Assessment of Climatic Variability on Water Quality, Quantity, and Crop Productivity in Mississippi Watersheds

Badde VPL Jayakody

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Assessment of climatic variability on water quality, quantity, and crop productivity in Mississippi watersheds

By

Badde Vidanelage Priyantha Lal Jayakody

A Dissertation
Submitted to the Faculty of
Mississippi State University
in Partial Fulfillment of the Requirements
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in Engineering
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Mississippi State, Mississippi

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By
Badde Vidanelage Priyantha Lal Jayakody

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This study was conducted on two Mississippi watersheds. The SWAT model was applied to the Upper Pearl River Watershed (UPRW) to evaluate flow, sediment, nutrients, and fecal coliform bacteria (FCB) transport. The model was further applied to evaluate crop and sediment yields from three tillage systems (Conventional, Reduce 1, and Reduce 2) of the Big Sunflower River Watershed (BSRW). In the UPRW, flow and sediment simulations showed good to very good model performances (for flow $R^2$ up to 0.76 and NSE up to 0.75; and for sediment $R^2$ up to 0.72 and NSE up to 0.54). Both total nitrogen (TN) and total phosphorous (TP) simulations showed fair to good model performances ($R^2$ up to 0.71 and NSE up to 0.63 for TN; $R^2$ up to 0.70 and NSE up to 0.59 for TP). The FCB simulation showed good model performance ($R^2$ up to 0.59 and NSE up to 0.58). In the BSRW, crop simulations showed good to very good model performances (for corn yield $R^2$ up to 0.5 and NSE up to 0.9; and for soybean yield $R^2$ and NSE up to 0.6). Furthermore, modeling outputs of the BSRW explained 64% of the water table fluctuations in the Mississippi alluvial aquifer.
The future climates of the UPRW and the BSRW were evaluated for three emission scenarios (A1B, A2, and B1) from the Intergovernmental Panel on Climate Change (IPCC) with the help of the general circulation model, CCSM3. Simulations predict future sediment yields will increase as much as 25% in the UPRW. Both TN and TP yields will also be elevated as much as 7.3% and 14.3% respectively in future climates of the UPRW. Four best management practices (BMPs) were applied to the current and future climates in the UPRW and results showed that BMPs were able to reduce 51% of flow, 55% of sediment, 44% of TN, and 88% of TP in the baseline climate. Moreover, the effectiveness of TN removal will increase in future climates, while the effectiveness of TP removal will remain unchanged. The effects of climate variability on corn and soybean yield were insignificant in the BSRW.
DEDICATION

This work is dedicated to my family, my parents, my wife, Anusha, my children, Tuvini and Nadil, my sister, Premalatha, my brothers, Premasiri, Ranjith, and Sarath, for all their love and encouragement
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CHAPTER I
INTRODUCTION

Global surface temperature has increased during the past 150 year interval between 1850 and 2000, and this trend is expected to continue in the future (IPCC, 2007). Elevated levels of greenhouse gases such as carbon dioxide (CO$_2$) in the atmosphere are causing the global mean temperature to increase (the greenhouse effect). Based on global circulation model (GCM) experiments, a rise in global mean temperature of between 1.4 $^0$C to 5.8 $^0$C and a doubling of current CO$_2$ concentration are expected by the late 21$^{st}$ century (IPCC, 2007). Sufficient scientific evidence exists that air and water temperatures have increased dramatically over the last 15 to 20 years (Barnett et al., 2005; IPCC, 2007), causing hydrological system consequences (Zhang et al., 2007). The greenhouse effect will not only cause global mean temperature to increase, but the form and pattern of precipitation and surface runoff will be altered as well (Mimikou et al., 1999; Lahmer et al., 2001; Legesse et al., 2003; Doris et al., 2007). The literature reports that climate variability has a greater effect on the changes in runoff than land use changes do (Hu et al., 2004; Guo et al., 2008).

Surface water chemical processes (e.g. chemical degradation) will be altered by increasing temperature resulting in a change in water quality. Additionally, droughts will increase pollutant concentrations of surface water, while floods will dilute the pollutant concentrations. Changes to the surface runoff will change the land based erosion,
pollutant transport and deposition processes (Macdonald et al., 2005; Doris et al., 2007). Researchers have reported the impacts of climate variability on water quality (Park et al., 2010; Wilson and Weng, 2011; Visser et al., 2012). Increasing temperature, drought, and extreme precipitation events are the most important changes caused by climate variability and these changes will affect water quality parameters such as pH (Van Vliet and Zwolsman, 2008), dissolved oxygen (Prathumratana et al., 2008), nutrients (Van Vliet and Zwolsman, 2008), and pathogens (Arheimer et al., 2005; Jöhnk et al., 2008).

Climatic variability has a major effect on, not only water quantity and quality, but on crop production as well (Abraha et al., 2006). Increasing temperatures, levels of CO₂, and rainfall variability will affect crop yields geographically. While increasing rainfall and temperature may have positive impact on crop yield (Akpalu et al., 2008), extreme rainfall events may have negative impacts (Challinor et al., 2007). Crop duration and yield will be affected by temperature increases (Wheeler et al., 2000; Challinor et al., 2005). Furthermore, elevated CO₂ levels will have notable impacts on crop growth and development (Challinor and Wheeler, 2007). A detailed review of the impact of climate variability on crop production can be found in Kang et al. (2009).

Water quality issues have become prominent in the U.S. About 44% of the assessed U.S. river miles are impaired (USEPA, 2009). Top listed impairments are pathogens, habitat alteration, oxygen depletion, impaired biota, nutrients, metals, sediments, flow alteration, and turbidity (USEPA, 2009). Agricultural pollutants such as sediment, fertilizers, pesticides, salts and trace elements, resulting from various crop management activities can cause the degradation of surface and ground water resources through soil erosion, chemical runoff and leaching (Zalidis et al., 2002; Thorburn et al.,
Southern U.S. states with abundant water resources such as Mississippi are experiencing runoff pollution problems (Schreiber et al., 2001).

Hydrological models are used extensively in climate change impact studies (Limbrick et al., 2000; Goderniaux et al., 2009; Mauser and Bach, 2009; Rasmussen et al., 2012; Chen et al., 2012). As commented by Bloschl and Montanari (2010) “the climate change impact studies are four step processes: selection of climate change scenario based on expected economy and global climate model (GCM); downscale the GCM outputs; simulate hydrological models using those data; and compare future simulations with current scenarios”. Even though, these modeling outputs may be associated with high levels of uncertainties (Covey et al., 2003; Blöschl et al., 2007; Koutsoyiannis et al., 2008), impact studies are beneficial for evaluating future water quality deteriorations and the consequences of preventive methods such as implementation of best management practices (BMP). Impacts of climate variability on crop production can also be evaluated using appropriate crop models (Reddy and Pachepsky, 2000; Xie and Eheart, 2004; Aggarwal et al., 2006; Tojo Soler et al., 2007).

Nonpoint source (NPS) pollutants are dominant in surface water (Corwin et al., 1997), and proper evaluation requires expensive and time-consuming field level observations involving the collection of sediment and nutrient data because long-term secondary data sets are non-existent. These costs can be averted by using hydrological models capable of simulating NPS pollutants, and their spatial and temporal distributions (Di Luzio et al., 2004; Yang and Wang, 2010). The following are some of the hydrological models that can be used to investigate water quality dynamics in watersheds: IHACRES (Jakeman et al., 1990); QUASAR (Whitehead et al., 1997);
DRAINMOD (Skaggs, 1999); HSPF (Johanson et al., 1984), and the Soil and Water Assessment Tool (SWAT) model (Arnold et al., 1998). The SWAT has been extensively used to evaluate nitrogen, phosphate, and sediment transport over watersheds (Grizzetti et al., 2005; Abbaspour et al., 2007; Lam et al., 2010; Akhavan et al., 2010; Kemanian et al., 2011; Yang et al., 2011; Panagopoulos et al., 2011; Girolamo and Porto, 2012).

Moreover, the SWAT model can be used for systematic evaluation of water quantity and quality (Yang et al., 2007; Mishra et al., 2007) including assessing the total maximum daily load (TMDL) for these pollutants in surface water (Kang et al., 2006; Richards et al., 2008). Various modeling scenarios can also be used to predict climatological and environmental outcomes (Krysanova et al., 2005; Højberg et al., 2007).

A number of studies evaluating climate variability impacts of hydrology in the U.S. regions can be found in chapter 4 of “Hydrology and Water Resources” (Arnell et al., 2001). Most climate variability studies have focused on the Western region of the U.S. (Miles et al., 2000; Stone et al., 2001; Rosenberg et al., 2003; Payne et al., 2003; Christensen et al., 2004). Fewer studies have been conducted in the Southern U.S., while several have been carried out in the Upper Mississippi River Regions, (Dean, 1999; Goolsby et al., 2001; Knox, 2002). Very few studies have focused specifically on Mississippi watersheds. For example, Parajuli (2010) has conducted a study assessing the effects of long-term potential future climate change on average mean monthly stream flow in central Mississippi. Cathcart et al. (2007) investigated the climatological basis for conserving groundwater and reducing overflow in aquaculture ponds of Mississippi. Moreover, Mississippi has a climatic gradient that ranges from a maritime, warm temperate climate along the Gulf Coast to more continental temperate in the Northern
portion of the state (Katarzyna Grala, 2010). There is a need for additional climate variability studies for watershed evaluation in Mississippi. Moreover, as a state proximal to the Gulf of Mexico, the consequences of agricultural and industrial activities in the state directly impact this important body of water.

Proper management of water is important for sustainable crop production, especially in vital agricultural areas such as the Mississippi Delta. Water abstracted from the Mississippi Delta currently exceeds the long-term recharge rate resulting in declining aquifer levels (Poweres, 2007). Additionally, sedimentation, pathogens, and nutrients are among top priority pollutants in Mississippi today (USEPA, 2008). Further, Parajuli (2010) reported that the Upper Pearl River watershed in Mississippi will be highly sensitive to future climate variability. Understanding the hydrologic response of watersheds to physical (land use) and climatic (rainfall and air temperature) changes are important components of water resource planning and management (Vorosmarty et al., 2000). Accordingly, water management studies are important in Mississippi watersheds.

Studies about water quantity, quality, and pollutant transport processes are important to the effective management of Mississippi watersheds. Studies on Mississippi crop production and related consequences are important as well. The current water quantity and quality needs to be evaluated adequately allowing for anticipated climate variability. This study was designed to fulfill the current knowledge gap regarding the effects of climate variability on water budget, NPS pollution, and crop productions in Mississippi watersheds. The SWAT model was chosen because of its proven capability of investigating climate variability (Lirong and Jianyun, 2012; Rajesh et al., 2012), water
quality (Pisinaras et al., 2010; Cho et al., 2012), and crop growth and developments (Masih et al., 2011; Kim et al., 2013) in many geographical regions of the world.

**Objective**

The overall goal of this study is to investigate the impacts of climate variability on water quality, water quantity, and crop production in two differently managed Mississippi watersheds using modeling approaches.

**Specific Objectives**

1. Evaluate the impacts of climate variability on hydrological responses of Mississippi watersheds by incorporating global climatic data to a hydrological model.
2. Quantify the impacts, sensitivity, and uncertainty of climatic change variability on the fate and transport of bacteria.
3. Develop relationships between the models predicted evapotranspiration with observed ground water table.
4. Assess the impacts of crop management practices and climate variability on crop and sediment yields.

**Study area**

This research focused on two watersheds in Mississippi: (i) Upper Pearl River Watershed (UPRW; 7,588 km²) in central Mississippi, dominated by forestland use; (ii) Big Sunflower River Watershed (BSRW; 7,660 km²) in North-Western Mississippi, dominated by cropland use (Figure 1.1).
Figure 1.1  Study area showing two Mississippi watersheds and River networks
References


CHAPTER II
EVALUATE THE IMPACTS OF CLIMATE VARIABILITY ON HYDROLOGICAL RESPONSES OF MISSISSIPPI WATERSHEDS BY INCORPORATING GLOBAL CLIMATIC DATA TO A HYDROLOGICAL MODEL

Abstract
Effectiveness of NPS pollution control methods may be altered due to future climate variability. This study investigated climate variability impacts on flow, sediment and nutrient transport processes, with the effectiveness of BMPs, in the UPRW in Mississippi. The SWAT model was applied to the UPRW using observed flow, sediment, and nutrient data. Water quality samples were collected at three USGS gauging stations. The model was successfully calibrated and validated for daily time steps using manual and automatic (SUFI-2) methods from February 2010 to May 2011 (NSE and $R^2$ up to 0.7). Future climate variability was simulated with the LARS-WG, a stochastic weather generator, using the global climate model named CCSM3 which was developed by National Center for Atmospheric Research (NCAR) in the U.S. The SRES (Special Report on Emissions Scenarios) A1B, A2, and B1 of the Intergovernmental Panel on Climate Change (IPCC) were simulated for the mid (2046-2065) and late (2080-2099) century. The effectiveness of four BMPs (Riparian buffer, stream fencing, nutrient management, and vegetative filter strips) on reducing sediment and nutrient was evaluated in current and future climate scenarios. Results showed that sediment, nitrogen,
and phosphorus loadings will increase up to a maximum of 26.3%, 7.3%, and 14.3% respectively in future climate scenarios. Furthermore, the efficiencies of BMPs on sediment removal decrease in future climates, and the effectiveness of nitrogen removal will increase, while phosphorus removal effectiveness will remain unchanged.

**Introduction**

Ross Barnett Reservoir, which provides drinking water to the state capital Jackson MS, receives discharges from the UPRW, and potentially receives NPS pollution. Anthropogenic activities such as land use changes and deforestation directly contribute to water quality degradations, but the effect of climate variability on water quality is indirect (Delpla et al., 2009). Even though many studies have reported future climate variability impacts on water quality in different geographical regions (Park et al., 2010; Wilson and Weng, 2011; Visser et al., 2012), further investigations in different climatic regions are required to improve the current knowledge of impacts of climate variability on water quality.

Global warming occurs as a result of carbon dioxide (CO$_2$) increases in the atmosphere, and many consequences can be expected on hydrological systems due to this change (Zhang et al., 2007). There is ample scientific evidence that temperature has increased over the last 15 to 20 years in both air and water (Barnett et al., 2005; IPCC, 2007). Precipitation form and pattern may change, and these changes will alter runoff and land based erosion, which lead to a change of transport and deposition process of contaminants (Macdonald et al., 2005; Doris et al., 2007). The climate variability impacts on hydrology in the different U.S. regions have been well documented and can be found in chapter 4 in Hydrology and Water Resources (Arnell et al., 2001). Most of these
studies have focused on the western U.S. (Miles et al., 2000; Stone et al., 2001; Rosenberg et al., 2003; Payne et al., 2003; Christensen et al., 2004), while studies from the southern U.S. were limited.

Hydrological models are extensively used in climate variability impact studies (Limbrick et al., 2000; Goderniaux et al., 2009; Mauser and Bach, 2009; Rasmussen et al., 2012; Chen et al., 2012). As commented by Bloschl and Montanari (2010) “the climate change impact studies are four step processes: Selection of climate change scenario based on expected economy and global climate model (GCM); downscale the GCM outputs; simulate the hydrological models using those data; and compare the simulations with current scenarios”. Even though these modeling outputs are associated with high level of uncertainties (Covey et al., 2003; Blöschl et al., 2007; Koutsoyiannis et al., 2008), those outputs help future watershed management plans, such as implementation of BMPs.

The SWAT model (Arnold et al., 1998) has been extensively used to evaluate nitrogen, phosphorus, and sediment transport over watersheds (Grizzetti et al., 2005; Abbaspour et al., 2007; Lam et al., 2010; Kemanian et al., 2011; Yang et al., 2011; Panagopoulos et al., 2011). Moreover, the SWAT model has been applied in several geographical locations to evaluate the effectiveness of BMPs on NPS pollution reduction (Bracmort et al., 2006; Gassman et al., 2007; Arabi et al., 2008; Richards et al., 2008; Parajuli et al., 2008; Parajuli et al., 2013; Laurent and Ruelland, 2011). However, only a few studies in the U.S. have reported the effectiveness of the SWAT model to assess the climate variability impacts on nutrients and sediment transport. Recently, Ficklin et al. (2010) has reported climate variability impacts on sediment, nitrate, phosphorus, and
pesticide transport in San Joaquin watershed in California but have not investigated prevention methods. Further, Woznicki et al. (2011) has reported the effectiveness of BMPs for an agriculture dominant watershed in a humid continental climate (Tuttle Creek Lake watershed in Kansas and Nebraska). Therefore, additional studies are needed to investigate future climate variability impacts on water quality with the effectiveness of potential BMPs implementation on forest dominant watersheds in the humid subtropical climate of the U.S.

**Materials and Methods**

**Study area**

This study was performed in the UPRW, located in east central Mississippi in the U.S. (Figure 2.1). The watershed drains (drainage area = 7,588 km²) to the Ross Barnett Reservoir, which provides drinking water to the city of Jackson, the state capital of Mississippi. The watershed extends across the following ten counties (smallest administrative boundaries) of Mississippi: Rankin, Scott, Newton, Kemper, Neshoba, Leake, Madison, Winston, Attala, and Choctaw.
Input variables

Weather and stream flow

Observed daily rainfall and temperature data from the National Climatic Data Center (NCDC, 2010) were used in this study. The NCDC data came from the Global Climate Observing and System (GCOS) and Surface Network (GSN). Further, this data has undergone thorough quality assurance reviews. There were 10 NCDC weather stations in or near the UPRW (Figure 2.1). The average annual rainfall (from 2000 to 2009) of the study area was 1400 mm. Daily stream flow data from 3 USGS (U.S. Geological Survey) stations were used for stream flow calibration and validation (Burnside: USGS 02481880; Lena: USGS 02483500; and Ofahoma: USGS 02484500).
This data is available on the USGS-Water Data for the Nation website (http://waterdata.usgs.gov/nwis/sw).

Water quality data

Samplings were performed at three locations (Burnside, Lena, and Ofahoma) of the UPRW from Feb 2010 to May 2011, and these locations coincided with the USGS flow stations. Two locations were in the main Pearl River, while the other was in the Yockanookany River, which is the largest tributary of Pearl River (Figure 2.1). Thirty seven (37) sampling events were performed during the study period. Samplings were performed on the same day for all three locations. Grab samples were collected using narrow, open mouth 500 ml polyethylene bottles. The samples were divided into three 125 ml bottles, and concentrated sulfuric acid (96%) was added to the nitrogen and phosphate samples to preserve them. Preserved samples were refrigerated until the analyses.

Analyses were performed at the chemical and hydrological lab at the Forestry Department of the Mississippi State University following the standard guidelines given by “Methods for chemical analysis of water and wastes” (USEPA, 1983). Total suspended solid (sediment) and total phosphorus (TP) were analyzed according to the EPA methods 160.2 and 365.4 respectively (Table 2.1). The EPA methods 351.2 and 353.2 were used to analyze total Kjeldahl nitrogen and nitrogen in nitrate-nitrite forms, respectively. Total nitrogen (TN) was calculated by summing nitrogen in nitrate-nitrite forms with total Kjeldahl nitrogen.
Table 2.1  EPA standard analytical methods for TSS, TN, and TP

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>EPA method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total suspended solid (TSS)</td>
<td>160.2</td>
<td>Gravimetric, Dried at 103-105°C</td>
</tr>
<tr>
<td>Total Nitrogen (TN)</td>
<td>Kjeldahl Total : 351.2</td>
<td>Colorimetric, Semi-Automated, Block Digester, AA II</td>
</tr>
<tr>
<td></td>
<td>Nitrate-Nitrite: 353.2</td>
<td>Colorimetric, Automated Cadmium Reduction</td>
</tr>
<tr>
<td>Total Phosphorus</td>
<td>365.4</td>
<td>Colorimetric, Automated, Block Digester, AA II</td>
</tr>
</tbody>
</table>

Source: Methods for chemical analysis of water and wastes” (USEPA, 1983)

**Geospatial**

Soil Survey Geographic Database (SSURGO) data was incorporated into the model to parameterize soils in the watershed (USDA, 2005). The SSURGO databases have been developed using field methods based on the National Cooperative Soil Survey (NCSS) mapping standards and 1:12000 to 1:63360 map scales (USDA, 1995). The SSURGO data for the UPRW shows 7 major soil textural classes (Clayey, coarse-loamy, coarse-silty, fine, fine-loamy, fine-silty, and loamy). The “Loamy soil” is the dominant soil textural class (60% of the watershed area). The cropland data layer, with a 30 x 30 m spatial resolution, was used for the watershed land use data (USDA/NASS, 2009). The UPRW is covered by forest (60%), pasture (20%), wetland (12%), residential (6%), and croplands (2%). The 30 x 30 m grid digital elevation model (DEM) data from the U.S Geological Survey (USGS, 2010) were used for the elevation data in this study.

**Future weather data**

Future climate variability was simulated using LARS-WG, a stochastic weather generator. The LARS-WG generates synthetic daily time series of maximum and minimum temperatures, precipitation, and solar radiation by using parameters, which were generated using observed daily weather data for a given site and the selected GCM.
More details about LARS-WG can be found in the model reference manual (Semenov, 2007). Furthermore, the weather generator converts observed sunshine hours into solar radiations. Observed sunshine hours were only available for the weather station at the Jackson, MS airport, which is in the vicinity of the study area. Those sunshine hours were used with all the other weather stations to generate synthetic daily time series. The CCSM3 (Collins et al., 2004), developed by National Center for Atmospheric Research (NCAR) in the U.S, was used as GCM to generate future weather data. The CCSM3 is a model with 1.4° x 1.4° grid resolution.

Three emissions scenarios were selected based on the special report on emissions scenarios (SRES; IPCC, 2000) to evaluate future climate variability. These scenarios are listed below:

- **A1B scenario:** very rapid economic growth is expected and global population will peak in mid-century and then decline. A rapid introduction of new and more efficient technologies is expected with a balance between fossil and non-fossil energy sources. The CO$_2$ concentrations vary from baseline 334 ppm to 418 ppm during the early century (2011-2030), 541 ppm in mid century (2046-2065), and 674 ppm in late century (2081-2100).

- **A2 scenario:** a very heterogeneous world with continuously increasing global population. Economic development is regionally oriented, and technological changes are fragmented and slower. The CO$_2$ concentrations vary from baseline 334 ppm to 414 ppm in early century, 545 ppm in mid century, and 754 ppm in late century.
• B1 scenario: a convergent world where the global population peaks in mid-century and then declines. A rapid change in economic structures toward a service and information economy is expected. Clean and resource-efficient technologies, global solutions to economic, social, and environmental sustainability are expected without additional climate initiatives. The CO₂ concentrations vary from baseline 334 ppm to 410 ppm in early century, 492 ppm in mid century, and 538 ppm in late century.

Future weather data was incorporated to the model as new input files. New input files were developed from 2012 to 2100. The LARS-WG generates precipitation, temperature, and solar radiation only. The wind and humidity input files were developed as missing data (-99). The weather generator inside the SWAT model (WXGEN) fills those missing data.

Model setup

*SWAT model description*

The SWAT is a semi-distributed watershed scale hydrological model which operates on daily or sub-daily time steps, and has the capability to simulate the management change impacts on water quality and quantity (Neitsch *et al.*, 2005). Weather, hydrology, plant growth, water quantity and quality routing are some of the major components of the SWAT model (Arnold *et al.*, 1998; Neitsch *et al.*, 2005; Gassman *et al.*, 2007). Moreover, sub-watersheds are further divided into smaller units called hydrological response units (HRUs). The HRUs are lumped land areas that consist of unique land cover, soil and management combinations. The SWAT model simulates
daily runoff using the curve number (CN) method when daily data are available, or simulates using Green Ampt method if sub-daily precipitation data are available. The SWAT predicts flow through each layer in root zones using storage routing technique. During simulation, the SWAT routes flow, sediment yield, and nutrients through the stream network. The detailed description of the SWAT model can be found in the SWAT theoretical manual 2005 (Neitsch et al., 2005).

**BMP implementation**

The main objective of the BMPs implementation was to reduce sediment and nutrients in the surface water. The following four BMPs were selected based on common application methods in the watershed and main land use types.

*Stream fencing*

Generally, livestock graze near the streams where they wallow and drink. The main objective of stream fencing was to reduce the availability of cattle fecal matters near the streams, hence reducing the nutrient availability for wash off with runoff. In addition, this BMP improves the soil quality by preventing soil compaction caused by cattle movements. To facilitate stream fencing, grasslands within 200 m of streams (buffer) were treated as a separate land use category in the SWAT model setup. The 200 m buffer distance was chosen because cattle travel a similar distance to drink water while grazing. A study from the University of Missouri by Gerrish et al. (2012) reported that grazing cattle tend to travel around 180 m to 240 m away from water sources. The grasslands within the 200 m buffer distance covers 2% of the UPRW. The SWAT calibration parameters, which control the runoff from grasslands, were altered to simulate stream
fencing BMP. Grazing and manure applications on grasslands (within 200 m buffer) were excluded from the SWAT management file. The initial SCS runoff curve number for moisture condition II (CN2) for the fenced grasslands was also changed (from 79 to 69) to facilitate more infiltrations. We assumed that prevention of cattle entering into grassland may reduce soil compaction and increase infiltration. The CANMX (Maximum canopy storage mm H₂O) was also changed (from 3.5 to 4) to increase the interception. The grasslands may show an optimal growth without frequent grazing, and fully-grown grasses may intercept more rainfall.

*Riparian buffer strip*

Riparian buffer strips were implemented along the streams where good forest covers are unavailable. The cropland data layer, with a 30 m X 30 m spatial resolution, indicated that the majority of the stream buffer zone was already covered with forest (USDA/NASS, 2009). The forest HRUs within 100 m distance of the streams were selected using “select by location” operations in ArcGIS. This operation selected 60 forest HRUs. Moreover, ortho photos (1 m resolution) for the study area from USDA Geospatial Data Gateway (http://datagateway.nrcs.usda.gov/) were clipped using 100 m buffer zone, and classified into three forest types as good, fair, and poor by performing supervised classification in ERDAS Imagine 9.3. Areas with fully grown canopies were ranked as good, while areas where logging took place and with visible open spaces were ranked as poor. Forests with intermediate conditions were ranked as fair. This classified map was then overlaid with the selected forest HRUs and HRUs were also ranked similarly. This was the baseline condition for the UPRW.
It was found that only 11 forest HRUs were within poor and fair category, while all other forest HRUs were already good forests. A total HRU area of 253 km$^2$ contributed to the riparian buffer, only 28 km$^2$ were poor or fair. This BMP was performed by converting all the poor and fair forestland use parameters to good forest parameters. The CN number for the fair and poor forest was 73 and 77 respectively, and was changed to 70 to represent good forest characteristics. Furthermore, the CANMX was also changed (from 4.2 to 5) to increase the interception. The $C_{usle}$ is the ratio between soils losses from the specified lands against clean till continuous fallow lands (Wischmier and Smith, 1978). Generally, good forests have very low $C_{usle}$ (example, $C_{usle} = 0.006$; Qiu et al., 2012). In this study, we changed $C_{usle}$ from 0.1 (poor and fair) to 0.001 (good).

**Nutrient management**

Livestock farming is common in the UPRW. Current grassland management allows free grazing for beef cattle, and accumulated poultry litters are broadcasted on a monthly basis on grasslands (MDEQ, 1999). Instead of broadcasting manure on grasslands, subsurface applications were performed by combining with tillage operations. Plow was performed to 8 cm of depth as current subsurface plows are made to plough the soil up to 8 cm of depth (Pote et al., 2011). Furthermore, we assumed this plow has 0.25 mixing efficiency to match with the SWAT tillage database. Subsurface applications enhance biological mixing in the topsoil, and parameter BIOMIX (biological mixing efficiency) was changed (from 0.2 to 0.5) to facilitate more mixing. The parameter FRT_SURFACE controls the fraction of fertilizer applied to the top 10 mm of soil, and this model allows sediment and nutrients in this layer to move with surface runoff.
The default condition was to apply 20% (FRT_SURFACE = 0.8) of the fertilizer into the top 10 mm of soil with the remainder going to the layer below. Subsurface applications decrease the amount of manure in the top 10 mm of soil, while increasing amount into the layer below. We assumed 90% (FRT_SURFACE = 0.1) of poultry manure goes to the soil layer, which is below the top 10 mm of soil, due to BMP implementation.

*Vegetative filter strip*

Filter strips, defined in HRUs, reduce sediment, nutrient, pesticide, and bacteria in surface runoff. Vegetative filter strips slow down the surface runoff and facilitate the settlement of larger soil and organic particles. The trapping efficiency of the filter strip was calculated using following equation (Neitsch et al., 2005).

\[
\text{Trapping efficiency} = 0.367 \times (\text{width of the filter strip})^{0.2967}
\]  

(2.1)

Vegetative filter strips were applied on all the sub-watersheds by keeping the strip length at 6 m (20 feet) in accordance with NRCS standards (CODE 393) minimum criteria for sediment (NRCS, 2010). Similar lengths have been reported by several studies in different geographical regions (4.6 m by Magette et al., 1989; 6 m by Chaubey et al., 1994; 6.1 m by Lim et al., 1998)

**Model calibration and validation**

Daily observed stream flows from Burnside for Feb 2010 to May 2011 (37 data points) were used to calibrate the SWAT hydrological model, and the daily observed stream flows from Lena and Ofahoma for the same period were used for model validation. These flow data points coincided with water quality sampling dates. Observed
discrete water quality data (sediment, TN, and TP) from Burnside for Feb 2010 to May 2011 were used to calibrate the SWAT water quality model and observed data at the Lena and Ofahoma were used to validate the model.

Model calibration (flow, sediment, TP, TN) was initially performed using SWAT-CUP SUFI-2 automatic calibration technique (Abbaspour et al., 2007) and followed by the manual calibration to incorporate calibration parameters from previous studies in the UPRW. The SWAT-CUP SUFI-2 has been used for previous similar studies (Abbaspour et al., 2007). The SUFI-2 algorithm evaluates uncertainty of input parameters as a uniform distribution, and uncertainty of the model output as 95% of the prediction uncertainty. This prediction uncertainty is calculated for 2.5% and 97.5% levels of the cumulative distribution, and Latin hypercube sampling technique is used to obtain the output variables (Abbaspour et al., 2007). The Nash–Sutcliffe efficiency (NSE) coefficient was used as an objective function. Moreover, soil parameters were eliminated from auto-calibration as SSURGO soil data contain all the required parameters such as soil bulk density and hydraulic conductivity (USDA, 2005). The initial SCS runoff curve number for moisture condition II (CN2) was manually changed based on a previous modeling study performed in the same watershed by Parajuli (2010). Furthermore, depending on the data availability, the SWAT calculates potential evapotranspiration (PET) using Penman-Monteith, Priestley-Taylor, or Hargreaves method. In this study, we used Penman-Monteith method to simulate PET.

Model performances

Coefficient of determination ($R^2$) and Nash-Sutcliffe efficiency index (NSE) were used to evaluate model performance. The NSE statistic indicates how consistently
measured values (range $-\infty$ to 1.0) match predicted values, and is given by the following equation (Nash and Sutcliffe, 1970).

$$NSE = 1 - \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} (O_i - O_m)^2} \tag{2.2}$$

Where $NSE$ is model efficiency index, $O_i$ is $i^{th}$ observed value, $P_i$ is $i^{th}$ predicted value, and $O_m$ is observed mean value.

Coefficient of determination explains the co-linearity among simulated and measured data. The value of $R^2$ varies from 0 to 1. Zero indicates no relationship between observed and measured, while a 1 indicates similar dispersion of both observed and predicted data.

$$R^2 = \left( \frac{\sum_{i=1}^{n} (O_i - O_m)(P_i - P_m)}{\sqrt{\sum_{i=1}^{n} (O_i - O_m)^2 \sum_{i=1}^{n} (P_i - P_m)^2}} \right)^2 \tag{2.3}$$

Where $R^2$ is coefficient of determination, $O_i$ is $i^{th}$ observed value, $O_m$ observed mean, $P_i$ is $i^{th}$ predicted value, and $P_m$ is the predicted mean.

Model evaluation was performed based on previously published methods (Moriasi et al., 2007; Parajuli et al., 2009). Model performance was classified as excellent for $R^2$ or $NSE \geq 0.90$, very good for 0.75–0.89, good for 0.50-0.74, fair for 0.25-0.49, poor for $NSE =0-0.24$, and unsatisfactory for $< 0$.

**Results and Discussion**

**Stream flow calibration and validation**

Daily flow calibration was performed from Feb-2010 to May-2011. The model was simulated with a one year warm-up period (2009). Limited daily data points were
selected for calibration and validation to coincide with water quality data. The model was calibrated to the upstream gauge (Burnside) and validated to the downstream gauges Lena and Ofahoma. The Lena gauge is in the Pearl River, while the Ofahoma is in a tributary. Burnside and Lena showed good to very good model performances, however, Ofahoma showed poor model performances in flow simulations (Figure 2.2). Sub-watershed 1 and 13 drains to the Ofahoma gauge, and the model was unable to simulate flow at the Ofahoma adequately due to unavailability of representative weather stations. Average daily flow at the Burnside and Lena were 8.73 m$^3$s$^{-1}$, and 41.19 m$^3$s$^{-1}$ (Lena gauge is the nearest gauge to the Ross Barnett reservoir) respectively. Similar model performances have been reported for monthly stream flow simulation by the previous study in the UPRW (Parajuli, 2010).

Eleven flow calibration parameters were used in this study (Table 2.2). Groundwater flow responses to changes in recharge is controlled by the base flow alpha factor (ALPHA_BF) (Smedema and Rycroft, 1983) and it was set to 0.76. A previous study in the UPRW reported 0.9 (Parajuli, 2010). Higher ALPHA_BF indicate rapid responses to the recharge. We assumed rapid recharge because the most abundant soil types of the UPRW are coarse and fine loamy soils which contain more than 55% sand. All other parameters were set from SUFI-2 auto calibration technique. The ESCO showed a small value (0.1) in this study, however, it is acceptable based on published literature (Akhavan et al., 2010).
Figure 2.2 Observed and predicted daily flow (m$^3$s$^{-1}$)

(a) Burnside: sub-watershed 6; (b) Ofahoma: sub-watershed 13; (c) Lena: sub-watershed 17
Table 2.2   Flow calibration parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Fitted Value</th>
<th>Min</th>
<th>Max</th>
<th>t-Stat*</th>
<th>P-Value*</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALPHA_BF</td>
<td>0.76</td>
<td>0.20</td>
<td>0.90</td>
<td>-11.60</td>
<td>0.00</td>
</tr>
<tr>
<td>GW_DELAY</td>
<td>26.68</td>
<td>2.00</td>
<td>45.00</td>
<td>-0.53</td>
<td>0.59</td>
</tr>
<tr>
<td>CH_N2</td>
<td>0.28</td>
<td>0.014</td>
<td>0.30</td>
<td>81.37</td>
<td>0.00</td>
</tr>
<tr>
<td>CH_K2</td>
<td>46.96</td>
<td>1.00</td>
<td>50.00</td>
<td>25.80</td>
<td>0.00</td>
</tr>
<tr>
<td>SURLAG</td>
<td>1.07</td>
<td>1.00</td>
<td>8.00</td>
<td>-46.23</td>
<td>0.00</td>
</tr>
<tr>
<td>RCHRG_DP</td>
<td>0.17</td>
<td>0.00</td>
<td>0.90</td>
<td>-0.94</td>
<td>0.34</td>
</tr>
<tr>
<td>EPCO</td>
<td>0.44</td>
<td>0.10</td>
<td>0.90</td>
<td>4.14</td>
<td>0.00</td>
</tr>
<tr>
<td>ESCO</td>
<td>0.10</td>
<td>0.10</td>
<td>0.90</td>
<td>-15.73</td>
<td>0.00</td>
</tr>
<tr>
<td>GW_REVAP</td>
<td>0.03</td>
<td>0.02</td>
<td>0.20</td>
<td>-0.46</td>
<td>0.64</td>
</tr>
<tr>
<td>GWQMN</td>
<td>339.32</td>
<td>2.00</td>
<td>1000.00</td>
<td>-2.07</td>
<td>0.03</td>
</tr>
<tr>
<td>REVAPMN</td>
<td>239.60</td>
<td>1.00</td>
<td>400.00</td>
<td>1.26</td>
<td>0.20</td>
</tr>
</tbody>
</table>

*t-stat is a measure of sensitivity (high sensitivity is represented by larger absolute values)
*p-value is a measure of the significance of the sensitivity (Values close to zero is more significance)

ALPHA_BF=Base flow alpha factor(days); GW_DELAY=Groundwater delay time (days); CH_N2=Manning’s “n” value for the main channel; CH_K2=Effective hydraulic conductivity (mm hr\(^{-1}\)); SURLAG=Surface runoff lags time; RCHRG_DP=Deep aquifer percolation fraction; EPCO=Plant uptake compensation factor; ESCO=Soil evaporation compensation factor; GW_REVAP=Groundwater "revap" coefficient; GWQMN=Threshold depth of water in the shallow aquifer required for return flow to occur; REVAPMN=Threshold depth of water in the shallow aquifer for "revap" to occur.

**Sediment calibration and validation**

The sediment yield followed the stream flow pattern and showed good to very good model performances (Figure 2.3). Previous studies in the U.S. have reported similar model performance statistics for monthly sediment simulations. In addition, few studies have also reported model performance statistics for daily simulations (Gassman *et al.*, 2007). Big Creek in Illinois (NSE=0.42; Muleta and Nicklow, 2007) and Upper North Bosque River in Texas (NSE=-2.5 to -3.5; Saleh and Du, 2004) have reported daily model performance statistics. Average daily observed sediment loads were 7.6 Mg, 17.2 Mg, and 77.8 Mg for Burnside, Ofahoma, and Lena respectively. The model
overpredicted sediment loads at the Burnside (9.4 Mg; 24% overprediction),
underpredicted at the Ofahoma (9.4 Mg; 46% underprediction), and overpredicted at the
Lena (97.8 Mg; 26% overprediction).

Discrepancies of the observed and predicted were mainly attributed by the
accuracy of peak flow predictions. Peak sediment loads were affected by peak flows, and
simulating peak flows with greater accuracy is crucial for model calibration (Benaman
and Shoemaker, 2005). Furthermore, this discrepancy may also be attributed to
limitations of the existing SCS-CN and MUSLE methods in the SWAT model.
Depending on the number of rainfall events per a single day, soil moisture level and CN2
vary from event to event (Kim and Lee, 2008). However, the SWAT consider only sum
of the rainfall and may underestimate the runoff (Choi et al., 2002) and the sediment
loads. Further, rainfall intensity affects runoff, but the SWAT has no capability to
incorporate rainfall intensities during simulations (Vahabi and Nikkami, 2008).
Moreover, limited understanding of the physical process in the watershed may also
encounter possible discrepancies. Understanding physical process occurring in the
watershed is crucial in soil erosion modeling (Setegn et al., 2009).
Accuracy of the modeling results is dependent upon accurate calibration parameters (Xu et al., 2009). The most significant parameter for sediment calibration was
channel erodibility factor (CH_EROD) (Table 2.3). We allowed the SWAT-CUP to set the optimal parameter values and any discrepancies with previously reported values were adjusted manually.

Table 2.3  Sediment calibration parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Final</th>
<th>Min</th>
<th>Max</th>
<th>t-Stat</th>
<th>p-Value</th>
<th>Used in previous studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>CH_EROD</td>
<td>0.40</td>
<td>-0.50</td>
<td>0.6</td>
<td>-1.17</td>
<td>0.24</td>
<td>0.60 (Qui et al., 2012); 0.0001 (Oeurng et al., 2011)</td>
</tr>
<tr>
<td>CH_COV</td>
<td>0.59</td>
<td>-0.0010</td>
<td>1.0</td>
<td>-0.41</td>
<td>0.67</td>
<td>0.31 (Qui et al., 2012); 1 (Oeurng et al., 2011);</td>
</tr>
<tr>
<td>SPCON</td>
<td>0.001</td>
<td>0.0001</td>
<td>0.01</td>
<td>-1.16</td>
<td>0.24</td>
<td>0.009 (Qui et al., 2012); 0.01 (Oeurng et al., 2011); 0.001 (Ouyang et al., 2010);</td>
</tr>
<tr>
<td>SPEXP</td>
<td>1.4</td>
<td>1.0</td>
<td>1.5</td>
<td>-0.71</td>
<td>0.47</td>
<td>1.52 (Qui et al., 2012); 2 (Oeurng et al., 2011); 1.21 (Ouyang et al., 2010);</td>
</tr>
<tr>
<td>PRF</td>
<td>0.98</td>
<td>0.0</td>
<td>2.0</td>
<td>-0.87</td>
<td>0.37</td>
<td>0.58 (Oeurng et al., 2011);</td>
</tr>
<tr>
<td>USLE_C</td>
<td>0.001</td>
<td>0.001</td>
<td>0.5</td>
<td></td>
<td></td>
<td>Wood (0.006 Qui et al., 2012; 0.1 Ouyang et al., 2010), Grass (0.12 Qui et al., 2012; 0.08 Ouyang et al., 2010), Residential (0.2 Qui et al., 2012)</td>
</tr>
</tbody>
</table>

*t-stat is a measure of sensitivity (high sensitivity is represented by larger absolute values)
*p-value is a measure of the significance of the sensitivity (Values close to zero is more significance)

CH_EROD=Channel erodibility factor; CH_COV=Channel cover factor; SPCON= linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing; SPEXP=Exponent parameter for calculating sediment reentrained in channel sediment routing; PRF=Peak rate adjustment factor for sediment routing in the main channel; USLE C=Universal soil loss equation C factor

TN calibration and validation

Daily TN simulation results showed fair to good model performances (Figure 2.4). Most of the previous studies in the U.S. have reported similar statistics for monthly TN simulations, but only few studies have reported daily simulation statistics (Gassman et al., 2007). Studies from the Upper north Bosque River in Texas (NSE= 0.01 to 0.68; Saleh and Du, 2004) and Walnut Creek Iowa (NSE=-0.14 to -0.41; Du et al., 2006) have reported daily model performance statistics. Daily average TN loads during the study
period at the Burnside was 635 kg, and model predicted was 681 kg (7% overprediction); at the Ofahoma was 384 kg and model predicted was 448 kg (16% overprediction); at the Lena was 2309 kg and model predicted was 2542 kg (10% overprediction).

We used eight calibration parameters to simulate the TN loads (Table 2.4). The rate factor for humus mineralization of active organic nitrogen (CMN) was the most sensitive parameter. The nitrogen uptake distribution parameter (N_UPDIS) was not used in the sensitivity analysis, as current SWAT-CUP version has no capability to use N_UPDIS. Parameter values set by SWAT-CUP was manually manipulated to reasonable with previously published literature.
Figure 2.4  Observed and predicted total nitrogen yield (Kg day\(^{-1}\))

(a) Burnside: sub-watershed 6; (b) Ofahoma: sub-watershed 13; (c) Lena: sub-watershed 17
### Table 2.4  Nitrogen calibration parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Final</th>
<th>Min</th>
<th>Max</th>
<th>t-Stat*</th>
<th>P-Value*</th>
<th>Used in previous studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>CMN</td>
<td>0.0018</td>
<td>0.0010</td>
<td>0.0030</td>
<td>-2.00</td>
<td>0.18</td>
<td>63-65 (Akhavan et al., 2010); 10 (Yang et al., 2011); 9.4 (Abbaspour et al., 2007);</td>
</tr>
<tr>
<td>N_UPDIS</td>
<td>10</td>
<td>0.00</td>
<td>100</td>
<td>0.42</td>
<td>0.71</td>
<td>0.06 (Yang et al., 2011); 0.05 (Lam et al., 2010); 0.04 (Giolamo and Porte, 2012);</td>
</tr>
<tr>
<td>RSDCO</td>
<td>0.05</td>
<td>0.02</td>
<td>0.10</td>
<td>0.99</td>
<td>0.42</td>
<td>0.1 (Akhavan et al., 2010); 1.3 (Abbaspour et al., 2007); 0.3 (Richards et al., 2008);</td>
</tr>
<tr>
<td>RCN</td>
<td>1.70</td>
<td>0.00</td>
<td>2.00</td>
<td>0.36</td>
<td>0.75</td>
<td>0.1-0.2 (Akhavan et al., 2010); 0.5 (Yang et al., 2011); Panagopoulos et al., 2011);</td>
</tr>
<tr>
<td>NPERCO</td>
<td>0.33</td>
<td>0.00</td>
<td>1.00</td>
<td>0.04</td>
<td>0.97</td>
<td>2.75 (Abbaspour et al., 2007); 5 (Richards et al., 2008);</td>
</tr>
<tr>
<td>ERORGN</td>
<td>4.37</td>
<td>0.00</td>
<td>5.00</td>
<td>0.56</td>
<td>0.25</td>
<td>10000 (Richards et al., 2008);</td>
</tr>
<tr>
<td>RSDIN</td>
<td>1475</td>
<td>0.00</td>
<td>10000</td>
<td>0.04</td>
<td>0.41</td>
<td>0.08 (Lam et al., 2010);</td>
</tr>
<tr>
<td>AI1</td>
<td>0.072</td>
<td>0.07</td>
<td>0.09</td>
<td>0.72</td>
<td>0.72</td>
<td>38% underprediction; 9% overprediction; 2% underprediction respectively for the three stations.</td>
</tr>
</tbody>
</table>

* t-stat is a measure of sensitivity (high sensitivity is represented by larger absolute values)

* p-value is a measure of the significance of the sensitivity (Values close to zero is more significance)

CMN=Rate factor for humus mineralization of active organic nitrogen;
N_UPDIS=Nitrogen uptake distribution parameter; RSDCO residue decomposition coefficient; RCN=Concentration of nitrogen in rainfall; NPERCO=Nitrogen percolation coefficient; ERORGN=Organic N enrichment ratio; RSDIN=Initial residue cover; AI1=fraction of algal biomass that is nitrogen

**TP calibration and validation**

Similar to sediment and TN transport, TP also followed the stream flow pattern and showed good to fair model performances (Figure 2.5). Previous studies in the U.S. have reported similar statistics for monthly TP simulations, but only few studies reported daily simulation statistics (Gassman et al., 2007). A study at upper north Bosque River in Texas has reported daily NSE (-0.74 to 0.59; Saleh and Du, 2004). Average daily TP loads at the Burnside were 221 kg, Ofahoma were 154 kg, and Lena were 1356 kg, and model predictions were 138 kg (38% underprediction), 168 kg (9% overprediction), and 1342 kg (2% underprediction) respectively for the three stations.
We used eight model parameters to simulate TP loads at the UPRW. The phosphorus sorption coefficient (PSP) and algal respiration rate at 20 °C (RHOQ) were the most sensitive parameters in this study (Table 2.5).
Table 2.5  Phosphorus calibration parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Final</th>
<th>Min</th>
<th>Max</th>
<th>t-Stat*</th>
<th>P-Value*</th>
<th>Previous studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>GWSOLP</td>
<td>2.15</td>
<td>0.00</td>
<td>5.00</td>
<td>-1.27</td>
<td>0.20</td>
<td>0.08 (Richards et al., 2008)</td>
</tr>
<tr>
<td>PSP</td>
<td>0.067</td>
<td>0.01</td>
<td>0.07</td>
<td>10.32</td>
<td>0.00</td>
<td>0.4 (Yang et al., 2011; Panagopoulos et al., 2011) 0.5-0.7 (Abbaspour et al., 2007)</td>
</tr>
<tr>
<td>PPERCO</td>
<td>32.03</td>
<td>10.00</td>
<td>175.00</td>
<td>0.72</td>
<td>0.47</td>
<td>10 (Richards et al., 2008; Panagopoulos et al., 2011)</td>
</tr>
<tr>
<td>ERORGPC</td>
<td>3.37</td>
<td>0.00</td>
<td>5.00</td>
<td>-8.16</td>
<td>0.00</td>
<td>2-4 (Abbaspour et al., 2007)</td>
</tr>
<tr>
<td>AI2</td>
<td>0.019</td>
<td>0.01</td>
<td>0.02</td>
<td>-9.50</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>RHOQ</td>
<td>0.096</td>
<td>0.05</td>
<td>0.50</td>
<td>19.54</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>BC4</td>
<td>0.11</td>
<td>0.01</td>
<td>0.70</td>
<td>-3.10</td>
<td>0.001</td>
<td>0.3-0.5 (Abbaspour et al., 2007)</td>
</tr>
<tr>
<td>RS5</td>
<td>0.0017</td>
<td>0.0001</td>
<td>0.10</td>
<td>3.14</td>
<td>0.001</td>
<td>0.08-0.1 (Abbaspour et al., 2007)</td>
</tr>
</tbody>
</table>

*t-stat is a measure of sensitivity (high sensitivity is represented by larger absolute values)
*p-value is a measure of the significance of the sensitivity (Values close to zero is more significance)
GWSOLP=Concentration of soluble phosphorus in groundwater contribution to stream flow from sub-basin; PSP=Phosphorus sorption coefficient; PPERCO=Phosphorus percolation coefficient; ERORGPC=Organic P enrichment ratio; AI2=Fraction of algal biomass that is phosphorus; RHOQ=Algal respiration rate at 20 °C; BC4=Rate constant for mineralization of organic P to dissolved P in the reach at 20 °C; RS5=Organic phosphorus settling rate in the reach at 20 °C

Spatial distribution of sediment and nutrient yield

Monthly average flow, sediment, TN, and TP from sub-watersheds outputs for 2007 to 2011 were analyzed. Outputs were categorized into sub-categories as very low, low, medium, and high. Sub-watersheds, which contribute higher sediment and nutrient concentrations to the streams, can be ranked using the SWAT simulation results (Figure 2.6). These rankings help to prioritize the sub-watersheds which need preventive methods or effective land use planning to protect surface water (Tripathi et al., 2003; Panagopoulos et al., 2011). Sub-watershed 3 and 10 showed high to medium runoff, and all other sub-watersheds showed low to very low runoff. Sub-watershed 3 and 10 include urban lands which have higher runoff potentials. Sub-watersheds 9 and 24 showed the
highest sediment yield and all other sub-watersheds showed low to very low sediment yield. Soil erosion and transportation is controlled by many factors such as land use, climate, topography, soil, and anthropogenic activities (Assouline and Ben-Hur, 2006). Sub-watersheds which have different land use, soil, slope, and management practices showed high spatial variation of sediment and nutrients loads. Sub-watersheds 23, 20, 12, and 17 showed medium level of TN yields, while the sub-watershed 3 showed the highest yield. Furthermore, rest of the sub-watersheds showed very low TN yields. It’s been noted that area covered by forest was negatively correlated with nitrate loads (Lam et al., 2010). Sub-watershed 1 showed very low TP yield while sub-watersheds 12, 18, and 23 showed the highest TP yield, rest of the sub-watersheds were medium to low.

Monthly average water yield varied from 40 mm to 60 mm across the watershed, and sediment yield varied from 0.01 to 0.03 Mg ha\(^{-1}\). The UPRW is a forest dominant watershed and low erosion rate can be expected. It has been reported that forests reduce the erosion rates (Garzía-Ruiz et al., 2008; Verbist et al., 2010). Previous SWAT simulations have reported similar sediment yields in different geographic locations (0.006-0.23 Mg ha\(^{-1}\): Abbaspour et al., 2007; 0.005-0.008 Mg ha\(^{-1}\): Ouyang et al., 2010; 0.04 Mg ha\(^{-1}\): Oeurng et al., 2011; 1.16 Mg ha\(^{-1}\): Panagopoulos et al., 2011. Total nitrogen yields varied from 0.7 to 0.9 Kg ha\(^{-1}\) and upper and lower sections of the watershed showed very low TN yields. Previous SWAT applications have reported similar ranges in different geographical regions (0.75-3.5: Abbaspour et al., 2007; 1.6: Panagopoulos et al., 2011). Total phosphorus yields from the watershed were varied from 0.05 to 0.13 Kg ha\(^{-1}\). Previous studies have also reported similar yields (0.008-0.35: Abbaspour et al., 2007; 0.23 Mg ha\(^{-1}\): Panagopoulos et al., 2011).
Future rainfall and temperature

Future temperature variations were evaluated with compared to the baseline temperature from 1992-2011. Maximum (Tmax) and minimum (Tmin) temperature, derived for mid (2046-2065) and late (2080-2099) centuries from LARS-WG, were averaged over the entire watershed to compare with baseline averages (Figure 2.7).
Average annual baseline Tmax was 24°C, and average annual mid century Tmax will be 26.1°C, 26.2°C, and 25.6°C for A1B, A2, and B1 scenarios respectively. During late century, the annual average Tmax will be 26.8°C (A1B), 26.4°C (A2), and 25.6°C (B1). The highest Tmax increases (from baseline) will be 2.5°C for A1B (September), 3.1°C for A2 (September), and 2°C for B1 (March) scenario during the mid century (Figure 2.7). In late century, the highest Tmax increase will be 3.4°C for A1B (June) and 3.3°C for A2 (September) and 2.2°C for B1 (November). November Tmax will be increased by more than 2 °C in all future scenarios. July and August are the warmest months in a year, but in future climate warmest period will be extended from June to September. The Tmin variations followed a similar pattern as Tmax.

Figure 2.7 Maximum and minimum future temperature changes °C

Note: Reference to the base period (1980-2011)
Mid and late century precipitation from 10 stations were evaluated with compared to the baseline precipitation from 1992 to 2011. Percentage changes of annual average future precipitation were calculated based on baseline annual averages (Table 2.6). The future rainfall in mid century will vary from a 6.3% reduction to an 11.8% increase. During late century, the rainfall will vary from an 8.3% reduction to a 13.1% increase. Moreover, Monthly precipitation patterns will be changed in future climate. Monthly baseline average precipitations showed a decreasing trend from March to June (Figure 2.8). All three future scenarios will have more rain in April compared to the baseline, and the lowest point will be shifted from March to June. The low rainfall months will be receiving further low rain in future. Furthermore, the summer will be drier than before as June will be receiving low rainfall compared to the baseline. It has been reported that future summers will be drier in the subtropics (Bates et al., 2008). After June, the baseline rainfall increased in July but future rainfall will only be increased in August (one-month shift). Peak rainfall in April, August, and December in future scenarios will be due to extreme rainfall events. There is evidence that extreme rainfall events have already increased in the U.S. (Karl and Knight, 1998), and are expected to increase in the future as subtropics will experience extreme rain events(Bates et al., 2008).
<table>
<thead>
<tr>
<th>Station name</th>
<th>Annual average (mm) 1992-2011</th>
<th>Scenario</th>
<th>% change 2046-2065</th>
<th>% change 2080-2099</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest 3S</td>
<td>1445</td>
<td>A1B</td>
<td>2.1</td>
<td>-4.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A2</td>
<td>-4.1</td>
<td>-0.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B1</td>
<td>-4.9</td>
<td>-1.9</td>
</tr>
<tr>
<td>Gholson 8W</td>
<td>1415</td>
<td>A1B</td>
<td>1.4</td>
<td>5.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A2</td>
<td>-3.9</td>
<td>-3.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B1</td>
<td>0.9</td>
<td>2.7</td>
</tr>
<tr>
<td>Louisville</td>
<td>1382</td>
<td>A1B</td>
<td>0.1</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A2</td>
<td>-6.0</td>
<td>-0.9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B1</td>
<td>-0.2</td>
<td>5.5</td>
</tr>
<tr>
<td>Philadelphia 1 WSW</td>
<td>1405</td>
<td>A1B</td>
<td>7.5</td>
<td>13.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A2</td>
<td>5.3</td>
<td>9.5</td>
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<td></td>
<td></td>
<td>B1</td>
<td>7.5</td>
<td>8.3</td>
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<td>B1</td>
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<td></td>
<td></td>
<td>A2</td>
<td>3.1</td>
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<td>B1</td>
<td>11.2</td>
<td>11.9</td>
</tr>
<tr>
<td>Goshen Spring 3 NW</td>
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<td>A1B</td>
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</tr>
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<td>Walnut Grove 2S</td>
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<td>A1B</td>
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</tr>
<tr>
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<td>-6.3</td>
<td>-8.3</td>
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<td>0.5</td>
<td>-1.4</td>
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<td>5.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A2</td>
<td>4.6</td>
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<td></td>
<td></td>
<td>B1</td>
<td>11.8</td>
<td>9.6</td>
</tr>
<tr>
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<td>A1B</td>
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</tr>
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<td></td>
<td></td>
<td>A2</td>
<td>-3.2</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>B1</td>
<td>11.4</td>
<td>10.5</td>
</tr>
</tbody>
</table>

*%change= ((Scenario-Base)/Base)*100
Future flow, sediment, and nutrients

Average annual changes of flow, sediment, TN, and TP yield from the baseline (2007-2011) due to climate variability were evaluated at the Lena gauge, which is immediately upstream of the Ross Barnnet reservoir. Average annual flow rate at the Lena was 90 m$^3$s$^{-1}$; there will be a 4.2% to 16% increase in the mid century, and a 19% to 19.5% increase in the late century based on which IPCC scenario was chosen (Table 2.7). This flow increase will be caused by high intensity rainfalls in the future climate. In addition, long dry periods will create surface crusting and will reduce infiltration capacity, which leads to extreme runoff events (Kostaschuk et al., 2002; Bouraoui et al., 2004).
Future sediment yields in the UPRW will be changed compared to the baseline. Several studies have already reported consequences of soil erosion due to climate variability (Zhang, 2007; Nunes and Nearing, 2011). Average annual sediment yield at the Lena gauge was 0.49 Mg ha\(^{-1}\)year\(^{-1}\) (baseline) and showed more than 20% increase in mid century, and about 25% increase in late century, will be expected (Table 2.7). A study of the forest dominant Cannonsville watershed in the Catskill region of New York State has reported similar sediment yield changes from 20.7% reduction to 25.5% increased in A1B scenario (in late century) based on nine climate models (Mukundan et al., 2012). Furthermore, Li et al. (2011) has reported 3 °C increase in temperature may lead to an increase of 13% of sediment loads in south China. This finding is similar to our future predictions in the UPRW. It has been reported that increasing rainfall intensity in
the future will increase the sediment loads (Kostaschuk et al., 2002; Bouraoui et al., 2004; Nearing et al., 2005).

Extreme dry and wet events may increase the decomposition and flushing of more organic matter to the stream (Evans et al., 2005) and may lead to increased nutrient concentration in surface water. The TN will be decreased 0.5% (A2) and increased up to 7.3% in mid century, and 2.1% to 5.5 % will be increased in late century at the Lena gauge. The TP will follow a pattern similar to TN, but with a different magnitude. The TP will be reduced by 3.9% (A2) and increased up to 14.3% (A2) during mid and late century respectively (Table 2.7). Increasing temperature due to climate variability will affect the transformation of nitrogen between different forms and leads to increased nitrogen mineralization (Whitehead et al., 2009). Furthermore, release of N and P from organic matter will also increase with increasing temperature (Ducharne et al., 2007). The SWAT uses PAPRAN mineralization model (Seligman and van Keulen, 1981) and this model mineralizes more nitrogen with increasing soil temperature and water content. Further, soil enzymatic activity may increase with the increasing temperature and increased nitrogen and phosphorus mobilization (Van Vliet and Zwolsman, 2008). Moreover, high intensity rainfall after long drought will increase pollutant loads to the streams (Delpla et al., 2009). Once the dry periods get longer, more nitrogen will be flushed into the stream at the beginning of the wet season (Wilby et al., 2006). Bhat et al. (2007) reported that 73% of the TN from forested watersheds was exported by surface runoff. Generally, high runoff tends to wash off more sediment, TN, and TP to the streams, and the major portion of TP washes off by attaching to sediment (Drewry et al., 2009).
Effect of BMPs

This study simulated four BMPs, and their efficiencies were evaluated in baseline (2007-2011) and future climate. Five years were chosen as baseline by assuming that the management practices in the UPRW have not been changed significantly during this period. Evaluation was performed to assess the effects of individual BMP as well as a combination of four BMPs (Figure 2.9). The efficiencies of BMPs were evaluated at the Lena gauge, which is the nearest to the Ross Barnett reservoir and at the each sub-watershed separately. The riparian buffer strip, stream fencing, and nutrient management (subsurface poultry manure applications) BMPs did not show noticeable impacts at the Lena gauge, but they did at the individual sub-watersheds in which BMPs were placed.

Riparian buffer strips were simulated using healthy forest covers as forests are capable of controlling erosions (Stott et al., 2001; Gökbulak et al., 2008). Generally, the undisturbed forests use as a benchmark to assess the erosion process (Sidle et al., 2006). It has been reported that sediment, TN, and TP may be reduced around 20%, 65, and 8% respectively by converting bare lands into forests (USEPA, 2008). Impacts of riparian buffer strips on reducing sediment and nutrient was not effective at the Lena gauge (Table 2.8). The UPRW is a forested watershed, and 100 m stream buffer zones were extended about 253 km² of lands. Out of that only 28 km² lands are poor or fair type forest, and most of the current buffer zones are currently with healthy forests. Implementation of riparian buffers on such a small land fractions may not improve the downstream water quality, but individual sub-watersheds, in which riparian buffers were placed, simulated noticeable reductions to sediment and nutrients loads (Figure 2.9).
Stream fencing BMP was simulated in the UPRW, as stream fencing improves the water quality (Godwin and Miner, 1996). Control grazing such as preventing the cattle movements near to the stream banks, helps to improve water quality and was reported by Larsen et al. (1994) in their excellent review. A significant reduction of sediment (90%), TN (54%), and TP (81%) can be achieved by restricting cattle from streams (Sheffield et al., 1997). Stream fencing was limited 2% of the UPRW, as availability of grasslands near to streams was limited. Results showed that the TN can be reduced around 5% at the sub-watersheds 3, 22, 25, 26, and 27, while other sub-watersheds got very low impacts (Figure 2.9). Overall impacts at the Lena gauge were also low as expected (Table 2.8), and TN can be reduced only about 1.5% in baseline. Furthermore, the effectiveness of the BMP will be increased in future climate. The TN yield can be reduced more than 5% using stream fencing in mid century climate (Table 2.8).

Subsurface poultry manure application was evaluated as a nutrient management BMP. We assumed that this BMP prevents nutrients wash off with surface runoff, and in addition, enhances the soil properties. Subsurface manure applications have no dominant effect on flow and sediment yield as expected, but were effective in reducing TN and TP. Simulation results showed that around 20% of TP and 30% of TN removal can be achieved at most of the sub-watershed outlets. Moreover, sub-watersheds such as 13 and 14 showed more than 30% of TN removal (Figure 2.9). Unlike riparian buffer and stream fencing, subsurface manure application has noticeable effects at the Lena gauge (Table 2.8). Both TN and TP can be reduced approximately 14% and 7% respectively at the Lena gauge. Moreover, effectiveness of TN removal will be increased in mid century,
while effectiveness of TP removal will be reduced in both mid and late century (Table 2.8).

Vegetative filter strips were applied for all sub-watersheds and their efficiencies for reduction of sediment and nutrient loading were evaluated. Flow, sediment, TN, and TP can be reduced considerably at all the sub-watersheds outlets by applying this BMP (Figure 2.9). The TP can be reduced about 80%, while sediment and TN can be reduced 20% to 40% in all sub-watershed outlets. Vegetative filter strips slowdown runoff and facilitate settling of larger materials. The TP attached to the sediments may also settled on filter strips, and reduce the overall TP yields into the streams. Even though, sediment and TP can be reduced notably, the effectiveness of this BMP on TN removal was low. The mineralization process, which occurred in streams, may contribute TN to existing TN loads in the stream. Moreover, we have used 6 m width of filter strips. A field study with 4.6 m buffer reported 66% of sediment, 0% of TN, and 27% of TP removal (Magette et al., 1989). Further, Lim et al. (1998) reported that 6.1 m filter strips were able to reduce 75% of the incoming nutrient and sediment. Chaubey et al. (1994) also reported that 6 m filter strips were able to remove 69% TN and 70% TP. Furthermore, these removal efficiencies can be as high as 90% removal (Coyne et al., 1995). Generally, physical dimensions of the filter strips change the effectiveness of sediment and nutrient removal. In addition, land uses determine the TN and TP loads in surface water (Wickham and Wade, 2002).
Vegetative filter strips reduced the runoff by 49% at the Lena gauge in baseline, but the effectiveness of the BMP in flow reduction will be reduced more than 10% in future climate (Table 2.8). Extreme rainfall events in the future may decrease the effectiveness of the vegetative filter strips. A field study reported that effectiveness of the vegetative filter strip decreases as the number of runoff events increases (Magette et al., 1989). In the baseline, this BMP was able to reduce 54% of the sediment load, but the effectiveness of the BMP will be reduced in a future climate. Moreover, vegetative filter strips were able to reduce 24.7% of TN and 87.1% of TP in baseline. The effectiveness of the BMP on TN removal will increase in the future. Further, the effectiveness of BMP for
TP removal will not be affected notably in the future climate. The combined applications of all the BMPs will help to reduce more sediment and nutrient loads at the Lena gauge. As the dominant effects come from vegetative filter strip, the combine effects also followed similar pattern as vegetative filter strip in baseline and future climate. The highest combine effect was observed in TN removal (44.4%).

Table 2.8 Effectiveness of BMPs at the Lena gauge

<table>
<thead>
<tr>
<th>BMP</th>
<th>Baseline value</th>
<th>% change at Baseline</th>
<th>% change mid century</th>
<th>% change late century</th>
</tr>
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<tr>
<td>Flow (m³s⁻¹)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>90</td>
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<td>-0.2</td>
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<tr>
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<td>-0.1</td>
<td>-0.3</td>
<td>-0.3</td>
</tr>
<tr>
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<td>0.1</td>
<td>0.1</td>
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<tr>
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<td>-39.4</td>
<td>-37.4</td>
</tr>
<tr>
<td>All combined</td>
<td></td>
<td>-51.0</td>
<td>-40.6</td>
<td>-38.5</td>
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<tr>
<td>Sediment (Mg month⁻¹)</td>
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<td></td>
<td></td>
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<td>-0.3</td>
<td>-0.2</td>
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<td>-0.2</td>
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<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>Vegetative filter strip</td>
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<tr>
<td>All combined</td>
<td></td>
<td>-55.5</td>
<td>-46.2</td>
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<tr>
<td>Total nitrogen (Kg month⁻¹)</td>
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<tr>
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<td></td>
<td>-44.4</td>
<td>-50.8</td>
<td>-45.3</td>
</tr>
<tr>
<td>Total phosphorus (Kg month⁻¹)</td>
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<td></td>
<td></td>
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Conclusions

The SWAT model was applied to a forest dominant watershed in the humid subtropical climate of the U.S. The model used climate, soil, and elevation as input data to simulate flow, sediment and nutrients from the UPRW. Simulated model outputs were evaluated against observed flow, sediment, total nitrogen (TN), and total phosphorus (TP). Flow and sediment simulations showed good to very good model performances (for flow $R^2$ up to 0.76 and NSE up to 0.75; and for sediment $R^2$ up to 0.72 and NSE up to 0.54). Both the TN and TP simulation showed fair to good model performances ($R^2$ up to 0.71 and NSE up to 0.63 for TN; $R^2$ up to 0.70 and NSE up to 0.59 for TP). Model simulation results agreed with previous similar studies.

The SWAT model was successfully applied to simulate mid and late century flows, sediment, TN, and TP from the UPRW with the help of LARS-WG stochastic weather generator. The synthetic weather data for IPCC scenarios SRES (A1B, A2, and B1) were generated by LARS-WG weather generated in accordance with the general circulation model, CCSM3. It was predicted that future temperature in the UPRW will be warmer by 2°C to 3.4°C. The future rainfall distributions will be highly variable across the watershed. Annual average future flow rates will be increased up to 19 % compared with baseline, and future sediment yield will also increase up to 25%. Moreover, both TN and TP yields will be higher (up to 7.3% and 14.3%, respectively) in future climates.

Four BMPs and their combinations were applied in baseline and future climate. Riparian buffer and stream fencing did not show a large impact on reducing flow, sediment, and nutrients in both baseline and future climate. The nutrient management BMP and vegetative filter strips were very effective in reducing flow, sediment, and nutrients.
Combined effects of all BMPs were able to reduce 51% of flow, 55% of sediment, 44% of TN, and 88% of TP in baseline climate. The effectiveness of BMPs on reducing flow and sediment will decline in a future climate. Moreover, the effectiveness of TN removal will be increased in future climate, while the effectiveness of TP removal will be unchanged. Results of this study can be used to make early mitigation plans.
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CHAPTER III
QUANTIFY THE IMPACTS, SENSITIVITY, AND UNCERTAINTY OF CLIMATIC CHANGE VARIABILITY ON THE FATE AND TRANSPORT OF BACTERIA

Abstract
This study investigated the impacts of climate variability on flow and fecal coliform bacteria (FCB) transport in the UPRW in Mississippi. The Soil and Water Assessment Tool (SWAT) was applied to the UPRW using observed flow and FCB concentrations. Water samples were collected for FCB analysis at three USGS gauging stations. The SWAT hydrologic model was successfully calibrated and validated for daily time steps using both manual and automatic (SUFI-2) methods from Feb 2011 to June 2012 (NSE and $R^2$ up to 0.79). Future climate variability was simulated with the LARS-WG, a stochastic weather generator, using the global climate model, CCSM3, which was developed by the U.S. National Center for Atmospheric Research (NCAR). The SRES (Special Report on Emissions Scenarios) A1B of the Intergovernmental Panel on Climate Change (IPCC) were simulated for the mid (2046-2065) and late (2080-2099) century. The FCB simulations showed good model performances ($R^2$ up to 0.59 and NSE up to 0.58). During the mid-century climate, the bacteria concentration varied between a 54% reduction to a 1,613% increase, while the late-century variation of FCB concentration will reduce by 56% to a 2,175% increase.
Introduction

Fecal coliform bacteria (FCB) are indicators of potential pathogenic organisms. Serious health risks arise when FCB contaminated water is a source of drinking water, irrigation, or recreational purposes. Surface waters receive FCB from agricultural operations (USEPA, 1998 & 2004), failing septic systems (Parajuli et al., 2006), and wildlife. Livestock animals, which are colonized with FCB, spread such micro-organisms via defecation during grazing (Nicholson et al., 2000). In addition, land application of livestock manure releases such micro-organisms into the environment. These bacteria in the environment may undergo die-off and/or re-growth depending on the stresses and resources of the physical, chemical, and biological nature of their surroundings (Cool et al., 2001). Climatic factors such as temperature, rainfall, and solar radiations play a significant role in determining FCB survival.

Global warming occurs because of carbon dioxide (CO2) increases in the atmosphere. There will be many consequences expected on hydrological systems resulting from this warming (Zhang et al., 2007). It has been reported that both air and water temperature has increased over the last 15 to 20 years (Barnett et al., 2005; IPCC, 2007). This warming alters the form and pattern of precipitation which in turn alters runoff, which changes the transport and deposition processes of contaminants (Macdonald et al., 2005; Doris et al., 2007). There is evidence that extreme rainfall events have already increased in the U.S. (Karl and Knight, 1998), and are expected to continue in the future. It has been reported that the subtropics (southern part of the U.S.) will experience frequent extreme rainfall events (Bates et al., 2008), and long dry periods, creating surface crusting, which reduces infiltration capacity and promotes
extreme runoff events (Kostaschuk et al., 2002; Bouraoui et al., 2004). Furthermore, future summers are anticipated to be drier in the subtropics (Bates et al., 2008).

Effect of temperature fluctuations on FCB survival and transport is complex. Soil and water temperature determine the rate of re-growth and die-off rates of FCB in the environment. Increasing temperatures reduce bacterial survival rates as bacteria die-off increases with increasing temperature (Reddy et al., 1981; Rice et al., 1992; Perrot et al., 1998; Wang et al., 1996). Moreover, effect of water temperature varies based on the water body type (Blaustein et al., 2013). Even though higher water temperature retard the growth of bacteria (Schijven and Husman, 2005) the initial growth may be accelerated (Freeman et al., 2009). A significant temperature increase is expected in future climates (IPCC, 2007) and the effect on survival and transport of bacteria is yet to be fully understood.

Suspended sediment affects the transport and survival of FCB as bacteria tend to attach to suspended solids (Maki and Hicks, 2002). High nutrient levels in the suspended sediments provide favorable conditions for bacteria to re-grow (Crump et al., 1998; Maki and Hicks, 2002). It has been suggested that bacteria attached to colloidal materials can travel many kilometers within the watershed (Palmateer et al., 1993), which often settle in river bottoms. During rainy seasons, increasing river flows create turbulence and resuspend settled bacteria (Garzio-Hadzick et al., 2010; Wu et al., 2009).

Several studies have been conducted that investigate the impacts of rainfall on bacterial transport into surface water (Abu-Ashour and Lee, 2000; Vinten et al., 2002). Successive rainfall events increase bacterial percolation, but this is often less compared to the overland transport of bacteria (Saini et al., 2003). Abu-Ashour and Lee, (2000) has
reported that rainfall controls both vertical and horizontal transport of bacteria in soil columns. Bacteria move through the soil profile when pores sizes are large enough and filled with water (Culley and Phillips, 1982; Bowen and Rovira, 1999). Livestock manure, which contains FCB, wash-off with runoff and increase FCB in surface water (Wilby et al., 2005). Severe storm events, which are high in energy, tend to wash-off more FCB into surface water. It has been shown that heavy storms may increase fecal bacteria levels in surface water by 100-folds (Rodgers et al., 2003). Furthermore, splash and flow detachment of soil due to kinetic energy of rainfall enhance the movement of bacteria since bacteria can travel by attaching to soil particles (Vinten et al., 2002; Heinonen-Tanski and Uusi-Kamppa, 2001).

Soil hydraulic conductivity is an important soil property, which affects the transport of bacteria through soil. Bacteria transport through soil increases with increasing hydraulic conductivity (Rahe et al., 1978). It has been reported that bacteria can move up to 75 cm deep if enough water is available for percolation (Culley and Phillips, 1982). Bacteria die-off increases with decreasing soil moisture content (Mubiru et al., 2000) as low moisture content is a stress factor for bacterial growth. It has been reported that high moisture content under grass buffer strips helped prolong bacterial survival (Entry et al., 2000). Soils with higher water holding capacity also support to survival of bacteria for longer period (Gerba and Bitton, 1994). Excessive moisture content dilutes usable organic carbon, and affects non-attached fecal coliform (Klein and Casida, 1967).

Future extreme dry weather may increase die-off of bacteria. However, dry weather may hasten the crust build-up on deposited feces and bacteria can survive under
this crust for a longer time (Buckhouse and Gifford, 1976; Thelin and Gifford, 1983). Bacteria in the upper most-layer of freshly deposited feces are generally affected by UV sunlight, however, bacteria under the crusts may live a longer period without influences. Bacteria (e.g. Escherichia coli) can survive 10 weeks within livestock manure once temperature is around 50 °C (Wang et al., 1996). Moreover, droughts may increase bacteria concentrations in surface water (Senhorst and Zwolsman, 2005) creating high environmental risks.

Watershed-based bacterial models are appropriate tools to understand behavior of bacteria in natural watersheds. Some of the models that can be used to investigate bacteria transport are MWASTE (Moore et al., 1989), COLI (Walker et al., 1990), HSPF (Hydrological simulation program FORTRAN; Bicknell et al., 1997), SEDMOD (Fraser et al., 1998), and WATFLOOD (Kouwen and Mousavi, 2002). In addition, the Soil and Water Assessment Tool (SWAT) is also a commonly used watershed model to simulate bacteria survival and transport in different environments, since it contains a microbial sub-model (Sadeghi and Arnold, 2002). The SWAT model has been applied to various geographic locations to evaluate the spatial and temporal variation of bacterial loadings (Baffaut and Benson, 2003; Parajuli et al., 2006; Chin et al., 2009; Coffey et al., 2010; Bougerad et al., 2011; Tang et al., 2011; Cho et al., 2010). Watershed-based hydrological models are capable of simulating pathogen transport, but capacity to account all governing factors is still uncertain (Coffey et al., 2010). Moreover, spatial and temporal variability of pathogen concentrations are poorly understood due to the largest sources of variability (Crowther et al., 2003), and these models have many limitations (Oliver et al., 2009; Pachepsky et al., 2006; Jamieson et al., 2004).
Impacts of climate variability on bacterial contamination have not been thoroughly investigated. Some reported that flooding has a direct correlation with disease outbreaks (Bowen and Rovira, 1999). Further, 3% of the world diarrhea cases may be caused by climate change (McMichael et al., 2009; Wang et al., 1996). Effects of climate variability on bacterial contamination are complex and depend upon study area and models used (Hofstra, 2011). Incorporating more observational data and evaluating models through validation and sensitivity analyses may help understand spatial and temporal pathogenic bacterial variation (Haydon and Deletic, 2009). Studies of climate variability on bacteria transport of the watersheds in southern U.S. are limited. Therefore, this research was formulated to investigate impacts of climate variability on FCB transport in watershed levels by using a modeling approach.

**Materials and Methods**

**Study area**

This study was performed in the UPRW (defined in chapter II), which is in the central east of Mississippi in the U.S.

**Input variables**

*Weather and stream flow*

Observed daily rainfall and temperature data from the National Climatic Data Center (NCDC, 2010) were used in this study. Daily stream flow data from 3 USGS (U.S. geological survey) station were used for stream flow calibration and validation (Burnside: USGS 02481880; Lena: USGS 02483500; and Ofahoma: USGS 02484500).
Water quality data

Samplings were performed in three locations of the UPRW from Feb 2011 to June 2012, and these locations coincided with the USGS flow stations. Two locations were in the main Pearl River, while the other was in the Yockanookany River, which is the largest tributary of Pearl River. Twenty-three (23) sampling events were performed during the study period. Sampling was performed during the same day for all three locations. Grab samples were collected using narrow, open mouth 500 ml polyethylene bottles.

Water samples for bacteria counts were analyzed by following EPA method 1103.1). Water samples were filtered onto a 0.45 µm membrane filter and placed onto mTEC agar plates mTEC plates were incubated at 35°C for 2 h to resuscitate injured or stressed bacteria, followed by further incubation at 44.5°C for 22 h. Incubated membranes were then transferred to a urea saturated filter pad and counted after 15 min. Detailed procedures can be found in the USEPA technical document, method 1103.1 (USEPA, 2002).

Geospatial

A Soil Survey Geographic Database (SSURGO) was incorporated into the model to parameterize soils in the watershed (USDA, 2005).

Future weather data

Future climate variability was simulated using LARS-WG, a stochastic weather generator. The LARS-WG generates synthetic daily time series of maximum and minimum temperatures, precipitation, and solar radiation by using parameters, which
were generated using observed daily weather data for a given site and the GCM. More
details about LARS-WG can be found in the model reference manual (Semenov, 2007).
Furthermore, the weather generator is capable of converting observed sunshine hours into
solar radiations. Observed sunshine hours were only available for the weather station in
the Jackson airport, which is near the study vicinity. Jackson airport sunshine hours were
used with all the other weather stations to generate synthetic daily time series. The
CCSM3 (Collins et al., 2004), developed by National Center for Atmospheric Research
(NCAR) in the U.S, was used as GCM to generate future weather data. The CCSM3 is a
model with 1.4 x 1.4° grid resolution.

The emission scenario, A1B, was selected based on the special report on
emissions scenarios (SRES; IPCC, 2000) to evaluate future climatic impacts. Similar
scenario have been used for previous studies (Kolstad and Johansson 2011). Very rapid
economic growth is expected under this scenario, and global population will peak in mid-
century and then decline. A rapid introduction of new and more efficient technologies are
expected with a balance between fossil and non fossil energy sources. The CO2
concentration varies from baseline 334 ppm to 418 ppm in early century (2011-2030),
541 ppm in mid-century (2046-2065), and 674 ppm in late-century (2081-2100).

Model setup

\textit{SWAT model description}

The SWAT model is a semi-distributed watershed scale hydrological model,
which operates on daily or sub-daily time steps, and has the capability to simulate
management impacts on water quality and quantity (Neitsch et al., 2005). Weather,
hydrology, plant growth, water quantity, and quality routing are some of the major
components of the SWAT model (Arnold et al., 1998; Neitsch et al., 2005; Gassman et al., 2007). Moreover, sub-watersheds are further divided into small units called hydrological response units (HRUs). The HRUs are lumped land areas that consist of unique land cover, soil and management combinations. The SWAT model simulates daily runoff using the curve number (CN) method when daily data are available, or simulated using the Green Ampt method if sub-daily precipitation data are available. The SWAT model predicts flow through each layer in root zones using storage routing technique. During the simulation, SWAT routes flow, sediment yield, and nutrients through the stream network. A detailed description about the SWAT model can be found in the SWAT theoretical manual (Neitsch et al., 2005).

**Bacteria equations**

The SWAT microbial sub-model uses first-order kinetics (Moore et al., 1989) to simulate fecal bacterial die-off and re-growth (Neitsch et al., 2005). The first-order decay equation below determines the quantity of bacteria that are removed or added by die-off and re-growth, as describes in SWAT 2005 (Sadeghi and Arnold, 2002; Neitsch et al., 2005).

\[
  B_{ct} = B_{ci} \times e^{-\beta_{20}^\gamma (T-20) t}
\]

where \(B_{ct}\) is the bacterial concentration at time \(t\) (counts per 100 mL), \(B_{ci}\) is the initial bacterial concentration (counts per 100 mL), \(\beta_{20}\) is the first–order die-off rate at 20°C (per day), \(t\) is the exposure time (days), \(\gamma\) is the temperature adjustment factor, and \(T\) is the temperature (°C).
Sources of Bacteria

The FCB total maximum daily loads (TMDL) report (MDEQ, 1999) from the Mississippi department of environmental quality indicated that livestock operations and failing septic system were the main sources of FCB in the UPRW watershed. Livestock operations in the UPRW watershed are made up of beef cow and poultry operations (USDA/NASS, 2011). Beef cows are managed in unconfined operations. Unconfined management is a type of extensive cattle farming, whereby animals freely roam over the portions of the watershed. While grazing, cattle drink water from streams and ponds in the watershed. Poultry operations are typically confined, and poultry litter are stacked in covered-farm yards before applying on grasslands and crop lands (MDEQ, 1999). The extent of crop agriculture under the UPRW area was minor; hence, manure applications were mainly considered on grasslands (USDA/NASS, 2007).

Numbers of annual beef cattle and poultry birds were collected from Quick Stats 1.0 (USDA/NASS, 2011) for the ten counties in the study area for the period of 2010 - 2011. Number of animals were divided by total grassland areas of the counties to calculate animal density (animal unit ha⁻¹). Animal densities were then multiplied by extent of sub-watershed grasslands to estimate the total number of animal per each sub-watershed. Similar methods have been implemented in Upper-Wakarusa watershed in northeast Kansas (Parajuli et al., 2009), and in the Irish Fergus catchment (Coffey et al., 2010). Moreover, numbers of animals were converted to number of animal units. One animal unit is defined as 1000-kg of live animal mass based on American Society of Agricultural Engineering (ASAE) standard (ASAE, 2003). For a single beef cow-calf pair, the animal unit was estimated to 0.549 (Parajuli et al., 2009). Average body weights
of layers and broiler chickens were assumed to be 1.8 kg and 0.9 kg per bird, respectively, and numbers of animal units per bird are 0.0018 (layer) and 0.0009 (broiler).

Manure production per animal unit was estimated based on ASAE standard production rates. Total manure production rate for an animal unit was 58 kg per day for beef, 64 kg per day for layers, and 85 kg per day for broilers (ASAE, 2003). Furthermore, the FCB levels of each manure type were estimated based on the ASAE standard (Beef manure = 4.8 x 10^6 colony-forming unit (cfu) gram⁻¹; Chicken manure = 1.0 x 10^6 cfu gram⁻¹).

Manure was one of the main sources of FCB considered in this study. Bacteria enter streams through runoff once manure is applied over grasslands (Bukhari et al., 1997). Moreover, fate and transport of FCB in the watershed were determined based on timing and rate of manure application. The timing and rate of manure applications in this study were based on the available manure productions, and seasonality. Similar methods have been reported in a previous study (Coffey et al., 2010). Manure applications closer to water bodies have more effect on FCB contamination than manure applied away from water bodies. In this study, we proposed variable manure application rates based on distance from the stream. To facilitate this method, grasslands were reclassified into three categories as grasslands within 100 m from stream (2.03%), grasslands within 100 m from ponds (4.41%), and general grasslands (13.05%). A study from the University of Missouri by Gerrish et al. (2012) reported that grazing cattle tend to travel around 180 m to 240 m away from water sources. About 1600 small ponds were identified after careful observation of ortho photos (1 m resolution) for the study area (USDA Geospatial Data Gateway) (http://datagateway.nrcs.usda.gov/) (Figure 3.1). The HRUs were formed.
separately for three grassland types. These help to change the manure application rates based on the types of the grasslands.

Figure 3.1 Watering ponds in the UPRW

It has been reported that cattle prefer to spend more time in-stream or closer to streams than away (Sheffield et al., 1997). We assumed that 2% of manure is directly deposited into the streams during wallowing. To accommodate this within the model, a portion of the total beef manure (2%) was converted to number of FCB colony-forming units (cfu) based on the ASAE standards (ASAE, 2003), and directly added to the respective sub-watershed as a point source. Previous studies have suggested 30% of manure as a direct stream deposition (VDEQ, 2007; Zeckoski et al., 2005). Based on our
experiences in the watershed, we assumed 2% of manure directly deposited in the stream at the UPRW and rest were distributed through grazing operations. Higher rates were implemented on grasslands within 100 m buffer zones to simulate more FCB transport from those lands. Poultry litter from the poultry houses was spread on grasslands as monthly applications. The TMDL report of the Pearl River Watershed (MDEQ, 1999) has used the similar methodologies.

Septic systems can contribute fecal coliform bacteria to streams due to failures, malfunctions, and direct pipe discharge. Septic system contributions are affected by the number of people served by a system, and number of systems failed. Mississippi Department of Environment Quality (MDEQ) has reported that one person in Mississippi discharges about 100 gallons of effluent, which has a fecal coliform concentration of $10^4$ cfu $100 \text{ mL}^{-1}$ (MDEQ, 1999). As reported by MDEQ TMDL report (MDEQ, 1999), we also assumed 40% of the septic systems were failed, and those failing systems directly contributed FCB to the streams as direct input source. Population data were taken from the Mississippi Automated Resource Information System (MARIS) databases, and were intersected with sub-watersheds to determine the number of people residing in each sub-watershed. The numbers of people were multiplied by 100 gallons to determine the total effluent discharge from the septic systems. Forty percent of the total discharge was then converted into fecal coliform bacteria load by multiplying by the $10^4$ cfu $100 \text{ mL}^{-1}$.

**Model calibration and validation**

Daily observed stream flows from Burnside for Feb 2011 to June 2012 (23 data points) were used to calibrate the SWAT hydrological model, and daily observed stream flows from Lena and Ofahoma for the same period were used for model validation. These
flow data points coincided with bacteria sampling dates. Observed discrete FCB concentrations at Burnside for Feb 2011 to June 2012 were used to calibrate the SWAT bacteria sub-model and observed FCB concentrations at the Lena and Ofahoma were used to validate the model.

Model calibration (flow, FCB) was initially performed using SWAT-CUP Sufi-2 automatic calibration technique (Abbaspour et al., 2007) and followed by the manual calibration to incorporate calibration parameters from previous studies in the UPRW. The SWAT-CUP Sufi-2 has been used for previous similar studies (Abbaspour et al., 2007). The Nash–Sutcliffe efficiency (NSE) coefficient was used as an objective function. Moreover, soil parameters were eliminated from auto-calibration as SSURGO soil data contain all the required parameters such as soil bulk density and hydraulic conductivity (USDA, 2005). The initial SCS runoff curve number for moisture condition II (CN2) was manually changed based on a previous modeling study performed in the same watershed by Parajuli (2010). In addition, depending on data availability, SWAT calculates potential evapotranspiration (PET) using Penman-Monteith, Priestley-Taylor, or Hargreaves method. In this study, we used Penman-Monteith method to simulate PET.

**Sensitivity analysis**

The SWAT-CUP Sufi-2 automatic calibration technique (Abbaspour et al., 2007) was used for sensitivity analysis of the bacteria calibration parameters. After automatic calibration, the manual calibration was performed based on sensitivity analysis results. Manual calibration helps to incorporate our knowledge about the watershed in flow and bacteria simulation. There were fourteen (14) parameters that were used for bacteria calibration.
Model performances

Model performances were evaluated using two statistical parameters; the coefficient of determination (R²) and Nash-Sutcliffe efficiency index (NSE) were used to evaluate model performance (as per chapter II).

Results and Discussion

Flow calibration

Daily flow calibration and validation were performed from Feb-2011 to June-2012. The model was run with a one year warm-up period (2010). A warm-up period helps model to stabilize during simulations. Discrete daily data points were selected for calibration and validation to coincide with FCB sampling dates. The model was calibrated to the upstream gauge (Burnside), and validated to the downstream gauges (Lena and Ofahoma). Burnside and Lena showed good to very good model performance, but Ofahoma showed poor model performance in flow simulations (Figure 3.2). Sub-watershed 1 and 13 drain to the Ofahoma gauge, and the model was unable to simulate flow from those sub-watersheds adequately due to unavailability of representative weather stations. Average daily observed flow at the Burnside and Lena were 14.2 m³s⁻¹, and 78.9 m³s⁻¹ during the study periods respectively. The model simulated 13.8 m³s⁻¹ at the Burnside (3 % underprediction) and 84.2 m³s⁻¹ at the Lena (7 % overprediction). Similar model performance has been reported for monthly stream flow simulation by the previous study in the UPRW (Parajuli, 2010).
Figure 3.2  Stream flow calibration and validation

FCB calibration

The SWAT bacterial model predicts FCB concentrations at the outlets of each sub-watershed. Observed data at the Burnside (sub-watershed 6), Ofahoma (sub-watershed 13), and Lena (sub-watershed 17) were evaluated against simulated FCB concentrations. The observed FCB data showed high variability at all the three sampling locations (Figure 3.3), because FCB transport over watershed affect by physical, chemical, and biological process in the watershed. Our modeling challenge was to achieve good model performances during model calibration and validation. The bacterial transport process is controlled by flow and sediment transport processes in the model. More runoff generally causes more bacteria wash-off into streams, but may reduce bacteria concentration due to dilution. Rainfall has a significant effect on transport of bacteria to surface water (Abu-Ashour and Lee, 2000; Vinten et al., 2002). In this study, most of the high stream flows accounted for high FCB concentrations (Figure 3.3). High rainfall driven runoff transports more bacteria, which are generally available in the soil solution and adsorbed to soil particles (Parajuli, 2007). Splash and flow detachment of
soil due to rainfall kinetic energy enhance the movement of bacteria since bacteria travel by attaching to soil particles (Vinten et al., 2002; Heinonen-Tanski and Uusi-Kamppa, 2001). Heavy storms increase fecal bacterial levels in surface water by 100-fold (Rodgers et al., 2003).

The lowest daily FCB concentrations were found from May to August (Figure 3.3). These months are generally dry months for the study area, which may affect the survival and transport of bacteria. Bacteria die-off rates increase with decreasing soil moisture content as low moisture content is a stress factor for bacteria (Gerba and Bitton, 1994; Mubiru et al., 2000). Summer months (June, July, and August) show warmer temperatures and longer exposure to UV sunlight due to long day times, and may lead to rapid bacterial die-off. It has been reported that the die-off rate of bacteria may double when temperature increases by 10 °C within the 5-30 °C range (Reddy et al., 1981). The upper most-layer of freshly deposited feces are generally affected by UV sunlight, but bacteria under the crust live a longer period without influences from UV lights. It is reported that bacteria (e.g. E. coli) can survive 10 weeks within livestock manure once temperature is around 5 °C (Wang et al., 1996).
Results showed a reasonable agreement between measured and simulated FCB concentrations at the outlets of the UPRW. According to the model performance...
guidelines, our bacteria model showed good model performances (Figure 3.4). Model performance statistics, such as $R^2$ and NSE were calculated up to 0.59 and 0.52 during calibration and validation, respectively, for the two sampling locations in the main Pearl River. The Ofahoma sampling location showed poor model performance due to poor stream flow calibration. These results were reasonable when compared to other published literature (Parajuli et al., 2009; Reddy et al., 1981; Tang et al., 2011). Furthermore, the SWAT bacteria sub-model under-simulated FCB concentrations at all the sampling locations. Average daily measured FCB concentrations were calculated as 208 cfu 100 mL$^{-1}$, 247 cfu 100 mL$^{-1}$, and 154 cfu 100 mL$^{-1}$ for Burnside, Ofahoma, and Lena respectively. Average daily model simulations were calculated as 134 cfu 100 mL$^{-1}$ (35% underprediction), 42 cfu 100 mL$^{-1}$ (83% underprediction), and 92 cfu 100 mL$^{-1}$ (40% underprediction) for Burnside, Ofahoma, and Lena respectively.

![Graphs showing observed vs. simulated fecal coliform bacteria](image)

**Figure 3.4** Observed vs. Simulated fecal coliform bacteria

This study applied 14 bacteria transport parameters during the SWAT bacteria sub-model calibration (Table 3.1). All the bacteria transport parameters are applicable
only on watershed wide transport of bacteria, and sub-watershed level adjustment was not allowed. This may sometimes yield poor model performances. The die-off factor for bacteria in soil solution at 20°C (WDPQ) and growth factor for bacteria in soil solution at 20°C (WGPQ) were highly sensitive in bacteria transport. After several iterations, we found that WDPQ = 0.125 and WGPQ = 0.12 gave the highest model performances. Previous studies suggested different values (Table 3.1)
**Table 3.1  Bacteria calibration parameters**

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<th>P-Value</th>
<th>Comments</th>
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<td>0.75</td>
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<td>12</td>
<td>-0.35</td>
<td>0.72</td>
<td>10(Baffaut and Benson, 2009; Baffaut, 2006; Parajuli et al., 2006, 2009; Chin et al., 2009), 5.6 (Chin et al., 2009)</td>
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<td>0.22 (Hutchison et al., 2005)</td>
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*t-stat is a measure of sensitivity (high sensitivity is represented by larger absolute values)
*p-value is a measure of the significance of the sensitivity (Values close to zero is more significance)

BACT_SWF= Fraction of manure applied to land areas that has active colony forming units; WGPS= Growth factor for bacteria adsorbed to soil particles at 20°C (1/day); BACTMINP= Minimum daily bacteria loss (#cfu/m²); WOF_P= Wash-off fraction for bacteria; BACTKDQ= Bacteria soil partitioning coefficient (m³/Mg); BACTMX= Bacteria percolation coefficient (10 m³/Mg); WDPS= Die-off factor for bacteria adsorbed to soil particles at 20°C (1/day); WDPRCH= Die-off factor for bacteria in streams (moving water) at 20°C; THBACT= Temperature adjustment factor for bacteria die-off/growth; WGPF= Growth factor for bacteria on foliage at 20°C (1/day); WDPRES= Die-off factor for bacteria in water bodies (still water) at 20°C (1/day); WDPF= Die-off factor for bacteria on foliage at 20°C (1/day); WGPQ= Growth factor for bacteria in soil solution at 20°C (1/day); WDPQ= Die-off factor for bacteria in soil solution at 20°C (1/day)

**Spatial distribution**

The simulated FCB concentrations from each sub-watershed were analyzed to investigate spatial variability of FCB concentration. The state of Mississippi water quality...
criteria for intrastate, interstate, and coastal water regulations observed two periods to set water quality standard as May to October and November to April (MDEQ, 1999). Sub-watershed FCB loadings were analyzed based on those periods (Figure 3.5). Sub-watershed characteristics determined transport differences between bacteria from each sub-watershed. The sub-watersheds with high elevation and higher population density showed higher FCB load contributions. High elevation and slope account for the rapid wash-off of FCB sources. This modeling study assumed constant FCB concentration from failing septic systems based on population density, so high FCB concentrations would be expected from high populated areas. Sub-watersheds with more grassland and grasslands that were closer to the stream network contributed higher FCB loadings. More grassland indicated more manure application, and grasslands closer to the streams received higher rates of manure deposition because of frequent grazing.

Soil bulk density, soil hydraulic conductivity, and percentage of sand were evaluated against bacteria concentrations at each sub-watershed outlet. Results showed that there was an inverse relationship ($R^2=0.6$) between soil bulk density and the bacteria concentrations at the sub-watershed outlets excluding sub-watersheds 21, 26, and 27, which transported extreme levels of bacteria concentrations. This study did not show any correlation of FCB concentrations with soil hydraulic conductivity, and percentage of sand. Transport and survival of FCB are controlled by many factors, and evaluating the significance of each controlling factor needs further research.
Figure 3.5  Daily average fecal coliform bacteria loadings from sub-watersheds.  
(a) May-October, (b) November- April

**Mid and late century climate**

Future temperature variations were evaluated with the baseline temperatures from 1992-2011. Maximum (Tmax) and minimum (Tmin) temperature, derived for mid (2046-2065) and late (2080-2099) centuries from LARS-WG for SRES A1B scenario, were averaged over the entire watershed to compare with baseline averages (Figure 3.6). Average annual baseline Tmax was 24°C, and average annual mid-century Tmax will be 26.1°C. During late century, the annual average Tmax will be 26.8°C. The highest Tmax increases (from baseline) will be 2.5°C in September (Figure 3.6). In late century, the highest Tmax increase will be 3.4°C in June. Moreover, November Tmax will increase by more than 2°C mid and late century. According to the baseline temperatures, July and August were the warmest months during the year, but in future climates the warmest
period will be extended to four months from June to September. The Tmin variations followed a similar pattern as Tmax (Figure 3.6).

![Image of temperature changes](image)

**Figure 3.6** SRES A1B maximum and minimum future temperature change (°C)

Referring to the base period (1992-2011); (a) Mid-century T_{max}, (b) Mid-century T_{min}, (c) Late-century T_{max}, (d) Late-century T_{min}.

Mid and late-century precipitation from 10 stations were evaluated with the baseline precipitation from 1992 to 2011. Percentage changes of annual average future precipitation were calculated based on baseline annual averages. The future rainfall in mid-century will vary from 0.3% reduction to 11.8% increase. During late century, the rainfall will vary from a 5.6% reduction to a 13.1% increase. Moreover, monthly precipitation patterns will be changed in future climates. Monthly baseline average precipitations showed a decreasing trend from March to June (Figure 3.7). The A1B future scenario will have more rain in April compared to the baseline, and the lowest
point will be shifted from March to June. The low rainfall months will receive even less rain in the future. Furthermore, the summer will be drier than before as June will receive lower rainfall compared to the baseline. It has been reported that future summers will be drier in subtropics (Bates et al., 2008). After June, the baseline rainfall increased in July but future rainfall will only be increased in August (one month shift). Peak rainfalls in April, August, and December in future scenarios will be due to extreme rainfall events. There is evidence that extreme rainfall events have already increased in the U.S. (Karl and Knight, 1998), and are expected to increase in the future as subtropics will experience extreme rain events (Bates et al., 2008).

![Figure 3.7 Mid-century, late-century, and baseline monthly average rainfall](image)

**Climate effects**

Mid and late-century average monthly simulated bacteria concentrations from the three sampling locations were evaluated against average monthly bacteria concentrations during baseline (2008-2012) at the same locations. Results showed that extreme bacteria
loadings (up to 10x10^4 cfu 100 mL^{-1}) will be possible from July to September during mid and late century at the Burnside and Lena locations (Figure 3.8). Extreme bacteria concentrations (up to 15x10^3 cfu 100 mL^{-1}) expected only in January at the Ofahoma gauge during both mid and late century. These extreme loadings may be due to high runoff caused by extreme rainfall and high rainfall variability (Table 3.2). July, August, and September will have the highest rainfall variability in mid and late-century climates based on SRES A1B scenario. Furthermore, these three months are in summer, during which, long dry periods tend to create surface crusting that may reduce infiltration capacity, leading to extreme runoff events (Kostaschuk et al., 2002; Bouraoui et al., 2004). Studies have reported increased runoff and sediment loads (Kostaschuk et al., 2002; Bouraoui et al., 2004; Nearing et al., 2005) in future climates causing increased waterborne pathogens in surface waters (Schijven and Husman, 2005).

The effects of increasing temperatures on future bacteria transport processes are complex because survivals of bacteria are influenced by many additional factors besides temperature. The first-order decay equation determines the quantity of bacteria that are removed or added by die-off and re-growth as described in SWAT 2005 (Sadeghi and Arnold, 2002; Neitsch et al., 2005). Studies have reported that temperature and bacteria die-off rates are directly related (Reddy et al., 1981; Rice et al., 1992; Perrot et al., 1998; Wang et al., 1996). Based on our climate predictions, the maximum temperature increase will be 2.5°C and 3.4°C during the mid and late-century, respectively. Daily maximum temperature could be high, up to 43°C, while daily minimum temperature might be as low as -17 °C. The effects of these extreme temperatures are difficult to isolate from final
bacteria concentrations at the sub-watershed outlets as there are many contributing factors related to bacteria survival and transport.

Figure 3.8  Monthly fecal bacteria concentrations in mid and late-century with flow
Stream flow and bacteria loadings from each sub-watershed were evaluated in mid and late-century climates against the baseline climate. Results indicated that mid-century flow increases can vary between a 15% to a 103%, while late-century variation will be up to 24% to 133% compared to the baseline water yields (Table 3.3). Bacteria concentrations at the sub-watershed outlets showed extreme variability. During the mid-century climate, the bacteria concentration may vary between a 54% reduction to a 1,613% extreme increase. Moreover, the late-century variation is shown to be a 56% reduction to a 2,175% increase. Most of the future monthly FCB concentrations will violate the water quality criteria of the state. Land applications of manure prior to extreme rain events tend to increase FCB loads in surface water. It has been demonstrated that severe storms may increase fecal bacteria levels in surface water by 100-fold (Rodgers et al., 2003). During bacteria transport to the watershed outlets, further die-off occurs in leading to moderate concentrations of bacteria. In this study, we used the SRES A1B scenario. Results from
other scenarios such as A2 and B1 will not be the same because they have different rainfall and temperature predictions. However, these results indicate that future climate variability may cause extreme levels of FCB concentrations in the surface waters.

Table 3.3  Flow and FCB concentrations in mid and late-century

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<th>Mid-century flow change (%)</th>
<th>Late-century flow change (%)</th>
<th>Baseline FCB (CFU 100 mL$^{-1}$)</th>
<th>Mid-century FCB change (%)</th>
<th>Late-century FCB change (%)</th>
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Conclusions

The SWAT model was applied to a forest dominant watershed in a humid subtropical climate of the U.S. The model used climate, soil, and elevation as input data to simulate flow and fecal coliform bacteria (FCB) concentrations from the UPRW. Simulated model outputs were evaluated against observed flow and FCB concentrations at three sub-watershed outlets. Flow simulations showed good to very good model performances ($R^2$ up to 0.79 and NSE up to 0.78). The FCB simulations showed good model performances ($R^2$ up to 0.59 and NSE up to 0.58). These model simulation results agreed with previous similar studies. Results further showed that there was a high variability of FCB transport among the individual sub-watersheds of the UPRW.

The SWAT model was successfully applied to simulate mid and late century flows and FCB concentrations from the UPRW with the help of LARS-WG stochastic weather generator. The synthetic weather data for IPCC scenarios SRES (A1B) were generated by LARS-WG weather generator in accordance with the general circulation model, CCSM3. Simulations suggest that future temperature in the UPRW will be warmer by 2.5°C to 3.4°C. Future rainfall distributions will be highly variable across the watershed, and future climates in the UPRW will experience longer summer periods. Results showed that mid-century stream flow increase can be varied from 15% to 103%, while late-century variation will be up 24% to 133% compared to the baseline stream flow. Bacteria concentrations at the sub-watershed outlets showed extreme variability. During the mid-century climate, the bacteria concentration can vary between a 54% reduction to a 1,613% increase and the late-century variations of FCB concentration will be a 56% reduction to a 2,175% increase.
This study evaluated the effects of future climate variability on FCB transport and the results should benefit watershed managers to prepare future plans. In this study, we used the SRES A1B scenario. Results from other scenarios such as A2 and B1 will not be similar due to different rainfall and temperature predictions. Therefore, further studies using different SRES scenarios and different GCM models on FCB transport in future climates is recommended. Comparison of different prediction results will assist watershed managers in choosing the proper future scenario.
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CHAPTER IV
DEVELOP RELATIONSHIPS BETWEEN THE MODELS PREDICTED EVAPO-TRANSPIRATION WITH OBSERVED GROUND WATER TABLE

Abstract

Agriculture management practices change the hydrological budget of watersheds. Changes in surface runoff are easily identified using the intensive USGS stream gauge network. However, changes to the water table are poorly understood due in part to inherent difficulties in obtaining accurate, detailed measurements. This research was designed to develop relationships among evapotranspiration (ET), percolation (PERC), groundwater discharge to the stream (GWQ), and depth to the water table through a modeling approach. The Soil and Water Assessment Tool (SWAT) hydrologic and crop models were applied to the BSRW (7,660 km²) within the Yazoo River Basin of the Lower Mississippi River alluvial plain. The hydrologic part of the model was calibrated and validated for the period between 1999 and 2009 using USGS monthly stream flow data. The crop model was calibrated and validated for the same period using corn and soybean yield data from the research plots. Results showed good to very good model performances with the coefficient of determination ($R^2$) and Nash-Sutcliff efficiency index (NSE) from 0.4 to 0.9 respectively during both hydrologic and crop model calibration and validation. An empirical relationship between ET, PERC, GWQ, and water table changes predicted 64% of the groundwater level variation in the alluvial plain.
in this study. Thematic maps were developed to identify areas overusing groundwater, which can help watershed managers to develop water resources programs.

**Introduction**

Over the last few decades, reliance on groundwater for irrigation has increased substantially, even in high rainfall areas, to ensure adequate crop production and quality (Evett *et al.*, 2003). Currently, approximately 17 million hectares of croplands in the U.S are irrigated using groundwater (Siebert *et al.*, 2010). The Mississippi river alluvial plain, an area colloquially known as the Delta, is the predominant area of row crop production in Mississippi, and relies heavily on groundwater as the primary source of irrigation (USGS, 2005). The sustained groundwater pumping associated with agricultural activities has resulted in groundwater depletion in many areas of the U.S. This may reduce the water in wells, streams, and lakes (USGS, 2007).

Water tables in the U.S follow a seasonal pattern, and recharge during the winter and spring because of high precipitation. Groundwater levels decline during the summer due to high evapotranspiration and abstraction for irrigation (Charles and William, 2001). Seasonal fluctuations and associated impacts can be investigated using an extensive network of groundwater level measurements. However, the availability of groundwater observations is limited in many parts of the world, compared to surface water observations. As an example, there are 135 USGS gauging stations to record stream flows in Mississippi, but only 4 stations record groundwater levels (USGS, 2012). Groundwater levels are commonly observed using piezometers, which are open wells or pipes installed into an aquifer. Piezometer readings give only point measurements of depth to the water table, and network of piezometers are required to understand the
spatial distribution of groundwater sources. But, lack of data availability and cost of the water table measurements leads to look for alternative methodologies to investigate groundwater resources.

Computer simulation models help to explore seasonal changes of groundwater levels and associated hydrological linkages. Some of the models having capabilities to simulate groundwater dynamics are FEFLOW (Finite Element subsurface FLOW system; Diersch, 1996), PLASM (Prickett lonnquist aquifer simulation model; Prickett and Lonnquist, 1971), MODFLOW-2000 (Modular three-dimensional, finite-difference computer model; Harbaugh et al., 2000), and HydroGeoSphere (Three-dimensional numerical model; Therrien et al., 2012). Even though the models are capable of simulating seasonal changes of groundwater levels, these models are data intensive. Remote sensing methods can be an alternative data provider (Brunner et al., 2007; Hendricks et al., 2008). Both modeling and remote sensing methods have been used to investigate seasonal groundwater changes with easily measurable hydrological parameters; the results strongly correlated with groundwater level changes.

Evapotranspiration (ET) and groundwater have strong hydrological linkages (Meyboom, 1967; William, 1994), and soil available water levels control the ET rates in plants (Emery, 1970; Sala et al., 1996; Devitt et al., 2002; Nichols, 2000). Plant ET rates are influenced by the dynamics of interconnected surface and groundwater systems (Woessner, 2000; Sophocleous, 2002). The strength of the relationship between ET and groundwater levels varies with depth to the Water Table (WT) from the land surface. Shallow unsaturated soil and deep saturated groundwater are hydrologically connected with ET in shallow groundwater systems (Thompson, 2003). The temporal fluctuation of
shallow water tables controls ET and root water uptake (Nachabe, 2002; Nachabe et al., 2005). Roots extract water from the unsaturated zone if water table is deeper than the root zone. Unsaturated zone is then replenished from the water table based on the hydraulic conductivity of the soil (Jury et al., 1991). High and low ET rates are associated with shallow and deep water tables respectively (Duell, 1990; Nichols, 1994). Relationships and functions between ET and groundwater levels have been derived based on interconnections among ET, the unsaturated soil zone, and the water table (Emery, 1970; Nichols, 1994a and 2000b).

Groundwater models have become useful tools to investigate relationships between ET and groundwater. TOPMODEL (Physically based, distributed watershed model; Beven and Kirkby, 1979), MODHMS (Physically based, spatially distributed, integrated surface/subsurface modeling framework hydrologic system; Panday and Huyakorn, 2004), MIKE SHE (Advanced integrated hydrological modeling system; Graham and Butts, 2006), GSFLOW (Coupled groundwater and surface-water FLOW model; Markstrom et al., 2008), MOGROW (MOdelling GROundwater flow and the flow in surface Water systems; Querner, 1997), InHM (Integrated Hydrology Model; Vanderkwaak, 1999), and the widely used MODFLOW (McDonald and Harbaugh, 1988) are some of the models which can be used to explore the hydrological relationships between ET and groundwater. The SWAT (Soil and Water Assessment Tool) is a semi distributed watershed scale level model and has its own module for groundwater simulations (Arnold et al., 1993). This model considers groundwater flow and hydraulic conductivities with quasi distributed groundwater flow. However, it considers overland flow process in the landscape with well distributed parameters. The SWAT groundwater
simulations are unable to express any spatial distribution of groundwater levels and recharge rates. These limitations can be overcome by coupling with other models such as MODFLOW (Kim et al., 2008) or by further analyzing SWAT groundwater outputs using separate models (Vazquez-Amábile et al., 2005).

Figure 4.1 Groundwater process in SWAT (Neitsch et al., 2005)

The SWAT model is a semi distributed, physically based, hydrological model. It simulates surface runoff, sediment and nutrient yields, pesticide, bacteria, and crop yields (Arnold et al., 1998; Neitsch et al., 2005). This model is categorized as a semi distributed model because it divides sub-watersheds into further small units called hydrological response units (HRUs). The SWAT calculates daily runoff using a curve number (CN) method if daily data are available, or using the Green Ampt method when sub-daily precipitation data are available. A storage routing technique is used by SWAT to predict...
flow through each layer in the root zones. Percolation occurs only when the moisture content of the soil layer exceeds the field capacity, and soil layer below is unsaturated. Flow rates within the soil layers are determined by saturated hydrologic conductivity. The SWAT model assumes that soil moisture content is evenly distributed within a given soil layer, and unsaturated flows are indirectly predicted by depth distribution of plant water uptake, soil water evaporation, and upward flow from a shallow aquifer. The EPIC model within the SWAT simulates crop growth functions, and heat units above the base temperature used for crop growth and development. Detail description about SWAT model can be found in SWAT theoretical manual 2005 (Neitsch et al., 2005).

The SWAT model considers two aquifers in the groundwater simulation: a confined aquifer and an unconfined aquifer (Figure 4.1). The unconfined aquifer, which is shallow, contributes to the main channel or reaches of the sub-watersheds. Water entering into the confined aquifer contributes to streams outside the watershed. The SWAT simulates the unconfined aquifer as a reservoir under the soil surface, and water storage changes are predicted by a water balance equation below

\[ Q_{\Delta} = Q_{rch} - Q_{gw} - Q_{revap} - Q_{pump} \]  

(4.1)

Where \( Q_{\Delta} \) is the amount of water change in the unconfined shallow aquifer compared to the previous time step (mm H\(_2\)O), \( Q_{rch} \) is the amount of water entering into the confined aquifer from upper soil layers (mm H\(_2\)O), \( Q_{gw} \) is the groundwater flow entering into the stream (mm H\(_2\)O), \( Q_{revap} \) is the amount of water moving into the upper soil layers in response to the water deficiencies (mm H\(_2\)O), and \( Q_{pump} \) is the amount of water removed from the aquifer due to pumping (mm H\(_2\)O). Detailed documentation can be found in the SWAT theoretical manual 2005 (Neitsch et al., 2005).
Understanding seasonal fluctuations of the water table helps to plan crop calendars, irrigation schedules, and crop field maintenance operations. But, lack of data availability and cost of the water table measurements hinder proper understanding of groundwater dynamics. As an alternative, groundwater models have become useful tools to investigate relationships between ET and water table. Semi distributed hydrological models such as the Soil and Water Assessment Tool (SWAT; Arnold et al., 1993) can be used to investigate the groundwater statues of large watersheds (Hua et al., 2010; Reshmidevi and Kumar, 2012). Therefore, this study was designed methodologies using hydrological outputs from the SWAT with observed water table fluctuations. The developed methodologies were then applied in groundwater irrigated crop lands for improved water management.

Materials and Methods

Study area

This study was conducted in the BSRW, which at 7,660 km2 is the major sub-watershed of the Yazoo river watershed in Mississippi (Figure 4.2). The BSRW covers most of the Delta region and eleven Mississippi counties (Coahoma, Bolivar, Tallahatchie, Sunflower, Leflore, Washington, Humphreys, Sharkey, Issaquena, Yazoo and Warren). Agriculture is the main land use (>80 %) in the watershed, and soybean, corn, and rice are intensively grown. The BSRW drains into the Mississippi River near Vicksburg.
Input variables

Geospatial

Soil Survey Geographic Database (SSURGO) was incorporated into the model to parameterize soils in the watershed (USDA, 2005). The SSURGO databases were developed using field methods based on the National Cooperative Soil Survey (NCSS) mapping standards and 1:12000 to 1:63360 map scales (USDA, 1995). The SSURGO data for the BSRW showed 12 major soil textural classes. “Fine-silty” constituted 62% of the watershed area and was the dominant soil textural class. The cropland data layer, with
a 30 m spatial resolution, was used to parameterize land use characteristics of the watershed (USDA/NASS, 2009). The 30 m x 30 m grid digital elevation model (DEM) data from the U.S Geological Survey (USGS, 2010) was used as elevation data in this study.

*Weather, stream flow and groundwater data*

Observed daily rainfall and temperature data from the National Climatic Data Center (NCDC, 2010) were used in this study. NCDC data come from Global Climate Observing and System (GCOS) and Surface Network (GSN), and has undergone through quality assurance reviews. There were six NCDC weather stations in or near the BSRW that provided daily precipitation and daily minimum and maximum temperature (Figure 4.2). One automatic weather station within the watershed was maintained by the Delta Research and Extension Center Weather Center at Stoneville (DAWC, 2012), and provided precipitation, both maximum and minimum temperatures, wind speed, solar radiation, and relative humidity. Monthly stream flow data from three USGS gauge stations (station number 7288280 in sub-watershed 5 at Merigold, 7288500 in sub-watershed 16 at Sunflower, and 7288650 in sub-watershed 26 at Leland) from 2001 to 2009 were used for stream flow calibration and validation. The gauge data is available in USGS-Water Data for the Nation website (http://waterdata.usgs.gov/nwis/sw). There were two types of observed groundwater level data available in USGS Groundwater Data for Mississippi website (http://nwis.waterdata.usgs.gov/ms/nwis/gw). Continuous time-series data which were obtained from automated recorders were only available for two locations in the study area. Discrete field-water-level measurements, which represented the Yazoo Management District (YMD), were available for 108 locations within the
watershed. The discrete field-water-level measurements reported only two extreme conditions of the water table during a year and available from 1980 to 2009. Measurements taken from April represented the lowest depth to the groundwater level while August measurement represented the highest. Out of 108 discrete field-water-level measurement locations within the watershed, only 33 wells were selected by overlaying groundwater well locations map with the sub-watersheds map to represent each sub-watershed by one well. Other than these discrete field-water-level measurement, there were two Continuous time-series data for two locations within watershed, which represent the sub-watershed 27 (Sunflower, station, Station number: 332826090441601) and sub-watershed 18 (Leflore station, Station number: 333315090151801) (Figure 4.2). These two stations reported monthly groundwater level measurements from Jan 1990 to September 1994.

**SWAT model setup**

The SWAT 2005, currently runs in ArcGIS 9.2, needs three main geospatial data inputs to parameterize physical properties of the watershed: elevation, soil, and land use. The BSRW boundaries and sub-watershed boundaries were delineated using the 30 m x 30 m DEM data. The 30 m cropland layer and SSURGO soil data layer were overlaid with sub-watersheds to create the number of hydrological response units (HRUs) required for the study. In this study, 37 sub-watersheds were delineated, and 1900 HRUs were also created during overlay operations. After creating HRUs, the weather data were incorporated. The model was run from 2000 to 2009 in monthly time steps. Stream flow calibration and validation was carried out for the period from 2002 to 2009.
Stream flow calibration and validation

Predicted monthly stream flows from three sub-watersheds (5, 16, and 26) correspond to observed monthly stream flows from USGS (Merigold, Sunflower, and Leland) were compared for the calibration and validation of the model. The SWAT hydrologic model was manually calibrated using data from January 2002 to December 2005, and validated from January 2006 to December 2009. Sensitivity analysis was carried out to identify the most sensitive parameters in flow simulation. Based on the sensitivity analysis results, manual calibration was performed using 11 calibration parameters by changing one parameter per time (Table 4.1). Descriptions about these parameters can be found in the SWAT theoretical manual (Neitsch et al., 2005). The SWAT utilizes exponential weighting decay functions (Venetis, 1969; Sangrey et al., 1984) to determine the time delay in aquifer recharge. The GW_delay is the delay time for aquifer recharge in days (or delay time of the overlying geologic formations; Neitsch et al., 2005), and was estimated by dividing average depth to the water table by saturated hydraulic conductivity of the sub-watersheds. Calibration was performed iteratively until acceptable model performance statistics were achieved. Mean, correlation-coefficient ($R^2$), and Nash-Sutcliffe efficiency ($E$) are some of the commonly used model performance indexes (Moriasi et al., 2007; Parajuli et al., 2009).

The SWAT model performance can be described by six ranking levels (Parajuli, 2010) varying from excellent model performance to unsatisfactory model performances: excellent if $R^2$ and $E \geq 0.90$; very good if $R^2$ and $E = 0.75 - 0.89$; good if $R^2$ and $E = 0.50 - 0.74$; fair if $R^2$ and $E = 0.25 - 0.49$, and poor if $R^2$ and $E = 0 - 0.24$; and unsatisfactory - $R^2$ and $E < 0$. 

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Table 4.1 Flow calibration parameters

<table>
<thead>
<tr>
<th>Sensitivity</th>
<th>Parameters</th>
<th>Range</th>
<th>Final</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CN2</td>
<td>45-92</td>
<td>65-92</td>
</tr>
<tr>
<td>2</td>
<td>ALPHA_BF</td>
<td>0.20-0.90</td>
<td>0.70</td>
</tr>
<tr>
<td>3</td>
<td>GW_DELAY</td>
<td>2.0-45.0</td>
<td>4.0 – 27.1</td>
</tr>
<tr>
<td>4</td>
<td>CH_N2</td>
<td>0.014-0.30</td>
<td>0.23</td>
</tr>
<tr>
<td>5</td>
<td>SOL_AWC</td>
<td>0.02-0.90</td>
<td>0.24</td>
</tr>
<tr>
<td>6</td>
<td>SURLAG</td>
<td>2.0-8.0</td>
<td>3.5</td>
</tr>
<tr>
<td>7</td>
<td>RCHRG_DP</td>
<td>0.0-0.9</td>
<td>0.67</td>
</tr>
<tr>
<td>8</td>
<td>EPCO</td>
<td>0.1-0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>9</td>
<td>ESCO</td>
<td>0.1-0.9</td>
<td>0.7</td>
</tr>
<tr>
<td>10</td>
<td>GW_REVAP</td>
<td>0.02-0.20</td>
<td>0.02</td>
</tr>
<tr>
<td>11</td>
<td>GWQMN</td>
<td>2.0-1000.0</td>
<td>251</td>
</tr>
<tr>
<td>12</td>
<td>REVAPMN</td>
<td>1.0-400.0</td>
<td>300</td>
</tr>
</tbody>
</table>

ALPHA_BF=Base flow alpha factor(days); GW_DELAY=Groundwater delay time (days); CH_N2=Manning’s “n” value for the main channel; CH_K2=Effective hydraulic conductivity (mm hr⁻¹); SURLAG=Surface runoff lags time; RCHRG_DP=Deep aquifer percolation fraction; EPCO=Plant uptake compensation factor; ESCO=Soil evaporation compensation factor; GW_REVAP=Groundwater "revap" coefficient; GWQMN=Threshold depth of water in the shallow aquifer required for return flow to occur; REVAPMN=Threshold depth of water in the shallow aquifer for "revap" to occur

**Corn and soybean yield simulation**

Accurate simulation of crop growth is essential to correctly determine ET from the land surface. The SWAT crop growth module incorporates crop management data provided by the user to simulate crop growth and development in each HRU. Crop management data was collected from field research plots at two agricultural experimental stations, Clarksdale and Stoneville, located within sub-watersheds 1 and 30 respectively. Corn and soybean are common crops in the Delta (NASS, 2011), and often planted in rotation. Both stations planted corn and soybeans using standard agricultural practices to maintain healthy, well-watered crops. Management practices for weed and insect control, fertilization, irrigation, planting dates, cultivars, harvest date and final yield were recorded for all crops grown. Both corn and soybeans were irrigated, but fertilizer
applications of nitrogen were carried out only on corn since soybean has nitrogen fixation capability. Land preparation was performed using a “furrow out cultivator” to create furrows and ridges for convenient irrigation. Tillage depth was 150 mm, and mixing efficiency was set in the model as 75% based on the field observations. Based on the available data, the SWAT crop growth model was calibrated using data from the Stoneville experiment station and validated using data from the Clarksdale experiment stations for the period from 2000 to 2009. Date of planting, harvesting, irrigation, and fertilization were used as management inputs to the crop model in addition to basic field preparation and tillage data.

At present, no limitations on use of groundwater for irrigation are imposed on farmers, so groundwater is used for irrigation on an as-needed basis. Most of the irrigation in the Delta is from groundwater, with some surface water sources (primarily streams or ponds) used as available. In the SWAT crop simulation, auto irrigation and auto fertilization was implemented to minimize water stress and nutrient stress, which represents field conditions. Water sources for each sub-watershed in the model were defined as the shallow aquifer option in the model assuming groundwater from each sub-watershed was used for its own irrigation. Six crop growth model parameters were adjusted during calibration period (Table 4.2). Those are WTRS (water stress), NTRS (nitrogen stress), BLAI (leaf area index), ESCO (soil evaporation compensation factor), EPCO (plant evaporation compensation factor), and HVSTI (harvest index).
Table 4.2  Crop calibration parameters

<table>
<thead>
<tr>
<th>Parameter/Crop</th>
<th>Corn</th>
<th></th>
<th>Soybean</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Range</td>
<td>Final</td>
<td>Range</td>
<td>Final value</td>
<td></td>
</tr>
<tr>
<td>WTRS</td>
<td>0.80-0.97</td>
<td>0.95</td>
<td>0.80-0.97</td>
<td>0.95</td>
<td></td>
</tr>
<tr>
<td>NTRS</td>
<td>0.80-0.97</td>
<td>0.95</td>
<td>default</td>
<td>default</td>
<td></td>
</tr>
<tr>
<td>BLAI</td>
<td>4-8</td>
<td>7</td>
<td>3-6</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>ESCO</td>
<td>0.2-0.4</td>
<td>0.3</td>
<td>0.2-0.4</td>
<td>0.3</td>
<td></td>
</tr>
<tr>
<td>EPCO</td>
<td>0.6-0.9</td>
<td>0.9</td>
<td>0.7-0.9</td>
<td>0.9</td>
<td></td>
</tr>
<tr>
<td>HVSTI</td>
<td>0.4-0.7</td>
<td>0.65</td>
<td>0.3-0.4</td>
<td>0.35</td>
<td></td>
</tr>
</tbody>
</table>


SWAT outputs and water table relationships

The SWAT simulates percolation (PERC), groundwater discharge to the stream (GWQ), and evapotranspiration (ET) for sub-watersheds. These simulated variables were utilized with continuous time-series groundwater levels from sub-watershed 27 to develop a descriptive relationship. The relationship was validated using continuous time-series groundwater levels from the Leflore station at sub-watershed 18. The developed relationship was then used to analyze discrete field-water-level measurement to investigate the groundwater usage in the BSRW.

Results and Discussion

Monthly stream flow calibration and validation results showed good to very good model performances (Table 4.3), similar to results reported by previous studies in the region (King et al., 1999; Arnold et al., 2000; Jha et al., 2006; Parajuli, 2010). The $R^2$ and NSE were varied from 0.73 to 0.86 and 0.67 to 0.85 respectively. Monthly average flow rates for the study period were underpredicted at the Marigold station by 4% and by 18% at the Leland station. Monthly average flow rate at the Sunflower station was equal
to the predicted average flow rate. The model was able to simulate peaks and base stream flows at all three of the stations (Figure 4.3). The SWAT underestimated monthly stream flows at all the three stations in 2003 and 2004. The Leland station underestimated the monthly stream flow in 2006 and 2009. Model overestimated the monthly stream flow at the Marigold and Sunflower stations in 2007 (Figure 4.3). The sub-watersheds outlets 5 (Marigold) and 16 (Sunflower) are in same reach and showed similar patterns in observed and predicted monthly flows. Model performances were good in both wet and dry years. The rainfall was high in 2006 and 2008 but the observed stream flows were low. The SWAT model was able to simulate those variations. The SWAT uses curve number method to simulate surface runoff (Neitsch et al., 2005), if the daily rainfall data is available. There were no rainfall intensity information was available for this study, hence model could only capture the temporal distribution of total depth of the rainfall during runoff calculation. The high rainfall years not necessarily yield high runoff as antecedent moisture condition plays a major role during runoff process. The disparity between observed and predicted flows may also be due to uncertainties associated with model input data and measurement errors in flow data. The SWAT considers only one climate station which is nearest to the centroid of the sub-watersheds, and cannot capture the spatial distribution of the rainfall. This may also lead to potential prediction errors. Annual total (cumulative total at the December) were well predicted by the model except at the Marigold and Sunflower stations in 2004 and 2009, and at the Leland station in 2003, 2006, and 2009.
Table 4.3  Model performance statistics for flow calibration

<table>
<thead>
<tr>
<th>Process</th>
<th>Parameter</th>
<th>Sub-watershed 5; Marigold</th>
<th>Sub-watershed 16; Sunflower</th>
<th>Sub-watershed 26; Leland</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration</td>
<td>R²</td>
<td>0.82</td>
<td>0.73</td>
<td>0.73</td>
</tr>
<tr>
<td>2002 – 2005</td>
<td>NSE</td>
<td>0.78</td>
<td>0.67</td>
<td>0.67</td>
</tr>
<tr>
<td>Validation</td>
<td>R²</td>
<td>0.86</td>
<td>0.85</td>
<td>0.73</td>
</tr>
<tr>
<td>2006 - 2009</td>
<td>NSE</td>
<td>0.85</td>
<td>0.83</td>
<td>0.71</td>
</tr>
</tbody>
</table>
Figure 4.3 Monthly cumulative observed and predicted water yield and rainfall

Period in months (2002-2005 for calibration and 2006-2009 for validation)
Crop yield simulation showed good to very good model performances for corn (R² 0.5 and NSE 0.8 – 0.9), and fair model performances for soybean (R² 0.4 – 0.6 and NSE 0.4 – 0.6). Similar results have been reported by a previous study in the region (Srinivasan et al., 2010). Observed and predicted average yield for the study period showed that the model was able to accurately predict observed crop yields (Table 4.4). The model very slightly (1%) over-predicted the corn yield at Stoneville, and under-predicted yield at Clarksdale. Soybean yield was under-predicted by 10% and 18% at the Stoneville and Clarksdale stations, respectively.

Table 4.4  Observed and predicted average corn and soybean yield

<table>
<thead>
<tr>
<th>Process</th>
<th>Crop</th>
<th>Observed (Mg ha⁻¹)</th>
<th>Predicted (Mg ha⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration- Stoneville</td>
<td>Corn</td>
<td>9.7</td>
<td>9.8</td>
</tr>
<tr>
<td></td>
<td>Soybean</td>
<td>3.0</td>
<td>2.66</td>
</tr>
<tr>
<td>Validation- Clarksdale</td>
<td>Corn</td>
<td>9.1</td>
<td>8.6</td>
</tr>
<tr>
<td></td>
<td>Soybean</td>
<td>3.2</td>
<td>2.6</td>
</tr>
</tbody>
</table>

**Water table**

The water table of the BSRW is recharged from rainfall, and discharged primarily through abstraction for irrigation. Maximum recharge typically occurs in spring following heavy rainfall during the winter. Once the primary crop growing season begins in May, intensive groundwater abstraction occurs. The highest drawdown is commonly observed in August following peak irrigation demand. Based on the discrete field-water-level measurements in the watershed, depth to the GWT changed from a minimum depth of 4.8 m in sub-watershed 01 to a maximum depth of 14.1 m in sub-watershed 16.
SWAT hydrological outputs and groundwater level relationship

The change in groundwater level showed a strong inverse correlation to the predicted monthly water balance (Figure 4.4) for 1990 to 1994. A relationship was developed to describe the correlation between groundwater level and ET, and included model predicted percolation and groundwater flows to the streams to relate the precipitation impact on groundwater recharge as below.

\[ \Delta GW = -6.1452 \times (ET-(PERC-GWQ)) + 440.17 \]  

(4.2)

Where, \( \Delta GW \) is the groundwater level changes (mm) compare to the previous month, ET is the evapotranspiration (mm), PERC is the percolation (mm), and GWQ is the amount of groundwater discharge to the stream (mm)

Figure 4.4 Relationship between models simulated variables (ET-(PERC-GWQ)) with observed monthly water table changes

The ET and water table are strongly related (Meyboom, 1967; William, 1994; Emery, 1970; Sala et al., 1996; Devitt et al., 2002; Nichols, 2000; Woessner, 2000;
Both linear and exponential decay have been proposed in previous studies to describe the relationship between ET and depth to the water table (Nachabe et al., 2005; McDonald and Harbaugh, 1988). Our results indicate a linear relationship between ET and monthly groundwater level fluctuations (Figure 4.4). Even though the GWT was below 7.9 m from the land surface, model outputs and water table fluctuations still showed a good relationship. Previous studies have reported similar relationships for the shallow water tables (Devitt et al., 2002; Nichols, 2000; Woessner, 2000; Sophocleous, 2002). Regular pumping of groundwater into the surface acts as a linkage between groundwater and ET. Crops always received adequate irrigation water from the aquifer in the simulation, as the model was set for the auto irrigation mode, and ET was mainly controlled by crop types and weather parameters. Model predicted ET was able to explain 32% ($R^2 = 0.32$) of the groundwater level changes. After incorporating model predicted PERC and GWQ, the groundwater model was able to explain 64% ($R^2 = 0.64$) of the water table variation for the study period. Similar results have been reported by a study in Muscatatuck river basin in southeast Indiana (Vazquez-Amábile et al., 2005).

The groundwater model may not be able to capture the entire observed variation due to a disparity of actual irrigation efficiencies and timing of irrigations. The developed empirical relationship was tested using monthly data from sub-watershed 18 (Leflore station) (Figure 4.4). The results showed that the developed groundwater model was able to predict groundwater levels of the sub-watershed 18 with a reasonable accuracy ($R^2 = 0.6$). From Jan 93 to Jun 93, the model over-predicted the groundwater levels by maximum 0.4 m, and under-predicted from August 93 to Jan 94 by maximum 0.9 m.
The water table has been shown in previous studies to be hydrologically connected with ET in shallow groundwater systems (Thompson, 2003). When the water table is deeper than the root zone, roots extract water from unsaturated zones and replenish from the water table based on the hydraulic conductivity of the soil (Jury et al., 1991). The ET rates are higher when the water table is shallow (< 1.2 m); deep water tables (3.2-4.7 m s) correspond to low ET rates (Duell, 1990). When depth to the water table increase, the ET rates are decreased exponentially (Nichols, 1994). This study showed an opposite trend, and sub-watersheds with deep water tables showed higher annual ET during 2000 to 2009 (Figure 4.5). This trend was observed in two depth categories. The sub-watersheds which are having water table less than 8 m below the land surface (14 sub-watersheds) and water table between 10 – 13 m (10 sub-watersheds), showed a linear relationships (R²=0.62 and R²=0.5 respectively) between depth to the water table and annual ET. Rests of the sub-watersheds were not shown any relationship between depth to the water table and annual ET. Sub-watersheds in which groundwater levels were more than 10 m below the land surface showed more than 700 mm of ET. Conversely, for those sub-watersheds in which groundwater levels were between 6 to 10 m, ET was less than 700 mm. This indicated that ET rates were not solely governed by the depth to the GWT. Other crop management practices such as crop, cultivar, tillage, planting dates or irrigation scheduling may influence the ET rates.
Seasonal ET and groundwater consumptions

Model predicted seasonal ET from sub-watersheds (April to October) were analyzed with seasonal observed groundwater level changes. Seasonal differences in groundwater levels are a better indicator of the total water abstractions from irrigation. These abstractions should be equal or closer to net water balances in the field (ET-(PER-GWQ)). Positive differences between net groundwater changes and net water balances indicate over abstraction of groundwater, and negative differences indicate groundwater recharge during growing season. Seasonal differences from 2000 to 2009 were analyzed.
for 33 sub-watersheds (Table 4.5). There were no groundwater level data was available for sub-watershed 35-37 for the analysis. Result showed a prominent spatial and temporal variation of groundwater usage among the sub-watersheds. Annual variation determined that some years (2000, 2002, 2005, and 2006) showed prominent over abstraction of groundwater, while years such as 2001 and 2004 showed balance groundwater usage. Annual variation was further changed over sub-watershed levels. Sub-watersheds 9 and 15 only showed less than +/-300 mm differences from 2000 to 2009, while sub-watersheds 3, 5, 6, 7, 11, 19, 26, 29, and 30 showed less than +/- 500 mm differences for the same period. Rest of the sub-watershed showed more than +/- 500 mm differences. The sub-watersheds 16, 24, and 32, showed high variability compare to other sub-watersheds, while sub-watersheds 6, 9, and 15 showed low variability of groundwater usage. These results can be used to formulate proper water management scenarios for each sub-watershed to minimize the positive differences which facilitate the sustainable groundwater abstractions.
Table 4.5  Seasonal differences between groundwater abstraction and simulated variables

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NOTE: Simulated variables= (ET-(PERC-GWQ)), and *data is not available.
Long term differences between average groundwater abstractions for the growing season and model predicted net water balances for two decades were analyzed; 1990 to 1999 and 2000 to 2009 (Figure 4.6). This helps to identify the areas where frequent over abstraction occurs. The zones with values below zero represent good water management or possible recharge during the growing season as a result of influent stream (recharge to the aquifer) or excessive rainfall. The zones with positive values indicate overuse of groundwater or effluent stream (abstraction from aquifer) was closer. Compared to the period from 1990 to 1999, water management from 2000 to 2009 was improved. More than 500 mm of groundwater per season was overused in 10 sub-watersheds (2,16,24,25,31,32,33,35,36, and 37) from 1990 to 1999, but only 5 sub-watersheds (25, 31, 33, 35, and 36) showed overuse of groundwater during the subsequent decade. Sub-watersheds such as 25 and 36 are very close to the Mississippi river, so greater loss of groundwater from the aquifer can be expected. Sub-watersheds in the middle part of the watershed showed good water balances compared to the sub-watersheds at the north and south ends of the watershed. Careful investigation of darker areas will help to improve water management and conserve the groundwater resources in the Mississippi Delta.
Groundwater abstractions from irrigation were influenced by farmers’ activities during crop management. Some farmers may over irrigate their field, while others may under irrigate. On the other hand, net water balance (ET-(PERC-GWQ)) was calculated by the model was only influenced by climatic forcing, crop types, and field management. We have compared those two (groundwater abstraction and net water balance) to identify the areas where proper water management occurs. It has been reported that evapotranspiration based irrigation scheduling is important for proper water management (Jonghan and Giovanni, 2009; Migliaccio et al., 2010). Currently, irrigation scheduling at
delta occurs based on farmers wish, but this study proved the inefficiency of such a system to protect the groundwater resources. Field level investigation of causes for the differences may help to improve the Delta water management.

Conclusions

This study demonstrated the benefits of the modeling tool and groundwater measurements in identifying areas where over abstraction of groundwater were taking place in the Mississippi Delta. Calibrated and validated SWAT model simulations can be used to develop hydrological relationships with observed water table. Both hydrological and crop models showed good to very good model performances during calibration and validation. The coefficient of determination ($R^2$) and Nash-Sutcliffe efficiency index (NSE) varied from 0.4 to 0.9 respectively during both hydrologic and crop model calibration and validation. This study determined an empirical relationship between groundwater consumption and model predicted evapotranspiration, percolation and groundwater movements to the streams. The model results explain 64% of the water table fluctuations. Net water balance ($\text{ET-(PERC-GWQ)}$) increases when depth to the water table increases across the 24 sub-watersheds. Seasonal differences between groundwater abstraction and net water balance indicate the years of groundwater over abstraction. Only 11 sub-watersheds are reasonable in water management (± 500 mm water), and 26 sub-watersheds require immediate attention. Results from this study are useful in the development of viable water management plans that protect the groundwater resources of the Mississippi Delta.
References


CHAPTER V
ASSESS THE IMPACTS OF CROP MANAGEMENT PRACTICES AND CLIMATE VARIABILITY ON CROP AND SEDIMENT YIELDS

Abstract

This study evaluated climate variability impacts on flow, crop yield, and soil erosion from three different tillage systems (Conventional, Reduce 1, and Reduce 2), in the BSRW in Mississippi. The Soil and Water Assessment Tool (SWAT) was applied to the BSRW using observed flow and crop yields. The model was successfully calibrated and validated using monthly time steps between 2001 and 2011 by applying manual and automatic (SUFI-2) methods. Flow and crop simulations showed good to very good model performances (for flow R² up to 0.78 and NSE up to 0.76; for corn yield R² up to 0.5 and NSE up to 0.9; and for soybean yield R² and NSE up to 0.6). Future climate variability was simulated with the LARS-WG, a stochastic weather generator, using the global climate model, CCSM3, which was developed by the U.S National Center for Atmospheric Research (NCAR). The SRES (Special Report on Emissions Scenarios) A1B, A2, and B1 of the Intergovernmental Panel on Climate Change (IPCC) were simulated for the mid (2046-2065) and late (2080-2099) century. Results showed no significant differences between average corn and soybean yields among three different tillage systems in the BSRW (P>0.05). Additional results indicated a significant difference between sediment yields from the three tillage systems (from corn fields...
p=0.002, and soybean fields p=0.003). Future average maximum simulated temperature increased as high as 4.8°C in the BSRW. Monthly precipitation patterns will be remained un-changed in future climate simulations but the BSRW will receive frequent extreme rainfall events. The effect of climate variability and tillage together failed to show notable changes to the future crop yields. The reduce tillage 2 system showed the highest responses to the climate variability on erosion control followed by the reduce tillage 1 and conventional tillage systems.

Introduction

The world crop productions need to be increased, and this has to be achieved by coping with several challenges such as soil erosion and anticipated climatic variability. Soil erosion can convert productive agricultural lands into unproductive barren lands, and climate variability can aggravate the problem. Consequences of the climate variability on crop production have been already visible, and future climatic variability will have a major effect on changing crop production in regional and global scale (Abraha et al., 2006). As an example, the damage to the future corn production due to climate variability will be $3 billion per year in the U.S. alone (Rosenzweig et al., 2002). Elevated carbon dioxide (CO₂) concentration in the atmosphere, changing precipitation, and temperature fluctuations are some of the anticipated climatic changes, and these changes will affect future cropland erosion and crop production in multiple way.

Global warming occurs as a result of CO₂ increases in the atmosphere, and this warming up will lead to have many consequences on hydrological systems (Zhang et al., 2007). There are enough scientific evidences that temperature has increased over the last 15 to 20 years in both air and water (Barnett et al., 2005; IPCC, 2007). This temperature
changes may have significant effects on future crop production. Based on IPCC (2007), future crop production may increase with increase of average temperature range 1 to 3°C but beyond that, yield may decrease. Moreover, most of the crops are currently near to their climatic thresholds and quantity and quality of the crop yield will be affected due to unfavorable climatic conditions (White et al., 2006). These effects may be positive or negative depending on the crop type and the locations. As an example, the moderate climate variability in the North American region may have positive impacts on crop yields (Reilly, 2002).

Future precipitation form and pattern may change, and these changes will alter runoff and land based erosion, which lead to a change of transport and deposition process of contaminants (Macdonald et al., 2005; Doris et al., 2007). These changes will affect on pollutant transport from agriculture lands as agriculture is the major contributor of NPS pollution of water resource (Duda, 1993). Currently agricultural pollutants such as sediment, resulting from crop management activities, caused degradation of surface water resources (Donoso et al., 1999; Zalidis et al., 2002; Thorburn et al., 2003). Moreover, soil erosion related to the crop management practices are spatially varied over the watershed and need to identify the critical areas for remedial measures (Dickinson et al., 1990; Mostaghimi et al., 1997). How to increase crop productivity without further degrading environment is one of the major challenge facing by agriculture scientists today.

Several studies have been conducted to evaluate effects of climate variability on crop productions (Challinor, 2009; Crane et al., 2011; Lobell et al., 2006), and these effects are varied spatially. A climate study on maize yield in South Africa found that
increasing rainfall and temperature under future climate change positively impact on maize yield. This study further concluded that precipitation is more important than the temperature for the final crop yield (Akpalu et al., 2008). Changes to the precipitation directly affect the crop yield if precipitation cannot fulfill the demand of evapotranspiration (Mera et al., 2006). Extreme temperatures have negative effect on crop yield compare to minimum and maximum temperature when irrigation water is available through growing season (Challinor et al., 2007). Similarly, Mera et al. (2006) has reported that temperature has limited impacts on crop yield. Detail review of the effects of precipitation and temperature on crop yield can be found in the excellent reviews of Yinhong et al. (2009). Not only precipitation and temperature, the elevated CO₂ level has positive effects on future crop production. Elevated CO₂ may increase the growth of future crops (Kimball et al., 2002). Detail reviews of effects of elevated CO₂ on crop growth can be found from the excellent reviews of Tubiello and Ewert, (2002).

It is important to predict the impact of climate variability on crop production, because adaptation and mitigation measures can be planned ahead of the consequences of future climate. Crop simulation models are the most widely used tool for predicting climate variability impact on crop growth and production. Many crop models have been used to assess the possible future impacts (Aggarwal et al., 2006). The impacts of temperature, rainfall, and CO₂ concentration on soybean yield have been studied using model GLYCIM (Reddy and Pachepsky, 2000). Xie and Eheart, (2004) conducted a study to investigate climate vulnerability of maize crop in Mackinaw watershed in the U.S., using SWAT model. Application of model CERES-Maize in Brazil has investigated suitable date of planting of maize crop in future climate (Tojo Soler et al., 2007). Crop
simulation models help to evaluate the status of future crop growth, contribute to the crop improvements, and design appropriate crop management practices in future climate (Matthews et al., 2012). Moreover, these models can also be used to investigate the environmental effects on crop physiology in future climate (Southworth et al., 2000).

Studies of climate variability on crop yield and soil erosion are limited in southern Mississippi, where climatic conditions are different from other part of the U.S. No studies focused on effects of climate variability on different tillage practices and resulting threat of soil erosion from crop lands. Moreover, southern U.S. states such as Mississippi, which has region’s abundant water resources are, aggravated the runoff pollution problems such as soil erosion. Few studies in the U.S. have already reported about soil erosion and crop productivity in future climate. O’Neal et al. (2005) has performed a study about crop management and erosion rate under climate change in Midwestern U.S. Mehta et al. (2012) has carried out a crop simulation studies in the Missouri River Basin. However, the effects of climate variability on crop production vary between locations (Southworth et al., 2000). In this study, we evaluated three tillage practices on corn and soybean production and their potential for soil erosion. Further, the effects of climate variability on crop production and soil erosion in future climate was evaluated from agriculture lands, which are belongs to subtropical humid climate.

**Materials and methods**

**Study area**

This study was conducted in the BSRW, and the BSRW, which extend over 7,660 km², is the major sub-watershed of the Yazoo river watershed in Mississippi.
Input variables

Weather and Stream Flow

Measured daily rainfall and temperature data from the National Climatic Data Center (NCDC, 2010) were used in this study. Monthly stream flow data from three USGS gauge stations (station number 7288280 in sub-watershed 5 at Merigold, 7288500 in sub-watershed 16 at Sunflower, and 7288650 in sub-watershed 26 at Leland) from 2001 to 2011 were used.

Geospatial

Soil Survey Geographic Database (SSURGO) was incorporated into the model to parameterize the soils in the watershed (USDA, 2005). The SSURGO databases were developed using field methods based on the National Cooperative Soil Survey (NCSS) mapping standards and 1:12000 to 1:63360 map scales (USDA, 1995). The SSURGO data for the BSRW showed 12 major soil textural classes. “Fine-silty”, which is constituted 62% of the watershed area, was the dominant soil textural class. The cropland data layer, with a 30 m spatial resolution, was used to parameterize the land use characteristics of the watershed (USDA/NASS, 2009). The 30 m x 30 m grid digital elevation model (DEM) data from the U.S Geological Survey (USGS, 2010) was used as elevation data in this study.

Crop yield and management data

The SWAT crop growth module incorporates crop management data provided by the user to simulate crop growth and development in each HRU. Detail 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 experiment stations. These stations were at Stoneville (USDA-ARS Crop Production Systems Research Unit) and Clarksdale, and were inside the sub-watershed 30 and sub-watershed 1 respectively. These are the variety trial experiment plots and they maintain yield and crop management records. Data related from 2000 to 2009 was utilized in this study. Date of plowing, planting, fertilizer application, irrigation, and harvesting were recorded to apply in crop model. Corn and soybean are common crops in the Delta (NASS, 2011), and often planted in rotation. The yield data were originally recorded as bushels per acre. These values were 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 that 25 kg of corn per bushel and 27 kg of soybean per bushel (Weiland and Smith, 2007; Parajuli et al., 2013).

*Future weather data*

Future climate variability was simulated using LARS-WG, a stochastic weather generator. The LARS-WG generates synthetic daily time series of maximum and minimum temperatures, precipitation, and solar radiation by using parameters, which were generated using measured daily weather data for a given site and the selected GCM. More details about LARS-WG can be found in the model reference manual (Semenov, 2007). The CCSM3 (Collins et al., 2004), developed by National Center for Atmospheric Research (NCAR) in the U.S, was used as GCM to generate future weather data. The CCSM3 is a model with 1.4° x 1.4° grid resolution.
Three emissions scenarios were selected based on the special report on emissions scenarios (SRES; IPCC, 2000) to evaluate future climate variability. Those scenarios are listed as below.

- **A1B scenario**: very rapid economic growth is expected and global population will be peak in mid-century and then declines. A rapid introduction of new and more efficient technologies are expected with a balance between fossil and non-fossil of energy sources. The CO₂ concentrations vary from baseline 334 ppm to 418 ppm in early century (2011-2030), 541 ppm in mid century (2046-2065), and 674 ppm in late century (2081-2100).

- **A2 scenario**: a very heterogeneous world with continuously increasing global population. Economic development is regionally oriented, and technological changes are fragmented and slower. The CO₂ concentrations vary from baseline 334 ppm to 414 ppm in early century, 545 ppm in mid century, and 754 ppm in late century.

- **B1 scenario**: a convergent world with the global population peaks in mid-century and then declines. A rapid change in economic structures toward a service and information economy is expected. Clean and resource-efficient technologies, global solutions to economic, social and environmental sustainability are expected without additional climate initiatives. The CO₂ concentrations vary from baseline 334 ppm to 410 ppm in early century, 492 ppm in mid century, and 538 ppm in late century.
Model setup

**SWAT model description**

The SWAT model is a semi distributed physically based, continuous, daily time step model and it allows predicting surface runoff, sediment and nutrient yields, pesticide, bacteria, and crop yields (Arnold *et al.*, 1998; Neitsch *et al.*, 2005). SWAT model divide sub-watersheds into further 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 subroutine within the SWAT and apply based on the user settings. The SWAT calculates daily runoff by curve number (CN) method using daily data or by Green Ampt method when the sub-daily precipitation data are available. The EPIC model within the SWAT simulates the crop growth functions and heat units above the base temperature use for crop growth and development. The SWAT calculates crop yield as a product of Harvest Index (HI) and above-ground biomass. Daily HI was calculated on the basis of an optimal HI and a fraction of potential heat units (Neitsch *et al.*, 2002). The crop growth module first calculates the plant growth under optimal conditions, and then computes the actual growth under stresses by water, temperature, nitrogen, and phosphorous. Detail description about SWAT model can be found in SWAT 2005 theoretical manual (Neitsch *et al.*, 2005).
Flow calibration and validation

Monthly measured stream flows from Merigold, Sunflower, and Leland from Jan 2001 to Sep 2011 were used to calibrate (2001-2005) and validate (2006-2011) the SWAT hydrological model. Model calibration (flow) was initially performed using SWAT-CUP SUFI-2 automatic calibration technique (Abbaspour et al., 2007) and followed by the manual calibration. The SWAT-CUP SUFI-2 has been used for previous similar studies (Abbaspour et al., 2007). The SUFI-2 algorithm evaluate uncertainty of input parameter as uniform distribution, and uncertainty of the model output as 95% of the prediction uncertainty. This prediction uncertainty is calculated for 2.5% and 97.5% levels of the cumulative distribution, and Latin hypercube sampling technique is used to obtain the output variables (Abbaspour et al., 2007). The Nash–Sutcliffe efficiency (NSE) coefficient was used as an objective function. Moreover, soil parameters were eliminated from auto-calibration as SSURGO soil data contain all the required parameters such as soil bulk density and hydraulic conductivity (USDA, 2005). Furthermore, depending on the data availability, the SWAT calculates potential evapotranspiration (PET) using Penman-Monteith, Priestley-Taylor, or Hargreaves method. In this study, we used Penman-Monteith method to simulate PET. This study also used 12 flow calibration parameters for the SWAT hydrologic model calibration (Table 5.1).
### Table 5.1 Flow calibration parameters

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Fitted Value</th>
<th>Range</th>
<th>Final (hybrid)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 CN2$^{*}$</td>
<td>Not used</td>
<td>45-92</td>
<td>45-92</td>
</tr>
<tr>
<td>2 ALPHA_BF</td>
<td>0.7</td>
<td>0.20-0.90</td>
<td>0.7</td>
</tr>
<tr>
<td>3 GW_DELAY</td>
<td>12.7</td>
<td>2.0-45.0</td>
<td>12.7</td>
</tr>
<tr>
<td>4 CH_N2</td>
<td>0.228</td>
<td>0.014-0.30</td>
<td>0.228</td>
</tr>
<tr>
<td>5 SOL_AWC</td>
<td>0.24</td>
<td>0.02-0.90</td>
<td>0.24</td>
</tr>
<tr>
<td>6 SURLAG</td>
<td>3.5</td>
<td>2.0-8.0</td>
<td>3.5</td>
</tr>
<tr>
<td>7 RCHRG_DP</td>
<td>0.67</td>
<td>0.0-0.9</td>
<td>0.67</td>
</tr>
<tr>
<td>8 EPCO</td>
<td>0.7</td>
<td>0.1-0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>9 ESCO</td>
<td>0.3</td>
<td>0.1-0.9</td>
<td>0.7</td>
</tr>
<tr>
<td>10 GW_REVAP</td>
<td>0.06</td>
<td>0.02-0.20</td>
<td>0.02</td>
</tr>
<tr>
<td>11 GWQMN</td>
<td>251</td>
<td>2.0-1000.0</td>
<td>251</td>
</tr>
<tr>
<td>12 REVAPMN</td>
<td>300</td>
<td>1.0-400.0</td>
<td>300</td>
</tr>
</tbody>
</table>

*CN2 didn’t include in the automatic calibration as it allowed only one CN2 number for all sub-watershed with the different land use. Manually calibrate this based on land use. (Sufi_2 Swat cup parameters 2003 to 2005 was used for SWAT-cup calibration)*

**Corn and soybean yield simulation**

Based on the available data, the SWAT crop growth model was calibrated using data from the Stoneville experiment station and validated using data from the Clarksdale experiment stations for the period from 2000 to 2009. Date of planting, harvesting, irrigation, and fertilization were used as management inputs to the crop model in addition to the basic field preparation and tillage data. Both stations planted corn and soybeans using standard agricultural practices to maintain healthy, well-watered crops. Both corn and soybeans were irrigated, but fertilizer applications were carried out only on corn since soybean has nitrogen fixation capability. Land preparation was performed using a “furrow out cultivator” to create furrows and ridges for convenient irrigation. Tillage depth was 150 mm, and mixing efficiency was set in the model as 75% based on the field observations. Corn and Soybean were established on seed beds where land was prepared to have furrows and ridges.
At present, no limitations on use of groundwater for irrigation are imposed on farmers, so groundwater is used for irrigation on an as-needed basis. In the SWAT crop simulation, auto irrigation and auto fertilization was implemented to minimize water stress and nutrient stress, which represents field conditions. Water sources for each sub-watershed in the model were defined as the shallow aquifer option, assuming groundwater from each sub-watershed was used for its own irrigation. Six crop growth model parameters were adjusted during calibration period (Table 5.2). Those are AUTO_WSTRS (water stress), AUTO_NSTRS (nitrogen stress), BLAI (leaf area index), ESCO (soil evaporation compensation factor), EPCO (plant evaporation compensation factor), and HVSTI (harvest index).

Table 5.2   Crop calibration parameters

<table>
<thead>
<tr>
<th>Parameter/Crop</th>
<th>Corn</th>
<th>Soybean</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUTO_WSTRS</td>
<td>0.80-0.97</td>
<td>0.80-0.97</td>
</tr>
<tr>
<td>AUTO_NSTRS</td>
<td>0.80-0.97</td>
<td>0.80-0.97</td>
</tr>
<tr>
<td>BLAI</td>
<td>4-8</td>
<td>4-8</td>
</tr>
<tr>
<td>ESCO</td>
<td>0.2-0.4</td>
<td>0.2-0.4</td>
</tr>
<tr>
<td>EPCO</td>
<td>0.6-0.9</td>
<td>0.7-0.9</td>
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<tr>
<td>HVSTI</td>
<td>0.4-0.7</td>
<td>0.3-0.4</td>
</tr>
</tbody>
</table>


Model performances

Model performances were evaluated using two statistical parameters. Coefficient of determination ($R^2$) and Nash-Sutcliffe efficiency index (NSE) were the two statistical parameters used in this study.
Tillage scenarios and crop rotations

Currently three different tillage practices were performed in the BSRW including conventional and two reduce tillage practices (Table 5.3). We evaluated crop and sediment yield from con-soybean rotation in the BSRW for the three tillage options. Soybean after corn is the most common rotation at the BSRW. Further, we simulated con-soybean rotation with three tillage options for mid and late-century climate for SRES A1B scenario. Most of the previous studies have used A1B SRES scenario for climate variability and crop production studies (Osborne et al., 2013). Using simulation results, we evaluated climate variability impacts on corn & soybean yield, and sediment transport from the respective croplands of the watershed. Date of planting (March 15) and date of harvesting (August 15) were kept unique for both crops to compare the result.

<table>
<thead>
<tr>
<th>Time</th>
<th>Operation</th>
<th>Mixing Efficiency</th>
<th>Tillage Depth</th>
<th>Plow Name</th>
</tr>
</thead>
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<tr>
<td>Conventional</td>
<td>Disk</td>
<td>0.85</td>
<td>100</td>
<td>Disk Plow Ge23ft</td>
</tr>
<tr>
<td></td>
<td>Sub-Soil</td>
<td>0.15</td>
<td>350</td>
<td>Para plow</td>
</tr>
<tr>
<td></td>
<td>Disk</td>
<td>0.85</td>
<td>100</td>
<td>Disk Plow Ge23ft</td>
</tr>
<tr>
<td></td>
<td>Row Up</td>
<td>0.65</td>
<td>150</td>
<td>Bedder Disk-Hipper</td>
</tr>
<tr>
<td>Just before planting</td>
<td>Do-All</td>
<td>0.3</td>
<td>150</td>
<td>Land all, Do-All</td>
</tr>
<tr>
<td>March 15 - June 31</td>
<td>Planting</td>
<td>Na</td>
<td>Na</td>
<td></td>
</tr>
</tbody>
</table>

Reduced tillage 1

<table>
<thead>
<tr>
<th>Time</th>
<th>Operation</th>
<th>Mixing Efficiency</th>
<th>Tillage Depth</th>
<th>Plow Name</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sub-Soil</td>
<td>0.15</td>
<td>350</td>
<td>Para plow</td>
</tr>
<tr>
<td></td>
<td>Row Up</td>
<td>0.65</td>
<td>150</td>
<td>Bedder Disk-Hipper</td>
</tr>
<tr>
<td>Just before planting</td>
<td>Do-All</td>
<td>0.3</td>
<td>150</td>
<td>Land all, Do-All</td>
</tr>
<tr>
<td>March 15 - June 31</td>
<td>Planting</td>
<td>Na</td>
<td>Na</td>
<td></td>
</tr>
</tbody>
</table>

Reduced tillage 2

<table>
<thead>
<tr>
<th>Time</th>
<th>Operation</th>
<th>Mixing Efficiency</th>
<th>Tillage Depth</th>
<th>Plow Name</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sub-Soil</td>
<td>0.15</td>
<td>350</td>
<td>Para plow</td>
</tr>
<tr>
<td>Just before planting</td>
<td>Roller</td>
<td>0.35</td>
<td>40</td>
<td>Roller Packer Flat Roller</td>
</tr>
<tr>
<td>March 15 - June 31</td>
<td>Planting</td>
<td>Na</td>
<td>Na</td>
<td></td>
</tr>
</tbody>
</table>
Results and discussion

Flow calibration

Monthly flow calibration and validation were performed from 2001 to 2011. The model was simulated with a one year warm-up period (2000), and warm-up period helps model to stabilize during simulations. Measured monthly stream flow data from Merigold, Sunflower, and Leland from 2001 to 2005 was used to calibrate the model, and data from 2006 to 2011 was used to validate the model. Results showed that model was able to capture most of the peak flows in all three gauges (Figure 5.1). Calculated model performance statistics showed good to very good model performance with $R^2$ up to 0.78 and NSE up to 0.76 in all three locations (Table 5.4). The SWAT under simulated the stream flows in all locations. Average monthly measured flow at the Merigold, Sunflower, and Leland were 24.1 m$^3$s$^{-1}$, 29.6 m$^3$s$^{-1}$, and 20.1 m$^3$s$^{-1}$ during the study period respectively. The model simulated 21.7 m$^3$s$^{-1}$ at the Merigold (10 % underprediction), 27.5 m$^3$s$^{-1}$ at the Sunflower (7 % underprediction), and 16.7 m$^3$s$^{-1}$ at the Leland (17 % underprediction).
Figure 5.1  Measured and simulated stream flows

(a) Merigold

(b) Sunflower

(c) Leland

Period in months (2001-2005 for calibration and 2006-2011 for validation)
Crop model calibration

The SWAT uses EPIC crop model for crop growth and simulations. Several previous studies have reported poor yield prediction of the EPIC model (Debaeke et al., 1996; Mearns et al., 1999). But in this study, crop yield simulation showed good to very good model performances for corn ($R^2$ 0.5 and NSE 0.8 – 0.9), and fair model performances for soybean ($R^2$ 0.4 – 0.6 and NSE 0.4 – 0.6) (Table 5.5). Similar results have been reported by a previous study in the region (Srinivasan et al., 2010). Measured corn yield showed less variability compare to the measured soybean yield (Figure 5.2). Corn was grown under good management with intensive fertilizer applications; however, there were no fertilizer applications for the soybean. Soybean crop has capability of fixing nitrogen using nitrogen fixing bacteria. The average measured corn yield was 9.7 Mg ha$^{-1}$ and 9.1 Mg ha$^{-1}$ at Stoneville and Clarksdale respectively, and the simulated average corn yield was 9.8 Mg ha$^{-1}$ (1% overprediction), and 8.6 Mg ha$^{-1}$ (6% underprediction) at Stoneville and Clarksdale respectively. Average measured soybean yield was 3.0 Mg ha$^{-1}$ and 3.6 Mg ha$^{-1}$ respectively for Stoneville and Clarksdale, and model was able to simulate 2.66 Mg ha$^{-1}$ (11% underprediction) at Stoneville, and 2.6 Mg ha$^{-1}$ (13% underprediction) at the Clarksdale.
Figure 5.2  Measured vs. simulated corn and soybean yield

Table 5.5  Model performance crop simulation

<table>
<thead>
<tr>
<th>Crop</th>
<th>Model performance Statistics</th>
<th>Calibration- Stoneville</th>
<th>Validation- Clarksdale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>$R^2$</td>
<td>0.50</td>
<td>0.46</td>
</tr>
<tr>
<td></td>
<td>NSE</td>
<td>0.83</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>1.4</td>
<td>1.0</td>
</tr>
<tr>
<td>Soybean</td>
<td>$R^2$</td>
<td>0.59</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>NSE</td>
<td>0.49</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>0.48</td>
<td>0.80</td>
</tr>
</tbody>
</table>
**Future rainfall and temperature**

Future temperature variations were evaluated with the baseline temperatures from 1992-2011. Maximum (T$_{\text{max}}$) and minimum (T$_{\text{min}}$) temperature, derived for mid (2046-2065) and late (2080-2099) centuries from LARS-WG, were averaged over the entire watershed to compare with baseline averages (Figure 5.3). Average annual baseline T$_{\text{max}}$ was 23.4°C, and average annual mid-century T$_{\text{max}}$ will be 25.5°C, 25.7°C, and 25.0°C for SRES A1B, A2, and B1 scenarios respectively. During late century, the annual average T$_{\text{max}}$ will be 26.2°C (A1B), 27.2°C (A2), and 24.9°C (B1). The highest T$_{\text{max}}$ increases (from baseline) will be in November during the mid century scenario, and the increase will be 2.8°C for A1B, 3.2°C for A2, and 2.3°C for B1 SRES scenarios (Figure 5.3). In late century, the highest T$_{\text{max}}$ increase will be 3.7°C for A1B (June) and 4.8°C for A2 (July) and 2°C for B1 (July). According to the baseline temperatures, July and August were the warmest months in a year, but in future climate warmest period will be extended to 5 months from June to November. This indicate that future climate in BSRW will be experienced longer summer periods. The T$_{\text{min}}$ variations will be followed a similar pattern as T$_{\text{max}}$ (Figure 5.3).
Mid and late century precipitations from 7 stations were evaluated with the baseline precipitation from 1992 to 2011. Percentage changes from baseline were calculated for mid and late-centuries. The future rainfall in mid-century will be varied from 0.8% reduction to 21.9% increase (Table 5.6). During late century, the rainfall increases will be varied between a 9% to a 23.1%. Future rainfall increase will be due to
extreme rainfall events. Results showed that number of rainfall events, which exceed 100 mm of rainfall per day, will be higher in both mid and late-century. Moreover, Monthly precipitation patterns will be remained un-changed in future climate, but the BSRW will get extreme rainfall events (Figure 5.4). There are evidences that extreme rainfall events have been already increased in the U.S. (Karl and Knight, 1998), and expected to be increased in future as subtropics (climate of the study area) will be experienced extreme rain events (Bates et al., 2008).

Table 5.6  Characteristics of rainfall in mid and late-century for A1B, A2, and B1 scenario

<table>
<thead>
<tr>
<th>Station</th>
<th>Average rainfall (mm)</th>
<th># of days &quot;&gt;100 mm&quot;</th>
<th>SRES</th>
<th>% Change</th>
<th># of days &quot;&gt;100 mm&quot;</th>
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<tr>
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<tr>
<td>Clarksdale</td>
<td>1313</td>
<td>7</td>
<td>A1B</td>
<td>10.1</td>
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</table>

*%change= ((Scenario-Base)/Base)*100
Tillage effects

*Tillage effect on crop yield*

Studies to evaluate the effect of conventional tillage and no-till on soil erosion, were common (Edwards et al., 1988; Norwood, 1999). In this study, we used three different tillage systems, which are currently practicing at the BSRW, to evaluate the impacts of tillage on corn and soybean yield. Conventional tillage practices in BSRW involve five different plows before the planting, while reduce tillage 1 and 2 use two to three plows. Reduce tillages were performed to make minimum disturbance to the soil. Further, the reduce 2 tillage is similar to the no-till condition as it makes minimum soil mixing during tillage operations. Results showed that there is no significant differences between average corn and soybean yield among three different tillage systems for entire watershed (P>0.05). Previous 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 yield in conventional tillage system was 8.39 Mg ha\(^{-1}\), while average corn yield for reduce tillage 1 and 2 was 8.35 Mg ha\(^{-1}\) and 8.38 Mg ha\(^{-1}\) respectively. Average soybean yield for the watershed was remained 2.77 Mg ha\(^{-1}\) for all three tillage systems.

Corn and soybean yields were analyzed at sub-watershed level, and results showed that corn yield can be increased by 0.3 % and 1.2 % and reduce by 2.7% and 1.8% in reduce tillage 1 & 2 respectively with compared to the conventional tillage (Figure 5.5). Sub-watershed level soybean yield also showed similar pattern but with different magnitude (yield increased up to 1.2% and reduce up to 0.1%). Previous studies showed mixed results. Hairston et al. (1990) has reported that tillage has no effects on soybean yield. A Study in Alabama has reported that 30% corn yield reductions and 16% soybean yield reduction by changing conventional tillage to no-tillage (Edwards et al., 1988). A study in Kansas State has reported that corn yield increased after 3 years of no-tillage and soybean yield increased after one year of no-tillage (Norwood, 1999). Pedersen and Lauer (2003) reported that corn yield can reduce 5% in no-tillage compare to the conventional but soybean yield can increase 6% in no-tillage compared to the conventional.
Effect of tillage practices on soil erosion was evaluated. Results showed that there is a significant difference between sediment yields of three tillage systems (from corn fields \( p=0.002 \), and soybean fields \( p=0.003 \)). Conventional tillage has the highest sediment yield followed by reduce tillage 1 to reduce tillage 2 for both crop fields. Average sediment yield from corn fields were 12.56 Mg ha\(^{-1}\) year\(^{-1}\), and sediment yields were reduced by 24% and 39% in reduce tillage 1 & 2 respectively. Average sediment yield from soybean fields were 14.11 Mg ha\(^{-1}\) year\(^{-1}\), and the sediment yields were reduced 30% and 51% in reduce tillage 1 & 2 respectively. Moreover, soybean fields were eroded 16%, 10%, and 4% higher than the soybean fields in conventional, reduce 1, and reduce 2 tillage system respectively. It is reported that reduce or no-till systems help to reduce soil erosion by preventing rill erosion (Fua et al., 2006). A previous study in the study area has reported that 97% sediment reduction (from 19 Mg ha\(^{-1}\) year\(^{-1}\) to 0.5 Mg ha\(^{-1}\) year\(^{-1}\)).

Figure 5.5  Percentage yield changes in reduce 1 and 2 tillage systems compared to the conventional tillage system

*Tillage effects on erosion*

Effect of tillage practices on soil erosion was evaluated. Results showed that there is a significant difference between sediment yields of three tillage systems (from corn fields \( p=0.002 \), and soybean fields \( p=0.003 \)). Conventional tillage has the highest sediment yield followed by reduce tillage 1 to reduce tillage 2 for both crop fields. Average sediment yield from corn fields were 12.56 Mg ha\(^{-1}\) year\(^{-1}\), and sediment yields were reduced by 24% and 39% in reduce tillage 1 & 2 respectively. Average sediment yield from soybean fields were 14.11 Mg ha\(^{-1}\) year\(^{-1}\), and the sediment yields were reduced 30% and 51% in reduce tillage 1 & 2 respectively. Moreover, soybean fields were eroded 16%, 10%, and 4% higher than the soybean fields in conventional, reduce 1, and reduce 2 tillage system respectively. It is reported that reduce or no-till systems help to reduce soil erosion by preventing rill erosion (Fua et al., 2006). A previous study in the study area has reported that 97% sediment reduction (from 19 Mg ha\(^{-1}\) year\(^{-1}\) to 0.5 Mg ha\(^{-1}\) year\(^{-1}\)).
Mg ha\(^{-1}\) year\(^{-1}\)) by changing conventional tillage to no-tillage in soybean crop lands (Schreiber et al., 2001).

Sediment yield from each sub-watersheds were evaluated. Results showed that annual sediment yield was reduced in reduce tillage systems with compared to the conventional system (Figure 5.6). Some sub-watersheds (ex sub-watershed 6) produced higher sediment yield irrespective of the tillage practices. These sub-watersheds generally are either in high slope area or soil contains more silt. Sub-watersheds in the western side of the basins are very close to the Mississippi river and more erosion can be expected (Sub-watershed 4, 6, 14, 22, 25, and 36). Sub-watersheds in north eastern of the watershed shows comparatively low sediment yield.
Figure 5.6   Tillage effects on sediment yield (Mg ha$^{-1}$ year$^{-1}$) at sub-watershed level

(a) Corn conventional tillage, (b) Corn reduce tillage 1
(c) Corn reduce tillage 2, (d) Soybean conventional tillage
(e) Soybean reduce tillage 1, and (f) Soybean reduce tillage 2
Climate effect

Climate effects on crop yield

Effects of climate variability on corn and soybean productions were evaluated for the mid and late-century climate. Average corn yield in BSRW will be increased in both mid and late century compared to the baseline, however the mid century increment is higher than the late century. Future soybean yield will be lower than the current soybean yield. Average corn yield in baseline was 8.4 Mg ha\(^{-1}\), 8.3 Mg ha\(^{-1}\), and 8.4 Mg ha\(^{-1}\) for conventional, reduce 1, and reduce 2 tillage systems respectively. The mid-century corn yield will be increased by 3% (conventional tillage), 2.8% (reduce tillage 1), and 2.6% (reduce tillage 2). Late-century corn yield increase will be about 1% in all tillage system. The mid and late-century soybean yield will be decreased by 3%, and 1.5% respectively for all the three tillage system. The soybean yield reduction may caused by the extreme temperature fluctuations. Rising temperature may increase the crop growth but the heat stress may reduce the final yield (Southworth et al., 2000), and it is reported that yield responses were linearly related to the local temperature fluctuations (Osborne et al., 2013). Impact of tillage on crop yield in future climate will be remained similar to the current climate in BSRW.

Sub-watersheds of the BSRW will show different yield responses to the future climate variability (Figure 5.7 & Figure 5.8). Sub-watershed level analysis showed that corn yield can be increased up to 34% and reduced up to 12 %, and soybean yield can be increased up to 12.5% and reduced up to 16.6 % in future climate under all tillage systems. A climate variability study using EPIC in U.S. has reported that corn and soybean yield increases in future climate (Izaurralde et al., 2003). Mid and late-century
climate of the BSRW will receive more rain with a long summer period and temperature will be increased maximum about 5°C from the baseline. These conditions may be favorable for the crop productions. Previous research suggested that precipitation is important in crop growth than temperature (Akpalu et al., 2008; Challinor et al., 2007). We used soybean after corn crop rotation and these results will be significantly changed if crop rotation is changed. Even though we changed the tillage practices, the effect of climate variability and tillage together did not show notable changes to the future crop yields. Moreover, we kept constant crop planting dates, but careful planning of the planting dates is important to capture the maximum soil moisture and effective rainfall. It is predicted that crop growing period will be reduced in future climate and planting dates need to be adjusted for optimal crop growth (Tojo Soler et al., 2007; Yinhong et al., 2009).
Figure 5.7 Corn yield changes (%)

(a) Conventional tillage mid-century, (b) Reduce tillage 1 mid-century (c) Reduce tillage 2 mid-century (d) Conventional tillage late-century (e) Reduce tillage 1 late-century and (f) Reduce tillage 2 late-century
Figure 5.8  Soybean yield changes (%)

(a) Conventional tillage mid-century, (b) Reduce tillage 1 mid-century
(c) Reduce tillage 2 mid-century (d) Conventional tillage late-century
(e) Reduce tillage 1 late-century and (f) Reduce tillage 2 late-century
Climate effects on sediment yield

Mid and late-century climate will generate more runoff in BSRW (Table 5.7). Water yield (river flow) from the watershed outlet will be higher by 7%-17% in future climate. A study from Midwestern U.S. has reported 10-310% runoff increase 2040-2059 compared to the 1990-1999 (O'Neal et al., 2005). Increase runoff ultimately increases the erosion rate in the watershed. Results showed that sediment yield will be increased in mid and late-century climate in all three tillage systems (Table 5.7). But only late century sediment yields showed a significant difference compared with baseline condition (p<0.02 for corn fields and p<0.003 for soybean fields). Sediment yield from cornfields will be increased 7% to 11% in mid-century and 13% to 21% in late-century depending on the tillage type. Reduce tillage 2 showed the lowest increase. Sediment yield from the soybean fields will be increased 6% to 9% in mid-century and 16% to 21% in late-century depending on the tillage type. Reduce tillage 2 has the highest responses to the climate variability on erosion control followed by reduce tillage 1 and conventional tillage.

Table 5.7   Effect of climate and tillage on water and sediment yield

<table>
<thead>
<tr>
<th>Type</th>
<th>Tillage</th>
<th>Corn</th>
<th>Soybean</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Baseline</td>
<td>Mid</td>
<td>Late</td>
</tr>
<tr>
<td>Sediment (Mg ha(^{-1}) year(^{-1}))</td>
<td>Conventional</td>
<td>12.6</td>
<td>13.4</td>
</tr>
<tr>
<td>Water yield (mm year(^{-1}))</td>
<td>Conventional</td>
<td>400</td>
<td>431</td>
</tr>
</tbody>
</table>
Effect of climate and tillage on erosion rates were varying between sub-watersheds. Future sediment yield will be reduced in some sub-watersheds, while some sub-watershed will increase (Figure 5.9). Maximum sediment yield increased in mid-century from the corn fields will be in sub-watershed 5 (42% conventional tillage, 49% reduce tillage 1 and 50% reduce tillage 2). During late-century, sub-watershed 12 showed the maximum sediment yield increased from corn fields (up to 58%). Sub-watersheds such as 21 and 22 showed sediment yield reduction up to 15% in all tillage systems of the corn fields. In soybean fields, maximum sediment yield increased in both mid and late-centuries will be from sub-watershed 10, and the sediment yield can be increased up to 45% to 69% depending on the tillage type. Similarly maximum sediment reduction from soybean fields will be observed in sub-watershed 19, and sediment yield will be reduced from 5.8% to 22% in mid and late-century depending on the tillage type. These results are comparable with previous studies. A study from Midwestern U.S. has reported 33-274% erosion increase in 2040-2059 compared to the 1990-1999 (O'Neal et al., 2005).

There is a climatic variability within the BSRW and corn & soybean growth and development will be different between sub-watersheds. Some sub-watersheds may experience temperature stress and will reduce the yield. It is reported that temperature stress to the crops may reduce the full canopy development and increase the erosion (O'Neal et al., 2005).
Figure 5.9  Sub-watershed level percentage sediment increases.

Different tillages for mid and late-century; (a) From corn fields; (b) From soybean fields

Sediment yield of Merigold, Sunflower, Leland, and watershed outlet were evaluated in three different tillage practices and mid and late-century climate for SRES A1B scenario (Figure 5.10). The gauge Merigold, which is the upstream, showed reducing sediment yield from reduces tillage compared to the conventional, and this is true for both mid and late-century climate. However, the downstream gauges didn’t show any notable differences of sediment yield among tillage systems. This is possible as BSRW is a flat watershed and eroded sediment may deposit on channels. This may reduce the channel capacity and increase future flooding. Mid century sediment yield will be reduced compare to the baseline and again increase in late-century. Watershed outlet will be received notable sediment reduction in future climate.
Conclusions

The SWAT model was applied to a crop dominant watershed in a humid subtropical U.S. climate. The model used climate, soil, and elevation as inputs to simulate flow, crop yield, and sediment from the BSRW (2000 – 2011). Simulated model outputs were evaluated against observed flow and crop yields (corn and soybean). Three tillage systems (Conventional, Reduce 1, and Reduce 2) were evaluated using crop and sediment yields from the BSRW. Flow and crop simulations showed good to very good model performances (for flow $R^2$ up to 0.78 and NSE up to 0.76; for corn yield $R^2$ up to 0.5 and NSE up to 0.9; and for soybean yield $R^2$ and NSE up to 0.6). Model simulation results agreed with previous similar studies. There were no significant differences between average corn and soybean yield among three different tillage systems in the BSRW.
(P>0.05). However, there was a significant difference between the sediment yields of the three tillage systems (from corn fields p=0.002, and soybean fields p=0.003).

The SWAT model with the help of LARS-WG stochastic weather generator successfully simulated the mid and late-century flows, sediment yield, and corn & soybean crop yields from the BSRW. The synthetic weather data for IPCC scenarios SRES (A1B, A2, and B1) were generated by the LARS-WG weather generator in accordance with the general circulation model, CCSM3. It was simulated that the future average maximum temperature increase can go up to 4.8°C in the BSRW, and future climates in BSRW will experience longer summer periods. Monthly precipitation patterns will remain un-changed in future climates but the BSRW will receive frequent severe rainfall events.

Compared to the baseline, average corn yields in the BSRW will increase in both the mid and late-century but the mid century incremental increase is predicted to be higher than the late century increase. Future soybean simulated yield predictions are lower than the current soybean yield. The combined effects of climate variability and tillage failed to indicate notable changes to the future crop yields. The future climates simulate significant effects on soil erosion in the BSRW. The reduce tillage 2 system has the highest responses to the climate variability input on erosion control followed by reduce tillage1 and conventional tillage systems. Sediment yield at the downstream locations failed to show notable differences in sediment transport between the three different tillage systems evaluated. Most of the eroded soils are deposited along the channels of the BSRW likely reducing the channel capacity and increasing the chance of future flooding in the watershed.
References


CHAPTER VI

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

Conclusions

Hydrological models can be used to study the impacts of climate variability on water quantity, quality, pollutant transport processes, and crop production in Mississippi watersheds. In this study, the UPRW was successfully evaluated for sediment, total nitrogen, total phosphorus, and fecal coliform bacteria transport in the current climate as well in mid and late-century future climates. Furthermore, the BSRW was also successfully evaluated for the impacts of tillage practices on crop and sediment yield considering current and future climate. In addition, the water table variations of the Mississippi alluvial aquifer were also evaluated.

The SWAT model was applied to a forest dominant watershed in a humid subtropical climate of the U.S. The model used climate, soil, and elevation as input data to simulate flow, sediment, nutrients, and fecal coliform bacteria (FCB) transport from the UPRW. Simulated model outputs were validated using observed flow, sediment, total nitrogen (TN), total phosphorus (TP), and FCB. Flow and sediment simulations showed good to very good model performances (for flow \( R^2 \) up to 0.76 and NSE up to 0.75; and for sediment \( R^2 \) up to 0.72 and NSE up to 0.54). Both TN and TP simulations showed fair to good model performances (\( R^2 \) up to 0.71 and NSE up to 0.63 for TN; \( R^2 \) up to 0.70 and
NSE up to 0.59 for TP). The FCB simulation showed good model performance ($R^2$ up to 0.59 and NSE up to 0.58).

The SWAT model was applied to the BSRW. Simulated model outputs were validated against observed flow and crop yield (corn and soybean). Three tillage systems (Conventional, Reduce 1, and Reduce 2) were evaluated on crop and sediment yield from the BSRW. Flow and crop simulations showed good to very good model performances (for flow $R^2$ up to 0.78 and NSE up to 0.76; for corn yield $R^2$ up to 0.5 and NSE up to 0.9; and for soybean yield $R^2$ and NSE up to 0.6). Moreover, results showed that there were no significant differences between average corn and soybean yields between three different tillage systems in the BSRW ($P>0.05$). However, there were significant differences between sediment yields of the three tillage systems (from corn fields $p=0.002$, and soybean fields $p=0.003$). Furthermore, a relationship was developed between the water table and simulated evapo-transpirations, and this relationship explained 64% of the water table fluctuations in the Mississippi alluvial aquifer.

The future climate of the UPRW and the BSRW was evaluated with the help of the LARS-WG stochastic weather generator. The synthetic weather data for IPCC scenarios (SRES A1B, A2, and B1) were generated by the LARS-WG in accordance with the general circulation model, CCSM3. Simulations predicted that future temperature in the UPRW will be 2°C warmer by mid-century and 3.4°C warmer by late century. The future average maximum temperature increase can be as high as 4.8°C in the BSRW. The future rainfall distributions will be highly variable across the UPRW while BSRW distributions will remain unchanged. Moreover, the future sediment yield will increase as
much as 25% in the UPRW. Both TN and TP yields will also be elevated as much as 7.3% and 14.3% respectively in future climates of the UPRW.

Four BMPs were applied individually and combined using current and future climate in the UPRW. Riparian buffer and stream fencing did not show large impact on reducing flow, sediment, and nutrients in either current or future climate. Nutrient management and vegetative filter strips were very effective on reducing flow, sediment, and nutrients. The combined effects of all BMPs were able to reduce 51% of flow, 55% of sediment, 44% of TN, and 88% of TP in baseline climate. The effectiveness of BMPs on reducing flow and sediment will be reduced in future climates. Moreover, the effectiveness of TN removal will be increased in future climates, while the effectiveness of TP removal will be unchanged.

**Recommendations**

**Nonpoint source pollution and best management practices**

Identifying the source and managing nonpoint pollution is problematic requiring special tools for proper evaluation. Sediment, total nitrogen (TN), and total phosphorus (TP) transport in the UPRW were evaluated in this study. The SWAT model, which has been used extensively for similar studies, was used as an evaluation tool (Kemanian et al., 2011; Yang et al., 2011; Panagopoulos et al., 2011). The water quality data from Feb 2010 to May 2011 were used, and the number of data points available for the calibration and subsequent validation was about 37. Ideally, a 2 to 3 year span of data points should be used in order to capture the inter-annual variation of the measured data. Optimally, more than three sampling locations should be utilized for a watershed the size of the UPRW (7,588 km²). It is recommended that future modeling studies should incorporate
additional diverse random sampling events. This dissertation explains the average situation of the entire watershed. Detailed studies of sub-watershed levels are recommended as a continuation of the results presented in this study.

The SWAT model has been applied in many geographical locations to evaluate the effectiveness of BMPs on NPS pollution control (Parajuli et al., 2013; Laurent and Ruelland, 2011). This dissertation evaluated only four BMPs but there are several others that should be evaluated using the SWAT in order to further the knowledge presented here. Additional studies may identify the most effective BMP(s) for the UPRW.

**Bacteria transport in watersheds**

The fecal coliform bacteria (FCB) are indicators of potential pathogenic organisms though their transport through other watersheds varies geographically. The SWAT model is one of the most effective tools available for evaluating FCB transport. This study evaluated FCB loadings from the UPRW with reasonable accuracy. The FCB data was available from Feb 2011 through June 2012 as a discrete dataset. Additional data should be utilized in order to increase the accuracy of this work. Incorporating more observational data and continued evaluation of the model through validation and sensitivity analysis may provide a greater understanding of the spatial and temporal variation of pathogen bacteria transport (Haydon and Deletic, 2009). The bacterial die-off factor in soil solution at 20°C (WDPQ) and growth factor for bacteria in soil solution at 20°C (WGPQ) were highly sensitive in bacterial transport. After several iterations, it was found that WDPQ = 0.125 and WGPQ = 0.12 yielded the highest model performances. These factors vary spatially and should be validated locationally using field experiments.
Crop management and soil erosion

Part of this research focused on the Mississippi Delta where corn and soybeans are grown extensively. The corn and soybean yields were simulated using the SWAT with reasonable accuracy. The SWAT uses the EPIC crop model for crop growth and simulations. However, several previous studies have reported poor yield predictions using the EPIC model (Debaeke et al., 1996; Mearns et al., 1999). Therefore, using other crop models such as DSSAT and AquaCrop and comparing these modeling results with those acquired using the SWAT in the Mississippi Delta is recommended for performance evaluation. This study showed significant differences between the sediment yields of the three tillage systems but measured data to validate the simulated sediment yield were not available for the Mississippi Delta region. Had measured sediment data been available, these study results could have been carried further into the validation process. Plot level studies are also suggested to validate the modeling results.

Climate variability

This dissertation evaluated effects of climate variability on stream flow, erosion, nutrient transport, fecal coliform transport, and crop yields of two differently managed watersheds. Most previous climate variability studies focused on the Western part of the U. S. (Miles et al., 2000; Stone et al., 2001; Rosenberg et al., 2003; Payne et al., 2003; Christensen et al., 2004), while fewer studies focused on the Southern portion of the U.S. This study offers an important addition to the existing literature. The SWAT model was chosen for its proven capability of modeling climate variability (Lirong and Jianyun, 2012; Rajesh et al., 2012), water quality (Pisinaras et al., 2010; Cho et al., 2012), and
crop growth and developments (Masih et al., 2011; Kim et al., 2013) in various geographical regions of the world

Future climate variability was simulated using the LARS-WG, a stochastic weather generator. The CCSM3, developed by the U.S. National Center for Atmospheric Research (NCAR) was used as the GCM to generate future weather data (Collins et al., 2004). The CCSM3 is a model with a 1.4° x 1.4° grid resolution. It is recommended that additional studies using a higher grid resolution be conducted.

This study used the LARS-WG version 4, though version 5 was recently released in 2013. The updated version 5.0 includes fourteen Global Climate Models (GCMs) which have been used in the latest IPCC 4th Assessment Report (2007). In order to gain a more comprehensive understanding of future climate variability on watersheds additional studies using the more flexible version 5.0 are recommended.
References


APPENDIX A

SUMMARY OF SSURGO SOIL DATA USED IN THIS STUDY
Table A.1  Soil properties of the study area, averaged over soil textural classes, based on SSURGO databases UPRW

<table>
<thead>
<tr>
<th>Soil texture</th>
<th>Total area (km²)</th>
<th>Depth of the top layer (mm)</th>
<th>Soil bulk density (g/cm³)</th>
<th>Saturated soil conductivity (mm/hr)</th>
<th>Clay %</th>
<th>Silt %</th>
<th>Sand %</th>
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<td>Clayey</td>
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<td>130</td>
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<td>33.0</td>
<td>12.8</td>
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<td>9.8</td>
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<td>32.0</td>
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<td>12.5</td>
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<td>30.9</td>
</tr>
</tbody>
</table>

Table A.2  Soil properties of the study area, averaged over soil textural classes, based on SSURGO databases BSRW

<table>
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<th>Soil texture</th>
<th>Total area (km²)</th>
<th>Depth of the top layer (mm)</th>
<th>Soil bulk density (g/cm³)</th>
<th>Saturated soil conductivity (mm/hr)</th>
<th>Clay %</th>
<th>Silt %</th>
<th>Sand %</th>
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</thead>
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<tr>
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<td>1.4</td>
<td>31</td>
<td>17</td>
<td>64</td>
<td>19</td>
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<td>Very-fine</td>
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<td>1.4</td>
<td>9</td>
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<td>42</td>
<td>11</td>
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</table>
APPENDIX B

LAND USE DATA USED IN THIS STUDY
Figure B.1  Land use data (2009) Upper Pearl River Watershed (UPRW)

Figure B.2  Land use data (2009) Big Sunflower River Watershed (BSRW)
APPENDIX C

DIGITAL ELEVATION MODEL (DEM) USED IN THIS STUDY
Figure C.1  Digital elevation model for the Upper Pearl River Watershed (UPRW)
Figure C.2  Digital elevation model for the Big Sunflower River Watershed (BSRW)