Calibration and validation of SWAT model by using hydrological remote sensing observables in the Lake Chad Basin

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Abstract: The distributed hydrological models are important tools potentially used for policy planning and decision-making in terms of water-soil balance at the catchment level in different environmental conditions. However, the model calibration and validation present a crucial challenging task in poorly gauged basins, e.g. many river basins in Africa. Our study contributed to providing an operational framework to calibrate hydrological models by using distributed geospatial remote sensing data. The Soil and Water Assessment Tool (SWAT) model was calibrated in monthly steps using only twelve months of satellite-based actual evapotranspiration (ETa) geospatially distributed in the 37 sub-basins of the Lake Chad Basin in Africa. The identification of influential model parameters was done based on global sensitivity analysis by applying the Sequential Uncertainty Fitting Algorithm–version 2 (SUFI-2), incorporated in the SWAT-Calibration and Uncertainty Program (SWAT-CUP). This technique is designed to deal with spatially variable parameters and estimates either multiplicative or additive corrections applicable to the entire model domain, which limits the number of unknowns while preserving spatial variability. Fifteen influential parameters were selected for calibration based on the sensitivity analysis. The optimized parameters set could achieve the best model performance judging by the high Nash–Sutcliffe Efficiency (NSE), Kling–Gupta Efficiency (KGE), and determination coefficient (R^2). Four sets of ET were tested for SWAT model calibration, i.e. ETMonitor, GLEAM, SSEBop and WaPOR. Overall, the calibration performance was very good, especially when matching the SWAT ET calculated with Hargreaves-equation based potential ET (ETp), to the ETMonitor ET and GLEAM ET, with performance metrics R^2> 0.9, NSE>0.8 and KGE>0.75. The ETMonitor ET product was finally adopted for the SWAT model calibration in this study for further application, since it showed the best calibration results. The calibrated SWAT model were further validated by comparing its outputs with the total water storage change (TWSC) derived from GRACE and surface soil moisture from ESA – CCI product. The validation during 2010-2015 using total water storage derived from GRACE gave an acceptable performance, i.e. R2=0.56 and NSE=0.55. The evaluation against the ESA – CCI soil moisture showed NSE=0.85.

Keywords: hydrological modeling; SWAT model; hydrological remote sensing observables; ETMonitor evapotranspiration; African Sahel; limited calibration

Introduction:

Hydrological models are most useful tool to reveal the hydrological processes that occur in a changing environment. Therefore, the accurate calibrated model is essential for understanding assessment of drought, impacts of climate change, impacts of land use/land cover change, assessment of Water scarcity, sediments and nutrients evaluation and water stress/conflict within basins. Model calibration is usually based on ground observations such as surface runoff. This kind of data must be available in long time series to get good calibration performance. Ground observation scarcity is the main problem for hydrological model calibration such as in Africa.

In solution, many studies found that retrievals of hydrological variables from remote sensing data may help to improve model performance. Many studies have used remote sensing ETa to calibrate and validate hydrological models:

* Ha et al., (2018) used three years of remote sensing ETa to calibrate the SWAT model for a tributary of the Red River in Vietnam.
* Poméon et al., (2018) validated the SWAT model using time series of remote sensing data in the Niger, Volta, and Senegal River Basins.
* Odusanya et al. (2019) calibrated the SWAT model using ETa from GLEAM and MOD16 in the Ogun catchment in Southwestern Nigeria.

All the previous studies showed good calibration and validation performance. However, they did not well emphasize the benefit of the geospatial distribution of remote sensing retrievals, which could resolve the problem of the lack of ground observation time series, e.g., discharge.

This presentation aims to provide a novel calibration approach of the SWAT model based on limited time series of earth observation data in a data-scarce Lake Chad Basin.

Objective:

The objectives of this study are:

1) to evaluate the performance of the SWAT model after a limited calibration period (one year) using multiple satellite remote sensing ETa products, which would be the novelty of this study.

2) to validate the model using remote sensing ETa, total water storage, and soil moisture in a distributed manner in the whole Lake Chad Basin.

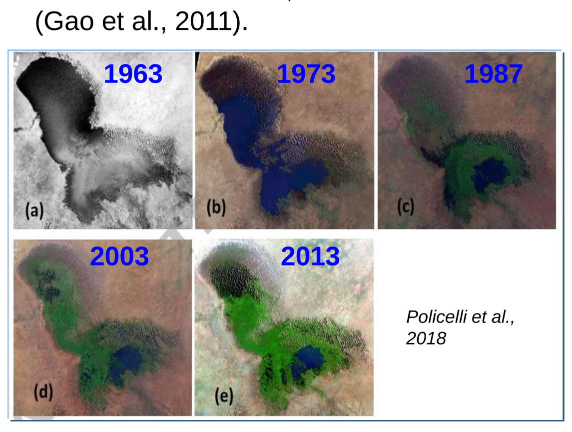
Study area

The Sahel :

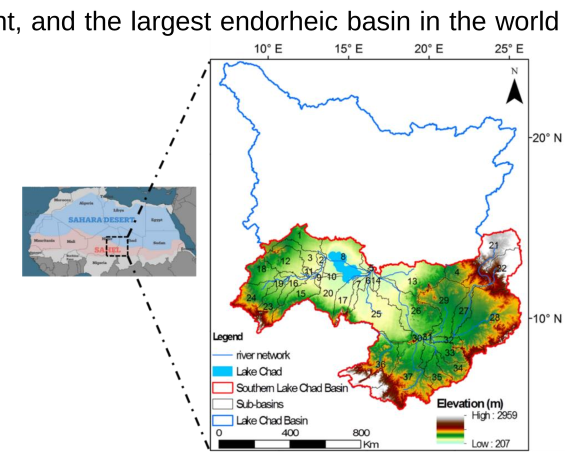
is a transitional zone between the Sahara desert to the north and the humid savannas to the south, its semi-arid climate is characterized by a very important variation in rainfall throughout years which oscillates between 300 and 600 mm also the temperature varies from one region to another and throughout years but generally it is high.

Chad Lake

was about 2.5 Mkm2, 8% of the African continent, and the largest endorheic basin in the world (Gao et al., 2011).



Evolution of Lake Chad. Optical imagery from (a) Argon satellite (b) 119 Landsat 1 (c) Landsat 5 (d) Landsat 7 (e) Landsat 8.



The location of the African Sahel, the Lake Chad Basin, the study area (Southern Lake Chad Basin), and the 37 sub-basins.

Method:

Input Data

* Meteorological data : precipitation (CHIRPS, 5 Km) other meteorological data (ERA5, 30 km).
* LULC: Tsinghua LULC maps for each year from 2009-2015 in resolution of 250 m.
* Soil data :The Harmonized World Soil Database (HWSD) version 1.2 .
* Digital Elevation Model (DEM): SRTM Shuttle Radar Topography Mission in 30 m resolution

Data for calibration and validation

* **Remote Sensing ET products : four products :**
  * ETMonitor_V1.1, GLEAM_V3.3a, SSEBop_V4 and WaPOR_V1.1.
* **Other Remote Sensing observable products :**
  * Total water storage change TWSC: GRACE
  * Remote Sensing Surface Soil Moisture ESA CCI SSM v5.2

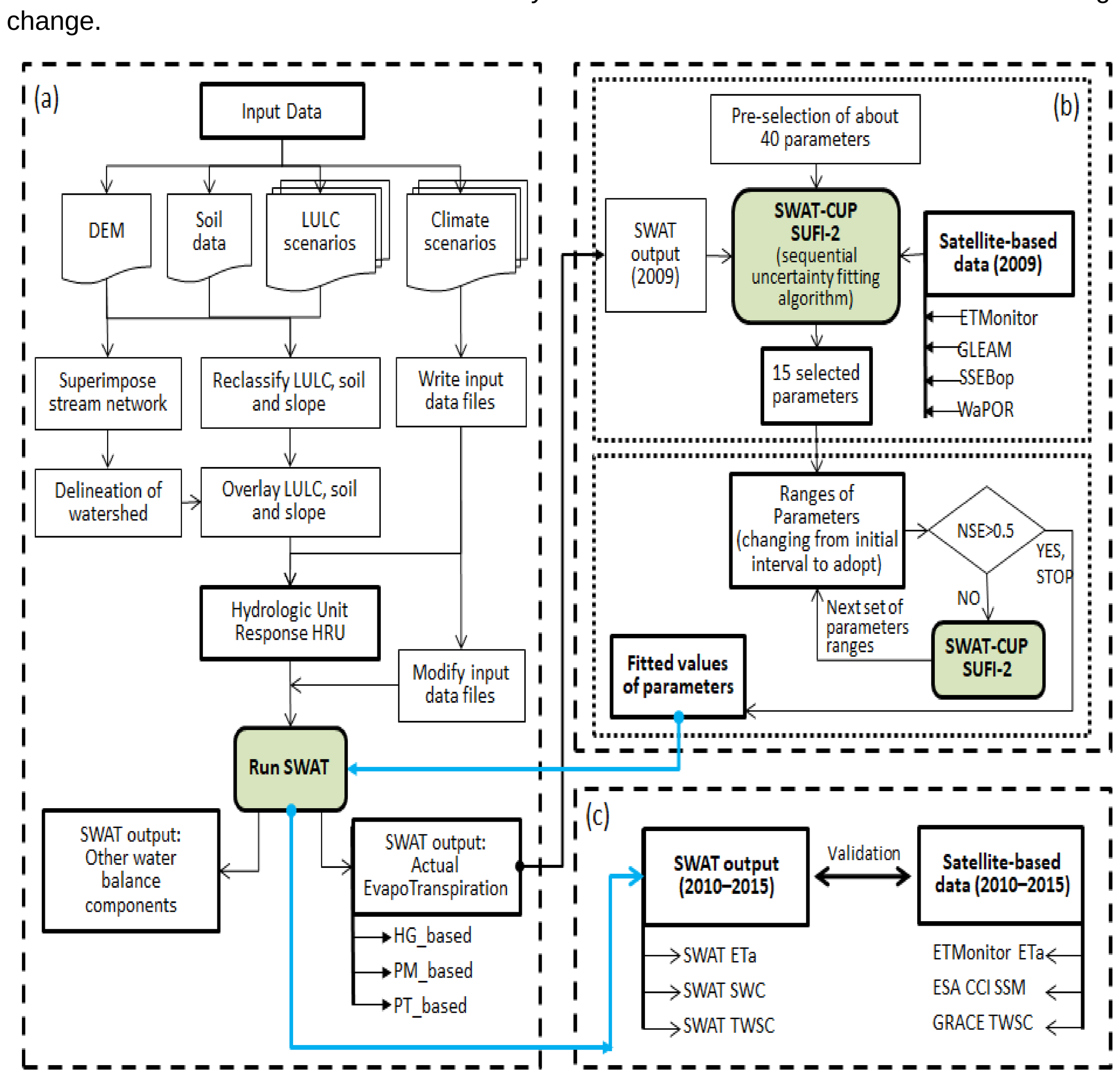
Soil and Water Assessment Tool model (SWAT)

The SWAT model is an open-source, process-based, and semi-distributed model is widely used to simulate different water balance components in a watershed **[1].**

In this study, three available ETp equations (Hargreaves, Priestley–Taylor, and Penman–Monteith) were used to configure the SWAT model to estimate the ETa.

Then using SWAT-CUP **[2]**, four satellite-observation-based ETa data products (ETMonitor, GLEAM, SSEBop and WaPOR) were evaluated, and the one with the best performance was used for further analysis.

For validation, the results from the calibrated SWAT were assessed by comparing with the satellite-based observations of surface layer soil moisture and terrestrial water storage change.



The conceptual framework of this study: (a) the SWAT flowchart (and uncalibrated model outputs), (b) SWAT-CUP flowchart (parameter selection and calibration), and (c) the validation schemes (using the calibrated model).

SWAT-CUP **[3]** provides three techniques to modify the selected model parameters through the iterations: (a) by a multiplicative factor "(1+α)"; (b) by adding a constant "β"; and (c) assigning a parameter a new value "γ". The default parameter value (P) is replaced with a new candidate value (Pnew) in each iteration by:

$$\text{Pnew} = \text{P} \times (1 + \alpha) \quad (1)$$

$$\text{Pnew} = \text{P} + \beta \quad (2)$$

$$\text{Pnew} = \gamma \quad (3)$$

where α, β and γ are the final values obtained by the calibration. In this study we have used (a) multiplicative and (c) replace techniques.

Selected Parameters description [4]

	Parameters	used range		full name	SWAT range		Unit	default values
		min	max		min	max		
1	r1__CN2.mgt	-0.5	0.25	SCS runoff curve number f	35	98	%	specific to HRU
2	r2__SOL_AWC().sol	-0.5	0.95	Available water capacity of the soil layer	0	1	mm H2O/mm soil	specific to soil
3	r3__SOL_BD().sol	-0.5	0.95	Moist bulk density	0.9	2.5	Mg/m3	specific to soil
4	r4__SOL_ALB().sol	-0.03	0.2	Moist soil albedo	0	0.25	%	specific to soil
5	v1__ESCO.hru	0.25	0.95	Plant uptake compensation factor	0	1	-	0.95
6	v2__BLAI{15,16}.plant	0	5	Max leaf area index	0	10	-	specific to plant
7	v3__GSI{15,16}.plant.	0	5	Max stomatal conductance	0	5	ms-1	specific to plant
8	v4__HRU_SLP.hru	0	1	Average slope steepness	0	1	m/m	HRU Specific
9	r5__SOL_CBN().sol	-0.03	0.2	Organic carbon content	0.05	10	% Soil weight	specific to soil
10	r6__SOL_Z().sol	-0.03	0.2	Depth from soil surface to bottom of layer	0	3500	mm	specific to soil
11	v5__SLSOIL.hru	0	150	Slope length for lateral subsurface flow	0	150	m	0
12	v6__FFCB.bsn	0	1	Initial soil water storage expressed as a fraction of field capacity water content	0	1	-	0
13	v7__DDRAIN.mgt	0	200	Depth to subsurface drain	0	2000	mm	0
14	v8__EPCO.hru	0	1	Soil evaporation compensation factor	0	1	-	1
15	v9__SURLAG.bsn	0.05	24	Surface runoff lag time	0.05	24	-	4

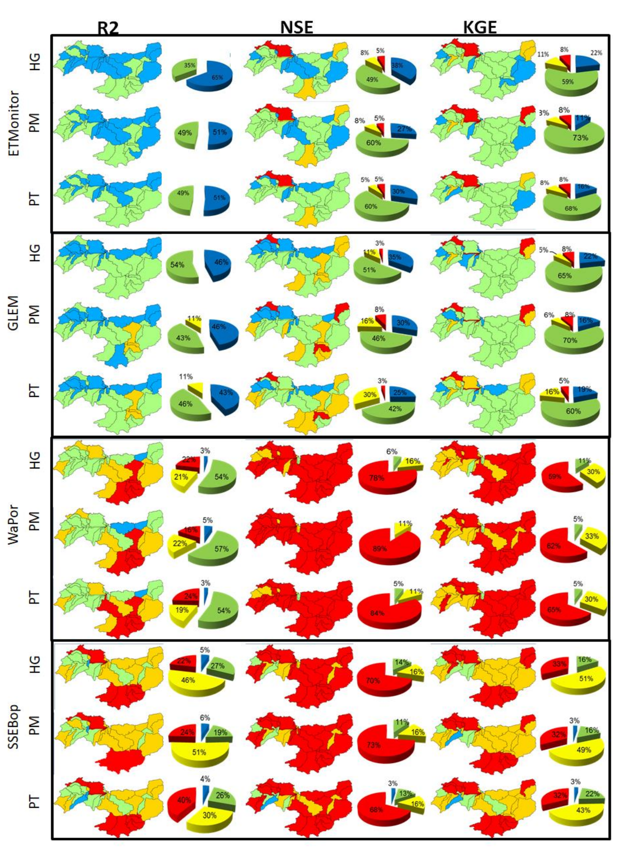
Performance metrics used to evaluate the calibration and validation **[5]**

Performance Metrics	Equations	Descriptions
Coefficient of determination	$R^2 = \frac{[\sum_i (ET_{Rs,i} - \overline{ET_{Rs}})(ET_{s,i} - \overline{ET_s})]^2}{\sum_i (ET_{s,i} - \overline{ET_s})^2 \sum_i (ET_{Rs,i} - \overline{ET_{Rs}})^2}$	where ET_{Rs} represents satellite-based ETa values; ET_s represents simulated ETa values; $\overline{ET_{Rs}}$ represents mean satellite-based ETa values; $\overline{ET_s}$ represents mean simulated ETa values. r is the Pearson product correlation coefficient between satellite-based ETa and the simulated ETa; α is the standard deviation of the simulated ETa over the standard deviation of the satellite-based ETa; β is the ratio of the mean simulated ETa to the satellite-based ETa.
Nash–Sutcliffe Efficiency	$NSE = 1 - \frac{\sum_i (ET_{Rs} - ET_s)_i^2}{\sum_i (ET_{s,i} - \overline{ET_s})^2}$	
Kling–Gupta Efficiency	$KGE = 1 - \sqrt{(r-1)^2(\alpha-1)^2(\beta-1)^2}$	
Percent bias	$\text{PBIAS} = \frac{\sum_{i=1}^{n}(ET_{Rs} - ET_s)i}{\sum_{i=1}^{n}(ET_{Rs})}$	

Results

Calibration by using actual evapotranspiration

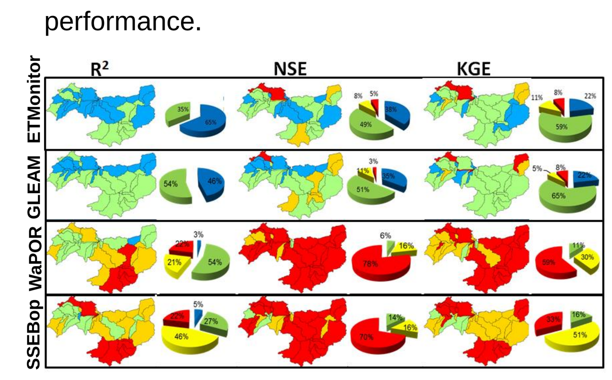
ETMonitor and GLEAM showed best performance while WaPOR and SSEBop indicated lower performance. The Hargreaves (HG) potential evapotranspiration equation showed better performance than Penman-Monteith (PM) and Priestley–Taylor (PT).



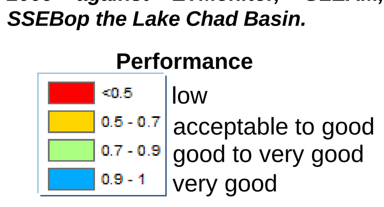
Spatial distribution of performance metrics (R^2, NSE, and KGE) of SWAT_Hargreaves, Penman-Monteith and Priestley-Taylor when calibrated in 2009 against ETMonitor, GLEAM, WaPOR, and SSEBop the Lake Chad Basin.

Spatial distribution of the performance metrics during calibration of SWAT configured using Hargreaves .

ETMonitor showed the best performance then GLEAM took place after that SSEBop is a little better than WaPOR but both indicated lower performance.

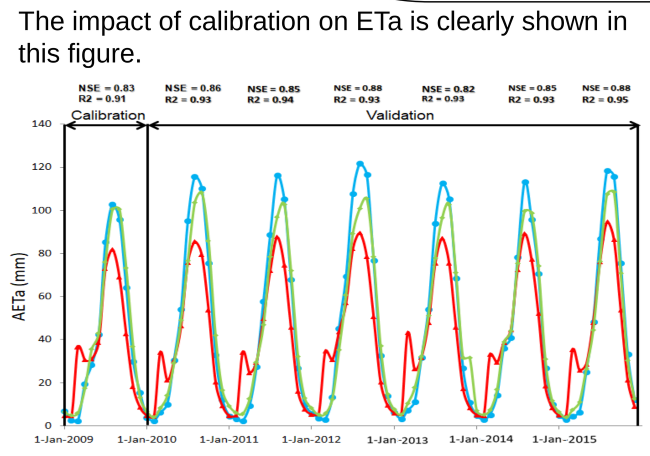


Spatial distribution of performance metrics (R^2, NSE, and KGE) of SWAT_Hargreaves, when calibrated in 2009 against ETMonitor, GLEAM, WaPOR, and SSEBop the Lake Chad Basin.

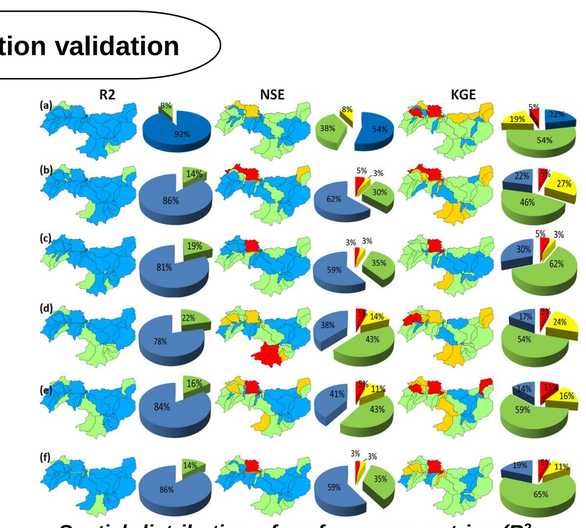


Actual evapotranspiration validation

The impact of calibration on ETa is clearly shown in this figure.

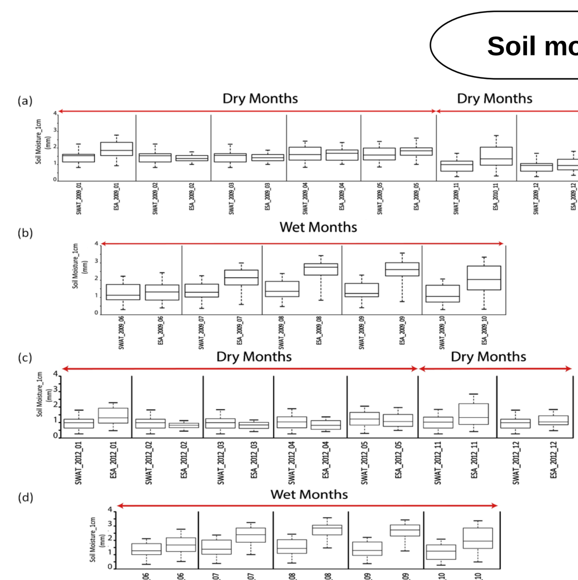


Comparison of monthly averaged ETs before and after calibration and ETM ETa.

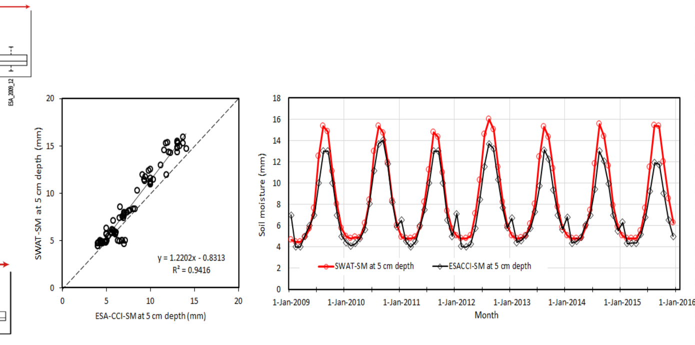


Spatial distribution of performance metrics (R^2, NSE, and KGE) of SWAT_Hargreaves when validated against ETMonitor in 2010, 2011, 2012, 2013, 2014, and 2015 (a,b,c,d,e,f), respectively, in the Lake Chad Basin.

Soil moisture validation

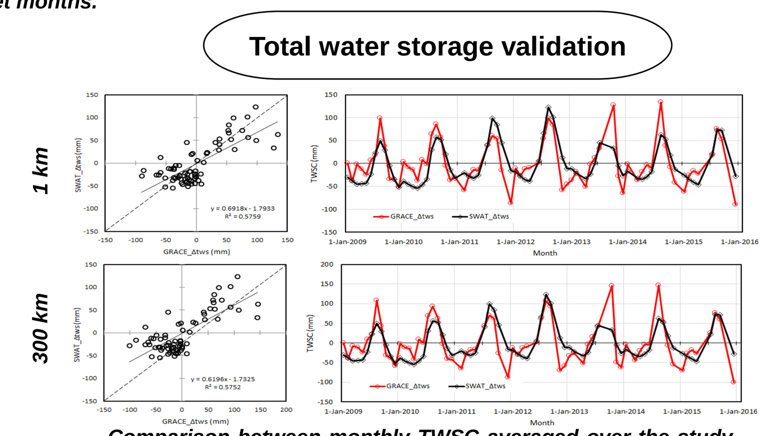


Seasonal comparison between monthly averaged SWAT and ESA CCI SSM at 1 cm on 2009 as driest year: (a) dry months, (b) wet months and on 2012 as wettest year: (c) dry months, and (d) wet months.



Comparison between monthly averaged SWAT SWC vs. ESA CCI SM at 50 mm during 2009–2015 in the study area in the Lake Chad Basin: the scatter plot, and the time series.

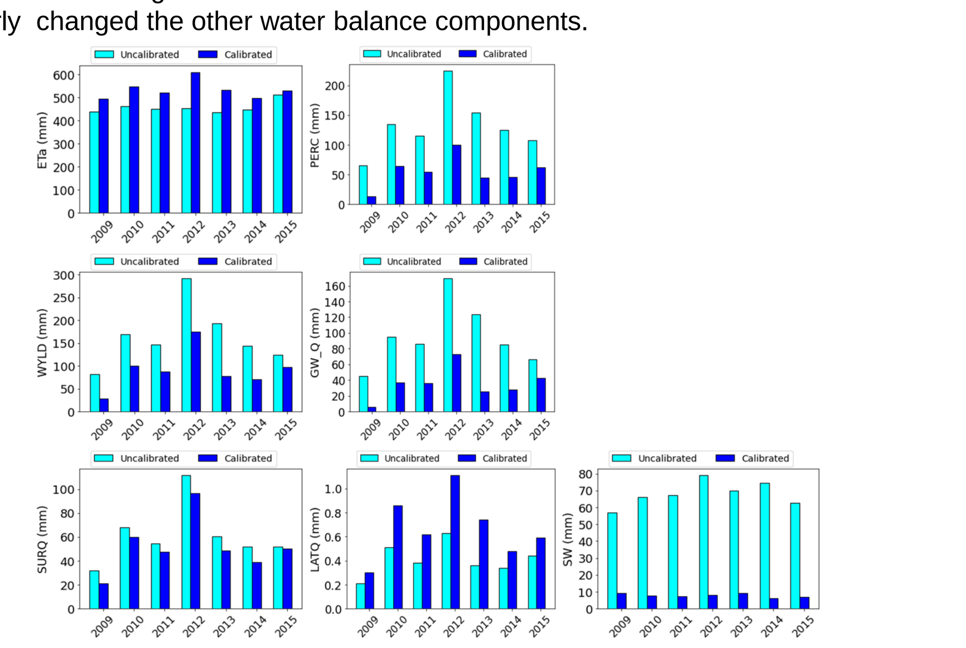
Total water storage validation



Comparison between monthly TWSC averaged over the study area in the Lake Chad Basin for 2009–2015: SWAT estimates and GRACE data product, at 1 km resolution: scatter plot, time series, and at 300 km resolution: scatter plot, time series.

Impact of calibration on different simulated water balance components

Not only the ETa was changed after calibration because it was the calibrated variable But the calibration clearly changed the other water balance components.



Average annual water balance components in the study area in the Lake Chad Basin based on SWAT-simulated output before (Uncalibrated) and after (Calibrated) calibration. (ETa: actual evapotranspiration; SW: soil water content; PERC: perception; SURQ: surface runoff; GW_Q: groundwater recharge; WYLD: water yield; LATQ: lateral runoff.

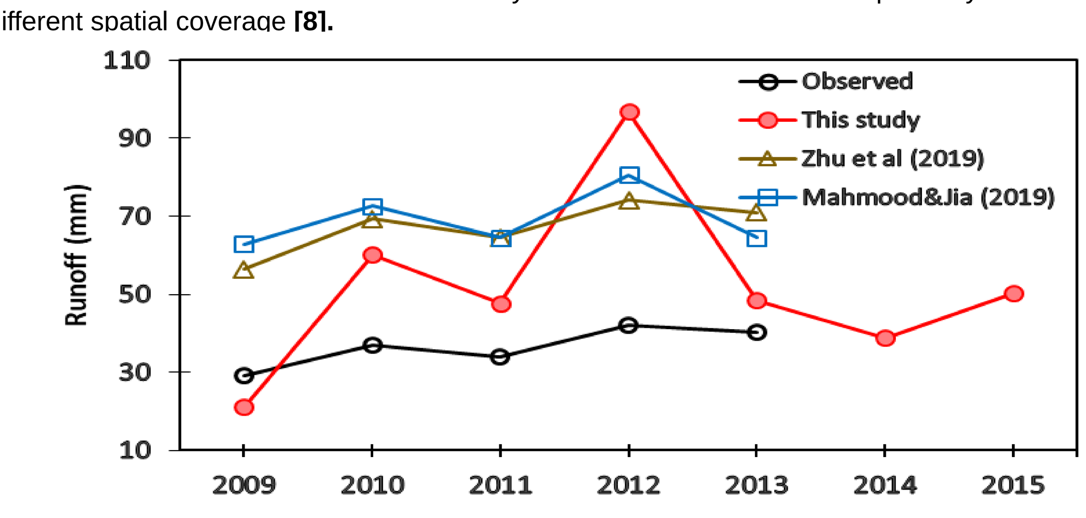
Discussion

* A very good performance of the SWAT model calibration and validation using ETa configured using Hargreaves ETp equation with both ETMonitor and GLEAM was indicated by all performance metrics while SSEBop and WaPOR ETa showed low performance. These findings showed better values than those found by other studies **[6].**
* the dynamic of the SWAT SM fit very well with the ESA CCI SSM (%) in the upper few centimeters of the soil profile in most of the basin at a monthly time step **[6,7].**
* the SWAT TWSC was in good agreement with the GRACE retrievals, although the differences in the wet months were at times large and not systematic **[7].**
* the runoff simulated by our study is comparable to the other studies in recent years (i.e., after 1970), notwithstanding the different temporal and spatial coverage of the study.

Comparison with previous studies

	Study	Time Period	Study Area	Mean Runoff (mm/Year)
1	LCBC, 2016	1954–1969	Lake Chad	170.7
2	Odada et al. 2006	Pre-1970	Lake Chad	90.8
3	Vuillaume, 1981	1954–1969	Chari-Logone Basin	67.67
4	Olivry et al. 1996	1932–1995	Chari-Logone Basin	52.64
5	Odada et al. 2006	1971–1990	Lake Chad	42.22
6	LCBC, 2016	1988–2010	Lake Chad	65.7
7	Zhu et al. 2017	1991–2013	Southern Pool of Lake Chad	40.52
8	Mahamat Nour et al. 2021	1960–2015	Chari-Logone Basin	42
9	Lemoalle et al. 2012	1960–2009	Chari-Logone Basin	41.35
10	Our study	2009–2015	Southern Lake Chad Basin	51.9

All the model studies and the observed runoff confirmed the increase in the runoff in the comparison period starting from 2009, and followed similar trends and fluctuations. The difference in some values between our study and the two other studies is probably due to the different spatial coverage **[8].**



Comparison with previous studies

Conclusions

* This study demonstrated that it is feasible to calibrate the semi-distributed regional hydrological model SWAT for the entire LCB, notwithstanding the scarcity of hydrological data, by using remote sensing data products of ETa
* The innovative aspect of the limited calibration (one year on a monthly timescale) results showed that the remote sensing products are useful to calibrate and validate the SWAT model in arid to semi-arid poorly gauged basins, even though the temporal coverage of the calibration was limited.
* Differences across the remote sensing ETa products were significant, consistently with the different algorithms used to estimate the ETa. The statistical analysis of both calibration and validation results indicated that the ETMonitor and GLEAM led to a better SWAT performance than SSEBop and WaPOR.
* SWAT estimates of SWC and TWSC were compared with satellite data products. Overall, the agreement was good, further confirming the usefulness of the proposed limited calibration in our data-scarce study area.
* The results of this study are comparable to previous studies results as well as to the observed data.
* The limited calibration of a hydrological model using remote sensing data is one of the solutions to deal with the scarcity of hydrological data, and it also needs less computational capacity and time, as opposed to a calibration done for several years which requires much computational time and resources.

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