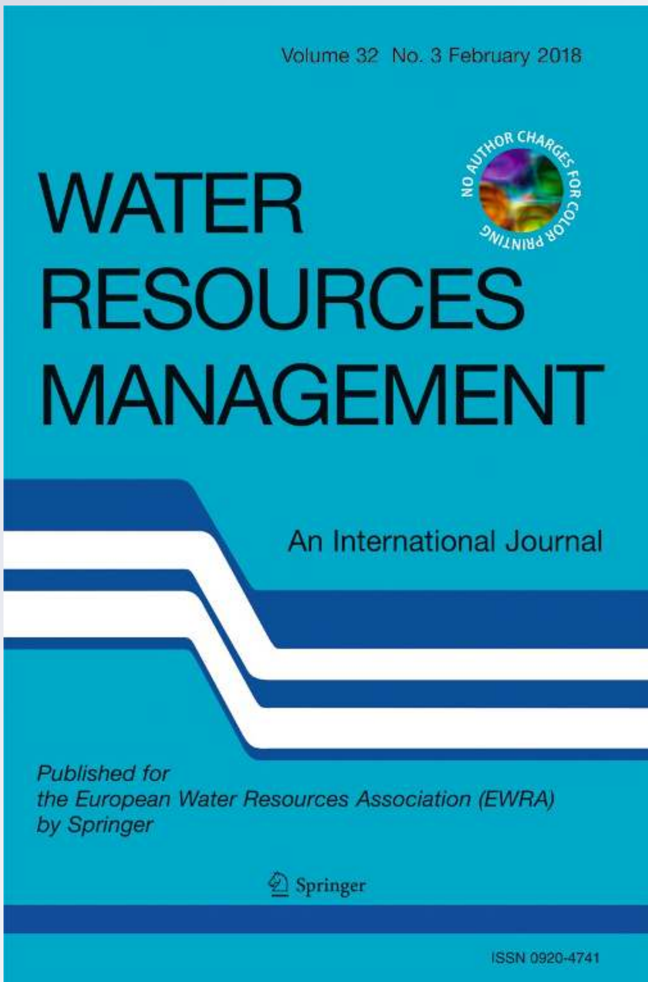
# Evaluation of Using Remote Sensing Evapotranspiration Data in SWAT

**Prem B. Parajuli, Priyantha Jayakody & Ying Ouyang**

**Water Resources Management**
An International Journal - Published for the European Water Resources Association (EWRA)

ISSN 0920-4741
Volume 32
Number 3

Water Resour Manage (2018)
32:985-996
DOI 10.1007/s11269-017-1850-z




Springer

Water Resour Manage (2018) 32:985–996
https://doi.org/10.1007/s11269-017-1850-z

CrossMark

# Evaluation of Using Remote Sensing Evapotranspiration Data in SWAT

Prem B. Parajuli[1] · Priyantha Jayakody[2] · Ying Ouyang[3]

Received: 16 March 2017 / Accepted: 31 October 2017 /
Published online: 7 November 2017


**Abstract** This study applied a time series evapotranspiration (ET) data derived from the remote sensing to evaluate Soil and Water Assessment Tool (SWAT) model calibration, which is a unique method. The SWAT hydrologic model utilized monthly stream flow data from two US Geological Survey (USGS) stations within the Big Sunflower River Watershed (BSRW) in Northwestern, Mississippi. Surface energy balance algorithm for land (SEBAL), which utilized MODerate Resolution Imaging Spectro-radiometer (MODIS) to generate monthly ET time series data images were evaluated with the SWAT model. The SWAT hydrological model was calibrated and validated using monthly stream flow data with the default, flow only, ET only, and flow-ET modeling scenarios. The flow only and ET only modeling scenarios showed equally good model performances with the coefficient of determination ($R^2$) and Nash Sutcliffe Efficiency (NSE) from 0.71 to 0.86 followed by flow-ET only scenario with the $R^2$ and NSE from 0.66 to 0.83, and default scenario with $R^2$ and NSE from 0.39 to 0.78 during model calibration and validation at Merigold and Sunflower gage stations within the watershed. The SWAT model over-predicted ET when compared with the Modis-based ET. The ET-based ET had the closest ET prediction (~8% over-prediction) as followed by flow-ET-based ET (~16%), default-based ET (~27%) and flow-based ET (~47%). The ET-based modeling scenario demonstrated consistently good model performance on streamflow and ET simulation in this study. The results of this study demonstrated use of Modis-based remote sensing data to evaluate the SWAT model streamflow and ET calibration and validation, which can be applied in watersheds with the lack of meteorological data.

**Keywords** Evapotranspiration · Stream flow · MODIS · SWAT · Remote sensing

✉ Prem B. Parajuli
pparajuli@abe.msstate.edu

[1] Department of Agricultural and Biological Engineering, Mississippi State University, Mississippi State, MS, USA

[2] New South Wales Department of Primary Industries, Orange, NSW, Australia

[3] USDA Forest Service, Mississippi State, MS, USA

## 1 Introduction

Hydrological models are developed with several model parameters, which are adjusted by the modeler during model calibration process. When the hydrological model predicts observed data satisfactorily as suggested by literatures, it may be considered as adequately calibrated (Moriasi et al. 2015). Precipitation, surface runoff, ET, and infiltration are major components in the hydrological cycle, in which precipitation and ET are the two crucial components. It is estimated that about 60% of the moisture input from the rain, yields back to the atmosphere due to the ET process within the hydrological cycle (Korzun et al. 1978; L'vovich and White 1990). In addition, the ET component uses about half of the solar energy captured by the earth surface (Hunt et al. 1986; Kiehl and Trenberth 1997). Hydrological model calibration process can be benefitted with the ET data derived from remote sensing (Immerzeel and Droogers 2008; Bastiaanssen et al. 1998; Doherty 2005). Land use and land cover conditions may impact on exchanges of water and energy between terrestrial and atmospheric layers. Therefore, Land use and land cover data, which generally provide vegetation information to the data layers are commonly utilized in hydrological modeling studies. Computer models utilize vegetation information variables or its richness based on maximum green vegetation fraction to estimate for ET, which are generally collected using remote sensing data (Broxton et al. 2014; Los et al. 2000). Vegetation absorbs fraction of photosynthetically active radiation such as leaf area index, fraction of green leaves measured by MODerate Resolution Imaging Spectroradiometer (MODIS). The MODIS data collection is carried by NASA's Terra and Aqua satellites, which provide biophysical and surface energy information or values for model input to estimate ET (Justice et al. 2002).

Terrestrial land use and land covers conditions, energy, carbon, and biogeochemical cycling are affected by hydrological processes (Potter et al. 2008). In addition, factors such as green vegetation fraction is important for agriculture and water related to agroecosystems (Asner and Lobell 2000; Lucht et al. 2002; Parmesan and Yohe 2003). In the terrestrial agroecosystems, the ET, which is a combined form of evaporation and the transpiration, is considered a major component of the hydrological cycle (Hussey and Odum 1992; Drexler et al. 2004; Parasuraman et al. 2007; Gao 2008; Zhou and Zhou 2009). Penman-Monteith, Priestley-Taylor, and the Hargreaves methods are generally used to estimate ET, which are based on climatological data such as heat flux, aerodynamic component, temperature etc. (Lopez-Urrea et al. 2006; Zhang et al. 2008). Depending upon the method used for estimating ET, different set of climatological daily input data are required in the hydrological model. These input data includes heat flux, daily maximum and the minimum air temperature, relative humidity, solar radiation and wind speed. The daily maximum and minimum air temperatures, solar radiation, and humidity data are needed to estimate ET using Priestley-Taylor method. The Hargreaves ET estimation equation needed daily maximum and minimum air temperatures data.

The actual ET estimation is a difficult process as it involves a complex instrumentation as well as physical and biological processes. The lack of measured meteorological data in the various watersheds to represent spatial conditions of the watershed can make ET estimation process even further complex. While field measured ET data are lacking, remote sensing data can be utilized to estimate net energy and the ET. Remote sensing data are widely available for the large scale watersheds or regional scale and easily accessible than the field measured data. The remote sensing data can provide essential information required to quantify the net energy and the aerodynamic effects of the evapotranspiration process (Tang et al. 2007; Gamage et al. 2011).

In the last few decades, development of hydrological models is growing to address the concerns from small to large scale watersheds modeling with distributed parameters. Especially for the large watershed scale modeling, the remote sensing (RS) data can provide a useful information for estimating ET (Overgaard et al. 2006). Accordingly, modeling methods are needed for validating the ET data retrieved from RS in the hydrological models. The objective of this study was to present an operational approach to validation of RS-derived ET data using a distributed hydrological model. The RS derived ET data, along with other field observed data including USGS stream flow data were used to calibrate and validate a hydrological model. In this study, the soil and water assessment tool (SWAT) model was applied and model predicted stream flow values were compared with observed stream flow data. The RS derived ET data were also validated accordingly. Among the advanced watershed scale, distributed parameter based hydrological models, the SWAT model has been widely applied for hydrological studies (Lirong and Jianyun 2012; Shrestha et al. 2012; Parajuli et al. 2013, 2016). In addition, the SWAT model was also applied to water quality (Pisinaras et al. 2010; Cho et al. 2012; Dakhlalla et al. 2016), and crop growth functions (Masih et al. 2011; Kim et al. 2013; Parajuli et al. 2013, 2016; Kim and Parajuli 2014) studies in various watersheds. The SWAT model has been used with appropriate calibration, validation, and sensitivity analysis (Kannan et al. 2007; Immerzeel and Droogers 2008; Thampi et al. 2010; Parajuli et al. 2013; Dakhlalla and Parajuli 2016; Daggupati et al. 2015; Yuan et al. 2015) as well as the climate change study (Ficklin et al. 2009). The method presented in this paper were tested and evaluated in the study area.

Calibration and validation of the SWAT model in the watershed studies are mostly focused on using stream flow data only (Stone et al. 2001; Rosenberg et al. 2003; Payne et al. 2003; Christensen et al. 2004; Parajuli 2010; Parajuli et al. 2013, 2016). In addition, lack of field measured weather data in the watersheds can make ET estimation process complex. While field measured ET data are lacking, RS data can be utilized in the model to estimate ET. This study offers an important addition to the existing literatures to evaluate the SWAT model streamflow and ET calibration based on remote sensing derived ET data. Four modeling scenarios were developed for the SWAT model simulation in this study. The specific objectives of this study was to compare SWAT model streamflow and ET calibration and validation using (i) default, (ii) stream flow only, (iii) MODIS ET only, and (iv) both stream flow and MODIS ET modeling scenarios, which are unique methods.

## 2 Material and Methods

### 2.1 Watershed and Model Use

The study area in this research is the Big Sunflower River Watershed (BSRW) which is located in the west central Mississippi, USA (Fig. 1). The watershed is located within the eleven Mississippi counties (Coahoma, Bolivar, Tallahatchie, Sunflower, Leflore, Washington, Humphreys, Sharkey, Issaquena, Yazoo and Warren). The watershed is dominated by agriculture with more than 72% croplands, primarily by corn and soybean crops. However other crops such as cotton, rice are also available in the watershed. Agricultural activities within the BSRW may have direct impact on the health or water quality of the Gulf of Mexico as it feeds the Mississippi River near Vicksburg, MS via the Sunflower and Yazoo Rivers.

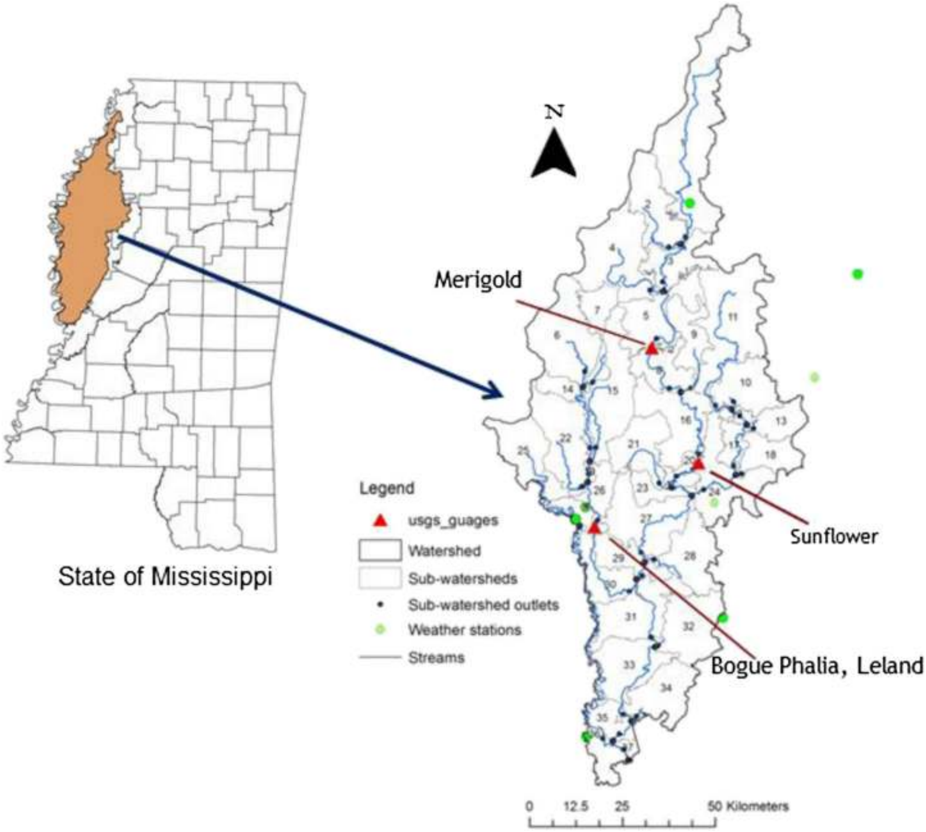



**Fig. 1** Big Sunflower River watershed showing USGS gages and sub-watersheds within the State of Mississippi

The SWAT model is a continuous, semi-distributed hydrological and water quality model with daily or sub-daily time scales, simulates surface runoff, sediment and nutrient yields, and crop yields from the agricultural watersheds (Arnold et al. 1998; Neitsch et al. 2011). The SWAT considers watershed, sub-watersheds, and hydrological responsive units (HRUs) as various spatial units in the model. The HRUs are lumped land areas in the watershed sub-basins, which consist of unique soil, land cover, and management conditions in the model (Neitsch et al. 2011). The SWAT model can be simulated in a daily, monthly, annually depending on need. Model calculates water yield, sediment yield, nutrient yield, lateral flow and groundwater flow, evapotranspiration, crop yield, and in-stream process of water quality parameters for each HRU in every sub-watersheds and the watershed outlet.

The SWAT model considers crop planting and harvesting, crop rotations, tillage operations, irrigation management, and fertilizer application inputs as described by users in the model. The SWAT model in this modeling study used the curve number (CN) method to estimate surface runoff. The SWAT model utilized Environmental Policy Integrated Climate (EPIC) model within the SWAT to estimate crop growths, potential heat units, hydrological parameters including ET (Neitsch et al. 2011). The detailed SWAT model sub-routine descriptions are available in the theoretical documentation (Neitsch et al. 2011).

## 2.2 Model Input and Modeling Scenarios

In this study rainfall and temperature data were utilized from seven weather stations in which six weather stations data were available from the National Climatic Data Center (NCDC 2013; Fig. 1) and one from the Delta Research and Extension Center (DREC) within the watershed (DAWC) 2012). This study utilized monthly stream flow data (2002 to 2009) from the Merigold, and Sunflower USGS gage stations available within the watershed. The soil data base in the SWAT model were created using Soil Survey Geographic Database (SSURGO) data (USDA 2005), which showed twelve major soils in the watershed. Primarily, fine-silty soil contributed about 62% of the watershed area (Parajuli et al. 2016). The USDA cropland data layer of 30 m by 30 m resolutions were utilized to generate land use data input in the model (USDA/NASS 2009). This study also utilized 30 m × 30 m pixel digital elevation model (DEM) data (USGS 2010) to delineate topographic characteristics of the watershed. Model inputs considered auto irrigation and auto fertilization only for corn crop. The common crop rotation in the watershed is corn after soybean crop rotation with conventional tillage (NASS 2013). The Penman Monteith equation was used to describe the potential evapotranspiration (PET) algorithms in the SWAT model (Neitsch et al. 2011). The MODIS data as carried by NASA's Terra and Aqua satellites was used for ET based model calibration (Mu et al. 2011).

Four modeling scenarios were considered for the hydrologic calibration of the SWAT model in this study. These modeling scenarios include: (i) SWAT model default scenario considered as a baseline condition after all inputs in the model representing the current watershed conditions, (ii) Flow-based modeling scenario considered calibration of flow related hydrological parameters in the model, (iii) ET-based modeling scenario considered use of Modis-based remote sensing ET data for hydrological calibration, and (iv) Flow-ET-based modeling scenario considered both flow-based and ET-based methods.

## 2.3 Streamflow Calibration and Validation

The SWAT-CUP SUFI-2 was used to automatically calibrate the SWAT model at the beginning (Abbaspour et al. 2007; Parajuli et al. 2013) then manually adjusted parameters to improve model performance. The SWAT model was calibrated and validated using monthly measured USGS stream flow data from the two USGS gage stations Merigold and Sunflower. In addition, to the twelve stream flow calibration parameters for the SWAT hydrologic model calibration as described in Parajuli et al. (2013); this study added two more parameters during refining model calibration. Therefore the total of fourteen hydrological parameters were selected for the model calibration. These parameters were curve number (cn2), base flow recession constant (alpha_bf), delay time for aquifer recharge (gw_delay), Manning's "n" value for the main channel (ch_n2), available water capacity (sol_awc), surface runoff lag coefficient (surlag), aquifer percolation coefficient (rchrg_dp), plant uptake compensation factor (epco), soil evaporation compensation factor (esco), revap coefficient (gw_revap), threshold water level in shallow aquifer in base flow (gwqmn), threshold water level in shallow aquifer for revap (revapmn), maximum canopy storage (canmx), and effective hydraulic conductivity in main channel alluvium (ch_k2). The canmx parameter was ranged from 0.00 to 100.00 with 2 as the final value considered during model calibration. Similarly, the ch_k2 parameter was ranged from 0.00 to 150.00 with 20 as the final value considered during model calibration. Model predicted outputs were statistically analyzed using Nash–Sutcliffe model efficiency index (NSE), and coefficient of determination (R2) based on previous literatures (Moriasi et al. 2007; Parajuli 2010; Parajuli et al. 2013; Kim and Parajuli 2014).

## 3 Results and Discussion

### 3.1 Monthly Stream Flow

The SWAT model predicted monthly stream flow values were calibrated and validated using eight years of monthly measured stream flow data from the Merigold and Sunflower USGS gage stations. The SWAT model simulation considered two years warm up period to improve hydrologic predictions. Monthly measured stream flow data from the Merigold, and Sunflower from January 2002 to December 2005 were used to calibrate the SWAT model, and data from January 2006 to December 2009 were used to validate the SWAT model (Table 1). The statistics of the model performance demonstrated the R2 values up to 0.86 and NSE values up to 0.83 in both Merigold and Sunflower gage stations (Table 1).

Monthly measured USGS mean stream flow at Merigold, and Sunflower were 24.1 $m^3\ s^{-1}$, and 32.4 $m^3\ s^{-1}$ respectively during the model calibration and validation period. The SWAT default modeling scenario over-estimated monthly mean stream flows in both the Merigold and Sunflower gage stations. The SWAT model default modeling scenario simulated monthly mean stream flow of 35 m3 s-1 at Merigold (~45% over-prediction, R2 and NSE from 0.39 to 0.78), and 47.5 m3 s-1 at Sunflower (~46% over-prediction, R2 and NSE from 0.42 to 0.78) gage stations within the watershed (Table 1, Figs. 2 and 3).

The SWAT model flow only modeling scenario simulated monthly mean stream flow of 26.9 m3 s-1 at Merigold (~11% over-prediction, R2 and NSE from 0.78 to 0.86), and 36.5 m3 s-1 at Sunflower (~13% over-prediction, R2 and NSE from 0.72 to 0.86) gage stations within the watershed (Table 1, Figs. 2 and 3).

The SWAT model ET only modeling scenario simulated monthly mean stream flow of 28.0 m3 s-1 at Merigold (~16% over-prediction, R2 and NSE from 0.75 to 0.82), and 38.4 m3 s-1 at Sunflower (~19% over-prediction, R2 and NSE from 0.71 to 0.79) gage stations within the watershed (Table, Figs. 2 and 3). The SWAT model both flow and ET modeling scenario simulated monthly mean stream flow of 27.0 m3 s-1 at Merigold (~12% over-prediction, R2 and NSE from 0.69 to 0.81), and 36.9 m3 s-1 at Sunflower (~14% over-prediction, R2 and NSE from 0.66 to 0.83) gage stations within the watershed (Table 1, Figs. 2 and 3).

**Table 1** Model calibration and validation efficiencies for Merigold and Sunflower stations with different modeling scenarios

| Modeling scenarios | Merigold | | Merigold | | Sunflower | | Sunflower | |
|---|---|---|---|---|---|---|---|---|
| | Calibration | | Validation | | Calibration | | Validation | |
| | $R^2$ | NSE | $R^2$ | NSE | $R^2$ | NSE | $R^2$ | NSE |
| Default | 0.78 | 0.39 | 0.78 | 0.44 | 0.74 | 0.52 | 0.78 | 0.42 |
| Flow only | 0.84 | 0.78 | 0.86 | 0.80 | 0.78 | 0.72 | 0.86 | 0.81 |
| ET only | 0.82 | 0.80 | 0.78 | 0.75 | 0.79 | 0.78 | 0.75 | 0.71 |
| Flow & ET | 0.77 | 0.69 | 0.81 | 0.79 | 0.73 | 0.66 | 0.83 | 0.81 |

*ET*, evapotranspiration; $R^2$, coefficient of determination; *NSE*, Nash-Sutcliffe Efficiency Index

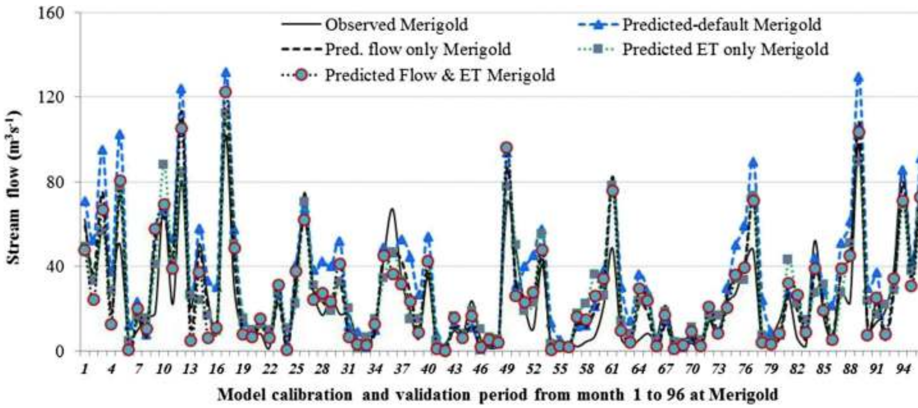



**Fig. 2** Model calibration and validation with four stream flow modeling scenarios at Merigold gage station

Based on monthly mean stream flow prediction, the SWAT model flow only scenario had the closest match with the USGS measured monthly mean stream flow during model calibration and validation as followed by both flow and ET stream flow modeling scenario, ET only stream flow modeling scenario and default stream flow modeling scenario. However, based on model efficiency (R2 and NSE) values ET only stream modeling scenario (R2 and NSE from 0.74 to 0.78) was equally good as flow only stream flow modeling scenario (R2 and NSE from 0.71 to 0.82) during model calibration and validation for monthly mean stream flow at Merigold and Sunflower USGS gage stations.

### 3.2 Evapotranspiration

In this study, spatial distribution of the MODIS-based ET on surface energy balance was utilized as an observed data as similar to previous studies (Venturini et al. 2007; Mu et al. 2011) to compare with SWAT model simulated ET outputs. The MODIS-based ET data was compared with the SWAT model simulated ET outputs for the prior model calibration and validation period from January 2002 to December 2009. The SWAT model simulation

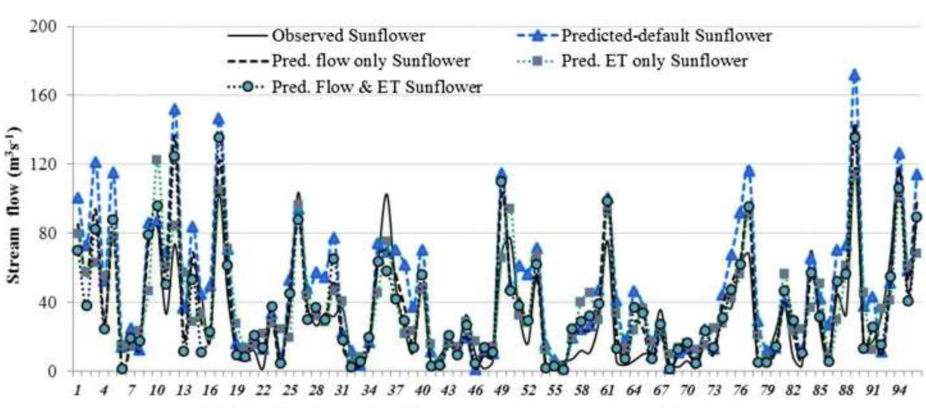



**Fig. 3** Model calibration and validation with four stream flow modeling scenarios at Sunflower gage station

**Table 2** Model calibration and validation efficiencies for the watershed with four ET modeling scenarios

| Modeling scenarios | Calibration | | Validation | |
|---|---|---|---|---|
| | $R^2$ | NSE | $R^2$ | NSE |
| Default ET | 0.71 | 0.28 | 0.70 | 0.27 |
| Flow-based ET only | 0.56 | −0.34 | 0.50 | −0.38 |
| ET-based ET only | 0.61 | 0.50 | 0.63 | 0.60 |
| Flow-ET-based ET | 0.68 | 0.50 | 0.72 | 0.60 |

*ET*, evapotranspiration; $R^2$ , coefficient of determination; *NSE*, Nash-Sutcliffe Efficiency Index

considered default ET, flow-based ET only, ET-based ET only, and flow-ET-Based ET modeling scenarios in this study. The statistics of the model predicted four modeling scenarios in Table 2 below showed the $R^2$ values up to 0.72 and NSE values up to 0.60 during model calibration and validation. The model performance in this study showed reasonable results as supported by previous studies (Venturini et al. 2007; Gamage et al. 2011; Bowman et al. 2015).

The average monthly MODIS-based ET for the model calibration and validation period (January 2002 to December 2009) was 46.8 mm. In this study, the SWAT model generally over-predicted ET in all modeling scenarios as compare to MODIS-based ET (Fig. 4). The default ET predicted average monthly ET of 59.8 mm (27.5% over-predicted), flow-based ET predicted average monthly ET of 69.1 mm (47.3% over-prediction), the ET-based ET predicted average monthly ET of 50.8 mm (8.4% over-prediction), and flow-ET-based ET predicted average monthly ET of 54.6 mm (16.5% over-prediction).

The SWAT model simulated annual average ET, water yield (WYLD) and precipitation outputs from 2002 to 2009 (Fig. 5). Water yield is generally estimated annually is a mean water depth in mm that leave from the watershed to the stream. Water yield in fact is a sum of surface flow, lateral flow, and ground water flow subtracted from the transmission loss including pond abstractions as described in the SWAT model documentation (Neitsch et al. 2011). Annual average precipitation values were determined generally greater than ET and WYLD values. However, average annual precipitation values for 2003, 2005 and 2007 were slightly lower than combined ET and WYLD values (Fig. 6).

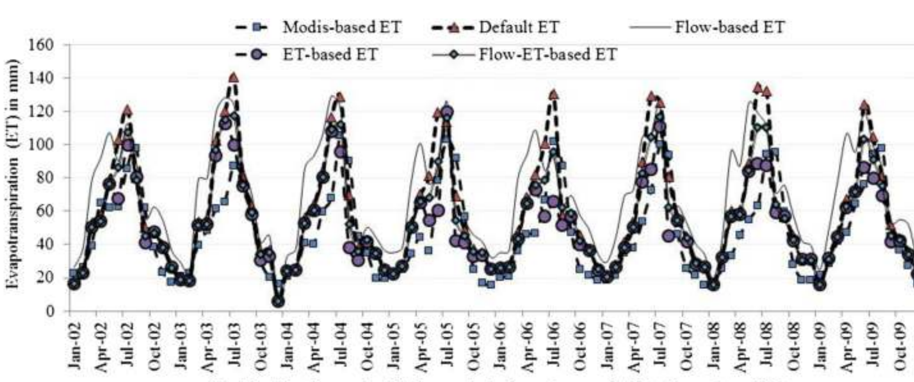



**Fig. 4** Simulated evapotranspiration (ET) with four ET modeling scenarios from the watershed

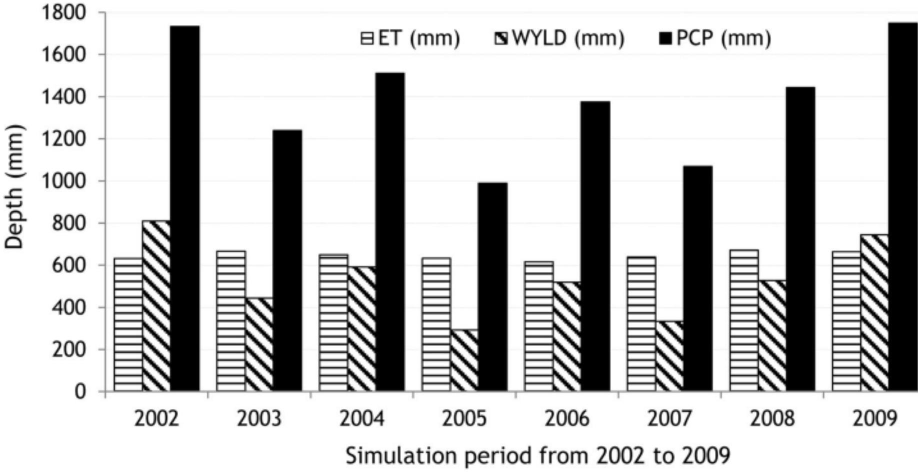



**Fig. 5** Simulated evapotranspiration (ET), water yield (WYLD), and precipitation (PCP) outputs in mm

Annual mean water balance was calculated by subtracting annual mean rainfall with the sum of ET and WYLD. The calculated annual mean water balance for the watershed during the model calibration and validation period (2002 to 2009) determined mostly greater with a positive values with 1.04% for default, 3.39% for flow only, 15.75% for ET only, and 14.31% for flow-ET modeling scenarios. However, annual mean water balance values were calculated slightly lower with a negative values for the individual years of 2003 by 65 mm, 2005 by 98 mm, and 2007 by 15 mm only with the default modeling scenario (Fig. 6). However, model simulated average annual water balance with slightly low negative values for 2003 by10 mm, 2005 by 57 mm, and 2007 by 2 mm only with flow only modeling scenario. It is possible to have a continuation of ET and WYLD processes, when there is no rainfall or more ET losses than rainfall due to other climatic factors including solar radiation (Hanson 1991). The SWAT model also permits movement of water from the bank storage into an unsaturated area to fulfill

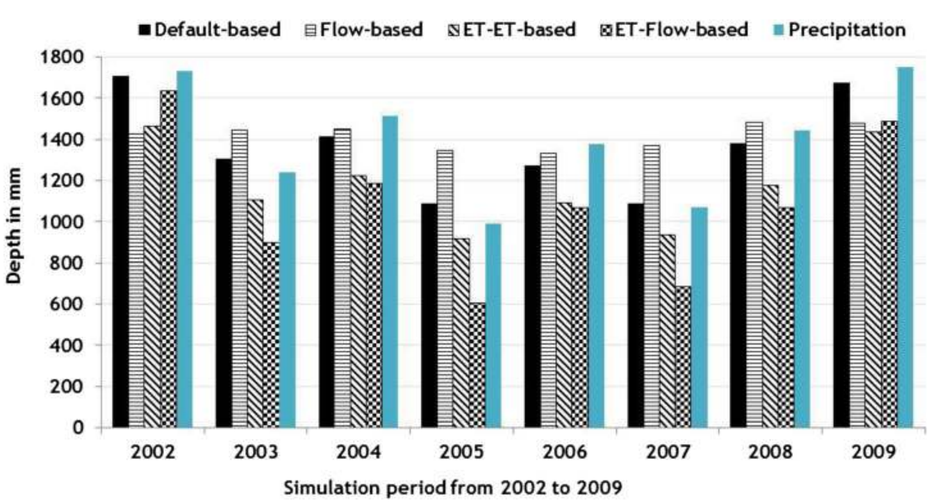



**Fig. 6** Comparison of simulated sum of water yield and evapotranspiration with precipitation for four modeling scenarios from the watershed

the water demand for ET, which is considered as “revap” process in the model (Neitsch et al. 2011). The revap process can be significant in the watershed like the BSRW, where deep-rooted plants are growing due to corn and soybean cropping system and saturated zones are not very far below the surface.

## 4 Conclusions

The SWAT hydrological model was calibrated and validated within the BSRW using monthly stream flow data from the two USGS gage stations and four modeling scenarios with the default, flow only, ET only, and flow-ET scenarios. The flow only and flow-ET modeling scenarios showed equally consistent model performances for both coefficient of determination (R2 from 0.66 to 0.87) and Nash Sutcliffe Efficiency (NSE from 0.59 to 0.84), followed by ET only (R2 and NSE from 0.74 to 0.78) and default (R2 and NSE from 0.33 to 0.78) scenarios during model calibration and validation at Merigold and Sunflower gage stations within the watershed.

This study used Modis-based ET data to compare the SWAT model simulated ET outputs with four modeling scenarios with the default, flow only, ET only, and flow-ET scenarios. The SWAT model generally over-predicted ET in all four modeling scenarios as compare to Modis-based ET. Out of four modeling scenarios, the ET-based ET predicted the closest average monthly ET (~8% over-predicted) followed by flow-ET (~16%), default (~27%), and flow based (~47%) ET scenarios. As discussed, the ET-based modeling scenario also had consistently good model performance on monthly streamflow simulation from both Merigold and Sunflower gage stations with R2 and NSE values from 0.74 to 0.78. This study demonstrated use of Modis-based remote sensing data to evaluate calibration and validation of hydrological model SWAT and ET, which can be applied in the watershed with the lack of meteorological data.

**Acknowledgements** We would like to acknowledge the partial financial support of AFRI competitive grant award # 2013-67020-21407 and 2017-67020-26375, from the USDA/NIFA; and Special Research Initiatives of the Mississippi Agricultural and Forestry Experiment Station at Mississippi State University. We would like to acknowledge the support of Yazoo Mississippi Delta Joint Water Management District; USGS; and all our collaborators.

## References

Abbaspour KC, Yang J, Maximov I, Siber R, Bogner K, Mieleitner J, Zobrist J, Srinivasan R (2007) Modeling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. J Hydrol 333:413–430

Arnold JG, Srinivasan P, Muttiah RS, Williams JR (1998) Large area hydrologic modeling and assessment. Part I. Model development. J Am Water Resour Assoc 34:73–89

Asner GP, Lobell DB (2000) A biogeophysical approach for automated SWIR un-mixing of soils and vegetation. Remote Sens Environ 74:99–112

Bastiaanssen WGM, Menenti M, Feddes RA, Holtslag AM (1998) A remote sensing surface energy balance algorithm for land (SEBAL)-formulation. J Hydrol 212–213:198–212

Bowman AL, Franz KJ, Hogue TS, Kinoshita AM (2015) MODIS-Based Potential Evapotranspiration Demand Curves for the Sacramento Soil Moisture Accounting Model. J Hydrol Eng 21(1):04015055–1-13

Broxton PD, Zeng X, Scheftic W, Peter AT (2014) A MODIS-based global 1-km maximum green vegetation fraction dataset. Am Meteorol Soc 53:1996–2004

Cho KH, Pachepsky YA, Kim JH, Kim JW, Park MH (2012) The modified SWAT model for predicting fecal coliforms in the Wachusett reservoir watershed, USA. Water Res 46(15):4750–4760
Christensen NS, Wood AW, Voisin N, Lettenmaier DP, Palmer RN (2004) The effects of climate change on the hydrology and water resources of the Colorado River basin. Clim Chang 62:337–363
Daggupati P, Pai N, Ale S, Douglas-Mankin KR, Zeckoski R, Jeong J, Parajuli PB, Saraswat D, Youssef MA (2015) A recommended calibration and validation strategy for hydrologic and water quality models. Trans Am Soc Agric Biol Eng 58(6):1705–1719
Dakhlalla AO, Parajuli PB (2016) Evaluation of the best management practices at the watershed scale to attenuate peak streamflow under climate change scenarios. Water Resour Manag 30(3):963–982
Dakhlalla AO, Parajuli PB, Ouyang Y, Schmitz DW (2016) Evaluating the impacts of crop rotations on groundwater storage and recharge in an agricultural watershed. Agric Water Manag 163:332–343
Delta Agricultural Weather Center (DAWC) (2012) Delta research and extension center, Mississippi State University, Stoneville. Available at: http://www.deltaweather.msstate.edu/. Accessed 5 Jan 2015
Doherty J. (2005) PEST: model independent parameter estimation 5th ed. Brisbane: watermark numerical Computing
Drexler J, Snyder R, Spano D (2004) A review of models and micrometeorological methods used to estimate wetland evapotranspiration. Hydrol Process 18(11):2071–2101
Ficklin D, Luo Y, Luedeling E, Zhang M (2009) Climate change sensitivity assessment of a highly agricultural watershed using SWAT. J Hydrol 374(1–2):16–29
Gamage N, Smakhtin V, Perera BJC (2011) Estimation of actual evapotranspiration using remote Sensing data. 19th International congress on modelling and simulation, Perth, Australia, 12–16 December 2011
Gao Y (2008) Intercomparison of remote sensing-based models for estimation of evapotranspiration and accuracy assessment based on SWAT. Hydrol Process 22(25):4850–4869
Hanson RL (1991) Evapotranspiration and droughts, in Paulson, RW, chase, EB, Roberts, RS, and moody, DW, compilers, National Water Summary 1988-89–hydrologic events and floods and droughts: U.S. Geol Surv Water-Supply Paper 2375:99–104
Hunt GE, Kandel R, Mecherikunnel AT (1986) A history of presatellite investigations of the earth's radiation budget. Rev Geophys 24:351–356
Hussey B, Odum W (1992) Evapotranspiration in tidal marshes. Estuar Coasts 15(1):59–67
Immerzeel WW, Droogers P (2008) Calibration of a distributed hydrological model based on satellite evapotranspiration. J Hydrol 349(3–4):411–424
Justice CO, Townshend JRG, Vermote EF, Masuoka E, Wolfe RE, Saleous N, Roy DP, Morisette JT (2002) An overview of MODIS land data processing and product status. Remote Sens Environ 83:3–15
Kannan N, White S, Worrall F, Whelan M (2007) Sensitivity analysis and identification of the best evapotranspiration and runoff options for hydrological modelling in SWAT-2000. J Hydrol 332(3–4):456–466
Kiehl JT, Trenberth KE (1997) Earth's annual global mean energy budget. Bull Am Meteorol Soc 78:197–208
Kim HK, Parajuli PB (2014) Impacts of reservoir outflow estimation methods in SWAT model calibration. Trans Am Soc Agric Biol Eng 57(4):1029–1042
Kim HK, Parajuli PB, Filip SD (2013) Assessing impacts of bioenergy crops and climate change on hydrometeorology in the Yazoo River basin, Mississippi. Agric For Meteorol 169:61–73
Korzun VI, Budyko MI, Sokolov AA, Voskresensky KP, Konoplyantsev AA, Kalinin GP (1978) Atlas of world water balance. USSR National Committee for the international hydrological decade. English translation. UNESCO, Paris
L'vovich MI, White GF (1990) Use and transformation of terrestrial water systems. In: Turner BL, Clark WC, Kates RW, Richards JF, Mathews JT, Meyer WB (eds) The Earth as Transformed by Human Action. Cambridge University Press, Cambridge, pp 235–252
Lirong S, Jianyun Z (2012) Hydrological response to climate change in Beijiang River basin based on the SWAT model. Procedia Eng 28:241–245
Lopez-Urrea R, Martin de Santa Olalla F, Fabeiro C, Moratalla A (2006) Testing evapotranspiration equations using lysimeter observations in a semiarid climate. Agric Water Manag 85(1–2):15–26
Los SO, Collatz GJ, Sellers PJ, Malmstroem CM, Pollack NH, DeFries RS, Bounoua L, Parris MT, Tucker CJ, Dazlich DA (2000) A global 9-year biophysical land surface data set from NOAA AVHRR data. J Hydrometeorol 1:183–199
Lucht W, Prentice IC, Myneni RB, Sitch S, Friedlingstein P, Cramer W, Bousquet P, Buermann W, Smith B (2002) Climatic control of the high-latitude vegetation greening trend and Pinatubo effect. Science 296: 1687–1689
Masih I, Maskey S, Uhlenbrook S, Smakhtin V (2011) Impact of upstream changes in rain-fed agriculture on downstream flow in a semi-arid basin. Agric Water Manag 100(1):36–45

Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL, Van Liew M (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans Am Soc Agric Biol Eng 50(3): 885–900

Moriasi DN, Gitau MW, Pai N, Daggupati P (2015) Hydrologic and water quality models: performance measures and evaluation criteria. Trans Am Soc Agric Biol Eng 58(6):1763–1785

Mu Q, Maosheng Z, Steven WR (2011) Improvements to a MODIS global terrestrial evapotranspiration algorithm. Remote Sens Environ 115:1781–1800

National Agricultural Statistics Service (NASS) (2013) Quick stats: agricultural statistics database. Washington, DC. Available at: http://www.nass.usda.gov/Quick_Stats/. Accessed 5 Jan 2015

National Climatic Data Center (NCDC) (2013) Climate Data Online. Available at: http://www.ncdc.noaa.gov/cdo-web. Accessed 15 Jan 2015

Neitsch SL, Arnold JG, Kiniry JR, Williams JR (2011) Soil and water assessment tool (SWAT), theoretical documentation, version 2009. Blackland Research Center: Temple

Overgaard J, Rosbjerg D, Butts M (2006) Land-surface modelling in hydrological perspective: a review. Biogeosciences 3(2):229–241

Parajuli PB (2010) Assessing sensitivity of hydrologic responses to climate change from forested watershed in Mississippi. Hydrol Process 24(26):3785–3797

Parajuli PB, Jayakody P, Sassenrath GF, Ouyang Y, Pote JW (2013) Assessing the impacts of crop rotation and tillage on crop yields and sediment yield using a modeling approach. Agric Water Manag 119:32–42

Parajuli PB, Jayakody P, Sassenrath GF, Ouyang Y (2016) Assessing the impacts of climate change and tillage practices on stream flow, crop and sediment yields from the Mississippi River basin. Agric Water Manag 168:112–124

Parasuraman K, Elshorbagy A, Carey S (2007) Modelling the dynamics of the evapotranspiration process using genetic programming. Hydrol Sci J 52(3):563–578

Parmesan C, Yohe G (2003) A globally coherent fingerprint of climate change impacts across natural systems. Nature 421:37–42

Payne JT, Wood AW, Hamlet AF, Palmer RN, Lettenmaier DP (2003) Mitigating the effects of climate change on the water resources of the Columbia River basin. Clim Chang 62(1–3):233–256

Pisinaras V, Petalas C, Gikas GD, Gemitzi A, Tsihrintzis VA (2010) Hydrological and water quality modeling in a medium-sized basin using the soil and water assessment tool (SWAT). Desalination 250(1):274–286

Potter C, Peggy G, Steven K, Matthew F, Vanessa G (2008) Storage of carbon in U.S. forests predicted from satellite data, ecosystem modeling, and inventory summaries. Clim Chang 90:269–282

Rosenberg NJ, Brown RA, Izaurralde RC, Thomson AM (2003) Integrated assessment of Hadley Centre (HadCM2) climate change projections on agricultural productivity and irrigation water supply in the conterminous United States. Part I: climate change scenarios and impacts on irrigation water supply simulated with the HUMUS model. Agric For Meteorol 117(1–2):73–96

Shrestha RR, Dibike YB, Prowse TD (2012) Modelling of climate-induced hydrologic changes in the Lake Winnipeg watershed. J Great Lakes Res 38(3):83–94

Stone MC, Hotchkiss RH, Hubbard CM, Fontaine TA, Mearns LO, Arnold JG (2001) Impacts of climate change on Missouri River basin water yield. J Am Water Resour Assoc 37(5):1119–1130

Tang R, Xia J, Zhang X, Yin X (2007) MODIS-based estimates of the regional evapotranspiration. Remote sensing for environmental monitoring and change detection. Proceedings of symposium HS3007 at IUGG2007, Perugia, July 2007. IAHS Publ 316, 2007

Thampi SG, Kolladi YR, Surya TV (2010) Influence of scale on SWAT model calibration for streamflow in a River Basin in the humid tropics. Water Resour Manag 24:4567–4578

U.S. Department of Agriculture (USDA) (2005) U.S. General soil map: Natural Resources Conservation Services. Available at: http://soildatamart.nrcs.usda.gov. Accessed 15 Jan 2013

U.S. Department of Agriculture, National Agricultural Statistic Services (USDA_NASS) (2009) Cropland data layer: Available at: http://www.nass.usda.gov. Accessed 15 Jan 2013

U.S. Geological Survey (USGS) (2010) National Elevation Dataset (NED): Available at: http://seamless.usgs.gov/ned1.php. Accessed 15 Jan 2013

Venturini V, Islam S, Rodriguez L (2007) Estimation of evaporative fraction and evapotranspiration from MODIS products using a complementary based model. Remote Sens Environ 112:132–141

Yuan Y, Khare Y, Wang X, Parajuli PB, Kisekka I, Finsterle S (2015) Hydrologic and water quality models: sensitivity. Trans Am Soc Agric Biol Eng 58(6):1721–1744

Zhang B, Kang S, Li F, Zhang L (2008) Comparison of three evapotranspiration models to Bowen ratio-energy balance method for a vineyard in an arid desert region of northwest China. Agric For Meteorol 148(10): 1629–1640

Zhou L, Zhou G (2009) Measurement and modelling of evapotranspiration over a reed (Phragmites Australis) marsh in Northeast China. J Hydrol 372(1–4):41–47