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Application of SWAT model in predicting water quantity and quality for U.S. and Thailand watersheds

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ABSTRACT

Evaluating processes which influence water quantity and quality can be achieved through either long-term on-site monitoring or with the use of simulation models. On-site monitoring can be time-consuming, labor-intensive, and expensive. Therefore, the use of simulation models has become viable and cost-effective. However, to ensure that the model is capable and reliable to describe hydrologic processes in various hydrologic conditions and to use it as an assessment tool, there is a strong need in testing the model against extensive field measured data for different scales, land use, topography, climate, and soil conditions prior to its application for solving natural resource problems within watersheds. For this reason, the objective of this research was to make an effort to calibrate and validate the surface and subsurface components of the Soil and Water Assessment Tool (SWAT) model for various hydrologic conditions in predicting surface and subsurface drain flows and their water quality.

Calibration and validation of the SWAT for the Upper Maquoketa River Watershed were performed by comparing measured and predicted stream flows and NO_3-N losses at the watershed outlet during the period of 1999-2001. The coefficient of determination (r^2) statistics found for the monthly stream flows and NO_3-N losses were equal to 0.73 and 0.72, respectively indicating that model performed reasonably well.

Evaluation of the SWAT tile flow components were performed by comparing the measured tile flows with the predicted tile flows at the Iowa State University's Northeastern Research Center for five years (1993-1997) using both STATSGO and SSURGO soil databases. SWAT simulation results indicated that the model reasonably predicted the cumulative annual tile flow volumes and reasonably tracked the observed trends for the calibration year. The SWAT model did not accurately predict cumulative annual tile flows

and monthly tile flows for the validation years. Therefore, the simulation results showed that the model predicted similar results regardless of soil data set.

Application of the SWAT was conducted for the Chi River Subbasin II located in the northeastern Thailand by comparing predicted stream flows and NO_3-N losses with corresponding in-stream for five years (2000-2003, 2005). Statistical comparisons between the simulated results and the observed data for the calibration year gave a reasonable agreement for both monthly r^2 and Nash-SutCliffe model efficiency (E) within ranges of 0.77-0.88 and 0.55-0.79, respectively, where as validation results showed lower values of r^2 and E values ranging from 0.23 to 0.77 and -7.98 to 0.66.

CHAPTER 1. GENERAL INTRODUCTION

Introduction

Public concerns over water quality have increased during recent decades. In particular, in coastal plains and other regions with shallow groundwater tables, water quality impairments resulting from point and non-point sources (NPS) of pollution have resulted in concerns for human health as well as harmful effects on natural ecosystems. In human populations, these pollutants are suspected to contribute to a range of illnesses, including various types of cancer. In the ecosystems of coastal environments, the pollutants are implicated in Harmful Algal Blooms and anoxia, which are believed to be caused by excessive amounts of plant nutrients entering coastal waters via surface runoff and/or subsurface flow emanating from agricultural croplands (Parry, 1998; Montas et al., 1999b; Djodjic et al., 2002).

Apart from pesticides, the two key diffuse pollutants in NPS pollution are nitrogen and phosphorous. Nitrogen is an essential plant nutrient that is applied to agricultural crops in greater quantity than any other fertilizer. In addition, vast quantities of nitrogen are contained in the ecosystems, including the organic matter in soil. Biological processes that convert nitrogen to its mobile form (nitrate-nitrogen, NO_3 -N) occur continuously in the soil-water-plant system. Due to the negative charges on both soil minerals and on nitrate, NO_3 -N can be repelled from mineral surfaces and readily leached from the root zone toward subsurface flow systems.

For these reasons, quantity and quality of surface and subsurface waters need to be evaluated. Evaluating processes which influence water quantity and quality can be achieved through either long-term on-site monitoring or with the use of simulation models. However, on-site monitoring, particularly in very large hydrologic areas, can be time-consuming, labor-intensive, and expensive. The use of simulation models has become a viable and cost-effective tool (Santhi et.al, 2001). Not only simulation models save time and money, but they also presents a more flexible approach for assessing different land use scenarios and impacts on single or interrelated components of the hydrologic cycle. Indeed, simulation models have been used quite frequently to provide guidelines in water resources management and to assist in management decision support. In simulation modeling, mathematical relationships are used to describe the behavior of the physical system or to quantitatively represent the process occurring within the system.

Numerous models have been developed that vary in terms of simulation capabilities, complexity for simulating hydrologic flows, and in some cases agricultural chemical movement, through the soil-water system. Some of these models are primarily designed to simulate subsurface drain flow processes. Dutt et al. (1972) and Duffy et al. (1975) developed mathematical models of biophysiochemical processes that could be applied to tile-drained agricultural areas. Kanwar et al. (1983) developed a computer simulation model to simulate NO_3-N losses with tile drainage water. Kirkham (1958) developed an analytical solution for steady-state flow to parallel tile drains in a homogeneous soil underlain by an impermeable layer. Scotter et al. (1990) developed a simple numerical model for transient soil water flow to a tile drain for assumed or measured values of rainfall, evaporation, deep percolation, drain spacing, and depth. The DRAINMOD model (Skaggs, 1982) was developed to support design and evaluation of different drainage systems including tile drains. The DRAINMOD-N model (Brevé et al., 1997) is an adaptation of DRAINMOD that also simulates NO_3 -N movement through tiles.

Other models have been developed that focus on surface runoff and leaching of water and agricultural chemicals rather than tile flow processes. For example, the Root Zone Water Quality Model (RZQWM) model (USDA-ARS, 1995) was developed for simulating the fate and movement of water, nutrients and pesticides in soil-plant environment by integrating physical, chemical, and biological processes in the root zone. The Chemical, Runoff, and Erosion from Agricultural Management Systems (CREAMS) model (Knisel, 1981) was designed to simulate the long-term impact of land management on water leaving the edge of a field. Several others models that are based on CREAMS include the Ground Water Loading Effects on Agricultural Management Systems (GLEAMS) model (Leonard et al., 1987), the Simulator for Water Resources in Rural Basins (SWRRB) model (Williams et al., 1985; Arnold et al., 1990), the Erosion-Productivity Impact Calculator (EPIC) model (Williams et al., 1990) , the Agricultural Non-point Source (AGNPS) model (Young et al., 1989), and recently, one of the most widely used water quality model, the Soil and Water Assessment Tool (SWAT) model (Arnold et al., 1998; Srinivasan et al., 1998).

The SWAT model was developed to predict the effects of different management scenarios on water quality, pollutant loadings and sediment yields by accounting for variations in soil, climate, and land use across a watershed or river basin. The model has been successfully applied numerous times for detailed long-term continuous simulations of stream and subsurface drain flows, soil erosion, and sediment and nutrient transport in watersheds of different scales/sizes, and having different hydrologic, geologic, and climatic conditions including tile drained croplands (Arnold et al., 1999; Ahmad et al., 2002; Du et al., 2003;

Srinivasan et al., 1998; Peterson and Hamlett, 1998; Shirmohammadi et al., 2001; Van Liew and Garbrecht, 2001; Benaman et al., 2001; Varanou et al., 2002; Vache et al., 2002; Santhi et al., 2001; Stone et al., 2001; Qiu and Prato, 2001; Arnold et al., 2000; Spruill et al., 2000; Stonefelt et al., 2000; Rosenthal and Hoffman, 1999; King et al., 1999; Bingner, 1996; and Rosenthal et al., 1995).

However, to ensure this model is capable and reliable to describe hydrologic process in various hydrologic conditions and to use as an assessment tool, there is an ongoing need for testing of the model against extensive field measured data for different scales, land use, topography, climate, and soil conditions prior to its application for solving natural resource problems. For this reason, a research effort was made to calibrate and validate the surface and subsurface drainage components of the SWAT model for various hydrologic conditions.

The specific objectives of this research were:

1. To calibrate and validate the SWAT model for the Upper Maquoketa River Watershed using measured watershed data on stream flows and water quality.
2. To calibrate and validate the SWAT's tile flow component under two different soil databases for the experimental site at Iowa State University's Northeastern Research Center, Nashua, Iowa.
3. To calibrate and validate the SWAT model for the Chi River Subbasin II in northeast Thailand.

Dissertation Organization

This dissertation is organized into five different chapters. The first chapter includes an introduction to the research and explanation of the organization of the dissertation. Chapter 2, 3, and 4 are manuscripts prepared for publication. The second chapter presents the manuscript entitled "Calibration and Validation of SWAT for the Upper Maquoketa River Watershed". This manuscript has been accepted for publication in the International Agricultural Engineering Journal. The third chapter contains the manuscript entitled "Effect of Spatial Variability in Soil Properties in Predicting Tile Flow by Using the SWAT Model". This manuscript was prepared for publication in the Transactions of the ASABE. The fourth chapter is entitled "Application of SWAT model in Simulating Stream Flow and NO_3-N Losses for the Chi River Subbasin II in Northeast Thailand". This manuscript was prepared for publication in the International Agricultural Engineering Journal. The final chapter, the fifth, summarizes the general conclusions of the research.

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CHAPTER 2. CALIBRATION AND VALIDATION OF SWAT FOR THE UPPER MAQUOKETA RIVER WATERSHED

A paper accepted by the International Agricultural Engineering Journal

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Abstract

A validation study has been performed using the Soil and Water Assessment Tool (SWAT) model with data collected for the Upper Maquoketa River Watershed (UMRW), which drains over 160 km^2 in northeast Iowa. Calibration and validation of the SWAT output was performed by comparing predicted flow and NO_3-N loadings with corresponding in-stream measurements at the watershed outlet during 1999-2001. Annual stream flows measured at the watershed outlet were greatly under-predicted when precipitation data collected within the watershed during 1999-2001 were used to drive SWAT. Selection of alternative nearby National Weather Service (NWS) climate data resulted in greatly improved average annual stream predictions, and also relatively strong r^2 values of 0.73 and 0.72 for the predicted average monthly flows and NO_3-N loads, respectively. The use of the alternative precipitation data resulted in 19 and 55% increases in average annual precipitation and average annual stream flow as compared to the precipitation data measured in the watershed. The results also indicate that the precipitation data collected in the watershed likely underreported the true rainfall amounts, although this cannot be established with absolute certainty. In summary, the results of this study show that SWAT can replicate

measured trends for this watershed and that climate inputs are very important for validating SWAT.

Keywords: SWAT, modeling, calibration, validation, water quality, nitrate

Introduction

Water quality modeling is emerging as a key component of Total Maximum Daily Load (TMDL) assessments and other watershed-based water quality studies. Numerous water quality models have been developed that differ greatly in terms of simulation capabilities, documentation, and technical support. One of the more widely used water quality models is the Soil and Water Assessment Tool (SWAT), which was developed to assess the water quality impacts of agricultural and other land uses for a range of watershed scales including large river basins (Arnold and Forher, 2005). Previous applications of SWAT have compared favorably with measured data for a variety of watershed scales and conditions (Gassman et al., 2006). However, an ongoing need regarding the use of SWAT is to test it with measured data for different scales, land use, topography, climate, and soil conditions.

The overall goal of this study was to test the ability of SWAT to simulate stream flow and nitrate (NO_3-N) for the Upper Maquoketa River Watershed (UMRW), which is a row-crop dominated watershed located in northeast Iowa that is typical of much of Iowa. The focus on NO_3-N in this study reflects concerns regarding elevated NO_3-N levels in many Iowa streams, as well as the larger Upper Mississippi River Basin (UMRB) stream system that drains the majority of the state including the UMRW. Investigation of alternative precipitation data inputs is also conducted in this study. Previous studies have shown that

SWAT stream flow and pollutant outputs can be very sensitive to precipitation inputs, and that accurate precipitation data is needed for optimum model performance (Chaplot et al., 2005 and Jayakrishnan et al., 2005). Thus, the specific objectives of the study were: (1) to perform a sensitivity analysis of key SWAT hydrologic input parameters, (2) calibrate and validate SWAT with measured streamflow and NO_3-N data collected at the UMRW outlet, and (3) assess the impact of using alternative climate data for performing the UMRW SWAT simulations.

Watershed description

The UMRW is located at 42° 40’ 44” N, 91° 35’ 34” W and covers an area of about 162 km^2 in portions of Buchanan, Clayton, Fayette, and Delaware counties in Iowa. The watershed lies within the upper reaches of the Maquoketa River Watershed (MRW), which drains a 4,867 km^2 region that is dominated by row crop and other agricultural land (Figure 1). In 1998, the MRW was listed as a priority watershed within the Iowa Department of Natural Resources Unified Watershed Assessment with the primary concern being nutrient and sediment losses from agricultural nonpoint sources.

Corn and soybean are the major crops in the UMRW, accounting for 66% of the total landuse (Gassman et al., 2002). Other key land uses included woodland (8.9%), alfalfa (7.5%), Conservation Reserve Program (CRP) land (4.1%), and pasture (4.0%). A total of 90 operations were identified in a 1999 survey (Osei et al., 2000) having one or more types of livestock (Figure 1), with production focused primarily on swine, dairy cows, beef cattle, feeder cattle, and/or calves and heifers. The survey also indicated that most of the livestock producers were not taking enough credit for the nutrient content from manure when it was applied to the crop fields. In general, the UMRW is characterized by low relief and poor natural surface drainage with elevation ranging from 300-380 m. Based on information from a previous study (Keith et al., 2000) and local sources, it was shown that a significant portion of cropland in the study area was tile drained. The tile drains are key conduit of NO_3-N to the UMRW stream system.

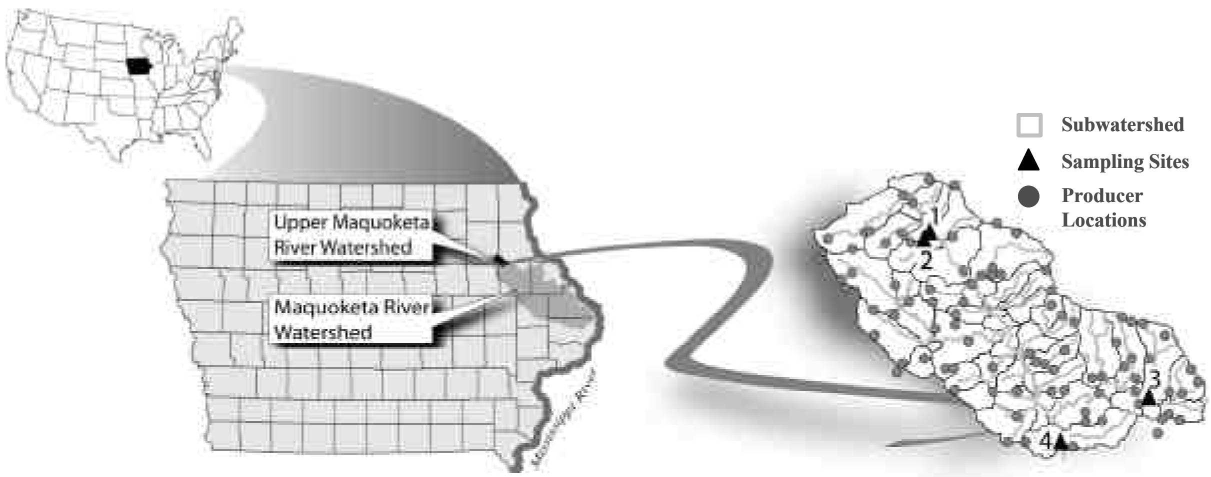

Figure 1. Location of the Upper Maquoketa River Watershed in relation to the Maquoketa River watershed and the Mississippi River, and the locations of the UMRW livestock operations and sampling sites

Four sampling sites were established within the watershed for monitoring stream flow and water quality in 1999-2001 (Figure 1). Analysis of water quality measurements at the UMRW outlet (sampling site 4) located in Backbone State Park showed elevated levels of NO_3-N and phosphate-phosphorus (PO_4-P), depending on the changes in the proportions of stream flow made up by the surface runoff and subsurface drainage components. During extended wet periods, but between surface runoff events when subsurface flow dominates stream flow, NO_3-N concentrations increased while PO_4-P concentrations decreased. In contrast, during rainfall surface runoff events, NO_3-N concentrations decreased while PO_4-P concentrations increased. A detailed summary of these water quality data were reported in Baker et al. (1999). In addition, total-catch and tipping-bucket rain gauges were installed within the watershed and used to record the amount of rain at sites 2 and 3 for 1999-2001.

SWAT input data and management assumptions

The SWAT model requires inputs on weather, topography, soils, land use, management, and stream channels. This SWAT validation study builds on a previous UMRW simulation study, in which a nested modeling approach was used, in which field-scale simulations performed with the Agricultural Policy EXtender (APEX) model (Williams et al., 2006; Saleh et al., 2004) were embedded within the SWAT watershed simulations (Gassman et al., 2002; Saleh et al., 2003). APEX was used to simulate the manured cropland and pasture areas due to its enhanced flexibility in simulating different manure application scenarios relative to SWAT. Edge-of-field sediment and nutrient losses simulated in APEX, coupled with losses simulated in SWAT from other land uses, were routed in SWAT through the stream system to the watershed outlet. This approach was also used in two other previous watershed studies that were conducted in Texas, as described in Gassman et al. (2002).

In this study, the entire watershed was simulated in SWAT rather than using APEX for the manured cropland and pastures. The input files that were created for the original set of the APEX-SWAT application were converted into equivalent SWAT hydrologic response units (HRUs) as described in Kanwar et al. (2003). The additional cropland HRUs were inserted only in SWAT subwatersheds that contained livestock operations. Small open lot and vegetative buffer strip areas that were simulated in APEX for swine open lot and cattle feeder operations were assumed to be non-grazed pasture areas for this simulation. The remaining pasture areas simulated within each SWAT subwatershed were split into separate dairy, calf/heifer, and beef cow pasture HRUs, to preserve differences in manure deposition rates and grazing periods that were assumed to occur between these different livestock species. The manure was assumed to be applied to cropland that was planted with corn. Manure generated by beef pasture and calf/heifer operations was relatively minor compared to the other types of operations and assumed to be deposited on pastures and/or corn fields via grazing rather than applied with a manure spreader. It was assumed that the livestock producers applied solid manure at an annual rate of 44.8 t ha^{-1} and liquid manure at the rate of 46,745 l ha^{-1}, resulting in the N and P application rates shown in Table 1.

Table 1. Manure N and P rates (kg ha^{-1}) applied to corn by farm type for the UMRW baseline simulations

Nutrient	Tie stall dairies	Small swine (open lot)	Large swine (confinements)	Cattle feeder
Manure N	234	278	293	262
Manure P	49	96	101	71

Based on expert opinion and survey results (Osei et al., 2000), it was assumed that the simulated primary N fertilizer applications were applied at the same rate for manured fields relative to nonmanured cropland (Table 2). An N fertilizer rate of 159 kg ha^{-1} was simulated for continuous corn, and the simulated fertilizer rates for corn following soybean and alfalfa were 128 and 100 kg ha^{-1}, respectively, reflecting some accounting of N credit from the legume crops. Additional "crop-removal" N and phosphate (P_2O_5) fertilizer were simulated for both manured and nonmanured fields following corn harvest (Table 2), for continuous corn, corn-soybean, and the second year of corn when rotated with alfalfa for the manured cropland. Smaller starter N and P fertilizer amounts of 10 and 11 kg ha^{-1} were assumed applied for corn in all rotations, regardless of manure inputs. Additional details regarding the distribution of livestock in the watershed and the nutrient management assumptions are given in Osei et al. (2000) and Gassman et al. (2002).

Table 2. Expected yields and fertilizer rates based on UMRW survey results

Crop	Crop sequence	Expected yield (bu/ac)	Primary N fert. appl. (kg ha^{-1})[a]	Fall crop removal fert. appls. (kg ha^{-1}) Manured fields		Nonmanured fields	
				N	P_2O_5	N	P_2O_5
Corn	after corn	155	159	18	46	28	68
Corn	after soybean	160	128	10	26	28	68
Corn	after alfalfa	158	100	10	26	28	68
soybean	after corn	55	0	15	39	28	68

[a]The same rate was assumed to be applied to both manured and nonmanured fields

The land use/cover, topographic, and soil data required for the SWAT simulations were generated as part of the previous UMRW modeling study, from maps developed within the Geographical Resource Analysis Support System (GRASS) Geographic Information System (GIS) using the GRASS/SWAT Interface Program (Srinivasan and Arnold, 1994). For modeling purposes in SWAT, a total of 52 subwatersheds were created for the UMRW (Figure 1), with the watershed outlet at sampling site 4. Each subwatershed delineated within SWAT was simulated as a homogeneous area in terms of climatic inputs. The subwatersheds were further subdivided into HRUs that were assumed to consist of homogeneous land use, management, and soil type. The percent of the subwatershed that was covered by a specific HRU is input to SWAT; however, the exact spatial location is not accounted for. A land use threshold of 10% was used when the HRUs were created, which limited the land use to categories that covered at least 10% of a given subwatershed. The HRU land use categories included pasture, urban land, continuous corn, corn-soybean, and a five-year rotation of corn and alfalfa. A total of 646 HRUs were used for the UMRW to reflect the differences in land use, management, and soil type.

The soil map and associated soil layer data used for the simulation were obtained from the Iowa Department of Natural Resources (IDNR-IGS, 2006). The soil slope length and percent slope were determined from an assessment of mean slope lengths that are given in the 1992 National Resource Inventory (NRI) database (USDA-NRCS, 1997; Nusser and Goebel, 1997). Roughly 80% of the cropped soils were depicted as being tile drained in the SWAT simulations, based on previous assumptions reported by Keith et al. (2000). The subsurface tile depths were set at 1.2 m below the soil surface in SWAT.

Precipitation and other climatic data inputs

The SWAT sensitivity simulations, and initial calibration and validation simulations, were performed using the daily precipitation data collected at sampling sites 2 and 3 (Figure 2) within the UMRW for the same three year period (1999-2001) that the in-stream monitoring data was collected for. Table 3 lists the annual and average annual precipitation levels for this period at these two sites. Two five-year average daily precipitation records for 1997-2001 were constructed by collating 1997-98 precipitation data collected near Fayette and Manchester (IEM, 2005) onto the site 2 and site 3 data, respectively; the Fayette and Manchester data were used because these two stations were determined to be the closest to sites 2 and 3, respectively (Figure 2). These five-year precipitation records enabled each SWAT simulation to encompass a complete cycle of the five-year corn and alfalfa rotations. They also provided a two-year “initialization period” prior to the three years that the monitoring data were collected for (1999-2001). The assignment of a specific precipitation record to a given subwatershed was determined based on which rain gauge (site 2 or 3) was closest to the subwatershed.

Further investigation of 1999-2001 precipitation levels was performed for seven National Weather Service (NWS) climate stations in the region surrounding the UMRW (Figure 2), including Fayette and Manchester.

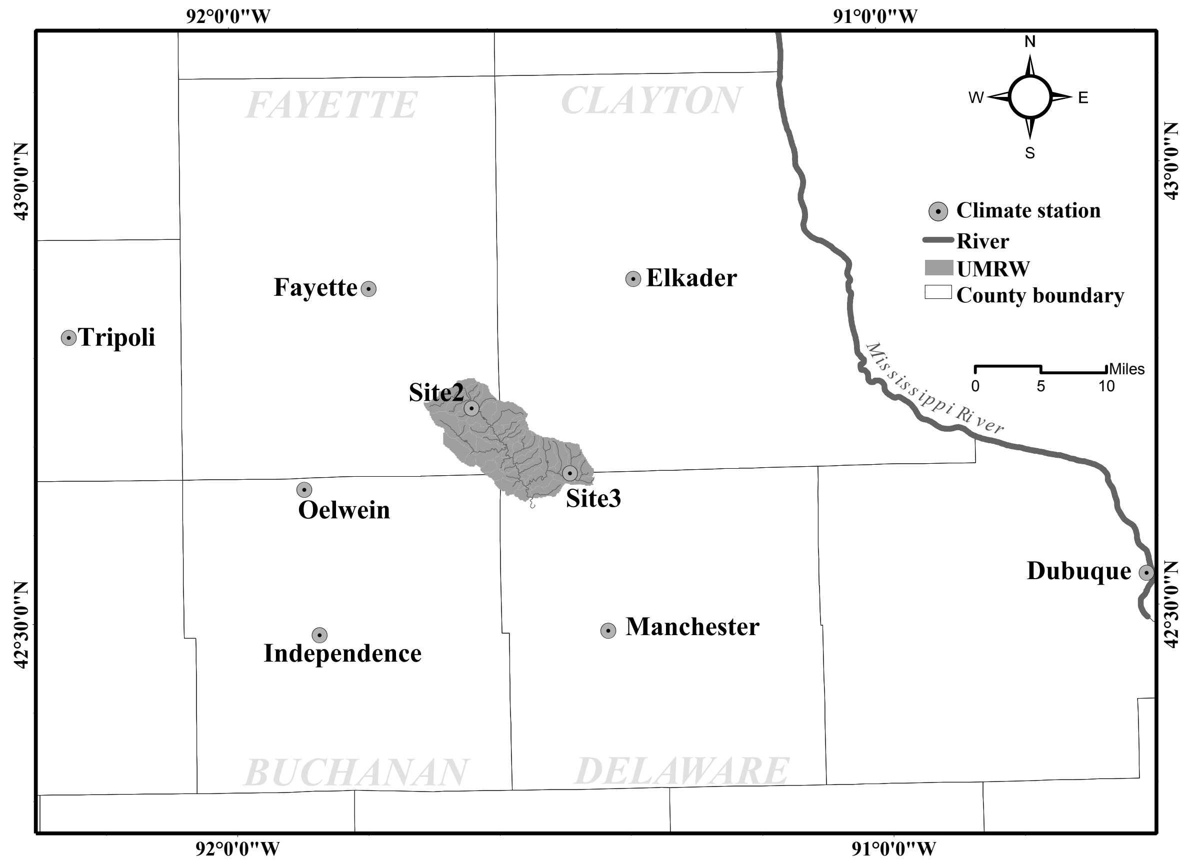

Figure 2. Locations of sites 2 and 3 precipitation gauges within the UMRW, and the locations of nearby NWS climate stations

Table 3 summarizes the 1999-2001 annual and annual average precipitation levels for these climate stations, based on data obtained from IEM (2005). A comparison of the precipitation amounts between sites 2 and 3 and the other climate stations reveals that the precipitation levels measured at site 2 and 3 were considerably lower than those recorded at the other climate stations. The percentage differences (Table 4) reveals that the precipitation at sites 2 and 3 were lower than the other climate stations by 9 to 30%. In addition, several tests of statistical analysis of variance (ANOVA) were performed using SAS© (SAS, 2006) to compare average annual precipitation between the alternative climate stations and sites 2 and 3. The results of the ANOVA tests confirmed that there was a significant difference between the average annual precipitation of sites 2 and 3 and the other climate stations.

These results suggest that there was an underreporting of precipitation amounts by the two automatic gauges used to record precipitation levels at sites 2 and 3. Shirmohammadi et al. (2006) state that typical measurement errors associated with tipping bucket type rain gauges are on the order of 1-5%. However, Humprhey et al. (1997) report underestimation of rainfall of up to 29% for rainfall rates ranging between 6 and 240 mm hr^{-1}. Unfortunately, the catch gauge data collected at sites 2 and 3 is not fully reliable and thus it cannot be established with certainty that there were underestimations of precipitation levels by the tipping bucket gauges at sites 2 and 3. Therefore, it was decided that five-year Fayette and Manchester precipitation records for 1997-01 should also be used as alternative precipitation inputs to perform the SWAT calibration and validation simulations. The execution of these additional simulations provides further insight into the sensitivity of SWAT to recorded precipitation amounts in the UMRW region.

Fayette and Manchester daily maximum and minimum temperature data for 1997-2001 were used for all of the five-year SWAT simulations. The daily air temperature inputs were used in the SWAT crop growth algorithms and evapotranspiration computations. The Hargreaves Method (Hargreaves and Samani, 1985) was used to estimate daily evapotranspiration rates.

Table 3. Summary of annual precipitation (mm) for sites 2 and 3 within the UMRW and nearby NWS stations

	Rain Gauge[a] or NWS Climate Stations[b]								
	Site 2[a]	Site 3[a]	Fayette	Manchester	Elkader	Oelwein	Tripoli	Dubuque	Independence
Year	(42.72, -91.65)[c]	(42.65, -91.50)	(42.85, -91.80)	(42.47, -91.45)	(42.86, -91.40)	(42.63, -91.90)	(42.80, -91.25)	(42.53, -90.63)	(42.47, -91.88)
1999	814.3	807.2	1052.1	943.6	924.0	987.3	1054.1	910.3	1057.1
2000	750.9	839.4	967.0	834.9	875.0	955.5	958.1	820.7	840.0
2001	794.7	795.4	1042.7	893.1	897.0	987.8	811.3	933.7	970.8
Average	786.6	814.0	1020.6	890.5	898.7	976.9	941.2	888.2	956.0

[a]Measured within the watershed at sampling sites 2 and 3
[b]Alternative NWS climate station data were obtained from IEM (2005)
[c]Latitude and longitude

Table 4. Precipitation differences (%) between sites 2 and 3 versus seven NWS rain gauges in the UMRW region

	Fayette	Manchester	Elkader	Oelwein	Tripoli	Dubuque	Independence
Site2	-29.74	-13.21	-14.24	-24.18	-19.65	-12.92	-21.53
Site3	-25.38	-9.40	-10.40	-20.01	-15.62	-9.12	-17.44

Sensitivity analysis

The SWAT model has numerous of hydrologically-related model inputs, some of which can vary greatly between different subwatersheds. Holvoet et al. (2005) found that the most sensitive SWAT parameter was the curve number, which is related to both soil and vegetation. Spruill et al. (2000) reported that the most sensitive parameters were saturated hydraulic conductivity, base flow factor, drainage area, channel length and channel width, for an application of SWAT to a central Kentucky watershed. Arnold et al. (2000) found that three different basins within the Upper Mississippi River Basin exhibited clear differences in hydrologic sensitivity.

The six input parameters selected for the sensitivity analysis in this study were based on literature references, personal judgments, and suggestions in the SWAT User's Manual (Neitsch et al., 2002a). These parameters were the runoff curve number, soil available water capacity, soil evaporation coefficient, base flow alpha coefficient, groundwater delay, and groundwater revap coefficient. Precipitation inputs were also evaluated as part of the sensitivity analysis. The first three parameters were evaluated by Arnold et al. (2000) in their sensitivity analysis of SWAT and were also found to be very sensitive in SWAT studies performed by Spruill et al. (2000), Santhi et al. (2001), Jha et al. (2003), and Chu and Shirmohammadi (2004). The curve number determines the partitioning of precipitation between surface runoff and infiltration as a function of soil hydrologic group, land use, and antecedent moisture condition (Mishra and Singh, 2003). The available water capacity is a key soil parameter that has been found to affect groundwater recharge estimates in simple water balance models (Finch, 1998). The soil evaporation coefficient values adjust the depth distribution for evaporation from soil to account for the effect of capillary action, crusting, and cracking (Neitsch et al., 2002b).

The base flow alpha factor for groundwater is defined within SWAT as the groundwater recession or the rate at which groundwater is returned to the stream. Base flow recession is a function of the overall topography, drainage pattern, soils, and geology of the watershed. The base flow alpha factor is a direct index of the intensity with which the groundwater outflow responds to changes in recharge (Smedema and Rycroft, 1983). The groundwater delay is defined as the time it takes for water leaving the bottom of the root zone to reach the shallow aquifer where it can become lateral groundwater flow. The groundwater revap coefficient is defined within SWAT as the fraction of the amount of water that can be moved from shallow aquifer into overlying unsaturated layers as a function of water demand for evapotranspiration. Water may move from the shallow aquifer into the overlying unsaturated zone. In periods when the material overlying the aquifer is dry, water in the capillary fringe that separates the saturated and unsaturated zones will evaporate and diffuse upward.

Van Liew and Garbrecht (2001) found that simulated surface runoff volume varied from 0% to 27% in response to variations in precipitation that ranged from -60% to +60%, relative to the baseline precipitation volume. Thus, further sensitivity analysis was also performed for the site 2 and site 3 precipitation inputs, to ascertain how much shifts in precipitation affect flow volumes predicted by SWAT at the UMRW outlet.

Several simulations were executed for each input parameter selected for the sensitivity analysis, which were performed within the allowable range of values for the specific parameter while holding all other input values constant. The sensitivity of each input parameter was calculated separately for surface runoff and base flow, as a function of average annual values. The range of annual precipitation was varied from -40 to 40% for both site 2 and site 3, to cover the amount of precipitation of those other climate stations in the region (Table 3). The curve numbers were allowed to vary between -6 to +6 of the original values to account for uncertainty in the soil and land use conditions of the watershed. The soil available water capacities were obtained from a soils database (USDA-NRCS, 1992) and were adjusted within a range of -0.04 to +0.04 of the original values. The soil evaporation coefficient can vary between 0.0 and 1.0, and was varied in this study from 0.5 to 1.0. The base flow alpha was varied from 0.1 for land with slow response recharge to 0.9 for land with a rapid response, while the groundwater delay was varied from 10 to 90 days. Based on a recommended value from the SWAT manual, the groundwater revap coefficient value can be vary between 0.02 and 0.2, and was varied in the study from 0.02 to 0.18.

Figure 3 shows the sensitivity of surface runoff and base flow to precipitation, curve number, soil evaporation coefficient, soil available water capacity, base flow alpha factor, groundwater delay, and groundwater revap coefficient. As expected, increased precipitation resulted in greater surface runoff and base flow (Figure 3a). An increase in precipitation of 30% resulted in surface runoff and base flow increases of roughly 200%. However, surface runoff and base flow declined by only 25% in response to a precipitation decrease of 30%. The sensitivities of surface runoff and base flow to curve number change are shown in Figure 3b. The resulting relationship confirms that base flow is inversely correlated to curve number, because infiltration decreases with increased surface runoff and vice versa.

Figure 3c shows that decreasing the soil evaporation coefficient allows lower soil layers to compensate for water deficits in the upper layers, resulting in higher soil evaporation. Consequently, with higher soil evaporation, there is less water available for surface runoff and base flow. Both surface runoff and base flow increased in response to decreasing soil water capacity (Figure 3d). This occurs because less pore space is available to hold water when the soil water capacity decreases, resulting in higher runoff and percolation. However, as shown in Figure 3e, 3f, and 3g, surface runoff was found to not be sensitive at all for the base flow alpha factor, groundwater revap coefficient, and groundwater delay, while base flow was found to be sensitive for all three parameters. Base flow increased in response to increasing base flow alpha factor and groundwater delay values, but decreased in response to increasing groundwater revap coefficient value.

Calibration and validation

Similar calibration steps were performed with both the five-year precipitation records that included the 1999-2001 data for sites 2 and 3, and for the alternative Fayette and Manchester five-year precipitation records. Graphical time series plots and statistical measures were used to evaluate the model performance based on measured stream flow and NO_3-N data. Three statistical criteria were used to evaluate goodness of fit (ASCE, 1993; Legates and McCabe, 1999; Nash and Sutcliffe, 1970): deviation of runoff volume (D_v); coefficient of determination (r^2); and model efficiency (E). The D_v value is the deviation of steam flow volume or NO_3-N load, which is a measure of the accumulation of differences in the observed and simulated values for the particular period. The r^2 value is the percentage of the variance in the measured data that is explained by the simulated data. The E value indicates how well the plot of observed versus simulated data corresponds to the 1:1 line. If the r^2 and E values are close to zero, the model prediction is considered unacceptable.

The D_v can be mathematically expressed as equation 1:

$$D_v = \frac{V_{sim} - V_{obs}}{V_{obs}} .100\% \tag{1}$$

where V_{obs} and V_{sim} are the measured and simulated yearly or seasonal tile flow volumes, respectively.

The r^2 can be calculated from equation 2:

$$r^2 = \frac{\left[\sum_{i=1}^{n} (O_i - O_{avg})(P_i - P_{avg}) \right]^2}{\sum_{i=1}^{n} (O_i - O_{avg}) \sum_{i=1}^{n} (P_i - P_{avg})} \tag{2}$$

where O_i and P_i are the observed and predicted values, O_{avg} and P_{avg} are the mean of the observed and predicted values, and i is the number of samples.

Finally, the E value is given by equation 3 below:

$$E = \frac{\sum_{i=1}^{n} (O_i - O_{avg})^2 - \sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} (O_i - O_{avg})^2} \tag{3}$$

where O_i and P_i are the observed and predicted values, O_{avg} is the mean of the observed values, and i is the number of samples.

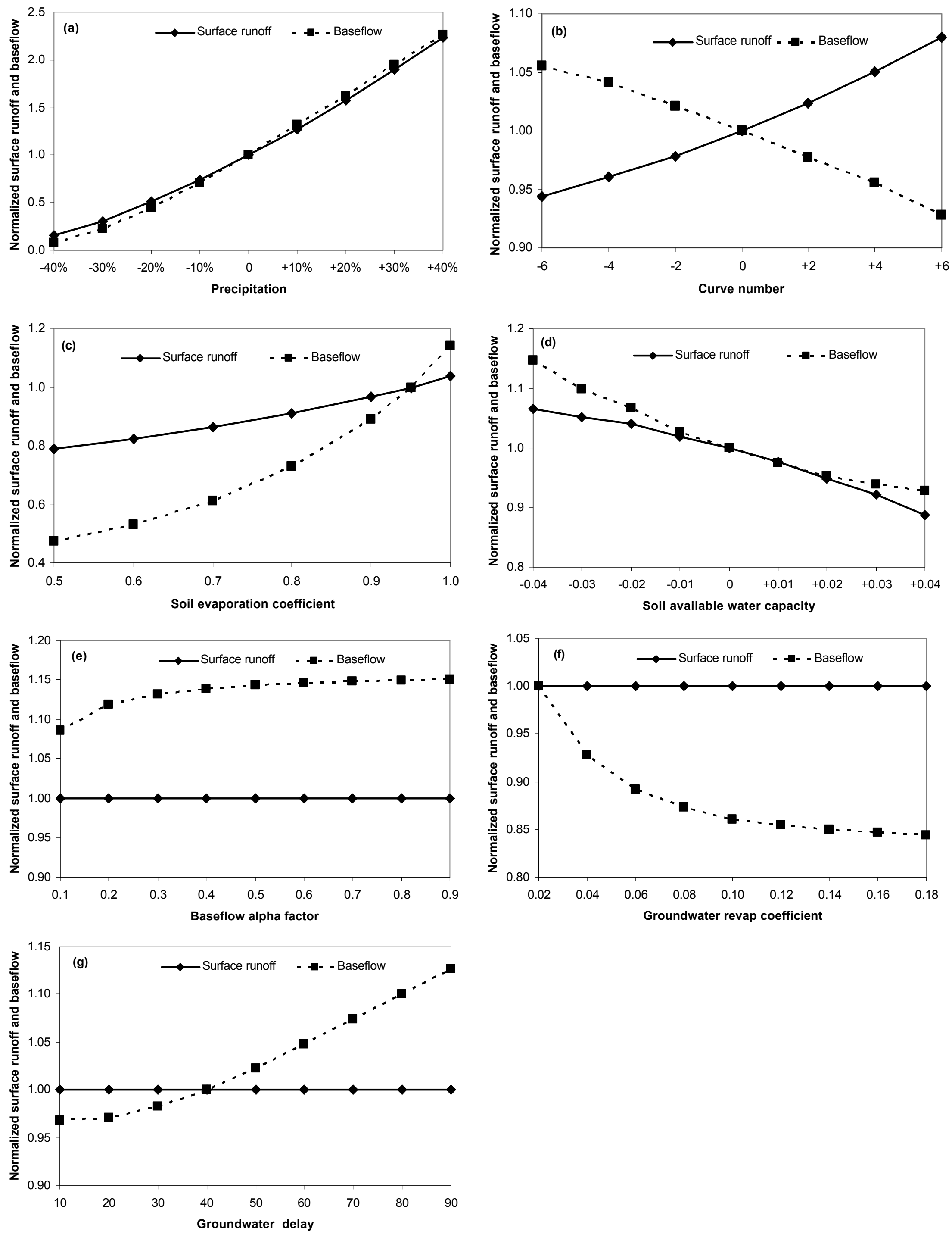

Figure 3. Sensitivity of surface runoff and base flow to (a) precipitation, (b) curve number, (c) soil evaporation coefficient, (d) soil available water capacity, (e) base flow alpha factor, (f) groundwater revap coefficient, and (g) groundwater delay

The following steps were then taken to complete the stream flow calibration and validation process for this study, based on comparisons between the simulated and measured data at the watershed outlet: 1) calculate initial estimates of surface runoff and base flow contributions to stream flow 2) calibrate the long-term average annual stream flow, 3) calibrate the monthly stream flows, and 4) validate the monthly stream flow. Adjustment of the nitrate percolation coefficient (NPERCO) was also performed in an attempt to perform further calibration for the NO_3-N loads. However, it was found that the NPERCO default value of 0.2 was the best choice for the UMRW conditions, and thus there was essentially no additional calibration performed for the NO_3-N simulations. Table 5 lists the initial and final values of the selected calibration parameters, as well as possible ranges for each parameter (where relevant) based primarily on ranges given by Neitsch et al. (2002a). These values reflect the final choice of calibrated parameters using the Fayette and Manchester precipitation data, which were the focus of the most intensive calibration efforts (similar calibration efforts were performed using the sites 2 and 3 precipitation data, although less in-depth due to weaknesses in the stream flow results as discussed in the Results and Discussion section.

An automated base flow separation method developed by Arnold and Allen (1999) was used to estimate the relative contributions of surface runoff and base flow at the outlet of the watershed for the calibration period. The base flow separation analysis yielded a subsurface contribution of about 58%. This base flow estimate was used as a guide in performing the total stream flow calibration. For the second step, the annual stream flow was calibrated against measured stream flow at the outlet of the watershed for 1999. This step was performed to ensure that the local water balance was realistic. Once the simulated annual stream flow was within 10% of the measured stream flow, the monthly stream flows and NO_3-N levels were then calibrated for 1999. For the validation step, the stream flows and NO_3-N levels were estimated for 2000 and 2001 using input parameter values determined during calibration step.

Table 5. Initial and final values of the calibration parameters, plus possible ranges where applicable

Parameter	Range[a]	Initial Value	Final Calibrated Value[b]
Curve number	±6		
- continuous corn		78	71
- corn-soybean or soybean-corn		78	71
- CCAAA or AAACC[c]		72	66
- hay and pasture		66	60
- forest		70	65
Soil available water capacity (SOIL_AWC)	±0.04	default values from STATSGO	-0.04 from STATSGO
Soil evaporation coefficient (ESCO)	0.01-1.0	0.95	0.85
Base flow alpha factor, days (ALPHA_BF)	0.1-1.0	0.025	0.9
Groundwater revap coefficient, (GW_REVAP)	0.02-0.2	0.02	0.04
Groundwater delay time, days (GW_DELAY)	0-100	40	50
Nitrate percolation coefficient (NPERCO)	0.01-1.0	0.2	0.2

[a]The ranges are based primarily on recommendations given in the SWAT User's Manual (Neitsch et al., 2002a); the curve number range was selected arbitrarily
[b]Final calibrated values using the Fayette and Manchester five-year precipitation data (calibrations were performed with the same parameters using the precipitation data for sites 2 and 3)
[c]CCAAA and AAACCC represent corn-corn-alfalfa-alfalfa-alfalfa and alfalfa-alfalfa-alfalfa-corn-corn rotations

Results and discussion

Stream flow simulations

Figure 4 shows the resulting time series comparing the monthly measured and simulated stream flows during both the calibration and validation periods, using the precipitation records that included the data for sites 2 and 3. The time series plots indicate that the simulated stream flow trends closely followed the measured stream flows most of the time, except when the model underestimated the flow. The statistical evaluations show that the r^2 values ranged between 0.81 and 0.96 for the three different years (Table 6), which further confirms that the model captured the monthly measured trends. The strong monthly E value of 0.84 for the calibration period (Table 6) also indicates that there was a strong correspondence between the measured and simulated stream flows for 1999, relative to the 1:1 line. However, the monthly E values of 0.23 and 0.64 (Table 6) for the validation period showed that the correspondence between the simulated and measured stream flows was much weaker during 2000 and 2001. The model also underestimated the total annual stream flow by 30% for the calibration period, and by 53% and 24% in 2000 and 2001 for the validation period (Table 6). Overall, the three-year average annual stream flow was underpredicted by 35.4%, with corresponding r^2 and E values of 0.84 and 0.62 (Table 6). The underprediction of the stream flows further underscores the possibility that the sites 2 and 3 precipitation levels were underestimated, as previously discussed.

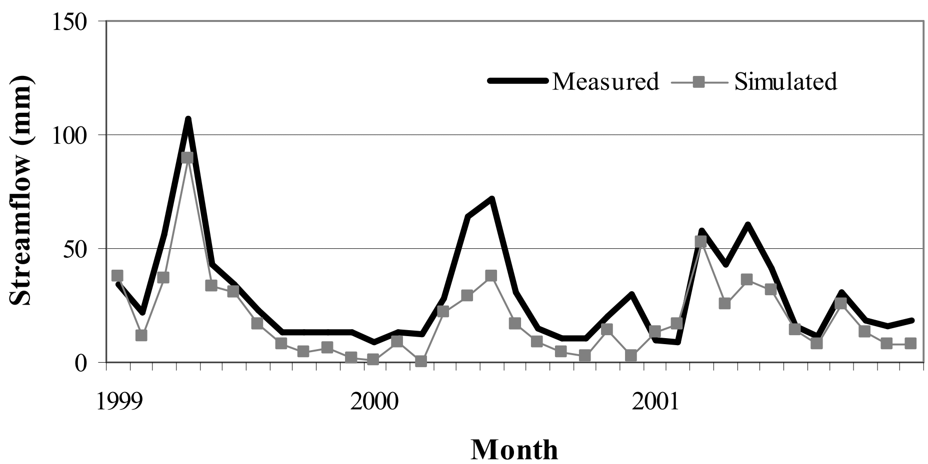

Figure 4. Simulated versus measured monthly stream flows at the UMRW outlet (1999-2001) using the precipitation data for sites 2 and 3

Table 6. Predicted versus measured annual stream flows, deviation of annual stream flow volumes, monthly coefficient of determination, and monthly modeling efficiencies using the precipitation data for sites 2 and 3

Year	Measured annual streamflow (mm)	Predicted annual streamflow (mm)	D_v(%)	Monthly r^2	Monthly E
1999	339	237	-30.08	0.96	0.84
2000	315	148	-52.92	0.82	0.23
2001	332	252	-24.19	0.81	0.64
Average	329	212	-35.40	0.84[a]	0.62[a]

[a]These r^2 and E statistics were computed on a monthly basis for the 36 months over 1999-2001

The persistent underpredictions of streamflow using the precipitation data for sites 2 and 3 led to the decision to cease further calibration efforts with those data, and focus instead on a more in-depth SWAT calibration effort using the alternative Fayette and Manchester precipitation data. Time series plot comparisons of monthly measured and simulated stream flow is shown in Figure 5, based on the alternative precipitation inputs. This figure shows that the simulated stream flows more accurately match the measured data in both the calibration and validation periods. Some of the high flow periods were over-predicted while other high flow periods were under-predicted. Evaluation of daily stream flows was also performed for the SWAT simulations using the alternative precipitation inputs. The simulated daily flow is shown relative to the corresponding measured flows for 1999-2001 at the UMRW outlet (Figure 6). The model accurately tracked most of the peak flow events that occurred during the year, although the peaks were usually over-predicted. In contrast, the majority of the low-flow periods were under-predicted by SWAT.

The predicted stream flow D_v values for the simulations using the alternative climate data (Table 7) show significant improvement as compared to the results shown in Table 6, for both the calibration (-3.8%) and validation (17 and -11.9%) periods. Figure 7 also reveals the improvement in the predicted annual stream flows that occurred using the alternative climate data. The three-year average annual stream flow was very accurately predicted, as indicated by the slight under-prediction of 0.14% (Table 7). The use of the alternative precipitation data resulted in a 19% increase in average annual precipitation and a corresponding increased in average annual stream flow of about 55% (Figure 7 and Table 8).

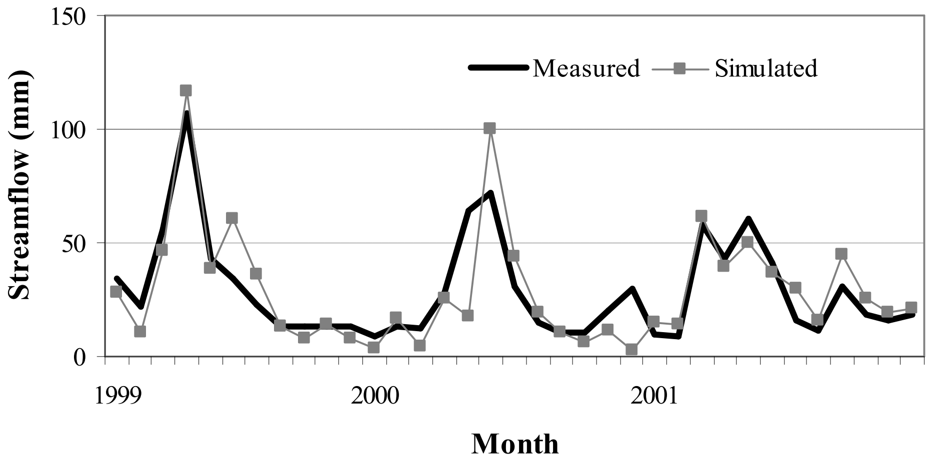

Figure 5. Simulated versus measured monthly stream flows at the UMRW outlet (1999-2001) using the alternative Fayette and Manchester precipitation data

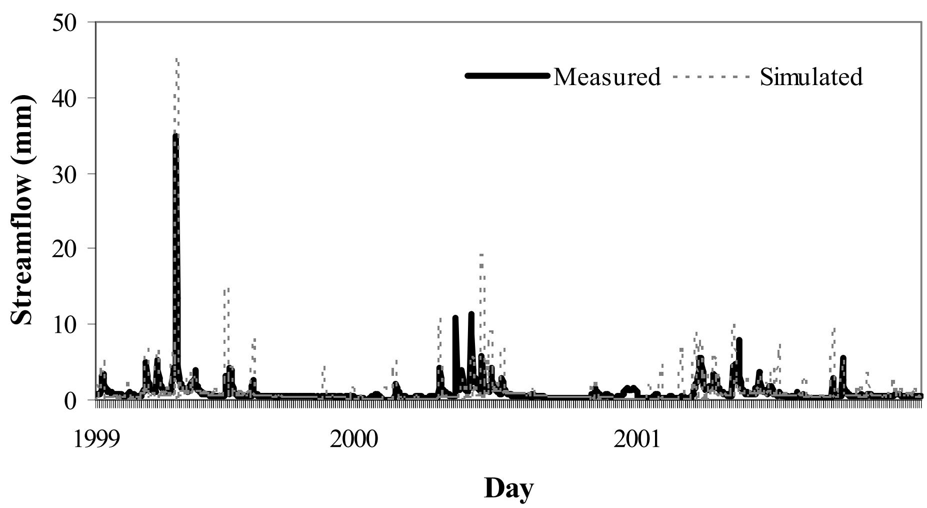

Figure 6. Simulated versus measured daily stream flows at the UMRW outlet (1999-2001) using the alternative Fayette and Manchester precipitation data

Table 7. Predicted versus measured annual stream flows, deviation of annual stream flow volumes, monthly coefficient of determination, and monthly modeling efficiencies using the alternative precipitation inputs

Year	Measured annual streamflow (mm)	Predicted annual streamflow (mm)	D_v(%)	Monthly r^2	Monthly E
1999	339	352	3.79	0.89	0.84
2000	315	262	-16.99	0.54	0.18
2001	332	371	11.85	0.87	0.82
Average	329	328	-0.14	0.73[a]	0.65[a]

[a]These r^2 and E statistics were computed on a monthly basis for the 36 months over 1999-01

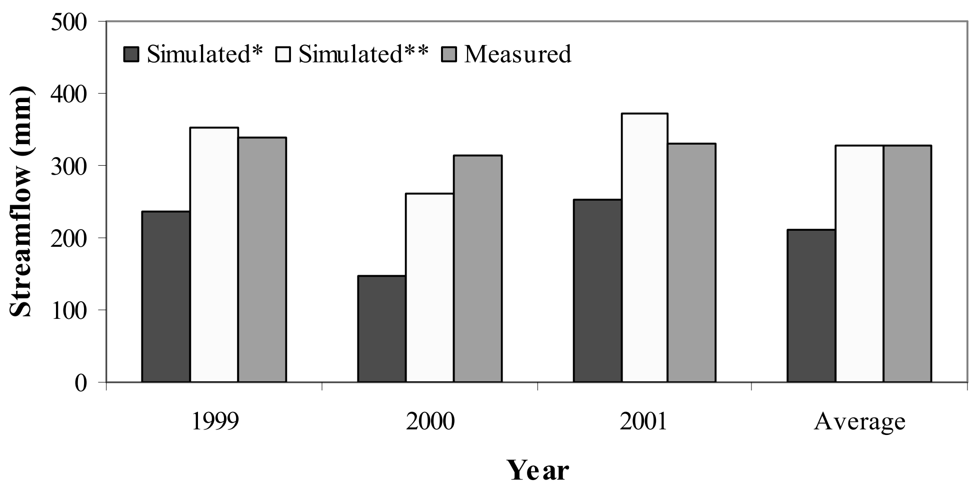

Figure 7. Comparison of measured versus simulated UMRW annual and 1999-2001 average stream flows (*=site 2 and site 3, **=Fayette and Manchester)

However, the r^2 and E values listed in Table 7 are somewhat lower than those reported in Table 6 for virtually all of the years, except 2001. Overall, these results indicate that the model performed fairly well using the alternative weather inputs without further adjustment of calibrated parameters. Improved results could potentially be obtained if additional model calibration were performed.

Table 8. Annual average 1999-2001 precipitation and stream flows over the Fayette and Manchester data versus the sites 2 and 3 data

Climate Stations	Fayette and Machester	site 2 and site 3	%difference
Average Annual Precipitation (mm.)	944	797	19
Average Annual Stream flow (mm.)	328	212	55

Simulation of NO_3-N loads

Based on the stream flow results, it was decided to use just the alternative climate data inputs to evaluate the NO_3-N transport predicted by SWAT. Calibration of the simulated NO_3-N loads was attempted using the NPERCO input parameter, but the final value chosen was the same as the default value as previously discussed. The simulated versus measured average monthly NO_3-N levels are plotted in Figure 8. The NO_3-N trend was reasonably tracked by SWAT, except for large discrepancy in the months of June and April in both 2000 and 2001. This was due in part to inaccuracies in predicted stream flows by the model. The statistical results of the model's NO_3-N prediction performance during the calibration and validation periods are shown in Table 9. The results indicate that the NO_3-N loads were accurately simulated during the calibration period, as reflected by the D_v, r^2, and E values of 18.3%, 0.96 and 0.81, respectively. In contrast, weaker results resulted for the validation period, especially for the E values which were 0.0 and -0.45 for 2000 and 2001, respectively. SWAT was judged to be a reasonably good predictor of the overall NO_3-N loads, based on the fact that the cumulative three-year NO_3-N load was under-predicted by SWAT by only 7.3%. The model results could again be potentially improved with further calibration.

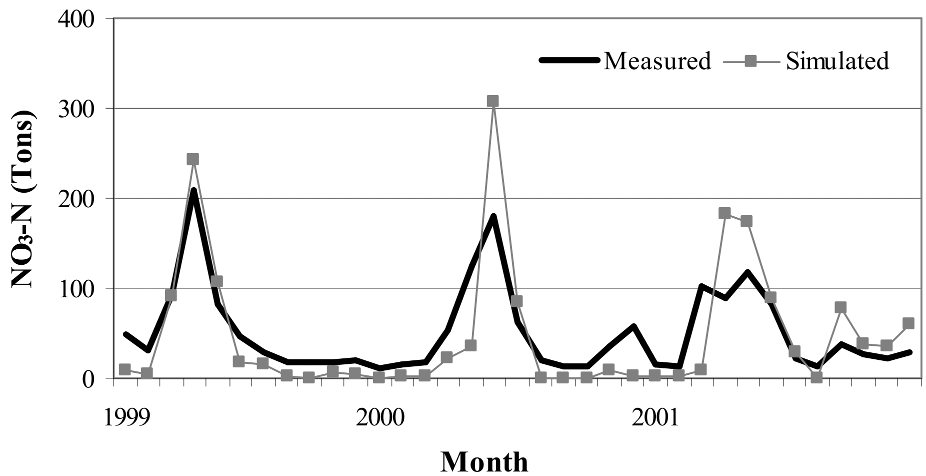

Figure 8. Simulated versus measured monthly NO_3-N loads at the watershed outlet during 1999-2001 using the Fayette and Manchester precipitation data

Table 9. Predicted versus measured NO_3-N annual loads, annual deviations, monthly coefficient of determinations, and monthly model efficiencies using the Fayette and Manchester precipitation data

Year	Measured annual NO_3-N load (tons)	Predicted annual NO_3-N load (tons)	D_v(%)	Monthly r^2	Monthly E
1999	612	500	-18.32	0.96	0.81
2000	608	469	-22.91	0.73	0.00
2001	576	696	20.96	0.49	-0.45
Average	599	555	-7.29	0.72[a]	0.24[a]

[a]These r^2 and E statistics were computed on a monthly basis for the 36 months over 1999-01

Summary and conclusions

Sensitivity analyses performed with SWAT showed that the simulated base flow and runoff was sensitive to variations in precipitation, curve number, soil available water capacity, and the soil evaporation coefficient. The choice of values of these inputs can clearly greatly impact the predicted stream flow results, underscoring that care must be taken in selecting correct input values as much as possible.

Annual stream flows measured at the UMRW outlet for 1999-2001 were greatly under-predicted when precipitation data collected within the watershed during 1999-2001 were used as input to SWAT. The predicted annual stream flows improved greatly when precipitation data were used that were measured at climate stations outside the watershed. These results were counter intuitive and pose the question as to whether measurement error might have occurred regarding the precipitation data collected at UMRW sampling sites 2 and 3. However, it is not possible to establish with absolute certainty that such error occurred. The results found here do point to the need to ensure that accurate precipitation data is collected for watershed studies, and that the output of SWAT is very sensitive to choice of precipitation inputs.

Further simulations with SWAT using only the climate data collected at the Fayette and Manchester climate stations showed that the model was able to reasonably track monthly measured stream flows and nitrate losses at the watershed outlet. The r^2 statistics found for the monthly stream flows and NO_3-N losses were equal to 0.73 and 0.72, respectively. These results compare favorably with previous r^2 values reported by Saleh et al. (2003) of 0.79 for stream flows and 0.74 for the NO_3-N loads, using the APEX-SWAT approach. However, the annual stream flows and three-year average annual stream flow were more accurately simulated in this study. It can be concluded that both the APEX-SWAT and SWAT-only methods are viable simulation approaches for the UMRW.

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CHAPTER 3. EFFECT OF SPATIAL VARIABILITY IN SOIL PROPERTIES IN PREDICTING TILE FLOW BY USING THE SWAT MODEL

A paper to be submitted to the Transactions of the ASABE

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Abstract

Nitrate-nitrogen from the application of commercial fertilizers and animal manure to croplands has been found in the surface and groundwater sources in many agricultural regions of the U.S. In many Midwestern U.S. states, subsurface drainage systems are key pathways to surface water contamination from nitrate-nitrogen (NO_3-N). In order to accurately simulate hydrologic balance and nitrate transport to subsurface drainage systems, data on soil properties is one of the crucial inputs needed by a model to access impacts of agricultural management practices on soil and water quality. Therefore, it is important to understand the extent of spatial variability in soil properties when using the model. This study attempts to quantify the effect of spatial variability in soil properties by employing STATSGO and SSURGO soil databases to predict the quantity of tile flows at Iowa State University's Northwest Research Center at Nashua, Iowa. For this purpose, the subsurface tile component of Soil and Water Assessment Tool (SWAT) model was calibrated and validated using field measured data from 0.4 ha plots for five years (1993-1997) and two soil databases (STATSGO and SSURGO). Three experimental treatments were selected for calibration and validation with varying land use, tillage and fertilizer management regimes against observed tile flow data. Continuous corn and corn-soybean rotations were the two crop production systems used at the research site with combinations of chisel plow and no-till systems, and a conventional fertilizer treatment. Statistical comparisons of measured and predicted results for the calibration year indicated reasonable agreement for both soil databases, while similar comparison for validation years showed that the model could not accurately predict the system performance. In summary, the overall evaluation of the SWAT tile flow component on both soil databases indicates that the model has the capability to predict system performance and predicted similar trends in flow regardless of the soil data set used.

Keywords: SWAT, SSURGO, STATSGO, modeling, calibration, validation, tile flow

Introduction

Nonpoint source (NPS) pollution from cropland is a widespread problem in Europe and North America. Concerns typically include sediment, nitrogen and phosphorus, as well as herbicides and pathogen loadings. In the Midwestern part of the U.S., subsurface water drained from croplands has been identified as a potential NPS of surface water contamination with nitrate–nitrogen (NO_3–N), which may have adverse effects on human and animal health (Kanwar et al., 1999; Jaynes et al., 1999; Cambardella et al., 1999; Bjorneberg et al., 1998; Gentry et al., 2000). Recently, the development of a hypoxic zone in the Gulf of Mexico has also been attributed to the increased loadings of nitrates in the Mississippi River (Rabalais et al., 1999). The higher NO_3–N concentrations in the Mississippi River have been linked to the stream tributaries and extensive subsurface drainage systems in the upper Midwest (Davis et al., 2000; Randall, 1998). In fact, the subsurface drainage systems are key pollution pathways to surface water in this region as reported by Kanwar et al. (1999), Jaynes et al. (1999), and Cambardella et al. (1999).

The subsurface flow response of a given soil system can be influenced by rainfall patterns, topography, soil type and agricultural management practices. Tillage practices directly affect the soil water properties of the surface soil and in turn the soil leaching characteristics (Kanwar et al., 1988). Tillage practices may can influence the distribution and continuity of macropores in soil that can act as preferential pathways for rapid movement of water and chemicals to the groundwater (Singh et al., 1991). Therefore, evaluation of subsurface drainage water quantity and quality for various cropping systems can provide useful information for accessing and improving the impact of agricultural management practices on soil and water quality (Bakhsh et al., 2000a; Kanwar et al., 1999; Andraski et al., 2000). The evaluation of subsurface drainage systems can be accomplished in two ways: 1) by collecting field data from a monitoring site over long time period, or 2) by using computer simulation models, developed from current scientific knowledge. However, it is impractical to monitor all the practices under various conditions due to time and cost constraints. Hence, computer simulation model provides an efficient and cost effective way to evaluate the impact of soils, crops, and agricultural management practices on subsurface drainage system (Bakhsh et al., 1999; Zacharias and Heatwole 1994). Nevertheless, testing and evaluation of computer models still require the use of extensive field data to ensure that the models are reliable for the prediction of the response effects.

To evaluate and assess environmental conditions that impact on soil and water quality, several computer models have been developed. These models include HSPF (Bicknell et al., 1993), AGNPS (Young et al., 1989), AnnAGNPS (Bingner and Theurer, 2001), ANSWERS (Beasley et al., 1980), ANSWERS-Continuous (Bouraoui et al., 2002), PRMS (Leavesley et al., 1983), KINEROS (Woolhiser et al., 1990), DWSM (Borah et al., 2002), CASC2D (Ogden and Julien, 2002), MIKE SHE (Refsgaard and Storm, 1995), and SWAT (Arnold et al., 1998). Recently, SWAT has been found to be one of the most widely used simulation models for evaluating and accessing the impacts of climate, soil, or landscape properties, and management alternatives on water quality, pollutants loadings and sediment yields. The model has been successfully applied numerous times for long-term continuous simulations of flow, soil erosion, and sediment and nutrient transport in watersheds of different sizes, and having different hydrologic, geologic, and climatic conditions including tile drained cropland (Arnold et al., 1999; Ahmad et al., 2002; Du et al., 2003; Srinivasan et al., 1998; Peterson and Hamlett, 1998; Shirmohammadi et al., 2001; Van Liew and Garbrecht, 2001; Benaman et al., 2001; Varanou et al., 2002; Vache et al., 2002; Santhi et al., 2001; Stone et al., 2001; Qiu and Prato, 2001; Arnold et al., 2000; Spruill et al., 2000; Stonefelt et al., 2000; Rosenthal and Hoffman, 1999; King et al., 1999; Bingner, 1996; and Rosenthal et al., 1995).

However, according to the model requirements, soil data is one of the crucial inputs needed to assess impacts of agricultural management practices on soil and water quality. At present, very little is known about the effects of spatial scale, especially on water quantity within the tile flow component of SWAT, when soil input is derived at varying spatial resolutions. This study attempts to quantify the effect of scale on water quantity by employing two spatially different soil databases commonly available in the United States. The Natural Resources Conservation Service (NRCS) has developed and distributes two digital soil databases, namely, STATSGO (STATe Soils GeOgraphic; 1:250,000 scale) (USDA, 1991) and SSURGO (Soil SURvey GeOgraphic; (1:12,000 to 1:63,360) (USDA, 1995), which can be used to derive soil input data needed for the model simulation. The amount of time and resources needed to use them varies significantly based on which soil database is used. The smallest soil map unit represented in STATSGO is about 625.1 ha, whereas the smallest unit is about 2 ha in the SSURGO database whereas we used experimental data from 0.4 ha plots. The main objective of this study was to determine if there are significant differences between the measured and predicted tile drained water quantity based on using the STATSGO versus SSURGO soil input databases. To achieve this goal, the specific objectives of this study were:

1. To calibrate the tile flow component of the SWAT model using observed tile flow data from the experimental site at Nashua, Iowa for the year 1995 for both STATSGO and SSURGO soil databases.

2. To apply the calibrated SWAT model to make comparisons between predicted tile flow and observed tile flow data for period 1993-1994 and 1996-1997, using both STATSGO and SSURGO soil databases.

SWAT model description

SWAT, Soil and Water Assessment Tool (Arnold et al., 1998; Neitsch et al., 2002) was developed by the U.S. Department of Agriculture (USDA) – Agricultural Research Service (ARS) at the Grassland Soil and Water Research Laboratory in Temple, Texas. It is a complex, conceptual model with spatially explicit parameterization. It emerged mainly from SWRRB (Arnold et al., 1990), and contains features from CREAMS (Knisel, 1981), GLEAMS (Leonard et al., 1987), EPIC (Williams et al., 1984), and ROTO (Arnold et al., 1995). It was developed to assist water resources managers in predicting and assessing the impact of management on water, sediment and agricultural chemical yields in large ungaged watersheds or river basins. It is an operational or conceptual model that operates on a daily time step. Although most of the applications have been on a daily time step, recent additions to SWAT are the Green and Ampt (1911) infiltration equation using rainfall input at any time increment and channel routing at an hourly time step. The model is intended for long term yield predictions and is not capable of detailed single-event flood routing. The model has eight major components include hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, pesticides, and agricultural management. A complete detailed description of SWAT model component is found in Arnold et al. (1998). A brief description of the SWAT key components are provided here as follow. To simulate with SWAT, first a watershed is divided into a number of subwatersheds or subbasins, which are grouped based on climate and main drainage/stream channels. To account for variability of land use, management, and soil characteristics regardless of spatially location, subwatershed or subbasin then further subdivided into several Hydrologic Response Units (HRUs). Hence, HRUs are lumped land areas within the subbasin comprised of unique land cover, soil, and management combinations. The water balance of each HRU in the watershed is represented by four storage volumes: snow, soil profile (0–2 m), shallow aquifer (2–20 m) and deep aquifer (>20 m). Flow, sediment, nutrient, and pesticide loadings from each HRU in a subwatershed or subbasin are summed together, and routed through channels, ponds, and/or reservoirs to the watershed outlet. Hydrology processes simulated include surface runoff estimated using SCS curve number (Mockus, 1969) or Green-Ampt infiltration equation; percolation modeled with a layered storage routing technique combined with a crack flow model; lateral subsurface flow; groundwater flow to streams from shallow aquifers; potential evaportranspiration by Hargreaves, Priestley-Taylor or Penman-Monteith; snowmelt; transmission losses from streams; and water storage and losses from ponds (Arnold et al., 1998).

The soil profile in each HRU can be divided into multiple layers. Soil water processes include infiltration, evaporation, plant uptake, lateral flow, and percolation to lower layers. The percolation of SWAT uses a storage routing technique to predict flow through each soil layer. Downward flow occurs when field capacity of the soil layer is exceeded and if the layer below is not saturated. The downward flow rate is governed by the saturated hydraulic conductivity of the soil layer. Percolation from the bottom of the soil profile recharges the shallow aquifer. The groundwater flow contribution to total stream flow is simulated by routing a shallow aquifer storage component to the stream (Arnold et al. 1998). Upward flow may occur when the field capacity of the next lower layer is exceeded. Movement from a lower layer to an adjoining upper layer is governed by the soil water to field capacity ratios of the two layers. Percolation is also affected by the soil temperature. No percolation is allowed from a layer if the temperature of that layer is 0° C or below. If snow is present, it is melted on days when the maximum temperature exceeds 0° C. Melted snow is treated the same as rainfall for estimating runoff and percolation.

To accurately predict surface runoff and infiltration in areas where preferential flow presented in soil, bypass flow or vertical movement of free water along macropores through unsaturated soil horizons must be modeled. In SWAT, when bypass flow is modeled, it calculates the crack volume of the matrix for each day of simulation by layer. Therefore, potential crack volume for the soil profile needs to be input by the user as a function of soil depth. On days in which precipitation events occur, infiltration and surface runoff is first calculated for the soil peds. If any surface runoff is generated, it is allowed to enter the cracks. A volume of water equivalent to the total crack volume for the soil profile may enter the profile as bypass flow. Surface runoff in excess of the crack volume remains characterized an overland flow. Water that enters the cracks fills the soil layers beginning with the lowest layer of crack development. After cracks in one layer are filled, the cracks in the overlying layer are allowed to fill.

To simulate tile drainage, the user must specify the depth from the soil surface to the drain, the amount of time required to drain the soil to field capacity, and the amount of lag between the time water enters the tile until it exits the tile and enters the main channel. Tile drainage occurs when the soil water content exceeds field capacity in the soil layer where the tile drains are installed. Water entering the tiles is treated like lateral flow. In large subbasins with a time of concentration greater than one day, only a portion of the tile or lateral flow will reach the main channel on the day it is generated. SWAT incorporates a tile or lateral flow storage to the main channel.

Materials and Methods

Experimental Site and Management Treatments

The experimental site for this study was located at Iowa State University’s Northeastern Research Center, Nashua, Iowa (Figure 1), on a predominantly Kenyon loam (fine–loamy, mixed, mesic Aquic Hapludoll) with 2% to 3% organic matter (USDA–SCS, 1982). These soils have a seasonally high water table and benefit from improved subsurface drainage. Sixty meters of pre–Illinoian till typically overlies a carbonate aquifer, although bedrock is near the surface in some areas. Topography of the site is relatively flat with elevation ranging from 320 to 327 m.

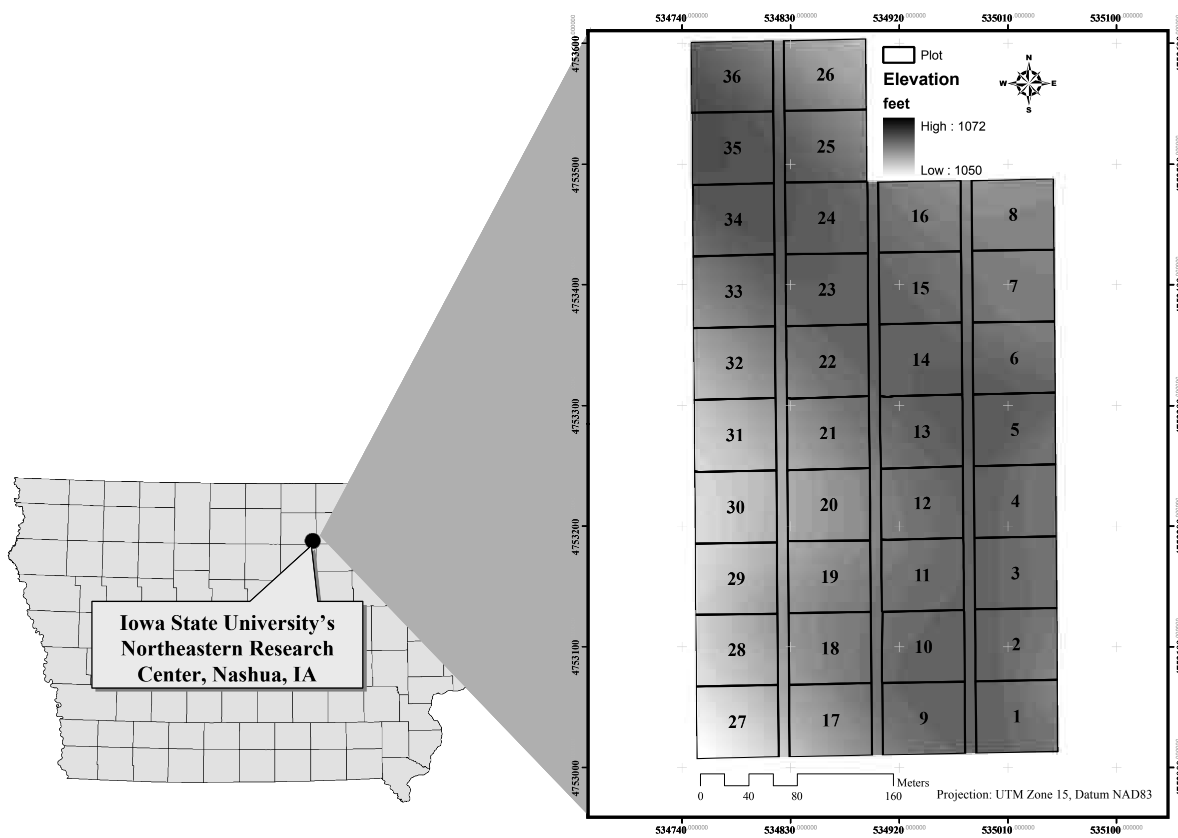

Figure 1. Location of the Iowa State University's Northeastern Research Center, Nashua, Iowa

The Nashua water quality research site has thirty-six 0.4–ha plots (each 58.5 X 67 m in size), with fully documented tillage and cropping records for the past 21 years. These plots have been managed under a randomized complete block design with four tillage systems (chisel, ridge, moldboard, and no–till) from 1979 to 1992 (Bjorneberg et al., 1996), from

1993 onwards only two tillage systems (no-till and chisel plow) were used. Data on water quality and crop yield were collected at this site from 1993 to 1997. The following treatments of various combinations of tillage, crop rotation, and N management systems were established and used for this study (Table 1).

Table 1. Management information for each treatment

Treatement 1 (CC-CP): Continuous corn, chisel plow constant UAN application			**Treatment 2 (CS-NT):** Corn-soybean rotation; no-till; late spring nitrogen test			**Treatment 3 (SC-NT):** Soybean-corn rotation; no-till; late spring nitrogen test		
Year	**Month/Day**	**Operation**	**Year**	**Month/Day**	**Operation**	**Year**	**Month/Day**	**Operation**
1993	May 14	Elem-N (135 kg/ha)	1993	May 17	Elem-N (28 kg/ha)	1993	May 26	Plant soybeans
	May 16	Chisel plow		May 17	Plant corn		Oct 7	Harvest soybeans
	May 17	Plant corn		Jul 7	Elem-N (144 kg/ha)	1994	May 2	Elem-N (28 kg/ha)
	Jul 21	Row cultivator		Oct 21	Harvest corn		May 2	Plant corn
	Oct 25	Harvest corn	1994	May 17	Plant soybeans		Jun 17	Elem-N (169 kg/ha)
1994	Apr 24	Elem-N (135 kg/ha)		Oct 6	Harvest soybeans		Oct 25	Harvest corn
	May 1	Chisel plow	1995	May 16	Elem-N (28 kg/ha)	1995	May 12	Plant soybeans
	May 2	Plant corn		May 16	Plant corn		Oct 11	Harvest soybeans
	Jun 2	Row cultivator		Jun 22	Elem-N (193 kg/ha)	1996	May 21	Elem-N (28 kg/ha)
	Sep 28	Harvest corn		Oct 22	Harvest corn		May 21	Plant corn
1995	May 12	Elem-N (135 kg/ha)	1996	May 30	Plant soybeans		Jun 24	Elem-N (195 kg/ha)
	May 15	Chisel plow		Oct 8	Harvest soybeans		Oct 21	Harvest corn
	May 16	Plant corn	1997	May 12	Elem-N (28 kg/ha)	1997	May 16	Plant soybeans
	Jun 14	Row cultivator		May 12	Plant corn		Oct 10	Harvest soybeans
	Sep 22	Harvest corn		Jun 19	Elem-N (125 kg/ha)			
1996	May 3	Elem-N (135 kg/ha)		Oct 10	Harvest corn			
	May 20	Chisel plow						
	May 21	Plant corn						
	Jun 24	Row cultivator						
	Oct 21	Harvest corn						
1997	May 12	Elem-N (135 kg/ha)						
	May 12	Chisel plow						
	May 12	Plant corn						
	Jun 19	Row cultivator						
	Oct 10	Harvest corn						

Each treatment was replicated three times in a randomized complete block design. Treatment means were separated using SAS (1989) with least significant difference (LSD; tests the difference, significant among all the treatment means) and constrast (tests the difference, significant between the specified treatment means) methods at the 5% probability level.

The subsurface drainage system was installed in 1979 at the Nashua water quality research site. Each plot is drained separately and has subsurface drainage lines installed in the center of the plot at a depth of 1.2 m below the ground surface with a drain spacing of

28.5 m. Cross contamination of each plot was avoided by installing subsurface drainage lines on the northern and southern borders of the plot and isolating the eastern and western borders with berms (Kanwar et al., 1999). The central subsurface drainage lines are intercepted at the end of the plots and are connected to individual sumps for measuring drainage effluents and collecting water samples for chemical analysis. Cumulative subsurface drain flows were recorded, and sampling bottles were removed two times per week beginning from mid–March to the beginning of December during the entire study period. A more detailed description of the automated subsurface drainage system installed at the site can be found in Kanwar et al. (1999).

Model Input data

SWAT, physically based model, requires inputs on topography, climate, land management, and soil. For this study, SWAT version 2000 (Neitsch et al., 2002) embedded within ArcView GIS software (ESRI, 2000) named ArcView Soil and Water Assessment Tool (AVSWAT) (Di Luzio et al., 2000), developed by the Texas A&M University Blacklands Research Center was used to prepare inputs and conduct model simulations for various experimental scenarios.

Climate data

On-site daily measured minimum and maximum temperatures, and precipitation data were used to prepare the climate input data for the model for year 1993 to 1997. While, other climate data such as average relative humidity, solar radiation and wind speed were internally generated within SWAT by using monthly weather statistics data obtained from Osage, Iowa, located approximately 50 km from the study site. In this study, the SCS curve number approach was used since sub-hourly precipitation was not available at sufficient detail. Figure 2 shows the monthly precipitation for 1993-1997 at this site.

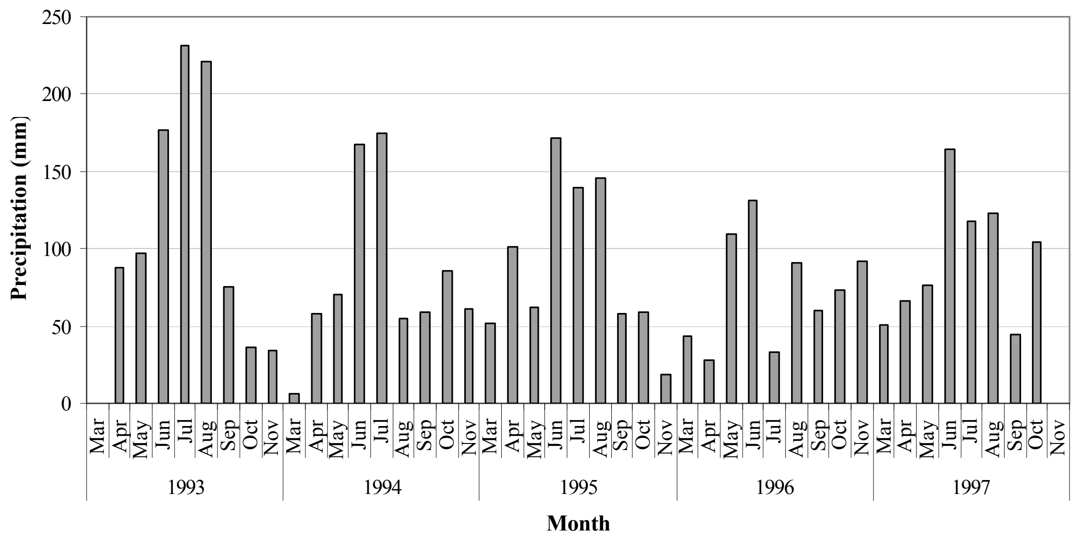

Figure 2. Monthly precipitation at the experimental site, Nashua , Iowa for year 1993-1997

Land use and management data

SWAT requires data for planting, harvest, irrigation application, nutrient application, pesticide application, and tillage operations. For this study, the three treatments (Table 1) on six plots were selected and simulated for 1993 to 1997; a) CC-CP (plot 21 and 26), b) SC-NT (plot 15 and 29) with soybeans planted in 1993, and c) CS-NT (plot 24 and 28) with corn planted in 1993.

Soil properties

The soil data used by SWAT can be divided into two groups: physical characteristics and chemical characteristics. The physical properties of the soil govern the movement of water and air through the profile and have a major impact on the cycling of water within the hydrologic response unit (HRU). Inputs for chemical characteristics are used to set initial levels of different chemicals in the soil. Input data for the physical properties are required, while the chemical property data is optional. The model requires the division of the soil profile into horizons. For this study, soil properties such as the depth of each horizon, particle size distribution, organic matter content, vertical hydraulic conductivity, and soil water release curve for each of the SSURGO and STATSGO soil map units were derived from the Map Unit Use File (MUUF) soil database (Baumer et al., 1994). Figure 3 shows STATSGO and SSURGO soil data sets for the experimental area that were obtained and processed from AVSWAT, while Table 2 lists selected soil properties as a function of horizon that were input into SWAT for these soils included in this study. Therefore, the spatial process model used in this study requires a set of modeling units known as HRUs. In this study, unique HRUs were identified by overlaying soil, tillage, land use and management layers using AVSWAT.

However, with the current version of AVSWAT, only the STATSGO database can be accessed directly from the program. Thus, to be able to utilize the SSURGO soil data, an ArcView extension was used to prepare the soil data. In general, this extension was developed to convert the SSURGO data set into the modified STATSGO format so AVSWAT can access the data. The detailed information about this extension is found in Peschel et al. (2003).

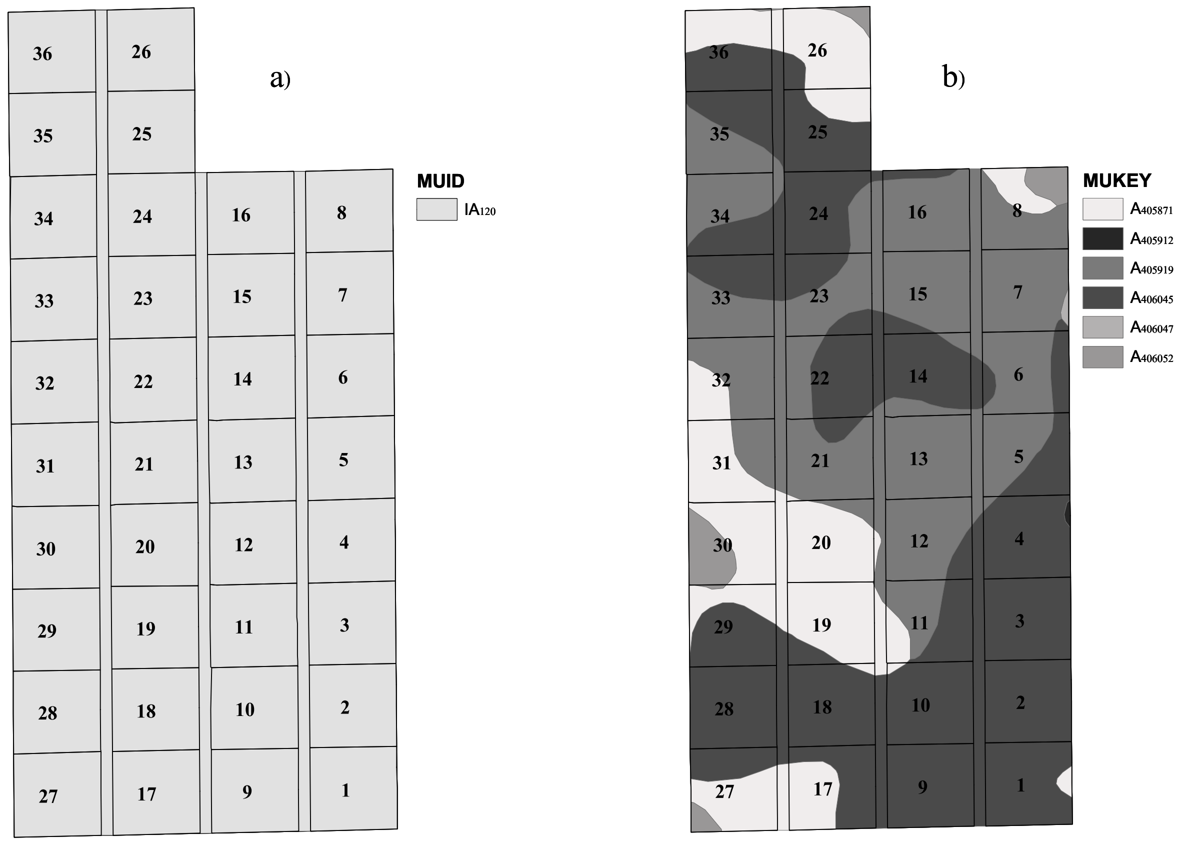

Figure 3. STATSGO (a) and SSURGO (b) data sets for the experimental site at Nashua, Iowa

Table 2. Selected soil properties for STATSGO and SSURGO soil for the experimental site, Nashua, Iowa

Horizon No.	Depth mm	Bulk density Mg/m^3	Organic carbon %	% Particle size distribution Clay	Silt	Sand	Hydraulic conductivity mm/hr
			IA120 (CLYDE, Hydrologic group B)				
1	0-584	1.38	4.36	30.00	52.15	17.85	9.6
2	584-1042	1.55	1.45	25.00	36.48	38.52	15.0
3	1042-1118	1.65	0.29	16.00	40.19	43.81	18.0
4	1118-1524	1.70	0.15	22.00	36.88	41.12	9.4
			A405871 (FLOYD, Hydrologic group B)				
1	0-510	1.57	3.20	23.00	37.50	39.50	32.4
2	510-810	1.58	0.87	21.00	37.40	41.60	32.4
3	810-1520	1.82	0.15	24.00	36.90	39.10	32.4
			A405912 (CLYDE-FLOYD COMPLEX, Hydrologic group B)				
1	0-530	1.58	4.36	30.00	52.20	17.80	32.4
2	530-890	1.78	1.45	25.00	36.50	38.50	32.4
3	890-990	1.74	0.29	16.00	18.90	65.10	100.8
			A405919 (READLYN, Hydrologic group B)				
1	0-250	1.44	2.91	21.00	37.40	41.60	32.4
2	250-910	1.61	1.74	25.00	36.50	38.50	32.4
3	910-1520	1.84	0.29	21.00	37.40	41.60	32.4
			A406045 (KENYON, Hydrologic group B)				
1	0-330	1.50	2.03	22.00	36.90	41.10	32.4
2	330-1140	1.63	0.44	25.00	36.50	38.50	32.4
3	1140-1520	1.79	0.15	22.00	36.90	41.10	32.4
			A406047 (KENYON, Hydrologic group B)				
1	0-330	1.50	1.57	22.00	36.90	41.10	32.4
2	330-1140	1.63	0.29	25.00	36.50	38.50	32.4
3	1140-1520	1.79	0.15	22.00	36.90	41.10	32.4
			A406052 (CLYDE, Hydrologic group B)				
1	0-530	1.58	4.36	30.00	52.20	17.80	32.4
2	530-890	1.78	1.45	25.00	36.50	38.50	32.4
3	890-990	1.74	0.29	16.00	18.90	65.10	100.8

Model evaluation criteria

To test the ability of the model to predict the system response, a graphical method (time series plot), and a statistical measurement were used to evaluate the model performance against measured subsurface drain flow data for the period from 1993-1997 for all three cropping systems on a plot-by-plot basis. Three statistical criteria were used to evaluate a goodness of fit (ASCE, 1993; Legates and McCabe, 1999) including deviation between observed and predicted values (D_v), coefficient of determination (r^2), and model efficiency

(E) (Nash and Sutcliffe, 1970). The D_v value is the deviation of tile flow, which is a measure of the accumulation of difference in observed and predicted values for the particular period. The r^2 represents the percentage of the variance in the measured data that is explained by the simulated data; it varies between 0 and 1. The E statistical parameter indicates how close the plot of the observed versus predicted values come to the 1:1 line. If r^2 and E values are close to zero, the model prediction is considered unacceptable. In contrast, if these values approach one, the model predictions become perfect.

Model calibration and validation

The model was calibrated using experimental data from the six different plots on both STATSGO and SSURGO soils for 1995. Previous studies (Ahmad et al., 2002; Bakhsh et al., 2002; and Chung et al., 2002) suggested that there was preferential movement of water through soil macropores for these plots; therefore crack flow model was simulated within this study. Initially for this simulation, the available water content (AWC) levels of these soils were set equal to the difference between the field capacity and wilting point. The AWC levels were adjusted some in the final simulations to ensure that the predicted tile flow started approximately the same time as the observed flows. The criterion used for calibrating the model was minimize the difference between observed and predicted cumulative annual levels and to match predicted cumulative monthly amounts with the observed values for tile flow. The calibration of the model for flow was done by adjusting the runoff curve number for condition II (CN2), potential crack volume of soil profile (SOIL_CRK), and the soil evaporation compensation coefficient (ESCO). The CN2 values affected the peak subsurface drain flow while the ESCO inputs affected the shape of the subsurface drain flow hydrograph. Therefore, the SOL_CRK affected the peak of subsurface drain tile flow as well due to after surface runoff was calculated; the amount of runoff is reduced by the volume of the cracks present on that day. The process was initiated by calibrating the ESCO values so that the shape of the simulated subsurface drain flow hydrographs matched the observed subsurface flow hydrographs as closely as possible. Because SWAT input data are physically based (based on readily observed or measured information), there is often considerable uncertainty in model inputs due to spatial variability, and measurement error. The ESCO values were allowed to vary between 0.75 and 1.0 with no compensation for depth. As the value for ESCO was reduced, the model was able to extract more evaporative demand from lower levels. The procedure was continued until the shapes of the simulated and observed subsurface drain flow hydrographs were in reasonable agreement. If the flow differences continued to exceed 10 percent, the SOL_CRK, and CN2 value were allowed to vary until the simulated total subsurface drain flows were within 10 percent of the observed total subsurface drain flows. Accounting for uncertainty in the hydrologic conditions of the field, the CN2 was allowed to vary within numerical range of ±6. Table 3 lists calibrated parameters after calibration of the SWAT model for the study area.

Table 3. Calibrated values of the SWAT parameters for the experimental site at Nashua, Iowa

Plot	**STATSGO**			**SSURGO**		
	CN2	**SOL_CRK (mm)**	**ESCO**	**CN2**	**SOL_CRK (mm)**	**ESCO**
15	74	5	0.95	72	9	0.95
21	70	5	0.95	70	11	0.95
24	70	5	0.95	71	18	0.95
26	68	5	0.95	68	9	0.95
28	76	7	0.95	77	11	0.95
29	65	5	0.95	74	5	0.95

To test the ability of the model to predict system response, the model was validated using observed tile flow data from 1993–94 and 1996–97 for three cropping systems without changing calibrated input parameters on a plot-by-plot basis. Available water capacity in the soil profile was adjusted for each simulation year in the same manner as in the case of 1995 simulation year.

Results and discussion

Using both STATSGO and SSURGO soil data sets for Iowa State University's Northeastern Research Center, Nashua, Iowa, SWAT simulations were conducted for the period 1993-1997. GIS overlay analysis resulted in one and six soil types for STATSGO and SSURGO soil databases, respectively. Calibration of SWAT was performed for year 1995, while 1993-1994 and 1996-1997 were used as the validation years. In the calibration phase, attempts were made to minimize the D_v and obtain r^2 and E values closest to a value of unity. As shown in Table 3, the ESCO values for both STATSGO and SSURGO were less affected to the predicted of tile flow in this study, the default value of 0.95 as defined by SWAT was found to be the best value during calibration periods for all six plots. The tiles were predicted for higher tile flows at plot 21 and 26, for CC-CP treatment on SSURGO soil whereas occurred at plot 26 and 29 for CC-CP and SC-NT treatments on STATSGO as indicted by lower CN2 values that were used for this simulation. Table 4 shows good agreement between observed and predicted cumulative annual tile flow for both STATSGO and SSURGO soils as indicated by low D_v values (ranged from -7.46 to 6.2 for STATASGO, and -5.85 to 4.16 for SSURGO). The r^2 values determined for the calibration year ranged from 0.49 to 0.69 for STATSGO and 0.62 to 0.76 SSURGO, whereas E values ranging from 0.49 to 0.69 for

STATSGO and 0.61 to 0.71 for SSURGO, except for plot 28 which had low values of r^2 (0.29) and E (0.24) in STATSGO soil data set. Overall, during the calibration period, the E values for both STATSGO and SSURGO soils indicate a good linear relationship fit between observed and predicted on the line of 1:1 plots. Scattergrams presented in Figure 4 supported these statistical results.

Table 4. Statistical results comparing observed and predicted values for each plot on STATSGO and SSURGO soil data sets for calibration period in 1995

Plot	Observed	Predicted tile flow (mm)		Dv (%)		r^2		E	
	tile flow (mm)	STATSGO	SSURGO	STATSGO	SSURGO	STATSGO	SSURGO	STATSGO	SSURGO
15	108.18	105.68	106.08	-2.31	-1.94	0.75	0.76	0.67	0.71
21	134.23	138.54	139.82	3.21	4.16	0.60	0.70	0.59	0.67
24	128.55	136.52	128.98	6.20	0.34	0.54	0.62	0.54	0.61
26	140.04	129.59	139.64	-7.46	-0.28	0.49	0.76	0.49	0.71
28	65.94	66.26	63.24	0.49	-4.09	0.29	0.67	0.24	0.61
29	119.96	120.11	112.94	0.13	-5.85	0.74	0.76	0.69	0.68

The predicted tile flows for the four validation years (1993-1994, and 1996-1997) were weak compared to the calibration years as indicated in Table 5. The model was unable to predict the cumulative annual tile flows for 1993 and 1994 as indicated by higher values of D_v using both soil data sets. Underestimated flows occurred in 1993 while an overestimation occurred in 1994. In contrast, for these two years, the r^2 and E values showed that the model reasonable tracked much of observed flow trends over the four years of the validation period. Surprisingly, in some plots, the r^2 and E values for year 1994 were higher than the calibration year in 1995 as indicated in plot 21, 24, and 29. Scattergrams for these two years also supported these statistical results as indicated a good linear relationship between observed and predicted on the line of 1:1 plots (Figure 5 and 6). For the period 1996-1997, the simulation results showed high values of D_v and low values of r^2 and E on both STATSGO and SSURGO soils. These results indicate that the model was not accurately predicting tile flows for three years. In addition, the negative E values indicated a poor model performance in predicting tile flows as presented unsatisfied plots of the line 1:1 (Figure 7 and 8). However, with the higher of r^2, E, and D_v, values, it suggests that there might be a possibility of crack volume change over these years due to changes in crops and management practices. Although, SWAT dynamically computes crack volume from crack potential, soil depth, and soil moisture, however, the potential crack volume for the soil profile was used as an input by the user as a constant value at the initial state and does not change over the year. For this study, the potential crack volume was adjusted only in the calibration phase for 1995 and was kept unchanged for the validation phase for 1993-1994 and 1996-1997. Never the less, if we look at the time series plots for observed and predicted flows as shown in Figures 11 through 15, it clearly showed that the model generally tracked the observed flows for each plot on both STATSGO and SSURGO soils in 1994-1995. However, some discrepancies between the timing of predicted and observed flows for 1996-1997 could be attributed to error involved with the linear interpolation of observed cumulative tile flow data. In general, comparison of model predictions based on statistical and graphical results indicated that the trends in predicted tile flow using STATSGO data were similar to these using SSURGO data. However, with the higher resolution on soil properties for SSURGO data compared to STATSGO data, the model might be able to improve the model predictions as indicated by higher values of r^2 and E, and lower values of D_v as shown in the Table 3 and 4. Scattergrams for five years simulation presented in Figure 9 also supported these statistical results as indicated in the plots of observed and predicted tile flows on the line 1:1 plots. The plots of observed and predicted tile flows for SSURGO data were better agree well on the line of 1:1 plots than STATSGO data.

Table 5. Statistical results comparing observed and predicted values for each plot on STATSGO and SSURGO soil data sets for validation periods in 1993-1994 and 1996-1997

Plot 15

Year	Observed	Predicted tile flow (mm)		Dv (%)		r^2		E	
	tile flow (mm)	STATSGO	SSURGO	STATSGO	SSURGO	STATSGO	SSURGO	STATSGO	SSURGO
1993	390.35	145.03	218.16	-62.85	-44.11	0.32	0.62	0.02	0.40
1994	43.56	80.42	86.04	84.61	97.51	0.70	0.66	0.46	0.26
1996	48.15	34.41	41.60	-28.54	-13.61	< 0.01	< 0.01	-0.44	-0.52
1997	71.25	73.45	72.28	3.09	1.45	0.01	0.08	-0.51	-0.19

Plot 21

Year	Observed	Predicted tile flow (mm)		Dv (%)		r^2		E	
	tile flow (mm)	STATSGO	SSURGO	STATSGO	SSURGO	STATSGO	SSURGO	STATSGO	SSURGO
1993	405.72	170.19	225.27	-58.05	-44.48	0.38	0.62	0.15	0.38
1994	87.55	119.64	116.20	36.65	32.72	0.91	0.95	0.86	0.90
1996	66.86	75.50	40.23	12.92	-39.83	0.03	0.01	-0.28	-0.37
1997	94.99	70.08	42.33	-26.22	-55.44	0.04	0.03	-0.29	-0.37

Plot 24

Year	Observed	Predicted tile flow (mm)		Dv (%)		r^2		E	
	tile flow (mm)	STATSGO	SSURGO	STATSGO	SSURGO	STATSGO	SSURGO	STATSGO	SSURGO
1993	318.69	170.15	151.11	-46.61	-52.58	0.49	0.66	0.32	0.37
1994	69.24	119.44	100.48	72.50	45.12	0.92	0.95	0.74	0.89
1996	54.90	75.49	51.33	37.51	-6.50	0.03	< 0.01	-0.44	-0.59
1997	82.85	70.07	41.17	-15.43	-50.31	< 0.01	0.13	-0.58	-0.11

Plot 26

Year	Observed	Predicted tile flow (mm)		Dv (%)		r^2		E	
	tile flow (mm)	STATSGO	SSURGO	STATSGO	SSURGO	STATSGO	SSURGO	STATSGO	SSURGO
1993	469.73	178.02	230.27	-62.10	-50.98	0.46	0.75	0.12	0.39
1994	67.65	121.27	102.46	79.27	51.46	0.83	0.70	0.31	0.42
1996	57.09	76.73	46.13	34.39	-19.20	0.05	0.11	-0.35	-0.06
1997	85.87	72.83	45.26	-15.19	-47.29	0.07	0.06	-0.31	-0.29

Plot 28

Year	Observed	Predicted tile flow (mm)		Dv (%)		r^2		E	
	tile flow (mm)	STATSGO	SSURGO	STATSGO	SSURGO	STATSGO	SSURGO	STATSGO	SSURGO
1993	184.41	165.31	98.75	-10.36	-46.45	0.52	0.34	0.46	0.20
1994	48.74	76.74	45.42	57.43	-6.82	0.89	0.50	0.78	0.50
1996	38.64	38.64	29.52	0.01	-23.60	< 0.01	< 0.01	-0.68	-0.30
1997	29.35	48.20	15.97	64.25	-45.58	0.19	0.14	-0.25	-0.07

Plot 29

Year	Observed	Predicted tile flow (mm)		Dv (%)		r^2		E	
	tile flow (mm)	STATSGO	SSURGO	STATSGO	SSURGO	STATSGO	SSURGO	STATSGO	SSURGO
1993	436.91	174.08	230.86	-60.16	-47.16	0.26	0.63	0.02	0.37
1994	82.78	96.92	85.62	17.08	3.43	0.94	0.92	0.92	0.89
1996	60.06	38.44	40.63	-36.00	-32.35	< 0.01	< 0.01	-0.38	-0.31
1997	67.05	87.49	86.44	30.49	28.92	< 0.01	0.06	-0.97	-0.37

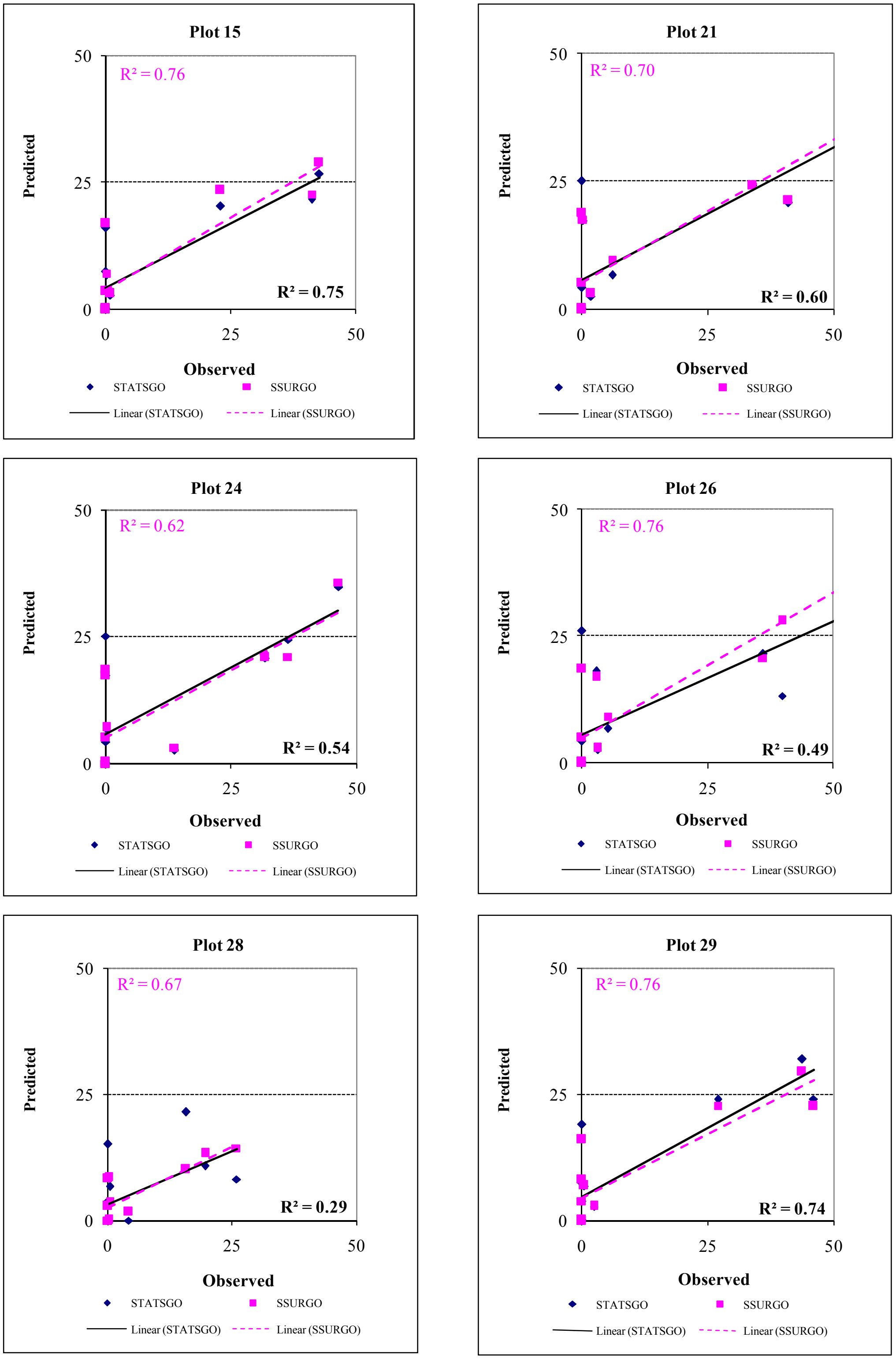

Figure 4. Scattergrams of observed and predicted tile flows for 1995

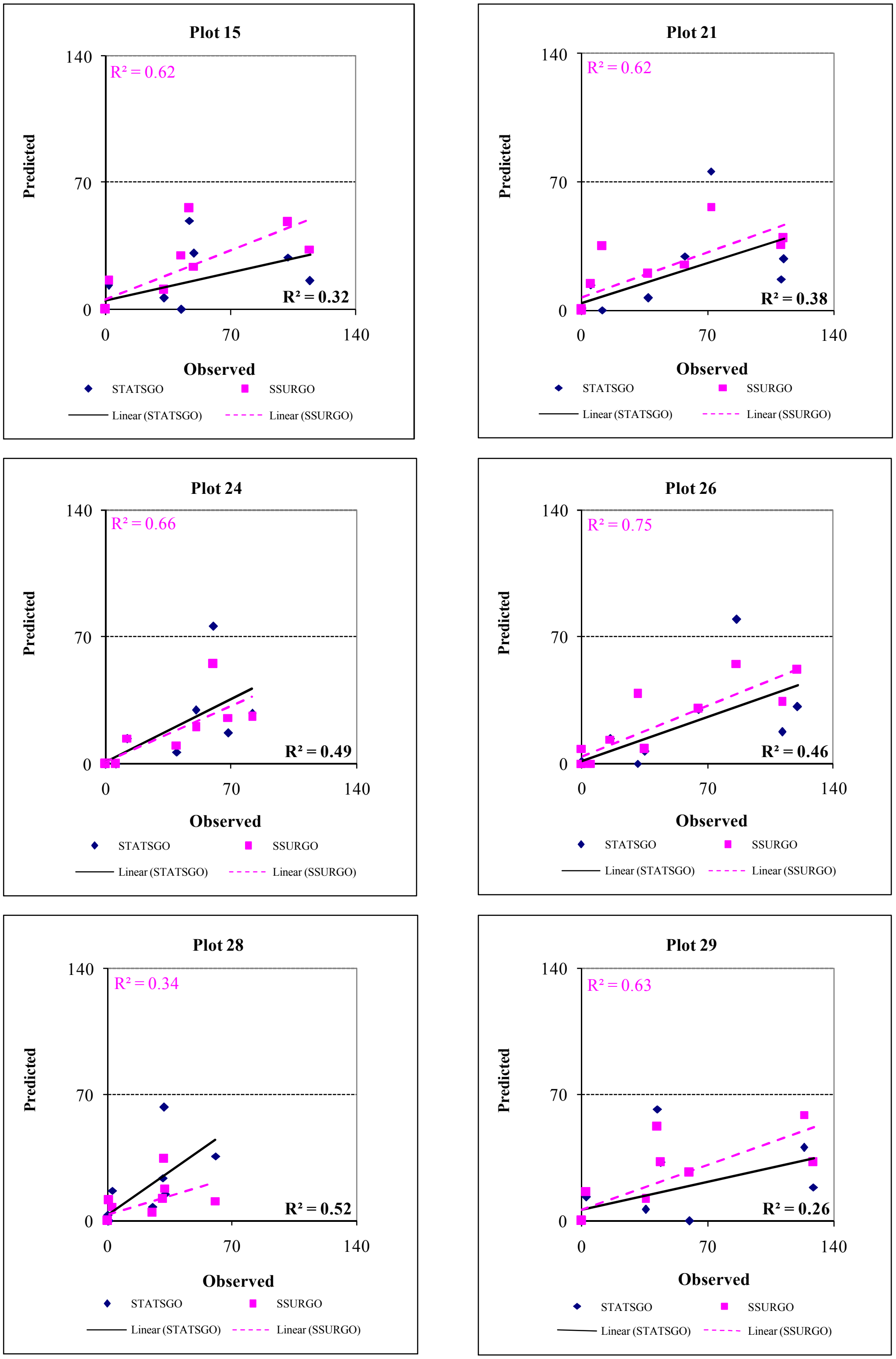

Figure 5. Scattergrams of observed and predicted tile flows for 1993

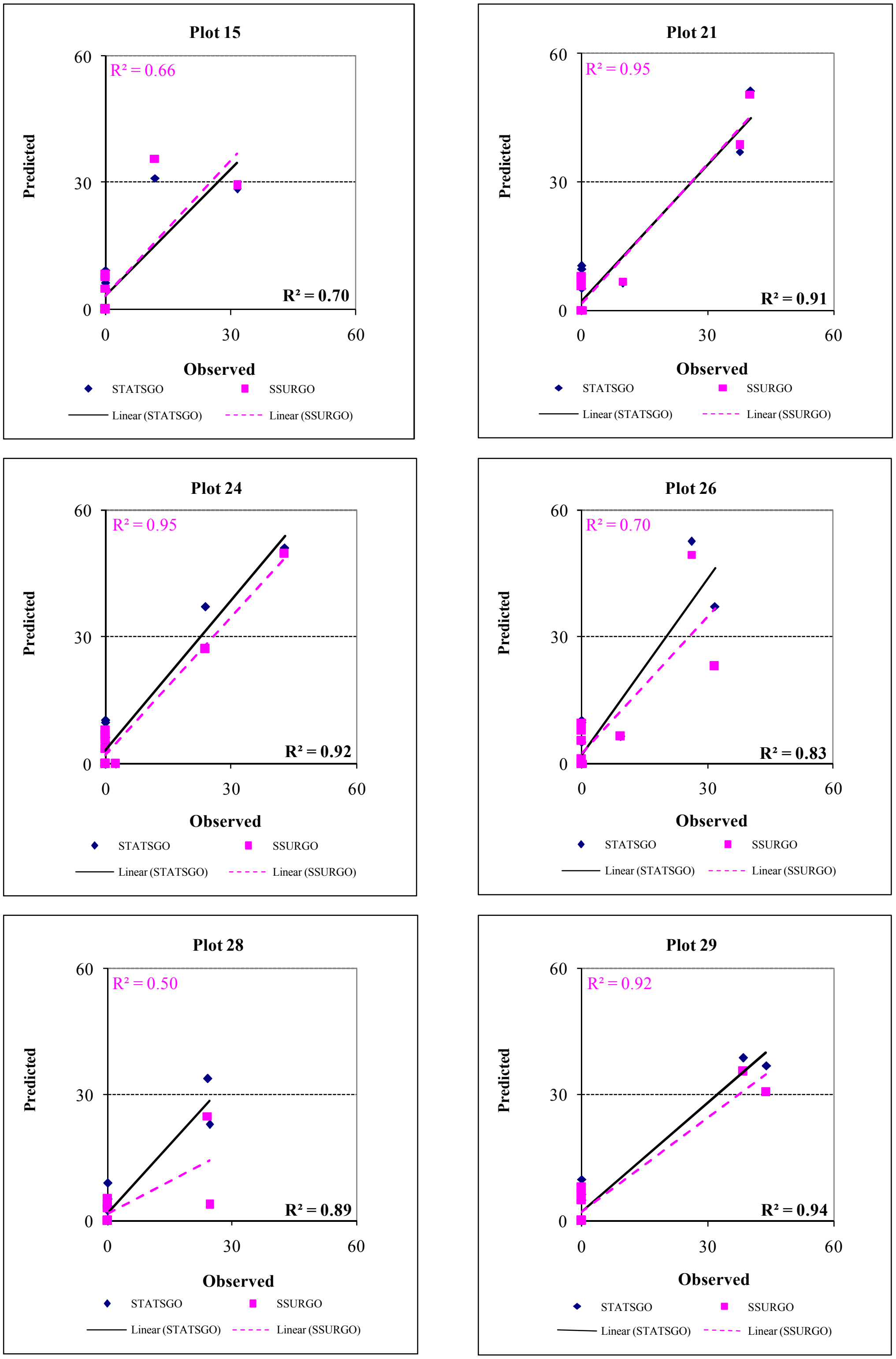

Figure 6. Scattergrams of observed and predicted tile flows for 1994

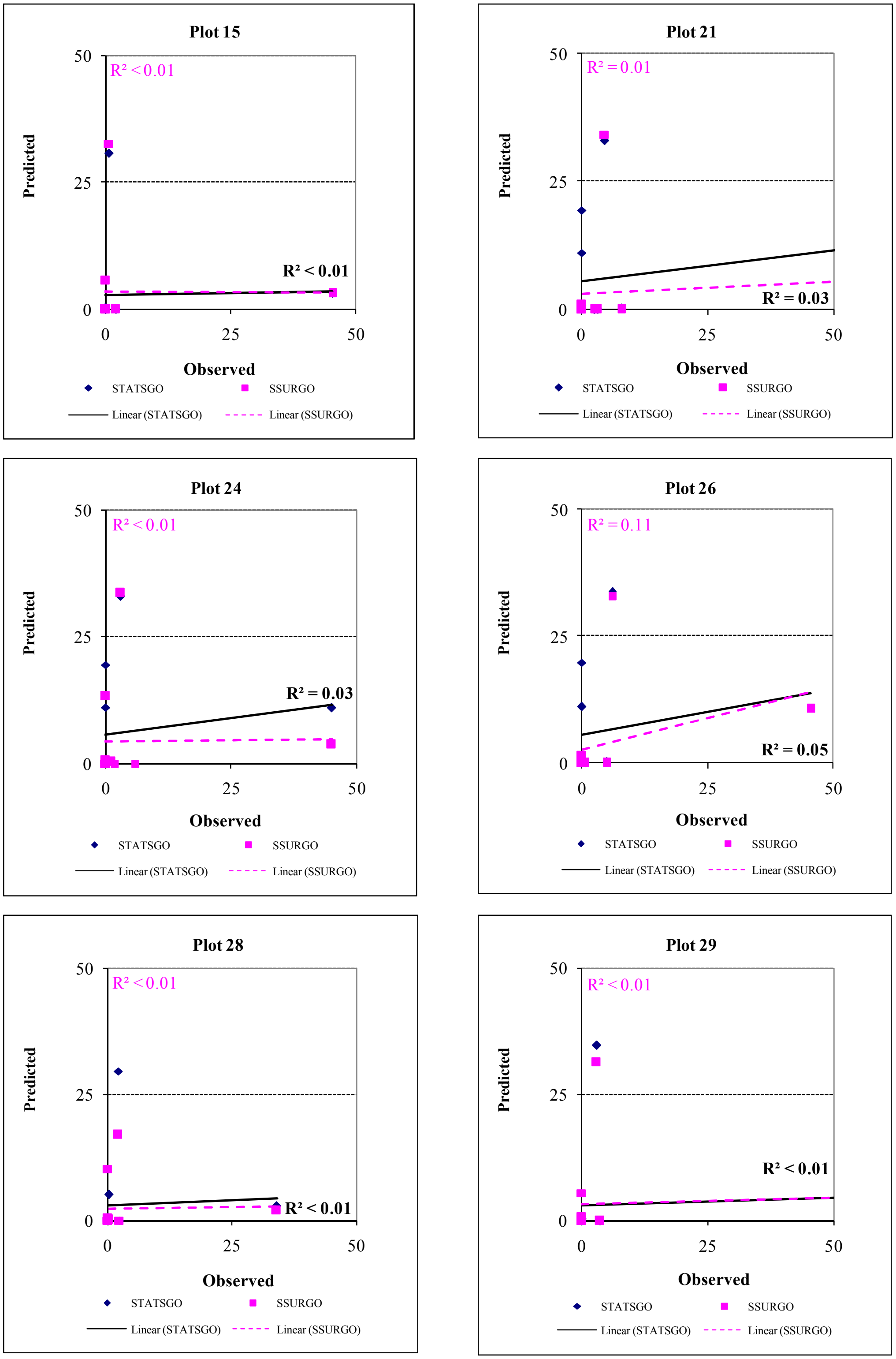

Figure 7. Scattergrams of observed and predicted tile flows for 1996

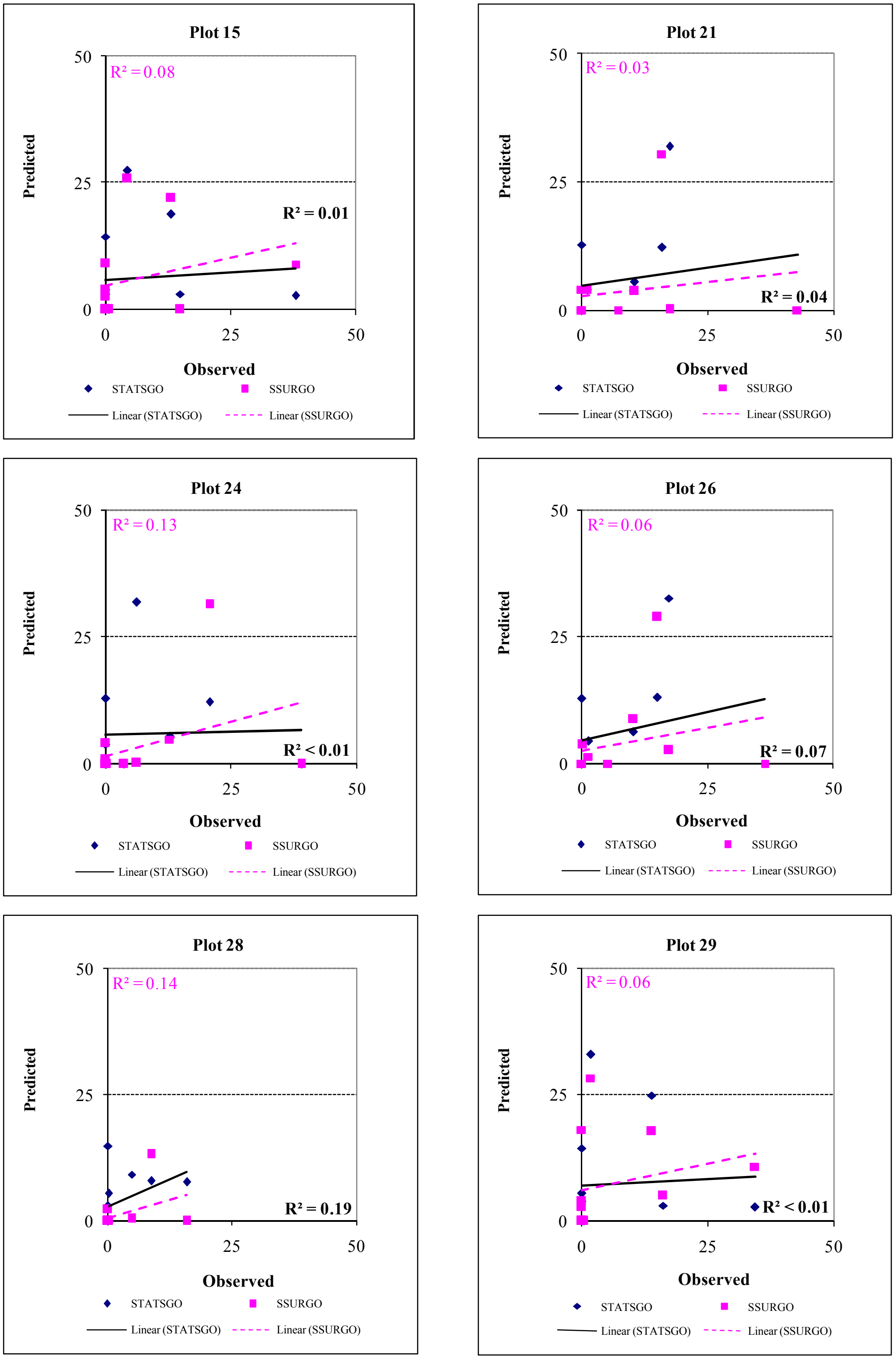

Figure 8. Scattergrams of observed and predicted tile flows for 1997

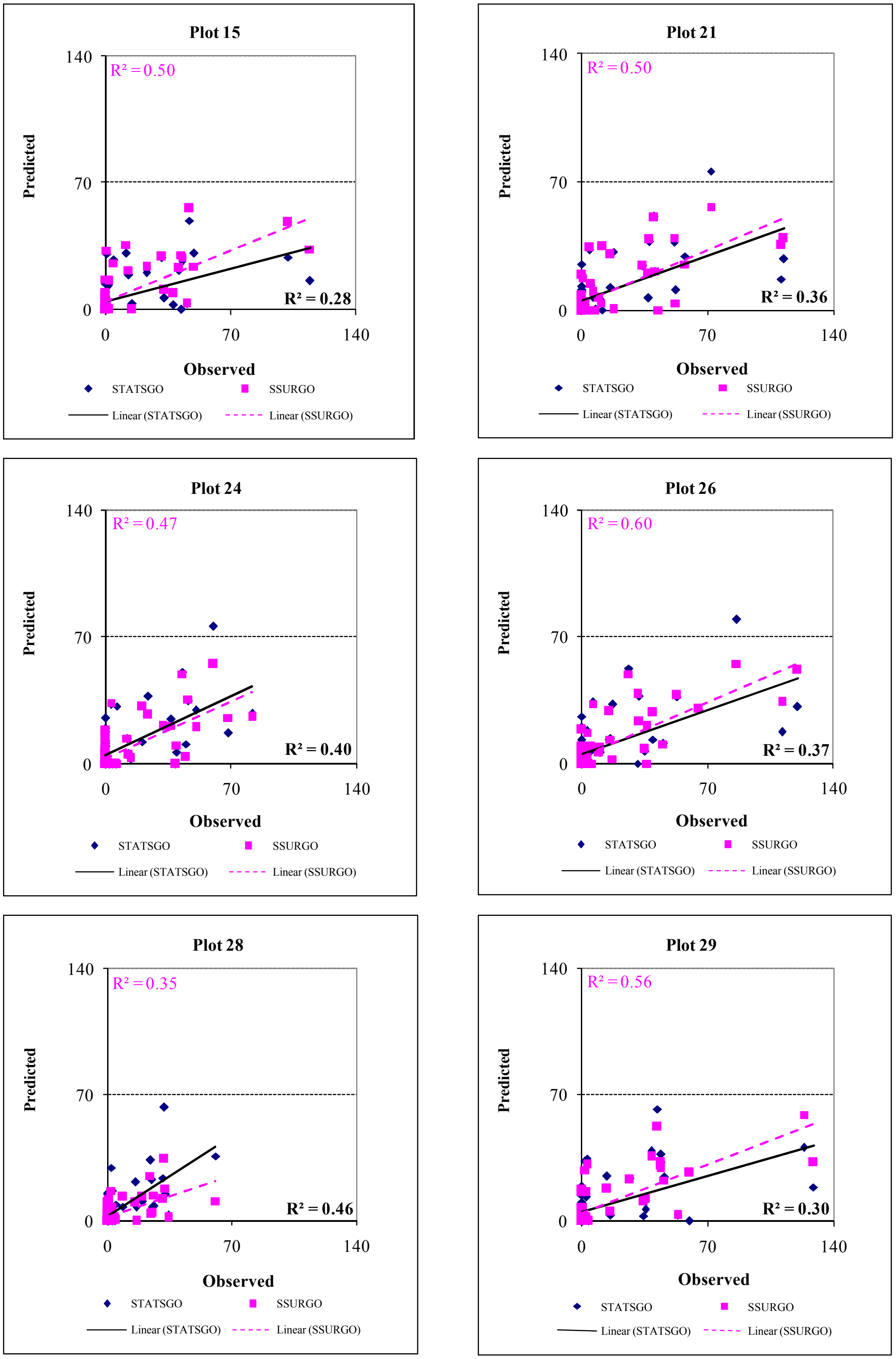

Figure 9. Scattergrams of observed and predicted tile flows for 1993-1997

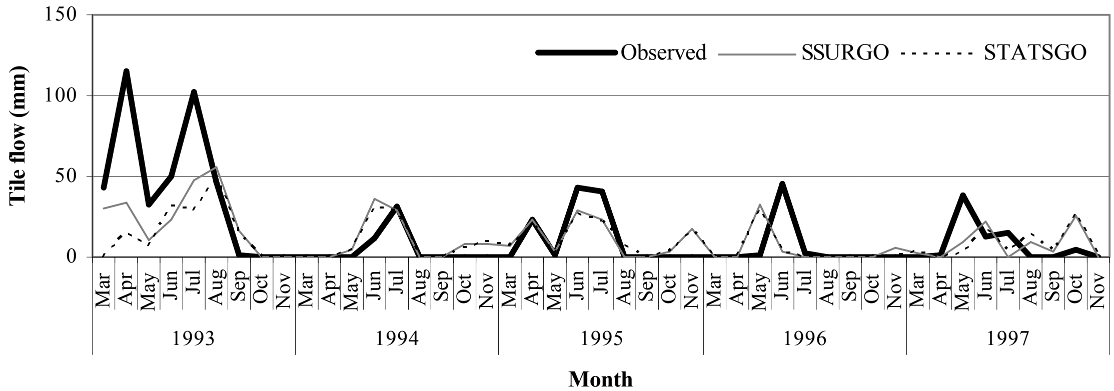

Figure 10. Monthly observed and predicted tile flows for plot 15

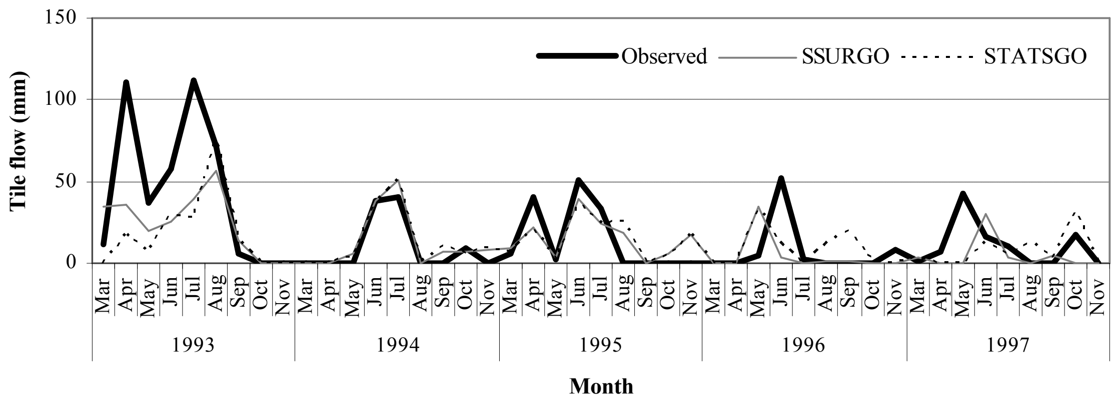

Figure 11. Monthly observed and predicted tile flows for plot 21

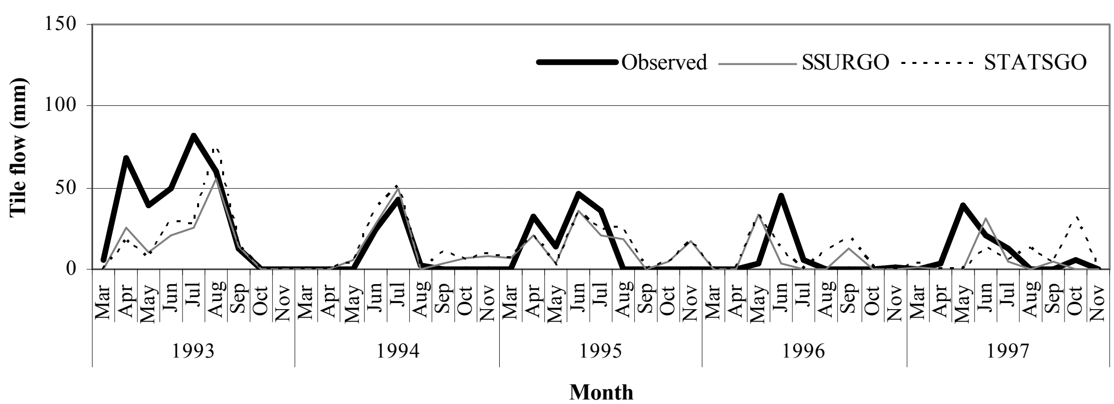

Figure 12. Monthly observed and predicted tile flows for plot 24

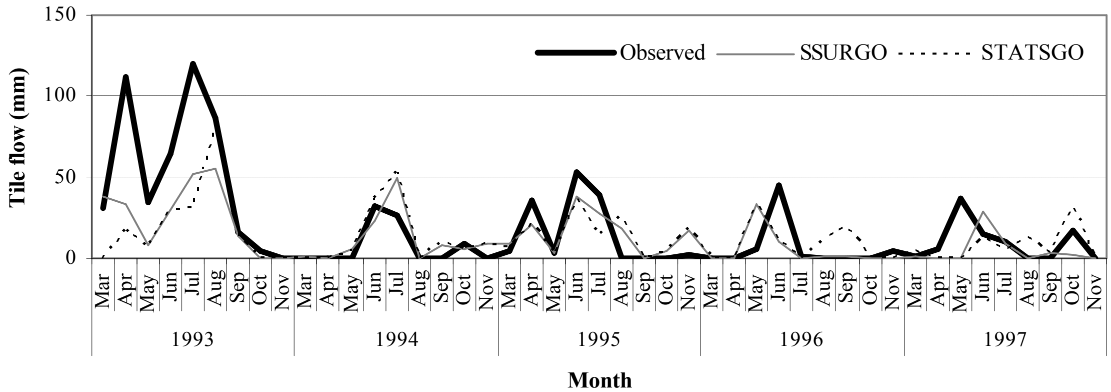

Figure 13. Monthly observed and predicted tile flows for plot 26

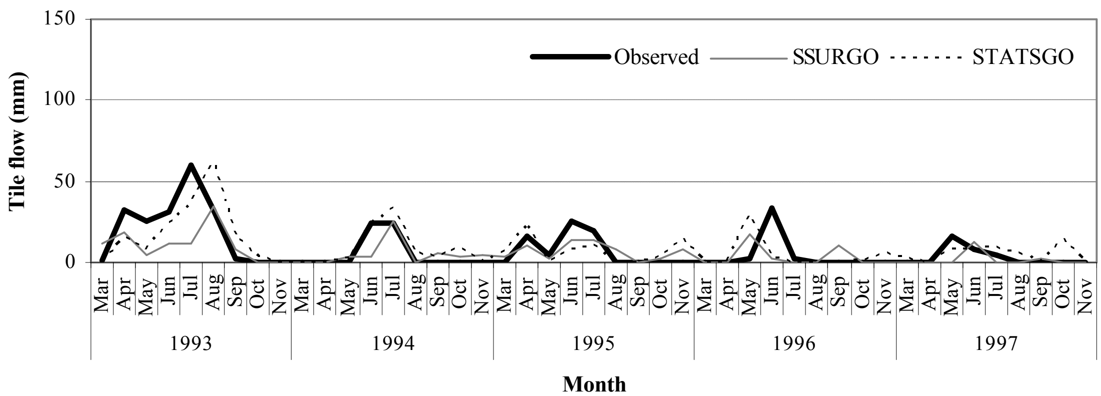

Figure 14. Monthly observed and predicted tile flows for plot 28

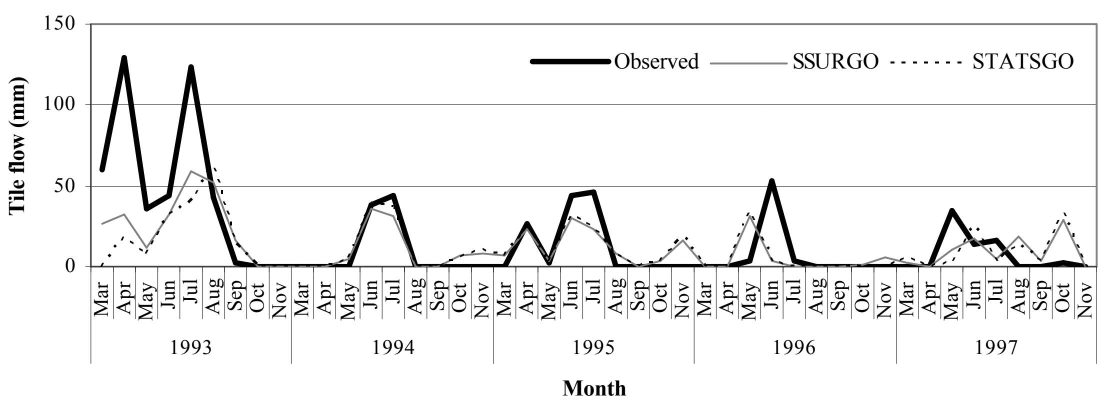

Figure 15. Monthly observed and predicted tile flows for plot 29

Summary and conclusions

The SWAT model was calibrated by minimizing the difference between the cumulative predicted and observed tile flows and shapes of tile flow hydrographs for three management systems for 1995 at the experimental site, Nashua, Iowa. The model was calibrated using STATSGO and SSURGO soil databases. The calibration process mainly involved adjusting the ESCO, SOL_CRK, and CN2 parameters but also included some adjustments to AWC levels. The 1995 cumulative annual tile flow volumes were reasonably predicted by SWAT as indicated by the D_v values of -7.46 to 6.2 on both soil data sets. The model also reasonably tracked the observed trends for the calibration year as evidenced by the r^2 values that ranged between 0.49 and 0.76 and by the E values that were between 0.49 and 0.71. Validation of SWAT was performed by predicting the tile flows for a total of four years: 1993–94 and 1996–97. The model did not accurately predict cumulative annual tile flows and monthly tile flows for year 1993-1994, and 1996-1997, respectively as indicated by the very high value of D_v and very low values of r^2 and E. The overall evaluation of the SWAT's tile flow component indicates that the model predicted similar results regardless of soil data sets. However, the model simulations did show that the prediction of the tile flow could be improved with the use of higher soil resolution databases. Further studies are needed to determine the effect of additional factors on tile flow performance, such as spatial correlation between soil type and land cover, or other uncertainties associated with the SSURGO soil data when used within the AVSWAT.

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CHAPTER 4. APPLICATION OF SWAT MODEL IN SIMULATING STREAM FLOW AND NO_3-N LOSSES FOR THE CHI RIVER SUBBASIN II IN NORTHEAST THAILAND

A paper to be submitted to the International Agricultural Engineering Journal

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Abstract

Hydrologic models have been used to assess the water quality performance of complex watersheds and river basins for managing water resources systems. Hydrologic models can provide essential information to policy makers for making decisions on sustainable management system of water resources within watersheds. A study was conducted on the application of a watershed scale simulation model, SWAT (Soil and Water Assessment Tool), for the Chi River Subbasin II located in the northeastern Thailand. Calibration and validation of the SWAT output were performed by comparing predicted stream flows and NO_3-N losses with corresponding in-stream measurements from four gaging stations within the watershed for five years (2000-2003, 2005). Statistical comparisons between the simulated results (for the calibration year) and the observed data gave a reasonable agreement for both, monthly coefficient of determination (r^2) and Nash-Sutcliffe Coefficient (E) within ranges of 0.77-0.88 and 0.55-0.79, respectively. The overall results of this simulation study indicated that although the model performance was poor with r^2 and E values ranging from 0.23-0.77 and -7.98-0.66 but SWAT model has the capability to

predict stream flows and NO_3-N losses within a desired range. Overall, the evaluation of the SWAT model demonstrated that this model can be used as a decision support tool for making decisions on sustainable management of water resources within the Chi River Subbasin II in the northeast Thailand.

Keywords: SWAT, modeling, calibration, and validation.

Introduction

The northeast region of Thailand, approximately an area of 170,000 km^2, supports about 22 million people. There are three main basins including Mekong, Chi, and Mun River Basin. The total water storage in the region is about 5,300 million m^3. The analysis from the National Water Resources Development Project, Royal Irrigation Department in 1993 found that water demand in this region was about 10,800 million m^3 and will be 14,300 million m^3 in 2006 (Khon Kaen University, 1998). Several surface water reservoirs and weirs have been constructed over the existing rivers. Use of some of the surface water systems was limited due to poor yield and quality (Arunin, 1980). Agriculture is the main occupation in northeast of Thailand. Common crops in this region are cassava, sugar cane, corn, kenaf, watermelon and tobacco. Within irrigated areas, farmers tend to grow rice, sweet corn, soybean, peanut and tomatoes (Ghassemi et al., 1995). Common problems related to water in this region are soil erosion, point and nonpoint source pollution, floods, insufficient water supply, and saline water. Improved assessment of both water quantity and quality is needed in order to provide possible future scenarios for water resource management and development in this region. In support of this goal, a watershed scale, continuous time, distributed hydrologic and water quality model, Soil and Water Assessment Tool (SWAT) model, was selected for testing its performance in predicting the hydrologic response and NO_3-N losses of 7,000 km^2 of mixed land use in the Chi River Subbasin located in the northeast region of Thailand. The SWAT 2000 version of the model was validated in this study. Four years of hydrologic data (2000-2003) were used to calibrate and validate the capability of SWAT in predicting stream flow, whereas NO_3-N concentration data for 2005 were used to validate the capability of SWAT's nutrient component in this study.

SWAT model description

SWAT, Soil and Water Assessment Tool (Arnold et al., 1998; Neitsch et al., 2002) was developed at the U.S. Department of Agriculture (USDA) – Agricultural Research Service (ARS) Grassland, Soil and Water Research Laboratory in Temple, Texas. It is a complex, conceptual model with spatially explicit parameterization. It emerged mainly from SWRRB (Arnold et al., 1990), and contained features from CREAMS (Knisel, 1981), GLEAMS (Leonard et al., 1987), EPIC (Williams et al., 1984), and ROTO (Arnold et al., 1995). It was developed to assist water resources managers in predicting and assessing the impact of management on water, sediment and agricultural chemical yields in large ungaged watersheds or river basins. It is an operational or conceptual model that operates on a daily time step. Although most of the applications have been on a daily time step, recent addition to SWAT is the Green and Ampt (1911) infiltration equation using rainfall input at any time increment and channel routing at an hourly time step. The model have been intended for long term yield predictions and is not capable of detailed single-event flood routing. The model has eight major components include hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, pesticides, and agricultural management. A complete detailed description of SWAT model component was found in Arnold et al. (1998). A brief description of the SWAT key components were provided here as follow. To simulate with SWAT, first a watershed is divided into a number of subwatersheds or subbasins, which were grouped based on climate and main channels. To account for variability of land use, management, and soil characteristics regardless of spatially location, subwatershed or subbasin was then further subdivided into several Hydrologic Response Units (HRUs). Hence, HRUs were lumped land areas within the subbasin comprised of unique land cover, soil, and management combinations. The water balance of each HRU in the watershed was represented by four storage volumes: snow, soil profile (0–2 m), shallow aquifer (2–20 m) and deep aquifer (>20 m). Flow, sediment, nutrient, and pesticide loadings from each HRU in a subwatershed or subbasin were summed together, and routed through channels, ponds, and/or reservoirs to the watershed outlet. Hydrology processes simulated included surface runoff estimated using SCS curve number (Mockus, 1969) or Green-Ampt infiltration equation; percolation modeled with a layered storage routing technique combined with a crack flow model; lateral subsurface flow; groundwater flow to streams from shallow aquifers; potential evaportranspiration by Hargreaves, Priestley-Taylor or Penman-Monteith; snowmelt; transmission losses from streams; and water storage and losses from ponds (Arnold et al., 1998).

Description of study site

The Chi River Subbasin II constitutes approximately 7,000 km^2 located in the northeast region of Thailand. It is part of the Chi River Basin that drains a total of 49,480 km^2 and lies between latitude 15° 24’ N and 16° 39’ N, and longitudes 101° 53’ E and 102°

57' E (Figure 1). The main river that passes through the sub basin is the Chi River, originating from the eastern slope of the Phetchabun Range. The main sources of surface water are rainfall bringing most of the flows to the rivers within the basin. Based on data collected from three selected rain gauges by Royal Irrigation Department (RID) for four years (2000-2005), the average annual precipitations for these three gaging stations were found to be 1,054, 1,321, and 1,204 mm for station 05013, 14022, and 14122, respectively (Figure 2). The highest annual precipitation of 1,593 mm occurred at station 14022 in 2003 whereas the lowest annual precipitation of 762 mm occurred at station 14122 in 2005. Approximately 85 percent of average annual precipitation occurred between May and October (raining season). Figure 3 shows the seasonal and spatial variation of the precipitation. Similar characteristic was also shown by stream flows (Figures 4, 5, 6, and 7) from four monitoring stations (E.6C, E21, E.9 and E.16) along the Chi River under the responsibility of the RID. These characteristics caused major problems on the efficient use of surface water due to large variation in annual stream flows. In fact, there is a big shortage of water for agriculture, domestic and industrial activities in the dry season (November to April). Land use types including rice (56%), field crops (e.g. sugar cane, cassava, sweet corn, etc) (15%), forest (10%), pasture (6%), and the rest is covered by the urban, and rural resident activities.

Most of the altitude of the sub basin is between 148 to 250 m except in the western part which has an average elevation of about 580 m. Soil types within the subbasin primarily consist of sandy clay, sandy loam, clay, and loam. Therefore, none of these soils are strongly favorable to agriculture and many are susceptible to erosion. In general, the soil quality within the Chi River basin is very poor.

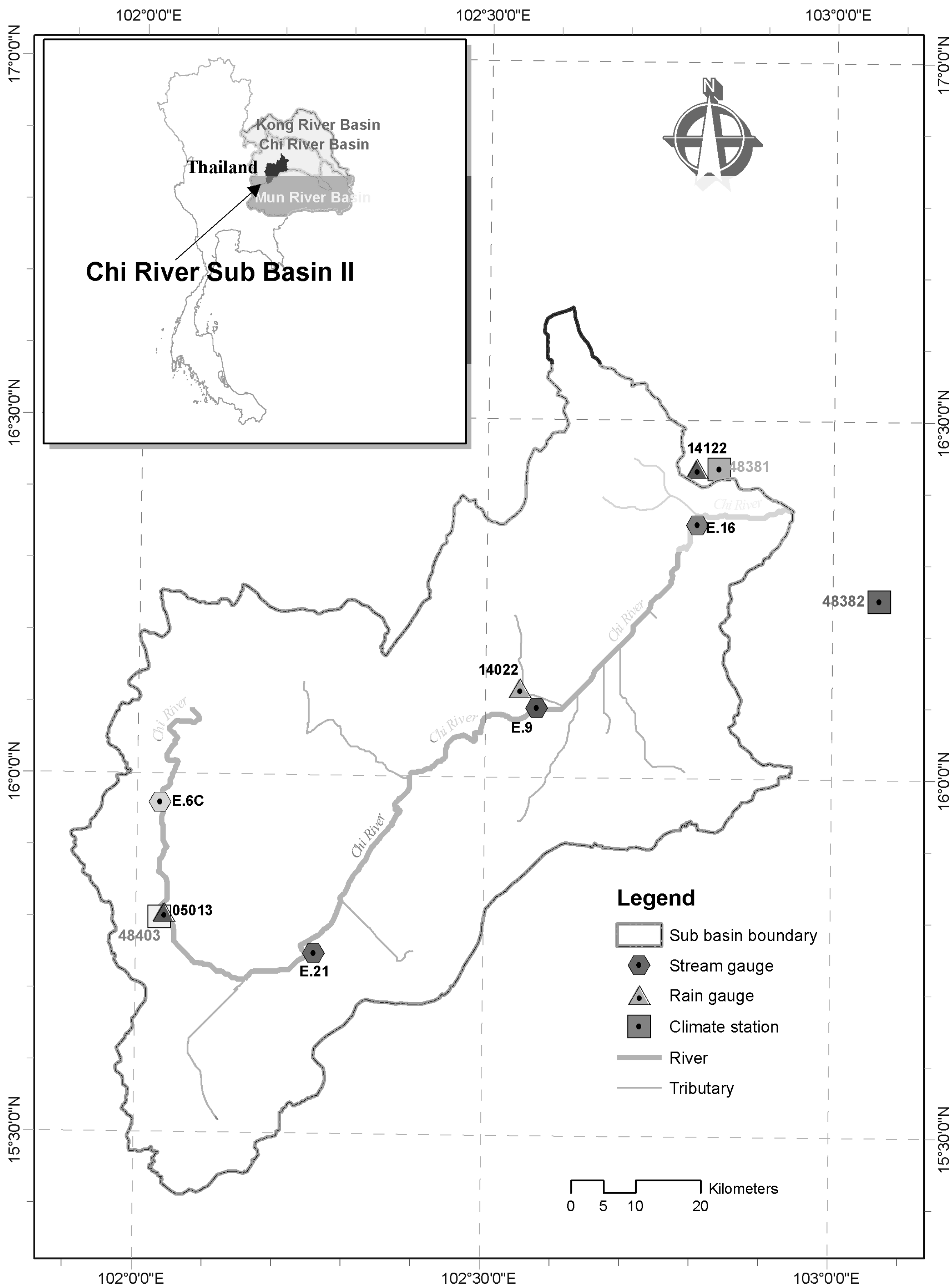

Figure 1. Location of the Chi River Subbasin II, monitoring stations, and climate stations, Northeast Thailand

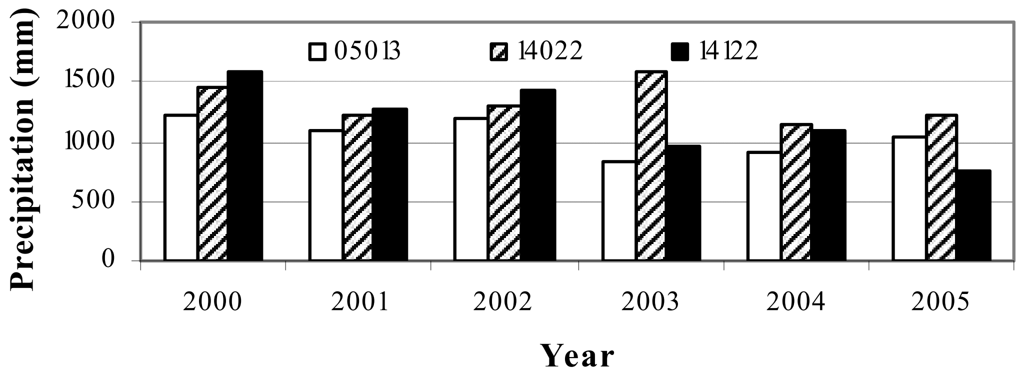

Figure 2. Annual precipitation at the Chi River Subbasin II

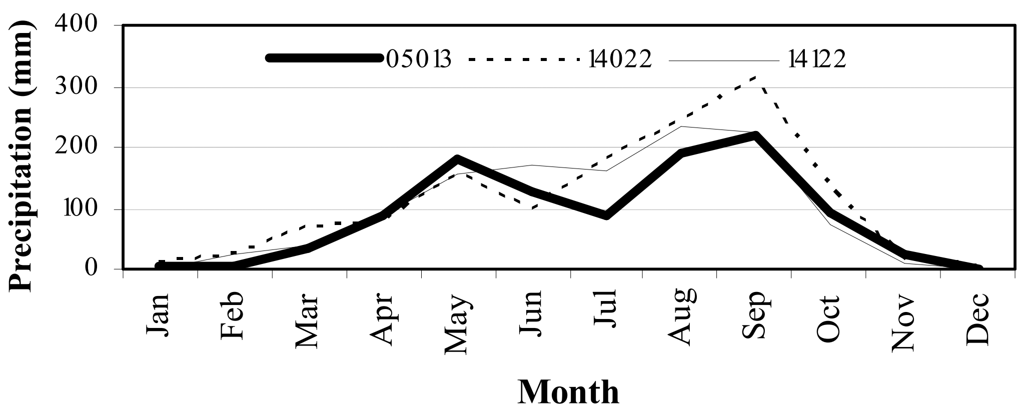

Figure 3. Seasonal and spatial variation of average precipitation at the Chi River Subbasin II

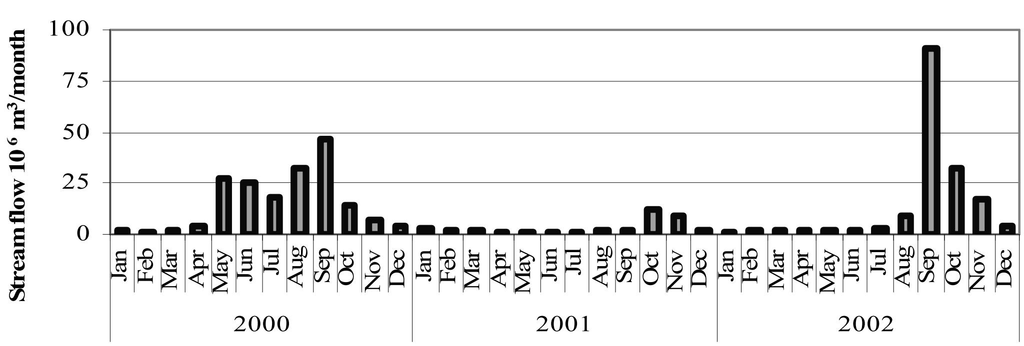

Figure 4. Stream flow seasonal pattern at Station E.6C

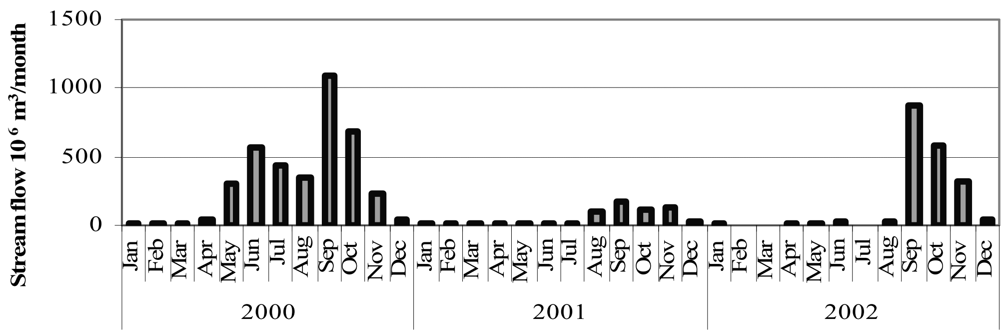

Figure 5. Stream flow seasonal pattern at Station E.21

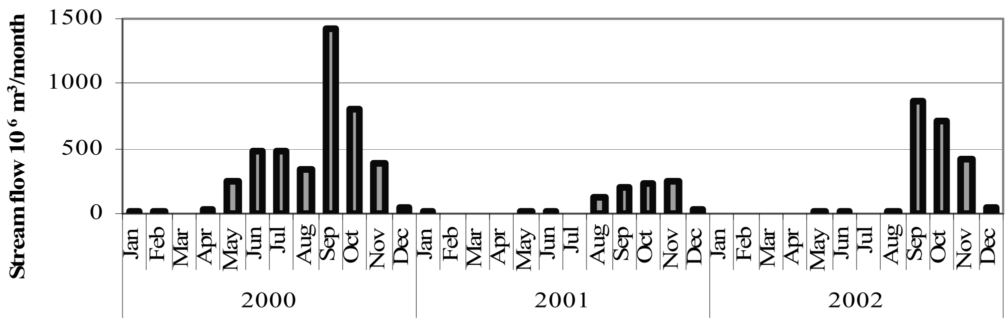

Figure 6. Stream flow seasonal pattern at Station E.9

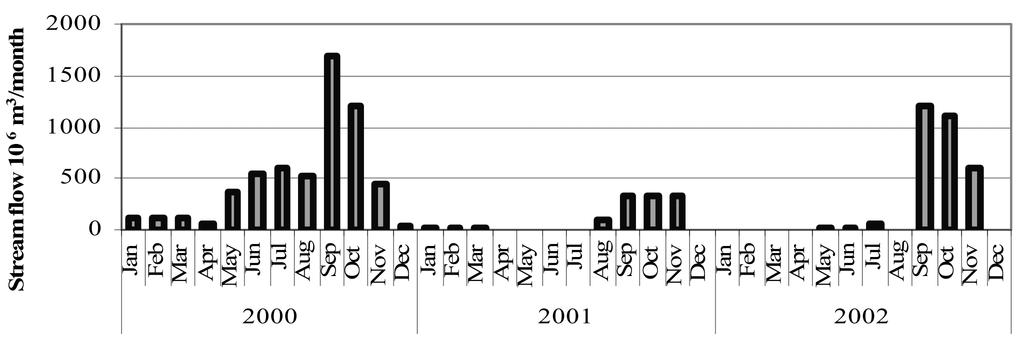

Figure 7. Stream flow seasonal pattern at Station E.16

Input data acquisitions for the SWAT model

SWAT, physically based model, requires data inputs on topography, climate, land management, and soil. For this study, SWAT version 2000 (Neitsch et al., 2002) embed within ArcView GIS software (ESRI, 2000) named ArcView Soil and Water Assessment Tool (AVSWAT) (Di Luzio et al., 2002), developed by the Texas A&M University Blacklands Research Center was used to prepare inputs and simulate experimental scenarios. Pertinent input parameter values for the model such as topography, land use, soils, and climate data were compiled using several different databases. These databases included both GIS data and information extracted from both soils and land use maps. The topographic map was extracted from the contour map provided by the Royal Survey Thailand Department. While the soils and land use database were extracted from the provincial soil survey maps from the Land Development Department. Therefore, before setting up land use for SWAT, the land use map was reclassified into the appropriate equivalent classification as embedded in the SWAT database. Similar to the land use map, the soil map was reclassified with a user soil database and inserted into SWAT soil database. However, the soil maps contain only soil unit without soil physical and hydraulic parameters which are required by SWAT. To obtain these parameters for the user on soil database, the sand, silt, clay, and organic matter components of each soil unit were derived first and then calculated the parameters by using equations found in Saxton et al. (1986). For this study, complete data set on daily precipitation for years 2000 through 2003, three rain gauge stations from RID were selected including station 05013, 14022, and 14122. While other climate data such as minimum and maximum temperatures, average relative humidity, solar radiation and wind speed were selected for the same period from three climate stations under the authority of Thai Meteorology Department including station 48381, 48382, and 48403 at Khon kaen, Mahasarakham, and Chaiyaphum province, respectively.

Model evaluations

To test the ability of the model to predict system response, a graphical method (time series plot), and a statistical measurement were used to evaluate the model performance against the measured stream flow data for the period of years (2000-2003) at four stream gaging stations. Two statistical criterion were used to evaluate a goodness of fit (ASCE, 1993; Legates and McCabe, 1999) including coefficient of determination (r^2), and model efficiency (E) (Nash and Sutcliffe, 1970). The r^2 represents the percentage of the variance in the measured data that is explained by the simulated data which varies between 0 and 1. The E statistic indicates how close the plot of the observed versus predicted values come to the 1:1 line. If r^2 and E values are close to zero, the model prediction is considered unacceptable. In contrast, if these values approach one, the model predictions become perfect.

Model calibration and validation

For modeling purposes in SWAT, the Chi River Subbasin II was divided into 29 virtual sub basins based on drainage network in the sub basin. Therefore, the sub basins were further subdivided into hydrologic response units (HRUs) that were assumed to consist of homogeneous land use and soil type. The percent of the sub basin that are covered by a specific HRU becomes an input to SWAT. However, the exact spatial location is not accounted for. For this study, a land use and soil thresholds of 10% were used when the

HRUs were created, which limited the land use and soil to categories that covered at least 10% of the sub basin.

For model calibration and validation, the predicted stream flows were compared to measured stream flows at four monitoring stations including station E.6C, E.21, E9, and E16 at Ban Tat Ton (Chaiyaphum province), Ban Kaeng Ko (Chaiyaphum province), Ban Tha Nang Luan (Khon Kaen province), and Ban Tha Phra (Khon Kaen province), respectively. The monthly measured stream flows data for 2002 were used for model calibration. The criterion used for calibrating the model was to minimize the difference between measured and predicted cumulative annual stream flows and to match the predicted cumulative monthly amounts with the measured values for stream flow. The calibration of the model for stream flow was done by adjusting the runoff curve number for condition II (CN2), soil available water capacity (SOL_AWC), and the soil evaporation compensation coefficient (ESCO). Hence, these three parameters were found to be very sensitive in SWAT studies performed by Spruill et al. (2000), Santhi et al. (2001), Jha et al. (2003), and Chu and Shirmohammadi (2004). The curve number determines the partitioning of precipitation between surface runoff and infiltration as a function of soil hydrologic group, land use, and antecedent moisture condition (Mishra and Singh, 2003). The available water capacity is a key soil parameter that has been found to affect groundwater recharge estimates in simple water balance models (Finch, 1998) whereas the soil evaporation coefficient values appear to adjust the depth distribution for evaporation from soil to account for the effect of capillary action, crusting, and cracking (Neitsch et al., 2002b). Because SWAT input data are physically based (based on readily observed or measured information), there is often considerable uncertainty in model inputs due to spatial variability and measurement error.

First, the CN2 was adjusted. Accounting for uncertainty in the hydrologic conditions of the field, the CN2 was allowed to vary within ±6. If the flow differences continued to exceed 10 percent, then ESCO and SOL_AWC were adjusted. The procedure was continued until the shapes of the simulated and observed stream flow hydrographs were in reasonable agreement. The ESCO values were allowed to vary between 0 and 1.0 with no compensation for depth, while the AWC values were allowed to vary within ±0.04. As the value for ESCO was reduced, the model was able to extract more evaporative demand from lower levels. Similar to the ESCO, decreasing SOL_AWC resulted in higher water available for both surface runoff and base flow. To test the ability of the model to predict system response, the model was validated with measured stream flow data for 2000, 2001 and 2003 without changing calibrated input parameters. Unfortunately, stream flow record at gauge E.16 was not available for 2003, therefore only the upstream three monitoring gauges were validated for 2003 in this study. Note that calibration and validation were performed on stream flow only, no attempt was made for base flow.

To test the ability of the SWAT's nutrient component, the model was validated with measuring NO_3-N concentrations collected from monitoring station E.6C, E.21, and E.9. Six samples of water quality data including NO_3-N concentrations from specific date in 2005 were used for model validation. Validation of NO_3-N predictions was performed primarily by adjusting the NPERCO parameters in SWAT. The NPERCO parameter controlled the concentration of NO_3-N in surface runoff relative to the NO_3-N that leached below the soil surface. The value of NPERCO can range from 0 to 1. If no value for NPERCO is entered, the model will automatically set it equal to 0.2.

Results and discussion

The SWAT simulations were conducted for the four year period (2000-2003). Calibration of SWAT was performed for year 2002 using data from the Chi River basin whereas the data from the years 2000, 2001, and 2003 were used for the model validation. Both graphic and statistical approaches were used to evaluate SWAT model's performance. The statistical results of the model performance for both calibration and validation periods are summarized in Table 1. Figure 8 through 11 present a time series comparison of simulated and measured stream flows during the calibration and validation years at station E.6C, E.21, E.9, and E.16, respectively. These figures clearly indicate that simulated stream flows reasonably match with the measured stream flows most of the time except for the year 2000 when model underestimated the stream flow and for the year 2002 when model overestimated the flow for all four monitoring stations. These trends in predictions of stream flow by SWAT might be due to the CN2 method used for simulations. The major weakness of the CN2 method is the absence of inclusion of spatial and temporal variability in precipitation. More specific, for stream flow calibration, the time series plots for all four monitoring stations showed that the simulated flows matched well with the measured flows except that some of the model generated peak flows did not occur on the same days of the measured flows from April to July in 2002. The r^2 values of 0.88, 0.85, 0.86, and 0.82 for stations E.6C, E.21, E.9, and E.16, respectively, indicated a strong linear relationship between the measured and simulated flows. The E values of 0.8, 0.58, 0.83, and 0.81 for the calibration period also suggested a very strong relationship between the measured and simulated stream flows and agree well on the line of 1:1 plots (Figures 12 and 13). Scattergram presented in Figure 12 supported these statistical results. For stream flow validation, the time series plots for all four monitoring stations showed that the simulated flows reasonably matched with measured flows with r^2 values in range of 0.23 to 0.77. The lowest r^2 value of 0.23 was found at station E.6C for year 2001, while the highest r^2 value of 0.77 was found at station E.6C for year 2003. However, the monthly E values between -7.89 and 0.67 were found during the validation periods. The negative E values indicated a poor model performance in predicting stream flows. These values indicate unsatisfied plot of the line 1:1 for validation period. Figure 13 also supported the statistical results during validation periods (2000, 2001, and 2003). Note that no validation was performed at station E.16 in 2003, due to the non-availability of recorded measured flows.

Validation of the model using 2005 data on NO_3-N concentrations and losses in stream flow was performed by adjusting the NPERCO parameter. The predicted NO_3-N concentrations were compared to the measured data collected on NO_3-N concentrations from four monitoring stations during the period from March to August, 2005. The measured and simulated NO_3-N concentrations for at each sampling date for four stations are summarized in Table 2. Statistical results given in Table 2 show that the model was unable to predict NO_3-N concentrations accurately as indicated by lower values of r^2 (0.14, 0.08, and 0.01 for station E.21, E.9, and E.16, respectively) except for station E.6C that has higher r^2 value of 0.65. In addition, the negative values of E (-12.4, -0.1, -0.1 and -0.3 for station E.6C, E.21, E.9, and E.16, respectively) indicate unsatisfied plot on the line 1:1 plot for validation period (Figure 14). Although SWAT performed poorly in predicting NO_3-N concentration for this study site, however, the model was capable of simulating NO_3-N concentrations for the sampling site E.6C with sufficient accuracy (r^2 = 0.65). The short-term availability of data used for model validation and the lack of detailed information on fertilization (both quantity and timing) may have added some errors in NO_3-N concentration predictions. In addition, the model predictions of NO_3-N concentrations without flow calibration could lead to some error in predictions.

Table 1. Statistical results comparing monthly measured and simulated stream flow data at monitoring station E.6C, E.21, E.9, and E.16

Year	Station	r^2	E	Station	r^2	E	Station	r^2	E	Station	r^2	E
2000	**E.6C**	0.70	0.67	**E.21**	0.49	-0.06	**E.9**	0.45	0.17	**E.16**	0.44	0.19
2001		0.23	-7.89		0.58	0.04		0.56	0.05		0.54	-0.25
*2002		0.88	0.80		0.85	0.58		0.86	0.83		0.82	0.81
2003		0.77	0.25		0.63	0.59		0.76	0.62		N/A	N/A

* = Calibration year
N/A = No record of measured stream flow

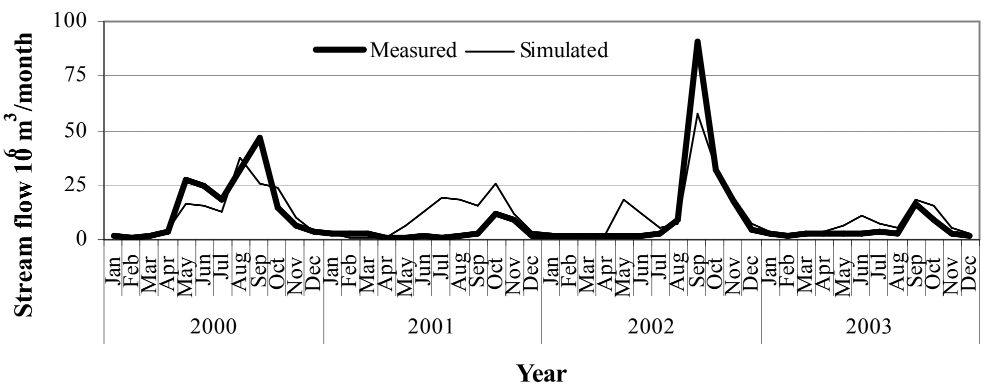

Figure 8. Time series of measured and simulated stream flow at station E.6C for 2000-2003

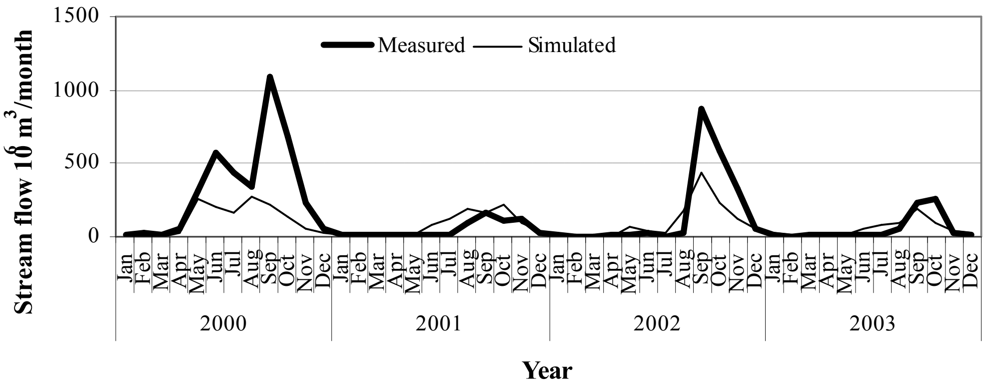

Figure 9. Time series of measured and simulated stream flow at station E.21 for 2000-2003

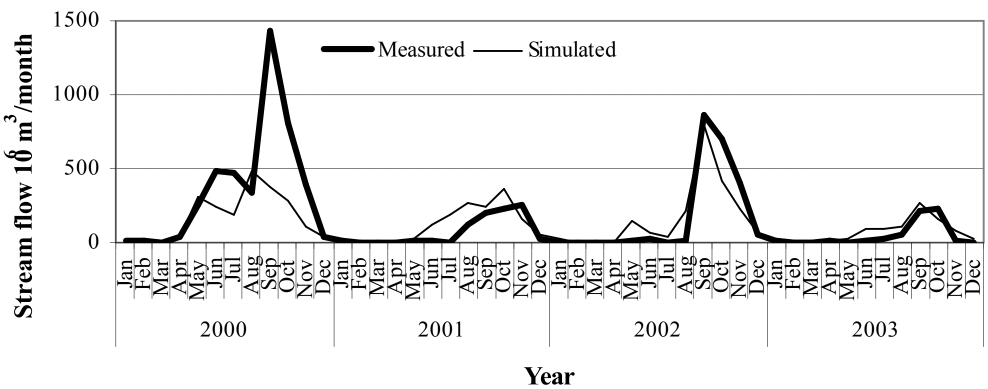

Figure 10. Time series of measured and simulated stream flow at station E.9 for 2000-2003

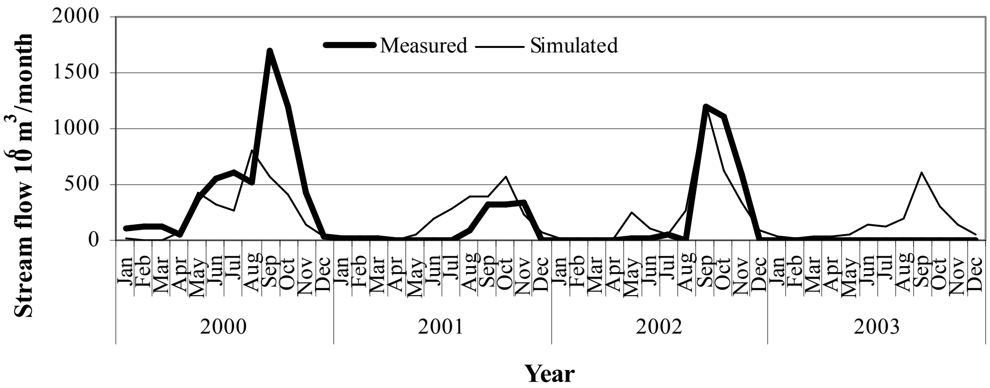

Figure 11. Time series of measured and simulated stream flow at station E.16 for 2000-2003

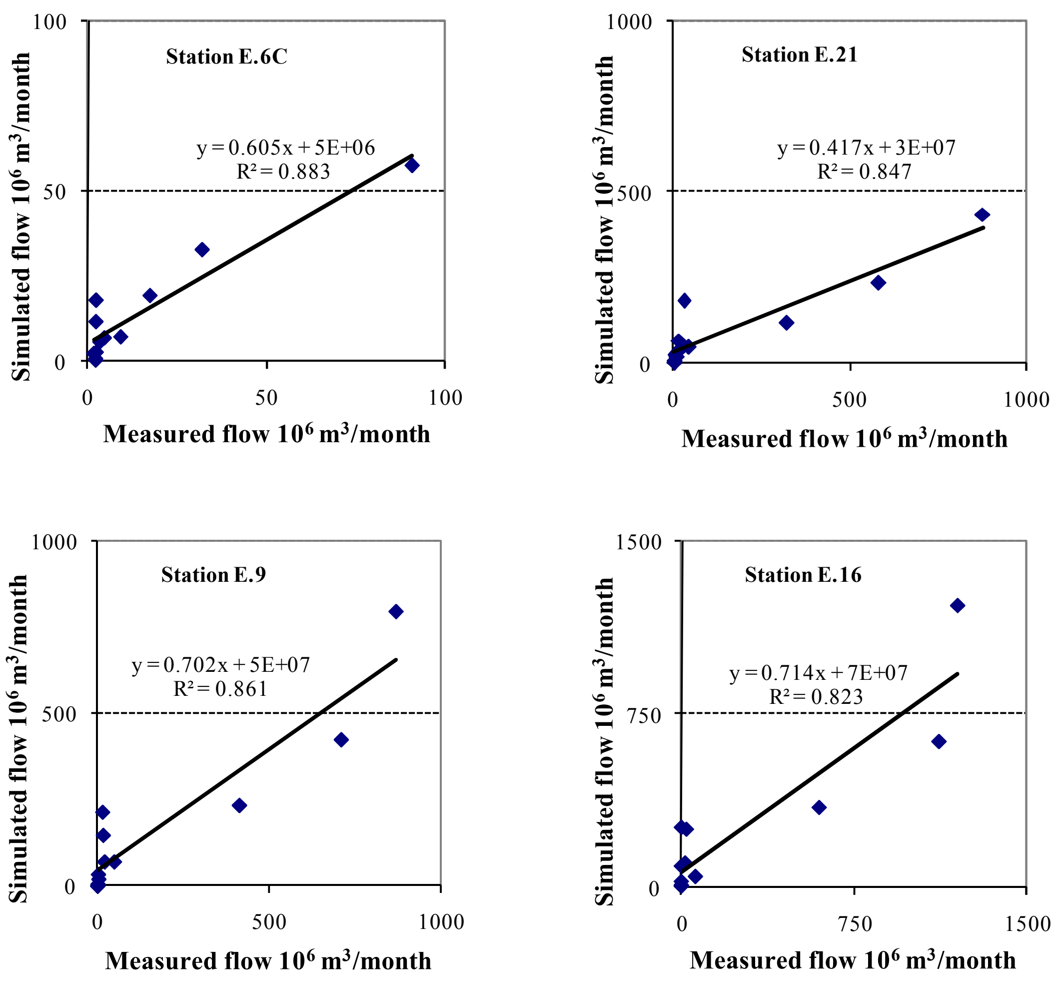

Figure 12. Scattergrams of measured and simulated stream flow during calibration period (2002)

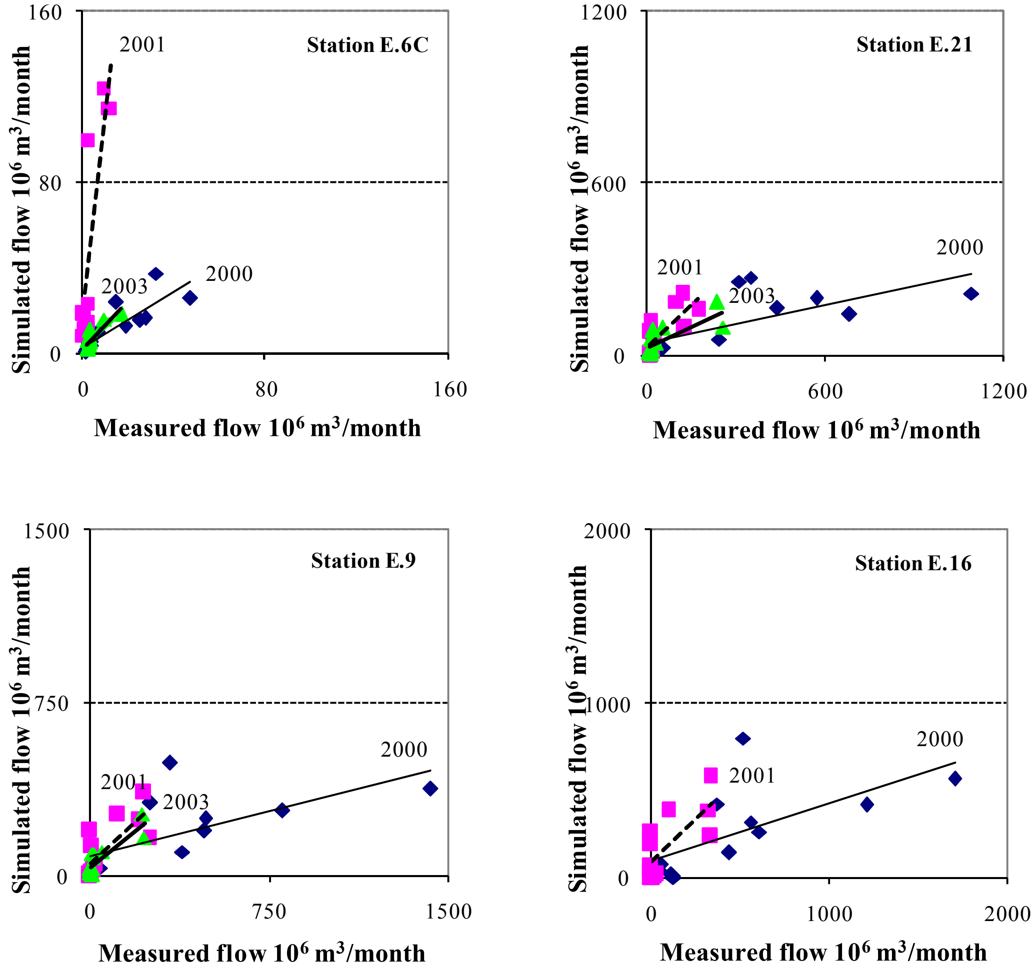

Figure 13. Scattergrams of measured and simulated stream flow during validation period (2000, 2001, and 2003)

Table 2. Statistical results comparing measured and simulated NO_3-N concentration (mg/L) at monitoring station E.6C, E.21, E.9, and E.16

Sample Date	Station E.6C				Station E.21				Station E.9				Station E.16			
	Measured	Simulated	r^2	E	Measured	Simulated	r^2	E	Measured	Simulated	r^2	E	Measured	Simulated	r^2	E
3/28/2005	1.30	0.00	0.65	-12.4	0.10	0.03	0.14	-0.1	0.30	0.00	0.08	-0.1	0.20	0.00	0.01	-0.3
4/28/2005	2.40	0.18			0.10	0.22			0.20	0.23			0.90	0.52		
5/26/2005	3.40	0.31			0.20	0.38			0.10	0.30			0.20	0.81		
6/28/2005	3.40	0.20			0.40	0.55			0.10	0.43			0.20	0.71		
7/29/2005	2.90	0.11			1.10	0.51			1.20	0.43			2.10	0.57		
8/24/2005	3.00	0.13			2.10	0.37			1.10	0.30			1.40	0.50		

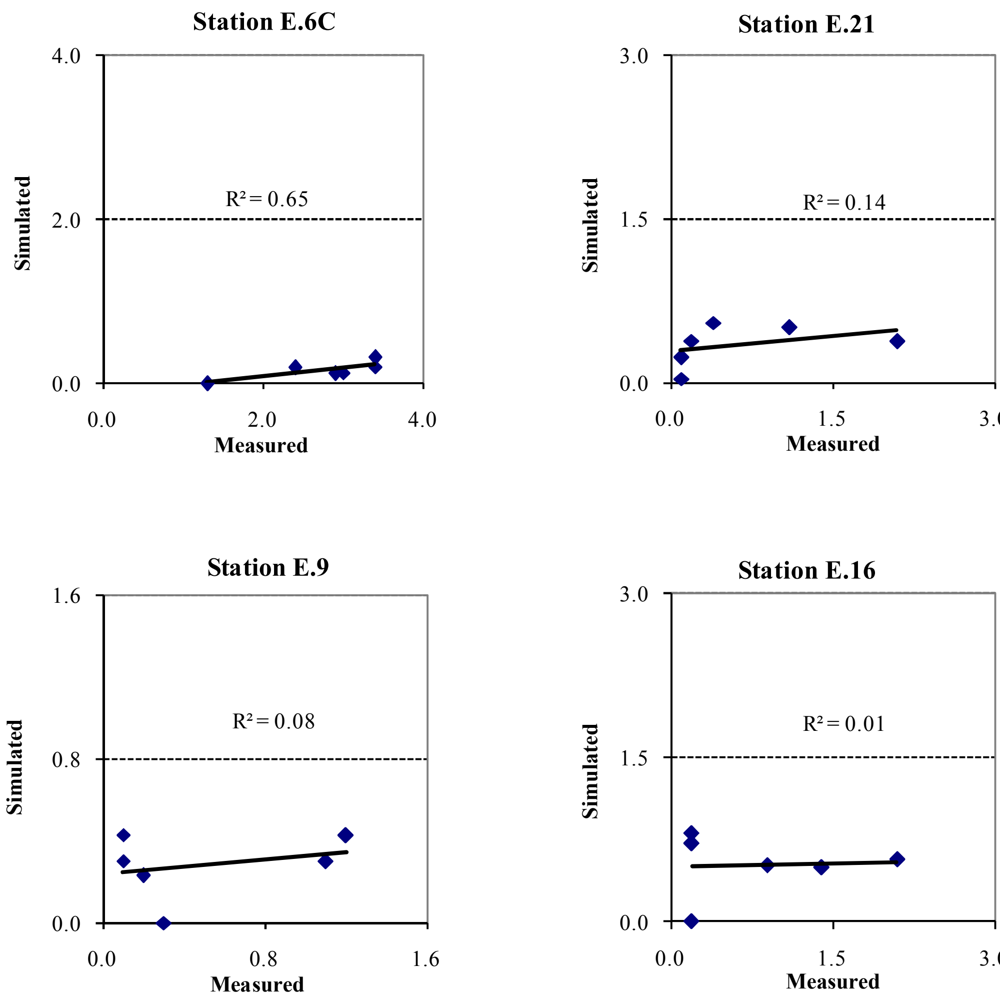

Figure 14. Scattergrams of measured and simulated NO_3-N concentration (mg/L) during validation period for 2005

Summary and conclusions

Calibration and validation of the SWAT's hydrologic component were performed by comparing predicted stream flows with corresponding in-stream measurements for four years (2000-2003) from four gaging stations within the Chi River Subbasin II in Northeast Thailand. Statistical comparisons of calibration results with observed data indicated a reasonable agreement for both monthly coefficient of determination (r^2) and Nash-Sutcliffe Coefficient (E) with the ranges of 0.77-0.88 and 0.55-0.79, respectively. The model validation results showed lower values of r^2 and E values ranging from 0.23 to 0.77 and -7.98 to 0.66. Validation of SWAT's nutrient component was also performed by predicting NO_3-N concentrations in stream flows at the same four gaging stations in 2005. The results of this study indicated that model was capable of simulating stream flow and NO_3-N concentrations satisfactorily. In summary, the overall evaluation of the SWAT demonstrated that the model can be used as a decision support tool for sustainable water resources management. Results of this study also indicated that more studies are needed to interpret accurately the soil physical and hydraulic parameters for SWAT's soil database. In addition to improving model performance, detailed and long-term data are needed for further analyses.

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CHAPTER 5. GENERAL CONCLUSIONS

Calibration and Validation of the SWAT model for the Upper Maquoketa River Watershed (UMRW) was conducted. Sensitivity analyses performed on the SWAT model showed that the simulated base flow and runoff was sensitive to variations in precipitation, curve number, soil available water capacity, and the soil evaporation coefficient. The choice of values for these input parameters can greatly impact the predicted stream flow results, underscoring that care must be taken in selecting correct input values. Annual stream flows measured at the UMRW outlet for 1999-2001 were greatly under-predicted when precipitation data collected within the watershed during 1999-2001 were used as input to SWAT. The predicted annual stream flows improved greatly when precipitation data were used that were measured at climate stations outside the watershed. The reasons for this cause-effect relationship are not clear to us. Further simulations with SWAT using only the climate data collected at the Fayette and Manchester climate stations showed that the model was able to reasonably track monthly measured stream flows and nitrate losses at the watershed outlet. The r^2 statistics found for the monthly stream flows and NO_3-N losses were equal to 0.73 and 0.72, respectively which was considered reasonably good. These results compare favorably with previous r^2 values reported by Saleh et al. (2003) of 0.79 for stream flows and 0.74 for the NO_3-N loads, using the APEX-SWAT approach. However, the annual stream flows and three-year average annual stream flow were more accurately simulated in this study. From these results, it can be concluded that both the APEX-SWAT and SWAT-only methods are viable simulation approaches for simulating the stream flow and NO_3-N loads for the UMRW.

Simulation results on the effects of spatial variability in soil properties on tile flow component of SWAT model indicated that the SWAT model reasonably predicted the 1995 cumulative annual tile flow volumes and also reasonably tracked the observed trends for the calibration year for both, STATSGO and SSURGO soil data sets. Validation of the SWAT model was performed by predicting tile flows for a total of four years: 1993 and 1994 and 1996 and 1997. The SWAT model did not accurately predict cumulative annual tile flows and monthly tile flows for years 1993 and 1994, and 1996 and 1997, respectively. The overall evaluation of the SWAT tile flow component indicates that the model predicted similar results regardless of which soil data set was used. However, the model simulations did show that the prediction of the tile flow could be improved by using higher resolution soil databases. Further studies are needed to collect accurate data on additional factors, such as spatial correlation between soil type and land cover, or other uncertainties associated with the SSURGO soil data when used within the AVSWAT.

Finally, the application of SWAT model was extended to an international watershed in Thailand. Application of a watershed scale model, SWAT was conducted for the Chi River Subbasin II located in the northeastern Thailand. Calibration and validation of the SWAT output were performed by comparing predicted stream flows and NO_3-N losses with corresponding data collected on in-stream measurements from four gaging stations within the Chi River Subbasin II watershed for five years (2000 through 2003, and 2005). Statistical comparisons between the simulated results and the observed data for the calibration year gave a reasonable agreement for both monthly r^2 and E within ranges of 0.77-0.88 and 0.55-0.79, respectively. The overall results of this simulation study indicated that although the model performance was less accurate with r^2 and E values ranging from 0.23 to 0.77 and from -7.98 to 0.66, respectively, but SWAT model can predict stream flows and NO_3-N losses within the desired range. Overall, the evaluation of the SWAT model demonstrated that this model can be used as a decision support tool for making decisions on sustainable management of water resources within the Chi River Subbasin II in the northeast Thailand.

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