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Challenges Calibrating Hydrology for Groundwater-Fed Wetlands: a Headwater Wetland Case Study

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Abstract

This study aims to adapt the Soil and Watershed Assessment Tool (SWAT), a ubiquitously used watershed model, for groundwater dominated surface waterbodies by accounting for recharge from the aquifers. Using measured flow to a headwater slope wetland in Alabama's coastal plain region as a case study, we present challenges and relatively simple approaches in using the SWAT model to predict flows from the draining watershed and relatively simple approaches to model groundwater upwelling. SWAT-simulated flow at the study watershed was limited by precipitation, and consequently, simulated flows were several times smaller in magnitude than observed flows. Thus, our first approach involved a separate stormflow and baseflow calibration which included the use of a regression relationship between observed and simulated baseflow (E_{NASH} = 0.67). Our next approach involved adapting SWAT to simulate upwelling groundwater discharge instead of deep aquifer losses by constraining the range of deep losses, β_{deep} parameter, to negative values (E_{NASH} = 0.75). Finally, we also investigated the use of artificial neural networks (ANN) in conjunction with SWAT to further improve calibration performance. This approach used SWAT-calibrated flow, evapotranspiration, and precipitation as inputs to ANN (E_{NASH} = 0.88). The methods investigated in this study can be used to navigate similar flow calibration challenges in other groundwater dominant watersheds which can be very useful tool for managers and modelers alike.

Keywords Wetland · Model · SWAT · Headwater slope wetland · High baseflow · Artificial neural networks

1 Introduction

The biogeochemical state or nutrient content of a drainage network is dictated by that of its headwaters which form the beginning of water movement from uplands into streams [6]. Headwater streams also comprise the highest proportion of stream miles [17, 32, 33], which explains their disproportionately high influence in the drainage [6, 32, 33]. Wetlands of headwater streams provide important ecosystem services such as habitat for aquatic life; nutrient uptake and cycling; clean drinking water; downstream temperature regime regulation; and reduce loads of nitrogen, phosphorous, and sediment to coastal waters [32, 33, 35]. As a class, wetlands on lower order streams have higher capacity for water quality mitigation from nonpoint source pollution since channel flow in higher order downstream reaches does not come in contact with the floodplain wetland surface very often (due to infrequent overbank flooding)—this calls for greater scrutiny of wetland alterations on low-order streams [6, 32].

Forested, groundwater-fed headwater slope wetlands occur throughout the Alabama–Mississippi coastal plain at the headwaters of coastal creeks [27]. Given their density on the landscape and their location at the interface of uplands and coastal creeks, these wetlands are likely to be extremely important in ameliorating runoff. However, headwater streams and associated wetlands have been severely altered in the Southeast, and

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data from headwater wetlands in the region are sparse [32]. Though watersheds draining into headwater wetlands tend to be small (< 1km^2 [9]), understanding the impact of human activities in these small headwater watersheds is critical to the restoration and management of headwater slope wetlands. In order to predict watershed impacts on headwater slope wetlands, models have to be applied and calibrated.

However, modeling involves several challenges because (1) models are essentially simpler representations of natural systems since it is not possible to account for the entire extent of real world complexity and (2) models are defined by the values of their parameters. This can cause even highly complex models to fail in simulating watershed processes. Disparities between surficial and ground watershed size in small watersheds can also introduce challenges to the model calibration process. Since ground watersheds cannot be observed from the land surface, defining their extent can be challenging [43]. Additionally, groundwater flow systems of different magnitudes may be superimposed on one another, or the groundwater divides themselves may move in response to dynamic recharge and discharge conditions [43]. These associations are further influenced by watershed size and its location within the groundwater flow system. For small watersheds located on terrains with high permeability and low regional topographic relief, as encountered in coastal Alabama, ground watershed area contributing water to the watershed can extend beyond the boundaries of the surficial watershed unless the watershed is situated on groundwater divides [43].

Subsurface processes are also difficult to observe or represent in watershed models because of the high level of soil/aquifer heterogeneity and the lack of data to characterize hydrogeological systems and their responses [29]. While the parameters of these processes maybe measured, they are prohibitive for use in larger watershed modeling since these are usually point scale measurements—for use in models, these may be averaged or used at grid scales, which are larger than the scale of variations of these processes and as such do not capture catchment heterogeneity [29]. While there is consensus about the holistic existence of surface water and groundwater systems, these integrated systems are not very well developed in models [38, 44].

A wide variety of models are utilized nowadays to understand hydrological and water quality responses to land use changes and environmental alterations. Watershed scale models such as the Soil and Watershed Assessment Tool (SWAT) have combined recent advancements in computational power with the use of Geographic Information Systems (GIS) technology to establish semi- to fully distributed hydrologic models to better represent physical processes governing complex natural systems. Since SWAT allows for manipulations of land use, soils, slope, and climate on watershed scales, it has wide applicability in determining impacts of different land use practices, climate, etc. on hydrological and water quality responses of a diversity of water bodies at multiple scales [20]. SWAT also has provisions for automated parameter calibration through the use of SWAT Calibration and Uncertainty Program, or SWAT-CUP, which enables sensitivity analysis, calibration and uncertainty analysis for SWAT models [1]. However, SWAT is typically applied to studies where flows are a fraction of precipitation over the watershed; it is structured to compute deep aquifer losses as opposed to recharge from deep aquifers. In areas of low topographical relief such as in low coastal plain regions, extensive belowground watersheds can result in localized upwelling zones creating high baseflows which may cause overall flows to exceed precipitation over the surficial watershed—a situation that SWAT has not been used to address to our knowledge. This study aims to adapt SWAT for such groundwater-dominated surface waterbodies by accounting for recharge from the aquifers. Using measured flow to a headwater slope wetland in Alabama's coastal plain region as a case study, we present challenges and relatively simple approaches in using the SWAT model to predict flows from the draining watershed and relatively simple approaches to model groundwater upwelling.

The coastal plain watershed in question (as delineated by SWAT) is small, 0.49 km^2, and drains into a slope wetland at the headwaters of Owen's Bayou in Foley, AL. In order to predict the nutrient loadings to the wetland, daily streamflow estimates from this watershed were needed. However, measured flow data was sparse and had significant gaps. A modeling approach therefore was used to fill these gaps. Flow, estimated at a discernible surface water inlet to the headwater slope wetland, was most peculiar in that it exceeded total precipitation over the watershed. Increasing the delineated watershed area to twice its current extent still did not alter this imbalance. Although not common, wetland hydrology can be dominated by groundwater discharge as a major source, which in some areas can be greater than the surface flow component (e.g., [43]). This establishes the need for models that can simulate groundwater discharge (upwelling) contributed by deep regional aquifers. However, the SWAT model has limited capability to accurately predict groundwater interactions, especially groundwater discharge from deep regional aquifers. In order to simulate the hydrology of such complex ecosystem, an integrated version of the SWAT model linking SWAT with groundwater model MODFLOW (SWAT-MODFLOW) is currently available, which links groundwater outputs from SWAT as inputs for MODFLOW [10]. However, this modeling approach is resource intensive (data, computational time and labor) and requires detailed hydrogeologic site characterization, all of which may be too high of an investment for project goals in a small watershed. Moreover, a separate MODFLOW model needs to be developed at appropriate spatial resolutions in order to be linked with SWAT. In the absence of any groundwater observations or associated aquifer data, there is no assurance that a highly complex model will yield better results. Instead, can a simpler approach be implemented using SWAT only to model watershed flows when observed flows exceed precipitation in the watershed? Indeed, SWAT can be adapted as shown in this study to model groundwater upwelling in the absence of more detailed hydrogeologic data.

Data-driven approaches such as the use of artificial neural networks (ANN) are other extensively used tools in hydrology modeling [28, 31, 39]. ANNs are black box models which can be trained to learn the relationships between inputs and outputs (including highly complex, multidimensional, nonlinear relationships) in a process without actually needing to delve into the physical characteristics of the process [28, 31, 39]. ANNs, therefore, provide a useful alternative for streamflow predictions while steering clear of issues affecting process-based models such as SWAT due to reasons such as large spatial scale and complex but poorly understood processes (as described in previous paragraphs). ANNs may also be applied together with a watershed model to enhance streamflow prediction capabilities. A few studies have compared the ability of SWAT and ANN in predicting streamflow [15, 39, 40], but only one study to our knowledge has tested the utility of coupling SWAT and ANN for improved streamflow prediction [28]. In [28], authors showed that SWAT–ANN coupling can predict daily streamflow in ungauged basins better than the standalone SWAT model. Our study also aims to add to the body of literature using ANN models in conjunction with SWAT to improve hydrological prediction ability.

The overarching goal of this paper is to present three approaches to predict flow in groundwater-dominated small headwater watersheds, as relatively simple alternatives to more complex models that have strong surface/groundwater coupling. The specific objectives are as follows: (1) to explore hydrological trends of the watershed outflows draining into a headwater slope wetland in coastal Alabama and (2) to apply different approaches of hydrology calibration using SWAT including applying an optimized adjustment factor to SWAT-calibrated baseflow, adapting SWAT to simulate groundwater discharge to the study wetland, and developing ANN model with inputs from SWAT to further improve calibration. The study will yield useful modeling approaches in SWAT to model flow in watersheds dominated by groundwater input as an alternative to more complex groundwater–surface water interaction models. Additionally, the study explores the use of artificial neural networks (ANN) in improving flow calibration.

2 Materials and Methods

2.1 Site Description and Hydrology Monitoring

Data for this study was collected from a discernible inlet to a headwater slope wetland in Baldwin County, AL: New Foley wetland (30.354°, − 87.631°) located at the headwaters of a smaller tributary to Owen's bayou (Fig. 1) within the city of Foley. Headwater slope wetlands in coastal Alabama occur above and alongside first-order streams—they are typically groundwater fed and exist as braided channels along a gradual slope [27, 37]. Wetland soils are generally alluvial [4, 21] and remain saturated or close to saturated throughout the year since these wetlands have fairly stable water levels that are at or slightly below the ground surface [27]. Land use in the watershed draining to the New Foley wetland is predominantly residential. A prominent feature of the draining area is a stormwater lake that drains into the NF wetland (Fig. 1). The study area is characterized by hot, humid summers, and mild winters with average annual temperatures of 19 °C and precipitation of 170 cm mostly evenly distributed throughout the year with peaks occurring in early spring and midsummer [4, 27, 34].

Hydrological data was collected at the study wetland from August 2013 to December 2014. Stage was measured every 15 min using InSitu Mini-Troll 500 pressure transducers and data loggers at a discernible inlet to the wetland. Surface water velocity and depth were measured at the site at twelve different instances for every 10 cm across the channel width and used to calculate average surface water discharge using the velocity–area method (based on USGS stream gauging guidelines, [30]). The surface water velocity was measured by using a Marsh-McBirney, Inc. Flo-Mate Model 2000 Portable Flowmeter. Discharge was associated with transducer stage reading from the nearest time of velocity measurement to develop stage-discharge relationship.

A modified Manning's equation was used to generate estimates of discharge as a function of measured stage. Manning's formula can be described as

$$Q = \frac{1}{n} A R^{\frac{2}{3}} \sqrt{S_0} \qquad (1)$$

$$Q = k A R^{\frac{2}{3}} \qquad (2)$$

where Q = flow (m^3/s), R = hydraulic radius (m), S_0 = friction slope, estimated as bedslope, n = Manning's roughness coefficient, A = channel cross-sectional area, and $k = \sqrt{S_0}/n$. From channel dimensions, channel cross-sectional areas, wetted perimeters, and hydraulic radius were calculated and applied to stage (h)–discharge (Q) data to calculate k for each data point from Eq. (2), and subsequently, a k–h relationship was developed through regression. This k–h relationship was combined with Eq. (2) to convert the measured stage time series at 15-min time intervals into discharge time series, which were then used to estimate average daily flow to the wetland through the discernible surface water inlet.

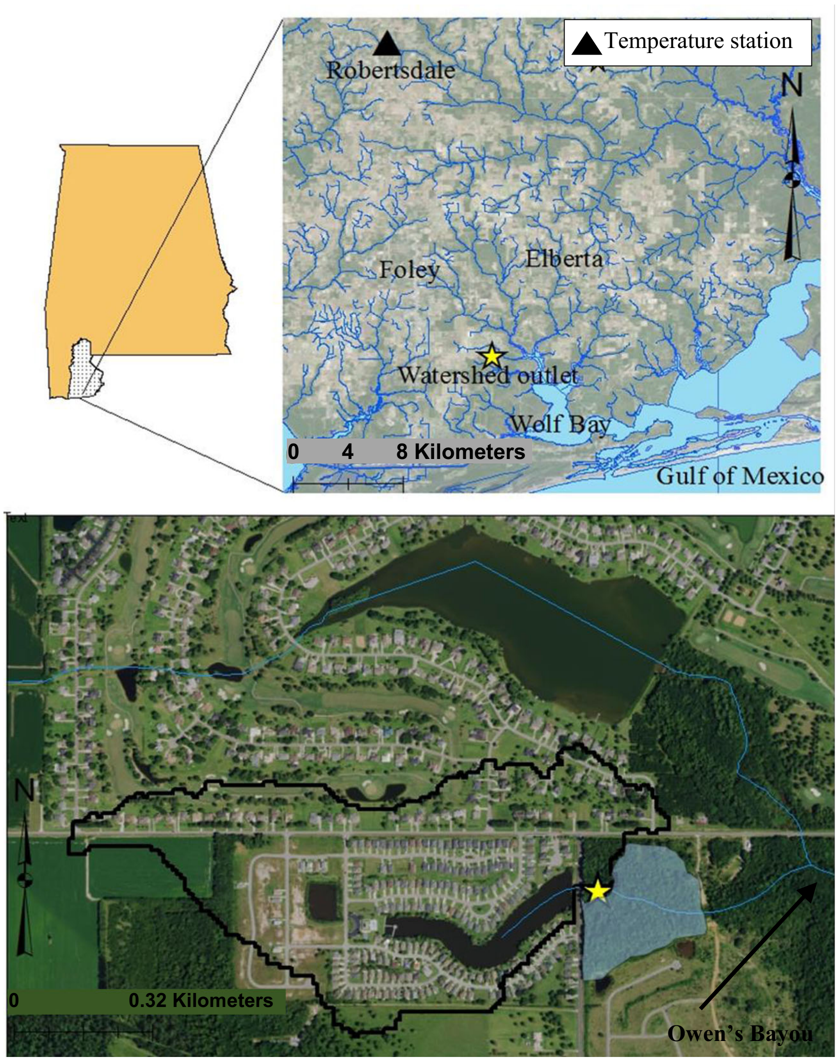

Fig. 1 The head watershed used for this study drains into a headwater slope wetland that feeds a tributary to Owens's bayou. The watershed area is 0.49 km^2 with ~ 57% classified as urban

2.2 SWAT and SWAT-CUP Model Descriptions

The Soil and Watershed Assessment Tool (SWAT) is a widely used watershed scale, process-based hydrologic model that was developed by the US Department of Agriculture [3, 7]. It can operate on hourly, daily, monthly or annual scales and has been used effectively for assessing nonpoint source pollution problems at different scales and environmental conditions all over the world [7]. SWAT divides the watershed into multiple subwatersheds which are further divided into hydrologic response units or HRUs—these represent percentages of the subwatershed area and are not identified visually within a SWAT simulation [8]. SWAT defines multiple HRUs each having unique land use, soil and slope combinations. Hydrology is separated into the land phase and the routing phase of the hydrologic cycle–water to the main channel is determined by the land phase of the hydrologic cycle while the routing phase determines water from the channel network to the outlet. SWAT uses either the Conservation Service Curve number (CN) method or the Green and Ampt infiltration method to estimate surface runoff. Three methods are included for evapotranspiration estimation based on the number of inputs required—the Penmen–Monteith method, the Priestly–Taylor method and the Hargreaves method. Surface, lateral subsurface, and baseflow waters reaching the stream channels are routed either through Muskingum or variable storage coefficient method. The water budget is developed for each HRU, and then aggregated for the subbasin by a weighted average [16].

Water enters groundwater primarily through infiltration/percolation from land surfaces and seepage from surface water bodies [26]. SWAT simulates two aquifers within each subbasin, a shallow aquifer which is unconfined and contributes baseflow to the reach or main channel of the subbasin, and a deep confined aquifer which contributes to streamflow somewhere outside the watershed. Below we describe the groundwater component of the SWAT model in more detail given its significant contribution to the study system.

SWAT calculates baseflow contribution to a channel on a given day as

$$Q_{gw,i} = Q_{gw,i-1}.\exp(-\alpha_{gw}.\Delta t) + w_{rchrg,sh}.(1-\exp[-\alpha_{gw}.\Delta t]), \text{ if } aq_{sh} > aq_{shthr,q} \quad (3)$$

$$Q_{gw,i} = 0, \ \text{ if } aq_{sh} < aq_{shthr,q} \quad (4)$$

where $Q_{gw,\ i}$ and $Q_{gw,\ i-1}$ are baseflow or groundwater flows into the main channel on days i and $i-1$ respectively (mm H_2O), Δt is the daily time step ($\Delta t = 1$ day), $w_{rchrge,\ sh}$ is the amount of recharge entering the shallow aquifer on day i (mm H_2O), aq_{sh} is the amount of water stored in the shallow aquifer at the beginning of day i, $aq_{shthr,\ q}$ is the threshold water level in the shallow aquifer for groundwater contribution to the main channel to occur (mm H_2O), and α_{gw} is the baseflow recession constant (a direct index of groundwater flow response to changes in recharge).

The amount of recharge entering the shallow aquifer, $w_{rchrge,\ sh}$, is a portion of the total aquifer recharge w_{rchrg} after accounting for percolation to the deep aquifer which is lost from the system. This is represented as

$$w_{rchrge,sh} = w_{rchrg} - w_{deep} \quad (5a)$$

where w_{rchrg} is the total aquifer recharge on day i (mm H_2O), and w_{deep} is the amount of water percolating from the shallow aquifer to the deep aquifer on day i (which is essentially lost since it does not contribute to flows within that subbasin) (mm H_2O); it is given by

$$w_{deep} = \beta_{deep}\, w_{rchrg} \quad (5b)$$

where β_{deep} is the aquifer percolation coefficient and assigned default positive values in the SWAT model.

Default parameter ranges for β_{deep} in the SWAT model ensures $w_{deep} \geq 0$ mm/day, i.e., SWAT only assumes water loss from the shallow aquifer to the deep aquifer. The reverse scenario of discharge from the deep aquifer into the shallow aquifer is not considered in SWAT. However, by constraining the range of default values of β_{deep} to negative values, SWAT can be adapted as shown later to simulate recharge to the shallow aquifer from the deep aquifer.

Aquifer recharge, w_{rchrg}, is comprised of water percolating past the lowest depth of the soil profile and bypass flow flowing through the vadose zone. An exponential decay weighting function is used to model recharge to the aquifers as

$$w_{rchrg,i} = \left(1-\exp\left[-\frac{1}{\delta_{gw}}\right]\right) w_{seep} + \exp\left[-\frac{1}{\delta_{gw}}\right] w_{rchrg,i-1} \quad (6)$$

where $w_{rchrg,\ i}$ is the amount of recharge entering aquifers on day i (mm H_2O), δ_{gw} is the delay time or drainage time of the overlying geologic formations which has been shown to remain somewhat constant within the same geomorphic area, w_{seep} is the total amount of water exiting the bottom of the soil profile on day i (mm H_2O), and $w_{rchrg,\ i-1}$ is the amount of recharge entering the aquifers on day $i-1$ (mm H_2O).

Parameters for the SWAT model can be calibrated through manual and automated methods—the former involves running SWAT model with manually modified deterministic values for parameters, while the latter allows the user to run SWAT models using parameters propagated within a range of specified feasible upper and lower values for parameters. An automated calibration software called SWAT Calibration and Uncertainty and Program (SWAT-CUP) was developed specifically to be used with SWAT in order to report uncertainty in the results by propagating parameter uncertainties [1]. Various SWAT parameters are identified for auto-calibration, through initial manual calibration as well as from literature. Parameter ranges are then propagated by Latin hypercube sampling using the SUFI-2 algorithm in SWAT-CUP [1]. Propagating parameter uncertainties results in uncertainties in the outputs which are represented as 95% confidence intervals of probability distributions—calculated at 2.5% and 97.5% levels of the cumulative output distributions—also known as the 95% prediction uncertainty or the 95PPU. The goal of the SWAT-CUP calibration process is to have the 95PPU envelop most of the observations (measured data). The fit between simulation results, i.e., the 95PPU, and the observations is represented by two main factors—the *P*-factor and *R*-factor. The *P*-factor represents the percentage of observations enveloped by the 95PPU, and the *R*-factor is the thickness of the 95PPU band. No firm values exist for these values—for flow, a *P*-factor ≥ 0.7 and *R*-factor ≤ 1 are considered acceptable [1]. A few iterations (usually < 5) of multiple simulations (300–500 depending on the time it takes) are performed in SWAT-CUP, where initially the user starts out with larger parameter ranges which get smaller with each iteration. Various criteria such as coefficient of determination (R^2), Nash–Sutcliffe efficiency (E_{NASH}) [24], and bias ratio (R_{BIAS}) [36] are used to measure the closeness of the model output and the observed data.

2.2.1 SWAT and SWAT-CUP Model Setup and Data

The SWAT model was developed and applied for the watershed draining into the New Foley wetland at the discernible surface water inlet to the wetland. We used SWAT version SWAT-2012 through the ArcSWAT interface in ArcGIS 10.0 for all SWAT simulations. All the GIS data required for ArcSWAT setup was downloaded from the USGS's online Seamless Data Warehouse (https://datagateway.nrcs.usda.gov). The watershed boundaries for the wetland were delineated by ArcSWAT using elevation data obtained from the National Elevation Dataset (NED) DEM with a resolution of one-third arc-second (10 m pixels) developed by USGS and hydrography data from the National Hydrography Dataset (NHD). Hydrography was further modified and digitized to include headwaters with channel extensions to improve watershed delineation and streamflow routing in ArcSWAT [2]. The delineated watershed contributing to the discernible wetland inflow where the transducer was located had an area of 0. 49 km^2 (49 ha).

Land use data was obtained from the 2011 National Land Cover Dataset (NLCD), and soil parameters were derived from the county level Soil Survey Geographic (SSURGO) dataset. Some classifications in the NLCD layer were edited slightly to reflect current land use in the watershed. About 57.2% of the watershed area was classified urban. Slopes were divided into 3% classes (1–3%, 3–6%, etc.). Threshold values of 5% were used for land use, soils, and slope definition. Daily maximum and minimum temperatures for the study period were available from a station in Robertsdale (station GHCND: USC00016988) in Baldwin County (Fig. 1). Daily precipitation was obtained from NEXRAD data for a period from 2008 to 2014, and the Hargreaves method was used for calculation of potential evapotranspiration.

The study area received very high rainfall of ~ 380 mm between April 28 and May 1, 2014, and fluctuations in transducer data after these dates were highly variable and exaggerated. We believe that the sudden extreme rainfall may have affected the functioning of the transducer and caused it to produce faulty data. Consequently, these dates were excluded from the calibration. Since the duration of observed data was so small (< 1 year), we did not split the data to perform validation—instead all the data was used for calibration alone. While the small duration of observed data is an important limitation to the study, it is not detrimental to the overall objectives of the study which are to present different approaches of dealing with challenging hydrology calibrations in a headwater watershed with extensive groundwater inputs.

Previously calibrated parameter values reported in [42] for Magnolia River watershed, which is situated adjacent (in the northeast side) to the Wolf Bay watershed of which the study watershed is a part (Fig. 2), were applied as starting values in the SWAT model for the study wetland (Table 1). Since the Magnolia River and Wolf Bay watersheds neighbor each other and have similar physical characteristics (soils, slope, geology), SWAT parameters calibrated for the Magnolia river watershed can be transferred to the Wolf Bay watershed [42]. Literature has shown that model simulations require a long warm-up period to accurately represent conditions being simulated such as antecedent moisture and initial groundwater table height which can influence predictions of streamflow and baseflows [5, 13, 42]. The SWAT model was run for 7 years, with a warm-up period of 5 years (2008–2012) prior to the 2-year period (2013–2014) of which the study period (August 10, 2013–April 28, 2014) is a part, to accurately initialize SWAT parameters.

SWAT-CUP requires that the default simulation (simulation that is fed into SWAT-CUP for calibration) to not be too different from observed data. For this reason, some manual calibration was done (in addition to applying parameter values from Table 1) to ensure some parity between simulated and observed flows at the wetland inlet. Procedures explained in [25] and personal communication with different SWAT users were used to adjust parameters for calibration. For baseflow-dominated areas, parameters such as groundwater delay (GWDELAY), deep aquifer recharge coefficient (RCHRGE_DP), and baseflow alpha factor (ALPHA_BF) were adjusted, along with SCS curve number (CN2). Model parameters were calibrated at daily timescales for flow. Following manual calibration, around sixteen parameters influencing different aspects of surface and subsurface flows were chosen for SWAT-CUP auto-calibration from literature (Table 2). SWAT-CUP 2012 version 5.1.6 was used to conduct auto-calibration runs.

2.3 Coupled SWAT–ANN Model Description and Setup

While hydrological models may be calibrated to some satisfying measure of performance ability, they may not always preserve all aspects of the hydrograph, i.e., not all simulated flow values will correspond to observed values [41]. For example, a model might have a reasonably high value of the objective function but fails in adequately capturing high or low flow extremes which may be critical in predicting specific ecological responses [41]. One way of dealing with this limitation involves a stepwise coupled approach by first calibrating with SWAT through a process-based hydrological understanding of the system followed by black box models such as artificial neural networks (ANN) to improve the former calibration.

ANNs are black box models where detailed understanding of the internal processes is not required to develop relationships between the inputs and outputs [12, 28, 39]. Many kinds of ANN exist, but the feed forward ANN is used most commonly in hydrological applications and consists of several nodes organized in layers. Between the input and the output layers, a number of user-defined hidden layers exist where most of the processing takes place. Input data is fed into the input layer, which communicates with nodes in the hidden layer(s), which then links to an output layer where the response of the ANN model is received [39]. A process called training corresponds with the calibration process in traditional models [39]. During training, the inputs together with the desired response (target response/observed data) are fed to the ANN model. The ANN model process is started with an initial random choice of weights, input data, and target response, and the model is allowed to compute responses which are compared with the desired response: this process is repeated in an iterative manner, each time adjusting the weights, until the desired subjective stopping criterion is reached. Training aims to minimize a predefined error function by

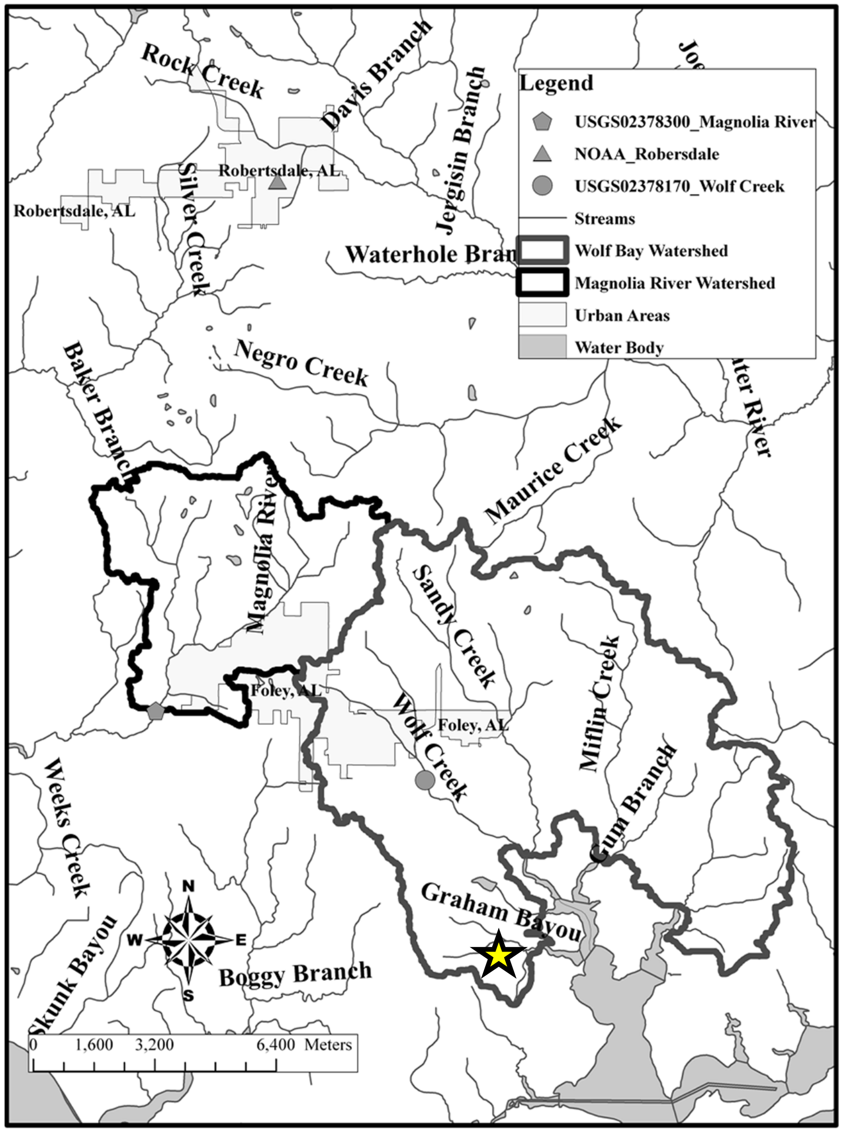

Fig. 2 Yellow star represents the location of study watershed which is part of the Wolf Bay watershed. The Magnolia River watershed is located adjacent to the Wolf Bay watershed on the northeast side. The image is borrowed from [42] to show the spatial proximity of Magnolia River watershed to the study watershed

searching for a set of connection strengths and threshold values so that ANN outputs are close or equal to the desired response/target [14, 39]. Inputs are usually normalized to avoid differences in magnitudes and variance from interfering with the training process [39].

The size of the hidden layer and the number of neurons are important considerations in ANN development. There is no singular setup structure; rather, trial and error is used to establish the optimum number of hidden layers and neurons [12]. We varied the number of neurons in the hidden layer from 5 to 10 but restricted the number of hidden layers to 1 to avoid over-fitting with such limited data. We also used two different transfer functions to translate input signals to output signals—the log-sigmoid and the hyperbolic tangent sigmoid functions [28]—and picked the one which gave better results. We used SWAT-calibrated streamflow at the inlet to the wetland (calibrated to observed flow at that location) together with precipitation and potential evapotranspiration (PET) calculated by the Hamon method [11] as inputs to the ANN model. The Hamon method calculates daily PET as a function of daily mean air temperature and hours of daylight and has been shown to work favorably in the southeastern USA [19, 28]. Here we checked to see if coupling ANN with SWAT-calibrated streamflow would yield better calibration results than calibrating with SWAT alone. We used MATLAB R2016a version 9.0.0 for model construction and implementation.

2.4 Performance Measures and Evaluation Criteria

Model performances were measured using metrics such as coefficient of determination (R^2), Nash–Sutcliffe efficiency (E_{NASH}) [24], and bias ratio (R_{BIAS}) [36]. The coefficient of determination (R^2) is a measure of linear

Table 1 Calibrated parameters for Magnolia River watershed, Baldwin County, AL from [42]

Parameters	Default	Wang and Kalin (2010) Magnolia River watershed
CN2	Varies	+3[a]
ESCO	0.95	1
GW_ DELAY	31	–
GWQMN	0	–
GWREVAP	0.02	–
SURLAG	4	1
SOL_AWC	Varies	− 0.01[a]
REVAPMN	10	500
ALPHA_BF	0.048	0.015
CH_N2	0.014	0.114

[a] Plus and minus sign indicate that parameter values are increased/decreased by adding/subtracting the given amount

correlation between the two quantities and explains the fraction of variance in the observed data explained by the model, while the Nash–Sutcliffe efficiency statistic (E_{NASH}) reflects the correspondence between observed and simulated data on 1:1 line. Contrary to R^2, which is varies between 0 and 1, E_{NASH} values vary from $-\infty$ to 1 where 1 corresponds to the perfect model. The bias ratio (R_{BIAS}) measures the degree to which the forecast is under- or overpredicted—negative values indicate underprediction and positive values indicate overprediction [36].

$$R^2 = \frac{\left[\sum_i \left(Q_{\mathrm{obs},i} - \overline{Q}_{\mathrm{obs}}\right)\left(Q_{\mathrm{sim},i} - \overline{Q}_{\mathrm{sim}}\right)\right]^2}{\sum_i \left(Q_{\mathrm{obs},i} - \overline{Q}_{\mathrm{obs}}\right)^2 \sum_i \left(Q_{\mathrm{sim},i} - \overline{Q}_{\mathrm{sim}}\right)^2}$$

$$E_{\mathrm{NASH}} = 1 - \frac{\sum_i \left(Q_{\mathrm{obs},i} - Q_{\mathrm{sim},i}\right)^2}{\sum_i \left(Q_{\mathrm{obs},i} - \overline{Q}_{\mathrm{obs}}\right)^2}$$

$$R_{\mathrm{BIAS}} = \frac{\overline{Q}_{\mathrm{sim}} - \overline{Q}_{\mathrm{obs}}}{\overline{Q}_{\mathrm{obs}}}$$

where Q is a variable of interest (e.g., discharge), $\overline{Q}$ is the average of variable Q over a specific period, and obs and sim indexes represent observed and simulated data, respectively.

Model performances for flow simulations were assessed based on the guidelines presented by [22] for assessments of flow and nutrients at monthly time scales. Since our study is assessed at a daily time scale, the modified relaxed constraints in [14] were adopted for the purposes of this study:

Table 2 Parameters chosen from manual calibration and literature for inclusion in SWAT-CUP

Parameter	Parameter description	Location
CN2	Initital SCS runoff curve number for moisture condition II	.mgt
ALPHA_BF	Baseflow alpha factor (1/days)	.gw
GW_DELAY	Groundwater delay time (days)	.gw
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm H_2O)	.gw
GW_REVAP	Groundwater revap coefficient which controls rate of water movement from shallow aquifer to the root zone	.gw
ESCO	Soil evaporation compensation factor	.hru
CH_N(2)	Manning's "*n*" value for the main channel	.rte
CH_K(2)	Effective hydraulic conductivity in main channel alluvium (mm/hr)	.rte
ALPHA_BNK	Baseflow alpha factor for bank storage (days)	.rte
SOL_AWC()	Available water capacity of the soil layer (mm H_2O)/mm soil)	.sol
SOL_K()	Saturated hydraulic conductivity (mm/hr)	.sol
SOL_BD()	Moist bulk density (Mg/m^3 or g/cm^3)	.sol
RCHRG_DP	Deep aquifer percolation fraction	.gw

Very Good: $E_{NASH} \geq 0.7$; $|R_{BIAS}| \leq 0.25$
Good: $0.5 \leq E_{NASH} < 0.7$; $0.25 < |R_{BIAS}| \leq 0.5$
Satisfactory: $0.3 \leq E_{NASH} < 0.5$; $0.5 < |R_{BIAS}| \leq 0.7$
Unsatisfactory: $E_{NASH} < 0.3$; $|R_{BIAS}| > 0.7$

3 Calibration Approaches

The hydrology at the watershed outlet (inlet to the wetland) showed distinctive trends consistent with ecological understanding of flow as a function of urbanization and coast proximity. As is seen in Fig. 3, observed flow had consistently high baseflow contribution. For the study period, observed flow at the watershed outlet ranged from 0.048 to 0.95 m^3/s and averaged around 0.15 m^3/s.

SWAT simulations, after transferring parameters from the adjacent Magnolia River watershed, failed to simulate the magnitude of observed flows (R^2 = 0.52, E_{NASH} = − 0.57, R_{BIAS} = − 0.82; Fig. 3). The figure indicates that the model simulations were able to capture trends but disproportionately (and consistently) underpredicts the magnitude. The watershed received a total of around 1726 mm of precipitation during the study period. It was, however, interesting to note that the sum of daily watershed outflows during this period equaled 6599 mm (depth calculated for ArcSWAT delineated watershed), which exceeded precipitation by a factor of 3.8, i.e., the percentage of precipitation converted to streamflow was 380%. So where is all this excess water coming from? The only logical conclusion is that there appears to be an upward flow to the shallow aquifer from the deeper aquifer contributing to high baseflows. SWAT assumes coinciding watershed and ground watershed areas and allows for groundwater losses out of the watershed through deep losses unless negative β_{deep} values are used. Thus, the remainder of this section is focused on the different approaches we used to calibrate a system with this unique hydrological behavior. As mentioned previously, extreme rainfall from April 28, 2014 seemed to have affected transducer functioning causing faulty and highly exaggerated fluctuations in the data—consequently, dates following April 28, 2014 were excluded from the calibration. The following calibration approaches are presented through a flowchart in Fig. 4.

3.1 Approach 1—Separate Calibration of Baseflow and Surface Runoff

In this approach, we followed a two-step calibration process where we separately calibrated baseflow trend and surface runoff components. First, we partitioned observed streamflow into baseflow and surface runoff components using the Web-based Hydrograph Analysis Tool (WHAT; [18]) using inbuilt BFI_{max} value (maximum value of long term ratio of base flow to total streamflow) of 0.80 for perennial streams with porous aquifers. We then constructed two SWAT models, one for baseflow and the other for surface runoff.

In the baseflow model, we manually adjusted different parameters to match the baseflow trend (not magnitude) by comparing GW_Q (groundwater contribution to streamflow) with observed baseflow. All parameters for Magnolia River watershed from [42] mentioned in Table 1 were applied such as REVAPMN, which is the threshold depth of water in the shallow aquifer for percolation to the deep aquifer to occur, and ALPHA_BF which is the baseflow recession constant and indicates the groundwater flow response to changes in recharge.

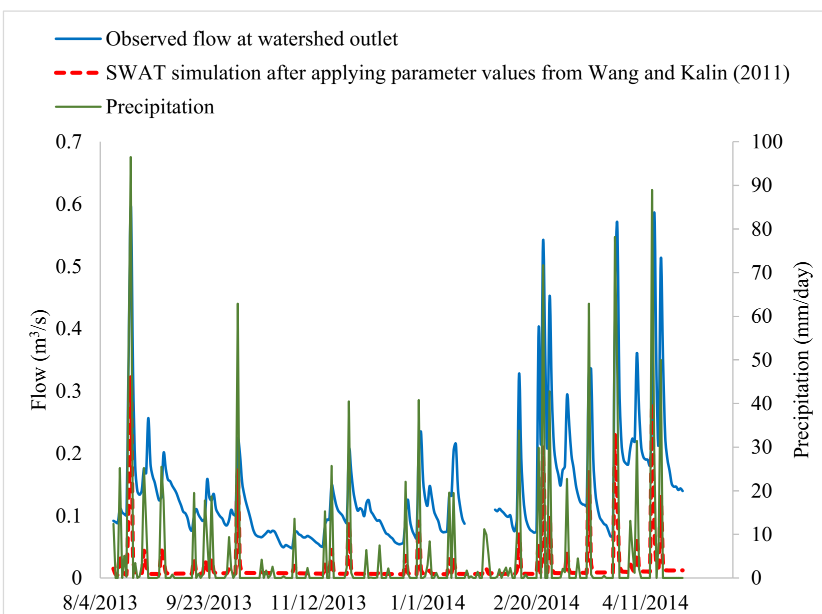

Fig. 3 Comparisons between observed flow from the study watershed and SWAT-simulated flow after applying parameters from [42] for the same. From the figure, the magnitude of observed flow is many times larger than the SWAT simulation

A separate calibration was carried out for the surface runoff component of observed streamflow. This calibration was done using SWAT-CUP software with 13 parameters concerned with both groundwater and surface water components (Table 2). Groundwater parameters where also considered in this calibration, but this does not affect actual baseflow estimates whose calibration was undertaken using a separate model. Three iterations of 500 simulations each were conducted to get calibrated parameter ranges and the values for the best simulation.

Finally, a regression relationship between the simulated baseflow, calibrated for trend, and observed baseflow was used to get final baseflow estimates that were calibrated for both trend and magnitude. This was added to the calibrated surface runoff component to get total calibrated streamflow.

3.2 Approach 2—Adjusting *RCHRGE_DP* to Allow for Groundwater Discharge

In this approach, we evaluated the parameter RCHRGE_DP for its role in removing surface water by percolation to the deep aquifer. The default value of this parameter (fraction) is set to 0.05, and its range extends between 0 and 1—a positive *RCHRGE_DP* indicates shallow aquifer losses to the deep aquifer. However, in certain cases, the deep aquifer may recharge the shallow aquifer, which can be addressed by assigning a negative value to *RCHRGE_DP*. To the best of our knowledge, adapting SWAT model for deep aquifer recharge to shallow aquifers as a strategy for simulating upwelling groundwater discharge to shallow aquifers has not been explored for the circumstances surrounding the watershed evaluated in this study (Fig. 3). As described earlier, if the fraction β_{deep} is made negative, this implies a flow from the deep aquifer into the shallow aquifer since w_{deep} will be negative which in turn increases $w_{\text{rchrge,sh}}$ allowing for higher baseflow contribution from the shallow aquifer to enter the reach.

In this approach of streamflow calibration, we first manually manipulated SWAT parameters to ensure some match between the simulated and observed flows, following which we used SWAT-CUP to complete the calibration. Like in the previous approach, parameters from [42] were first applied following which GW_DELAY was reduced to 1 and ALPHA_BF_D was changed to 0. Instead of a 2-step calibration like the previous approach, we changed *RCHRGE_DP* to − 13 (rounding off coefficient from Eq. (8)). In order for this to work, ranges in the ArcSWAT database should be changed before applying negative *RCHRGE_DP* values in the model. We then used SWAT-CUP to further calibrate the model using three iterations of 500 simulations each.

3.3. Approach 3—ANN-SWAT Coupling

To improve upon any limitations from prior calibrations, previously calibrated streamflow from approach 2 was fed into ANN together with daily precipitation and PET as inputs (Fig. 4). Due to the small calibration dataset (249 data points) and to maintain consistency with the different approaches, we used all of the data for training (or calibration) alone. Through

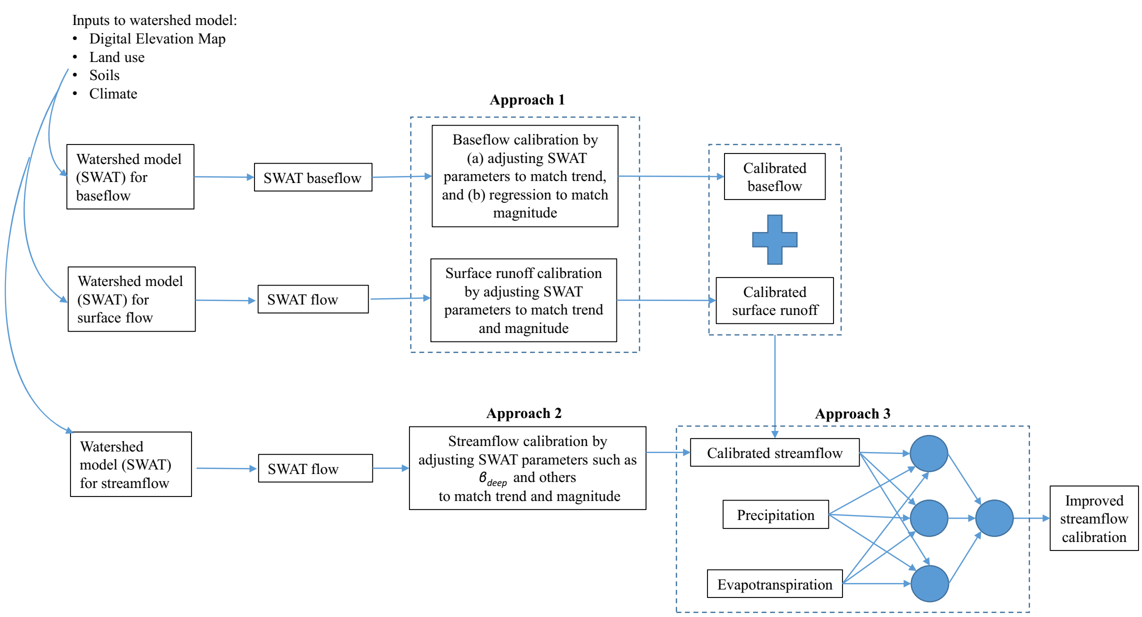

Fig. 4 The figure represents the three calibration approaches used in this study. In approach 1, baseflow and surface flow components are calibrated separately and then summed to get calibrated streamflow. In approach 2, calibration is done by specifically tweaking the deep recharge parameter to allow for groundwater recharge into the system. In approach 3, ANN and SWAT are coupled to improve calibrated streamflow predictions

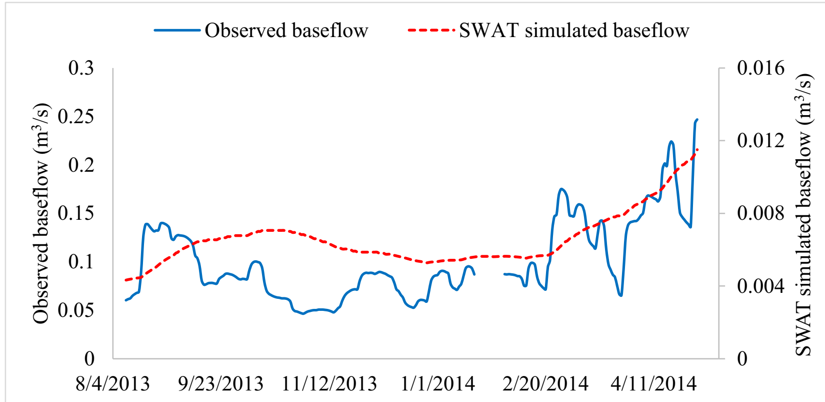

Fig. 5 Comparisons between observed baseflow and SWAT-simulated baseflow after applying parameters from [42]. From the figure, the magnitude of observed baseflow is many times larger than the SWAT simulation, and the trend is different as well ($E_{NASH} = -5.6$)

trial-and-error, the ANN model with one hidden layer, 8 nodes, and a log-sigmoid transfer function was used to calibrate streamflow.

4 Results

4.1 Approach 1

On comparing observed baseflow and surface runoff with that simulated by ArcSWAT (Figs. 5 and 6), we observed that surface runoff matched "satisfactorily" ($R^2 = 0.59$, $E_{NASH} = 0.44$, $R_{BIAS} = -0.55$), which was not the case for baseflows which greatly differed in magnitude or the match was "unsatisfactory" ($R^2 = 0.28$, $E_{NASH} = -5.6$, $R_{BIAS} = -0.93$). So, we then constructed two SWAT models: one for baseflow and the other for surface runoff.

The parameters which were critical in matching baseflow trend were GW_DELAY which is the time required for water leaving the bottom of the root zone to reach the shallow aquifer and RCHRGE_DP which is the deep aquifer percolation fraction. GW_DELAY was decreased to 1 day to mimic the high permeability of sandy soils in the coastal plain area where flow from the root zone to the aquifer is rapid [5]. We also decreased ALPHA_BF_D, which is the alpha factor for groundwater recession curve of the deep aquifer, from the default value of 0.01 (1/day) to 0. RCHRGE_DP (i.e., β_{deep}) was set to 0 (from default value of 0.05) which prevents percolation loss to the deep aquifer. Trends of simulated and observed baseflows now yielded a good match ($R^2 = 0.72$; Fig. 7). The relationship between observed baseflow and simulated baseflow, calibrated for trend, can be described using a linear regression relationship as

$$y = 13.247x - 0.003; R^2 = 0.72 \quad (7)$$

where y is the observed baseflow (m³/s) and x is the ArcSWAT-simulated trend-calibrated baseflow (m³/s). Since the intercept was not significant at $\alpha = 0.05$ ($p = 0.48$), we used a regression equation with zero intercept as

$$y = 12.894x; R^2 = 0.72 \quad (8)$$

This was used to magnify and determine calibrated baseflow estimates which had a "very good" match with observed baseflow ($R^2 = 0.72$, $E_{NASH} = 0.72$, $R_{BIAS} = 0.00$).

Calibrated parameter ranges and values for the best simulation for the surface runoff component are presented in Table 3. The best simulation from this calibration had a "good" match with observed surface runoff ($R^2 = 0.72$, $E_{NASH} = 0.62$, $R_{BIAS} = -0.5$). ArcSWAT-calibrated

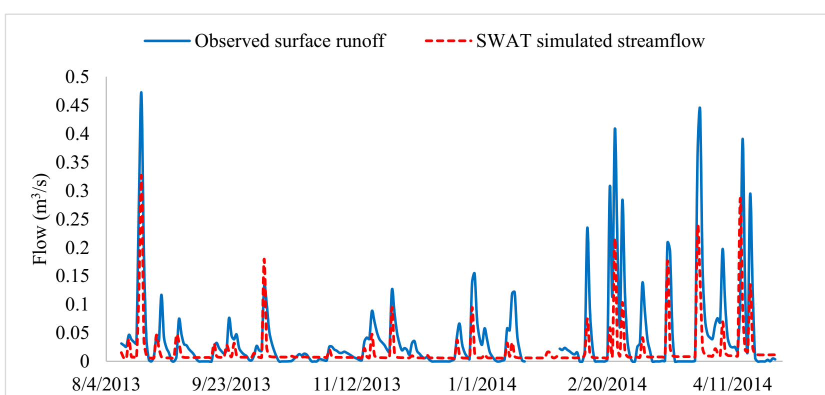

Fig. 6 Comparisons between observed surface runoff and SWAT-simulated streamflow after applying parameters from [42] to the SWAT model for the study watershed. From the figure, there is some parity between the magnitude of observed surface runoff and SWAT-simulated streamflow ($E_{NASH} = 0.44$)

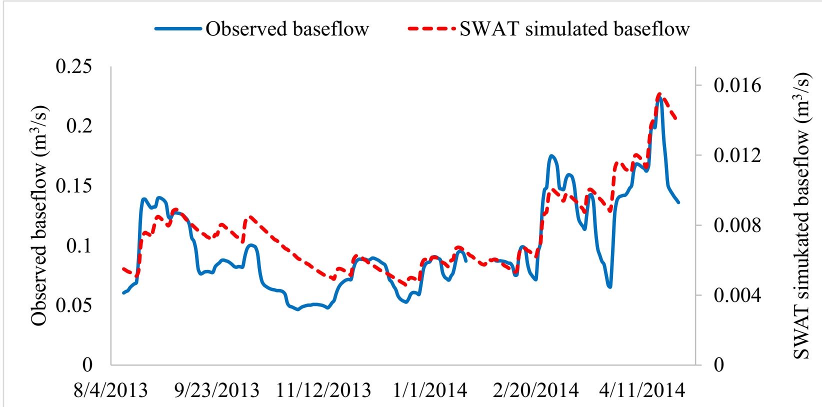

Fig. 7 Comparisons between observed baseflow and SWAT-simulated baseflow after manually calibrating the trend. Here SWAT baseflow trend was adjusted to match observed baseflow. On average, observed baseflow is about 13 times simulated baseflow. Hence, simulated baseflow was manually magnified by using the regression relationship between observed and simulated baseflow. This calibration procedure is described in approach 1

streamflow was calculated as the sum of calibrated baseflow, estimated using regression Eq. (8), and calibrated surface runoff, which yielded a "good" match with that of the observed streamflow ($R^2 = 0.74$, $E_{\mathrm{NASH}} = 0.67$, $R_{\mathrm{BIAS}} = -0.15$; Fig. 8). While this approach resulted in a decent calibration, a look at the flow exceedance curve (Fig. 8) shows that flows > 0.08 m^3/s are slightly but consistently underpredicted.

4.2 Approach 2

Calibrated parameter ranges are presented in Table 4. The best streamflow simulation matched well with observed streamflow, and the 95PPU enveloped 84% of the observations (*P*-factor = 0.84, *R*-factor = 1.04, $R^2 = 0.78$, $E_{\mathrm{NASH}} = 0.75$, $R_{\mathrm{BIAS}} = -0.03$; Fig. 9). From the flow exceedance curve in Fig. 9, it can be observed that the hydrograph is mostly well preserved, except for low flows (< 0.1 m^3/s) which are slightly underestimated.

4.3 Approach 3

If accurately predicting low flows is an important concern, then the previous approach is slightly lacking (flow exceedance curve in Fig. 9). Following approach 3, predicted flows had "very good" match with observed flows ($R^2 = 0.89$, $E_{\mathrm{NASH}} = 0.89$, $R_{\mathrm{BIAS}} = -0.012$; Fig. 10). Coupling SWAT calibration with ANN in this hybrid approach much improved streamflow calibration compared to the previous approaches discussed in the study. From the flow exceedance curve in Fig. 10, all aspects of the hydrograph are well estimated and the previously observed limitation of low flow underestimation has been resolved.

Table 3 Final parameter ranges and the fitted values for the best simulation resulting from SWAT-CUP auto-calibration with observed stormflow

Parameter_Name	Fitted_Value	Min_value	Max_value
1: r__CN2.mgt	0.015	− 0.015	0.121
2: v__ALPHA_BF.gw	0.690	0.418	0.812
3: v__GW_DELAY.gw	0.362	0.001	2.527
4: v__GWQMN.gw	21.741	5.071	24.614
5: v__GW_REVAP.gw	0.199	0.134	0.200
6: v__ESCO.hru	0.842	0.796	0.887
7: v__CH_N2.rte	0.224	0.191	0.352
8: v__CH_K2.rte	32.122	0.010	43.114
9: v__ALPHA_BNK.rte	0.884	0.549	0.986
10: r__SOL_AWC(..).sol	− 0.151	− 0.240	0.048
11: r__SOL_K(..).sol	0.014	− 0.116	0.370
12: r__SOL_BD(..).sol	− 0.809	− 0.855	− 0.173
13: v__RCHRG_DP.gw	0.006	0.001	0.284

v__ means the existing parameter value is to be replaced by a given value

a__ means a given value is added to the existing parameter value

r__ means an existing parameter value is multiplied by (1+ a given value)

Table 4 Final parameter ranges and the fitted values for the best simulation resulting from SWAT-CUP auto-calibration with observed flow, and assigning negative values for RCHRGE_DP

Parameter_Name	Fitted_Value	Min_value	Max_value
1: r__CN2.mgt	0.285	0.126	0.421
2: v__ALPHA_BF.gw	0.082	0.001	0.173
3: v__GW_DELAY.gw	0.563	0.001	3.104
4: v__GWQMN.gw	41.312	25.939	43.589
5: v__GW_REVAP.gw	0.094	0.026	0.101
6: v__ESCO.hru	0.952	0.916	0.985
7: v__CH_N2.rte	0.144	0.125	0.254
8: v__CH_K2.rte	131.781	85.332	142.185
9: v__ALPHA_BNK.rte	0.386	0.232	0.740
10: r__SOL_AWC(..).sol	− 0.435	− 0.441	− 0.068
11: r__SOL_K(..).sol	0.241	− 0.098	0.442
12: r__SOL_BD(..).sol	0.029	− 0.217	0.134
13: v__RCHRG_DP.gw	− 15.293	− 19.559	− 13.066

v__ means the existing parameter value is to be replaced by a given value

a__ means a given value is added to the existing parameter value

r__ means an existing parameter value is multiplied by (1+ a given value)

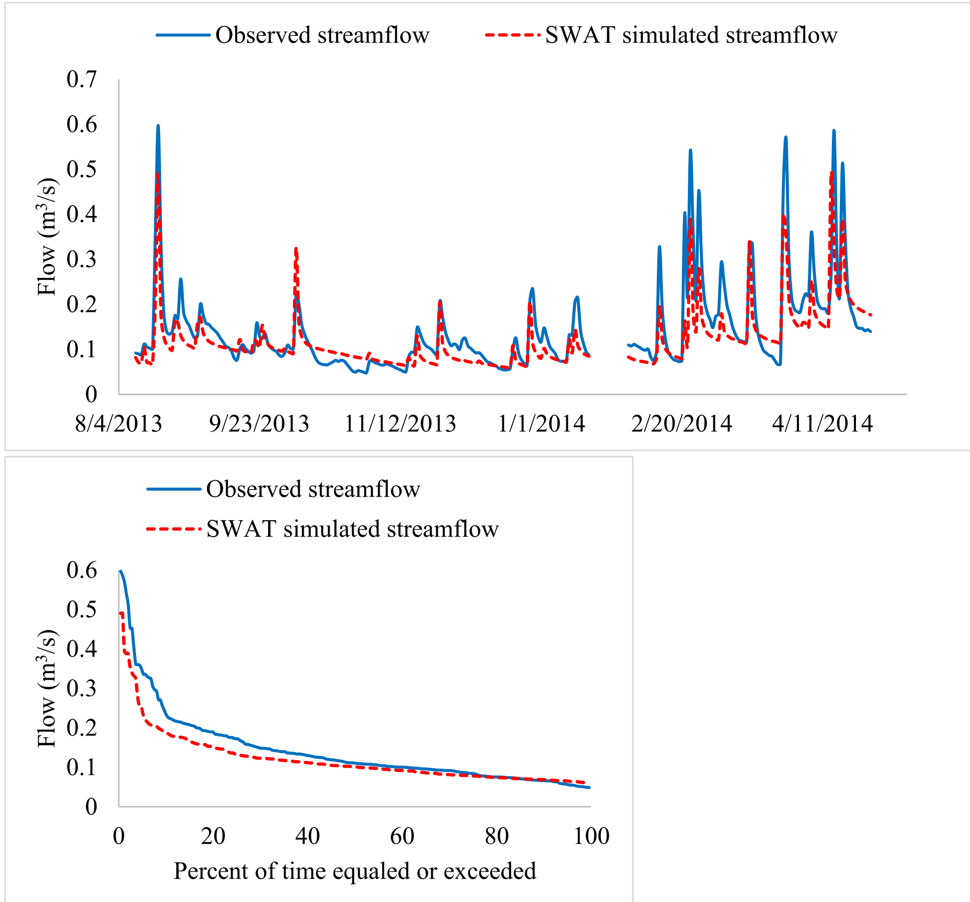

Fig. 8 Top plot compares observed flow and SWAT-calibrated flow from calibration approach 1. Here SWAT flow was calibrated in two parts—(1) the trend of simulated baseflow was first matched to observed baseflow, following which a regression equation between trend-matched simulated baseflow and observed baseflow was applied to match the magnitudes and (2) SWAT streamflow was calibrated to observed surface runoff—and then (1) and (2) were summed. From the figure, the magnitude of observed flow has "very good" match with the SWAT simulation (E_{NASH} = 0.67). Bottom plot compares the flow exceedance curves for observed and simulated flows

Sometimes process-based models, through advanced physical understanding of the system, can allow for model calibration up until a certain point beyond which the model faces difficulties improving calibration, perhaps due to system complexity and our limited understanding thereof. The use of ANN allows further attempts at improving calibration without delving into the process details. Thus, ANN serves as a tool to improve upon deficiencies observed in SWAT-simulated (and SWAT-CUP calibrated) flows.

5 Discussion and Conclusions

In this study, we explored different options for calibrating a very small head watershed in Alabama's coastal plain region draining into a headwater slope wetland which feeds Owen's bayou and eventually, Wolf Bay. This watershed exhibited unique characteristics most notably that flows exceeding precipitation—total precipitation and flows for the study period were 1726 mm and 6599 mm respectively—potentially due to high amounts of groundwater discharging to the watershed. In general, models such as SWAT despite their capabilities show limitations in modeling surface and groundwater interactions, which may be redeemed by using SWAT in conjunction with groundwater models such as MODFLOW. However, this comes with the added cost of increased complexity, heavy data requirements, technical expertise, and computing prowess. Moreover, this level of integrated modeling may not be appropriate for the case at hand where very limited data are available and the watershed size is too small to warrant the use of very complex integrated models. In this study, we evaluated the use of SWAT to tackle calibration of this groundwater-fed head watershed system with minimal observed data.

The three approaches evaluated for calibration had "good" to "very good" performance with $E_{NASH} > 0.66$. In the first approach, baseflow and stormflow components were calibrated separately and summed to yield total streamflow: ArcSWAT-simulated baseflow trend was matched to that observed and then manually amplified to the observed magnitude using a regression relationship between trend-matched baseflow and observed baseflow. The second approach involved adapting SWAT to reverse deep aquifer losses and simulate upward recharge to the shallow aquifer. This was done by attributing a negative value to the parameter RCHRGE_DP, which controls loss of surface water to the deep aquifer by percolation, to allow for recharge and discharge into streamflow instead. The

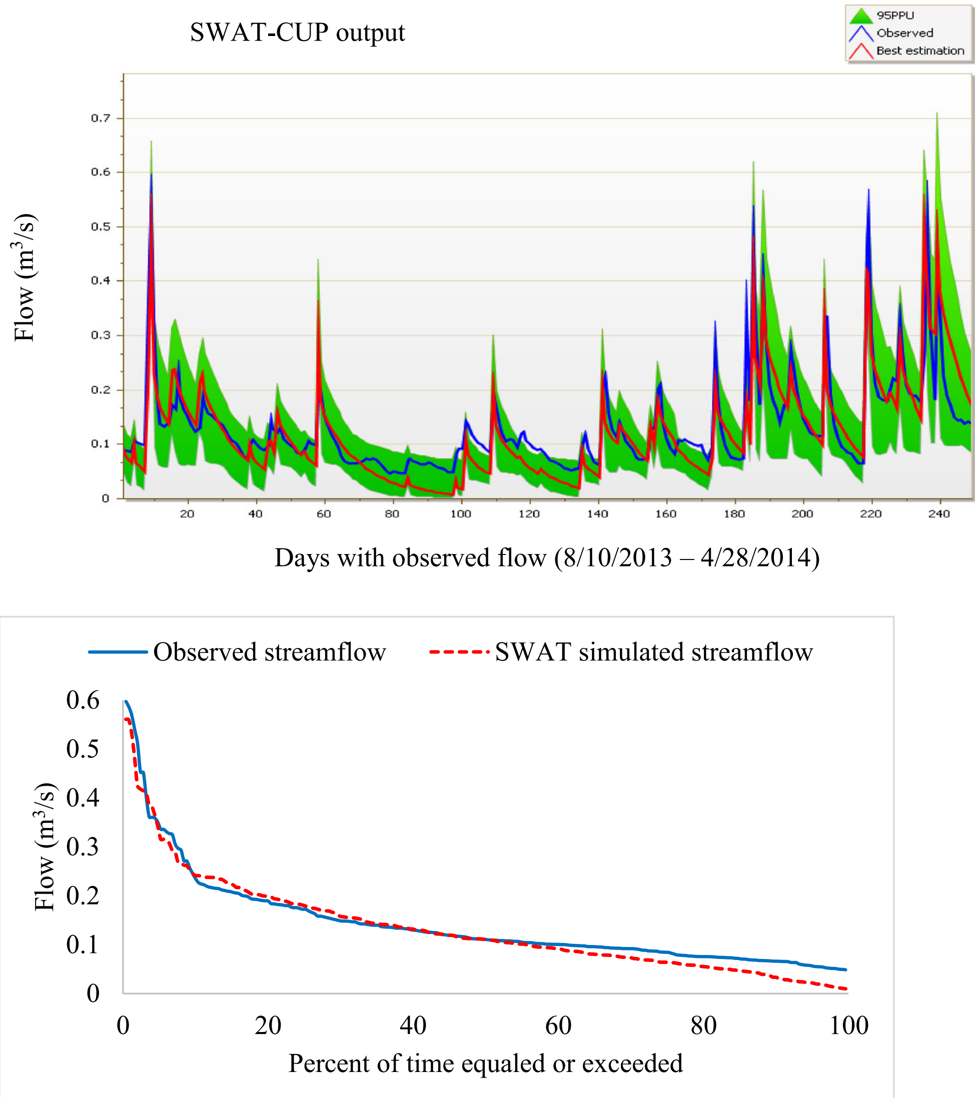

Fig. 9 Top plot includes SWAT-CUP results for calibrating total streamflow using the approach that assigns a negative value for RCHRGE_DP parameter. Performance, in this case, was "very good" with $E_{NASH} = 0.75$. This is described in calibration approach 2. Bottom plot represents the comparison of flow exceedance curves for the "best simulation" from SWAT-CUP calibration and observed flow

calibrated range for this parameter from the SWAT-CUP calibration ranged from − 13 to − 20. The second approach yielded an improved model performance. Whether and how changing the value of RCHRGE_DP so far outside its range affects other aspects of streamflow and nutrient dynamics is unknown and worthy of future investigation. However, if hydrology calibration is the ultimate goal of the study, then tweaking RCHRGE_DP in this manner is a useful strategy to be aware about. Although this approach may appear trivial, there is no published literature evaluating this approach to the best of our knowledge.

In this study, we further attempted to improve hydrology calibration through the application of ANN in conjunction with SWAT. Feeding calibrated streamflow from SWAT together with precipitation and PET to the ANN model resulted in a much improved performance with E_{NASH} of 0.88. Using ANN together with SWAT in this hybrid approach has the advantage of better calibration by letting ANN deal with complexities that we have less knowledge about and cannot be modeled, while also incorporating a process-based hydrological understanding of the system through the SWAT model. The limitation of using a constant groundwater discharge, estimated using the first two approaches, should be recognized in future model runs as groundwater discharge may change in time due to regional groundwater dynamics. Moreover, a good model calibration does not necessarily guarantee a satisfactory model validation or prediction. We acknowledge our limitations in model validation given the very short study period. While ANN could be a useful calibration tool, its capability in hydrologic model validation and prediction deserves further investigation. Nevertheless, we reiterate that this study is intended as a demonstration of three calibration approaches that one might employ without advocating for one over the other—rather the choice of calibration approach and its modification thereof is left to the user based on the study system at hand.

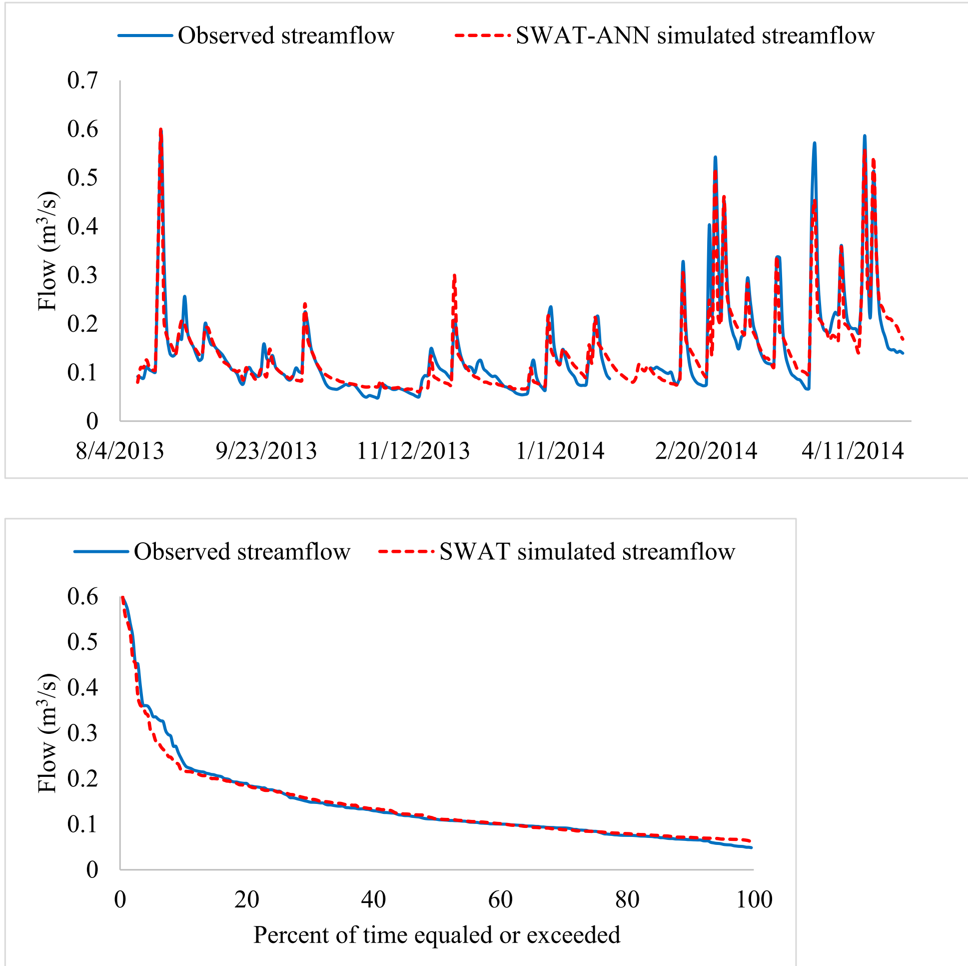

Fig. 10 Top plot compares ANN-simulated flow using SWAT-calibrated flow, precipitation, and PET as inputs, with observed inflow. This combination SWAT–ANN calibration yielded superior performance compared to using just SWAT with $E_{\mathrm{NASH}} = 0.88$. This is described in calibration approach 3. Bottom plot compares flow exceedance curves for SWAT–ANN predicted flow and observed flow

The study watershed is located at an elevation of 4 to 15 m above mean sea level where depth to water table is probably lower than 1.2 m below ground surface [23]. In parts of the Graham Creek Nature preserve immediately south of the study watershed, the water table was found to be as close as 12 inches below the ground surface (personal communication with Preserve manager). This indicates that high baseflows are natural to the system. However, baseflows may be still higher than natural conditions due to some upland contribution from an impounded lake in the residential area just upstream of the wetland.

Most headwater streams in Alabama originate from headwater slope wetlands [27, 37]. However, these systems are highly imperiled due to pressure from various land use activities such as transportation, construction, poorly planned residential and commercial developments, and channel excavation, among others [27, 37]. These headwater slope wetlands, impacted to varying degrees by modifications to hydrological regimes and connectivity, will also exhibit differences in functioning along a gradient of land use pressure. Documenting existing hydrological trends of headwater slope wetlands and providing tools for hydrology calibration provides a very valuable tool for understanding impacts of watershed land use on wetland function, thus aiding in the understanding, protection and preservation of these systems. This study adds to that body of knowledge and gives managers useful tools for hydrology calibration in groundwater dominated wetlands when accurate predictions of hydrology are necessary.

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Compliance with Ethical Standards

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