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A simulation assessment of the Boone River watershed: baseline calibration/validation results and issues, and future research needs

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A simulation assessment of the Boone River watershed: baseline calibration/validation results and issues, and future research needs

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CHAPTER 1. GENERAL INTRODUCTION

Introduction

Iowa stands at a fascinatiing and challenging agricultural crossroads at the state moves forward into the 21st century. On one hand, Iowa has become a model of agricultural productivity with ever increasing corn and soybean yields, phenomenal swine output, and other highly productive agricultural sectors (Tables 1 and 2). Iowa has further emerged as a national leader in biofuel production and the pursuit of value-added crop bioenergy options will likely intensify in the future. However, the state also finds itself positioned at the epicenter of agricultural pollution controversy, due to the intensity of crop and livestock production, crop production nutrient inputs, altered hydrological landscapes, and other factors. Ongoing and at times contentious debate regarding the severity of the pollution problem and appropriate solutions has continued unabated during my 20-year history at the Center for Agricultural and Rural Development (CARD). It is this debate that I hope to enter into in a constructive way with this study, with the goal of providing useful insights that will assist in the overall pursuit of nonpoint source pollution mitigation in Iowa.

At the outset, it is important to recognize that tremendous effort has been made by federal, state, county, local, and other agencies, private organizations, and individual landowners in both Iowa and across the nation to establish conservation practices, re-establish riparian zones and wetlands, improve cropland nutrient management practices, and provide other rural landscape improvements. The annual average investment cost of installing terraces, grassed waterways, Conservation Reserve Program (CRP) land, and four other key conservation practices was estimated by Feng et al. (2008) to exceed $430 million

Table 1. Key Iowa crop production statistics for 2005[a].

Selected Crop Category	Rank	% of U.S. total
Corn (grain)	1	17
Corn (silage)	7	4
Soybeans	1	14
Oats	5	7
Winter Wheat	37	-
Alfalfa Hay & Mixtures	6	6
Total area of principal crops harvested	1	8

[a]Source: IDALS (2006).

Table 2. Key Iowa livestock production statistics for 2005[a].

Selected Livestock Category	Rank	% of U.S. total
All hogs	1	27
Beef cows (that have calved)	10	3
Dairy cows (that have calved)	12	2
Cattle & calves on feed	5	7
All sheep & lambs	9	4
All egg layers	1	14

[a] Source: IDALS (2006).

in Iowa, based on cost share and other data obtained from state and federal sources. Extrapolation of this figure to the complete set of supported conservation practices at the national level would indicate an investment of tens of billions of dollars over the past several decades. Clear successes have resulted from these investments. National estimates of soil erosion rates exceeding soil loss tolerance rates show declines of 35 and 45% between 1982 and 2003 for highly erodible land (HEL) and non-HEL land (USDA-NRCS, 2003).

Argabright et al. (1996) further report that erosion rates declined 42% between 1930 and 1992 in the northern Mississippi Loess Hills Region (Major Land Resource Area 105), which transcends portions of Iowa, Illinois, and Wisconsin. Another Indicator of environmental improvement is surveyed statewide average fertilizer rates (USDA-ERS, 2007) that declined in the late 1980s and have remained relatively stable since the late 1990s[1], while corn grain yields (USDA-NASS, 2007) have steadily increased (Figure 1), implying better utilization of nitrogen inputs. Other examples of environmental benefits can be observed including sizeable enrollments of HEL and other vulnerable land in the CRP and similar programs.

Despite these clear signs of progress, acute nonpoint source environmental problems persist in Iowa, including areas where intensive efforts to reduce pollutant losses have occurred. For example, extensive installation of terraces in the Sny Magill Creek watershed in northeast Iowa resulted in only a 7% reduction in sediment after 10 years of monitoring (Fields et al., 2005). Similar results were reported by Schilling et al. (2006) for the Walnut Creek watershed in Jasper County, Iowa, where restoration of prairie grasses from 1992 to 2005 (ultimately about 23.5% of the watershed area) resulted in no measurable reduction in sediment loss after 10 years of monitoring (although declines in nitrate losses were found). Monitoring data collected by the Des Moines Water Works, which serves over 300,000 people in central Iowa (DMWW, 2007), reveals that five-year running average nitrate concentrations have steadily increased near the outlet of the Raccoon River during the years of 1978 to 2004 (Jones, 2005) in spite of ongoing upstream conservation efforts.

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[1]Statewide average fertilizer application rates derived from fertilizer sales data generally show somewhat higher application rates (see ISUE, 2004). It is not clear if the upward trend in application rates shown in 2003 and 2005 is a short-term anomaly or gradual increase in fertilizer application rates.

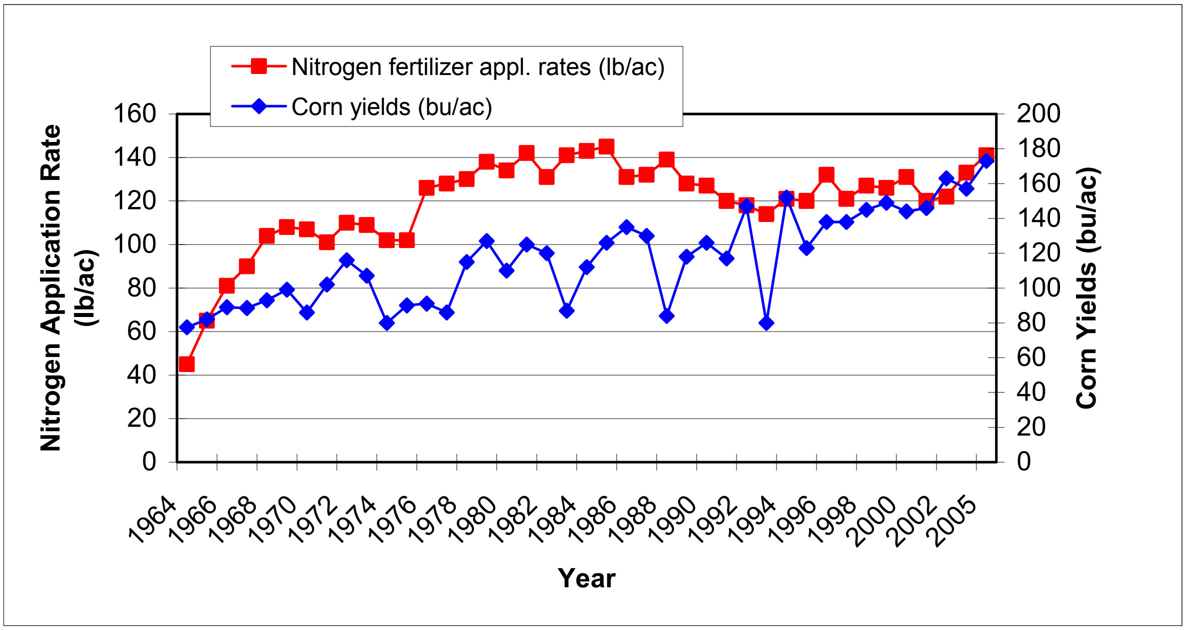

Figure 1. Iowa average annual nitrogen application rate and corn yield trends between 1964 and 2005 (data not reported for 2004 due to lack of reported nitrogen application rate data; Sources: USDA-NASS, 2007; USDA-ERS, 2007).

Other studies performed for larger regions including parts or all of Iowa further underscore the pervasiveness of the nonpoint source pollution problem in Iowa. Kalkoff et al. (2000) report that nitrogen and phosphorus levels measured in several large eastern Iowa watersheds, which drain to the Mississippi River, were among the highest found in the Corn Belt region and in the entire U.S. as part of the U.S. Geological Survey (USGS) National Water-Quality Assessment Program. Libra et al. (2004) estimated that Iowa contributed 20% of the nitrogen load to the Gulf of Mexico via the Mississippi River during 2000-2002, based on a statewide nutrient balance study that included nutrient load estimations for 68 watersheds that drain roughly 80% of the state. Goolsby et al. (2001) report that streams draining Iowa and Illinois accounted for an estimated 35% of the nitrogen discharge to the Gulf of Mexico for “average years” during 1980-1996. Alexander et al. (2007) suggest somewhat lower nitrogen loads originating from Iowa and the Upper Mississippi River Basin (UMRB), with the UMRB Gulf of Mexico nitrogen contribution estimated at about 33% (and 18% of the phosphorus load). Regardless of the exact contributions, Iowa is clearly a major source of the nitrogen and phosphorus discharged from the mouth of the Mississippi River. These nutrients have been implicated as the primary cause of the seasonal oxygen-depleted hypoxic zone which occurs in the Gulf of Mexico (USEPA 2007a; b), that has covered upwards of 20,000 km^2 in recent years (Rabalais et al., 2002; Turner et al., 2006).

Corn Ethanol Production: Increased Water Quality Pollution?

The explosive growth of biofuel production has dominated news headlines during much of the past three years in Iowa (2004-2007). Corn-based ethanol production has especially skyrocketed, with Iowa production levels reaching approximately 1.5 billion gallons in 2006, which equaled 28% of the total U.S. production (Figure 2). Brasher et al. (2007) reports that current U.S. ethanol production capacity has reached 6.9 billion gallons, with an expected increase to 13.5 billion gallons once all new facilities or facility expansions under construction are completed; equivalent Iowa production numbers stand at 1.98 and 3.8 billion gallons[2] (Hart, 2007). However, Brasher further reports that overcapacity already exists in the ethanol market, and that increasing production levels portend greater uncertainty in future ethanol markets and prices for corn producers in Iowa and other states. A number of factors will ultimately determine the future profitability of ethanol production, including critical decisions made at the federal congressional and state legislative levels.

[2]Both the U.S. volumes reported by Brasher and the Iowa volumes reported by Hart were for October 2007. Hart further reports expected U.S. future capacity at 14.5 billion gallons; the difference between the two estimates may reflect planned projects that were canceled, underscoring the volatile and fluid nature of the industry at this time.

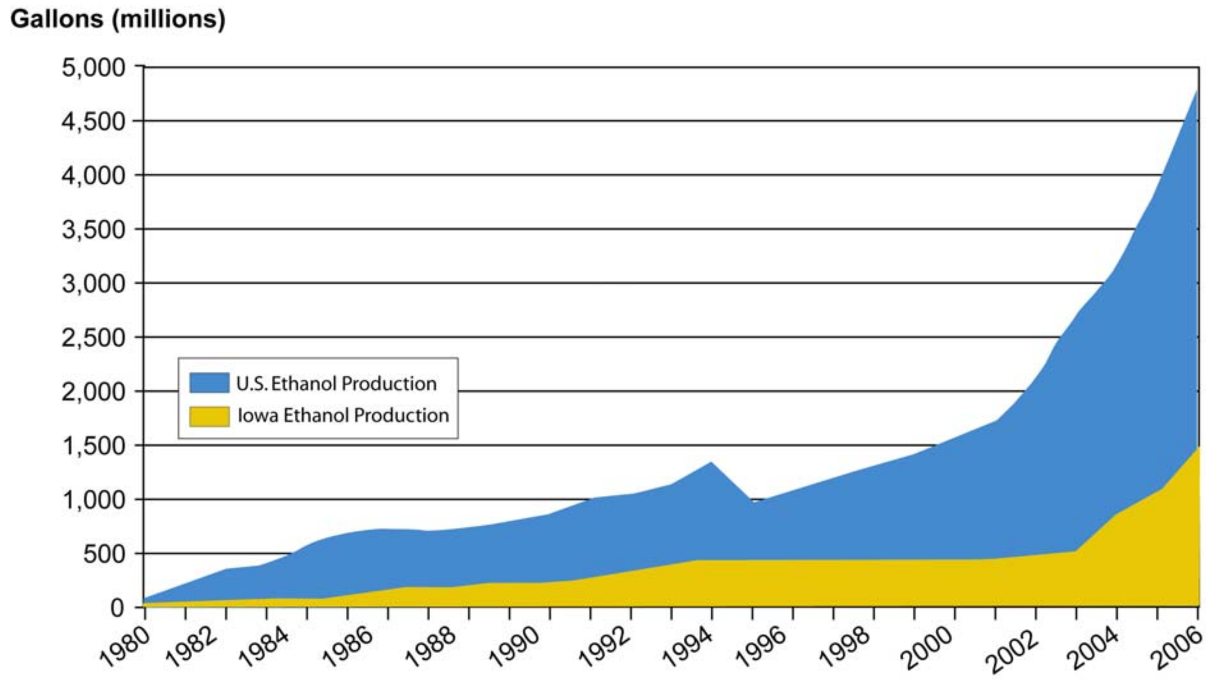

Figure 2. Total ethanol production in the United States and Iowa between 1980 and 2006 (Source: ICA, 2007).

Meanwhile, ongoing debate has focused on the true net energy balance and the associated real environmental impacts of grain-based biofuel production, especially corn ethanol production. Leading critics argue that corn ethanol production results in net negative energy benefits (e.g., Patzek et al., 2005; Pimental and Patzek, 2005). However, recent reviews by Farrell et al. (2006) and Hammerschlag (2006) counter the net negative energy balance argument, by pointing to an overall research consensus that corn ethanol production does yield a positive net energy balance and clearly requires less fossil fuel inputs than gasoline. Farrell et al. and Hammerschlag also show that the net energy benefits of cellulosic-based ethanol production would be much greater than the current grain-based approach that is standard in the industry. This fact has important implications for future cropping systems and potential resulting environmental impacts.

Quantifying the environmental impacts of corn ethanol production is also complex and controversial. Patzek et al. (2005) and Pimental and Patzek (2005) again argue that corn-based ethanol production results in multiple negative environmental externalities including drawdown of groundwater supplies that exceed recharge rates, increased atmospheric emissions of green house gases (GHGs), and greater export of pesticides and nutrients to stream systems from expanded corn production. A rising chorus of voices echo one or more of these concerns, including recent articles or reports published by the National Geographic Society (Bourne, 2007), the National Research Council (NAS, 2007), the Worldwatch Institute (2007), and the Des Moines Register (Clayworth, 2007; Elbert, 2007). However, conflicting results have been reported between different environmental impact studies, including recent analyses of GHG emissions resulting from corn ethanol production. Pimental and Patzek (2005) and Patzek et al. (2005) state that corn ethanol production results in overall greater atmospheric pollution and increased or neutral GHG emissions, as compared to petroleum-based fuel production. However, Babcock et al. (2007) concluded that corn ethanol production will result in reduced GHG emissions based on a life-cycle analysis of biofuel feedstocks, providing crop production shifts in other countries don't negate the GHG gains. A second life-cycle study performed by Adler et al. (2007) concluded that corn ethanol and soybean biodiesel production reduced GHGs by almost 40% relative to gasoline and diesel production

Complex questions also emerge regarding the more pertinent question of corn ethanol production impacts on water quality. Pimental and Patzek (2005), Patzek et al. (2005), NAS (2007), Bourne (2007), and Widenoja (2007) all point to increased fertilizer and pesticide use in corn production that will result inevitable increased nonpoint source pollution. The concerns expressed by these authors are based largely on anecdotal information rather than actual data. However, two recent studies (Simpson et al., 2008; Donner and Kucharik et al., 2008) do provide validation of the water quality concerns raised in the above studies. Simpson et al. project that increased acreage of corn could lead to higher losses of nitrogen and phosphorus by 37% and 25%, respectively, based primarily on inferences from previous field and large regional assessments. They further state that the resulting negative effects would be particularly acute in the Mississippi River Basin and that the use of dried distiller's grains (which are a by-product of the ethanol production process) as a livestock feed supplement could further exacerbate water quality problems. Donner and Kucharik project that export of dissolved inorganic nitrogen via the Mississippi and Atchafalaya rivers to the Gulf of Mexico could increase by 10-34% in response to meeting federal biofuel goals of 15 to 36 billion gallons by 2022.

In contrast, there are signals from some field studies in Iowa and Minnesota that indicate that current ethanol-driven cropping shifts from typical corn-soybean to rotations with more corn may not necessarily result in large nonpoint source pollution increases. Randall et al. (1997) report that total nitrate (NO_3-N) losses measured in tile drain effluent over 1990-1993 in southern Minnesota were only 7% higher for continuous corn (218 kg ha^{-1}) versus corn-soybean (203 kg ha^{-1}). Similar differences were also reported during 1990-93 for comparisons of NO_3-N measured in tile drains beneath continuous corn and corn-soybean cropping systems near Gilmore City in north central Iowa (IDALS, 1994). Baksh and Kanwar (2007) further found that average NO_3-N loadings measured in tile drainage outflow during 1993-1998 for continuous corn were 16.9 kg ha^{-1}, versus 13.7 and 13.3 kg ha^{-1} for two cropping systems of corn rotated with soybean. However, they also reported that average NO_3-N losses beneath continuous corn (64.9 kg ha^{-1}) were almost double those of the two corn-soybean cropping systems (both about 35.0 kg ha^{-1}) during 1990-92. The results of these studies reveal that NO_3-N leaching losses from soybeans can be similar to those reported for corn, but the results were influenced by several factors including variations in nitrogen application rates and precipitation that could warrant further investigation.

There are other potential impacts of biofuel production that also warrant investigation including shifts from CRP and other grassland into corn-dominated crop rotation, biomass removal of corn stover, and shifts into switchgrass or other biofuel crops that could greatly alter present Iowa agricultural landscapes. Secchi et al. (2007) show in a recent simulation study for Iowa that conversion from CRP land to corn-dominated cropping systems could result in proportionally much greater environmental impacts. They further point out that shifts to conventional tillage are expected for rotations with increased corn production, which could lead to greater soil erosion. On the other hand, shifts into switchgrass and similar perennial crops could provide extensive environmental benefits. Overall, these issues point to the need for further research on cropping and management system impacts on nonpoint source pollution in Iowa watersheds.

Statement of the Problem

It is clear that nonpoint source pollution remains a vexing and difficult problem to solve in Iowa and the Upper Midwest in general, and current corn ethanol production trends may exacerbate those problems. Questions linger about the effectiveness of in-field nutrient management adjustments and related practices in reducing nitrogen losses from cropland, and what exactly the best suite of practices is to reduce nutrient losses to Iowa stream systems.

One interesting potential mitigation strategy is the placement of more perennials/close grown crops on agricultural landscapes that will result in reduced nonpoint source pollution including nitrogen losses. To date, evaluation of perennial impacts on water quality at the watershed scale in Iowa have been very limited, and further research is definitely needed. Therefore, there is a need for systematic analysis of the potential environmental impacts of biofuel/ethanol-based production scenarios, such as expanded corn acreage and expanded acreage of perennials (such as switchgrass), should cellulosic ethanol production become reality (which has an obvious tie-in to the use of perennials to reduce nonpoint source pollution).

Simulation models can be an effective tool for evaluating biofuel cropping scenarios for cropping conditions. However, there is a need to further test existing models for current Iowa conditions, to ensure they are accurately replicating the effects of typically used cropping systems and management practices, before applying them to emerging and potential future biofuel scenarios. This research seeks to address this testing need by performing in-depth testing of a widely used water quality model that holds promise for application to biofuel related scenarios.

Case Study: The Boone River Watershed

The Boone River Watershed (BRW) is an intensively cropped region located in north central Iowa which exemplifies the Iowa agricultural production characteristics and water quality issues described above. The BRW was identified by Libra et al. (2004) as discharging some of the highest nitrogen loads during 2000-2002 among the 68 Iowa watersheds that were analyzed within their statewide nutrient balance study. The BRW has also been identified within the UMRB as both an area of freshwater biodiversity significance and a priority area for biodiversity conservation (Weitzell et al., 2003). The biodiversity conservation designation reflects the fact that the watershed has been identified as currently possessing a “relatively un-degraded stream ecosystem,” but that it is also very vulnerable to future increased degradation (Neugarten and Braun, 2005). Potential biodiversity threats listed by Neugarten and Braun include consistently high in-stream nitrogen concentrations, farm production methods that may be ecologically harmful, and inadequate treatment of wastewater. Ethanol production also poses potential environmental impacts, with one ethanol refinery located within the watershed and several others in operation or under construction in the north central Iowa region.

The research I present here has been performed in the context of a larger CARD research study, which was initiated to evaluate a broad set the potential economic and environmental impacts of alternative land use and management practices for the BRW. I specifically focus on the environmental component of the modeling system, which features the Soil and Water Assessment Tool (SWAT) model (Arnold and Forher, 2005; Gassman et al., 2007) that is used worldwide and has been foundational in much of our CARD research team’s efforts during the past decade. The goal of the overall CARD BRW study is to identify strategies that can potentially mitigate loss of nitrates and other pollutants from agricultural cropland, which could lead to improved water quality in the BRW stream network as well as in downstream ecosystems such as the Gulf of Mexico. The specific research I report here is centered on testing SWAT for BRW baseline conditions, including accounting for the tile drained landscapes and intensive nutrient inputs from fertilizer and livestock manure. Insights gained from this research may also be transferable to other watersheds that drain parts of the Des Moines Lobe, which are generally characterized as regions of high nitrogen export.

Overview of Dissertation Chapters

The study is divided into seven chapters including this initial general introduction. The remaining chapters are: (2) the Soil and Water Assessment Tool: Developmental History, Applications, and Future Directions, (3) Development of a Common Land Unit (CLU) – Based Modeling System Framework for the Boone River Watershed, (4) SWAT Baseline Simulation Results for the Boone River Watershed: Analysis and Issues Regarding Two Simulation Approaches, (5) An In-Depth Assessment of Corn and Soybean Yields Predicted with SWAT for the Boone River Watershed, and (6) General Conclusions.

Chapter Two is an extensive invited paper (Gassman et al., 2007) which was published in *Transactions of the American Society of Agricultural and Biological Engineers* and chronicles the development of SWAT, worldwide applications, strengths and weaknesses, and future research needs. This chapter documents the successful application of SWAT for a wide variety of environmental conditions and watershed scales, and that it has proven to be a very flexible tool for assessing a wide range of land use, climatic, management, and other scenarios for hydrologic and/or pollutant impact assessments. However, the review also reveals that the model has performed poorly for some conditions and that a wide range of improvements are required to address emerging 21st century water quality research and water resources needs. The literature review performed within this chapter undergirds the research presented in chapters three through seven.

Chapter 3 describes the modeling framework that has been developed for the Boone River Watershed. The framework has been constructed on the basis of Common Land Units (CLUs), which are essentially field-sized land parcels and are further described by NAS (2007a). Land use, conservation practices, and soil data have been collected at the CLU level, forming an extremely intensive data set to support simulation scenarios for the watershed. These data are described in detail in this chapter, along with climate, topographic, distribution of tile drainage, and other data key data inputs. The interface between the data inputs and the suite of available models at CARD is described, with an emphasis on the modeling structure used to support the SWAT simulations including the interactive SWAT (i_SWAT) software developed in-house at CARD which is a key model interface tool in our simulation approach.

The SWAT baseline calibration and validation results for the Boone River watershed are reported in Chapter 4. Two different calibration/validation approaches are described which reflect differences between the “traditional” (USDA-NRCS, 2004) and “new” (Kannan et al., 2007) Runoff Curve Number (RCN) options provided in SWAT2005, as well as other differences in input assumptions. Differences in the hydrologic and pollutant loss predictions are presented including problems encountered in fully calibrating the model with the new RCN approach. The implications of the two approaches are also discussed, particularly in regards to the different hydrologic balance and nitrogen movement results.

Chapter 5 presents an in-depth assessment of the SWAT corn and soybean yield results for the two baseline approaches discussed in Chapter 4, and also introduces yield predictions generated with the Environmental Policy Impact Climate (EPIC) model (Williams et al., 1990; Gassman et al., 2005) for comparison purposes. Very few studies report comparisons of SWAT crop yield predictions with measured data and thus there is an urgent need to test the biomass and grain yield capabilities of the model. The results provide some interesting insights into the effects of the two hydrologic calibration approaches on the crop yield predictions and reveal weaknesses that need to be addressed in future SWAT development efforts. The results also show that SWAT corn yield predictions are very sensitive to tillage, and that further research is needed to verify if the current responses are consistent with field measurements.

The final chapter (Chapter 6) provides an overall set of conclusions for the study including recommendations for future research.

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CHAPTER 2: THE SOIL AND WATER ASSESSMENT TOOL: HISTORICAL DEVELOPMENT, APPLICATIONS, AND FUTURE DIRECTIONS

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Abstract

The Soil and Water Assessment Tool (SWAT) model is a continuation of nearly 30 years of modeling efforts conducted by the USDA Agricultural Research Service (ARS). SWAT has gained international acceptance as a robust interdisciplinary watershed modeling tool as evidenced by international SWAT conferences, hundreds of SWAT-related papers presented at numerous other scientific meetings, and dozens of articles published in peer-reviewed journals. The model has also been adopted as part of the U.S. Environmental Protection Agency (USEPA) Better Assessment Science Integrating Point and Nonpoint Sources (BASINS) software package and is being used by many U.S. federal and state agencies, including the USDA within the Conservation Effects Assessment Project (CEAP). At present, over 250 peer-reviewed published articles have been identified that report SWAT applications, reviews of SWAT components, or other research that includes SWAT. Many of

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these peer-reviewed articles are summarized here according to relevant application categories such as streamflow calibration and related hydrologic analyses, climate change impacts on hydrology, pollutant load assessments, comparisons with other models, and sensitivity analyses and calibration techniques. Strengths and weaknesses of the model are presented, and recommended research needs for SWAT are also provided.

Introduction

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

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

SWAT Developmental History and Overview

The development of SWAT is a continuation of USDA Agricultural Research Service (ARS) modeling experience that spans a period of roughly 30 years. Early origins of SWAT can be traced to previously developed USDA-ARS models (Figure 1) including the Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) model (Knisel, 1980), the Groundwater Loading Effects on Agricultural Management Systems (GLEAMS) model (Leonard et al., 1987), and the Environmental Impact Policy Climate (EPIC) model (Izaurralde et al., 2006), which was originally called the Erosion Productivity Impact Calculator (Williams, 1990). The current SWAT model is a direct descendant of the Simulator for Water Resources in Rural Basins (SWRRB) model (Arnold and Williams, 1987), which was designed to simulate management impacts on water and sediment movement for ungauged rural basins across the U.S.

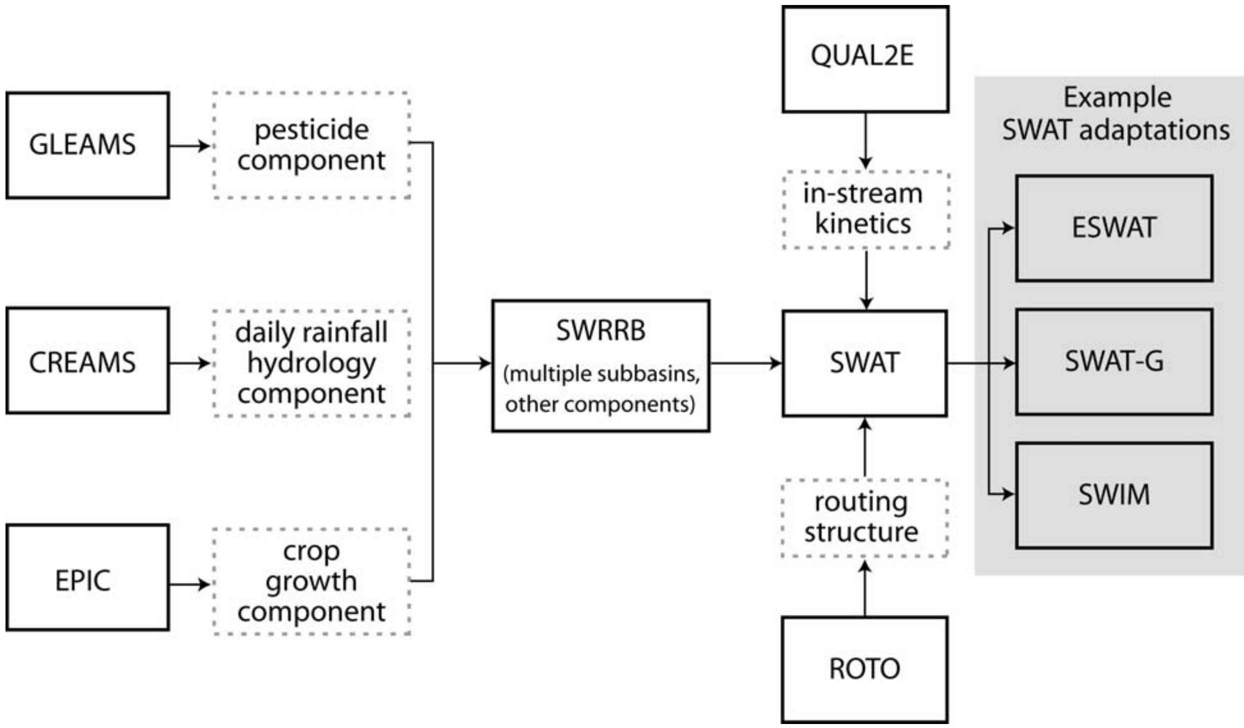

Figure 1. Schematic of SWAT developmental history, including selected SWAT adaptations.

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

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

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

Swat Overview

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

Climatic Inputs and HRU Hydrologic Balance

Climatic inputs used in SWAT include daily precipitation, maximum and minimum temperature, solar radiation data, relative humidity, and wind speed data, which can be input from measured records and/or generated. Relative humidity is required if the Penman-Monteith (Monteith, 1965) or Priestly-Taylor (Priestly and Taylor, 1972) evapotranspiration (ET) routines are used; wind speed is only necessary if the Penman-Monteith method is used. Measured or generated sub-daily precipitation inputs are required if the Green-Ampt infiltration method (Green and Ampt, 1911) is selected. The average air temperature is used to determine if precipitation should be simulated as snowfall. The maximum and minimum temperature inputs are used in the calculation of daily soil and water temperatures. Generated weather inputs are calculated from tables consisting of 13 monthly climatic variables, which are derived from long-term measured weather records. Customized climatic input data options include: (1) simulation of up to ten elevation bands to account for orographic precipitation and/or for snowmelt calculations, (2) adjustments to climate inputs to simulate climate change, and (3) forecasting of future weather patterns, which is a new feature in SWAT2005.

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

A storage routing technique is used to calculate redistribution of water between layers in the soil profile. Bypass flow can be simulated, as described by Arnold et al. (2005), for soils characterized by cracking, such as Vertisols. SWAT2005 also provides a new option to simulate perched water tables in HRUs that have seasonal high water tables. Three methods for estimating potential ET are provided: Penman-Monteith, Priestly-Taylor, and Hargreaves

(Hargreaves et al., 1985). ET values estimated external to SWAT can also be input for a simulation run. The Penman-Monteith option must be used for climate change scenarios that account for changing atmospheric CO_2 levels. Recharge below the soil profile is partitioned between shallow and deep aquifers. Return flow to the stream system and evapotranspiration from deep-rooted plants (termed "revap") can occur from the shallow aquifer. Water that recharges the deep aquifer is assumed lost from the system.

Cropping, Management Inputs, and HRU-Level Pollutant Losses

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

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

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

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

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

A final feature in SWAT2005 is a new automated sensitivity, calibration, and uncertainty analysis component that is based on approaches described by van Griensven and

Meixner (2006) and van Griensven et al. (2006). Further discussion of these tools is provided in the Sensitivity, Calibration, and Uncertainty Analyses Section.

SWAT Adaptations

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

Geographic Information System Interfaces and Other Tools

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

The ArcView-SWAT (AVSWAT) interface tool (Di Luzio et al., 2004a, 2004b) is designed to generate model inputs from ArcView 3.x GIS data layers and execute SWAT2000 within the same framework. AVSWAT was incorporated within the U.S. Environmental Protection Agency (USEPA) Better Assessment Science Integrating point and Nonpoint Sources (BASINS) software package versions 3.0 (USEPA, 2006a), which provides GIS utilities that support automatic data input for SWAT2000 using ArcView (Di Luzio et al., 2002). The most recent version of the interface is denoted AVSWAT-X, which provides additional input generation functionality, including soil data input from both the

USDA-NRCS State Soils Geographic (STATSGO) and Soil Survey Geographic (SSURGO) databases (USDA-NRCS, 2007a, 2007b) for applications of SWAT2005 (Di Luzio et al., 2005; SWAT, 2007b). Automatic sensitivity, calibration, and uncertainty analysis can also be initiated with AVSWAT-X for SWAT2005. The Automated Geospatial Watershed Assessment (AGWA) interface tool (Miller et al., 2007) is an alternative ArcView-based interface tool that supports data input generation for both SWAT2000 and the KINEROS2 model, including options for soil inputs from the SSURGO, STATSGO, or United Nations Food and Agriculture Organization (FAO) global soil maps. Both AGWA and AVSWAT have been incorporated as interface approaches for generating SWAT2000 inputs within BASINS version 3.1 (Wells, 2006).

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

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

SWAT Applications

Applications of SWAT have expanded worldwide over the past decade. Many of the applications have been driven by the needs of various government agencies, particularly in the U.S. and the European Union, that require direct assessments of anthropogenic, climate change, and other influences on a wide range of water resources or exploratory assessments of model capabilities for potential future applications.

One of the first major applications performed with SWAT was within the Hydrologic Unit Model of the U.S. (HUMUS) modeling system (Arnold et al., 1999a), which was implemented to support USDA analyses of the U.S. Resources Conservation Act Assessment of 1997 for the conterminous U.S. The system was used to simulate the hydrologic and/or pollutant loss impacts of agricultural and municipal water use, tillage and cropping system trends, and other scenarios within each of the 2,149 U.S. Geological Survey (USGS) 8-digit Hydrologic Cataloging Unit (HCU) watersheds (Seaber et al., 1987), referred to hereafter as "8-digit watersheds". Figure 2 shows the distribution of the 8-digit watersheds within the 18 Major Water Resource Regions (MWRRs) that comprise the conterminous U.S. SWAT is also being used to support the USDA Conservation Effects Assessment Project, which is designed to quantify the environmental benefits of conservation practices at both the national and watershed scales (Mausbach and Dedrick, 2004). SWAT is being applied at the national level within a modified HUMUS framework to assess the benefits of different conservation practices at that scale. The model is also being used to evaluate conservation practices for watersheds of varying sizes that are representative of different regional conditions and mixes of conservation practices.

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

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

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

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

Specific SWAT Applications

SWAT applications reported in the literature can be categorized in several ways. For this study, most of the peer-reviewed articles could be grouped into the nine subcategories listed in Table 1, and then further broadly defined as hydrologic only, hydrologic and

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

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

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

pollutant loss, or pollutant loss only. Reviews are not provided for all of the articles included in the Table 1 summary; a complete list of the SWAT peer-reviewed articles is provided at the SWAT web site (SWAT, 2007c), which is updated on an ongoing basis.

Hydrologic Assessments

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

An extensive list of R^2 and NSE statistics is presented in Table 2 for 115 SWAT hydrologic calibration and/or validation results reported in the literature. These statistics provides valuable insight regarding the hydrologic performance of the model across a wide spectrum of conditions. To date, no absolute criteria for judging model performance have been firmly established in the literature. However, Moriasi et al. (2007) propose that NSE values should exceed 0.5 in order for model results to be judged as satisfactory for hydrologic and pollutant loss evaluations performed on a monthly time step (and that appropriate relaxing and tightening of the standard be performed for daily and annual time step evaluations, respectively). Assuming this criterion for both the NSE and R^2 values at all time steps, the majority of statistics listed in Table 2 would be judged as adequately replicating observed streamflows and other hydrologic indicators. However, it is clear that poor results resulted for parts or all of some studies. The poorest results generally occurred for daily predictions, although this was not universal (e.g., Grizzetti et al., 2005). Some of the

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

					Calibration						Validation					
		Drainage Area		Time Period (C = calib.,	Daily		Monthly		Annual		Daily		Monthly		Annual	
Reference	Watershed	(km^2)[a]	Indicator	V = valid.)	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
Afinowicz et al. (2005)	North Fork of the Upper Guadalupe River (Texas)	60	Stream flow	C: 1992-1996 V: 1997 - Sept. 2003		0.4		0.29				0.09		0.5		
Arabi et al. (2006b)[b]	Dreisbach and Smith Fry (Indiana)	6.2 and 7.3	Stream flow	C: 1975 - May 1977 V: June 1977 - 1978			0.92 and 0.86	0.84 and 0.73					0.87 and 0.81	0.73 and 0.63		
			Surface runoff				0.91 and 0.84	0.80 and 0.62					0.88 and 0.84	0.75 and 0.63		
Arnold and Allen (1996)	Goose Creek, Hadley Creek, and Panther Creek (Illinois)	122 to 246	Surface runoff	Varying periods									0.79 to 0.94			
			Ground water flow										0.38 to 0.51			
			Total stream flow										0.63 to 0.95			
Arnold et al. (2000)	Upper Mississippi River (north central U.S.)	491,700	Stream flow	C: 1961-1980 V: 1981-1985			0.63						0.65			
Arnold et al. (2005)	USDA-ARS Y-2 (Texas)	0.53	Crack flow	1998-1999							0.84					
			Surface runoff	1998-1999							0.87					
Arnold et al. (1999a)[c]	Conterminous U.S. (Figure 2)	--	Runoff (by state)	20-year period											0.78	
			(by soils)												0.66	
Arnold et al. (1999b)	35 8-digit watersheds (Texas)	2,253 to 304,620	Stream flow	1965-1989											0.23 to 0.96	-1.1 to 0.87
	Three 6-digit watersheds[c] (Texas)	--	Stream flow	1965-1989									0.57 to 0.87	0.53 to 0.86		
Bärlund et al. (2007)[c],[d]	Lake Pyhäjärvi (Finland)	--	Stream flow	1990-1994		0.48										
Behera and Panda (2006)	Kapgari (India)	9.73	Surface runoff	C: 2002 V: 2003 (rainy season)	0.94	0.88					0.91	0.85				

Table 2 (continued)

		Drainage		Time Period	Calibration						Validation					
		Area		(C = calib.,	Daily		Monthly		Annual		Daily		Monthly		Annual	
Reference	Watershed	(km^2)[a]	Indicator	V = valid.)	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
Benaman et al. (2005)	Cannonsville Reservoir (New York); C: four gauges, V: two gauges	37 to 913	Stream flow	C: 1994 - July 1999 V: 1990-1993			0.72 to 0.80	0.63 to 0.78					0.73 and 0.80	0.62 and 0.76		
Benham et al. (2006)	Shoal Creek (Missouri); upstream gauge	367	Stream flow	C: May 1999 - June 2000 V: June 2001 - Sept. 2002	0.40	0.21	0.70	0.63			0.61	0.54	0.61	0.66		
Binger (1996)[e]	Goodwin Creek (Mississippi); 14 gauges	0.05 to 21.3	Stream flow	V: 1982-1991 (140 r^2 statistics)											93 ≥ 0.90	
Bosch et al. (2004)[f,g]	Subwatershed J, Little River (Georgia, U.S.)	22.1	Stream flow	1997-2002								-0.24 to -0.03		0.55 to 0.80		
Bouraoui et al. (2005)[h]	Medjerda River (Algeria and Tunisia); three gauges	163 to 16,000	Stream flow	Sept. 1988 - March 1999							0.44 to 0.69	0.23 to 0.41	0.62 to 0.84	0.53 to 0.84		
Bouraoui et al. (2002)	Ouse (U.K.); three gauges	980 to 3,500	Stream flow	1986-1990		0.39 to 0.77										
Bouraoui et al. (2004)	Vantaanjoki (Finland)	1,682	Stream flow	1965-1984										0.87		
	Subwatershed	295		1982-1984		0.81										
Cao et al. (2006)	Motueka River (New Zealand); seven gauges	47.9 to 1,756.6	Stream flow	C: 1990-1994 V: 1995-2000	0.52 to 0.82	0.36 to 0.78			0.64 to 0.95		0.41 to 0.75	0.35 to 0.72				
Cerucci and Conrad (2003)	Townbrook (New York)	36.8	Stream flow	Oct. 1998 - Sept. 2000			0.72									
Chanasyk et al. (2003)	Three watersheds (Saskatchewan)	0.015 to 0.023	Surface runoff	1999-1900		-35.7 to -0.005										
Chaplot et al. (2004)	Walnut Creek (Iowa)	51.3	Stream flow	1991-1998			0.73									
Cheng et al. (2006)	Heihe River (China)	7,241	Stream flow	C: 1992-1997 V: 1998-1999			0.80	0.78					0.78	0.76		
Chu and Shirmohammadi (2004)[i]	Warner Creek (Maryland)	3.46	Stream flow	C: 1994-1995 V: 1996-1999			0.66	0.52					0.69	0.63		
			Surface runoff				0.43	0.35					0.88	0.77		
			Sub-surface runoff				0.56	0.27					0.47	0.42		

Table 2 (continued)

Reference	Watershed	Drainage Area (km^2)[a]	Indicator	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Coffey et al. (2004)[e]	University of Kentucky ARC (Kentucky)	5.5	Stream flow	1995 and 1996	0.26 and 0.40	0.09 and 0.15	0.70 and 0.88	0.41 and 0.61								
Conan et al. (2003a)[c,i]	Coët-Dan (France)	12	Stream flow	C: 1995-1996 V: 1997-1999		0.79						0.42		0.87		
	Subwatershed		Stream flow	V: 1994 - Feb. 1999										0.83		
Conan et al. (2003b)	Upper Guadiana River (Spain)	18,100	Stream flow	1975-1991								0.45				
Cotter et al. (2003)	Moores Creek (Arkansas)	18.9	Stream flow	1997-1998	0.76											
Di Luzio et al. (2005)	Goodwin Creek (Mississippi)	21.3	Surface runoff	1982-1993									0.90 to 0.95	0.81 to 0.97		
Di Luzio and Arnold (2004)[j]	Blue River (Oklahoma)	1,233	Stream flow	1994-2000 (auto. calib.)	0.24 to 0.99	0.15 to 0.99										
				(manual calib.)	0.01 to 0.98	-102 to 0.80										
Di Luzio et al. (2002)	Upper North Bosque River (Texas)	932.5	Stream flow	1993 - July 1998										0.82		
Du et al. (2005)[c]	Walnut Creek (Iowa); Subwatershed (site 310) and watershed outlet	51.3	Stream flow	C: 1992-1995 V: 1996-1999 (SWAT2000)		0.39 and 0.47		0.36 to 0.72				0.35 and 0.32		0.13 and 0.56		
	Subwatershed (site 210)	--	Tile flow	(SWAT2000)		-0.15		-0.33				-0.16		-0.42		
	Subwatershed (site 310) and watershed outlet	51.3	Stream flow	(SWAT-M)[i]		0.55 and 0.51		0.84 and 0.88				-0.11 and 0.49		0.72 and 0.82		
	Subwatershed (site 210)	--	Tile flow	(SWAT-M)[i]		-0.23		0.67				-0.12		0.70		
Eckhardt et al. (2002)	Dietzhölze (Germany)	81	Stream flow	1991-1993 (SWAT99.2)		-0.17										
				(SWAT-G)[i]		0.76										
El-Nasr et al. (2005)	Jeker (Belgium)	465	Stream flow	C: June 1986 - April 1989 V: June 1989 - April 1992	0.45	0.39					0.55	0.60				

Table 2 (continued)

Reference	Watershed	Drainage Area (km^2)[a]	Indicator	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Fontaine et al. (2002)	Wind River (Wyoming)	4,999	Stream flow	1991-1996 (new snowmelt routine)												0.86
				1991-1996 (old routine)												-0.70
Fontaine et al. (2001)	Spring Creek (South Dakota)	427	Stream flow	1987-1995			0.62		0.94							
Francos et al. (2001)[k]	Kerava River (Finland)	400	Stream flow	1985-1994										0.65		
Geza and McCray (2007)	Turkey Creek (Colorado)	126	Stream flow	1998-2001 (SSURGO soils)				0.70								
				(STATSGO soils)				0.61								
Gikas et al. (2005)[c,d]	Vistonis Lagoon (Greece); nine gauges	1,349	Stream flow	C: May 1998 - June 1999 V: Nov. 1999 - Jan. 2000	0.71 to 0.89						0.72 to 0.91					
Gitau et al. (2004)	Town Brook (New York)	36.8[l]	Stream flow	1992-2002			0.76	0.44	0.99	0.84						
Gosain et al. (2005)[c,i]	Palleru River (India)	--	Stream flow	1972-1994									0.61	0.87		
Govender and Everson (2005)	Cathedral Park Research C VI (South Africa)	0.68	Stream flow	C: 1991 V: 1990-1995 (auto. calib.)	0.86						0.65					
				V: 1990-1995 (manual calib.)							0.68					
Green et al. (2006)	South Fork of the Iowa River (Iowa)	580.5	Stream flow	C: 1995-1998 V: 1999-2004 (scenario 1)	0.7	0.7	0.9	0.9	1.0	0.7	0.5	0.4	0.6	0.5	0.7	0.6
				C: 1995-2000 V: 2001-2004 (scenario 2)	0.7	0.7	0.9	0.8	0.9	0.9	0.3	0.2	0.6	0.5	0.7	-0.8
Grizzetti et al. (2005)[c]	Parts of four watersheds (U.K.); C: one gauge, V: two gauges, annual: 50 gauges	8,900	Stream flow	C and V: 1995-1999		0.75		0.86								0.66
Grizzetti et al. (2003)[c]	Vantaanjoki (Finland); C: one gauge, V: three gauges	295 and 1,682	Stream flow	Varying periods		0.81					0.57 to 0.66	0.75 to 0.81				
Hanratty and Stefan (1998)	Cottonwood (Minnesota)	3,400	Stream flow	1967-1991				0.78								
Hao et al. (2004)	Lushi (China)	4,623	Stream Flow	C: 1992-1997 V: 1998-1999			0.87	0.87			0.84	0.81				

Table 2 (continued)

Reference	Watershed	Drainage Area (km^2)[a]	Indicator	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Hernandez et al. (2000)	Watershed 11, Walnut Gulch (Arizona)	8.2	Stream flow	1966-1974 (1 vs. 10 rain gauges)					0.33 and 0.57							
Heuvelmans et al. (2006)[j]	25 watersheds (Schelde River basin, Belgium)	2.2 to 209.9	Stream flow	C: 1990-1995 V: 1996-2001		0.70 to 0.95						0.67 to 0.92				
Holvoet et al. (2005)	Nil (Belgium)	32	Stream flow	Nov. 1998 - Nov. 2001		0.53										
Jha et al. (2004a)[c]	Maquoketa River (Iowa)	4,776	Stream flow	1981-1990							0.68		0.76		0.65	
Jha et al. (2004b)	Upper Mississippi River (north central U.S.)	447,500	Stream flow	C: 1989-1997 V: 1980-1988			0.75	0.67	0.91	0.91			0.70	0.59	0.89	0.86
Jha et al. (2006)	Upper Mississippi River (north central U.S.)	447,500	Stream flow	C: 1968-1987 V: 1988-1997	0.67	0.58	0.74	0.69	0.82	0.75	0.75	0.65	0.82	0.81	0.91	0.90
Jha et al. (2007)[m]	Raccoon River (Iowa); Van Meter gauge	8,930	Stream flow	C: 1981-1992 V: 1993-2003			0.87	0.87	0.97	0.97			0.89	0.88	0.94	0.94
Kalin and Hantush (2006)[c,i]	Pocono Creek (Pennsylvania)	98.8	Base flow	C: July 2002 - May 2004 V: June 2004 - April 2005 (rain gauge)			0.30	0.08					0.13	-0.26		
			Surface runoff	(rain gauge)			0.77	0.77					0.83	0.73		
			Stream flow	(rain gauge)	0.74	0.74	0.85	0.83			0.70	0.64	0.81	0.66		
			Base flow	(NEXRAD)			0.31	0.05					0.06	-0.40		
			Surface runoff	(NEXRAD)			0.79	0.79					0.84	0.77		
			Stream flow	(NEXRAD)	0.74	0.73	0.85	0.84			0.66	0.62	0.89	0.75		
Kang et al. (2006)[k]	Baran (South Korea)	29.8	Surface runoff	C: 1996-1997 V: 1999-2000	0.93	0.93					0.87	0.87				
Kannan et al. (2007b)[g]	Colworth (U.K.)	1.4	Stream flow	C: Oct. 1999 - 2001 V: 2001 - May 2002 (CN approach)		0.60 and 0.61						0.54 and 0.60				
				(Green-Ampt)		0.51 and 0.54						0.56 and 0.51				
Kaur et al. (2004)	Nagwan (India)	9.58	Surface runoff	Varying periods	0.76	0.71					0.83	0.54				

Table 2 (continued)

Reference	Watershed	Drainage Area (km^2)[a]	Indicator	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
King et al. (1999)[e]	Goodwin Creek (Mississippi)	21.3	Stream flow	1982-1989 (curve number)								0.43		0.84		0.55
				(Green-Ampt)								0.53		0.69		0.81
Kirsch et al. (2002)	Rock River (Wisconsin); two gauges	23.2 and 190	Stream flow	1989-1995											0.86 and 0.74	0.41 and 0.61
	12 USGS gauges[c]	9,708	Stream flow	Varying periods					0.28 to 0.98	0.18 to 0.84						
Limaye et al (2001)	Dale Hollow (Tennessee); subwatershed	523	Stream flow	C: 1966-1990 V: 1991-1993		0.42		0.74				0.45		0.80		
Lin and Radcliffe (2006)	Upper Etowah River (Georgia, U.S.)	1,580	Stream flow	C: 1983-1992 V: 1993-2001		0.61		0.86				0.62		0.89		
Manguerra and Engel (1998)[g]	Greenhill (Indiana)	113.4	Stream flow	1991-1995				0.93 to 1.0								
Mapfumo et al. (2004)[i]	Three watersheds (Saskatchewan)	1.53 to 2.26	Soil water	C: 1998 V: 1999-2000 (overall results)	0.84	0.77					0.72	0.70				
Mishra et al. (2007)	Banha (India)	17	Surface runoff	C: 1996 V: 1997-2001	0.93	0.70	0.99	0.99			0.78	0.60	0.92	0.88		
Moon et al. (2004)[i]	Cedar Creek (Texas)	2,608	Stream flow	1999-2001 (rain gauge)							0.53	0.48	0.86	0.78		
				(NEXRAD)							0.58	0.57	0.84	0.82		
Moriasi et al. (2007)[c]	Leon River (Texas); C: seven gauges, V: five gauges	9,312	Stream flow	--				0.66 to 1.0						0.69 to 1.0		
Muleta and Nicklow (2005a)	Big Creek (Illinois)	86.5	Stream flow	1999-2001		0.69										
Muleta and Nicklow (2005b)	Big Creek (Illinois); separate gauges for C and V	23.9 and 86.5	Stream flow	C: June 1999 - Aug. 2001 V: April 2000 - Aug. 2001		0.74						0.23				
Narasimhan et al. (2005)[c]	Six watersheds (Texas); 24 gauges	10,320 to 29,664	Stream flow	Varying periods (overall annual average)					0.75	0.75					0.70	0.70
				(range across 24 gauges)					0.54 to 0.99	0.52 to 0.99					0.63 to 1.00	0.55 to 0.97

Table 2 (continued)

Reference	Watershed	Drainage Area (km^2)[a]	Indicator	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Nasr et al. (2007)[d]	Clarianna, Dripsey, and Oona Water (Ireland)	15 to 96	Stream flow	Varying periods		0.72 to 0.91										
Olivera et al. (2006)	Upper Seco Creek (Texas)	116	Stream flow	C: 1991-1992 V: 1993 - June 1994		0.67		0.88				0.33		0.90		
Perkins and Sophocleous (1999)[h]	Lower Republican River (Kansas)	2,569	Stream flow	1977-1994			0.85									
Peterson and Hamlet (1998)[i]	Ariel Creek (Pennsylvania)	39.4	Stream flow	May 1992 - July 1994		0.04		0.14								
				May 1992 - July 1994 (no snowmelt events)		0.2		0.55								
Plus et al. (2006)[h]	Thau Lagoon (France); two gauges	280	Stream flow	Sept. 1993 - July 1996	0.68 and 0.45											
Qi and Grunwald (2005)	Sandusky River (Ohio); five gauges	90.3 to 3,240	Surface water	C: 1998-1999 V: 2000-2001				0.31 to 0.65						-0.04 to 0.75		
			Ground water					-9.1 to 0.60						-0.57 to 0.22		
			Total flow					0.31 to 0.81						0.40 to 0.73		
Rosenberg et al. (2003)[c]	Conterminous U.S. (18 MWRRs; Figure 2)		Water yield	1961-1990 (overall mean)											0.92	
				1961-1990 (8-digit means by MWRR)											0.03 to 0.90	
Rosenthal and Hoffman (1999)	Leon River (Texas)	7,000	Stream flow	1972-1974										0.57		
Rosenthal et al. (1995)[c,f,i]	Lower Colorado River (Texas); Bay City gauge	8,927	Stream flow	1980-1989									0.75	0.69		
	Upstream gauges												0.69 to 0.90			
Saleh et al. (2000)[n]	Upper North Bosque River (Texas); C: one gauge, V:11 gauges	932.5	Stream flow	Oct. 1993 - Aug. 1995				0.56						0.99		

Table 2 (continued)

Reference	Watershed	Drainage Area (km^2)[a]	Indicator	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Saleh and Du (2004)	Upper North Bosque River (Texas)	932.5	Stream flow	C: 1994 - June 1995 V: July 1995- July 1999		0.17		0.50				0.62		0.78		
Salvetti et al. (2006)	Lombardy Plain Region (Po River basin, Italy)	16,000	Stream flow	1984-2002		0.50		>0.70								
Santhi et al. (2001a)[c,o]	Bosque River (Texas); two gauges	4,277	Stream flow	Varying periods			0.80 and 0.89	0.79 and 0.83	0.88 and 0.66	0.86 and 0.72			0.92 and 0.80	0.87 and 0.62		
Santhi et al. (2006)[c]	West Fork (Texas); two gauges	4,554	Stream flow	1982-2001			0.61 and 0.81	0.12 and 0.72	0.88 and 0.86	0.84 and 0.78						
Schomberg et al. (2005)[c]	Three watersheds (Minnesota); two watersheds (Michigan)	829 to 3,697	Stream flow	Varying periods	0.10 to 0.28	-1.3 to 0.25	0.35 to 0.58	-1.4 to 0.49								
Secchi et al. (2007)[c]	13 watersheds (Iowa)	2,051 to 37,496	Stream flow	Varying periods (composite statistics)									0.76	0.75	0.91	0.90
Singh et al. (2005)	Iroquois River (Illinois and Indiana)	5,568	Stream flow	C: 1987-1995 V: 1972-1986		0.79		0.88				0.74		0.84		
Spruill et al. (2000)	University of Kentucky ARC (Kentucky)	5.5	Stream flow	C: 1996 V: 1995		0.19		0.89				-0.04		0.58		
Srinivasan et al. (2005)[i]	Watershed FD-36 (Pennsylvania)	0.395	Stream flow	1997-2000		0.62										
Srinivasan and Arnold (1994)	Upper Seco Creek (Texas)	114	Stream flow	Jan. 1991 - Aug. 1992			0.82									
Srinivasan et al. (1998)[c]	Richland-Chambers Reservoir (Texas); two gauges	5,000	Stream flow	C: 1965-1969 V: 1970-1984			0.87 and 0.84	0.77 and 0.84					0.65 and 0.82	0.52 and 0.82		
Srivastava et al. (2006)[i]	West Fork Brandywine Creek (Pennsylvania)	47.6	Base flow	C: July 1994 - Dec. 1997 V: Jan. 1999 - May 2001			0.51	-0.16					0.29	-1.2		
			Surface flow				0.38	0.20					0.39	-0.35		
			Total flow				0.57	0.54					0.34	-0.17		
Stewart et al. (2006)	Upper North Bosque River (Texas)	932.5	Stream flow	C: 1994-1999 V: 2001-1902			0.87	0.76					0.92	0.80		
Stonefelt et al. (2000)	Wind River (Wyoming)	5,000	Stream flow	1990-1997			0.91									

Table 2 (continued)

Reference	Watershed	Drainage Area (km^2)[a]	Indicator	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Thomson et al. (2003)[c,p]	Conterminous U.S. (18 MWRRs; Figure 2)	--	Water yield	1960-1989 (overall mean)												0.96
				1960-1989 (8-digit means by MWRR)												0.05 to 0.94
Tolson and Shoemaker (2007)[c,i]	Cannonsville Reservoir (New York); six gauges	37 to 913[q]	Stream flow	Varying periods	0.64 to 0.80	0.59 to 0.80					0.69 to 0.88	0.43 to 0.88	0.88 to 0.97	0.88 to 0.97		
Tripathi et al. (2003)	Nagwan (India)	92.5	Surface runoff	1997 (daily) 1992-1998 (month) (June - Oct.)							0.91	0.87	0.97	0.98		
Tripathi et al. (2006)[g]	Nagwan (India)	90.3	Surface runoff	1995-1998									0.86 to 0.90			
Vaché et al. (2002)	Buck Creek and Walnut Creek (Iowa)	88.2 and 51.3	Stream flow	Varying periods			0.64 and 0.67									
Van Liew et al. (2003a)[i]	Little Washita River (Oklahoma); C: two gauges, V: six gauges	2.9 to 610	Stream flow	Varying periods		0.56 and 0.58		0.66 and 0.79				-0.35 to 0.72		-1.1 to 0.89		
Van Liew and Garbrecht (2003)	Little Washita River (Oklahoma); C: two gauges, V: three gauges	160 to 610	Stream flow	Varying periods		0.60 and 0.40		0.75 and 0.71				-0.06 to 0.71		0.45 to 0.86		
Van Liew et al. (2003b)[c]	Little Washita River (Oklahoma); two gauges	160	Stream flow	Oct. 1992 - Sept. 2000		0.55 and 0.59		0.78 and 0.77								
Van Liew et al. (2007)[r]	Little River (Georgia, U.S.); two gauges	114 and 330	Stream flow	C: 1997-2002 V: 1972-1996		0.64 and 0.71		0.83 and 0.90				0.66 and 0.68		0.88 and 0.89		
	Little Washita River (Oklahoma); three gauges	160 to 600	Stream flow	C: 1993-1999 V: varying periods		0.54 and 0.63		0.68 and 0.76				0.13 to 0.56		-0.36 to 0.60		
	Mahantango Creek (Pennsylvania); two gauges	0.4 and 7	Stream flow	C: 1997-2000 V: varying periods		0.46 and 0.69		0.84 and 0.88				0.35 to 0.54		0.46 to 0.75		
	Reynolds Creek (Idaho); three gauges	36 to 239	Stream flow	C: 1968-1972 V: varying periods		0.51 to 0.73		0.52 to 0.79				-0.17 to 0.62		0.21 to 0.74		
	Walnut Gulch (Arizona); three gauges	24 to 149	Stream flow	C: 1968-1972 V: 1973-1982		0.30 to 0.76		0.48 to 0.86				-1.0 to -1.8		-0.62 to -2.5		

Table 2 (continued)

Reference	Watershed	Drainage Area (km^2)[a]	Indicator	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Varanou et al. (2002)	Ali Efenti (Greece)	2,796	Stream flow	1977-1993		0.62		0.81								
Vazquez-Amabile and Engel (2005)[c]	Muscatatuck River (Indiana); three gauges	2,952	Stream flow	C: 1980-1994 V: 1995-2002		-0.23 to 0.28		0.59 to 0.80				-0.35 to 0.48		0.49 to 0.81		
			Ground water table depth			-0.12 to 0.28		0.36 to 0.61				-0.74 to 0.33		-0.51 to 0.38		
Vazquez-Amábile et al. (2006)	St. Joseph River (Indiana, Michigan, and Ohio); C: three gauges, V: four gauges	2,800	Stream flow	C: 1989-1998 V: 1999-2002		0.46 to 0.65		0.64 to 0.74			0.50 to 0.66	0.33 to 0.60	0.73 to 0.76	0.64 to 0.74		
Veith et al. (2005)	Watershed FD-36 (Pennsylvania)	0.395	Stream flow	1997-2000 (April to Oct.)			0.63	0.75								
Von Stackelberg et al. (2007)[h]	Research watersheds D1 and D2 (Uruguay)	0.69 and 1.08	Stream flow	July 2000 - June 2004 (reduced ET scenario)	0.92 and 0.93	0.77 and 0.71										
				(added groundwater scenario)	0.93 and 0.94	0.78 and 0.72										
Wang and Melesse (2005)[i]	Wild Rice River (Minnesota); two gauges	2,419 and 4,040.3	Stream flow	Varying periods	0.73 and 0.68	0.64 and 0.67	0.89 and 0.86	0.86 and 0.86	0.82 and 0.73	0.80 and 0.72	0.69 and 0.52	0.62 and 0.50	0.93 and 0.83	0.90 and 0.83	0.93 and 0.82	0.90 and 0.68
Wang and Melesse (2006)[i]	Elm River (North Dakota); subwatershed	515.4	Stream flow	C: Dec. 1984 - Nov. 1986 V: Dec. 1981 - Nov. 1984 (STATSGO soils)	0.53	0.51	0.89	0.88			0.55	0.31	0.53	0.50		
				(SSURGO soils)	0.51	0.49	0.92	0.92			0.55	0.26	0.53	0.49		
Wang et al. (2006)[g,i]	Wild Rice River (Minnesota); two gauges	2,419 and 4,040.3	Stream flow	Varying periods	0.68 to 0.76	0.64 to 0.70	0.86 to 0.92	0.86 to 0.90	0.73 to 0.91	0.72 to 0.90	0.52 to 0.69	0.46 to 0.64	0.83 to 0.93	0.80 to 0.91	0.82 to 0.93	0.68 to 0.91

Table 2 (continued)

Reference	Watershed	Drainage Area (km^2)[a]	Indicator	Time Period (C = calib., V = valid.)	Calibration Daily		Calibration Monthly		Calibration Annual		Validation Daily		Validation Monthly		Validation Annual	
					R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
Watson et al. (2005)[k]	Woady Yaloak River (Australia)	306	Stream flow	C: 1978-1989 V: 1990-2001		0.54		0.77		0.77		0.47		0.79		0.91
Weber et al. (2001)	Aar (Germany)	59.8	Stream flow	1986-1987 (daily), 1983-1987 (mon.)								0.63		0.74		
White and Chaubey (2005)[e,s]	Beaver Reservoir (Arkansas); three gauges	362 to 1,020	Stream flow	C: 1999 and 2000 V: 2001 and 2002			0.41 to 0.91	0.50 to 0.89					0.77 to 0.91	0.72 to 0.87		
Wu and Johnston (2007)	South Branch Ontonagon River (Michigan)	901	Stream flow	C: 1948-1949 V: 1950-1965 (drought years for calib.)				0.8						0.8		
				C: 1969-1970 V: 1950-1965 (average years for calib.)				0.9						0.4		
Wu and Xu (2006)[c]	Amite, Tamgipahoa, and Tickfaw Rivers (Louisiana)	662.2 to 3434.9	Stream flow	C: 1975-1977 V: 1979-1999		0.83 to 0.93		0.94 to 0.96				0.69 to 0.78		0.81 to 0.87		
Zhang et al. (2007)	Luohe River (China)	5,239	Stream flow	C: 1992-1996 V: 1997-2000	0.82	0.65	0.82	0.64			0.74	0.54	0.86	0.82		

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

weaker results can be attributed in part to inadequate representation of rainfall inputs, due to either a lack of adequate rain gauges in the simulated watershed or subwatershed configurations that were too coarse to capture the spatial detail of rainfall inputs (e.g., Cao et al., 2006; Conan et al., 2003b; Bouraoui et al., 2002; Bouraoui et al., 2005). Other factors that may adversely affect SWAT hydrologic predictions include a lack of model calibration (Bosch et al., 2004), inaccuracies in measured streamflow data (Harmel et al., 2006), and relatively short calibration and validation periods (Muleta and Nicklow, 2005b).

Example Calibration/Validation Studies

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

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

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

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

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

km^2 Ariel Creek watershed in northeast Pennsylvania, due to the presence of soil fragipans. Chu and Shirmohammadi (2004) found that SWAT was unable to simulate an extremely wet year for a 3.46 km^2 watershed in Maryland. After removing the wet year, the surface runoff, base flow, and streamflow results were within acceptable accuracy on a monthly basis. Subsurface flow results also improved when the base flow was corrected.

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

Afinowicz et al. (2005) modified SWAT in order to more realistically simulate rapid subsurface water movement through karst terrain in the 360 km^2 Guadalupe River watershed in southwest Texas. They report that simulated base flows matched measured streamflows after the modification, and that the predicted daily and monthly and daily results (Table 2) fell within the range of published model efficiencies for similar systems. Eckhardt et al.

(2002) also found that their modifications for SWAT-G resulted in greatly improved simulation of subsurface interflow in German low mountain conditions (Table 2).

Soil Water, Recharge, Tile Flow, and Related Studies

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

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

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

Snowmelt-Related Applications

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

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

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

Irrigation and Brush Removal Scenarios

Gosain et al. (2005) assessed SWAT's ability to simulate return flow after the introduction of canal irrigation in a basin in Andra Pradesh, India. SWAT provided the assistance water managers needed in planning and managing their water resources under various scenarios. Santhi et al. (2005) describe a new canal irrigation routine that was used in SWAT. Cumulative irrigation withdrawal was estimated for each district for each of three different conservation scenarios (relative to a reference scenario). The percentage of water that was saved was also calculated. SWAT was used by Afinowicz et al. (2005) to evaluate the influence of woody plants on water budgets of semi-arid rangeland in southwest Texas.

Baseline brush cover and four brush removal scenarios were evaluated. Removal of heavy brush resulted in the greatest changes in ET (approx. 32 mm year^{-1} over the entire basin), surface runoff, base flow, and deep recharge. Lemberg et al. (2002) also describe brush removal scenarios.

Applications Incorporating Wetlands, Reservoirs, and Other Impoundments

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

Green-Ampt Applications

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

Pollutant Loss Studies

Nearly 50% of the reviewed SWAT studies (Table 1) report simulation results of one or more pollutant loss indicator. Many of these studies describe some form of verifying pollutant prediction accuracy, although the extent of such reporting is less than what has been published for hydrologic assessments. Table 3 lists R^2 and NSE statistics for 37 SWAT pollutant loss studies, which again are used here as key indicators of model performance. The majority of the R^2 and NSE values reported in Table 3 exceed 0.5, indicating that the model was able to replicate a wide range of observed in-stream pollutant levels. However, poor

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

Reference	Watershed	Drainage Area (km^2)[a]	Indicator[b]	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Arabi et al. (2006b)[c]	Dreisbach and Smith Fry (Indiana)	6.2 and 7.3	Suspended solids	C: 1974-1975 V: 1976 - May 1977			0.97 and 0.94	0.92 and 0.86					0.86 and 0.85	0.75 and 0.68		
			Total P				0.93 and 0.64	0.78 and 0.51					0.90 and 0.73	0.79 and 0.37		
			Total N				0.76 and 0.61	0.54 and 0.50					0.75 and 0.52	0.85 and 0.72		
Bärlund et al. (2007)[d,e]	Lake Pyhäjärvi (Finland)	--	Sediment	1990-1994		0.01										
Behera and Panda (2006)	Kapgari (India)	9.73	Sediment	C: 2002 V: 2003 (rainy season)	0.93	0.84					0.89	0.86				
			Nitrate		0.93	0.92					0.87	0.83				
			Total P		0.92	0.83					0.94	0.89				
Bouraoui et al. (2002)	Ouse (Yorkshire, U.K.)	3,500	Nitrate	1986-1990				0.64								
			Ortho P					0.02								
Bouraoui et al. (2004)	Vantaanjoki (Finland); subwatershed	295	Susp. solids	1982-1984		0.49										
			Total N			0.61										
			Total P			0.74										
	Entire watershed	1,682	Nitrate	1974-1998										0.34		
			Total P											0.62		
Bracmort et al. (2006)[c]	Dreisbach and Smith Fry (Indiana)	6.2 and 7.3	Mineral P	C: 1974-1975 V: 1976 - May 1977			0.92 and 0.90	0.84 and 0.78					0.86 and 0.73	0.74 and 0.51		
Cerucci and Conrad (2003)[f]	Townbrook (New York)	36.8	Sediment	Oct. 1999- Sept. 2000			0.70									
			Dissolved P				0.91									
			Particulate P				0.40									
Chaplot et al. (2004)	Walnut Creek	51.3	Nitrate	1991-1998			0.56									
Cheng et al. (2006)	Heihe River (China)	7,241	Sediment	C: 1992-1997 V: 1998-1999			0.70	0.74					0.78	0.76		
			Ammonia	C: 1992-1997 V: 1998-1999			0.75	0.76					0.74	0.72		

Table 3 (continued)

Reference	Watershed	Drainage Area (km^2)[a]	Indicator[b]	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Chu et al. (2004)[g]	Warner Creek	3.46	Sediment	Varying periods			0.10	0.05					0.19	0.11	0.91	0.90
			Nitrate				0.27	0.16					0.38	0.36	0.96	0.90
			Ammonium										0.38	-0.05	0.80	0.19
			Total Kjeldahl N										0.40	0.15	0.66	-0.56
			Soluble P				0.39	-0.08					0.65	0.64	0.87	0.80
			Total P										0.38	0.08	0.83	0.19
Cotter et al. (2003)	Moores Creek (Arkansas)	18.9	Sediment	1997-1998				0.48								
			Nitrate					0.44								
			Total P					0.66								
Di Luzio et al. (2002)	Upper North Bosque River (Texas)	932.5	Sediment	Jan. 1993 - July 1998										0.78		
			Organic N											0.60		
			Nitrate											0.60		
			Organic P											0.70		
			Ortho P											0.58		
Du et al. (2006)[d,h,i]	Walnut Creek (Iowa); subwatershed (site 310) and watershed outlet	51.3	Nitrate (stream flow)	C: 1992-1995 V: 1996-2001 (SWAT2000)		-0.37 and -0.41		-0.21 and -0.26				-0.14 and -0.18		-0.21 and -0.22		
	Subwatershed (site 210)	--	Nitrate (tile flow)	(SWAT2000)		-0.60		-0.08				-0.16		-0.31		
	Subwatershed (site 310) and watershed outlet	51.3	Nitrate (stream flow)	(SWAT-M)[j]		0.61 and 0.53		0.91 and 0.85				0.41 and 0.26		0.80 and 0.67		
	Subwatershed (site 210)	--	Nitrate (tile flow)	(SWAT-M)		0.25		0.73				0.42		0.71		
	Subwatershed (site 310) and watershed outlet	51.3	Atrazine (stream flow)	(SWAT2000)		-0.05 and -0.12		-0.01 and -0.02				-0.02 and -0.39		-0.04 and 0.06		
	Subwatershed (site 210)	--	Atrazine (tile flow)	(SWAT2000)		-0.47		-0.04				-0.46		-0.06		
	Subwatershed (site 310) and watershed outlet	51.3	Atrazine (stream flow)	(SWAT-M)		0.21 and 0.47		0.50 and 0.73				0.12 and - 0.41		0.53 and 0.58		
	Subwatershed (site 210)	--	Atrazine (tile flow)	(SWAT-M)		0.51		0.92				0.09		0.31		

Table 3 (continued)

Reference	Watershed	Drainage Area (km²)[a]	Indicator[b]	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Gikas et al. (2005)[d,k]	Vistonis Lagoon (Greece); nine gauges	1,349	Sediment	C: May 1998 - June 1999 V: Nov. 1999 -Jan. 2000			0.40 to 0.98						0.34 to 0.98			
			Nitrate				0.51 to 0.87						0.57 to 0.89			
			Total P				0.50 to 0.82						0.43 to 0.97			
Grizzetti et al. (2005)[d]	Parts of four watersheds (U.K.); C: one gauge, V: two gauges, annual: 50 gauges	1,380 to 8,900	Nitrate and nitrite	1995-1999		0.24		0.32				0.004 and 0.28		-0.66 and 0.38		0.68
Grizzetti et al. (2003)	Vantaanjoki (Finland); three gauges	295 to 1,682	Total N	Varying periods		0.59						0.43 and 0.51		0.10 and 0.30		
			Total P			0.74						0.54 and 0.44		0.63 and 0.64		
Grunwald and Qi (2006)	Sandusky (Ohio); three gauges	90.3 to 3,240	Suspended sediment	C: 1998-1999 V: 2000-2001				-5.1 to 0.2						-1.0 to 0.02		
			Total P					-0.89 to 0.07						0.08 to 0.45		
			Nitrite					-4.6 to 0.19						-0.16 to 0.48		
			Nitrate					-0.12 to 0.29						-0.1 to 0.57		
			Ammonia					-0.44 to -0.24						-0.44 to -0.21		
Hanratty and Stefan (1998)	Cottonwood (Minnesota)	3,400	Suspended sediment	1967-1991				0.59								
			Nitrate and nitrite					0.68								
			Total P					0.54								

Table 3 (continued)

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

Table 3 (continued)

Reference	Watershed	Drainage Area (km^2)[a]	Indicator[b]	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Plus et al. (2006)[d,m]	Thau Lagoon (France); two gauges	280	Nitrate	1993-1999							0.44 and 0.27					
			Ammonia								0.31 and 0.15					
			Organic N								0.66 and 0.20					
Plus et al. (2006)[d,m]	Thau Lagoon (France); two gauges	280	Nitrate	1993-1999							0.44 and 0.27					
			Ammonia								0.31 and 0.15					
			Organic N								0.66 and 0.20					
Saleh et al. (2000)[n]	Upper North Bosque River (Texas); C: one gauge, V: 11 gauges	932.5	Sediment	Oct. 1993 - Aug. 1995				0.81						0.94		
			Nitrate					0.27						0.65		
			Organic N					0.78						0.82		
			Total N					0.86						0.97		
			Ortho P					0.94						0.92		
			Particulate P					0.54						0.89		
			Total P					0.83						0.93		
Saleh and Du (2004)	Upper North Bosque River (Texas)	932.5	Total suspended solids	C: Jan. 1994 - June 1995 V: July 1995 - July 1999		-2.5		0.83				-3.5		0.59		
			Nitrate and nitrite			0.04		0.29				0.50		0.50		
			Organic N			-0.07		0.87				0.69		0.77		
			Total N			0.01		0.81				0.68		0.75		
			Ortho P			0.08		0.76				0.45		0.40		
			Particulate P			-0.74		0.59				0.59		0.73		
			Total P			-0.08		0.77				0.63		0.71		

Table 3 (continued)

Reference	Watershed	Drainage Area (km^2)[a]	Indicator[b]	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Santhi et al. (2001a)[d,o]	Bosque River (Texas); two gauges	4,277	Sediment	C: 1993-1997 V: 1998			0.81 and 0.87	0.80 and 0.69					0.98 and 0.95	0.70 and 0.23		
			Mineral N				0.64 and 0.72	0.59 and -0.08					0.89 and 0.72	0.75 and 0.64		
			Organic N				0.61 and 0.60	0.58 and 0.57					0.92 and 0.71	0.73 and 0.43		
			Mineral P				0.60 and 0.66	0.59 and 0.53					0.83 and 0.93	0.53 and 0.81		
			Organic P				0.71 and 0.61	0.70 and 0.59					0.95 and 0.80	0.72 and 0.39		
Stewart et al. (2006)	Upper North Bosque River (Texas)	932.5	Sediment	C: 1994-1999 V: 2001-2002			0.94	0.80					0.82	0.63		
			Mineral N				0.80	0.60					0.57	-0.04		
			Organic N				0.87	0.71					0.89	0.73		
			Mineral P				0.88	0.75					0.82	0.37		
			Organic P				0.85	0.69					0.89	0.58		
Tolson and Shoemaker (2007)[d,j,p]	Cannonsville (New York)	37 to 913[q]	Total suspended solids	Varying periods			0.70 (0.47)	0.67 (0.24)			0.42 and 0.83	0.33 and 0.83	0.72 and 0.83	0.52 and 0.76		
			Total dissolved P				0.79 (0.84)	0.78 (0.84)			0.62 and 0.71	0.61 and -5.3	0.93 and 0.89	0.89 and -6.5		
			Particulate P				0.67 (0.50)	0.61 (0.26)			0.37 and 0.85	0.32 and 0.85	0.63 and 0.88	0.48 and 0.79		
			Total P				0.73 (0.58)	0.78 (0.37)			0.43 and 0.87	0.40 and 0.78	0.75 and 0.92	0.63 and 0.92		
Tripathi et al. (2003)	Nagwan (India)	92.5	Sediment	June-Oct. 1997							0.89	0.89	0.89	0.79		
			Nitrate								0.89					
			Organic N								0.82					
			Soluble P								0.82					
			Organic P								0.86					

Table 3 (continued)

Reference	Watershed	Drainage Area (km^2)[a]	Indicator[b]	Time Period (C = calib., V = valid.)	Calibration Daily R^2	Calibration Daily NSE	Calibration Monthly R^2	Calibration Monthly NSE	Calibration Annual R^2	Calibration Annual NSE	Validation Daily R^2	Validation Daily NSE	Validation Monthly R^2	Validation Monthly NSE	Validation Annual R^2	Validation Annual NSE
Vazquez-Amabile et al. (2006)[i]	St. Joseph River (Indiana, Michigan, and Ohio); ten sampling sites	628.2 to 1620	Atrazine	1996-1999		0.14		0.42								
	Main outlet at Fort Wayne, Indiana	2,620	Atrazine	2000-2004							0.27	-0.31	0.59	0.28		
Veith et al. (2005)	Watershed FD-36 (Pennsylvania)	0.395	Sediment	1997-2000			0.04	-0.75								
White and Chaubey (2005)[r,s]	Beaver Reservoir (Arkansas); three gauges	362 to 1,020	Sediment	C: 2000 or 2001 V: 2001 or 2002			0.45 to 0.85	0.23 to 0.76					0.69 to 0.82	0.32 to 0.85		
			Nitrate and nitrite				0.01 to 0.84	-2.36 to 0.29					0.59 and 0.71	0.13 and 0.49		
			Total P				0.50 to 0.82	0.40 to 0.67					0.58 and 0.76	-0.29 and 0.67		

[a] Based on drainage areas to the gauge(s)/sampling site(s) rather than total watershed area where reported (see footnote [d] for further information).

[b] The reported indicators are listed here as reported in each respective study; the standard SWAT variables for relevant in-stream constituents are: sediment, organic nitrogen (N), organic phosphorus (P), nitrate (NO_3-N), ammonium (NH_4-N), nitrite (NO_2-N), and mineral P (Neitsch et al., 2005b).

[c] Arabi et al. (2006b) and Bracmort et al. (2006) reported the same set of r^2 and NSE statistics for sediment and total P; the calibration time periods were reported by Arabi et al. (2006b), and the validation time periods were inferred from graphical results reported by Bracmort et al. (2006).

[d] Explicit or estimated drainage areas were not reported for some or all of the gauge sites; the total watershed area is listed for those studies that reported it.

[e] The exact time scale of comparison was not explicitly stated and thus was inferred from other information provided.

[f] The statistics reported for sediment and organic P excluded the months of February and March 2000; large underestimations of both constituents occurred in those two months.

[g] The nutrient statistics were based on adjusted flows that accounted for subsurface flows that originated from outside the watershed as reported by Chu and Shirmohammadi (2004); the annual sediment, nitrate, and soluble P statistics were based on the combined calibration and validation periods.

[h] The daily and monthly statistics were based only on the days that sampling occurred.

[i] Other statistics were reported for different time periods, conditions, gauge combinations, and/or variations in selected in input data.

[j] A modified SWAT model was used.

[k] The exact time scale of comparison was not explicitly stated and thus was inferred from other information provided.

[l] A similar set of Raccoon River watershed statistics were reported for slightly different time periods by Secchi et al. (2007).

[m] Specific calibration and/or validation time periods were reported, but the statistics were based on the overall simulated time period (calibration plus validation time periods).

[n] The APEX model (Williams and Izaurralde, 2006) was interfaced with SWAT for this study. The calibration statistics were based on a comparison between simulated and measured flows at the watershed outlet, while the validation statistics were based on a comparison between simulated and measured flows averaged across 11 different gauges.

[o] The calibration and validation statistics were also reported by Santhi et al. (2001b).

[p] The calibration statistics in parentheses include January 1996; an unusually large runoff and erosion event occurred during that month.

[q] As reported by Benamen et al. (2005).

[r] These statistics were computed on the basis of comparisons between simulated and measured data within specific years, rather than across multiple years.

[s] The statistics for the War Eagle Creek subwatershed gauge were also reported by Migliaccio et al. (2007).

results were again reported for some studies, especially for daily comparisons. Similar to the points raised for the hydrologic results, some of the weaker results were due in part to inadequate characterization of input data (Bouraoui et al., 2002), uncalibrated simulations of pollutant movement (Bärlund et al., 2007), and uncertainties in observed pollutant levels (Harmel et al., 2006).

Sediment Studies

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

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

SWAT sediment simulations have also been evaluated in Asia, Europe, and North Africa. Behera and Panda (2006) concluded that SWAT simulated sediment yield satisfactorily throughout the entire rainy season based on comparisons with daily observed data (Table 3) for an agricultural watershed located in eastern India. Kaur et al. (2004)

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

Nitrogen and Phosphorus Studies

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

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

Bracmort et al. (2006) and Arabi et al. (2006b) found that SWAT could account for the effects of best management practices (BMPs) on phosphorus and nitrogen losses for two small watersheds in Indiana, with monthly validation NSE statistics ranging from 0.37 to

0.79 (Table 3). SWAT tended to underpredict both mineral and total phosphorus yields for the months with high measured phosphorus losses, but overpredicted the phosphorus yields for months with low measured losses. Cerucci and Conrad (2003) calibrated SWAT soluble phosphorus predictions using measured data obtained for the Townbrook watershed in New York. They reported monthly NSE values of 0.91 and 0.40, if the measured data from February and March were excluded. Kirsch et al. (2002) reported that SWAT phosphorus loads were considerably higher than corresponding measured loads for the Rock River watershed Wisconsin. Veith et al. (2005) found that SWAT-predicted losses were similar in magnitude to measured watershed exports of dissolved and total phosphorus during a 7-month sampling period from a Pennsylvania watershed.

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

Pesticide and Surfactant Studies

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

Scenarios of BMP and Land Use Impacts on Pollutant Losses

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

Climate Change Impact Studies

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

SWAT Studies Reporting Climate Change Impacts on Hydrology

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

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

Stone et al. (2001) predicted climate change impacts on Missouri River basin (Figure 2) water yields by inputting downscaled climate projections into SWAT, which were generated by nesting the RegCM RCM (Giorgi et al., 1998) within the CISRO GCM (Watterson et al., 1997) into the previously described version of SWAT that was modified by

Hotchkiss et al. (2000). A structure similar to the HUMUS approach was used, in which 310 8-digit watersheds were used to define the subwatersheds. Water yields declined at the basin outlet by 10% to 20% during the spring and summer months, but increased during the rest of the year. Further research revealed that significant shifts in Missouri River basin water yield impacts were found when SWAT was driven by downscaled CISRO GCM projections only versus the nested RegCM-CISRO GCM approach (Stone et al., 2003).

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

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

SWAT Studies Reporting Climate Change Impacts on Pollutant Loss

Several studies report climate change impacts on both hydrology and pollutant losses using SWAT, including four that were partially or completely supported by the EU CHESS project (Varanou et al., 2002; Bouraoui et al., 2002; Boorman, 2003; Bouraoui et al., 2004). Nearing et al. (2005) compared runoff and erosion estimates from SWAT versus six other models, in response to six climate change scenarios that were simulated for the 150 km^2 Lucky Hills watershed in southeastern Arizona. The responses of all seven models were similar across the six scenarios for both watersheds, and it was concluded that climate change could potentially result in significant soil erosion increases if necessary conservation efforts are not implemented. Hanratty and Stefan (1998) found that streamflows and P, organic N, nitrate, and sediment yields generally decreased for the 3,400 km^2 Cottonwood River watershed in southwest Minnesota in response to a downscaled 2×CO_2 GCM climate change scenario. Varanou et al. (2002) also found that average streamflows, sediment yields, organic

N losses, and nitrate losses decreased in most months in response to nine different climate change scenarios downscaled from three GCMs for the 2,796 km^2 Pinios watershed in Greece. Bouraoui et al. (2002) reported that six different climate change scenarios resulted in increased total nitrogen and phosphorus loads of 6% to 27% and 5% to 34%, respectively, for the 3,500 km^2 Ouse River watershed located in the Yorkshire region of the U.K. Bouraoui et al. (2004) further found for the Vantaanjoki River watershed, which covers 1,682 km^2 in southern Finland, that snow cover decreased, winter runoff increased, and slight increases in annual nutrient losses occurred in response to a 34-year scenario representative of observed climatic changes in the region. Boorman (2003) evaluated the impacts of climate change for five different watersheds located in Italy, France, Finland, and the UK., including the three watersheds analyzed in the Varanou et al. (2002), Bouraoui et al. (2002), and Bouraoui et al. (2004) studies.

Sensitivity, Calibration, and Uncertainty Analyses

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

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

Sensitivity Analyses

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

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

Calibration Approaches

The manual calibration approach requires the user to compare measured and simulated values, and then to use expert judgment to determine which variables to adjust, how much to adjust them, and ultimately assess when reasonable results have been obtained.

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

Automated techniques involve the use of Monte Carlo or other parameter estimation schemes that determine automatically what the best choice of values are for a suite of parameters, usually on the basis of a large set of simulations, for a calibration process. Govender and Everson (2005) used the automatic Parameter Estimation (PEST) program

(Doherty, 2004) and identified soil moisture variables, initial groundwater variables, and runoff curve numbers to be some of the sensitive parameters in SWAT applications for two small South African watersheds. They also report that manual calibration resulted in more accurate predictions than the PEST approach (Table 2). Wang and Melesse (2005) also used PEST to perform an automatic SWAT calibration of three snowmelt-related and eight hydrologic-related parameters for the 4,335 km^2 Wild Rice River watershed in northwest Minnesota, which included daily and monthly statistical evaluation (Table 2).

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

Uncertainty Analyses

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

Benaman and Shoemaker (2004) developed a six-step method that includes using Monte Carlo runs and an interval-spaced sensitivity approach to reduce uncertain parameter ranges. After parameter range reduction, their method reduced the model output range by an order of magnitude, resulting in reduced uncertainty and the amount of calibration required for SWAT. However, significant uncertainty remained with the SWAT sediment routine. Lin and Radcliffe (2006) performed an initial two-stage automatic calibration streamflow prediction process with SWAT for the 1,580 km^2 Etowah River watershed in Georgia in which an SCE algorithm was used for automatic calibration of lumped SWAT input parameters, followed by calibration of heterogeneous inputs with a variant of the Marquardt-Levenberg method in which "regularization" was used to prevent parameters taking on unrealistic values. They then performed a nonlinear calibration and uncertainty analysis using PEST, in which confidence intervals were generated for annual and 7-day streamflow estimates. Their resulting calibrated statistics are shown in Table 2. Muleta and Nicklow (2005b) describe a study for the Big Creek watershed that involved three phases: (1) parameter sensitivity analysis for 35 input parameters, in which LH samples were used to reduce the number of Monte Carlo simulations needed to conduct the analysis; (2) automatic calibration using a genetic algorithm, which systematically determined the best set of input parameters using a sum of the square of differences criterion; and (3) a Monte Carlo-based GLUE approach for the uncertainty analysis, in which LH sampling is again used to generate input samples and reduce the computation requirements. Uncertainty bounds corresponding to the 95% confidence limit are reported for both streamflow and sediment loss, as well as final calibrated statistics (Tables 2 and 3). Arabi et al. (2007b) used a three-step procedure that included OAT and interval-spaced sensitivity analyses, and a GLUE analysis to assess uncertainty of SWAT water quality predictions of BMP placement in the Dreisbach and Smith Fry watersheds in Indiana. Their results point to the need for site-specific calibration of some SWAT inputs, and that BMP effectiveness could be evaluated with enough confidence to justify using the model for TMDL and similar assessments.

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

Inputs (CANOPI), which evaluates uncertainty associated with climatic data and other inputs.

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

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

HRU and Subwatershed Delineation Effects

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

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

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

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

DEM, Soil, and Land Use Resolution Effects

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

Effects of Different Spatial and Temporal Transfers of Inputs

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

Historical and Hypothetical Land Use Effects

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

Climate Data Effects

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

Comparisons of SWAT with Other Models

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

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

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

Interfaces of SWAT with Other Models

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

SWAT with MODFLOW and/or Surface Water Models

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

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

SWAT with Environmental Models or Genetic Algorithms for BMP Analyses

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

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

SWAT with Economic and/or Environmental Models

A farm economic model was interfaced with the Agricultural Policy Extender (APEX) model (Williams and Izaurralde, 2006) and SWAT to simulated the economic and environmental impacts of manure management scenarios and other BMPs for the 932.5 km^2 upper North Bosque River and 1,279 km^2 Lake Fork Reservoir watersheds in Texas and the 162.2 km^2 upper Maquoketa River watershed in Iowa (Gassman et al., 2002). The economic and environmental impacts of several manure application rate scenarios are described for each watershed, as well as for manure haul-off, intensive rotational grazing, and reduced fertilizer scenarios that were simulated for the upper North Bosque River watershed, Lake Fork Reservoir watershed, and upper Maquoketa River watershed, respectively. Osei et al. (2003) report additional stocking density scenario results for pasture-based dairy productions in the Lake Fork Reservoir watershed. They concluded that appropriate pasture nutrient management, including stocking density adjustments and more efficient application of commercial fertilizer, could lead to significant reductions in nutrient losses in the Lake Fork

Reservoir watershed. Gassman et al. (2006) further assessed the impacts of seven individual BMPs and four BMP combinations for upper Maquoketa River watershed. Terraces were predicted to be very effective in reducing sediment and organic nutrient losses but were also the most expensive practice, while no-till or contouring in combination with reduced fertilizer rates were predicted to result in reductions of all pollutant indictors and also positive net returns.

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

SWAT with Ecological and Other Models

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

SWAT Strengths, Weaknesses, and Research Needs

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

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

Hydrologic Interface

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

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

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

Hydrologic Response Units (HRUs)

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

Simulation of BMPs

A key strength of SWAT is a flexible framework that allows the simulation of a wide variety of conservation practices and other BMPs, such as fertilizer and manure application rate and timing, cover crops (perennial grasses), filter strips, conservation tillage, irrigation management, flood-prevention structures, grassed waterways, and wetlands. The majority of conservation practices can be simulated in SWAT with straightforward parameter changes. Arabi et al. (2007a) have proposed standardized approaches for simulating specific conservation practices in the model, including adjustment of the parameters listed in Table 4. Filter strips and field borders can be simulated at the HRU level, based on empirical functions that account for filter strip trapping effects of bacteria or sediment, nutrients, and pesticides (which are invoked when the filter strip width parameter is set input to the model). However, assessments of targeted filter strip placements within a watershed are limited, due to the lack of HRU spatial definition in SWAT. There are also further limitations in

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

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

[a]Soil incorporation of residue by tillage implements is also a key aspect of simulated residue management in SWAT.

[b]Setting a filter strip width triggers one of two filter strip trapping efficiency functions (one for bacteria and the other for sediment, pesticides, and nutrients) that account for the effect of filter strip removal of pollutants.

simulating grassed waterways, due to the fact that channel routing is not simulated at the HRU level. Arabi et al. (2007a) proposed simulating grassed waterways by modifying subwatershed channel parameters, as shown in Table 4. However, this approach is generally only viable for relatively small watersheds such as the example they present in their study. Wetlands can be simulated in SWAT on the basis of one wetland per subwatershed, which is assumed to capture discharge and pollutant loads from a user-specified percentage of the overall subwatershed. The ability to site wetlands with more spatial accuracy within a subwatershed would clearly provide improvements over the current SWAT wetland simulation approach, although this can potentially be overcome for some applications by subdividing a watershed into smaller subwatersheds. The lack of spatial detail in SWAT also hinders simulation of riparian buffer zones and other conservation buffers, which again need to be spatially defined at the landscape or HRU level in order to correctly account for upslope pollutant source areas and the pollutant mitigation impacts of the buffers. The riparian and wetland processes recently incorporated into the SWIM model (Hatterman et al., 2006) may prove useful for improving current approaches used in SWAT.

Bacteria Life Cycle and Transport

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

In-Stream Kinetic Functions

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

Additional Research Needs

Many other research needs have been identified that will also improve the ability of SWAT to replicate land use, management, and other effects on watershed hydrology and pollutant transport. Several of the most important needs are listed here including some that are being actively investigated in ongoing research:

- Development of concentrated animal feeding operation and related manure application routines, that support simulation of surface and integrated manure application techniques and their influence on nutrient fractionation, distribution in runoff and soil, and sediment loads. Current development is focused on a manure cover layer.
- All aspects of stream routing need further testing and refinement, including the QUAL2E routines as discussed above.
- Improved stream channel degradation and sediment deposition routines are needed to better describe sediment transport, and to account for nutrient loads associated with sediment movement, as discussed by Jha et al. (2004a). Channel sediment routing could be improved by accounting for sediment size effects, with separate algorithms for the wash and bed loads. Improved flood plain deposition algorithms are needed, and a stream bank erosion routine should be incorporated.
- SWAT currently assumes that soil carbon contents are static. This approach will be replaced by an updated carbon cycling submodel that provides more realistic accounting of carbon cycling processes.
- Improvements to the nitrogen cycling routines should be investigated based on the suggestions given by Borah et al. (2006). Other aspects of the nitrogen cycling process should also be reviewed and updated if needed, including current assumptions of plant nitrogen uptake. Soil phosphorus cycling improvements have been initiated and will continue. The ability to simulate leaching of soil phosphorus through the soil profile, and in lateral, groundwater, and tile flows, has recently been incorporated into the model.

- Expansion of the plant parameter database is needed, as pointed out by Heuvelmans et al. (2005), to support a greater range of vegetation scenarios that can be simulated in the model. In general, more extensive testing of the crop growth component is needed, including revisions to the crop parameters where needed.
- Modifications have been initiated by McKeown et al. (2005) in a version of the model called SWAT2000-C to more accurately simulate the hydrologic balance and other aspects of Canadian boreal forest systems including: (1) incorporation of a surface litter layer into the soil profile, (2) accounting of water storage and release by wetlands, and (3) improved simulation of spring thaw generated runoff. These improvements will ultimately be grafted into SWAT2005.
- Advancements have been made in simulating subsurface tile flows and nitrate losses (Du et al., 2005, 2006). Current research is focused on incorporating a second option, based on the DRAINMOD (Skaggs, 1982) approach, that includes the effects of tile drain spacing and shallow water table depth. Future research should also be focused on controlled drainage BMPs.
- Routines for automated sensitivity, calibration, and input uncertainty analysis have been added to SWAT (van Griensven and Bauwens, 2003). These routines are currently being tested on several watersheds, including accounting of uncertainty encountered in measured water quality data, as discussed by Harmel et al. (2006).
- The effects of atmospheric CO_2 on plant growth need to be revised to account for varying stomatal conductance and leaf area responses as a function of plant species, similar to the procedure developed for SWAT-G by Eckhardt et al. (2003).

Conclusions

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

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CHAPTER 3. DEVELOPMENT OF A COMMON LAND UNIT (CLU)-BASED MODELING FRAMEWORK FOR THE BOONE RIVER WATERSHED

A paper to be submitted to *Environmental Management*

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Abstract

A modeling framework has been constructed to support analyses of alternative management practice and/or cropping system scenarios for the Boone River Watershed in north central Iowa. The core of the system is the Soil and Water Assessment Tool (SWAT) model (version 2005), which is a widely used water quality model that has been applied for several previous Iowa water quality studies. The required input files for the baseline SWAT simulation are initially constructed using the standard ArcView SWAT (AVSWATX) interface and supporting databases, including hydrologic response units (HRUs) that reflect monoculture crop rotations based on a 2002 Iowa land use data layer. The monoculture crop rotation HRUs are subsequently converted into more realistic crop rotations for every Common Land Unit (CLU) in the watershed, based on survey data collected in the watershed during the spring of 2005. Tillage and conservation practices, nutrient applications, and soil type are also incorporated into the CLU-based crop rotation HRUs. These updated HRUs and other input files are then imported into an Access database and the interactive SWAT (i_SWAT) software program, which facilitates execution of the SWAT. An overview of the

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modeling system is provided followed by an in-depth description of the land use, tillage practices, and conservation practices that were collected in the survey, as well as soil, topographic, tile drainage, climate, and other data layers that are used in the modeling system. Weaknesses in some of the current data layers are discussed as well as potential future improvements for those data layers. Limitations within SWAT and other models to fully utilize all of the currently available data in the modeling system is also discussed, including how such limitations might be overcome. Finally, the potential to port the approach to other watersheds in the immediate region and the greater UMRB is presented.

Introduction

Simulation modeling has emerged globally as a key water resources and water quality management tool. Both point and nonpoint source water quality assessments are needed by a wide range of local, regional, state/provincial, and federal/national government agencies, as well as non-governmental organizations (NGOs) such as watershed improvement councils, commodity groups, and environmental organizations. Many of these analyses are required for agriculturally dominated watersheds or regions and can span a wide range of water use, land use/cropping system, alternative tillage and nutrient management strategies, climate sensitivity and change, and conservation practice scenarios as documented in Chapter 2 for worldwide applications of the Soil and Water Assessment Tool (SWAT) model.

A foundational aspect of the application of SWAT and other models is the accuracy and resolution of key land use, topographic, climate, and other input data. Only very coarse input data are available for some model applications, such as the application of SWAT described by Schuol and Abbaspour (2007) for the 4 million km^2 region encompassing the

Senegal, Niger, and Volta river basins in the western horn of Africa. They found that using generated weather instead of measured precipitation and temperature data resulted in better simulated stream discharge, when compared with measured discharge data in the region. In another example, Jha et al. (2006) report using relatively coarse data provided in the Better Assessment Science Integrating Point and Nonpoint Sources (BASINS) package version 3.0 (USEPA, 2001) for a climate change sensitivity assessment of the Upper Mississippi River Basin (URMB), which consisted of 1:250,000 scale soil data, 90 m resolution digital elevation model (DEM) data, and low resolution land use data (e.g., only one category for agricultural land use is provided that is defined as "Agricultural Generic"). They found the BASINS data to be sufficient for the UMRB hydrologic sensitivity analysis but pointed to the need for using more detailed land use data to perform future UMRB scenarios, including water quality scenarios assessments of alternative cropping and management systems.

One alternative source of data for UMRB and other watershed studies is the U.S. Department of Agriculture (USDA) – Natural Resource Conservation Service (NRCS) 1997 National Resource Inventory (NRI) that contains land use, conservation practice, soil type, and other data for over 800,000 points across the U.S. (USDA-NRCS, 2007a), and provides the capability to estimate crop rotations for intensive cropland areas based on cropping history data. The 1997 NRI has been used in several Center for Agricultural and Rural Development (CARD) SWAT applications including the UMRB (Gassman et al., 2006), the Raccoon River Watershed in west central Iowa (Jha et al., 2007), and 13 major watersheds covering over 80% of Iowa (Secchi et al., 2007). However, the NRI approach has serious limitations due to a lack of spatial resolution for watersheds smaller than the U.S. Geological

Survey (USGS) “8-digit watershed level”[4] and the fact that it was last compiled a decade ago.

Jha et al. (2007) described reallocating 1997 NRI data to 26, 10-digit watersheds within the two 8-digit watersheds that comprise the Raccoon River watershed, in an attempt to provide more detailed spatial inputs for the SWAT simulation study they conducted. However, this approach was found to be cumbersome and was replaced with a more straightforward digital land use-based approach that was used to simulate the Raccoon River watershed in a subsequent SWAT Total Maximum Daily Load (TMDL) nitrogen simulation study (Schilling and Wolter, 2007), based on a watershed subdivision scheme of 116, 12-digit watersheds[4]. Improved methods of simulating livestock concentration and associated nutrient inputs, distribution of tile drainage, distribution of soil types and corresponding soil layer properties, and point source nutrient inputs to the stream system were also incorporated in the second Raccoon River SWAT study.

The research described for the present study builds on the work reported by Schilling and Wolter by using several of the same input data methods and assumptions, but also incorporating new refinements that further extend the modeling capabilities currently used at CARD. The specific simulation framework described here has been developed for the Boone River watershed, which is an intensively cropped region located in north central Iowa. The development of the framework is described primarily in the context of supporting SWAT simulations for the Boone River watershed. However, a brief description is also provided regarding use of the modeling framework for three other environmental models. The key

[4]See Seaber et al. (1987) and USDA-NRCS (2007b) for a description of the different USGS and/or USDA-NRCS watershed classifications (i.e., 2-, 4-, 8-, 10-, and 12-digit watersheds) and Santhi et al. (2007) for a comparison of NRI 8-digit watershed land use estimates with two other land use data sources for the UMRB.

advancement of the system is the development of a framework constructed using Common Land Units (CLUs), which are described by NAS (2007) and allows land use data, tillage and conservation practices, and soil data to be input to receiving models at a field-scale level, or at any desired aggregation of the field-level land parcels. Different approaches for incorporating crop rotations into the simulation framework are also presented, which are critical to account for in many agricultural scenario studies and can not be derived from remote sensing databases available for only a single year; e.g., see discussion provided in Chinnasamy et al. (2008).

The specific objectives of this research are to present: (1) an overview of the modeling system including key software tools required to build the data inputs for the BRW SWAT simulations, (2) a description of the CLU-based data layers and other data layers required for the modeling system, (3) limitations within SWAT and other models to fully utilize all of the currently available data in the modeling system, and other limitations of the modeling system, and (4) the potential to port the approach to other watersheds in the immediate region and the greater UMRB. Weaknesses in some of the current data layers are also discussed as well as potential future improvements for those data layers.

Description of the Boone River Watershed

The Boone River watershed covers over 237,000 ha in six north central Iowa counties and is one of 131 8-digit watersheds that are located in the UMRB (Figure 1). It lies within the Des Moines Lobe geologic formation, which is the southern most portion of the central North American Prairie Pothole Region. An extensive network of subsurface tile drains and surface ditches have been installed throughout the watershed, resulting in the elimination of

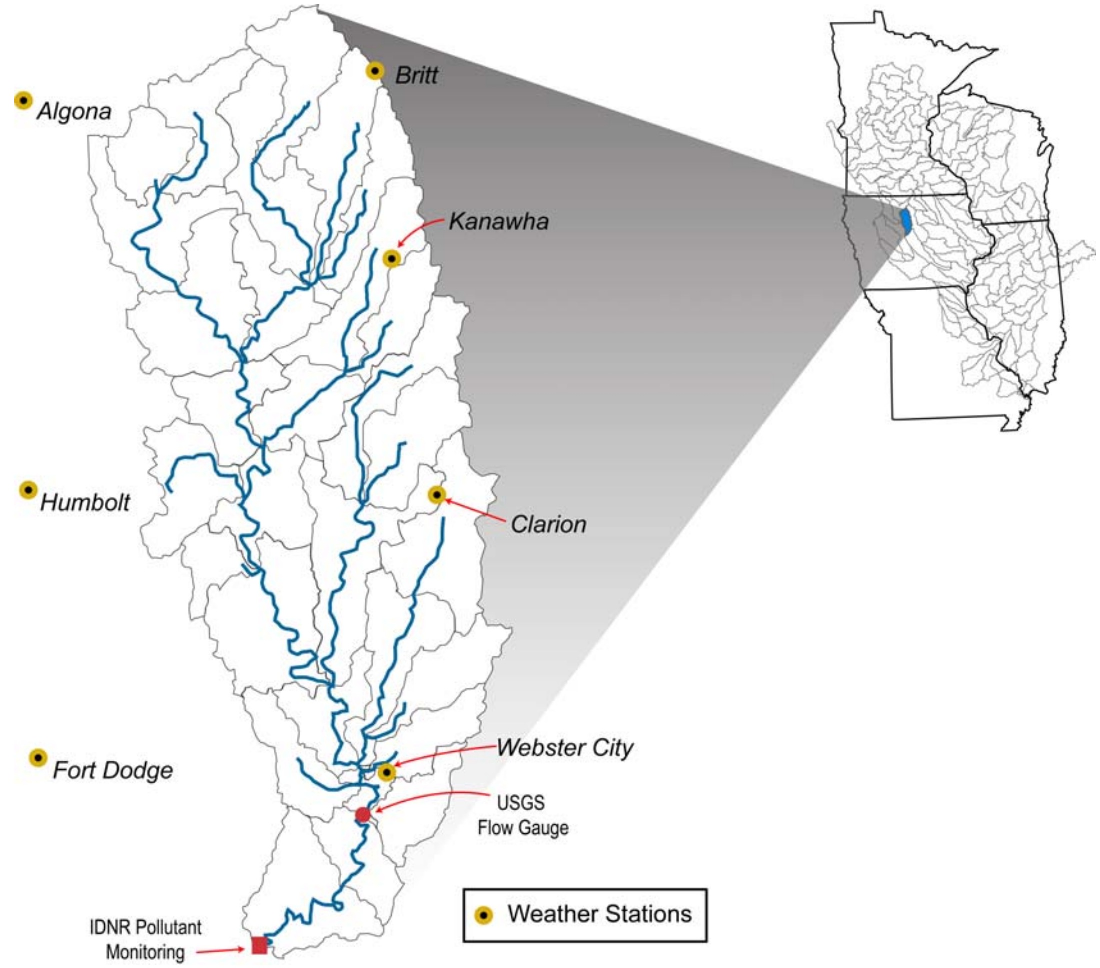

Figure 1. Location of the Boone River Watershed within the UMRB, and the subwatersheds, climate stations, and monitoring sites used for the SWAT simulations.

most wetland areas and an intensively cropped landscape. The watershed is dominated by corn and soybean production as discussed further in subsection 3.3.1.3 (Boone River Watershed Land Use). The watershed is also characterized by intensive livestock production, with a total of 128 confined animal feeding operations (CAFOs) including 109 swine operations that produce about 480,000 head annually (IDNR, 2007b). Land-applied manure from these livestock operations and commercial fertilizer applications are the primary sources of nutrients to the watershed stream system. The 1997 NRI indicated that grassed waterways were the only structural best management practices (BMPs) in the watershed, and that very few acres were affected by the practice. However, a 2005 field-level survey (Kiepe, 2005) revealed some additional structural conservation practices and extensive use of mulch tillage; these findings are discussed in more detail below in the context of the CLU-based simulation framework.

The locations of climate stations in the region, SWAT baseline subwatershed boundaries, USGS flow gauge, and Iowa Department of Natural Resources (IDNR) in-stream pollutant monitoring site are shown in Figure 1. The pollutant sampling at the watershed outlet reveals elevated levels of nitrates, especially during the spring runoff season. The watershed was identified by Libra et al. (2004) as discharging some of the highest nitrogen loads during 2000-2002 among the 68 Iowa watersheds that were analyzed within their statewide nutrient balance study. The Boone River has also been identified within the UMRB as both an area of freshwater biodiversity significance and a priority area for biodiversity conservation by the Nature Conservancy (Weitzell et al., 2003), and the 42 km (26 mile) stretch of the river from Webster City to the watershed outlet has been designated by the Iowa Department of Natural Resources (IDNR) as a Protected Water Area (ICC, 1985; Wikipedia, 2007)[5]. The biodiversity conservation designation reflects the fact that the watershed has been identified as currently possessing a “relatively un-degraded stream ecosystem,” but that it is also very vulnerable to future increased degradation (Neugarten and Braun, 2005). Potential biodiversity threats listed by Neugarten and Braun include

[5]The Protected Water Area designation and corresponding management plan was originally established in 1985 by the Iowa Conservation Commission. The vision for the plan apparently dimmed shortly after it was written and thus the Protected Water Area status became dormant for roughly two decades. However, it has recently been revived and measurable outcomes of the designation are being pursued by IDNR staff.

consistently high in-stream nitrogen concentrations, farm production methods that may be ecologically harmful, and inadequate treatment of wastewater.

Modeling System Overview

Figure 2 shows a schematic of the SWAT modeling system that has been constructed for the BRW simulations. The system supports both SWAT versions 2000 and 2005 (SWAT2000 and SWAT2005); SWAT2005 is the latest release of the model that features several enhancements as described in Chapter 2. SWAT is a conceptual, physically based long-term continuous watershed scale simulation model that operates on a daily time step. In SWAT, a watershed is divided into multiple subwatersheds, which are then usually further subdivided into Hydrologic Response Units (HRUs) that consist of homogeneous land use, management, and soil characteristics that represent percentages of the respective subwatershed are (i.e., they are not spatially defined within the model). Flow generation, sediment yield, and non-point-source loadings from each HRU in a subwatershed are summed, and the resulting loads are routed through channels, ponds, and/or reservoirs to the watershed outlet. Key components of SWAT include hydrology, plant growth, erosion, nutrient transport and transformation, pesticide transport and management practices. Further description of the model is provided in Chapter 2.

A variety of digital data layers are available for constructing the BRW modeling system. Table 1 lists the digital data layers that have been investigated so far, the status of each data layer regarding application in the modeling system, and whether the data layer can be accessed in the Iowa Department of Natural Resources (IDNR) on-line library. The role of some of the data layers within the modeling system is briefly discussed in this modeling

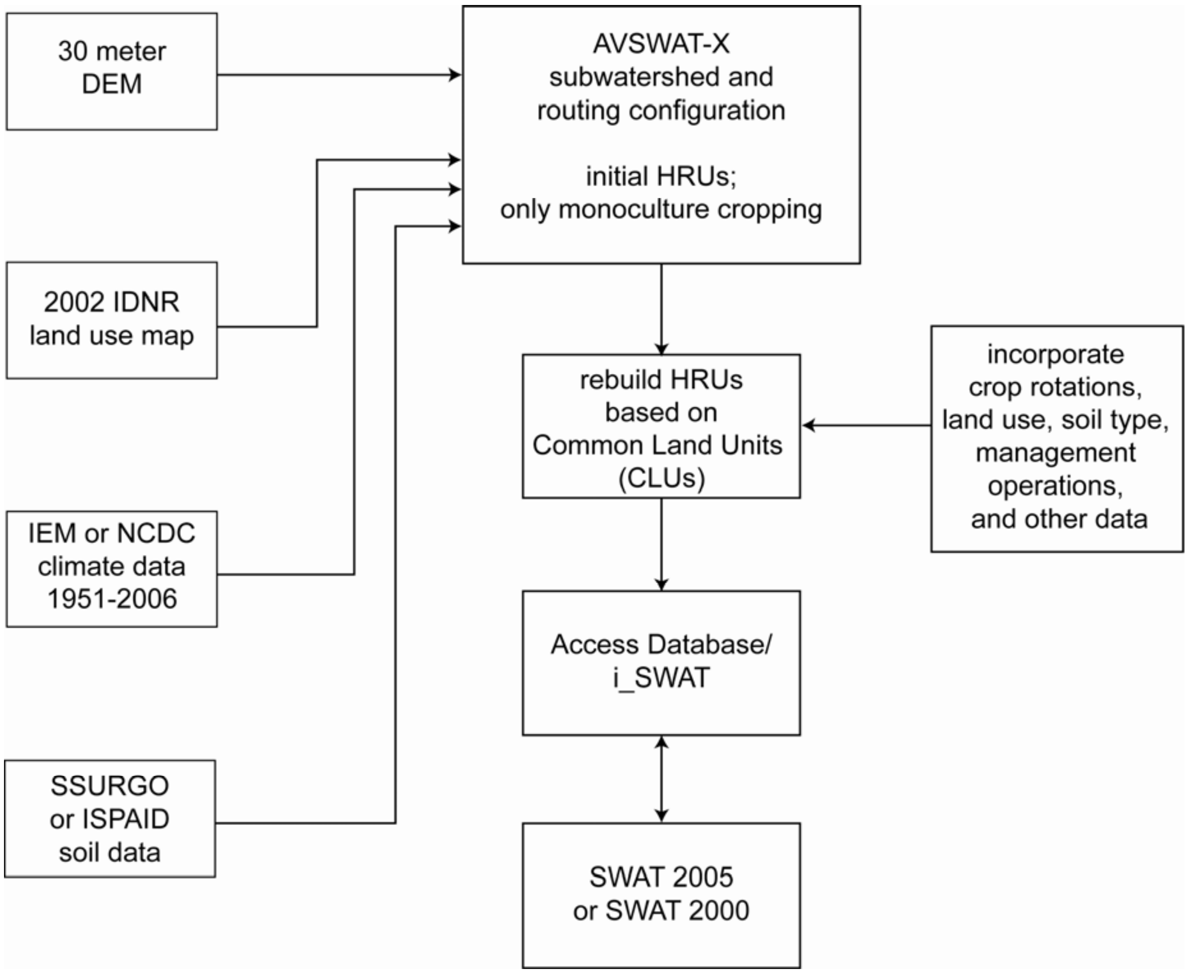

Figure 2. Schematic of the Boone River watershed SWAT modeling system.

system overview. The data layers are further described in subsequent sections, including characteristics of the data layers and key processing steps required for the modeling system. The modeling system is initiated by processing digital topographic, land use, climate, and soil data (Figure 2) within the ArcView SWAT-X (AVSWAT-X) interface (Di Luzio et al., 2004a), which is an application built for the ArcView Geogrpahic Information System (GIS) package (ESRI, 2007b) and is an extension of the original AVSWAT interface (Di Luzio et al., 2004b) as discussed in Chapter 2. The AVSWAT-X interface is a standard interface

Table 1. Digital data layers available for developing the BRW modeling system

Data Type	Data layer description (source[a])	Currently used?	In IDNR on-line library[c]?
Soil	Soil Survey Geographic (SSURGO) Database (USDA-NRCS, 2006a)	Yes	Yes
	Iowa Soil Properties and Interpretations Database (ISPAID) Version 7.2 (ISU, 2004)	Yes	Yes[d]
Topographic	Resampled IDNR 30 m Digital Elevation Model	Yes	No
	National Elevation Data (NED) 30 m GRID of Iowa	No	Yes
	National Elevation Data (NED) 10 m GRID of Iowa	No	Yes
Climate data	Iowa Environmental Mesonet (ISU, 2007)	Yes	No
	NOAA Satellite and Information Service (NCDC, 2007)	Yes	No
Field boundaries	Common Land Units (NAS, 2007)	Yes	Yes
Livestock operations	2005 Confined animal feeding operations (CAFOs)	Yes	Yes
Drainage districts	Public Drainage Districts of Iowa	No[b]	Yes
Point sources	Waste Water treatment plants of Iowa	No[b]	Yes
Land cover	2002 land cover grid of Iowa	Yes	Yes
	2005 Boone River watershed field-level survey (Kiepe, 2005)	Yes	No
	2000-2006 USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (USDA-NASS, 2007)	No	No
Tillage distribution	2005 Boone River watershed field-level survey (Kiepe, 2005)	Yes	No
Conservation Practices	2005 Boone River watershed field-level survey (Kiepe, 2005)	Yes	No

[a]Metadata documentation is provided for each data layer included in the IDNR on-line library; additional sources are provided here if available.
[b]Development has been initiated to include these data layers into the BRW modeling system.
[c]See IDNR (2007b) for on-line library access information.
[d]ISPAID attribute data can be linked to Iowa Cooperative Soil Survey (ICSS) soil polygons available in the IDNR on-line library.

provided for developing SWAT input data and is used worldwide for supporting a variety of SWAT applications. A SWAT interface compatible with ArcGIS (ESRI, 2007a) has recently been developed (Olivera et al., 2006) which could be used for future BRW modeling system development and is also discussed further in Chapter 2.

A resampled 30 m DEM layer (Table 1) was processed in AVSWAT-X to delineate the subwatersheds and routing configuration required for SWAT (Figure 2). These subwatersheds and associated routing structure are held constant across the BRW baseline and scenario simulations. Climate data were obtained for 1951-2006 (Table 1; Figure 2) and were assigned to specific subwatersheds within AVSWAT-X. The 2002 IDNR land use layer (Table 1) and a combination of SSURGO and ISPAID soil data[6] (Table 1) were used to build the initial cropland and other HRUs for the modeling system; the current structure of AVSWAT-X cannot accept a land use layer with crop rotations, thus a static land use layer such as the 2002 IDNR dataset must be used. As a result, the initial cropland HRUs created in AVSWATX consisted only of monoculture cropping systems dominated by continuous corn and continuous soybean. Some editing tools are provided in AVSWATX to convert such monoculture HRUs into crop rotations, and to add tillage, fertilizer application, and other management operations as appropriate. However, these editing tools are limited and did not provide the desired flexibility for building the cropping system and management inputs for the BRW SWAT simulations. In addition, these HRUs also represent lumped areas within each subwatershed that do not allow model users the ability to account for other specific land parcel units of interest such as the CLUs used in this study.

[6]SSURGO data were not available for two of the six counties that encompass the BRW when the initial set of monoculture HRUs were created. Thus, ISPAID data was converted by Di Luzio (2005) into SSURGO format to complete the required soil input data layer. SSURGO soil data has since become available for all six counties.

Common Land Units (CLUs): Framework for Input Data Integration

Recognizing these weaknesses, a method was developed to provide a more accurate representation of cropping systems, soil and landscape characteristics, and management at the CLU level. The CLU coverage is being developed by the USDA Farm Service Agency (FSA) for the entire U.S., which will include over 33 million farm and field boundaries when completed (NAS, 2007). At present, the majority of the U.S. CLU coverage has been completed including the entire state of Iowa (NAS, 2007). Further description of the CLU data is presented in Gelder et al. (2007a).

The CLU boundaries for the Boone River watershed portion of the Iowa coverage are shown in Figure 3. A total of 16,434 CLUs are located within the Boone River watershed; this number increases to 22,372 CLUs and CLU fragments when the 30 subwatershed boundaries (Figure 1) are overlayed on the CLU coverage. This Boone River watershed CLU coverage provides a framework for building model inputs at a much more refined spatial scale than in previous modeling efforts. It also provides a consistent basis for lumping data to various levels of aggregation, depending on the needs of the specific analysis.

External software was developed to convert the monoculture HRUs into crop rotation HRUs at the CLU level (Figure 2); fertilizer and manure applications, tillage practices, and conservation practices were also incorporated into the HRU management schemes in this step. The crop rotation, tillage practices, and conservation practices were all determined on the basis of a field-level survey performed in 2005 (Table 1). The crop rotation and management data were interfaced with dominant soil types determined from the SSURGO soil layer (Table 1) for every CLU in the watershed, resulting in a cropping system data set for essentially every field in the watershed.

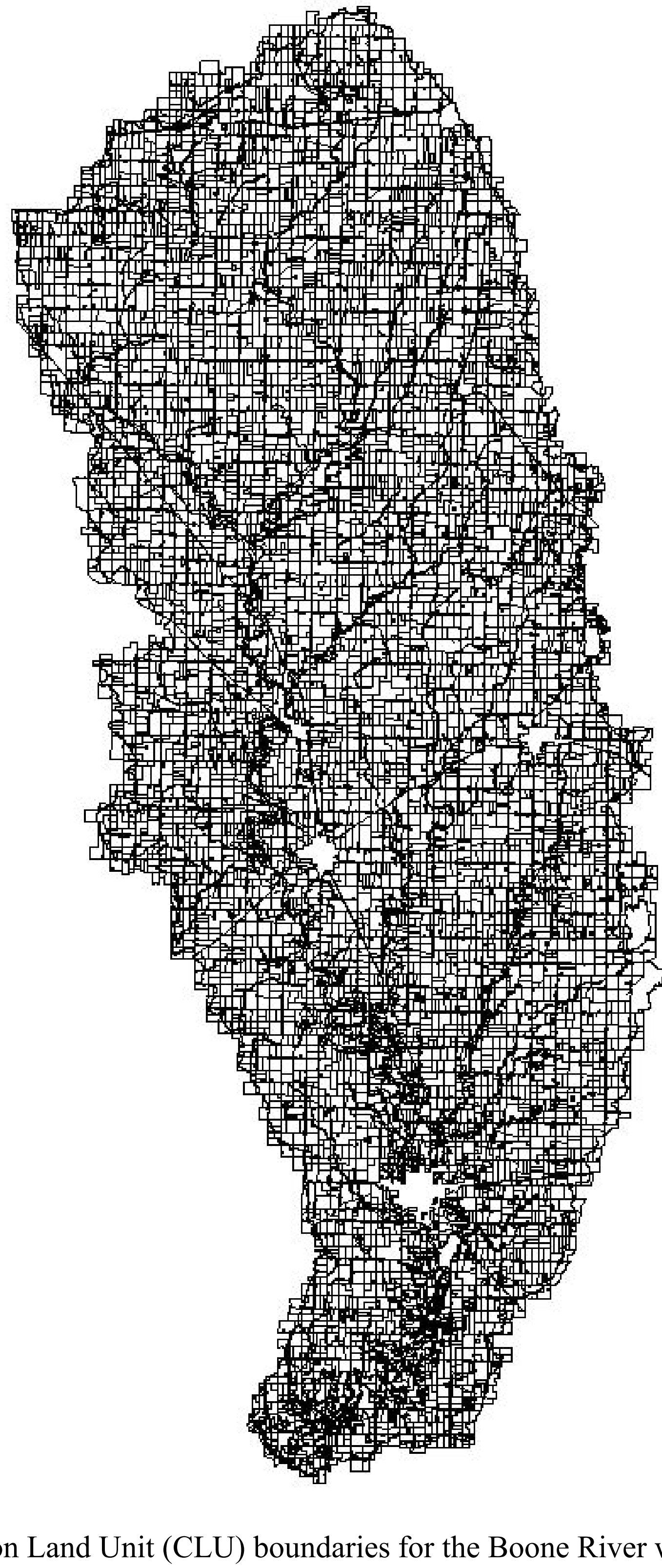

Figure 3. Common Land Unit (CLU) boundaries for the Boone River watershed.

The HRUs for the modeling system can be based on the individual CLUs and CLU fragments, or on aggregations of the CLU-based data as a function of homogeneous CLU characteristics. Either approach represents only percentages of land use in each subwatershed in SWAT rather than spatially defined land parcels, due to the inability of SWAT to recognize spatially defined HRUs at this time. However, the CLU framework allows the output to be mapped back to specific spatial units if desired. And it also provides the basis for accommodating anticipated future developments in SWAT that will support simulation of more spatial detail at the subwatershed level (see Chapter 2). The CLU-based data were further aggregated for the Boone River simulations, resulting in a total of 2212 HRUs that were used for both the SWAT baseline and scenario simulations.

The aggregated input data for each SWAT simulation were inserted into an Access database (Figure 2), which is used to manage the input and output data for the respective SWAT simulation. The SWAT simulations were managed with the interactive SWAT (i_SWAT) software (CARD, 2007), which translates the data in Access into the required input file formats, executes SWAT, and inserts output data back into the Access database (Figure 2). Other i_SWAT features include the option to import (and then execute) existing SWAT datasets, print and print preview options of management system lists, modification of management and other input data, charts of output by subbasins or HRUs, subbasin routing structure maps, and computation of average crop yields at the subwatershed or entire watershed levels. This approach provides increased flexibility for modifying SWAT inputs using Access queries and is in general a very straightforward method for managing the input and output data for a SWAT simulation.

Adaptation of the Modeling System for other Environmental Models

The Boone River modeling system has also been adapted for three other models used at CARD (Figure 4): the Environmental Policy Impact Climate (EPIC) model (Izaurralde et al., 2006; Williams, 1990; Gassman et al., 2005), the Agricultural Policy EXtender (APEX) model (Williams et al., 2006; Williams and Izaurralde, 2006), and the Century model (Parton et al., 1988; Kelly et al., 1997). Interactive software has been developed for each of these models (CARD, 2007) which are designed to support large simulations sets required for regional analyses. Data are input directly at the CLU level because these models operate at a field-scale level. Output data generated at the CLU level can be aggregated to various CLU aggregations, depending on the needs of the analysis. A current Boone River watershed EPIC application is being tested that consists of over 18,000 individual simulations that are simulated at the CLU level using the interactive EPIC (i_EPIC) software package.

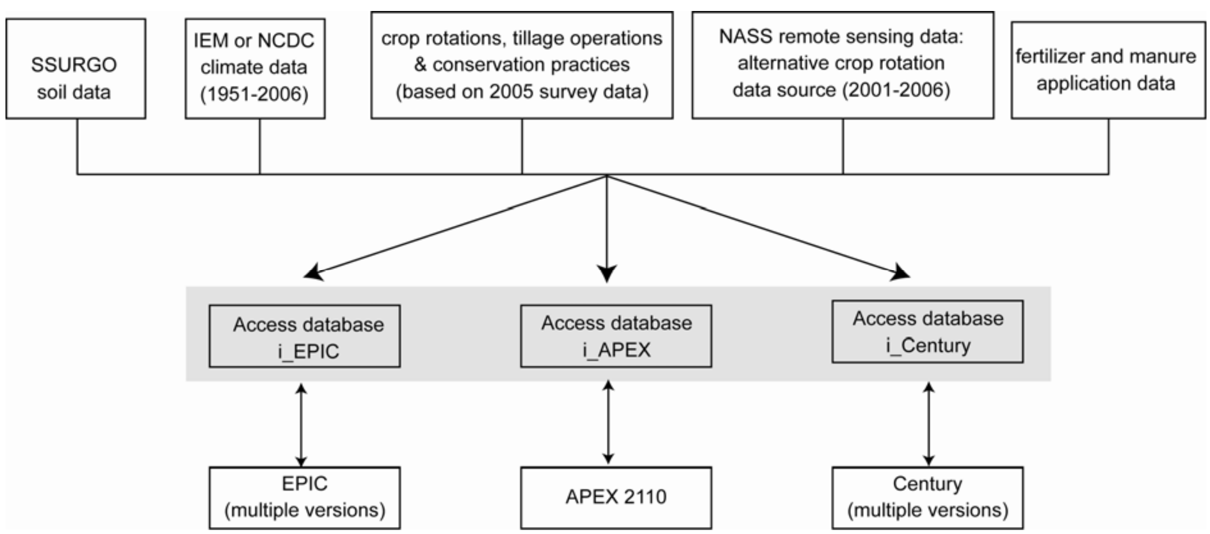

Figure 4. Schematic of the Boone River watershed modeling system for the EPIC, APEX, and Century models.

Data Layer Development and Characteristics

The following discussion provides in-depth descriptions of the development and characteristics of each of the key data layers used in the modeling system. The initial subsections focus on the data developed at the CLU level, including conservation practice, land use, nutrient applications, and soil data. The remaining subsections describe other key data layers that are required for the modeling system that are not currently linked directly at the CLU level.

Field-Level Survey of Tillage Practices, Conservation Practices, and Land Use

The field-level survey (BRW survey) was performed by Kiepe[7] (2005) during the spring of 2005 for the entire Boone River watershed in order to obtain land use and conservation practice data at the CLU level. The key data collected in the BRW field-level survey included current land use, crop rotation, tillage practice, and conservation practices. The location of livestock operations and eroded gullies or stream banks was also recorded; these data are currently not used in the modeling system because: (1) other confined animal feeding operation (CAFO) data are available, and (2) there was not an immediate need to apply the eroded gulley/streambank data in SWAT. The survey was performed primarily via visual reconnaissance, although local USDA-NRCS and other agency experts were also consulted to obtain additional insights regarding practices in certain parts of the watershed. There are obvious weaknesses in the approach due to the subjective judgments involved, especially when determining crop rotations. However, this approach was the only way to obtain detailed field-level practice data at the current time.

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[7]This work was performed by Mr. Charles Kiepe during the spring of 2005. Mr. Kiepe is a former USDA-NRCS employee and has performed similar surveys for several smaller watersheds in different parts of Iowa.

Field-Level Survey: Tillage Practices

A key set of data collected in the BRW field-level survey was the distribution of tillage practices and residue cover quality (categorized as good, average, or poor) at the CLU level. Figure 5 shows the resulting distribution of tillage in terms of three tillage levels: conventional (< 30% residue cover), mulch (30% < residue cover < 90%), and notill (> 90% residue cover[8]). Both Figure 5 and Table 2 reveal the extensive use of mulch till throughout the watershed, and that conventional till and no till were used on relatively small areas. Table 2 further shows the areal distribution of tillage type by current crop (2005 growing season) and residue cover quality. Nearly 95% of the row crop area was classified as being managed with mulch till at the time of spring planting in 2005. However, 11.6 and 21.6% of the mulch tilled corn and soybean were categorized as having poor residue quality. At present, the tillage assumptions used in the BRW baseline SWAT simulation mirror the three broad tillage category distributions shown in Table 2. However, future simulations could take into account the additional residue quality designations by incorporating more refined tillage system treatments in the model simulations.

The only other source of tillage data currently available for the BRW is county-level survey data collected on a biannual basis by the Conservation Tillage Information Center (CTIC), using primarily expert opinion and supporting transect surveys of selected cropland areas (typically drive-by surveys of residue on crop fields) to determine the distribution of five different tillage categories at the county level (Hill, 2006). Table 3 lists the area (ha) reported in the 2004 CTIC survey for no till (including ridge till), mulch till, and

[8]The residue cover demarcation between mulch and notill can fluctuate some due to the effect of planter passes and/or fertilizer application equipment that can bury some residue in a notill system, and also because of differences in coverage that occur between corn and soybean residue.

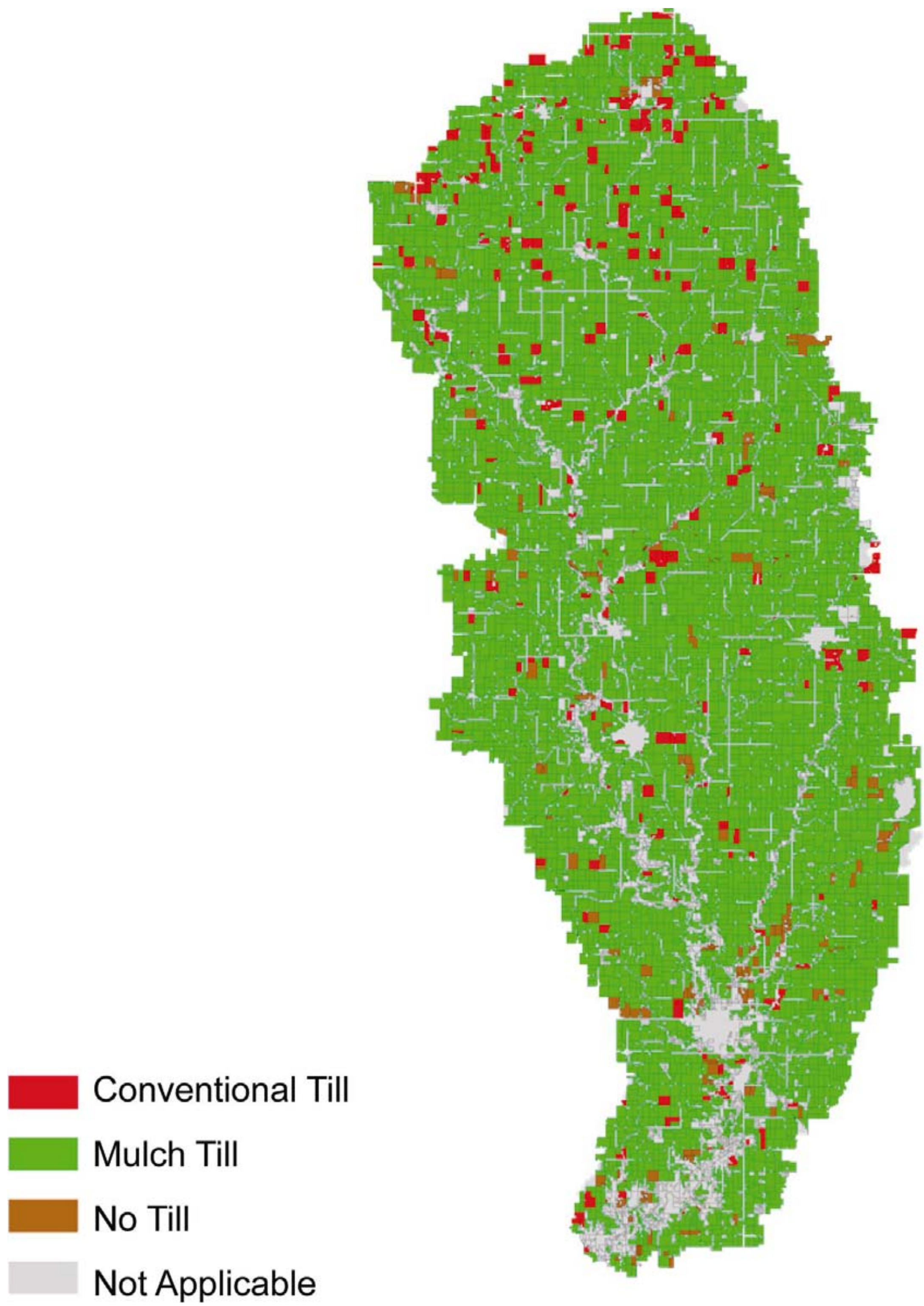

Figure 5. Distribution of tillage practices for the Boone River watershed determined from the field level survey.

Table 2. Distribution of tillage type and associated residue quality by crop as determined in the 2005 field-level survey.

2005 Crop	Tillage type	Residue quality	Number recorded[a]	Total area (ha)	Percentage of row crop area
Corn	Conventional Till	Good	23	396.3	0.2
Corn	Conventional Till	Poor	345	5290.7	2.6
Corn	Mulch Till	Average	2	16.3	0.01
Corn	Mulch Till	Good	4749	76845.6	37.7
Corn	Mulch Till	Poor	1576	23676.6	11.6
Corn	No Till	Good	210	3581.5	1.8
Corn	No Till	Poor	4	105.3	0.05
Soybean	Conventional Till	Average	2	45.1	0.02
Soybean	Conventional Till	Good	2	48.4	0.02
Soybean	Conventional Till	Poor	180	2799.1	1.4
Soybean	Mulch Till	Average	7	107.0	0.05
Soybean	Mulch Till	Good	2784	45131.2	22.2
Soybean	Mulch Till	Poor	2938	43899.3	21.6
Soybean	No Till	Good	71	1445.9	0.7
Soybean	No Till	Poor	7	125.3	0.06

[a]The number recorded for conventional tilled corn and mulch tilled soybean include 5 (34.6 total ha) and 8 (143.8 total ha) records, respectively, that were marked as “not applicable”; these were assumed to be in the “good” residue quality category for the data reported here.

conventional till (including reduced till) for the six counties that the BRW is located in. These CTIC survey results are markedly different than those found in the BRW survey; the vast majority of corn area was indicated to be managed with conventional till, and a sizeable portion of the soybean area was also reported to be managed with conventional till. Some of the inconsistencies between the BRW and CTIC surveys can be attributed to two different years of data collection and different overall areas used in the data collection process.

Table 3. Distribution of tillage levels reported in the 2004 Conservation Tillage Information Center (CTIC) survey by county and crop for the BRW region.

	Corn			Soybean		
County	Notill	Mulch	Conventional	Notill	Mulch	Conventional
	(ha)					
Hamilton	3,151	7,396	55,242	4,829	30,213	26,496
Hancock	0	9,393	55,685	4,066	37,606	9,148
Humboldt	209	29,545	22,354	632	41,917	2,665
Kossuth	1,230	6,149	115,594	2,879	63,340	29,751
Webster	615	4,539	71,774	2,641	17,540	47,540
Wright	630	25,366	44,074	5,716	51,445	3,009

However, the comparisons between the two survey approaches clearly points out the need for more accurate survey methods, if realistic accounting of tillage practices are going to be obtained on a watershed-by-watershed basis.

It is clear that using field-level reconnaissance will not be a viable approach for gathering tillage and residue information on a wide scale. A more realistic method would be to use the remote sensing approach described by Gelder et al. (2007b), who successfully demonstrated that remote sensing techniques could be used to estimate residue cover for 83 fields in Boone, Hamilton, and Story counties in the north central Iowa Des Moines Lobe region. Further application of this approach is needed at the large regional scale, such as the entire state of Iowa to provide consistent and reliable assessment of tillage practices for watershed simulation and other studies.

Field-Level Survey: Conservation Practices

Conservation practice data collected in the field-level survey are shown in Figures 6 and 7. Figure 7 reveals that structural practices such as terraces, field borders, and water and sediment control basins are scattered throughout the watershed and that contouring is also practiced to a limited extent. The use of terraces and contouring are concentrated in subareas with higher slopes, including areas characterized by glacial moraine formations such as the far southern and northern portions of the watershed (Figure 7). Grass field borders are used along several stream channel segments in the flatter areas of the watershed, which dominate the majority of the BRW topography.

Table 4 summarizes the total areas of different conservation practices and conservation practice combinations in the BRW, based on the areas of the affected CLUs. These tabulated results underscore the fact that the use of such practices is not extensive across the BRW, but are definitely important in specific BRW subareas. In contrast, the statistical sampling approach used in the 1997 NRI found that grassed waterways were the only conservation practice used in the watershed, which affected almost 2,700 ha. Grassed waterways were not reported in the BRW survey, which may indicate that the grassed waterways reported in the 1997 NRI were actually field borders instead. Whether this is true or not, the survey conducted for this study clearly reveals the weaknesses that can occur when using a statistical sampling approach for determining conservation practices, especially in a region dominated by relatively flat topography.

At present, both terraces and contouring are directly accounted for in the BRW SWAT simulations. The possibility of incorporating field borders, ponds, and water and sediment control basins can be investigated for future BRW SWAT applications, although

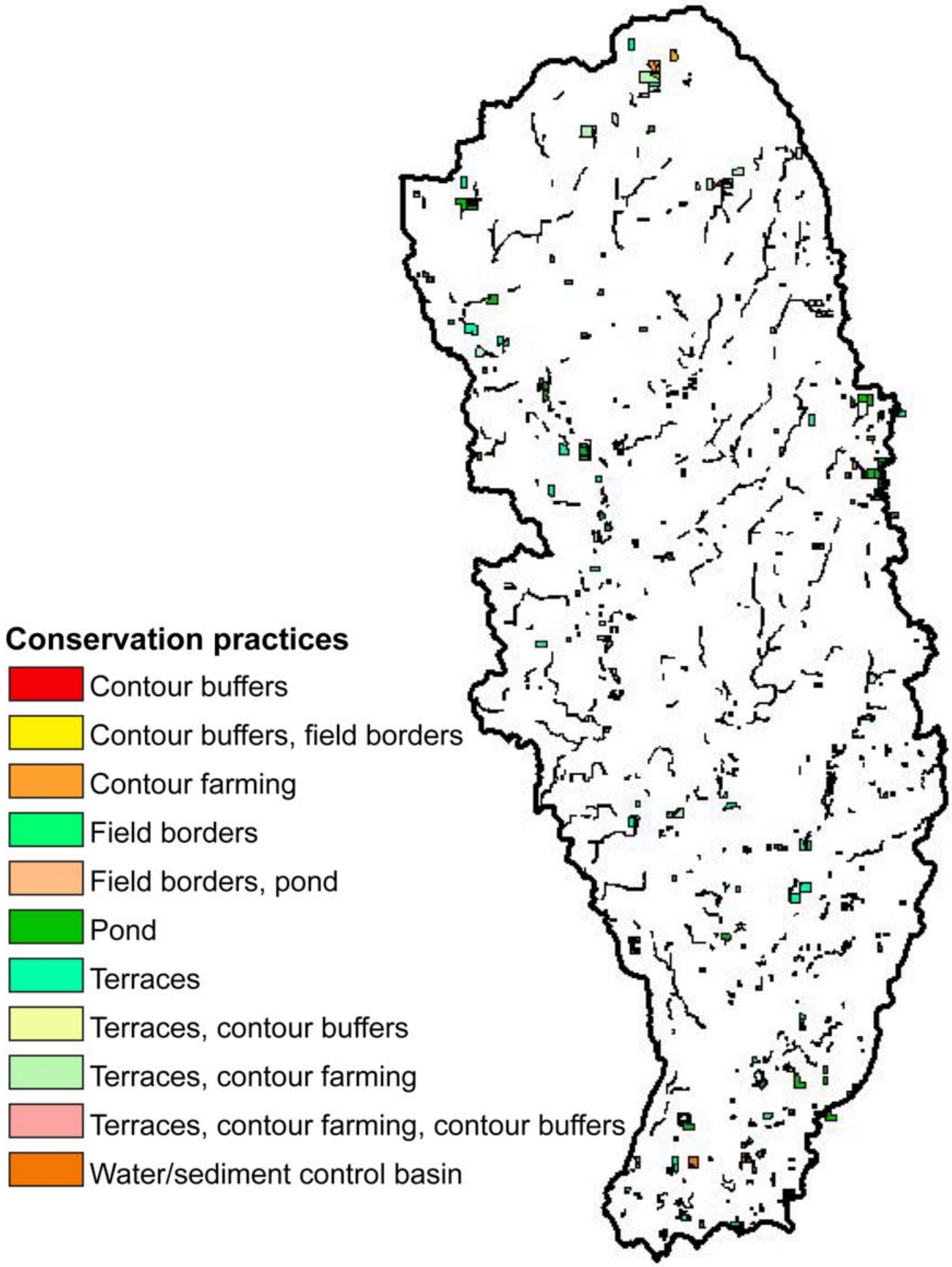

Figure 6. Locations of structural conservation practices and contour farming identified in the BRW Survey.

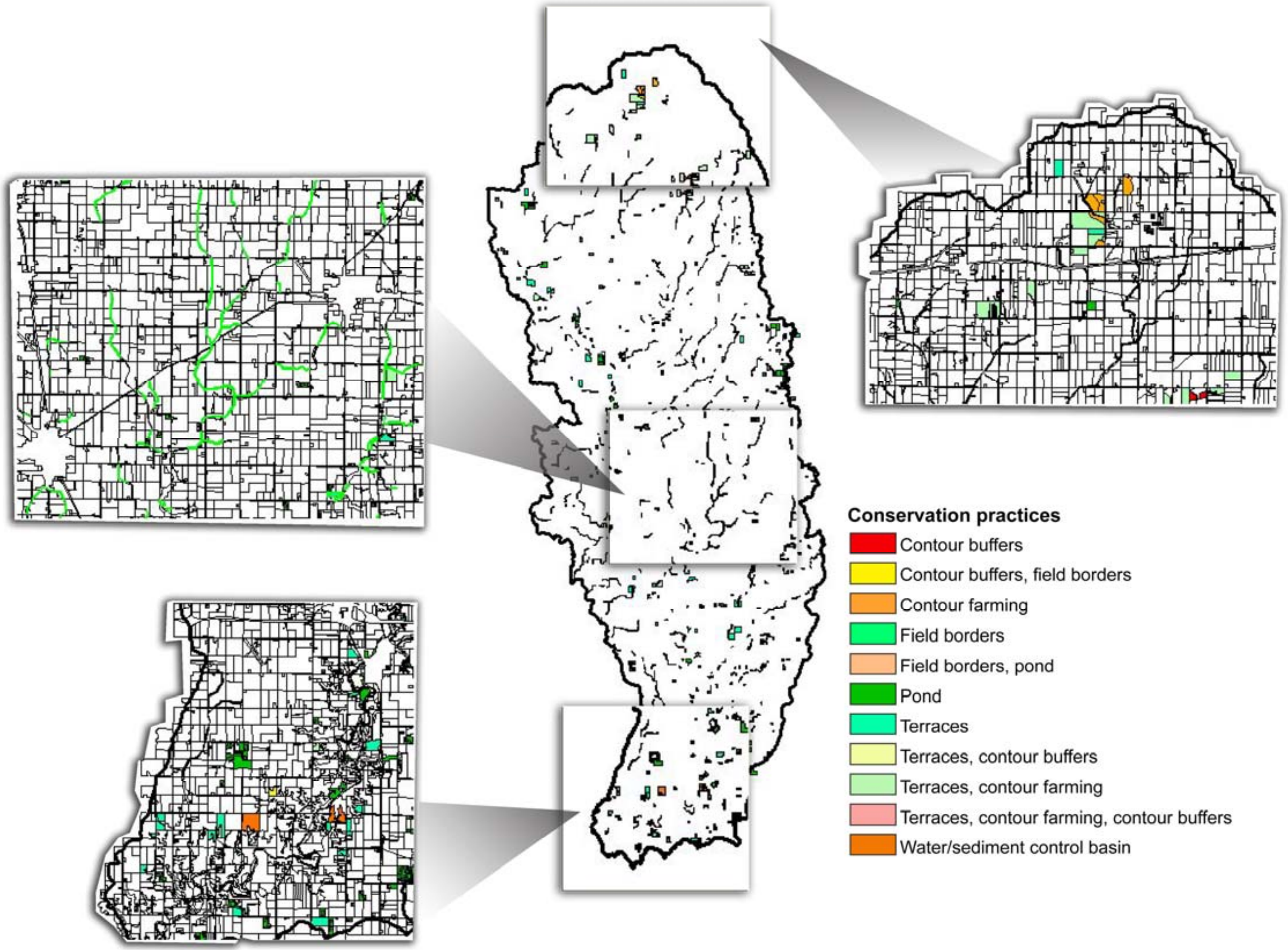

Figure 7. Examples of zoomed-in subregions showing extent of conservation practices recoded in the BRW field-level survey.

Table 4. Total number and area of different conservation practice types found in the field-level BRW survey.

Conservation Practice(s)	Number recorded	Total area affected (ha)
Terraces, Contour Farming, Contour Buffers	1	1.3
Contour Buffers, Field Borders	2	1.2
Terraces, Contour Buffers	3	17.3
Water/Sediment Control Basin	8	99.2
Field Borders, Pond	9	15.1
Contour Farming	15	158.8
Contour Buffers	20	30.0
Terraces, Contour Farming	54	737.5
Terraces	89	955.6
Pond	1,089	2,944.7
Field Borders	1,545	1,997.4
No practices documented	20,037	219,977.0

the impacts of ponds and water and sediment control basins would be expected to be minor. Improvement in the process of determining conservation practices reported here is not foreseeable, due to a lack of viable alternative approaches presently available.

Field-Level Survey: Land Use

Current land use and crop rotations were two of the key sets of information that were gathered in the survey. Determination of crop rotations is vital for accurately assessing nutrient management and other scenarios in SWAT and similar models, by accounting for rotation effects on nutrient application rates, tillage practices, and other rotation-driven management decisions. The specific crops or the cropland CLUs were determined based on observation of the crops that were being planted during the survey period. The crop rotations were determined for each field based on observed plant residue remaining from the previously harvested crop and on supplemental expert opinion provided by local agency experts for some fields.

Figure 8 shows the 2005 land use map, overlayed on the CLU boundaries, which was generated from the BRW survey and clearly demonstrates the dominance of corn and soybean across the majority of the watershed. Figure 9 shows a comparable 2005 land use map that is based on the USDA-NASS Cropland Data Layer (NASS CDL) listed in Table 1, which was developed from remote sensing data. The NASS CDL land use map confirms the dominance of corn and soybean. However, some differences can be observed between the two data sources regarding whether corn or soybean was identified in specific land parcels.

The percentage of primary land use categories are compared in Table 5 between the BRW survey, 2005 NASS CDL, and the 2002 IDNR land use data layer (Table 1), which was also derived from remote sending data. The land use distributions of the two remote sending data sets are very similar, with roughly 95% of the land use indicated to be in corn, soybean, or some type of grassland. The BRW survey also indicates that about 95% of the watershed area is managed with corn, soybean, or grass, but the combined corn and soybean area is about 5% higher than the corresponding combined areas reported by the other two land use sources (and the BRW survey grassland area is lower than the corresponding estimates for the other two sources by a similar percentage).

Error in the 2005 (and 2002) land use estimates could have occurred for several possible reasons. Visual misinterpretation and data entry errors may have occurred during the course of the BRW survey. Misclassification can also occurred for data collected via remote

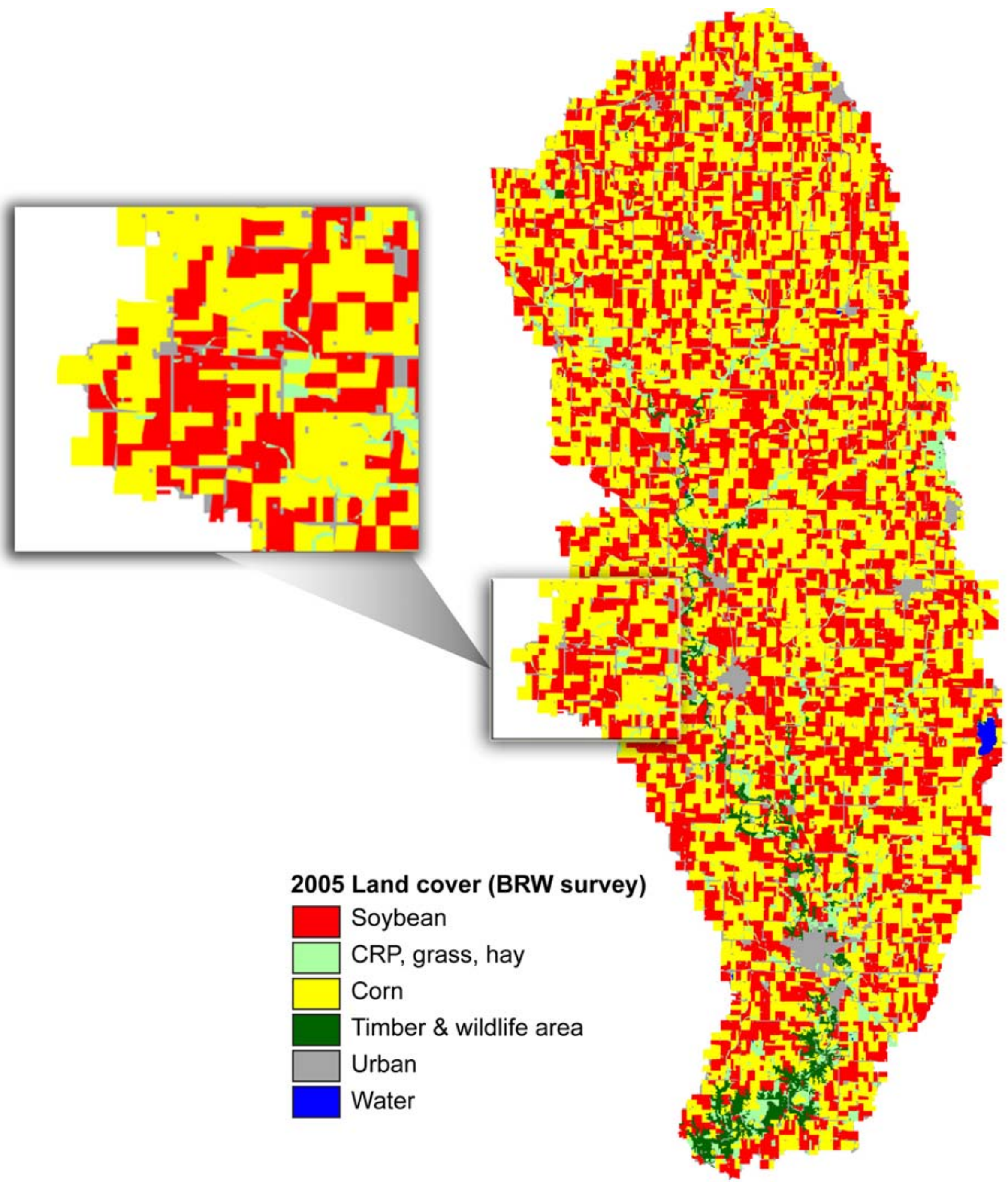

Figure 8. 2005 Boone River watershed land use based on the BRW Survey results.

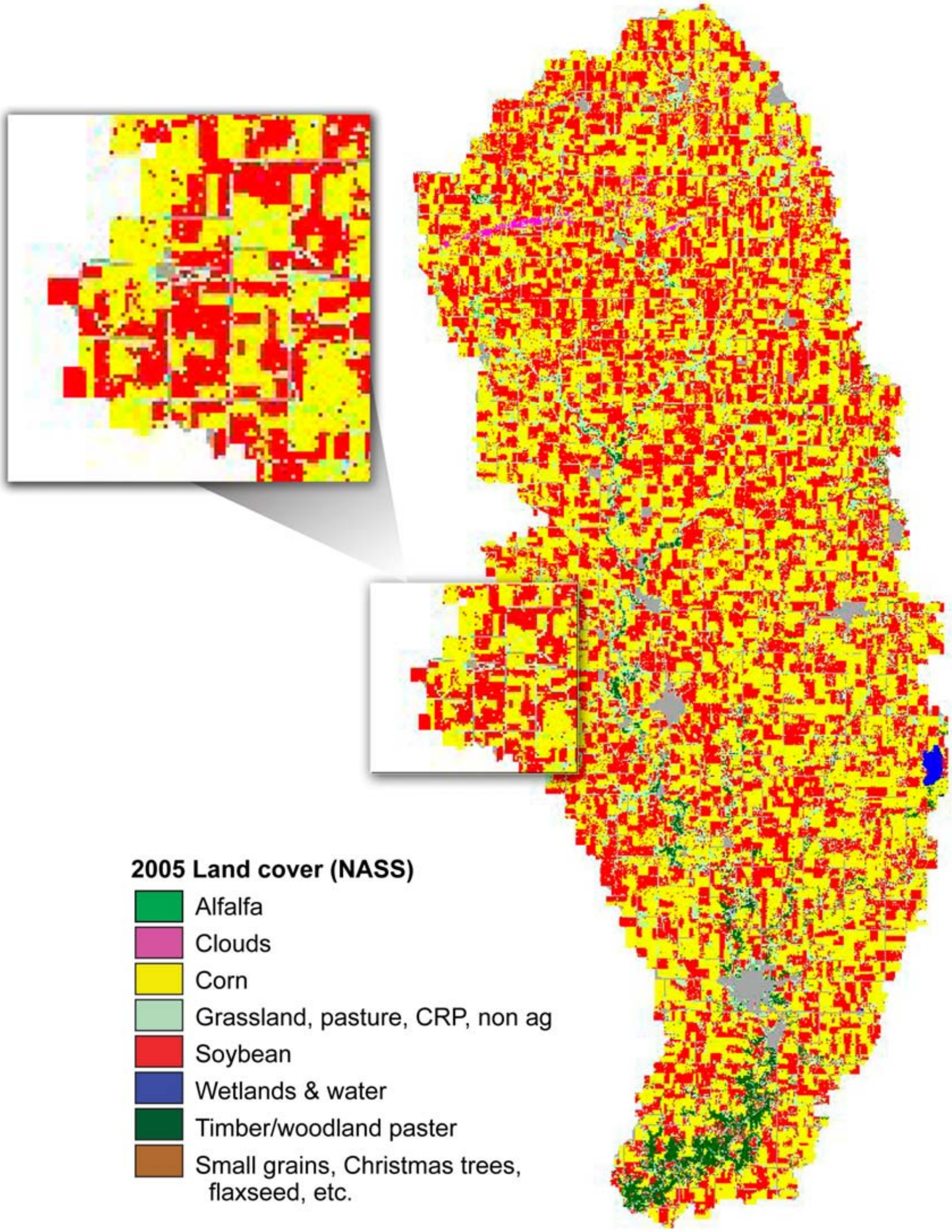

Figure 9. 2005 Boone River watershed land use based on the USDA-NASS Cropland Data Layer.

Table 5. Comparison of percentages reported for Boone River watershed land use from three different sources[a]

Landuse	2005 BRW Survey	2005 NASS CDL	2002 IDNR
Alfalfa	-	0.3[c]	0.75
Corn	48.5	44.6	44.0
Soybean	41.4	38.9	39.7
Pasture/CRP/grassland	5.4[b]	12.3[d]	10.9
Urban	2.0	0.43	1.6
Water/Wetland	0.03	0.06	0.6
Woodland	2.6	2.3	2.2
Other	-	1.2[e]	-

[a]See Table 1 for further information on data sources.
[b]Includes hay and oats.
[c]Includes small grains, hay, flaxseed, and oats.
[d]Includes a cryptic category called "Non ag."
[e]Includes "other crops", areas shrouded by clouds, fallow/idle cropland, Christmas trees, and sunflowers.

sensing (Gelder et al., 2007a). This clearly occurred with the 2005 NASS CDL, as evidenced by curious land use categories such as flaxseed and sunflowers which are obvious errors. Two key apparent discrepancies include: (1) areas interpreted by the remote sensing process as grassland, which were found to be corn or soybean in the BRW survey, and (2) CLUs that were recorded as corn in the BRW survey that were interpreted as soybean by the NASS CDL remote sensing data and vice versa (see zoomed-in areas in Figures 8 and 9). It is difficult to establish with absolute certainly which approach was the most accurate. These results do point for the need for further research to better confirm the accuracy of using NASS CDL and other remote sensing data at the CLU level.

Land use data in the form of crop rotations were also collected in the BRW survey and derived from multiple successive years of the NASS CDL. Figures 10 and 11 show the respective crop rotation maps that were based on the BRW survey and the 2002-2006

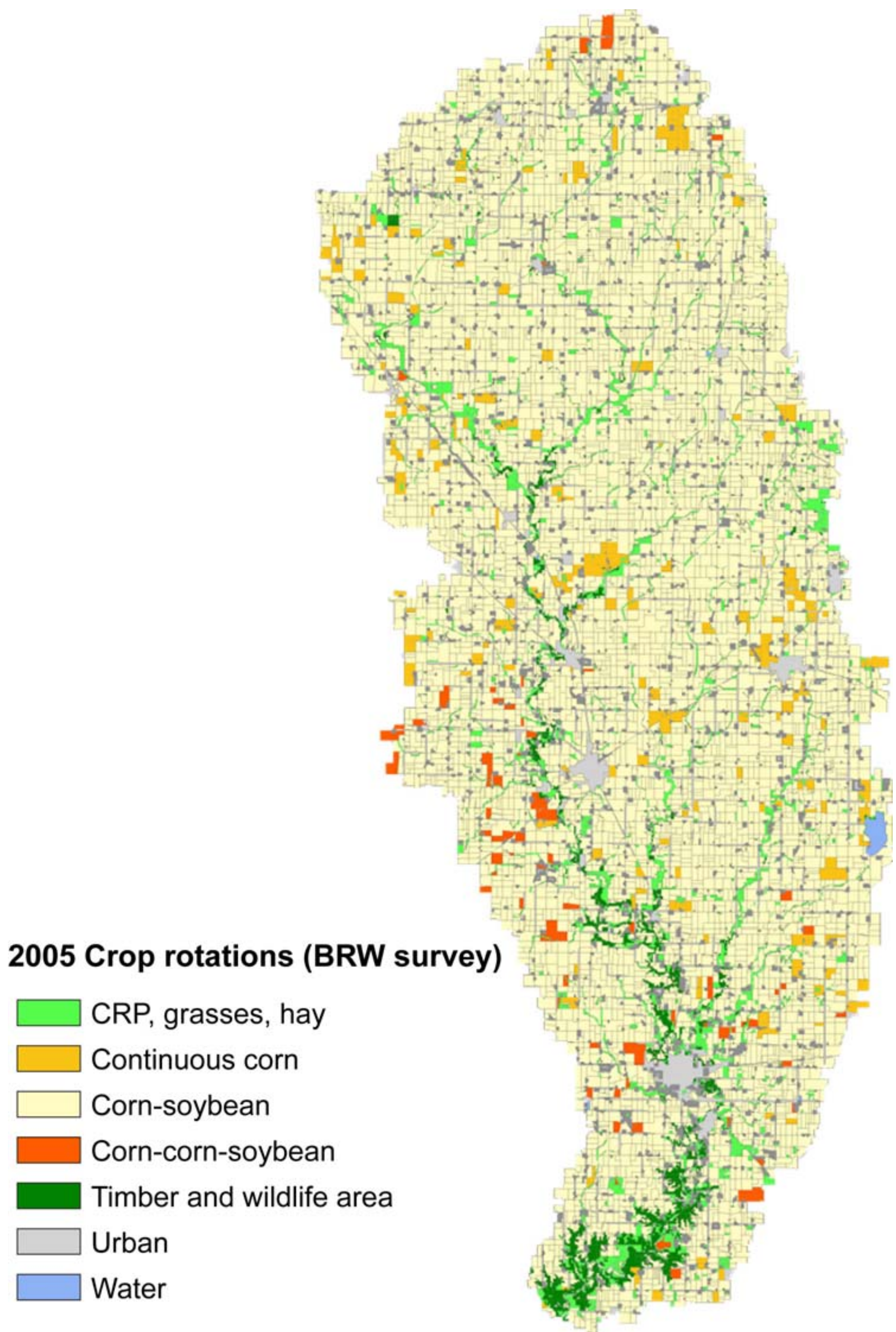

Figure 10. Boone River watershed land use map showing key crop rotations, based on data collected in the 2005 BRW field-level survey.

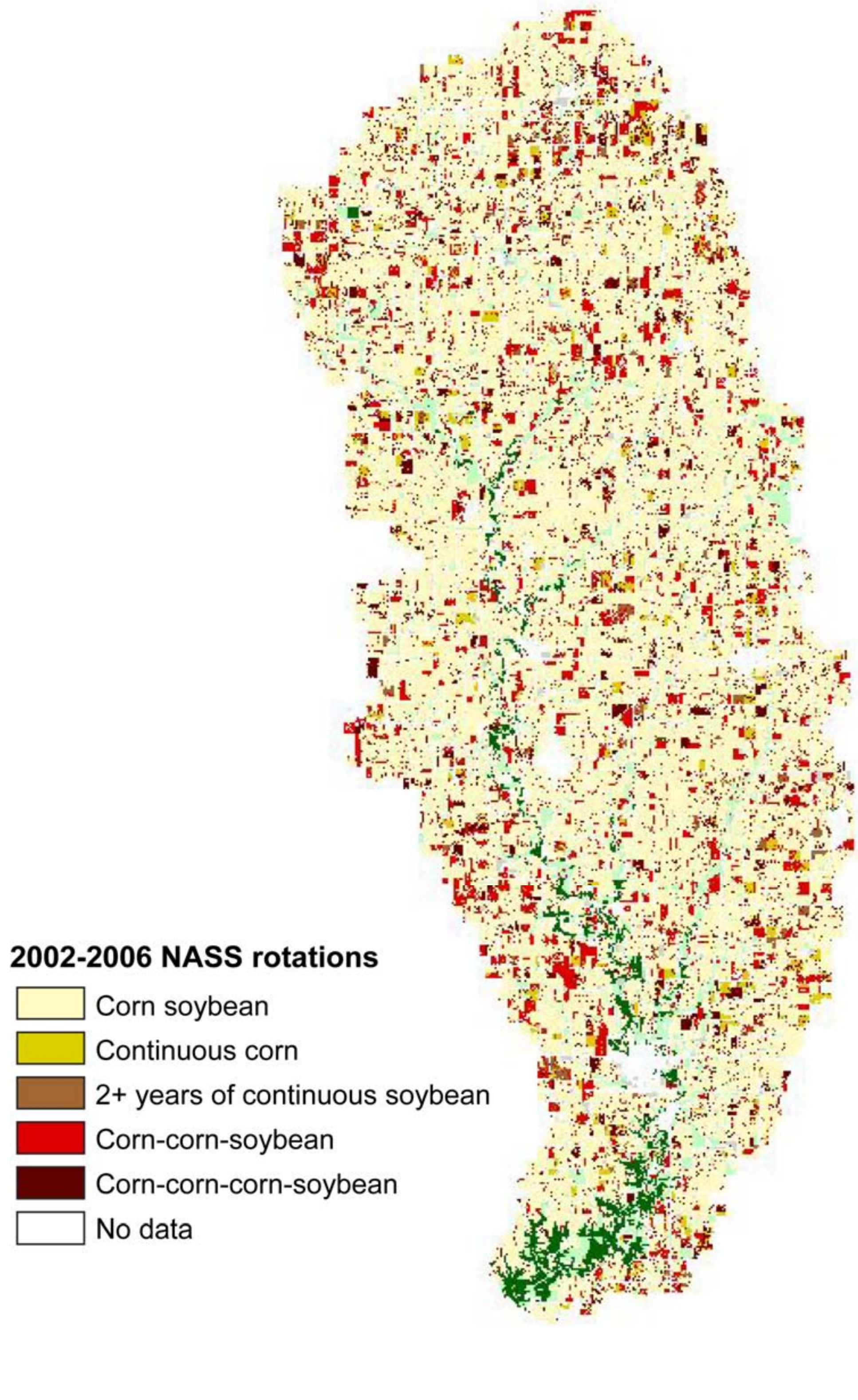

Figure 11. Boone River watershed land use map showing key crop rotations, based on remote sensing data reported in the 2002-2006 NASS Cropland data layers.

NASS CDL[9]. Both maps show that a two-year sequence of corn-soybean was by far the dominant rotation in the watershed and that relatively small areas of continuous corn were present. However, the crop rotation map based on the 2002-2006 NASS CDL shows a much greater occurrence of three- and four-year rotations with multiple years of corn and only one year of soybean. These differences reflect the inherent subjectivity of estimating rotation patterns within a field-level survey and also the likelihood of corn acreage expansion that was occurring during the 2006 growing season due to increased demand from regional corn-based ethanol production (Table 6). However, subjective judgments were also used in determining some of the crop rotations for the 2002-2006 NASS CDL, which may have introduced errors in those estimations.

The percentage of each crop rotation reported in the BRW survey, on the basis of total cropland area (as opposed to total land area), is compared with similar percentages in Table 6 that were determined from the 1997 NRI and the 2002-2006 NASS data. The tabulated data shows that the percentage of cropland planted in a corn-soybean rotation was 17% higher than what was derived from the NASS CDL. Similarly, the NASS CDL shows almost 16% more area planted to corn-corn-soybean and corn-corn-corn-soybean relative to the BRW survey. The 1997 NRI indicates proportions of corn-soybean and corn-corn-soybean that are in between the estimates provided by the other two land use data sources. The NRI also indicates that slightly over 3% of the cropped area in the watershed was planted in soybean-soybean-corn in 1997, which contrasts with the NASS CDL estimate of 2.2% of the cropped area being planted in continuous soybean during 2002-2006 (and

[9]The BRW Survey reportd that a small percentage of the grassland CLUs were planted in alfalfa. These CLUs with alfalfa were simulated as a five-year rotation (two years of corn followed by three years of alfalfa) which is not shown in either Figure 10 or 11.

Table 6. Percentages of different crop rotations reported from three land use data sources, within the overall Boone River watershed cropland area.

Crop rotation	Percentage of overall cropland area		
	BRW Survey	1997 NRI	NASS CDL[a]
Continuous corn	4.3	3.7	3.4
Corn-soybean	94.0	86.7	77.0
Corn-corn-soybean	1.5	6.1	10.6
Corn-corn-corn-soybean	-	-	6.7
Soybean-soybean-corn	-	3.3	-
Continuous soybean	0.1	-	2.2
Corn-alfalfa (5-year)	0.3	0.3	-

[a]Developed from the NASS CDL (Table 1) for the 2002-2006 growing seasons.

virtually no continuous soybean based on the BRW survey results). Both the BRW survey and the 1997 NRI show very small percentages (0.3%) of the cropland being devoted to rotations that include alfalfa.

At present, the crop rotation estimates provided by the BRW survey have been used for the SWAT baseline simulations. However, the fact that the NASS CDL can be mapped at the CLU level points to it being an excellent alternative source of land use data for the BRW, with the ability to account for specific crop rotations. Improved crop rotation estimates based on the NASS CDL can also be obtained using a filtering approach similar to the one described by Gelder et al. (2007a). The option does exist to adjust the survey data with the NASS CDL, to reflect greater proportions of corn-corn-soybean, soybean-soybean-corn, or continuous soybean rotations. It is also possible to use the NASS CDL instead of the BRW survey data, which may be considered for future research. It is clear that the NASS CDL approach is the only viable option, in terms of both cost and time, for building similar crop rotation-based land use data sets for multiple watershed studies in the UMRB region, especially for watersheds similar in size to the BRW. Recent expansion of the NASS CDL for other upper midwest states also points to the potential to build a land use layer with crop rotations for the entire UMRB in the near future (Chinnasamy et al., 2008).

Nutrient Inputs From Livestock Production

Figure 12 shows the distribution of confined animal feeding operations (CAFOs) located in and near the BRW, based on 2005 IDNR data (Table 1), overlayed on the SWAT subwatersheds. Some of the operations shown just outside of the watershed in Figure 12 would actually lie on the watershed border, if standard 12-digit watershed boundaries were used instead of the delineated SWAT subwatershed boundaries (see the Topographic Data section for further discussion of DEM dataset effects on the watershed boundaries). The vast majority of the 128 CAFOs are swine, which are clearly also the dominant species in terms of total head and equivalent animal units (Table 7). However, over 25% of the approximately 266,000 animal units in the BRW region are layer chickens distributed across just six operations. The concentration of animal units by CAFO are shown in Figure 13, which further demonstrates the large relative size of the layer chicken operations and some of the swine operations as compared to the other livestock operations in the BRW.

The CAFO operations represent a significant source of cropland-applied nutrients in the watershed. Several challenges arise when attempting to assess exactly how manure nutrients are managed within any watershed including determination of: (1) the composition of the applied manure nitrogen and phosphorus as a function of inorganic and organic subcomponents, (2) how much of the manure nutrients (mainly nitrogen) are lost prior to land application, (3) the rate the manure nutrient applications are applied at, (4) which

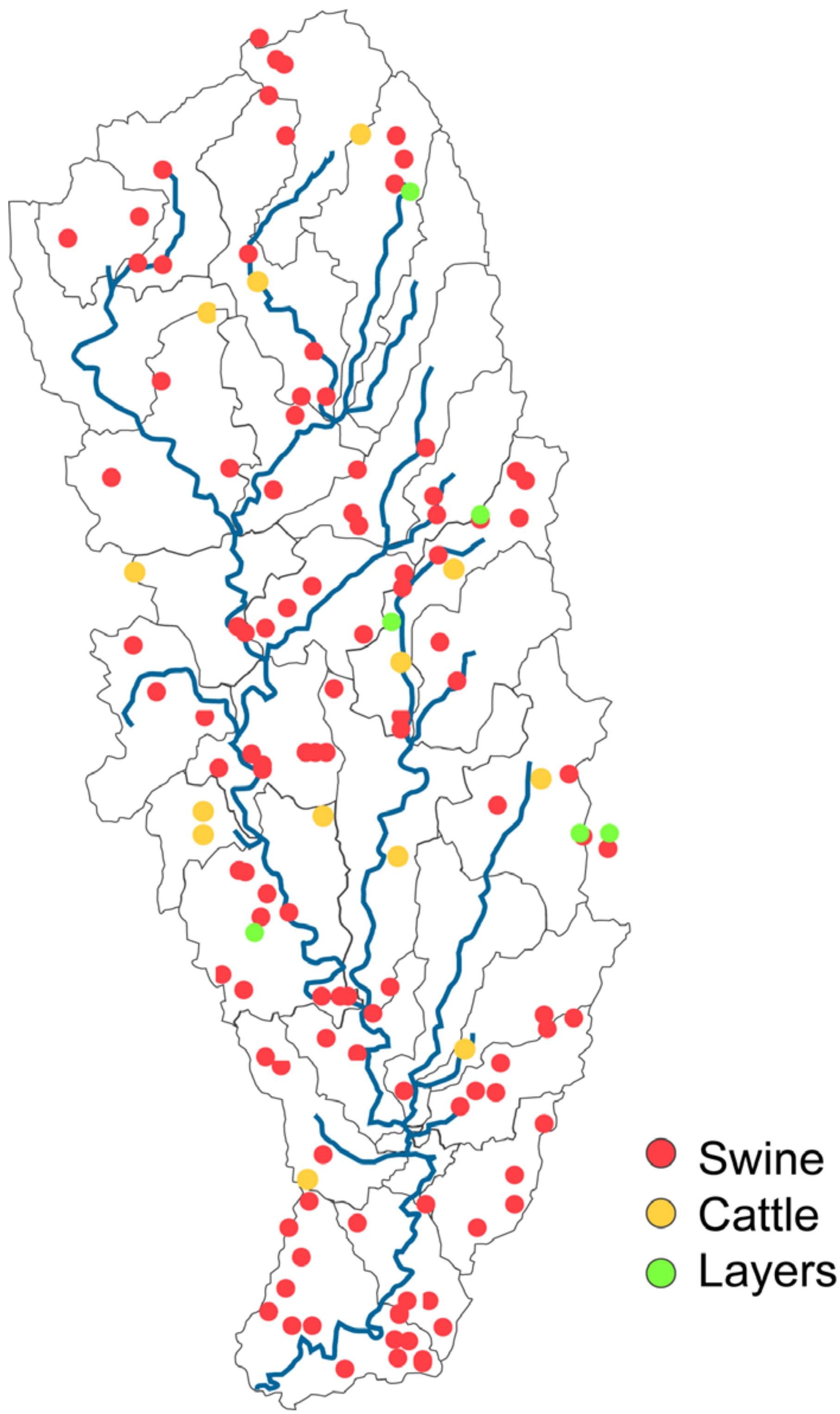

Figure 12. Locations of confined animal feeding operations in the Boone River watershed.

Table 7. Total number of confined animal feeding operations (CAFOs), and corresponding livestock numbers and animal units, in the Boone River watershed[b]

Livestock type	Total number of operations	Total number of livestock	Total animal units[c]
Swine	109[a]	480,478	192,191
Cattle	13	4,265	4,265
Chickens (layers)	6	6,962,116	69,621

[a]97 are finishing operations and the other 12 are gestating/nursery operations.
[b]Source: IDNR (2007b).
[c]Animal unit equivalencies: swine = 0.4; cattle = 1.0; layer chickens = 0.01.

specific cropland the manure is applied to, and (5) when the manure is applied.

A "composite manure" was developed for the BRW SWAT simulations, which reflects the overall relative contributions of the three different livestock species produced in the watershed. Annual nutrient production per animal was first determined for each type of livestock based on the livestock manure nutrient production data and nitrogen loss assumptions for typical manure handling systems reported by Libra et al. (2004), which are shown in Table 8. The inorganic and organic fractions for the manure nitrogen and phosphorus, that are required to characterize manure nutrient composition in SWAT, were based on the fractions used for the study by Gassman et al. (2002) and are shown in Table 9 by livestock species. The composite manure inorganic and organic fractions used in the SWAT simulations are shown in the bottom line of Table 9, which reflect the relative amounts of manure contributed by the three livestock species.

Determination of where the manure would be applied was based on the approach described by Schilling and Wolter (2007) for the Raccoon River SWAT TMDL study. The initial step in this approach is to estimate manure application zones around each CAFO, using software developed at the USDA National Soil Tilth Laboratory (Tomer et al., 2008). The resulting manure application zones are shown in Figure 14, which represent concentric

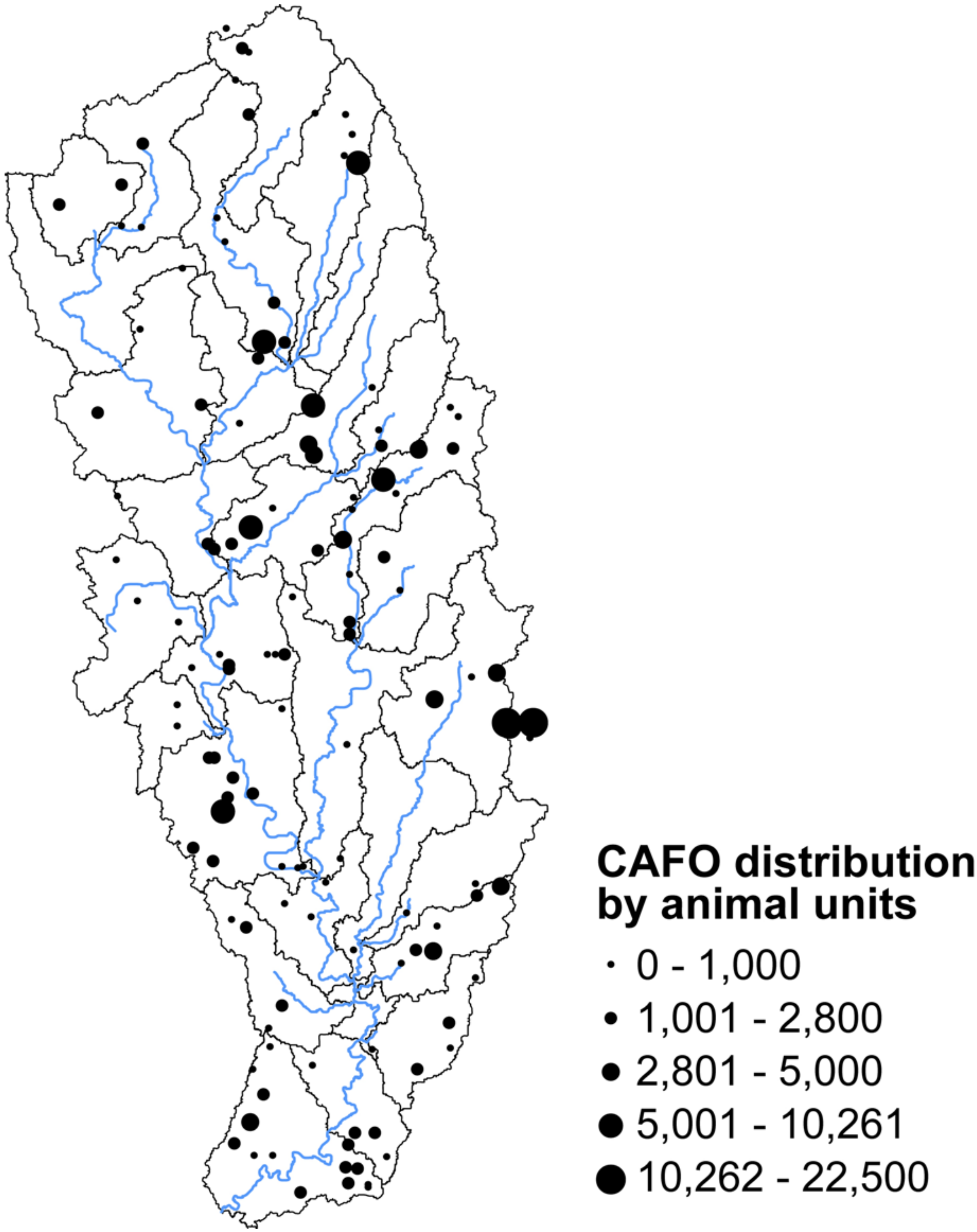

Figure 13. Concentration of animal units by confined animal feeding operation for the Boone River Watershed.

Table 8. Percentage nitrogen loss for typical manure handling systems and total annual amount of manure nitrogen and phosphorus by livestock species[a]

Livestock species	% nitrogen losses for typical manure handling systems	Total manure nitrogen per animal	Total manure nitrogen per animal after losses are accounted for	Total manure phosphorus per animal
		---------------------- kg yr^{-1} (lb yr^{-1})	--------------------	
Swine	25	13.2 (29.2)	9.9 (21.9)	3.2 (6.9)
Cattle	45	54.6 (120.4)	30.0 (66.2)	10.9 (24.1)
Layer chickens	40	0.5 (1.1)	0.3 (0.7)	0.2 (0.3)

[a]Based on data reported in Libra et al. (2004).

Table 9. Manure inorganic and organic nutrient fractions by livestock species and for the composite manure that was used for the BRW SWAT simulations

Livestock species	Inorganic nitrogen	Inorganic phosphorus	Organic nitrogen	Organic phosphorus	% NH_4
Swine	0.5695	0.2045	0.1898	0.0361	100
Cattle	0.2420	0.0881	0.4913	0.1787	75
Layer chickens	0.1225	0.2357	0.5442	0.0977	94
Composite	0.4302	0.2117	0.3010	0.0571	97.8

circles around each CAFO (or CAFO cluster). These zones were created on the assumption of manure being applied at 100 kg ha^{-1} (89 lb ac^{-1}) on all corn and soybean fields within a given zone, or at an equivalent application rate of 200 kg ha^{-1} (178 lb ac^{-1}) to corn during the corn year of a corn-soybean rotation. Some of the zones lie outside of the watershed, which represent CAFOs just over the watershed border. Some of the other zones straddle the

Figure 14. Locations of confined animal feeding operations in the Boone River watershed.

boundary including zones generated for some of the large layer chicken operations. These zones represent manure application areas that transcend the BRW region.

The manure applications for the BRW SWAT simulations were assumed to occur in CLUs (or CLU frgaments) that were at least 50% located within one of the manure application zones shown in Figure 14 and that were also located within the BRW. The initial assumption of 200 kg/ha of equivalent manure nitrogen applied on corn every two years within the manure application zones was then modified in two ways for the BRW SWAT simulations. First, the assumption was made that 80% of the manure nutrients were applied to corn and the remaining 20% was applied to soybean in any given year. This step was taken in response to apparent excess manure nitrogen available in the BRW, as discussed below, which leads to the conclusion that some of the manure nutrients are being applied to soybean (even though soybean does not need the nitrogen). Second, the manure was assumed to be applied at an equivalent nitrogen application rate of 190 kg ha^{-1} on all manured corn and soybean fields. This rate was arrived at based on calculations of how much manure nitrogen would be required to be spread to CLUs cropped with corn that were at least 50% located within a manure zone (Figure 14), and that when summed met the constraint of 80% of the overall BRW manure nitrogen being applied to fields planted in corn. The resulting equivalent manure phosphorus application rate was 69.8 kg ha^{-1}. All manure applications were assumed to occur in the spring for the BRW baseline simulation.

The modeling system is very flexible and can accommodate variations in these manure nutrient application assumptions. Different scenarios can also be simulated that reflect differing manure application scenarios, both in terms of location, the crops the manure is applied to, and the timing of the manure applications.

Nutrient Inputs From Fertilizer

Table 10 lists the simulated nitrogen fertilizer application rates for corn within a corn-soybean rotation that are currently used for the BRW SWAT baseline. These rates are based on aggregated data obtained by the Iowa Soybean Association (ISA) in collaboration with producers in the watershed. A nitrogen application rate of 196 kg ha^{-1} (175 lb ac^{-1}) was assumed for corn grown in a continuous corn rotation and a phosphate (P_2O_5) application of 49 kg ha^{-1} was simulated for corn in all rotations. Fertilizer applications were not simulated for soybean in the BRW SWAT baseline. These application rates can be easily adjusted, similar to the manure nutrient application assumptions.

Table 10. Nitrogen application rates on corn, within a corn-soybean rotation, based on 2004-05 Iowa Soybean Association aggregated collaborator data

Time of year	Number of Observations	Application rate (kg ha^{-1})[a]
Fall	21	183
Spring	100	172

[a]Equivalent application rates in lb/ac are 163 and 154 for fall and spring, respectively.

The spring nitrogen application rate of 172 kg ha^{-1} is very similar to the average BRW corn nitrogen fertilizer application rate of 169.4 kg ha^{-1} derived for the IDNR statewide nutrient balance study (not reported in Libra et al., 2004). However, the calculations for that study indicate that nitrogen fertilizer was applied on all corn fields at that rate, including fields that received manure. It is difficult to determine what percentage of the manured fields in the BRW also receive nitrogen fertilizer. Thus it was assumed that 50% of the BRW manured corn fields also receive nitrogen fertilizer at the rates described above. This results in the overall nutrient inputs shown in Table 11 between the two studies. The overall

Table 11. Comparison of total annual watershed nutrient inputs between the BRW modeling system and the IDNR nutrient balance study

Nutrient input	BRW modeling system	IDNR nutrient balance study[a]
	--------------- million kg (million lb) ----------------	
Fertilizer N	15.8 (34.9)	18.0 (39.7)
Manure N	6.3 (13.8)	5.1 (11.3)
Fertilizer P	2.2 (5.0)	2.2 (4.8)
Manure P	2.3 (5.1)	2.4 (5.2)

[a]Calculations performed in support of the study performed by Libra et al. (2004).

phosphorus inputs were similar between the two studies. Somewhat higher manure nitrogen inputs were assumed for the BRW modeling system as compared to the IDNR nutrient balance study. However, over 2 million kg more of nitrogen fertilizer was determined to be input to the watershed for the IDNR nutrient balance study as compared to the BRW modeling system.

Soil Inputs

The previously described AVSWAT-X interface was developed to provide automated translation of various soil, topographic, land use and other required digital data into formats that are directly readable by SWAT. The original AVSWAT version of the interface was limited to only being able to directly process relatively coarse 1:250,000 scale U.S. General Soil Map (STATSGO) data (USDA-NRCS, 2007c) into compatible file structures readable by SWAT, although other soil data could be entered into SWAT by using alternative methods. However, the updated AVSWAT-X version of the interface supports both direct input of STATSGO and the much more refined Soil Survey Geographic (SSURGO) data

(Table 1), which can range in scale between 1:12,000 to 1:63,000 depending on the U.S. subregion. Several previous studies have been conducted (Chapter 2) which evaluated the impacts of differing soil resolution on SWAT predictions and found that the model was generally sensitive to the resolution of soil data inputs, and that predictions usually improved with finer soil data resolution. These findings underscore the need to use the most accurate soil data available for SWAT simulations designed to evaluate alternative land use and management practice scenarios for the BRW and other watersheds.

The BRW soil layer has been developed from SSURGO data available at a 1:15,860 scale, which is the most refined soil data available for Iowa. The resulting soil map for the watershed is shown in Figure 15. Distinct lines can be seen in the map which reveal county boundaries associated with the county-level SSURGO soil data. This phenomena is an artifact of differences in soil ID labels used between the different counties; however, the processing of the soil data for input to SWAT is not hindered by this anomaly. Some distinct geological features can also be discerned in the soil map including the main Boone River alluvial channel and the glacial moraine in the southern and northeastern portions of the watershed, respectively. The dominant SSURGO soil type was determined for each CLU in order to establish the set of soil landscape characteristics and layer properties that should be used to represent the respective CLU.

Topographic Data

Characterization of watershed topography with digital elevation model (DEM) data is another key input to SWAT. SWAT predictions usually improve with increasing DEM resolution as discussed in Chapter 2, similar to the previously discussed soil input data

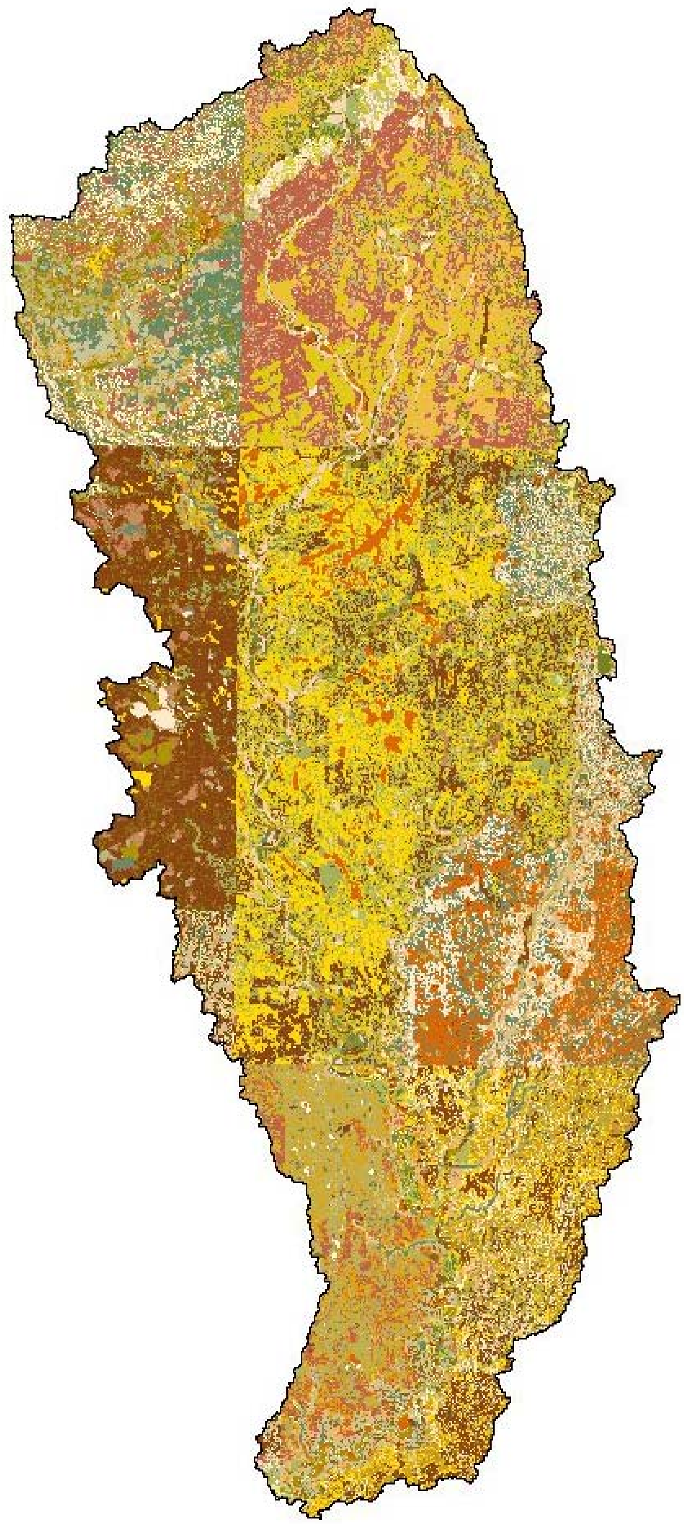

Figure 15. SSURGO soil map for the Boone River watershed.

effects. Several sources of DEM data were available to characterize the BRW topography. Both 10 and 30 m resolution National Elevation Data (NED) DEMs (Table 1) were initially assessed to determine the utility of using the two DEM layers in the modeling system. Attempts to process the 10 m DEM in AVSWAT-X failed, because the size of the data file overwhelmed the ArcView GIS software. At the same time, the accuracy of the 30 m DEM was inadequate in replicating the BRW topography and stream channel network. Thus a 30 m DEM that was resampled from a 10 m DEM was used instead (Table 1).

The resulting topographic surface developed with the resampled 30 m DEM is shown in Figure 16. A total relief of approximately 91 m (300 ft) occurs from the BRW upper stream reaches to it's confluence with the Des Moines River. The changes in elevation are gradual across most of the watershed, underscoring the level terrain present in most of the region. Some relatively sharp relief occurs in the southern portion of the watershed near the Boone River channel and in the Moraine region in the northern part of the watershed.

A comparison of the boundaries delineated for the 30 subwatersheds[10] with standard 12-digit boundaries (Table 1) shows that SWAT subwatershed boundaries coincide well with the 12-digit boundaries for much of the watershed, and that the main stream system channels were adequately delineated (Figure 17). However, some obvious disagreement also resulted, especially for the northern part of the watershed including portions of the watershed that "disappeared". These discrepancies point to inadequacies in the resampled 30 m DEM to accurately capture all of the subtle terrain changes that occur across the predominantly flat subregions of the BRW, assuming the 12-digit boundary delineations are accurate.

[10]The delineation of the 30 swat subwatersheds was performed in AVSWAT-X in a manner to ensure as close an alignment with the 12-digit boundaries as possible. There are actually only 29 12-digit subwatersheds; an additional subwatershed was delineated in AVSWAT-X to allow a direct correspondence between the outlet of subwatershed 27 and the location of the USGS flow gauge (shown in Figure 1).

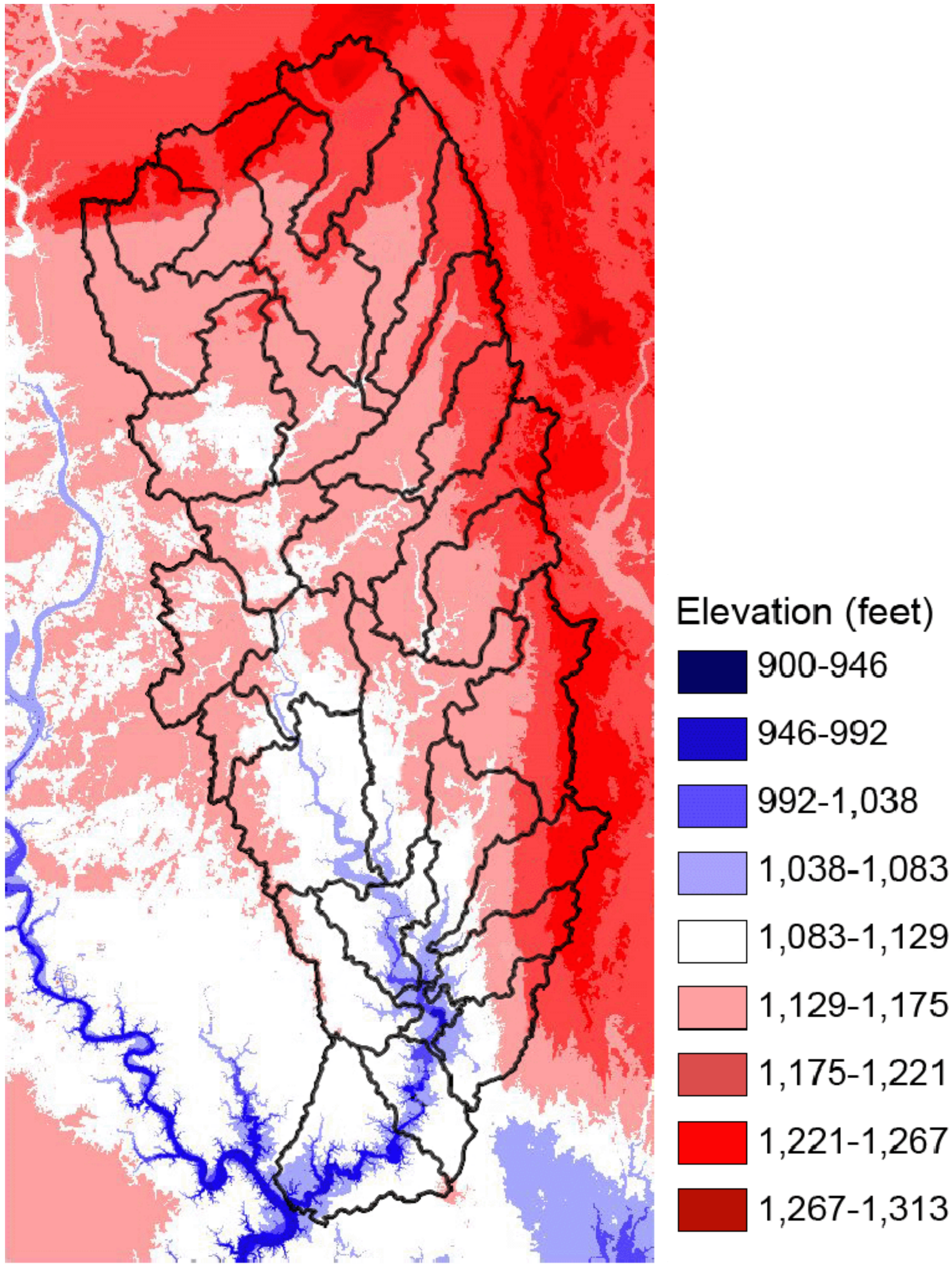

Figure 16. Overlay of SWAT subwatershed boundaries on the Boone River watershed topographic surface, which was created from the resampled 30 m DEM.

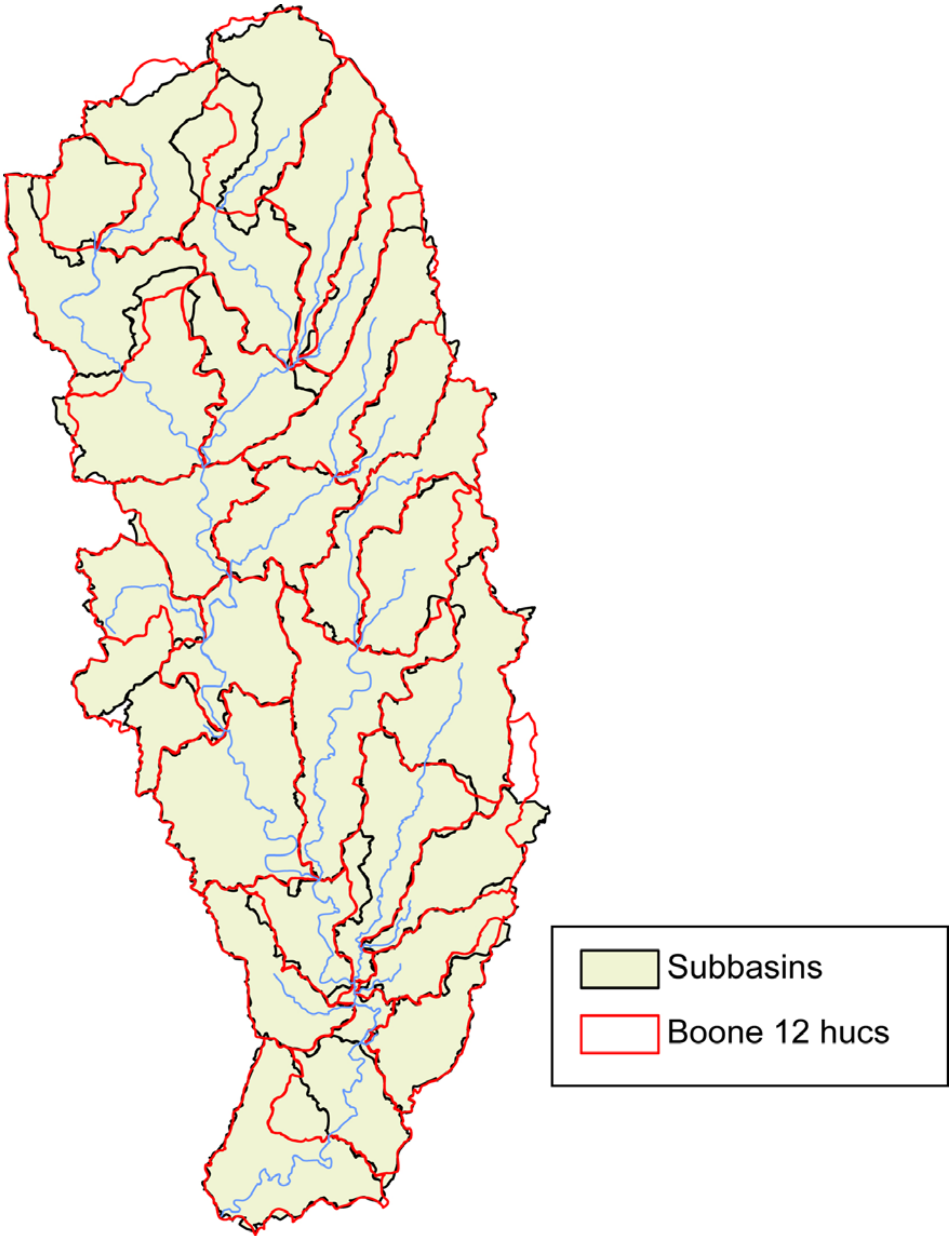

Figure 17. Comparison of delineated SWAT subwatershed boundaries (subbasins) with 12-digit watershed boundaries.

The most promising option for improved characterization of the BRW topography is Light Detection and Ranging (LiDAR) data, which is currently being collected for the entire state of Iowa (IDNR, 2007a) and is projected for completion in 2009 (Giglierano, 2007). The completed LiDAR data will have a spatial resolution of approximately ± 1.5 m (± 5 ft) and provide elevation estimations within an accuracy of 0.2 m (8 in). Improvement in GIS software will be required in order to process such an intensive data layer, and aggregation of the LiDAR data (e.g., 5 m resolution) will likely be required for realistic processing in future GIS interface tools. At present, the recently released ArcGIS SWAT interface (Olivera, 2006) appears to have the potential for processing aggregated LiDAR data. Further investigation of this option can be pursued when BRW LiDAR data becomes available.

Tile Drainage Data

Extensive installation of tile drainage has occurred in the BRW over the past century or more, resulting in a drastically altered hydrologic landscape. Most of the pre-settlement wetland system has vanished, and seasonally wet soils can be managed much easier due to the presence of subsurface drainage. The exact extent of tile drainage in the watershed is not known. However, the fact that tile drainage districts have been established across most of the primary cropland areas (Figure 18) would indicate that subsurface tiles have been installed beneath the majority of cropland in the watershed. The 1992 NRI estimates that 50% of the BRW cropland was tile drained at that time, which was one of the most intensively tile drained 8-digit watersheds in the UMRB according to that NRI dataset. Never the less, it is likely that the 1992 NRI BRW tile drain estimate greatly underestimated the true extent of.

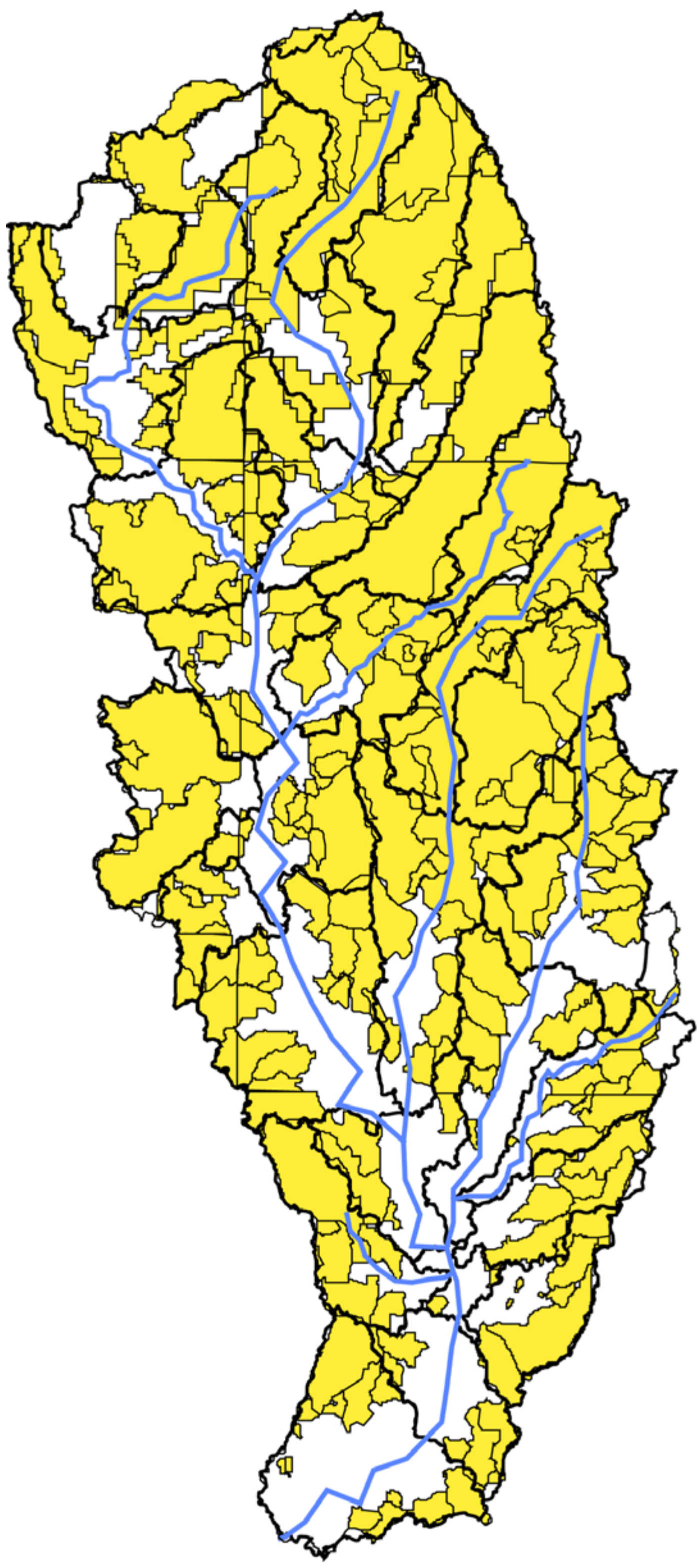

Figure 18. Tile drainage districts established in the Boone River Watershed.

tile drained cropland in the watershed, based on the alternative approach of estimating soils needing tile drainage that is described here.

Two alternative approaches exist to estimate which soils would most likely require tile drainage in the BRW (and in other watersheds). These methods are both simple algorithms developed by Miller (2007) and Jaynes (2007) and are compared in Table 12. Data provided in the ISPAID database (Table 1) can be used in either the Jaynes or Miller methods, and SURRGO data (Table 1) can also be used for Jaynes method.

Table 12. Comparison of Jaynes and Miller algorithms for estimating which soils require subsurface tile drainage[a].

Algorithm criteria	Jaynes Method	Miller Method
Soil slope (%)	≤ 2	≤ 5
Drainage class	Poor or very poor	-
Drainage class code	-	> 40
Hydrologic group	D	-
Subsoil group	-	1 or 2

[a]Data provided in the ISPAID database (Table 1) can be used as inputs for both algorithms; the SSURGO database (Table 1) can also be used for the Jaynes method.

The results of applying the criteria in the two algorithms separately and in combination are presented in Figure 19. Both methods result in estimating extensive need for tile drainage across the BRW, with the Miller method resulting in a denser tile drainage coverage as compared to the Jaynes method. Both methods also point to tiles not being needed along the alluvial channels, especially in the southern portion of the watershed, and along the glacial moraine feature in the northern part of the BRW. The combined map closely resembles the Miller method map, due to its denser coverage, and is assumed to provide the

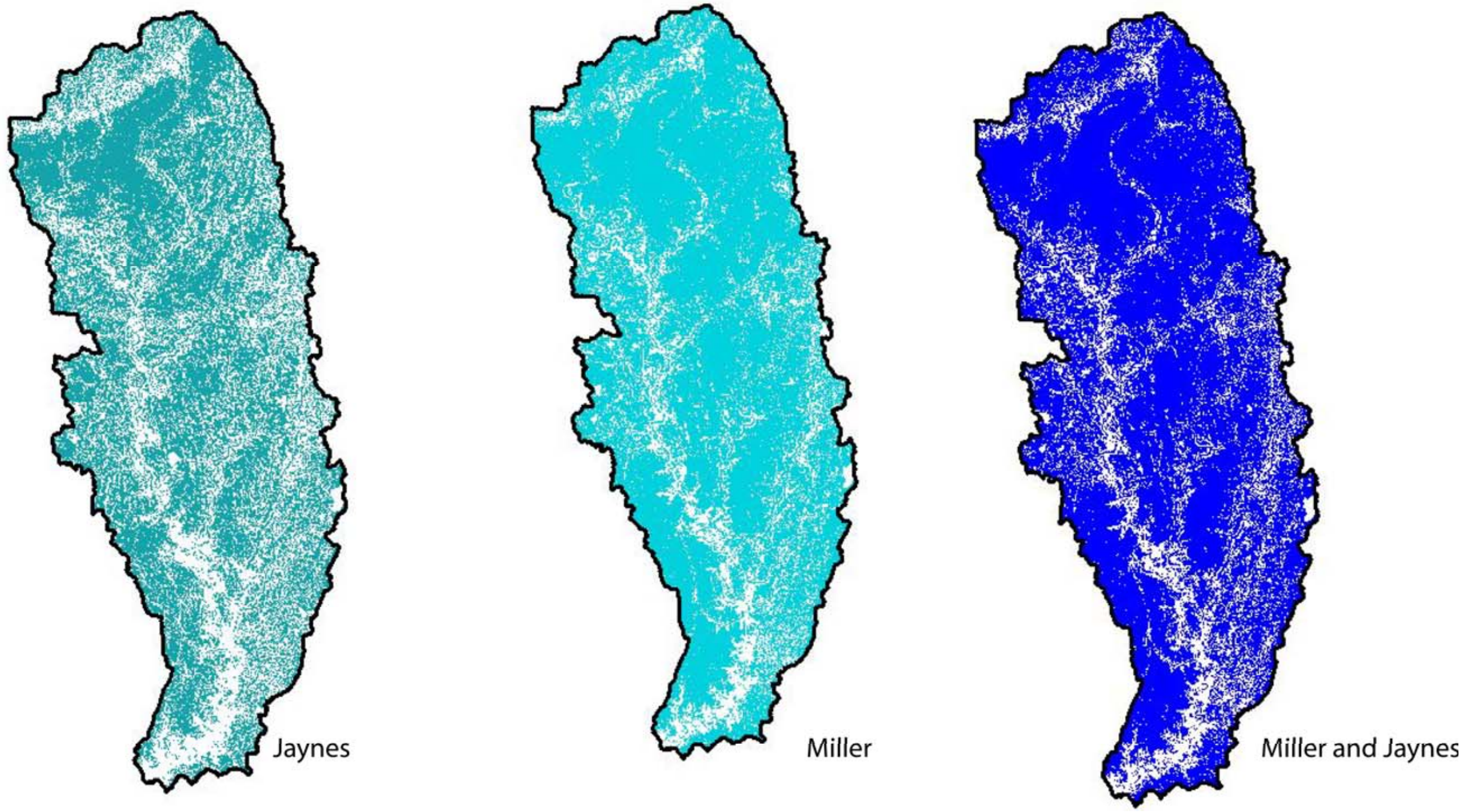

Figure 19. Results of applying the Jaynes and Miller algorithms separately, and in combination, for estimating the extent of soils that require tile drainage in the Boone River watershed (colored areas are the soils indicated to need subsurface tile drains).

most accurate picture of tile drainage usage across the BRW. As a result, tile drainage is simulated in SWAT for virtually all cropland in the watershed.

Tile drainage district records and other similar information could be researched with a goal of obtaining improved estimates of tile drainage distribution in the BRW. However, this would be an exacting process that may yield little additional useful data. Allred et al. (2004) report that ground penetrating radar was also found to have excellent potential to locate the presence of tile drains down to a depth of 1 m in different soil materials in Ohio. But the method did not work well at all sites and would likely be a very expensive and intensive procedure to use for a watershed the size of the BRW. Kalita et al. (2007) describe such geophysical and geotechnical approaches as “tedious” and found that aerial color infrared images taken following spring thaw can be used more effectively to identify locations of tile lines for Illinois. However, this again would likely be a very labor intensive process for a watershed the size of the BRW. In summary, the estimated tile drainage distribution determined using the combined Miller and Jaynes methods appears to be the most efficient available and also likely provides a reasonably accurate reflection of the extent of tile drainage in the watershed.

Daily Climate Data Inputs

Daily climate inputs to SWAT include precipitation, maximum and minimum temperature, solar radiation, wind, and relative humidity. Wind and relative humidity are only required for specific evapotranspiration options in the model. Both measured and/or generated climate data can be used in SWAT; most applications rely on measured precipitation and temperature data, and generated data for the other climate inputs.

Inadequate coverage and/or spatial characterization of precipitation data for a watershed can result in poor hydrologic results. Further discussion of the climate data inputs and hydrologic calibration issues related to precipitation data input accuracy is presented in Chapter 2.

Daily precipitation and temperature data measured at every climate station in the watershed region (Figure 1) were obtained for the period of 1951-2006 from the IEM and NCDC sources listed in Table 1, for possible inclusion in the BRW SWAT simulations. The NCDC data obtained for Kanawha included only precipitation measurements. Thus, Clarion temperature measurements were incorporated into the Kanawha data to construct a complete climatic record. Annual precipitation and temperature statistics computed for each station are given in Tables 13 and 14. The precipitation statistics reveal a distinct gradient of increasing precipitation amounts going from north to south in the BRW region (see station locations in Figure 20), with the highest average annual precipitation occurring at Fort Dodge[11]. The annual precipitation extremes ranged from a low of 135.6 mm at Britt in 1987 (a year of severe statewide drought) to 1,396.5 mm at Webster City in 1993 (a year of severe statewide flooding). A slight north to south temperature gradient is also indicated by the statistics in Table 14, with the highest average annual maximum and minimum temperatures recorded for Fort Dodge and Webster City.

Figure 20 shows which subwatersheds the measured precipitation and temperature data were assigned to in AVSWAT-X, based on proximity of the climate station locations to the geographic centroids of the different subwatersheds. The majority of subwatersheds were assigned to three of the climate stations: Kanawha, Clarion, and Webster City. The Fort

[11]Climate normals reported by MRCC (2007) for 1971-2000 show nearly the same ranking of the seven climate stations based on average precipitation, ranging from 873.5 mm for Fort Dodge to 779.5 mm for Algona (only the order of Britt and Kanawha are reversed from what is shown in Table 12).

Table 13. Annual precipitation statistics (mm) computed over 1951-2006 for the climate stations in the BRW region

Climate station	Data source[a]	Mean	Maximum	Minimum	Standard Deviation
		------------------------ (mm) ------------------------			
Algona	IEM	748.5	1158.5	357.1	182.1
Britt	IEM	758.3	1182.4	135.6	206.4
Clarion	IEM	805.3	1221.2	519.4	156.2
Fort Dodge	IEM	844.4	1200.7	556.3	163.8
Humboldt	IEM	790.8	1156.0	514.1	155.9
Kanawha	NCDC	773.2	1225.3	386.3	175.6
Webster City	IEM	815.0	1396.5	463.8	187.2

[a]See Table 1 for more information.

Table 14. Temperature statistics computed over 1951-2006 for the climate stations in the BRW region.

Climate station	Data source[b]	Maximum Temperature				Minimum Temperature			
		Mean	Max.	Min.	St. Dev.	Mean	Max.	Min.	St. Dev.
		---------------------------- (°C) ----------------------------							
Algona	IEM	13.8	40.6	-27.2	13.3	2.1	27.2	-34.4	11.9
Britt	IEM	13.7	40.0	-26.7	13.2	2.2	30.0	-35.0	12.1
Clarion	IEM	13.8	39.4	-27.8	13.2	2.0	25.6	-35.6	12.1
Fort Dodge	IEM	14.6	41.1	-24.4	13.0	2.7	26.1	-34.4	11.8
Humboldt	IEM	14.1	40.0	-26.1	13.0	2.5	25.6	-36.1	11.9
Kanawha[a]	NCDC	13.8	39.4	-27.8	13.2	2.0	25.6	-35.6	12.1
Webster City	IEM	14.6	40.6	-24.4	12.9	2.6	25.6	-35.6	11.8

[a]Clarion temperature data was also used for Kanawha.
[b]See Table 1 for more information.

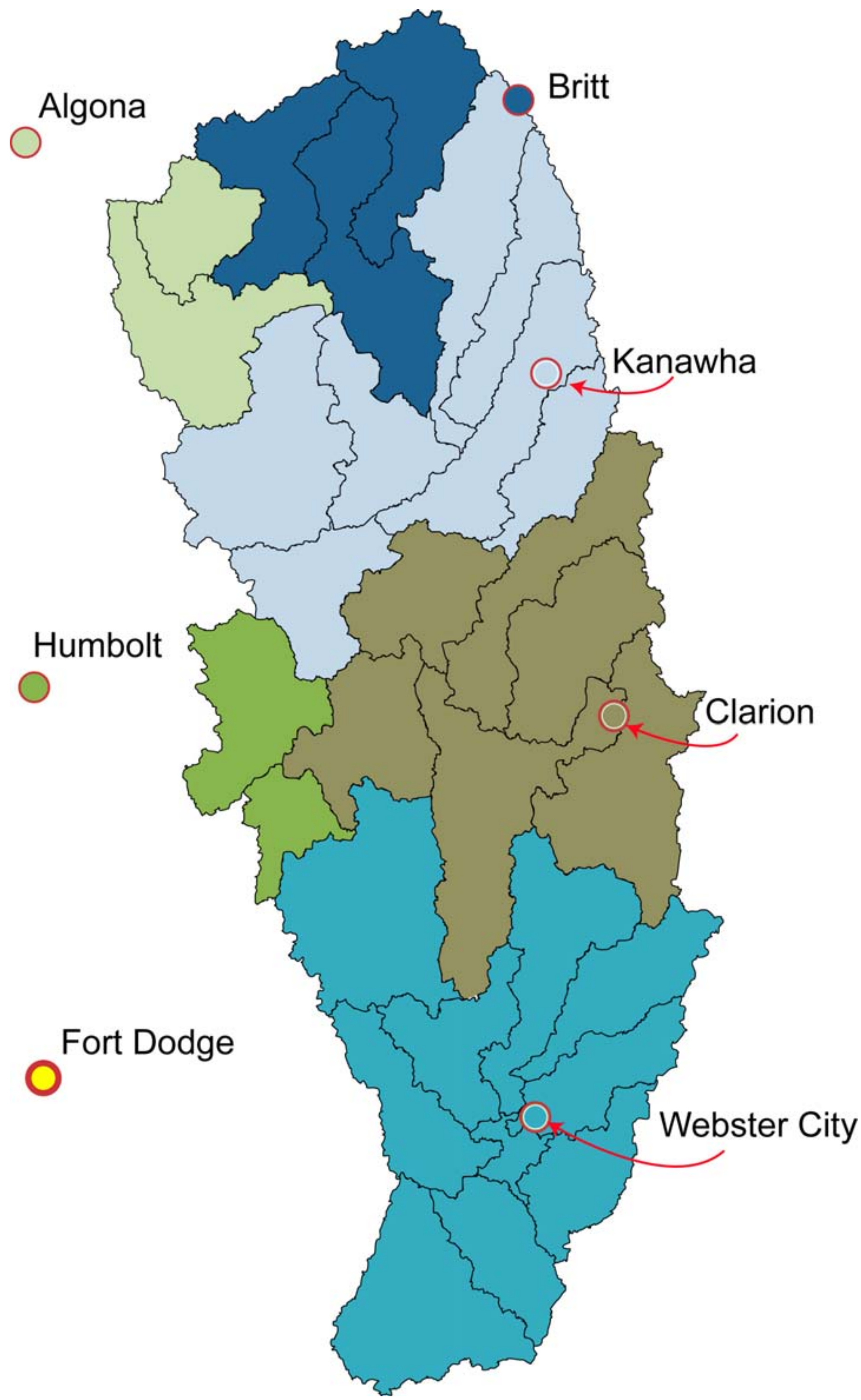

Figure 20. Assignment of measured climate data to the subwatersheds used for the BRW SWAT simulations (Fort Dodge climate station data are not used).

Dodge climate station was too far from any of the subwatersheds to be used in the SWAT simulations. Generated weather is also configured in SWAT via automated functions provided in the AVSWAT-X interface. This includes assignment of climate station data, consisting of monthly climate normals, from a database that covers the entire U.S. Figure 21 shows similar assignments for daily climate inputs generated internally in SWAT from the three climate stations that were closest to the BRW. Solar radiation was the only generated climate data used for the BRW simulations.

Nitrogen and Phosphorus Point Sources

Libra et al. (2004) report that nonpoint sources contributed 92% of the total nitrogen load and 80% of the phosphorus load to Iowa streams, based on their statewide nutrient balance conducted for 2000-2002. The remaining 8 and 20% of the nitrogen and phosphorus loads were attributed to point sources. Specific point source nitrogen and phosphorus contributions to the BRW stream system were estimated by Libra et al. to be 8 and 9.4%, respectively. Point source nutrient contributions are currently not incorporated in the BRW SWAT simulations. However, incorporation of point sources into the modeling framework has been initiated, which will provide point source assessments to be performed in future BRW scenario simulations. Figure 22 shows the location of 14 different key point sources in the BRW, most of which are municipal waste treatment plants. Nitrogen and phosphorus inputs from these sources to the BRW stream system will be calculated using the assumptions developed by Libra et al. for municipal and industrial waste sources, and which were also used for the Raccoon River SWAT nitrogen TMDL study (Schilling and Wolter, 2007).

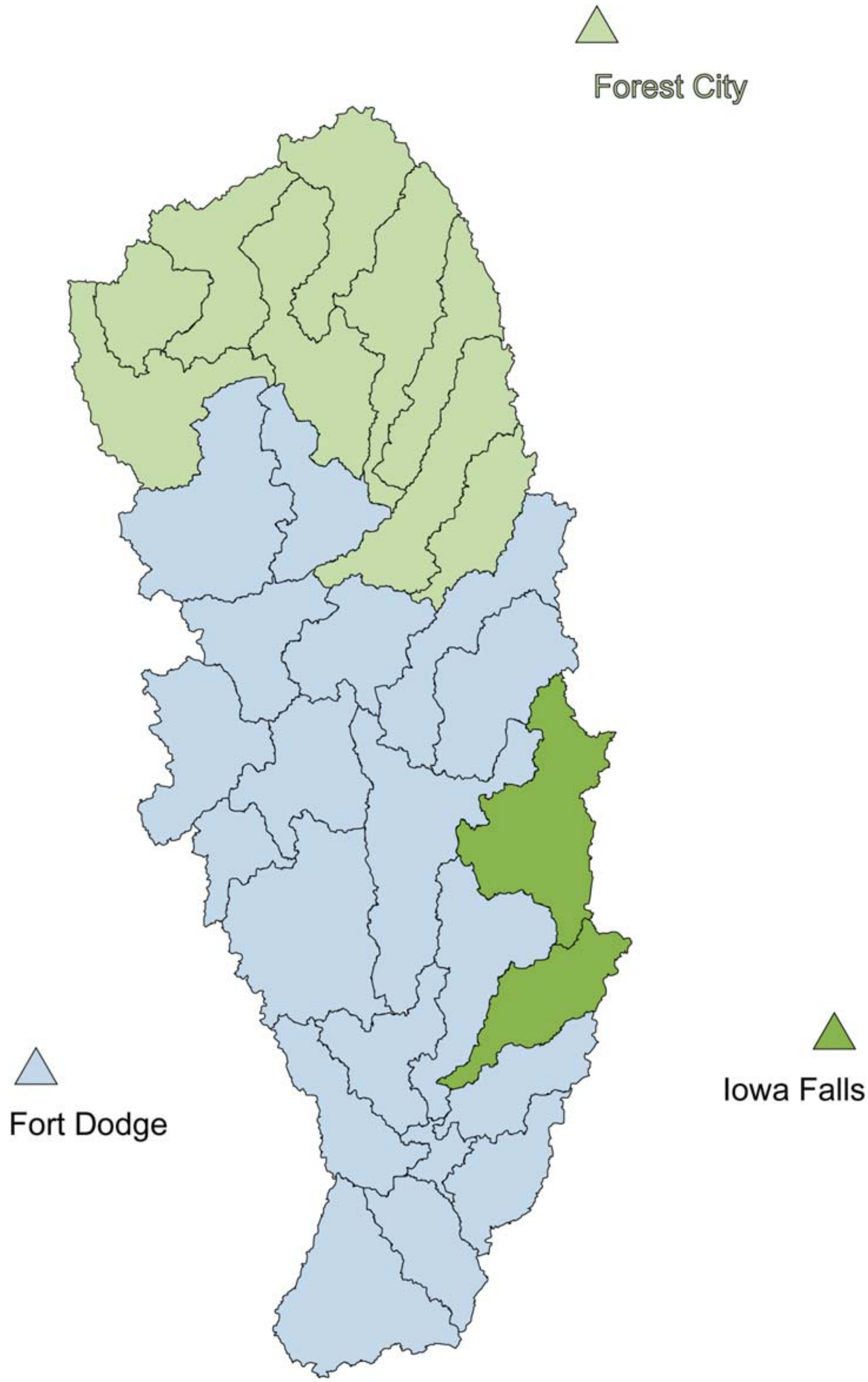

Figure 21. Assignment of generated climate data (solar radiation) to the subwatersheds used for the BRW SWAT simulations.

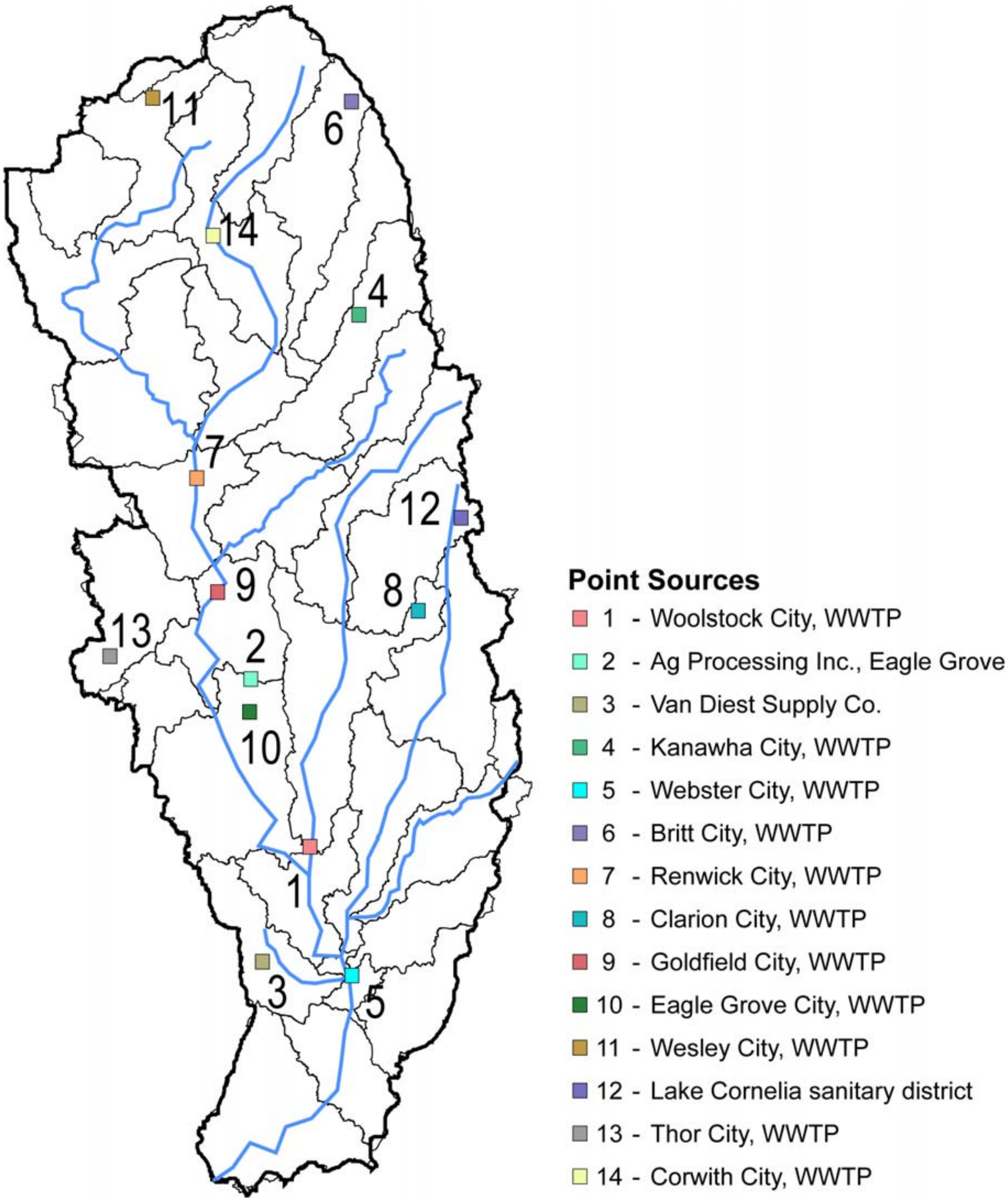

Figure 22. Location of primary waste treatment plant and industry point sources in the Boone River watershed.

Monitoring Data

In-stream pollutant monitoring data has been collected in the form of single monthly grab samples near the watershed outlet (Figure 1) since October of 1999. Nearly 80 different pollutant indicators have been measured for at least part of the sampling period. The primary indicators of interest for the BRW SWAT simulation study that have been collected near the watershed outlet are sediment, nitrate, organic nitrogen, inorganic (mineral) phosphorus, and total phosphorus. Figure 23 shows a time series of the nitrate concentrations measured between October 1991 and December 2006. The highest nitrate concentrations were usually recorded in the spring and early summer, although high concentrations were measured at times during the fall and winter seasons (e.g., November 2000 to January 2001). The concentrations often exceed the drinking water standard of 10 mg l^{-1} (USEPA, 2007) and exceed 15 mg l^{-1} at times. These nitrate, and other nutrient and sediment concentrations, form the basis for estimating pollutant loads which are used for the model calibration and validation as discussed in Chapter 4.

Additional collection of in-stream pollutant monitoring data was initiated at 30 sites (Figure 24) by the Iowa Soybean Association (Seeman, 2007) beginning in the 2007 growing season. These data are being collected at the outlets of the 29 12-digit BRW subwatersheds and also at the location of the USGS flow gauge shown in Figure 1 (site BR003 in Figure 24). These data are not currently being collected with flow data, except for the data collected coincident with the USGS flow data and a second flow gauge located near the town of Goldfield[12], and thus cannot be used to estimate pollutant loads. However, the measurements

[12]These streamflow measurements were initiated by the U.S. Army Corps of Engineers in 2004 and can be accessed at USACE (2007).

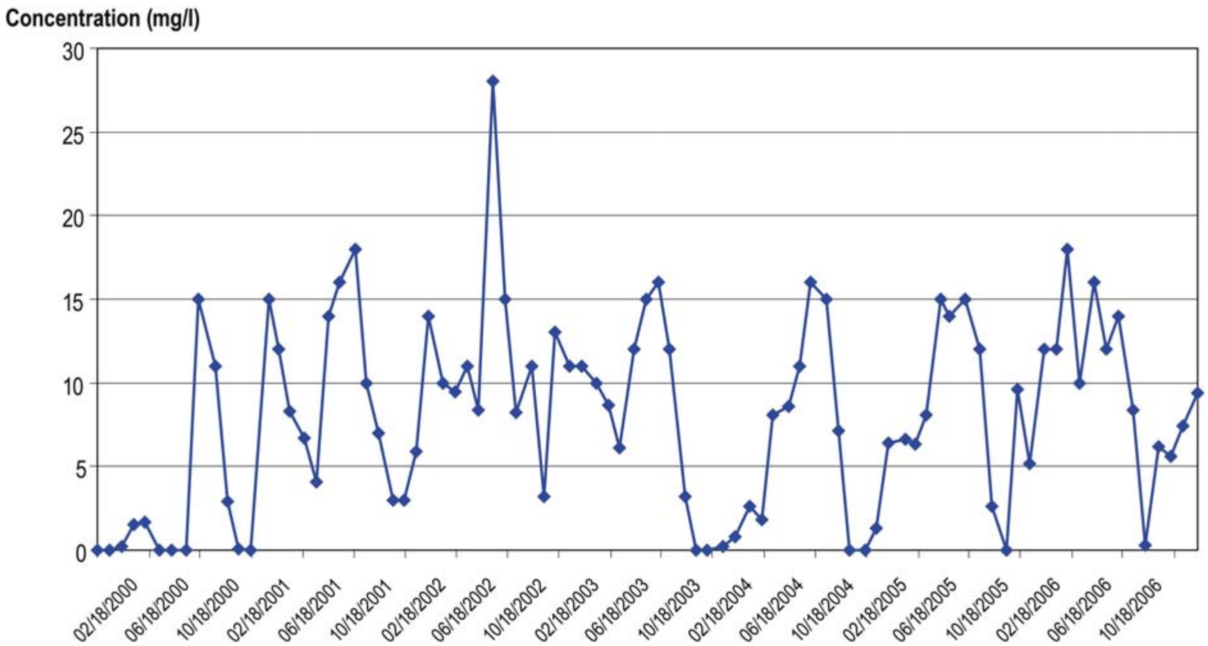

Figure 23. Time series of nitrate concentrations measured between October 1999 and December 2006 near the outlet of the Boone River watershed.

will provide critical insights regarding pollutant trends at the subwatershed level. This is illustrated in Figure 25, which shows the average nitrate concentrations measured in each 12-digit subwatershed over the 2007 growing season (spanning April 4 to October 15). The 2007 trends clearly show greater nitrate concentrations for the subwatersheds located in the southeastern portion of the BRW. These trends can also be compared with other BRW data, such as the distribution of CAFO animal units that are overlayed on the subwatershed in Figure 25. Samples are currently being collected on a bi-weekly basis year round at 13 of the sites and only during the growing season at the other sites. Additional support has been announced to support future BRW monitoring efforts as reported by TNC (2007).

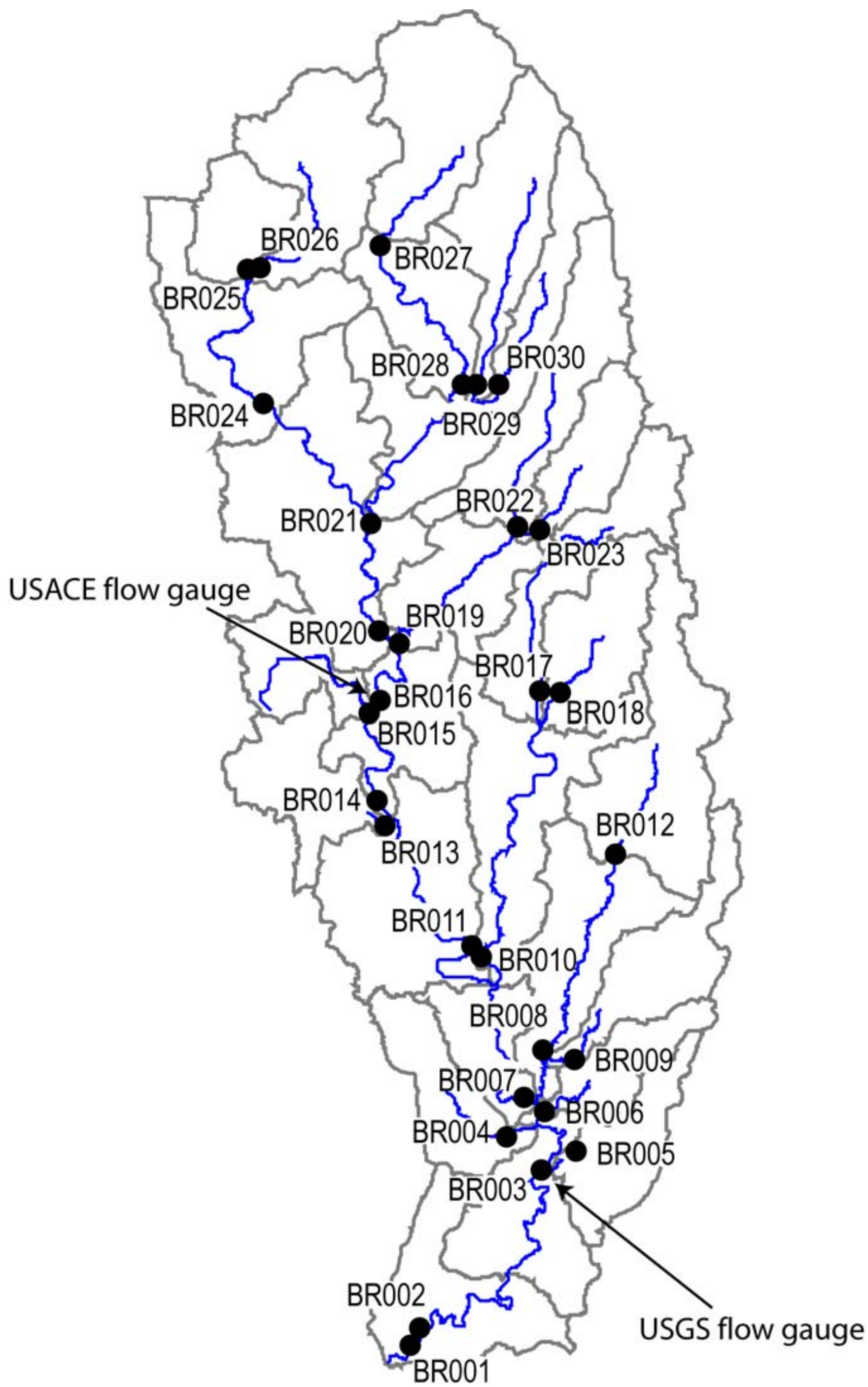

Figure 24. Location of Iowa Soybean Association 2007 growing season sampling sites in the Boone River watershed.

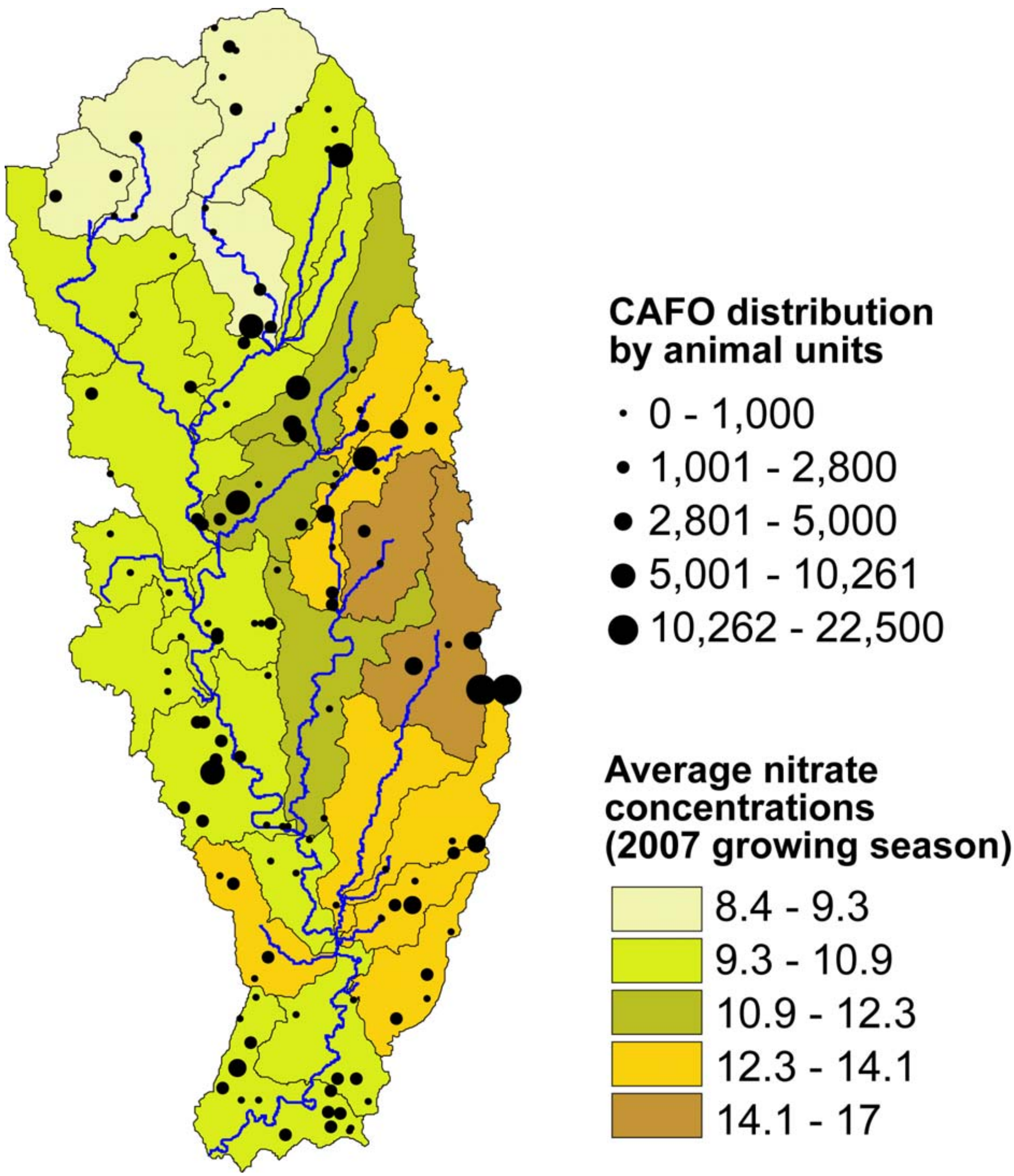

Figure 25. Distribution of confined animal feeding units (by animal units) overlayed on average nitrate concentrations determined for each 12-digit watershed during the 2007 growing season in the Boone River watershed.

SWAT Application Issues

The BRW modeling system contains one of the most detailed data sets that has been assembled for a watershed at the 8-digit scale in Iowa (and possibly the U.S.). The design of the system allows for land use, tillage and conservation practices, fertilizer and manure applications, and soil data to be directly interfaced at the CLU level. Identification of tile drained soils can also be linked to the CLUs using Access database queries or other software tools. Other data layers are less detailed, including the 30 m resolution DEM data that has obvious weaknesses. The LiDAR data currently being collected by the IDNR will provide greatly refined topographic data for the system, once it becomes available.

Unfortunately, these data layer advancements cannot be fully utilized by SWAT at this time because the SWAT HRUs are currently not spatially referenced within the simulated subwatersheds, as previously discussed in the Modeling System Overview and in Chapter 2. At present, the model will simply recognized CLU-level HRUs as lumped land parcels within a subwatershed, instead of accounting for the explicit landscape position of each CLU. Thus a total of 2,212 HRUs are used in the current BRW SWAT simulations, which represent aggregations of CLUs with homogeneous land use, management, soil, and landscape characteristics. Output from these HRUs can be viewed at the subwatershed or other aggregated levels, or at a disaggregated level for individual CLUs. The CLU-level data does provide the foundation for performing more refined BRW simulations in the future, as improved spatial accounting is built into SWAT including simulation of explicit landscape positions as discussed in Chapter 2. The CLU data also provides the basis for developing the economic model component of the overall BRW modeling study, which will be interfaced with SWAT in the next phase of the broader project.

Other limitations exist in SWAT that affect the accuracy of the model output besides the lack of spatially referenced HRUs. Several of these limitations are discussed in Chapter 2, including the Runoff Curve Number (RCN) approach which is investigated in more detail in Chapter 4. One additional limitation that is important to recognize for the BRW modeling system is the relatively simplistic subsurface tile drainage routine that is currently used in SWAT. This routine has been recently improved based primarily on testing of the model for the Walnut Creek watershed in Story County, Iowa (Du et al., 2005; 2006) and further refinements reported by Green et al. (2006). However, tile drainage effects are represented in the model only via tile drainage depth, depth to an impervious layer, and two other input variables related to subsurface flow dynamics, and no accounting of tile drain spacing or landscape position is provided. Therefore, pattern tile and irregular tile networks are simulated in an identical manner in the current approach used in SWAT. It can be expected that these simplifications misrepresent some aspects of BRW subsurface tile drainage flow dynamics. Development of an alternative tile drainage method in SWAT, which is based on the DRAINMOD approach (Singh et al., 2006), is being performed by Moriasi (2007) and will provide expanded options for simulating tile drainage systems in future BRW SWAT applications.

Other data limitations can hinder the accuracy of simulation results for the watershed. For example, the previously described set of available measured precipitation data may not accurately cover all the precipitation events that occurred in different parts of the watershed during the 1984-2006 baseline simulation period (see Chapter 4). Improved coverage could be obtained by the placement of additional rain gauges in the watershed, but this would obviously only benefit future applications of SWAT or other models. Another option would be to use Next Generation Weather Radar (NEXRAD)[13] precipitation data (Crum et al., 1998) which has been successively used in previous SWAT applications as discussed in Chapter 2. However, modifications would be required for SWAT to input the data using a refined 4 x 4 km^2 grid such as described by Cruse et al. (2006) for their Iowa modeling application, and this data would cover only a later portion of the baseline period used in this study. The testing of the model is also limited by the amount and accuracy of available in-stream flow and pollutant monitoring data. Harmel et al. (2006) document occurrences of errors in both streamflow and pollutant measurements, which can exceeded over 100% for some nutrient samples. The fact that only single monthly grab samples at a single site are the only pollutant data available for testing the SWAT BRW simulations up through 2006 is a clear limitation of the current modeling system. Further discussion of monitoring data issues is provided in Chapter 4.

Transferability of the Modeling System Approach

There are several challenges that arise when considering the transferability of the modeling system approach described here. The most obvious is the reliance on a field-level survey to gather land use, tillage practices, and conservation practice data at the CLU level. This can be feasible if adequate resources are available, particularly for smaller watersheds. For example, similar data sets have been developed for five watersheds as part of the Iowa State University USDA-funded Conservation Effects Assessment Project (CEAP), which included field-level surveys to develop CLU-based data in some of the watersheds[14]. In

[13]The precipitation and other weather data is collected with a network of 166 Weather Surveillance Radar-1988 Doppler (WSR-88D) systems (Crum et al., 1998).
[14]See Tomer et al. (2008) and Schilling et al. (2007) for descriptions of some of the watersheds and/or practices.

general, resource constraints will preclude such intensive survey data gathering approaches, especially for watersheds similar or larger in size to the BRW.

The development of remote sensing approaches as previously discussed are the only realistic land use and tillage practice data gathering approach for developing CLU-based datasets for a wide range of watersheds, and especially for large systems such as the UMRB. These approaches would overcome the significant labor requirements of field-surveys and could be updated on an annual basis, which overcomes the limitation of single-year surveys such as the 2005 data collected for the BRW. At present, no systematic approach seems available to collect other conservation practice data such as terraces, contouring, and grassed waterways. Field-level surveys focused on these data alone may be useful supplements to remote sensing data used to characterize land use and tillage practices.

Other key data such as SSURGO soil data, locations of CAFOs, and DEM data are readily available for any watershed in Iowa. Estimates of tile drained land have been generated for the entire state as well. LiDAR data should become available before the end of this decade, which will be a greatly improved topographic layer. Estimates of fertilizer application rates and some other management practices can be obtained on the basis of local expert opinion, or through surveys of producers or agribusinesses, or from groups such as the ISA who have or are working directly with producers in a watershed. However, some of these data, such as CAFO locations, may not be as easily accessible for watersheds in neighboring states or throughout the UMRB.

Conclusions

A SWAT CLU-based modeling system has been built for the Boone River watershed that will support a range of alternative land use and management practice scenario analyses. The modeling system contains very detailed land use, tillage practice, and conservation practice data that were obtained for each CLU during a field survey conducted in the spring of 2005. Crop rotation data was also generated as a part of the survey effort. Alternative USDA-NASS CDL remote sensing data has also been obtained that can be used to create crop rotations. Soil data and tile drainage practices can also be interfaced at the CLU-level. Limitations in the current SWAT structure preclude using the full potential of the CLU-based data at this time. However, aggregated CLU data used for creating the HRUs used in the SWAT simulations retain much of the CLU-level land use and management information. The modeling system can be updated as better data becomes available; e.g., LiDAR topographic data or tillage distributions based on remote sensing data. And enhancements in the modeling approach will also be realized as improved versions of SWAT become available in the future.

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CHAPTER 4. SWAT BASELINE SIMULATION RESULTS FOR THE BOONE RIVER WATERSHED: ANALYSIS AND ISSUES REGARDING TWO HYDROLOGIC CALIBRATION APPROACHES

A paper to be submitted to the *Journal of Environmental Quality*

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Abstract

The Boone River Watershed (BRW) covers over 237,000 ha in north central Iowa. The watershed is dominated by corn and soybean production, which together account for over 85% of the land use. Fertilizer and livestock manure applications to cropland are key sources of nutrient loads to the watershed stream system. Nitrate losses are of particular concern, which escapes the cropland via multiple pathways including subsurface tiles that drain the predominantly flat landscapes that persist throughout the watershed. This study describes the application of the Soil and Water Assessment Tool (SWAT) model for the BRW, using two different hydrologic simulation approaches that were based on the standard runoff curve number (RCN) option versus a new alternative RCN option available in version 2005 of SWAT. These two different approaches were used to reflect differing assumptions regarding the relative contributions of surface runoff and baseflow to the total BRW streamflow. Strong annual and monthly R^2 and Nash-Sutcliffe modeling efficiency (E)

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statistics were found for both the 1986-1996 calibration and 1996-2006 validation periods, which ranged from 0.74 to 0.99. The R^2 and E statistics determined for the calibrated annual and monthly sediment, nitrate, organic nitrogen, and total phosphorus loads for the period of 2000-2006 were also generally strong for the SWAT simulations that were performed with the standard RCN approach, ranging from 0.50 to 0.92 with the majority of the statistics exceeding 0.70. However, the accuracy of the predicted pollutant loads generally declined when the alternative RCN approach was used, especially for the organic nitrogen estimates. The results show that specific calibration is necessary for pollutant-related input parameters for the alternative RCN approach, in order to obtain improved results. The results also show weaknesses in the overall nitrogen balance predicted for the SWAT simulations, especially for the approach based on the standard RCN method.

Introduction

Water quality degradation has emerged as a major issue within the Upper Mississippi River Basin (UMRB). The Mississippi River and tributary streams have been greatly impacted by excess nitrogen, phosphorus, and sediment loadings from cropland and other sources. The nutrient load discharged from the mouth of the Mississippi River has also been implicated as a key cause of the Gulf of Mexico seasonal oxygen-depleted hypoxic zone (USEPA, 2007), which has covered an extent equal to or greater than 20,000 km^2 in recent years (Rabalais et al., 2002). Goolsby et al. (1999) estimated that the UMRB was the source of nearly 39% of the Mississippi nitrate load discharged to the Gulf between 1980 and 1996; 35% of this load was attributed solely to Iowa and Illinois tributary rivers for average discharge years during the same time period (Goolsby et al., 2001). The UMRB was also reported to contribute 39 and 26% of the total nitrogen and phosphorus loads to the Gulf of Mexico during 2001-2005 (USEPA, 2007). Libra et al. (2004) further estimated that Iowa streams contributed approximately 20% of the long-term nitrogen load to the Gulf of Mexico based on in-stream measurements performed during 2000-2002.

The Boone River Watershed (BRW) is an intensively cropped region located in north central Iowa which was identified by Libra et al. as discharging some of the highest nitrogen loads during 2000-2002 among the 68 Iowa watersheds that were analyzed within their study. The Boone River Watershed has also been identified within the UMRB as both an area of freshwater biodiversity significance and a priority area for biodiversity conservation (Weitzell et al., 2003). The biodiversity conservation designation reflects the fact that the watershed has been identified as currently possessing a "relatively un-degraded stream ecosystem," but that it is also very vulnerable to future increased degradation (Neugarten and Braun, 2005). Potential biodiversity threats listed by Neugarten and Braun include consistently high in-stream nitrogen concentrations, farm production methods that may be ecologically harmful, and inadequate treatment of wastewater. Thus the mitigation of nitrogen losses to the BRW stream system is essential for maintaining the long-term viability of the stream ecosystem.

A simulation project has been initiated in response to these issues that is designed to evaluate the potential economic and environmental impacts of alternative land use and management practices in the Boone River Watershed. The goal of the overall study is to identify strategies that can potentially mitigate loss of nitrates and other pollutants from agricultural cropland, which could lead to improved water quality in the Boone stream network as well as in downstream ecosystems such as the Gulf of Mexico. Insights gained from the research may also be transferable to other watersheds that drain parts of the Des Moines Lobe, which are generally characterized as regions of high nitrogen export. Environmental impacts will be assessed within the study with the Soil and Water Assessment Tool (SWAT) model (Arnold and Forher, 2005), which has been used for a wide range of environmental conditions, watershed scales, and scenario analyses as described in Chapter 2.

Calibration and validation of baseline SWAT streamflow and pollutant loss estimates are foundational for the subsequent scenario analyses that will be performed for the BRW. The relatively flat topography and intensely tile-drained landscapes that characterize the watershed as discussed in Chapter 3 pose challenges for calibrating the model. As discussed in Chapter 2, the vast majority of the SWAT studies reported in the peer-reviewed literature have relied on using the Runoff Curve Number (RCN) approach (USDA-NRCS, 2004) for partitioning precipitation between surface runoff and infiltration, as opposed to using the Green-Ampt method (Green and Ampt, 1911) which requires sub-daily precipitation inputs and other less readily available inputs. Successful applications of the standard RCN approach in SWAT have been reported for several previous Iowa studies (e.g., Jha et al., 2007; Secchi et al., 2007; Schilling and Wolter, 2007), which links the RCN runoff calculations with the available soil moisture capacity of the soil.

Kannan et al. (2007) describe a modified RCN approach that relates the RCN runoff calculations to soil moisture depletion (computed as a function of evapotranspiration) rather than available moisture capacity, which has been added as an RCN option in SWAT version 2005 (SWAT2005). They demonstrated that the modified RCN method can be calibrated by simply adjusting the “depletion coefficient,” and that better water yield prediction results were obtained with the alternative approach for watersheds representative of three U.S.

regions. Green et al. (2006) also used the modified RCN approach for a SWAT2005 hydrologic calibration and validation study of the South Fork of the Iowa River watershed, which is located to the east of the BRW and is similarly characterized by intensive tile-drained and cropped landscapes. They reported a 5:1 ratio of subsurface flow (mainly tile flow) to surface runoff, which according to Green (2007) was only attainable using the modified RCN approach. The implication of their results is that baseflow contributions to streamflow is much greater than what has been previously estimated with streamflow separation techniques or SWAT simulation studies for other watersheds in the region. This presents two interesting questions: (1) are their results correct?, and (2) what ratio of baseflow to surface runoff would be most representative of BRW hydrology, considering the flat topography, extensive tile drainage, and widespread depressional "pothole" features that characterize the majority of the watershed?

Kannan et al. did not compare the two RCN methods for midwestern tile-drained soil conditions and also did not report the impacts of the two approaches on pollutant losses. Green et al. reported the overall hydrologic balance of the South Fork of the Iowa River watershed for SWAT simulations with and without tile drains, but did not compare the effects of the two RCN methods on the hydrologic balance of the simulated system. They also did not report pollutant loss impacts for the simulations they performed with the alternative RCN approach. Thus, there is a need to further investigate the effects of the two RCN methods on both the hydrologic balance and pollutant losses in an intensively tile-drained watershed system. This research seeks to carry out this task in the context of a traditional RCN SWAT calibration/validation study for both BRW streamflow and pollutant losses, which includes comparisons with the results of applying the alternative RCN method.

Investigation of two specific nitrogen balance components is also performed: (1) the balance of predicted nitrate versus organic nitrogen loss at the landscape level, and (2) nitrogen fixation associated with soybean which was shown to be overpredicted in a recent SWAT study performed for Embarrass River watershed in Illinois (Hu et al., 2007). Hu et al. further point out that nitrogen balance assessments have rarely been performed in previously reported SWAT studies, underscoring the need for more research to ascertain the accuracy of nutrient cycling estimates provided by the model for different environmental conditions.

Thus the specific objectives of this research are: (1) to calibrate and validate SWAT streamflow, sediment, nitrogen and phosphorus predictions for 2005 BRW baseline conditions (Chapter 3) using both the standard and alternative RCN methods, (2) to perform hydrologic sensitivity analyses for the alternative RCN approach, (3) to assess differences between the two RCN methods including implications for future SWAT applications in Iowa, and (4) to investigate predictions of nitrogen losses at the field level and also the amount of nitrogen fixation predicted for soybean.

Watershed Description

The BRW covers over 237,000 ha in six north central Iowa counties and is one of 131 U.S. Geological Survey (USGS) 8-digit hydrologic unit code (HUC) watersheds (Seaber et al., 1987) that are located in the UMRB (Figure 1). It lies within the Des Moines Lobe geologic formation, which is the southern most portion of the central North American Prairie Pothole Region. An extensive network of subsurface tile drains and surface ditches have been installed throughout the watershed, resulting in the elimination of most wetland areas and an intensively cropped landscape. The watershed is dominated by corn and soybean production,

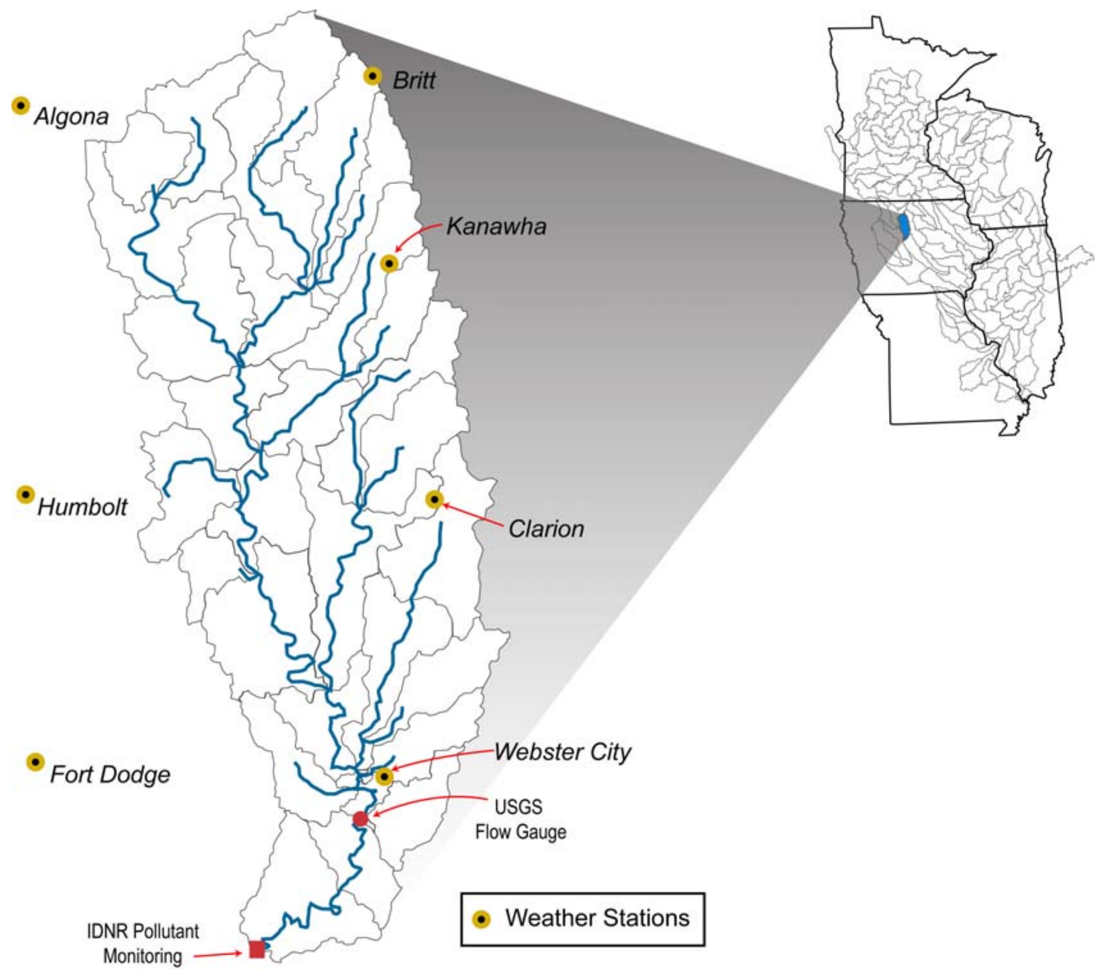

Figure 1. Location of the Boone River Watershed within the UMRB, and the subwatersheds, climate stations, and monitoring sites used for the SWAT simulations.

which together account for almost 90% of the land use based on a field-level survey of the watershed performed in 2005 as described in Chapter 3. The survey also revealed that the use of mulch tillage is very extensive, that a limited number of terraces and other conservation practices are used on cropland with steeper slopes, and that field borders are used along some stream channels in flatter areas of the watershed. A total of 128 confined animal feeding operations (CAFOs) are also located in the BRW; 109 of these are swine operations with a total of about 480,000 head (Chapter 3).

The BRW has been subdivided into 30 subwatersheds for the SWAT simulations (Figure 1), which roughly align with 12-digit watersheds as discussed in Chapter 3. The location of available measured streamflow data, pollutant data, and climate data are also shown in Figure 1. An in-depth description of land use, conservation practices, and other BRW characteristics is provided in Chapter 3.

Description of SWAT

SWAT is a conceptual, physically based long-term continuous watershed scale simulation model that operates on a daily time step. In SWAT, a watershed is divided into multiple subwatersheds, which are then usually further subdivided into Hydrologic Response Units (HRUs) that consist of homogeneous land use, management, and soil characteristics that represent percentages of the respective subwatershed are (i.e., they are not spatially defined within the model). Flow generation, sediment yield, and non-point-source loadings from each HRU in a subwatershed are summed, and the resulting loads are routed through channels, ponds, and/or reservoirs to the watershed outlet. Key components of SWAT include hydrology, plant growth, erosion, nutrient transport and transformation, pesticide transport and management practices. Several enhancements have been built into SWAT2005 including the alternative RCN approach and improved simulation of subsurface tile drain functions as described by Du et al. (2005; 2006). Further description of the model and summaries of a broad array of applications is provided in Chapter 2. The remaining discussion in this section focuses on the RCN approaches available in SWAT.

SWAT2005 RCN Options

The RCN method was originally developed by Mockus (1969); recently updated documentation has been released by USDA-NRCS (2004) which includes a set of rainfall-runoff tables for selected RCN values. The standard form of the RCN equation is:

$$Q = \frac{(P - 0 \cdot 2S)^2}{(P + 0 \cdot 8S)} \tag{1}$$

where Q is the runoff depth (mm), P is the rainfall depth (mm), and S is the retention parameter (mm). The retention parameter is calculated as a function of the curve number:

$$S = \frac{1000}{CN} - 10 \tag{2}$$

where CN is a dimensionless number ranging from 0 to 100 is referred to as the RCN in this discussion. The retention parameter S is related to watershed characteristics and antecedent moisture conditions (Kannan et al., 2007) and also represents the maximum difference that can occur between precipitation (P) and runoff (Q) for a specific storm and watershed conditions (Mishra and Singh, 2003).

Traditionally, S has been allowed to vary in SWAT (and many other models) as a function of the soil water content (Neitsch et al., 2005a) and is calculated as:

$$S = S_{\max} \cdot \left(1 - \frac{SW}{\left[SW + \exp\left(w_1 - w_2 \cdot SW\right)\right]}\right) \tag{3}$$

where S_{max} is the maximum value that the retention parameter can reach on any given day (mm), SW is the soil water content (mm) of the entire soil profile (excluding the soil water amount that is held in the soil at wilting point), and w_1 and w_2 are shape coefficients that are computed as function of field capacity (mm), soil water content for totally saturate conditions (mm), and other parameters.

The alternative RCN method uses a different retention parameter calculation approach first introduced by Williams and LaSeur (1976), in which S is varied as a function of accumulated evapotranspiration (ET). This is calculated in SWAT2005 (Neitsch et al., 2005a) on a daily basis as:

$$S = S_{prev} + E_o * \exp\left(\frac{-CNCOEF - S_{prev}}{S_{\max}}\right) - R_{day} - Q_{surf} \tag{4}$$

where S is the retention parameter calculated for a specific day, S_{prev} is the retention parameter calculated for the previous day, E_o is the potential ET for the day, the CNCOEF is a weighting coefficient used in the calculations of the daily curve number based on the ET level (and is referred to as the "depletion coefficient" by Kannan et al.), and P and Q are the same as defined in equation 1. The basic effect of the alternative RCN approach is that S declines as the hydrologic system becomes more "ET dominated", resulting in a lower CN and thus increased infiltration of rainfall. The reverse effect occurs as rainfall begins to dominate ET in the hydrologic regime. Williams (2007) points out that this approach tends to more realistically capture the water balance effects of gradual soil recharge processes, such as often happens over much of the U.S. during the transition from ET dominated summer periods into fall periods characterized by increased rainfall and subsequent soil water recharge.

The effects of the S parameter calculations (equations 3 and 4) are updated in SWAT on a daily basis. Thus, the range of RCN values can vary widely over a long-term simulation such as the 21-year simulations reported in this study (as discussed below).

Previous Applications of the Alternative RCN Approach

Kannan et al. state the alternative RCN approach provides better results for shallow soils and soils that are characterized by low water storage. They demonstrated the effects of varying the CNCOEF in SWAT2005 over a theoretical range of 0.0 to 2.0 for two 8-digit watersheds located in the New England and Texas Gulf Major Water Resource Regions (MWRRs)[6]. They also stated that the "practical limits" of the CNCOEF were from 0.5 to 1.5, but did not further explain the reasons for these practical bounds[7]. Total water yield and ET remained relatively constant over the range of simulated CNCOEF values in both 8-digit watersheds. However, surface runoff and subsurface flow varied dramatically for the two simulated watersheds, but in different ways.

Green et al. also used the alternative SWAT2005 RCN method to simulate the deeper tile-drained soils in the South Fork of the Iowa River watershed. Their calibrated 10-year hydrologic balance was split between 38.1 mm of surface flow and 154.3 mm of subsurface flow, with 136.4 mm being attributed to tile flow. They set CNCOEF to 0.2 for their calibrated simulations, which is outside the practical limits reported by Kannan et al. and the recommendations in the SWAT Users Manual (Neitsch et al., 2005b). They do not provide any further discussion regarding the theoretical implications of their choice of CNCOEF value. However, this does not appear to be a violation of any specific hydrologic principles based on insights provided by Williams (2007) as referenced above.

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[6]See Figure 2 in Chapter 2 for a map of the 18 MWRRs that comprise the conterminous U.S.
[7]Williams (2007) does not see any problem in applying the method outside the "practical bounds" or applying it to deeper soils; it was initially included in SWAT2005 to overcome problems of accurately simulating the water balance of soils characterized by low water storage in the Bosque River watershed in Texas.

Input Data

The input data for the baseline BRW simulations are described in detail in Chapter 3 and are briefly reviewed here. The baseline land use, tillage practice, and conservation practice data were collected via a field survey in 2005, which included estimates of crop rotation patterns as well as the growing season land use for that year. According to historical cropping patterns reported by USDA-NASS (2007), the BRW has been dominated by corn and soybean production since the early 1960s. Thus the 2005 land use is representative of the 1986-2006 simulation period used for the baseline simulations. It is probable that conservation tillage increased during 1986-2006, but it is assumed for this study that the 2005 tillage patterns are representative of the entire simulation period. It is not clear how the distribution of conservation practices has varied over time. However, the influence of these practices is relatively minor on both the baseline hydrologic and nonpoint source pollution estimates.

The nutrient application rates are listed in Table 1, which were derived from 2005 confined animal feeding operation (CAFO) information and fertilizer application rates reported during 2004 and 2005 as discussed in Chapter 3. These cropland nutrient inputs were applied as a function of crop rotation (Table 1) and are realistically consistent with the period in which in-stream nutrient measurements have been collected (October 1999 to the present). An additional key management input for the baseline simulations was that virtually all cropland was tile drained, following the methodology discussed in Chapter 3.

Soil, topographic, climate and other required input data for the BRW SWAT baseline simulations are also discussed in detail in Chapter 3. The Hargreaves ET and the Variable Storage channel routing options were also used for the BRW simulations.

Table 1. Nutrient application rates on corn by nutrient source.

Nutrient source	Time of Year	Crop rotation	Application rate (kg ha^{-1})[a,b]
Fertilizer (nitrogen)	Fall	Corn-soybean	183
Fertilizer (nitrogen)	Spring	Corn-soybean	172
Fertilizer (nitrogen)	Spring	Continuous corn	196
Fertilizer (P_2O_5)	Fall or spring	Corn-soybean & continuous corn	49
Manure nitrogen	Spring	Corn-soybean & continuous corn	190
Manure phosphorus	Spring	Corn-soybean & continuous corn	69.8

[a]Multiply these rates by 1.12 to obtain Equivalent application rates in lb/ac.
[b]Total nitrogen applied for each application rate.

SWAT Calibration and Validation

The SWAT calibration and validation approach used in this study is based on the approach described by Jha et al. (2007) for their study of the Raccoon River watershed in west central Iowa. A 21-year (1986-2006) simulation period was chosen to perform the BRW model testing, which was split into a 10-year (1986-1995) calibration period and an 11-year (1996-2006) validation period. The calibration period includes both the most extreme drought year (1987) and wet year (1993) of the past 56 years (1951-2006) as discussed further in Chapter 3.

The calibration process was performed manually by adjusting key hydrologic, sediment, and nutrient related parameters (described below) including several suggested by Jha et al. (2007), Neitsch et al. (2005b), Santhi et al. (2001), and Green et al. (2006), and then comparing the model output with measured data. The initial focus of the calibration process was on the overall watershed-level hydrologic balance and annual streamflows. Further hydrologic calibration was then performed by comparing the simulated monthly streamflows with corresponding measured values. The streamflow comparisons were performed by normalizing the predicted streamflows at the watershed outlet with the measured streamflows at the USGS flow gauge, which is located at the outlet of subwatershed 27 (Figure 2). This process was accomplished by converting both the predicted and measured streamflows from flow rates (m^3 s^{-1}) to equivalent depths (mm), which provides a consistent basis for comparisons between the two different locations.

A fundamental question considered in the hydrologic calibration process was the partitioning of total flow between surface runoff and subsurface flow (baseflow) components. Schilling and Wolter (2005) reported that the total Boone River streamflow was comprised essentially of equal base flow and surface runoff contributions, based on assessment of long-term streamflow records near the watershed outlet using an automated streamflow hydrograph separation program. This contrasts sharply with the results that Green et al. found for the neighboring South Fork of the Iowa River watershed, who reported that overall streamflow was comprised of 80% baseflow and 20% surface runoff. Further BRW streamflow analysis performed with an automated digital filter technique (Arnold and Allen, 1999) for this study resulted in an estimated range of baseflow contribution between 40 and 65%, with a mid-range estimate of 49% (which is generally the recommended estimate). Thus, an initial guide for the streamflow separation was to assume that 50% each was contributed from baseflow and surface runoff. However, specific investigation was also

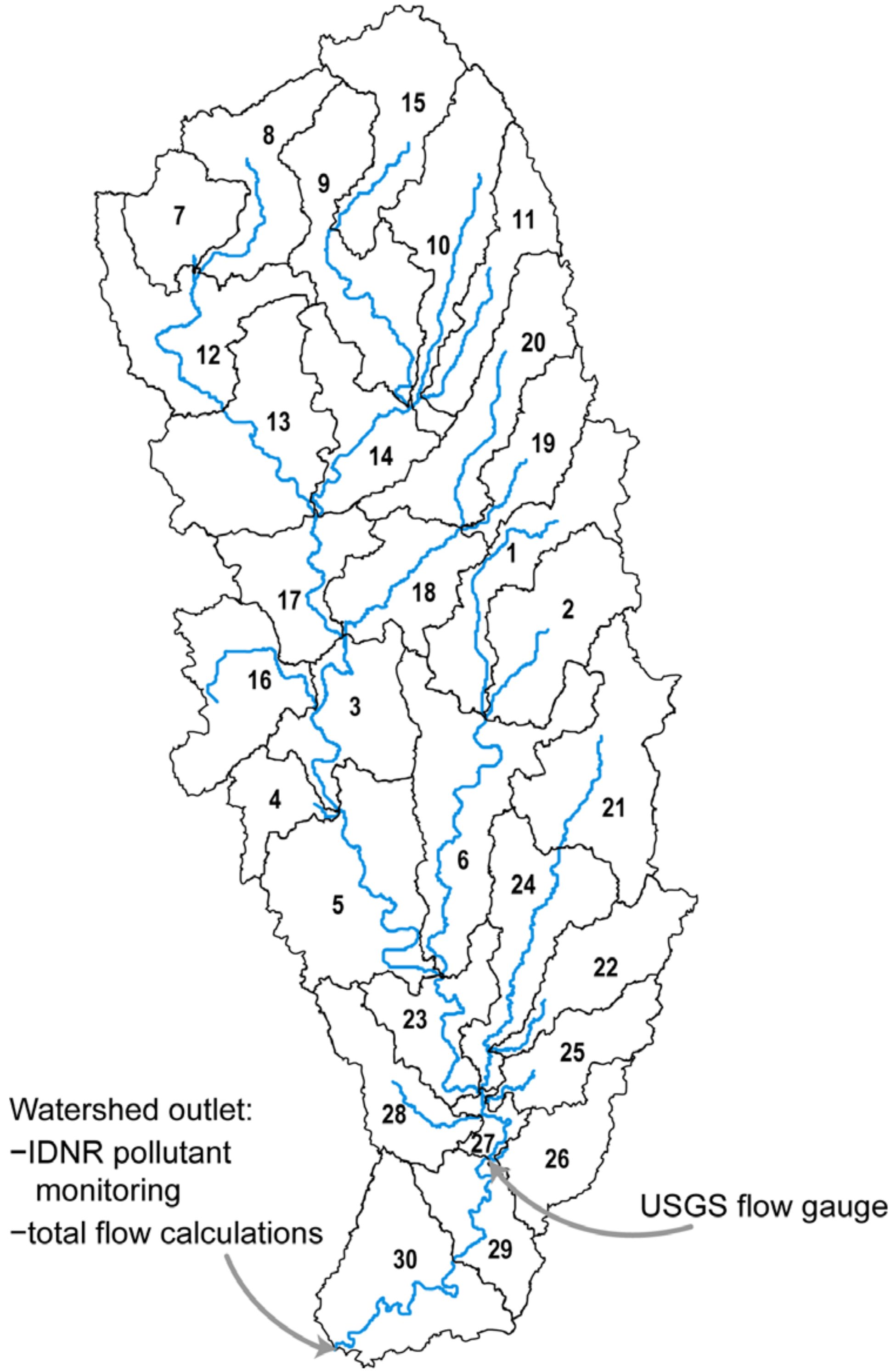

Figure 2. Location of the USGS flow gauge at the outlet of subwatershed 27 relative to the watershed outlet (outlet of subwatershed 30), the location at which the predicted streamflows and pollutant loads results are reported for.

performed on the differing hydrologic balance responses of the two RCN methods, with a particular focus on differences in predicted relative contributions of surface runoff and baseflow to overall streamflow at the watershed outlet.

Calibration of the sediment and nutrient outputs were performed following completion of the hydrologic calibration process. The pollutant calibration was performed on the basis of single monthly grab samples collected between January 2000 and December 2006 at the watershed outlet (Figure 2), which are discussed further in Chapter 3. Validation of the pollutant estimates was not performed due to the limited number of measurements available for model testing. The water quality samples were extrapolated into equivalent monthly pollutant loads using the USGS Load Estimator (LOADEST) regression model (Runkel et al., 2004), which was developed from the predecessor LOADEST2 (Crawford, 1996) and ESTIMATOR (Cohn et al., 1989) models. In-stream pollutant loads are estimated with LOADEST by developing a regression model as a function of streamflow, pollutant concentration, and other data inputs. The model is well documented and is accepted as a valid means of calculating annual solute load from a limited number of water quality measurements. However, the load estimation process of the model is complicated by the same problems experienced with other approaches; e.g., retransformation bias, data censoring, and non-normality. For example, Ferguson (1986) reported that the rating curve estimates of instantaneous load were biased and may have underestimated the true load by as much as 50 percent.

Calibrated Input Parameters

The hydrologic calibration/validation process was carried out in what is best described as "parallel phases", with the first phase centered on testing the traditional RCN method while the second phase focused on further testing of the alternative RCN method. The hydrologic-related calibration assumptions for the two SWAT simulation approaches are listed in Table 2. The key parameter adjustments for the standard RCN approach included reducing the CN values by 10%, the available water capacity (AWC) by .04 in the soil layer file, and the ESCO ET parameter to .82, and adjustment of the tile drainage parameters. The CN and AWC reductions resulted in less surface runoff, which was observed to be an initial problem due to overprediction of the total streamflow. A tile drainage depth of 1.2 m (4 ft) was assumed for all fields with subsurface drainage. The same depth was assumed for the "impervious soil layer", which was added by Green et al. to SWAT2005 to further improve the simulated tile drainage response as reported. Green et al. assumed an impervious soil layer depth of 2.5 m for their SWAT simulation study. However, the model response was not adequate using deeper impervious depths such as 2.5 m for the BRW simulations, so 1.2 m was used. The time to drain soil to field capacity and drain tile lag time were set to 24 and 48 hours, respectively. Several other parameters were also adjusted (Table 2) that had relatively minor effects on the hydrologic balance and streamflow results.

The same values were used for the majority of the calibrated parameters for the BRW baseline based on the alternative RCN method (Table 2). A CNCOEF value of 0.6 was selected for the alternative method based on testing across the range of possible CNCOEF values, as discussed further in the Results and Discussion Section. No adjustments were made to the soil AWC inputs, because greater infiltration and subsurface flow occurred with

Table 2. Calibrated hydrologic parameters for the BRW baseline simulations

Definition of adjusted SWAT parameter (or description of adjustment)	SWAT parameter name	Standard RCN approach	Alternative RCN approach
Curve number calculation method (0 versus 1)	ICN	0	1
Curve number reduction	CN2	10%	10%
Curve number coefficient (depletion coefficient)	CNCOEF	-	0.6
Reduction in available water capacity	AWC	-0.04	-
Soil evaporation compensation factor	ESCO	0.82	0.90
Depth to subsurface drain (mm)	DDRAIN	1200	1200
Depth to impervious layer in soil profile (mm)	DEP_IMP	1200	1200
Time to drain soil to field capacity (hours)	TDRAIN	24	24
Drain tile lag time (hours)	GDRAIN	48	48
Surface runoff lag	SURLAG	0.5	0.5
Delay time for aquifer recharge (days)	GW_DELAY	30	30
Baseflow recession constant	ALPHA_BF	0.9	0.9
Threshold water level in shallow aquifer for base flow (mm)	GWQMN	0	0
Revap coefficient	GW_REVAP	0.02	0.02
Threshold water level in shallow aquifer for revap (mm)	REVAPMN	2	2
Aquifer percolation coefficient	RCHRG_DP	0	0

the alternative RCN method. The ESCO ET parameter was set at 0.90 rather than 0.82 as used for the standard RCN method. All other values were held constant for the alternative RCN method simulations. The hydrologic calibration also formed the foundation for the calibration of the pollutant input parameters. Further calibration was then performed for the nutrient, sediment, and in-stream water quality parameters listed in Table 3. The exact

Table 3. Calibrated pollutant-related parameters for the BRW baseline simulations

Definition of adjusted SWAT parameter (or description of adjustment)	SWAT parameter name	Standard RCN approach	Alternative RCN approach
Nutrient parameters			
Nitrate percolation coefficient	NPERCO	0.8	0.8
Organic N enrichment ratio for loading with sediment.	ERORGN	4	4
Organic P enrichment ratio for loading with sediment.	ERORGP	2	2
Initial concentration of nitrate in shallow aquifer (mg N L^{-1})	SHALLST_N	10	10
Concentration of soluble phosphorus in groundwater (mg P L^{-1})	GWSOLP	0.05	0.05
Sediment parameters			
Sediment re-entrainment parameter	SPCON	0.0006	0.0006
Sediment re-entrainment parameter	SPEXP	2.2	2.2
Channel erodibility factor	CH_EROD	0.028	0.028
Channel cover factor	CH_COV	0.5	0.5
In-stream parameters			
Rate coefficient for organic N settling	RS4	0.001	0.001
Rate constant for hydrolysis of organic N to NH_4	BC3	0.35	0.35
Rate constant for biological oxidation of NO_2 to NO_3	BC2	1.5	1.5
Rate constant for biological oxidation of NH_4 to NO_2	BC1	2.5	2.5
Organic phosphorus settling rate	RS5	0.1	0.1
Rate constant for mineralization of organic P to dissolved P	BC4	0.02	0.02

same set of calibrated pollutant-related parameters was used for both the standard and alternative RCN method simulations. However, further adjustment of some of the calibrated input values would likely be necessary to obtain improved pollutant loss results with the alternative RCN method, as is discussed below in the Results and Discussion Section.

Statistical Evaluation

The predicted streamflows and pollutant loads were statistically evaluated with the regression correlation coefficient (R^2) and the Nash-Sutcliffe model efficiency (E) coefficient (Nash and Sutcliffe, 1970). Both of these statistics have been used extensively to evaluate SWAT output in past studies as discussed in Chapter 2. The r^2 is defined as:

$$R^2 = \frac{\left(\sum_{i=1}^{n} (O_i - \bar{O})(P_i - \bar{P})^2 \right)}{\sum_{i=1}^{n} \left((O_i - \bar{O}) \sum_{i=1}^{n} (P_i - \bar{P})^2 \right)} \tag{5}$$

where n is the number of observations, O_i and P_i are the individual corresponding observed and predicted values, and O and P are the arithmetic means of the observed and predicted values. The R^2 measures how well the simulated versus observed regression line approaches an ideal match and ranges from 0 to 1, with a value of 0 indicating no correlation and a value of 1 representing that the predicted dispersion equals the measured dispersion (Krause et al., 2005). Krause et al. further point out that simulated predictions which systematically over- or under-predict observed values can still result in strong R^2 values, which is an inherent weakness of the statistic and an important reason why it should not be the sole method used to evaluate model output. The E is defined as:

$$E = \frac{\sum_{i=1}^{n}\left(O_i - \bar{O}\right)^2 - \sum_{i=1}^{n}\left(P_i - O_i\right)^2}{\sum\left(O_i - \bar{O}\right)^2} \tag{6}$$

Krause et al. explain that the E ranges from -∞ to 1 and measures how well the simulated versus observed data match the 1:1 line (regression line with slope equal to 1). An E value of 1 again reflects a perfect fit between the simulated and measured data. A value of 0 or less than 0 indicates that the mean of the observed data is a better predictor than the model output. Green et al. further state that the E can be used to judge the ability of a model to replicate individual observed values, which cannot be performed with the R^2 statistic. The statistical results were judged to be acceptable if the R^2 and E values exceeded 0.5, based on criterion proposed by Moriasi et al. (2007) as discussed in more detail in Chapter 2.

Results and Discussion

Table 4 presents the overall predicted 21-year hydrologic balances for the two different calibrated RCN approaches. The final calibrated results for the standard RCN approach result in a slightly higher total baseflow (tile flow plus groundwater and lateral subsurface flows) of 51.3% versus 48.7% of the total streamflow being attributed to surface runoff. The average annual ET result of 572.7 mm was 68.5% of the total respective precipitation input, which is in the expected range of 60 to 70% as suggested by Hatfield (2006). Small in-stream transmission losses were also predicted.

The results of the SWAT baseline that was based on the alternative RCN method (Table 4) were one of several hydrologic balances generated with the alternative RCN method (Table 5). The seven sets of output reported in Table 4 reveal that the predicted surface runoff and subsurface flow components were very sensitive to the choice of

Table 4. Predicted 21-year (1986-2006) average annual BRW water balances for the two SWAT baselines.

Water balance component	Standard RCN approach (mm)	Alternative RCN approach (mm)
Precipitation	836.7	836.7
Snowmelt	90.9	90.7
Surface runoff	128.6	110.1
Tile flow	110.1	121.3
Groundwater flow	24.4	20.4
Lateral subsurface flow	1.31	1.7
Evapotranspiration (ET)	572.7	581.8
Stream flow	264.2	253.3
Transmission losses	3.1	2.4

CNCOEF, with the balances estimated with CNCOEF=0.2 and 1.5 being virtual opposites of each other. At the same time, the estimated average annual ET and total streamflow remained almost constant across the range of CNCOEF values. Setting CNCOEF to 0.2 resulted in baseflow being predicted as contributing 80% of the total streamflow, which was essentially identical to the results found by Green et al. The CNCOEF value of 0.6 resulted in relative predicted contributions of 43.5 and 56.6% for surface runoff and the combined baseflow components, which was the closest set of results as compared to the standard RCN method results while still maintaining a higher level of relative baseflow input. Thus, the alternative SWAT baseline was based on using a CNCOEF value of 0.6 (Table 3). This assumption reflects a position that a greater amount of overall streamflow could be contributed from baseflow sources, but not as great as the results reported by Green et al.

Table 5. Predicted 21-year (1986-2006) average annual BRW water balances for different CNCOEF values used in the SWAT simulations based on the alternative RCN method

	CNCOEF value						
	.2	.5	.6	.8	1.0	1.2	1.5
Precipitation	836.7	836.7	836.7	836.7	836.7	836.7	836.7
Snowmelt	90.7	90.7	90.7	90.7	90.7	90.7	90.7
Surface runoff	43.0	97.1	110.1	132.0	150.2	165.9	185.9
Tile flow	180.1	132.8	121.3	102.3	86.4	72.8	55.8
Groundwater flow	27.3	23.0	20.4	19.9	18.3	17.0	15.4
Lateral subsurface flow	2.1	1.8	1.7	1.6	1.5	1.4	1.2
Evapotranspiration	583.8	582.0	581.8	580.8	580.0	579.0	577.3
Stream flow	252.5	254.7	253.3	255.8	256.4	257.1	258.3
Transmission losses	1.3	2.2	2.4	2.7	2.9	3.1	3.3

Comparisons between simulated and measured annual streamflows are shown for the two SWAT approaches in Figures 3 and 4, and corresponding monthly streamflow comparisons are shown in Figures 5 and 6. The results of both the annual and monthly comparisons were similar between the standard RCN method (Figures 3 and 5) and the alternative RCN method (Figures 4 and 6). Both approaches resulted in strong calibration and validation statistics that ranged from 0.74 to 0.99 for the annual streamflow comparisons and from 0.88 to 0.92 for the monthly comparisons. The overall annual average streamflow predicted with the alternative RCN method was virtually identical to the measured streamflow (Figure 4), while the long-term annual average was slightly overpredicted (3%) when the standard RCN method was used (Figure 3). The streamflows were generally underpredicted during the 1986-1995 calibration period and overpredicted during the

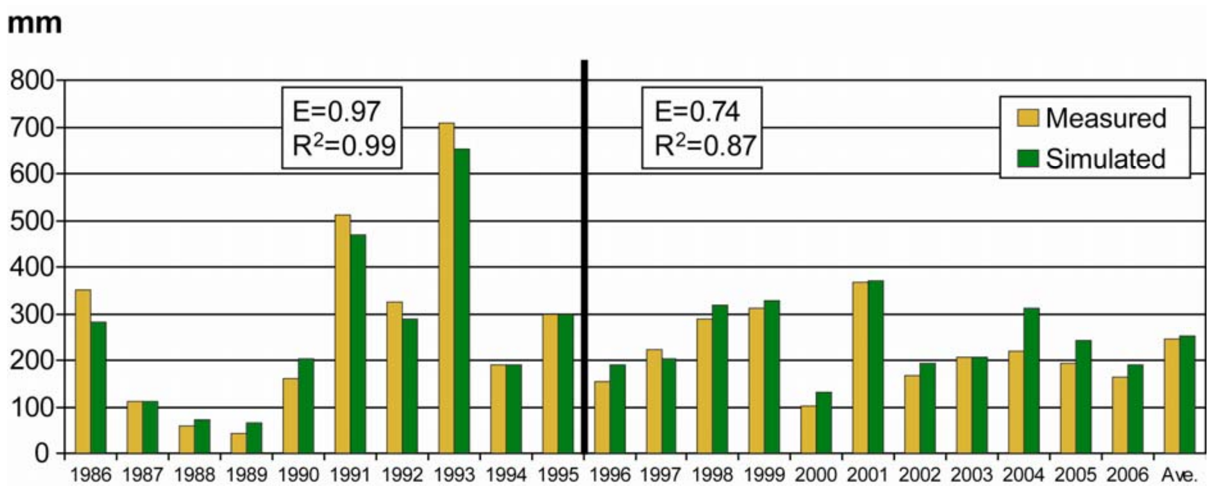

Figure 3. Simulated versus measured BRW annual streamflows during the 1986-1995 calibration and 1996-2006 validation periods for the Boone River watershed using the standard RCN method.

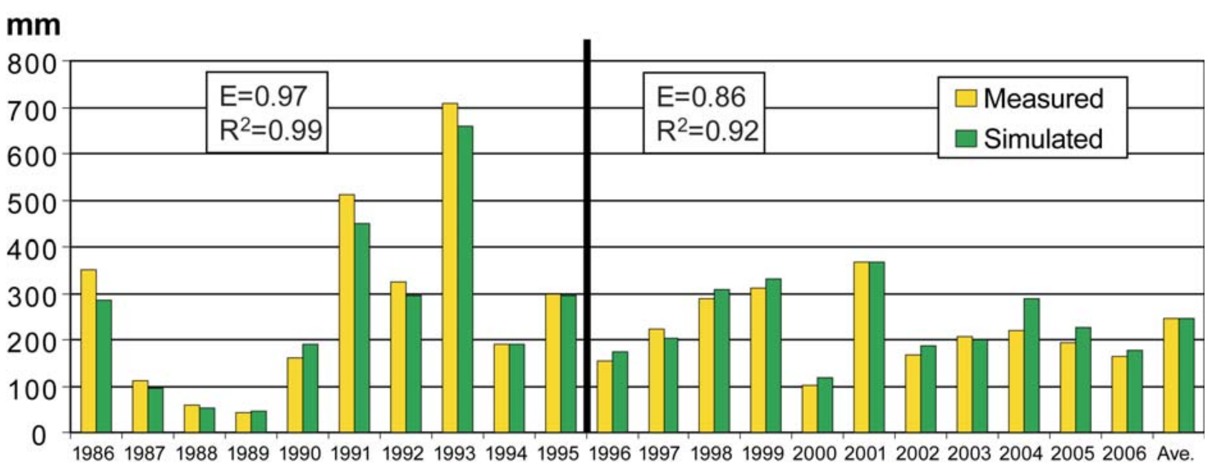

Figure 4. Simulated versus measured BRW annual streamflows during the 1986-1995 calibration and 1996-2006 validation periods for the Boone River watershed using the alternative RCN method (CNCOEF=0.6).

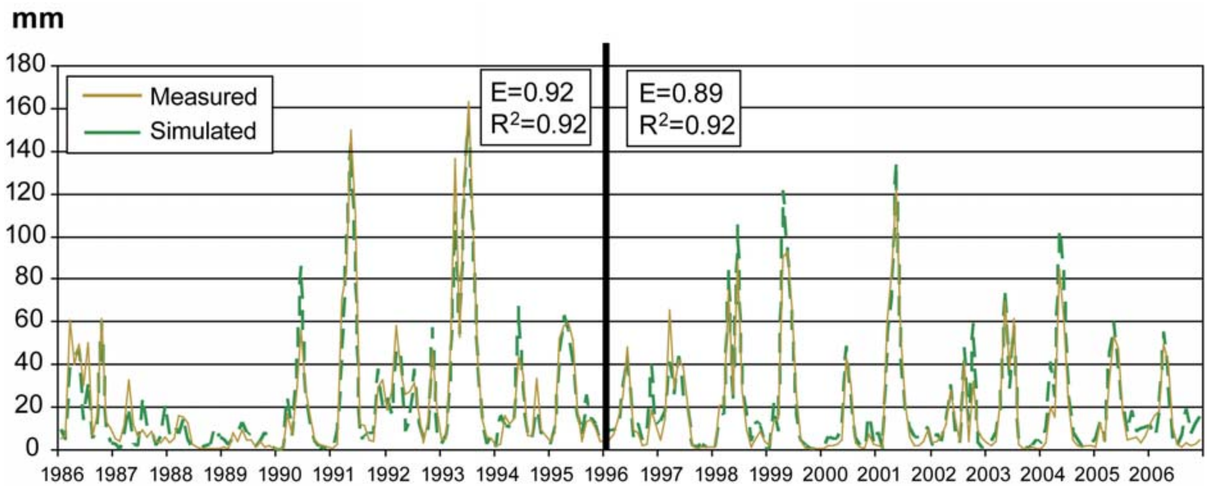

Figure 5. Simulated versus measured BRW monthly streamflows during the 1986-1995 calibration and 1996-2006 validation periods for the Boone River watershed using the standard RCN method.

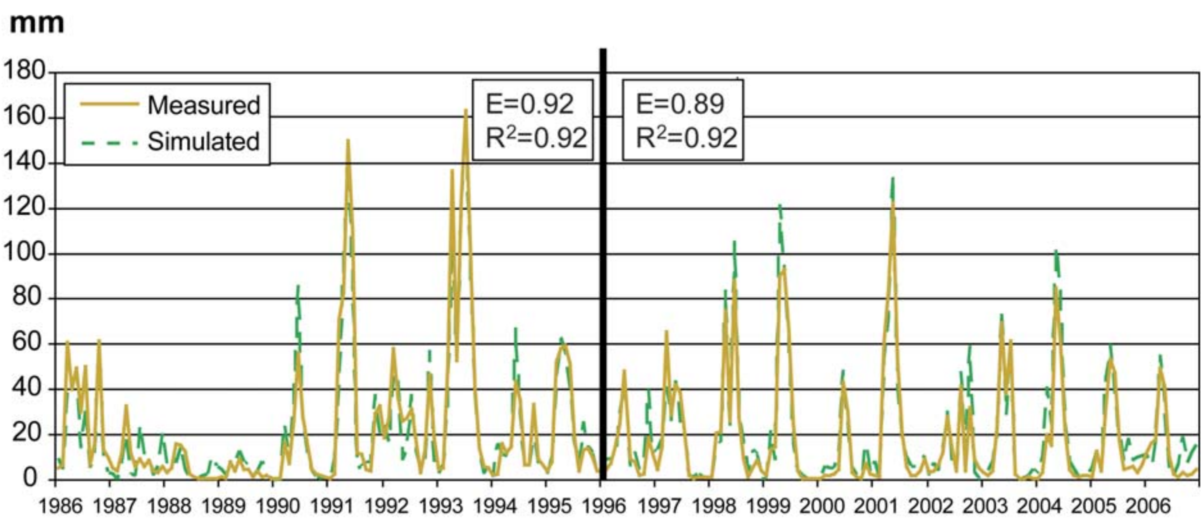

Figure 6. Simulated versus measured BRW monthly streamflows during the 1986-1995 calibration and 1996-2006 validation periods for the Boone River watershed using the alternative RCN method (CNCOEF=0.6).

1996-2006 validation period. Using the alternative RCN method resulted in noticeable improvement of the computed statistics for the annual streamflow validation, with the R^2 and NSE statistics shifting from 0.87 to 0.92 and 0.74 to 0.88 between Figures 3 and 4, respectively. This was due mainly to the increased overprediction of annual streamflows that occurred when the standard RCN method was used. However, the overpredictions shown between the two methods for the monthly streamflow comparisons (Figures 5 and 6) were very similar, which was reflected in the similar R^2 and NSE statistics computed between the two baselines. It is also useful to note that any of the CNCOEF values (Table 4) would result in similar streamflow comparison results for the alternative RCN simulations reported here.

Environmental Indicators

Comparisons between the predicted annual sediment loads and the measured sediment loads estimated with LOADEST are shown in Figures 7 and 8. Similar results are shown for monthly comparisons in Figures 9 and 10. The predicted annual sediment loads (and overall annual average sediment load) declined slightly between the SWAT baseline executed with the standard RCN method (Figure 7) and the alternative SWAT baseline (Figure 8), which would be expected due to the lower surface runoff that was predicted using the alternative RCN approach. The computed annual statistics were very similar between the two simulations, and the E statistic actually improved for SWAT baseline based on the alternative RCN method. The monthly statistics predicted for both approaches ranged from .67 to .79, and weakened slightly for the alternative SWAT baseline (Figure 10). Minor improvements could be obtained by performing additional calibration for the sediment loads estimated with the alternative RCN method.

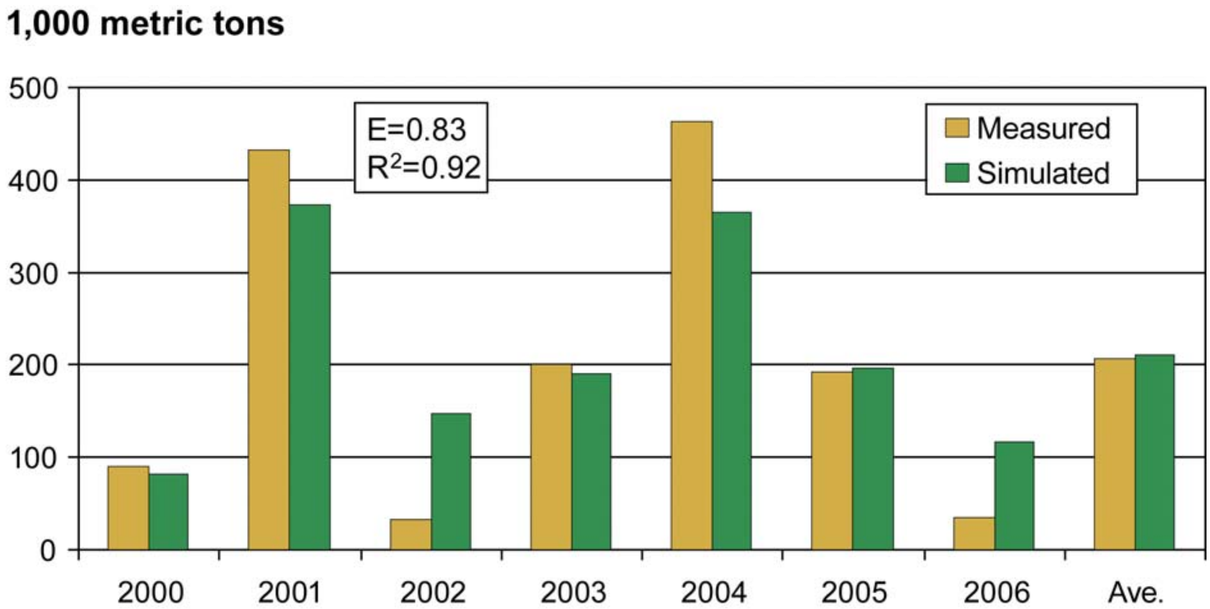

Figure 7. Simulated versus measured BRW annual sediment loads during 2000-2006 for the Boone River watershed using the standard RCN method.

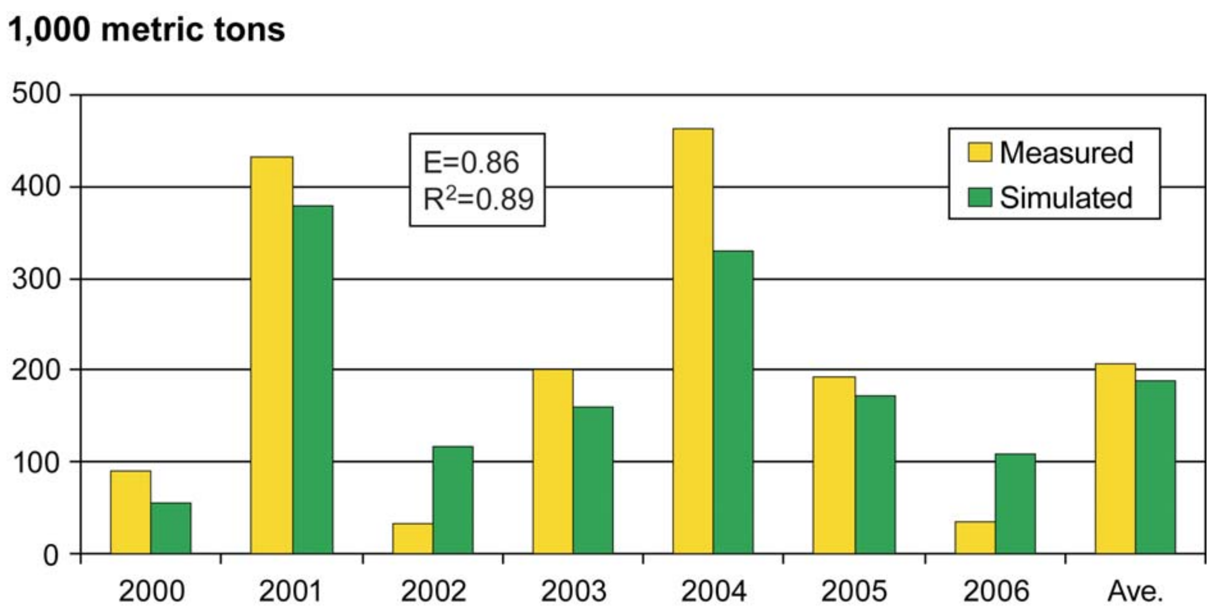

Figure 8. Simulated versus measured BRW annual sediment loads during 2000-2006 for the Boone River watershed using the alternative RCN method (CNCOEF=0.6).

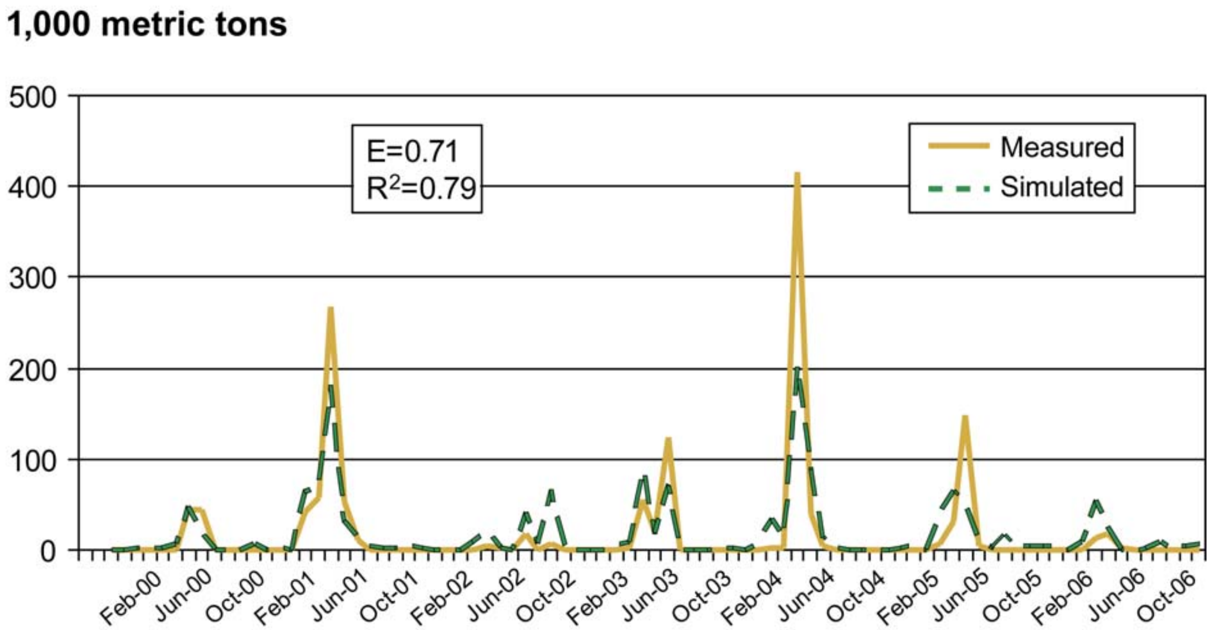

Figure 9. Simulated versus measured BRW monthly sediment loads during 2000-2006 for the Boone River watershed using the standard RCN method.

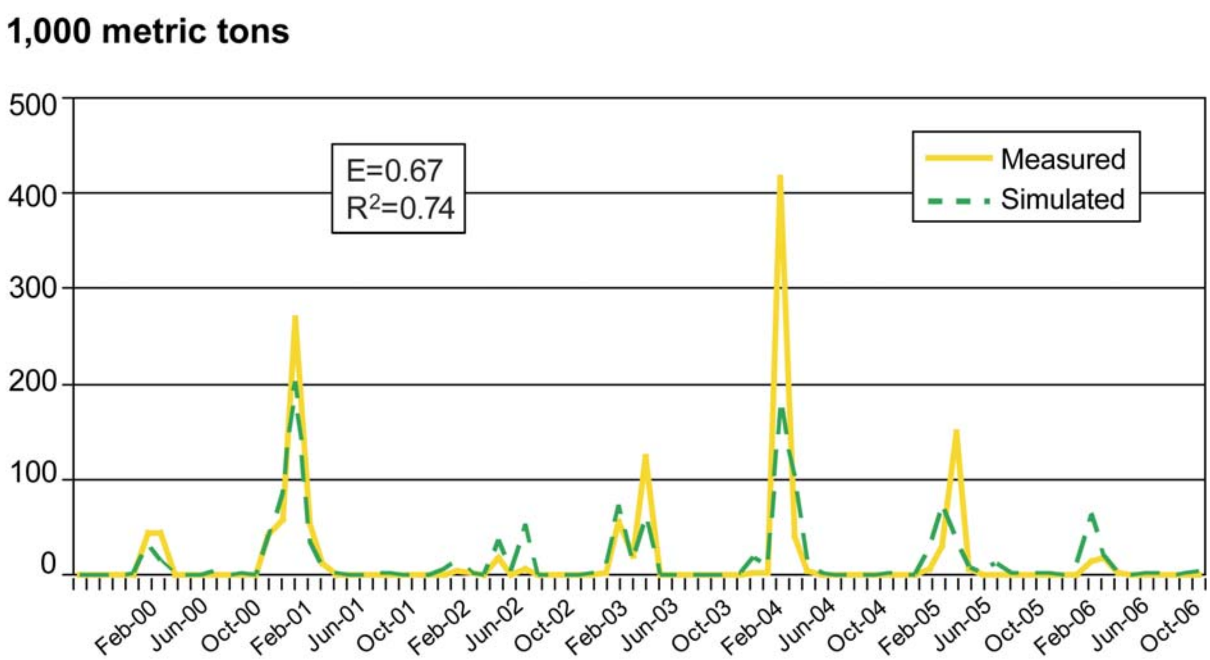

Figure 10. Simulated versus measured BRW monthly sediment loads during 2000-2006 for the Boone River watershed using the alternative RCN method (CNCOEF=0.6).

Comparisons of predicted versus measured annual total phosphorus loadings are shown in Figures 11 and 12. Counterpart comparisons on a monthly basis are shown in Figures 13 and 14. The total phosphorus loads were more accurately simulated using the standard RCN method as evidenced by the more accurate annual average load (Figure 11) and the stronger E statistic (0.66 versus 0.57 for the alternative approach). However, the estimated measured load was greatly underestimated in 2001 for the standard SWAT baseline (Figure 11), and the 2004 and 2005 annual total phosphorus loads were more accurately simulated when the alternative RCN method was used (Figure 12).

The R^2 and E statistics computed for the monthly total phosphorus load comparisons in Figures 13 and 14 were generally stronger than those determined for the annual comparisons in Figures 11 and 12. The monthly statistics ranged from an E value of 0.66 for the alternative SWAT baseline to an R^2 of 0.79 for the SWAT simulation based on the standard RCN method. However, several total phosphorus peaks were clearly more weakly predicted using the alternative RCN method including the peak loads estimated in 2000, 2003, 2004, and 2006 (Figure 14). Overall, the relatively strong statistics generated for the monthly comparisons indicate that the model accurately tracked both the magnitudes and trends of the measured total phosphorus loads, for both of the baseline simulation approaches.

The weaker total phosphorus outputs that resulted from using the alternative RCN method further demonstrate the need to re-calibrate some of the parameters listed in Table 3 that were specifically calibrated for the SWAT baseline using the standard RCN method. This recalibration issue is more acute for the nitrogen simulations as discussed below.

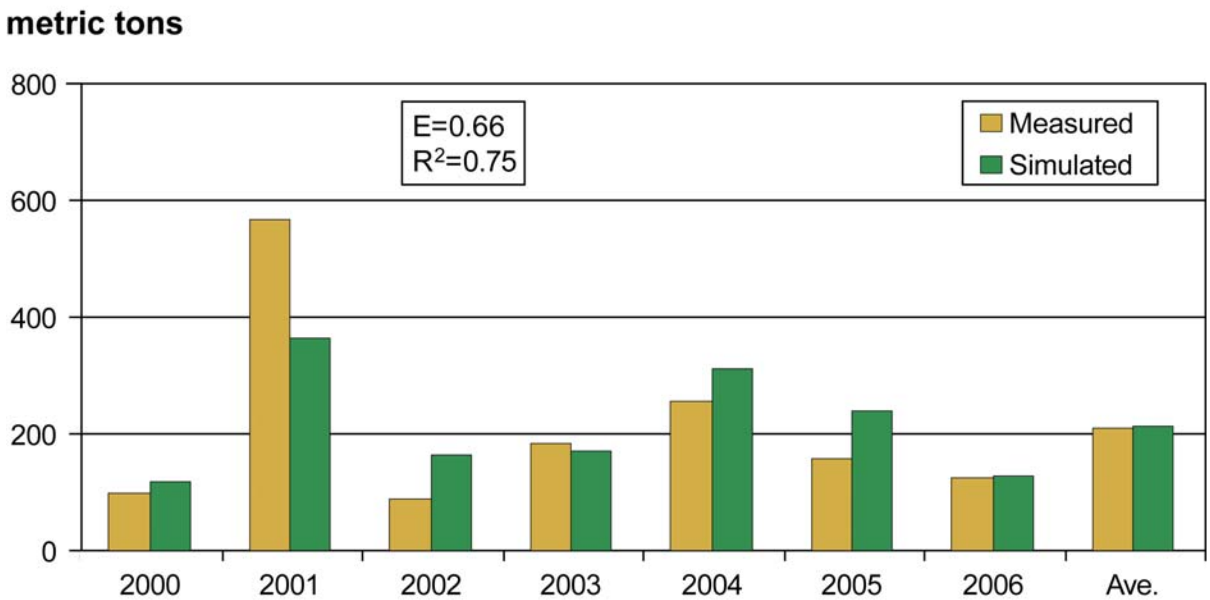

Figure 11. Simulated versus measured annual total phosphorus loads during 2000-2006 for the Boone River Watershed using the standard RCN method.

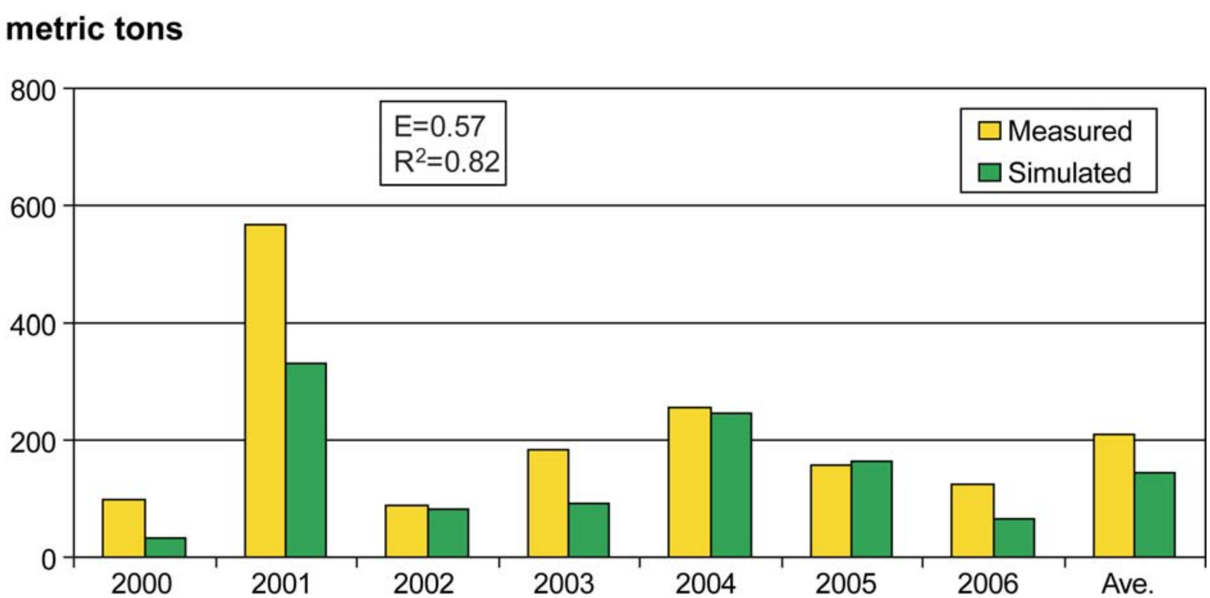

Figure 12. Simulated versus measured annual total phosphorus loads during 2000-2006 for the Boone River Watershed using the alternative RCN method (CNCOEF=0.6).

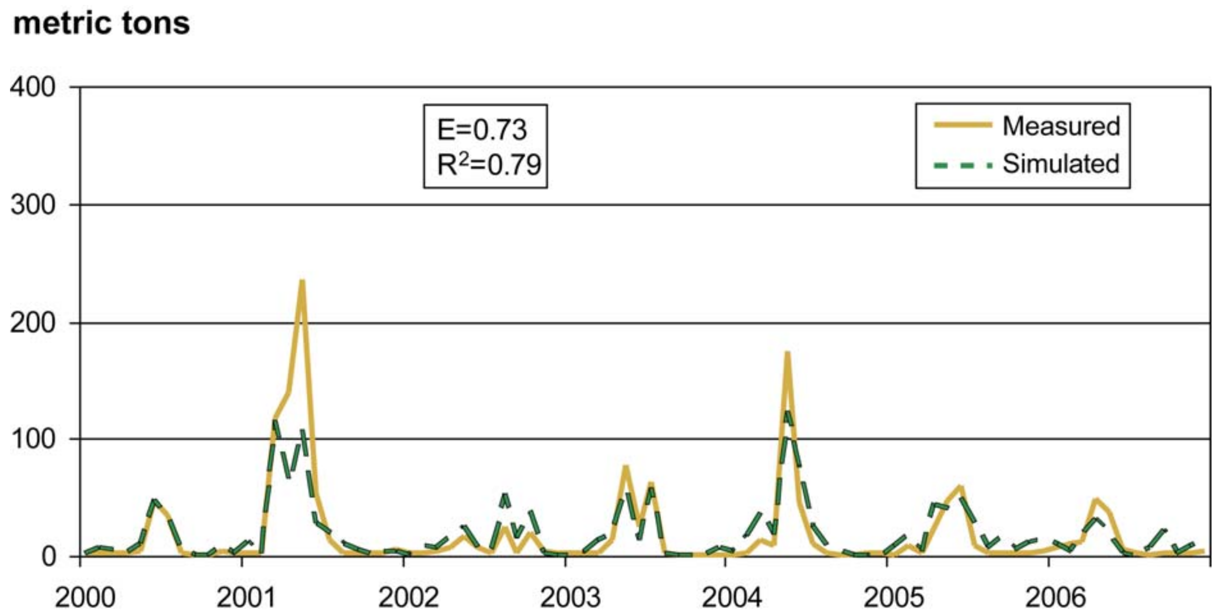

Figure 13. Simulated versus measured monthly total phosphorus loads during 2000-2006 for the Boone River Watershed using the standard RCN method.

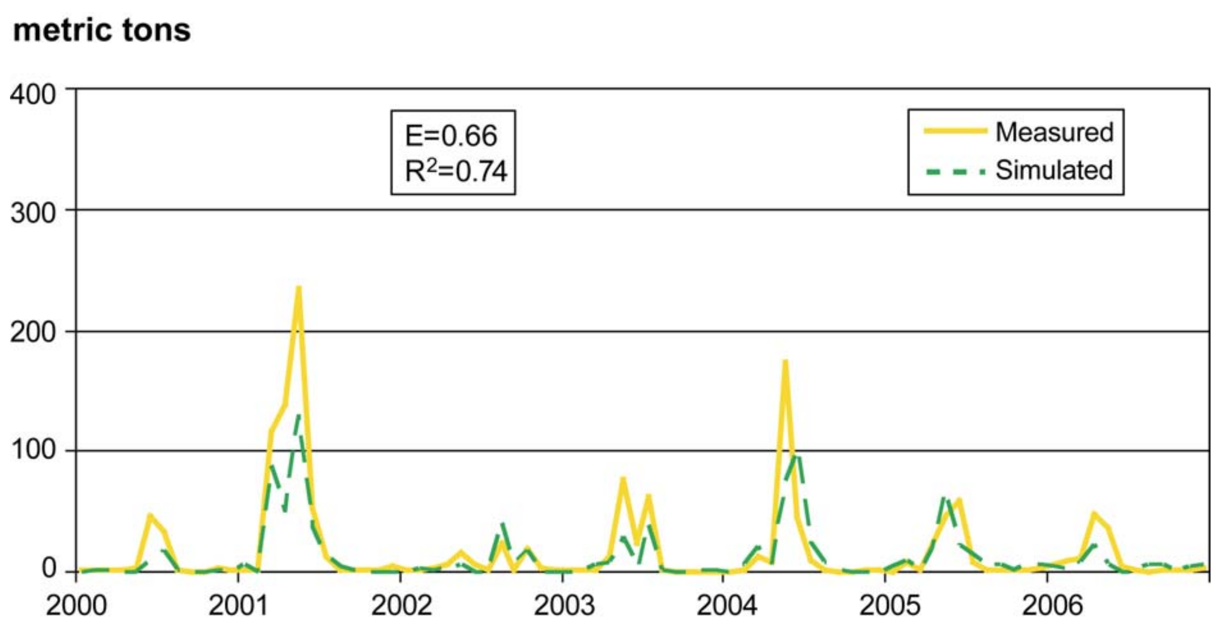

Figure 14. Simulated versus measured monthly total phosphorus loads during 2000-2006 for the Boone River Watershed using the alternative RCN method (CNCOEF=0.6).

Figures 15 and 16 show comparisons of predicted and measured annual nitrate loads. Similar monthly comparisons are shown in Figures 17 and 18. The annual average nitrate loads predicted with the standard RCN method (Figure 15) and the alternative RCN method (Figure 16) were both slightly below the estimated measured load and also similar in magnitude to each other. The predicted annual nitrate loads for the alternative SWAT baseline were higher in some years, such as 2001 and 2004, as compared to the baseline based on the standard RCN method. The reverse was also true, with lower loads predicted in 2000 and 2001 for the alternative RCN method relative to the corresponding loads predicted using the standard RCN method. These results can also be observed from the plots of monthly loads for the standard and alternative baselines in Figures 17 and 18, respectively.

The computed statistics showed some degradation in the results when the alternative RCN method was used, especially for the E value which declined from 0.50 (Figure 15) to 0.35 (Figure 16). Almost all of the r^2 and E statistics exceeded 0.50 for both the annual and monthly comparisons; the monthly statistics showed the greatest accuracy, which ranged from 0.61 for the alternative SWAT baseline to 0.70 and 0.71 for the standard SWAT baseline. However, several of the monthly peaks were underpredicted by both approaches, as shown for 2002, 2003, and 2006 in Figures 17 and 18, which indicates some weakness in SWAT's ability to capture all of the pertinent nitrate loss trends.

The comparisons of the predicted organic nitrogen loads with the corresponding estimated measured loads are shown on an annual basis in Figures 19 and 20 and for the monthly results in Figures 21 and 22. The graphical results and strong r^2 and E statistics shown in Figure 19 confirm that the annual organic nitrogen loads were accurately simulated when the standard RCN method was used, both on an annual and annual average basis.

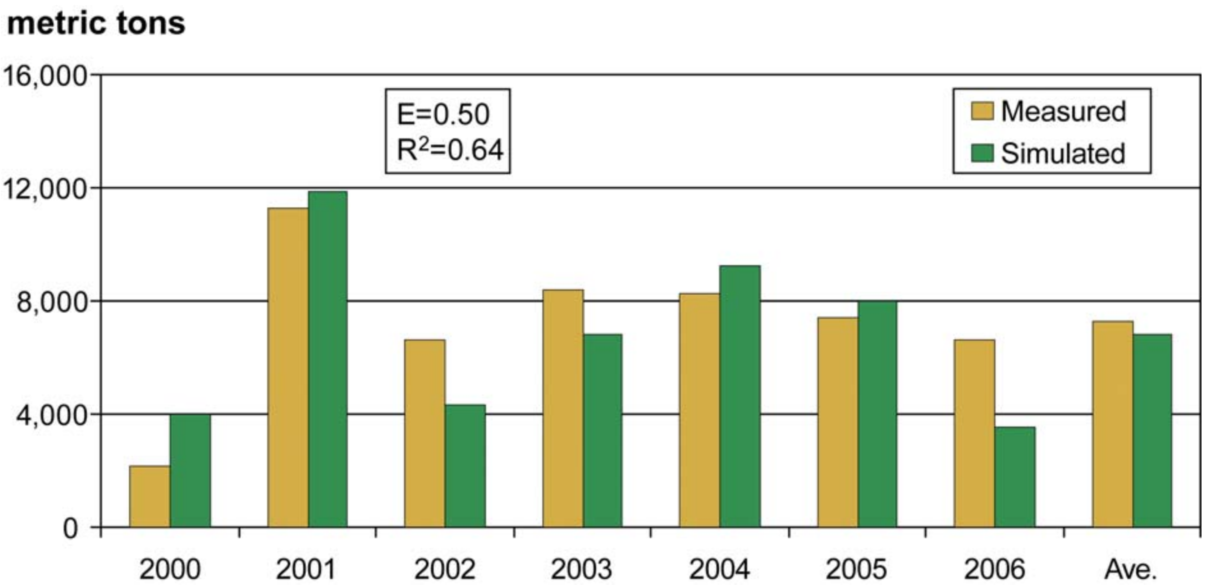

Figure 15. Simulated versus measured annual nitrate loads during 2000-2006 for the Boone River Watershed using the standard RCN method.

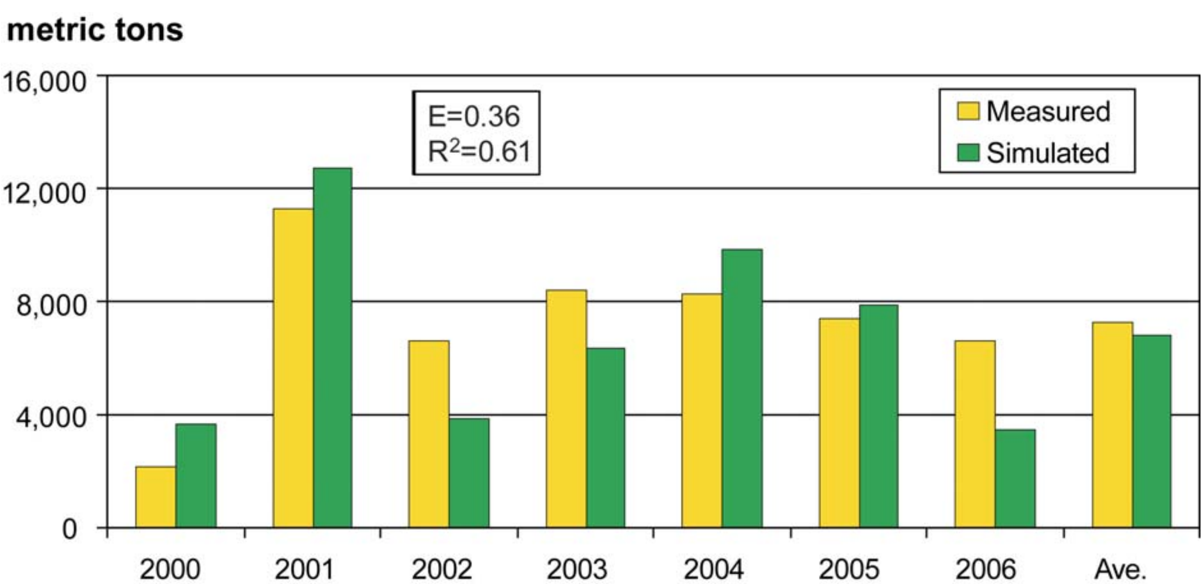

Figure 16. Simulated versus measured annual nitrate loads during 2000-2006 for the Boone River Watershed using the alternative RCN method (CNCEOF=0.6).

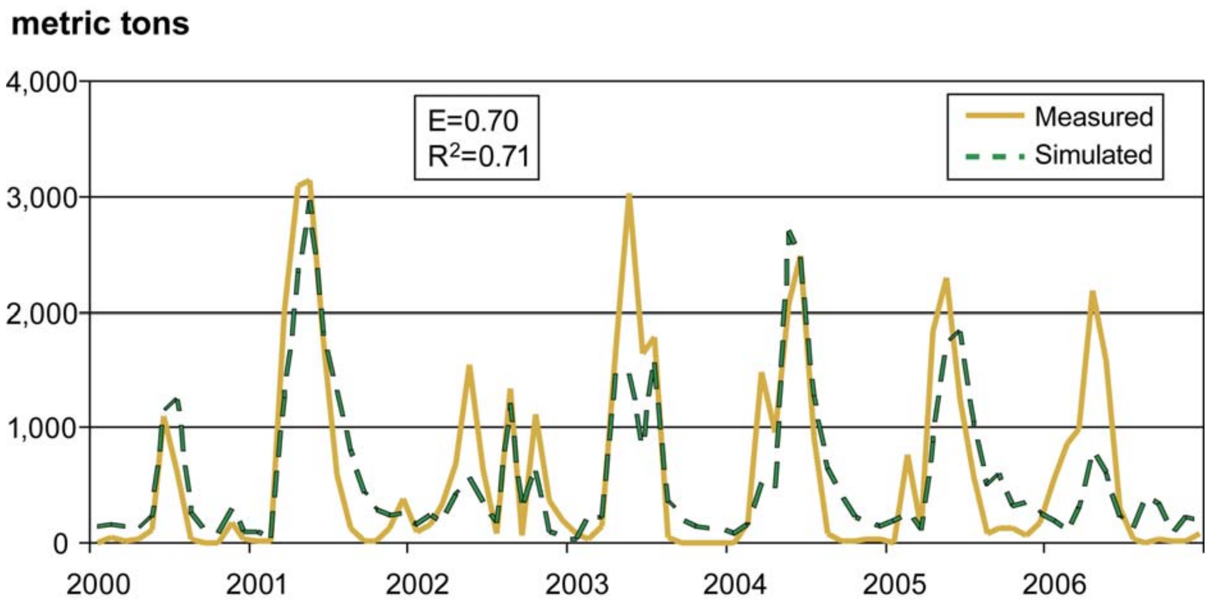

Figure 17. Simulated versus measured monthly nitrate loads during 2000-2006 for the Boone River Watershed using the standard RCN method.

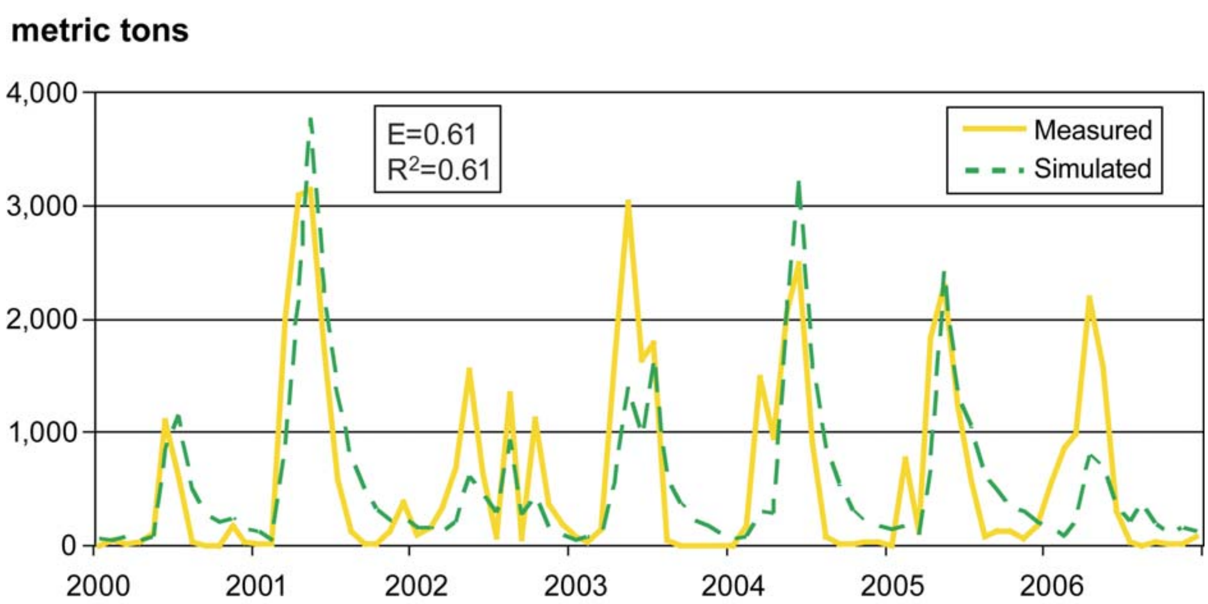

Figure 18. Simulated versus measured monthly nitrate loads during 2000-2006 for the Boone River Watershed using the alternative RCN method (CNCOEF =0.6).

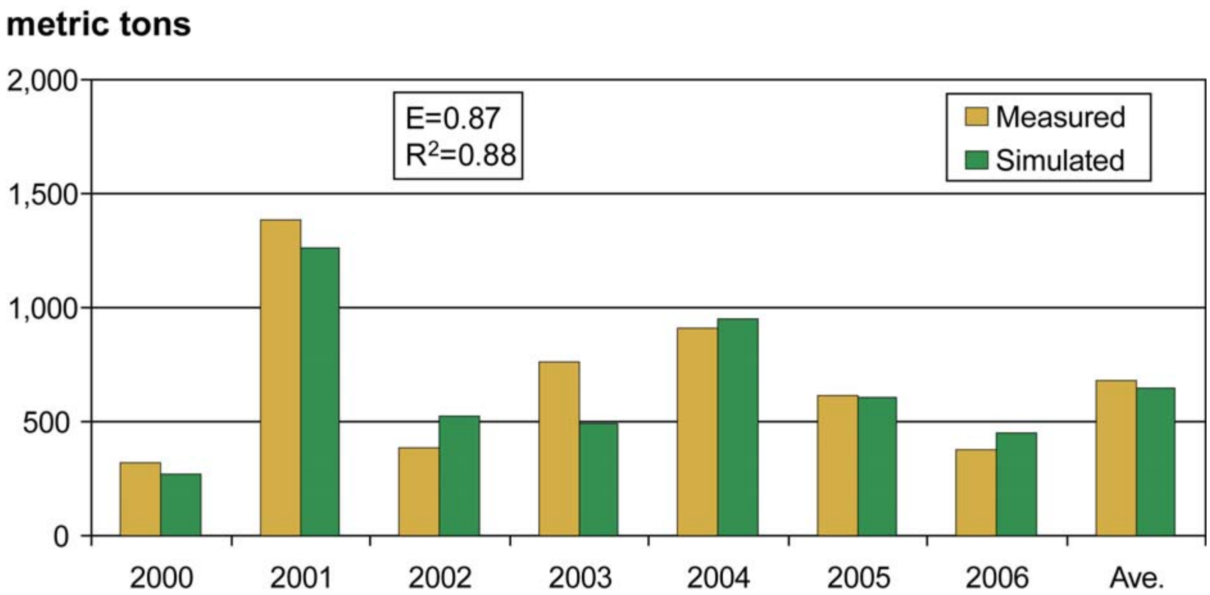

Figure 19. Simulated versus measured annual organic nitrogen loads during 2000-06 for the Boone River Watershed using the standard RCN method.

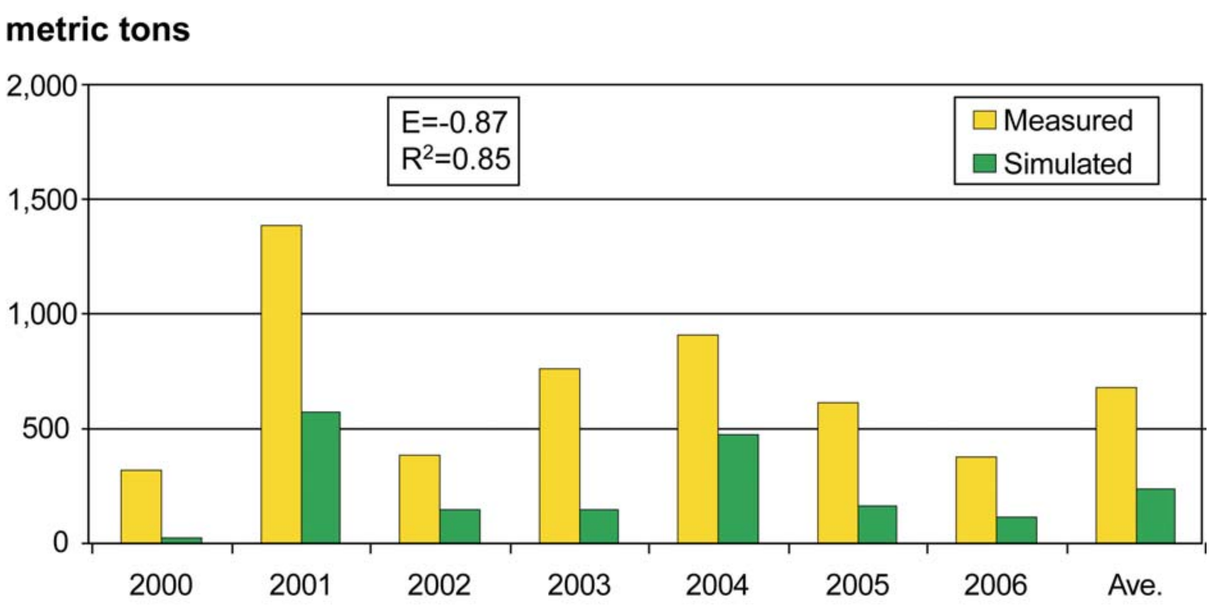

Figure 20. Simulated versus measured annual organic nitrogen loads during 2000-06 for the Boone River Watershed using the alternative RCN method (CNCOEF=0.6).

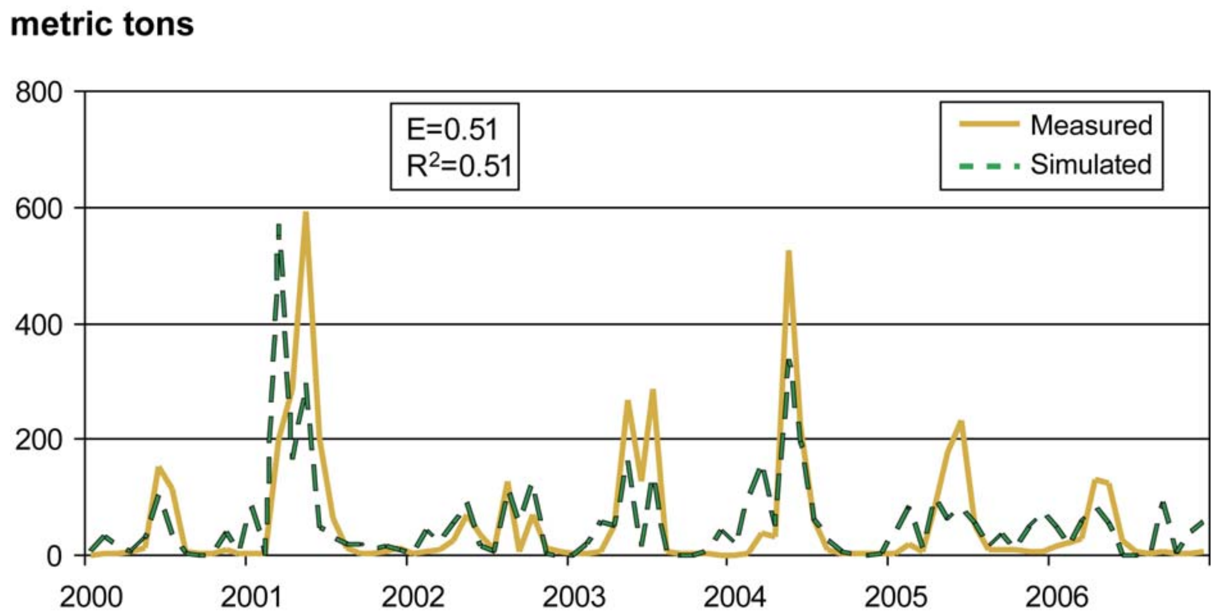

Figure 21. Simulated versus measured monthly organic nitrogen loads during 2000-06 for the Boone River Watershed using the standard RCN method.

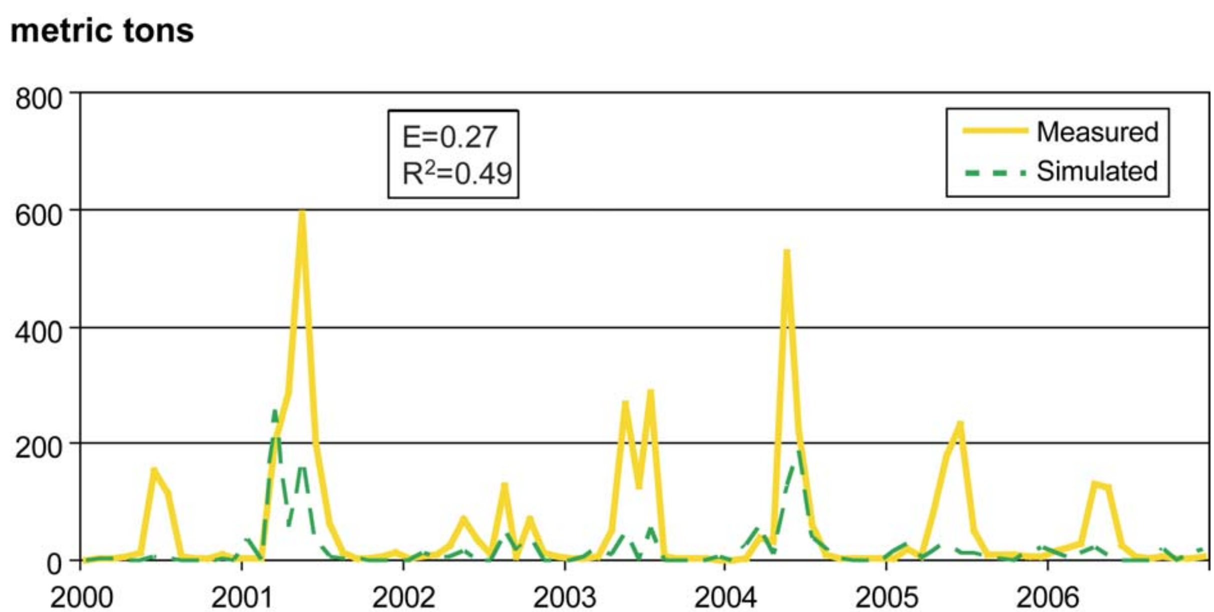

Figure 22. Simulated versus measured monthly organic nitrogen loads during 2000-06 for the Boone River Watershed using the alternative RCN method.

However, the graphical comparisons shown in Figure 20 reveal immediately that the calibrated nutrient parameters failed for the annual organic nitrogen loads estimated with the alternative RCN method. A strong R^2 value of 0.85 still resulted (Figure 20), indicating that the alternative SWAT approach captured the general trends in annual organic nitrogen loads. But the E value of -0.87 (Figure 20) that resulted when the alternative RCN method was used confirms that the model did not accurately simulate the annual organic nitrogen loads during the 2000 to 2006 time period.

The monthly R^2 and E statistics of 0.51 listed in Figure 21 reveal that the monthly organic N load trends were not captured as accurately by SWAT as the corresponding annual organic nitrogen loads (Figure 19), when the standard RCN method was used. However, both the annual and monthly organic nitrogen load results shown in Figures 19 and 21 confirm that the model replicated the magnitude of organic nitrogen loads in an accurate manner. However, this positive outcome collapsed when the alternative RCN method was used, as already discussed for the annual organic N estimates and further shown by the weak monthly comparison results shown in Figure 22.

Additional Nitrogen Loss and Cycling Investigations

Further investigation was performed regarding: (1) the effect of modifying the alternative RCN CNCOEF value on nitrogen losses, and (2) assessing other aspects of the predicted nitrogen cycling in these simulations. The additional testing of the alternative RCN method was performed using the same calibrated parameters listed in Tables 2 and 3, with the exception that the CNCOEF set equal to 0.2. The effect of this change on the annual and monthly nitrate loadings at the BRW outlet is shown in Figures 23 and 24. The average

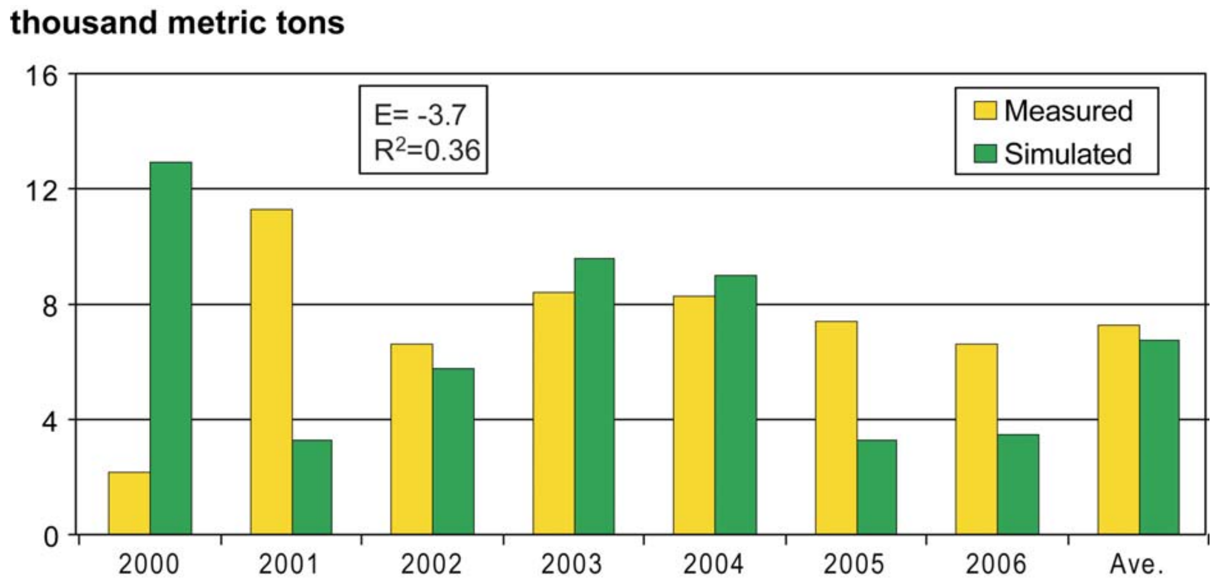

Figure 23. Simulated versus measured annual nitrate loads during 2000-06 for the Boone River Watershed using the alternative RCN method (CNCEOF=0.2).

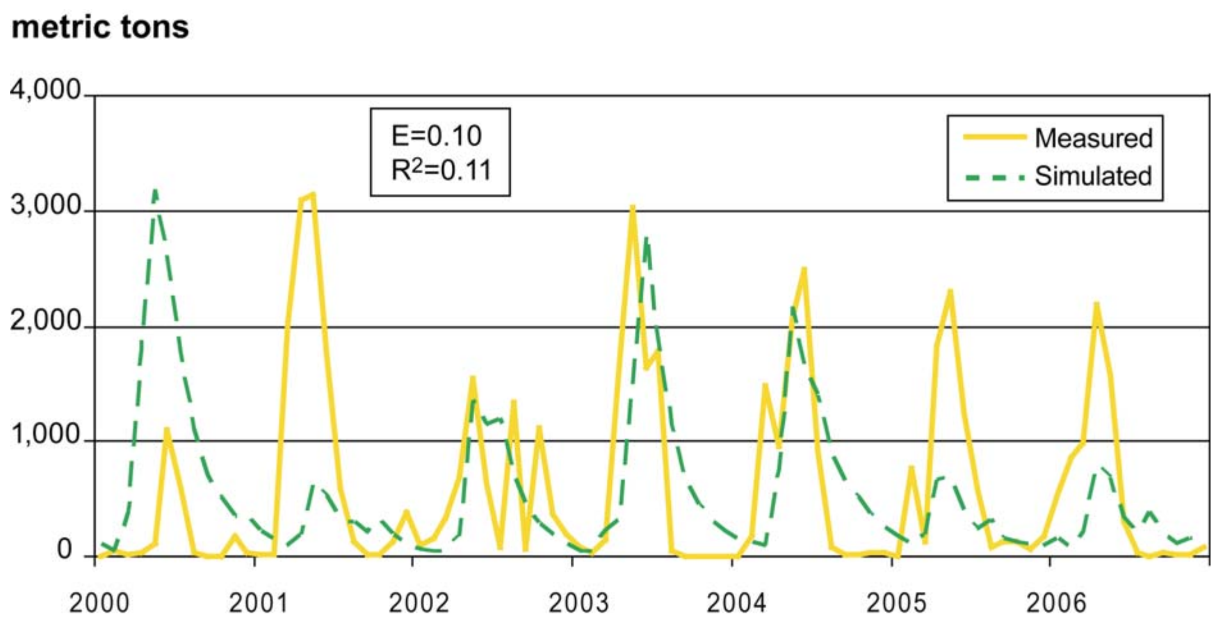

Figure 24. Simulated versus measured monthly nitrate loads during 2000-06 for the Boone River Watershed using the alternative RCN method (CNCEOF=0.2).

annual load shown in Figure 23 was slightly below the corresponding measured value and was also similar to the previously discussed average annual nitrate loads shown in Figures 15 and 16. However, the annual predicted nitrate loads in Figure 23 varied greatly from those shown in Figures 15 and 16, especially for 2000 and 2001 which were essentially the reverse of the estimated measured loads for those two years. The predicted monthly patterns of nitrate loss (Figure 24) also varied greatly from the monthly nitrate series predicted for the other two simulations (Figures 17 and 18). The weak R^2 and E statistics shown in Figures 23 and 24 further confirm the inadequacy of this third simulation option. Even worse results occurred for predictions of organic nitrogen loadings using this second version of the alternative RCN method (not shown); the organic N loads were essentially nonexistent due to a lack of simulated surface runoff and apparently inappropriate values for other parameters.

These results with the CNCOEF set equal to 0.2 for the alternative RCN method reinforce the need to recalibrate SWAT with more appropriate parameter values than those currently used as listed in Table 3, when using the alternative RCN method. The results also help frame issues regarding the relative amounts of organic nitrogen versus nitrate losses predicted by the model at the landscape level, and the subsequent effects of in-stream kinetics and transformation effects on the ultimate predicted levels of the nitrogen indicators at the watershed outlet.

Table 6 lists the average watershed unit loadings for the three simulations described in this study. These loadings are generated in the standard SWAT output file and represent an average over all land use in the watershed, with cropland the obvious dominant influence. The average per hectare loadings predicted with the calibrated SWAT baseline that was based on the standard RCN method were nearly identical, at just under 17 kg ha^{-1} for both

Table 6. Average predicted nitrogen loadings per hectare over the entire BRW for the standard RCN method and two different versions of the alternative RCN method

Simulation approach	Organic nitrogen loadings ($kg\ ha^{-1}$)	Nitrate loadings ($kg\ ha^{-1}$)
Standard RCN method	16.9	16.7
Alternative RCN method (CNCOEF=0.6)	14.4	20.4
Alternative RCN method (CNCOEF=0.2)	5.6	27.1

indicators. However, the predicted nitrate loadings at the watershed outlet were roughly an order of magnitude higher than the predicted organic nitrogen loadings (e.g., Figure 17 versus 19), which was consistent with the estimated measured loads. This resulted from the application of the calibrated in-stream parameters listed in Table 3, which transformed much of the initial organic nitrogen loadings into nitrate and also generated smaller amounts of ammonia (NH_4-N) and nitrite, as well as affecting the phosphorus loadings.

In contrast, the amount of unit losses of nitrate increased relative to the organic loading levels as the CNCOEF was reduced for the alternative RCN method (Table 6), resulting in 59 and 82% of the total landscape-level nitrogen loadings being attributed to nitrate when the CNCOEF was set to 0.6 and 0.2, respectively. These increased amounts of landscape-level nitrate losses are intuitive for a system such as the BRW, which would be expected to export high loadings of nitrate via subsurface tile drains to the internal stream network. The weaker overall watershed nitrate and organic nitrogen loading results found with the alternative RCN method, especially when the CNCOEF was set to 0.2, are clearly due in part to calibrated in-stream and other parameters (Table 3) which are inconsistent with this approach. However, an interesting outcome of the model testing for this study is the fact that all three simulation approaches resulted in essentially the same overall annual average nitrate loading at the watershed level. The reason for this result is not currently clear, but may be due to the effects of the in-stream parameters that needs to be further researched.

One additional noteworthy outcome of this research is the fact that the SWAT results were very sensitive to the choice of in-stream parameter values. This result differs from previous research reported by Migliaccio et al. (2007) who found that SWAT was generally insensitive to the in-stream kinetic functions provided in the model in their study of the 60 km^2 War Eagle Creek watershed in northwest Arkansas. One reason for these differences may be the much larger size of the BRW as compared to the Arkansas watershed. These results echo the point made in Chapter 2 that additional research of the SWAT in-stream routines is needed, including for future BRW applications.

Soil Nitrogen Fixation

Hu et al. report that soybean nitrogen fixation was predicted by SWAT to be in the range of 172 to 206 kg ha^{-1} in their study of the Embarras River in central Illinois, which was considerably higher than the commonly accepted range of 102 to 124 kg ha^{-1} for the region. The average soybean nitrogen fixation rate predicted for this study was 174 kg ha^{-1}, which again is much higher than the soybean nitrogen fixation range of 0 to 100 kg ha^{-1} reported by Russelle and Birr (2007) for most of Iowa, and the specific rate of only 31 kg ha^{-1} estimated for the BRW as part of the overall study (Russelle, 2007). Assuming the approach used by Russelle and Birr is accurate, it can be concluded that SWAT is currently greatly overpredicting soybean nitrogen fixation. It is not totally clear what all the implications are of this weakness for policy scenario analyses with the model. However, it is clear that this problem should be addressed in future SWAT applications. Additional constraints have already been incorporated in more recent versions of the code that appear to predict more accurate soybean nitrogen fixation estimates for the BRW, based on initial test simulations. Additional testing will be pursued of these modified routines in future BRW research.

Conclusions

This study reports a successful calibration and validation of SWAT version 2005 for the Boone River watershed (BRW) located in north central Iowa. The testing of the model using the standard runoff curve number (RCN) method resulted in strong hydrologic and pollutant loss estimates, as evidenced by the graphical and statistical results presented in the paper. The SWAT2005 simulation approach based on the standard RCN method will be used for current scenario simulations for the BRW. However, there is a need to further investigate issues regarding the relative amounts of organic nitrogen versus nitrate losses that were predicted to occur at the field level and also apparent overprediction of soybean nitrogen fixation. Improved simulation of these processes is likely needed to obtain the most accurate results possible for different scenarios of interest for the BRW, including scenarios depicting different levels of expanded corn acreage in response to increased ethanol production demands. Efforts have already been initiated by the SWAT developers to address these issues and improved accuracy can be expected in future versions of the model.

An alternative hydrologic simulation approach was also investigated in this study that was based on a new RCN option available in SWAT2005. This alternative RCN method relates the daily curve number estimation in the model to water depletion caused by evapotranspiration (ET), rather than to available soil water as has been traditionally used with the RCN technique. The results of applying the alternative RCN method show that the

SWAT hydrologic response is very sensitive to the choice of curve number coefficient (CNCOEF), which is the depletion coefficient referred to by Kannan et al. Decreasing levels of CNCOEF result in increasing levels of baseflow, especially tileflow, and corresponding decreasing levels of surface runoff. A second set of SWAT calibration/validation results presented for the alternative RCN method with the CNCOEF set to 0.6 again showed that the model accurately replicated streamflows and also provided reasonably accurate sediment, total phosphorus, and nitrate results, although the accuracy was weaker than the results found for the standard RCN method. However, very inadequate predictions resulted for the organic nitrogen load predictions. The pollutant loss results using the alternative RCN method point to the clear need to recalibrate sediment- and nutrient-related calibration parameters as well as in-stream parameters used in the calibration process. This need was underscored even more when a CNCOEF value of 0.2 was used with the alternative RCN method, which resulted in very unsatisfactory nitrate and organic nitrogen predictions.

The results of this study also raise questions as to which hydrologic simulation approach is the most appropriate for the BRW. The traditional approach using the standard RCN method results in an overall hydrologic balance that is consistent with hydrologic separation techniques applied to the watershed. However, a reduction in the available soil water capacity for the inputted soil layer data had to be used in order to obtain this balance. This step has negative effects on the estimation of corn yields as discussed in Chapter 5, while better corn yield estimates resulted from using the alternative RCN method. The alternative RCN method also results in a greater relative level of subsurface flow, and also increased amounts of nitrate losses from the BRW agricultural landscapes. These results may more accurately reflect the actual hydrologic and nitrogen loss processes occurring in the

BRW. An additional "pothole routine" option is available in SWAT2005 that was successfully used by Du et al. (2005; 2006) in their simulations of the Walnut Creek watershed. Invoking this option could more accurately capture depressional area processes occurring in the BRW and better simulate the hydrologic and nitrogen balances.

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CHAPTER 5: AN IN-DEPTH ASSESSMENT OF CORN AND SOYBEAN YIELDS PREDICTED WITH SWAT FOR THE BOONE RIVER WATERSHED

A paper to be submitted to the *Environmental Modelling & Software*

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Abstract

The Soil and Water Assessment Tool (SWAT) has been extensively used for hydrologic and water quality analyses over a wide range of watershed scales and conditions. However, testing of the crop growth component in the model has rarely been reported. In this study, SWAT-predicted corn and soybean yields generated from two separate baseline simulations were compared with comparable historical yields for the Boone River watershed in north central Iowa. The two SWAT baselines represent applications of the standard runoff curve number (RCN) versus an alternative RCN method in the model. Corn and soybean yields estimated with the Environmental Policy Impact Climate (EPIC) model are also compared with the SWAT yields and measured yields, as an additional benchmark. The 1986-2006 long-term average corn yields estimated with the standard and alternative SWAT baselines were 127.1 and 143.3 bu ac^{-1}, respectively; these yields underestimated the historical average of 147.9 bu ac^{-1} as reported by USDA-NASS. The long-term average corn yield estimated by EPIC was 165.4 bu ac^{-1}, which greatly exceeded the 1986-2006 average

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historical yield but was close to the 1997-2006 average corn yield of 163.5 bu ac^{-1}. In contrast, the 1986-2006 average soybean yields estimated for the standard and alternative SWAT baselines were 49.3 and 51.6 bu ac^{-1}, which were considerably higher than the mean historical yield of 43.6 bu ac^{-1}. The mean EPIC soybean yield was 41.6 bu ac^{-1} was slightly below the measured means and was again closer in magnitude to recent historical yields. Statistical analysis of annual yield comparisons indicates weak year-to-year replication of the historical yields by both models, except for the SWAT yields predicted in 1986-1997 (if 1993 is ignored). The SWAT model greatly underpredicted corn yields for the 1998-2006 time period, indicating a lack of accounting for recent genetic advances. Further analysis indicated that the SWAT corn yield predictions were sensitive to tillage, with higher yields predicted for corn managed with conventional tillage as compared to mulch and no till. The SWAT soybean yield predictions and the EPIC corn and soybean yield predictions were generally insensitive to tillage. Overall, the results indicate a need to update crop parameters in SWAT especially, to more accurately simulate current corn and soybean yields in the region. Modifications to the generic crop growth routine used in both models may also improve annual predictions of both crops.

Introduction

Field-, watershed-, and regional-scale models have emerged as key tools for evaluating water quality, climate change, soil carbon sequestration, and other environmental problems over a wide range of conditions. Models that are used for environmental assessments of agricultural production systems require the ability to depict a broad array of cropping systems and generate reliable estimates of crop biomass and yields. Models used for agricultural-related water quality analyses also need to be able to estimate the impacts of different cropping and management systems on sediment, nutrient, and other nonpoint source losses from cropland at the scale the model is designed for.

Two models that have been widely used for assessing the nonpoint source pollution impacts of different cropping and management systems are the Environmental Policy Impact Climate (EPIC) model (Williams, 1990; Izaurralde et al., 2006; Gassman et al., 2005) and the Soil and Water Assessment Tool (SWAT) model, which is described in Chapter 2. A generic crop growth routine is used in the EPIC model which has also been directly adapted in SWAT. The generic crop growth modeling approach provides a very flexible platform in both models for simulating complex modeling systems consisting of both annual and perennial crops, as well as other vegetation. This approach also supports assessments of different tillage, nutrient application, and other management practices on water quality impacts. However, the generic approach also represents a trade-off in modeling flexibility versus accuracy of replicating crop growth and yields; in general, this approach is designed to replicate long-term average yields more accurately than interannual yield variability.

A number of studies have been reported in the literature that describe comparisons between EPIC-predicted crop yields and measured crop yields, including several studies that focused only on EPIC's ability to replicate measured yield data (Gassman et al., 2005) Gassman et al. report that several studies found that EPIC could replicate both long-term and annual yields while other studies concluded that EPIC could replicate measured mean or median yields but not observed yield variability. Some studies found that EPIC tended to underestimate peak crop yields and overestimate low crop yields (Bryant et al., 1992; Touré et al., 1994) while Warner et al. (1997) found that EPIC exhibited a bias toward overprediction of corn yields. Overall, EPIC has been found to be able to replicate long-term mean yields for a variety of cropping systems, management practices, and environmental conditions (Gassman et al. 2005).

In contrast, very few SWAT studies report comparisons with measured crop yields, which was highlighted as a future research need in Chapter 2. Kannan et al. (2007) reported the need to estimate heat units external to the model and then enter those for each simulated HRU, for a SWAT simulation of a 1.4 km^2 watershed in the United Kingdom. They report using locally published values for some of the crop parameters including maximum leaf area index, canopy height, and root depth. They state that these changes resulted in much improved yields although they do not provide any actual comparisons between simulated and measured yields. Nelson et al. (2006) report using an iterative process for a SWAT simulation of the 3,000 km^2 Delaware River watershed in Kansas, in which they adjusted selected SWAT crop growth parameters until the simulated yields were considered acceptable in comparison with U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) historical yields (USDA-NASS, 2007) estimated for 1991-94. However, they did not report which parameters they adjusted or show comparisons between the measured and simulated yields.

Two SWAT studies report crop yields for the U.S. Corn Belt region. Hu et al. (2007) show graphical comparisons of predicted versus measured corn and soybean yields for a SWAT application of the Embarras River watershed in eastern Illinois. The average predicted yields were close to the corresponding measured yields in both the 1994-2002 calibration and 1985-1993 validation periods as demonstrated by relative errors that ranged from -10 to +6%. The Nash-Sutcliffe modeling efficiencies (E) values (Nash and Sutcliffe, 1970; Chapters 2 and 4) were poor for the calibration period; the authors point out that the weak soybean E result was due in part to the fact that there was little variation in the measured soybean yields. No mention is made of the possible implications of increasing crop yields, which are discernible for the plotted measured corn yields. Jha et al. (2007) reported a SWAT-predicted average dry weight corn yield of 7.1 t ha^{-1} for the Raccoon River watershed in west central Iowa, which translates to an average yield of 128.5 bu ac^{-1}. This corn yield result is well below measured corn yields reported by USDA-NASS (2007) for the Raccoon River region in recent years, which indicates a need to improve the SWAT corn yield predictions for that watershed area as well as Iowa in general.

The goal of this study is to build on this previous research by further investigating the accuracy of SWAT-predicted corn and soybean yields versus corresponding measured yields for the Boone River watershed (BRW) in north central Iowa, which is briefly described here and is discussed in more detail in Chapter 3. Comparisons with EPIC yields are also reported as an additional benchmark and to provide more insight into possible ways to improve the SWAT yield predictions (and vice versa). Investigation of tillage effects on crop yields was also performed with both models. This is a relevant issue for the BRW and the U.S. Corn Belt region in general, due to expansion of corn-dominated crop rotations driven by increasing ethanol production. A concurrent shift into greater use of conventional tillage is also likely, to maintain higher yields in continuous corn sequences as discussed by Secchi et al. (2007). This shift into continuous corn managed with conventional tillage could also result in increased negative environmental externalities, due to the reduction of protective residue cover for agricultural landscapes.

The specific objectives of the study are: (1) to compare SWAT-predicted corn and soybean yields versus historical USDA-NASS yield data for the BRW region over 1986-2006 (simulation period described in Chapter 4), (2) to compare EPIC-predicted yields for the same time period and region with the USDA-NASS yield data and SWAT yields, and (3) investigate the effects of tillage practices on SWAT- and EPIC- predicted yields.

Watershed Description

The BRW covers over 237,000 ha in six north central Iowa counties and is one of 131 U.S. Geological Survey (USGS) 8-digit hydrologic unit code (HUC) watersheds (Seaber et al., 1987) that are located in the UMRB (Figure 1). It lies within the Des Moines Lobe geologic formation, which is the southern most portion of the central North American Prairie Pothole Region. An extensive network of subsurface tile drains and surface ditches have been installed throughout the watershed, resulting in the elimination of most wetland areas and an intensively cropped landscape. The watershed is dominated by corn and soybean production, which together account for almost 90% of the land use based on a field-level survey of the watershed performed in 2005 as described in Chapter 3. The survey also revealed that the use of mulch tillage is very extensive, that a limited number of terraces and other conservation practices are used on cropland with steeper slopes, and that field borders are used along some stream channels in flatter areas of the watershed. A total of 128 confined animal feeding operations (CAFOs) are also located in the BRW; 109 of these are swine operations with a total of about 480,000 head (Chapter 3).

The locations of climate stations in the region, SWAT subwatershed boundaries, USGS flow gauge, and Iowa Department of Natural Resources (IDNR) in-stream pollutant

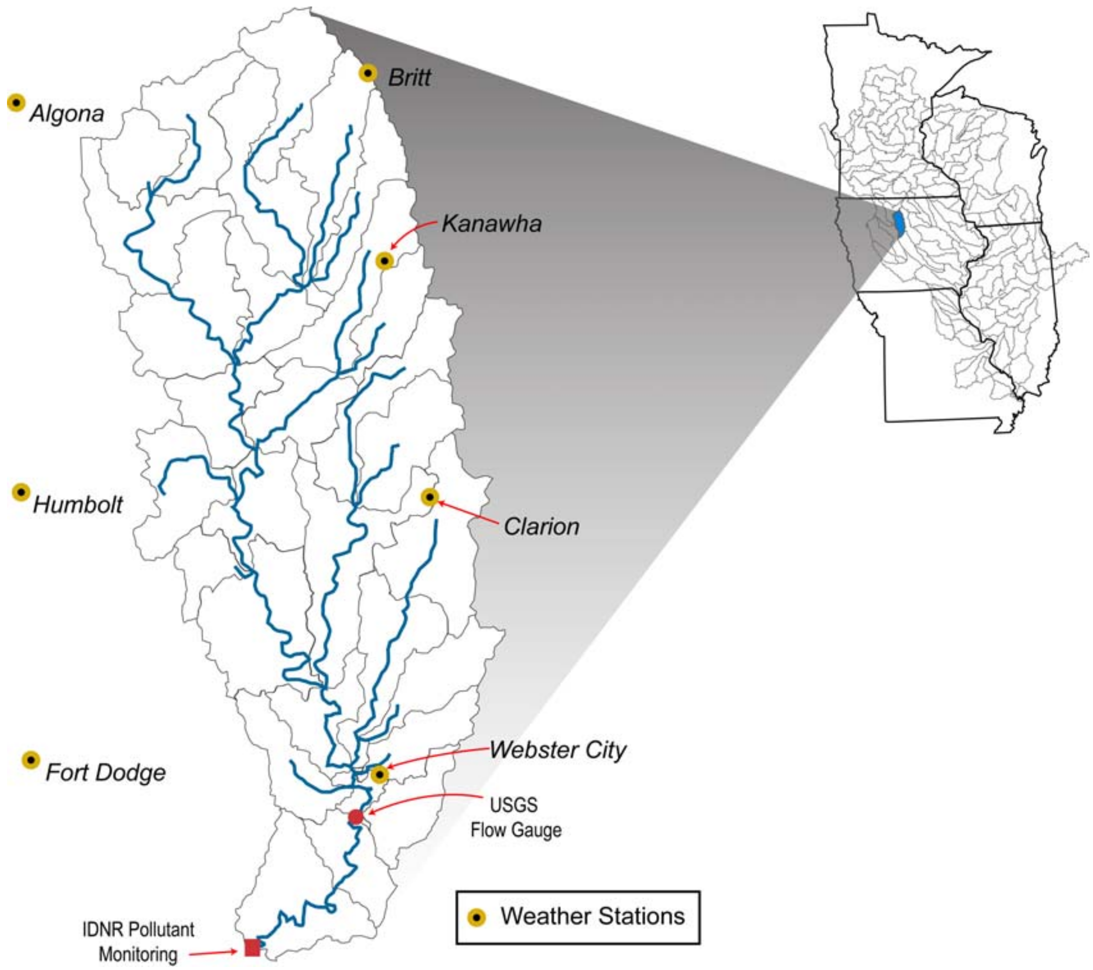

Figure 1. The location of the Boone River watershed within Iowa and the Upper Mississippi River Basin.

monitoring are shown in Figure 1. The pollutant sampling at the watershed outlet reveals elevated levels of nitrates, especially during the spring runoff season. The BRW was identified by Libra et al. (2004) as discharging some of the highest nitrogen loads during 2000-2002 among the 68 Iowa watersheds that were analyzed within their study; their study further concluded that 20% of the nitrogen load discharged via the Mississippi River to the Gulf of Mexico originated in Iowa during that three-year time period.

Methodology

The SWAT corn and soybean yields described in this study were generated as part of the baseline simulations reported in Chapter 4 and reflect averages calculated across the 2,927 HRUs that were constructed for the baseline simulations. The baseline simulations were performed for 1986-2006 which were split into calibration (1986-1995) and validation (1996-2006) periods. Two sets of SWAT simulated yields are presented here that correspond to the two SWAT baselines described in Chapter 4, which were based on the standard runoff curve number (RCN) method (standard baseline) and the alternative RCN method (alternative baseline) in which the curve number coefficient was set to 0.6. These yields were then compared with historical crop yield data that were derived from USDA-NASS county level averages as described below, and with a single set of EPIC-predicted corn and soybean yields that were averaged across 18,325 BRW simulations performed at the Common Land Unit (CLU) level as discussed in Chapter 3.

BRW Historical Crop Yields

Historical corn and soybean yield estimates were obtained from USDA-NASS (2006) for 1951-2006 for the six counties shown in Figure 2. These yields were then averaged across the six counties to create a single annual historical yield dataset for 1951-2006 (Figure 3). The yield data in Figure 3 serve as the measured yields for assessing the accuracy of the SWAT and EPIC simulated yields during 1986-2006. These historical yields also illustrate the extraordinary yield increases that have occurred since the middle of the previous century, especially for corn. Strong linear relationships result when regressions are plotted for both crops for the entire 1951-2006 historical period, with r^2 values of 0.83 and 0.76 for the long-

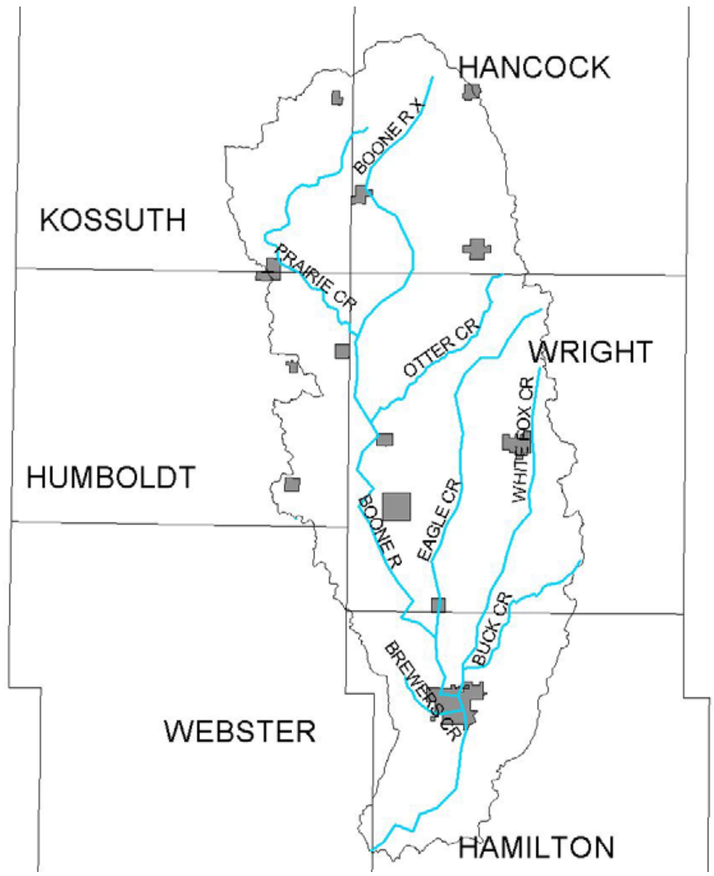

Figure 2. The location of the BRW in reference to the six north central Iowa counties.

term corn and soybean yield trends, respectively. Hart (2005) has advanced the theory that recent genetic advances have resulted in even greater accelerated yield gains for corn since approximately 1993; this idea warrants further exploration but is not pursued here.

Both SWAT and EPIC provide crop yield estimates on a dry-weight basis. These simulated yields were translated from a dry-weight basis to a wet-weight basis using the following equation (Atwood, 2005):

$$\text{yield} = \text{model\_yield} * 0.4461 * 2000 * \text{moisture factor} / \text{unit conversion factor} \tag{1}$$

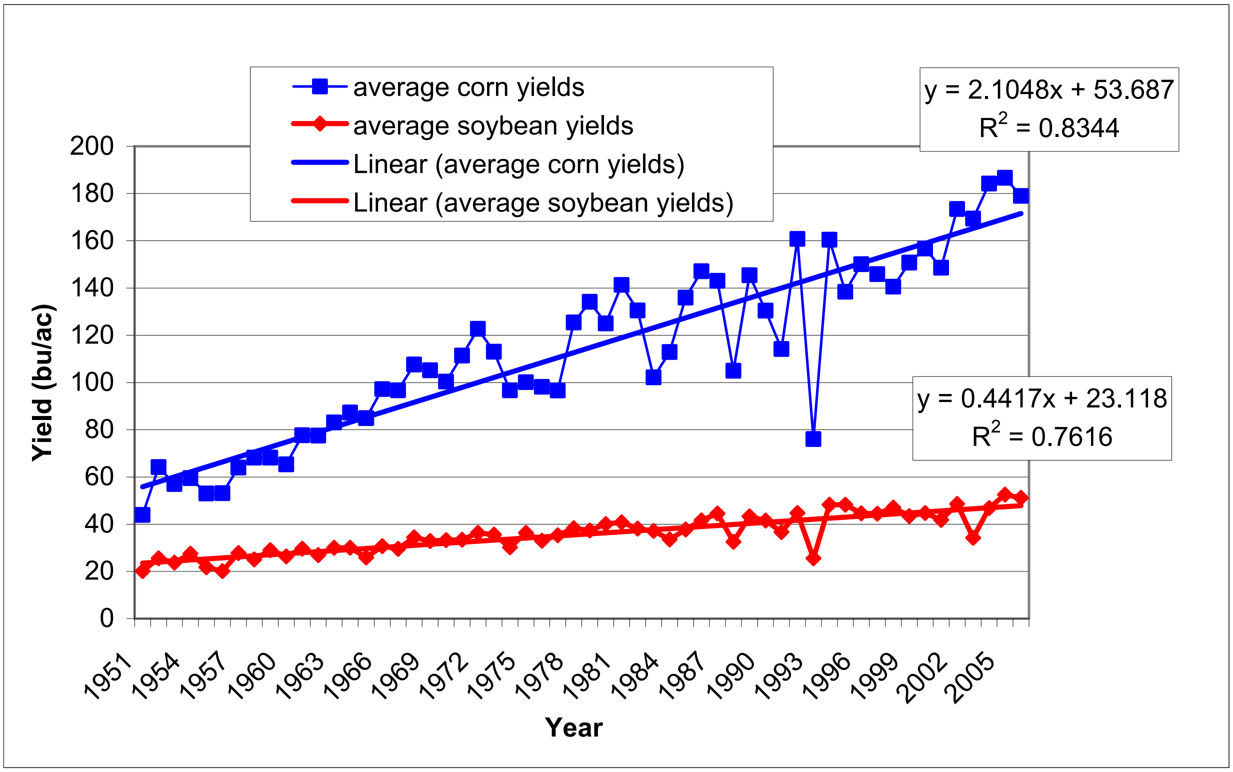

Figure 3. Long-term average six-county average NASS corn and soybean yields which are assumed to be the Boone River watershed measured yields for the same time period.

where yield is the translated crop yield (bu ac^{-1}), model_yield is the SWAT or EPIC predicted yield (t ha^{-1}), the moisture factor equals 1.13 for both corn and soybean (which assumes a 13% for the wet weight basis), and the unit conversion factor equal 55.7 for corn and 60 for soybean. A different moisture content assumption could be used in these conversions such as a moisture factor equal to 1.15 which would be equivalent to 15% moisture content for both crops. The simulated yields were evaluated graphically and with E and r^2 statistics, which are described in detail in Chapters 2 and 4.

Results and Discussion

The 1986-2006 predicted yields averaged across the two SWAT baselines and the EPIC simulations are plotted versus the long-term measured NASS yields for corn in Figure 4 and soybean in Figure 5. Both plots show that the crop yields predicted with the alternative SWAT baseline were higher than the standard SWAT baseline; this was much more pronounced for predicted corn yields, where 145.7 bu ac^{-1} was predicted for the alternative baseline versus 127.1 bu ac^{-1} for the standard baseline. The previously discussed reduction of the available water capacity (AWC) was observed over iterative simulations to be a key factor in the lower yields predicted for the accepted SWAT baseline. The use of the alternative CN method may have also benefited the yield predictions for the alternative baseline, by routing more water through the soil subsurface.

Both the standard and alternative SWAT baseline average corn yields underpredicted the 1986-2006 measured corn yield average of 147.9 bu ac^{-1}, although the mean yield predicted for the alternative baseline was less than 2 bu ac^{-1} below the historical mean. The difference becomes more pronounced when considering the 1997-2006 measured average corn yield, which was 163.5 bu ac^{-1}. In contrast, the average corn yield predicted by EPIC was 165.4 bu ac^{-1}, which exceeded both the 1986-2006 and 1997-2006 measured averaged corn yields. It appears that the SWAT yield predictions need upward adjustment while the opposite could be considered for the EPIC corn yields, although the average is consistent with more recently measured yields and is closer to realistic yield predictions for future scenarios projecting from 2007 onward[6].

[6]The USDA 2007 average corn yield estimate for Iowa is 175 bu ac^{-1} (Brasher, 2007); yields exceeding 180 bu ac^{-1} or even higher appear to be more realistic for future scenarios based on the 2007 Iowa average estimate and current measured corn yield trends for the BRW

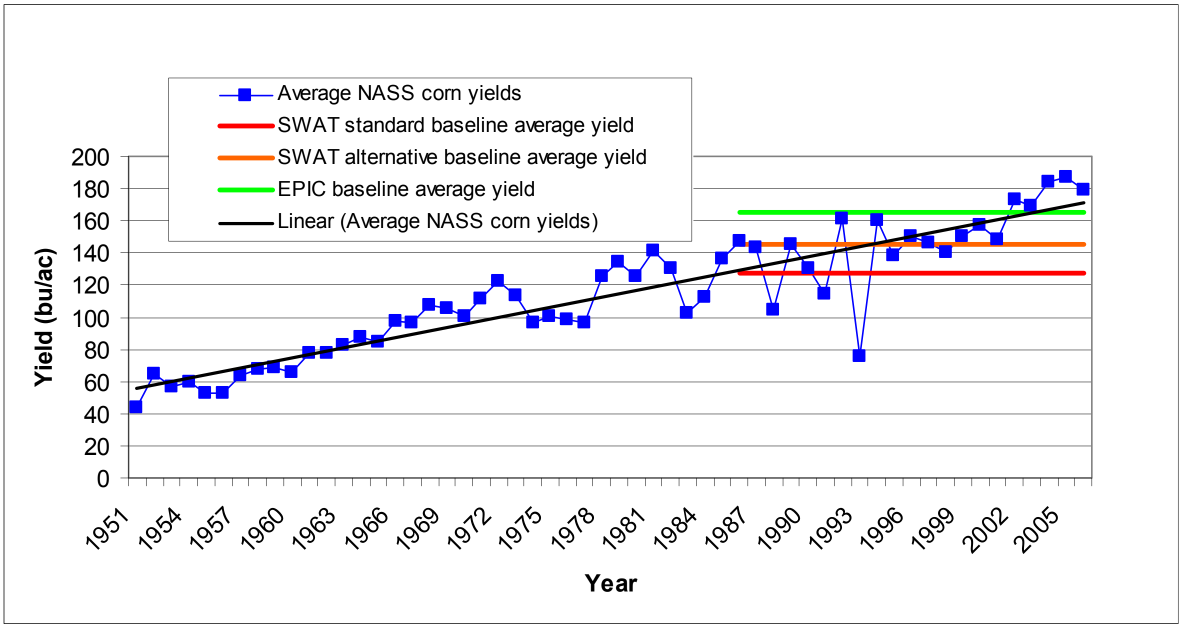

Figure 4. Average simulated corn yields for 1986-2006 versus NASS average six-county corn yields for the Boone River Watershed.

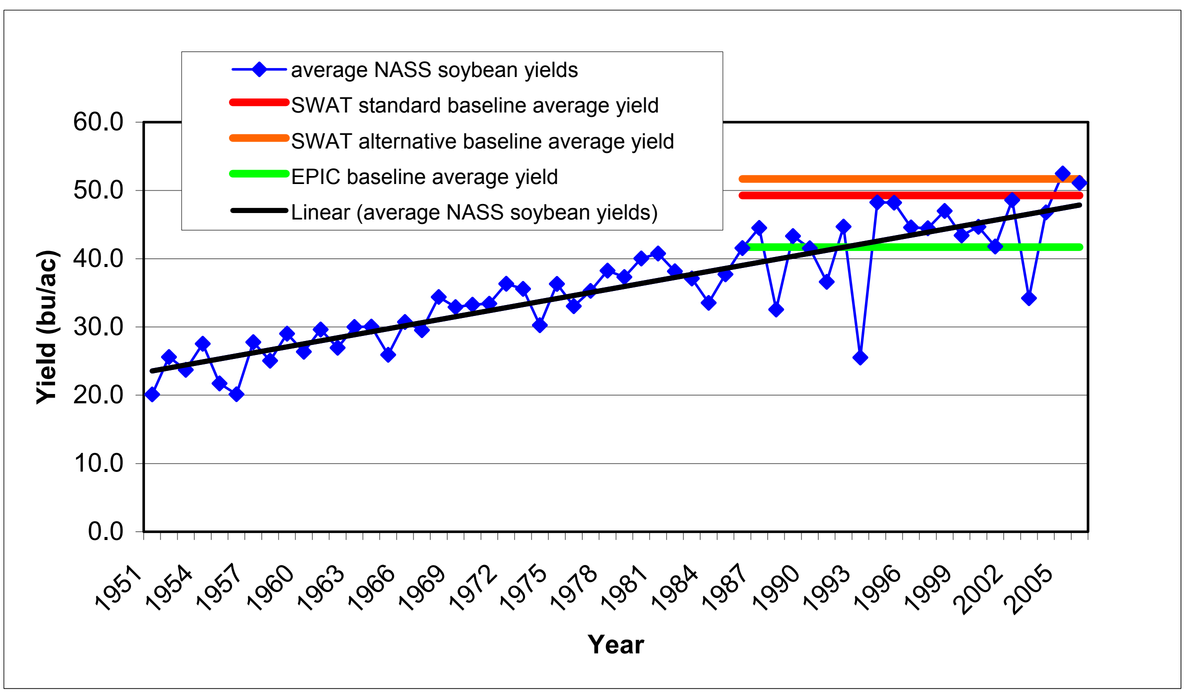

Figure 5. Average simulated soybean yields for 1986-2006 versus NASS average six-county soybean yields for the Boone River Watershed.

An opposite result was found for the average soybean yields predicted with the two SWAT baselines (Figure 3), which were 49.3 and 51.6 bu ac^{-1} during 1986-2006 for the standard and alternative baselines; both average yields exceeded the measured average yield of 43.6 bu ac^{-1} for the same time period. Both the standard and alternative SWAT average soybean yield estimates were in the range of the most recent measured soybean yields reported in 2005-2006 and would be more realistic for future scenario projections than the previously discussed corn yields. However, these predicted SWAT yields are too high for the 1986-2006 time period. The EPIC average yield (41.7 bu ac^{-1}) was considerably lower than the two yields estimated with SWAT, which again is an opposite result of the predicted corn yields shown in Figure 2. However, the EPIC average yield was much closer to the measured average yield of 43.6 bu ac^{-1} for 1986-2006. These soybean yield results also point to the need for some parameter adjustments in both models.

Annual yield comparisons

Figures 6 and 7 show 1986-2006 annual comparisons between the SWAT- and EPIC-predicted corn and soybean yields, and the corresponding measured yields. The relative differences between the different simulated and measured yields reflect the previous discussion regarding average simulated yields.

The standard SWAT baseline corn yields clearly underpredict most of the measured yields across the entire time period (Figure 6), except for 1993, 1994, and 1997; 1993 was an extreme flood year in which all 99 Iowa counties were declared disaster areas, so it is not surprising the models overpredicted the corn yields that year. Despite underpedicting the yields in most years, the standard SWAT baseline accurately mirrors the measured corn yield

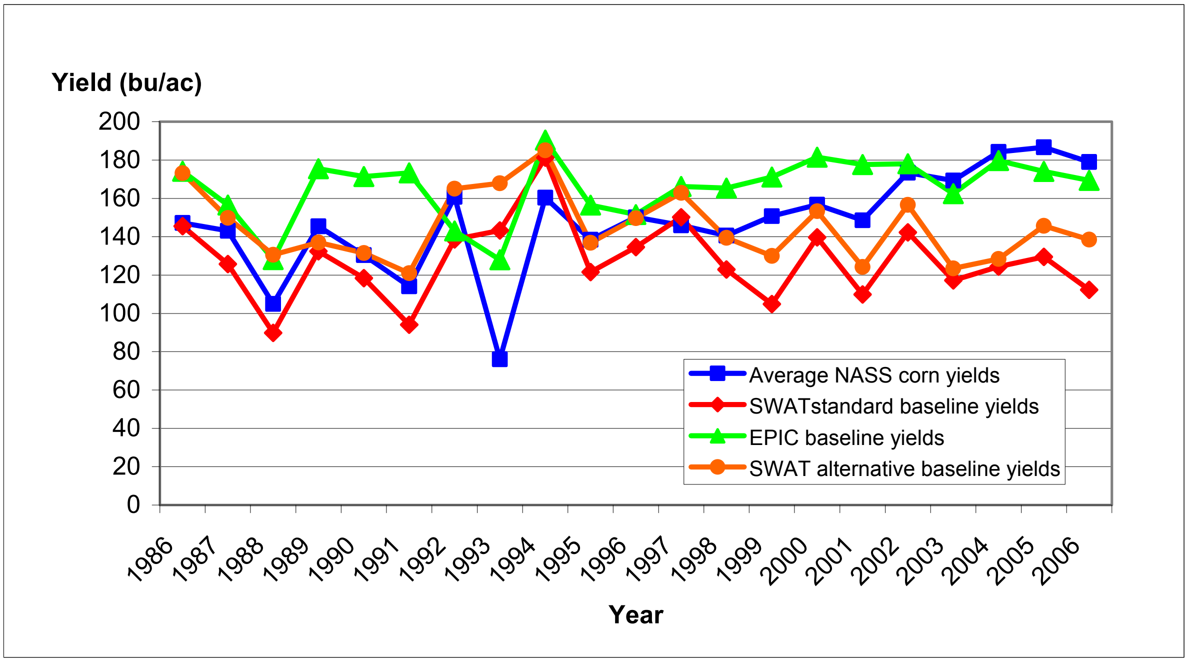

Figure 6. Measured versus simulated corn yields for 1986-2006.

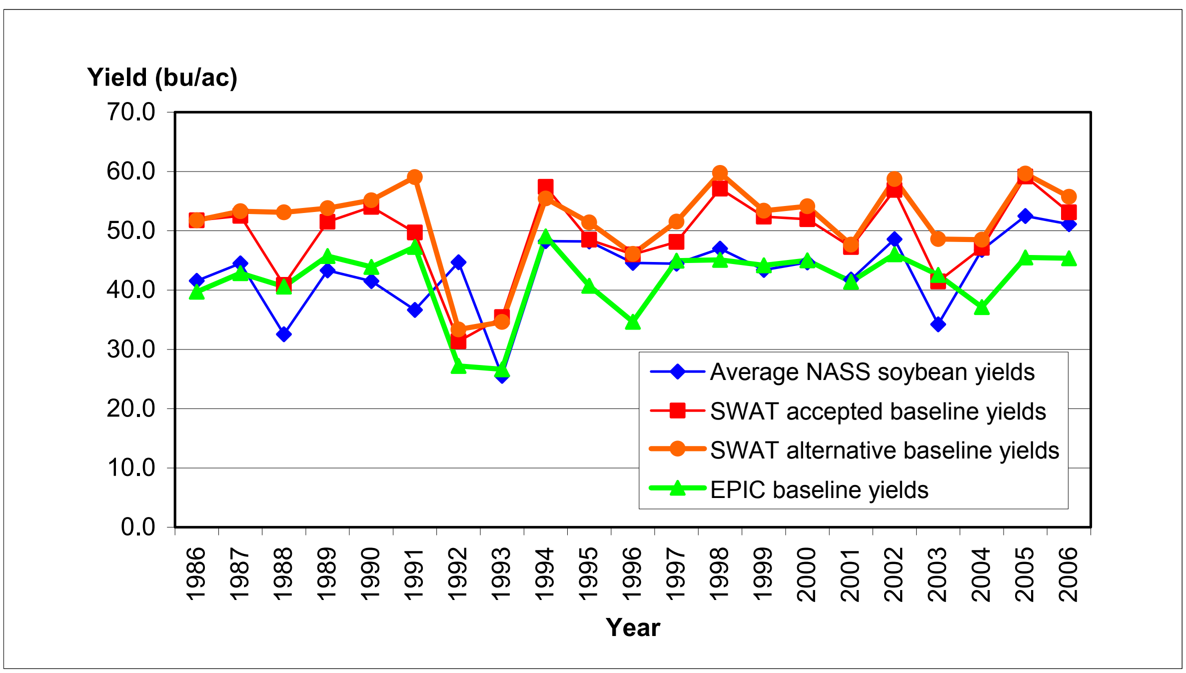

Figure 7. Measured versus simulated soybean yields for 1986-2006.

trends for virtually the entire 1986-1997 period, and particularly picks up well on the 1988 and 1991 drought years. The standard SWAT baseline yields begin to diverge from the measured yields in noticeably greater magnitudes starting about 1998, and the underpredictions reach approximately 50-60 bu ac^{-1} by the end of the simulation period.

The alternative SWAT baseline corn yields are consistently higher throughout the 1986-2006 simulation period as compared to the standard baseline yields (Figure 6). The year-to-year corn yield estimates are also generally consistent with the measured yields, although the alternative corn yields do not appear as accurate as the standard baseline yield estimates (but there are several years in which the alternative baseline yields are, or are almost, identical to the measured yields). The same divergence from the measured corn yields begins again around 1998 (Figure 6), although the differences are not as extreme in most years. The weak predictions in the latter half of the simulation period for both SWAT approaches indicates that the current SWAT corn parameters need updating to capture the most recent scientific advances that have been incorporated into current corn hybrids, which are resulting in ever-increasing yield gains.

The predicted EPIC corn yields overpredict the measured corn yields in most years, in contrast to the SWAT corn yield estimates (Figure 6). The 1991 EPIC prediction does not capture the drought impacts reflected in the measured data of that year, and 1992 is greatly overpredicted too. However, EPIC does capture more of the yield loss that occurred in 1993 as compared to the SWAT predictions. The EPIC corn yield estimates track the annual measured yields reasonably well during much of the 1986-2006 simulation period. The undepredictions that occur during 2002-2006 may again reflect the need for crop parameter updates in order to capture the most recent genetic gains.

The soybean yield comparisons shown in Figure 7 further draw out the overpredictions of the SWAT simulations versus the lower predictions of the EPIC yields, that were discussed previously for the annual average soybean yield comparisons shown in Figure 5. The general soybean yield trends of the standard SWAT baseline again accurately reflect the measured yield trends across most of the 1986-2006 simulation period. The standard SWAT baseline clearly captures soybean yield declines in 1988 and 1991 that the alternative SWAT baseline totally misses, and also replicates the 2003 yield decline more accurately. This result is likely an artifact of the AWC reduction, in which the reduced soil AWC is better reflecting drought conditions that existed during these years. The yield trends of the two SWAT baselines are very similar apart from those three years and nearly identical in many of the years.

The EPIC-predicted soybean yields are much closer to the measured yields throughout the entire simulation period and are essentially identical in some of the years (Figure 7). The 1988-1991 and 2003 soybean yields were overpredicted while the 1992, 1994-1995, and 2004-2006 were underpredicted by EPIC. These results would suggest that crop parameter adjustments may improve the predictions of both models. However, it does not appear that the model parameters are out-of-sync with current soybean genetics, unless the EPIC underpredictions at the end of the simulation period reveal an ongoing trend.

Effect of Harvest Index adjustment

One suggested step to improve the SWAT corn yield predictions was an adjustment of the Harvest Index (HI) value from 0.50 to 0.55 (Kiniry, 2007), which is one of the inputs included in the crop parameter table. The resulting corn yield prediction shift for the standard

SWAT baseline is shown in Figure 8. This adjustment does bring the simulated yields closer to the measured yields for most of the years during the 1986-2000 period. However, the yield estimates degraded to some degree in a few of the years relative to the original predicted yields; e.g., in 1992 and 1997. The predicted yields in most of the last eight years (except 2000) still greatly lag the measured yields, especially in 2003-2006. This would indicate that HI adjustments alone are not going to address recent genetic advances.

Regression lines computed for the NASS measured yields and the SWAT accepted baseline yields (HI=0.50) reinforce the divergence that occurs between the simulated and measured yields as the simulation period progresses towards 2006, and that SWAT is not able to capture the upward technology trend corn hybrids. In fact, the SWAT yields decrease slightly over the simulation period, which may be climatically driven or a function of slightly increasing nitrogen stress over the duration of the simulations.

Statistical Assessment

Tables 1 and 2 list R^2 and E statistics (described in Chapters 2 and 4) for three different time periods are presented (1986-1997, 1998-2006, and 1986-2006) for the previously described SWAT and EPIC simulations. The 1986-1997 time period reflects the early half of the simulation period in which the SWAT corn yields were closer to the measured yields, while 1998-2006 reflects the time period of increasing divergence between the SWAT and measured corn yields. Statistics for the entire time period are also presented. Additional statistics are also presented for 1986-1997 and 1986-2006 without 1993, which was the year corn yields were greatly overestimated in SWAT due to inability to account for extreme ponding in fields. The same time periods are used for the soybean yield estimates for

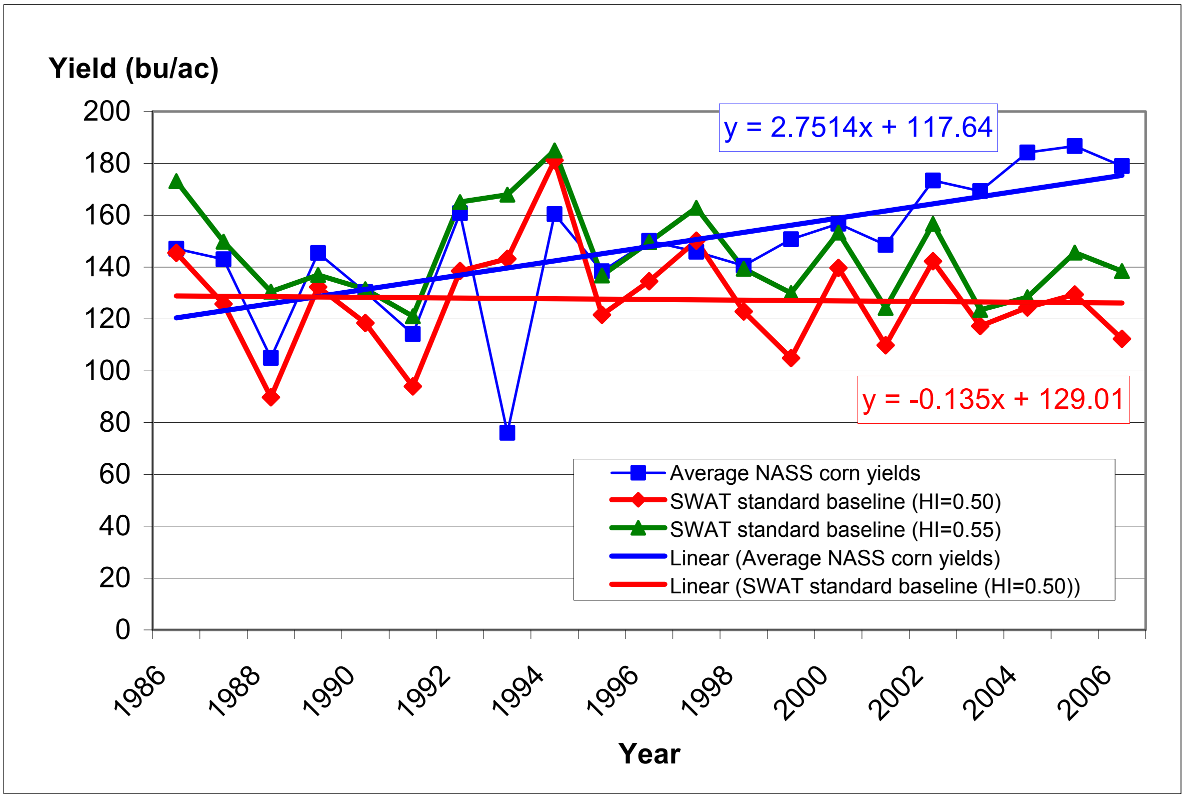

Figure 8. Measured versus simulated yields with two HI values for the SWAT accepted baseline yield estimates.

consistency. However, additional statistics were generated without 1992 for the 1986-1997 and 1986-2006 soybean statistics; the simulated soybean yield estimates greatly underpredicted the measured yields in 1992.

The majority of the corn statistics are quite poor; the E statistics are dominated by negative values and most of the R^2 values are very low. However, strong statistics were computed for the SWAT corn yields during 1986-1997, if 1993 was not included. The SWAT corn yield statistics were all poor for the 1986-2006 time period and for the entire simulation duration, reflecting the problems with the large yield underpredictions that occurred during most of 1998-2006. The EPIC statistics were in general poor across all three

Table 1. Regression and Nash-Sutcliffe statistics computed for corn yield estimates

Simulation run	1986-1997 with 1993 R^2	1986-1997 with 1993 E	1986-1997 without 1993 R^2	1986-1997 without 1993 E	1998-2006 R^2	1998-2006 E	1986-2006 with 1993 R^2	1986-2006 with 1993 E	1986-2006 Without 1993 R^2	1986-2006 Without 1993 E
SWAT (standard baseline; HI=0.50)	.22	-.06	.79	.60	.12	-7.5	.05	-2.8	.18	-.57
SWAT (standard baseline; HI=0.55)	.23	-.29	.79	.66	.12	-4.3	.05	-.48	.18	-.02
SWAT (alternative baseline; HI=0.50)	.10	-.59	.64	.65	.05	-3.4	.0	-.49	.05	.12
EPIC	.34	-.79	.12	-.39	.01	-.25	.39	-.08	.20	.12

Table 2. Regression and Nash-Sutcliffe statistics computed for soybean yield estimates

Simulation run	1986-1997 with 1992 R^2	1986-1997 with 1992 E	1986-1997 without 1992 R^2	1986-1997 without 1992 E	1998-2006 R^2	1998-2006 E	1986-2006 with 1992 R^2	1986-2006 with 1992 E	1986-2006 without 1992 R^2	1986-2006 without 1992 E
SWAT (standard baseline; HI=0.50)	.25	-1.1	.64	-.69	.74	-.82	.41	-.54	.68	-.76
SWAT (alternative baseline; HI=0.50)	.09	-2.5	.29	-2.2	.55	-2.2	.21	-1.9	.38	-2.0
EPIC	.16	-.35	.36	.28	.11	-.07	.19	-.11	.31	.26

time periods, although stronger than SWAT for the entire 1986-2006 simulation period. Removing 1993 weakens the EPIC R^2 results for the corn statistics, but does provide some improvement in the E values. However, the 1993 EPIC corn yield was more accurate than the 1993 corn yields estimated in the two SWAT simulations.

The majority of the R^2 and E statistics for the predicted soybean yields were again poor, and all but two of the E values were negative. The standard SWAT baseline yields were the most accurate in terms of replicating the yield trends, especially when 1992 was removed, as evidenced by the stronger R^2 values. The SWAT alternative baseline also captured the 1998-2006 soybean yield trends reasonably well. The EPIC predictions were generally weaker, although positive E values of .28 and .26 was computed for 1986-1997 and 1986-

2006, if 1992 was excluded. The stronger E values found with EPIC reflect the overall more accurate magnitude of the EPIC soybean predictions.

Sensitivity to tillage effects

The sensitivity of SWAT and EPIC yield predictions to different tillage levels was also evaluated for the BRW. The baseline tillage levels were based on a field-level survey performed for the 2005 growing season as described in Chapter 3. Figure 9 shows the resultant distribution of tillage across the BRW, which are defined in terms of the following three tillage levels: conventional (< 30% residue cover), mulch (30% < residue<90% cover), and notill (> 90% residue cover); mulch tillage was by far the dominant tillage practice in the watershed.

The yield estimations were split out by tillage for the SWAT simulations by: (1) defining a different crop number in the SWAT crop parameter table for each crop-tillage combination , (2) setting an appropriate minimum C factor for the crop-tillage combination in the SWAT crop parameter table, (3) simulating appropriate tillage passes for each crop-tillage combination, and (4) retrieving the yield estimates using the "Output Yield Summary" reporting function available in the latest versions of the interactive SWAT (i_SWAT) software (CARD, 2007). This approach results in three different corn and soybean parameter lines being set up in the SWAT crop parameter table; the only difference between the three corn entries and between the three soybean entries are the different minimum C factor values. EPIC estimates the C factor internally on a daily basis, so there is no need to split out separate crop-tillage combinations in the EPIC crop parameter table.

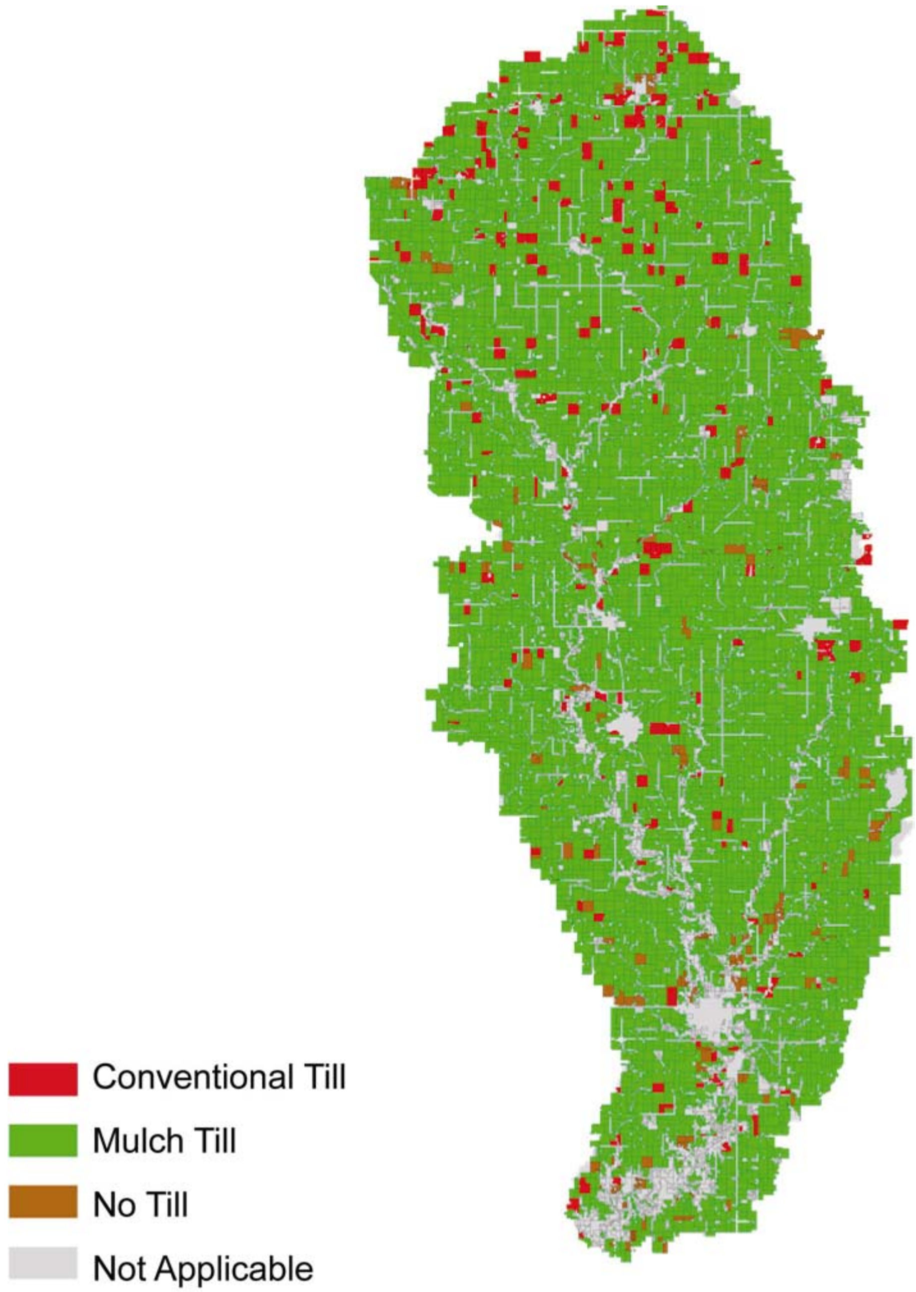

Figure 9. Distribution of tillage in the BRW based on the 2005 field-level survey.

The resultant yield estimations for the two SWAT baselines (HI=0.50) and the EPIC simulations are listed in Table 3 by crop and tillage level (conventional, mulch, or no-till). At present it is not clear if the choice of C factor has any effect on the predicted SWAT yields.

Table 3. BRW average yields by tillage level for the two SWAT baselines (HI=.50) and EPIC

Simulation run	Crop	Tillage level	Crop number[a]	USLE C factor[a]	Estimated average yield (t ha^{-1})	Estimated average yield (bu ac^{-1})	Area (km^2)
SWAT (standard baseline)	corn	conventional	100	.3	7.88	142.5	54.3
		Mulch	101	.15	6.99	126.5	1016.8
		Notill	102	.04	6.66	120.5	27.3
	soybean	conventional	103	.3	2.84	47.7	40.0
		Mulch	104	.15	2.94	49.4	940.1
		Notill	105	.08	2.92	49.1	26.4
SWAT (alternative baseline)	corn	conventional	100	.3	8.71	157.6	54.3
		Mulch	101	.15	7.89	142.8	1016.8
		Notill	102	.04	7.46	135.0	27.3
	soybean	conventional	103	.3	3.00	50.5	40.0
		Mulch	104	.15	3.07	51.6	940.1
		Notill	105	.08	3.11	52.3	26.4
EPIC[b]	corn	conventional	-	-	9.05	163.2	37.5
		Mulch	-	-	9.21	165.9	908.1
		Notill	-	-	9.10	162.0	27.7
	soybean	conventional	-	-	2.56	43.0	53.5
		Mulch	-	-	2.50	42.0	986.6
		Notill	-	-	2.50	41.7	24.2

[a]The crop numbers and corresponding USLE minimum C factors are input to the SWAT simulations via the SWAT Crop Parameter table.
[b]The EPIC areas are preliminary and need to be further checked.

However, it would be expected that the tillage passes are affecting soil properties which in turn could impact the estimated yields. It is also possible that the specific soils that were simulated within each tillage class could impact the overall average crop yield for the given

tillage category. The predicted yields clearly show that SWAT is favoring the conventional tilled corn over conservation tillage and that yields decrease as tillage decreases. The percentage differences in yields ranged from 9 to 15% less for mulch till and notill corn relative to conventionally tilled corn (Table 4). An opposite relationship was generally predicted for soybean, although the effects were generally minor (Tables 3 and 4).
The tillage effects on EPIC corn and soybean predictions were minor (Tables 3 and 4). The highest corn yield predicted by EPIC was for mulch tillage rather than conventional, although the difference in yield estimates was only 2%. EPIC predicted higher yields for conventionally tilled soybean relative to soybean managed with mulch tillage or no till, but the maximum absolute percentage difference was only 3%. Overall, EPIC exhibited less sensitivity to tillage differences as compared to SWAT.

Wilhelm and Wortman (2004) report that mean corn yields measured over 16 years near Lincoln, Nebraska were 19% less in continuous corn managed with no till versus a moldboard plow system used in continuous corn. Continuous corn managed with different mulch tillage systems (chisel plow, disk, or ridge till) resulted in mean yields in between the moldboard plow and no till yields. However, tillage effects were smaller for the 16-year mean corn yields measured in a rotation of corn and soybean, with the moldboard plow yields be only 5% higher than the no till yields. Wilhelm and Wortman also found that soybean yields were unaffected by tillage treatment. Vetsch and Randall (2002) report similar corn yield results in a four-year (1996-2000) study near Waseca, Minnesota, in which corn yields were significantly higher in coventionally tilled continuous corn versus two mulch tillage systems and no till (which had the lowest mean corn yields). They also found

Table 4. Percentage differences between tillage categories for the BRW SWAT baselines (HI=.50) and EPIC simulations.

Simulation run	Crop	Tillage comparsion	Percentage difference
SWAT (standard baseline)	Corn	mulch relative to conventional	-11
		notill relative to conventional	-15
		Notill relative to mulch	-5
	soybean	mulch relative to conventional	4
		notill relative to conventional	3
		Notill relative to mulch	-.5
SWAT (alternative baseline)	Corn	Mulch relative to conventional	-9
		notill relative to conventional	-14
		Notill relative to mulch	-5
	soybean	Mulch relative to conventional	2
		notill relative to conventional	4
		Notill relative to mulch	1
EPIC	Corn	Mulch relative to conventional	2
		notill relative to conventional	-.7
		Notill relative to mulch	-2
	soybean	Mulch relative to conventional	-2
		notill relative to conventional	-3
		Notill relative to mulch	-.6

that tillage effects did not signficantly impact corn yields for corn grown in rotation with soybean. However, Vetsch et al. (2007) report that greater corn yields and economic returns occurred within a corn-soybean rotation when the soybeans were managed with zone-tillage or 20-cm deep fall strip-tillage versus full-with tillage, for a second study conducted during 2000-2004 near Waseca. Some effect of tillage was observed on soybean yields, but this did not affect economic returns. Perez-Bidegan et al. (2007) also found that mean corn yields for corn grown in rotation with soybean and managed with a disk-chisel tillage system were 0.8 t ha^{-1} higher than corresponding corn yields produced with strip tillage and no till systems, in a three-year (2002-2004) experiment near Newton, Iowa.

The tillage effects reported here for the SWAT and EPIC crop yields were dominated by a cropping sequence of corn grown in rotation with soybean. The lack of tillage impact on soybean yields are consistent with the field studies reviewed above. However, the same studies provide conflicting reports regarding the effect of tillage on corn yields within a corn-soybean rotation. Further research is needed to confirm the reasons why the tillage effects on corn, within a corn-soybean cropping system, are occurring in SWAT and whether these effects are consistent with published research. Comparisons of tillage effects on corn yields simulated within continuous corn versus a corn-soybean cropping system are also needed for both models.

Conclusions

Corn and soybean yield predictions generated with SWAT and EPIC were compared with historical yields reported by USDA-NASS over a 21-year time period (1986-2006) for the Boone River watershed (BRW) that covers over 237,000 ha in north central Iowa. The SWAT yields were generated for two different baselines reported in Chapter 4, which represent applications of the standard runoff curve number (RCN) versus an alternative RCN method in the model. The 1986-2006 long-term average corn yields estimated with the standard and alternative SWAT baselines were 127.1 and 143.3 bu ac^{-1}, respectively; these yields underestimated the historical average of 147.9 bu ac^{-1}. The SWAT model greatly underpredicted corn yields for the 1998-2006 time period, indicating a lack of accounting for recent genetic advances. The long-term average corn yield estimated by EPIC was 165.4 bu ac^{-1}, which greatly exceeded the 1986-2006 average historical yield but was close to the 1997-2006 average corn yield of 163.5 bu ac^{-1}. In contrast, the 1986-2006 average soybean yields estimated for the standard and alternative SWAT baselines were 49.3 and 51.6 bu ac^{-1}, which were considerably higher than the mean historical yield of 43.6 bu ac^{-1}. The mean EPIC soybean yield was 41.6 bu ac^{-1} was slightly below the measured means and was again closer in magnitude to recent historical yields.

Statistical analysis of annual yield comparisons indicated generally weak year-to-year replication of the historical yields by both models, except for the estimated SWAT yields predicted in the first half of the simulation period. The majority of the E statistics were negative and over half of the r^2 statistics were below 0.3. However, the SWAT corn yield predictions resulted in r^2 and E statistics ranging between .60 and .79 for 1986-1997, if 1993 was ignored. The comparison of the simulated SWAT soybean yields with the historical yields also resulted in an r^2 values of 0.74 and 0.55, respectively, for the overall 1986-2006 time period. These statistics indicate that SWAT is tracking the year-to-year pattern of the measured soybean yields. However, the negative E statistics found for the same comparisons underscore that the magnitude of the yields were too high, and that the yield estimates need to be corrected in order to obtain overall reliable predictions. In general, the trends estimated with the EPIC were less accurate as compared to SWAT, which is an interesting result considering that the EPIC crop growth submodel is considered to be more refined and updated as compared to the SWAT counterpart.

Further analysis indicated that the SWAT corn yield predictions were sensitive to tillage, with higher yields predicted for corn managed with conventional tillage as compared to mulch and no till. The SWAT soybean yield predictions and the EPIC corn and soybean yield predictions were generally insensitive to tillage. An overview of several field studies reveals that corn yields are sensitive to tillage when grown in a monoculture corn rotation, with conventional tilled corn usually outyielding corn managed with mulch or no till systems. Similar results can result for corn yields in a corn-soybean rotation, although some studies show that the tillage effects are much less pronounced.

Overall, the results indicate a need to update crop parameters, especially in SWAT, to more accurately simulate current corn and soybean yields in the region. Modifications to the generic crop growth routine used in both models may also improve annual predictions of both crops. There is also a need to further study the effects of tillage on crop yields in both SWAT and EPIC, to ascertain whether current simulated effects are logical, and to determine if modifications are needed in both models to improve their sensitivity to the effects of tillage.

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CHAPTER 6. GENERAL CONCLUSIONS

The state of Iowa faces a complex set of agricultural production and environmental issues, which are being compounded due to emerging biofuel production trends. Concern is intensifying that corn-based ethanol production will result in greater nonpoint source pollution, in both Iowa waterways and further downstream including the Gulf of Mexico. Enhanced tools are needed to evaluate the ramifications of current biofuel production trends on water quality and other environmental indicators. Watershed-scale computer models are key tools that will likely be increasingly used to assess the impacts of biofuel production and other alternative management and cropping system scenarios on water quality.

The Soil and Water Assessment Tool (SWAT) model has emerged as a viable option for watershed-scale water quality assessments. The extensive review in Chapter 2 underscores the fact that SWAT has been successfully used for a wide range of watershed sizes, environmental conditions, management practices, and cropping systems in many regions across the globe. However, the review also revealed that SWAT has performed inadequately for some conditions, that further testing is needed to strengthen the predictive accuracy of the model, and that code enhancements will be needed in future versions to expand the range of conditions and practices that the model can reliably be applied to.

The development of the Boone River watershed (BRW) data layers and modeling system (Chapter 3) provides an excellent framework for further testing of SWAT, especially in regards to conditions representative of the Des Moines Lobe ecological region which covers the north central region of Iowa including the BRW. The compilation of data at the Common Land Unit (CLU) level provides a very intensive set of land use, soil, conservation practice, and management practice data at the field-scale level, which can be aggregated in different ways to create the SWAT hydrologic response units (HRUs). This framework supports both testing of SWAT for baseline conditions as well as applications of the model for alternative BRW biofuel simulations and other alternative management and cropping practice scenarios. The framework also supports execution of the field-scale models such as Century and the Environmental Policy Impact Climate (EPIC) model, which can be configured at the CLU level for evaluations of soil carbon sequestration and other environmental indicators in response to various BRW scenarios.

Two different methods were used for performing the SWAT BRW hydrologic calibration and validation that were described as the standard runoff curve number (RCN) approach and the alternative RCN approach (Chapter 4), in which the curve number coefficient (CNCOEF) value was set to 0.6. The simulated annual and monthly streamflows at the watershed outlet were similar for both approaches over the 1986 to 2006 simulation period, even though the surface runoff and subsurface runoff (including tile flow) components differed markedly between the two methods. Furthermore, it was found that varying the CNCOEF for the alternative approach resulted in tremendous differences between the relative balances of surface runoff and subsurface flow, but very little variation occurred in the overall predicted streamflow. Strong graphical and statistical agreement was found for both methods in evaluations of simulated annual and monthly streamflows versus measured streamflow values at the watershed outlet.

Additional calibration of SWAT for the BRW showed that simulations based on standard RCN approach adequately replicated measured annual and monthly loads of sediment, total phosphorus, nitrate, and organic nitrogen, based on graphical and statistical evaluations (Chapter 4). Corresponding simulations using the alternative RCN approach revealed weaker predictions by the model, especially for organic nitrogen, which point to the need for additional or different calibration steps. However, further analyses showed that there may be fundamental problems underlying the environmental calibrations performed in this study, including overestimation of soybean nitrogen fixation and underestimation of nitrate levels predicted to escape cropped landscapes. The latter appears to be a particularly acute problem for the standard RCN approach, which resulted in equal levels of predicted nitrate and organic nitrogen losses from cropped HRUs. This result appears inconsistent with typical BRW nitrogen loss pathways (e.g., nitrate losses to streams via subsurface drainage tile) and nitrogen constituents measured in the BRW stream system.

Corn and soybean yields predicted with the two alternative SWAT hydrologic approaches and with the EPIC model were compared versus historical yields measured in the BRW region (Chapter 5). The average annual corn yield estimated with the standard RCN approach was over 20 bu ac^{-1} below the counterpart historical average annual corn yield for the 21-year simulation period of 1986 to 2006. The average annual corn yield estimated with the alternative RCN approach was only about 4.5 bu ac^{-1} below the historical average. Both SWAT approaches tracked the annual corn yield trends well for 1986 to 1997 (with the exception of 1993), but the corn yields for 1997 to 2006 were greatly underpredicted by both SWAT approaches. Corn yields were also found to be sensitive as a function of tillage level in SWAT, but not in EPIC. The EPIC model predicted a much higher average annual corn yield across the entire 21-year simulation period, which exceeded the historical average corn yield by over 17 bu ac^{-1} but which was close to the 1997-2006 historical average corn yield. The annual historical corn yields were not well predicted by EPIC. The average annual predicted soybean yields for 1986 to 2006 were overpredicted by the two SWAT approaches by an average of almost 7 bu ac^{-1}. The corresponding EPIC average annual soybean yield underpredicted the long-term historical soybean yield by 2 bu $^{-1}$. Trends in annual historical soybean yields were generally accurately predicted by SWAT (i.e., high R^2 values), especially using the standard RCN approach. The crop yield predictions reveal the need for further testing and refinement of the crop yield estimates in both SWAT and EPIC, the need to update the SWAT corn growth parameters to better reflect current hybrids, and the possible need to modify the code to better simulate annual and long-term average crop yields.

Recommendations

The results of this study indicate that further testing of SWAT is needed for the BRW. Precise water balance, nitrate loss, and other measurements are lacking for the region, which interjects uncertainty regarding which SWAT hydrologic simulation approach is the most accurate option to use for the BRW. However, the flat, heavily-tiled cropped landscapes that dominant the watershed and the large proportion of nitrate found in in-stream nitrogen measurements intuitively suggest a streamflow system dominated by subsurface flow components (including tile drains) that carry large amounts of nitrate. Thus, the next testing phase should focus on using the alternative RCN approach, perhaps with a lower CNCOEF value than the value of 0.6 used for this study. This would result in more water being routed through subsurface pathways. In turn, this would result in greater nitrate fluxes being simulated via subsurface flows, especially tile drains, as compared to the lower nitrate amounts estimated using the standard RCN approach in this study. The second phase of testing should also investigate more thoroughly other aspects of nutrient cycling, including estimates of soybean nitrogen fixation and corn nitrogen uptake.

There is also a need to improve crop yield estimates for the BRW SWAT simulations, especially the corn yield estimates. Initial progress should be obtainable through simple adjustments of both corn and soybean crop growth parameters, in consultation with model developers. However, more extensive adjustments will likely be required for corn, to obtain yield estimates that are more consistent with present day hybrids. Further investigation is also warranted regarding the apparent tillage effect on corn yields found for the SWAT simulations in this study.

Finally, it is recommended that a recently updated SWAT2005 model be used in future BRW testing, rather that the present code which is over two years old now. The SWAT code is continuously evolving and current 2005 versions contain a number of updates relative to older versions of the SWAT2005 model[1]. Some testing of a more recent SWAT2005 code has already been performed for the BRW, which showed more accurate predictions of crop yields as compared to the version of the model used for this study. The latest release of SWAT2005 will also support enhanced scenarios for the BRW and other watersheds, including newly introduced capabilities to simulate biomass removal of corn and other crops (an important biofuel scenario option) and more realistic depiction of grassed waterways.

[1]It could be more straight forward to update the model version more frequently; e.g., to SWAT2007 or SWAT2005.1. However, the current reality is that the model name is being held static as SWAT2005, and several versions of that version now exist.

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