doi:10.2489/jswc.64.1.17

Soil and Water Assessment Tool evaluation of soil and land use geographic information system data sets on simulated stream flow

G.C. Heathman, M. Larose, and J.C. Ascough II

Abstract: The integration of geographic information systems (GIS) and hydrologic models provides the user with the ability to simulate watershed-scale processes within a spatially digitized computer-based environment. Soil type and land use data are essential GIS data layers used in a wide array of government and private sector activities, including resource inventory, land management, landscape ecology, and hydrologic modeling. This investigation was conducted to evaluate the use of different combinations of Soil Survey Geographic (SSURGO) and State Soil Geographic (STATSGO) soil classification systems and the USDA National Agricultural Statistics Service (NASS) and national Gap Analysis Project (GAP) land use data sets and their effects on modeled stream flow using the Soil and Water Assessment Tool (SWAT2005). Performance of the model was tested on the Cedar Creek Watershed in northeastern Indiana, one of 14 benchmark watersheds in the USDA Agricultural Research Service Conservation Effects Assessment Project (CEAP) watershed assessment component. CEAP comprises two main components: (1) a national assessment that provides model estimates of conservation benefits for annual reporting and (2) a watershed assessment component aimed at quantifying the environmental benefits from specific conservation practices at the watershed scale. Model performance for daily, monthly, and annual uncalibrated stream flow responses in SWAT was assessed using the Nash-Sutcliffe efficiency coefficient (ENS), coefficient of determination (R^2), root mean square error (RMSE), ratio of RMSE to the standard deviation of measured data (RSR), and percent bias (PBIAS). We found that the range of relative error (e.g., PBIAS) and ENS values for uncalibrated stream flow predictions in this study were similar to others that have been reported in the literature. Simulated stream flow values ranged from slight overestimations of approximately 5%, to underestimating stream flow by 25% to 41% depending on the combination of soil and land use input data sets. Overall, the NASS SSURGO data sets gave the best model performance for monthly stream flow having an ENS value of 0.58, R^2 of 0.66, RSR of 0.65, and PBIAS equal to 21.93. The poorest model performance results were obtained using the GAP SSURGO data sets that had an ENS value of -2.58, R^2 of 0.49, RSR of 1.89, and a PBIAS value of 27.92. The results of this study indicate that in using the SWAT model, several factors regarding GIS input data sets may affect stream flow simulations and, consequently, water quality assessment studies. In addition to the effect of GIS source data on model output (e.g., SSURGO, STATSGO, NASS, GAP), there is evidence shown in this study that the interaction, pre-processing, and aggregation of unique combinations of GIS input layers within SWAT also influence simulated stream flow output. Overall, results of the study indicate that the use of different land use GIS layers has a greater effect on stream flow estimates than different soil data layers.

Key words: Conservation Effects Assessment Project (CEAP)—geographic information system (GIS)—hydrologic modeling—Soil and Water Assessment Tool (SWAT)—stream flow

Recent advances in computing capability and geographic information systems (GIS) have led to increasingly sophisticated watershed scale models that incorporate climatic, soil, topographic, and land use characteristics and are capable of addressing multiple issues related to water quality concerns and environmental assessments. Notable examples of continuous watershed simulation models include the Hydrologic Simulation Program-Fortran (HSPF) (Johanson et al. 1984), Soil and Water Assessment Tool (SWAT) (Arnold et al. 1993), and Annualized Agricultural Non-Point Source (AnnAGNPS) model (Yuan et al. 2001). These conceptually based watershed scale models are computationally efficient, operate on a daily or subdaily time step, and often lump hydrologic processes that occur over short time steps into simplified assumptions.

Integrated GIS hydrologic models require as primary input geospatial data sets characterizing the soils, topography, and land use. Fundamental to optimum model performance are the quality, consistency, compatibility, and structure of the geographic data sets used as model input. Furthermore, the combination and subsequent model interaction of primary GIS input layers often influences the initialization of several hydrologic input parameters (Di Luzio et al. 2005). Di Luzio et al. (2005) applied the SWAT model in the Goodwin Creek, MS, watershed and found that using a coarser digital elevation model (DEM) caused inaccuracies for erosion and sediment yields, less detailed land use maps caused significant variations in runoff, and that the SWAT model was less sensitive to the scale of soil maps. Romanowicz et al. (2005) investigated the sensitivity of SWAT to the preprocessing of soil and land use data for modeling rainfall runoff processes in the Thyle watershed in Belgium. Their results suggest that the SWAT model is extremely sensitive to the quality of the soil and land use data. Wang and Melesse (2006) studied the effects of State Soil Geographic (STATSGO)

Gary C. Heathman is a soil scientist at the National Soil Erosion Research Laboratory, USDA Agricultural Research Service, West Lafayette, Indiana. **Myriam Larose** is a research graduate assistant in the Agronomy Department, Purdue University, West Lafayette, Indiana. **James C. Ascough II** is a hydrologic engineer at the Agricultural Systems Research Unit, USDA Agricultural Research Service, Fort Collins, Colorado.

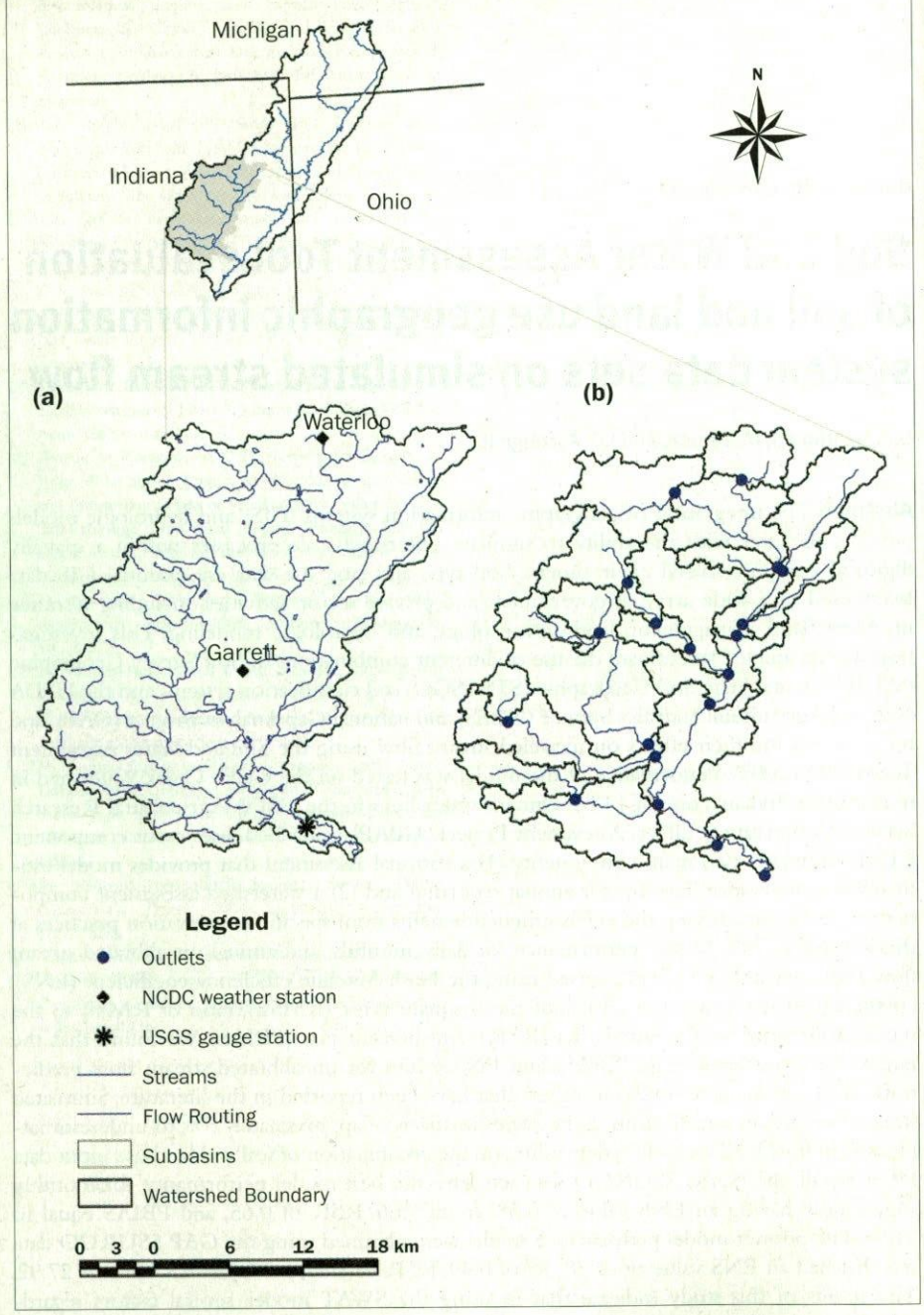
and Soil Survey Geographic (SSURGO) soil data as inputs for SWAT to simulate stream flows that were predominantly generated from melting snow and found that the SWAT SSURGO simulation provided an overall better prediction of the discharges. Other than these studies, there seems to be a dearth of literature on the topic.

In an effort to better understand the effects of using different types of GIS data sources for soil and land use, we conducted an investigation to assess estimates of stream flow using the Soil and Water Assessment Tool (SWAT2005) watershed scale, conceptual model, and readily available soil and land use GIS data sets. The AVSWAT-X (version 2005) ArcView 3.3 GIS interface (Di Luzio et al. 2002) was used to input both the STATSGO database (1:250,000 scale) and the SSURGO database (1:12,000 scale) from the USDA Natural Resources Conservation Service (NRCS). Two types of land use GIS data sets were used in the investigation and also input into the AVSWAT-X GIS interface: (1) the 2001 USDA National Agricultural Statistics Service (NASS) Indiana Cropland Data Layer (USDA NASS 2001) and (2) the 1994 United States Geological Survey (USGS) National Gap Analysis Program (GAP) data set.

The overall objective of this study was to determine to what extent the use of different combinations of the above soil and land use geospatial data sets affects uncalibrated stream flow estimates using SWAT2005. We chose to compare noncalibrated simulation estimates given that SWAT was developed for applications on ungaged watersheds, as well as to eliminate any bias due to parameter optimization as a result of calibration (thus potentially masking the effects of using different GIS input data sets). Model performance was evaluated on the Cedar Creek watershed (CCW) within the St. Joseph River watershed in northeastern Indiana. The St. Joseph River watershed is one of 14 benchmark watersheds in the USDA Agricultural Research Service (ARS) Conservation Effects Assessment Project (CEAP) watershed assessment studies. The CEAP watershed assessment studies are a combined effort by NRCS and ARS to quantify the environmental benefits of conservation practices supported by the USDA in the 2002 farm bill. A complete description of the CEAP watershed assessment studies is reported in Mausbach and Dedrick (2004), Duriancik et al. (2008), and Richardson et al. (2008).

Figure 1

(a) Cedar Creek watershed stream network, weather stations, and USGS gauging station and (b) Cedar Creek watershed subbasins, flow routing, and subbasin outlets for SWAT modeling.



Materials and Methods

Study Area. The CCW is located within the St. Joseph River Basin in northeastern Indiana (41°04'48" to 41°56'24" N and 84°52'12" to 85°19'48"W). The CCW drains two 11-digit hydrologic unit code (HUC) watersheds, the Upper Cedar (04100003080) and Lower Cedar (04100003090), covering an area of approximately 707 km^2 (273 mi^2) (figure 1a). Topography of the watershed varies from rolling hills in Noble County to nearly level plains in DeKalb and Allen Counties, with a maximum altitude above sea level of 326 m (1,069 ft) and average land surface slope of 3%.

Soil types on the watershed were formed from compacted glacial till. The predomi-

nant soil textures in the immediate Cedar Creek are silt loam, silty clay loam, and clay loam. The majority of soils along Cedar Creek are comprised of the Morley-Blount and Eel-Martinsville-Genesee associations. The Morley-Blount association usually occurs on the uplands and indicates deep, moderately to poorly drained, nearly level to steep, medium-textured soils. The Eel-Martinsville-Genesee association consists of deep, moderately well drained, nearly level, and medium- to moderately fine-textured soils on bottomlands and stream terraces (SJRWI 2004).

The average annual precipitation in the watershed area is approximately 900 mm (35 in). The average temperature during crop growth seasons ranges from 10°C to 23°C (50°F to 75°F). Approximately 76% of the watershed area is agriculture, 21% forested lands, and 3% urban. The majority of the agricultural lands are rotationally tilled, predominantly with corn and soybeans, with lesser amounts of wheat and hay.

Table 1

Number of subbasins and hydrologic response units (HURs) within the Cedar Creek watershed for each land use and soil geographic information system data set.

Land use database	Soil database	Number of subbasins	Number of HRUs
NASS 2001	SSURGO	20	259
	STATSGO	20	164
GAP 1994	SSURGO	20	143
	STATSGO	20	91

Table 2

Cedar Creek watershed SWAT soil parameters for each land use and soil geographic information system data set.

Land use	Soil	Hydrologic soil group	CN	SOL_AWC (mm mm^{-1})	SOL_K (mm h^{-1})
GAP 1994	SSURGO	A	55	0.36	186.8
NASS 2001		B	72	0.14	57.6
		C	80	0.16	32.3
GAP 1994	STATSGO	A	55	0.4	240.0
NASS 2001		B	72	0.2	41.0
		C	80	0.2	7.0

Note: CN = curve number. SOL_AWC = soil available water capacity. SOL_K = soil saturated hydraulic conductivity.

SWAT Model Overview. The SWAT model was originally developed by the USDA ARS to predict the impact of land management practices on water, sediment, and agricultural chemical yields in large ungaged basins (Arnold et al. 1998). SWAT incorporates features of several ARS models (Knisel 1980; Leonard et al. 1987; Williams et al. 1984) and is a direct outgrowth of the Simulator for Water Resources in Rural Basins (SWRRB) (Williams et al. 1985). The Soil Conservation Service (SCS) runoff curve number (CN) is used to estimate surface runoff from daily precipitation. The curve number is adjusted according to moisture conditions in the watershed (Arnold et al. 1993). SWAT can also be executed on a subdaily time step using the Green and Ampt infiltration method (Green and Ampt 1911). Other hydrologic processes simulated by the model include evapotranspiration (ET), infiltration, percolation losses, channel transmission losses, channel routing, and surface, lateral, shallow aquifer, and deep aquifer flow (Arnold and Allen 1996).

In the SWAT model, watershed discretization consists of partitioning the watershed into 20 subbasins (figure 1b), which are further subdivided into hydrologic response units (HRUs) (table 1). Each subbasin is simulated as a homogenous area in terms of climatic conditions, with additional HRU subdivisions representing distinct combinations of soil and land use that are determined based on soil and land use threshold values specified by the user. HRUs are assumed to be spatially uniform in terms of soil, land use, topographic, and climatic data. In this study, the AVSWAT-X (version 2005) ArcView 3.3 GIS interface was used for expediting SWAT model input and output.

A warm-up period for SWAT is recommended to initialize and then approach reasonable starting values for model variables. Mamillapalli (1998) used a five-year warm-up period to minimize model initialization problems. Tolson and Shoemaker (2007) used a two-year warm-up period in order to provide reasonable initial channel sediment levels. In a SWAT sensitivity analysis by White and Chaubey (2005), initial values were established by simulating a seven-year period, allowing the model to stabilize during the first three years and considering the fourth year to be representative of conditions in the watershed. In this study, model simulations were initialized in 1992, thus providing a five-year warm-up period.

SWAT Model Input. In this study, daily precipitation and maximum/minimum air temperatures were obtained from the National Oceanic and Atmospheric Administration National Climate Data Center (NOAA NCDC 2004) for the Garret and Waterloo weather stations for the years 1997 through 2005 (see figure 1a for CCW station locations). Data for solar radiation, wind speed, and relative humidity were generated in SWAT. The AVSWAT-X interface automatically distributed the precipitation and temperature data from the two gauges over the watershed by assigning the data from the closest gauge station to the geometric centroid of each subbasin within the watershed. The Penman-Monteith method was selected to compute ET, and the SCS CN method was used to calculate surface runoff (versus the Green-Ampt method that requires subdaily precipitation data supplied by the user). Channel water routing, needed to predict the changes in the magnitude of the peak and the corresponding stage of flow, was based on the Muskingum River routing method, which is a variation of the kinematic wave model described in Chow et al. (1998). Although SWAT also provides users with a variable storage method for flow routing, the Muskingum approach is considered by the model developers to be more reliable in describing the flood routing network (J.R. Arnold, personal communication, 2008).

A list of SWAT parameter values affecting stream flow that are dependent on the land use and soil GIS input data sets are given in table 2. Due to the lack of measured data and to maintain consistency for all simulations, SWAT default values were used

Table 3
SWAT model input for Cedar Creek watershed management dates, operation types, and fertilizer/pesticide types and amounts for a typical two-year corn–soybean rotation.

Year	Month	Day	Operation/crop	Implement	Fertilizer (kg ha^{-1})	Pesticide (kg ha^{-1})
No-till						
1	May	3	Fertilizer	Surface applied	95 (10-34-00)	
1	May	3	Tillage	No-till mixing		
1	May	4	Corn			
1	May	4	Pesticide			1.5 (Atrazine)
1	May	25	Fertilizer	Injected	145 (ANH-NH_3)	
2	April	20	Fertilizer	Surface applied	32 (Elemental P)	
2	May	20	Tillage	No-till mixing		
2	May	20	Soybean			
2	June	1	Pesticide			0.7 (Roundup)
2	October	1	Harvest and kill			
Conventional tillage						
1	April	1	Tillage	Spring plowing		
1	April	15	Tillage	Field cultivator		
1	May	3	Fertilizer	Surface applied	95 (10-34-00)	
1	May	4	Corn			
1	May	4	Pesticide			1.5 (Atrazine)
1	May	25	Fertilizer	Injected	145 (ANH-NH_3)	
1	October	30	Harvest and kill			
1	November	1	Tillage	Fall plowing		
2	April	15	Tillage	Tandem disk		
2	April	20	Fertilizer	Surface applied	32 (Elemental P)	
2	May	20	Soybean			
2	June	1	Pesticide			0.7 (Roundup)
2	September	20	Harvest and kill			

Note: ANH-NH_3 = Anhydrous ammonia.

for those parameters affecting baseflow and groundwater, i.e., baseflow recession constant (ALPHA_BF = 0.05 days), delay time for aquifer recharge (GW_DELAY = 31 days), threshold water level in the shallow aquifer for return flow to occur (GWQMN = 0.0 mm), coefficient for controlling the movement of water into the overlying unsaturated zone (GW_REVAP = 0.02), and threshold water level in the shallow aquifer for movement of water to the unsaturated zone or percolation to the deep aquifer (REVAPMN = 1.0 mm).

For agricultural management data, area-specific information on management activities was provided by the St. Joseph River Watershed Initiative (SJRWI) project and the Soil and Water Conservation Districts (SWCD) of Allen, DeKalb, and Noble Counties. Table 3 shows the management dates, operation types, and fertilizer and pesticide types and amounts used for a typical two-year corn-soybean (the predominant crops in the CCW) rotation. Corn and soybeans are usually planted between late April and early May (Indiana Agricultural Statistics

Table 4
NASS 2001 and GAP 1994 land use for the Cedar Creek watershed.

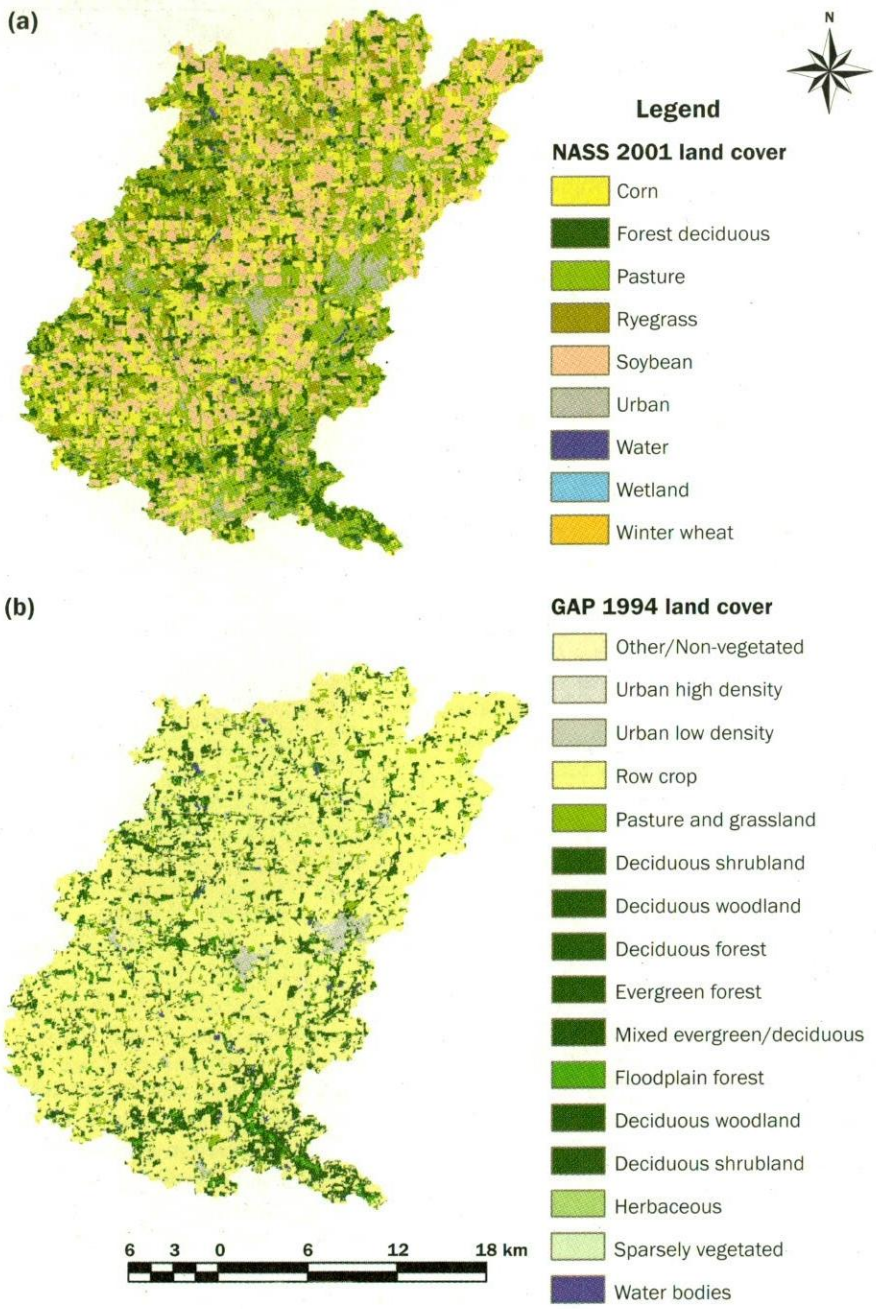
	NASS 2001		GAP 1994	
Land use	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**
Agriculture row crops			528.0	74.6
Corn	121.2	17.1		
Soybeans	175.9	24.9		
Winter wheat	4.3	0.6		
Other small grains and hay	6.1	0.9		
Double-cropped winter Wheat/soybeans	0.8	0.1		
Popcorn	0.2	0.03		
Fallow/idle cropland	37.4	5.3		
Pasture/grassland/non-agriculture	249.5	35.3	35.0	5.0
Deciduous forest			126.6	17.9
Evergreen forest			0.6	0.1
Mixed forest			0.1	0.02
Woods	88.8	12.5		
Urban	16.8	2.4		
Transportation/commercial			1.9	0.3
High density residential			2.5	0.6
Low density residential			9.1	1.3
Water	5.6	0.9	3.0	0.4
Wetlands	1.0	0.1	0.7	0.1

Service 2003). Nitrogen fertilizer is primarily applied as anhydrous ammonia to corn, phosphorus is usually applied to corn and soybeans in granular form blended in various combinations with other nutrients, and atrazine-based herbicides are widely used to control weeds in corn and are surface applied as a liquid solution (table 3). However, the amount of atrazine applied is being reduced over time due to increased popularity of glyphosate-tolerant corn hybrids being used in conjunction with reduced tillage practices. The DeKalb County SWCD estimated that greater than 75% of all soybeans planted in the watershed are glyphosate-tolerant cultivars.

Conservation tillage has been widely adopted in the watershed. In DeKalb County, 28% of all corn and 82% of all soybeans planted in 2004 were under a no-till system (Indiana Conservation Tillage Reports 2004). The tillage practices in Noble and Allen counties differed only slightly from that in DeKalb County. However, the Noble and Allen Counties SWCD offices regard tillage in the Cedar Creek portion of their county to be similar to that of neighboring DeKalb County. In general, all three counties exhibit similar agricultural trends within the watershed. Furthermore, the management input scenarios for SWAT shown in table 3 were in accordance with the most current data available as provided by the SJRWI, SWCD, Indiana Agricultural Statistics Service, and Indiana Conservation Tillage Reports.

Although the soils within the watershed are considered highly productive, the majority are comprised of slowly permeable glacial till material that require agricultural producers to use artificial drainage (Smith and Pappas 2007). Approximately 80% to 90% of the cropland in DeKalb County is tile drained (DeKalb County Department of Watershed Management 2008). Thus, tile drainage was specified in the model for cropland areas. Based on the most current information available for the CCW (as provided by county soil conservation personnel), SWAT parameters describing tile drainage include the average depth of the tile drain area (DDRAIN = 80 mm), drainage time after a rain for the soil to reach field capacity (TDRAIN = 48 hr), and the drain tile lag time (GDRAIN = 2 hr) (DeKalb County Department of Watershed Management 2008). In SWAT, water entering tiles is treated like lateral flow with the input variables defined in the management (.mgt) input files.

Figure 2
(a) National Agricultural Statistics Service (NASS) 2001 GIS land use map layer and (b) National Gap Analysis Program (GAP) 1994 GIS land use map layer.



A digital elevation model (DEM) is required in order to delineate the watershed and subwatershed boundaries, stream routing (figure 1b), and other topographic input needed for the SWAT model. The elevation data used in this study were obtained from the USGS, at 10-m elevation resolution, 1/3 arc second, and a map scale of 1:24,000 quadrangle sheet (available at http://seamless.usgs.gov/website/seamless/viewer.htm). Based on the study by Di Luzio et al. (2005), the use of DEM data greater than 30 m resolution causes inaccuracies for erosion and sediment yield predictions. Thus, a 10 m DEM was used to delineate the subwatershed slopes, stream network, and the watershed

and subwatershed boundaries. The DEM was projected to Universal Transverse Mercator (UTM) North American Datum (NAD) 83, Zone 16 north for the state of Indiana.

Soil and Land Use Data Layers. A significant portion of the uncertainty associated with stream flow modeling results can be attributed to uncertainty in estimates of the input parameters that are derived from various soil and land use data sets (Shirmohammadi et al. 2006). In particular, the interaction and aggregation of different combinations of soil and land use GIS data layers in SWAT, at the HRU level, play an important role in describing the hydrologic response of the system in a realistic manner (Di Luzio et al. 2005). In this study, four different combinations of land use and soil GIS data sets were used as input to model stream flow: (1) NASS SSURGO (NSS), (2) NASS STATSGO (NST), (3) GAP SSURGO (GSS), and (4) GAP STATSGO (GST). Each data set is described in greater detail below.

The NASS land use map is a raster, georeferenced, categorized land use data layer produced using satellite imagery from the Thematic Mapper (TM) instrument on Landsat 5 and the Enhanced Thematic Mapper (ETM+) on Landsat 7. The imagery was collected between the dates of April 29, 2001, and September 5, 2001. The approximate scale is 1:100,000 with a ground resolution of 30 by 30 m (98 by 98 ft). The remotely sensed land use data is used to produce a GIS data layer that is interfaced with SWAT as model input. As listed in table 4 and shown in figure 2a, the major percentages of land use are corn (17%), soybeans (25%), pasture (35%), and forests (12%). The second land use classification was obtained from the 1994 USGS GAP data set. The purpose of the GAP project is to assess the conservation status of all components of the nation's biodiversity. In 1994, the first full set of Landsat Thematic Mapper satellite imagery (scale of 1:100,000) of the 48 contiguous states was assembled for state-by-state mapping of floristically defined vegetation types (Jennings 2000). The land use mapping process for GAP is adopted from the National Vegetation Classification system (FGDC 1997). Major GAP land use categories in the Cedar Creek watershed are agricultural land row-crop (75%), forest (18%), pasture (5%), and urban/residential (~2%) (table 4 and figure 2b). A small fraction of open water, wetlands, and transportation make up the remaining cover. Pastureland is comprised of grassland used for grazing, hay, and land enrolled in conservation programs such as the Conservation Reserve Program (CRP). For a more comprehensive review on the use of satellite sensor imagery utilized for land use and land use classification the reader is referred to Yuksel et al. (2008) or the most recent US Climate Change Science Report (2007).

Detailed information on soil type is needed to improve simulation results based on an increase or reduction in the number of HRUs (Mamillapalli 1998). The AVSWAT-X GIS interface can accept either the NRCS STATSGO (from the 1:250,000 scale underlying map) or the SSURGO (from the 1:12,000 to 1:63,000 scale underlying map) geospatial soil databases. In the CCW, eight STATSGO soil associations are represented (figure 3a). STATSGO polygon IN004 (52.86% of the watershed area) is dominated by the Crosby and Treaty soil series, Blount-Glynwood-Morley; STATSGO polygon IN005 (26.71%) is comprised primarily of the Crosby and Cyclone soil series, Blount-Pewamo-Glynwood; STATSGO polygon IN025 (7.98%) is dominated by Sebewa-Gilford-Homer; IN016 (6.86%) is dominated by Miami-Wawasee-Crosier; IN019 (3.56%) is comprised of Houghton-Adrian-Carlisle; and IN028 (2.04%) is comprised of Martinsville-Whitaker-Rensselaer (table 5). STATSGO is one of the predefined data sets provided within the AVSWAT-X interface software. SSURGO GIS soils data consist of county-level maps, metadata, and tables, which define the proportionate extent of the component soils and their properties for

Figure 3
(a) STATSGO database GIS soil map layer and (b) SSURGO database GIS soil map layer.

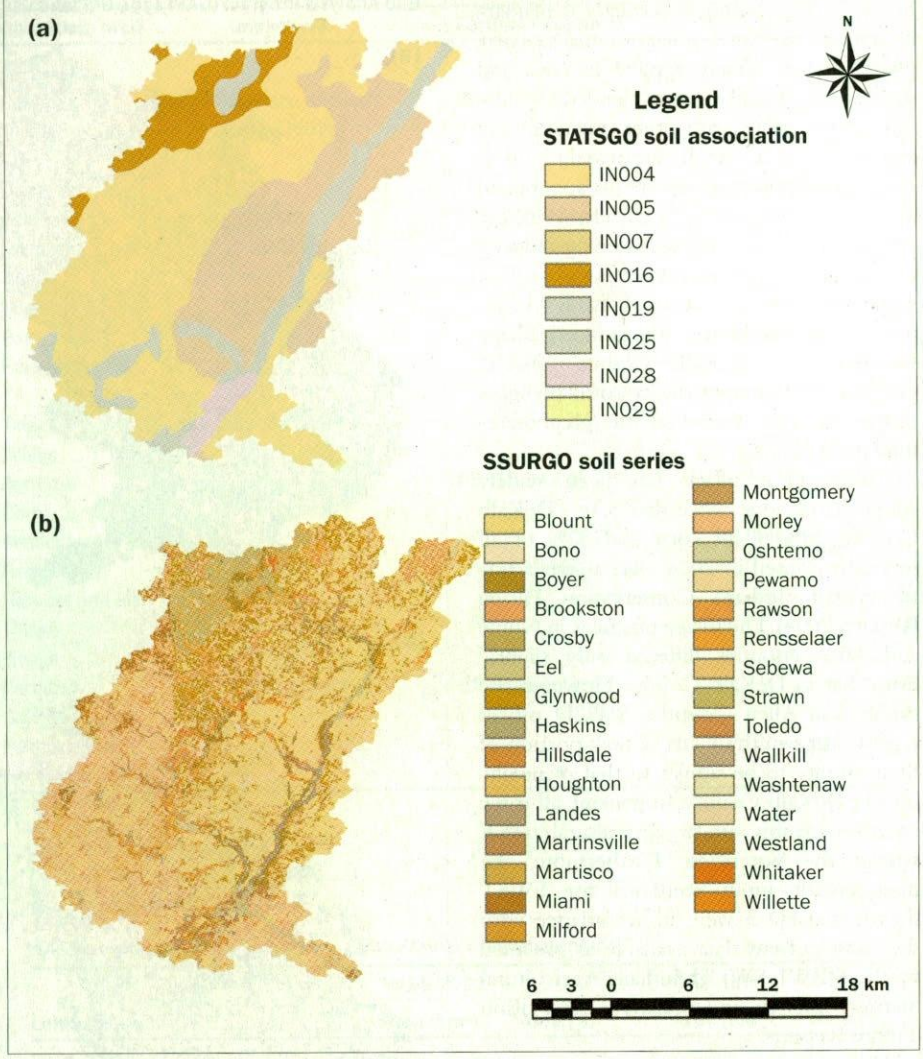


Table 5
STATSGO soil associations and dominant SSURGO soil series in the Cedar Creek watershed.

Soil	Texture	Hydrologic soil group	Area (km^2)	Area (%)
STATSGO soil association				
Blount-Glynwood-Morley (IN004)	SIL	C	374.0	52.9
Blount-Pewamo-Glynwood (IN005)	SIL	C	189.0	26.7
Sebewa-Gilford-Homer (IN025)	SIL	B	56.5	8.0
Miami-Wawasee-Crosier (IN016)	SIL-L	B	48.5	6.9
Houghton-Adrian-Carlisle (IN019)	SIL	B	25.2	3.6
Martinsville-Whitaker-Rensselaer (IN028)	L	B	14.4	2.0
SSURGO soil series				
Blount	SIL-SIC-SICL	C	171.3	24.2
Morley	SIL-CL-SICL	C	117.4	16.6
Pewamo	SILCL-SIC-CL	C	112.3	15. 7
Glynwood	SIL-C-CL	C	72.5	10.2
Houghton	MUCK-MUCK	A	28.1	4.0
Rawson	SL-SLC-SIC	B	27.4	3.9
Strawn	L-SICL-CL	B	23.2	3.3
Rensselaer	SIL-SCL-L-SIL	B	22.8	3.2
Boyer	LS-LS-L-GR-S	B	20.3	2.9
Miami	SIL-CL-L-L	B	9.4	1.3
Haskins	L-GR-SCL-SIC	C	7.4	1.1
Eel	SIL-L-SL	B	7.2	1.0
Martinsville	L-CL-SCL-SIL	B	5.5	0.8
Washtenaw	SIL-L-SICL-L	C	5.0	0.7

each map unit (table 5 and figure 3b). For the counties intersecting the watershed, the SSURGO soil database is at a map scale of 1:12,000 and was created primarily for farm, landowner, township, or county natural resource planning and management. Thirty soil SSURGO series are present in the CCW with Blount being dominant (24.46% of the watershed), following by Morley (16.36%), Pewamo (15.87%), and Glynwood (10.36%). The remaining 32.95% of soil types are less than 2% each.

Hydrologic Response Units. In SWAT, hydrologic response units (HRUs) are determined by the combination of land use and soil within each subbasin based on user-specified threshold values for dominant soil and land use percentages. Based on the study by Haverkamp et al. (2002) and the information provided in Neitsch et al. (2002), the threshold frequencies for land use and soil chosen in this study were 5% and 10%, respectively, representing HRUs that are comprised of at least 5% of land use of the area in each subbasin, combined with soil types that occupy at least 10% of the area of that land use.

Several studies have investigated the effect that different levels of discretization (i.e., subbasin and HRU number and size) have on simulated stream flow while trying to maintain a balance between maximum level of aggregation and minimum information loss (Muleta et al. 2007; Di Luzio et al. 2005; Haverkamp et al. 2002). According to Neitsch et al. (2002), a given subbasin should have between 1 and 10 HRUs depending on the level of complexity one wishes to incorporate into the data set. Di Luzio et al. (2005) used 20% and 10% for land use and soil threshold values, respectively, resulting in the number of HRUs ranging from 273 to 940 within the watershed (depending upon the type of GIS input data). A recent study by Muleta et al. (2007) used a value of 20% for both the land use and soil threshold values, with the total number of HRUs ranging from 9 to 352. The number of subbasins delineated for the CCW was 20 for each model simulation. The number of HRUs within the watershed was different for each simulation, ranging between 91 and 259 (table 1) due to the interaction between the unique combination of GIS soil and land use layers and the assigned threshold values.

SWAT Model Statistical Evaluation. During the past two decades, computer-based watershed models have become powerful tools for simulating hydrologic processes, as well as the effects of management practices on water quality. Although modeling applications have increased substantially during this period of time, the modeling community has yet to adopt a comprehensive set of model performance standards. Thus, the statistical evaluation of modeling results has been rather capricious. A recent report by Moriasi et al. (2007) provides a comprehensive review of model evaluation techniques and recommends several quantitative statistics, as well as performance ratings for the recommended statistical metrics. Although we do not necessarily consider their report as the definitive reference on what is satisfactory or not in terms of model performance, we use several statistical criteria that have been proposed by Moriasi et al. (2007) to evaluate SWAT model performance for daily, monthly, and annual simulated stream flows. In addition to graphical representation, we use the Nash-Sutcliffe Efficiency coefficient (ENS), coefficient of determination, root mean square error (RMSE), ratio of RMSE to the standard deviation of measured data (RSR), and percent bias (PBIAS) to evaluate the overall correspondence of simulated output to measured values. The ENS, RMSE, and PBIAS statistics are defined as follows:

$$\mathrm{ENS} = \frac{\sum (O-\overline{O})^2 - \sum (O_i-P_i)^2}{\sum (O_i-\overline{O})^2}, \quad (1)$$

$$\mathrm{RMSE} = \sqrt{\left(\frac{\sum (P-O)^2}{n}\right)}, \quad (2)$$

$$\mathrm{PBIAS} = \frac{\sum (O-P) \times 100}{\sum (O)}, \quad (3)$$

where P is stream flow ($m^3\ s^{-1}$) predicted by the SWAT model, $\overline{O}$ is observed stream flow ($m^3\ s^{-1}$), is the average observed stream flow during the simulation period ($m^3\ s^{-1}$), and n is the number of observations. ENS indicates how well the plot of observed versus simulated values fits a 1:1 line. The value of ENS in Equation 1 may range from $-\infty$ to 1.0, with 1.0 representing a perfect fit of the data. The coefficient of determination (R^2) represents a measure of the strength of the linear relationship between predicted stream flow and observed measurements, whereas the RMSE is indicative of the error associated with estimated stream flow. Based on

Table 6
List of SWAT parameters considered for the sensitivity analysis and the sensitivity coefficients and overall rankings for SWAT average monthly stream flow output response.

Parameter	Description	Range	S_i coefficient (SSURGO)	S_i coefficient (STATSGO)	Sensitivity ranking (SSURGO)	Sensitivity ranking (STATSGO)
CN2	Initial SCS runoff curve number for moisture condition II	35 to 98	1.84	1.52	1	1
SLSUBBSN	Average slope length (m)	20 to 200	0.26	0.36	6	5
ESCO	Soil evaporation compensation factor	0 to 1	0.16	0.22	8	7
GWQMN	Threshold depth of water in shallow aquifer required for return flow to occur (mm)	0 to 1,000	0.53	0.50	4	4
ALPHA_BF	Baseflow alpha factor (days)	0 to 1	0.18	0.19	7	8
HRU_SLP	Average slope steepness (m m^{-1})	0 to 0.5	0.38	0.33	5	6
SOL_K	Saturated hydraulic conductivity (mm h^{-1})	0 to 400	0.69	0.96	3	2
SOL_AWC	Available water capacity of the soil layer (mm H_2O mm^{-1} soil)	0 to 1	0.73	0.85	2	3
GW_REVAP	Groundwater "revap" time	0.02 to 0.2	0.12	0.10	9	11
GW_DELAY	Groundwater delay time (days)	0 to 500	0.08	0.13	11	10
REVAPMN	Threshold depth of water in shallow aquifer required for "revap" or percolation to the deep aquifer (mm)	0 to 1,000	0.10	0.15	10	9

the reported ranges of values in the review by Moriasi et al. (2007), SWAT model performance for CCW stream flow was judged to be satisfactory if ENS > 0.50, RSR ≤ 0.70, and PBIAS is ± 25%. Again, we realize that model performance is somewhat of a subjective area; however, we have chosen to use the above values based on the most current review available. In addition to assessing model performance based on the criteria mentioned above, Tukey's statistical least significant difference (LSD) test was also used at the $\alpha = 0.05$ level for all possible pairs of average stream flow values.

SWAT Model Sensitivity Analysis. Sensitivity is measured as the response of an output variable to a change in an input parameter, with the greater change in output response corresponding to a greater sensitivity (White and Chaubey 2006). In general, sensitivity analysis evaluates how different model input parameters influence a predicted model output response. As previously discussed, SWAT model outputs depend on input parameters related to the climate, soil type, management, land use, watershed routing configuration, underlying aquifer, and reservoirs. Parameters identified in sensitivity analysis that influence predicted output responses are typically used for model calibration. For this research, a sensitivity analysis was performed on a range of values in order to ensure that values for parameters critical to stream flow estimation were appropriate. Table 6 summarizes SWAT parameters selected for sensitivity analysis in this study. These parameters were identified by Eckhardt and Arnold (2001), Santhi et al. (2001), White and Chaubey (2005), and Bracmort et al. (2006) as being important for the estimation of stream flow. Sensitivity of SWAT mean monthly stream flow output responses to the selected parameters was determined by perturbing model parameters "one at a time" and calculating a linear sensitivity coefficient (S_i), defined as follows (Bracmort et al. 2006):

$$S_i = \frac{(y_{2,i}-y_{1,i}) \big/ (y_{2,i}+y_{1,i})}{(X_{2,i}-X_{1,i}) \big/ (X_{2,i}+X_{1,i})}, \qquad (4)$$

where $y_{1,i}$ and $y_{2,i}$ are SWAT mean monthly stream flow responses corresponding to perturbation of the ith element of the parameter vector from $x_{1,i}$ to $x_{2,i}$, while other parameters were kept constant. S_i is essentially a normalized estimate of sensitivity of input design variables for stream flow to parameter perturbation, with higher values indicating higher sensitivity (Bracmort et al. 2006). There are limitations to using the S_i coefficient for SWAT sensitivity analysis; i.e., it is assumed that the response of model outputs to parameter perturbation is linear and correlations are not considered between parameters. Table 6 shows the sensitivity of SWAT average monthly stream flow output response to the selected input parameters for both the SSURGO and STATSGO soil data sets (i.e., sensitivity results were averaged across the GAP and NASS land use data sets). The results are similar to those of Bracmort et al. (2006) and White and Chaubey (2006) with respect to ranking order for stream flow parameters; i.e., in those studies, CN2, SOL_AWC, GWQMN, HRU_SLP, and SLSUBBSN were found to produce the five highest sensitivity coefficients for SWAT surface runoff or stream flow output responses. In addition, sensitivity coefficient magnitudes were within the ranges reported by Bracmort et al. (2006), who used a similar coefficient for calculating sensitivities for stream flow, sediment yield, and total phosphorus SWAT output responses. The results of the sensitivity analysis are significant in confirming that the parameters most influenced by using different combinations of soil and land use are CN2, SOL_AWC, and SOL_K. The values for these parameters were determined based on the type of soil and land use GIS data sets that are used in SWAT as input data layers (table 2). By running the model without calibration, these parameter values remained constant for each model simulation. Due to the lack of available measured data, SWAT

Table 7

Statistical evaluation for SWAT simulated daily, average monthly, and average annual Cedar Creek watershed stream flows for each land use and soil geographic information system data set (January 1997 to December 2005).

Statistical evaluation metric	NASS 2001 land use and SSURGO soil data sets (NSS)			NASS 2001 land use and STATSGO soil data sets (NST)			GAP 1994 land use and SSURGO soil data sets (GSS)			GAP 1994 land use and STATSGO soil data sets (GST)		
	Daily	Monthly	Annual	Daily	Monthly	Annual	Daily	Monthly	Annual	Daily	Monthly	Annual
ENS	0.41	**0.58**	-1.45	0.41	**0.57**	-1.44	0.40	**0.53**	-2.58	0.40	**0.54**	-2.24
R^2	0.47	**0.66**	0.46	0.46	**0.65**	0.42	0.47	**0.65**	0.49	0.47	**0.64**	0.46
RMSE	9.21	4.55	1.92	9.21	4.61	1.91	9.29	4.79	2.32	9.31	4.78	2.20
RSR	0.77	**0.65**	1.57	0.77	**0.66**	1.56	0.77	**0.68**	1.89	0.78	**0.68**	1.80
PBIAS	**21.90**	**21.93**	**21.91**	**21.54**	**21.60**	**21.56**	27.91	27.91	27.92	26.17	26.20	26.19

Notes: ENS = Nash-Sutcliffe efficiency; R^2 = coefficient of determination; RMSE = root mean square error ($m^3 s^{-1}$); RSR = ratio of RMSE to standard deviation; PBIAS = bias (%).Values in bold represent model performance ratings that are considered satisfactory according to Moriasi et al. (2007); all other values are considered less than satisfactory.

default values were used for all of the remaining parameters listed in table 6 to maintain consistency in the simulations and to avoid introducing any bias due to parameter optimization. Additional analysis was also performed to determine differences in sensitivity coefficients for parameters in table 6 (both magnitudes and rankings) as a result of using an inverse distance weighting (IDW) scheme to distribute historical precipitation and temperature across the watershed (as opposed to assigning the data from the closest gauge station to the geometric centroid of each subbasin within the watershed). Sensitivity coefficients calculated in conjunction with using the IDW scheme to distribute climate data were within ±4% of the values in table 6 (for both the SSURGO and STATSGO soil coverages), with no change in the overall sensitivity rankings (data not shown). In a recent study on the impact of rainfall distribution on parameterization of a soil-moisture balance model in equatorial Africa, Mileham et al. (2008) showed a 7% increase in mean catchment precipitation using an IDW interpolation procedure relative to point-based station data. Recalibration of the model using the gridded precipitation data required a 3% reduction in potential ET and a 12% increase in the runoff coefficient (Mileham et al. 2008).

Results and Discussion

Results. Historical measured data for Cedar Creek stream flow from the USGS for a nine-year period, from January 1997 to December 2005, at Gauge 04180000 (41°13'08"N, 85°04'35"W) near Cedarville, Indiana, was compared with daily, monthly, and annual SWAT noncalibrated stream flows for all four soil and land use data set combinations. The stream flow data obtained from the USGS are composed of baseflow

Figure 4

(a) Daily Cedar Creek watershed stream flow for observed and SWAT simulated values using NASS and SSURGO (NSS) data sets (January 2004 to December 2004). (b) Daily Cedar Creek watershed stream flow for observed and SWAT simulated values using GAP and SSURGO (GSS) data sets (January 2004 to December 2004).

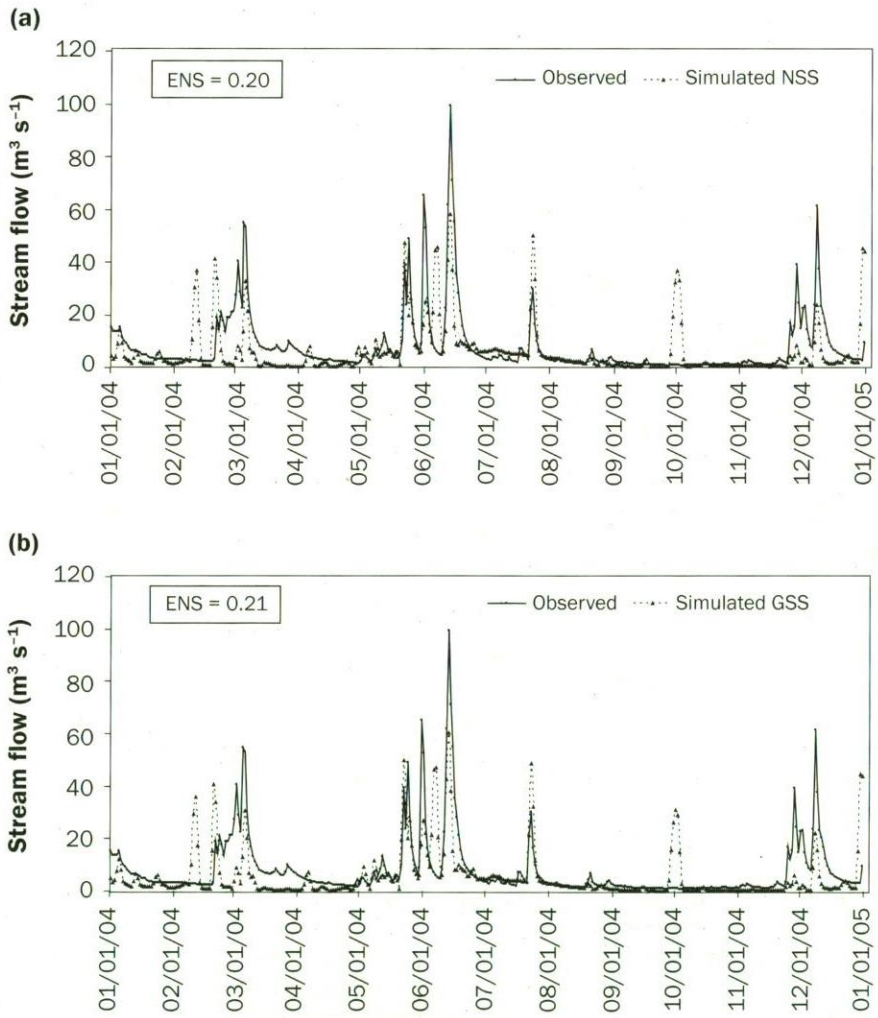
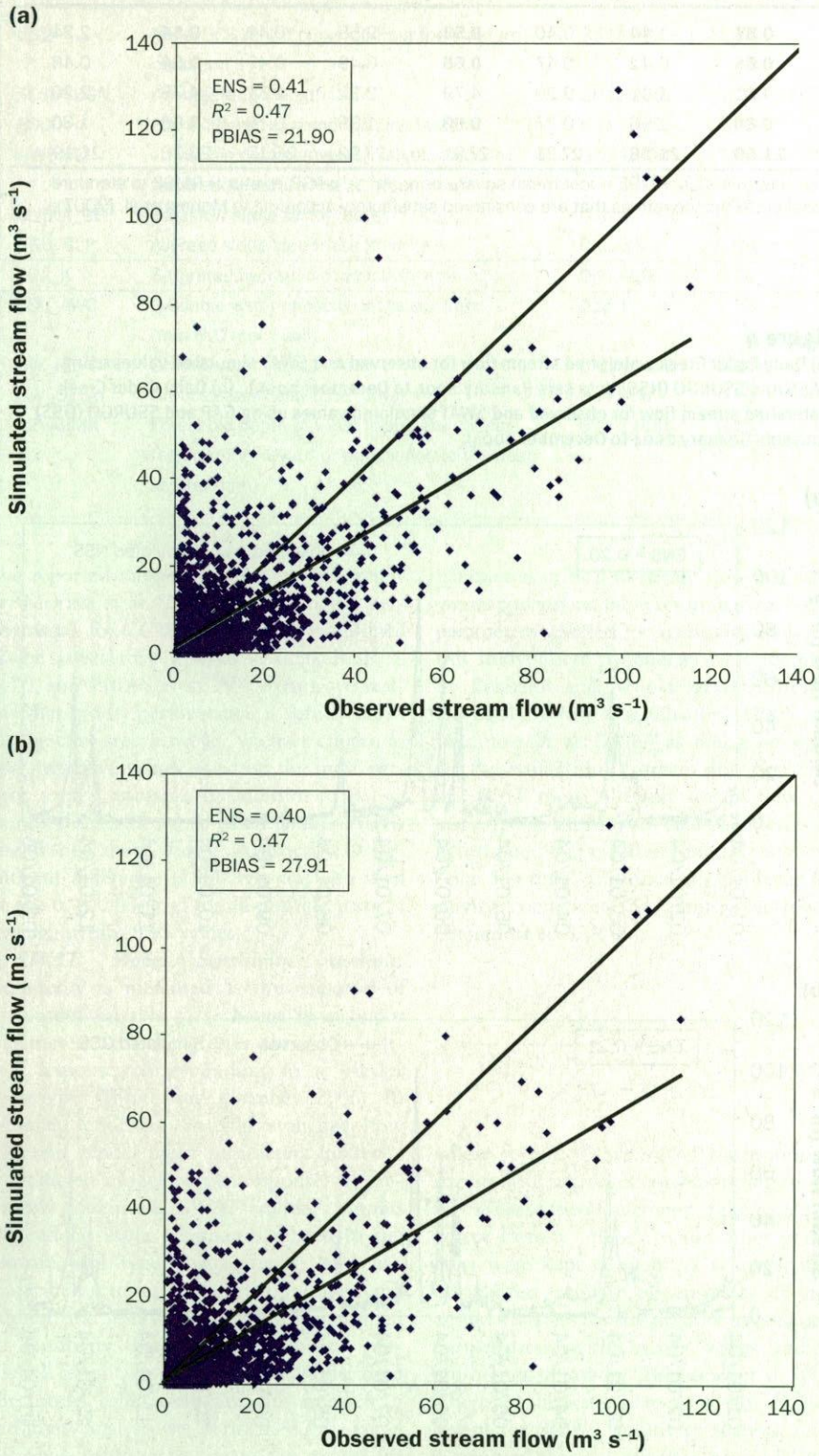


Figure 5

(a) Daily Cedar Creek watershed stream flow 1:1 plot of SWAT simulated values using NASS and SSURGO (NSS) data sets versus observed (January 1997 to December 2005). (b) Daily Cedar Creek watershed stream flow 1:1 plot of SWAT simulated values using GAP and SSURGO (GSS) data sets versus observed (January 1997 to December 2005).



and surface runoff; therefore, no baseflow filter program was applied to the SWAT stream flow predictions.

Although the SWAT model was run uncalibrated, modeled water balance predictions for the simulation period (e.g., ET, surface runoff) were compared with historical averages that are representative of hydrologic conditions on the watershed. The Indiana Department of Natural Resources (1980) reported that the long-term average annual net supply to surface water in the northeastern part of the state is 305 mm (12.01 in), distributed as 213 to 229 mm (8.39 to 9.02 in) in diffused surface water and 76 to 91 mm (2.99 to 3.58 in) in recharge to groundwater. Furthermore, the average annual precipitation in this part of Indiana is approximately 965 mm (37.99 in), with evaporation and transpiration accounting for 660 mm (25.98 in). For this study, average annual measured precipitation on the CCW was 909.3 mm (35.8 in), SWAT average annual simulated ET ranged from 611 mm (24.06 in) for the NASS land use data set to 633 mm (24.92 in) for the GAP land use data set, and SWAT average annual simulated surface runoff ranged from 222 mm (8.74 in) for the NASS land use data set to 237 mm (9.33 in) for the GAP land use data set. Evaluation statistics for each time scale are shown in table 7. Due to the large amount of data analyzed for each data set combination and the similarity in results for the soil and land use GIS data set combinations, we have limited the graphical presentation of results to only those using SSURGO data sets for the daily and monthly time scales.

Graphs for daily observed and simulated stream flows for the NSS and GSS data sets from January 2004 to December 2004 are presented in figures 4a and 4b, respectively. These graphs serve as a one-year subset of results from the nine-year simulation period. For uncalibrated conditions, overall model performance on a daily time step was poor for both the NSS and GSS 2004 data sets. In general, the trend in stream flow was captured using either data set; however, there were significant overestimations by the model on some days compared to the measured data. The overestimation may be due in part to having rainfall input data for only two weather stations in the CCW.

Upon closer inspection of the 2004 daily rainfall records for the Garret and Waterloo weather stations, we found that during the

period of time in February when simulated stream flow experienced a significant peak, 9 mm (0.35 in) and 29 mm (1.1 in) of total rainfall were recorded at the Garret and Waterloo weather stations, respectively. This was also the case during other times of the year when spikes appeared in the simulated stream flow data and no response was observed in the USGS discharge data at the watershed outlet. Perhaps, these were localized rainfall events that did not significantly contribute to the total measured watershed stream flow. However, the modeled distribution of rainfall over the entire watershed area was based on the input data from the two weather stations which, in some cases, could result in higher rainfall amounts than actually occurred being used as input. This in turn would result in elevated simulated stream flow levels at the watershed outlet.

In general, both the NSS and GSS simulations underestimated stream flow on a daily time step, with the GSS data set being slightly worse, as shown in the 1:1 plots in figures 5a and 5b where it was more plausible to include all data points for the nine-year period. The positive values for PBIAS in both figures indicate that the model underestimated stream flow and that the GSS data set resulted in lower estimates having a value of 27.91%, compared to 21.90% for the NSS results. The ENS and R^2 values are considered unsatisfactory for both data sets, with NSS having an ENS value of 0.41 and R^2 of 0.47 (figure 5a) and GSS values of 0.40 and 0.47, for ENS and R^2, respectively (figure 5b). This was the case for all daily data set combinations as indicated by the ENS and R^2 statistics in table 7. The results of the Tukey's LSD test (α = 0.05) for the difference in average values between observed and simulated stream flows are given in table 8. The results for the 2004 daily stream flow analysis show that all simulated averages are significantly different from the observed with the exception of the NASS STASGO data sets. However, there was no significant difference between the simulated values.

Average monthly observed and simulated stream flows for NSS and GSS data sets from January 1997 to December 2005 are plotted in figures 6a to 7b. For both data set combinations, figures 6a and 6b show that the trend in simulated average monthly stream flow followed the observed values much more closely than the simulated daily stream flow results. Furthermore, it is much easier to discern that the simulated average monthly stream flow in figures 6a and 6b was underestimated for much of the nine-year simulation period. Again, similar to the daily output, it is difficult to determine visually that the monthly stream flow output for the GSS data sets is slightly lower than the NSS output. However, the 1:1 plots in figures 7a and 7b show that deviation from the 1:1 line for the GSS regression was greater (figure 7b) than that of the NSS regression line in figure 7a, indicating a slightly greater degree of underestimation. The statistical results for average monthly output in table 7 for PBIAS values show that a PBIAS value of 27.91% for the GSS output is beyond the satisfactory range of ±25% and is nearly 6% higher than the PBIAS of 21.93% for NSS output. Table 7 also shows that analysis of the average monthly output for the NSS and NST data set combinations are the only cases where the evaluation statistics for all three of the model performance indicators (i.e., ENS, RSR, and PBIAS) are considered satisfactory according to Moriasi et al. (2007). Furthermore, the results in table 8 for Tukey's test (α = 0.05) indicate no significant difference between the observed and the NST and NSS average monthly stream flow values, which supports the performance evaluation criteria and suggests that the higher PBIAS values for the GST and GSS data sets resulted

Figure 6

(a) Monthly Cedar Creek watershed stream flow for observed and SWAT simulated values using NASS and SSURGO (NSS) data sets (January 1997 to December 2005). (b) Monthly Cedar Creek watershed stream flow for observed and SWAT simulated values using GAP and SSURGO (GSS) data sets (January 1997 to December 2005).

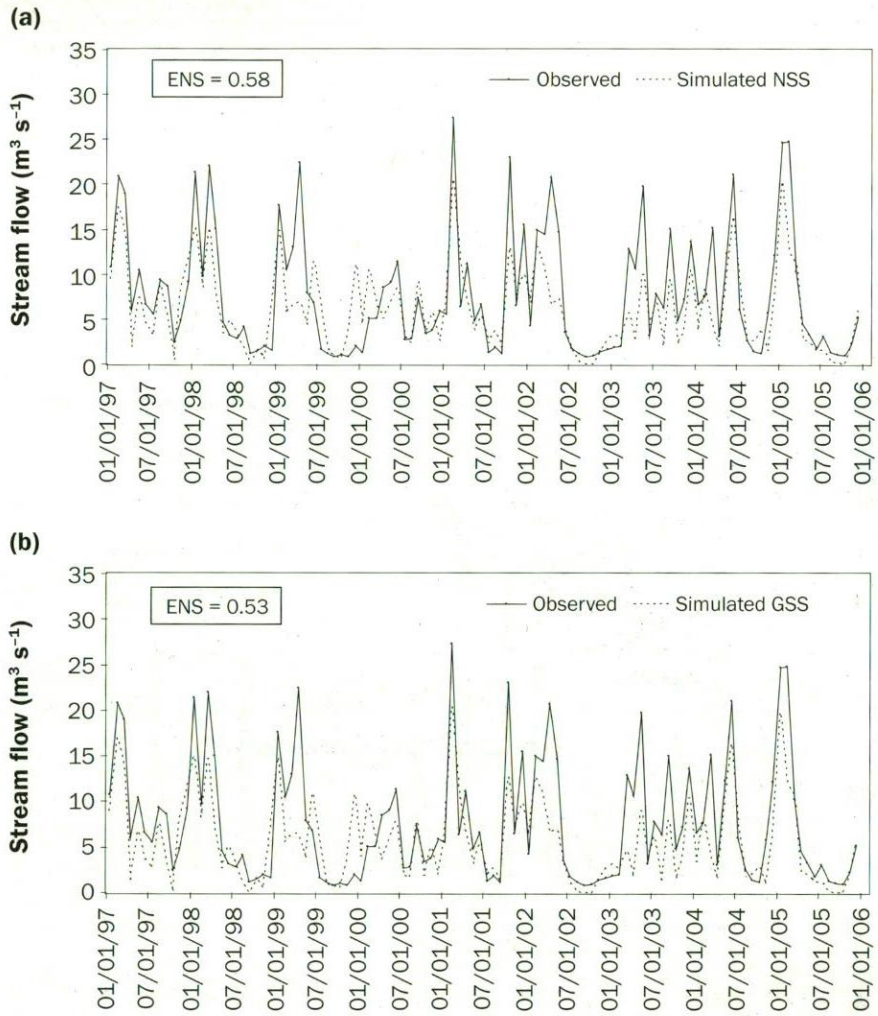
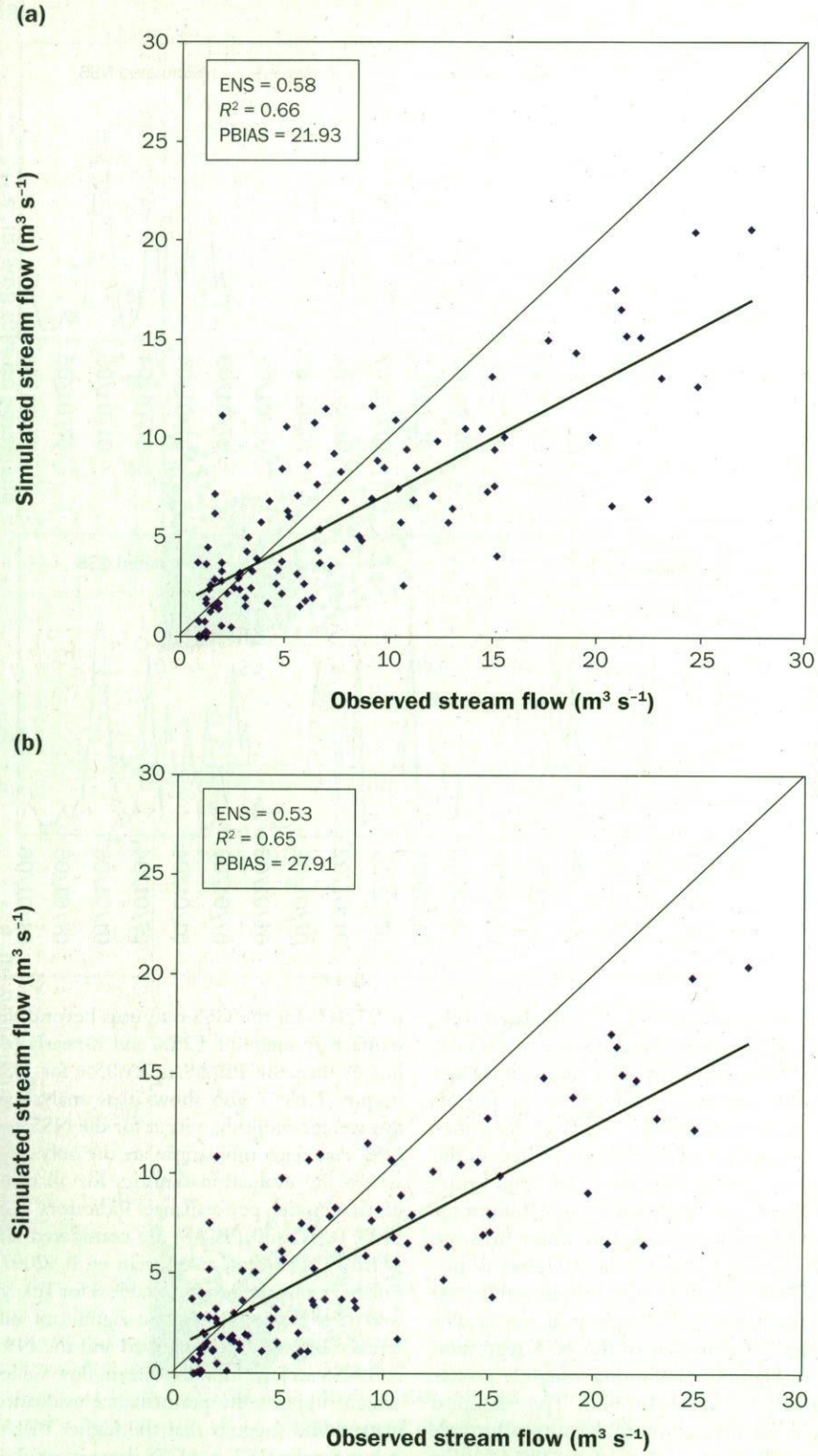


Figure 7

(a) Monthly Cedar Creek watershed stream flow 1:1 plot of SWAT simulated values using NASS and SSURGO (NSS) data sets versus observed (January 1997 to December 2005). (b) Monthly Cedar Creek watershed stream flow 1:1 plot of SWAT simulated values using GAP and SSURGO (GSS) data sets versus observed (January 1997 to December 2005).



in those means being significantly different from the observed.

The data for average annual observed and simulated stream flows for all data set combinations are shown in figure 8 for the nine-year simulation period. The simulated data clearly indicate the underpredicted values for all data set combinations, with the exception of the simulation runs in 2000 for the NST and NSS data sets. It is also much easier to see that the GSS and GST data sets consistently underestimate average annual stream flow to a greater degree than the NSS and NST data set combinations throughout the study period. SWAT model performance based on the statistical analysis in table 7 indicates that stream flow simulation results at the annual output time scale were very poor, with all data sets having negative ENS values and RSR values ranging between 1.56 and 1.89. The PBIAS values are very close to those calculated at the daily and monthly time scales, with the GSS and GST data sets again having the highest percentages of underestimation (table 7). The results for the Tukey's LSD test (α = 0.05) in table 8 for average annual stream flow show that all simulated stream flow values were significantly different from the observed values.

However, it is important to note that on a year-by-year basis, the data in figure 8 indicate that simulated average annual stream flow is underestimated to a much lesser degree for the years 1997 to 2001, ranging from a slight overestimation (<5%) for the NASS data sets in 2000 to approximately 22% underestimation in 1997. In comparison, the 2002 to 2005 simulation period shows that average annual stream flow was underestimated by 25% to 41%. Since the input parameters remained constant throughout the nine-year study period, it is possible that (1) there may be errors in the rainfall input data that we are not aware of or (2) as mentioned earlier, perhaps the rainfall distribution over the watershed is not adequately captured by the two weather stations, especially during the latter part of the simulation study. Irregardless, the greater degree of underestimation in simulated average annual stream flow for the last four years of the study resulted in lower ENS values for the average annual stream flow results over the entire nine-year period.

Discussion. The range of relative error (e.g., PBIAS) and ENS values for uncalibrated daily stream flow predictions in this study are simi-

lar to others that have been reported in the literature. For a small watershed in Kentucky, Spruill et al. (2000) found that the differences between observed and calibrated daily stream flow rates ranged between ±17% to 25% over a two-year period, and that the size of the drainage area influenced SWAT discharge predictions. Van Liew and Garbrecht (2003), in a 15-year study, reported uncalibrated daily stream flow ENS values as low as -3.24 that were improved with calibration to values as high as 0.60 for the Little Washita River watershed in Oklahoma, which is comparable in size to the CCW. More recently, a 5-year study by Wang and Melesse (2006) showed that for the Elm River in North Dakota, calibrated daily stream flow predictions ranged from 5% over prediction to 35% under prediction, compared to the observed data. There is a considerable cache of literature that demonstrate the use of SWAT in effectively modeling monthly stream flow (e.g., Spruill et al. 2000; Cotter et al. 2003; Van Liew and Garbrecht 2003; Di Luzio et al. 2005; White and Chaubey 2005; Wang and Melesse 2006; Larose et al. 2007). The statistical parameters reported in this study for uncalibrated monthly stream flow estimates fall well within the range of those found throughout the literature. The ENS values for uncalibrated model simulations for all data set combinations were within the satisfactory range (0.53 to 0.58). However, the GAP data set simulations gave less than satisfactory results for the PBIAS statistic (table 7). In the study by Van Liew and Garbrecht (2003), their evaluation results show that SWAT underestimated average annual stream flow by 18.4% using default values for model parameters affecting stream flow prediction. On a year-by-year basis, SWAT model estimates for annual stream flow were within plus or minus 20%, underestimating one year by as much as 98.4%, while overestimating another year by 156.9%. Several of the other studies we have cited also report a considerable range in SWAT results for uncalibrated, as well as calibrated, stream flow (e.g., Di Luzio et al. 2005; White and Chaubey 2005; Wang and Melesse 2006; Larose et al. 2007).

Di Luzio et al. (2005) indicated that "further investigations are needed to determine the influence of the input GIS data distribution on different watersheds with various sizes, in varying geoclimatic and land resource regions," and emphasized the lack of research on this topic. In their work, they found that land use maps had a significant effect on both runoff and sediment yield predictions, and that soil maps had little influence on model results. We have shown in this study that the use of different land use maps has only a slight effect on stream flow estimates, and that the use of two different soil maps shows no effect. It is significant to note that the work by Di Luzio et al. (2005) in the Goodwin Creek Watershed (21.3 km^2 [8 mi^2]) in Mississippi covers considerably less area than the Cedar Creek Watershed (707 km^2 [273 mi^2]) modeled in this study, and that there is also a considerable difference in climatic conditions and soil types. Furthermore, the results of this study indicate that in using the SWAT model, several factors regarding GIS input data sets may affect stream flow simulations and, consequently, water quality assessment studies. In addition to the effect of GIS source data on model output (e.g., SSURGO, STATSGO, NASS, GAP), there is evidence shown in this study that the interaction, preprocessing, and aggregation of unique combinations of GIS input layers within SWAT also influence simulated stream flow output. There are several general implications of this work that merit further discussion and consideration from a broader perspective in terms of the application of different GIS input data sets in hydrologic modeling. The following topics highlight the main points of consideration in this study.

Calibrated versus noncalibrated stream flow analysis: As mentioned earlier, we chose to evaluate noncalibrated stream flow results considering that SWAT was developed for applications on ungaged watersheds (Neitsch et al. 2002). More importantly, however, is

Table 8

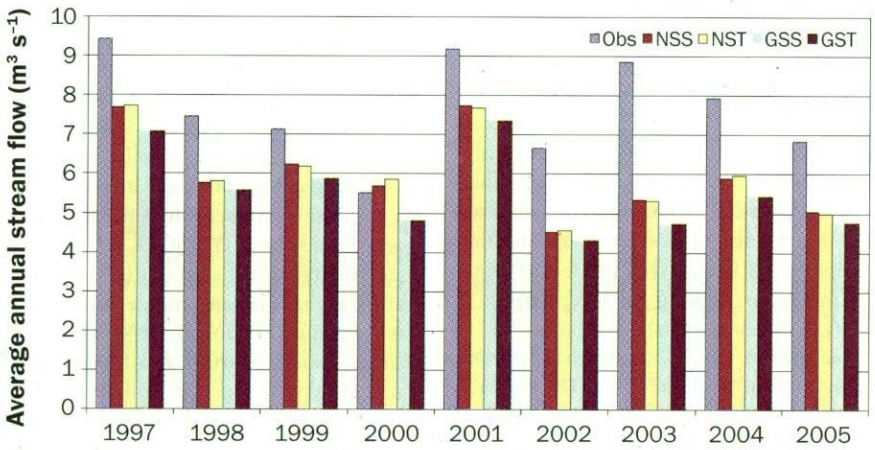
Tukey's LSD analysis for observed and 2004 daily simulated stream flows and 1997 to 2005 monthly and annual simulated stream flows.

	Average daily stream flow for 2004 ($m^3 s^{-1}$)	Average monthly stream flow from 1997 to 2005 ($m^3 s^{-1}$)	Average annual stream flow from 1997 to 2005 ($m^3 s^{-1}$)
Observed	7.92a	7.70a	7.66a
NST	5.96ab	6.03ab	6.01b
NSS	5.88b	6.01ab	5.98b
GST	5.59b	5.68b	5.66b
GSS	5.42b	5.55b	5.52b

Note: Average values followed by the same letter are not significantly different using Tukey's LSD test with $\alpha = 0.05$.

Figure 8

Annual average Cedar Creek watershed stream flow for observed and all SWAT simulated combinations of soil and land use geographic information system data sets (January 1997 to December 2005).



the potential for calibration to introduce various levels of bias to each data set that could ultimately eliminate any differences between results. A case in point would be the data shown in figure 8 for average annual stream flow. Based on our previous experience in using SWAT, it is very likely that each of the SWAT simulated data set combinations in figure 8 could be calibrated to within satisfactory levels of performance, thus masking any effects due to the use of different GIS data layers. However, our future modeling efforts will consider this factor in comparison with our current findings.

Land use GIS input: Both the 1994 USGS GAP and 2001 NASS land use maps were derived from similar sensor technology (Landsat TM imagery), digital processing, and based on the same nominal scale (1:100,000). The argument could be made that both are considered appropriate since the 1994 GAP coverage may be considered the most applicable for the beginning of the nine-year simulation period (1997 to 2005), whereas the 2001 NASS coverage may be more representative of the latter part of simulation period. Obviously, this brings into question what time period of land use maps are most appropriate to use as GIS input data layers for simulations running for long periods of time (i.e., 10 to 50 years).

The data in table 4 shows that approximately 49% of land use in the 2001 NASS coverage was classified as some type of agricultural land. On the other hand, table 4 shows that, in the 1994 GAP coverage, 75% of the land use was classified as being in agriculture row crops. Perhaps both data sets accurately represent the spatial distribution of land use for time period they were produced, and there has been approximately a 25% reduction in agricultural land use over a seven- or eight-year period. The differences between the land use data sets are most likely due to a combination of several factors, such as actual changes in land use as mentioned above, as well as differences in the classification schemes used to produce the products and the nature of the objectives associated with each product (i.e., agricultural statistics, landscape ecology, and conservation areas). These differences are precisely why we chose to use these two data sets that have both been applied to a variety of issues involving the management of natural resources, including watershed scale hydrologic modeling.

Soil GIS input: Although we used smaller threshold values in SWAT for land use (5%) and soil (10%) coverages compared to several values reported in the current literature (i.e., 20% and 10%, or 20% and 20% for land use and soil, respectively), our results indicate that there was an effect due to the aggregation of soil input properties. This appears to explain why there is no significant difference in modeled stream flow values when using either SSURGO or STATSGO soil maps for a given land use layer. The purpose of the threshold function is to aggregate the soil data layer such that only the dominant soil types and properties are represented. The SSURGO soil data layer (figure 3b) provides more detailed information on soil types and properties since it is based on soil series descriptions. In comparison, the STATSGO soil layer describes the taxonomy at the much coarser soil association scale (figure 3a). However, according to the values in table 5, once a 10% threshold has been applied to the SSURGO data set, only the Blount, Morley, Pewamo, and Glynwood soil series remain to be assigned to the final input data layer for a given land use. Although soil associations define the STATSGO data, the same four soil types are also found in the two remaining associations once a 10% threshold has been applied (table 5). It stands to reason that the soil properties and final input soil parameters for each GIS soil data set (e.g., CN2, SOL_AWC, and SOL_K) would be very similar. These findings imply that careful consideration must be given in setting the threshold value for soil coverage in SWAT if SSURGO data are available for the watershed area. Having a threshold value set too high could have a considerable effect on modeling sediment and chemical transport under different agricultural management practices. Based on the results presented in this study, our current and future modeling efforts will reassess what is the most appropriate soil threshold value to use to insure that the hydrologic soil properties are most effectively parameterized over the geographical area.

Time scale of statistical analysis: This study is unique in assessing overall SWAT model performance at three temporal scales for four soil and land use data sets. There are only small differences between the statistical metrics for simulated versus observed daily, monthly, and annual stream flows and the four soil and land use data set combinations (table 6). However, the model evaluation statistics in table 6 indicate that the time scale of output for each of the data set combinations can influence the performance evaluation. The data in table 6 show that for the uncalibrated conditions, model performance ratings were highest based on average monthly stream flow output and considered satisfactory for the NSS and NST data sets. All output based on daily and annual time scales, as well as the GSS and GST data set combinations, proved less than satisfactory according to the Moriasi et al. (2007) performance criteria discussed earlier. This implies that it is important to consider model output at all time scales in the process of model evaluation, and further work will include a comparison of the current results with those obtained for calibrated stream flow using SWAT.

Summary and Conclusions

There are several issues to consider in compiling primary input GIS data sets for use in watershed scale hydrologic modeling. This is especially true when using the model as an environmental assessment tool or as a decision-support system for soil and water resource management. The objective of this study was to determine to what extent the use of various combinations of soil and land use GIS input data layers affected noncalibrated stream flow estimates in a large-scale agricultural watershed. Based on our results, the SWAT model shows the most variation in stream flow estimates using different land use data sets. In this study, we found that the 2001 NASS data set provided the best estimates for stream flow in the CCW. We suggest that our study agrees with the results of Shirmohammadi et al. (2006), and that a significant portion of the uncertainty associated with stream flow modeling is due to the uncertainty in estimates of the input parameters, including soils, land use, and climate. It should be noted that although the SWAT model is sensitive to soil properties, the scale and extent of soil information did not have a substantial impact on CCW stream flow modeling results.

Although the use of a distributed parameter hydrologic model such as SWAT may facilitate the simulation of various watershed assessment studies regarding the effects of different conservation programs (i.e., the USDA CEAP project), it is important that the users exercise prudence in choosing the most appropriate GIS input. This research

demonstrates the significance associated with using different soil and land use GIS input for simulating stream flow, which is a fundamental requirement of any watershed hydrology model. Inadequate parameterization of soil property data and land use coverage due to either GIS input data or model processing of the GIS data may lead to the misinterpretation of model output for not only stream flow but, ultimately, for sediment yield and nutrient/pesticide transport. It would make it very difficult to adequately assess the benefits of conservation practices if the modeling results were based on less than optimal GIS input and, therefore, improper parameterization. This not only applies to a specific watershed but also to any modeling comparisons and assessments made between watersheds in different regions.

Finally, the results of this study suggest that in determining the effects of farm conservation practices on diverse watersheds, it is important to maintain as much consistency as possible in GIS input data sets, while using the most appropriate data sets available. Indeed, this is a relatively uninvestigated area of research, where further studies are necessary to better understand the effects of GIS data applications in watershed hydrologic modeling. Perhaps future versions of SWAT will incorporate the use of dynamic GIS input data sets to accommodate changes in land use over time, as well as the use of NEXRAD rainfall observations or remotely sensed surface soil moisture as geospatial input data to account for errors associated with limited or point-scale rainfall observations.

Acknowledgements

The authors would like to express their sincere gratitude to the reviewers of this manuscript for their time, insight, and very constructive comments and suggestions that have served to improve the scope and quality of this manuscript considerably. We would also like to thank Mr. Scott McAfee for his assistance in editing the manuscript.

References

Arnold, J.G., P.M. Allen, and G. Bernhardt. 1993. A comprehensive surface-groundwater flow model. Journal of Hydrology 142:47-69.

Arnold, J.G., and P.M. Allen. 1996. Estimating hydrologic budgets for three Illinois watersheds. Journal of Hydrology 176:57-77.

Arnold, J.G., R. Srinivasan, R.S. Muttiah, and J.R. Williams. 1998. Large area hydrologic modeling and assessment, part I: Model development. Journal of the American Water Resources Association 34(1):73-89.

Bracmort, K.S., M. Arabi, J.R. Frankenberger, B.A. Engel, and J.G. Arnold. 2006. Modeling long-term water quality impact of structural BMPs. Transactions of the American Society of Agricultural and Biological Engineers 49(2):367-374.

Bultot, F., and G.L. Dupriez. 1976. Conceptual hydrological model for an average-sized catchment area. Journal of Hydrology 29:251-292.

Chow, V.T., D.R. Maidment, and L.W. Mays. 1998. Applied Hydrology. New York, NY: McGraw-Hill Inc.

Cotter, A.S., I. Chaubey, T.A. Costello, T.S. Soerens, and M.A. Nelson. 2003. Water quality model output uncertainty as affected by spatial resolution of input data. Journal of the American Water Resources Association 39(4):977-986.

DeKalb County Department of Watershed Management. 2008. County data, GIS Department. http://www.dekalbwatershed.com/GIS/projects_watermapping.htm.

Di Luzio, M., R. Srinivasan, J.G. Arnold, and S.L. Neitsch. 2002. Soil and Water Assessment Tool. ArcView GIS Interface Manual:Version 2000. GSWRL Report 02-03, BRC Report 02-07. College Station, TX: Texas Water Resources Institute TR-193.

Di Luzio, M., J.G. Arnold, and R. Srinivasan. 2005. Effects of GIS data quality on small watershed stream flow and sediment simulations. Hydrological Processes 19:629-650.

Duriancik, L.F., D. Bucks, J.P. Dobrowolski, T. Drewes, S.D. Eckles, L. Jolley, R.L. Kellogg, D. Lund, J.R. Makuch, M.P. O'Neill, C.A. Rewa, M.R. Walbridge, R. Parry, and M.A. Weltz. 2008. The first five years of the Conservation Effects Assessment Project. Journal of Soil and Water Conservation 63(6):185A-197A.

Eckhardt, K., and J.G. Arnold. 2001. Automatic calibration of a distributed catchments model. Journal of Hydrology 251(1-2):103-109.

FGDC (Federal Geographic Data Committee). 1997. Vegetation information and classification standard. Reston, VA: Federal Geographic Data Committee, US Geological Survey.

FitzHugh, T.W., and D.S. Mackay. 2000. Impacts of input parameter spatial aggregation on an agricultural nonpoint source pollution model. Journal of Hydrology 236:35-53.

Gassman, P.W., M.R. Reyes, C.H. Green, and J.G. Arnold. 2007. The soil water and assessment tool: Historical development, applications, and future research directions. Transactions of the American Society of Agricultural and Biological Engineers 50(4):1211-1250.

Green, W.H., and G.A. Ampt. 1911. Studies on soil physics, 1. The flow of air and water through soils. Journal of Agricultural Science 4:11-24.

Haverkamp, S., R. Srinivasan, H.G. Frede, and C. Santhi. 2002. Subwatershed spatial analysis tool: Discretization of a distributed hydrological model by statistical criteria. Journal of the American Water Resources Association 38(6):1723-1733.

Indiana Agricultural Statistics Service. 2003. County data. West Lafayette, IN: Indiana Agricultural Statistics Service, Purdue University.

Indiana Conservation Tillage Reports. 2004. Indiana Department of Natural Resources, Division of Soil Conservation. http://www.in.gov/isda/2384.htm.

Indiana Department of Natural Resources. 1980. The Indiana Water Resource: Availability, Uses, and Needs (G.D. Clark, Ed.). Indianapolis, IN: Indiana Department of Natural Resources.

Jennings, M.D. 2000. Gap analysis: Concepts, methods, and recent results. Landscape Ecology 15:5-20.

Johanson, R.C., J.C. Imhoff, J.L. Little, and A.S. Donigian. 1984. User's Manual for the Hydrological Simulation Program (HSPF). Athens, GA: US Environmental Protection Agency.

Knisel, W.G. 1980. CREAMS, a field scale model for chemicals, runoff and erosion from agricultural management systems. Conservation Research Report No. 26. Washington, DC: USDA.

Larose, M., G.C. Heathman, D.L. Norton, and B. Engle. 2007. Hydrologic and atrazine simulation in the cedar creek watershed using the SWAT model. Journal of Environmental Quality 36:521-531.

Leavesley, G.H., R.W. Lichty, B.M. Troutman, and L.G. Sindon. 1983. Precipitation-runoff modeling system: user's manual. US Geological Survey Water Resource Investment Report 83-4238.

Leonard, R.A., W.G. Knisel, and D.A. Still. 1987. GLEAMS: Groundwater loading effects on agricultural management systems. Transactions of the American Society of Agricultural Engineers 30(5):1403-1428.

Mamillapalli, S. 1998. Effect of spatial variability on river basin streamflow modeling. PhD dissertation, Purdue University.

Mausbach, M.J., and A.R. Dedrick. 2004. The length we go measuring environmental benefits of conservation practices. Journal of Soil and Water Conservation 59(5):96-103.

Mileham, L., R. Taylor, J. Thompson, M. Todd, and C. Tindimugaya. 2008. Impact of rainfall distribution on the parameterization of a soil-moisture balance model of groundwater recharge in equatorial Africa. Journal of Hydrology (forthcoming).

Moriasi, D.N., J.G. Arnold, M.W. Van Liew, R.L. Binger, R.D. Harmel, and T.L. Veith. 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Transactions of the American Society of Agricultural and Biological Engineers 50(3):885-900.

Muleta, M.K., J.W. Nicklow, and E.G. Bekele. 2007. Sensitivity of a distributed watershed simulation model to spatial scale. Journal of Hydrologic Engineering 12(2):163-172.

NOAA NCDC (National Oceanic and Atmospheric Administration National Climate Data Center). 2004. Weather Data. http://www.ncdc.noaa.gov/oa/climate/research/monitoring.html.

Neitsch, S.L., J.G. Arnold, J.R. Kiniry, R. Srinivasan, and J.R. Williams. 2002. Soil and water assessment tool theoretical documentation:Version 2000. TWRI report TR-191. College Station, TX: Texas Water Resources Institute. http://www.brc.tamus.edu/swat/downloads/doc/swat-2000theory.pdf.

Richardson, C.W., D.A. Bucks, and E.J. Sadler. 2008. The Conservation Effects Assessment Project benchmark watersheds: Synthesis of preliminary findings. Journal of Soil and Water Conservation 63(6):590-604.

Romanowicz, A.A., M. Vanclooster, M. Rounsevell, and I. La Junesse. 2005. Sensitivity of the SWAT model to soil and land use data parametrisation: A case study in the Thyle catchment, Belgium. Ecological Modelling 187(1):27-39.

Santhi, C., J.G. Arnold, J.R. Williams, W.A. Dugas, R. Sirinivasan, and L.M. Hauck. 2001. Validation of the SWAT model on a large river basin with point and nonpoint sources. Journal of the American Water Resources Association 37(5):1169-1188.

Shirmohammadi, A., I. Chaubey, R.D. Harmel, D.D. Bosch, R. Munoz-Carpena, C. Dharmasri, A. Sexton, M. Arabi, M.L. Wolfe, J. Frankenberger, C. Graff, and T.M. Sohrabi. 2006. Uncertainty in TMDL models. Transactions of the American Society of Agricultural and Biological Engineers 49(4):1033-1049.

Smith, D.R., and E.A. Pappas. Effects of ditch dredging on the fate of nutrients in deep drainage ditches of the Midwestern United States. Journal of Soil and Water Conservation. 62(4):252-261.

Spruill, C.A., S.R. Workman, and J.L. Taraba. 2000. Simulation of daily and monthly stream discharge from small watersheds using the SWAT model. Transactions of the American Society of Agricultural Engineers 43(6):1431-1439.

SJRWI (St. Joseph River Watershed Initiative). 2004. Cedar Creek watershed management plan. ARN 01-383. http://www.sjrwi.org/documents/CCWMP-final-draft081505.pdf.

Tolson, B.A., and C.A. Shoemaker. 2007. Cannonsville Reservoir Watershed SWAT2000 model development, calibration and validation. Journal of Hydrology 337:68-86.

US Climate Change Science Program. 2007. Our Changing Planet: The U.S. Climate Change Science Program for Fiscal Year 2008. Washington, DC: Climate Change Science Program Office. http://www.gcrio.org/orders/product_info.php?cPath=22&products_id=184.

USDA NASS (National Agricultural Statistics Service). 2001. National Agricultural Statistics. http://www.nass.usda.gov/index.asp.

Van Liew, M.W., and J. Garbrecht. 2003. Hydrologic simulation of the Little Washita River experimental watershed using SWAT. Journal of the American Water Resources Association 39(2):413-426.

Wang, X., and A.M. Melesse. 2006. Effects of STATSGO and SSURGO as inputs on SWAT model's snowmelt simulation. Journal of the American Water Resources Association 42(5):1217-1236.

White, K.L., and I. Chaubey. 2005. Sensitivity analysis, calibration, and validation for a multisite and multivariable SWAT model. Journal of the American Water Resources Association 41(5):1077-1089.

Williams, J.R., A.D. Nicks, and J.G. Arnold. 1985. Simulator for water resources in rural basins. Journal of Hydraulic Engineering 111(6):970-986.

Williams, J.R., C.A. Jones, and P.T. Dyke. 1984. A modeling approach to determining the relationship between erosion and soil productivity. Transactions of the American Society of Agricultural and Biological Engineers 27(1):129-144.

Yuan, Y., R.L. Bingner, and R.A. Rebich. 2001. Evaluation of AnnAGNPS on Mississippi Delta MSEA Watersheds. Transactions of the American Society of Agricultural Engineers 44(5):1183-1190.

Yüksel, A., A.E. Akay, and R. Gundogan. 2008. Using ASTER imagery in land use/cover classification of eastern Mediterranean landscapes according to CORINE land cover project. Sensors 8:1237-1251.