SWAT Ungauged: Hydrological Budget and Crop Yield Predictions in the Upper Mississippi River Basin

R. Srinivasan, X. Zhang, J. Arnold

Abstract. *Physically based, distributed hydrologic models are increasingly used in assessments of water resources, best management practices, and climate and land use changes. Model performance evaluation in ungauged basins is an important research topic. In this study, we propose a framework for developing Soil and Water Assessment Tool (SWAT) input data, including hydrography, terrain, land use, soil, tile, weather, and management practices, for the Upper Mississippi River basin (UMRB). We also present a performance evaluation of SWAT hydrologic budget and crop yield simulations in the UMRB without calibration. The uncalibrated SWAT model ably predicts annual streamflow at 11 USGS gauges and crop yield at a four-digit hydrologic unit code (HUC) scale. For monthly streamflow simulation, the performance of SWAT is marginally poor compared with that of annual flow, which may be due to incomplete information about reservoirs and dams within the UMRB. Further validation shows that SWAT can predict base flow contribution ratio reasonably well. Compared with three calibrated SWAT models developed in previous studies of the entire UMRB, the uncalibrated SWAT model presented here can provide similar results. Overall, the SWAT model can provide satisfactory predictions on hydrologic budget and crop yield in the UMRB without calibration. The results emphasize the importance and prospects of using accurate spatial input data for the physically based SWAT model. This study also examines biofuel-biomass production by simulating all agricultural lands with switchgrass, producing satisfactory results in estimating biomass availability for biofuel production.*

Keywords. *Crop yield, Soil and Water Assessment Tool, Streamflow, Ungauged basin, Upper Mississippi River basin.*

Watershed computer models have long been an integral part of any assessment, and model types vary with intended application. The application of most hydrological models often requires a large amount of spatially variable input data and a large number of parameters. Due to the lack of high-quality input data and conceptual simplification of hydrological processes, these models need to be calibrated, by varying degrees, to the observed hydrologic variables (Beven and Binley, 1992; Beven, 2006; Wagener et al., 2004; Gupta et al., 2008). In the past two decades, model calibration has progressed significantly (e.g., Duan et al., 1992; Beven and Binley, 1992; Beven, 2006; Gupta et al., 1998; Vrugt et al., 2003). Model calibration requires sufficiently long, high-quality observations of streamflow and other variables, but observed data on both spatial and temporal scales of interest are always very limited, especially in ungauged basins (Sivapalan et al., 2003). For predictions of future environmental impacts (e.g., land use) on hydrologic variables, Wagener (2007) pointed out that many researchers face the fact that no gauging stations exist in their area of study. In addition, it is worth noting that uncertainties associated with input data and measured hydrologic variables may lead to biased estimation of parameters calibrated using one or several stream gauges. For example, under typical conditions, errors ranged from 6% to 16% for streamflow measurements (Harmel et al., 2006). A case study in Reynolds Creek Experimental Watershed showed that a parameter set with high streamflow simulation performance at the watershed outlet can have much lower performance at some internal points within the watershed (X. Zhang et al., 2008a). Very frequently, the calibrated model is user-dependent, as it is based on the model user's experience and knowledge about the watershed, model, chosen parameters, and their ranges. Therefore, calibrated models may be limited to their intended purpose.

Different methods have been used to build hydrologic modeling systems in ungauged basins, including the extrapolation of response information from gauged to ungauged basins, measurements by remote sensing, the application of process-based hydrological models in which climate inputs are specified or measured, and the application of combined meteorological-hydrological models that do not require the user to specify precipitation inputs (Sivapalan et al., 2003). Recently, many studies have examined approaches that improve the applicability of hydrologic models in ungauged basins, including *a priori* parameter estimation from physical watershed characteristics (e.g., Atkinson et al., 2003), regionalization of model param-

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eters (e.g., Vandewiele and Elias, 1995), regionalization of hydrologic indices (e.g., Yadav et al., 2007; Z. Zhang et al., 2008), application of satellite remote sensing (e.g., Lakshmi, 2004), and the use of process-based, distributed hydrologic models (e.g., Moretti and Montanari, 2008).

One approach to addressing the use of hydrological models in ungauged basins is developing a model that uses physically based inputs both spatially and temporally along with comprehensiveness in the model's interrelationships and ability to predict ungauged basins reasonably well. The Soil and Water Assessment Tool (SWAT) model was originally developed to operate in large-scale ungauged basins with little or no calibration efforts (Arnold et al., 1998). It attempts to incorporate spatially distributed and physically distributed watershed inputs to simulate a set of comprehensive processes, such as hydrology (both surface and subsurface up to the shallow aquifer), sedimentation, crop/vegetative growth, pesticides, bacteria, and comprehensive nutrient cycling in soils, streams, and crop uptake. Most SWAT parameters can be estimated automatically using the GIS interface and meteorological information combined with internal model databases (Srinivasan et al., 1998; X. Zhang et al., 2008b). The USEPA incorporated SWAT into the Better Assessment Science Integrating Point and Nonpoint Sources (BASINS) software package (Di Luzio et al., 2004), and the USDA is applying it in the Conservation Effects Assessment Project (CEAP, 2008). Over 600 published, peer-reviewed articles have reported SWAT applications, reviews of SWAT components, or other research including SWAT (Gassman et al., 2007; https://www.card.iastate.edu/swat_articles/). However, most model applications involve calibration procedures (e.g., van Griensven et al., 2008; Abbaspour, 2008; X. Zhang et al., 2009a, 2009b). Therefore, the main objective of this study was to produce datasets for the Upper Mississippi River basin that can be used to evaluate the long-term effects on hydrologic budget and crop/biomass production by the SWAT model without calibration.

The Upper Mississippi River basin (UMRB) (fig. 1) is a "hot spot" for studies of the hydrological cycle and nutrient transport and fate. Agricultural land accounts for more than 40% of the UMRB total area (approximately 491,665 km^2). Nitrate-nitrogen flowing to the Mississippi River basin from agricultural lands is implicated as the major source of nutrients leading to hypoxia in the Gulf of Mexico (Goolsby et al., 1999, Dale et. al., 2007). The UMRB comprises only 15% of the Mississippi River basin's drainage area but contributes more than half of the nitrate-nitrogen reaching the Gulf of Mexico (Goolsby et al., 1997). The existing critical environmental issues of the U.S. Midwest region and the Gulf of Mexico could be worsened by the emphasis on future increases in renewable and alternative biofuels (Simpson et al., 2008, Powers, 2007). The USDA and EPA have both applied the SWAT model to simulate and evaluate strategies for more effectively managing water resources and nutrient inputs (Jewett et al., 2007; CEAP, 2008). Several previous studies applied the SWAT model in the UMRB to simulate water budgets and nutrient movement. The first SWAT application at the entire UMRB scale was conducted by Arnold et al. (2000). Recently, Jha et al. (2004) and Wu and Tanaka (2005) also used SWAT in UMRB studies to evaluate climate change effects on water yield and estimate the social cost of reducing nitrogen loads. In all three previous UMRB applications of SWAT, the authors implemented parameter calibration procedures to match simulated and observed streamflow. In this study, we are focusing on hydrologic simulation, which is the basis for sediment and nutrient predictions. The hypothesis of this study is that, given appropriate spatial input data, SWAT can provide a satisfactory simulation of the water budget. We present a framework for developing spatial climate and watershed configuration data for the entire UMRB, assess the performance of an uncalibrated SWAT model in predicting water and crop yield, and compare the uncalibrated SWAT model with calibrated SWAT models applied in previous studies. The results of this study are expected to provide valuable information on the applicability of SWAT in medium to large-scale ungauged basins.

Materials and Methods

Study Area Description

The location of the UMRB, which is shown in figure 1, includes large parts of the states of Illinois, Iowa, Minnesota, Missouri, and Wisconsin and smaller portions of Indiana, Michigan, and South Dakota. The Upper Mississippi River flows through a 2100 km waterway from Lake Itasca in northern Minnesota to its confluence with the Ohio River at the southern tip of Illinois. The Upper Mississippi River System is the only water body in the nation recognized by Congress as both a "nationally significant ecosystem" and a "nationally significant commercial navigation system" (www.umrba.org/facts.htm). The river system supports commercial navigation, recreation, and a wide variety of ecosystems. In addition, the region contains more than 30 million residents who rely on river water for public and industrial supplies, power plant cooling, wastewater assimilation, and other uses (Jha et al., 2004). Physically based models that can simulate the hydrologic cycle, crop yield, soil erosion, and nutrient transport and fate are useful tools for evaluating Upper Mississippi River System sustainability, best management practices, and climate and land use/land cover changes. In the following sections, SWAT and its setup are introduced.

SWAT Model Description

SWAT is a continuous-time, long-term, distributed-parameter model (Arnold et al., 1998). SWAT divides a watershed into subbasins connected by a stream network and further delineates each subbasin into hydrologic response units (HRUs), which consist of unique combinations of land cover, slope, and soil type. It is assumed that there is no interaction between HRUs. In other words, the HRUs are non-spatially distributed. HRU delineation can minimize a simulation's computational costs by lumping similar soil and land use areas into a single unit (Neitsch et al., 2005). SWAT is able to simulate surface and subsurface flow, sediment generation and deposit, and nutrient movement and fate through the watershed system. For this study, only SWAT components concerned with runoff simulation are briefly introduced. Hydrologic routines within SWAT account for snowfall and melt, vadose zone processes (i.e., infiltration, evaporation, plant uptake, lateral flows, and percolation), and groundwater flows (Neitsch et al., 2005). Surface runoff volume is estimated using a modified version of the Soil Conservation Service (SCS) curve number (CN) method (USDA-SCS, 1972). A kinematic storage model is used to predict lateral flow, whereas return flow is simulated by creating a shallow aquifer (Arnold et al., 1998). The Muskingum method is used for channel flood routing. Outflow from a channel is adjusted for transmission losses, evaporation, diversions, and return

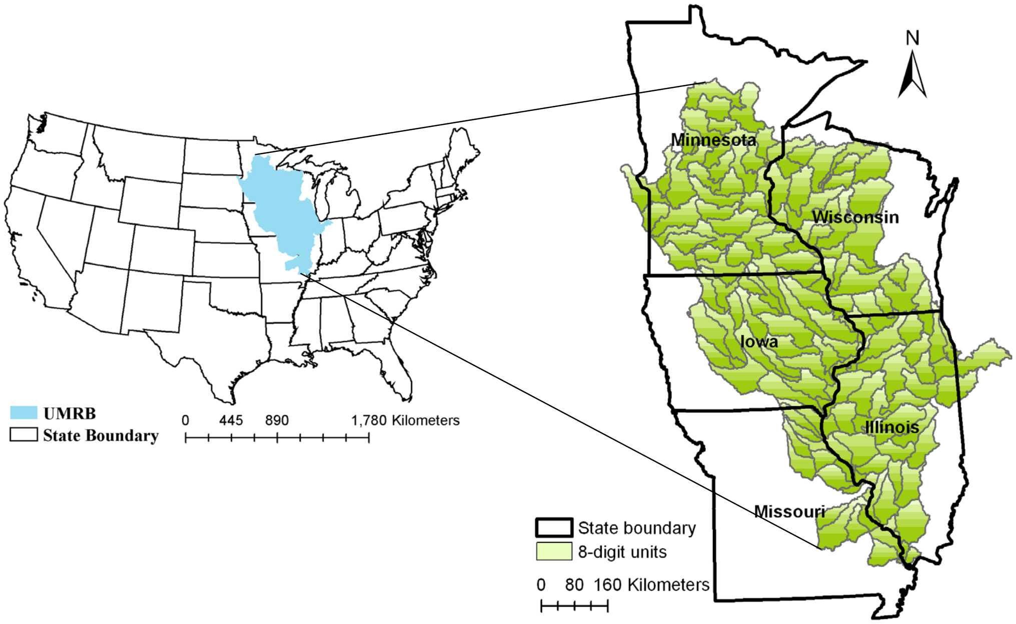

Figure 1. Location of the Upper Mississippi River basin with eight-digit HUCs and state boundaries.

flow. As a physically based hydrological model, SWAT requires a great deal of input data in order to derive parameters that control the hydrologic processes in a given watershed. Major input datasets include weather, hydrography, topography, soils, land use/land cover data, and management practices. The methods used to develop UMRB input data for SWAT are introduced as follows.

SWAT Model Setup

Hydrography and Digital Elevation Model (DEM)

In the ArcSWAT interface (Winchell et al., 2007) user-defined watershed boundary option, we used the eight-digit USGS hydrologic unit codes (HUCs), National Hydrography Dataset (NHD) stream dataset, and a 90 m (3 arc second) digital elevation model (DEM) as SWAT inputs to provide watershed configuration and topographic parameter estimation. We defined a total of 131 HUCs in the UMRB. The main inputs provided by the DEM were channel length (of both the main routing stream and tributary routing streams), channel slope, and overland slope by HRU. We tested both a 30 m (1:24000) DEM and 90 m (1:100000) DEM, both of which are available from the USGS. The differences in overland slope between 30 m and 90 m DEM data were not substantial given the size of the HRUs and subbasin HUCs. We also found no substantial difference in model prediction at the monthly and annual scales of streamflow. Hence, we chose the 90 m DEM for this study in order to reduce the project size. In addition, we identified 15 major reservoirs on the main stream (shown in fig. 4) of the UMRB and inserted them into the ArcSWAT interface.

Land Use/Land Cover

The land use map is the next critical SWAT input. Crop rotation and management data are essential for accurate estimation of water and crop yield. In this study, we obtained the land use map from two sources of information, the Cropland Data Layer (CDL) (www.nass.usda.gov/research/Cropland/SARS1a.htm) and 2001 National Land Cover Data (NLCD2001) (Homer et al, 2004). The CDL contains crop-specific digital data layers, suitable for use in geographic information system (GIS) applications. The CDL program focuses on classifying corn, soybean, rice, and cotton agricultural regions in many Midwestern and Mississippi Delta states using remote sensing imagery and on-the-ground monitoring programs through the USDA (www.nass.usda.gov/research/Cropland/SARS1a.htm). The CDL focuses on cultivated land use, but defines non-agricultural land use types very broadly. Therefore, we suggest referring to NLCD for non-agricultural land cover information (www.nass.usda.gov/research/Cropland/sarsfaqs2.html).

In this study, we propose a framework for combining both NLCD2001 and CDL to generate the final land use map. General procedures for generating the UMRB land use map are described as follows: (1) overlay multiple years of CDL information to produce crop rotation maps, and (2) use NLCD to judge whether one pixel is cultivated or not. If cultivated, assign a crop rotation type from the overlaid CDL map to that pixel. Otherwise, that pixel will acquire an NLCD value. Currently, the CDL is available from the Geospatial Data Gateway (http://datagateway.nrcs.usda.gov/) free of charge. CDL data are available for the following years: 2000-2006 for Iowa, 2000-2006 for Illinois, 2003-2006 for Wisconsin, 2006 for Minnesota, and 2006 for Missouri. Based on an analysis of a three-year rotation in Iowa, Illinois, and Wisconsin from 2004-2006, corn-soybean or soybean-corn rotations constitute a significant portion (approximately 25%) of the UMRB land use. We assumed that these two rotation types are also the major rotation types for Minnesota and Missouri due to a lack of multi-year CDL maps in these two states. For the small portion of the UMRB located in South Dakota and Indiana, we derived eight cropland rotation types involving corn and soybean (coded from 301 to 308), and three other land use types (coded as 223, 236, 262) were from the CDL. The final land use map is shown in figure 2, and the areas of each land use type and classification system are shown in table 1. The land use types with values less than 100 use the NLCD classi-

Table 1. Land use classification system for the UMRB using NLCD and CDL data layers.

Value	Area (km^2)	Percentage (%)	Land Use Type
11	13,651.9	2.8	Open water
21	23,080.2	4.7	Developed, open space
22	13,014.3	2.6	Developed, low intensity
23	3,823.5	0.8	Developed, medium intensity
24	1,458.4	0.3	Developed, high intensity
31	348.8	0.1	Barren
41	95,611.4	19.4	Deciduous forest
42	6,879.8	1.4	Evergreen forest
43	3,978.0	0.8	Mixed forest
52	2,664.5	0.5	Shrubland
61	1,149.5	0.2	Cropland reserve program
71	13,999.3	2.8	Grassland herbaceous
81	56,641.8	11.5	Hay
82	36,981.5	7.5	Cultivated crop
90	13,997.6	2.8	Woody wetlands
95	11,543.8	2.3	Herbaceous wetlands
223	701.4	0.1	Spring wheat
236	1,522.0	0.3	Alfalfa
262	24,259.6	4.9	Pasture
301	61,531.7	12.5	Corn/soybean
302	57,784.8	11.8	Soybean/corn
303	9,827.9	2.0	Soybean/corn/corn
304	7,569.6	1.5	Corn/corn/soybean
305	15,652.5	3.2	Continuous corn
306	2,215.2	0.5	Corn/soybean/soybean
307	4,741.9	1.0	Soybean/soybean/corn
308	7,034.4	1.4	Continuous soybean

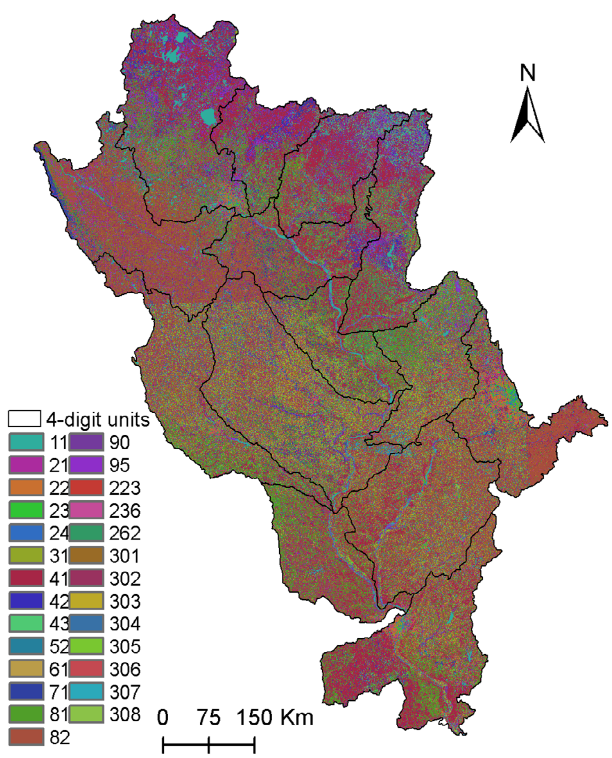

Figure 2. UMRB land use map (refer table 1 for legend).

fication system, while values larger than 200 use the new crop rotation types from the CDL.

Soils

For soils, we used the STATSGO (USDA-NRCS, 1995) 1:250000 scale soil map since the county-level SSURGO map was not available for all counties within the UMRB. We extracted the associated soil properties needed for SWAT directly from the national STATSGO layer and distributed them with ArcSWAT software.

Hydrologic Response Units (HRUs)

HRUs are the basic building blocks of SWAT at which all landscape processes are computed. The unique combination of subbasin land use, soil, and slope overlay determine HRUs. Using the ArcSWAT interface, we overlaid land use, soil, and slope layers to create a unique combination of HRUs by subbasin. The slope classes used for this process were 1% to 2%, 2% to 5%, and 5% and above, resulting in 109,507 HRUs. However, using a threshold operation of 5% for land use, 10% for soil, and 5% for slope reduced the number of HRUs to 14,568, and the number of HRUs per HUC ranged from 58 to 216.

Tile Drainage

Tiles are critical man-made hydrology structures that change the natural hydrological cycle significantly at both surface and subsurface (lateral flow) levels. The tile system is designed to drain excess water and nutrients in a timely manner. However, no clear record of tile locations is available within the UMRB other than a few research articles attempting to estimate the location and extent of tile coverage. In this study, we used values similar to those in the literature to estimate and identify HRUs with the tile drainage system. First, we used the STATSGO database to identify very poorly drained soils, somewhat poorly drained soils, and poorly drained soils. Since STATSGO is component-based, one polygon may contain as many as 21 soil series. Therefore, we added poorly drained soils by their component percent within a STATSGO polygon. Candidates for the tile drainage system included soil polygons with a soil area threshold of 40% or more. Then, we overlaid slope and land use maps on these poorly drained soils to identify the potential tile drainage system. HRUs potentially served by the tile drainage system included only those with slopes less than 1% and agricultural land uses. Figure 3 shows the spatial distribution of potential tile drainage systems considered for the UMRB modeling efforts.

Tillage

We obtained county-level UMRB tillage practice information from the Conservation Technology Information Center (CTIC; www.ctic.purdue.edu/). There are five major tillage types. Conservation tillage includes no tillage, ridge tillage, and mulch tillage. On the other hand, non-conservation tillage includes reduced tillage and intensive tillage. We used county acreages to estimate the spatial distribution of conservative and non-conservative tillage percentages for all crops, including corn and soybean. To estimate the tillage practice percent by crop for each HUC, we overlaid tillage information on eight-digit HUCs. When assigning tillage practices to HRUs, we tried to assign conservation tillage to HRUs with steep slope and non-conservation tillage to HRUs with small slope.

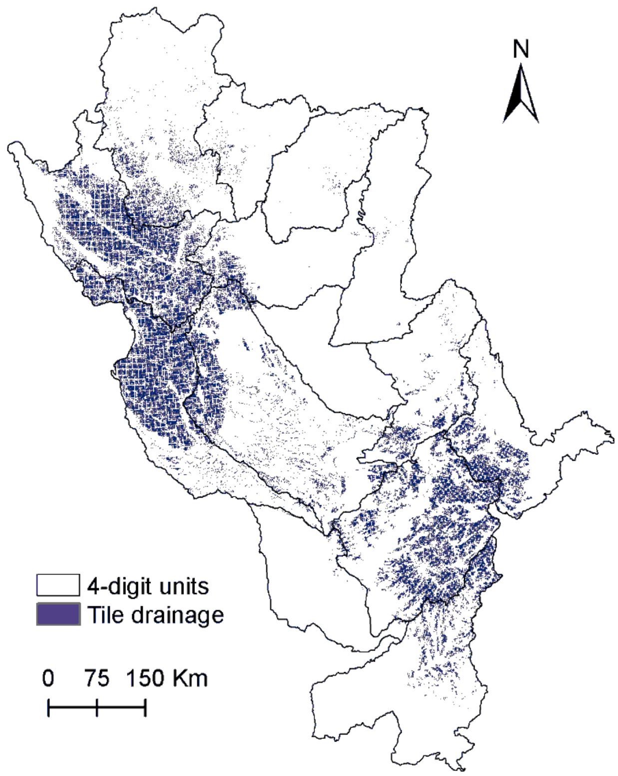

Figure 3. UMRB potential tile drainage map.

Fertilizer and Manure

We used county statistics from the 2002 Census of Agriculture to calculate the number of animals (cattle and hogs) for each eight-digit HUC. Then, we multiplied the number of animals and the manure production rates as outlined in ASABE Standard D384 (*ASABE Standards*, 2005) to obtain the manure production of each eight-digit HUC. If manure production exceeded 20% of the estimated total fertilizer application in one HUC, we included manure and chemical fertilizer applications as SWAT model input in that HUC. Even during rotation, only HRUs with agricultural land use received manure applications. More specifically, only hay, corn, and row crops received manure application, not legume crops such as alfalfa or soybean. Therefore, an HRU classified as having a corn and soybean rotation would only receive manure during corn-growing periods. Although manure was applied, we initialized the management file in SWAT with an auto-fertilizer operation used to supplement manure applications with chemical fertilizer where and when needed. In HRUs without manure applications, SWAT relied on the auto-fertilizer option as chemical input to allow the agricultural crops to grow.

Weather

Di Luzio et al (2008) developed a method for constructing long-range, large-area spatiotemporal datasets of daily precipitation and temperature (maximum and minimum) by combining daily observations from the National Climatic Data Center (NCDC) digital archives with maps from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM). These datasets provide daily precipitation and temperature values at 2.5 min (around 4 km) resolution for the years 1960 to 2001. Using their method, we used the GIS-based precipitation and temperature interpolation program (Zhang and Srinivasan, 2009) to set up the baseline model with long-term historical weather inputs from 1960-2001. Then, we aggregated the 4 km gridded daily precipitation and maximum and minimum temperature to the eight-digit subbasins using standard ArcGIS aggregation procedures. This created 131 weather stations, one for each HUC subbasin, to input into the SWAT model from 1960-2001. Although there are several point sources within the UMRB, this study did not consider them due to their relatively small overall contribution to flow.

Model Evaluation

The major hydrological budget components evaluated in this study are actual evapotranspiration (AET), soil moisture storage, and streamflow. In the recent scientific literature, these components are also called green water flow, green water storage, and blue water, respectively (Schuol et al., 2008). Comparing streamflow is relatively straightforward since it is generally observed with well-established instrumentation that produces fewer measurement errors. However, reproducing green water flow and green water storage with a hydrologic model is not straightforward in large-scale watersheds because there are not enough monitoring locations. Furthermore, green water flow and storage cannot be easily extrapolated from a few site-specific studies to large watersheds. Therefore, we compared model predictions of green water flow and green water storage with observations at site locations. Another approach is to compare observed and modeled crop yield. Crop yield or biomass generally accounts for both evapotranspiration and soil moisture required for vegetative growth. Therefore, crop yield can be used as an alternative for evaluating combined AET and soil moisture within the hydrological budget. In this study, we compared uncalibrated SWAT model predictions of streamflow and crop yield with observed data from 11 streamflow locations and the 14 four-digit HUC basin level for crop yield. All the parameters required by SWAT are determined based on Neitsch et al. (2005). The default values of major parameters that control water cycle in SWAT are listed in table 2.

Streamflow

We obtained all monthly and annual streamflow observation data for verification from the USGS website (www.umesc.usgs.gov/data_library/sediment_nutrients/sediment_nutrient_page.html). Figure 4 shows the USGS monitoring station locations that provided observed streamflow data used in comparisons with SWAT outputs. Table 3 shows the drainage area estimated by USGS and SWAT and the time period during which observed data were available for comparison with predicted data. The SWAT estimated drainage areas are within 3% of the basin areas estimated by the USGS (table 3). The difference in drainage area is due to the fact that SWAT estimates its cumulative drainage area based on HUC outlet location. However, the USGS gauge location may not always correspond to the outlet of the HUCs. Thus, there will be some difference between the two areas. In addition, table 3 provides the time period of data available for comparison of streamflow and water quality parameters, which ranges from 6 to 37 years.

Table 2. Default values of major parameters in SWAT.

No.	Parameter	Description	Default Value[a]
1	CN2	Curve number	25-92
2	ESCO	Soil Evaporation compensation factor	0.85
3	OV_N	Manning's coefficient value for overland flow	0.14
4	EPCO	Plant evaporation compensation factor	1.0
5	EVLAI	Leaf area index at which no evaporation occurs from water surface (m^2 m^{-2})	3.00
6	SOL_AWC	Available soil water capacity (mm H_2O mm^{-1} soil)	0.01-0.4
7	Slope	Slope steepness (m m^{-1})	0.0-0.24
8	SOL_Kast	Soil saturated hydraulic conductivity (mm h^{-1})	0.05-400
9	GW_REVAP	Ground water re-evaporation coefficient	0.02
10	REVAPMN	Threshold depth of water in the shallow aquifer for re-evaporation to occur (mm).	1.0
11	GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	1.0
12	GW_DELAY	Groundwater delay (days)	31.0
13	ALPHA_BF	Base flow recession constant	0.048
14	RCHRG_DP	Deep aquifer percolation fraction	0.05
15	GW_SPYLD	Specific yield of the shallow aquifer (m^3 m^{-3})	0.003
16	CH_K2	Effective hydraulic conductivity in main channel alluvium (mm h^{-1})	1.0
17	CH_N	Manning's coefficient for channel	0.014
18	TIMP	Snow pack temperature lag factor	1.00
19	SURLAG	Surface runoff lag coefficient (day)	4.0
20	SMTMP	Snow melt base temperature (°C)	0.5
21	SFTMP	Snowfall temperature (°C)	1.0
22	SMFMX	Maximum snowmelt factor for June 21 (mm H_2O °C^{-1} day^{-1})	4.5
23	SMFMN	Minimum snowmelt factor for Dec. 21 (mm H_2O °C^{-1} day^{-1})	4.5
24	SNOCOVMX	Minimum snow water content that corresponds to 100% snow cover (mm)	1.00
25	SNO50COV	Fraction of snow volume represented by SNOCOVMX that corresponds to 50% snow cover	0.5

[a] For CN2, SOL_AWC, Slope, and SOL_Kast, range of values of all HRUs are listed.

Table 3. The drainage area of each monitoring station, the corresponding SWAT simulated drainage area and the time period of observation data used in this study.

USGS Gauge	Location	Eight-Digit HUC	SWAT Area (km^2)	USGS Area (km^2)	(SWAT Area)/ (USGS Area)	Time Period of Validation
05267000	Royalton, Minn.	07010104	30,180	29,696	1.02	1975-1993
05331000	Hastings, Minn.	07010206	95,940	94,863	1.01	1961-1997
05330000	Jordan, Minn.	07020012	43,720	43,126	1.01	1980-1996
05340500	St. Croix Falls, Wisc.	07030005	20,030	19,768	1.01	1976-1996
05385000	Houston, Minn.	07040008	4,301	4,250	1.01	1991-1996
05369500	Durand, Wisc.	07050005	24,720	24,338	1.02	1991-1996
05474500	Keokuk, Iowa	07080104	309,400	304,640	1.02	1975-1987
05474000	Augusta, Iowa	07080107	11,250	11,016	1.02	1976-1995
05465500	Wapello, Iowa	07080209	32,800	31,997	1.03	1976-1995
05586100	Valley City, Ill.	07130011	74,600	73,656	1.01	1991-1996
05587450	Grafton, Ill.	07110004	447,500	444,185	1.01	1980-1997

Crop Yield

For the duration of simulation from 1991 to 2001, we examined two major crop yields (corn and soybean). The choice of crops represents the watershed land use map well, and the temporal selection does a good job of capturing climatic variability over the 11 years. It is believed that, starting in the 1990s, the climatic norm began to change with shifting temperature and precipitation patterns. SWAT- simulated crop yields were compared with county-level USDA National Agricultural Statistical Survey (NASS) data obtained for each year of interest from the NASS website (www.nass.usda.gov/Data_and_Statistics/Quick_Stats/index.asp). NASS data are reported by county, but many counties have missing data. Thus, we aggregated the data to four-digit HUCs based on the area proportion method and compared the results with the aggregated corn and soybean yields from the SWAT model baseline run for the same four-digit HUCs. NASS reports crop yield in bushel per acre. However, SWAT reports yield in tons per hectare, so we used the following equation to convert bushels per acre to tons per hectare:

$$1\frac{\text{bushel}}{\text{acre}} = \frac{\text{tons}}{\text{hectare}} \times (1+\text{moisture}) \times \frac{\dfrac{2205}{2.471}}{\dfrac{\text{lbs}}{\text{bushel}}} \tag{1}$$

The SWAT model estimates crop yield at 20% moisture content during harvest time, so in equation 1, moisture is 0.2 and pounds per bushel (lbs/bushel) is 56 for corn and 60 for soybean, based on standard literature. Hence, for corn, a yield of 8 tons per hectare would be equivalent to 147 bushels per acre, and a yield of 10 tons per hectare will be about 183 bushels per acre. More details about the corn and soybean weight can be found at the following website: www.unc.edu/~rowlett/units/scales/bushels.html.

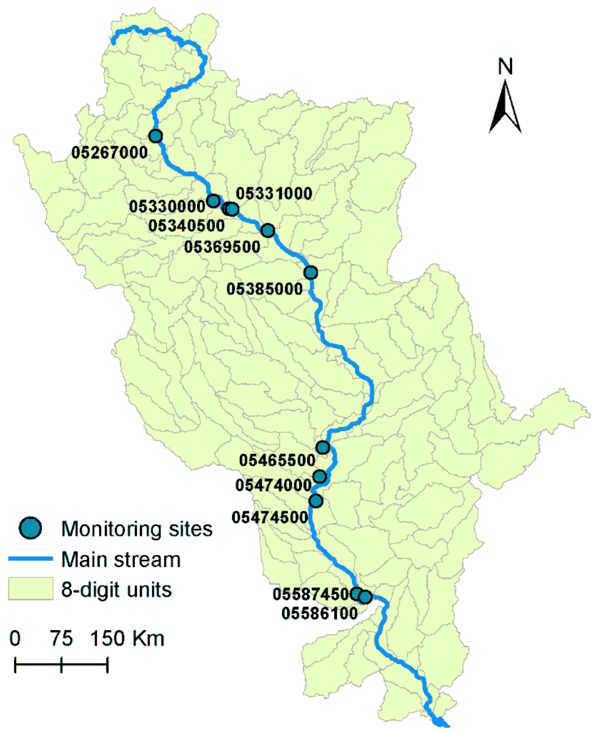

Figure 4. Locations of USGS monitoring stations used in comparison with SWAT results.

Evaluating the Performance of the SWAT Predictions

Previous studies (e.g., Santhi et al., 2001; Moriasi et al., 2007) proposed statistics for evaluating calibrated SWAT performance, but there are no explicit guidelines for evaluating the uncalibrated SWAT model. We investigated two evaluation methods in this study: (1) using evaluation coefficients proposed in previous studies, and (2) comparing the performance of the uncalibrated SWAT model developed in this research with models developed in previous work. Following statistical guidelines set by Santhi et al. (2001) and Moriasi et al. (2007), the evaluation coefficients for deterministic predictions include percent bias (PBIAS), coefficient of determination (R^2), and Nash-Sutcliffe efficiency (NSE). PBIAS is calculated as:

$$\text{PBIAS} = \left(\frac{\sum_{t=1}^{T} (f_t - y_t)}{\sum_{t=1}^{T} (y_t)} \right) \times 100 \qquad (2)$$

where f_t is the model simulated value at time t, and y_t is the observed data value at time t (t = 1, 2, ..., T). PBIAS measures the average tendency of simulated data to be larger or smaller than the observed counterparts (Gupta et al., 1999). PBIAS values with small magnitude are preferred. Positive values indicate model overestimation bias, and negative values indicate underestimation model bias (Gupta et al., 1999).

The formula for calculating the R^2 value is as follows:

$$R^2 = \left\{ \frac{\sum_{t=1}^{T} (y_t - \bar{y})(f_t - \bar{f})}{\left[\sum_{t=1}^{T} (y_t - \bar{y})^2 \right]^{0.5} \left[\sum_{t=1}^{T} (f_t - \bar{f})^2 \right]^{0.5}} \right\}^2 \qquad (3)$$

where $\bar{y}$ is the mean of observed data values for the entire evaluation time period, and $\bar{f}$ is the mean of simulated data values for the entire evaluation time period. The other symbols have the same meanings as defined in the preceding equation. The R^2 value is equal to the square of Pearson's product-moment correlation coefficient (Legates and McCabe, 1999). It represents the proportion of total variance in the observed data that can be explained by the model. R^2 ranges from 0.0 to 1.0. Higher values equate to better model performance.

NSE is calculated as follows:

$$\text{NSE} = 1.0 - \sum_{t=1}^{T} \frac{(y_t - f_t)^2}{\sum_{t=1}^{T} (y_t - \bar{y})^2} \qquad (4)$$

NSE indicates how well the plot of observed versus simulated values fits the 1:1 line. It ranges from $-\infty$ to 1 (Nash and Sutcliffe, 1970), and larger NSE values denote better model performance.

Results and Discussion

Streamflow Comparison

Tables 4 and 5 show the annual and monthly statistics, respectively, for the uncalibrated SWAT model at all 11 USGS gauges. Available data and time period determined the number of data points for comparison, as shown in table 3. Tables 4 and 5 include statistical comparisons of long-term means, standard deviations, R^2, NSE, and PBIAS. The NSE values range from 0.51 to 0.95 on an annual scale and from -0.10 to 0.80 on a monthly scale. The R^2 values range from 0.78 to

Table 4. Comparison of simulated and observed annual streamflow at 11 monitoring sites in the UMRB.

USGS	Average		Standard Deviation				
Gauge	Simulated	Observed	Simulated	Observed	NSE	R^2	PBIAS
05267000	166.20	148.16	77.30	56.59	0.55	0.85	12.18
05331000	456.31	427.02	231.79	181.77	0.71	0.86	6.86
05330000	177.07	192.97	130.38	119.57	0.86	0.90	-8.24
05340500	165.07	176.26	59.73	51.43	0.72	0.83	-6.35
05385000	36.84	37.58	16.86	10.44	0.51	0.93	-1.96
05369500	260.05	264.63	37.61	31.07	0.65	0.78	-1.73
05474500	2354.65	2214.71	813.37	622.88	0.65	0.85	6.32
05474000	91.18	90.16	59.58	56.58	0.95	0.95	1.13
05465500	250.10	277.73	168.27	169.52	0.92	0.95	-9.95
05586100	705.28	882.70	346.04	312.10	0.64	0.98	-20.10
05587450	3206.07	3374.88	1220.56	1029.89	0.80	0.88	-5.00

Table 5. Comparison of simulated and observed monthly streamflow at 11 monitoring sites in the UMRB.

USGS Gauge	Average		Standard Deviation		NSE	R^2	PBIAS
	Simulated	Observed	Simulated	Observed			
05267000	165.37	149.04	149.49	110.14	-0.10	0.42	10.96
05331000	454.82	427.27	448.75	382.99	0.34	0.54	6.45
05330000	180.56	200.29	228.62	228.46	0.48	0.56	-9.85
05340500	164.70	176.58	120.09	125.27	0.11	0.29	-6.73
05385000	36.98	37.50	29.45	23.79	0.20	0.49	-1.40
05369500	263.84	266.11	157.41	140.55	0.06	0.34	-0.86
05474500	2346.73	2205.19	1543.52	1239.83	0.14	0.47	6.42
05474000	91.03	89.49	98.27	103.09	0.80	0.81	1.73
05465500	249.60	275.37	260.05	270.39	0.78	0.80	-9.36
05586100	674.20	869.72	626.21	552.80	0.48	0.69	-22.48
05587450	3204.26	3311.38	2262.37	2054.29	0.50	0.60	-3.23

0.99 on an annual scale and from 0.29 to 0.81 on a monthly scale. PBIAS values are less than 10% for 10 out of the total 11 monitoring sites for both annual and monthly comparisons.

In order to save space, two USGS gauges, one (05587450) with the largest drainage area and another (05586100) with the largest PBIAS, were used to exemplify the process of illustrating simulated and observed streamflow. The simulated and observed streamflow at these two gauges is shown in figure 5 (annual) and figure 6 (monthly).

It is worth noting that, on average, the evaluation coefficients are less on a monthly temporal scale than an annual scale, which may be attributable to one or more of the following factors: snowmelt simulation, seasonal variation in ET and soil moisture conditions, or operation of large reservoirs. By not accounting for all UMRB dams and reservoirs, the accuracy of simulated monthly streamflow variation was diminished. There are over 3,000 reservoirs in the basin. Their flood storage volume of about 49 billion m^3 would take over three months to flow past St. Louis, Missouri, at average discharge rates (www.umrba.org/facts.htm). In this study, we only added the 15 major reservoirs, which account for about 46% (23 billion m^3) of the total storage volume (49 billion m^3) on the main stream (as shown in fig. 4) to the SWAT simulation. It would be worthwhile to collect and compile information about all reservoirs and dams within the UMRB to further improve monthly streamflow simulations. Overall, the uncalibrated model compared very well at an annual temporal scale across all 11 monitoring sites, which indicates that SWAT can adequately produce long-term water yield in ungauged meso-scale and large-scale basins, given the input data developed in this study. Again, for further improvements in monthly streamflow, more detailed information (e.g., reservoirs, dams, and irrigation) needs to be collected.

The streamflow observed at monitoring gauges is composed of combined contributions from surface water and base flow. The mechanisms controlling these two processes are very different from one another. In order to test different land use practices on a watershed's hydrologic budget, a model should be able to realistically simulate contributions from surface flow and base flow (Arnold et al., 2000). There are no observed base-flow data available for the entire UMRB. Therefore, to evaluate SWAT's ability to simulate base-flow contribution, we used the base-flow ratio estimated by Arnold et al. (2000), which uses the base-flow filter method (Arnold et al., 1995). The average observed total flow and estimated base-flow depths from 1961 to 1980 are listed in table 6. These results indicate that the uncalibrated SWAT model can estimate the contribution from base flow well.

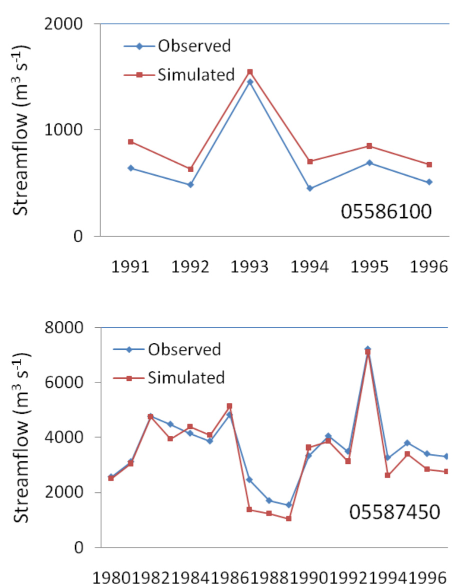

Figure 5. Simulated and observed annual streamflow at two USGS gauges (05586100 and 05587450).

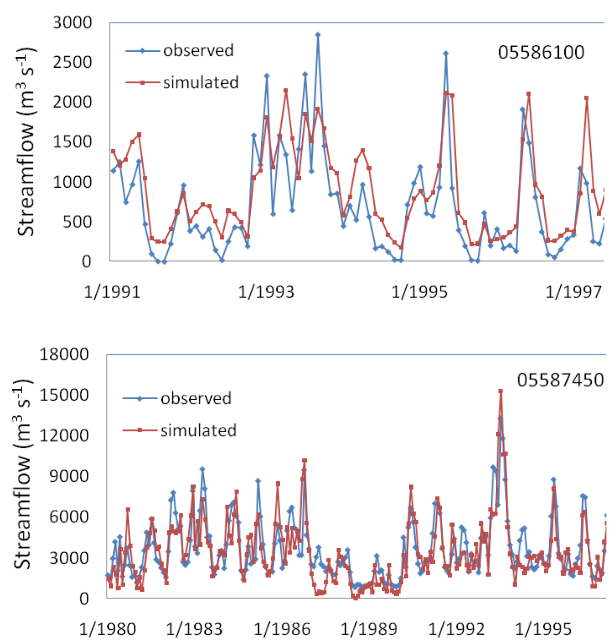

Figure 6. Simulated and observed monthly streamflow at two USGS gauges (05586100 and 05587450).

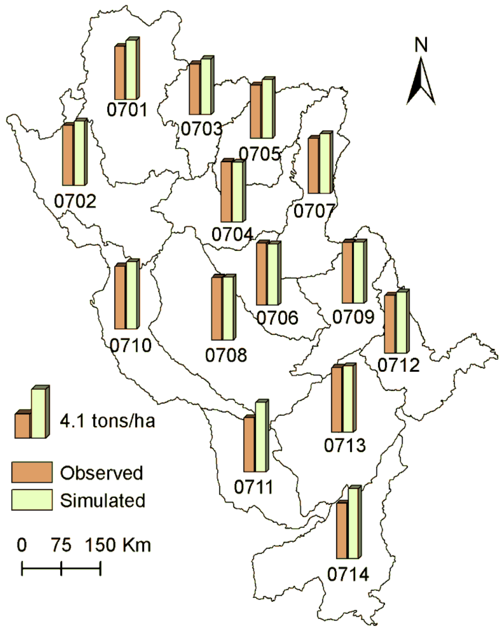

Figure 7. Comparison between SWAT-simulated and NASS-observed corn yield at the four-digit HUC level in the UMRB.

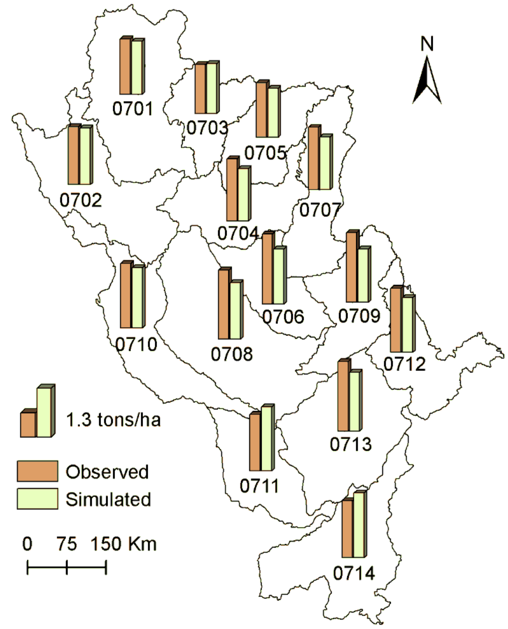

Figure 8. Comparison between SWAT-simulated and NASS-observed soybean yield at the four-digit HUC level in the UMRB.

Table 6. Evaluation of base-flow contribution to total flow.

Methods	Total Flow (mm)	Base Flow (mm)	Base Flow Fraction (%)
Base-flow filter and USGS gauges	207	83	40
SWAT by Arnold et al. (2000)	192	80	42
SWAT in this study	218	98	45

In general, the SWAT model developed in this study provides a good baseline model for use in various analysis scenarios without any user bias. In addition, this study validates how well spatially distributed models are able to produce acceptable results using readily available, physically based input parameters in watersheds ranging from small to very large. Given further information about the watershed's physiographic characteristics, we expect that better simulation results would be obtained, especially on a monthly temporal scale.

Crop Yield Analysis

Differences between SWAT and NASS yields are presented in figure 7 for corn and in figure 8 for soybean for each four-digit HUC in the UMRB. As exhibited in these figures and in tables 7 and 8, the SWAT model predicts observed yield well with a small PBIAS, which is defined as:

$$\frac{(\text{NASS observed yield} - \text{SWAT predicted yield})}{\text{NASS observed yield}} \tag{5}$$

However, in HUC regions 0711 and 0714, SWAT predictions are higher than USDA-NASS reported yields. This could be because SWAT was configured for a baseline run. For example, SWAT uses STATSGO soils, which represent a large area. Thus, SWAT may potentially be using a better, more productive soil set than what is actually in the watershed. In addition, SWAT does not handle pest impact or extreme flooding situations well. Therefore, SWAT-estimated yields represent the typical or potential yield.

Table 7. Analysis of SWAT-simulated and NASS-observed corn yield at the four-digit HUC level for the time period 1991 to 2001.

Four-Digit HUC	Average (tons ha^{-1})		Standard Deviation (tons ha^{-1})		Range (tons ha^{-1})		PBIAS (%)
	Observed	Simulated	Observed	Simulated	Observed	Simulated	
0701	6.27	7.01	0.74	0.96	4.85-7.26	5.46-9.16	12
0702	7.12	7.62	0.67	0.99	6.26-8.08	5.67-9.50	7
0703	5.96	6.56	0.73	0.69	4.50-6.78	5.63-8.16	10
0704	7.15	7.07	0.76	0.90	5.69-8.26	5.73-8.77	-1
0705	6.27	6.93	0.71	0.53	4.51-7.06	6.32-8.10	11
0706	7.33	7.22	0.60	0.64	6.31-8.04	6.47-8.30	-1
0707	6.50	7.05	0.65	0.52	5.48-7.51	6.40-8.08	8
0708	7.39	7.43	0.64	0.73	5.97-8.03	6.07-8.60	1
0709	7.19	7.22	0.71	0.70	5.99-8.11	6.16-8.51	0
0710	7.38	7.89	0.57	0.89	6.06-8.18	6.17-9.29	7
0711	6.38	8.18	0.95	1.34	4.71-8.30	5.43-9.86	28
0712	6.87	7.24	1.13	0.91	4.06-8.18	5.41-8.52	5
0713	7.65	7.85	0.79	1.08	6.19-8.74	5.72-9.52	3
0714	6.53	8.27	0.86	1.13	5.28-7.67	5.79-9.91	27

Table 8. Analysis of SWAT-simulated and NASS-observed soybean yield at the four-digit HUC level for the time period 1991 to 2001.

Four-Digit HUC	Average (tons ha^{-1})		Standard Deviation (tons ha^{-1})		Range (tons ha^{-1})		PBIAS (%)
	Observed	Simulated	Observed	Simulated	Observed	Simulated	
0701	2.02	1.94	0.30	0.13	1.41-2.40	1.62-2.07	-4
0702	2.13	2.08	0.31	0.19	1.29-2.42	1.55-2.23	-2
0703	1.79	1.82	0.27	0.10	1.24-2.19	1.58-1.95	2
0704	2.28	1.92	0.33	0.18	1.62-2.67	1.46-2.15	-16
0705	1.99	1.79	0.27	0.23	1.35-2.34	1.27-2.02	-10
0706	2.56	2.02	0.29	0.17	1.84-2.90	1.64-2.28	-21
0707	2.28	1.93	0.27	0.14	1.73-2.67	1.64-2.17	-15
0708	2.52	2.06	0.25	0.18	1.86-2.85	1.59-2.24	-18
0709	2.55	1.95	0.20	0.15	2.32-2.93	1.55-2.16	-23
0710	2.35	2.20	0.31	0.20	1.50-2.74	1.65-2.41	-6
0711	2.07	2.34	0.24	0.23	1.47-2.40	1.92-2.64	14
0712	2.35	2.00	0.24	0.15	1.77-2.65	1.70-2.24	-15
0713	2.55	2.16	0.11	0.23	2.34-2.72	1.76-2.52	-15
0714	2.07	2.36	0.16	0.21	1.78-2.29	1.90-2.64	14

Furthermore, we compared SWAT and NASS yields on an annual basis. To illustrate, we present two best and two poorly predicted four-digit HUCs in figure 9 for corn and in figure 10 for soybean. Figure 9 shows the annual comparison of predicted and observed corn yield in four-digit HUCs 0708 and 0714 for the years 1991-2001, except the year of 1993. Figure 10 shows the annual comparison of predicted and observed soybean yield in four-digit HUCs 7020 and 0709 for the years 1991-2001, except the year of 1993. One of the worst years for crop production was 1993 due to extended periods of flooding in the UMRB. Therefore, SWAT's prediction was significantly higher than the USDA-NASS reported yield because SWAT did not capture the extended flooding and height of the crops under flood conditions. It is worth noting that SWAT cannot capture annual variation in crop yields very well. For example, in four-digit HUC 0708, SWAT predicted higher corn yield in 1997 than 1996, while the NASS observed data indicated the reverse. Another example is in four-digit HUC 0709 where SWAT predicted lower soybean yield in 1998 than in 1997 and 1999, while NASS observed the highest soybean yield in 1998. One main reason for these inconsistencies is the lack of information on management practices at the farm scale (e.g., tillage, fertilizer and manure application). In the model, we must assign tillage practices according to the tillage area percentage within one eight-digit HUC and use the fertilizer auto-application. These estimated management practices may not reflect actual farm-scale conditions. In previous studies (e.g., Thomson et al., 2005) that applied the Erosion Productivity Impact Calculator (EPIC), which uses a plant growth module similar to SWAT's, researchers usually used average, multi-year crop yields to evaluate model performance because of the difficulties in collecting detailed crop management practices. Overall, the crop yield validation results are satisfactory considering the uncalibrated nature of this study. Another advantage of the uncalibrated model is its extendibility to other various studies, such as the potential expansion of corn production for biofuels or the combined effects of climate change on biofuel production on a large scale.

From the above analysis, SWAT, in general, is able to predict crop yield satisfactorily over the long-term average for most four-digit HUCs, with PBIAS values less than 15%. However, it is worth noting that the PBIAS values can be larger than 20% for several four-digit HUCs (tables 7 and 8). Further information on crop management (e.g., fertilizer, tillage,

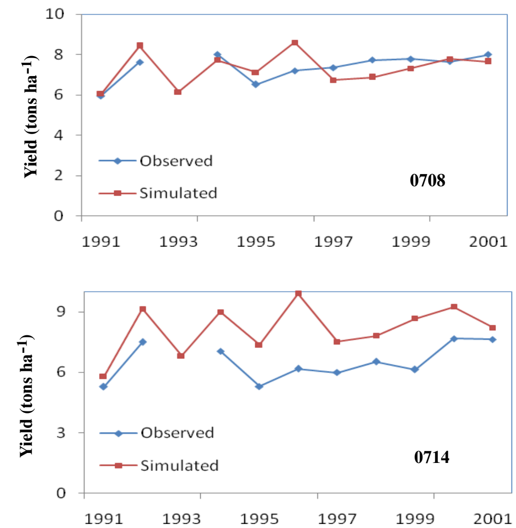

Figure 9. Annual comparison of SWAT-simulated and NASS-observed corn yield for the period 1991 to 2001 for two HUCs (0708 and 0714).

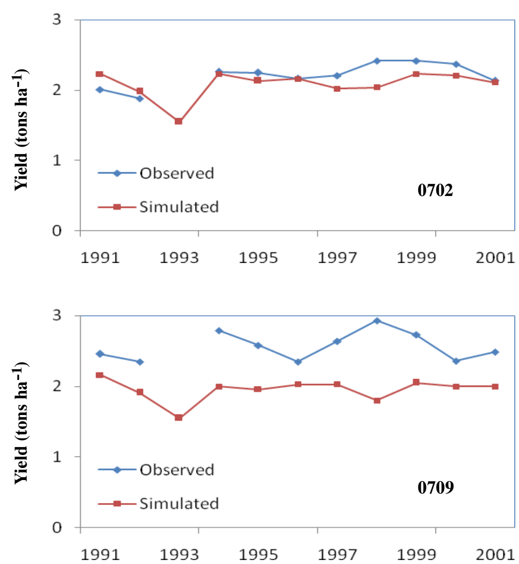

Figure 10. Annual comparison of SWAT-simulated and NASS-observed soybean yield for the period 1991 to 2001 for two HUCs (0702 and 0709).

Table 9. Comparison of annual and monthly streamflow simulations between two SWAT models at USGS gauge 05587450 near Grafton, Illinois.

		PBIAS		R^2		NSE	
		Jha et al. (2004)	This study	Jha et al. (2004)	This study	Jha et al. (2004)	This study
Calibration (1989-1997)	Annual	N/A	-9.1	0.91	0.97	0.91	0.90
	Monthly	N/A	-9.1	0.75	0.75	0.67	0.74
Validation (1980-1988)	Annual	N/A	-4.5	0.89	0.93	0.86	0.81
	Monthly	N/A	-4.6	0.70	0.58	0.57	0.69

and harvest) may improve SWAT's performance for those HUCs. Since crop growth depends on properly predicting AET and soil moisture storage, one could extend the validity and confidence in the model prediction of AET and soil moisture using a well-compared model on crop yield. Arnold and Allen (1996) discussed the application of SWAT for estimating AET in three small watersheds in Illinois (Goose Creek, Hadley Creek, and Panther Creek). Their results indicated that SWAT can produce AET values that are very similar to those observed in the 1950s. The Goose Creek, Hadley Creek, and Panther Creek watersheds are located in eight-digit HUCs 07130006, 07110004, and 07130004, respectively. Due to the space and time mismatch (1950s vs. 1961-2001) and the small area (122 to 250 km^2) of the three watersheds vs. the large area (3018 to 5156 km^2) of the three HUCs, we cannot directly use the observed AET at these three small watersheds to evaluate SWAT performance. However, we expect that the simulated and observed AET values are similar to one another. The average simulated AET values from 1961-2001 are 624 mm (with a range of 548 to 689 mm) in 07130006, 688 mm (with a range of 633 to 747 mm) in 07110004, and 649 mm (with a range of 566 to 712 mm) in 07130004. These values match well with the observed AET values of 617 mm in Goose Creek, 627 mm in Hadley Creek, and 608 mm in Panther Creek, having less than 10% deviation. To some extent, the comparison results indicate that SWAT produced the AET values with reasonable success. Hence, the uncalibrated SWAT model, with its crop growth component, could prove to be instrumental in developing long-term strategies concerning hydrologic budgets and crop and vegetative biomass yield for strategic biofuel production planning.

Comparison with Previous Applications of SWAT in the UMRB

Several SWAT model applications have been developed for the UMRB. In this study, we compare the performance of the uncalibrated SWAT model developed in this study to other SWAT models developed in previous studies. Arnold et al. (2000) created a UMRB-scale SWAT model that was shown to successfully simulate monthly streamflow with R^2 values larger than 0.6 at Alton, Illinois. Jha et al. (2004) calibrated SWAT for streamflow simulation in the UMRB using monthly and annual streamflow data from the USGS gauge near Grafton, Illinois. Wu and Tanaka (2005) evaluated a SWAT model using monthly average streamflow with data from a USGS gauge station near Grafton, Illinois. Their results showed that the difference between simulated and observed average monthly streamflow values (1980-1999) was less than 5%. Because the difference between the drainage areas of USGS gauges at Grafton and Alton is very small (443,667 vs. 442,185 km^2), we used the evaluation coefficients obtained at Grafton, Illinois, in comparisons between the three SWAT studies. Because the three SWAT models use different time periods for model calibration and validation, we compared them separately. Compared with Wu and Tanaka (2005), the PBIAS of the average monthly streamflow simulation from 1980-1997 is less than 5% (-3.23%). Using monthly flow from 1981-1985, Arnold et al. (2000) obtained an R^2 value of 0.65 and a PBIAS of -15.09%, which compare to an R^2 of 0.58 and a PBIAS of 2% calculated using the simulated results in this study. In general, the evaluation coefficients obtained in this study are similar to those reported by Arnold et al. (2000) and Wu and Tanaka (2005), who used calibrated SWAT models. Our comparison between this research and the results of Jha et al. (2004) is illustrated in table 9. Annual and monthly streamflow data for the same time period (1980-1997) were available, allowing us to calculate evaluation coefficients for both studies. All annual streamflow simulation R^2 and NSE values are greater than 0.8. For monthly streamflow simulation, this study obtained a greater NSE value than Jha et al. (2004) (0.74 vs. 0.67) during the calibration period. During the validation period, Jha et al. (2004) obtained a greater R^2 value (0.70 vs. 0.58), but this study obtained a greater NSE value (0.69 vs. 0.57). Overall, the uncalibrated SWAT model performed similarly to the calibrated SWAT model of Jha et al. (2004) in terms of R^2 and NSE.

The above results indicate that the uncalibrated SWAT model's performance is comparable to calibrated SWAT models used in previous studies. One major difference between the SWAT model developed in this study and those developed in previous research lies in the input data. Although all four SWAT models used eight-digit HUCs and STATSGO soil maps, the DEM, land use map, climate input data, and management practices are different from one another. Since we do not have access to the SWAT project files from other studies, a detailed comparison between the input data and derived parameters (e.g., slope, elevation, land use, precipitation, temperature, tillage, and fertilizer) cannot be completed. In the future, the effect of input data on SWAT simulation should be further explored.

UMRB Biomass Availability

In the current energy debate, renewable, clean energy derived from plant biomass is a major potential commodity. The UMRB contains some of the most fertile land in the U.S. We extended this study to estimate potential annual biomass production for the entire UMRB by converting all arable crop lands into fields of switchgrass. The SWAT model has the ability to simulate various bioenergy crops. Switchgrass was chosen as one of the most promising bioenergy crops for both cellulose and biomass process-based biofuel production. Hence, all agricultural fields were modified from the typical corn and soybean rotations to switchgrass. Figure 11 shows the average biomass production results for each eight-digit HUC in the UMRB. The 41-year, average yield for the entire

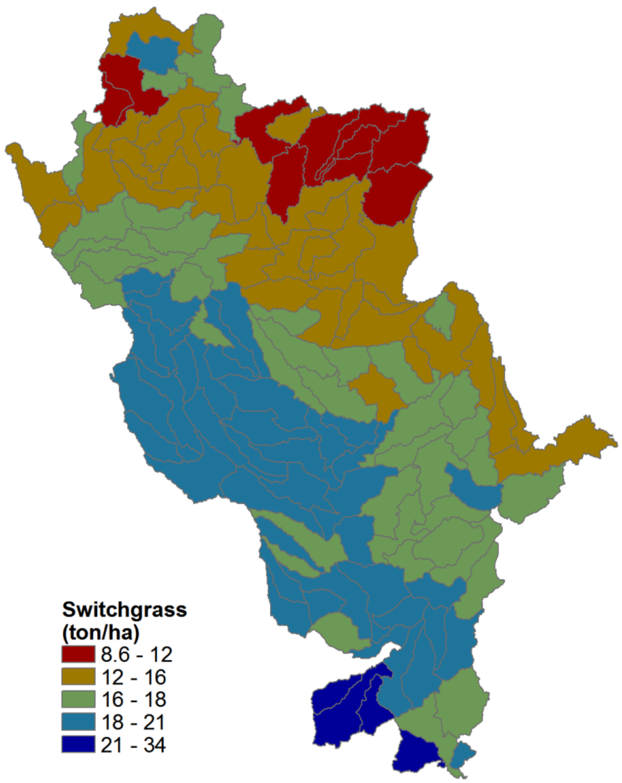

Figure 11. Average annual SWAT simulated Switchgrass yield at the eight-digit HUC level in the UMRB.

basin is 17.44 tons per hectare, and individual eight-digit HUCs vary from 8.6 to 33.9 tons per hectare, showing tremendous variability in biomass production. Thus, the model can help identify high-yielding areas as potential biofuel production facility locations to reduce the cost of hauling and transport. These yield ranges are very similar to those observed in field trails throughout the Midwest as described by Dr. Jim Kiniry, research agronomist with the USDA-ARS in Temple, Texas. The overall average, annual estimated production of switchgrass energy crop within the UMRB is 0.38 billion tons. This provides a good estimate for energy production capabilities and informs policy makers of biofuel production potential within the UMRB in lieu of grain production. In addition, figure 11 provides a very good spatial pattern for high-yielding bioenergy crop production sites, which is not much different from that of high-yielding grain crops. However, the figure also shows the spatial location of marginal lands that could potentially be used for renewable energy production.

Conclusions

Scientists and planners have been using physically based, distributed hydrologic models increasingly for the assessment of water resources, best management practices, and climate and land use changes. Our research involved the application of the physically based, spatially distributed SWAT model for hydrologic budget and crop yield predictions from an ungauged perspective. We proposed a framework for developing spatial input data, including hydrography, terrain, land use, soil, tile, weather, and management practices, for SWAT in the UMRB and tested the uncalibrated SWAT model for streamflow, base flow, and crop yield simulation. We used annual and monthly streamflow from 11 USGS monitoring gauges to test SWAT, and found that SWAT can capture the amount and variability of annual streamflow very well (PBIAS is less than 10% for 11 monitoring stations, R^2 values range between 0.78 and 0.99, and NSE ranges between 0.51 and 0.95). For monthly streamflow simulation, the performance of SWAT is slightly degraded (R^2 values range from -0.10 to 0.80, and NSE ranges between 0.29 and 0.81), which may be mainly attributed to incomplete information about the reservoirs and dams within the UMRB. Further validation indicates that the simulated base-flow contribution ratio (BFR) of 45.1% is very close to the filtered BFR of 40% calculated by Arnold et al. (2000). At the four-digit HUC scale, SWAT can predict corn and soybean yields well (PBIAS is less than 20% for 11 out of 14 four-digit HUCs for both corn and soybean). In addition, the uncalibrated SWAT model developed in this study produced similar evaluation statistics to those calculated using calibrated SWAT models from three previous studies. Overall, the SWAT model can satisfactorily predict the UMRB hydrologic budget and crop yield without calibration. This makes it a readily extendible SWAT model for assessing the consequences of management practices and predicting the effects of climate and land use changes such as biofuel crop and biomass production. The results emphasize the importance and prospects of using accurate spatial input data for the physically based SWAT model. Furthermore, we extended the study to assess total UMRB biofuel energy crop production by converting all agricultural land into switchgrass production. The UMRB has the potential to produce 0.38 billion tons of biomass per year, with an average production of 17.44 tons per hectare.

Acknowledgements

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