8-10-2018

Evaluation of Impacts of Conservation Practices on Surface Water and Groundwater at Watershed Scale

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By

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A Dissertation
Submitted to the Faculty of
Mississippi State University
in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy
in Biological Engineering
in the Department of Agricultural and Biological Engineering

Mississippi State, Mississippi

August 2018

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Pages in Study 121

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For an agricultural watershed, best management practice (BMP) is a conservational way to prevent non-point source pollution, soil and water loss and mitigate groundwater declination. In this dissertation, several BMPs of tail water recovery system, conservation tillage system and crop rotation were selected and evaluated in order to demonstrate the impacts of those activities on stream water quality and quantity. Besides, a land use change scenario was also evaluated. In order to evaluate the scenarios comprehensively, Soil and Water Assessment Tool (SWAT) and Annualized Agricultural Non-point Source Pollution (AnnAGNPS) were applied to simulate surface hydrology scenarios, and Modular flow (MODFLOW) models was

used to simulate groundwater level change. This dissertation contains several novel methods regarding to model simulation including (i) using satellite imagery data to detect possible tail water recovery ponds, (ii) simulating surface and groundwater connected, (iii) selecting land use change area based on local trend and spatial relationship, (iv) comparing scenarios between two models. The outcomes from this dissertation included scenarios comparison on surface water quantity and quality, groundwater level change for long term simulation, and comparison between surface water models.

ACKNOWLEDGEMENTS

I am grateful to all my committee members for their help on this dissertation. I am thankful to my major advisor, Dr. Prem Parajuli, for his patient and valuable guidance and advices on not only the individual studies, but the overall strategy of my four-years PhD study. I am thankful to Dr. Ouyang Ying and Dr. Padmanava Dash for their intelligence and valuable advices on the methods used in this dissertation. And I am thankful to Dr. Courtney Siegert and her lab team for great support on water quality data analysis. I am thankful to all my colleagues for their help on any questions I have encountered. Thank for my families and important one for their support and patient during my PhD study and during the process preparing this dissertation. As a member of this project, I would like to acknowledge the partial financial support of AFRI national competitive grant award (2013-67020-21407, and 2017-67020-26375) from the USDA/NIFA for this project. I would like to acknowledge the support of Yazoo Mississippi Delta Joint Water Management District; USGS; and all the data collaborators.

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CHAPTER I

INTRODUCTION

In the last several decades, agricultural best management practices (BMPs), referring to the conservation managements that are both environmentally friendly and agriculturally productive, were gradually adopted by more and more farms and have demonstrated their effectiveness in agricultural non-point source (NPS) pollution control (Dressing, 2003; Prokopy et al., 2008). Big Sunflower River Watershed, as the study area, is considered as an intensive crop production region with the majority of the land covered by soybean, corn, rice, and cotton crops. Crop production activities have the potential to impact water quality of the watershed because it affects soil nutrient structure (Vaché et al., 2002). BMPs have been applied in this area over the last several decades to improve watershed management and prevent the impacts of agricultural activities on the environment. In this dissertation, four studies were conducted to quantity the impacts of various BMPs on different parameters including surface water quantity, surface water quality and groundwater level change at watershed scale.

Chapter II describes combing pond detection and surface hydrologic model to demonstrate the impact of BMPs. Three BMPs including tail water recovery, conservation tillage and crop rotation were evaluated in order to assess the impacts on water quality and quantity. Satellite imagery data were used to detect potential tail water recovery ponds. The Soil and Water Assessment Tool (SWAT) was applied to evaluate

BMPs at watershed scale. The major objectives of this study were, first, demonstrate the impact of BMPs on surface water, and secondly, obtained the groundwater recharge calculated from the surface water model to serve as the input of study 2.

The objective of study 2 in Chapter III was to simulate the impacts of BMPs on groundwater level in a sub-area of the major study area. Agricultural water usage is the major consumptive use of groundwater in Mississippi. Ceasing pumping is a common way to mitigate groundwater declination. However, without considering crop water need, ceasing pumping may affect crop production. Two conservation plans were simulated and discussed in this study referring to changing the irrigation source and schedule, which were tail water recovery system and crop rotation. This study combined the different BMPs regarding irrigation applications with groundwater modeling to simulate the impacts of surface agricultural activities on groundwater level. Manually coupled MODFLOW and SWAT model with monthly surface and groundwater water interaction was used in this study. In the study area, groundwater modeling combining with process-based watershed modeling regarding to BMPs has not been established before this study.

Land use and cover change impacts on hydrology related analysis have come into academic attention since late 1960s. Recent studies focus on land urbanization and its impact on hydrology and surface water quality, as well as predicting land use change among urban, cropland and other land use categories. Crop land is the major land use in the study watershed and had an increasing trend based on the historical data analysis. Study 3 in Chapter IV was conducted in order to demonstrate the impact of local land use change trend on downstream hydrology and water quality. The methods used involve surface water modeling and land use change selection based on spatial relationship among land use and covers. This study provided a process to randomly select Hydrologic Response Units (HRUs) applied in land use change scenario, which is suifor an agricultural domain watershed to project a land use change scenario.

The surface water model tool used in study 1 through 3 was the SWAT model, which is a convenient and comprehensive agricultural watershed modeling tool. However, SWAT is not the only comprehensive agricultural watershed modeling tool. Annunlized-Agricultural Non-Point Source Pollution Model (AnnANGPS) is a relatively user friendly watershed modeling tool, which emphasis on agricultural homogeneous area, developed by Natural Resources Conservation Service (NRCS) of United States Department of Agriculture (USDA). Study 4 in Chapter V was conducted in order to compare the performances of two models (SWAT and AnnAGNPS) and demonstrate the differences and consistency of the results from different modeling tools of same scenarios. In this study, two BMPs including conservation tillage operation and crop rotation, and a land use change scenario were evaluated by using SWAT and AnnAGNPS. The calibrated model in study 3 was applied as the baseline model of SWAT. The land use scenario simulated in study 3 was compared with AnnAGNPS since the potential ability of AnnAGNPS to simulate land use change scenario.

CHAPTER II

EVALUATION OF THE IMPACTS OF BMPs AND TAIL WATER RECOVERY SYSTEM ON SURFACE AND GROUNDWATER USING SATELLITE IMAGERY DATA AND SWAT RESERVOIR FUNCTION

2.1 Introduction

Watershed management contributes to the essential agro-ecosystem services. The studies focusing on water management in an agricultural watershed became popular in 1950s, which were mainly related to flood control (Brakensiek, 1959; Brown and Winsett, 1960). Later in 1970s, the studies were broadened to nonpoint source pollution and erosion control focusing on management practices (Summer, 1970; Seay, 1970). According to Environmental Protection Agency (EPA), the agricultural nonpoint source (NPS) pollution is one of the major sources that impacts water quality of the rivers and streams in U.S. The concept of best management practices (BMP) early used in Yoon (1970) were applied more and more in 1990s referring to the conservation managements that are both environmentally friendly and agriculturally productive. The Big Sunflower River Watershed, as the study area, is considered as an intensive crop production region with about 76% of the area covered by soybean, corn, rice, and cotton crops (USDA/NASS, 2009). Crop production activities have the potential impacts on surface water quality of the watershed, because it affects soil nutrient structure (Vaché et al., 2002). BMPs have been applied in this area over the last several decades to improve watershed management and prevent the impacts of agricultural activities on environment.

Tail water recovery system is constructed as an irrigation water storage system helping reduce groundwater use. It contains an irrigation reservoir and corresponding pumping system. According to USDA-NRCS (2011) conservation practice standard 447, it helps to collect irrigation runoff flows and improves offsite water quality. The way it affects hydrologic processes at watershed level is mainly through adjusting surface water runoff and water use structure. Mississippi River Valley is the main source of the water use (Kenny et al., 2009; Clark et al., 2011; Maupin et al., 2010) in Mississippi. And irrigation is the major water use in Big Sunflower River Watershed (BSRW) (Clark et al., 2011), which makes the groundwater resource directly relate to economy of the state of Mississippi. Since 2011, tail water recovery system started to be constructed as a BMP in Mississippi in order to reduce groundwater usage and mitigate groundwater depletion. Ceasing pumping could improve groundwater level depletion situation in this area according to Clark et al. (2011). Evaluating the performance of the tail water recovery system on recovering groundwater level is necessary at this point although other BMPs continued to be applied in this area. Nakasone and Kuroda (1999) discussed the relationship between in-pond water quality and land use and cover of upland field. They indicated that there was high correlation between in-pond water quality, such as sediment, total nitrogen (TN) and total phosphorus (TP), and upland agricultural land use. The study showed the down-stream water quality from reservoir depended on the capacity of the pond and in-pond water quality. Thus, it is necessary to evaluate the impact of tail water recovery system on water quality in BSRW. And this is the first study evaluating the tail water recovery system at watershed scale. In order to conduct a scenario representing tail water recovery pond in watershed model, satellite imagery was used to detect potential tail water pond.

Tillage management is usually used as a preparation of seedbed before planting in order to provide a good environment for seeds. There were two types of tillage management considered in this study, conventional tillage and conservational tillage management. Conventional tillage is a traditional tillage management used by farmers in study area, which leaves only few residues cover after operation. Although conventional tillage is usually considered as a method for maximum crop yield (Triplett et al., 1968, Kapusta, 1979), it has some drawbacks regarding to energy consuming and as the potential cause of soil erosion (Montgomery, 2007). Comparing to conventional tillage, conservational tillage system, for example strip tillage operation, reduces tillage operation by tillage depth, frequency, and amount of removal residual. This could reduce energy input and prevent erosion. For these reasons, conservational tillage management is usually considered as a soil protection method and suggested to be applied to field to improve off-site water quality (EPA, 2017). Since tillage management is a common management in a crop field, and according to previous studies, tillage management may affect surface water runoff (Shipitalo and Edward, 1998) and water quality including TN, TP and sediment (Tan et al., 2002; Vaché et al., 2002), it is necessary to evaluate the impact of different kinds of tillage managements in study area.

Crop rotation is a common agricultural practice that growing different crops in a same area in different seasons or years. The main purpose of crop rotation is adjusting the nutrients ratio of soil. Many of the studies focused on how crop rotation affects soil quality and productive capacity (Karlen et al., 2006). The experiments showed that soil quality, including extracphosphorus, varies among different crop rotation scenarios (Karlen et al., 2006). Besides, experiments conducted by Klocke et al. (1999) and Power et al. (2000) showed the different crop rotation plans affect the amount of nitrogen leaching through soil profile to subsurface. The nutrients on the surface or in shallow profile of the soil could be moved with water by erosion and enter into surface water body (Novotny, 1999). The way crop rotation affecting surface water is mainly on surface water quality (Vaché et al., 2002) caused by the different fertilizing demand of rotated crops. Corn and soybean rotation is one of the most commonly used rotation plan in study area. It was one of the main scenarios in studies mentioned above when investigating the relationship between nutrient loss in drainage water and crop rotation. Four crop rotation scenarios were evaluated in this study including baseline, continuous corn, continuous soybean and corn/soybean rotation for investigating the impacts of crop rotation on surface water body. Since both of tillage operation and crop rotation practice are agricultural activities during crop growing season, the two managements were usually crossed evaluated to conducting different scenarios (Power et al., 2000; Parajuli et al., 2013).

Evaluating the impacts of agricultural management on the water quality and quantity at watershed scale requires the modeling tools considering both watershed hydrological factors and agricultural activity factors. The Soil and Water Assessment Tool (SWAT) was selected to evaluate BMPs scenarios in this study. It is a process-based watershed-modeling tool, which considers physical characteristics of the watershed including surface elevation, soil type, land use, and factors affecting water routing within the watershed (Neitsch et al., 2011). It contains modules simulating agricultural activities such as irrigation, fertilizing, and tillage. SWAT was widely used by previous studies focusing on agricultural watershed management and BMPs simulation. Arabi et al. (2008) systematically discussed the representation of conservational managements using SWAT including crop rotation. Lee et al. (2010) described and simulated four BMP scenarios including controlling the amount of crop fertilization, conversion of bare soil to grassland, application of riparian buffer system, and installation of vegetative filter strip. The study used stream discharge, sediment, TN and TP as indicators to evaluate the impacts of BMPs on stream water quality. Specific to tail water recovery system simulation, the reservoir function in SWAT was used to simulate potential tail water recovery ponds grouped by sub-basins, which is the main novelty of this study.

The main objectives of this study were to (i) detecting potential tail water recovery ponds satellite imagery data; (ii) evaluating impacts of BMPs including conservational tillage and tail water recovery systems; and (iii) evaluating the impacts of crop rotation change on surface water hydrology and water quality.

2.2 Material and method

2.2.1 SWAT model

SWAT model was developed as a physically based continuous time watershed scale model (Arnold et al., 1993). The BSRW was divided into 22 sub-basins in this study based on surface elevation. The sub-basins were further divided into Hydrologic Response Units (HRUs) based on soil type, land use type, and slope length. The soil type with area less than 5% of the sub-basin area would not be simulated in this study. Similar for land use type and slope length, the thresholds were 3%, and 5% of sub-basin area respectively. Input data include Digital Elevation Model (DEM) (USGS, 1999), soil type from SSURGO database (USDA, 2005), land use and cover data from the USGS Land Cover Institute (LCI) (USDA/NASS, 2009) and climate information including precipitation, temperature, solar radiation, wind speed and relative humidity from Climate Forecast System Reanalysis (CFSR) database (NCDC, 2015). Crop management schedules including the date and amount of irrigation and fertilizing were summarized from MS Agricultural and Forest Experiment Station (MAFES) annual report (MAFES, 2000-2014). The source of irrigation was the groundwater deep aquifer of each sub-basin. The total irrigation depth from tail water recovery pond was set as 3.5 inch in the tail water recovery system scenario. Other cropland was set as auto irrigation based on the default crop needs in SWAT model. The tillage management setting was according to Parajuli et al. (2013).

For SWAT hydrologic model calibration and validation, simulated monthly stream flow were compared with monthly stream flow data from three USGS gaging stations located in the BSRW. The auto-calibration program, SWAT-Cup SUFI2, was used to find the proper parameters' values that resulted in the high coefficient of determination (R^2) and Nash–Sutcliffe model efficiency coefficient (NSE) from comparing simulated monthly stream flow rate and USGS gaging station data. Manual calibration based on the Soil Conservation Service (SCS) curve number method (NRCS, 1986) was applied after auto-calibration. 2.1 shows the calibrated parameters and the fitted values for hydrologic model. There are three USGS gaging stations in BSRW including Merigold, Sunflower and Leland, shown in Figure 2.1. Previous studies (Jayakody et al., 2014; Parajuli et al., 2016) applied these three gaging stations to calibration of BSRW simulation. In order to take advantage of long-term stream flow data, USGS gaging station of Big Sunflower River near Merigold and its' corresponding sub-basins, which are shown in Figure 2.1, were calibrated from 1998 to 2015. The calibrated parameters were later applied to the model with the boundary of sub-basins corresponded with USGS gaging station of Bogue Phalia near Leland for validation, shown in Figure 2.1. And a scale-up to the model with the boundary of entire BSRW with all three USGS gaging stations was applied as re-validation from 1998 to 2015 in order to obtain the response from BSRW during scenario analysis.

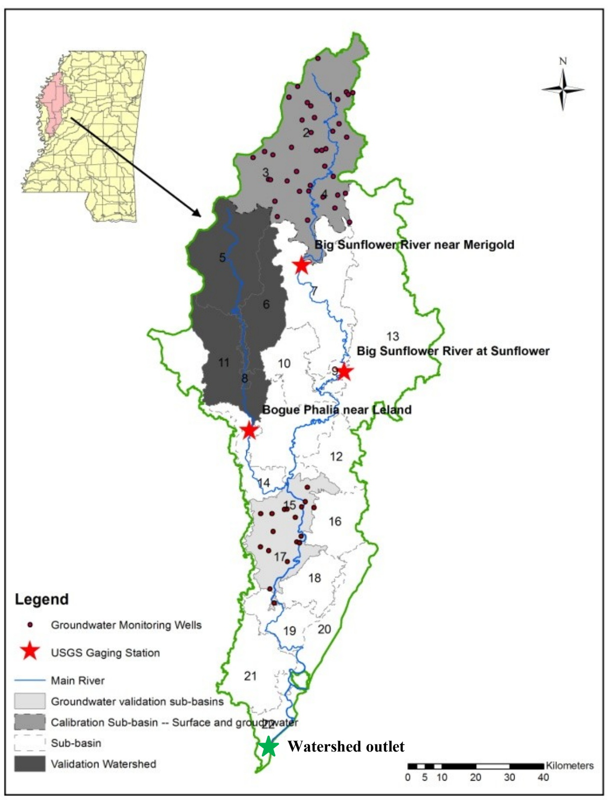

Figure 2.1 USGS gaging stations and corresponding calibration and validation sub-basins for surface water and groundwater

Table 2.1 Monthly stream flow calibration parameters

	Parameter Name		Fitted Value
1	ESCO	Soil evaporation compensation coefficient	0.660
2	ALPHA_BF	Base flow recession constant	0.690
3	GW_DELAY	Delay of time for aquifer recharge	40.700
4	CH_N2	Manning's coefficient for the main channel	0.157
5	SOL_AWC	Available water capacity	0.108
6	RCHRG_DP	Aquifer percolation coefficient	0.090
7	GW_REVAP	Groundwater revap coefficient	0.146
8	GWQMN	Threshold water level in shallow aquifer for base flow	501.000
9	EPCO	Plant uptake compensation factor	0.660
10	SURLAG	Surface runoff lag coefficient	3.800
11	REVAPMN	Threshold water level in shallow aquifer for revap	40.900
12	CN2	SCS curve number	68--93, vary by land use and soil type

The calibrated hydrologic parameters were later applied to the daily water quality model with the boundary of BSRW from 2013 to 2015. The calibration water quality parameters are shown in 2.2. The calibrated factors included total suspended sediment, TN and TP. According to Santhi et al. (2001), White and Chaubey (2005), and Shen et al. (2008), some of the parameters are only affect single calibrated factor, while some parameters affect all three factors. Therefore, the auto-calibration process using SWAT-CUP program was repeated for each calibrated factor with unique calibration parameters. Daily data at three USGS gaging stations with around two weeks interval of sediment, TN and TP were used for calibration.

Table 2.2 Water-quality-related calibrated parameters

Affected Factor	Parameter	File	Description	Fitted Value
Sediment Only	PRF	.bsn	Peak rate adjustment factor for sediment routing in the main channel	2

Table 2.2 Water-quality-related calibrated parameters (continued)

	SPEXP	.bsn	Exponent parameter for calculating sediment reentrained in channel sediment routing	1.5
	SPCON	.bsn	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing.	0.01
	CH_ERODMO	.rte	Channel erosion ability	0.07 to 0.86, vary by month
	CH_COV	.rte	The channel erodibility factor	-0.03
TP only	PSP	.bsn	Phosphorus availability index	0.29
	ERORGP	.hru	Phosphorus enrichment ratio for loading with sediment	4.5
	BC4	.swq	Rate constant for mineralization of organic P to dissolved P in the reach at 20°C (day-1)	0.523
	PPERCO	.bsn	Phosphorus percolation coefficient	12.8
	RS5	.swq	Organic phosphorus settling rate in the reach at 20o C (day-1)	0.047
TN only	ERORGN	.hru	Organic N enrichment ratio for loading with sediment	2.97
	NPERCO	.bsn	Nitrate percolation coefficient	0.0285
All Parameters	ADJ_PKR	.bsn	Peak rate adjustment factor	2
	USLE_K	.sol	KUSLE: USLE soil erodibility factor (0.013 metric ton m^2 hr/(m^3-metric ton cm))	0.2
	USLE_C	crop.dat	CUSLE,mn: Minimum value for the cover and management factor for the land cover	0.001 to 0.2, vary by crops
	USLE_P	.mgt	PUSLE: USLE support practice factor	1

In order to evaluate the impact of tail water recovery system on groundwater level changes, it is necessary to validate the groundwater storage change during irrigation season. Since the SWAT model does not simulate the changes on groundwater depth, the simulated groundwater storage changes for shallow aquifer was used to compare with groundwater level changes from monitoring wells, which was a similar method adopted by Dakhlalla et al. (2016). Their study used the relationship between groundwater storage change and actual groundwater level change to validate the groundwater simulation in SWAT model. They indicated that the groundwater level change equals the ratio of change in groundwater storage and specific yield. In this way, the groundwater level change can be validated in SWAT model. The groundwater specific yield for the unconfined aquifer in SWAT is not active, which means the model itself does not use the parameter in calculation. The Solver tool in Microsoft Excel was used to adjust specific yield based on the performance of validation evaluated by R^2 and NSE. The validation of groundwater storage change during the irrigation season was applied in two sub-basins, shown in Figure 2.1. Dakhlalla et al. (2016) validated the SWAT model by applying the sub-basin wide average in two chosen sub-basins with little spatial variation of groundwater level. The reason was the simulated groundwater storage in SWAT is HRU-based without spatial information. In this study, the groundwater level from 57 monitoring wells provided by Yazoo Mississippi Delta Joint Water Management District (YMD), measured before and after irrigation season twice a year on April and October, were used to validate the model-simulated groundwater storage change through 1998 to 2012. The simulated groundwater storage difference between April and October were compared with monitored groundwater level change that was obtained by water level of April subtracting water level of October every year. Two areas of the sub-basins 1 through 4 and sub-basins 15 and 17 (Figure 2.1) in the watershed were selected to validate the model due to the little spatial variation of the groundwater level change according to YMD monitoring well data.

2.2.2 Detection of potential tail water pond

As a relative new BMP constructed in BSRW, the watershed wide tail water recovery pond data was not comprehensive. In this case, conducting a scenario that could represent the location and dimension of tail water recovery pond in watershed scale was one of the objectives in this study. The processes contain two parts. First, a method, that combines water body detection and spatial characters of tail water recovery pond, was used to detect water bodies simulated as potential tail water recovery pond in BSRW. A simplified digital density slicing method based on near-infrared (NIR) band (Campbell and Wynne, 2011) was used to detect the water body within BSRW using ERDAS Imagine. Based on the relationship among adjacent features, ArcGIS was used to distinguish crop, mixed forest and all the other land use such as urban area. In order to distinguish cropland and wetland forest, National Agriculture Imagery Program (NAIP) near-infrared image from USDA with 1 m resolution (USDA/FSA, 2015) during crop growing season of 2015 were used in this study.

According to the basic spectral response of water, vegetation and other features on NIR region, water absorbs more NIR energy than vegetation. Since the images were obtained during the crop-growing season, the vegetation would have the most reflection on NIR among water, other feature, and vegetation. The NAIP data of BSRW was divided into 278 blocks with dimension of around 8 km by 8 km grid. Each block was the unit of the density slicing process. Due to the variation of data quality and acquired date of each block, the gray level divisions of different classes varied by blocks. Figure 2.2 shows the histogram of NIR image of one block. From NIR index 0 to 90, the pixels were assigned to water body due to the low reflection of NIR energy for these pixels. From 90 to 120, the pixels were assigned to all other land use. From 120 to 255, the pixels were assigned to vegetation due to the high reflection on NIR. Figure 2.3 shows (a) the NIR image, (b) the reclassified image after level slicing, (c) the polygon feature of cropland pixels, and (d) detected potential tail water pond of the example block in BSRW.

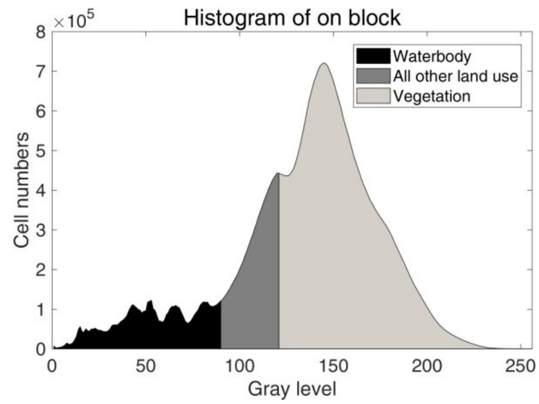

Figure 2.2 Histogram and level slicing of one example block in BSRW

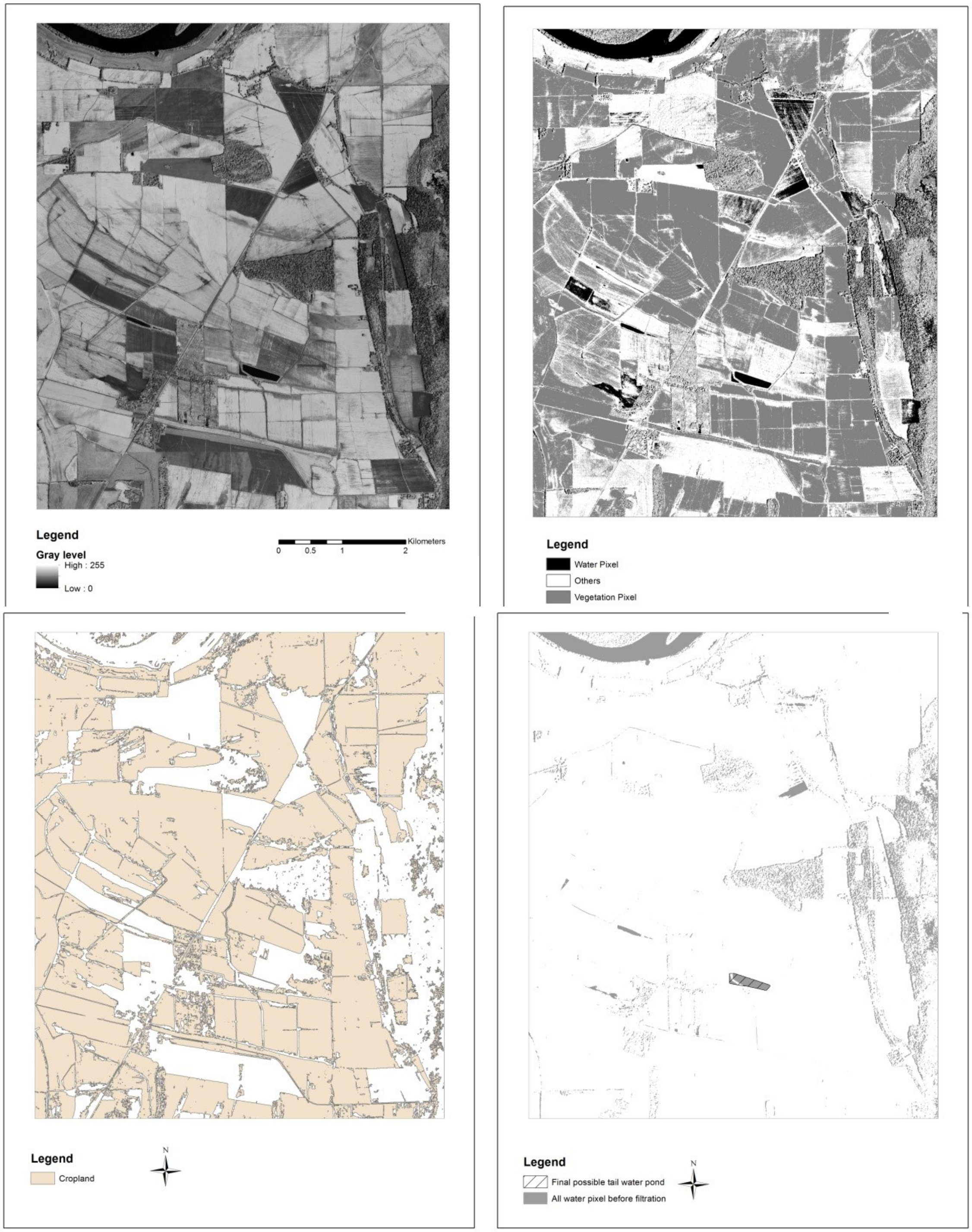

Figure 2.3 Image process for an example block in watershed

Note: (a) original near-infrared image from NAIP, (b) reclassified image after level slicing with three classes of water, vegetation and others, (c) cropland feature after aggregation and distinguished from other vegetation, and (d) all detected water pixels and final potential tail water pond after filtration and manual calibration

Figure 2.3 (a) shows the original NAIP satellite imagery data. Figure 2.3 (b) shows the three classes of pixels including water body, vegetation and all other land uses after density slicing. The main task was to distinguish cropland and other vegetation land cover within the vegetation pixels after density slicing. For example, wetland forest is one of the major land uses in addition to cropland in BSRW. The main difference between the level sliced images of cropland and wetland forest is that the raster values of cropland were relatively uniform across the farm, while the pixels were distributed unevenly in the wetland forest that may be the mixture of vegetation pixels and water body pixels. Therefore, aggregation tool in ArcGIS was used to delete the vegetation pixels in all other land cover class, so that the area with uniform vegetation pixels could be considered as cropland, which is shown in Figure 2.3 (c). Cropland layer would be used later for filtration of potential tail water pond.

The detected water bodies included rivers, natural and artificial ponds such as tail water ponds and catfish ponds, and small water bodies in wetland forest, shown in Figure 2.3 (d). After aggregation of water body pixels, filtering potential tail water recovery ponds from all the water bodies was another challenge in this study. The filtration includes three steps that were area filtration, regular shape filtration and adjacent objects filtration. The tail water recovery ponds in study area were mainly used by farmers for one farm or cropland irrigation. In this study, the medium-size from 1 acre to 40 acres was considered as the size of potential tail water recovery ponds. This step was useful for filtering out rivers, fishponds, and water pixels in the wetland those usually with larger size. Due to the procedure of aggregation water pixels, some of the water pixels within the wetland forest were falsely considered as water bodies. However, this kind of water body usually had irregular shape that differed from tail water ponds. In this study, the index as the ratio of perimeter and area of the detected water body shown in equation 2.1 helped determine the regular shape. And the process of the index is shown in equation 2.2 through 2.4.

(2.1)

Where P is the perimeter of the water body, A is the area of the water body

Assuming the tail water recovery pond has rectangular shape, than

(2.2)

(2.3)

(2.4)

Where a is the length and b is the width of the rectangle

The index less than 7 indicating small ratio of the length and width, which was summarized from some existing tail water ponds in study area, was applied to define regular shape with smooth edge of the water body.

The third step of filtration was utilizing the function of tail water ponds. Tail water pond is used to capture tail water and irrigate in irrigation season in order to decrease groundwater use. Therefore, the potential tail water ponds need to be located adjacent to the cropland, which are shown in Figure 2.3 (c).

After the three filtrations, 134 regular shape ponds were determined adjacent to the cropland. Figure 2.3 (d) shows the final ponds in this block. Manual validation of the

134 ponds comparing with Google satellite map was applied to confirm the pond locations.

2.2.3 Scenarios setting

2.2.3.1 Tail water pond scenario

The water body in baseline scenario was simulated as full pond, which indicated the water body level is maximum and constant during the simulation. The original land use and cover data were updated with tail water ponds' locations and corresponding irrigated cropland. The NRCS design guidelines of tail water recovery and on-farm storage (NRCS/USDA, 2011) defined the storage requirement of the tail water recovery pond as that the stored water in pond need to fulfill at least 3.5 inch depth irrigation for irrigated land. Based on this requirement and the area of each detected tail water pond from satellite data, the area of irrigated cropland could be estimated. The type of the irrigated cropland also affects the water use management in the watershed, which could be determined by adjacent cropland of the tail water pond.

In order to model tail water pond in SWAT model at watershed scale, a reservoir of aggregation of tail water recovery ponds in each sub-basin was applied at sub-basin wide. The reservoir was located at the outlet of each sub-basin. The area of the reservoir was the sum of all the tail water ponds in the sub-basin. Nielsen et al. (2013) used the SWAT model to simulate a drinking water reservoir in order to assess the eutrophication including TN and TP. Nielsen et al. (2013) studied the in-pond nutrient dynamics, while this study paid more attention to off-site water quality over the watershed. The study (Nielsen et al., 2013) showed the sensitive analysis of nutrient dynamics related parameters including NPERCO and PPERCO using in-pond field data. Since evaluating the impact of tail water recovery pond on watershed scale was the concern of this study, and the stream water quality was used for calibration and validation in the model, the statements of impacts on in-pond water quality was helpful to this study. Tiessen et al. (2011) indicated the reservoir would averagely decrease TP, TN and TSS by 10%, 18% and 70%, respectively, of the inlet of reservoir. The universal settling rate through all reservoirs were adjusted to the values that could result in averagely 10%, 18% and 70% reduction of sediment, TN and TP of inlet of every reservoirs. The final phosphorus settling rate and nitrogen settling rate were set as 0.05 and 0.2 meter/year respectively. The area of each reservoir was determined by the sum of area of detected potential tail water recovery ponds which were ranged from 2.5 to 89 ha.

2.2.3.2 Crop rotation and tillage management setting

In addition to the tail water recovery ponds, different tillage operations and crop rotation management practices were evaluated in this study. Kirsch et al. (2002) described the different tillage operation scenarios setting using SWAT model. They considered the SCS curve number as the main parameter to represent different tillage scenarios. According to Arabi et al. (2008) and Feyereisen et al. (2008), the curve number of the conventionally tilled land is 6 units lower than conservational tilled land.

Tillage management and crop rotation scenarios were cross evaluated as 8 scenarios shown in 2.3. The original continuous land use representing the original land use data (USDA/NASS, 2009) was applied in the baseline scenario. All the cropland including soybean, cotton and others were converted to corn in continuous corn scenario, and similarly in continuous soybean and corn/soybean rotation scenarios. Original continuous land use with conventional tillage management as scenario A; original continuous land use with conservation tillage management as scenario B; continuous corn with conventional tillage management as scenario C; continuous corn and conservation tillage management as scenario D; continuous soybean with conventional tillage management as scenario E; continuous soybean with conservation tillage management as scenario F; corn-soybean rotation with conventional tillage management as scenario G; corn-soybean rotation with conservation tillage management as scenario H. The crop rotation management practices were set as Parajuli et al. (2013).

Table 2.3 Crop rotation and tillage management cross evaluated scenario setting

Treatment	Original Land Use	Continuous Corn	Continuous Soybean	Corn-Soybean Rotation
Conventional Tillage Management	A	C	E	G
Conservation Tillage Management	B	D	F	H

2.3 Results and discussion

2.3.1 Calibration and validation results

2.3.1.1 Watershed model calibration and validation

2.1 and 2.2 show the final fitted values of parameters for auto-calibration of the hydrologic model. The coefficient of determination (R^2), Nash–Sutcliffe model efficiency coefficient (NSE) and percent bias (PBIAS) were used to evaluate the model performance. 2.4 shows the model evaluation of monthly hydrologic model. The hydrological model shows good statistic with R^2 up to 0.61 and NSE up to 0.56. The consistency of statistical performance among models with different boundaries indicated the fitted parameters calibrated in a small area could be used in the whole BSRW. Figure 2.4 shows the stream flow calibration from 1998 to 2015. The model showed accepperformance (Moriasi et al., 2015) on the simulation of stream flow variation trend during modeling time period. 2.5 shows the performance of daily water quality model for three evaluation factors of suspended sediment, TN and TP. Although the statistic was not as good as hydrologic model, the calibration could simulate the trend of stream water quality. One of the reasons of the lower NSE is that the daily based model requires higher quality of water quality data. Considering the temporary scale and number of data points, the performance were accepbased on the reported statistic from literatures (Tuppad et al., 2011; Moriasi et al., 2015).Those literatures indicated the NSE of TN could be as low as 0.2 for satisfactory model performance. Moriasi et al. (2015) indicated the model could be considered as satisfactory performance with the PBIAS for daily sediment simulation of less than 55%, and for TN and TP simulation of less than 70%. The Leland station shows unsatisfactory performance of sediment and TN according to Moriasi et al. (2015). The reason might be land use structure difference among the calibration region, validation region and BSRW. The land use structure in calibration sub-basins was more similar to the BSRW than in the corresponding validation sub-basins with Leland gage (USDA/NASS, 2009). The scenario analysis in this study was mainly conducted in BSRW instead of sub-basin wide.

Table 2.4 Hydrological model calibration and validation statistics

Models	R^2	NSE
Calibration Sub-basin-Merigold	0.57	0.55
Validation Sub-basin-Leland	0.59	0.46
Re-validation-BSRW-Merigold	0.61	0.51
Re-validation-BSRW-Leland	0.61	0.58
Re-validation-BSRW-Sunflower	0.61	0.56

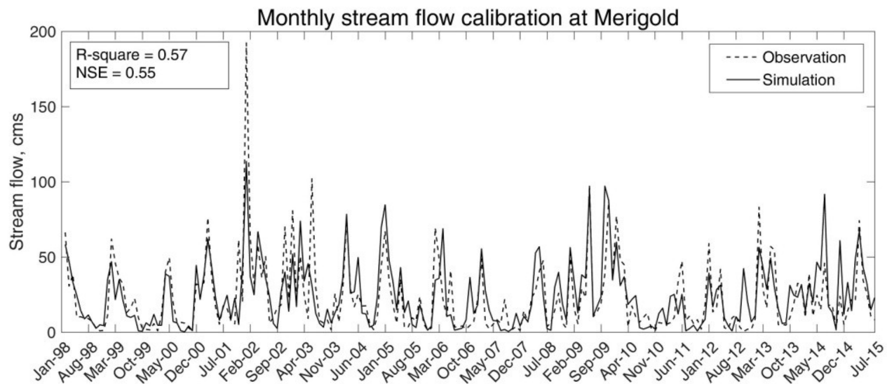

Figure 2.4 Calibration stream flow at the Merigold station through 1998 to 2015

Table 2.5 Water quality statistics for sediment, total nitrogen and total phosphorus calibration at three USGS gaging stations using daily model with boundary of BSRW from 2013 to 2015

	TSS			TN			TP		
	R^2	NSE	PBIAS	R^2	NSE	PBIAS	R^2	NSE	PBIAS
Merigold	0.45	0.29	30.0%	0.58	0.24	54.4%	0.72	0.57	26.3%
Sunflower	0.67	0.37	31.9%	0.54	0.26	54.5%	0.55	0.51	18.4%
Leland	0.54	0.15	37.2%	0.08	-0.11	56.1%	0.81	0.62	32.2%

2.3.1.2 Validation of groundwater level change during irrigation season

Figure 2.5 (a) and (b) shows the validation results for different areas of groundwater level change during the irrigation season. The R^2 are 0.68 and 0.52 with NSE of 0.44 and 0.43 for two regions shown in Figure 2.1 respectively. The optimal specific yield value was estimated as 0.17 using solver tool in Microsoft Excel. Brown (1947) indicated that this aquifer is mixed sand and gravel with specific yield of 0.10-0.45 (Gupta, 2008). The Figure 2.5 shows the 95% confidence interval indicating the performance of simulating groundwater level change during the irrigation season.

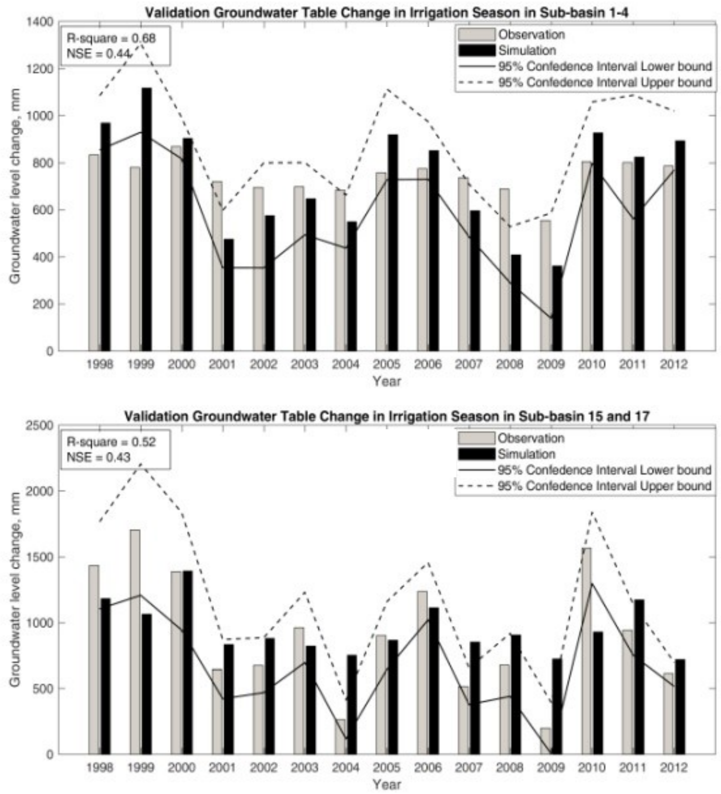

Figure 2.5 Observed vs. simulated ground water level changes in irrigation season with 95% confidence levels for the area of sub-basins 1 to 4 and the area of sub-basin 15 and 17 from 1998 to 2012

Note: (a) sub-basin 1 to 4 (b) sub-basin 15 and 17

2.3.2 Tillage management and crop rotation

Figure 2.6 shows the nutrient and sediment loss to the stream resulted from scenarios A and B at the out let of BSRW. For the stream flow comparison of scenario A and B (Figure 2.6(a)), the monthly runoff was changed from -5% to 53% in conservational tillage scenario compared with conventional tillage scenario from 2013 to 2015. In order to evaluate the long term difference between conventional and conservational tillage scenarios, cumulative TN, TP and sediment are shown in Figure 2.6(c), (d) and (b), respectively. For the three indicators, the results indicated that more loss to stream with 30%, 18% and 20% for TN, sediment and TP respectively in scenario A compared with scenario B. Kirsch et al. (2002) indicated that there would be 14% loss of phosphorus for the tillage improvement with nutrient control scenarios. The higher reduction in this study may be caused by the difference from nutrient sources of their studied areas. The only simulated nutrient source loss to stream in BSRW was the non-point source, while there was 40% of nutrient loss to stream from point source in Kirsch et al. (2002). For the comparison of different tillage scenarios with continuous corn crop management (scenario C and D), the results showed 38%, 11%, and 17% more TN, sediment and TP respectively in conventional tillage scenario. These numbers were 32%, 8% and 17% in the comparison between scenario E and F, and 35%, 11%, and 19% in the comparison between scenario G and H.

Figure 2.7 shows the comparison of scenario A, C, E and G. Corn-Soybean rotation scenario had 11% higher TP and 40% lower TN cumulative yield than continuous corn scenario. The low TN loss to stream from continuous soybean scenario was resulted from less applied nitrogen fertilization for soybean planting (MAFES, 2000-2014). The sediment loss to stream resulted from scenario A, C, E and G was not visually different as TN and TP. The reason of that there was more phosphorus loss to stream in corn-soybean rotation scenario was that there were more simulated crop yield of corn than soybean. The test of P removed in grain conducted by Eghball et al. (2003) suggested that corn would be the more effective crop in terms of reducing soil P than soybean due to the differences in magnitude of crop yield of corn and soybean (Parajuli et al., 2013). This indicated that the P in corn residue might be larger than in soybean residue. The tillage operation was applied before crop planting instead of after harvesting.

The P in residue was back to the soil via degradation. Thus, TP in continuous corn were large than continuous soybean.

Continuous soybean (SS) had 31% less phosphorus loss than continuous corn (CC) and 38% less than corn-soybean rotation (CS). Figure 2.8 shows the temporal difference between three crop rotation scenarios. There was more phosphorus loss to stream in scenario CS than CC during soybean year. However comparing to SS, the phosphorus loss was more during soybean year in CS. This indicated that corn production was affecting phosphorus yield in CS scenario during soybean year. The reason may be that there was larger amount of corn residuals than soybean residuals left on the field during simulation. One of the phosphorus sources considered in SWAT model was crop residual. Even though there was no phosphorus fertilizer in corn year, the phosphorus left from corn residual led to larger amount of available phosphorus in soil. This part of phosphorus would not be affected by tillage management and would enter to stream through runoff eventually. Thus, for corn and soybean rotation scenario, because the residues were considered not removed from field right after harvest, the large amount of corn residue would lead more phosphorus loss to the soil. The second year crop, soybean, had less phosphorus removal ability due to its smaller yield. The cumulative phosphorus was simulated to be larger in corn/soybean rotation scenario.

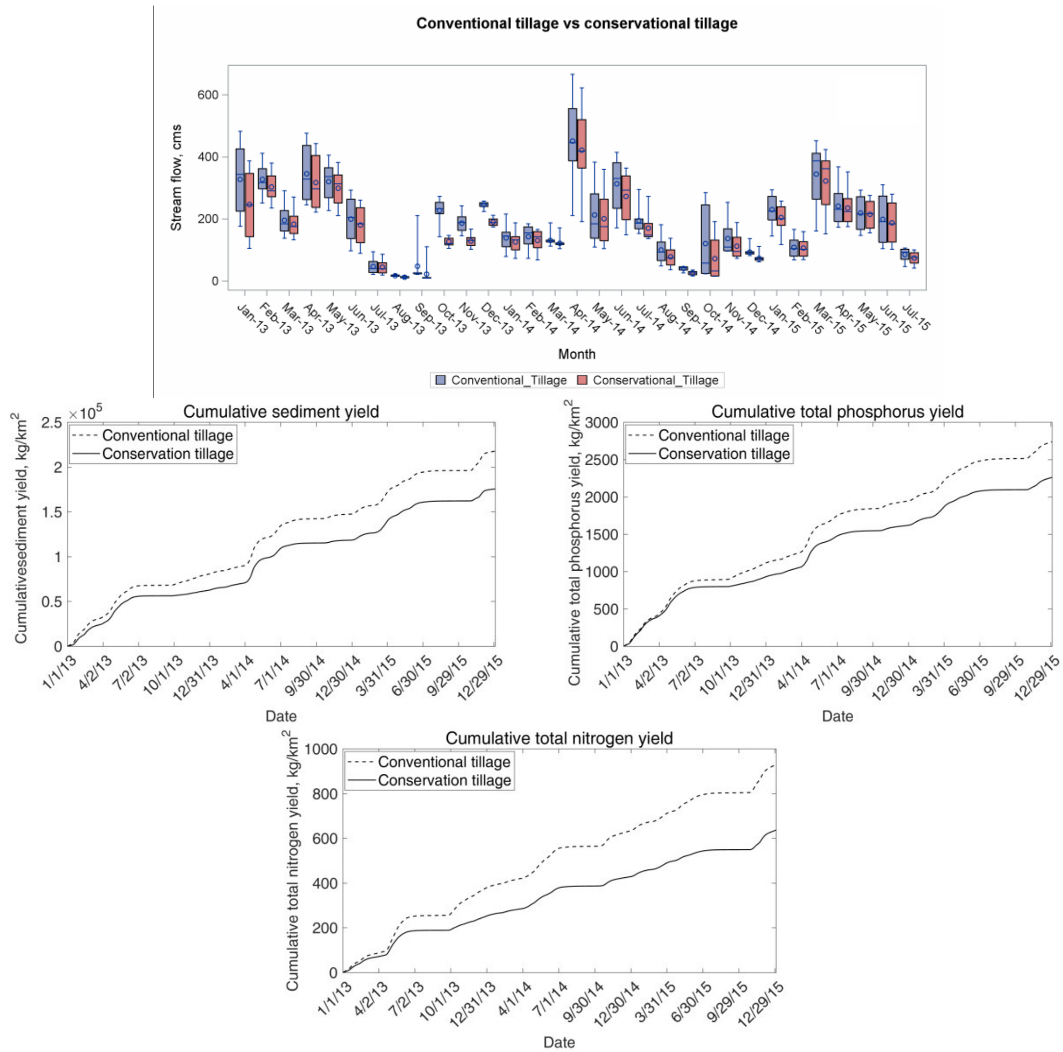

Figure 2.6 Watershed outlet cumulative daily yields from 2013 to 2015

Note: (a) stream flow, (b) sediment, (c) total nitrogen, (d) total phosphorus

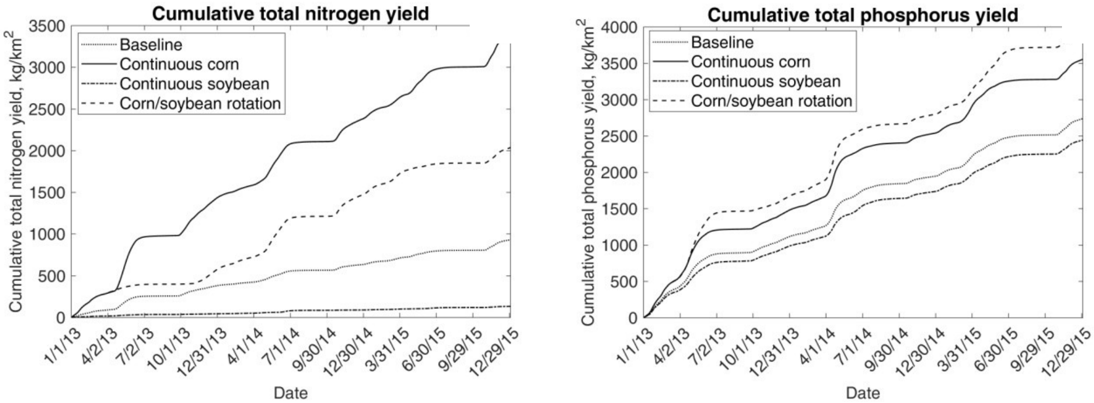

Figure 2.7 Nutrient and sediment loss comparison of crop rotation scenarios with conventional tillage from the daily water quality model from 2013 to 2015

Note: (a) total nitrogen, (b) total phosphorus

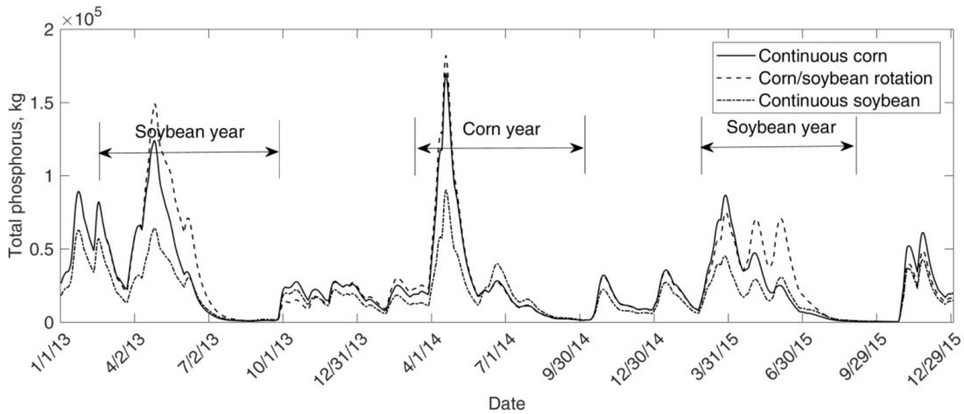

Figure 2.8 Daily phosphorus loading from continuous corn (CC), continuous soybean (SS), corn-soybean (CS) rotation scenarios

2.3.3 Tail water recovery pond analysis

The reservoir function was used to simulate the impacts of tail water recovery pond in SWAT at watershed level. Figure 2.9 shows the impacts of the stream flow at BSRW outlet by the reservoir. Stream flow was only slightly affected by reservoirs distributed among 19 sub-basins out of 22 sub-basins in whole watershed. Reservoirs could reduce stream flow from 2% to 6%. Summer season was affected more than other seasons with average of 5% reduce of stream flow.

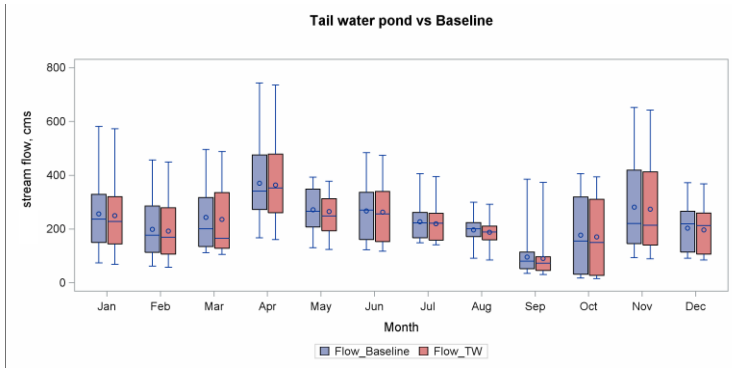

Figure 2.9 Monthly stream flow at watershed Outlet affected by reservoirs

Figure 2.10 shows the monthly average sediment concentration at the watershed outlet. Sediment concentration was slightly affected by the functional reservoirs. Unlike stream flow, there was more reduction for sediment concentration in stream during fall season than other seasons. The reduction rates were from 3% to 20% based on the size of the reservoirs and seasons. Larger reservoirs would have higher reduction rates. The results showed strong correlation between sediment concentration and stream flow. However the reduction rates of sediment concentration in stream and stream flow did not have same trend. Figure 2.11 showed that months with low sediment concentration would have more reduction rate due to the functional reservoirs. This was resulted from using constant settling rate through all the reservoirs. With constant settling rate, the method of sediment settling used in SWAT (Haan et al., 1994; Arnold et al., 2013) led to an inverse proportion relationship between the inlet and outlet sediment concentration in the reservoirs, which could be considered as the comparison of tail water recovery pond scenario and baseline scenario.

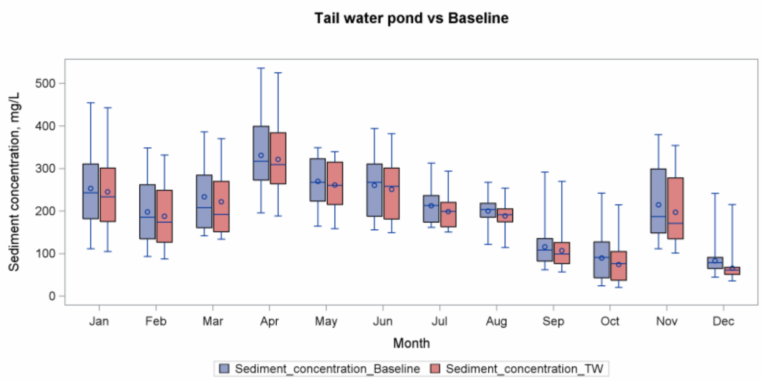

Figure 2.10 Monthly average sediment concentration at watershed outlet

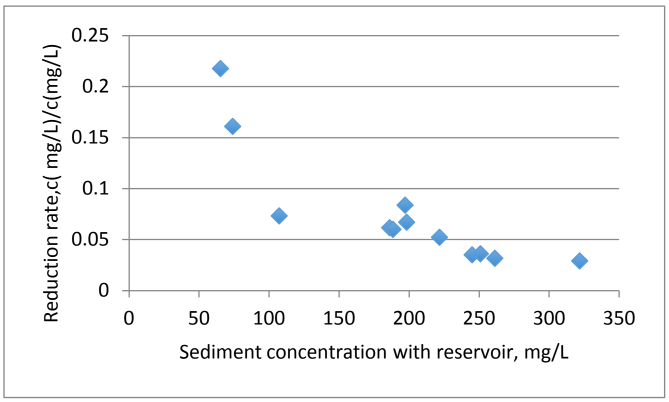

Figure 2.11 Sediment concentration vs reduction rate

Figure 2.12 shows the increasing rate of groundwater storage in tail water pond scenario, which ranged from 0 to 20%. There was more increase in groundwater storage in sub-basins with larger reservoirs, shown in Figure 2.12. This indicated that using reservoir to irrigate has potential ability to reduce groundwater use and mitigate groundwater depletion caused by irrigation.

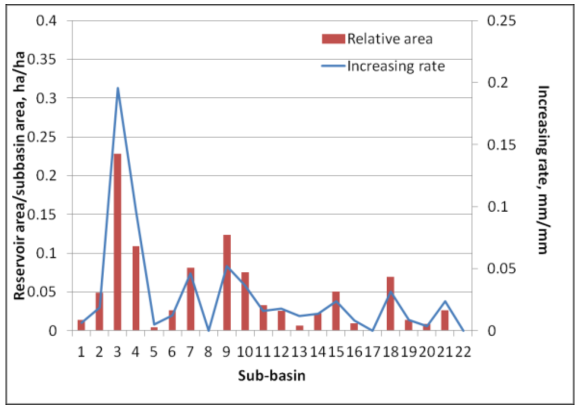

Figure 2.12 Groundwater storage changes of tail water pond scenario and baseline scenario vs relative area of reservoirs

2.4 Conclusion

The model showed better performance on simulating monthly stream flow in hydrological model compared to daily water quality indicators. For evaluation of BMPs, using conservational tillage operation, stream flow decreased up to 53% compared with conventional tillage scenario from 2013 to 2015. Cumulative sediment, TN and TP yield decreased by using conservational tillage as similar to other studies (Kanwar et al., 1988; Sharpley et al., 1994; Tuppad et al., 2010). For crop rotation scenarios analysis, sediment and flow were not sensitive to crop rotation management as TN and TP. Corn-soybean rotation scenario had higher TP and lower TN yield than continuous corn scenario. The lower TN loss to stream from continuous soybean scenario was resulted from less nitrogen fertilization during soybean growing. And the reason of that corn-soybean rotation had larger phosphorus loss to stream was that there were more simulated crop yields for corn than soybean. Thus, to prevent the high TP release in corn/soybean rotation scenario, residues might need to be removed after harvesting.

Satellite imagery was a good source to detect water bodies that could be used as tail water recovery pond. By detecting existing ponds, this could be a more economical way to find potential tail water recovery ponds and reducing the construction spending of installing new tail water recovery pond from digging. By using the reservoir function in SWAT, tail water recovery ponds could reduce sediment up to 20% and helping recover groundwater storage based on the simulation.

In order to see the overall impacts on the downstream outlet in BSRW, the nutrient reduction rate was set as universal for all reservoirs based on literature. In the future, it is necessary to do field verification as conducting field test to obtain the nutrient settling rate and related parameters of tail water recovery ponds, such as the inlet TN and TP data for calibrating the model, and conducting the relationship between tail water recovery ponds and reservoirs regarding to nutrient removal.

CHAPTER III

ASSESSING THE IMPACT OF CONSERVATION PRACTICES ON GROUND WATER USING A GROUNDWATER MODEL

3.1 Introduction

During the last several decades, groundwater resource, as a continuous water supplement, has become one of the most important natural resources in U.S. providing approximately 40% of nation's water supply (Alley et al., 1999). More and more usage of groundwater and the consequential groundwater resource depletion motivated the discussion of sustainability of groundwater resource (Logan, 1990; Wada et al., 2010). Due to the limitation of precipitation as a temporally discontinuous source and surface water as a spatially discontinuous source of irrigation, groundwater is one of the major sources of irrigation in U.S. (Siebert et al., 2010). In 2010, 43% of total irrigated water of cropland in U.S. was from groundwater (Maupin et al., 2014). In west Mississippi, also referred to as the Mississippi Delta region, the intense crop production, including corn, soybean, cotton and rice, results in large groundwater consumption. In late 1970s, groundwater level decline was starting observed in this area (YMD, 2006). Since early 1990s, the Yazoo Mississippi Delta Joint Water Management District (YMD) has monitored groundwater levels in the Mississippi Delta region through irrigation wells, and has observed steady 0.23 meter/year decline of groundwater in some of the Central Delta area (YMD, 2006). Since 2005, as a part of United States Geological Survey

(USGS) Ground-Water Resource program (Dennehy, 2005), a series of studies focusing on the Mississippi embayment regional aquifer has been established in order to investigate the groundwater resource in the Mississippi embayment including state of Mississippi and seven other states. Hart et al. (2008) indicated the most used aquifers in the Delta region, with a relative thin average thickness of 40 meter aquifer, but provided the largest water yield and is used primary for agricultural irrigation. Clark and Hart (2009) built an embayment scale numerical model using MODFLOW with long-term (137 years) seasonal simulation to estimate groundwater resource within the embayment. It provided the general idea of this study, using model to present the aquifer condition and evaluate related activities. Using the model, Barlow and Clark (2011) evaluated several groundwater conservation plans with reducing groundwater pumping by 5% and 25%. The results showed reducing groundwater consumption brought an increase of groundwater storage and recovery of groundwater level from 2% to 31.7% while the recharge rate stayed same. Reducing groundwater consumption is the most direct method to recover the groundwater level. Meanwhile, it is important to be both economic and environmental friendly for an agriculture dominant area without affecting the crop production. BMPs including crop rotation and tail water recovery pond may affect irrigation schedule and amount of water consumed from aquifer (USDA, 2011; Dakhlalla et al., 2016). In this case, the current irrigation plan and the impacts of BMPs on groundwater level change need to be evaluated before decreasing groundwater consumption.

There were two conservation plans discussed in this study regarding to changing the spatial or temporal irrigation water use. One was tail water recovery system and another was crop rotation. There was about average annual of 1400 mm precipitation in Mississippi, which was ranked as third wettest state in U.S. from 1971 to 2000 (Osborn, 2010a). The irrigation season was from May to September, while the average monthly precipitation of May to September in Mississippi was about 30% less than other months (Osborn, 2010b). Thus, the difficulty to use rainwater is mainly due to the temporal discontinuity of precipitation. The stream could be irrigation source usually for the cropland located near stream. And the excess irrigation water is not usually conserved to be reused, which make the main irrigation source in the study area is groundwater shallow aquifer (Hart et al., 2008). In this case, the tail water recovery system is constructed as an irrigation water storage system that can help collect and store the runoff to irrigate so that groundwater use reduced. Since 2011, tail water recovery system has been constructed as a BMP in Mississippi in order to reduce groundwater usage and recover groundwater storage (Tagert et al., 2018). Evaluating the performance of the tail water recovery system on mitigate groundwater depletion is necessary.

Crop rotation is a management practice that grows different crops in a same area in different seasons or years. Brouwer and Heibloem (1986) introduced the difference of water need among crops. From 1991, YMD started recording and estimating the water use by main crops and catfish ponds based on energy consumption in the Delta area (Powers, 2007). The surveys showed the differences among the amount of irrigation water of different crops. The variations of irrigation amount and frequency, which may vary by crops, will affect the amount of water percolated into underground (Rice et al., 1986; Scanlon et al., 2003; Scanlon et al., 2005). Up to 70% of the sum of precipitation and irrigation water will percolate into the aquifer (Kendy et al., 2004) as groundwater recharge that is a variable affecting groundwater level (Freeze and Cherry, 1979). Thus, crop rotation was another simulated conservation plan in this study. Corn and soybean rotation is one of the potential commonly used rotation plans in Mississippi Delta region (Heatherly, 2017). Four crop rotation scenarios were evaluated in this study including original continuous crops, continuous corn, continuous soybean and corn-soybean rotation for investigating the impacts of crop rotation on groundwater level.

Integration of surface and ground water models to simulate ground water resource has been reported (Arnold et al., 1993; Kollet and Maxwell, 2008; Sulis et al., 2010). One of the focuses was to estimate groundwater recharge based on water balance (Sharma, 1986). Evaluating the impacts of agricultural management on groundwater recharge requires the modeling tools considering both hydrological factors and agricultural activity factors. The SWAT has been widely applied on agricultural watershed management and BMPs simulation. Arabi et al. (2008) systematically discussed the representation of crop rotation using SWAT. Gosain et al. (2005) indicated the potential use of SWAT to simulate irrigation return flow with good model performance. The ability of simulating irrigation source and schedule using SWAT was successfully indicated by several studies (Rosenthal et al., 1995; Dechmi and Skhiri, 2013; Dakhlalla et al., 2016).

In order to capture the difference of recharge among BMPs, SWAT was chosen as the tool to simulate the watershed in this study. Since SWAT does not simulate the groundwater level and the pumping activity, a comprehensive groundwater modeling tool was needed in this study. There were studies focusing on automatically integrating MODFLOW and SWAT model, such as Kim et al. (2008) and Guzman et al. (2013). Kim et al. (2008) described the framework of the integrated model and a hydrologic response unit (HRU) to cell conversion interface. The model applied to a small catchment in Korea for testing with good performance. Since SWAT model is a daily time step based watershed model, the framework of automatically integrated model developed by Guzman et al. (2013) was also daily based. These two studies provided the basic framework and process of connecting watershed modeling and groundwater modeling in this study. To simplify the task, manually coupled MODFLOW and SWAT model with monthly surface and groundwater interaction was used in this study. In the study area, groundwater modeling combined with process-based watershed modeling regarding to BMPs has not been established before this study. To evaluate the impacts of BMPs on the groundwater level, this study could be benefit to future BMPs and groundwater flow analysis.

The specific objectives of this study were to (i) simulate BMPs using SWAT and obtain the monthly recharge of different scenarios; (ii) connect and represent the surface activities including recharge and pumping to the groundwater model; and (iii) evaluate the impacts of BMPs on groundwater level.

3.2 Material and method

3.2.1 SWAT model

A calibrated surface water model of the Big Sunflower River Watershed (BSRW) using SWAT (Neitsch et al., 2011) conducted in study 1 was used to simulate conservation managements including crop rotations and tail water recovery system. The BSRW in this study was divided into 22 sub-basins based on surface elevation. The sub-watershed was further divided into HRUs based on soil type, land use type and slope length. The soil type with area less than 5% of sub-basin area would not be simulated in this study. Similar for land use type and slope length, the thresholds were 3%, and 5% of sub-basin area respectively. Input data include Digital Elevation Model (DEM) (USGS, 1999), soil type from SSURGO database (USDA, 2005), land use and cover data from the USGS Land Cover Institute (LCI) (USDA/NASS, 2009) and climate information including precipitation, temperature, solar radiation, wind speed and relative humidity from Climate Forecast System Reanalysis (CFSR) database (NCDC, 2015).

Both surface water and groundwater model were evaluated by coefficient of determination (R^2) and Nash–Sutcliffe model efficiency coefficient (NSE). In addition to R^2 and NSE, the mean absolute error (MAE) and mean squared error (RMSE) were used to evaluate the model performance during validation. The auto-calibration program, SWAT-Cup SUFI2, was used to find the proper parameters' values that result in high R^2 and NSE from comparing simulated monthly stream flow rate with USGS gaging station stream flow rate. Manual calibration based on the Soil Conservation Service (SCS) curve number method (NRCS, 1986) was applied after auto-calibration. For SWAT hydrologic model calibration and validation, monthly stream flow data from three USGS gaging stations located in the BSRW were used to compare with outflows from corresponding sub-basins, shown in Figure 3.1. The model had a R^2 of 0.59 , NSE of 0.59 calibration and R^2 of up to 0.63 , NSE of 0.62 for validation.

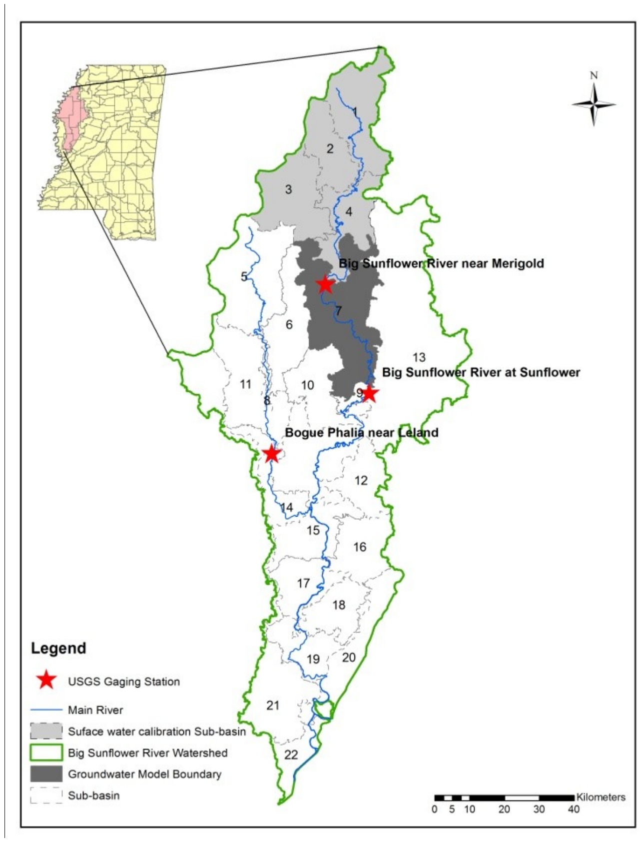

Figure 3.1 USGS gaging stations and boundaries of surface and groundwater model

The groundwater model study area was conducted in sub-basin 7 in SWAT model of the BSRW with the area around 690 km^2, which was contained by the area that considered with severe groundwater declination in Mississippi Delta region (Barlow and Clark, 2011; Dakhlalla et al., 2016). Figure 3.1 shows the surface water model and groundwater model boundaries. There were two USGS gaging stations in sub-basin 7, which were applied to calibrate the surface water condition in SWAT model. Pumping rate and recharge amount varied by BMPs due to the change of irrigation amount and schedule. Within the groundwater model boundary, the HRU-based monthly recharge was input into groundwater model. With the specific pumping rate by crops calculated from Yazoo Management District groundwater use annual reports (YMD, 2002-2010), the BMPs could be represented in groundwater model.

Table 3.1 Calibration parameters and final fitted value for SWAT watershed model

	Parameter name	Description	Fitted value
1	ESCO	Soil evaporation compensation coefficient	0.66
2	ALPHA_BF	Base flow recession constant	0.69
3	GW_DELAY	Delay of time for aquifer recharge	40.70
4	CH_N2	Manning's coefficient for the main channel	0.16
5	SOL_AWC	Available water capacity	0.11
6	RCHRG_DP	Aquifer percolation coefficient	0.09
7	GW_REVAP	Groundwater revap coefficient	0.15
8	GWQMN	Threshold water level in shallow aquifer for base flow	501
9	EPCO	Plant uptake compensation factor	0.66
10	SURLAG	Surface runoff lag coefficient	3.80
11	REVAPMN	Threshold water level in shallow aquifer for revap	40.90

3.2.2 MODFLOW model

The MODFLOW model is a finite-difference distributed-parameter groundwater model developed by USGS (Harbaugh et al., 2000). It considers the geological structure of the aquifer, pumping rate and location, and recharge distribution. The inputs of MODFLOW included aquifer dimension, aquifer characteristics, such as hydraulic conductivity and storativity, sources and sinks referring to rechargeand well-pumping, and river properties.

The lithology information (Brown, 1947) and status of Delta water supplies (Byrd, 2014) indicated that the Mississippi Alluvial aquifer could be simulated as two layers. One was a vadose zone layer of surficial clay simulated as unconfined aquifer with thickness of 11 m, and another was an unconfined aquifer with thickness of 50 m. Layer 1 was interacted with streams, while layer 2 was the source of the water use from pumping. DEM was considered as the top of Layer 1 with elevation around 40 m. According to over 20 years monitored groundwater level, the groundwater level is around 27 m, which was in Layer 2 in this model. The conceptual aquifer is shown in Figure 3.2. The no-flow boundary condition was used for the watershed boundary with cell dimension of 90 m * 90 m.

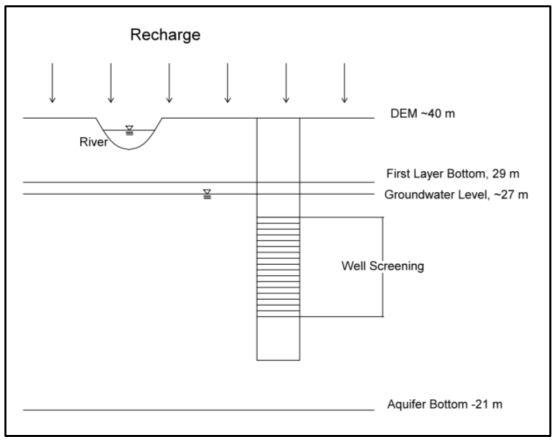

Figure 3.2 Conceptual aquifer with elevation of each layer

A mathematical governing equation described water balance of the aquifer was applied in MODFLOW. In order to solve the equation, boundary conditions describing the head or flux at the boundary (Anderson and Woessner, 1992) were needed. The agricultural pumpage for crop irrigation was considered as one of the boundary conditions in groundwater model. To simulate irrigation pumping, well location and pumping rate were inputted as time series. The monitoring wells that used to provide seasonal observed groundwater level are shown in Figure 3.3. Most of the monitoring wells were active irrigation wells (YMD, 2002-2010). However, the actual total active irrigation wells were much more than the monitoring wells. Since lack of data of pumping rate and operating schedule of active irrigation wells, the pumping rate of the monitoring was altered to present the irrigation wells in study area.

Due to lack of the data of the temporal pumping rate specific to each pump, the pumping rates were assumed to be constant over irrigation season of each year and calculated from the average crop usage from YMD groundwater use annual reports (YMD, 2002-2010). YMD groundwater use annual reports showed the average water usage for cotton, soybean, corn and rice from 2002 to 2010, which were the main crop in Mississippi Delta region. The irrigation crop of each well was decided depending on adjacent land use of the irrigation well. There were total 32 wells simulated in this area. 26 of the wells were located adjacent to cropland including 4 corn field, 2 rice field and 20 soybean filed. Pumping occurred in irrigation season from May to September and varies by crop types. Average pumping rate was applied to represent the average water usage during non-irrigation season, which were indicated in Clark et al. (2011). The average irrigation season usage height from May to September is shown in Figure 3.4. The depth of usage for rice was the most, while soybean was the crop with the most area of irrigation with irrigation season from June to September in the modeling area. Figure 3.5 shows the total estimated usage of the main crop in this area. Thus, the Figure 3.4 and 3.5 indicated the most water consuming crops were soybean and rice considering both unit usage and area of crops. According to Byrd (2014), the well pumping occurs in the Layer 2 of the model as shown in Figure 3.2.

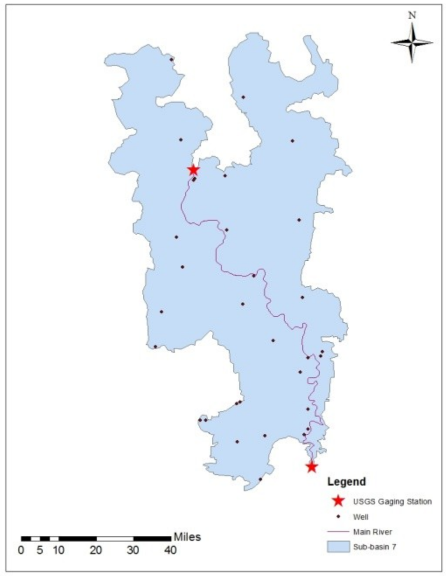

Figure 3.3 Simulated wells and river location

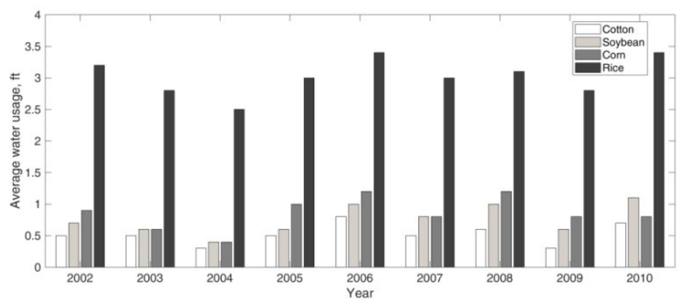

Figure 3.4 Average irrigation season water usage for main crops in the modeling area

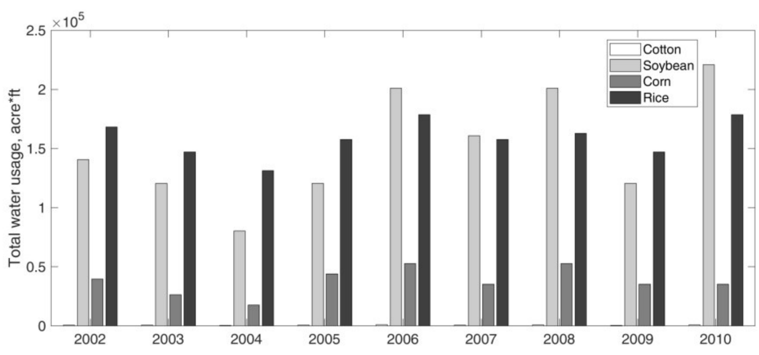

Figure 3.5 Total water usage of main crops in modeling area

Stress period is a term used to describe a time period with same boundary conditions, including recharge, pumping rate and river stage, in MODFLOW, which is a month in this study. The modeling stress periods in this study contained 1 steady state indicating average groundwater level 2002 and 108 transient states from January 2002 to December 2010. Time step was daily as 28 to 31 time steps in each stress period. The steady state stress period described the average status of groundwater level before transient stress period. In order to calculate the average status of groundwater level, the pumping rate used in steady state stress period was set as average monthly pumping rate summarized from 2002 to 2010. Besides, average recharge rate and average river stage from previous 4 years were applied in steady state stress period. Monthly HRU-based recharge was calculated through SWAT model simulation from 1998 to 2014. There were 70 and 173 recharge zones in each stress period based on different conservation management scenarios, which was as same as the number of HRUs simulated in corresponding SWAT model scenarios. Two USGS gaging stations shown in Figure 3.3 were used to interpolate river stages in every river cell in MODFLOW. The "stream" package is used to simulate the river.

3.2.3 Modeling scenarios

Connecting the surface agricultural activities to the groundwater was one of the main objectives in this study. There were clear impacts of the BMPs, including tail water recovery system and crop rotation in this study, on irrigation plan and simulated recharge in surface water model. To evaluate the impacts of these practices on groundwater, recharge and irrigation plan corresponding parameters in groundwater model need to be altered for different BMP scenarios setting.

The Baseline scenario from the SWAT model was considered as original land use, including corn, soybean, cotton and rice, with the tail water pond simulated as regular water body. The tail water recovery ponds were treated as regular water body in the baseline scenario without the function of providing irrigation water. The irrigation source in this scenario was from shallow aquifer (Layer 2 in groundwater model) in SWAT model. The monthly recharge calculated from baseline surface water model and well pumping rate calculated for different crops were as input into the baseline groundwater model. . This scenario was the one used to calibrate the groundwater model by comparing to the monitoring groundwater level data.

To evaluate the crop rotation scenarios' impacts on groundwater level, representing the different scenarios with the groundwater recharge and well pumping were the main objectives. The irrigation amount and schedules varied by crops according to YMD (2002-2010) and MAFES (2000-2014). There were three crop rotation scenarios, including continuous corn, continuous soybean, and corn-soybean rotation, simulated in this study. For continuous corn planting, all agriculture fields were converted to planting corn continuously and with the irrigation schedule for corn. Similarly, all agriculture fields were assumed to plant soybean continuously or corn/soybean rotation in other two scenarios with corresponding irrigation plans. The calculated monthly recharge from SWAT model was applied to the groundwater model to represent different scenarios of crop rotation from 2002 to 2010. Figure 3.6 shows the average monthly recharge from different crop rotation plans. The high recharge rate occurred from October to May, while there was few recharge during irrigation season. That is also an explanation of why groundwater use for irrigation could cause the water declination. The average recharge of scenario of continuous corn was higher than continuous soybean. This was caused by that the defaulted curve number of SWAT model was set to be lower for corn than soybean. The reason was that during the non-planting season, the curve number was mainly depending on the crop residue from the crop of the year before. Due to the high yield of corn, there were more residues for corn during the non-planting season, which resulted in higher residue cover (Dickey et al., 1986). The recharge from all the crop rotation scenarios was less than the scenario with original land use. The reason was that the crop rotation scenarios considered in this study only involve corn and soybean. Figure 3.4 indicated rice was a high water consuming crop in this area. Rice was simulated in the models with original land use and cover including baseline and two tail water recovery system related scenarios. Thus, the irrigation water use in the models with original land use and cover was averagely around 24% higher than crop rotation scenarios, which resulted in averagely around 30% higher recharge throughout the year.

In addition to recharge variation among different crop rotation scenarios, water usage from simulated irrigation wells in groundwater model was altered according to the crop water usage to represent the irrigation schedules of crop rotation scenarios in SWAT. In continuous corn scenario, the daily pumping rates of the simulated wells in irrigation season were calculated by corn water use from YMD water use reports (YMD, 2002-2010). Those reports were also used to generate Figure 3.4 and Figure 3.5. Similarly, the pumping rates were calculated by the water use of soybean in continuous soybean scenario. The first year pumping rates were set as the corn pumping rate, while the second year pumping rates were set as the soybean pumping rate in corn/soybean rotation scenario.

To evaluate tail water recovery pond, a surface water model, with updated tail water recovery pond and corresponding irrigation farm, was developed with same modeling parameters as in baseline SWAT scenario. The tail water recovery ponds were simulated using the reservoir function in SWAT model and grouped by sub-basins, which described in Chapter II. Figure 3.7 shows the regular shaped ponds considered as tail water recovery ponds and assumed corresponding irrigation cropland with the area calculated based on NRCS design guidelines (USDA, 2011). There were 15 ponds treated as tail water recovery ponds in study area. Three of them were for corn field irrigation, and twelve were for soybean field irrigation.

The amounts of pond-irrigation were calculated based on the irrigation frequency of these two crops. The reservoir function in SWAT was used to simulated tail water recovery pond with the total area of detected regular shaped ponds in each sub-basin. The reservoirs located at the outlet of each sub-basin in SWAT model were treated as irrigation source in the tail water recovery pond scenarios. The irrigation rate depended on the size of the detected ponds and were calculated based on NRCS design guidelines (USDA, 2011). The irrigation amount of water from pond may be less than the total crop needs. In this case, the shallow aquifer in the SWAT model was another source of irrigation in order to meet the crop need summarized from YMD (2002-2010). The pumping rate in tail water pond groundwater scenario was reduced to 96% of the one in baseline scenario based on the ratio of the area of irrigated farm to the area of total cropland. From above, the calculated recharge and altered pumping rate were compatible to represent the scenario of tail water recovery pond in the groundwater model. Figure 3.6 shows the average monthly recharge comparison for the baseline scenario and tail water recovery ponds scenario. Since the total irrigation amounts of baseline scenario and tail water pond scenario were the same, the calculated groundwater recharge of these two scenarios was same.

The scenario comparisons were conducted by band collection statistic, basic static, and area comparison among groundwater level categories. The band collection statistic is a tool in ArcGIS used to calculate the correlation among raster datasets (ESRI, 2016), which were groundwater level maps of different scenario in this study. Basic statistics comparison includes comparison among average, maximum, minimum, and standard deviation of the groundwater level in study area. Area comparisons among categories were based on the area of each groundwater level categories in different scenarios, which used to indicate groundwater level difference within a same category.

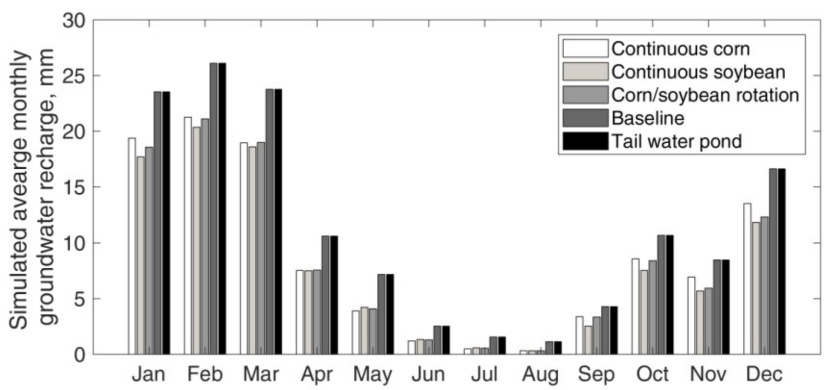

Figure 3.6 Average monthly recharge from SWAT model of modeling area

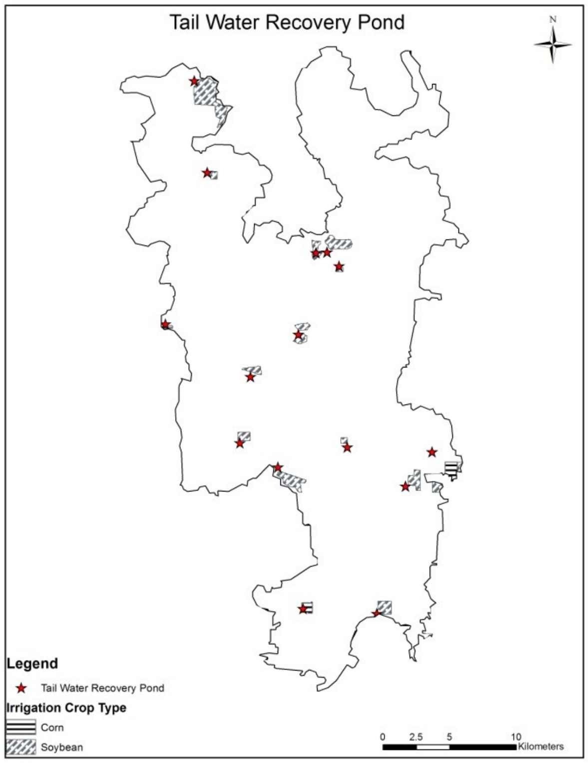

Figure 3.7 Tail water recovery pond and corresponding irrigated crop

3.2.4 Calibration and validation of groundwater model

Monitoring groundwater levels measured by YMD from 2002 to 2010 were used to calibrate and validate the groundwater model. The monitoring groundwater level was conducted in every April and October, twice a year. The calibration time period was from April 2002 to April 2006, while validation period was from October 2006 to October 2010. For the reason of irrigation well data availability, the monitoring wells were treated as the irrigation wells. Each monitoring well was used to represent the several irrigation wells nearby. The parameters had been altered during calibration including hydrological conductivity, specific yield, and the number of wells that one monitoring well represents. Because of the relatively small area of groundwater model and no flow boundary condition, the wells located at southeast had higher weight in this model. Calibrated hydrology conductivity was considered as homogeneous through the modeling area with value of sand of 120 m/day and 40 m/day for two directions. Specific yield was set as typically number which was 0.01. Each monitoring well represented 8 irrigation wells nearby during irrigation season.

3.3 Results and discussion

3.3.1 Calibration and validation

Figure 3.8 shows the calibration results with R^2 of 0.81 and no seasonal bias for calibration time period. Figure 3.9 shows the results of validation with 6.25 m of RMSE and 2.02 m of MAE and small seasonal bias for validation time period. The model shows accepstatistic as compared with literatures using MODFLOW (Scanlon et al., 2003; Xu et al., 2011).

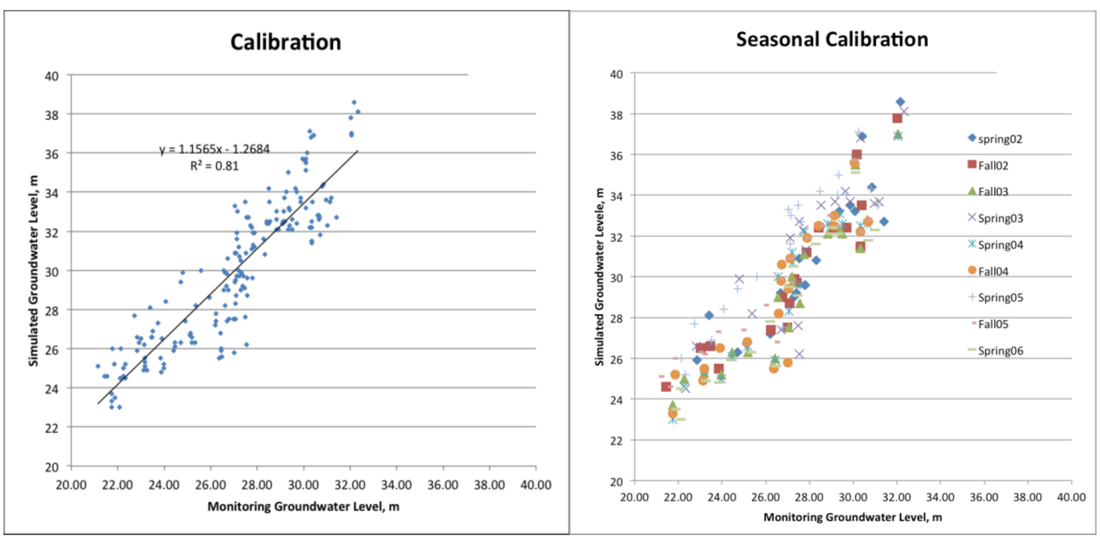

Figure 3.8 Calibration statistics and seasonal bias from April, 2002 to April, 2006

Note: a) Calibration statistics, b) Calibration seasonal bias

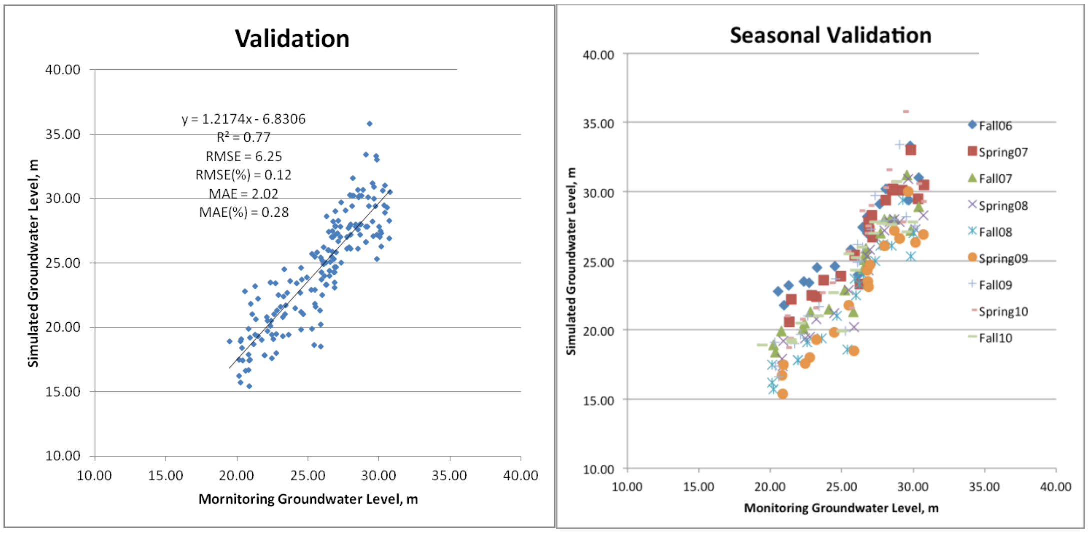

Figure 3.9 Validation statistics and seasonal bias from October, 2006 to October, 2010

Note: (a) Calibration statistics, (b) Calibration seasonal bias

3.3.2 Scenario analysis

Figure 3.10 shows the groundwater level distribution of all the simulated scenarios, which indicated the changes of well pumping rate and recharge could affect the spatial variation of groundwater level and critical area defined as the area with groundwater level less than 30 m which was the lowest groundwater level category in this study. The area with lower groundwater level was the location of concern. Tail water pond active scenario and all the crop rotation scenarios had smaller area of the groundwater level less than 30 m than the baseline scenario, which indicated all the simulated scenarios could help alleviate groundwater depletion. From the correlation matrix calculated from band collection statistic in ArcGIS, the correlation of the groundwater levels of any two scenarios was large than 0.98, which indicated the scenarios have little impact on the groundwater level trend. The location with higher groundwater level in baseline scenario would still have high value in other scenarios.

3.2 shows the basic statistics of the groundwater level at the end of the simulation including mean, maximum, minimum and standard deviation of groundwater level. The average groundwater level and standard deviation of simulated groundwater level for each simulated cell were not far from each other. Since Figure 3.6 shows the monthly average groundwater recharge calculated from SWAT model of baseline scenario and tail water recovery pond scenario, the main difference between baseline scenario and tail water recovery pond scenario was the irrigation water use represented by the different pumping rate. The pumping was reduced in tail water pond scenario by 4% due to the cropland area irrigated by tail water pond. This resulted in the area with simulated groundwater level less than 30 m of tail water recovery pond scenario (27 km^2) is less than the baseline model (73 km^2) by 63% (Figure 3.11). The total area of groundwater level less than 35 m of baseline scenario and tail water recovery pond scenario was about the same, which was around 375 km^2. Thus, reducing the pumping for this area could help reduce the area with the critical situation.

The area with simulated groundwater level less than 30 m in all of the crop rotation scenarios were less than baseline scenario by 14% for continuous soybean scenario, 25% for corn-soybean rotation scenario and 35% for continuous corn scenario. Figure 3.6 indicated the groundwater recharge in crop rotation scenarios were less than baseline scenario. The reason that the area with simulated groundwater level less than 30 m in crop rotation scenario was less than baseline scenarios was that the water uses in crop rotation scenarios were less. Rice as one of the top two water consumption crops in study area was simulated in baseline scenario, but not in crop rotation scenarios. This resulted in the total amount of pumped water for crop rotation scenario was also less than the baseline scenario. In this case, less recharge may not result in more critical area with lower groundwater level.

For the three crop rotation plans comparison, the area with simulated groundwater level less than 30 m in continuous corn scenario was less than the one in continuous soybean scenario by 24%. The groundwater recharge was on average 7% more in continuous corn scenario compared to continuous soybean scenario, while the pumping rate in continuous corn scenario was on average 29% more compared to continuous soybean scenario. The larger recharge was mainly from non-planting season (Figure 3.6) according to SWAT model simulation. In this case, increasing recharge in non-planting season could help the critical situation even with the increasing of pumping in irrigation season. The groundwater recharge calculated from SWAT in corn and soybean rotation was on average 3% less than the one in continuous corn scenario but 4% higher than in continuous soybean scenario. Since the pumping rate applied in corn/soybean rotation scenario switched every year between corn and soybean, the average pumping rate in corn/soybean rotation scenario during the modeling period was between continuous corn scenario and continuous soybean scenario. The moderate groundwater recharge and pumping rate resulted in the area with critical condition was between the one in continuous corn scenario and continuous soybean scenario. The total area with groundwater less than 35 m was similar for all three crop rotation scenarios, which is around 403 km^2. From above, the change of groundwater and pumping rate in all the scenarios had little impacts on groundwater level trend represented by 4 contour intervals. The area with critical groundwater level changed with the change of recharge and pumping by different scenarios.

Table 3.2 Statistic of groundwater level at the end of simulation in different scenarios

Scenarios	MIN (m)	MAX (m)	MEAN (m)	STD (m)
Baseline	27.20	44.40	35.20	4.54
TWActive	28.00	51.00	36.40	5.86
CC	29.60	45.10	35.13	4.16
SS	29.40	44.00	35.00	4.01
CS	29.50	44.70	35.17	4.16

Note: TWActive: tail water recovery pond active scenario, CC: continuous corn scenario, SS = continuous soybean scenario, CS = corn and soybean rotation scenario, STD: standard deviation

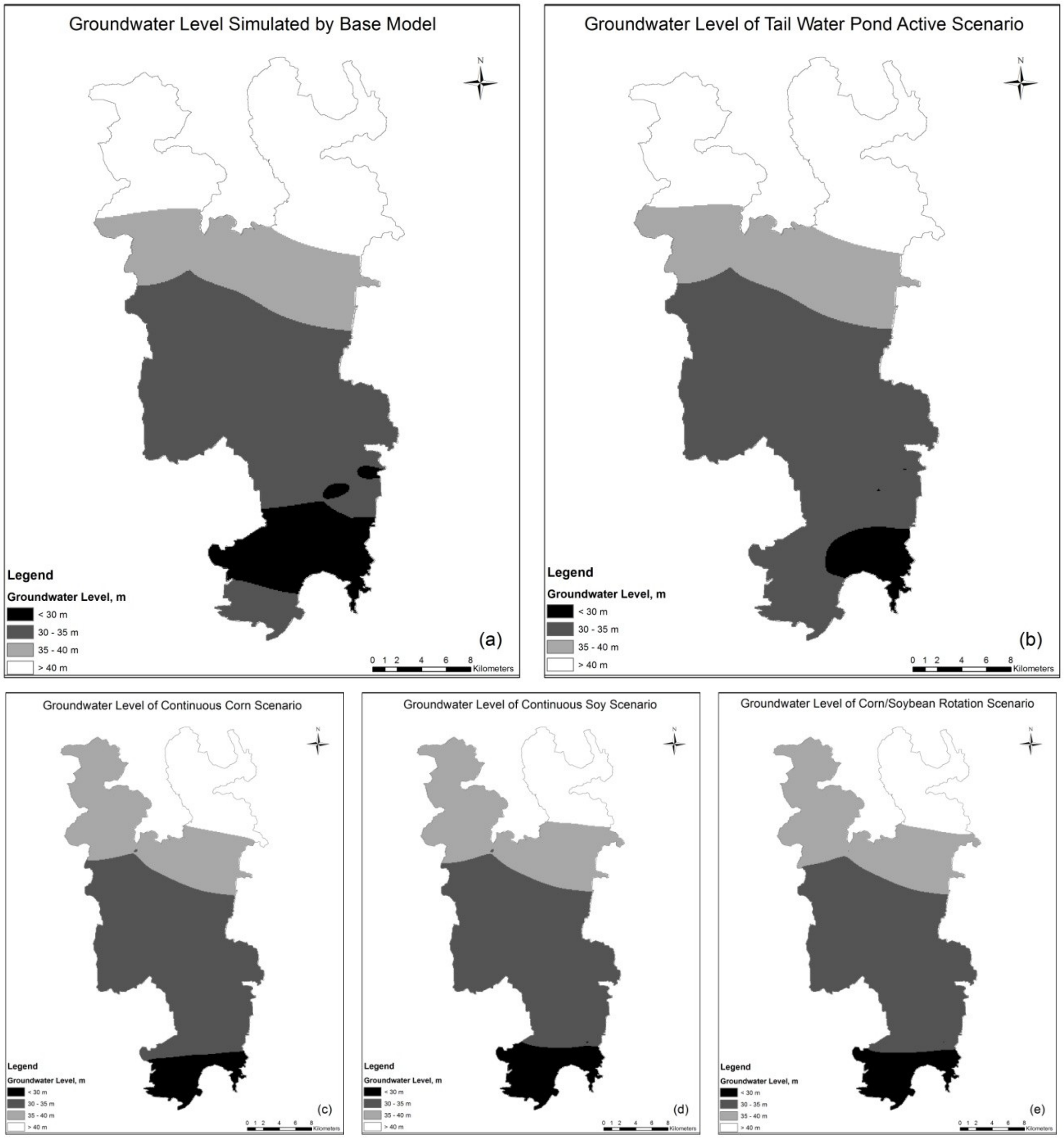

Figure 3.10 Groundwater level in modeling area at the end of simulation

Note: a) baseline scenario; b) tail water recovery pond active scenario; c) continuous corn scenario; d) continuous soybean scenario; e) corn and soybean rotation scenario

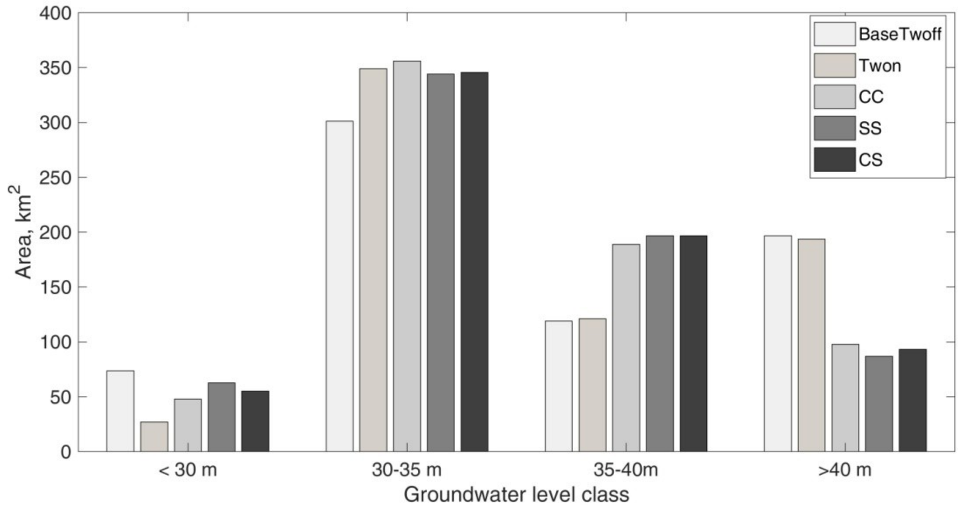

Figure 3.11 Watershed area covered by five groundwater level classes at the end of simulation

Note: BaseTwoff = baseline scenario, Twon = tail water recovery pond active scenario, CC = continuous corn scenario, SS = continuous soybean scenario, CS = corn and soybean rotation scenario

The Figure 3.12 shows the groundwater level change from 2002 to 2010 period for all the scenarios. Except for the north-east area of the modeling area, the groundwater level had declined up to 5 m, which means water consumption was more than groundwater recharge in this area. The area with more than 4 m declination was located at south and south-east region of study area. These regions were also the area with lowest groundwater level shown in Figure 3.10. The groundwater recharge calculated from SWAT was based on the water balance in each HRUs and varied by the crop type. The land uses and covers of baseline scenario and tail water recovery pond scenario area were same. And the cropland in crop rotation scenario was changed to unified corn, soybean or corn and soybean rotation. This affected the distribution of recharge amount of each HRUs in SWAT and caused that the groundwater level change correlation between baseline scenario and tail water recovery pond scenario (Figure 3.12 (a) and (b)) was 0.97, which was higher than correlation with three crop rotation scenarios ranged from 0.82 to 0.88.

Figure 3.13 shows the class comparison of groundwater level changes from December 2002 to December 2010 in different scenarios. The area with declination larger than 4 m occurred only in baseline scenario and tail water recovery pond scenario. Since the groundwater level was declined, compare to groundwater recharge, pumping was the reason cause the high declination. The total amount of pumped water in baseline (Figure 3.12 (a)) and tail water recovery pond active scenario (Figure 3.12 (b)) were on average 24% more than the rate in crop rotation scenarios (Figure 3.12 (c), (d) and (e)) caused by converting rice to continuous corn, continuous soybean or corn-soybean rotation during scenario setting, which caused more declination. Comparing to baseline scenario (Figure 3.12 (a)), tail water recovery pond (Figure 3.12 (b)) helped to reduce the area with groundwater level change more than 4 m by 20% (65 km^2). The area with high fluctuation of 4 m to 3 m in continuous corn scenario (Figure 3.12 (c)) was 20 km^2 larger than the one in continuous soybean scenario (Figure 3.12 (d)) and 23 km^2 larger than in corn and soybean rotation scenario (Figure 3.12 (e)). The area with change more than 3 m in corn-soybean rotation scenario was slightly less than continuous soybean scenario, shown in Figure 3.12 (d) and e. The initial groundwater levels at December 2002 for both of these two scenarios were same, since year 2002 was soybean year. Recharge in corn-soybean rotation scenario, shown in Figure 3.6, was 4% more than continuous soybean scenario, while the pumping rate was 5% more than continuous soybean scenario. Increasing non-planting season recharge also helped reduce the fluctuation of groundwater level change even with slightly higher pumping during irrigation season. Figure 3.14 shows the water balance from 2002 to 2010 in modeling area. Compared with baseline scenario, cumulative volume of the water losing to stream was 4% less. The cumulative volume of the water losing to stream in crop rotation scenarios was on average 23% less than in baseline and tail water recovery pond scenarios due to the less recharge.

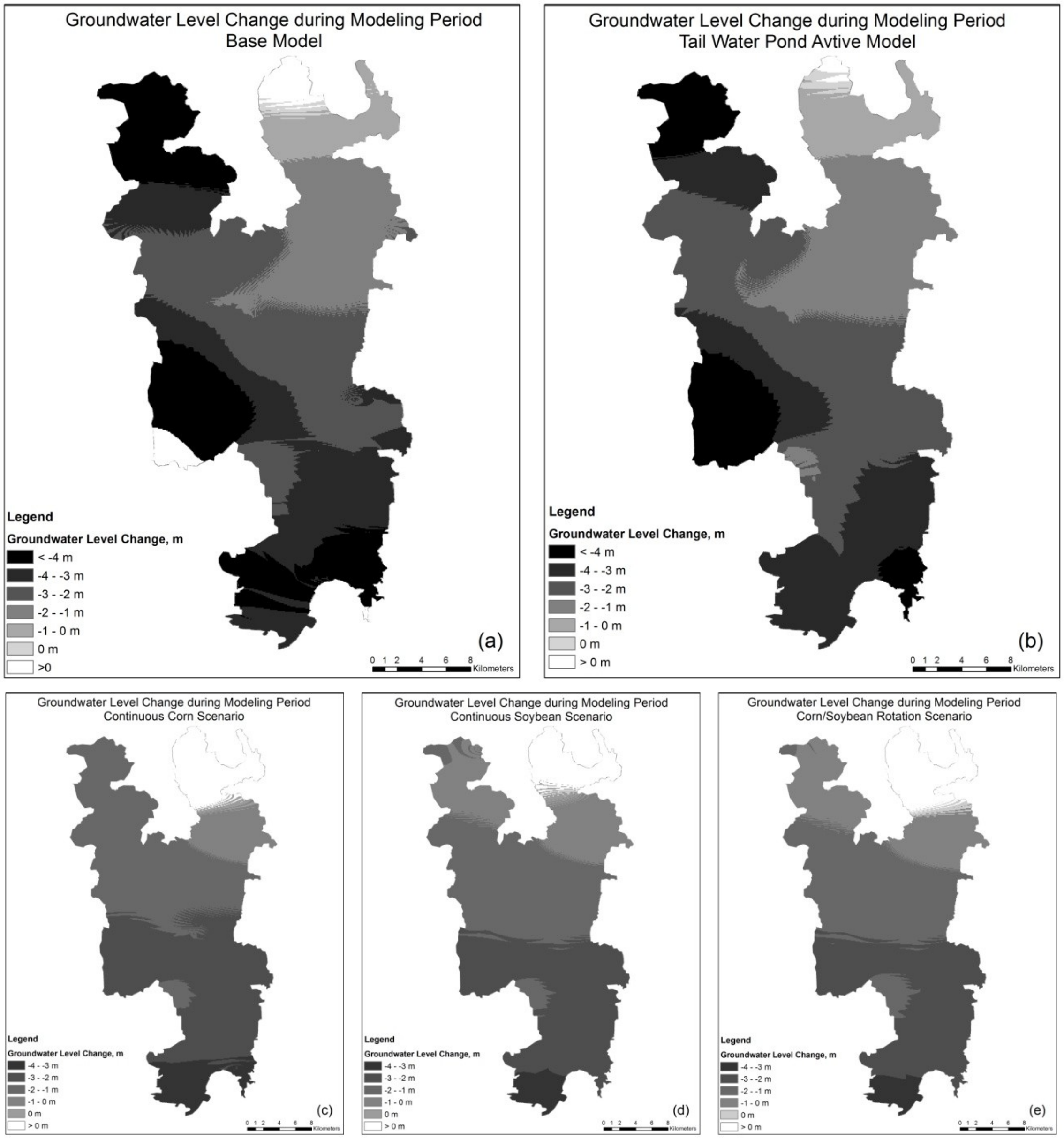

Figure 3.12 Groundwater level changes during modeling time period in modeling area

Note: a) baseline scenario; b) tail water recovery pond active scenario; c) continuous corn scenario; d) continuous soybean scenario; e) corn and soybean rotation scenario

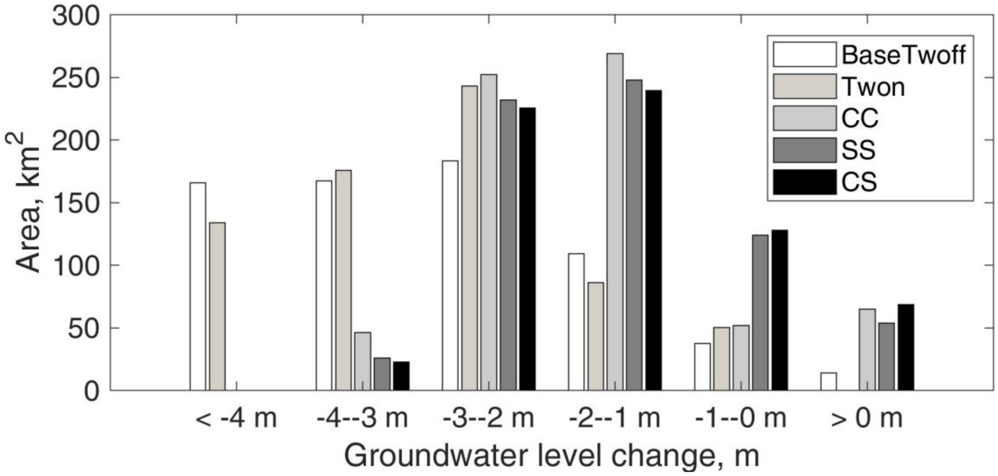

Figure 3.13 Comparison of groundwater level change from December 2002 to December 2010

Note: BaseTwoff = baseline scenario, Twon = tail water recovery pond active scenario, CC = continuous corn scenario, SS = continuous soybean scenario, CS = corn and soybean rotation scenario

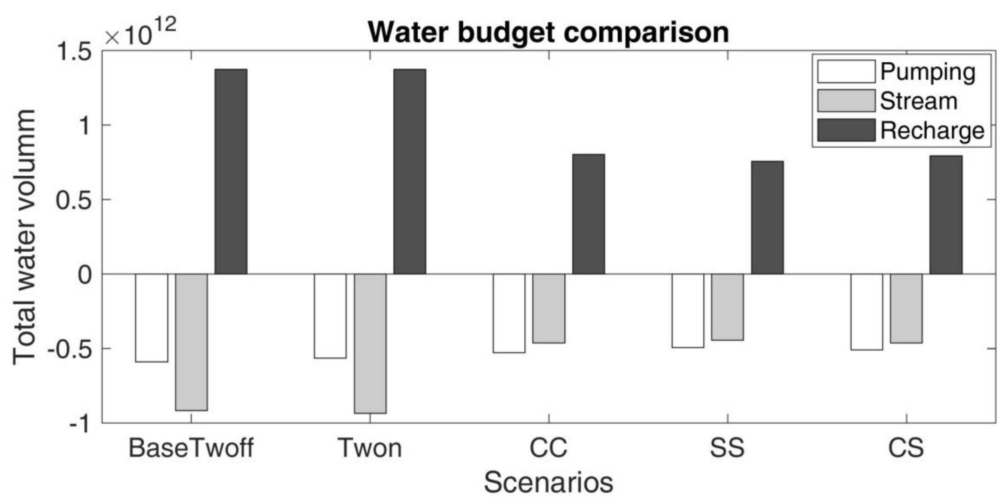

Figure 3.14 Water balance comparison in modeling area during the modeling time period

Note: BaseTwoff = baseline scenario, Twon = tail water recovery pond active scenario, CC = continuous corn scenario, SS = continuous soybean scenario, CS = corn and soybean rotation scenario

3.4 Conclusion

This paper combined the different BMPs regarding the irrigation plans and groundwater modeling, and simulated the impacts of surface agricultural activities on groundwater level. The model performance was determined as accepwith R^2 of 0.81 and no seasonal bias for calibration time period, and 6.25 m of RMSE and 2.02 m of MAE and small seasonal bias for validation time period compared with literatures. Thus, within the modeling period, the model could represent the change of groundwater level.

The changes of well pumping rate and recharge could affect the spatial variation of groundwater level. The results of scenario analysis indicated all the simulated scenarios, including one tail water recovery pond scenario and three crop rotation scenarios, could help with the groundwater depletion in different levels. And all the scenario setting had little impact on groundwater distribution trend, which indicated by correlation among scenarios. The pumping rate difference between tail water pond scenario and baseline scenario, which was 4%, caused a 63% reduction of critical area with groundwater level less than 30 m. The area with simulated groundwater level less than 30 m of all of the crop rotation scenarios were less than baseline scenario by 14% for continuous soybean scenario, 25% for corn-soybean rotation scenario and 35% for continuous corn scenario. This was mainly resulted from the less pumping rate caused by converting rice to continuous corn, continuous soybean or corn-soybean rotation during scenario setting. Continuous corn was the most effective scenario to reduce critical region area among three crop rotation scenarios.

The comparison among simulated groundwater level at the end of simulation of the scenarios showed the non-planting season recharge might be the major impact of the simulated groundwater level and groundwater level fluctuation within modeling period, even with the increasing of pumping rate during irrigation season. Although, this should be tested with longer and more comprehensive pumping rate data. And the sensitive analysis of non-planting season recharge and irrigation pumping rate should be investigated in the future in order to determine limitation of using monitoring wells as irrigation wells.

CHAPTER IV

EFFECT OF LOCAL LAND USE CHANGE TREND ON DOWNSTREAM HYDROLOGY AND WATER QUALITY IN BIG SUNFLOWER RIVER WATERSHED WITH SPATIAL DEPENDENT SELECTION OF LAND USE CHANGE AREA USING GIS AND SWAT MODEL

4.1 Introduction

Land use and cover change impacts on hydrology related analysis have come into academic attention since late 1960s (Leopold, 1968; DeCoursey, 1970). Studies were focus on how the land use and cover affected hydrological process as runoff (Howe et al., 1967; Onstad and Jamieson, 1970), base-flow (Harrold, 1962) and erosion (Ursic and Dendy, 1965). In last few decades, studies were conducted in the fields mentioned above and expanded to include water quality. The previous research studies indicated the land use and cover change could affect on both hydrology and water quality. Nelson and Booth (2002) summarized the sediment sources and types, including urban, agriculture, forest, landfill and so on, and corresponding simulation methods from varied previous studies (Reinelt, 1996; Horner, 1992; Wischmeier and Smith, 1978) in a mixed land use watershed. Wang et al. (2009) analyzed the spatial relationship between the soil nutrients percentage including soil total nitrogen (TN) and soil total phosphorus (TP) and different land use in a small watershed in China, which showed the correlation between land use and soil nutrients. Schilling and Spooner (2006) indicated changing cropland to forest and grassland would result in an increase in stream nitrate concentration in the past 10 years of the study.

Recent studies focused on land urbanization and its' impact on hydrology and water quality and predicting land use change among urban, cropland and other land use categories (Nelson and Booth, 2002; Weng, 2002). Classified by the method used to determine land use change trend, the models predicting land use change evolves static-trend based method as the Conversion of Land Use and its Effects modeling framework (CLUE) (Verburg et al., 2002) and stochastic-trend based method (Bell, 1974; Muller and Middleton, 1994; Guan et al., 2011). CLUE model combines user defined trend based on target land use change area and change probability of land use cell to simulate land use change in the future. The change probability of a land use cell is based on factors including geology, policy and spatial relation to city and stream. There were other studies (Luo et al., 2010; Britz et al., 2011) focusing on improving the change probability of land use by adding other factors including socioeconomic and agricultural policy. The model requires that the users are familiar with the study area and all the impact factors of each modeling unit. Stochastic-trend based method using Markov model and cellular automaton considers the randomness and spatial relationship among simulated land use unit. The Markov method is used to obtain the spatial change trend within historical land use data (Britz et al., 2011). The Markov method requires the land use data with high quality in order to figure out the spatial change trend.

In order to evaluate the effect of local land use change trend on downstream hydrology and water quality in Mississippi Big Sunflower River Watershed (BSRW), the background of the study area was the major concern to select method to analysis the trend and predicting the land use in the future. The BSRW is the major sub-watershed of the Mississippi Delta region, which are known of its' heavy crop production. About over 80% of the area covered by crops due to the Crop data layer (CDL) from USDA (USDA/NASS, 2016). The CDL data, with on average over 90% of both producer's and user's accuracy (USDA/NASS, 2006 to 2016) for crop type, were widely used in previous studies focusing on agricultural watershed hydrology (Srinivasan et al., 2010; Giri et al., 2012). However, the limitation of CDL data is that the accuracy of the other land use including pasture, urban and wetland forest were depending on the accuracy of National Land Cover Database (Homer et al., 2007; Fry et al., 2011; Homer et al., 2015), which was ranged from 28% to 76% (Wickham et al., 2010, 2017) relatively lower than the cropland data. Thus, the models based on either static or stochastic-trend were not suifor this study. In this study, due to the local availability of the land use data and small area of other land use besides cropland, the area change trend of cropland was obtained by using simple regression with cropland area and year. The change availability was considered mainly depending on the adjacent cropland and the area.

The objectives of this study were (i) obtaining the local land use change trend using simple regression, (ii) conducting a method of land use change area selection suiin study area, (iii) evaluating the impacts on stream water quality including monthly trend and cumulative trend.

4.2 Material and method

4.2.1 SWAT model

In order to simulate the complex crop management operation in the study area, Soil and Water Assessment Tool (SWAT) (Neitsch et al., 2011) with comprehensive operation simulating module were select to conduct hydrological model in the Big Sunflower River Watershed (BSRW) this study. The BSRW was divided into 22 sub-basins based on surface elevation, which is shown in Figure 4.1. The sub-watershed was further divided into Hydrology respond units (HRUs) based on soil type, land use type, and slope length. The soil type with area less than 5% of sub-basin area would not be simulated in this study. Similar for land use type and slope length, the thresholds were 1%, and 5% of sub-basin area respectively. Input data included Digital Elevation Model (DEM) (USGS, 1999), soil type from SSURGO database (USDA, 2005), land use and cover data were the Crop Data Layer (CDL) from USDA (USDA/NASS, 2016) and climate information including precipitation, temperature, solar, wind and relative humidity from Climate Forecast System Reanalysis (CFSR) database (NCDC, 2015) and Global Historical Climatology Network (GHCN)–Daily database (NOAA, 2016). The crop management is shown in 4.1 according to Parajuli et al. (2013) and MS Agricultural and Forest Experiment Station (MAFES) annual report (MAFES, 2000-2014).

There were two major methods to analysis land use change in SWAT. One is using the land use data from different years to conduct different models with same modeling time period (Li et al., 2009; Nie et al., 2011; Zhang et al., 2013). Another one is taking advantage of the comprehensive management schedule feature of SWAT. The land use changes are represented by different management schedule within the modeling time period (Pai and Saraswat, 2011). The single land use type could be modeled as a unit in SWAT model so that changing the parameters only in the land use change area is possible in the tool. In this study, the land use change was presented by different management schedule combination from the 4.1, where shows the management schedules for different crop types.

The SWAT model was set up and calibrated by two steps based on the hydrological and water quality parameters. Coefficient of determination (R^2) and Nash–Sutcliffe model efficiency coefficient (NSE) were used to evaluate the model performance. The final fitted values of hydrological parameter were determined as those resulting in the high R^2 and NSE from comparing simulated monthly stream flow with USGS gaging station data from 2006 to 2016, with one year of warming-up time. The water quality related parameters from a daily SWAT model with calibrated hydrologic parameters was calibrated with measured water quality data including total nitrogen (TN), total phosphorus (TP) and total suspended sediment (TSS) those were obtained every two weeks at three USGS gaging stations in BSRW shown in Figure 4.1 from 2013 to 2015. The calibration process included auto and manual calibration. The auto-calibration program, SWAT-Cup SUFI2, was applied to obtain the final fitted values of hydrological and water quality parameters. Manual calibration based on the Soil Conservation Service (SCS) curve number method (NRCS, 1986) was applied after auto-calibration of hydrologic model.

For SWAT hydrologic model calibration and validation, in order to take advantages of long term stream flow data, the USGS gaging station of Merigold and its' corresponding sub-basins were used to calibrate the hydrological parameters of BSRW from 2007 to 2016. The other two gaging stations, which are Leland and Sunflower, were used as validation by comparing the simulated monthly stream flow with stream flow data from 2007 to 2016, which is shown in Figure 4.1. 4.2 shows the hydrological parameters used to calibrate stream flow at the USGS gaging stations and their final fitted values.

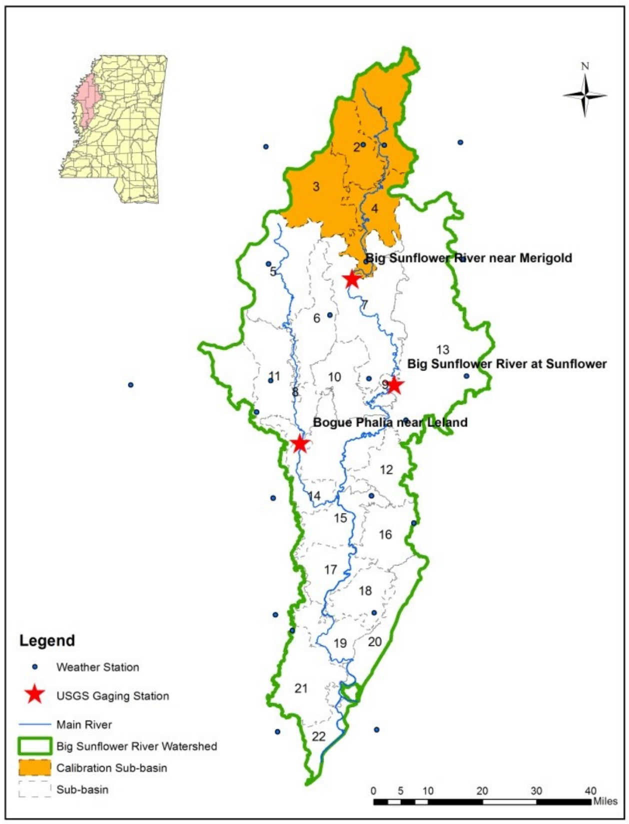

Figure 4.1 USGS Gaging Stations and Corresponding Calibration and Validation Watershed

Table 4.1 Management calendar of crop field simulated in SWAT model

Field	February	March	April	May	June	July	August	September	October
Soybean		Tillage	Tillage Planting	Fertilizing (12-22-22)	Irrigation	Irrigation	Irrigation	Irrigation	Harvesting

Table 4.1 Management calendar of crop field simulated in SWAT model (continued)

Corn	Tillage	Tillage Planting	Fertilizing (Element N)	Fertilizing Irrigation	Irrigation	Irrigation	Irrigation	Harvesting	
Cotton			Tillage	Tillage Planting	Fertilizing (03-27-06) Irrigation	Irrigation	Irrigation		Harvesting
Rice	Tillage	Tillage	Planting	Fertilizing (Urea) Irrigation	Irrigation	Irrigation	Irrigation		Harvesting

Note: 12-22-22, Element N, 03-27-06 and Urea were set according to Arnold et al. (2013)

Table 4.2 Hydrology calibration parameters

	Parameter Name		Fitted Value
1	ESCO	Soil evaporation compensation coefficient	0.537
2	ALPHA_BF	Base flow recession constant	0.675
3	GW_DELAY	Delay of time for aquifer recharge	93.278
4	CH_N2	Manning's coefficient for the main channel	0.014
5	RCHRG_DP	Aquifer percolation coefficient	0.468
6	GW_REVAP	Groundwater revap coefficient	0.170
7	GWQMN	Threshold water level in shallow aquifer for base flow	884.565
8	EPCO	Plant uptake compensation factor	0.896
9	SURLAG	Surface runoff lag coefficient	9.362
10	REVAPMN	Threshold water level in shallow aquifer for revap	261.813

The calibrated hydrological parameters were later applied to a daily SWAT model of BSRW from 2013 to 2015 in order to calibrate the water quality parameters in the modeling area. As the process of calibrating hydrologic model, both auto and manual calibration were involved. And in order to take advantage of the full length of data, the water quality factors at Merigold USGS gaging station were used to calibrate, while the ones at Sunflower and Leland USGS gaging stations were used to validate the model from 2013 to 2015. According to Santhi et al. (2001), White and Chaubey (2005) and Shen et al. (2008), some of the parameters only affect TN or TP, while some parameters affect the simulation of all three factors by affecting TSS, which were shown in 4.3. Therefore, the calibration process repeated for each calibrated factor with unique calibration parameters. 4.3 is the calibrated water quality related parameters and their final fitted values.

Table 4.3 Water quality calibration parameters and final fitted values

Calibrated factor	Parameters	Description	Fitted value
TSS	CH_COV1.rte	Channel erodibility factor	0.192
	CH_COV2.rte	Channel cover factor	0.208
	USLE_K.sol	USLE equation soil erodibility (K) factor	0.040--0.390
	SPCON.bsn	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	0.004
	CHERODMO.rte	Channel erodability factor	0.600
TN	ERORGN.hru	Organic N enrichment ratio	0.318
	CH_ONCO.rte	Organic nitrogen concentration in the channel (ppm)	14.700
	RS4.swq	Rate coefficient for organic N settling in the reach	0.090
	BC1.swq	Rate constant for biological oxidation of NH4 to NO2 in the reach	0.177
	BC2.swq	Rate constant for biological oxidation of NO2 to NO3 in the reach	1.817
	BC3.swq	Rate constant for hydrolysis of organic N to NH4 in the reach	0.314
	RCN.bsn	Concentration of nitrogen in rainfall	1.775
	N_UPDIS.bsn	Nitrogen uptake distribution parameter	98.567
	NPERCO.bsn	Nitrogen percolation coefficient	0.739
TP	PSP.bsn	Phosphorus sorption coefficient	0.436
	ERORGP.hru	Organic P enrichment ratio	4.878
	BC4.swq	Rate constant for mineralization of organic P to dissolved P in the reach	0.068
	RS5.swq	Organic phosphorus settling rate in the reach	0.009
	P_UPDIS.bsn	Phosphorus uptake distribution parameter	1.567
	PPERCO.bsn	Phosphorus percolation coefficient	16.428
	CH_OPCO.rte	Organic phosphorus concentration in the channel (ppm)	17.900
	PPERCO_SUB.chm	Phosphorus percolation coefficient	16.543

4.2.2 Land use change scenario

4.2.2.1 Cropland area changing trend

In order to set up reasonable land use change scenario, it is necessary to obtain the local land use and cover change trend. In the study area, cropland is the dominant land use and it occupied more than 80% area of the BSRW watershed according to the CDL data (USDA/NASS, 2016). Even through the CDL data is annually updated, it does not show a clear trend within all land uses changed by year. This might be caused by the change of the original satellite data sources and improving technology of the process of CDL data generating. Due to the accuracy of the CDL data, the cropland areas were regressed with the year using simple linear regression. The annual cropland area change was simulated as increasing of around 68 km^2 per year within BSRW, which was around 0.8% of the BSRW.

4.2.2.2 HRUs selection

After obtaining the annual increasing area of cropland, the next goal was to select the HRU change to cropland every year. The assumption was that each HRU with changeable land use has same probability to change to cropland. The crop planted on the land use change area was determined by longest adjacent boundary method. In this study, there were other two land uses and covers categories were simulated by SWAT model including the area considered as urban and wetland forest in CDL data. According to CDL data of 2016 (USDA/NASS, 2016), 15% of the BSRW area were wetland forest, while 4% of the BSRW area were urban. Due to the larger area of wetland forest compared to urban and lower accuracy toward wetland forest land in CDL data compared to cropland, land use and cover category of the wetland forest was considered as changeable area to cropland. The wetland forest category were contained the Delta National Forest that were around 4% of BSRW. Thus, to determine where the change would occur, first step was to subtract the national forest area from wetland forest category. The second step was to determine the changed area to each cropland category. There were four types of main crops considered in this study, which were soybean, corn, cotton and rice. According to the CDL data (USDA/NASS, 2016), the percentage of cropland planting soybean, corn, cotton and rice are 62.6%, 27.4%, 4.7% and 5.3%, respectively. The annual increasing cropland area was divided into four parts as the increasing area of each crop according to the current cropland ratio.

After determining how much area changed for each crop every year, the locations of changed HRUs and the crops planted on the HRUs need to be decided. In this process, the HRUs with both changeable land use category and cropland category were intersected with itself in ArcGIS in order to extract the boundary of HRUs with two different land use categories on both sides. One side was cropland with crop type, and another side was the changeable HRUs. The crop types that changeable HRUs changed to were decided by the longest shared boundary with changeable HRUs. As shown in Figure 4.2, the blue dotted line is the boundary of changeable HRUs shared with soybean field, while the maroon bold solid line was the one shared with corn field. In this case, the HRU were determined as the one would change to soybean field. If the HRU were not adjacent to a crop field, the HRU would not be mark as changeable. Figure 4.3 shows the final projected crop planted on the changeable HRUs.

The changeable HRUs were not necessary changing to crop field since the annual change area of each crop was estimated. To select the transferred HRU, Matlab was used as the tool to achieve choosing the random HRU without replacement till the target changing area of each crop reached every year. Figure 4.4 shows the selected changeable HRUs in every year from 2017 to 2022. After the HRUs were selected to be converted to cropland for each year, the crop managements of corresponding crop types were applied to the selected HRUs from 2017 to 2022. The management of a HRU began changing only after the year that the HRU were selected in Figure 4.4. In order to make the scenario comparable with the current modeling situation, the weather data used in SWAT model from 2017 to 2022 were as same as 2011 to 2016, so that the land use and cover change would be the only variable changed during simulating the scenario.

Figure 4.2 Process to determining crop planted on changeable HRUs

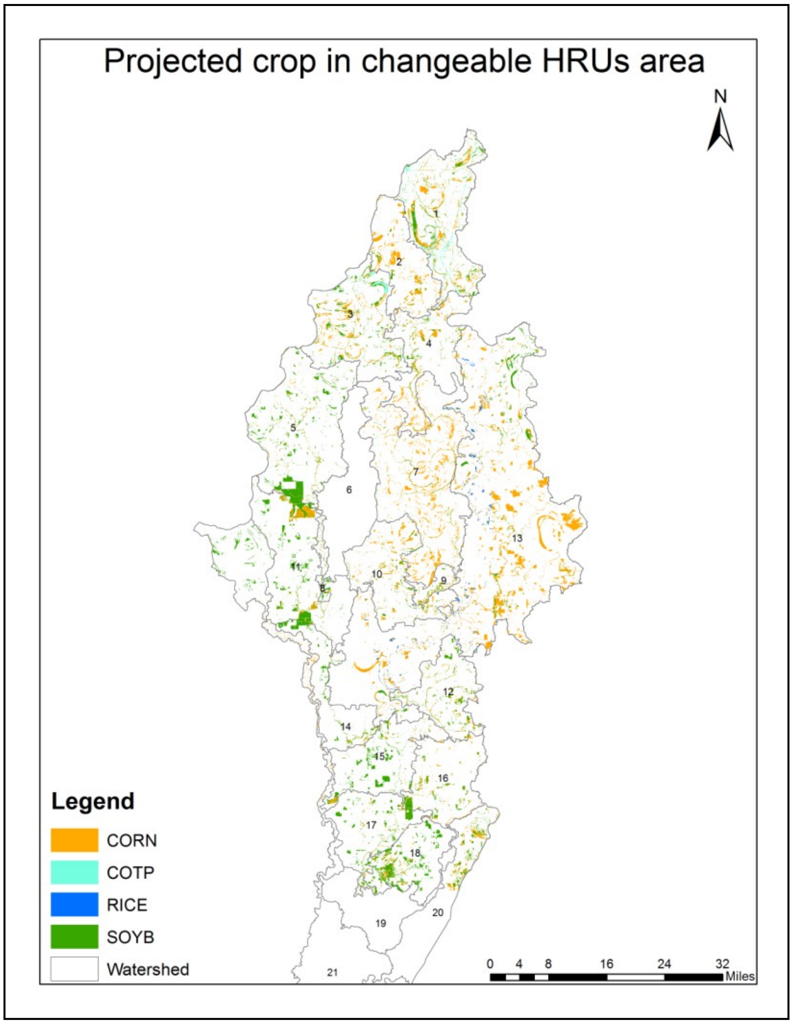

Figure 4.3 Projected crop type planted on changeable HRUs

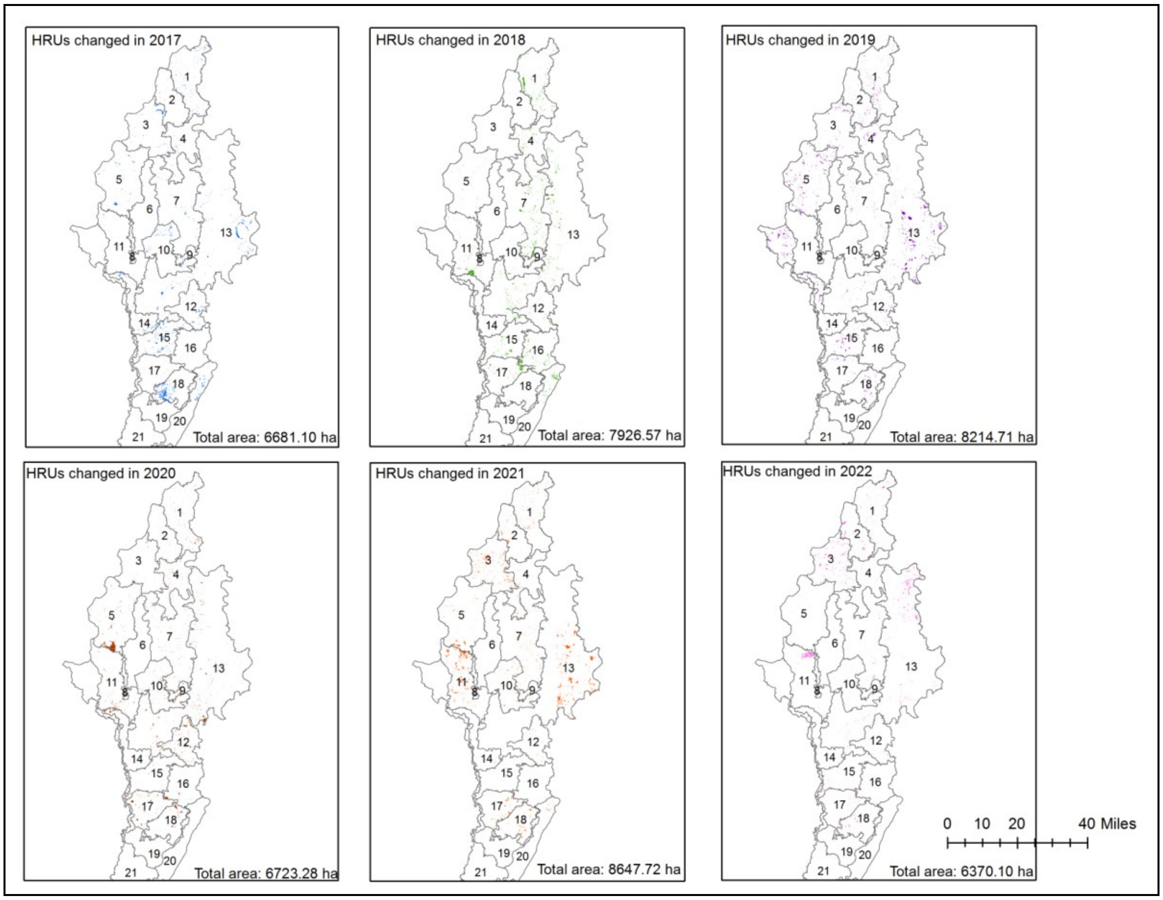

Figure 4.4 Selected changeable wetland forest HRUs converted to cropland each year

4.3 Results and discussion

4.3.1 Calibration and validation

In order to obtain the baseline situation representing current watershed condition, calibration and validation of both hydrological and water quality factors were necessary. R^2 and NSE were used for calibration in order to evaluate the model performance. In addition to R^2 and NSE, MAE and RMSE were used to evaluate the model performance during validation and water quality factors. Due to the large magnitude range of water quality factor, modified relative MAE and RMSE, shown in equation 4.1 and 4.2, used by Dash et al. (2011) were applied as evaluation coefficients instead of MAE and RMSE in this study.

Relative MAE = MAE/(maximum measured value - minimum measured value) (4.1)

Relative RMSE = RMSE/(maximum measured value - minimum measured value) (4.2)

Figure 4.5 shows the calibration and validation results of stream flow at three USGS gaging stations in BSRW from 2007 to 2016. The calibration performance was evaluated by R^2 of 0.61 and NSE of 0.6, which was considered as accepaccording to previous study in this area (Parajuli et al., 2013; Dakhlalla et al., 2016). The validation R^2s were 0.69 and 0.70 for Sunflower gaging station and Leland gaging station respectively. The relative MAEs were 10.37% and 9.94%, while the relative RMSEs are 9.16% and 13.41% for Sunflower and Leland gaging stations respectively.

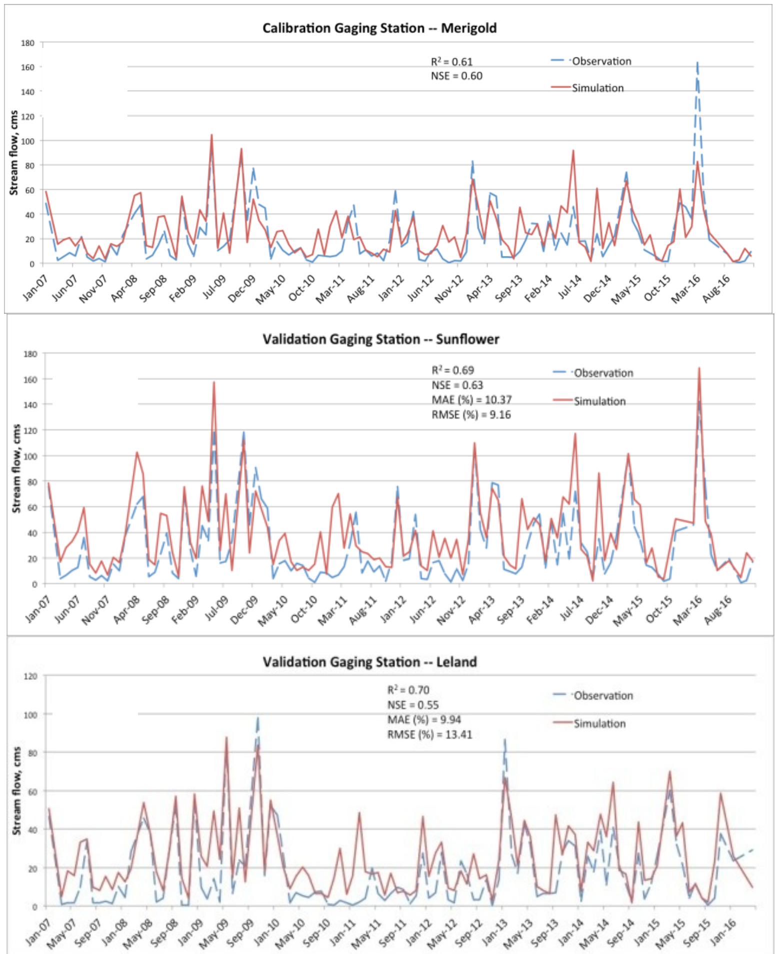

Figure 4.5 Stream flow calibration and validation results

Note: (a) Merigold (b) Sunflower (c) Leland

The statistic coefficients used to evaluate the daily water quality model from 2013 to 2015 are shown in 4.4. The R^2s for calibration were 0.46, 0.49 and 0.83 for TSS, TN and TP respectively, while for validation were from 0.56 to 0.88. The NSEs for calibration were 0.47, 0.56 and 0.45 respectively, while for validation were from 0.34 to 0.64. Due to the large magnitude of the data range, the MAE and RMSE were up to 8366 mg/L. The relative MAEs were ranged from 5% to 15% and the relative RMSE were ranged from 15% to 21%. The water quality calibration and validation performance were not as good as hydrologic calibration and validation. This might be caused by the smaller sample size of water quality dataset (Oeurng et al., 2011) compared to the stream flow dataset and the uncertainty from bi-weekly sampling frequency of the water quality monitoring (Glavan et al., 2011).

Table 4.4 Model performance for daily water quality model from 2013 to 2015

		R2	NSE	MAE (mg/L)	RMSE (mg/L)	Relative MAE	Relative RMSE
TSS	Calibration--Merigold	0.49	0.47	105.94	155.71	0.11	0.15
	Validation--Sunflower	0.57	0.44	72.08	83.82	0.15	0.18
	Validation--Leland	0.56	0.52	75.23	102.37	0.12	0.16
TN	Calibration--Merigold	0.46	0.56	267.13	484.76	0.10	0.18
	Validation--Sunflower	0.65	0.34	1658.11	4172.09	0.07	0.18
	Validation--Leland	0.75	0.50	227.26	545.69	0.07	0.16
TP	Calibration--Merigold	0.83	0.45	3331.93	8365.66	0.07	0.18
	Validation--Sunflower	0.88	0.64	2992.62	7871.56	0.05	0.12
	Validation--Leland	0.82	0.38	1021.39	2285.28	0.09	0.21

4.3.2 Downstream hydrology and water quality

In the land use change scenario, the area of HRUs selected to change to cropland was 5.4% of BSRW and the change was gradually occurred throughout the 6 comparison years. In order to evaluate the impacts of land use change scenario on BSRW watershed, the simulated parameters including stream flow rate, TSS, TN, TP, runoff, and sediment yield from land use change scenario were compared with the results of baseline scenario from 2017 to 2022. The discussion focused on the impacts occurring at the downstream outlet of BSRW and the whole watershed area instead of only at USGS gaging stations' locations and corresponding sub-basins.

Figure 4.6 shows the comparison of monthly stream flow rate between land use change scenario and baseline scenario at the watershed outlet from 2017 to 2022. There was with up to ±10% change of monthly stream flow rates through 2017 to 2022. The average monthly stream flow rate through 2017 to 2022 of the land use change scenario was slightly higher as 162 m^3/s compared to 161 m^3/s in baseline scenario.

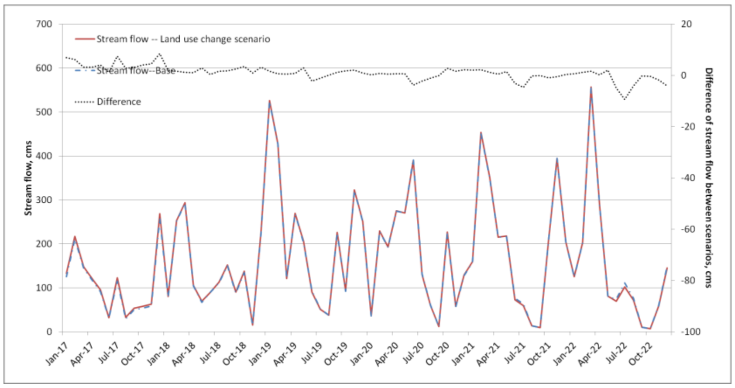

Figure 4.6 Comparison of stream flow of baseline scenario and land use change scenario at the watershed outlet 2017 to 2022

Figure 4.7 shows the comparison of total sediment concentration in stream between land use change scenario and baseline scenario at the watershed outlet from 2017 to 2022. The percentage change rate was from -3% to 25% of sediment concentration simulated based on baseline scenario. There was 1.9% increasing regarding to the average sediment concentration in land use change scenario compared to baseline scenario through 2017 to 2022. The cumulative sediment yield through 2017 to 2022 from the entire watershed in land use change scenario was on average 1.8% higher than the one in baseline scenario.

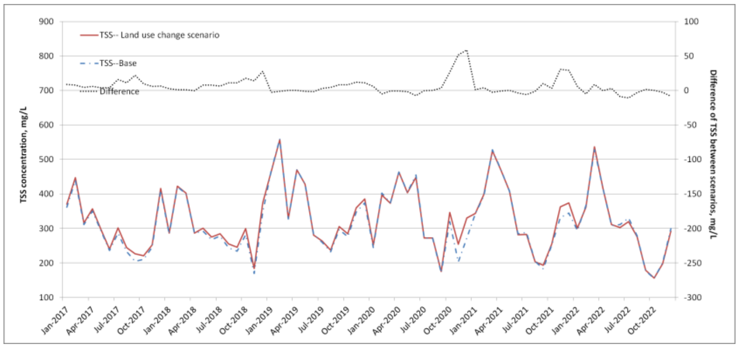

Figure 4.7 Comparison of TSS concentration of baseline scenario and land use change scenario at the watershed outlet from 2017 to 2022

Figure 4.8 (a) and Figure 4.9 (a) shows the comparison of total nitrogen and total phosphorus yield in surface runoff from the entire BSRW between land use change scenario and baseline scenario at the watershed outlet from 2017 to 2022. And the (b)s show the cumulative change through the comparison period. The percentage change rate was from -26% to 96% based on TN in surface runoff simulated in baseline scenario with the change ranged from -0.05 kg/ha to 0.22 kg/ha. The cumulative TN from 2017 to 2022 from the entire watershed was averagely 18.9 kg/ha in land use change scenario, which was 12.7% higher than the one in baseline scenario. The percentage change rate was from -1.7% to 30.2% based on TP yield in surface runoff simulated in baseline scenario with the change ranged from -1.31 kg/ha to 1.02 kg/ha. There was 10.2% increasing regarding to the cumulative TP yield in surface runoff from 2017 to 2022 in land use change scenario compared to baseline scenario. The linear trend of percentage change of both TN and TP yield in surface runoff shown in Figure 4.8 (a) and Figure 4.9 (a) indicated that there were slightly increasing trends on both factors if cropland continuously increased.

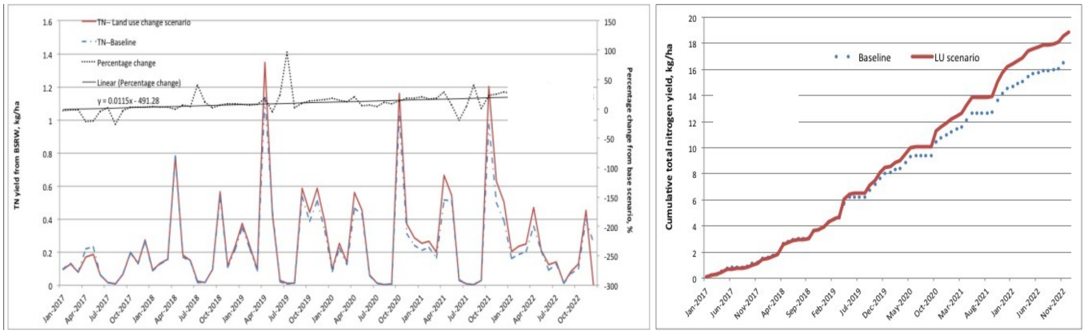

Figure 4.8 Comparison of TN in surface runoff from BSRW of baseline scenario and land use change scenario at the watershed outlet from 2017 to 2022

Note: (a) monthly TN yield (b) Cumulative TN yield

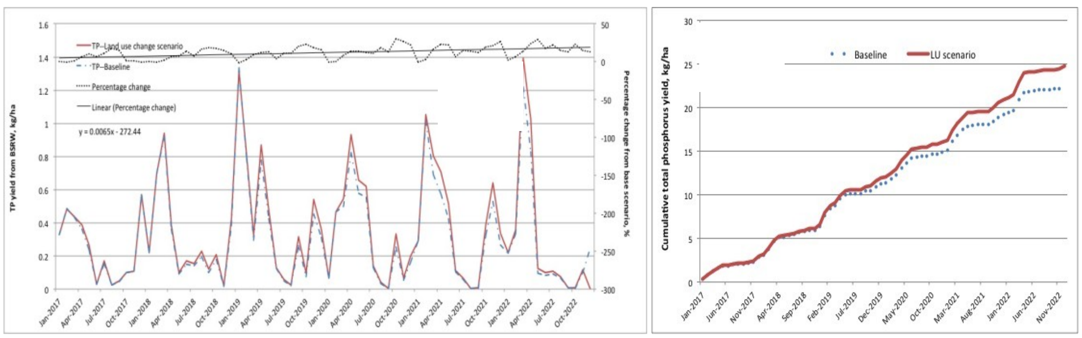

Figure 4.9 Comparison of TP in surface runoff from BSRW of baseline scenario and land use change scenario at the watershed outlet from 2017 to 2022

Note: (a) monthly TP yield (b) Cumulative TP yield

Figure 4.10 (a) shows the comparison of monthly TN yield in surface runoff from BSRW between two scenarios. The monthly average TN yields in surface runoff in land use scenario from all months were higher than the baseline scenario by 0.04% to 16.9%. The increasing of TN yield in surface water runoff was caused by the additional fertilizing operation in land use change scenario. Although there were no outstanding months with large relative percentage changes, the large increasing amount occurs in April and October with 86 mg/ha and 81 mg/ha difference. As shown in 4.1, the cornfield with 27.4% of area within land use change region was the main source of nitrogen fertilizer, which caused the high change on TN yield on April. The harvesting operation of corn occurred on September, while harvesting operation of other crops occurs on October. The nitrogen removal rates for crops were set as default based on Kiniry et al. (1995), which indicated that the nitrogen removal rate was the lowest for corn compared with other crops simulated in this study. And the corn covered around 22% of the BSRW (USDA/NASS, 2016), while other crops covered 58% of the BSRW. These 58% of the BSRW area with high nitrogen removal ability harvested on October led to a relative larger change of 81 mg/ha on TN yield in surface water runoff, which might be caused by that the harvesting operation stopped the nitrogen consuming by crops in BSRW.

For the monthly TP yield in surface runoff from BSRW, shown in Fiugre 4.10 (b), the largest yield occurred in March, while the large difference of 97 mg/ha between the two scenarios occurred in April. The percentage change based on the baseline scenario ranged from -0.8% in January to 20.3% in October. There were 62.6% of area with land use changing changed to soybean field each year. And the soybean field were fertilized with 12-22-22 (4.1) containing 9.6% mineral phosphorus (Arnold et al., 2013) in April. Thus, soybean as the dominant crop in the gained cropland was the main source of TP yield in runoff and caused the most change of TP in runoff inApril.

Figure 4.10 (c) shows the comparison between sediment yields from BSRW in two scenarios. Before crop growning season, the sediment yield from BSRW in land use change scenario was on average 5.7% less than the one in baseline scenario, while the trend inversed after May. From July to December, the sediment yield in land use scenario was increasedby 10% to 95% compared tothe baseline scenario with the original land use of wetland forest. The average monthly sediment yield in land use change scenario ranged from 97 kg/ha to 835 kg/ha, which the one in baseline scenario ranged from 49 kg/ha to 896 kg/ha. From the annual monthly sediment yield throughout 6 years, there was no regularity among different years regarding to monthly sediment yield change. Thus, the smaller range of the sediment yield in the land use change scenario might caused by randomness of selecting HRUs location, whichwould cause the uncertainty of selecting different soil type with varies of eroson factors.

The land use change affect less on monthly average surface runoff compared to the impacts on total TN and TP yield in surface runoff and sediment yield (Fiugre 4.10. (d)). The percentage change ranged from -1.7% to 1.6% of the runoff in baseline scenario. The differences of runoff raged from -0.68 to 0.7 mm.

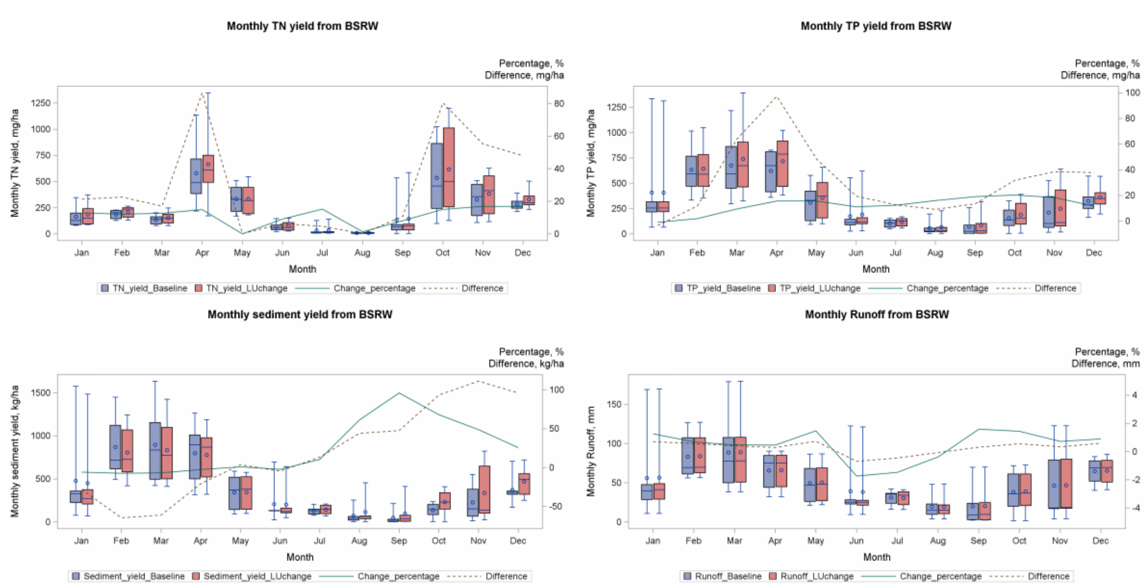

Figure 4.10 Monthly TN and TP in surface runoff, sediment yield and runoff from BSRW comparison between land use change scenario and baseline scenario

Note: (a) monthly TN yield in surface runoff from BSRW; (b) monthly TP yield in surface runoff from BSRW; (c) monthly sediment yield from BSRW (d) monthly runoff from BSRW

4.4 Conclusion

This study provided a process to random select HRUs applied in land use change scenario, which was suifor an agricultural domain watershed to evaluate the hydrological impacts by the land use change. The method involved combining the land use change availability and spatial relationships between the changeable HRUs and original land use HRUs. Taking advantages of the comprehensive crop management setting in SWAT model, the scenario could represent the land use change through 6 years. A comprehensive calibration of hydrologic and water quality parameters were presented in this study. The model calibrated using selected sub-basins and applied to the whole watershed for validation with accepR^2 and NSE compared to literatures.

The scenario comparison indicated that there were significant impacts on TN and TP yield in the runoff from BSRW. There was 1.9% increasing regarding to the average sediment concentration at BSRW outlet in land use change scenario compared to baseline scenario with percentage change rate from -3% to 25%. There were 12.7% and 10.2% increasing regarding to the cumulative TN and TP yield in surface runoff in land use change scenario respectively through 2017 to 2022. This indicated that indicated that there were slightly increasing trends on both factors if cropland continuously increased. For the monthly average TN and TP yield in surface runoff from BSRW, the impact factors were the cropland management operations including fertilization and harvesting. The results of monghly average sediment yield transported to stream showed a smaller range of simulated monthly sediment yeild in land use change scenario, while the evidence was not strong in monthly sediment yield throughout the comparison period through 2017 to 2022. The conservative of the land use change scenario might caused by randomness of selecting HRUs locations, which would cause the uncertainty of selecting different soil type with varies of eroson factors. The land use change affected less on monthly average surface runoff compared to the impacts on TN and TP yield in surface runoff and sediment yield. However, the modeling peroid should be longer in order to obtain the evidence of the impacts on stream flow and the sediment yield changing trend.

CHAPTER V

COMPARISON OF BEST MANAGEMENT PRACTICES SIMULATION USING SWAT AND ANNAGNPS

5.1 Introduction

With the deeper understanding of watershed mechanisms, various modeling tools were developed to simulate the physical hydrological processes in watershed scale. Each watershed model has its' emphasis on different aspect. For example, TR-55 (NRCS, 1986) and TR-20 developed by Natural Resources Conservation Service (NRCS) are classic watershed runoff models for single event focusing on small urban watershed runoff simulation. Hydrologic Modeling System (HEC-HMS) (Feldman, 2000) developed by The United States Army Corps of Engineers Hydrologic Engineering Center is a runoff modeling tool with options of varies methods for simple continuous modeling.

In order to choose appropriate tool to simulate target watershed, understanding the characteristics of the watershed and the study objectives are the essential. The Big Sunflower River Watershed (BSRW), as the target watershed in this study, is a major sub-basin of Mississippi Delta region that was known for the intensive crop production (Parajuli and Jayakody, 2012). About over 80% of the area covered by crops according to Crop Data Layer (CDL) data from USDA (USDA/NASS, 2016). Crop production activities have potential impacts on the surface water quality and quantity of the watershed (Ayers and Westcot, 1985; Shipitalo and Edwards, 1998; Vaché et al., 2002). To improve watershed management and prevent the impacts of agricultural activities on environment, Best Management Practices (BMPs) were applied in this area over last several decades. In order to simulate BMPs impacts on watershed hydrology, the selected modeling tool is needed to have both hydrologic and agricultural activities factors. Soil and Water Assessment Tool (SWAT) is a process based watershed modeling tool focusing on an agricultural region with comprehensive modules to simulate agricultural activities such as tillage operation and crop rotation (Kirsch et al., 2002; Arabi et al., 2008; Neitsch et al. 2011). Annualized Agricultural Non-Point Source Pollution Model (AnnAGNPS), as another relative user friendly watershed modeling tool emphasizing on agricultural homogeneous area, has abilities modeling BMPs such as conservational tillage (Yuan et al., 2001; Bingner et al., 2015). Thus, as two comprehensive agricultural watersheds modeling tools, SWAT and AnnAGNPS were applied in this study to simulate BMPs in order to demonstrate the differences and consistency of the results.

Comparisons among watershed models were conducted by previous studies. Van Liew et al. (2003) compared the performance of HSPF and SWAT on runoff simulation in an agricultural watershed by comparing the performances of the stream flow rate simulation in varies time scales from the two models evaluated by deviation, coefficient of efficiency and prediction efficiency. The results showed different performances observed in different simulated watershed. SWAT was a more robust model than HSPF. Nasr et al. (2007) compared SWAT with HSPF and Systeme Hydrologique Europeen TRANsport (SHETRAN) on total phosphorus (TP) yield simulation by comparing the results with observations. As a conclusion, they recommended SWAT as the tool to estimate TP yield. Parajuli et al. (2009) compared the performances of SWAT and AnnAGNPS evaluated by coefficient of determination (R^2), Nash–Sutcliffe model efficiency coefficient (NSE), root-mean-square error (RMSE), RMSE-observations standard deviation ratio (RSR), and percentage bias (PBIAS). They also summarized the differences in methods used to simulate same physical process in two models. Both model had fair to good performance simulating stream flow rate and sediment yield. The previous studies were mainly focus on comparing the performance among models. Performances of different models indicate the ability to simulate watershed condition, which are important for choosing appropriate models for a specific application. After selecting an appropriate model for a specific application, making decisions based on the scenario simulations is the next step. Thus, the evaluations of the results from concerned scenarios from different models are necessary. In this study, the main objective was to compare the results and verify if the conclusions were consistent from a different model. The specific objectives included (i) demonstrating the performances of SWAT and AnnAGNPS comparing with observations over stream flow and water quality factors, (ii) comparing the results of scenarios from SWAT and AnnAGNPS, (iii) demonstrating the differences and consistency of the results of scenarios of SWAT and AnnAGNPS

5.2 Material and method

5.2.1 Model parameters

To ensure that two models were comparable, the same input data were applied in both models including Digital Elevation Model (DEM) (USGS, 1999), soil type from SSURGO database (USDA, 2005), land use and cover data from the Crop Data Layer (CDL) database (USDA/NASS, 2016) and climate information including precipitation, temperature, solar radiation, wind speed, and relative humidity from Climate Forecast System Reanalysis (CFSR) database (NCDC, 2016) and Global Historical Climatology Network (GHCN)–Daily database (NOAA, 2016). The crop management is shown in 4.1 according to Parajuli et al. (2013) and MS Agricultural and Forest Experiment Station (MAFES) annual report (MAFES, 2000-2014).

There were some similar methodologies used in modules in both models describing same physical procedure. Both model used Soil Conservation Service (SCS) curve number (SCS, 1985) based method to simulate runoff (King et al., 1999; Parajuli et al., 2009) and Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978) based method to simulate sediment yield (Borah and Bera, 2003; Parajuli et al., 2009). For those parameters (shown in 5.1) involved in both models were kept consistent as inputting to both models.

5.2.1.1 SWAT model

The BSRW was divided into 22 sub-basins based on surface elevation in SWAT model. The sub-basins were further divided into 1799 Hydrology Respond Units (HRUs) based on soil type, land use type and slope length. The soil type with area less than 5% of sub-basin area would not be simulated in this study. Similar for land use type and slope length, the thresholds were 1%, and 5% of sub-basin area respectively. The calibration process included auto and manual calibration. The auto-calibration program, SWAT-Cup SUFI2, was used to obtain the final fitted values of parameters resulting in the highest R^2 and NSE from comparing the simulated results and monthly stream flow, total nitrogen (TN), total phosphorus (TP) and total suspended sediment (TSS) measured at the USGS gaging station locations. Manual calibration based on the Soil Conservation Service

(SCS) curve number method (NRCS, 1986) was applied after auto-calibration of hydrologic model. The calibrated hydrological parameters were later applied to a daily SWAT model of BSRW from 2013 to 2015 in order to calibrate the water quality parameters in the modeling area.

5.2.1.2 AnnAGNPS model

The BSRW was divided into 193 cells as the modeling units in the subsequent simulation in AnnAGNPS based on surface elevation by TopAGNPS. The spatial data including soil type, weather stations and land use and cover were summarized as the majority and inputted to each cell. The modeling areas of both models are shown in Figure 5.1.

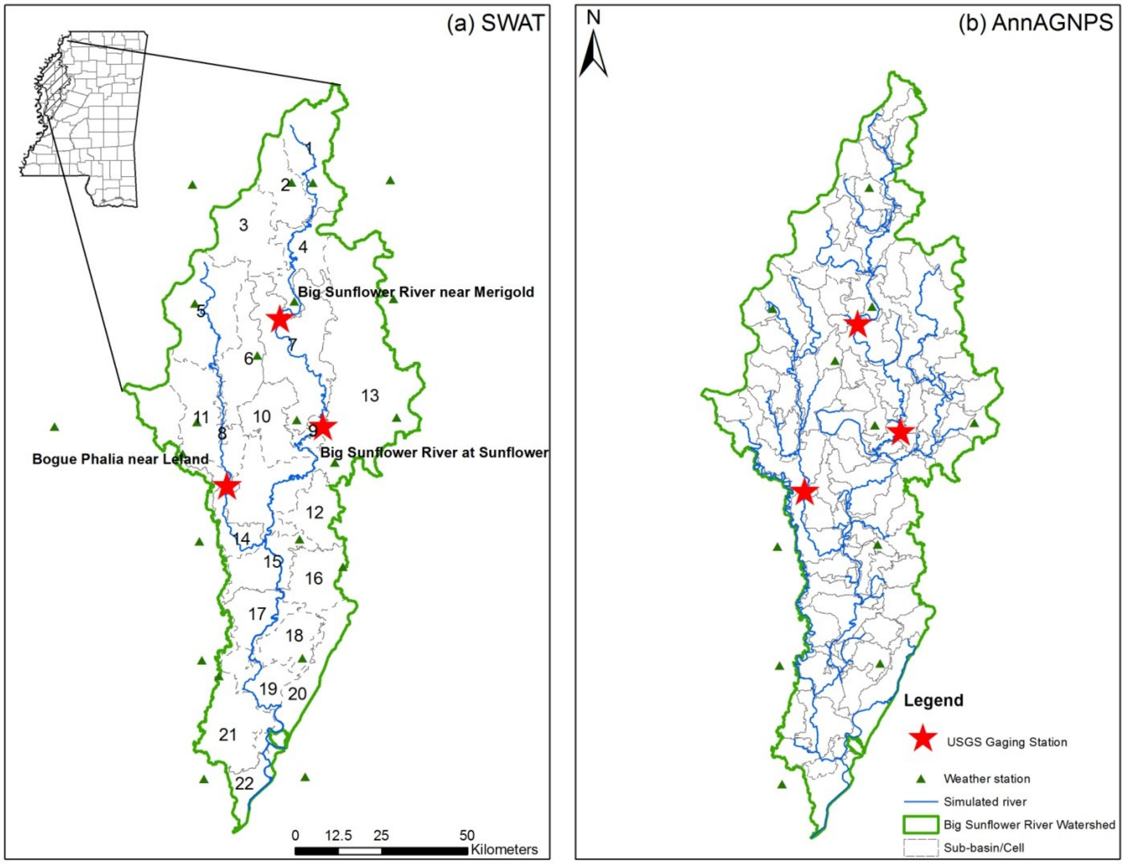

Figure 5.1 Study area in SWAT and AnnAGNPS model

Note: (a) SWAT and (b) AnnAGNPS

5.2.2 Scenarios

In this study, two kinds of BMPs of conservation tillage operation and crop rotations and one land use change scenario were evaluated by using SWAT and AnnAGNPS in BSRW. Both SWAT and AnnAGNPS are models designed emphasizing on agricultural field hydrology and water quality. Tillage managements and crop rotations from study 1 and land use change from study 3 were selected to be simulated using both models in order to compare the consistency and differences of the results from two models. In tillage scenario, conventional tillage and conservation tillage managements were simulated by mainly changing curve number, which was described in study 1. Crop rotation scenarios included continuous corn (CC), continuous soybean (SS) and corn and soybean rotation (CS) scenarios, which were simulated by converting all crop fields to CC, SS or CS, respectively. Land use change scenario simulated in study 3 was simplified in AnnAGNPS due to the modeling units (cells) in AnnAGNPS were much larger and unified than HRUs in SWAT. The trend used in both model were same, which is 68 km^2/year increase of crop fields from 2017 to 2019, but the locations were varied. The land use change cell selection in AnnAGNPS was mainly based on the size of the cells with changeable land use as considered in SWAT that was close to the target changing land use area.

5.2.3 Calibration and validation

Both models were calibrated by two steps based on the hydrological and water quality parameters. Coefficient of determination (R^2) and Nash–Sutcliffe model efficiency coefficient (NSE) were used in order to evaluate the model performance. For the hydrological model, final fitted values of parameters were determined as those resulting in highest R^2 and NSE from comparing the simulated monthly stream flow and USGS gaging station data from 2007 to 2016. The daily output from both models were compared with measured water quality data including total nitrogen (TN), total phosphorus (TP) and total suspended sediment (TSS) obtained every two weeks at three USGS gaging stations in BSRW from 2013 to 2015 in order to calibrate water quality related parameters. In order to take advantage of the limit number of water quality data, the Merigold station was used to calibrate the model from 2013 to 2015, while Sunflower and Leland were served as validation stations. For hydrologic model calibration and validation, the calibration period was from 2007 to 2011, while the validation period was from 2012 to 2016 for all three USGS gaging stations.

In SWAT model, parameters used in study 3 were applied in this study. The calibrated parameters and their fitted values of both models are shown in 5.1. Other parameters were set as default of both models.

Table 5.1 Calibration parameters in both SWAT and AnnAGNPS model

Description	SWAT		AnnAGNPS	
	Parameters	Fitted value	Parameters	Fitted value
Soil evaporation compensation factor	ESCO	0.54		
Base flow recession constant	ALPHA_BF	0.68		
Delay of time for aquifer recharge	GW_DELAY	93.28	Delay Time	93.28
Manning's coefficient for the main channel	CH_N2	0.01	Reach Manning's n	0.01
Deep aquifer percolation coefficient	RCHRG_DP	0.47		
Groundwater returning to zoot zone coefficient	GW_REVAP	0.17		
Threshold water level in shallow aquifer for base flow	GWQMN	884.56		
Plant uptake compensation factor	EPCO	0.9		
Surface runoff lag coefficient	SURLAG	9.36		
Threshold water level in shallow aquifer for revap	REVAPMN	261.81		
SCS curve number	CN2	68--93	Runoff curve number	68--93
Channel erodibility factor	CH_COV1	0.19		
Channel cover factor	CH_COV2	0.21		
USLE equation soil erodibility (K) factor	USLE_K	0.04--0.39	USLE K factor	0.04--0.39
Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	SPCON	0.004		
Channel erodability factor	CHERODMO	0.6		
Watershed-scale calibration factors from sediment sources			Sediment calibration factor	15--70
Organic N enrichment ratio	ERORGN	0.32		
Organic nitrogen concentration in the channel (ppm)	CH_ONCO	14.7		
Rate coefficient for organic N settling in the reach	RS4	0.09		
Rate constant for biological oxidation of NH4 to NO2 in the reach	BC1	0.18		

Table 5.1 Calibration parameters in both SWAT and AnnAGNPS model (continued)

Rate constant for biological oxidation of NO2 to NO3 in the reach	BC2	1.82		
Rate constant for hydrolysis of organic N to NH4 in the reach	BC3	0.31		
Concentration of nitrogen in rainfall	RCN	1.78		
Nitrogen uptake distribution parameter	N_UPDIS	98.57		
Nitrogen percolation coefficient	NPERCO	0.74		
Nitrogen uptake per yield unit			N Uptake	0.04--1
Phosphorus uptake per yield unit			P Uptake	0.08--0.63
Phosphorus sorption coefficient	PSP	0.44		
Organic P enrichment ratio	ERORGP	4.88		
Rate constant for mineralization of organic P to dissolved P in the reach	BC4	0.07		
Organic phosphorus settling rate in the reach	RS5	0.01		
Phosphorus uptake distribution parameter	P_UPDIS	1.57		
Phosphorus percolation coefficient	PPERCO	16.43		
Organic phosphorus concentration in the channel (ppm)	CH_OPCO	17.9		
Phosphorus percolation coefficient	PPERCO_SUB	16.54		
Watershed-scale calibration factors from phosphorus sources			Phosphorus calibration factor	1--5

5.3 Results and discussion

5.3.1 Calibration and Validation

The calibration results of hydrologic models showed satisfactory to good performance for both models (Moriasi et al., 2015), shown in 5.2. The SWAT model showed higher R^2 and similar NSE value compared to AnnAGNPS. The similar results were predicsince both model used SCS curve number (SCS, 1985) based methods to estimate runoff that were the major source of stream flow (Bingner et al., 2015; Neitsch et al., 2011). 5.3 shows the TN, TP and TSS calibration and validation results from SWAT and AnnAGNPS. For sediment, both models gave satisfactory performances according to Moriasi et al. (2015) evaluated by R^2 and NSE around 0.5. Both model used USLE based methods (Bingner et al., 2015, Neitsch et al., 2011) to estimate sediment yield, which was a wide-used method to simulate sediment in an agricultural watershed (Nelson and Booth, 2002). SWAT model gave accepperformance for predicting TN and TP. R^2s were from 0.46 to 0.75 and 0.82 to 0.83 for TN and TP respectively. NSEs were from 0.34 to 0.56 and 0.38 to 0.64 for TN and TP respectively. AnnAGNPS could predict the trend of TP through 2013 to 2015 with R^2 of 0.22 for calibration and 0.34 for validation at Leland station, but with unsatisfactory performance at Sunflower station. NSEs used to evaluate the bias of the model were from -0.41 to 0.23, which indicated AnnAGNPS was performed as a biased model (McCuen et al., 2006) in this study predicting TP. For TN prediction, AnnAGNPS did not give accepresults at any of the USGS gaging stations. The performances of predicting TN and TP in AnnAGNPS were close to the reported results in Parajuli et al. (2009). For TN and TP simulation, the methods used in SWAT and AnnAGNPS were different regarding to the sources and routing process simulation (Parajuli et al., 2009). The method used in SWAT is more comprehensive than the method used in AnnAGNPS. The number of parameters used to describe the simulation process is also larger than in AnnAGNPS.

Table 5.2 Stream flow calibration and validation performance for SWAT and AnnAGNPS

	SWAT		AnnAGNPS	
	R2	NSE	R2	NSE
Calibration--Merigold	0.71	0.65	0.54	0.48
Calibration--Sunflower	0.67	0.46	0.56	0.50
Calibration--Leland	0.75	0.60	0.57	0.59
Validation--Merigold	0.53	0.51	0.49	0.48
Validation--Sunflower	0.76	0.61	0.59	0.52
Validation--Leland	0.66	0.44	0.46	0.38

Table 5.3 Water quality calibration and validation for SWAT and AnnAGNPS

		SWAT		AnnAGNPS	
		R2	NSE	R2	NSE
TSS	Calibration--Merigold	0.49	0.47	0.52	0.48
	Validation--Sunflower	0.57	0.44	0.52	0.50
	Validation--Leland	0.56	0.52	0.49	0.48
TP	Calibration--Merigold	0.83	0.45	0.22	-0.02
	Validation--Sunflower	0.88	0.64	0.003	-0.41
	Validation--Leland	0.82	0.38	0.34	0.23
TN	Calibration--Merigold	0.46	0.56		
	Validation--Sunflower	0.65	0.34		
	Validation--Leland	0.75	0.50		

The comparison among SWAT, AnnAGNPS and observations at Sunflower gaging station is shown in Figure 5.2. The average monthly stream flow from SWAT was 38.9 cms, while it was 29.1 cms from AnnAGNPS and 28.5 cms for observation. The R^2 in SWAT simulation were higher than AnnAGNPS, while NSEs were similar. With using same curve number for homogeneous modeling unit with same land use and soil type, the differences might be resulted from the different modifications of SCS curve number methods used to simulate runoff in SWAT and AnnAGNPS. AnnAGNPS considered the retention parameter that is an important parameter in SCS curve number method varies with soil moisture content, while SWAT considered the retention parameter varies with plant potential evapotranspiration in addition to soil moisture content (Bingner et al., 2015, Neitsch et al., 2011).

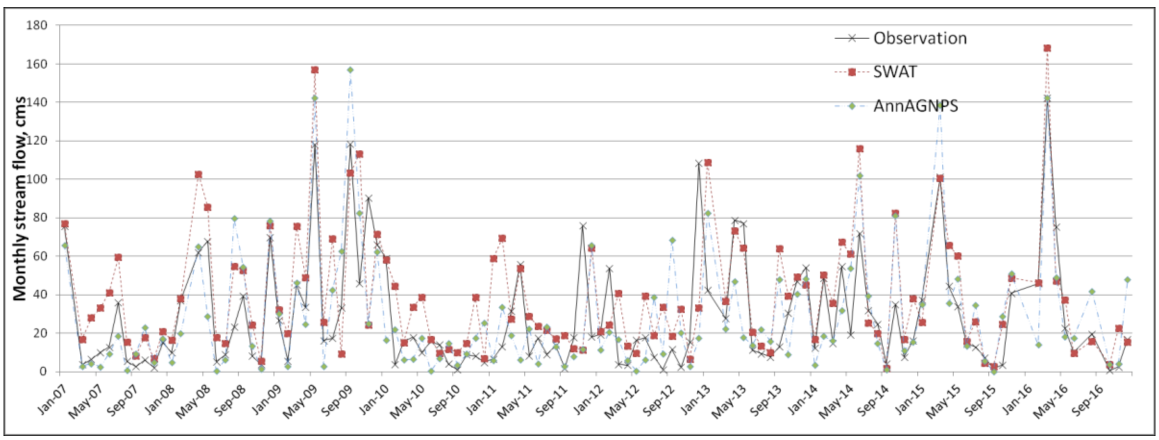

Figure 5.2 Baseline comparison between SWAT and AnnAGNPS at Sunflower gaging station

5.3.2 Scenarios comparison

In order to obtain comparable results for different scenarios between SWAT and AnnAGNPS, the comparison were conducted at three USGS gaging stations where the baseline scenario was compared with observations during calibration and validation processes. Figure 5.3 shows the scenario comparisons between conventional tillage and conservational tillage from SWAT and AnnAGNPS at three USGS gaging stations. The change variation among three stations were small with average reduction of monthly stream flow of 43%, 42% and 32% for Merigold, Sunflower and Leland respectively in AnnAGNPS, and 12%, 11% and 13% in SWAT. Both model showed the reduction of stream flow in conservational tillage comparing with conventional tillage. The stream flow was more sensitive to changed curve number in AnnAGNPS than in SWAT. This might be caused from the difference between modeling units in two models. The modeling units in AnnAGNPS were depended on the surface elevation, while the modeling units in SWAT were depended on the combination of land use, soil type and slope length. SCS curve number method calculate runoff by considering the different infiltration conditions of land cover, soil group and land treatment (SCS, 1985) Thus the modeling units in SWAT were more compatible with SCS curve number method. The majority of land use and soil type of the modeling units were applied in AnnAGNPS. This caused that changing of curve number might be not compatible with the tillage management occurring on the cropland.

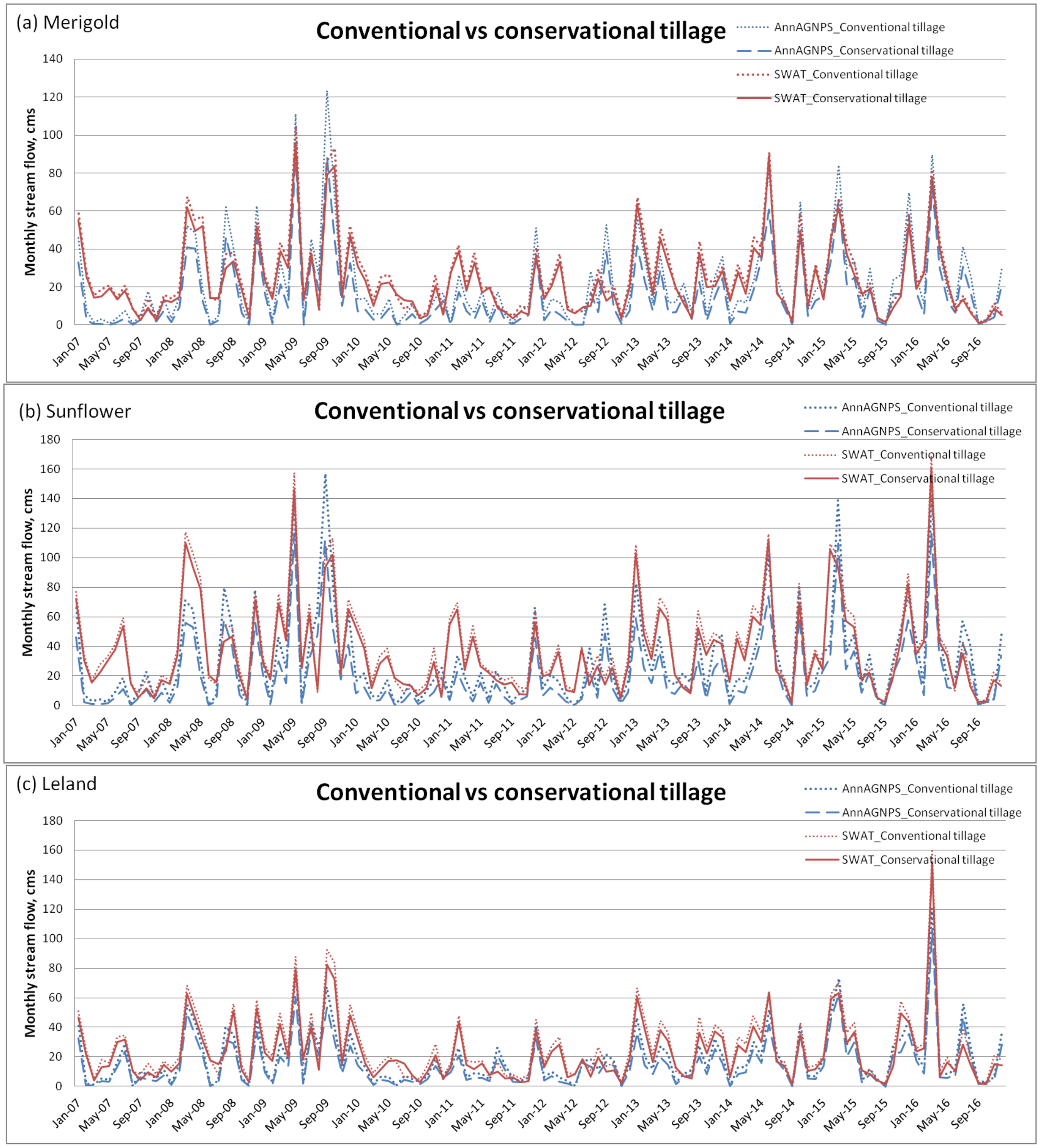

Figure 5.3 Conventional tillage and conservational tillage monthly flow comparison between SWAT and AnnAGNPS

Note: (a) Merigold (b) Sunflower (c) Leland

Figure 5.4 shows the impacts of conventional tillage and conservational tillage on cumulative sediment yield at Sunflower station. The changes within three gaging stations were similar. The sediment yields at the end of simulation were reduced by 7% and 13% in AnnAGNPS and SWAT, respectively. The change in sediment yields in SWAT was more sensitive than in AnnAGNPS. SWAT used MUSLE (Williams, 1975), while AnnAGNPS used RUSLE (Renard et al., 1997) and HUSLE (Theurer and Clarke, 1991). Both models used USLE-based methods, but with different power and weight of factors used in USLE method. This might result in the differences during scenario analysis, though the calibration and validation results of baseline scenario evaluated by R^2 and NSE were close.

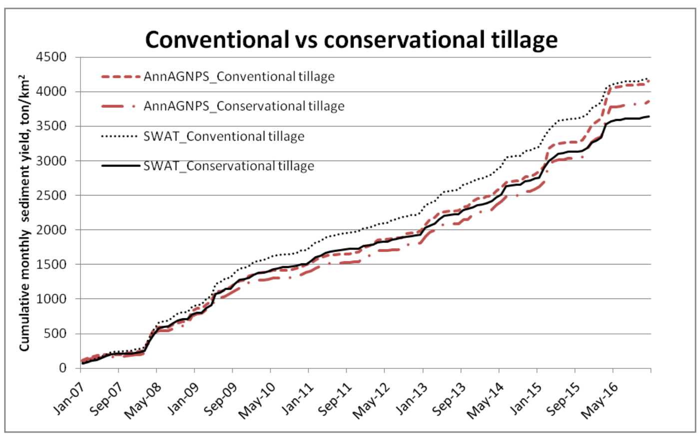

Figure 5.4 Conventional and conservational tillage comparison of cumulative monthly sediment yield between SWAT and AnnAGNPS at Sunflower station

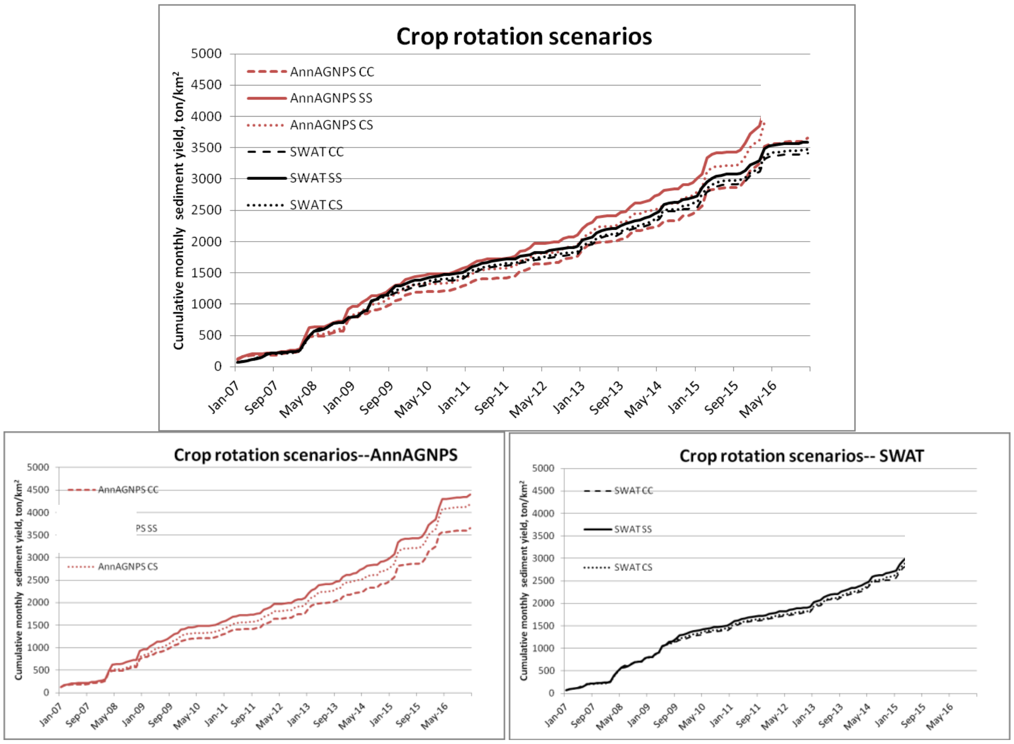

Figure 5.5 Cumulative monthly sediment yield from crop rotation scenarios of SWAT and AnnAGNPS at Sunflower station

Note: CC: continuous corn, SS: continuous soybean, CS: corn/soybean rotation (a) model comparison (b) AnnAGNPS (c) SWAT

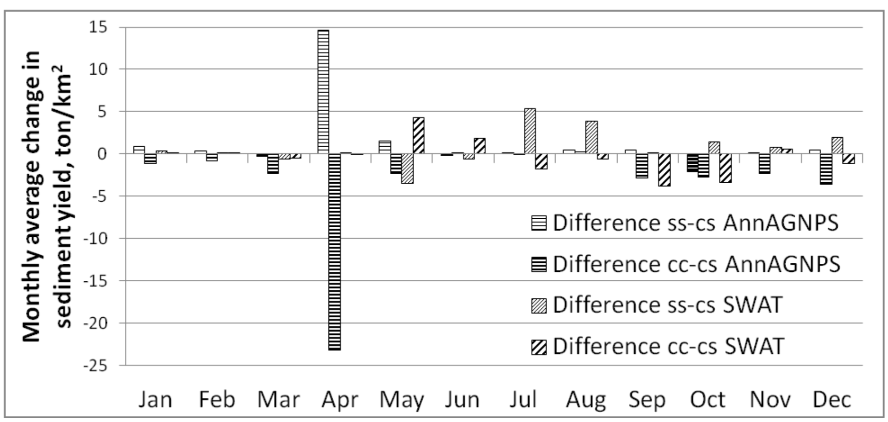

Figure 5.6 Monthly average change in sediment yield comparison of SWAT and AnnAGNPS

Note: CC: continuous corn, SS: continuous soybean, CS: corn/soybean rotation, Difference: difference between scenarios, ss-cs: results from SS subtract results from CS, cc-cs: results from CC subtract results from CS

Figure 5.5 shows the cumulative monthly sediment yield simulated in crop rotation scenarios in SWAT and AnnAGNPS at Sunflower station. The changes simulated by SWAT of cumulative monthly sediment yield at the end of simulation were 5% in SS and 2% in CS increase comparing with CC. The changes simulated by AnnAGNPS were 20% in SS and 14% in CS increase comparing with CC. Figure 5.6 shows the monthly average change in sediment yield in SWAT and AnnAGNPS. The changes occurred in different months in two models. In AnnAGNPS, the changes occurring mainly in April were mainly caused by the change of time of the tillage operations. The tillage operation of corn field occurred in February and March, while it occurred in March and April in soybean field, which discussed in study 1. The changes in SWAT mainly occurred in crop growing season from May to October, which was caused from the difference of management schedule of crop rotation scenarios and different crop parameters as C factor used in USLE method. Thus, the sediment simulation in AnnAGNPS was more sensitive to the temporal curve number change than SWAT, while the crop properties affected sediment simulation more in SWAT.

Because of the modeling unit difference between SWAT and AnnAGNPS, the modeling area were more homogeneous in AnnAGNPS than in SWAT. This caused the changeable modeling unit of two models in land use change scenario with different locations. In this case, the comparison of land use scenario between two models conducted at the outlet of the watershed instead of USGS gaging stations. Figure 5.7 shows the comparison of stream flow affected by land use change scenario for both models. For SWAT model, there was up to ±10% change of monthly stream flow rates through 2017 to 2019. For AnnAGNPS model, the change was from -66% to 600%

between land use change scenario and baseline scenario. The higher impacts in AnnAGNPS model were resulted from that the cell size was larger than HRUs and the locations difference among two land use change scenario. The cell with changed land use in AnnAGNPS was determined by the closest area with land use change HRUs in SWAT model. However, due to the cell size, the total area with changed land use was larger than total HRUs with changed land use area in SWAT. The land use change regions were located at the downstream of the watershed in AnnAGNPS, while the land use change regions were distributed more evenly across the watershed. These also affected the large change of cumulative sediment yield in AnnAGNPS. The cumulative sediment load at the end of simulation was increased 85% in land use change scenario compared to the baseline scenario, while this number was only 3% in SWAT model. The SWAT model, due to its flexibility of choosing modeling unit with land use change, was more appropriate for simulating land use change in an agricultural watershed. However, results from both models showed the increasing trend of flow and sediment.

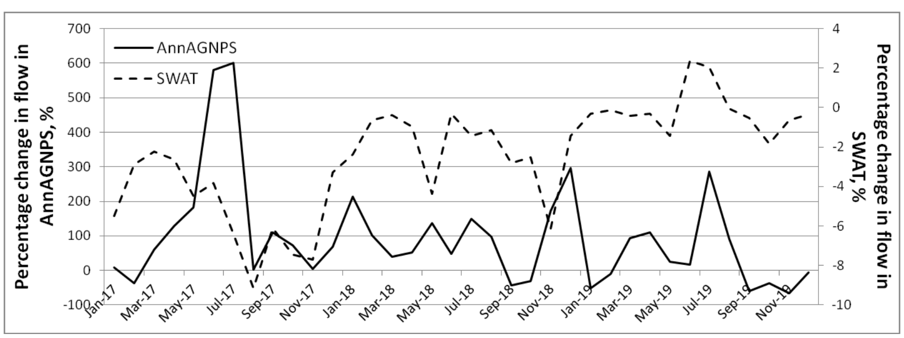

Figure 5.7 Land use change scenario comparison of percentage change in flow between SWAT and AnnAGNPS

5.4 Conclusion

Both SWAT and AnnAGNPS gave accepstream flow and sediment results during calibration and validation processes in modeling time period. The ability of modeling nutrients in SWAT was better than AnnAGNPS. With the similar inputs in two models, the result showed that the simulated stream flow and sediment varied with scenarios due to the different modifications of the SCS and USLE methods applied in SWAT and AnnAGNPS. For tillage scenarios, both model showed the reduction of stream flow in conservational tillage compared to conventional tillage. The change in sediment yields in SWAT was more sensitive than in AnnAGNPS in tillage scenarios because of the differences of the methods used to simulate sediment. For crop rotation scenarios, both model showed CC had lowest sediment yield, while the highest sediment yield was simulated in SS scenarios. But the reasons varied with models. In AnnAGNPS, the changes were mainly caused by the change in schedules of the tillage operations, while the changes in SWAT mainly occurred in crop growing season. The sediment simulation in AnnAGNPS was more sensitive to the temporal curve number change than SWAT, while the crop properties affected sediment simulation more in SWAT. The results of both stream flow and sediment were more sensitive to temporal and quantitative curve number in AnnAGNPS than in SWAT. In land use change scenarios, the impacts in AnnAGNPS model were higher than in SWAT model, which may be resulted from the differences in land use change regions' locations caused by the difference in modeling units between SWAT and AnnAGNPS. This also affected the large change of cumulative sediment yield in AnnAGNPS. Because of the flexibility of changing land use in small region in SWAT, SWAT is more suias the tool to modeling land use change.

The conclusions were consistent of all scenarios, comparing to study 1 through 3. However, the changes in magnitude were different. Both models have ability to model BMPs including tillage management and crop rotations, but the modeler need to pay attention to the different responds from different models. SWAT and AnnAGNPS have different sensitivities to the parameters and inputs. Even with the similar conclusions, the effect of the factors on results may vary. More studies need to be conducted focusing on the comparison of parameters sensitivities in each scenario.

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