Hydrol. Earth Syst. Sci. Discuss., 9, 2071–2120, 2012
www.hydrol-earth-syst-sci-discuss.net/9/2071/2012/
doi:10.5194/hessd-9-2071-2012

Hydrology and Earth System Sciences Discussions

Calibration and evaluation of a semi-distributed watershed model of sub-Saharan Africa using GRACE data

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Received: 29 December 2011 – Accepted: 11 January 2012 – Published: 17 February 2012

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Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

Irrigation development is rapidly expanding in mostly rainfed Sub-Saharan Africa. This expansion underscores the need for a more comprehensive understanding of water resources beyond surface water. Gravity Recovery and Climate Experiment (GRACE) satellites provide valuable information on spatio-temporal variability of water storage. The objective of this study was to calibrate and evaluate a semi-distributed regional-scale hydrological model, or a large-scale application of the Soil and Water Assessment Tool (SWAT) model, for basins in Sub-Saharan Africa using seven-year (2002–2009) 10-day GRACE data. Multi-site river discharge data were used as well, and the analysis was conducted in a multi-criteria framework. In spite of the uncertainty arising from the tradeoff in optimizing model parameters with respect to two non-commensurable criteria defined for two fluxes, it is concluded that SWAT can perform well in simulating total water storage variability in most areas of Sub-Saharan Africa, which have semi-arid and sub-humid climates, and that among various water storages represented in SWAT, the water storage variations from soil, the vadose zone, and groundwater are dominant. On the other hand, the study also showed that the simulated total water storage variations tend to have less agreement with the GRACE data in arid and equatorial humid regions, and the model-based partition of total water storage variations into different water storage compartments could be highly uncertain. Thus, future work will be needed for model enhancement in these areas with inferior model fit and for uncertainty reduction in component-wise estimation of water storage variations.

1 Introduction

Sub-Saharan Africa (SSA) is used as a collective term that refers to African nations which lie (or partially lie) south of the Sahara. The region makes up about 80 % of the African and 10 % of the global population. Agriculture forms the backbone of the SSA economy; however, SSA countries largely missed the green revolution. The agricultural productivity in SSA countries remains low relative to other parts of the world, and the region is still beset with food insecurity. It was estimated that the number of undernourished people in SSA in 2010 reached 239 million (FAO, 2010). SSA is also the only region where childhood malnutrition is projected to increase as a result of rapid population growth, climate change, and continued low productivity in agriculture (Rosegrant et al., 2009). Annual population growth in SSA is 2.2 %, much higher than average global growth of 1.1 % per year (World Bank, 2009). In addition, SSA is regarded as the region with a particularly low capacity to adapt to climate change (IPCC, 2001).

Sustainable intensification of agriculture, with a focus on irrigation development is considered a key pillar for increasing agricultural productivity in SSA (Rosegrant et al., 2002; Molden, 2007; Rockström et al., 2007). SSA straddles the Equator and is dominated by tropical and sub-tropical climate. Rainfall in SSA is highly variable both spatially and temporally and constitutes a more critical factor than temperature for agriculture. Limited water availability, particularly during droughts, is a key reason for crop failure, especially considering the fact that SSA agriculture is predominantly rainfed with only 3 % of cultivated area irrigated (Siebert, 2010; FAO, 2011). Both international development banks and African governments have pledged to significantly increase irrigation development to address low agricultural productivity, rural poverty, and food security challenges in the region.

Significant expansion of irrigated agriculture in SSA, however, will require a more comprehensive understanding of water resources in the region. Mathematical models are important tools for scientific investigation and to support policy decisions. They provide a feasible and economical way to explore key hydrologic processes and to evaluate alternative management options where direct observation and experimentation are not possible, are costly, or both. However, hydrological modeling is a challenging process, particularly for regions with limited data. Models are only a rough representation of the reality. It is advisable to calibrate and evaluate model performance by using information contained in monitoring of past behavior of the hydrologic system whenever such data are available before the model can be used to provide reliable results.

HESSD

9, 2071–2120, 2012

In this study, we presented a study on the calibration and evaluation of a regional-scale semi-distributed watershed model developed for Sub-Saharan African countries using GRACE Data. The semi-distributed watershed model here refers to the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998), which is a physically-based comprehensive river basin model with a proven track record of successful application globally, including in agricultural water management (e.g., Kim et al., 2008; Xie et al., 2008, 2011; Dhar and Mazumdar, 2009; Oeurng et al., 2011). The size of the study river basins in reported SWAT applications typically range from a few square kilometers to tens of thousands of square kilometers. However, the model also shows potential for watershed studies at very large scales. Related to Africa, Schuol et al. (2008a,b) reported SWAT model applications for West Africa and the entire continent for the assessment of blue and green water resources.

The application of the SWAT model may have wide-ranging focuses. However, regardless of the primary goal of the SWAT modeling, evaluating and ensuring the model's capacity in hydrologic simulation is always essential because water movement is the driving force behind other processes simulated in SWAT. Conventional processes for evaluating and validating hydrologic models generally use stream discharge data. In the Schuol et al. (2008a,b) studies, the SWAT model was calibrated and validated using river discharge time series data for 1975–1990 compiled by the Global Runoff Data Centre (GRDC). In the study reported in this paper, a newly developed data set, satellite-based observations of total water storage (TWS) variations derived from the Gravity Recovery And Climate Experiment (GRACE) were applied to the SWAT model of Sub-Sahahran Africa (SWAT-SSA). The GRACE mission is a joint mission between NASA and the German Space Agency (DLR). The twin satellites for GRACE were launched in March 2002 and were designed to accurately map the Earth's gravity field. After corrections for tidal and atmospheric mass variations, the hydrologic cycle is the primary source of variations in the Earth's gravity field on the continents. Total water storage variations (or deviations of water storages integrated over all water storage layers from their temporal means) can be inferred from the GRACE gravity signals.

HESSD
9, 2071–2120, 2012

Including additional state observations to complement river discharge expands the data base for model evaluation and may help generate additional insights into model performance (Fenicia et al., 2008; Parajkaet al., 2010; Konz and Seibert, 2010). In this study, the merits of incorporating GRACE-based hydrological observations into the development of the SWAT-SSA model are two-fold: firstly, the river systems in SSA are poorly monitored and many river basins are ungauged. The GRACE-based TWS variation data have a global coverage, and thus offer the opportunity to calibrate and evaluate the model for those areas where river discharge data are not available or sparse. Secondly, river discharge is part of "blue" water, which is the traditional focus of water resources planning and management but only accounts for a small portion of total water resources. Over the past decade, the definition of agricultural water management has widened to include the entire hydrologic cycle (e.g., Falkenmark and Rockström, 2006). GRACE data provide direct measurements to help verify the capacity of the SWAT model to simulate spatio-temporal variability across all water resources.

There is keen interest in applying GRACE data to hydrologic studies since the launch of the GRACE mission. Several hydrologic modeling studies that involved use of monthly GRACE-based TWS variations have been reported. To date most studies that use GRACE data are limited to model validation without significant calibration or model parameter tuning procedures (Niu and Yang, 2006; Ngo-Duc et al., 2007; Syed et al., 2008; Yirdaw et al., 2009; Alkama et al., 2010; Tang et al., 2010). Werth et al. (2009, 2010) may be the first to present calibration analyses for water storage variability in global hydrological modeling. In their studies, GRACE-based water storage variations were used to calibrate and validate the WaterGAP Global Hydrology Model (WGHM) for 28 major river basins globally. More recently, Milzow et al. (2011) combine GRACE data with altimetry and SAR surface soil moisture data to calibrate and validate the SWAT model for the Okavango catchment in Southern Africa. The study presented in this paper includes calibration of SWAT, and the modeled area covers all SSA. Furthermore, the GRACE data used in this study have a finer temporal scale, having a 10-day time interval.

HESSD
9, 2071–2120, 2012

The rest of the paper is organized as follows: the setup of the SWAT model is depicted in Sect. 2, and the key data sets and steps for calibrating and evaluating the SWAT-SSA models are described in Sects. 3 through 5. Section 6 presents the results of the model calibration and validation. A summary of the major findings from this study and their implications are provided in Sect. 7.

2 SWAT model setup

The area of the region being modeled in this study is ~21 million km^2 (Fig. 1). The major data sets used for the setup or initial parameterization of the SWAT-SSA model are listed in Table 1. The data acquisition and processing strategy in our study are similar to those described in Schuol et al. (2008 a,b), but updated data or alternative options were selected in most cases.

The drainage topology of the study region is represented in SWAT modeling by partitioning the river basins into subbasins and defining the corresponding drainage network of the river system with one river channel segment in each subbasin. Elevation data used in this step of watershed delineation were clipped from the HydroSHEDS database (Lehner et al., 2008). HydroSHEDS is a derivative mapping product from NASA's 3 arc-second (approximately 90 m in equatorial area) SRTM (Shuttle Radar Topography Mission) elevation data and is the best currently available (with highest resolution) hydrologically conditioned digital elevation data set for SSA. Based on topographic analysis of HydroSHEDS elevation data, SSA was divided into 1488 subbasins (Fig. 1).

Within a subbasin, SWAT allows multiple hydrologic response units (HRUs) to be defined that reflect spatial variability in soil and land cover distributions. However, due to computational limitations, only one HRU with the dominant land cover and soil was created for each subbasin (Winchell et al., 2007). The soil and land cover data used to set up the model were obtained from the Harmonized World Soil Database (HWSD, v 1.1, FAO/IIASA/ISRIC/ISSCAS/JRC, 2009) and the Global

HESSD
9, 2071–2120, 2012

Land Cover 2000 database (European Commission, Joint Research Centre, 2003, http://bioval.jrc.ec.europa.eu/products/glc2000/glc2000.php), respectively. The HWSD contains updated soil data for eastern, central, and southern African countries relative to the FAO/UNESCO Soil Map of the World. The soil attribute data in HWSD can meet most requirements for SWAT model parameterization; however, two important parameters that describe the hydrologic properties of soils (available water capacity and saturated hydraulic conductivity) are missing and were estimated using pedotransfer functions (Saxton et al., 1986; Schaap et al., 2001).

Climate forcing data for the SWAT model include 1° daily (1 DD) precipitation, temperature, solar radiation, and relative humidity, and were obtained from the NASA Langley Research Center POWER Project. These data were spatially re-aggregated to calculate basin-wide estimates for each subbasin. The original source of the precipitation data is the Global Precipitation Climate Project (GPCP, http://precip.gsfc.nasa.gov). The 1-DD GPCP data set combined observations from multiple sensors (Huffman et al., 2001) and missing values in the GPCP data were filled with data from the Tropical Rainfall Measurement Mission (TRMM) Daily Global and Regional Rainfall derived data sets (TMPA-RT-3B42RT, http://trmm.gsfc.nasa.gov/). The data for other climate variables were imported from NASA's Surface meteorology and Solar Energy (SSE) database (Release 6.0) and were primarily used for the estimation of potential evapotranspiration (PET). SWAT includes three different methods for estimating PET (Neitsch et al., 2005); the three methods have varying amount of data requirements, and the Priestley-Taylor method (Priestley and Taylor, 1972) was selected because it is considered more accurate than the Hargreaves method (Hargreaves et al., 1985), which is temperature-based, and reliable estimates of wind speed required for the Penman-Monteith method (Monteith, 1965) were not available at the time of this study.

SWAT also provides two options for simulating the flow routing in river channels. The variable storage method was used to route water in river channels because pilot simulations suggested that this is more robust than the Muskingum method option in this study. Anthropogenic impacts on water resources were considered to be negligible

HESSD
9, 2071–2120, 2012

in SSA. Agriculture is the dominant water use sector. However, current agriculture in SSA is mainly rainfed; the area of SSA equipped for irrigation only accounts for 3 % of the total cultivated area (Siebert, 2010; FAO, 2011). Therefore, existing irrigation was not simulated in this study.

SSA has a number of large fresh water bodies, such as Lake Victoria, the world's second largest fresh water lake in terms of surface area (239 000 km^2), and Lake Volta, the largest reservoir in the world by surface area (8,502 km^2). The major lakes and reservoirs in SSA were defined in our SWAT-SSA model (Fig. 2). Locations and storage capacities of these water impoundments were obtained from the Global Lakes and Wetlands Database (GLWD) (Lehner and Döll, 2004). Due to signal leakage, mass variations in these lakes and reservoirs may have a significant contribution to GRACE TWS observations (e.g., Becker et al., 2010), even if their size is much less than the GRACE foot print (~450 km, i.e., 200 000 km^2 in area). We compared the simulated water level change data and water level variation data obtained with satellite altimetry (Crétaux et al., 2011, see http://www.legos.obs-mip.fr/en/soa/hydrologie/hydroweb/) and found that it is difficult to adequately simulate water storage variations in these lakes and reservoirs because of a lack of detailed bathymetry and reservoir operation data. In this study, an alternative modeling strategy was taken, i.e., lake and reservoir mass correction was applied in GRACE TWS data according to the height and volume variations of 22 largest lakes and reservoirs in SSA (Table 2) from the satellite altimetry data analysis for a fair comparison between GRACE and hydrological model. Accordingly, the simulated water mass variations lakes and reservoirs were excluded from the model-based TWS variation calculation.

SWAT is a semi-distributed watershed model. A parameter may take on different values for different subbasins/reaches. To reflect the spatial variability of SWAT parameters in calibration and considering computational efficiency, SSA was divided into ten sub-continental regions; one SWAT model was setup and calibrated separately for each sub-continental region (Fig. 1; Table 3).

3 GRACE data

GRACE data used in this study were obtained from CNES-GRGS (Centre National d'Etudes Spatiales-Groupe de Recherches de Géodésie Spatiale), RL2 product (Bruinsma et al., 2010). The data are provided as spherical harmonics as 10 day means. The Stokes coefficients are truncated at degree 50 to remove high frequency noise. No further filtering is required for these solutions. Stokes coefficients were recombined following Wahr et al. (1998) and projected on a 0.5° latitude/longitude grid. In terms of time frame of the data, we used 232 10-d periods from 29 July 2002 through 22 April 2009 (with missing values from 26 November 2002 to 23 February 2003, 25 May 2003 to 3 July 2003, and 20 January 2004 to 29 January 2004).

The GRACE CSR RL04 product (Center for Space Research, University of Texas at Austin, monthly timescales, Bettadpur, 2007) was also used to estimate GRACE errors at a 10-day timescale. CSR data were destriped according to Swenson et al. (2006). For error calculation, both GRGS and CSR GRACE products were then truncated at degree 30 and smoothed using a 300-km Gaussian smoother to evaluate large-scale errors. Error is computed at a monthly time step as the difference between CSR and GRGS data, and resampled as 10-day errors.

In the mass correction, the impact of 22 lakes and reservoirs were first forward modeled at GRACE GRGS resolution, prior to subtraction to GRACE. Lake volume variations were distributed on a grid, projected on spherical harmonics. They were then recombined up to degree 50 on a 0.5° grid.

4 Total water storage variation calculation in SWAT

SWAT was developed to provide continuous simulations of the basin hydrology at a daily timescale. During each day of the simulation, the model first computes the water yields on land, and then routes the water through the defined river channel network. In the land phase simulation, SWAT uses the SCS curve number method (SCS 1972) to

HESSD
9, 2071–2120, 2012

estimate the volume of overland flow and storage routing techniques to simulate percolation and lateral movement of water through the soil profile. The water leaving the bottom of the soil profile does not enter aquifers immediately but is time lagged based on transport through the vadose zone. The vadose zone defined in SWAT denotes the unsaturated zone beneath the bottom of the soil profile and above the groundwater table. An exponential decay weighting function, proposed by Venetis (1969), was used to account for the time delay of water drainage in vadose zone and to predict effective recharge into shallow aquifers (Sangrey et al., 1984). It is further assumed in the baseflow rate estimation that the variation in groundwater return flow to rivers is linearly related to changes in the elevation of the water table.

SWAT simulates several water storage components that make up total water storage to compare with GRACE TWS. The storages related to the calculation of model-based TWS variation in this study include:

1. Overland water storage (V_1), including river channels, bank storage and canopy storage. Due to the mass correction in GRACE data processing, the water storage variations in lakes/reservoirs were not taken into account.

2. Storages ($V_2 + V_3$) for lagged surface runoff and lateral flow. The two storages are defined in SWAT for estimating the amount of overland and lateral flow reaching river channels on a daily time step. SWAT allows for delayed release of overland flow and later flow yielded in river basins with time of concentration greater than one day.

3. Soil profile (V_4).

4. Vadose zone (V_5). Water storage in vadose zone is typically not considered as a storage in SWAT water balance analysis because the Venetis' exponential decay weighting function (1969) doesn't alter the quantity of water from soil into aquifers. However, the time delay for water to move through the vadose zone results in variationsin water storage and needs to be addressed in TWS variation calculations (Milzow et al., 2011).

HESSD
9, 2071–2120, 2012

5. Groundwater (V_6). SWAT simulates an unconfined shallow aquifer and a confined deep aquifer in each subbasin. Water storage in shallow aquifers may contribute to flow in main river channels or re-evaporated into the soil. By contrast, there is no simulated outlet for water in deep aquifers except pumpage. "Water that enters deep aquifer is assumed to contribute to streamflow somewhere outside of the watershed" and therefore "is not considered in future water budget calculations and can be considered to be lost from the system" (Neitsch et al., 2005). While this assumption may hold in the studies for small size river basins, it is no longer valid at continental scale. Under this assumption, an upward trend in water storage in deep aquifers would be observed which is unrealistic and due to the accumulation of water percolated from shallow aquifer. Because of these problems, the deep aquifer was excluded from the simulations and from the simulation and TWS calculation by setting the percolation rate to the deep aquifer to zero.

For each subbasin, the model-based TWS for each 10-day period was calculated as:

$$\mathrm{TWS}_t = V_{1,t} + V_{2,t} + V_{3,t} + V_{4,t} + V_{5,t} + V_{6,t} \tag{1}$$

where t is the index for the 10-day period. The series of SWAT subbasin-wide anomalies TWSV_t was computed by differencing the total water storage for each 10-day period TWS_t and the mean of the TWS over the entire GRACE data period:

$$\mathrm{TWSV}_t = \mathrm{TWS}_t - \overline{\mathrm{TWS}} \tag{2}$$

where $\overline{\mathrm{TWS}}$ is the mean of the TWS_t over the GRACE data period.

5 Calibration approach

Similar to the studies by Werth et al. (2009, 2010), calibration and evaluation of the SWAT-SSA model in this study was carried out using a multi-criteria framework. The

HESSD
9, 2071–2120, 2012

multi-criteria approach extends the traditional calibration approach by casting the calibration into a multi-objective optimization problem, and for independent data, allows evaluating model performance against more than one objective to improves model robustness and predictability capacities (Gupta et al., 1998). The solution to the multi-criteria optimization program consists of the non-dominated calibration parameter sets, which are optimal in a Pareto efficiency sense. The trade-off reflects the minimum parameter uncertainty (Vrugt et al., 2003) caused by errors in the input and measured data as well as by model structure.

For the calibration of the SWAT-SSA model, two objective functions were defined. Their definitions and calculations are explained in detail below. The multi-objective optimization problems defined in the multi-criteria calibration of the SWAT-SSA models were solved using the Non-dominated Sorting Genetic Algorithm II (NSGA-II, Deb et al., 2002), a population-based heuristic evolutionary optimization technique with proven track record of success in solving many large-scale optimization problems. The population sizes chosen in the optimizations varied from 150 to 300, and the optimizations last for 50 ~ 100 generations until no significant improvements in the solution were observed.

5.1 Comparison of model-based and GRACE-derived TWS variations

As GRACE provides a filtered image of reality, the modeled storage variations from SWAT are first converted to GRACE resolution to provide storage values at the same spatial scales for comparison. This mathematical process involves projecting SWAT modeled spatial fields to Spherical Harmonics (SH) up to degree 50 (in this study, SH transformation was conducted using SHTOOLS, http://www.ipgp.fr/~wieczor/SHTOOLS/SHTOOLS.html) in which the SWAT-based basin-wide TWS variations for each 10-day period were first disaggregated into a 0.5 by 0.5° grid prior to the transformation. In order to allow for a comparison between GRACE- and SWAT-based TWS variations for sub-continental regions, simulated variations in TWS by the Noah land surface model (Ek et al., 2003) in NASA's Global Land Data Assimilation System

HESSD

9, 2071–2120, 2012

(GLDAS) (Rodell et al., 2004) were used as a priori information to fill areas outside of the SSA sub-region of interest in the SH transformation.

Agreement between GRACE-derived and model-based TWS variations was evaluated using a weighted total square error (WTSE) function:

$$\mathrm{WTSE} = \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j}^{J} I_\mathrm{s} \times w_{i,j,t} \times \left(\mathrm{TWS}V_{i,j,t,\mathrm{SWAT}} - \mathrm{TWS}V_{i,j,t,\mathrm{GRACE}}\right)^2 \quad (3)$$

where $\mathrm{TWS}V_{i,j,t,\mathrm{SWAT}}$ and $\mathrm{TWS}V_{i,j,t,\mathrm{GRACE}}$ are SWAT- and GRACE-based TWS variations for 10-day period t and grid cell (i, j), respectively. I_s is an indicator function. $I_\mathrm{s} = 1$ if the grid cell is located within the study region; otherwise, $I_\mathrm{s} = 0$, w is the weight, an inverse of the estimated standard deviation of GRACE-based TWS variations $\mathrm{TWS}V_{i,j,t,\mathrm{GRACE}}$.

Finally, following the convention in hydrologic model calibration, available GRACE data were divided into two groups: the first 112 10-day periods (29 July 2002–December 2005) were used for calibration, and the remaining data were reserved for validation.

5.2 Criterion/objective function for evaluating goodness of model fit in runoff field simulation

Observed monthly river discharge data were obtained from Global Runoff Data Centre (GRDC), a primary source of information for global river discharge to support large-scale hydrological studies. For stations in SSA, river discharge data are only available up to the early 1990s. The different time frames among the GRDC river discharge data, GRACE data (2002-2009), and GPCP 1-DD precipitation data (1997–2009) pose difficulty for model calibration. In this study, we focused on evaluating performance of SWAT for modeling TWS variability: SWAT was run for 2002–2009 (with five additional years 1997–2001 as the spin-up period) and, following the approach by Werth et al. (2009, 2010), simulated and observed monthly river discharge rates were compared for two time frames on a multi-year average basis. The fit of the SWAT model at each GRDC station was measured using the Nash-Sutcliffe Efficiency (NSE) coefficient (Nash and Sutcliffe, 1970), which is defined as

$$\mathrm{NSE} = 1 - \frac{\sum_{t=1}^{T} \left(Q_{t,\mathrm{obs}} - Q_{t,\mathrm{sim}}\right)^2}{\sum_{t=1}^{T} \left(Q_{t,\mathrm{obs}} - \overline{Q}_{t,\mathrm{obs}}\right)^2} \tag{4}$$

where $T = 12$ is sample size $Q_{t,\mathrm{obs}}$ is the observed flow at time t ($\mathrm{m}^3\,\mathrm{s}^{-1}$), $Q_{t,\mathrm{sim}}$ is simulated flow at time t ($\mathrm{m}^3\,\mathrm{s}^{-1}$), and $\overline{Q}_{t,\mathrm{obs}}$ is mean observed flow ($\mathrm{m}^3\,\mathrm{s}^{-1}$). The NSE coefficient can range from $-\infty$ to 1; a value of one indicates a perfect model fit.

Discharge data from 187 stations were used for this calibration study (Fig. 2). Due to the limited spatial resolution of the SWAT-SSA model, many stations are located on tributaries which were undefined in the model; therefore, the data from these stations could not be utilized in this study. As shown in Fig. 2, the GRDC station network is relatively dense in West Africa, but limited in other regions. This highlights the benefit of applying GRACE data to support hydrologic simulations in SSA. The NSE values for all selected GRDC stations in a sub-regional model were further spatially aggregated:

$$\mathrm{WNSE} = \sum_{i} w_i \cdot \mathrm{NSE}_i \tag{5}$$

where NSE_i is the NSE coefficient at GRDC station i, and w_i is the weighting factor proportion to the length of the monthly river discharge data time series at that station. The weighted NSE (WNSE) serves as the criteria for evaluating performance of SWAT in simulating river discharge.

HESSD
9, 2071–2120, 2012

5.3 Calibration parameters

The hydrologic processes and watershed properties in SWAT are characterized by a multitude of parameters. A list of SWAT parameters selected for calibration, together with their lower and upper bounds of adjustable ranges, are shown in Table 4. This list was determined through literature review, numerical sensitivity analysis (Morris, 1991) and according to the results from several test runs of the calibration programs.

In these SWAT calibration parameters, SCS curve number is a key parameter for surface runoff estimation. It is defined to characterize the potential maximum soil moisture retention capacity. A low value indicates low runoff, but high infiltration potential. Surface runoff lag coefficient (SURLAG) determines how much total available runoff enters into reach on a given day and is a sensitivity parameter for simulating river discharge hydrographs. ESCO (soil evaporation compensation factor) is defined to specify the depth distribution used to meet soil evaporative demand. As the value of ESCO decreases, more water is allowed to be evaporated from deeper soil layers. SOL_AWC, SOL_K, and SOL_D are soil available water capacity, saturated conductivity, and the soil layer depth, respectively. All three soil attribute parameters are highly uncertain. Values of the first two parameters were derived using pedotransfer functions; no reliable information about the actual depth of soil layer in Africa is available from HWSD, only a reference value (in most cases 1 m) was assigned. GW_ELAY (groundwater delay coefficient) characterizes the delay time of the recharge into aquifer, is a single controlling parameter in determining the water storage variation in the vadose zone. The remaining four parameters in the table, GW_REVAP (groundwater revap coefficient), ALPHA_BF (baseflow alpha factor), REVAPMN (threshold depth of water in the shallow aquifer for “revap” to occur) and GWQMN (threshold depth of water in the shallow aquifer required for groundwater flow to occur) control the behavior of shallow aquifers.

The ten SWAT sub-regional models were calibrated with the parameters shown in Table 4. The model for each sub-region was calibrated independently, but within a region, the same percentage changes were made for those parameters which may

HESSD
9, 2071–2120, 2012

Title Page
Abstract | Introduction
Conclusions | References
Tables | Figures
◀| |▶
◀ ▶
Back | Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

have spatially varying values (or parameters other than SURLAG and ESCO), except for the SCS curve number (CN2), based on spatial fields of their initial estimates. The CN2 values are correlated with land cover and soil permeability. In this study, within a sub-region the CN2 parameters were grouped by land cover, and the CN2 values for major land covers/uses were considered as independent calibration parameters.

6 Results

The Pareto fronts in the two-dimensional objective space found via multi-criteria calibration for all ten SSA sub-regions are shown in Fig. 3. Paired values of weighted root mean square error (RMSE) and weighted NSE coefficients are plotted on horizontal and vertical axes, respectively (weighted RMSE is a monotonic function of weighted TSE). A model with a perfect fit to GRACE data and river discharge data would have weighted RMSE value of 0 and weighted NSE coefficient value of 1. Thus, the Pareto front curves are convex towards the point (0, 1), reflecting the tradeoffs between the ability to fully describe discharge or total water storage variations.

With regard to the performance of calibrated models in river discharges simulation, the highest values of weighted NSE coefficient obtained vary from −2.55 to 0.66 and are negative for five out of ten sub-region models (West Africa, Nile, Congo, Zambezi and Madagascar). This measure of goodness of fit statistic is also sensitive to different solutions of parameter sets in Pareto fronts. The deterioration of its value is greater than 2 in models for all sub-regions other than West Africa, Nile, and Zambezi when the parameter set in the Pareto frontier that most closely matches the simulation of GRACE TWS variations was used. The NSE model coefficients for each individual GRDC gauging station are shown in Fig. 4. When the "best-fit" solutions for river discharge simulation were taken, 20 % of stations have NSEs ≥ 0.7, 43 % ≥ 0.4, and the NSEs at 64 % of the GRDC stations used are positive. These percentages decrease from 20 to 6 %, 43 to 17 % and 64 to 30 % if the models are run with the "least-fit" solutions for river discharge simulation.

HESSD
9, 2071–2120, 2012

More satisfactory model fits were achieved in simulation of TWS variations after the calibration. The ensembles of time series of zonally averaged simulated TWS variations over ten sub-regions and associated with Pareto optimal solutions found in multi-criteria calibration are plotted in Fig. 5, together with the time series of zonally averaged GRACE –based mean TWS variations and the related one-sigma (68.7 %) confidence interval (CI). The NSE coefficients for the time series of model-based TWS variations with respect to the GRACE-based mean TWS variations were also calculated and summarized, for calibration and validation periods respectively, in Table 5. Overall, simulated and GRACE-based zonally averaged time series are in good agreement in sub-regions of West Africa, Volta, Chad, Nile, Eastern African, Zambezi and Madagascar during both calibration and validation periods. The means of the NSE coefficients for these sub-regional models range from 0.66 to 0.91. Larger discrepancies were observed in the Congo and Horn of Africa. In the simulation of temporal variations of TWS for these two sub-regions, the model still captures the general trends/phase changes of TWS variations but the mismatch in amplitude is greater. For the Southern African model, the model fit was poorer during the calibration period; however, the model performs much better during the validation period.

The NSE coefficients calculated on a gridded basis are shown in Fig. 6a and b. The "best-fit" and "least-fit" solutions were determined according to model fits with respect to the GRACE TWS variations. Figure 6c and d show the agro-climatic zonation (derived from FAO Agroecological Zones crafted by HarvestChoice, Z. Guo, personal communication, 2011), and the density of cropland (fraction of farming land area in 5 min × 5 min grid, Ramankutty et al., 2008) in SSA. Generally, the model performs well in simulating TWS variations in semiarid and sub-humid areas, which encompass most farming land in SSA. The largest discrepancies in TWS variation simulation (NSE coefficients ≤ 0) occurred in arid areas, where is water storage amplitude is lower or equivalent to GRACE error (the Sahara, Somalia, western Ethiopia, northwest Kenya, south Namibia and most of Southern Africa) and the equatorial humid area (notably in central Democratic Republic of the Congo).

HESSD
9, 2071–2120, 2012

GRACE TWS data integrate water mass variations from all storage components. Sometimes, interest is focused on estimating water mass variations in certain storage (e.g., groundwater; Rodell et al., 2009; Tiwari et al., 2009). Temporal variability of zonally aggregated water mass in six terrestrial water storages parameterized in the SWAT model are characterized by calculating ratios between variances of these storage variables $\sigma^2_{V_i\text{Total}}$ ($i = 1, \ldots 6$) and variance of model-based total storage variance $\sigma^2_{V_\text{total}}$ (in unfiltered space), or $\sigma^2_{V_i}/\sigma^2_{V_\text{Total}}$. Means and ranges of calculated normalized variances for each storage variable and each sub-region are listed in Table 6 (note that the water mass variations in six storages are not independent; thus $\sigma^2_{V_\text{Total}}$ may not equal $\sum_{i=1} \sigma^2_{V_i}$). These statistics show that the three principal water storage components that have largest temporal variability, thus, contributing most to the TWS, are soil, vadose zone and groundwater storages. By contrast, contributions from overland flow, surface runoff and later flow lags are trivial. Zonally aggregated time series of soil water, vadose zone water, and groundwater storage variations obtained from the calibrated SWAT models are shown in Fig. 7 in further detail. Systematic phase differences exist among the time series for the three storage variables: in each annual cycle when the rainy season begins the soil moisture is first replenished and reaches its peaks, followed by vadose zone, and the groundwater.

The statistics in Table 6 and the graphs in Fig. 7 also indicate that there could be even larger uncertainties in the estimation of component-wise water storages than what is seen in TWS estimation. For example, the model gives divergent estimates for water storage variations in vadose zone and groundwater in Eastern Africa when the model was run with parameters sets across the Pareto frontier. The estimated time series for water storage variations in the vadose zone and groundwater fall into two groups: one group has large variations in the vadose zone water storage but relatively smaller variation in groundwater storage; in another group, vadose zone water storage variations are almost zero and variations in groundwater storage are much larger. Figure 8 shows the Pareto fronts in parameter space with normalized parameter values in [0,

HESSD
9, 2071–2120, 2012

1] intervals (zero values represent the lower bounds of the adjustable ranges of the parameters and one corresponds to the upper bounds). The disparate estimates for vadose zone and groundwater storage variations can be explained by the dichotomy in the estimated values of GW_DELAY. As the value of GW_DELAY approaches zero, water exiting the bottom of the soil profile can enter aquifers immediately causing no variation in vadose water storage and larger variations in groundwater storage, and the situation is opposite with large values for GW_DELAY. Similar divergent estimates in vadose zone water storage and groundwater storage variations caused by different GW_DELAY estimates were also found in the Congo model. For Chad, Nile and Southern Africa, there are large uncertainties in estimating soil water storages, which is most likely related to divergent estimates of SOL_AWC_X.

7 Conclusions and discussion

The study presented in this paper concerns calibration/evaluation of a semi-distributed regional-scale hydrological simulation model, or a large-scale application of the SWAT model of Sub-Saharan African countries. The SWAT-SSA models we set up were calibrated and evaluated in a multi-criteria framework to both river discharge and GRACE TWS data, but with more focus on assessing the model's capacity in modeling the TWS variability using GRACE data. In spite of the uncertainty arising from the tradeoff in optimizing model parameters with respect to two model fitting criteria and in the estimation of storage variations contributed by different storage components, the study showed that the calibrated SWAT-SSA model performs well in simulating TWS variations in semi-arid and semi-humid areas, where agriculture in SSA is concentrated, and therefore is capable of acting as an effective modeling tool for agricultural water management in SSA.

Any modeling/model calibration and validation exercises are subject to certain limitations. A major limitation in this study originated from the use of multi-year average monthly river discharge data within a time frame different from the one in which the

HESSD
9, 2071–2120, 2012

models were actually run as a result of limited availability and accessibility of recent stream flow data in Sub-Saharan countries. Therefore, it is difficult to evaluate the model's adequacy in modeling the surface water system. The climate and land use change may alter the flow regimes of rivers (e.g., Amogu et al., 2010) and potentially bias the calibration for river discharge and the estimation of the contribution of water mass variation in river systems to the TWS variation. Furthermore, an interesting question often raised in the model calibration/evaluation study that involve the use of multiple observation data sets is what values are brought to the calibration and evaluation of the model by the use of additional data set(s). The limitation with river discharge data also makes it hard to give a definite and complete answer to this question. However, the outcome of SWAT model calibration and validation in this study tends to suggest that the use of GRACE data may only provide little additional constraints to reduce the parametric uncertainties of the model since the NSEs shown in Fig. 3 and Table 5 indicate that there might exist stronger equifinality (Beven and Binley, 1992) in the TWS simulation than in discharge simulation. On the other hand, it is apparent that GRACE data are of great value in that they provide valuable information and unprecedented opportunity to validate and evaluate the model's capacity in simulating spatio-temporal variability in TWS.

Finally, it was found that there is less agreement between model and GRACE-based TWS variations in arid and equatorial humid areas. A few possible reasons for the larger discrepancies include: Firstly, uncertainties associated with GRACE TWS variations themselves. Noticeable disagreement between model- and GRACE-based TWS variations in arid regions were also reported by Ngo-Duc et al. (2007) in a global-scale model validation study, who attributed the disagreements in arid areas to the weak GRACE signals and the resulting larger errors in GRACE TWS variations. Secondly, errors in climatic forcing data, especially in precipitation data. Due to the lack of ground-based observations in precipitation, regional or global scale hydrologic simulations typically rely on use of precipitation field estimates from different satellite-based or meteorological reanalysis data products. Uncertainty associated with these precipitation data

HESSD
9, 2071–2120, 2012

sets is often a principle source of uncertainty for hydrologic simulation (e.g., Fiedler and Döll, 2007). Thirdly, inadequacy of SWAT parameterization or algorithms in simulating hydrology in arid and humid areas might also help explain the discrepancy. Future work will be required to identify physical reasons for model misfits and for model enhancement.

Acknowledgements. This study was funded by a grant from the Bill & Melinda Gates Foundation. The findings and conclusions contained within are those of the authors and do not necessarily reflect positions or policies of the Bill & Melinda Gates Foundation. The meteorological data were obtained from the NASA Langley Research Center POWER Project funded through the NASA Earth Science Directorate Applied Science Program.

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HESSD
9, 2071–2120, 2012

Calibration and evaluation of a semi-distributed watershed model

H. Xie et al.

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HESSD

9, 2071–2120, 2012

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HESSD
9, 2071–2120, 2012

Table 1. The data sets for SWAT model setup.

Category	Source
Elevation	HydroSHEDS
Soil	Harmonized world soil database (HWSD)
Land cover	Global land cover (GLC) 2000
Lakes & reservoirs	Global lake and wetland database (GLWD)
Climate	Surface meteorology and Solar Energy (SSE) Release 6.0 – Global Precipitation Climate Project (GPCP) & Tropical Rainfall Measuring Mission (TRMM)

HESSD
9, 2071–2120, 2012

Table 2. Lakes/reservoirs to which mass correction in GRACE data processing were applied.

1. Albert	6. Kainji	11. Malawi	17. Tana	22. Volta
2. Bangweulu	7. Kariba	12. Mweru	18. Tanganyika	
3. Buyo	8. KhashmGirba	13. Nasser	19. Chad	
4. CahoraBassa	9. Kivu	15. Roseires	20. Turkana	
5. Edward	10. Kyoga	16. Rukwa	21. Victoria	

HESSD
9, 2071–2120, 2012

Table 3. The sub-regions in SWAT-SSA model setup and calibration.

Name	Area ($\times 10^3 km^2$)	Name	Area ($\times 10^3 km^2$)
West Africa	3550	Congo	4474
Volta	534	Eastern Africa	808
Chad	2576	Southern Africa	2928
Nile	2841	Zambezi	1365
Horn of Africa	1477	Madagascar	309
Total: 20 862			

HESSD
9, 2071–2120, 2012

Table 4. SWAT hydrologic calibration parameters.

Parameter	Level	Possible range
CN2: SCS curve number	HRU/subbasin	35 ~ 90
ESCO: Soil evaporation compensation factor	Basin	0 ~ 1
GW_DELAY: Groundwater delay coefficient [days]	HRU/subbasin	0 ~ 100
GW_REVAP: Groundwater revap coefficient	HRU/subbasin	0.02 ~ 0.2
ALPHA_BF: Baseflow alpha factor [days]	HRU/subbasin	0 ~ 1
REVAPMN: Threshold depth of water in the shallow aquifer for "revap" to occur [mm]	HRU/subbasin	0 ~ 500
GWQMN: Threshold depth of water in the shallow aquifer required for groundwater flow to occur [mm H_2O]	HRU/subbasin	0 ~ 1000
SURLAG: Surface runoff lag coefficient	Subbasin	1 ~ 10
SOL_AWC_X*: Calibration factor for soil water available capacity	Soil layer/subbasin	0.5 ~ 2
SOL_D_X*: Calibration factor for depth from soil surface to bottom of layer	Soil layer/sbubasin	1 ~ 2
SOL_K_X*: Calibration factor for saturated hydraulic conductivity	Soil layer/sbubasin	0.5 ~ 1.5

* These factors are defined for model calibration purpose only. The actual values of these parameter used in simulation are equal to their default values multiplied by the calibration factors.

HESSD
9, 2071–2120, 2012

Table 5. The Nash-Sutcliffe efficiency coefficients for calibrated SWAT models in TWS variation simulation.

	Calibration			Validation		
	Mean	Max.	Min.	Mean	Max.	Min.
West Africa	0.91	0.92	0.89	0.91	0.92	0.90
Volta	0.86	0.90	0.75	0.91	0.94	0.82
Chad	0.81	0.83	0.79	0.66	0.73	0.55
Nile	0.856	0.865	0.84	0.75	0.78	0.72
Horn of Africa	0.41	0.45	0.40	0.31	0.34	0.25
Congo	0.34	0.19	−0.44	0.12	0.30	−0.80
Eastern Africa	0.85	0.91	0.71	0.80	0.87	0.67
Zambezi	0.91	0.92	0.90	0.91	0.93	0.89
South Africa	0.46	0.54	0.40	0.80	0.83	0.75
Madagascar	0.81	0.85	0.76	0.82	0.84	0.79

HESSD

9, 2071–2120, 2012

Table 6. Temporal variability of zonally averaged component-wise water storage variations (%).

	West Africa	Volta	Chad	Nile	Horn of Africa	Congo	Eastern Africa	Zambezi	South Africa	Madagascar
					Soil					
Avg	55.2	11.5	31.5	37.9	44.8	10.0	28.8	18.9	20.8	9.1
Max	61.1	16.2	58.5	48.9	48.8	31.0	38.9	21.4	38.5	13.8
Min	50.3	8.5	20.8	31.4	37.0	5.3	17.1	17.4	8.6	6.8
					Vadose					
Avg	5.2	46.7	26.9	4.5	9.8	37.1	19.4	16.8	13.9	42.6
Max	9.5	55.0	34.2	11.6	13.1	51.5	31.0	19.8	40.8	59.2
Min	2.7	8.1	3.0	0	6.0	0.24	0	12.5	3.1	21.6
					Groundwater					
Avg	1.6	15.3	6.2	13.0	11.3	8.4	5.1	8.4	25.3	2.9
Max	3.6	56.4	24.8	24.5	16.2	59.1	25.5	16.2	41.5	8.6
Min	0.42	5.3	2.0	6.7	8.1	0.01	2.7	6.6	11.5	0.08
					Overland water					
Avg	0.03	0.04	0.01	0.4	0.007	0.10	0.004	0.01	0.03	0.0004
Max	0.05	0.10	0.02	0.58	0.009	0.30	0.01	0.02	0.06	0.001
Min	0.02	0.01	0.01	0.25	0.006	0.01	0.002	0.005	0.01	0.0002
					Surface water lag					
Avg	0.003	0.20	0.07	0.03	0.01	0.06	0.01	0.22	0.31	0.02
Max	0.005	1.23	0.52	0.14	0.01	0.32	0.02	0.59	0.83	0.03
Min	0.002	0.001	0.003	0.005	0.01	0.03	0.002	0.04	0.02	0.01
					Lateral flow lag					
Avg	0.0007	0.0001	0.0001	0.004	0.001	0.01	0.005	0.00042	0.0009	0.011
Max	0.0010	0.0002	0.0001	0.04	0.00	0.02	0.03	0.001	0.0015	0.03
Min	0.0004	0.0001	0.00004	0.001	0.001	0.001	0.001	0.00036	0.0005	0.006

HESSD
9, 2071–2120, 2012

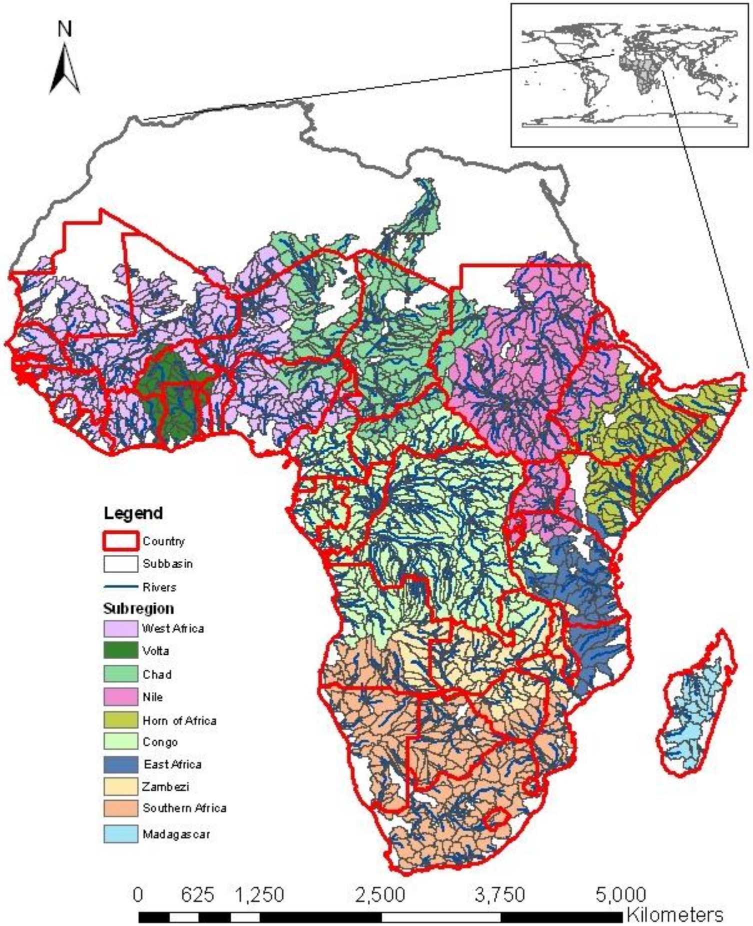


Fig. 1. Study area boundary, sub-region division, and watershed delineation in SWAT-SSA model setup.

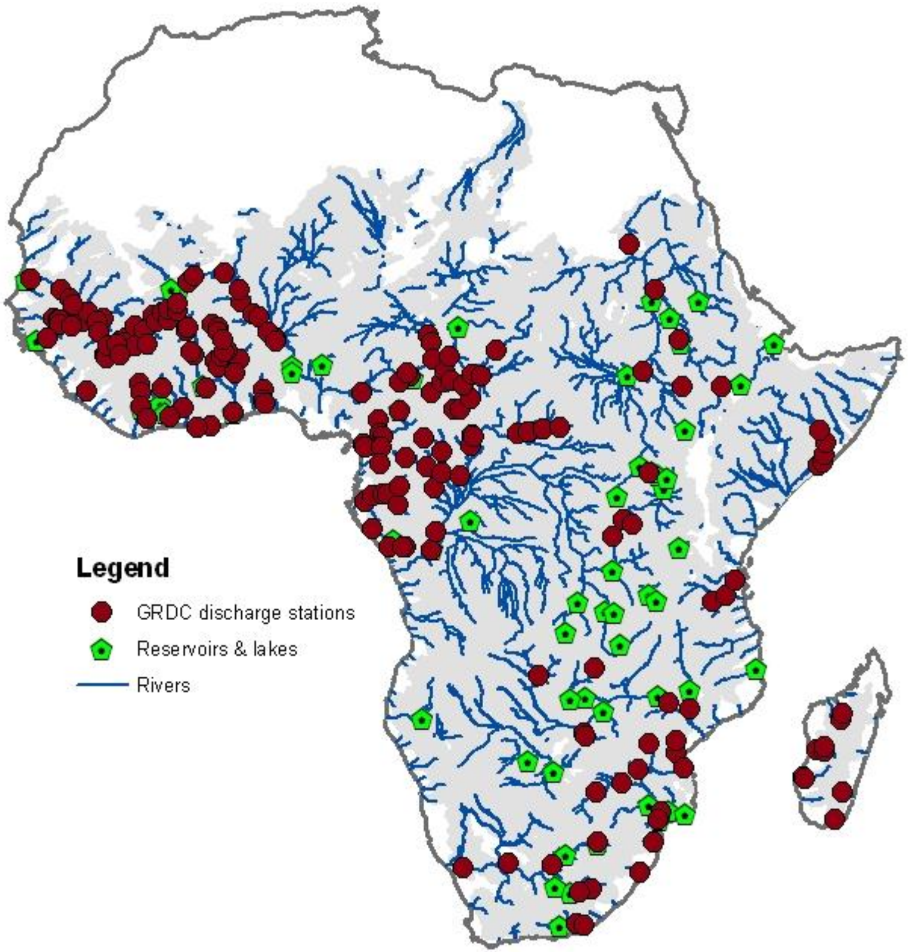


Fig. 2. Global Runoff Data Centre (GRDC) stations and reservoirs/lakes included in the SWAT-SSA model setup and calibration.

HESSD
9, 2071–2120, 2012

Calibration and evaluation of a semi-distributed watershed model

H. Xie et al.

Title Page
Abstract | Introduction
Conclusions | References
Tables | Figures
◀| |▶
◀ ▶
Back | Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

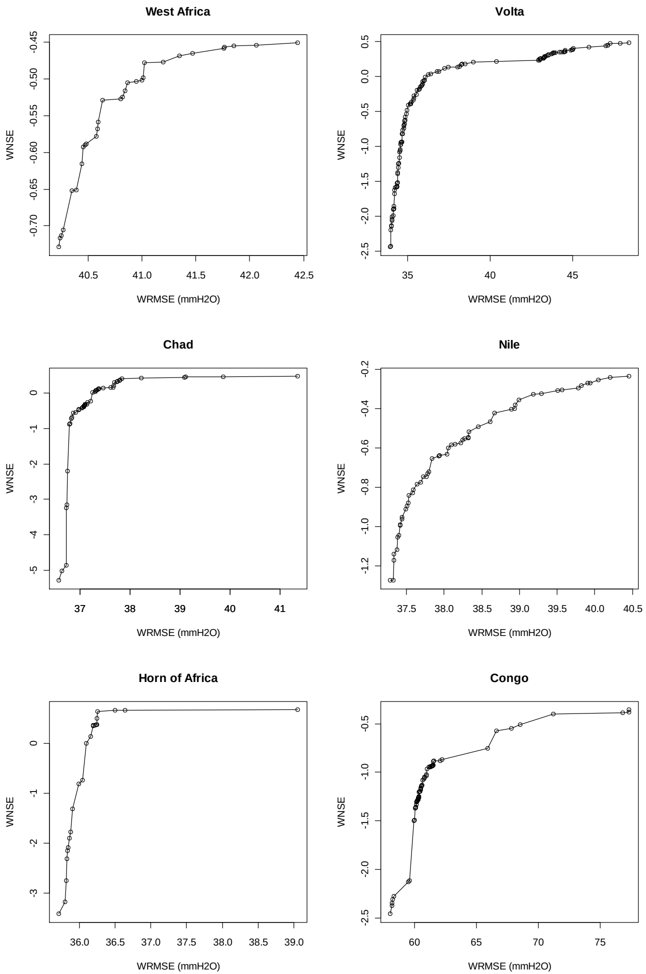


Fig. 3. See caption on next page.

HESSD

9, 2071–2120, 2012

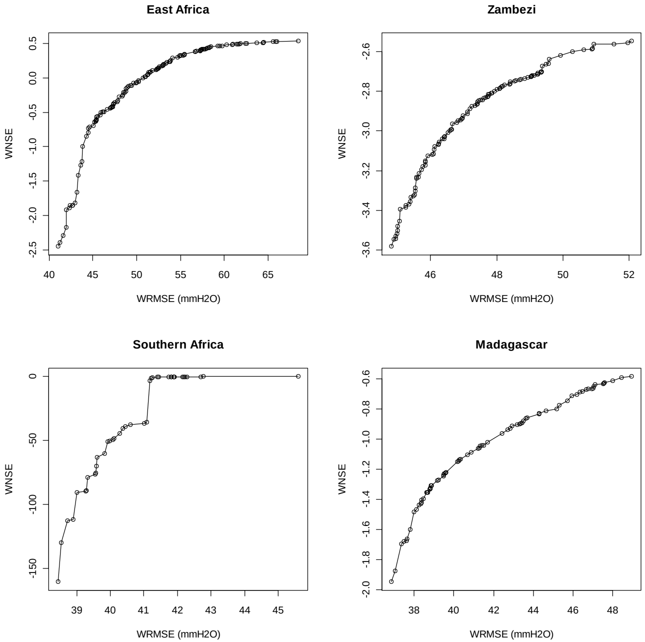


Fig. 3. The Pareto front in objective space.

HESSD
9, 2071–2120, 2012

Calibration and evaluation of a semi-distributed watershed model

H. Xie et al.

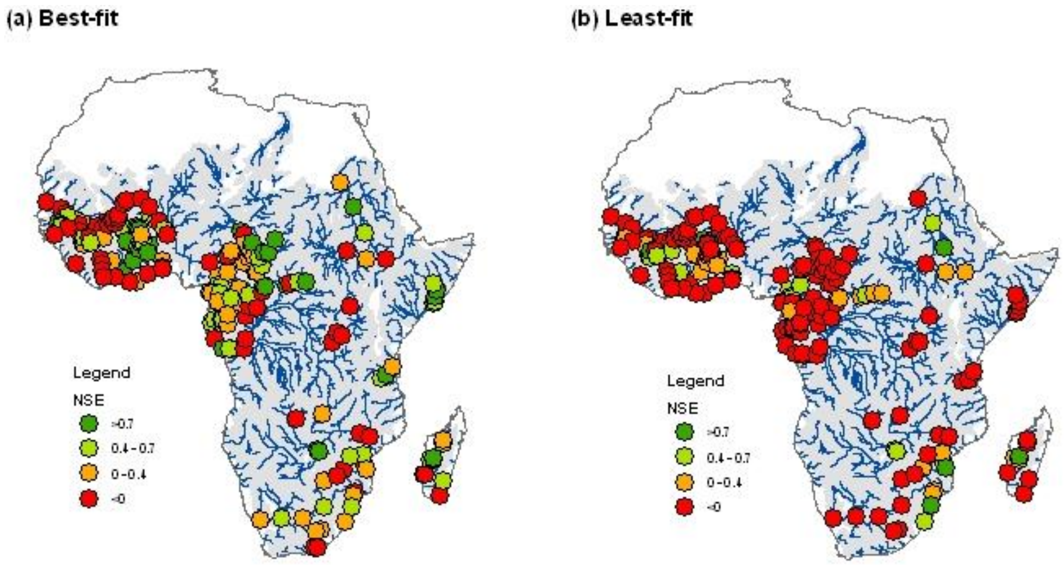
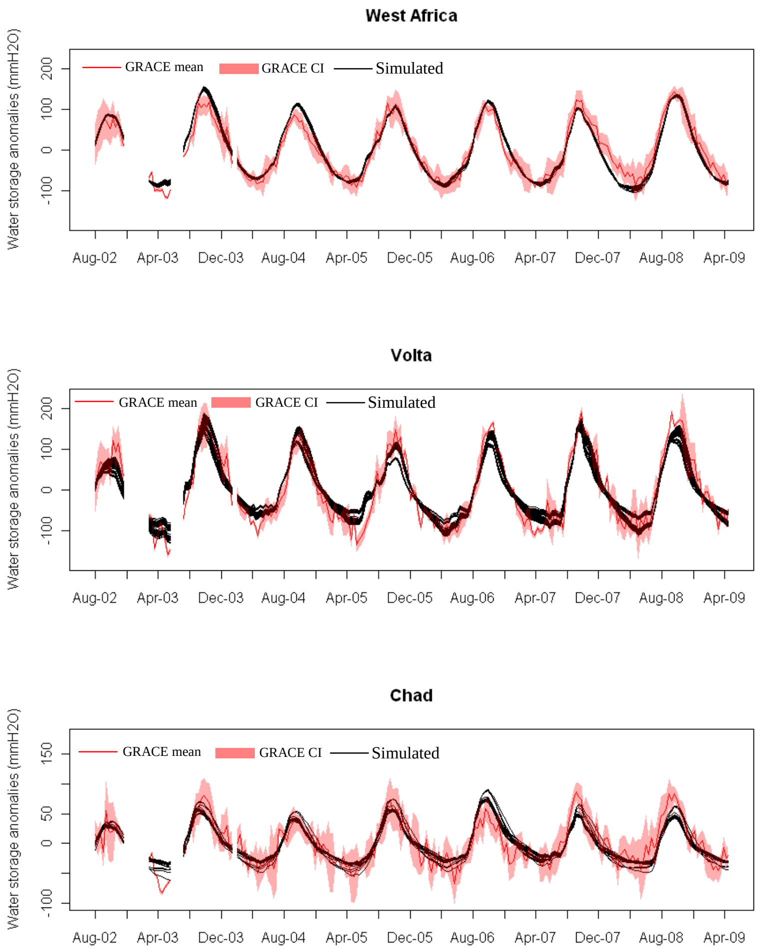


Fig. 4. The model fit in river discharge simulation.

HESSD
9, 2071–2120, 2012

Calibration and evaluation of a semi-distributed watershed model

H. Xie et al.



(a)

Fig. 5. See caption on p. 2111.

HESSD
9, 2071–2120, 2012

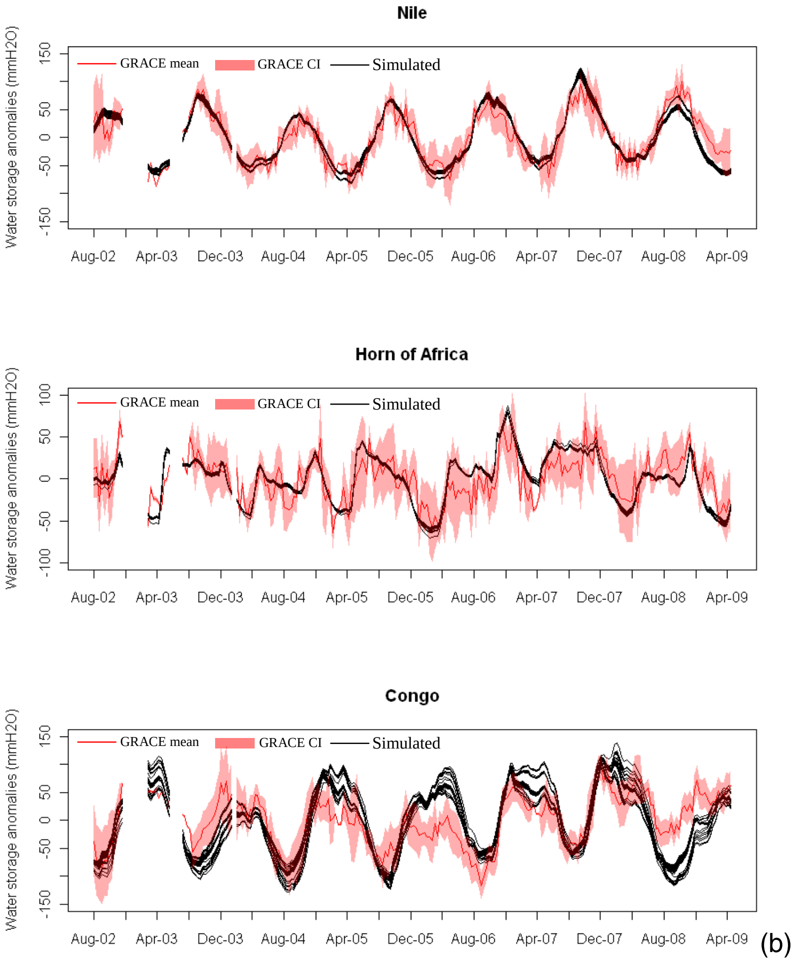


Fig. 5. See caption on p. 2111.

HESSD

9, 2071–2120, 2012

Calibration and evaluation of a semi-distributed watershed model

H. Xie et al.

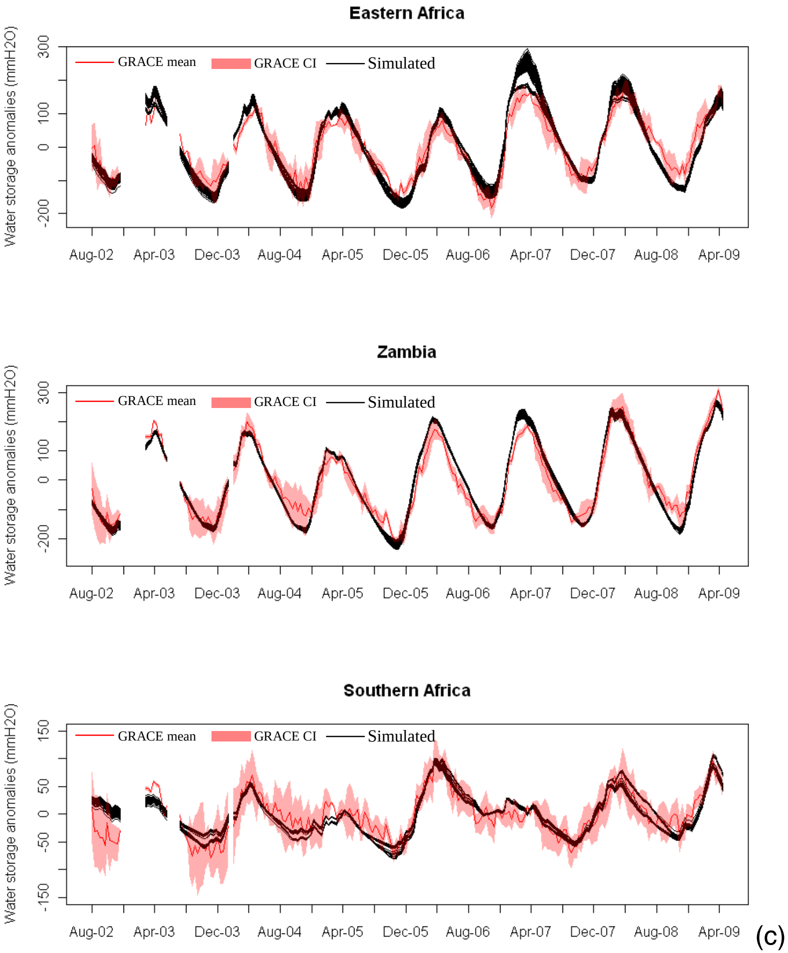
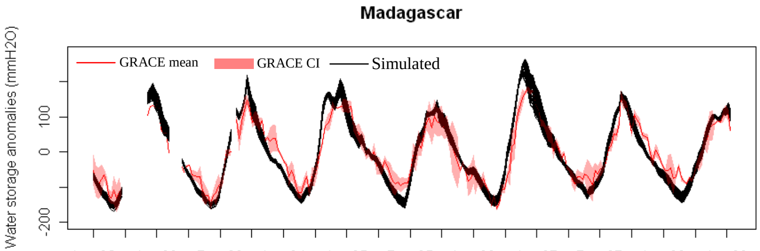


Fig. 5. See caption on p. 2111.

HESSD
9, 2071–2120, 2012



(d)

Fig. 5. The observed and the zonally averaged simulated TWS variations over ten sub-continental regions.

HESSD

9, 2071–2120, 2012

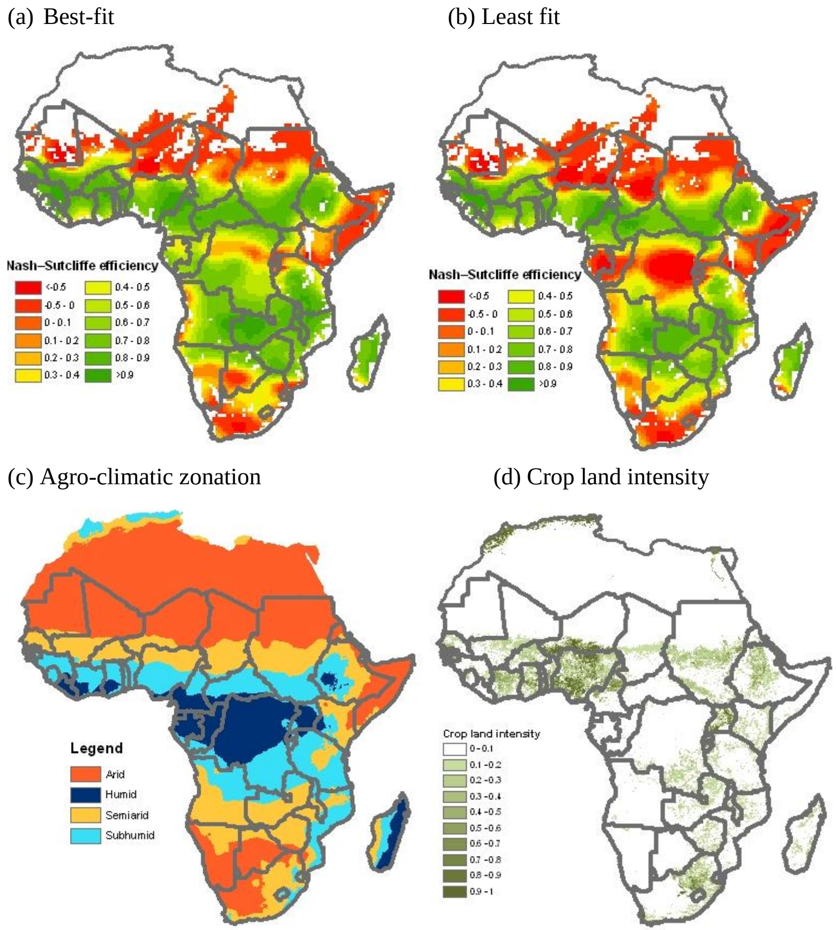


Fig. 6. Spatial comparison of SWAT model fits in simulations of total water storage variations in Sub-Saharan Africa (country boundaries are shown).

HESSD
9, 2071–2120, 2012

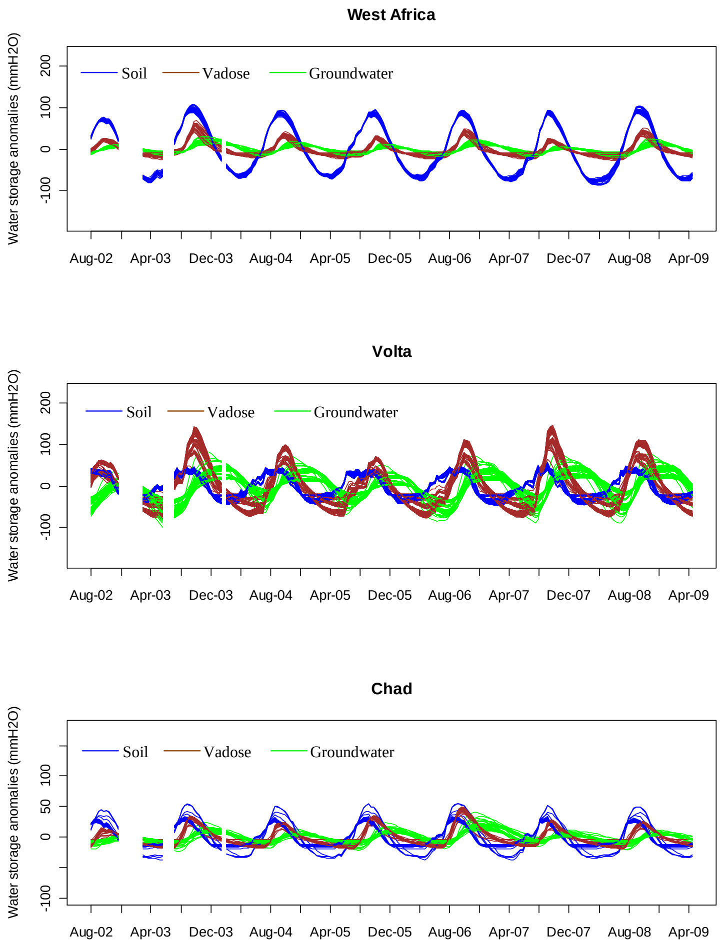


Fig. 7. See caption on p. 2116.

HESSD
9, 2071–2120, 2012

Calibration and evaluation of a semi-distributed watershed model

H. Xie et al.

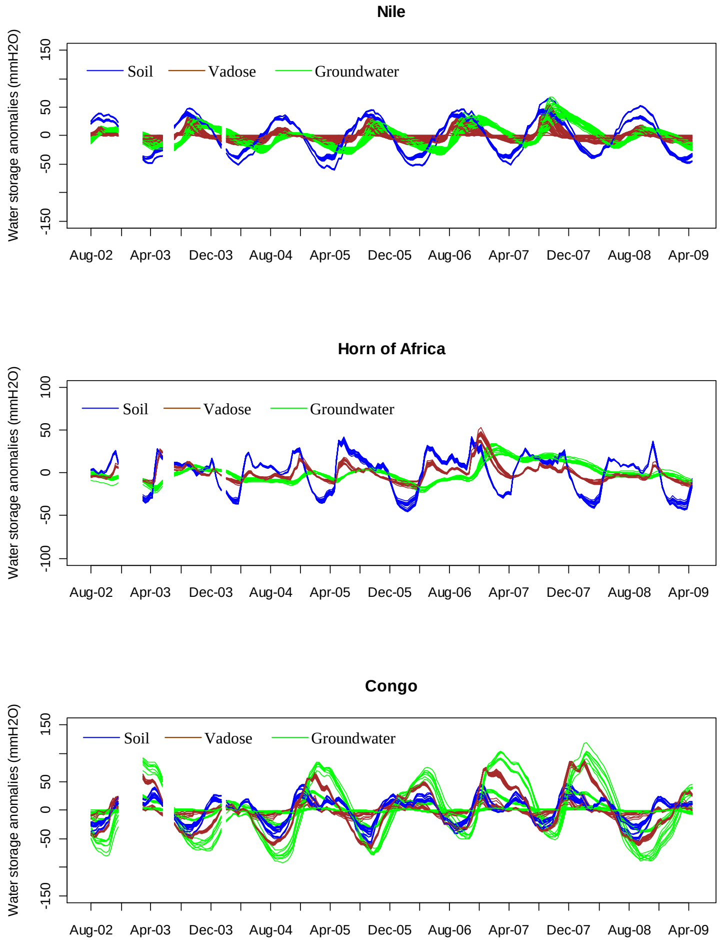


Fig. 7. See caption on p. 2116.

HESSD
9, 2071–2120, 2012

Calibration and evaluation of a semi-distributed watershed model

H. Xie et al.

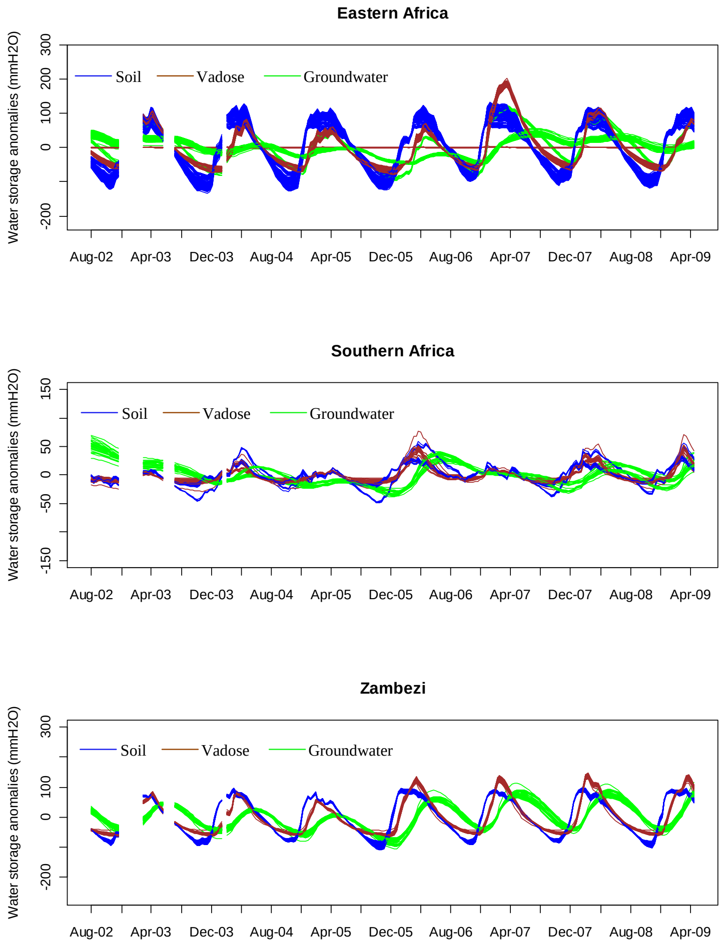


Fig. 7. See caption on p. 2116.

HESSD
9, 2071–2120, 2012

Calibration and evaluation of a semi-distributed watershed model

H. Xie et al.

Title Page
Abstract
Introduction
Conclusions
References
Tables
Figures
◀▌ ▌▶
◀ ▶
Back
Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

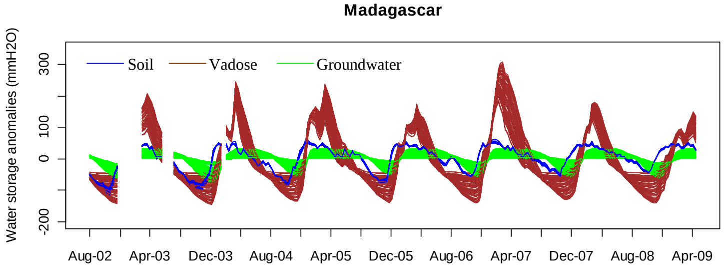


Fig. 7. The zonally averaged water variations in soil, vadose zone and groundwater storages.

HESSD
9, 2071–2120, 2012

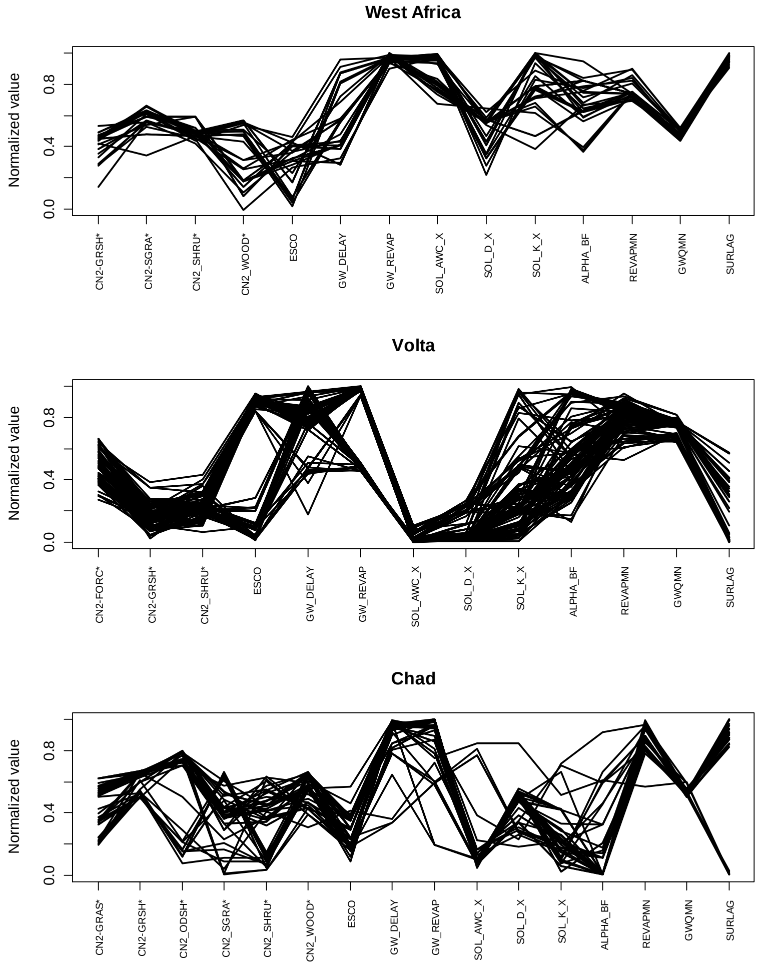


Fig. 8. See caption on p. 2120.

HESSD
9, 2071–2120, 2012

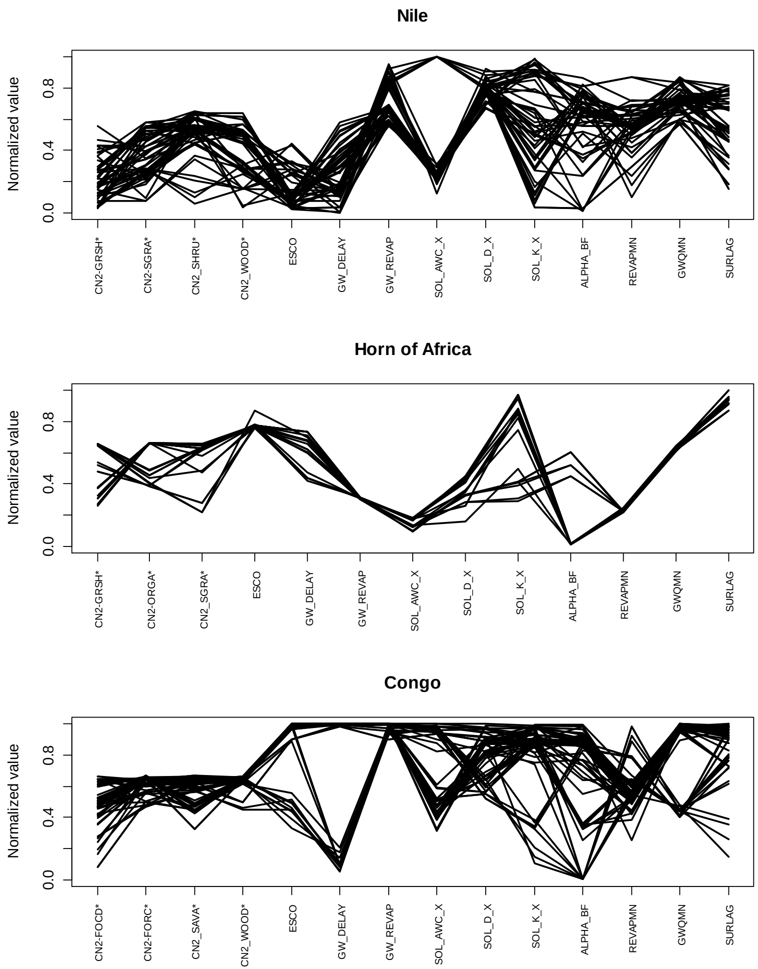


Fig. 8. See caption on p. 2120.

HESSD
9, 2071–2120, 2012

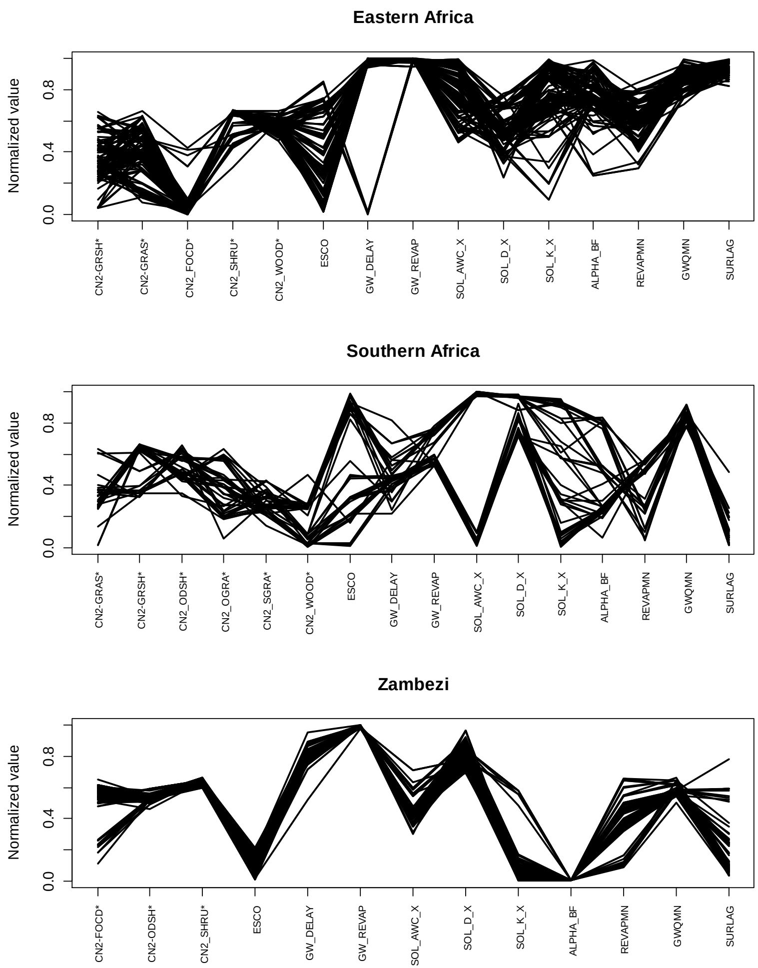


Fig. 8. See caption on p. 2120.

HESSD

9, 2071–2120, 2012

Calibration and evaluation of a semi-distributed watershed model

H. Xie et al.

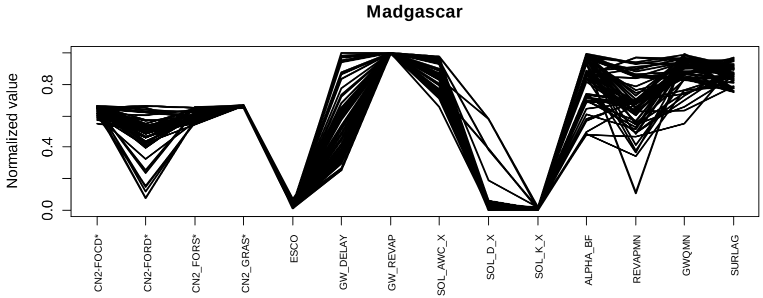


Fig. 8. The estimates of SWAT calibration parameters obtained from mutli-criteria calibration (abbreviations of the land cover type: FOCD – Closed deciduous forest; FORC – Closed evergreen lowland forest; FORD – Degraded evergreen lowland forest; FORS – Submontane forest; GRAS – Closed grassland; GRSH – Open grassland with sparse shrubs; ODSH – Open deciduous shrubland; OGRA – Open grassland; SAVA – Mosaic Forest/Savanna; SGRA – Sparse grassland; SHRU – Deciduous shrubland with sparse trees; WOOD – Deciduous woodland).

HESSD
9, 2071–2120, 2012

Calibration and evaluation of a semi-distributed watershed model

H. Xie et al.