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MODELING WATER QUANTITY AND QUALITY IN AN AGRICULTURAL
WATERSHED IN THE MIDWESTERN US USING SWAT: ASSESSING IMPLICATIONS
DUE TO AN EXPANSION IN 'BIOFUEL' PRODUCTION AND CLIMATE CHANGE

by

Sudipta Kumar Mishra

A thesis submitted in partial fulfillment
of the requirements for the Doctor of
Philosophy degree in Civil and Environmental Engineering
in the Graduate College of
The University of Iowa

December 2013

Thesis Supervisors: Professor Jerald L. Schnoor
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CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

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To Mom and Dad for your love and support

Nature shrinks as capital grows. The growth of the market cannot solve the very crisis it creates.

Vandana Shiva
Soil Not Oil: Environmental Justice in an Age of Climate Crisis

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ABSTRACT

Iowa finds itself positioned at the epicenter of agricultural pollution due to the intensity of crop and livestock production, fertilizer inputs, altered hydrological landscapes, and other factors. To address such issues, the overarching objective of this research work was to understand the implications of an expansion in bioenergy crops as mandated by the Environmental Protection Agency's Renewable Fuel Standard 2 (through 2022) on hydrology and water quality in an agricultural watershed.

In this research, the Soil Water Assessment Tool (SWAT) model was calibrated and validated using field data obtained through water quality sensors and grab samples at Clear Creek watershed in the state of Iowa, and then model parameters were estimated for sensitivity and uncertainty analysis. Scenarios were generated based on Renewable Fuel Standards and evaluated for understanding the impacts of expanding bioenergy production on hydrology and water quality. Also output from an agent-based model was incorporated into SWAT for simulating watershed responses to different crop market scenarios. Finally SWAT model output under eighteen scenarios, was generated for six different climate models and analyzed to see changes in various water quantity outputs e.g. surface flow, base flow, and ET.

The SWAT Model was calibrated and validated within statistically acceptable limits e.g. $R^2 > 0.85$ of observed monthly hydrologic mass and $R^2 > 0.7$ for nutrients loads. Sediment load was reduced by 15% due to conversion of corn acreage into switch grass on high elevation land with a slope of $>5\%$ (roughly 12% of the watershed). Model simulations also showed that linear climatic inputs (i.e. linear temporal trends increase in precipitation and max/min air temperature) can generate non-linear responses amongst different components of the water cycle (i.e. surface flow, base flow, ET, and deep percolation rates) in the watershed model. This research effort will

help to produce a prototype Intelligent Digital Watershed (IDW) to understand the interactions between water and human systems, with the goal of a sustainable agricultural economy. The IDW should enable discovery of scenarios that result in water quality that meets water quality standards.

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CHAPTER 1

INTRODUCTION

1.1 Perspective

In recent times, the state of Iowa has come forth as a national leader in biofuel production and the chase for value added bioenergy crops is likely to continue in the future too. Meanwhile the state has also emerged as a hot spot of agricultural pollution debate because of the high intensity of crop production and associated fertilizer inputs that goes on lands, changes in hydrologic landscape and some other factors. Corn-based ethanol production has jumped in recent times in Iowa and reached approximately 14 billion gallons in 2012 which almost amounts to 40% of the total U.S. corn production (<http://www.neo.ne.gov/statshtml/121.htm>). There are many potential impacts of biofuel production which need intense observation e.g.: domination of corn rotation in crop lands, stover removal from corn fields, and the adoption of biofuel crop ‘switch grass’ which can potentially change Iowa’s landscape in future. Some studies (Secchi et al 2007) showed that the shift from CRP land to a corn dominant cropping system in Iowa has resulted in an adverse environmental impact on soil erosion and pollutant loads while shifting to more switch grass production in high eroding crop lands would result in a wide range of environmental benefits. Hence, there is need for robust studies to understand the environmental impact of crop rotation and associated management practices on the agricultural pollution load and sediment yield in many more watersheds in Iowa.

1.2 Problem statement

Agricultural runoff is a major source of pollution in the watersheds in Iowa and the problem may intensify in the future due to intense biofuels production. What is the possible

environmental impact of the emerging biofuel driven landscape in Iowa? How can that impact be minimized in future? What are the best management practices to reduce agricultural pollutant runoff in the watershed? What should be an environmentally sustainable cropping system in Iowa considering those ambitious biofuel goals? To answers such questions, there is a strong need to do a systematic study on the environmental impact, at a watershed scale in Iowa, of the possible biofuel production scenarios, e.g., increase in corn rotation years, removal of stover from corn fields, and shifting to switch grass.

1.3 Research objectives

The overarching objective of this research work is to understand the implications of an expansion in bioenergy crops as mandated by the Environmental Protection Agency's Renewable Fuel Standard 2 (through 2022) on hydrology and water quality in an agricultural watershed (<http://www.epa.gov/otaq/fuels/renewablefuels/regulations.htm>). To complete the main objective, the following specific-objectives and associated hypothesis will be tested through this work:

Specific-Objective #1: Use the water quality model 'SWAT' to accurately model/represent watershed related processes and environmental indicators, i.e. water quality parameters (sediment and nutrients) for a representative agricultural watershed 'Clear Creek watershed' to within predetermined acceptable statistical criteria.

Hypothesis # 1: SWAT Modeling is an accurate representation of watershed processes (for discharge, suspended sediment, and nitrate load) within statistically acceptable limits (e.g. $R^2 > 0.8$) of observed monthly hydrologic mass and nutrients loads.

Hypothesis # 2: Certain modeling parameters (i.e. soil available water capacity, soil evaporation compensation factor, nitrate percolation coefficient) for water and nutrient cycling are the most sensitive parameters.

Specific-Objective #2: Model the impact of an expansion in bioenergy crops (i.e. corn, corn stover, and switch grass) on hydrology and water quality by linking water quality model 'SWAT' with inputs generated from land use conversion schemes based on Renewable Fuel Standard 2 guidelines (RFS 2) and/or a socioeconomic model.

Hypothesis # 1: Stream water quantity and quality (monthly average values) can change in a statistically significant manner due to shifts from traditional crops to alternative biofuel feedstock production (switch grass, corn stover).

Hypothesis #2: More cellulosic biofuel crop yields (corn stover, switch grass) can be achieved without impairing water quality based on adaptive land use conversion strategies depending on the local land slope and soil properties.

Specific-Objective #3: Understand patterns in different components of the hydrologic cycle at the watershed scale by utilizing output from regional climate models in conjunction with SWAT.

Hypothesis #1: Linear climatic inputs (i.e. increasing precipitation or changes in max/min air temperatures) can generate non-linear responses amongst different components of water cycle (surface flow, base flow, ET, and deep percolation rates).

1.4 Thesis Organization

This thesis contains eight chapters to address the specific objectives described above. Chapter 2 contains review of literature on various application area of SWAT model e.g.: on

hydrology, sediment and nutrient studies, pollutant loss studies, biofuel, and climate change studies. It also contains basics about water quality model SWAT.

Chapter 3 describes the Clear Creek watershed where specific objectives were tested. It also describes in details the set of input and output data used for this research.

To achieve the specific-objectives #1 in this research, following tasks were performed: Calibration and validation of the SWAT model using field data obtained through water quality sensors and grab samples, and model parameter estimation for sensitivity and uncertainty analysis. These steps are discussed in details in chapter 4.

Tasks under specific-objective #2 include: Scenario generation and evaluation for understanding the impacts of expanding bioenergy production on hydrology and water quality (based on RFS 2 standards), result of which is incorporated in chapter 5. Biofuel scenarios were alternatively generated using an agent-based model under different crop market price and then outputs were ingested into SWAT model to understand watershed responses, details of which is also discussed in chapter 5.

Under specific-objective #3, eighteen SWAT simulations (three each under six climate models) were generated under different climate models and then model outputs were analyzed for discovering patterns, trends in different water balance component which is discussed in chapter 6 in details.

A cyber-framework namely Intelligent Digital Watershed is introduced in Chapter 7. It links different model (namely ABM and SWAT) and should enable discovery of scenarios that result in water quality that exceeds water quality standards.

Chapter 8 summaries the findings from this research and makes recommendations based on this research. Significance of the current research along with future research prospect is also

discussed in the chapter. Some relevant data on water quality, input data with statistics, and model configuration are put on Appendix A at the end.

CHAPTER 2

LITERATURE REVIEW AND MODEL BACKGROUND

The Soil and Water Assessment Tool 'SWAT' (Arnold et al., 1998; Arnold and Fohrer, 2005) has emerged as a useful tool for modeling water quantities and non-point source pollution in various part of the world. SWAT was selected in this study to model the hydrologic and water quality response of the watershed. SWAT was developed in USDA Agricultural Research Services as an outcome of their long years of expertise in related area and derived many of its modeling processes from some earlier models like: Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) model (Knisel, 1980), the Groundwater Loading Effects on Agricultural Management Systems (GLEAMS) model (Leonard et al., 1987), and the Environmental Impact Policy Climate (EPIC) model (Izaurrealde et al., 2006). However SWAT is more closely linked to the Simulator for Water Resources in Rural Basins (SWRRB) model (Arnold and Williams, 1987), which was typically used for simulating sediment and water movement under different soil management practices. Following sections go through a brief literature review on SWAT model categorized based on their application areas.

2.1 Literature review on SWAT based on application areas

2.1.1 Hydrologic modeling studies

Hydrologic balance simulation is the basic for any SWAT application and it is reported for any watershed analysis studies regardless of its focus. Many studies on SWAT application also report on the hydrologic calibration and validation for stream flow and/or other hydrologic component. In one of the earliest reported application of SWAT model, Arnold et al (1996) successfully validated surface flow as well as groundwater flow, and evapotranspiration of the

water component in three watersheds in Illinois. In another similar study in a larger watershed in Texas, Santhi et al (2001) successfully validated SWAT model for different water balance component e.g. surface flow, base flow. Arnold et al (1999) used a large number of stream monitoring gauge and validated stream flow in watersheds in Texas. In another earlier studies in northern Mississippi, Bingner (1996) validated SWAT model for stream flow in multiple sub basins on daily and annual basis. Srinivasan et al (1998) was successful in validating stream flow in a watershed in Texas using limited period of data. White and Chaubey (2005) used multiple stream gauges to calibrate and validate their model successfully in Illinois.

2.1.2 Sediment modeling studies

SWAT is a robust model for simulating sediment load and has been widely used across large number of watersheds around the world. In a study in North Bosque River watershed in north Texas, Saleh et al (2000) used SWAT model for evaluating sediment load and observed that SWAT simulated sediment load matched well with the observed sediment load at monthly basis but they found SWAT predicted daily load was not so good. However Santhi et al 2001 was successful in simulating sediment loads at different time scale in two sub watersheds in Bosque River in Texas. In a similar study in Mill Creek watershed in Texas, Srinivasan et al 1998 was able to predict sediment load accurately. Arnold et al 1999, used SWAT model for five major Texas river basins and observed that sediment yields predicted by SWAT was within reasonable range of sediment yields derived from rating curves in the watersheds.

2.1.3 Nitrogen and Phosphorus modeling studies

There are many studies around the world that show the robustness of SWAT for modeling nutrient losses. Saleh et al (2000), Santhi et al (2001) used SWAT model to evaluate nitrogen losses in watersheds in Texas. They found that SWAT was able to predict nitrogen losses within reasonable limit of NSE value which was obtained as greater than 0.60 and phosphorus losses was also simulated within reasonable limit of NSE ranging from 0.39 to 0.93. NSE stands for 'Nash–Sutcliffe model efficiency' coefficient and is a widely used statistics to evaluate efficiency in hydrologic predictions. In a similar study in Iowa at Walnut Creek watershed, Chaplot et al (2004) used SWAT model with nine years of data to calibrate nitrate load and found that predicted loads were close to the observed loads at the Creek site. Hanratty and Stefan (1998) used data collected from Cottonwood River, Minnesota to calibrate SWAT model and concluded that SWAT was a suitable model for simulating water quality variable under climate change. They simulated both nitrate-nitrogen and phosphorus for their study. Arabi et al (2006) studied the effect of best management practices (BMPs) on nitrogen and phosphorus losses in two small watersheds in Indiana and found SWAT as an effective tool to do so. But they also noticed that SWAT under predicted phosphorus yield in those months when measured phosphorus losses were higher and over predicted it for the months with low phosphorus losses.

2.1.4 Land Use Impacts on Pollutant Losses

Borah et al (2006) reviewed some recent applications of SWAT model in United States that includes: Total Maximum Daily Load (TMDL) analysis, evaluate effectiveness of conservation practices under CEAP program. Hypothetical land use scenarios can be constructed in SWAT to evaluate pollutant losses under different land use or BMPs. In one such study in

Texas, Santhi et al (2006) documented the impact of manure and other BMPs on the water quality. Kirsch et al (2002) reported that improved tillage practice, in a watershed in Wisconsin, reduced sediment yield by 20%. Vache et al (2002) studied the effect of BMPs in Walnut Creek watershed in Iowa and observed that suitable BMPs could largely reduce the sediment load at the watershed outlet. In the same watershed, Chaplot et al (2004) observed that nitrogen losses was largely impacted by the tillage practices, fertilizer application rates and land use changes.

2.1.5 SWAT with Economic Models

There are many studies that show how effectively SWAT model was interfaced with an economic model in the past. William et al (2006) used Agricultural Policy Extender model with SWAT in two watersheds in Texas and evaluated the impact of manure management scenarios and other BMPs on the overall environment and economy of the watershed. Gassman et al (2002) did a similar study in Maquoketa River watershed in Iowa. Lemberg et al (2002) studied the economic impact of brush control in a Texas watershed and they used SWAT along with two other economic models in their analysis. Qiu et al (1998) studied the benefit of riparian buffer in reducing pollutant load in Goldwater Creek, Missouri. They used SWAT with a budget generator and an economic model and found that implementation of riparian buffer increased net economic return in the study area because of reduction in CRP rental payment. In a further study, Qiu (2005) created five alternative management scenarios of BMPs and evaluated the economic and environmental impact under those scenarios in the same watershed. Secchi et al (2001) used an economic model to convert landuse under corn expansion in Upper Mississippi Basin. Then they applied the land use in SWAT model and studied the water quality impact under those conversions.

2.1.6 Biofuel issues

Cultivated cropland in the Corn Belt is projected to reach up to 1.6 million acres by 2016 (Malcolm and Aillery, 2009; Donner and Kucharik, 2008) of which corn stover could approximately provide 25 percent of the biofuel crop biomass targeted by 2030 (Wilhelm et al., 2007). Mann et al (2002) observed that corn stover residue on the soil surface helps in controlling surface runoff, soil erosion, nutrient losses and contamination of water resources. According to Graham et al (1995) producing environmentally and economically competitive bioenergy crops relies on the availability of low-cost and high biomass feedstocks. In this regard, switch grass has been identified as an energy crop that can successfully grow across a wide range of climatic conditions (Vogel, 1996). In many recent studies, SWAT model was widely used for understanding the impact of alternative biofuel crop, e.g. corn stover, switch grass, on the environment (Babcock et al 2007; Secchi et al 2008; Costello et al 2009; Demissie et al 2012).

2.1.7 Climate change studies

Stream flow characteristics, both mean and variance, of the Upper Mississippi River Basin (UMRB) has large influence, e.g. environmental effects, economic effects etc., for the Central United States (Changnon et al 1996). Many studies have explored the impact of climate change on the hydrology (stream flow changes and other flow characteristics) at different spatial scale e.g. basin, watershed level at UMRB. Stone et al 2001 applied a regional Climate model 'RegCM' in Missouri River Basin to study the effect of climate change on the basin water resources and in subsequent study Stone et al 2003 used SWAT model to analyze the impact of climate model resolution on the water yield in the same basin. They observed that water yield obtained from SWAT run under regional climate model (RCM) was higher than the yield

obtained from running SWAT under Global climate models (GCMs). They also found that water yield in the sub basins were significantly different under different climate models and concluded that resolution of climate model played an important role in estimating water yield at the basin. In a similar study in UMRB, Arnell et al 2003 constructed different climate scenarios from a single climate model, compared runoff generated under each of them, and found that the runoff varied by 10-20%.

2.1.8 Conclusion from literature review

The above studies clearly suggest that SWAT is widely and successfully used to model hydrology and pollutant transport in agricultural watersheds. More recent efforts have been aimed towards coupling SWAT with agro economical models. Since focus of this work was aimed towards modeling, and understanding implications of hydrology and water quality under expansion in biofuel production, SWAT emerged as a promising choice for this research.

2.2 Basics of water quality model 'SWAT' (Adapted from SWAT 2005 documentation)

In SWAT, the watershed is divided into two layers: the entire watershed area is divided into some smaller areas called 'sub watershed' and then each sub watershed is divided into further smaller areas called hydrologic response units (HRUs). Sub watersheds are created by defining threshold value for critical source area during the watershed delineation step in SWAT model. HRUs are formed by using a threshold values for land use and soil type as percentages of sub watershed area. Land use and soil type of area lower than the specified limits are not taken into consideration in the SWAT model and corresponding areas are assigned proportionately to the land use and soil types with higher percentage area in corresponding sub watersheds. Hence

HRU is a unique combination of land use, slope and soil type in a sub watershed. All calculations in SWAT are performed at the HRU level. A brief description of SWAT hydrologic component is provided in the following section along with the sediment and water quality components. Further details for each component can be found at SWAT Theoretical Documentation (Neitsch et al., 2005) from which following descriptions are based on. Key processes, which impact water quality and quantity in SWAT model, are discussed below.

2.2.1 Water Yield

Water balance is the basic driver of SWAT model and the water balance equation formulated in the model as:

$$SW_t = SW_0 + \Sigma(R_{\text{day}} - Q_{\text{surf}} - E_a - w_{\text{seep}} - Q_{\text{gw}})$$

where SW_t is the final soil water content (mm water), SW_0 is the initial soil water content (mm water), R_{day} is the amount of precipitation for the day (mm water), Q_{surf} is the amount of surface runoff for the day (mm water), E_a is the amount of evapotranspiration for the day (mm water), w_{seep} is the amount of water entering the vadose zone from the soil profile for the day (mm water), and Q_{gw} is the amount of return flow to groundwater for the day (mm water). As SWAT model does computation at daily time step, the water balance at each hydrologic response units is assessed every day of the simulation in SWAT.

The water yield from a given land parcel is important in the model since it controls the water discharge from the upper soil and it affects the concentration of pollutants being removed from the land area. The leading component of water yield is surface runoff and the quantity of surface runoff also controls the amount of soil erosion that takes place.

2.2.2 Hydrologic components

2.2.2.1 Surface Runoff

SWAT follows two methods for the estimating of surface runoff: (1) SCS curve number method, and (2) Green-Ampt infiltration method. Kannan et al. 2007 observed that SCS curve number generally performed suitably than Green-Ampt method. Besides that, Green-Ampt infiltration method needs hourly precipitation data, and flow routing at hourly time step (rather than daily), and that resulted in the model being computationally demanding for long-term simulations. Therefore SCS Curve Number method is employed in this study. Curve Number for antecedent moisture condition II (CN2) are adapted for sub watershed slope in the model, and these values are modified on a daily time step depending on soil moisture conditions in the root zone.

2.2.2.2 Percolation

Soil is categorized into multiple layers in SWAT and water is assumed to permeate through these layers to reach shallow aquifer based on moisture conditions in each layer. Water can permeate to another layer below when soil moisture content in a layer is more than field capacity. Percolation rate is maximum (saturated hydraulic conductivity) at saturation and decreases to zero at field capacity. A storage routing technique aggregated with crack flow is utilized to model flow through each soil layer. When the soil is dry and cracked, water can just percolate through the cracked layer without impacting its water content. Temperature also influence the percolation rate, which falls to zero when soil temperature is below zero degree C. Water that percolates through all layers becomes part of groundwater and contribute as part of base flow to a stream.

2.2.2.3 Lateral flow

Soil water above saturation directly reaches to streams. A kinematic storage model is utilized to model lateral flow through each soil layer. In SWAT volume of lateral flow relies on soil layer properties (saturated hydraulic conductivity and porosity), terrain slope, and flow length.

2.2.2.4 Snowpack accumulation

Snowmelt and snow formation parameters are influential hydrology calibration parameters in the SWAT model. In SWAT snowmelt events are treated in the same way as rainfall events. Snowfall accumulation and snowmelt depends on the daily mean air temperature. The parameters that control the snowpack accumulation and melt are delineated at the watershed scale. Heterogeneity between different HRUs that control the snow melts dynamics can be explained through the following SWAT model parameters:

- The snowpack temperature lag factor TIMP, it indicates how fast the snowpac temperature is influenced by air temperature;
- The snowmelt base temperature SMTMP, above which the snowpack melts;
- The maximum and minimum temperature-index snowmelt factors SMFMX and SMFMN;

2.2.2.5 Groundwater flow

Groundwater component in SWAT is treated as two aquifer systems including shallow (unconfined) and deep aquifer (confined) (Figure 4.1). Recharge to shallow aquifer from percolation is categorized into two parts: one part that percolates into deep aquifer and never reaches to the stream, while the remaining part in shallow aquifer adds to the stream as base flow

and also satisfies a portion of evaporative demand in the root zone (revap). The time for water parting the root zone and getting into shallow aquifer is characterized through groundwater delay factor (Gw_dealy). A user defined fraction (deep aquifer percolation coefficient) is applied to divide total recharge into deep aquifer recharge and shallow aquifer recharge. If water in shallow aquifer exceeds user defined threshold value (Gwqmn), then it will reach to stream as base flow. Water table fluctuations are estimated as change in baseflow rate from shallow aquifer to the stream using a constant factor defined as baseflow recession constant (α_{bf}). If top soil profile is unable to meet its evaporative demand, then a part of the evaporative demand (defined by revap coefficient) is fulfilled by shallow aquifer if it has more water than the specified threshold value (revap threshold).

2.2.2.6 Evapotranspiration

SWAT has three alternatives methods to calculate potential evapotranspiration: Hargreaves (Hargreaves et al 1985), Priestley-Taylor (Priestley and Taylor, 1972) and Penman-Monteith (Monteith, 1965). Hargreaves method needs only daily air temperature; Priestley-Taylor needs solar radiation and air temperature, whereas Penman-Monteith method needs solar radiation, air-temperature, wind-speed, and relative humidity as inputs. Kannan et al. (2007) observed that performance of Hargreaves method is comparable to complex energy based Penman-Monteith method. Potential evapotranspiration is the maximum amount of evapotranspiration that can occur in a HRU. Actual evapotranspiration in SWAT is estimated based on availability of water in various storage volumes e.g. canopy storage and soil moisture. Actual evapotranspiration may or may not equate to potential evapotranspiration. Evaporative demand is satisfied in a successive order i.e., at any stage in the sequence if potential

evapotranspiration demand is attained, no further demand will be there from the stages below. First all canopy water is extracted and then subsequent evaporative demand is met by plant transpiration and soil moisture evaporation. If ground is covered with snow then soil evaporation demand is first met by sublimation of snow.

2.2.2.7 Transmission loss

When a channel runs through a semi-arid region, it releases water when water table is at lower level compared to the channel bottom. SWAT calculates transmission loss using Lane's method as a function of channel width, length and flow duration.

2.2.3 Flow Routing

Volume of water to be routed (surface runoff + lateral flow + baseflow– transmission loss) are estimated for each HRU and then summed up to find out total volume of water to be routed from a sub watershed. Channel length in each sub watershed is calculated using stream network, and channel dimension are supplied by user (bank full width, depth and side slope). Cross sectional area for flow is estimated by dividing volume of flow to be routed by length of the channel. Manning's equation (manning's n is supplied by user) for uniform flow is deployed to determine flow rate and velocity. In SWAT, water can be routed through channel network by selecting either the variable storage method or Muskingum River routing method using daily time step. Besides transmission loss, channel also loses water through evapotranspiration, which is a function of water surface area in the channel. Evaporation loss in each reach (channel segment) is deducted from total volume before routing the flow through next reach.

2.2.4 Sediment Yield

The predicted soil erosion rate and sediment yield is estimated for each hydrologic response unit (HRU) with the Modified Universal Soil Loss Equation (MUSLE). This equation utilize surface runoff volume and peak rate to predict erosion rate and sediment delivery from small watersheds. MUSLE is derived from the Universal Soil Loss Equation (USLE) developed by Wischmeier and Smith (1965, 1978). The MUSLE equation adapted for use in the model is:

$$\text{Sed} = 11.8(Q_{\text{surf}} * q_{\text{peak}} * \text{area}_{\text{hru}})^{0.56} * K_{\text{USLE}} * C_{\text{USLE}} * P_{\text{USLE}} * LS_{\text{USLE}}$$

where Sed is the sediment yield (metric tons), 11.8 is a unit conversion constant, Q_{surf} is the surface runoff volume (mm water/ha), q_{peak} is the peak runoff rate (m^3/s), area_{hru} is the area of the hydrologic unit area (HRU) in hectares, K_{USLE} is the USLE soil erodibility factor (dimensionless), C_{USLE} is the USLE cropping and management factor (dimensionless), P_{USLE} is the USLE conservation support practices factor (dimensionless), and LS_{USLE} is the USLE slope length (in meter) and steepness factor (unit less).

2.2.5 Nutrients

Nitrogen and phosphorus management and movement are estimated in SWAT using the modeling approach of GLEAMS. SWAT assumes the movement and transformations of nitrogen for two mineral species (ammonium and nitrate) and for three organic species (active, stable and fresh) in soil nitrogen pools (as N). Whereas it simulates the movement and transformation of phosphorus for three mineral (labile in solution, labile on soil surface and fixed in soil) and three organic pools (active, stable and fresh).

The major in-soil processes for nitrogen and phosphorus cycles in SWAT model are: Mineralization, decomposition, and immobilization. These processes are activated in model

simulation when the temperature of the soil layer reaches above zero. SWAT estimate the nitrate load at various pathways e.g. export with runoff, lateral flow, and percolation and it is calculated as a function of the volume of water and the average concentration of nitrate in the soil layer. In-stream nutrient dynamics are replicated in SWAT model by incorporating the kinetic routines of QUAL2E model (Brown and Barnwell, 1987).

2.2.6 Crop Growth

The crop growth routines in SWAT model were adapted from EPIC (Erosion Productivity Impact Calculator, Williams et al., 1984). SWAT estimates potential plant growth under optimal conditions with adequate water and nutrient supply and a favorable climate. It then estimates the actual plant growth under stresses of temperature, water and nutrients. All crop growth parameters are summarized in the crop growth database in SWAT and the crop growth cycle is controlled by the management operations information in SWAT model. The major components used for crop growth simulation in the model are: Leaf area development, fraction of nutrients in the total plant biomass at different stages of crop growth, radiation use efficiency and its conversion to biomass etc.

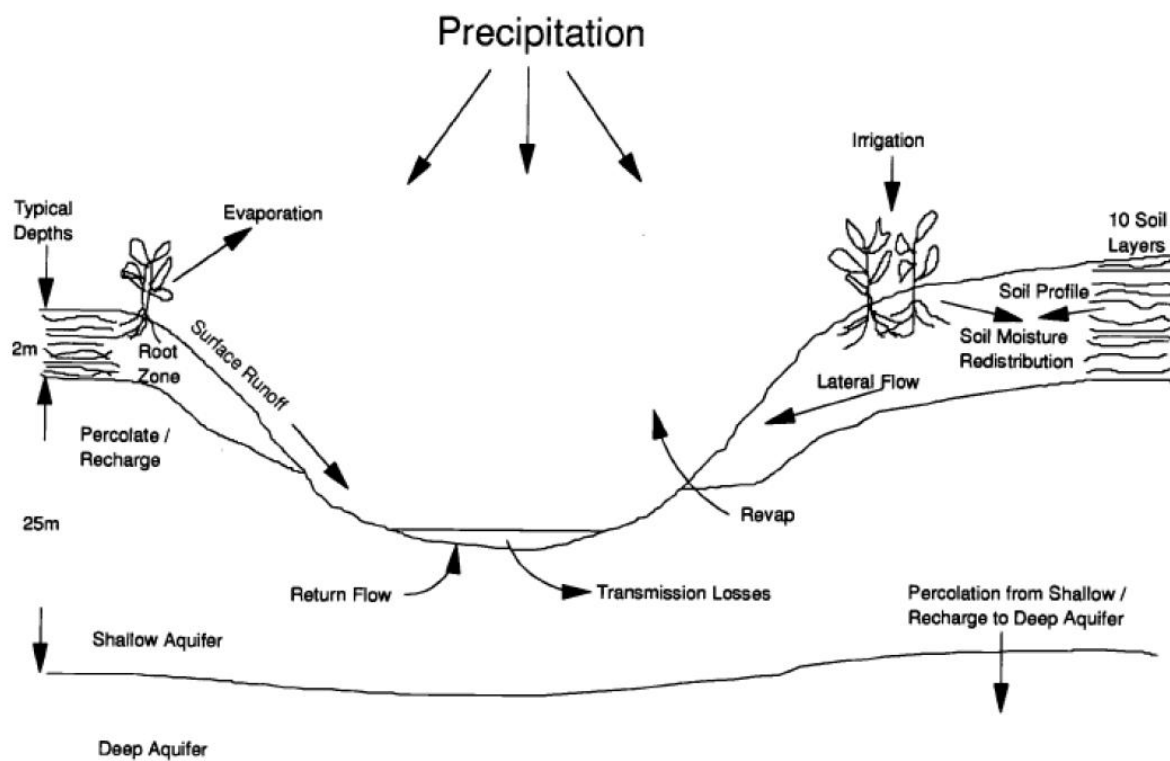


Figure 2.1 Hydrologic components in a HRU (adopted from Arnold et al. 1998)

NITROGEN

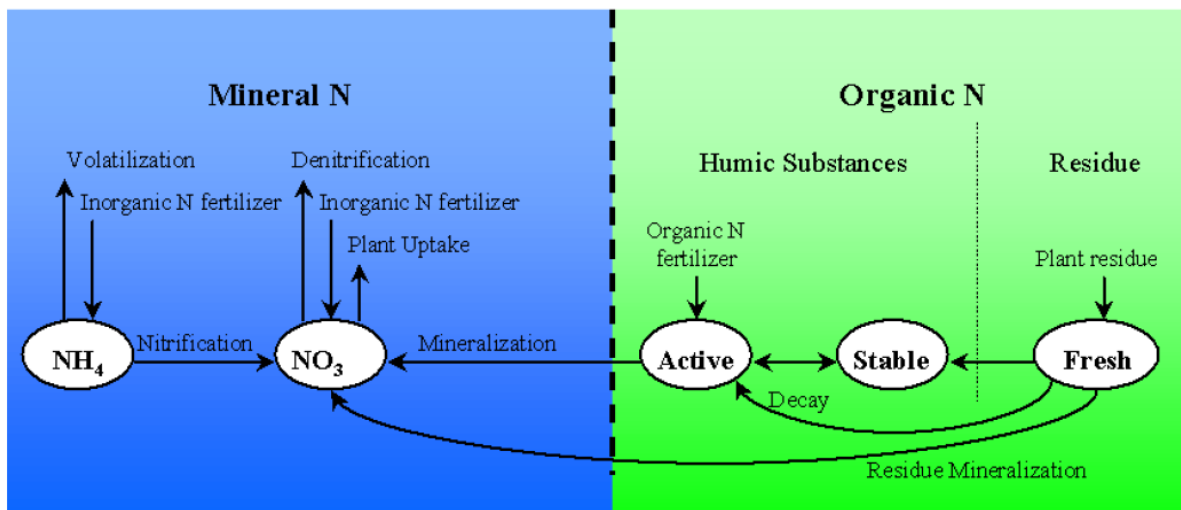


Figure 2.2 SWAT nitrogen pools and nitrogen cycle processes (adopted from SWAT 2005 documentation)

PHOSPHORUS

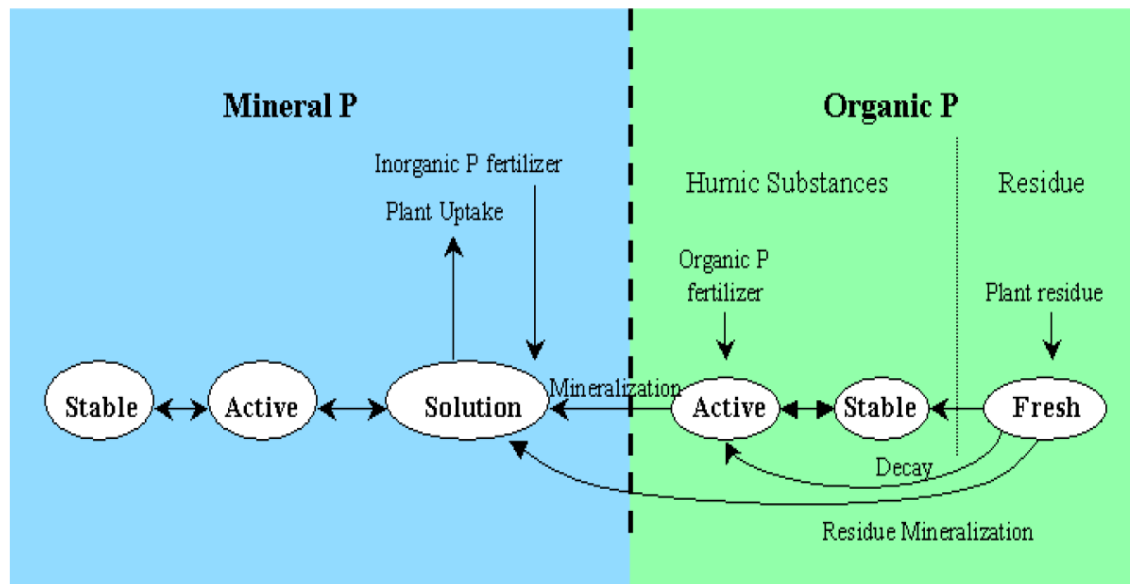


Figure 2.3 SWAT phosphorus pools and phosphorus cycle processes (adopted from SWAT 2005 documentation)

CHAPTER 3

STUDY AREA AND DATA USED

3.1 Study area

The Clear Creek watershed (CCW) is a 267 km² HUC 10 watershed (Hydrologic Unit Code) situated in east-central Iowa. It is part of the larger Lower Iowa HUC 8 basin and discharges into the Iowa River. Approximately 85% of the land cover in the watershed is agricultural or grassland, 8% is forest, 6% is roads or urban, and the remaining area is water or barren (Iowa DNR 2008). The main channel of CCW is approximately 47 km long (Figure 3.1).

Though CCW is largely dominated by agricultural landscape, downstream section of it is partly urbanized and provides a unique site to study the impact of human interferences on natural landscape. CCW falls within high erodible region in the state of Iowa and contributes large amount of agricultural pollutant runoff to Mississippi River, which then contribute to the creation of “dead zone” in Gulf of Mexico (www.iowacdi.net)

3.2 Data used

Data used for modeling was grouped into two categories: Static data and dynamic data. Static data included: DEM, Soil, Land use and dynamic data includes: Weather data, discharge data. In addition to it some auxiliary data e.g. CLU layer information was used in his study. Discharge was measured at two US Geological Survey (USGS) gauging stations located in the middle of the watershed at Oxford, and near the outlet of the watershed at Coralville. There were three (near) real-time sensing stations with high frequency measurements (every 20 minutes) of pH, temperature, stage-discharge, conductivity, dissolved oxygen, and nitrate.

3.2.1 Input data

Following set of data is required in order to set up a SWAT model and can be categorized into two classes, static and dynamics datasets. Static data broadly includes DEM, soil and land use whereas dynamics data includes climatic variables, discharge and water quality. Source of each data set is shown in Table 3.1.

Climate data includes: Daily precipitation, maximum/minimum air temperature, solar radiation, wind speed and relative humidity. Clear Creek observed an average precipitation of 2.7 mm over last decade with maximum precipitation is 152.9 mm. Average max temperature observed was 16.8 C whereas min average was 5.03 C (Table 3.4).

Discharge data: There are two USGS gauging stations in Clear Creek watershed, one is at Coralville and other is near Oxford. In this study, Coralville station was selected as an outlet point of the watershed where model was calibrated and validated. Average discharge observed at Coralville was 2.37 cms and maximum discharge recorded was 204.68 cms over last three decade (Table 3.4).

Water quality data: Nitrate data ($\text{NO}_3\text{-N}$) was obtained from Nitratax sensor at Coralville and turbidity data was obtained from DTS sensor deployed at Coralville, at the watershed outlet. Some of the nitrate, turbidity data obtained through those sensors is plotted in Figure 3.10 and Figure 3.11 below. Original data had a time step of 15 min which was aggregated into daily and then into monthly before using for calibrating the model. Periods where data were missing or not recorded was filled up with a linear interpolation scheme so to estimate corresponding daily or monthly loads. Alternatively LOADEST software can also be used to do the same. To convert turbidity data, which has its unit as NTU, into Total Suspended Solid (TSS in mg/l) following relationship was used (Loperfido et al 2009):

$$\text{Log}_{10} \text{TSS} = 1.53 * \text{Log}_{10} \text{Turbidity (NTU)} - 0.52$$

where coefficient of correlation value obtained was 0.87 using turbidity data of 2007-2008. Ideally more data years (say at least 5 years of data) should be used to obtain accurate relationship.

3.2.2 Output data

Erosion and sediment yield were estimated for each HRU with MUSLE (modified universal soil loss equation). The movement and transformation of nutrient (nitrogen and phosphorus) in the watershed and into the stream network via surface runoff with GLEAMS model (Groundwater Loading Effects of Agricultural Management Systems model). It also generates hydrologic data: surface runoff, lateral subsurface flow, evapotranspiration, infiltration, canopy storage, redistribution, etc.

3.3 Discussion

Input data were collected from above sources and imported into ArcGIS. The shape file of Clear Creek was used to extract data. The following figures show the raster input data used in the model. As seen in Figure 3.2, upstream part of the watershed is of higher elevation and partly hilly in nature with elevation 270 m while as lowest elevation is the watershed is 190 m. Majority of watershed falls with slope 5% with below 3% slope coming next as shown in Figure 3.8. Figure 3.9 show the distribution of land elevation in Clear Creek Watershed. Red curve shows the cumulative curve formed with % area in the watershed below certain elevation level.

The watershed contains considerable amount of agricultural land (almost 85%) with corn being dominant crop cultivated in 35% of the watershed as shown in Figure 3.6. Soybean comes

next with almost 27% of watershed area in the base line year whereas urban area in the watershed falls below 10%.

Variation in SSURGO soil categories over the entire watershed is shown in Figure 3.4. FAYETTE is the majority soil class in Clear Creek which approximately contains 31% of the watershed area. This soil class mainly consists of very deep, well drained soils formed in loess. The next majority soil class is Colo which approximately contains 17% of the watershed area (Figure 3.7).

Land use distribution in Clear Creek watershed is shown in Table 3.2 whereas soil distribution from SSURGO dataset is shown in Table 3.3 below.

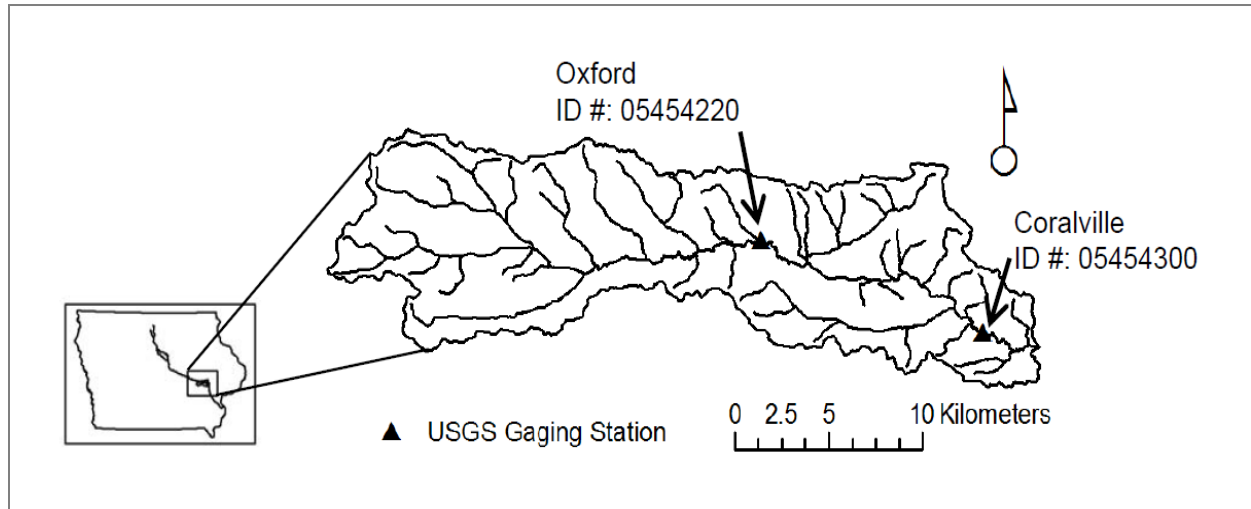
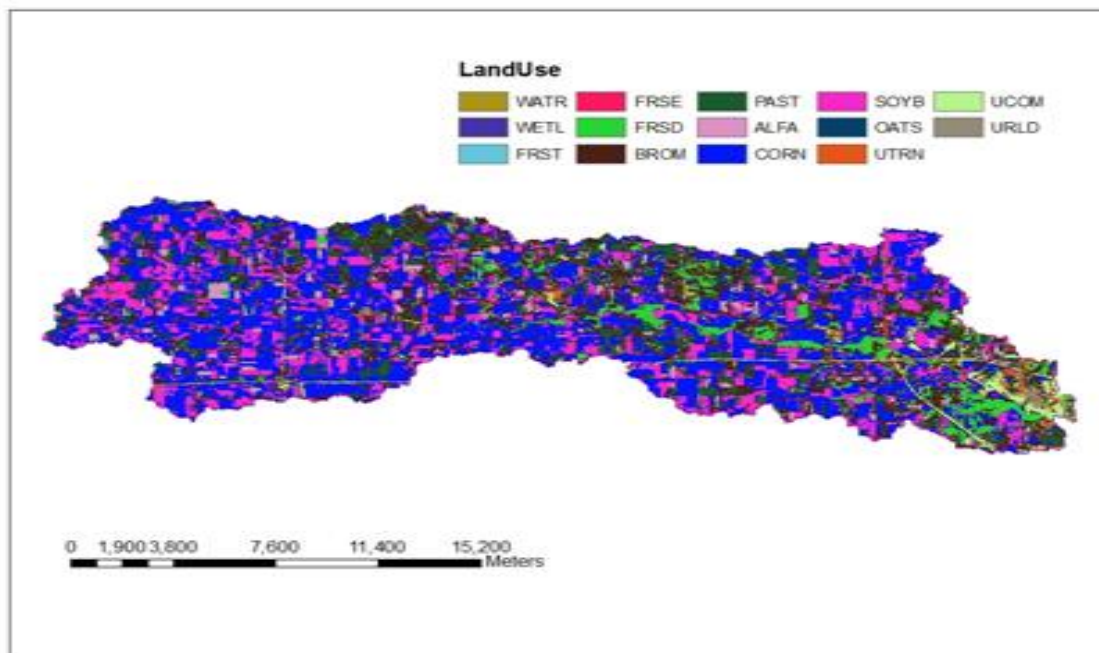
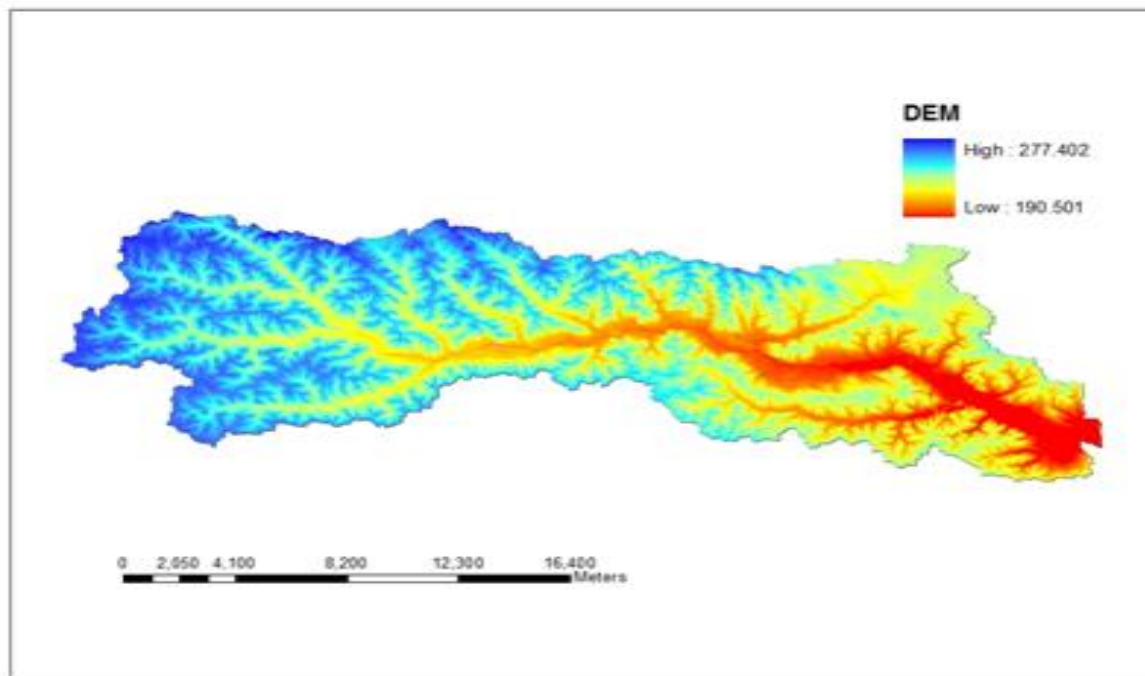


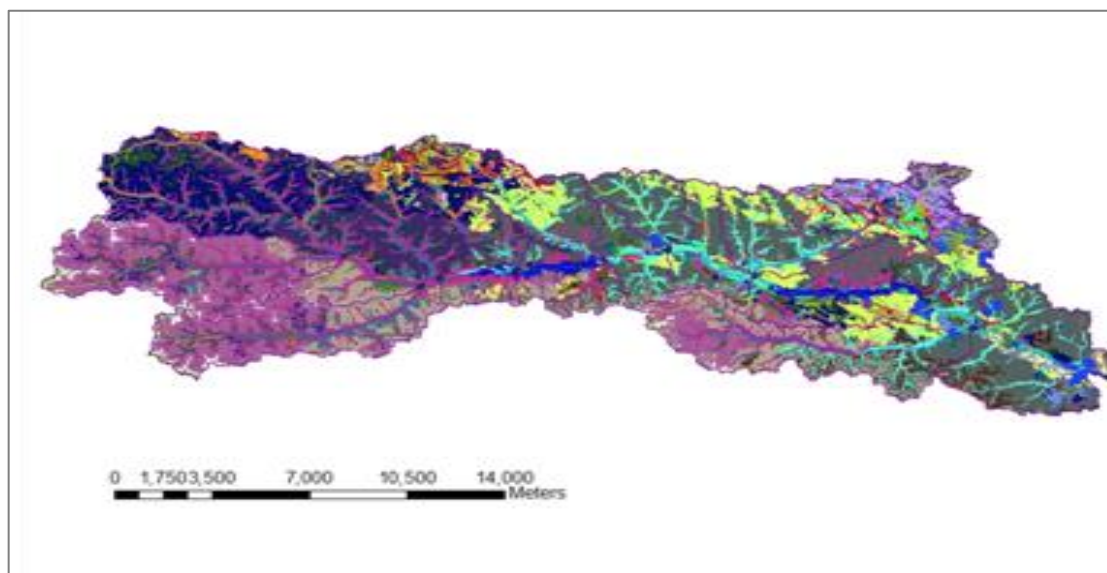
Figure 3.1 The Clear Creek Watershed located in east-central Iowa. USGS gauging stations are present in the middle of the watershed and at the outlet which drains to the Iowa River (source: iowacedarbasin.org).



Figures 3.2 Model input data for clear creek: Land use and land cover map obtained from Iowa Department of natural resources (IDNR 2001).

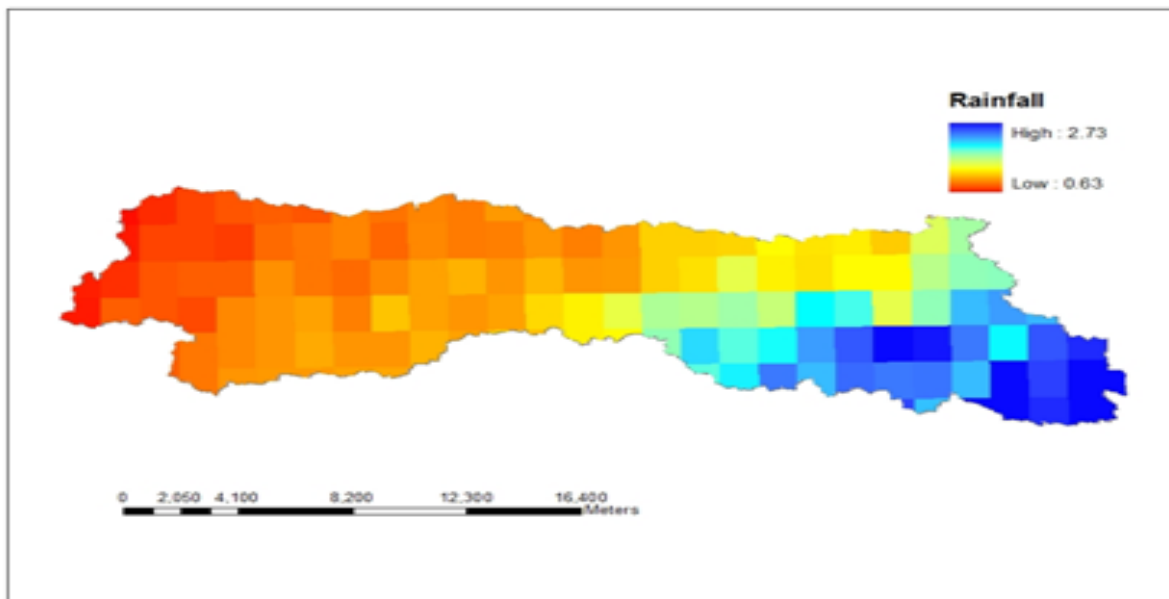


Figures 3.3 Model input data for Clear Creek: 30 m DEM obtained from National Elevation dataset.

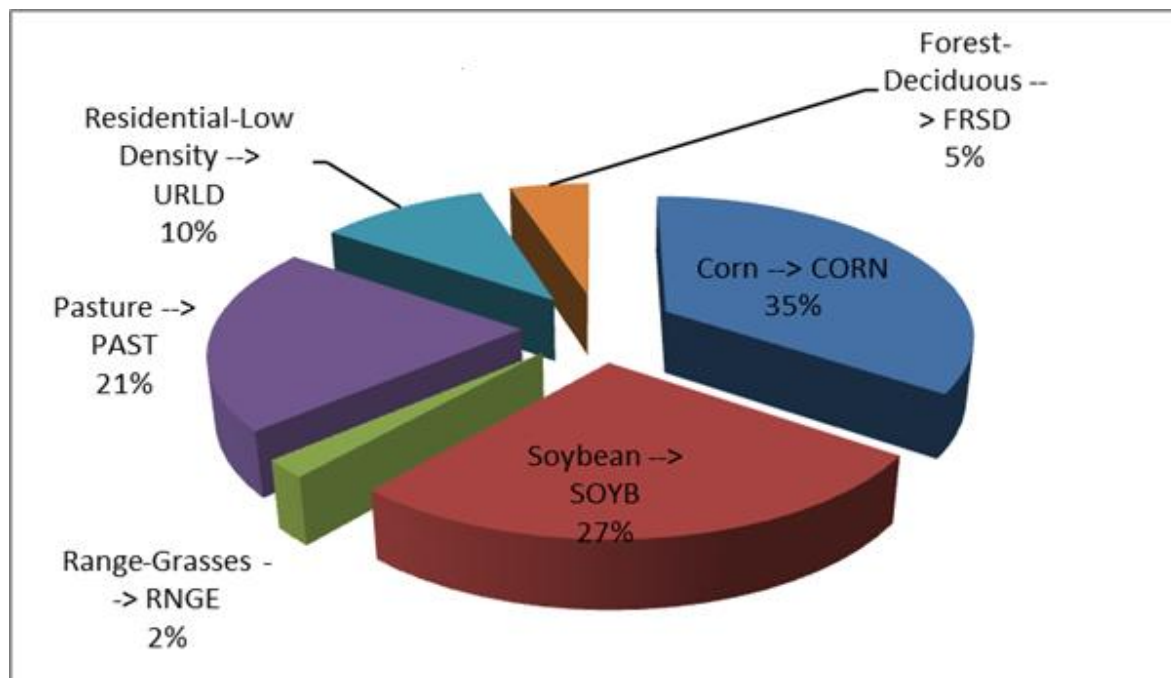


SwatSoilClass(LandSoils11)									
Classes									
Fayette	Watseka	Lawler	Bremer	Franklin	Adair				
Muscatine	Lawson	Taintor	Tuskeego	Ladoga	Judson				
Walford	Spillville	Mahaska	Pits	Waubeek	Shelby				
Garwin	Marshan	Otley	Orthents	Sattre	Sewage lagoon				
Colo	Downs	Chelsea	Coppock	Armstrong	Pits_ sand and gravel				
Tama	Stronghurst	Arenzville	Zook	Bertrand	Udorthents_ loamy				
Sperry	Bassett	Waukegan	Lindley	Clinton	Intermittent water				
Nodaway	Hoopeston	Whittier	Watkins	Rowley	Seaton				
Atterberry	Bolan	Dinsdale	Koszta	Kenyon	Ackmore				
Perks	Dickinson	Maxfield	Wiota	Nevin	Tell				
Coland	Waukee	Sparta	Udolpho	Elvira	Vesser				
	Gara	Amana	Givin	Raddle	Hayfield				
	Klinger	Ely	Ansgar	Water	Pilot				

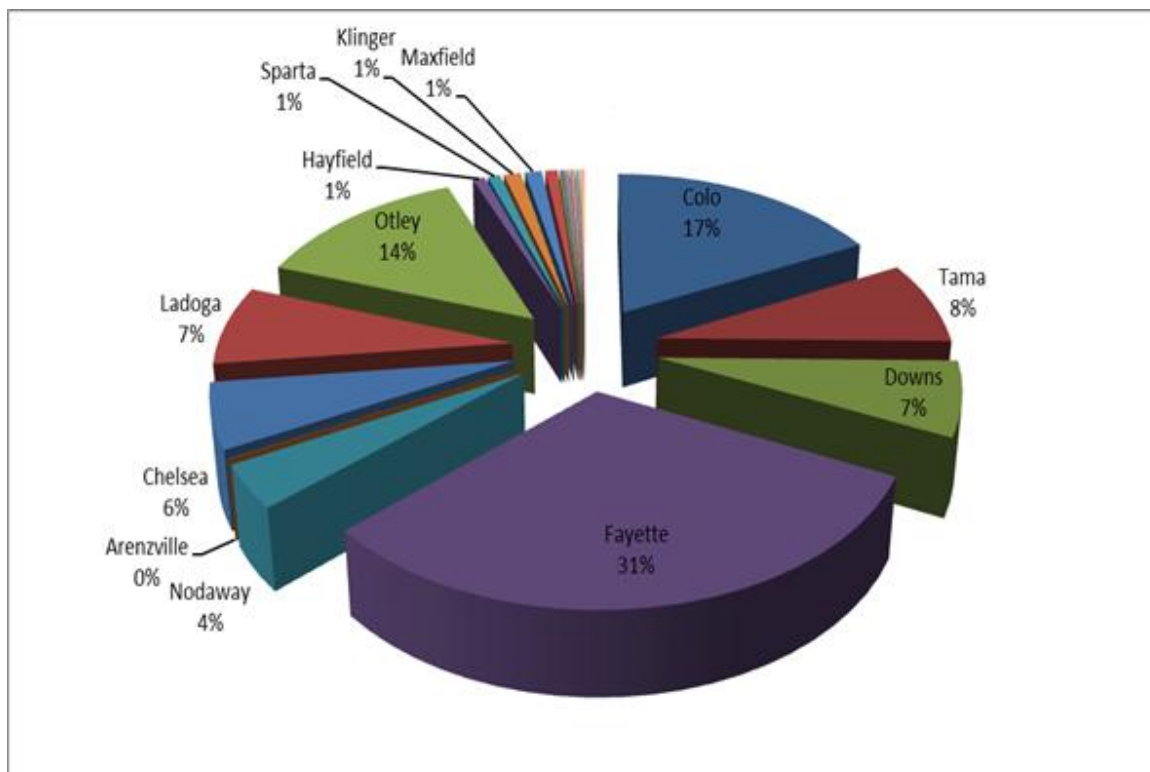
Figures 3.4 Model input data for Clear Creek: SSURGO soil data with legend shown above (source: <http://soils.usda.gov/survey/geography/ssurgo/>)



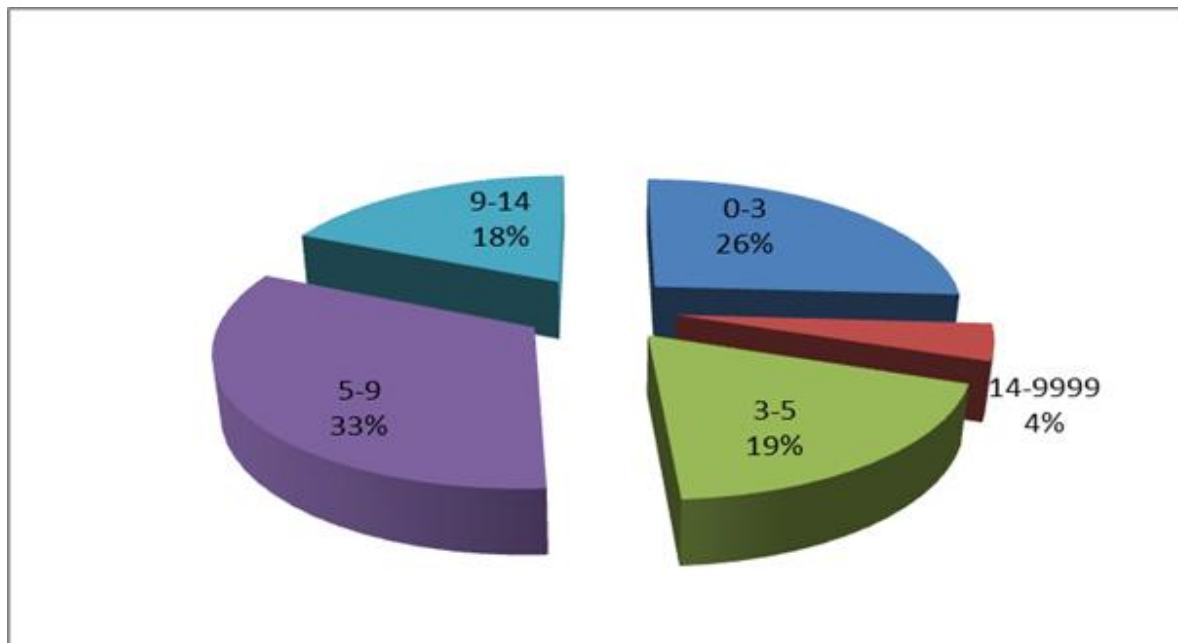
Figures 3.5 Model input data for Clear Creek: Gridded NEXRAD data showing sample rainfall variability in CCW



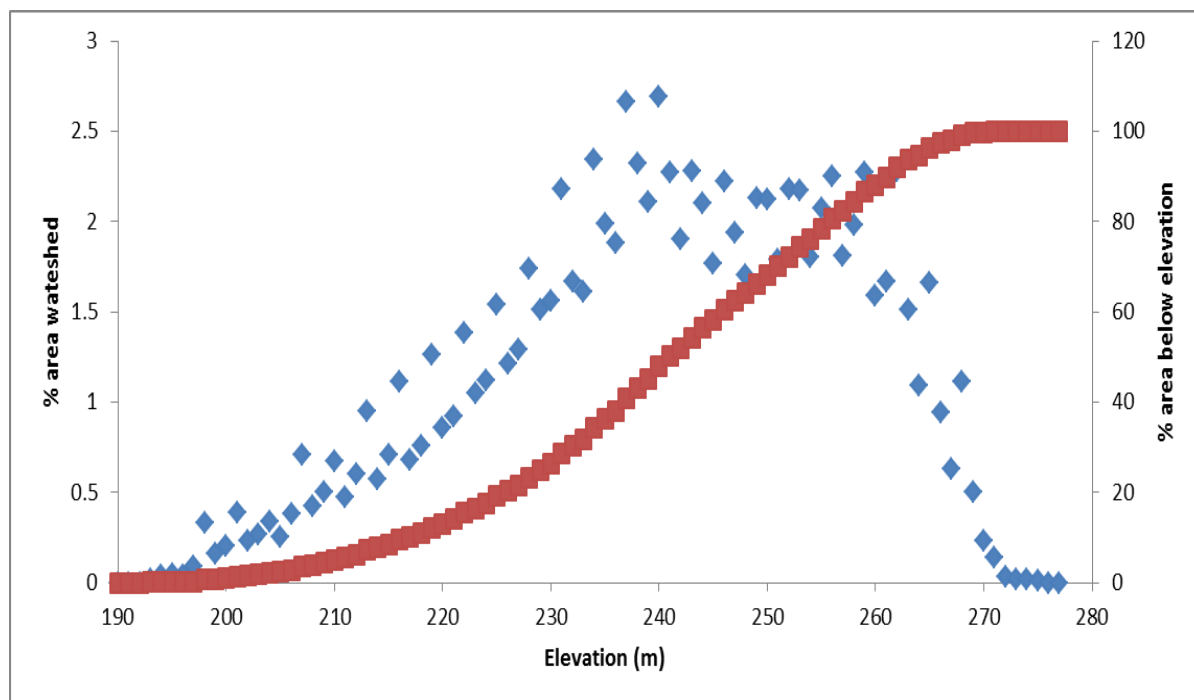
Figures 3.6 Land use distribution in Clear Creek Watershed (source: Iowa Department of natural resources, IDNR 2001).



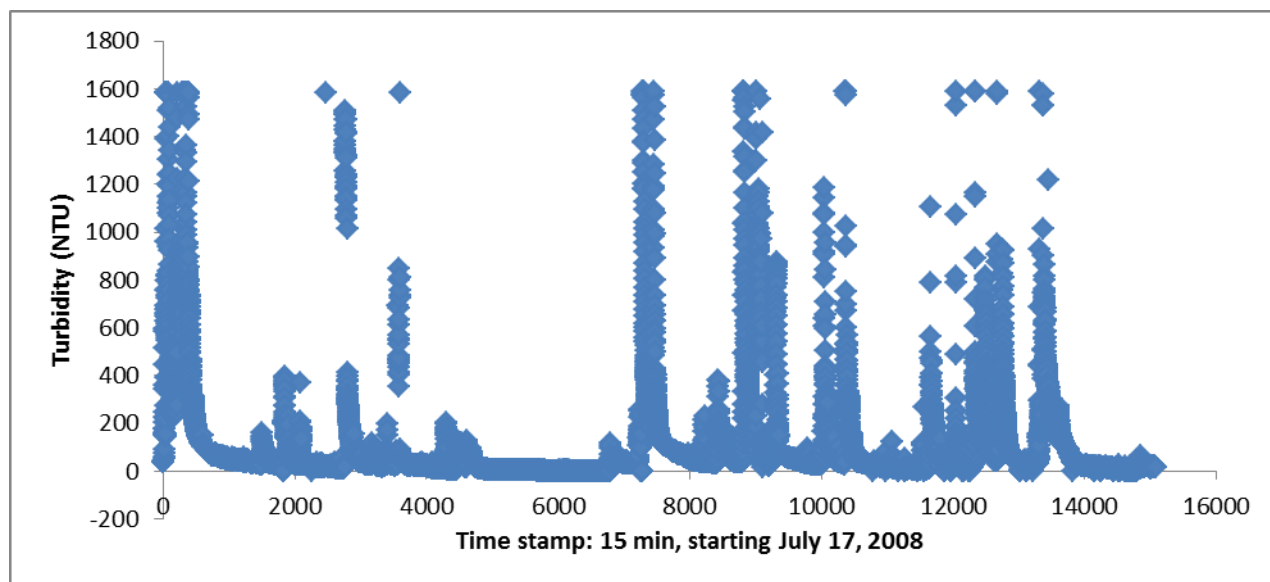
Figures 3.7 SSURGO soil distribution in Clear Creek Watershed (source: <http://soildatamart.nrcs.usda.gov/>).



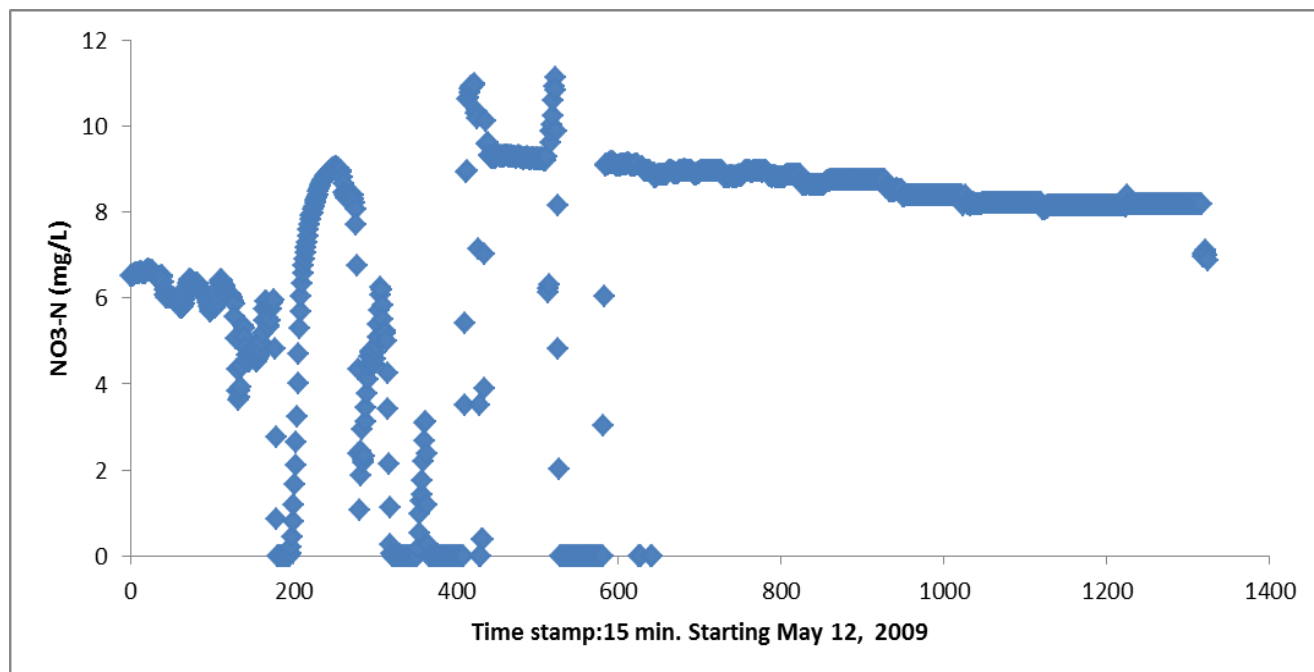
Figures 3.8 Land slope categories in Clear Creek Watershed, in percentage watershed area (source: 30 m DEM obtained from National Elevation dataset).



Figures 3.9 Distribution of land elevation in Clear Creek watershed where red dots represent cumulative percentage of watershed area under particular elevation. Whereas blue dots represent percentage of area below a particular elevation (source: 30 m DEM obtained from National Elevation dataset).



Figures 3.10 Turbidity data at Coralville, Clear Creek obtained from DTS sensor for July 17, 2008 through October 23, 2009



Figures 3.11 NO₃-N data at Coralville, Clear Creek obtained from Nitratex sensor from May 12, 2009 to October 23, 2009.

Table 3.1 Input data required to set up SWAT model and their sources

Data inputs	scale	Data sources
DEM	One arc second (30m resolution)	http://seamless.usgs.gov/
Landuse, Landcover	15 m	NRGIS (http://www.igsb.uiowa.edu/nrgislibx/)
Soil	1:24,000	SSURGO (http://soildatamart.nrcs.usda.gov/)
Stream flow data	Daily	http://waterdata.usgs.gov/ia/nwis/
Weather data	Daily	http://www.ncdc.noaa.gov/oa/ncdc.html
Water quality	Daily, Sub daily	STORET, local sensors
CLU (common land units)	Farm field	NRGIS (http://www.igsb.uiowa.edu/nrgislibx/)
Farmer's survey	2009-2010	University of Iowa and SIU

Table 3.2 Landuse distribution in Clear Creek Watershed (source: source: Iowa Department of natural resources, IDNR 2001)

Watershed		Area [ha]	Area[acres]	% Wat.Area
		26972.9	66651.38	
		Area [ha]	Area[acres]	% Wat.Area
LANDUSE:	Corn --> CORN	9343.714	23088.78	34.64
	Soybean --> SOYB	7206.145	17806.75	26.72
	Range-Grasses --> RNGE	561.5958	1387.731	2.08
	Pasture --> PAST	5725.151	14147.13	21.23
	Residential-Low Density -- > URLD	2816.536	6959.802	10.44
	Forest-Deciduous --> FRSD	1319.757	3261.185	4.89

Table 3.3 SSURGO soil distribution in Clear Creek Watershed (source: <http://soildatamart.nrcs.usda.gov/>).

Watershed		Area [ha]	Area[acres]	% Wat.Area
		26972.9	66651.38	
		Area [ha]	Area[acres]	
SOILS:	Colo	4718.959	11660.78	17.5
	Tama	2092.099	5169.682	7.76
	Downs	1850.3	4572.184	6.86
	Fayette	8372.812	20689.64	31.04
	Nodaway	1059.191	2617.314	3.93
	Arenzville	6.7655	16.7178	0.03
	Chelsea	1613.877	3987.971	5.98
	Ladoga	1985.862	4907.165	7.36
	Otley	3672.283	9074.396	13.61
	Hayfield	212.555	525.234	0.79
	Sparta	218.1215	538.9892	0.81
	Klinger	296.848	733.5262	1.1
	Maxfield	292.9421	723.8745	1.09
	Lawson	209.6853	518.1429	0.78
	Ely	26.8466	66.3394	0.1
Franklin	24.8801	61.48	0.09	
Dinsdale	28.7188	70.9655	0.11	

Table 3.3 Continued

	Waubeek	29.4226	72.7048	0.11
	Bassett	38.7378	95.723	0.14
	Orthents	71.9544	177.803	0.27
	Atterberry	12.2705	30.3211	0.05
	Bertrand	14.8172	36.6141	0.05
	Clinton	29.9913	74.1099	0.11
	Perks	92.9586	229.705	0.34

Table 3.4 Discharge, precipitation and temperature statics in CCW (sources: <http://waterdata.usgs.gov/ia/nwis/>, <http://www.ncdc.noaa.gov/oa/ncdc.html>)

	Discharge (cms) at Coralville (period: 1980-2010)	Precipitation mm (2000-2010)	Temp C (2000-2010)	
			Max	Min
Mean	2.37	2.66	16.76	5.03
Median	1.04	0.00	18.89	5.56
Standard deviation	5.68	7.76	12.19	11.12
Max	204.68	152.91	39.44	26.67
Min	0.02	0.00	-17.22	-33.89
99 -percentile	24.40	37.46	35.00	23.33
Q1	0.42	0.00	6.67	-2.78
Q2	1.04	0.00	18.89	5.56
Q3	2.35	0.76	27.78	14.44

CHAPTER 4

SWAT MODEL CALIBRATION, VALIDATION FOR CLEAR CREEK

Hydrologic processes are the governing forces that control any kind of pollutant transport within a watershed and hence understanding those hydrological processes is very important for assessing the environmental and economic well-being for Clear Creek Watershed (CCW) in Iowa. The Clear Creek drains an area of 267 km² and the daily mean flow is 2.37 m³/sec at the watershed outlet in Coralville gauge station for thirty years of data record, 1980-2010. The peak flow season in CCW typically ranges between three months of April to June and the low flows occur during the months of Dec-Jan. There are number of hydrologic processes that control the spatial and temporal variability of the CCW hydrology and the primary step to understand those surface and subsurface hydrological processes was achieved by separating the base flow in this study. This was followed by a sensitivity analysis of SWAT model input parameters. All other required steps for building a CCW SWAT model are discussed in the following sections.

4.1 Model setup

In SWAT a watershed is initially sub divided into smaller spatial units consisting of sub-basins in the model configuration procedure. Sub-basin delineation in the CCW was obtained following the matches of available flow and water quality monitoring stations at Coralville, Oxford and South Amana using a 5% contributing source area (CSA) threshold in the model. The slope and flow direction in CCW was obtained from a 30m digital elevation map by using the watershed delineation algorithms in Arc SWAT, which was then used to determine the sub-basin outlets and the contributing areas that discharged to those outlets. Thus Clear Creek watershed was subdivided into 23 sub-basins with the outlets at all three gauging sites as shown

in Figure 4.2. The soil types were delineated based on SSURGO (Soil Survey Geographic database) soils database while further discretization of the sub-basins was obtained by aggregating areas with same soil types, land use and slope. This thereby formed the computational units in SWAT that were assumed to be homogeneous in hydrologic response, which is also called as 'Hydrologic Response Units' (HRUs). Each HRU has its own set of unique parameters that are applied during hydrologic simulation process to generate spatially heterogeneous hydrologic responses in the watershed. In each sub-basin, each land use representing over 10% of the sub basin area was included in the model; and then each soil class representing 10% or more of that land use area were also included and finally each land slope class representing 10% or more of that soil area were merged together to form an unique HRU. By following these steps, CCW was subdivided in to 644 HRUs with 23 sub basins in total.

4.2 Base flow Separation

A major construct in many of the current watershed models is the process of baseflow discharging to streams and the parameters like 'Baseflow recession coefficients' can be utilized to control the recharge amount (Arnold et al., 1995, Leavesley et al., 1983). Estimating the correct average annual ratio of surface runoff to baseflow can significantly improve the SWAT model output and hence, application of some type of baseflow separation techniques is essential for any successful calibration of SWAT model. Baseflow separation method obtains the baseflow signature by using the time-series record of stream flow for given outlet. There are two different methods for baseflow separation: Firstly the graphical method in which the points where baseflow intersects the rising and falling limbs of the quick flow response are defined, and secondly the filtering method in which the entire stream hydrograph can be utilize to derive a

baseflow hydrograph through filtering. The baseflow recession constant alpha factor, which is one of the input parameters to the SWAT model in shallow ground water flow simulation routine, can be obtained from the baseflow separation process. High alpha value is an indication of steep recession thereby indicating rapid drainage and little storage in the watershed while low alpha value shows very slow drainage (Arnold et al., 1995). In the case of CCW, baseflow separation was obtained using Eckhardt's (2004) automated recursive digital filter method applied in the Web-based Hydrograph Analysis Tool (WHAT). Through adjusting the ALPHA BF factor, the estimated baseflow was used to calibrate the shallow groundwater flow component against the measured stream flow at the watershed outlet and was performed prior to the setting up and calibration of the CCW SWAT model.

Baseflow separation for the CCW showed that 60 % of the total stream flow was contributed by baseflow and the maximum amount of baseflow occurred during the summer months. Further analysis showed that the month of May has the largest baseflow fraction (almost 75%), while the month of August has the smallest fraction of 0.28% (Figure 4.3). The high baseflow fraction of the CCW indicates to the large contributing area that increases baseflow, as well as snowmelt during late spring months that increases hydrostatic pressure.

4.3 Sensitivity analysis of model parameters

For effectively characterizing the spatially changing properties of a watershed through model simulation, it needs to conceive the heterogeneity in the environmental variables e.g. soil types, land uses, topographic features, and weather parameters. Realistic representation of a watershed, through any physically based spatially distributed models like SWAT, is often confined by the scarcity of input data information which is spatially discrete and temporally

continuous in nature and often not available easily. Hence any hydrological models which can be applied over large areas using deficient input data must also include the model sensitivity analysis as part of its methodological framework. Muleta et al. (2005) suggested a systemic approach of parameter screening, spatial parameterization, and parameter sensitivity analysis to minimize the SWAT model calibration parameters.

In order to get a good understanding on the calibration parameters in CCW SWAT model simulation, a sensitivity analysis was first performed as a screening tool in this study which helped in selecting the number of parameters to be adjusted during calibration. The sensitivity of SWAT hydrologic parameters is typically influenced by the topography, geomorphology of the landscape, size and the land-use variations of the watershed. Using the Latin-Hypercube (LH) One-factor-At-a-Time (OAT) random sampling procedures inbuilt in SWAT, the most sensitive parameters were identified first, details of the steps can be found in SWAT 2005 (van Griensven, 2005). A summary of the ten most sensitive parameters in the Clear Creek watershed is shown in Table 4.4.

4.4 Baseline scenario constructs

A corn-bean rotation was the dominant rotation pattern (almost in 30% of the land) in the watershed as an analysis of eight years (2001-2008) of USDA National Agricultural Statistics Service-NASS data showed (Figure 4.1). Large part of the watershed was tile drained as inferred from field trips during this study whereas USDA ARS documents suggest that mainly conservation tillage is practiced on corn fields in the Iowa corn-belt (<http://www.ars.usda.gov/>). Based on the above knowledge and information, a baseline calibration configuration was constructed as: (a) Corn-bean rotation was employed on row crop land; (b) Conservation

(mulch) till in corn, no till in soybean fields; and (c) Tile flow was activated in the entire watershed.

4.5 Model Calibration/validation

The CCW SWAT model was calibrated under baseline scenario, details of which are described in section 4.4. Soon after the calibration parameters were finalized through the sensitivity analysis step, SWAT model calibration was performed with the data at Coralville gauge site near the watershed outlet and the value of calibration parameters were obtained manually based on its upper and lower boundary limits and by using objective function e.g. regression coefficient and Nash–Sutcliffe efficiency measure (Nash and Sutcliffe, 1970). A number of iterations were performed in order to obtain good sets of calibration parameter values and this was subsequently tested by validating the model over next ten year period.

The land use in the CCW is dominantly (85%) agricultural, with a two year rotation of corn and soybean. That upper part of the Clear Creek watershed is highly erodible and has substantial channel erosion at downstream (Papanicolau et al 2008), helped in calibrating the upland hydrological and sediment transport processes in CCW SWAT model. SWAT model was calibrated for the years 1990-2000 and the calibration values were obtained after an adjustment of ten most sensitive model input parameters (Figure 4.4). The adjustments were made based on available measured data, knowledge about the watershed and an extensive literature review of SWAT model applications.

4.5.1 Calibration of Parameters governing the entire watershed hydrology

The basin level hydrology parameters used during the model calibration were: snow hydrology parameters, surface runoff lag time (SURLAG), Channel hydraulic conductivity (CH_K2), soil evaporation compensation factor (ESCO), and plant evaporation compensation factor (EPCO). The most sensitive parameter for snow hydrology was obtained as snow pack temperature lag factor 'TIMP' which controls the previous day snow pack temperature effect on the current day's snow pack temperature and the final calibrated value of it was set at 0.85. The calibrated values for the rest of the snow parameters and basin level inputs are shown in Table 4.2. As seen from Table 4.4 below, most influencing parameters from calibrating water balance were: Curve number, available soil water content, soil evaporation compensation factor etc.

The calibration period was chosen as 1990-2000 and validation as 2000-2010. Due to lack of water quality data, the SWAT model was calibrated over the entire period for water quantity whereas shorter period with good data availability was chosen for calibrating water quality (Table 4.1). In order to perform hydrologic calibration, the observed stream flow was separated into surface and base flow and the ratio of the two fractions was calculated as 0.6 on annual scale. This ratio along with ET/P, which was 0.7 for annual average, served as benchmark for further model calibration.

Figures 4.4 show the comparison between observed and simulated discharge at Coralville gauge stations in the watershed. Model was first calibrated with monthly data and then fine-tuned with daily data. Nash–Sutcliffe efficiency (NSE) values (Krause et al 2005) were obtained with daily simulations at Oxford and Coralville as 0.53 and 0.60, respectively. Validation of stream flow was conducted using calibrated model parameters. On an annual scale, water volume

differences obtained from observed and simulated discharge at Oxford and Coralville were: 2.8% and 4.4% respectively. This was calculated as accumulated difference in water volume between observed and simulated. These results indicate that the SWAT model can accurately simulate the hydrology of the CCW (Figure 4.4). The estimated average daily stream flow for CCW is 2.37 m³/s. The daily flow ranges from zero in the low flow season, to 204.68 m³/s during the high flow season. Timing of occurrence of both low and peak flows as predicted by the SWAT model generally agreed with observed data. Overall, model predictions showed very good agreement with field measured data (Figure 4.4).

4.5.2 Water Budget

Annual water budget in the CCW can be obtained by applying the following principle of conservation of mass:

$$\Delta SW = P - (ET + \text{tile}Q + \text{surf}Q + \text{gw}Q + \text{daq}Q)$$

Where ΔSW is the change in soil water storage (mm), P is the total annual precipitation (mm), ET the evapotranspiration (mm), $\text{tile}Q$ is the tile flow (mm), $\text{surf}Q$ is the surface runoff flow (mm), $\text{gw}Q$ is the groundwater flow (mm) and $\text{daq}Q$ is the deep aquifer recharge (mm).

During baseline simulation (years: 1990-2000) in CCW, ET accounts for 69% of the water budget, the largest of all water components and the base flow is the second largest component, consists of 18% of the total water budget. Surface runoff forms another 12% of the water budget. Available water holding capacity of the CCW soils varies considerably. About 47% of the water yield is contributed by tile drainage, 38% is from surface runoff, 11% is groundwater flow, 4% is lateral flow, and 1% is deep aquifer recharge. The months of March to

June are the period in which over 70% of the surface runoff, tile flow and total water yield of CCW occurs (Table 4.8).

4.6 Calibration for sediment load

Detailed descriptions of sources for primary input data required to build the model, (weather, topography, soils, land use, stream network etc) were described in Chapter 3. SWAT sediment modeling has additional requirements including information about tillage management practices and measured Total Suspended Solid (TSS) levels. These data were obtained from IIHR sensors (Table 4.1).

In the model formulation, stream flow quantity as well as stream flow velocity control the transport and deposition of sediment along a stream reach. And hence to simulate sediment load correctly, estimation of stream flow quantities is quite important. Sediment transport processes in SWAT is influenced by many parameters some of which also control the hydrologic components in the model. Certain sediment transport parameters are highly influential in the model while some others are less significant which can be found through the parameter sensitivity analysis. Some of the known parameters that significantly affect the sediment transport processes in the model are: PRF, SPCON, SPEXP, CH_N, CH_K2, CH_Cov, USLE-C and USLE-P (Jha et al., 2004; Kirsch et al., 2004). A sensitivity analysis of the CCW sediment parameters was performed by utilizing the SWAT inbuilt sensitivity analysis routine which is based on Monte Carlo simulations and called Latin Hypercube One factor At a Time (LH-OAT) routine. The initial step in LH-OAT routine begins with generating random values of the model parameters and then distribution of each parameter set is subdivided into n ranges of 1/n equal probability of occurrence, each range being sampled only once. Finally the model is run n times, with random

combinations of the parameters. By changing value of a single input parameter, one at a time, the output values obtained from the model runs are compared and the relative changes are recorded for making the ranking of the parameters. The sensitivity analysis of CCW sediment was obtained by using ten intervals in the LH_OAT routine. It is hard to estimate the values of some of the highly sensitive sediment related parameters from soil or topographic information e.g. PRF, SPCON, SPEXP, CH_N, and CH_K2. So generally their values are estimated based from research in similar areas or by following calibration procedures.

Sediment calibration was made manually using the year 2000-2009 as a calibration year. Calibration started using SWAT model default values and then adjusting sensitive parameters based on available data and knowledge about the CCW. Calibration was made by changing one variable at a time and then comparing the fitness of simulated monthly sediment outputs against measured loads based on the NSE efficiency index. Validation of the pollutant estimates was not performed due to the limited number of measurements available for model testing.

4.6.1 Sediment Input Parameters

The CCW SWAT model requires numerous input parameters most of which were generated using ARCGIS during model development, and several others were developed for the purpose of CCW hydrology modeling. Inputs parameters that are specific to sediment transport were developed during management input data organization, during parameter optimization through sensitivity analysis, and through calibration procedures described in previous sections. Tillage operations have a major impact on sediment loss and the tillage management operations under baseline simulation are shown in Table 4.7.

4.6.2 Sensitivity analysis

The most sensitive parameters obtained for sediment load prediction during calibration and parameterization were: peak rate adjustment factor for sediment routing in the main channel (PRF), linear parameter for calculating the maximum amount of sediment that can be re-entrained during channel sediment routing (SPCON), exponent parameter for calculating sediment re-entrained in channel sediment routing (SPEXP), USLE cover factor (USLE-C), Manning's "n" value for the tributary channels (CH_N), effective hydraulic conductivity of main channel (CH_K2), soil available water capacity (AWC) and soil evaporation compensation factor (ESCO). Most of the parameters are important for simulation of sediment losses and control the upland sediment transport and deposition processes.

4.6.3 Calibration and Validation of Sediment load

The SWAT model was calibrated over 2008-2009 by aggregating observed sub daily data into daily, and then into a monthly time step but validation was not performed due to lack of sufficient amount of data.. Since the model did not perform well in daily simulations, monthly data was used in this study. R^2 values obtained for the monthly simulations were: 0.78, but for the daily it was 0.6 (Figure 4.5). Parameters used in sediment calibration are shown in Table 4.5. Parameters obtained from model calibration and validation for water quantity is shown in Table 4.2. Overall, the time to peaks of the simulated sediment yield consistently matched the time to measured peaks of sediment yield in different seasons. Since the model only predicts upland sediment sources, the predicted sediment load was consistently under predicted at the mouth of the CCW. Annual average Sediment load obtained was 5.2 MT/ha, which is close to reported value for similar watershed in Iowa (Gassman et al 2006).

4.7 Calibration for nitrate load

The nitrogen model development was made after calibration and validation of SWAT's hydrology and sediment components. The management operations file was organized based on knowledge about the watershed and it included the information about: the time, rate and sources of fertilizer applied, application methods and tillage operations. Monitoring results for nitrogen collected through IIHR sensor for year 2008-2009 were used for the calibration and validation of the model. Monthly calibration was made on the watershed for the year 2008-2009, and validation was not performed due to lack of sufficient data. Procedures similar to those used in hydrology and sediment predictions were applied for sensitivity analysis, and calibration and validation of nitrogen. Nitrogen was applied to corn fields of the CCW at a rate of about 143 kg N/hectare from commercial fertilizer (anhydrous ammonia). The application was made following the previous year's soybean crop. Table 4.13 shows the baseline scheduled management operations for a Corn-Soybean (CS) rotation.

4.7.1 Sensitivity Analysis of Nitrogen Parameters

There are over 14 input parameters specific to nitrogen simulation in the SWAT model, soil organic and mineral nitrogen concentration and rate of mineralization were the most sensitive ones. Other related parameters like the curve number and USLE factors were calibrated for hydrology and sediment modeling as described in previous section. Nitrate losses were very sensitive to the humus mineralization rate (CMN) and small changes in CMN can result into huge difference in the amount of nitrate available for plant and microbial uptake, leaching, denitrification, and ammonia/ammonium available for biological microbial uptake and volatilization. The most sensitive seven parameters obtained were: Rate coefficient for

mineralization of the residue fresh organic nutrients (RSDCO), Nitrate percolation coefficient (NPERCO), Organic nitrogen enrichment ratio (ERORGN), amount of organic carbon in the soil layer (SOL-CBN), (SOL-NO3), humus mineralization rate (CMN) and Initial NO3 concentration in soil layer (SOL-ORGN).

4.7.2 Calibration and Validation of Nitrogen

Calibration and validation of nitrate- nitrogen in SWAT model is important because of the complexity of the nitrogen components and its intensive input data requirements. The CCW SWAT model nitrogen calibration and validation was made on a monthly basis using visual comparisons and statistical comparison e.g. regression coefficient, NSE values etc. The SWAT model under-predicted denitrification and organic nitrogen mineralization with default settings for the exponential rate coefficient of denitrification (CDN) and the rate factor for humus mineralization of active organic nitrogen (CMN). Therefore the CDN and CMN were increased to 0.032 and 0.5 respectively during baseline calibration. Changes were also made to the organic nitrogen enrichment ratio and some other default parameters as listed in Table 4.6.

Model was calibrated over 2008-2009 aggregating observed sub daily data into daily and then into monthly time step but validation was not performed due to lack of sufficient amount of data. Since the model did not perform well with daily simulation, we rather used monthly data in this study. R^2 obtained for monthly simulation was: 0.72, but for the daily it was 0.53 (Figure 4.6). Parameters used in nitrate calibration are shown in Table 4.6. The ratio of predicted to measured annual N loads was about 89%. Annual average Nitrate load was obtained as 25 kg/ha which is close to reported value in similar watershed in Iowa (Gassman et al 2006)

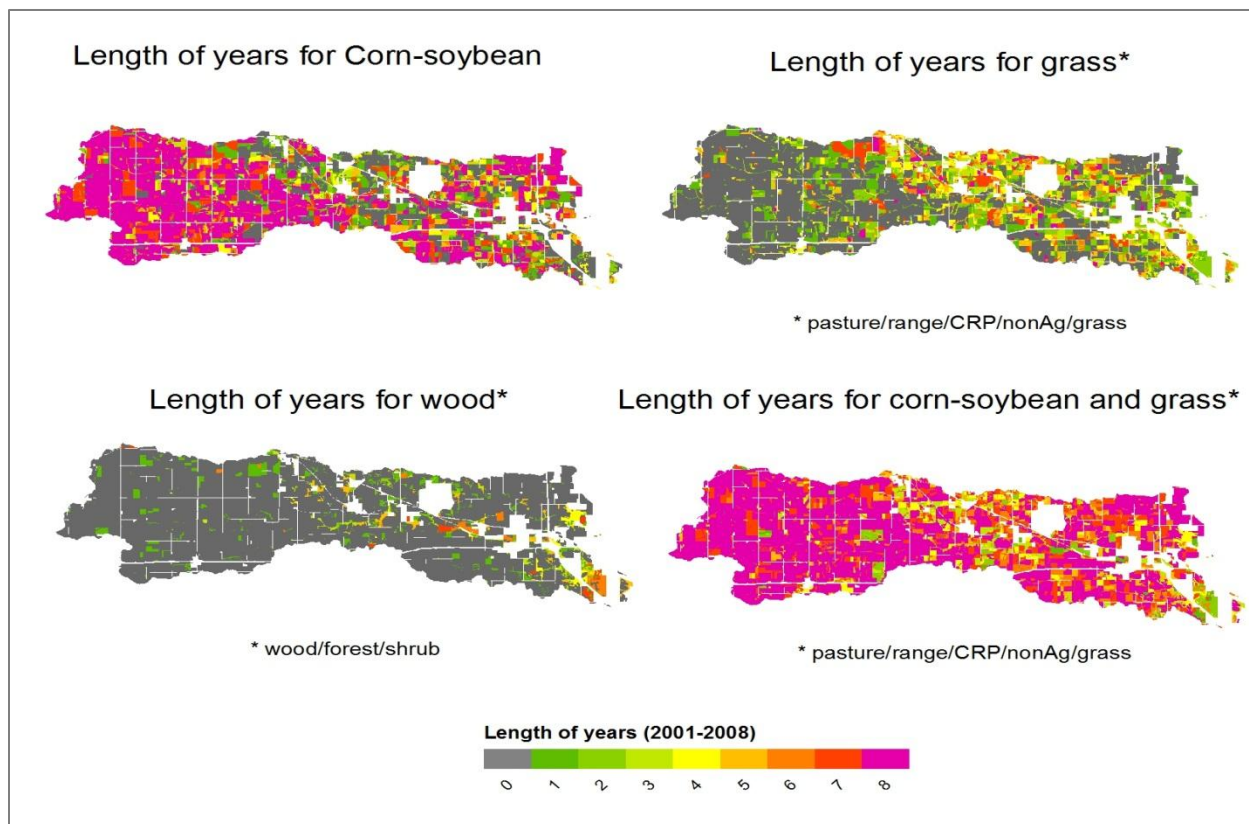


Figure 4.1 Length of year of different land use from NASS data.

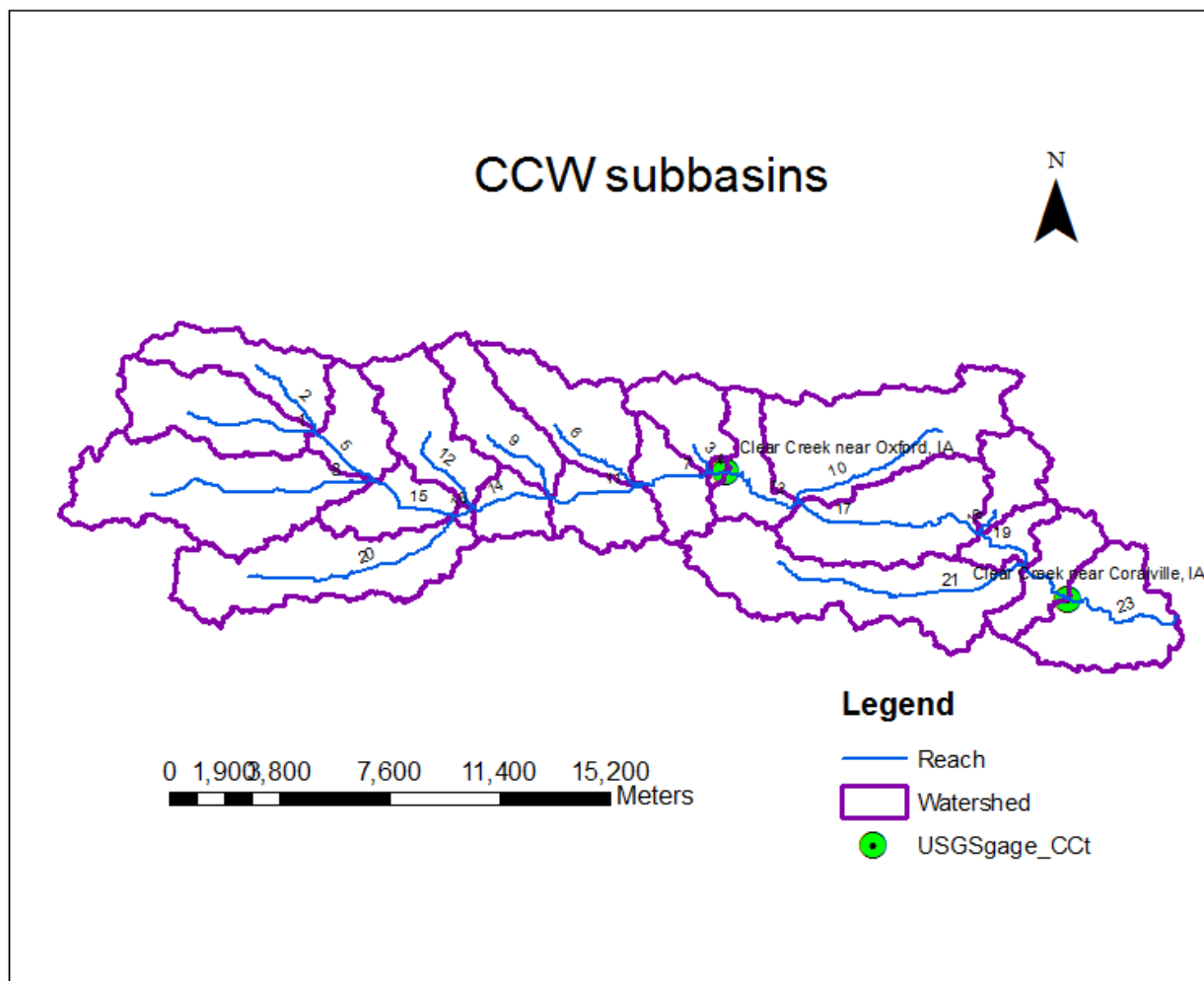


Figure 4.2 Twenty three sub basins created in the CCW SWAT model.

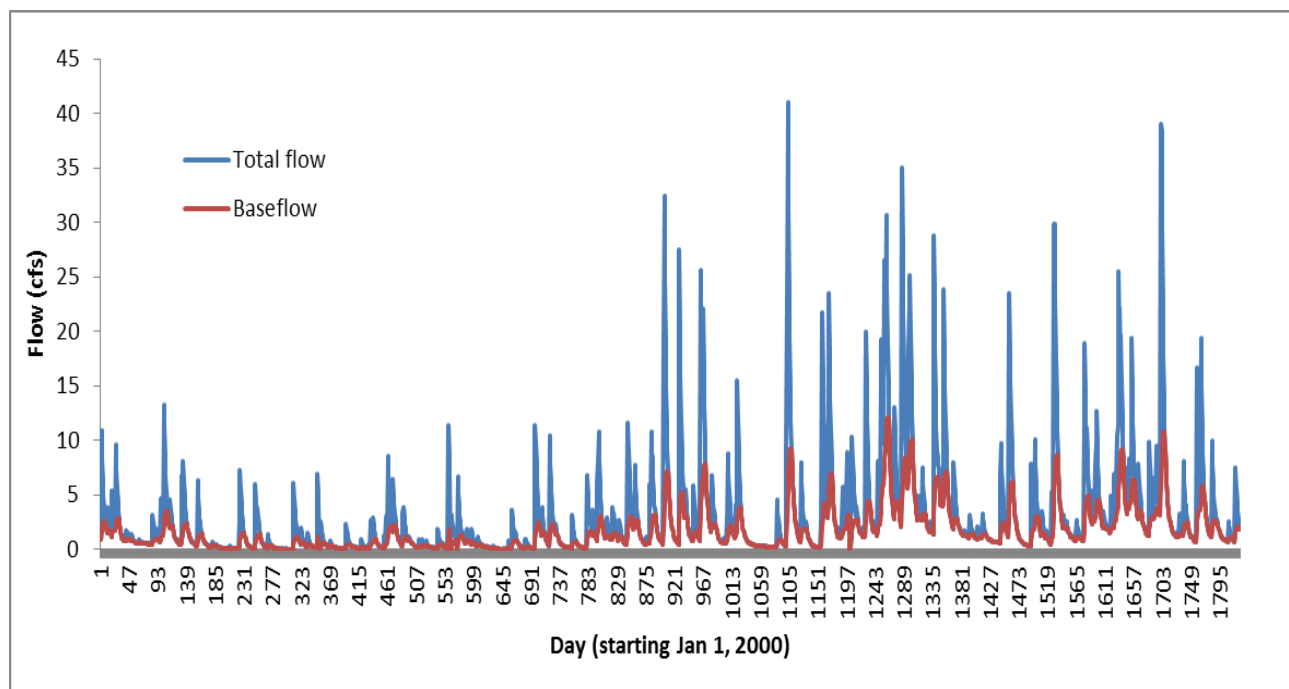
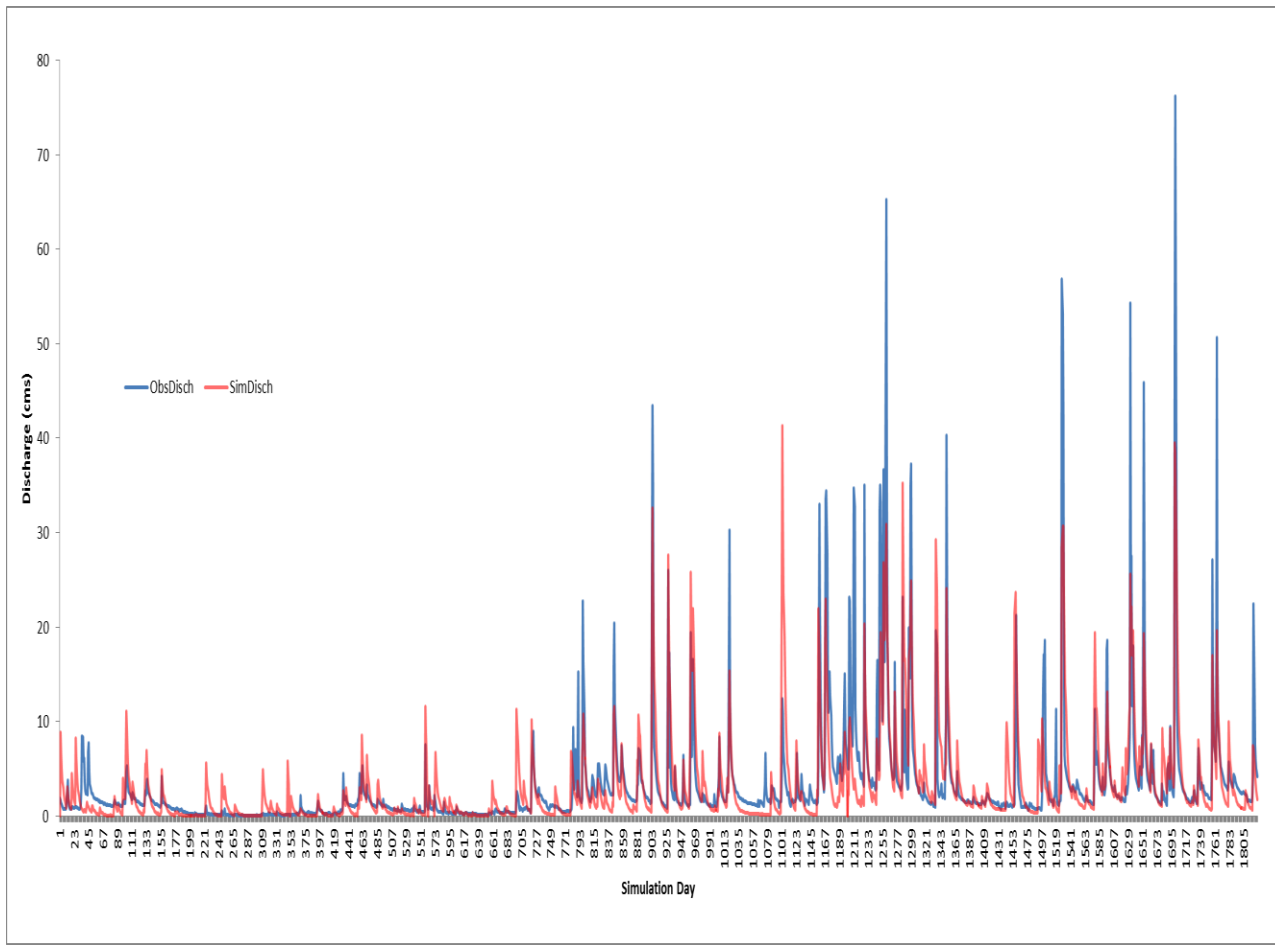
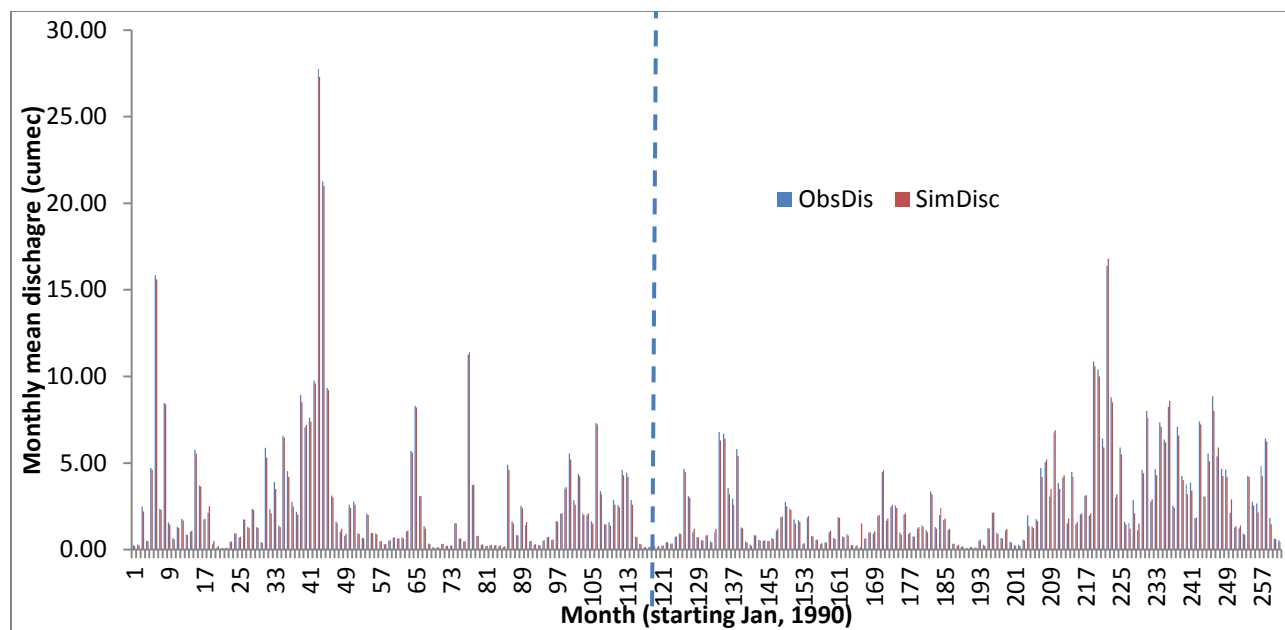


Figure 4.3 Discharge and base flow separated using Web-based Hydrograph Analysis Tool (WHAT) at Clear Creek outlet for the years 2000-2004 shown above.



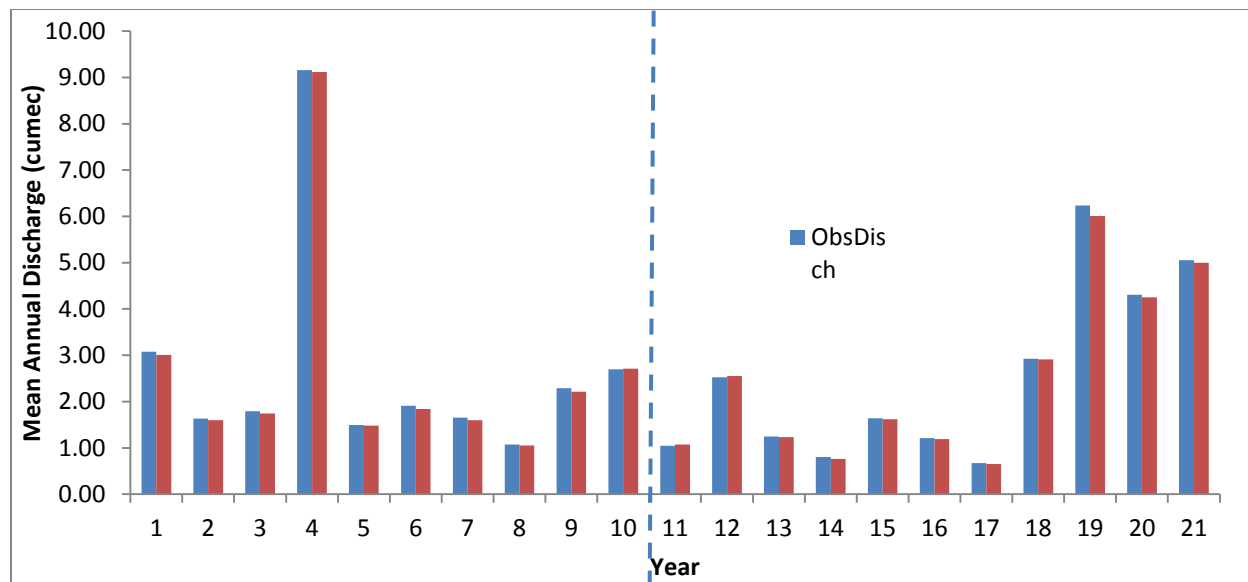
(a)

Figure 4.4 Model calibration and validation (1990-2010, starting 1st January, 1990): (a) Part of daily simulation of the total period (b) monthly simulation (c) yearly simulation. Dotted line in figure symbolizes demarcation between calibration and validation period. NOTE: cumec = cubic meters per second



(b)

Figure 4.4 Continued



(c)

Figure 4.4 Continued

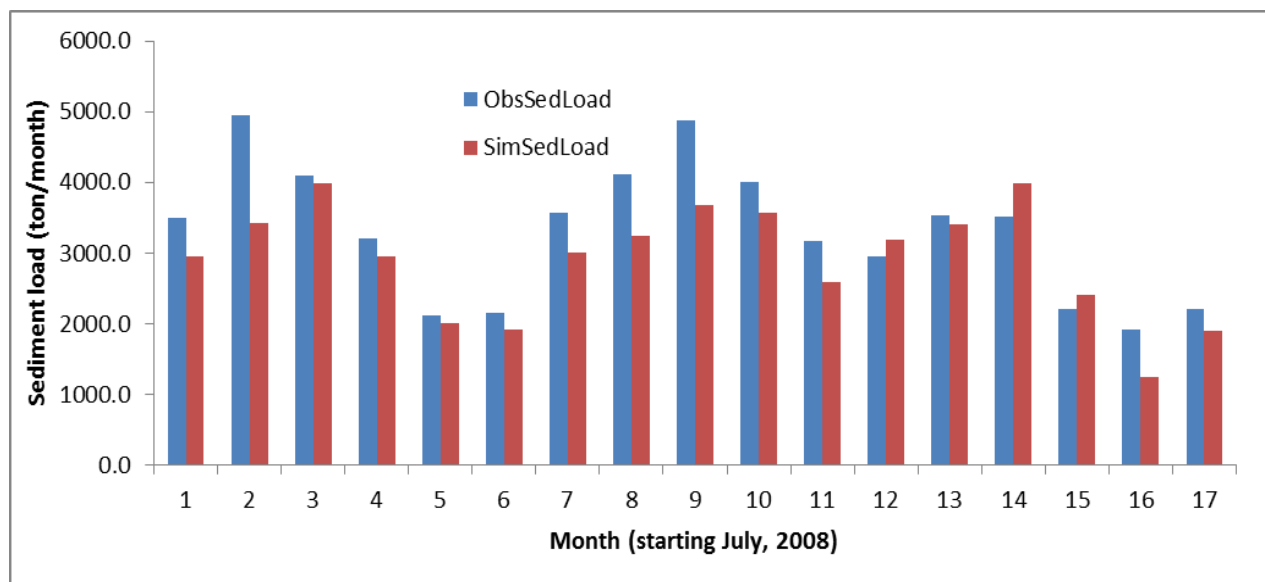


Figure 4.5 Simulation of SWAT model for monthly sediment load, 2008-2009 ($R^2=0.78$)

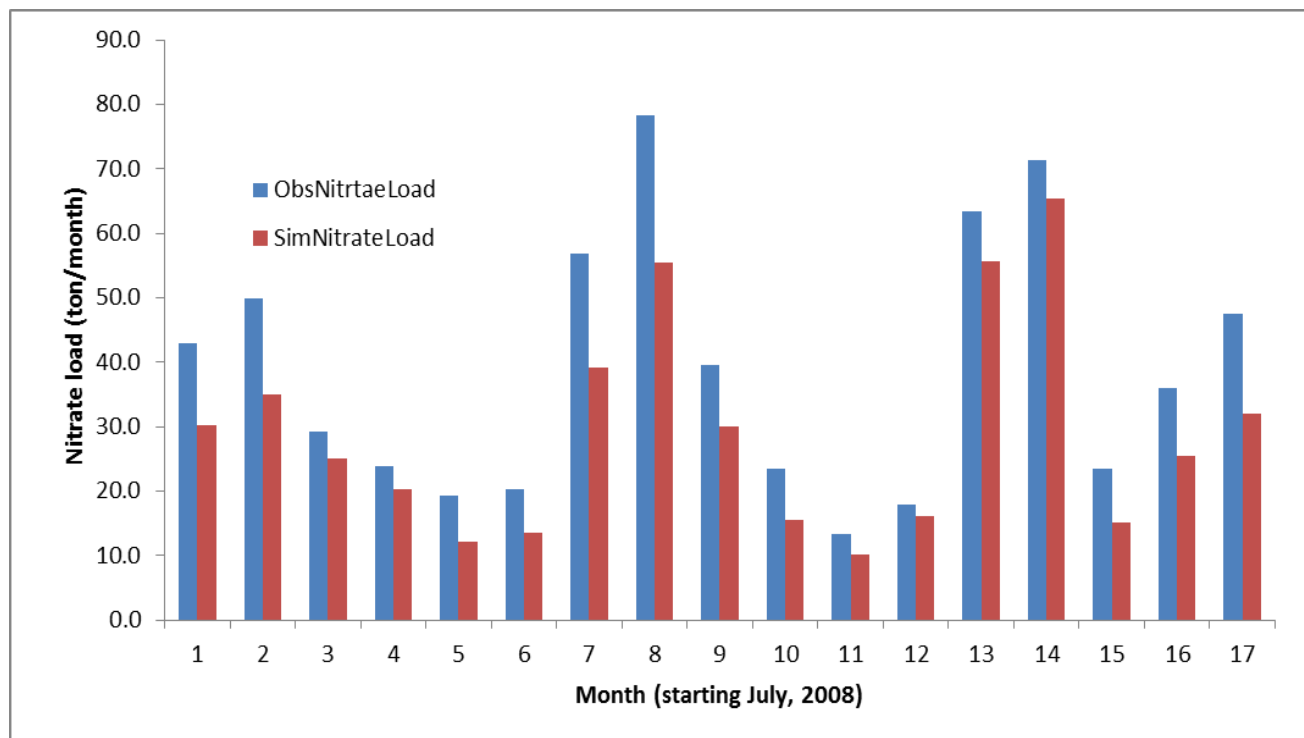


Figure 4.6 Simulation of SWAT model for monthly nitrate load, 2008-2009 ($R^2=0.72$)

Table 4.1 Data used in CCW model for calibration/validation of the model with period of data availability.

Data inputs	Period	Data sources
DEM	30 m NED	http://seamless.usgs.gov/
Landuse, Landcover	2001 Resolution: 15 m	NRGIS (http://www.igsb.uiowa.edu/nrgislib x/)
Soil	1:24,000	SSURGO (http://soildatamart.nrcs.usda.gov/)
Stream flow data	Daily over 1990- 2010	http://waterdata.usgs.gov/ia/nwis/
Weather data	Daily over 1990- 2010	http://www.ncdc.noaa.gov/oa/ncdc.h tml
Sediment data	Daily aggregated over 2008-2009 Sub daily	Local sensors by IIHR
NO ₃ -N	Daily aggregated over 2008-2009 Sub daily	Local sensors by IIHR
Phosphate	2007-2008	Grab samples by IIHR

Table 4.2 SWAT parameters selected for hydrologic calibration

Variable	Description	Calibrated value	Process calibrated	Lower bound	Upper bound
cn2	SCS runoff curve number for moisture condition II	10% decrease from default	Surface flow	35	98
sol_awc	Available water capacity of the soil layer	0.04	Surface flow	0	1
Esco	Soil evaporation compensation factor	0.85	Surface flow	0	1
gw_revap	Groundwater "revap" coefficient	0.02	Subsurface flow	0.02	0.2

Table 4.2 Continued

revapmn	Threshold depth of water in the shallow aquifer for "revap" to occur (mm)	2	Subsurface flow	0	500
gwqmn	Threshold depth of water in the shallow aquifer required for return flow to occur (mm).	0	Subsurface flow	0	5000
alpha_bf	Baseflow alpha factor	0.9	Temporal flow	0	1
ch_n2	Manning's "n" value for the main channel.	0.05	Temporal flow	0.01	0.5
SURLAG	Surface runoff lag time (days)	4	Surface flow	--	--

Table 4.3 SWAT hydrological calibration and validation statics for discharge (calibration: 1990-2000, validation: 2000-2010)

Time step	Discharge Regression Correlation coefficient (R^2) for predicted values versus observed values	
	Calibration	Validation
Daily	0.78	0.76
Monthly	0.85	0.83
Yearly	0.91	0.90

Table 4.4 Sensitivity ranking of SWAT calibration parameters using Latin-Hypercube (LH) procedure which is inbuilt in ArcSWAT.

Parameter	Description	Sensitivity ranking
CN2	Initial SCS CN 2 value	1
Esco	Soil evaporation compensation factor	2
SOL_AWC	Available water capacity	3
Alfa_Bf	Baseflow alpha factor	4
Surlag	Surface runoff lag time (days)	5
Sol_Z	Soil depth (mm)	6
Ch_K2	channel effective hydraulic conductivity	7
Blai	Maximum potential leaf area index	8
Gwqmn	Threshold water depth in shallow aquifer flow	9
Canmx	Maximum canopy storage (mm)	10

Table 4.5 Sediment calibration parameters used in the CCW model for calibrating sediment load at the watershed outlet for period 2008-2009.

Parameter description	SWAT name	value used
Sediment re-entrainment parameter	SPCON	0.0005
Sediment re-entrainment parameter	SPEXP	2.3
Channel erodibility factor	CH_EROD	0.03
Channel cover factor	CH_COV	0.5

Table 4.6 Nitrate calibration parameters used in the CCW model for calibrating nitrate load at the watershed outlet for period 2008-2009.

Parameter description	SWAT name	value used
Nitrate percolation coefficient	NPERCO	0.9
Organic N enrichment ratio for loading with sediment.	ERORGN	3.2
Organic P enrichment ratio for loading with sediment.	ERORGP	2.1
Initial concentration of nitrate in shallow aquifer (mg N L ⁻¹)	SHALLST_N	11
Concentration of soluble phosphorus in groundwater (mg P L ⁻¹)	GWSOLP	0.05

Table 4.7 Typical management operations for Corn Bean rotation implemented in CCW SWAT model.

CORN-SOYBEAN		
YR (generic)	DATE	OPERATION
1	May 3	Generic Conservation till (Mulch)
	May 5	Fertilizer application
		(N-based, Anhydrous Ammonia@143kg/ha)
		(P-based, elemental P@70 kg/ha)
	May 10	Plant CORN
	May 13	Pesticides application (Atrazine @1.46 kg/ha)
	Oct 15	Harvest & Kill
2	May 3	Generic No till
	May 5	Fertilizer application
		(P-based, elemental P@70 kg/ha)
	May 10	Plant Soybean
	May 13	Pesticides application (Metalachor@1.59 Kg/ha)
	Oct 15	Harvest & Kill

Table 4.8 Water balance fraction in CCW model baseline calibration

Water balance fraction	Values during baseline calibration
Runoff Coefficient Q/P	0.29
Actual ET/P	0.69
Potential ET/P	1.26
Recharge/P	0.01
Baseflow/Q	0.60
RB Flashiness Index	0.53
Annual avg P (mm)	971.90
Avg daily T max (c) over 10 yrs sim	16.82
Avg daily T min (c) over 10 yrs sim	5.05

CHAPTER 5

BIOFUEL SCENARIOS ASSESSMENT USING SWAT*

5.1 Introduction

According to the ethanol council report (<http://www.ndethanol.org/>): *“The Renewable Fuel Standards (RFS) program was created under the Energy Policy Act (EPAct) of 2005, and established the first renewable fuel volume mandate in the United States. As required under EPAct, the original RFS program (RFS1) required 7.5 billion gallons of renewable- fuel to be blended into gasoline by 2012. Under the Energy Independence and Security Act (EISA) of 2007, the RFS program was expanded in several key ways (RFS2): EISA expanded the RFS program to include diesel, in addition to gasoline; EISA increased the volume of renewable fuel required to be blended into transportation fuel from 9 billion gallons in 2008 to 36 billion gallons by 2022; EISA established new categories of renewable fuel (including cellulosic and advanced biofuels), and set separate volume requirements for each one. Also, a greenhouse gas performance life-cycle standard was added on all new feedstock and biofuel production implemented after 2008. “* (Table 5.1; NRC 2008)

Donner and Kutchrick 2008 suggested that to meet the 2022 goal of 15-billion-gallon ethanol production, an increase in corn production would increase the size of the Gulf hypoxic zone by 10-18%. Instead of all efforts on technological advancement to use cellulosic biofuel production, presently available technology is largely based on corn grain ethanol production and

* Adapted from Mishra et al 2013, "Modeling the Effects of Increasing Biofuels Mandate on Water Quantity and Quality at Clear Creek, Iowa", manuscript in preparation which also includes some parts from Chapter 4.

biodiesel from soybeans. Graham et al 2007, identified corn residue and switchgrass as promising biofuel feedstocks for cellulosic ethanol production. Corn stover, which consists of stalks, leaves, and cobs left over above ground after the kernel is reaped, constitutes main biomass source to produce cellulosic ethanol and adds up to 220 million tons of dry biomass weight in the United States. According to Perlack et al 2005 study, 30-60% of the corn stover can be harvested to meet up to 10% of total gasoline demands. Corn stover is composed of 70% cellulose and hemicellulose, which can be transformed to ethanol, and 15-20% lignin which is used as a boiler fuel for generating electricity. Glassner et al 1998 estimated that using a ton of corn stover, around 130 gallons of cellulosic ethanol could be generated. However Mann et al 2002 identified that the shortage of commercial biomass conversion technologies has obstructed the wider scale harvesting of corn residue in US. According to Wilhelm et al 2007 estimate, corn stover can provide up to 25 percent of the biofuel crop biomass needed by 2030. Mann et al 2002 suggests that maintaining crop residue on the soil surface has many prominent environmental benefits such as in controlling surface runoff, soil erosion, and nutrient losses. As an alternative to stover, switch grass has emerged as promising energy crop and can be harvest in wide range of climate (Vogel, 1996). According to Lemus et al 2002 study, switch grass has many assuring biofuel attributes which includes: high biomass production, low chloride and ash contents. Moreover switch grass can provide cover to soil layer for longer years and thus help in reducing soil erosion and potential water contamination of water resources from sediment and nutrient runoff losses. These gains can be attributed to the density of switch grass stems and roots, which facilitate soil stability, increase infiltration, and slow runoff (Redfearn et al., 1997).

5.2 Scenario constructs

EPA's renewable fuel standards (Table 5.1) suggest that there needs to be a major increase in U.S. cellulosic biofuel production to meet 2022 goals. Cellulosic biofuel in the Midwest is likely to come from corn stover and switch grass (DoE US Billion Ton Update 2011). In addition, there will be a small increase from traditional sources, i.e., corn grain by 2015. How is this alternative biofuel driven landscape going to affect hydrology and water quality in the long run? Can the conversion schemes be made such that adverse effects can be reduced? To answer such questions alternative scenarios were constructed as discussed in next section. Based on these scenarios, land use and associated land management practices were implemented in SWAT model. Its implications are discussed in the following sections.

The following scenarios were constructed based on RFS2 guideline to understand the impact of an expansion in bioenergy crops (primarily corn stover). The impact of possible perennial alternatives (e.g. switch grass) was also studied. RFS2 mandate were simulated by the following cases:

(a) Expansion in corn from corn-bean to corn-corn-bean rotation: Management operations for the baseline condition were described in previous chapter.

(b) Corn stover harvesting: This scenario involved removal of crop residue for cellulosic ethanol production with three different stover removal rates e.g. by 0% (no removal), 25% and 50%.

(c) Switch grass expansion: This scenario involved extensive switch grass plantings on crop lands, pasture and on crop fields with slopes steeper than 3%.

The main objective of this part of the research was to quantify the impacts of increases in cellulosic ethanol production on the water quality and quantity in Clear Creek watershed. The

Soil Water Assessment Tool (SWAT) model was used in this study to evaluate the overall impacts of increase in corn acreage on water quality in terms of sediment, nutrient losses. Simulation of CCW alternative biofuel crop growth and yield was made based on temporal variation of weather (temperature, precipitation, solar radiation, and humidity conditions), soil and management conditions for the ten years simulation from 2001 to 2010. The crop growth parameters (such as maximum leaf area index, canopy height, and root depth) were set to the SWAT model default values. Crop growth was modeled using growth parameters, management operation and estimated plant heat units based on the approach presented in the SWAT theoretical documentation (Neitsch et al., 2005).

5.3 Results and discussion

5.3.1 Baseline Crop Production Scenario

The baseline crop production scenario consisted of a two-year corn-bean rotation as followed in the majority of land parcels in CCW. The planting dates of corn and soybean were set at May 10 for all simulation years. Fall chisel plowing and spring field cultivation was used for corn soybean production on flat, poorly drained soils of the CCW. Management operation input data for a corn soybean rotation operation is shown in Table 5.2. The base temperature required to start growth of corn, soybean and switch grass in the watershed was set at 10 C. The optimum temperature was set at 25 C for corn and soybean, and 30 C for switch grass. When optimum temperature is exceeded, the growth rate will slow down until a maximum temperature is reached, at which time growth ceases. The average annual PHU (Plant Heat Unit) for the simulation period from 2000-2010 in the watershed was about 1714. There was no temperature stress to grow these crops as the total heat units required for growing corn, soybean and switch

grass in the CCW are 1490 HU, 1256 HU and 1350 HU respectively. SWAT plant growth database contains all crop nutrient uptake and growth parameters needed to estimate biomass yield. Figure 5.4 shows the SWAT simulated leaf area index (LAI) in comparison with the LAI derived from MODIS data and as seen, the model estimated yield was close to MODIS LAI.

5.3.2 Scenario 1: Corn-bean rotation to corn-corn bean rotation (CS to CCS)

The difference between management operations in the CS rotation from those in the CCS rotation was in the changes in tillage practices (from chisel plow to moldboard plow) and a 43 kg/ha of incremental N-fertilizer was applied during the second year of corn. An increase in corn cultivated years in the watershed resulted in an increase in amount of fertilizer applied in land parcels. This is because of the fact that corn requires more nitrogen than any other crops and it must be replaced annually as the corn is harvested in each year. A typical land management operation for Corn bean rotation is shown in Table 5.2.

SWAT simulations show that the shift from a corn-bean to a corn-corn-bean rotation has no pronounced effect on the hydrology of the CCW. However this has increased the annual average sediment yield by 6% (+/- 1.5%) and annual average nitrate-N losses by 15% (+/-2.3%) at the watershed outlet as shown in Figure 5.1 and Table 5.8. This large increase in nitrate losses can be attributed to the application of extra amount of fertilizer for CCS rotation and the changes in tillage operations, e.g. a shift from conventional to mulch tillage in corn fields (Table 5.2).

5.3.3 Scenarios 2: With different corn

stover removal rates

Corn stover is typically enriched with cellulose which is an important source for producing bio-ethanol. In this study, the nitrate application rates, which are typically calculated as a function of biomass yield, were increased with increase in stover removal rates and for the corn residue removal scenario, every 1% of corn residue removed required an additional 0.6 kg of N fertilizer, assuming there is 60 kg/ha N in the corn residue. This assumption was based on Burgess et al., (2002) in which they reported corn residues can contain 40-80 kg N/ha depending on yield and N concentrations. In this study, I implemented the following cases with different corn stover removal rates at corn hrus which consists of about 35% of the watershed area: 50% stover removal, 25% stover removal, and no stover removal.

Under CS rotation, stover removal did not change much water yield in the CCW, however, shifting to a CCS rotation reduced water yield by 3-7 mm, based on the different residue removal rates. The reduction in water yield can be explained as with more residues was removed, surface roughness decreased. As shown in Figure 5.2, due to increase in stover removal rate to 50% the annual average sediment load was increased by 19% and annual average Nitrate-N load was increased by 4%. The increase in sediment load suggests that soil tends to erode more with higher stover removal. Figure 5.3 shows that, sediment load was maximum for 50% stover removal case and minimum with no stover removal case. Nitrate load also changed with stover removal rate; being maximum under 50 percent stover removal rate and minimum with no stover removal case. Removing crop residue causes a linear increase in sediment yield under both the C-S and C-C-S rotations (Figure 5.3). For each of the three rates of residue removal (0%, 25% and 50%), the CCS rotation lost roughly 0.5 ton/ha more sediment than the

corresponding CS rotation. Impairment under the CS rotation would worsen by the increased removal of crop residue for cellulosic ethanol production. The sediment impairment would also be worsened by shifting to a CCS rotation and removing crop residue under the CCS rotation. The unwanted impacts on sediment load, due to crop residue removal or shifting to a CCS rotation, could be partly off-set by agricultural BMPs such as riparian buffer strips or cover crops. Nitrate losses did not change much with different stover removal under the CS rotation but nitrate-N losses increased by about 60% in the shift from a C-S to a C-C-S rotation with no residue removal. An 8 percent increase in nitrate-N losses to Clear Creek was observed for the CCS rotation with the high residue removal rate. T-test results are shown in Table 5.8. It shows that nutrient loads are statistically significantly different under different Stover removal rates.

5.3.4 Scenario 3: With Switch grass

Switch grass is a perennial grass used in biofuel production and a typical management operation for switch grass, as implemented in SWAT, is shown in Table 5.4 below. With 112 kg/ha fertilizer application rate SWAT simulated switch grass yield was around 9000 kg/ha/yr. which was almost 1.5 times of the yield simulated without fertilizer. Switch grass was planted in the watershed without tillage, however, atrazine (1.46 kg/ha) was applied during the establishment year, and 112 kg/ha of nitrogen fertilizer was applied annually. CCW SWAT model was set to achieve a targeted biomass yield of 9 ton/ha for switch grass assuming employing switch grass cultivar can produce higher biomass yield.

The water quality impacts of planting switch grass were estimated using three different strategies (Table 5.5). The major scenario in these schemes was constructed as planting switchgrass on all crop fields with a slope steeper than three percent. For each of the three

scenarios, the SWAT model was set to achieve a dry biomass yield of 9 ton/ha. Compared to the baseline simulation, switchgrass production scenarios trended to increase the overall evapotranspiration and there was a 7 mm or 0.8% decrease in the surface runoff and total water yield in CCW. There are many water quality benefits of switchgrass plantings depending upon the planting strategies. Planting switchgrass on highly erodible land can produce much greater water quality benefits than planting switchgrass on all croplands or on the marginal croplands. For example, planting switchgrass on the land parcels with slopes steeper than 3 percent, reduced sediment yield by 30% and nitrate-N losses by 8% relative to the baseline rotation in Clear Creek watershed (Table 5.6). Also sediment load was reduced by almost 11% due to conversion of corn acreage into switchgrass on high elevation land with a slope >5% which consists of approximately 12% of the total watershed area. This shows the potentiality of switchgrass for improving the impairment of watersheds such as CCW.

5.4 Assessing the impact of high crop prices on hydrology and water quality in an agricultural watershed⁺

5.4.1 Introduction

Increased corn production for meeting biofuel goals has associated environmental and economic consequences such as increasing the commodity price of corn (Secchi et al 2007). Increased prices are good for the bottom line of farmers, but it has a tendency to cause them to

⁺ Adapted from Mishra, S. K., G. Kanade, D. Ding, D. A. Bennet, J. L. Schnoor, S. Secchi, and M. Muste, 2010. "Development of a field based Decision support Tool integrated with socio-economical model for managing Water Quality and Quantity", 2010 International SWAT Conference, Korea Institute of Construction Technology, Seoul, South Korea, publication on CD ROM.

plant more corn in the next year which could result in increased runoff and environmental impact. Previous works have used different water quality models, e.g. SWAT model, to study such consequences by using rules of thumb for allocating crop land to increased acreage of biofuel feedstock based on historical land use or other heuristics. To improve understanding, it is necessary to have a proper representation of the expansion in crop land acreage in the watershed which is often linked to external market forces. In this study, the water quality model ‘SWAT’ was linked to an agent based land use model (ABM) which was then used to generate an improved representation on crop land allocation, crop choices or crop rotation throughout the watershed based on associated crop market prices. Increased fertilizer applications, which have consequences may occur through different crop rotations or by changes in the corn acreage throughout the watershed.

The ABM model was developed by *Dr. Dave Bennett and Deng Ding of University of Iowa*. It simulates the landscape as a result of decisions by the farmer (as agent) under different market policy conditions. This dissertation benefitted from the collaboration with Deng and Bennett as a part of the NSF CDI Type II project, and it is expected that a joint publication will follow. For this work, the likely landscape generated under different biofuel markets was taken from the ABM model and then fed as input to the SWAT model for understanding water quality responses under those scenarios. The impact of these alternative landscapes, generated through the ABM model under various corn market scenarios, was studied through the following cases: a linear increase in corn price.

The entire model coupling and relevant workflow is discussed in the following sections.

4.2 Linking ABM output to SWAT

Output from the socio-economic model, ABM, is in the granular unit of common land unit or land parcel (CLUs) and the corresponding physical unit in SWAT is Hydrologic response unit (HRUs). In order to incorporate feedback from ABM, CLUs were mapped with the physical hydrologic response units of SWAT i.e. HRUs. The entire process consists of two sub-modules (Figure 5.5):

5.4.2.1 CLU-HRU reconfiguration sub-module

The next steps were: (a) Converting CLU and HRU layer into georeferenced raster layers. (b) Creating a new index system accounting grid index from both above layers (mentioned in step a) using the algorithm: $\text{NewHRUIndex} = \text{OldHRUIndex} * B + \text{CLUIndex}$; where OldHRUIndex is the default hru index created by ArcSWAT whereas CLUIndex is the unique field identifier of a land unit. B is a suitable constant in form of 10k, where k value depends on total number of digits in the maximum OldHRUIndex. (c) Using NewHRUIndex notation (resulted from step b) CLU-HRU transformation module rebuilds HRU.

5.4.2.2 SWAT preprocessor Catchment

attributes sub-module

Using NewHRUIndex notation (resulted from step b), this sub-module rebuilds HRU, updates the information about crop rotation, fertilizer application, conservation practices and other management operations using output from ABM simulation. It also creates all other configuration files for SWAT simulation (see figure 6.1). The key feature of above sub-modules includes tracking of Meta information of CLUIndex, OldHRUIndex, and NewHRUIndex etc.

into simulation archive. This information is critical to the post processing phase where the SWAT outputs based on the NewHRUIndex are re-converted back to CLUIndex in order to help ABM to re-learn. The entire process is explained in Figure 5.5.

5.4.3 Simulating SWAT model under different market scenarios

Three scenarios about the corn grain market were constructed by Ding et al. As an external input to the agent-based model, in Scenario 1, the time series of yearly cash corn price (2000-2008) was the actual data obtained from Iowa Agricultural Statistics. In Scenario 2, the cash corn price during the last 8 years from 2000 to 2008 was increased by 25% comparing to the actual price in Scenario 1. In Scenario 3, the price increase was 50% comparing to the actual price. By running the ABM model with the external inputs at three levels of cash corn price, we obtained the CLU-specific management information respectively for the three scenarios. Figure 5.6 shows the original prices of the two crops from 1960 to 2008 and illustrates that the number of land parcels in which corn or soybean was planted during this period. It shows that there have been more corn parcels than soybean parcels in overall during 1960 and 2008. In Figure 5.6c, the corn price has increased by 20% since 2001. Therefore, in Figure 5.6d, the difference between the numbers of corn parcels and soybean parcels has become bigger since 2001, which indicates a positive influence of corn price on the number of corn parcels.

In order to incorporate landscape maps generated through ABM model into SWAT, first HRUs were reconfigured based on CLU map and then management parameters from ABM simulation were written as explained in Figure 5.5 above. Then SWAT was run for three different corn price scenarios as defined below:

Scenario1: original corn price in year 2000-2008

Scenario2: 25% increase on original corn price, 2000-2008

Scenario3: 50% increase on original corn price, 2000-2008

An increase in the corn price from scenario 1 to 3 resulted in an increase in annual average nitrate load by 2.5% and 8.4% from baseline to scenario 2 and 3 (Figure 5.7 and Figure 5.9). This also amounted to an increase in sediment yield by 11% and 30% in successive scenarios at the watershed outlet (Figure 5.8 and Figure 5.10). This can be explained as more amount of land parcel converted into corn in successive scenarios, would subsequently increase the amount of nitrate input in the watershed. Detailed statics on sediment and nitrate load under all three scenarios are explained in Table 6.2. Annual average sediment yield and nitrate load obtained from ten year model simulation was 5.08 t/ha and 29.38 kg/ha respectively under scenario 1. This was taken as baseline sediment, nitrate load and then compared with the sediment yield and nitrate load obtained under other two scenarios.

5.4.4 Feedback from SWAT model simulations

Figure 5.11 shows advantages of using back to back SWAT and ABM runs. For example, the output values for sediment or nutrient load provided by the SWAT simulations can be used to train the response of agents. Based on water quality simulation data, agents can then reduce fertilizer application rate in their fields. Such reduction strategies can be many fold: either a linear reduction in fertilizer application rate proportional to the reduction in total load, or it can be any other nonlinear response in such model runs. In an example illustrated through Figure 5.11 shows that if SWAT model was run in stand-alone for a ten year simulation, it would result in an annual average nitrate concentration of 6.2 mg/l at the watershed outlet where the

corresponding acceptable values is, say, 5 mg/l. So in order to achieve this goal SWAT model was run in series of two years and then was checked if water quality threshold was not met or not. Then fertilizer application rate in ABM was altered based on the difference in loads. The SWAT model was rerun for the next two years with new set of ABM outputs. With a couple of such iterations, the goal was met as shown in the plot on Fig. 5.11.

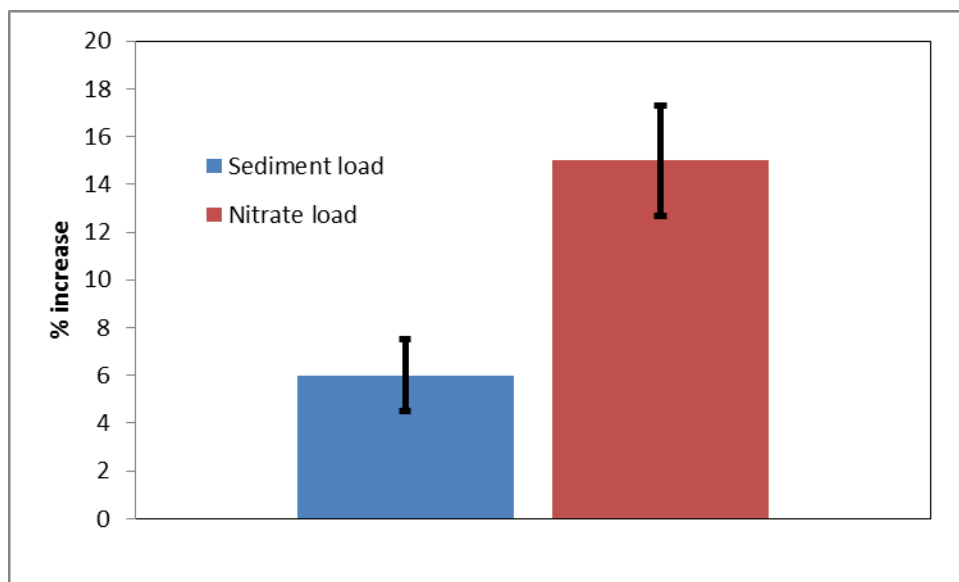


Figure 5.1 Increase in nutrient and sediment export at watershed outlet (annual average over entire simulation period) due to shift from CS to CCS rotation on 35% of watershed area in CCW.

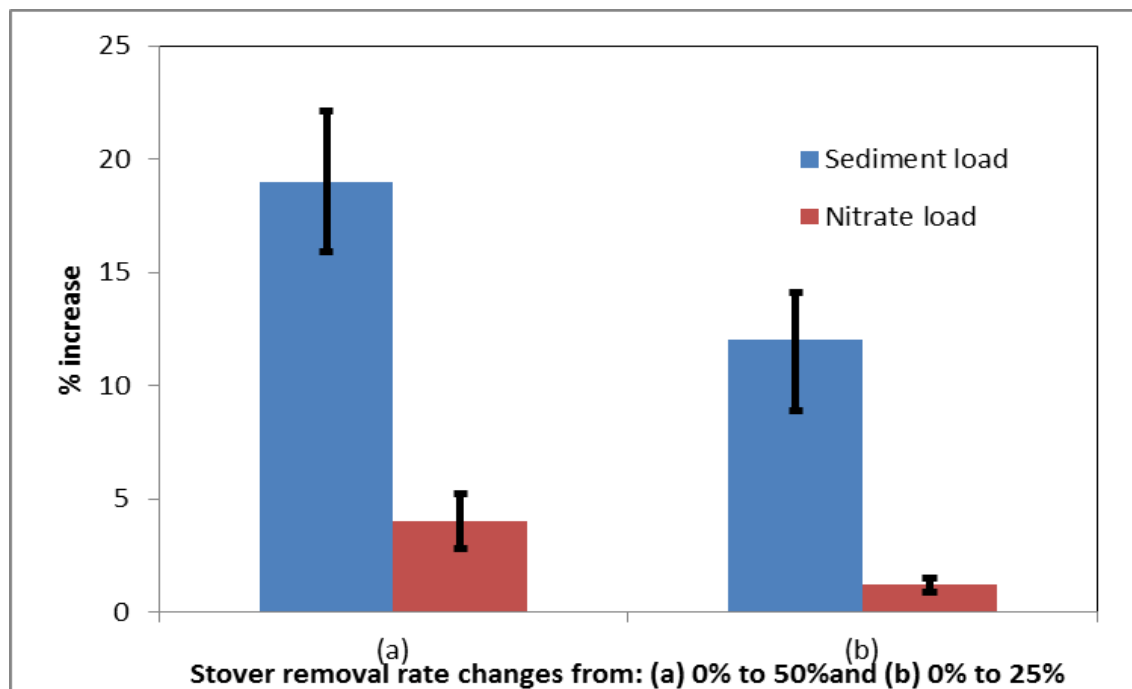
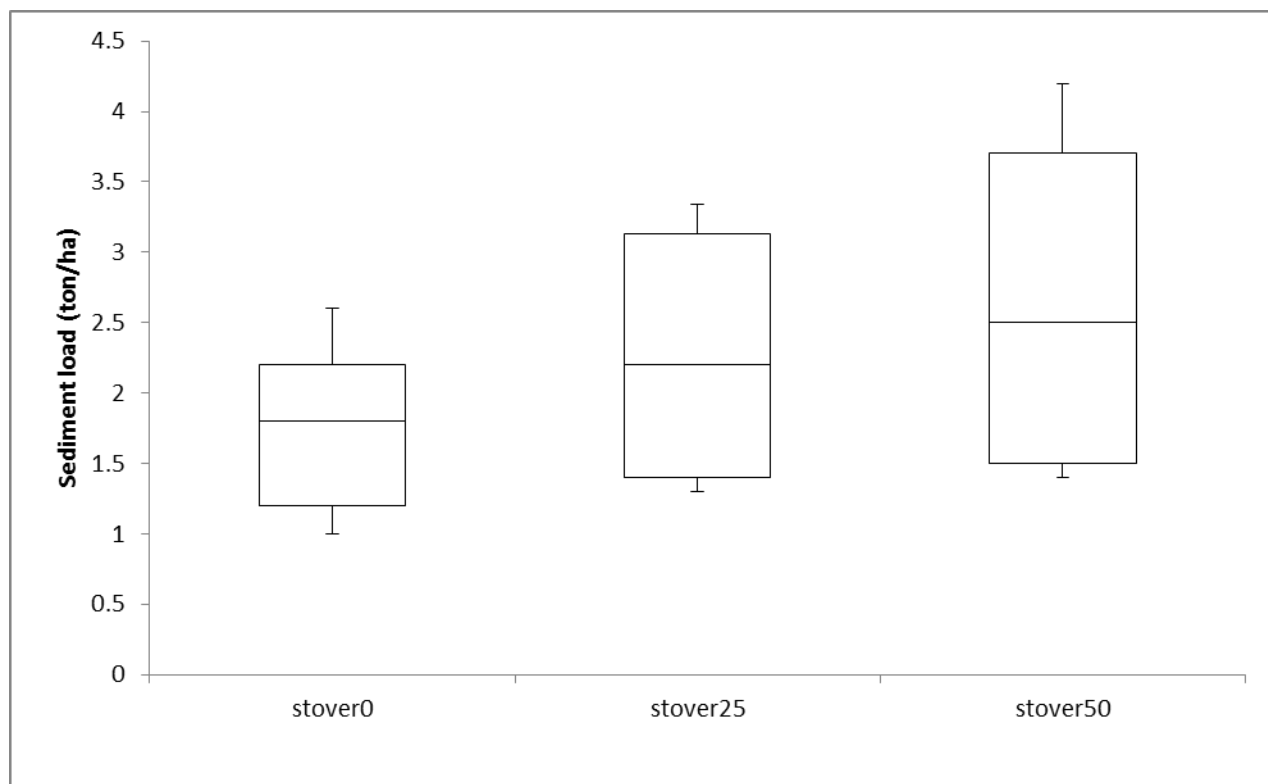
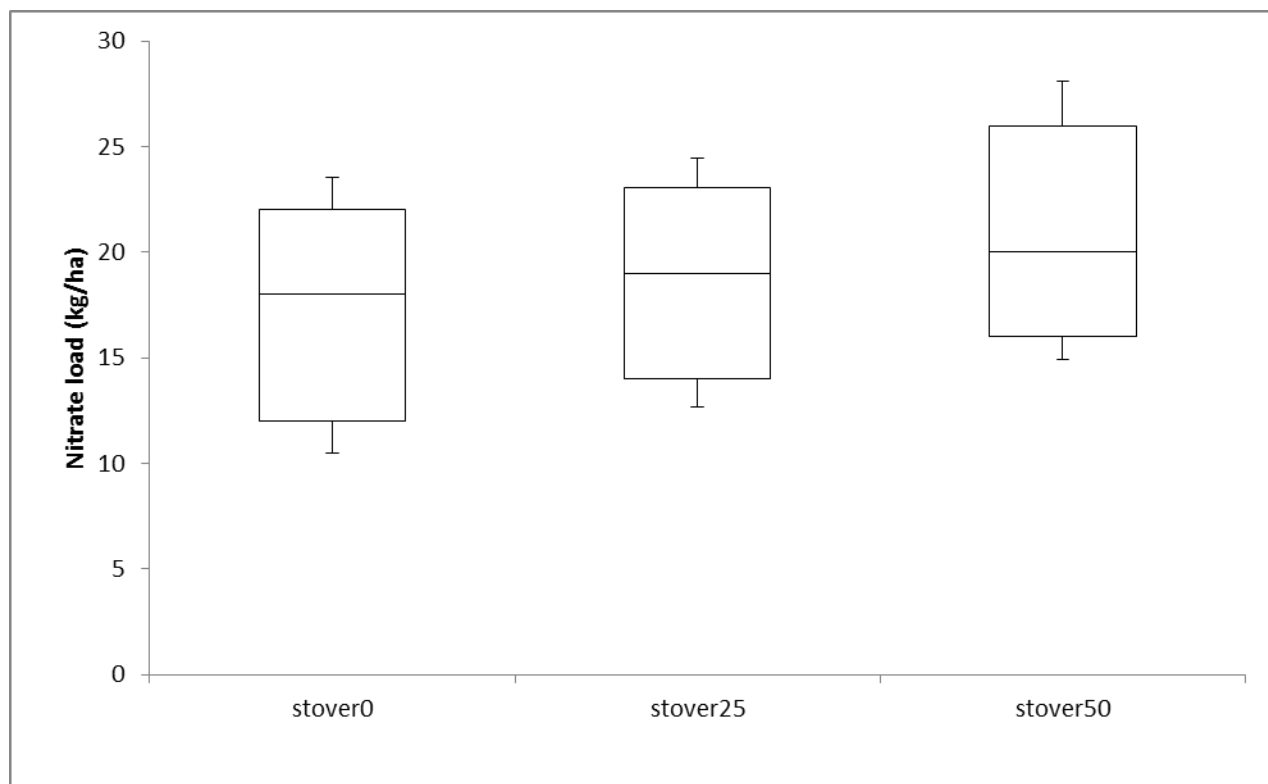


Figure 5.2 Increase in nutrient and sediment loads (annual average over entire simulation period) due to change in corn stover removal rate from 0% to 50% removal.



(a)

Figure 5.3 Box whisker plots on: (a) Sediment yield with different stover removal rates: 0, 25%, and 50% (b) Nitrate load with different stover removal rates: 0, 25%, and 50%



(b)

Figure 5.3 Continued

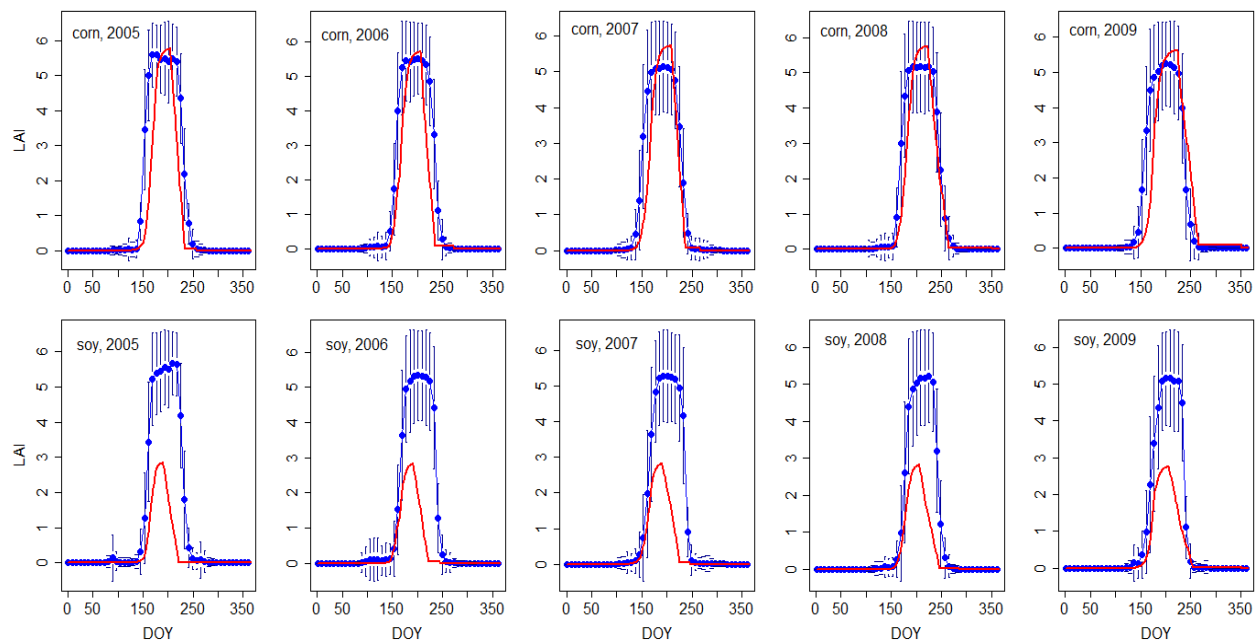


Figure 5.4 LAI obtained from MODIS data compared with SWAT LAI, DOY=day of year (adapted from Ding et al 2013, “Integration of Remote Sensing vegetation data into parsimonious modeling of hydrological responses in Midwestern landscapes” paper in preparation)

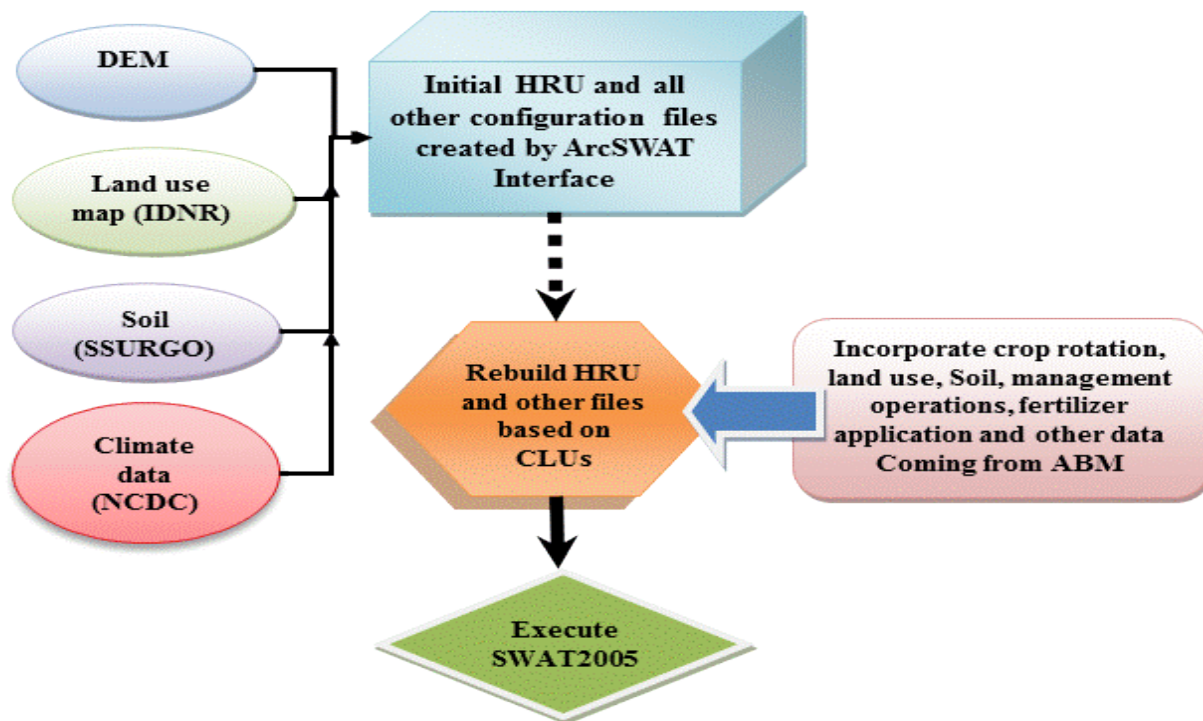


Figure 5.5 Flowchart showing steps for building CLU based modeling framework for SWAT

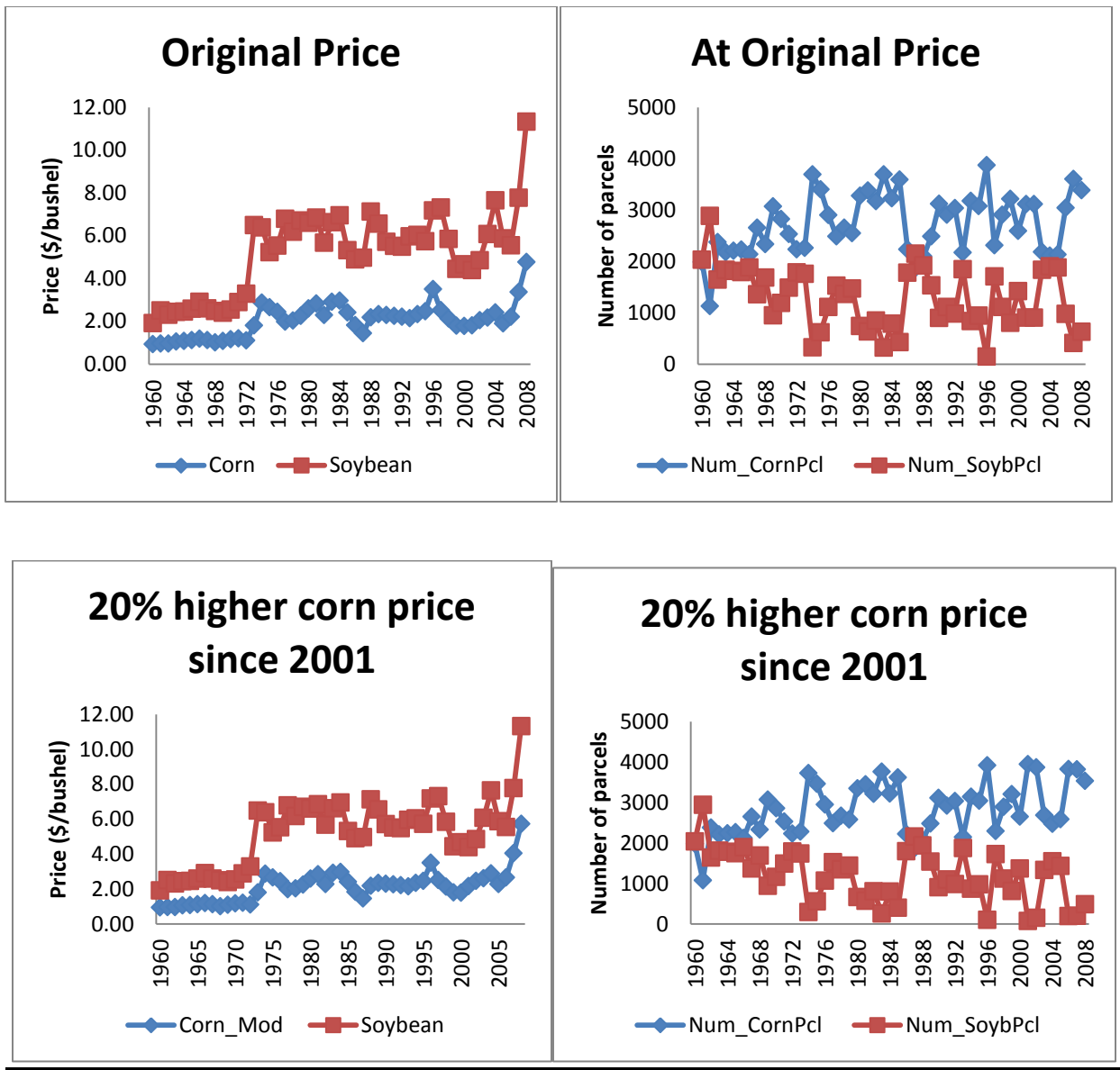


Figure 5.6 Corn prices scenarios: Original corn price and 20% increase in corn price with corresponding land parcel distribution for corn and bean over Clear Creek watershed for the year 1960-2008 (source: ABM output from Deng Ding of UI)

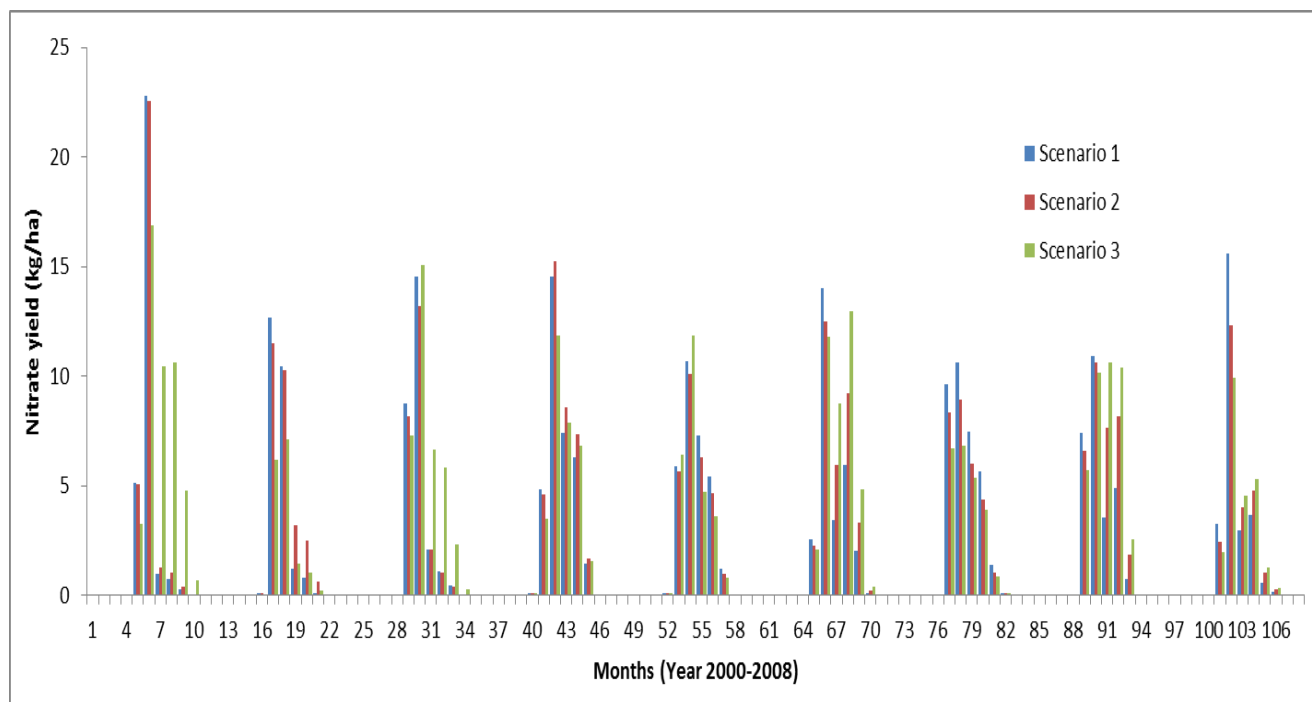


Figure 5.7 Monthly Nitrate load at Clear Creek watershed outlet at Coralville station under different corn price scenarios (Scenario1: original corn price in year 2000-2008, Scenario2: 25% increase on original corn price since 2000-2008, Scenario3: 50% increase on original corn price since 2000-2008)

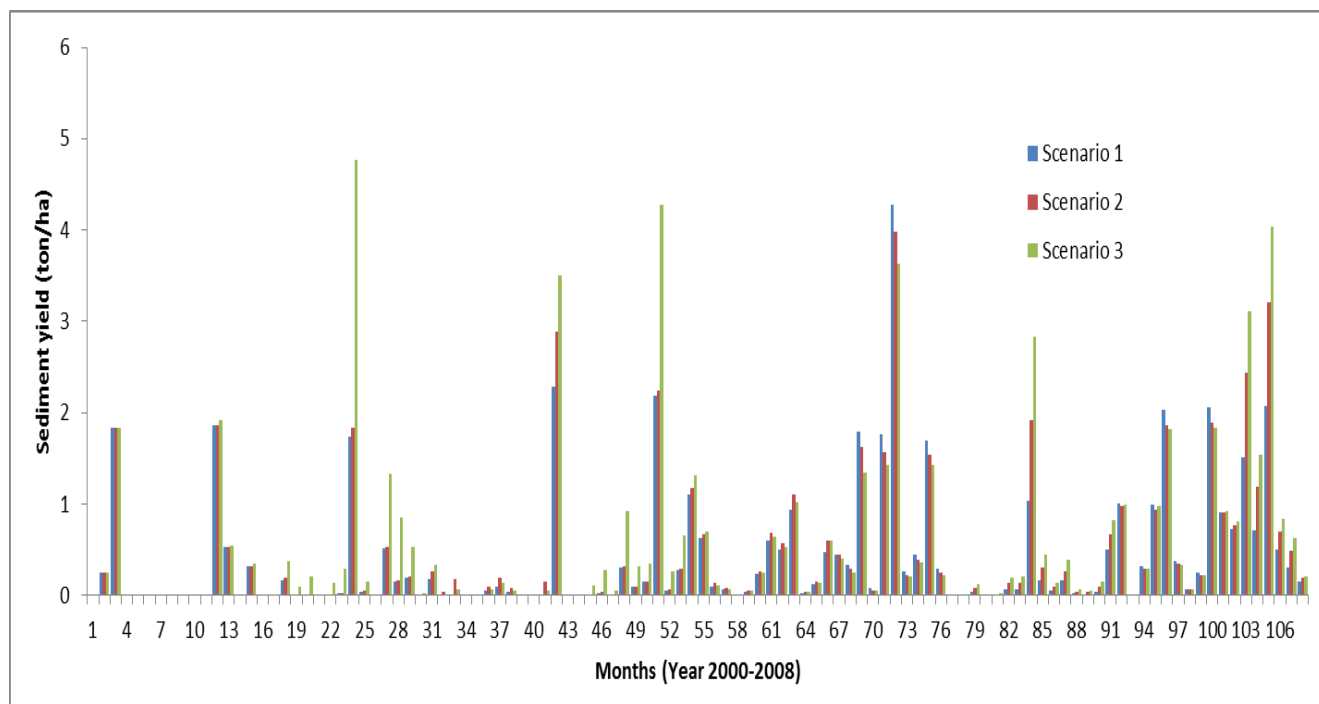


Figure 5.8 Monthly sediment yield at Clear Creek watershed under different scenarios (Scenario1: original corn price in year 2000-2008, Scenario2: 25% increase on original corn price since 2000-2008, Scenario3: 50% increase on original corn price since 2000-2008).

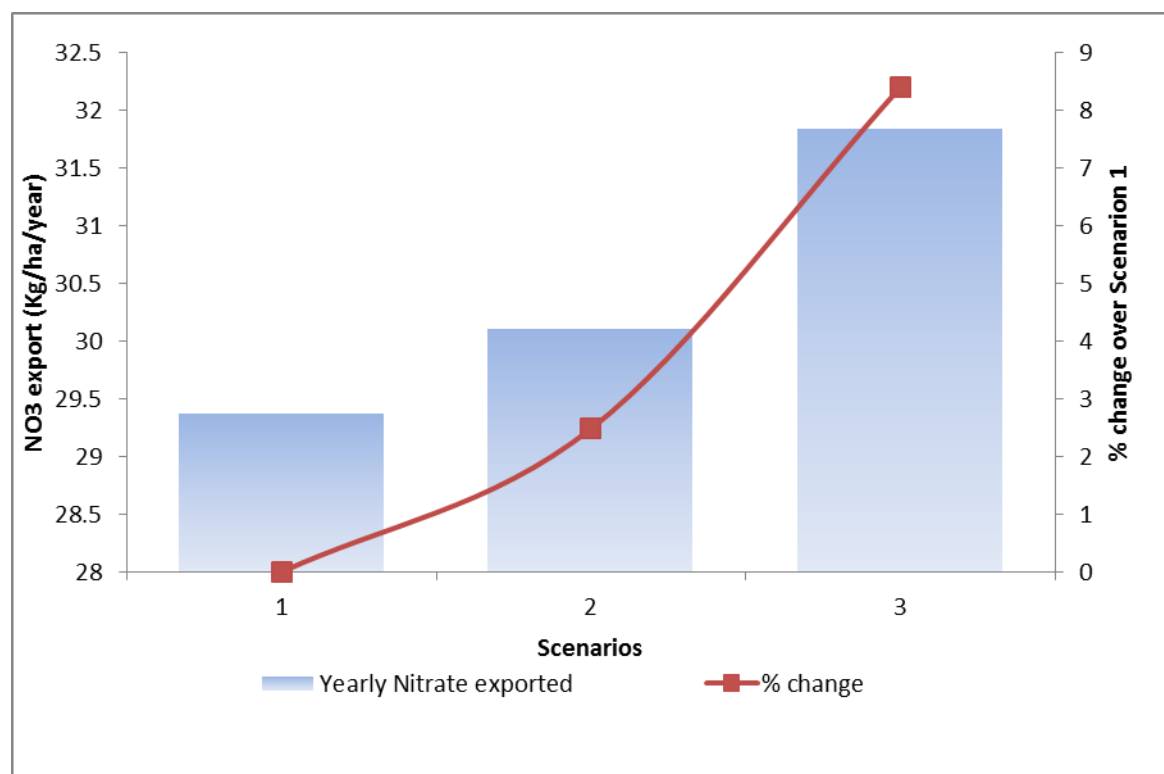


Figure 5.9 Yearly nitrate load at Clear Creek watershed outlet (at Coralville) for different scenarios (Scenario1: original corn price in year 2000-2008, Scenario2: 25% increase on original corn price since 2000-2008, Scenario3: 50% increase on original corn price since 2000-2008) with % change from baseline. Fertilizer applied was 143 Kg/ha for Corn land parcels under each scenarios.

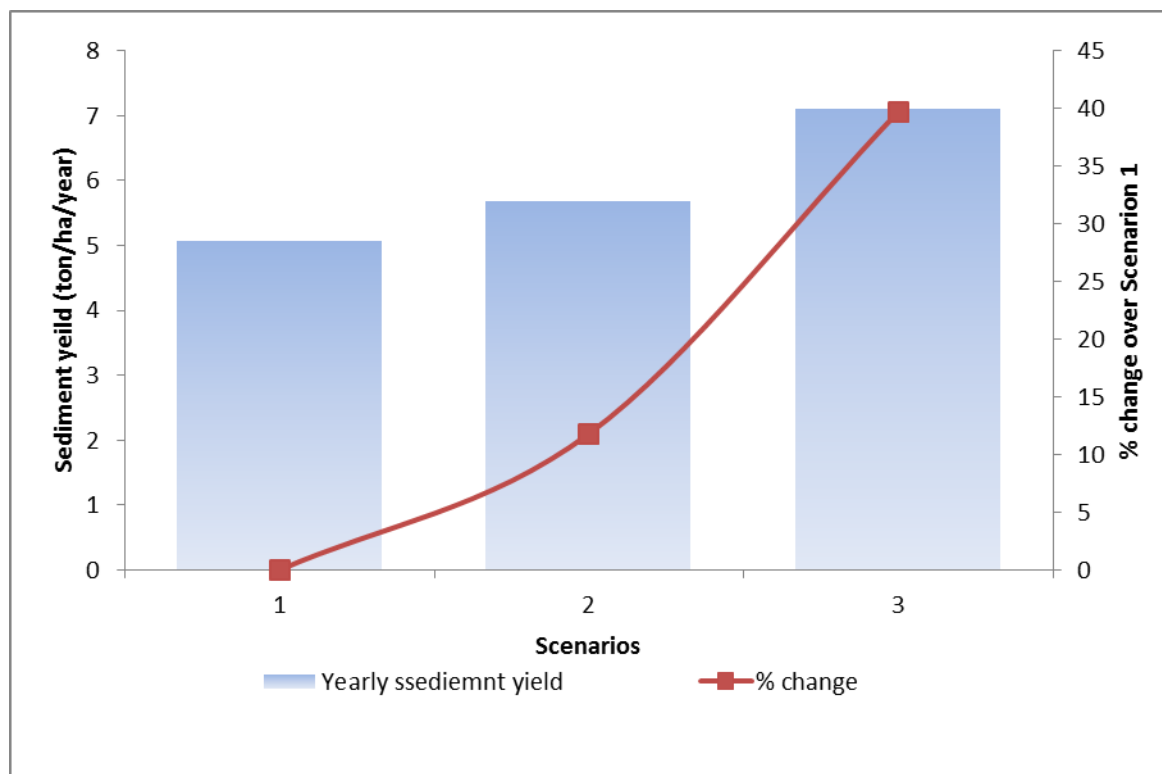


Figure 5.10 Yearly sediment yield at Clear Creek watershed under different scenarios (Scenario1: original corn price in year 2000-2008, Scenario2: 25% increase on original corn price since 2000-2008, Scenario3: 50% increase on original corn price since 2000-2008) with % change from baseline.

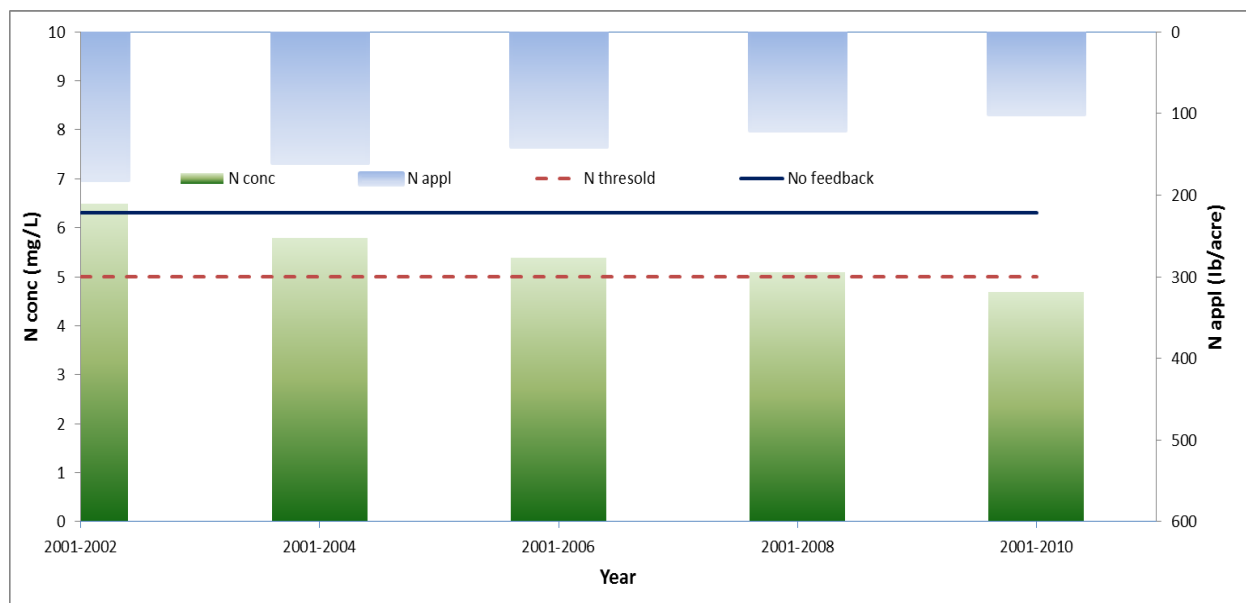


Figure 5.11 Illustrative example of iterative SWAT runs back to back with ABM in order to meet nitrate concentration goal at the watershed outlet.

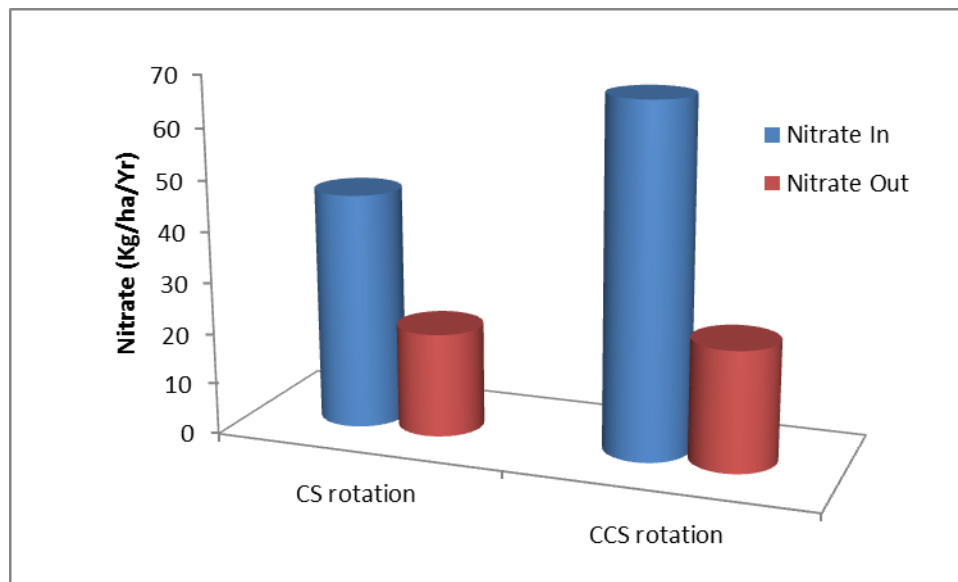


Figure 5.12 Nitrate inputs/outputs at watershed outlet (annual average over entire simulation period) due to shift from CS to CCS rotation.

Table 5.1 EPA Renewable Fuel Standard (RFS2) in billion gallons per year (NRC 2008)

	2005	2010	2015	2020	2022
Conventional bio-fuels	4	12	15	15	15
Biomass diesel	0	1	1	1	1
Advanced biofuels	0	0.1	1.5	3.5	4
Cellulosic Biofuels	0	0.4	3	13	16
TOTAL			20		36

Table 5.2 Operations for Corn Bean rotation used in SWAT

CORN-SOYBEAN		
YR (generic)	DATE	OPERATION
1	May 3	Generic Conservation till (Mulch)
	May 5	Fertilizer application
		(N-based, Anhydrous Ammonia@143kg/ha)
		(P-based, elemental P@70 kg/ha)
	May 10	Plant CORN
	May 13	Pesticides application (Atrazine @1.46 kg/ha)
	Oct 15	Harvest & Kill
2	May 3	Generic No till
	May 5	Fertilizer application
		(P-based, elemental P@70 kg/ha)
	May 10	Plant Soybean
	May 13	Pesticides application (Metalachor@1.59 Kg/ha)
	Oct 15	Harvest &Kill

Table 5.3 Water balance and nutrient results under CS to CCS rotation in the CCW from SWAT simulations, year 2000-2010

	C-S rotation	CCS rotation
Water Yield (mm)	150	148.4
Sediment yield (t/ha)	2.51	2.66
Nitrate (kg/ha)	20.4	23.5

Table 5.4 Typical switch grass operation schedule used in SWAT

Switch grass		
Year	Date	Operation
1	May 15	Plant Switch grass
	June 1	Fertilizer application
		(N-based, Anhydrous Ammonia@112 kg/ha)
		(P-based, elemental P@70 kg/ha)
	June 2	Pesticides application (Atrazine @1.46 kg/ha)
	Oct 25	Harvest only
Other parameters: LAI_INIT=0.5, BIO_INIT=500		

Table 5.5 Switchgrass production potential in the CCW based on IDNR 2001 landuse dataset

Scenario	Planted Area, ha
SG on all CS land	13,932
SG on CS land > 3% slope	10,310
SG on all CS, pasture lands	19,435

Table 5.6 Water balance and nutrient components under Switch grass production in the CCW

		SG conversion on		
		C-S	All CS	CS with slope>3%
Water Yield (mm)	150	148.1	147	147.3
Sediment yield (t/ha)	2.51	1.89	1.76	2.43
Nitrate (kg/ha)	20.4	19.6	18.8	19.41

Table 5.7 Sediment yield and nitrate load statistics under different market scenarios

	Scenario1		Scenario2		Scenario3	
	Sediment yield (t/ha)	Nitrate load (kg/ha)	Sediment yield (t/ha)	Nitrate load (kg/ha)	Sediment yield (t/ha)	Nitrate load (kg/ha)
Monthly average load	0.42	2.45	0.47	2.51	0.59	2.65
Std deviation	0.71	4.38	0.76	4.21	0.97	4.06
Sum	45.74	264.39	51.15	270.95	63.92	286.60
Yearly yield	5.08	29.38	5.68	30.11	7.10	31.84

Table 5.8 T-test result for nitrate load under different land use rotations

Rotation	P-value (Two tail, two sample equal variance)	P-value (Single tail, paired)
Stover 0% to Stover 25%	0.994	0.042
Stover 0% to Stover 50%	0.961	0.019
Stover 25% to Stover 50%	0.967	0.021
Corn-Bean to Corn-Corn-Bean	0.922	0.014

CHAPTER 6

ASSESSING CHANGES IN THE HYDROLOGIC CYCLE AT WATERSHED SCALE UNDER REGIONAL CLIMATE MODEL PROJECTIONS USING SWAT*

6.1 Introduction

Stream flow characteristics, both mean and variance, of the Upper Mississippi River Basin (UMRB) has large influence, e.g. environmental effects, economic effects etc., for the Central United States (Changnon et al 1996). Many studies have explored the impact of climate change on the hydrology (stream flow changes and other flow characteristics) at different spatial scale e.g. basin, watershed level at UMRB. Stone et al 2001 applied a regional Climate model 'RegCM' in Missouri River Basin to study the effect of climate change on the basin water resources, and in a subsequent study, Stone et al 2003 used the SWAT model to analyze the impact of climate model resolution on water yield in the same basin. They observed that water yield obtained from SWAT runs under the regional climate model (RCM) was higher than the yield obtained from running SWAT under Global climate models (GCMs). They also found that water yield in the sub basins were significantly different under different climate models and concluded that resolution of climate model played an important role in estimating water yield at the basin. In a similar study in UMRB, Arnell et al 2003 constructed different climate scenarios from a single climate model, compared runoff generated under each of them, and found that the runoff varied by 10-20%.

SWAT has been widely used to study the impact of climate change on basin hydrology.

* Adapted from Mishra et al 2013, "Evaluating watershed scale response to Regional Climate Change at Clear Creek, Iowa", manuscript in preparation.

Some of the important meteorological inputs required to run or sub daily precipitation, maximum and minimum air temperature, solar radiance, wind speed and relative humidity. SWAT also has an inbuilt weather generator that uses its statistical database and generates representative values for any missing meteorological variables at every sub basin. In this study daily values of precipitation and temperature, under present climate and different regional climate models, were supplied to SWAT.

6.2 Methodology

6.2.1 Building RCM driven SWAT

model for Clear Creek

This study built on using an existing calibrated and validated SWAT model to assess the impacts of climate change scenarios on the hydrologic responses at the watershed scale. A baseline scenario was first constructed with the current climate variable for years 2000-2010. Then climate scenarios were generated under each RCM by altering present climatic time series by a % increase or decrease as suggested by respective climate models (Figure 6.1 and Figure 6.2). The objective of this exercise was to detect changes various component of water cycle e.g. surface runoff, base flow, evapotranspiration etc.

In this study precipitation, maximum and minimum temperature, between present and future projections under NARCAAP climate models were used to generate climate series which then used to run SWAT. According to NARCCAP website (narccap.ucar.edu): *“The North American Regional Climate Change Assessment Program (NARCCAP) is an international program to produce high resolution climate change simulations in order to investigate uncertainties in regional scale projections of future climate and generate climate change*

scenarios for use in impacts research. NARCCAP modelers are running a set of regional climate models (RCMs) driven by a set of atmosphere-ocean general circulation models (AOGCMs) over a domain covering the conterminous United States and most of Canada.” RCM models used in this work are shown in Table 6.1.

Figure 6.4 shows the annual average precipitation and temperature under different RCMs for near future condition. These values were obtained after altering present weather time series in SWAT (for precipitation, maximum and minimum temperature) by the percentage change obtained by analyzing corresponding RCM models. After running SWAT with altered weather time series data, output files were analyzed to understand the trend in different hydrologic components e.g. surface flow, base flow, evapotranspiration and deep recharge. Annual average values of those components were then normalized with corresponding precipitation values in order to get fractional quantities e.g. runoff ratios, ET ratios etc.

6.2.2 Flow statistics and flow indices:

Richards-Baker Flashiness Index

Richards-Baker Flashiness Index (Baker et al 2004) measures: “*oscillations in flow (or discharge) relative to total flow (or discharge). R-B Index has much less annual variability and reveals many more trends in discharge data*”. R-B index is given by:

$$\text{R-B Index} = \frac{\sum_{i=1}^n q_i - q_{i-1}}{\sum_{i=1}^n q_i}$$

Where the value of q_i and q_{i-1} are treated as daily discharge volumes (m^3) or as average daily flows (m^3/s) at time step i and $i-1$ respectively.

6.2.3 Budyko diagram

Budyko curve is a widely used diagram in hydrologic science which represents the characteristics of annual water balance for a watershed. It basically represents different water balance fraction in a watershed, plotted in an X-Y coordinate system. X axis denotes the ratio E/P and Y axis denotes the E_p/P fraction where E is actual evapotranspiration and E_p is potential evapotranspiration. E/P represents annual water balance and it denotes how rainfall is separated into evaporation and runoff whereas E_p/P ratio is a representation of the climate, and is often called as the dryness index (or index of dryness). Large value of dryness index (>1) denotes dry climate whereas a small value of it (<1) means wet climate (source: http://civil.colorado.edu/~balajir/CVEN5333/Lectures/OLE2_MSpart1.pdf).

6.3 Results and Discussion

SWAT model was run under different RCMs with altered weather time series and was able to simulate the seasonal trend in runoff in CCW with an estimated annual average runoff of 281.9 mm. Runoff is proportional to the difference between precipitation and evapotranspiration in SWAT model. Seasonal distribution of SWAT generated stream flow shows that precipitation in winter months generated high spring stream flow whereas lower precipitation during summer months resulted in low stream flow in the late summer. Stream flow was analyzed at monthly and annual time steps whereas base flow, ET was estimated on annual scale in this study.

Figure 6.1, 6.2 and 6.3 below show changes in precipitation, minimum and maximum temperature in near future over present climate. Most of the RCM models show similar trends in precipitation change throughout the seasons except for June, July August. Amongst the models, HRM3 shows highest change in precipitation while RCM3 shows the least. The pattern of

maximum and minimum temperature change was similar throughout. Significant changes occur during June-July-August period for both maximum and minimum temperature, and it is lowest during March-April-May period.

Figure 6.5 show that runoff coefficient is highest under MM5 model projection and lowest under CRCM model projection. This is in agreement with Figure 6.1 which shows that the seasonal precipitation increase at the pre crop period (March-April-May) is a maximum under MM5 and minimum under CRCM. This is in agreement to the fact that at pre crop period ET would be lower and the surface runoff would tend to be higher. Figure 7.6 shows that ET/P ratio is lowest for MM5 and highest under CRCM which is in agreement with the plots in Figure 6.5, as higher runoff ratio would result into lower ET/P values.

Figure 6.5 suggest that runoff coefficient is going to be higher under most of the RCMs and it will increase the monthly stream flow under future climate scenarios. The mean annual precipitation is estimated to increase maximum by 14.3% under MM5 model and minimum by 0.4% under CRCM model. Annual average stream flow is expected to increase maximum by 4.2% under MM5 model due to the precipitation changes discussed before. This non proportional (Figure 6.14) changes in the stream flow due to the change in precipitation; can be explained by the fact that more precipitation falling on saturated soil will generate higher runoff in the watershed.

Figure 6.8 shows the monthly runoff coefficient distribution over ten year simulation under different climate models. A higher runoff coefficient during early spring months indicates precipitation falling in saturated soil and thus creating fast runoff response. Base flow fraction (backflow to total flow) in the simulation data was widely distributed with the lower values of 10 % which went up to 90% during extreme cases (Figure 6.9). The broader-scale effects of climate

change on the flow regime of the CCW indicate an overall slight drying of the basin as a consequence of increased evapotranspiration (Christiansen et al 2012).

Figure 6.10 shows RB index calculated over monthly discharge data from SWAT runs under different RCM models. Figure 6.11 plots 99 percentile of monthly discharges obtained from all model runs (by changing precipitation, temperature and both) with RB index, although there was not any specific trend observed for the watershed. Variation of monthly average discharge data over the 10 years simulation period can be represented by a box whisker plot as shown in Figure 6.12. MM5 model created maximum variation in discharge obtained from SWAT simulation, which is due to the fact that maximum change in precipitation and temperature occurred under MM5 model. But all the models showed a median monthly Q of 14.44 +/- 4.37 mm

Figure 6.13 shows Budyko curve for Clear Creek watershed plotted with data from obtained from different RCM model runs. CCW slightly falls under water limit region according to Budyko curve and will remain the same under the future climates too (Figure 6.13).

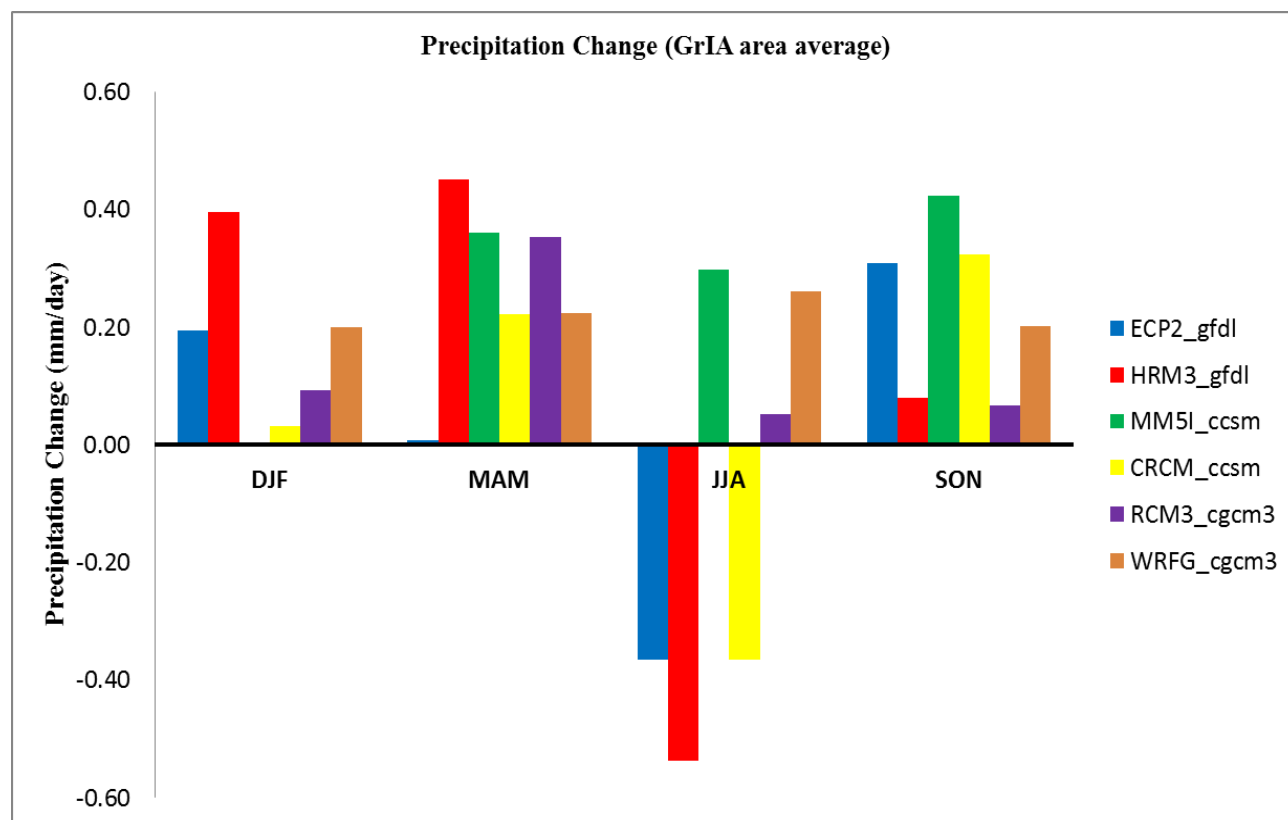


Figure 6.1 Seasonal changes in precipitation under different RCMs from present (1971-2000) to near future (2041-2070) (source: narccap.ucar.edu, data processed by Prof William Gutowski of ISU)

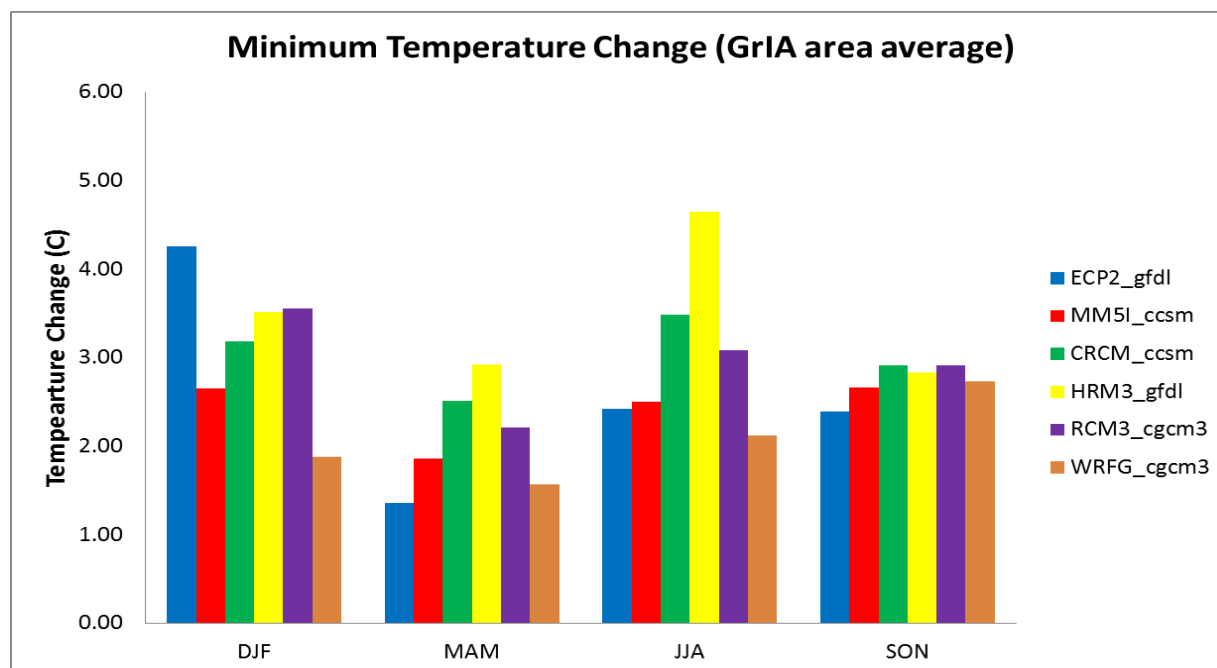


Figure 6.2 Seasonal changes in minimum temperature under different RCMs from present (1971-2000) to near future (2041-2070) (source: narccap.ucar.edu, data processed by Prof William Gutowski of ISU)

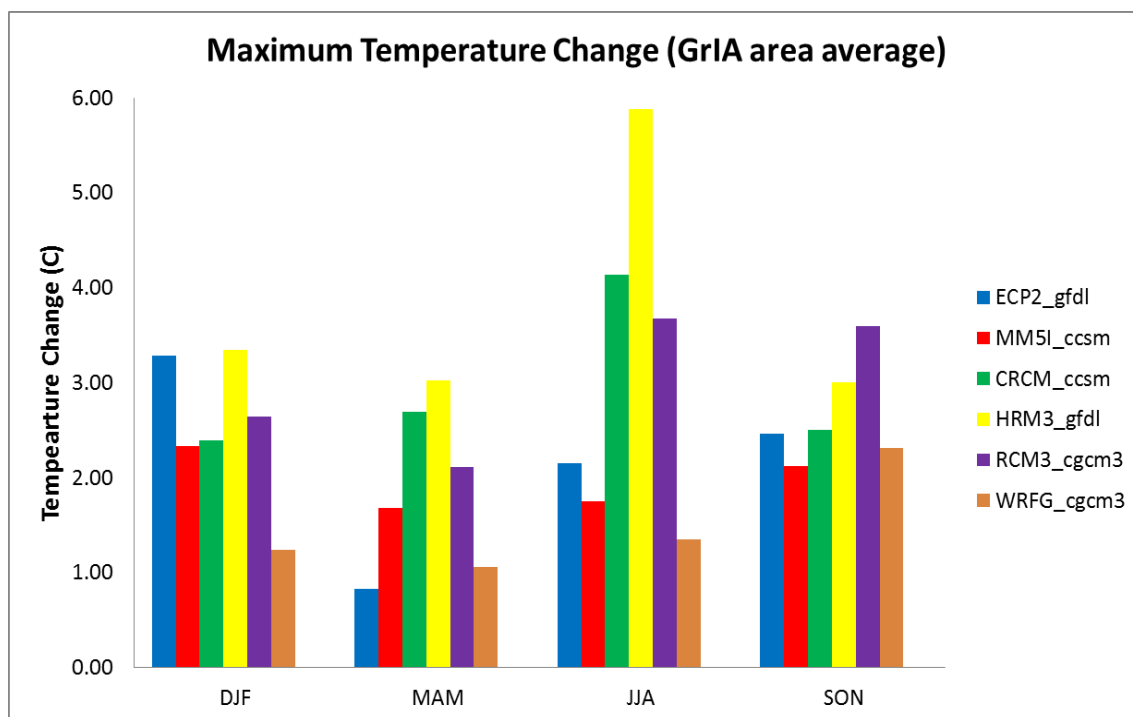


Figure 6.3 Seasonal changes in maximum temperature under different RCMs from present (1971-2000) to near future (2041-2070) (source: narccap.ucar.edu, data processed by Prof William Gutowski of ISU)

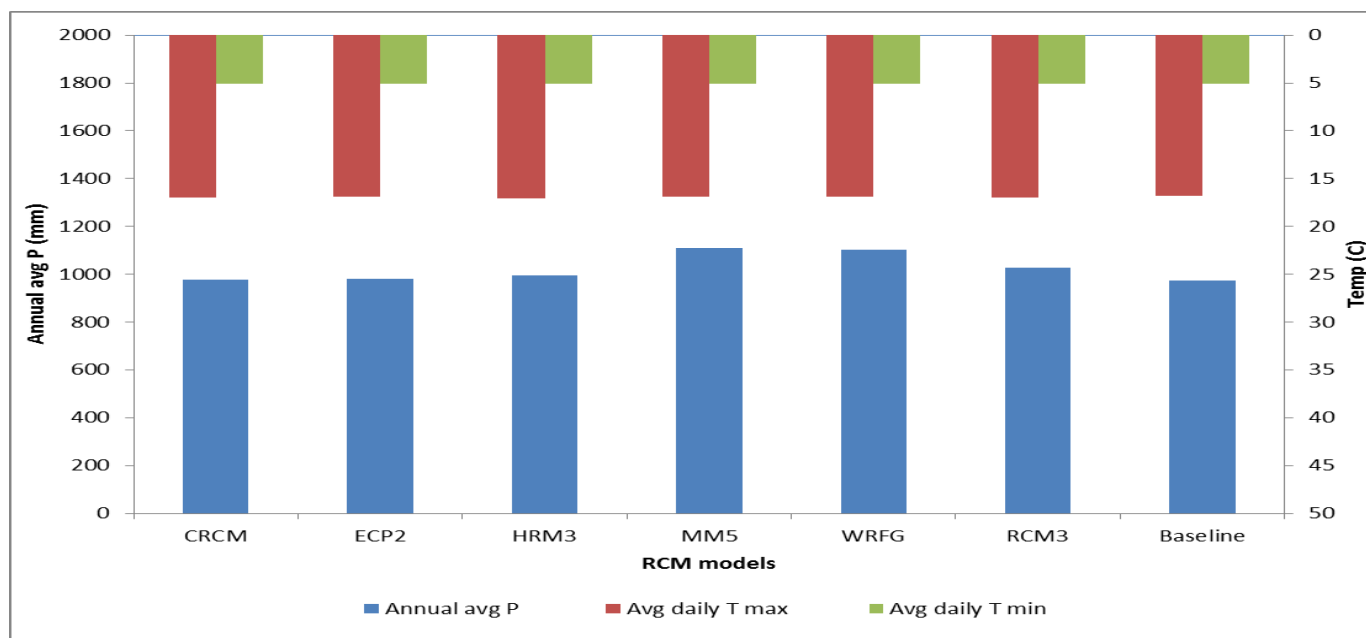


Figure 6.4 Annual average precipitation and average daily maximum, minimum temperature under different RCMs for near future condition (2041-2070) (source: narccap.ucar.edu, data processed by the author)

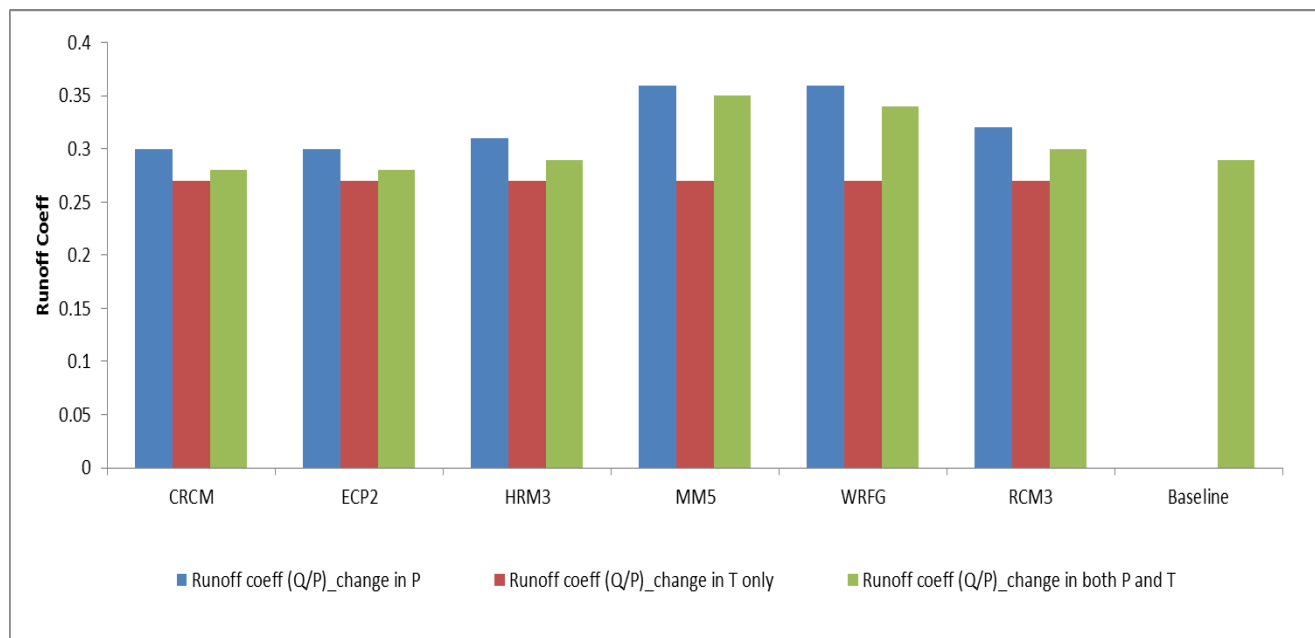


Figure 6.5 Annual runoff coefficients under different RCMs with cases considering changes in precipitation, temperature and both under ten years simulation, 2000-2010 (using values obtained from figure 6.1 and 6.2).

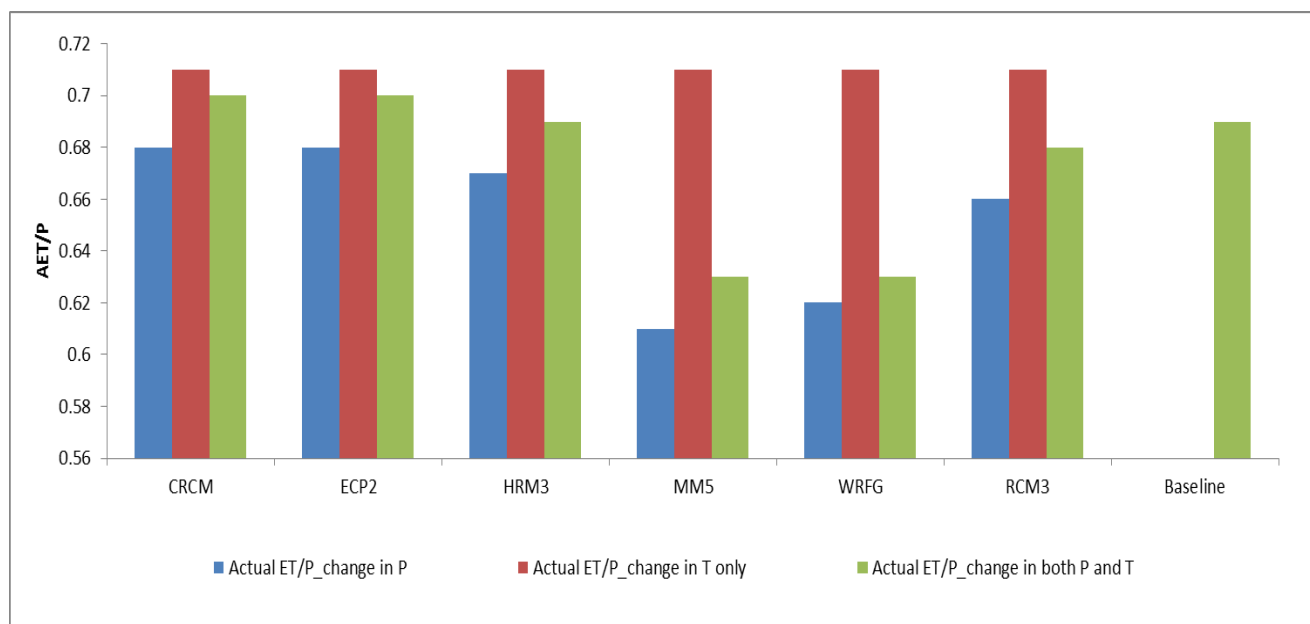


Figure 6.6 Annual actual evapotranspiration to precipitation ratio under different RCMs with cases considering changes in precipitation, temperature and both under ten years simulation, 2000-2010 (using values obtained from figure 6.1 and 6.2).

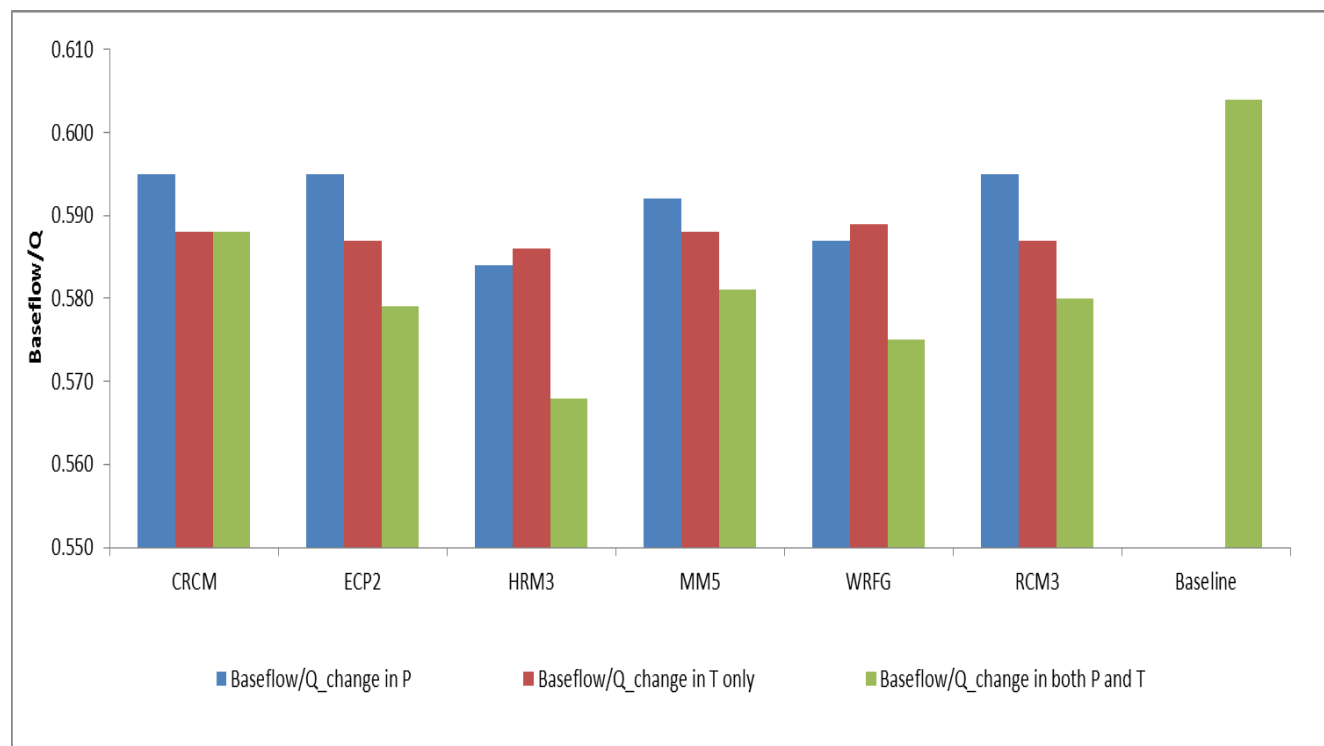


Figure 6.7 Annual base flow to discharge ratio under different RCMs with cases considering changes in precipitation, temperature and both under ten years simulation, 2000-2010 (using values obtained from figure 6.1 and 6.2).

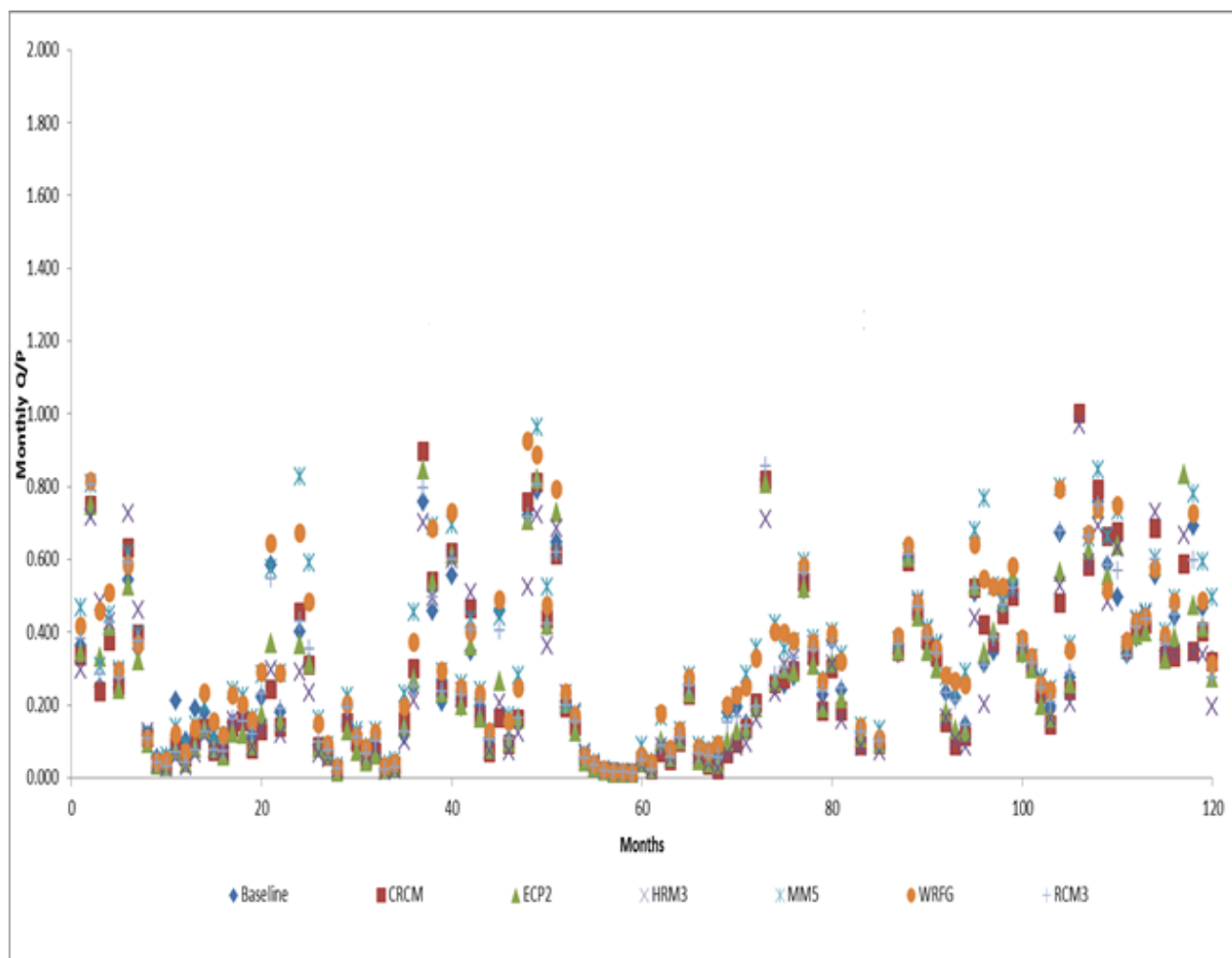


Figure 6.8 Monthly runoff coefficient distribution under different climate models under ten years simulation, 2000-2010 (using values obtained from figure 6.1 and 6.2).

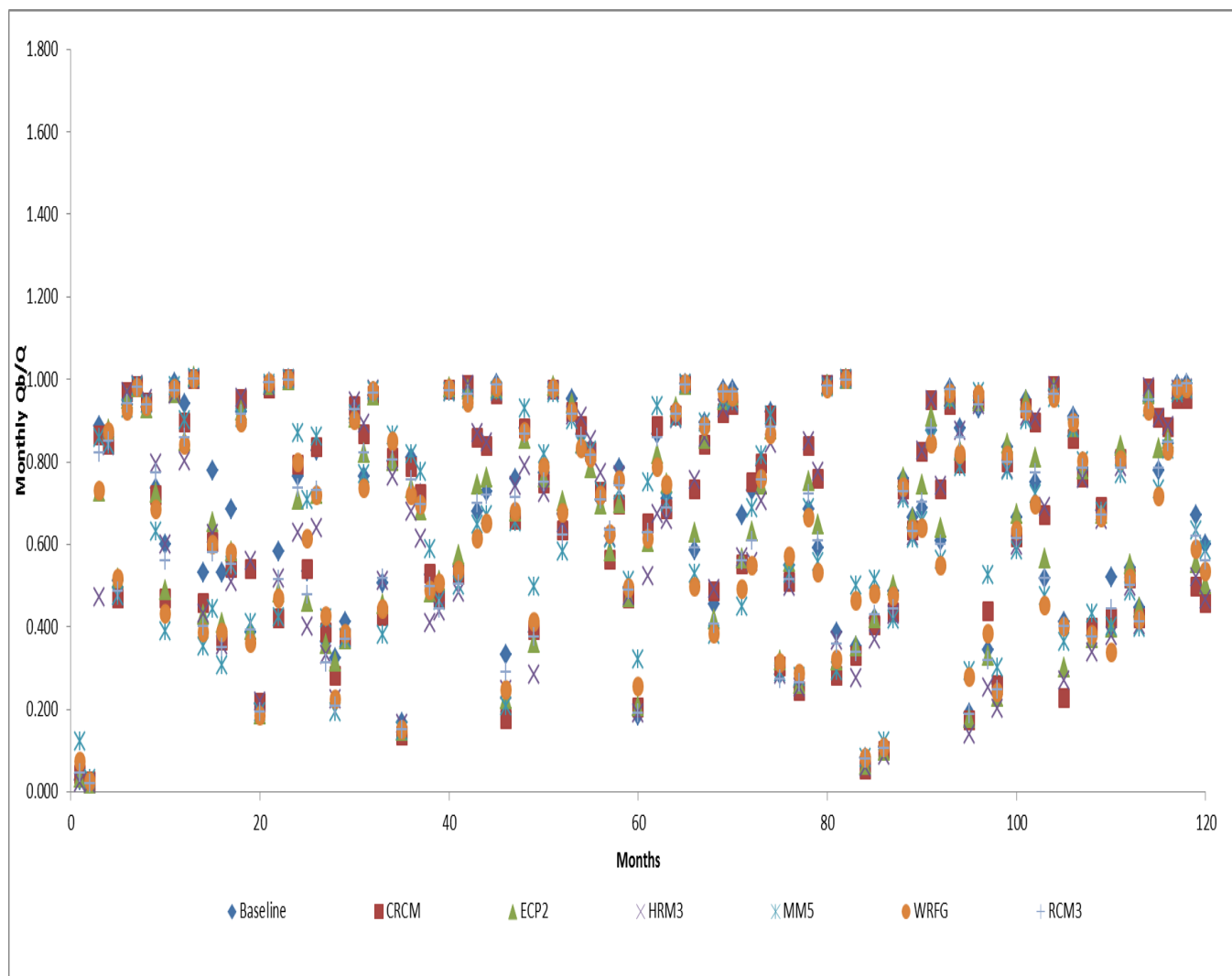


Figure 6.9 Monthly base flow fraction distribution over ten year simulation period under different climate models under ten years simulation, 2000-2010 (using values obtained from figure 6.1 and 6.2).

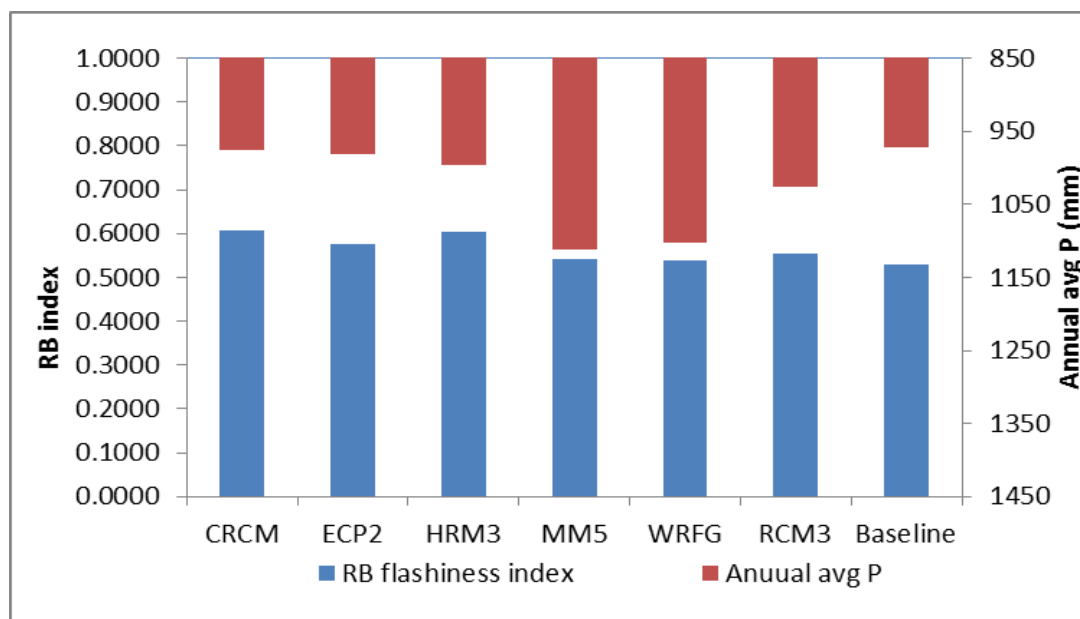


Figure 6.10 Richard Baker flashness index and annual average precipitation obtained under different RCM under ten years simulation, 2000-2010 (using values obtained from figure 6.1 and 6.2).

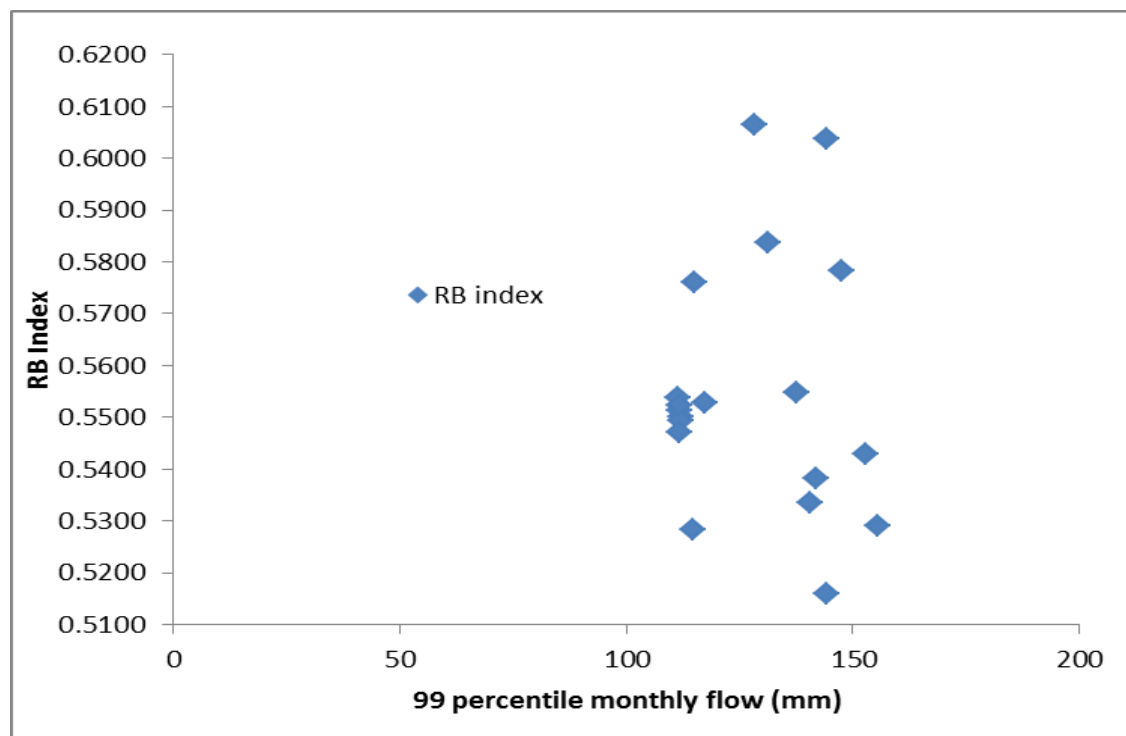


Figure 6.11 RB index plotted against 99 percentile of monthly flows under all runs under ten years simulation, 2000-2010 (using values obtained from figure 6.1 and 6.2).

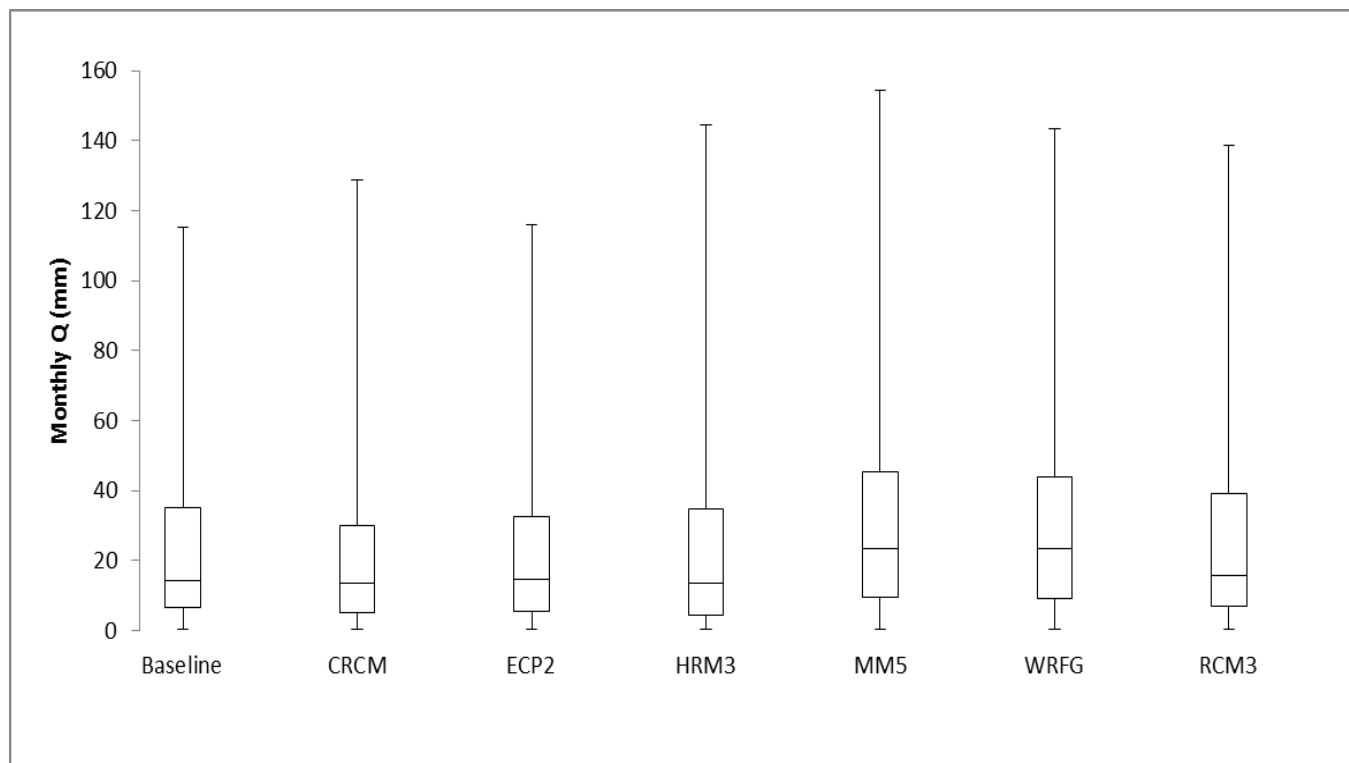


Figure 6.12 Box whisker plots of monthly flows under different RCMs under ten years simulation, 2000-2010 (using values obtained from figure 6.1 and 6.2).

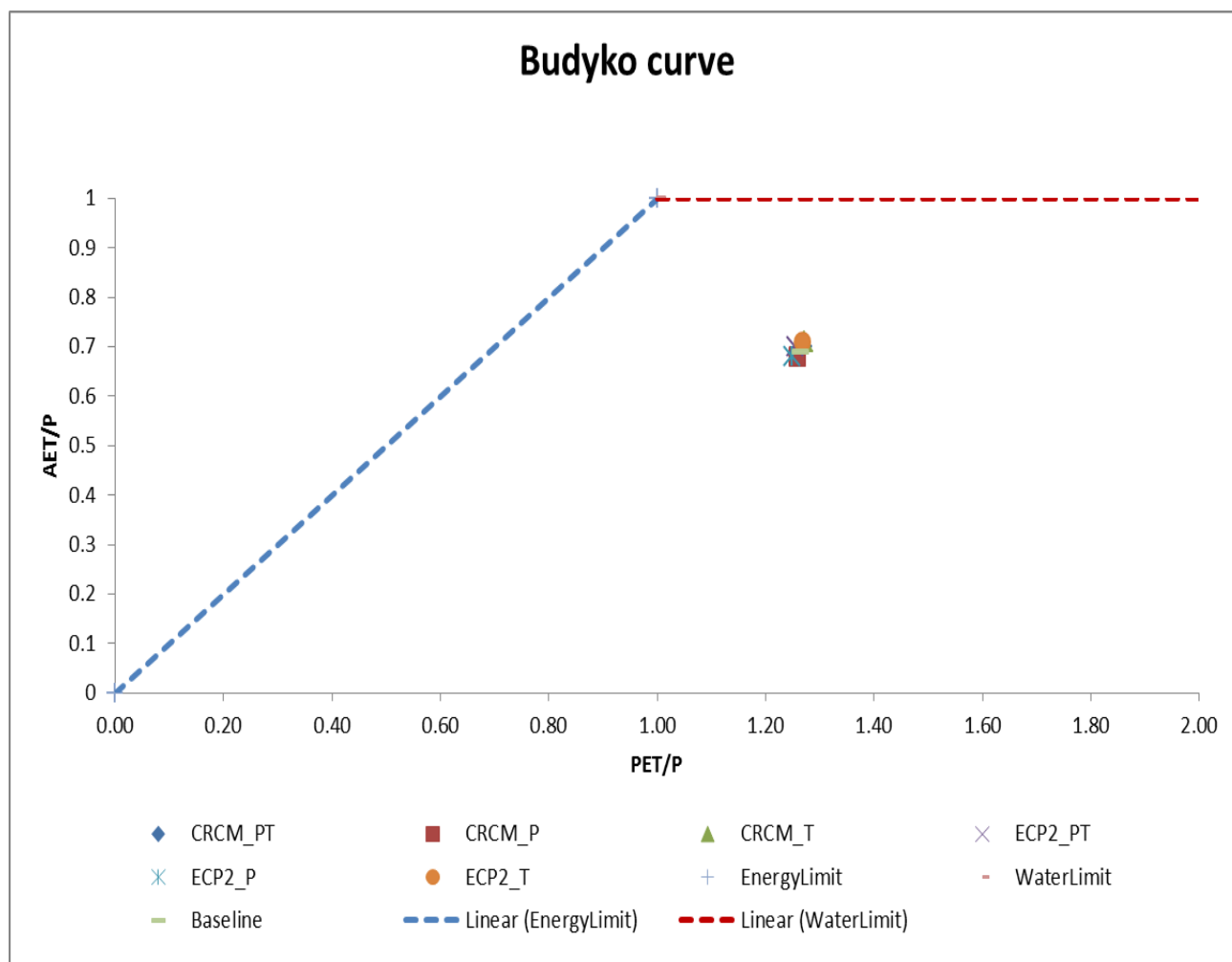


Figure 6.13 Budyko plot for different RCM for Clear Creek watershed under ten years simulation, 2000-2010 (using values obtained from figure 6.1 and 6.2).

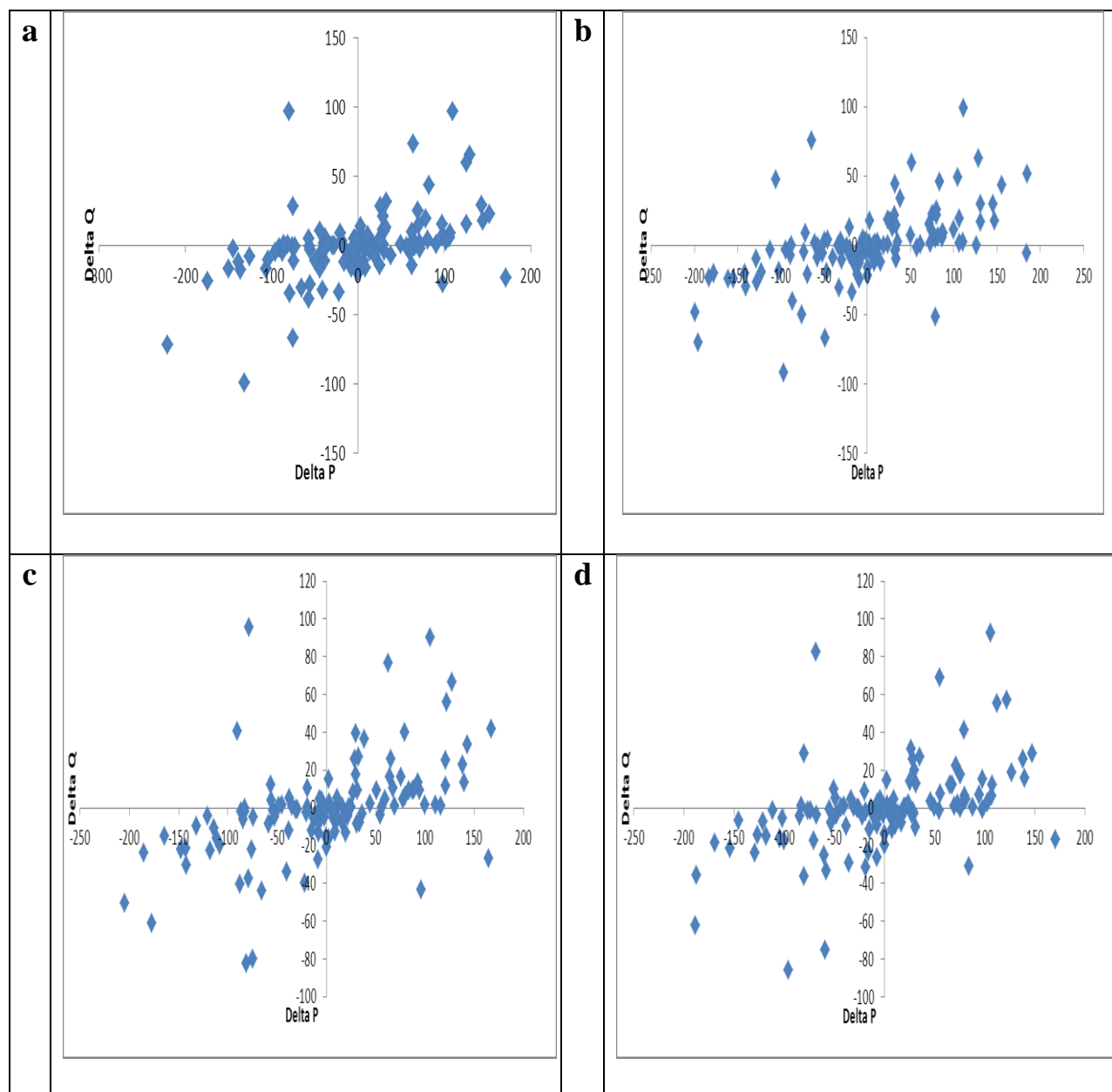


Figure 6.14 Delta P Vs Delta Q plots of monthly data under different RCMs for ten years simulation, 2000-2010: a) HRM3 b) MM5 c) WRFG d) RCM3

Table 6.1 Different climate model used in this simulation (source: www.narccap.ucar.edu)

Regional Model	Model Center
CRCM	OURANOS / UQAM, Canada
ECP2	UC San Diego / Scripps Institute of Oceanography, USA
HRM3	Hadley Centre for Climate Prediction and Research, UK
MM5	Iowa State University, USA
RCM3	UC Santa Cruz, USA
WRFG	Pacific Northwest National Lab, USA

Table 6.2 Statistics of monthly precipitation distribution under different climate models

	Baseline	CRCM	ECP2	HRM3	MM5	WRFG	RCM3
Monthly mean (mm)	80.99	81.85	82.38	83.49	93.22	92.52	86.14
Monthly standard deviation	57.22	56.67	55.28	57.95	66.01	63.28	60.77

CHAPTER 7

INTELLIGENT DIGITAL WATERSHED*

7.1 Introduction

The amount of data and information needed to support decision-making processes in the current complexity of integrated watershed approaches is daunting because decision support systems must capture the functionality of water-cycle centered natural systems and its dynamic and multiple interactions with human systems. Given this key role played by data and information in the decision-making process, there is a critical need to develop and implement monitoring and information management systems based on new information technologies and system architectures. Given that today's natural scale processes are intrinsically connected with the management practices of humans and much of the observational infrastructure is operated by practitioners, the watershed-related scientific and research communities recognize the need to develop common platforms that can be used both for scientific explorations and decision making.

This chapter aims to illustrate the utility of an advanced CI implementation designed to help understanding of the impact of alternative watershed management scenarios on ecological processes, conservation efforts, economic return and public perception about environmental health. The scientific inferences facilitated by these developmental efforts are also relevant to decision makers and actually difficult to estimate using alternative tools.

This chapter illustrates an implementation of an end-to-end CI system for understanding of

* Adapted from Muste, M., Bennett, D.A., Secchi, S., Schnoor, J.L., Kusiak, A., Arnold, N.J., Mishra, S.K., Ding, D., Rapolu, U. 2012. "End-to-End Cyberinfrastructure for Decision-Making Support in Watershed Management," Special issue on Cyberinfrastructure – Journal of Water Resources Planning and Management, American Society of Civil Engineers, Reston, Va., doi: 10.1061/(ASCE)WR.1943-5452.0000289

the ecological threats, shifts in soil conservation practices, and public perception of environmental health with preservation of the economic benefits of agricultural production at the watershed scale. The systems were implemented in a 270 km² Clear Creek catchment in eastern Iowa.

7.2 Architecture of the CI Systems for Decision-Making Support

The CI-based systems discussed herein are electronic representations of the watersheds and their processes as documented by data and the spatio-temporal representation of the data, simulation models, and the analysis and synthesis of the available data and information. They contain the means to track the movement of water, sediments, contaminants and nutrients through the environmental system. These systems must embrace the best available information to provide the digital description of the natural environment and the man-made constructed infrastructure (e.g., dams, water abstraction and discharge systems) using a variety of data sources. Although the internet has improved access to these disparate data sources, gathering the data required for most eco-hydrologic studies requires visiting multiple online sites, each with its own access protocols and data exporting formats. For systems as complex as watersheds, the CI-based technologies hold the greatest promise for advancing both scientific insights and management. Given the variety and extent of information, however, the CI design is driven by the needs of scientific and management communities and increasingly developed with a collaborative perspective in mind.

In the last several years, efforts in the U.S. to develop CI-based systems for integrated watershed studies have been led by two National Science Foundation (NSF) communities: the Consortium of Universities for the Advancement of Hydrologic Science, Inc. (CUAHSI) and the

WATER and Environmental Research Systems Network (WATERS Network). The latter initiative was dissolved in 2010. CUAHSI and WATERS Network promoted alliances among U.S. universities and the development and implementation of CI-based observatories for the examination of watersheds. These communities labeled the CI investigation platform with the term Digital Observatories. The term observatory was adopted from the astronomical community to suggest the massive datasets and information that are acquired over large spatio-temporal scales. The CI-based observatories promoted by CUAHSI and WATERS Network are not unique to the U.S. or world scientific communities. In the past decade, a number of similar initiatives have been launched in the U.S (e.g., National Ecological Observatory Network, Long Term Ecological Network, Earthscope) and around the world (e.g. World Meteorological Organization's World Hydrological Cycle Observing System). They focus on distributed data collection, management, and the operation of a network of observing stations and interactions among scientific activities across time and space.

Currently, there are no comprehensive frameworks, or off-the-shelf components and modules available that can be integrated into an operational end-to-end CI system for scientific enquiry. Their design and implementation is guided by the practical needs of specific scientific investigations or management-related concerns. While providing a detailed technical architecture for a CI-instrumented system is challenging, an attempt is made in Figure 7.2 to illustrate the system's overall architecture and its key CI elements (Muste 2007). This architecture continues to evolve through an open and participatory community-driven effort similar to other Internet projects. In general, these CI systems are based on an open services-oriented architecture (SOA) that machine-to-machine communication capabilities using internet protocols and standards. This architecture loosely couples self-contained services that

communicate with each other, and that can be called by multiple clients in a standardized fashion (Maidment 2005). This architecture facilitates the automation of time-consuming activities, allowing scientists and engineers to spend more time interpreting data and developing insight into associated processes (Foster 2005). Additional benefits associated with the service-oriented architectures include: scalability, security, easier monitoring, standards-reliance, interoperability across a range of resources, and plug-and-play interfaces. Provided below is a brief description of the CI system modules and the CI tools and functions associated with each module.

7.2.1 Observing Systems and Networks (OSN)

This component entails instruments and communication technologies for data collection within the targeted watershed. The measured variables are related to a wide range of watershed processes and are increasingly acquired and reported in near-real time using specialized CI (hard wired or wireless communication). Data can be acquired by “third parties” (i.e., typically federal or state agencies) as well as local individual investigators. Typical examples of 3rd party-data are point source time-series observations acquired by the National Water Information System, National Water Quality Assessment, EPA STORET and Climate Data Online (with USGS, EPA, NCDC as providing agencies) and spatially distributed observations usually obtained with remote sensing (with NASA, NOAA, USGS as primary provider agencies). The parameters that guide automatic and real-time sampling (e.g., temporal or spatial resolution) of the variables of interest must balance issues related to power requirements and availability, sampling requirements given the dynamic nature of the processes under investigation, and the funds available. Continuous unsupervised operation and data quality control are often implemented to ensure that the delivered data are continuous (no missing values) and fulfil the accuracy levels

required by data consumers. Future deployed instruments can be clustered in observational networks, remotely operated, and equipped with capabilities to communicate among themselves to adjust operating parameters (e.g., sampling rates) through feed-back loops connected to the central monitoring server. The link between CI and sensor networks is strong and necessary as many of the implemented sensor networks will generate significant quantities of data that must be managed by the CI. The acquired data is used for monitoring, analysis, in conjunctions with modelling, and for extraction of information and knowledge.

7.2.2 Digital Watershed (DW)

Central to the engineered system is the digital watershed that seamlessly connects data models (DM), modeling and synthesis (MS) and digital libraries (DL). DW is a comprehensive characterization of ecohydrologic systems that use integrated data and simulation models to facilitate the study of the multi-scaled, multi-process dynamics of watersheds (Maidment 2006). DW are populated with data and information from the best available data sources, both hosted by the observatory and stored in external data repositories and from the metadata associated with the sources. In most of the cases, data are also available as a result of running numerical simulations for water-related processes. Using data from these varied sources requires visiting multiple websites, each with its own access protocols, terminology and data export formats. These inconsistencies in format (syntactic differences) and terminology (semantic differences) inhibit integrated analyses (Maidment 2010). Valuable data exists that are not being used to their fullest, solely because it is too difficult to find, interpret, access and/or transform into a format suitable for analysis.

Many DW aspects presented herein stem from the CUAHSI-Hydrologic Information System (CUAHSI-HIS) project as this research group is familiar with them and they illustrate well the concepts and functionalities assembled in CI-based systems. CUAHSI-HIS project has the goal of developing standards, systems, and software to enhance access to and interoperability among water data from multiple sources and to facilitate the discovery, publishing, cataloging, and visualizing of these data in support of analysis (Tarboton et al. 2009). The data formats for transmission among various CUAHSI-HIS functions follow strict protocols, ontologies, lexicons, and standards (e.g., Open Geospatial Consortium, Geographic Markup Language). Recently, several U.S. water-related management agencies have also adopted some of these standards for their data management systems.

Data Model (DM) in this context refers to a permanent information infrastructure that stores data on water-cycle fluxes and the related environmental processes over large domains and multiple scales. DM applies to any type of waterbody, i.e., watershed, lake, estuary, coastal area. It digitally describes watershed features including GIS data (terrain, stream network, soils, land cover, geology), hydrologic observations (streamflow, groundwater levels), weather and remotely sensed data, data produced by weather and climate models, upland and in-stream water quality data collected using in situ sensors (pollutant types and levels, habitat characteristics), and socio-economic data within the boundaries of the waterbody. The type of data hosted in DM can include time series, static geographic data, slowly varying geographical data (vegetation), and high frequency gridded data (from observations or models). Collectively they are referred to as “data packets” (Tarboton and Hooper 2010). Historical data and recent observational information are stored in a relational database (Codd 1970). In addition to the actual data, this database accommodates the associated metadata, i.e., attributes that accompany the data such as

their names, data type, and context for getting high granularity information about the data (Horsburgh et al. 2008). Controlled vocabulary, rigorous and uniform metadata specifications, ontologies, and semantic mapping are associated with the DM construct facilitate data selection and discovery functionality.

Besides storing the data, DMs are equipped with specialized CI that facilitates the efficient communication (loading and retrieval), organization, editing, querying, visualization, analysis, and publication of the stored data (Horsburgh et al. 2011). Access to 3rd party and locally acquired data relevant to a broad array of disciplines and water-related problems is made available through web services and dedicated web portals. Web services are applications that provide the ability to pass information between computers over the Internet, typically based on a platform independent markup language, such as eXtensible Markup Language (Goodall 2005). Standardized markup languages exist that fulfill the needs of various research communities and are built on common interfaces and formats within a SOA. Web services are used in conjunction with the access, transmission, and publication of the data. The DM developed by the CUAHSHIS project classifies the publication of the data packets as: data cart and themes. The first type designates a list of datapackets (usually formed as a result of a query) with all the specifications needed to access the information that contains the pointers to the data. The second type of data packets contain the data and metadata (usually created through downloading a data cart, for example) as well as various value added work done after the theme was created. Access control is maintained at the level of the datapacket.

Finally, data visualization is vitally important as a way to communicate to user exactly what the data to be acquired represents and as a way for them to inspect and explore the data prior to downloading large datasets. Monitoring sites can, for example, be superposed onto watershed

maps to provide geographic context via the web portal. Visualization can be highly automated (and often running in real time) and represented as maps, plots, or numerical information within conventional web browsers that do not require the user to possess special technical skills. The DM equipped with the features described above enables geographically remote users to discover, query, visualize and retrieve data of interest from various sources using map-based, point-and-click web-portals (Horsburgh et al. 2011). Beyond accessing the data, the role of the portal is to provide a uniform view over multiple concurrent project efforts, preliminary data analysis and visualization, and to organize multiple resources into executable workflows.

7.2.3 Modeling and Synthesis (MS)

Modeling entails process conceptualization and methodologies that map inputs to outputs. They create a unifying framework for the synthesis of field information, improvement of sampling strategies, testing of hypotheses, and identification of optimal management strategies for complex systems that minimize cost (including environmental degradation) and maximize the performance of a water body through feedback loops. Conventional model-based simulation approaches make use of a sequential process, based on difficult data collection and preparation, periodic and disconnected simulations, followed by post-processed visualization and analyses. This approach increases cost through the inefficient use of human and computer resources, loss of information, and excessive offline operations that increase the time lag between questions and answers. This fragmented approach forces individuals to think inside the box by using highly simplified models over small geographic areas, and results in a significant gap between what is possible and what is practical, and between basic research and the practice of modeling/visualization. Customized meta workflows allow software operations that are typically

executed manually and in sequence because of data dependencies and required data transformations to automate as user-friendly interactive systems where the data/ model fusion takes place in real time to produce simulations.

Data ingestion, conversion, and transformation are tedious processes involving a large number of small tasks of various kinds that often take a great deal of time. A workflow sequence is a defined set of operations that can be executed in order with data passing automatically from one operation in the sequence to the next. Several workflow sequencing environments are available (e.g., the ModelBuilder for ArcGIS). Regardless of the type of workflow sequence, the principles are the same – take a graph of operations and execute them in a defined way that can include standard programming control structures like branching and looping. These operations may be preprogrammed software modules built as standard tools for a workflow environment, or they may be custom tools created by an investigator within the problem-specific environment to execute specific simulation models. Thus, a simulation model can be thought of simply as a tool in an information system, which takes in information from other tools, and produces information which goes on to other tools.

7.3 Prototype CI-based System for Clear Creek Watershed in Iowa

The CI implementation examples provided below have been developed with support from the National Science Foundation (<http://nsf.gov>) thought projects carried out by University of Iowa interdisciplinary research teams since 2003. These successive projects has enabled the assembly of a suite of CI-based systems associated with watersheds (or jurisdictions) of widely different areas, as illustrated in Figure 7.3.

7.3.1 Data storage and information production

The applications presented herein were prototyped for the 270 km² Clear Creek watershed, an intensively instrumented and investigated site located near the university campus. Since 2003, this catchment has been subject of intensive interdisciplinary research with strong emphasis on CI, hence becoming an ideal location for researchers to demonstrate how an information-centric approach can be used to address complex and unresolved science questions and support decision-making. The watershed was one of the 11 national test beds serving as beta test locations for the deployment of CUAHSI-HIS project products (Just et al. 2007; Schnoor et al. 2008). The initial goal of these efforts was to access and store data provided by diverse sensors and communication means with simple numerical models into an end-to-end system that can describe electronically the watershed through data and information (Figure 7.4). The CI-based system, labeled Clear Creek Digital Watershed (CCDW), operates via the Internet in real time through a user-friendly browser that does not require technical or computer skills (<http://his08.iuhr.uiowa.edu/uicc>).

7.3.2 Knowledge extraction from data and information

The complexity of the models and workflows connecting data and model embedded in CCDW has gradually increased leading to fully functional CI systems that are capable of extracting knowledge from the data stored and information produced by the system. The most recent development of our team is the assemblage of a prototype “intelligent” CI platform that not only accesses, stores, and displays a variety of heterogeneous data, but also enables understanding of the links between shifts in soil conservation practices and the water quantity and quality in watershed streams as well as the public perception of environmental health. To

help explore these connections an Agent-based Model (ABM) and Soil Water Assessment Tool (SWAT) models are used. The overall CI architecture and the operational steps for the user are illustrated in Figure 7.3

ABM was developed to simulate land use change based on decisions made by farmers given alternative assumptions about market forces, farmer characteristics, and water quality regulations (Bennett et al. 2012). SWAT is a widely used semi distributed watershed model for predicting the impact of land management practices on water, sediment, and agricultural chemical yields in large, complex watersheds with varying soils, land use, and management conditions over long periods of time (Arnold et al 1998). SWAT model is used to simulate the impact of these decisions on the movement of sediment, nitrogen, and phosphorus across the landscape. The SWAT and ABM models are embedded in a CI platform that links the two models through a web-based interface and provides a feedback loop that connects land use to water quality, and subsequently water quality back to land use.

7.3.3 ABM workflow

ABM simulates actions and interactions of heterogeneous autonomous agents in complex adaptive systems (Bennett and McGinnis 2008). Agents are autonomous but ranked in terms of importance to reflect the system complexities. Agents in the system make decisions and behave based on specific decision-making heuristic, learning and adaption rules. To simplify the system simulated in an ABM, external variables in a non-agent environment are specified and parameterized instead of involving high-level agents in the system. The ABM developed by this research team is focused on land use modeling. It was developed to capture and represent: 1) the heterogeneous set of driving forces on land-use decisions, 2) the interactions among agents, and

between agents and environment, and 3) the complex feedback mechanisms and non-linear dynamics. The workflow elements and operational steps to execute the ABM workflow are illustrated in Figure 7.3.

The ABM presented in the paper anticipates farm-based decision-making in response to alternative scenarios of: climate, federal energy and agricultural policies, and market value of crops and fuels. Before simulating the decision-making process data about commodity prices, soils, and parcel boundaries are loaded into the system to create and initialize farmer agents, farm fields and farmer net objects. With a scenario selected, ABM is ready to run. The ABM process is composed of a single initialization on Common Land Units (CLU), and multiple simulations with different sets of attributes specified for all the farms and farmer agents. The input files for ABM are: 1) prescribed physical attributes of CLUs, which includes CLU-farm relationship, previous crop, soil fertility and erodibility, and CLU geometry, etc.; 2) prescribed monetary values of crops and fuels, which integrates both market prices, and federal energy and agricultural policies. Specifications for the social-economic attributes of farm and farmers involve are based on statistical distributions derived from a land use survey data. Each set of attributes specified with a particular random seed corresponds to a single simulation and consequently one ABM output. Repetitions of simulations produce multiple ABM outputs at the CLU level and suggest the amount of variability resulting from heterogeneous land owners.

A special routine is included in the ABM workflow to mediate the different spatial granularity of ABM output and SWAT input (Step 3, in Figure 8.3). The SWAT input dataset is classified in the present context as static and dynamic. The static input is obtained by combining a set of soil, digital elevation model (DEM), and landuse represented as Hydrologic Response Units. The HRUs are produced by ArcSWAT geoprocessor in conjunction with other

configuration files such management operation, crop rotation, fertilizer application (SWAT 2005). The dynamic dataset is described in the following section. The routine linking ABM and SWAT consists in the following operations: a) convert CLU and the original HRU layer into georeferenced raster layers; b) map the two through an indexing matrix; and c) create new HRUs with the new land use created by ABM. The routine updates the information about crop rotation, fertilizer application, conservation practices and other management operations using the output from ABM simulations. The routine tracks the CLU-HRU transformation such that the mapping is can be conducted in both directions.

7.3.4 SWAT workflow

This workflow entails the preparation of the static data as described above using mostly freely-available data. The dynamic data, i.e., stream flow, weather data, and water quality are stored in the CCDW using the workflows described above. The dynamic data is coupled with the SWAT through customized software that enables the: 1) discovering and downloading time series data from heterogeneous point measurement sources via WoF web services and spatial search, 2) processing and importing spatially-distributed (non-point) NEXRAD precipitation data, and, 3) data transformation and injection into a SWAT simulation. These components were constructed utilizing many technologies including Microsoft Visual Studio with C# .NET, ESRI's ArcMap and the ArcObjects API, CUAHSI WoF web services, and the HIS-Central Metadata Repository and associated web service. The one-time effort to create these workflows was significant, but the developed CI automates and decreases proportionally the domain specialist workload. The workflow elements and operational steps to execute the workflow are illustrated in Figure 7.3.

The ability to discover available time series of point measurement data in a source-independent manner entails the definition of an area of interest (AOI) to limit the area searched and the actual search. Search parameters include the variable name (precipitation, humidity, etc.), the time range for which data is required, and the service that will be utilized to conduct the search. The specification of the AOI can be accomplished either by specifying the location of a shapefile from a locally available dataset or selecting a polygon feature using the map interface. Sites that match the specified parameters are filtered through a spatial clipping algorithm that only returns sites within the AOI. If the requested data is not found within the AOI the system can be instructed to search within a user defined bounding neighborhood. Following the AOI selection the variable name, time range, and search parameters are recorded.

In addition to discovering and downloading point measurement data, the SWAT workflow has capabilities to handle gridded data. The first application of this kind was applied for importing and aggregating high-resolution precipitation intensity data produced by the Hydro-NEXRAD project (<http://hydro-nexrad.net>). These data are provided as ArcASCII-formatted text files representing accumulated rainfall over a certain time period. Each file contains the measurement for a grid cell in the measured area. Importing this time series data into a SWAT simulation involves three steps: a) converting an ArcASCII grid file to a polygon based gridded shapefile, b) transforming the time series data from a directory of ArcASCII-formatted files to separate time series datafiles for each grid cell within the AOI, and, c) aggregating the spatially distributed data points to each sub basin used for the SWAT simulation.

The production of a gridded shapefile allows the spatially distributed radar data to be represented by and linked to what we call virtual measurement sites, where each site represents one of the Hydro-NEXRAD grid cells. An algorithm was devised and implemented using the

ArcObjects API that reads ArcASCII files into memory, calculates the geometries of each of the polygons that make up a grid, and writes the resulting shapefiles to disk. Each grid cell, known as a feature, was given a unique numerical name that corresponds to the location in the ArcASCII grid that it represents. A spatial clip is applied to the data to retain only those grid cells that intersect with the AOI. The next step for ingesting the Hydro-NEXRAD data entails processing a directory of ArcASCII files containing the time series data. One-by-one the files are read into memory and the numerical identifier that was assigned to each feature in the gridded shapefile is used to locate the precipitation value within the file's data section. After the data import is complete the SWAT workflow creates one time series for each of the grid cells covering the AOI. Lastly, data from each grid cell was aggregated to the subbasin level to match SWAT input requirements. Spatial overlay algorithms available in the ArcObjects library were used build a list of grid cells that correspond to each sub basin. Each time series' in each grid cell within a sub basin is then processed to produce a virtual time series of mean values.

The obtained point or gridded dynamic time series data (irrespective of their nature i.e., precipitation, temperature, humidity) are subsequently ingested by the SWAT workflow in SWAT simulations. This task is accomplished by first loading a sub basin shapefile created with ArcSWAT and associating to each sub basin the closest gage station (real or virtual) by means of measuring the Euclidian distance from the centroid of each sub basin to each gage station. Next the previously downloaded time series is chosen along with a time frame that matches the time frame of the SWAT simulation. Then the location of the SWAT input file directory is specified followed by a check to make sure that the required input files are in place. The SWAT workflow also entails a set of routines developed as a C# class library that allow users to modify the files used as input for SWAT simulation. Following editing and checkup the SWAT simulations are

triggered from the workflow interface. SWAT output provides information on water quantity as well as water quality (sediment yield, Nitrate, and phosphorus loads). They can be tracked at CLU, HRU, sub watershed or whole watershed scales.

7.3.5 Feedback workflow

The user can choose to run SWAT or SWAT alone or connected in a loop as illustrated in Figure 7.3(b). Moreover users can visualize, interact and generate reports for each unique simulation. Repeated simulations using alternative scenarios composed in an incremental manner produces a wealth of information that can relate the effect of changes in the input variables to model outputs (sensitivity analysis). More relevant in the present context is the capability of the repeated simulations to reciprocally inform the two domain models on extrogeous driving forces or imposed thresholds not included in the individual simulations (e.g., the impact of environmental regulation on farmer decision-making). The feedback from SWAT to the ABM allows the simulated farmer decisions to be constrained by environmental outcomes (e.g., maximum allowable nitrogen loss). The SWAT-ABM feedback subsequently described illustrates the utility of this approach for the creation of actionable knowledge for decision-making processes.

All farmer agents in the ABM are able to perceive complete information on prescribed physical attributed of CLUs, but they are not able to perfectly predict or perceive the monetary value of crops and fuels. They will, therefore, generate different estimations based on their own experience and via interactions with neighbors and friends in social networks. The output information provided by SWAT simulations is integrated with the response of agents representing higher level decision makers (e.g. USDA or DNR). These agents determine and

suggest specific threshold values of N fertilizer rate based on simulated water quality outcomes at scales larger than HRU or CLU. Alternatively, they may subsidize N reduction programs or penalize for the overuse of N, and the rates of subsidy or penalty adapted from the simulated water quality in the past. In response to various decisions made by the higher-level agents, farmer agents may adopt different management strategies. Farmer agents who are environmentally-concerned might, for example, set constraints on nitrogen fertilizer input to reduce the total nitrogen loss from their farm fields while maximizing the total farm profit. Farm agents who are not environment-concerned stick with the profit maximization without nitrogen-based constraints. Both agents respond to subsidies (penalties) associated with N reduction policy.

The number of possible scenarios and time frames that can be explored by successive ABM, SWAT, and end-to-end (i.e., executing ABM, SWAT, and feedback workflows as a continuous flow) simulations is large and the relations among driving forces complex. After multiple simulations are executed users can evaluate the impact of various driving forces. To help explore the complex relationships embedded in this collaborative modeling loop a database is maintained that maps model inputs (e.g., assumptions about market prices, climate, policy, or farmer characteristics) to model outcomes (e.g., economic return, nitrogen and sediment in streams). This database (see Figure 7.4) stores: a) user attributes and their role; b) unique scenario identification associated with process and parcel data and simulation output; c) linkage between user-id and master-id generated for each SWAT simulations; and, d) hydrologic and data quality indicators. The indicators include runoff, nitrate export, sediment export, Phosphorus export as simulated by the SWAT model in multiple spatial resolutions at HRU, sub-basin, reach or watershed respectively. Statistics captured are monthly maximum, minimum,

mean, standard deviation and variance for the above indicators. Microsoft SQL 2008 Database server (DB) is used for storing all important parameters: metadata for input file sets and the transactional data from each steps mentioned in Figure 7.4. SQL operations can be used to view, or compare scenarios, and save the results back to the DB. Rendering of reports is achieved by reporting controls supported by .NET framework and C# programming language is used for complete IDW application development excluding CLU-HRU transformation module.

7.3.6 Database design for the workflow

The entire database is divided into multiple smaller database files and linked with each other through a set of primary keys or IDs. Each of those files and their contents are discussed in the following paragraph.

a) SWAT fields: Watershed level variables are Water Yield, Ground water yield, Sediment yield, Total Nitrate. Max, min, average, and standard deviation of these quantities from the daily simulation are stored under each month. Besides that monthly statistics, yearly data are also stored in the database.

Sub watershed level variables stored are Sub watershed ID, monthly Sediment yield, monthly lateral NO₃, and monthly water yield. Monthly values are then used to aggregate at annual scale.

HRU level variables stored are Water Yield and water quality variables e.g. sediment yield, Organic Nitrate, Inorganic Nitrate, crop nitrate uptake, Organic and Inorganic Phosphorus for each HRUs. HRUs are tracked by keeping HRU ID and the sub watershed to which it belongs.

Reach level database files store Monthly water flux variables e.g. water in and water out in each reach. Primary key of reach files is reach id which is linked to the sub watershed. Many unique water quality variables e.g. Biological oxygen demand, Dissolved oxygen, nitrate concentration

are stored in reach files. Nitrate concentration is an important variable to track in reach files as federal agencies are interested to know whether it crosses certain threshold value in any part of the watershed.

b) ABM fields: The purpose of this database is to track and link certain ABM model output to SWAT output. For this information e.g. Price input information, policy input information, ABM scenario ID are stored in the database. Scenario ID is the primary key that is linked with other SWAT database files.

c) Inter linking fields: In order to track and link different component tables, a Master database tables is created. It contains information e.g. User ID, scenario ID, Master ID e.g. watershed ID, sub basin ID, HRU counts. A uniquely generated mastered field is used as Primary key for this table. All other database files are linked to it as shown in Figure 7.4.

7.4 Conclusion

Through the exploration of this database users can identify conditions that lead to desirable socio-economic outcomes with preservation of water quantity and quality in the watershed streams. Using this “intelligent” CI system, managers can find answers to such questions as (Schnoor et al. 2008; Bennett et al. 2012):

- What is the response of the hydrologic system to shifts in economic drivers (e.g., in response to changes in the ethanol content of gasoline) or emerging technologies (the development of economically viable cellulosic ethanol production)?
- What is the time lag between changes in management practices and their impact on water quality?
- What motivates individuals as they make decisions that affect land management?

- What planning horizon is important to decision-makers, how does this vary based on public policy, economic condition, or available technology?
- What is the effect of uncertainty and risk behavior land use decisions, perceived important of competing objectives such economic return and environmental quality?
- What impact does improved knowledge about environmental effects of decisions have on the decision-making process?

The platform is available over the Internet, so a variety of users in watershed science & management (researchers, educators, students, farmers, managers, and the public) can monitor and engage in exploration and dialogue about this watershed.

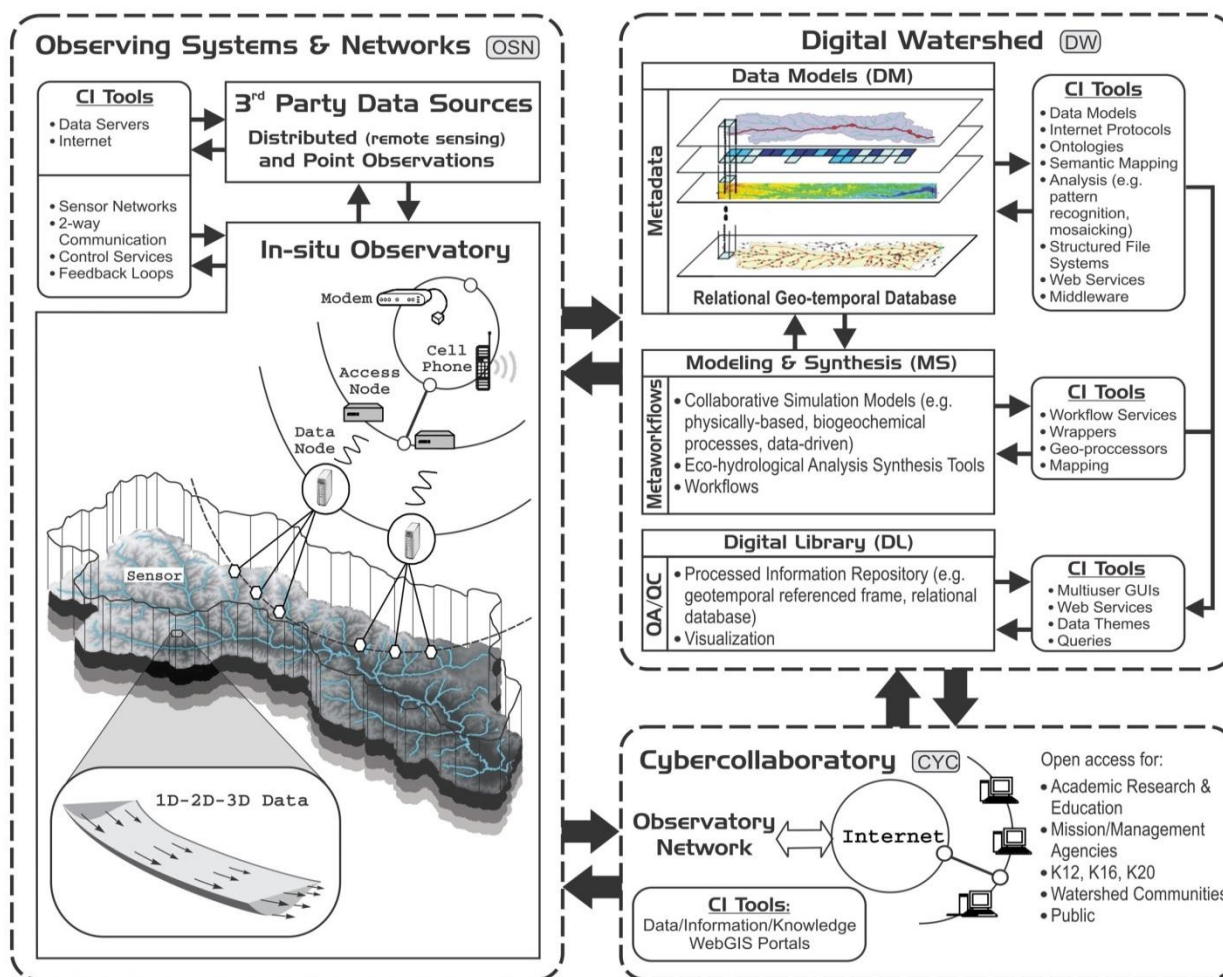


Figure 7.1 Conceptual framework for the CI-based end-to-end prototype (adapted from Muste 2007).

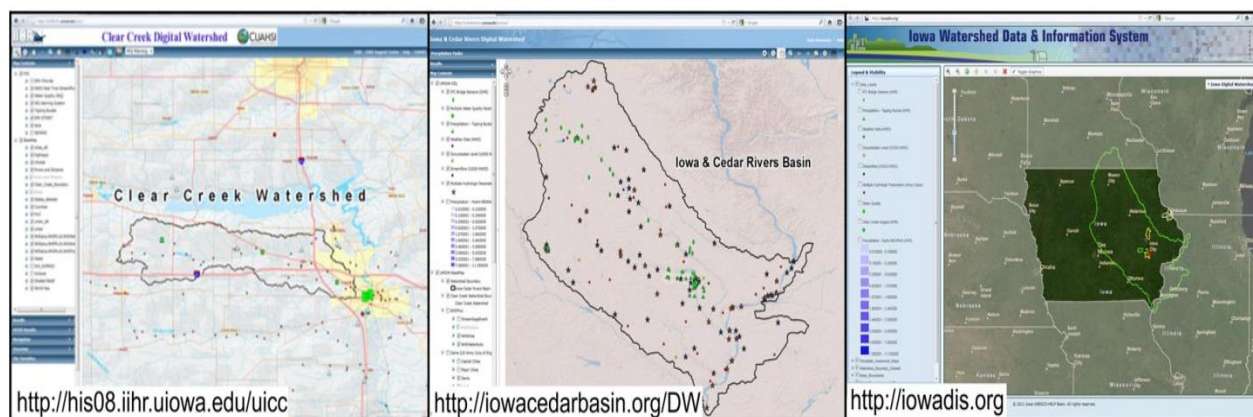
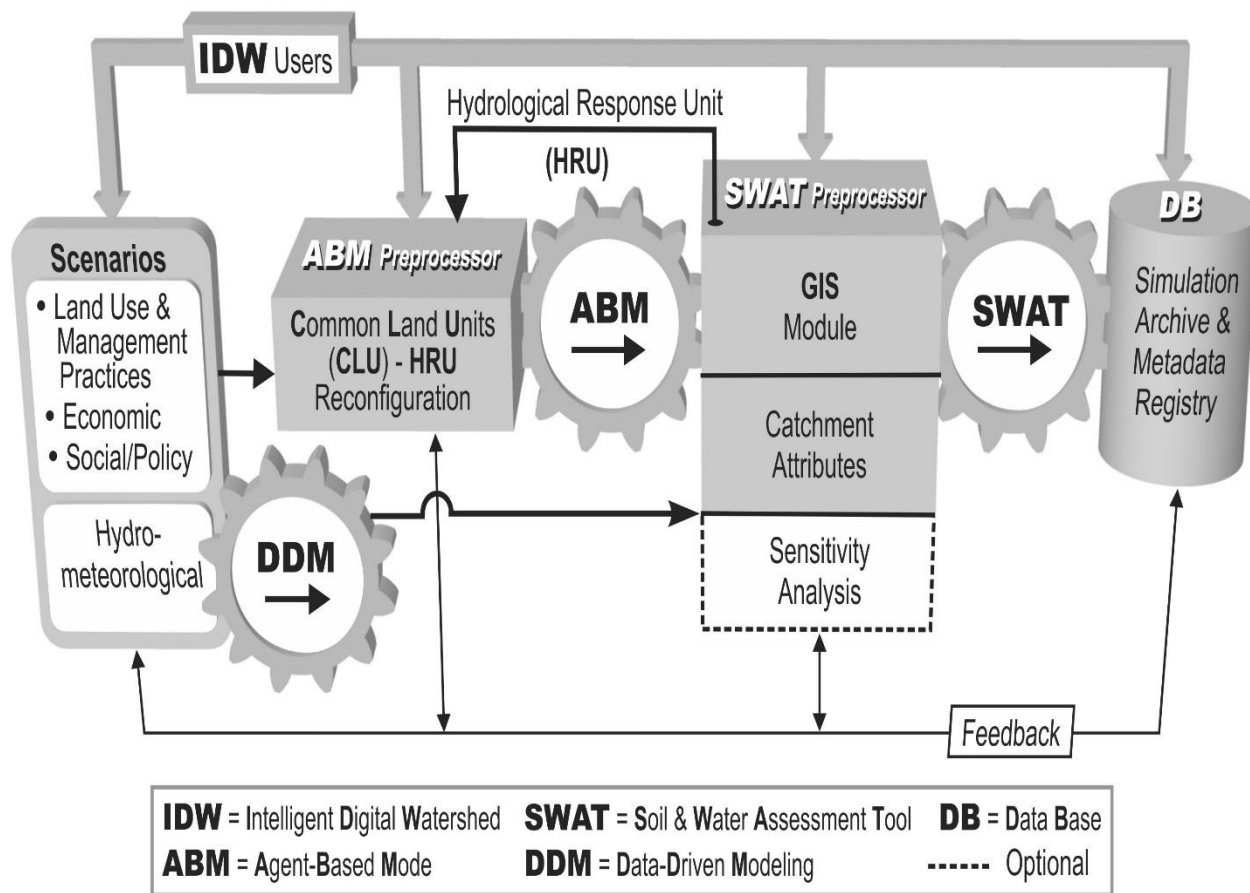
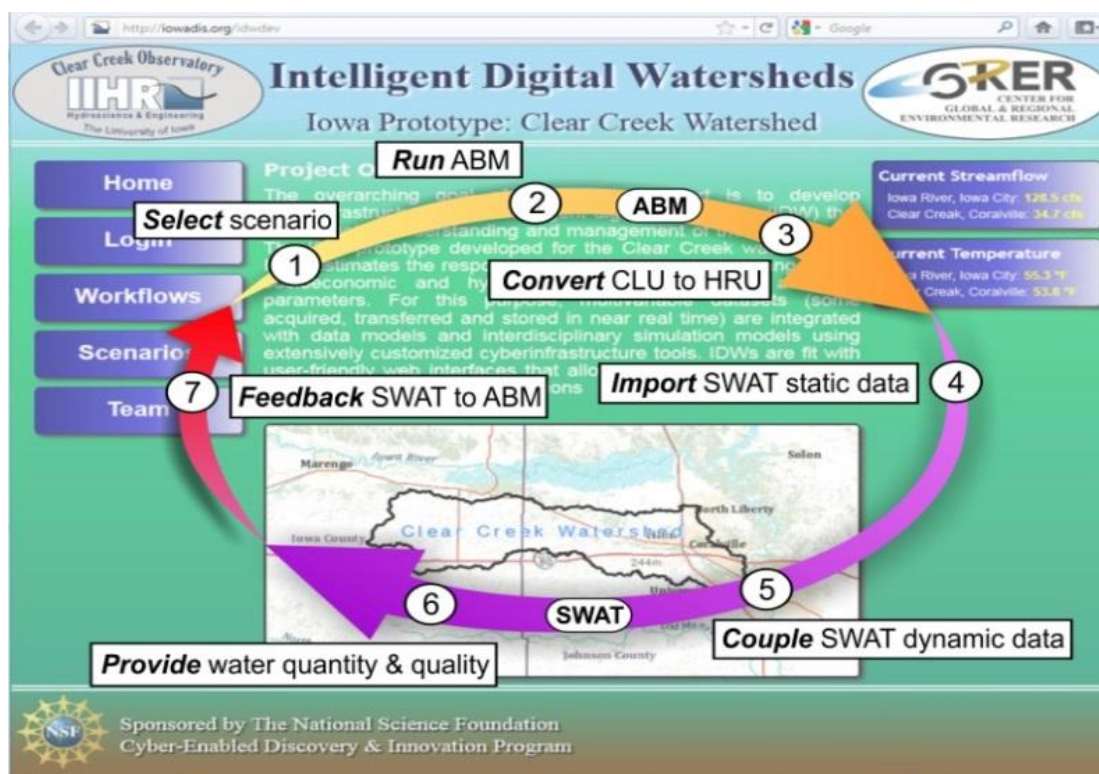


Figure 7.2 CI-based systems built with off-the-shelf community-developed components for Iowa watersheds (from left to right): Clear Creek (270 km²); Iowa-Cedar River (59,378 km²); State of Iowa (145,754 km²).



(a)

Figure 7.3 The “intelligent” digital watershed (IDW): (a) flowchart of the flux of data and information between the models. (b) The “intelligent” digital watershed (IDW): IDW connected ABM-SWAT workflows including the feedback loop as embedded in the website. (c) The “intelligent” digital watershed (IDW): User interface for IDW operation (<http://iowadis.org/idwdev>).



(b)

Figure 7.3 Continued

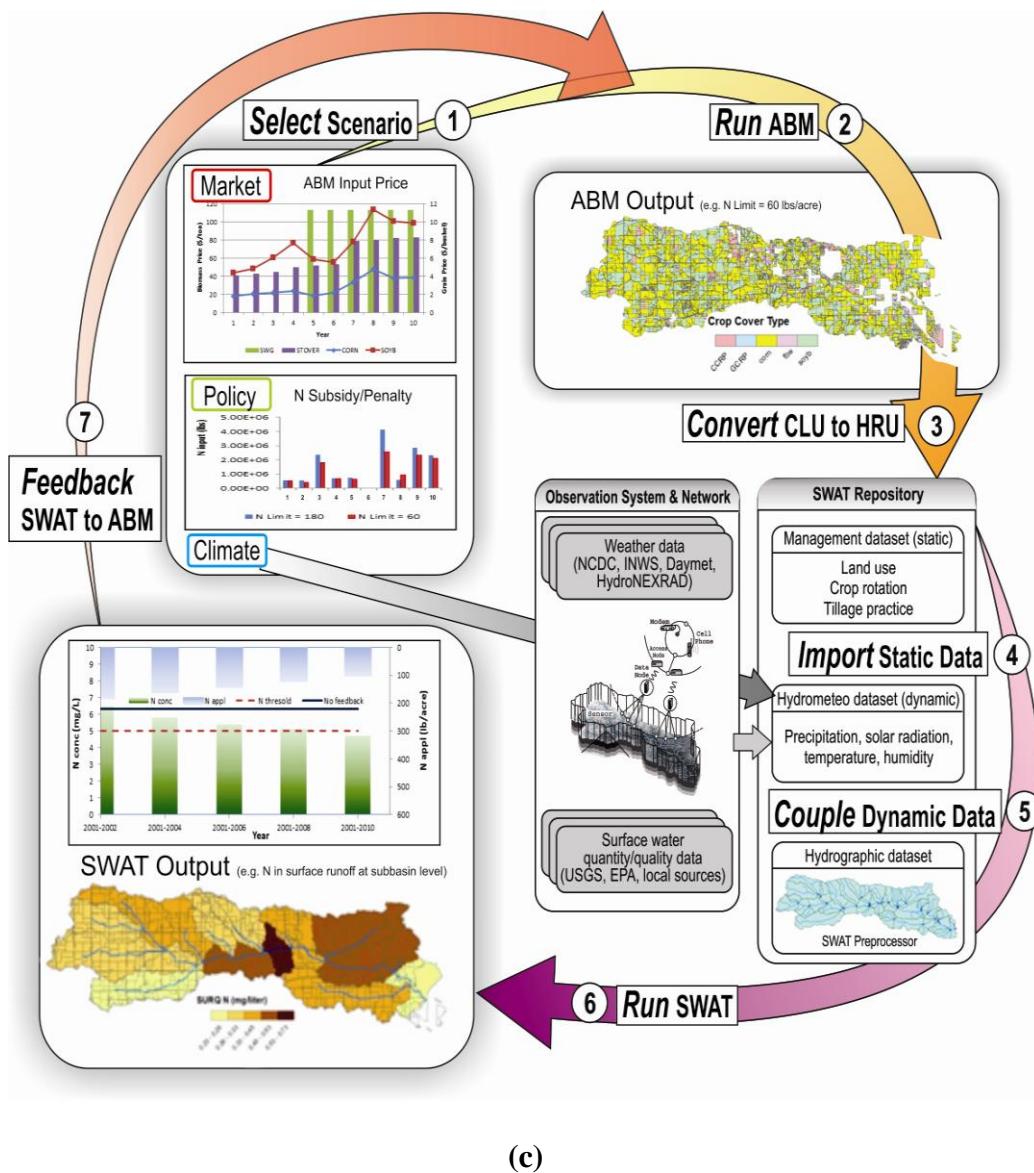


Figure 7.3 Continued

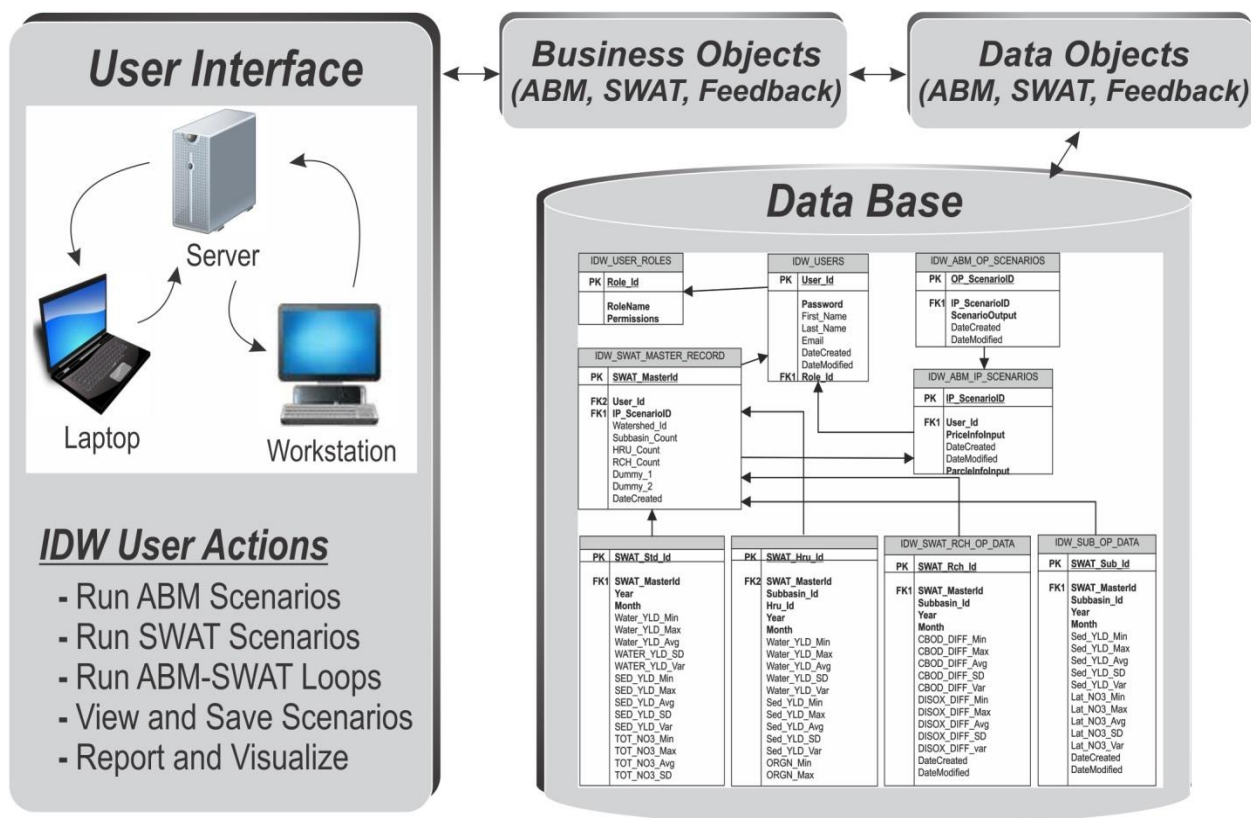


Figure 7.4 The Intelligent Digital Watershed operational flux and ancillary database.

CHAPTER 8

CONCLUSIONS AND RECOMMENDATIONS

8.1 Conclusion and recommendations

The SWAT Model was calibrated and validated with data from 1990-2010, and it proved to be an accurate representation of watershed processes (for discharge, suspended sediment, and nitrate load) to within statistically acceptable limits e.g. $R^2 > 0.85$ of observed monthly hydrologic mass and $R^2 > 0.7$ for nutrients loads. In order to perform the hydrologic calibration, the observed stream flow was separated into surface and base flow components, and the ratio of the two fractions was calculated as 0.6 on annual average (varies between 0.28 to 0.89). This ratio along with P/ET, which was 0.7 (range: 0.2 to 0.9) for annual average, was close to what is reported in similar watersheds in Iowa (Schilling et al 2008; Jha et al 2007) and served as benchmark for further model calibration.

The annual average sediment load over the simulation period was 5.2 MT/ha, and the annual average nitrate load was 25 kg/ha, which is close to reported values of the similar watershed in Iowa (Gassman et al 2006). Soil erosion rates were simulated as >10 MT/ha/year in the upper part of the watershed but were lower in the downstream part which is similar to what was reported by Papanicolau et al 2008. Nitrate loadings were calibrated at a monthly time interval in this study, but nitrate concentrations were found to be greater than 10 mg/l/day at the watershed outlet, the water quality standards, for a couple of days during each crop growth season (May-Oct) in CCW.

Stream water quantity and quality (monthly average values) changed significantly due to shifts from traditional crops to alternative biofuel crops production (switchgrass, corn stover). Sediment load was reduced by 11% due to a conversion of corn acreage into switchgrass on high

elevation land with a slope of >5% (roughly 12% of the watershed). The results of this research showed that the RFS2 biofuel mandate will decrease sediment and nitrate loadings to Clear Creek (improve the environment) as cellulosic biofuels come into production between now and 2022. This is because more land will come into switchgrass production instead of corn-bean rotation, and also because the harvesting of corn stover will not seriously impact sediment and nitrate runoff.

Through coupled SWAT-ABM model simulations, it was observed that increases in corn prices resulted in increases in annual average nitrate loads and increases in sediment yield at the watershed outlet. This can be explained as more amounts of land parcels were converted into corn which then resulted in more nitrogen fertilizer application and more nitrate runoff from land. The output information provided by SWAT simulations can be integrated with the response of farmer agents who will then determine and suggest specific threshold values of N fertilizer rates based on simulated water quality outcomes at scales larger than local land parcels to sub regional scale.

It was observed, through multiple regional climate model driven SWAT simulations, that a certain increase/decrease in climate variables (i.e. precipitation) generated a disproportionate increase/decrease in different components of the water cycle (i.e. surface flow, base flow, ET, and deep percolation rates). For example, a 4.2% increase in average annual precipitation resulted in a 14.3% increase in average annual stream flow in CCW. This disproportionate change can be ascribed to the fact that more precipitation falling on saturated soils can then generate non proportional runoff, and the CCW model was broadly able to capture those dynamics.

Through this modeling work, it was observed that most sensitive parameters for hydrologic balance in the water quality model were: Curve number, available soil water content, soil evaporation compensation factor and plant evaporation compensation factor. Snow melt parameters e.g. snow pack temp, were found to play an important role in CCW model. For making accurate sediment load budgets the following parameters were found to be significant: MUSLE parameters, sediment re-entrainment parameters, and the channel erodibility factor. The most sensitive parameters for nitrate load were found as: nitrate percolation coefficient, Org N enrichment ratio, and initial nitrate concentration.

.2 Significance and future research

Recent developments indicate the RFS2 may change in the future, affecting corn prices and land use change. Implications of such changes can be studied through this work. Moreover NARCAP is improving on the spatial resolution of its regional climate models. In order to understand the sensitivity of those new models on the hydrologic cycle at a watershed scale, presently built SWAT can be used effectively.

The research effort carried out through this work will help to produce a prototype Intelligent Digital Watershed (IDW) which will help to understand the interaction between water and human systems, in the context of a sustainable agricultural economy. The IDW should also be able to find all scenarios that result in water quality that exceeds a user specified threshold level. It can address issues like finding all scenarios that result in economic return which exceeds a user specified threshold level under alternative scenarios. Projections can be made for questions like: What agricultural land use patterns will emerge in the Clear Creek Watershed by 2050? What is the likely impact of this land use pattern on water quality in the Clear Creek Watershed?

Furthermore, the CI end-to-end systems enable wide-access to data and information represented in a language that can be understood by various user categories (including the general public). They facilitate efficient and timely stakeholder engagement through traditional forms (joining local watershed groups, donating time or money to a local project, voting or commenting on plans, implementing a conservation practice, attending training courses or public meetings) as well as through more contemporary technologies (web collaboratory, mobile devices, and online social networking tools). Collectively, these forms of involvement inject local (public) knowledge into the decision-making process. This engagement brings to the techno-scientific aspects of the decision-making important human dimensions such as health and economic well-being, vulnerability, cultural, spiritual, ownership rights.

The prototype implementations described in this work illustrates that the translation of theoretical concepts regarding integrative management approaches to practical application is achievable. Furthermore, these implementations point toward new, and unprecedented perspectives on the stresses that currently threaten watershed resources and comprehensive approaches to educate and engage decision-makers and relevant stakeholders. These end-to-end engineering systems are poised to create a new paradigm for watershed science and management, enabling interdisciplinary teams to collaboratively understand and manage complex watershed issues to achieve long-term sustainability.

**APPENDIX
CLEAR CREEK DATA**

A.1 Sample water quality data from WQ sensors in CCW

Query Parameters:

QueryDate: 10/7/2011 12:30:16 PM
Location: Water Quality: 05454300
Variable: Water Quality: NO3N
DateRange: 7/16/2008 12:00:00 AM - 10/23/2009 12:00:00 AM

QueryURL:

OD Web Service

#

Source Information:

Organization: IIHR - University of Iowa
SourceID: 1
Source Desc: Sensor data collected from the Iowa River.
Email: craig-just@uiowa.edu
Address: University of Iowa, Iowa City, Iowa 52240-
TypeOfContact: main
ContactName: Craig Just
Phone: (319) 335-5051

#

Site Information:

Name: Clear Creek near Coralville, IA
Code: 05454300

Location: SRS EPSG: 26915: 41.676701,-91.598801

#

Variable Information:

Name: Nitrogen, nitrate (NO3) as N, unfiltered

Code: NO3N

Vocabulary: CCDO

Valuetype: Sample

Datatype: Unknown

GeneralCategory: Water Quality

NoDataValue: -9999

Units: Unknown mg/L, code: 199

#

Data Value Count: 14895

#

DATETIME,VALUE

7/16/2008 12:45:00 PM,0

7/16/2008 1:00:00 PM,0

7/16/2008 1:15:00 PM,0

7/16/2008 1:30:00 PM,0

7/16/2008 1:45:00 PM,0

7/16/2008 2:00:00 PM,0

7/16/2008 2:15:00 PM,0

7/17/2008 4:15:00 PM,8.59

7/17/2008 4:30:00 PM,8.59
7/17/2008 4:45:00 PM,8.6
7/17/2008 5:00:00 PM,8.59
7/17/2008 5:15:00 PM,8.61
7/17/2008 5:30:00 PM,8.61
7/17/2008 5:45:00 PM,8.61
7/17/2008 6:00:00 PM,8.63
7/17/2008 6:15:00 PM,8.64
7/17/2008 6:30:00 PM,8.64
7/17/2008 6:45:00 PM,8.64
7/17/2008 7:00:00 PM,8.62
7/17/2008 7:15:00 PM,8.62
7/17/2008 7:30:00 PM,8.55
7/17/2008 7:45:00 PM,8.54
7/17/2008 8:00:00 PM,8.56
7/17/2008 8:15:00 PM,8.5
7/17/2008 8:30:00 PM,8.2
7/17/2008 8:45:00 PM,6.576
7/17/2008 9:00:00 PM,5.782
7/17/2008 9:15:00 PM,5.885
7/17/2008 9:30:00 PM,6.172
7/17/2008 9:45:00 PM,6.456
7/17/2008 10:00:00 PM,6.542

7/17/2008 10:15:00 PM,6.583
7/17/2008 10:30:00 PM,6.546
7/17/2008 10:45:00 PM,6.347
7/17/2008 11:00:00 PM,6.186
7/17/2008 11:15:00 PM,6.197
7/17/2008 11:30:00 PM,6.293
7/17/2008 11:45:00 PM,6.3
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7/18/2008 12:15:00 AM,6.296
7/18/2008 12:30:00 AM,6.305
7/18/2008 12:45:00 AM,6.259
7/18/2008 1:00:00 AM,6.189
7/18/2008 1:15:00 AM,6.178
7/18/2008 1:30:00 AM,6.104
7/18/2008 1:45:00 AM,5.943
7/18/2008 2:00:00 AM,5.639
7/18/2008 2:15:00 AM,4.803
7/18/2008 2:30:00 AM,3.479
7/18/2008 2:45:00 AM,3.506
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7/18/2008 3:15:00 AM,3.115
7/18/2008 3:30:00 AM,3.117
7/18/2008 3:45:00 AM,3.054

7/18/2008 4:00:00 AM,3.023
7/18/2008 4:15:00 AM,2.962
7/18/2008 4:30:00 AM,2.921
7/18/2008 4:45:00 AM,2.961
7/18/2008 5:00:00 AM,3.068
7/18/2008 5:15:00 AM,3.23
7/18/2008 5:30:00 AM,3.38
7/18/2008 5:45:00 AM,3.62
7/18/2008 6:00:00 AM,3.809
7/18/2008 6:15:00 AM,3.839
7/18/2008 6:30:00 AM,3.687
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7/18/2008 9:45:00 AM,4.041
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7/18/2008 10:30:00 AM,3.728
7/18/2008 10:45:00 AM,4.001
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7/18/2008 11:30:00 AM,3.918
7/18/2008 11:45:00 AM,3.655
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7/18/2008 12:15:00 PM,3.95
7/18/2008 12:30:00 PM,4.096
7/18/2008 12:45:00 PM,3.917
7/18/2008 1:00:00 PM,3.554
7/18/2008 1:15:00 PM,3.322
7/18/2008 1:30:00 PM,3.105
7/18/2008 1:45:00 PM,2.934
7/18/2008 2:00:00 PM,2.781
7/18/2008 2:15:00 PM,2.702
7/18/2008 2:30:00 PM,2.624
7/18/2008 2:45:00 PM,2.568
7/18/2008 3:00:00 PM,2.561
7/18/2008 3:15:00 PM,2.526

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7/19/2008 4:45:00 AM,5.764
7/19/2008 5:00:00 AM,5.84
7/19/2008 5:15:00 AM,5.877
7/19/2008 5:30:00 AM,5.939
7/19/2008 5:45:00 AM,5.97
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7/19/2008 6:30:00 AM,6.043
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7/19/2008 7:15:00 AM,6.092
7/19/2008 7:30:00 AM,6.113
7/19/2008 7:45:00 AM,6.141
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7/19/2008 8:15:00 AM,6.208
7/19/2008 8:30:00 AM,6.282

7/19/2008 8:45:00 AM,6.312

A.2 Land use, soil and slope distribution in CCW

Watershed	Area	Area[acres]	% Wat.Area
	[ha]		
	26972.9	66651.38	
<hr/>			
	Area	Area[acres]	% Wat.Area
	[ha]		
LANDUSE:			
Corn --> CORN	9343.714	23088.78	34.64
Soybean --> SOYB	7206.145	17806.75	26.72
Range-Grasses --> RNGE	561.5958	1387.731	2.08
Pasture --> PAST	5725.151	14147.13	21.23
Residential-Low Density --> URLD	2816.536	6959.802	10.44
Forest-Deciduous --> FRSD	1319.757	3261.185	4.89
SOILS:			
Colo	4718.959	11660.78	17.5
Tama	2092.099	5169.682	7.76
Downs	1850.3	4572.184	6.86
Fayette	8372.812	20689.64	31.04
Nodaway	1059.191	2617.314	3.93
Arenzville	6.7655	16.7178	0.03
Chelsea	1613.877	3987.971	5.98
Ladoga	1985.862	4907.165	7.36
Otley	3672.283	9074.396	13.61
Hayfield	212.555	525.234	0.79
Sparta	218.1215	538.9892	0.81
Klinger	296.848	733.5262	1.1
Maxfield	292.9421	723.8745	1.09
Lawson	209.6853	518.1429	0.78
Ely	26.8466	66.3394	0.1
Franklin	24.8801	61.48	0.09
Dinsdale	28.7188	70.9655	0.11
Waubeek	29.4226	72.7048	0.11
Bassett	38.7378	95.723	0.14
Orthents	71.9544	177.8028	0.27
Atterberry	12.2705	30.3211	0.05
Bertrand	14.8172	36.6141	0.05
Clinton	29.9913	74.1099	0.11
Perks	92.9586	229.7054	0.34

SLOPE:

3-5	4970.104	12281.37	18.43
0-3	5185.942	12814.72	19.23
5-9	10354.09	25585.47	38.39
9-14	5662.352	13991.96	20.99
14-9999	800.4109	1977.855	2.97

A.3 Land use, soil and slope distribution in sub basin 1 in CCW

		Area [ha]	Area[acres]	% Wat.Area	% Sub.Area
SUBBASIN #	1	1475.477	3645.978	5.47	
LANDUSE:					
	Corn -- >				
	CORN	1035.571	2558.947	3.84	70.19
	Soybean -->				
	SOYB	453.677	1121.059	1.68	30.75
SOILS:					
	Colo	360.9478	891.9202	1.34	24.46
	Tama	1128.3	2788.086	4.18	76.47
SLOPE:					
	3-5	377.1975	932.0739	1.4	25.56
	0-3	320.8202	792.7628	1.19	21.74
	5-9	641.2774	1584.629	2.38	43.46
	9-14	149.9528	370.5408	0.56	10.16

A.4 Land use, soil and slope distribution in HRUs in CCW

SUBBASIN #	HRUs	Area [ha]	Area[acres]	% Wat.Ar ea	%Sub.Ar ea
		1475.4			
1	Corn --> CORN/Colo/3-5	4	232.8011	0.35	6.39
2	Corn --> CORN/Colo/0-3	04	263.3901	0.4	7.22
3	Corn --> CORN/Colo/5-9	64.743	159.9831	0.24	4.39
4	Corn --> CORN/Tama/5-9	77	945.0227	1.42	25.92
5	Corn --> CORN/Tama/0-3	21	287.166	0.43	7.88
6	Corn --> CORN/Tama/3-5	07	435.9196	0.65	11.96
7	Corn --> CORN/Tama/9-14	6	234.6647	0.35	6.44
8	Soybean --> SOYB/Colo/3-5	2	84.8217	0.13	2.33
9	Soybean --> SOYB/Colo/5-9	3	64.9325	0.1	1.78
10	Soybean --> SOYB/Colo/0-3	6	85.9917	0.13	2.36
11	Soybean --> SOYB/Tama/9-14	2	135.876	0.2	3.73
12	Soybean --> SOYB/Tama/0-3	1	156.2151	0.23	4.28
13	Soybean --> SOYB/Tama/3-5	2	178.5315	0.27	4.9
14	Soybean --> SOYB/Tama/5-9	94	414.6902	0.62	11.37

A.5 Elevation statistics in CCW

Min.	Elevation: 190
Max.	Elevation: 277
Mean.	Elevation: 240.569820834441
Std.	Deviation: 16.488210269643

Elevation	% Area	
	Below Elevation	% Area Watershed
190	0	0
191	0	0
192	0	0
193	0.02	0.02
194	0.06	0.04
195	0.12	0.05
196	0.16	0.04
197	0.25	0.09
198	0.58	0.33
199	0.74	0.16
200	0.94	0.2
201	1.33	0.39
202	1.57	0.23
203	1.83	0.27
204	2.18	0.34
205	2.43	0.25
206	2.81	0.38
207	3.52	0.71
208	3.94	0.42
209	4.44	0.5
210	5.11	0.67
211	5.58	0.47
212	6.18	0.6
213	7.13	0.95
214	7.7	0.57
215	8.41	0.71
216	9.52	1.11
217	10.19	0.68
218	10.96	0.76

219	12.22	1.26
220	13.08	0.86
221	14	0.92
222	15.37	1.38
223	16.43	1.05
224	17.54	1.12
225	19.08	1.54
226	20.29	1.21
227	21.58	1.29
228	23.33	1.74
229	24.84	1.51
230	26.4	1.56
231	28.58	2.18
232	30.25	1.67
233	31.86	1.61
234	34.19	2.34
235	36.18	1.99
236	38.06	1.88
237	40.72	2.66
238	43.04	2.32
239	45.15	2.11
240	47.84	2.69
241	50.11	2.27
242	52.01	1.9
243	54.29	2.28
244	56.39	2.1
245	58.15	1.77
246	60.37	2.22
247	62.31	1.94
248	64.01	1.7
249	66.14	2.13
250	68.26	2.12
251	70.05	1.79
252	72.23	2.18
253	74.4	2.17
254	76.2	1.8
255	78.27	2.07
256	80.52	2.25
257	82.33	1.81
258	84.31	1.98
259	86.58	2.27
260	88.17	1.59
261	89.84	1.67

262	92.12	2.28
263	93.63	1.51
264	94.72	1.09
265	96.38	1.66
266	97.31	0.94
267	97.95	0.63
268	99.06	1.11
269	99.56	0.5
270	99.78	0.23
271	99.92	0.14
272	99.96	0.03
273	99.97	0.02
274	99.99	0.02
275	100	0.01
276	100	0
277	100	0

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