Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-170
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 23 April 2018

Hydrology and Earth System Sciences
Discussions

Multi-site calibration and validation of SWAT with satellite-based evapotranspiration in a data sparse catchment in southwestern Nigeria

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Abstract. The main objective of this study was to calibrate and validate the eco-hydrological model Soil and Water Assessment Tool (SWAT) with satellite based actual evapotranspiration (AET) data (Global Land Evaporation Amsterdam Model (GLEAM_v3.0a) and Moderate Resolution Imaging Spectroradiometer Global Evaporation (MOD16) for the Ogun River Basin (20 292 km^2) located in southwestern Nigeria. The novelty of the study is the use of freely available satellite derived AET data for calibration/validation of each of the SWAT delineated subbasins, thereby obtaining a better performing model at the local scale as well as at the whole watershed level. The Sequential Uncertainty Fitting technique (SUFI-2) in the SWAT-Calibration and Uncertainty Program was used for the sensitivity analysis, model calibration, validation, and uncertainty analysis. Three different structures of the SWAT model were used in which each model structure was a set-up of SWAT with a different potential evapotranspiration (PET) equation. The two global AET products (GLEAM_v3.0a and MOD16) were subsequently used to calibrate the SWAT simulated AET outputs from each model structure resulting in six calibration/validation procedures at a monthly time scale. The model performance for the three SWAT model structures was evaluated for each of the 53 subbasins through the six calibrations/validations, which enabled the best model structure with the highest performing AET product to be chosen. A verification of the simulated AET variable was carried out by: (i) comparing the simulated AET of the calibrated model to GLEAM_v3.0b AET, this is a product that has a different forcing data to version of GLEAM used for the calibration, and (ii) assessing the long-term average annual and average monthly water balances at the outlet of the watershed. Overall, the SWAT model structure composed of Hargreaves PET equation and calibrated using the GLEAM_v3.0a data performed well for the simulation of AET and provided a good level of confidence for using the SWAT model as a decision support tool. The 95% uncertainty of the SWAT simulated variable bracketed most

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of the satellite based AET data in each subbasin. The SWAT model also proved efficient in capturing the seasonal variability of the water balance components at the outlet of the watershed. This study demonstrated the potential to use remotely sensed evapotranspiration data for hydrological model calibration and validation in a sparsely gauged large river basin with reasonable accuracy.

1. Introduction

Hydrological modelling in data sparse catchments has always been a challenging task due to lack of ground observations, and insufficient or poor quality data. Data scarcity is the main limitation in tropical regions for setting up hydrological models for watershed simulations, which could be used as significant decision support tools for sustainable water resources management. Water resources globally are becoming increasingly vulnerable as a result of escalating water demand arising from population growth, expanding industrialisation, increased food production and pollution due to various anthropogenic activities, climate and land use change impacts (Carroll et al., 2013; McDonald et al., 2014; Goonetilleke et al., 2016). The situation is more evident and critical in many developing countries where no water resources monitoring plans or water management strategies are in place for the future. Like many developing countries, Nigeria cannot satisfy its domestic water needs as only 47% of the total population have access to water from improved sources (Ishaku et al., 2012).

The Ogun River is the main source of public water supply for the people living in the States of Lagos and Ogun in southwestern Nigeria. The prevalent situation of insufficient hydrological data associated with lack of up to date streamflow data (Sobowale and Oyedepo, 2013) and the poor level of data quality in this watershed can be attributed to a gradual decline in hydrological stations number and their management. Water management planners are facing considerable uncertainties in terms of future availability and quality of the water resource. Therefore, a clear understanding of the on-going challenges and innovative management approaches are needed. One of the many ways to tackle this task is by using hydrological models as tools coupled with the use of increasingly available global and regional datasets to run the models.

Numerous mechanistic, continuous, physically based distributed (PBD) models are available to simulate water quality variables for example, among others: the Soil and Water Assessment Tool (SWAT; Arnold et al., 1998), which is able to represent detailed agricultural management practices and simulate water quality and quality variables; the Hydrologic Simulation Program Fortran (HSPF, Bicknell et al., 1997) that is used in predicting hydrology with in-stream nutrient transport processes; and SHETRAN (Ewen et al., 2000) which has capabilities for modelling subsurface flow and transport. . These PBD models attempt to explain hydrological phenomena through their underlying physical mechanisms, and explicitly represent (through mathematical equations) the biological, chemical and physical processes of a basin.

At the African continental level, Schuol et al. (2008) have successfully applied the hydrological model SWAT to quantify the freshwater availability for the whole of Africa at a detailed subbasin level and on a monthly time scale. Using the SUFI-2 (Sequential Uncertainty Fitting Algorithm) program with three different objective functions, the model was calibrated and validated at 207 discharge stations. They reported the models' inability to simulate runoff adequately in some areas in the

East and South Africa, but also reported that the model results were quite satisfactory for such a large-scale application although containing large prediction uncertainties in some areas. Many of the limitations reported within this continental modelling study in Africa were data related. Abaho et al. (2009) applied an uncalibrated SWAT model to evaluate the impacts of climate change on river flows and groundwater recharge in Sezibwa catchment, Uganda. They observed a 40% increase in groundwater recharge for the period of 2070-2100 and a 47% increase in average river flow. However, there are high levels of uncertainty associated with the model predictions since the model was not calibrated due to insufficient data.

In West Africa, the SWAT model has been widely applied to different river basins with satisfactory results. For example, Schuol and Abbaspour (2006) applied SWAT to model a 4×10^6 km^2 area; mainly the basins of the Niger, Volta and Senegal, addressing calibration and uncertainty issues. Measured river discharges at 64 stations to which many of these stations available data doesn't cover the whole simulation period were used for annual and monthly calibration using SUFI-2 algorithm. Although the results obtained are preliminary with basis for discussion of further improvement, Schuol and Abbaspour (2006) reported that the annual and monthly simulations with the calibrated SWAT model for West Africa showed promising results for the freshwater quantification despite the modelling shortcomings of lack of dams management operation long-term dataset. They also pointed out the importance of evaluating the conceptual model uncertainty as well as the parameter uncertainty. Laurent and Ruelland (2010) successfully calibrated SWAT for the Bani catchment (1×10^6 km²) in Mali, a major tributary of the upper Niger River. The calibration and validation results were satisfactory at the catchment outlet and also in various gauging stations located in tributaries. They showed the model performance by reporting discharge and biomass calibration results, but did not assess the model prediction uncertainty.

In northwestern Nigeria, Xie et al. (2010) evaluated the SWAT model performance in a large watershed (30 300 km^2). Due to the short data period available, all the data obtained were used for calibration. In their study, the model parameters were first optimized with a genetic algorithm, and the uncertainty in the calibration was further analysed using the generalized likelihood uncertainty estimation (GLUE) method; the study presented a reasonably good calibrated model performance without validation. Adeogun et al. (2014) successfully calibrated and validated the SWAT model for the prediction of streamflow at the upstream watershed of Jebba reservoir (area 12 992 km^2) located in north central Nigeria. The model results showed a good Nash-Sutcliffe efficiency (NSE) and Coefficient of determination (R^2) value for monthly average streamflow as well as for water balance components, but the model prediction uncertainty was not quantified.

The findings from these past studies call for continued improvement in the SWAT model performances in Africa, especially in data sparse regions. One solution is to use freely available global datasets to improve the model performance.

Recently, Ha et al. (2017) used remotely sensed precipitation, actual evapotranspiration (AET) and leaf area index (LAI) from open access data sources to calibrate the SWAT model for the Day Basin, a tributary of the Red River in Vietnam. The calibration was performed in SWAT-CUP using the Sequential Uncertainty Fitting algorithm (SUFI-2). In this study simulated monthly AET correlations with remote sensing estimates showed an R^2 of 0.71. Remote sensing technologies offer large scale spatially distributed observations and have opened up new opportunities for calibrating hydrologic models. This advancement enables several global evapotranspiration products to be used. Extensive reviews of earth observation based methods for deriving AET have been carried out by several research groups (Anderson et al., 2012; Bateni et al., 2013; Li et al., 2013; Savoca et al., 2013; Senay et al., 2013; Nouri et al., 2015; Wang-Erlandsson et al., 2016).

Two global-scale AET products derived from satellite observation have become available. The Global Land Evaporation Amsterdam Model (GLEAM, http://www.gleam.eu) is an evapotranspiration product developed by the VU University of Amsterdam (Miralles et al., 2011a, 2011b) and contains a set of algorithms that separately estimate the different components of terrestrial evaporation (i.e. transpiration, interception loss, bare soil, evaporation, snow sublimation and open water evaporation), as well as variables such as the evaporative stress, potential evaporation, root-zone soil moisture and surface soil moisture based on daily satellite observations of meteorological drivers of terrestrial evaporation, vegetation characteristics and soil moisture (Miralles et al., 2011a; Martens et al., 2017). Recently, the GLEAM_v3.0 AET has been validated against measurements from 64 eddy-covariance towers and 2338 soil moisture sensors across a broad range of ecosystems with varying level of success (Martens et al., 2017). In this study GLEAM_v3.0a and v3.0b were used and the datasets differ only in their forcing variables and spatial-temporal coverage. GLEAM_v3.0a is a dataset spanning the 35-year period 1980-2014 and is based on reanalysis net radiation and air temperature, a combination of gauged-based, reanalysis and satellite-based precipitation and satellite-based vegetation optical depth. GLEAM_v3.0b is a dataset spanning the 13-year period 2003-2015 and is driven by satellite data only (Miralles et al., 2011a; Martens et al., 2017)..

The MOD16 global evapotranspiration data is based on a 1 km^2 grid of land surface AET that was developed with an energy balance model using satellite data as input (Mu et al., 2011). The MOD16 product estimates actual evapotranspiration using Moderate Resolution Imaging Spectroradiometer, landcover, albedo, LAI, an Enhanced Vegetation Index (EVI), and a daily meteorological reanalysis data set from NASA's Global Modelling and Assimilation office. The non-satellite input data are NASA's MERRA GMAO (GEOS-5) daily meteorological reanalysis data from 2000 to 2010. MOD 16 has been validated using measurement from eddy covariance station in different tropical sites (Ruhoff et al., 2013; Ramoelo et al., 2014). Ruhoff et al. (2013) validated MOD16 AET using ground-based measurements of energy fluxes obtained from eddy covariance sites installed in tropical sites in the Rio Grande basin Brazil. Likewise, Ramoelo et al. (2014) validated MOD16 using data from two eddy covariance flux towers installed in a savannah and woodland ecosystem within the Kruger National Park, South Africa.

The objective of our study was to obtain a high performing eco-hydrological model for the Ogun River basin in southwestern Nigeria that can be used as a decision-support tool. To this effect, the specific objectives were to calibrate/validate the Soil and Water Assessment Tool model with remotely sensed actual evapotranspiration products; namely the Global Land Evaporation Amsterdam Model (GLEAM_v3.0a) and the Moderate Resolution Imaging Spectroradiometer Global Evaporation (MOD16), and also to verify the results of the model AET simulations and the water balance components.

The novelty of this study include: (i) the use of satellite based actual evapotranspiration data for calibration/validation of the SWAT hydrological model in each of the SWAT delineated subbasins and (ii) the calibration/validation of SWAT simulated AET from the three SWAT model structures using the satellite derived AET data sets.

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2. Materials and methods

2.1 Description of the study site

The study area is a sub-watershed (20 292 km^2) of the Ogun River basin (23 700 km^2) located in southwestern Nigeria (Fig. 1), bordered geographically by latitudes 7^o 7' N and 8^o 59' N and longitudes 2^o 4' E and 4^o 9' E. About 2 % of the catchment area is located in the Benin Republic. The study area encompasses the Sepeteri, Iseyin, Olokemeji, Oyan and Abeokuta catchments and cut across the Oyo and Ogun state administrative boundaries. The Ogun River, which literarily means the River of Medicine, springs from Igaran Hills in Oyo state, near Saki, at an elevation of about 624 m above the mean sea level. The elevation ranges from 624 m to 23 m. The mean annual rainfall for the watershed is 1224 mm year-^{1} and the mean annual temperature is about 27^{o}C. Mean annual potential evapotranspiration (PET) estimated by Hargreaves method (Hargreaves and Samani, 1985) is 1720 mm year-^{1} and the mean AET is about 692 mm year^{-1}. Two seasons are distinguishable in the watershed, a dry season from November to March and a wet season between April and October. The watershed area is characterized by strong climatic variation and an irregular rainfall (Eruola et al. 2012). The geology of the study area can be described as a rock sequence that starts with Precambrian Basement; which consists of quartzites and biotite schist, hornblende-biotite, granite and gneisses (Bhattacharya and Bolaji, 2010). The major soils of the basin are sandy clayey loam, sandy loam, clayey loam and silt loam. The landuse in the watershed is primarily forest (75 %), cropland (24 %), and urban (1 %). The basin, in which two large dams (Oyan and Ikere Geroge dams) are located, is of great importance for the economic advancement both at the federal and state level. The dams are the main principal provider of water to Lagos and Ogun States Water Corporation for municipal drinking water production. The Oyan reservoir is located at the confluence of Oyan and Ofiki rivers at an elevation of 43.3 m above mean sea level and was built in 1984, it has a surface area of 4 ×10^3 ha, and a catchment area of 9 × 10^3 km^2, with a dead storage capacity of 16 × 10^6 m^3, a gross storage capacity of 270 × 10^6 m^3, an embankment crest length of 1044 m, a height of 30.4 m, four spillway gates (each 15 m wide and 7 m high) and three outlet valves (each 1.8 m diameter). The Ikere Gorge is an uncontrolled dam, which started operation in 1991. The dam crosses Ogun River in Iseyin local government area of Oyo state. Ikere Gorge has a capacity of 690 × 10^6 m^3. The reservoir is adjacent to the Old Oyo National Park, providing recreational facilities for tourists, and the river flows through the park (Oyegoke and Sojobi, 2012). Twenty-five local government areas fall within the study area. In densely populated areas, the Ogun River is used for bathing, washing and drinking.

(Fig.1)

2.2 SWAT model description

The Soil and Water Assessment Tool (Arnold et al., 1998) is an open source eco-hydrological model developed for the USDA Agricultural Research Services. SWAT is a semi-distributed, process based, continuous model that uses weather, soil, topography and landuse for hydrologic modelling of a basin and runs at a daily time step. It was developed to predict the impact of agricultural land management practices on discharge, sediments, nutrients, bacteria, pesticides and biomass in large complex watersheds with varying soils, land use and management conditions over long periods of time. For modelling purpose in SWAT, the watershed is divided into subwatersheds which are then further subdivided into hydrologic response units (HRUs) that consist of homogeneous landuse, soil types and slope (Arnold et al., 1998). The soil water balance (WB) is conducted for each HRU and the equation comprises six variables and is estimated in SWAT using the following Eq. (1)

$$SW_t = SW_0 + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right) \quad (1)$$

Where SW_t is the final soil water content (mm of water), SW_o is the initial soil water content on day i (mm of water), t is the time (days), R_{day} is the amount of precipitation on day i (mm of water), Q_{surf} is the amount of surface runoff on day i (mm of water), E_a is the amount of evapotranspiration on day i (mm of water), W_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm of water), and Q_{gw} is the amount of return flow on day i (mm of water)

2.2.1 Evaporation estimation in SWAT

Evapotranspiration is a key process of the water balance and one of the more difficult components to determine. Although different empirical methods for the estimation of PET are widely adopted, AET is difficult to quantify and it usually requires the reduction of PET through a factor that describes the level of stress experienced by plants. This relationship has been described in detail by several researches (e.g. Morton, 1986; Hobbins et al., 1999; Wang et al., 2006). Numerous methods have been developed to estimate PET (Lu et al., 2005) and SWAT offers three PET estimation options from which the user can choose one depending on e.g the data availability: the Penman-Monteith method (Monteith, 1965; Allen, 1986), the Priestley-Taylor method (Priestley and Taylor, 1972), and the Hargreaves method (Hargreaves and Samani, 1985). Any one of these three PET equations can be chosen to run in SWAT, but they vary in the amount of required input data. Hargreaves method (HG) is temperature-based and requires only average daily air temperature as input. The Penman-Monteith method (P-M) requires air temperature, solar radiation, relative humidity and wind speed as input. The Priestley-Taylor (P-T) equation is a radiation-based method and it provides PET estimates for low advective conditions. The P-T method requires solar radiation, air temperature and relative humidity as input. Once the total PET is determined, AET must be estimated in SWAT, whereby first, SWAT evaporates any rainfall intercepted by the plant canopy. Second, it calculates the maximum amount of transpiration and sublimation/soil evaporation. Finally, the actual amount of sublimation and evaporation from the soil surface is calculated. If snow is presented in the HRU, sublimation can occur. When there is no snow (such as this case study), only evaporation from the soil surface is calculated. A complete description of the SWAT model and the model equations can be found in Neitsch et al. (2002, 2005) and in Arnold et al. (1998).

(Table 1)

2.3 Model set-up

The ArcView GIS interface for SWAT2012 (Winchell et al., 2013) was used to configure and parameterize the SWAT model. SWAT model inputs included a 30 m spatial resolution digital elevation model (DEM), 17 soil classes, 17 landuse classes, 3 slope categories, meteorological data and landuse with its management (Table 1). After the SWAT model set-up, the watershed was delineated into 53 subbasins, with the main outlet in Abeokuta. Daily precipitation data (1984-2012) and minimum and maximum temperature data (1984-2012) at four weather stations (Fig. 1) were used as observed input data. The missing values of daily precipitation and minimum and maximum temperatures, along with solar radiation, wind speed and relative humidity were simulated by the ArcSWAT CSFR_World weather generator. The CFSR_World weather database contains monthly weather data covering for the entire globe that can be used with ArcSWAT. The topHRU program (Strauch et al., 2017) was used to determine the optimum number of HRUs to use in the watershed. The topHRU program allows the identification of a pareto-optimal threshold which minimizes the spatial error to 0.01 ha for a given number of HRUs and thereby minimizes the trade-off between SWAT computation time and number of HRUs. In this case, topHRU determined the optimum number of HRUs to be 1397 for the Ogun River basin. Thresholds of 0 ha for landuse, 150 ha for soil and 250 ha for slope were used in the SWAT set-up.

The surface runoff in SWAT was estimated using the modified Soil Conservation Society Curve Number method. The SWATfarmR program (Schürz et al., 2017) was used to write the management files in SWAT. All SWAT simulations included a warm-up period of 5 years for the simulation period from 1984 to 2012. The SWAT model was set-up three times (each set-up is henceforth referred to as a model structure). In each model structure, a different PET equation available in SWAT (HG, P-M or P-T) was used for the simulation. The three SWAT model structures (SWAT_HG, SWAT_P-T, and SWAT_P-M) were used to evaluate the model performance by comparing the calibrations/validations implemented with two global AET products (GLEAM_3.0a and MOD16), thus allowing for six calibrations of SWAT (GS1 through MS6). Structure SWAT_HG represents the SWAT set-up using the Hargreaves PET equation to simulate AET and that was calibrated and validated with the AET from GLEAM_v3.0a (GS1) and MOD16 (MS4). Structure SWAT_P-T represents the SWAT set-up using the Priestley-Taylor PET equation to simulate AET and that was calibrated and validated with the AET from GLEAM_v3.0a (GS2) and MOD16 (MS5). Structure SWAT_P-M represents the SWAT set-up using the Penman-Monteith PET equation to simulate AET and that was calibrated and validated with the AET from GLEAM_v3.0a (GS3) and MOD16 (MS6) (Fig. 2). The three SWAT structures calibrated and validated with the two AET data products enabled the most efficient model structure with the highest performing simulated AET product to be chosen for further use.

(Fig. 2)

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Manuscript under review for journal Hydrol. Earth Syst. Sci.
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2.5 Satellite evaporation dataset

Due to the unavailability of sufficient long-term recorded gauging station data for discharge measurements in the watershed, two satellites based AET products (GLEAM_v3.0a and MOD16) were used for the SWAT calibration and validation. The criteria for choosing GLEAM and MOD16 products are based on their spatial-temporal coverage and resolution and the fact that they are freely available and because these two AET data sets have been validated in several countries in Africa.

2.5.1 GLEAM

The Global Land Evaporation Amsterdam Model (GLEAM) developed in 2011, has been continuously revised and updated. Two (GLEAM_v3.0a and GLEAM_v3.0b) of the three datasets produced in 2016 using GLEAM v3.0 were downloaded for this study. The overview of the different forcing variables used to produce GLEAM_v3.0a and GLEAM_v3.0b dataset can be found in Martens et al. (2017). GLEAM_v3.0a was used for SWAT calibration and validation while GLEAM_v3.0b was used for the verification of the SWAT simulated AET. The Priestley and Taylor equation used in GLEAM calculates potential evaporation (mm/day) based on observations of surface net radiation and near-surface air temperature. The estimates of potential evaporation for the land fractions of bare soil, tall canopy and short canopy are converted into actual evaporation using a multiplicative evaporative stress factor (S) based on observations of microwave Vegetation Optical Depth (VOD) and estimates of root-zone soil moisture. The datasets are provided on a 0.25^0 by0.25^0 regular grid. For more information on GLEAM the reader is referred to Miralles et al. (2011b) and Martens et al. (2017).

2.5.2 MOD16

The MOD16 retrieval algorithm (Mu et al., 2007, 2011) is based on the Penman–Monteith framework (Monteith, 1965) with modifications to account for parameters not readily available from space (Cleugh et al., 2007). Mu et al. (2011) estimated PET with the Penman-Monteith equation driven by NASA's MERRA GMAO (GEOS-5) daily meteorological reanalysis data and MODIS derived vegetation data. Mu et al. (2007) derived actual evaporation from potential evaporation data by using multipliers to halt plant transpiration and soil evaporation. MOD16 is described in detail by Mu et al. (2007, 2011).

2.6 SWAT calibration, validation and uncertainty analysis

A multi-objective calibration and validation of SWAT simulated AET using satellite derived AET from GLEAM_v3.0a and MOD16 was implemented in SWAT-CUP. SWAT-CUP (Abbaspour, 2015) is a package used to carry out sensitivity analysis, calibration and validation of the SWAT model. SUFI-2 (Abbaspour et al., 2004) is one of the programs available in SWAT-CUP that is a multi-site, semi-automated, inverse modelling procedure used for calibrating parameters. SUFI-2 is based on a stochastic procedure for drawing independent parameter sets using Latin Hypercube sampling (LHS). An initial pre-selection of parameters based on literature research (Bicknell et al., 1997; Wang et al., 2006; Rafiei Emam et al., 2016; Ha et al., 2017; Lopez Lopez et al., 2017) was undertaken to choose the most sensitive parameters to AET. The initial parameter ranges were based on Neitsch et al.(2002, 2005, 2011). Furthermore, a global sensitivity analysis based on multiple regression method (Abbaspour, 2015) was carried out in which parameter sensitivities are determined by numerous rounds of LHS (each comprising of 1000 simulations) to obtain the most sensitive parameters by examining the resulting p-value and the t-stat value. The t-stat provides a measure of parameter sensitivity (a larger absolute values is more sensitive) and p-value determines the significance of the sensitivity (a value close to zero has more significance). Based on the sensitivity analysis, 11 of the most sensitive parameters were selected for further calibration using SUFI-2.

In this study, the first three calibration/validation procedures GS1, GS2 and GS3 use the AET from GLEAM_v3.0a for SWAT calibration (1989-2000) and validation (2001-2012) while the last three calibration/validation procedures MS4, MS5 and MS6 use the AET from MOD16 for SWAT calibration (2000-2006) and validation (2007-2012). The three model structures were run at the monthly time step for each of the 53 subbasins. The three model structures were calibrated (GS1 through MS6) by adjusting the 11 most sensitive parameters found in SUFI-2. In the calibration of SWAT with the AET from GLEAM a sample size of 1000 was chosen for the first iteration and a sample size of 500 for the second iteration, resulting in 1500 simulations. In the calibration of SWAT with AET from MOD16 a sample size of 1000 was chosen for two iterations of LHS, resulting in 2000 simulations. The validation process involved running the model using parameters that were determined during the calibration process and comparing the SWAT AET simulations to satellite based AET data.

The three SWAT model set-ups calibrated and validated using six procedures (GS1 through MS6) were evaluated with four objective functions, in which their mathematical formulations are described below. The statistics used in the evaluation of each SWAT structure performance were: Nash-Sutcliffe efficiency (NSE, (Nash and Sutcliffe, 1970)), Kling-Gupta efficiency (KGE,(Gupta et al., 2009)), Percent bias (PBIAS) and Coefficient of determination (R^2).

The NSE quantifies the relative magnitudes of the residual variance ("noise") compared to the measured data variance. NSE ranges from $-\infty$ to 1, where NSE > 0.5 indicates a good agreement (Moriasi et al., 2007, 2015) between simulated and satellite based evapotranspiration and NSE of 1 being the optimal value. NSE is computed as shown in Eq.2:

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2} \tag{2}$$

Where P_i and O_i are the ith simulated and observed AET, $\bar{O}$ is the mean value of observed AET, and n is the total number of observations.

The R^2 is the percent of variance explained by the model. It is a statistical measure of how close the data are to the fitted regression line (Eq. 3). R^2 ranges from 0 to 1 with higher values indicating less error variance. R^2 is computed as shown in Eq.3:

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$$R^2 = \left(\frac{\sum_{i=1}^{n} (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n} (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^{n} (P_i - \bar{P})^2}} \right)^2 \quad (3)$$

Where P_i and O_i are the ith simulated and observed AET, $\bar{P}$ and $\bar{O}$ are the mean value of simulated and observed AET, respectively and n is the total number of observations.

Percent bias (PBIAS) is the deviation of data being evaluated expressed as a percentage It measures the average tendency of the simulated data to be larger or smaller than the observations (Gupta et al., 1999) (Eq. 4). Negative values indicate model overestimating (overprediction) and positive values indicate model underestimating (underprediction). It ranges from - ∞ to ∞, where low magnitude values indicate better simulations. The optimum value of PBIAS is 0. It is computed in percentage terms as shown in Eq.4:

$$PBIAS = 1 - \frac{\sum_{i=1}^{n} (O_i - P_i)}{\sum_{i=1}^{n} O_i} \, x \, 100 \quad (4)$$

Where P_i and O_i are the ith simulated and observed AET, and n is the total number of observations.

The KGE goodness-of-fit measure provides an analysis of the relative importance of different components (correlation, bias and variability) in hydrologic simulations. KGE is calculated as shown in Eq.5:

$$KGE = 1 - \sqrt{(r-1)^2 + (\propto - 1)^2 + (\beta - 1)^2} \quad (5)$$

Where r is the Pearson product moment correlation coefficient between observed AET and the simulated AET, $\propto$ is the standard deviation of the simulated AET over the standard deviation of the observed AET (measure of variability), and β is the mean of simulated AET over the mean of observed AET. KGE ranges from 0 to 1, where KGE of 1 is the optimal value.

In this paper, the model performance ratings criteria for recommended statistics for a monthly time step are based on Kouchi et al.(2017) and Moriasi et al.(2007, 2015). NSE>0.50, R^2>0.60, KGE≥0.50 and PBIAS ≤ ±25% are the required satisfactory threshold (Kouchi et al., 2017; Moriasi et al., 2007, 2015) used in this study for assessing the model performance.

SUFI-2 was also used for the uncertainty analysis of the AET modelling process. In this step, the procedure depicts the 95% prediction uncertainty (95PPU) of the model compared with satellite based AET. The 95PPU was estimated at the 2.5% and 97.5% levels of the cumulative distribution of the AET simulated output variable derived through LHS. The uncertainties were quantified by two indices referred to as P-factor and R-factor (Abbaspour et al., 2004). The P-factor represents the percentage of observed data plus its error bracketed by the 95% predictive uncertainty (95PPU) band and varies from 0 to 1. Where 1 indicates a 100% bracketing of the observed data within model prediction uncertainty. While the R- factor is the ratio of the average width of the 95PPU and the standard deviation of the observed variable, this value ranges between 0 and infinity. These two indices were also used to judge the strength of the calibration and validation in which the ideal situation would be to account for 100% of the satellite AET data in the 95PPU while at the same time have an R-factor close to zero.

2.7 SWAT Model Verification

In some modelling studies (EPA, 2013; Faramarzi et al., 2017), the term model verification is used to refer to the examination of the numerical technique and computer code to ascertain that it truly represents the conceptual model and that there are no inherent numerical problems with obtaining a solution. In this study, to further examine the accuracy of the calibrated SWAT model, a verification of the simulated variables was carried out by: (i) a graphical comparison of AET of the calibrated and validated model to GLEAM_v3.0b AET time-series (2003-2012), and (ii) assessment of the long-term average annual and average monthly water balances at the outlet of the watershed. The SWAT water balance equations used for the assessment are:

$$WYLD = SURQ + LAT\_Q + GW\_Q - Q\_TLOSS \quad (6)$$

$$\text{Water Balance: } PRECIP = WYLD + AET + \Delta SW + PERC - GW\_Q \quad (7)$$

Where PRECIP is the observed precipitation; AET is the actual evapotranspiration; WYLD is the net amount of water that leaves the subbasin and contributes to stream flow in the reach; SURQ is the surface runoff contribution to stream flow; GW_Q is the groundwater contribution to stream flow; PERC is the water percolating past the root zone; LAT_Q is the lateral flow contribution to stream flow; Q_TLOSS is the transmission loss and ΔSW is the change in soil water content. The soil water content for both monthly and annual output is the average soil water content for the time period. Hence, the initial soil water content is the average for the time period of 25 years.

3. Results

The results of global sensitivity analysis revealed that the SCS runoff curve number (CN2.mgt) is the most sensitive to SWAT's simulations of AET for all the three SWAT model structures in this study. The sensitivity ranking of the remaining 10 parameters varies significantly according to the model structure through procedures GS1 to MS6 (Table 2). In this paper, only the spatial representation of the SWAT structure SWAT_HG with the highest (GS1) and SWAT structure SWAT_P-M with the lowest (MS6) model performance are included for the purpose of showing the two extreme results obtained (Fig. 3, Fig. 4, Fig. 5 and Fig. 6). Figure 7 and 8 show the overall model performance results of the three SWAT model structures when calibrated/validated with GLEAM_v3.0a (GS1, GS2 and GS3) and MOD16 AET (MS4, MS5 and MS6).

(Table 2)

Results indicate that the SWAT model structure SWAT_HG of calibration/validation procedure GS1 exhibits a model performance superior to the remaining two model structures for AET simulation (through GS2 to MS6).

Result from each subbasin for model structure SWAT_HG of procedure GS1 show a model performance of Nash-Sutcliffe efficiency NSE>0.50, Kling-Gupta efficiency KGE>0.50, coefficient of determination R^2 >0.6 in more than half of the 53 subbasins with a percent bias PBIAS < ±15% in all of the 53 subbasins (Fig.3 and Fig 4). In summary, the results of model structure SWAT_HG performance in both calibration/validation (GS1) for the entire catchment were satisfactory (GS1, Fig.7 and Fig. 8) except for the validation period, where a lower NSE (average value of 0.45) was obtained (GS1, Fig. 8).

(Fig.3)

(Fig 4)

For the SWAT model structure SWAT_P-T of procedure GS2, a model performance NSE<0.50, KGE>0.50, R^2 ≥0.60 and PBIAS < ±10% was achieved in more than half of the 53 subbasins (see Fig. S1 and Fig. S2). The overall result of model structure SWAT_P-T performance in both calibration/validation (GS2) for the entire catchment were satisfactory judging by the KGE, PBIAS, and R^2 criteria and unsatisfactory with a lower NSE average values of 0.43 in calibration and 0.32 in validation (GS2, Fig. 7 and Fig.8).

For the SWAT model structure SWAT_P-M of procedure GS3, a model performance NSE<0.50, KGE>0.50, R^2<0.60 and PBIAS < ±10% was achieved in more than half of the 53 subbasins (see Fig. S3 and Fig. S4). The overall result of model structure SWAT_P-M performance in both calibration/validation (GS3) for the entire catchment were satisfactory judging by the KGE, and PBIAS criteria and unsatisfactory assessing the performance of the NSE and R^2 criteria (GS3, Fig. 7 and Fig. 8).

For the SWAT model structure SWAT_HG of procedure MS4 a model performance of NSE<0.50, R^2<0.60 and PBIAS < ±25% was achieved in more than half of the 53 subbasins (see Fig.S5 and Fig.S6). A KGE >0.50 was obtained in in more than half of the 53 subbasins during the calibration and a KGE<0.50 was obtained in more than half of the 53 subbasins during the validation. The overall result of model structure SWAT_HG (MS4) performance for the entire catchment was merely satisfactory judging by the KGE and PBIAS metrics in the calibration period and was also only satisfactory in the validation period assessing the performance with the PBIAS criteria (MS4, Fig. 7 and Fig. 8).

For the SWAT model structure SWAT_P-T of procedure MS5 a model performance of KGE >0.50 and PBIAS < ±25% was achieved in more than half of the 53 subbasins in the calibration (see Fig.S7). A PBIAS< ±25% was obtained in more than half of the 53 subbasins during the validation (see Fig. S8). The overall result of model structure SWAT_P-T (MS5) performance for the entire catchment was merely satisfactory judging by R^2, and PBIAS metrics in the calibration period and was also only satisfactory in the validation period assessing the performance with PBIAS (MS5, Fig. 7 and Fig. 8)

For the SWAT model structure SWAT_P-T of MS6 a model performance of KGE >0.50 and PBIAS < ±25% was achieved in more than half of the 53 subbasins in the calibration (Fig.5). A PBIAS< ±25% was obtained in more than half of the 53 subbasins during the validation (Fig. 6) The overall result of model structure SWAT_P-M (MS6) performance for the entire catchment in both calibration/ validation (MS6) were unsatisfactory judging with NSE, KGE, and R^2 metrics but the PBIAS value obtained in the validation and calibration period were satisfactory (MS6, Fig. 7 and Fig.8).

(Fig. 5)

(Fig. 6)

The results of the AET calibration for SWAT model structures carried out at the monthly time step for the period 1989-2000 and the validation for the period 2001-2012 was better when performed with GLEAM_v3.0a (GS1, GS2 and GS3) than calibration (2000-2006) and validation (2007-2012) with MOD16 satellite based AET (MS4, MS5 and MS6). The results of the performance metrics revealed that the calibration period gives a higher model performance than the validation period (Fig. 7 and Fig. 8).

The validation results of model structure SWAT-HG of procedure GS1 showed a satisfactory SWAT predictive capability judging by the four objective functions except for the average NSE value of 0.45. Considering that NSE>0.50 was achieved in 32 (60%) subbasin, meaning that, more than half of the 53 subbasin have a satisfactory model performance, therefore the average NSE value of 0.45 obtained in the validation period can be considered acceptable.

(Fig.7)

(Fig.8)

3.3 Uncertainty analysis of SWAT model structure

The SWAT model performance results of the SWAT-HG structure when calibrated/validated with the AET from GLEAM_v3.0a (GS1) proved to be the most efficient of the three structures (through GS1 to MS6), therefore, this model structure was used to further predicted the uncertainty associated with the AET simulations (GS1) for each of the 53 subbasin to map error sources. In the calibration period, the values of the P-factor obtained were between 0.50 and 0.90 and the values of the R-factor were between 1.40 and 2.4. In the validation period, the values of P-factor were between 0.6 and 0.88, and that of the R-factor were between 1.43 and 2.5. The P-factor values revealed that more than half of the earth observation derived AET plus its error are bracketed by the 95% predictive uncertainty. The predictive uncertainty were adequate in the 53 subbasins and had a satisfactory performance for monthly AET simulations using the Hargreaves equation, though the R-factor was quite large in all the 53 subbasins indicating large model uncertainties. Extracts of the monthly calibration/validation results showing the 95% prediction uncertainty intervals along with the satellite based AET (GLEAM_v3.0a) are presented in Fig.9.

(Fig.9)

3.4 Model verification result

It was found that the AET from GLEAM_v3.0b was bracketed within the 95 percent uncertainty prediction (Fig. 10). The long-term average monthly water balance assessment performed at the outlet of the watershed shows a seasonal fluctuation which agrees with previous water balance studies conducted within and at the outlet of the of the study area located in Abeokuta (Ufoegbune et al., 2011; Eruola et al., 2012; Ufoegbune et al., 2012; Sobowale and Oyedepo, 2013), namely: (i) the study area is characterized by bimodal rainfall pattern, (ii) the AET increases in February from 55mm to 76mm as the wet season approaches and decreases in October from 72 mm to 54 mm in November as the dry season approaches (Ufoegbune et al., 2011), (iii) rainfall commences in March (66 mm) and is plentiful in June (165 mm) and September (167 mm), (iv) in August there is a decrease in precipitation to 96 mm and a decrease in AET to 94 mm, the dry spell often experienced in August is termed “August break” (Ufoegbune et al., 2011), (iii) The dry period extends from November to March, the months of low rainfall, AET, and soil moisture values (Ufoegbune et al., 2011), (v) with moderate rain in March soil water increases from 83 mm to 200 mm in July (Ufoegbune et al., 2011), (vi) as dry season commences, the soil water gradually declines.

The differences in the long term mean monthly water balance values obtained in the past studies conducted within the catchment are due to the variation in duration of years considered. Also, Eruola et al. (2012) revealed the two peak rainfalls in July and September agree with the current study, while Ufoegbune et al. (2011) showed the two peak rainfall to be in the month of June and September. All these previous studies and the current study water balance results are in the same range. Figure 11 shows the seasonal fluctuation of the SWAT estimated water balance components at the outlet of watershed, located in Abeokuta town. Our results show, the average long-term annual water balance estimated by SWAT to be within a reasonable percentage error of closure of ±15% (Table 3).

(Table 3)

(Fig. 10)

(Fig. 11)

4. Discussion

The global sensitivity analysis revealed that for the three SWAT model structure calibrations (GS1 to MS6), the same SWAT hydrologic parameters governing AET were sensitive. However, when different PET equations were applied to SWAT, different simulated AET values were obtained and the overall sensitivity ranking of the parameters varied significantly. The CN2.mgt is the most sensitive parameter of the three structures, indicating that it is the dominant parameter controlling the AET processes in SWAT in the Ogun River basin.

Assessing the model performance with the objective function and their optimal threshold values used in this study and as described in Moriasi et al. (2007, 2015) and Kouchi et al. (2017), the calibration/validation with the AET from

GLEAM_v3.0a showed an overall satisfactory SWAT model performance when the Hargreaves PET equation was used in SWAT to simulate AET (GS1), compared to the other model structures (GS2 to MS6). The calibration/validation with the AET from MOD16 yielded a lower SWAT model performance regardless which of the three PET equations was applied to SWAT.

Using the guidelines in Moriasi et al. (2007, 2015) and Kouchi et al. (2017) for evaluating the SWAT model performance at a monthly time step, the PBIAS values showed a satisfactory model performance (PBIAS ≤±25) in the six calibrations/validations of the three SWAT model structures (Fig. 7). The positive PBIAS obtained in the calibration/validation of the three SWAT model structures using the AET from MOD16 (MS4, MS5 and MS6) indicated a tendency for the SWAT model to underestimate monthly AET, or the MOD16 algorithm overestimated AET at the Ogun River Basin site. The positive PBIAS result obtained using MOD16 for calibrating agrees with previous studies conducted at a site in tropical region. Ruhoff et al. (2013) validated MOD16 AET using ground-based measurements of energy fluxes obtained from eddy covariance sites installed in tropical sites in the Rio Grande basin Brazil and from a hydrological model (MGB-IPH) at both local and regional scales and found that at the natural savannah vegetation site, the annual AET estimate derived by the MOD16 algorithm was 19% higher than the measured amount. Ruhoff et al. (2013) found that misclassification of land use and land cover was identified as the largest contributor to the error from the MOD16 algorithm. Ramoelo et al. (2014) validated MOD16 using data from two eddy covariance flux towers installed in a savannah and woodland ecosystem within the Kruger National Park, South Africa and found that, one flux tower results showed inconsistent comparisons with MOD16 AET and the other site achieved a poorer comparison with MOD16 ET. In their study, they found that, the inconsistent comparison of MOD16 and flux tower-based AET can be attributed to the parameterization of the Penman-Monteith model, flux tower measurement errors, and flux tower footprint vs MODIS pixel. From our results, we agree that the AET from MOD16 tends to overestimate AET.

The PBIAS result of the model structure SWAT-HG (GS1) showed the highest calibration/validation performance. The satisfactory SWAT model GS1 performance was achieved for all objective functions, except for the average NSE value obtained of 0.45 in the validation period. During the validation period (GS1), the Kling-Gupta efficiency especially revealed the SWAT model to be satisfactory (Fig 8). Also, the low PBIAS result of -0.02% and 0.45% (GS1, Fig 7 and Fig 8) corresponded to a performance rating “very good” indicating predictive capability of accurate model simulation. An NSE>0.50 was achieved in 32 (60%) subbasins, showing that over half of the 53 subbasins have a satisfactory model performance during the validation period. The Hargreaves PET equation uses the observed minimum and maximum temperature to calculate AET, whereas a limitation of GLEAM, is that is uses an algorithm to convert PET into AET using a multiplicative evaporation stress factor (S). The derivation of S is based on microwave observation of the vegetation optical depth-used as a proxy for the vegetation water content and simulations of root zone soil moisture. Therefore, the Hargreaves equation used in SWAT has high tendency to better represent the dynamic hydrological processes due to its connection to the observed meteorological data in the calibration and validation periods.

The SWAT model structures which were based on calibration/validation with AET from MOD16 (MS4, MS5 and MS6) had lower SWAT model performances, with a few exceptions. MOD16 estimation of PET is based on the Penman-Monteith equation which is also a function of its derived AET; yet the SWAT model run with the Penman-Monteith PET equation for the simulated AET also gave an unsatisfactory result both for the calibration and validation periods.

The results of our study are in agreement with Trambauer et al. (2014) who found that MOD16 did not show good agreement in most parts of Africa with evaporation products such as Era-Land, GLEAM and AET derived from three alternative versions of the PCR-GLOBWB global hydrological model , while the aforementioned products were more consistent. The differences in GLEAM and MOD16 products are due to their input and forcing data (Trambauer et al. 2014). Furthermore, in GLEAM, evaporation from open water is considered while in MOD16, the contribution of lakes and rivers is not (Trambauer et al. 2014). Hence, AET estimated from MOD16 accounts only for the land evaporation. Another study found that AET from GLEAM performed satisfactory for the calibration of a large-scale hydrological model set up in Morocco (Lopez et al., 2017).

The SWAT model structure using the Hargreaves equation had a superior model performance which might be linked with the climate variables that stem from the observed precipitation and maximum and minimum temperatures while the Penman Monteith and the Priestly-Taylor equations are driven by simulated variables (wind speed, relative humidity and solar radiation). The 95% predictive uncertainty of the best SWAT model performance was quantified, and the 95% predictive uncertainty bracketed most of the satellite based AET, although the R-factor was quite large in all of the subbasins signifying a large model uncertainty which can be ascribed to the uncertainty in satellite derived AET, the forcing climate data, the conceptual model and the model parameters. The 95PPU are the combined outcome of the uncertainties, these uncertainty sources are not separately evaluated in SUFI-2 but attributed as a total model uncertainty to the parameters which are visualized through the simulated model output ranges. The first verification of the SWAT model structure with the highest model performance was carried out using another version of GLEAM (GLEAM_v3.0b) as independent dataset and we found that the AET from GLEAM_v3.0b was bracketed within the 95PPU of our model. The second verification of the SWAT model structure with the highest model performance was carried out by assessing the output of SWAT water balance components. The result obtained from the long-term mean monthly water balance agrees with the previous water balance studies conducted within the study area. The differences in the water balance components values of the past and the current study are due to variation in the length of years considered. The average long-term annual of the water balance at the outlet of the study area shows a satisfactory percentage error of closure of ±15%. These we considered as our SWAT model verification which further raises our confidence in the predictive capability of SWAT as a decision support tool for further research.

5. Conclusion

This study examined an alternative method to calibrate the SWAT hydrological model using a freely available satellite based product for the Ogun River Basin in southwestern Nigeria. Due to the scarcity of measured hydrological datasets in the region and different algorithms of the available satellite based AET products, the SWAT model was set-up three times, each time using a different PET equation. The three different structures of SWAT were used with two different global AET product to calibrate the SWAT simulated AET outputs from each model structure resulting in six calibration/validation procedures implemented on a monthly time scale. The performance of SWAT model in simulating AET in a data sparse tropical region was quantified. The results of this study revealed that, an alternative approach to calibrating the SWAT model can be the use of globally available GLEAM_v3.0a AET product; this yielded a satisfactory model performance in predicting monthly actual evapotranspiration in the Ogun River basin with an acceptable predictive uncertainty.

Our analysis shows that the temperature based Hargreaves PET equation performed well when implemented in SWAT and is therefore the most efficient equation to use with the satellite based AET from GLEAM for the calibration and validation in a tropical region. Our findings suggest that the SWAT model structure using the Hargreaves equation can be used as a potential decision support tool for further studies and predictions on basin hydrology in the Ogun River Basin.

There is still a need for further research on: (i) improving the model calibration performance in those subbasins where the performances are unsatisfactory and (ii) validation of other simulated variable (e.g. stream flow) of the calibrated SWAT model using observed datasets when these are available.

The results from this research contribute to a better understanding of the ease and suitability of using freely available satellite based actual evapotranspiration datasets in a tropical sparsely gauged catchment for calibration/validation by subbasin of the SWAT hydrological model and thereby reducing the uncertainty associated with the long-established calibration on a limited number of observed streamflow datasets. Furthermore, a new contribution of this study is the better understanding of calibration of the three different estimated AET in SWAT to derive the model with the best goodness of fit and a satisfactory predictive capability. Therefore, we recommend testing the three available PET equations in SWAT to estimate simulated AET whenever SWAT calibration is carried out with any satellite based AET product. The work presented in this paper is a first step of hydrological modelling that will set the basis for future modelling applications within the study area.

Author Contributions: Abolanle E. Odusanya, Bano Mehdi and Karsten Schulz designed the methodological framework and advised and contributed to the entire strategic and conceptual framework of the study. Abolanle E. Odusanya performed the simulations, analyzed the results and prepared the manuscript under supervision of Bano Mehdi and Karsten Schulz. Christoph Schürz prepared the landuse and soil maps, wrote the SWATfarmR script, and modified topHRU code for this study. Adebayo O. Oke, carried out the field work for point source water pollution data collection used in the SWAT configuration. Olufiropo. S. Awokola, Julius A. Awomeso and Joseph O. Adejuwon carried out the field work for the necessary data input for the two reservoirs used in the SWAT configuration.

6. Acknowledgements

The authors wish to thank those persons, institutions, authorities and agencies, especially Olusegun Orekoya (Nigerian Meteorological Agency) and Basiru Olatunde Bakare (Ogun state Agricultural Development Authority, Nigeria) that assisted in accessing research data and information.

Conflicts of Interest: The authors declare no conflict of interest

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Table 1. Description and sources of input data used to configure SWAT for the Ogun River Basin

Data type	Description/Resolution	Sources
Topography	Digital Elevation model (DEM). 1 arc-second global coverage (approx. 30m resolution)	Shuttle Radar Topography Mission (SRTM)
Soil	Soil property map (250m resolution)	Soil property maps of Africa
Landuse	Landuse classification 2010 (300m resolution)	European Space Agency global land cover map
Weather	Daily Precipitation, Max. and Min. Temperature (1984-2012) (24hrs temporal resolution)	Nigerian Metrological Agency
Reservoir outflow	Reservoir discharge (24hrs temporal resolution) Oyan:2007-2012	Ogun-Oshun River Basin Authority Nigeria
Reservoir Water level	Daily Water level Oyan:1984-2012	Ogun-Oshun River Basin Authority Nigeria
Management practices	Major crop management practices	Ogun state Agricultural Development Authority, Nigeria Oyo state Agricultural Development Authority, Nigeria

Table 2. Sensitivity rank and calibrated parameters with their optimal value of the three SWAT model structures through the six procedures of calibration

		Rank (optimal value)					
SWAT Parameter	**Description**	**GS1**	**GS2**	**GS3**	**MS4**	**MS5**	**MS6**
r__CN2.mgt	SCS runoff curve number	1 (-0.01)	1 (-0.13)	1 (0.08)	1 (-0.48)	1 (-0.48)	1 (-0.47)
v__ESCO.hru	Soil evaporation compensation factor	2 (0.02)	4 (0.20)	3 (0.20)	4 (0.23)	8 (0.33)	5 (0.50)
v__CANMX.hru	Maximum canopy storage	3 (6.96)	2 (0.61)	2 (3.86)	5 (82.11)	9 (33.9)	4 (15.6)
r__SOL_BD.sol	Moist bulk density	4 (-0.19)	3 (0.11)	4 (-0.20)	3 (-0.82)	3(-0.005)	2 (-0.07)
v__ALPHA_BF.gw	Base flow alpha factor	5 (0.66)	5 (0.62)	7 (0.13)	6 (0.42)	6 (0.9)	8 (0.14)
r__SOL_K.sol	Saturated hydraulic conductivity	6 (0.23)	10 (-0.26)	8 (0.24)	10 (0.49)	10 (-0.19)	10 (0.26)
v__EVRSV.res	Lake evaporation coefficient	7 (0.59)	7 (0.55)	10 (0.62)	8 (0.22)	7 (0.23)	7 (0.74)
v__GSI.plant.dat	Maximum stomatal conductance	8 (4.7)	11 (1.66)	11 (3.4)	7 (2.34)	5 (1.9)	6 (0.34)
v__FFCB.bsn	Initial soil water storage expressed as a fraction of field capacity water content	9 (0.59)	6 (0.82)	5 (0.15)	11 (0.99)	11 (0.4)	11 (0.83)
v__EPCO.hru	Plant uptake compensation factor	10 (0.47)	9 (0.61)	9 (0.07)	9 (0.95)	4 (0.88)	9 (0.47)
r__SOL_AWC.sol	Soil available water storage capacity	11 (0.8)	8 (0.92)	6 (0.77)	2 (0.96)	2 (0.89)	3 (0.93)

"v_" means a replacement (initial or existing parameter value is to be replaced by a given value);
"r_" means a relative change (initial or existing parameter value is multiplied by 1+ given value within the range)

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Table 3: Average annual water balance at the outlet of the watershed in Abeokuta Town

Year	PRECP (mm)	AET (mm)	SW (mm)	PERC (mm)	SURQ (mm)	GW_Q (mm)	WYLD (mm)	LAT_Q (mm)	ΔSW (mm)	*Estimated PRECP	Balance Year	PBIAS (%)
1989	1357	941	57	188	294	147	456	5	5	1442	-85	-6
1990	1094	882	82	69	145	52	207	4	-25	1081	13	1
1991	1161	881	54	117	228	84	321	4	27	1263	-101	-9
1992	1066	806	57	113	177	86	274	4	-3	1104	-38	-4
1993	1185	862	63	55	305	38	351	4	-5	1225	-41	-3
1994	870	768	47	34	96	17	118	3	16	918	-48	-6
1995	1166	858	55	116	225	83	317	4	-8	1200	-34	-3
1996	1457	885	45	201	460	148	621	5	10	1569	-112	-8
1997	1341	851	110	151	342	122	478	5	-65	1292	50	4
1998	1107	767	81	124	290	93	394	4	29	1222	-114	-10
1999	1515	900	100	223	458	183	656	5	-19	1577	-62	-4
2000	1198	814	55	175	306	143	463	4	45	1355	-157	-13
2001	841	738	35	27	108	12	128	3	20	900	-60	-7
2002	1241	758	64	146	375	108	492	4	-29	1260	-19	-2
2003	1456	845	56	216	488	177	681	5	8	1572	-117	-8
2004	1156	922	44	90	186	69	265	4	12	1220	-64	-6
2005	915	792	41	27	114	14	134	3	3	942	-27	-3
2006	1153	804	46	128	263	94	365	4	-5	1198	-45	-4
2007	1600	910	50	229	552	175	742	6	-4	1702	-103	-6
2008	1395	832	55	221	416	174	605	5	-4	1480	-85	-6
2009	1338	872	65	185	334	151	500	5	-10	1397	-59	-4
2010	1609	928	91	232	519	189	722	6	-26	1667	-58	-4
2011	1264	815	64	172	367	134	515	5	27	1395	-130	-10
2012	1409	839	60	265	386	205	609	6	4	1512	-103	-7

PRECIP: precipitation; AET: actual evapotranspiration; SW: soil water content; PERC: percolation; SURQ: surface runoff; GW_Q: groundwater recharge; WYLD: water yield; LAT_Q: lateral flow; ΔSW: change in soil water content; * Estimated PRECP is WYLD + AET + ΔS + PERC - GW_Q, expressed in mm.

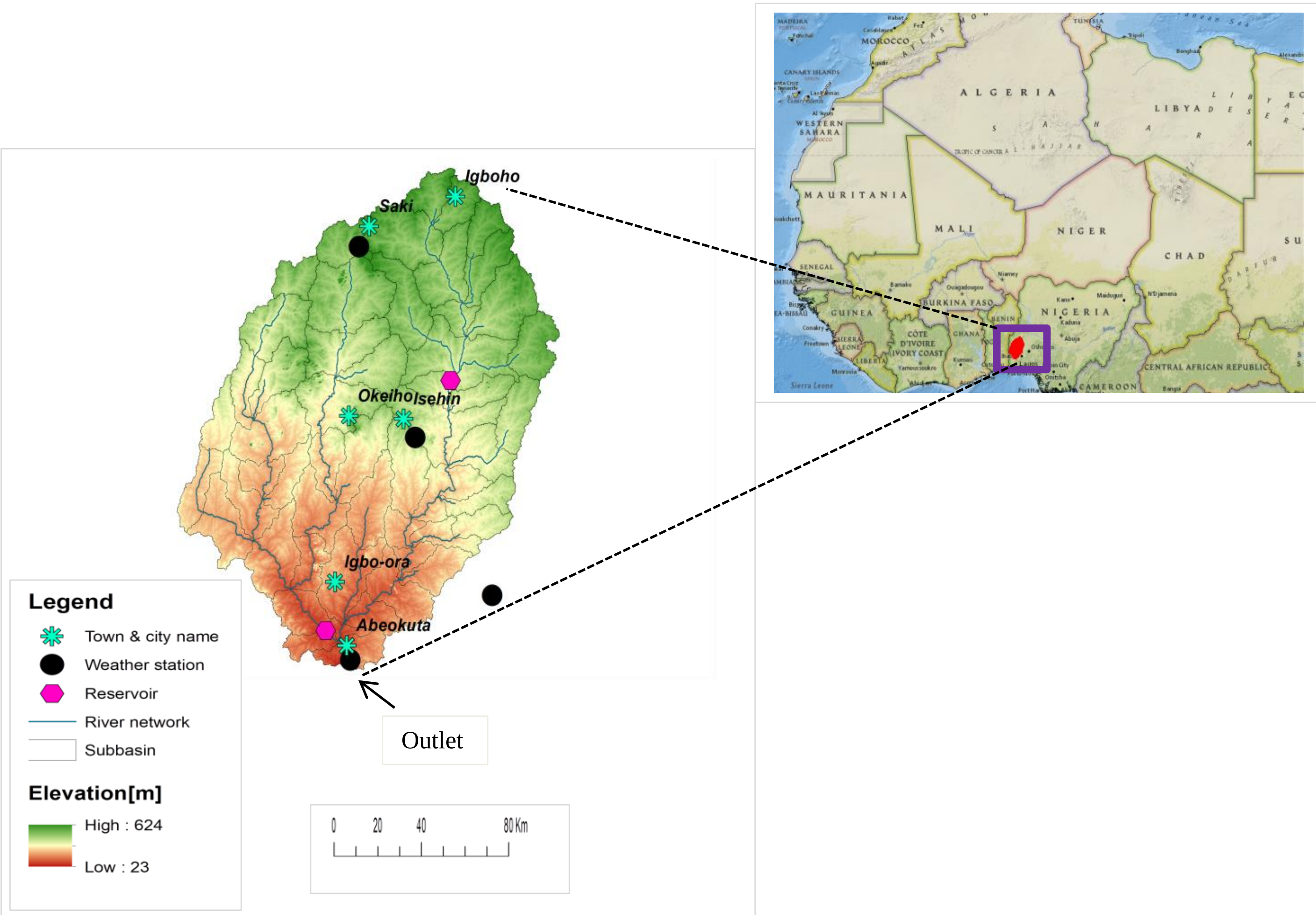


Figure 1: The Ogun River Basin located in Nigeria showing the SWAT-delineated subbasins, weather stations and river network

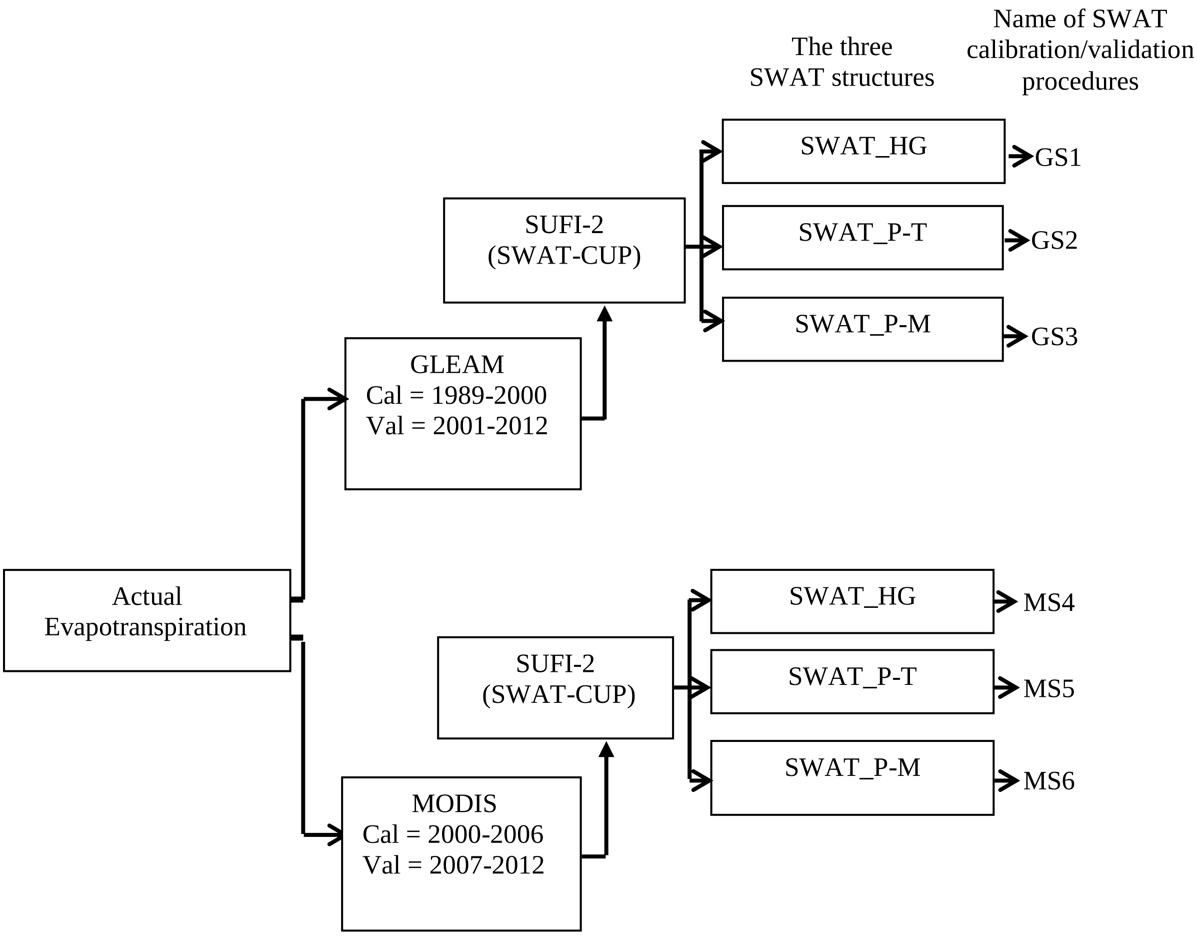
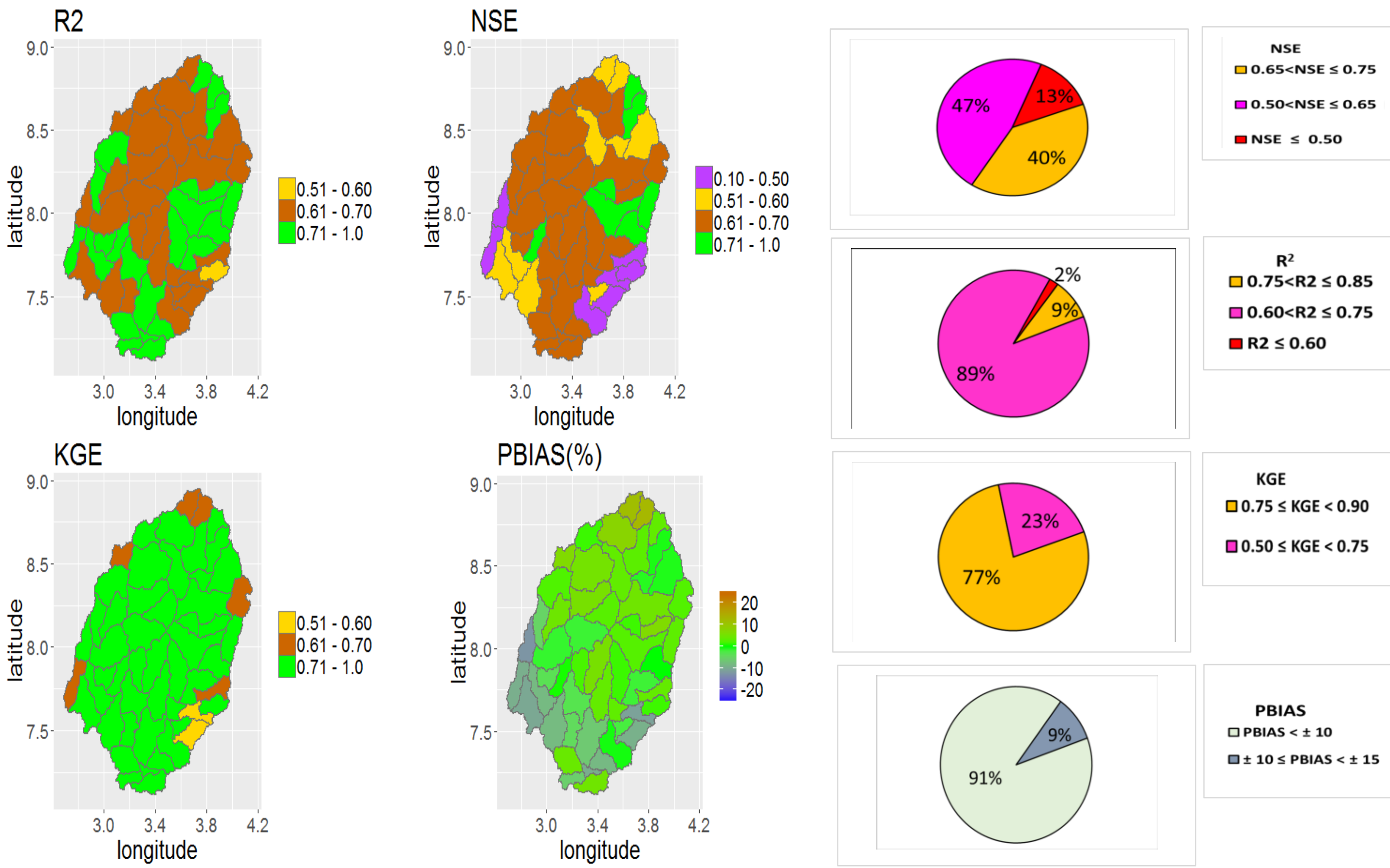


Figure 2: Schematic diagram showing the three structures of the SWAT model, the two global AET products, and the resulting six calibration and validation procedures for the Ogun River Basin.



5 **Figure 3: Performance metrics (NSE, KGE, R^2, and PBIAS) of SWAT (SWAT_HG) when calibrated with GLEAM_v3.0a (GS1).**

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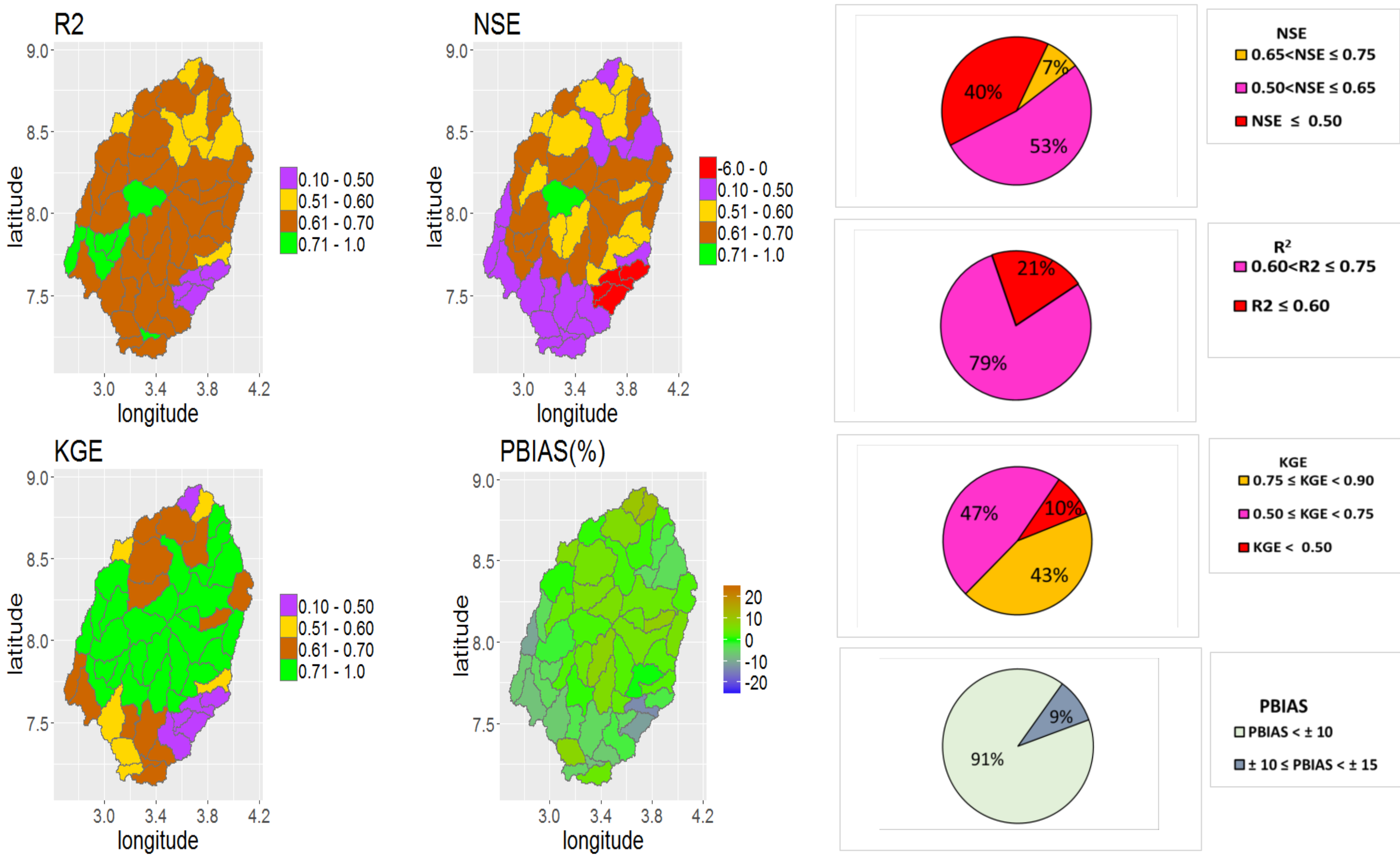

5 **Figure 4: Performance metrics (NSE, KGE, R^2, and PBIAS) of SWAT (SWAT_HG) when validated with GLEAM_v.3.0a (GS1)**

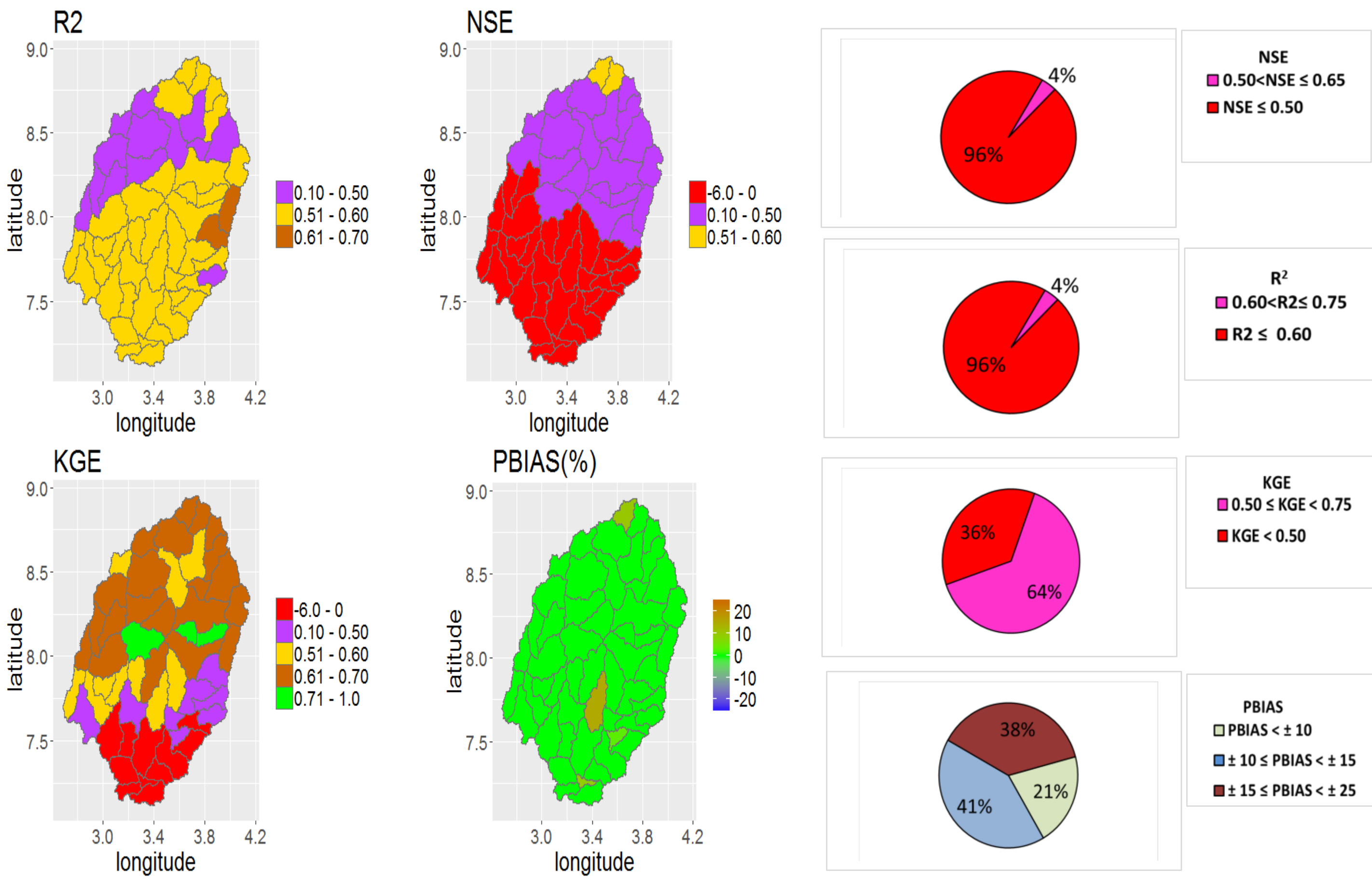

Figure 5: Performance metrics (NSE, KGE, R^2, and PBIAS) of SWAT (SWAT_P-M) when calibrated with MOD16 (MS6)

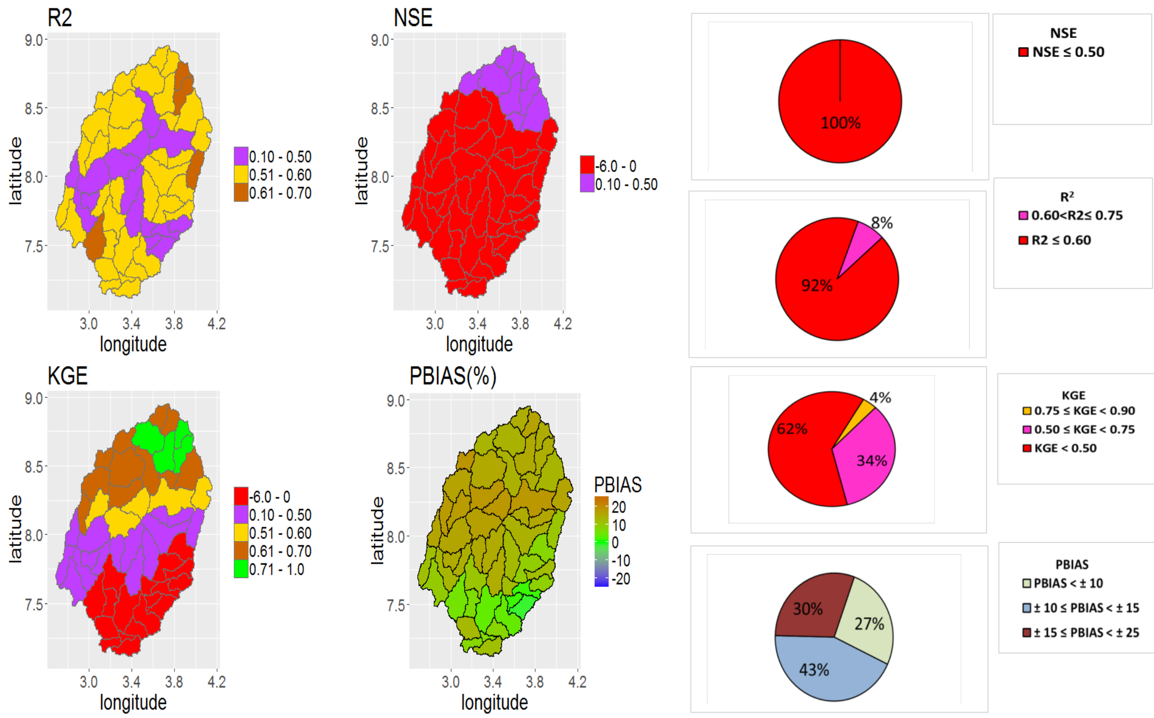

Figure 6: Performance metrics (NSE, KGE, R^2, and PBIAS) result of SWAT (SWAT_P-M) when validated MOD16 (MS6)

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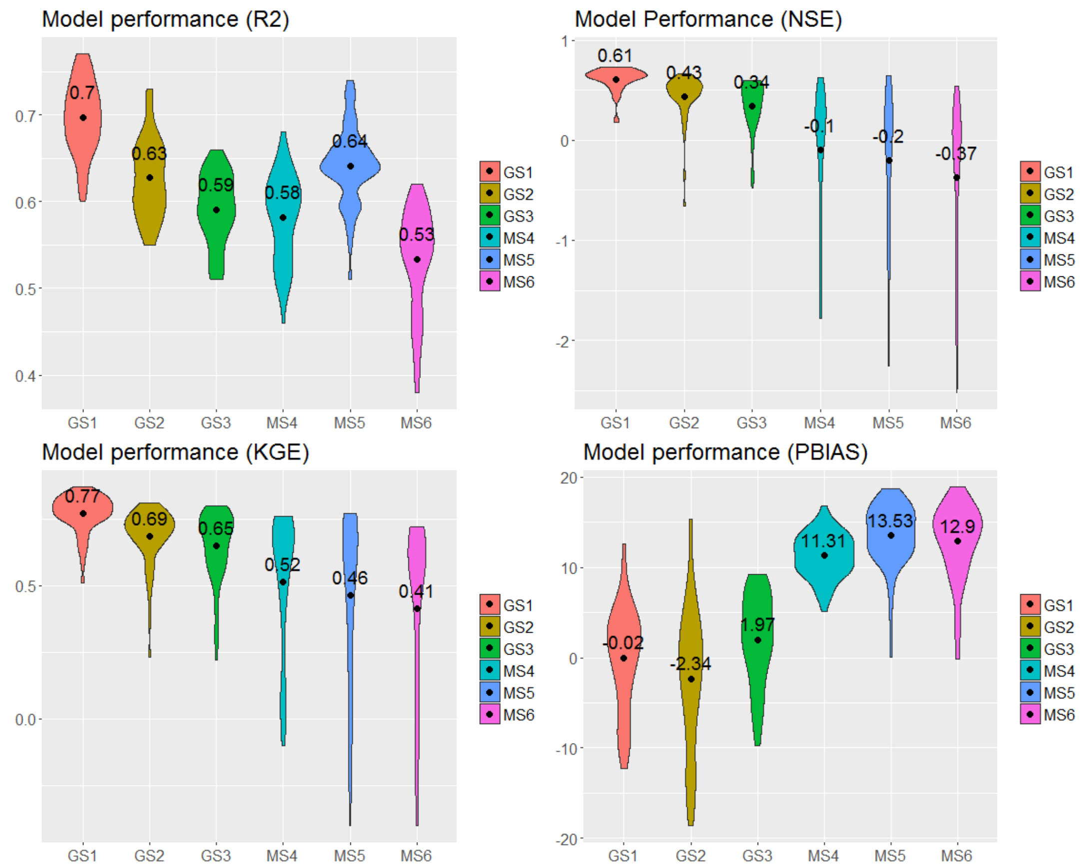

Figure 7: The plots of the performance result of SWAT in simulating actual evapotranspiration. The values and the black dot symbol ("•") depicts the average value of, R^2, NSE, KGE and PBIAS obtained for each of the calibration.

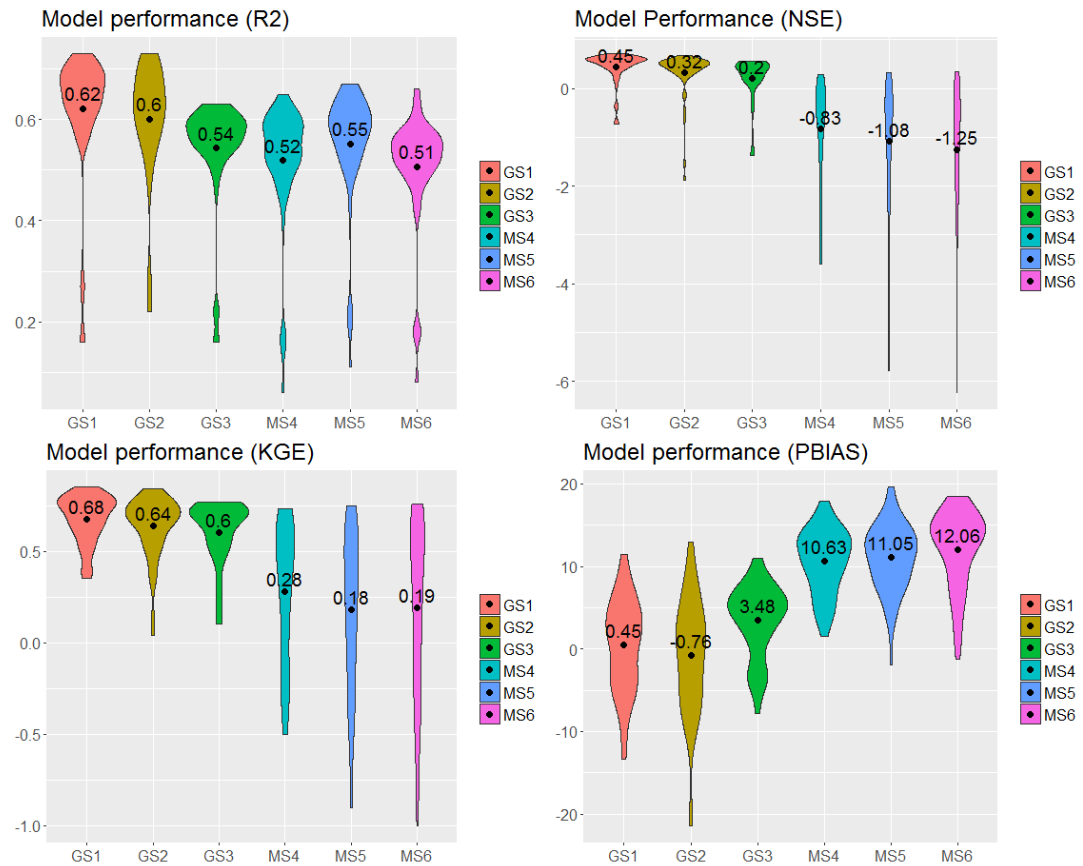

Figure 8: The plots of the performance result of SWAT in simulating actual evapotranspiration. The values and the black dot symbol ("•") depicts the average value of, R^2, NSE, KGE and PBIAS obtained for each of the validation.

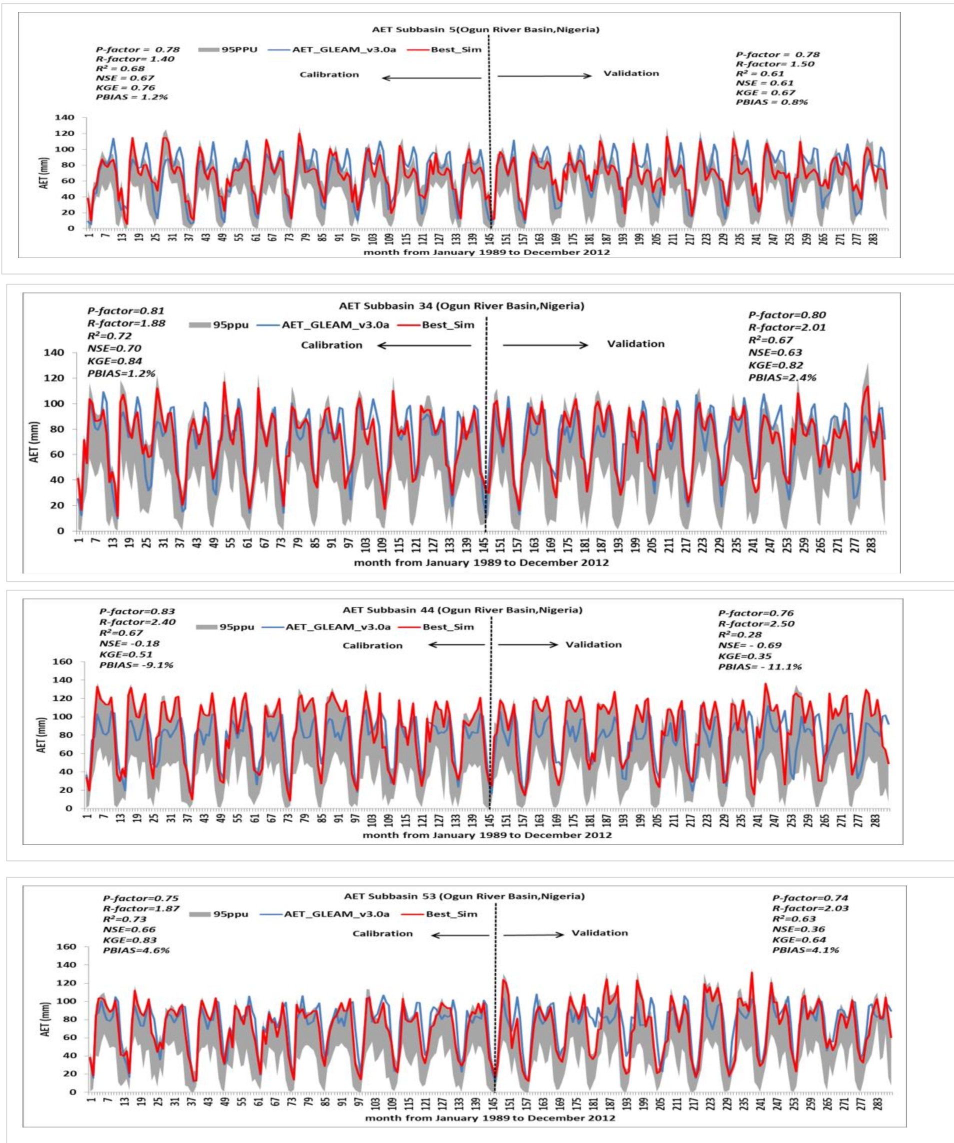

Figure 9: Extracts of the monthly calibration and validation results (GSI) showing the 95% prediction uncertainty interval along with the best SWAT simulated actual evapotranspiration and the satellite based actual evapotranspiration (GLEAM-v3.0a)

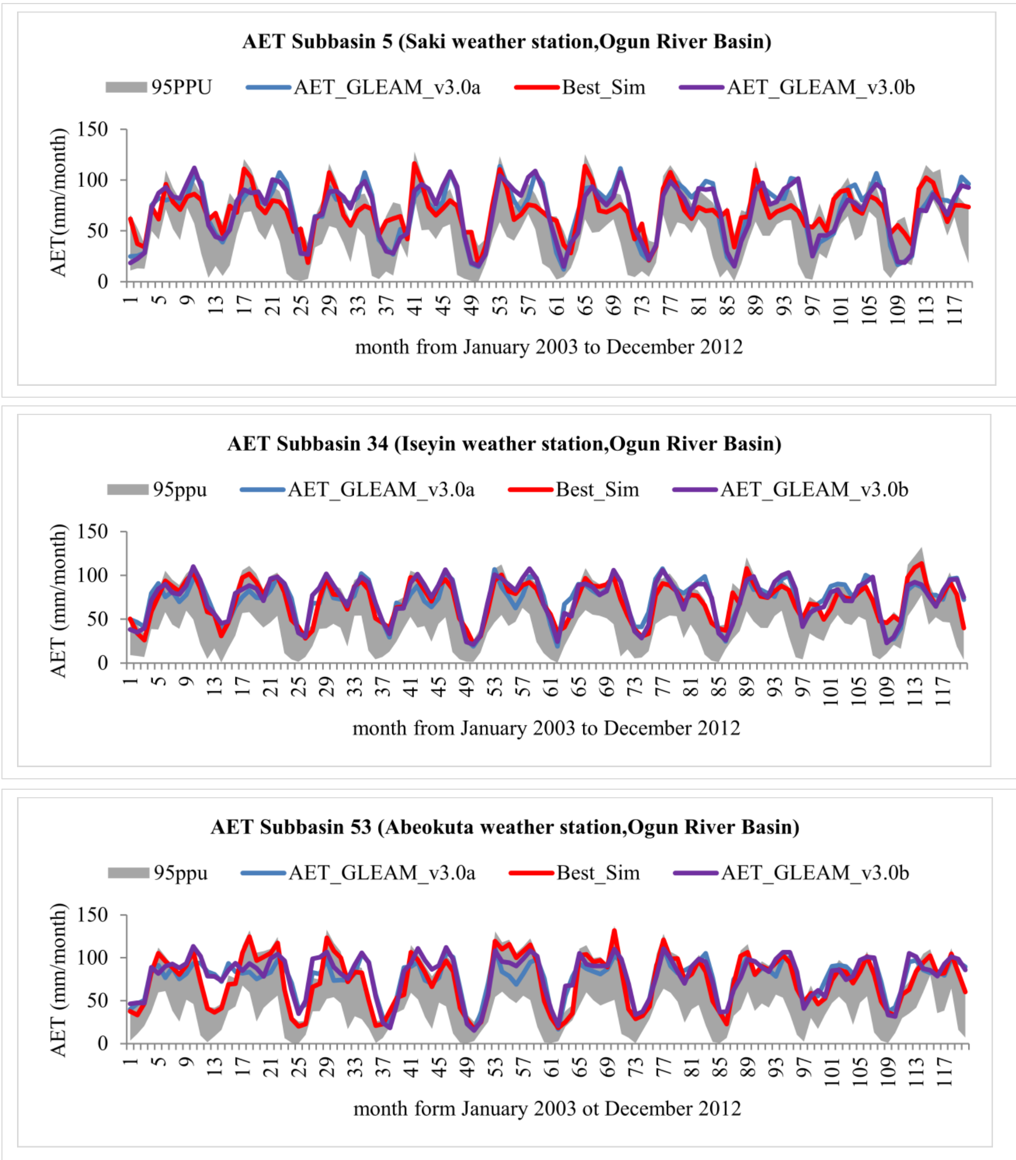

Figure 10: SWAT model verification results showing the satellite based AET GLEAM_v3.0a used for the model calibration/validation, the best SWAT simulated actual evapotranspiration (GS1), and an independent GLEAM_v3.0b time series bracketed by 95% predictive uncertainty.

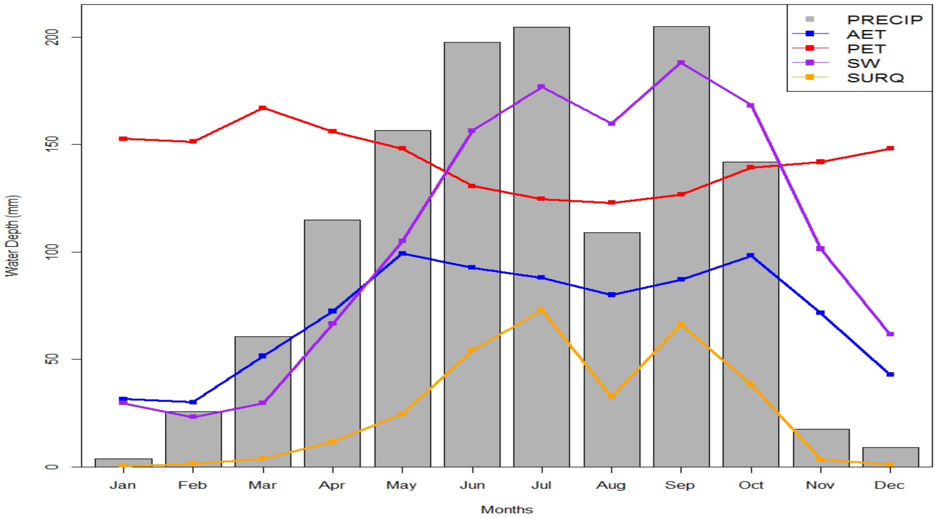

Figure 11: Seasonal fluctuation of water balance components at the outlet of the watershed located in Abeokuta Town