APPLICATIONS OF THE SWAT MODEL FOR COASTAL WATERSHEDS: REVIEW AND RECOMMENDATIONS

Review

Pawan Upadhyay[1], Anna Linhoss[3,*], Chris Kelble[4], Steve Ashby[2], Naja Murphy[5], Prem B. Parajuli[2]

[1] Water Resources, Shoshone-Paiute Tribes, Owyhee, Nevada, USA.
[2] Department of Agricultural and Biological Engineering, Mississippi State University, Starkville, Mississippi, USA.
[3] Department of Biosystems Engineering, Auburn University, Auburn, Alabama, USA.
[4] NOAA Atlantic Oceanographic and Meteorological Laboratory, Miami, Florida, USA.
[5] College of Marine Science, University of South Florida, Tampa, Florida, USA.
[*] Correspondence: alinhoss@auburn.edu

HIGHLIGHTS

- A systematic review was performed of SWAT applications in coastal watersheds.
- Three percent of SWAT applications have occurred in coastal watersheds.
- SWAT performed better at a monthly time step versus a daily time step.
- Nash-Sutcliffe efficiency (NSE) was the most common metric used for evaluating simulations.
- More research should be conducted on coupling SWAT with hydrodynamic models in tidal systems.

ABSTRACT. *The Soil and Water Assessment Tool (SWAT) is a watershed to river basin scale model widely used to simulate the quality and quantity of surface water and groundwater. SWAT has been applied in a wide variety of geographical landscapes around the world. This review presents a comprehensive summary of SWAT applications for coastal watersheds. Thirty-four articles were identified as coastal applications of SWAT, which account for 3% of the total published studies using SWAT. Nash-Sutcliffe efficiency (NSE) was the most common metric used to evaluate SWAT simulations. The SWAT model calibration and validation studies in coastal watersheds reported higher NSE values for monthly flow simulation (NSE up to 0.95) than for daily flow simulation (NSE up to 0.89). Among all the studies, 34% of the reported NSE values (flow and water quality combined) were >0.75. The majority (58%) of flow values were reported daily, while the majority (81%) of water quality values were reported monthly. Only two studies combined SWAT with a hydrodynamic model to account for tide-storm surge processes. SWAT may be applied more readily and successfully to coastal watersheds if a user-friendly method is developed for coupling SWAT with hydrodynamic models to simulate the tidal influence.*

Keywords. *Bay, Coast, Estuary, Gulf, Hydrologic model, Soil and Water Assessment Tool, Water quality model, Watershed model.*

Approximately 40% of the global human population lives within 100 km of the shore (Agardy and Alder, 2005) in coastal zones (Crossland et al., 2005). This puts immense pressure on the living and non-living resources in these areas. In recent decades, the use and development of coastal zones by humans has greatly increased. As a result, coasts are undergoing tremendous socio-economic and environmental changes, a trend that is expected to continue into the future (Amatya et al., 2008; Neumann et al., 2015). Understanding the functional links between terrestrial and marine environments is fundamental to sustainably manage coastal zones and accommodate the rapidly expanding wildland/urban interface (Amatya et al., 2008).

According to the U.S. Environmental Protection Agency (EPA), the physical boundaries of coastal watersheds begin with the streams and rivers that ultimately flow to coastal areas. Coastal watersheds include upstream areas, estuaries, beaches, nearshore waters, and offshore habitats such as coral reefs. Fares and El-Kadi (2008) argued that coastal watersheds differ from other watersheds because of their proximity to the ocean, weather and rainfall patterns, subsurface features, and land cover.

Hydrologic and water quality information at the coastal/terrestrial interface is a critical element for resource managers, planners, and decision-makers for protecting human health and natural resources (Amatya et al., 2008). The use of hydrological models for water resource management

Submitted for review on 13 September 2021 as manuscript number NRES 14848; approved for publication as a Review Article by the Natural Resources & Environmental Systems Community of ASABE on 2 February 2022.

Mention of company or trade names is for description only and does not imply endorsement by the USDA. The USDA is an equal opportunity provider and employer.

and planning has become fundamental and commonplace. Detailed field observations are time-consuming and economically inefficient, especially in coastal areas that are characterized by the presence of many coastal creeks, bayous, and brooks (Rollo and Robin, 2010). In contrast, hydrological models allow resource managers to assess the condition of a watershed efficiently and economically. When modeling, observed data are used for model parameterization, calibration, and validation. The developed model can then be used to produce a much larger, simulated dataset, which can then be further analyzed to make meaningful conclusions.

Despite the large human populations in coastal watersheds, they have received less attention than inland watersheds in the literature (Burke and Ficklin, 2017). There are several challenges to hydrologic modeling of coastal watersheds. For example, when applying a watershed model to a coastal watershed, it is important to consider the influence of tides on flow and salinity. However, most watershed hydrological models do not simulate the effect of tides, which often leads to the selection of a downstream boundary above the influence of tides. Furthermore, in flatland watersheds, such as in the Coastal Plain of the southeast U.S., identifying watershed boundaries is complex because high and low elevations may differ by only a few centimeters (Edwards et al., 2015).

One model that is immensely popular among water resource engineers is the Soil and Water Assessment Tool (SWAT). SWAT is a physically based, spatially distributed, continuous time, hydrological model (Arnold et al., 1998; Griensven et al., 2012). SWAT was developed based on decades of modeling experience at the USDA Agricultural Research Service (ARS). Many previously developed USDA-ARS models have been incorporated into SWAT to make it a comprehensive model. A detailed history of SWAT model development is provided by Gassmann et al. (2007). SWAT has been applied across the globe for predicting the quality and quantity of surface and groundwater. SWAT has been used extensively in hydrological modeling to improve our understanding of watershed systems. A quick search of the term "Soil and Water Assessment Tool" AND "watershed" in Scopus results in thousands of publications, most of which have been published in the last decade.

Researchers in the field of watershed management and modeling find review articles useful, especially when there is abundant literature on a given subject. Many review articles on SWAT can be found over a broad range of topics, from showing its applicability worldwide (Krysanova and White, 2015) to showing its various applications (Gassman et al., 2007). Review articles have been published that describe how SWAT has been used on specific topics such as ecosystem services (Francesconi et al., 2016) and simulating hydro-climatic extremes (Tan et al., 2020) as well as describing how SWAT performs in specific areas such as the Nile River basin (Griensven et al., 2012). Because no article explicitly summarizes the information on SWAT for coastal watersheds, researchers often have to do their own literature review to shortlist the parameters for model calibration (López-Ballesteros et al., 2019; Wu and Chen, 2013). Other models are available for simulating watershed hydrology, such as HSPF, SWMM, and AGNPS. All of these models function similarly to SWAT in that they only simulate downstream flow and are incapable of simulating tidal fluctuations.

Various factors determine the selection of a hydrological model for a particular study. In the case of SWAT, tools such as SWAT-CUP, which is an auto-calibration/uncertainty or sensitivity feature; global weather data, which are available in SWAT file format; and SWAT workshops provide SWAT a wider acceptability and ease model development compared to other hydrological models. Our goal is to provide a synthesis of findings from applications of SWAT to coastal watersheds. To the best of our knowledge, no review article synthesizes such information. The objective of this article is to provide a systemic review of peer-reviewed articles and a guideline for the application range and selection of SWAT for coastal watersheds, and to list the most commonly used SWAT parameters for systematic calibration.

Study Area

The articles included in this review were selected from projects in which SWAT was applied to coastal environments. The SWAT articles were selected based on the criteria described in the Methods section, which resulted in the selection of articles from around the world. The specific countries from which the articles were selected are shown in figure 1 and are also listed in the Results section.

Methods

The selection of research articles for this study was based on the method recommended in "Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement" (Moher et al., 2009). PRISMA is a publication selection protocol that is used to narrow down specific publications based on predefined criteria while clearly stating the outcome at each step. It improves the reporting of systematic reviews and meta-analyses. PRISMA has four steps. The first step is identification, which includes identification of all relevant publications through searches of databases and other sources. The second step is screening, which removes duplications. The third step is setting an eligibility criterion and excluding publications that do not meet the criterion. Finally, the fourth step includes further analysis of the filtered publications. Only peer-reviewed articles were included, and "gray" literature was excluded (i.e., reports, non-peer-reviewed conference papers, unpublished articles, theses, and book sections). The Scopus, Academic Search Complete, Environment Complete, CAB Abstracts, GeoRef, and Agricola databases were searched for this review. In addition to these databases, we searched the SWAT literature database, which is an exclusive database for SWAT peer-reviewed journal articles. No restrictions were placed on the year or language of publication.

The searches were based on search terms from the title, the abstract, or the keywords. A keyword search of these databases was performed in March 2020 using a basic search statement: ("Soil and Water Assessment Tool" OR "Soil &

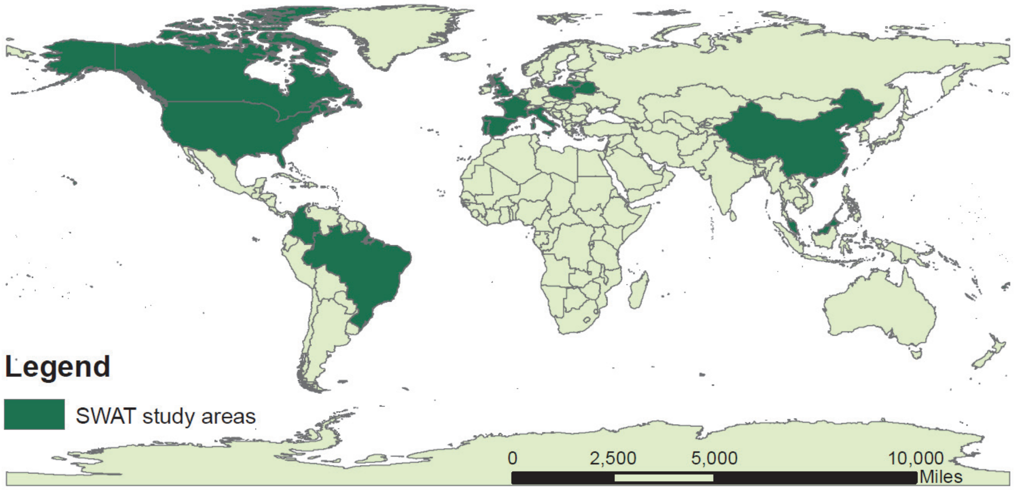

Figure 1. Countries where SWAT studies were selected based on our selection criteria (data source: services.arcgis.com).

Water Assessment Tool" OR "Soil Water Assessment Tool" OR "SWAT") AND (watershed* OR catchment* OR basin*). The results were refined to include only studies that focused on coastal watersheds by applying a filter statement (coast/coastal OR bay OR gulf OR estuary). The SWAT literature database was also searched for the terms SWAT and coast/coastal/bay/gulf, without excluding duplicated articles. The articles were further narrowed down by reading the abstracts. Studies that mentioned the watershed to be coastal but had no direct contact with a coast/bay/gulf (Bosch et al., 2004; Feyereisen et al., 2005; Sexton et al., 2010; Wu and Tanaka, 2005) were not considered for this review. The Appendix provides a summary of the 34 articles included in this review.

It is unlikely that every article that has reported the use of SWAT in coastal environments was captured by this method and included in this review. Nevertheless, we took a systematic approach to search the literature for this review article to enable us to draw reliable conclusions and offer a broad overview of SWAT applications in coastal environments.

Results

A total of 7,334 unique peer-reviewed published articles were found in the library databases using the basic search statement: ("Soil and Water Assessment Tool" OR "Soil & Water Assessment Tool" OR "Soil Water Assessment Tool" OR "SWAT") AND (watershed* OR catchment* OR basin*). Only 220 of these studies focused on coastal watersheds, as determined by applying the filter statement (coast/coastal OR bay OR gulf OR estuary). After reading each abstract, these 220 studies were further narrowed down to only 32 studies that had direct contact with a coast, gulf, or bay to address the research goal regarding application of SWAT in coastal environments according to the criteria described in the Methods section. Two new articles were found in the SWAT literature database after excluding the articles that were already selected from the other databases mentioned above. In sum, a final total of 34 articles are included in this review.

Of the total number of SWAT-related publications found, based on the basic and filter statements described above, only about 3% were located in coastal watersheds. Of the 34 articles included in this review of coastal SWAT applications, 16 were located in the U.S. Other locations included Canada, U.K., France, Italy, Poland, Portugal, Spain, Lithuania, Belarus, Fiji, Brazil, Colombia, Jamaica, China, Singapore, and Malaysia (fig. 1). SWAT was applied to different sizes of watersheds, ranging from less than 100 ha to mmore than 300,000 ha. The digital elevation model (DEM) used in the studies ranged from 5 m to 90 m resolution, with 30 m resolution being the most common. Only 30% of the studies reported the average slope within their watersheds. This information is important to understand the diversity of coastal watersheds to which SWAT has been applied across the world.

In most of the articles included in this review, flow was simulated on a daily and/or monthly basis. Thirty-three of the studies reported simulated flow on a daily time step, and 24 studies reported simulated flow on a monthly time step. Eight studies reported simulated flow on both daily and monthly time steps. A single article can have multiple watersheds or subwatersheds that are calibrated or validated and hence can have multiple reported values of Nash-Sutcliffe efficiency (NSE; Nash and Sutcliffe, 1970). The monthly NSE values were always better than the daily NSE values, as shown in figure 2. SWAT can also be run on an hourly time step. For example, Bacopoulos et al. (2017) applied SWAT on an hourly time step to simulate coastal flooding in Florida from Tropical Storm Fay in 2008. When hourly simulations are performed, the routing parameters become very sensitive. Thus, the scientific community does not yet embrace results at an hourly resolution (Singh et al., 2015).

Most of the studies reported more than one NSE value for either flow or water quality. Many studies reported both monthly and daily NSE values for a give study area. Many studies also included more than one calibrated and validated study subwatershed, each with its own NSE value. Table 1 shows the percentages of reported daily and monthly NSE

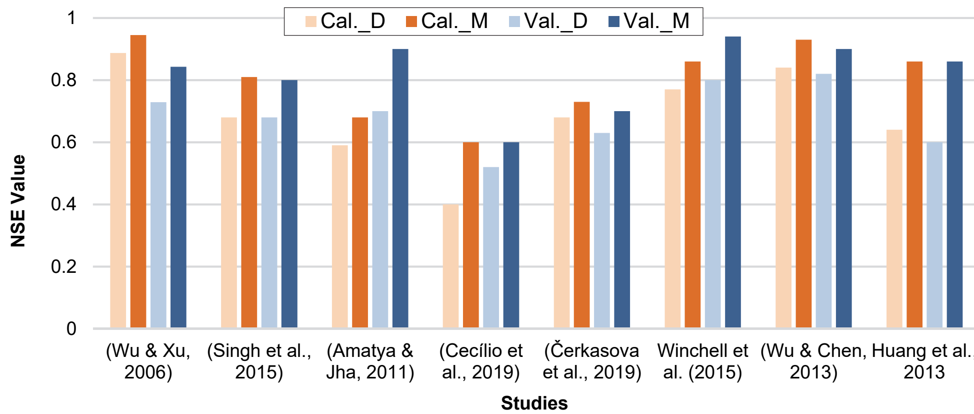

Figure 2. Comparison of daily and monthly calibrated/validated NSE values for flow (Cal._D = daily calibration, Cal._M = monthly calibration, Val._D = daily validation, and Val._M = monthly validation). Čerkasova et al. (2019) and Winchell et al. (2015) reported more than one NSE value for calibration and validation; therefore, the highest reported NSE values were used for this figure.

values for flow and water quality. Of all the reported NSE values, 46% were for daily simulations and 54% were for monthly simulations.

While all the studies simulated flow, only nine studies (26%) simulated water quality in SWAT. Again, a single study often reported more than one NSE value. Seven studies reported water quality simulations on a monthly time step, and two studies reported water quality simulations on a daily time step. The other time steps used in the studies were bimonthly (Piniewski et al., 2014) and seasonal (Pesce et al., 2018). Table 2 shows the variables simulated in each study, including flow, total suspended solids (TSS), sediment, total nitrogen (TN), total phosphorus (TP), nitrate (NO_3^-), organic nitrogen, and organic phosphorus.

A wide range of metrics were used to evaluate SWAT simulations, including deviation of discharge (D), mass balance error (MBE), coefficient of determination (R^2), percent bias (PBIAS), ratio of RMSE to the standard deviation of measured data (RSR), relative error (E_{rel}), root mean square error (RMSE), mean square error (MSE), and Kling-Gupta efficiency (KGE). Among all the studies, NSE was the most common evaluation metric (table 2).

Moriasi et al. (2007) suggested guidelines for model evaluation. Their evaluation criteria were based on three quantitative statistics (NSE, PBIAS, and RSR). While Moriasi et al. (2007) suggested robust watershed model evaluation guidelines, most of the studies did not follow this standard protocol for model evaluation. However, all of the studies we investigated that reported model evaluation metrics, except one, reported NSE.

Therefore, lacking other common metrics for this article, we use the NSE criteria from Moriasi et al. (2007) to interpret model performance. For simulations of flow at a daily time step, 37% of the studies reported NSE values >0.75, 33% of the studies reported NSE values between 0.65 and 0.75, 27% of the studies reported NSE values between 0.50 and 0.65, and 3% of the studies reported NSE values <0.50. For simulations of flow at a monthly time step, 46% of the studies reported NSE values >0.75, 25% of the studies reported NSE values between 0.65 and 0.75, 25% of the studies reported NSE values between 0.50 and 0.65, and 4% of the studies reported NSE values <0.50. According to the model evaluation metrics in the articles that we reviewed, SWAT yielded very good to satisfactory hydrological results in most of its applications to coastal watersheds, as shown in table 1.

Table 1. Percentages (and counts) of reported daily and monthly values of Nash-Sutcliffe efficiency (NSE) for flow and water quality.

	NSE Value				Total
	>0.75	0.65–0.75	0.50–0.65	<0.50	Reported
Flow					
Daily	37 (12)	33 (11)	27 (9)	3 (1)	100 (33)
Monthly	46 (11)	25 (6)	25 (6)	4 (1)	100 (24)
Water quality					
Daily	20 (1)	40 (2)	40 (2)	0 (0)	100 (5)
Monthly	19 (4)	24 (5)	28.5 (6)	28.5 (6)	100 (21)

For daily simulation of nutrients, 20% of the studies reported NSE values >0.75, 40% of the studies reported NSE values between 0.65 and 0.75, 40% of the studies reported NSE values between 0.50 and 0.65, and 0% of the studies reported NSE values <0.50. For monthly simulation of nutrients, 19% of the studies reported NSE values >0.75, 24% of the studies reported NSE values between 0.65 and 0.75, 28.5% of the studies reported NSE values between 0.50 and 0.65, and 28.5% of the studies reported NSE values <0.50. According to the model evaluation metrics in the studies that we reviewed, SWAT yielded very good to satisfactory nutrient results in most of its applications to coastal watersheds, but this conclusion is based on a relatively small number of studies. A key difference in reported NSE values between flow and water quality is that, in the case of water quality, an overwhelming majority (81%) of the NSE values were reported on a monthly basis. Only two studies (Huang et al., 2013; Rollo and Robin, 2010) reported a combined five NSE values (table 1) on a daily basis for water quality, with NSE values ranging from 0.49 to 0.76.

SWAT has an auto-calibration tool called SWAT-CUP (Abbaspour, 2012) that can be used for sensitivity analysis, calibration, and validation. The optimized values of specified SWAT parameters are derived during model calibration by modifying the parameter values during iterations. The modified parameters are then used for model validation. SWAT has a large number of parameters available for calibration. Calibrating one model to all of these parameters is computationally expensive and inefficient. A more efficient

Table 2. Summary of SWAT parameters used by various studies in coastal modeling.

Reference and Study Location	Watershed Size (km^2)	Time Step[a]	Simulation Period	Variables Simulated: Flow	Variables Simulated: Nutrients	Variables Simulated: TSS and Sediment	Model Performance (NSE, calibration/validation)[b]: Flow (Daily)	Flow (Monthly)	Nutrients (Daily)	Nutrients (Monthly)	Sensitivity Analysis	DEM Resolution (m)	Evaluation Metrics[c]	How Tides are Handled	Model Use
Amatya and Jha (2011), South Carolina															
	72.6	D, M, Y	2003-2010	Yes	-	-	0.59/0.70	0.68/0.90	-	-	Yes	10	NSE, RSR	Gauge station not affected by tidal inflows (located upstream)	-
Bacopoulos et al. (2017), Florida															
	9892, 2023, 3 × 1000, 3 × 100	H	2007-2008	Yes	-	-	0.85/0.45 (hourly)	-	-	-	Yes	30	NSE, E_{rel}	SWAT integrated with hydrodynamic (ADCIRC) model	Analysis of river flooding due to storm
Bougeard et al. (2011), France															
	113	D	2000-2006	Yes	-	-	0.84/0.82	-	-	-	Yes	15	NSE, R^2	Grid created to account for tidal forcing	SWAT coupled with other models
Burke and Ficklin (2017), Washington, Oregon, and California															
	42 to 718	D, M	1963-2011	Yes	-	-	0.76–0.91/ 0.61–0.81	-	-	-	Yes	10	NSE, PBIAS, RSR	No information	SWAT coupled with other models
Cecílio et al. (2019), Brazilian Atlantic rainforest															
	2220	D, M	-	Yes	-	-	0.40/0.52	0.60/0.60	-	-	Yes	30	NSE, R^2, RSR, PBIAS	No information	Simulating land use change scenarios
Čerkasova et al. (2016), Belarus (48%), Lithuania (46%), Kaliningrad Oblast and Poland (6%)															
	100,458	M	-	Yes	Yes	Yes	-	0.79/0.60	-	-	Yes	51	NSE, R^2	No information	Assessment of climate change scenarios
Čerkasova et al. (2019), Lithuania															
	3097.04	D, M	1995-2010	Yes	Yes	Yes	0.65–0.68/ 0.60–0.63	0.72–0.73/ 0.68–0.70	-	N: 0.40–0.80/ 0.39–0.62; P: 0.39–0.64/ 0.35–0.62; Sed: 0.54/0.53	Yes	35	NSE, R^2, PBIAS	No information	Assessing climate change impact
Chen et al. (2014), Apalachicola River, Florida															
	3589	D	1984-1994	Yes	-	-	0.92/0.88	-	-	-	Yes	30	NSE	Soil textures documented to understand tidal effects	Assessing climate change impact

[a] D = daily, H = hourly, M = monthly, and Y = yearly.

[b] NSE = Nash-Sutcliffe efficiency (Nash and Sutcliffe, 1970), N = nitrogen, NH_3 = ammonia, P = phosphorus, Sed = sediment, and TSS = total suspended solids.

[c] D = deviation of discharge, E_{rel} = relative error, KGE = Kling-Gupta efficiency, MAE = mean absolute error, MBE = mass balance error, MSE = mean square error, PBIAS = percent bias, r = correlation coefficient, R^2 = coefficient of determination, RMSE = root mean square error, and RSR = RMSE-observations standard deviation ratio.

Table 2 (continued). Summary of SWAT parameters used by various studies in coastal modeling.

Reference and Study Location	Watershed Size (km^2)	Time Step[a]	Simulation Period	Variables Simulated: Flow	Variables Simulated: Nutrients	Variables Simulated: TSS and Sediment	Model Performance (NSE, calibration/validation)[b]: Flow (Daily)	Flow (Monthly)	Nutrients (Daily)	Nutrients (Monthly)	Sensitivity Analysis	DEM Resolution (m)	Evaluation Metrics[c]	How Tides are Handled	Model Use
Dadhich and Nadaoka (2012), Viti Levu Island, Fiji															
	1994.5	D	1993-2007	Yes	-	-	R^2: 0.84 and 0.92; NSE: 0.83 and 0.75	-	-	-	Yes	25	NSE, R^2	Integrated modeling framework with land use change was constructed	SWAT coupled with other models
Ferreira et al. (2014), Portugal															
	627	D	-	Yes	Yes	Yes	-	-	-	-	No	30	-	SWAT integrated with Delft3D for ocean circulation	SWAT coupled with other models
Gao et al. (2018), California															
	337	M	1980-2010	Yes	-	-	-	0.86/0.71	-	-	Yes	30	NSE, R^2, E_{rel}	No information	Separating wet and dry years to improve SWAT calibration
Hoyos et al. (2019), Colombia															
	~300	M	1982-2008	Yes	-	-	-	0.79/0.72	-	-	Yes	30	NSE, PBIAS, RSR, R^2	No information	Response of streamflow to persistent drought
Huang et al. (2013), China															
	10,000	D, M	2000-2007	Yes	Yes	-	0.64/0.60	0.86/0.86	-	N: 0.69/0.57; P: 0.56/0.49	Yes	30	NSE, R^2	No information	Assessing land use and land cover impacts
Lin et al. (2015), China															
	5042	D, M, Y	2001-2010	Yes	-	-	>0.75/>0.75	>0.9/>0.9 (annual and monthly)	-	-	Yes	30	NSE, R^2, PBIAS	Not mentioned	Assessing land use and land cover impacts
López-Ballesteros et al. (2019), Spain															
	6	M	2000-2015	Yes	-	-	-	0.58/0.53	-	-	Yes	5	NSE, KGE, R^2, PBIAS	No information	Best management practice (BMP) evaluation
Mirhosseini and Srivastava (2016), Alabama															
	80.24	M	1950-2008	Yes	Yes	-	-	0.60/0.60	-	N: 0.73/0.51; P: 0.43/0.30	Yes	30	NSE, R^2, MBE	No information	Quantify effects of irrigation and ENSO

[a] D = daily, H = hourly, M = monthly, and Y = yearly.

[b] NSE = Nash-Sutcliffe efficiency (Nash and Sutcliffe, 1970), N = nitrogen, NH_3 = ammonia, P = phosphorus, Sed = sediment, and TSS = total suspended solids.

[c] D = deviation of discharge, E_{rel} = relative error, KGE = Kling-Gupta efficiency, MAE = mean absolute error, MBE = mass balance error, MSE = mean square error, PBIAS = percent bias, r = correlation coefficient, R^2 = coefficient of determination, RMSE = root mean square error, and RSR = RMSE-observations standard deviation ratio.

Table 2 (continued). Summary of SWAT parameters used by various studies in coastal modeling.

Reference and Study Location	Watershed Size (km^2)	Time Step[a]	Simulation Period	Variables Simulated: Flow	Nutrients	TSS and Sediment	Model Performance (NSE, calibration/validation)[b]: Flow (Daily)	Flow (Monthly)	Nutrients (Daily)	Nutrients (Monthly)	Sensitivity Analysis	DEM Resolution (m)	Evaluation Metrics[c]	How Tides are Handled	Model Use
Omani et al. (2014), Texas															
	16,100 and 11,600	D, M	1975-2008	Yes	Yes	Yes	-	-	-	Sed: 0.55–0.75/ 0.43–0.52; -4.36–0.85/ -6.91–0.87	Yes	30	NSE, PBIAS, RSR	Gauge stations not affected by tidal inflows	Sediment and nutrient loading
Pesce et al. (2018), Italy															
	140	D, Y	-	Yes	Yes	-	-	0.58/ 0.20	-	N: 0.60/0.25 NH_3: 0.51/-0.10	Yes	5	NSE, R^2	Effects of tide and sea level rise have been neglected	Assessing climate change impact
Piniewski et al. (2014), Poland															
	482	D, M	1991-2010	Yes	Yes	Yes	0.75/0.61	-	-	Sed: 0.55/0.22; N: 0.62/0.64; P: 0.53/-1.78	Yes	50	NSE, R^2, PBIAS	No information	Nutrient loading
Rezaeianzadeh et al. (2018), Alabama															
	0.84	D	1948-2005	Yes	-	-	0.73/0.52	-	-	-	No	-	NSE, RMSE	No information	SWAT coupled with other models
Rollo and Robin (2010), France															
	128 and 43	D	2001-2004	Yes	Yes	-	Yes/ 0.65–0.82	-	Yes; P: 0.54–0.76	-	No	50	NSE	No information	Identify critical source areas for coastal watershed loadings
Samadi et al. (2017), North Carolina and South Carolina															
	3116.85	D	2000-2007	Yes	-	-	0.79/0.87	-	-	-	Yes	-	NSE, MSE	No information	Assessing SWAT parameter uncertainty
Setegn et al. (2014), Jamaica															
	646	D, M, Y	1997-2008	Yes	-	-	-	0.52/0.51; 0.58/0.54 (annual)	-	-	Yes	90	NSE, R^2, RSR	Not reported	Assessing land use, land cover, and climate change impacts
Shao et al. (2017), Ontario, Canada															
	14.3	-	-	-	-	-	-	-	-	-	No	-	-	No information	SWAT coupled with other models to evaluate BMPs
Singh et al. (2011), Fish River, Alabama															
	398	D, M	1990-2007	-	-	Yes	>0.75/>0.75	-	-	-	Yes	10	NSE, R^2, MBE	Not reported	Sediment and nutrient loading

[a] D = daily, H = hourly, M = monthly, and Y = yearly.

[b] NSE = Nash-Sutcliffe efficiency (Nash and Sutcliffe, 1970), N = nitrogen, NH_3 = ammonia, P = phosphorus, Sed = sediment, and TSS = total suspended solids.

[c] D = deviation of discharge, E_{rel} = relative error, KGE = Kling-Gupta efficiency, MAE = mean absolute error, MBE = mass balance error, MSE = mean square error, PBIAS = percent bias, r = correlation coefficient, R^2 = coefficient of determination, RMSE = root mean square error, and RSR = RMSE-observations standard deviation ratio.

Table 2 (continued). Summary of SWAT parameters used by various studies in coastal modeling.

Reference and Study Location	Watershed Size (km^2)	Time Step[a]	Simulation Period	Variables Simulated: Flow	Variables Simulated: Nutrients	Variables Simulated: TSS and Sediment	Model Performance (NSE, calibration/validation)[b]: Flow (Daily)	Flow (Monthly)	Nutrients (Daily)	Nutrients (Monthly)	Sensitivity Analysis	DEM Resolution (m)	Evaluation Metrics[c]	How Tides are Handled	Model Use
Singh et al. (2015), Alabama															
	398	D, M	1990-2010	Yes	Yes	Yes	0.68/0.68	0.81/0.80	-	TSS: 0.26–0.87/ 0.12–0.82; N: 0.13–0.31/ -5.34–0.96; P: -0.96–0.88/ 0.12–0.74	Yes	10	NSE, R^2, MBE	No calibration, validation, or post-validation was performed at the main outlet due to tidal influence	Assessing land use and land cover impacts
Sun et al. (2015), Texas															
	1828	D	1999-2006	Yes	Yes	Yes	-	-	-	-	Yes	-	-	-	SWAT outputs used to develop three metamodels
Vale and Holman (2009), United Kingdom															
	-	-	1983-2005	Yes	-	-	0.67–0.74/ 0.56–0.74	-	-	-	Yes	10	NSE	Not reported	Hydrological assessment
Wang and Kalin (2011), Wolf Bay and Magnolia River, Alabama															
	130 and 44.8	D, M, Y	1999-2009	Yes	-	-	-	0.82/0.65	-	-	Yes	-	NSE, R^2, MBE	Not reported	Assessing land use land cover impact
Wang et al. (2014), Wolf Bay, Alabama															
	126	D, M, Y	1984-2008	Yes	-	-	-	-	-	-	No	-	-	Not reported	Assessing land use, land cover, and climate change impacts
Winchell et al. (2015), Québec, Canada (42%) and Vermont, USA (58%)															
	3105.27	D, M	-	Yes	Yes	Yes	0.54–0.77/ 0.58–0.80	0.68–0.86/ 0.73–0.94	-	Sed: 0.65–0.86/ 0.60–0.86; P: 0.67–0.91/ 0.61–0.90	Yes	10	NSE, PBIAS, RSR	No tides	Identification of P critical source areas
Wu and Chen (2013), China															
	25,325 and 7699	D, M	1970-1988	Yes	-	-	0.84/0.82	0.93/0.90	-	-	Yes	90	NSE, RSR, PBIAS, R^2	Not reported	Hydrological response to monsoonal climate
Wu and Xu (2006), Louisiana															
	8728	D, M	1975-1999	Yes	-	-	0.83–0.93/ 0.69–0.78	0.94–0.96/ 0.81–0.87	-	-	Yes	60	NSE, D	No information	Assessing SWAT suitability
Xu and Chua (2017), Singapore and Malaysia															
	3055.71	D	2001 and 2006	Yes	Yes	-	0.75/0.89 and 0.87	-	-	-	No	92.6	MAE, RMSE, r, NSE	Coupled hydrologic-hydrodynamic model (SWAT-SUNTANS) used tidal currents for model validation	SWAT coupled with other models

[a] D = daily, H = hourly, M = monthly, and Y = yearly.

[b] NSE = Nash-Sutcliffe efficiency (Nash and Sutcliffe, 1970), N = nitrogen, NH_3 = ammonia, P = phosphorus, Sed = sediment, and TSS = total suspended solids.

[c] D = deviation of discharge, E_{rel} = relative error, KGE = Kling-Gupta efficiency, MAE = mean absolute error, MBE = mass balance error, MSE = mean square error, PBIAS = percent bias, r = correlation coefficient, R^2 = coefficient of determination, RMSE = root mean square error, and RSR = RMSE-observations standard deviation ratio.

method of calibration is selecting only the most important or most sensitive parameters for calibration. We noted the calibration parameters for each article to provide a summary of the most common calibration parameters used in coastal watershed SWAT modeling. Table 3 lists all the flow and water quality parameters that were used in at least two studies presented in this review article. The seven most common parameters for coastal watersheds are the SCS runoff curve number (CN2), soil evaporation compensation factor (ESCO), groundwater delay (GW_DELAY), baseflow alpha factor (ALPHA_BF), groundwater revap coefficient (GW_REVAP), available water capacity of the soil layer (SOL_AWC), and surface runoff lag time (SURLAG).

In table 3, the calibration parameters are grouped according to their input category as specified in the SWAT input-output document. This is not a comprehensive list of parameters. Table 3 only lists parameters that were used in at least two studies. Some input categories were used more often for calibration, and some were used less often for calibration. For example, for flow, the groundwater category was used more frequently for calibration than the soil water category. For flow, the input categories that were most frequently used included groundwater, soil water, evapotranspiration, and surface runoff. For water quality, the most frequently used input categories were channel sediment routing, residue decomposition coefficient, nitrogen cycle/runoff, phosphorus cycle/runoff, and channel nutrient routing.

This information can serve as a guideline for systematic SWAT calibration. For a coastal watershed, a SWAT user can start calibration based on the seven most common parameters mentioned above and then gradually include the lesser used parameters in table 3. At the same time, it is important to prioritize the input categories. Prioritization might vary based on the site geography, climate, land use, or soils. The parameters listed in table 3 are based only on their occurrence in calibration and not on their sensitivity.

DISCUSSION

Coastal watersheds are different from inland watersheds due to their hydraulic connections between groundwater levels, which are impacted by sea level rise and climate change, which may make future rainfall events less frequent but of higher intensity (Chen et al., 2014). Coastal areas are also more prone to tropical storms and flooding rains, and SWAT is not an event-based model. As pointed out by Wang and Kalin (2011), SWAT has limitations for extreme events, although it works reasonably well for long-term simulations. SWAT does not simulate the back-and-forth hydrodynamic

Table 3. SWAT parameters used at least twice for calibration in various research studies of coastal watershed modeling.

Input Category	Name	Definition	No. of Studies
Flow Parameters			
Surface runoff	CN2	SCS runoff curve number	25
	SURLAG	Surface runoff lag time	14
Evapotranspiration	ESCO	Soil evaporation compensation factor	21
	GW_REVAP	Groundwater revap coefficient	16
	EPCO	Plant uptake compensation factor	8
	CANMX	Maximum canopy storage	6
Groundwater	ALPHA_BF	Baseflow alpha factor (days)	19
	GW_DELAY	Groundwater delay (days)	15
	GWQMN	Threshold depth of water in a shallow aquifer required for return flow to occur (mm)	13
	REVAPMN	Threshold depth of water in a shallow aquifer required for revap to occur (mm)	10
	RCHRG_DP	Deep aquifer percolation fraction	8
Soil water	SOL_AWC	Available water capacity of the soil layer	17
	SOL_K	Saturated hydraulic conductivity	13
	SOL_BD	Moist bulk density	7
	SOL_Z	Depth from soil surface to bottom of layer	5
Channel water routing	CH_N2	Manning's n value for the main channel	12
	CH_K2	Effective hydraulic conductivity in main channel alluvium	9
Time of concentration	OV_N	Manning's n value for overland flow	5
Sediment erosion	SLSUBBSN	Average slope length	5
Water Quality Parameters			
Channel sediment routing	SPCON	Linear parameter for calculating the maximum amount of sediment that can be re-entrained during channel sediment routing	4
	SPEXP	Exponent parameter for calculating the amount of sediment re-entrained in channel sediment routing	4
Residue	RSDCO	Residue decomposition coefficient	4
Nitrogen cycle/runoff	NPERCO	Nitrogen percolation coefficient	4
	BIOMIX	Biological mixing efficiency	4
	SDNCO	Denitrification threshold water content	3
	CDN	Denitrification exponential rate coefficient	3
Phosphorus cycle/runoff	PPERCO	Phosphorus percolation coefficient	3
	PSP	Phosphorus sorption coefficient	3
	GWSOLP	Concentration of soluble phosphorus in groundwater contribution to streamflow from subbasin (mg P L^{-1})	3
Channel nutrient routing	BC4	Rate constant for mineralization of organic P to dissolved P in the reach at 20°C (d^{-1})	3
	AI2	Fraction of algal biomass that is phosphorus	3

flow of tides. The studies in this review addressed this shortcoming in several ways. Most commonly, coastal applications defined the downstream boundary conditions above the tidally influenced point (Niazi et al., 2015), thereby allowing the study to ignore tidal effects. Some studies calibrated and validated SWAT for the subwatersheds upstream of the main outlet separately from when the main outlet was tidally influenced (Singh et al., 2015).

A more robust way to deal with tides is to couple SWAT with a hydrodynamic model (Bacopoulos et al., 2017). In those cases, the hydrodynamic model uses SWAT's flow and water quality outputs as inputs. For example, Bougeard et al. (2011) modeled the impact of *E. coli* loads in the Daoulas estuary in France with a hydrodynamic model (MARS 2D) using the daily *E. coli* fluxes simulated by SWAT in an upstream catchment as input. Another potential solution is to link SWAT with a simple tidal prism model. To date, existing links between SWAT and hydrodynamic or tidal prism models are not hard-coded.

One of the main limitations reported by many users of SWAT (not just in coastal watersheds) is the limited availability of hydrological data. Data limitations can be of many types, most commonly periodic (occasional spot measurements, 7 to 10 day intervals, or monthly), spatial (data collected at only one location or at too few locations), data available for different time periods (e.g., a mismatch between the flow data and water quality data periods), and with different temporal scales (ranging from instantaneous to monthly averages). Coastal watersheds are always associated with a coastal boundary, so the water is likely to be used recreationally and water quality is especially important. It can be noted from our review that water quality data are less available than flow data, which creates additional limitations for model development. Vale and Holman (2009) used limited but diverse data (stream discharges, lake levels, periods of hydraulic connection between lake arms, groundwater levels, and lake outflows) to develop a calibrated and validated SWAT model for a shallow lake system in Wales.

Because of the lack of data, researchers may have to resort to calibrating a model for only flow (Singh et al., 2011) or calibrating water quality on a limited number of data points (Bougeard et al., 2011), even when the modeling priority is water quality. For example, Singh et al. (2011) chose to calibrate a SWAT model for flow and not sediment when studying critical source areas because only some snapshot sediment concentration data were available and no corresponding flow data existed. Wang and Kalin (2011) studied the impacts of land use and land cover changes on flow in the Wolf Bay watershed in coastal Alabama, for which no flow data were available at the start of the study. They developed a SWAT model for the neighboring Magnolia River watershed and then transferred the relevant model parameters, and they calibrated the model for the Wolf Bay watershed with limited data that became available later during the study. These might be the reasons for the low number of modeling studies in coastal watersheds.

Although SWAT has proven to be effective in modeling coastal basin hydrology (Wu and Xu, 2006), other watershed models have been used in coastal applications. Im et al. (2007) compared SWAT and HSPF models to predict runoff and sediment yield in the Polecat Creek watershed in Virginia. They found that the SWAT and HSPF watershed models both performed sufficiently well in the simulation of streamflow and sediment yield, with HSPF performing moderately better than SWAT for simulation time steps greater than a month. While SWAT does a good job of simulating coastal hydrology, other models should also be evaluated based on the study objective and data availability.

Summary

We reviewed the findings from applications of SWAT in coastal watersheds because of SWAT's wide applicability and immense popularity among water resource engineers. This review provides a guideline for the application range and the most common parameters used in SWAT model calibration for coastal watersheds. A total of 34 articles were selected for this review, consisting of 3% of the total studies on SWAT. Studies that mentioned the watershed to be coastal but had no direct contact with a coast, bay, or gulf were not considered. NSE was the most common metric used to evaluate SWAT simulations. NSE values were used to evaluate daily (54%) and monthly (46%) simulations. NSE values for water quality were predominately based on monthly simulations (85%) compared to daily simulations (15%). Water quality measurements were more commonly made on a monthly time step, rather than a daily time step, making calibration at the finer temporal resolution of the model difficult. According to the model evaluation metrics, SWAT yielded very good, good, or satisfactory hydrological results in most of its applications to coastal watersheds. The SWAT results for water quality were more mixed and had a wide range of NSE values.

We identified the seven most common parameters used for SWAT calibration, which included the SCS runoff curve number (CN2), soil evaporation compensation factor (ESCO), groundwater delay (GW_DELAY), baseflow alpha factor (ALPHA_BF), groundwater revap coefficient (GW_REVAP), available water capacity of the soil layer (SOL_AWC), and surface runoff lag time (SURLAG). We also identified the most frequently used parameter categories. For flow, these input categories included groundwater, soil water, evapotranspiration, and surface runoff. For water quality, the most frequently used input categories included channel sediment routing, residue decomposition coefficient, nitrogen cycle/runoff, phosphorus cycle/runoff, and channel nutrient routing.

The information about the most frequently used input categories, input parameters, model performance, and evaluation metrics (NSE values for daily and monthly flow and for monthly water quality were mostly good to satisfactory) can serve as a guideline for systematic calibration. While SWAT has done a good job in simulating coastal hydrology, other models should also be evaluated based on the objective of the study and data availability. One of the drawbacks of SWAT for coastal watershed modeling is that it does not simulate the back-and-forth hydrodynamic flow of tides. To overcome this limitation, SWAT is often coupled with a hydrodynamic model. If a user-friendly method can be developed for coupling SWAT with hydrodynamic models to simulate tidal influence, then SWAT may be more readily and successfully applied to coastal watersheds.

Acknowledgements

This research was funded by a NOAA Atlantic Oceanographic and Meteorological Laboratory grant to the Northern Gulf Institute (Award No. NA160AR4320199). This material is also based on work supported by the USDA National Institute of Food and Agriculture under Project No. 1022505: Costs and Benefits of Natural Resources on Public and Private Lands: Management, Economic Valuation, and Integrated Decision-Making.

References

Abbaspour, K. C. (2012). *SWAT-CUP-2012: SWAT calibration and uncertainty programs: A user manual*. Dübendorf, Switzerland: Swiss Federal Institute of Aquatic Science and Technology (Eawag).

Agardy, T., & Alder, J. (2005). Chapter 19: Coastal systems. In *Ecosystems and human well-being: Current state and trends, Volume 1* (pp. 515-549). Washington, DC: Island Press. Retrieved from https://www.millenniumassessment.org/documents/document.288.aspx.pdf

Amatya, D. M., & Jha, M. K. (2011). Evaluating the SWAT model for a low-gradient forested watershed in coastal South Carolina. *Trans. ASABE, 54*(6), 2151-2163. https://doi.org/10.13031/2013.40671

Amatya, D. M., Callahan, T. J., Radecki-Pawlik, A., Drewes, P., Trettin, C., & Hansen, W. F. (2008). Hydrologic and water quality monitoring on Turkey Creek watershed, Francis Marion National Forest, SC. *Proc. 2008 South Carolina Water Resources Conf.* Clemson, SC: Clemson University.

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

Bacopoulos, P., Tang, Y., Wang, D., & Hagen Scott, C. (2017). Integrated hydrologic-hydrodynamic modeling of estuarine-riverine flooding: 2008 Tropical Storm Fay. *J. Hydrol. Eng., 22*(8), article 04017022. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001539

Bosch, D. D., Sheridan, J. M., Batten, H. L., & Arnold, J. G. (2004). Evaluation of the SWAT model on a coastal plain agricultural watershed. *Trans. ASAE, 47*(5), 1493-1506. https://doi.org/10.13031/2013.17629

Bougeard, M., Le Saux, J. C., Pérenne, N., Baffaut, C., Robin, M., & Pommepuy, M. (2011). Modeling of *Escherichia coli* fluxes on a catchment and the impact on coastal water and shellfish quality. *JAWRA, 47*(2), 350-366. https://doi.org/10.1111/j.1752-1688.2010.00520.x

Burke, W. D., & Ficklin, D. L. (2017). Future projections of streamflow magnitude and timing differ across coastal watersheds of the western United States. *Intl. J. Climatol., 37*(13), 4493-4508. https://doi.org/10.1002/joc.5099

Cecílio, R. A., Pimentel, S. M., & Zanetti, S. S. (2019). Modeling the influence of forest cover on streamflows by different approaches. *Catena, 178*, 49-58. https://doi.org/10.1016/j.catena.2019.03.006

Čerkasova, N., Ertürk, A., Zemlys, P., Denisov, V., & Umgiesser, G. (2016). Curonian Lagoon drainage basin modeling and assessment of climate change impact. *Oceanologia, 58*(2), 90-102. https://doi.org/10.1016/j.oceano.2016.01.003

Čerkasova, N., Ertürk, A., & Umgiesser, G. (2019). Assessing climate change impacts on streamflow, sediment, and nutrient loadings of the Minija River (Lithuania): A hillslope watershed discretization application with high-resolution spatial inputs. *Water, 11*(4), 676. http://dx.doi.org/10.3390/w11040676

Chen, X., Alizad, K., Wang, D., & Hagen, S. C. (2014). Climate change impact on runoff and sediment loads to the Apalachicola River at seasonal and event scales. *J. Coastal Res., 68*, 35-42. https://doi.org/10.2112/SI68-005.1

Crossland, C. J., Baird, D., Ducrotoy, J.-P., Lindeboom, H., Buddemeier, R. W., Dennison, W. C., ... Swaney, D. P. (2005). The coastal zone: A domain of global interactions. In C. J. Crossland, H. H. Kremer, H. J. Lindeboom, J. I. Marshall Crossland, & M. D. Le Tissier (Eds.), *Coastal fluxes in the Anthropocene: The land-ocean interactions in the coastal zone project of the international geosphere-biosphere programme* (pp. 1-37). Berlin, Germany: Springer. https://doi.org/10.1007/3-540-27851-6_1

Dadhich, A. P., & Nadaoka, K. (2012). Analysis of terrestrial discharge from agricultural watersheds and its impact on nearshore and offshore reefs in Fiji. *J. Coastal Res., 28*(5), 1225-1235. https://doi.org/10.2112/JCOASTRES-D-11-00149.1

Edwards, P. J., Williard, K. W., & Schoonover, J. E. (2015). Fundamentals of watershed hydrology. *J. Contemp. Water Res. Educ., 154*(1), 3-20. https://doi.org/10.1111/j.1936-704X.2015.03185.x

Fares, A., & El-Kadi, A. I. (2008). *Coastal watershed management*. Southampton, UK: WIT Press.

Ferreira, J. G., Saurel, C., Lencart e Silva, J. D., Nunes, J. P., & Vazquez, F. (2014). Modelling of interactions between inshore and offshore aquaculture. *Aquaculture, 426-427*, 154-164. https://doi.org/10.1016/j.aquaculture.2014.01.030

Feyereisen, G. W., Strickland, T. C., Bosch, D. D., & Batten, H. L. (2005). Evaluation of SWAT input parameter sensitivity for the Little River watershed. ASABE Paper No. 052167. St. Joseph, MI: ASAE. https://doi.org/10.13031/2013.19808

Francesconi, W., Srinivasan, R., Pérez-Miñana, E., Willcock, S. P., & Quintero, M. (2016). Using the Soil and Water Assessment Tool (SWAT) to model ecosystem services: A systematic review. *J. Hydrol., 535*, 625-636. https://doi.org/10.1016/j.jhydrol.2016.01.034

Gao, X., Chen, X., Biggs, T. W., & Yao, H. (2018). Separating wet and dry years to improve calibration of SWAT in Barrett watershed, southern California. *Water, 10*(3), article 274. https://doi.org/10.3390/w10030274

Gassman, P. W., Reyes, M. R., Green, C. H., & Arnold, J. G. (2007). The Soil and Water Assessment Tool: Historical development, applications, and future research directions. *Trans. ASABE, 50*(4), 1211-1250. https://doi.org/10.13031/2013.23637

Griensven, A. V., Ndomba, P., Yalew, S., & Kilonzo, F. (2012). Critical review of SWAT applications in the upper Nile basin countries. *Hydrol. Earth Syst. Sci., 16*(9), 3371-3381. https://doi.org/10.5194/hess-16-3371-2012

Hoyos, N., Correa-Metrio, A., Jepsen, S. M., Wemple, B., Valencia, S., Marsik, M., ... Velez, M. I. (2019). Modeling streamflow response to persistent drought in a coastal tropical mountainous watershed, Sierra Nevada de Santa Marta, Colombia. *Water, 11*(1), article 94. https://doi.org/10.3390/w11010094

Huang, J., Zhou, P., Zhou, Z., & Huang, Y. (2013). Assessing the influence of land use and land cover datasets with different points in time and levels of detail on watershed modeling in the North River watershed, China. *Intl. J. Environ. Res. Public Health, 10*(1), 144-157. https://doi.org/10.3390/ijerph10010144

Im, S., Brannan, K. M., Mostaghimi, S., & Kim, S. M. (2007). Comparison of HSPF and SWAT models performance for runoff and sediment yield prediction. *J. Environ. Sci. Health A, 42*(11), 1561-1570. https://doi.org/10.1080/10934520701513456

Krysanova, V., & White, M. (2015). Advances in water resources assessment with SWAT: An overview. *Hydrol. Sci. J., 60*(5), 771-783. https://doi.org/10.1080/02626667.2015.1029482

Lin, B., Chen, X., Yao, H., Chen, Y., Liu, M., Gao, L., & James, A. (2015). Analyses of land use change impacts on catchment runoff using different time indicators based on SWAT model. *Ecol. Indic., 58*, 55-63. https://doi.org/10.1016/j.ecolind.2015.05.031

López-Ballesteros, A., Senent-Aparicio, J., Srinivasan, R., & Pérez-Sánchez, J. (2019). Assessing the impact of best management practices in a highly anthropogenic and ungauged watershed using the SWAT model: A case study in the El Beal watershed (southeast Spain). *Agronomy, 9*(10), article 576. https://doi.org/10.3390/agronomy9100576

Mirhosseini, G., & Srivastava, P. (2016). Effect of irrigation and climate variability on water quality of coastal watersheds: Case study in Alabama. *J. Irrig. Drain. Eng., 142*(2), article 976. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000976

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Med., 6*(7), e1000097. https://doi.org/10.1371/journal.pmed.1000097

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Trans. ASABE, 50*(3), 885-900. https://doi.org/10.13031/2013.23153

Nash, J. E., & Sutcliffe, J. V. (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

Neumann, B., Vafeidis, A. T., Zimmermann, J., & Nicholls, R. J. (2015). Future coastal population growth and exposure to sea-level rise and coastal flooding: A global assessment. *PLoS One, 10*(3), e0118571. https://doi.org/10.1371/journal.pone.0118571

Niazi, M., Obropta, C., & Miskewitz, R. (2015). Pathogen transport and fate modeling in the Upper Salem River watershed using SWAT model. *J. Environ. Mgmt., 151*, 167-177. https://doi.org/10.1016/j.jenvman.2014.12.042

Omani, N., Srinivasan, R., & Lee, T. S. (2014). Estimation of sediment and nutrient loads to bays from gauged and ungauged watersheds. *Appl. Eng. Agric., 30*(6), 869-887. https://doi.org/10.13031/aea.30.10162

Pesce, M., Critto, A., Torresan, S., Giubilato, E., Santini, M., Zirino, A., ... Marcomini, A. (2018). Modeling climate change impacts on nutrients and primary production in coastal waters. *Sci. Total Environ., 628-629*, 919-937. https://doi.org/10.1016/j.scitotenv.2018.02.131

Piniewski, M., Kardel, I., Gielczewski, M., Marcinkowski, P., & Okruszko, T. (2014). Climate change and agricultural development: Adapting Polish agriculture to reduce future nutrient loads in a coastal watershed. *Ambio, 43*(5), 644-660. https://doi.org/10.1007/s13280-013-0461-z

Rezaeianzadeh, M., Hantush, M. M., & Kalin, L. (2018). An integrated approach for modeling wetland water level: Application to a headwater wetland in coastal Alabama, USA. *Water, 10*(7), article 879. http://dx.doi.org/10.3390/w10070879

Rollo, N., & Robin, M. (2010). Relevance of watershed modeling to assess the contamination of coastal waters due to land-based sources and activities. *Estuarine Coastal Shelf Sci., 86*(3), 518-525. https://doi.org/10.1016/j.ecss.2009.10.025

Samadi, S., Tufford, D. L., & Carbone, G. J. (2017). Assessing parameter uncertainty of a semi-distributed hydrology model for a shallow aquifer dominated environmental system. *JAWRA, 53*(6), 1368-1389. https://doi.org/10.1111/1752-1688.12596

Setegn, S. G., Haiduk, A., Melesse, A. M., Webber, D., McClain, M. E., & Wang, X. (2014). Modeling hydrological variability of fresh water resources in the Rio Cobre watershed, Jamaica. *Catena, 120*, 81-90. https://dx.doi.org/10.1016/j.catena.2014.04.005

Sexton, A. M., Sadeghi, A. M., & Shirmohammadi, A. (2010). Impact of rainfall data source on hydrologic and water quality model response of a coastal plain watershed. ASABE Paper No. 1009640. St. Joseph, MI: ASABE.

Shao, H., Yang, W., Lindsay, J., Liu, Y., Yu, Z., & Oginskyy, A. (2017). An open-source GIS-based decision support system for watershed evaluation of best management practices. *JAWRA, 53*(3), 521-531. https://doi.org/10.1111/1752-1688.12521

Singh, H. V., Kalin, L., & Srivastava, P. (2011). Effect of soil data resolution on identification of critical source areas of sediment. *J. Hydrol. Eng., 16*(3), 253-262. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000318

Singh, H. V., Kalin, L., Morrison, A., Srivastava, P., Lockaby, G., & Pan, S. (2015). Post-validation of SWAT model in a coastal watershed for predicting land use/cover change impacts. *Hydrol. Res., 46*(6), 837-853. https://doi.org/10.2166/nh.2015.222

Sun, A., Miranda, R., & Xu, X. (2015). Development of multi-metamodels to support surface water quality management and decision making. *Environ. Earth Sci., 73*(1), 423-434. https://doi.org/10.1007/s12665-014-3448-6

Tan, M. L., Gassman, P. W., Yang, X., & Haywood, J. (2020). A review of SWAT applications, performance, and future needs for simulation of hydro-climatic extremes. *Adv. Water Resour., 143*, article 103662. https://doi.org/10.1016/j.advwatres.2020.103662

Vale, M., & Holman, I. P. (2009). Understanding the hydrological functioning of a shallow lake system within a coastal karstic aquifer in Wales, U.K. *J. Hydrol., 376*(1-2), 285-294. https://doi.org/10.1016/j.jhydrol.2009.07.041

Wang, R. Y., & Kalin, L. (2011). Modeling effects of land use/cover changes under limited data. *Ecohydrology, 4*(2), 265-276. https://doi.org/10.1002/eco.174

Wang, R., Kalin, L., Kuang, W., & Tian, H. (2014). Individual and combined effects of land use/cover and climate change on Wolf Bay watershed streamflow in southern Alabama. *Hydrol. Proc., 28*(22), 5530-5546. https://doi.org/10.1002/hyp.10057

Winchell, M. F., Folle, S., Meals, D., Moore, J., Srinivasan, R., & Howe, E. A. (2015). Using SWAT for sub-field identification of phosphorus critical source areas in a saturation excess runoff region. *Hydrol. Sci. J., 60*(5), 844-862. https://doi.org/10.1080/02626667.2014.980262

Wu, J., & Tanaka, K. (2005). Reducing nitrogen runoff from the upper Mississippi River basin to control hypoxia in the Gulf of Mexico: Easements or taxes? *Marine Resour. Econ., 20*(2), 121-144. https://doi.org/10.1086/mre.20.2.42629465

Wu, K., & Xu, Y. J. (2006). Evaluation of the applicability of the SWAT model for coastal watersheds in southeastern Louisiana. *JAWRA, 42*(5), 1247-1260. https://doi.org/10.1111/j.1752-1688.2006.tb05298.x

Wu, Y. P., & Chen, J. (2013). Analyzing the water budget and hydrological characteristics and responses to land use in a monsoonal climate river basin in south China. *Environ. Mgmt., 51*(6), 1174-1186. https://doi.org/10.1007/s00267-013-0045-5

Xu, M., & Chua V. P. (2017). A numerical study on land-based pollutant transport in Singapore coastal waters with a coupled hydrologic-hydrodynamic model. *J. Hydro-environ. Res., 14*, 119-142. https://dx.doi.org/10.1016/j.jher.2016.09.002

APPENDIX

Amatya amd Jha (2011) calibrated and validated the SWAT model with limited field measurements for the 72.6 km^2 low-gradient forested third-order Turkey Creek watershed in the South Carolina Coastal Plain. They used the SWAT model with an improved one-parameter "depletion coefficient" for plant evapotranspiration in the SCS curve number (CN), which eliminated the limitation of runoff overprediction in shallow soils and soils with low storage, often found in low-gradient coastal landscapes. The model performance was "good" (E = 0.68, RSR = 0.56) to "very good" (E = 0.90, RSR = 0.31) for the monthly calibration and validation periods but only "satisfactory" (E = 0.59, RSR = 0.64) to "good" (E = 0.70, RSR = 0.55) for the daily calibration and validation periods. However, the authors concluded that the refined SWAT model was still unable to accurately capture the flow dynamics and suggested further investigations of this forest ecosystem with shallow, high water table soils for events preceded by wet saturated conditions during the dry summer and wet winter periods. This study added to the existing limited knowledge on SWAT modeling of low-gradient forested watersheds, especially during the early days of SWAT modeling when only a handful of such studies existed.

Bacopoulos et al. (2017) integrated SWAT with an advanced circulation (ADCIRC) model to generate a hydrologic (SWAT) hydrodynamic (ADCIRC) model applicable for flood prediction in coastal areas. They used the integrated model for analysis of the flooding in the lower St. Johns River basin (northeast Florida) caused by Tropical Storm Fay in 2008, which was an approximately 100-year return period rainfall event. The model validation and inundation assessment demonstrated the need to apply watershed runoff as an additional boundary condition to more fully capture the peak surge and recession, which added approximately 0.5 m to the storm tide elevation in the lower St. Johns River, extended the surge recession by nearly 5 days, and increased the inundated watershed area by almost 50%.

Bougeard et al. (2011) coupled SWAT with a hydrodynamic model (MARS 2D) to simulate the impacts of *E. coli* loads in the Daoulas catchment and estuary in France. The daily *E. coli* fluxes simulated by SWAT were used as input in the MARS 2D model to calculate *E. coli* concentrations in the estuarine water and shellfish. Model validation was based on a comparison of frequencies, and a strong relationship was found between calculated and measured *E. coli* concentrations for river quality (R^2 = 0.99) and shellfish quality (R^2 = 0.89). The important influence of agricultural practices and rainfall events on the rapid and large fluctuations in *E. coli* fluxes from the watershed (reaching three orders of magnitude in <24 h) is one main result of the study. Response time in terms of seawater quality degradation ranged from one to two days after any important rainfall event (greater than 10 mm d^{-1}), and the time for the estuary to recover good water quality also mainly depended on the duration of the rainfall. In the estuary, three effects (rainfall, tidal dilution, and manure spreading) were identified as important influences.

Burke and Ficklin (2017) coupled the SWAT hydrologic model with projected temperature and precipitation from general circulation models (GCMs) for five small coastal basins (42 to 718 km^2) in Washington, Oregon, and California to simulate future hydrology for each watershed. They found that the three northernmost watersheds, in Washington, Oregon, and northern California, showed increases in peak winter streamflow, and the two southernmost watersheds, in central and southern California, were projected to decrease in streamflow.

Cecílio et al. (2019) used SWAT to simulate land use change scenarios with increasing and decreasing forest cover in a Brazilian Atlantic rainforest watershed and examined the effects on streamflow. The influence of the geographic location on afforestation was evaluated with two approaches: (1) a random approach (RA) in which the locations of reforested areas did not matter, and (2) an imposed approach (IA) in which the locations of afforestation were precisely defined. The RA results showed little tendency of reduction in the simulated average and minimum flows with afforestation. The IA approach showed that the locations of afforestation did not significantly interfere with the average flows but interfered with the simulated minimum flows. Afforestation concentrated in areas close to streams caused a reduction in minimum flows, while afforestation concentrated in the upper parts of the basin managed to increase streamflows.

Čerkasova et al. (2016) developed a SWAT model for assessing the impacts of climate change scenarios on runoff to the Nemunas River and the Minija River, which are located in the Curonian Lagoon drainage basin. The model was calibrated and validated using monthly streamflow data, and the calculated R^2 and NSE values for the Nemunas and Minija stations were respectively 0.81 and 0.79 for calibration and 0.679 and 0.602 for the validation period. Two potential climate-change scenarios were developed within the general patterns of near-term climate projections, as defined by the IPCC Fifth Assessment Report: pessimistic (substantial changes in precipitation and temperature) and optimistic (insubstantial changes in precipitation and temperature). Both simulations produced similar general patterns in river discharge change, including a strong increase (up to 22%) in the winter months, especially in February, a decrease during the spring (up to 10%) and summer (up to 18%), and a slight increase during the fall (up to 10%).

Čerkasova et al. (2019) developed a SWAT model for the Minija River basin in Lithuania for assessing the impact of near-term (up to 2050) and long-term (up to 2099) climate change on streamflow, sediment, and nutrient loadings. They adopted a multi-site manual calibration approach to calibrate and validate the model. They found that net decreases in flow (up to 35%), TN (up to 34%), and TP (up to 50%) loads were projected under both scenarios.

Chen et al. (2014) used SWAT to assess the potential impacts of climate change on runoff and sediment load in the Apalachicola River basin in Florida. Two regional climate models (HRM3-HADCM3 and RCM3-GFDL) were used to project the climate for use as input to SWAT and project streamflow and sediment load. The streamflow NSE values for the simulation and validation periods (1984-1989 and

1990-1994 years) were 0.92 and 0.88, respectively. The sediment NSE values for the simulation and validation periods were 0.46 and 0.36, respectively, with an excellent description of trend variability. The results showed that the average daily level of streamflow and sediment load will not vary significantly, but the peak flow and peak sediment load will increase dramatically due to more intense and less frequent rainfall events. The impact of climate change during an extreme rainfall event was also investigated. A storm event with a 25-year return period and a 24-hour duration in 1991 was used as the baseline event. Based on the projection using the RCM3-GFDL scenario, streamflow and sediment load may increase by 50% and 89%, respectively.

Dadhich and Nadaoka (2012) assessed the change in benthic cover as influenced by terrestrial loadings from 14 adjoining, agriculturally dominated (especially sugarcane), coastal watersheds. They coupled SWAT with a geographic information system (GIS) and remote sensing technique to ascertain how land use changes affect hydrological processes, erosion, and waterborne transport of eroded materials in catchments. The impact of terrestrial discharge on the coastal ecosystem was investigated by spatio-temporal analysis (1992 to 2007) of the benthic cover using Landsat TM/ETM+ data. Due to cropland expansion, significant amounts of surface runoff, sediment, and nutrient discharge were generated during 1992 to 2007 from the steeply sloping watersheds. The hydrological response results from areas with different land use conditions (1992 to 2007) revealed that conversion of forestland (7.88%) and shrubland (7.59%) to agricultural (10.04%) and barren land (3.06%) had the greatest impact on the potential risk of surface runoff. The researchers found that during the study period, the coral cover was reduced by 33.5%, while the algae and seagrass cover increased by 139.3% and 70.6%, respectively. During the same time, the degraded reef area around these coastal watersheds increased by 59.39% due to the increased sediment and nutrients, mainly from the sugarcane fields.

Ferreira et al. (2014) developed a dynamic modeling framework that integrate SWAT for the watershed, Delft3D for ocean circulation, and the EcoWin model for long-term (10-year) ecological simulations for integrated analysis of catchment, inshore waters, and offshore aquaculture, providing an approach that addressed production, environmental effects, and disease interactions. This framework was tested using a case study in southeast Portugal for a system-scale modeling domain with an ocean area of 470 km^2 and a coastal watershed area of 627 km^2. The SWAT simulations of the watershed indicated that 55% of the nitrogen and 70% of the phosphorus load came from diffuse sources, which was contrary to the perception of clam culture stakeholders that nutrients were mainly linked to the point-source discharges from wastewater treatment plants.

Gao et al. (2018) calibrated SWAT separately for dry and wet years in the semi-arid Barrett watershed on the west coast of the U.S. and analyzed differences in the most sensitive parameters between the wet and dry year series. The results showed that (1) SWAT calibrated to the entire runoff series produced significant differences in simulation efficiency between wet years and dry years, with lower efficiency during dry years; (2) calibration with separate wet and dry years greatly enhanced SWAT's simulation efficiency for both wet and dry years; and (3) differences in hydrological conditions between wet and dry years were represented by changes in the six most sensitive parameters, including baseflow recession rate, channel infiltration rate, SCS curve number, soil evaporation, shallow aquifer flow, and soil water holding capacity.

Hoyos et al. (2019) developed a SWAT model for assessing the streamflow response to drought for a watershed in the Colombian Caribbean by analyzing the effects of drought length and land cover on streamflow recovery. The model was used to predict water yields for selected land covers (wet forest, shade coffee, shrub, and dry forest) in annual and monthly drought scenarios created from rainfall records. The annual scenarios resulted in water yield reductions of ~15 mm month^{-1} (for wet forest, coffee, and shrub) and 5 mm month^{-1} (for dry forest) for the first month after a two-year drought. Maximum water yield reductions for the monthly scenarios occurred after a 10-month drought and were ~100 mm month^{-1} (for wet forest, coffee, and shrub) and 20 mm month^{-1} (for dry forest). Streamflow recovered within nine months (for annual scenarios) and within two to eight months (for monthly scenarios) after drought termination.

Huang et al. (2013) tested the applicability of SWAT in the Jiulong River basin, which is a medium-sized subtropical coastal watershed in southeast China. They assessed the sensitivity of SWAT to land use and land cover (LULC) datasets with different points in time and levels of detail. They found good agreement between observed and simulated values for both monthly and daily streamflow, with NSE values of 0.86 and 0.85, respectively, for calibration and 0.86 and 0.64, respectively, for validation. Monthly NH_4^+-N and TP loads were also acceptable, with NSE values of 0.69 and 0.56, respectively, for calibration and 0.57 and 0.49, respectively, for validation. The sensitivity of SWAT to LULC datasets with different points in time and levels of detail was lower for monthly and daily streamflow simulation than for monthly NH_4^+-N and TP load prediction.

Lin et al. (2015) used SWAT to analyze the land use change impacts on catchment runoff on daily, monthly, and annual time scales and quantitatively compared the impacts of time scales with different time indicators for a coastal catchment in southeast China with a humid subtropical climate. First, SWAT was calibrated to produce satisfactory reproduction of annual, monthly, and daily runoff processes over a nine-year (2002 to 2010) period at three gauging stations. Runoff was then simulated and compared using the same meteorological input but two different land use scenarios (1985 and 2006, with reduced forest and increased cropland and urbanized area). The results showed varying changes in runoff among the three time scales and three catchments. Annual runoff had the smallest increase between two scenarios, monthly runoff had medium rates (increasing in all months except October and November), and daily runoff had the largest rates with a increase in flood peaks but a decrease in drought flows because of the variable influence of interception, evapotranspiration loss, percolation, and antecedent soil water storage.

López-Ballesteros et al. (2019) developed SWAT for the El Beal watershed, an anthropogenic and ungauged basin in southeast Spain that drains into a coastal lagoon of high environmental value, to quantify the effectiveness of five BMPs (contour planting, filter strips, reforestation, fertilizer application, and check dam restoration). The BMPs were tested both individually and in combination to test their impacts on sediment and nutrient reduction. For calibration and validation processes, actual evapotranspiration data obtained from a remote sensing dataset, the Global Land Evaporation Amsterdam Model (GLEAM), were used. SWAT achieved good performance in the calibration period, with values of 0.78 for Kling-Gupta efficiency (KGE), 0.81 for coefficient of determination (R^2), 0.58 for NSE, and 3.9% for percent bias (PBIAS), as well as in the validation period (KGE = 0.67, R^2 = 0.83, NSE = 0.53, and PBIAS = -25.3%). The results showed that check dam restoration was the most effective BMP, with reductions of 90% in sediment yield (S), 15% in total nitrogen (TN), and 22% in total phosphorus (TP) at the watershed scale, followed by reforestation (S = 27%, TN = 16%, and TP = 20%). All effectiveness values improved when BMPs were assessed in combination.

Mirhosseini and Srivastava (2016) used SWAT to quantify the effects of irrigation and El Niño Southern Oscillation (ENSO) on nutrient transport in the Big Creek watershed in southwest Alabama. The model parameters were optimized using 15 years of observed data. The results showed that total nitrogen (TN) and total phosphorus (TP) loads increased by 4% and 3%, respectively, when irrigation was applied to cropland subwatersheds. TN was found to be more sensitive to irrigation compared to TP.

Omani et al. (2014) used SWAT in lower watersheds of the Texas coastal region to estimate terrestrial sediment and nutrient loads from non-tidal freshwater inflows to Texas bays. Two separate models were established for an urbanized watershed (Galveston) and a rural watershed (Matagorda) as a pilot study. Applying SWAT enabled the researchers to predict the temporal and spatial distributions of freshwater, sediment, and nutrient loads in an ungauged watershed as they used parameter settings from a gauged watershed for the ungauged watershed. The monthly sediment calibration showed good agreement compared with the observed total suspended sediment, with NSE values ranging from 0.55 to 0.75 and PBIAS values ranging from +10.3% to +51.0%. The predicted monthly total nitrogen (TN) and total phosphorus (TP) (loads or concentrations) at gauge stations exhibited a poor correlation with the observed values in the urbanized subwatershed but good to acceptable correlation in the other watershed, with NSE values ranging from -0.15 to 0.85 and PBIAS values ranging from +13.3% to +84.0%. The calibration results showed that applying the global average calibrated parameter values for urbanized ungauged subwatersheds led to poor results compared with the estimated loads. However, extending the regional parameterization values resulted in better agreement with the estimated loads.

Pesce et al. (2018) developed an integrated modeling framework consisting of climate simulations derived by coupling a general circulation model (GCM) and a regional climate model (RCM) under alternative emission scenarios, the hydrological model SWAT, and the ecological model AQUATOX. The framework was applied to the Zero River basin in Italy, one of the main contributors of freshwater and nutrient to the Palude di Cona salt marsh, a coastal waterbody in the Venetian Lagoon. Climate projections indicated an increase in precipitation in the winter and a decrease in the summer, while temperature showed a significant increase over the whole year. Water discharge and nutrient loads simulated by SWAT showed a tendency to increase in the winter and decrease in the summer. AQUATOX projected changes in the concentration of nutrients in the Palude di Cona salt marsh and variations in the biomass and species of the phytoplankton community.

Piniewski et al. (2014) used SWAT for scenario modeling in a small (482 km^2) agricultural coastal watershed in northern Poland. SWAT was used to quantify the effects of future climate, land cover, and management changes for multiple scenarios up to the 2050s. The combined effects of climate and land use change on N-NO_3 and P-PO_4 loads were increases of 20% to 60% and 24% to 31%, respectively, depending on the intensity of future agricultural use. The scenario that assumed a major shift toward more intensive agriculture, following the Danish model, resulted in significantly higher crop yields but caused a great deterioration in water quality. Using vegetative cover in winter and spring would be a very efficient way to reduce future P-PO_4 loads to levels lower than those observed at present. However, even the best combination of measures (vegetative cover, buffer zones, reduced fertilization, and constructed wetlands) would not help to remediate the heavily increased N-NO_3 loads due to climate change and agricultural intensification.

Rezaeianzadeh et al. (2018) used an integrated approach by coupling SWAT with an artificial neural network (ANN) to predict water levels in a headwater wetland in coastal Alabama. They first estimated the baseflow and stormflow from the watershed draining to the wetland using an uncalibrated SWAT model. These estimates were then used as input to the ANN model along with other meteorological variables. The hybrid model was used to successfully predict water levels in the headwater wetland. The model was then used to predict water levels in the studied wetland from 1951 to 2005 to explore the possible teleconnections between the El Niño Southern Oscillation (ENSO) and water level. The results showed that precipitation and the variations in water level were both partially affected by ENSO in the study area.

Rollo and Robin (2010) used SWAT for assessing the contamination of coastal waters due to land-based sources and activities on the coastal watersheds of the Pen-Bé estuary and Le Croisic bay on the west coast of France. Despite limited existing data, the simulated flows were close to the measurements, according to the NSE values. The NSE values ranged from 0.65 to 0.82 for streamflow and from 0.54 to 0.76 for phosphorus flow. The continuous flows simulated by SWAT complemented the intermittent water quality sampling and streamflow measurements and helped to identify the subwatersheds that contributed the most nutrients. The simulations could be used to suggest priority areas for intervention to decrease coastal watershed loadings.

Samadi et al. (2017) examined the performance of SWAT using sequential uncertainty fitting (SUFI-2), generalized likelihood uncertainty estimation (GLUE), parameter solution (ParaSol), and particle swarm optimization (PSO) in the Waccamaw watershed, a shallow aquifer dominated Coastal Plain watershed in the southeastern U.S. They found that SWAT performed best during intervals with wet and normal antecedent conditions, with varying sensitivity to effluent channel shape and characteristics. In addition, the calibration of all models depended mostly on Manning's n value for the tributary channels as the surface friction resistance factor to generate runoff. SUFI-2 and PSO simulated the same relative probability distribution tails as observed at an upstream outlet, while all methods (except ParaSol) exhibited longer tails at a downstream outlet. ParaSol exhibited large skewness, suggesting that a global search algorithm was less capable of characterizing parameter uncertainty. These findings provide insights regarding parameter sensitivity and uncertainty as well as modeling diagnostic analysis that can improve hydrologic theory and prediction in complex watersheds.

Setegn et al. (2014) used SWAT to analyze the temporal variability of hydrological processes in the Rio Cobre watershed in Jamaica. The ability of a watershed model to accurately predict the hydrological processes was evaluated through parameter sensitivity analysis, model calibration, and validation. The three most sensitive parameters were the soil evaporation compensation factor, initial SCS curve number, and base flow alpha factor. The model evaluation metrics for streamflow prediction showed good agreement between the measured and simulated flows, and the R^2 and NSE values were greater than 0.5. The hydrological water balance analysis indicated that more than 52% of the annual precipitation was lost to evapotranspiration in the basin. Surface runoff contributed more than 12% of the total water yield, while the groundwater contributed more than 42%. This indicated that ET and groundwater are the two most important hydrological processes in the basin.

Shao et al. (2017) integrated SWAT (for estimating water quantity and quality benefits of BMPs) with a farm economic model (for quantifying the costs of BMPs) and an optimization model (for examining the cost-effectiveness of BMPs) within Whitebox Geospatial Analysis Tools. The researchers developed an open-source GIS-based decision support system (DSS) called Watershed Evaluation of BMPs (WEBs). WEBs was then applied to the 14.3 km^2 Gully Creek watershed, a coastal watershed in southern Ontario, Canada, for creating BMP scenarios and simulating economic costs and water quantity and quality benefits at the field, subbasin, and watershed scales.

Singh et al. (2011) used SWAT to evaluate if two commonly used soil data sets, State Soil Geographic (STATSGO) and the Soil Survey Geographic (SSURGO) data, could lead to differences in the locations of critical source areas (CSAs) of sediment in the Fish River watershed in coastal Alabama. Identification of CSAs in a watershed is important for effective implementation of best management practices (BMPs). Flow data from a USGS gauging station located within the watershed were used for model calibration for five years (1990 to 1994) and validation for four years (1995 to 1998). The results showed that the locations of the CSAs were different for the two soil data sets. The use of STATSGO soil data resulted in higher soil erodibility and surface runoff. The locations of the CSAs varied at both the subwatershed and HRU level. At the HRU level, about 7% of the watershed area was identified as contributing to almost half of the entire sediment yield from the watershed. At the subwatershed level, about 27% of the watershed area was identified as contributing half of the total sediment yield. This suggests that the order of CSAs might change depending on the resolution of the input data. Therefore, careful selection of the soil input data set is necessary for the identification of CSAs within a watershed.

Singh et al. (2015) explored the performance of SWAT in predicting water quality and quantity in response to changing land use and land cover (LULC) in a coastal watershed in Alabama. They first calibrated and validated SWAT using a 1992 LULC dataset and then evaluated its performance in predicting flow and TSS, NO_3^-, and total P loads using a 2008 LULC dataset. SWAT showed good performance, with R^2 and NSE values >0.80 and mass balance error (MBE) <10% for both the calibration and validation periods. SWAT also showed good performance in predicting changes in flow and water quality during the post-validation period.

Sun et al. (2015) developed three metamodels that were trained using an existing SWAT model to support decision-making activities related to surface water quality management in the Arroyo Colorado watershed, a coastal watershed in Texas. The main objective of the metamodels was to support web-based decision-making, including near-term nutrient load forecasting, online sensitivity studies, and long-term load reduction planning. All three metamodels either replicated or extended the capabilities of the original SWAT model and thus provided proxies for regulators and stakeholders to examine and discuss model results interactively. This multi-metamodel methodology would be useful for supporting multigroup decision-making and public education and provides an effective way to leverage existing investment in watershed models.

Vale and Holman (2009) applied SWAT to improve understanding of the hydrological functioning of the Bosherston Lakes in western Wales. The lakes receive surface water inflows but have an uncertain interaction with the underlying karstic Carboniferous limestone. Temporally variable and limited observational data were used in a two-step calibration process. The simulated surface water inflows and groundwater levels were calibrated, followed by the lake volumes (NSE ranging from 0.67 to 0.74). Finally, the simulated lake volumes were validated (NSE ranging from 0.56 to 0.74), and the simulated lake outflows were shown to be plausible. The simulations revealed that three of the four linked water bodies lose significant water to the underlying aquifer. The simulated water balance demonstrated that the catchment outputs are dominated by evapotranspiration, surface outflow from the lake system to the sea, and coastal groundwater discharge, with abstraction and lake evaporation of lesser importance. The coastal groundwater discharge originates from leakages from the lakes and from previously unrecognized larger-scale groundwater flow paths in the limestone aquifer. This study provided an improved basis for future hydrological management of the catchment and lakes and demonstrated the wide utility of SWAT in simulating karstic systems.

Wang and Kalin (2011) used SWAT to study the impacts of land use and land cover (LULC) changes in the Wolf Bay watershed in coastal Alabama, where flow data did not exist for the study site. SWAT was set up in the neighboring Magnolia River watershed, and relevant model parameters were transferred to the Wolf Bay watershed. Impacts of LULC changes on hydrology in the Wolf Bay watershed were studied by running the model with the default parameters, with the transferred model parameters (from the Magnolia River watershed), and with parameters for the Wolf Bay watershed that were calibrated with limited data that became available later during the study. The relative changes in flow duration curves (FDCs) due to differing LULC showed a similar pattern for each parameter set: There was a clear threshold of about 1% probability of exceedance where the relative change was at its maximum. The relative change in flow due to LULC change dropped drastically with an increasing probability of exceedance beyond 2% until it reached a plateau at 20%. Hence, small to medium range flows were less sensitive to the parameter set. Further, the impact of LULC change on flow gradually decreased with the size of the storm for very large events (probability of exceedance <1%).

Wang et al. (2014) used SWAT to analyze the individual and combined impacts of future LULC and climate change on hydrologic processes in the Wolf Bay watershed. The LULC map for 2005 was used to represent the baseline period, and three future (2030) development scenarios were used: LPR, MPR, and HPR, indicating low, medium, and high population increasing rates, respectively. To demonstrate the variability of future climate, outputs from four global circulation models (GCMs), including GFDL_cm2_0, GISS_model_e_r, NCAR_ccsm3_0, and UKMO_hadcm3, under three Special Report Emission Scenarios (SRES), including A2, A1B, and B1, were used to estimate potential monthly precipitation and temperature in the Wolf Bay watershed for the period 2016 to 2040. In the climate change scenarios, the study area was predicted to experience increased precipitation in the future, especially in the fall, and the temperature was expected to rise, especially in summer and fall. A redistribution of daily streamflow was projected when either climate or LULC change were considered. High flows were predicted to increase, while low flows were expected to decrease. The combined change effects resulted in a more noticeable and uneven distribution of daily streamflow. Monthly average streamflow and surface runoff were projected to increase in spring and winter, and especially in the fall. LULC change did not have a significant effect on monthly average streamflow, but the change affected the partitioning of streamflow, causing higher surface runoff and lower baseflow. The combined effect led to a dramatic increase in monthly average streamflow with a stronger increasing trend in surface runoff and a decreasing trend in baseflow.

Winchell et al. (2015) used SWAT in the Missisquoi Bay watershed, located along the U.S.-Canada border, for identification of phosphorus critical source areas (CSAs). They developed a novel approach for adjusting the SCS curve number based on the local compound topographic index. SWAT was run for a 30-year period to identify the phosphorus CSAs throughout the watershed, determining that 20% of the watershed produces 74% of the total phosphorus load.

Wu and Chen (2013) assessed the performance of SWAT in representing the hydrological cycle in a coastal area dominated by a monsoonal climate in the East River basin of southern China. The SWAT model was calibrated with eight years of daily streamflow data and then validated with another eight years of data. The calibration and validation results showed that the model could predict monthly and daily streamflow in the East River, with monthly NSE values of 0.93 for calibration and 0.90 for validation. Water budget analysis of the key hydrological components showed that subsurface lateral flow and baseflow contributed more than two-thirds of the water yield over the long term (16-year annual average), while the contribution of surface runoff could reach 40% during the intense rainfall period (May and June). Moreover, the hydrological responses to forest areas produced relatively low surface runoff and high subsurface and baseflow compared to agriculture and pasture lands.

Wu and Xu (2006) evaluated the applicability of SWAT in three coastal watersheds: the Amite, Tickfaw, and Tangipahoa River watersheds in southeastern Louisiana. Their study found that Manning's roughness coefficient for the main channel, SCS curve number, and soil evaporation compensation factor were the most sensitive parameters for these coastal watersheds. Manning's roughness coefficient showed a significant effect and higher sensitivity for runoff response. SWAT demonstrated excellent performance, with NSE values for daily and monthly flow calibration of 0.926 and 0.935 for the Amite River watershed, 0.902 and 0.940 for the Tickfaw River watershed, and 0.834 and 0.960 for the Tangipahoa River watershed. The NSE values for daily and monthly flow validation were 0.784 and 0.851 for the Amite River watershed, 0.713 and 0.811 for the Tickfaw River watershed, and 0.689 and 0.867 for the Tangipahoa River watershed. The performance of SWAT demonstrated that it is capable of simulating hydrologic processes for medium-scale to large-scale coastal lowland watersheds in Louisiana.

Xu and Chua (2017) coupled SWAT with a hydrodynamic model (SUNTANS) by transferring streamflow and pollutant concentrations at nine rivers along common boundaries. The coupled hydrologic-hydrodynamic model (SWAT-SUNTANS) simulated the hydrodynamic process and output velocities, the evolution of depth-averaged pollutants, and the dispersion coefficients to illustrate the circulation pattern, pollutant transport, and dispersion processes in Singapore coastal waters. The coupled hydrologic-hydrodynamic model was validated for sea surface elevations and velocities. A low RMSE of 0.10 m and a high correlation coefficient of 0.98 were observed for sea surface elevations. The coupled model predicted depth-averaged U and V velocities accurately, with low RMSE values of 0.06 and 0.07 m s^{-1}, respectively, and high correlation coefficients exceeding 0.95.