SOIL AND WATER ASSESSMENT TOOL (SWAT) MODEL: CURRENT DEVELOPMENTS AND APPLICATIONS

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ABSTRACT. *This article introduces a special collection of 20 research articles that present current developments and applications of the Soil and Water Assessment Tool (SWAT). The first objective is to review and introduce the research addressed within this special collection. The second objective is to summarize and synthesize the model performance statistics and parameters published in these articles to provide a succinct guide to complement a previous SWAT model summary. Recent SWAT developments in landscape representation, stream routing, and soil P dynamics are presented in this collection. Numerous critical applications of the SWAT model were conducted across a variety of landscape scales, climatic and physiographic regions, and pollutant sources. In this article, model performance in terms of coefficient of determination, Nash-Sutcliffe efficiency, and percent bias across all the studies is summarized and found to be satisfactory or better in all cases. These results are then compiled with a previous synthesis of results to generate a comprehensive assessment of SWAT. Model parameters used to calibrate the model for streamflow, sediment, N, and P in numerous studies are also summarized. This collection demonstrates that research in development and application of the SWAT model and associated tools continues to grow internationally in a wide range of settings and applications.*

Keywords. *Hydrologic modeling, Hydrology, SWAT, Water quality, Watershed.*

The Soil and Water Assessment Tool (SWAT) model is a physically based, deterministic, continuous, watershed-scale simulation model developed by the USDA Agricultural Research Service (Arnold et al., 1998; Neitsch et al., 2004, 2005). SWAT has evolved from numerous individual models over a 30-year period and has been tested for a wide range of regions, conditions, practices, and time scales (Gassman et al., 2007). Gassman et al. (2007) summarized more than 250 refereed journal articles reporting research using SWAT around the world. Evaluation of daily, monthly, and annual streamflow and pollutant outputs indicate that SWAT functioned well in a wide range of watersheds.

This article introduces an effort to present recent developments of the SWAT model and current applications of the model to address a range of issues. The ASABE SWAT 2010 Special Collection assembles 20 research articles, largely selected from 113 papers, presentations, and posters presented at the 2009 International SWAT Conference (Twigg et al., 2009). New research in this special collection summarizes results of streamflow, sediment, nitrogen, phosphorus, and bacteria simulation at watershed scales ranging from 0.004 to 491,665 km^2.

The objectives of this article are to review and introduce the research addressed by this SWAT special collection and to summarize and synthesize the model performance statistics and parameters reported in these articles, and thus to provide a succinct guide to complement the SWAT model summary by Gassman et al. (2007).

SWAT MODEL

Five versions of the SWAT model are currently being distributed: SWAT2009 (documentation currently is not available), SWAT2005 (Neitsch et al., 2004, 2005), SWAT2000 (Di Luzio et al., 2002; Neitsch et al., 2002), SWAT99.2 (Neitsch et al., 1999b), and SWAT98.1 (Neitsch et al., 1999a). SWAT uses spatially distributed data on topography, soils, land cover, land management, and weather to predict water, sediment, nutrient, pesticide, and fecal bacteria yields. In the current versions, a modeled watershed is divided spatially into subwatersheds using digital elevation data according to the density specified by the user. Subwatersheds are further subdivided into lumped, nonspatial hydrologic response units (HRUs) consisting of all areas within the subwatershed having similar landscape characteristics. Versions 2000 and earlier model subwatersheds as having uniform slope and climatic conditions, and HRUs as having similar soil, land use, and land management characteristics. Versions 2005 and 2009 allow slope to be included at the HRU level.

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The SWAT model includes subbasin, reservoir, and channel routing components, each of which are addressed in this collection. The subbasin component simulates runoff and erosion processes, soil water movement, evapotranspiration, crop growth and yield, soil nutrient and carbon cycling, and pesticide and bacteria degradation and transport. SWAT simulates a wide array of agricultural structures and practices, including tillage, fertilizer and manure application, subsurface drainage, irrigation, ponds and wetlands, and edge-of-field buffers. The reservoir component detains water, sediments, and pollutants and degrades nutrients, pesticides, and bacteria during detention. The channel component routes flows, settles and entrains sediment, and degrades nutrients, pesticides, and bacteria during transport. SWAT typically produces daily results for every subwatershed outlet, each of which can be summed to provide monthly and annual load estimates.

SWAT MODEL PERFORMANCE SUMMARY

Most SWAT modeling studies in this collection report calibration and/or validation statistics either at the daily, monthly, or annual scale. Moriasi et al. (2007) recommend using multiple statistics and criteria in assessing model performance. In table 1, the reported statistics of coefficient of determination (R^2), Nash-Sutcliffe model efficiency (E_f), and percent bias (PBIAS) are summarized. These statistics provide insight regarding model performance in simulating streamflow, sediment load, N and P loads, and *E. coli* and fecal coliform bacteria loads across a wide spectrum of watershed conditions.

Calibration and validation results from this collection (table 1) add substantially to the previous compilation of model results by Gassman et al. (2007). Table 2 summarizes the combined results of more than 100 model runs/applications calibrated for daily flow and 80 runs/applications validated for daily flow from this collection and from Gassman et al. (2007). Adapting the threshold of $E_f \geq 0.50$ for satisfactory model performance for monthly flow (Moriasi et al., 2007), and recognizing that monthly model performance statistics generally are better than daily statistics (Gassman et al., 2007), all reported daily flow calibration statistics in this collection were reported to be satisfactory or better. Very good performance for daily flow ($E_f \geq 0.75$, adapting monthly flow criteria from Moriasi et al., 2007) was achieved in one of the seven calibration results and none of the validation results. Combined with data from Gassman et al. (2007), 69% of 107 calibration results and 56% of 86 validation results rated as satisfactory or better, and 21% of calibration results and 10% of validation results rated as very good.

Several studies report the parameters used to calibrate the model. These parameters are summarized in table 3 for streamflow, table 4 for sediment, and table 5 for nutrients. Baffaut and Sadeghi (2010) provide a review of fecal bacteria modeling using SWAT and report a detailed summary of calibrated bacterial parameters and statistics. Model parameters used in calibration and the values found to produce optimal calibration for each parameter vary substantially among studies and watersheds. Interpretation of model results is aided by detailed reporting of model parameterization and calibration procedures, as found in many of the studies in this collection. However, gaps in reported methods and results were evident in many cases. Improved reporting of calibration and validation procedures and results, perhaps guided by a set of standard reporting guidelines, is essential for adequate interpretation of each study and comparison among studies in the future. This increased information would also form the basis for assigning typical parameters and ranges for use in either manual or automatic calibration and uncertainty processes.

MODEL DEVELOPMENTS

LANDSCAPE ROUTING

The use of HRUs in SWAT allows soil, topographic, and land use heterogeneity to be simulated within each subwatershed but ignores pollutant attenuation between the source area and stream and limits spatial representation of wetlands, buffers, and other best management practices (BMPs) within a subwatershed. In this collection, Arnold et al. (2010) and Bosch et al. (2010) present and assess new model developments that will allow these limitations to be addressed.

Arnold et al. (2010) present an enhancement to the SWAT model that allows landscapes to be subdivided into catenas comprised of upland, hillslope, and floodplain units and flow to be routed through these catenas. This catena method was tested against three other methods (using a lumped method with a single HRU, using an HRU-based method to delineate unique land use and soil combinations, and using a grid-based method with distributed land use, soil, and slope cells). These methods performed similarly in simulating streamflow, with daily E_f of 0.63 to 0.67, in the 17.3 km^2 Brushy Creek, Texas, watershed, with clay soils (Vertisols), pasture (on hillslopes and valley bottoms), and tilled cropland (on uplands) and slopes of 1% (on uplands and valleys) and 4% (on hillslopes).

In another study, the catena method was compared with a single-HRU method at the 1.77 ha Fox Den field site near Tifton, Georgia (Bosch et al., 2010). The study area had loamy sand soils and included a 0.93 ha tilled cropland of corn, peanuts, and pearl millet and a 0.84 ha, multi-zone, 70 m buffer consisting of 8 m of biannually harvested grass followed by 45 to 55 m of mature pine and 10 m of hardwoods adjacent to the stream. At this site, surface runoff for the upland HRU was simulated with very good annual E_f of 0.83 but unsatisfactory (negative) E_f for monthly runoff. The model tended to overpredict winter runoff and underpredict summer runoff. In this study area, groundwater contribution was estimated to range from 7% to 32% of annual precipitation from a separate study and was substantially overestimated by the catena method (40%). Although Bosch et al. (2010) conclude that further revisions are needed to adequately redistribute flow among surface runoff, lateral subsurface flow, and groundwater flow at the landscape scale, they expect dramatic potential benefits in representing water quality fate and transport. Further development is expected to include sediment and nutrient routing components to the catena method (Arnold et al., 2010).

STREAMFLOW ROUTING

Accurate simulation of fluvial processes is essential to watershed-scale modeling. Kim et al. (2010) compared flow and pollutant loads from SWAT2005, using the Muskingum

Table 1a. Summary of reported SWAT hydrology calibration and validation statistics.[a]

Reference	Model	Watershed	Drainage Area (km^2)	Indicator	Warm-up Period (years)	Time Period	Time Scale	C or V	R^2	E_f	PBIAS (%)
Arnold et al., 2010	SWAT HRU	Brushy Creek (TX)	17.3	Streamflow	--[b]	1968-1974	D	C	0.67	0.67	7.8
	SWAT Catena						D	C	0.65	0.65	4.4
	SWAT HRU	Brushy Creek (TX)	17.3	Streamflow	--	1975-1981	D	V	0.63	0.63	40
	SWAT Catena						D	V	0.55	0.54	23
Baskaran et al., 2010	SWAT2005	Current River (AR, MO)	6817	Streamflow	--	1985-1996	M	C	--	0.74	--
		Southern Beaver (TX)	1780				M	C	--	0.78	--
	SWAT2005	Current River (AR, MO)	6817	Streamflow	--	1997-2003	M	V		0.75	
		Southern Beaver (TX)	1780				M	V		0.65	
Bosch et al., 2010	SWAT Catena	Fox Den Field (GA)	0.0177	Field runoff	1	1992-1994	A	C	--	0.83	--
							M	C		<0	
Chiang et al., 2010	SWAT2009	Lincoln Lake (AR, OK)	32	Streamflow	2	2001-03, 06-07	M	C	0.55	0.52	--
						1997-2000	M	V	0.76	0.60	
Ghebremichael et al., 2010	SWAT2000	Rock River (VT)	71	Streamflow	4	2001-2004	M	C	--	0.74	--
						2004-2007	M	V		0.70	
	SWAT2000	Rock River (VT)	71	Streamflow	4	2001-2004	D	C	--	0.60	--
						2004-2007	D	V		0.60	
Kim et al., 2010	SWAT2005	Chungju Dam (S. Korea)	6,648	Streamflow	--	1998-2006	D	C	0.51	0.51	--
	SWAT-NSR						D	C	0.81	0.80	
Lee et al., 2010	SWAT2000	G1 Coal Creek (TX)	--	Streamflow	--	1966-1987	M	C	0.82	0.81	--
		G2 Coal Creek (TX)				1966-1987	M	C	0.89	0.83	
		R Coal Creek (TX)				1980-2002	M	V	0.76	0.80	
Meng et al., 2010	SWAT2005	Rappahannock River (VA)	7,405	Streamflow	--	1995-2002	D	C	0.74	0.73	6.24
						2003-2008	D	V	0.71	0.70	7.26
Narasimhan et al., 2010	SWAT2000	Cedar Creek (TX)	--	Streamflow	3	1966-1987	M	C	0.82	0.81	--
						1980-2000	M	V	0.76	0.79	
		King's Creek (TX)	--	Streamflow	3	1966-1987	M	C	0.89	0.83	--
Rahman et al., 2010	SWAT2005	Ruscom River (Ontario)	175	Streamflow	--	1990-1994	M	C	0.80	0.81	--
						1980-84	M	V	0.74	0.76	
Sexton et al., 2010	SWAT2005	German Branch (MD)	50	Streamflow	--	2005-2006	D	C[c]	0.60	0.58	-11.80
						2007	D	V	0.75	0.73	-10.33
Srinivasan et al., 2010	SWAT2005	07010104[d]	29,696	Streamflow	--	1975-1993	A	V	0.85	0.55	12.18
		07010206	94,863			1961-1997	A	V	0.86	0.71	6.86
		07020012	43,126			1980-1996	A	V	0.90	0.86	-8.24
		07030005	19,768			1976-1996	A	V	0.83	0.72	-6.35
		07040008	4,250			1901-1996	A	V	0.93	0.51	-1.96
		07050005	24,338			1991-1996	A	V	0.78	0.65	-1.73
		07080104	304,640			1975-1987	A	V	0.85	0.65	6.32
		07080107	11,016			1976-1995	A	V	0.95	0.95	1.13
		07080209	31,997			1976-1995	A	V	0.95	0.92	-9.95
		07130011	73,656			1981-1996	A	V	0.98	0.64	-20.10
		07110009	444,185			1980-1997	A	V	0.88	0.80	-5.00
	SWAT2005	07010104	29,696	Streamflow	--	1975-1993	M	V	0.42	-0.10	10.96
		07010206	94,863			1961-1997	M	V	0.54	0.34	6.45
		07020012	43,126			1980-1996	M	V	0.56	0.48	-9.85
		07030005	19,768			1976-1996	M	V	0.29	0.11	-6.73
		07040008	4,250			1901-1996	M	V	0.49	0.20	-1.40
		07050005	24,338			1991-1996	M	V	0.34	0.06	-0.86
		07080104	304,640			1975-1987	M	V	0.47	0.14	6.42
		07080107	11,016			1976-1995	M	V	0.81	0.80	1.73
		07080209	31,997			1976-1995	M	V	0.80	0.78	-9.36
		07130011	73,656			1981-1996	M	V	0.69	0.48	-22.48
		07110009	444,185			1980-1997	M	V	0.60	0.50	-3.23
Tuppad et al., 2010a	SWAT2000	Kanopolis Lake (KS)	6,316	Streamflow	--	1995-2002	D	V	0.54	0.52	--
Veith et al., 2010	SWAT[e]	Mahantango (PA)	7.2	Streamflow	--	--	M	C	--	0.84	0.07
		Little River (GA)	329.9				M	C		0.90	-13.92
		Little Washita (OK)	159.9				M	C		0.90	-14.36
		Walnut Gulch (AZ)	23.7				M	C		0.83	24.14
		Reynolds Creek (ID)	239.0				M	C		0.80	4.75

method of stream routing, with a version of SWAT adapted to include a new nonlinear storage routing method. The nonlinear storage method was found to improve estimation of stream peak-flow magnitude and timing in the watershed draining to the Chungju Dam, China. They also found the nonlinear storage method to result in improved model

Table 1b. Summary of reported SWAT sediment calibration and validation statistics.

Reference	Model	Watershed	Drainage Area (km^2)	Indicator	Warm-up Period (years)	Time Period	Time Scale	C or V	R^2	E_f	PBIAS (%)
Chiang et al., 2010	SWAT2009	Lincoln Lake (AR, OK)	32	Sediment	2	2001-03, 06-07	M	C	0.73	0.58	--
						1997-2000	M	V	0.67	0.25	
Ghebremichael et al., 2010	SWAT2000	Rock River (VT)	71	Sediment	4	2001-2004	M	C	--	0.7	--
						2004-2007	M	V		0.6	
	SWAT2000	Rock River (VT)	71	Sediment	4	2001-2004	D	C	--	0.4	--
						2004-2007	D	V		0.4	
Kim et al., 2010	SWAT2005	Chungju Dam (S. Korea)	6,648	Sediment	--	1998-2006	D	C	0.55	<0	--
	SWAT-NSR						D	C	0.65	<0	
Meng et al., 2010	SWAT2005	Rappahannock River (VA)	7,405	Sediment	--	1995-2002	D	C	0.64	0.63	-16.15
						2003-2008	D	V	0.31	0.25	24.26

Table 1c. Summary of reported SWAT nutrient (N and P) calibration and validation statistics.

Reference	Model	Watershed	Drainage Area (km^2)	Indicator	Warm-up Period (years)	Time Period	Time Scale	C or V	R^2	E_f	PBIAS (%)
Chiang et al., 2010	SWAT2009	Lincoln Lake (AR, OK)	32	Total N	2	2001-03, 06-07	M	C	0.66	0.50	--
						1997-2000	M	V	0.50	0.33	
Douglas-Mankin et al., 2010	SWAT99.2	Field TILL2 (KS)	0.0039	Total N	2	2001-2004	M	C	0.54	0.48	31
		Field TILL1 (KS)	0.0056				M	V	0.44	0.25	57
		Field NT/DB2 (KS)	0.0076				M	C	0.61	0.59	17
		Field NT/DB1 (KS)	0.0040				M	V	0.27	0.26	46
		Field NT/SB2 (KS)	0.0146				M	C	0.37	0.50	7
		Field NT/SB1 (KS)	0.0049				M	V	0.39	0.60	-22
	SWAT99.2	Field TILL2 (KS)	0.0039	Total N	2	2001-2004	D	C	0.47	0.46	31
		Field TILL1 (KS)	0.0056				D	V	0.57	0.33	57
		Field NT/DB2 (KS)	0.0076				D	C	0.71	0.62	19
		Field NT/DB1 (KS)	0.0040				D	V	0.50	0.34	46
		Field NT/SB2 (KS)	0.0146				D	C	0.60	0.57	7
		Field NT/SB1 (KS)	0.0049				D	V	0.58	0.65	-22
Kim et al., 2010	SWAT2005	Chungju Dam (S. Korea)	6,648	Total N	--	1998-2006	D	C	0.46	0.03	--
	SWAT-NSR						D	C	0.64	0.54	
Meng et al., 2010	SWAT2005	Rappahannock River (VA)	7,405	Nitrate	--	1995-2002	D	C	0.65	0.52	-10.41
						2003-08	D	V	0.62	0.61	11.18
Chiang et al., 2010	SWAT2009	Lincoln Lake (AR, OK)	32	Total P	2	2001-03, 06-07	M	C	0.72	0.60	--
						1997-2000	M	V	0.89	0.73	
Douglas-Mankin et al., 2010	SWAT99.2	Field TILL2 (KS)	0.0039	Total P	2	2001-2004	M	C	0.85	0.76	-48
		Field TILL1 (KS)	0.0056				M	V	0.59	0.58	19
		Field NT/DB2 (KS)	0.0076				M	C	0.71	0.75	-4
		Field NT/DB1 (KS)	0.0040				M	V	0.46	0.65	-25
		Field NT/SB2 (KS)	0.0146				M	C	0.22	0.49	2
		Field NT/SB1 (KS)	0.0049				M	V	0.46	-0.43	-135
	SWAT99.2	Field TILL2 (KS)	0.0039	Total P	2	2001-2004	D	C	0.58	0.29	-48
		Field TILL1 (KS)	0.0056				D	V	0.38	0.39	21
		Field NT/DB2 (KS)	0.0076				D	C	0.65	0.55	-4
		Field NT/DB1 (KS)	0.0040				D	V	0.47	0.50	-25
		Field NT/SB2 (KS)	0.0146				D	C	0.33	0.49	2
		Field NT/SB1 (KS)	0.0049				D	V	0.42	0.64	-135
Ghebremichael et al., 2010	SWAT2000	Rock River (VT)	71	Total P	4	2001-2004	M	C	--	0.7	--
						2004-2007	M	V		0.6	
Kim et al., 2010	SWAT2005	Chungju Dam (S. Korea)	6,648	Total P	--	1998-2006	D	C	0.43	<0	--
	SWAT-NSR						D	C	0.57	0.55	
Meng et al., 2010	SWAT2005	Rappahannock River (VA)	7,405	Phosphate	--	1995-2002	D	C	0.51	0.50	0.07
						2003-2008	D	V	0.30	0.19	29.57

performance of daily streamflow, sediment, total N, and total P simulation.

SOIL SOLUTION P

Algorithms used in SWAT continually evolve to incorporate current scientific understanding of fate and transport processes. Vadas and White (2010) validated the routines used in SWAT2000 and SWAT2005 to initialize the size of soil P pools and simulate changes in soil solution P, and they tested these routines against a new equation for estimating P sorption coefficient (or P availability index). After P addition to soil, soil solution P was found to be underestimated by SWAT, potentially resulting in 30% underprediction of dissolved inorganic P in runoff, but not by the proposed routines.

Table 1d. Summary of reported SWAT fecal bacteria calibration and validation statistics.

Reference	Model	Watershed	Drainage Area (km^2)	Indicator	Warm-up Period (years)	Time Period	Time Scale	C or V	R^2	E_f	PBIAS (%)
Baffaut and Sadeghi, 2010	SWAT[e]	James River (MO)	3,600	*E. coli*	--	1 year (*n*=18-33)	--	C[f]	0.24	0.11	--
								V[f]	0.26	0.21	
	SWAT2005	Rock Creek (KS)	75	Fecal coliforms	--	2004-06 (*n*=60)	D	C	0.42	0.20	--
	SWAT2005	Deer Creek (KS)	51	Fecal coliforms	--	2004-06 (*n*=60)	D	V	0.41	0.31	--
	SWAT2005	Auburn (KS)	152	Fecal coliforms	--	2004-06 (*n*=60)	D	V	0.36	-2.2	--
	SWAT[e]	Litter River (GA)	16.7	Fecal coliforms	--	7 years (*n*=53)	--	C	--	0.73	--
	SWAT[e]	#1 (Brittany, France)	68	*E. coli*	--	2009 (*n*=49)	--	C	0.0	-1.0	--

[a] Abbreviations: D = daily, M = monthly, A = annual, C = calibration, V = validation, R^2 = coefficient of determination, E_f = Nash-Sutcliffe efficiency, and PBIAS = percent bias.

[b] Values for all empty cells (--) were not specified in the cited article.

[c] Best calibration statistics (and corresponding validation statistics) for given watershed from among three calibration methods.

[d] HUC corresponding to USGS stream gauging station in the Upper Mississippi River basin.

[e] SWAT version not specified.

[f] Best statistics from range reported.

Table 2. Frequency analysis of SWAT daily hydrologic calibration and validation statistics.[a]

	SWAT 2010 Collection				Gassman et al. (2007)				Combined			
	Calibration		Validation		Calibration		Validation		Calibration		Validation	
	R^2	E_f	R^2	E_f	R^2	E_f	R^2	E_f	R^2	E_f	R^2	E_f
n	6	7	5	6	41	100	39	80	47	107	44	86
0.90-1.00	0	0	0	0	9	5	3	1	19	5	7	1
0.80-0.89	1	1	0	0	6	6	6	6	15	7	14	7
0.70-0.79	1	1	2	2	9	24	7	7	21	23	20	10
0.60-0.69	3	3	1	2	5	16	11	17	17	18	27	22
0.50-0.59	1	2	2	2	3	16	9	11	9	17	25	15
0.40-0.49	0	0	0	0	4	8	2	11	9	7	5	13
0.30-0.39	0	0	0	0	0	5	1	8	0	5	2	9
0.20-0.29	0	0	0	0	3	5	0	4	6	5	0	5
0.10-0.19	0	0	0	0	1	4	0	1	2	4	0	1
0.00-0.09	0	0	0	0	1	2	0	1	2	2	0	1
<0.00	0	0	0	0	0	9	0	13	0	8	0	15

[a] R^2 = coefficient of determination, E_f = Nash-Sutcliffe efficiency, and *n* = number of models analyzed.

MODEL PARAMETERIZATION AND UNCERTAINTY

Uncertainty, defined as the amount by which an estimated value differs from the true value, is a major concern in watershed modeling (Haan, 1989; Haan et al., 1995; Shirmohammadi et al., 2006; Harmel et al., 2010). In watershed modeling, uncertainty can arise from uncertainty in model inputs, such as precipitation (Sexton et al., 2010; Tuppad et al., 2010a) or representation of land use, management, or structures (Lee et al., 2010; Srinivasan et al., 2010); from model representation, such as landscape routing (Arnold et al., 2010; Bosch et al., 2010); or from model parameterization (Veith et al., 2010; Whittaker et al., 2010).

Parameter sensitivity was assessed for SWAT using calibrated models from five USDA-ARS experimental watersheds across a range of climatic, physiographic, and land use conditions (Veith et al., 2010). Parameter sensitivity varied by climatic region, with important implications on model performance. Runoff uncertainty was greater in regions with high evaporation rates and localized storm patterns. Uncertainty in streamflow prediction was less in humid than arid climatic regions. Users were cautioned that optimal values for different parameters may lie in the upper, middle, or lower portion of the SWAT user-defined range, depending upon the parameter.

The SWAT model has at least 25 major hydrologic parameters (table 2 in Srinivasan, 2010), although fewer parameters are often used in model calibration, as seen in tables 3, 4, and 5 in this article. Whittaker et al. (2010) argue that SWAT may be calibrated with a very large number of parameters to achieve a stable solution without overfitting. They applied a genetic algorithm to generate optimum solutions and used common statistical measures, including E_f and PBIAS, to assess model performance. Constraints in the large, complex SWAT model may allow the use of a large number of parameters in calibration without overparameterization and overfitting, although Whittaker et al. (2010) suggest that further work is needed to address the issue of parameter sensitivity.

One study addressed the uncertainty in model simulations resulting from precipitation input uncertainty by combining the results of multiple SWAT simulations using a Bayesian model averaging procedure (Sexton et al., 2010). This procedure, which derives an expected mean prediction and uncertainty interval from the multiple simulations, produced reasonable uncertainty estimation and improved deterministic model performance over any individual simulation.

APPLICATIONS OF NEXRAD PRECIPITATION DATA

Accurate simulation of watershed processes depends on spatially and temporally accurate soil moisture, soil water movement, surface runoff, baseflow, and streamflow simulation, all of which require temporally and spatially accurate

Table 3. Streamflow-related SWAT calibration parameter values or change (Δ) from default values.

Reference	Model	CN2	AWC (mm_{H2O} $\text{mm}_{\text{soil}}^{-1}$)	ALPHA _BF (d^{-1})	ESCO	EPCO	SUR LAG	OV _N	SOL_ K (mm h^{-1})	CH_ N2	CH_ K2 (mm h^{-1})	GW REVAP	GW DELAY (d)	GW QMN (mm)	REVAP MN	Other
Arnold et al., 2010	SWAT Catena	Δ-5.4	Δ0.0016		0.96		1.92									
	SWAT HRUs	Δ-6.0	Δ-0.04		0.90		6.10									
Baskaran et al., 2010	SWAT 2005	Δ-0.34%	Δ2.03%	0.06	0.80	0.44	1.79				6.86			Δ503.76	Δ-95.58	--[a]
		Δ4.73%	Δ-21.03%	0.06	0.01		1.00				8.06		Δ9.84	Δ-868.14	Δ99.81	--[b]
Bosch et al., 2010	SWAT Catena	Crop: 88			0.95			0.09	400/ 44[c]							
		Grass: 48			0.74			0.41	8000/ 1000							
		Pine: 50			0.74			0.50	600/ 22							
		Poplar: 63			0.74			0.50	600/ 22							
Chiang et al., 2010	SWAT 2009	Δ-10%			0.26											--[d]
Ghebremichael et al., 2010	SWAT 2000	Δ-10%	Δ-14.9%	0.45	0.63		0.30				53.17	Δ-0.025		750		
Kim et al., 2010	SWAT2005 SWAT-NSR			0.5	0.80					0.03			100			--[e]
Narasimhan et al., 2010	SWAT 2000	Δ±3		0.0420-0.2006	0.85					0.075	0.1 4.0	0.10	135	1.00	1.60	
Srinivasan et al., 2010	SWAT 2005[f]	25-92	0.01-0.4	0.048	0.85	1.0	4.0	0.14	0.05-400	0.014	1.0	0.02	31.0	1.0	1.0	

[a] SOL_Z (mm) = Δ-3.18%.
[b] SOL_Z (mm) = Δ24.95%.
[c] Layer 1/Layer 2.
[d] MSK_CO2 = 3000.
[e] SLSOIL (m) = 20, MSK_CO2 = 1.1.
[f] Default values.

Table 4. Sediment-related SWAT calibration parameter values or change (Δ) from default values.

Reference	Model	USLE-C_{min}	USLE-K	SLOPE (m m^{-1})	ADJ_ PKR	AMP	PRF	RSDIN (kg ha^{-1})	SPCON	SPEXP	CH_ COV	CH_ EROD
Chiang et al., 2010	SWAT 2009		Δ-50%	Δ-50%	2							
Douglas-Mankin et al., 2010	SWAT 99.2	--[a]										
Ghebremichael et al., 2010	SWAT 2000				n/s[b]		n/s[b]					
Kim et al., 2010	SWAT 2005					0.5	0.1		0.00001	1.05	0.3	0.038
Narasimhan et al., 2010	SWAT 2000	0.007[c]						1000	0.01	1.4	0.1-1.0	0.3-0.8

[a] Grain sorghum/soybean: 0.31/0.23 (disc till), 0.13/0.10 (no-till, deep-banded fertilizer), and 0.39/0.30 (no-till, surface-broadcast fertilizer).
[b] Parameters used for calibration, but value not specified.
[c] Pastureland, fair condition.

precipitation data. In this collection, radar-based enhancements to the spatial representation of precipitation data within SWAT were evaluated by two studies (Sexton et al., 2010; Tuppad et al., 2010a).

The Next Generation Weather Radar (NEXRAD) system is maintained by the National Weather Service across the U.S. and at selected overseas locations. NEXRAD provides information on many types of weather, including thunderstorms, hail, tornadoes, hurricanes, flash floods, snow, and freezing precipitation. Reflectivity data from NEXRAD are converted to precipitation depths by the National Weather Service and made available in the form of several different classification products, including Stage III (Tuppad et al., 2010a) and Multisensor Precipitation Estimator (MPE) (Sexton et al., 2010). Most river forecast centers in the U.S. used Stage III from 1996-2001 and MPE from 2002-2006 to estimate spatial precipitation data.

SWAT assigns precipitation to each subwatershed in a basin according to the nearest raingauge to the subwatershed centroid. At about 4 km resolution, NEXRAD data allow

Table 5. Nutrient-related SWAT calibration parameter values.[a]

Reference	Model	CMN	UBN	UBP	NPERCO	PPERCO	RSDCO	BIOMIX	PHOSKD	PSP	SOL_NO3	SOL_ORGN	GWNO3	SOL_SOLP	SOL_ORGP	GWMINP
Chiang et al., 2010	SWAT 2009	0.004			1	17.5			100							
Douglas-Mankin et al., 2010	SWAT 99.2			50	1.0	10	0.05	0.2	175							
Kim et al., 2010	SWAT 2005				0.3						100	5000	0.45	0.1	200	0.01
Narasimhan et al., 2010	SWAT 2000	0.003	20	100	0.2	10			200	0.4						

[a] SOL_NO3 and SOL_ORGN are in mg N kg^{-1}, GWNO3 is in mg N L^{-1}, SOL_SOLP and SOL_ORGP are in mg P kg^{-1}, and GWMINP is in mg P L^{-1}.

more refined spatial precipitation data than most raingauge networks. Tuppad et al. (2010a) found that the increased resolution of Stage III precipitation data resulted in similar or improved SWAT2000 streamflow estimation compared to raingauge data, but that bias adjustment with upper and lower threshold limits was required. Sexton et al. (2010) found that in most cases SWAT2005 streamflow estimation was improved using MPE data compared to raingauge data and that bias-correcting MPE data with local raingauge data improved hydrologic simulation.

CLIMATE AND LAND USE CHANGE

Global climate variability and change are likely to alter trends and timing of precipitation and other weather drivers and impact terrestrial and aquatic ecosystem responses. Similarly, land use changes associated with major shifts in crop production can have major impacts on watershed hydrologic and water quality response, such as the recent shift to corn production associated with ethanol-based bioenergy development (Simpson et al., 2008). Several studies in this collection address these issues.

Climate change impacts were assessed for a watershed in Canada (Rahman et al., 2010). Rahman et al. (2010) used SWAT2005 to study low-flow response to the A2 (high economic growth, low technology development, high population growth) climate-change scenario. Using a weather generator to apply global climate model projections to stochastic distributions of historical observed weather data, they developed daily future weather data. Projections for 2041 to 2070 showed increased winter and spring low-flow rates and decreased low-flow rates in fall.

Bioenergy impacts of shifting cropland to switchgrass were assessed for the Upper Mississippi River basin with SWAT2005 (Srinivasan et al., 2010). The 41-year average switchgrass production across 131 eight-digit HUC level subwatersheds ranged from 8.6 to 33.9 Mg ha^{-1}, showing potential spatial distribution of lands, including marginal lands, with the greatest potential for renewable energy production. This assessment of both spatial and temporal variability of corn and soybean crop yields was the first of its kind in the SWAT model application literature. A second regional-scale study found that SWAT2005-simulated switchgrass yields adequately characterized the geographic distribution of potential bioenergy yields in the midwestern and eastern U.S. (Baskaran et al., 2010). Baskaran et al. (2010) also calibrated SWAT2005 for flow in two subbasins and functionally validated the results for 86 other subbasins in the Arkansas-White-Red River basin, providing information that they hope will allow them to characterize the flow, and ultimately water quality, response of land use shifts to switchgrass production in the U.S.

MODELING POLLUTANTS AND PRACTICES

SWAT is often used to predict hydrologic and water quality responses to land use changes, including implementation of best management practices. Although models can be calibrated for "current conditions," accurate simulation requires careful selection of model parameters used to define the future conditions. Douglas-Mankin et al. (2010) used field-scale data to calibrate and validate SWAT99.2 parameters used to simulate tillage (no-till or conventional till) and nutrient application (surface broadcast or deep banded) practices. In a previous study, Maski et al. (2008) found that unique changes to curve number (CN), saturated conductivity, available water capacity, and USLE minimum crop factor ($C_{\min}$) for each combination of practices provided satisfactory model performance (daily and monthly $E_f > 0.5$). However, for nutrient simulation, there was no differentiation among practices for the best-fit set of revised model parameters (NPERCO, RSDCO, and BIOMIX for total N; PPERCO, PHOSKD, and UBP for total P; tables 4 and 5), which indicates that differences in management practices might be adequately captured by calibration of runoff and erosion parameters.

Chiang et al. (2010) assessed individual impacts of land use change and pasture management on sediment, N, and P losses with SWAT2009. With 12 years of detailed spatial land use data, they differentiated the impacts of land use change from conservation practice implementation. They used these results to determine the relative contribution of sediment and nutrients from pastureland, including the impacts of land application and intensive grazing, and urban areas, and demonstrated the importance of modeling in pollutant source identification. Tuppad et al. (2010b) simulated field-scale and watershed-scale reductions in runoff, sediment, total N, and total P from several structural and non-structural management practices using APEX, a field-scale model that has similar functions as SWAT and has recently been linked to SWAT (Gassman et al., 2010).

Watershed models are valuable for assessing contamination from various pollutant sources, including fecal bacteria (Benham et al., 2006). Recent research using the bacteria module of SWAT was reviewed by Baffaut and Sadeghi (2010). They summarize the bacteria module equations and present the results of four model applications across the U.S.

and France, and they conclude that SWAT reasonably simulated the range and frequencies of bacterial concentrations at the watershed scale, although this conclusion was based on a limited number of available studies.

TARGETING AND WATERSHED MANAGEMENT

Watershed models can inform watershed management and planning by assisting with prioritization of practices, spatial targeting of critical source areas for potential action, and temporal assessment of pollutant delivery. Articles in this collection address many issues related to targeting and watershed management.

Ghebremichael et al. (2010) assessed critical source areas for P contribution to Lake Champlain in a dairy agricultural watershed in Vermont using SWAT2000. They found that 80% of total P loss originated from 24% of the watershed area. These high runoff and sediment loss areas were dominated by lower infiltrations rates (hydrologic soil groups C and D) and corn production.

Several studies demonstrated modeling approaches to assist watershed planning to achieve water quality goals. Narasimhan et al. (2010) linked SWAT2000 with a lake eutrophication model to develop a watershed-scale total P reduction target of 35% needed to achieve algal control goals in Cedar Creek reservoir, Texas. Subsequently, Lee et al. (2010) used SWAT2000 to target management practice implementation to achieve the 35% total P load reduction to Cedar Creek reservoir. They simulated successive implementation of eight management practices on the highest-ranked subwatersheds (by total P load), and the total implementation area for each practice was selected according to a pre-determined marginal adoption rate.

Meng et al. (2010) demonstrated the use of SWAT2005 as the land module in the Chesapeake Bay Forecast System to simulate hydrologic and water quality responses to weather forecast ensembles. Finally, SWAT model performance for the large Upper Mississippi River basin using uncalibrated default parameters was demonstrated for hydrology and crop yields by Srinivasan et al. (2010) with satisfactory results.

SUMMARY AND CONCLUSIONS

The SWAT model continues to evolve as an internationally applied, multidisciplinary simulation tool. Since the last major summary of the literature (Gassman et al., 2007), SWAT has incorporated improved model routines and been applied to address numerous watershed issues, as demonstrated by the articles in this collection.

This collection presents recent SWAT developments in landscape representation, stream routing, and soil P dynamics. Numerous critical applications of SWAT were conducted across a variety of landscape scales, climatic and physiographic regions, and pollutant sources, and model performance was found to be satisfactory or better in all cases. Representation of structural and non-structural practices within SWAT is evolving, but model algorithms currently are not sufficient to simulate complex nutrient cycling and transport processes. Thus, the improved routines for soil P dynamics and stream routing presented in this collection represent important model enhancements.

SWAT is increasingly being used to assist watershed planning with increased sophistication for targeting critical pollutant source areas and practices. Modelers have demonstrated the importance of temporally and spatially accurate model input data, such as precipitation and land use, to make accurate targeting recommendations. However, the simplistic approaches presented in this collection to assess the watershed-scale impacts of major shifts in climate and bioenergy related land use will likely require further enhancement. Future watershed planning would benefit from further improved simulation of climate change and variability and better representation of market-induced shifts in land use, such as those involved in the current movement toward bioenergy development. In addition, no studies were presented in this collection that connected SWAT hydrologic and water quality results to their broader impacts on ecosystem services. These observations point to the need for increased integration of SWAT and other watershed models with climatic, ecologic, and socio-economic models to better represent the impacts of landscape management on society.

Results of this collection were compiled with a previous synthesis of results to generate a comprehensive assessment of SWAT. Model parameters used to calibrate the model for streamflow, sediment, N, and P in numerous studies were also summarized. It is not evident if the overall improvement in model performance of the reported studies relative to those in the Gassman et al. (2007) synthesis indicates a general improvement in model algorithms, input data quality, or modeler procedures and expertise. The variety of parameters used to calibrate each model application might reflect the necessity to adjust parameters differently for different physiographic and climatic conditions, but it also might reflect modeler preferences. Improved consistency is needed in reporting the process of selecting model parameters during calibration, and in assessing the resulting model performance. This would allow better interpretation of model application results and more consistent comparison among studies.

Transactions of the ASABE and *Applied Engineering in Agriculture* have long been important sources of literature on watershed modeling innovations and advancements; this collection continues that tradition. It is hoped that this collection provides a body of new research on the SWAT model that enhances the efforts of both model developers and model users and sets the stage for future model developments as well as more insightful model applications.

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