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Assessing the impacts of crop-rotation and tillage on crop yields and sediment yield using a modeling approach

P.B. Parajuli[a,*], P. Jayakody[a], G.F. Sassenrath[b], Y. Ouyang[c], J.W. Pote[a]

[a] Department of Agricultural and Biological Engineering, Mississippi State University, Mississippi State, MS, USA
[b] USDA/ARS, Stoneville, MS, USA
[c] USDA/FS, Mississippi State, MS, USA

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ABSTRACT

This study was conducted in the Big Sunflower River Watershed (BSRW), north-west, Mississippi. The watershed has been identified as "impaired waters" under Section 303(d) of the Federal Clean Water Act due to high levels of sediment and total phosphorus. This excess is then transported to the Gulf of Mexico via the Yazoo River, further damaging the nation's water resources. The specific objectives of this study were to assess the impact of corn (*Zea mays* L.), soybean (*Glycine max* (L.) *Merr.*, and rice (*Oryza sativa*, L.) crop-rotations (corn after soybean, soybean after rice, continuous soybean) and tillage practices (conventional, conservation, no-till) on crop yields and sediment yield using the Soil and Water Assessment Tool (SWAT) model.

The SWAT model was calibrated from January 2001 to December 2005 and validated from January 2006 to September 2010 for monthly stream flow with good to very good performance [coefficient of determination (R^2) values from 0.68 to 0.83 and Nash Sutcliffe Efficiency index (NSE) values from 0.51 to 0.63] using stream flow data from three spatially distributed USGS gage stations within the BSRW. The SWAT model was further calibrated for corn and soybean yields from research fields at Stoneville and validated using research fields at the Clarksdale experiment stations with fair to excellent statistics (R^2 values from 0.43 to 0.59 and NSE values from 0.34 to 0.96). The SWAT model simulation results suggested that corn yields were greater in the corn after soybean rotation under conventional tillage (mean = 9.88 Mg ha^{-1}) than no-tillage (mean = 8.81 Mg ha^{-1}) practices. However, tillage practices had no effects on soybean yield for the corn after soybean rotation. Soybean yields under conventional tillage practice indicated greater yields (mean = 3.01 Mg ha^{-1}) for the soybean after rice rotation than for soybean after corn. Continuous soybean under conventional tillage had the lowest simulated crop yield (mean = 2.07 Mg ha^{-1}) and the greatest sediment yield (5.2 Mg ha^{-1}) in this study. The cumulative (1981–2009) sediment yield at the end of the simulation period (2009) indicated a maximum difference of about 8 Mg ha^{-1} between no-till and conventional tillage practices, with no-till contributing the lowest sediment yield. The cumulative difference of the sediment yield between no-till and conservation till was about 2 Mg ha^{-1}. The results of this study will help to better understand the impact of management practices on watershed crop management and water quality improvement within the BSRW. This information can be applied to other agricultural watersheds.

1. Introduction

According to the Food and Agriculture Organization (FAO) statistics approximately 850 million people in the world are struggling with food shortages and hunger. Greater levels of crop production are needed to meet the growing global demand for food. Simultaneously, farmers are being increasingly required to reduce the negative environmental impacts of their production practices. Crop yield is influenced by internal (e.g. soil properties) and external factors including crop management practices, fertilizer, irrigation, climate and others. These choices of crop management that improve yield can also have serious negative consequences to the environment, such as impacting water quality through erosion and chemical runoff. Knowledge of how farming practices impact the environment can help to improve water quality, crop yield, and water use efficiency. Pimentel and Patzek (2005) indicated that traditional U.S. crop production systems, especially corn, have been rapidly degrading environmental sustainability, for example

* Corresponding author at: Department of Agricultural and Biological Engineering, Mail Box 9632, Mississippi State University, Mississippi State, MS 39762, USA. Tel.: +1 662 325 7350; fax: +1 662 325 3853.
E-mail address: pparajuli@abe.msstate.edu (P.B. Parajuli).

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through increased soil erosion. Unless major changes are made in the cultivation of this crop, continued environmental impairment will hinder future productive capacity. Corn is a raw material for ethanol production, but cannot be considered to provide a renewable energy source. One of the major challenges currently facing agricultural practitioners and scientists is how to increase crop productivity without further degrading the environment.

Agriculture is the major contributor of non-point source pollution to water quality (Parajuli et al., 2008; Lam et al., 2009), and the major user of soil and water natural resources. Agriculture-related pollution may include sediment, nutrients, and pesticides that cause water quality degradation (Zalidis et al., 2002; Thorburn et al., 2003). Application of nutrients such as fertilizer is essential for sustaining food production, but it can become a nonpoint pollutant to surface water resources due to poor agricultural practices. Changes in crop rotation and tillage management offer alternative production practices that can preserve soil resources and minimize contamination (Ma et al., 2007; Jaynes et al., 1999; Cambardella et al., 1999). An increase in agricultural water productivity is necessary to improve water management and reduce environmental problems (Ali and Talukder, 2008). Improvements in water productivity and quality are related to the improved management of water and nitrogen application (Nangia et al., 2008).

There is no doubt that crop management and water quality are inter-related. It is essential to know where and when pollution is generated and how crop management choices impact crop yields in the southern U.S. states like Mississippi in order to develop realistic pollution abatement approaches. Water quality responses related to the crop management practices such as crop-rotations and tillage managements are spatially varied over the watershed, which need to be identified to implement improved management practices (Singer et al., 2011; Ullrich and Volk, 2009). About 70% of the state's soybean crop and 43% of the state's corn crop are grown in the resource abundant Mississippi River Valley alluvial flood plain in the northwest section of the state, colloquially known as the Delta (MAFES, 2009).

Assessing the impact of farming practices on soil and water quality is essential to provide the information for developing more economically and environmentally sustainable agricultural management systems (Bakhsh et al., 2000). Agricultural management practices such as crop rotation, tillage practices, and conservation practices can have significant impacts on water entry and retention of water and nutrient processes in the soil profile (Weed and Kanwar, 1996; Boddy and Baker, 1990).

Tillage intensity in the region ranges from the currently conventional tillage (CT) practice of chisel-plowing, with maximal soil disruption, to the reduced till (RT) or conservation till (CST) practice, and no-tillage (NT). Tillage operations affect nutrient cycling in several ways by altering soil structure and the decomposition of crop residues and soil organic matter (Katupitiya et al., 1997). As a result, the structure of soils in NT fields is often very different from that in CT fields. Macropores, including cracks, worm burrows, and root channels, are generally larger in size and form a better connected network in NT than CT soil (Singh and Kanwar, 1991). Also, as the intensity of tillage is decreased, the quantity of mulch remaining on the soil surface from a previous crop increases. The increased mulch helps to reduce evaporation and runoff while increasing infiltration (Green et al., 1995). In addition, combined with mulch and well-developed network of macropores, help to reduce evaporation and runoff by enhancing infiltration and greater soil water contents (Smith and Cassel, 1991).

Previous research on crop yield has found that within-field spatial variations play an important role in crop yield within a given year (Cox et al., 2006). This spatial variability arises from soil properties and landscape features that affect patterns in plant available water-holding capacity or soil drainage and aeration (Jaynes and Colvin, 1997; Mulla and Schepers, 1997). Bakhsh et al. (2000) found that crop yield variability may not only be controlled by inherent soil properties but also by other external factors such as climate, agricultural management practices, and topographic characteristics of the fields. Yang et al. (1998) conducted crop yield research using the Geographic Information Systems (GIS). They reported that topographic attributes have an influence on crop yield variability in the Palouse region in the northwest U.S. Several researchers have used map overlay analysis, a GIS techniques to determine the combined effect of various factors within agricultural fields (Diaz et al., 1998; Hashmi et al., 1995; Wesseling and Feddes, 2006). The GIS tools and techniques have the ability to create and overlay various data layers in order to examine their interaction with each other over the space and time (Tim and Jolly, 1994).

A watershed hydrologic and water quality model use a set of mathematical descriptions to simulate hydrologic cycles, and they are accepted tools to evaluate hydrological processes (Singh and Woolhiser, 2002). Hydrological models can be used to simulate stream flow, water and nutrient yields from spatially variable watershed source areas. Hydrological models such as the Soil and Water Assessment Tool (SWAT; Arnold et al., 1998) offer a useful means of evaluating the effects of agricultural management practices, human impact, and conservation scenarios, and help make watershed management decisions (Fohrer et al., 2005; Lin et al., 2007).

Baffaut and Benson (2003) used the SWAT model in the Shoal Creek watershed, Missouri, to consider the physical properties of the watershed and the farming practices for the simulation period (1990–2001). One of the parameters used in the model calibration was crop yield (hay) data for the Barry and Newton Counties. They demonstrated that the correct representation of the crop yields can ensure the correct amounts of moisture and nutrient uptake by the vegetation and removal from the hydrologic system. The average crop yield simulated by SWAT for the 12 year periods under-predicted crop yield by 5% (4.25 Mg ha^{-1} vs. 4.48 Mg ha^{-1}) from the average reported yield for Barry and Newton Counties. However, the model was not validated at the small field scale using crop yield data.

The ability to predict crop yields prior to harvest and its water quality impacts covering large-scale watershed areas are important concerns for many countries. Crop yield is an outcome of several complex soils and climate related factors, and their effect on crop yield can be better predicted using GIS-based watershed models. Crop yield prediction requires the application of crop growth models (Soria-Ruiz and Ordonez, 2006). The plant growth models such as the Erosion-Productivity Impact Calculator (EPIC; Williams, 1995) in conjunction with hydrologic simulation tools such as the SWAT (Arnold et al., 1998) model can be used to investigate potential crop yields, water quality and hydrologic impacts due to land use change. Several previous studies applied, calibrated and validated the SWAT model to assess surface runoff, sediment and nutrient yields, and bacteria loadings from several geographically referenced locations (Wang et al., 2006; Gassman et al., 2007; Parajuli, 2007; Parajuli et al., 2008; 2009; Lin et al., 2009; Parajuli, 2010). However, most of these applications and evaluations have considered only the hydrology and water resource implications.

The specific objectives of the study were to: (a) calibrate and validate the SWAT simulated results using field measured corn and soybean crop yield data and (b) assess various crop management practices and their impact on crop yields and sediment yields using a modeling approach. This study examines current crop management practices, stream flow, and crop yields in the BSRW in Northwest, Mississippi. Management practices, crop rotations and tillage management and their impact on crop yields and sediment yields were assessed.

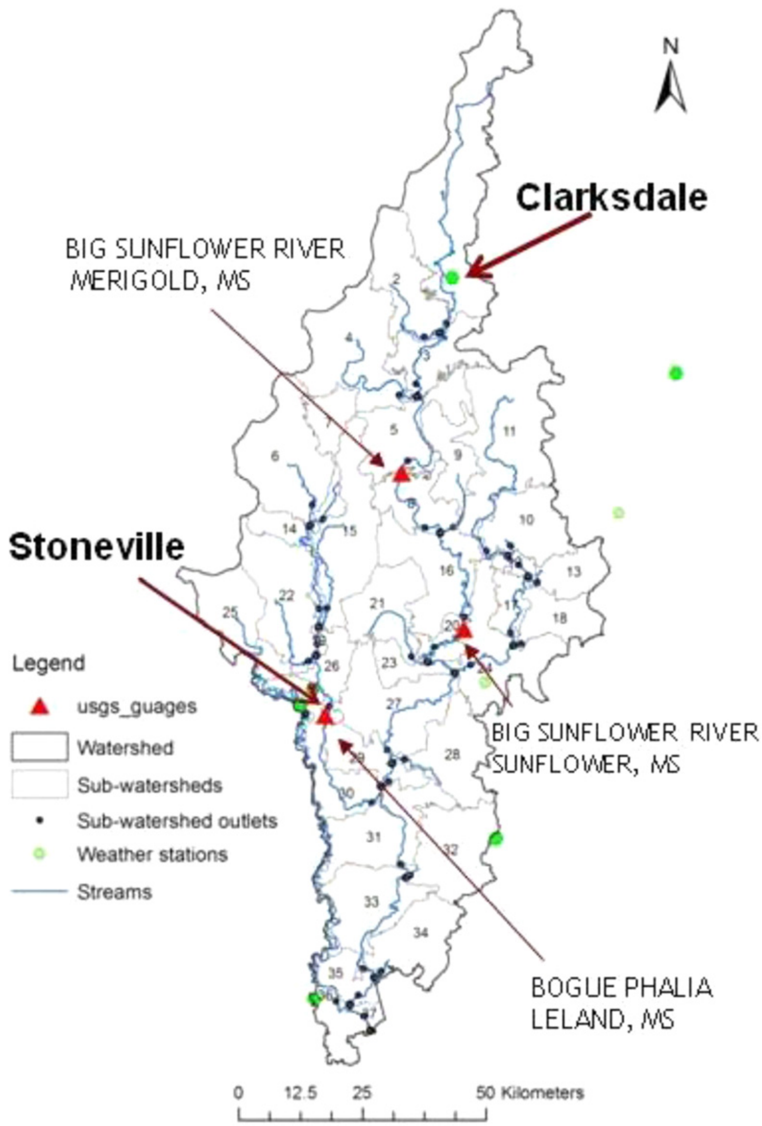

Fig. 1. Location of the Big Sunflower River watershed showing Stoneville and Clarksdale agriculture experiment stations.

2. Materials and methods

2.1. Watershed

The BSRW (Fig. 1; 10,488 km^2) is an area of intensive row crop production, mainly soybean, corn, cotton (*Gossypium hirsutum* L.) and rice. The BSRW covers most of the Delta region including eleven Mississippi counties (Coahoma, Bolivar, Tallahatchie, Sunflower, Leflore, Washington, Humphreys, Sharkey, Issaquena, Yazoo and Warren). Land use in the watershed is predominantly agricultural (>80%; USDA/NASS, 2009). The BSRW drains into the Mississippi River near Vicksburg, MS. The BSRW (HUC-08030207) is one of the forty-one watersheds in the twelve Mississippi River Basin Initiative (MRBI) states. The NRCS State Conservationists identified the BSRW as one of the high priority or focused watersheds to improve water conservation and water quality (USDA/NRCS, 2010).

2.2. SWAT model

The SWAT model (Arnold et al., 1998; Neitsch et al., 2005) is a physically based, continuous, daily time step model, which predicts surface runoff, sediment and nutrient yields, pesticide, bacteria, and crop yields. The SWAT model sub-divides a watershed into sub-basins as delineated using a digital elevation model (DEM) and small spatial units called the hydrologic response units (HRUs). The HRUs are generated based on the intersection of unique land use and soil conditions within the model; spatially variable input parameters can be provided for the simulation. These input parameters can directly impact the hydrology, water quality and crop yields. The SWAT model estimates daily time-period parameters (e.g. runoff and evapo-transpiration), which are largely driven by daily rainfall inputs, other climate parameters and irrigation in the model. The variability in the crop growth functions is simulated in the SWAT model utilizing the EPIC model. In the SWAT model all the available heat units above the base temperature helps crop-growth and crop-development. The SWAT model keeps the records of the daily sum of the heat units and daily average temperature must be greater than the base temperature for the crop to grow (Neitsch et al., 2005).

The SWAT model requires several geospatial data inputs that cover the watershed boundary (e.g. DEM, land use, and soil). The model uses these geospatial input parameters to develop specific model inputs for each HRU, and sub-basins in the watershed. The 30 m × 30 m grid DEM data from the U.S. Geological

Table 1
Hydrologic parameters used to auto-calibrate the SWAT model.

	Parameters	Fitted value (Sufi-2)	Range	Final (hybrid)
1	Cn2[a]	Not used	45–92	45–92
2	Alpha_bf	0.70	0.20–0.90	0.70
3	Gw_delay	12.70	2.0–45.0	12.70
4	Ch_n2	0.23	0.014–0.30	0.23
5	Sol_awc	0.24	0.02–0.90	0.24
6	Surlag	3.5	2.0–8.0	3.5
7	Rchrg_Dp	0.67	0.0–0.9	0.67
8	Epco	0.7	0.1–0.9	0.9
9	Esco	0.3	0.1–0.9	0.7
10	Gw_Revap	0.06	0.02–0.20	0.02
11	Gwqmn	251	2.0–1000.0	251
12	Revapmn	300	1.0–400.0	300

Note: Cn2 = curve number, Alpha_bf = base flow recession constant, Gw_delay = delay of time for aquifer recharge, Ch_n2 = Manning's "*n*" value for the main channel, Sol_awc = available water capacity, Surlag = surface runoff lag coefficient, Rchrg_Dp = aquifer percolation coefficient, Epco = plant uptake compensation factor, Esco = soil evaporation compensation coefficient, Gw_Revap = ground water revap coefficient, Gwqmin = threshold water level in shallow aquifer for base flow, Revapmn = threshold water level in shallow aquifer for revap.

[a] Not included in the calibration.

Survey (USGS, 1999) was used to create the UPRW watershed boundaries; soil input data was developed using the Soil Survey Geographic Database (SSURGO, USDA, 2005). The cropland data layer (USDA/NASS, 2009) was used to create land use data for the entire watershed for model input. The model also used daily measured rainfall and temperature data as a climate data input from the ground based climate stations maintained by the National Climatic Data Center (NCDC, 2012). Daily climate data were utilized from seven weather stations within or near the watershed including the Stoneville experiment station, which collects precipitation, both maximum and minimum temperatures, wind speed, and relative humidity. The BSRW was divided into 37 sub-watersheds. Three USGS gage stations (7288280 at Merigold, 7288500 at Sunflower, and 7288650 at Leland) provided monthly stream flow data.

2.3. Stream flow calibration and validation

The SWAT model was parameterized to assess the long term stream flows from three spatially distributed USGS gage stations in the BSRW. A one year warm-up period was considered prior to the model simulation starting date. The model was calibrated from January 2001 to December 2005 and validated from January 2006 to September 2010 using USGS monthly stream flow data. The SWAT model literature described model calibration and validation procedures by changing one key parameter at a time manually (Parajuli, 2010). This study used the Sequential Uncertainty Fitting (Sufi-2) SWAT Calibration and Uncertainty Procedures (Swat-cup2) automatic calibration technique to determine the final model input values of twelve hydrologic parameters (Table 1, Abbaspour et al., 2007). The Swat-cup2 is a SWAT calibration and uncertainty program developed to estimate various statistical values and provide model evaluation statistics to assess model efficiency and Sufi-2 is a program procedure where Swat-cup2 can be linked (Abbaspour et al., 2009).

The Cn2 is the moisture condition II curve number, which was used to represent land use conditions of the watershed; Alpha_bf is the base flow recession constant, which considered watershed land areas with rapid response; Gw_delay is the delay of time for aquifer recharge, which was estimated by simulating aquifer recharge using different values; Ch_n2 is the Manning's "*n*" value for the main Channel, which was considered for the natural channel with good conditions grass; Sol_awc is the available water capacity, which was estimated by determining the amount of water released between in situ field capacity and the permanent wilting point by the model; Surlag is the surface runoff lag coefficient, which considered more water held in storage; Rchrg_Dp is the aquifer percolation coefficient, which considered a good fraction of percolation from the root zone to recharges the deep aquifer; Epco is the plant uptake compensation factor, which allowed more of the water uptake demand to be met by lower layers in the soil in this condition; Esco is the soil evaporation compensation coefficient, which allowed model to consider depth distribution used to meet the soil evaporative demand; Gw_Revap is the ground water revap coefficient, which allowed minimum water movement of from the shallow aquifer to the root zone in this model simulation; Gwqmn is the threshold water level in shallow aquifer for base flow, which was adjusted to simulate threshold depth of water in shallow aquifer required for the base flow to occur and Revapmn is the threshold water level in shallow aquifer for revap or percolation to deep aquifer, which allowed to decrease water movement between two aquifers to occur revap in the SWAT model (Neitsch et al., 2005). As long as upper and lower values of the model calibration parameters are within the range of values, they are considered good. Consequences of lower limit or upper limit values in the physical condition of the watershed are specific to each parameter. For example, the "esco" parameter value close to "0" allows more water extraction from the lower soil layers to meet the evaporative demands. However the "esco" value close to 1 allows less water extraction from the lower soil layers. Therefore, every watershed is unique in its hydrologic characteristics. The detailed descriptions of parameter used in Table 1 are available in the SWAT documentation (Neitsch et al., 2005).

The Cn2 value was not included in the automatic calibration as the model allowed only one Cn2 number for all sub-watersheds with a different land use. However, the Cn2 value was manually calibrated based on land use and the Sufi-2–Swat-cup2 parameters (Abbaspour et al., 2007). Monthly observed USGS gage data from three stations (Merigold, Sunflower, and Leland) were compared with monthly model predicted data.

2.4. Crop yield calibration and validation

The SWAT crop growth module can simulate the crop growth and crop yield. The detailed crop management data for corn and soybean are not available for all the agricultural cropland areas in the BSRW. However, management data from the two agricultural experiment stations, located at Stoneville and Clarksdale within the BSRW provided representative data for the watershed. These experiment stations maintain records of crop management practices and crop yields. Stoneville and Clarksdale are located within the sub-watersheds 30 and 1, respectively of the BSRW (Fig. 1), where field test plots and variety trial experiments were carried out. The model was calibrated using crop yield data from research plots at the USDA-ARS Crop Production Systems Research Unit (CPSRU) Stoneville and validated using crop yield data at Clarksdale. Both locations are used for research test plots using standard agricultural practices for row crop production. Soils are typical alluvial soils ranging from rapidly draining sandy and silty loams to slowly drained clays (Vanderford, 1962). Field preparation after harvesting in the fall includes disking and hipping to establish seed beds on 96.5 cm rows. Deep tillage is performed to break up the soil structure and improve water infiltration into the soil. Prior to spring planting, seed beds are firmed using a do-all or roller.

Model input parameters were unchanged during the model validation process. The crop management data include planting date, harvesting dates, irrigation, and fertilization. Rates of irrigation and fertilization were assumed to address crop needs, as the research stations maintained a controlled growth environment in comparison to the production crop fields in the BSRW. These assumptions in the model minimize water stress and nutrient stress in the

Table 2
Crop rotations and tillage management practices used in the model.

Crop rotation	Tillage	Planting date	Harvesting date	Fertilized crop
Corn after soybean	Conventional	March 15	August 15	Corn only
Corn after soybean	No-Till	March 15	August 15	Corn only
Soybean after soybean	Conventional	March 15	August 15	None
Soybean after soybean	No-Till	March 15	August 15	None
Rice after soybean	Conventional	April 15	September 15	Rice only
Rice after soybean	No-Till	April 15	September 15	Rice only

Note: All the crops were under auto-irrigation.

crop fields. The current crop rotation in the watershed was considered soybean after corn. One crop per year is very common in the watershed based on the local climatic conditions. Model input data includes: planting corn on March 15 and harvesting on August 15, which represent typical field conditions within the watershed. Soybeans have a much broader planting and harvesting window in the area (Table 2). For simplicity in the simulations, the planting and harvesting dates for soybean were assumed to be similar to corn. Both soybean and corn crops were irrigated. Model inputs considered an auto-fertilization (28-10-10) only for corn, which is similar to the suggested rates based on anticipated yield (Larson, 2008); the model assumed soybean had nitrogen fixation capability. Corn and soybean were established on seed beds to allow adequate early-season drainage and within-season irrigation through furrows, as is the standard practice in the region. In this study we used the furrow out cultivator to create furrows in the model simulation. The measured crop yield data were recorded in bushels per acre unit, using the standard bushel dry weights of 56 lbs bu^{-1} for corn and 60 lbs bu^{-1} for soybeans, and converted to dry weight megagrams per hectare of land for comparison to the SWAT yield prediction. The standard conversion rate estimates 25 kg of corn per bushel and 27 kg of soybean per bushel (Weiland and Smith, 2007). Table 3 presented four crop parameters water stress (AUTO_WSTRS), nitrogen stress (AUTO_NSTRS), leaf area index (BLAI), and harvest index (HVSTI) used for corn and soybean yields calibration in the model. Detailed descriptions of these calibration parameters are available in the SWAT model documentation (Neitsch et al., 2005).

Among crop parameters, the harvest index (HVSTI) parameter in the model has been commonly utilized to predict crop yield in the model simulation studies (Soltani et al., 2005; Craufurd et al., 2002). The HVSTI is also used in the field level experimental studies to analyze crop yields. The SWAT model defined HVSTI as the fraction of the above-ground plant dry biomass removed as dry economic yield, which is calculated by the model every day of the plant's growing season during the model simulation period (Neitsch et al., 2005). The HVSTI values for the common crops harvested above the ground are generally used from 0 to 1. The HVSTI values are relative to obtainable soil-water-content in the water-limited conditions after anthesis (Nix and Fitzpatrick, 1969; Passioura, 1986). Since the HVSTI values are dependent on obtainable soil-water-content, they are not considered as an independent value to impact on crop yield (Kang et al., 2003).

Table 3
Crop parameters calibrated and suggested final values.

Parameter/crop	Corn		Soybean	
	Range	Final value	Range	Final value
AUTO_WSTRS	0.85–0.98	0.95	0.82–0.98	0.95
AUTO_NSTRS	0.85–0.98	0.95	NA	NA
BLAI	5–8	7	3–5	4
HVSTI	0.5–0.7	0.65	0.3–0.4	0.35

AUTO_WSTRS: water stress, AUTO_NSTRS: nitrogen stress, BLAI: leaf area index, HVSTI: harvest index, NA = not applicable as soybean was not fertilized.

2.5. Statistical analysis

The SWAT model predicted results were compared with the field measured data utilizing commonly used statistical parameters such as mean, correlation-coefficient (R^2), and Nash-Sutcliffe efficiency (NSE) categories as recommended by previous studies (Moriasi et al., 2007; Parajuli et al., 2009). Parajuli (2010) classified the SWAT model performances of the monthly flow simulations using six categories (excellent for R^2 and NSE $\geq$ 0.90; very good for R^2 and NSE = 0.75–0.89; good for R^2 and NSE = 0.50–0.74; fair for R^2 and NSE = 0.25–0.49, and poor for R^2 and NSE = 0–0.24; and unsatisfactory for R^2 and NSE < 0).

The Swat-cup2 and Sufi-2 program calibration method uses percentage of measured data within the 95% prediction uncertainty (*P*-factor), which referred a degree of all uncertainties. The strength of a calibration/uncertainty analysis is determined by *R*-factor, which shows the thickness of the 95% prediction uncertainty band divided by the standard deviation of the measured data. Coefficient of determination (R^2) multiplied by the coefficient of the regression line is bR^2. The sum of the squares (SSQR) method measures frequency distributions of the measured or observed and the simulated values. The mean square error (MSE) measures the average of the squares of the errors between measured and simulated values. More information on *P*-factor, *R*-factor, br^2, SSQR and MSE are available in Swat-cup2 calibration and uncertainty programs (Abbaspour et al., 2009).

3. Results and discussion

This study calibrated and validated monthly stream flow within the BSRW, corn and soybean yields at two agricultural experiment stations within the watershed, and then assessed crop rotation and tillage impacts on crop yields and water quality (e.g. water yield, and sediment yield) from the entire BSRW using the SWAT model. Detailed model calibration, validation, and simulation results and interpretations are given below.

3.1. Stream flow

Initially the SWAT model simulations were performed using default model parameters. The default SWAT model results provided good model performance based on the R^2 values but poor performances with regards to the NSE, which indicated the need for model calibration. Before conducting a manual calibration, an automatic calibration was performed using the SWAT-cup2 and Sufi-2 algorithms (Abbaspour et al., 2009) within the SWAT model. Automatic calibration of the SWAT model identified the most sensitive parameters (Tables 1 and 4). The SWAT simulated results were used to estimate these statistics using SWAT-cup2 (Table 4). In addition other factors should also be considered to evaluate model performance. The *P*-factor is the scale to which uncertainties are explained within the percentage of measured data banded by the 95% prediction uncertainty (95PPU) as described by Abbaspour et al., 2009. The *P*-factor ranges from 0 to 1; *P*-factor exactly equivalent to 1 indicates exact agreement between simulated and

Table 4
Statistical values determined by SWAT-Cup2 Sufi-2 calibration method.

Gage/variables	*P*-factor	*R*-factor	R^2	NSE	br^2	MSE (m^6/s^2)	SSQR (m^6/s^2)
Marigold	0.33	0.15	0.81	0.79	0.77	103.39	16.70
Sunflower	0.42	0.21	0.77	0.75	0.65	84.61	41.61
Leland	0.22	0.22	0.67	0.61	0.56	114.47	24.73

measured values. In this study the *P*-factor ranged from 0.22 to 0.42. The Sunflower gage station had the best *P*-factor (0.42) among three gage stations.

The *R*-factor is defined by the average thickness of the 95PPU range divided by the standard deviation of the measured data (Abbaspour et al., 2009) and can vary from 0 to infinity. The *R*-factor equal to 0 indicates perfect model simulation that corresponds exactly to measured values. In this study the *R*-factor was found to be from 0.15 to 0.22. The watershed outlet at Merigold showed the best *R*-factor value of 0.15 in this study. The R^2 values, which varies from 0 to 1 with one indicating perfect regression between observed and simulated values simulation was determined to be good to very good (R^2 from 0.67 to 0.81) from all three watershed outlets tested in this study. The NSE values can vary from negative infinity to 1, with one indicating perfect efficiencies between observed and simulated values simulation; the results from this study indicated good to very good NSE (NSE from 0.61 to 0.79) from all three watershed outlets. The Marigold outlet showed the best R^2 and NSE values among the three stations compared in this study. The br^2, MSE, and SSQR factors as described by Abbaspour et al. (2009) also showed good model performance in this study.

Considering all the performance statistics estimated by the Sufi-2–SWAT-cup2, we can conclude that the model is performing reasonably well when predicting stream flows at the given watershed outlets. The SWAT model performances were further improved by manual calibration as described in Section 2.3. Table 5 shows the model statistics (R^2, NSE) using defaults and manually improved model calibration.

Van Liew et al. (2003) investigated hydrologic conditions of the Delaware Creek watershed in Oklahoma using the SWAT model. The SWAT model performed well (R^2 = 0.68 and NSE = 0.84) for monthly stream flow simulation in their study. King et al. (1998) applied the SWAT model in the Goose Creek watershed (21.3 km^2) in Mississippi Delta using two methods of simulating excess rainfall: (a) the SCS daily curve number method (CN) and (b) Green-Ampt Mein-Larson (GAML). The simulated and monthly measured stream flows were evaluated at the watershed outlet. Uncalibrated SWAT model results indicated good model performances (R^2 from 0.70 to 0.82 and NSE from 0.63 to 0.78) in both methods used in their study.

Parajuli (2010) applied the SWAT model in the Upper Pearl River watershed to assess the hydrologic impact of long-term climate

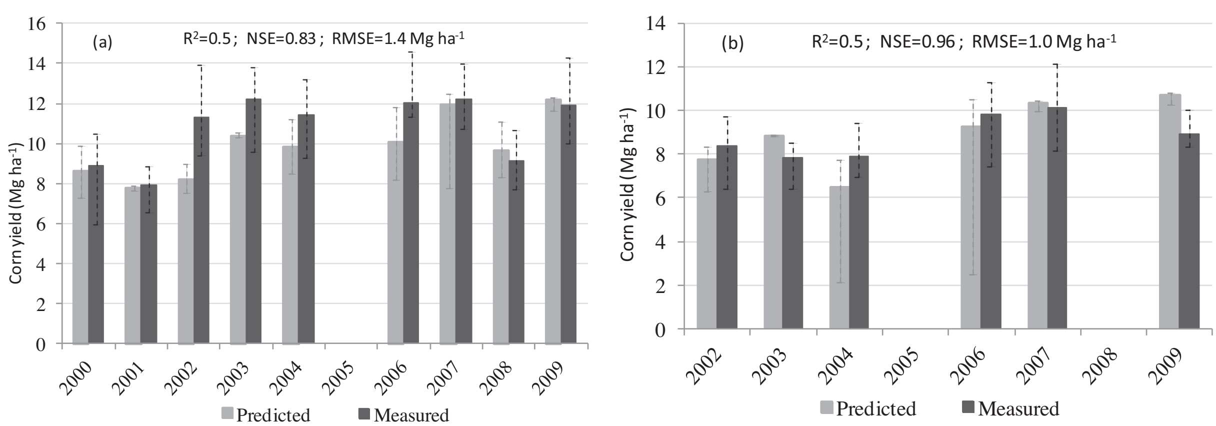

Fig. 2. Model responses to the observed corn yield for model calibration at: (a) Stoneville, and model validation at: (b) Clarksdale agricultural experiment stations.

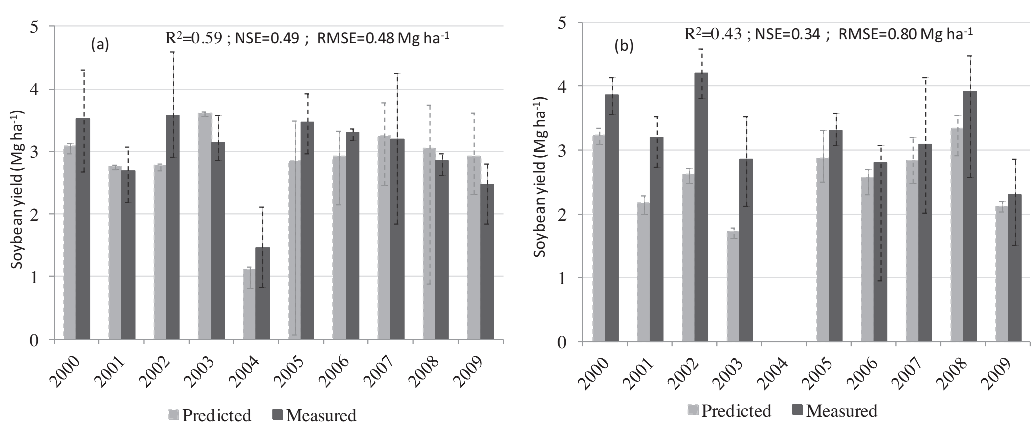

Fig. 3. Model responses to the observed soybean yield during model calibration at: (a) Stoneville, and model validation at: (b) Clarksdale agricultural experiment stations.

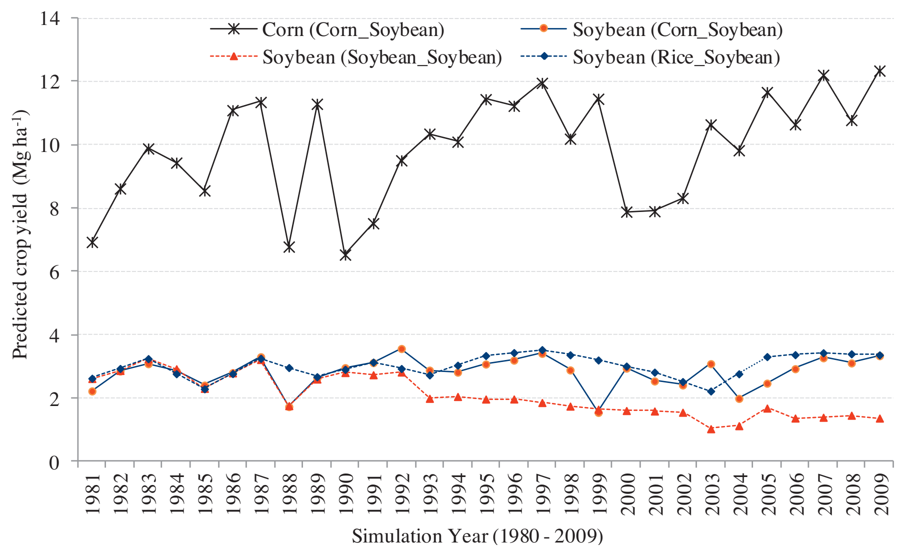

Fig. 4. Long-term model responses to corn and soybean yields in three crop-rotations under conventional tillage practice in the Big Sunflower River watershed.

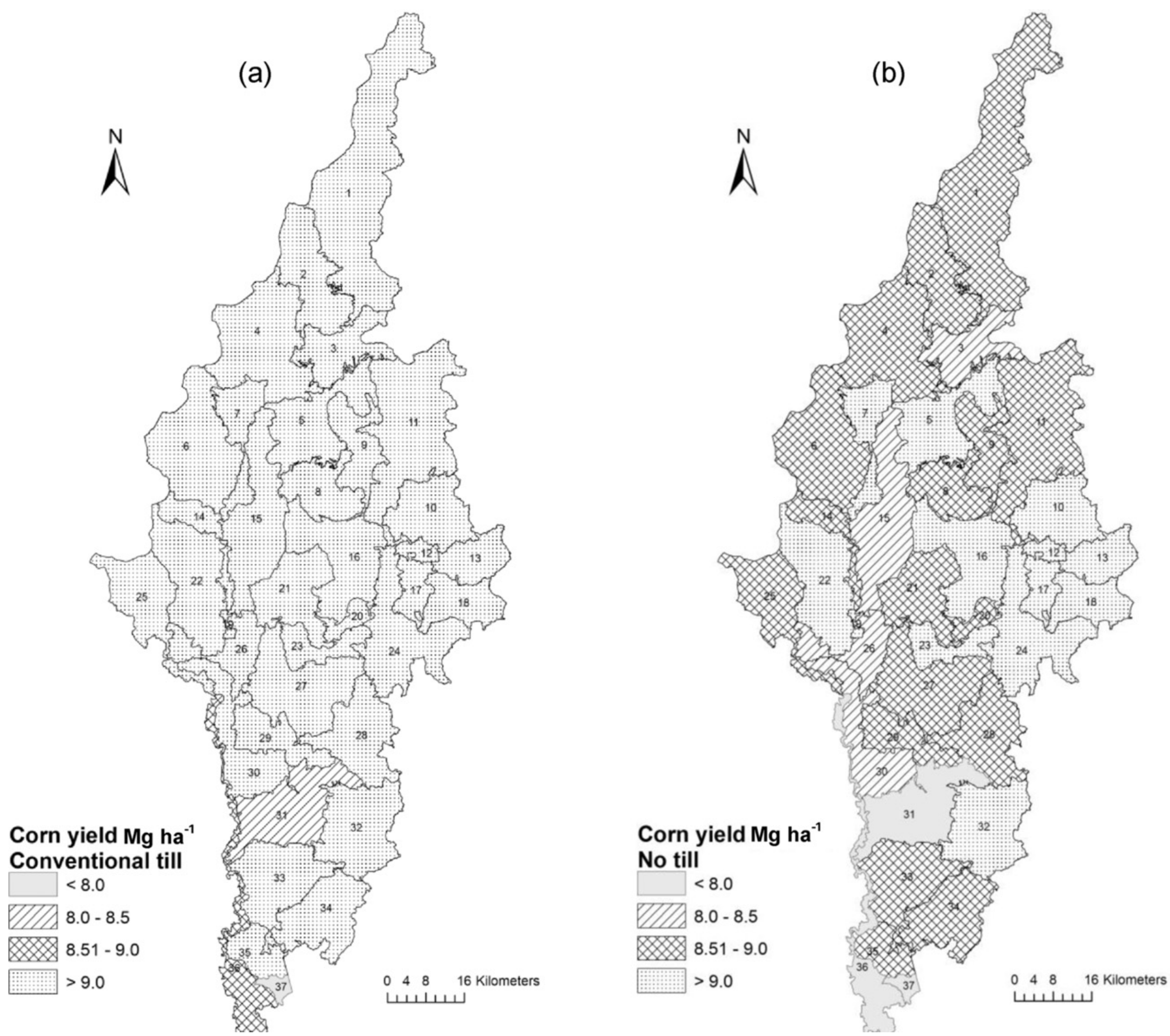

Fig. 5. Model predicted corn yields from corn after soybean rotation under (a) conventional till and (b) no-till fields in the watershed.

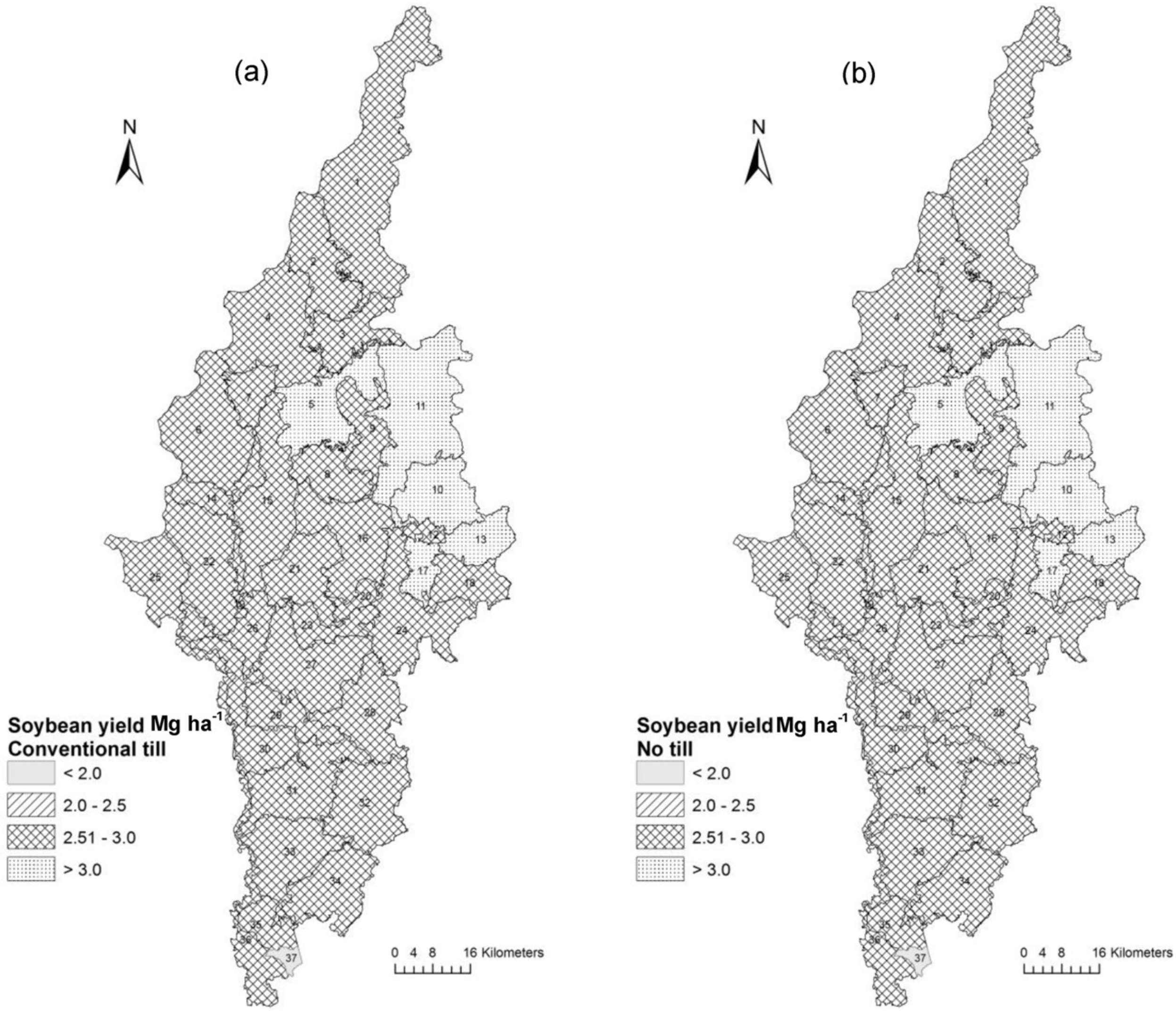

Fig. 6. Model predicted soybean yield from corn–soybean rotation under (a) conventional till and (b) no-till fields in the watershed.

change (e.g. precipitation, temperature, CO_2). The calibrated and validated SWAT model showed good to very good performances (R^2 from 0.69 to 0.79 and NSE from 0.68 to 0.79) when predicting monthly stream flows from various USGS gage stations in the watershed. The watershed stream flows were shown to be sensitive to the climate changes.

The stream flow calibration and validation results of this study showed good agreement with other research studies reviewed by Gassman et al. (2007), which utilized the SWAT hydrologic model calibration and validation research.

3.2. Crop yield

This study calibrated and validated the SWAT model to predict crop yield at Stoneville and Clarksdale agricultural experiment stations. Annual average harvest weight corn and soybean yields from research plots at the experiment stations were compared with the model simulated crop yields. The model simulated results from the silty clay loam soil texture HRU in the sub-watershed where the experiment stations are located were utilized to compare with the measured crop yield data. The corn crop yield data from 2000 to 2009 were used for model calibration and validation, except from 2005 for both stations and 2008 for Clarksdale station due to data unavailability (Fig. 2). Simulated average annual corn yields from model calibrated (Fig. 2a) and validated (Fig. 2b) experiment stations showed good to excellent model performances (R^2 of 0.50, NSE from 0.83 to 0.96, and RMSE from 1.0 to 1.4).

The soybean crop yield data from 2000 to 2009 were used for model calibration and validation (Fig. 3) except for 2004 for the Clarksdale station due to data unavailability. Simulated average annual soybean yields from model calibrated (Fig. 3a) and validated (Fig. 3b) stations showed lower model performance (fair to good) than was observed for corn (R^2 from 0.43 to 0.59, NSE from 0.34 to 0.49, and RMSE from 0.48 to 0.80).

The model under-predicted annual average corn yields by 8.8% at Stoneville and by 0.2% at Clarksdale experiment stations (Fig. 2). Similarly, the model under-predicted annual average soybean yields by 4.3% at Stoneville and 16.8% at the Clarksdale experiment stations (Fig. 3). The corn and soybean yield results of this study were comparable to previous studies using the SWAT model in the Lower Mississippi River Basin (Srinivasan et al., 2010).

The calibrated and validated SWAT model was further applied to the entire BSRW to simulate the impact of long-term (1981–2009) crop rotation and tillage management on corn and soybean yields (Fig. 4), and sediment yield. Model simulated corn and soybean yields for corn after soybean rotation using conventional tillage practices were compared. The corn yield was found to be the highest in a corn-soybean rotation (mean = 9.88, max = 12.34,

Table 5
Final values after automatic and manual calibration of the model at three gage stations.

Process	Parameter	Default statistics	Merigold	Sunflower	Leland
Calibration	R^2	From 0.55 to 0.66	0.69	0.75	0.68
Validation	R^2	From 0.55 to 0.71	0.83	0.82	0.77
Calibration	NSE	From −0.31 to −0.75	0.63	0.51	0.62
Validation	NSE	From −0.18 to −2.26	0.53	0.52	0.62

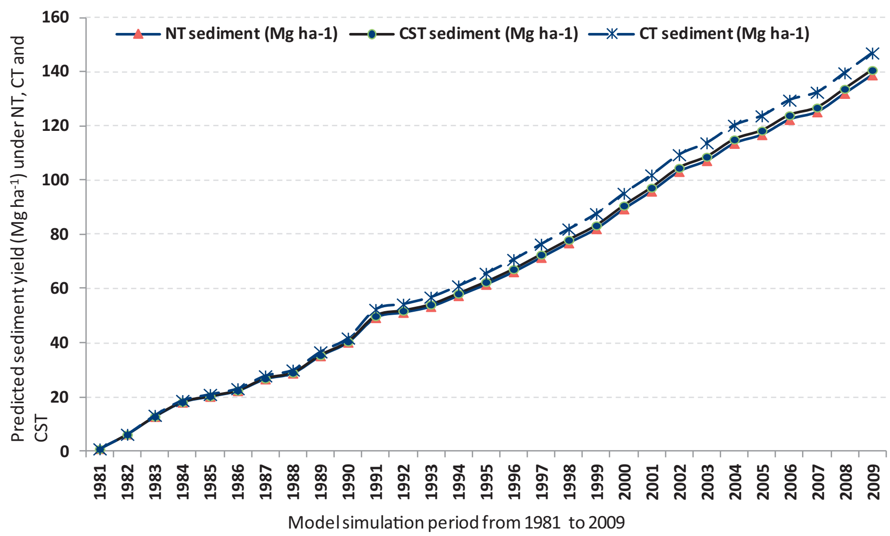

Fig. 7. Model predicted cumulative annual average sediment yield for no-till, conservation till and conventional till from continuous soybean production fields in the watershed. Note: NT = no-till, CST = conservation-till, CT = conventional till.

min = 6.53 Mg ha^{-1}; Fig. 4). Model results were generally affected by climate change parameters including annual rainfall in the preceding year.

Simulated long-term average soybean yields for soybean after rice for conventional tillage practices were the highest (mean = 3.01, max = 3.53, min = 2.22 Mg ha^{-1}) as the soil moisture remaining after the rice crop would help grow the soybean crop. Soybean yield for the soybean after rice rotation consistently simulated higher yields than soybean after corn and soybean after soybean rotations in most of the years (Fig. 4; Kurtz et al., 1997). Soybean yield under continuous soybean production had the lowest soybean yield simulated in this study (mean = 2.07, max = 3.24, min = 1.03 Mg ha^{-1}), which is very similar to other studies (Kurtz et al., 1997). Simulated corn yield for corn after soybean for conventional tillage showed higher corn yields than no-till practices in the watershed (Fig. 5), which is similar to other studies (e.g. Hargrove, 1985).

Conversely, soybean yields were not influenced by tillage practices under the soybean after corn rotation (Fig. 6). Similar results have been reported previously (Hairston et al., 1990).

3.3. Sediment yield

The cumulative average annual sediment yield simulated by the model showed that continuous soybean production under conventional tillage resulted in the greatest sediment yield from the fields within the BSRW. Although the difference in sediment yield at the beginning of the time period was not significantly greater, it showed consistent increases at the end of the simulation period (Fig. 7). By the end of the simulation period (2009), a maximum difference of about 8 Mg ha^{-1} was observed between the no-till and conventional tillage practices. No-tillage management resulted in the lowest sediment yield. The cumulative difference of the sediment yield between no-till and reduced till was about 2 Mg ha^{-1}.

4. Conclusion

This study calibrated and validated the SWAT model for the monthly stream flow using measured USGS gage station data from three spatially distributed gage stations and crop yields using annual corn and soybean yield data from the two agricultural experiment stations (Stoneville and Clarksdale) within the BSRW. Further, three crop rotation and three tillage management scenarios were developed for the entire BSRW to assess their effects on corn and soybean yields as well as sediment yield.

This study successfully evaluated the impact of spatially distributed crop rotation and tillage practices on crop yield and sediment yield from the BSRW. The results of this study allow development of future watershed management strategies based on best crop and tillage management practices to reduce environmental impacts. The model simulation results indicated that corn yields for a corn–soybean rotation under conventional tillage practice produced the greatest yields (mean = 9.88 Mg ha^{-1}). The corn yields under conventional tillage practice were greater than those for no-tillage practices. However, tillage practices had no effects on the soybean yield under the corn–soybean rotation. The soybean yields in conventional tillage practice under the rice–soybean rotation showed greater yields than corn–soybean rotation. The continuous soybean production under conventional tillage had the lowest simulated crop yield (mean = 2.07 Mg ha^{-1}) and the greatest sediment yield (mean = 5.2 Mg ha^{-1}) in this study. Overall, the long-term average soybean yields were the greatest (mean = 3.01 Mg ha^{-1}) under soybean–rice crop rotation. The cumulative (1981–2009) difference of the sediment yield at the end of the simulation period (2009) showed about 8 Mg ha^{-1} between no-till and conventional tillage practices. The no-till practice resulted in the lowest sediment yield from the fields within the watershed. The cumulative difference of the sediment yield between no-till and conservation till was found to be about 2 Mg ha^{-1}. Further study with more crop-rotations and tillage management scenarios within or outside the current watershed would help to determine crop yields and sediment loads from the watershed. Results of this study will help to practically compare the spatial variation of potential corn and soybean yielding areas within the BSRW. The results of this study will help to guide watershed crop management and water quality improvement in the BSRW or any other crop dominated watersheds.

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