Comparison of Data-Driven Groundwater Recharge Estimates with a Process-Based Model for a River Basin in the Southeastern USA

Mauricio Osorio Gonzalez, M.ASCE[1]; Pooja Preetha, Aff.M.ASCE[2]; Mukesh Kumar, Aff.M.ASCE[3]; and T. Prabhakar Clement, Aff.M.ASCE[4]

Abstract: Reliable estimates of aquifer recharge have the potential to help develop sustainable groundwater management policies. Despite its importance, quantifying this flux continues to be a challenge and remains one of the most uncertain components of the hydrological cycle. Here, we obtain a spatially explicit estimate of recharge using a semi-distributed hydrologic model for a major river basin in the Southeastern United States. A comparison of these process-based estimates with a data-driven recharge product (developed by USGS), which was obtained using a set of empirical regression equations, shows good agreement at the basin scale, but significant discrepancies at finer spatial resolutions. Overall, the semi-distributed model shows a higher degree of spatial heterogeneity across the basin than the USGS study results, which likely indicates that the empirical relationships modeled at the basin scale by the USGS empirical equations might not hold at smaller spatial scales. However, more ground-truthing recharge datasets are necessary to properly evaluate subbasin-scale models and reduce the uncertainty of estimates at these scales. **DOI: 10.1061/JHYEFF.HEENG-5882.** © *2023 American Society of Civil Engineers.*

Practical Applications: Groundwater recharge information at local scales is essential for various tasks: It is critical in the assessment of groundwater contamination from point sources, determining rates of change in response to pumping, quantifying local scale climate-induced storage change effects, assessing climate impacts on land cover changes and water supply, to name a few (Scanlon and Cook 2002) (Reitz et al. 2017). Because precipitation, pumping rates, land cover changes, and other important factors that affect groundwater recharge can vary significantly at a local scale (on the order of 1 to 10 km^2), having recharge estimates at a similarly fine scale will be useful for groundwater managers to evaluate the effectiveness of various practices that impact different stakeholders within the basin, and use this information to develop more effective water management plans.

Introduction

Groundwater depletion (larger withdrawals than natural recharge) is a growing threat to groundwater management and water security. Particularly in the Southeastern US, the Mississippi embayment section of the Gulf Coastal Plain, groundwater depletion has occurred at a rate of 1.2 km^3/year between 1900 and 2008 (Konikow 2015). The consequences of this groundwater depletion have been widely documented (Konikow 2015; Konikow and Kendy 2005; Landes et al. 2014; Pranjal et al. 2021). Increasing water demand, driven by agricultural development and population growth, and decreasing surface water availability due to droughts, are some of the major causes that have led water users worldwide to turn to groundwater to meet freshwater demands. However, this practice has imposed significant stress on various major groundwater aquifers around the world (Famiglietti 2014). Accurate and timely information, at various spatiotemporal scales, on the amount of water stored in groundwater aquifers, is necessary to develop more sustainable and flexible water management policies. A better understanding of when and where recharge happens within watersheds allows water managers to better orient resources and design tailored solutions where needed. One of the 23 unsolved problems in hydrology identified by the hydrology community in 2018 related to time variability and change is the question: "What are the impacts of land cover change and soil disturbances on water and energy fluxes at the land surface, and on the resulting groundwater recharge?" Blöschl et al. (2019). One of the goals of this study is to address this question.

Reitz et al. (2017) employed a data-driven approach to estimate annual values of recharge, runoff, and evapotranspiration (ET) [we will refer to these data as United States Geological Survey (USGS) datasets or USGS products] at an 800 m resolution for the period 2000–2013 for the continental United States (CONUS). As per our knowledge, this is the only fine-scale recharge product available for mapping recharge over the entire CONUS. Reitz et al. validated their long-term recharge estimates (averaged over 14 years, from 2000 to 2013) using a relatively small number of point observations reported by McMahon et al. (2011). The McMahon et al. study compiled the apparent water age distribution in a few groundwater aquifers by using various networks of wells located at 45 field sites distributed over the entire CONUS. The groundwater recharge values were calculated based on age-depth distribution data. However, validating a large-scale dataset with a small number of point estimates is not adequate, because a sample of 45 sites in an area as big as the United States is not representative. Furthermore, several

[1]Dept. of Civil, Construction, and Environmental Engineering, Univ. of Alabama, Tuscaloosa, AL 35487.

[2]Assistant Professor, Dept. of Mechanical and Civil Engineering, Alabama A&M Univ., Huntsville, AL 35811 (corresponding author). Email: pooja.preetha@aamu.edu

[3]Associate Professor, Dept. of Civil, Construction, and Environmental Engineering, Univ. of Alabama, Tuscaloosa, AL 35487.

[4]Professor, Dept. of Civil, Construction, and Environmental Engineering, Univ. of Alabama, Tuscaloosa, AL 35487.

Note. This manuscript was submitted on July 22, 2022; approved on January 31, 2023; published online on April 24, 2023. Discussion period open until September 24, 2023; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Hydrologic Engineering***, © ASCE, ISSN 1084-0699.

states did not have a single measurement, and some states had limited information that is based on other secondary studies. For example, there was just one recharge estimate for the entire state of Alabama. This estimate was based on a groundwater quality study completed by Robinson (2002) that reported samples collected in 1993 from a network of 12 wells located predominantly in residential/commercial zones near Montgomery, Alabama. Based on these data, McMahon et al. estimated the long-term recharge for each well with values ranging from 26 to 540 mm/year with a median value of 120 mm/year. The corresponding average estimate predicted by the USGS empirical model for the Montgomery region, is about 175 mm/year. The large difference in the two estimates is a concern; furthermore, the discrepancy in the estimation time is another concern. Note that the McMahan et. al. values were based on groundwater data collected in 1993, whereas the USGS product was developed based on a water budget evaluated for the period 2000 to 2013. Other than this rather weak validation exercise, to the best of our knowledge there have not been any field studies completed to validate the USGS annual recharge product. More recently, a modeling study was completed by Li et al. (2021) to compare the USGS long-term product against a set of land surface model (LSM) simulation results. The results show that the greatest discrepancies between the ensemble of LSMs and the USGS long-term recharge product are in the southeastern and northwestern portions of the CONUS.

Because a full validation is not possible due to the lack of direct measurements, we hypothesize that a comparison with a process-based model that explicitly resolves hydrological processes at a scale similar to the USGS product would still provide insights into the strengths and limitations of the data-driven approach of the USGS product. Therefore, the objective of this study is to implement a process-based, semi-distributed hydrological model for a major river basin in Alabama, the Black Warrior-Tombigbee Basin, using the Soil and Water Assessment Tool (SWAT) (Arnold et al. 1998), and compare the model results with the recharge product developed by the Reitz et al. USGS study.

Study Area

The basin region selected for this study drains at a USGS gauging station located in Coffeeville, Alabama (station ID 02469761). The drainage basin include Tombigbee River and the Black Warrior River. The entire drainage area, referred to herein as the Basin, includes the hydrologic unit level 6 (HUC-6) Black Warrior-Tombigbee Basin, and extends to a portion of the HUC-6 Mobile Bay-Tombigbee Basin (Fig. 1). The streamflow record available at the Basin outlet is for January 2000 to December 2013 period, and the USGS recharge product includes this period.

The Basin drains an area of approximately 48,300 km^2, overlying portions of Mississippi and Alabama. The Tombigbee River is a tributary of the Mobile River, and it is approximately 320 km long. The Tombigbee watershed is part of the coastal plain of Western Alabama and Northeastern Mississippi, flowing generally southward. The Tombigbee River merges with the Alabama River to form the Mobile River that drains into Mobile Bay on the Gulf of Mexico. The Tombigbee River became an important commercial navigation route after the construction of the Tennessee-Tombigbee Waterway, which consists of a series of dams and locks.

The Black Warrior River, approximately 286 km long, is a tributary of the Tombigbee River. Its upper drainage area is part of the southern end of the Appalachian Mountains, while the downstream portion drains forest land of the coastal plain regions. The main branch of the Black Warrior River is impounded by a series of narrow reservoirs constructed for navigation, hydropower, and water supply. According to the National Land Cover Database (NLCD), the Basin is covered by various types of forests and pastures over approximately 65% of the area; about 13% is woody wetland, 7% is urban, 3% is agricultural land, and the remaining 12% is divided among other land cover types (Dewitz 2016).

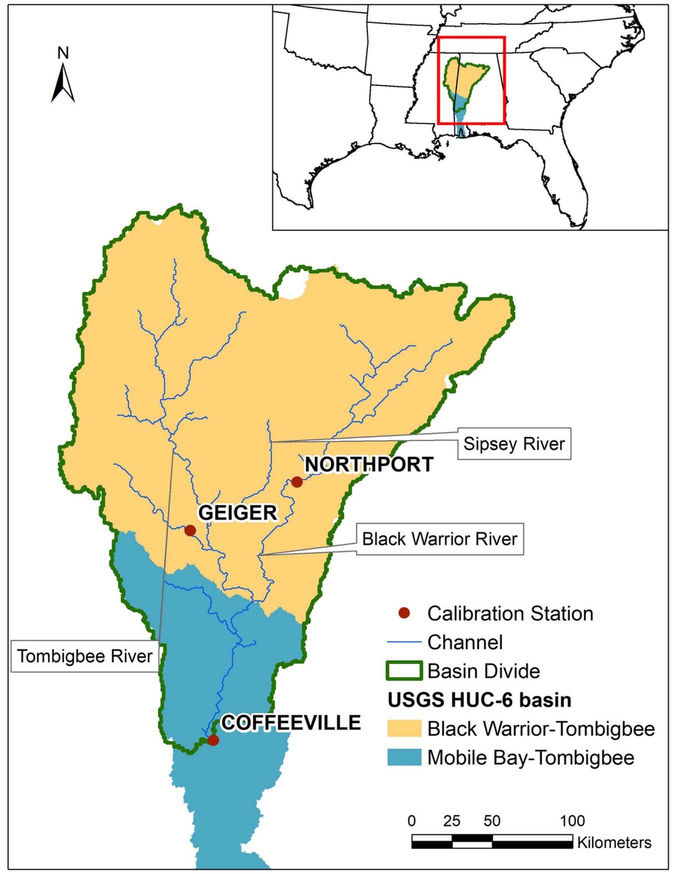

Fig. 1. Study area.

Methodology

We developed a semi-distributed hydrological model (referred to herein as the SWAT model) using the Soil and Water Assessment Tool (Neitsch et al. 2011; Preetha and Al-Hamdan 2020) to produce independent estimates of groundwater recharge, and compared the results with the USGS annual recharge product. The modeling steps used are summarized in Fig. 2.

SWAT Model Details

SWAT is a semi-distributed hydrological model developed by the USDA Agricultural Research Service to predict the impacts of land management practices on water, sediment, and chemical yields (Neitsch et al. 2011). It simulates spatial variability by discretizing the watershed into subbasins, and these are further discretized into hydrologic response units (HRUs). The HRUs are areas within a subbasin with a unique combination of land use, soil type, and slope. SWAT does not simulate the interactions between different HRUs. The hydrological cycle is simulated by using two phases: the land phase, and the routing phase. The land phase controls the amount of water that reaches the main channel within each subbasin, and it is calculated at the HRU level. The routing phase is calculated at a subbasin scale, and it defines the movement of water through the channel network of the basin.

J. Hydrol. Eng., 2023, 28(7): 04023019

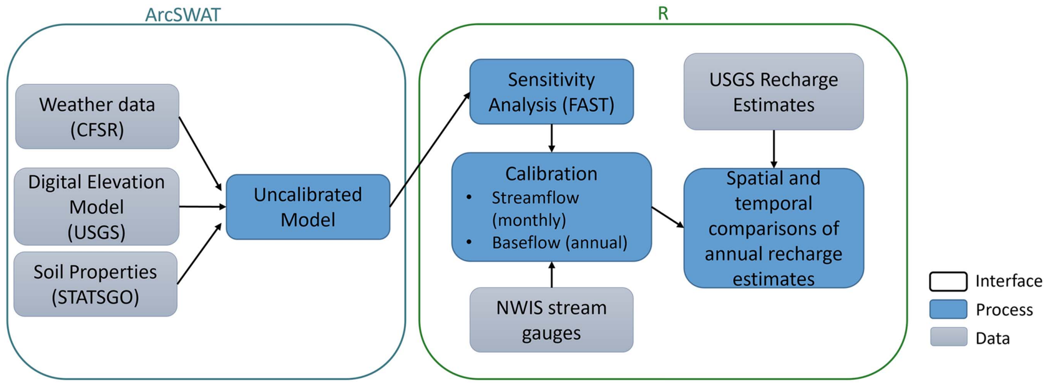

Fig. 2. Modeling methodology.

The land phase is modeled using the following water balance equation:

$$SW_t = SW_0 + \sum_{i=1}^{t} (R - Q - ET - P - Q_{gw})_i \tag{1}$$

where SW_t is the soil water content at time t; SW_0 is the initial soil water content; R is precipitation; Q is surface runoff; ET is evapotranspiration; P is percolation exiting the bottom layer of the soil profile; and Q_{gw} is return flow.

Surface runoff is estimated by two methods: the SCS curve number method (Mishra et al. 2012), or the Green & Ampt infiltration method (Green and Ampt 1911). For this study, we used the SCS curve number method.

SWAT employs three methods to estimate potential ET (PET), Penman-Monteith (selected for this study), Priestley-Taylor, and Hargreaves. Once PET is calculated, actual ET is estimated by first evaporating water available in canopy storage, and then SWAT calculates the maximum amount of transpiration along with the maximum amount of sublimation/soil evaporation.

Percolation is calculated for each layer of the soil profile, and it is determined by

$$W_{ly} = SW_{ly,excess}\left(1 - exp\left[\frac{-\Delta t}{TT_{perc}}\right]\right) \tag{2}$$

$$SW_{ly,excess} = SW_{ly} - FC_{ly} \quad for\ SW_{lY} > FC_{ly}, \quad 0\, otherwise \tag{3}$$

where $W_{ly,excess}$ is the drainable volume of water in the soil layer at a given time step; Δt is the length of the time step; TT_{perc} is the time for percolation; SW_{ly} is the soil water content of a given layer; and FC_{ly} is the field capacity.

The baseflow (return flow) is determined by the water balance for the shallow aquifer (SWAT models two aquifers for each subbasin, a shallow unconfined aquifer, and a deep aquifer):

$$aq_{sh,i} = aq_{sh,i-1} + w_{rech,sh} - Q_{gw} - w_{revap} - w_{pump} \tag{4}$$

where $aq_{sh,i}$ is the volume of water stored in the shallow aquifer on Day i; $aq_{sh,i-1}$ is the volume stored on the previous day; $w_{rech,sh}$ is the amount of recharge entering the shallow aquifer on Day i; Q_{gw} is the return flow or baseflow into the main channel on Day i; w_{revap} is the amount of water moving into the soil zone in response to water deficiencies on Day i; and w_{pump} is the amount of water extracted by pumping on Day i.

Total recharge (for both aquifers) w_{rech} is calculated by

$$w_{rech,i} = \left(1 - exp\left(-\frac{1}{\delta_{gw}}\right)\right)P + exp\left(-\frac{1}{\delta_{gw}}\right)w_{rech,i-1} \tag{5}$$

where $w_{rech,i}$ is the recharge entering aquifers on Day i; and δ_{gw} is the drainage time of the overlying geologic formations. The partitioning of total recharge into shallow and deep aquifer recharge is controlled by the percolation coefficient β_{deep}:

$$w_{rech,sh} = w_{rech}(1 - \beta_{deep}) \tag{6}$$

In this study, the total recharge computed using Eq. (5) at the HRU scale will be used to compare with the USGS recharge product.

Finally, the return flow or baseflow due to groundwater discharging into the main channel is estimated as

$$Q_{gwi} = Q_{gwi-1}\exp(-\alpha_{gw}\Delta t) + w_{rech,sh}(1 - exp(-\alpha_{gw}\Delta t)) \tag{7}$$

where α_{gw} is the baseflow recession constant.

For further details, the reader should refer to the SWAT theoretical documentation report (Neitsch et al. 2011).

Model Setup

The model for the Basin was created using the automatic watershed delineator available in the ArcGIS interface for SWAT; specifically ArcSWAT version 2012.10.24 for ArcGIS 10.7. The final model consists of 40 subbasins and 3,774 HRUs. Three locations along the river network were identified for later use as calibration/validation points, including the outlet of the Basin. These locations coincide with the location of USGS Streamgauges. The details of these gauges are discussed in the "Datasets Used" section.

As mentioned in the "SWAT Model Details" section, SWAT allows one to choose between different methods for modeling various hydrological processes. In this study, the SCS curve number method was selected for surface runoff modeling and the Penman-Monteith method for modeling potential ET. The model was set to run from January 1, 1997, to December 31, 2013, using a daily time step, with a warm-up period of three years, generating results from January 1, 2000, to December 31, 2013.

Sensitivity Analysis and Model Calibration

Total streamflow and baseflow were chosen as the calibration target variables for the developed SWAT model using the Nash-Sutcliffe Efficiency (NSE) coefficient (Nash and Sutcliffe 1970) as the objective function. Total stream flow is an important water balance component of any hydrological system, and it is commonly used as the target variable for calibrating the model (Joseph et al. 2021; Preetha and Al-Hamdan 2019). Additionally, baseflow was selected because it is closely related to the groundwater component of the water balance.

Baseflow was estimated using PART, the same method used by Reitz et al. (2017). PART is a USGS-developed software that uses a hydrograph separation method to split streamflow into quick-flow and baseflow components (Rutledge 1998). According to the PART documentation, the baseflow estimates from this software, despite being calculated at a daily time step, are valid only if the values are aggregated at least at a quarterly time scale. Therefore, baseflow values were calibrated using annual estimates for the period 2000–2013. For total streamflow (which was based on directly observed data from USGS Streamgauges), a monthly time scale was selected for calibration.

To identify the optimal set of parameters for performing the calibration step, we first quantified the sensitivity of several important model parameters for predicting both streamflow and baseflow patterns. The sensitivity analysis of model parameters and calibration of the model was carried out in RStudio (Fig. 2), with the help of the package *SWATplusR* (Schuerz 2021). This package allows the user to execute, modify and read SWAT models within the R environment, enabling the user to leverage other packages written in R for further analysis. Additionally, *SWATplusR* performs multiple runs in parallel, which optimizes the computational time. Because the calibration targets involve two different temporal resolutions (annual for baseflow and monthly for streamflow), the sensitivity analysis and calibration steps had to be carried out independently for each target variable. Then, based on the results of both calibrations, a common set of sensitive parameters were adjusted through a trial-and-error process to obtain adequate joint performance.

The sensitivity analysis was performed using the Fourier Amplitude Sensitivity Test (FAST) (Cukier et al. 1973). This test is a variance-based global sensitivity analysis method that uses a periodic sampling procedure and a Fourier transform to decompose the variance of a model into partial variances contributed by different model parameters (Xu and Gertner 2011). The test indicates the fraction of the objective function variance that can be attributed to each parameter. FAST was implemented using the R package *fast* (Reusser 2020). Musyoka et al. (2021) implemented this method to perform a sensitivity analysis for SWAT model parameters.

We tested the sensitivity of the most common parameters used for streamflow and baseflow calibration in SWAT models (Bailey et al. 2016; Li et al. 2013; Musyoka et al. 2021; Preetha and Al-Hamdan 2022) (and for posterior calibration). The parameters considered are summarized in Table 1. The possible values selected for each parameter include a range of likely values according to the level of parameter uncertainty. For example, curve number values were varied by ±10%, while soil available water content was varied by ±50%, because we expected less uncertainty in the actual curve number value for a certain type of land use than in soil available water content.

To identify the parameter combination that produces the best model performance, the most sensitive parameters were perturbed in the model with a Latin hypercube sampler (LHS) (Loh 1996), using the R package *lhs*. The range of possible values for each parameter was selected according to the model performance shown in the sensitivity analysis. After this step, the combination of parameter values that produced the highest model performance was selected.

Parameter changes were applied for the entire basin: Calibration at the outlet of the basin (Station Coffeeville), and validation at the other two stations (Geiger and Northport). Because performance was adequate at these three stations, subbasin-wise calibration at these points was not necessary. Arsenault et al. (2018) suggest that is best to include all available years in the dataset for the calibration process, instead of using a split-sample method. In our study, the entire period of interest (2000–2013) was used for model calibration.

Datasets Used

Different types of datasets were used to accomplish various model development objectives. These include data for setting up the hydrological model, model forcing (weather data), calibration targets, and ET and recharge for model comparisons. Further details of these datasets are described in the following sections and are summarized in Table 2.

SWAT Inputs

To build the hydrological model, SWAT needs a digital elevation model (DEM), soil, and land use/land cover data. The DEM was obtained from the USGS *The National Map* download service. The 1-arc-second DEM version was selected. ArcSWAT was used to retrieve the STATSGO soil dataset from the US Department of Agriculture. Finally, land cover-land use data was retrieved from National Land Cover Database version 2016.

Hydrometeorological data from the National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) is available on the SWAT website. This dataset provides daily precipitation, wind, relative humidity, and solar data in SWAT 2012 file format from 1979 to 2014 (Preetha et al. 2021). For this study, we downloaded data between January 1, 1997, and December 31, 2013. Studies have found that using CFSR precipitation and temperature estimates to force SWAT models produces equal or better streamflow simulations than does using traditional weather stations (Dile and Srinivasan 2014; Fuka et al. 2014).

Reitz et al. (2017) included groundwater-sourced irrigation to estimate effective precipitation. They argue that most groundwater irrigation comes from deep aquifers not affected streams and these

Table 1. Selected parameters for sensitivity analysis

Parameter	SWAT parameter name	Target (streamflow/baseflow)	Adjustment range
Curve number for moisture condition II (unitless)	CN2	S/B	−10% to 10%
Soil available water content (unitless)	SOL_AWC	S/B	−50% to 50%
Delay time for aquifer recharge (δ_{gw}) (days)	GW_DELAY	S/B	−50% to 50%
Soil saturated hydraulic conductivity (mm/h)	SOL_K	S	−50% to 50%
Channel Manning's roughness coefficient (unitless)	CH_N2	S	−50% to 50%
Soil evaporation compensation factor (unitless)	ESCO	S/B	0.01–1.0
Baseflow recession constant (α_{gw}) (unitless)	ALPHA_BF	S/B	0–1
Threshold water level for baseflow to occur (mm)	GWQMIN	S/B	1–50

Table 2. Datasets

Data	Source	Notes
Digital elevation model[a]	USGS National Map Download Service	Resolution: 1 arc-second (30 m approximately)
Soil data	STATSGO	Provided in Arc SWAT
Land use/land cover[b]	NLCD	NLCD 2016
Weather data[c]	NCEP CFSR	Daily data from January 1, 1997 to December 31, 2013
Streamflow[d]	USGS NWIS	Daily data from January 1, 1997 to December 31, 2013
Annual recharge[e]	Science-Base Catalog	Annual averages from 2000 to 2013
Annual ET[e]	Science-Base Catalog	Annual averages from 2000 to 2013

[a]https://data.usgs.gov/datacatalog/data/USGS:3a81321b-c153-416f-98b7-cc8e5f0e17c3.
[b]https://www.mrlc.gov/data/nlcd-2016-land-cover-conus.
[c]https://swat.tamu.edu/data/cfsr.
[d]https://waterdata.usgs.gov/nwis.
[e]https://doi.org/10.5066/f7pn93p0.

volume would add to local water budgets. In our study area, agricultural land accounts only 3% of the area. Moreover, groundwater comes mainly from shallow aquifers. Therefore, irrigation water was considered negligible.

Calibration Targets

Streamflow and baseflow data were selected as calibration targets. Streamflow was obtained from USGS Streamgauges within the Basin. Streamgauges with less than 5% of gaps between 2000 and 2013, and a drainage area greater than 10% of the Basin, were selected; a total of three stations meet these criteria, including the outlet of the Basin (see Table 3)

The locations of the USGS gauge station are shown in Fig. 1. Because no direct measurements of baseflow are available, a baseflow separation method was used to estimate it from daily streamflow data, as described in the "Sensitivity Analysis and Model Calibration" section.

USGS Annual Estimates of ET and Groundwater Recharge

Reitz et al. (2017) provided estimates of annual quick-flow runoff, ET, and groundwater recharge for CONUS (in this study we focus on recharge and ET datasets); these datasets are available in the USGS Science Base Catalog. As mentioned before, these estimates were developed by the authors by fitting empirical regression equations to the long-term average (14 years), basin-scale quick-flow runoff, and ET data, and then applied directly to annual and pixel scale (800 m resolution) data to predict quick-flow runoff and ET for the CONUS. Annual effective recharge estimates were then obtained by closing the water budget to sum to the total influx from precipitation using the equation

$$R = P - Q - ET - \Delta S \tag{8}$$

where R (m/year) is effective recharge or baseflow; P (m/year) is precipitation; Q (m/year) is quick-flow runoff; and ΔS (m/year) is the change in subsurface water storage. The authors assumed that the change in sub-surface storage is negligible compared to the volumes of the other components over long time scales. To account for the effective recharge that is intercepted by riparian vegetation near streams, the authors added 5% of ET uniformly to the effective recharge (this dataset is called Total Recharge). This correction method is derived from a previous result in a study conducted in Virginia (Sanford et al. 2012). In the current study, the total recharge product is compared with SWAT recharge estimates.

Table 3. USGS Streamgauges used for calibration

Station ID	USGS station name
02465000	Black Warrior River, Northport AL
02448500	Noxubee River Nr, Geiger, AL
02469761	Tombigbee R At, Coffeeville, AL

Results and Discussion

Sensitivity Analysis and Calibration Results

To identify the optimal set of parameters for performing the calibration step, we first quantified the sensitivity of several important model parameters for predicting both streamflow and baseflow patterns commonly used for calibration, especially in SWAT models (Table 1). These results are summarized in Fig. 3. For streamflow, the model is most sensitive to the soil evaporation compensation factor (ESCO), as labeled in SWAT 2012, followed by the baseflow recession constant (ALPHA_BF), soil available water content (SOL_AWC), and curve number (CN2), coinciding with Musyoka et al. (2021), except for the baseflow recession constant, as the most sensitive factors for streamflow. For baseflow, the model is most sensitive to curve number, followed by the soil compensation factor, and soil available water content. These results agree with Musyoka et al. (2021), who found that the most sensitive parameters for streamflow were curve number, soil available water content, and soil compensation factor; for groundwater flow, the threshold depth for return flow of water in the shallow aquifer (GWQMN), curve number, soil available water content, deep aquifer percolation fraction (RCHRG_DP), groundwater revap coefficient (GW_REVAP), saturated hydraulic conductivity (mm/hr) (SOL_K), and soil compensation factor. After identifying the most sensitive parameters, these values were perturbed again, using the Latin hypercube sampling method to fine-tune and calibrate the model to obtain the best performance. The results of this analysis are shown in Figs. 4 and 5. These figures show that there is an agreement among the values of ALPHA_BF and SOL_AWC that are needed to achieve good model performance for predicting both streamflow and baseflow. However, the level of adjustment to the curve number needed to achieve the best performance in streamflow prediction is around −3%, while for baseflow prediction is around +10%. Similarly, the best performance in streamflow is achieved with an ESCO = 0.85. In contrast, ESCO = 1 produces the best performance when the target is baseflow prediction.

The comparison of data presented in Figs. 4 and 5 indicates that the model was able to better reproduce monthly streamflow values (NSE values above 0.8) than annual baseflow values (maximum NSE values around 0.4). Based on these results, various combinations of curve numbers and ESCO values were adjusted

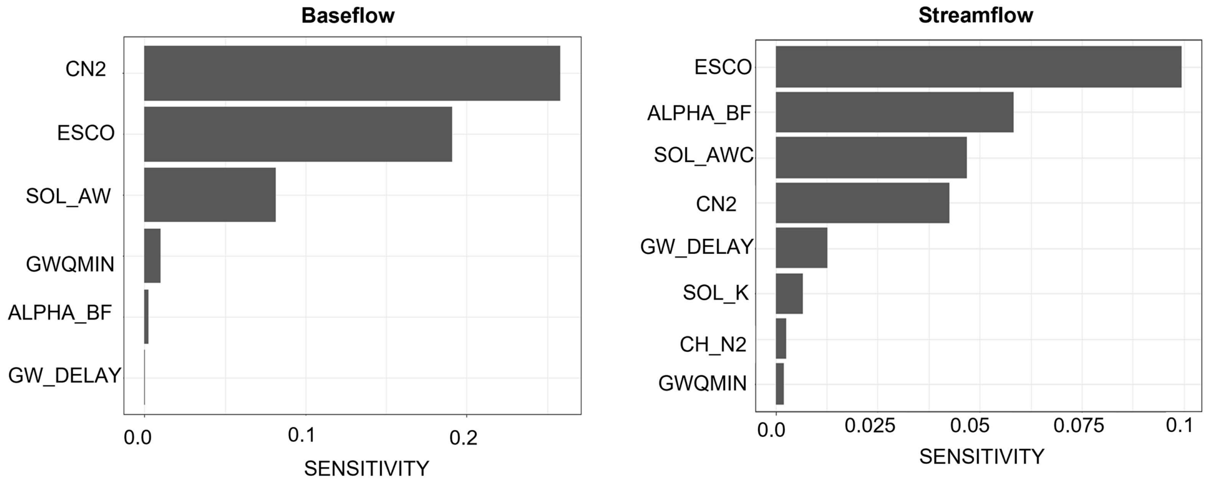

Fig. 3. FAST relative sensitivity [fraction of variance attributed to each parameter (unitless)] of baseflow and monthly streamflow at the Coffeeville Basin outlet to various parameters.

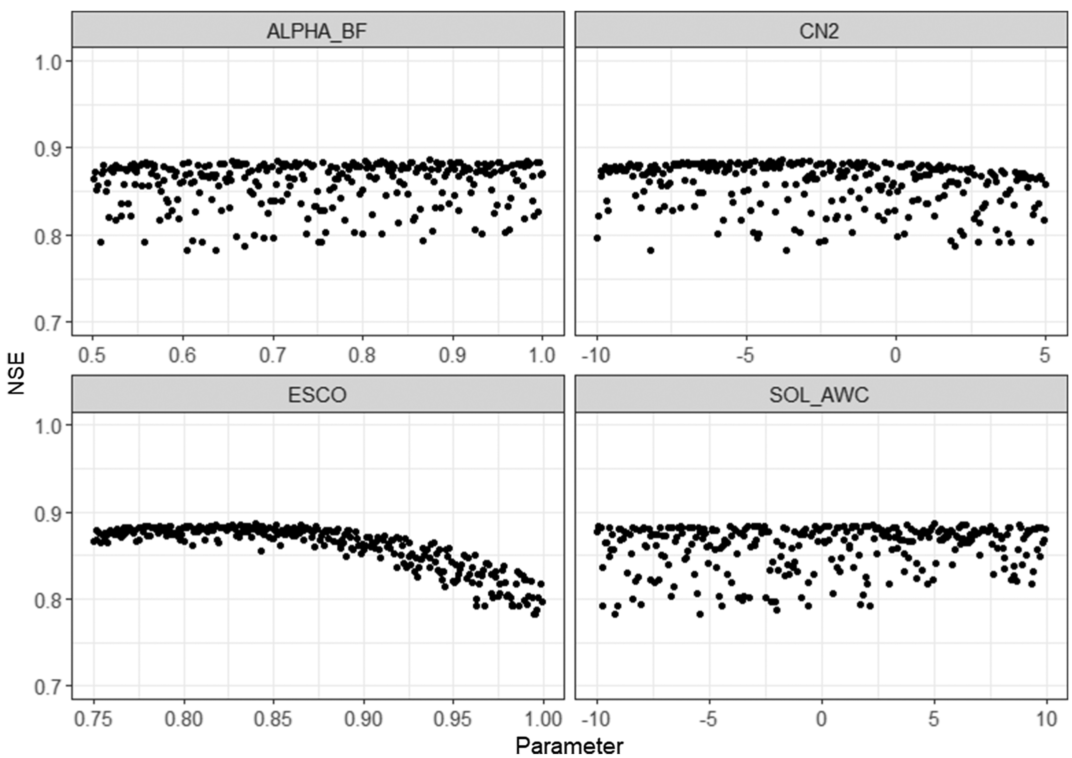

Fig. 4. Variations in model performance (monthly streamflow) to the most sensitive model parameters (ALPHA-BF, CN2, ESCO, SOL, and_AWC) at the Coffeeville Basin outlet, generated using the Latin hypercube sampling method.

manually through a trial-and-error process to calibrate the model to yield acceptable fits for both streamflow and baseflow datasets. The calibrated optimal model parameter values are presented in Table 4.

Monthly streamflow and annual baseflow values simulated by the calibrated SWAT model are compared with the field data measured at the outlet of the Basin in Figs. 6 and 7, respectively. In addition, the model performance metrics for the three calibration/validation stations are summarized in Table 5. Streamflow prediction performance is good for the three locations; coefficient of determination (R^2) values are above 0.65 for all stations, while NSE values are greater than 0.61. For baseflow prediction, R^2 values are above 0.53. While the NSE values at Northport and Geiger are a bit low, the simulated values closely follow the estimates given by PART. The reason for these low NSE values is that baseflow predictions for the year 2009 (the wettest in the period of analysis) deviated significantly from PART estimates, and because the time series contains only 11 points, the NSE value is highly penalized by this outlier. Overall, the SWAT model can adequately reproduce the dynamics of streamflow and baseflow in the Basin.

Comparison of Temporal Variations in Basin-Scale Recharge Estimates

Total recharge estimates from Reitz et al. (2017) were compared with the SWAT model's shallow aquifer recharge estimates (output as GW_RCHG in SWAT files). For temporal comparison, results

J. Hydrol. Eng., 2023, 28(7): 04023019

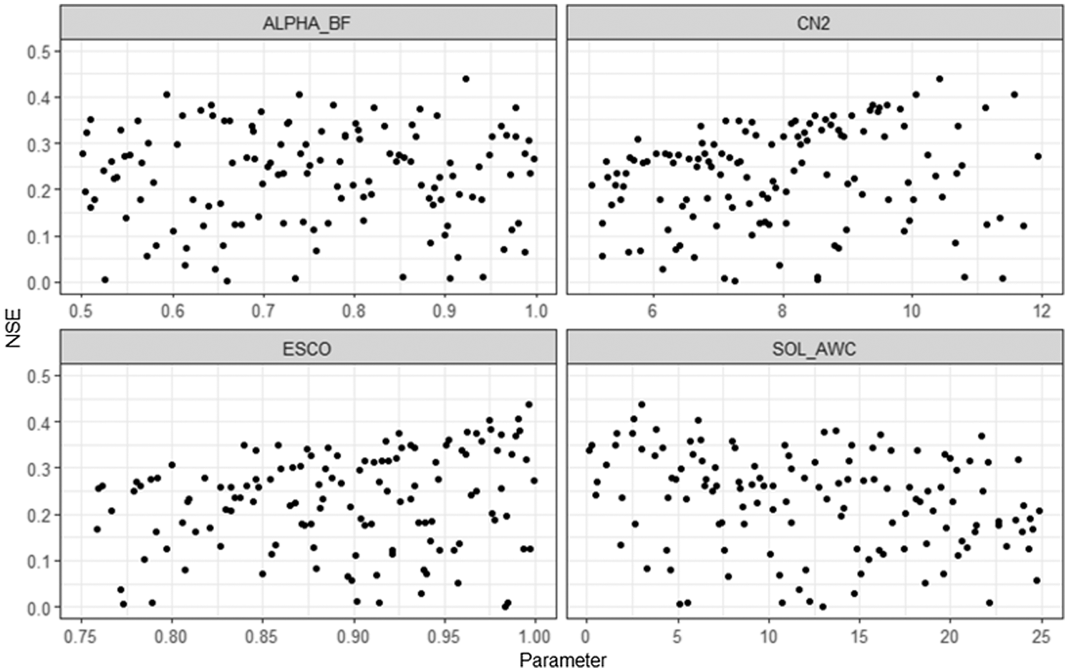

Fig. 5. Variations in model performance (annual baseflow) to the most sensitive parameters (ALPHA-BF, CN2, ESCO, SOL, and_AWC) at the Coffeeville Basin outlet, generated using the Latin hypercube sampling method.

Table 4. Range of calibrated model parameter values

Parameter	Parameter name in SWAT	Values
Curve number for moisture condition II (unitless)	CN2	62–92
Soil available water content (unitless)	SOL_AWC	0.1–0.24
Soil evaporation compensation factor (unitless)	ESCO	0.88
Baseflow recession constant (α_{gw}) (unitless)	ALPHA_BF	0.89

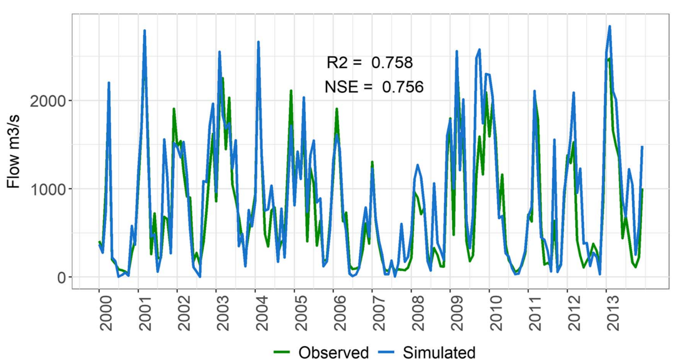

Fig. 6. Simulated versus observed monthly streamflow at the Basin outlet near Coffeeville.

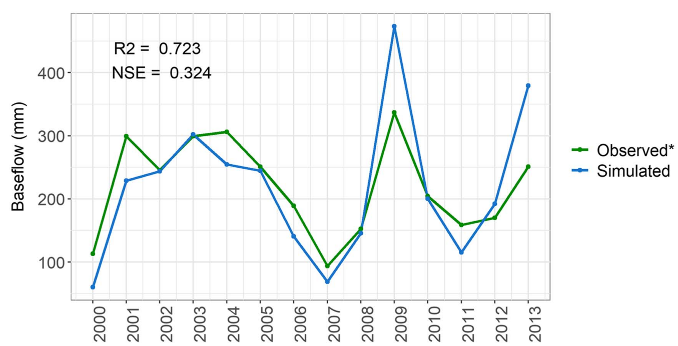

Fig. 7. Simulated versus observed annual baseflow at the Basin outlet near Coffeeville (baseflow values estimated by PART).

from both models (USGS and SWAT) were spatially averaged over the entire Basin. Fig. 8 shows the annual average recharge volumes for the Black Warrior—Tombigbee Basin, along with the baseflow values derived using PART and the precipitation estimates used in each model. We can observe that the two recharge estimates are in good agreement. The NSE is equal to 0.84, R^2 is equal to 0.83, percent bias (PBIAS) is equal to 0.4, and the root mean squared error (RMSE) is equal to 46 mm.

Between 2000 and 2013, the mean recharge value was 256 mm/year (12.36 km^3) (18% of precipitation) according to the SWAT model, while the USGS model estimate is 257 mm (12.41 km^3), which is equivalent to 17% of precipitation. It is important to note that each model uses a different data source for precipitation. The SWAT model uses precipitation from the CFSR dataset, which estimates an average annual rate equal to 1,415 mm (68.34 km^3). The USGS model uses the PRISM dataset from the PRISM Climate Group at the University of Oregon. Average precipitation from the PRISM dataset is slightly higher and equals 1,481 mm/year (71.53 km^3). From Fig. 8 we can observe a strong correlation

Table 5. Model performance at the calibration stations

	Streamflow		Baseflow	
Station name	NSE	R^2	NSE	R^2
Northport	0.72	0.68	−0.09	0.54
Geiger	0.61	0.67	0.01	0.53
Coffeeville	0.76	0.76	0.32	0.72

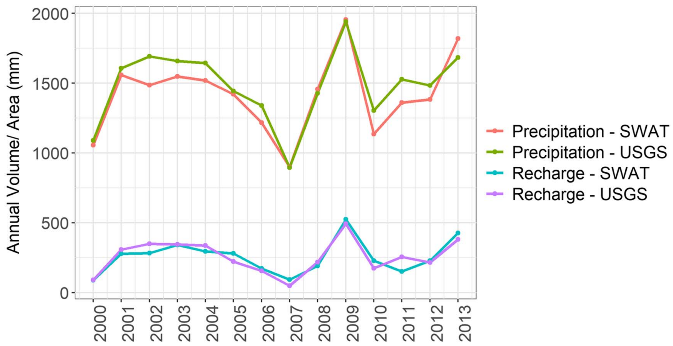

Fig. 8. Comparison of SWAT model predicted recharge averaged over the entire Basin compared to USGS. The figure also compares CFSR precipitation data used by SWAT with the PRISM data used by USGS. (Data from Reitz et al. 2017.)

between precipitation estimates ($R^2 = 0.85$); however, PRISM tends to slightly overestimate with respect to CFSR (PBIAS = 4.7) based estimates.

Recharge Estimates—Spatial Comparison

The annual recharge estimates for the driest (2007) and the wettest (2009) years were selected for the spatial analysis. The SWAT model estimates at the HRU level were rasterized at an 800 m resolution to allow comparison with the USGS data products at every pixel.

Fig. 9 presents the following information: (a) the SWAT model annual recharge estimates throughout the Basin for the year 2007, (b) USGS recharge estimates, and (c) the difference between USGS estimates and SWAT estimates. Note, Fig. 9(c) helps to show regions where USGS data underpredicts with respect to the SWAT estimates (positive values), where USGS data overpredicts (negative values), and where both data products agree (values near zero).

In 2007, the Black Warrior-Tombigbee basin received 92 mm (4.44 km^3) of recharge according to the SWAT model, while the USGS model estimates 48 mm (2.32 km^3), an average difference of 44 mm, or a relative error of 48% (considering the SWAT model as the true value). The USGS model generally underpredicts for this dry year across the Basin, as we can observe in Fig. 9(c), with positive values (blue) more commonly observed through the entire Basin.

Discrepancies at the 800 m scale are significantly larger when compared to discrepancies observed at the basin scale in the temporal analysis. The coefficient of determination between recharge estimates at the 800 m scale across the Basin is $R^2 = 0.16$, and the RMSE is 65 mm. We The SWAT model predictions are more heterogeneous in space than the USGS model, as indicated by the coefficient of variation (CV). The mean CV of SWAT recharge estimates between 2000 and 2013 is 0.67, while USGS recharge estimates present a lower mean value equal to 0.51.

Because the annual recharge estimates from the USGS model are the residual of the water budget after estimating ET, it is expected that differences in ET estimates between models are to some degree related to the differences in recharge estimates. For the year 2007, the SWAT model predicts 733 mm of ET, while the USGS model predicts 745, a difference of 12 mm or a relative error of 2%. As noted in the comparison of recharge products, the agreement between models reduces significantly at finer scales. As we can observe in Fig. 10(c), the models show absolute differences of 300 mm at the 800 m resolution. The correlation coefficient for this year is $R^2 = 0.04$, and the RMSE is equal to 135 mm.

As we can observe in Fig. 10(c), the USGS model overpredicts ET and underpredicts recharge in the northern portion of the Basin, as shown in Fig. 9(c). Similarly, on the east bank of the Tombigbee River (in the eastern portion of the Basin), the USGS model underpredicts ET, while it overpredicts recharge. Overall, there is no agreement in the spatial pattern of ET between the two models. The SWAT model predicts higher ET values in the southern region, while the USGS model has no specific pattern. There are some local agreements; for example, in a small portion of the eastern bank of the Tombigbee River, both models predict lower ET than in its surroundings.

The wettest year during the period of analysis is 2009, having an average annual precipitation of 1,955 mm (94.43 km^3). As shown in Fig. 11, recharge is estimated as 524 mm (25.31 km^3) according to the SWAT model, and 493 mm (23.81) according to USGS estimates, a difference of 31 mm or a relative error of 6%. The spatial distribution of recharge for this year is marginally more consistent between the two models: $R^2 = 0.29$, and RMSE = 227 mm. In Fig. 11, we can observe a half-moon-shaped region of lower

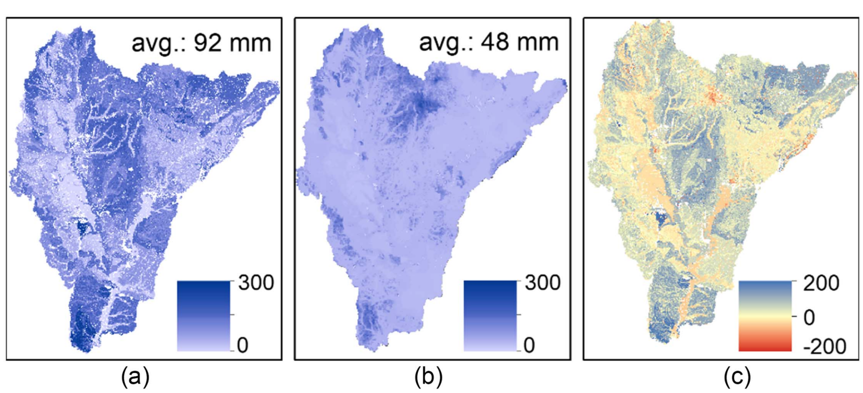

Fig. 9. Dry year recharge estimates (2007): (a) SWAT estimates; (b) USGS estimates; and (c) difference (a – b).

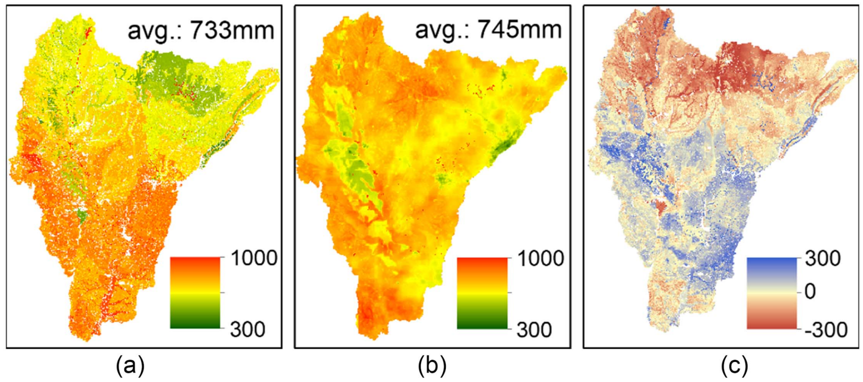

Fig. 10. ET estimates (2007): (a) SWAT estimates; (b) USGS estimates; and (c) difference (a − b).

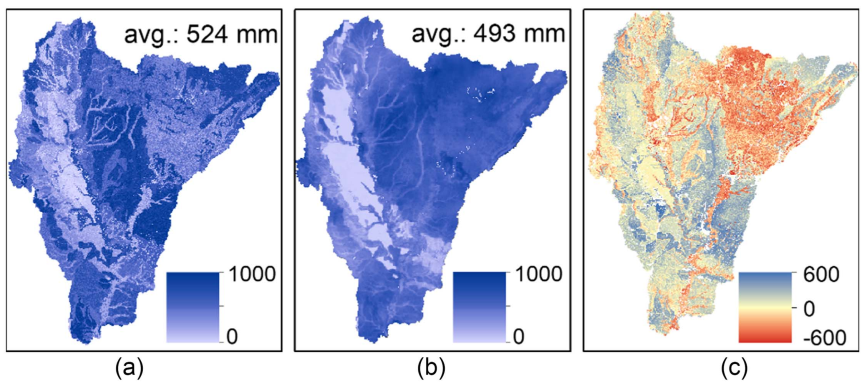

Fig. 11. Wet year recharge estimates (2009): (a) SWAT estimates; (b) USGS estimates; and (c) difference (a − b).

recharge that is present in both models, indicating higher values on the eastern bank of the Tombigbee River. However, while the SWAT model predicts a low-recharge zone in the northeastern portion of the Basin, the USGS model fails to capture this lower recharge zone.

ET in 2009 is estimated to be 826 mm by the SWAT model, while the USGS model estimates 940 mm, a difference of 114 mm or a relative error of 14%. There is not much consistency in the spatial pattern, as indicated by the low correlation coefficient value of $R^2 = 0.06$, and RMSE = 160 mm. The USGS model estimates very high values throughout the Basin except for a small portion on the western bank of the Tombigbee River. As shown in Fig. 12(c), there are very few areas that show good agreement (shaded in yellow).

Influences Various Forcing on Seasonal Groundwater Recharge Dynamics

The finer temporal resolution of the SWAT model allows us to assess the seasonal dynamics of recharge and the impact of precipitation, ET, and soil moisture on it. Fig. 13 shows the monthly dynamics of the net water flux into the surface precipitation minus ET (PCP − ET), the water flux into the subsurface precipitation minus ET minus runoff (PCP–ET − QF), soil water content (SWC), and groundwater recharge. During the period of analysis, recharge occurred mainly from December to May, when the monthly net water flux (PCP − ET) correlates better with monthly recharge according to Pearson's correlation coefficient (ρ) ($\rho = 0.45$). The period from December to May also coincides with high values of soil water content. In contrast, between June and November, when the soil water content is low, monthly recharge correlates less with the flux of water into the surface ($\rho = 0.33$). As we can observe, during this period (June–November) the net water flux increases consistently on average, while recharge remains constant at values near zero. The result highlights that soil moisture helps to determine the extent to which PCP-ET influences groundwater recharge.

Conclusion and Recommendations

In this study, we modeled the groundwater recharge pattern over a 48,300 km^2 river basin in the southeastern US using a semi-distributed hydrologic model, SWAT. We compared the process-model-based recharge results with the data-derived USGS recharge product provided by Reitz et al. (2017). The two datasets exhibited good agreement (NSE = 0.84, $R^2 = 0.83$) at the basin scale. The study also found that notable discrepancies exist at the finer 800 m scale estimates of groundwater recharge. There is a weak correlation ($R^2 = 0.16$ for the driest year, and $R^2 = 0.29$ for the wettest year), and the RMSEs are significantly large relative to basin-wide mean values. These results suggest that the application of the empirical equations derived by Reitz et al. (2017) at the basin scale might not be valid at lower scales. While we cannot conclude that the SWAT model results at the HRU or 800 m scale are more accurate, we do point out the need for groundwater recharge data at finer spatial and temporal scales to better calibrate and verify recharge models. The study outcomes also highlight that soil moisture conditions could better determine the extent to which

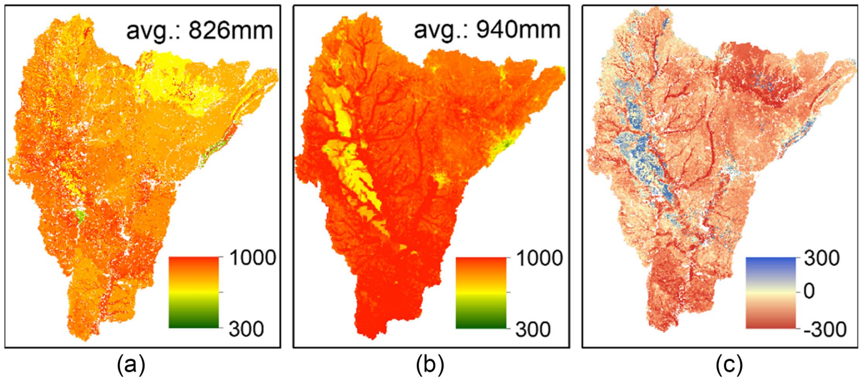

Fig. 12. ET estimates (2009): (a) SWAT estimates; (b) USGS estimates; and (c) difference (a − b).

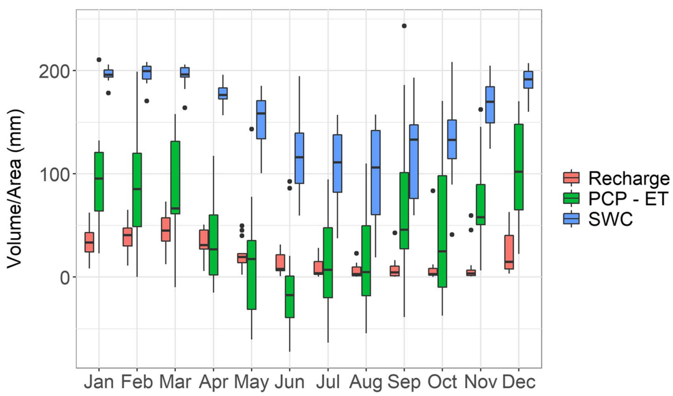

Fig. 13. Distribution of monthly recharge, precipitation minus ET (PCP − ET), precipitation minus ET minus runoff (PCP–ET − QF), and SWAT estimated SWC.

precipitation and evapotranspiration processes influence groundwater recharge.

The USGS recharge and ET products are based on regression equations fitted with data at a basin scale, which might explain why the agreement between model estimates occurs at larger scales. When these equations were used to obtain recharge and ET values at the fine 800 m scale, the relationships found at the basin scale by the regression equations were not necessarily preserved. We hypothesize that this mismatch of scales is a potential cause of the poorer agreement between the two estimates. However, our model, and also other models available in the literature, require validation and ground-truthing recharge datasets evaluated at subbasin scales to further test this hypothesis. In general, more direct recharge measurements are needed to validate hydrologic models that aim to resolve processes at subbasin scales. While using baseflow as a proxy for groundwater recharge might be adequate for coarser scales (regional or larger), there are limitations in using baseflow data to resolve processes at finer scales. Having more fine recharge measurements will help accelerate the process of model development and testing, advancing our understanding of the recharge processes. However, because large-scale measurement campaigns are cost prohibitive, the next intermediate step could be to study an area where other recharge models are available and use three-point estimation methods to assess the uncertainty of these recharge models and identify the physical characteristics associated with high-uncertainty areas to identify appropriate benchmarking field sites for conducting detailed water balance studies. Additionally, probabilistic models could be developed to provide a range of values for recharge estimates.

Data Availability Statement

All data that support the findings of this study, such as SWAT model and code, are available from the corresponding author upon reasonable request.

Acknowledgments

Funding for this project was provided in part by the National Science Foundation Grants OIA 2019561 and OIA 1854631, and by CIROH Grant GR29007 awarded through the NOAA's Cooperative Agreement with The University of Alabama, NA22NWS4320003.

References

Arnold, J. G., R. Srinivasan, R. S. Muttiah, and J. R. Williams. 1998. "Large area hydrologic modeling and assessment Part 1: Model development." *J. Am. Water Resour. Assoc.* 34 (1): 73–89. https://doi.org/10.1111/j.1752-1688.1998.tb05961.x.

Arsenault, R., F. Brissette, and J. L. Martel. 2018. "The hazards of split-sample validation in hydrological model calibration." *J. Hydrol.* 566 (Nov): 346–362. https://doi.org/10.1016/j.jhydrol.2018.09.027.

Bailey, R. T., T. C. Wible, M. Arabi, R. M. Records, and J. Ditty. 2016. "Assessing regional-scale spatio-temporal patterns of groundwater-surface water interactions using a coupled SWAT-MODFLOW model." *Hydrol. Processes* 30 (23): 4420–4433. https://doi.org/10.1002/hyp.10933.

Blöschl, G., et al. 2019. "Twenty-three unsolved problems in hydrology (UPH)—A community perspective." *Hydrol. Sci. J.* 64 (10): 1141–1158. https://doi.org/10.1080/02626667.2019.1620507.

Cukier, R. I., C. M. Fortuin, K. E. Shuler, A. G. Petschek, and J. H. Schaibly. 1973. "Study of sensitivity of coupled reaction systems to uncertainties in rate coefficients. 1. Theory." *J. Chem. Phys.* 59 (8): 3873–3878. https://doi.org/10.1063/1.1680571.

Dewitz, J. 2016. *National land cover database*. Washington, DC: US Geological Survey.

Dile, Y. T., and R. Srinivasan. 2014. "Evaluation of CFSR climate data for hydrologic prediction in data-scarce watersheds: An application in the Blue Nile River Basin." *J. Am. Water Resour. Assoc.* 50 (5): 1226–1241. https://doi.org/10.1111/jawr.12182.

Famiglietti, J. S. 2014. "The global groundwater crisis." *Nat. Clim. Change* 4 (11): 945–948. https://doi.org/10.1038/nclimate2425.

Fuka, D. R., M. T. Walter, C. MacAlister, A. T. Degaetano, T. S. Steenhuis, and Z. M. Easton. 2014. “Using the climate forecast system reanalysis as weather input data for watershed models.” *Hydrol. Processes* 28 (22): 5613–5623. https://doi.org/10.1002/hyp.10073.

Green, W. H., and G. Ampt. 1911. “Studies of soil physics, Part I, The flow of air and water through soils.” *J. Agric. Sci.* 1911 (4): 1–24.

Joseph, N., P. P. Preetha, and B. Narasimhan. 2021. “Assessment of environmental flow requirements using a coupled surface water-groundwater model and a flow health tool: A case study of Son river in the Ganga basin.” *Ecol. Indic.* 121 (Feb): 107110. https://doi.org/10.1016/j.ecolind.2020.107110.

Konikow, L. F. 2015. “Long-term groundwater depletion in the United States.” *Groundwater* 53 (1): 2–9. https://doi.org/10.1111/gwat.12306.

Konikow, L. F., and E. Kendy. 2005. “Groundwater depletion: A global problem.” *Hydrogeol. J.* 13 (1): 317–320. https://doi.org/10.1007/s10040-004-0411-8.

Landes, A. A. L., L. Aquilina, J. De Ridder, L. Longuevergne, C. Page, and P. Goderniaux. 2014. “Investigating the respective impacts of groundwater exploitation and climate change on wetland extension over 150 years.” *J. Hydrol.* 509 (Feb): 367–378. https://doi.org/10.1016/j.jhydrol.2013.11.039.

Li, B. L., M. Rodell, C. Peters-Lidard, J. Erlingis, S. Kumar, and D. Mocko. 2021. “Groundwater recharge estimated by land surface models: An evaluation in the conterminous United States.” *J. Hydrometeorol.* 22 (2): 499–522. https://doi.org/10.1175/JHM-D-20-0130.1.

Li, Y., A. Huo, R. Liu, S. Chen, X. Wang, and J. Li. 2013. “Water resources responses to climate changes in Xi’an Heihe River Basin based on SWAT model.” *J. Water Resour. Res.* 2 (5): 301–308.

Loh, W.-L. 1996. “On Latin hypercube sampling.” *Ann. Stat.* 24 (5): 2058–2080. https://doi.org/10.1214/aos/1069362310.

McMahon, P. B., L. N. Plummer, J. K. Bohlke, S. D. Shapiro, and S. R. Hinkle. 2011. “A comparison of recharge rates in aquifers of the United States based on groundwater-age data.” *Hydrogeol. J.* 19 (4): 779–800. https://doi.org/10.1007/s10040-011-0722-5.

Mishra, S. K., A. Pandey, and V. P. Singh. 2012. “Special issue on soil conservation service curve number (SCS-CN) methodology.” *J. Hydrol. Eng.* 17 (11): 1157. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000694.

Musyoka, F. K., P. Strauss, G. J. Zhao, R. Srinivasan, and A. Klik. 2021. “Multi-step calibration approach for SWAT model using soil moisture and crop yields in a small agricultural catchment.” *Water* 13 (16): 2238. https://doi.org/10.3390/w13162238.

Nash, J. E., and J. V. Sutcliffe. 1970. “River flow forecasting through conceptual models part I—A discussion of principles.” *J. Hydrol.* 10 (3): 282–290. https://doi.org/10.1016/0022-1694(70)90255-6.

Neitsch, S. L., J. G. Arnold, J. R. Kiniry, and J. R. Williams. 2011. *Soil and water assessment tool—Theoretical documentation—Version 2009*. Rep. No. 406. College Station, TX: Texas Water Resources Institute.

Pranjal, P., N. Kadiyan, R. S. Chatterjee, D. Kumar, and M. S. Sati. 2021. “Interpreting land subsidence impacts due to groundwater depletion using remote sensing-based GRACE gravity anomaly and DInSAR technique: A study on north-western parts of India.” *Environ. Earth Sci.* 80 (17): 596. https://doi.org/10.1007/s12665-021-09905-y.

Preetha, P., and A. Al-Hamdan. 2020. “Developing nitrate-nitrogen transport models using remotely-sensed geospatial data of soil moisture profiles and wet depositions.” *J. Environ. Sci. Health Part A* 55 (Aug): 615–628. https://doi.org/10.1080/10934529.2020.1724503.

Preetha, P., and A. Al-Hamdan. 2022. “A union of dynamic hydrological modeling and satellite remotely-sensed data for spatiotemporal assessment of sediment yields.” *Remote Sens.* 14 (2): 400. https://doi.org/10.3390/rs14020400.

Preetha, P. P., and A. Z. Al-Hamdan. 2019. “Multi-level pedotransfer modification functions of the USLE-K factor for annual soil erodibility estimation of mixed landscapes.” *Model. Earth Syst. Environ.* 5 (3): 767–779. https://doi.org/10.1007/s40808-018-0563-5.

Preetha, P. P., N. Joseph, and B. Narasimhan. 2021. “Quantifying surface water and ground water interactions using a coupled SWAT_FEM model: Implications of management practices on hydrological processes in irrigated river basins.” *Water Resour. Manage.* 35 (9): 2781–2797. https://doi.org/10.1007/s11269-021-02867-7.

Reitz, M., W. E. Sanford, G. B. Senay, and J. Cazenas. 2017. “Annual estimates of recharge, quick-flow runoff, and evapotranspiration for the contiguous U.S. using empirical regression equations.” *J. Am. Water Resour. Assoc.* 53 (4): 961–983. https://doi.org/10.1111/1752-1688.12546.

Reusser, D. 2020. “Fast.” Accessed October 12, 2021. https://rdrr.io/cran/fast/.

Robinson, J. L. 2002. *Ground-water quality beneath an urban residential and commercial area, Montgomery, Alabama, 1999–2000*. Rep. No. 02–4052. Washington, DC: US Geological Survey.

Rutledge, A. T. 1998. *Computer programs for describing the recession of ground-water discharge and for estimating mean ground-water recharge and discharge from streamflow records—Update*. Rep. No. 98-4148. Washington, DC: US Geological Survey.

Sanford, W. E., D. L. Nelms, J. P. Pope, and D. L. Selnick. 2012. *Quantifying components of the hydrologic cycle in Virginia using chemical hydrograph separation and multiple regression analysis*. Rep. No. 2011-5198. Washington, DC: US Geological Survey.

Schuerz, C. 2021. “SWATplusR.” Accessed October 12, 2021. https://github.com/chrisschuerz/SWATplusR.

Xu, C. G., and G. Gertner. 2011. “Understanding and comparisons of different sampling approaches for the Fourier amplitudes sensitivity test (FAST).” *Comput. Stat. Data Anal.* 55 (1): 184–198. https://doi.org/10.1016/j.csda.2010.06.028.