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Assessing the impacts of climate change and tillage practices on stream flow, crop and sediment yields from the Mississippi River Basin

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ABSTRACT

This study evaluated climate change impacts on stream flow, crop and sediment yields from three different tillage systems (conventional, reduced 1–close to conservation, and reduced 2–close to no-till), in the Big Sunflower River Watershed (BSRW) in Mississippi. The Soil and Water Assessment Tool (SWAT) model was applied to the BSRW using observed stream flow and crop yields data. The model was calibrated and validated successfully using monthly stream flow data (2001–2011).

The model performances showed the regression coefficient (R^2) from 0.72 to 0.82 and Nash–Sutcliffe efficiency index (NSE) from 0.70 to 0.81 for streamflow; R^2 from 0.40 to 0.50 and NSE from 0.72 to 0.86 for corn yields; and R^2 from 0.43 to 0.59 and NSE from 0.48 to 0.57 for soybeans yields. The Long Ashton Research Station Weather Generator (LARS-WG), was used to generate future climate scenarios. The SRES (Special Report on Emissions Scenarios) A1B, A2, and B1 climate change scenarios of the Intergovernmental Panel on Climate Change (IPCC) were simulated for the mid (2046–2065) and late (2080–2099) century. Model outputs showed slight differences among tillage practices for corn and soybean yields. However, model simulated sediment yield results indicated a large difference among the tillage practices from the corn and soybean crop fields. The simulated future average maximum temperature showed as high as 4.8 °C increase in the BSRW. Monthly precipitation patterns will remain un-changed based on simulated future climate scenarios except for an increase in the frequency of extreme rainfall events occurring in the watershed. On average, the effect of climate change and tillage practice together did not show notable changes to the future crop yields. The reduced tillage 2 practices showed the highest responses of erosion control to climate change followed by the reduced tillage 1 and conventional tillage in this study.

1. Introduction

An increase in the world crop production is essential to feed the anticipated increase in world population. Several challenges including soil erosion and the anticipated impact of climatic change on crop yield must be addressed. Soil erosion can convert productive agricultural lands into unproductive barren lands, and climate change can aggravate the problem. Consequences of the climate change on crop production are already visible, and future climatic change will have a major effect on changing crop production at regional and global scale (Abraha and Savage, 2006). For example, the damage to future corn yields due to climate change will be $3 billion per year in the U.S. (Rosenzweig et al., 2002). Elevated carbon dioxide (CO_2) concentration in the atmosphere, changing precipitation, and temperature fluctuations are some of the anticipated climatic changes that will affect future crop production and erosion in multiple ways.

Global warming occurs because of CO_2 increases in the atmosphere, which could have many consequences on hydrological systems (Zhang et al., 2007). There is sufficient scientific evidence that temperature has increased over the last 15–20 years in both air and water (Barnett et al., 2005; IPCC, 2007). These temperature changes may have significant effects on future crop production. Based on IPCC (2007) findings, future crop production may increase with an increase of average temperature range from 1 to 3 °C but beyond that, yield is expected to decline. Moreover, most of the crops are currently near to their climatic thresholds; shifts away from these thresholds will impair the quantity and quality of the

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crop yields due to unfavorable climatic conditions (White et al., 2006). These effects may be positive or negative depending on the crop type and locations. For example, the moderate climate change in the North American region may have positive impacts on crop yields (Reilly, 2002). Future rainfall patterns may change and modify runoff and erosion processes, which lead to a change of the transport and deposition process of contaminants (Macdonald et al., 2005; Doris et al., 2007). These changes will have an effect on non-point sources pollutant transport from agricultural landuses. Currently agricultural pollutants such as sediment, generated by crop management activities, have caused visible degradation of surface water resources (Zalidis et al., 2002; Thorburn et al., 2003; Howarth et al., 2011; Thorburn et al., 2013). Soil erosion related to crop management practices can vary spatially indicating a need to identify critical areas for implementation of remedial measures (Marshall and Randhir 2008; Howarth et al., 2011).

Several studies have been conducted to evaluate the effects of climate change on crop production (Boxall et al., 2009; Biggs et al., 2013; Challinor, 2009; Webster et al., 2009; Crane et al., 2011; Jeppesen et al., 2011; Lobell et al., 2006), and account for the spatial variability of these effects. A climate change study on maize yield in South Africa found that increasing rainfall and temperature under future climate change positively influenced maize yield. The results indicated that precipitation is a more important factor than temperature in determining crop yield (Akpalu et al., 2008). Changes to precipitation amounts directly affect crop yield if precipitation cannot fulfill the demand of evapotranspiration (Mera et al., 2006), especially for non-irrigated crops. A detailed review of the effects of precipitation and temperature on crop yield is available in the work of Yinhong et al. (2009). Precipitation and temperature are not the only climatic variables that impact crop performance; the elevated CO_2 levels predicted in climate models will have positive effects on future crop production by increasing the growth of future crops (Kimball et al., 2002). A detailed review of the effects of elevated CO_2 on crop growth is available from Tubiello and Ewert (2002).

Implementation of adaptation and mitigation measures prior to the consequences of future climate changes is essential to improve crop production and water quality. Crop simulation models are useful tools for predicting the impact of climate change on crop growth and production. Moreover, these models can investigate the environmental effects on crop physiology in the future climate (Southworth et al., 2000). Despite the interest of international audiences, most of the previous climate change studies focused on conditions in the western U. S. (Stone et al., 2001; Rosenberg et al., 2003; Payne et al., 2003; Christensen et al., 2004; Villarini and Strong, 2014). Climate change studies on crop and sediment yields are limited in the south-eastern U.S., especially in Mississippi where climatic conditions are different from other regions of the U.S. Although beneficial for crop production, the abundant water resources and high rainfall levels common to the southern U.S. states such as Mississippi have high runoff related pollution problems. Some studies in the U.S. have reported anticipated soil erosion and crop productivity levels under future climate conditions. O'Neal et al. (2005) have investigated crop management and erosion rate under climate change in the Midwestern U.S. Mehta et al. (2012) has carried out a crop simulation study in the Missouri River Basin. However, the effects of climate change on crop production vary between locations (Southworth et al., 2000).

The Mississippi River is one of the world's major river systems in size, habitat diversity and biological productivity. The Mississippi River watershed is the largest watershed of all other rivers discharging into U.S. Gulf waters combined, which drains 40% of continental U.S. including parts of 31 states and 2 Canadian provinces (Kemp et al., 2011). The Mississippi River outlet dominates ecosystem processes in northern Gulf of Mexico. These ecosystem processes include freshwater inflow as the Mississippi River provides 80–90% of freshwater entering the northen Gulf of Mexico from rivers, creating critically important freshwater (Kemp et al., 2011). The Mississippi River contributes about 95% of all sediment entering the northern Gulf of Mexico with an average of 436,000 tons of sediment each day and up to 550 million tons of sediment during a major flood year (MRR, 2015). The U.S. Geological Survey identified the watersheds that are the largest contributors of nutrient loading to the Gulf of Mexico, which includes the Yazoo River Basin (Robertson et al., 2009). The BSRW in this study is the largest portion of the Yazoo River Basin in Mississippi (Parajuli et al., 2013), which contributes pollutants to the Gulf of Mexico via The Mississippi River.

To address the internationally important discharge of agricultural pollutants from the Mississippi River into the Gulf of Mexico, the current study evaluated the effects of three tillage practices on corn and soybean production and their potential for soil erosion in the humid mid-south. Further, the effects of climate change on crop and sediment yields in future climates scenarios were evaluated for the BSRW using a modeling approach.

2. Material and methods

2.1. Study area and model description

This study was conducted in the Big Sunflower River Watershed (BSRW), which extends over 7660 km^2 and is a major sub-watershed of the Yazoo River Basin in Mississippi (Fig. 1). The BSRW encompasses eleven counties in Mississippi (Coahoma, Bolivar, Tallahatchie, Sunflower, Leflore, Washington, Humphreys, Sharkey, Issaquena, Yazoo and Warren), which is a majority of the land area in Mississippi River Alluvial Flood Plain, colloquially known as the Mississippi Delta. Agriculture is the main land use (>80%) in the watershed. Soybean and corn are major crops in the watershed. The BSRW drains into the Mississippi River near Vicksburg via the Sunflower and Yazoo Rivers.

The SWAT model was chosen for this study as it has been used for modeling climate change (Lirong and Jianyun, 2012; Shrestha et al., 2012), water quality (Pisinaras et al., 2010; Cho et al., 2012), and crop growth and development (Masih et al., 2011; Kim et al., 2013) in various geographical regions around the world. The SWAT model is a semi distributed physically based, continuous, daily time-step model and it allows for predicting surface runoff, sediment and nutrient yields, pesticide, bacteria, and crop yields (Arnold et al., 1998; Neitsch et al., 2005). The SWAT model divides a watershed into a number of sub-watersheds, which are further divided into small spatial units called hydrological response units (HRUs). The HRUs are lumped land areas within the sub-watershed and consist of unique land cover, soil and management combinations (Neitsch et al., 2005).

The SWAT computes on a daily basis, for each HRU in every sub-watershed, the soil water balance, lateral flow and channel routing (main and tributary), groundwater flow, evapotranspiration, crop growth and nutrient uptake, soil pesticide degradation, and in-stream transformation of water quality parameters. Irrigation, fertilization, tillage, and drainage are subroutines within SWAT and applied based on the user settings. The SWAT calculates daily surface runoff using either curve number (CN) or Green Ampt method when the sub-daily precipitation data are available. The Erosion Productivity Impact Calculator (EPIC) model within the SWAT simulates the crop growth functions and heat units above the base temperature used for crop growth and development. The SWAT model determines crop yield as a function of Harvest Index (HI) and the biomass above the ground. The daily HI is calculated based on an optimal HI and a fraction of potential heat units (Neitsch et al., 2002). The crop-growth module in the SWAT model

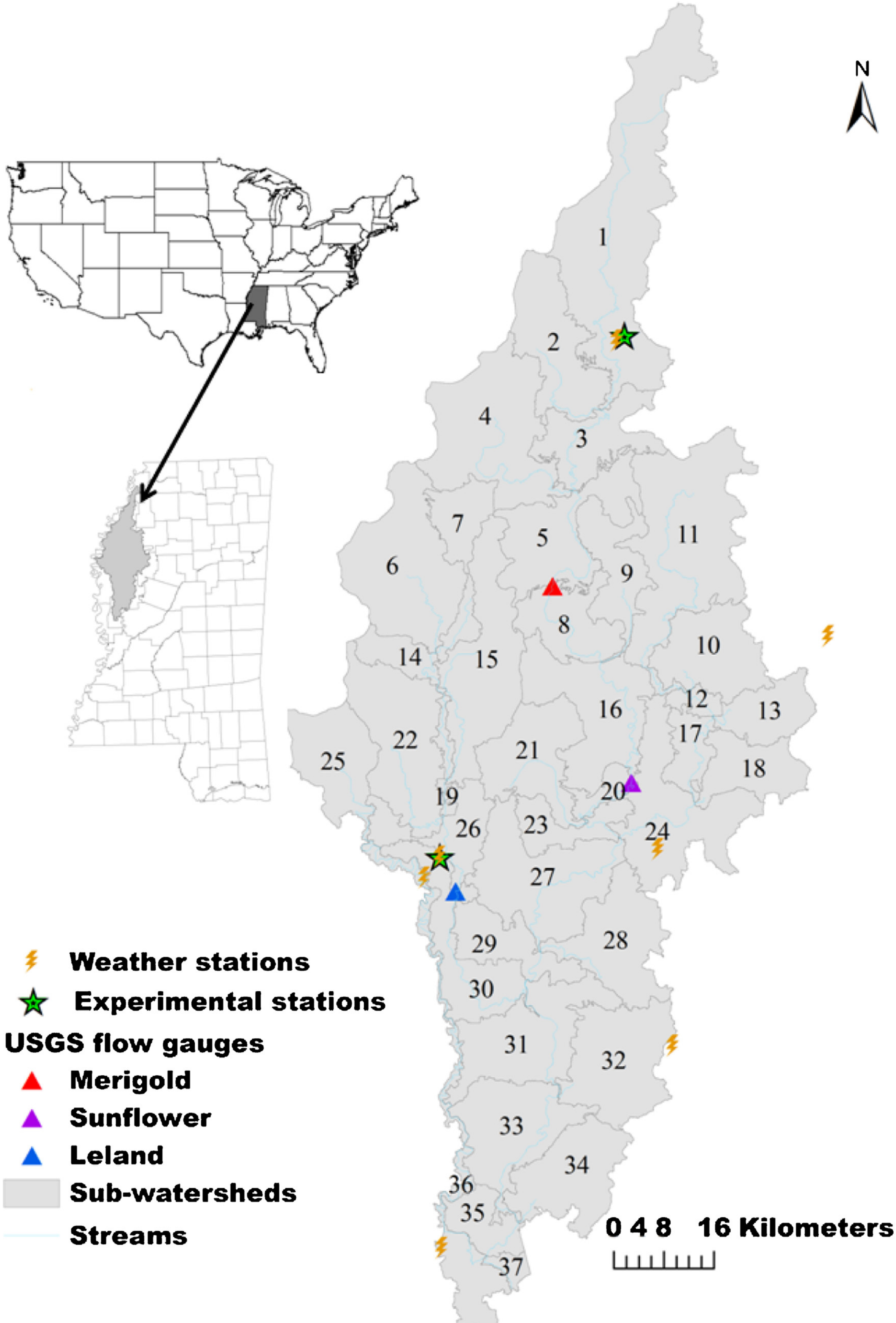

Fig. 1. Big Sunflower River Watershed showing locations of USGS gage, weather, agricultural experiment stations and labeled sub-watersheds.

quantifies plant growth under optimal conditions, and then calculates the actual crop growth under water, temperature, nitrogen, and phosphorus stresses. A detailed description of the SWAT model and its subroutines is available in the SWAT 2005 theoretical manual (Neitsch et al., 2005).

2.2. Model input

This study utilized measured daily rainfall and temperature data from the National Climatic Data Center (NCDC, 2013). There were 6 NCDC weather stations in or near the BSRW, which provided daily precipitation and daily minimum and maximum temperature (Fig. 1). In addition, one automatic weather station within the watershed was maintained by the Delta Research and Extension Center Weather Center at Stoneville (DAWC, 2012), which provided precipitation, both maximum and minimum temperatures, wind speed, solar radiation, and relative humidity data. Monthly stream flow data from 2001 to 2013 used from three USGS gage stations (Merigold at sub-watershed 5; Sunflower at sub-watershed 16; and Leland at sub-watershed 26).

Soil Survey Geographic Database (SSURGO) used to generate soil data input in the model (USDA, 2005). The SSURGO database developed using field surveys based on the National Cooperative Soil Survey (NCSS) mapping standards and 1:12,000 to 1:63,360 map scales (USDA, 1995). The SSURGO data for the BSRW showed 12 major soil textural classes. The "fine-silty" soil texture class dominated the watershed and constituted about 62% of the watershed area. The land use data input in the model was developed by utilizing a 30 m spatial resolution cropland data layer (USDA_NASS, 2009). The 30 m × 30 m grid digital elevation model (DEM) data were used for elevation data (USGS, 2010) in this study.

The SWAT crop growth module incorporates crop management data provided by the user to simulate crop growth and development in each HRU. Specific crop management data was not available for all the croplands in BSRW. Crop yield and associated management data were only available for the two agricultural experimental stations. These stations were Stoneville (USDA-ARS Crop Production Systems Research Unit) and Clarksdale, located within the watershed (Fig. 1). Stoneville is located at sub-watershed 30 and Clarksdale at sub-watershed 1. These research plots maintain the records of crop yields and most crop management practices. The field crop management (e.g., date of plowing, planting, fertilizer application, irrigation, and harvesting) information was used in the crop model. Corn and soybean are commonly grown in Mississippi Delta (NASS, 2011), and often planted in rotation with conventional tillage, which was assumed in the model for the entire BSRW. The crop yield data originally recorded as bushels per acre was converted to mega grams per hectare (Mg ha^{-1}) using standard bushel dry weights of 56 lbs bu^{-1} for corn and 60 lbs bu^{-1} for soybeans. This conversion resulted in 25 kg of corn per bushel and 27 kg of soybean per bushel (Weiland and Smith, 2007; Parajuli et al., 2013).

The three tillage practices that are implemented in the BSRW (conventional and two reduced tillage practices, Table 1) were considered in this study. Conventional tillage practices in the BSRW involve 5 different tillage events before planting, while reduced tillage 1 and 2 use two to three tillage practices. The reduced 2 tillage practices are similar to the no-till condition as they generate minimum soil mixing. Crop production in the BSRW is commonly performed on raised beds to provide a drier, warmer soil for planting in the wet springs. Subsoiling is also beneficial to break up the compaction layer. The minimum tillage performs these tasks, and rolls the ground in the early spring to form the planting bed (reduced Till 2). More extensive tillage practice separates the subsoiling and rowing operations, and uses a Do-All in the early spring to prepare the seed bed (reduced Till 1). Conventional tillage practices in the alluvial soils of the BSRW also include one or more tillage operations with a chisel plow or disk harrow after harvest to manage crop residue. The soil may be deep-tilled or "subsoiled" to a depth of 12 to 18″ (30–45 cm). The conventional tillage operation removes most of the crop residue from the soil surface. The reduced tillage operations leave crop residue on the soil surface, and include fewer disk operations.

This study evaluated crop and sediment yield from corn–soybean rotation in the BSRW for these three tillage practices. Soybean after corn is the most common crop rotation at the BSRW. Further, this study simulated corn–soybean rotation with three tillage practices for mid and late-century climate change for SRES A1B scenario. The SRES A1B scenario represents the best scenario for climate change and crop production studies (Osborne et al., 2013). Using simulation results, climate change impacts on corn and soybean yield and sediment transport from the respective croplands of the watershed were evaluated. Date of planting (March 15) and date of harvesting (August 15) were kept unique for both crops to compare the results.

2.3. Climate change, model calibration and validation

The LARS-WG, a stochastic weather generator was used to simulate future climate change scenarios. The LARS-WG generates synthetic precipitation, temperature (maximum and minimum), and solar radiation on a daily time series by using ground observed weather data for a location with the selected Global Climate Model (GCM). The LARS-WG model reference manual provides more information (Semenov, 2007). Future weather data were generated using the CCSM3 with 1.4° × 1.4° grid resolution as GCM, developed by National Center for Atmospheric Research (NCAR) in the U.S. (Collins et al., 2004). Based on the special report on emissions scenarios (SRES) three emissions scenarios (A1B, A2, and B1) were selected to evaluate future climate change. A1B scenario considers global population peaks in mid century and then declines. A1B scenario estimates the CO_2 concentration variability from 541 ppm in mid century (2046–2065) to 674 ppm in late century (2081–2100). A2 scenario considers continuously increasing global population. In A2 scenario, estimates CO_2 concentration variation from 545 ppm in mid century to 754 ppm in late century. B1 scenario considers global population peaks in mid century then declines. B1 scenario estimates CO_2 concentration variation from 492 ppm in mid century to 538 ppm in late century. More detailed descriptions of A1B, A2, and B1 are provided in previous publications (IPCC, 2000, 2013; Jayakody et al., 2013). Mid and late century daily rainfall data from seven weather stations were compared with the baseline measured rainfall from 1992 to 2011. Percentage changes from baseline were calculated for mid and late-centuries.

Monthly measured stream flows at Merigold, Sunflower, and Leland from January 2001 to September 2013 were used to calibrate (2001–2006) and validate (2007–2013) the SWAT hydrological model. Model calibration (stream flow) was initially performed using SWAT-CUP SUFI-2 automatic calibration technique (Abbaspour et al., 2007) and followed by a manual calibration. The SWAT-CUP SUFI-2 has been used previously for similar studies (Abbaspour et al., 2007). The SUFI-2 algorithm determines the uncertainty of model input parameters at 95% accuracy level. The cumulative distribution of uncertainty is calculated for 2.5% and 97.5% levels using a Latin hypercube sampling technique (Abbaspour et al., 2007). Furthermore, the SWAT Penman–Monteith potential evapotranspiration (PET) was used. This study also used 12 flow calibration parameters for the SWAT hydrologic model calibration as described in Parajuli et al. (2013). These calibration parameters were curve number (CN_2), base flow recession constant (alpha_bf), delay of time for aquifer recharge (gw_delay), Manning's "n" value for the main channel (ch_n2), available water capacity (sol_awc), surface runoff lag coefficient (surlag),

Table 1
Tillage practices[a] for corn and soybean.

Time	Operation	Mixing efficiency	Tillage depth (mm)	Plow name
Conventional				
Fall (September–November)	Disk	0.85	100	Disk Plow Ge23 ft
	Sub-soil	0.15	350	Paraplow
	Disk	0.85	100	Disk Plow Ge23 ft
	Row up	0.65	150	Bedder Disk-Hipper
Just before planting	Do-All	0.3	150	Landall, Do-All
March 15 to June 31	Planting	Na	Na	
Reduced tillage 1				
Fall (September–November)	Sub-soil	0.15	350	Paraplow
	Row up	0.65	150	Bedder Disk-Hipper
Just before planting	Do-All	0.3	150	Landall, Do-All
March 15 to June 31	Planting	Na	Na	
Reduced tillage 2				
Fall (September–November)	Sub-soil	0.15	350	Paraplow
Just before planting	Roller	0.35	40	Roller Packer Flat Roller
March 15 to June 31	Planting	Na	Na	

[a] Implementation of operation, mixing efficiency, tillage depth, and plow names are included in the SWAT tillage database (Arnold et al., 2009). Na = Not available.

aquifer percolation coefficient (rchrg_dp), plant uptake compensation factor (epco), soil evaporation compensation coefficient (esco), ground water revap or percolation coefficient (gw_revap), threshold water level in shallow aquifer for base flow (gwqmin), and threshold water level in shallow aquifer for revap or percolation (revapmn).

The calibrated and validated SWAT model for the stream flow was further calibrated using Stoneville (2001–2009 except 2005) and validated using Clarksdale (2002–2010 except 2005 and 2008) agricultural experiment stations data respectively for corn and soybean yields. In addition to basic field preparation and tillage data, date of planting, harvesting, irrigation, and fertilization were used as management inputs to the crop model. Both agricultural experiment stations planted corn and soybeans using standard agricultural practices to maintain healthy, well-watered crops. Both corn and soybeans crop were irrigated, but fertilizer applications were carried out only on corn since soybean has nitrogen fixation capabilities. Land preparation was performed using a "furrow out cultivator" to create furrows and ridges for gravity flow irrigation. Tillage depth was 150 mm, and mixing efficiency was set in the model as 75% based on field observations. Irrigation was applied based on crop needs to fully replace the demand for evapotranspiration. The auto-irrigation and auto-fertilization management operations were considered to minimize water and nutrient stress, which represents field conditions. Fertilizer and irrigation inputs were not changed for different tillage types. Water sources for each sub-watershed in the model were defined as the shallow aquifer option, assuming groundwater from each sub-watershed is used for irrigation. Four model parameters were adjusted during calibration period as described by Parajuli et al. (2013). Those parameters were AUTO_WSTRS (water stress), AUTO_NSTRS (nitrogen stress), BLAI (leaf area index), and HVSTI (harvest index).

For the statistical analysis of the model performances, this study utilized two commonly used methods (Parajuli, 2012; Kim and Parajuli, 2014): the regression coefficient (R^2), and Nash–Sutcliffe efficiency index (NSE). The root mean square error (RMSE) was also used to evaluate crop yield prediction (Kim et al., 2013). The calibrated and validated model for stream flow and crop yields was applied for climate change effects on hydrologic (stream flow), crop yields, and water quality (sediment) assessments. Further, model simulated results were used for comparative evaluations.

Table 2
Statistical efficiency of monthly stream flow calibration and validation.

Period	Parameter	Merigold	Sunflower	Leland
Calibration (2001–2006)	R^2	0.72	0.73	0.72
Validation (2007–2013)	R^2	0.82	0.81	0.73
Calibration (2001–2006)	NSE	0.71	0.79	0.70
Validation (2007–2013)	NSE	0.81	0.71	0.71

3. Results and discussion

3.1. Stream flow and crop yields calibration and validation

The SWAT model was calibrated and validated using monthly stream flow data from three USGS stations. The model simulation considered one year (2000) of hydrologic warm-up, 6 years (2001–2006) of model calibration and 7 years (2007–2013) of model validation periods. Results showed that the model was able to capture most of the peak flows at all three gage stations (Fig. 2).

The statistics of the model performance showed R^2 values from 0.72 to 0.82 and NSE values from 0.70 to 0.81 in all three locations (Table 2). Model performance was slightly better (R^2 values) during model validation as compared to calibration, which is relevant as compared with previous literature (Parajuli et al., 2009). The SWAT under-estimated the stream flows in all gage stations. Average monthly measured stream flows at Merigold, Sunflower, and Leland were 23.3 $m^3 s^{-1}$, 29.1 $m^3 s^{-1}$, and 19.5 $m^3 s^{-1}$ respectively during the study period. The model simulated average monthly stream flow of 21.2 $m^3 s^{-1}$ at Merigold (9% underprediction), 28.7 $m^3 s^{-1}$ at Sunflower (1% underprediction), and 16.2 $m^3 s^{-1}$ at Leland (17% underprediction). Lower model prediction efficiency at Leland may have been due to inadequately represented weather stations in the Bogue Phalia River sub-watershed, which drains into the Big Sunflower River near Leland within the BSRW.

Although the model slightly under-predicted (~9% on average) stream flows from 3 USGS gage stations within the watershed, model consistency between observed vs predicted values with 1:1 line showed very good efficiency (NSE = 0.75).

The SWAT model uses the EPIC crop model for crop growth and crop yield simulations. Some of the previous studies have reported poor crop yield prediction using the EPIC model (Debaeke et al., 1996; Mearns et al., 1999). In this study, crop yield simulation produced with R^2 from 0.40 to 0.50 and NSE from 0.72 to 0.86 for corn; R^2 from 0.43 to 0.59 and NSE from 0.48 to 0.57 for soybean; and RMSE from 0.43 to 2.73 for all (Table 3). These results are similar

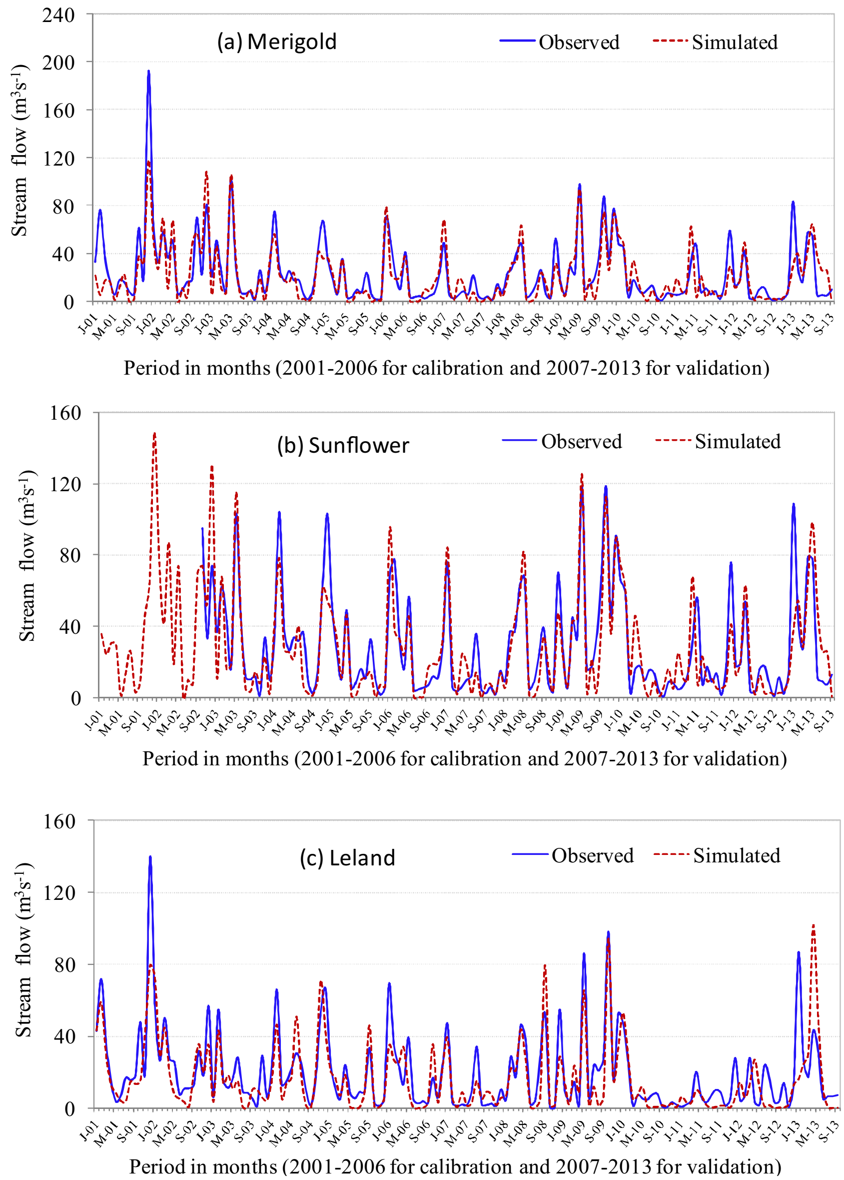

Fig. 2. Measured and simulated stream flows from (a) Merigold, (b) Sunflower, and (c) Leland gage stations.

Table 3
Model performance for corn and soybean yield simulation.

Crop	Model performance statistics	Calibration-Stoneville	Validation-Clarksdale
Corn	R^2	0.50	0.40
	NSE	0.86	0.72
	RMSE	1.48	2.73
Soybean	R^2	0.59	0.43
	NSE	0.48	0.57
	RMSE	0.43	0.81

to previous studies reported in the watershed (Parajuli et al., 2013) and in the region (Srinivasan et al., 2010).

Measured corn yield showed less variability compared to the measured soybean yield. The corn crop was grown under good management with intensive fertilizer applications; however, there were no fertilizer applications for the soybean because of its considerable capability to fix nitrogen. The average measured corn yields were 11.02 Mg ha^{-1} and 8.94 Mg ha^{-1} at Stoneville and Clarksdale respectively, and the model simulated average corn yields were 10.01 Mg ha^{-1} (9% underprediction), and 8.43 Mg ha^{-1} (6% underprediction) at Stoneville and Clarksdale respectively. Average measured soybean yields were 2.91 Mg ha^{-1} and 3.21 Mg ha^{-1} respectively for Stoneville and Clarksdale, and model simulated average soybean yields were 2.81 Mg ha^{-1} (3% underprediction) at Stoneville, and 2.53 Mg ha^{-1} (21% underprediction) at Clarksdale.

As with the streamflow prediction, the model slightly underpredicted (~9.7%) overall corn and soybean yields from the Stoneville and Clarksdale agriculture experimental stations within the watershed. The model consistency between observed vs predicted values with 1:1 line showed very good efficiency (NSE = 0.66) for corn and soybean prediction as compared to literature (Srinivasan et al., 2010).

3.2. Climate change

The temperature variations during future climate were assessed using the baseline temperatures from 1992–2011. The baseline

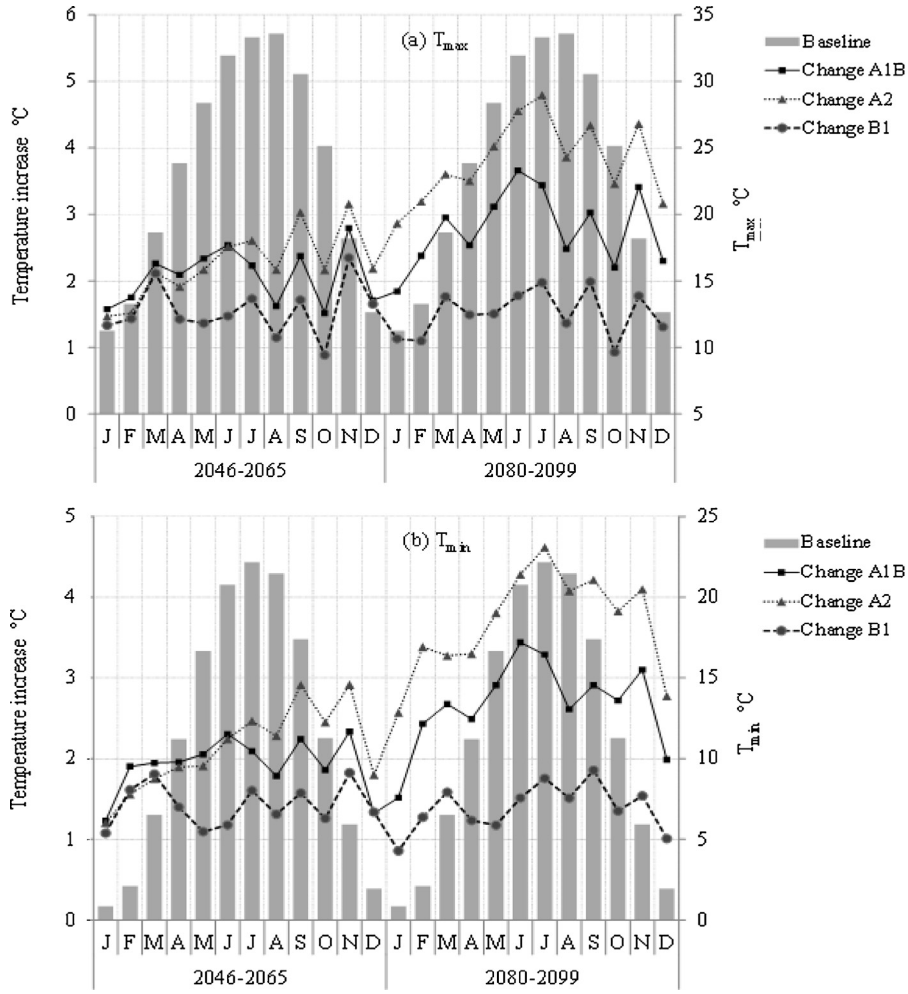

Fig. 3. Maximum (a) minimum (b) future temperature change °C reference to base period (1992–2011).

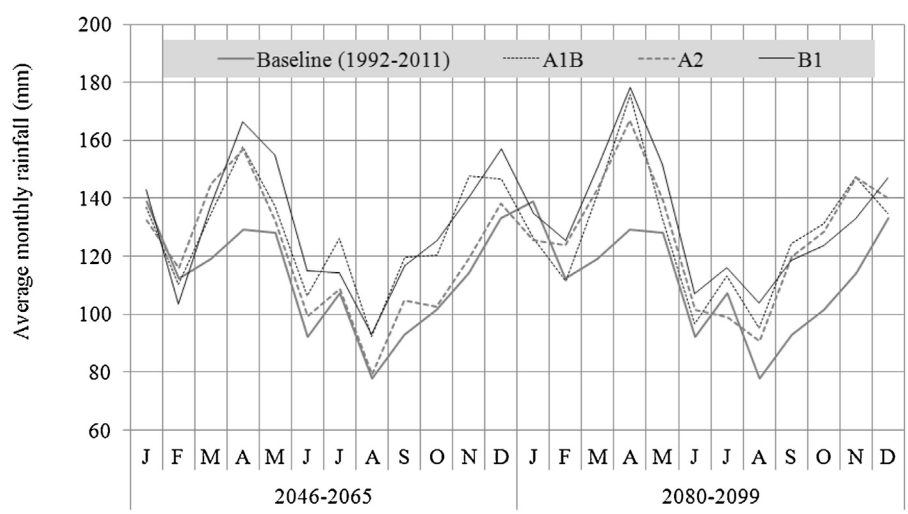

Fig. 4. Average monthly rainfall distribution scenarios (A1B, A2, and B1) in mid and late centuries as compared to baseline conditions.

average temperatures were compared with average maximum (T_{max}) and minimum (T_{min}) temperatures for the entire watershed, which were estimated for mid (2046–2065) and late (2080–2099) centuries using the LARS-WG (Fig. 3). Average annual baseline observed T_{max} was 23.4 °C, and average annual mid-century T_{max} were predicted as 25.5 °C, 25.7 °C, and 25.0 °C for SRES A1B, A2, and B1 scenarios respectively. During the late century, the annual average T_{max} were predicted to be 26.2 °C (A1B), 27.2 °C (A2), and 24.9 °C (B1). The highest T_{max} increase (from baseline) was predicted for the month of November during the mid century scenario, and the increase is 2.8 °C for A1B, 3.2 °C for A2, and 2.3 °C for B1 SRES scenarios (Fig. 3). In late century, the highest T_{max} increase

Table 4
Characteristics of average annual rainfall in mid (2046–2065) and late (2080–2099) century for A1B, A2, and B1 scenario.

Station	Average annual rainfall (mm)	#of days per year with rainfall >100 mm	Special report on emissions scenarios (SRES)	%Change*		#of days per year with rainfall >100 mm	
				Mid (2046–2065)	Late (2080–2099)	Mid (2046–2065)	Late (2080–2099)
Clarksdale	1313	7	A1B	10.1	9.0	19	16
			A2	4.5	9.4	21	24
			B1	14.9	12.2	18	23
Stoneville research center	1308	6	A1B	5.1	9.3	15	10
			A2	−0.8	9.4	9	13
			B1	6.3	12.3	18	15
Moorhead	1339	8	A1B	17.0	13.0	23	23
			A2	8.8	14.2	22	23
			B1	18.2	17.9	25	26
Minter city	1405	10	A1B	15.8	17.8	32	31
			A2	8.9	17.9	23	31
			B1	15.7	22.3	37	35
Stoneville experimental station	1315	7	A1B	14.6	16.6	13	17
			A2	9.0	14.1	14	11
			B1	18.6	23.2	14	14
Belzoni	1376	11	A1B	19.2	18.6	26	23
			A2	5.0	15.6	17	21
			B1	21.9	23.1	25	21
Rolling fork	1368	13	A1B	16.3	11.4	25	18
			A2	9.8	12.0	20	17
			B1	18.7	15.2	30	18

* %change = ((Scenario − Base)/Base) × 100.

was predicted as 3.7 °C for A1B (June) and 4.8 °C for A2 (July) and 2 °C for B1 (July). The analysis of annual baseline temperatures indicated that the July and August would be the warmest months. The warmest period for future climate was projected to occur from June to November. This indicates that future climate in BSRW will experience longer summer periods. The T_{min} variations followed a similar pattern to that predicted for T_{max} (Fig. 3).

The future annual rainfall in mid-century was predicted to change by a decrease of up to 0.8% to an increase of up to 21.9% (Table 4). During late century, the rainfall was projected to increase from 9% to 23.1%. This increase may be caused by extreme rainfall events. Results showed that the number of rainfall events that exceed 100 mm per day would be higher in both mid and late-century. Previous literature reported an increase in the number of intense precipitation events in the U.S. (Karl and Knight, 1998; Bates et al., 2008). Although monthly precipitation patterns projected to remain unchanged (Fig. 4), the BSRW will experience more frequent intense precipitation events based on projected future climate study.

3.3. Tillage effects on crop and sediment yields

Few studies have evaluated the effect of conventional tillage and no-till on soil erosion (Edwards et al., 1988; Norwood, 1999). This study compared the impacts of tillage management practices on corn and soybean yield. The predicted results showed that there is a slight difference between average corn and soybean yield among tillage practices in the watershed (p value > 0.05). Previous field studies also reported that average U.S. corn and soybean yield has no notable differences between no-tillage and conventional tillage (Edwards et al., 1988; Norwood, 1999). Average corn yields in the conventional tillage system were predicted to be 8.39 Mg ha^{-1}, while average corn yields for reduced tillage 1 and 2 were predicted to be 8.35 Mg ha^{-1} and 8.38 Mg ha^{-1} respectively. Average soybean yield predicted for the watershed remained at 2.77 Mg ha^{-1} for all tillage practices.

The predicted corn and soybean yields were analyzed at each of the sub-watersheds within the BSRW (Fig. 5). The model predicted results showed that corn yield could increase between 0.3% and 1.2% or decrease between 2.7% and 1.8% in reduced tillage 1 and 2 respectively in comparison to conventional tillage (Fig. 5). Sub-watershed soybean yield also showed similar patterns in response to tillage practices but with different magnitude (yield increased up to 1.2% and reduced up to 0.1%). Previous studies also showed similar mixed results. Hairston et al. (1990) reported that tillage has no effects on measured soybean yield. A study in Alabama reported 30% reduction in measured corn yield and 16% reduction in measured soybean yield by changing from conventional tillage to no-tillage (Edwards et al., 1988). A study in Kansas reported that measured corn yield increased after 3 years of no-tillage and measured soybean yield increased after one year of no-tillage (Norwood, 1999). Pedersen and Lauer (2003) reported that measured corn yield may decline 5% in no-tillage compared to the conventional system but measured soybean yield may increase 6% in no-tillage compared to the conventional.

Model simulated uncalibrated sediment yields showed that there is a large difference in sediment yield between tillage practices from corn and soybean fields due to tillage. Conventional tillage has the highest sediment yield followed by reduced tillage 1 and reduced tillage 2 for both crop fields. Average sediment losses from corn crop fields were 12.56 Mg ha^{-1} year $^{-1}$, which decreased by 24% and 39% for reduced tillage 1 and 2 respectively. Average sediment losses under conventional tillage from soybean fields were 14.11 Mg ha^{-1} year^{-1}, which decreased by 30% and 51% in reduced tillage 1 and 2 respectively. Model simulated sediment yield output from each sub-watershed showed

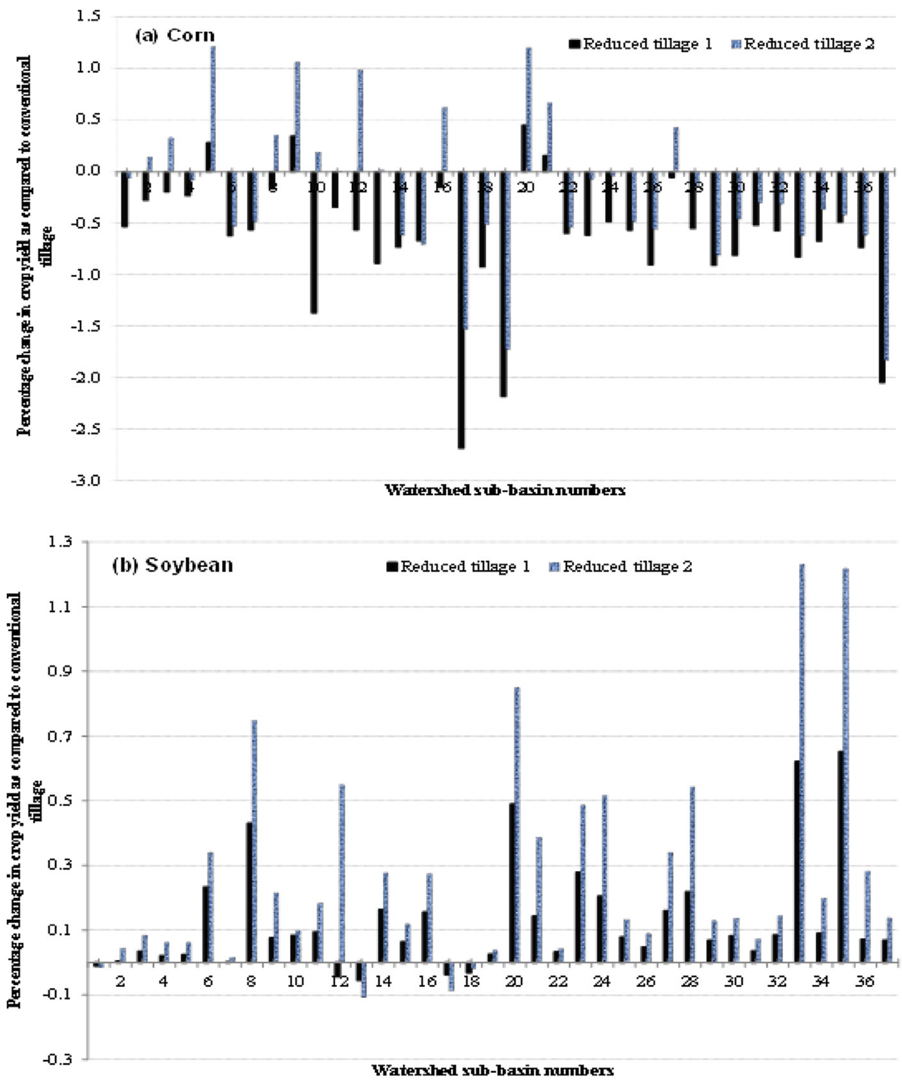

Fig. 5. Percentage yield changes in reduced 1 and 2 tillage practices compared to conventional tillage system calculated for each sub-watershed within the BSRW.

that annual sediment yield declined in reduced tillage systems as compared to the conventional system. The reduced or no-till practices can help to reduce soil erosion by preventing rill erosion (Fua et al., 2006). Although field measured long-term data were not available from conventional and no-till croplands to show correlation between measured vs model simulated results, some previous studies supported that the SWAT simulated uncalibrated results of this study were reasonable. A previous field study in this area reported sediment yield of about 10.95 Mg ha^{-1} year^{-1} (Schreiber et al., 2001). The Total Maximum Daily Load (TMDL) report from the Mississippi Department of Environmental Quality (MDEQ, 2003) reports the similar trends of sediment yields from the watershed. In the MDEQ's TMDL report the sediment yield was estimated with average high of 18.98 Mg ha^{-1} year^{-1}, average medium of 7.08 Mg ha^{-1} year^{-1} and average low of 3.68 Mg ha^{-1} year^{-1} (MDEQ, 2003). Results of this study are somewhat consistent with the previous USGS regional modeling study using SPARROW model. The USGS estimated increase in the nutrient loads from the Yazoo River Basin with crop rotation scenarios (Welch et al., 2010).

3.4. Climate change effects on crop and sediment yields

The modeled effects of climate change on corn and soybean production determined that the average corn yield averaged across all sub-watersheds in the BSRW is projected to increase in both mid and late century compared to the baseline; however the mid century crop yield increase will be higher than that of the late century. The predicted future soybean yield will be lower than the current soybean yield for both mid and late century periods. The average baseline corn yield was 8.4 Mg ha^{-1}, 8.3 Mg ha^{-1}, and 8.4 Mg ha^{-1} for conventional, reduced 1, and reduced 2 tillage practices respectively. The predicted mid-century corn yield was projected to increase by 3% (conventional tillage), 2.8% (reduced tillage 1), and 2.6% (reduced tillage 2). The predicted late-century corn yield will increase by 1% for all tillage practices. The predicted mid and late-century soybean yields will decrease by 3%, and 1.5% respectively for all tillage practices. The soybean yield reduction might be caused by the extreme temperature fluctuations. Rising temperature may increase crop growth but the heat stress may reduce the final crop yield (Southworth et al., 2000), and it is reported that crop yield responses are linearly correlated to the local temperature fluctuations (Osborne et al., 2013). The impact of tillage practices on crop yield in future climate scenarios will remain similar to the current climate conditions in the BSRW.

Sub-watersheds of the BSRW showed variable response in crop yield prediction due to the future climate change. Sub-watershed level analysis showed that corn yield could change from an increase of up to 34% to a reduction of up to 12%. The soybean yield could

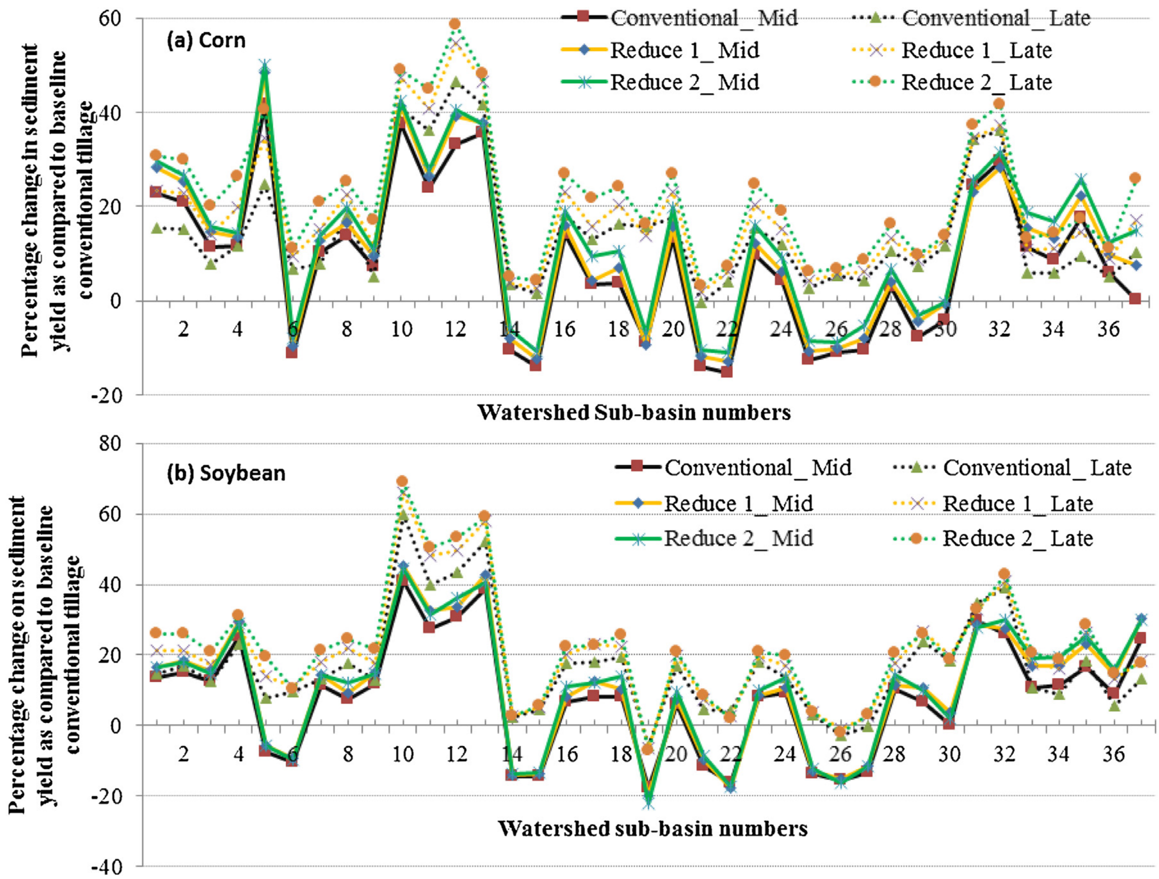

Fig. 6. Percentage change in sediment yield during mid and late centuries due to tillage compared to baseline conventional tillage from sub-watersheds.

Table 5
Effect of climate change on sediment and water yields for each tillage system.

Type	Tillage	Corn			Soybean		
		Baseline (1992–2011)	Mid (2046–2065)	Late (2080–2099)	Baseline (1992–2011)	Mid (2046–2065)	Late (2080–2099)
Sediment (Mg ha^{-1} yr^{-1})	Conventional	12.6	13.4	14.2	14.1	15.0	16.3
	Reduced 1	10.2	11.1	11.9	11.1	12.0	13.2
	Reduced 2	8.7	9.6	10.5	9.0	9.8	10.9
Water yield (mm yr^{-1})	Conventional	400	431	461	404	441	473
	Reduced 1	405	438	468	409	447	479
	Reduced 2	407	441	471	411	450	482

increase up to 12.5% or decline up to 16.6% in future climate under all tillage practices. A climate change study using the EPIC model in the U.S. reported that corn and soybean yields were expected to increase in future climate conditions (Izaurralde et al., 2003).

Mid and late-century climate of the BSRW will exhibit more rain with a longer summer period and higher temperature (maximum up to 5 °C) as compared to the baseline conditions, which may be favorable for crop production. However, the results could be significantly different if the crop rotation is changed. In addition, crop growing periods would be reduced in future climate conditions. Those changes would require some adjustments in crop rotations and planting dates for optimal crop growth (Yinhong et al., 2009). Spatial variability of the climate change within the BSRW can affect corn and soybean growth and development due to temperature stress (O'Neal et al., 2005).

Mid and late-century climate change will generate more runoff in the BSRW. Water yield from the watershed outlet was projected to be higher by 7–17% in future climate conditions. A study from the Midwestern region of the U.S. reported (O'Neal et al., 2005) runoff increase from 10 to 310% in future climate (2040–2059) as compared to their baseline (1990–1999). Increased runoff ultimately increases the erosion rate from the watershed. In this study, simulated results showed that sediment yield will increase in mid and late-century climate conditions from all tillage practices (Table 5).

However, only the late century sediment yields showed a large difference as compared to the baseline conditions. Sediment yield from corn crop fields will increase from 7% to 11% in mid-century and 13% to 21% in late-century depending on the tillage type. Reduced tillage 2 showed the lowest sediment yield increase as compared to baseline levels. Sediment yield from the soybean fields was projected to increase from 6% to 9% in mid-century and from 16% to 21% in late-century depending on tillage type. Effect of climate change and tillage practices on erosion rates varied among sub-watersheds, because of spatially variable inputs in the model within the watershed (Fig. 6). A study from the Midwestern U.S. reported an expected 33–274% increase in erosion during 2040–2059 compared to the 1990–1999 (O'Neal et al., 2005).

4. Conclusions

The SWAT model was first calibrated and validated for monthly stream flow and then for corn and soybean yields from the BSRW. Observed flow and crop yields for corn and soybean were utilized to evaluate model performances. The crop and sediment yields from the watershed were assessed based on implementation of three tillage practices (conventional, reduced 1, and reduced 2). Model simulated stream flow and crop yield simulations produced with R^2 from 0.72 to 0.82 and NSE from 0.70 to 0.81 for stream flow; R^2 from 0.40 to 0.50 and NSE from 0.72 to 0.86 for corn yield; and R^2 from 0.43 to 0.59 and NSE from 0.49 to 0.57 for soybean yield. There were slight differences between average corn and soybean yield for the three different tillage practices in the BSRW. However, there was a large difference between the sediment yields due to tillage practices.

The Gulf of Mexico is one of the major source area for the U.S. seafood industry. The Gulf of Mexico supplies 72% of U.S. harvested shrimp, 66% of harvested oysters, and 16% of commercial fish (in Bruckner, 2015 – Potash and Phosphate Institutes of the U.S. and Canada, 1999). If the hypoxic zone in the Gulf degrades due to sediment and nutrient depositions, coastal state economies might be greatly impacted. Increased sediment and nutrient yields can negatively affect the hypoxia zone in the Gulf of Mexico. Nutrients enter the river through upstream runoff of soil erosion, fertilizers, and animal wastes. The size of the dead zone in the Gulf fluctuates seasonally or year to year due to sediment and nutrient input. It is also affected by climate changes conditions. Sediment and nutrient loading to the Gulf of Mexico has increased since 1980. The size of the hypoxia zone has also increased after 1980 (Rabalais et al., 2002). The expansion of this zone indicates increased annual sediment and nutrient loading to the Gulf from the Mississippi River, which may be partially contributed by agricultural water management practices in the upstream watersheds. The predicted increased sediment yield from this study with specific agricultural practices may also have adverse impacts on the Gulf ecosystems. Studies on agricultural tillage managements with crop rotation and climate change from this study provided additional useful information to help to measure progress toward meeting the sediment and nutrient reduction targets as specified by the Mississippi River/Gulf of Mexico Watershed Nutrient Task Force.

For future climate change, this study used the synthetic weather data for IPCC scenarios SRES (A1B, A2, and B1), which was generated by the LARS-WG weather generator in accordance with the general circulation model, CCSM3. According to LARS-WG prediction, future average maximum temperature might increase up to 4.8 °C with longer summer periods in the BSRW. Future climate conditions of the BSRW may experience similar monthly rainfall patterns but frequent severe rainfall events. Agricultural practices in the BSRW should be adopted to reduce sediment and nutrient loadings to the Gulf of Mexico but keeping economic feasible cropping practices in the watershed. Average corn yields within the BSRW will increase in both the mid and late centuries as compared to the baseline conditions. However, the increment will be higher in mid century than in late century. The predicted future soybean yield was lower than the current soybean yield. The predictions showed high effects on sediment yield due to late century climate change within the BSRW. The reduced tillage 2 practice has the greatest responses to reducing sediment loss followed by reduced tillage 1 and conventional tillage practice for future climate change. Note also that unlike crop yields, sediment loss is cumulative over time. This study indicates the importance of implementing appropriate agricultural conservation management protocols to preserve topsoil and maintain agricultural crop field productivity. This study provides useful information about the consequences of climate change to watershed managers and policy makers for agricultural water management.

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