2017 International SWAT Conference

Warsaw, Poland

Hydrologic modeling of sparsely gauged West African river basins using SWAT

- a remote sensing approach -

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Contents

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1 Introduction

- Water is a crucial natural resource in West Africa, where large parts of the population depend on rain-fed agriculture
- Hydrologic modelling is an important tool to aid in water resource management
- Temporal and spatial observations are necessary to accurately model a watershed
- Ground-based observation networks are sparse

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Can we build a model using remotely-sensed data?
Can remotely-sensed data be used to further validate the model?

SRTM

TERRA

SMAP

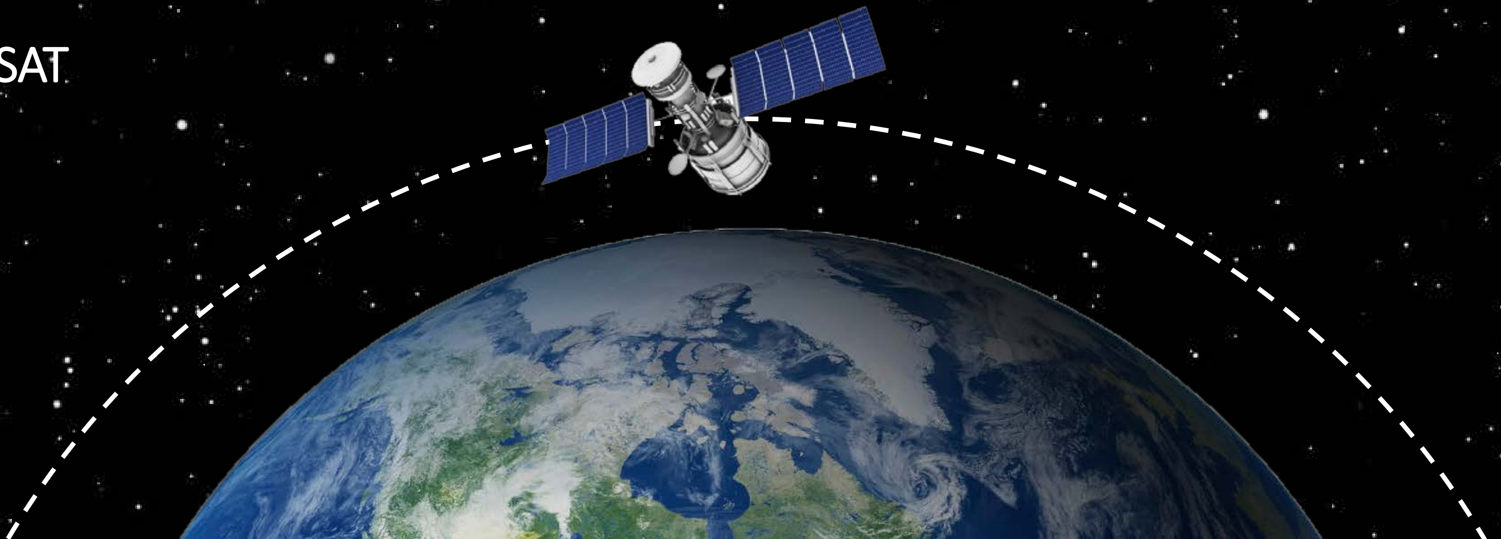
GRACE

TRMM

AQUA

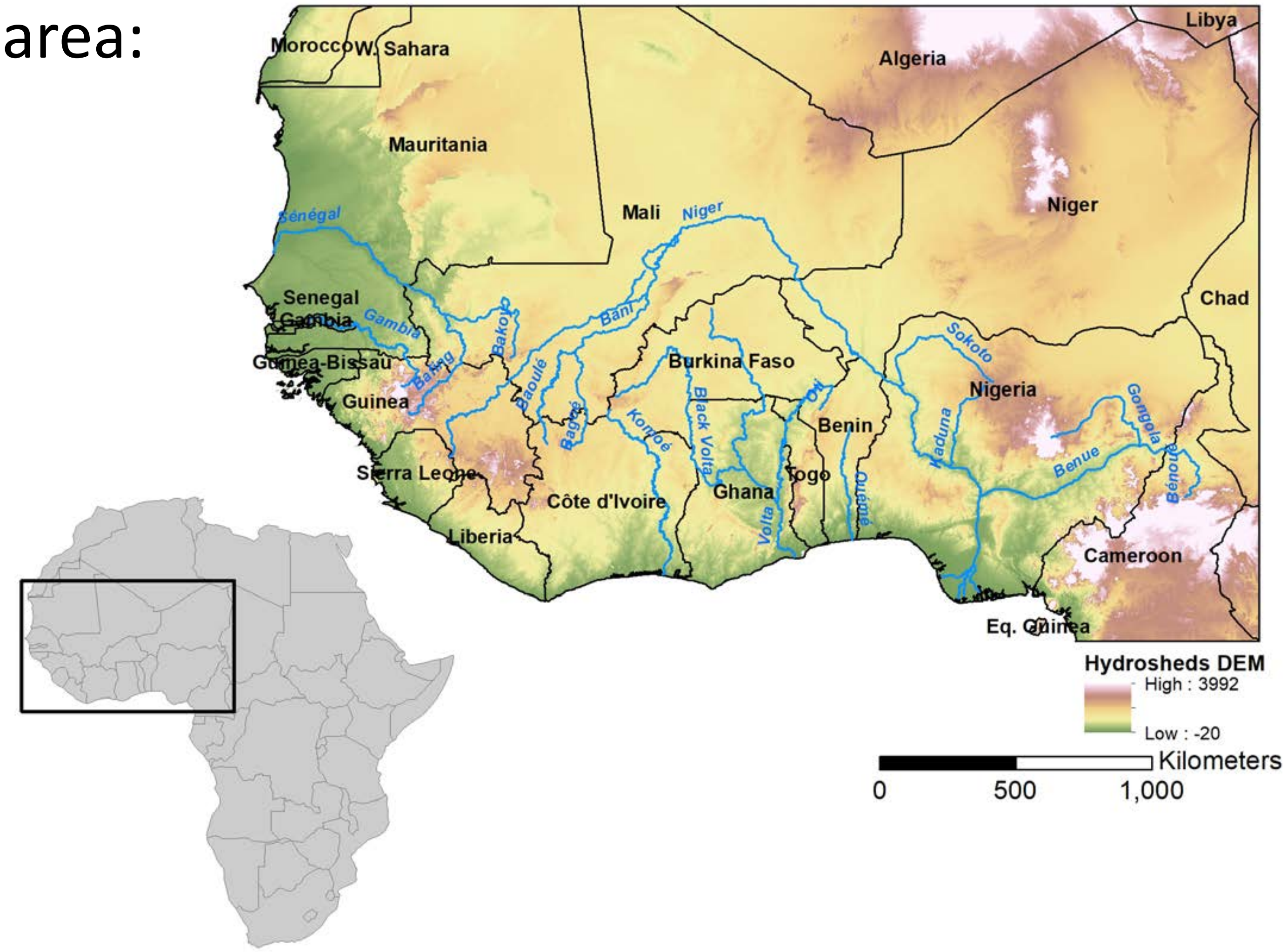
SMOS

ENVISAT



1 Introduction

- The COAST project (*Studying changes of sea level and water storage for coastal regions in West Africa using satellite and terrestrial data sets*)
- Research area:



2 Model inputs

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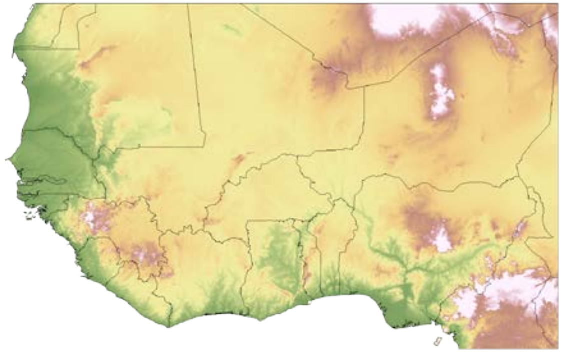
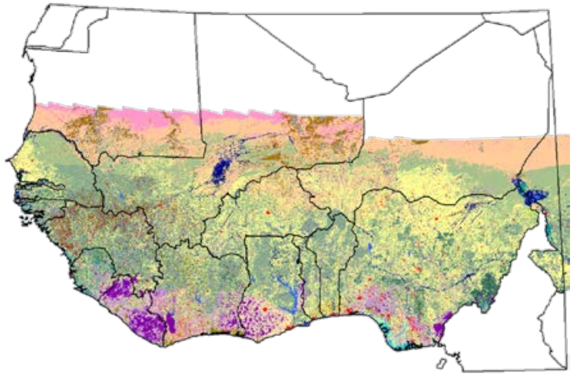
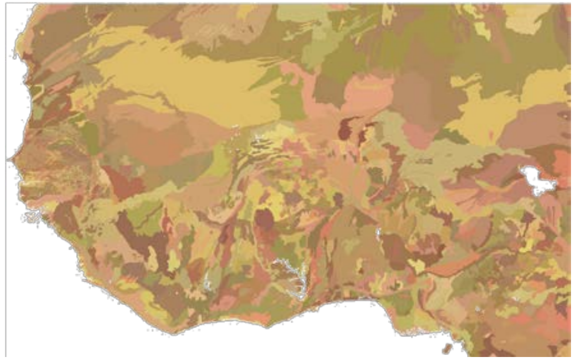
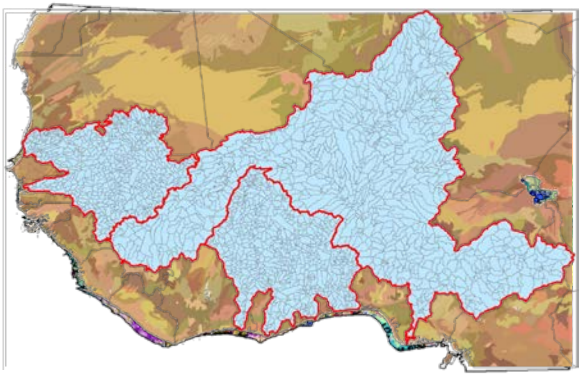


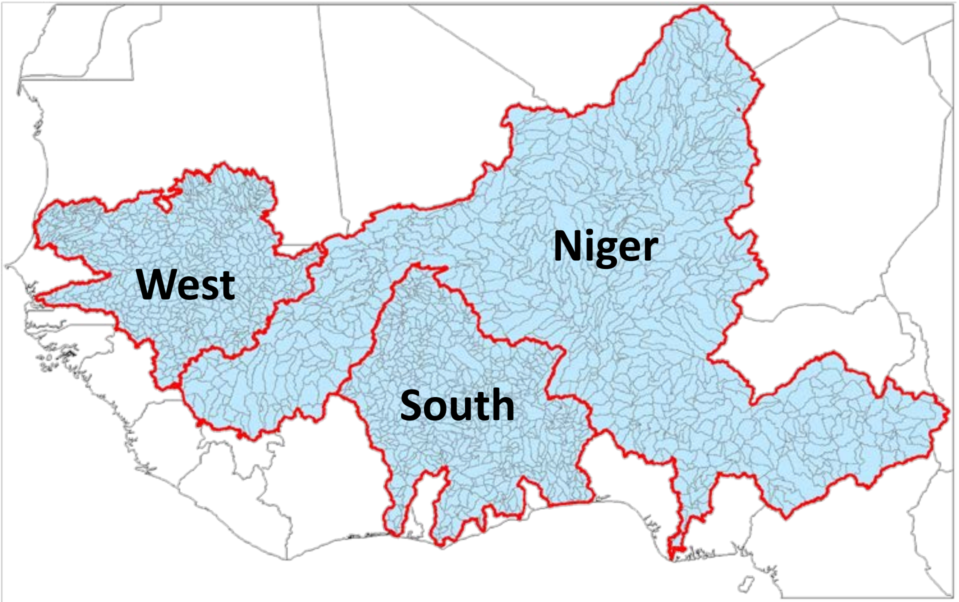




Layer	Product
Digital Elevation Model	Hydrosheds (2000) - hydrologically corrected SRTM - 90 or 500m resolution
Landuse and Landcover	Landscapes of West Africa (2013) - based on local data and remote sensing - 2000 m resolution - 25 landuse classes
Soil	HWSD (2012) - 1000 m resolution - many attributes available

2 Model inputs





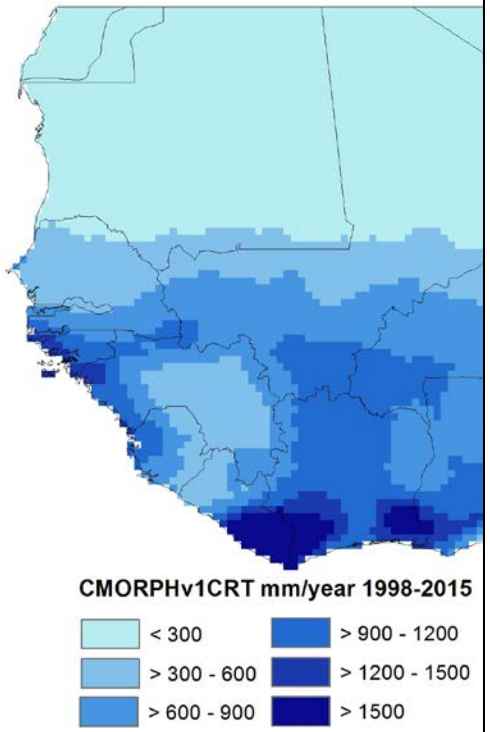
Basin	No. of Subbasins	Area (Mio. km^2)	Average Subbasin (km^2)
South	712	0.63	889
West	630	0.56	887
Niger	811	2.2	2770
TOTAL	2153	3.44	1597

- 500 km^2 minimum drainage threshold (1500 km^2 for Niger)
- Dominant landuse, soil and slope were used for HRU delineation

2 Model inputs

hold (1500

were used



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ELSEVIER

Research papers

Evaluating the performance of remotely sensed and reanalysed precipitation data over West Africa using HBV light

CrossMark

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A R T I C L E I N F O

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A B S T R A C T

Water is a crucial resource in West Africa, where large parts of the population rely on rainfed agriculture. Therefore, accurate knowledge of the water resources is of the utmost importance. Due to the declining number of rain gauging stations, the use of satellite and reanalysis precipitation datasets in hydrological modelling is steadily rising. However, accurate information on the benefits and deficits of these datasets is often lacking, especially in the West African subcontinent. For validation purposes, these products are commonly compared to freely available rain gauge data, which has in some cases already been used to bias correct the products in the first place. We therefore explored the possibility of a hydrological evaluation, where a model is calibrated for each dataset using streamflow as the observed variable. In this study, ten freely available satellite and reanalysis datasets (CFSR, CHIRPS, CMORPHv1.0 CRT, CMORPHv1.0 RAW, PERSIANN CDR, RFE 2.0, TAMSAT, TMPA 3B42v7, TMPA 3B42 RTv7 and GPCC FDDv1) were thus evaluated for six differently sized and located basins in West Africa. Results show that while performances differ, most datasets manage to somewhat accurately predict the observed streamflow in a given basin. Best results were achieved by datasets which use a multitude of input data, namely infrared and microwave satellite data, as well as observations from rain gauges (usually GPCC) for bias correction. If considering only the Nash Sutcliffe Efficiency averaged for all six basins during the calibra-

Details
0.25° daily
0.5° daily
0.31° daily

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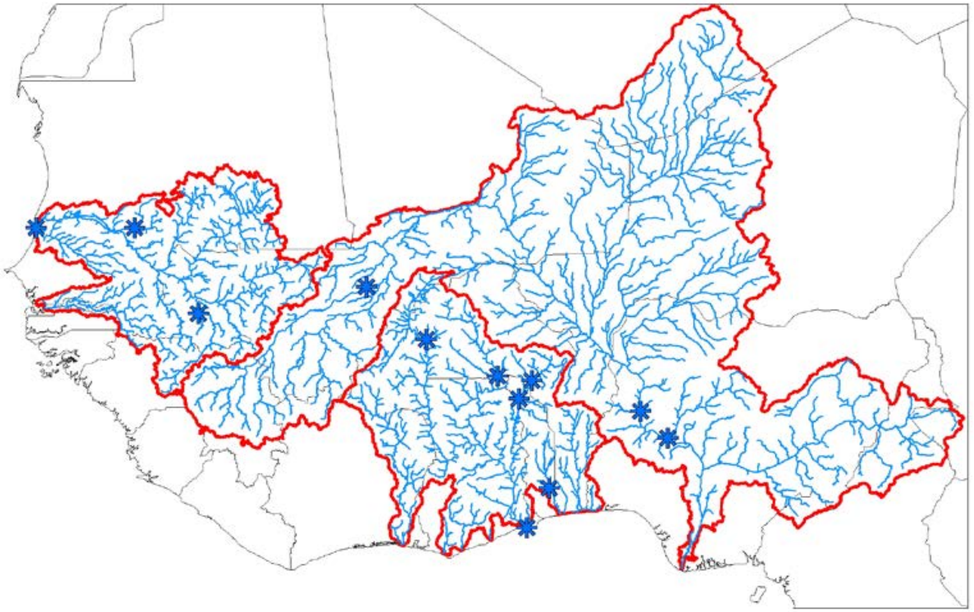
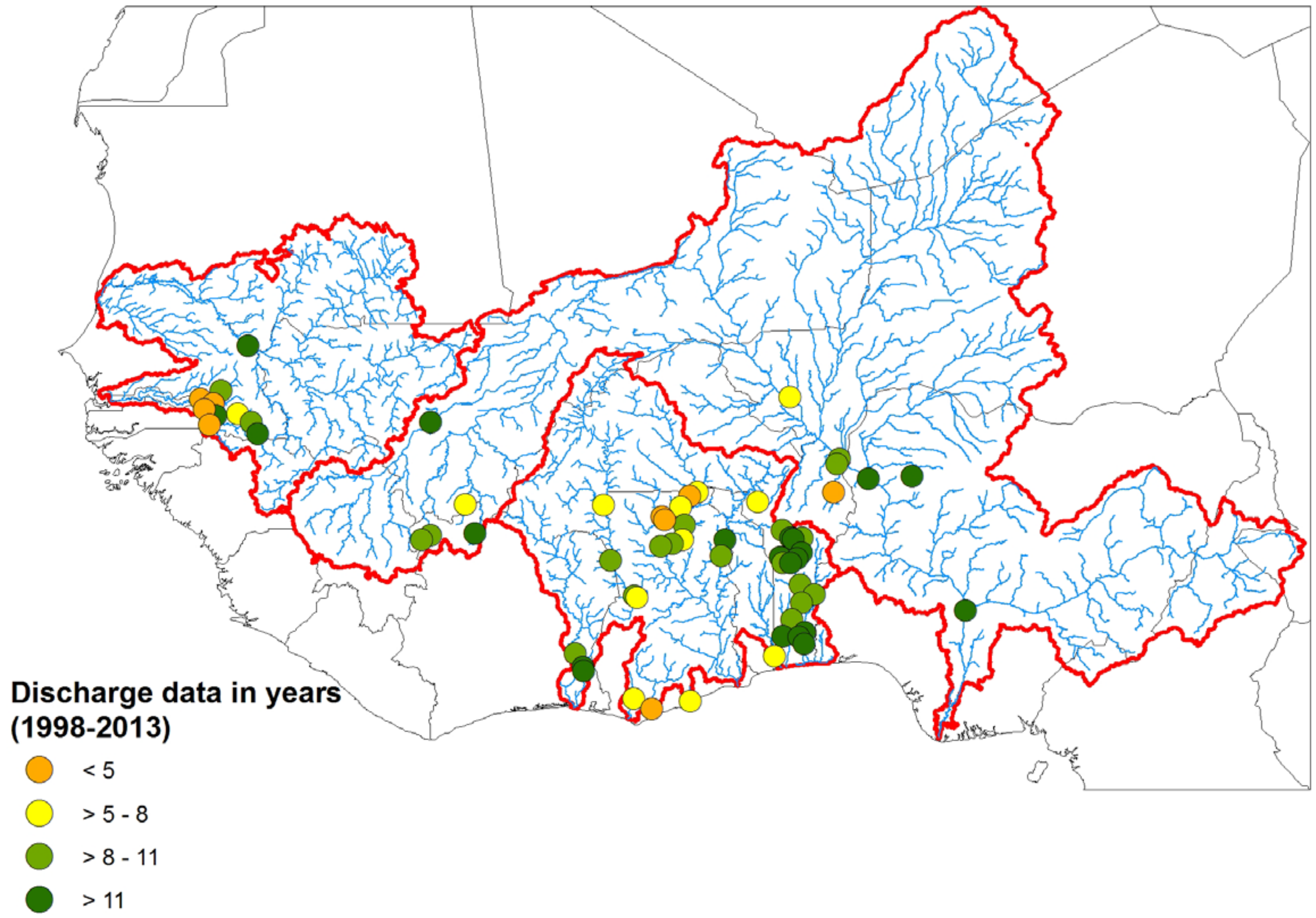


- 500 km² minimum drainage threshold (1500 km² for Niger)
- Dominant landuse, soil and slope were used for HRU delineation

Climate Input	Product	Details
Precipitation	CMORPHv1 CRT	0.25° daily
Temperature	MERRA v2	0.5° daily
Relative humidity, windspeed, radiation	CFSR	0.31° daily

- 12 reservoirs added from GRanD database (2008)



- Discharge data was acquired from the GRDC, AMMA-CATCH, and local cooperation
- A total of 64 stream gauges were used for calibration

- Custom plant management patterns were developed to better reflect tropical plant growth
- Calibration was performed using Sequential Uncertainty Fitting (SUFI2) routine in SWAT-CUP
- The model was calibrated at a monthly time step

Warm-up	Calibration	Validation
1996-1997	first $\frac{2}{3}$ of discharge data	last $\frac{1}{3}$ of discharge data
total simulation period: 1996-2013		

see also Abbaspour et al. 2015

3 Model results and multi-objective validation approaches

Sensitivity analysis

- Parameters influencing streamflow using realistic ranges (Literature)
- Iterate using Kling-Gupta Efficency ($- \infty < KGE \leq 1$) (Gupta et al. 2009)
- Remove non-sensitive parameters ($p_s > 0.05$)

Calibration/ validation

- Iterate 3-4 times (500 runs)
- Validate (500 runs)

Multi-objective validation

- Validate furter parameters using remote-sensing data

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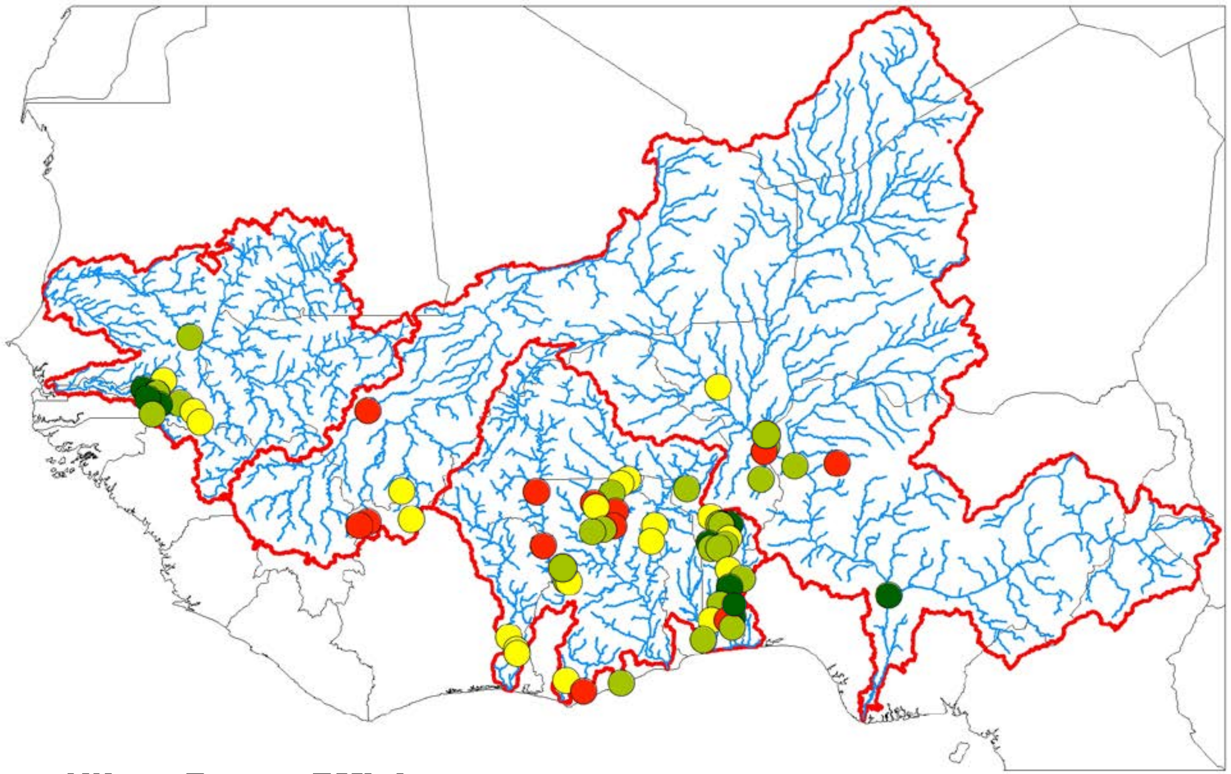
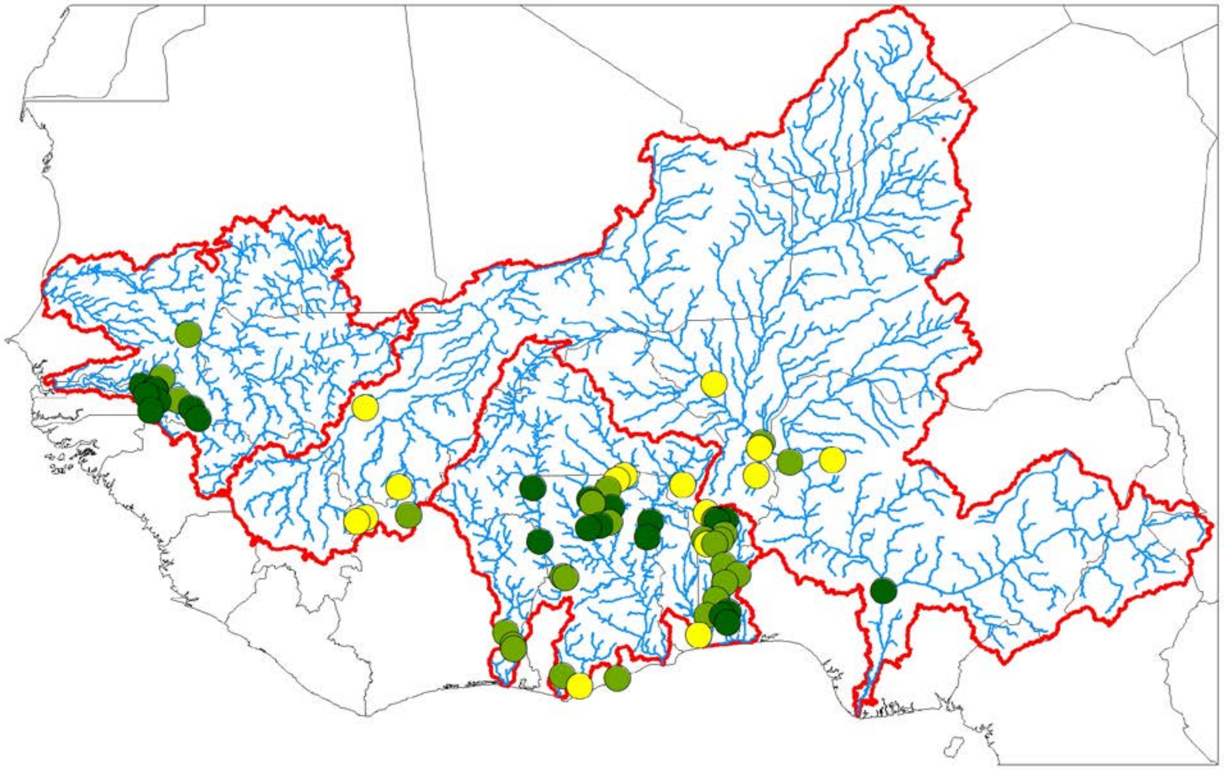
Calibration results:



Kling-Gupta Efficiency

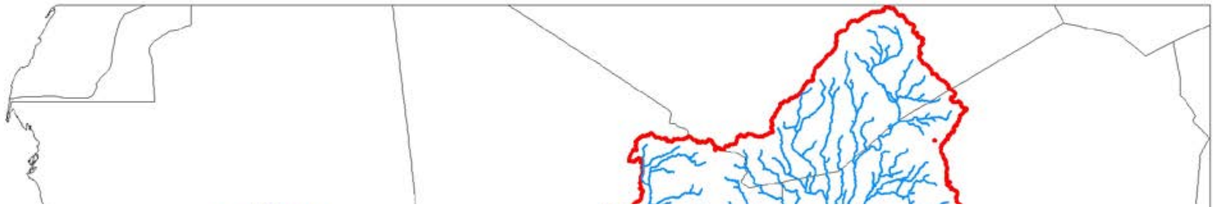
- < 0
- 0 < 0.5
- 0.5 < 0.7
- 0.7 - 1



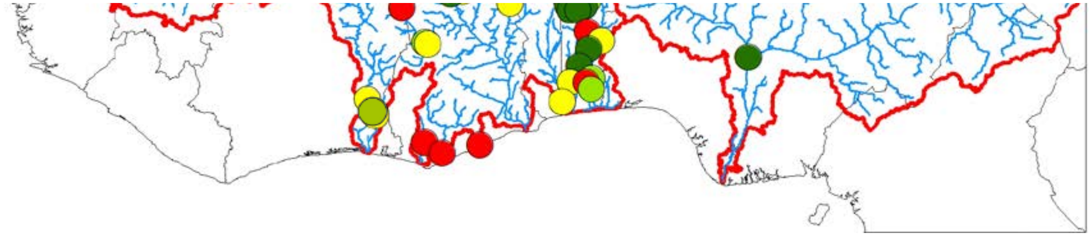
p Factor (% of data bracketed by the 95 PPU)

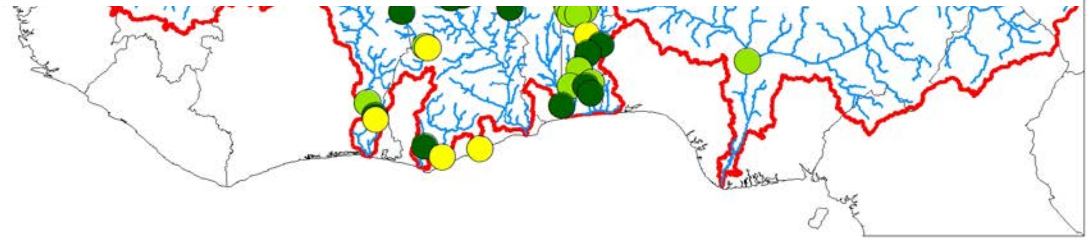
- < 0.3
- 0.3 < 0.5
- > 0.5 - 1.0

Validation results:



Calibration (KGE > 0)					Validation (KGE > 0)				
p Factor	r Factor	R^2	PBIAS	KGE	p Factor	r Factor	R^2	PBIAS	KGE
0.46	0.60	0.58	9.27	0.50	0.42	0.91	0.70	25.07	0.48





Kling-Gupta Efficiency

- < 0
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- 0.7 - 1

p Factor (% of data bracketed by the 95 PPU)

- < 0.3
- 0.3 < 0.5
- > 0.5 - 1.0

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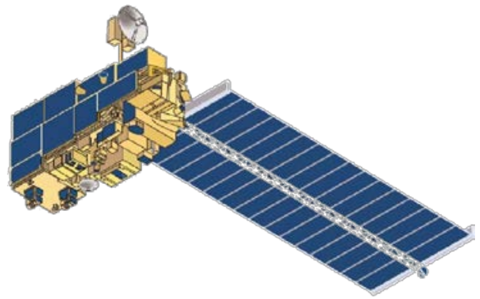
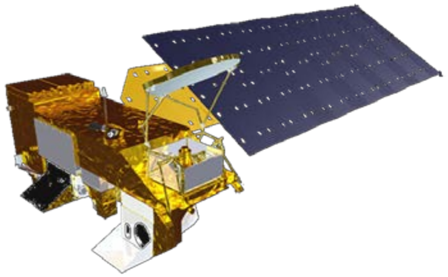
- Validating model actual evapotranspiration using NASA MODIS MOD16 data

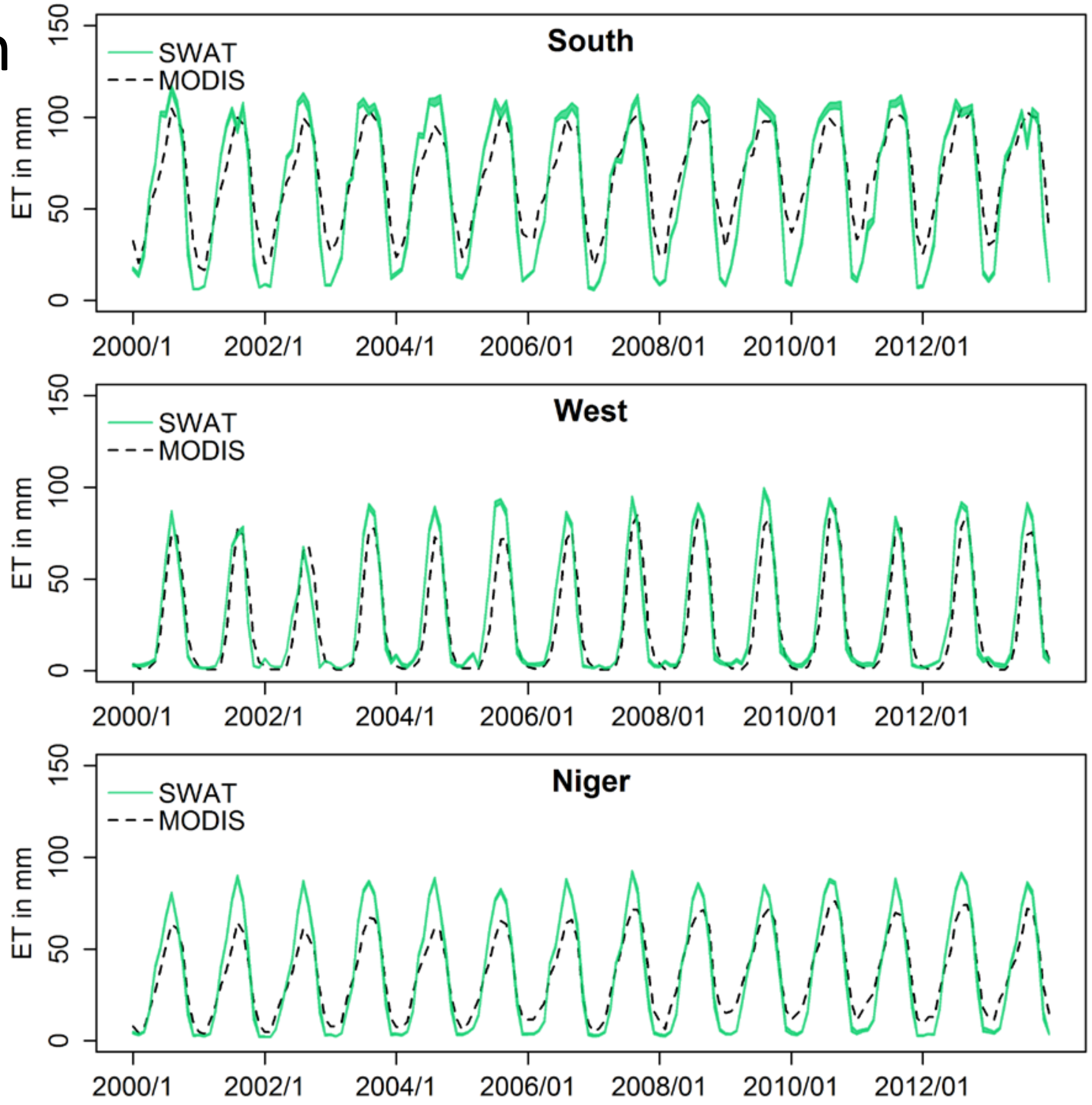


TERRA

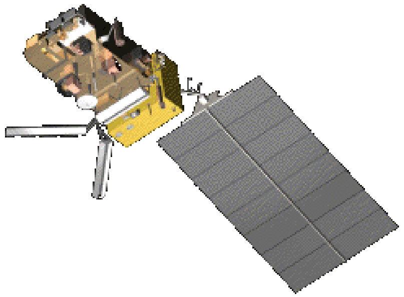


AQUA

Basin	Pearson's r	R^2	p	PBIAS	KGE	NSE
South	0.95	0.90	<0.001	-6	0.55	0.63
West	0.95	0.90	<0.001	14.1	0.81	0.85
Niger	0.97	0.93	<0.001	2.3	0.60	0.74
AVERAGE	0.96	0.91		3.5	0.65	0.74



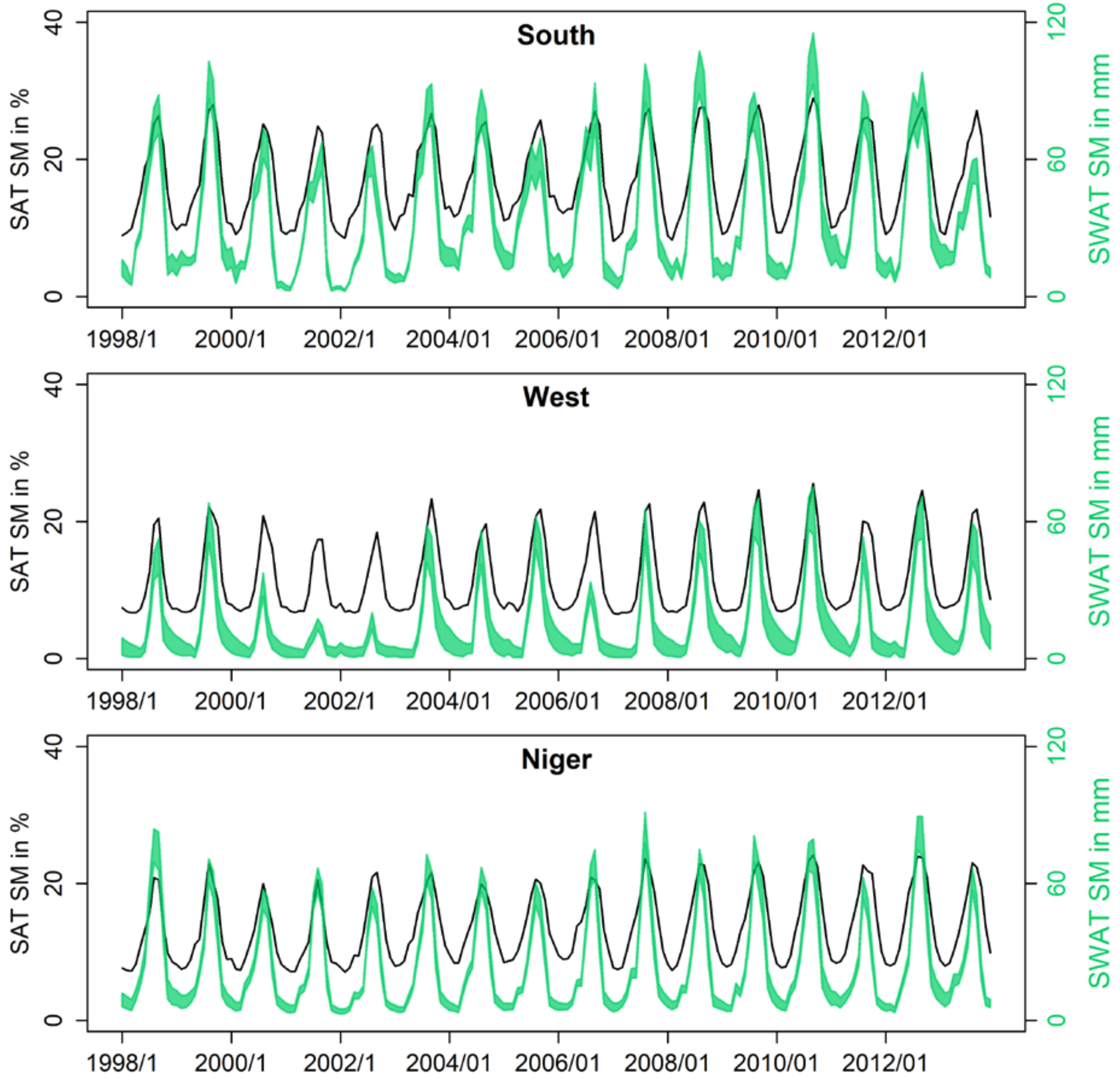
- Validating model soil moisture using esa CCI 3.2 data



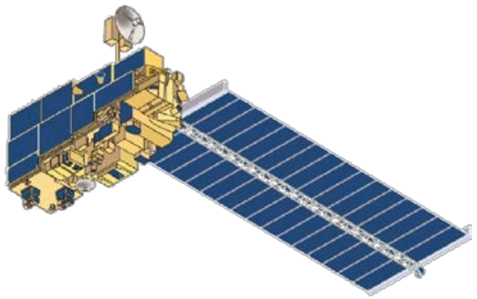
MetOp-A

ERS-1, ERS-2

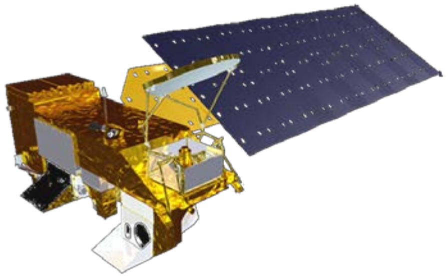
Basin	Pearson's r	R^2	p
South	0.92	0.84	<0.001
West	0.89	0.79	<0.001
Niger	0.91	0.83	<0.001
AVERAGE	0.91	0.82	



- Validating model leaf area index using NASA MODIS MOD15A2 data

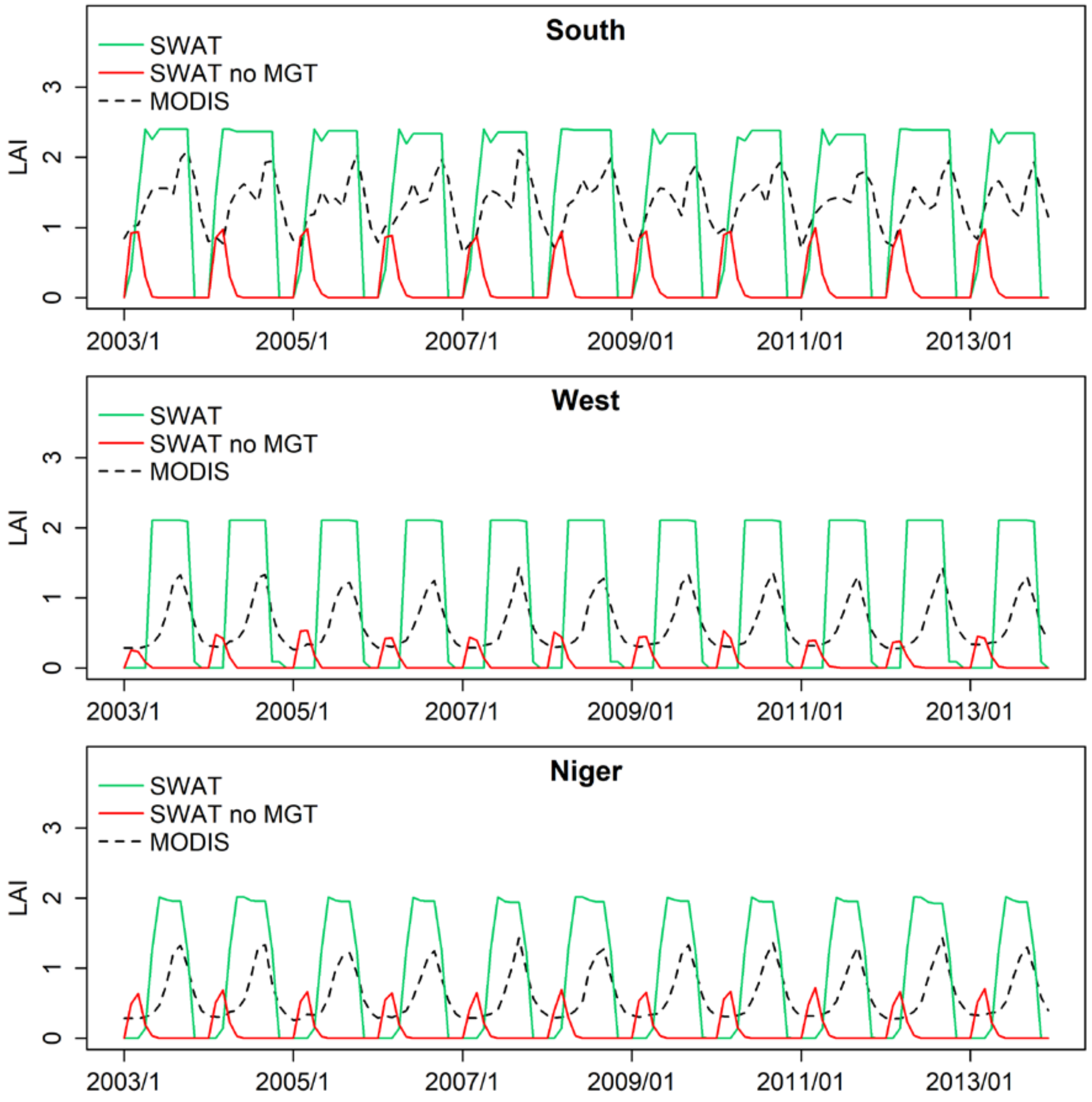


TERRA



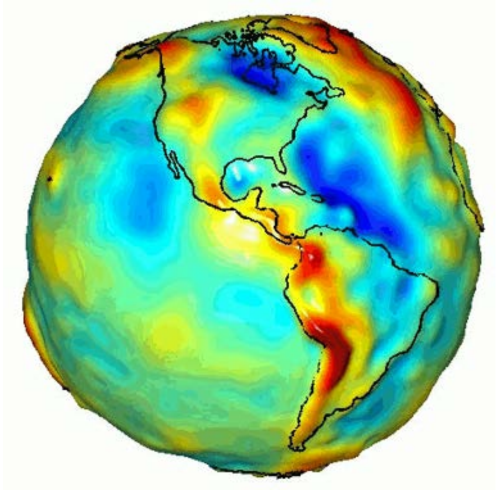
AQUA

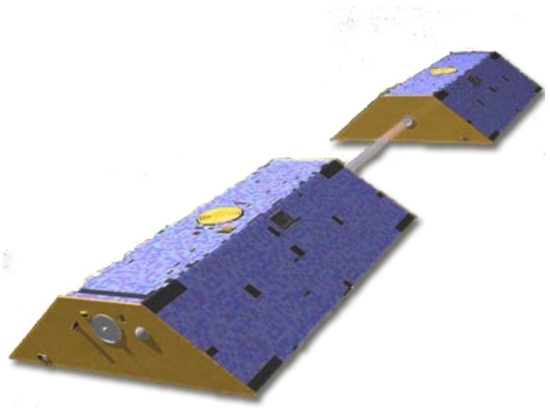
	With management				Without management			
Basin	Pearson's r	R^2	p	PBIAS	Pearson's r	R^2	p	PBIAS
South	0.52	0.27	<0.001	-13.7	-0.50	0.25	<0.001	676
West	0.64	0.41	<0.001	-42.2	-0.45	0.20	<0.001	630.7
Niger	0.70	0.49	<0.001	-33.6	-0.46	0.21	<0.001	418.9
AVERAGE	0.62	0.39		-29.8	-0.47	0.22		575.2



3 Model results and multi-objective validation approaches

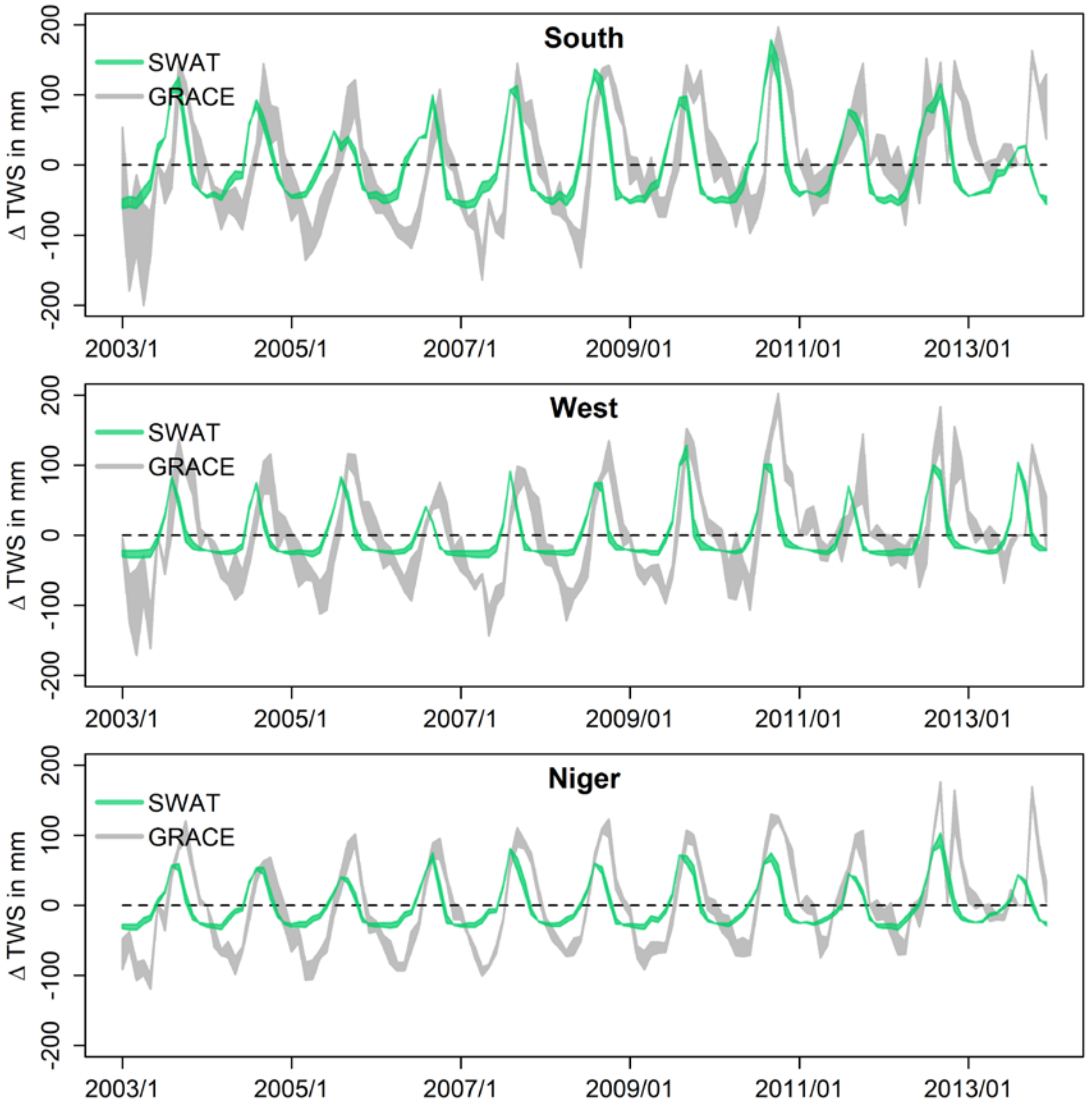
- Validating model total water storage using NASA and DLR GRACE data





GRACE 1, GRACE 2

Basin	Pearson's r	R^2	p	PBIAS	KGE	NSE
South	0.45	0.20	<0.001	-93	-0.11	0.12
West	0.47	0.20	<0.001	-117	-3.6	0.22
Niger	0.67	0.44	<0.001	-111	-2.6	0.42
AVERAGE	0.53	0.28		-107	-2.10	0.25



GIF Source: https://grace.jpl.nasa.gov/resources/6/

3 Model results and multi-objective validation approaches

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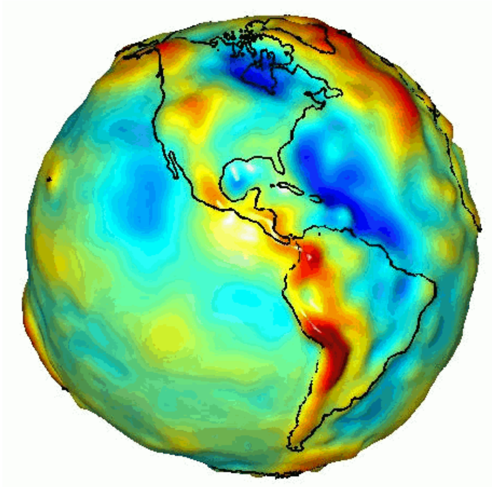

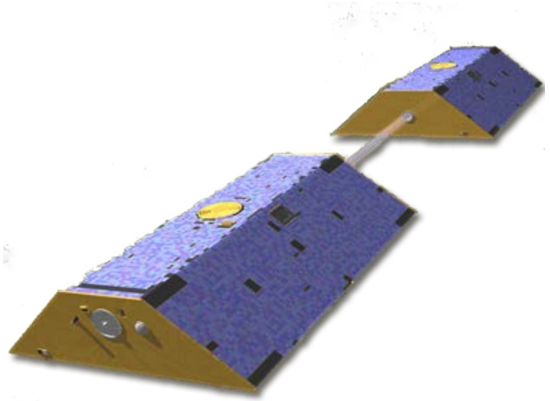

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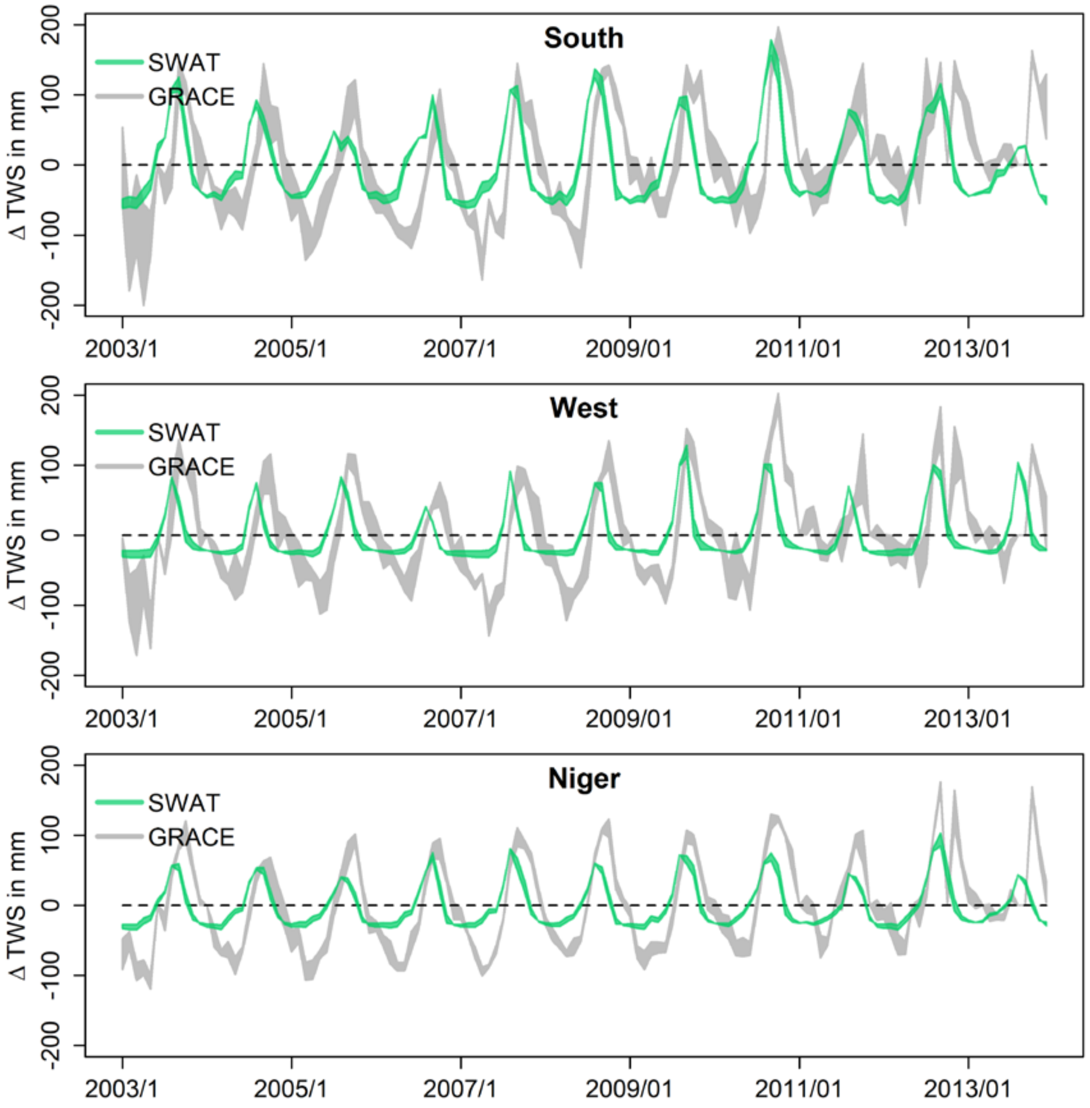

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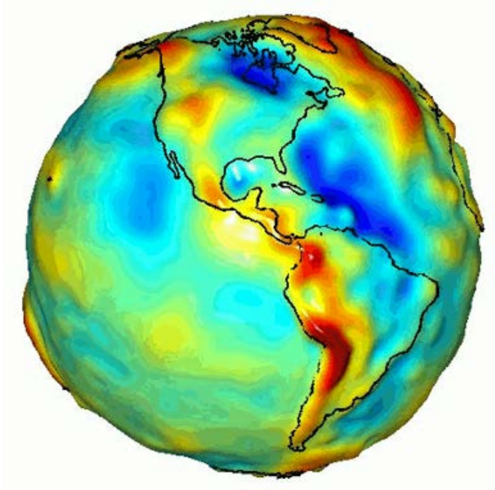
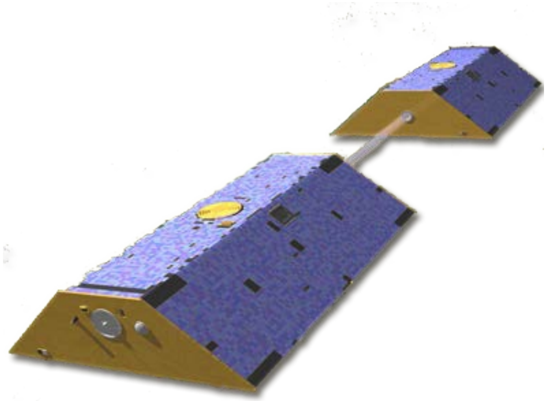
GIF Source: https://grace.jpl.nasa.gov/resources/6/

- Validating model total water storage using NASA and DLR GRACE data





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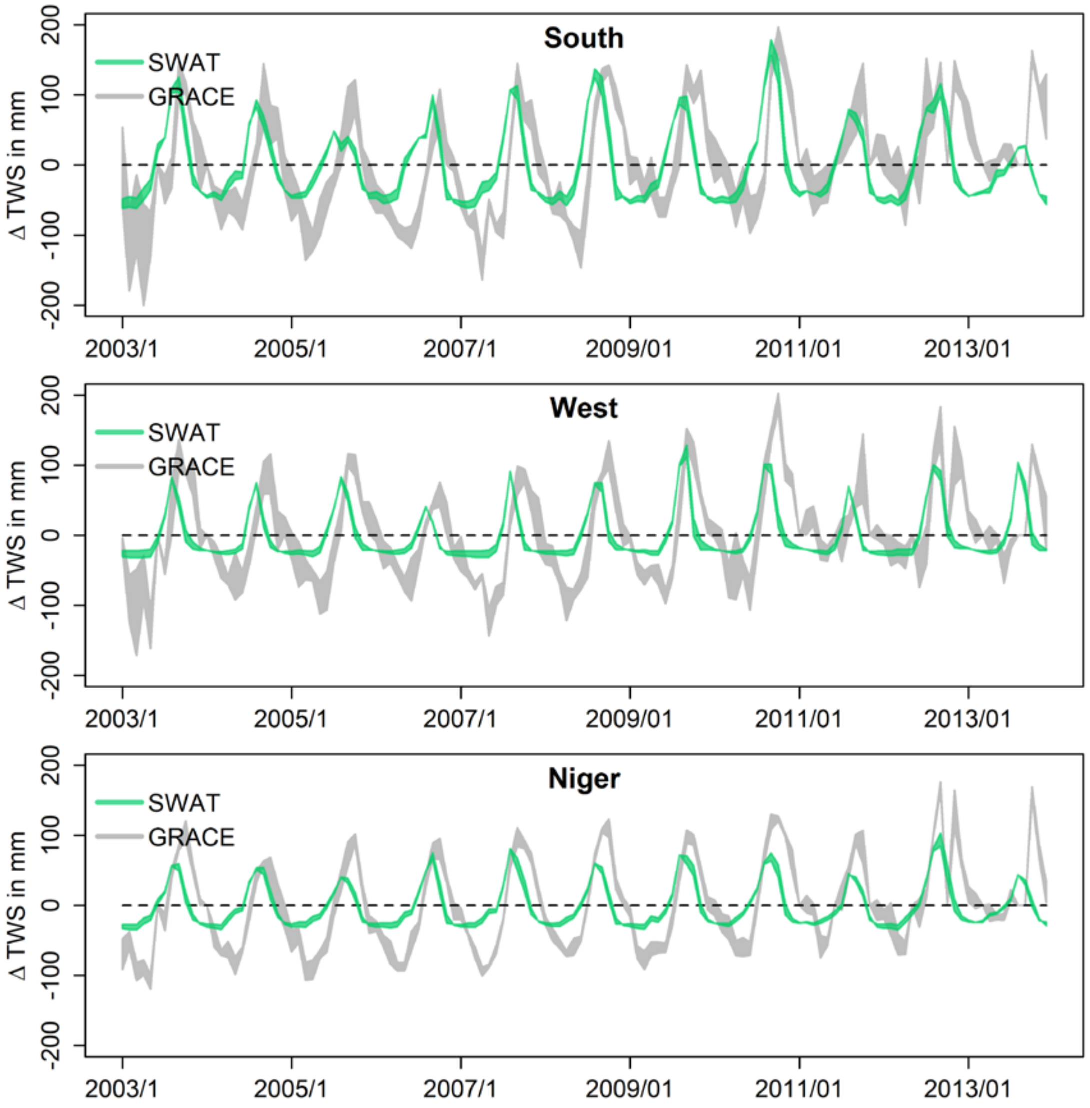


GIF Source: https://grace.jpl.nasa.gov/resources/6/

4 Conclusion and Outlook

- Remote sensing offers an inexpensive opportunity to model sparsely gauged catchments
- Some temporal measurements are still needed for calibration
- Multi-objective validation approaches deliver promising results and may be used to improve parametrization
- Inner Niger Delta will be added and plant growth revised
- Further investigate gauging stations and revise initial parameters
- Combined calibration using Q and ETa

Thank you for your attention!

Looking for info on:

- Remote-sensing data?
- Data preparation?
- netCDF?
- R?

COAST e-workshop

Check out the COAST Online Tutorial/Workshop. It's free! Come talk to us or write an e-mail to: thomas.pomeon@uni-bonn.de

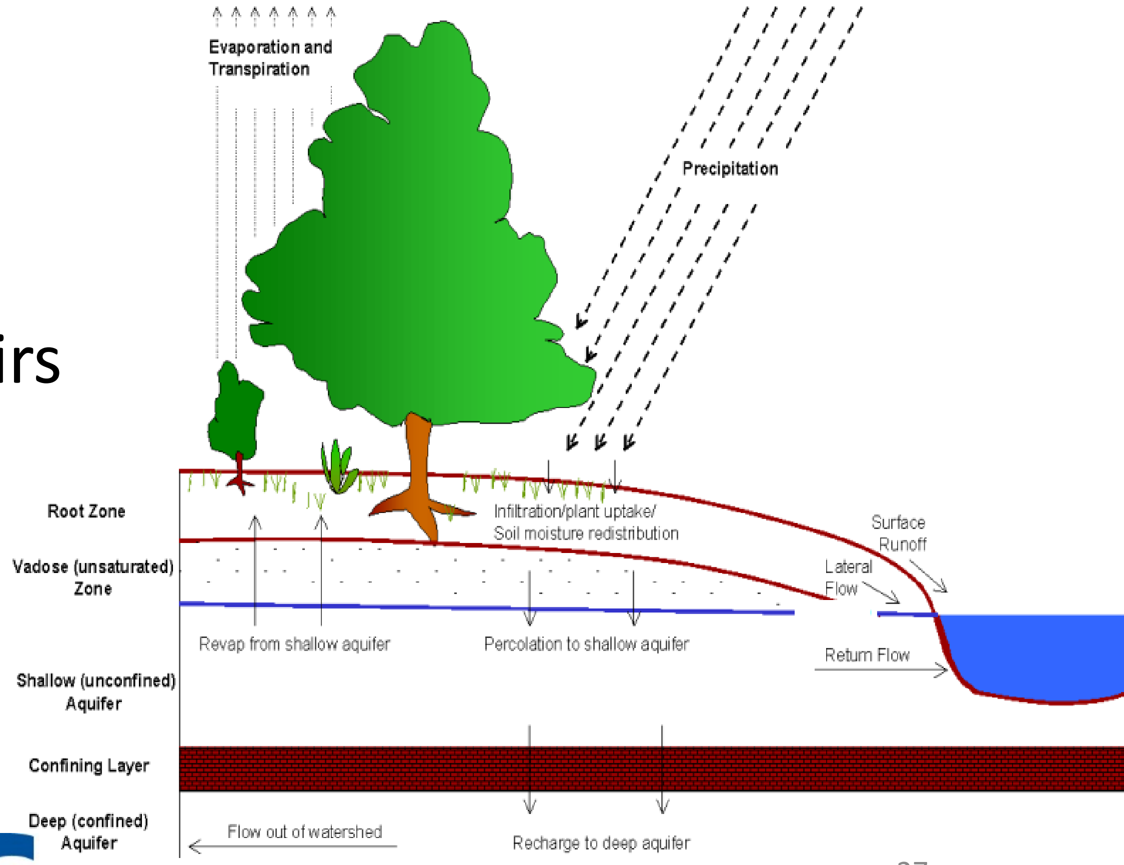
	Calibration (KGE > 0)					Validation (KGE > 0)				
Basin	p Factor	r Factor	R^2	PBIAS	KGE	p Factor	r Factor	R^2	PBIAS	KGE
South	0.42	0.30	0.50	10.81	0.48	0.44	0.35	0.65	17.21	0.51
West	0.63	1.03	0.71	4.58	0.58	0.57	2.03	0.72	34.05	0.44
Niger	0.32	0.38	0.52	12.43	0.44	0.25	0.34	0.74	23.94	0.51
AVERAGE	0.46	0.60	0.58	9.27	0.50	0.42	0.91	0.70	25.07	0.48

Most sensitive parameters		
South	West	Niger
CN2 (LULC)	CN2 (LULC)	CN2 (LULC)
SOL AWC (TEX)	SOL AWC (TEX)	SOL AWC (TEX)
SOL BD (TEX)	SOL BD (TEX)	SOL BD (TEX)
EPCO		EPCO
ESCO (LULC)	ESCO (LULC)	ESCO (LULC)
GW GELAY	GW GELAY	GW GELAY
GWQMN	GWQMN	GWQMN
RCHRG DP	RCHRG DP	
GW REVAP	GW REVAP	GW REVAP
REVAPMN	REVAPMN	REVAPMN
ALPHA BF		
CANMX (LULC)		CANMX (LULC)
RES RR (RES)		
	SOL K (TEX)	
	RES K (RES)	
		EVRSV (RES)

The Soil and Water Assessment Tool (SWAT)

- Mainly physically-based, semi-distributed, continuous-time, basin-scale model
- Designed to predict impacts of management on water supplies
- Major components are: hydrology, weather, soil, plant growth and reservoirs
- Developed especially for use in undergauged catchments

SWAT Soil & Water Assessment Tool



http://swat.tamu.edu/software/swat-check/

$$\mathrm{KGE} = 1 - \sqrt{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2}$$

where: r is the correlation, α is the relative variability and β is the bias in the observed and simulated variables. The term within the root describes the Euclidian distance from the ideal point.

$$TWS^t = P^t + SW^{t-1} + \left(WYLD^{t-1} - WYLD^{t-1}_{outlets}\right) - ET^t - DA\_RCHG^t$$

where: TWS is the total water storage at timestep t, P is precipitation, SW is soil water, $WYLD$ is water yield, ET is evapotranspiration and DA_RCHG is the deep aquifer recharge

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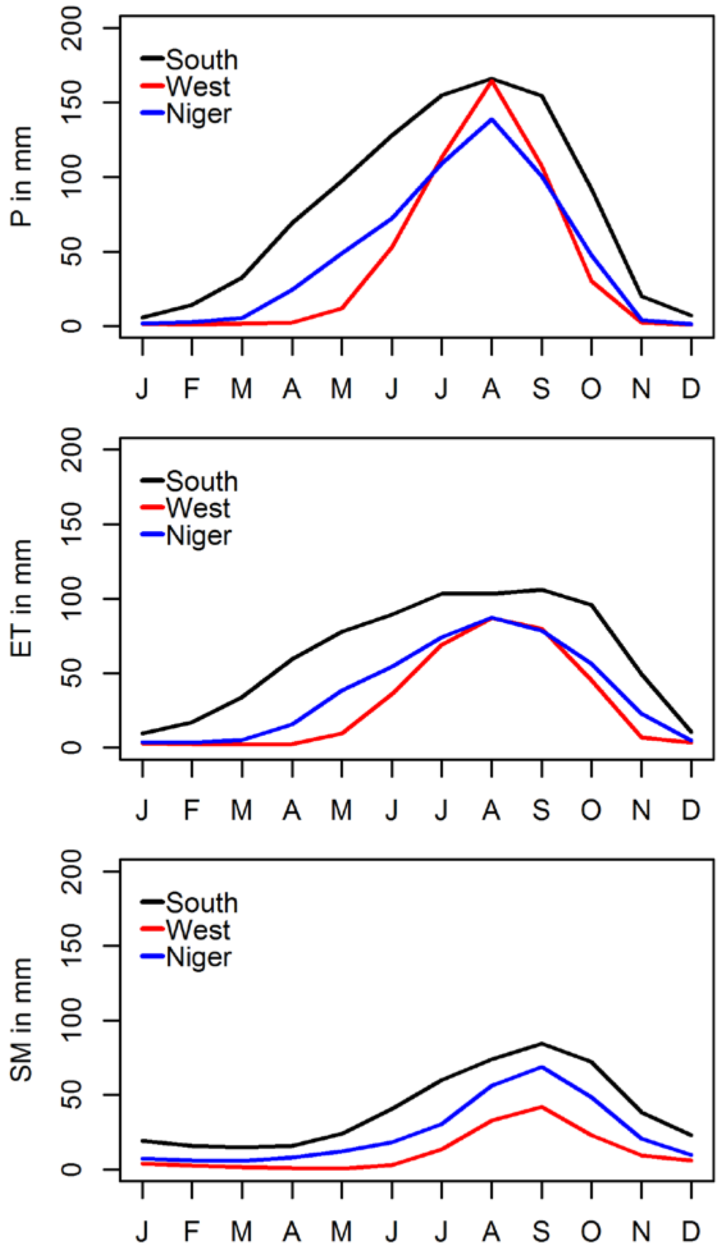
P in mm
ET in mm
SM in mm
South
West
Niger
0
50
100
150
200
J F M A M J J A S O N D

3 Model results and multi-objective validation approaches

- Sensitivity analysis was performed for parameters influencing flow using suggested, realistic ranges
- Non-sensitive parameters ($p_s > 0.05$) were removed from the selection
- For model optimization, the Kling-Gupta Efficiency (Gupta et al. 2009) was used ($-\infty < KGE \leq 1$)
- Further validation approaches using remote-sensing data were explored