Analyzing different ways of assimilating volume change estimates for surface water bodies into a hydrological model

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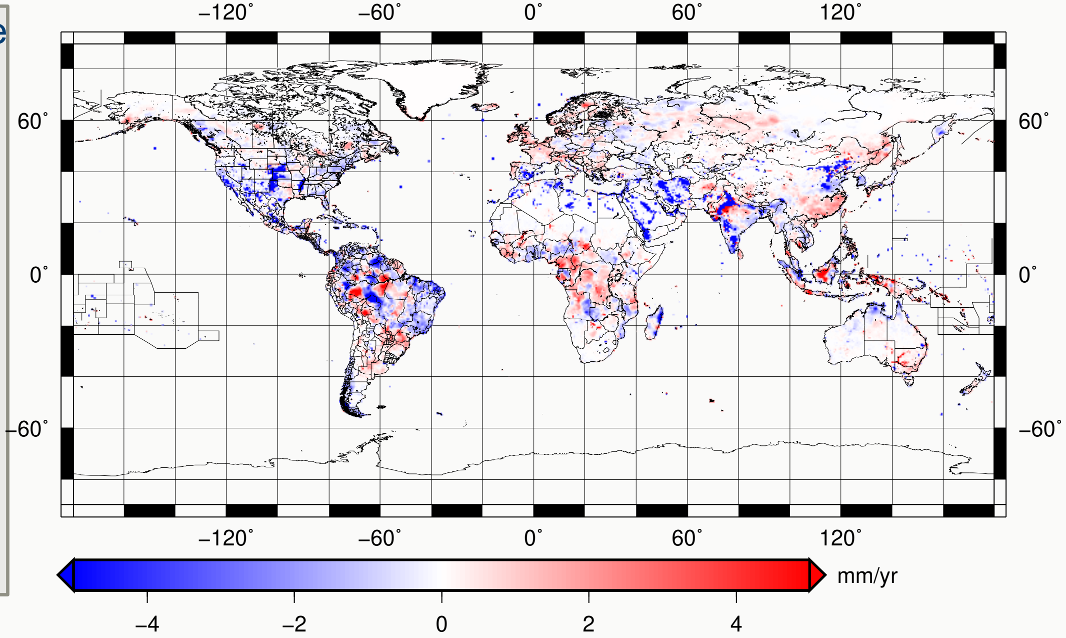
EGU2020: Sharing Geoscience Online

WGHM = WaterGAP Global Hydrology Model 2.2 d

- Conceptual model = simplification of the reality
- Sources of uncertainty:
  - Climate forcing data
  - Model parameters (so-called calibration parameters)
  - Simplified equations behind complex physical processes
  - Initial water states
- WGHM is applied to
  - globally assess droughts/floods
  - quantify the impact of human actions on freshwater

https://en.wikipedia.org/wiki/WaterGAP

WGHM-based linear trend in groundwater storage over 2003-2016



Motivation

To improve the realism of the model → Combine model with observations using Data Assimilation (DA)

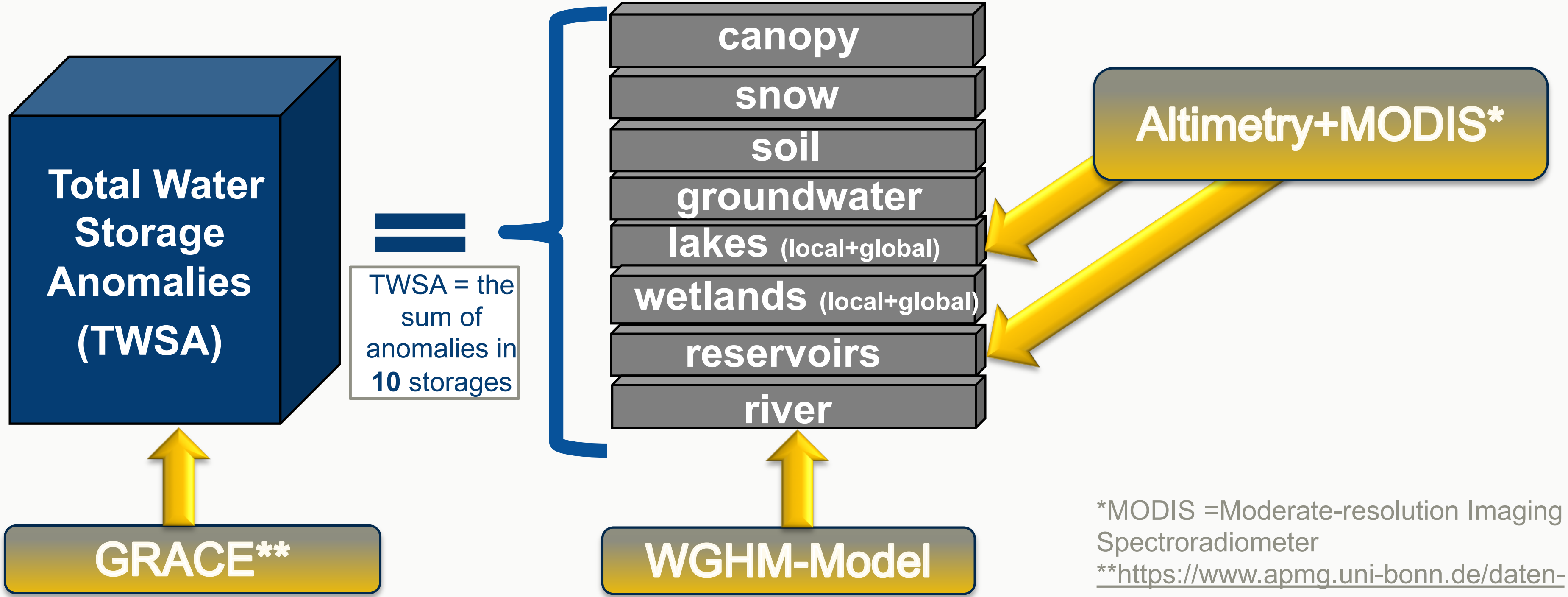
To inform model beyond the observational period → Combine model with observations using **Calibration** and Data Assimilation (CDA)

- ➢ estimate water storages **and** calibration parameters simultaneously*

www.globalcda.de

*Eicker et al., 2014

This study: WGHM & Observations



*MODIS =Moderate-resolution Imaging Spectroradiometer

**https://www.apmg.uni-bonn.de/daten-und-modelle/grace-monthly-solutions

Relation between GRACE and Altimetry+MODIS

UNIVERSITÄT BONN igg Global CDA

Altimetry: water level time series*

+

MODIS: extent of water bodies**

=

High-resolution mass changes in: reservoirs, lakes(local+global)

→ **Forward modelling*** = how would GRACE 'see' this signal? GRACE-like spatial resolution (ca. 300 x 300 km)**

→ **GRACE:** TWSA (reservoirs, lakes(local+global))

*created by DAHITI (Schwatke et al., 2015); **based on MODIS (Klein et al., 2017); ***Deggim et al., in prep

Different ways of assimilating GRACE & Altimetry+MODIS (AM) into WGHM

1 Use GRACE as it is:
- Assimilate the sum of **10** storages
- So-called '**GRACE**'-solution

2 Remove AM-based forward-modelled mass changes from GRACE
- Assimilate the sum of **7** storages
- So-called '**Removed**'-solution

3 Remove AM-based **forward-modelled** mass changes from GRACE **AND** add AM-based **high-resolution** mass changes back
- Assimilate the sum of **10** storages
- So-called '**Relocated**'-solution

4 Use Altimetry+MODIS-based high-resolution mass changes
- Assimilate the sum of **3** storages
- So-called '**Altimetry**'-solution

- We always estimate all 10 storages of WGHM for DA (+ calibration parameters for CDA)
- Depending on how many storages are assimilated, a so-called **observation operator** is different. Observation operator (or design matrix) relates model states to observations.

Calibration & Data Assimilation (CDA)

- **PDAF** = Parallel Data Assimilation Framework (http://pdaf.awi.de)

- Initialization (1995-2000)
- Spin-Up (2001-2002)
- 30 Ensembles

- Temporal disaggregation (Schumacher et al, 2018)

- Forgetting factor = 0.8 to increase error estimate before analysis

Ensemble Kalman Filter* (EnKF)

*Evensen, 1994

Initial sampling = initial state estimate with corresponding errors

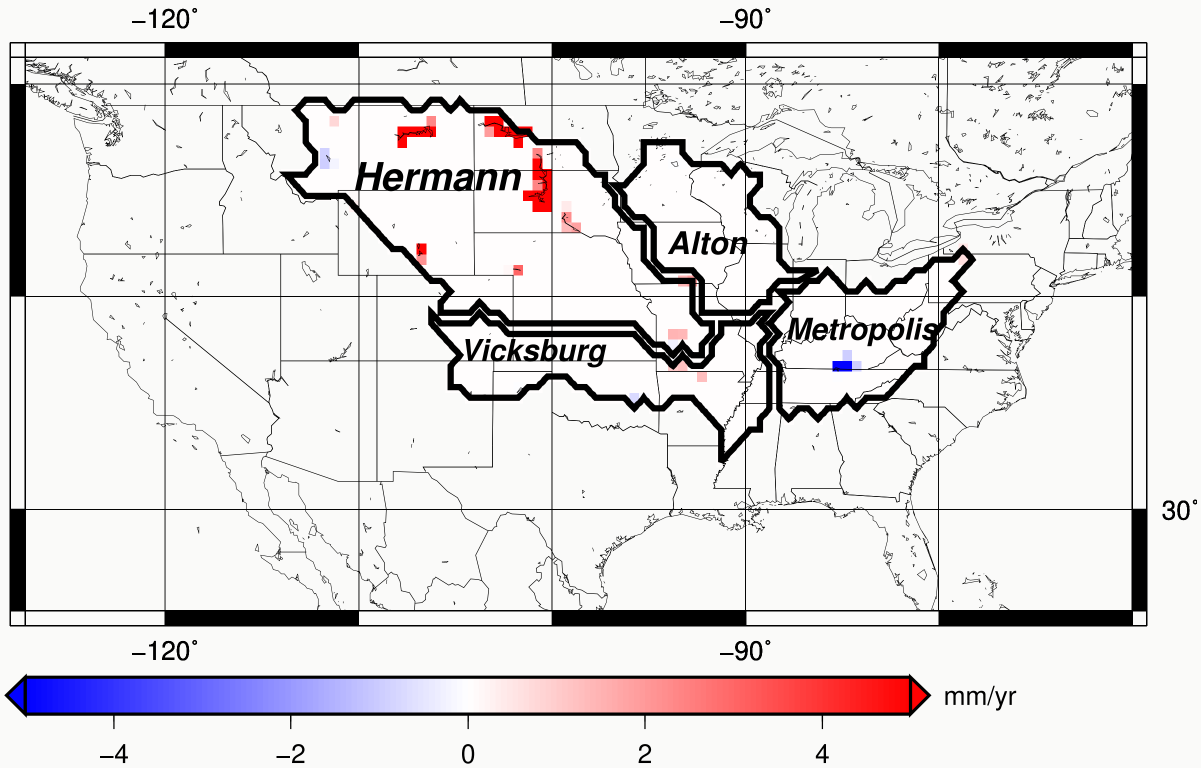
Ensemble Forecast = model integration

Analysis:

- combine monthly WGHM state estimates with observations based on corresponding errors
- observations are averaged over subbasins in the study region

Study region: Mississippi River Basin

- Linear trend on 0.5 x 0.5° grid for 01.2003 – 12.2016 based on 'altimetry' data
- Lake size (e.g. in Hermann) below GRACE resolution, but the magnitude of mass variations is large enough to have an influence if used to correct GRACE



Calibration Parameters of WGHM

- WGHM calibration parameters are not measurable
- But related to different processes along the water path
- Calibration = adjusting model parameters of important processes within a particular region towards observations
- ➢ to improve model simulations

compartment	calibration parameter
soil	root_depth_multiplier
	runoff_coeff
surface water bodies	river_roughness_coeff_mult
	lake_depth
	wetland_depth
	surfacewater_outflow_coefficient
	evapo_red_fact_exp_mult
evapotranspiration (ET)	PT_coeff_humid
	PT_coeff_arid
	max_daily_PET
canopy evapotranspiration	Max canopy water height per leaf area
	Specific leaf area multiplier
snow	snow_freeze_temp
	snow_melt_temp
	degree_day_factor_mult
	temperature_gradient
groundwater (GW)	gw_factor_mult
	rg_max_mult
	pcrit_aridgw
	groundwater_outflow_coeff
water abstractions	net_abstraction_surfacewater_mult
	net_abstraction_groundwater_mult
	precip_mult

Most sensitive* calibration parameters that will be calibrated during CDA

Hermann	runoff coefficient	Root Depth Multiplier		Wetland Depth	Surface Water Outflow Coefficient	PT** Coefficient for Humid		
Alton	runoff coefficient	Root Depth Multiplier		Wetland Depth	Surface Water Outflow Coefficient	PT Coefficient for Humid		
Metropolis	runoff coefficient	Root Depth Multiplier		Wetland Depth		PT Coefficient for Humid	Groundwater Outflow Coefficient	
Vicksburg		Root Depth Multiplier	River Roughness Coefficient Multiplier	Wetland Depth	Surface Water Outflow Coefficient	PT Coefficient for Humid		Net Groundwater Abstraction Multiplier
Compartment:	soil		surface water bodies			ET	GW	water abstractions

*based on the sensitivity study performed by Mehedi Hasan from GFZ Potsdam
**Priestley-Taylor–alpha factor as indicator of water demand of the atmosphere for humid areas

Summary 1 from 2

- We have 4 alternative observation types to be assimilated into WGHM: (1) GRACE (2) Removed (3) Relocated (4) Altimetry
  Note: (2) and (3) are based on both, GRACE and Altimetry.

- We perform: (1) DA (2) CDA (3) OL (Open Loop = model run for 30 ensembles without assimilating any observations)

➢ 9 methods:

OL	DA-GRACE	DA-Removed	DA-Relocated	DA-Altimetry	CDA-GRACE	CDA-Removed	CDA-Relocated	CDA-Altimetry

- We assimilate over 4 subbasins of the Mississippi River Basin

Alternative observation types to be assimilated

After assimilating the shown 4 alternative observation types, we expect the results being dependent on

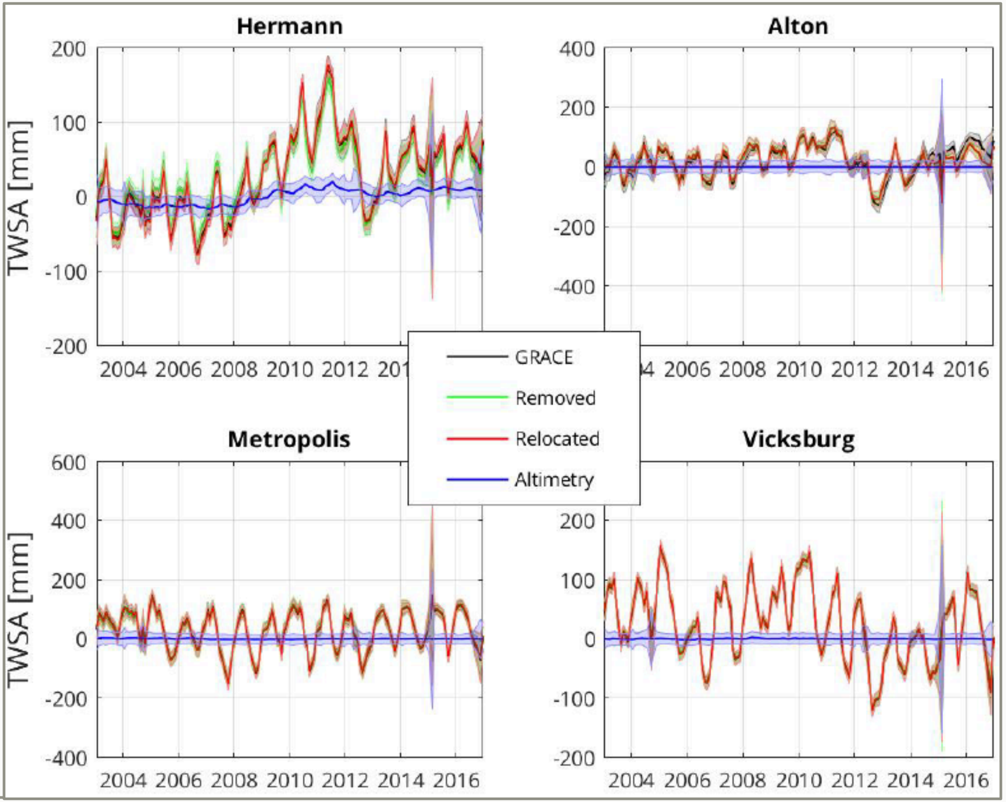
(1) Observation operator

(2) Observational error

To isolate (1), we apply

the same error covariance matrix (based on GRACE) for all observation types

- ➢ low signal-to-noise ratio of ‚altimetry'



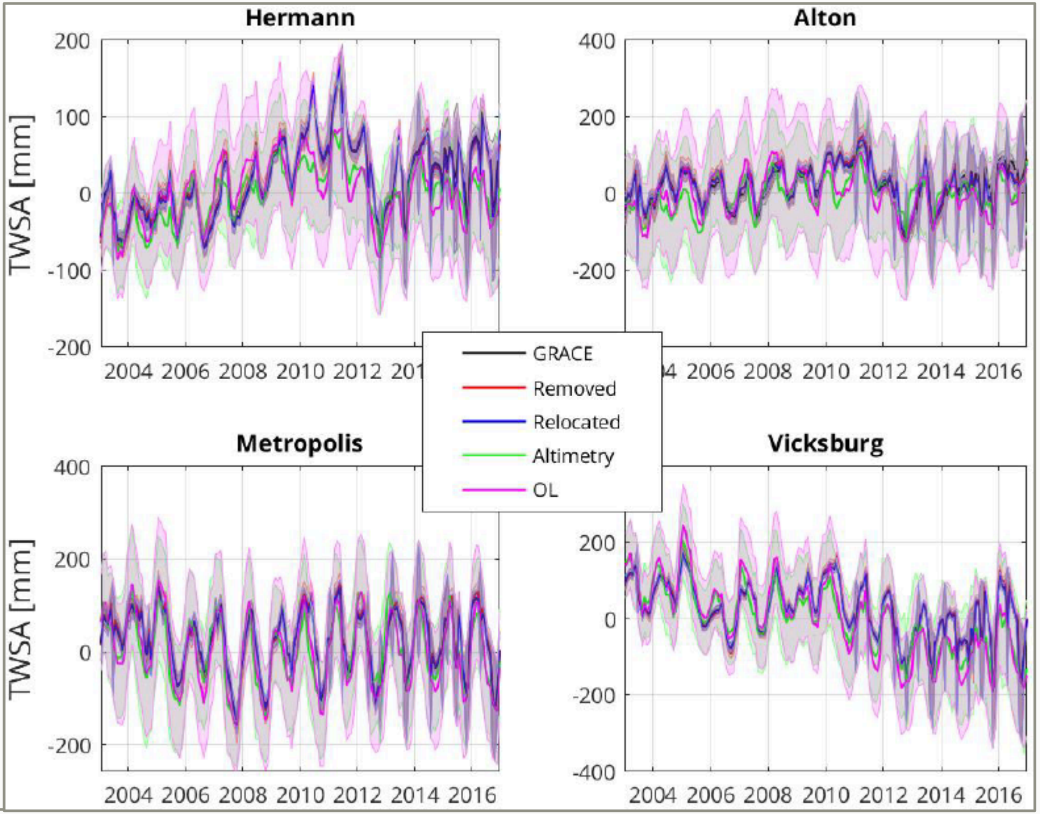
Data Assimilation-Results for TWSA

After assimilating observations that were averaged over subbasin

- methods (1) – (3)

provide similar TWSA-results

- method (4) provides TWSA-results close to OL-TWSA



What is similar across all 9 methods?

- Based on linear trends, we analyze how much percent each compartment does contribute to the TWSA
- The table shows the mean (over 9 methods) percentage of the TWSA-based linear trends for compartments that contribute the most to the total signal
- For all subbasins, groundwater storage contributes > 30% to the TWSA-based linear trend (in Vicksburg, even 80%)

Hermann	Mean % of the TWSA-based linTrend
LOCALWETLAND	33
GROUNDWATER	29
RESERVOIR	18
Alton	
GROUNDWATER	35
LOCALWETLAND	33
Metropolis	
GROUNDWATER	33
SOIL	29
RESERVOIR	19
Vicksburg	
GROUNDWATER	80
RIVER	8

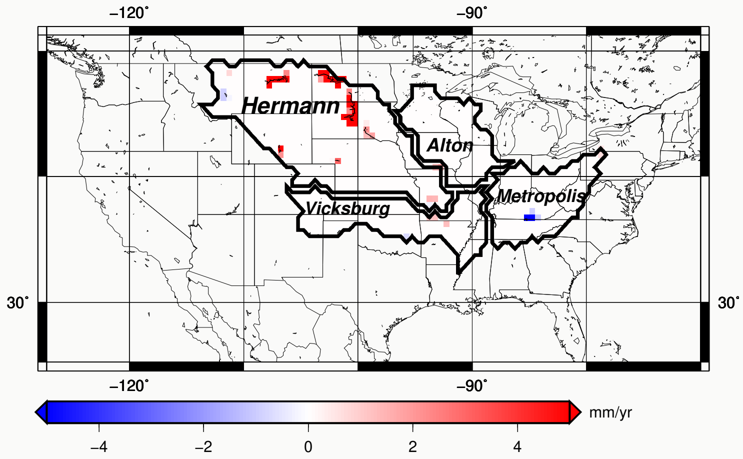
On the next slides

- We will analyze the differences between the 9 methods:

OL	DA-GRACE	DA-Removed	DA-Relocated	DA-Altimetry	CDA-GRACE	CDA-Removed	CDA-Relocated	CDA-Altimetry

- For 4 subbasins in the study area

- Based on linear trends and percentage that each compartment contributes to the TWSA-based linear trend



Analysis of the results: Hermann
Comparison between the 9 methods

		OL	DA-GRACE	DA-Removed	DA-Relocated	DA-Altimetry	CDA-GRACE	CDA-Removed	CDA-Relocated	CDA-Altimetry
linear trend in mm ewh per yr	TWSA	1,66	6,40	5,83	6,09	3,47	5,37	5,50	6,26	3,49
percentage of the TWSA-based linear trend	LOCALWETLAND	42	32	28	27	53	29	20	15	50
	RESERVOIR	19	14	20	18	25	12	14	15	29
	GROUNDWATER	28	21	36	33	10	39	43	52	4
	SNOW	1	20	6	9	1	6	10	3	1
	RIVER	5	6	7	7	6	5	7	7	9

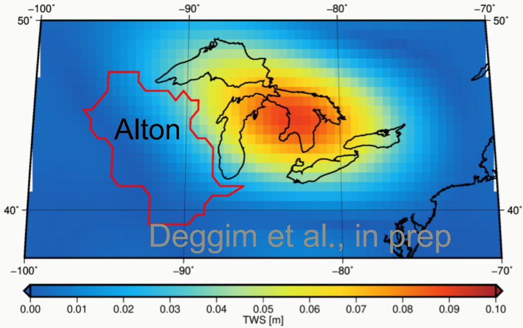
- For all methods, the shown 5 storages represent > 90% of the TWSA-based linear trend
- All the assimilation runs yield significantly increased TWSA-based linear trends compared to model-based results (OL)
- Max. difference of 19% between the contributions of single storages to the total signal for CDA versus DA occurs in groundwater (GW) compartment (without calibrating GW-related parameters)

Analysis of the results: Alton
Comparison between the 9 methods

		OL	DA-GRACE	DA-Removed	DA-Relocated	DA-Altimetry	CDA-GRACE	CDA-Removed	CDA-Relocated	CDA-Altimetry
linear trend in mm ewh per yr	TWSA	0,80	2,52	0,90	1,14	3,36	3,11	0,21	1,60	2,67
percentage of the TWSA-based linear trend	SOIL	6	11	2	7	1	0	10	3	13
	LOCALLAKE	8	7	7	14	0	7	12	9	1
	LOCALWETLAND	38	38	25	15	63	27	26	29	38
	RIVER	7	11	12	16	5	3	2	3	9
	GROUNDWATER	32	18	44	35	22	46	40	49	32

- For all methods, the shown 5 storages represent > 80% of the TWSA-based linear trend
- In our study area, Alton is the closest subbasin to Great Lakes, i.e. here is the largest GRACE-correction for leakage-in effect

➢ expected significant difference between (C)DA-GRACE and (C)DA-Removed in terms of TWSA linear trend



Analysis of the results: Metropolis
Comparison between the 9 methods

		OL	DA-GRACE	DA-Removed	DA-Relocated	DA-Altimetry	CDA-GRACE	CDA-Removed	CDA-Relocated	CDA-Altimetry
linear trend in mm ewh per yr	TWSA	-1,69	-0,89	-0,37	-0,73	-0,64	-0,85	-0,06	-0,63	3,92
percentage of the TWSA-based linear trend	SOIL	44	13	38	20	56	18	45	5	18
	LOCALWETLAND	3	4	10	7	9	8	14	1	0
	RESERVOIR	4	19	23	25	17	19	25	26	9
	RIVER	14	8	10	12	8	2	5	6	1
	GROUNDWATER	30	50	9	30	1	43	4	58	70

- For all methods, the shown 5 storages represent > 90% of the TWSA-based linear trend
- All the assimilation runs yield less negative (or even positive) TWSA-based linear trends compared to model-based results (OL)
- Significant difference between DA- and CDA-Altimetry regarding the redistribution of the signal between the different compartments (69% difference for groundwater compartment)
- Across all the methods, groundwater compartment is the most variable

Analysis of the results: Vicksburg
Comparison between the 9 methods

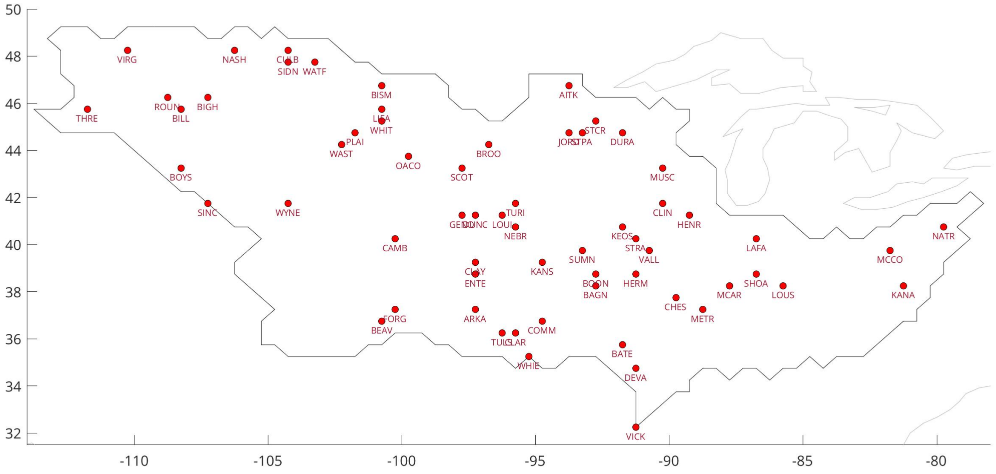
		OL	DA-GRACE	DA-Removed	DA-Relocated	DA-Altimetry	CDA-GRACE	CDA-Removed	CDA-Relocated	CDA-Altimetry
linear trend in mm ewh per yr	TWSA	-17,5	-8,3	-8,0	-8,3	-15,2	-8,1	-8,0	-6,4	-21,2
percentage of the TWSA-based linear trend	SOIL	3	1	4	2	3	2	6	12	3
	LOCALWETLAND	0	4	4	2	4	6	5	13	2
	RIVER	0	8	11	11	2	12	14	10	4
	GROUNDWATER	97	83	76	80	90	76	72	61	89

- For all methods, groundwater + river represent > 70% of the TWSA-based linear trend
- All the assimilation runs yield significantly less negative trends than OL (except (C)DA-Altimetry)
- All the assimilation runs yield smaller conribution of GW storage to the total signal than OL
- In our study area, Vicksburg is the most robust basin against different assimilation methods

Comparison with independent in-situ discharge observations from GRDC*

	OL	DA-GRACE	DA-Removed	DA-Relocated	DA-Altimetry	CDA-GRACE	CDA-Removed	CDA-Relocated	CDA-Altimetry
median correlation	0,58	0,64	0,60	0,62	0,58	0,58	0,59	0,56	0,61

- By assimilating GRACE and/or Altimetry (i.e. updating storages), we do not lose the fit against in-situ discharge observations (i.e. fluxes)
- Note: the correlation value is highly dependent on the choice of the stations (we used all the stations shown)



GRDC*= The Global Runoff Data Centre, 56068 Koblenz, Germany

Summary 2 from 2

Assimilating GRACE and/or Altimetry into WGHM

- changes (mostly) significantly the TWSA-trend compared to OL model runs
- yields redistribution of the mass between the most sensitive storages
- BUT keeps the fit to independent in-situ discharge observations

We identified which processes dominate each subbasin in the Mississippi River Basin

- Across all methods and subbasins, groundwater compartment contributes the most to the total signal and is the most sensitive storage wrt different methods

OUTLOOK: Is there the most appropriate way of assimilating volume change estimates of surface water bodies into WGHM? What about the average based on different assimilation results?

- ➢ Comparison to further in-situ data is required
- ➢ what can we learn when switching off the anthropogenic mode in the WGHM?

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