THE SOIL AND WATER ASSESSMENT TOOL: HISTORICAL DEVELOPMENT, APPLICATIONS, AND FUTURE RESEARCH DIRECTIONS

SWAT

Invited Review Series

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ABSTRACT. *The Soil and Water Assessment Tool (SWAT) model is a continuation of nearly 30 years of modeling efforts conducted by the USDA Agricultural Research Service (ARS). SWAT has gained international acceptance as a robust interdisciplinary watershed modeling tool as evidenced by international SWAT conferences, hundreds of SWAT-related papers presented at numerous other scientific meetings, and dozens of articles published in peer-reviewed journals. The model has also been adopted as part of the U.S. Environmental Protection Agency (USEPA) Better Assessment Science Integrating Point and Nonpoint Sources (BASINS) software package and is being used by many U.S. federal and state agencies, including the USDA within the Conservation Effects Assessment Project (CEAP). At present, over 250 peer-reviewed published articles have been identified that report SWAT applications, reviews of SWAT components, or other research that includes SWAT. Many of these peer-reviewed articles are summarized here according to relevant application categories such as streamflow calibration and related hydrologic analyses, climate change impacts on hydrology, pollutant load assessments, comparisons with other models, and sensitivity analyses and calibration techniques. Strengths and weaknesses of the model are presented, and recommended research needs for SWAT are also provided.*

Keywords. *Developmental history, Flow analysis, Modeling, SWAT, Water quality.*

The Soil and Water Assessment Tool (SWAT) model (Arnold et al., 1998; Arnold and Fohrer, 2005) has proven to be an effective tool for assessing water resource and nonpoint-source pollution problems for a wide range of scales and environmental conditions across the globe. In the U.S., SWAT is increasingly being used to support Total Maximum Daily Load (TMDL) analyses (Borah et al., 2006), research the effectiveness of conservation practices within the USDA Conservation Effects Assessment Program (CEAP, 2007) initiative (Mausbach and Dedrick, 2004), perform "macro-scale assessments" for large regions such as the upper Mississippi River basin and the entire U.S. (e.g., Arnold et al., 1999a; Jha et al., 2006), and a wide range of other water use and water quality applications. Similar SWAT application trends have also emerged in Europe and other regions, as shown by the variety of studies presented in four previous European international SWAT conferences, which are reported for the first conference in a special issue of *Hydrological Processes* (volume 19, issue 3) and proceedings for the second (TWRI, 2003), third (EAWAG, 2005), and fourth (UNESCO-IHE, 2007) conferences.

Reviews of SWAT applications and/or components have been previously reported, sometimes in conjunction with comparisons with other models (e.g., Arnold and Fohrer, 2005; Borah and Bera, 2003, 2004; Shepherd et al., 1999). However, these previous reviews do not provide a comprehensive overview of the complete body of SWAT applications that have been reported in the peer-reviewed literature. There is a need to fill this gap by providing a review of the full range of studies that have been conducted with SWAT and to highlight emerging application trends. Thus, the specific objectives of this study are to: (1) provide an overview of SWAT development history, including the development of GIS interface tools and examples of modified SWAT models; (2) summarize research findings or methods for many of the more than 250 peer-reviewed articles that have been identified in the literature, as a function of different application categories; and (3) describe key strengths and weaknesses of the model and list a summary of future research needs.

SWAT DEVELOPMENTAL HISTORY AND OVERVIEW

The development of SWAT is a continuation of USDA Agricultural Research Service (ARS) modeling experience that spans a period of roughly 30 years. Early origins of SWAT can be traced to previously developed USDA-ARS models (fig. 1) including the Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) model (Knisel, 1980), the Groundwater Loading Effects on

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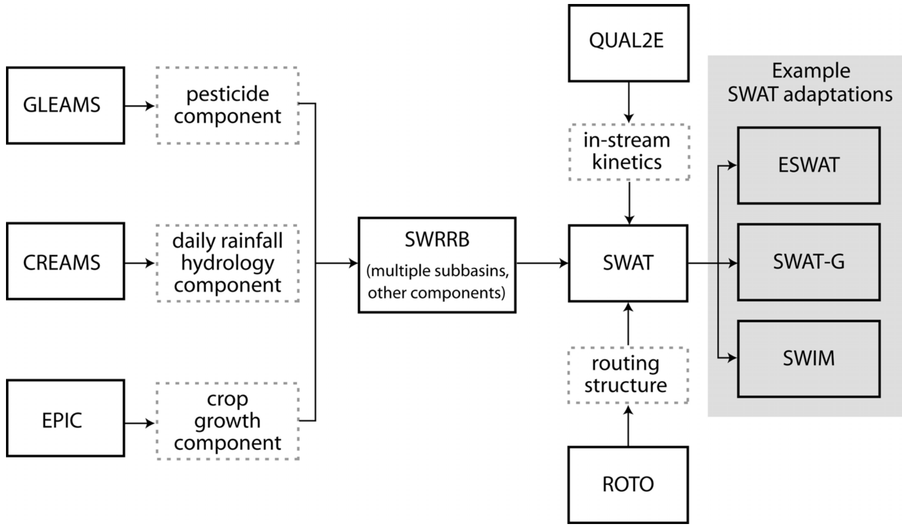

Figure 1. Schematic of SWAT developmental history, including selected SWAT adaptations.

Agricultural Management Systems (GLEAMS) model (Leonard et al., 1987), and the Environmental Impact Policy Climate (EPIC) model (Izaurralde et al., 2006), which was originally called the Erosion Productivity Impact Calculator (Williams, 1990). The current SWAT model is a direct descendant of the Simulator for Water Resources in Rural Basins (SWRRB) model (Arnold and Williams, 1987), which was designed to simulate management impacts on water and sediment movement for ungauged rural basins across the U.S.

Development of SWRRB began in the early 1980s with modification of the daily rainfall hydrology model from CREAMS. A major enhancement was the expansion of surface runoff and other computations for up to ten subbasins, as opposed to a single field, to predict basin water yield. Other enhancements included an improved peak runoff rate method, calculation of transmission losses, and the addition of several new components: groundwater return flow (Arnold and Allen, 1993), reservoir storage, the EPIC crop growth submodel, a weather generator, and sediment transport. Further modifications of SWRRB in the late 1980s included the incorporation of the GLEAMS pesticide fate component, optional USDA-SCS technology for estimating peak runoff rates, and newly developed sediment yield equations. These modifications extended the model's capability to deal with a wide variety of watershed water quality management problems.

Arnold et al. (1995b) developed the Routing Outputs to Outlet (ROTO) model in the early 1990s in order to support an assessment of the downstream impact of water management within Indian reservation lands in Arizona and New Mexico that covered several thousand square kilometers, as requested by the U.S. Bureau of Indian Affairs. The analysis was performed by linking output from multiple SWRRB runs and then routing the flows through channels and reservoirs in ROTO via a reach routing approach. This methodology overcame the SWRRB limitation of allowing only ten subbasins; however, the input and output of multiple SWRRB files was cumbersome and required considerable computer storage. To overcome the awkwardness of this arrangement, SWRRB and ROTO were merged into the single SWAT model (fig. 1). SWAT retained all the features that made SWRRB such a valuable simulation model, while allowing simulations of very extensive areas.

SWAT has undergone continued review and expansion of capabilities since it was created in the early 1990s. Key enhancements for previous versions of the model (SWAT94.2, 96.2, 98.1, 99.2, and 2000) are described by Arnold and Fohrer (2005) and Neitsch et al. (2005a), including the incorporation of in-stream kinetic routines from the QUAL2E model (Brown and Barnwell, 1987), as shown in figure 1. Documentation for some previous versions of the model is available at the SWAT web site (SWAT, 2007d). Detailed theoretical documentation and a user's manual for the latest version of the model (SWAT2005) are given by Neitsch et al. (2005a, 2005b). The current version of the model is briefly described here to provide an overview of the model structure and execution approach.

SWAT Overview

SWAT is a basin-scale, continuous-time model that operates on a daily time step and is designed to predict the impact of management on water, sediment, and agricultural chemical yields in ungauged watersheds. The model is physically based, computationally efficient, and capable of continuous simulation over long time periods. Major model components include weather, hydrology, soil temperature and properties, plant growth, nutrients, pesticides, bacteria and pathogens, and land management. In SWAT, a watershed is divided into multiple subwatersheds, which are then further subdivided into hydrologic response units (HRUs) that consist of homogeneous land use, management, and soil characteristics. The HRUs represent percentages of the subwatershed area and are not identified spatially within a SWAT simulation. Alternatively, a watershed can be subdivided into only subwatersheds that are characterized by dominant land use, soil type, and management.

Climatic Inputs and HRU Hydrologic Balance

Climatic inputs used in SWAT include daily precipitation, maximum and minimum temperature, solar radiation data, relative humidity, and wind speed data, which can be input from measured records and/or generated. Relative humidity is required if the Penman-Monteith (Monteith, 1965) or

Priestly-Taylor (Priestly and Taylor, 1972) evapotranspiration (ET) routines are used; wind speed is only necessary if the Penman-Monteith method is used. Measured or generated sub-daily precipitation inputs are required if the Green-Ampt infiltration method (Green and Ampt, 1911) is selected. The average air temperature is used to determine if precipitation should be simulated as snowfall. The maximum and minimum temperature inputs are used in the calculation of daily soil and water temperatures. Generated weather inputs are calculated from tables consisting of 13 monthly climatic variables, which are derived from long-term measured weather records. Customized climatic input data options include: (1) simulation of up to ten elevation bands to account for orographic precipitation and/or for snowmelt calculations, (2) adjustments to climate inputs to simulate climate change, and (3) forecasting of future weather patterns, which is a new feature in SWAT2005.

The overall hydrologic balance is simulated for each HRU, including canopy interception of precipitation, partitioning of precipitation, snowmelt water, and irrigation water between surface runoff and infiltration, redistribution of water within the soil profile, evapotranspiration, lateral subsurface flow from the soil profile, and return flow from shallow aquifers. Estimation of areal snow coverage, snowpack temperature, and snowmelt water is based on the approach described by Fontaine et al. (2002). Three options exist in SWAT for estimating surface runoff from HRUs, which are combinations of daily or sub-hourly rainfall and the USDA Natural Resources Conservation Service (NRCS) curve number (CN) method (USDA-NRCS, 2004) or the Green-Ampt method. Canopy interception is implicit in the CN method, while explicit canopy interception is simulated for the Green-Ampt method.

A storage routing technique is used to calculate redistribution of water between layers in the soil profile. Bypass flow can be simulated, as described by Arnold et al. (2005), for soils characterized by cracking, such as Vertisols. SWAT2005 also provides a new option to simulate perched water tables in HRUs that have seasonal high water tables. Three methods for estimating potential ET are provided: Penman-Monteith, Priestly-Taylor, and Hargreaves (Hargreaves et al., 1985). ET values estimated external to SWAT can also be input for a simulation run. The Penman-Monteith option must be used for climate change scenarios that account for changing atmospheric CO_2 levels. Recharge below the soil profile is partitioned between shallow and deep aquifers. Return flow to the stream system and evapotranspiration from deep-rooted plants (termed "revap") can occur from the shallow aquifer. Water that recharges the deep aquifer is assumed lost from the system.

Cropping, Management Inputs, and HRU-Level Pollutant Losses

Crop yields and/or biomass output can be estimated for a wide range of crop rotations, grassland/pasture systems, and trees with the crop growth submodel. New routines in SWAT2005 allow for simulation of forest growth from seedling to mature stand. Planting, harvesting, tillage passes, nutrient applications, and pesticide applications can be simulated for each cropping system with specific dates or with a heat unit scheduling approach. Residue and biological mixing are simulated in response to each tillage operation. Nitrogen and phosphorus applications can be simulated in the form of inorganic fertilizer and/or manure inputs. An alternative automatic fertilizer routine can be used to simulate fertilizer applications, as a function of nitrogen stress. Biomass removal and manure deposition can be simulated for grazing operations. SWAT2005 also features a new continuous manure application option to reflect conditions representative of confined animal feeding operations, which automatically simulates a specific frequency and quantity of manure to be applied to a given HRU. The type, rate, timing, application efficiency, and percentage application to foliage versus soil can be accounted for simulations of pesticide applications.

Selected conservation and water management practices can also be simulated in SWAT. Conservation practices that can be accounted for include terraces, strip cropping, contouring, grassed waterways, filter strips, and conservation tillage. Simulation of irrigation water on cropland can be simulated on the basis of five alternative sources: stream reach, reservoir, shallow aquifer, deep aquifer, or a water body source external to the watershed. The irrigation applications can be simulated for specific dates or with an auto-irrigation routine, which triggers irrigation events according to a water stress threshold. Subsurface tile drainage is simulated in SWAT2005 with improved routines that are based on the work performed by Du et al. (2005) and Green et al. (2006); the simulated tile drains can also be linked to new routines that simulate the effects of depressional areas (potholes). Water transfer can also be simulated between different water bodies, as well as "consumptive water use" in which removal of water from a watershed system is assumed.

HRU-level and in-stream pollutant losses can be estimated with SWAT for sediment, nitrogen, phosphorus, pesticides, and bacteria. Sediment yield is calculated with the Modified Universal Soil Loss Equation (MUSLE) developed by Williams and Berndt (1977); USLE estimates are output for comparative purposes only. The transformation and movement of nitrogen and phosphorus within an HRU are simulated in SWAT as a function of nutrient cycles consisting of several inorganic and organic pools. Losses of both N and P from the soil system in SWAT occur by crop uptake and in surface runoff in both the solution phase and on eroded sediment. Simulated losses of N can also occur in percolation below the root zone, in lateral subsurface flow including tile drains, and by volatilization to the atmosphere. Accounting of pesticide fate and transport includes degradation and losses by volatilization, leaching, on eroded sediment, and in the solution phase of surface runoff and later subsurface flow. Bacteria surface runoff losses are simulated in both the solution and eroded phases with improved routines in SWAT2005.

Flow and Pollutant Loss Routing, and Auto-Calibration and Uncertainty Analysis

Flows are summed from all HRUs to the subwatershed level, and then routed through the stream system using either the variable-rate storage method (Williams, 1969) or the Muskingum method (Neitsch et al., 2005a), which are both variations of the kinematic wave approach. Sediment, nutrient, pesticide, and bacteria loadings or concentrations from each HRU are also summed at the subwatershed level, and the resulting losses are routed through channels, ponds, wetlands, depressional areas, and/or reservoirs to the watershed outlet. Contributions from point sources and urban areas are also accounted for in the total flows and pollutant losses exported from each subwatershed. Sediment transport is simulated as a function of peak channel velocity in SWAT2005, which is a simplified approach relative to the stream power methodology used in previous SWAT versions. Simulation of channel erosion is accounted for with a channel erodibility factor. In-stream transformations and kinetics of algae growth, nitrogen and phosphorus cycling, carbonaceous biological oxygen demand, and dissolved oxygen are performed on the basis of routines developed for the QUAL2E model. Degradation, volatilization, and other in-stream processes are simulated for pesticides, as well as decay of bacteria. Routing of heavy metals can be simulated; however, no transformation or decay processes are simulated for these pollutants.

A final feature in SWAT2005 is a new automated sensitivity, calibration, and uncertainty analysis component that is based on approaches described by van Griensven and Meixner (2006) and van Griensven et al. (2006b). Further discussion of these tools is provided in the Sensitivity, Calibration, and Uncertainty Analyses Section.

SWAT Adaptations

A key trend that is interwoven with the ongoing development of SWAT is the emergence of modified SWAT models that have been adapted to provide improved simulation of specific processes, which in some cases have been focused on specific regions. Notable examples (fig. 1) include SWAT-G, Extended SWAT (ESWAT), and the Soil and Water Integrated Model (SWIM). The initial SWAT-G model was developed by modifying the SWAT99.2 percolation, hydraulic conductivity, and interflow functions to provide improved flow predictions for typical conditions in low mountain ranges in Germany (Lenhart et al., 2002). Further SWAT-G enhancements include an improved method of estimating erosion loss (Lenhart et al., 2005) and a more detailed accounting of CO_2 effects on leaf area index and stomatal conductance (Eckhardt and Ulbrich, 2003). The ESWAT model (van Griensven and Bauwens, 2003, 2005) features several modifications relative to the original SWAT model including: (1) sub-hourly precipitation inputs and infiltration, runoff, and erosion loss estimates based on a user-defined fraction of an hour; (2) a river routing module that is updated on an hourly time step and is interfaced with a water quality component that features in-stream kinetics based partially on functions used in QUAL2E as well as additional enhancements; and (3) multi-objective (multi-site and/or multi-variable) calibration and autocalibration modules (similar components are now incorporated in SWAT2005). The SWIM model is based primarily on hydrologic components from SWAT and nutrient cycling components from the MATSALU model (Krysanova et al., 1998, 2005) and is designed to simulate "mesoscale" (100 to 100,000 km^2) watersheds. Recent improvements to SWIM include incorporation of a groundwater dynamics submodel (Hatterman et al., 2004), enhanced capability to simulate forest systems (Wattenbach et al., 2005), and development of routines to more realistically simulate wetlands and riparian zones (Hatterman et al., 2006).

Geographic Information System Interfaces and Other Tools

A second trend that has paralleled the historical development of SWAT is the creation of various Geographic Information System (GIS) and other interface tools to support the input of topographic, land use, soil, and other digital data into SWAT. The first GIS interface program developed for SWAT was SWAT/GRASS, which was built within the GRASS raster-based GIS (Srinivasan and Arnold, 1994). Haverkamp et al. (2005) have adopted SWAT/GRASS within the Input-OutputSWAT (IOSWAT) software package, which incorporates the Topographic Parameterization Tool (TOPAZ) and other tools to generate inputs and provide output mapping support for both SWAT and SWAT-G.

The ArcView-SWAT (AVSWAT) interface tool (Di Luzio et al., 2004a, 2004b) is designed to generate model inputs from ArcView 3.x GIS data layers and execute SWAT2000 within the same framework. AVSWAT was incorporated within the U.S. Environmental Protection Agency (USEPA) Better Assessment Science Integrating point and Nonpoint Sources (BASINS) software package versions 3.0 (USEPA, 2006a), which provides GIS utilities that support automatic data input for SWAT2000 using ArcView (Di Luzio et al., 2002). The most recent version of the interface is denoted AVSWAT-X, which provides additional input generation functionality, including soil data input from both the USDA-NRCS State Soils Geographic (STATSGO) and Soil Survey Geographic (SSURGO) databases (USDA-NRCS, 2007a, 2007b) for applications of SWAT2005 (Di Luzio et al., 2005; SWAT, 2007b). Automatic sensitivity, calibration, and uncertainty analysis can also be initiated with AVSWAT-X for SWAT2005. The Automated Geospatial Watershed Assessment (AGWA) interface tool (Miller et al., 2007) is an alternative ArcView-based interface tool that supports data input generation for both SWAT2000 and the KINEROS2 model, including options for soil inputs from the SSURGO, STATSGO, or United Nations Food and Agriculture Organization (FAO) global soil maps. Both AGWA and AVSWAT have been incorporated as interface approaches for generating SWAT2000 inputs within BASINS version 3.1 (Wells, 2006).

A SWAT interface compatible with ArcGIS version 9.1 (ArcSWAT) has recently been developed that uses a geodatabase approach and a programming structure consistent with Component Object Model (COM) protocol (Olivera et al., 2006; SWAT, 2007a). An ArcGIS 9.x version of AGWA (AGWA2) is also being developed and is expected to be released near mid-2007 (USDA-ARS, 2007).

A variety of other tools have been developed to support executions of SWAT simulations, including: (1) the interactive SWAT (i_SWAT) software (CARD, 2007), which supports SWAT simulations using a Windows interface with an Access database; (2) the Conservation Reserve Program (CRP) Decision Support System (CRP-DSS) developed by Rao et al. (2006); (3) the AUTORUN system used by Kannan et al. (2007b), which facilitates repeated SWAT simulations with variations in selected parameters; and (4) a generic interface (iSWAT) program (Abbaspour et al., 2007), which automates parameter selection and aggregation for iterative SWAT calibration simulations.

SWAT Applications

Applications of SWAT have expanded worldwide over the past decade. Many of the applications have been driven by the needs of various government agencies, particularly in the U.S. and the European Union, that require direct assessments of anthropogenic, climate change, and other influences on a

Figure 2. Distribution of the 2,149 8-digit watersheds within the 18 Major Water Resource Regions (MWRRs) that comprise the conterminous U.S.

wide range of water resources or exploratory assessments of model capabilities for potential future applications.

One of the first major applications performed with SWAT was within the Hydrologic Unit Model of the U.S. (HUMUS) modeling system (Arnold et al., 1999a), which was implemented to support USDA analyses of the U.S. Resources Conservation Act Assessment of 1997 for the conterminous U.S. The system was used to simulate the hydrologic and/or pollutant loss impacts of agricultural and municipal water use, tillage and cropping system trends, and other scenarios within each of the 2,149 U.S. Geological Survey (USGS) 8-digit Hydrologic Cataloging Unit (HCU) watersheds (Seaber et al., 1987), referred to hereafter as "8-digit watersheds". Figure 2 shows the distribution of the 8-digit watersheds within the 18 Major Water Resource Regions (MWRRs) that comprise the conterminous U.S.

SWAT is also being used to support the USDA Conservation Effects Assessment Project, which is designed to quantify the environmental benefits of conservation practices at both the national and watershed scales (Mausbach and Dedrick, 2004). SWAT is being applied at the national level within a modified HUMUS framework to assess the benefits of different conservation practices at that scale. The model is also being used to evaluate conservation practices for watersheds of varying sizes that are representative of different regional conditions and mixes of conservation practices.

SWAT is increasingly being used to perform TMDL analyses, which must be performed for impaired waters by the different states as mandated by the 1972 U.S. Clean Water Act (USEPA, 2006b). Roughly 37% of the nearly 39,000 currently listed impaired waterways still require TMDLs (USEPA, 2007); SWAT, BASINS, and a variety of other modeling tools will be used to help determine the pollutant sources and potential solutions for many of these forthcoming TMDLs. Extensive discussion of applying SWAT and other models for TMDLs is presented in Borah et al. (2006), Benham et al. (2006), and Shirmohammadi et al. (2006).

SWAT has also been used extensively in Europe, including projects supported by various European Commission (EC) agencies. Several models including SWAT were used to quantify the impacts of climate change for five different watersheds in Europe within the Climate Hydrochemistry and Economics of Surface-water Systems (CHESS) project, which was sponsored by the EC Environment and Climate Research Programme (CHESS, 2001). A suite of nine models including SWAT were tested in 17 different European watersheds as part of the EUROHARP project, which was sponsored by the EC Energy, Environment and Sustainable Development (EESD) Programme (EUROHARP, 2006). The goal of the research was to assess the ability of the models to estimate nonpoint-source nitrogen and phosphorus losses to both freshwater streams and coastal waters. The EESD-sponsored TempQsim project focused on testing the ability of SWAT and five other models to simulate intermittent stream conditions that exist in southern Europe (TempQsim, 2006). Volk et al. (2007) and van Griensven et al. (2006a) further describe SWAT application approaches within in the context of the European Union (EU) Water Framework Directive.

The following application discussion focuses on the wide range of specific SWAT applications that have been reported in the literature. Some descriptions of modified SWAT model applications are interspersed within the descriptions of studies that used the standard SWAT model.

Table 1. Overview of major application categories of SWAT studies reported in the literature.[a]

Primary Application Category	Hydrologic Only	Hydrologic and Pollutant Loss	Pollutant Loss Only
Calibration and/or sensitivity analysis	15	20	2
Climate change impacts	22	8	--
GIS interface descriptions	3	3	2
Hydrologic assessments	42	--	--
Variation in configuration or data input effects	21	15	--
Comparisons with other models or techniques	5	7	1
Interfaces with other models	13	15	6
Pollutant assessments	--	57	6

[a] Includes studies describing applications of ESWAT, SWAT-G, SWIM, and other modified SWAT models.

Specific SWAT Applications

SWAT applications reported in the literature can be categorized in several ways. For this study, most of the peer-reviewed articles could be grouped into the nine subcategories listed in table 1, and then further broadly defined as hydrologic only, hydrologic and pollutant loss, or pollutant loss only. Reviews are not provided for all of the articles included in the table 1 summary; a complete list of the SWAT peer-reviewed articles is provided at the SWAT web site (SWAT, 2007c), which is updated on an ongoing basis.

Hydrologic Assessments

Simulation of the hydrologic balance is foundational for all SWAT watershed applications and is usually described in some form regardless of the focus of the analysis. The majority of SWAT applications also report some type of graphical and/or statistical hydrologic calibration, especially for streamflow, and many of the studies also report validation results. A wide range of statistics has been used to evaluate SWAT hydrologic predictions. By far the most widely used statistics reported for hydrologic calibration and validation are the regression correlation coefficient (R^2) and the Nash-Sutcliffe model efficiency (NSE) coefficient (Nash and Sutcliffe, 1970). The R^2 value measures how well the simulated versus observed regression line approaches an ideal match and ranges from 0 to 1, with a value of 0 indicating no correlation and a value of 1 representing that the predicted dispersion equals the measured dispersion (Krause et al., 2005). The regression slope and intercept also equal 1 and 0, respectively, for a perfect fit; the slope and intercept are often not reported. The NSE ranges from $-\infty$ to 1 and measures how well the simulated versus observed data match the 1:1 line (regression line with slope equal to 1). An NSE value of 1 again reflects a perfect fit between the simulated and measured data. A value of 0 or less than 0 indicates that the mean of the observed data is a better predictor than the model output. See Krause et al. (2005) for further discussion regarding the R^2, NSE, and other efficiency criteria measures.

An extensive list of R^2 and NSE statistics is presented in table 2 for 115 SWAT hydrologic calibration and/or validation results reported in the literature. These statistics provides valuable insight regarding the hydrologic performance of the model across a wide spectrum of conditions. To date, no absolute criteria for judging model performance have been firmly established in the literature. However, Moriasi et al. (2007) proposed that NSE values should exceed 0.5 in order for model results to be judged as satisfactory for hydrologic and pollutant loss evaluations performed on a monthly time step (and that appropriate relaxing and tightening of the standard be performed for daily and annual time step evaluations, respectively). Assuming this criterion for both the NSE and r^2 values at all time steps, the majority of statistics listed in table 2 would be judged as adequately replicating observed streamflows and other hydrologic indicators. However, it is clear that poor results resulted for parts or all of some studies. The poorest results generally occurred for daily predictions, although this was not universal (e.g., Grizzetti et al., 2005). Some of the weaker results can be attributed in part to inadequate representation of rainfall inputs, due to either a lack of adequate rain gauges in the simulated watershed or subwatershed configurations that were too coarse to capture the spatial detail of rainfall inputs (e.g., Cao et al., 2006; Conan et al., 2003b; Bouraoui et al., 2002; Bouraoui et al., 2005). Other factors that may adversely affect SWAT hydrologic predictions include a lack of model calibration (Bosch et al., 2004), inaccuracies in measured streamflow data (Harmel et al., 2006), and relatively short calibration and validation periods (Muleta and Nicklow, 2005b).

Example Calibration/Validation Studies

The SWAT hydrologic subcomponents have been refined and validated at a variety of scales (table 2). For example, Arnold and Allen (1996) used measured data from three Illinois watersheds, ranging in size from 122 to 246 km^2, to successfully validate surface runoff, groundwater flow, groundwater ET, ET in the soil profile, groundwater recharge, and groundwater height parameters. Santhi et al. (2001a, 2006) performed extensive streamflow validations for two Texas watersheds that cover over 4,000 km^2. Arnold et al. (1999b) evaluated streamflow and sediment yield data in the Texas Gulf basin with drainage areas ranging from 2,253 to 304,260 km^2. Streamflow data from approximately 1,000 stream monitoring gauges from 1960 to 1989 were used to calibrate and validate the model. Predicted average monthly streamflows for three major river basins (20,593 to 108,788 km^2) were 5% higher than measured flows, with standard deviations between measured and predicted within 2%. Annual runoff and ET were validated across the entire continental U.S. as part of the Hydrologic Unit Model for the U.S. (HUMUS) modeling system. Rosenthal et al. (1995) linked GIS to SWAT and simulated ten years of monthly streamflow without calibration. SWAT underestimated the extreme events but produced overall accurate streamflows (table 2). Bingner (1996) simulated runoff for ten years for a watershed in northern Mississippi. The SWAT model produced reasonable results in the simulation of runoff on a daily and annual basis from multiple subbasins (table 2), with the exception of a wooded subbasin. Rosenthal and Hoffman (1999) successfully used SWAT and a spatial database to simulate flows, sediment, and nutrient loadings on a 9,000 km^2 watershed in central Texas to locate potential water quality monitoring sites. SWAT was also successfully validated for streamflow (table 2) for the Mill Creek watershed in Texas for 1965-1968 and 1968-1975 (Srinivasan et al., 1998). Monthly streamflow rates were well predicted, but the model overestimated streamflows in a few years during the spring/summer months. The overestimation may be accounted for by variable rainfall during those months.

Table 2. Summary of reported SWAT hydrologic calibration and validation coefficient of determination (R^2) and Nash-Sutcliffe model efficiency (NSE) statistics.

Reference	Watershed	Drainage Area (km^2)[a]	Indicator	Time Period (C = calib., V = valid.)	Calibration						Validation					
					Daily		Monthly		Annual		Daily		Monthly		Annual	
					R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
Afinowicz et al. (2005)	North Fork of the Upper Guadalupe River (Texas)	60	Stream flow	C: 1992-1996 V: 1997 to Sept. 2003		0.4		0.29				0.09		0.5		
Arabi et al. (2006b)[b]	Dreisbach and Smith Fry (Indiana)	6.2 and 7.3	Stream flow	C: 1975 to May 1977 V: June 1977 to 1978			0.92 and 0.86	0.84 and 0.73					0.87 and 0.81	0.73 and 0.63		
			Surface runoff				0.91 and 0.84	0.80 and 0.62					0.88 and 0.84	0.75 and 0.63		
Arnold and Allen (1996)	Goose Creek, Hadley Creek, and Panther Creek (Illinois)	122 to 246	Surface runoff	Varying periods									0.79 to 0.94			
			Ground water flow										0.38 to 0.51			
			Total stream flow										0.63 to 0.95			
Arnold et al. (2000)	Upper Mississippi River (north central U.S.)	491,700	Stream flow	C: 1961-1980 V: 1981-1985			0.63						0.65			
Arnold et al. (2005)	USDA-ARS Y-2 (Texas)	0.53	Crack flow	1998-1999							0.84					
			Surface runoff	1998-1999							0.87					
Arnold et al. (1999a)[c]	Conterminous U.S. (fig. 2)	--	Runoff (by state)	20-year period											0.78	
			(by soils)												0.66	
Arnold et al. (1999b)	35 8-digit watersheds (Texas)	2,253 to 304,620	Stream flow	1965-1989											0.23 to 0.96	-1.1 to 0.87
	Three 6-digit watersheds[c] (Texas)	--	Stream flow	1965-1989									0.57 to 0.87	0.53 to 0.86		
Bärlund et al. (2007)[c],[d]	Lake Pyhäjärvi (Finland)	--	Stream flow	1990-1994		0.48										
Behera and Panda (2006)	Kapgari (India)	9.73	Surface runoff	C: 2002 V: 2003 (rainy season)	0.94	0.88					0.91	0.85				
Benaman et al. (2005)	Cannonsville Reservoir (New York); C: four gauges, V: two gauges	37 to 913	Stream flow	C: 1994 to July 1999 V: 1990-1993			0.72 to 0.80	0.63 to 0.78					0.73 and 0.80	0.62 and 0.76		
Benham et al. (2006)	Shoal Creek (Missouri); upstream gauge	367	Stream flow	C: May 1999 to June 2000 V: June 2001 to Sept. 2002	0.40	0.21	0.70	0.63			0.61	0.54	0.61	0.66		
Binger (1996)[e]	Goodwin Creek (Mississippi); 14 gauges	0.05 to 21.3	Stream flow	V: 1982-1991 (140 r^2 statistics)											93 ≥ 0.90	
Bosch et al. (2004)[f],[g]	Subwatershed J, Little River (Georgia, U.S.)	22.1	Stream flow	1997-2002								-0.24 to -0.03		0.55 to 0.80		
Bouraoui et al. (2005)[h]	Medjerda River (Algeria and Tunisia); three gauges	163 to 16,000	Stream flow	Sept. 1988 to March 1999							0.44 to 0.69	0.23 to 0.41	0.62 to 0.84	0.53 to 0.84		
Bouraoui et al. (2002)	Ouse River (U.K.); three gauges	980 to 3,500	Stream flow	1986-1990		0.39 to 0.77										

Table 2 (cont'd). Summary of reported SWAT hydrologic calibration and validation coefficient of determination (R^2) and Nash-Sutcliffe model efficiency (NSE) statistics.

Reference	Watershed	Drainage Area (km^2)[a]	Indicator	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Bouraoui et al. (2004)	Vantaanjoki (Finland)	1,682	Stream flow	1965-1984										0.87		
	Subwatershed	295		1982-1984		0.81										
Cao et al. (2006)	Motueka River (New Zealand); seven gauges	47.9 to 1,756.6	Stream flow	C: 1990-1994 V: 1995-2000	0.52 to 0.82	0.36 to 0.78			0.64 to 0.95		0.41 to 0.75	0.35 to 0.72				
Cerucci and Conrad (2003)	Townbrook (New York)	36.8	Stream flow	Oct. 1998 to Sept. 2000			0.72									
Chanasyk et al. (2003)	Three watersheds (Saskatchewan)	0.015 to 0.023	Surface runoff	1999-1900		-35.7 to -0.005										
Chaplot et al. (2004)	Walnut Creek (Iowa)	51.3	Stream flow	1991-1998			0.73									
Cheng et al. (2006)	Heihe River (China)	7,241	Stream flow	C: 1992-1997 V: 1998-1999			0.80	0.78					0.78	0.76		
Chu and Shirmohammadi (2004)[i]	Warner Creek (Maryland)	3.46	Stream flow	C: 1994-1995 V: 1996-1999			0.66	0.52					0.69	0.63		
			Surface runoff				0.43	0.35					0.88	0.77		
			Sub-surface runoff				0.56	0.27					0.47	0.42		
Coffey et al. (2004)[e]	University of Kentucky ARC (Kentucky)	5.5	Stream flow	1995 and 1996	0.26 and 0.40	0.09 and 0.15	0.70 and 0.88	0.41 and 0.61								
Conan et al. (2003a)[c],[i]	Coët-Dan (France)	12	Stream flow	C: 1995-1996 V: 1997-1999		0.79						0.42		0.87		
	Subwatershed		Stream flow	V: 1994 to Feb. 1999										0.83		
Conan et al. (2003b)	Upper Guadiana River (Spain)	18,100	Stream flow	1975-1991								0.45				
Cotter et al. (2003)	Moores Creek (Arkansas)	18.9	Stream flow	1997-1998	0.76											
Di Luzio et al. (2005)	Goodwin Creek (Mississippi)	21.3	Surface runoff	1982-1993									0.90 to 0.95	0.81 to 0.97		
Di Luzio and Arnold (2004)[j]	Blue River (Oklahoma)	1,233	Stream flow	1994-2000 (auto. calib.)	0.24 to 0.99	0.15 to 0.99										
				(manual calib.)	0.01 to 0.98	-102 to 0.80										
Di Luzio et al. (2002)	Upper North Bosque River (Texas)	932.5	Stream flow	1993 to July 1998										0.82		
Du et al. (2005)[c]	Walnut Creek (Iowa); Subwatershed (site 310) and watershed outlet	51.3	Stream flow	C: 1992-1995 V: 1996-1999 (SWAT2000)		0.39 and 0.47		0.36 and 0.72				0.35 and 0.32		0.13 and 0.56		
	Subwatershed (site 210)	--	Tile flow	(SWAT2000)		-0.15		-0.33				-0.16		-0.42		
	Subwatershed (site 310) and watershed outlet	51.3	Stream flow	(SWAT-M)[i]		0.55 and 0.51		0.84 and 0.88				-0.11 and 0.49		0.72 and 0.82		
	Subwatershed (site 210)	--	Tile flow	(SWAT-M)[i]		-0.23		0.67				-0.12		0.70		
Eckhardt et al. (2002)	Dietzhölze (Germany)	81	Stream flow	1991-1993 (SWAT99.2)		-0.17										
				(SWAT-G)[i]		0.76										
El-Nasr et al. (2005)	Jeker (Belgium)	465	Stream flow	C: June 1986 to April 1989 V: June 1989 to April 1992	0.45	0.39					0.55	0.60				

Table 2 (cont'd). Summary of reported SWAT hydrologic calibration and validation coefficient of determination (R^2) and Nash-Sutcliffe model efficiency (NSE) statistics.

		Drainage Area		Time Period	Calibration						Validation					
				(C = calib.,	Daily		Monthly		Annual		Daily		Monthly		Annual	
Reference	Watershed	(km^2)[a]	Indicator	V = valid.)	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
Fontaine et al. (2002)	Wind River (Wyoming)	4,999	Stream flow	1991-1996 (new snowmelt routine)												0.86
				1991-1996 (old routine)												-0.70
Fontaine et al. (2001)	Spring Creek (South Dakota)	427	Stream flow	1987-1995			0.62		0.94							
Francos et al. (2001)[k]	Kerava River (Finland)	400	Stream flow	1985-1994										0.65		
Geza and McCray (2007)	Turkey Creek (Colorado)	126	Stream flow	1998-2001 (SSURGO soils)				0.70								
				(STATSGO soils)				0.61								
Gikas et al. (2005)[c],[d]	Vistonis Lagoon (Greece); nine gauges	1,349	Stream flow	C: May 1998 to June 1999 V: Nov. 1999 to Jan. 2000	0.71 to 0.89						0.72 to 0.91					
Gitau et al. (2004)	Town Brook (New York)	36.8[l]	Stream flow	1992-2002			0.76	0.44	0.99	0.84						
Gosain et al. (2005)[c],[i]	Palleru River (India)	--	Stream flow	1972-1994									0.61	0.87		
Govender and Everson (2005)	Cathedral Park Research C VI (South Africa)	0.68	Stream flow	C: 1991 V: 1990-1995 (auto. calib.)	0.86						0.65					
				V: 1990-1995 (manual calib.)							0.68					
Green et al. (2006)	South Fork of the Iowa River (Iowa)	580.5	Stream flow	C: 1995-1998 V: 1999-2004 (scenario 1)	0.7	0.7	0.9	0.9	1.0	0.7	0.5	0.4	0.6	0.5	0.7	0.6
				C: 1995-2000 V: 2001-2004 (scenario 2)	0.7	0.7	0.9	0.8	0.9	0.9	0.3	0.2	0.6	0.5	0.7	-0.8
Grizzetti et al. (2005)[c]	Parts of four watersheds (U.K.); C: one gauge, V: two gauges, annual: 50 gauges	8,900	Stream flow	C and V: 1995-1999		0.75		0.86								0.66
Grizzetti et al. (2003)[c]	Vantaanjoki (Finland); C: one gauge, V: three gauges	295 and 1,682	Stream flow	Varying periods		0.81					0.57 to 0.66	0.75 to 0.81				
Hanratty and Stefan (1998)	Cottonwood (Minnesota)	3,400	Stream flow	1967-1991				0.78								
Hao et al. (2004)	Lushi (China)	4,623	Stream Flow	C: 1992-1997 V: 1998-1999			0.87	0.87			0.84	0.81				
Hernandez et al. (2000)	Watershed 11, Walnut Gulch (Arizona)	8.2	Stream flow	1966-1974 (1 vs. 10 rain gauges)					0.33 and 0.57							
Heuvelmans et al. (2006)[j]	25 watersheds (Schelde River basin, Belgium)	2.2 to 209.9	Stream flow	C: 1990-1995 V: 1996-2001		0.70 to 0.95						0.67 to 0.92				
Holvoet et al. (2005)	Nil (Belgium)	32	Stream flow	Nov. 1998 to Nov. 2001		0.53										
Jha et al. (2004a)[c]	Maquoketa River (Iowa)	4,776	Stream flow	1981-1990							0.68		0.76		0.65	
Jha et al. (2004b)	Upper Mississippi River (north central U.S.)	447,500	Stream flow	C: 1989-1997 V: 1980-1988			0.75	0.67	0.91	0.91			0.70	0.59	0.89	0.86
Jha et al. (2006)	Upper Mississippi River (north central U.S.)	447,500	Stream flow	C: 1968-1987 V: 1988-1997	0.67	0.58	0.74	0.69	0.82	0.75	0.75	0.65	0.82	0.81	0.91	0.90
Jha et al. (2007)[m]	Raccoon River (Iowa); Van Meter gauge	8,930	Stream flow	C: 1981-1992 V: 1993-2003			0.87	0.87	0.97	0.97			0.89	0.88	0.94	0.94

Table 2 (cont'd). Summary of reported SWAT hydrologic calibration and validation coefficient of determination (R^2) and Nash-Sutcliffe model efficiency (NSE) statistics.

		Drainage		Time Period	Calibration						Validation					
		Area		(C = calib.,	Daily		Monthly		Annual		Daily		Monthly		Annual	
Reference	Watershed	(km^2)[a]	Indicator	V = valid.)	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
Kalin and Hantush (2006)[c],[i]	Pocono Creek (Pennsylvania)	98.8	Base flow	C: July 2002 to May 2004 V: June 2004 to April 2005 (rain gauge)			0.30	0.08					0.13	-0.26		
			Surface runoff	(rain gauge)			0.77	0.77					0.83	0.73		
			Stream flow	(rain gauge)	0.74	0.74	0.85	0.83			0.70	0.64	0.81	0.66		
			Base flow	(NEXRAD)			0.31	0.05					0.06	-0.40		
			Surface runoff	(NEXRAD)			0.79	0.79					0.84	0.77		
			Stream flow	(NEXRAD)	0.74	0.73	0.85	0.84			0.66	0.62	0.89	0.75		
Kang et al. (2006)[k]	Baran (South Korea)	29.8	Surface runoff	C: 1996-1997 V: 1999-2000	0.93	0.93					0.87	0.87				
Kannan et al. (2007b)[g]	Colworth (U.K.)	1.4	Stream flow	C: Oct. 1999 to 2001 V: 2001 to May 2002 (CN approach)		0.60 and 0.61						0.54 and 0.60				
				(Green-Ampt)		0.51 and 0.54						0.56 and 0.51				
Kaur et al. (2004)	Nagwan (India)	9.58	Surface runoff	Varying periods	0.76	0.71					0.83	0.54				
King et al. (1999)[e]	Goodwin Creek (Mississippi)	21.3	Stream flow	1982-1989 (curve number)								0.43		0.84		0.55
				(Green-Ampt)								0.53		0.69		0.81
Kirsch et al. (2002)	Rock River (Wisconsin); two gauges	23.2 and 190	Stream flow	1989-1995											0.86 and 0.74	0.41 and 0.61
	12 USGS gauges[c]	9,708	Stream flow	Varying periods					0.28 to 0.98	0.18 to 0.84						
Limaye et al (2001)	Dale Hollow (Tennessee); subwatershed	523	Stream flow	C: 1966-1990 V: 1991-1993		0.42		0.74				0.45		0.80		
Lin and Radcliffe (2006)	Upper Etowah River (Georgia, U.S.)	1,580	Stream flow	C: 1983-1992 V: 1993-2001		0.61		0.86				0.62		0.89		
Manguerra and Engel (1998)[g]	Greenhill (Indiana)	113.4	Stream flow	1991-1995				0.93 to 1.0								
Mapfumo et al. (2004)[i]	Three watersheds (Saskatchewan)	1.53 to 2.26	Soil water	C: 1998 V: 1999-2000 (overall results)	0.84	0.77					0.72	0.70				
Mishra et al. (2007)	Banha (India)	17	Surface runoff	C: 1996 V: 1997-2001	0.93	0.70	0.99	0.99			0.78	0.60	0.92	0.88		
Moon et al. (2004)[i]	Cedar Creek (Texas)	2,608	Stream flow	1999-2001 (rain gauge)							0.53	0.48	0.86	0.78		
				(NEXRAD)							0.58	0.57	0.84	0.82		
Moriasi et al. (2007)[c]	Leon River (Texas); C: seven gauges, V: five gauges	9,312	Stream flow	--				0.66 to 1.0						0.69 to 1.0		
Muleta and Nicklow (2005a)	Big Creek (Illinois)	86.5	Stream flow	1999-2001		0.69										
Muleta and Nicklow (2005b)	Big Creek (Illinois); separate gauges for C and V	23.9 and 86.5	Stream flow	C: June 1999 to Aug. 2001 V: April 2000 to Aug. 2001		0.74						0.23				

Table 2 (cont'd). Summary of reported SWAT hydrologic calibration and validation coefficient of determination (R^2) and Nash-Sutcliffe model efficiency (NSE) statistics.

Reference	Watershed	Drainage Area (km^2)[a]	Indicator	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Narasimhan et al. (2005)[c]	Six watersheds (Texas); 24 gauges	10,320 to 29,664	Stream flow	Varying periods (overall annual average)					0.75	0.75					0.70	0.70
				(range across 24 gauges)					0.54 to 0.99	0.52 to 0.99					0.63 to 1.00	0.55 to 0.97
Nasr et al. (2007)[d]	Clarianna, Dripsey, and Oona Water (Ireland)	15 to 96	Stream flow	Varying periods		0.72 to 0.91										
Olivera et al. (2006)	Upper Seco Creek (Texas)	116	Stream flow	C: 1991-1992 V: 1993 to June 1994		0.67		0.88				0.33		0.90		
Perkins and Sophocleous (1999)[h]	Lower Republican River (Kansas)	2,569	Stream flow	1977-1994			0.85									
Peterson and Hamlet (1998)[i]	Ariel Creek (Pennsylvania)	39.4	Stream flow	May 1992 to July 1994		0.04		0.14								
				May 1992 to July 1994 (no snowmelt events)		0.2		0.55								
Plus et al. (2006)[h]	Thau Lagoon (France); two gauges	280	Stream flow	Sept. 1993 to July 1996	0.68 and 0.45											
Qi and Grunwald (2005)	Sandusky River (Ohio); five gauges	90.3 to 3,240	Surface water	C: 1998-1999 V: 2000-2001				0.31 to 0.65						-0.04 to 0.75		
			Ground water					-9.1 to 0.60						-0.57 to 0.22		
			Total flow					0.31 to 0.81						0.40 to 0.73		
Rosenberg et al. (2003)[c]	Conterminous U.S. (18 MWRRs; fig. 2)		Water yield	1961-1990 (overall mean)											0.92	
				1961-1990 (8-digit means by MWRR)											0.03 to 0.90	
Rosenthal and Hoffman (1999)	Leon River (Texas)	7,000	Stream flow	1972-1974										0.57		
Rosenthal et al. (1995)[c],[f],[i]	Lower Colorado River (Texas); Bay City gauge	8,927	Stream flow	1980-1989									0.75	0.69		
	Upstream gauges												0.69 to 0.90			
Saleh et al. (2000)[n]	Upper North Bosque River (Texas); C: one gauge, V:11 gauges	932.5	Stream flow	Oct. 1993 to Aug. 1995				0.56						0.99		
Saleh and Du (2004)	Upper North Bosque River (Texas)	932.5	Stream flow	C: 1994 to June 1995 V: July 1995 to July 1999		0.17		0.50				0.62		0.78		
Salvetti et al. (2006)	Lombardy Plain Region (Po River basin, Italy)	16,000	Stream flow	1984-2002		0.50		>0.70								
Santhi et al. (2001a)[c],[o]	Bosque River (Texas); two gauges	4,277	Stream flow	Varying periods			0.80 and 0.89	0.79 and 0.83	0.88 and 0.66	0.86 and 0.72			0.92 and 0.80	0.87 and 0.62		
Santhi et al. (2006)[c]	West Fork (Texas); two gauges	4,554	Stream flow	1982-2001			0.61 and 0.81	0.12 and 0.72	0.88 and 0.86	0.84 and 0.78						

Table 2 (cont'd). Summary of reported SWAT hydrologic calibration and validation coefficient of determination (R^2) and Nash-Sutcliffe model efficiency (NSE) statistics.

Reference	Watershed	Drainage Area (km^2)[a]	Indicator	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Schomberg et al. (2005)[c]	Three watersheds (Minnesota); two watersheds (Michigan)	829 to 3,697	Stream flow	Varying periods	0.10 to 0.28	-1.3 to 0.25	0.35 to 0.58	-1.4 to 0.49								
Secchi et al. (2007)[c]	13 watersheds (Iowa)	2,051 to 37,496	Stream flow	Varying periods (composite statistics)									0.76	0.75	0.91	0.90
Singh et al. (2005)	Iroquois River (Illinois and Indiana)	5,568	Stream flow	C: 1987-1995 V: 1972-1986		0.79		0.88				0.74		0.84		
Spruill et al. (2000)	University of Kentucky ARC (Kentucky)	5.5	Stream flow	C: 1996 V: 1995		0.19		0.89				-0.04		0.58		
Srinivasan et al. (2005)[i]	Watershed FD-36 (Pennsylvania)	0.395	Stream flow	1997-2000		0.62										
Srinivasan and Arnold (1994)	Upper Seco Creek (Texas)	114	Stream flow	Jan. 1991 to Aug. 1992			0.82									
Srinivasan et al. (1998)[c]	Richland-Chambers Reservoir (Texas); two gauges	5,000	Stream flow	C: 1965-1969 V: 1970-1984			0.87 and 0.84	0.77 and 0.84					0.65 and 0.82	0.52 and 0.82		
Srivastava et al. (2006)[i]	West Fork Brandywine Creek (Pennsylvania)	47.6	Base flow	C: July 1994 to Dec. 1997 V: Jan. 1999 to May 2001			0.51	-0.16					0.29	-1.2		
			Surface flow				0.38	0.20					0.39	-0.35		
			Total flow				0.57	0.54					0.34	-0.17		
Stewart et al. (2006)	Upper North Bosque River (Texas)	932.5	Stream flow	C: 1994-1999 V: 2001-1902			0.87	0.76					0.92	0.80		
Stonefelt et al. (2000)	Wind River (Wyoming)	5,000	Stream flow	1990-1997			0.91									
Thomson et al. (2003)[c],[p]	Conterminous U.S. (18 MWRRs; fig. 2)	--	Water yield	1960-1989 (overall mean)												0.96
				1960-1989 (8-digit means by MWRR)												0.05 to 0.94
Tolson and Shoemaker (2007)[c],[i]	Cannonsville Reservoir (New York); six gauges	37 to 913[q]	Stream flow	Varying periods	0.64 to 0.80	0.59 to 0.80					0.69 to 0.88	0.43 to 0.88	0.88 to 0.97	0.88 to 0.97		
Tripathi et al. (2003)	Nagwan (India)	92.5	Surface runoff	1997 (daily) 1992-1998 (monthly) (June - Oct.)							0.91	0.87	0.97	0.98		
Tripathi et al. (2006)[g]	Nagwan (India)	90.3	Surface runoff	1995-1998									0.86 to 0.90			
Vaché et al. (2002)	Buck Creek and Walnut Creek (Iowa)	88.2 and 51.3	Stream flow	Varying periods			0.64 and 0.67									
Van Liew et al. (2003a)[i]	Little Washita River (Oklahoma); C: two gauges, V: six gauges	2.9 to 610	Stream flow	Varying periods		0.56 and 0.58		0.66 and 0.79				-0.35 to 0.72		-1.1 to 0.89		
Van Liew and Garbrecht (2003)	Little Washita River (Oklahoma); C: two gauges, V: three gauges	160 to 610	Stream flow	Varying periods		0.60 and 0.40		0.75 and 0.71				-0.06 to 0.71		0.45 to 0.86		
Van Liew et al. (2003b)[c]	Little Washita River (Oklahoma); two gauges	160	Stream flow	Oct. 1992 to Sept. 2000		0.55 and 0.59		0.78 and 0.77								

Table 2 (cont'd). **Summary of reported SWAT hydrologic calibration and validation coefficient of determination (R^2) and Nash-Sutcliffe model efficiency (NSE) statistics.**

Reference	Watershed	Drainage Area (km^2)[a]	Indicator	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Van Liew et al. (2007)[r]	Little River (Georgia, U.S.); two gauges	114 and 330	Stream flow	C: 1997-2002 V: 1972-1996		0.64 and 0.71		0.83 and 0.90				0.66 and 0.68		0.88 and 0.89		
	Little Washita River (Oklahoma); three gauges	160 to 600	Stream flow	C: 1993-1999 V: varying periods		0.54 and 0.63		0.68 and 0.76				0.13 to 0.56		-0.36 to 0.60		
	Mahantango Creek (Pennsylvania); two gauges	0.4 and 7	Stream flow	C: 1997-2000 V: varying periods		0.46 and 0.69		0.84 and 0.88				0.35 to 0.54		0.46 to 0.75		
	Reynolds Creek (Idaho); three gauges	36 to 239	Stream flow	C: 1968-1972 V: varying periods		0.51 to 0.73		0.52 to 0.79				-0.17 to 0.62		0.21 to 0.74		
	Walnut Gulch (Arizona); three gauges	24 to 149	Stream flow	C: 1968-1972 V: 1973-1982		0.30 to 0.76		0.48 to 0.86				-1.0 to -1.8		-0.62 to -2.5		
Varanou et al. (2002)	Ali Efenti (Greece)	2,796	Stream flow	1977-1993		0.62		0.81								
Vazquez-Amabile and Engel (2005)[c]	Muscatatuck River (Indiana); three gauges	2,952	Stream flow	C: 1980-1994 V: 1995-2002		-0.23 to 0.28		0.59 to 0.80				-0.35 to 0.48		0.49 to 0.81		
			Ground water table depth			-0.12 to 0.28		0.36 to 0.61				-0.74 to 0.33		-0.51 to 0.38		
Vazquez-Amábile et al. (2006)	St. Joseph River (Indiana, Michigan, and Ohio); C: three gauges, V: four gauges	2,800	Stream flow	C: 1989-1998 V: 1999-2002		0.46 to 0.65		0.64 to 0.74			0.50 to 0.66	0.33 to 0.60	0.73 to 0.76	0.64 to 0.74		
Veith et al. (2005)	Watershed FD-36 (Pennsylvania)	0.395	Stream flow	1997-2000 (April to Oct.)			0.63	0.75								
Von Stackelberg et al. (2007)[h]	Research watersheds D1 and D2 (Uruguay)	0.69 and 1.08	Stream flow	July 2000 to June 2004 (reduced ET scenario)	0.92 and 0.93	0.77 and 0.71										
				(added groundwater scenario)	0.93 and 0.94	0.78 and 0.72										
Wang and Melesse (2005)[i]	Wild Rice River (Minnesota); two gauges	2,419 and 4,040.3	Stream flow	Varying periods	0.73 and 0.68	0.64 and 0.67	0.89 and 0.86	0.86 and 0.86	0.82 and 0.73	0.80 and 0.72	0.69 and 0.52	0.62 and 0.50	0.93 and 0.83	0.90 and 0.83	0.93 and 0.82	0.90 and 0.68
Wang and Melesse (2006)[i]	Elm River (North Dakota); subwatershed	515.4	Stream flow	C: Dec. 1984 to Nov. 1986 V: Dec. 1981 to Nov. 1984 (STATSGO soils)	0.53	0.51	0.89	0.88			0.55	0.31	0.53	0.50		
				(SSURGO soils)	0.51	0.49	0.92	0.92			0.55	0.26	0.53	0.49		
Wang et al. (2006)[g],[i]	Wild Rice River (Minnesota); two gauges	2,419 and 4,040.3	Stream flow	Varying periods	0.68 to 0.76	0.64 to 0.70	0.86 to 0.92	0.86 to 0.90	0.73 to 0.91	0.72 to 0.90	0.52 to 0.69	0.46 to 0.64	0.83 to 0.93	0.80 to 0.91	0.82 to 0.93	0.68 to 0.91
Watson et al. (2005)[k]	Woady Yaloak River (Australia)	306	Stream flow	C: 1978-1989 V: 1990-2001		0.54		0.77		0.77		0.47		0.79		0.91
Weber et al. (2001)	Aar (Germany)	59.8	Stream flow	1986-1987 (daily), 1983-1987 (monthly)								0.63		0.74		
White and Chaubey (2005)[e],[s]	Beaver Reservoir (Arkansas); three gauges	362 to 1,020	Stream flow	C: 1999 and 2000 V: 2001 and 2002			0.41 to 0.91	0.50 to 0.89					0.77 to 0.91	0.72 to 0.87		

Table 2 (cont'd). Summary of reported SWAT hydrologic calibration and validation coefficient of determination (R^2) and Nash-Sutcliffe model efficiency (NSE) statistics.

					Calibration						Validation					
		Drainage Area		Time Period (C = calib.,	Daily		Monthly		Annual		Daily		Monthly		Annual	
Reference	Watershed	(km²)[a]	Indicator	V = valid.)	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
Wu and Johnston (2007)	South Branch Ontonagon River (Michigan)	901	Stream flow	C: 1948-1949 V: 1950-1965 (drought years for calib.)				0.8						0.8		
				C: 1969-1970 V: 1950-1965 (average years for calib.)				0.9						0.4		
Wu and Xu (2006)[c]	Amite, Tamgipahoa, and Tickfaw Rivers (Louisiana)	662.2 to 3434.9	Stream flow	C: 1975-1977 V: 1979-1999		0.83 to 0.93		0.94 to 0.96				0.69 to 0.78		0.81 to 0.87		
Zhang et al. (2007)	Luohe River (China)	5,239	Stream flow	C: 1992-1996 V: 1997-2000	0.82	0.65	0.82	0.64			0.74	0.54	0.86	0.82		

[a] Based on drainage areas to the gauge(s) rather than total watershed area where reported (see footnote [d] for further information).
[b] The same statistics were also reported by Bracmort et al. (2006); the validation time period was not reported and thus was inferred from graphical results reported by Bracmort et al. (2006).
[c] Explicit or estimated drainage areas were not reported for some or all of the gauge sites; the total watershed area is listed for those studies that reported it.
[d] The exact time scale of comparison was not explicitly stated and thus was inferred from other information provided.
[e] These statistics were computed on the basis of comparisons between simulated and measured data within specific years, rather than across multiple years.
[f] The SWAT simulations were not calibrated.
[g] These statistics represent ranges for different input data configurations for either: (1) different combinations of land use, DEM, and/or soil resolution inputs; (2) different subwatershed/HRU configurations; or (3) different ET equation options.
[h] Specific calibration and/or validation time periods were reported, but the statistics were based on the overall simulated time period (calibration plus validation time periods).
[i] Other statistics were reported for different time periods, conditions, gauge combinations, and/or variations in selected in input data.
[j] The comparisons were performed on an hourly basis for this study, for 24 different runoff events, because the Green and Ampt infiltration method was used.
[k] A modified SWAT model was used.
[l] As reported in Cerucci and Conrad (2003).
[m] A similar set of Raccoon River watershed statistics were reported for slightly different time periods by Secchi et al. (2007).
[n] The APEX model (Williams and Izaurralde, 2006) was interfaced with SWAT for this study. The calibration statistic was based on a comparison between simulated and measured flows at the watershed outlet, while the validation statistic was based on a comparison between simulated and measured flows averaged across 11 different gauges including the watershed outlet.
[o] The calibration and validation statistics were also reported by Santhi et al. (2001b).
[p] Similar statistics for the same time periods were reported by Thomsen et al. (2005).
[q] As reported by Benaman et al. (2005).
[r] Previous NSE statistics were reported by Van Liew et al. (2005) for the same Little River and Little Washita River subwatersheds and time periods for four different sets of simulations (one set was based on a manual calibration approach, while the other three sets were based on an automatic calibration approach with different objective functions and/or selected calibration input parameters).
[s] The statistics for the War Eagle Creek gauge were also reported by Migliaccio et al. (2007).

Van Liew and Garbrecht (2003) evaluated SWAT's ability to predict streamflow under varying climatic conditions for three nested subwatersheds in the 610 km² Little Washita River experimental watershed in southwestern Oklahoma. They found that SWAT could adequately simulate runoff for dry, average, and wet climatic conditions in one subwatershed, following calibration for relatively wet years in two of the subwatersheds. Govender and Everson (2005) report relatively strong streamflow simulation results (table 2) for a small (0.68 km²) research watershed in South Africa. However, they also found that SWAT performed better in drier years than in a wet year, and that the model was unable to adequately simulate the growth of Mexican Weeping Pine due to inaccurate accounting of observed increased ET rates in mature plantations.

Qi and Grunwald (2005) point out that, in most studies, SWAT has usually been calibrated and validated at the drainage outlet of a watershed. In their study, they calibrated and validated SWAT for four subwatersheds and at the drainage outlet (table 2). They found that spatially distributed calibration and validation accounted for hydrologic patterns in the subwatersheds. Other studies that report the use of multiple gauges to perform hydrologic calibration and validation with SWAT include Cao et al. (2006), White and Chaubey (2005), Vazquez-Amábile and Engel (2005), and Santhi et al. (2001a).

Applications Accounting for Base Flow and/or for Karst-Influenced Systems

Arnold et al. (1995a) and Arnold and Allen (1999) describe a digital filter technique that can be used for determining separation of base and groundwater flow from overall streamflow, which has been used to estimate base flow and/or groundwater flow in several SWAT studies (e.g., Arnold et al., 2000; Santhi et al., 2001a; Hao et al., 2004; Cheng et al., 2006; Kalin and Hantush, 2006; Jha et al., 2007). Arnold et al. (2000) found that SWAT groundwater recharge and discharge (base flow) estimates for specific 8-digit watersheds compared well with filtered estimates for the 491,700 km² upper Mississippi River basin. Jha et al. (2007) report accurate estimates of streamflow (table 2) for the 9,400 km² Raccoon River watershed in west central Iowa, and that their predicted base flow was similar to both the filtered estimate and a previous base flow estimate. Kalin and Hantush (2006) report accurate surface runoff and streamflow results for the 120 km^2 Pocono Creek watershed in eastern Pennsylvania (table 2); their base flow estimates were weaker, but they state those estimates were not a performance criteria. Base flow and other flow components estimated with SWAT by Srivastava et al. (2006) for the 47.6 km^2 West Branch Brandywine Creek watershed in southwest Pennsylvania were found to be generally poor (table 2). Peterson and Hamlett (1998) also found that SWAT was not able to simulate base flows for the 39.4 km^2 Ariel Creek watershed in northeast Pennsylvania, due to the presence of soil fragipans. Chu and Shirmohammadi (2004) found that SWAT was unable to simulate an extremely wet year for a 3.46 km^2 watershed in Maryland. After removing the wet year, the surface runoff, base flow, and streamflow results were within acceptable accuracy on a monthly basis. Subsurface flow results also improved when the base flow was corrected.

Spruill et al. (2000) calibrated and validated SWAT with one year of data each for a small experimental watershed in Kentucky. The 1995 and 1996 daily NSE values reflected poor peak flow values and recession rates, but the monthly flows were more accurate (table 2). Their analysis confirmed the results of a dye trace study in a central Kentucky karst watershed, indicating that a much larger area contributed to streamflow than was described by topographic boundaries. Coffey et al. (2004) report similar statistical results for the same Kentucky watershed (table 2). Benham et al. (2006) report that SWAT streamflow results (table 2) did not meet calibration criteria for the karst-influenced 367 km^2 Shoal Creek watershed in southwest Missouri, but that visual inspection of the simulated and observed hydrographs indicated that the system was satisfactorily modeled. They suggest that SWAT was not able to capture the conditions of a very dry year in combination with flows sustained by the karst features.

Afinowicz et al. (2005) modified SWAT in order to more realistically simulate rapid subsurface water movement through karst terrain in the 360 km^2 Guadalupe River watershed in southwest Texas. They report that simulated base flows matched measured streamflows after the modification, and that the predicted daily and monthly and daily results (table 2) fell within the range of published model efficiencies for similar systems. Eckhardt et al. (2002) also found that their modifications for SWAT-G resulted in greatly improved simulation of subsurface interflow in German low mountain conditions (table 2).

Soil Water, Recharge, Tile Flow, and Related Studies

Mapfumo et al. (2004) tested the model's ability to simulate soil water patterns in small watersheds under three grazing intensities in Alberta, Canada. They observed that SWAT had a tendency to overpredict soil water in dry soil conditions and to underpredict in wet soil conditions. Overall, the model was adequate in simulating soil water patterns for all three watersheds with a daily time step. SWAT was used by Deliberty and Legates (2003) to document 30-year (1962-1991) long-term average soil moisture conditions and variability, and topsoil variability, for Oklahoma. The model was judged to be able to accurately estimate the relative magnitude and variability of soil moisture in the study region. Soil moisture was simulated with SWAT by Narasimhan et al. (2005) for six large river basins in Texas at a spatial resolution of 16 km^2 and a temporal resolution of one week. The simulated soil moisture was evaluated on the basis of vegetation response, by using 16 years of normalized difference vegetation index (NDVI) data derived from NOAA-AVHRR satellite data. The predicted soil moistures were well correlated with agriculture and pasture NDVI values. Narasimhan and Srinivasan (2005) describe further applications of a soil moisture deficit index and an evapotranspiration deficit index.

Arnold et al. (2005) validated a crack flow model for SWAT, which simulates soil moisture conditions with depth to account for flow conditions in dry weather. Simulated crack volumes were in agreement with seasonal trends, and the predicted daily surface runoff levels also were consistent with measured runoff data (table 2). Sun and Cornish (2005) simulated 30 years of bore data for a 437 km^2 watershed. They used SWAT to estimate recharge in the headwaters of the Liverpool Plains in New South Wales, Australia. These authors determined that SWAT could estimate recharge and incorporate land use and land management at the watershed scale. A code modification was performed by Vazquez-Amábile and Engel (2005) that allowed reporting of soil moisture for each soil layer. The soil moisture values were then converted into groundwater table levels based on the approach used in DRAINMOD (Skaggs, 1982). It was concluded that predictions of groundwater table levels would be useful to include in SWAT.

Modifications were performed by Du et al. (2006) to SWAT2000 to improve the original SWAT tile drainage function. The modified model was referred to as SWAT-M and resulted in clearly improved tile drainage and streamflow predictions for the relatively flat and intensively cropped 51.3 km^2 Walnut Creek watershed in central Iowa (table 2). Green et al. (2006) report a further application of the revised tile drainage routine using SWAT2005 for a large tile-drained watershed in north central Iowa, which resulted in a greatly improved estimate of the overall water balance for the watershed (table 2). This study also presented the importance of ensuring that representative runoff events are present in both the calibration and validation in order to improve the model's effectiveness.

Snowmelt-Related Applications

Fontaine et al. (2002) modified the original SWAT snow accumulation and snowmelt routines by incorporating improved accounting of snowpack temperature and accumulation, snowmelt, and areal snow coverage, and an option to input precipitation and temperature as a function of elevation bands. These enhancements resulted in greatly improved streamflow estimates for the mountainous 5,000 km^2 upper Wind River basin in Wyoming (table 2). Abbaspour et al. (2007) calibrated several snow-related parameters and used four elevation bands in their SWAT simulation of the 1,700 km^2 Thur watershed in Switzerland that is characterized by a pre-alpine/alpine climate. They report excellent SWAT discharge estimates.

Other studies have reported mixed SWAT snowmelt simulation results, including three that reported poor results for watersheds (0.395 to 47.6 km^2) in eastern Pennsylvania. Peterson and Hamlett (1998) found that SWAT was unable to account for unusually large snowmelt events, and Srinivasan et al. (2005) found that SWAT underpredicted winter streamflows; both studies used SWAT versions that predated the modifications performed by Fontaine et al. (2002). Srivastava et al. (2006) also found that SWAT did not adequately predict winter flows. Qi and Grunwald found that SWAT did not predict winter season precipitation-runoff events well for the 3,240 km^2 Sandusky River watershed. Chanasyk et al. (2003) found that SWAT was not able to replicate snowmelt-dominated runoff (table 2) for three small grassland watersheds in Alberta that were managed with different grazing intensities. Wang and Melesse (2005) report that SWAT accurately simulated the monthly and annual (and seasonal) discharges for the Wild Rice River watershed in Minnesota, in addition to the spring daily streamflows, which were predominantly from melted snow. Accurate snowmelt-dominated streamflow predictions were also found by Wang and Melesse (2006) for the Elm River in North Dakota. Wu and Johnston (2007) found that the snow melt parameters used in SWAT are altered by drought conditions and that streamflow predictions for the 901 km^2 South Branch Ontonagon River in Michigan improved when calibration was based on a drought period (versus average climatic conditions), which more accurately reflected the drought conditions that characterized the validation period. Statistical results for all these studies are listed in table 2.

Benaman et al. (2005) found that SWAT2000 reasonably replicated streamflows for the 1,200 km^2 Cannonsville Reservoir watershed in New York (table 2), but that the model underestimated snowmelt-driven winter and spring stream–flows. Improved simulation of cumulative winter streamflows and spring base flows were obtained by Tolston and Shoemaker (2007) for the same watershed (table 2) by modifying SWAT2000 so that lateral subsurface flow could occur in frozen soils. Francos et al. (2001) also modified SWAT to obtain improved streamflow results for the Kerava River watershed in Finland (table 2) by using a different snowmelt submodel that was based on degree-days and that could account for variations in land use by subwatershed. Incorporating modifications such as those described in these two studies may improve the accuracy of snowmelt-related processes in future SWAT versions.

Irrigation and Brush Removal Scenarios

Gosain et al. (2005) assessed SWAT's ability to simulate return flow after the introduction of canal irrigation in a basin in Andra Pradesh, India. SWAT provided the assistance water managers needed in planning and managing their water resources under various scenarios. Santhi et al. (2005) describe a new canal irrigation routine that was used in SWAT. Cumulative irrigation withdrawal was estimated for each district for each of three different conservation scenarios (relative to a reference scenario). The percentage of water that was saved was also calculated. SWAT was used by Afinowicz et al. (2005) to evaluate the influence of woody plants on water budgets of semi-arid rangeland in southwest Texas. Baseline brush cover and four brush removal scenarios were evaluated. Removal of heavy brush resulted in the greatest changes in ET (approx. 32 mm year^{-1} over the entire basin), surface runoff, base flow, and deep recharge. Lemberg et al. (2002) also describe brush removal scenarios.

Applications Incorporating Wetlands, Reservoirs, and Other Impoundments

Arnold et al. (2001) simulated a wetland with SWAT that was proposed to be sited next to Walker Creek in the Fort Worth, Texas, area. They found that the wetland needed to be above 85% capacity for 60% of a 14-year simulation period, in order to continuously function over the entire study period. Conan et al. (2003b) found that SWAT adequately simulated conversion of wetlands to dry land for the upper Guadiana River basin in Spain but was unable to represent all of the discharge details impacted by land use alterations. Wu and Johnston (2007) accounted for wetlands and lakes in their SWAT simulation of a Michigan watershed, which covered over 23% of the watershed. The impact of flood-retarding structures on streamflow for dry, average, and wet climatic conditions in Oklahoma was investigated with SWAT by Van Liew et al. (2003b). The flood-retarding structures were found to reduce average annual streamflow by about 3% and to effectively reduce annual daily peak runoff events. Reductions of low streamflows were also predicted, especially during dry conditions. Mishra et al. (2007) report that SWAT accurately accounted for the impact of three checkdams on both daily and monthly streamflows for the 17 km^2 Banha watershed in northeast India (table 2). Hotchkiss et al. (2000) modified SWAT based on U.S. Army Corp of Engineers reservoir rules for major Missouri River reservoirs, which resulted in greatly improved simulation of reservoir dynamics over a 25-year period. Kang et al. (2006) incorporated a modified impoundment routine into SWAT, which allowed more accurate simulation of the impacts of rice paddy fields within a South Korean watershed (table 2).

Green-Ampt Applications

Very few SWAT applications in the literature report the use of the Green-Ampt infiltration option. Di Luzio and Arnold (2004) report sub-hourly results for two different calibration methods using the Green-Ampt method (table 2). King et al. (1999) found that the Green-Ampt option did not provide any significant advantage as compared to the curve number approach for uncalibrated SWAT simulations for the 21.3 km^2 Goodwin Creek watershed in Mississippi (table 2). Kannan et al. (2007b) report that SWAT streamflow results were more accurate using the curve number approach as compared to the Green-Ampt method for a small watershed in the U.K. (table 2). However, they point out that several assumptions were not optimal for the Green-Ampt approach.

Pollutant Loss Studies

Nearly 50% of the reviewed SWAT studies (table 1) report simulation results of one or more pollutant loss indicator. Many of these studies describe some form of verifying pollutant prediction accuracy, although the extent of such reporting is less than what has been published for hydrologic assessments. Table 3 lists R^2 and NSE statistics for 37 SWAT pollutant loss studies, which again are used here as key indicators of model performance. The majority of the R^2 and NSE values reported in table 3 exceed 0.5, indicating that the model was able to replicate a wide range of observed in-stream pollutant levels. However, poor results were again reported for some studies, especially for daily comparisons. Similar to the points raised for the hydrologic results, some of the weaker results were due in part to inadequate characterization of input data (Bouraoui et al., 2002), uncalibrated simulations of pollutant movement (Bärlund et al., 2007), and uncertainties in observed pollutant levels (Harmel et al., 2006).

Sediment Studies

Several studies showed the robustness of SWAT in predicting sediment loads at different watershed scales. Saleh et al.

Table 3. Summary of reported SWAT environmental indicator calibration and validation coefficient of determination (R^2) and Nash-Sutcliffe model efficiency (NSE) statistics.

Reference	Watershed	Drainage Area (km^2)[a]	Indicator[b]	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Arabi et al. (2006b)[c]	Dreisbach and Smith Fry (Indiana)	6.2 and 7.3	Suspended solids	C: 1974–1975 V: 1976 to May 1977			0.97 and 0.94	0.92 and 0.86					0.86 and 0.85	0.75 and 0.68		
			Total P				0.93 and 0.64	0.78 and 0.51					0.90 and 0.73	0.79 and 0.37		
			Total N				0.76 and 0.61	0.54 and 0.50					0.75 and 0.52	0.85 and 0.72		
Bärlund et al. (2007)[d],[e]	Lake Pyhäjärvi (Finland)	--	Sediment	1990–1994		0.01										
Behera and Panda (2006)	Kapgari (India)	9.73	Sediment	C: 2002 V: 2003 (rainy season)	0.93	0.84					0.89	0.86				
			Nitrate		0.93	0.92					0.87	0.83				
			Total P		0.92	0.83					0.94	0.89				
Bouraoui et al. (2002)	Ouse River (Yorkshire, U.K.)	3,500	Nitrate	1986–1990				0.64								
			Ortho P					0.02								
Bouraoui et al. (2004)	Vantaanjoki (Finland); subwatershed	295	Susp. solids	1982–1984		0.49										
			Total N			0.61										
			Total P			0.74										
	Entire watershed	1,682	Nitrate	1974–1998										0.34		
			Total P											0.62		
Bracmort et al. (2006)[c]	Dreisbach and Smith Fry (Indiana)	6.2 and 7.3	Mineral P	C: 1974–1975 V: 1976 to May 1977			0.92 and 0.90	0.84 and 0.78					0.86 and 0.73	0.74 and 0.51		
Cerucci and Conrad (2003)[f]	Townbrook (New York)	36.8	Sediment	Oct. 1999–Sept. 2000			0.70									
			Dissolved P				0.91									
			Particulate P				0.40									
Chaplot et al. (2004)	Walnut Creek	51.3	Nitrate	1991–1998			0.56									
Cheng et al. (2006)	Heihe River (China)	7,241	Sediment	C: 1992–1997 V: 1998–1999			0.70	0.74					0.78	0.76		
			Ammonia	C: 1992–1997 V: 1998–1999			0.75	0.76					0.74	0.72		
Chu et al. (2004)[g]	Warner Creek	3.46	Sediment	Varying periods			0.10	0.05					0.19	0.11	0.91	0.90
			Nitrate				0.27	0.16					0.38	0.36	0.96	0.90
			Ammonium										0.38	–0.05	0.80	0.19
			Total Kjeldahl N										0.40	0.15	0.66	–0.56
			Soluble P				0.39	–0.08					0.65	0.64	0.87	0.80
			Total P										0.38	0.08	0.83	0.19
Cotter et al. (2003)	Moores Creek (Arkansas)	18.9	Sediment	1997–1998				0.48								
			Nitrate					0.44								
			Total P					0.66								
Di Luzio et al. (2002)	Upper North Bosque River (Texas)	932.5	Sediment	Jan. 1993 to July 1998										0.78		
			Organic N											0.60		
			Nitrate											0.60		
			Organic P											0.70		
			Ortho P											0.58		

Table 3 (cont'd). Summary of reported SWAT environmental indicator calibration and validation coefficient of determination (R^2) and Nash-Sutcliffe model efficiency (NSE) statistics.

Reference	Watershed	Drainage Area (km²)[a]	Indicator[b]	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Du et al. (2006)[d],[h],[i]	Walnut Creek (Iowa); subwatershed (site 310) and watershed outlet	51.3	Nitrate (stream flow)	C: 1992-1995 V: 1996-2001 (SWAT2000)		-0.37 and -0.41		-0.21 and -0.26				-0.14 and -0.18		-0.21 and -0.22		
	Subwatershed (site 210)	--	Nitrate (tile flow)	(SWAT2000)		-0.60		-0.08				-0.16		-0.31		
	Subwatershed (site 310) and watershed outlet	51.3	Nitrate (stream flow)	(SWAT-M)[j]		0.61 and 0.53		0.91 and 0.85				0.41 and 0.26		0.80 and 0.67		
	Subwatershed (site 210)	--	Nitrate (tile flow)	(SWAT-M)		0.25		0.73				0.42		0.71		
	Subwatershed (site 310) and watershed outlet	51.3	Atrazine (stream flow)	(SWAT2000)		-0.05 and -0.12		-0.01 and -0.02				-0.02 and -0.39		-0.04 and 0.06		
	Subwatershed (site 210)	--	Atrazine (tile flow)	(SWAT2000)		-0.47		-0.04				-0.46		-0.06		
	Subwatershed (site 310) and watershed outlet	51.3	Atrazine (stream flow)	(SWAT-M)		0.21 and 0.47		0.50 and 0.73				0.12 and -0.41		0.53 and 0.58		
	Subwatershed (site 210)	--	Atrazine (tile flow)	(SWAT-M)		0.51		0.92				0.09		0.31		
Gikas et al. (2005)[d],[k]	Vistonis Lagoon (Greece); nine gauges	1,349	Sediment	C: May 1998 to June 1999 V: Nov. 1999 to Jan. 2000			0.40 to 0.98						0.34 to 0.98			
			Nitrate				0.51 to 0.87						0.57 to 0.89			
			Total P				0.50 to 0.82						0.43 to 0.97			
Grizzetti et al. (2005)[d]	Parts of four watersheds (U.K.); C: one gauge, V: two gauges, annual: 50 gauges	1,380 to 8,900	Nitrate and nitrite	1995-1999		0.24		0.32				0.004 and 0.28		-0.66 and 0.38		0.68
Grizzetti et al. (2003)	Vantaanjoki (Finland); three gauges	295 to 1,682	Total N	Varying periods		0.59						0.43 and 0.51		0.10 and 0.30		
			Total P			0.74						0.54 and 0.44		0.63 and 0.64		
Grunwald and Qi (2006)	Sandusky (Ohio); three gauges	90.3 to 3,240	Suspended sediment	C: 1998-1999 V: 2000-2001				-5.1 to 0.2						-1.0 to 0.02		
			Total P					-0.89 to 0.07						0.08 to 0.45		
			Nitrite					-4.6 to 0.19						-0.16 to 0.48		
			Nitrate					-0.12 to 0.29						-0.1 to 0.57		
			Ammonia					-0.44 to -0.24						-0.44 to -0.21		

Table 3 (cont'd). Summary of reported SWAT environmental indicator calibration and validation coefficient of determination (R^2) and Nash-Sutcliffe model efficiency (NSE) statistics.

					Calibration						Validation					
					Daily		Monthly		Annual		Daily		Monthly		Annual	
Reference	Watershed	Drainage Area (km^2)[a]	Indicator[b]	Time Period (C = calib., V = valid.)	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
Hanratty and Stefan (1998)	Cottonwood (Minnesota)	3,400	Suspended sediment	1967-1991				0.59								
			Nitrate and nitrite					0.68								
			Total P					0.54								
			Organic N and ammonia					0.57								
Hao et al. (2004)	Lushi (China)	4,623	Sediment	C: 1992-1997 V: 1998-1999			0.72	0.72					0.98	0.94		
Jha et al. (2007)[l]	Raccoon River (Iowa)	8,930	Sediment	C: 1981-1992 V: 1993-2003			0.55	0.53	0.97	0.93			0.80	0.78	0.89	0.79
			Nitrate				0.76	0.73	0.83	0.78			0.79	0.78	0.91	0.84
Kang et al. (2006)[k]	Baran (South Korea)	29.8	Suspended solids	C: 1996-1997 V: 1999-2000	0.77	0.70					0.89	0.89				
			Total N		0.84	0.73					0.85	0.65				
			Total P		0.81	0.42					0.85	0.19				
Kaur et al. (2004)	Nagwan (India)	9.58	Sediment	C: 1984 and 1992 V: 1981-1983, 1985-1989, and 1991	0.54	-0.67					0.65	0.70				
Kirsch et al. (2002)	Rock River (Wisconsin); Windsor gauge	190	Sediment	1991-1995					0.82	0.75						
			Total P						0.95	0.07						
Mishra et al. (2007)	Banha (India)	17	Sediment	C: 1996 V: 1997-2001	0.82	0.82	0.99	0.98			0.77	0.58	0.89	0.63		
Muleta and Nicklow (2005a)	Big Creek (Illinois)	86.5	Sediment	1999-2001		0.42										
Muleta and Nicklow (2005b)	Big Creek (Illinois); separate gauges for C and V	23.9 and 86.5	Sediment	C: June 1999 to Aug. 2001 V: Apr. 2000 to Aug. 2001		0.46						-0.005				
Nasr et al. (2007)[c]	Clarianna, Dripsey, and Oona Water (Ireland)	15 to 96	Total P	Varying periods		0.44 to 0.59										
Plus et al. (2006)[d],[m]	Thau Lagoon (France); two gauges	280	Nitrate	1993-1999							0.44 and 0.27					
			Ammonia								0.31 and 0.15					
			Organic N								0.66 and 0.20					
Saleh et al. (2000)[n]	Upper North Bosque River (Texas); C: one gauge, V: 11 gauges	932.5	Sediment	Oct. 1993 to Aug. 1995				0.81						0.94		
			Nitrate					0.27						0.65		
			Organic N					0.78						0.82		
			Total N					0.86						0.97		
			Ortho P					0.94						0.92		
			Particulate P					0.54						0.89		
			Total P					0.83						0.93		

Table 3 (cont'd). Summary of reported SWAT environmental indicator calibration and validation coefficient of determination (R^2) and Nash-Sutcliffe model efficiency (NSE) statistics.

Reference	Watershed	Drainage Area (km^2)[a]	Indicator[b]	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Saleh and Du (2004)	Upper North Bosque River (Texas)	932.5	Total suspended solids	C: Jan. 1994 to June 1995 V: July 1995 to July 1999		−2.5		0.83				−3.5		0.59		
			Nitrate and nitrite			0.04		0.29				0.50		0.50		
			Organic N			−0.07		0.87				0.69		0.77		
			Total N			0.01		0.81				0.68		0.75		
			Ortho P			0.08		0.76				0.45		0.40		
			Particulate P			−0.74		0.59				0.59		0.73		
			Total P			−0.08		0.77				0.63		0.71		
Santhi et al. (2001a)[d],[o]	Bosque River (Texas); two gauges	4,277	Sediment	C: 1993-1997 V: 1998			0.81 and 0.87	0.80 and 0.69					0.98 and 0.95	0.70 and 0.23		
			Mineral N				0.64 and 0.72	0.59 and −0.08					0.89 and 0.72	0.75 and 0.64		
			Organic N				0.61 and 0.60	0.58 and 0.57					0.92 and 0.71	0.73 and 0.43		
			Mineral P				0.60 and 0.66	0.59 and 0.53					0.83 and 0.93	0.53 and 0.81		
			Organic P				0.71 and 0.61	0.70 and 0.59					0.95 and 0.80	0.72 and 0.39		
Stewart et al. (2006)	Upper North Bosque River (Texas)	932.5	Sediment	C: 1994-1999 V: 2001-2002			0.94	0.80					0.82	0.63		
			Mineral N				0.80	0.60					0.57	−0.04		
			Organic N				0.87	0.71					0.89	0.73		
			Mineral P				0.88	0.75					0.82	0.37		
			Organic P				0.85	0.69					0.89	0.58		
Tolson and Shoemaker (2007)[d],[j],[p]	Cannonsville (New York)	37 to 913[q]	Total suspended solids	Varying periods			0.70 (0.47)	0.67 (0.24)			0.42 and 0.83	0.33 and 0.83	0.72 and 0.83	0.52 and 0.76		
			Total dissolved P				0.79 (0.84)	0.78 (0.84)			0.62 and 0.71	0.61 and −5.3	0.93 and 0.89	0.89 and −6.5		
			Particulate P				0.67 (0.50)	0.61 (0.26)			0.37 and 0.85	0.32 and 0.85	0.63 and 0.88	0.48 and 0.79		
			Total P				0.73 (0.58)	0.78 (0.37)			0.43 and 0.87	0.40 and 0.78	0.75 and 0.92	0.63 and 0.92		
Tripathi et al. (2003)	Nagwan (India)	92.5	Sediment	June-Oct. 1997							0.89	0.89	0.89	0.79		
			Nitrate								0.89					
			Organic N								0.82					
			Soluble P								0.82					
			Organic P								0.86					
Vazquez-Amabile et al. (2006)[i]	St. Joseph River (Indiana, Michigan, and Ohio); ten sampling sites	628.2 to 1620	Atrazine	1996-1999		0.14		0.42								
	Main outlet at Fort Wayne, Indiana	2,620	Atrazine	2000-2004							0.27	−0.31	0.59	0.28		

Table 3 (cont'd). Summary of reported SWAT environmental indicator calibration and validation coefficient of determination (R^2) and Nash-Sutcliffe model efficiency (NSE) statistics.

					Calibration						Validation					
		Drainage Area		Time Period (C = calib.,	Daily		Monthly		Annual		Daily		Monthly		Annual	
Reference	Watershed	(km^2)[a]	Indicator[b]	V = valid.)	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
Veith et al. (2005)	Watershed FD-36 (Pennsylvania)	0.395	Sediment	1997-2000			0.04	-0.75								
White and Chaubey (2005)[r],[s]	Beaver Reservoir (Arkansas); three gauges	362 to 1,020	Sediment	C: 2000 or 2001 V: 2001 or 2002			0.45 to 0.85	0.23 to 0.76					0.69 to 0.82	0.32 to 0.85		
			Nitrate and nitrite				0.01 to 0.84	-2.36 to 0.29					0.59 and 0.71	0.13 and 0.49		
			Total P				0.50 to 0.82	0.40 to 0.67					0.58 and 0.76	-0.29 and 0.67		

[a] Based on drainage areas to the gauge(s)/sampling site(s) rather than total watershed area where reported (see footnote [d] for further information).
[b] The reported indicators are listed here as reported in each respective study; the standard SWAT variables for relevant in-stream constituents are: sediment, organic nitrogen (N), organic phosphorus (P), nitrate (NO_3-N), ammonium (NH_4-N), nitrite (NO_2-N), and mineral P (Neitsch et al., 2005b).
[c] Arabi et al. (2006b) and Bracmort et al. (2006) reported the same set of r^2 and NSE statistics for sediment and total P; the calibration time periods were reported by Arabi et al. (2006b), and the validation time periods were inferred from graphical results reported by Bracmort et al. (2006).
[d] Explicit or estimated drainage areas were not reported for some or all of the gauge sites; the total watershed area is listed for those studies that reported it.
[e] The exact time scale of comparison was not explicitly stated and thus was inferred from other information provided.
[f] The statistics reported for sediment and organic P excluded the months of February and March 2000; large underestimations of both constituents occurred in those two months.
[g] The nutrient statistics were based on adjusted flows that accounted for subsurface flows that originated from outside the watershed as reported by Chu and Shirmohammadi (2004); the annual sediment, nitrate, and soluble P statistics were based on the combined calibration and validation periods.
[h] The daily and monthly statistics were based only on the days that sampling occurred.
[i] Other statistics were reported for different time periods, conditions, gauge combinations, and/or variations in selected in input data.
[j] A modified SWAT model was used.
[k] The exact time scale of comparison was not explicitly stated and thus was inferred from other information provided.
[l] A similar set of Raccoon River watershed statistics were reported for slightly different time periods by Secchi et al. (2007).
[m] Specific calibration and/or validation time periods were reported, but the statistics were based on the overall simulated time period (calibration plus validation time periods).
[n] The APEX model (Williams and Izaurralde, 2006) was interfaced with SWAT for this study. The calibration statistics were based on a comparison between simulated and measured flows at the watershed outlet, while the validation statistics were based on a comparison between simulated and measured flows averaged across 11 different gauges.
[o] The calibration and validation statistics were also reported by Santhi et al. (2001b).
[p] The calibration statistics in parentheses include January 1996; an unusually large runoff and erosion event occurred during that month.
[q] As reported by Benamen et al. (2005).
[r] These statistics were computed on the basis of comparisons between simulated and measured data within specific years, rather than across multiple years.
[s] The statistics for the War Eagle Creek subwatershed gauge were also reported by Migliaccio et al. (2007).

(2000) conducted a comprehensive SWAT evaluation for the 932.5 km^2 upper North Bosque River watershed in north central Texas, and found that predicted monthly sediment losses matched measured data well but that SWAT daily output was poor (table 3). Srinivasan et al (1998) concluded that SWAT sediment accumulation predictions were satisfactory for the 279 km^2 Mill Creek watershed, again located in north central Texas. Santhi et al. (2001a) found that SWAT-simulated sediment loads matched measured sediment loads well (table 3) for two Bosque River (4,277 km^2) subwatersheds, except in March. Arnold et al. (1999b) used SWAT to simulate average annual sediment loads for five major Texas river basins (20,593 to 569,000 km^2) and concluded that the SWAT-predicted sediment yields compared reasonably well with estimated sediment yields obtained from rating curves.

Besides Texas, the SWAT sediment yield component has also been tested in several Midwest and northeast U.S. states. Chu et al. (2004) evaluated SWAT sediment prediction for the Warner Creek watershed located in the Piedmont physiographic region of Maryland. Evaluation results indicated strong agreement between yearly measured and SWAT-simulated sediment load, but simulation of monthly sediment loading was poor (table 3). Tolston and Shoemaker (2007) modified the SWAT2000 sediment yield equation to account for both the effects of snow cover and snow runoff depth (the latter is not accounted for in the standard SWAT model) to overcome snowmelt-induced prediction problems identified by Benaman et al. (2005) for the Cannonsville Reservoir watershed in New York. They also reported improved sediment loss predictions (table 3). Jha et al. (2007) found that the sediment loads predicted by SWAT were consistent with sediment loads measured for the Raccoon River watershed in Iowa (table 3). Arabi et al. (2006b) report satisfactory SWAT sediment simulation results for two small watersheds in Indiana (table 3). White and Chaubey (2005) report that SWAT sediment predictions for the Beaver Reservoir watershed in northeast Arkansas (table 3) were satisfactory. Sediment results are also reported by Cotter et al. (2003) for another Arkansas watershed (table 3). Hanratty and Stefan (1998) calibrated SWAT using water quality and quantity data measured in the Cottonwood River in Minnesota (table 3). In Wisconsin, Kirsch et al. (2002) calibrated SWAT annual predictions for two subwatersheds located in the Rock River basin (table 3), which lies within the glaciated portion of south central and eastern Wisconsin. Muleta and Nicklow (2005a) calibrated daily SWAT sediment yield with observed sediment yield data from the Big Creek watershed in southern Illinois and concluded that sediment fit seems reasonable (table 3). However, validation was not conducted due to lack of data.

SWAT sediment simulations have also been evaluated in Asia, Europe, and North Africa. Behera and Panda (2006) concluded that SWAT simulated sediment yield satisfactorily throughout the entire rainy season based on comparisons with daily observed data (table 3) for an agricultural watershed located in eastern India. Kaur et al. (2004) concluded that SWAT predicted annual sediment yields reasonably well for a test watershed (table 3) in Damodar-Barakar, India, the second most seriously eroded area in the world. Tripathi et al. (2003) found that SWAT sediment predictions agreed closely with observed daily sediment yield for the same watershed (table 3). Mishra et al. (2007) found that SWAT accurately replicated the effects of three checkdams on sediment transport (table 3) within the Banha watershed in northeast India. Hao et al. (2004) state that SWAT was the first physically based watershed model validated in China's Yellow River basin. They found that the predicted sediment loading accurately matched loads measured for the 4,623 km^2 Lushi subwatershed (table 3). Cheng et al. (2006) successfully tested SWAT (table 3) using sediment data collected from the 7,241 km^2 Heihe River, another tributary of the Yellow River. In Finland, Bärlund et al. (2007) report poor results for uncalibrated simulations performed within the Lake Pyhäjärvi watershed (table 3). Gikas et al. (2005) conducted an extensive evaluation of SWAT for the Vistonis Lagoon watershed, a mountainous agricultural watershed in northern Greece, and concluded that agreement between observed and SWAT-predicted sediment loads were acceptable (table 3). Bouraoui et al. (2005) evaluated SWAT for the Medjerda River basin in northern Tunisia and reported that the predicted concentrations of suspended sediments were within an order of magnitude of corresponding measured values.

Nitrogen and Phosphorus Studies

Several published studies from the U.S. showed the robustness of SWAT in predicting nutrient losses. Saleh et al. (2000), Saleh and Du (2004), Santhi et al. (2001a), Stewart et al. (2006), and Di Luzio et al. (2002) evaluated SWAT by comparing SWAT nitrogen prediction with measured nitrogen losses in the upper North Bosque River or Bosque River watersheds in Texas. They all concluded that SWAT reasonably predicted nitrogen loss, with most of the average monthly validation NSE values greater than or equal to 0.60 (table 3). Phosphorus losses were also satisfactorily simulated with SWAT in these four studies, with validation NSE values ranging from 0.39 to 0.93 (table 3). Chu et al. (2004) applied SWAT to the Warner Creek watershed in Maryland and reported satisfactory annual but poor monthly nitrogen and phosphorus predictions (table 3). Hanratty and Stefan (1998) calibrated SWAT nitrogen predictions using measured data collected for the Cottonwood River, Minnesota, and concluded that if properly calibrated, SWAT is an appropriate model to use for simulating the effect of climate change on water quality; they also reported satisfactory SWAT phosphorus results (table 3).

In Iowa, Chaplot et al. (2004) calibrated SWAT using nine years of data for the Walnut Creek watershed and concluded that SWAT gave accurate predictions of nitrate load (table 3). Du et al. (2006) showed that the modified tile drainage functions in SWAT-M resulted in far superior nitrate loss predictions for Walnut Creek (table 3), as compared to the previous approach used in SWAT2000. However, Jha et al. (2007) report accurate nitrate loss predictions (table 3) for the Raccoon River watershed in Iowa using SWAT2000. In Arkansas, Cotter et al. (2003) calibrated SWAT with measured nitrate data for the Moores Creek watershed and reported an NSE of 0.44. They state that SWAT's response was similar to that of other published reports.

Bracmort et al. (2006) and Arabi et al. (2006b) found that SWAT could account for the effects of best management practices (BMPs) on phosphorus and nitrogen losses for two small watersheds in Indiana, with monthly validation NSE statistics ranging from 0.37 to 0.79 (table 3). SWAT tended to underpredict both mineral and total phosphorus yields for the months with high measured phosphorus losses, but overpredicted the phosphorus yields for months with low measured losses. Cerucci and Conrad (2003) calibrated SWAT soluble phosphorus predictions using measured data obtained for the Townbrook watershed in New York. They reported monthly NSE values of 0.91 and 0.40, if the measured data from February and March were excluded. Kirsch et al. (2002) reported that SWAT phosphorus loads were considerably higher than corresponding measured loads for the Rock River watershed Wisconsin. Veith et al. (2005) found that SWAT-predicted losses were similar in magnitude to measured watershed exports of dissolved and total phosphorus during a 7-month sampling period from a Pennsylvania watershed.

SWAT nutrient predictions have also been evaluated in several other countries. In India, SWAT N and P predictions were tested using measured data within the Midnapore (Behera and Panda, 2006) and Hazaribagh (Tripathi et al., 2003) districts of eastern India (table 3). Both studies concluded that the SWAT model could be successfully used to satisfactorily simulate nutrient losses. SWAT-predicted ammonia was close to the observed value (table 3) for the Heihe River study in China (Cheng et al., 2006). Three studies conducted in Finland for the Vantaanjoki River (Grizzetti et al. 2003; Bouraoui et al. 2004) and Kerava River (Francos et al., 2001) watersheds reported that SWAT N and P simulations were generally satisfactory. Plus et al. (2006) evaluated SWAT from data on two rivers in the Thau Lagoon watershed, which drains part of the French Mediterranean coast. The best correlations were found for nitrate loads, and the worst for ammonia loads (table 3). Gikas et al. (2005) evaluated SWAT using nine gauges within the Vistonis Lagoon watershed in Greece and found that the monthly validation statistics generally indicated good model performance for nitrate and total P (table 3). SWAT nitrate and total phosphorus predictions were found to be excellent and good, respectively, by Abbaspour et al. (2007) for the 1700 km^2 Thur River basin in Switzerland. Bouraoui et al. (2005) applied SWAT to a part of the Medjerda River basin, the largest surface water reservoir in Tunisia, and reported that SWAT was able to predict the range of nitrate concentrations in surface water, but lack of data prevented in-depth evaluation.

Pesticide and Surfactant Studies

Simulations of isoaxflutole (and its metabolite RPA 202248) were performed by Ramanarayanan et al. (2005) with SWAT for four watersheds in Iowa, Nebraska, and Missouri that ranged in size from 0.49 to 1,434.6 km^2. Satisfactory validation results were obtained based on comparisons with measured data. Long-term simulations indicated that accumulation would not be a problem for either compound in semistatic water bodies. Kannan et al. (2006) report that SWAT accurately simulated movement of four pesticides for the Colworth watershed in the U.K. The results of different application timing and split application scenarios are also described. Two scenarios of surfactant movement are described by Kannan et al. (2007a) for the same watershed. Prediction of atrazine greatly improved using SWAT-M as reported by Du et al. (2006) for the Walnut Creek watershed in Iowa (table 3), which is a heavily tile-drained watershed. Vazquez-Amabile et al. (2006) found that SWAT was very sensitive to the estimated timing of atrazine applications in the 2,800 km^2 St. Joseph River watershed in northeast Indiana. The predicted atrazine mass at the watershed outlet was in close agreement with measured loads for the period of September through April during 2000-2003. Graphical and statistical analyses indicated that the model replicated atrazine movement trends well, but the NSE statistics (e.g., table 3) were generally weak.

Scenarios of BMP and Land Use Impacts on Pollutant Losses

Simulation of hypothetical scenarios in SWAT has proven to be an effective method of evaluating alternative land use, BMP, and other factors on pollutant losses. SWAT studies in India include identification of critical or priority areas for soil and water management in a watershed (Kaur et al., 2004; Tripathi et al., 2003). Santhi et al. (2006) report the impacts of manure and nutrient related BMPs, forage harvest management, and other BMPs on water quality in the West Fork watershed in Texas. The effects of BMPs related to dairy manure management and municipal wastewater treatment plant effluent were evaluated by Santhi et al. (2001b) with SWAT for the Bosque River watershed in Texas. Stewart et al. (2006) describe modifications of SWAT for incorporation of a turfgrass harvest routine, in order to simulate manure and soil P export that occurs during harvest of turfgrass sod within the upper North Bosque River watershed in north central Texas. Kirsch et al. (2002) describe SWAT results showing that improved tillage practices could result in reduced sediment yields of almost 20% in the Rock River in Wisconsin. Chaplot et al. (2004) found that adoption of no tillage, changes in nitrogen application rates, and land use changes could greatly impact nitrogen losses in the Walnut Creek watershed in central Iowa. Analysis of BMPs by Vaché et al. (2002) for the Walnut Creek and Buck Creek watersheds in Iowa indicated that large sediment reductions could be obtained, depending on BMP choice. Bracmort et al. (2006) present the results of three 25-year SWAT scenario simulations for two small watersheds in Indiana in which the impacts of no BMPs, BMPs in good condition, and BMPs in varying condition are reported for streamflow, sediment, and total P. Nelson et al. (2005) report that large nutrient and sediment loss reductions occurred in response to simulated shifts of cropland into switchgrass production within the 3,000 km^2 Delaware River basin in northeast Kansas. Benham et al. (2006) describe a TMDL SWAT application for a watershed in southwest Missouri. Frequency curves comparing simulated and measured bacteria concentrations were used to calibrate SWAT. The model was then used to simulate the contributions of different bacteria sources to the stream system, and to assess the impact of different BMPs that could potentially be used to mitigate bacteria losses in the watershed.

Climate Change Impact Studies

Climate change impacts can be simulated directly in SWAT by accounting for: (1) the effects of increased atmospheric CO_2 concentrations on plant development and transpiration, and (2) changes in climatic inputs. Several SWAT studies provide useful insights regarding the effects of arbitrary CO_2 fertilization changes and/or other climatic input shifts on plant growth, streamflow, and other responses, including Stonefelt et al. (2000), Fontaine et al. (2001), and Jha et al. (2006). The SWAT results reported below focus on approaches that relied on downscaling of climate change projections generated by general circulation models (GCMs) or GCMs coupled with regional climate models (RCMs).

SWAT Studies Reporting Climate Change Impacts on Hydrology

Muttiah and Wurbs (2002) used SWAT to simulate the impacts of historical climate trends versus a 2040-2059 climate change projection for the 7,300 km^2 San Jacinto River basin in Texas. They report that the climate change scenario resulted in a higher mean streamflow due to greater flooding and other high flow increases, but that normal and low streamflows decreased. Gosain et al. (2006) simulated the impacts of a 2041-2060 climate change scenario on the streamflows of 12 major river basins in India, ranging in size from 1,668 to 87,180 km^2. Surface runoff was found to generally decrease, and the severity of both floods and droughts increased, in response to the climate change projection.

Rosenberg et al. (2003) simulated the effect of downscaled HadCM2 GCM (Johns et al., 1997) climate projections on the hydrology of the 18 MWRRs (fig. 2) with SWAT within the HUMUS framework. Water yields were predicted to change from –11% to 153% and from 28% to 342% across the MWRRs in 2030 and 2095, respectively, relative to baseline conditions. Thomson et al. (2003) used the same HadCM2-HUMUS (SWAT) approach and found that three El Niño/Southern Oscillation (ENSO) scenarios resulted in MWRR water yield impacts ranging from –210% to 77% relative to baseline levels, depending on seasonal and dominant weather patterns. An analysis of the impacts of 12 climate change scenarios on the water resources of the 18 MWRRs was performed by Thomson et al. (2005) using the HUMUS approach, as part of a broader study that comprised the entire issue of volume 69 (number 1) of *Climatic Change.* Water yield shifts exceeding $\pm 50\%$ were predicted for portions of Midwest and Southwest U.S., relative to present water yield levels. Rosenberg et al. (1999) found that driving SWAT with a different set of 12 climate projections generally resulted in Ogallala Aquifer recharge decreases (of up to 77%) within the Missouri and Arkansas-White-Red MWRRs (fig. 2).

Stone et al. (2001) predicted climate change impacts on Missouri River basin (fig. 2) water yields by inputting downscaled climate projections into SWAT, which were generated by nesting the RegCM RCM (Giorgi et al., 1998) within the CISRO GCM (Watterson et al., 1997) into the previously described version of SWAT that was modified by Hotchkiss et al. (2000). A structure similar to the HUMUS approach was used, in which 310 8-digit watersheds were used to define the subwatersheds. Water yields declined at the basin outlet by 10% to 20% during the spring and summer months, but increased during the rest of the year. Further research revealed that significant shifts in Missouri River basin water yield impacts were found when SWAT was driven by downscaled

CISRO GCM projections only versus the nested RegCM-CISRO GCM approach (Stone et al., 2003).

Jha et al. (2004b), Takle et al. (2005), and Jha et al. (2006) all report performing GCM-driven studies for the 447,500 km^2 upper Mississippi River basin (fig. 2), with an assumed outlet at Grafton, Illinois, using a framework consisting of 119 8-digit subwatersheds and land use, soil, and topography data that was obtained from BASINS. Jha et al. (2004b) found that streamflows in the upper Mississippi River basin increased by 50% for the period 2040-2049, when climate projections generated by a nested RegCM2-HadCM2 approach were used to drive SWAT. Jha et al. (2006) report that annual average shifts in upper Mississippi River basin streamflows, relative to the baseline, ranged from −6% to 38% for five 2061-2090 GCM projections and increased by 51% for a RegCM-CISRO projection reported by Giorgi et al. (1998). An analysis of driving SWAT with precipitation output generated with nine GCM models indicated that GCM multi-model results may be used to depict 20th century annual streamflows in the upper Mississippi River basin, and that the interface between the single high-resolution GCM used in the study and SWAT resulted in the best replication of observed streamflows (Takle et al., 2005).

Krysanova et al. (2005) report the impacts of 12 different climate scenarios on the hydrologic balance and crop yields of a 30,000 km^2 watershed in the state of Brandenburg in Germany using the SWIM model. Further uncertainty analysis of climate change was performed by Krysanova et al. (2007) for the 100,000 km^2 Elbe River basin in eastern Germany, based on an interface between a downscaled GCM scenario and SWIM. Eckhardt and Ulbrich (2003) found that the spring snowmelt peak would decline, winter flooding would likely increase, and groundwater recharge and streamflow would decrease by as much as 50% in response to two climate change scenarios simulated in SWAT-G. Their approach featured variable stomatal conductance and leaf area responses by incorporating different stomatal conductance decline factors and leaf area index (LAI) values as a function of five main vegetation types; these refinements have not been adopted in the standard SWAT model.

SWAT Studies Reporting Climate Change Impacts on Pollutant Loss

Several studies report climate change impacts on both hydrology and pollutant losses using SWAT, including four that were partially or completely supported by the EU CHESS project (Varanou et al., 2002; Bouraoui et al., 2002; Boorman, 2003; Bouraoui et al., 2004). Nearing et al. (2005) compared runoff and erosion estimates from SWAT versus six other models, in response to six climate change scenarios that were simulated for the 150 km^2 Lucky Hills watershed in southeastern Arizona. The responses of all seven models were similar across the six scenarios for both watersheds, and it was concluded that climate change could potentially result in significant soil erosion increases if necessary conservation efforts are not implemented. Hanratty and Stefan (1998) found that streamflows and P, organic N, nitrate, and sediment yields generally decreased for the 3,400 km^2 Cottonwood River watershed in southwest Minnesota in response to a downscaled $2 \times CO_2$ GCM climate change scenario. Varanou et al. (2002) also found that average streamflows, sediment yields, organic N losses, and nitrate losses decreased in most months in response to nine different climate change scenarios downscaled from three GCMs for the 2,796 km^2 Pinios watershed in Greece. Bouraoui et al. (2002) reported that six different climate change scenarios resulted in increased total nitrogen and phosphorus loads of 6% to 27% and 5% to 34%, respectively, for the 3,500 km^2 Ouse River watershed located in the Yorkshire region of the U.K. Bouraoui et al. (2004) further found for the Vantaanjoki River watershed, which covers 1,682 km^2 in southern Finland, that snow cover decreased, winter runoff increased, and slight increases in annual nutrient losses occurred in response to a 34-year scenario representative of observed climatic changes in the region. Boorman (2003) evaluated the impacts of climate change for five different watersheds located in Italy, France, Finland, and the UK., including the three watersheds analyzed in the Varanou et al. (2002), Bouraoui et al. (2002), and Bouraoui et al. (2004) studies.

Sensitivity, Calibration, and Uncertainty Analyses

Sensitivity, calibration, and uncertainty analyses are vital and interwoven aspects of applying SWAT and other models. Numerous sensitivity analyses have been reported in the SWAT literature, which provide valuable insights regarding which input parameters have the greatest impact on SWAT output. As previously discussed, the vast majority of SWAT applications report some type of calibration effort. SWAT input parameters are physically based and are allowed to vary within a realistic uncertainty range during calibration. Sensitivity analysis and calibration techniques are generally referred to as either manual or automated, and can be evaluated with a wide range of graphical and/or statistical procedures.

Uncertainty is defined by Shirmohammadi et al. (2006) as "the estimated amount by which an observed or calculated value may depart from the true value." They discuss sources of uncertainty in depth and list model algorithms, model calibration and validation data, input variability, and scale as key sources of uncertainty. Several automated uncertainty analyses approaches have been developed, which incorporate various sensitivity and/or calibration techniques, which are briefly reviewed here along with specific sensitivity analysis and calibration studies.

Sensitivity Analyses

Spruill et al. (2000) performed a manual sensitivity/calibration analysis of 15 SWAT input parameters for a 5.5 km^2 watershed with karst characteristics in Kentucky, which showed that saturated hydraulic conductivity, alpha base flow factor, drainage area, channel length, and channel width were the most sensitive parameters that affected streamflow. Arnold et al. (2000) show surface runoff, base flow, recharge, and soil ET sensitivity curves in response to manual variations in the curve number, soil available water capacity, and soil evaporation coefficient (ESCO) input parameters for three different 8-digit watersheds within their upper Mississippi River basin SWAT study. Lenhart et al. (2002) report on the effects of two different sensitivity analysis schemes using SWAT-G for an artificial watershed, in which an alternative approach of varying 44 parameter values within a fixed percentage of the valid parameter range was compared with the more usual method of varying each initial parameter by the same fixed percentage. Both approaches resulted in similar rankings of parameter sensitivity and thus could be considered equivalent.

A two-step sensitivity analysis approach is described by Francos et al. (2003), which consists of: (1) a "Morris" screening procedure that is based on the one factor at a time (OAT) design, and (2) the use of a Fourier amplitude sensitivity test (FAST) method. The screening procedure is used to determine the qualitative ranking of an entire input parameter set for different model outputs at low computational cost, while the FAST method provides an assessment of the most relevant input parameters for a specific set of model output. The approach is demonstrated with SWAT for the 3,500 km^2 Ouse watershed in the U.K. using 82 input and 22 output parameters. Holvoet et al. (2005) present the use of a Latin hypercube (LH) OAT sampling method, in which initial LH samples serve as the points for the OAT design. The method was used for determining which of 27 SWAT hydrologic-related input parameters were the most sensitive regarding streamflow and atrazine outputs for 32 km^2 Nil watershed in central Belgium. The LH-OAT method was also used by van Griensven et al. (2006b) for an assessment of the sensitivity of 41 input parameters on SWAT flow, sediment, total N, and total P estimates for both the UNBRW and the 3,240 km^2 Sandusky River watershed in Ohio. The results show that some parameters, such as the curve number (CN2), were important in both watersheds, but that there were distinct differences in the influences of other parameters between the two watersheds. The LH-OAT method has been incorporated as part of the automatic sensitivity/calibration package included in SWAT2005.

Calibration Approaches

The manual calibration approach requires the user to compare measured and simulated values, and then to use expert judgment to determine which variables to adjust, how much to adjust them, and ultimately assess when reasonable results have been obtained. Coffey et al. (2004) present nearly 20 different statistical tests that can be used for evaluating SWAT streamflow output during a manual calibration process. They recommended using the NSE and R^2 coefficients for analyzing monthly output and median objective functions, sign test, autocorrelation, and cross-correlation for assessing daily output, based on comparisons of SWAT streamflow results with measured streamflows (table 2) for the same watershed studied by Spruill et al. (2000). Cao et al. (2006) present a flowchart of their manual calibration approach that was used to calibrate SWAT based on five hydrologic outputs and multiple gauge sites within the 2075 km^2 Motueka River basin on the South Island of New Zealand. The calibration and validation results were stronger for the overall basin as compared to results obtained for six subwatersheds (table 2). Santhi et al. (2001a) successfully calibrated and validated SWAT for streamflow and pollutant loss simulations (tables 2 and 3) for the 4,277 km^2 Bosque River in Texas. They present a general procedure, including a flowchart, for manual calibration that identifies sensitive input parameters (15 were used), realistic uncertainty ranges, and reasonable regression results (i.e., satisfactory r^2 and NSE values). A combined sensitivity and calibration approach is described by White and Chaubey (2005) for SWAT streamflow and pollutant loss estimates (tables 2 and 3) for the 3,100 km^2 Bear Reservoir watershed, and three subwatersheds, in northwest Arkansas. They also review calibration approaches, including calibrated input parameters, for previous SWAT studies.

Automated techniques involve the use of Monte Carlo or other parameter estimation schemes that determine automatically what the best choice of values are for a suite of parameters, usually on the basis of a large set of simulations, for a calibration process. Govender and Everson (2005) used the automatic Parameter Estimation (PEST) program (Doherty, 2004) and identified soil moisture variables, initial groundwater variables, and runoff curve numbers to be some of the sensitive parameters in SWAT applications for two small South African watersheds. They also report that manual calibration resulted in more accurate predictions than the PEST approach (table 2). Wang and Melesse (2005) also used PEST to perform an automatic SWAT calibration of three snowmelt-related and eight hydrologic-related parameters for the 4,335 km^2 Wild Rice River watershed in northwest Minnesota, which included daily and monthly statistical evaluation (table 2).

Applications of an automatic shuffled complex evolution (SCE) optimization scheme are described by van Griensven and Bauwens (2003, 2005) for ESWAT simulations, primarily for the Dender River in Belgium. Calibration parameters and ranges along with measured daily flow and pollutant data are input for each application. The automated calibration scheme executes up to several thousand model runs to find the optimum input data set. Similar automatic calibration studies were performed with a SCE algorithm and SWAT-G by Eckhardt and Arnold (2001) and Eckhardt et al. (2005) for watersheds in Germany. Di Luzio and Arnold (2004) described the background, formulation and results (table 2) of an hourly SCE input-output calibration approach used for a SWAT application in Oklahoma. Van Liew et al. (2005) describe an initial test of the SCE automatic approach that has been incorporated into SWAT2005, for streamflow predictions for the Little River watershed in Georgia and the Little Washita River watershed in Oklahoma. Van Liew et al. (2007) further evaluated the SCE algorithm for five watersheds with widely varying climatic characteristics (table 2), including the same two in Georgia and Oklahoma and three others located in Arizona, Idaho, and Pennsylvania.

Uncertainty Analyses

Shirmohammadi et al. (2006) state that Monte Carlo simulation and first-order error or approximation (FOE or FOA) analyses are the two most common approaches for performing uncertainty analyses, and that other methods have been used, including the mean value first-order reliability method, LH simulation with constrained Monte Carlo simulations, and generalized likelihood uncertainty estimation (GLUE). They present three case studies of uncertainty analyses using SWAT, which were based on the Monte Carlo, LH-Monte Carlo, and GLUE approaches, respectively, within the context of TMDL assessments. They report that uncertainty is a major issue for TMDL assessments, and that it should be taken into account during both the TMDL assessment and implementation phases. They also make recommendations to improve the quantification of uncertainty in the TMDL process.

Benaman and Shoemaker (2004) developed a six-step method that includes using Monte Carlo runs and an interval-spaced sensitivity approach to reduce uncertain parameter ranges. After parameter range reduction, their method reduced the model output range by an order of magnitude, resulting in reduced uncertainty and the amount of calibration required for SWAT.

However, significant uncertainty remained with the SWAT sediment routine. Lin and Radcliffe (2006) performed an initial two-stage automatic calibration streamflow prediction process with SWAT for the 1,580 km^2 Etowah River watershed in Georgia in which an SCE algorithm was used for automatic calibration of lumped SWAT input parameters, followed by calibration of heterogeneous inputs with a variant of the Marquardt-Levenberg method in which "regularization" was used to prevent parameters taking on unrealistic values. They then performed a nonlinear calibration and uncertainty analysis using PEST, in which confidence intervals were generated for annual and 7-day streamflow estimates. Their resulting calibrated statistics are shown in table 2. Muleta and Nicklow (2005b) describe a study for the Big Creek watershed that involved three phases: (1) parameter sensitivity analysis for 35 input parameters, in which LH samples were used to reduce the number of Monte Carlo simulations needed to conduct the analysis; (2) automatic calibration using a genetic algorithm, which systematically determined the best set of input parameters using a sum of the square of differences criterion; and (3) a Monte Carlo-based GLUE approach for the uncertainty analysis, in which LH sampling is again used to generate input samples and reduce the computation requirements. Uncertainty bounds corresponding to the 95% confidence limit are reported for both streamflow and sediment loss, as well as final calibrated statistics (tables 2 and 3). Arabi et al. (2007b) used a three-step procedure that included OAT and interval-spaced sensitivity analyses, and a GLUE analysis to assess uncertainty of SWAT water quality predictions of BMP placement in the Dreisbach and Smith Fry watersheds in Indiana. Their results point to the need for site-specific calibration of some SWAT inputs, and that BMP effectiveness could be evaluated with enough confidence to justify using the model for TMDL and similar assessments.

Additional uncertainty analysis insights are provided by Vanderberghe et al. (2007) for an ESWAT-based study and by Huisman et al. (2004) and Eckhardt et al. (2003), who assessed the uncertainty of soil and/or land use parameter variations on SWAT-G output using Monte Carlo-based approaches. Van Greinsven and Meixner (2006) describe several uncertainty analysis tools that have been incorporated into SWAT2005, including a modified SCE algorithm called "parameter solutions" (ParaSol), the Sources of Uncertainty Global Assessment using Split Samples (SUNGLASSES), and the Confidence Analysis of Physical Inputs (CANOPI), which evaluates uncertainty associated with climatic data and other inputs.

Effects of HRU and Subwatershed Delineation and Other Inputs on SWAT Output

Several studies have been performed that analyzed impacts on SWAT output as a function of: (1) variation in HRU and/or subwatershed delineations, (2) different resolutions in topographic, soil, and/or land use data, (3) effects of spatial and temporal transfers of inputs, (4) actual and/or hypothetical shifts in land use, and (5) variations in precipitation inputs or ET estimates. These studies serve as further SWAT sensitivity analyses and provide insight into how the model responds to variations in key inputs.

HRU and Subwatershed Delineation Effects

Bingner et al. (1997), Manguerra and Engel (1998), FitzHugh and Mackay (2000), Jha et al. (2004a), Chen and Mackay (2004), Tripathi et al. (2006), and Muleta et al. (2007) found that SWAT streamflow predictions were generally insensitive to variations in HRU and/or subwatershed delineations for watersheds ranging in size from 21.3 to 17,941 km^2. Tripathi et al. (2006) and Muleta et al. (2007) further discuss HRU and subwatershed delineation impacts on other hydrologic components. Haverkamp et al. (2002) report that streamflow accuracy was much greater when using multiple HRUs to characterize each subwatershed, as opposed to using just a single dominant soil type and land use within a subwatershed, for two watersheds in Germany and one in Texas. However, the gap in accuracy between the two approaches decreased with increasing numbers of subwatersheds.

Bingner et al. (1997) report that the number of simulated subwatersheds affected predicted sediment yield and suggest that sensitivity analyses should be performed to determine the appropriate level of subwatersheds. Jha et al. (2004a) found that SWAT sediment and nitrate predictions were sensitive to variations in both HRUs and subwatersheds, but mineral P estimates were not. The effects of BMPS on SWAT sediment, total P, and total N estimates was also found by Arabi et al. (2006b) to be very sensitive to watershed subdivision level. Jha et al. (2004a) suggest setting subwatershed areas ranging from 2% to 5% of the overall watershed area, depending on the output indicator of interest, to ensure accuracy of estimates. Arabi et al. (2006b) found that an average subwatershed equal to about 4% of the overall watershed area was required to accurately account for the impacts of BMPs in the model.

FitzHugh and Mackay (2000, 2001) and Chen and Mackay (2004) found that sediment losses predicted with SWAT did not vary at the outlet of the 47.3 km^2 Pheasant Branch watershed in south central Wisconsin as a function of increasing numbers of HRUs and subwatersheds due to the transport-limited nature of the watershed. However, sediment generation at the HRU level dropped 44% from the coarsest to the finest resolutions (FitzHugh and Mackay, 2000), and sediment yields varied at the watershed outlet for hypothetical source-limited versus transport-limited scenarios (FitzHugh and Mackay, 2001) in response to eight different HRU/subwatershed combinations used in both studies. Chen and Mackay (2004) further found that SWAT's structure influences sediment predictions in tandem with spatial data aggregation effects. They suggest that errors in MUSLE sediment estimates can be avoided by using only subwatersheds, instead of using HRUs, within subwatersheds.

In contrast, Muleta et al. (2007) found that sediment generated at the HRU level and exported from the outlet of the 133 km^2 Big Creek watershed in Illinois decreased with increasing spatial coarseness, and that sediment yield varied significantly at the watershed outlet across a range of HRU and subwatershed delineations, even when the channel properties remained virtually constant.

DEM, Soil, and Land Use Resolution Effects

Bosch et al. (2004) found that SWAT streamflow estimates for a 22.1 km^2 subwatershed of the Little River watershed in Georgia were more accurate using high-resolution topographic, land use, and soil data versus low-resolution data obtained from BASINS. Cotter et al. (2003) report that DEM resolution was the most critical input for a SWAT simulation of the 18.9 km^2 Moores Creek watershed in Arkansas, and provide minimum DEM, land use, and soil resolution recommendations to obtain accurate flow, sediment, nitrate, and total P estimates. Di Luzio et al. (2005) also found that DEM resolution was the most critical for SWAT simulations of the 21.3 km^2 Goodwin Creek watershed in Mississippi; land use resolution effects were also significant, but the resolution of soil inputs was not. Chaplot (2005) found that SWAT surface runoff estimates were sensitive to DEM mesh size, and that nitrate and sediment predictions were sensitive to both the choice of DEM and soil map resolution, for the Walnut Creek watershed in central Iowa. The most accurate results did not occur for the finest DEM mesh sizes, contrary to expectations. Di Luzio et al. (2004b) and Wang and Melesse (2006) present additional results describing the impacts of STATSGO versus SSURGO soil data inputs on SWAT output.

Effects of Different Spatial and Temporal Transfers of Inputs

Heuvelmans et al. (2004a) evaluated the effects of transferring seven calibrated SWAT hydrologic input parameters, which were selected on the basis of a sensitivity analysis, in both time and space for three watersheds ranging in size from 51 to 204 km^2 in northern Belgium. Spatial transfers resulted in the greatest loss of streamflow efficiency, especially between watersheds. Heuvelmans et al. (2004b) further evaluated the effect of four parameterization schemes on SWAT streamflow predictions, for the same set of seven hydrologic inputs, for 25 watersheds that covered 2.2 to 210 km^2 within the 20,000 km^2 Scheldt River basin in northern Belgium. The highest model efficiencies were achieved when optimal parameters for each individual watershed were used; optimal parameters selected on the basis of regional zones with similar characteristics proved superior to parameters that were averaged across all 25 watersheds.

Historical and Hypothetical Land Use Effects

Miller et al. (2002) describe simulated streamflow impacts with SWAT in response to historical land use shifts in the 3,150 km^2 San Pedro watershed in southern Arizona and the Cannonsville watershed in south central New York. Streamflows were predicted to increase in the San Pedro watershed due to increased urban and agricultural land use, while a shift from agricultural to forest land use was predicted to result in a 4% streamflow decrease in the Cannonsville watershed. Hernandez et al. (2000) further found that SWAT could accurately predict the relative impacts of hypothetical land use change in an 8.2 km^2 experimental subwatershed within the San Pedro watershed. Heuvelmans et al. (2005) report that SWAT produced reasonable streamflow and erosion estimates for hypothetical land use shifts, which were performed as part of a life cycle assessment (LCA) of CO_2 emission reduction scenarios for the 29.2 km^2 Meerdaal watershed and the 12.1 km^2 Latem watersheds in northern Belgium. However, they state that an expansion of the SWAT vegetation parameter dataset is needed in order to fully support LCA analyses. Increased streamflow was predicted with SWAT for the 59.8 km^2 Aar watershed in the German state of Hessen, in response to a grassland incentive scenario in which the grassland area increased from 20% to 41% while the extent forest coverage decreased by about 70% (Weber et al., 2001). The impacts of hypothetical forest and other land use changes on total runoff using SWAT are presented by Lorz et al. (2007) in the context of comparisons with three other models. The impacts of other hypothetical land use studies for various German watersheds have been reported on hydrologic impacts with SWAT-G (e.g., Fohrer et al., 2002, 2005) and SWIM (Krysanova et al., 2005) and on nutrient and sediment loss predictions with SWAT-G (Lenhart et al., 2003).

Climate Data Effects

Chaplot et al. (2005) analyzed the effects of rain gauge distribution on SWAT output by simulating the impacts of climatic inputs for a range of 1 to 15 rain gauges in both the Walnut Creek watershed in central Iowa and the upper North Bosque River watershed in Texas. Sediment predictions improved significantly when the densest rain gauge networks were used; only slight improvements occurred for the corresponding surface runoff and nitrogen predictions. However, Hernandez et al. (2000) found that increasing the number of simulated rain gauges from 1 to 10 resulted in clear estimated streamflow improvements (table 2). Moon et al. (2004) found that SWAT's streamflow estimates improved when Next-Generation Weather Radar (NEXRAD) precipitation input was used instead of rain gauge inputs (table 2). Kalin and Hantush (2006) report that NEXRAD and rain gauge inputs resulted in similar streamflow estimates at the outlet of the Pocono Creek watershed in Pennsylvania (table 2), and that NEXRAD data appear to be a promising source of alternative precipitation data. A weather generator developed by Schuol and Abbaspour (2007) that uses climatic data available at 0.5° intervals was found to result in better streamflow estimates than rain gauge data for a region covering about 4 million km^2 in western Africa that includes the Niger, Volta, and Senegal river basins. Sensitivity of precipitation inputs on SWAT hydrologic output are reported for comparisons of different weather generators by Harmel et al. (2000) and Watson et al. (2005). The effects of different ET options available in SWAT on streamflow estimates are further described by Wang et al. (2006) and Kannan et al. (2007b).

Comparisons of SWAT with Other Models

Borah and Bera (2003, 2004) compared SWAT with several other watershed-scale models. In the 2003 study, they report that the Dynamic Watershed Simulation Model (DWSM) (Borah et al., 2004), Hydrologic Simulation Program – Fortran (HSPF) model (Bicknell et al., 1997), SWAT, and other models have hydrology, sediment, and chemical routines applicable to watershed-scale catchments and concluded that SWAT is a promising model for continuous simulations in predominantly agricultural watersheds. In the 2004 study, they found that SWAT and HSPF could predict yearly flow volumes and pollutant losses, were adequate for monthly predictions except for months having extreme storm events and hydrologic conditions, and were poor in simulating daily extreme flow events. In contrast, DWSM reasonably predicted distributed flow hydrographs and concentration or discharge graphs of sediment and chemicals at small time intervals. Shepherd et al. (1999) evaluated 14 models and found SWAT to be the most suitable for estimating phosphorus loss from a lowland watershed in the U.K.

Van Liew et al. (2003a) compared the streamflow predictions of SWAT and HSPF on eight nested agricultural watersheds within the Little Washita River basin in south-western Oklahoma. They concluded that SWAT was more consistent than HSPF in estimating streamflow for different climatic conditions and may thus be better suited for investigating the long-term impacts of climate variability on surface water resources. Saleh and Du (2004) found that the average daily flow, sediment loads, and nutrient loads simulated by SWAT were closer than HSPF to measured values collected at five sites during both the calibration and verification periods for the upper North Bosque River watershed in Texas. Singh et al. (2005) found that SWAT flow predictions were slightly better than corresponding HSPF estimates for the 5,568 km^2 Iroquois River watershed in eastern Illinois and western Indiana, primarily due to better simulation of low flows by SWAT. Nasr et al. (2007) found that HSPF predicted mean daily discharge most accurately, while SWAT simulated daily total phosphorus loads the best, in a comparison of three models for three Irish watersheds that ranged in size from 15 to 96 km^2. El-Nasr et al. (2005) found that both SWAT and the MIKE-SHE model (Refsgaard and Storm, 1995) simulated the hydrology of Belgium's Jeker River basin in an acceptable way. However, MIKE-SHE predicted the overall variation of river flow slightly better.

Srinivasan et al. (2005) found that SWAT estimated flow more accurately than the Soil Moisture Distribution and Routing (SMDR) model (Cornell, 2003) for 39.5 ha FD-36 experimental watershed in east central Pennsylvania, and that SWAT was also more accurate on a seasonal basis. SWAT estimates were also found to be similar to measured dissolved and total P for the same watershed, and 73% of the 22 fields in the watershed were categorized similarly on the basis of the SWAT analysis as compared to the Pennsylvania P index (Veith et al., 2005). Grizzetti et al. (2005) reported that both SWAT and a statistical approach based on the SPARROW model (Smith et al., 1997) resulted in similar total oxidized nitrogen loads for two monitoring sites within the 1,380 km^2 Great Ouse watershed in the U.K. They also state that the statistical reliability of the two approaches was similar, and that the statistical model should be viewed primarily as a screening tool while SWAT is more useful for scenarios. Srivastava et al. (2006) found that an artificial neural network (ANN) model was more accurate than SWAT for streamflow simulations of a small watershed in southeast Pennsylvania.

Interfaces of SWAT with Other Models

Innovative applications have been performed by interfacing SWAT with other environmental and/or economic models. These interfaces have expanded the range of scenarios that can be analyzed and allowed for more in-depth assessments of questions that cannot be considered with SWAT by itself, such as groundwater withdrawal impacts or the costs incurred from different choices of management practices.

SWAT with MODFLOW and/or Surface Water Models

Sophocleus et al. (1999) describe an interface between SWAT and the MODFLOW groundwater model (McDonald and Harbaugh, 1988) called SWATMOD, which they used to evaluate water rights and withdrawal rate management scenarios on stream and aquifer responses for the Rattlesnake Creek watershed in south central Kansas. The system was used by Sophocleus and Perkins (2000) to investigate irrigation effects on streamflow and groundwater levels in the lower Republican River watershed in north central Kansas and on streamflow and groundwater declines within the Rattlesnake Creek watershed. Perkins and Sophocleous (1999) describe drought impact analyses with the same system. SWAT was coupled with MODFLOW to study for the 12 km^2 Coët-Dan watershed in Brittany, France (Conan et al., 2003a). Accurate results were reported, with respective monthly NSE values for streamflow and nitrate of 0.88 and 0.87.

Menking et al. (2003) interfaced SWAT with both MODFLOW and the MODFLOW LAK2 lake modeling package to assess how current climate conditions would impact water levels in ancient Lake Estancia (central New Mexico), which existed during the late Pleistocene era. The results indicated that current net inflow from the 5,000 km^2 drainage basin would have to increase by about a factor of 15 to maintain typical Late Pleistocene lake levels. Additional analyses of Lake Estancia were performed by Menking et al. (2004) for the Last Glacial Maximum period. SWAT was interfaced with a 3-D lagoon model by Plus et al. (2006) to determine nitrogen loads from a 280 km^2 drainage area into the Thau Lagoon, which lies along the south coast of France. The main annual nitrogen load was estimated with SWAT to be 117 t year^{-1}; chlorophyll a concentrations, phytoplankton production, and related analyses were performed with the lagoon model. Galbiati et al. (2006) interfaced SWAT with QUAL2E, MODFLOW, and another model to create the Integrated Surface and Subsurface model (ISSm). They found that the system accurately predicted water and nutrient interactions between the stream system and aquifer, groundwater dynamics, and surface water and nutrient fluxes at the watershed outlet for the 20 km^2 Bonello coastal watershed in northern Italy.

SWAT with Environmental Models or Genetic Algorithms for BMP Analyses

Renschler and Lee (2005) linked SWAT with the Water Erosion Prediction Project (WEPP) model (Ascough et al., 1997) to evaluate both short- and long-term assessments, for pre- and post-implementation, of grassed waterways and field borders for three experimental watersheds ranging in size from 0.66 to 5.11 ha. SWAT was linked directly to the Geospatial Interface for WEPP (GeoWEPP), which facilitated injection of WEPP output as point sources into SWAT. The long-term assessment results were similar to SWAT-only evaluations, but the short-term results were not. Cerucci and Conrad (2003) determined the optimal riparian buffer configurations for 31 subwatersheds in the 37 km^2 Town Brook watershed in south central New York, by using a binary optimization approach and interfacing SWAT with the Riparian Ecosystem Model (REMM) (Lowrance et al., 2000). They determined the marginal utility of buffer widths and the most affordable parcels in which to establish riparian buffers. Pohlert et al. (2006) describe SWAT-N, which was created by extending the original SWAT2000 nitrogen cycling routine primarily with algorithms from the Denitrification-Decomposition (DNDC) model (Li et al., 1992). They state that SWAT-N was able to replicate nitrogen cycling and loss processes more accurately than SWAT.

Muleta and Nicklow (2005a) interfaced SWAT with a genetic algorithm and a multiobjective evolutionary algorithm to perform both single and multiobjective evaluations for the 130 km^2 Big Creek watershed in southern Illinois. They found that conversion of 10% of the HRUs into conservation programs (cropping system/tillage practice BMPs), within a maximum of 50 genetic algorithm generations, would result in reduced sediment yield of 19%. Gitau et al. (2004) interfaced baseline P estimates from SWAT with a genetic algorithm and a BMP tool containing site-specific BMP effectiveness estimates to determine the optimal on-farm placement of BMPs so that P losses and costs were both minimized. The two most efficient scenarios met the target of reducing dissolved P loss by at least 60%, with corresponding farm-level cost increases of $1,430 and $1,683, respectively, relative to the baseline. SWAT was interfaced with an economic model, a BMP tool, and a genetic algorithm by Arabi et al. (2006a) to determine optimal placement for the Dreisbach and Smith Fry watersheds in Indiana. The optimization approach was found to be three times more cost-effective as compared to environmental targeting strategies.

SWAT with Economic and/or Environmental Models

A farm economic model was interfaced with the Agricultural Policy Extender (APEX) model (Williams and Izaurralde, 2006) and SWAT to simulated the economic and environmental impacts of manure management scenarios and other BMPs for the 932.5 km^2 upper North Bosque River and 1,279 km^2 Lake Fork Reservoir watersheds in Texas and the 162.2 km^2 upper Maquoketa River watershed in Iowa (Gassman et al., 2002). The economic and environmental impacts of several manure application rate scenarios are described for each watershed, as well as for manure haul-off, intensive rotational grazing, and reduced fertilizer scenarios that were simulated for the upper North Bosque River watershed, Lake Fork Reservoir watershed, and upper Maquoketa River watershed, respectively. Osei et al. (2003) report additional stocking density scenario results for pasture-based dairy productions in the Lake Fork Reservoir watershed. They concluded that appropriate pasture nutrient management, including stocking density adjustments and more efficient application of commercial fertilizer, could lead to significant reductions in nutrient losses in the Lake Fork Reservoir watershed. Gassman et al. (2006) further assessed the impacts of seven individual BMPs and four BMP combinations for upper Maquoketa River watershed. Terraces were predicted to be very effective in reducing sediment and organic nutrient losses but were also the most expensive practice, while no-till or contouring in combination with reduced fertilizer rates were predicted to result in reductions of all pollutant indictors and also positive net returns.

Lemberg et al. (2002) evaluated the economic impacts of brush control in the Frio River basin in south central Texas using SWAT, the Phytomass Growth Simulator (PHYGROW) model (Rowan, 1995), and two economic models. It was determined that subsidies on brush control would not be worthwhile. Economic evaluations of riparian buffer benefits in regards to reducing atrazine concentration and other factors were performed by Qiu and Prato (1998) using SWAT, a budget generator, and an economic model for the 77.4 km^2 Goodwater Creek watershed in north central Missouri (riparian buffers were not directly simulated). The implementation of riparian buffers was found to result in substantial net economic return and savings in government costs, due to reduced CRP rental payments. Qiu (2005) used a similar approach for the same watershed to evaluate the economic and environmental impacts of five different alternative scenarios. SWAT was interfaced with a data envelope analysis linear programming model by Whittaker et al. (2003) to determine which of two policies would be most effective in reducing N losses to streams in the 259,000 km^2 Columbia Plateau region in the northwest U.S. The analysis indicated that a 300% tax on N fertilizer would be more efficient than a mandated 25% reduction in N use. Evaluation of different policies were demonstrated by Attwood et al. (2000) by showing economic and environmental impacts at the U.S. national scale and for Texas by linking SWAT with an agricultural sector model. Volk et al. (2007) and Turpin et al. (2005) describe respective modeling systems that include interfaces between SWAT, an economic model, and other models and data to simulate different watershed scales and conditions in European watersheds.

SWAT with Ecological and Other Models

Weber et al. (2001) interfaced SWAT with the ecological model ELLA and the Proland economic model to investigate the streamflow and habitat impacts of a "grassland incentive scenario" that resulted in grassland area increasing from 21% to 40%, and forest area declining by almost 70%, within the 59.8 km^2 Aar watershed in Germany. SWAT-predicted streamflow increased while Skylark bird habitat decreased in response to the scenario. Fohrer et al. (2002) used SWAT-G, the YELL ecological model, and the Proland to assess the effects of land use changes and associated hydrologic impacts on habitat suitability for the Yellowhammer bird species. The authors report effects of four average field size scenarios (0.5, 0.75, 1.0, and 2.0 ha) on land use, bird nest distribution and habitat, labor and agricultural value, and hydrological response. SWAT is also being used to simulate crop growth, hydrologic balance, soil erosion, and other environmental responses by Christiansen and Altaweel (2006) within the ENKIMDU modeling framework (named after the ancient Sumerian god of agriculture and irrigation), which is being used to study the natural and societal aspects of Bronze Age Mesopotamian cultures.

SWAT Strengths, Weaknesses, and Research Needs

The worldwide application of SWAT reveals that it is a versatile model that can be used to integrate multiple environmental processes, which support more effective watershed management and the development of better-informed policy decisions. The model will continue to evolve as users determine needed improvements that: (1) will enable more accurate simulation of currently supported processes, (2) incorporate advancements in scientific knowledge, or (3) provide new functionality that will expand the SWAT simulation domain. This process is aided by the open-source status of the SWAT code and ongoing encouragement of collaborating scientists to pursue needed model development, as demonstrated by a forthcoming set of papers in *Hydrological Sciences Journal* describing various SWAT research needs that were identified at the 2006 Model Developer's Workshop held in Potsdam, Germany. The model has also been included in the Collaborative Software Development Laboratory that facilitates development by multiple scientists (CoLab, 2006).

The foundational strength of SWAT is the combination of upland and channel processes that are incorporated into one simulation package. However, every one of these processes is a simplification of reality and thus subject to the need for improvement. To some degree, the strengths that facilitate widespread use of SWAT also represent weaknesses that need further refinement, such as simplified representations of HRUs. There are also problems in depicting some processes accurately due to a lack of sufficient monitoring data, inadequate data needed to characterize input parameters, or insufficient scientific understanding. The strengths and weaknesses of five components are discussed here in more detail, including possible courses of action for improving current routines in the model. The discussion is framed to some degree from the perspective of emerging applications, e.g., bacteria die-off and transport. Additional research needs are also briefly listed for other components, again in the context of emerging application trends where applicable.

Hydrologic Interface

The use of the NRCS curve number method in SWAT has provided a relatively easy way of adapting the model to a wide variety of hydrologic conditions. The technique has proved successful for many applications, as evidenced by the results reported in this study. However, the embrace of the method in SWAT and similar models has proved controversial due to the empirical nature of the approach, lack of complete historical documentation, poor results obtained for some conditions, inadequate representation of "critical source areas" that generate pollutant loss (which can occur even after satisfactory hydrologic calibration of the model), and other factors (e.g., Ponce and Hawkins, 1996; Agnew et al., 2006; Bryant et al., 2006; Garen and Moore, 2005).

The Green-Ampt method provides an alternative option in SWAT, which was found by Rawls and Brakenseik (1986) to be more accurate than the curve number method and also to account for the effects of management practices on soil properties in a more rational manner. However, the previously discussed King et al. (1999) and Kannan et al. (2007b) SWAT applications did not find any advantage to using the Green-Ampt approach, as compared to the curve number method. These results lend support to the viewpoint expressed by Ponce and Hawkins (1996) that alternative point infiltration techniques, including the Green-Ampt method, have not shown a clear superiority to the curve number method.

Improved SWAT hydrologic predictions could potentially be obtained through modifications in the curve number methodology and/or incorporation of more complex routines. Borah et al. (2007) propose inserting a combined curve number-kinematic wave methodology used in DWSM into SWAT, which was found to result in improved simulation of daily runoff volumes for the 8,400 km^2 Little Wabash River watershed in Illinois. Bryant et al. (2006) propose modifications of the curve number initial abstraction term, as a function of soil physical characteristics and management practices, that could result in more accurate simulation of extreme (low and high) runoff events. Model and/or data input modifications would be needed to address phenomena such as variable source area (VSA) saturated excess runoff, which dominants runoff in some regions including the northeast U.S., where downslope VSA saturated discharge often occurs due to subsurface interflow over relatively impermeable material (Agnew et al., 2006; Walter et al., 2000). Steenhuis (2007) has developed a method of reclassifying soil types and associated curve numbers that provides a more accurate accounting of VSA-driven runoff and pollutant loss for a small watershed in New York. The modified SWAT model described by Watson et al. (2005), which accounts for VSA–dominated hydrology in southwest Victoria, Australia, by incorporating a saturated excess runoff routine in SWAT, may also provide useful insights.

Hydrologic Response Units (HRUs)

The incorporation of nonspatial HRUs in SWAT has supported adaptation of the model to virtually any watershed, ranging in size from field plots to entire river basins. The fact that the HRUs are not landscape dependent has kept the model simple while allowing soil and land use heterogeneity to be accounted for within each subwatershed. At the same time, the nonspatial aspect of the HRUs is a key weakness of the model. This approach ignores flow and pollutant routing within a subwatershed, thus treating the impact of pollutant losses identically from all landscape positions within a subwatershed. Thus, potential pollutant attenuation between the source area and a stream is also ignored, as discussed by Bryant et al. (2006) for phosphorus movement. Explicit spatial representation of riparian buffer zones, wetlands, and other BMPs is also not possible with the current SWAT HRU approach, as well as the ability to account for targeted placement of grassland or other land use within a given subwatershed. Incorporation of greater spatial detail into SWAT is being explored with the initial focus on developing routing capabilities between distinct spatially defined landscapes (Volk et al., 2005), which could be further subdivided into HRUs.

Simulation of BMPs

A key strength of SWAT is a flexible framework that allows the simulation of a wide variety of conservation practices and other BMPs, such as fertilizer and manure application rate and timing, cover crops (perennial grasses), filter strips, conservation tillage, irrigation management, flood-prevention structures, grassed waterways, and wetlands. The majority of conservation practices can be simulated in SWAT with straightforward parameter changes. Arabi et al. (2007a) have proposed standardized approaches for simulating specific conservation practices in the model, including adjustment of the parameters listed in table 4. Filter strips and field borders can be simulated at the HRU level, based on empirical functions that account for filter strip trapping effects of bacteria or sediment, nutrients, and pesticides (which are invoked when the filter strip width parameter is set input to the model). However, assessments of targeted filter strip placements within a watershed are limited, due to the lack of HRU spatial definition in SWAT. There are also further limitations in simulating grassed waterways, due to the fact that channel routing is not simulated at the HRU level. Arabi et al. (2007a) proposed simulating grassed waterways by modifying subwatershed channel parameters, as shown in table 4. However, this approach is usually only viable for relatively small watersheds, such as the example they present in their study.

Wetlands can be simulated in SWAT on the basis of one wetland per subwatershed, which is assumed to capture discharge and pollutant loads from a user-specified percentage of the overall subwatershed. The ability to site wetlands with more spatial accuracy within a subwatershed would clearly provide improvements over the current SWAT wetland simulation approach, although this can potentially be overcome for some applications by subdividing a watershed into smaller subwatersheds.

The lack of spatial detail in SWAT also hinders simulation of riparian buffer zones and other conservation buffers, which again need to be spatially defined at the landscape or HRU level in order to correctly account for upslope pollutant source areas and the pollutant mitigation impacts of the buffers. The riparian and wetland processes recently incorporated into the SWIM model (Hatterman et al., 2006) may prove useful for improving current approaches used in SWAT.

Bacteria Life Cycle and Transport

Benham et al. (2006) state that SWAT is one of two primary models used for watershed-scale bacteria fate and transport assessments in the U.S. The strengths of the SWAT bacteria component include: (1) simultaneous assessment of fecal coliform (as an indicator pathogen) and a more persistent second pathogen that possesses different growth/die-off characteristics, (2) different rate constants that can be set for soluble versus sediment-bound bacteria, and (3) the ability to account for multiple point and/or nonpoint bacteria sources such as land-applied livestock and poultry manure, wildlife contributions, and human sources such as septic tanks. Jamieson et al. (2004) further point out that SWAT is the only model that currently simulates partitioning of bacteria between adsorbed and non-adsorbed fractions; however, they also state that reliable partitioning data is currently not available. Bacteria die-off is simulated in SWAT on the basis of a first-order kinetic function (Neitsch et al., 2005a), as a function of time and temperature. However, Benham et al. (2006), Jamieson et al. (2004), and Pachepsky et al. (2006) all cite several studies that show that other factors such as moisture content, pH, nutrients, and soil type can influence die-off rates. Leaching of bacteria is also simulated in SWAT, although all leached bacteria are ultimately assumed to die off. This conflicts with some actual observations in which pathogen movement has been observed in subsurface flow (Pachepsky et al., 2006; Benham et al., 2006), which is especially prevalent in tile-drained areas (Jamieson et al., 2004). Benham et al. (2006), Jamieson et al. (2004), and Pachepsky et al. (2006) list a number of research needs and modeling improvements needed to perform more accurate bacteria transport simulations with SWAT and other models including: (1) more accurate characterization of bacteria sources, (2) development of bacteria life cycle equations that account for different phases of die-off and the influence of multiple factors on bacteria die-off rates, (3) accounting of subsurface flow bacteria movement including transport via tile drains, and (4) depiction of bacteria deposition and resuspension as function of sediment particles rather than just discharge.

In-Stream Kinetic Functions

The ability to simulate in-stream water quality dynamics is a definite strength of SWAT. However, Horn et al. (2004) point out that very few SWAT-related studies discuss whether the QUAL2E-based in-stream kinetic functions were used or not. Santhi et al. (2001a) opted to not use the in-stream functions for their SWAT analysis of the Bosque River in central Texas because the functions do not account for periphyton (attached algae), which dominates phosphorus-limited systems including the Bosque River. This is a common limitation of most water quality models with in-stream components, which focus instead on just suspended algae. Migliaccio et al. (2007) performed parallel SWAT analyses of total P and nitrate (including nitrite) movement for the 60 km^2 War Eagle Creek watershed in northwest Arkansas by: (1) loosely coupling SWAT with QUAL2E (with the SWAT in-stream component turned off), and (2) executing SWAT by itself with and without the in-stream functions activated. They found no statistical difference in the results generated between the SWAT-QUAL2E interface approach versus the stand-alone SWAT approach, or between the two stand-alone SWAT simulations. They concluded that further testing and refinement of the SWAT in-stream algorithms are warranted, which is similar to the views expressed by Horn et al. (2004). Further investigation is also needed to determine if the QUAL2E modifications made in ESWAT should be ported to SWAT, which are described by Van Griensven and Bauwens (2003, 2005).

Additional Research Needs

- Development of concentrated animal feeding operation and related manure application routines, that support simulation of surface and integrated manure application techniques and their influence on nutrient fractionation, distribution in runoff and soil, and sediment loads. Current development is focused on a manure cover layer.
- All aspects of stream routing need further testing and refinement, including the QUAL2E routines as discussed above.

Table 4. Proposed key parameters to adjust for accounting of different conservation practice effects in SWAT (source: Arabi et al., 2007a).

Conservation Practice	Channel Depth	Channel Width	Channel Erodibility Factor	Channel Cover Factor	Channel Manning Roughness Coeff.	Channel Slope Segment	Filter Strip Width[a]	Hillside Slope Length	Manning N for Overland Flow	SCS Runoff Curve Number	USLE C Factor	USLE P Factor
Contouring										X		X
Field border							X					
Filter strips							X					
Grade stabilization structures			X			X						
Grassed waterways	X	X		X	X							
Lined waterways	X	X	X		X							
Parallel terraces								X		X		X
Residue management[b]									X	X	X	
Stream channel stabilization	X	X	X		X							
Strip cropping									X	X	X	X

[a] Setting a filter strip width triggers one of two filter strip trapping efficiency functions (one for bacteria and the other for sediment, pesticides, and nutrients) that account for the effect of filter strip removal of pollutants.
[b] Soil incorporation of residue by tillage implements is also a key aspect of simulated residue management in SWAT.

- Improved stream channel degradation and sediment deposition routines are needed to better describe sediment transport, and to account for nutrient loads associated with sediment movement, as discussed by Jha et al. (2004a). Channel sediment routing could be improved by accounting for sediment size effects, with separate algorithms for the wash and bed loads. Improved flood plain deposition algorithms are needed, and a stream bank erosion routine should be incorporated.
- SWAT currently assumes that soil carbon contents are static. This approach will be replaced by an updated carbon cycling submodel that provides more realistic accounting of carbon cycling processes.
- Improvements to the nitrogen cycling routines should be investigated based on the suggestions given by Borah et al. (2006). Other aspects of the nitrogen cycling process should also be reviewed and updated if needed, including current assumptions of plant nitrogen uptake. Soil phosphorus cycling improvements have been initiated and will continue. The ability to simulate leaching of soil phosphorus through the soil profile, and in lateral, groundwater, and tile flows, has recently been incorporated into the model.
- Expansion of the plant parameter database is needed, as pointed out by Heuvelmans et al. (2005), to support a greater range of vegetation scenarios that can be simulated in the model. In general, more extensive testing of the crop growth component is needed, including revisions to the crop parameters where needed.
- Modifications have been initiated by McKeown et al. (2005) in a version of the model called SWAT2000-C to more accurately simulate the hydrologic balance and other aspects of Canadian boreal forest systems including: (1) incorporation of a surface litter layer into the soil profile, (2) accounting of water storage and release by wetlands, and (3) improved simulation of spring thaw generated runoff. These improvements will ultimately be grafted into SWAT2005.
- Advancements have been made in simulating subsurface tile flows and nitrate losses (Du et al., 2005, 2006). Current research is focused on incorporating a second option, based on the DRAINMOD (Skaggs, 1982) approach, that includes the effects of tile drain spacing and shallow water table depth. Future research should also be focused on controlled drainage BMPs.
- Routines for automated sensitivity, calibration, and input uncertainty analysis have been added to SWAT (van Griensven and Bauwens, 2003). These routines are currently being tested on several watersheds, including accounting of uncertainty encountered in measured water quality data, as discussed by Harmel et al. (2006).
- The effects of atmospheric CO_2 on plant growth need to be revised to account for varying stomatal conductance and leaf area responses as a function of plant species, similar to the procedure developed for SWAT-G by Eckhardt et al. (2003).

Conclusions

The wide range of SWAT applications that have been described here underscores that the model is a very flexible and robust tool that can be used to simulate a variety of watershed problems. The process of configuring SWAT for a given watershed has also been greatly facilitated by the development of GIS-based interfaces, which provide a straightforward means of translating digital land use, topographic, and soil data into model inputs. It can be expected that additional support tools will be created in the future to facilitate various applications of SWAT. The ability of SWAT to replicate hydrologic and/or pollutant loads at a variety of spatial scales on an annual or monthly basis has been confirmed in numerous studies. However, the model performance has been inadequate in some studies, especially when comparisons of predicted output were made with time series of measured daily flow and/or pollutant loss data. These weaker results underscore the need for continued testing of the model, including more thorough uncertainty analyses, and ongoing improvement of model routines. Some users have addressed weaknesses in SWAT by component modifications, which support more accurate simulation of specific processes or regions, or by interfacing SWAT with other models. Both of these trends are expected to continue. The SWAT model will continue to evolve in response to the needs of the ever-increasing worldwide user community and to provide improved simulation accuracy of key processes. A major challenge of the ongoing evolution of the model will be meeting the desire for additional spatial complexity while maintaining ease of model use. This goal will be kept in focus as the model continues to develop in the future.

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