The Soil and Water Assessment Tool: Historical Development, Applications, and Future Research Directions

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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 U.S. Department of Agriculture (USDA), Agricultural Research Service. 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 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's BASINS (Better Assessment Science Integrating Point & Nonpoint Sources) software package and is being used by many U.S. federal and state agencies, including the USDA within the Conservation Effects Assessment Project. 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 provided.

Keywords: developmental history, flow analysis, modeling, SWAT, water quality.

INTRODUCTION

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 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 (; research the effectiveness of conservation practices in the U.S. Department of Agriculture (USDA) Natural Resource Conservation Service (NRCS) Conservation Effects Assessment Program (CEAP) (Mausbach and Dedrick, 2004; http://www.nrcs.usda.gov/technical/NRI/ceap/); perform "macro-scale assessments" such as for the Upper Mississippi River Basin (e.g., Arnold et al., 2000; Jha et al., 2006b) and the entire U.S. (e.g., Arnold et al., 1999a; Rosenberg et al., 2003); and for a wide variety of other water use and water quality applications. Similar SWAT application trends have also emerged in Europe and other regions, as indicated by the variety of studies presented in three previous European international SWAT conferences; these are reported in part for the first conference in a special issue of *Hydrological Processes* (volume 19, issue 3), the SWAT2003 2nd International Conference Proceedings (http://www.brc.tamus.edu/swat/pubs_2ndconf.html), and in the SWAT2005 3rd International Conference Proceedings (http://www.brc.tamus.edu/swat/pubs_3rdconf.html).

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; Borah and Bera, 2004; Horn et al., 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. Thus, the main objective of this study is to fill this gap by providing a review of the full range of studies that have been conducted with SWAT, drawing primarily from peer-reviewed literature. Research findings or methods are summarized here for most of the approximately 220 peer-reviewed articles that have been identified in the literature, based on relevant application categories. A brief overview of SWAT development history is also provided, as well as summaries of the strengths and weaknesses of the model and 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 (Figure 1), including the Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) model (Knisel et al., 1980), the Groundwater Loading Effects on Agricultural Management Systems (GLEAMS) model (Leonard et al., 1987), and the Environmental Impact Policy Climate (EPIC) model (Gassman et al., 2005; 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 (Williams et al., 1985; 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 10 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 Soil Conservation Service (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.

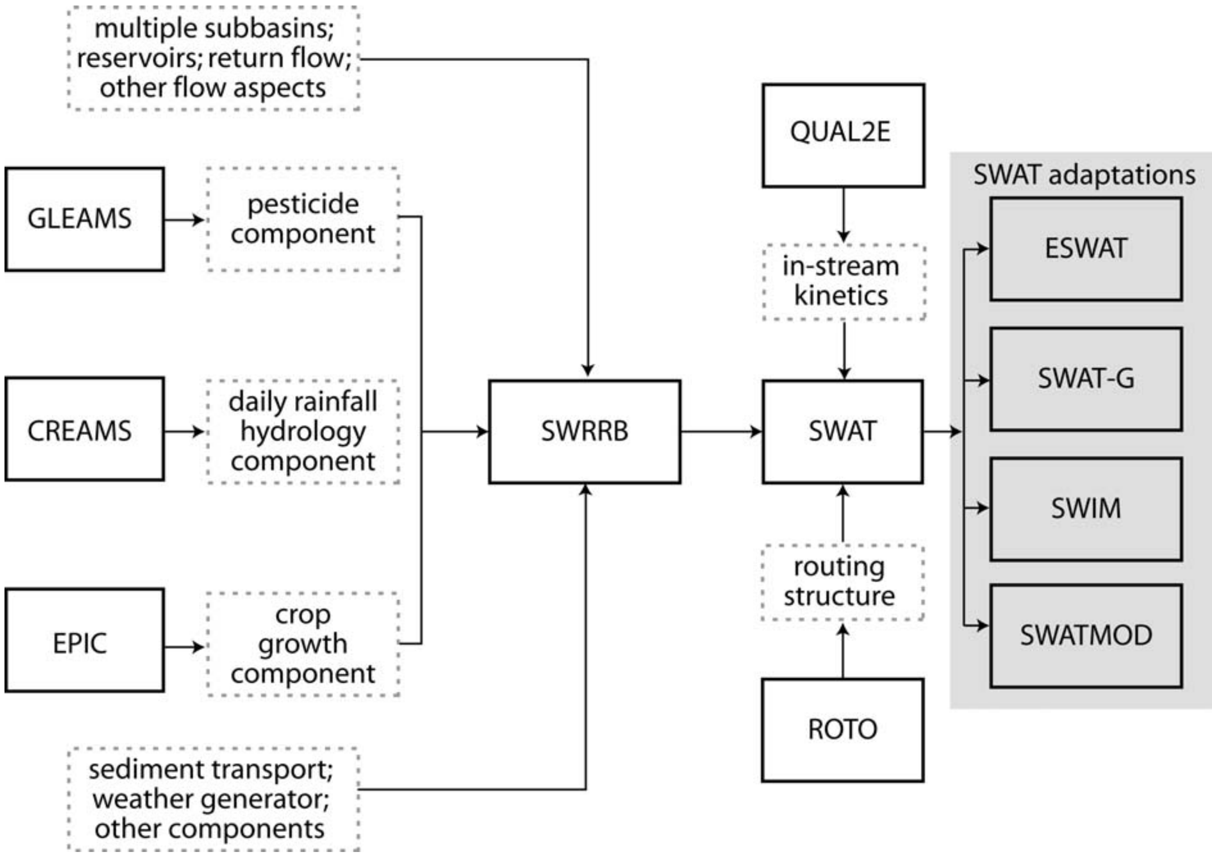

Figure 1. Schematic of SWAT developmental history, including selected SWAT adaptations.

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 10 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 (Figure 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. (2005), including the incorporation of in-stream kinetic routines from the QUAL2E model (Brown and Barnwell, 1987). Theoretical documentation of previous versions of the model is provided by Arnold et al. (1998) and is posted at www.brc.tamus.edu/swat/soft_model.html. A detailed theoretical documentation and user's manual for the latest version of the model (SWAT2005) is given in 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, plant growth, nutrients, pesticides, 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 subdaily precipitation inputs are required if the Green and 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 10 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 area 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 NRCS Curve Number (CN) method (USDA-NRCS, 2004) or the Green and Ampt method. Canopy interception is implicit in the CN method while explicit canopy interception is simulated for the Green and 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 for simulating 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 ET 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 auto fertilizer routine can be used to simulate nitrogen 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. Arabi et al. (2007) present standardized methods for simulating these and other practices (see additional discussion in the SWAT Strengths, Weaknesses, and Future Research Directions section). Simulation of irrigation water on cropland can be accomplished based on five alternative sources: stream reach, reservoir, shallow aquifer, deep aquifer, or a waterbody 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 can "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 (N) and phosphorus (P) 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., 2005), both of which are 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 more 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, N and P cycling, carbonaceous biological oxygen demand, and dissolved oxygen are performed based on routines developed for the QUAL2E model. Degradation, volatilization, and other in-stream processes are simulated for pesticides, as is the 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), van Griensven et al. (2006), and van Griensven (2006). These routines can be implemented for any subset of SWAT input parameters, unless the AVSWAT-X interface options are used as discussed further in the Geographic Information System Interface Tools subsection.

SWAT Adaptations

A notable 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 (Figure 1) include the Extended SWAT (ESWAT) model, the Soil and Water Integrated Model (SWIM), SWAT-G, and SWATMOD. 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 the QUAL2E model (Brown and Barnwell, 1987) 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 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 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 – 100,000 km^2) watersheds. Recent improvements to the model 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). The SWATMOD model (Sophocleous et al., 2000) is an interface between SWAT and the MODFLOW groundwater model and is discussed further in the Model Interface section. The SWATMOD model (Sophocleus et al., 1999) is an interface between SWAT and the MODFLOW groundwater model, and is discussed further in the Model Interface Section.

GEOGRAPHIC INFORMATION SYSTEM INTERFACE TOOLS

A second trend that has paralleled the historical development of SWAT is the creation of various Geographic Information System (GIS) 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 InputOutputSWAT (IOSWAT) software package, which generates inputs and provides output mapping support for both SWAT and SWAT-G. Other tools incorporated in IOSWAT include the Topographic Parameterization Tool (TOPAZ), Subwatershed Spatial Analysis Tool (SUSAT), and OUTGRASS, which, respectively, are used to delineate subwatershed maps, determine appropriate levels of subwatershed/HRU discretization, and to assign model output values to specific watershed grids.

The ArcView-SWAT (AVSWAT) interface tool (Di Luzio et al., 2004a,b) 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's (USEPA) Better Assessment Science Integrating point and Non-point Sources (BASINS) software package version 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, denoted AVSWAT-X, provides additional input generation functionality, including soil data input from both the USDA-NRCS State Soils Geographic (STATSGO) and Soil Survey Geographic (SSURGO) databases (Di Luzio et al., 2004a; SWAT, 2007b) for applications of SWAT2005. Automatic sensitivity, calibration, and uncertainty analysis can also be initiated with AVSWAT-X for SWAT2005, for a pre-selected subset of 41 input parameters. The Automated Geospatial Watershed Assessment (AGWA) interface tool (Miller et al., 2006) is an alternative ArcView-based interface tool that supports data input generation for both SWAT2000 and the KINEROS2 model, including soil inputs from the SSURGO, STATSGO, or global FAO soil maps. AGWA and AVSWAT have both been incorporated as interface approaches for generating SWAT2000 inputs within BASINS version 3.1 (D. Wells, personal communication. USEPA).

A SWAT interface compatible with ArcGIS version 9.x is currently being tested and is projected for release sometime in the fall of 2006 (Olivera et al., 2006; SWAT, 2007a). An ArcGIS 9.x version of AGWA (AGWA2) is also under development and is expected to be released around mid-2007 (USDA-ARS, 2006). A variety of other tools have been developed to support executions of SWAT simulations, including: (1) the interactive SWAT (i_SWAT) software, which is described by Gassman et al. (2003) and further documented and provided for download by Campbell (2006); and (2) the AUTORUN system, as described by Kannan et al. (2007b).

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 United States and the European Union, that require direct assessments of anthropogenic, climate change, and other influences on a 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 United States 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; USDA-NRCS, 2006); 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 45% of the nearly 39,000 currently listed impaired waterways still require TMDLs (USEPA, 2006c); SWAT, BASINS, and a variety of other modeling tools will be used to help determine the pollutant sources and potential solutions for these forthcoming TMDLs. Extensive discussion of applying SWAT and other models for TMDLs is presented in Borah et al. (2006), Benham et al. (2006), Shirmohammadi et al. (2006), and Vellidis et al. (2006).

SWAT has also been used extensively in the context of 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

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

N and P 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). Eight models including SWAT have also been incorporated into the AgriBMPWater modeling system to evaluate different agricultural BMPs in eight watersheds in five European countries (Turpin et al., 2005).

The remaining 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.

SPECIFIC SWAT APPLICATIONS

The numerous SWAT applications reported in the literature can be categorized in a variety of ways. For this study, the articles were grouped into nine subcategories and then further broadly defined as hydrologic only, hydrologic and pollutant loss, or pollutant loss only (Table 1). The summary given in Table 1 includes most of the articles found in the literature. However, some of the articles could not be categorized according to the Table 1 criteria, and reviews are not provided for all of the articles included in the Table 1 summary. A complete list of the SWAT-related peer reviewed articles is provided at www.brc.tamus.edu/swat, which is updated on a regular basis.

Table 1. Overview of major application categories of SWAT studies reported in the literature. †

Primary Application Category	Hydrologic Only	Hydrologic & Pollutant Loss	Pollutant Loss Only
Calibration and/or sensitivity analysis	14	20	2
Climate change impacts	21	7	-
GIS interface descriptions	3	3	2
Hydrologic assessments	40	-	-
Variation in configuration or data input effects	18	14	-
Comparisons with other models/techniques	5	7	-
Interfaces with other models	13	16	6
Pollutant assessments	-	52	5

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

HYDROLOGIC STUDIES

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 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 usually not reported for most studies. The NSE ranges from -• 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 implications of the r^2, NSE, and other efficiency criteria measures.

An extensive list of r^2 and NSE statistics are presented in Table 2 for 100 SWAT hydrologic calibration and/or validation results reported in the literature. This set of statistics provides valuable insight regarding the hydrologic performance of the model across a wide spectrum of conditions. No absolute criteria for judging model performance has been firmly established to date in the literature. However, Moriasi et al. (2006) have suggested that NSE values should exceed 0.5 in order for model results to be judged as being satisfactory. Assuming this criterion for both the NSE and r^2 values, 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 were obtained 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; Jayakrishnan et al., 2005), 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 gages from 1960 to 1989 were used to calibrate and validate the model. Predicted average monthly streamflow data from three six-digit HUA were 5% higher than measured flows with standard deviations between measured and predicted within 2%. Arnold et al. (2000) compared SWAT groundwater recharge and discharge (base flow) estimates with filtered estimates for the 491,700 km^2 Upper Mississippi River Basin. Annual runoff and ET were validated across the entire continental U.S. as part of the HUMUS (Hydrologic Unit Model for the United States) project (Arnold et al., 1999a).

Table 2. Summary of reported SWAT streamflow and other hydrologic calibration and validation results.

Reference	Watershed(s)	Area (km^2)	Indicator	Time period (C = calibration; V = validation)	Calibration Daily		Calibration Monthly		Calibration Annual		Validation Daily		Validation Monthly		Validation 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 Guadalope River (Texas)	60	stream flow	C: 1992-96 V: 1997-Sept 03		0.4		0.29				0.09		0.5		
Arabi et al. (2006)	Dreisbach & Smith Fry (Indiana)	6.2 & 7.3	stream flow	C: 1975 – May 1977 V: 1974-75			.92 and .86	.84 and .73					.87 and .81	.73 and .63		
			surface runoff				.91 and .84	.80 and .62					.88 and .84	.75 and .63		
Arnold and Allen (1996)	Goose Creek, Hadley Creek, & Panther Creek (Illinois)	122 – 246	surface runoff	1951-52, 1955-57, or 1956-58									.79 to .94			
			ground water flow	"									.38 to .51			
			total stream flow	"									.63 to .95			
Arnold et al. (2000)	Upper Mississippi River Basin (north central U.S.)	491,700	stream flow	C: 1961-80 V: 1981-85			.63						.65			
Arnold et al. (2005)	USDA-ARS Y-2 (Texas)	.534	crack flow	1998-99							.84					
			surface runoff	1998-99							.87					
Arnold et al. (1999a)	Conterminous U.S. (Figure 2)	-	stream flow?	runoff											.80	
Arnold et al. (1999b)	35 USGS 8-digit watersheds (Texas)	2,253 – 304,620	stream flow	1965-89					.23 to .96	-1.1 to .87						
	Sequin, Neches, & Colorado Rivers (Texas)	9,104 – 108,788	stream flow	1965-89									.40 to .95	.53 to .86		
Behera & Panda (2006)	Kapgari (India)	9.73	surface runoff	C: 2002 V: 2003 (rainy season)	.94	.88					.91	.85				

Table 2. Continued

Reference	Watershed	Area (km^2)	Indicator	Time period (C = calibration; V = validation)	Calibration Daily		Calibration Monthly		Calibration Annual		Validation Daily		Validation Monthly		Validation Annual	
					r^2	NSE	r^2	NSE	r^2	NSE	r^2	NSE	r^2	NSE	r^2	NSE
Benaman et al. (2005)	Cannonsville (New York); 4 sub-watersheds: 3, 5, 11, & & 78 % of total area	1,178 (total area)	stream flow	1994-99			.72 to .80	.63 to .78								
	2 subwatersheds: 30 & 78% of total area		stream flow	1990-93									.73 & .80	.62 & .76		
Benham et al. (2006)	Shoal Creek (Missouri); upsteam gauge	367	stream flow		.40	.21	.70	.63			.61	.54	.61	.66		
Binger (1996)	Goodwin Creek (Mississippi)	21.3	stream flow	V: 1982-91 (140 r^2 statistics)											93 ≥ .90	
Bosch et al. (2004)	Subwatershed of the Little River (Georgia, USA)	22.1	stream flow	1997-02 (uncalibrated)								-.24 to -.03		.55 to .80		
Bouraoui et al. (2005)	Medjerda River (Algeria and Tunisia)	16,000	stream flow	Sept. 1988 – March 1999	.44	.23	.75	.53								
	Medjerda subwatershed	314	"		.66	.33	.62	.59								
	"	163	"		.69	.41	.84	.84								
Bouraoui et al. (2002)	Ouse (Yorkshire, United Kingdom)	3,500	stream flow	1986-90		.77										
	Ouse subwatershed	1,470	"			.39										
	Ouse subwatershed	980	"			.45										
Bouraoui et al. (2004)	Vantaanjoki (Finland)	1,682	stream flow	1965-84										.87		
	Vantaanjoki subwatershed	295	"	1982-84		.81										
Cao et al. (2006)	Motueka River (South Island, New Zealand); primary calibration subwatershed	1,756.6	stream flow	C: 1990-94 V: 1995-00	.82	.78					.75	.72				
	Six other subwatersheds	81.6 to 479	stream flow	C: 1990-94 V: 1995-00	.52 to .62	.36 to .60					.41 to .61	.35 to .57				
Cerucci & Conrad (2003)	Townbrook (New York)	37	stream flow	Oct. 1999 – Sept. 2000			.72									

Table 2. Continued

Reference	Watershed	Area (km^2)	Indicator	Time period (C = calibration; V = validation)	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
Chanasyk et al. (2003)	3 watersheds (Saskatchewan)	1.53 – 2.26	surface runoff	1999-00		-35.7 to -.005										
Chaplot et al. (2004)	Walnut Creek	51.3	stream flow	1991-98			.73									
Cheng et al. (2006)	Heihe River (China)	7,241	stream flow	C: 1992-97 V: 1998-99			.80	.78					.78	.76		
Chu & Shirmohammadi (2004)	Warner Creek	3.46	stream flow	C: 1994-95 V: 1996-99			.66	.52					.69	.63		
			surface runoff	C: 1994-95 V: 1996-99			.43	.35					.88	.77		
			subsurface runoff	C: 1994-95 V: 1996-99			.56	.27					.47	.42		
Coffey et al. (2004)	University of Kentucky ARC (Kentucky)	5.5	stream flow	1995	.26	.09	.70	.41								
				1996	.40	.15	.88	.61								
Conan et al. (2003a)	Coët-Dan (Brittany, France)	12	stream flow	C: 1995-96 V: 1994-99		.79						.42		.87		
	Coët-Dan subwatershed		stream flow	V: 1994-99										.83		
Conan et al. (2003b)	Upper Guadiana River (Spain)	18,100	stream flow	1975-91								.45				
Cotter et al. (2003)	Moores Creek (Arkansas)	18.9	stream flow	1997-98	.76											
Di Luzio et al. (2005)	Goodwin Creek (Mississippi)	21.3	surface runoff	1982-93									.90 to .95	.87 to .97		
Di Luzio & Arnold (2004)	Blue River (Oklahoma)	1,233	stream flow	1994-2000 (24 separate runoff events; auto. calib.)	.24 to .99[†]	.15 to .99										
				manually calibrated[a]	.01 to .98	-102 to .80										
Di Luzio et al. (2002)	Upper North Bosque River (Texas)	932.5	stream flow	Jan. 1993 – July 1998										.82		

Table 2. Continued

-0-.333Reference	Watershed	Area (km^2)	Indicator	Time period (C = calibration; V = validation)	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. (2005)	Walnut Creek (Iowa); subwatershed & watershed outlet	51.3 (total area)	stream flow	C: 1992-95 V: 1996-99 (SWAT2000)		.39 & .47		.36 to .72				.32 & .35		.13 & .56		
	Subwatershed (site 210)	-	tile flow	(SWAT2000)		-.15		-.33				-.16		-.42		
	subwatershed & watershed outlet	51.3 (total area)	stream flow	(SWAT-M)		.51 & .55		.84 & .88				-.11 & .49		.72 & .82		
	Subwatershed (site 210)	-	tile flow	(SWAT-M)		-.23		.67				-.12		.70		
Eckhardt et al. (2002)	Dietzhölze (Germany)	81	stream flow	Nov. 1990 – Aug. 1993 (SWAT99.2)		-.17										
				Nov. 1990 – Aug. 1993 (SWAT-G)		.76										
El-Nasr et al. (2005)	Jeker (Belgium)	465	stream flow	C: June 1986 – May 1989 V: June 1989 – May 1992	.45	.39					.55	.60				
Fontaine et al. (2002)	Wind River (Wyoming)	4,999	stream flow	1991-96 (new snowmelt routine)												.86
				1991-96 (old routine)												-.70
Fontaine et al. (2001)	Spring Creek (South Dakota)	427	stream flow	1987-95			.62		.94							
Francos et al. (2001)	Kerova River (Finland)	460	stream flow	1985-94										.65		
Gikas et al. (2005)[a]	Vistonis Lagoon (Greece); 9 gauges in four subwatersheds	1,349	stream flow	C: May 1998 – June 1999 V: Nov. 1999 – Jan. 2000			.71 to .89						.72 to .91			
Gitau et al. (2004)	Town Brook subwatershed (New York)	3	stream flow	1992-02			.76	.44	.99	.84						
Gosain et al. (2005)	Palleru River (India)	-	stream flow	1972-94									.61	.87		

Table 2. Continued

Reference	Watershed	Area (km^2)	Indicator	Time period (C = calibration; V = validation)	Calibration Daily		Calibration Monthly		Calibration Annual		Validation Daily		Validation Monthly		Validation Annual	
					r^2	NSE	r^2	NSE	r^2	NSE	r^2	NSE	r^2	NSE	r^2	NSE
Govender & Everson (2005)	Cathedral Park Research C VI (South Africa)	677	stream flow	C: 1991 V: 1990-95 (auto. calib.)	.86						.65					
				V: 1990-95 (manual calib.)							.68					
Green et al. (2006)	South Fork of the Iowa River (Iowa)	775	stream flow	C: 1995-98 V: 1999-04 (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: 1995-00 V: 2001-04 (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)	Parts of four watersheds (United Kingdom)	8,900 (total area)	stream flow	C&V: 1995-99		.75		.86								.66
Grizzetti et al. (2003)	Vantaanjoki (Finland)	1,682	stream flow	1989-93 (daily) 1989-97 (mon.)							.66	.76				
	Vantaanjoki subwatershed	295		various time periods		.81					.57	.75				
Hanratty & Stefan (1998)	Cottonwood (Minnesota)	3,400	stream flow	1967-91				.78								
Hao et al. (2004)	Lushi (Yellow River Basin, China)	4,623	stream flow	C: 1992-97 V: 1998-04			.87	.87			.84	.81				
Hernandez et al. (2000)	Subwatershed within 150 km^2 Walnut Gulch (Arizona)	8.23	stream flow	1966-74 (1 or 10 rain gauges)											.33 & .57	
Heuvelmans et al. (2006)	25 watersheds (Schelde River Basin, Belgium)	2 – 210	stream flow	C: 1990-95 V: 1996-01		.70 to .95						.67 to .92				
Holvoet et al. (2005)	Nil (Belgium)	32	stream flow	Nov. 1998 to Nov. 2001		.53										
Jayakrishnan et al. (2005)	Four watersheds (Texas)	196 – 2,227	stream flow	1995-99 (rain gauge; uncalibrated)										-7.4 to .22		
				1995-99 (NEXRAD; uncalibrated)										-.75 to .59		
Jha et al. (2004a)	Maquoketa River (Iowa)	4,776	stream flow	1981-90 (average daily, etc.)							.68		.76		.65	

Table 2. Continued

Reference	Watershed	Area (km²)	Indicator	Time period (C = calibration; V = validation)	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
Jha et al. (2004b)	Upper Mississippi River (north central U.S.)	447,500	stream flow	C: 1989-97 V: 1980-88			.75	.67	.91	.91			.70	.59	.89	.86
Jha et al. (2006b)	Upper Mississippi River (north central U.S.)	447,500	stream flow	C: 1968-87 V: 1988-97	.67	.58	.74	.69	.82	.75	.75	.65	.82	.81	.91	.90
Kang et al. (2006)	Baran (South Korea)	2,979	surface runoff	C: 1996-97 V: 1999-00	.93	.93					.87	.87				
Kaur et al. (2004)	Nagwan (India)	9.58	surface runoff	C: 1984 & 92 V: 1981-83; 1985-89; 1991	.76	.71					.83	.54				
Kannan et al. (2007b)	Colworth (United Kingdom)	1.4	stream flow	C: Oct/1999–01 V: 2001–May/02 (CN approach)		.61						.60				
				Green Ampt		.50						.56				
King et al. (1999)	Goodwin Creek (Mississippi)	21.3	stream flow	1982-89 (curve number; not calibrated)										.84		
				1982-89 (Green Ampt; not calibrated)										.69		
Kirsch et al. (2002)	Rock River (Wisconsin): Windsor gauge	9,708	stream flow	1989-95					.74	.61						
	12 USGS gauges	-		1989-96 (most gauges)					.28 to .98							
Limaye et al. (2001)	Dale Hollow (Tennessee)	2,345	stream flow	C: 1966-90 V: 1991-93		.42		.74				.45		.80		
Lin & Radcliffe (2006)	Upper Etowah River (Georgia, USA)	1,580	stream flow	C: 1983-92 V: 1993-01		.61		.86				.62		.89		
Manguerra & Engel (1998)	Greenhill (Indiana);	113.4	stream flow	1991-95				.93 to 1.0								
Mapfumo et al. (2004)	3 watersheds (Saskatchewan)	1.53 – 2.26	soil water	C: 1998 V: 1999-00 (selected days)	.85	.77					.72	.70				
Moon et al. (2004)	Cedar Creek (Texas)	2,608	stream flow	1999-01 (rain gauge)	.53	.48					.86	.78				
				1999-01 (NEXRAD)	.58	.57					.84	.82				

Table 2. Continued

Reference	Watershed	Area (km^2)	Indicator	Time period: C = calibration & V = validation (notes)	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
Muleta & Nicklow (2005a)	Big Creek (Illinois)	133	stream flow	1999-01		.69										
Muleta & Nicklow (2005b)	Big Creek (Illinois): PRS station for calibration and CRS station for validation	133	stream flow	C: June/1999-Aug/01 V: April/2000-Aug/01		.74						.23				
Narasimhan et al. (2005)	Six watersheds (Texas); 24 different gauges	10,320 – 29,664	stream flow	varying periods (overall annual average)					.75	.75					.70	.70
				varying periods (range across 24 gauges)					.54 to .99	.52 to .99					.63 to 1.00	.55 to .97
Perkins & Sophocleous (1999)	Lower Republican River (Kansas)	2,569	stream flow	1977-94 (separate C & V stat. not given)									.85			
Peterson & Hamlet (1998)	Ariel Creek (Pennsylvania)	39.4	stream flow	May 1992 – July 1994		.04		.14								
				May 1992 – July 1994 (no snowmelt events)		.2		.55								
Plus et al. (2006)	Thau Lagoon (France); gauges on two rivers	280 (total area)	stream flow	1993-99							.68 & .45‡					
Qi & Grunwald (2005)	Sandusky River (Ohio); five gauges	90.3 - 3,240	surface water	C: 1998-99 V: 2000-01				.31 to .65						-.04 to .75		
			ground water					-9.1 to .60						-.57 to .22		
			total flow					.31 to .81						.40 to .73		
Rosenberg et al. (2003)	18 major water resource regions for conterminous U.S. (48 states)	-	water yield	1961-90 (overall annual average)											.92	
				1961-90 (at 8-digit watershed level)											.03 to .90	

Table 2. Continued

Reference	Watershed	Area (km^2)	Indicator	Time period (C = calibration; V = validation)	Calibration Daily		Calibration Monthly		Calibration Annual		Validation Daily		Validation Monthly		Validation Annual	
					r^2	NSE	r^2	NSE	r^2	NSE	r^2	NSE	r^2	NSE	r^2	NSE
Rosenthal & Hoffman (1999)	Leon River (Texas)	9,000	stream flow	1972-74										.52		
Rosenthal et al. (1995)	Lower Colorado River (Texas)	8,927	stream flow	1980-89			.75	.69								.86
	upstream gauges						.69 to .90									
Saleh et al. (2000)	Upper North Bosque (Texas); outlet for calibration & composite of 11 gauges for validation	932.5	stream flow	C: Oct. 1993 – Aug. 1995 V: July 1995 – July 1999 (with APEX)				.56						.99		
Saleh & Du (2004)	Upper North Bosque (Texas)	932.5	stream flow	C: Jan. 1994 – June 1995 V: July 1995 – July 1999		.17		.50				.62		.78		
Salvetti et al. (2006)	Lombardy Region of the Po River (Italy)	16,000	stream flow	1984-02		.50		>.70								
Santhi et al. (2001a)	Bosque (Texas); gauges for two subwatersheds	4,277	stream flow	C: 1962-97 (annual) C: 1993-97 V: 1998			.80 & .89	.79 & .83	.86 & .66	.88 & .72			.92 & .80	.87 & .62		
Santhi et al. (2006)	West Fork (Texas): gauges for two subwatersheds	4,554	stream flow	1982-2001			.61 & .81	.12 & .72	.88 & .86	.84 & .78						
Schomberg et al. (2005)	Straight, Whitewater, & Zumbro Rivers (Minnesota); Brent Run & South Branch Cass Rivers (Michigan)	829 – 3,697 (3 are not given)	stream flow	multiple time periods (10-year records)	.10 to .28	-1.3 to .25	.35 to .58	-1.4 to .49								
Singh et al. (2005)	Iroquois River (Illinois & Indiana)	5,568	stream flow	C: 1987-95 V: 1972-86		.79		.88				.74		.84		
Spruill et al. (2000)	University of Kentucky ARC (Kentucky)	5.5	stream flow	C: 1996 V: 1995		.19		.89				-.04		.58		
Srinivasan et al. (2005)	Upland watershed (Pennslyvania)	.395	stream flow	1997-2000		.62										
Srinivasan & Arnold (1994)	Upper Seco Creek (Texas)	114	stream flow	Jan. 1991 – Aug. 1992			.82									

Table 2. Continued

Reference	Watershed	Area (km^2)	Indicator	Time period (C = calibration; V = validation)	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
Srinivasan et al. (1998)	Richland-Chambers Reservoir (Texas): two gauges	5,000	stream flow	C: 1965-69 V: 1970-84			.87 & .84	.77 & .84					.65 & .82	.52 & .82		
Stewart et al. (2006)	Upper North Bosque (Texas)	932.5	stream flow	C: 1994-99 V: 2001-02			.87	.76					.92	.80		
Stonefelt et al. (2000)	Wind River (Wyoming)	4,999	stream flow	1990-97			.91									
Thomson et al. (2003)	18 major water resource regions for conterminous U.S. (48 states)	-	water yield	1960-89 (overall mean)						.96						
				1960-89 (8-digit means by MWRR)						.05 to .94						
Thomson et al. (2005)	18 major water resource regions for conterminous U.S. (48 states)	-	water yield	1960-89 (overall annual average)						.94						
Thomson et al. (2005)	18 major water resource regions for conterminous U.S. (48 states)	-	water yield	1960-89 (8-digit means by MWRR)						.04 to .81						
Tripathi et al. (2003)	Nagwan (India)	92.5	surface runoff	June – Oct. 1997							.91	.87				
Tripathi et al. (2006)	Nagwan (India); 3 different watershed delineations	92.5	surface runoff	1995-98									.86 to .90			
Vaché et al. (2002)	Walnut Creek (Iowa)	51.3	stream flow	1991-97			.67									
	Buck Creek (Iowa)	88.2	stream flow	1991-97			.64									
Van Liew et al. (2003a)	Little Washita (Oklahoma); calib. – 2 gauges; valid. – 8 gauges	2.9 – 610	stream flow	Varying time periods		.56 to .72		.66 to .85				-.35 to .63		-1.1 to .89		
Van Liew & Garbrecht (2003)	Little Washita (Oklahoma); calib. – 2 gauges; valid. – 2 gauges	160 – 610	stream flow	Varying time periods		.60 & .40		.75 & .71				-.06 to .71		.45 to .86		
Van Liew et al. (2003b)	Little Washita (Oklahoma)	610	stream flow	Oct. 1992 – Sept. 2000		.55		.78								

Table 2. Continued

Reference	Watershed	Area (km^2)	Indicator	Time period (C = calibration; V = validation)	Calibration Daily		Calibration Monthly		Calibration Annual		Validation Daily		Validation Monthly		Validation Annual	
					r^2	NSE	r^2	NSE	r^2	NSE	r^2	NSE	r^2	NSE	r^2	NSE
Van Liew et al. (2006)[#]	Walnut Gulch (Arizona)	149	stream flow	varying time periods		.30 to .76		.48 to .86				-1.0 to -1.8		-.62 to -2.3		
	Little River (Georgia, USA)	334	stream flow	varying time periods		.64 & .71		.83 & .90				.66 & .68		.88 & .89		
	Reynold's Creek (Idaho)	239	stream flow	varying time periods		.51 to .73		.52 to .79				-.17 to .62		.21 to .74		
	Little Washita 526 (Oklahoma)	160	stream flow	varying time periods		.54 & .63		.68 & .76				.13 to .56		-.11 to .60		
	Mahantango Creek (Pennslyvania)	7	stream flow	varying time periods		.46 & .69		.84 & .88				.35 to .54		.46 to .75		
Varanou et al. (2002)	Ali Efenti (Greece)	2,796	stream flow	1977-93		.62		.81								
Vazquez-Amábile & Engel (2005)	Muscatatuck River (Indiana); gauges for 3 subwatersheds	2,952	stream flow	C: 1980-94 V: 1995-02		-.23 to .28		.59 to .80				-.35 to .48		.49 to .81		
			ground water			-.12 to .28		.36 to .61				-.74 to .33		-.51 to .38		
Vazquez-Amábile et al. (2006)	St. Joseph River (Indiana, Michigan, & Ohio); 3 gauges for calib. & 4 gauges for valid.	2,800	stream flow	C: 1989-98 V: 1999-02		.46 to .65		.64 to .74			.50 to .66	.33 to .60	.73 to .76	.68 to .74		
Veith et al. (2005)	FD-36 (Pennslyvania)	.395	stream flow	April – Oct. of 1997-2000			.63	.75								
Wang & Melesse (2005)	Wild Rice River (Minnesota); gauges for two subwatersheds	2,419 – 4,040	stream flow	varying time periods		.64 & .33		.87 & .87				.49 & .45		.87 & .82		
Watson et al. (2005)	Woady Yaloak River (Australia)	306	stream flow	C: 1978-89 V: 1990-01 (modified SWAT)		.54		.77		.77		.47		.79		.91
Weber et al. (2001)	Aar (Germany)	59.8	stream flow	1986-87 (daily) 1983-87 (mon.)								.63		.74		

Table 2. Continued

Reference	Watershed	Area (km^2)	Indicator	Time period (C = calibration; V = validation)	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
White & Chaubey (2005)	Beaver Reservoir (Arkansas); gauges for three subwatersheds	362 – 1,020	stream flow	C: 1999 & 2000 V: 2001 & 2002 (stats. by year)			.41 to .91	.50 to .89					.77 to .91	.72 to .87		

†The comparisons were performed on an hourly basis for this study because the Green and Ampt infiltration method was used.
‡Exact time period of comparison was not stated in study and thus was inferred.
#Multiple gauges were used for each watershed, with some variation between calibration and validation periods for some of the watersheds.

Rosenthal et al. (1995) linked GIS to SWAT and with no calibration simulated 10 years of monthly streamflow. SWAT underestimated the extreme events but had a significant relationship (r^2=0.75). Bingner (1996) simulated runoff for 10 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, 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 and sediment loads for the Mill Creek Watershed in Texas for 1965-68 and 1968-75 (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.

Hernandez et al. (2000) utilized existing data sets (i.e., STATSGO soil database and NALC land cover classification) for parameterizing SWAT to simulate hydrologic response to land cover change for a small semi-arid watershed (150 km^2) in southeastern Arizona. These authors found that calibration was required to improve model efficiency for simulation of runoff depth. Manguerra and Engel (1998) identify parameterization issues when modeling watershed hydrology for runoff prediction when using SWAT. Areas specified were the sensitivity of runoff to spatial variability, watershed decomposition, and spatial and temporal adjustment of curve numbers and subsurface flow. Van Liew and Garbrecht (2003) evaluated SWAT's ability to predict streamflow under varying climatic conditions for three nested subwatersheds in the 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) also found that the model performed better in drier years than in wet years. However, they also found that the model was unable to simulate adequately the growth of Mexican Weeping Pine, due to the lack of simulating increased ET rates in mature plantations.

Hao et al. (2004) used an automated digital filter technique to separate and calibrate direct runoff from base flow for a five-year period for monthly streamflow. The NSE values were above 0.70 for both the calibration and validation periods with a relative error within 20%. Chu and Shirmohammadi (2004) evaluated SWAT's capability to predict surface and subsurface flow for a 33.4 km^2 watershed in Maryland. They found that SWAT was unable to simulate an extremely wet year; with the wet year removed, the surface runoff, base flow and streamflow results were within acceptable accuracy on a monthly basis. Subsurface flow results improved when the base flow was corrected.

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

Applications for Karst Influenced Systems

Spruill et al. (2000) calibrated and validated SWAT with one year of data each for a small experimental watershed in Kentucky. The daily NSE values reflected poor peak flow values and recession rates (Table 2). However, the NSE values for monthly total flows were 0.58 and 0.89 for 1995 and 1996, respectively. 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). 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 baseflows accurately matched measured streamflows after the modification, and that the predicted daily and monthly and daily resultes (Table 2) fell within the range of published model efficiencies for similar systems. Benham et al. (2006) report that SWAT streamflow results (Table 2) did not meet calibration criteria for a karst influenced 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.

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 (1962-91) 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 ET 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; these measures were then converted into groundwater table levels based on DRAINMOD theory. 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 over streamflow predictions for the 51.3 Walnut Creek Watershed in central Iowa (Table 2). Green et al. (2006) report a further application of the improved tile drainage routine using SWAT2005 for a large tile-drained watershed in north central Iowa. The addition of this routine significantly improved the model's ability to simulate a more adequate water balance for a tile-drained region in Iowa (Table 2). This study also showed 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

In Finland, Francos et al. (2001) adapted the model by adding a weather generator and a snowmelt submodel. These authors calibrated at a subbasin level and then scaled-up to the Vantaa watershed-level. They emphasize the importance of using good input data and adjusting the relevant parameters. Benaman et al. (2005) used the SWAT2000 model to calibrate and validate the runoff for the 1,200 km^2 Cannonsville River Watershed in South Central New York. These authors found the validated runoff NSE value was reasonable (0.76); however, they identified both model and data input limitations regarding estimation of snowmelt, erosion, and sediment transport. Wang and Melesse (2005) used the SWAT model to simulate streamflows for the Wild Rice River Watershed in Minnesota, which involves snowmelt hydrology. SWAT simulated the monthly, seasonal, and annual discharges well, in addition to the spring daily streamflows, which were predominantly from melted snow. Chanasyk et al. (2003) simulated the impacts of grazing on hydrology and soil moisture, respectively, using small grassland watersheds under three grazing intensities in Alberta, Canada. They evaluated SWAT's ability to simulate low flow conditions that included snow-melt events. Chanasyk et al. (2003) and Peterson and Hamlet (1998) found that SWAT was better suited for long simulation periods and suggested that the snowmelt routine be improved. The modifications performed by Fontaine et al. (2002) have clearly improved the snowmelt routine, as evidenced by an NSE increase from -0.70 to 0.86 for a six-year SWAT simulation of the Upper Wind River Basin in Wyoming.

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 ET (~32 mm/yr reduction over the entire basin), surface runoff, baseflow, and deep recharge. Lemberg et al. (2002) also describe brush removal scenarios.

Wetlands and Reservoir Applications

Arnold et al. (2001) found that a simulated wetland near Dallas, Texas, needed to be at or above 85% capacity for 60% of a 14-year simulation period. Conan et al. (2003b) found that SWAT adequately simulated the change from wetlands to dry land for the Upper Guadiana River Basin in Spain. SWAT, however, was unable to represent all of the discharge details impacted by land use alterations. The impact of flood-retarding structures on streamflow with varying climatic conditions in Oklahoma was investigated with SWAT by Van Liew et al. (2003b). It was found that flood-retarding structures are effective at reducing annual peak runoff events. Low streamflow was also impacted, showing that maintenance of a minimum base flow is vital for stream habitat preservation. Hotchkiss et al. (2000) modified SWAT to more accurately simulate U.S. Army Corp of Engineers reservoir rules for major Missouri River reservoirs. As a result, the reservoir dynamics were much more accurately simulated over a 25-year period.

Green-Ampt Applications

Very few SWAT applications in the literature report the use of the Green and Ampt infiltration option. Di Luzio and Arnold (2004) report subhourly results for two different calibration methods using the Green and Ampt method (Table 2). King et al. (1999) found that the Green and Ampt option resulted in better annual streamflow predictions but that monthly streamflows were more accurately predicted using the curve number approach (Table 2), for uncalibrated SWAT simulations for the 21.3 km^2 Goodwin Creek Watershed in Mississippi. Kannan et al. (2007b) also report that streamflow results were more accurate using the curve number approach as compared with the Green and Ampt method for a small watershed in the United Kingdom. They also report that the Hargreaves ET method outperformed the Penman-Monteith ET equation.

POLLUTANT LOSS STUDIES

Nearly 50% of the reviewed SWAT papers (Table 1) report simulation results of one or more pollutant loss indicators. Many of these studies describe some form of verifying pollutant prediction accuracy, although the extent of such reporting is much less than what has been published for hydrologic assessments. Table 3 lists r^2 and NSE statistics for 30 SWAT pollutant loss studies, which again are used here as key indicators of model performance. The majority of the r^2 and NSE values shown in Table 3 exceed 0.5, indicating that the model is able to replicate a wide range of observed in-stream pollutant levels. Relatively poor results were again reported for some studies, especially for daily comparisons. Similar to the points raised for the hydrologic results, some of weaker results were due in part to inadequate characterization of input data (e.g., description of P input gaps in Bouraoui et al., 2002), uncalibrated simulations of pollutant movement (Bärlund et al., 2006), 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. (2000) conducted a comprehensive SWAT evaluation for the 932.5 km^2 Upper North

Bosque River Watershed (UNBRW) 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) compared estimated and SWAT simulated average annual sediment loads for five major Texas river basins (20,593 to 569,000 km^2) and concluded that in all the river basins, SWAT simulated sediment yields compared reasonably well with estimated sediment yields obtained from rating curves.

Table 3. Summary of reported SWAT environmental indicator calibration and validation results.

Reference	Watershed(s)	Area (km^2)	Indicator†	Time period (C = calibration; V = validation)	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
Bärlund et al. (2006)‡	Lake Pyhäjärvi (Finland)	-	sediment	1990-94		.01										
Behera & Panda (2006)	Kapgari (India)	9.73	sediment	C: 2002 V: 2003 (rainy season)	.93	.84					.89	.86				
			nitrate		.93	.92					.87	.83				
			total P		.92	.83					.94	.89				
Bouraoui et al. (2002)	Ouse (Yorkshire, United Kingdom)	3,500	nitrate	1986-90				.64								
			soluble P					.02								
Bouraoui et al. (2004)	Vantaanjoki (Finland)	295 - 1,682	sediment	varying time periods		.44								.87		
	Vantaanjoki subwatershed	295	total N			.61										
			total P			.74		.62								
			nitrate			.34										
Bracmort et al. (2006)	Two subwatersheds the Black Creek Watershed (Indiana)	6.2 and 7.3	suspended solids				.97 & .94	.92 & .86					.86 & .85	.75 & .68		
			soluble P				.92 & .90	.84 & .78					.86 & .73	.74 & .51		
			total P				.93 & .64	.78 & .51					.90 & .73	.79 & .37		
Cerucci & Conrad (2003)	Townbrook (New York)	37	soluble P	Oct. 1999 – Sept. 2000			.91									
Chaplot et al. (2004)	Walnut Creek	51.3	nitrate	1991-98			.56									
Cheng et al. (2006)	Heihe River (China)	7,241	sediment	C: 1992-97 V: 1998-99			.70	.74					.78	.76		
			Ammonia	C: 1992-97 V: 1998-99			.75	.76					.74	.72		

Table 3. Continued

Reference	Watershed	Area (km^2)	Indicator	Time period (C = calibration; V = validation)	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
Chu et al. (2004)	Warner Creek	3.46	sediment	varying time periods			.10	.05					.19	.11	.91	.90
			nitrate				.27	.16					.38	.36	.96	.90
			ammonia										.38	-.05	.80	.19
			TKN										.40	.15	.66	-.56
			soluble P				.69	-.08					.65	.64	.87	.80
			total P				.38	.08					.65	.64	.83	.19
Cotter et al. (2003)	Moores Creek (Arkansas)	18.9	sediment	1997-98				.48								
			nitrate					.44								
			total P					.66								
Di Luzio et al. (2002)	Upper North Bosque River (Texas)	932.5	Sediment	Jan. 1993 – July 1998										.78		
			organic N											.60		
			Nitrate											.60		
			organic P											.70		
			soluble P											.58		
Du et al. (2006)[#]	Walnut Creek (Iowa); subwatershed & watershed outlet	51.3 (total area)	nitrate (stream flow)	C: 1992-95 V: 1996-99 (SWAT2000)		-.37 & -.41		-.21 & -.26				-.14 & -.18		-.21 & -.22		
	Subwatershed (site 210)	-	nitrate (tile flow)	(SWAT2000)		-.60		-.08				-.16		-.31		
	subwatershed & watershed outlet	51.3 (total area)	nitrate (stream flow)	(SWAT-M)		.41 & ,61		.80 & .91				.26 & .53		.67 & .85		
	Subwatershed (site 210)	-	nitrate (tile flow)	(SWAT-M)		.25		.73				.42		.71		
	Walnut Creek (Iowa); subwatershed & watershed outlet	51.3 (total area)	atrazine (stream flow)	(SWAT2000)		-.05 & -.12		-.01 & -.02				-.02 & -.39		-.04 & .06		
	Subwatershed (site 210)	-	atrazine (tile flow)	(SWAT2000)		-.47		-.04				-.46		-.06		

Table 3. Continued

Reference	Watershed	Area (km^2)	Indicator	Time period (C = calibration; V = validation)	Calibration Daily		Calibration Monthly		Calibration Annual		Validation Daily		Validation Monthly		Validation Annual	
					R^2	NSE	r^2	NSE	R^2	NSE	r^2	NSE	r^2	NSE	r^2	NSE
Du et al. (2006)	subwatershed & watershed outlet	51.3 (total area)	atrazine/ stream flow	C: 1992-95 V: 1996-99 (SWAT-M)		.21 & .47		.50 & .73				.12 & -.41		.53 & .58		
	Subwatershed (site 210)	-	atrazine/ tile flow	(SWAT-M)		.51		.92				.09		.31		
Gikas et al. (2005)[a]	Vistonis Lagoon (Greece); 9 gauges in four subwatersheds	1,349	Sediment	C: May 1998 – June 1999 V: Nov. 1999 – Jan. 2000			.40 to .98						.34 to .98			
			Nitrate				.51 to .87						.57 to .89			
			total P				.50 to .82						.43 to .97			
Grizzetti et al. (2005)	parts of four watersheds (United Kingdom); multiple gauges	1,380 - 8,900	total organic N	1995-99		.24		.32				.28		.38		.68
Grizzetti et al. (2003)	Vantaanjoki (Finland); 3 gauges	295 - 1,682	total N	varying time periods		.59						.43 & .51		.10 & .30		
			total P			.74						.54 & .44		.63 & .64		
Hanratty & Stefan (1998)	Cottonwood (Minnesota)	3,400	sediment	1967-91				.59								
			nitrate					.68								
			total P					.54								
			organic N & ammonia					.57								
Hao et al. (2004)	Lushi (Yellow River Basin, China)	4,623	sediment	C: 1992-97 V: 1998-04			.72	.72					.98	.94		
Kaur et al. (2004)	Nagwan (India)	9.58	sediment	C: 1984 & 92 V: 1981-83; 1985-89; 1991	.54	-.67					.65	.70				

Table 3. Continued

Reference	Watershed	Area (km^2)	Indicator	Time period (C = calibration; V = validation)	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
Kirsch et al. (2002)	Rock River (Wisconsin): Windsor gauge	9,708	sediment	1991-95					.82	.75						
			total P						.95	.07						
Muleta & Nicklow (2005a)	Big Creek (Illinois)	133	sediment	1999-01		.42										
Muleta & Nicklow (2005b)	Big Creek (Illinois): PRS station for calibration and CRS station for validation	133	sediment	C: June 1999 to Aug. 2001 V: April 2000 – Aug. 2001		.46						-.005				
Plus et al. (2006)	Thau Lagoon (France); gauges on two rivers	280	nitrate	1993-99	.44 & .27											
			NH_4+		.31 & .15											
Saleh et al. (2000)	Upper North Bosque (Texas); outlet for calibration & composite of 11 gauges for validation	932.5	sediment	C: Oct. 1993 – Aug. 1995 V: July 1995 – July 1999 (with APEX)				.81						.94		
			nitrate					.27						.65		
			organic N					.78						.82		
			total N					.86						.97		
			soluble P					.94						.92		
			organic P					.54						.89		
			total P					.83						.93		

Table 3. Continued

Reference	Watershed	Area (km^2)	Indicator	Time period (C = calibration; V = validation)	Calibration Daily		Calibration Monthly		Calibration Annual		Validation Daily		Validation Monthly		Validation Annual	
					r^2	NSE	r^2	NSE	R^2	NSE	r^2	NSE	r^2	NSE	r^2	NSE
Saleh & Du (2004)	Upper North Bosque (Texas)	932.5	sediment	C: Jan. 1994 – June 1995 V: July 1995 – July 1999		-2.5		.83				-3.5		.59		
			nitrate			.04		.29				.50		.50		
			organic N			-.02		.87				.69		.77		
			total N			.01		.81				.68		.75		
			soluble P			.08		.76				.45		.40		
			organic P			-.74		.59				.59		.73		
			total P			-.08		.77				.63		.71		
Santhi et al. (2001a)	Bosque (Texas); gauges for two subwatersheds	4,277	Sediment	C: 1993-97 V: 1998			.81 & .87	.80 & .69					.98 & .95	.70 & .23		
			Nitrate				.64 & .72	.59 & -.08					.89 & .72	.75 & .64		
			organic N				.61 & .60	.58 & .57					.92 & .71	.73 & .43		
			soluble P				.60 & .66	.59 & .53					.83 & .93	.53 & .81		
			organic P				.71 & .61	.70 & .59					.95 & .80	.72 & .39		
Stewart et al. (2006)	Upper North Bosque (Texas)	932.5	Sediment	C: 1994-99 V: 2001-02			.92	.80					.82	.63		
			Nitrate				.80	.60					.57	-.04		
			organic N				.87	.71					.89	.73		
			soluble P				.88	.75					.82	.37		
			organic P				.85	.69					.89	.58		

Table 3. Continued

Reference	Watershed	Area (km^2)	Indicator	Time period (C = calibration; V = validation)	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
Tripathi et al. (2003)	Nagwan (India)	92.5	Sediment	June – Oct. 1997							.89	.89	.92	.86		
			Nitrate								.89					
			organic N								.82					
			soluble P								.82					
			organic P								.86					
Vazquez-Amábile et al. (2006)	St. Joseph River (Indiana, Michigan, & Ohio); mean area weighted of multiple gauges	2,800	Atrazine	1996-99		.14		.42								
	main outlet at Fort Wayne	2,620	Atrazine	2000-04							.27	-.31	.59	.28		
White & Chaubey (2005)	Beaver Reservoir (Arkansas); gauges for three subwatersheds	362 – 1,020 (3,100 total)	Sediment	C: 1999 & 2000 V: 2001 & 2002 (stats. by year)			.45 to .85	.23 to .76					.69 to .77	.32 to .45		
			Nitrate				.01 to .84	-2.36 to .29					.59 to .71	.13 to .49		
			total P				.50 to .82	.40 to .67					.58 to .76	-.29 to .76		

[†]Soluble P is also report as ortho-phosphate and mineral P for some studies.
[‡]Exact time period of comparison was not stated in study and thus was inferred.
[#]Comparisons shown for Du et al. (2006) are for sampling days only.

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 from a 346 ha Warner Creek watershed located in the Piedmont physiographic region of Maryland. Evaluation results indicated a strong agreement between yearly measured and SWAT simulated sediment load but simulation of monthly sediment loading was poor (Table 3). Jha et al. (2006a) found that the sediment loads predicted by SWAT were consistent with sediment loads measured for the Raccon River Watershed (RRW) in west central Iowa, as evidenced by monthly and annual NSE values of 0.78 and 0.79, respectively. Bracmort et al. (2006) report satisfactory SWAT sediment simulation results for two small watersheds in Indiana (Table 3). Benaman and Shoemaker (2005) and found that SWAT underestimated observed load by 29% for the Cannonsville Reservoir Watershed in New York, primarily because of underestimation of surface runoff during snow melt events. Cotter et al. (2003) report a calibrated NSE value of 0.48 for monthly SWAT predictions for the Moores Creek Watershed in Arkansas, while White and Chaubey (2005) report NSE values of 0.43 to 0.76 for three Beaver Reservoir watershed sites in northeast Arkansas. Hanratty and Stefan (1998) calibrated SWAT using water quality and quantity data measured in the Cottonwood River near New Ulm, 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 with an r^2 of 0.42. However, no verification procedure was conducted because of 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. (2005) compared SWAT with observed daily sediment yield for the same watershed and found a close agreement with r^2 of 0.89 and NSE of 0.89. Hao et al. (2004) stated 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) tested SWAT using sediment data collected from the Heihe River, another tributary of the Yellow River (Table 3); the resulting monthly NSE statistics were 0.74 and 0.76 for the calibration and validation periods, respectively. In Finland, Bärlund et al. (2006) report poor results for uncalibrated simulations performed within the Lake Pyhäjärvi Watershed (Table 3). Gikas et al. (2005) conducted an extensive evaluation of SWAT in Vistonis Lagoon, a mountainous agricultural watershed in northern Greece, and concluded that agreement between observed and SWAT 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 are 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 (2006), and Di Luzio et al. (2002) evaluated SWAT by comparing SWAT N prediction with measured N losses in the Upper North Bosque or Bosque River watersheds in Texas. They unanimously concluded that SWAT reasonably predicted N loss, with most of the average monthly validation NSE greater than or equal to 0.60 (Table 3). They also found that SWAT satisfactorily predicted P losses, 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 N and P predictions (Table 3). Hanratty and Stefan (1998) calibrated SWAT N predictions using measured data collected for the Cottonwood River in 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 P results (Table 3).

In Iowa, Chaplot et al. (2004) calibrated SWAT from a nine-year data at flat and intensively cultivated Walnut Creek Watershed and concluded that SWAT gave accurate predictions of nitrate load

(Table 3). Du et al. (2006) also showed that the modified tile drainage functions in SWAT-M resulted in far superior nitrate loss predictions for Walnut Creek (Table 3), as compared with the previous approach used in SWAT2000. However, Jha et al. (2007) report very strong nitrate loss predictions for the Raccoon River Watershed using SWAT2000, with monthly r^2 and NSE values that ranged between 0.73 and 0.79 for the calibration and validation periods. In Arkansas, Cotter et al. (2003) calibrated SWAT measured nitrate and got an NSE of 0.44 in the Moores Creek Watershed; the authors stated that SWAT had a response similar to those in other published reports.

Bracmort et al. (2006) and Arabi et al. (2006) found that SWAT could account for the effects of BMPs on phosphorus and nitrogen losses for the Dreisbach and Smith Fry 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 P 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 P loads were considerably higher than corresponding measured loads for the Rock River Watershed in Wisconsin. Veith et al. (2005) found that measured watershed exports of dissolved P and total P during a seven-month sampling period from a watershed in Pennsylvania were similar in magnitude to SWAT predicted losses.

SWAT nutrient predictions have also been evaluated in several other countries (Table 3). In India, SWAT N and P predictions were tested in two studies using measured data within the Midnapore (Behera and Panda, 2006) and Hazaribagh (Tripathi et al., 2003) districts of eastern India. Both studies concluded that the SWAT model could be successfully used to satisfactorily simulate nutrient losses. SWAT predicted NH_3-N was close to the observed value for the Heihe River study in China (Cheng et al., 2006), as indicated by the validation NSE of 0.72. Three studies conducted in Finland for the Vantaanjoki River (Grizzetti et al., 2003, and 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 with data from two rivers in the Thau Lagoon Watershed, which drains to 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, with r^2 values of 0.57 to 0.89. 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 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 .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 terbuthylazine, tebutryn, cyanazine, and bentazone for the 1.41 km^2 Colworth Watershed in the United Kingdom. The results of different application timing and split application scenarios are also described. 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-Amábile et al. (2006) found that the estimated timing of atrazine applications in the 2,800 km^2 St. Joseph Watershed in northeast Indiana was a very sensitive parameter regarding calibration and validation of atrazine in SWAT. The predicted atrazine mass at the watershed outlet was in close agreement with measured loads for the period of September through April during the 2000-2003 period. 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

Several SWAT scenario studies report the effects of various BMPs, cropping systems, and other factors on pollutant losses. Kirsch et al. (2002) describe SWAT results, which indicated that the implementation of improved tillage practices can reduce sediment yields by almost 20% in the Rock River in Wisconsin. Chaplot et al. (2004) found that adoption of no-tillage, changes in N application rates, and land use changes could greatly affect N losses in the 51.3 km^2 Walnut Creek Watershed in central Iowa. Further analysis of BMPs by Vaché et al. (2002) for Walnut Creek and a second Iowa watershed 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. 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. Santhi et al. (2006) report the impacts of manure and nutrient-related BMPs, forage harvest management, and other BMPs on water quality for the West Fork Watershed of the Trinitiy River Basin in Texas. SWAT studies in India include identification of critical or priority areas for soil and water management in a watershed (Kaur et al., 2004 and Tripathi et al., 2003). 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. 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. Graphical and tabular 2-4,D and nitrate losses are reported by King and Balogh (2001) for 99-year simulations of four treatment scenarios: continuous corn, undisturbed forest, golf course conversion from forest, and golf course conversion from cropland. Two scenarios of surfactant movement are described by Kannan et al. (2007a) for the Colworth Watershed. Sensitivity analyses were also performed. Benham et al. (2006) describe a TMDL application of SWAT for the 367 km^2 Shoal Creek 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 the standard SWAT model by accounting for (1) the effects of increased atmospheric CO_2 concentrations, in the range of 330-660 ppmv, on plant development and transpiration; and (2) changes in climatic inputs. Several SWAT studies report the effects of arbitrary climate changes on streamflow. These include Eheart and Tornil (1999), Stonefelt et al. (2000), Fontaine et al. (2001), and Jha et al. (2006b), which report useful insights on plant growth and streamflow responses to CO_2 fertilization effects and/or other climatic input shifts. The SWAT results reported next 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

Ritschard et al. (1999) and Limaye et al. (2001) describe climate change impacts on the hydrology of selected watersheds in the U.S. southeast region, using SWAT and downscaled climate projections from the HadCM2 GCM. Ritschard et al. found that future water availability could decline by up to 10% within 20 to 40 years during critical agricultural growing seasons in the Gulf Coast. A second key finding (Limaye et al., 2001) was that GCM interfaces with hydrologic models may only work for regional assessments of seasonal and annual climate change rather than for short-term watershed-level analyses.

Rosenberg et al. (2003) simulated the effect of downscaled HadCM2 climate projections (CO_2 level of 560 ppmv) on the hydrology of the 18 MWRRs (Figure 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 *Climatic Change* volume 69, number 1. Water yield shifts exceeding ±50% were predicted for portions of the 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 (Figure 2).

Stone et al. (2001) predicted the impact of climate change on Missouri River Basin (Figure 2) water yields by inputting downscaled climate projections, which were generated by nesting the RegCM RCM within the CISRO GCM, 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 eight-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 (Figure 2), with an assumed outlet at Grafton, Illinois, using a framework consisting of 119 eight-digit subwatersheds and land use, soil, and topography data that was obtained from BASINS. Jha et al. (2004b) found that Upper Mississippi River Basin streamflows increased by 50% for the 2040-2049 period, when climate projections generated by a nested RegCM2-HadCM2 approach were used to drive SWAT. Jha et al. (2006b) 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 twentieth century Upper Mississippi River Basin annual streamflows, 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. (2006) 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 values as a function of five main vegetation types; this approach has 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 and the 1.1 km^2 Ganspoel Watershed in Belgium. 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 2xCO_2 GCM climate change scenario. Varanou et al. (2002) also found that average stream flows, 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 N and P loads of 6%-27% and 5%-34%, respectively, for the 3,500 km^2 Ouse River Watershed located in the Yorkshire region of the United Kingdom. Bouraoui et al. (2004) found for the Vantaanjoki River Watershed, which covers 1,682 km^2 in southern Finland, that snow cover decreased, winter runoff increased, and annual nutrient losses increased slightly 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 analysis approaches 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. Some calibration steps occur prior to application of SWAT, such as the common use of automated methods that determine separation of base and groundwater flow from overall streamflow (Arnold et al., 1995a; Arnold and Allen, 1999).

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; the latter two are further discussed in the next section. Several automated uncertainty analyses approaches have been developed, which incorporate various sensitivity and/or calibration techniques. These techniques 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 United Kingdom 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. (2006) 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 based on a large set of simulations, for the 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 did the automatic PEST approach (Table 2). Wang and Melesse (2005) also used PEST to perform an automatic SWAT calibration of three snowmelt- 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). Muleta and Nicklow (2005a) describe using a genetic algorithm to perform automatic calibration of daily streamflow and sediment yield estimates (Tables 2 and 3).

The monthly applications of a shuffled complex evolution (SCE) optimization scheme are described by van Griensven and Bauwens (2003, 2005) and Vandenberghe et al. (2001) for ESWAT simulations, primarily for the Dender River in Belgium. The user inputs calibration parameters and ranges along with measured daily flow and pollutant data. The automated calibration scheme controls 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 the 81 km^2 Dietzhölze and 134 km^2 Aar watersheds in Germany, respectively. Di Luzio and Arnold (2004) describe 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. (2003) 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. (2005) further evaluated the SCE alogrithm for five watersheds with widely varying climatic characteristics, including the same two in Georgia and Oklahoma and three others located in Arizona, Idaho, and Pennslyvania.

Uncertainty Analyses

Shirmohammadi et al. (2006) state that Monte Carlo simulations 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 essentially been derived from these two basic strategies, 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 simulations, LH-Monte Carlo simulations, 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 simulations 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 from taking on unrealistic values. They then performed a nonlinear calibration and uncertainty analysis using PEST, in which confidence intervals were generated for annual and seven-day streamflow estimates. Their resulting calibrated statistics are shown in Table 2. Muleta and Nicklow (2005b) describe a second 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) an 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 for the final calibrated statistics (Tables 2 and 3).

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), which further evaluates results obtained with ParaSol for a different time period (to ascertain bias in the initial confidence region, etc.); and the Confidence ANalysis Of Physical Inputs (CANOPI), which evaluates uncertainty associated with climatic data and other inputs. Additional uncertainty analysis insights are provided by Vanderberghe et al. (2006) 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 MC-based approaches.

EFFECTS OF HRU/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) different resolutions of precipitation input. These studies serve as additional types of SWAT sensitivity analyses and provide valuable insight into how the model responds to variations in key inputs.

HRU and Subwatershed Delineation Effects

The majority of the HRU/subwatershed delineation studies were based on arbitrary subdivision criteria. However, Haverkamp et al. (2002) used a statistically based approach called the SUbwatershed

Spatial Analysis Tool (SUSAT) to find the most efficient SWAT flow predictions as a function of the number of simulated subwatersheds. Further application of SUSAT in combination with SWAT-G, IOSWAT, and other software tools is described by Fohrer et al. (2005) and Haverkamp et al. (2005).

Bingner et al. (1997), Manguerra and Engel (1998), FitzHugh and Mackay (2000), Jha et al. (2004a), and Chen and Mackay (2004) 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) also found that little variation occurred in predicted surface runoff across three subwatershed delineation schemes (1, 12, and 22 subwatersheds) for the 90.2 km^2 Nagwan Watershed in northeast India, but that evapotranspiration, percolation, and soil water content estimates did vary between 5% to 48%, 2% to 26%, and 0.3% to 22%, respectively, between the three configurations. 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 suggested 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 were also found by Arabi et al. (2006) 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. (2006) found that an average subwatershed equal to about 4% of the overall watershed area is 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, because of 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.

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 1,890 ha Moores Creek Watershed in Arkansas, and that minimum DEM, land use, and soil resolutions should be between 30 and 300, 300 and 500, and 300 and 500 m, respectively, to obtain accurate flow, sediment, NO_3-N, and TP 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. Romanowicz et al. (2005) report that SWAT streamflow estimates were very sensitive to both soil and land use inputs, on the basis of 36 different soil and land use map combinations that were used in uncalibrated SWAT simulations for the 59.1 km^2 Thyle Watershed in central Belgium.

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 had been 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 were found to result 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 1,200 km^2 Cannonsville Watershed in south central New York. Streamflows were predicted to increase in the San Pedro Watershed because of 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) also 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 and 12.1 km^2 Latem watersheds in the Flanders region of 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). Huisman et al. (2004) describe the impacts of hypothetical cropland and pasture 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 Resolution 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 51.3 km^2 Walnut Creek Watershed in central Iowa and the UNBRW in north central Texas. Sediment predictions improved significantly when the densest rain gauge networks were used; only slight improvements occurred for the corresponding surface runoff and N 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 efficiency improved (Table 2) when Next Generation Weather Radar (NEXRAD) precipitation input was used instead of rain gauge inputs. Jayakrishnan et al. (2005) also found that NEXRAD precipitation input resulted in improved streamflow estimates relative to rain gauge data (Table 2). Further sensitivity of precipitation input on SWAT hydrologic output is reported for comparisons of different weather generators by Harmel et al. (2000) and Watson et al. (2005).

COMPARISONS OF SWAT WITH OTHER MODELS

Borah and Bera (2003, 2004) compared SWAT with several other watershed-scale models. In the 2003 paper, they report that DWSM, HSPF, 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 paper, they compiled 17 SWAT, 12 HSPF, and 18 DWSM applications and concluded that SWAT and HSPF were suitable for predicting yearly flow volumes, sediment loads, and nutrient 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, nutrient, and pesticides at short time intervals. Shepherd et al. (1999) evaluated 14 models and found SWAT to be the most suitable for estimating P loss from a lowland English catchment.

Van Liew et al. (2003a) compared the streamflow predictions of SWAT and HSPF on eight nested agricultural watershed within the 610 km^2 Washita River Basin in southwestern Oklahoma. They found that differences in model performance were mainly attributed to the runoff production mechanisms of the two models. Furthermore, they concluded that SWAT gave more consistent results than HSPF in estimating streamflow for agricultural watersheds under various 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) calibrated SWAT and HSPF with daily flow, sediment, and nutrients measured at five stream sites of the 933 km^2 Upper North Bosque River Watershed (UNBRW) located in central Texas. They concluded that the average daily flow, sediment, and nutrient loading simulated by SWAT were closer to measured values than was HSPF during both the calibration and verification periods. Singh et al. (2005) found that SWAT flow predictions were slightly better than corresponding HSPF estimates for the 5,508 km^2 in eastern Illinois and western Indiana, primarily because of better simulation of low flows by SWAT. El-Nasr et al. (2005) found that both SWAT and MIKE-SHE 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 (Soil and Water Lab, 2002) for a 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 N loads for two monitoring sites within the 1,380 km^2 Great Ouse Watershed in the United Kingdom. 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.

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 have allowed for more in-depth assessments of questions that cannot be considered with SWAT alone, such as groundwater withdrawal impacts or the costs incurred from different choices of management practices.

SWAT-MODFLOW and/or Surface Water Model Interfaces

A linkage was performed between SWAT and the MODFLOW groundwater model (McDonald and Harbaugh, 1988) that is described in detail by Perkins and Sophocleous (1999) and Sophocleous and Perkins (2000) and referred to as SWATMOD by Sophocleous et al. (1999). Sophocleous et al. (1999) used SWATMOD 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 Sophocleous and Perkins (2000) to study irrigation effects on streamflow and groundwater levels in the Lower Republican River Watershed in north central Kansas and to investigate streamflow into a wildlife refuge and streamflow and groundwater declines within the Rattlesnake Creek Watershed. Additional SWATMOD testing and scenario results are reported by Perkins and Sophocleous (1999) for the Lower Republican River. 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 also interfaced with a 3-D lagoon model by Plus et al. (2006) to determine N loads from a 280 km^2 drainage area into the Thau Lagoon, which lies along the south coast of France. The main annual N load was estimated with SWAT to be 117 t yr^{-1}; chlorophyll a concentrations, phytoplankton production, and related analyses were performed with the lagoon model.

SWAT Interfaces with Environmental Models or Genetic Algorithms for BMP Analyses

Renschler and Lee (2005) linked SWAT with the Water Erosion Prediction Project (WEPP) model 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 similar. 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). The analysis determined the marginal utility of buffer widths and the most affordable parcels in which to establish riparian buffers.

Nicklow and Muleta (2005a) have interfaced SWAT with both a GA and a Strength Pareto Evolutionary Algorithm (SPEA) to perform single and multi-objective evaluations, respectively. They show an example for the 130 km^2 Big Creek Watershed in southern Illinois, in which conversion of 10% of the HRUs into conservation programs (cropping system/tillage practice BMPs) for a maximum of 50 GA generations would result in reduced sediment yield of 19%. Optimal land use–tillage combinations were determined for each HRU within a maximum of 50 GA generations. Gitau et al. (2004) interfaced baseline P estimates from SWAT, with a GA 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-Economic and/or Environmental Model Interfaces

Osei et al. (2003a; 2003b) simulated the impacts of nutrient losses from grazing dairy cows within the 1,279 km^2 Lake Fork Reservoir Watershed (LFRW) in northeast Texas and dairy manure applications to cropland within the UNBRW in north central Texas, respectively, by interfacing a Farm Economic Model (FEM) with the APEX model and SWAT. It was 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 LFRW, and that manure incorporation reduced P losses at a relatively small to moderate cost to producers in the UNBRW. Gassman et al. (2006) assessed the impacts of seven individual BMPs and four BMP combinations with the same integrated modeling system for the 162.2 km^2 Upper Maquoketa River Watershed in northeast Iowa, which is dominated by cropland and mixed livestock production. 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 yield positive net returns. Additional scenario results for all three watersheds are reported in Gassman et al. (2002).

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 regard 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, because of 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 was 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. Other examples of SWAT interfaces with economic models are reported in Whittaker (2005) and Turpin et al. (2005).

Interfaces 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 model 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 (.5, .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 in honor of 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 that 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 will (1) enable more accurate simulation of currently supported processes, (2) incorporate advancements in scientific knowledge, and/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 recent Model Developer's Workshop at the Institute for Climate Research Impact 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; i.e., 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 this method in SWAT and similar models has proved controversial because of 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., see Ponce and Hawkins, 1996; Agnew et al., 2006; Bryant et al., 2006).

The Green and Ampt method provides an alternative hydrologic option in SWAT, which Rawls and Brakensiek (1986) found 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, King et al. (1999) and Kannan et al. (2007b) found that the curve number method was more accurate than the Green and Ampt approach in their respective SWAT applications, as previously discussed. These conflicting results lend support to the viewpoint expressed by Ponce and Hawkins (1996) that alternative point infiltration techniques, including the method developed by Green and Ampt, have not demonstrated a clear superiority to the curve number method.

Improved SWAT hydrologic predictions potentially could be obtained through modifications in the curve number methodology and/or incorporation of more complex routines. For example, 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. Borah et al. (2006) further propose inserting the combined curve number-kinematic wave methodology used in the Dynamic Watershed Simulation Model (DWSM) into SWAT, which was found to result in improved simulation of daily runoff volumes for 8,400 km^2 Little Wabash River Watershed in Illinois. Model modifications would be needed to address phenomena such as variable source area (VSA) saturated excess runoff which dominants surface runoff in some regions including the northeast U.S., where down-slope VSA saturated discharge often occurs because of subsurface interflow over relatively impermeable material (Agnew et al., 2006; Walter et al., 2000). The modified SWAT versions described by Eckhardt et al. (2002) and Watson et al. (2005) may provide useful insights for regions that are characterized by VSA hydrology, in which the respective modifications were made to address subsurface interflow in low mountain conditions in Germany (SWAT-G version) and to simulate VSA dominated hydrology in southwest Victoria, Australia, by incorporating a saturated excess runoff routine in SWAT.

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. Consequently, potential pollutant attenuation between the source area and a stream is also ignored, as discussed by Bryant et al. (2006) for P movement. The current SWAT HRU provides neither explicit spatial representation of riparian buffer zones, wetlands, and other BMPs nor 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 currently being explored, with the initial focus on constructing spatially defined landscapes that can then 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/manure application rate and timing, cover crops (perennial grasses), filter strips, grassed waterways, and wetlands. However, there are limitations in how these practices are represented in the model, and some practices such as riparian buffer zones cannot be directly simulated at the present time.

The majority of conservation practices can be simulated in SWAT with straightforward parameter changes; Arabi et al. (2007) have proposed standardized approaches for simulating specific conservation practices in the model including the 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 because of the lack of HRU spatial definition in SWAT. There are also further limitations in simulating grassed waterways, because channel routing is not simulated at the HRU level. However, a viable option for some applications may be to configure a watershed using subwatersheds without HRUs, which maintains a more realistic representation of channel structure throughout the simulated watershed. Overall, the empirical basis used for simulating most of these practice effects is a definite limitation in accurately depicting the impacts of such BMPs in the model. However, this weakness is a reflection of much of the current state-of-the-art understanding of conservation practice effects and is inherent in most available simulation tools.

Virtually any combination of fertilizer or manure application rate and timing can be simulated in SWAT at the HRU level. Nutrient injection or incorporation, in response to tillage passes, can also be accounted for, although the model assumes that the nutrients are distributed in the top soil layer rather than injected or distributed at a specific depth. Also, side dressing or similar fertilizer placement application practices cannot be realistically simulated at present in SWAT. Depiction of cover crops can be carried out in various ways such as inclusion of alfalfa or other forages within a crop rotation, and as perennial vegetation planted after crop harvest in the fall or in land set-aside programs such as CRP. Only a single plant species can be simulated at a given time, which precludes performing scenarios such as mixed perennial grasses for a CRP field.

Constructed wetlands have been identified as a key N loss mitigation strategy in the Mississippi River Basin (Mitsch et al., 2001) and in other regions. Representation of constructed wetlands or other wetland areas 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. Riparian buffers and other conservation buffers have also been demonstrated to reduce N and other pollutant losses to streams in many locations (Lovell and Sullivan, 2006). 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. Flexible simulation of riparian and other buffers for a wide range of watershed scales and conditions will likely require the incorporation of buffer zone components from REMM (or a similar model) into SWAT, which, together with spatially explicit landscape/HRU functionality, would allow for realistic assessments of riparian buffer impacts along stream channels. The riparian and wetland processes recently incorporated into the SWIM model (Hatterman et al., 2006) may also prove useful for improving current approaches used in SWAT.

Table 5. Proposed key parameters to adjust for accounting of different conservation practice effects in SWAT. [†]

	Suggested parameters that should be adjusted for each conservation practice											
Conservation practice	Channel depth	Channel width	Channel erodibility factor	Channel cover factor	Channel Manning's roughness coefficient	Channel slope segment	Filter strip width[#]	Hillside slope length	Manning's N coeff. 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[‡]									X	X	X	
Stream channel stabilization	X	X	X		X							
Strip Cropping									X	X	X	X

[†]Source: Arabi et al., 2007.
[‡]Soil incorporation of residue by tillage implements is also a key aspect of simulated residue management in SWAT.
[#]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.

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. SWAT bacteria component strengths 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 based on 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 avenues 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 not to 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 dominants P-limited systems including the Bosque River. This is a common limitation of most water quality models with in-stream components, which focus instead just on suspended algae. Migliaccio et al. (2006) performed parallel SWAT analyses of total P and nitrate (including nitrite) movement for the 60 km^2 War Eagle Creek 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, a finding 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 is described by Van Griensven and Bauwens (2003, 2005).

Additional Research Needs

1. Routines for concentrated animal feeding operations and related manure application should be developed 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 and subsurface transport of phosphorus.
2. All aspects of stream routing need further testing and refinement, including the QUAL2E routines as previously discussed.

3. Improved stream channel degradation and sediment deposition routines are needed to better describe sediment transport, using the simple channel and degradation routines described by Allen et al. (2002) for their modified SWAT-DEG model, and to account for nutrient loads associated with sediment movement (Jha et al., 2004a). Channel sediment routing could be improved by accounting for sediment size effects, with separate algorithms for wash load and bed load. Improved flood plain deposition algorithms are needed, and a stream bank erosion routine should be incorporated into the model.
4. SWAT currently assumes that soil carbon contents are static. This approach should be replaced by an updated carbon cycling submodel such as a simplified version of the one described by Izaurralde et al. (2006).
5. 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.
6. 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, especially in light of recent corn and other crop hybrid developments that have resulted in ever-increasing yields.
7. 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 (a) incorporation of a surface litter layer into the soil profile, (b) accounting of water storage and release by wetlands, and (c) improved simulation of spring-thaw-generated runoff. These improvements will ultimately be grafted into SWAT2005.
8. 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 that is based on the

DRAINMOD model approach (Skaggs, 1982) that includes the effects of tile drain spacing and shallow water table depth. Future research should also be focused on controlled drainage BMPs.

9. 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 and the uncertainty analysis is being broadened to account for uncertainty in regression during validation (Harmel et al., 2006).
10. 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). General revisions of the atmospheric CO_2 effects are also needed, to reflect more recent findings that elevated CO_2 concentrations will result in crop yield increases that are only about 50% of previously report yield impacts (Long et al., 2006) and other issues discussed by Jha et al. (2006b).
11. Further investigations are being conducted by a variety of researchers to expand the utility of SWAT by interfacing it with other models. Two examples include (a) passing forest growth estimates from a more advanced crop growth component in the ALMANAC model to SWAT for Canadian Boreal Forest conditions (MacDonald et al., 2005), and (b) the SWAP model that is a fully integrated APEX-SWAT modeling system (Saleh and Du, 2004).

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 creating component modifications, which support more accurate simulation of specific processes or regions, or by interfacing SWAT with other models. Both of these trends are likely 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 to meet the desire for additional spatial complexity while maintaining ease of model use. This goal should be kept in focus as the model continues to develop in the future.

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