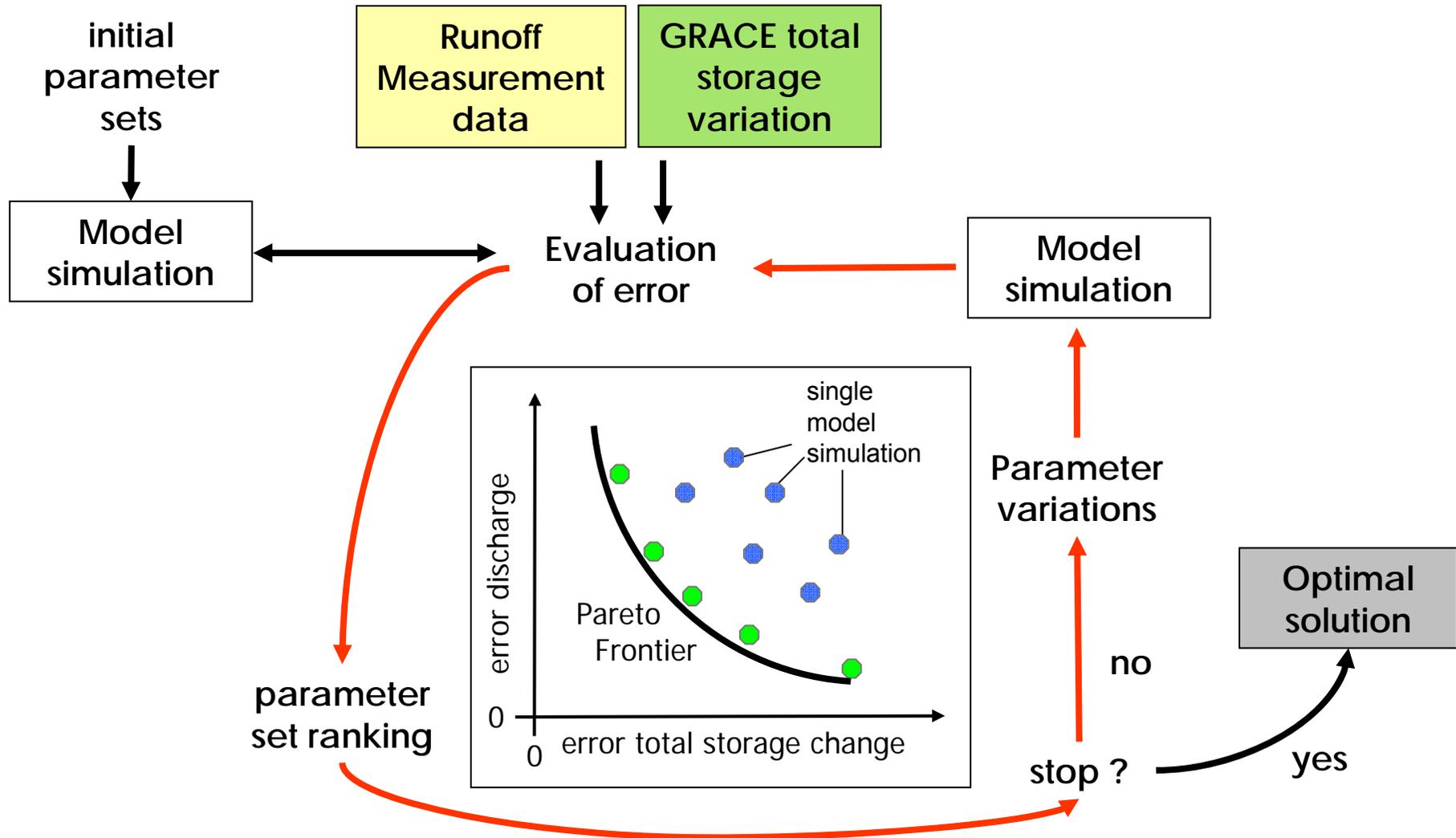
- 2) Select adequate GRACE data and filter tools

- 3) Perform multi-objective model calibration

Step 3.1) Test for single-objective calibration



Step 3.2) Multi-objective calibration approach



Step 3.3) Implementation of multi-objective calibration algorithms into WGHM

DDS Dynamically Dimension Search

- ▶ single-objective calibration algorithm extended for multi-objective problems

NSGA-II Non-dominated Sorting Genetic Algorithm

- ▶ evolutionary multi-objective calibration algorithm

Conclusions

- **Model parameter sensitivity for water storage change varies regionally with the dominant storage components**
- **GRACE data help to identify structural model errors during model uncertainty assessment**
- **Adequate filter tools to derive basin-average storage change from GRACE vary with location and river basin characteristics**
- **GRACE data are highly valuable to constrain large-scale hydrological models in a multi-objective calibration framework**

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