12-2015

SWAT Model Simulation of Bioenergy Crop Impacts on Water Quality in Cache River Watershed

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SWAT Model Simulation of Bioenergy Crop Impacts on Water Quality in Cache River Watershed

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in Biological Engineering

By

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Bachelor of Technology in Agricultural Engineering, 2013

December 2015
University of Arkansas

This thesis is approved for recommendations to the Graduate Council.

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Abstract

Energy security through increased biofuel production is one of the components of the Energy Independence and Security Act (EISA) 2007. As per EISA 2007 mandate**,** appropriate independent research institutes are required to assess concerns to natural biodiversity due to biofuel production and report it to the Congress through the Environment Protection Agency (EPA). Planners, researchers, and agencies concerned with environmental regulations, ideally, would like to have location-specific information about the impacts for developing appropriate management interventions. This study examines long-term impacts on water quality in response to targeted (i.e. marginal lands) production of biofuel crops by setting up two SWAT models. One of the SWAT model was set-up using typical modeling practice i.e. by using a single land use layer, whereas, the second SWAT model was set-up by incorporating dynamic land use change data. The Cache River Watershed in Arkansas, a watershed selected for Biomass Crop Assistance Program (BCAP) by the United States Department of Agriculture (USDA), was used for this case study. The crops of interest were Giant Miscanthus (*Miscanthus x giganteus*) and Switchgrass (*Panicum virgatum L*). Results indicated that sediment, total phosphorus and total nitrogen loadings decreased at the watershed outlet when these crops were cultivated on marginal crop lands thereby making them potentially useful for improving water quality in Cache River Watershed.

Acknowledgements

My academic journey would not have been completed without the help and unwavering support of some wonderful people.

Dr. Dharmendra Saraswat, you have always inspired me to become an independent researcher along with the power of critical thinking. Thank you for all that you have done to me.

Dr(s) Thomas Costello and Andy Pereira, many thanks for serving on my research committee, for all your time, supporting and guiding me all this while. Arkansas High Performance Computing Center (AHPCC), Dr. Pawel Wolinski and Mr. Bruce Gorham requires a special mention for helping and providing me with resources that sailed through tough computational components of this research work.

To my friends, for all the joy and happiness, this journey would have been incomplete without you all, especially Gurdeep, for helping and accompanying me till wee hours in office. Mansoor, thanks are also due to you for providing quick solutions to my questions. Priyanka and Pooja, thank you for listening and offering me advice all the time.

Mom, Dad and my sister, Richa, I am the most fortunate one to have such a wonderful family, grateful to you all for being by my side in my endeavors.

BAEG staff and our department chair: Dr. Lalit Verma, thanks for all the support. Linda no words can express my heartfelt gratitude towards you. Thanks are also due to the Arkansas Natural Resource Commission (ANRC) for providing financial assistance for this research work.

Dedication

To my family heritage.

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I. INTRODUCTION

1.1 Problem Statement

The United States Energy Independence and Security Act (EISA) 2007 was enacted to bring energy security through increased biofuel production. As per EISA 2007 Section 204, appropriate independent research institutes are required to assess concerns to natural biodiversity due to biofuel production and report it to the congress through the Environment Protection Agency (EPA) not later than three years after enactment of this section and every three years thereafter (EISA, 2007). In reality, planners, researchers, and agencies concerned with environmental regulations would also like to have location-specific information about these impacts before developing appropriate management interventions. In the meantime, Biomass Crop Assistance Program (BCAP) was created in the 2008 Farm Bill to expand acreage under bioenergy crops by providing financial assistance to farmers in twelve states of the United States including Arkansas (BCAP, 2015).

It is pertinent to note that a key driver for an interest in biofuel crop production was a target set to produce 36 billion gallons of renewable fuels by 2022 (EPA, 2013). The target has been revised to 16.3 and 17.4 billion gallons by 2015 and 2016 respectively due to a variety of reasons such as constraints in accommodation of increasing volumes of ethanol in the fuel market, limited ability of industries to produce qualifying renewable fuel, etc (EPA, 2015). Despite downward revisions in the targeted renewable fuel production, the need to study environmental footprint of biofuel crop production is still relevant.

As per the estimates of the United States Department of Agriculture (USDA), 27 million acres of cropland would be required to meet the goals of EISA bio-feedstock production (USDA

Biofuel Strategic Production Report, 2010). Smeets and Faaij (2007) have predicted that till the end of 2050, 54 Mha to 348 Mha of surplus agricultural land may be available for bioenergy cultivation. Currently, a major portion of biofuel in the form of ethanol comes from food crops such as (corn, soybean, etc.) which can lead to a competition for food and fuel (Trostle, 2008) resulting in increase of agricultural commodities by 26% for cereals, 18% for other crops and 5% for livestock by 2020 (Fischer et al., 2009). To decrease this competition, EISA estimated that, 15 billion gallons of ethanol may come from first generation crop such as sugar crops, starch crops, oil seed crops and animal fats (Lee and Lavoie, 2013). The rest of 21 billion gallons is expected to be contributed by second generation biofuel crops comprising of cellulosic crops or non-food crops and third generation biofuel sources such as algal biomass (Dragone et al., 2010; NCEE, 2014). The additional agricultural land for production of energy crops motivates to explore the potential of bioenergy crop production. Targeted or marginal lands have gained attention for bioenergy research (Lewis and Kelly, 2014). Cultivation of second-generation bioenergy feedstock on abandoned or marginal land can decrease competition of land for growing bioenergy crops (Post et al., 2013). These lands may be considered marginal or non-productive for cultivation of traditional agriculture but could be suitable for bioenergy crop production or other utilizations (Gopalakrishnan et al., 2011). Reports suggest that biofuels help to decrease greenhouse gas emissions in comparison to conventional petroleum fuels (RFS2, 2010; Hertel et al., 2010). Thus, bioenergy feed stock cultivation may provide an opportunity to reduce greenhouse gas (GHG) emissions (NCEE, 2014).

Since actual implementation of land use change and cultivation of biofuel crops would take a considerable amount of time, implementation of computer based watershed modeling tools is gaining momentum to analyze the fate of nutrients as a result of production of such crops. This research work examines production of bioenergy crops and its impacts on water quality using the SWAT (Soil Water Assessment Tool) Model (Arnold et al., 1998).

Several SWAT studies have highlighted changes in water quality in response to biofuel crop production. Ng et al. (2010) reported that 30% nitrate load was reduced in the Salk Creek Watershed, Illinois by converting 50% of the area under corn and soybean to Miscanthus grown with nitrogen application rate of 90 kg/ha. A reduction in the nitrogen losses was seen when the biofuel crop matured (Sarkar and Miller, 2014). Production of Switchgrass or Miscanthus has also been reported to result in reduced sediment loss compared to corn production in the Iowa River Basin (Wu and Liu, 2012). However, conversion of native grasses to bioenergy crops resulted in a decrease in water yield but increase in nitrate-nitrogen load in the same watershed (Wu and Lee, 2012). Kim et al. (2013) reported that land use change to Miscanthus and Switchgrass coupled with climate change altered the hydrometeorology of the Yazoo River Basin, Mississippi. A decrease in sediment and nutrients load was reported at the watershed outlet in Michigan by conversion of marginal lands to Miscanthus (Love and Nejadhashemi, 2011). A detailed account of other studies on bioenergy crop production is presented in the research background chapter.

A limited number of peer reviewed papers are available that have used dynamic land use change feature for setting up SWAT model at a scale of single (Chiang et al., 2010) to multiple sub-watersheds (Pai and Saraswat, 2011). No study has so far been reported that provides a comparative account of water quality impacts of bioenergy crop production on targeted land (i.e. marginal land) by setting up SWAT model using traditional approach (i.e. single land use dataset) and dynamic land use approach (using multiple land use datasets). In a watershed where land use has changed, hydrology and sediment transport are affected (White and Chaubey, 2005).

Using multiple land use datasets in SWAT model can help to remove stationarity of model responses that are present due to using a traditional modeling approach where a single land use layer is used (Pai and Saraswat, 2011). The dynamic land use change feature was introduced in SWAT model since SWAT2009 release, therefore, the present study is expected to be a good contributor to the existing SWAT literature base.

1.2 Research objectives

The primary purpose of this research is to study water quality impacts of bioenergy crops production using the Soil and Water Assessment Tool (SWAT) Model. Cache River Watershed has been chosen for this study, as it is a part of the area selected for BCAP program implementation in Arkansas.

The methodology adopted to test the hypothesis is outlined below in form of three objectives:

1. Setup, calibration and validation of two SWAT models.
2. Analysis of water quality impacts by simulation of biofuels on marginal lands at a watershed scale.
3. Comparison of two SWAT models.

1.3 Research hypothesis

Long term land use change in the Cache River Watershed has no significant effect on sediment and nutrient loadings at the watershed outlet.

1.4 Scope of study

The overall purpose of this study is to use SWAT model for simulating water quality impacts of Miscanthus (*Miscanthus* x *giganteus*, - to be mentioned as Miscanthus in rest of the chapters*)* and 'Alamo' Switchgrass (*Panicum virgatum L,* - to be mentioned as Switchgrass in rest of the chapters*)* production on targeted land (marginal land) in the Cache River Watershed. The results of this study could be useful for planners, researchers and all other relevant persons interested in utilizing SWAT model for assessing long-term impacts on water quality in response to biofuel crop production on targeted areas within 8-digit hydrologic unit code (HUC) watersheds.

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II. RESEARCH BACKGROUND

The primary purpose of this study is to analyze water quality impacts of bioenergy crop production in Cache River Watershed using the Soil and Water Assessment Tool (SWAT) model. Several studies have been conducted in the past that have used the SWAT model at plot, watershed and regional scale to simulate bioenergy crops and analyze their impacts. This chapter provides an account of these studies (Section 2.1). Development of SWAT models that includes, sensitivity analysis, calibration and validation, and uncertainty analysis are also discussed (Sections 2.2 to 2.4). A brief discussion about crop growth database in SWAT, and yield analysis for biofuel crops are also presented in this chapter (Sections 2.5 and 2.6). In closing, a summary along with the works cited are provided (Section 2.7 and 2.8).

2.1 Simulation of bioenergy crops in watershed models

In order to quantify bioenergy crop production impacts on water quantity and quality, computer based models have proved to be effective tools (Engel et al., 2010). They give answers to 'what-if' scenarios to address questions of long-term effects related to land use changes (Thomas et al., 2009) and their use may be helpful to understand non-point source levels before any type of field monitoring (Thomas et al., 2007). Four hydrologic/water quality models: Groundwater Loading Effects of Agricultural Management Systems and National Agricultural Pesticide Analysis (GLEAMS-NAPRA, Leonard et al., 1986; Lim et al., 2003; Bagdon et al., 1994), Environmental Policy Integrated Climate (EPIC, Izaurralde et al., 2006), Agricultural Policy/Environmental Extender (APEX, Williams et al., 2006), and Soil Water Assessment Tool (SWAT, Arnold et al., 1998) have been used in the past to analyze bioenergy crop production impacts on hydrology and water quality.

Thomas et al. (2009) used the GLEAMS-NAPRA model to analyze impacts on hydrology and water quality by production of corn-based feedstock. This study quantified long-term changes in surface runoff, percolation and nutrients as a result of increased corn productions in existing row crops to meet increasing corn-based ethanol demands for biofuels. Another study (Thomas et al., 2011) used the GLEAMS-NAPRA model to analyze corn stover removal rates on water quality. This study suggested that corn stover removal at 38% and 70% in combination with no-till crop management practice resulted in high erosion losses at an annual scale in comparison to no residue removal scenario.

The EPIC model was used in the Conservation Reserve Program (CRP) in Iowa to analyze soil erosion, nutrient losses and carbon sequestration by production of corn based bio-feedstock production in the Conservation Reserve Program (CRP) in Iowa (Secchi et al., 2009). The authors reported that sediment and nitrogen losses increased approximately five hundred percent (from one million tons to five million tons-sediment and 11,000 tons to 50,000 tons-N) in response to approximately 67 percentage increases in CRP land conversion to corn. For continuous corn rotation on the entire CRP area, the sediment and nitrogen losses were reported to exceed nine million tons and 75,000 tons respectively. Thus, the authors concluded that environmental impacts increased when more environmentally fragile land was brought under corn production to bear higher corn prices. A change in targeting strategies was suggested to keep sensitive lands intact within CRP.

The APEX model was also applied in Iowa to analyze the impacts on soil and water quality by feedstock-production involving crop rotation and Switchgrass production (Powers et al., 2008). The authors reported that production of Switchgrass indicated a decrease in soil losses by 20% in compared to corn-soy rotation, lead to an increase in soil carbon content to about

1.5% of initial after 16 years of simulation and considerable reduction in nitrogen discharges to surface and ground water (about 10% less). According to the results of this study, total yield and soil quality should be included towards a sustainable approach to produce of biofeed-stock.

The SWAT model has been widely used to predict and analyze impacts of land use and crop management on water quality and sediment loadings (Goldstein et al., 2014, Kim et al., 2013, Moriasi et al., 2012, Ngo et al., 2015, and Santhi et al., 2001). There are about 2,231 peer-reviewed journal articles on the use of SWAT model (till November 7, 2015; SWAT literature database, available at: https://www.card.iastate.edu/swat_articles/). The SWAT model is open-source, continuously upgraded with improvements (Panagopoulos et al., 2015), has a large user base with well-documentation. Also, Borah and Bera (2004) had reviewed various continuous simulation models. They have analyzed these models for prediction of nutrient export at a watershed scale and reported that the SWAT model was found better than other models for analyzing long-term impacts of management scenarios and prediction of nutrient loads from predominantly agricultural watersheds. Some of the other strengths of SWAT include: prediction of long term or relative impacts of scenarios for example changes in land use, crop management practices or climate on water quality or quantity, ability to perform spatially differentiated analyses, and ability to model ungauged or poorly gauged watersheds (Mutenyo et al., 2013, Schmalz and Fohrer, 2009, and Ullrich and Volk, 2009). The SWAT literature database also contains modeling protocols to evaluate, interpret and communicate performance of SWAT, considering its intended use (Engel et al., 2007, Harmel et al., 2014, and Panagopoulos et al., 2015). Thus, considering a vast application domain and suitability for modeling agricultural watersheds, SWAT was chosen for this study.

2.1.1 Bioenergy crop simulation using SWAT model

Some of the studies that have conducted analysis of water quality effects as a result of production of bioenergy crops are presented in this section and have been organized according to scale of simulation ranging from plot, watershed and regional.

2.1.1.1 Plot scale studies

In a study conducted at a research center in South Carolina by Sarkar et al. (2011), Switchgrass and cotton were simulated in the SWAT model on two plots (size 510 square meters). Cotton was simulated for the initial years (1985 to 2006) followed by Switchgrass (2007 to 2021). According to the results of this study, total nitrogen losses decreased by 87% and 92% (annual scale) for one-cut and two-cut Switchgrass (nitrogen fertilizer rate 68 kg/ha) respectively in comparison to cotton (nitrogen fertilizer rate of 90 kg/ha). Nitrogen losses were reported to be 14% and 3% at nitrogen fertilizer rates of 68 kg/ha for short and long term average annual conditions for Switchgrass respectively.

Trybula et al. (2014) simulated Miscanthus and upland variety of Switchgrass in SWAT by defining most sensitive parameters with region-specific data and literature values at a study conducted on a plot scale at Water Quality Field Station (size 518 square meters) at Purdue University. They made three improvements in the SWAT 2009 code to facilitate correct representation of the bioenergy crops in the model: to have a below ground biomass the harvest code was modified, an improved-DLAI (fraction of growing season as leaf area begins to decrease) was used to represent maturity and leaf senescence in a better way to enhance plant respiration, and in order to allow the crop to respond to stresses a revision was also made for the nutrient uptake codes. The authors' reported improvements in biomass yield simulations in addition to enhanced leaf area index were as per the expectations for the region. The results also indicated an improved nutrient storage and uptake for Switchgrass and Miscanthus.

2.1.1.2 Watershed scale studies

In a research work conducted in the Khlong Phlo Watershed (size 202.8 square kilometers) in Thailand by Babel et al. (2011), a total of twenty scenarios were simulated in the SWAT model to study effects of bioenergy crop cultivation on hydrology and water quality. These scenarios included oil palm expansion (some land uses converted to oil palm), cassava expansion (some land uses converted to cassava), sugarcane expansion (some land uses converted to sugarcane) and combined expansion (some land uses converted to combinations of oil palm, cassava and sugarcane). They reported that an increase in nitrate loading from 1.3 to 51.7 % would occur in the surface water with oil palm expansion scenario however a negligible change in evapotranspiration from 0.5 to 1.6% and water yield from -0.5 to -1.1 % would occur. A decrease in evapotranspiration by 11% and increase in water yield by 16.4% was reported while simulating cassava and sugarcane expansion scenario. Also, this decrease in evapotranspiration and increase in water yield resulted in increased sediments by 80%, nitrate by 42% and total phosphorus by 155%. A negative impact was reported by this study on water quality of the watershed by production of bioenergy crops.

Gassman et al. (2008) assessed twelve scenarios for Boone River Watershed (size 2370 square kilometers) in north-central Iowa using the SWAT model for bioenergy crops. The baseline scenario was corn-soybean acreage. The other scenarios included 15%, 50% and 100% corn-soybean acreage converted to continuous corn, 15%, 50% and 75% corn-soybean acreage converted to Switchgrass and 15%, 50% and 75% of corn soybean acreage converted to fescue with different nitrogen fertilizer rates. All scenarios were executed for a 30-year period (1977 to 2006) and a decrease of 2% to 11% in sediment, an increase of 9% to 100% in nitrate in continuous corn scenario when compared to baseline was observed. A decrease of 5 to 39% in sediments and 3 to 26% in nitrate losses was also reported in the perennial grasses (Switchgrass and fescue) scenarios.

Goldstein et al. (2014) analyzed hydrologic impacts of Switchgrass cultivation by replacing of winter wheat and range grasses with Switchgrass (no fertilizer applied), and Switchgrass with application of fertilizer with harvest on specific dates in the Middle North Canadian River (MNCR) Watershed (size 1,649 square kilometers) located in Western Oklahoma. By conversion of any land use to Switchgrass, a decrease in median stream flow discharges from 5.6% to 20.6% during the spring season and from 6.4% to 31.2% during the summer season was reported. Further, an increase in spring and summer evapotranspiration from 3.4% to 32% and from 1.5% to 18.9% respectively, was also reported under the same scenarios. The authors also reported greater (48% to 300%) water stress days with Switchgrass than in the baseline scenario.

Hoque et al. (2014) analyzed hydrological and water quality impacts by changes in land use and climate in St. Joseph River watershed (size 2,825 square kilometers) in Indiana. They used three different risk indicators that were reliability, resilience and vulnerability. Sediment and nutrients (total phosphorus and total nitrogen) risk indicator values improved with the production of Miscanthus and Switchgrass had the potential to improve sediment and nutrients risk indicator values. Approximately 30% (sediment), 16% (total nitrogen) and 33% (total phosphorus) reductions in loadings were observed at the watershed outlet. Also, risk indicator values were found to be sensitive to a greater degree for precipitation-driven climate change scenarios when compared to climate change scenarios driven by temperature.

Moon et al. (2012) simulated Switchgrass on three land use types, namely, HRUs with slopes steeper than 2%, critical land with high nutrient and sediment losses and land with corn yield less than 15% in the Le Sueur River Watershed in southern Minnesota. The size of this watershed is approximately 2,280 square kilometers. A three-year corn-corn-soybean rotation in addition to a two-year corn-soybean rotation with four stover removal rates (0%, 10%, 30% and 60%) was also included to analyze the water quality impacts. For Switchgrass scenarios, nitrate-nitrogen losses ranged from 10 kg/ha to 14 kg/ha, phosphorus losses ranged from 0.01 kg/ha to 0.1 kg/ha and sediment losses ranged from 0.02 kg/ha to 0.38 kg/ha. The two-year crop rotation scenario with four different stover removal rates resulted in nitrate-nitrogen losses (18 to 19 kg/ha), phosphorus losses (0.7 to 1 kg/ha) and sediment losses (2 to 3 kg/ha). A reduction of 29 kg/ha to 34 kg/ha for nitrate-nitrogen losses, 0.8 kg/ha to 1 kg/ha for phosphorus losses and 2 kg/ha to 3 kg/ha for sediment losses was observed for three-year crop rotations. Lower nutrient losses occurred with Switchgrass in comparison to other scenarios.

In a study conducted by Nelson et al. (2006), Switchgrass was simulated on corn, soybean, sorghum and wheat crop rotations with different fertilizer application rates (0 to 224 kg-N/ha) in the Delaware basin. The size of this basin is approximately 3,000 square kilometers and lies in northeast Kansas. This study reported reductions in sediment yield (99%), runoff (55%), nitrate losses (34%) and soil erosion (98%).

Ng et al. (2010) simulated Miscanthus in a watershed in Illinois. The size of this watershed was approximately 303 square kilometers. A total of five scenarios in SWAT model were considered: a baseline scenario with no change, conversion of corn-soybean 1:1 rotation to

Miscanthus (10%, 25%, and 50%) using three different fertilizer rates (30, 60 and 90 kg-N/ha) and soybean conversion to all agriculture land with 90 kg-N/ha fertilizer applied. A decrease in nitrate-nitrogen load was observed when the percentage of Miscanthus conversion increased. Using the three fertilizer rates (mentioned above) and 50% land use conversion to Miscanthus, nitrate-nitrogen losses reduced (34%, 32%, and 29%) at the outlet of the watershed.

Sarkar and Miller (2014) assessed total nitrogen loss by conversion of agricultural croplands to Switchgrass in the Black Creek Watershed. This watershed lies in South Carolina and is about 756 square kilometers in size. The modeling period was from 1995 to 2021. During the initial years (1995 to 2006) cotton was simulated and then cotton was converted to Switchgrass from 2007 to 2021. Reductions in nitrogen losses was observed for one-cut Switchgrass (73%) and two-cut Switchgrass (80%) system when compared to cotton over a fifteen-year period.

2.1.1.3 Regional scale studies

In addition to the above studies that were conducted either at watershed scale or plot scale, the SWAT model has also been used at regional scale. Baskaran et al. (2010) simulated **S**witchgrass in SWAT model to evaluate its sustainability as a bioenergy crop in the Arkansas-White-Red River basin (size approximately 50,000 square kilometers) and validate SWAT predictions of water quantity (flow). Switchgrass was designated as a perennial crop by reclassifying all the land uses to Switchgrass except area underwater. Increase in differences in SWAT flow predictions and USGS measurements were observed in the downstream subwatersheds and in subwatersheds with greater water percentage which helped to identify potential areas for biofeedstock production.

Einheuser et al. (2013) simulated fourteen biofuel crop rotations with two scenarios where biofuel crops were simulated on all marginal lands and all agricultural and marginal lands in the SWAT model in the Saginaw River Watershed in Michigan (size 16,000 square kilometers). The primary purpose of this research work was to analyze effects of bioenergy crop expansions on health of streams using adaptive neural-fuzzy inference system (ANFIS). Water quantity and quality results obtained from SWAT were supplied to ANFIS. It was found that macroinvertebrate measures to assess stream health had a negative impact under the row crops scenario, but improved under perennial crops scenarios. Native grass, Switchgrass and Miscanthus expansion affected the fish biological integrity (Miscanthus had the greatest impact of 17% decrease) in a negative way in comparison to conventional bioenergy crops (corn stover improved the biological integrity by an increase of 9%).

Kim et al. (2013) assessed impacts of simulation of two biofuel crops (Switchgrass and Miscanthus) and change in climate on hydrometeorology in the Yazoo River Basin (YRB, size 34,589 square kilometers) in Mississippi. An increase of 16 mm and 27mm (annual scale) was reported in evapotranspiration with Switchgrass and Miscanthus respectively. Reductions in surface water on an annual scale (4% for Switchgrass and 6% for Miscanthus), water yield (3% for Switchgrass and 2% for Miscanthus) and streamflow (5% for Switchgrass and 3% for Miscanthus) was also reported. Future climate change scenarios showed decreases in annual evapotranspiration (3% to 10%), annual surface runoff (1% to 6%), water yield (3% to 11%) and streamflow (5% to 15%). A greater effect of climate change was observed on the hydrometeorology of the basin than growing bioenergy crops.

Wu and Liu (2012) evaluated effects of bioenergy crop production on soil erosion/ nitrate-nitrogen concentrations, water quantity and quality. This study was conducted in the Iowa River Basin which is approximately 32,686 square kilometers in size. Eight scenarios were simulated where 0, 40, 80 and 100% corn stover removal rate was assumed on all corn fields. Other scenarios included 10% corn fields converted to Switchgrass, 10% corn fields converted to Miscanthus, 100% of native grass changed to Switchgrass and lastly 100% conversion of native grasses to Miscanthus. Results indicated a significant increase in sediment yield from 4.7% to 70.6%, decrease in water yield from 1.2% to 3.2% and decrease in nitrate load from 6% to 10.1% with stover removal rate ranging from 40% to 100%. In addition to this, Switchgrass or Miscanthus reduced sediment loss by about 4.5% in comparison to corn, conversion of native grass to bioenergy crops resulted in a decrease of 2.1% (Switchgrass) and 4.6% (Miscanthus) in water yield and increase in nitrate-nitrogen load by 1.2% for Switchgrass and 5.1% for Miscanthus. Among Switchgrass and Miscanthus, the latter was reported to be more productive in generating biomass (6.3 t/ha for Switchgrass and 25 t /ha for Miscanthus) but higher water demand was a problem.

2.2 Sensitivity analysis of the SWAT model

Sensitivity analysis is basically done to decrease the number of parameters to be adjusted during calibration phase of any model. Topography, sixe of watershed, geomorphology of landscape, land-use pattern and human impacts influence the sensitivity of different parameters (Folle et al. 2007). Sensitivity analysis evaluates how the output is affected by different parameters. Reduction of large and uncertain parameter ranges also aids calibration (Benaman and Shoemaker, 2004). Sensitivity analysis can be performed in two different ways, a global analysis or a local analysis.

Global sensitivity analysis procedure works on entire parameter distribution while local sensitivity analysis examines sensitivity relative to point estimates of parameter values (Hamby 1994). Since sensitivity of a parameter may be affected by the value of another parameters, therefore it is tough to determine correct values of other parameters while conducting a local sensitivity analysis (Arnold et al., 2012). A greater number of model runs may be required while performing the global sensitivity analysis to obtain robust results (Arnold et al., 2012, Sanadhya et al., 2014). The initial limitation of long hours of simulation periods can be easily handled with the availability of high speed computing facilities nowadays. In summary, performing sensitivity analysis before proceeding to calibration phase is an important step.

2.3 SWAT model calibration and validation

In order to reduce prediction uncertainty it is essential to calibrate a model. Model calibration is done to parameterize it according to the measured data by changing selected parameters and comparing simulated outputs to their measured counter parts (Arnold et al., 2012). Validation of models is done to demonstrate its capability in performing and making sufficiently accurate site-specific hydrologic, sediment or nutrient predictions (Arnold et al., 2012).

A multi-site calibration approach combined with the use of multi-variables can result in enhanced simulation of hydrological processes in a watershed (Lu et al., 2015). This method of calibration has been used by many studies (White and Chaubey, 2005, Cao et al., 2006, Zhang et al., 2008, Pai et al., 2011, and Lu et al., 2015). The calibration procedure should start from an upstream gauge followed by downstream gauges (White and Chaubey, 2005) and the model needs to be calibrated at all gauges simultaneously for better parameterization (Migliaccio and Chaubey, 2007). Multi-variable calibration involves calibration of flow followed by sediment, phosphorus and nitrogen. It is also recommended that calibration should be first done on an annual basis to reduce relative error and then on a monthly time scale so that model accounts for seasonal trends or variations (Santhi et al., 2001).

A standalone program called SWAT Check (White et al., 2014) is available to screen for potential model application issues and is a good companion for model calibration (Arnold et al., 2012). The warnings generated by the tool are usually resolved by changing selected parameters. Many studies have used SWAT Check before starting the calibration process and periodically thereafter to ensure that model simulations were reasonable (Cerro et al., 2014, Santhi et al., 2014, Saraswat et al., 2013, and Zabaleta et al., 2014). Thus, the use of SWAT Check as part of calibration process is helpful to modelers for keeping check on SWAT outputs on ensuring reasonable simulations.

2.4 SWAT model uncertainty analysis

Although calibration and validation provides a sufficient measure of performance of a SWAT model, an additional analysis is performed to assess degree of uncertainty related to measured data or other measures of interest (Shirmohammadi et al., 2006). In water resources research, uncertainty analysis has gained attention over the last two decades and it is expected to become an integral part of modeling studies in future (Pappenberger and Beven, 2006). Uncertainty in any hydrologic modeling study can be attributed to three forms: structural, input uncertainty or parameter uncertainty. Structural uncertainty in the SWAT model can occur due to incorporation of assumptions for simplifying equations such as MUSLE (Modified Universal Soil Loss Equation), physical processes such as erosion caused by wind or landslides that may be happen in a watershed but are not represented in the model, or phenomena whose occurrences are included but actually unknown in the model such as representations of reservoirs or water transfer etc. Error in some of the input variables account to input uncertainty such as rainfall or temperature etc. Since parameters represents processes in a watershed and due to a large number of parameters complex watershed models, input uncertainty can increase (Abbaspour, 2013). Thus, presenting uncertainty estimates for a model can help to assess and quantify confidence in observed and predicted values (Harmel et al., 2014; Harmel et al., 2010).

2.5 SWAT model plant growth database

The crop growth component in SWAT was adopted from the Environmental Impact Policy Climate (EPIC) model (Williams, 1990). Plant growth and development, biomass, yield, nutrient and water uptake are driven by the parameters present in the crop database. The model initiates the annual crop growth via scheduled planting whereas in case of perennial plants crop growth starts when the mean daily temperature reaches a base threshold temperature. For perennial plants the root depth always equals the maximum allowed for the plant species and soil and dormancy is reached when day length is less than the threshold day length. Also, these perennial plants/grasses are able to maintain a nutrient pool as they do not require replanting and keep yielding for many years (Ng et al., 2010).

The SWAT crop growth database contains parameters for crop growth for many crops including Switchgrass. In comparison to Switchgrass, Miscanthus is a relatively new crop and SWAT crop growth database lacks its parameters. Ng et al. (2010) adapted crop growth parameters from another model, BioCro (Miguez et al., 2009). Love and Nejadhashemi (2011) used literature values for Switchgrass and agronomists' advice to represent Miscanthus in SWAT. Trybula et al., (2014) also suggested parameters for simulation of Miscanthus based on field data (agronomic and weather data) from at a research station in northwestern Indiana and literature value comparisons. They reported that new suggested parameter values in addition to code changes made in SWAT resulted in more accurate predicted biomass yields in addition to leaf area index values. Therefore, using values suggested by Trybula et al. (2014) would better simulate the Miscanthus crop growth in SWAT.

2.6 Yield analysis for bioenergy crops

Hydrology and nutrient balance can be affected by crop yields in an agricultural watershed and performing an analysis for simulated yields can add more confidence to model results aiding to a realistic benefit cost analysis (Nair et al., 2011). Many studies in the past have made a comparison for SWAT simulated yields with reported literature values and field data. Trybula et al. (2014) compared the yields of Switchgrass and Miscanthus and found them to be consistent with reported values. Ng et al. (2010) also presented estimates of simulated and field data yields for Miscanthus in a watershed in Illinois. Parajuli (2011) evaluated yields and water quality benefits of bioenergy crops at a watershed scale in Upper Pearl River Watershed, Mississippi. Baskaran et al. (2010) validated predicted yields from SWAT using a second model (PLOYSYS) to evaluate Switchgrass production sustainability at a regional scale for the eastern United States.

2.7 Summary

The second generation bioenergy crops (Switchgrass and Miscanthus) have gained attention from the scientific community. In the past, several hydrologic or water quality models have been used to study the pros and cons of bioenergy crop cultivation out of which the use of SWAT model has gained attention. A modeler has to go through a number of steps in order to develop a SWAT model. Sensitivity analysis is conducted to aid in calibration by identifying parameters affecting model outputs to a greater degree in comparison to other parameters. In order to analyze bioenergy crop impacts on water quality, a robust calibrated and validated SWAT model is required. Correct representation of crop growth parameters is essential to facilitate simulation of bioenergy crops in SWAT. Uncertainty analysis adds to the recognition of potential errors in modeling work and an additional yield analysis is done to gain confidence in model simulations.

The present scientific literature lacks a comparison of bioenergy crop impacts on water quality by their production on targeted (marginal land) by setting up SWAT model using traditional approach (using a single land use dataset) and dynamic land use approach (using multiple land use dataset). The results of this research work would give direction to future SWAT studies by providing a comparison of water quality impacts at a watershed scale. The next chapter (Methods) presents a detailed account for methodology adopted in this research work.

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III. METHODS

3.1 Study watershed description

This research work was conducted in the Cache River Watershed (CRW) that lies within the White River Basin and located in northeast Arkansas. It is represented by hydrologic unit code (HUC) 08020302 (Figure 3.1). The drainage area of the watershed is 5,066 square kilometers and eleven counties are covered: Clay, Craighead, Cross, Greene, Jackson, Lawrence, Monroe, Poinsett, Prairie, Randolph, and Woodruff. The watershed is about 230 kilometers in length and 29 kilometers at the widest point. About 4,403 square kilometers of the watershed lies in the Western Lowlands geological division of the Mississippi Alluvial Valley (MAV) except the remaining portion of the watershed (about 673 square kilometers) lies in the headwater areas along the western slope of Crowley's Ridge. The elevation ranges from 44 m from its lowest point to 170 m at its highest point. CRW is relatively flat with 48 percent of the watershed have slopes ranging from 0 to 1 percent. Land use and land cover in CRW consists of soybean (29%), forest (25%), rice (14%), corn (9%), cotton (3%), pasture (3.5%), urban (2.8%) and water (1.6%) (Gorham and Tullis, 2007). The dominating soils fall in hydrological soil groups C and D and cover approximately 64% of the area of the watershed (Figure 3.2).

The Cache River has been listed under impaired water bodies by the Arkansas Department of Environmental Quality (ADEQ, 2012). The CRW has been identified as a priority watershed for 2011-16 by the Arkansas Natural Resources Commission due to a number of reasons such as sediments and nutrients losses from row crop agriculture, industrial point source discharges, elevated levels of chlorides, total dissolved solids and impacts on aquatic life (ANRC, 2012).

Subwatershed level information for CRW including HUC 12 code, county, drainage area, elevation, slope, soil and major crops is presented in Appendix A.

3.2 Input data description

A wide range of inputs are required by the SWAT model that include spatial data (watershed boundary, topography, land use and land cover, soils and stream network), weather data, point source/water quality data and crop management data (Table 3.1).

Table 3.1- Input data requirements for SWAT model

Data type	Scale	Data Provider	Source	Date Accessed	Description
Spatial data					
Watershed boundary	1:24000	United States Department of Agriculture-Natural Resources Conservation Service (USDA-NRCS)	http://datagateway.nrcs.usda.gov	02/27/2014	8-digit and 12-digit HUC shapefiles
Topography	10 m	Center for Advanced Spatial Technologies (CAST) and GeoStor	http://gis.arkansas.gov/	03/01/2014	Digital Elevation Model
Land Use/ Land Cover (LULC)	28.5/30 m	Center for Advanced Spatial Technologies (CAST) and National Land Cover Database (NLCD)	http://gis.arkansas.gov/ & http://www.mrlc.gov/	03/01/2014	1999, 2004,2006 (CAST) 1992,2001,2011 (NLCD)
Soil	10 m	United States Department of Agriculture-Natural Resources Conservation Service (USDA-NRCS)	https://gdg.sc.egov.usda.gov/	03/03/2014	Soil Survey Geographic (SSURGO) database
Stream network	1:24000	National Hydrography Dataset-USGS (NHD-USGS)	ftp://nhdftp.usgs.gov/DataSets/Staged/States/FileGDB/HighResolution	03/10/2014	High resolution stream reaches
Non spatial data					
Weather	Subwatershed	National Oceanographic and Atmospheric Association (NOAA)	http://amazon.nws.noaa.gov/hdsb/data/nexrad/nexrad.html & http://www.ncdc.noaa.gov/cdo-web/	03/10/2014	
Stream flow	Daily measurements	United States Geological Survey (USGS)	http://waterdata.usgs.gov/nwis	03/10/2014	3 gage stations
Water quality		United States Geological Survey (USGS)	http://waterdata.usgs.gov/nwis	02/27/2014	1 gage station
Point Sources	Monthly measurements	Environment Protection Agency (EPA)	http://www.epa.gov/enviro/facts/pcs-icis/search.html	02/27/2014	Flow, sediment and nutrients for 22 facilities
Crop management data					
Crop Management Information	County level	University of Arkansas, Division of Agriculture, Cooperative Extension Service	Personal communication with County Staff Chairs	05/20/2014	Fertilizer and pesticides application rates, tillage practices, crop planting and harvesting timings and information

3.2.1 Spatial Data

Spatial data inputs for the SWAT model include watershed boundary, topography (digital elevation model), land use raster, soil raster and stream network. All input data were downloaded from either state or national agencies distribution channels. The coordinate system for all the input data was kept consistent to North America Datum 1983 (NAD83) Universal Transverse Mercator Zone 15 N (UTM-Zone 15 N) projection system. This was ensured from the metadata information and if the projection system was different then 'project (data management)' tool in ArcMap toolbox was used to change the projection of the data layers.

3.2.2.1 Topography

The topography of CRW was defined by a 10 m spatial resolution, digital elevation model (DEM) (Figure 3.3) data type downloaded from the Arkansas GIS office's website. The boundary of DEM was processed to overlap with the watershed boundary by using an additional mask layer using 'extract by mask' tool in ArcMap toolbox. To ensure correct DEM projection setup, the z-unit of DEM layer consistent with x-y units (meters) during watershed delineation.

3.2.2.2 User-defined watersheds

The 8-digit and 12-digit HUC shapefiles for CRW were obtained from the USDA Geospatial Data Gateway website and was processed as per requirements of SWAT (Winchell et al., 2013). In the attribute table, all fields were removed but FID and shape. Two new long-integer type fields were added as per SWAT requirements (GRIDCODE and Subwatershed).SWAT provides two options for a watershed to be divided into subwatersheds: DEM-based or user-defined. In this study, a user-defined approach was used so as to match delineated subwatershed boundaries with the 12-digit HUC boundaries that were defined by the U.S. Geological Survey (USGS). It was followed to avoid impacts of size, scale and number of subwatersheds affecting a watershed modeling processes and the model outputs (Jha et al., 2004). The final data layer represented 57 subwatersheds in CRW (Figure 3.4) and was used in watershed delineation process during the model setup. An additional exercise to identify nested subwatersheds in CRW to ensure correct networking and routing of flow between subwatersheds was also done. (Appendix B). It was noticed that 19, 27 and 4 headwater subwatersheds were part of Egypt, Patterson and Cotton Plant USGS gauge stations respectively and a total of 28 nested subwatersheds were present in CRW.

3.2.2.3 User-defined streams

User-defined streams (Figure 3.5) approach was used for generating a stream network, since it is a recommended practice to be followed with user-defined watershed delineation process for model set-up (Winchell et al., 2013). This differs from a DEM based approach, where the subwatershed boundaries and reach network do not exactly match with the reality, thus, affecting routing processes (Luo et al., 2011). To generate user-defined streams network, a high resolution (1:24,000) stream geodatabase was obtained from USGS-National Hydrology Dataset (NHD) website and processed (as discussed below) to force the SWAT subwatershed reaches to flow in directions of stream locations (Winchell et al., 2013). In the attribute table of the user streams layer, along with FID and shape fields, five new long integer type fields were also added (GRID_CODE, FROM_NODE, TO_NODE, Subwatershed and SubwatershedR). The GRID_CODE, FROM_NODE and Subwatershed values were set equal to subwatershed number and TO_NODE and SubwatershedR values were kept to match downstream subwatershed's number so as to make sure that the flow occurs correctly from the corresponding subwatershed. This ensured that watersheds and streams are geometrically consistent with the requirement of having one stream feature per subwatershed.

3.2.2.4 Mask

The mask layer was used to extract DEM data to match with watershed boundaries. It was created by “polygon to raster” in toolbox in ArcMap using HUC_8 layer generated in the user-defined watersheds process.

3.2.2.5 Land use and land cover (LULC) layer

Land use and land cover in CRW has changed over the years from 1992, 1999, 2001, 2004, 2006 and 2011 (Figure 3.6). The cropped area varied from 32% to 77%, urban varied from 0.7% to 5.1%, forest varied from 8.2% to 25.2%, pasture varied from 3% to 34.8%, barren varied from 0.1% to 36%, water varied from 0.9% to 5.8%, and wetlands varied from 2.9% to 12% during the modeling period (1992 to 2012). A single land use layer was used for the first SWAT model whereas multiple land use layers were used for setting-up the second SWAT model. For CRW, six LULC layers (1992, 1999, 2001, 2004, 2006 and 2011) were obtained from the state and federal sources, respectively. LULC data layers for 1999, 2004 and 2006 (Figure 3.7) were downloaded from the Center for Advanced Spatial Technologies (CAST), University of Arkansas and the remaining three years of data (1992, 2001, and 2011) was downloaded from the National Land Cover Dataset (NLCD) website. CAST and NLCD have defined different categories or schemes for classification for forest, urban and pasture land use categories (Gorham and Tullis, 2007). To gain parity, some of the similar land uses were merged together (Appendix C) to keep a common level I land use classification for the model. Residential or recreational area and urban (other) intensity 1 was merged to urban low intensity, commercial, industrial, transportation and intensity 2 and 3 were merged to urban high intensity, different tree types were merged to forest and warm and cool season grasses were merged to pasture. A land use look-up table was also prepared to match each category in the land use raster supplied to the model.

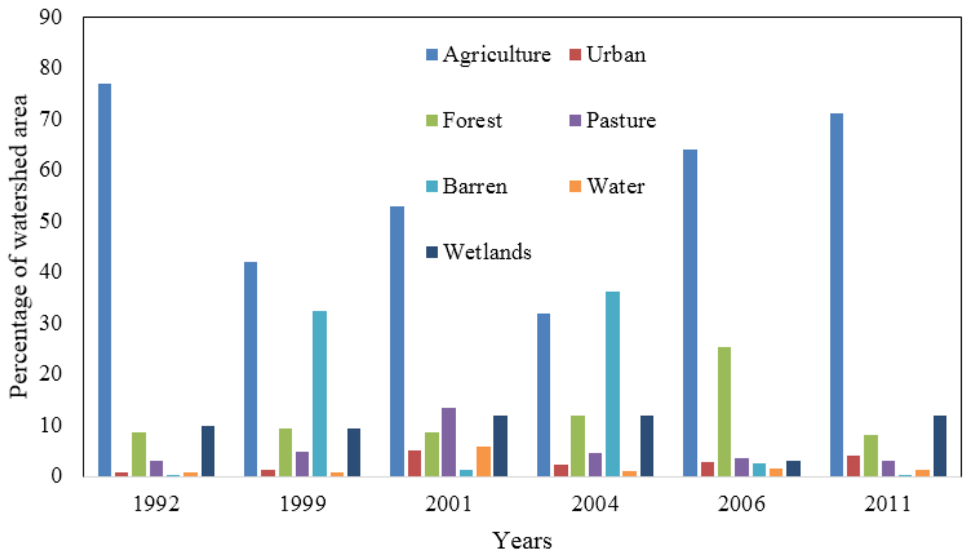

Figure 3.6- Land use and land cover change in Cache River Watershed.

3.2.2.7 Soil data layer

The Soil Survey Geographic Database (SSURGO) data layer was obtained from USDA Geospatial Data Gateway website for each county in CRW. Soil layers for all eleven counties that fall in CRW were merged together in ArcMap to generate a single soil layer and extracted using HUC_8 boundary for CRW. To meet the input soil layer requirements of SWAT, in the attribute table, all fields were deleted but MUKEY, MUNAME, FID and shape so that the soils are linked to the SSURGO database. This layer was then converted to a raster of 10 m spatial resolution using MUKEY which was related with the soils database in ArcSWAT to identify soil types in CRW. The soils in the watershed belonged to 27 different soil series. The major soils were being Grubbs (12.9%), Calhoun (11.6%), Forestdale (9.6%) and Askew (9.1%). Askew is categorized into hydrologic soils group C and all other three major soil types are categorized into hydrologic soils group D and have high runoff potential.

3.2.2 Weather data

Historical daily precipitation data for 21 years (1992 to 2012) was downloaded from the National Oceanic and Atmospheric Administration (NOAA) website. The NEXRAD (Next-Generation Radar) data stage III and rain gauge data together were used to cover the complete modeling period from 1/1/1992 to 31/12/2012. The temperature data (minimum and maximum) on daily basis were obtained from the NOAA website for HUC_8 08020302 in tenths of a degree centrigrade from 1/1/1992 to 31/12/2012 in csv format. SWAT generated the additional weather inputs such as wind velocity, relative humidity and solar radiation. A user can make a selection from three available methods in SWAT (Penman-Monteith, Priestly-Taylor or Hargreaves) for the calculation of potential evapotranspiration (PET). If any other method, apart from the above mentioned, is used to calculate PET then a user has to supply daily PET values in the ".pet" file in SWAT (neitsch et al., 2011). In this study, Penman-Monteith method was used for the calculation of PET. In this method, weather measurements are required at a single reference level instead of measurements at different gradients and is considered another advantage for using this method (Hydrology Handbook, ASCE Manuals and Reports on Engineering, 1996). Penman-Monteith method not only yields good results under a range of climate scenarios but is also the most desirable method to calculate evapotranspiration (Drooger and Allen, 2002, Liciardello et al., 2011 and Subedi et al., 2013). The Food and Agriculture Organization of the United Nations

(FAO-UN) also recommends the use of Penman-Monteith method to calculate evapotranspiration (FAO, Corporate Document Repository).

3.2.3 Point source/water quality data

Point source data was obtained from the Environment Protection Agency (EPA) website (http://www.epa.gov/enviro/facts/pcs-icis/search.html) that contains information based on counties and watersheds. Twenty-two major point source pollution facilities are present in CRW (Appendix D). The point source constituents such as, flow, sediment, chemical oxygen demand, carbonaceous oxygen demand, ammonia-N, phosphorus, and metal (copper, lead) discharge were converted into subwatershed discharge data in appropriate units (mass flow) to represent the respective 22 subwatersheds. This data was converted to SWAT compatible subwatershed discharge data for individual subwatersheds on a monthly scale (csv format) and provided as input to the model.

3.2.4 Crop management inputs

Crop management practices for four crops (cotton, corn, rice and soybean) grown in CRW were obtained by personal communication with the county extension personnel (staff chairs) of counties that fall within the watershed (Appendix E to H). The management practices included fertilizers/pesticides and their application rates, tillage practices, and typical crop sowing/harvesting dates. The application rate measurement units were converted to kg/ha. This data was provided in the management input files in the model as schedule of management operations occurring at specific times. Crop management practices for both the bioenergy crops

(Switchgrass and Miscanthus) were adapted from Singh (2012). These are provided in Appendix I.

3.3 Identification of marginal lands

In order to facilitate accurate simulation of bioenergy crops in a model, it is important that identification of marginal lands is done correctly in a watershed (Kiniry et al., 2008). In this study, marginal lands in CRW were identified based on two criteria: soil health issues (poorly drained and frequently flooded; Gopalakrishnan et al., 2011) and land capability classes.

The USDA land capability classification system categorizes soils into eight classes. Classes I to IV are suitable for cultivation whereas classes V to VIII are unfit for agriculture (Table 3.2).

Table 3.2- Description of land capability classes

Land Capability Class	Description
I	Soils having slight limitations that restrict their use
II	Soils that require moderate conservation practices
III	Soils that require special conservation practices
IV	Soils that require very careful management
V	Pasture, range, forest land or wildlife
VI	Soils unsuitable for cultivation, pasture, range, forestland or wildlife
VII	Soils unsuitable for cultivation, grazing, forestland or wildlife
VIII	Recreation, wildlife, water supply or aesthetic purposes.

According to information for CRW from the SSURGO database, about 50% of the watershed falls under class III and poorly drained category, 18% falls class IV constitutes about

18% along with poorly drained and frequently flooded soils, and 1% falls under class V. LCC classes IV (soils requiring very careful management) and V (pasture, range, forest land or wildlife) were considered as marginal cropland (Figure 3.8) for cultivation of biofuel crops.

Once marginal lands in the watershed were identified, a modified land use and land cover layer was generated following an approach developed by Singh (2012). The procedure to create this modified land use layer is presented in Appendix J. Also, marginal croplands area varied in the watershed during the years. It was about 11.3% in 1992, 5.7% in 1999, 6.8% in 2001, 3.3% in 2004, 8.2% in 2006 and 10.1% in 2011 according to different land use and land cover layers (discussed before in Section 3.2.2.6).

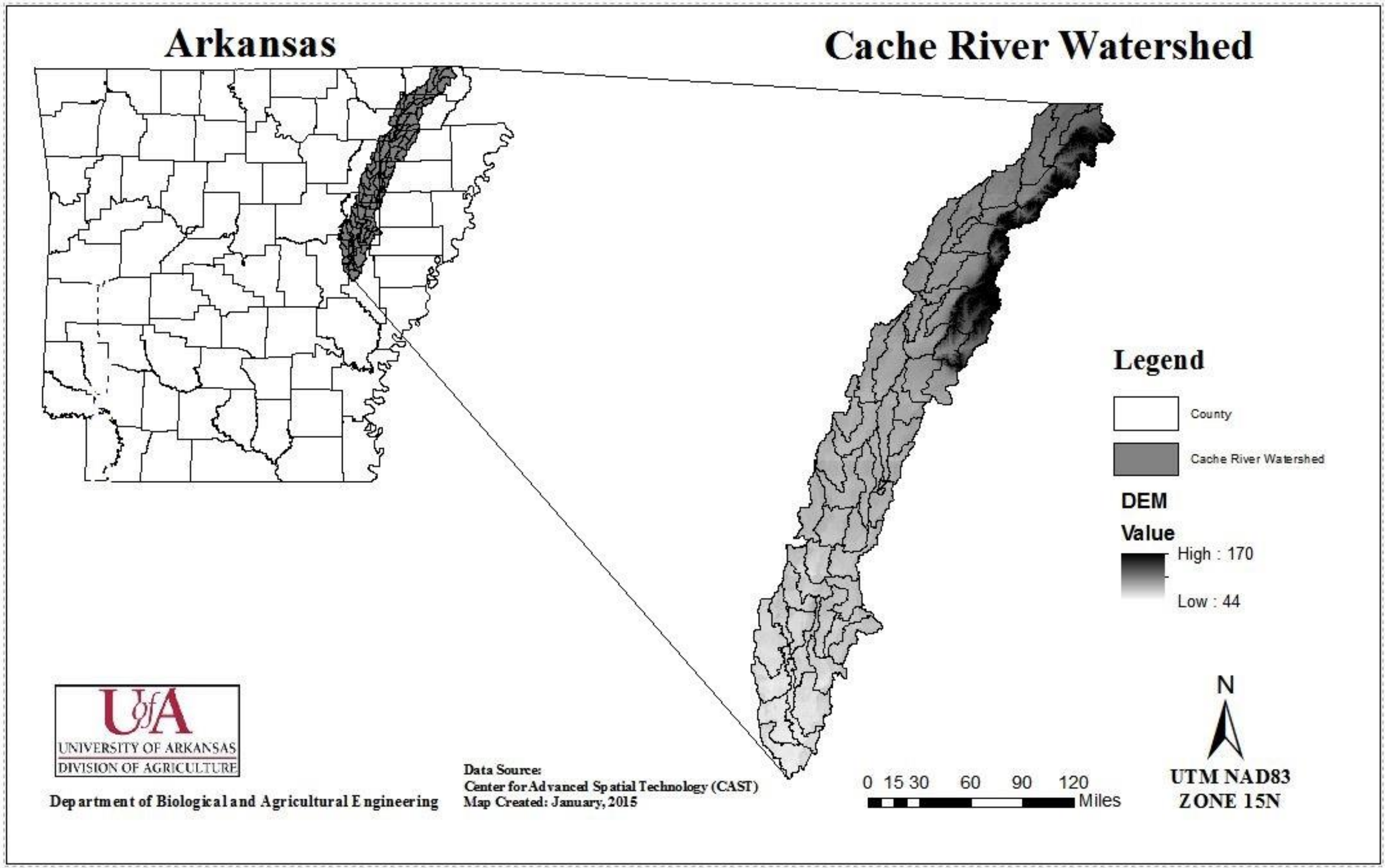

Figure 3.1- Study area: Cache River Watershed.

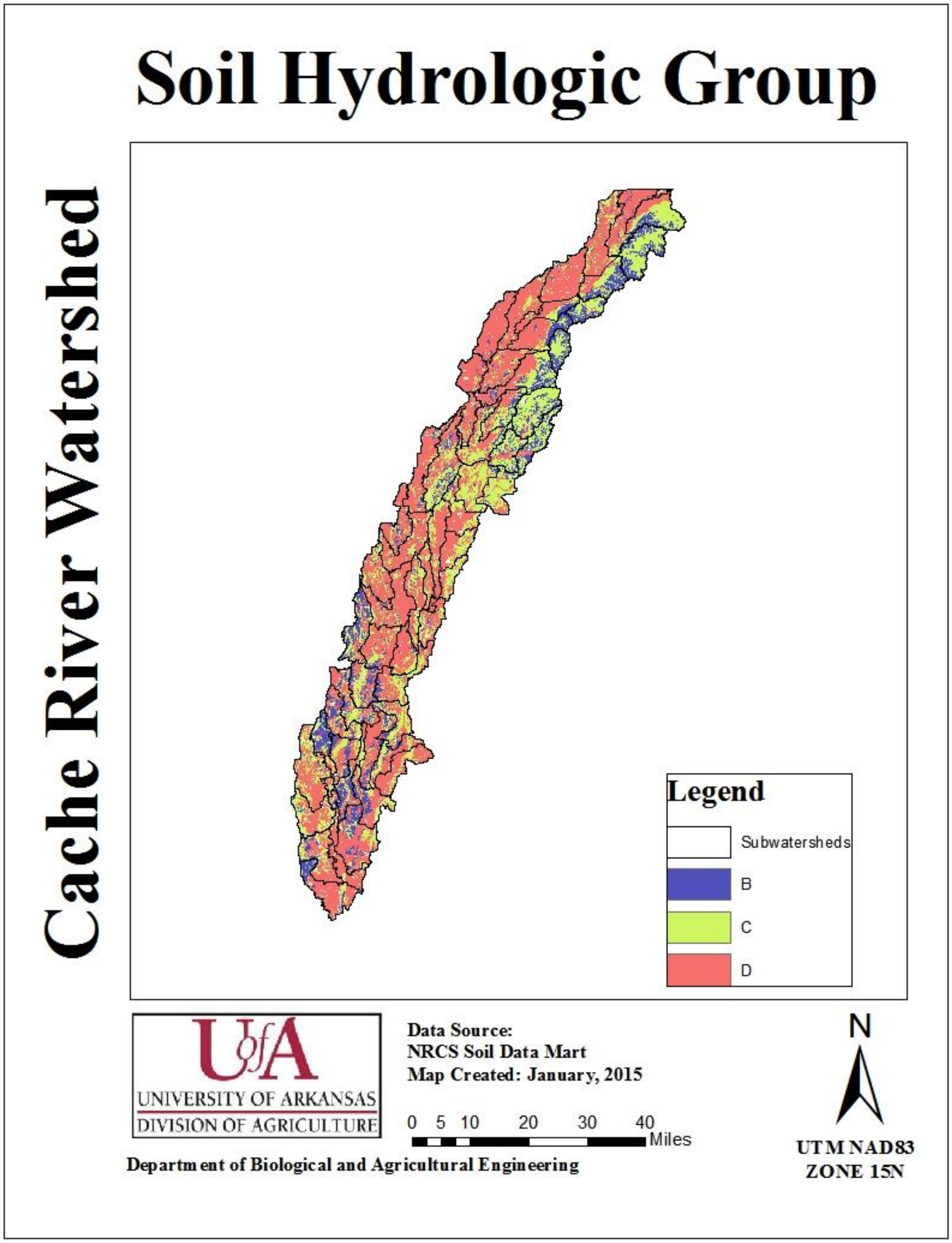

Figure 3.2- Soil hydrologic group for Cache River Watershed.

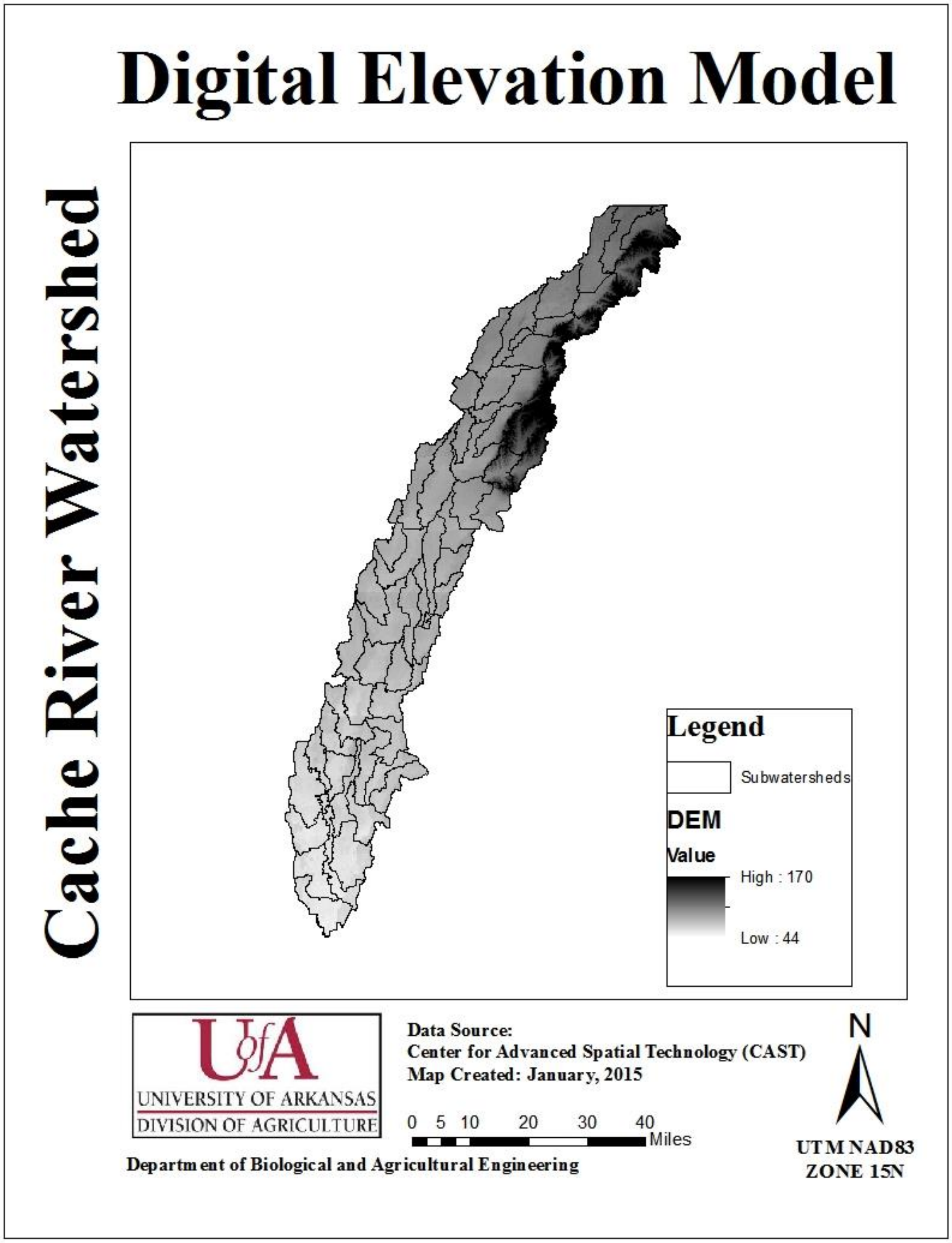

Figure 3.3- Digital Elevation Model (DEM) for Cache River Watershed.

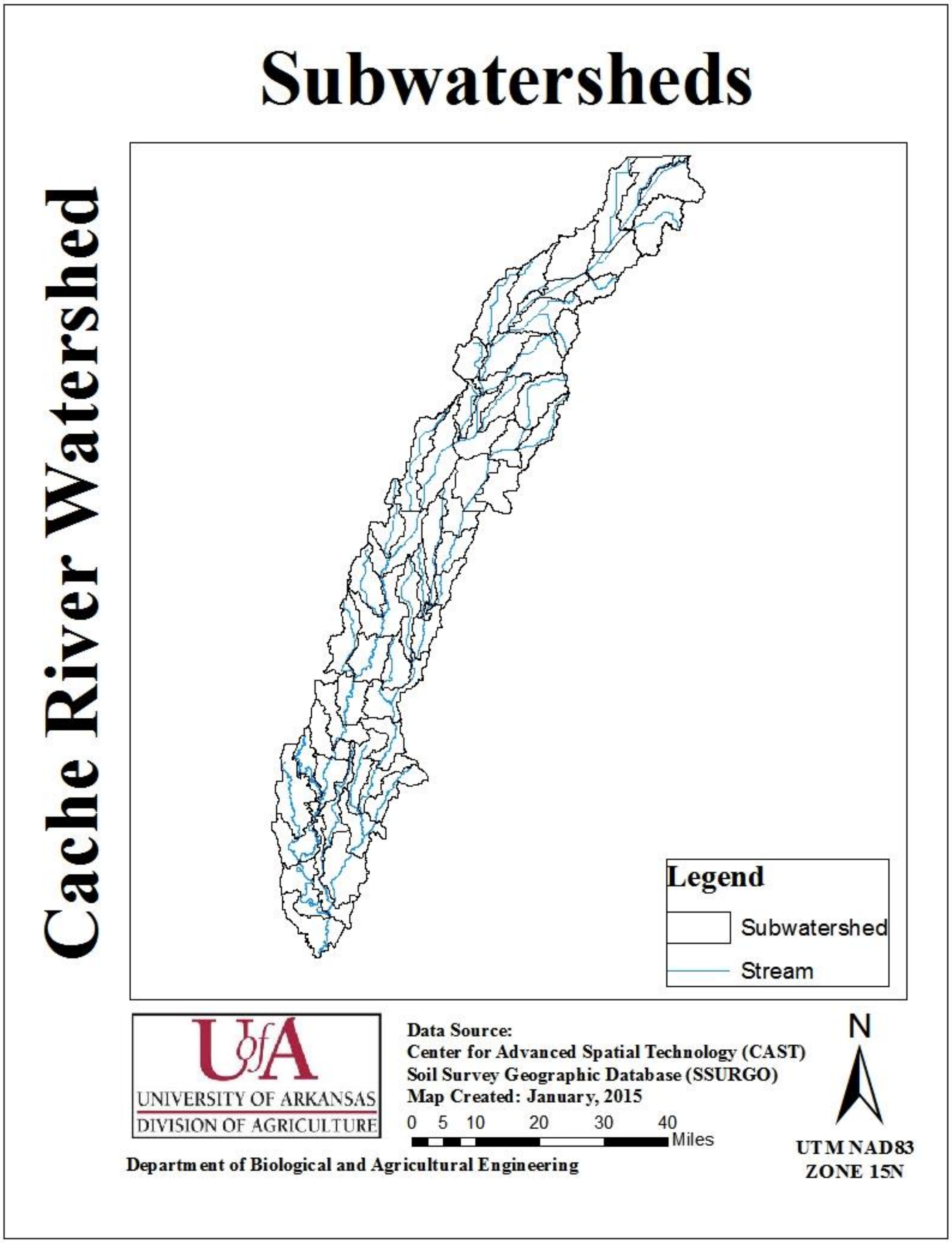

Figure 3.4- Subwatersheds in Cache River Watershed.

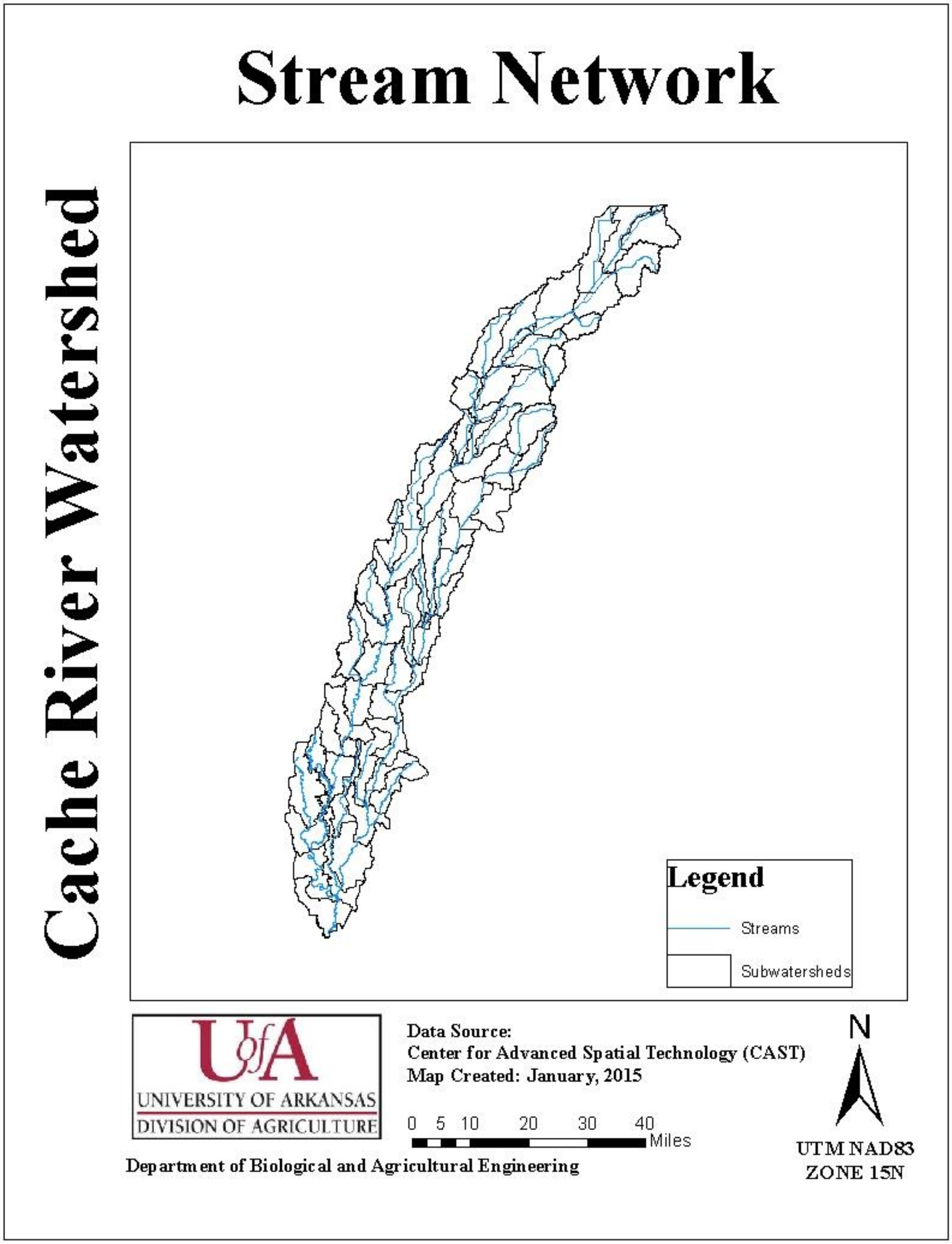

Figure 3.5- Stream network for Cache River Watershed

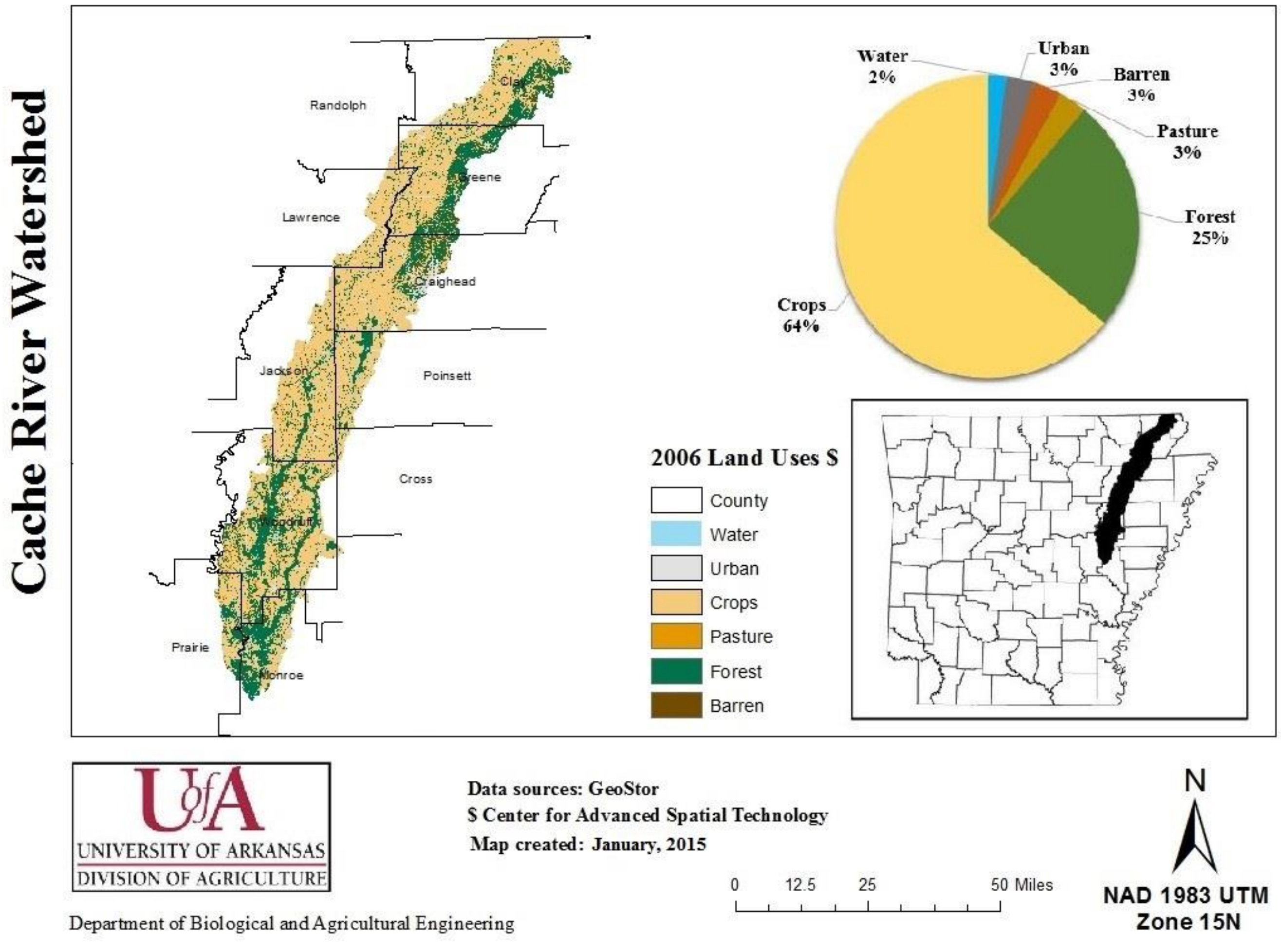

Figure 3.7- Land use land cover layer for Cache River Watershed.

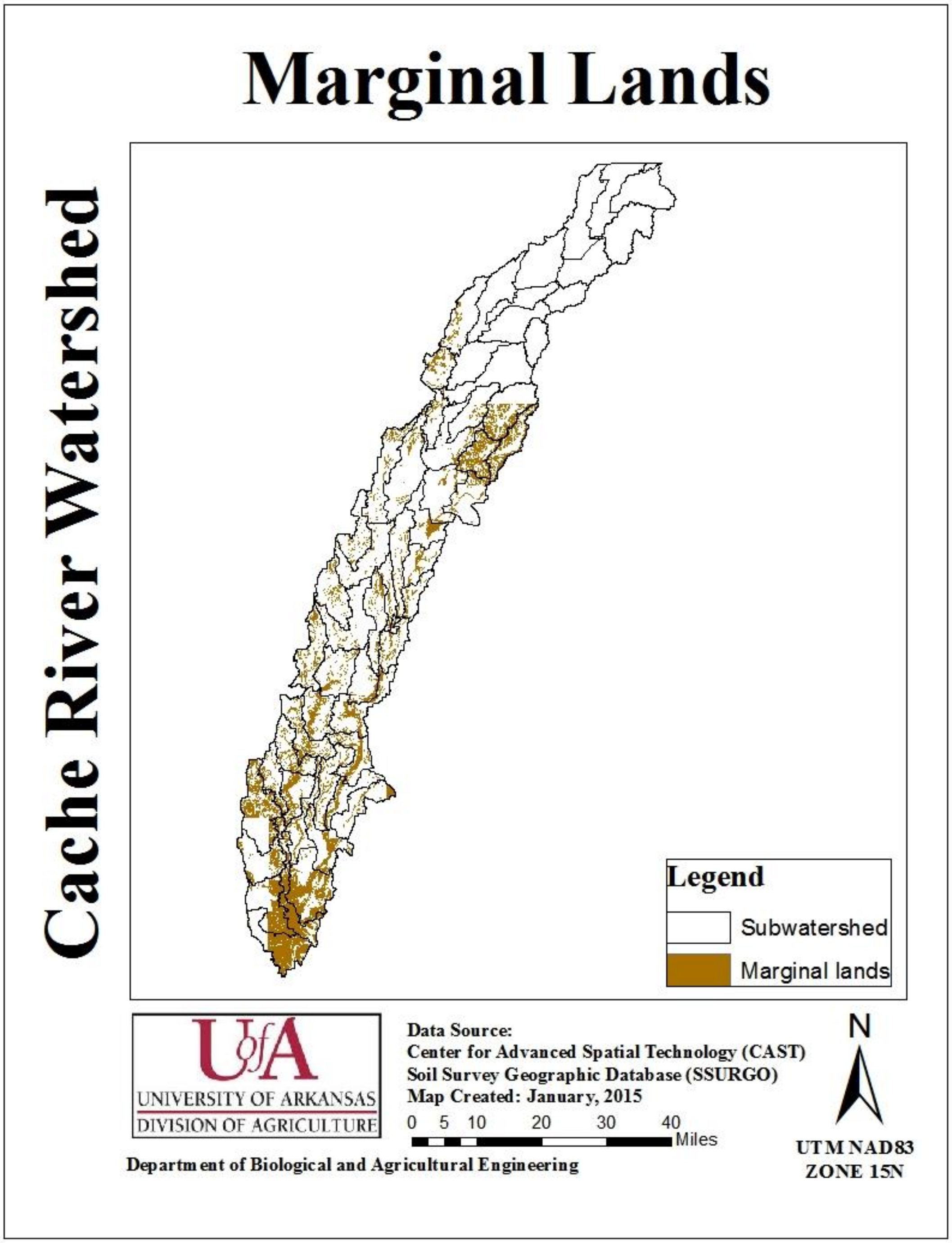

Figure 3.8- Marginal lands in Cache River Watershed.

3.4 SWAT model setup

ArcSWAT 2012.10.15 for ArcGIS 10.1 Service Pack 1, released on June 24, 2014, which was used in this study to develop two watershed models. One SWAT model was setup following a traditional practice, i.e., by using a single land use layer and the second model was built using multiple land uses by activating the land use change (LUC) module/land use update (lup.dat, Neitsch et al., 2011) using the SWAT LUC tool by Pai and Saraswat (2011) (available at http://130.184.161.242:15555/SwatTool/login). The LUC module updated the hydrologic response unit (HRU) areas defined by the variable HRU_FR. HRUs are unique combination of land use, soil and slope in a subwatershed. The value of HRU_FR ranges from 0 to 1. These values depict the fractional area covered by a HRU within the subwatershed (Pai and Saraswat, 2011). An un-published tool (LUU Checker tool, Dr. D. Saraswat, Associate Professor - Department of Agricultural and Biological Engineering, personal communication 15 January, 2015) was also used to re-update the SWAT model if a change was observed in land use layers and was not incorporated in the base raster used to setup the model. Since CRW was a watershed where the land use had changed during the study period, therefore it was important to incorporate that information within the second SWAT model before simulating various processes and it was the main reason behind using LUU Checker tool. A comprehensive base layer generated from the LUU Checker tool was used to setup the second SWAT model with HRUs created from the comprehensive base layer. Then the SWAT LUC tool was used to generate LUP.dat files which resulted in the final desired SWAT simulations during SWAT run.

For both the SWAT models, while creating HRUs no thresholds were used to preserve heterogeneity and prevent loss of information in relation to watershed landscape that could impact nutrient loads in a watershed (Her et al., 2015). HRU definition resulted in 14,053 HRUs for the first SWAT model and 12,321 HRUs for the second SWAT model. Since different land use layers were used to set-up the two models, a difference in number of HRUs was observed. A reduction in the number of HRUs may be possible due to less number of unique combinations of land use, soil and slope within a subwatershed in the two SWAT models. Weather, point source inputs and crop management practices were also provided. After model setup was complete, model checking, sensitivity analysis, calibration/validation and uncertainty analysis were performed for both the models. It was followed by creating scenarios for biofuel crop production on marginal lands and analyzing impacts on water quality.

3.5 Model checking

SWAT Check tool (Version 1.1.15-Released August 13, 2014; White et al., 2014) was used to identify potential model application problems. SWAT Check, with the help of process based figures, reads SWAT output files (such as Output.std, Output.hru etc.) and displays warning messages for values outside typical ranges. These warning messages indicate errors which are resolved while changing selected sensitive parameters during calibration phase and does not indicate serious issues in the modeling work. This tool identifies potential modeling errors classified in ten sections which include hydrology, sediment, nitrogen cycle, phosphorus cycle, plant growth, landscape nutrient losses, land use summary, in-stream processes, point sources, and reservoirs. SWAT Check indicated warnings related to hydrology (excessive water yields), high erosion rates, phosphorus and nitrogen stresses in crops and point sources. A detailed description of warning messages and their potential solutions are provided in appendices K and L. SWAT Check is generally used before and during calibration phase to have an idea if modeling results are well within the physically practical ranges and it was made sure that all the warnings disappeared during the calibration phase for both the SWAT models.

3.6 Sensitivity analysis

Since SWAT contains a very large number of parameters that could be calibrated by a user, it was important to determine those parameters that greatly affected the model outputs. Thus, sensitivity analysis was conducted to decrease the number of parameters to be adjusted during calibration phase of a model. In this study SUFI2 (Sequential Uncertainty Fitting version 2) algorithm (Abbaspour et al., 2013) was used in a parallel framework on AHPCC (Arkansas High Performance Computing Center) supercomputer for performing global sensitivity analysis. The advantage of using SUFI2 is that it requires smaller model runs (about 500) in comparison to other methods which require more simulations (~1000 to 3000) and a user can choose an objective function according to requirement (Yang et al., 2008).

In SUFI2, sensitivity of parameters are determined with the help of a multiple regression system that regresses latin hypercube generated parameter values against a specified objective function (Abbaspour, 2013). A t-test (with the null hypothesis that the given parameter had no effect on NSE) and corresponding p-values calculated by the program determine the sensitivity of a parameter (Abbaspour, 2013). In each case, a large t-value (and smaller p-value) indicates higher sensitivity with $p<0.05$ considered significant. Appendix M describes the procedure to run SWAT CUP on supercomputer.

Twenty six parameters were chosen based on literature review and physical characteristics of the watershed and 500 simulations were made for each SWAT model. Nash Sutcliffe Efficiency (NSE) was used as the objective function. As mentioned by Moriasi et al.

(2007), NSE is recommended by ASCE (1993) and Legates and McCabe (1999). It is a commonly used objective function in hydrology and has extensive information available on its reported values, thus making it a good choice (Schoul et al., 2008 and Yang et al., 2008). The threshold value that was chosen for the objective function was 0.60 (Abbaspour, 2013).

3.7 Calibration and Validation

Both the SWAT models were run for a period of 21 years from 1992 to 2012. A warm-up period is normally recommended to initialize and aid in the development of model variables (Tolson and Shoemaker, 2004). In this study the first four years were taken as warm-up years for both the models. Considering the availability of observed data (Table 3.3), the models were calibrated from 1996 to 2005 and validated from 2006 to 2012. However, there were some periods of missing data within the calibration and validation periods and were not included for calibration or validation. Calibration was first performed on annual scale followed by calibration on monthly time scale. The purpose of annual calibration was to decrease elative error at the annual scale for total flow, total phosphorus and total nitrogen. To address seasonal trends or variations both the models were calibrated on monthly basis (Chiang et al., 2010). Both the models were calibrated at the upstream gauge (Egypt) followed by downstream gauges (Patterson and Cotton Plant) to reduce the spatial accumulation of error (Arnold et al., 2012). Calibration of variables (outputs) was also done in a logical order as recommended by Arnold et al. (2012): hydrologic outputs (total flow, surface runoff and baseflow) calibrated first as they have effect on other output variables (White and Chaubey, 2005), followed by sediments, total phosphorus and total nitrogen. To calibrate the models at three USGS gauges: Cache River at Egypt (USGS 07077380), Cache River at Patterson (USGS 07077500) and Cache River at

Cotton Plant (USGS 07077555); outputs from subwatersheds 16, 50 and 57 were extracted from output.rch and output.sub files generated by SWAT.

Additional qualitative validation was performed for the period 2013-2014 for both the SWAT models by using recent water quality data. Since 2013 and 2014 were years that lie outside the modeling period for both the SWAT models, an approach reported by McCarty (James McCarty, Program Associate-Department of Biological and Agricultural Engineering, personal communication July 2, 2015) was used to test the model's ability to predict loads using data collected outside the modeling period. It serves as a criteria for post-model validation using measured data. Loads predicted by both the SWAT models were validated based on their qualitative similarities with the measured data loads. The comparison with recent monitoring data could be used as an additional measure to increase confidence in watershed models outputs.

For comparing the monitoring data and SWAT output at two gauges (Egypt and Cotton Plant), ellipses were generated by JMP Pro statistical software (SAS Institute Inc., Cary, NC) and set to cover 90% of the measured and simulated data for load regressions (McCarty). Ellipses depict covariance in linear regression model and provide information about the mean, variance, correlation and regression slopes of the two models in comparison (Friendly, 2006).

Table 3.3- List of available period of measured streamflow and nutrients at 3 USGS gauges.

USGS gauge	**Coordinates**	**Subwater shed**	**Drainage area (sq. miles)**		**Streamfl ow**	**TN**	**TP**
07077380	Lat:35°51'27", Long:90°55'59"	16	701	Calibration	1996/1-2005/12		
				Validation	2006/01-2014/12		2013/01-2014/12
07077500	Lat:35°16'11", Long:91°14'11"	50	1040	Calibration	1996/1-1997/10 2002/10-2005/12	1997/1-1997/10 2002/10-2005/12	1996/1-1997/10 2002/10-2005/12
				Validation	2006/01-2011/02	2006/01-2011/02	2006/01-2011/02
07077555	Lat:35°02'08", Long:91°19'21"	57	1170	Calibration	1996/1-2005/12		
				Validation	2006/01-2014/12		2013/01-2014/12

3.7.1 Model performance assessment

The annual time scale performance of both the SWAT models was assessed using relative error (RE) statistic (Santhi et al., 2001). The following equation was used for its calculation:

$$RE\ (\%) = \frac{|\,O-P\,|}{O}\ X\ 100 \qquad \ldots(1)$$

In the above equation, O represents the average annual measured value and P represents the average annual simulated value. To minimize relative error between observed and simulated values, performance ratings mentioned by Santhi et al. (2001) were used to judge annual time scale performance of the models (RE < 15% for average annual measured total flow and RE <25% for nutrients).

Statistical functions such as coefficient of determination (R^2), Nash-Sutcliffe efficiency, percent bias (PBIAS) and RMSE- observation standard deviation ratio (RSR) were used to judge the performance of the models on a monthly time scale (Table 3.4). These statistics are discussed below:

Standard regression statistic:

Coefficient of Determination (R^2): It describes the degree of collinearity between simulated and observed data. It represents the proportion of variance in observed data reported by the model. This varies from 0 to 1, higher values meaning less error variance and generally values above 0.5 are considered acceptable (Moriasi et al., 2007; Santhi et al., 2001). R^2 was calculated by equation 2:

$$R^2 = \left[\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_{mean}^{obs}\right)\left(Y_i^{sim} - Y_{mean}^{sim}\right)}{\left[\sum_{i=1}^{n}\left(Y_i^{obs} - Y_{mean}^{obs}\right)^2 \sum_{i=1}^{n}\left(Y_i^{sim} - Y_{mean}^{sim}\right)^2\right]}\right]^2 \quad \ldots (2)$$

Dimensionless statistic:

Nash-Sutcliffe Efficiency (NSE): It represents relative magnitude of residual variance (noise i.e. error sum of squares SSE) compared to observed data variance. NSE ranges from -∞ to 1, with 1 as the ideal value (Moriasi et al., 2007). NSE was calculated by equation 3:

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs} - Y^{mean}\right)^2}\right] \quad \ldots (3)$$

Error Index:

Percent Bias (PBIAS): It determines average tendency of simulated data to be greater or lesser than their observed counterparts. The ideal value of PBIAS is zero, positive values represent underestimation and negative values represent overestimation of results by a model (Moriasi et al., 2007). It was calculated by equation 4:

$$PBIAS = \left[\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)*(100)}{\sum_{i=1}^{n}\left(Y_i^{obs}\right)}\right] \quad \ldots (4)$$

RMSE-observations standard deviation ratio (RSR): RMSE (Root Mean Square Error) is commonly used as an error index statistics. RSR standardizes RMSE using observations standard deviation which is calculated as a ratio of RMSE and standard deviation of measured data (Moriasi et al., 2007; Singh et al., 2004). RSR was calculated by equation 5:

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\left[\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}\right]}{\left[\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - Y^{mean}\right)^2}\right]} \quad \ldots (5)$$

In the above equations 2 to 5, Y_i^{obs} is measured value, Y_i^{sim} is simulated value, Y^{mean} is the mean of observed values, and i is the number of values.

Table 3.4- Performance ratings used for evaluating monthly model results (adapted from Moriasi et al., 2007)

Rating	NSE	RSR	PBIAS (%)		
			Streamflow	Sediment	N, P
Very good	0.75 ≤ E ≤ 1.00	0.00 ≤ RSR ≤ 0.50	PBIAS ≤ ±10	PBIAS ≤ ±15	PBIAS ≤ ±25
Good	0.65 ≤ E ≤ 0.75	0.50 ≤ RSR≤ 0.60	±10 ≤ PBIAS ≤ ±15	±15 ≤ PBIAS ≤ ±30	±25 ≤ PBIAS ≤ ±40
Satisfactory	0.50 ≤ E ≤ 0.65	0.60 ≤ RSR ≤ 0.70	±10 ≤ PBIAS ≤ ±25	±30 ≤ PBIAS ≤ ±55	±40 ≤ PBIAS ≤ ±70
Unsatisfactory	E < 0.50	RSR < 0.70	PBIAS > ±25	PBIAS > ±55	PBIAS > ±70

Table 3.5 – Parameters adjusted during calibration phase of SWAT

Parameter	Description	Unit	Range	Default value
Parameters affecting surface water				
CN2	SCS runoff curve number	None	35-98	Varies
ESCO	Soil evaporation compensation factor	None	0-1	0.95
CANMX	Canopy storage capacity	Mm	0-100	0
Parameters affecting subsurface water				
ALPHA_BF	Baseflow recession constant	1/Day	0-1	0.048
GW_REVAP	Ground water revap coefficient	None	0.02-0.2	0.02
GW_DELAY	Ground water delay time	Days	0-500	31
REVAPMN	Threshold depth of water in shallow aquifer for percolation	Mm	0-1000	750
GWQMN	Threshold depth of water in shallow aquifer for return flow	Mm	0-5000	1000
RCHRG_DP	Deep aquifer percolation fraction	None	0-1	0.05
Parameters affecting phosphorus				
PSP	Phosphorus sorption coefficient	None	0.01-0.7	0.4
SOL_SOLP	Initial soluble P concentration	mg/kg	0-100	5
PHOSKD	Phosphorus soil partitioning coefficient	m^3/mg	100-200	175
BC4	Rate constant for mineralization of organic P	1/Day	0.01-0.7	0.35
RS5	Organic P settling rate	1/Day	0.001-0.1	0.05
BIOMIX	Biological mixing efficiency	None	0-1	0.2
USLE_P	USLE crop practice factor	None	0-1	1
Parameters affecting nitrogen				
RCN	Concentration of N in rainfall	mg/L	0-15	1
SHALLST_N	Initial concentration of nitrate in shallow aquifer	mg/L	0-1000	0
ERORGN	Organic N enrichment ratio for loading with sediment	None	0-5	0
SDNCO	Denitrification threshold water content	None	0-1	0.8
CDN	Denitrification exponential coefficient	None	0-3	1.4
N_UPDIS	Nitrogen uptake distribution parameter	None	0-100	20

3.7.2 Hydrology calibration

Hydrology was calibrated first starting from the upstream gauge (Egypt). The parameters affecting surface water and subsurface water were varied within their recommended ranges (Table 3.6) to fine-tune the model outputs. In order to capture the hydrograph peaks and recessions, parameters such as CN2 (SCS runoff curve number) and canopy storage capacity (CANMX; 0 to 100 mm) were changed. Soil evaporation compensation factor (ESCO; 0 to 1) which controls the depth distribution in order to meet the soil evaporative demand to address effects of capillary action, cracks and crusting was also adjusted to calibrate surface runoff (Neitsch et al. 2011). Baseflow was calibrated by changing parameters such as baseflow recession factor (ALPHA_BF; 0 to 1). Threshold depth of water in shallow aquifer for percolation (REVAPMN; 0 to 1000 mm), threshold depth of water in shallow aquifer for return flow to occur (GWQMN 0 to 5000 mm), ground water "revap" coefficient (GW_REVAP; 0.02 to 0.2) and ground water delay (GW_DELAY; 0 to 500 days) were adjusted. Once hydrology was calibrated at the upstream gauge (Egypt), parameter adjustments were made for the downstream gauges (Patterson and Cotton Plant) followed by calibration of total phosphorus and total nitrogen at Patterson gauge due to nutrient data availability at only this gage. Lack of observed sediments data at any of the gages did not allow sediment calibration or validation. Therefore, after satisfactory hydrologic calibration, total phosphorus and total nitrogen were calibrated.

3.7.3 Modeling phosphorus in SWAT

Phosphorus can be added to soil by applying fertilizer, manure or residue. Removal of phosphorus from soil can happen by plant uptake and erosion (Neitsch et al., 2011). In SWAT soil phosphorus is divided into six pools as shown in figure 3.9 (Neitsch et al., 2011). The default values of initial concentration of solution phosphorus (SOL_P) are 5 mg P kg^{-1} and 25 mg P kg^{-1} for unmanaged land under native vegetation and soil for cropland conditions (Chaubey et al., 2006). This initial amount of solution or labile P can be specified by a user. Soil test data that was available for three counties: Craighead, Cross and Clay from 1992 to 2012, was used to model phosphorus in SWAT. The data was reported as percentage of clay and organic carbon were found from the SSURGO database for the top layer of the three major soils. The order and suborder for the soils were determined from USDA website and Brady and Weil (2002).

The following equation (6) given by Sharpley et al. (1984) and Vadas and White (2010) was used to calculate phosphorus sorption coefficient (PSP):

$$PSP = -0.053 \text{ X } \ln(\%\text{ Clay}) + 0.001\text{X } (\text{Sol P, mg/kg}) - 0.029 \text{ X } (\%\text{ Org Carbon}) + 0.42 \quad \ldots (6)$$

The value of solution P (32.1 mg/kg) was taken as half of the Mehlich 3 test phosphorus values (Vadas and White, 2010; Vadas et al., 2006). The final value of PSP was 0.28 which was used in the SWAT model. Solution P was taken equal to 32.1 mg/kg for subwatersheds that lie in Craighead, Cross and Clay counties (1,2,4,5,8,9,10,11,13,14,16,17,18,19,20,22) and for the remaining subwatersheds (3,6,7,12,15,21 and 23 to 57) default Solution P values were retained.

Other sensitive parameters that were adjusted within their recommended ranges (Table 3.5) to calibrate total phosphorus were: USLE crop practice factor (USLE_P), phosphorus soil partitioning coefficient (PHOSKD), rate constant for mineralization of organic phosphorus (BC4), organic phosphorus settling rate (RS5), and biological mixing efficiency (BIOMIX).

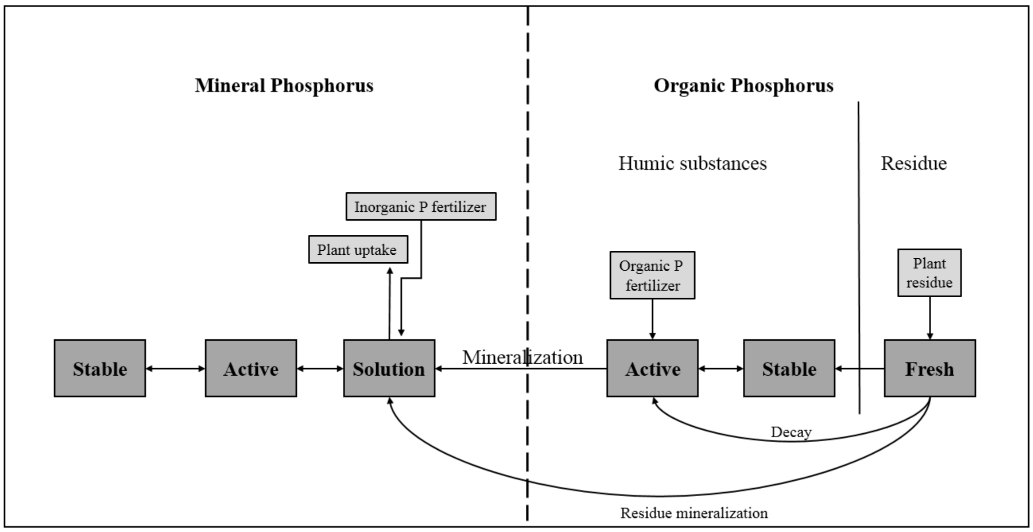

Figure 3.9- Components of phosphorus cycle in SWAT. Adapted from Neitsch et al. (2011).

3.7.4 Modeling nitrogen in SWAT

Similar to phosphorus, nitrogen can also be added to soil by fertilizer, manure or residue application (Neitsch et al., 2011). Five pools of nitrogen are simulated in SWAT, of these, two are inorganic nitrogen (NH_4^+ and NO_3^-) pools and the other three are organic forms of nitrogen (Figure 3.10, Neitsch et al., 2011) .

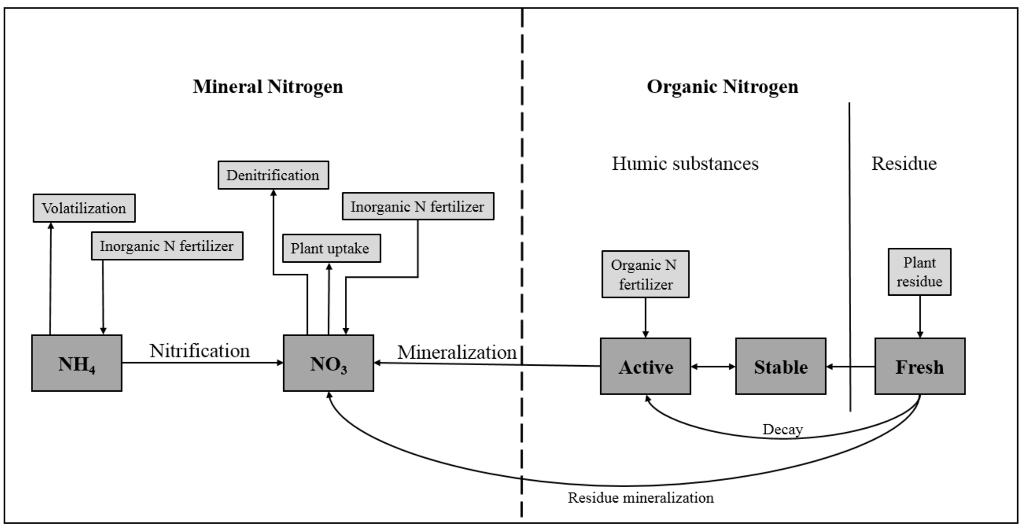

Figure 3.10- Components of nitrogen cycle in SWAT. Adapted from Neitsch et al. (2011).

In SWAT, a user can specify the amount of nitrate and organic nitrogen contained in soil layers according to soil test data. SWAT can automatically simulate and initialize levels of nitrogen in the different pools if no values are provided. Two parameters were changed as per available data, and several other parameters were perturbed to calibrate nitrogen.

Though default value of nitrogen concentration in rainfall is set to 1 (RCN=1 mg N/L), other values have also been mentioned in the literature (RCN=0.05 by Jiang et al., 2014 and RCN=1.03 by Folle, 2010). To determine the value of RCN in the current work, information of atmospheric deposition of nitrogen was retrieved from the National Atmospheric Deposition Program (NADP) website (http://nadp.sws.uiuc.edu/ntn/annualmapsByYear.aspx#2012). The information was provided as nitrate and ammonium ion concentration (year 2012), therefore, these concentrations were converted to total nitrogen concentration at each station. For two stations (Buffalo National River-Buffalo Point in Marion County and Caddo Valley in Clark County) in Arkansas, concentration of nitrate ion was 0.63 mg/L and 0.67 mg/L and ammonium ion was 0.22 mg/L and 0.18 mg/L respectively. The total nitrogen concentration from nitrate ions at Buffalo National River-Buffalo Point station was calculated as 0.14 mg N/L and at Caddo Valley station it was 0.15 mg N/L (since nitrate molecule weighs 62 grams per mole; the nitrogen content of nitrate is 22.5% of the total weight of the molecule equals to 0.63*0.22 and 0.67*.22). Similarly, total concentration of nitrogen from ammonium ion was 0.17 mg N/L and 0.14 mg N/L for the two stations (0.77*0.22 and 0.77*0.18 as 77% of nitrogen from ammonium whose molecular weight is 18 grams per mole). The value of total nitrogen concentration (sum of nitrogen from nitrate and ammonium) was taken as 0.3 mg-N/L and provided as input in the ".bsn file" in the models.

The initial concentration of nitrate in shallow aquifer (SHALLST_N, mg N/L) is equal to zero (Neitsch et al., 2011). Some other values have also been used in literature (SHALLST_N=0.1 by Hu et al., 2007 and SHALLST_N=0.001 mg N/L by Folle, 2010). Ground water nitrate concentration values for CRW were obtained from the USGS website on a county basis (for Prairie county its value was 1.7 mg N/L, for Woodruff county the value was 1.33 mg

N/L, for Jackson county the value was 0.12 mg N/L and for Clay county the value was 0.05 mg N/L). These values were changed on a subwatershed basis as per the counties in the ".gw file" in the models.

In addition to concentration of nitrogen in rainfall (RCN) and initial concentration of nitrate in shallow aquifer (SHALLST_N), other parameters adjusted to calibrate total nitrogen included denitrification threshold water content (SDNCO), denitrification exponential coefficient (CDN), organic nitrogen enrichment ratio for loading with sediment (ERORGN) and nitrogen uptake distribution parameter (N_UPDIS). All these parameters were varied within the recommended ranges (Table 3.6).

3.8 Uncertainty analysis

SWAT-CUP software (Abbaspour et al., 2013) with SUFI2 algorithm was used to perform uncertainty analysis for both the SWAT models developed for CRW. SUFI2 finds uncertainty parameters that affect the forecast for most of the observed data (Schoul et al., 2008). It allows a user to choose an arbitrary likelihood/objective function, requires smaller model runs to get good prediction uncertainty bands and identifies critical sources of uncertainty (Xue et al., 2014; Yang et al., 2008).

AHPCC supercomputer was used to make a total 1000 simulations performed in two successive iterations of 500 each (Yang et al., 2008; Abbaspour, 2013) for both the SWAT models. Two iterations were made to achieve good prediction uncertainty bands. After completion of simulations, SWAT CUP produced results in form of 95 PPU plots. The degree to which all uncertainties are reported is quantified by p-factor: determining percentage of observed data bracketed by the 95% prediction uncertainty (95PPU) and r-factor which represents thickness of the 95PPU band (Abbaspour, 2013).

3.9 Simulation of bioenergy crops in SWAT

Plant growth and development, biomass, yield, nutrient and water uptake are driven by parameters present in the SWAT crop database. In case of perennial plants like Switchgrass and Miscanthus, crop growth starts when the mean daily temperature reaches a base threshold temperature. Also, these perennial plants/grasses are able to maintain a nutrient pool as they do not require replanting and keep yielding for many years (Ng et al., 2010).

In this study, Miscanthus and Switchgrass were simulated on targeted (marginal) lands identified as separate land use categories: CORM (marginal corn), COTM (marginal cotton), RICM (marginal rice), SOYM (marginal soybean) and AGRM (marginal generic agriculture). The total available marginal cropland for bioenergy crop simulation for the first SWAT model was 8% (407 square kilometers) of the watershed area. Since the second SWAT model used six different land use layers, the marginal crop land available for bioenergy crops varied. As the land use land cover and cropped area in CRW had changed during the modeling period, for 1992, 1999, 2001, 2004, 2006 and 2011, the available marginal croplands also changed by occupying 11 % (557 square kilometers), 6 % (303 square kilometers), 7 % (355 square kilometers), 3 % (153 square kilometers), 8 % (407 square kilometers) and 10 % (508 square kilometers) of the watershed area respectively.

The SWAT crop growth model already contains parameters for a lowland cultivar of Switchgrass called ‘Alamo’ (Arnold et al., 2013). However, two parameters: maximum potential leaf area index (BLAI) which indicates the leaf area development of a plant species during the growing season and maximum canopy height (CHTMX) which indicates the measurement of maximum canopy height of a crop were changed to represent its growth in Arkansas (Singh, 2012). The value of BLAI was changed from 6 m to 10 m and CHTMX was changed from 2.5 m to 3 m because with an increase in growing degree days crop growth is affected.

Miscanthus, being a relatively new crop, SWAT model lacks its growth parameters. Ng et al. (2010) and Trybula et al. (2014) have proposed parameter values for Miscanthus modeling in SWAT. Values defined by Trybula et al. (2014) (Appendix N) were used in this study to represent Miscanthus in both the SWAT models. Out of 27 crop growth parameters, 22 parameters were changed but 5 parameters were retained from the database values for Switchgrass. To represent harvest scenario for Miscanthus, value of harvest efficiency (HARVEFF) was taken equal to 0.7 and harvest index (HI) was taken equal to 1. This represents Miscanthus yield of 70% of above ground biomass is totally removed and remaining 30% goes to the residue pool and below ground biomass is retained for the next year (Trybula et al., 2014). For Switchgrass the default value of HARVEFF was taken as 0.9 and HI was taken as 1 (Parajuli, 2011, Singh, 2012). Both the bioenergy crops were harvested once in a year (one-cut system).

Management practices (Appendix I) that included fertilizer and pesticides application timings and rates, tillage operations, crop planting and harvesting dates for both the bioenergy crops were adapted from Singh (2012).

Simulation of bioenergy crops in SWAT resulted in a total of three scenarios: baseline scenario (no bioenergy crop growing on marginal lands), Switchgrass scenario (all marginal cropland converted to Switchgrass) and Miscanthus scenario (all marginal cropland converted to Miscanthus). Section 3.10 describes the analysis of impacts of production of bioenergy crops.

3.10 Water quality impacts of bioenergy crops

In order to analyze the impacts of production of Switchgrass and Miscanthus on targeted marginal land/HRUs, loadings of sediments, total phosphorus and total nitrogen over a period of 17 years (excluding warm-up years) were analyzed. Since both the models were calibrated on a monthly scale and SWAT was set to print outputs on a monthly basis, the outputs at a watershed scale (watershed outlet) were evaluated for mean-monthly changes in nutrient loadings (Cibin et al., 2012; Ng et al., 2010). No bioenergy crops growing on marginal lands was considered as a baseline scenario for both the models. Mean-monthly simulated loads were compared for the baseline scenario and Switchgrass or Miscanthus scenario. The percentage change from baseline were reported for sediment, total phosphorus and total nitrogen loadings at the watershed outlet.

3.11 Yield analysis for bioenergy crops

To gain confidence in modeling simulations, an additional yield analysis for Switchgrass and Miscanthus was conducted. This was performed to compare the model predicted yields with the Arkansas reported literature values. Mean-annual simulated yields for the bioenergy crops were obtained for the SWAT models. The relationship between nitrogen uptake and biomass yield on an annual basis was also determined for Switchgrass and Miscanthus. Changes in leaf area index (LAI) were also analyzed as the crops matured towards harvest on a monthly simulation scale. The relationship between for LAI and biomass yield was also explored.

3.12 Comparison of SWAT models

In this study two SWAT models were developed following two different approaches of modeling. The first SWAT model used a single land use layer whereas the second model was developed using the land use update feature in SWAT using multiple land use layers with the help of SWAT LUC tool.

For both the SWAT models, a comparison was made between calibration/validation results, bioenergy scenario effects on sediment, total phosphorus and total nitrogen loadings at the watershed outlet along with biomass yields for Switchgrass and Miscanthus.

3.13 Hypothesis testing

The hypothesis developed in this study was that long term land use change in the Cache River Watershed has no significant effect on sediment and nutrient loadings at the watershed outlet. This hypothesis was tested by simulating two biofuel crop scenarios (Switchgrass and Miscanthus) during the modeling period (1992 to 2012) on marginal lands in the watershed. A linear regression analysis was performed using JMP Pro statistical software (SAS Institute Inc., Cary, NC) for the baseline scenario (no biofuel crop growing on marginal lands) and Switchgrass/Miscanthus scenarios. The analysis was performed for sediment, total phosphorus and total nitrogen loadings at the watershed outlet.

3.14 References

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IV. RESULTS AND DISCUSSION

4.1 Sensitivity analysis

For the first SWAT model it was found that CN2 (initial SCS runoff curve number for AMC II condition) was the most sensitive with a t-stat value of -16.81 and a p-value of 0 (Table 4.1). The t-stat, which is the coefficient of the parameter divided by its standard error (in multiple regression analysis) has a corresponding lower p-value (<0.05) which indicated that the result is significant, which implies that changes in parameter values have significant effect on the value of objective function (NSE). According to the SSURGO soils data layer, C and D classes are the dominant hydrological soils group in the Cache River Watershed. These two soil groups have high runoff potentials (Nielsen and Hjelmfelt, 1998) which in turn relates to the fact that flow in Cache River Watershed was mainly affected by overland processes. Also, modified soil conservation service (SCS) curve number equation relates flow and CN2 therefore, CN2 was observed as the most sensitive parameter. SURLAG (surface runoff lag coefficient) was the most sensitive parameter for the second SWAT model with a t-stat value of -16.51 and a p-value of 0 (Table 4.2). In large watersheds time of concentration may be greater than 1 and only a portion of the surface runoff will reach the main channel it is generated which can be controlled by SURLAG to lag a portion of the surface runoff released to the main channel (Neitsch et al., 2011). Since Cache River Watershed is a large-sized (5,066 square kilometers) watershed, there is no surprise that SURLAG came out to be a very sensitive parameter. Groundwater revap coefficient (GW_REVAP) which controls movement of water from shallow aquifer to root zone was found to be sensitive for subsurface flow. The t-stat value was -1.5 and 0.03 for the first and second SWAT model respectively. The p-value was 0.13 and 0.98 for the first and second SWAT model. The results indicate that GW_REVAP was not a sensitive parameter (Table 4.2) for the second model but it was found to affect the model outputs. It was because global sensitivity gives relative sensitivities based on linear approximations and does not consider correlations between parameters (Abbaspour, 2013; White and Chaubey, 2005) so, sometimes parameters that are sensitive may be neglected by SWAT CUP or those parameters may be reported which are not sensitive at all. Another parameter that affected subsurface flow was the baseflow recession factor (ALPHA_BF) which is the direct index of groundwater flow response to changes in recharge. The t-stat value was 1.44 and -1.59 for the first and second SWAT model respectively. The p-value was 0.15 and 0.11 for the first and second SWAT model.

The most sensitive parameters related to total phosphorus were the universal soil loss equation practice factor (USLE_P) and phosphorus enrichment ratio for loading with sediment (ERORGP). The t-stat value for USLE_P was -7.55 and -8.84 for the first and second SWAT model and the p-value was 0 for both the models. The t-stat value for ERORGP was -4.91 and -9.98 for the first and second SWAT models respectively. Similarly, the p-values for the corresponding t-stat values indicate that there is significant effect of the parameter value on the objective function, hence meaning that parameter is sensitive.

Initial concentration of nitrate in shallow aquifer (SHALLST_N) was the most sensitive parameter for total nitrogen for both the SWAT models. The t-stat value was -1.31 and -1.48 for the first and second SWAT model respectively. The p-value was 0.18 and 0.14 for the first and second SWAT model.

Table 4.1- Global sensitivity analysis results for the first SWAT model.

Rank	Parameter	t-stat value	p-value
1	CN2- Initial SCS runoff curve number for AMC II	-16.81	0
2	SURLAG- Surface runoff lag coefficient	-13.48	0
3	USLE_P- USLE practice factor	-7.55	0
4	ERORGP- Phosphorus enrichment ratio for loading with sediment	-4.91	0
5	USLE_K- Soil erodibility factor	-4.58	0
6	PSP- Phosphorus availability index	-1.94	0.05
7	GW_REVAP- Ground water revap coefficient	-1.50	0.13
8	ALPHA_BF- Baseflow alpha factor	1.44	0.15
9	SHALLST_N- Initial concentration of nitrate in shallow aquifer	-1.31	0.18
10	ESCO- Soil evaporation compensation factor	-1.21	0.22
11	SOL_K- Saturated hydraulic conductivity	-0.88	0.37
12	SPCON- Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	0.79	0.43
13	REVAPMN- Threshold depth of water in the shallow aquifer for revap or percolation to occur	-0.76	0.44
14	PPERCO- Phosphorus percolation coefficient	0.65	0.51
15	RCHRG_DP- Deep aquifer percolation fraction	-0.63	0.57
16	GWQMN- Threshold depth of water in the shallow aquifer required for return flow to occur	-0.56	0.58
17	SOL_AWC- Plant available water	0.52	0.59
18	RS5- Organic phosphorus settling rate in reach	0.38	0.70
19	SPEXP- Exponent parameter for calculating sediment re-entrained in channel sediment routing	-0.38	0.70
20	GW_DELAY- Ground water delay time	0.37	0.70
21	RCN- Concentration of nitrogen in rainfall	0.31	0.75
22	SOL_BD- Moist bulk density	0.28	0.77
23	BC4- Rate constant for mineralization of organic P to dissolved P in the reach at 20^0 C	0.15	0.88
24	NPERCO- Nitrate percolation coefficient	0.14	0.89
25	ANION_EXCL- Fraction of porosity from which anions are excluded	-0.04	0.96
26	EPCO- Plant uptake compensation factor	0.03	0.98

Table 4.2- Global sensitivity analysis for the second SWAT model.

Rank	Parameter	t-stat value	p-value
1	SURLAG- Surface runoff lag coefficient	-16.51	0
2	ERORGP- Phosphorus enrichment ratio for loading with sediment	-9.98	0
3	USLE_P- USLE practice factor	-8.84	0
4	CN2- Initial SCS runoff curve number for AMC II	-6.98	0
5	USLE_K- Soil erodibility factor	-6.59	0
6	SOL_BD- Moist bulk density	-4.38	0
7	PSP- Phosphorus availability index	2.76	0.01
8	ESCO- Soil evaporation compensation factor	-2.42	0.02
9	ALPHA_BF- Baseflow alpha factor	-1.59	0.11
10	SHALLST_N- Initial concentration of nitrate in shallow aquifer	-1.48	0.14
11	RCN- Concentration of nitrogen in rainfall	-1.24	0.21
12	BC4- Rate constant for mineralization of organic P to dissolved P in the reach at 20^0 C	1.15	0.25
13	RCHRG_DP- Deep aquifer percolation fraction	0.90	0.37
14	SOL_AWC- Plant available water	0.60	0.55
15	SOL_K- Saturated hydraulic conductivity	-0.57	0.57
16	GWQMN- Threshold depth of water in the shallow aquifer required for return flow to occur	-0.56	0.58
17	REVAPMN- Threshold depth of water in the shallow aquifer for revap or percolation to occur	0.45	0.65
18	NPERCO- Nitrate percolation coefficient	0.42	0.67
19	GW_DELAY- Ground water delay time	-0.41	0.68
20	PPERCO- Phosphorus percolation coefficient	-0.34	0.73
21	SPEXP- Exponent parameter for calculating sediment re-entrained in channel sediment routing	0.24	0.81
22	RS5- Organic phosphorus settling rate in reach	0.18	0.86
23	EPCO- Plant uptake compensation factor	0.15	0.88
24	ANION_EXCL- Fraction of porosity from which anions are excluded	-0.12	0.91
25	SPCON- Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	0.10	0.92
26	GW_REVAP- Ground water revap coefficient	0.03	0.98

4.2 Model calibration and validation

4.2.1 Annual calibration

For total flow, relative error (RE) for the first SWAT model were 3.6%, 14.9% and 6.4% at Egypt, Patterson and Cotton Plant USGS gauges respectively. RE for total phosphorus and total nitrogen were 17.7% and 62.7% respectively at the Patterson USGS gauge. For the second SWAT model, RE for total flow were 0.8%, 12% and 5.3% for Egypt, Patterson and Cotton Plant USGS gauges respectively. RE for total phosphorus and total nitrogen were 19.9% and 5.3% respectively at the Patterson USGS gauge. The first SWAT model over-predicted total flow for: 1996, 2004, and 2005 at Egypt USGS gauge; 1996, 2004, and 2005 at Patterson USGS gauge; and 1996, 2000, 2004, and 2005 at Cotton Plant USGS gauge (Figures 4.1 and 4.2). For rest of the years the first model under-estimated total flow. The second SWAT model over-predicted total flow for: 1996, 1999, 2000, 2002, 2004, and 2005 at Egypt USGS gauge; 1996, 2004, and 2005 at Patterson USGS gauge; and 1996, 2000, 2004, and 2005 at Cotton Plant USGS gauge. For rest of the years the second model under-estimated the flows. Past studies have indicated that the main reason for under and over prediction is spatial variability (Santhi et al., 2001; Srinivasan et al., 1998). Against an average rainfall of 849.0 mm, during the under/over prediction period, the rainfall in Cache River Watershed varied from 619.7 mm to 1353 mm. As nutrients depend on the hydrology calibration, a similar trend was seen for phosphorus and nitrogen. Both the SWAT models under predicted total phosphorus loadings during the calibration period except in 2004 at the Patterson USGS gauge. In the second SWAT model, an over-prediction in total nitrogen loads was observed in 2004.

Both the models were able to successfully capture hydrology (<15% RE) and nutrients (total phosphorus and total nitrogen; <25% RE) within the recommended ranges by Santhi et al. (2001) except total nitrogen in the first SWAT model.

Table 4.3- Comparison of annual-scale observed and simulated results for the first SWAT model

Gauge	Output	Average		Standard Deviation		RE (%)
		Observed	Simulated	Observed	Simulated	
Egypt	Total Flow (cms)	22.7	21.9	4.5	3.8	3.6
Patterson	Total Flow (cms)	26.4	30.4	6.9	5.6	14.9
	TP (kg)	212426	174880	51255.2	65724.2	17.7
	TN (kg)	1227171	457200	312153	200851.4	62.7
Cotton Plant	Total Flow (cms)	34.1	31.9	7.8	5.6	6.4

Table 4.4- Comparison of annual-scale observed and simulated results for the second SWAT model

Gauge	Output	Average		Standard Deviation		RE (%)
		Observed	Simulated	Observed	Simulated	
Egypt	Total Flow (cms)	22.7	22.5	4.5	3.8	0.8
Patterson	Total Flow (cms)	26.5	29.6	6.9	4.9	12.0
	TP (kg)	212426	154200	51255.2	51113.2	19.9
	TN (kg)	1227171	743275	312153	377199.4	8.01
Cotton Plant	Total Flow (cms)	34.1	32.3	7.8	5.4	5.3

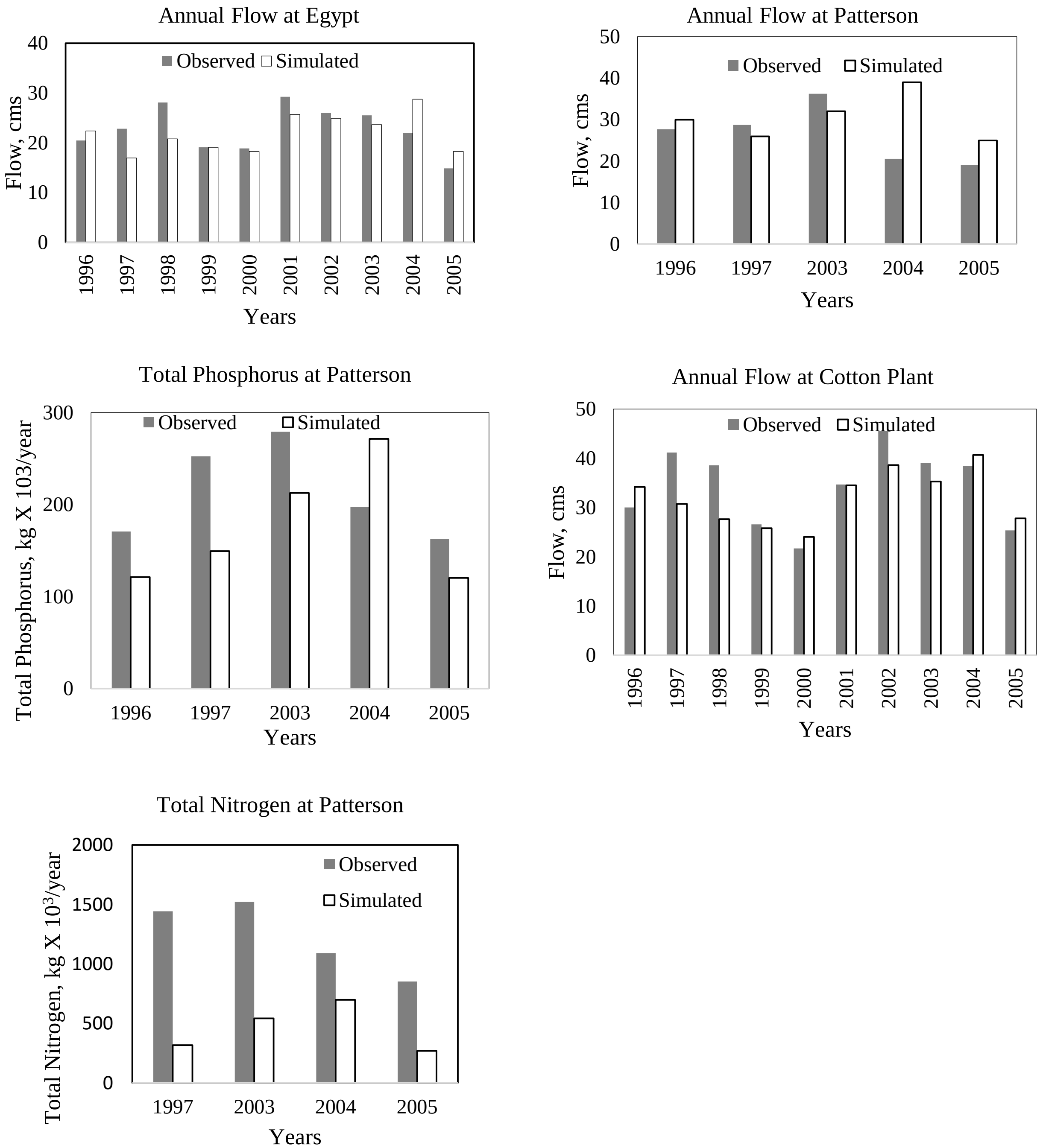


Figure 4.1- Graphical results for the performance of the first SWAT model at annual scale

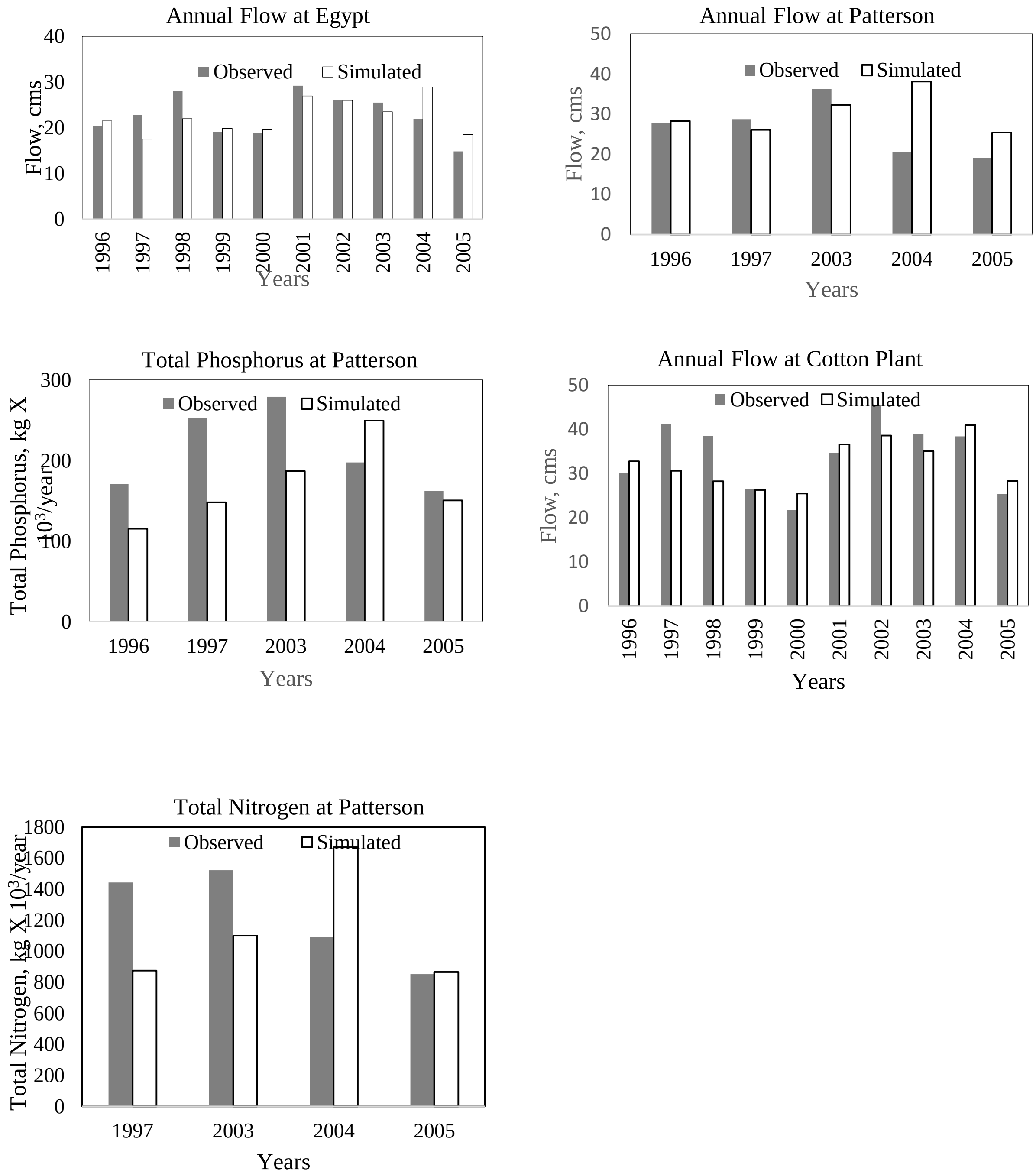


Figure 4.2- Graphical results for the performance of the second SWAT model at annual scale

4.2.2 Monthly calibration and validation

4.2.2.1 Hydrology calibration and validation

For the first SWAT model, coefficient of determination (R^2) varied from 0.5 to 0.6, Nash-Sutcliffe efficiency (NSE) values ranged from 0.5 to 0.6, percent-bias (PBIAS) was less than 25% except for baseflow at Patterson in the validation period and RSR varied from 0.6 to 0.7 (Tables 4.5). The first SWAT model under predicted total flow and surface runoff during the spring season for most of the years (1997 to 2003; 2007 and 2008; 2011 and 2012) at Egypt and Cotton Plant USGS gauge stations. At Patterson USGS gauge station, the model under-predicted total flow during the spring season of 1997 and 2008, however it over-predicted surface runoff in 2007 and 2009. Similarly, the second SWAT model also under-predicted flows during the spring season for 1997, 1998 and 1999. Identical under-prediction trend was also seen for 2011 in the validation period at Cotton Plant USGS station. At Patterson gauge, under-prediction was seen in 1997 and 2007 whereas over-prediction in flows was also observed in 2009. The watershed received high rainfall from 2007 to 2010 which resulted in slight over-prediction of flows. Also, studies have indicated that spatial variability and size of watershed is a major reason for under and over prediction (Santhi et al., 2001; Srinivasan et al., 1998). The hydrology results were slightly on the lower side since the parameters dealing with lesser understood processes, such as subsurface flows and interaction between groundwater and rivers became dominant in the watershed. A number of parameters affecting subsurface water were sensitive for the two models which showed that subsurface flow processes were dominant in the watershed which in turn added to the uncertainty in models and also affected the calibration results (Abbaspour et al., 2007). However, hydrology calibration and validation results for both the models were within the satisfactory ranges (Moriasi et al., 2007).

Table 4.5- Statistical results for calibration and validation of the first SWAT model

Gauge	Monthly output	Calibration				Validation			
		R^2	NSE	PBIAS	RSR	R^2	NSE	PBIAS	RSR
Egypt	Total flow	0.5	0.5	3.1	0.7	0.6	0.5	8.4	0.7
	Surface flow	0.5	0.5	4.6	0.7	0.6	0.6	4.9	0.7
	Baseflow			14.1				23.2	
Patterson	Total flow	0.6	0.5	-14.0	0.7	0.6	0.6	-6.8	0.6
	Surface flow	0.6	0.6	-14.4	0.7	0.6	0.5	-23.1	0.7
	Baseflow			-13.1				29.0	
	Total phosphorus	0.6	0.5	12.3	0.7	0.5	-0.4	-7.5	1.2
	Total nitrogen	0.2	-0.1	40.5	1.1	0.1	-0.3	5.3	1.1
Cotton Plant	Total flow	0.5	0.5	6.3	0.7	0.6	0.6	9.0	0.6
	Surface flow	0.6	0.5	1.2	0.7	0.6	0.6	-2.1	0.6
	Baseflow			10.3				22.7	

Table 4.6- Statistical results for calibration and validation of the second SWAT model

Gauge	Monthly output	Calibration				Validation			
		R^2	NSE	PBIAS	RSR	R^2	NSE	PBIAS	RSR
Egypt	Total flow	0.5	0.5	0.4	0.7	0.6	0.6	6.8	0.7
	Surface flow	0.5	0.5	8.4	0.7	0.6	0.6	3.2	0.7
	Baseflow			-11.1				21.7	
Patterson	Total flow	0.6	0.6	-13.1	0.7	0.6	0.6	-2.0	0.6
	Surface flow	0.6	0.5	-9.7	0.7	0.6	0.5	-12.6	0.7
	Baseflow			-21.4				21.5	
	Total phosphorus	0.6	0.6	30.0	0.7	0.5	-0.3	-0.1	1.2
	Total nitrogen	0.4	-0.6	21.2	1.3	0.1	-1.9	5.1	1.7
Cotton Plant	Total flow	0.6	0.5	5.4	0.7	0.7	0.6	9.2	0.6
	Surface flow	0.5	0.5	2.5	0.7	0.6	0.6	3.5	0.6
	Baseflow			9.0				16.4	

4.2.2.2 Total phosphorus calibration and validation

R^2 values for both the models was 0.6, NSE values were 0.5 and 0.6 for first and second model respectively, RSR values were 0.7 for both the models and PBIAS was 12.3 and 30.0 for the first and second model respectively. The first model over-predicted the phosphorus loads from April to July in 2003 and January to July in 2009. Similarly, second model also over-predicted phosphorus loads from April to July in 2003, January to July in 2009 and slight over-prediction from April to June in 2010. The possible reason for over-prediction in phosphorus loads could be relatively high precipitation during 2003, 2009 and 2010. Since nutrient calibration also depends on hydrology, under/over prediction also propagated to nutrients from hydrology. During the validation period, PBIAS was in very good range and R^2 was within the satisfactory range for both the SWAT models, however, NSE and RSR values were not within the satisfactory limits. Similar results were reported by Bracmort et al. (2006) where the SWAT model performed well within the satisfactory ranges during the calibration period and unsatisfactory values of R^2 and NSE during the validation period. This poor performance of the SWAT model was found due to over-prediction and under-prediction of the phosphorus loads. A common problem called the “second storm” effect which affects sediments and phosphorus loadings after a storm has passed was also found to exist in both the SWAT models (Years 1996-1997, 2009-2010 in Figures 4.6 and 4.10) since it uses modified universal soil loss equation (Abbaspour et al., 2007; Arnold et al., 2012). SWAT does not account for this effect which in turn results in uncertainty in prediction and affecting model results (Abbaspour et al., 2007; Arnold et al., 2012). Parajuli et al. (2008) also reported poor NSE values for total phosphorus modeling in the validation period for a watershed in south-central Kansas because of a larger watershed area with greater spatial variability. Arabi et al. (2006) also reported unsatisfactory value of NSE during the validation period for a watershed in Indiana.

4.2.2.3 Total nitrogen calibration and validation

First SWAT model: Total nitrogen PBIAS values were within the satisfactory ranges (Moriasi et al., 2007) 40.5% for calibration and 5.3% for the validation period. Other statistics: R^2 varied from 0.1 to 0.2, NSE from -0.1 to -0.3 and RSR was 1.1 during the calibration and validation period.

Second SWAT model: Total nitrogen PBIAS values were in very good range: 21.2% for calibration and 5.1% for validation period. Other statistics: R^2 varied from 0.1 to 0.4, NSE from -0.1 to –0.3 and RSR from 1.3 to 1.7 during the calibration and validation period respectively.

Since calibration of nutrients depends on hydrology, a comparable trend of under-prediction was observed for total nitrogen. From March to June in 2004 and 2009, the first SWAT model was able to capture the peaks. Over-prediction in total nitrogen outputs was observed during June to September in 2009 and 2010 during which relatively high precipitation was received in the watershed.

Comparing the results of this study with other similar studies determined reasonable results. Woznicki et al. (2011) calibrated a SWAT model for Tuttle Creek Lake Watershed lying in Nebraska and Kansas and reported unsatisfactory results for nitrogen simulation during the calibration/validation period. The poor performance of SWAT model was because of lack of observed data and unknown manure application rates. Glavan et al. (2012) also reported unsatisfactory nitrogen simulation results due to under-estimation of peak flows and small amount of observed data. In this study, availability of observed data for nitrogen posed a challenge to calibrate the models. Planting dates of a crop depends on soil moisture and rainfall (Espinoza and Ross, 2004) therefore it is not possible to represent actual planting dates in crop management practices for each year due to rainfall asymmetry. The planting dates in turn affect the nitrogen fertilization application dates which may cause in shift of peaks and affect the model calibration which implies there is a slight change in the crop development as per the model in contrast to the actual field applications (Dr. Andy Pereira, Professor-Crop Soil and Environmental Sciences-University of Arkansas, personal communication, 23 June 2015).

Similarly, the second SWAT model showed under-prediction for total nitrogen loads. The percent bias (PBIAS) was in the good range of performance during the calibration and validation period. During the validation period over-prediction was seen during June to September in 2010.

To further analyze the nitrogen modeling in SWAT, nitrogen budget for both the models was calculated. A complete mass balance of the inputs provided to the model and outputs was used to reflect the nitrogen budget of both the models. This was given by the equation below:

$$N_{inputs} - N_{outputs} = \text{Change in soil nitrogen storage} \ldots \text{(i)}$$

The nitrogen balance seemed to be reasonable and change in nitrogen storage in the soil was approximately same for both models (Tables 4.7 and 4.8). The nitrogen balance indicated that the two models were able to simulate the nitrogen budgets satisfactorily. With the current production system, the net change in soil nitrogen storage was 3.9 kg/ha for the first model whereas it was 3.8 kg/ha for the second model and this increase in the soil nitrogen storage constitutes about 2% of the total inputs for the first and the second SWAT model.

Table 4.7- Nitrogen budget for the first SWAT model.

Inputs	**kg/ha**	**%**	**Outputs**	**kg/ha**	**%**
N-fertilizer applied	49.1	27.2	Active to stable org N	2.7	1.5
Min from fresh org N	50.9	28.2	N-uptake	146.3	82.7
Min from active org N	4.5	2.5	Ammonia volatilization	3.1	1.8
N fixation	76.3	42.2	Denitrification	9.9	5.6
			NO3 yield (sq)	5.8	3.3
			NO3 yield (lat)	0.1	0.0
			NO3 leached	8.9	5.0
TOTAL	180.8	100	TOTAL	176.9	100

Table 4.8- Nitrogen budget for the second SWAT model.

Inputs	**kg/ha**	**%**	**Outputs**	**kg/ha**	**%**
N-fertilizer applied	106.3	61.5	Active to stable org N	1.7	1.0
Min from fresh org N	36.1	20.8	N-uptake	120.4	71.1
Min from active org N	3.4	1.9	Ammonia volatilization	4.3	2.5
N fixation	27.3	15.8	Denitrification	35.1	20.7
			NO3 yield (sq)	4.1	2.4
			NO3 yield (lat)	0.1	0.1
			NO3 leached	3.5	2.1
Total	173.0	100	Total	169.2	100

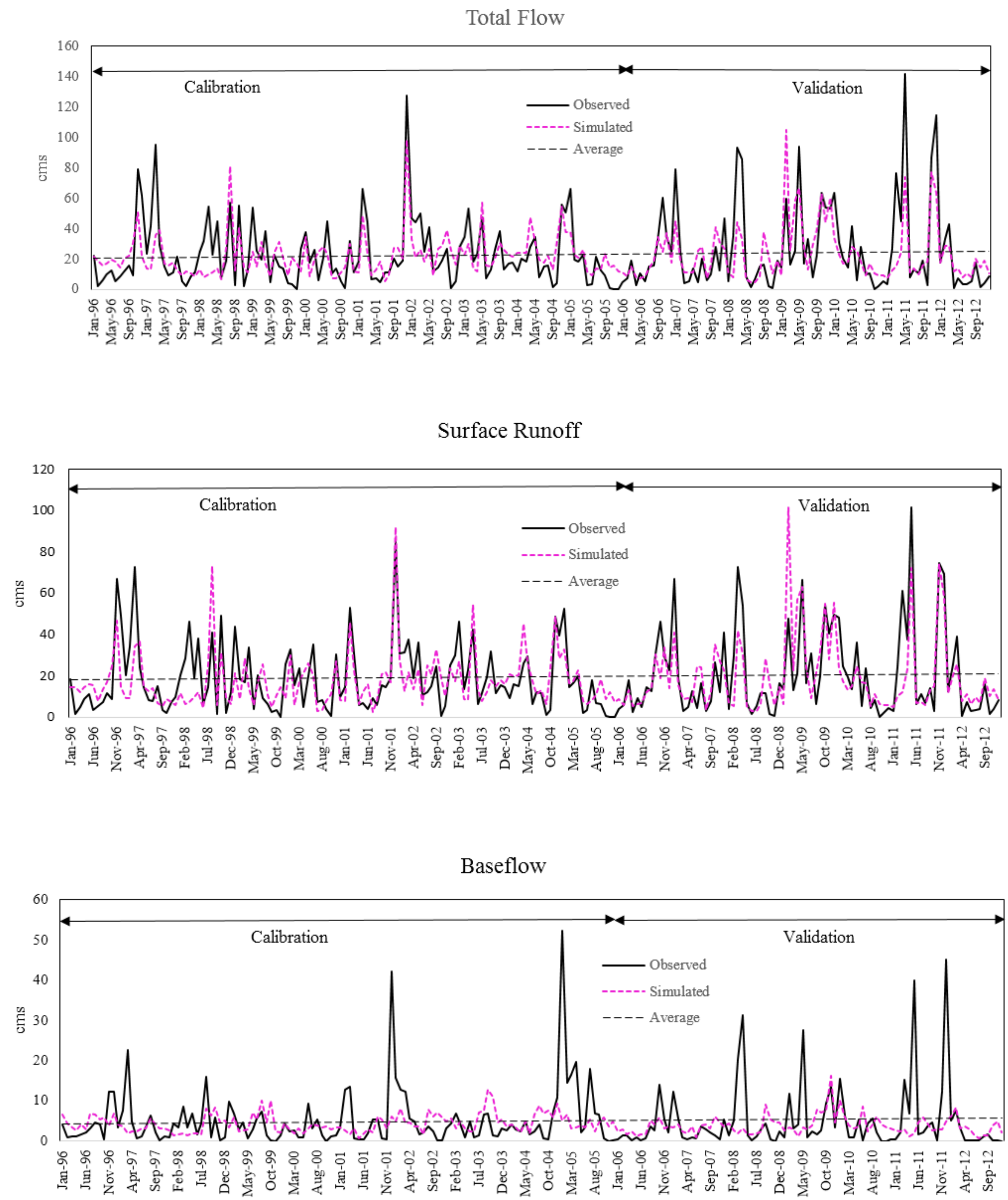


Figure 4.3- Time series plots for total flow, surface runoff and baseflow at Egypt for the first SWAT model.

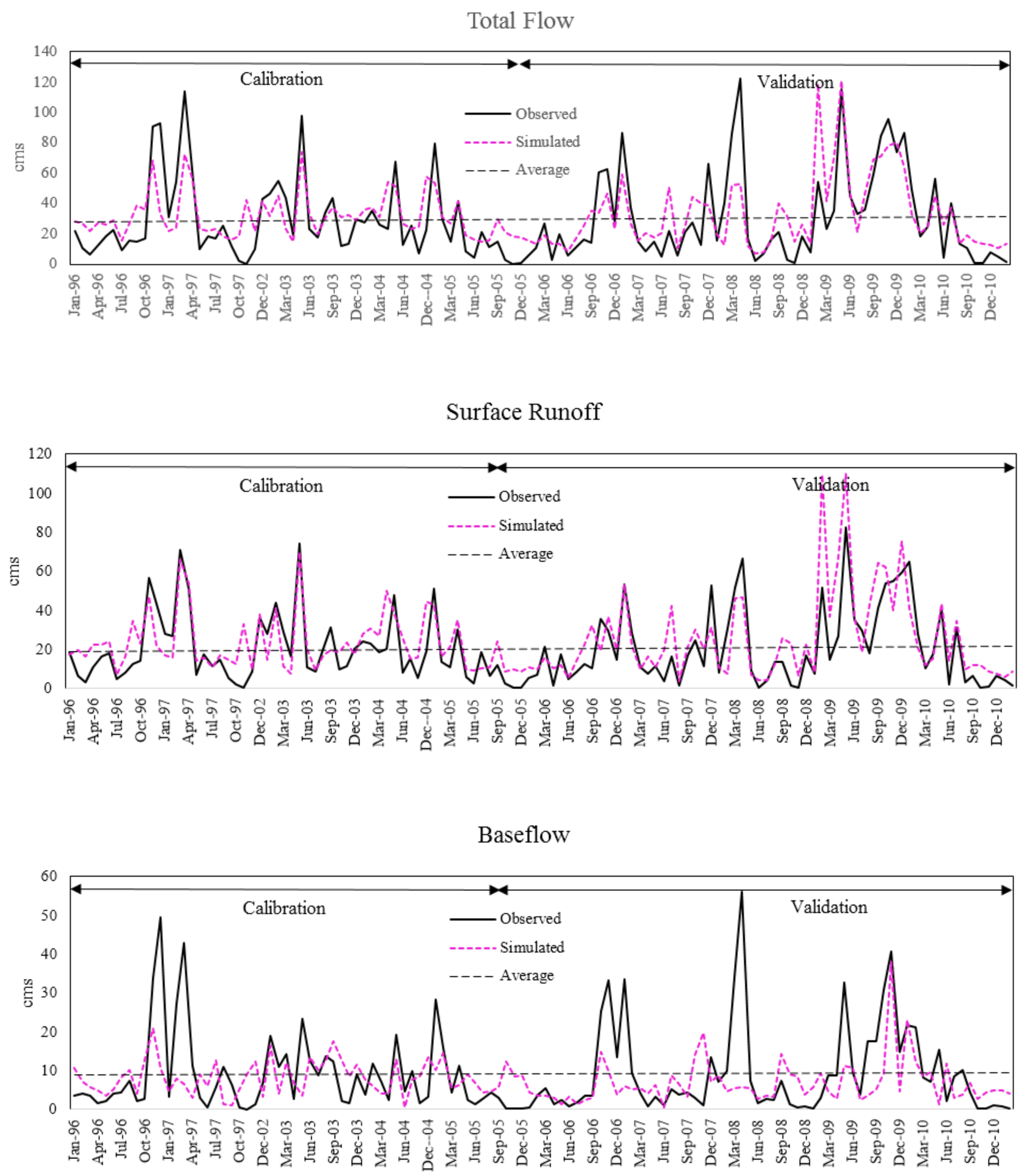


Figure 4.4- Time series plots for total flow, surface runoff and baseflow at Patterson for the first SWAT model.

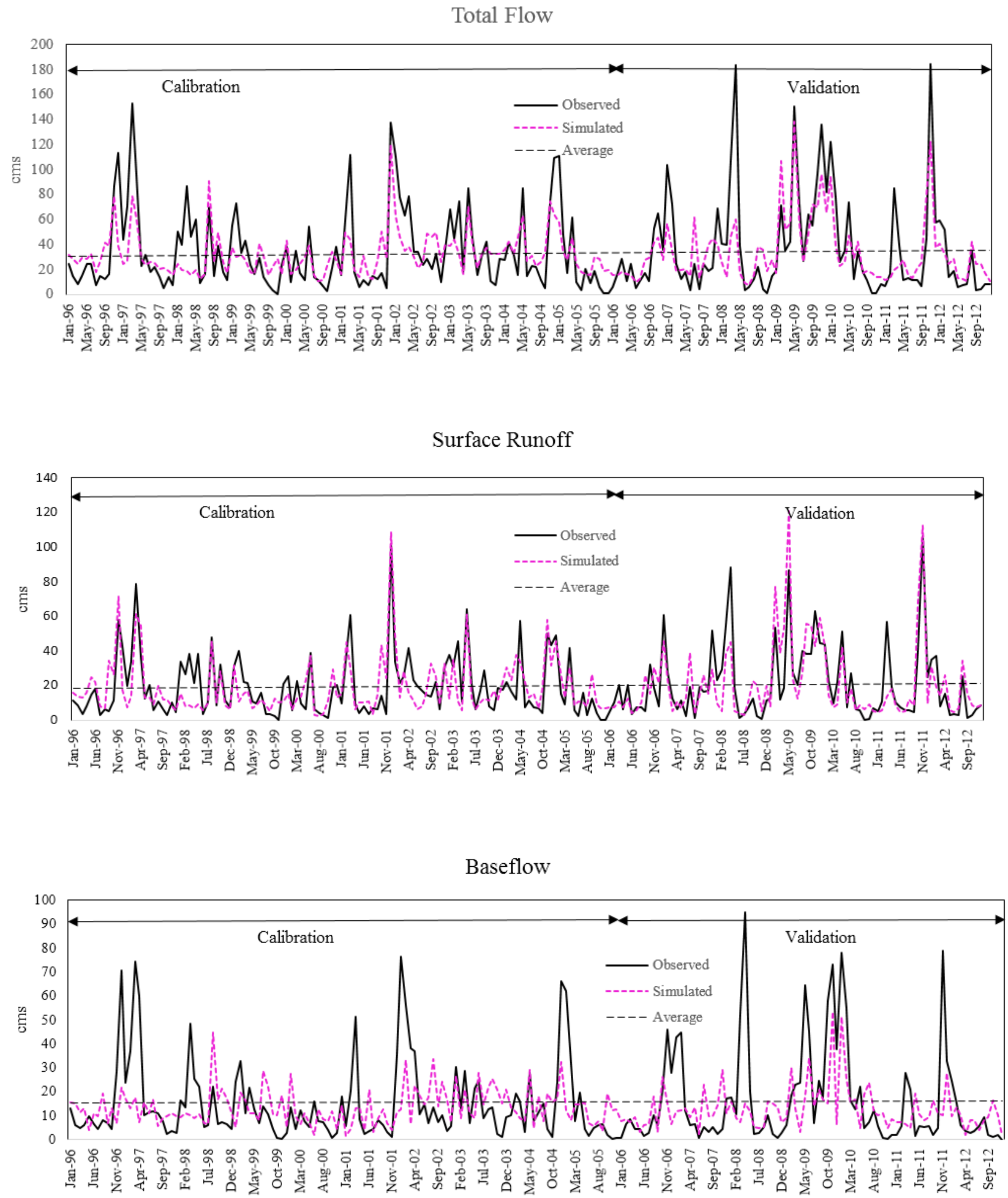
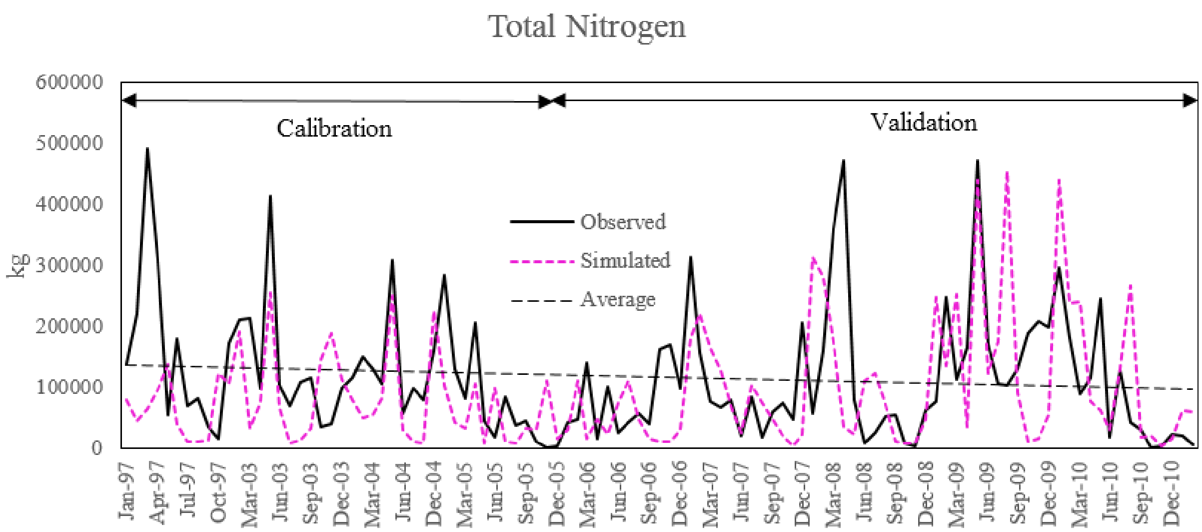


Figure 4.5- Time series plots for total flow, surface runoff and baseflow at Cotton Plant for the first SWAT model.



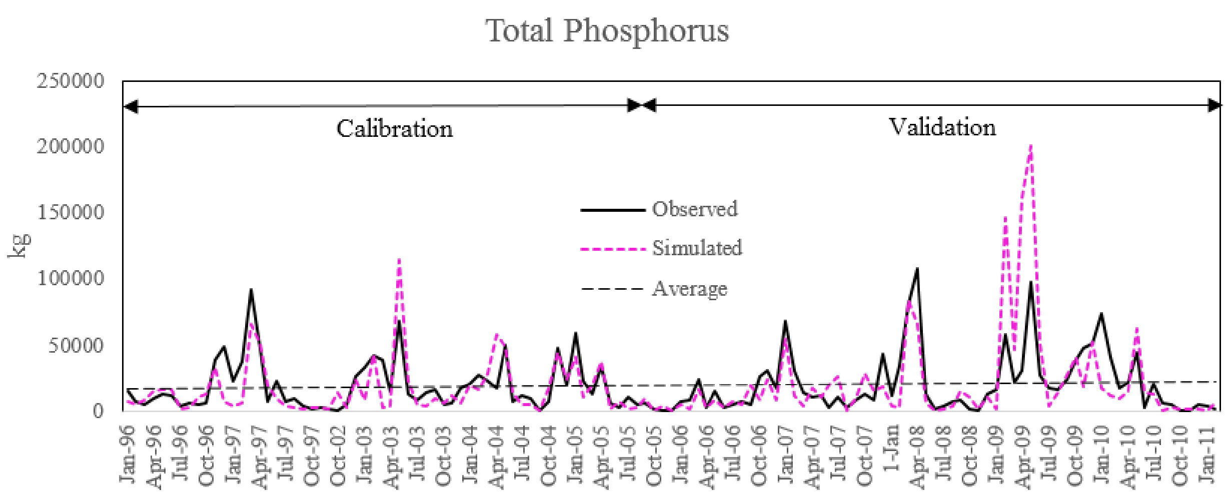


Figure 4.6- Time series plots for total nitrogen and total phosphorus at Patterson for the first SWAT model.

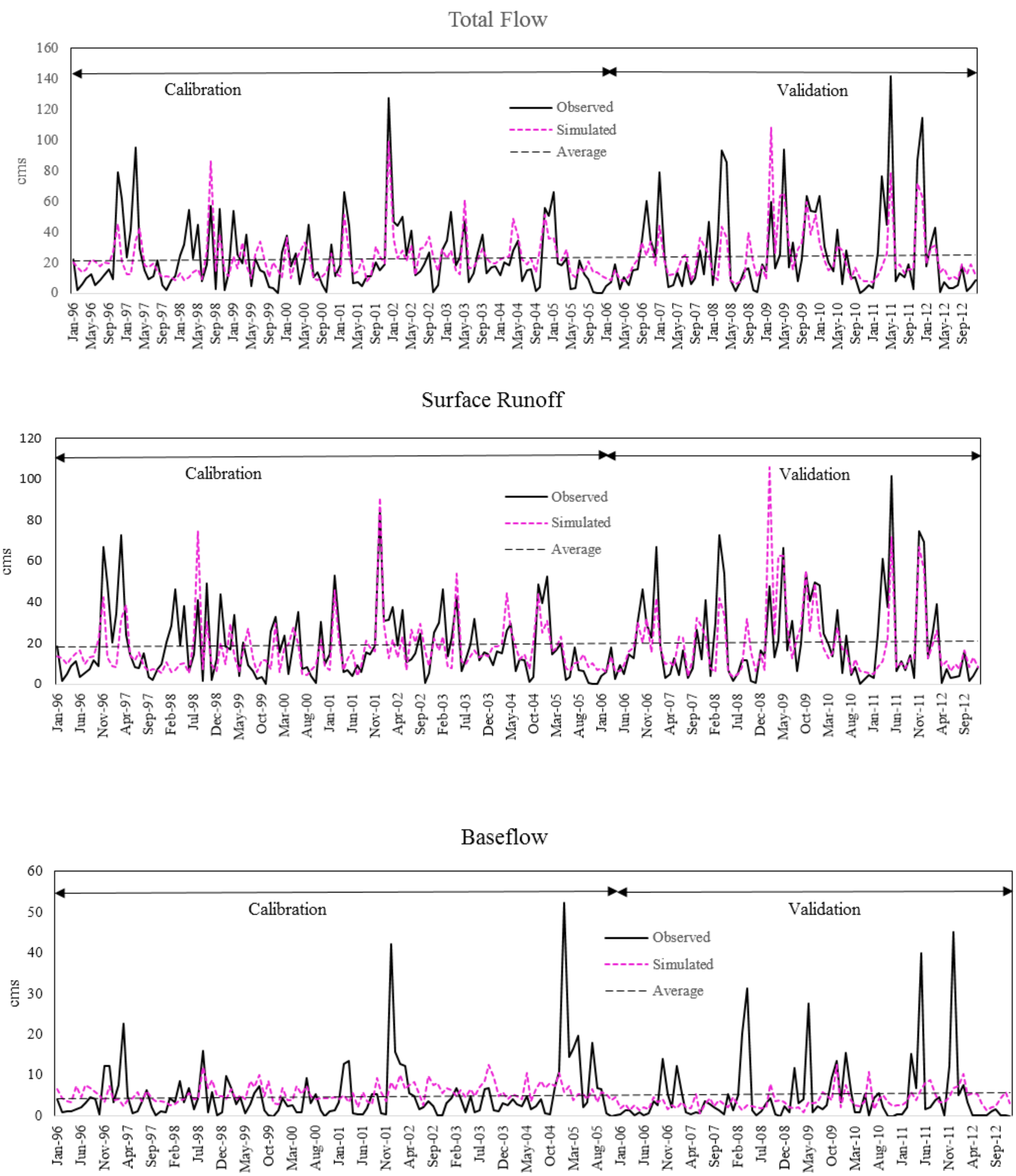


Figure 4.7- Time series plots for total flow, surface runoff and baseflow at Egypt for the second SWAT model.

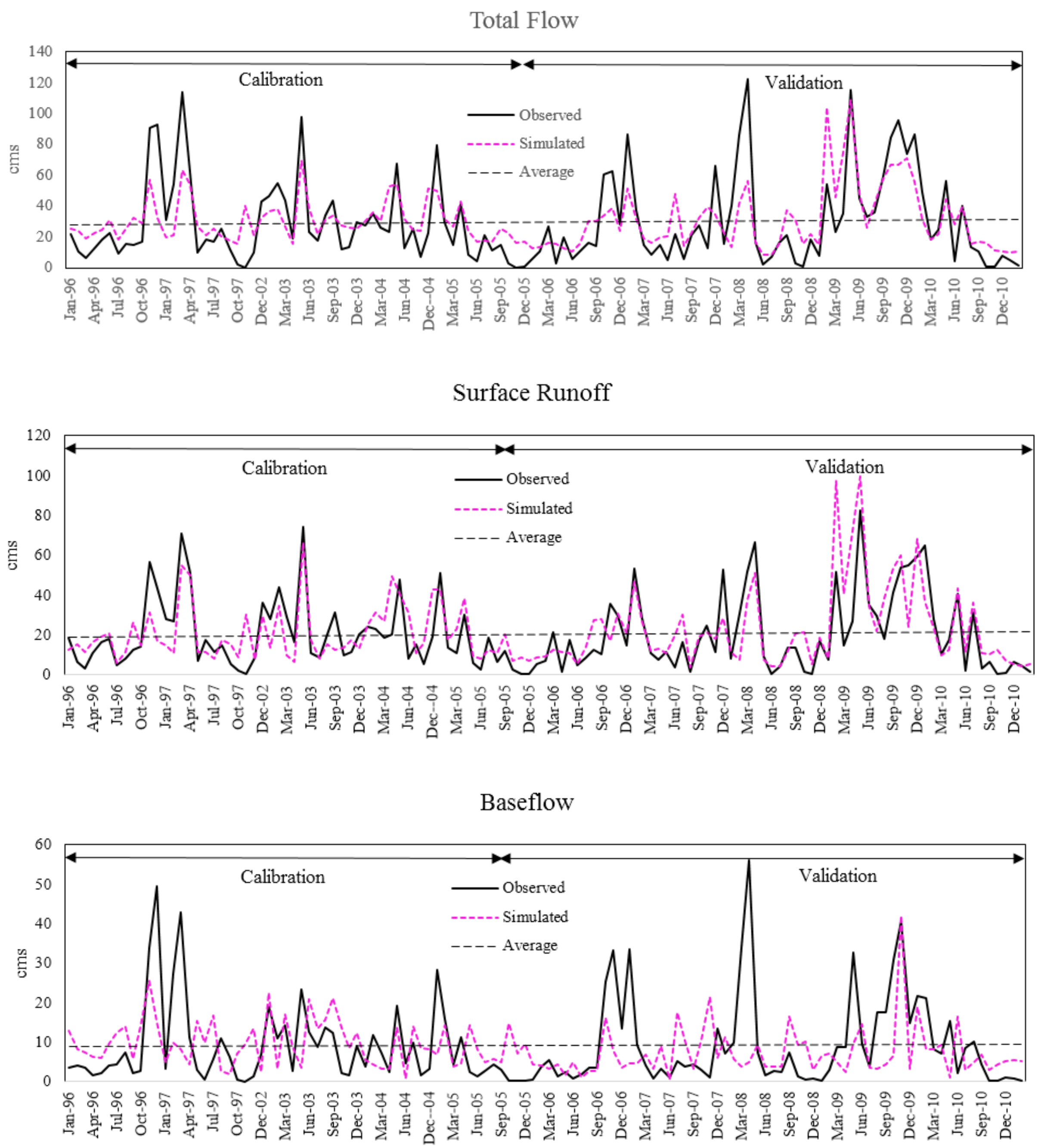


Figure 4.8- Time series plots for total flow, surface runoff and baseflow at Patterson for the second SWAT model.

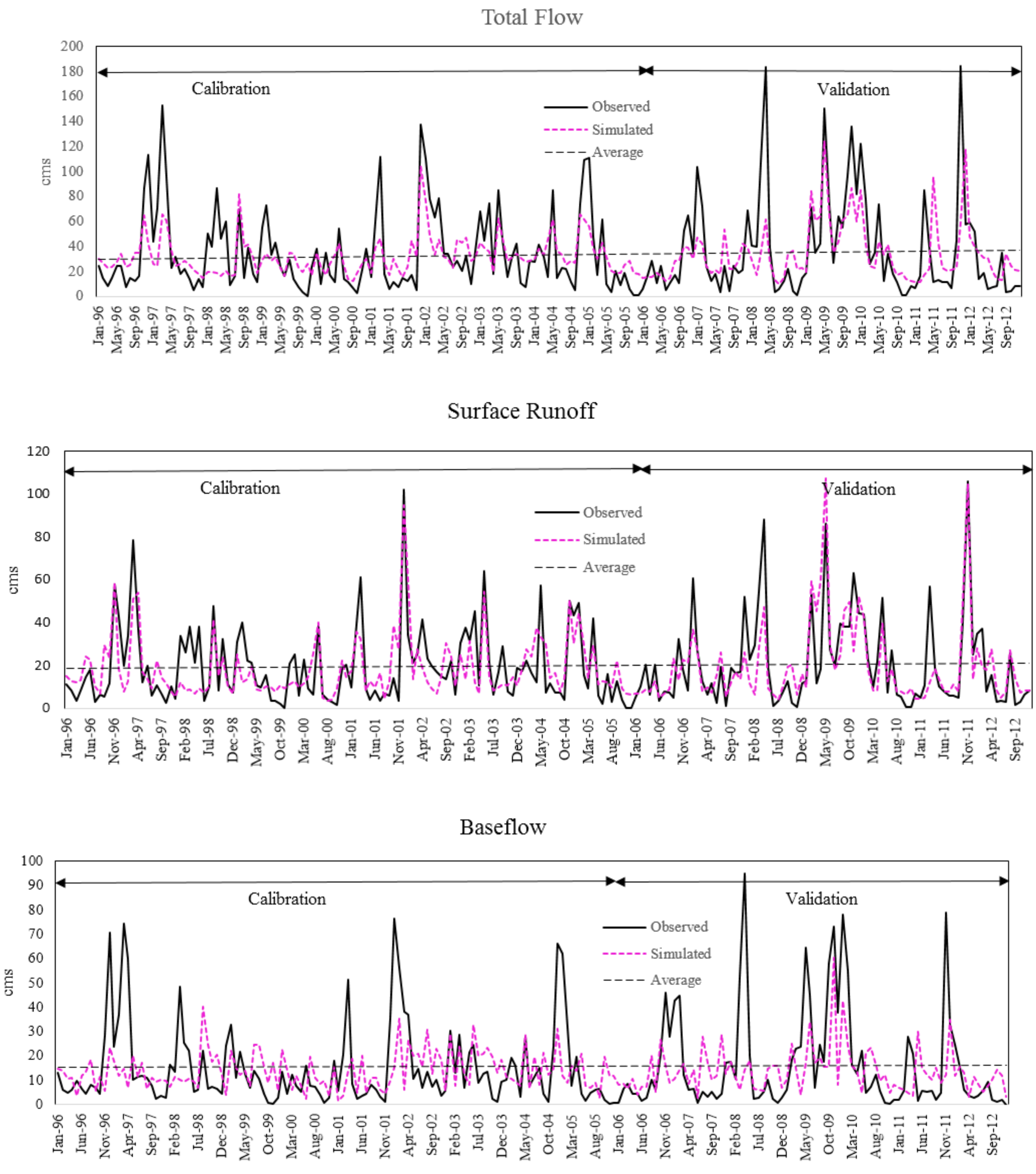
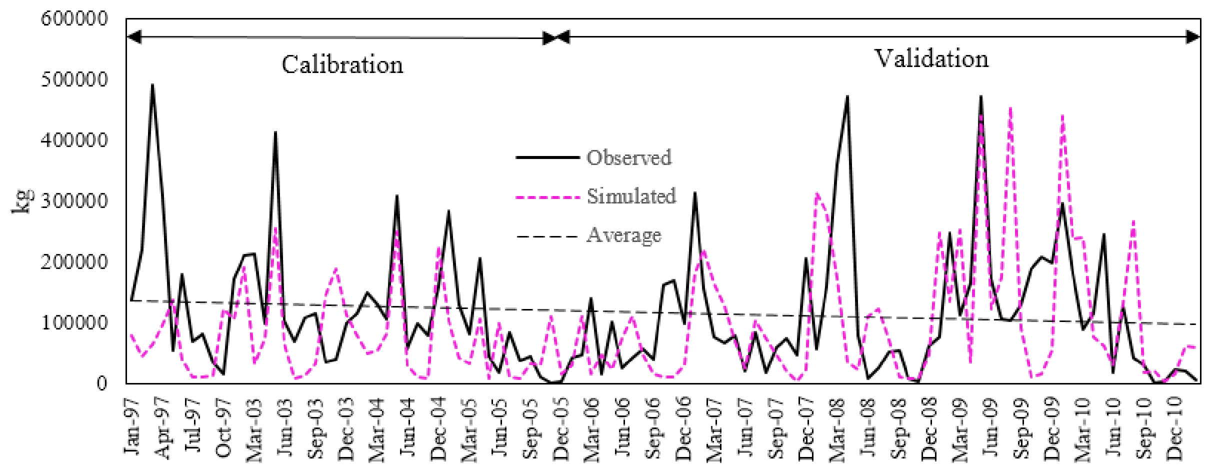


Figure 4.9- Time series plots for total flow, surface runoff and baseflow at Cotton Plant for the second SWAT model.

Total Nitrogen



Total Phosphorus

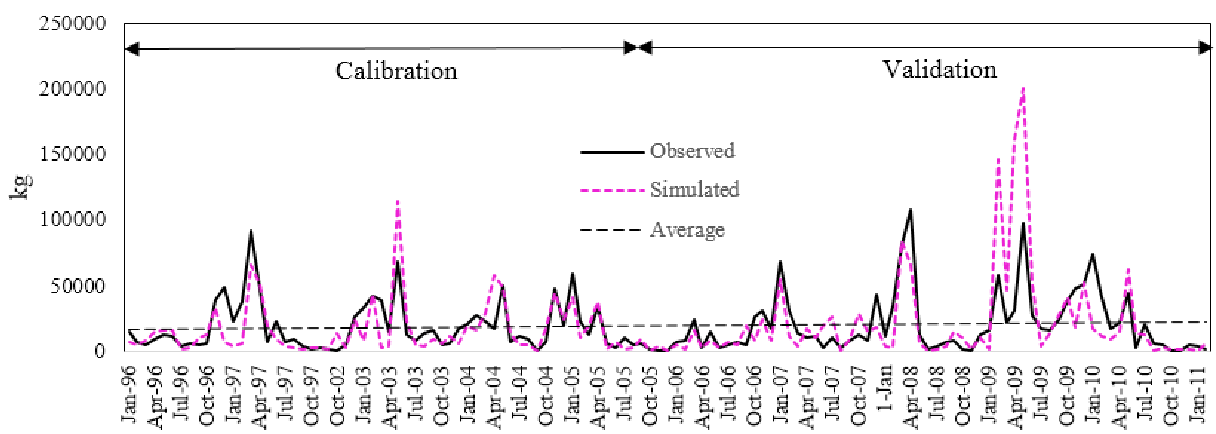


Figure 4.10- Time series plots for total nitrogen and total phosphorus at Patterson for the second SWAT model.

4.2.3 Comparison with recent water quality data and post-model validation

A comparison with recent monitoring data can increase the confidence in watershed models. For comparing the monitoring data and SWAT output at two gauges (Egypt and Cotton Plant), ellipses were generated by JMP statistical software and set to cover 90% of the measured and simulated data for load regressions (Figure 4.13 to 4.16). These ellipses give indications about mean, variance, correlation and regression slopes of the two models (Friendly, 2006). Similar ellipse orientation, range and variance were observed from both the measured and simulated datasets. A similar ellipse orientation for both the SWAT models indicated a general agreement between the observed and simulated loads. Although an overall agreement can be seen between the simulated and observed loads, slight differences in the ellipses are seen due to temporal difference as land use and management change over the years and affect the relationship between hydrologic transport and potential sources (James McCarty, Program Associate-Department of Biological and Agricultural Engineering, personal communication July 2, 2015). Since precipitation has a primary role in water balance for a watershed, another reason for differences in the ellipse orientation could be the input data for precipitation which was taken from two different sources (NEXRAD and rain gauge data, discussed in chapter 3).

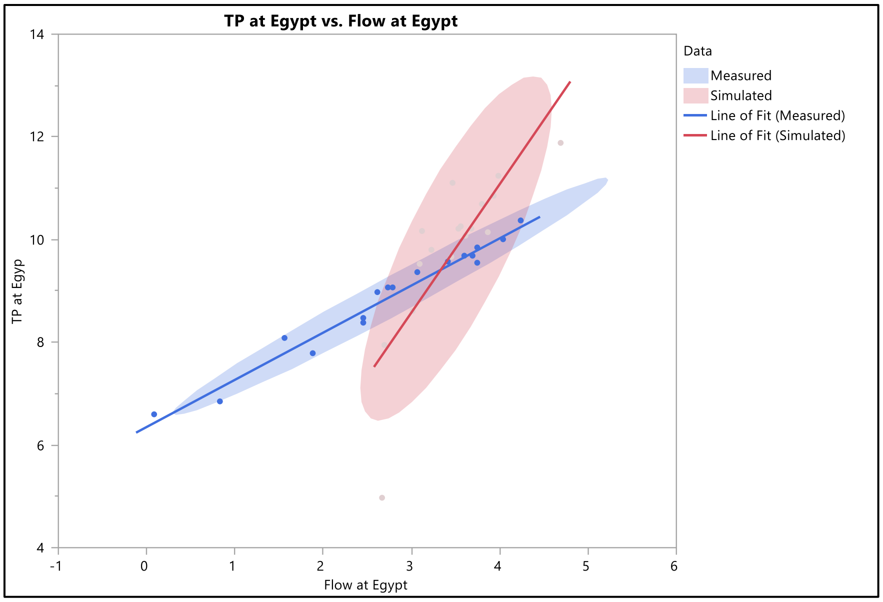


Figure 4.11- Graphical comparison of monthly total phosphorus loads from the first SWAT model and the monitoring data at Egypt as a function of discharge.

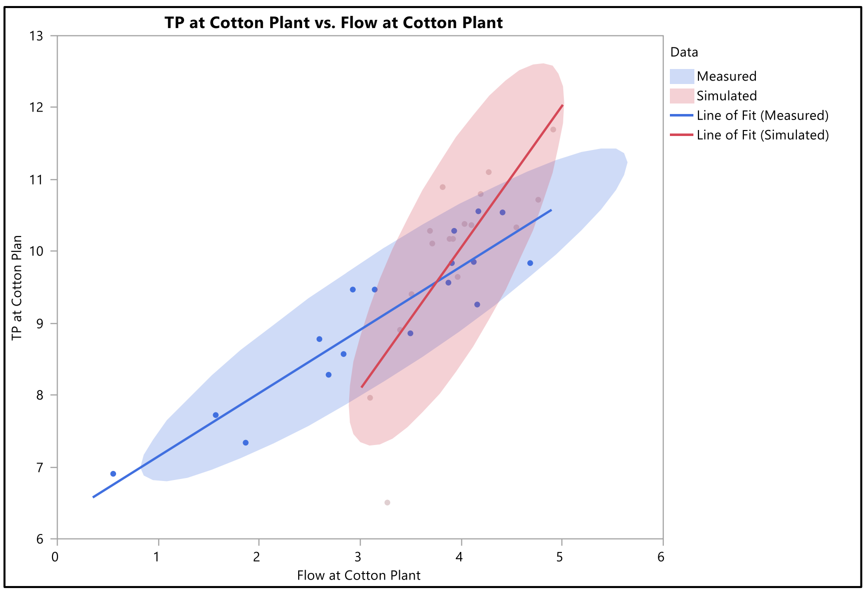


Figure 4.12- Graphical comparison of monthly total phosphorus loads from the first SWAT model and the monitoring data at Cotton Plant as a function of discharge.

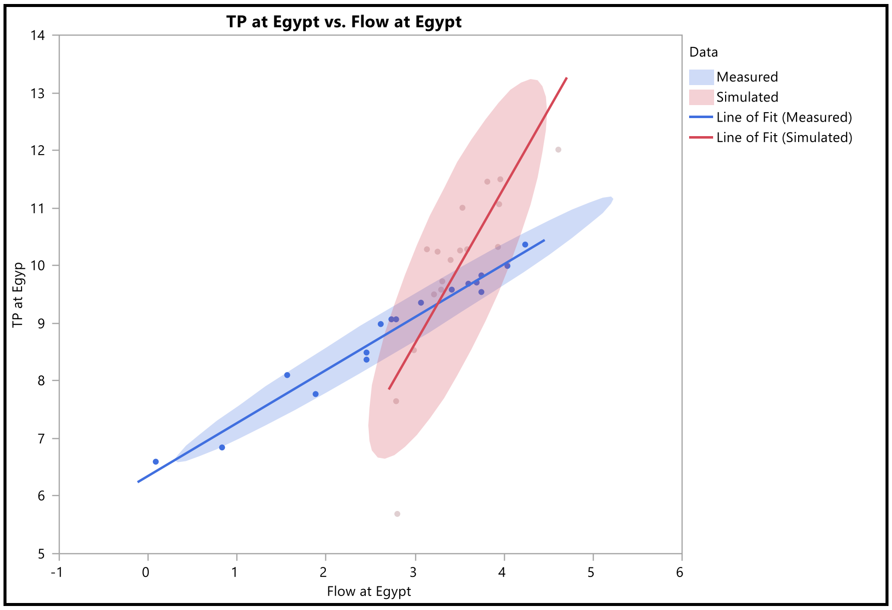


Figure 4.13- Graphical comparison of monthly total phosphorus loads from the second SWAT model and the monitoring data at Egypt as a function of discharge.

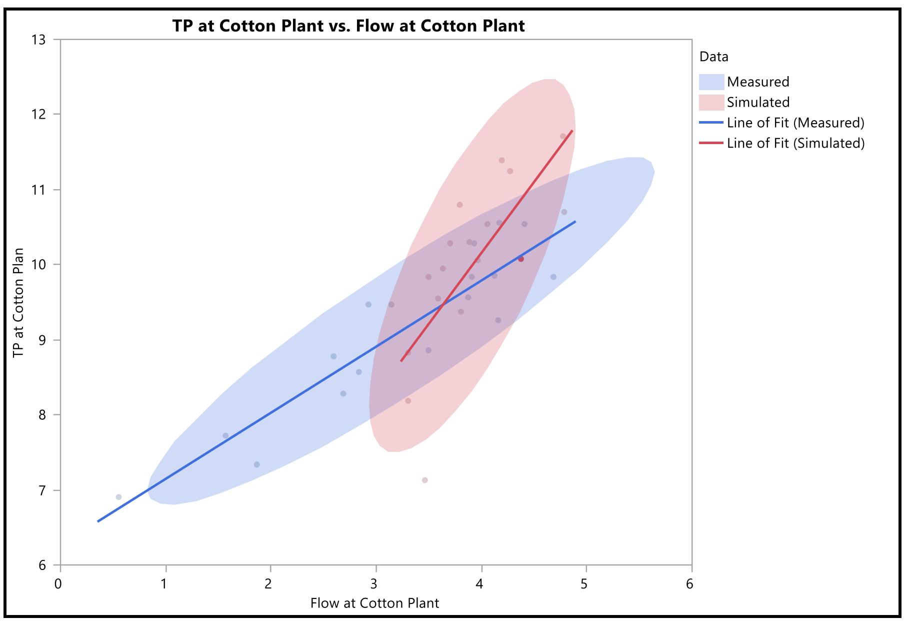


Figure 4.14- Graphical comparison of monthly total phosphorus loads from the second SWAT model and the monitoring data at Cotton Plant as a function of discharge.

4.3 Uncertainty analysis

Uncertainties in large scale watershed models make calibration a challenging task which can exist in the form of process simplification, processes not accounted in the model and unknown to the modeler (Abbaspour et al., 2007). In SUFI2, parameter uncertainty accounts for all these uncertainties. The degree to which all uncertainties are accounted for is quantified by a p-factor which is the percentage of measured data bracketed by the 95% prediction uncertainty (Abbaspour 2013; Figures 4.15 to 4.19). The green area in these plots represent the extent of effect of parameter uncertainty on the model results.

For the first SWAT model 45% of observed data for flow at Egypt; 43%, 66%, and 57% of observed data for flow, total phosphorus and total nitrogen respectively at Patterson and 54% of observed data for flow at Cotton Plant were found to be within the 95% confidence interval of the simulation. Similarly, for the second SWAT model 61% of observed data for flow at Egypt; 67%, 69%, and 43% of observed data for flow, total phosphorus and total nitrogen respectively at Patterson and 73% of observed data for flow at Cotton Plant were found to be within the 95% confidence interval of the best simulation.

One of the major reasons for uncertainty in flow in the Cache River Watershed was due the importance of interaction between groundwater-rivers, since a number of parameters governing the groundwater flow were found to be sensitive and disturbed during the calibration phase (Section 4.2). A common problem in prediction of phosphorus as reported by Abbaspour et al. (2007) and Arnold et al. (2012) which is called "second storm" effect was found to exist in both the models (Figures (4.18 (a-b)). The SWAT model does not account for this effect which affects the sediment and phosphorus loadings after a storm which results in conceptual uncertainty and adds to the overall uncertainty in the model. In case of total nitrogen, a greater degree of uncertainty was observed and 54% and 43% of the observed data for the first model and second SWAT models respectively were bracketed by the 95PPU (Figures 4.19 (a-b)).

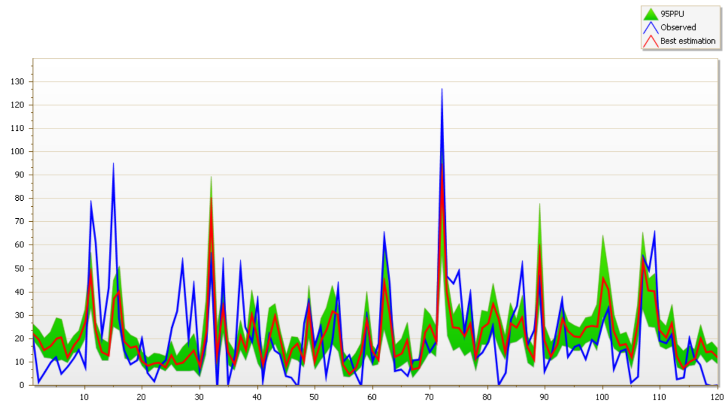


Figure 4.15(a) - SWAT model uncertainty 95PPU plot for flow at Egypt (First SWAT model).

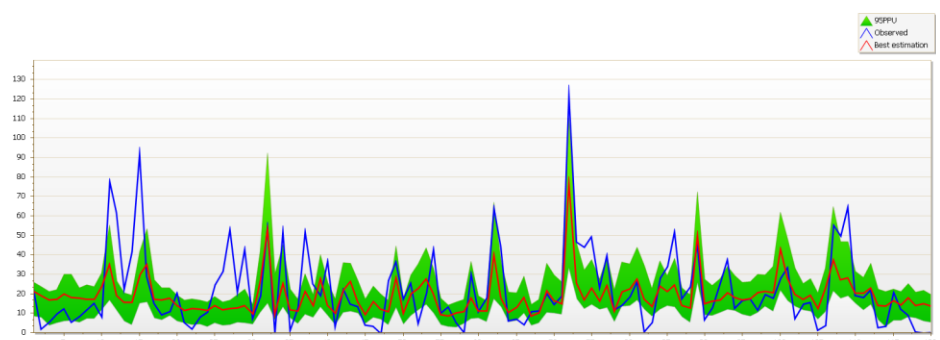


Figure 4.15(b) - SWAT model uncertainty 95PPU plot for flow at Egypt (Second SWAT model).

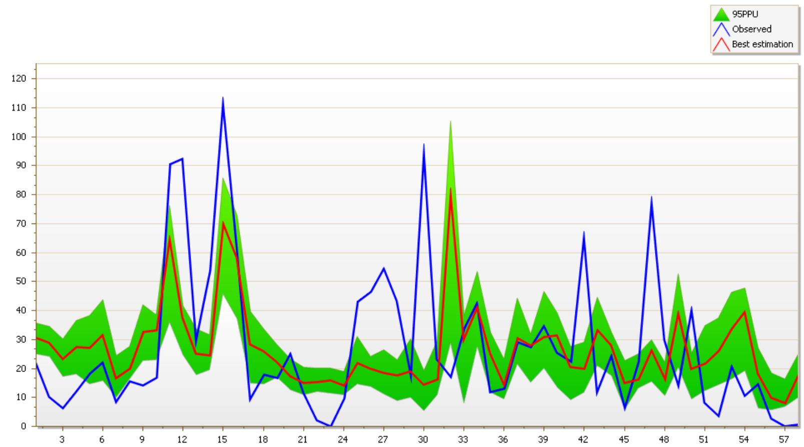


Figure 4.16(a) -SWAT model uncertainty 95PPU plot for flow at Patterson (First SWAT model).

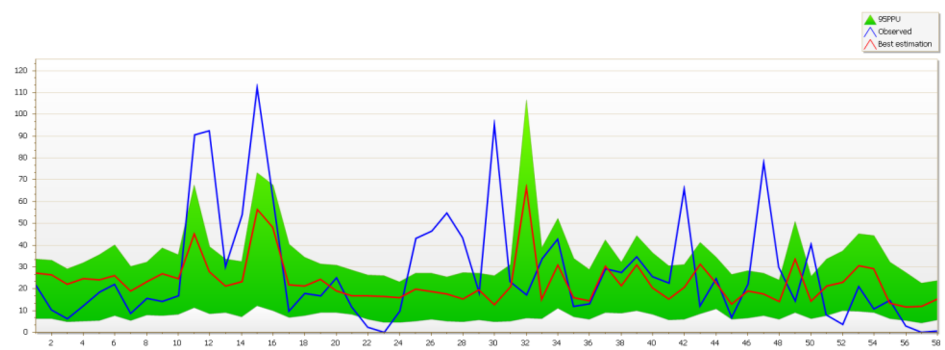


Figure 4.16(b)-SWAT model uncertainty 95PPU plot for flow at Patterson (Second SWAT model).

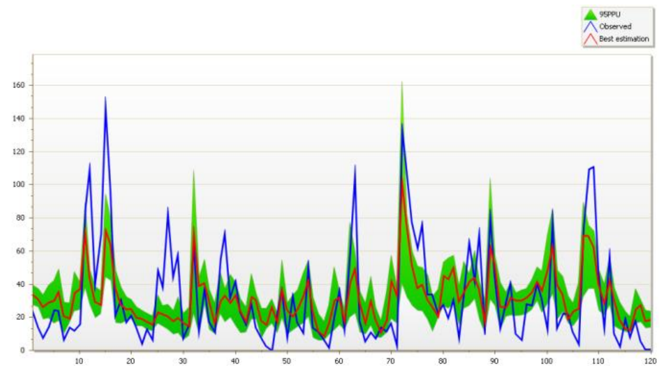


Figure 4.17(a)-SWAT model uncertainty 95PPU plot for flow at Cotton Plant (First SWAT model).

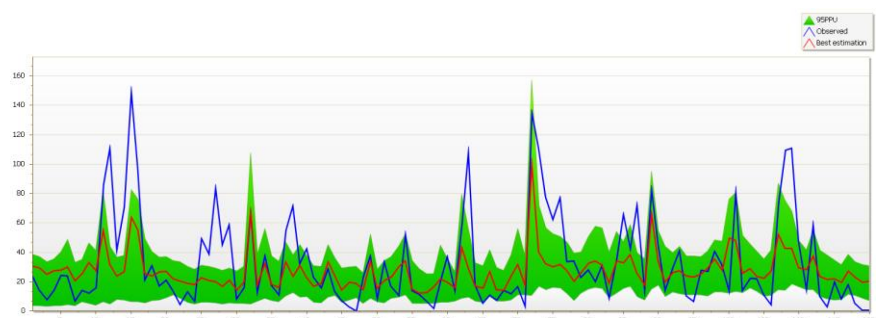


Figure 4.17(b)-SWAT model uncertainty 95PPU plot for flow at Cotton Plant (Second SWAT model).

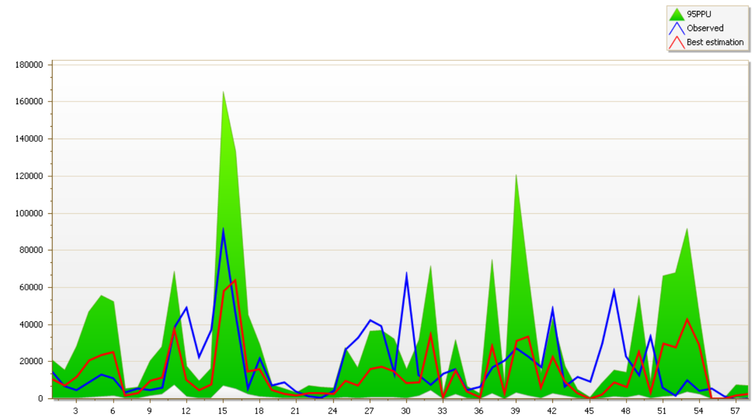


Figure 4.18 (a) - SWAT model uncertainty 95PPU plot for total phosphorus at Patterson (First SWAT model).

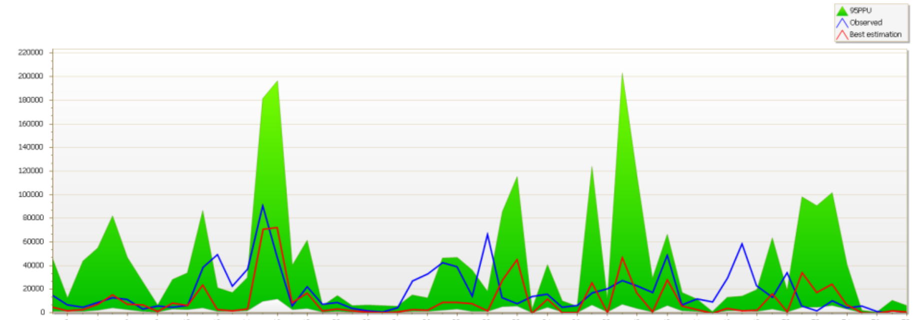


Figure 4.18 (b) - SWAT model uncertainty 95PPU plot for total phosphorus at Patterson (Second SWAT model).

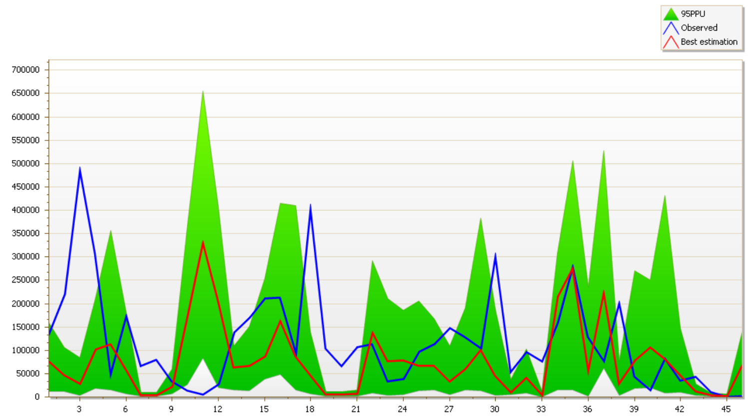


Figure 4.19 (a)- SWAT model uncertainty 95PPU plot for total nitrogen at Patterson (First SWAT model).

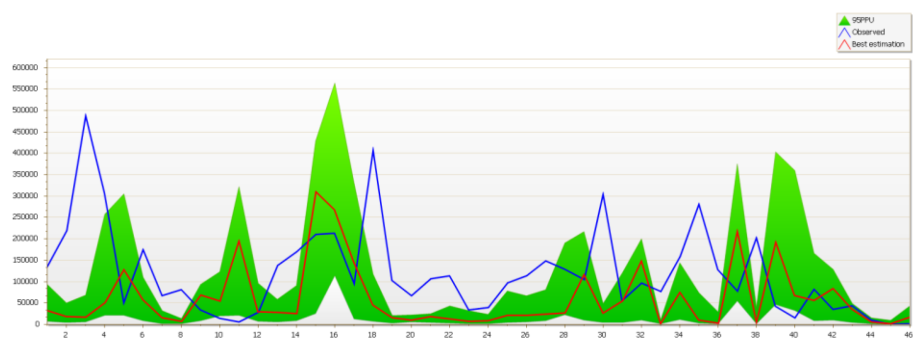


Figure 4.19 (b)- SWAT model uncertainty 95PPU plot for total nitrogen at Patterson (Second SWAT model).

4.4 Water quality impacts of bioenergy crops

Sediment, total phosphorus and total nitrogen loads were evaluated at the watershed outlet and a comparison was made with the baseline scenario where no biofuel crop were growing (Figures 4.20 to 4.25).

For the first SWAT model, when all marginal cropland was converted to Switchgrass, a reduction of 13.7%, 17.3% and 15.7% was observed in sediment, total phosphorus (TP) and total nitrogen (TN) loadings respectively at the watershed outlet. Conversion of same land to Miscanthus resulted in a decrease of 13.7%, 17.2% and 15.8% for sediment, TP loadings and TN loadings respectively at the watershed outlet.

For the second SWAT model, when all marginal cropland was converted to Switchgrass, a reduction of 11.9%, 20% and 13.6% was observed in sediment, TP and TN loadings respectively at the watershed outlet. Further, when the same land was converted to Miscanthus, a reduction of 12.1%, 20% and 13.3% was observed in sediment, TP and TN loadings respectively at the watershed outlet.

Mean-monthly reductions in sediments, TP and TN losses for individual crop scenarios was also calculated and it was found that individual crops resulted in different sediment and nutrient losses (Figures 4.22 to 4.25). In the first SWAT model, when soybean marginal (SOYM) was converted to Switchgrass (SWCH), maximum reductions in sediment (10%), TP (13%) and TN (11.1%) loadings were observed. Similarly, conversion of SOYM to Miscanthus (MXGS) resulted in maximum reductions in sediment (10%), TP (13%) and TN (11.3%) loadings. When corn marginal (CORM) was converted to SWCH, 1.5%, 1% and 2% reductions were observed in sediment, TP and TN loadings respectively. Conversion of cotton marginal (COTM) to SWCH resulted in 0.9%, 1.8% and 1.2% reductions in sediment, TP and TN loadings respectively.

Conversion of rice marginal (RICM) to SWCH resulted in 1.1%, 1.8% and 1.5% reductions in sediment, TP and TN respectively. Similarly, CORM conversion to MXGS resulted in 1.4%, 0.9% and 1.9% reductions in sediment, TP and TN loadings respectively. COTM conversion to MXGS resulted in 0.9%, 1.8% and 1.2% reductions in sediment, TP and TN loadings respectively. When RICM was converted to MMXGS, 1.1%, 1.8% and 1.6% reductions were observed in sediment, TP and TN loadings respectively. The reason behind maximum reductions for conversion of SOYM to SWCH or MXGS was due to the fact that out of 8.2 % marginal croplands in the first SWAT model, SOYM alone comprised of 5.1% of the acreage, CORM (1.1%), COTM (0.6%) and RICM (1.4%) comprised of the remaining 3.1% of the marginal cropland. Since SOYM acreage was greater than other crops, resulting in greater acreage for SWCH and MXGS (by simulation) leading to greater reductions in sediment, TP and TN loadings.

Mean-monthly reductions in sediment, total phosphorus and total nitrogen loadings by conversion of individual crops to bioenergy crops for the second SWAT model were different from the first SWAT model (Figure 4.24 and 4.25). When SOYM was converted to SWCH, about 6%, 10.5% and 4.4% reductions were observed in sediment, TP and TN loadings respectively. Similarly, SOYM conversion to MXGS resulted in 5.9%, 10.5% and 3% reductions for sediment, TP and TN loadings. When CORM was converted to SWCH, it resulted in 2.1%, 2.6% and 2.9% reductions in sediment, TP and TN loadings respectively and when converted to MXGS, 2%, 2.6% and 3% reductions were observed for sediment, TP and TN loadings respectively. COTM conversion to SWCH or MXGS resulted in 0.1%, 0.8% and 0.3% reductions in sediments, TP and TN loadings. RICM conversion to SWCH or MXGS resulted in 1.7%, 4% and 1.7% reductions in sediment, TP and TN loadings respectively. Maximum reductions in sediment and nutrient loadings was observed when SOYM was converted to SWCH or MXGS because SOYM occupied maximum acreage in comparison to other crops in the watershed.

Fertilizer input is a major contributor to nutrient exports from agricultural watersheds (Ng et al., 2010). A decrease in total nitrogen loadings at the watershed outlet was mainly because Switchgrass and Miscanthus require lower nitrogen fertilizer inputs as compared to baseline crops. Total phosphorus loadings were observed to decrease at the watershed outlet due to absence of tillage operations after the first year of establishment of bioenergy crops. In past, studies have reported decrease in sediment losses in absence of tillage operations (Giri et al., 2012; Tang et al., 2011) which also affects phosphorus loadings since total phosphorus and sediments are closely related. Also, a slight difference was observed between reductions in losses for the two bioenergy crops. Crop management operations and crop growth parameters are the two factors that affect nutrient loadings. In this study, crop management operations were kept same for Switchgrass and Miscanthus whereas the crop growth parameters differed which caused difference in nutrient loads for the two crops.

A difference between the results for reductions in sediment and nutrient loadings for the first and the second SWAT model was also observed. This was mainly due to the fact that the first SWAT model used a single land use layer which caused the marginal croplands to remain static (8.2% of the total watershed area). Therefore, the bioenergy crops simulated on marginal croplands in the first SWAT model was simulated on 8.2% of the watershed area during the modeling period (1992 to 2012). Whereas, in the second SWAT model, the percentage of marginal croplands changed during the modeling period (Table 4.9) which resulted in change of acreage in bioenergy crops during the modeling period. As seen from Table 4.9 below, the percentage of marginal lands simulated during 1999 to 2005 varied from 3.3% to 6.8% which was clearly lesser than the marginal lands simulated in the first SWAT model during the complete modeling period (8.2%). It should also be noted that the baseline scenarios were different for the two SWAT models.

The hypothesis formulated in the beginning of the study that long term land use change in the watershed has no significant effect on sediment and nutrient loadings at the watershed outlet is rejected. This is because a significant change was observed between the baseline and Switchgrass/Miscanthus scenarios for sediment and nutrient loadings at the watershed outlet.

Table 4.9- Change in percentage of marginal lands in CRW during modeling period.

Period	% of marginal lands in CRW
1992 to 1998	11.3
1999 to 2000	5.7
2001 to 2003	6.8
2004 to 2005	3.3
2006 to 2010	8.2
2010 to 2012	10.1

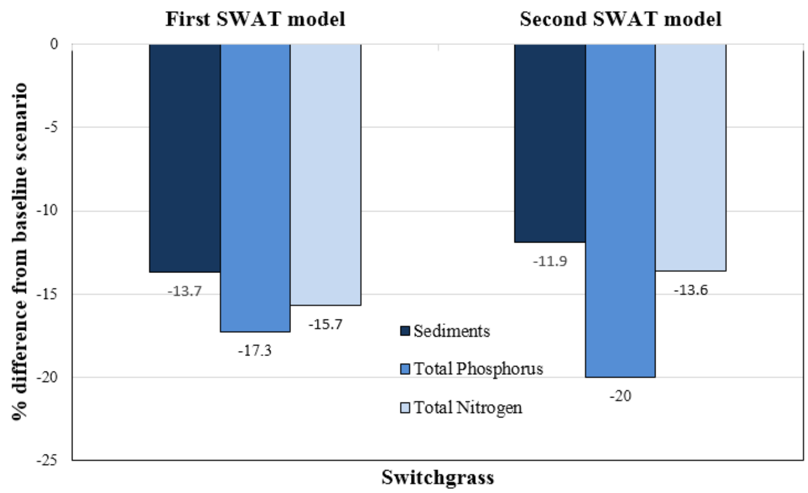


Figure 4.20- Mean-monthly changes in sediment, total phosphorus and total nitrogen losses by Switchgrass production.

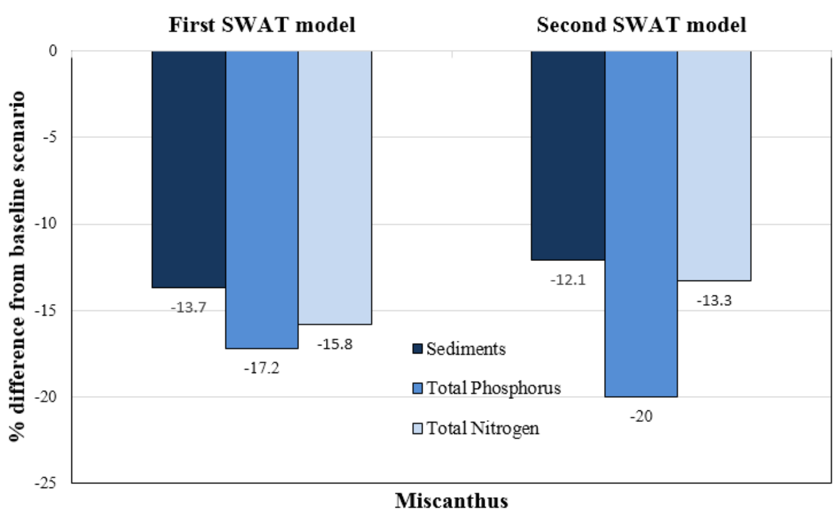


Figure 4.21- Mean-monthly changes in sediment, total phosphorus and total nitrogen losses by Miscanthus production.

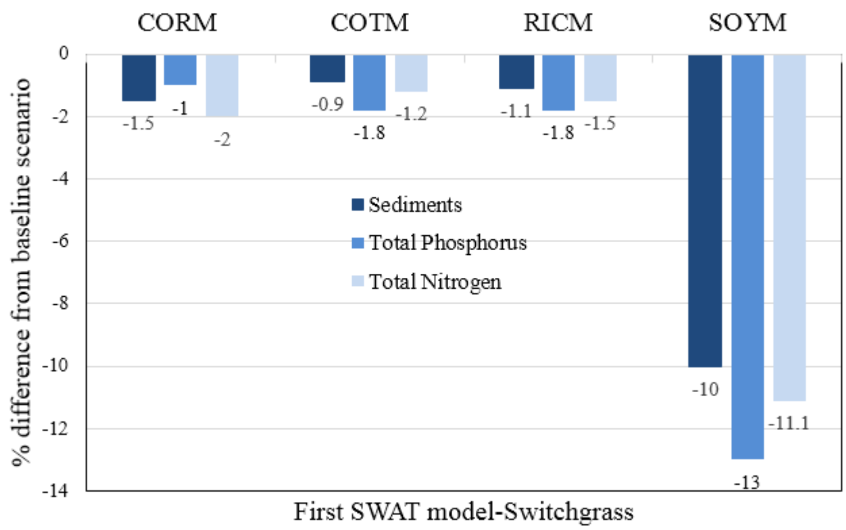


Figure 4.22-Mean-monthly changes in sediment, total phosphorus and total nitrogen losses by converting individual crops to Switchgrass (First SWAT model).

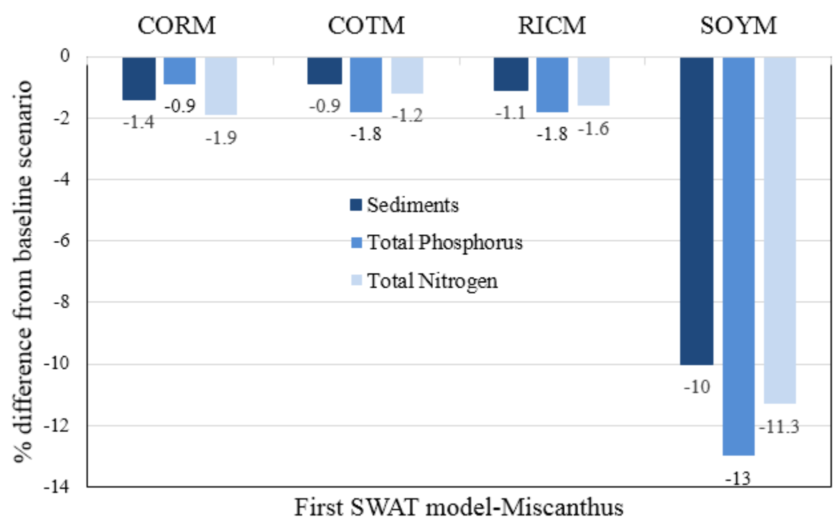


Figure 4.23-Mean-monthly changes in sediment, total phosphorus and total nitrogen losses by converting individual crops to Miscanthus (First SWAT model).

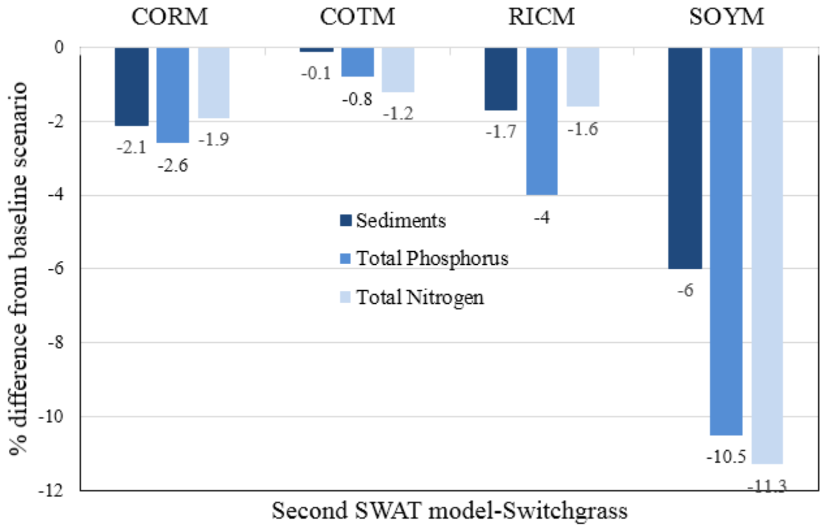


Figure 4.24- Mean-monthly changes in sediment, total phosphorus and total nitrogen losses by converting individual crops to Switchgrass (Second SWAT model).

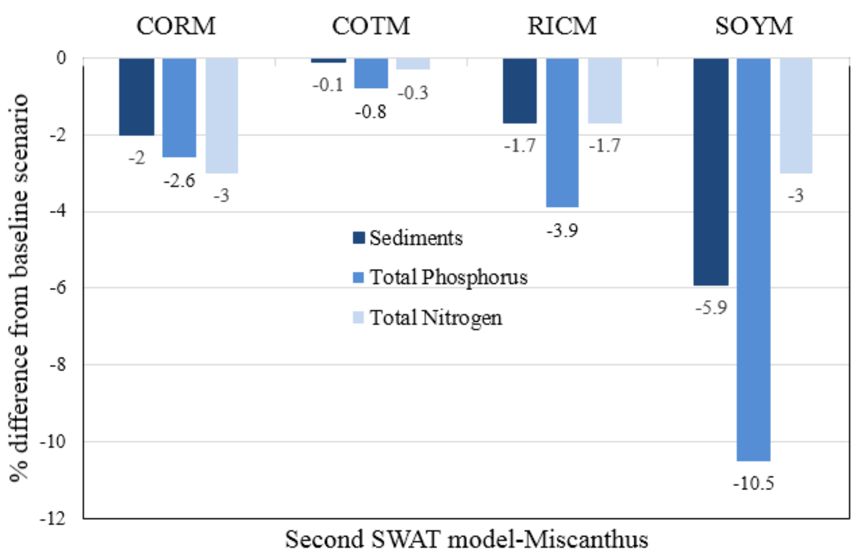


Figure 4.25- Mean-monthly changes in sediment, total phosphorus and total nitrogen losses by converting individual crops to Miscanthus (Second SWAT model).

4.5 Yield analysis for bioenergy crops

To gain confidence in modeling simulations, an additional yield analysis for Switchgrass and Miscanthus was conducted. This additional analysis was performed to compare the simulated yields with the Arkansas reported literature values. The first SWAT model simulated yields were 7.02 and 12.17 Mg/ha for Switchgrass and Miscanthus respectively. The second model simulated yields were 7.55 and 11.42 Mg/ha for Switchgrass and Miscanthus respectively. Miscanthus showed greater yield in comparison to Switchgrass. The yields were considered to be in satisfactory ranges (Dr. Andy Pereira, Professor-Crop Soil and Environmental Sciences-University of Arkansas, personal communication, 25 August 2015). Heaton et al. (2008) and Iqbal et al. (2015) reported superior yields for Miscanthus in comparison to Switchgrass due to higher yield potentials of Miscanthus. Additionally, Miscanthus is expected to have higher profits in comparison to Switchgrass (Farm Futures, 2015).

Average annual yields of Switchgrass in the US is about 11.2 Mg/ha, which ranges from 4.5 Mg/ha in the north to 23.0 Mg/ha in Alabama (McLaughlin and Kszos, 2005). Popp (2007) has reported that Switchgrass yield can vary from 7-12 Mg/ha on marginal croplands in Arkansas. The SWAT simulated yields for Miscanthus and Switchgrass were slightly on the lower side which can be considered normal (Baskaran et al., 2010).

Further, relation between mean-annual nitrogen uptake and biomass yield for Switchgrass and Miscanthus was determined with the help of scatterplots (Figures 4.26 to 4.29). It was found that both bioenergy crops exhibited a linear relationship. Miscanthus showed greater correlation in comparison to Switchgrass. The reason could be lower yields simulated by SWAT for Switchgrass. Higher yields resulted in higher nitrogen uptakes and vice-versa (Figures 4.26-4.29). A similar trend between nitrogen-uptake and biomass yield was reported by Singh (2012).

Mean-annual nitrogen uptake for the first SWAT model was 37 kg/ha and 42 kg/ha for Switchgrass and Miscanthus respectively and for the second SWAT model the mean-annual nitrogen uptake was 33 kg/ha and 39 kg/ha for Switchgrass and Miscanthus respectively. Slightly lower nitrogen uptake rates for the second SWAT model were due to the changing land use percent of marginal crop land for the second SWAT model.

In order to determine a relationship between leaf area index (LAI) and biomass yields scatter plots were plotted for Switchgrass and Miscanthus (Figures 4.30 to 4.33). These plots were generated on a mean-monthly basis. It was observed that when LAI increased, the biomass yield increased, reached to a maximum and then began to decline. LAI curves were different for Switchgrass and Miscanthus since crop growth parameters are different for the two crops resulting in a different crop growth cycle. LAI was observed to be maximum after one to two months after application of fertilizer which increased the nutrient uptake in the crops hence results more growth during in the months of June and July. Once LAI reached the maximum, it started to decrease since leaves fall off and temperature decreases, the crops begin to dry resulting in lower LAI values till the harvest time in November. Miscanthus showed high LAI values during the whole summer period due to optimization of solar radiation through the C4 pathway (Di Nasso et al., 2011).

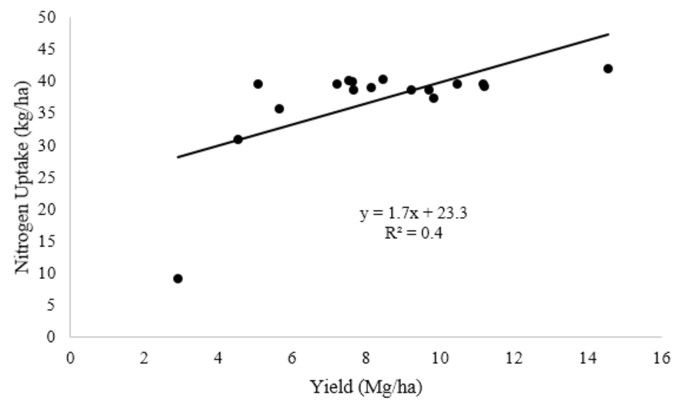


Figure 4.26– Scatterplot for mean-annual nitrogen uptake and biomass yield for Switchgrass for the first SWAT model.

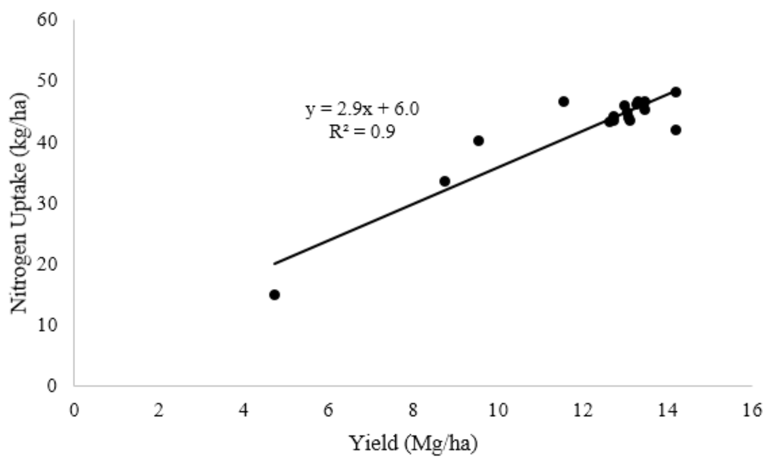


Figure 4.27– Scatterplot for mean-annual nitrogen uptake and biomass yield for Miscanthus for the first SWAT model.

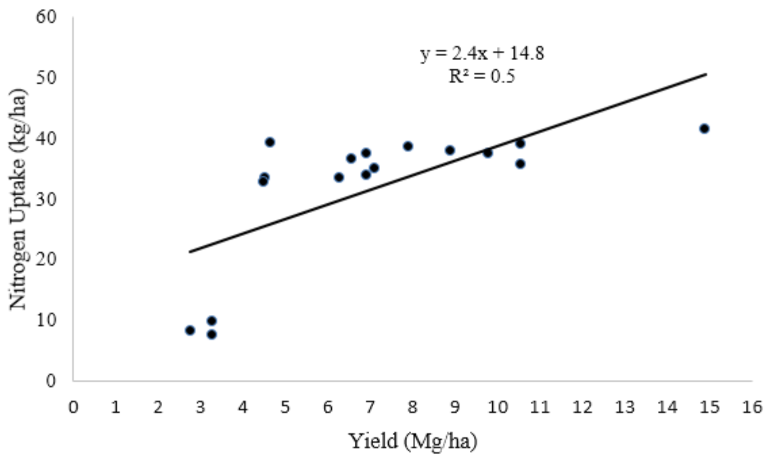


Figure 4.28- Scatterplot for mean-annual nitrogen uptake and biomass yield for Switchgrass for the second SWAT model.

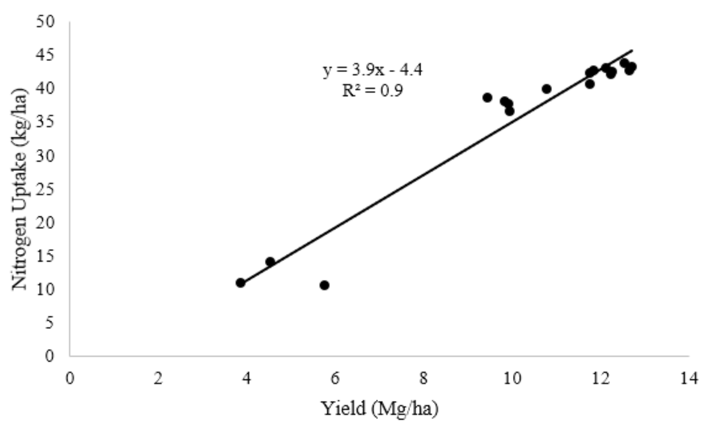


Figure 4.29 – Scatterplot for mean-annual nitrogen uptake and biomass yield for Miscanthus for the second SWAT model.

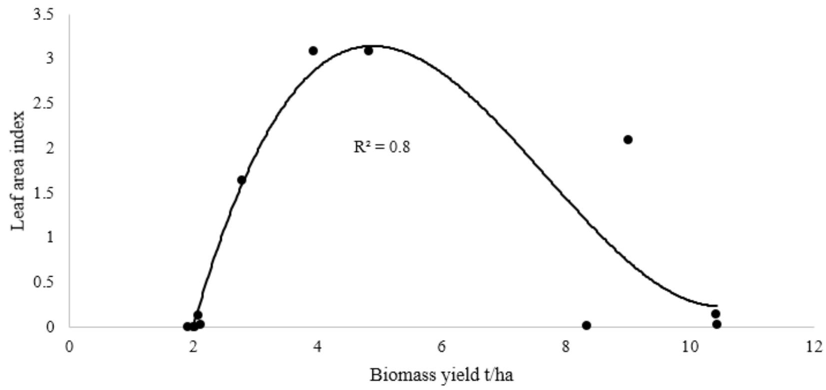


Figure 4.30- Scatterplot for mean-monthly leaf area index and biomass yield for Switchgrass for the first SWAT model.

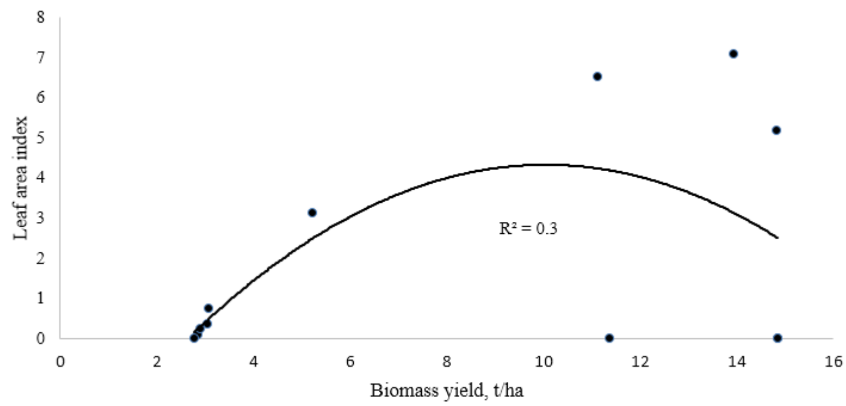


Figure 4.31- Scatterplot for mean-monthly leaf area index and biomass yield for Miscanthus for the first SWAT model.

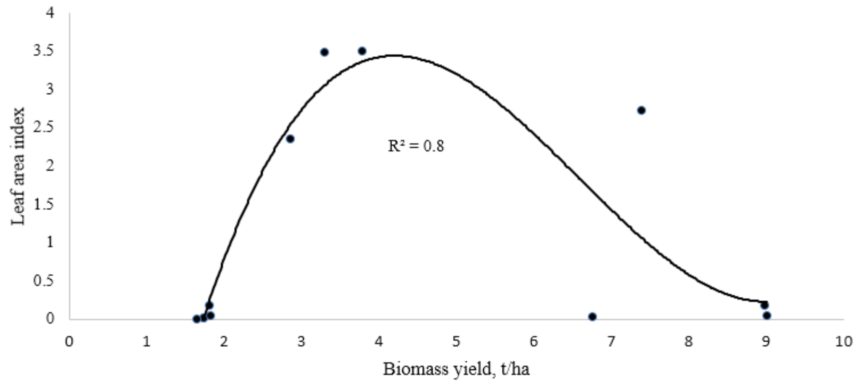


Figure 4.32- Scatterplot for mean-monthly leaf area index and biomass yield for Switchgrass for the second SWAT model.

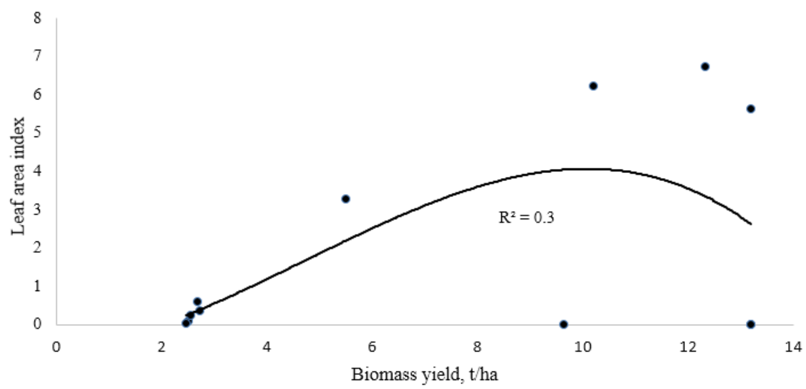


Figure 4.33- Scatterplot for mean-monthly leaf area index and biomass yield for Miscanthus for the second SWAT model.

4.6 Comparison of SWAT models

In this study two SWAT models were developed. The first SWAT model was developed following a traditional approach, i.e. using a single land use layer whereas the second model was developed using the land use update feature in SWAT using multiple land use layers with the help of SWAT LUC tool. Using a single land use layer for the complete modeling period limits the model's ability to simulate water quality impacts of temporal land use changes and benefits of conservation practices could be masked by simultaneous negative impacts of land use changes (Chiang et al., 2010; Pai, 2011). Therefore, the second SWAT model, using six different temporal land use maps, was able to represent the land use change in the Cache River Watershed by updating the HRU areas as observed from the "output.hru" output file. The LUC module was able to update HRU_FR (HRU land cover fractions) for the HRUs in the second SWAT model for each LULC year (1992, 1999, 2001, 2004, 2006 and 2011) using the SWAT_LUC tool (Pai and Saraswat, 2011).

The calibration and validation results were comparable for the two models however, the reductions in nutrient loadings (total phosphorus and total nitrogen) at the watershed outlet was slightly different. When all marginal crop lands were converted to Switchgrass, the first SWAT model showed a reduction of 13.7% in sediment loadings, 17.3% in total phosphorus loadings and 15.7% reduction in total nitrogen loadings and when marginal croplands were converted to Miscanthus, a reduction of 13.7% in sediment loadings, 17.2% in total phosphorus loadings and 15.8% reduction in total nitrogen loadings were observed at the watershed outlet. For the second SWAT model, when all marginal lands were converted to Switchgrass, a reduction of 11.9% in sediment loadings, 20% in total phosphorus loadings and 13.6% reduction in total nitrogen loadings and when all marginal crop land was converted to Miscanthus, a reduction of 12.1% in sediment loadings, 13.3% in total phosphorus loadings and 12.1% reduction in total nitrogen loadings were observed at the watershed outlet. Since the marginal cropland area remained static for the first model and changed in different years (1992, 1996, 1999, 2001, 2004, 2006 and 2011) according to different land use layers, a difference was observed between the reductions in sediment, total phosphorus and total nitrogen loadings for the two SWAT models (discussed in section 4.4). From this study, it can be said that the second approach does not introduce bias while simulating bioenergy crops. This is because it represents the physical characteristics of the watershed using six temporally different land use layers.

4.7 References

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V. CONCLUSIONS

The overarching goal of this study was to assess water quality impacts of production of two bioenergy crops, Miscanthus and Switchgrass, on targeted land (marginal land) in the Cache River Watershed located in Northeast Arkansas. Two SWAT models were setup in this study following two approaches of modeling. The first SWAT model was developed following a traditional modeling approach, i.e. using a single land use layer whereas the second SWAT model was developed using temporally different multiple land use layers to capture the dynamic land use change occurring in the watershed. The performance of both the models was judged by statistics such as coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS) and RMSE- observed standard deviation ratio (RSR). Two biofuel crops were simulated and their impacts on water quality were analyzed at the watershed outlet.

The observations made under respective objectives of the study are presented as follows:

Objective 1

The first objective of the study was to develop two SWAT models and calibrate and validate them.

Two SWAT models were developed for the Cache River Watershed following two different approaches. After the model set up, in order to identify most sensitive parameters that affected the model outputs, a global sensitivity analysis was conducted using the AHPCC supercomputer. Both models were run for the same modeling period, i.e., 1992 to 2012. First four years (1992 to 1995) were taken as the warmup period for the models. The models were calibrated from 1996 to 2005 and validated from 2006 to 2012 using the USGS monitoring data. Both the models were further validated using a qualitative modeling approach using recent water quality data for 2013-2014. Overall, both the models performed well within the satisfactory ranges with a few exceptions to total nitrogen and total phosphorus. As indicated in the methods chapter about the availability of observed data for flow at all three monitoring USGS stations but only at one station for total phosphorus and total nitrogen, in future more observed data without missing periods would be required for a robust calibration/validation.

Objective 2

The second objective of the study was to conduct analysis of potential water quality impacts resulting from land use change in the watershed by the simulation of biofuel crops at watershed scale.

Miscanthus and Switchgrass were simulated on marginal croplands in the watershed. Changes in nutrient loadings at the watershed outlet in comparison to the baseline scenario were analyzed for these crops at the monthly scale. Sediments, total phosphorus and total nitrogen loadings were found to decrease when Miscanthus or Switchgrass was simulated on the marginal lands. Soybean grown on marginal lands when converted to bioenergy crops was found to contribute the maximum reduction for sediment and nutrient loadings.

Objective 3

The third objective was to compare the results of biofuel crops simulation of the two models.

When all marginal lands were converted to Switchgrass, the first SWAT model showed a reduction of 13.7 % in sediment loadings, 17.3% in total phosphorus loadings and 15.7% in total nitrogen loadings at the watershed outlet and the second SWAT model showed a reduction of 11.9% in sediment loadings, 20% in total phosphorus loadings and 13.6% in total nitrogen loadings at the watershed outlet. When Miscanthus was simulated on marginal lands, the first model showed a reduction of 13.7% in sediment loadings, 17.2% in total phosphorus loadings and 15.8% reduction in total nitrogen loadings at the watershed outlet and the second model showed a reduction of 12.1% in sediment loadings, 20% in total phosphorus loadings and 13.3% in total nitrogen loadings at the watershed outlet. For the first SWAT model the percentage acreage of marginal lands remained static since a single land use layer was used. The acreage of marginal lands which in turn affected the acreage of bioenergy crops changed during the modeling period for the second SWAT model since six temporally different land use layers were used to setup the second SWAT model. The second model thus, did not introduce bias while simulating Switchgrass and Miscanthus on targeted lands. Also, the hypothesis formulated at the beginning of the study that long term land use change has no effect on sediment and nutrient loadings at the watershed outlet is rejected.

Appendices

Appendix A- Subwatershed level information for Cache River Watershed

Subbasin No.	HUC_12	County	Drainage Area (km^2)	Min elevation (m)	Max elevation (m)	Slope range/%		Soil group/%		Major crops/%	
1	080203020104	Clay	119	86	165	0-1	9.5	A	0.0	Soybean	23.0
						1-3	19.2	B	40.8	Rice	2.8
						3-8	41.3	C	49.6	Cotton	2.5
						8<	29.9	D	9.6	Corn	5.3
2	080203020102	Clay	106	84	165	0-1	28.0	A	0.0	Soybean	38.1
						1-3	30.8	B	50.6	Rice	16.7
						3-8	21.8	C	30.1	Cotton	5.5
						8<	19.4	D	19.3	Corn	5.2
3	080203020202	Clay & Green	117	75	90	0-1	52.0	A	0.0	Soybean	51.3
						1-3	41.8	B	36.9	Rice	22.8
						3-8	6.1	C	49.5	Cotton	0.2
						8<	0.1	D	13.6	Corn	6.7
4	080203020106	Clay & Green	88	76	164	0-1	27.9	A	0.0	Soybean	28.4
						1-3	26.8	B	22.6	Rice	14.8
						3-8	20.8	C	68.8	Cotton	4.0
						8<	24.4	D	8.6	Corn	5.5
5	080203020103	Clay	97	80	138	0-1	53.8	A	0.0	Soybean	41.7
						1-3	38.5	B	62.1	Rice	30.7
						3-8	5.5	C	29.7	Cotton	9.0
						8<	2.2	D	8.3	Corn	7.7
6	080203020206	Clay & Green	101	73	95	0-1	50.3	A	0.0	Soybean	42.6
						1-3	41.9	B	25.6	Rice	20.0
						3-8	7.6	C	61.0	Cotton	0.2
						8<	0.2	D	13.4	Corn	13.4
7	080203020101	Clay	6	87	97	0-1	61.4	A	0.0	Soybean	48.0
						1-3	34.2	B	38.5	Rice	35.5

Subbasin No.	HUC_12	County	Drainage Area (km^2)	Min elevation (m)	Max elevation (m)	Slope range/%		Soil group/%		Major crops/%	
						3-8	4.5	C	53.8	Cotton	5.0
						8<	0.0	D	7.7	Corn	3.9
8	080203020105	Clay	128	78	94	0-1	59.3	A	0.0	Soybean	50.4
						1-3	37.6	B	30.7	Rice	26.1
						3-8	3.0	C	55.9	Cotton	3.7
						8<	0.0	D	13.4	Corn	6.9
9	080203020503	Craighead	70	73	133	0-1	17.6	A	0.0	Soybean	16.9
						1-3	24.7	B	46.8	Rice	2.5
						3-8	39.6	C	27.3	Cotton	0.0
						8<	18.1	D	25.9	Corn	5.8
10	080203020305	Craighead &	114	56	84	0-1	59.6	A	0.0	Soybean	50.7
		Jackson				1-3	36.2	B	37.8	Rice	19.8
						3-8	4.1	C	54.6	Cotton	0.4
						8<	0.1	D	7.6	Corn	11.8
11	080203020302	Greene &	74	67	143	0-1	46.2	A	0.0	Soybean	44.0
		Craighead				1-3	31.7	B	38.5	Rice	13.0
						3-8	11.8	C	39.6	Cotton	0.1
						8<	10.3	D	22.0	Corn	11.1
12	080203020402	Poinsett &	107	58	84	0-1	52.8	A	0.0	Soybean	42.3
		Jackson				1-3	42.7	B	31.0	Rice	12.6
						3-8	4.4	C	50.0	Cotton	0.5
						8<	0.1	D	19.0	Corn	11.0
13	080203020501	Greene &	115	84	162	0-1	10.6	A	0.0	Soybean	12.2
		Craighead				1-3	23.2	B	53.9	Rice	1.8
						3-8	45.0	C	22.4	Cotton	0.0
						8<	21.3	D	23.7	Corn	4.0
14	080203020505	Craighead &	104	66	113	0-1	64.6	A	0.0	Soybean	63.4
		Poinsett				1-3	32.5	B	7.1	Rice	15.7
						3-8	2.8	C	36.3	Cotton	0.3

Subbasin No.	HUC_12	County	Drainage Area (km^2)	Min elevation (m)	Max elevation (m)	Slope range/%		Soil group/%		Major crops/%	
						8<	0.1	D	56.6	Corn	5.3
15	080203020601	Craighead &	89	62	75	0-1	54.6	A	0.0	Soybean	52.9
		Poinsett				1-3	41.7	B	26.9	Rice	17.1
						3-8	3.8	C	59.1	Cotton	0.3
						8<	0.0	D	14.0	Corn	12.6
16	080203020306	Lawrence &	145	65	82	0-1	62.0	A	0.0	Soybean	53.0
		Craighead				1-3	34.4	B	28.6	Rice	18.5
						3-8	3.6	C	32.8	Cotton	0.4
						8<	0.0	D	38.6	Corn	11.5
17	080203020303	Lawrence &	50	69	81	0-1	62.7	A	0.0	Soybean	55.3
		Craighead				1-3	33.8	B	33.7	Rice	13.7
						3-8	3.4	C	48.3	Cotton	0.2
						8<	0.0	D	18.0	Corn	13.7
18	080203020502	Craighead &	153	68	162	0-1	34.2	A	0.0	Soybean	32.1
		Poinsett				1-3	34.7	B	56.8	Rice	11.1
						3-8	26.1	C	24.1	Cotton	0.2
						8<	5.1	D	19.1	Corn	3.8
19	080203020304	Lawrence &	111	68	138	0-1	58.2	A	0.0	Soybean	51.7
		Craighead				1-3	32.0	B	37.2	Rice	15.8
						3-8	6.3	C	35.4	Cotton	0.2
						8<	3.6	D	27.4	Corn	9.8
20	080203020506	Craighead &	76	66	77	0-1	63.8	A	0.0	Soybean	41.9
		Poinsett				1-3	34.2	B	19.0	Rice	10.3
						3-8	2.0	C	42.9	Cotton	0.1
						8<	0.0	D	38.1	Corn	9.3
21	080203020301	Greene	134	72	163	0-1	42.4	A	0.0	Soybean	47.8
						1-3	31.4	B	36.4	Rice	9.8
						3-8	15.5	C	47.1	Cotton	0.2
						8<	10.8	D	16.4	Corn	8.1

Subbasin No.	HUC_12	County	Drainage Area (km^2)	Min elevation (m)	Max elevation (m)	Slope range/%		Soil group/%		Major crops/%	
22	080203020607	Cross &	101	56	72	0-1	52.4	A	0.0	Soybean	48.2
		Woodruff				1-3	42.5	B	13.9	Rice	9.2
						3-8	5.0	C	42.4	Cotton	0.3
						8<	0.1	D	43.7	Corn	6.4
23	080203020604	Cross &	60	63	73	0-1	56.6	A	0.0	Soybean	45.9
		Poinsett				1-3	40.2	B	32.9	Rice	18.6
						3-8	3.2	C	15.9	Cotton	0.2
						8<	0.0	D	51.2	Corn	9.9
24	080203020205	Greene	97	74	171	0-1	50.7	A	0.0	Soybean	42.3
						1-3	28.0	B	18.6	Rice	19.2
						3-8	7.9	C	71.2	Cotton	0.2
						8<	13.4	D	10.2	Corn	6.7
25	080203020203	Greene	57	74	169	0-1	42.4	A	0.0	Soybean	46.0
						1-3	38.5	B	26.7	Rice	17.5
						3-8	10.0	C	53.3	Cotton	0.2
						8<	9.1	D	20.0	Corn	6.7
26	080203020209	Greene	90	71	82	0-1	65.2	A	0.0	Soybean	49.8
						1-3	31.8	B	32.4	Rice	23.6
						3-8	3.0	C	59.2	Cotton	0.2
						8<	0.0	D	8.5	Corn	10.3
27	080203020207	Greene &	100	72	85	0-1	56.5	A	0.0	Soybean	48.1
		Lawrence				1-3	39.8	B	31.5	Rice	20.9
						3-8	3.7	C	53.7	Cotton	0.2
						8<	0.0	D	14.8	Corn	14.5
28	080203020201	Greene	50	78	171	0-1	5.1	A	0.0	Soybean	9.9
						1-3	15.8	B	20.8	Rice	1.0
						3-8	35.5	C	67.5	Cotton	0.5
						8<	43.7	D	11.7	Corn	3.4
29	080203020204	Greene	51	84	165	0-1	6.4	A	0.0	Soybean	11.7

Subbasin No.	HUC_12	County	Drainage Area (km^2)	Min elevation (m)	Max elevation (m)	Slope range/%		Soil group/%		Major crops/%	
						1-3	15.4	B	19.1	Rice	1.3
						3-8	34.7	C	73.5	Cotton	0.0
						8<	43.5	D	7.4	Corn	2.5
30	080203020401	Jackson	76	62	78	0-1	67.0	A	0.0	Soybean	49.3
						1-3	31.6	B	31.2	Rice	20.6
						3-8	1.3	C	54.4	Cotton	0.3
						8<	0.1	D	14.4	Corn	16.6
31	080203020404	Jackson	125	60	74	0-1	53.6	A	0.0	Soybean	43.4
						1-3	42.9	B	25.0	Rice	14.2
						3-8	3.5	C	65.8	Cotton	0.2
						8<	0.0	D	9.2	Corn	12.4
32	080203020405	Jackson &	97	59	74	0-1	57.1	A	0.0	Soybean	53.4
		Woodruff				1-3	38.7	B	40.8	Rice	5.2
						3-8	4.1	C	36.3	Cotton	0.2
						8<	0.0	D	22.9	Corn	19.1
33	080203020606	Jackson &	70	58	70	0-1	61.8	A	0.0	Soybean	47.1
		Woodruff				1-3	36.7	B	28.6	Rice	19.0
						3-8	1.5	C	51.8	Cotton	0.2
						8<	0.0	D	19.6	Corn	14.1
34	080203020403	Jackson	90	61	75	0-1	52.1	A	0.0	Soybean	44.6
						1-3	43.7	B	28.6	Rice	23.8
						3-8	4.1	C	58.0	Cotton	0.5
						8<	0.0	D	13.4	Corn	15.3
35	080203020605	Jackson,	85	62	76	0-1	53.6	A	0.0	Soybean	46.7
		Poinsett &				1-3	42.6	B	36.2	Rice	22.8
		Cross				3-8	3.8	C	44.7	Cotton	0.4
						8<	0.0	D	19.1	Corn	14.5
36	080203020406	Jackson &	94	58	71	0-1	54.6	A	0.0	Soybean	46.7
		Woodruff				1-3	42.1	B	40.1	Rice	12.5

Subbasin No.	HUC_12	County	Drainage Area (km^2)	Min elevation (m)	Max elevation (m)	Slope range/%		Soil group/%		Major crops/%	
						3-8	3.3	C	46.3	Cotton	0.1
						8<	0.0	D	13.6	Corn	10.4
37	080203020602	Poinsett	42	61	74	0-1	48.3	A	0.0	Soybean	63.8
						1-3	46.0	B	11.5	Rice	15.9
						3-8	5.6	C	73.1	Cotton	0.2
						8<	0.1	D	15.4	Corn	8.6
38	080203020208	Lawrence &	63	71	82	0-1	75.7	A	0.0	Soybean	49.4
		Greene				1-3	23.1	B	41.2	Rice	25.4
						3-8	1.2	C	45.1	Cotton	0.2
						8<	0.0	D	13.7	Corn	15.1
39	080203020704	Woodruff	82	52	69	0-1	45.1	A	0.0	Soybean	27.6
						1-3	45.8	B	1.6	Rice	38.0
						3-8	9.0	C	50.8	Cotton	10.4
						8<	0.1	D	47.6	Corn	2.2
40	080203020707	Woodruff &	69	49	73	0-1	43.8	A	0.0	Soybean	22.9
		Monroe				1-3	49.5	B	26.9	Rice	7.1
						3-8	6.7	C	38.3	Cotton	18.1
						8<	0.1	D	34.7	Corn	11.1
41	080203020708	Woodruff &	77	44	61	0-1	52.1	A	0.0	Soybean	22.0
		Monroe				1-3	42.7	B	13.6	Rice	8.8
						3-8	5.2	C	50.8	Cotton	10.8
						8<	0.1	D	35.6	Corn	5.3
42	080203020705	Woodruff &	82	49	69	0-1	49.9	A	0.0	Soybean	25.0
		Monroe				1-3	44.0	B	28.2	Rice	7.8
						3-8	6.0	C	29.8	Cotton	14.9
						8<	0.1	D	42.0	Corn	5.3
43	080203020808	Monroe &	105	43	62	0-1	48.7	A	0.0	Soybean	17.4
		Prairie				1-3	44.2	B	14.0	Rice	3.5
						3-8	6.9	C	74.0	Cotton	7.5

Subbasin No.	HUC_12	County	Drainage Area (km^2)	Min elevation (m)	Max elevation (m)	Slope range/%		Soil group/%		Major crops/%	
						8<	0.2	D	12.0	Corn	5.7
44	080203020706	Monroe	141	46	66	0-1	47.0	A	0.0	Soybean	19.1
						1-3	46.5	B	40.3	Rice	6.8
						3-8	6.5	C	37.6	Cotton	8.9
						8<	0.1	D	22.2	Corn	6.9
45	080203020807	Prairie,	100	44	63	0-1	43.6	A	0.0	Soybean	24.5
		Woodruff &				1-3	45.1	B	11.4	Rice	4.5
		Monroe				3-8	10.7	C	62.7	Cotton	9.4
						8<	0.6	D	25.9	Corn	5.0
46	080203020507	Poinsett	67	63	77	0-1	54.5	A	0.0	Soybean	43.0
						1-3	42.1	B	4.4	Rice	15.6
						3-8	3.3	C	55.9	Cotton	0.2
						8<	0.0	D	39.7	Corn	5.5
47	080203020603	Poinsett	49	61	76	0-1	46.8	A	0.0	Soybean	43.3
						1-3	46.1	B	8.8	Rice	22.0
						3-8	6.9	C	61.4	Cotton	0.2
						8<	0.1	D	29.8	Corn	8.6
48	080203020805	Woodruff &	139	47	64	0-1	43.6	A	0.0	Soybean	44.2
		Prairie				1-3	48.3	B	12.3	Rice	9.1
						3-8	8.0	C	46.0	Cotton	9.2
						8<	0.1	D	41.8	Corn	2.4
49	080203020806	Woodruff &	102	45	64	0-1	38.3	A	0.0	Soybean	34.8
		Prairie				1-3	49.1	B	11.2	Rice	8.8
						3-8	12.3	C	47.3	Cotton	9.2
						8<	0.3	D	41.5	Corn	4.3
50	080203020407	Woodruff	81	51	69	0-1	52.3	A	0.0	Soybean	32.9
						1-3	43.7	B	37.9	Rice	3.7
						3-8	3.8	C	33.3	Cotton	0.2
						8<	0.2	D	28.7	Corn	5.3

Subbasin No.	HUC_12	County	Drainage Area (km^2)	Min elevation (m)	Max elevation (m)	Slope range/%		Soil group/%		Major crops/%	
51	080203020701	Woodruff	76	57	70	0-1	57.1	A	0.0	Soybean	46.2
						1-3	40.0	B	28.6	Rice	10.6
						3-8	2.9	C	31.4	Cotton	1.9
						8<	0.0	D	40.0	Corn	4.4
52	080203020802	Woodruff	77	53	73	0-1	44.8	A	0.0	Soybean	31.3
						1-3	48.2	B	31.9	Rice	4.8
						3-8	6.9	C	36.3	Cotton	1.2
						8<	0.1	D	31.9	Corn	7.0
53	080203020702	Woodruff	87	52	70	0-1	49.9	A	0.0	Soybean	33.7
						1-3	45.5	B	24.3	Rice	8.8
						3-8	4.5	C	53.3	Cotton	9.8
						8<	0.1	D	22.4	Corn	12.2
54	080203020803	Woodruff	57	53	71	0-1	38.8	A	0.0	Soybean	27.3
						1-3	49.0	B	18.9	Rice	1.9
						3-8	11.7	C	30.6	Cotton	19.2
						8<	0.4	D	50.5	Corn	7.2
55	080203020703	Woodruff	62	54	70	0-1	43.2	A	0.0	Soybean	28.2
						1-3	49.2	B	21.4	Rice	19.2
						3-8	7.5	C	29.6	Cotton	10.7
						8<	0.0	D	49.0	Corn	8.3
56	080203020801	Woodruff	88	53	68	0-1	54.2	A	0.0	Soybean	37.0
						1-3	42.4	B	38.0	Rice	5.2
						3-8	3.4	C	32.8	Cotton	0.3
						8<	0.0	D	29.2	Corn	8.9
57	080203020804	Woodruff	71	51	69	0-1	46.1	A	0.0	Soybean	10.6
						1-3	46.7	B	27.3	Rice	2.8
						3-8	7.2	C	33.1	Cotton	10.1
						8<	0.0	D	39.7	Corn	17.3

APPENDIX B- Nested subwatersheds in Cache River Watershed

S.No.	Subwatershed Name	From	To	Area (acres)	Cumulative Area (acres)	Flows into	
1	South Fork Big Creek-Big Creek	1	4	29306	29306		
2	Little Cache River Ditch	2	5	26143	26143		
3	Big Gum Lateral-Cache River	3	6	29003	63260	4,28	Nested
4	Cache River Ditch Number One-Big Creek	4	3	21809	83443	1,8	Nested
5	North Big Creek-Cache River Ditch Number One	5	8	41874	83882	2,7	Nested
6	Petersburg Ditch-Cache River	6	26	25022	92065	3,24,25	Nested
7	Fish Trap Slough	7	5	15865	15865		
8	East Slough-Cache River Ditch Number One	8	4	32328	116210	5	Nested
9	Rogers Bayou-Big Creek Ditch	9	14	17175	83394	13,18	Nested
10	Willow Ditch	10	16	28262	28262		
11	Gum Slough Ditch	11	19	18208	18208		
12	Browns Creek-Cache River	12	31	26424	81042	16,30	Nested
13	Mud Creek Big Creek Ditch	13	9	28346	28346		
14	Whitsle Ditch-Big Creek Ditch	14	20	25767	25767		
15	Flag Slough Ditch	15	47	21984	21984		
16	Podo Creek-Cache River	16	12	35852	91645	10,19	Nested
17	West Cache River Ditch	17	19	12257	12257		
18	Lost Creek Ditch	18	9	37873	37873		
19	Whaley Slough Ditch-Cache River	19	16	27531	91169	11,17,21	Nested
20	OK Lake-Bayou DeView	20	46	18714	18714		
21	Number Twenty Six Ditch-Cache River	21	19	33173	55444	26	Nested
22	Old Channel Bayou DeView-Bayou DeView	22	51	24915	78033	23,33,35	Nested
23	Town of Pittinger-Bayou DeView	23	22	14718	26911	47	Nested
24	Swan Pond Ditch-Cache River	24	6	24023	36521	29	Nested
25	Town of Evening Star-Cache River Ditch	25	6	14017	14017		
26	Buffalo Head Slough Cache River	26	21	22271	139084	6,27	Nested
27	Beaver Dam Ditch	27	26	24748	24748		
28	Scatter Creek-Big Creek	28	3	12448	12448		
29	Sugar Creek-Cache River	29	24	12498	12498		
30	Skillet Ditch	30	12	18766	18766		
31	Overcup Slough-Cache River	31	36	30827	134106	12,34	Nested
32	Overcup Ditch	32	36	23965	23965		
33	May Branch Lateral	33	22	17358	17358		
34	Cyprus Creek Ditch	34	31	22237	22237		
35	Cow Lake Ditch	35	22	21042	21042		

36	Town of Gourd Neck-Cache River	36	50	23329	181400	31,32	Nested
37	Threemile Creek	37	47	10444	10444		
38	Kellow Ditch	38	26	15592	15592		
39	Caney Creek-Buffalo Creek	39	42	20270	20270		
40	Gum Flat Bayou	40	41	17039	17039		
41	Robe Bayou-Bayou DeView	41	43	19080	70858	40,44	Nested
42	Turkey Creek-Bayou DeView	42	44	20394	77533	39,53,55	Nested
43	Reeses Fork-Cache River	43	**OUT**	25873	25873		
44	Channey Slough-Bayou DeView	44	41	34739	112272	42	Nested
45	Maloy Bayou-Cache River	45	43	24810	49991	49	Nested
46	Lake Hogue-Bayou DeView	46	47	16625	35339	20	Nested
47	Town of Waldenburg-Bayou DeView	47	23	12193	79960	15,37,46	Nested
48	Bear Slough-Culotches Bay Slough	48	49	34269	34269		
49	Culotches Bay Slough-Cache River	49	45	25181	77000	48,57	Nested
50	Town of Patterson-Cache River	50	56	19913	201313	36	Nested
51	Possom Creek-Bayou DeView	51	55	18782	96815	22	Nested
52	Beard Lake-Cache River	52	57	18990	18990		
53	Buffalo Creek	53	42	21591	21591		
54	Cache Bayou	54	57	14147	14147		
55	Morrison Lake-Bayou DeView	55	42	15278	112093	51	Nested
56	Miller Branch-Cache River	56	52	21874	223187	50	Nested
57	James Ferry-Cache River	57	49	17550	128512	52,54	Nested

Appendix C- LULC Merged Categories for CAST and NLCD layers

Agency	Year	Categories	Category Name	SWAT Merged Name/Codes
NLCD	1992	22,23	High intensity residential, Commercial/Industrial/Transportation	URHD
		31,32,33	Bare Rock/Sand/Clay, Quarries/Strip Mines/Gravel Pits, Transitional	BARR
		41,42,43	Deciduous Forest, Evergreen Forest, Mixed Forest	FRST
		82,83	Row Crops, Small Grains	AGRR
		91,92	Woody Wetlands, Emergent Herbaceous Wetlands	WETL
NLCD	2001	22,23,24	High intensity residential, Commercial/Industrial/Transportation, Developed High Intensity	URHD
		41,42,43	Deciduous Forest, Evergreen Forest, Mixed Forest	FRST
		52,71,81	Shrub/Scrub, Grasslands/Herbaceous, Pasture/Hay	PAST
		90,95	Woody Wetlands, Emergent Herbaceous Wetlands	WETL
CAST	1999	11,14	Urban Level 1, Urban Other (Park, Golf Course, Cemetery, etc.)	URLD
		12,13	Urban Level 2, Urban Level 3	URHD
		31,208	Barren Land (Sand Bars/Mining Operations/Exposed Rock), Bare Soil/Seedbed/Fallow	BARR
		41,42	Perennial Water, Flooded	WATR
		51,101,105,109,117,118,119,120,121,122,123,124,126,127	Herbaceous/Woody/Transitional, Forest Unclassified, White Oak/Northern Red Oak/Shortleaf Pine/Hickory, White Oak/Mixed Hardwoods, Overcup Oak (Quercus Lyrata), Water Hickory (Carya Aquatica), Cherrybark Oak (Quercus Falcata var. Pagodifolia), Sugarberry (Celtis Laevigata), Nuttall Oak (Quercus Nuttallii), Willow Oak (Quercus Phellos), Sweetgum (Liquidambar Styraciflua), Baldcypress/Mixed Hardwoods, Baldcypress (Taxodium Distichum), Tupelo/Gum (Nyssa), Willow/Cottonwood (Salix, Populus)	FRST
		209,210	Warm Season Pasture, Cool Season Pasture	PAST
CAST	2004	31,208	Barren Land, Bare Soil/Seedbed	BARR
		51,100	Herbaceous/Woody/Transitional, Forest Unclassified	FRST
		209,210	Warm Season Grasses, Cool Season Grasses	PAST
CAST	2006	31,208	Barren Land, Bare Soil/Seedbed	BARR
		51,100	Herbaceous/Woody/Transitional, Forest Unclassified	FRST
		209,210	Warm Season Grasses, Cool Season Grasses	PAST
NLCD	2011	22,23,24	High intensity residential, Commercial/Industrial/Transportation, Developed High Intensity	URHD
		41,42,43	Deciduous Forest, Evergreen Forest, Mixed Forest	FRST
		52,71,81	Shrub/Scrub, Grasslands/Herbaceous, Pasture/Hay	PAST
		90,95	Woody Wetlands, Emergent Herbaceous Wetlands	WETL

Appendix D- Point source facilities in Cache River Watershed

Point source facility	County name	Latitude	Longitude
City of Weiner	Poinsett	-90.9135	35.62317
City of Bono	Craighead	-90.805	35.90467
City of Brinkley	Monroe	-91.2058	34.88403
City of Fisher	Poinsett	-90.9844	35.49333
City of Cotton Plant	Woodruff	-91.2435	34.99939
City of Grubbs	Jackson	-91.0606	35.64953
City of Hickory Ridge	Cross	-91.0018	35.41178
Arkansas Dept. of Parks and Tourism-Crowley's Ridge State Park	Greene	-90.6665	36.04478
Riceland-Waldenburg rice division	Poinsett	-90.9153	35.59417
City of Water and Light (CWL)-Westside WWTP Jonesboro	Craighead	-90.7486	35.85611
City of Patterson	Woodruff	-91.242	35.25408
Westside Consolidated School District #5	Craighead	-90.8043	35.85731
McDougal Municipal Water	Clay	-90.7992	35.85111
City of Knobel	Clay	-90.3884	36.44311
City of Sedgwick	Lawrence	-90.5967	36.31397
Tri-city Utilities, Inc.	Randolph	-90.8621	35.97178
Egypt Sewer System	Craighead	-90.8113	36.16536
City of McCrory	Woodruff	-91.2104	35.25192
City of Cash	Craighead	-90.9366	35.80217
City of Pollard	Clay	-90.2725	36.43611
City of Beedeville	Jackson	-91.1342	35.43694
Breckenridge-Union Water Treatment Facility	Jackson	-91.2302	35.47486

Appendix E- Management practices for corn

Month	Day	Operation	SWAT Practice	Fertilizer (Kg/ha)	Pesticide (Kg/ha)	Irrigation(mm)
March	2	Burn Down	Burn down			
March	2	Pesticide	Dicamba		2.135	
March	5	Tillage	Hipper 12 Row			
April	3	Fertilizer	Elemental Nitrogen	100.8		
April	3	Fertilizer	Elemental Potassium	67.76		
April	3	Fertilizer	Elemental Phosphorus	50.4		
April	5	Plant/Begin growing season	Corn			
April	30	Pesticide	Atrazine		3.44	
May	1	Fertilizer	Elemental Nitrogen	140		
May	15	Pesticide	Halex GT		2.24	
May	20	Irrigation				55.55
May	30	Irrigation				55.55
June	10	Irrigation				55.55
June	20	Irrigation				55.55
June	30	Irrigation				55.55
July	5	Fertilizer	Urea	50.4		
July	10	Irrigation				55.55
July	20	Irrigation				55.55
July	30	Irrigation				55.55
August	10	Irrigation				55.55
August	31	Harvest and Kill operation				

Appendix F- Management practices for rice

Month	Day	Operation	SWAT Practice	Fertilizer (Kg/ha)	Pesticide (Kg/ha)	Irrigation(mm)
March	23	Fertilizer	Elemental Potassium	67.2		
March	25	Plant/Begin growing season	Rice			
April	4	Pesticide	Clomazone		1.14	
May	11	Pesticide	Propanil		2.63	
May	13	Fertilizer	Elemental Phosphorus	33.6		
May	13	Fertilizer	Urea	224		
May	27	Pesticide	Lambda-Cyhalothrin		0.016	
May	30	Release/Impound	Initiate water impound			
June	8	Irrigation				82
June	11	Fertilizer	Urea	112		
June	18	Irrigation				82
June	25	Irrigation				82
July	5	Irrigation				82
July	15	Irrigation				82
July	25	Irrigation				82
August	4	Irrigation				82
August	15	Irrigation				82
August	26	Irrigation				82
August	27	Release/Impound	Initiate water release			
September	6	Harvest and Kill Operation				

Appendix G- Management practices for cotton

Month	Day	Operation	SWAT Practice	Fertilizer (Kg/ha)	Pesticide (Kg/ha)	Irrigation(mm)
March	10	Burn down	Burn down			
March	10	Pesticide	Dicamba		2.135	
March	16	Tillage	Disk Plow Ge23ft			
April	1	Fertilizer	Elemental Phosphorus	53.76		
April	1	Fertilizer	Elemental Potassium	67.2		
April	3	Tillage	Field Cultivator Ge 15 ft.			
April	4	Pesticide	Trifluralin		1.98	
April	24	Tillage	Land-all, Do-all			
April	26	Pesticide	Reflex		1.11	
April	28	Plant/Begin growing season	Upland Cotton			
May	10	Pesticide	Cotoran		1.66	
May	12	Pesticide	Asana		0.28	
May	15	Pesticide	Valor		0.14	
May	23	Fertilizer	Elemental Nitrogen	52.69		
June	19	Fertilizer	Elemental Nitrogen	59.41		
July	15	Irrigation				50.8
August	15	Irrigation				50.8
August	20	Irrigation				50.8
August	30	Irrigation				50.8
September	10	Irrigation				50.8
September	15	Irrigation				50.8
September	20	Pesticide	Def+Prep		0.56+0.7	
October	5	Pesticide	Def+Prep		0.56+0.7	
October	26	Harvest and Kill				

Appendix H- Management practices for soybean

Month	Day	Operation	SWAT Practice	Fertilizer (Kg/ha)	Pesticide (Kg/ha)	Irrigation(mm)
March	1	Burndown				
March	1	Pesticide	Dicamba		2.135	
March	7	Pesticide	Glyphosate Amine		2.24	
March	7	Pesticide	Paraquat		2.24	
April	12	Tillage	Bedder Roller			
May	13	Fertilizer	Elemental Phosphorus	44.8		
May	15	Plant begin/Growing season	Soybean			
May	25	Pesticide	Glyphosate Amine		2.24	
May	25	Pesticide	Metachlor		1.12	
May	30	Pesticide	Valor		2.24	
May	30	Pesticide	Fomesafen		1.12	
June	12	Irrigation				70
June	22	Irrigation				70
July	1	Irrigation				70
July	15	Irrigation				70
July	31	Irrigation				70
September	12	Irrigation				70
September	20	Irrigation				70
September	30	Irrigation				70
October	10	Harvest and Kill				

Appendix I- Management practices to be used for Miscanthus/Switchgrass simulation.

Date	Practice	Amount/acre	SWAT practice	SWAT kg/ha
First Year				
April 20	Phosphorus, Potassium application	36 lb phosphate (P2O5), 60 lb K12	Fertilizer application (0-40-60)	112 (19.5 Elemental P, 55.7 Elemental K)
April 20	Disking		Tillage (Disk Plow Ge23ft)	
April 21	Roller		Tillage (Roller Packer Attachment)	
May 20	Burn down with Glyphosate	1 lb active ingredient (a.i.)	Pesticide Application (Glyphosate amine)	1.12
May 21	Plant switchgrass		Plant/Begin Growing season (Switchgrass)	
June 20	Weed control	0.25 lb a.i.	Pesticide application (2,4-D Amine)	0.28
Second year				
April 1	Nitrogen Application	70 lb urea	Fertilizer Application (Urea)	78.46
June 20	Weed control	0.25 lb a.i.	Pesticide application (2,4-D Amine)	0.28
November 1	Harvest		Harvest Only	
Third year onwards				
April 1	Nitrogen Application	70 lb urea	Fertilizer Application (Urea)	78.46
November 1	Harvest		Harvest Only	

Appendix J- Marginal lands processing

1. Soil classes IV and V were identified in the soil raster layer.
2. Using extract by attribute and soil mukey as the query in the attribute Table soil classes IV and V were extracted.
3. The new raster that resulted in step 2 was combined to a single raster using the mosaic tool.
4. Reclassify tool was then used to reclassify the two different classes to a single marginal to result in the final marginal soils layer.

With the help of the marginal soils layer land uses were extracted using ArcGIS processes in ArcMap. These steps are presented below.

1. The land use layer for CRW with the final marginal soils layer as mask with extract by mask tool was used to create a raster that contained marginal land use types (eg urban marginal, barren marginal etc.)
2. The old values were reclassified to new values in order to avoid conflict. For example 1 was reclassified to 100, 2 was reclassified to 200 etc.
3. Further, it is important to create a distinction between marginal and non-marginal land use types. To identify the non-marginal land use types the resulting layer in step 2 was reclassified. The no data values were changed to zero and others to no data using the reclassify tool.
4. Using the raster layer generated in the step 3 and land use layer for CRW as the mask layer non-marginal lands were extracted using extract by mask tool. This resulted in the non-marginal land use layer.

5. To extract the non-marginal land use types from the land use layer for CRW, the raster created in the step 4 was used as mask.
6. At this step, there were two raster layers, one raster layer contained marginal land use types and other was non-marginal land use layer.
7. To get a single land use layer that contained marginal as well as non-marginal land use types, these two land use layers were mosaicked to get a single land use layer. This was done using the mosaic tool.
8. The land use layer generated in step 7 was the final layer to be used as input into the SWAT model.
9. All other land use layers were also prepared using the same process.

APPENDIX K- SWAT Check warnings and their potential solutions for the first SWAT model

Warning	Potential Solution
Section 1: Hydrology	
Water yield may be excessive	It is due to the Streamflow to Precipitation ratio which is 0.61. Water yield to precipitation ratio is 0.63.
Surface runoff may be excessive	Surface runoff to total flow ratio is 0.57 whereas as per the monitoring data from Egypt this ratio is about 0.56. In the calibration phase surface runoff needs to be decreased slightly at this station but if all three stations on Cache River are considered then this ratio is 0.68 which indicates that surface runoff needs to be increased during the calibration process.
Section 2: Sediment	
Maximum sediment yield is greater than 50 MT/ha in at least one HRU: In HRU number 7201, subbasin 29 where the land use type is barren, soil is loring and slope is 8-12% (which is high).	This HRU makes almost 0% area of the watershed (18.7/506584.5 hectares). To resolve this some cover (range grasses) can be simulated on similar HRUs.
Section 3: Nitrogen Cycle	
No warnings	
Section 4: Phosphorus Cycle	
No warnings	
Section 5: Plant Growth	
Unusually low phosphorus stress	It is because the default value of solution P set by SWAT is 5 mg/kg whereas according to soil test data this value was 32.1 mg/kg. During the calibration phase this warning should disappear.
Section 6: Landscape nutrient losses	
Total nitrogen losses are greater than 40% of applied N	Changing relevant parameters will cause this warning to disappear.
Solubility ratio for phosphorus in runoff is low, may indicate a problem	Due to difference in solution P values simulated and measured. This warning should disappear after calibration for phosphorus.
Section 7: Land use summary	
1. Crop BERM: less than 22% of water yield is baseflow 2. Crop BARR: sediment yield may be too high 3. Crop BARR: more than 1/2 precipitation is runoff 4. Crop BARR: surface runoff may be excessive 5. Crop BARR: biomass may be too low 0.00 mg/ha 6. Crop BARR: less than 22% of water yield is baseflow 7. Crop PAST: biomass may be too low 0.54 mg/ha	These warning are related to hydrology and sediment loss and should disappear during the calibration phase.

Warning	Potential Solution
8. Crop PAST: less than 22% of water yield is baseflow 9. Crop SOYB: sediment yield may be too high 10. Crop SOYB: surface runoff may be excessive 11. Crop RICE: surface runoff may be excessive 12. Crop COTP: surface runoff may be excessive 13. Crop COTP: less than 22% of water yield is baseflow 14. Crop CORN: surface runoff may be excessive 15. Crop SOYM: sediment yield may be too high 16. Crop SOYM: surface runoff may be excessive 17. Crop RICM: surface runoff may be excessive 18. Crop CORM: surface runoff may be excessive 19. Crop COTM: sediment yield may be too high 20. Crop COTM: surface runoff may be excessive 21. Crop COTM: less than 22% of water yield is baseflow	
Section 8: Instream processes	
No warnings	
Section 9: Point Source	
Inlets/point sources contribute flow, but not sediment and nitrogen. Inlets/point sources N:P ratio less than 2.8	These warnings are due to some no data values for nutrients and sediments in point source files.
Section 10: Reservoirs	
No warnings	

APPENDIX L- SWAT Check warnings and their potential solutions for the second SWAT model.

Warning	Potential Solution
Section 1: Hydrology	
Water yield may be excessive	It is due to the streamflow to precipitation ratio which is 0.48 considered excessive by SWAT Check.
Section 2: Sediment	
Maximum sediment yield is greater than 50 MT/ha in at least one HRU: In HRU number 2604, subbasin 13, land use type is barren, soil is dundee and slope is 8-12% (which is high).	To resolve this some cover can be simulated on similar HRUs. Warning similar to the first model.
Section 3: Nitrogen Cycle	
No warnings	
Section 4: Phosphorus Cycle	
No warnings	
Section 5: Plant Growth	
Unusually low phosphorus stress	It is because the default value of solution P set by SWAT is 5 mg/kg where as it is 32.1 mg/kg as per the soil test data. During the calibration phase this warning should disappear.
Section 6: Landscape nutrient losses	
Solubility ratio for phosphorus in runoff is low, may indicate a problem	It is because the default value of solution P set by SWAT is 5 mg/kg where as it is 32.2 mg/kg as per the soil test data. This value was changed as per the soil test data.
Nitrate leaching is less than 21% of the applied fertilizer	Changing relevant parameters will cause this warning to disappear.
Section 7: Land use summary	
1. Crop BERM: less than 22% of water yield is baseflow 2. Crop BARR: sediment yield may be too high 3. Crop BARR: surface runoff may be excessive 4. Crop BARR: biomass may be too low 0.00 mg/ha 5. Crop BARR: less than 22% of water yield is baseflow 6. Crop PAST: sediment yield may be too high 7. Crop PAST: biomass may be too low 0.50 mg/ha 8. Crop AGRR: sediment yield may be too high 9. Crop AGRR: less than 22% of water yield is baseflow 10. Crop WETL: sediment yield may be too high	These warning are related to hydrology and sediment loss and should disappear during the calibration phase.

Warning	Potential Solution
11. Crop SOYB: sediment yield may be too high 12. Crop SOYB: surface runoff may be excessive 13. Crop RICE: sediment yield may be too high 14. Crop RICE: surface runoff may be excessive 15. Crop COTP: sediment yield may be too high 16. Crop COTP: surface runoff may be excessive 17. Crop CORN: sediment yield may be too high 18. Crop CORN: surface runoff may be excessive 19. Crop AGRM: sediment yield may be too high 20. Crop AGRM: less than 22% of water yield is baseflow 21. Crop SOYM: sediment yield may be too high 22. Crop SOYM: surface runoff may be excessive 23. Crop RICM: surface runoff may be excessive 24. Crop CORM: surface runoff may be excessive 25. Crop COTM: sediment yield may be too high 26. Crop COTM: surface runoff may be excessive 27. Crop COTM: less than 22% of water yield is baseflow	
Section 8: Instream processes	
No warnings	
Section 9: Point Source	
Inlets/point sources contribute flow, but not sediment and nitrogen. Inlets/point sources N:P ratio less than 2.8	These warnings are due to some no data values for nutrients and sediments in point source files.
Section 10: Reservoirs	
No warnings	

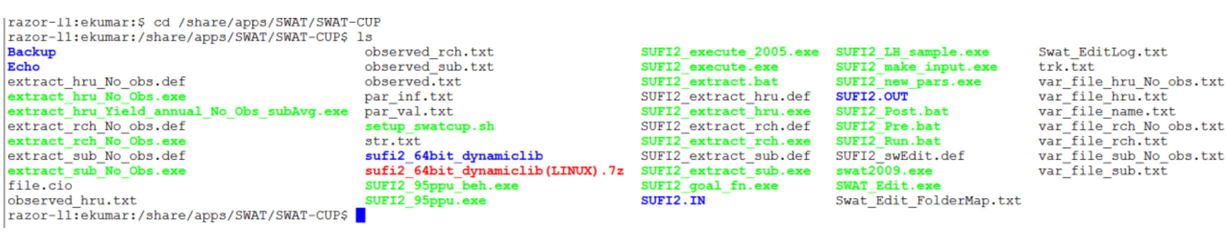
Appendix M- Running SWAT CUP (SUFI2) on Supercomputer

1. Login to cluster with username and password using secure shell client on Windows or terminal on Mac/Ubuntu.

2. Specify appropriate modules of SWAT and Mono in ".bashrc" file (environmental modules) so that they get loaded automatically at startup. This file contains the following code:

```
razor-l2:ekumar:$ cat .bashrc
. /etc/profile.d/env-modules.sh
ulimit -s unlimited 2>/dev/null
ulimit -l unlimited 2>/dev/null
#if using goto/mkl blas with mpi these should be set to 1 unless you want hybrid
mpi/openmp
export GOTO_NUM_THREADS=1
export OMP_NUM_THREADS=1
export MKL_NUM_THREADS=1
#enter your modules here
module load intel
module load openmpi
module load mkl
module load swat/rev622
module load mono/3.10.0
#export PATH=/share/apps/mono/3.10.0/bin:$PATH
#export LD_LIBRARY_PATH=/share/apps/mono/3.10.0/lib:$LD_LIBRARY_PATH
#export LD_LIBRARY_PATH=/share/apps/mono/3.10.0/lib/mono/4.5:$LD_LIBRARY_PATH
#export PKG_CONFIG_PATH=/share/apps/mono/3.10.0/lib/pkgconfig:$PKG_CONFIG_PATH
[ -z "$PS1" ] && return
  PS1='`/bin/hostname -s`:`whoami`:`echo $PWD | sed "s=$HOME=="`$ '
  alias ls='ls --color=auto'
  module list
echo "Welcome Eeshan!"
```

3. Go to the directory where SWAT CUP has been installed (/share/apps/SWAT/SWAT-CUP). A screenshot is shown below.



```
razor-l1:ekumar:$ cd /share/apps/SWAT/SWAT-CUP
razor-l1:ekumar:/share/apps/SWAT/SWAT-CUP$ ls
Backup                                   observed_rch.txt                    SUFI2_execute_2005.exe  SUFI2_LH_sample.exe       Swat_EditLog.txt
Echo                                     observed_sub.txt                    SUFI2_execute.exe       SUFI2_make_input.exe      trk.txt
extract_hru_No_obs.def                   observed.txt                        SUFI2_extract.bat       SUFI2_new_pars.exe        var_file_hru_No_obs.txt
extract_hru_No_Obs.exe                   par_inf.txt                         SUFI2_extract_hru.def   SUFI2.OUT                 var_file_hru.txt
extract_hru_Yield_annual_No_Obs_subAvg.exe  par_val.txt                      SUFI2_extract_hru.exe   SUFI2_Post.bat            var_file_name.txt
extract_rch_No_obs.def                   setup_swatcup.sh                    SUFI2_extract_rch.def   SUFI2_Pre.bat             var_file_rch_No_obs.txt
extract_rch_No_Obs.exe                   str.txt                             SUFI2_extract_rch.exe   SUFI2_Run.bat             var_file_rch.txt
extract_sub_No_obs.def                   sufi2_64bit_dynamiclib              SUFI2_extract_sub.def   SUFI2_swEdit.def          var_file_sub_No_obs.txt
extract_sub_No_Obs.exe                   sufi2_64bit_dynamiclib(LINUX).7z    SUFI2_extract_sub.exe   swat2009.exe              var_file_sub.txt
file.cio                                 SUFI2_95ppu_beh.exe                 SUFI2_goal_fn.exe       SWAT_Edit.exe
observed_hru.txt                         SUFI2_95ppu.exe                     SUFI2.IN                Swat_Edit_FolderMap.txt
razor-l1:ekumar:/share/apps/SWAT/SWAT-CUP$
```

Copy the "setup_swatcup.sh" file in the project directory. The project directory should be created in the /scratch/$user directory. This ".sh" file contains the following code which creates symbolic links to all the SUFI2 executables in the project directory.

```
#!/bin/bash
```

```
# make .exe links
ln -s /share/apps/SWAT/SWAT-CUP/extract_hru_No_Obs.exe ./extract_hru_No_Obs.exe
ln -s /share/apps/SWAT/SWAT-CUP/extract_hru_Yield_annual_No_Obs_subAvg.exe
./extract_hru_Yield_annual_No_Obs_subAvg.exe
ln -s /share/apps/SWAT/SWAT-CUP/extract_rch_No_Obs.exe ./extract_rch_No_Obs.exe
ln -s /share/apps/SWAT/SWAT-CUP/extract_sub_No_Obs.exe ./extract_sub_No_Obs.exe
ln -s /share/apps/SWAT/SWAT-CUP/SUFI2_95ppu_beh.exe ./SUFI2_95ppu_beh.exe
ln -s /share/apps/SWAT/SWAT-CUP/SUFI2_95ppqu.exe ./SUFI2_95ppu.exe
ln -s /share/apps/SWAT/SWAT-CUP/SUFI2_execute_2005.exe ./SUFI2_execute_2005.exe
ln -s /share/apps/SWAT/SWAT-CUP/SUFI2_execute.exe ./SUFI2_execute.exe
ln -s /share/apps/SWAT/SWAT-CUP/SUFI2_extract_hru.exe ./SUFI2_extract_hru.exe
ln -s /share/apps/SWAT/SWAT-CUP/SUFI2_extract_rch.exe ./SUFI2_extract_rch.exe
ln -s /share/apps/SWAT/SWAT-CUP/SUFI2_extract_sub.exe ./SUFI2_extract_sub.exe
ln -s /share/apps/SWAT/SWAT-CUP/SUFI2_goal_fn.exe ./SUFI2_goal_fn.exe
ln -s /share/apps/SWAT/SWAT-CUP/SUFI2_LH_sample.exe ./SUFI2_LH_sample.exe
ln -s /share/apps/SWAT/SWAT-CUP/SUFI2_make_input.exe ./SUFI2_make_input.exe
ln -s /share/apps/SWAT/SWAT-CUP/SUFI2_new_pars.exe ./SUFI2_new_pars.exe
ln -s /share/apps/SWAT/SWAT-CUP/SWAT_Edit.exe ./SWAT_Edit.exe
ln -s /share/apps/SWAT/SWAT-CUP/SWAT_Edit.exe ./Swat_Edit.exe

#make swat2012 link
ln -s /share/apps/SWAT/rev62/swat2012_622 ./swat2009.exe
//(make sure you use correct version of SWAT)
#make .bat links
ln -s /share/apps/SWAT/SWAT-CUP/SUFI2_extract.bat ./SUFI2_extract.bat
ln -s /share/apps/SWAT/SWAT-CUP/SUFI2_Post.bat ./SUFI2_Post.bat
ln -s /share/apps/SWAT/SWAT-CUP/SUFI2_Pre.bat ./SUFI2_Pre.bat
ln -s /share/apps/SWAT/SWAT-CUP/SUFI2_Run.bat ./SUFI2_Run.bat
```

4. Before proceeding further, replace SWAT2009.exe with SWAT2012.exe and rename it to SWAT2009.exe (Only if the symbolic link created has some conflicts).
5. Create directories “SUFI2.IN”, “SUFI2.OUT”, “Echo” and “Backup” in the project directory and copy all TxtInOut files in the project directory.
6. Copy all input files to the SUFI2.IN directory.
7. Rename file Tmp1.Tmp to tmp1.tmp.
8. Copy file Swat_Edit.exe.config.txt, SUFI2_extract.def, SUFI2_swEdit.def and Absolute_SWAT_Values.txt in the project folder from a sample SUFI2 project.
9. Specify correct number of years to run SWAT in file.cio and it should match with SUFI2_extract.def.
10. Execute ./SUFI2_Pre.bat to perform latin hypercube sampling and creating parameter values.
11. Now execute ./SUFI2_Run.bat via pbs script.
12. Keep track of “model.in” file which contains the values from the par_inf.txt file for the current simulation. The values should change as next simulation runs.
13. The file “Par_Name.out” created in the process should contain all the names of the parameters that were specified in “par_inf.txt” file in SUFI2.IN directory.

14. The “Echo” directory contains a copy of files that are created during the different steps if any error occurs a close look at the files in this directory could be helpful.

15. Write a pbs script (shown below) to submit the job.

```
#PBS -N CUP_SUFI2
#PBS -q med12core (or use med16core as per queue length qstat -q)
#PBS -j oe
#PBS -m abe
#PBS -M ish.ascent@gmail.com
#PBS -o SUFI2.$PBS_JOBID
#PBS -l nodes=1:ppn=12
#PBS -l walltime=72:00:00 (could be increased as per job requirement)

module load mono/3.10.0
module load swat/rev622

cd $PBS_O_WORKDIR

./SUFI2_Pre.bat
./SUFI2_Run.bat
//The .bat commands can be run separately.
```

16. Output files are generated in SUFI2.OUT folder.

Appendix N- Description of parameters for modeling Miscanthus in SWAT

S. No.	SWAT Parameter	Definition	Value (Trybula et al., 2014)	
			Suggested	Range
1.	bio_e	Radiation use efficiency (RUE)	4.1	
2.	ext_coef	Light extinction efficiency	0.55	0.45-0.65
3.	blai	Maximum leaf area index (LAI)	11	10-13
4.	frgrw1	Fraction of the growing season corresponding to point 1 on the LAI-time curve	0.1	
5.	laimx1	Fraction of the maximum LAI corresponding to point 1 on the LAI-time curve	0.1	
6.	frgrw2	Fraction of the growing season corresponding to point 2 on the LAI-time curve	0.45	
7.	laimx2	Fraction of the maximum LAI corresponding to point 2 on the LAI-time curve	0.85	
8.	heat units	Total accumulated heat units required for the plant to reach maturity	1830	2100-1600
9.	t_base	Base temperature, minimum temperature for growth	8 ^{0}C	7-10 ^{0}C
10.	dlai	Fraction of the growing season when leaf senescence exceeds leaf growth	1.1	
11.	cnyld	Optimal fraction of nitrogen in yield	0.0035	0.0034-0.0035
12.	pltnfr(1)	Optimal fraction of nitrogen in the plant at emergence	0.0100	0.0097-0.0104
13.	pltnfr(2)	Optimal fraction of nitrogen in the plant at 50% maturity	0.0065	0.0062-0.0070
14.	pltnfr(3)	Optimal fraction of nitrogen in the plant at maturity	0.0057	0.0053-0.0060
15.	cpyld	Optimal fraction of phosphorus in yield	0.0003	0.0003-0.0004
16.	pltpfr(1)	Optimal fraction of phosphorus in the plant at emergence	0.0016	0.0016-0.0017
17.	pltpfr(2)	Optimal fraction of phosphorus in the plant at 50% maturity	0.0012	0.0010-0.0014
18.	pltpfr(3)	Optimal fraction of phosphorus in the plant at maturity	0.0009	0.0007-0.0011
19.	hvsti	Fraction of above ground biomass removed in harvest	1.0	
20.	wsyf	Lower harvest index under water stress	1.0	
21.	chtmx	Maximum canopy height	3.5 m	
22.	rdmx	Maximum root depth	3 m	2-4 m
23.	t_opt	Optimal temperature for plant growth		
24.	rsdco_pl	Plant residue decomposition coefficient		
25.	alai_min	Minimum LAI during dormancy		
26.	usle_c	Minimum value of the USLE C factor for water erosion		
27.	wavp	Rate of decline in the RUW per unit increase in vapor pressure deficit		