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Article

Comparison of SWAT and MODIS Evapotranspiration Data for Multiple Timescales

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Abstract: Evapotranspiration (ET) provides important information for hydrological studies, including estimating plant water requirements which can be derived from remote sensing data or simulated using hydrological models. In this study, ET derived from the Moderate Resolution Imaging Spectrometer (MODIS) was compared with ET simulated by the calibrated and validated Soil and Water Assessment Tool (SWAT) model for the Big Sunflower River watershed (BSRW) in Mississippi. The comparisons were made based on 8-day, 1-month, seasonal, and annual timescales. The coefficients of variation (COVs) for the 8-day, 1-month, seasonal, and annual ET simulated by SWAT were 0.42, 0.40, 0.32, and 0.04, respectively, whereas the COVs for the ET derived from MODIS were 0.06, 0.12, 0.08, and 0.01 for the respective time scales. Lower COVs for the ET derived from MODIS indicated lower sensitivity to crop growth in the field. SWAT-simulated ET was the highest during crop growing season and lowest during dormant season, but MODIS-derived ET did not vary considerably according to crop growing or harvesting seasons. As MODIS-derived ET accounts for only climatic conditions and vegetation cover, SWAT-simulated ET is recommended for the short-term estimation of crop water requirements because it accounts for climatic, land use, soil, and slope conditions.

Keywords: MODIS; evapotranspiration; remote sensing; SWAT; water balance

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1. Introduction

About 60% of the water received by the earth's surface in the form of precipitation is transferred back to atmosphere through the evaporation process from the soil and water surfaces and the transpiration process from plants in the hydrologic cycle [1,2]. This combined process of soil-moisture/surface-water evaporation and plant transpiration is referred to as evapotranspiration (ET). ET is an important component of the hydrologic system as it accounts for moisture lost by both plants and the land surface to the atmosphere [3]. Thus, like precipitation and runoff, ET is also one of the basic driving factors of the water balance and is a key component of the hydrologic cycle since it has a vital role in energy–moisture exchanges between the earth and the atmosphere [4–6]. Estimation of ET is very essential for the evaluation of the water consumption requirements for different crops and the management of agricultural watersheds. In general, rates of ET are measured using ground-based measuring devices, such as large-aperture scintillometers [7] and lysimeters [8]. When such ground-based ET measurements are not available, ET rates are either estimated from climate and land surface data using modeling techniques or derived directly from remote sensing data [9]. Since ground-based measuring methods are very cost intensive and limited to a specific place and time, modeling techniques and remote sensing data analysis are the most effective methods for estimating ET at local, regional, or global levels. Main sources of ET data include global remote sensing data that may be available in various spatial/temporal resolutions, data derived using different surface energy balance models, and data derived from simulation by different hydrologic models [10,11]. Remotely sensed ET mostly depends on soil and land-use type, whereas ET values simulated by hydrologic models mostly depend on groundwater availability and weather input [12].

The Soil and Water Assessment Tool (SWAT) employs three ET methods, namely the Penman–Monteith, the Priestley–Taylor, and the Hargreaves methods to calculate ET. All these methods require different climatologic inputs, such as the maximum and the minimum air temperature, solar radiation, relative humidity, wind speed, etc. Some methods require fewer inputs, while others require a greater number of climatic inputs. Among these methods, the Penman–Monteith method [13] was used in this study. The SWAT model has been extensively used all around the world in the estimation of ET [12–14]. SWAT was calibrated for ET using remotely sensed ET data obtained from the MODIS and Global Land Evaporation Amsterdam Model (GLEAM) and validated using soil moisture data obtained from European Space Agency Climate Change Initiative in Nigeria [15]. Similarly, ET data obtained from GLEAM were used to improve the model performance for streamflow simulation in one of the gauged basins with some missing data in Kenya and Tanzania [16]. SWAT was calibrated using area-weighted remotely sensed ET data, along with observed streamflow, which showed improved ET-based model calibration but had no effect on streamflow output [12]. Although it is desirable to calibrate the model for ET, calibration for longer periods using remotely sensed ET data can impose propagated error on the model output [17]. The previous studies have directly used remotely sensed ET data, as observed data, for model calibration and validation [12,16,18].

Although remotely sensed ET data are easily accessible to download from various sources, these data should not be considered true since they have a lot of uncertainties due to the misinterpretation of the models, types of input, differences in scale and temporal/spatial resolution, and data coverage [19,20]. For the continental United States, the uncertainty in ET data due to vegetation fractional cover ranged from around 6% to 31%, that due to the Leaf Area Index ranged from around 2% to 14%, that due to surface temperature ranged from around 4% to 34%, and that due to net radiation ranged from around 4% to 18% [21].

Since ET has an important part in maintaining the water balance, hydrologic models must be calibrated not only for streamflow but also for ET [12]. Higher resolution remotely sensed data, along with data from monitoring sites, can be helpful in the more precise evaluation of hydrologic conditions [22]. Remotely sensed ET data has been used by various researchers around the world to improve discharge simulation, flood forecasting, and agricultural yield simulation [23,24]. However, remotely sensed ET data have some uncertainties due to fractional vegetative cover, model falsifications, coverage, and inputs [20]. If these remotely sensed ET data are used without much care, it can lead to propagated error in model simulations [18]. Therefore, the remotely sensed ET must be carefully evaluated and compared with other sources before applying them in estimating water resources. Relative accuracy of the data obtained from different sources should be extensively explored to improve the understanding of ET estimation. ET estimated by single and double source models like SEBAL, SEBS, P-TSEB, and S-TSEB using remotely sensed data were compared to examine their utilities and limitations under a wide range of land cover conditions, where S-TSEB was found to have the highest accuracy with reference to SWAT-based ET [25]. Two satellite-based ET (MODIS and AVHRR) were compared with SWAT-simulated ET for in the watersheds in Ethiopia, which showed that AVHRR ET better agreed with SWAT-simulated ET than MODIS ET [20]. MODIS ET of various spatial resolutions were compared with SWAT ET for one of the watersheds in Australia, which showed that the difference between the MODIS and SWAT ET were 31, 19, 15, 11, and 9%, respectively, for 1, 4, 9, 16, and 25 km^2 spatial resolutions [4].

In this study, ET simulated by SWAT and derived from the MODIS [26] aboard the National Aeronautics and Space Administration (NASA) Terra satellite are compared.

MODIS-ET data are available for each 8-day interval. Since ET estimation is also linked to crop water requirement sand crop growth, it may not be accurate to evaluate the performance of crop growth in the 8-day interval. Thus, evaluation of monthly and yearly ET needs to be performed to observe the effect of ET on crop growth. Crop yield can be better analyzed according to season; the evaluation of seasonal ET is therefore beneficial for the evaluation of ET effects on crop yield. The main goal of the study is to compare SWAT-estimated ET with MODIS-derived ET for the study area and gain a better understanding of the difference between them. Moreover, the goal of the study is to also analyze the possible causes of these differences. Although the MODIS ET product has been widely studied and compared with other ET methods, such as energy balance and hydrologic models, SWAT ET has not been compared with MODIS ET for the different timescales for this watershed. This study evaluated the hypothesis that SWAT-simulated ET can capture seasonal variation in comparison to MODIS-derived ET by comparing these two datasets for the BSRW using statistics such as mean, standard deviation, COV, and coefficient of variation (R^2).

The specific objectives of this study were to: (a) simulate and develop time series for SWAT-simulated and MODIS-derived ET data for the BSRW sub-basins; (b) compare the ET estimated by SWAT with ET derived by MODIS for 8-day, 1-month, seasonal, and annual timescales; and (c) discuss the possible causes of the differences in ET derived from MODIS and simulated by SWAT.

2. Materials and Methods

2.1. Study Area

The BSRW, located in the northwestern part of Mississippi (Figure 1) and having drainage area of about 10,500 km^2, was selected for this study. The watershed has a plain topography with maximum slope of 1% in south and 3% in north [27]. The major soil types found in the watershed were Sharkey, Dowling, Forestdale, Alligator, and Dundee, having higher percentages of clay and silt. Moreover, about 70% of the watershed area is covered by agricultural fields with good vegetation that are utilized by modeling algorithms to estimate ET [28].

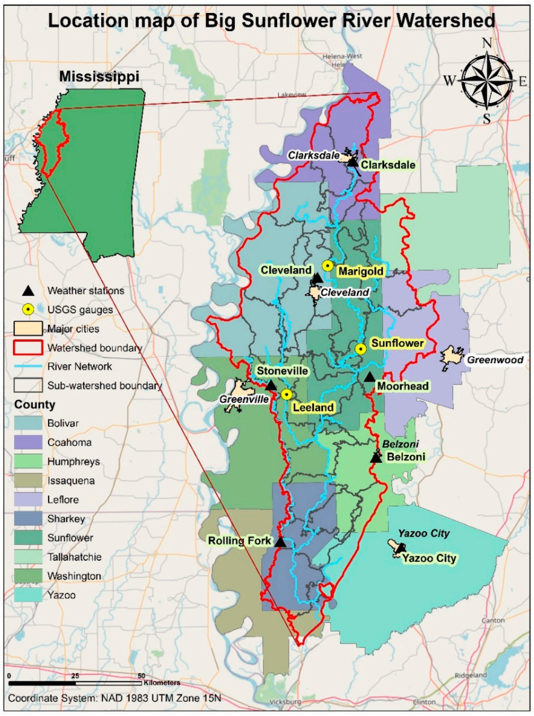

Figure 1. Location of study area: Big Sunflower River watershed, showing weather stations, USGS gauge stations, major cities, counties, sub-watershed, and river network.

2.2. Climate of the Study

Average annual rainfall received by the watershed area was 1371 mm and the average annual temperature was 18°C [29,30]. The watershed received the highest rainfall during the month of March with an average monthly precipitation of 219 mm and lowest rainfall during September with average monthly precipitation of 70 mm (Figure 2). The mean monthly maximum temperature from June to September was very high, in the range 31–33 °C, and the mean monthly minimum temperature from November to February was very low, in the range 0–4 °C (Figure 2). Only 30% of annual rainfall occurred during the period from May to September, which is the growing season for crops in the BSRW.

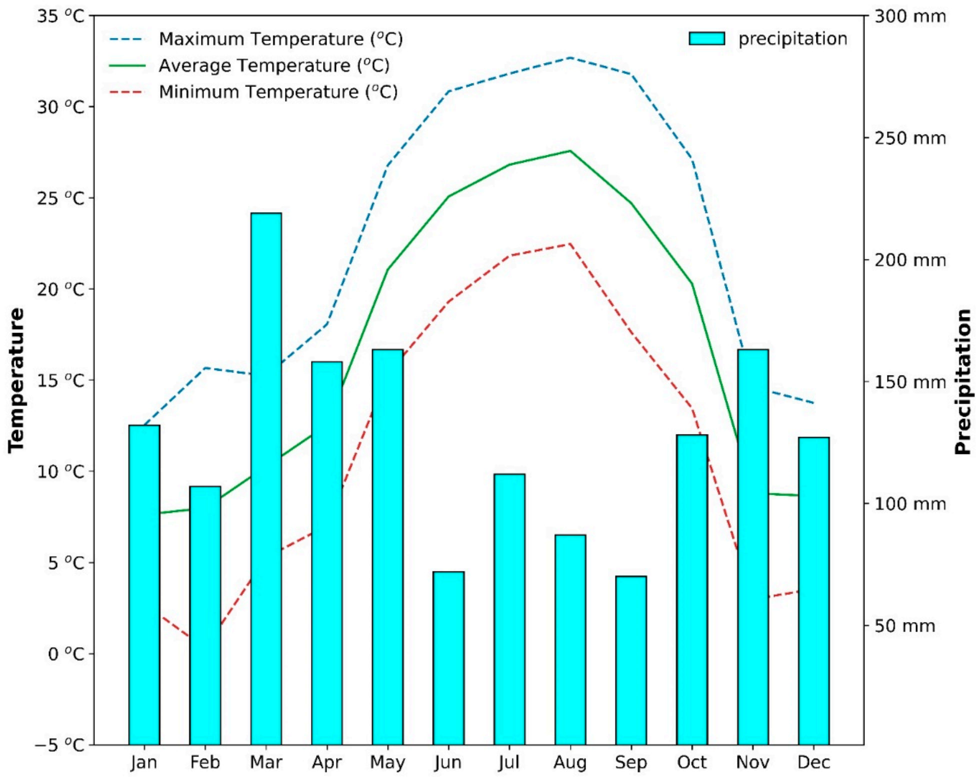

Figure 2. Average monthly minimum, maximum, and average temperature, and precipitation in Big Sunflower River watershed.

2.3. Evapotranspiration Data

MODIS Global Terrestrial Evapotranspiration ET data (MOD16A2) of 1-kilometer spatial resolution, similar to other studies [2,20,26], was downloaded for 8-day intervals for the 109.03 million square kilometers of global vegetated land areas [31]. The algorithm of MOD16 for ET estimation was based on the Penman–Monteith equation using daily meteorological reanalysis data and with MODIS data products such as vegetation property dynamics, albedo, and land cover, and the ET value for each pixel was sum of all 8-day intervals [31]. MODIS 16A2 from 2010 to 2018 was obtained from the USGS-Global Visualization (GLOVIS) portal [32]. Among 300 available global land tiles, tile h10v05 (horizontal tile: 10 and vertical tile: 5), where BSRW falls, was downloaded.

2.4. Generation of Sub-Basin Wise ET Timeseries

8-day interval ET data from 01/01/2010 to 12/27/2018 for tile h10v05 were used to generate a time series of 8-day average ET data for each sub-basin of BSRW using a GIS model builder in ArcGIS 10.7. The 8-day interval MODIS ET data were downloaded and placed in a folder. The "Iterate Raster" function was applied to pick one ET raster at a time and provide input to "Zonal Statistics as Table" tool, which also takes input of sub-basin layer of BSRW to develop average ET data for each BSRW sub-basin. Average ET values for each BSRW sub-basin at 8-day intervals were appended in a new database file (.dbf), which was further processed to obtain time-series average ET data for each sub-basin of BSRW. A schematic diagram of model to generate sub-basin-wise time-series of average ET data is given in Figure 3.

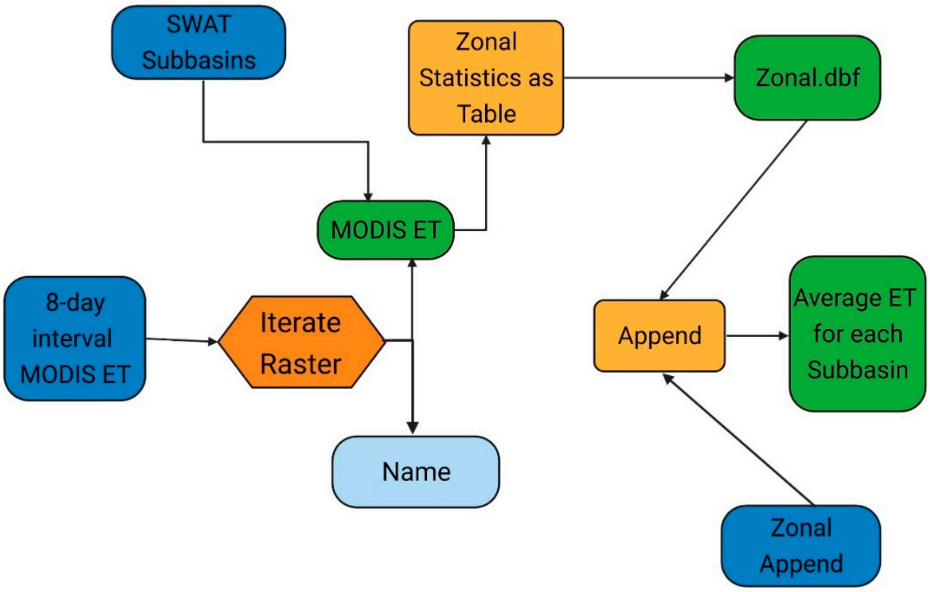

Figure 3. GIS-based model schematic to obtain average sub-basin-level MODIS evapotranspiration data for the watershed.

2.5. SWAT Model

The SWAT is a watershed scale model which is based on water balance concept that can predict impact of land management on hydrology and water quality [33,34]. SWAT can simulate runoff, sediment, nutrient, pesticide, and fecal bacteria loads using inputs such as topography, soils, land-use/land-cover, weather, fertilizers, manures, point-source pollutants, and management practices adopted [34]. Spatial inputs, such as Digital Elevation Model (DEM) data of 30 meters resolution, were obtained from United States Geologic Survey [35]; soil data (SSURGO) were obtained from USDA Natural Resource Conservation Service [36], and land-use/land-cover data were obtained from USDA National Agricultural Statistics Service [37]. Similarly, daily time series of weather data, such as precipitation, maximum and minimum temperature, relative humidity, solar radiation, and wind speed for six weather stations within BSRW were obtained from NOAA [38]. Major crops cultivated in the BSRW are soybean and cotton [39]. The data on planting and harvesting, tillage, fertilization, irrigation, and other management operations for cotton and soybean were obtained from MAFES [40].

2.6. SWAT Model Setup

The sub-watersheds and drainage network for the BSRW were delineated using DEM in Arc-SWAT interface. BSRW sub-watersheds were further divided into multiple Hydrologic Response Units (HRU), the smallest unit consisting of similar land use, soil, and slope for the land use and soil type information. The SCS curve number method was used for the estimation of surface runoff and Penman–Monteith method was used to estimate ET considering air temperature, relative humidity, solar radiation, and wind speed [41,42]. Since ET data in SWAT model was predicted using meteorological data obtained from limited weather stations, their evaluation with remotely sensed ET was necessary.

The crop growth and yield in SWAT was simulated using the plant growth module based on the concept of Environmental Policy Impact Climate" (EPIC) model [43].The annual crop schedule, including tillage, plantation, fertilization, irrigation, and harvest for soybean crop is presented in Table 1.

Table 1. Annual crop schedules for soybean crops established in the Big Sunflower.

Date	Operation
April 26	Tillage
May 6	Planting
June 14	Auto-Irrigation
June 20	Auto-Fertilization
October 20	Harvest and Kill

2.7. SWAT Calibration and Validation

2.7.1. Hydrology

SWAT was calibrated and validated for streamflow at three USGS gauge stations within the BSRW using flow data obtained from Marigold, Sunflower, and Leland. Sequential Uncertainty Fitting (SUFI-2) algorithm in SWAT Calibration and Uncertainty Procedures (SWAT-CUP) [44] was used for streamflow calibration. Observed monthly streamflow data from January 2012 to December 2015 were used for calibration, and data from January 2016 to December 2018 were used for validation. Nine parameters were used during calibration (Table 2), out of which CN2, GW_DELAY, SOL_AWC, and CH_N2 were the most sensitive parameters. More details of procedures for streamflow calibration and validation are available in previous paper [30].

Table 2. SWAT parameters used for the calibration of Streamflow at Marigold, Sunflower, and Leland gauge stations.

Parameter	Description	Minimum Value	Maximum Value
CH_N2.RTE	Manning's roughness coefficient for channel	0.2	0.4
CN2.MGT	Initial SCS runoff curve number	−40%	4%
GWQMN.GW	Threshold depth of water in the shallow aquifer for return flow	2376.1	7128.9
SURLAG.BSN	Surface runoff lag time	5.3	13.8
ALPHA_BF.GW	Base flow alpha factor	0.3	0.7
GW_DELAY.GW	Ground water delay	154.8	462.5
SOL_AWC.SOL	Available water capacity of soil layer	−26%	24%
GW_REVAP.GW	Groundwater re-evaporation coefficient	0.021	0.140
ESCO.HRU	Soil evaporation compensation factor	37%	112%

2.7.2. Crop Yield

Crop yields are one of the indicators of the amount of moisture and nutrient uptake by vegetation from the hydrological system. Soybean was one of the major crops cultivated in the BSRW, and crop yield was calibrated (2008–2018) for BSRW sub-basins using soybean yield data from Delta Branch Farms in Stoneville and validated (2008–2018) using Dulaney Farms in Clarksdale. The soybean-yield data were extracted from MAFES [40]. For the crop yield calibration, four parameters, as shown in Table 3, were adjusted.

Table 3. SWAT parameters used for the calibration of annual crop yield at Delta Branch Farms in Stoneville.

Parameter	Description	Calibrated Value	Default	Range
BIO_E	Radiation-use efficiency or Biomass-energy ratio (kg/ha)/(MJ/m^2)	30	39	30–39
HVSTI	Harvest index	0.35	0.50	0.30–0.50
WSYF	Lower limit of harvest index	0.25	0.30	0.25–0.35
BLAI	Maximum potential leaf area index	5	6	4–6

2.8. Comparison of SWAT Simulated and MODIS Derived ET

Differences in SWAT-simulated and MODIS-derived ET were mainly evaluated for the BSRW using coefficient of determination (R^2). Apart from this, mean, standard deviations, and COVs for each 8-day, monthly, seasonal, and yearly ET datasets were also analyzed. For seasonal analysis, only three seasons (spring (15 January–30 April), summer (1 May–14 September) and fall (15 September–14 January)) were considered, leaving out winter season because the climate of BSRW is characterized by very short duration of severe cold weather and the region does not have a winter season at all [38]. Comparison of long-term average monthly and seasonal ET for both datasets were also performed.

3. Results

3.1. SWAT Calibration and Validation

3.1.1. Streamflow Calibration and Validation

Monthly SWAT calibration (01/2008–12/2012) and validation (01/2013–12/2017) of streamflow, conducted at three USGS gauge stations (Marigold, Sunflower, and Leland) within the BSRW, showed that the model performances were reasonable in predicting streamflow [30,45]. After model calibration, SWAT-simulated streamflow at the outlet of sub-basins, when compared with the observed flow data at the respective gauging stations, yielded R^2 ranging from 0.73 to 0.79 and NSE ranging from 0.71 to 0.86 (Figure 4) [45]. The SWAT performance was considered as good based on the statistics obtained during calibration and validation, as per the recommendations from previous SWAT studies [46,47].

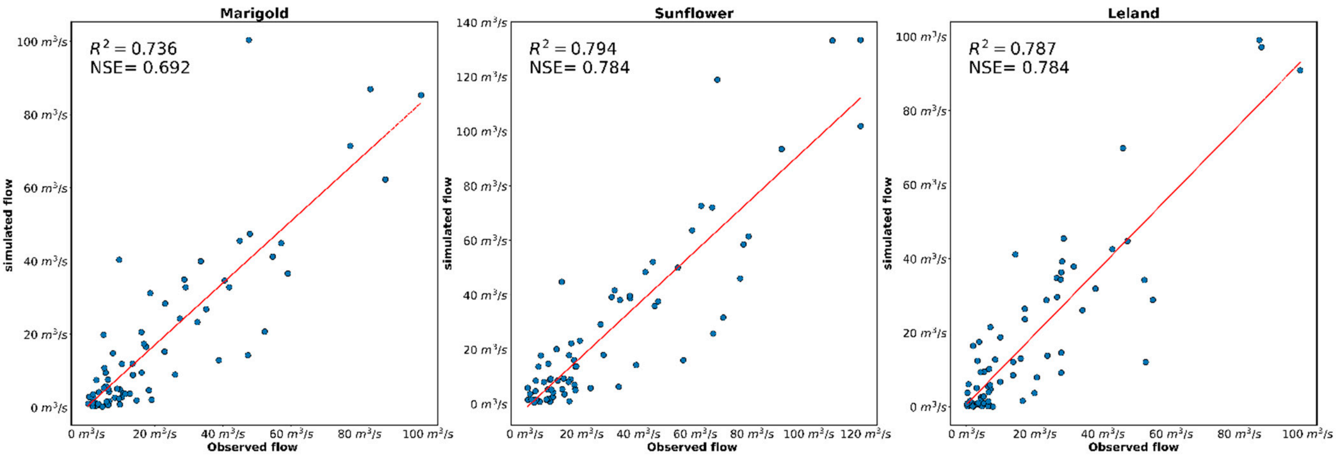

Figure 4. Comparisons of observed vs. simulated flow during model calibration and validation at Marigold, Sunflower, and Leland gauge stations.

3.1.2. Crop Yield Calibration and Validation

Soybean crop yield during model calibration (2008–2018) at Delta Branch Farms, Stoneville, showed that the model was capable of simulating crop yield satisfactorily. The R^2 value during model calibration was 0.55 and NSE was 0.45. Similarly, SWAT model validation (2008–2018) at Dulaney Farms, Clarksdale, showed good agreement with observed data with R^2 of 0.62 and NSE of 0.07 (Figure 5). The gradual increase in soybean yield was observed, possibly due to the planting of higher yielding soybean varieties and the adoption of proper management decisions, including but not limited to the adjustment of planting/harvesting dates, irrigation management, pest management, and nutrient management.

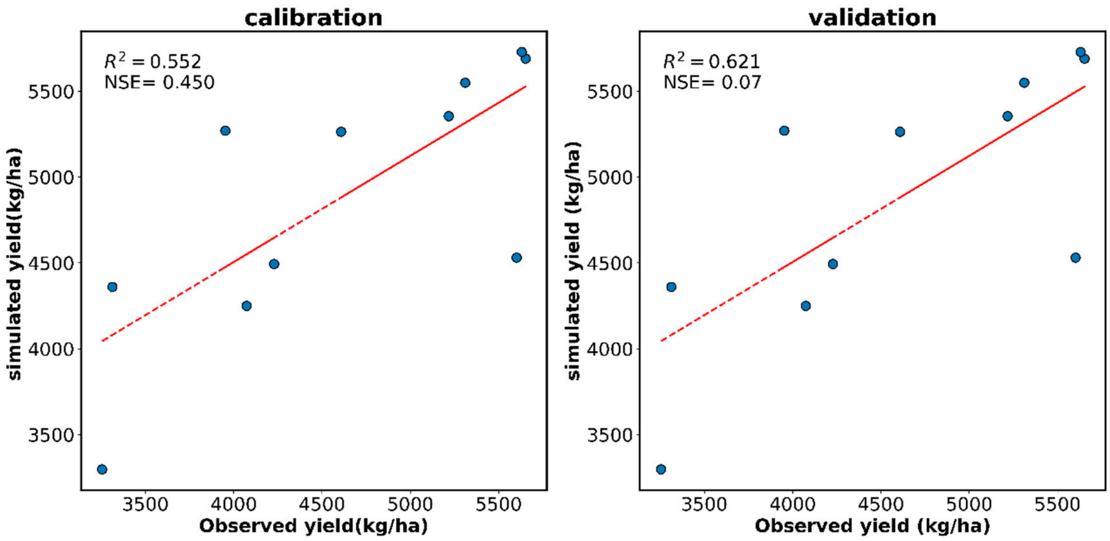

Figure 5. Comparison of observed vs. simulated annual soybean yield during model calibration and validation.

3.2. Comparison between SWAT-Simulated and MODIS-Derived ET

3.2.1. Eight-Day ET

Average 8-day ET for the BSRW, as simulated by the SWAT model, was 4.09 mm and that obtained from MODIS was 4.75 mm. Standard deviation and COV for SWAT-simulated 8-day ET were 1.72 mm and 0.42, respectively, and MODIS ET for the corresponding time period were 0.28 mm and 0.06. The R^2 obtained during comparison of 8-day SWAT-simulated and MODIS-obtained ET was 0.36. Comparison of 8-day SWAT-simulated ET and MODIS ET from 01/01/2010 to 12/27/2018 for the BSRW is presented in Figure 6.

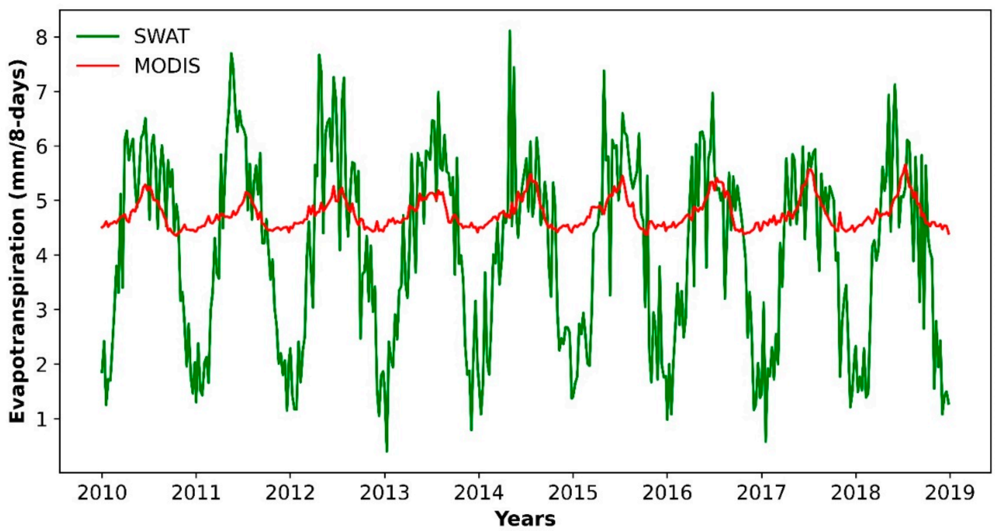

Figure 6. Comparison of 8-day SWAT-simulated vs. MODIS evapotranspiration data.

The maximum value of 8-day ET derived from MODIS was 5.66 mm while that simulated by SWAT was 8.11 mm. Similarly, the minimum value of MODIS-derived ET was 4.35 mm and that simulated by SWAT was 0.40 mm. SWAT simulated higher ET than MODIS during summer days but lower ET during winter days, possibly because SWAT accounts for both daily meteorological data (maximum and minimum air temperature, relative humidity, wind speed) and actual land surface conditions (land use, soil, and slope) for daily ET estimation, while MODIS accounts for only climatic data and remotely sensed vegetation cover data to estimate ET data for each 8-day interval [48].

3.2.2. Monthly ET

The mean monthly ET for BSRW, as simulated by SWAT, was 15.62 mm and that obtained from MODIS was 18.17 mm. The standard deviation and COV for SWAT-simulated monthly ET were 6.18 and 0.40, respectively, and that for MODIS-obtained monthly ET were 0.22 and 0.12, respectively. The R^2 obtained during comparison of monthly SWAT-simulated and MODIS-obtained ET was 0.21 (Figure 7).

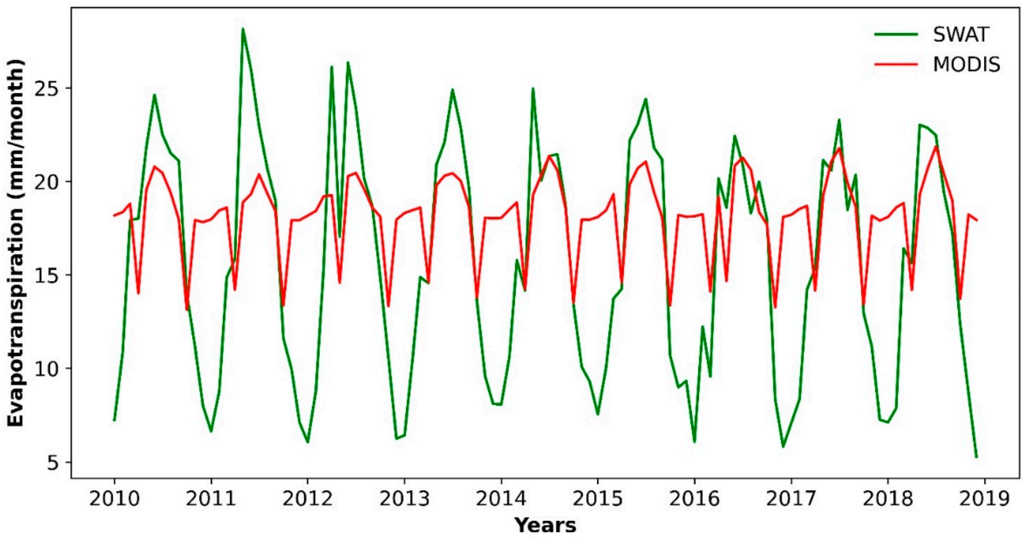

Figure 7. Comparison of monthly SWAT-simulated vs. MODIS evapotranspiration data.

The maximum value of MODIS-derived monthly ET was 22 mm (20% greater than mean monthly ET derived from MODIS) and the minimum value was 13 mm (27% less than mean monthly ET derived from MODIS). The maximum and minimum values of SWAT-simulated ET were 28 mm (80% greater than mean monthly ET simulated by SWAT) and 5 mm (66% less than mean monthly ET simulated by SWAT), respectively.

The long-term average monthly value of SWAT-simulated ET was maximum (23 mm per month) during June and July and was minimum during January (7 mm per month). The long-term average monthly value of MODIS ET during June was 21 mm (maximum) and 17 mm in November (minimum). Although the value of both SWAT-simulated and MODIS-derived ET varied according to months, more variability was seen in SWAT-simulated ET than in MODIS-derived ET (Figure 8).

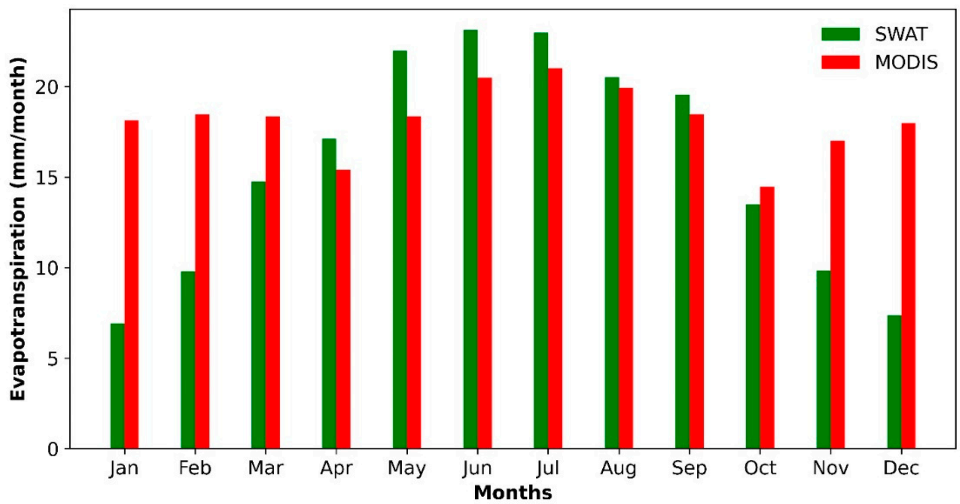

Figure 8. Comparison of long-term monthly SWAT-simulated vs MODIS evapotranspiration data.

Although the trend of both SWAT-simulated monthly ET and MODIS-derived monthly ET was similar, more fluctuations were observed for SWAT-simulated ET data. The SWAT model includes climatic data (maximum and minimum air temperature, relative humidity, wind speed) and actual land surface conditions (land use, soil, and slope) for ET estimation, while MODIS includes only climatic data and vegetation data [48].

3.2.3. Seasonal ET

The average value of SWAT-simulated ET for the period of 4 months was 63 mm and that obtained for MODIS was 73 mm. The standard deviation and COV for SWAT-simulated ET, averaged for four months, were 20 mm and 0.32, respectively, and that for MODIS-obtained seasonal ET were 6 mm and 0.08, respectively. The R^2 obtained during comparison of seasonal SWAT-simulated and MODIS-derived ET was 0.86 (Figure 9).

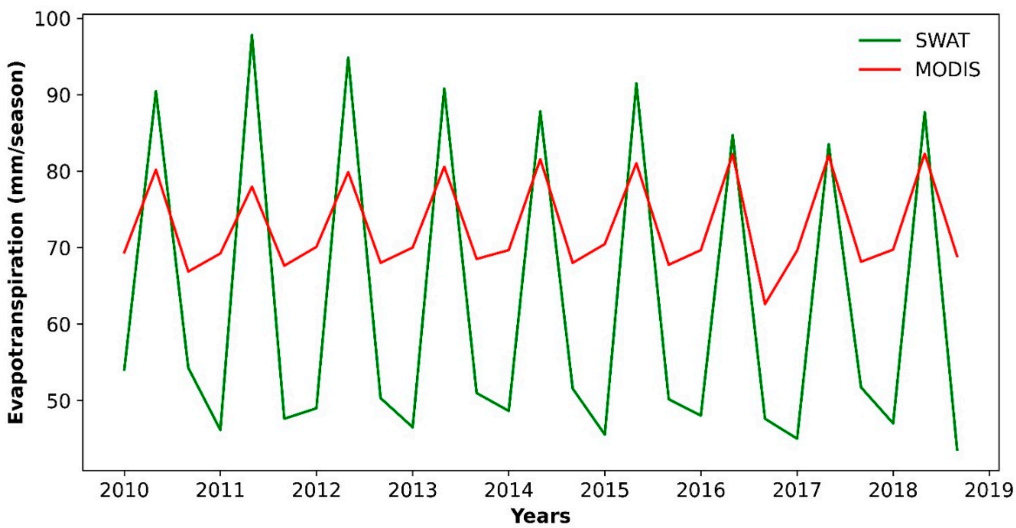

Figure 9. Comparison of seasonal SWAT-simulated and MODIS evapotranspiration data.

For MODIS, the maximum and minimum values of seasonal ET were 82.3 mm (13% greater than mean seasonal ET) and 62.6 mm (14% less than mean seasonal ET), respectively. On the other hand, for SWAT-simulated seasonal ET, the maximum and minimum values of seasonal ET were 97.8 mm (56% greater than mean seasonal ET) and 43.6 mm (30% less than mean seasonal ET), respectively.

The long-term average seasonal SWAT-simulated ET was maximum during summer, with 90 mm/4 months and was minimum during Spring with 47.7 mm. The long-term average seasonal MODIS ET was also maximum during summer, with 80.9 mm, and minimum during fall and spring, with 49 mm and 48 mm, respectively. However, the ET was highest during summer when crops are present on the field and lowest during spring and fall when fields were mostly fallow. For both the ET datasets, more variability was seen in SWAT-simulated ET than MODIS ET (Figure 10).

Previous studies on average seasonal ET conducted for 20 stations in the Nile valley and Nile Delta of Egypt also showed that the highest value of ET (7.5 mm/day) was observed in summer, and the lowest value of ET (2.3 mm/day) was observed in winter [41].

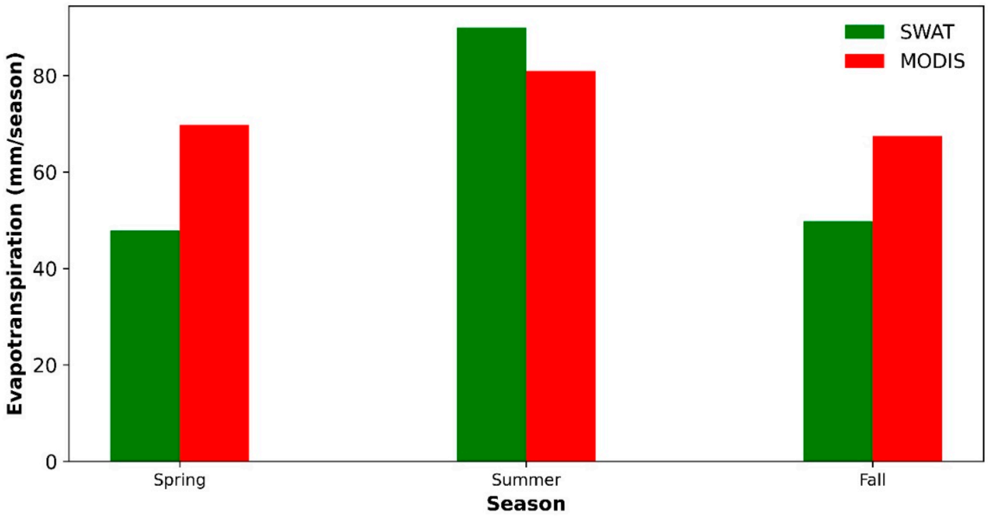

Figure 10. Comparison of long-term average seasonal SWAT-simulated vs. MODIS evapotranspiration data.

3.2.4. Annual ET

The average annual ET for BSRW, as simulated by SWAT, was 187.5 mm and that obtained from MODIS was 218 mm. The standard deviation and COV for SWAT-simulated annual ET were 6.87 and 0.04, respectively, and that for MODIS-obtained seasonal ET were 2.25 and 0.01, respectively. The R^2 during comparison of annual SWAT-simulated vs. MODIS-obtained ET was 0.13 (Figure 11).

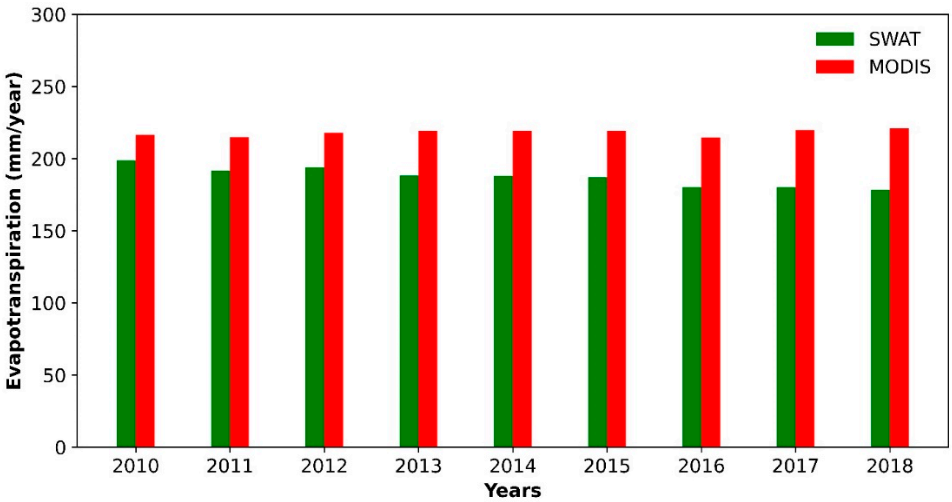

Figure 11. Comparison of annual SWAT-simulated vs. MODIS evapotranspiration data.

For MODIS, the maximum and minimum values of annual ET were 220.9 mm (1% greater than mean annual ET) and 214.5 mm (2% less than mean annual ET), respectively. On the other hand, SWAT-simulated annual maximum and minimum values of ET were 198.8 mm (6% greater than mean annual ET) and 178.3 mm (5% less than mean annual ET), respectively.

A previous study on average monthly ET, conducted for 20 stations in the Nile valley and Nile Delta of Egypt, also showed that the highest ET of 9.9 mm/day was observed in July and the lowest ET of 1.6 mm/day was observed in December [49]. The trend of seasonal ET for both SWAT-simulated, and MODIS were similar, but more fluctuations were observed for SWAT-simulated monthly ET data, as seen during the monthly and 8-day analyses. The fluctuation was much lower for annual ET than for 8-day, monthly, or seasonal ET values.

4. Discussion

In this study, comparisons of ET data obtained from two different sources, SWAT-simulated and MODIS, were presented for each 8-day, monthly, seasonal, and annual timescales. The trends of seasonal ET for both SWAT-simulated ET and that obtained from MODIS were similar. However, more fluctuations were observed for SWAT-simulated ET data. The fluctuation for SWAT-simulated ET ranged from −90% to +98% for 8-day, −66% to +80% for monthly, −30% to +56% for seasonal, and −5% to +6% for annual data. However, the fluctuation for MODIS ET ranged from −8% to +19% for 8-day, −27% to +20% for monthly, −13% to +14% for seasonal, and −2% to +1% for annual data. MODIS ET datasets use sensor-derived parameters such as land surface temperature, leaf area index, fraction of photosynthetically active radiation, enhanced vegetation index, albedo, and land cover, and these data may have some uncertainties [20].

The ET estimation is linked with crop growth; it is not practicable to evaluate the performance of crop growth in each 8-day period or in a month. The MODIS-derived ET on an annual basis was higher than the SWAT-simulated ET. It is recommended to use MODIS-derived yearly ET for long-term and seasonal estimations and SWAT-simulated ET for short-term estimations of crop water requirements. SWAT-simulated ET was the highest during the crop growing season and the lowest during the dormant season, whereas MODIS-simulated ET did not vary much according to crop growing or dormant season. SWAT-simulated ET is more reliable than MODIS-derived ET during the winter season as SWAT accounts for climatic, land use, soil, and slope conditions, while MODIS accounts for climatic condition and vegetation cover for ET estimation.

MODIS can provide ET data at higher spatial resolution, whereas SWAT can continuously simulate ET at higher temporal scales. Thus, if MODIS ET is in agreement with SWAT-simulated ET, both MODIS and SWAT ET can be used in combination for higher spatial resolution [25]. Instead of comparing the SWAT-simulated ET with MODIS-derived ET, the MODIS ET data can also be useful in further improving the water balance component and streamflow simulation of SWAT [2]. Accuracy of the model, in terms of both water and energy balance, can be enhanced by utilizing remotely sensed MODIS ET data during model calibration [2,18].

Moreover, apart from the methodology for assessing ET data used in this study, remotely sensed ET data can also be assessed with other methodologies using land use data, weather data, and hydrological models [20]. The method used in this study, along with other methods, can be very useful in enhancing our knowledge of the application of re-mote sensing ET for sustainable water resource management.

5. Conclusions

This study determined that SWAT-simulated ET was able to capture growing and dormant seasons more accurately than MODIS-derived ET, possibly because SWAT includes both climatic (maximum and minimum air temperature, relative humidity, wind speed) and actual land surface conditions (land use, soil, and slope) for ET estimation, while MODIS includes climatic conditions and remotely sensed vegetation data for ET estimation [40].

The SWAT-simulated ET data showed reasonable variations for all time periods, as expected and analyzed in this study. MODIS-obtained ET data were determined as reasonable for the annual time period. This study can be very helpful and applied to other watersheds, especially in data-scarce regions, to predict crop water requirements and irrigation scheduling.

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