MODELING AND ANALYSIS OF MANAGEMENT FOR AN AGRO-ECOSYSTEM USING AN AGENT-BASED MODEL INTERFACE FOR THE SOIL AND WATER ASSESSMENT TOOL (SWAT)

BY

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THESIS

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ABSTRACT

Poor water quality across the Mississippi River basin and its outlet, the Gulf of Mexico, is undermining the health of ecosystems, economies, and public health. Agricultural production in the watershed has been identified as the dominant factor contributing to poor water quality. Substantial investment by communities, governments, and research is dedicated to identifying appropriate agricultural management and practices to mitigate pollutants entering these waterbodies. Efforts must acknowledge diversity in agricultural production, stakeholders, environmental and societal factors to successfully address water quality issues. Consequently, it is important to develop comprehensive tools that can inform decision-makers with practical solutions with respect to environmental, economic, societal, and policy goals.

In this study, a coupled human-natural systems model and software interface was developed to simulate feasible agricultural management and policy changes in an east-central Illinois watershed to identify strategies suitable for producers and policy-makers. The Soil and Water Assessment Tool (SWAT) was calibrated using publicly available sources and comparable previous studies for nutrient loads, water yield, tile-drained flow, and crop yields (natural-systems outcomes). SWAT modeling performance was satisfactory or better with respect to previous studies (annual PBIAS for nitrogen, phosphorous, water flow, and crop yields < 20%). An agent-based model was developed for community and farmer behavior to simulate hypothetical policy initiatives, economic returns, best management practice adoption (human-systems outcomes). The models were coupled to form a software interface, ITEEPGAM (the Integrated Tool for Environmental Economic and Policy Goals in Agricultural Management). ITEEPGAM was used to perform an analysis of watershed-specific BMPs (winter cover

cropping, nutrient application timing, and drainage water management) along with fertilizer reductions and hypothetical tax, incentive, cost share policy initiatives.

The development of ITEEPGAM and scenario analysis demonstrated that significant and complex natural systems and human systems phenomenon can be satisfactorily modeled and analyzed for potentially greater environmental and economic gains. The study showed a lower potential for environmental gains (8%-10% reductions in nitrogen and phosphorous) that other BMP studies in similar areas due to a smaller set of BMPs considered and an incorporation of an agent-based model to drive adoption behavior. Modeling results and agent behavior highlighted the importance of agent profiles, focusing input ranges and practical management choices to achieve useful conclusions. In this study, it was evident that enforcing fertilizer reductions beyond 15% were impractical for farmers. The scenario analysis highlighted effective policy instruments and potential redundancies. Incentives presented the most cost-effective return for designing community policy, but were not suitable to budgets beyond $1,000,000 as incentives served to supplement farmer returns without environmental benefit. Cost shares were effective at increasing adoption, but only up to a threshold of adopters. Small tax schemes could promote adoption and generate revenue for the community. Winter cover cropping coupled with small fertilizer reductions with the greatest potential for preserving economic performance and improving environmental gains while maintaining adoption rates. In the case of nutrient management paired with fertilization reductions, it could only offset very small fertilizer reductions and was therefore not economical.

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CHAPTER 1

INTRODUCTION

1.1 Problem Statement

The most recent EPA report on our nation's water quality found that 64% of lakes and 45% of rivers and streams are impaired, the percentage of impaired waterbodies has increased over the last 12 years, and non-point source pollution from agriculture is a key limiting factor in improving water quality (U.S. Environmental Protection Agency, 2009). In particular, agricultural nutrient export from the Mississippi River watershed is contributing to poor surface and groundwater water quality in the Midwest and hypoxia in the Gulf of Mexico (Burkart & James, 1999). The excess nutrients contribute to eutrophication, an increase in algal growth and a rapid consumption of oxygen as the algae decays. With increased eutrophication and lower oxygen levels, aquatic life cannot sustain itself and results in a "Dead Zone" (Rabalais et al., 2001). The consequences of poor water quality and the hypoxia or "Dead Zone" in the Gulf of Mexico are widespread and significant. Hypoxia and elevated nutrient levels threaten ecosystem stability, degrades drinking water supplies, contributes to closed beaches and limits waterfront usage, endangers human, animal, and pet health, and suppresses tourism, property values, and fisheries (Rabalais et al., 2002). The Louisiana Universities Marine Consortium, which has mapped the dead zone each year for nearly three decades, reports that the amount of nitrates flowing into the Gulf of Mexico has increased by up to 300% since the consortium began mapping the "Dead Zone" in 1985 (Blooming horrible: Nutrient pollution is a growing problem all along the Mississippi, 2012).

Midwestern agriculture and its production practices are of particular importance in addressing the hypoxia. Land use in the Upper Mississippi River basin has been identified as the dominant factor contributing to elevated water nitrate concentrations and the hypoxia in the Gulf of Mexico (David et al., 2010). The National Water Quality Assessment Program at the United States Geological Survey estimates that these regions contribute nearly 60% of the nitrogen in the Gulf of Mexico, mostly from corn and soybean cropping, and 54% of the phosphorus primarily from corn and soybeans and non-recoverable animal manure on pastures (Alexander et al., 2008). In areas like East-Central Illinois, which is the subject of this study, land use is predominantly intensive corn and soybean production with high nitrogen inputs. In addition, agricultural production utilizes extensive hydrological modifications, including channelization of the headwater streams and intensive tile (subsurface, artificial) drainage, in fields to lower water tables and efficiently route water to streams (Baker et al., 2008; David et al., 2010). These modifications have been implemented in areas historically rich with wetlands due to the flat terrain, humid climate, and poorly drained soils. Implementing drainage and converting lands for agricultural production expedites water flow and diminishes the capacity of the river basin to remove nutrients and, in turn, creates larger nutrient loads to surface waters (Baker & Johnson, 1981; Mississippi River/Gulf of Mexico Watershed Nutrient Task Force, 2008).

The most recent Gulf Hypoxia Action Plan, put forth by the USEPA, established targets for the size of the hypoxia and identified needs and actions for achieving its goals. The plan called for a 45% reduction in total nitrogen and phosphorus loads with the goal of a 5,000 km^2 hypoxic region in 2015 (Mississippi River/Gulf of Mexico Watershed Nutrient Task Force, 2008). The task force recommended comprehensive watershed management plans and implementing conservation and best management practices to mitigate nutrient transport in agricultural watersheds as a critical area in addressing the problem of the hypoxic region (Mississippi River/Gulf of Mexico Watershed Nutrient Task Force, 2008). Watershed management plans involving implementation of best management practices (BMPs) can help reduce pollution from agricultural sources. BMPs are structural or non-structural control measures that can be implemented to mitigate pollutant loads at their source or their transport to receiving water bodies. Structural practices are physical modifications such as waterways, terraces, wetlands and diversions and can help reduce erosion, or sediment loss. Sediment loss and erosion degrade agricultural productivity by consuming cropland area and soil resources. Non-structural measures are management-related changes like planting decisions and fertilizer application timing and technique. Non-structural measures can help prevent nutrient and soil loss. A large-scale assessment of conservation practices in the Upper Missouri River basin from 2003-2007 showed that implementing these conservation practices have reduced the loss from agricultural area to receiving waterbodies of sediment by 61%, total nitrogen loss by 20%, and total phosphorus loss by 44% (USDA-NRCS, 2012a). Identifying and treatment of areas with a critical need, referred to as targeting, is the most effective way to achieving further gains (USDA-NRCS, 2012b)

In order to effectively deploy strategies and programs, large-scale policies and targeted technical solutions are needed to regulate nonpoint source nutrients (Mississippi River/Gulf of Mexico Watershed Nutrient Task Force, 2008). The 2008 Farm Bill provided more than $7 billion for promoting agricultural production and environmental quality by supporting implementation of structural or non-structural management practices under its Environmental Quality Incentives Program (EQIP) (Alexander et al., 2008). Further, as a part of the Farm Bill, the USDA-NRCS initiated the Conservation Effect Assessment Program (CEAP) to account for how society would benefit from the substantial funds dedicated to promoting conservation in agriculture (USDA-NRCS, 2012a). In addition, The Clean Water Act (U.S. Environmental Protection Agency, 1972), in combination with government oversight from the EPA, require states to identify impaired and polluted watersheds, reasons for their impairment, and Total Maximum Daily Loads (TMDL) for nutrients to restore the health of targeted watersheds (U.S. Environmental Protection Agency, 1972). Such watershed management initiatives are on-going interdisciplinary efforts involving collection of data, field and basin studies, model development and application, and research.

Informing watershed management and meeting the needs of initiatives to improve water quality must recognize interconnected human and natural influences. Watersheds encompass diverse natural influences with numerous land-uses, terrains, river networks, and climates and these landscapes interact with hydrologic processes ultimately affecting the fate and transport of nutrients (Wortmann, 2008). Environmental outcomes are also linked to diverse human influences like agricultural production, economic returns, land development, legal structures and government policy. Acknowledging both sides of the equation is necessary. Interactions and feedback from the natural or human environments have compromised water management goals in many areas of the world (McDonnell, 2008). Further, integrated watershed analysis is a dynamic process and must acknowledge changing circumstances across time and space. Enacting changes may result in the emergence of new problems or opportunities, or changed perspectives and values of stakeholders (Walter et al., 2007).

In agricultural watershed management, an integrated approach must identify the appropriate strategy for the farmer with respect to agricultural production with natural and socio-cultural systems. Identifying areas for the appropriate conservation strategies should account for ecological effects, associated implementation costs, while recognizing stakeholder interests and behaviors unique to the area. A farmer's adoption or non-adoption of a select practice, and the reasons underlying that choice, are critical dimensions for a comprehensive understanding of watershed management (Nowak & Korsching, 1998). Finally, management plans must use monitoring, modeling, extension, and other evaluation methods to measure progress toward established goals (Wortmann, 2008).

1.2 Objectives

The goal of this study is to identify suitable conservation strategies and initiatives as part of an ongoing University of Illinois at Urbana-Champaign (UIUC) study of a typical East-Central Illinois agricultural watershed. The study models environmental outcomes with respect to, and as a result of, producer goals and behavior. The study develops, implements, utilizes a coupled natural-human systems model to form conclusions about the economic and environmental performance of varied watershed management. The research objectives can be outlined in four parts:

1. The development, calibration, and validation of a hydrological (natural systems) model to quantify, characterize and predict nutrient flux, hydrologic flow, and crop yield in the study area.
2. Integrate modeled agricultural conservation practices and management techniques for the area.
3. Model government and producer behavior with an agent-based model to reflect observed adoption of conservation practices and management.
4. Couple the agent-based model with the hydrologic model and design testing of conservation strategies, producer outcomes and watershed management

This study focuses on the Upper Salt Fork watershed in East-Central Illinois. The Upper Salt Fork watershed is an agricultural area which is predominantly row-cropped in corn and soybeans. The watershed is monitored for water quality and engaged with extension outreach (David et al., 2011) by the University of Illinois at Urbana-Champaign (UIUC). In addition, UIUC has partnered with area producers to test mitigation techniques and technologies. The hydrologic and agent-based models are calibrated with observed metrics characterizing typical producers and a feasible set of best management practices in the area. This study incorporates information on established best management practices and observed adoption rates derived from the partnership between UIUC and area producers.

Conservation practices and funded initiatives designed to improve water quality are available through UIUC and USDA-NRCS programs within the study area in East-Central Illinois (David et al., 2011; NRCS-USDA, 2012b). However, effective implementation of these technologies and initiatives is often undermined in watersheds by a lack of knowledge regarding optimal locations and suitable adopters (Pannell, 2006). To remedy this disconnect between technology and adopters, it is important to understand how strategies perform in specific locations and how key stakeholders such as regulators, producers, and communities respond to such strategies. The comprehensive watershed modeling tool developed in this study – one that places agricultural and water-use strategies in a broad technical, economic, and social contexts – can more effectively capture site-specific characteristics (e.g., climate, topography, and soil) and evaluate multiple scenarios that would be very expensive to address with field studies. The model utilizes a "what-if" scenario analysis to provide scientific information on the impacts of various management alternatives and can assist stakeholders in achieving effective integrated water resources management and protection of the watershed and downstream consequences in the

Gulf of Mexico. This study seeks to inform decision-making for selection of mitigating strategies and provision of water quality forecasts. Integrating a natural-systems model with a human-systems component provides a rationale for adoption that is correlated with both productivity goals and improvements in water quality. This approach can have broad applicability for other water systems affected by non-point source pollution, such as: parking lots, roads, sub-urban developments, forestry areas, surface-mining, and construction sites.

1.3 Thesis Outline

Chapter 2 of this study begins with a review of modeling approaches for agricultural processes and human systems to predict environmental and behavioral outcomes. The review presents the considerations and examples of coupling human-systems and hydrological modeling for decision making in agricultural management. Chapters 3 and 4 outline the methodology of the study. Chapter 3 details the development and results of the hydrological modeling component along with the implementation of best management practices. Chapter 4 summarizes the agent-based modeling approach and integration into the hydrological model. Chapter 5 summarizes the scenario analysis and results from the modeling. Chapter 6 provides a discussion of the results and conclusions. Chapter 7 provides recommendations for further work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Agricultural production practices and management in the study area and similar Midwestern watersheds are contributing to poor water quality and harmful environmental outcomes, primarily ‘the Dead Zone’ in the Gulf of Mexico (Baker et al., 2008; Mississippi River/Gulf of Mexico Watershed Nutrient Task Force, 2008; Royer et al., 2006). Poor water quality contributes to human and animal health concerns, ecosystem instability, economic loss, and food insecurity (Rabalais et al., 2002). There is significant investment by communities and institutions to address the consequences. Tools that help decision-makers identify successful strategies are important in facilitating an analysis of the underlying factors contributing to poor water quality. These tools necessitate models to quantify and link environmental outcomes with land management, conservation practices, and economic outcomes.

This study sought to model the effect and the adoption of conservation practices in an East-Central Illinois watershed using a coupled natural-human systems model to identify initiatives and technologies to address poor water quality while acknowledging economic yields. The coupled model is an approach that acknowledges the interconnected and complex nature of the issue. This section introduces the two systems modeling domains (natural and human) and the underlying processes they address. A discussion of the body of work identifying necessary tools and data for this analysis along with and implementing and applying models follows.

2.1.1 Natural Systems - Watershed Hydrology

Watersheds are complex human-natural systems that incorporate geographic, environmental, hydrologic, economic, human and social interactions. Hydrologic processes like stream flow and nutrient loads in watersheds are the result of interactions between environmental and physical processes such as precipitation, infiltration, percolation, runoff, and evapotranspiration. A review of surface water phenomena is essential to understanding the physical processes this study will model.

The Earth’s hydrologic cycle is driven by the sun (Black, 1991). The sun’s radiation warms surface water causing evaporation. Evaporation transforms surface water from the liquid to the gaseous state, to form part of the atmosphere. Cycling energy in the atmosphere and interaction of gaseous water with land mass changes the water vapor back to the liquid state again through the process of condensation to form clouds. When the atmosphere is saturated with moisture, precipitation (rain or snow) is produced. The precipitation either to falls back to surface water storage or encounters the land surface. Rainfall reaching the ground surface collects to form surface runoff or it may infiltrate into the ground. Additionally, rainfall may be intercepted by vegetation on the ground and evaporated back to the air by evaporation. The liquid water in the soil then percolates through the unsaturated layers to reach the water table, where the ground becomes saturated, or it is taken up by vegetation from which it may be transpired back into the atmosphere. The net effect of transpiration and evaporation is called evapotranspiration. Surface runoff and groundwater flow to surface streams and rivers, may be held in lakes, but finally flows into the ocean or evaporates. Nutrients and particles adhere to water, moving through the system as well. Once the water returns to a waterbody and evaporates, the perpetual cycle continues. This cycle sustains all life on earth and human populations. In the context of planning and management of water resources, evaporation together with precipitation governs the amount of runoff available for human needs (Yeh et al., 1998).

2.1.2 Natural Systems - Nutrient Cycling

Along with the hydrology, nutrient cycling and availability, particularly of nitrogen, is of primary importance in agricultural ecosystems. All amino acids, the building blocks of biological organisms and proteins, contain nitrogen. It is essential for photosynthesis. While the atmosphere is composed of 78% nitrogen, which exists in its gaseous form, this form cannot be utilized by plants. The nitrogen cycle (fixation, uptake, mineralization, nitrification, and denitrification) describes how nitrogen and nitrogen containing compounds transform for incorporation into biological organisms. Nitrogen must be converted to ammonium (NH_4^+), nitrate (NO_3^-), or urea ($(NH_2)_2CO$) for utilization in plants. Nitrogen fixation is the process by which gaseous nitrogen is converted to ammonium. Application of fertilizer, cultivation of legumes, and burning fossil fuels all fix nitrogen. Uptake is the incorporation of ammonium into a plant. Mineralization is the decay of organic matter nitrogen (dead plant matter) into ammonium. Nitrification is the conversion of ammonium into nitrate by bacteria; the bacteria derive energy from nitrification. It is important because ammonium is positively charged, whereas nitrate is negatively charged. Ammonium is attracted to negatively charged soil particles and nitrate is repelled. Therefore, nitrate is susceptible to washing away (leaching) from soil. Finally, denitrification is the process by which nitrate is converted back to gaseous nitrogen and nitrite. The nutrient cycle facilitates and limits plant growth, governs nitrogen transport and determines the amount of pollutants delivered to receiving waterbodies.

2.1.3 Human Systems - Watershed Management and Use

In addition to the water and nutrient cycle, watershed hydrology is also the result of human impacts like terrain modification and influences by institutions such as government and society. For example, urban development has changed wind patterns, temperature, and vegetation to affect evaporation and runoff (Shaw, 1994). Urbanization of an area tends to increase peak runoffs because of the efficient delivery of rainwater to streams through sewer systems and the decrease in losses to infiltration because of large expanses of impervious areas (Singh, 1987). Further, agricultural production modifies species and spatial patterns of vegetation and therefore infiltration and evapotranspiration. In the Midwestern agricultural watersheds, water is drained artificially from row-cropped agricultural areas, affecting surface runoff and stream flow processes (Schilling & Helmers, 2008). In addition, modifications to the natural water network in Midwestern agricultural watersheds can include widening, deepening, straightening of streams, rivers, and ditches (Singh et al., 1987). Such modifications are important factors in characterizing the hydrology of a watershed.

2.1.4 Watershed modeling

Watershed modeling is necessary to characterize, quantify, and analyze these natural and human systems. It is impossible to observe, measure, and predict watershed processes like precipitation, nutrient flux, and agricultural operations across every point in a watershed. It is unwieldy and unfeasible to manually observe the large-scale effects of physical phenomena on a watershed across area and time. Watershed models simplify complex human-natural systems, like agricultural drainage systems, and their interconnected components in order to simulate and predict these phenomena (Black, 1991). Better watershed and modeling techniques are facilitating the deployment and application of tools, information, and decision-making in managing these watersheds for land-use and environmental integrity. It is helpful to be able to forecast changes in the river flows, nutrient flux and the state of the catchment in order to determine beneficial watershed management schemes (Shaw, 1994). The Soil and Water Assessment Tool (SWAT) is one particular model that has been broadly applied to characterize and forecast watershed processes. SWAT model depends on data sources for topography, precipitation, land-use and management. These models integrate ecology, economics, hydrology, and natural resources and environmental sciences.

Watersheds are coupled human-natural systems where human decisions affect the environment (e.g., water quality, streamflow), and environmental outcomes affect human decision-making (e.g., resource quality, water availability). As a result, comprehensive modeling of such systems for planning, management and other purposes requires an approach that considers both the human and natural aspects (Ng et al., 2011). In models characterizing the behavior of entities, an agent-based model (ABM) is one particular approach, and is most natural for describing and simulating a behavioral system (Bonabeau, 2002). For coupled natural-human systems, integrating biophysical models like SWAT with these socioeconomic ABM's is an area of expanding multi-disciplinary work to better inform decision-making, management, and optimal resource utilization in watersheds (Nejadhashemi et al., 2011).

2.1.5 Overview

This literature review is a summary of the body of research regarding the implementation and application of SWAT and other biophysical models, and their integration with socioeconomic models like agent-based modeling. Applying watershed models, like SWAT with sufficient input data can accurately quantify nutrient and pollutant loads and crop yields for varied management to identify appropriate conservation strategies. Pairing these environmental models (natural models) with human models (economic, social) can help identify cost-effective management and policy initiatives, and provide decision-support for stakeholders. This section summarizes the body of work supporting this proposal in the following sections: data sources, modeling and simulation, and decision support in human and natural systems modeling.

For sources of input data, modeling and simulation, and decision support, each is arranged into an overview of the topic; then specifics on applications, usages, and considerations; and finally, conclusions on the methods, advantages, and shortcomings. The data sources section outlines types of input data necessary to perform coupled human-natural systems modeling in watershed management. There are example data sources, and considerations to make when selecting input data. The modeling and simulation section presents examples, performance and applications of natural and human systems models independently, followed by coupled techniques. Finally, the decision-support section presents types of tools and their use in watershed management.

2.2 *Data Sources*

2.2.1 Data Sources Overview

Data sources for coupled natural-human systems models can be categorized into five categories:

- Physical,
- Environmental,
- Societal/institutional,
- Economic, and
- Behavioral.

Both human and natural models incorporate societal/institutional information. Natural models incorporate observed physical and environmental input data. Human models rely on information describing economic and behavioral/adoption phenomenon. There are two considerations to make when assessing input data needs: the scale/resolution of input data, and software/programming/formatting needs to utilize input data. This review will highlight several publications to illustrate the types of data sources (Table 2.1) needed and the considerations in selecting input data.

Sources of input data for coupled natural-human systems modeling for watershed management are generally available publicly and electronically (Table 2.1). Sources for natural systems modeling are available through government agencies (national, state, county, local) and university extension or research centers. Watershed management information is generally provided by national agencies or local agencies specific to the study area. The diversity of geography, environment, and management techniques for watersheds require a diverse set of sources to model them. The modeling goals, area, and modeling techniques for a study determine input data requirements. For example, in this study of an agricultural watershed spanning two counties in East-Central Illinois, the Illinois Agronomy Handbook (Hollinger & Angel, 2009) and Illinois State Water Survey (Illinois State Water Survey, 2012) provided information for weather, crops, fertilizers, drainage guidelines for the agricultural practices typified by the counties in the state of Illinois, while the USDA (USDA-NASS, 2012) provided county-level average crop yields for the entire United States. Other necessary information typifies physical processes like nutrient uptake and radiation utilization in crops across agricultural watersheds. Information may be specific for a model for Midwestern corn with tile drainage, or tillage types generalized for the entire Midwest. These considerations demonstrate that scale, modeling outcomes, and model selection are determinants of selecting input data and source (Table 2.1 – 2.2). Tables 2.1 and 2.2 provide an overview of data sources within the two domains of natural and human systems, with a description of the type of data source.

Table 2.1: Natural Systems Data Sources Overview

Natural Systems	Input Data Type	Data Source	Reference
Physical	Topography	National Elevation Dataset and GIS Portal	(USGS, 2012a)
		Illinois Geospatial Clearinghouse	(Illinois Natural Resources Geospatial Data Clearinghouse, Illinois Height Modernization: Digital Elevation Data)
	Stream Network	National Hydrography Dataset and GIS Portal	(USGS, 2012b)
	Land Cover	National Land Cover Dataset GIS Portal	(USGS-NLCD, 2012)
	Soil Type and Properties	National Soil Dataset GIS Portal	SSURGO (USDA-NRCS, 2012d) STATSGO2 (USDA-NRCS, 2012d)
Environmental	Precipitation, Temperature, Water Balance	National Climatic Data Center	(NOAA, 2012)
		Local weather databases Local research centers	(Ohio Agricultural Research and Development Center, 2012) (Illinois State Water Survey, 2012)(Winstanley et al., 2006)
		Local water budget studies	(Arnold, 1996) (Mitchell, Banasik, Hirschi, Cooke, & Kalita, 2001)
	Streamflow	National Water Information System	(USGS, 2012c)

Table 2.1: Natural Systems Data Sources Overview (Cont.)

Natural Systems	Input Data Type	Data Source	Reference
Environmental (Cont.)	Water Quality (Nutrient Flux)	National Water Information System	(USGS, 2012c)
		Local Agency Monitoring and Sampling	(M. W. Gitau, Chaubey, Gbur, Pennington, & Gorham, 2010)(Vendrell et al., 1997) (U.S. Environmental Protection Agency, 2009)
	Nutrient Balance, Accumulation (Crop)	University Extension Area Studies	(Iowa Learning Farms & Practical Farmers of Iowa, June 2011) (McIsaac & Hu, 2004b)
Societal/ Institutional	Point Source Impact	National Agency Monitoring	(Environmental Protection Agency, 2012a; Environmental Protection Agency, 2012b)
	Crop Yield	National and Local Surveys	(USDA-NASS, 2012) (UIUC-ACES, 2003-2012)
	Agricultural Management BMP Modeling	Research and University Reports	(Vitosh, Johnson, & Mengel, 1995)(Sustainable Agriculture Network, 2007)(CES (Cooperative Extension Service), 1987)
		Industry Reports	(Illinois Department of Agriculture, 2010)
		Area Studies	(David, Gentry, Starks, & Cooke, 2003)(Green, Tomer, Di Luzio, & Arnold, 2006)(USDA-NRCS, 2012a; USDA, 2009)(M. W. Gitau et al., 2010)(St. John & Ogle, October 2008)

Table 2.2: Human Systems Data Sources Overview

Human Systems	Input Data Type	Data Source	Reference
Economic	Financial	University Research Agency Extension	(University of Illinois at Urbana-Champaign (UIUC) College of Agricultural, Consumer and Environmental Sciences (ACES), 2003-2012)
		Professional Societies	(Illinois Society of Professional Farm Managers and Rural Appraisers, 2012)(O'Brien & Duncan, 2011)
		National Agency	(USDA, 2009)(Economic Research Service, United States Department of Agriculture, 2007)
Behavioral	Management Decisions, Land Use, Adoption	Survey Results / University Extension	(Pennington et al., 2008)(Upper Salt Fork Status Update and Report, 2011)(Lant, Loftus, Kraft, & Bennett, 2001) (USDA, 2007; USDA - NRCS, 2011; USDA-Farm Service Agency, 2004)
		Government, National Reporting	(Butler & Srivastava, 2007; Limnotech, 2007) (USDA, 2006)
		Local Studies	(Claasen, 2009; Lambert, Sullivan, Claassen, & Foreman, 2006)
Societal Institutional	Policy, Tax, Regulation	Government Agencies	(USDA-NRCS, 2012a-c)(USDA-FSA, 2013)
	Farmer, Farm Demographics,	Government Agencies	(USDA 2009)
	Legal boundaries		(Champaign County GIS Consortium 2013) (USDA-FSA 2013)

2.2.2 Data Sources in Natural Systems Modeling

Natural systems modeling of hydrologic processes, nutrient transport, and crop growth for watershed management rely on physical, environmental, and societal/institutional input data. Physical input data include elevation, land use, soil properties, and crop growth and nutrient consumption. Environmental data include weather, streamflow measurements, water balance estimates, flow partitioning and nutrient monitoring. Institutional data include crop planting patterns and locations, crop yield statistics, agricultural management inputs, and point source loadings delivered to rivers and streams. All three categories of data are utilized for modeling the placement and effect of conservation strategies.

Physical input data in natural systems models are comprised of static features within a study area: topography, location of streams, soils, and land cover. The scale and resolution of data depends on the model objectives and availability. Elevation data such as LiDAR (Light Imaging Detection and Radar) are available through local or statewide agencies such as Illinois Natural Resources Geospatial Clearinghouse (Illinois Natural Resources Geospatial Data Clearinghouse, 2011). LiDAR elevation data for Champaign County in Illinois have an average sampling rate of 1.2 meters (Aero-Metric, 2008). Lower resolutions of elevation data are available through agencies like the USGS National Elevation Dataset (USGS, 2012a). The USGS compiles elevation data with resolutions of 10, 30, and 90 meters depending on availability for the United States (USGS, 2012d).

Selecting the scale of data is study-area specific. Natural systems modeling scales from a specific field to an entire watershed of a major river like the Mississippi River. The hydrologic budget and crop yields for the Upper Mississippi River Basin (UMRB), approximately 491,665 km^2, were modeled using the Soil and Water Assessment Tool (SWAT)(Srinivasan et al., 2010).

The study tested using a 30 meter (1:24000) and a 90 meter (1:1000000) digital elevation map for the National Hydrography Dataset (NHD) (USGS, 2012b), land-use the study used data from USDA Cropland Data Layer (USDA-NASS, 2013) and the USGS National Land Cover Data (USGS-NLCD, 2012) processed in ArcGIS/ArcSWAT (Srinivasan, 2009). The study did not find a substantial difference in their slope calculations and consequently their predictions of streamflow. The larger resolution reduced the size of the input data files and expedited processing.

While a low resolution map did not affect modeling performance in a large watershed, resolution of elevation data was a significant factor in modeling watershed size, runoff, and soil erosion in the 21.3 km^2 Goodwin Creek watershed in Mississippi (Di Luzio et al., 2005). In the 18.9 km^2 Moores Creek watershed in Arkansas, the effect of DEM resolution depended on model output variable of interest: resolution of elevation data varying between 100 meters to 200 meters produced streamflow, nitrate-nitrogen, and total phosphorus within a relative error of +10% (Chaubey et al., 2005). An upper limit of 50 meters for resolution of elevation data was proposed for satisfactory modeling of streamflow, and soil map scale of 1:25000 for satisfactory modeling of sediment loading (Chaplot, 2005).

In addition to terrain, physical features like land cover and soil properties determine the movement of water and nutrients through watersheds (Shaw, 1994). The USGS Land Use and Land Change dataset (1:250000) and National Land Cover Dataset (30 meter resolution) (USGS-NLCD, 2012) are commonly used in SWAT simulations. While the resolution of elevation data is the most critical input for SWAT simulations, satisfactory streamflow modeling performance requires a maximum land use resolution of 300 meters (Cotter et al., 2003). USDA-NRCS provides two soil databases for properties and types of soils. SSURGO (The Soil Survey and

Geographic) (USDA - NRCS, Soil Survey Geographic (SSURGO) Database) has a resolution of 1:24,000 and its predecessor STATSGO (The State Soil and Geographic) has a 1:250,000 scale. SWAT model output for Walnut Creek watershed in central Iowa was compared to measure the effects of using three resolutions of soil data: 1:25,000 SSURGO,1:250,000 STATSGO, and 1:500,000 soil data derived from STATSGO (USDA-NRCS, 2013) (Chaplot, 2005). Runoff was not significantly affected by resolution of soil data, but nitrogen and sediment load were significantly reduced for coarser scale of soil data. Modeling performance for nitrogen and sediment was best with the finest resolution of SSURGO data.

Physical data modeling needs depend on studies in tile-drained areas for observed flow partitioning between surface runoff, percolation, crop nutrient uptake and growth. Three studies employed a GIS software, ArcGIS (ESRI, 2010), to manage, arrange, and format spatial data layers. In addition, SWAT has been integrated into ArcGIS (Srinivasan, 2009) to facilitate managing data for the analysis. A simulation of fertilizer reduction strategies in an Illinois watershed (Hu et al., 2007; Mitchell et al., 2000) was calibrated by enforcing a minimum tile drainage water yield of 75% of total water yield based on area field studies (Mitchell et al., 2000). Using observed data for nitrogen content, fixation, uptake, and leeching in Midwestern watershed (McIsaac & Hu, 2004a), the study identified the need for a denitrification parameter in SWAT for calibration. Similarly, a simulation of streamflow and water balance in the tile-drained South Fork Watershed in Iowa (Moriasi et al., 2009) was initialized with drainage design parameters from Iowa State Extension (CES (Cooperative Extension Service), 1987) and calibrated the model to partition 76% of total flow as tile flow based on previous estimates (Green et al., 2006). SWAT was applied to the Upper Big Walnut Creek in Ohio and utilized observations of tile drainage flow partitioning, observed corn and soybean biomass accumulation, harvested nitrogen content, uptake, and fixation to model nitrogen flux and crop yield (Nair et al., 2011).

Environmental and institutional input data needs are more common across studies and natural systems models. Studies utilize daily precipitation, temperature, evapotranspiration data from agencies such as the National Climatic Data Center (NCDC) (National Climate Data Center, 2012; NOAA, 2012), or local agencies relevant to the study area like the Ohio Agricultural Research and Development Center (Nair et al., 2011; Ohio Agricultural Research and Development Center, 2012) or the Illinois State Water Survey Climatologist (Hu et al., 2007; Illinois State Water Survey, 2012). On the field-scale, on-site meteorological measurements for a 22-hectare plot in Iowa were used to model nitrate dynamics and hydrologic budgets using the field-scale natural systems models DRAINMOD-II (Skaggs, 1980) and RZWQM (Root Zone Water Quality Model) (Agricultural Systems Research Unit, 2009)(Thorp et al., 2009). Crop yield information for grain weight and moisture content was obtained through a previous study for the study area (Colvin, 1990). On the basin-scale, one study found that the effect of the number of precipitation stations for a modeling runoff and nitrogen flux in a 51 km^2 watershed in Iowa and a 918 km^2 watershed in Texas did not result in a significant decrease in model accuracy (Chaplot, 2005). However, in a comparative analysis of precipitation station density, Moriasi & Starks (2009) found modeling conservation practice effectiveness should utilize the highest number of precipitation stations available. In a separate watershed and study, Moriasi & Starks (2010) also recommended the finest resolution of precipitation stations and mix of STATSGO and SSURGO soil datasets for nutrient transport studies.

Similarly, models utilize daily, monthly and annual streamflow measurements from national and local agencies like the USGS (USGS, 2012c), and county-level yearly crop yield statistics from the USDA-NASS (USDA-NASS, 2013), or study-area specific data sources like UIUC FarmDoc (University of Illinois at Urbana-Champaign (UIUC) College of Agricultural, Consumer and Environmental Sciences (ACES), 2003-2012). The Upper Mississippi River Basin study (Srinivasan et al., 2010) used streamflow measurements from 11 USGS stations (USGS, 2012c) to calibrate and validate SWAT simulations. The chosen stations corresponded to the nearest subbasin outlet based on ArcSWAT's (Srinivasan, 2009) delineation of the hydrology of the watershed. The study used USDA-NASS crop yield statistics (USDA-NASS, 2012), which is available yearly county-by-county, and aggregated it into SWAT subbasins. The analysis of the much smaller watershed in East-Central Illinois (Hu et al., 2007) incorporated one USGS (USGS, 2012c) streamflow gauge, and USDA-NASS (USDA-NASS, 2012) crop yields, which were weighted by the proportion of each county in the watershed.

SWAT has built-in functionality to implement and simulate the effect of human activities (Neitsch et al., 2009). For example, estimates from the Illinois Commercial Fertilizer Tonnage Reports from the Illinois Department of Agriculture (Illinois Department of Agriculture, 2010), the USDA-NASS (2012), and the Illinois Agronomy Handbook (Hollinger & Angel, 2009) were used to initialize existing SWAT cropping, fertilizer and tillage modeling routines to simulate the fertilizer reduction scenarios in the East-Central Illinois watershed study (Hu et al., 2007). County-level estimates from the Conservation Technology Information Center in Ohio, and the USDA Census of Agriculture (USDA-NASS, 2009) were used with SWAT routines for tillage practices and fertilizer applications in the Ohio crop yield calibration study (Nair et al., 2011). Similar built-in routines in SWAT have been modified and extended with study-area specific input data to assess varied management. Using input data from the USDA-NRCS, the Texas State Soil and Water Conservation Board (TSSWCB), and the Irrigation Technology Center at

Texas A&M University, an analysis of different irrigation amounts, timings, and frequencies was performed in the intensively canal irrigated Arroyo Colorado Basin in Texas (Kannan et al., 2011). The study initialized SWAT routines for: point source inputs for municipal treatment plants and shrimp farms (Rains & Miranda, 2002); irrigation schedules for sorghum, cotton, and sugar cane (Texas Water Development Board (TWDB), 2005); and land leveling or water management irrigation BMPs (Texas Water Development Board (TWDB), 2005). Similarly, data from the Texas Natural Resource Conservation Commission (McFarland & Hauck, 1995) on the location, size, herd size, and waste application management plans for dairy cow operations in the North Bosque River watershed in Texas were used to identify the effect of manure application on nitrate levels (Saleh et al., 2000). Increasing availability and frequency of data have expanded modeling capabilities, and ways to calibrate and verify natural-systems models (Gassman et al., 2007).

2.2.3 Data Sources in Human Systems Modeling

While natural systems models produce accurate simulation of hydrologic process, adoption of BMPs in agricultural management is dependent on accurate modeling of hydrologic processes, but economic, social and institutional forces as well (Nowak & Korsching, 1998). Studies regarding management in watershed and conservation strategy adoption rely on economic, behavioral and institutional data to characterize human influences on environmental outcomes. Institutional data sources are organizations that define considerations like laws, taxes, standards, and codes; they span both human and natural systems modeling (Section 2.2.2). It is recommended to include empirical observations when available to relate the model in real-world outcomes (Robinson et al., 2007). Economic and behavioral data sources are generally derived from local research agencies and surveying or government reporting like the USDA agricultural census (USDA-NASS, 2009). Similar to natural-systems data, scale and resolution must be considered. Like precipitation, single point measurement may not be available, and input data need to be defined in terms of a region, which involves establishing a boundary that is meaningful but does not actually exist (McDonnell, 2008). Moreover, surveying or voluntary participation in data collection, like the USDA Census, may not accurately represent behavior in a defined area.

Modeling economic outcomes for human systems in agriculture draws on data related to prices, costs, profitability, and market performance. Typical Central Illinois farmer balance sheets from University of Illinois extension (UIUC-ACES, 2003-2012), and carbon credit pricing from the Chicago Climate Exchange (InterContinental Exchange, 2013) was used to model planting decisions with respect to the adoption of the bioenergy crop Miscanthus (Ng et al., 2011). Empirical data on prices, costs of production, property law from government reports (Muchnik et al., 1996) in a Chilean watershed were used to model household adoption behavior with respect to government policy changes (Berger, 2001). Using data from the European Farm Accountancy Data Network (FADN) (European Commision, 2013) on farm size, farmer demographics, costs, and labor utilization, an analysis was performed on policy changes on European farms with respect to rent, interest rates, and income (Happe et al., 2006). The FADN data were used to define farmer behavior, socioeconomic status, and managerial ability and simulate policy outcomes.

Decision-making in human-systems models has also incorporated empirical socioeconomic observations. Le et al. (2008) identified one challenge in modeling land-use change in Vietnamese agriculture was developing an empirically grounded decision-making mechanism. Empirical typological Vietnamese farm data were used to define human, social, physical and financial, along with natural constraints, to model agricultural policy adoption (Le et al., submitted for publication). For a watershed in Southern Illinois, future adoption of BMPs and economic outcomes were forecasted (Sengupta et al., 2005) using used survey results (Lant et al., 2001) regarding participation in the Conservation Reserve Program (CRP). The survey polled 235 area producers for possibility of adoption, age, experience in farming, income. The study also used USDA-NASS (2013) spatial data defining farm acreage in CRP, and economic incentive rates from the Farm Service Agency (USDA-FSA, 2013). Similarly, data for the cost of BMP implementation estimates were obtained from by the USDA-NRCS (2012c).

In a similar approach to characterize adoption behavior and its impact, a broader-scale assessment of conservation practice effectiveness in the Upper Mississippi River Basin (USDA-NRCS, 2012b), employed a 3-year USDA-NRCS survey (USDA-NRCS, 2007) of adoption and the 2007 Census of Agriculture (USDA-NASS, 2009) to typify farms in the area. The NRI-CEAP survey (USDA-NRCS, 2007) provided 3,703 survey points in the Upper Mississippi River Basin, which were used to designate areas and their associated farming practices. The study extrapolated the survey data across subregions within the UMRB, and were deemed reliable reporting at that scale. The extrapolation was used to target critical areas for adopting conservation practices.

2.2.4 Data Sources Conclusions

Data sources in paired human-natural systems can be categorized into five categories: physical, environmental, social, economic, and behavioral. There are considerations of scale, resolution, processing time, and modeled area. In general, lower resolutions and larger areas result in and less predictive power (Srinivasan et al., 2010). Higher resolutions result in more processing time and are highly predictive (Gitau et al., 2011). Precipitation and topography data resolution has been identified as the most significant factor for the accuracy of hydrologic assessment (Moriasi et al., 2007).

It is important to recognize that the necessary sources of input data are widely and freely available. Data sources range from university extension agencies to government sources. Data may not come ready to use out of the box. There is processing required for different model input requirements. Fortunately, advances in GISs have facilitated and expedited data processing for analysis. Data management software is also necessary to process model output and input.

Natural systems data range from the slope of a hill to the water to the nitrogen content of corn growing downstream. Data are obtained from government, research agency, and related studies. Human processes information is generally available through survey-based research and reporting through government initiatives by agencies like the USDA and NRCS or local surveys specific to the study area. Extrapolating input data for areas where data are not available is necessary. Further, it is important to recognize that some private production methods like fertilizer application rates and timing are generalized by industry or government reports for areas where input data are not available (Illinois Department of Agriculture, 2010). Input data for modeling BMPs are derived from institutional data sources that measure their adoption, field studies on their effectiveness, and previous modeling studies where these strategies have been parameterized. Further, GIS software facilitates a location-specific analysis of BMP installations. BMP modeling data sources are at the nexus between human and natural systems modeling. Finally, data describing human systems for economic, policy, and social factors are drawn from government agencies, surveys, and trade/industry organizations/publications. Grounding human-systems models with empirical data is an important consideration. Implementing a model for phenomena like land-use change should be informed and assessed with observations of the real-world phenomenon when available and feasible. Incorporating empirical observations, like survey results, is improving their usefulness in applications, reflecting realistic assumptions and practical outcomes (Matthews et al., 2007).

2.3 Modeling and Simulation

2.3.1 Introduction

Modeling of coupled human-natural systems in agriculture is a useful tool for stakeholders where it is not practical or too expensive to perform long-term physically-based studies. This is due to diverse production approaches, diffusive impact, and expansive geography in agriculture. Direct water monitoring and field studies are usually costly and labor intensive, and require many years of monitoring to sufficiently account for climatic fluctuations. Acknowledging human interactions and accounting for their impact increases the complexity of the system but facilitates a more robust modeling outcome (McDonnell, 2008).

Coupled human-natural systems models can be described and selected using the following considerations: known or available model inputs, desired scale, and desired model output. Inputs select from the various data sources discussed (Section 2.2): streamflow partitioning, plant growth, crop yields, conservation adoption rates, and financial benchmarks. The availability of this input data informs model selection and facilitates verification of outputs like: scenario and sensitivity analysis, forecasting, and management recommendations. This study summarizes some of the widely used hydrological/physical models used in agriculture and their applications in long-term coupled analyses. The summary outlines the capabilities, performance and applications of these models with a focus on SWAT studies of BMP effectiveness and watershed management in Midwestern agriculture. Of particular importance for this thesis are the applications of SWAT to model hydrology, nutrient flux (specifically nitrate), tile drainage, and Midwestern corn and soybean BMPs.

2.3.2 Natural-Systems Models

This section will introduce commonly applied natural-system models in agricultural watersheds. The reviewed models can be categorized by scale: field-scale and watershed scale. The discussion is divided into capabilities, performance, and applications of these models.

2.3.2.1 Natural-systems models capabilities

The Soil and Water Assessment Tool (SWAT) is a basin-watershed scale, continuous-time model that operates on a daily/monthly/yearly time step and is designed to predict the impact of management on water, sediment, and agricultural chemical yields in ungauged watersheds (Neitsch et al., 2011).

As outlined in the SWAT Theoretical Documentation: "SWAT conceptualizes watershed by dividing similar topographic, soil, and land-use areas into hydrologic response units (HRUs) which are connected by the stream network. Published equations on soil water content, precipitation, surface runoff, evapotranspiration, percolation, and groundwater return (base) flow are employed to model daily water budgets. Plant nutrient consumption, which is estimated by supply in the soil and cropping demands, and nutrient and sediment routing routines are documented as well. The model is physically based, computationally efficient, and capable of continuous simulation over long time periods with built-in modeling of BMPs like tile-drainage, filter strips, animal grazing." (Neitsch et al., 2011; Parajuli et al., 2008) These routines are adaptable to diverse watersheds. As a result, SWAT is a parameter-intensive model using physically based and empirical relationships. Sources of input data are readily available from government and local agencies (Section 2.2.2).

The Hydrological Simulation Program − Fortran (HSPF) is a continuous watershed-scale model for simulating hydrology and water quality for a wide range of conventional and toxic organic pollutants (Bicknell et al., 2001). The documentation for HSPF describes the capabilities and underlying design features: "HSPF can be operated on an hourly time-scale, and BMPs can be simulated either through land use changes, or add-on modules. HSPF conceptualizes watersheds as a collection of pervious and impervious subwatersheds routing to a stream segment or mixed-use reservoir. Empirical equations govern the water budget and account for interception, infiltration, evapotranspiration, snowmelt, surface runoff, interflow, groundwater loss and recharge, and base flow. Physical properties and published equations determine pervious land surface erosion and transport, in-stream sediment transport, and deposition. HSPF employs subroutines of nutrient dynamics and calculates individual nutrient balances at a user-specified time step. HSPF allows for detailed inputs of field operations and fertilization rates (management activities) through its special actions module. It simulates in-stream fate and transport of a wide variety of pollutants, such as nutrients, sediment, dissolved oxygen, biochemical oxygen demand, temperature, bacteria, and user-defined constituents, including pesticides." (Bicknell et al., 2001) Boreh et al. (Borah et al., 2006) concluded in a review of HSPF for TMDL applications that: HSPF is chosen for modeling because of its flexibility, ability to simulate a wide range of user-configurable inputs, modular structure that allows use of only those components needed for a specific application, and USEPA and USGS support. Its limitations include large requirements of input data, the need for monitored data in order to perform calibration, and a steep learning curve (Borah et al., 2006). Like SWAT, it is also a long-term model and is not suitable for single event simulation.

Both SWAT and HSPF are approved by the EPA to perform TMDL reporting requirements (Shoemaker et al., 2005). Both are comprehensive watershed models with a focus on agricultural applications that model agricultural practices like irrigation, drainage, wetlands and BMPs (Borah et al., 2006). In addition, HSPF and SWAT include modeling of atmospheric deposition, which is an important consideration in large watershed or estuaries (Gassman et al., 2007). Fertilizer and manure application are also included which is a significant factor in the nutrient cycle in many agriculturally oriented watersheds models (Gassman et al., 2007).

Watershed-basin models provide a resolution of their smallest reporting unit. SWAT assigns an HRU based on area, soil type, and slope, for example. Field-scale models, on the other hand, have a resolution of the study area provided by the user. The Root Zone Water Quality Model (RZWQM) is a "field scale, physical, biological, and chemical process model that simulates plant growth and movement of water, nutrients, and pesticides over and through the root zone at a representative area of an agricultural cropping system. It is a one-dimensional, vertically into the soil profile, model designed to simulate conditions on a unit-area basis. Built-in agricultural management alternatives include evaluation of conservation tillage and residue cover versus conventional tillage, methods and timing of fertilizer and pesticide applications, manure and alternative chemical formulations, irrigation and drainage technology, methods and timing of water applications, and different crop rotations." (Ma et al., 2001) DRAINMOD is also a "one-dimensional, field-scale computer model designed to simulate the effects of artificial surface and subsurface drainage systems on the hydrology and nutrient flux of agricultural fields. DRAINMOD can simulate cropping decisions, fertilizer applications, tillage practices, and drainage system design." (Skaggs, 1980)

2.3.2.2 Natural-systems models performance

A model's performance is usually assessed by its ability to model observed outcomes specific to modeling objectives. In the context of watershed management, the hydrologic balance, the amount of precipitation, infiltration, runoff, and streamflow are usually described and compared to observed data where possible. Assessing performance is done statistically, graphically, or by reporting validated results. The two most common statistical measures are the regression coefficient, R-squared (R^2), and the Nash-Sutcliffe model efficiency (NSE) (Nash & Sutcliffe, 1970) coefficient. R-squared measures how close the modeled outcome's regression line matches the observed values' regression line. A value of 1 for R-squared indicates perfectly correlated regression lines, and a value of zero indicates no correlation. NSE measures how well simulated values versus observed data match the 1:1 line. NSE ranges from negative infinity to 1. A value less than 0 indicates that the mean of the observed data is a better indicator than the model. R-squared and NSE are, by far, the most widely used performance statistics used in SWAT model calibrations and validations (Gassman et al., 2007). Percent bias is also used to categorize model accuracy for less sampled outcomes like crop yield, which is an annual event (Gassman et al., 2007).

Moraisi et al. (2007) proposed a NSE greater than 0.5 (daily) and 0.65 (monthly) and percent bias within 25 percent (daily) and 10 percent (monthly) for hydrologic assessments, and percent bias within 70% for nitrogen in a review of performance criteria for SWAT and HPSF applications (Moriasi et al., 2007). Gassman et al. (2007) compiled R-squared and NSE performance statistics for SWAT applications for 115 hydrologic assessments and 37 pollutant studies (Gassman et al., 2007). Most studies with sufficient sources of input data exceeded Moriasi's criteria (Arabi et al., 2008; Hu et al., 2007; Moriasi et al., 2012), with weaker results for daily performance, inadequate input data (low precipitation resolution for large study areas), and simulations with uncalibrated parameters (Gassman et al., 2007).

Experience and environmental analysis are important in initializing models to achieve satisfactory performance (Shoemaker et al., 2005). Parameter-intensive models require some sort of calibration. Calibration of parameters can be done by applying known values directly, manually testing combinations and values, or automating the selection. Mixing the approaches can also improve performance and reduce uncertainty in the model. Manual calibration involves changing parameters within a desired range and evaluating performance statistics, elements of the hydrograph, or chosen modeling objectives. In cases where manual calibration is too laborious, automatic calibration in the form of an objective function and a range of parameters may be searched.

Moriasi et al. (2007) recommended guidelines for watershed calibration procedures as well. To form a robust model, a calibration should include the full range of hydrologic events in a watershed. Average, wet, and dry years should be included in a calibration (Bracmort et al., 2006). Calibration procedures should consider water balance components like peak flow, tile-flow, surface runoff (Moriasi et al., 2007). Observed values of the water balance like evapotranspiration should be verified along with reasonable estimates of plant growth and biomass production. The calibration procedures with respect to these guidelines for relevant studies in this analysis will be covered in the application section.

2.3.2.3 Natural-systems models applications

This study focuses on modeling agricultural Midwestern watershed and the effectiveness of conservation strategies with respect to water quality and producer behavior. To demonstrate the capabilities of the discussed models and provide a measure of their performance in this domain, a few relevant applications will be presented in the following three categories with a concentration on SWAT: hydrologic assessments, crop yield and nutrient modeling, and BMP analyses.

2.3.2.3.1 SWAT Hydrologic Assessments

One of the first SWAT hydrologic assessments validated flow partitioning and evapotranspiration models over three years for three Illinois watersheds (Arnold, 1996), ranging in size from 122 to 246 km^2. SWAT was calibrated manually by adjusting the soil available water capacity and the surface runoff coefficient or curve number with an R-squared of between 0.63 and 0.95 for the three gauges monthly total stream flow, and annual water balance components within 25% of observed values. Both SWAT and HSPF were applied to the much larger Iroquois River Watershed (5568 km^2) in Central Illinois by manually calibrating 5 SWAT parameters (surface runoff coefficient, plant evapotranspiration, tile drain depth, baseflow recession coefficient) and 14 HSPF parameters (describing soil infiltration rate, evapotranspiration rate, surface runoff rate) (Singh et al., 2005). The study assessed 15-year model verification period and showed that both models performed with a NSE of 0.88 for monthly flow and 0.80 for daily flow. The study noted that SWAT required considerably less effort to apply and may have resulted in better performance as a result of tile drainage capabilities (Singh et al., 2005). The 2012 version of SWAT with DRAINMMOD tile drainage routines was calibrated manually and used to model streamflow and water balance spanning a three-year calibration and five-year validation period in the South Fork Watershed in Iowa (Moriasi et al., 2012). By varying tile drainage design parameters, surface runoff and evapotranspiration parameters over fixed intervals within feasible regions, daily flows were modeled with NSE of 0.76 (0.85) and 0.5 (0.7) for daily (monthly) calibration and validation periods respectively.

2.3.2.3.2 SWAT Crop Yield and Nutrient Modeling

Modeling nutrient flux and pollutant levels with respect to crop yields is of primary importance in agricultural watersheds for this analysis. In an analysis of fertilizer reduction strategies East-Central Illinois Embarras watershed, SWAT modeled monthly streamflows with an NSE of 0.85 (0.69), monthly NO_3 fluxes with an NSE of 0.2 (0.31) for calibration (validation) regions, along with corn and soybean yields within 10% for an 18 year period (Hu et al., 2007). The calibration was performed in three stages for hydrology, nutrient flux, and finally crop yield using an automated trial-and-error search of parameter ranges. Nutrient flux was calibrated using past estimates the nitrogen balance for past field studies (McIsaac & Hu, 2004b) in the region. The nitrogen fixation in soybeans and harvested nitrogen was overestimated, and the study recommended additional parameterization in SWAT. SWAT was calibrated using four-stage iterative calibration procedure, by assessing model outcome performance after each step and repeating if insufficient, and applied to the Upper Big Walnut Creek (UBWC) watershed in central Ohio (Nair et al., 2011). The four stages were: parameter selection, hydrology calibration, crop yield calibration, and nutrient loading calibration. The parameter set included the surface runoff coefficient, evapotranspiration rates, crop nutrient uptake rates, nitrogen content in biomass, and leaf area indices. The study modeled daily streamflow over a 10-year validation period with a NS of 0.5, monthly nitrogen flux with an NS of 0.66, and corn, soybean, and winter wheat yields all within 10 percent. The harvested crop nitrogen was assessed for accuracy using the estimates same field studies (McIsaac & Hu, 2004a) as performed in Hu et al. (2007). While the calibration procedure is significant and utilizing as much input data as possible is recommended, in an uncalibrated SWAT model applied to the Upper Mississippi

River Basin, crop yields were modeled within 25%, and monthly streamflows with an NS between -.10 and .8 across 11 subbasins (Srinivasan et al., 2010).

2.3.2.3.3 SWAT BMP Analyses

SWAT has built-in functionality for modeling several agricultural practices including changes in fertilizer and pesticide application, tillage operations, crop rotation, dams, wetlands, and ponds (Neitsch et al., 2011; Srinivasan et al., 2010). The model also has the capacity to represent many other commonly used management practices in agriculture. SWAT was calibrated using a manual and automatic procedure across 39 SWAT parameters, and applied to a Central Illinois watershed to develop a coupled optimization-watershed model (Bekele et al., 2011) for optimal selection and placement of best management practices. Daily streamflow performance was NSE of 0.68, and annual sediment, phosphorus, nitrogen were all modeled within 6% error. The BMPs incorporated in the coupled model were based on typical management in the study area: filter strips, grassed waterways, and constructed wetlands. SWAT directly simulated filter strips and constructed wetlands. The built-in routines for grassed waterways are represented in the model using parameters governing channel processes such as channel roughness, cover, and erodibility factors (Bekele et al., 2011). The study identified preferred placement locations or HRUs in the watershed for a particular BMP type linking pollutant reduction at the watershed outlet and minimizing BMP costs.

SWAT was also applied to the Silver Creek watershed in Southwest Illinois to identify appropriate BMP placement (Kaini et al., 2012). The calibration identified parameters and used an automated calibration routine to vary the parameters to minimize R-squared for 14 streamflow parameters first and then 4 sediment parameters. Daily streamflow modeling performance over two years was NSE of 0.73, and sediment with a NSE of 0.76. Grassed waterways, filter strips, terracing, and stabilization structures were simulated using built-in SWAT implementations which modify parameters average slope length, erodibility, and runoff coefficients (Neitsch et al., 2011). The study identified costs and optimized locations for 20%, 40%, and 60% reductions in sediment. As part of USDA Conservation Effectiveness Assessment Program (CEAP), SWAT was applied to a 32 km^2 watershed in Northwest Arkansas to model non-structural BMPs. The study considered reduced poultry litter and commercial fertilizer application rates, application timing and chemical amendment to poultry litter, improved grazing and pasture management, and edge-of-field and riparian buffer zones. The study included weather variations as well to assess BMP effectiveness across spatial and temporal scales. The application required more than 43,000 runs of the SWAT model over 2 weeks using Condor, a free public domain software system for high throughput computing (Condor Team, 2013; TeraGrid, 2013). SWAT output was processed for analysis using MATLAB. The study concluded that N losses were greatest for fall fertilizer application for all grazing management and P losses were not sensitive to fertilizer application timing for no grazing and optimum grazing management. The interaction effects between litter application timing and grazing management on P losses indicated that low-intensity grazing management had greater impacts on P losses than litter application timing.

2.3.2.3.4 Other Analyses

A few applications of the other discussed models are presented to demonstrate their capabilities, calibration, and performance. The Root Zone Water Quality Model (RZWQM) was applied to a field near Story City, Iowa to model tile flow, NO_3 flux, and crop yields (Bakhsh et al., 2001). Over a three year period the model simulated tile flow, NO_3 losses in tile water, and yields by showing a percent difference of –8%, 15%, and –4%, respectively, between measured and simulated values. The calibration was performed sequentially with the hydrologic component first, then nutrients, and finally crop parameters (Bakhsh et al., 2001). Drainable porosity and saturated hydraulic conductivity of the soils, nutrient transfer coefficients, and plant growth parameters were used.

DRAINMOD was compared to SWAT for the Embarras watershed (Gentry et al., 2009) in East-Central Illinois discussed in the SWAT section to simulate the nitrogen budget. DRAINMOD was calibrated with evapotranspiration coefficients, crop rooting depths, physical soil parameters, and drainage system design. DRAINMOD underperformed SWAT with a prediction efficiency of 0.80 and 0.53 for monthly streamflow and nitrate flux respectively, and over predicted crop yields by 5-8% for a 10 year period. It's important to note that the comparisons were made on a representative unit area, as DRAINMOD is a field-scale model.

Best management practices have also been modeled on a representative unit area basis (specific plot, or field scale modeling). Nine plots in Minnesota, ranging from .6 to 2.4 ha, were assessed using DRAINMOD to show that shallow drainage and controlled drainage, two alternative drainage practices receiving much attention in the region, were both predicted to reduce annual drainage volumes and NO_3-nitrogen losses, with the latter appearing to be the most effective (Luo et al., 2010). Drainage design, crop nutrient uptake, denitrification, nutrient transport parameters were all manually calibrated first for physical properties of the area like the depth to the impermeable layer, then for hydrology, and then for nutrient flux. Flow predictions ranged from 2 to 24 percent error across the 9 plots and 7 years. Nutrient predictions ranged from 0 to 85 percent error, and crop yields were predicted within 5 percent error (Luo et al., 2010). 36 one acre plots in Nashua, IA were studied (L. Ma et al., 2007) using the RZWQM to simulate the trends of tillage practices, crop rotation, and controlled drainage on yearly drain flow and yearly N loss in drain flow, their effects on corn yield were less adequately simulated.

The tillage practices, soil properties, and manure applications from one plot were used to calibrate the model. Singer et al. (2011) used the RZWQM to demonstrate that N loads to tile drains can be reduced 19–28% using winter annual cover crops in Midwestern maize–maize–soybean and maize–soybean rotations.

2.3.2.4 Natural-Systems Models Conclusions

Four natural systems models have been presented to demonstrate the capabilities and performance of modeling the hydrology, pollutant transport, and yield in Midwestern agricultural watersheds. Criteria for sufficient modeling performance were presented to serve as benchmarks for applications. The analysis shows that the SWAT is one model that can provide functionality and meet these criteria. SWAT is a basin-scale model, provides a resolution for placement of structural and non-structural BMPs through a watershed, is accepted for TMDL analyses which serve as a plan for improving water quality, and is the most extensively applied model for Midwestern agricultural watersheds (Gassman et al., 2007).

2.3.3 Human-Systems Models

Integrating the human dimension in watershed management is important in determining both the effectiveness and efficiency of resource management programs. Human dimensions of water and land use have been modeled for forecasting, planning, and conservation. Modeling of the behavior of agricultural stakeholders and the economic tradeoffs posed by production have been utilized to improve outcomes. In agricultural conservation, modeling of a farmer's adoption or lack of adoption of a select practice and the reasons underlying that choice are critical dimensions for a comprehensive understanding of agricultural processes. Government agencies and agricultural extension entities have developed decision-making models to assist producers and researchers for conservation planning. This section summarizes specific human-systems models in agricultural, along with broader approaches taken in modeling human systems along like agent-based modeling, with an overview of some of the efforts to model human-systems employed in agricultural watershed management, and descriptions of their capabilities, performance. The reviewed models have coupled natural components. As a result, the review of applications is presented in the context of coupled analyses.

2.3.3.1 Overview of Models

One model designed to capture farm decision-making is the Comprehensive Economic and Environmental Optimization Tool and the related Farm Economic Model (FEM) developed by the EPA (Keith et al., 2000; Osei et al., 2000). The model operates on an annual time step and can be executed for extended periods of 30 years or more. Key sources of input data required to simulate a farm in FEM include type of livestock system, manure management methods, cropping systems, facilities and equipment, field characteristics and other external factors. Economic outputs generated by FEM include total revenue, components (crop and livestock, fertilizer, labor, etc.), total cost, net returns, costs of individual production, debt payment, and owner's equity (Osei et al., 2000).

Another tool to model farm decision-making is the Integrated Farm System Model available through the USDA – ARS (Rotz et al., 2012). The model considers crop rotations, feeding strategies, equipment, facilities, among other management options that can be evaluated. The model requires considerable calibration because of the number of options available to the user. The farm model is designed to represent the performance and economics of a farm firm by considering all major production costs and income for products leaving a farm. This assumption allows the measure of system performance to reflect one year’s use of resources to produce that year’s production. End-of-year crop inventories are sold and feed shortages are purchased to maintain steady state accounting of resources (Rotz et al., 2012). The ISFM was calibrated to predict farm yields for a 100 hectare pasture with four forage species for dairy cow production (Corson et al., 2007). Along with calibrated parameters like forage growth rate, rooting depth, nutrient uptake, yields and pasturing parameters (Rotz et al., 2012) for economic yields were calibrated. Net returns per cow for each species were simulated, with a correlation to yields of at least 0.92.

ISFM and FEM are models that are designed to typify a single farm unit. Modeling human decision-making on a larger-scale in communities and watersheds increases the complexity. The dynamics of a watershed is influenced both by environmental factors and by actions of individuals and institutions. Its behavior is characterized by interactions, emergence and non-linearities. It is difficult to observe and recognize feedback loops and unpredictable consequences in social and biophysical systems. ISFM and FEM provide results with a resolution of the study area only. A broader scale model, SEAMLESS, conceptualizes typical agricultural actors, members of the production chain, government entities, and market forces for the European Union (van Ittersum et al., 2008). The model requires a calibrated baseline with selected agro-technological options, and simulates economic and environmental outcomes over 15 years. SEAMLESS provides international, national and regional policies for simulation. SEAMLESS requires extensive calibration across components to account for diversity within the European Union.

Two broad modeling approaches to human-systems that have been applied beyond agricultural watershed management to areas like urban land use, water demand and pricing, are cellular automation and agent-based modeling. These modeling approaches can be constructed for study-specific applications, and therefore do not have generic properties. Each approach may use a top-down or bottom-up approach (Matthews et al., 2007). Top-down models define criteria or objectives to dictate how an area should be spatially structured. Bottom-up models are developed with rules specifying interactions among individual decision-makers (e.g., residents, businesses, institutions, etc.) or, at a higher level of abstraction, interactions among individual land use parcels to simulate the emergence of land use patterns over time (Bone et al., 2011).

Cellular automation conceptually divides a surface into cells and associates with each cell an automaton, an entity that independently executes its own state-transition rules, taking into account the nearby cells (Jantz et al., 2010). In land use change, implementation of the model occurs in two general phases: calibration, where historic growth patterns are simulated; and prediction, where historic patterns of growth are projected into the future.

Agent-based modeling is another technique used to describe human processes (Robinson et al., 2007). Agent-based modeling facilitates forecasts, decision-making, and scenario analysis for large-scale, diverse, otherwise complex human processes like watershed management. Such models can be valuable tools to identify potential mechanisms of resilience of specific social-ecological systems. In agent-based modeling, rules determine how autonomous entities behave and interaction with other entities in a modeled system. The agents can be programmed and calibrated according to real-world observations but there is limited validation of agent-based modeling result because it is an abstraction of larger immeasurable system. However, the abstraction can characterize systems beyond mathematical classification. The ABM mindset consists of describing a system from the perspective of its constituent. It has several advantages: ABM captures emergent phenomena, provides a natural description of a system, and is flexible. ABMs also have their disadvantages: human behavior is difficult to quantify, calibrate, and sometimes justify (Bonabeau, 2002).

2.3.3.2 Applications of Coupled Natural-Human Systems Models

Because of the coupled nature of these analyses and the direction of this study, applications of human-systems models are summarized in a review of coupled studies. The review focuses on agricultural management with respect to environmental and economic costs.

The Farm Economic Model (FEM) with SWAT was used to evaluate the impacts of a late spring nitrate test (LSNT) and a fall and winter cover crop (rye) on the a Northern Iowa agricultural watershed (Saleh et al., 2007). The simulation results were compared to a field test of a 25% reduction in NO_3-N due to the LSNT scenario (Jaynes et al., 2004). The FEM was used to generate several scenarios and relate environmental impacts to economic costs. The application of LSNT resulted in a reduction (31%) of nitrate losses a cost of about $6/ha. Using rye as cover crop during fall and winter resulted in reduction of sediment and all nutrients at a cost of about $26/ha if planted after corn harvest only and about $34/ha if planted after both corn and soybean harvests.

The Integrated Farm System Model (ISFM) was applied (Rotz et al., 2011) to evaluate methods for applying manure in Pennsylvania pastures. The model predicted ammonia emissions, nitrate leaching, and phosphorus runoff losses similar to those measured over four years of field trials. Each application method was considered on three Pennsylvania farms over 25 years. The ISFM related farm profits to nutrient losses. On a swine and cow-calf beef operation under grass production, shallow disk injection increased profit by $340 while reducing ammonia nitrogen and soluble phosphorus losses by 48% and 70%, respectively. On a corn-and-grass-based grazing dairy farm, shallow disk injection reduced ammonia loss by 21% and soluble P loss by 76% with little impact on farm profit. Incorporation by tillage and band application with aeration provided less environmental benefit with a net decrease in farm profit. On a large corn-and-alfalfa-based dairy farm where manure nutrients were available in excess of crop needs, incorporation methods were not economically beneficial, but they provided environmental benefits with relatively low annual net costs ($13 to $18 cow). In all farming systems, shallow disk injection provided the greatest environmental benefit at the least cost or greatest profit for the producer.

An agent-based model was constructed to determine and assign BMP installations (filter strips, no-till, and permanent vegetation) in a Northern Kansas watershed management plan (Nejadhashemi et al., 2011). The ABM used the cost of implementing each BMP using one-time and annual costs over a given time horizon for each BMP on each farm. The price of targeted nutrient was calculated as the government budget for reducing that nutrient (per unit nutrient). Adoption would occur if BMP cost per reduction in the nutrient exceeded the government budget per unit nutrient. The study coupled the ABM with SWAT and varied BMP costs and government budgets to find an optimal reduction strategy: government funds could be allocated up to $1 million on BMP implemention before allocating any funds for dredging to address sediment loading (Nejadhashemi et al., 2011).

An agent-based model was built to simulate biofuel cropping and carbon credit adoption in a Central Illinois watershed (Ng et al., 2011). The study formed the agent-based model defining initial perceptions of prices, costs, yields and the weather, and how they update those perceptions with time. Agents were diverse in their land holdings, quality of land, economic advantage, yields, time discount rates, foresights, and risk aversions as well. Farmer behavior adapted over time regarding initially unknown practices with respect to their neighbors and experience. The ABM was coupled with SWAT. The results of the study highlighted potential market instruments that would be more successful and nitrate mitigation strategies. Ng et al. (2011)

identified the need for better ways to verify ABM conclusions and incorporate observations and empirical data in model formulation.

Researchers performed a large-scale simulation of The Chesapeake Bay Watershed using a coupled natural-human agent-based model to identify stakeholders and policy initiatives to improve the ecological health of watershed (Learmonth et al., 2011). The study conducted the University of Virginia Bay Game to simulated decision-making and calibrated the simulation to observed watershed health. Results from the game showed a dramatic reduction in the nutrients flowing into the bay from the agriculture sector, and an increase in overall bay health and a sustainable fishing industry. Watershed improvement positively affected farming sector profitability, suggesting an opportunity for policy incentives to support the transition to new practices (Learmonth et al., 2011).

In land-use modeling, Zellner (2007) developed Water-Use Land-Use Model, an agent-based model to simulated land-use changes in Southeast Michigan and the linkage to groundwater aquifer depletion. The study defined hydrological processes using physical groundwater dynamics. The model defined agents as residents, stone quarries, golf courses and farmers) based on empirical and survey-based attributes. The conclusions identified zoning practices were the most important policy point in groundwater effects.

Additionally, there have been studies to incorporate empirical data from surveys and experiments for defining agent decision-making and verifying model behavior. Gilli and Winker (2003) modeled the foreign currency exchange market using an ABM and validated their results with observed market data. Castella et al. (2005) demonstrated that land-use scenarios in agricultural watersheds in Northern Vietnam could be validated using an ABM with observed data. The model was initialized with data from village surveys on population, ethnicity, number of buffaloes, and presence of reforestation or development projects. Agent behavior was seeded with behavior rules for typical farmer resource profiles.

2.3.3.3 Coupled Natural-Human Systems Models Conclusions

Physical models like SWAT are highly predictive for water processes like flow and water quality. They have capabilities for reliably simulating crop yields, management, and BMP installations. Physical models found to be highly integrative, synthetic, and useful for local stakeholders and regional policy makers at the field and watershed scale. Human systems models are helpful and necessary to form a more comprehensive description of an agricultural system, but difficult to verify because human behavior and decisions making is difficult to model and input data relies on unobservable outcomes over time. Integrating the two biophysical processes and socioeconomic processes in agriculture, water use, land use is a necessary and emerging research area. Increasing the use of empirical data is facilitating validation of paired physical-human models and making them more integrative. They can lead to insights on achieving optimal watershed management strategies. They provide policy makers with decision-making support for resource allocation, especially by taking into account the diversity of stakeholder trajectories and by eliciting the driving forces of land change and water use associated with each type of agro-ecosystem.

2.4 Decision Support

2.4.1 Decision Support Overview

Coupled human-natural systems models are leading to conclusions on the hydrology, management, land use, nutrient transport, economic tradeoffs, and conservation practice adoption in agriculture In practice, these models are meant to inform the stakeholders with information and analysis that would otherwise be too expensive or infeasible to obtain. It is important to model optimal placement of agricultural BMPs with respect to the trade-offs between multiple objectives can control diffuse pollution and lower costs for varied entities and across many scales. The modeling has led to the development of decision-support tools in agricultural management. Two important decision support tools, discussed in the following sections, are DSSAT and TMDL reporting.

2.4.2 Decision Support Tool Overview

The decision support system for agrotechnology transfer (DSSAT) is an approach to understand, predict and manage agricultural decisions. DSSAT can simulate field-scale single crop production systems considering weather, crop genetics, soil water, soil carbon and nitrogen, and management in single or multiple seasons and in crop rotations and incorporate factors such as soil phosphorus and plant diseases (Jones et al., 2003). DSSAT provides a platform that allows one to easily compare alternatives for specific inputs. DSSAT provides a user interface for the user to specify parameters, management, season/time frame, and outputs.

Total Maximum Daily Load (TMDLs) specify the amount of pollutant that needs to be reduced to meet standards, allocates pollutant load reductions, and provides recommendations to achieve those reductions (Shoemaker et al., 2005). A TMDL is the allowable load of any pollutant that a stream can receive and still achieve water quality standards and support its designated use. A TMDL is comprised of loads from permitted point, diffused and natural background sources. While a coupled human-natural systems modeling approach represents one option to meet reporting requirements, integrated models are important resources for decision-makers to identify viable strategies. Selecting the appropriate model is crucial in developing a feasible, defensible and equitable TMDL (Shoemaker et al., 2005). Likely benefits and drawbacks associated with various loading alternatives are central to effective management.

Modeling analyses can be used to test multiple scenarios, with various allocations to nonpoint and point sources. For example, coupled SWAT models are being used in TMDL analyses to inform policy regulating discharges into waterbodies.

2.4.3 Decision Support Tool Applications

DSSAT was coupled with RZWQM to simulate subsurface drainage, nitrate concentration in flow, and crop yield under various nitrogen application rates with winter cover cropping in a corn-soybean system in central Iowa (Li et al., 2008).The model results suggest that cover cropping did not reduce main crop yield with nitrogen application rates above 61 kg/ha nitrogen.

SWAT is being used in TMDL analyses to inform policy regulating discharges into waterbodies. Rosenthal et al. (2001) conducted an analysis in the Arroyo Colorado River watershed in Texas as part of a TMDL study to determine the impacts of placing BMPs in different areas of the watershed. The watershed had a mixture of urban and agricultural lands and excessive sediment and nutrient loads in the waterways. Sediment and nutrient loadings were simulated by SWAT for the outlet of the watershed. The SWAT model estimated an in-stream reduction of 50% for nitrate and phosphorus with a 50% reduction in fertilizer application rate. Saleh et al. (2007) studied the largest dairy producing area in Texas as part of a TMDL-related study. It was suspected that manure application in the North Bosque River watershed was delivering excessive nutrients to the waterways. The study utilized the Agricultural Practice Extender (APEX) to simulate the effect of buffer strips on the edge of field loadings of nutrients and sediment, and the output loadings were then input into the SWAT model to simulate transport and fate through the watershed. The study evaluated various phosphorus control scenarios, removal of dairy cow manure from the watershed, reductions of phosphorus in dairy cow diets, and reduced manure application rates.

In addition, larger scale studies are utilizing coupled natural-human systems models to assess the effectiveness and direct future efforts of policy initiatives on agriculture management. The USDA-NRCS utilized SWAT to analyze the Conservation Effect Assessment Project (CEAP) which funds conservation practices in U.S. farms (USDA-NRCS, 2011). CEAP estimated conservation benefits for reporting at the national and regional levels and to establish the scientific understanding of the effects and benefits of conservation practices at the watershed scale. Producers were able to install structural practices like terraces and filter strips, adopt nutrient management and retire land with assistance from the USDA. The study assessed the options available to producers and most beneficial opportunities in the future using SWAT and APEX and found that conservation practices have reduced wind erosion by 64%, sediment losses by water erosion by 61%, surface nitrogen loss by 45% while subsurface nitrogen loss by 9%, phosphorus loss by 44%. The study identified the most critical conservation needs in the future: sediment loss, nitrogen loss through surface and subsurface flow, and phosphorus loss. In addition, the study identified nutrient management as the most effective way to improve environmental outcomes in the Upper Mississippi River Watershed (USDA - NRCS, 2011).

2.4.4 Decision Support Conclusions

Coupled natural-human systems are helpful for determining the effects and optimal placement of agricultural BMPs and the trade-offs between multiple objectives in order to cost-effectively control diffuse pollution at varied scales (i.e. field and watershed scales). These tools are assisting decision making for producers and institutions. The use of these tools is limited with respect to physical and socio-economic data needs and usually requires advanced user skills to be successfully adjusted in various spatial scales and situations. The tools are good for researchers for simplified and generalized scenario analysis. As recent studies indicate, the models are informing policy-makers and producers.

2.5 Literature Review Conclusions

Coupled human-natural models can accurately characterize and quantify processes in agricultural systems. Data and modeling tools are widely available and largely free. Depending on the scale (spatial and stakeholder) and modeled process (nutrient, crop, social), there are many approaches and tools to consider. Natural systems models are more precise in quantifying verifiable data like flow and concentration. Human systems models are less rigid and may not be verifiable. Integrating both domains leads to more robust, practical conclusions. The approach is being employed in watershed management and policy decision-making for all stakeholders.

This study draws on the procedures, model selection, data requirements, and performance metrics to formulate a decision-making tool for an East-Central Illinois watershed. The literature demonstrates that policy instruments and agricultural management decisions can be reliably modeled for testing and forming conclusions to improve environmental and economic outcomes. This study is guided by past coupled analysis in similar watersheds in geography and management. The benchmarks and model development are informed by the discussed literature. These studies have established modeling performance benchmarks, recommended procedures, and BMP parameterizations to develop defensible and comprehensive models. The studies have produced recommendations and insights for improving water quality that are informed by practical real-world outcomes, which are used to validate and compare the results of this study.

CHAPTER 3

METHODS – NATURAL SYSTEMS MODEL

3.1 Introduction

This study sought to answer the following question: how can agricultural stakeholders improve environmental outcomes while preserving economic gains. The study took the following approach: model agricultural producer behavior and economic returns with respect to conservation strategy planning, environmental outcomes, and community/government policy. To model these outcomes, this study coupled a natural systems model and a human systems model in an East-Central Illinois watershed (Figure 3.1).

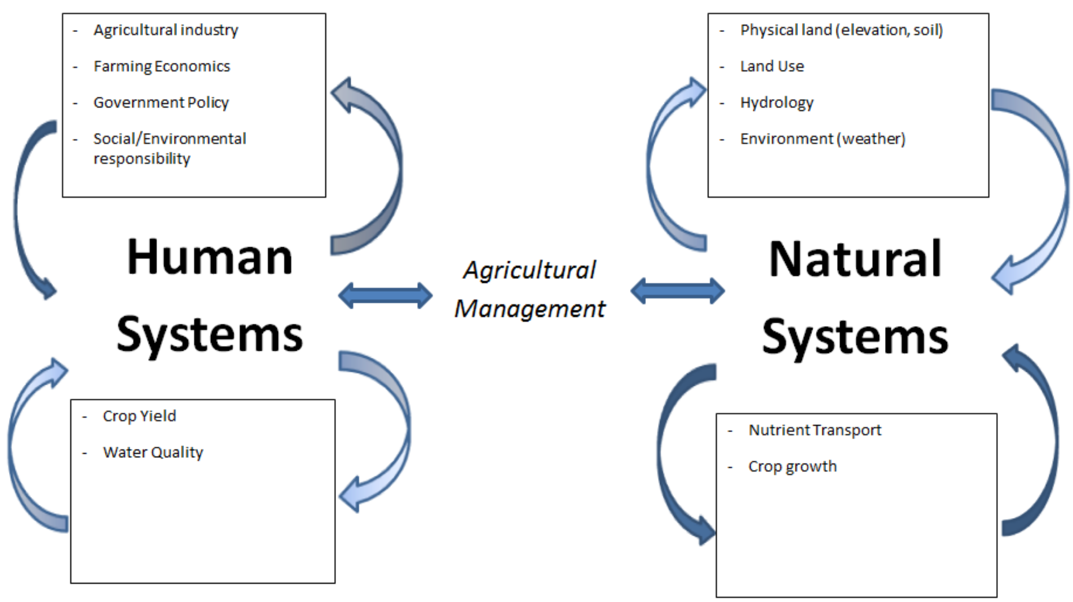

Figure 3.1: Coupled Natural-Human Systems Model

The metrics used to assess performance were water quality (nitrate and phosphorus levels), economic gains (yield, producer returns, government expenses/profit), and conservation practice adoption. Each model was calibrated to reflect observed environmental outcomes and producer behavior in the watershed. Once a calibrated model was formed, the model was employed to test different design features of conservation strategies and proposed government subsidies and taxes to find potential cost-effective and beneficial ways to accomplish the research objective.

The first part of the methodology is a presentation of the natural-systems model. The Soil and Water Assessment Tool was used to deliver natural systems outcomes: water quality, crop yields, and BMP modeling. The watershed description, calibration procedure and final SWAT model, and representation of conservation strategies are presented in Chapter 3. Three best management practices currently being employed in the watershed by producers were considered in this study: nutrient management, drainage water management, and winter cover cropping. Chapter 4 presents the human-systems model. An agent-based model was calibrated for cropping decisions, economic returns, and adoption of conservation strategies in the watershed. Finally, the coupling of the models, its interface, and the scenario analysis is presented. The agent-based model directed SWAT to implement farm decisions, and SWAT generated environmental outcomes for the agent-based model to consider in a feedback loop (Figure 3.2).

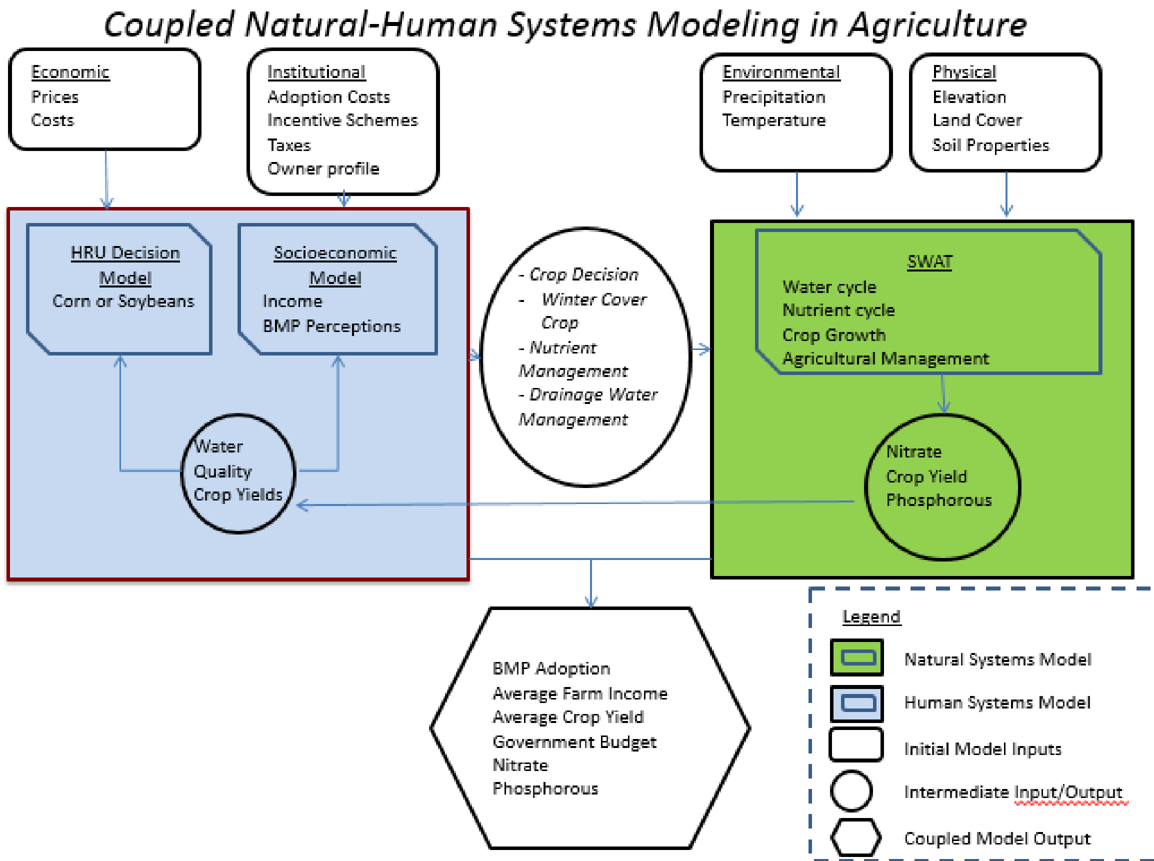

Figure 3.2: SWAT Agent-based Model

The coupled model produced the metrics for analyzing BMP adoption, effectiveness, and expense. The nexus of the coupled model are the management decisions: cropping and BMP decisions. The natural-systems model delivers environmental outcomes to the human-systems model; the human-systems model determines management decisions and invokes the natural-systems model in a feedback loop.

3.2 SWAT MODEL DEVELOPMENT

3.2.1 SWAT Model Overview

The natural systems component of the coupled analysis provided measures of water quality, hydrology, and crop growth for model development. SWAT was selected to model natural systems outcomes (water quality, crop growth, and hydrology). SWAT has a successful precedent of modeling these outcomes in Midwestern watersheds similar to the study area (Arnold, 1996; Bekele et al., 2011; Hu et al., 2007; Nair et al., 2011; Ng et al., 2010; Singh et al., 2005). This study focuses on four prior works that successfully utilized SWAT to model nitrate and phosphorus flux, hydrology, and crop yield in tile-drained Midwestern watersheds: Hu et al. (2007) studied the Upper Embarras River watershed in East-Central Illinois, Nair et al. (2011) studied the Upper Big Walnut Creek watershed in Central Ohio, Ng et al. (2010) studied the Salt Creek Watershed in Central Illinois, and Moriasi et al. (2012) modeled the water balance in the Salt Fork Watershed in Iowa. The calibration and performance of SWAT is presented with respect to these studies and other selected studies.

The SWAT model and software to initialize an analysis has changed over different version since SWAT's beginning in the 1990's. All four studies used a version of the SWAT model and followed the procedures detailed in the Theoretical Documentation (Neitsch et al., 2009) and the ArcSWAT Manual (Srinivasan, 2009) using the AVSWAT-X interface. This study employed the 2012 version of SWAT (Rev. 588) (Neitsch et al., 2009) and the ArcSWAT 10.1 (Srinivasan, 2009) interface. The watershed extent and hydrology are determined by the initialization procedure. For that reason, the results of the initialization are presented after an introduction of the location, climate and data sources for modeling the study area using SWAT.

3.2.2 Study Location

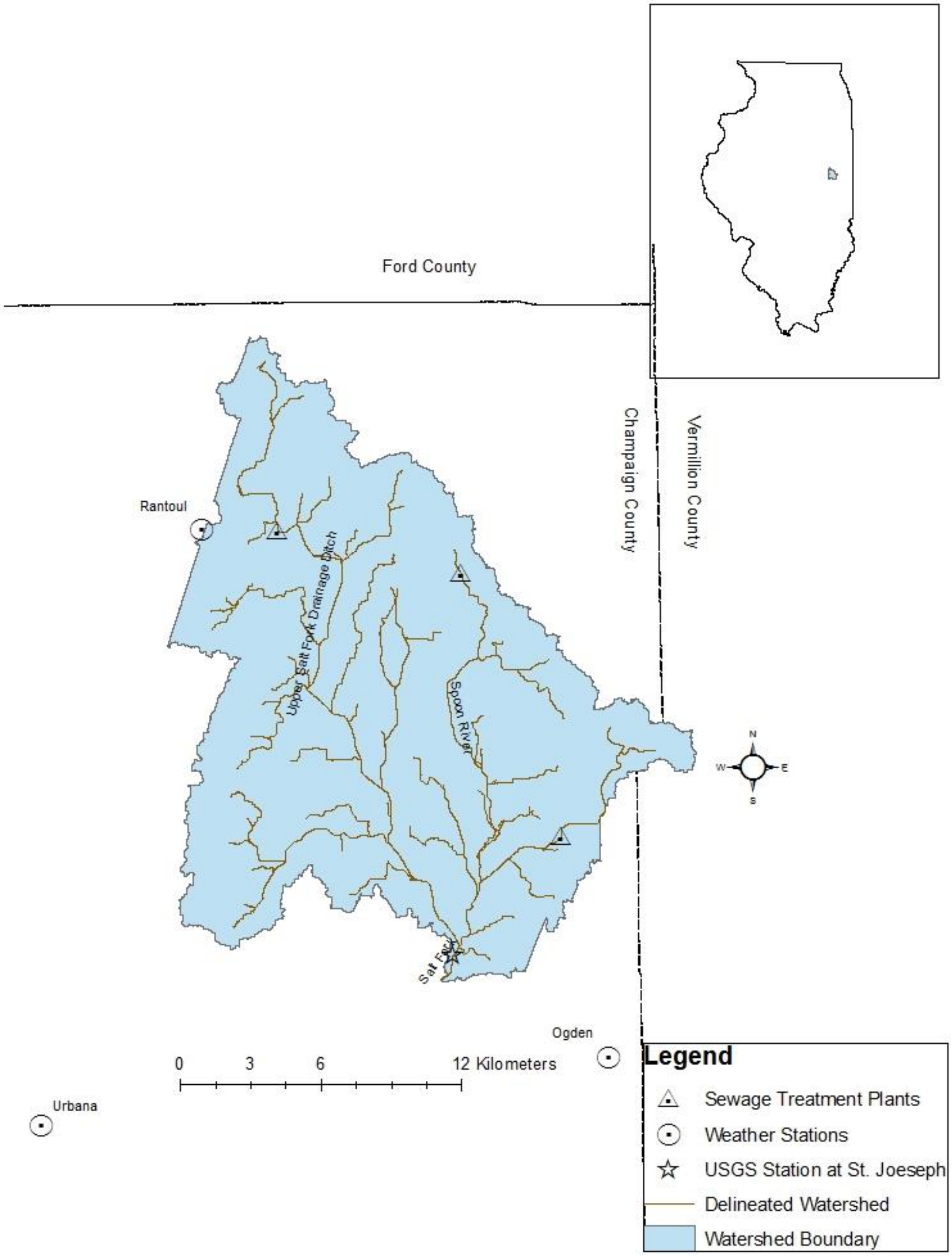

Figure 3.3: Upper Salt Fork Watershed

The Upper Salt Fork Basin is located in East-Central Illinois (Figure 3.3). The watershed is located in Champaign and Vermillion counties. The Upper Salt Fork Drainage Ditch and the Spoon River flow north to south and merge into the Salt Fork River. The Upper Salt Fork Basin flows through a network of artificially constructed ditches and channelized streams. The Upper Salt Fork Drainage Ditch was constructed with a 60-foot bottom width, tapering upstream to a 20-foot bottom width near Rantoul (Singh et al., 1987). The construction of these channels was to achieve the higher gradient for expedited flow. The Salt Fork and Vermillion River are currently listed as impaired under 303(d) of the 1972 Clean Water Act (U.S. Environmental Protection Agency, 1972) for the following reasons: fish kills, ammonia (total), total suspended solids, pH, nitrogen (total), phosphorus (total), nitrate-nitrogen. The Spoon River is listed as impaired for habitat assessment and dissolved oxygen (Limnotech, 2007).

The climate is temperate, with four distinct seasons. Based on the weather data for the Urbana weather station (Illinois State Water Survey, 2012), the mean annual precipitation was 1006.5 mm for the years 1995-2012, and the mean annual snowfall was 539.6 mm. Figure 3.4 shows the seasonality of the precipitation for the Urbana weather station, 25% of the annual precipitation occurs in the months of May and June (Illinois State Water Survey, 2012). Figure 3.5 shows the monthly average temperature (Illinois State Water Survey, 2012).

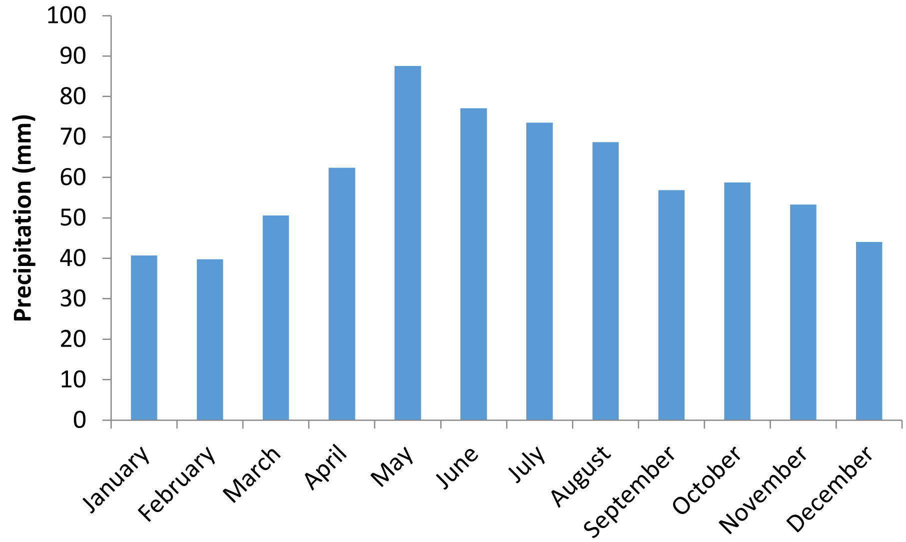

Figure 3.4: Monthly Precipitation for Upper Salt Fork watershed (1995-2012) (Illinois State Water Survey, 2012)

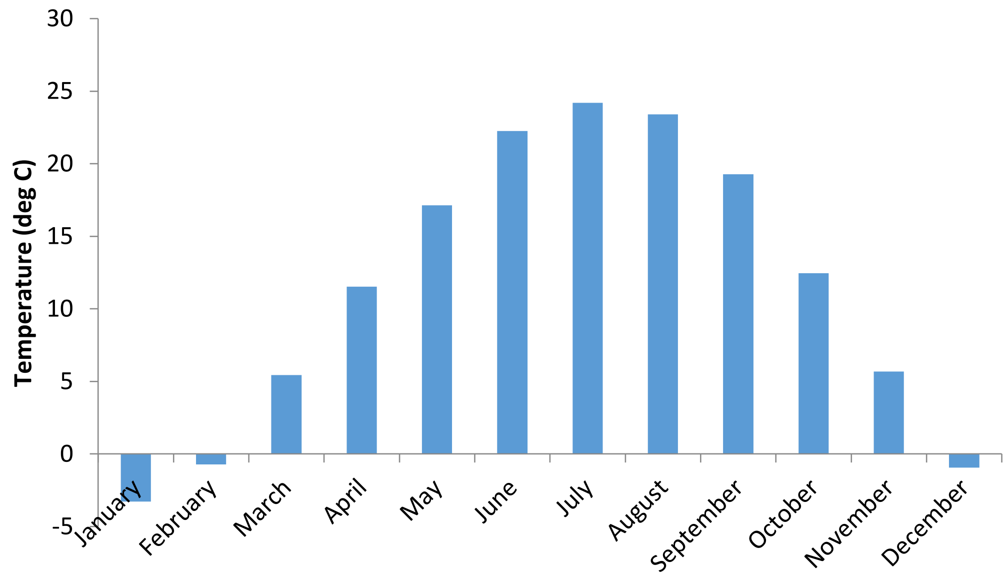

Figure 3.5: Monthly Temperature for Upper Salt Fork watershed (1995-2012) (Illinois State Water Survey, 2012)

3.2.3 Data Sources

The SWAT initialization was performed in ArcGIS 10.1 (ESRI, 2012) per the instructions in the ArcSWAT manual (Srinivasan, 2009). Data sources for this specific study incorporated:

elevation, soils, land cover, point source inputs, precipitation, temperature, wind speed, relative humidity, solar radiation, potential evapotranspiration, stream flow, nitrate-nitrogen, and dissolved reactive phosphorous.

3.2.3.1 Elevation

LiDAR (Light Detection and Ranging) digital elevation data were used for areas within Champaign County. LiDAR data were acquired in 2008 by Aero-Metric for the USGS and accessed through the Illinois Natural Resources Geospatial Data Clearinghouse (Illinois Natural Resources Geospatial Data Clearinghouse, 2012) (available at: http://www.isgs.uiuc.edu/nsdihome/webdocs/ilhmp/county/champaign.html). LiDAR data for Champaign County had an average sampling rate of 1.2 meters. LiDAR data were used to form a 3-meter resolution raster, ensuring at least twice the sample rate (Crawford, 2008). For areas in Vermillion County, digital elevation data with a resolution of 3 meters were merged with LiDAR data. Vermillion County elevation data were derived from the USGS Seamless Server (USGS, 2012b).

3.2.3.2 Land Cover and Soils

Land Cover data were derived from USGS Seamless Server 30-meter NLCD 2006 data and resampled to 3 meters (USGS, 2012b). Soil type and properties were accessed through the SSURGO database built-in to the ArcSwat 10.1 interface (Sheshukov et al., 2009; USDA - NRCS, Soil Survey Geographic (SSURGO) Database). SSURGO data for the area had a scale of 1:12000.

3.2.3.3 Climate Data

Daily precipitation and temperature data were obtained through the National Ocean AA for weather stations in Urbana (COOPID = 118740), Rantoul (COOPID = 117150), Ogden (COOPID = 116344) (National Climate Data Center, 2012). Urbana data were used for years of missing data at Ogden. Estimates of wind speed, relative humidity, solar radiation, and potential evapotranspiration were obtained through the Water and Atmospheric Resources and Monitoring Program (WARM) at the Illinois State Water Survey (Water and Atmospheric Resources Monitoring Program, 2013). The closest station to the study area was located in Champaign, IL (available at http://www.isws.illinois.edu/warm/data/cdfs/cmiday.txt). The Champaign station was used for wind speed, humidity, radiation, and potential evapotranspiration (PET) data for the entire study region. WARM-ISWS potential evapotranspiration estimates were calculated using the Penman-Monteith method (Monteith, 1965); the monthly average estimates are shown in Figure 3.6. Data collection began in 1989, and missing values were replaced with the average for that day over the 23 years.

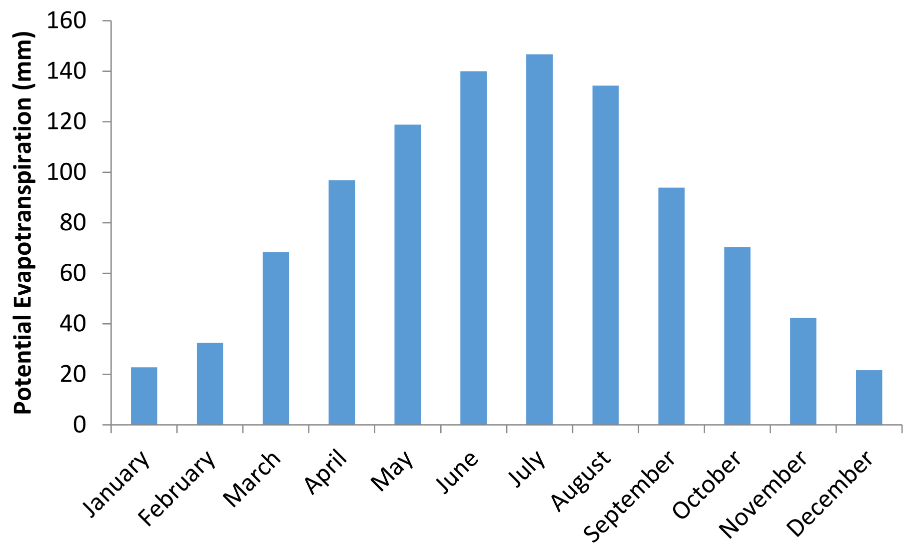

Figure 3.6: Monthly PET for Upper Salt Fork watershed (1989-2012) (Water and Atmospheric Resources Monitoring Program, 2013)

3.2.3.4 Point source inputs

Monthly effluent and nitrogen loads for the three sewage treatment plants were obtained from the Environmental Protection Agency Enforce & Compliance History Online (ECHO) for Rantoul Sewage Treatment Plant (STP) East (Source ID = IL0022128), Gifford STP (Source ID = ILG580214), and Royal Water Treatment Plant (WTP) (Source ID = ILG640131). (Environmental Protection Agency, 2012). The daily averages for 2012 are shown in Table 3.1.

Table 3.1: Point Sources – Sewage Treatment Plants (Environmental Protection Agency, 2012)

	Average Daily Flow (m^3)	Average Daily Nitrogen Load (kg NO_2 +NH_3)	Average Daily Dissolved Oxygen Load (kg O_2)	Average Daily Dissolved Phosphorous Load (kg P)
Rantoul	10874	90.3	88.86	25
Gifford	138.12	n/a	n/a	n/a
Royal	0.31	n/a	n/a	n/a

3.2.3.5 Streamflow and Nutrient Data

Daily streamflow data were obtained from the USGS for the station at St. Joseph (site no. 03336900) for 2005-2012 (USGS, 2012a) (available at http://waterdata.usgs.gov/usa/nwis/uv?site_no=03336900). The site sampled average daily flow from 1952 – 2012, with the exception of 1991 – 2004, for which no flow data were available. Nitrate and phosphorous sampling was obtained through Urbana-Champaign Sanitary District (UCSD) and University of Illinois (UIUC) Department of Natural Resources & Environmental Sciences (NRES) Biochemistry Group (UCSD & UIUC-NRES Biochemistry Group, 2013) (available at: saltfork.nres.uiuc.edu/water_quality.html). Samples were taken for a least a bi-weekly basis for April 15, 2008 through December 28, 2012. This resulted in a total of 242 total samples. To calculate loads, a linear interpolation method was use to extrapolate nitrate and phosphorous concentrations when not available, multiplied by the USGS measured for that date as performed by Hu et al. (2007). Figure 3.7 shows the monthly USGS flow values; Figure 3.8 shows the total monthly nitrate loads using the USGS flow and nitrate concentrations; Figure 3.9 shows the average monthly nitrate concentrations. The nitrate loads and concentrations peak in during the wet spring months and diminish during the dry late summer months. Figures 3.10

through 3.11 show the phosphorous loads and concentrations. Phosphorous exhibits a similar seasonality, and consequently during the dry summer months, the Rantoul Sewage Treatment plant loading comprises a larger percentage of the total load.

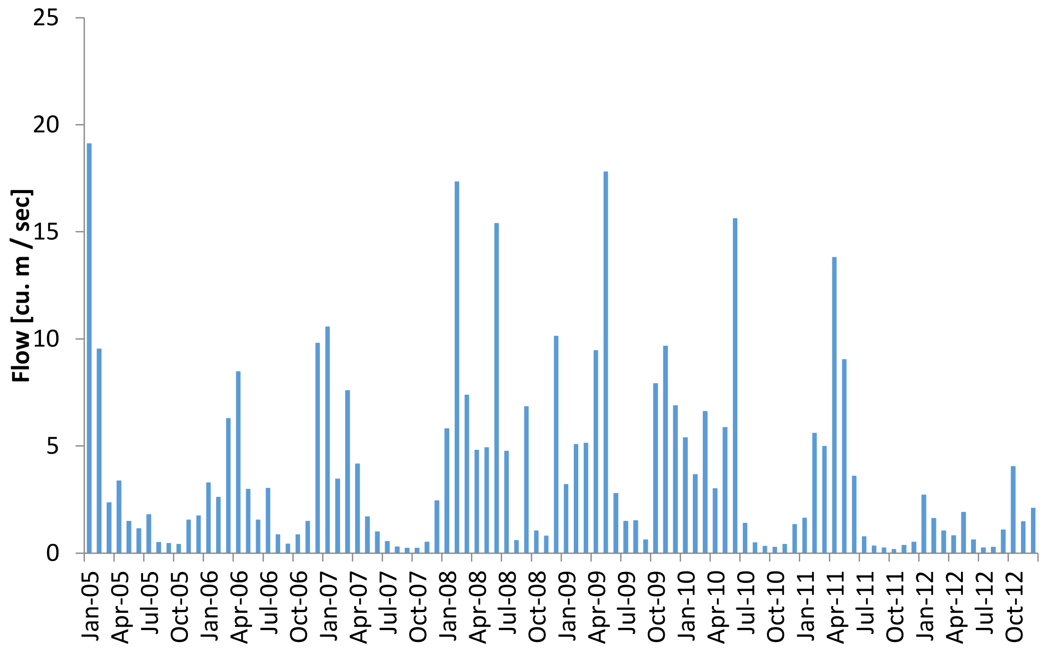

Figure 3.7: Average Monthly Flow Salt Fork River (USGS, 2012a)

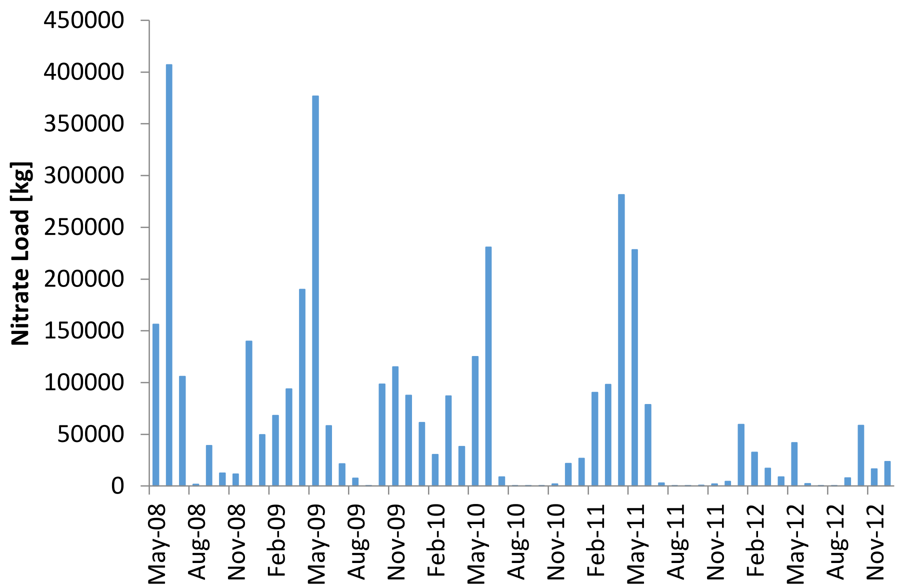

Figure 3.8: Total Monthly Nitrate Load Salt Fork River, Linear Interpolation Method 2008-2012 (UCSD & UIUC-NRES Biochemistry Group, 2013)

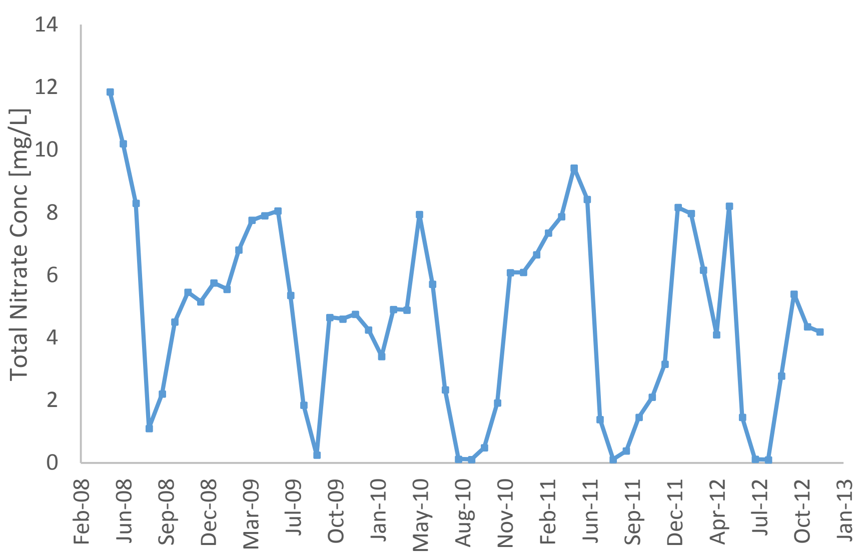

Figure 3.9: Average Monthly Nitrate Concentration (2008-2012) (UCSD & UIUC-NRES Biochemistry Group, 2013)

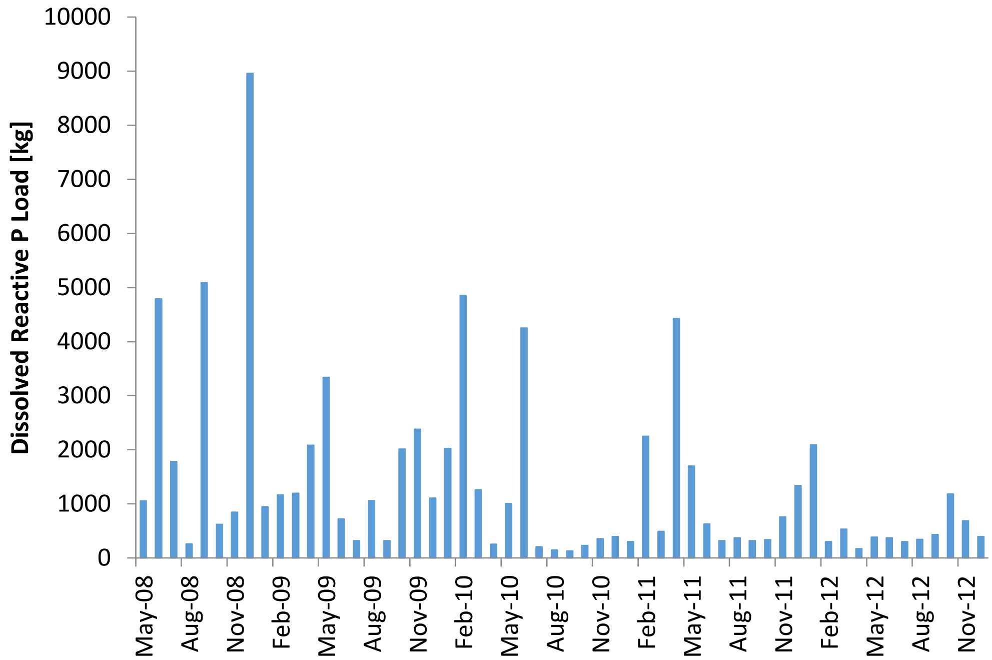

Figure 3.10: Average Monthly Dissolved Reactive Phosphorous Load (2008-2012) (UCSD & UIUC-NRES Biochemistry Group, 2013)

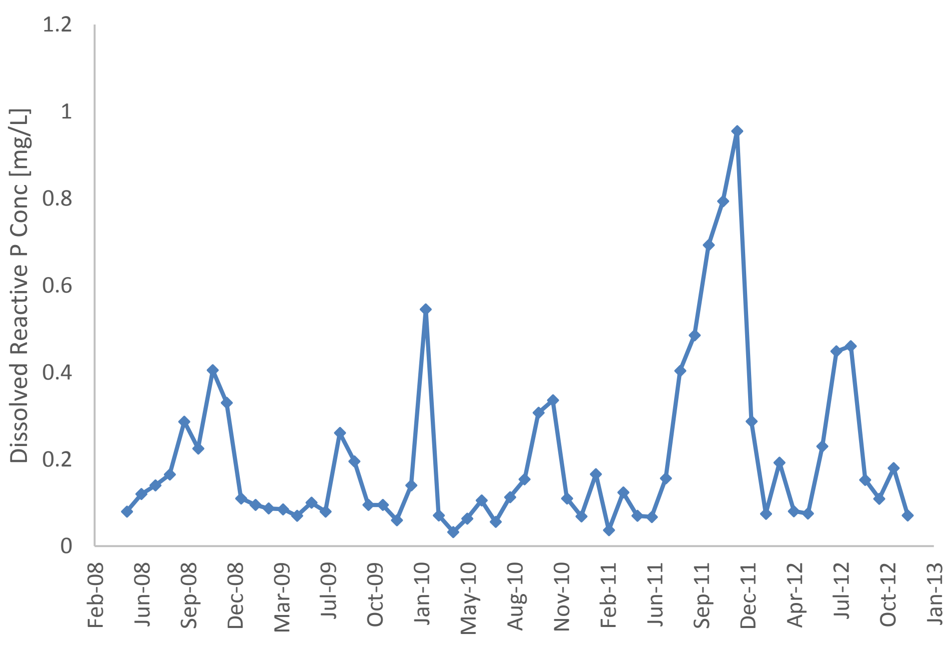

Figure 3.11: Average Monthly Dissolved Reactive Phosphorous Concentration (2008-2012) (UCSD & UIUC-NRES Biochemistry Group, 2013)

3.2.4 Watershed delineation

All watershed processing and delineation was done using the data sources specified in section 3.2.3 with the AVSWAT-X plugin (Srinivasan, 2009) for ArcGIS (ESRI, 2010) according to the procedures in the ArcSWAT manual (Neitsch et al., 2013). The watershed outlet was set to the USGS station at St. Joseph. The threshold for stream definition was set to 200 hectares as suggested by AVSWAT-X and performed in past studies (Hu et al., 2007; Nair et al., 2011). This resulted in 119 subbasins which were defined by dominant soil type, land use, and slope. The HRU definition was chosen to correspond to average farm size region as performed by Nair et al. (2011). This corresponded to an HRU definition of at least 55% of an area dedicated to a single land use, at least 28% of the area composed of a single soil, and and at least 28% of an area exhibiting a uniform slope. The agricultural HRU sizes ranged from 2 hectares to 1022 hectares with an average size of 149 hectares (368 acres). The USDA-NASS reported an average farm size for Champaign County of 160 hectares (USDA-NASS, 2009).

The resultant watershed was 328 km^2 is area. 88% of the watershed was row-cropped agriculture. 80% of the watershed was composed of poorly or moderately-poorly drained soils according to SSURGO soil data (USDA-NRCS, Soil Survey Geographic (SSURGO) Database). The dominant soil type was Drummer, which is poorly drained (Cooke, 2011). The terrain was flat; 76% of the watershed had a slope less than 2%. The distribution of soils in the resultant watershed and their drainage class are shown in Table 3.2. The drainage classes are derived from the Illinois Drainage Guide (Cooke, 2011).

Table 3.2: Soil Type and Class (USDA - NRCS, Soil Survey Geographic (SSURGO) Database)(Cooke, 2011)

Soil Name	% Area	Hydrologic Group	Drainage Class
Drummer silty clay loam, 0 to 2 percent slopes	39.519	D	Poorly drained
Raub silt loam, 0 to 2 percent slopes	7.449	B	Somewhat poorly drained
Ashkum silty clay loam, 0 to 2 percent slopes	6.682	D	Poorly drained
Elliott silty clay loam, 2 to 4 percent slopes, eroded	6.099	C	Somewhat poorly drained
Brenton silt loam, 0 to 2 percent slopes	5.689	B	Somewhat poorly drained
Varna silt loam, 2 to 4 percent slopes, eroded	4.138	C	Moderately well drained
Flanagan silt loam, 0 to 2 percent slopes	3.685	B	Somewhat poorly drained
Dana silt loam, 2 to 5 percent slopes	2.421	B	Moderately well drained
Selma loam, 0 to 2 percent slopes	2.397	D	Poorly drained

3.2.5 Model Calibration

SWAT provides default values for all the parameters necessary to run a simulation. However, according the SWAT manual (Neitsch et al., 2013), the default parameter values assigned by the interface are highly generic. The interface does not vary input values based on watershed size or location in the world. As a result, the model requires calibration. The calibration procedure for SWAT was derived from Hu et al. (2007) and Nair et al. (2011), and performed in a similar step-wise fashion for hydrology, nutrient flux, crop growth: incorporating meaningful physical parameters from past studies, and utilizing both manual and automated search procedures.

3.2.5.1 Uncalibrated Initialization

Some physical parameters were drawn from previous SWAT studies (Hu et al., 2007; Ng et al., 2010; J. Singh et al., 2005) were set and not considered for calibration. Table 3.3 describes the parameters adopted from previous studies and not adjusted further. The parameters were associated with climate and agricultural management typical of the area, so watersheds with similar characteristics from previous studies were selected (Hu et al., 2007; Ng et al., 2010; J. Singh et al., 2005; Nair et al., 2011).

Table 3.3: Calibrated Initial Values From Previous Studies

Parameter	Description (units)	Min.	Max.	Calibrated	Source
SFTMP	Snowfall Temperature (^{O}C)	-3	5	0.5	(Singh et al., 2005)
SMFMX	The maximum snow melt factor (mm d^{-1} $^{O}C^{-1}$)	1.4	6.9	6.5	(Hu et al., 2007; Ng et al., 2010)
SMFMN	The minimum snow melt factor (mm d^{-1} $^{O}C^{-1}$)	1.4	6.9	2.5	(Hu et al., 2007; Ng et al., 2010)
FFCB	Initial soil water storage expressed as a fraction of field capacity water content	0	1	.8	(Nair et al., 2011)
FRT_LY1	Fraction of fertilizer applied to top 10 mm of soil	0	0.2	0.01	(Hu et al., 2007)

In addition to climate parameters, soil saturated hydraulic conductivity and soil available water capacity properties for selected soils in Champaign County were available through the USDA-NRCS (USDA-NRCS, 2012) for the study area. The soil survey gives a range of values. In this study, the mean of the values provided in the survey were used and then calibrated around the mean within the range specified in the Champaign County survey. Table 3.4 shows the mean values for the selected soils. The depth of the deepest layer was not adjusted as shown in Table 3.4. The depth to the impermeable layer was calibrated in a separate SWAT parameter, DEP_IMP in the .ops file (Neitsch et al., 2013).

Table 3.4: USDA-NRCS mean soil saturated hydraulic conductivity and soil available water capacity initial values [depth (mm); K_{sat} (mm/hr); Soil AWC (mm/mm)] (USDA-NRCS, 2011b)

	Layer 1	Layer 2	Layer 3	Layer 4
Ashkum	250; 25; .17	380; 22.7; .16	580; 13.5; .16	810; 16; .13
Drummer	180; 28.6; .22	480; 19.4; .23	810; 16.2; .23	990; 20.4; .23
Elliot	360; 8.4; .22	910; 15.2; .16	5000; 5.8; .1	
Flannagan	460; 25.8; .23	580; 34.9; .23	970; 19.9; .2	1140; 17.3; .2
Brenton	410;33;.24	890;33;.19	1350;33;.18	1830;83.8;.17
Raub	460; 33; .23	810;33; .19	1270;33;.17	
Varna	300;33;.21	690;3.3;.15	990;10.1;.08	1520;3.3;.08
Selma	410;33;.23	800;33;.22	1140;33;.18	2500:33:.17
Kishwaukee	280;33;.23	1370;33;.17	3500;1524;.03	
Swygert	300;11;.2	460;11;.12	790;3;.12	5000;1.26;.08
Wyanet	250;33;.23	690;33;.17	790;10.1;.12	2030;10.1;.08
Ambraw	200;33;.16	990;33;.14	1270;33;.13	1520;33;.17
Catlin	280;33;.25	1140;33;.19	1450;33;.17	1780;10;.08
Camden	230;33;.23	360;33;.22	560;33;.21	890;33;.19
Sawmill	250;33;.22	810;33;.22	1470;33;.2	1650;33;.16

Table 3.4 (cont.): USDA-NRCS mean soil saturated hydraulic conductivity and soil available water capacity initial values [depth (mm); K_{sat} (mm/hr); Soil AWC (mm/mm)] (USDA-NRCS, 2011b)

	Layer 5	Layer 6
Ashkum	1220; 26.25; .13	1520; 26.7; .13
Drummer	1520; 76.8; .2	
Elliot		
Flannagan	1520; 83.4, .2	
Brenton		
Raub		
Varna		
Selma	5000;83.4;.09	
Kishwaukee		
Swygert		
Wyanet		
Ambraw		
Catlin		
Camden	1320;33;.16	2030;.14;83.4
Sawmill		

SWAT requires farm management parameters like crop type, planting date, and fertilization beyond the generic setup. The entire watershed was planted in a corn and soybean rotation as in Hu et al. (2007). Half of the agricultural HRU's were planted with corn then soybeans and half of the agricultural HRU's were planted soybeans then corn. Based on the Illinois Agronomy Handbook (Hollinger & Angel, 2009) and previous SWAT simulations the timing of planting, tillage, and heat units to maturity were set and not calibrated further. Fertilizer inputs in the nearby Embarras watershed were modeled using a split fall and spring application at a rate of 190 kg/ha nitrogen in previous studies (Hu et al., 2007; McIsaac & Hu, 2004). For this study, nitrogen was applied during the fall (December 2nd) prior to corn years at a rate of 224 kg/ha (200 lbs/ac) in the form of anhydrous ammonia. David et al. (2008) estimated anhydrous ammonia application rates of between 150 to 225 kg/ha of nitrogen for typical Midwestern corn production. Also, nitrogen inputs on the high end of the range and above Hu et al. (2007) were selected after a discussion with UIUC extension (Czapar, November 9, 2012) and fall application was chosen to facilitate an analysis between spring and fall application. In addition, phosphorous was applied prior to soybean years in the form of monoammonium phosphate (MAP) at a rate of 126.6 kg/ha (Hollinger & Angel, 2009). The rate and timing was derived from recommendation s in the Illinois Agronomy Handbook and generic conservation tillage was performed on April 20th, corn planting on April 27th, and harvest on October 15th. For soybean years, generic conservation tillage occurred on May 14th, planting on May 21st, and harvest on October 15th (David et al., 1997; Hollinger & Angel, 2009). The heat units until maturity were set according to results for corn (1400) and soybeans (1400) from the Potential Heat Units Program (Grassland Soil and Water Research Laboratory, 2013) (available at: http://swat.tamu.edu/software/potential-heat-unit-program/)

3.2.5.2 Calibration Procedure

Calibration was done with the following two objectives: ensure the model reflects observed watershed phenomenon like flow partitioning and nitrogen fixation, and then search other parameters to improve model performance. The calibration followed a step-wise procedure similar to the Hu et al. (2007) and Nair et al. (2011), and incorporated their considerations of modeling watershed phenomenon. Each step involved selecting a modeling outcome (first streamflow, then nutrient flux, finally crop yield) and parameters for calibrating that outcome. Previous SWAT studies informed which parameters and the range of values over which to calibrate. After each update to parameters, the performance of the previous outcome was assessed for any changes.

3.2.5.3 Calibration Performance

A measure of simulation performance was established to observe parameter sensitivity and assess the ability or inability of the simulation to model watershed events. For this study, the statistical measures of R-squared (Equation 3.1) and Nash-Sutcliffe (Equation 3.2)(Nash & Sutcliffe, 1970) were used as in similar SWAT studies:

$$R^2 = \frac{[\sum(X_{sim} - \overline{X_{sim}})\,(X_{obs} - \overline{X_{obs}})]}{[\sum(X_{sim} - \overline{X_{sim}})^2 \sum(X_{obs} - \overline{X_{obs}})^2]} \tag{3.1}$$

$$NS = 1 - \frac{\sum(X_{sim} - X_{obs})}{\sum(X_{obs} - \overline{X_{obs}})^2} \tag{3.2}$$

Where X_{sim} and X_{obs} are individual simulated and observed values, respectively; and $\overline{X_{sim}}$ and $\overline{X_{obs}}$ are average simulated and observed values. Nash-Sutcliffe measures the relationship of observed and modeled data and a 1:1 line. A value near 1 implies a close agreement. A negative value implies that the mean of observed data would be a better predictor. R-squared is a measure of the model's ability to predict the variation in observed data. The dispersion of modeled and observed data is equal with R-squared is 1.

In addition, percent bias (Equation 3.3) was used to express underestimation and overestimation.

$$P_{BIAS} = \frac{\sum(X_{sim} - X_{obs})}{\sum X_{obs}}\ x\ 100 \tag{3.3}$$

Model performance was compared to similar studies along with established benchmarks. Moriasi et al. (2007) conducted a review of hydrological studies and proposed the following recommendations for satisfactory modeling on a monthly timestep: streamflow (NS > .5, PBIAS < 25%), nitrate and phosphorous loads (PBIAS < 70%). Statistics better than these thresholds were deemed 'good' or 'very good'. Moriasi et al. (2007) also concluded that satisfactory modeling is dependent on the availability of data. Ideal model setup should include 3-5 years of varied precipitation (wet, dry, average), use multiple evaluation techniques (visual inspection, manual calibration), and calibration of all constituents involved (all relevant nutrient parameters). As a result, the 'ideal' model is study specific, and relevant studies guided acceptable modeling outcomes at each step.

3.2.5.4 Selected Calibration Outcomes

The calibration was performed in a step wise procedure adapted from Hu et al. (2007), Nair et al. (2011), Ng et al. (2010), Arnold (1996), and Moriasi et al. (2012). Arnold (1996) and Moriasi et al. (2012) did not calibrate nutrient flux and crop yield, but the studies informed parameter selection and outcome ranges in this study. Each modeling outcome was calibrated in stages: starting with hydrology, then nutrient flux, and finally crop yield. For each modeling outcome the process was to: first select parameters for calibration and set others, vary the parameters, assess optimum, check previous outcome, and proceed to next outcome.

Observed data were partitioned into years of flow data for calibrating, and years of flow data for validating. The recent available flow data for the USGS gauge at St. Joseph span 2004 through 2012 at the time of analysis. Figure 3.12 shows the observed precipitation and flow data for 2005-2012.

The time-scale of the calibration was an important consideration. In developing the natural-systems model, the objective was to facilitate an analysis of environmental and crop production outcomes. Crop production is determined on an annual basis: planting in the spring, harvest in the fall, with related seasonal field operations. While environmental processes are constantly changing, the model was calibrated to best describe outcomes on the time-scale of annual crop production. Finer time-scale (daily, monthly) data were utilized where available to improve modeling performance, but the goal of forecasting annual outcomes guided model development.

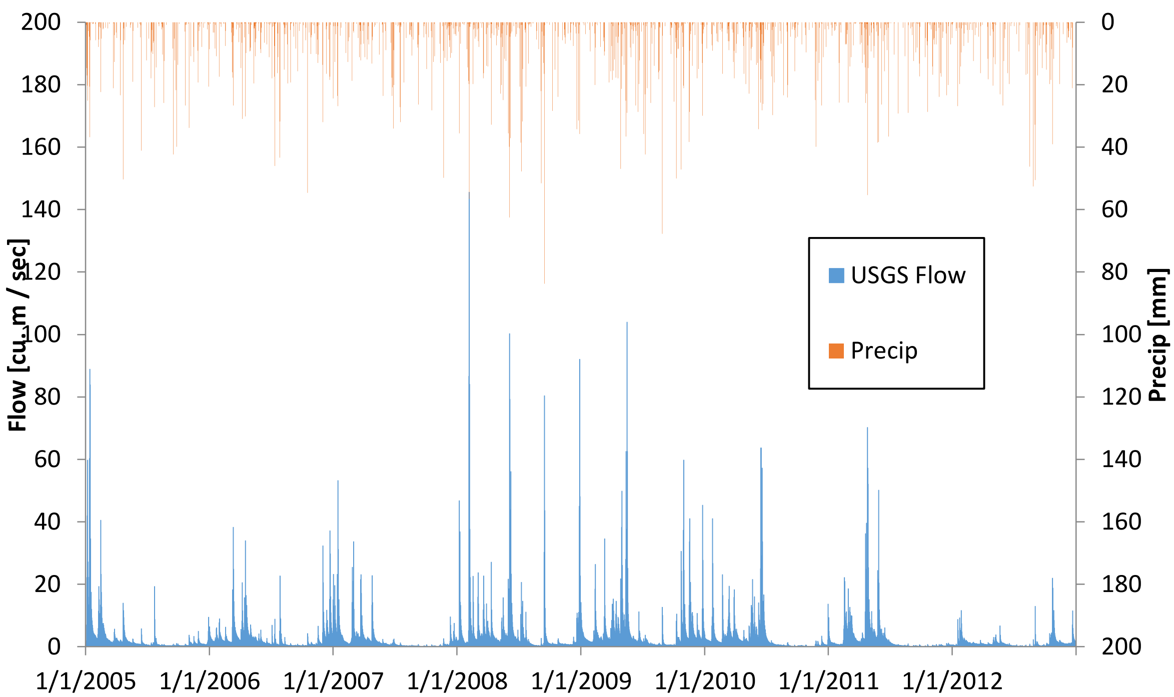

Figure 3.12: Precipitation and Flow (NOAA, 2012; USGS, 2012a)

A calibration period of observed data was used to vary SWAT parameters and assess their effect. The parameters were varied to find a "best-fit" for the calibration period, and then that set of parameters was used, and not modified, for a different, independent period called the validation period. The "best-fit" may not be the highest measure of statistical accuracy. Rather, a "best-suited" simulation may capture desired events or characteristics for a SWAT study. For this study, the a calibration period was set to 2007-2010 to incorporate a wet year following a wet year, a dry year following a wet year, and a wet year following a dry year. The time period also includes high flow events, which indicate high tile flow. This study concentrated on modeling high flow events. The validation period was limited to remaining years of data, 2005-2006, and 2011-2012.

3.2.5.4.1 Hydrologic Calibration

Hydrologic calibration was performed first as done in Hu et al. (2007) and Nair et al. (2011). The range and group of parameters selected for calibration were selected from multiple studies (Arnold, 1996; Hu et al., 2007; Moriasi et al., 2012; Nair et al., 2011). Moriasi et al. (2007) recommended calibrating for all watershed processes intended for study. Based on the previous work informing this study for tile-drained watersheds, the model was calibrated to model total water yield, tile drainage yield, surface runoff yield, evapotranspiration, and daily streamflow. A manual calibration of the water budget was conducted first, followed by a manual and automatic calibration of streamflow.

To start, this study sought to model annual water yield within 10% as set forth in Hu et al. (2007) and monthly streamflow with a NS greater than .5 for a monthly time step, which would exceed the recommendation for satisfactory modeling by Moriasi et al. (2007). The calibration procedure for the water budget was performed manually by varying selected parameters to model observed USGS water yields.

Modeling the tile drainage flow component of the water yield is an important consideration. The abundance of poorly-drained soils and flat terrain contributes to extensive tile-drainage for agricultural production. Many watersheds in east-central Illinois have less than 1% surface gradient and poorly drained soils, yet subsurface drains have made these lands some of the most productive farmland in the world. Subsurface drainage enhances productivity and reduces sediment transport and phosphorous losses from fields; however, it increases nitrate delivery to the receiving water bodies (Kalita et al., 2007). David et al. (1997) estimated that 75 to 80% of the fields have tile drainage in the nearby Embarras watershed which has similar topography and management.

Hu et al. (2007) calibrated SWAT for the nearby Embarras River watershed to model 75% of the total water yield as tile-drained flow. Similarly, Moriasi et al. (2012) estimated 71% of total water yield as tile drained, combined groundwater and lateral flow as 6%, and surface runoff at 23%. Mitchell et al. (2001) estimated that tile drainage comprised 80-90% of total flow across four East-Central Illinois watersheds. This study sought to model greater than 75% of total flow as tile-drained.

Cooke's (2011) Illinois Drainage Guide informed the design specifications of tile-drainage systems throughout the watershed. Cooke (2011) provides general recommendations for tile drainage systems in Illinois. These typical installation specification were used to develop ranges of parameters for calibration. The Drainage Guide's recommendations for sizing drainage systems are generalized by soil type and rating by drain spacing, drainage coefficient, and mean drain depth as outlined Table 3.5.

Table 3.5: Illinois Drainage Guide General Recommendations (Cooke, 2011)

		Drain Spacing (m)			
Soil Type	Permeability	Fair DC = 6.5 mm	Good DC = 9.5 mm	Excellent DC = 12.5 mm	Mean Drain Depth (mm)
Clay Loam	Very Low	21.3	15.24	10.7	991
Silty Clay Loam	Low	29	19.8	13.7	1036
Silt Loam	Moderately Low	39.6	30	18.3	1143
Loam	Moderate	61	42.7	29	1234
Sandy Loam	Moderately High	91	64	45.7	1295

As performed in Hu et al. (2007), Ng et al. (2010) and Moriasi et al. (2012) a single drainage system design was applied uniformly to the study area. In this study, agricultural HRUs with a slope less than 2% were considered tile drained. This resulted in treating 80% of the watershed as tile-drained. Similar to Moriasi et al.'s (2012) consideration of the Iowa Drainage Guide for establishing ranges for calibrating tile drainage parameters, this study considered ranges from the Illinois Drainage Guide. The primary soil in the study area was Drummer, a silty clay loam, and ranges were selected as shown in Table 3.6. The study also considered Moriasi et al.'s (2012) calibrated values.

Table 3.6: Manual Tile Drainage Parameters Calibration (Hu et al., 2007; Moriasi et al., 2012; Nair et al., 2011; Ng et al., 2010)

Parameter	Description (units)	Min.	Max.
DDRAIN	Depth to Drain (mm)	950	1200
DEP_IMP	Depth to impermeable layer (mm)	1550	2000
RE_BSN	Effective Radius of Drains (mm)	20	40
SDRAIN_BSN	Drain Spacing (m)	20	30
DRAIN_CO_BSN	Drainage Coefficient (mm)	5	20
LATKSATF_BSN	Lateral K_{sat} factor	.5	1.5
GDRAIN	Tile drain lag time (hours)	0	100
TDRAIN	Time to drain soil to field capacity (hours)	10	50

The other primary calibrated water budget component was evapotranspiration. The Illinois State Water Survey estimated annual evapotranspiration varies across Champaign County between 610 and 685 mm. Evapotranspiration was estimated between 610 and 635 mm by Arnold et al. (1996) and Winstanley et al. (2006) for nearby watersheds.

The selection of parameters for calibrating the water budget and the considered ranges were derived from previous studies as detailed in Table 3.7. These parameters were selected for manual calibration based on Moriasi et al.'s (2012) identification of these parameters as significant in hydrologic calibration. Further, these parameters were common across Hu et al. (2007), Ng et al. (2010), and Nair et al. (2011). The considered range for this study's calibration bookended the calibrated value from all three studies.

Table 3.7: Manual Water Budget Parameters Calibration (Hu et al., 2007; Moriasi et al., 2012; Nair et al., 2011; Ng et al., 2010)

Parameter	Description (units)	Min.	Max.
CN2	Runoff curve number	60	80
SOL_AWC	Soil Available Water Capacity	-10%	+20%
ESCO	Soil Evaporation Compensation Factor	.8	1
EPCO	Soil Evaporation Compensation Factor	.5	1
CNCOEF	CN coefficient	.1	1
ICN	Daily CN Calculation Method	0	1

Although Moriasi et al. (2012) achieved 'very good' model performance for the water budget and streamflow only considering the parameters in Table 3.7, the other three studies considered other SWAT parameters for calibrating streamflow. While the parameters were not common across all three, this study incorporated those parameters for an automatic calibration of streamflow following the manual calibration of significant parameters. Table 3.8 presents those parameters and the ranges. Again, the considered range included the calibrated range from each study.

Table 3.8: Automatic Streamflow Parameters Calibration (Hu et al., 2007; Moriasi et al., 2012; Nair et al., 2011; Ng et al., 2010)

Parameter	Description (units)	Min.	Max.
GW_REVAP	Groundwater Revap Coefficient	0.02	0.1
REVAPMN	Threshold depth for revap (mm)	0	500
GWQMN	Threshold depth for baseflow (mm)	0	100
ALPHA_BF	Baseflow Alpha Factor	0	1
RCHRG_DP	Deep aquifer percolation factor	0	1
GW_DELAY	Groundwater delay time (days)	0	100
CH_N1	Manning's N for tributary channels	0	0.3
OV_N	Manning's N for overland flow	0	0.3
SURLAG	Surface lag coefficient	.1	4
CANMX	Maximum Canopy Storage (mm)	0	10
CH_K1	Hydraulic Conductivity for tributary channels (mm/hr)	0	1

The manual calibration was performed first by varying the selected parameters observing the resultant water yield. After satisfactorily modeling evapotranspiration within the targeted range, tile-drained flow greater than 75% of total yield, and total water yield within 10% of USGS observed levels for the calibration region, SWAT-CUP was used to perform the automatic calibration for streamflow. SWAT-CUP is a standalone program that links to SWAT's output text files (Rouholahnejad et al., 2012) and applies algorithms to find a 'best-fit'. SWAT-CUP's SUFI-2 (Sequential Uncertainty Fitting) (Abbaspour et al., 2004) was applied to the parameter set. SWAT-CUP and SUFI-2 have been applied to watersheds to search for an optimum SWAT parameter for hydrological processes (Zhou et al., 2012). In this study, 1000 simulations were performed. The parameter set values were narrowed according to SWAT-CUP suggested ranges and user judgment and rerun to assess for further modeling performance. An optimum and the uncertainty of the fit was not the focus of this study, and the automated procedure served as a suggestion for parameter set. The suggested parameter set was compared to the related studies' calibrated values. Finally, the 'best-fit' parameter set was checked with the manually calibrated parameter set. Once a satisfactory hydrologic model was established, the calibration proceeded with the nitrogen calibration.

3.2.5.4.2 Nutrient Calibration

This study calibrated the SWAT model for annual nitrate loads observed at the outlet to quantify water quality outcomes. For that purpose, the entire nitrogen cycle was considered in the calibration. A similar procedure of manual and automatic calibration for the nitrogen budget first and then an automatic calibration of observed nitrate loads was performed. The significant parameters for calibration were derived from Hu et al. (2007) and Nair et al. (2011).

The target ranges of modeled outcomes for the nitrogen budget were derived from David et al. (2008) and Gentry et al. (2009). David et al. (2008) modeled the nitrogen budget for the nearby Embarras River watershed using six models, including SWAT, and compared performance. Hu et al. (2007) and Nair et al. (2011) both incorporated the ranges for comparing the performance of their SWAT models as well. Gentry et al. (2009) estimated field nitrogen budgets for the Big Ditch Watershed in East-Central Illinois. The ranges for the modeled outcomes are shown in Table 3.9.

Table 3.9: Estimated Annual Nitrogen Budget in Upper Embarras River Watershed (David et al., 2008; Hu et al., 2007)

Nitrogen Process (units)	Estimate
Fertilizer (Corn) (kg N ha^{-1})	183
Nitrate-N Load (kg N ha^{-1})	20-50
N_2 Fixation (Soy) (kg N ha^{-1})	102-124
Grain N Harvest (kg N ha^{-1})	116
Denitrification (kg N ha^{-1})	15-23
Mineralization (kg N ha^{-1})	77-90

Model performance was assessed with respect to Moriasi et al.'s (2007) recommendations and performance of Hu et al. (2007) and Nair et al. (2011). Based on the studies, nitrogen budget performance was satisfactory when within 25% of target estimates (Hu et al., 2007), and monthly flux modeling performance with a NS greater than .5 and percent bias within 70%. Model calibration prioritized annual load prediction over daily and monthly. The annual load prediction was used as an input for the coupled analysis, and the nutrient budgets were used to ground the model in estimated ranges.

Manual calibration focused on denitrification and mineralization along with parameters. The parameters and ranges are shown in Table 3.10. Calibrated values were informed by Ng et al. (2010), Hu et al. (2007), and Nair et al. (2011).

Table 3.10: Manual Denitrification Parameters Calibration (Neitsch et al., 2009)

Parameter	Description (units)	Min.	Max.
SDNCO	Denitrification threshold water content	0.01	2
CDN	Denitrification exponential rate coefficient	0.001	3
CMN	Humus mineralization of active nutrients N/P	0.0001	.01

Automatic calibration was used for nitrate load, soybean fixation, and grain nitrogen harvest. The parameters comprised of the union of nitrogen parameters considered in Hu et al. (2007), Nair et al. (2011), and Ng et al. (2010). Table 3.11 shows the parameters and range of values considered. The ranges were constrained based on the calibrated values in three studies.

Table 3.11: Automatic Nitrogen Parameters Calibration (Hu et al., 2007; Nair et al., 2011; Ng et al., 2010)

Parameter	Description (units)	Min.	Max.
N_UPDIS	N uptake distribution parameter	1	70
RSDCO	Residue decomposition coefficient	.03	.09
NPERCO	Nitrate Percolation Coefficient	.01	1
ANION_EXCL	Fraction of porosity from which anions are excluded	.1	.4
CMN	Humus mineralization of active nutrients N/P	0.0001	.01
CNYLD (Corn)	Fraction of N in harvested biomass [(kg N/kg seed)]	0.011	0.015
BN1 (Corn)	Fraction of N in plant at emergence [(kg N / kg biomass)]	0.011	0.015
BN2 (Corn)	Fraction of N in plant at .5 maturity [(kg N / kg biomass)]	0.03	0.07
BN3 (Corn)	Fraction of N in plant at maturity [(kg N / kg biomass)]	0.011	0.015
CNYLD (Soy)	Fraction of N in harvested biomass [(kg N/kg seed)]	0.04	0.07
BN1 (Soy)	Fraction of N in plant at emergence [(kg N / kg biomass)]	0.04	0.07
BN2 (Soy)	Fraction of N in plant at .5 maturity [(kg N / kg biomass)]	0.03	0.06
BN3 (Soy)	Fraction of N in plant at maturity [(kg N / kg biomass)]	0.01	0.03

Automatic calibration was performed iteratively to maximize NS performance of modeling observed monthly nitrate loads (NS>.5) and minimize error in predicting total annual loads (<25%) using SWAT-CUP. After each set of 1000 iterations, the nitrogen balance was checked and parameters adjusted to achieve budget estimates.

Once nitrogen modeling targets were reached, the similar SWAT nutrient parameters relevant for phosphorous (Neitsch et al., 2009) were selected and calibrated in the same manner. The nutrient generic parameters RSDCO, ANION_EXCL, and CMN were not calibrated further.

The target ranges of modeled outcomes for the phosphorous budget were derived from Mallarino et al. (2011) and Gentry et al. (2007). David et al. (2008) measured the phosphorus loadings for the nearby tile-drained Embarras River watershed and two other Illinois watersheds. Mallarino et al. (2011) measured phosphorus removal in corn and soybean harvests across 11 sites in Iowa. Further, the Illinois Agronomy Handbook provided estimates for phosphorus removal (Hollinger & Angel, 2009). The phosphorus budgets targets were derived from these three studies as shown in Table 3.12.

Table 3.12: Estimated Annual Phosphorus Budget in Upper Embarras River Watershed (Hollinger & Angel, 2009; Mallarino et al., 2011; Gentry et al., 2007)

Phosphorous Budget (units)	Estimate
Fertilizer (Biannual) (kg P ha^{-1})	64
Dissolved Reactive P Load (kg N ha^{-1})	.30-.80
Grain P Harvest (kg N ha^{-1})	52

The related parameters for phosphorus as with nitrogen were considered in the automatic calibration. The values were derived from the SWAT Theoretical Handbook as shown in Table 3.13 (Neitsch, 2009).

Table 3.13: Automatic Phosphorus Parameters Calibration (Neitsch, 2009)

Parameter	Description (units)	Min.	Max.
P_UPDIS	Phosphorus Uptake Distribution Parameter	0	100
PHOSKD	Phosphorus Soil Partitioning Coefficient	100	200
PSP	Phosphorus Sorption Coefficient	0	1
PPERCO	Phosphorus Percolation Coefficient	10	17.5
CPYLD (Corn)	Fraction of P in harvested biomass [(kg P/kg seed)]	0.003	0.004
BP1 (Corn)	Fraction of P in plant at emergence [(kg P / kg biomass)]	0.0035	0.006
BP2 (Corn)	Fraction of P in plant at .5 maturity [(kg P / kg biomass)]	0.0006	0.003
BP3 (Corn)	Fraction of P in plant at maturity [(kg P / kg biomass)]	0.0004	0.0028
CPYLD (Soy)	Fraction of P in harvested biomass [(kg P/kg seed)]	0.0062	0.0072
BP1 (Soy)	Fraction of P in plant at emergence [(kg P / kg biomass)]	0.006	0.009
BP2 (Soy)	Fraction of P in plant at .5 maturity [(kg P / kg biomass)]	0.0025	0.005
BP3 (Soy)	Fraction of P in plant at maturity [(kg P / kg biomass)]	0.0025	0.005

3.2.5.4.3 Crop Yield Calibration

Crop yield calibration was similarly informed by past studies. Crop yields were calculated from SWAT output as performed in Srinivasan et al. (Srinivasan et al., 2010). The leaf area index parameter for corn and soybean was set to according to Nair et al. (2011), Ng et al. (2010), and Hu et al. (2007) and not calibrated further as shown in Table 3.14.

Table 3.14: Inputted Crop Yield Parameters (Hu et al., 2007; Nair et al., 2011)

Parameter	Description (units)	Value
BLAI (Corn)	Leaf Area Index	5
BLAI (Soy)	Leaf Area Index	4

Finally, only the harvest index (HI) and bioenergy utilization rate (BIO_E) parameter for corn and soybeans was used to manually calibrate crop yields within 10% of observed values as a performance target as shown in Table 3.15. All other parameters were set to the default in the SWAT Theoretical Documentation (Neitsch et al., 2009).

Table 3.15: Manually Calibrated Crop Yield Parameters (Hu et al., 2007; Nair et al., 2011)

Parameter	Description (units)	Range
HI (Corn)	Harvest Index	.48-.52
HI (Soy)	Harvest Index	.28-.33
BIO_E (Corn)	Biomass/Energy Ratio ((kg ha^{-1})/(MJ/m^2))	35-45
BIO_E (Soy)	Biomass/Energy Ratio ((kg ha^{-1})/(MJ/m^2))	20-30

3.2.6 Model Results

Table 3.16 shows the parameter values from the calibration procedure. Each environmental outcome modeling results and performance are presented in the section.

Table 3.16: Calibrated Parameter Values

Hydrologic Parameters	
Parameter	Value
CN2	70.1
SOL_AWC	-12.6%
SOL_K	-30.4%
DEP_IMP	1724
ITDRN	1
IWTDN	1
DDRAIN	1072
TDRAIN	40.25
GDRAIN	1
ESCO	.9
EPCO	.71
CNCOEF	.43
ICN	1
GW_REVAP	.017
REVAPMN	1
GWQMN	1
ALPHA_BF	.684
RCHRG_DP	.01
GW_DELAY	39
GW_SPYLD	.01
CH_N1	.035
OV_N	.101
SURLAG	1
CH_N2	.062
IWQ	0
RE_BSN	20
SDRAIN_BSN	22000
DRAIN_CO_BSN	10.75
LATKSATF_BSN	.989

Nutrient Parameters	
Parameter	Value
SDNCO	.95
CDN	.013
N_UPDIS	29.9
NFIXMX	1.05
RSDCO	.20
NPERCO	0.89
ANION_EXCL	.091
CMN	.0005
P_UPDIS	20.20
PSP	.048
PHOSKD	169.5
PPERCO	10.04
CNYLD (Corn)	.0146
BN1 (Corn)	.0405
BN2 (Corn)	.0151
BN3 (Corn)	.0154
CNYLD (Soy)	.064
BN1 (Soy)	.0319
BN2 (Soy)	.0168
BN3 (Soy)	.0166
CPYLD (Corn)	0016
BP1 (Corn)	.004
BP2 (Corn)	.003
BP3 (Corn)	.002
CPYLD (Soy)	.0101
BP1 (Soy)	.007
BP2(Soy)	.004
BP3(Soy)	.003

Crop Yield Parameters	
Parameter	Value
HI (Corn)	.5
HI (Soy)	.31
BIO_E (Corn)	39
BIO_E (Soy)	22
PHU (Corn)	1800
PHU (Soy)	1800

3.2.6.1 Hydrologic Model Results

Table 3.17 shows the model results for the water budget over the entire 8-year period (1995-2012, 10 years of warm-up). Tile-drained flow comprised 84% of total water yield, surface runoff 6%, and lateral and groundwater flow 10%.

Table 3.17: Average Annual Water Balance SWAT Model (2005-2012)

Average Annual Water Budget Component	Value (mm)
Total Water Yield	365.6
Tile-drained Water Yield	306.7
Surface Runoff Yield	22.3
Lateral and Groundwater Yield	36.5
Average Evapotranspiration	650

Figure 3.13 shows the calibration and validation region for the water balance. The total water yield percent bias for the calibration and validation regions was +2%. The percent bias for the calibration period achieved targeted performance (-8%), but resulted in over estimation of flows for the validation region (+12%). The percent bias exceeded the target 10% because of the calibration region selection included the wet years of 2008 and 2009. The calibration sufficiently modeled flows for the wet years, but established a bias for large flows that was evident in overprediction for dry and normal years in the validation region. Over prediction was particularly evident in 2012, which was an extreme drought year. According to Illinois State Water Survey, precipitation was 243 mm below the 1981-2010 average, and 30% of Illinois was in severe drought, and 36% of Illinois was in moderate drought (Illinois State Water Survey, 2013). Other water budget modeling targets were met: evapotranspiration, surface, and tile-drained partitioning were modeled within 10% of targeted estimates.

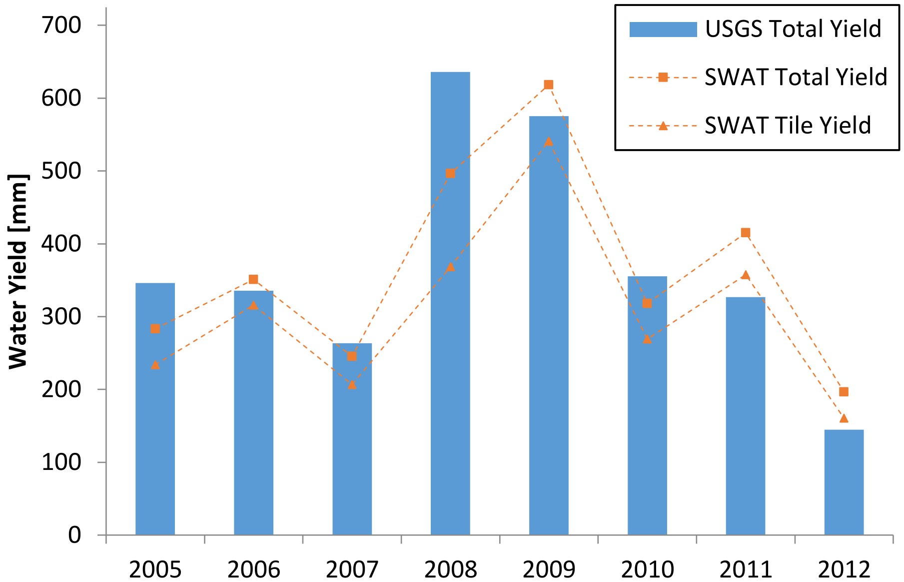

Figure 3.13: Observed and Simulated total and tile-drained yield (NOAA, 2012; USGS, 2012a)

Figures 3.14 and 3.15 show improvement in model performance across daily and monthly time scales. Infrequent large peak daily flows are persistently underestimated, while the more frequent medium and low flows are predicted well. Modeled monthly flows were predicted well across seasons. Table 3.18 provides the statistical improvement for modeling flow across time scales; the modeling objectives were met.

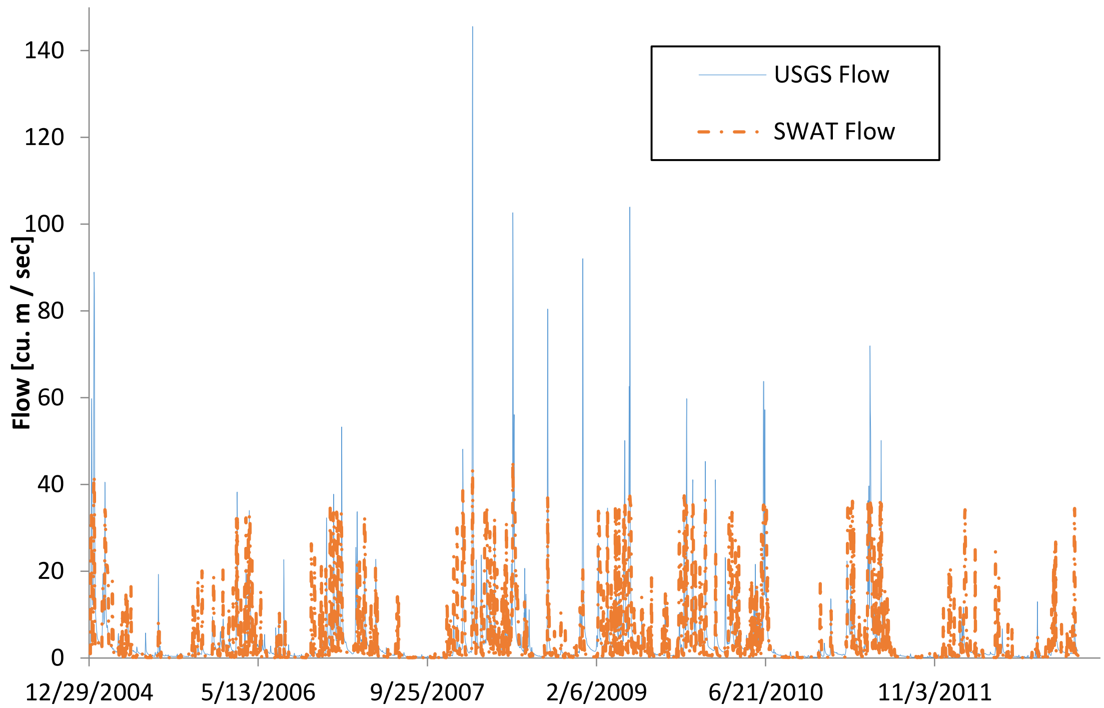

Figure 3.14: Modeled and observed daily flow (NOAA, 2012; USGS, 2012a)

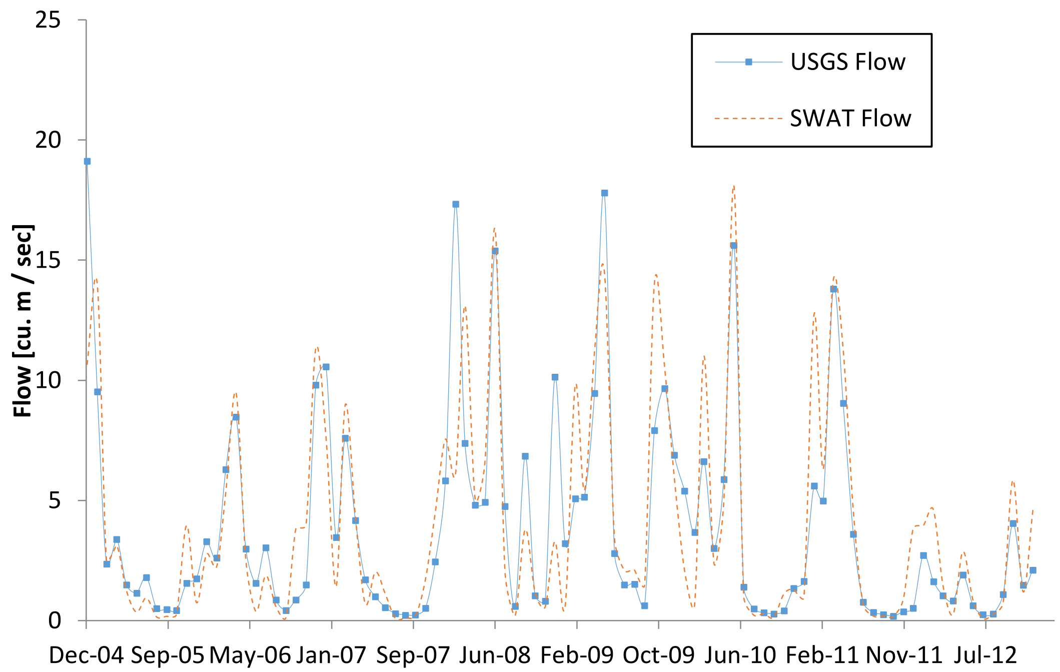

Figure 3.15: Modeled and observed monthly flow (NOAA, 2012; USGS, 2012a)

Table 3.18: Flow Model Performance

Time Period	Daily			Monthly		
	NS	R^2	PBIAS	NS	R^2	PBIAS
Calibration 2007-2010	0.41	0.45	-2.40%	0.63	0.67	-2.60%
Validation 2005-06, 2011-12	0.24	0.46	13.80%	0.69	0.74	14.50%

Flow modeling was 'very good' with respect to Moriasi et al. (2007), with monthly Nash Sutcliffe greater than .5. The results are on par with Hu et al.'s (2007) results (Monthly NS = .85 for validation and .69 for calibration). Annual flow was predicted within a percent bias of 10% across the entire simulation (+2%), with an overprediction in the validation region due the choice of two wet years in the calibration region. Figures 3.16 and 3.17 show the relationship of observed and simulated daily flows with respect to the 1:1 line (perfect correlation). The underestimation of large daily flows is evident, with an improvement on the monthly scale.

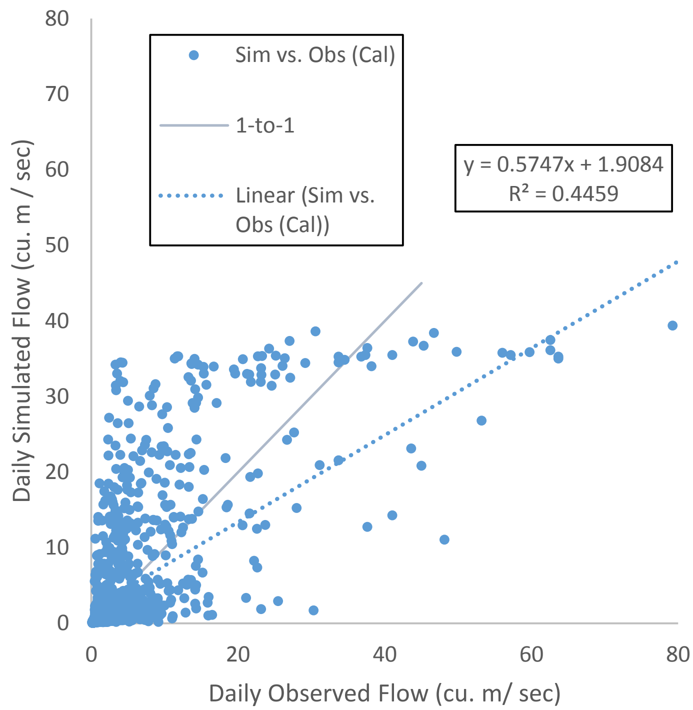

Figure 3.16: Modeled vs Observed Daily Flow Calibration (NOAA, 2012; USGS, 2012a)

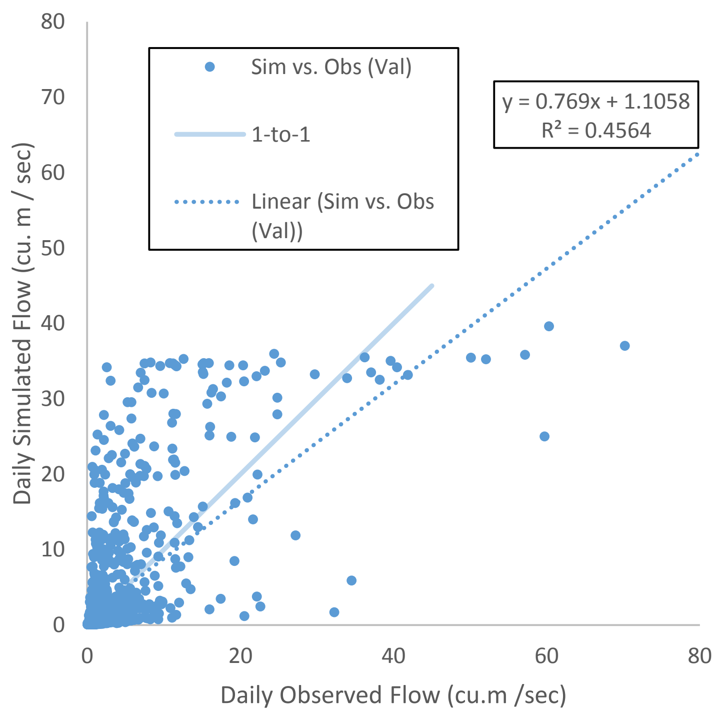

Figure 3.17: Modeled vs Simulated Daily Flow Validation (NOAA, 2012; USGS, 2012a)

The calibrated model underpredicted infrequent daily peak flows, while overpredicting the more frequent low flows. The overprediction of the model during the dry days is responsible for the bias below the 1:1 line. With all other water budget benchmarks satisfied, this overprediction of more frequent low flows and underprediction of peak flows may be related to the tile drainage flow hydrograph as related to the uniform drainage system design. Modeling higher daily peak flow during wet periods would lower flows for drier periods, bringing the correlation closer to alignment. Also, the choice to calibrate solely on monthly and annual flow components pre-selected away from modeling daily outcomes. The broader time-scale was selected because it would be used in the coupled analysis, and therefore a priority was placed on monthly and annual prediction. Figures 3.18 and 3.19 show the correlation of observed and simulated monthly flows and how the underprediction of peak flows and overprediction of low flows was less evident on a broader time-scale.

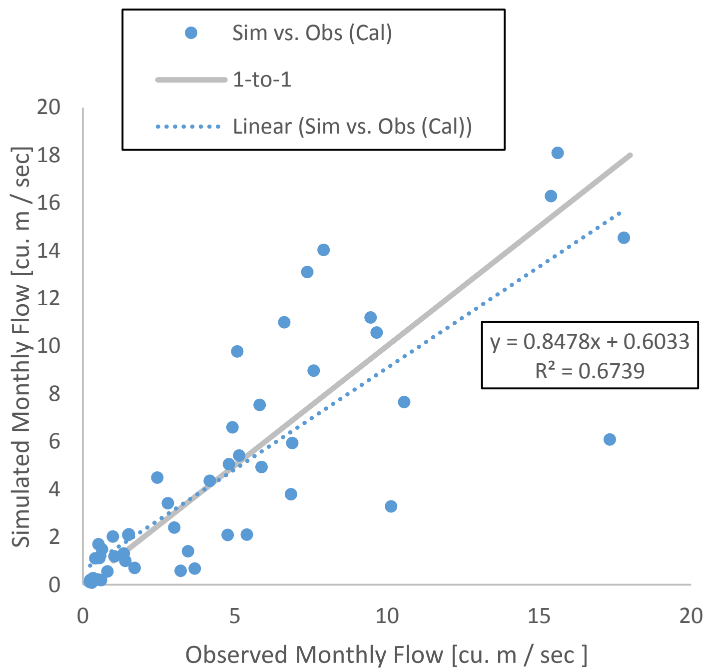

Figure 3.18: Observed vs Modeled Monthly Flow Calibration (NOAA, 2012; USGS, 2012a)

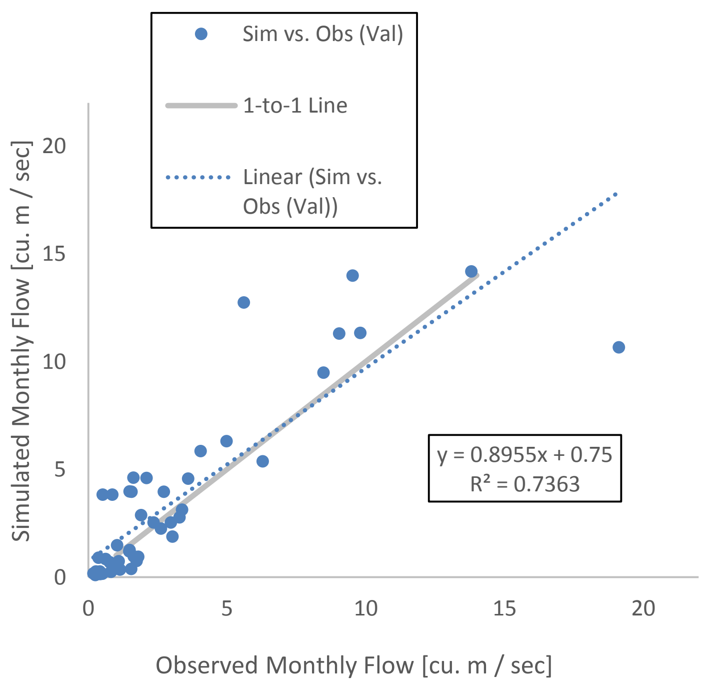

Figure 3.19: Observed vs Modeled Monthly Flow Validation (NOAA, 2012; USGS, 2012a)

Modeled flow outcomes in this study were contrary to Hu's (2007) overestimation of high flow events. The selection of a tile drain depth of 1072 mm was shallower than comparable studies, in addition to the use of new tile drainage routines in the 2012 SWAT release. A depth of 1072, spacing of 22 meters, and drainage coefficient of 10.75 mm would be classified between 'average and good drainage' for Silty Clay and Silt Loams according to the Illinois Drainage Guide, and may not be uniformly true for the watershed. The depth was shallower than the values in Hu et al. (2007) (1100 mm) and Ng et al. (2010) (two estimates of approx. 1200 mm). A deeper drain would deliver larger single event loads, leaving less water for low flow longer duration periods.

3.2.6.2 Nitrate Model Results

Table 3.19 shows the modeled annual nitrogen budget components. Percent bias is reported were modeled values were outside of targeted ranges.

Table 3.19: Average Nitrogen Balance SWAT Model (2005-2012)

Average Annual Nitrogen Budget Component	Value (kg N / ha)	Estimate (kg N / ha)	PBIAS
Nitrate-N Load (total)	23.4	20-50	-
Nitrate-N Load (surface)	1.7	-	-
Organic N	1.4		-
Nitrate-N Load (sub-surface)	21.7	-	-
Mineralization	71	77-90	-8%
N_2 Fixation	96	84-104	-
Grain N Harvest	123	116	6%
Denitrification	16.6	15-23	-

Nitrogen budgets were all modeled within 10% of targets. Hu et al. (2007) reported overestimation of nitrogen fixation (176 kg N ha^{-1}), although Hu et al. (2007) did not calibrate intermediate nitrogen uptake parameters, and did not employ the maximum nitrogen fixation parameter. In addition, Hu et al. (2007) reported an overestimation of harvested nitrogen in yield. This calibration focused on fixing nitrogen budget parameters and then searching other parameters which resulted in a closer fit for the budgets. Nitrate modeling results are shown on daily, monthly, and annual time scales in Figures 3.20 – 3.23. Performance statistics are shown in Table 3.20.

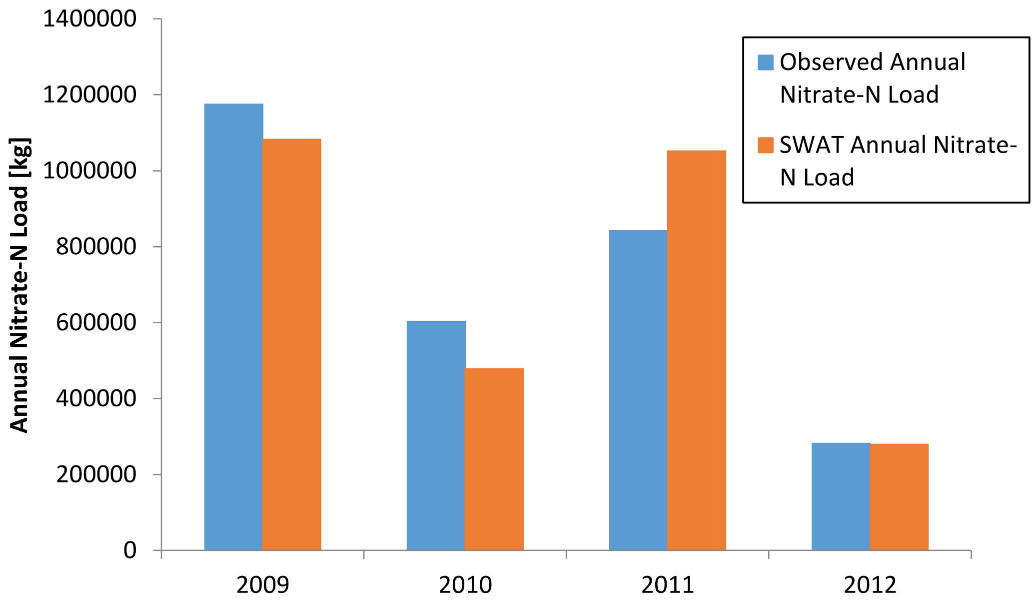

Figure 3.20: Modeled and observed annual cumulative nitrate loads (UCSD & UIUC-NRES Biochemistry Group, 2013)

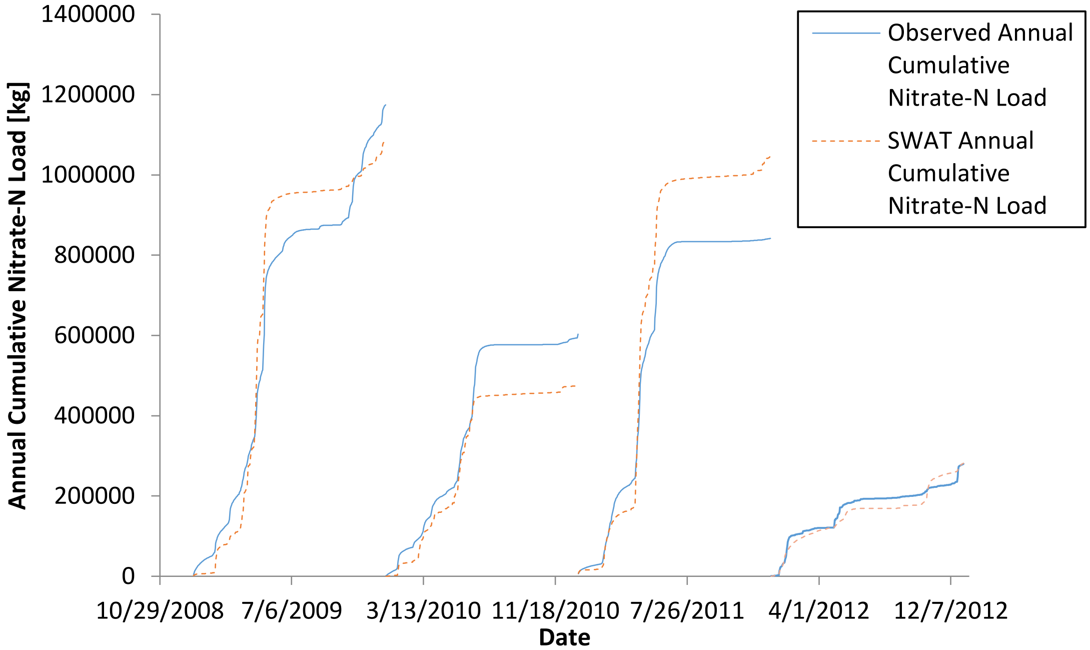

Figure 3.21: Modeled and observed annual cumulative Nitrate-N loads (annual totals) (NOAA, 2012; UCSD & UIUC-NRES Biochemistry Group, 2013; USGS, 2012a)

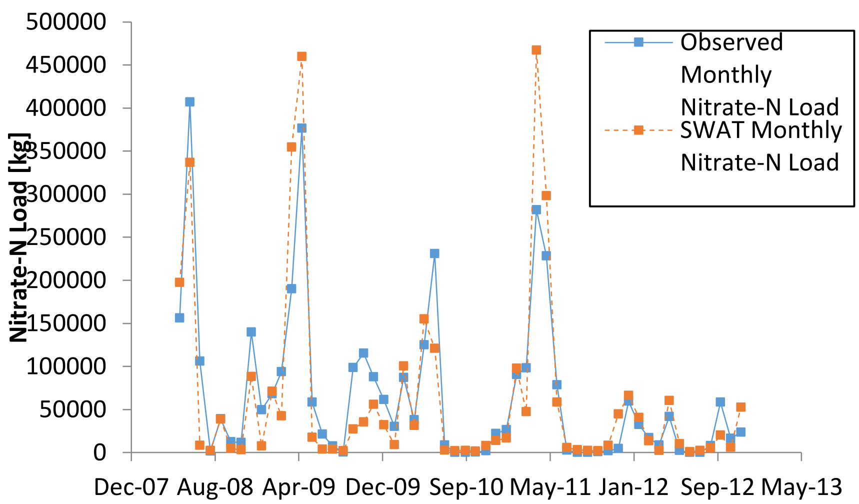

Figure 3.22: Modeled and observed monthly Nitrate-N loads (NOAA, 2012; UCSD & UIUC-NRES Biochemistry Group, 2013; USGS, 2012a)

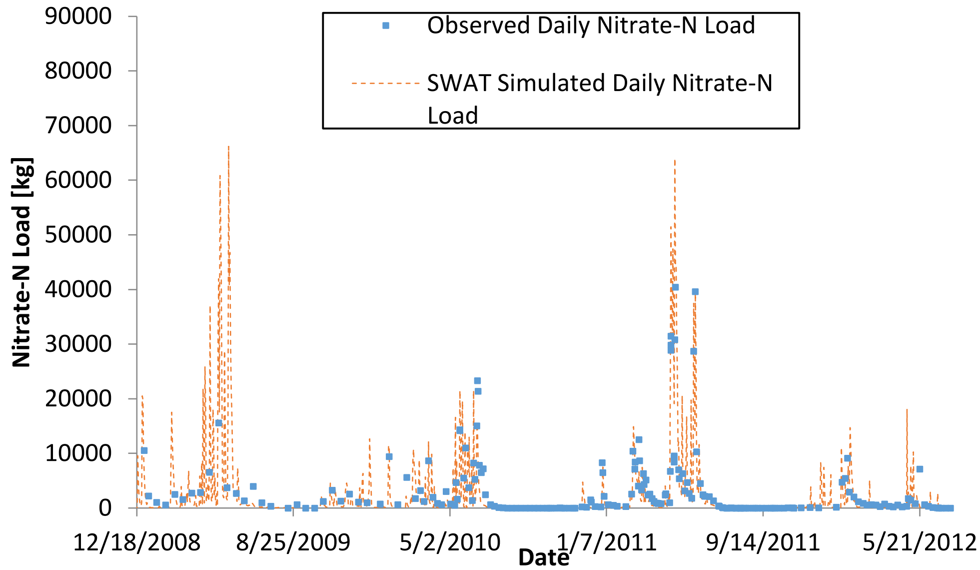

Figure 3.23: Modeled and observed daily Nitrate-N loads (NOAA, 2012; UCSD & UIUC-NRES Biochemistry Group, 2013; USGS, 2012a)

Table 3.20: Nitrate-N Model Performance

Time Period	Daily			Monthly			Annual
	NS	R^2	PBIAS	NS	R^2	PBIAS	PBIAS
Calibration 2008-2010	0.24	0.56	-17.8%	0.73	0.80	-15.4%	-14%
Validation 2011-2012	0.55	0.87	18.0%	0.60	0.91	23.0%	+16%

Nitrate modeling prioritized forecasting annual loads and accurately representing the nitrogen budget. Nitrogen budgets were all modeled within 10% and annual loads within 25%. On a monthly scale, nitrate modeling performance would be deemed ‘very good’ (monthly NS > .5, BIAS < 70%) with respect to Moriasi et al. (2007), and exceeded performance in Hu et al. (2007) (.2 for calibration, and .31 for validation). Even daily modeling performance were comparable to Moriasi et al.’s (2007) monthly benchmarks. Figures 3.24 and 3.25 show the relationship between observed nitrate loads and modeled loads with respect to perfect correlation (1:1 line).

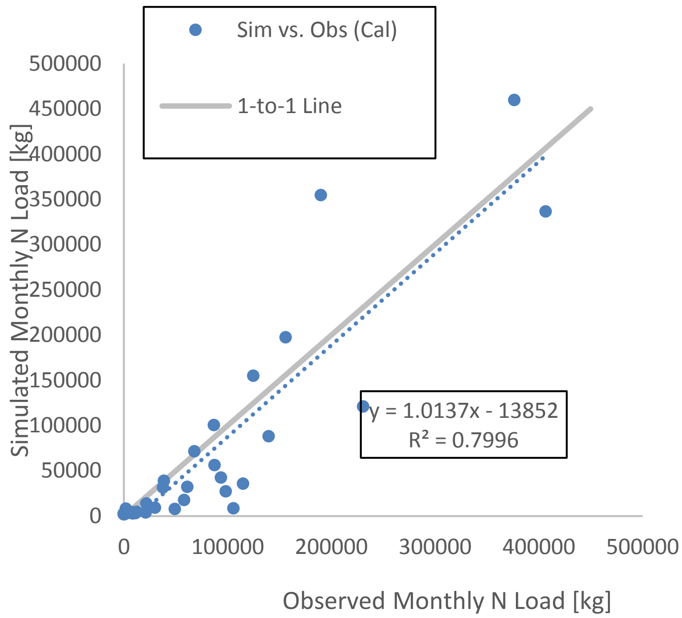

Figure 3.24: Correlation between modeled and observed monthly Nitrate-N loads (calibration) (NOAA, 2012; UCSD & UIUC-NRES Biochemistry Group, 2013; USGS, 2012a)

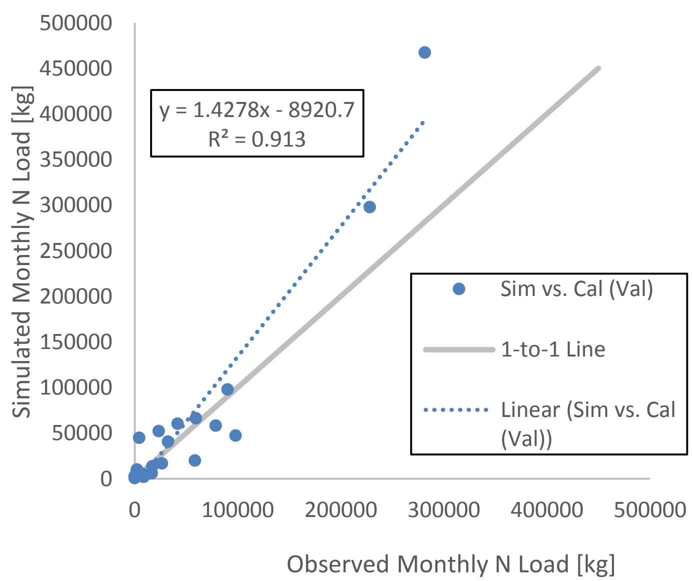

Figure 3.25: Correlation between modeled and observed monthly Nitrate-N loads (validation) UCSD & UIUC-NRES Biochemistry Group, 2013; USGS, 2012a)

As figures 3.22 and 3.23 show there was an overestimation of high nitrate loads. As with flow, the selection of the calibration region was a significant factor in performance. There was a high flow, high load event in May 2009 that the calibration procedure consistently overpredicted. SWAT overestimated the nitrate load for that month by 20%. It was determined during the calibration procedure that this load could not be modeled sufficiently while meeting overall nitrogen budgets and total annual load was prioritized for 2009 instead. The overestimation could have been related to the assumption of universal fall application of fertilizer. Some application of spring fertilizer in the watershed prior the high flow event would have contributed to less leaching in the spring months and more plant uptake. It wasn't possible to calibrate for the event and improve performance, and the modeling phenomenon persisted in the validation region, with further overpredictions of high nitrate loads. This calibration decision to prioritize annual prediction was confirmed in the validation region with 'very good' performance with respect to Moriasi et al. (2007): even daily performance met Moriasi's monthly recommendations.

Nitrate concentration was not incorporated into the calibration procedure because SWAT does not provide it as a direct output on a monthly or annual time step (Neitsch et al., 2009). Figures 3.26 and 3.27 show the results of the load divided by the volume of flow for that time period performed after the calibration.

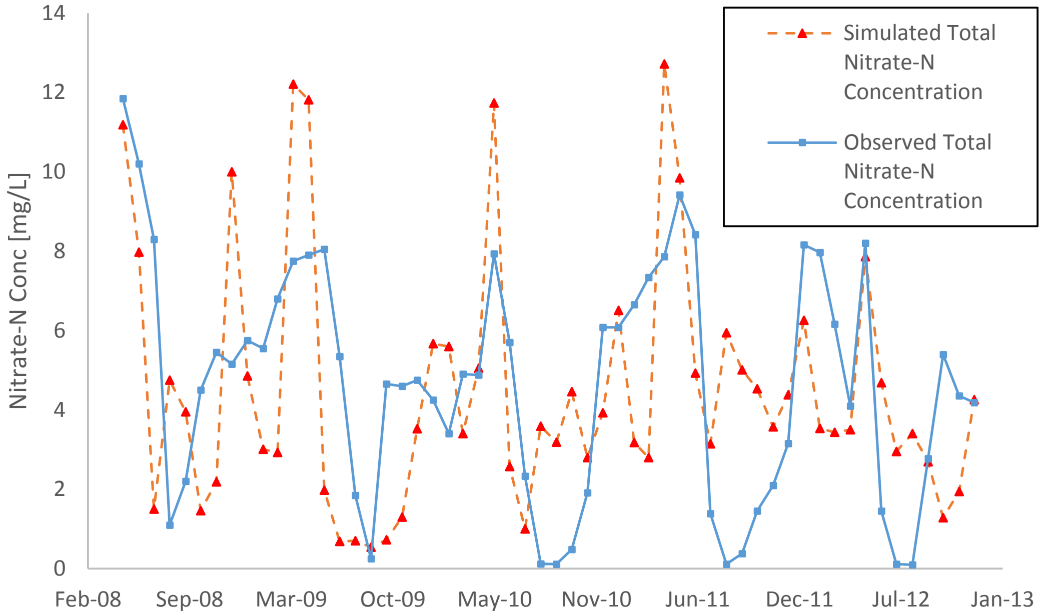

Figure 3.26: Modeled and observed monthly Nitrate-N concentrations (NOAA, 2012; UCSD & UIUC-NRES Biochemistry Group, 2013; USGS, 2012a)

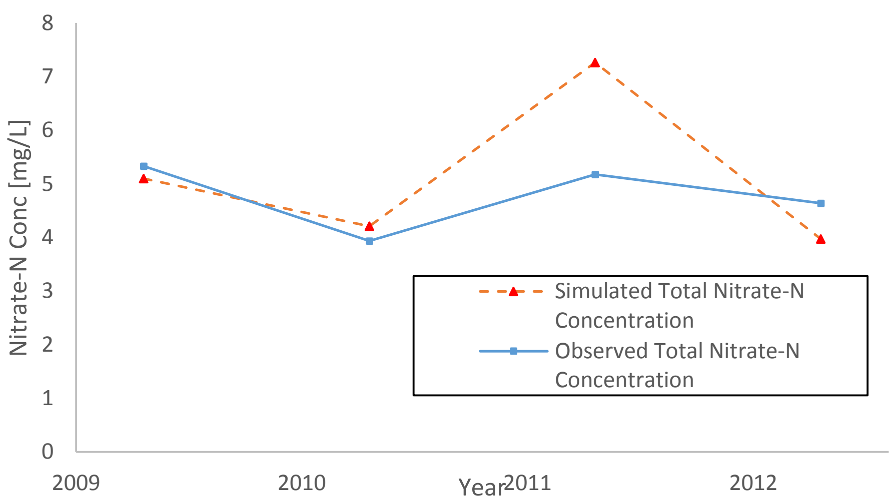

Figure 3.27: Modeled and observed annual Nitrate-N concentrations (NOAA, 2012; UCSD & UIUC-NRES Biochemistry Group, 2013; USGS, 2012a)

Monthly concentrations were modeled with a percent bias of -3.4%, Nash-Sutcliffe of -.13, and R^2 of .21. Annual nitrate concentrations were modeled with a percent bias of +7%. Annual concentrations are utilized in the coupled analysis as a measure of water quality.

Table 3.21 shows the modeled annual phosphorus budget components. Percent bias is reported where modeled values were outside of targeted ranges.

Table 3.21: Average Dissolved Reactive Phosphorus Balance SWAT Model (2005-2012)

Average Annual Phosphorus Budget Component	Value (kg P / ha)	Estimate (kg P / ha)	PBIAS
P Load (total)	.548	.5-1.1	-
DRP Load	.354	.3-.8	-
Grain P Yield	38	52	-27%

Total phosphorus and dissolved reactive phosphorus budgets were all modeled within 10% of targets. Harvested phosphorus in grain could not be raised sufficiently to meet the targets, while still meeting the targeted range of phosphorus at the outlet. Figures 3.28 – 3.31 show the daily, monthly, and annual modeled phosphorous loads. Table 3.22 shows the modeling performance.

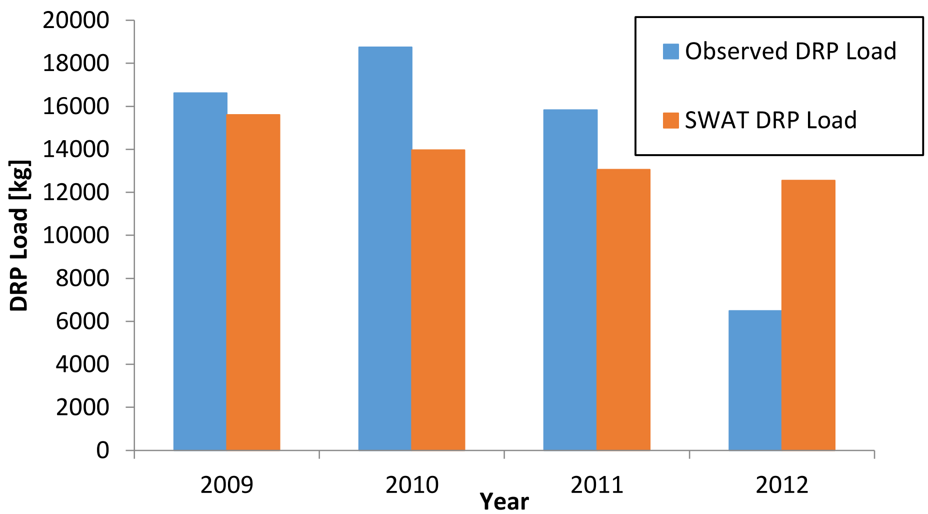

Figure 3.28: Modeled and observed annual cumulative dissolved reactive phosphorus loads (NOAA, 2012; UCSD & UIUC-NRES Biochemistry Group, 2013; USGS, 2012a)

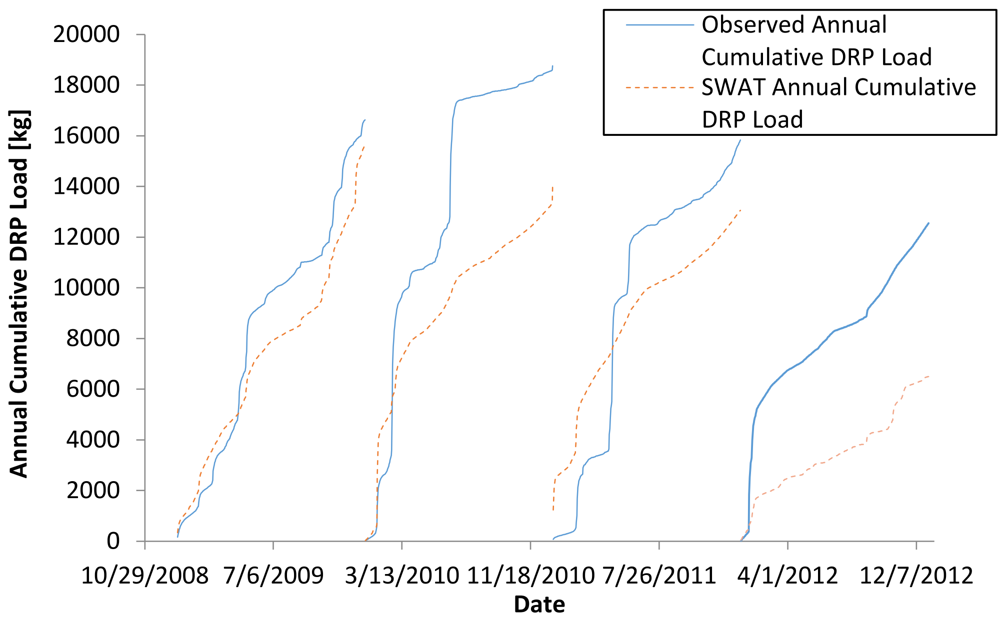

Figure 3.29: Modeled and observed daily cumulative DRP loads (annual totals) (NOAA, 2012; UCSD & UIUC-NRES Biochemistry Group, 2013; USGS, 2012a)

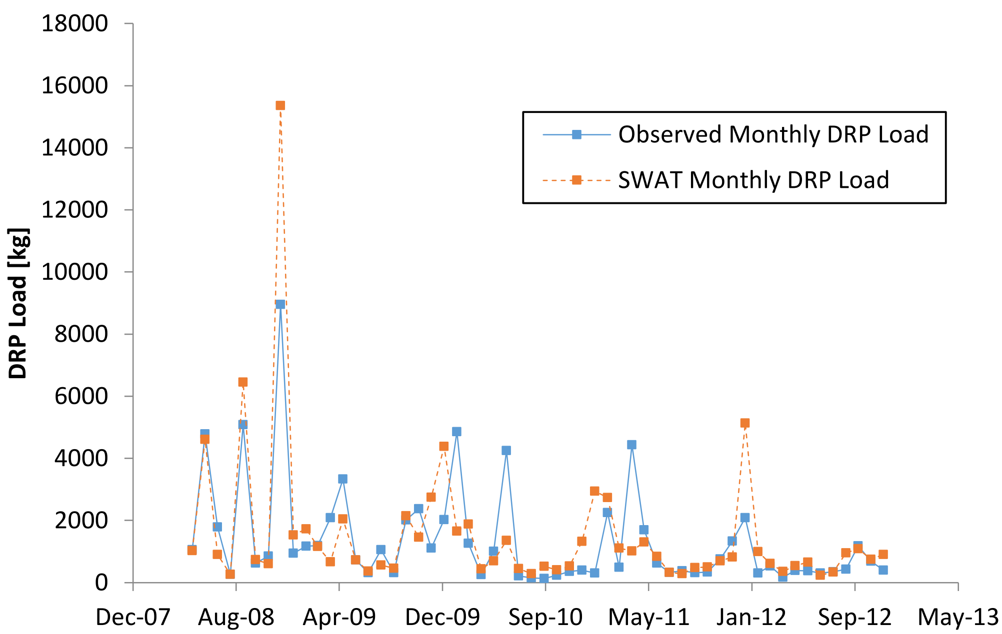

Figure 3.30: Modeled and observed monthly DRP loads (NOAA, 2012; UCSD & UIUC-NRES Biochemistry Group, 2013; USGS, 2012a)

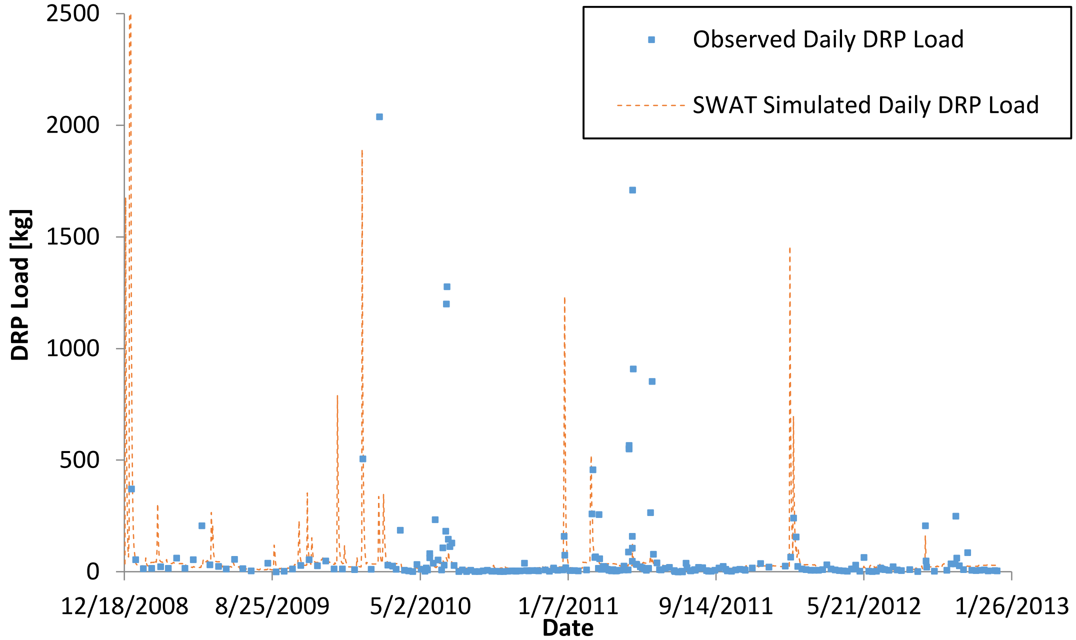

Figure 3.31: Modeled and observed daily DRP loads (NOAA, 2012; UCSD & UIUC-NRES Biochemistry Group, 2013; USGS, 2012a)

Table 3.22: Phosphorus Model Performance

Time Period	Daily			Monthly			Annual
	NS	R^2	PBIAS	NS	R^2	PBIAS	PBIAS
Calibration 2008-2010	0.05	0.12	-32.8%	0.35	0.71	7.9%	-20%
Validation 2011-2012	-0.28	0.02	-25.2	-0.42	0.16	25.2%	13%

Daily and monthly phosphorus modeling performance did not meet targets. Large monthly phosphorus loads were over predicted, and individual large day loads were missed or underpredicted. While daily and monthly loads were not predicted well, annual loads were prioritized for modeling, meeting 25% percent bias targets. Figures 3.32 and 3.33 show the correlation between observed and simulated loads.

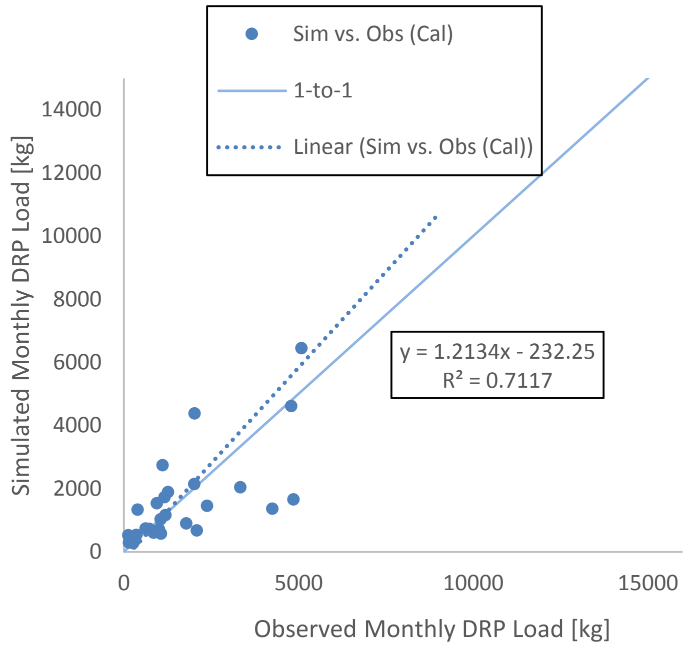

Figure 3.32: Correlation between modeled and observed monthly DRP loads (calibration) (NOAA, 2012; UCSD & UIUC-NRES Biochemistry Group, 2013; USGS, 2012a)

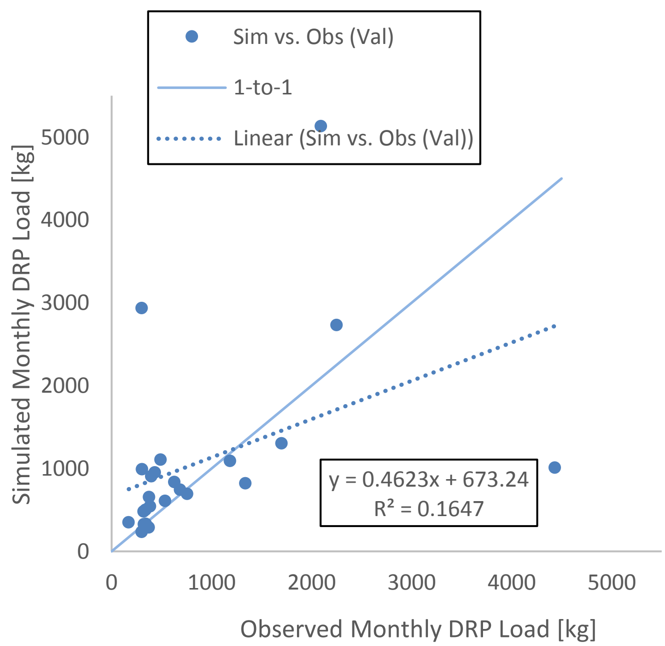

Figure 3.33: Correlation between modeled and observed monthly DRP loads (validation) (NOAA, 2012; UCSD & UIUC-NRES Biochemistry Group, 2013; USGS, 2012a)

As figures 3.30 and 3.31 show there was an overestimation of high phosphorus loads while underestimation of low phosphorus loads. While, this could not be remedied in the calibration, the procedure instead prioritized annual loads (within 20%), after no further improvement could be achieved. The under-performance may have been improved by calibrating phosphorus before nitrate and selecting for phosphorus targets, but nitrate was prioritized. In addition, phosphorus loadings for the Rantoul Sewage Treatment plant were only available for 2012. Incorporating measured loadings from the Rantoul plant may have improved performance for years outside of 2012. The tile drainage calibration also constrained the ability to improve phosphorous modeling performance. Tile drainage was calibrated for water budgets and then not considered for phosphorous. Increasing surface drainage tends to increase phosphorous loss (Skaggs, 1994). As a result, implementing drainage across 80% of the study area and partitioning 84% of flow into tile drainage would limit phosphorous loss, which is indicated by the model's persistent underestimation. Further, the surface drainage parameters were only considered during the water budget calibration.

As with nitrate concentration, phosphorus concentration was not incorporated into the calibration procedure because SWAT does not provide it as a direct output on a monthly or annual time step. Figures 3.34 and 3.35 show the results of the load divided by the volume of flow for that time period performed after the calibration (Neitsch et al., 2009).

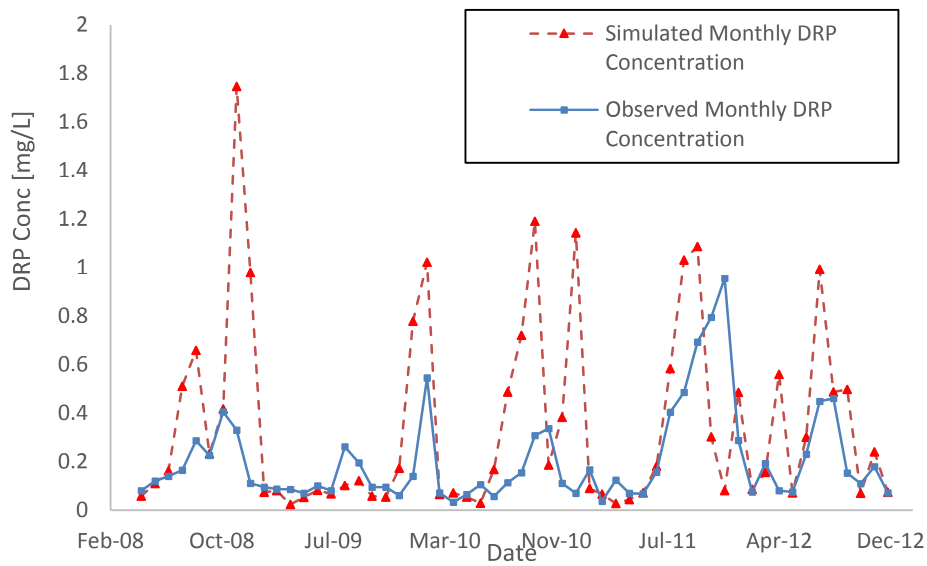

Figure 3.34: Modeled and observed monthly DRP concentrations (NOAA, 2012; UCSD & UIUC-NRES Biochemistry Group, 2013; USGS, 2012a)

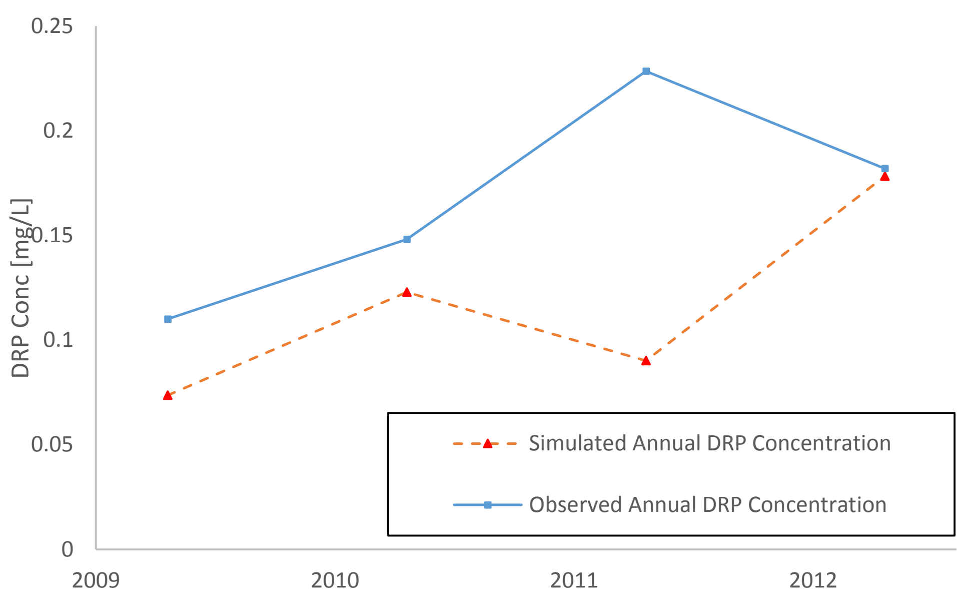

Figure 3.35: Modeled and observed annual DRP concentrations (NOAA, 2012; UCSD & UIUC-NRES Biochemistry Group, 2013; USGS, 2012a)

Monthly phosphorus concentrations were modeled with a percent bias of 70.6%, Nash-Sutcliffe of -3.06, and R^2 of .16. Annual nitrate concentrations were modeled with a percent bias of -30%. Annual concentrations are utilized in the coupled analysis as a measure of water quality.

3.2.6.3 Crop Growth Model Results

Figure 3.36 shows the crop yield model results. Annual crop yields were modeled within 10% percent bias: 3% for corn, and 1% for soybeans.

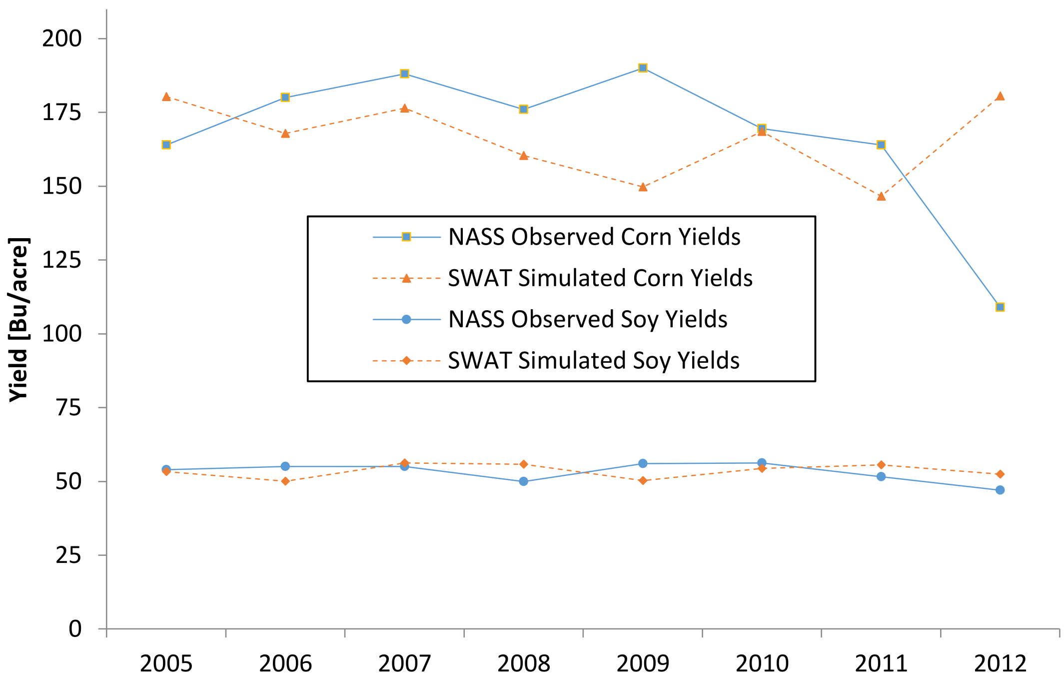

Figure 3.36: Modeled and observed annual crop yields (USDA-NASS, 2012)

Performance benchmarks were achieved despite poorly predicting the 2012 drought yield. The model overpredicted the yield by 72%. Corn yield modeling performance was -6% without considering 2012 yields. The 2012 overprediction could have been related to the overprediction of water yield in 2012, and consequently more water available for plant uptake. The calibration decision not to modify additional crop parameters could have addressed plant water uptake processes, but possibly adversely affecting the more frequently observed yields. The decision was made to treat 2012 as an exception, and to prioritize the modeling of the other years.

3.2.7 SWAT Model Conclusions

SWAT model performance met or exceeded 'satisfactory' benchmarks. Underestimating low-flow periods during the summer and one high nutrient load in 2009 affected performance measures. Calibration decisions including a deep drain to constrain tile-flow partitioning, and uniform fall fertilizer application may have affected performance. Water budget, nutrient budgets, and crop yield model performance are met target benchmarks to facilitate a coupled analysis. These model constraints accurately represented observed environmental outcomes and sufficiently characterized watershed phenomena with a few exceptions. Notably, finer time-scale modeling of phosphorous may have been undermined by the calibration procedure to address phosphorous last and lack of sewage loading data. In addition, the extreme drought year of 2012 was modeled poorly and could not be accounted for in the calibration procedure without adversely affecting the performance of more frequent yield outcomes.

3.3 Modeling Best Management Practices

3.3.1 Overview

While Illinois producers have a wide variety of management options and techniques to operate their businesses and improve land stewardship, this study focuses on three potential strategies for analysis: rye cover cropping, drainage water and nutrient management. Research has shown that these conservation practices are suitable for the region and effective measures for improving water quality in Midwestern watersheds (Upper Salt Fork Project Report and Status Update, 2011). The installation, effectiveness, and economics of these conservation strategies are well documented in the region (Cooke et al., 2001; Li et al., 2008; Randall & Vetsch, 2005; St. John & Ogle, 2008).

3.3.2 Rye cover cropping

Cover crops are small grain or legume crops that are planted in early fall to protect and improve water quality during the winter months. Planting cover crops has been shown to cut fertilizer costs, reduce the need for herbicides and other pesticides, improve yields by enhancing soil health, prevent soil erosion, conserve soil moisture, protect water quality, and help safeguard personal health (Sustainable Agriculture Network, 2007). The use of fall-planted cover crops crops can affect the water balance, reduce the soil NO_3–N level, and provide residue cover on agricultural fields that are normally fallow between summer crops (Feyereisen et al., 2006; Li et al., 2008; Singer et al., 2011). Studies show that the phosphorus and nitrate leaching reduction achieved by cover cropping ranges between 0% and 50% (Villamil et al., 2006; Logsdon et al., 2002). Cover cropping has been shown to not affect yield with nitrogen application rates above 80 lbs/acre, but may decrease yields below that threshold (Li et al., 2008). In Central Illinois potential cover crops are winter rye, winter wheat or hairy vetch. A producer must invest additional time, resources, and labor to successfully achieve the benefits of cover cropping.

3.3.3 Nutrient Management

Timing of fertilizer application can have a significant impact on nitrate export and economic benefit. Studies show that nitrogen utilization is greater, nitrate export is lower, and economic return is greater with spring application versus fall (Randall & Vetsch, 2005; Vetsch & Randall, 2004). Producers consider fall application because of equipment availability and lower input costs. However, it has been demonstrated that more nitrogen is available for plant uptake, and there is less time for denitrification and leeching to occur the nearer fertilizer is applied to planting (Fox et al., 1986). Randall & Vetsch (2005) estimated the reduction in nitrate losses at 17% in an 8 year study in Minnesota and increased yields by as much as 7%.

3.3.4 Drainage Water Management

Drainage water management is the use of a control structure to vary the depth of the drainage outlet. The depth is raised following harvest to limit flow and nutrient leaching during the off-season. The depth is then lowered previous to spring operations, and then raised again to potentially store more water during the dry summer months. Drainage water management (DWM) has been shown to reduce water flow and nitrate losses through drains by as much as 50% on the long term (25 years) (Thorp et al, 2008). Phosphorous reductions can be as much as 35% (Skagss et al., 2010). In addition, yields have been shown to increase by as much as 5% in Midwestern watersheds, when precipitation levels are sufficient and drains flow for a long time after planting (Frankenberger et al., 2006). These watersheds would allow for greater water storage through management.

3.4 BMP Representation in SWAT

3.4.1 Overview

Section 3.2 details how SWAT was initialized to model and predict the hydrology, nutrient loads, and crop yields for the watershed. This study sought to employ this model facilitate an analysis of management decisions in the watershed. Management decisions chosen for the analysis included: performing winter cover cropping, and switching fertilizer application to the spring, and managing the water table depth. The set of management decisions to include was based on SWAT's built-in functionalities, methods to extend them, and survey results of producers' adoption of these strategies in the watershed (Upper Salt Fork Project Report and Status Update, 2011). SWAT provides an extensive and customizable set of configuration files for simulating many different agricultural management practices. Drainage water management, fertilizer applications and timing, and cropping decisions are provided through existing SWAT functionality (Neitsch et al., 2013).

3.4.2 Rye Cover Cropping

Incorporating a winter cover crop has been shown to reduce nitrate leeching in Midwestern cropping systems (Li et al., 2008; Singer et al., 2011). Winter cover cropping ties up nitrogen during times of the year when corn and soybeans are not growing and taking up nutrients and water (Kaspar et al., 2007). The SWAT management (.mgt) file was used to add rye cover cropping operations. Rye cover cropping was implemented in SWAT by moving up corn/soybean harvest operations and inserting a rye planting operation by October 15th to comply with NRCS conservation practices requirements (Iowa Learning Farms & Practical Farmers of Iowa, 2011). The following spring, a kill operation was used two weeks before the next crops' planting as outlined in rye cover cropping operation manuals (Sustainable Agriculture Network, 2007). The management file was also used to apply a user-inputted fertilizer reduction for a cover cropping year. The user-inputted fertilizer reduction amount was based on cover cropping manuals estimate that cereal rye can add 60 lbs/acre of nitrogen to a field (Sustainable Agriculture Network, 2007).

3.4.3 Nutrient Management

The management (.mgt) file was also used to switch fall application to spring. Application date was at least two weeks before corn planting, centered around April 1st as in Hu et al. (2007).

3.4.4 Drainage Water Management

The operations (.ops) file was used to raise and lower the depth to the tile drain by entering a new operation for each depth change. To implement drainage water management for any year, the depth of the drain was raised from the default 1072 mm to 152.4 mm on November 30th in the preceding year. The tile was lowered to the default 1072 mm on March 21st, raised to 304.8 mm on June 1st, and then returned to 1072 on September 15th. This configuration ensured that all field operations (planting, tillage, fertilizer) were performed with the drain at default depth. The protocol was adapted from university extension and previous studies (Ale et al., 2009; Frankenberger et al., 2006; Thorp et al., 2008)

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CHAPTER 4

METHODS – HUMAN SYSTEMS MODEL

4.1 Introduction

This study interfaced a natural and human systems model to assess environmental outcomes with respect to economic performance and agricultural stakeholder decision-making. Chapter 3 documented the natural-systems model implementation in the Soil and Water Assessment Tool (SWAT). The modeling of environmental outcomes including crop yield, nitrate-N, and dissolved reactive phosphorous along with a suite of three Best Management Practices (BMPs) were presented in Chapter 3.

Modeling of environmental outcomes alone is not sufficient for identifying cost-effective and impactful conservation strategies (Nejadhashemi et al., 2011). Any analysis must consider the motivation and behavior of human entities to form useful conclusions. An analysis must also address societal, economic motivations of stakeholders to assess the adoption and effectiveness of conservation (Nowak & Korsching, 1998). This study formulated a model to incorporate these considerations. The output from SWAT in Chapter 3 was coupled with a human-systems model to form conclusions about the adoption of the BMPs, conservation policy initiatives, environmental and economic impact (Figure 4.1).

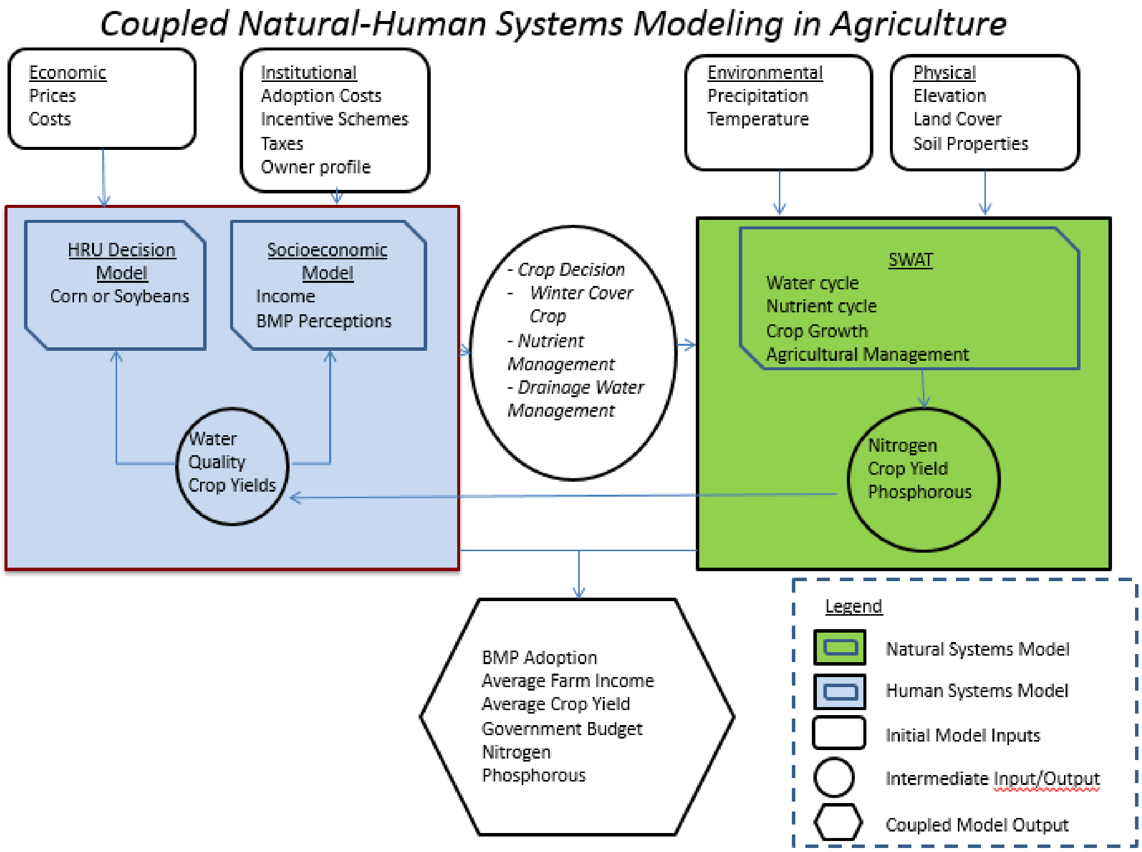

Figure 4.1: Coupled Natural-Human Systems Model (Chapter 3)

This chapter details the development of the human-systems model: the procedure, algorithm, calibration, and scenario test design. The model was implemented using the technique of agent-based modeling. First, the approach of agent-based modeling is discussed. The chapter proceeds with the parameterization of the model and presents its development using guidelines from past studies for agent-based. Then the logic and progression of the model is presented. Following the outlining of model logic, the rationale for initial model parameters values and then the calibration procedure is presented. The calibrated baseline results are presented along with the formulation of default input values for performing an analysis of different model scenarios. Finally, the calibrated model is used to perform a scenario analysis to answer the questions about environmental impacts related to economic outcomes and policy instruments.

4.2 Agent-based modeling

4.2.1 Introduction

Agent-based modeling (ABM) simulates the behavior of actors (agents) in a population and the interactions among actors within a specific environment (Gilbert, 2007). In an agent-based model, behavioral rules of individual agents and their interactions are established and enacted within the environment (Kanta & Zechman, 2010). The system evolves according to agent behavior. The model can be tested to form conclusions and better understand the relationship between agents and their role in the environment. The applications are broad and span many disciplines; ABMs have been used to model predator-prey relationships (Mock & Testa, 2007), electricity markets (Cirillo, 2006), and agricultural practice adoption (Ng et al., 2011) as discussed in Chapter 2. With the diversity of applications, there is a great flexibility in ABM modeling.

4.2.2 Agent-based model development

Macal and North (2010) characterized the development of agent-based models and their conclusions provided the framework for the ABM in this study. This study adopted Macal and North's (2010) general steps for model development, outlined as:

1. Identify the agents and get a theory of agent behavior
2. Identify the agent relationships and get a theory of agent interaction
3. Get the requisite agent-related data, initialize agents
4. Validate the agent behavior models (in addition to the model as a whole)
5. Run the model and analyze the output from the standpoint of linking the micro-scale behaviors on the agents to the macro-scale behaviors of the system.

The resultant Macal and North (2010) model had three elements: agents, environment, and relationships. Agents were self-contained, autonomous, social, adaptive, and goal-oriented. The environment defined information about the placement and surroundings of agents. Relationships governed the behavior of agents with their environment and each other. Macal and North's (2010) general model development steps and model components form the structure of this chapter. In addition to Macal and North's (2010) general guidelines, two types of data were necessary for development as described by Kanta & Zechman (2010): top-down, and bottom-up data. Top-down data described the overall performance of the system and bottom-up data governed the behavior of individual agents. In this study, top-down data types (macro) included: nitrogen at the outlet, phosphorous at the outlet, average crop yields, and crop prices. Bottom-up data types in this study included: farmer acreage, soil productivity, and the amount of BMP costs shared by the community.

4.3 Agent-based model development

4.3.1 Agents

Macal and North (2010) recommend first identifying agents and data in the development of an agent-based model. The ABM in this study defined two agents: a farmer agent and a community agent. The farmer and community agent exist in the watershed study area. The farmer agent represented a typical agricultural producer in the watershed. The community agent conceptually represented societal and government institutions. The next step in developing the agent-based model was to establish a theory of behavior for the agents and a method to parameterize that theory. Each agent's theory of behavior is presented in this section along with the model parameters used to govern their behavior.

4.3.1.1 Farmer Agent

The theory of farmer behavior in this study was based on studies of farmer priorities and motivations. Each farmer makes decisions about the operations of the farm. The farmer's behavioral theory is to operate to maximize their goals. A farmers' primary goal is to remain on their land and continue the farming way of life (Ohlmer et al., 1998). This primary goal encompasses motivations and priorities: economic profitability, environmental stewardship, social achievement (Brodt et al., 2006; Walter, 1997). Walter (1997) describes these values in four images of the successful Illinois farmer: sustainer of land resources, analytical operator, long-term business manager, and exemplary agrarian life-style member. Similarly, Brodt (2006) formed three categories of the motivations of farmers: environmental stewardship, production maximization, and networking entrepreneurship. These common themes of economic awareness, social responsibility, and environmental stewardship form the basis for the farmer agent. In addition, farmer behavior is dependent on their time engaged with a piece of land (Brodt 2006). Producers make different economic investments and decisions based on the duration farming one piece of land and their anticipated time continuing to farm that land (Hoag et al., 2012). The farmer agent was parameterized to reflect these motivations: sociability, environmental awareness, economic awareness, and farming time horizon. To incorporate these themes into the development of the ABM, each farmer agent was parameterized with measures of these motivations (Table 4.1). A farmer's social network consisted of nearby producers within a specified distance. The list of neighbors was based on that user-inputted geographic distance. All neighbors that were located within a user-defined distance were added to the list. The farmer agent parameters were initialized according to Section 4.3.4 to include diverse farmer behavior across the watershed. The calculations for anticipated crop yields and BMP opinions used for making management decisions are documented in Section 4.3.2. The feasible ranges of S, E, and M, were established to adjust a random variable that tested the likelihood of management decisions, as detailed in Section 4.3.2. These parameters were employed to weigh outcomes and facilitated increasing or decreasing the likelihood of making one management decision or another.

Table 4.1: Farmer Agent parameterization

Parameter	Description (units)	Range
S	Sociability	$-1 - 1$
E	Environmental Awareness	$-1 - 1$
M	Economic Awareness	$-1 - 1$
t_f	Farmer Time Horizon (years)	> 0
D	Farmer Neighborhood Distance (km)	> 0

The model parameterization was not necessarily a metric by which to make judgments about typical East-Central Illinois producers, but a means to facilitate and affect distinct agent behavior and, as outlined in Macal and North (2010) for defining agents. Farm decision-making may involve many different strategies and combinations of these priorities, and these parameters were used to express that diversity in agents, not as a commentary on the personalities of area producers.

Macal and North (2010) recommended locating and incorporating practical data in parameterizing agents. In this study, farmer agent parameterization with respect to economic behavior was derived from studies on the financial structure and performance of typical Illinois farms. The economics of each farmer agent were represented by annual net return basis for corn and soybean production in Central Illinois as reported in the Illinois Farm Management Handbook (Table 4.2) (UIUC-ACES, 2012).

Table 4.2: Central Illinois Farm Returns 2005-2012 (UIUC - ACES, 2003-2012)

	High Productivity		Low Productivity	
Year	Corn Net Return ($/acre)	Soy Net Return ($/acre)	Corn Net Return ($/acre)	Soy Net Return ($/acre)
2005	15	-9	-33	-22
2006	86	3	79	-3
2007	298	161	253	142
2008	158	52	139	66
2009	-90	1	-54	15
2010	201	144	121	118
2011	241	81	175	98
2012	174	79	144	102

The Handbook provided estimates for all costs, revenues, and returns for high and low productivity farms. The ABM grouped the cost data (fertilizers, grain handling, machinery, labor, interest on debt, power, repairs, disaster insurance) and revenue data (crop, government payments, off-farm, investments, insurance) from the Handbook into an annual performance (net return). In this manner, the ABM abstracted costs like labor and insurance to facilitate an analysis of returns with respect to BMP installations.

Farmer agent net returns were implemented in the ABM with a forecast at the beginning of the year for planning, and then calculating actual returns at the end of a year (Table 4.3).

Table 4.3: Farmer Agent Economic Parameterization

Parameter	Description [units]
i	year
$Y_f(i)$	Farmer Observed Yields (year) [bu/ac]
$Y_n(i)$	Farmer Neighbors' Observed Yields (year) [bu/ac]
$F[Y_f(i)]$	Farmer Forecasted Yields (year) [bu/ac]
$P_f(i)$	Farmer Observed Revenue Per Yield (year) [$ / bu/ac]
$F[P_f(i)]$	Farmer Forecasted Revenue Per Yield (year) [$ /
$C_f(i)$	Farmer Observed Cost Per Yield (year) [$ / bu/ac]
$F[C_f(i)]$	Farmer Forecasted Cost Per Yield (year) [$ / bu/ac]
$I_f(i)$	Farmer Observed Revenue (year) [$]
$F[I_f(i)]$	Farmer Forecasted Revenue (year) [$]

Returns were calculated by multiplying by the revenue per unit yield less the cost per unit yield by the yield, less BMP and policy costs (Equation 4.1), which are introduced in 4.3.3.

$$I_f(i) = Y_f(i) * \left(P_f(i) - C_f(i)\right) - BMP\ Costs - Policy\ Costs \tag{4.1}$$

Farmer adoption of BMPs was similarly driven by economics, sociability, and environmental awareness. The USDA-NRCS multi-year study of the CEAP (Conservation Effectiveness Assessment Program) in Upper Mississippi River Basin discussed in Chapter 2 provided important conclusions on why and what was driving conservation practice adoption (Hoag et al., 2012; USDA - NRCS, 2011). This model incorporated those conclusions in the logic for farmer BMP adoption. The CEAP assessment found that producers adopt first and foremost if practices increase profits. Producers also adopt if there are observable benefits such as reduced erosion, whereas nutrient management where benefits are abstracted are less likely to be adopted. Receiving a positive recommendation from a trusted source like an agricultural supplier or neighbor also drives adoption. Also, some producers are simply more interested in implementing conservation practices. In addition, producers with a strong network of peers to discuss changing management and the finances reflect higher adoption rates (Hoag et al., 2012). These factors driving adoption were parameterized in a BMP opinion that would decide the likelihood of adoption for each farmer along with their neighbors' opinions (Table 4.4). Farmer agent BMP opinions were the result of logic detailed in Section 4.2.3 and similar to farmer agent characteristic parameters, served as the likelihood of adoption (0-1). In addition, as farmer agents adopted practices, they tabulated their perceived reduction of nutrient loads for assessing BMP performance later. Perceived reduction was represented as a fraction of load delivered to the farmer's outlet (0-1).

Table 4.4: Farmer BMP Opinions

Parameter	Description	Range
$B_{BMP\ NAME}(i)$	Initial Farmer BMP Opinion (year)	0 - 1
$B_{n,BMP\ name}(i)$	Neighbors' Average BMP Opinion (year)	0 - 1
$E_N(i)$	Farmer Nitrate Reduction from BMPs (year)	0 - 1
$E_P(i)$	Farmer Phosphorous Reduction from BMPs (year)	0 - 1

Each farmers' BMP opinion was updated annually using a BMP scoring system (Table 4.5). The BMP scoring system measured a farmers' perception of the effectiveness of a BMP, their neighbors' perceptions, their general environmental awareness, and influence of the community. How the score was updated annually, along with its effect on opinions, and assessing the costs and benefits of a BMP is described in detail in the ABM logic section (Section 4.3.2). Each score was a measure of the four motivations (effectiveness, neighbors' perceptions, environmental awareness, and community) and used to form an updated BMP opinion (range of 0-1).

Table 4.5: BMP Score

Parameter	Description	Range
$R_{index}(i)$	BMP Score (year)	0 - 1

The parameters governing the behavior of farmer agents have been presented in this section. The community agent is presented next, and then logic of the model follows.

4.3.1.2 Community Agent

The community agent represented a hypothetical institution that at the very least reveals top-down data for the watershed to farmer agents. If specified by the user, the community agent could also apply regulatory or incentive measures. The core community agent was initialized with average yield data, average revenue and costs for corn and soybeans, and a community policy time horizon (Table 4.6).

Table 4.6: Community Agent parameterization

Parameter	Description (units)	Range
$Y_c(i)$	Average Community Yield (bu /acre)	> 0
$C_c(i)$	Average Farmer Costs (year) [$ / acre]	> 0
$P_c(i)$	Average Farmer Crop Revenue (year) [$ / bushel]	> 0
t_c	Community Time Horizon (years)	> 0

The community agent also incorporated user inputted parameters for water quality thresholds, incentives and BMP cost shares, and tax levies (Table 4.7). The community policy time horizon was used to enforce policy instruments. For example, if an incentive for BMP installations was available, it was available for farmers for the community time horizon. With respect to an East-Central Illinois, these functions (taxes, incentives, cost-shares) and data (crop yield, average price received) originate from a group of organizations in the area. The community agent could be conceived as serving functions of the local/state/federal government, extension agencies like the USDA and NRCS, and university research and extension. For example, the USDA-NRCS EQIP program implements a cost-sharing agreement for a BMP like winter cover crop (USDA-NRCS, 2012a), the University of Illinois disseminates annual financial performance metrics and crop yields in conjunction with the USDA (UIUC-ACES, 2012), and a potential incentive scheme could be implemented by local government. The community agent housed and revealed top-down data to farmer agents as the simulation evolved. Water quality at the outlet was also recorded by the community agent. Nitrogen and phosphorous levels are monitored by University of Illinois and the Urbana-Champaign Sanitary District (UCSD & UIUC, 2013) in the Upper Salt Fork watershed (Table 4.7). In addition, the averaged crop yields for the watershed were tabulated by the community agent and disseminated to farmer agents. The ranges for policy initiatives were derived from observed concentrations for nutrient thresholds and rates that would result in initiatives that would affect farmers' revenues so that an analysis could be performed. Nutrient concentrations were used as the measure of water quality because of the availability of direct measurements by UCSD & UIUC. In addition, nutrient concentration reflects both the nutrient load and water flow, providing a consistent measure across wet and dry years. As discussed in Chapter 3, monthly nutrients ranged from .07 to 1 mg/L for phosphorous and 0 to 12 mg/L for nitrogen. The ranges for policy initiatives were designed to facilitate an analysis of scenarios with minimal impact to excessive. For example, a high tax rate of $3,000,000 with a low threshold of 5 mg/L would result in a tax of $6,000,000 for a year with a simulated nitrogen concentration of 7 mg/L. The average owner tax amount of nearly $60,000 would be excessive for the 119 farmer agents in the simulations, but established an upper bound for scenario analysis. The upper bound was set to keep policy initiatives in line with farmer revenues and facilitate scenario testing from the upper bound to those policies with no impact.

Table 4.7: Community Policy parameterization

Parameter	Description	Range
$N_{OBS\ CONC}$	Modeled Annual Nitrate Conc at Outlet (mg/L)	0 - 15
$P_{OBS\ CONC}$	Modeled Annual Phosphorous Conc at Outlet (mg/L)	0 - .3
$X_{BMP\ NAME}$	Cost Share $(0 - 100\%)$	0-100
$N_{INC\ RATE}$	Nitrogen Incentive Payment Rate [$/(mg/L)]	$0 - 3000000$
$N_{INC\ CONC}$	Nitrogen Incentive Threshold (mg/L)	5 - 10
$N_{TAX\ RATE}$	Nitrogen Tax Rate [$/(mg/L)]	$0 - 3000000$
$N_{TAX\ CONC}$	Nitrogen Tax Threshold (mg/L)	5 - 10
$P_{INC\ RATE}$	Phosphorous Incentive Payment Rate [$/(mg/L)]	$0 - 30000000$
$P_{INC\ CONC}$	Phosphorous Incentive Threshold (mg/L)	.025 - .2
$P_{TAX\ RATE}$	Phosphorous Tax Rate [$/(mg/L)]	$0 - 30000000$
$P_{TAX\ CONC}$	Phosphorous Tax Threshold (mg/L)	.025 - .2
$N_{COM\ CONC}$	Community Nitrate Threshold (mg/L)	5 - 10
$P_{COM\ CONC}$	Community Phosphorous Threshold (mg/L)	.025 - .2

The community agent allowed for the user to enforce incentive schemes, taxes, and cost shares over the community policy time horizon. The user entered an annual nutrient threshold that was used for calculating costs or revenues to apply to farmer agents. For a simulated tax, the user specified a threshold annual nutrient concentration and a rate to apply for observed levels above that concentration. For each concentration unit beyond the threshold, every owner was taxed in proportion to the size their farm to the watershed size. Similarly, for a simulated incentive scheme, the user specified a threshold annual nutrient concentration and a price per unit concentration. A farmer considered a user-inputted effectiveness of a BMP and the potential payment of the incentive scheme distributed to farmers in proportion to their fraction of area within the watershed. An incentive scheme represented potential income for a farmer, a tax posed mandatory losses. In a cost share, a portion of the cost of a BMP was offset by the community agent.

In addition, the community agent initialized and revealed top-down BMP data to farmer agents. Each BMP was parameterized by the user with an initial opinion, annualized cost, perceived effect on yield, perceived nutrient removal effectiveness, and if considered, a reduction in fertilizer amount for pairing BMPs with fertilizer reductions (Table 4.8). The BMP costs are initialized using levels in section 4.3.3. Cost share schemes ranged from zero to all of the cost. Yield effects of BMPs were taken from studies presented in section 4.3.3. Scenarios were also designed to couple BMPs with fertilizer reductions. The yield effect for BMPs with fertilizer reductions were computed by varying fertilizer amounts and observing the modeled yield effect as in section 4.3.6. Similar to with policy initiatives, an upper bound of fertilizer reductions was established to facilitate a scenario analysis. While a fertilizer reduction of 45% could not be considered in practice, it served as an upper bound for scenarios from that level down to a 0% reduction.

Table 4.8: BMP parameterization

Parameter	Description (units)	Range
$C_{BMP\ NAME}$	BMP annualized Cost ($)	>0
$X_{BMP\ NAME}$	Cost Share (%)	0 – 100
$Y_{BMP\ NAME}$	Effect on yield (+/−%)	-25 – 7
$N_{BMP\ NAME}$	Nitrate Removal Effectivness (+/−%)	0 – 45
$P_{BMP\ NAME}$	Phosphorous Removal Effectiveness (+/−%)	0 – 45
$F_{BMP\ NAME}$	Fertilizer Reduction/Increase (+/−%)	-45 – 0

4.3.2 ABM Logic

The two agents implemented in the ABM along with their parameterization and sources for top-down and bottom-up data have been introduced. Macal and North (2010) recommend defining agent relationships and implementing the model theory next. Relying on the parameters introduced in Section 4.3.1, the logic governing the ABM in this study is presented in this section with an overview and in a detailed sequence.

4.3.2.1 ABM Logic Overview

The ABM logic determines how the parameters for the agents and modeling outcomes evolve over the length of a simulation. The logic utilizes the parameters discussed and establishes relationships to drive agent behavior year-by-year (Figure 4.2).

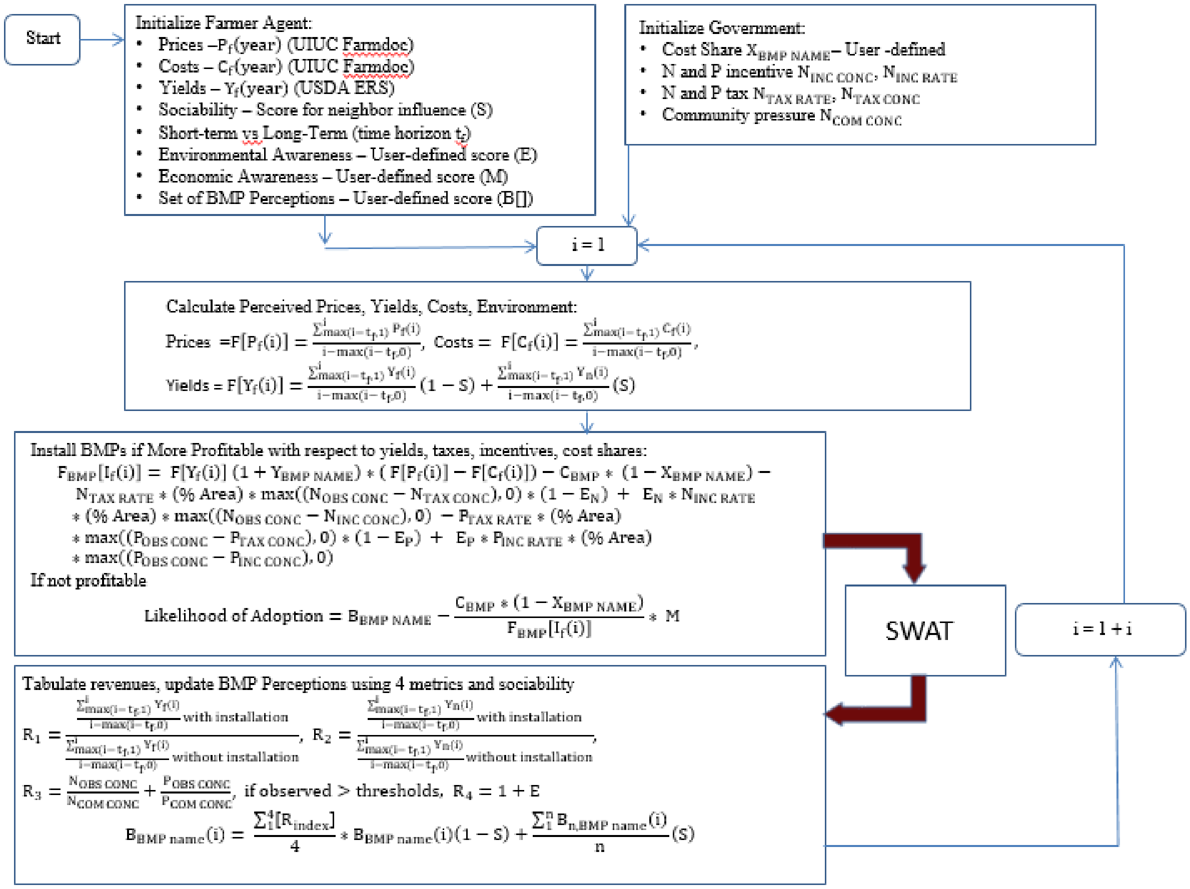

Figure 4.2: ABM Logic Overview

A farmer began a year by assessing their management options and anticipated farming returns. Each farmer considered crop yields, costs of production, community policy, pollutant levels, and BMP installations at the beginning of the year. The simulation invoked SWAT to simulate the farmer decisions. After running SWAT, farmers observed yield and pollutant data for the year. At the end of each year, farmers used this information to tabulate their returns. The progression continued for the beginning of the next year.

4.3.2.2 Farmer Yearly Planning

At the beginning of each year, each farmer computed the expected returns for corn and soybeans using the history of their personal yields weighted by their sociability (Equation 4.2).

$$F[Y_f(i)] = \frac{\sum_{\mathrm{j}=\max(i-\ t_f,1)}^{i} Y_f(j)}{i - \max(i-\ t_f,0)}(1-S) + \frac{\sum_{\mathrm{j}=\max(i-\ t_f,1)}^{i} Y_n(j)}{i - \max(i-\ t_f,0)}(S) \tag{4.2}$$

Each farmer also anticipated prices and costs for their crop using their past prices over their time horizon (Equations 4.3 – 4.4).

$$F[P_f(i)] = \frac{\sum_{\mathrm{j}=\max(i-\ t_f,1)}^{i} P_f(j)}{i - \max(i-\ t_f,0)} \tag{4.3}$$

$$F[C_f(i)] = \frac{\sum_{\mathrm{j}=\max(i-\ t_f,1)}^{i} C_f(j)}{i - \max(i-\ t_f,0)} \tag{4.4}$$

Each farmer initially anticipated income using prices, costs, and tax for the size of their farm as measured and enforce by the community agent's policy time horizon (Equation 4.5).

$$\begin{aligned} F[I_f(i)] = {} & F[Y_f(i)] * \left(F[P_f(i)] - F[C_f(i)] \right) - \widehat{N}_{TAX\ RATE} * (\%\ Area) \\ & * \max\left(\left(\frac{\sum_{j=\max(i-\ t_c,1)}^{i} \mathrm{N_{OBS\ CONC}}(j)}{i - \max(i-\ t_c,0)} - N_{TAX\ CONC} \right), 0 \right) - \widehat{P}_{TAX\ RATE} \\ & * (\%\ Area) * \max(\left(\frac{\sum_{\mathrm{j}=\max(i-\ t_c,1)}^{i} \mathrm{P_{OBS\ CONC}}(j)}{i - \max(i-\ t_c,0)} - P_{TAX\ CONC} \right), 0) \end{aligned} \tag{4.5}$$

Each farmer also considered BMP adoption at the beginning of the year. Adoption was determined by the economics and the perceptions of each BMP. The first identified goal in adoption from the USDA-NRCS study was economics (Hoag et al., 2012; USDA-NRCS, 2011). In the ABM, economics of a BMP were: compare the forecasted income with and without the BMP. The forecasted income without the BMP was calculated according to Equation 4.6. If the forecasted income was negative, there was no chance of a BMP installation as the farmer was already anticipating a loss on the year's farming. The forecasted income with the BMP was: the baseline income, less the cost of the BMP not offset by the government cost share, plus the savings on a farmers portion of the tax, plus the revenues of a the owners portion of the incentive scheme, less the perceived effect on yields over the owners time horizon. The difference between the tax and incentive is shown in the equation of the forecasted income (4.7). A BMP saves on an enforced cost (tax), and the incentive generates income. If the forecasted income with the BMP was greater, the BMP was installed. If the BMP was not profitable, then logic to test an uneconomical BMP was tested. First, a farmer did not install a BMP that constituted all of his/her forecasted income for the year. If the farmer could afford the BMP, then farmer's economic awareness (M: 0-1) was subtracted from the owners' perception of the BMP ($B_{BMP\ NAME}$: 0-1). The economic awareness was scaled for the fraction of income required to cover the cost of the BMP. This difference (BMP opinion – scaled economic awareness) was a random variable representing the likelihood of adoption (Equation 4.8). The random variable compared to a randomly generated number (0-1) and if greater, an installation occurred. Each farmer also perceived their reduction of nutrients via BMP installations as discussed in Section 4.3.1. As BMPs were installed, only the perceived remaining nutrient level was considered as eligible for further reduction. The tabulated total reduction was used for calculating taxes and incentives (Equation 4.7).

$$F_{NO\ BMP}\left[I_f(i)\right] = F\left[Y_f(i)\right] * \left(F\left[P_f(i)\right] - F\left[C_f(i)\right]\right) - \widehat{N}_{TAX\ RATE} * (\%\ Area)$$
$$* \max\left(\left(\frac{\sum_{\mathrm{j=max}(i-\ t_c,1)}^{i} \mathrm{N_{OBS\ CONC}}(j)}{i - \max(i-\ t_c, 0)} - N_{TAX\ CONC}\right), 0\right)$$
$$- \ \widehat{P}_{TAX\ RATE} * (\%\ Area)$$
$$* \max(\left(\frac{\sum_{\mathrm{j=max}(i-\ t_c,1)}^{i} \mathrm{P_{OBS\ CONC}}(j)}{i - \max(i-\ t_c, 0)} - P_{TAX\ CONC}\right), 0) \tag{4.6}$$

$$F_{BMP}\left[I_f(i)\right] = F\left[Y_f(i)\right](1 + Y_{BMP\ NAME}) * \left(F\left[P_f(i)\right] - F\left[C_f(i)\right]\right) - C_{BMP}$$
$$* \ (1 - X_{BMP}) - \left(1 - \ E_N(i)\right) * \ \widehat{N}_{TAX\ RATE} * (\%\ Area)$$
$$* \max(\left(\frac{\sum_{\mathrm{j=max}(i-\ t_c,1)}^{i} \mathrm{N_{OBS\ CONC}}(j)}{i - \max(i-\ t_c, 0)} - N_{TAX\ CONC}\right), 0)$$
$$* (1 - \ N_{BMP}) \ + (E_N(i)) * \ N_{BMP} * \widehat{N}_{INC\ RATE} * (\%\ Area)$$
$$* \max(\left(\frac{\sum_{\mathrm{j=max}(i-\ t_c,1)}^{i} \mathrm{N_{OBS\ CONC}}(j)}{i - \max(i-\ t_c, 0)} - N_{INC\ CONC}\right), 0)$$
$$+ \left(1 - \ E_P(i)\right) * \ \widehat{P}_{TAX\ RATE} * (\%\ Area)$$
$$* \max(\left(\frac{\sum_{\mathrm{j=max}(i-\ t_c,1)}^{i} \mathrm{P_{OBS\ CONC}}(j)}{i - \max(i-\ t_c, 0)} - P_{TAX\ CONC}\right), 0)$$
$$* (1 - \ P_{BMP}) \ + (E_P(i)) * \ P_{BMP} * \widehat{P}_{INC\ RATE} * (\%\ Area)$$
$$* \max(\left(\frac{\sum_{\mathrm{j=max}(i-\ t_c,1)}^{i} \mathrm{P_{OBS\ CONC}}(j)}{i - \max(i-\ t_c, 0)} - P_{INC\ CONC}\right), 0) \tag{4.7}$$

$$If\ not\ profitable, Likelihood\ of\ Adoption = B_{BMP\ NAME} - M * \frac{C_{BMP} * \left(1 - X_{BMP\ NAME}\right)}{F_{BMP}\left[I_f(i)\right]} \tag{4.8}$$

4.3.2.3 Farmer End of Year Analysis

At the end of each year, each owner saw the yield from the SWAT output for their HRU, their neighbors' yields, and the average yield for corn and soybeans for the entire watershed. The farmer calculated the end of year returns for the observed yield, costs of BMPs, assessed tax and income from incentives (Equation 4.7). Perceived reductions in nutrients from BMPs were updated for whatever nitrate remained after previous installations by the perceived reductions from installed BMPs that year. The perceived reductions from BMP installations reduced tax expenditures and generated revenue from incentives. Each farmer updated their BMP perceptions as well. BMP perceptions were updated based on farmer yields with and without an installation, farmer yields with an installation versus neighbors' yields, prevailing water quality, environmental concern, and neighbors' perceptions (Equations 4.9-4.12). The four scores quantified a farmers observations regarding each BMP: the yield benefits a farmer sees on their own farm, the yield benefits their neighbors see, community pressure, and environmental awareness. The first score assessed whether yields with BMP installations are greater than without. The second score assessed whether neighbors yields are greater with an installation than without. The third score assessed the measure of community pressure: if the nitrate concentration exceeded the user threshold, the score increased. The third score was the measure of a farmers' environmental awareness. The four scores were averaged and weighted by a farmers' sociability with the neighbors' perceptions (Equations 4.9 – 4.13)

$$R_1 = \frac{\dfrac{\sum_{\mathrm{j}=\max(i-\ t_f,1)}^{i} Y_f(j)}{i - \max(i -\ t_f, 0)}\ with\ installation}{\dfrac{\sum_{\mathrm{j}=\max(i-\ t_f,1)}^{i} Y_f(j)}{i - \max(i -\ t_f, 0)}\ without\ installation} \tag{4.9}$$

$$R_2 = \frac{\dfrac{\sum_{\mathrm{j}=\max(i-\ t_f,1)}^{i} Y_n(j)}{i - \max(i -\ t_f, 0)}\ with\ installation}{\dfrac{\sum_{\mathrm{j}=\max(i-\ t_f,1)}^{i} Y_n(j)}{i - \max(i -\ t_f, 0)}\ without\ installation} \tag{4.10}$$

$$R_3 = 1 + \frac{\dfrac{\sum_{\mathrm{j}=\max(i-\ t_c,1)}^{i} \mathrm{N}_{\mathrm{OBS\ CONC}}(j)}{i - \max(i -\ t_c, 0)}}{N_{COM\ CONC}} + \frac{\dfrac{\sum_{\mathrm{j}=\max(i-\ t_c,1)}^{i} \mathrm{P}_{\mathrm{OBS\ CONC}}(j)}{i - \max(i -\ t_c, 0)}}{P_{COM\ CONC}} \tag{4.11}$$

$$R_4 = 1 + E \tag{4.12}$$

$$B_{BMP\ name}(i) = \frac{\sum_1^4 [R_{index}]}{4} * B_{BMP\ name}(i)(1 - S) + \frac{\sum_1^n B_{n,BMP\ name}(i)}{n}(S) \tag{4.13}$$

The formulation of the BMP score and perceptions put the USDA-NRCS conclusions into practice with a bottom-up approach in the agent-based model. A farmer agent and their perceptions of adoption evolved over the course of a simulation according to these scores, which were derived from the USDA-NRCS conclusions. To start, a farmer agent was initialized with user-inputted measures of sociability, environmental awareness, time horizons, and economic awareness. Some farmer agents were more sociable, environmentally aware and prone to adoption, others were more economically aware, and some were short-term and others long-term. The system evolved by consideration yield benefits, environmental awareness, community engagement, and sociability.

After tabulating at the end of the year, the simulation started a new year.

4.3.3 Agent Parameter Initialization

The next step after defining agents, their relationships, and theory of behavior was to identify sources and data for parameter values. In this study, agents and their behavior were initialized with data gathered from farmers and community organizations relevant for the watershed. To begin a simulation, each farmer was linked to one SWAT HRU as defined in Chapter 3. That HRU had an adjusted soil productivity index (PI) calculated from the SWAT dominant soil type of the HRU as specified in the SWAT setup in Chapter 3. Each soils' PI is calculated using UIUC Bulletin 811 (UIUC-ACES, 2000). Based on a user inputted productivity index threshold the land was classified as high or low productivity. Class A soil had a PI greater than 133, Class B has a PI between 117 and 133, and Class C soils have a PI less than 117. Based on the classification between high and low productivity, a farmer perceived his/her yields and costs differently. The community agent assigned the appropriate amount to each agent based on Champaign County averages (2005-2012) revenues and costs for their productivity, and yields as the simulation proceeds per UIUC Farm Management Handbook (UIUC-ACES, 2012). Revenues include crop returns, government payments, insurance. Costs were all-inclusive as well, to facilitate the annualized net return analysis (Table 4.9 – 4.10).

Table 4.9: Corn Bean Prices, Costs, Yields (Central Illinois High/Low Productivity) (UIUC - ACES, 2003-2012)

	High Productivity			Low Productivity		
Year	Revenue ($/Bu.)	Cost ($/Acre)	Obs. Yields (Bu./Acre)	Revenue ($/Bu.)	Cost ($/Acre)	Obs. Yields (Bu./Acre)
2005	2.86	478	172	2.9	460	147
2006	3.26	501	180	3.26	481	172
2007	4.24	555	201	4.21	542	189
2008	4.30	699	199	4.30	682	191
2009	3.81	822	192	3.83	770	187
2010	5.67	752	168	5.39	725	157
2011	6.23	841	174	6.25	812	158
2012	6.1	864	109	6.12	826	109
Average	4.55	689	174	4.53	663	164

Table 4.10: Soy Bean Prices, Costs, Yields (Central Illinois High/Low Productivity) (UIUC - ACES, 2003-2012)

	High Productivity			Low Productivity		
Year	Revenue ($/Bu.)	Cost ($/Acre)	Obs. Yields (Bu./Acre)	Revenue ($/Bu.)	Cost ($/Acre)	Obs. Yields (Bu./Acre)
2005	6.71	378	55	6.74	359	50
2006	7.13	389	55	7.12	373	52
2007	10.58	421	55	10.54	406	52
2008	11.52	524	50	11.34	501	50
2009	10.53	578	55	10.42	527	52
2010	11.95	573	60	11.96	528	54
2011	12.9	641	56	13.04	580	52
2012	13	651	53	13.06	590	51
Average	10.54	519	55	10.53	483	52

Prices in this study were held constant and set to the average calculated in Tables 4.9 and 4.10. Each owner was initialized with the average prices and costs from Champaign County for 2005-2012 to start a simulation run. Each farmer computed their returns using these average prices and costs to choose corn or soybeans. Prices were held constant to observe average long-term decision-making and not short-term market fluctuations. The price expectations were simplistic, as the vagaries of the marketing and hedging in the commodities market were beyond the scope of this study. In addition, the crop yield model in SWAT does not incorporate technologic and management improvements over time, so using historical prices for specific years would not result in accurate returns.

The simulation was also initialized with planting ratios. Farmers selected the most profitable choice between corn and soybeans up to a user-inputted percentage. Historic plantings ratios in Champaign County are 55% corn and 45% soybeans (Table 4.11) (Illinois Office USDA-NASS, 2005-2011). A user could enforce these ratios if desired or observe the simulation without stipulating ratios.

Table 4.11: Planting Ratio Champaign County 2005-2011 (Illinois USDA-NASS 2005-2011)

Year	2005	2006	2007	2008	2009	2010	2011
Corn	292000	280000	319000	285000	305000	292000	306500
Soybeans	241000	246000	215000	239000	224000	245000	227000
Total	533000	526000	534000	524000	529000	537000	533500
%Corn	0.547842	0.532319	0.597378	0.543893	0.57656	0.543762	0.574508

The returns, set of neighbors, planting ratios served to initialize the owners.

BMP annual costs, cost share amounts, yield effects, and perceived effectiveness were all left to the user to initialize with established metrics from past studies or institutional data. The default initialization used, for this study, compiled estimates based on extension resources. The Illinois office of the NRCS estimated (2011-2012) the costs for rye cover cropping including installation costs and maintenance costs as $29 / acre, and offered a 50% cost share (USDA - NRCS, 2012). Nutrient management costs were estimated from a study that compared fall fertilizer prices versus spring and found an average increase of 10% over 2002-2010 (Borchers et al., 2011). Drainage water management costs were estimated via University of Illinois extension at $80/acre for installation, and $10/acre annually (Frankenberger et al., 2006). The installation costs were annualized using an internal rate of return of 3.5% and a 10-year time horizon (Equation 4.14):

$$Annual\ DWM\ Install\ Cost = \sum_{i=0}^{10} \frac{Installation}{(1+r)^i} \tag{4.14}$$

Drainage water management installations were eligible for a cost share through the University of Illinois (Frankenberger et al., 2006).

The effectiveness and yield effects were estimated from the discussion of BMPs in Chapter 3 along with a hypothetical universal adoption applied to the watershed for each BMP and observed average yield and water quality response. The default initialization used the midpoints of the ranges for yield effect and removal effectiveness for each BMP. From the discussion in Chapter 3, rye cover cropping (Table 4.12) did not affect yields at fertilizer levels considered in this study (Li et al., 2008) and removal effectiveness ranged 0 to 50% (Logsdon et al., 2002; Villamil et al., 2006).

Table 4.12: BMP Default Parameters Rye Cover Cropping (RCC)

Parameter	Description	Default Value
C_{RCC}	BMP annualized Cost ($/acre)	29
Y_{RCC}	Effect on yield (+/−%)	0
N_{RCC}	Nitrate Removal Effectivness (+/−%)	25
P_{RCC}	Phosphorous Removal Effectiveness (+/−%)	25

Nutrient management (Table 4.13) has been shown to increase yields as much as 7% (Randall & Vetsch, 2005) nutrient loss reduced by 17% (Randall & Vetsch, 2005).

Table 4.13: BMP Default Parameters Nutrient Management (NM)

Parameter	Description	Default Value
C_{NM}	BMP annualized Cost (% fertilizer \$/ac)	10
Y_{NM}	Effect on yield (+/−%)	4
N_{NM}	Nitrate Removal Effectivness (+/−%)	10
P_{NM}	Phosphorous Removal Effectiveness (+/−%)	10

Drainage water management (Table 4.14) was shown to increase yields as much as 5% (Frankenberger et al., 2006), with reductions of 50% (35%) for nitrogen (phosphorous) (Li et al., 2008; Skaggs et al., 2010).

Table 4.14: BMP Default Parameters Drainage Water Management (DWM)

Parameter	Description	Default Value
C_{NM}	BMP annualized Cost (\$/acre)	18
Y_{NM}	Effect on yield (+/−%)	2
N_{NM}	Nitrate Removal Effectivness (+/−%)	25
P_{NM}	Phosphorous Removal Effectiveness (+/−%)	17

With all values for agent parameters established; the baseline scenarios, fertilizer reduction scenarios, and ABM initialization are presented in the next section.

4.3.4 Baseline Model (No-BMP)

The model was initially run and calibrated for a no-BMP scenario to establish corn/soybean planting ratios, baseline yields, and nutrient loads. Corn and soybean plantings were each set at 50%. The USDA-NRCS CEAP study found that producers with a farming time-line of more than 5 years were more likely to implement conservation practices (Hoag et al., 2012). As a result, the time horizon for producers was set to 5 years. Producers did not consider implementing BMPs in the baseline case. The baseline setup was used to assess the performance of the coupled model and establish benchmarks for comparison of the economic and environmental metrics in future scenarios discussed in section 4.5.

A baseline scenario was established without any BMPs implemented in the watershed. The no-BMP baseline established the benchmarks for the performance of environmental and human-systems metrics considered in this study: crop yields (Figures 4.3– 4.4), crop returns (Figures 4.5 – 4.6), nutrient loads and concentrations (Figures 4.7 – 4.10), and water yield (Figure 4.11). As presented in Chapter 3 for the natural-systems model (SWAT) output, a measure of error (Table 4.15) with respect to observed values is presented here for the no-BMP output.

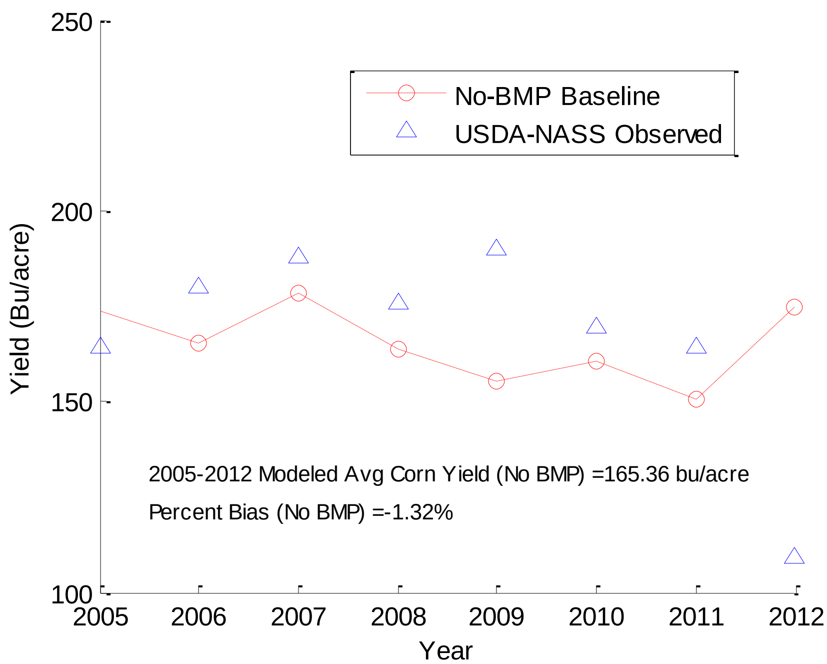

Figure 4.3: No-BMP modeled and observed corn yields (USDA-NASS, 2012)

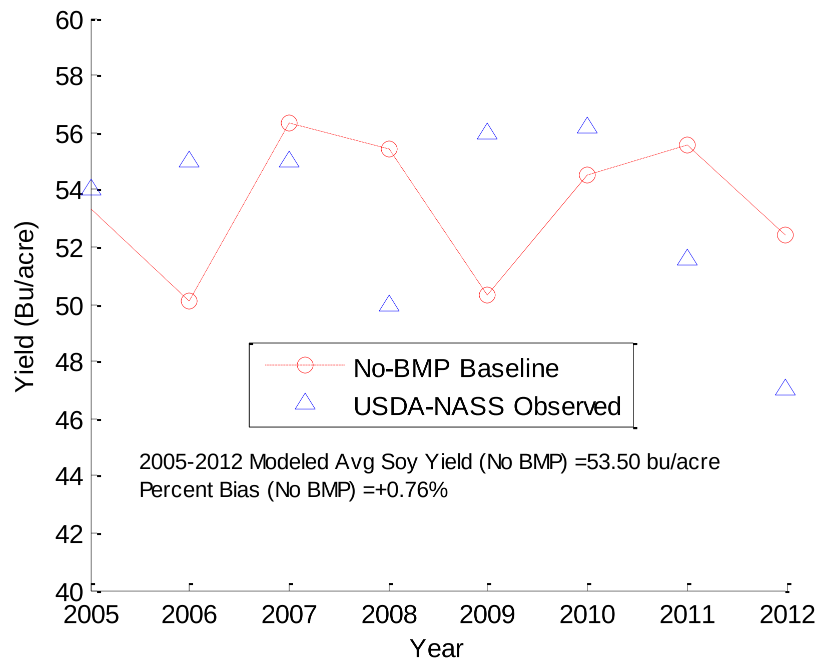

Figure 4.4: No-BMP modeled and observed soy yields (USDA-NASS, 2012)

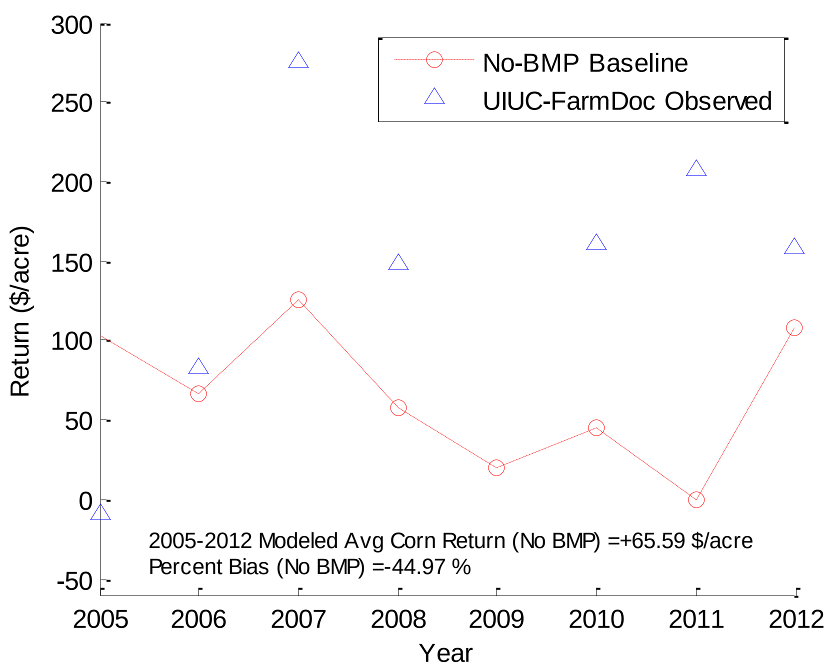

Figure 4.5: No-BMP modeled and observed corn returns (UIUC - ACES, 2003-2012)

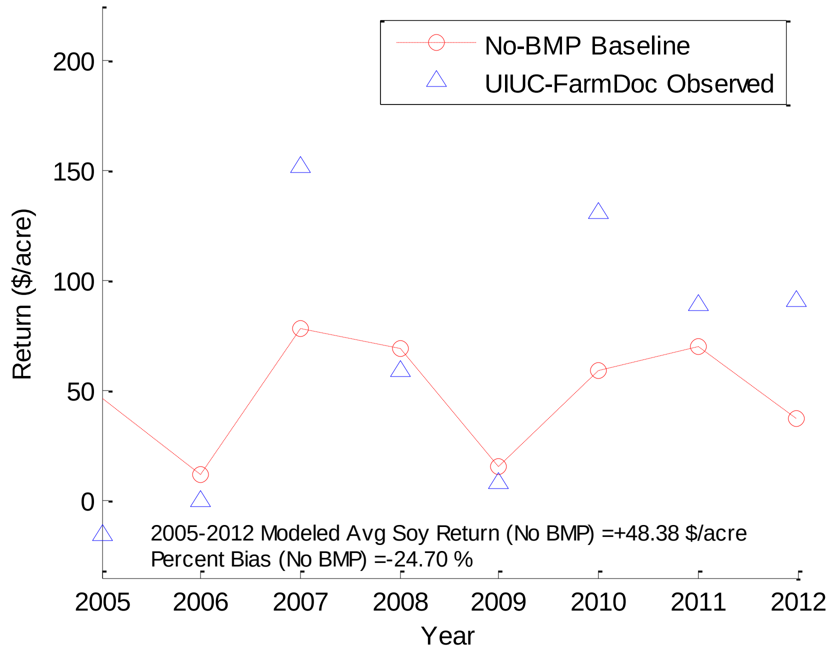

Figure 4.6: No-BMP modeled and observed soy returns (UIUC - ACES, 2003-2012)

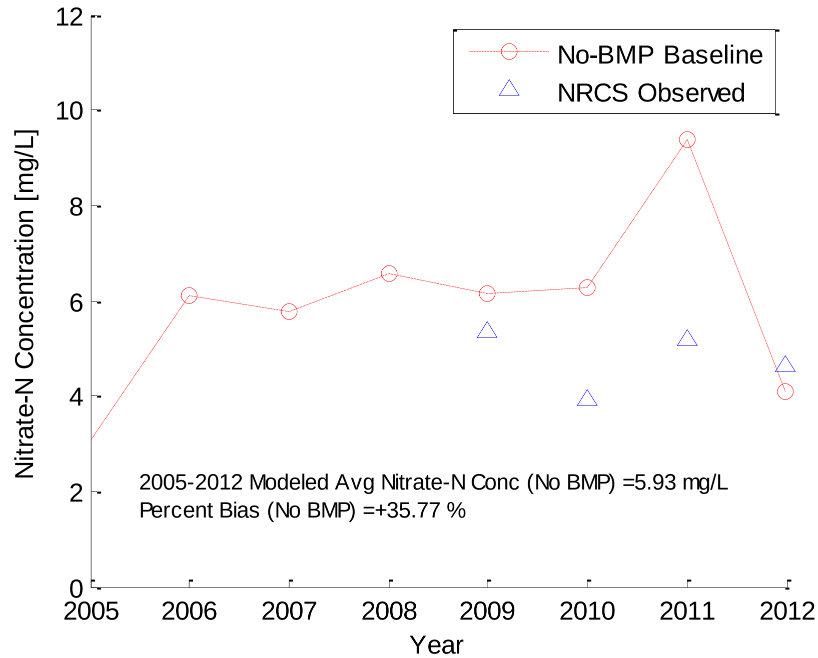

Figure 4.7: No-BMP modeled and observed nitrate-N concentrations (UCSD & UIUC-NRES Biochemistry Group, 2013)

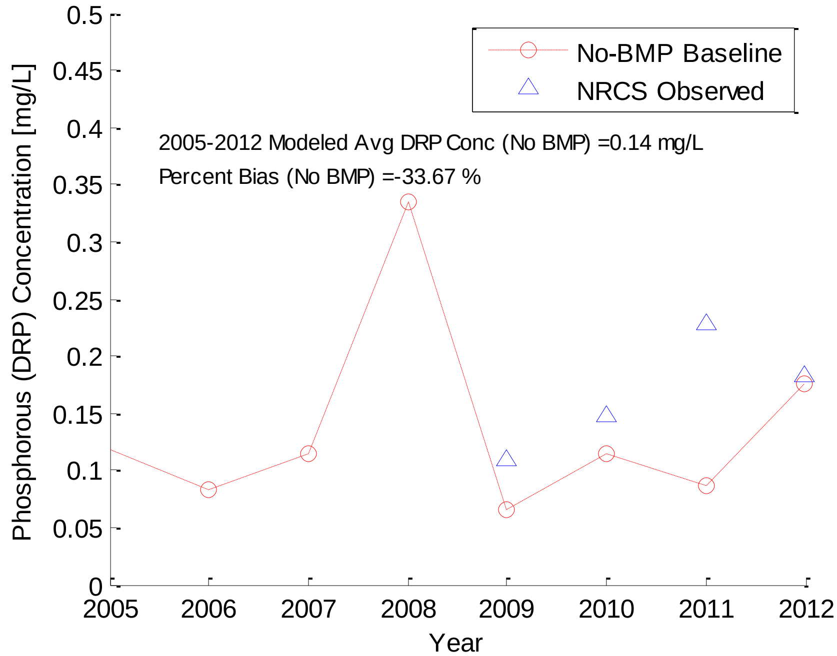

Figure 4.8: No-BMP modeled and observed phosphorous (DRP) concentrations (UCSD & UIUC-NRES Biochemistry Group, 2013)

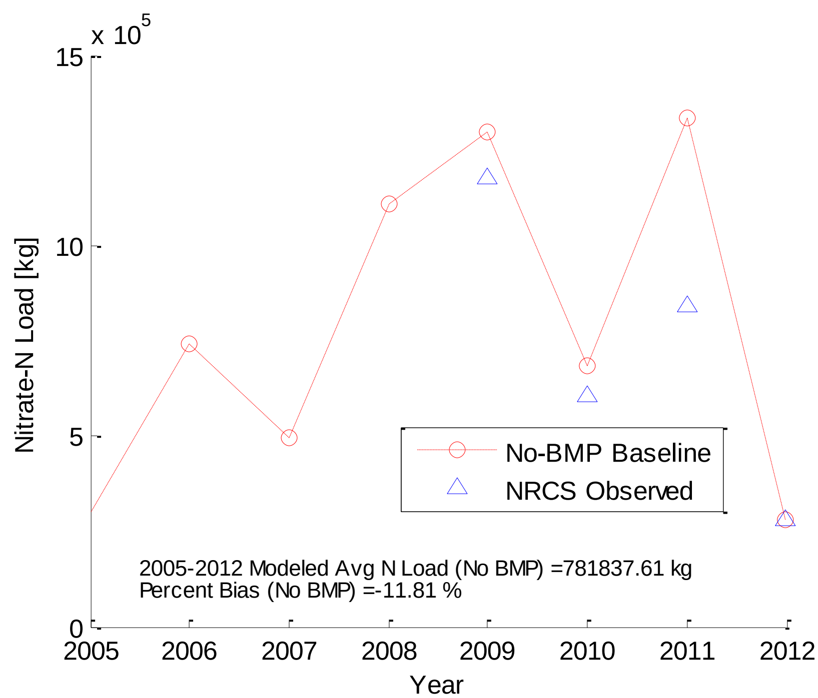

Figure 4.9: No-BMP modeled and observed nitrate-N loads (UCSD & UIUC-NRES Biochemistry Group, 2013)

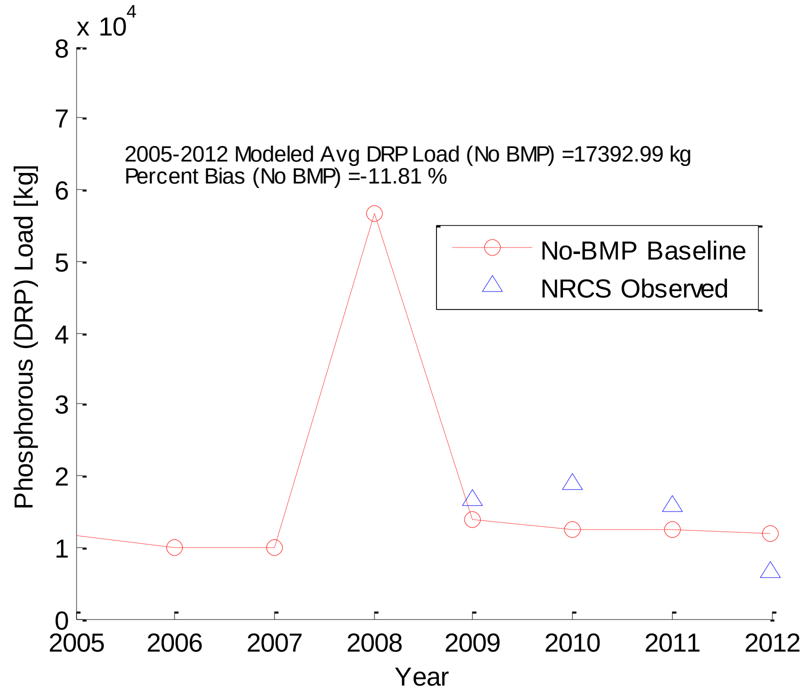

Figure 4.10: No-BMP modeled and observed phosphorous (DRP) loads (UCSD & UIUC-NRES Biochemistry Group, 2013)

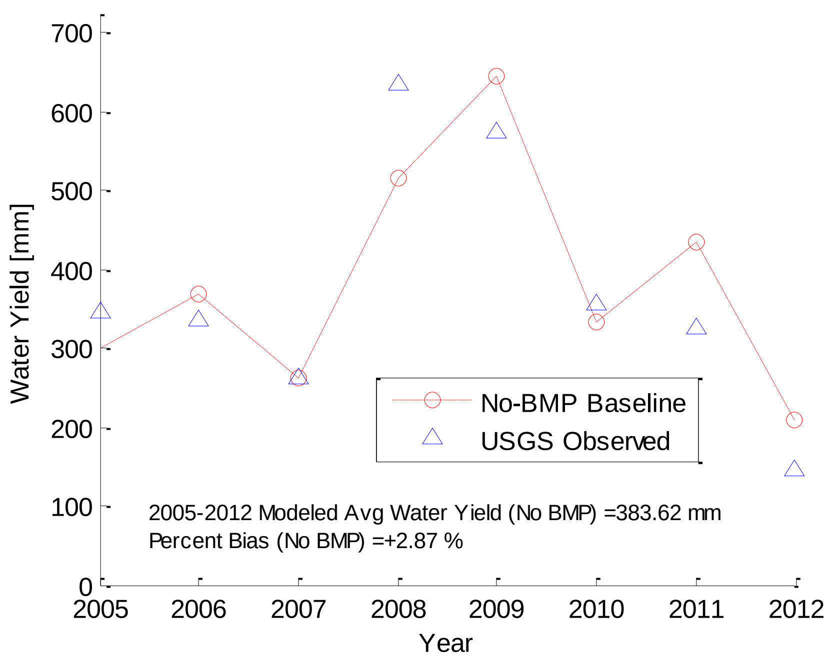

Figure 4.11: No-BMP modeled and observed water yields (USGS, 2012)

Table 4.15: No-BMP Baseline Results vs Observed

	No-BMP ABM Scenario 2005-2012 (0% RCC, 0% NM, 0% DWM)		
	Simulated Average	Observed Average	% Bias
Avg Annual N Load	900150 kg	725522.7 kg	+24.1%
Avg Annual P Load	12720 kg	14426.2 kg	-11.8%
Avg Annual N Conc	6.47 mg/L	4.77 mg/L	+35.8%
Avg Annual P Conc	.11 mg/L	.167 mg/L	-33.7%
Avg Annual Water Yield	383.62 mm	372.9 mm	+2.87%
Avg Annual Corn Yield	165.36 bu/ac	167.56 bu/ac	-1.32%
Avg Annual Soy Yield	53.5 bu/ac	53.1 bu/ac	+0.80%
Avg Annual Corn Return	+65.59 $/ac	+119.19 $/ac	-45%
Avg Annual Soy Return	+48.38 $/ac	+64.3 $/ac	-25%

4.3.5 No-BMP Baseline Discussion

The no-BMP baseline reflected the modeling accuracy of the natural-systems component presented in Chapter 3. The percent bias between the no-BMP baseline results and observed values can be attributed to differences in modeling the location and timing of corn-soybean rotations between SWAT and coupled model output. Half of the watershed was statically assigned to corn-soybean rotations in the isolated SWAT model, and the other half to soybean-corn rotations. In the no-BMP baseline, the cropping decisions were made dynamically according to the human-systems component. While half of the watershed was still in one rotation or in the other, the specific HRU in one rotation or the other varied in the coupled model. Consequently, the natural-systems modeling results were perpetuated in the no-BMP baseline: underestimation of phosphorous loadings, overestimation of nitrogen loadings (particularly in 2011), and overestimation of water yield in 2009 (Table 4.15).

Similarly, the no-BMP output modeled crop yields accurately with the exception of the 2012 drought year. Outside of the 2012 drought year, crop yields were underestimated and this persisted in underestimating crop returns.

4.3.6 No-BMP Fertilizer Reduction Initialization

The scenarios included an assessment of fertilizer reductions coupled with best management practices. To initialize coupled fertilizer reduction scenarios, the farmers' expectations for yield effects in adoption were established by stress testing the no-BMP model for different fertilizer amounts. The default fertilizer rates used in Chapter 3 were scaled up and down uniformly across the entire watershed. The average effect on yields was used to set farmers expectations for adopting that coupled strategy. Varying fertilizer amounts across the watershed was performed without any BMPs to achieve yield estimates that could be assessed with respect to fertilizer amounts only.

4.3.7 No-BMP Fertilizer Reduction Results

Fertilizer reductions (applied over the whole study watershed) scenarios were tested to observe the effect fertilizer reductions had on crop yields. The scenarios were performed to compare the effect on yield with results from field studies in the Illinois Agronomy Handbook (Figure 4.12) (Hollinger & Angel, 2009) and Hu et. al's (2007) results for universal fertilizer reductions in the nearby Embarras watershed (Table 4.16).

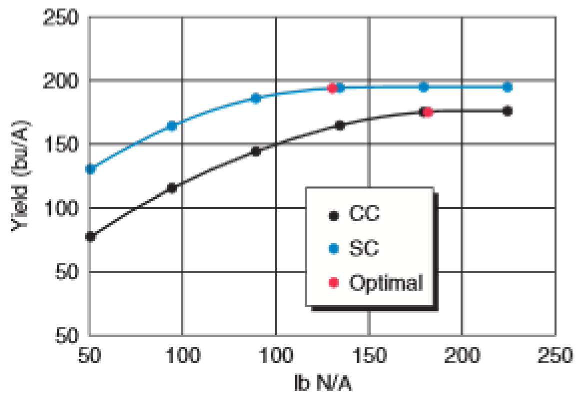

Figure 4.12: Corn Yield Response to Applied Nitrogen Champaign County Field Studies (Hollinger & Angel, 2009; Nafziger et al., 2010)

Table 4.16: Hu et al. (2007) Fertilizer Effect on Yield in SWAT

Fertilizer Reduction (%)	Effect on Yield (%)	
	Corn	Soybeans
0	0	0
10	-5.8	0
20	-13	0
30	-20	0
50	-37.6	0

Fertilizer reductions alone were not considered as a BMP in the coupled model, but as a stress test of universal application rate changes for comparison to the Agronomy Handbook (Hollinger & Angel, 2009) and Hu (2007). As outlined in Chapter 3, the baseline fertilizer application rates were 224 kg/ha of fall-applied anhydrous ammonia (AA) prior to corn plantings and 126.6 kg/ha of fall-applied monoammonium phosphate (MAP) prior to soybean plantings. Both applications rates were adjusted between a fertilizer application reduction of 70%, to a fertilizer application increase of 40%, in 1% increments. The results were compiled with respect to the cumulative applied nitrogen amount (AA is composed of 82% nitrogen, and MAP is 5% nitrogen), and a quadratic fit of the results for corn was computed (Figures 4.13 – Figure 4.14).

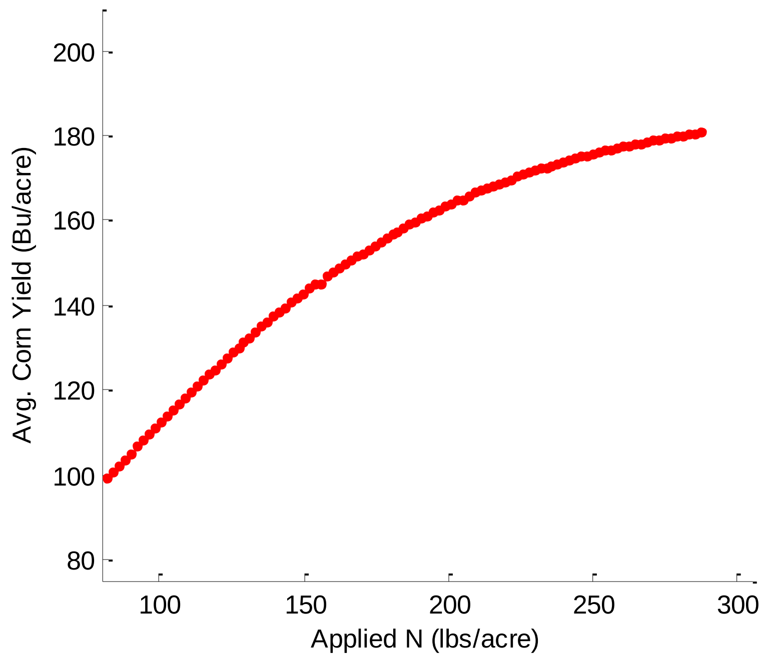

Figure 4.13: No-BMP Modeled Corn Yield Response to Applied Fertilizer Amount

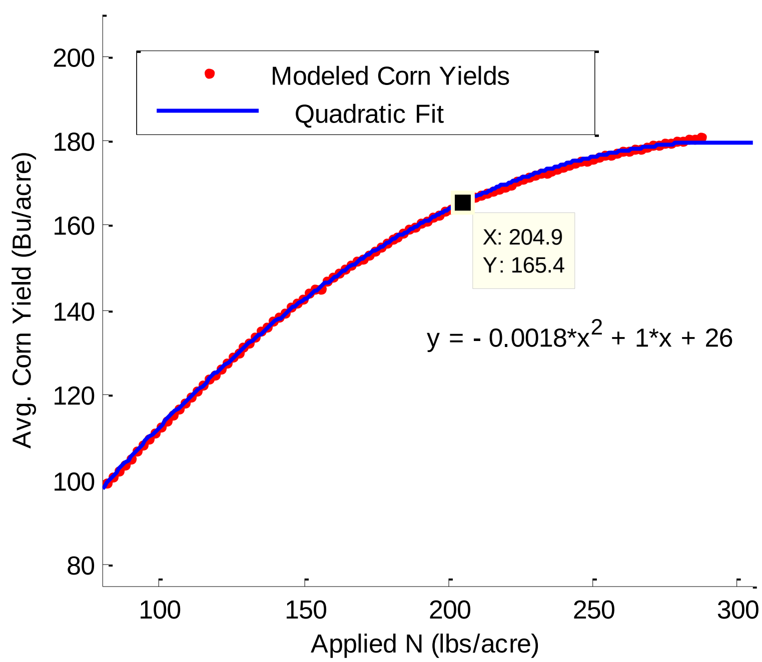

Figure 4.14: No-BMP Modeled Corn Yield Response to Applied Fertilizer Amount with Quadratic Fit

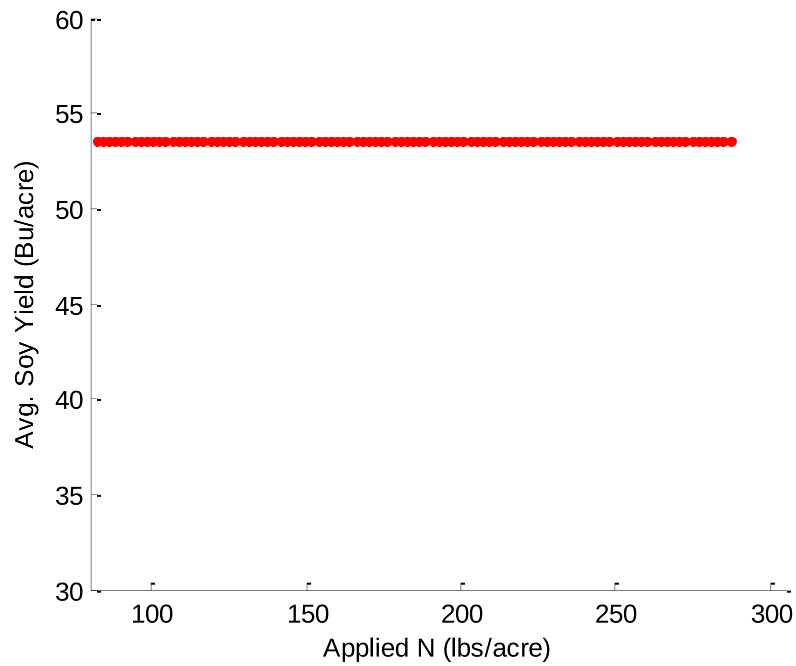

Figure 4.15: No-BMP Modeled Soy Yield Response to Applied Fertilzer Amount

The results (reductions in yield) were used as input for the scenarios presented in the next two sections (Table 4.17).

Table 4.17: SWAT and no-BMP Fertilizer Amount Effects on Yield

Fertilizer Reduction (%)	SWAT % Effect on Yield (Hu et al, 2007)		Fertilizer % Effect on Yield	
	Corn	Soybeans	Corn	Soybeans
0	0	0	0	0
10	-5.8	0	-4.2	0
20	-13	0	-10	0
30	-20	0	-18	0
50	-37.6	0	-45	0

Universal fertilizer reductions tracked Hu et al.'s (2007) results on a percentage change basis (Table 4.17). In the Illinois Agronomy Handbook's (Hollinger & Angel, 2009; Nafziger et al., 2010) also used a percent change approach, with a maximum achievable yield that was higher (195 bu/ac) than the no-BMP modeled fertilizer increases (180 bu/ac). Nafziger's (2010) field trials were concentrated near Urbana on 11 plots, whereas the study area for the model encompassed the 328 km^2 Salt Fork Watershed area with diverse soil types as described in Chapter 3. Both the Illinois Agronomy Handbook (Hollinger & Angel, 2009; Nafziger et al., 2010) and He et al. (2007) demonstrated no soybean yield response to changes in nitrogen. Soybeans are a nitrogen fixer when sufficiently nodulated, and there is no benefit to nitrogen application in Illinois fields typical of the study area.

4.3.8 ABM Initialization

With a baseline established, along with estimates for yield effects associated with fertilizer reductions, the ABM was initialized by varying the farmer agent parameters (sociability, environmental awareness, and economic awareness), time horizon and initial BMP perceptions to reflect observed farmer behavior in the watershed. In addition, the three parameters defining farmer agents (sociability, environmental awareness, and economic awareness), were randomly up and down from their initial value by a random value no greater than a parameter (V). For example, in the initialization of the model, the variability parameter (V) was 0.17, a farmer might have an environmental awareness plus or minus a value less than 0.17 from the user-defined environmental awareness, and sociability might be differently adjusted from the user-defined sociability differently plus or minus a value less than 0.17. In this manner, no two producers were exactly alike.

The USDA-NRCS CEAP study found that one-third of Midwestern farms are not farmed by the owner of the land (Hoag et al., 2012). One-third of the farmer agents were set to time horizons of 3 years, and the other two-thirds were set with a time horizon of 7 years. Then, calibrating the ABM involved manually varying the four parameters and observing the effect on adoption rates, yields, and economic returns while prioritizing knowledge about the behavior of producers in the area. The procedure included the following steps:

1. Set all initial BMP perception to 0.5
2. Prioritized one parameter and manually varied it over its range. In addition, varied the variability parameter (V) across farmer agents, leaving the unselected parameters in the middle of their ranges (0)
3. Observed adoption rates and economic performance versus the no BMP case
4. Selected the next parameter (sociability, environmental awareness, economic awareness), leaving the first and variability (V) set, and repeat
5. Once all three parameters were decided, varied the BMP perception up and down to achieve adoption rates in line with observations
6. With a suitable set of parameters, ran 100 simulations and calculate mean adoption rate for each BMP to assess average response, instead of just a single simulation in step 5.
7. Adjusted parameters after assessing average response, and, if necessary, and rerun the 100 simulations

A satisfactory calibration targeted modeling adoption rates within 10% averaged over the 8 year study period, to find a stasis in the model setup. The parameter selection and modeling outcomes were guided by survey results for area producers. UIUC extension conducted a survey conducted a survey of 86 farmers in the Upper Salt Fork Watershed area in 2011 (Upper Salt Fork Project Report and Status Update, 2011) to assess their perceptions, opinions, and values in farming. The calibration procedure started with those perceptions to choose parameters in the stepwise procedure.

The UIUC survey qualified factors driving water quality management and their level of importance to producers. 95% of producers reported that “Improving or maintaining the appearance and integrity of my farm” as important or very important (Upper Salt Fork Project Report and Status Update, 2011). 93.8% of producers reported that “Improving or maintaining the conditions of my farm for future generations of farmers in my family” as important or very important (Upper Salt Fork Project Report and Status Update, 2011). 92.5% of producers reported that “Improving or maintaining my relationships with neighboring farmers” as important or very important (Upper Salt Fork Project Report and Status Update, 2011). 83.8% of producers reported that “Improving my farm production and bottom line” as important or very important (Upper Salt Fork Project Report and Status Update, 2011).

Calibration also employed survey results observed BMP adoption rates. The UIUC survey showed that 58% of respondents were employing nutrient management, 11% were using an annual cover crop, and 4% were using drainage water management. The ABM incorporated survey results to set farmer opinions and perceptions. 62% of survey respondents rated the water quality as excellent or good, and 37% of respondents rated the water as average (Upper Salt Fork Project Report and Status Update, 2011). The survey respondents also rated their concern about water quality issues from 1 to 5 (1 not at all concerned to 5 very concerned): 9% rated their concern as a 1, 17% rated it a 2, 27% rated it a 3, 25% rated it a 4, 22% rated it a 5 (Upper Salt Fork Project Report and Status Update, 2011).

Informed by the survey results, the calibration procedure first selected economic awareness (and the variability of all three parameters), then sociability, and finally environmental awareness. BMP perceptions were then adjusted up and down to model adoption rates within 10%.

4.3.9 Calibrated Model

The final calibrated model parameters for farmer agents achieved the modeling targets of 10% error, and steady levels of adoption (Table 4.18). The modeling results of economic and environmental benchmarks are presented in the next chapter, Chapter 5, with the input parameters discussed in this section.

Table 4.18: Farmer Agent Initial Parameter Calibration

Parameter	Description	Calibrated Value
t_f	Time Horizon (years)	3 (33%); 7 (66%)
M	Economic Awareness	0.36
S	Sociability	0.2
E	Environmental Awareness	0.04
V	M, S, E Standard Deviation	0.17

The calibrated values do not necessarily reflect measures by which to categorize or compare farmers in the watershed to other watersheds. The parameters are relevant only in the context of the ABM defined in the study. The initial BMP perceptions were adjusted up and down from .5 to model adoption rates (Table 4.19).

Table 4.19: BMP Initial Parameter Calibration

Parameter	Description	Calibrated Value
B_{RCC}	RCC Initial Perception	0.31
B_{NM}	NM Initial Perception	0.97
B_{DWM}	DWM Initial Perception	0.24

Similarly, these parameters are relevant only in the context of the ABM defined in the study. For the considerations of the study, the perceptions define how farmer agents assess their effectiveness, their neighbors' opinions, and profitability.

The average of 100 simulations was validated with adoption rates from the UIUC Upper Salt Fork producer survey (Table 4.20).

Table 4.20: Calibrated Adoption Rates (Upper Salt Fork Project Report and Status Update, 2011)

Description	Calibrated Value	Observed
RCC Adoption Rate	11%	12%
NM Adoption Rate	56%	58%
DWM Adoption Rate	4%	4%

4.4 Coupled Model Scenario Analysis

The development of an agent-based model, input parameters, and calibration sequence were discussed in this chapter. The model, an interface to perform a scenario analysis along with inputting the parameter values was developed in Matlab using an object-oriented programming approach. The ABM output/input for cropping decisions, BMP installations, nutrient loads and concentrations, crop yields was formatted and inputted in the proper SWAT configuration files within the ABM architecture in Matlab. The SWAT configuration files for implementing BMPs are explained in Chapter 3. Farmer agents invoke BMP helper functions to access a SWAT configuration file, for example, the .mgt file for a cropping decision, rebuild the file, inserting SWAT the value to change. The file is then saved. SWAT runs for the entire life of the simulation for each year. The SWAT output for the current year is opened, formatted, and fed back to the ABM for decisions before the year turns, and another SWAT run begins. The code with comments and SWAT configuration files are available on a UIUC server. A single simulation can be run from a Matlab figure (Figure 4.16), while batch simulations can be run with custom scripts. This study named coupled model and Matlab interface the Integrated Tool for Economic, Environmental, and Policy Goals in Agricultural Management (ITEEPGAM).

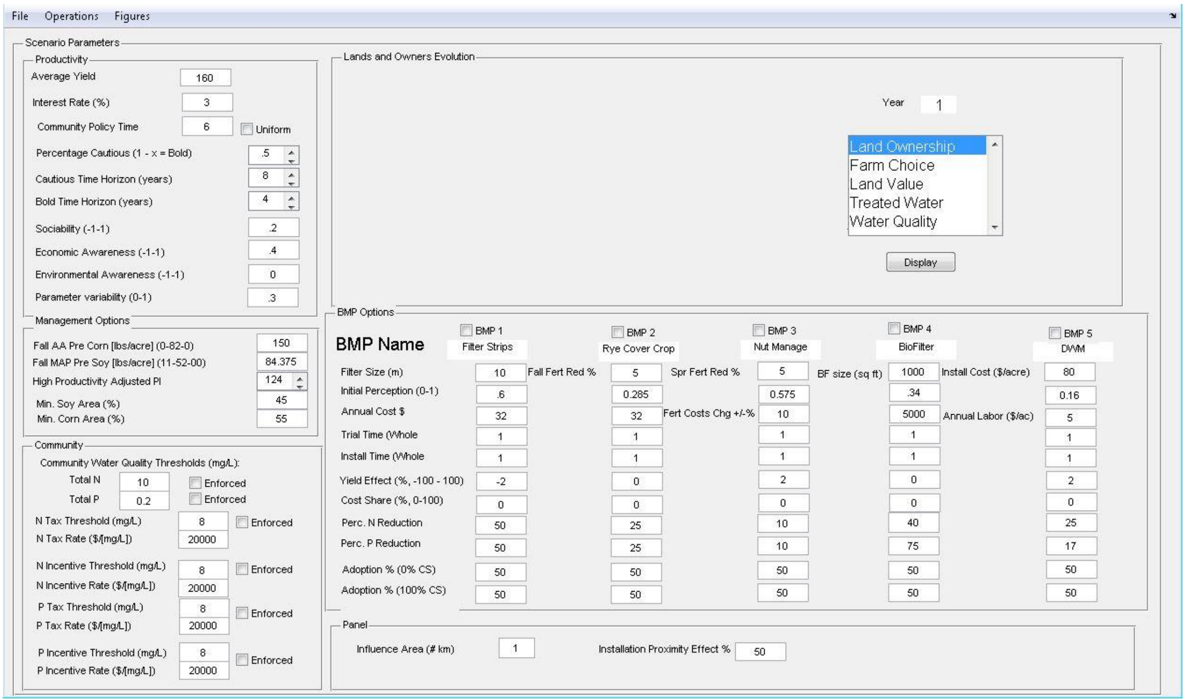

Figure 4.16: ITEEPGAM Matlab Interface

ITEEPGAM was applied to address the following: what features of BMPs and policy initiatives lead to optimizing economic and environmental performance? This study designed scenarios to quantify the relationship between economic and environmental performance with respect to varied management and policy (Table 4.21). The scenarios were run using the calibrated BMP baseline configuration described in this chapter.

Each scenario varied the parameters listed in the table row, while maintaining all the others. In this fashion, the analysis varied that input only; isolating one aspect of management or policy. The scenarios and their objectives are described in detail.

Table 4.21: ITEEPGAM Scenario Parameter and Ranges Outline

Scenario Category	Selected Scenario Parameters an Ranges
Cover Cropping + Fertilizer Savings (% Change)	Baseline BMP Configuration AA and MAP Rate (% Change) = -45 to 0, in 2.5 step increments
Nutrient Management + Fertilizer Savings (% Change)	Baseline BMP Configuration AA and MAP Rate (% Change) = -35 to 0, in 2.5 step increments
Cost Share Amounts (% Offset)	Baseline BMP Configuration X_{RCC}, X_{NM}, X_{DWM} = 15,5,5; 25,10,10; 35,15,15; 50,25,25; 50,50,50; 65,50,50; 80,75,75; 90,90,90; 100,100,100
Tax Policy	Baseline BMP Configuration $N_{TAX\ CONC} = 5, 6, 7, 8, 9, 10\ \frac{mg}{L}$ $N_{TAX\ RATE} = 25000, 50000, 75000, 100000, 150000, 250000, 500000, 1000000, 1500000, 2000000, 3000000\ \frac{\$}{\frac{mg}{L}}$ $P_{TAX\ CONC} = 0.025, 0.05, 0.075, 0.1, 0.15, 0.2\ \frac{mg}{L}$ $P_{TAX\ RATE} = 250000, 500000, 750000, 1000000, 1500000, 2500000, 5000000, 10000000, 15000000, 20000000, 30000000\ \frac{\$}{\frac{mg}{L}}$
Incentive Policy	Baseline BMP Configuration $N_{INC\ CONC} = 5, 6, 7, 8, 9, 10\ \frac{mg}{L}$ $N_{INC\ RATE} = 25000, 50000, 75000, 100000, 150000, 250000, 500000, 1000000, 1500000, 2000000, 3000000\ \frac{\$}{\frac{mg}{L}}$ $P_{INC\ CONC} = 0.025, 0.05, 0.075, 0.1, 0.15, 0.2\ \frac{mg}{L}$ $P_{INC\ RATE} = 250000, 500000, 750000, 1000000, 1500000, 2500000, 5000000, 10000000, 15000000, 20000000, 30000000\ \frac{\$}{\frac{mg}{L}}$

What level of fertilizer reduction can cover cropping supplement economic performance and mitigate nutrient loss? The default configuration for simulating cover cropping adoption accounted for a fertilizer reduction amount of 0%. To assess the adoption and performance of varied fertilizer amounts coupled with cover cropping, percentage reductions of 0 to 45, in 2.5% increments were simulated using the results from the universal fertilizer reduction scenarios for inputted anticipated yield reductions as presented in Section 4.3.6. Rye cover cropping with fertilizer reductions was assessed within the calibrated ABM as one of the suite of BMPs to see how adoption would be affected.

What level of fertilizer reduction can nutrient management supplement economic performance and mitigate nutrient loss? The default configuration for simulating switch fall-applied fertilizer to spring accounted for a fertilizer reduction amount of 0%. To assess the adoption and performance of varied fertilizer amounts coupled with switching application times, percentage reductions of 0 to 35, in 2.5% increments were simulated. Farmer's yield effect expectations were set according to the results from Section 4.3.6. Nutrient management with fertilizer reductions was assessed within the calibrated ABM as one of the suite of BMPs to see how adoption would be affected.

How do cost share levels produce additional environmental gains and at what financial cost? Only cover cropping is currently eligible for cost sharing through the NRCS (Iowa Learning Farms & Practical Farmers of Iowa, June 2011) at a 50% rate. The cost share was varied up to 100% for cover cropping, and 100% for the expenses associated with drainage water management, and nutrient management. The resultant cost share budgets were used to assess the return in environmental gains and adoption rates.

What level of tax encourages adoption with gains in water quality? Tax thresholds of 5 to 10 mg/L for nitrogen, and 0.025 to 0.2 mg/L for phosphorous were tested with rates of $25000, $50000, $75000, $100000, $150000, $250000, $500000, $1000000, $1500000, $2000000, $3000000 per mg/L for nitrate, and $250000, $500000, $750000, $1000000, $1500000, $2500000, $5000000, $10000000, $15000000, $20000000, $30000000 per mg/L for phosphorous. For example, a threshold of 5 mg/L for nitrogen and 0.025 mg/L for phosphorous was enforced with tax rates of $25000 per mg/L of nitrogen and $250000 per mg/L of phosphorous. The rates for those thresholds were scaled up through the listed amounts to $3000000 per mg/L of nitrogen and $30000000 per mg/L of phosphorous. Each scenario is assessed by the revenue for the government, cost to producers, and water quality gains. The varied thresholds and rates were used to find total tax budgets that encouraged adoption, improved environmental outcomes, at the lowest cost to producers.

What level of incentive encourages adoption with gains in water quality? Similar to the implementation of a tax, the same parameters were tested for an incentive. Each scenario is assessed by the cost to the government, revenue for producers, and water quality gains.

Each proposed scenario was run 10 times and the average response across the 10 replicates was used. The results of the scenario analysis are presented in the next chapter.

CHAPTER 5

RESULTS

5.1 Introduction

This study coupled a natural systems model with an agent-based human systems model to simulate the adoption of conservation practices with respect to environmental, economic, and policy goals in the Upper Salt Fork Watershed in East-Central Illinois. The SWAT (Soil and Water Assessment Tool) model was calibrated to model natural systems outcomes (nitrogen, phosphorous, crop yields) as detailed in Chapter 3. An agent-based model (ABM) was calibrated to model human systems outcomes and policy instruments (farming revenue, taxes, and incentives) along with the adoption of best management practices (rye cover cropping - RCC, drainage water management - DWM, nutrient management - NM) as presented in Chapter 4. The two models were coupled to form the Integrated Tool for Economic, Environmental, and Policy Goals in Agricultural Management (ITEEPGAM), and a schedule of scenarios was designed to observe the effect of the best management practices and how policy initiatives (taxes, incentives, and cost shares) influence environmental and economic outcomes. The objectives of each scenario were discussed in Section 4.4. Each scenario was run using the calibrated BMP baseline configuration described in this Chapter 4. All scenarios varied management or policy options with respect to all three BMPs. Each scenario varied the parameters listed Table 5.1, while maintaining all the others. In this fashion, the analysis varied a single input parameter only; isolating one aspect of management or policy. The model parameters selected for performing the scenarios discussed in Chapter 4 are repeated in Table 5.1. The selected parameters and the ranges used for performing each scenario were also outlined in Chapter 4, and are repeated in Table 5.2. Each scenario was repeated 10 times and the average of environmental and economic outcomes was used to perform the analysis. The scenario results are presented in this chapter. Each indexed row in Table 5.2 represents scenario category and serves to organize this chapter's sections.

Table 5.1: Scenario Parameters

Parameter	Description	Range
$X_{BMP\ NAME}$	BMP Cost Share (%)	0– 100
$N_{TAX\ RATE}$	Nitrogen Tax Rate [$/(mg/L)]	0-3000000
$N_{TAX\ CONC}$	Nitrogen Tax Threshold (mg/L)	5-10
$P_{TAX\ RATE}$	Phosphorous Tax Rate [$/(mg/L)]	0-30000000
$P_{TAX\ CONC}$	Phosphorous Tax Threshold (mg/L)	0.025-0.2
$N_{INC\ RATE}$	Nitrogen Incentive Payment Rate [$/(mg/L)]	0-3000000
$N_{INC\ CONC}$	Nitrogen Incentive Threshold (mg/L)	5-10
$P_{INC\ RATE}$	Phosphorous Incentive Payment Rate [$/(mg/L)]	0-30000000
$P_{INC\ CONC}$	Phosphorous Incentive Threshold (mg/L)	0.025-0.2
$Y_{BMP\ NAME}$	Effective on Yield (%)	-25 - 7

Table 5.2: Scenario Parameter and Ranges Outline

Scenario Category	Section	Selected Scenario Parameters and Ranges
Nutrient Management + Fertilizer Savings (% Change)	1	BMP Baseline Configuration AA and MAP Rate (% Change) = -35 to 0, in 2.5 step increments
Cover Cropping + Fertilizer Savings (% Change)	2	BMP Baseline Configuration AA and MAP Rate (% Change) = -45 to 0, in 2.5 step increments
Cost Share Amounts (% Offset)	3	BMP Baseline Configuration $X_{RCC}, X_{NM}, X_{DWM} = 15,5,5; 25,10,10; 35,15,15; 50,25,25; 50,50,50; 65,50,50; 80,75,75; 90,90,90; 100,100,100$
Incentive Policy	4	BMP Baseline Configuration $N_{TAX\ CONC} = 5, 6, 7, 8, 9,10\ mg/L$ $N_{TAX\ RATE} = 25000, 50000, 75000, 100000, 150000, 250000\ 500000, 1000000, 1500000, 2000000, 3000000\ \ \$/\frac{mg}{L}$ $P_{TAX\ CONC} = 0.025, 0.05, 0.075, 0.1, 0.15,0.2\ mg/L$ $P_{TAX\ RATE} = 250000, 500000, 750000, 1000000, 1500000, 2500000, 5000000, 10000000, 15000000, 20000000, 30000000\ \ \$/\frac{mg}{L}$
Tax Policy	5	BMP Baseline Configuration $N_{INC\ CONC} = 5, 6, 7, 8, 9,10\ mg/L$ $N_{INC\ RATE} = 25000, 50000, 75000, 100000, 150000, 250000\ 500000, 1000000, 1500000, 2000000, 3000000\ \ \$/\frac{mg}{L}$ $P_{INC\ CONC} = 0.025, 0.05, 0.075, 0.1, 0.15,0.2\ mg/L$ $P_{INC\ RATE} = 250000, 500000, 750000, 1000000, 1500000, 2500000, 5000000, 10000000, 15000000, 20000000, 30000000\ \ \$/\frac{mg}{L}$

5.2 Scenario Results

5.2.1 Results Overview

The natural systems model (SWAT) established nitrogen (nitrate-N), phosphorous (dissolved reactive phosphorous - DRP), and crop yields as metrics for assessing environmental and economic yields. The human systems model component initialized annualized returns and BMP adoption rates as benchmarks for economic and management outcomes. The two components were coupled into ITEEPGAM. To start, a no-BMP baseline case using ITEEPGAM established benchmarks for which to compare all scenarios against (farmers did not consider any BMPs for installations, but planted crops according to ITEEPGAM logic, as presented in Chapter 4).

Next, the coupled model (ITEEPGAM) was calibrated for adoption rates with respect to a survey of farmers in the Salt Fork Watershed (Upper Salt Fork Project Report and Status Update, 2011) for the three BMPs considered in this study. Using the resulting calibrated setup, the parameter values shown in Table 5.2 were inputted into ITEEPGAM for a schedule of scenarios. For scenario analysis, the output of the scenarios was assessed relative to the no-BMP baseline. Each scenario in the schedule, utilizing the calibrated model, was compared to the no-BMP baseline case. In this way, the analysis assessed the relative effect of changing management and policy. This section presents the results of the BMP baseline and scenario schedule shown in Table 5.2. The baseline model results are presented and then each table row forms a section of the chapter. The performance metrics are presented graphically and in a table format with a focus on the average response over the length of the simulation (2005-2012).

5.2.2 BMP Baseline

The ITEEPGAM no-BMP baseline was used as a benchmark to assess the environmental, economic, and policy changes for the schedule of scenarios in Table 5.2. The results for the

BMP baseline scenario (Figures 5.1 – 5.11) that was calibrated for adoption rates in Chapter 4 are presented in this section. The results are presented with respect to the no-BMP baseline to form conclusions on the effect of changes in management and maintain uniformity in the benchmark used (Table 5.4).

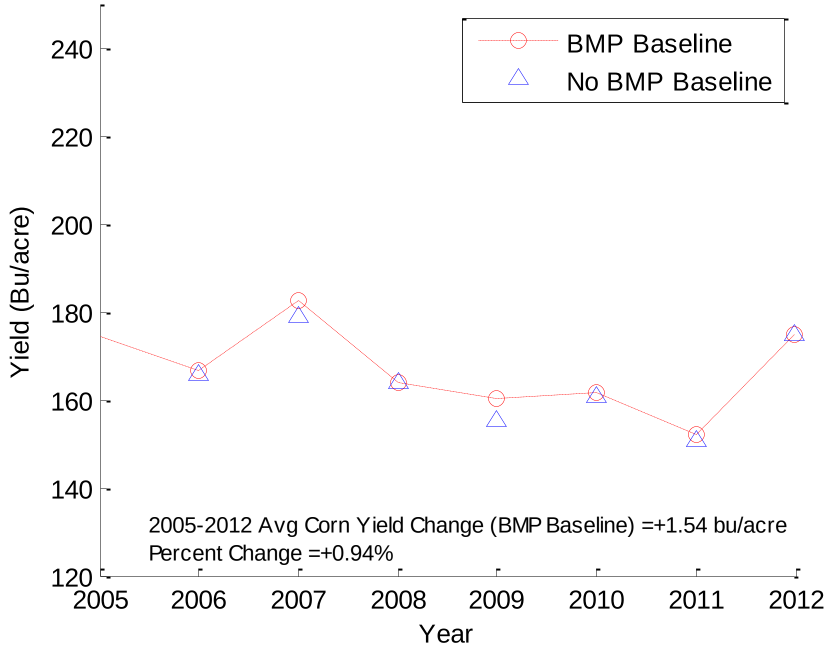

Figure 5.1: **ITEEPGAM BMP Baseline and No-BMP modeled corn yields**

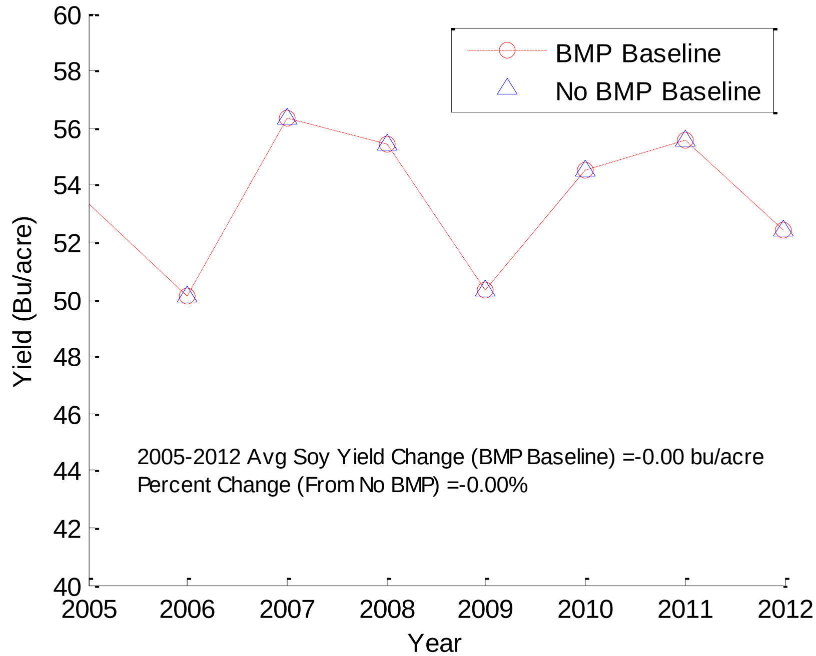

Figure 5.2: **ITEEPGAM BMP Baseline and No-BMP modeled soy yields**

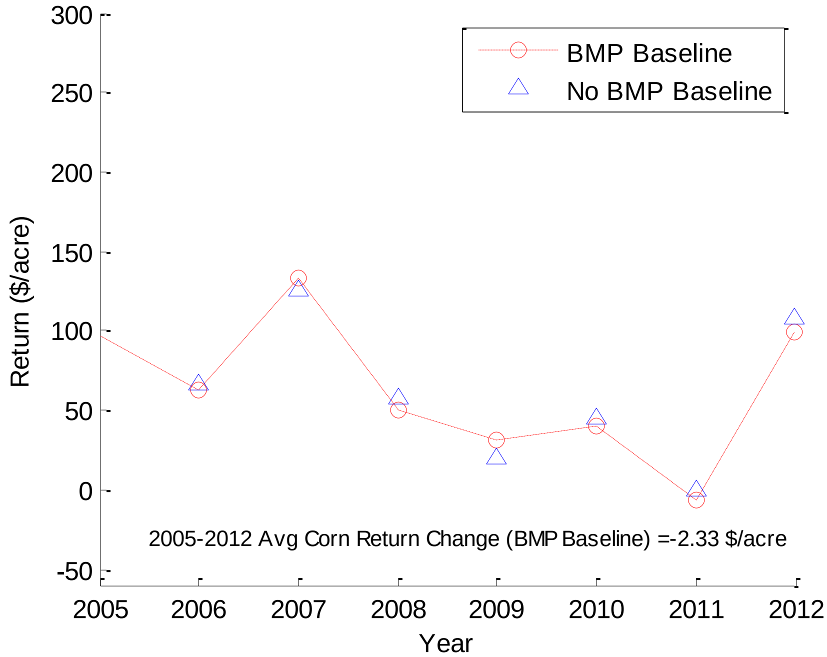

Figure 5.3: ITEEPGAM BMP Baseline and No-BMP modeled corn returns

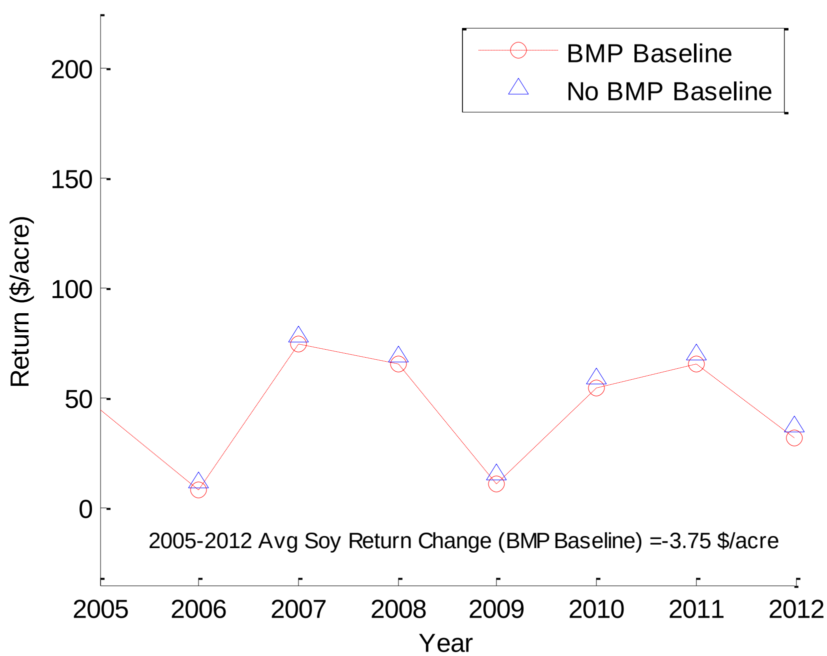

Figure 5.4: ITEEPGAM BMP Baseline and No-BMP modeled soy returns

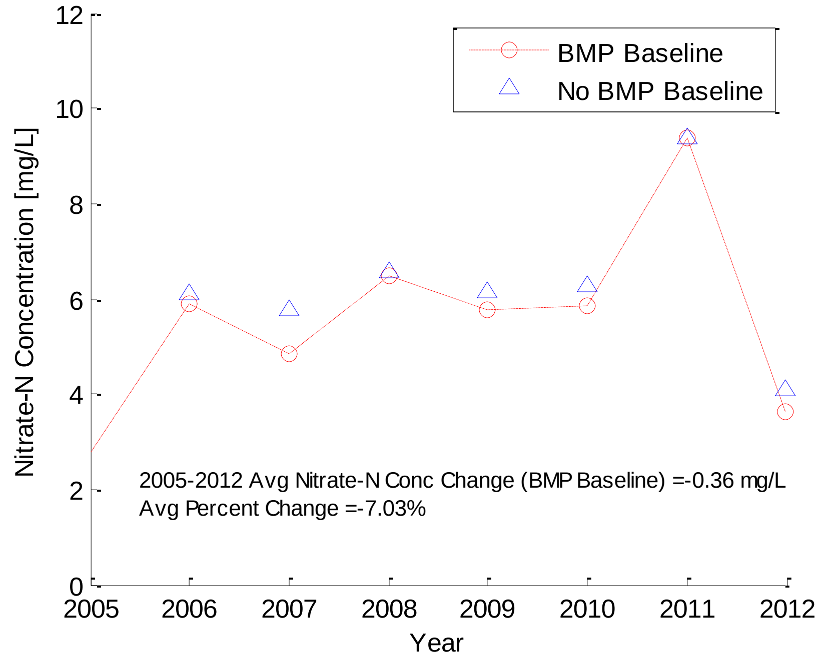

Figure 5.5: ITEEPGAM BMP Baseline and No-BMP modeled Nitrate-N Concentrations

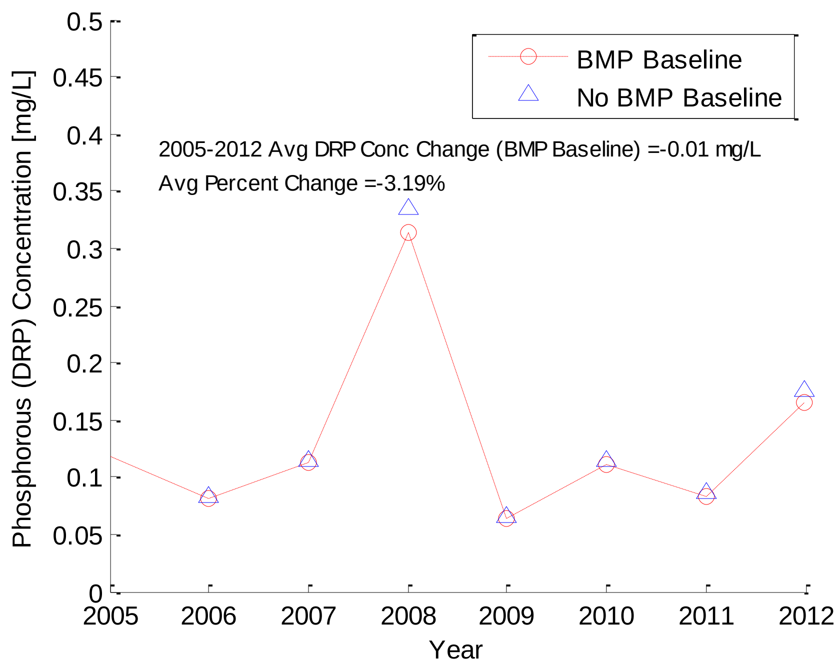

Figure 5.6: ITEEPGAM BMP Baseline and No-BMP modeled phosphorous (DRP) concentrations

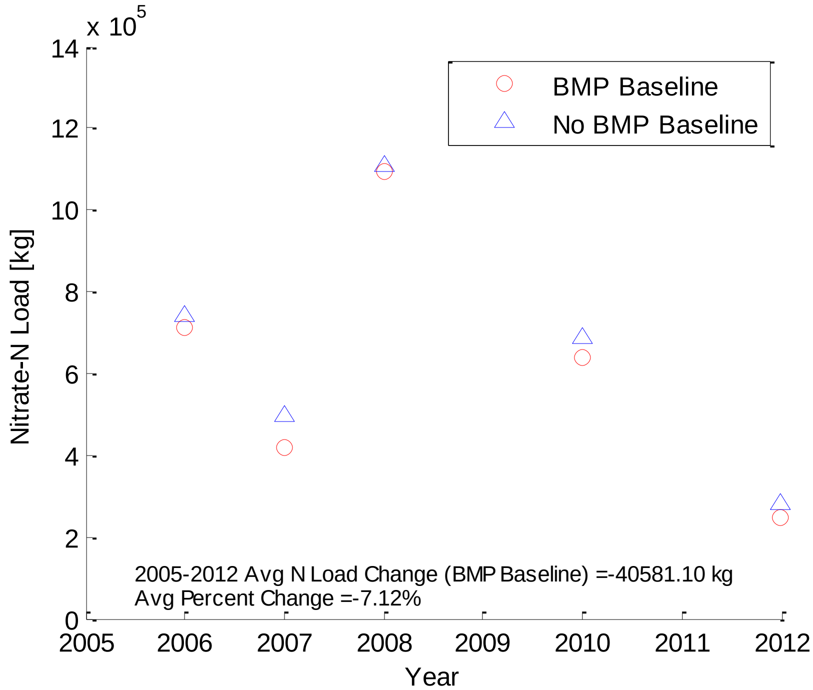

Figure 5.7: ITEEPGAM BMP Baseline and No-BMP modeled Nitrate-N loads

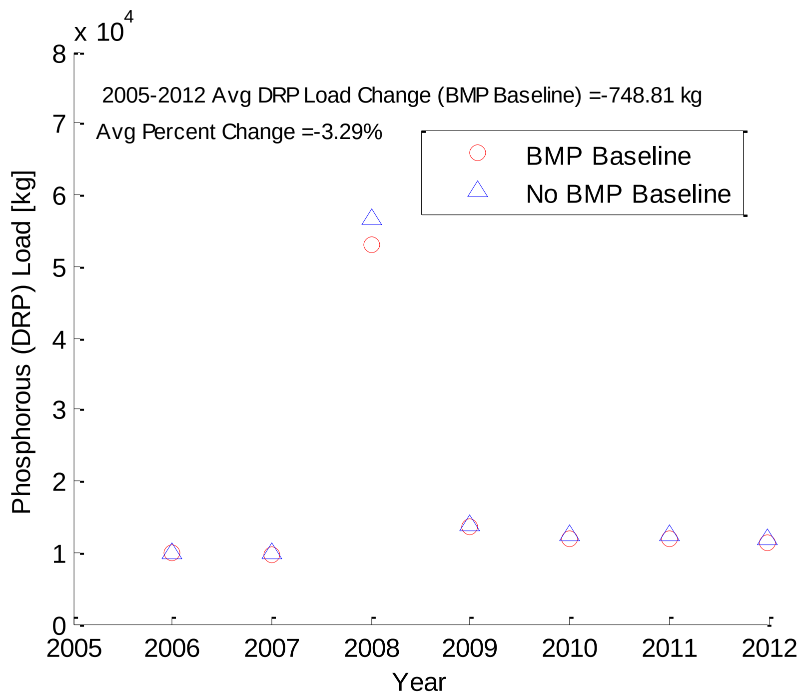

Figure 5.8: ITEEPGAM BMP Baseline and No-BMP modeled phosphorous (DRP) loads

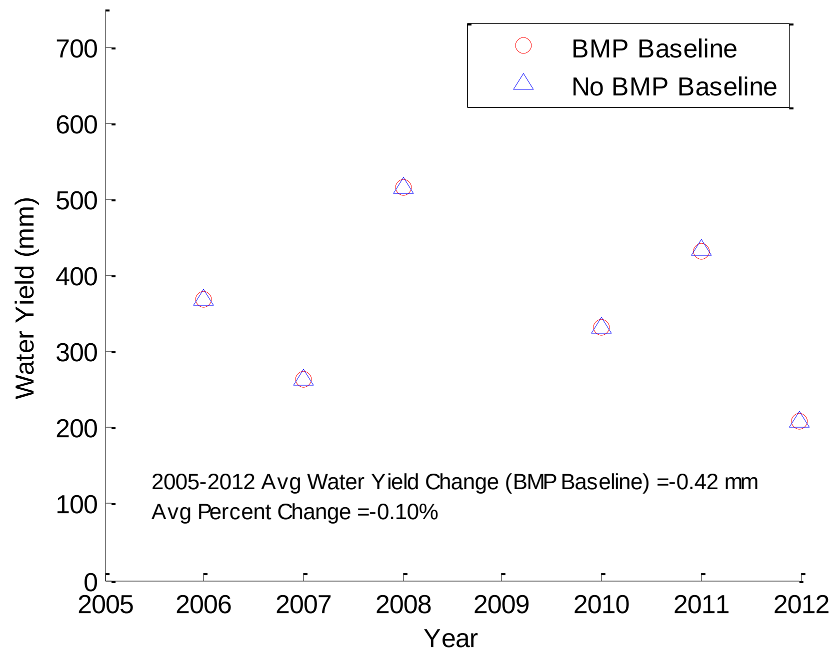

Figure 5.9: ITEEPGAM BMP Baseline and No-BMP modeled water yields

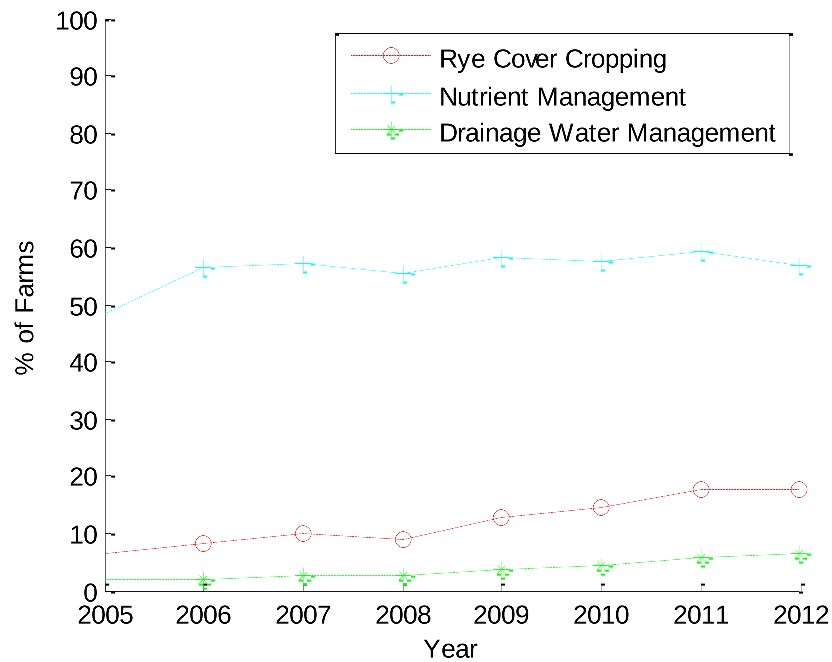

Figure 5.10: ITEEPGAM BMP Baseline modeled adoption rates

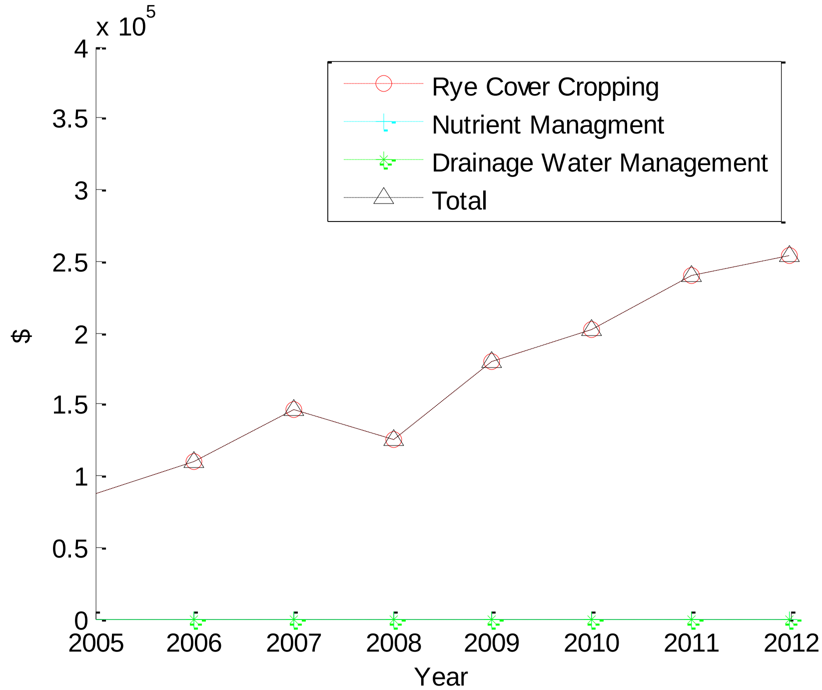

Figure 5.11: ITEEPGAM BMP Baseline modeled cost share budget

Table 5.3: BMP Baseline Results

Baseline BMP Scenario 2005-2012		
Adoption Rates	12% RCC, 56% NM, 4% DWM	
	Change From No-BMP	
	Amount	%
Avg Annual N Load	-40581 kg	-7.1%
Avg Annual P Load	-748 kg	-3.3%
Avg Annual N Conc	-0.36 mg/L	-7%
Avg Annual P Conc	-0.01 mg/L	-3%
Avg Annual Water Yield	-0.42 mm	-0.1%
Avg Annual Corn Yield	+1.54 bu/ac	+1%
Avg Annual Soy Yield	Unchanged	Unchanged
Avg Annual Corn Return	-2.33 $/ac	-3.6%
Avg Annual Soy Return	-3.75 $/ac	-7.8%
Avg Annual Cost Share	$167,740	

5.2.2.1 BMP Baseline Discussion

The ITEEPGAM BMP baseline results attributed a 7% reduction in nitrogen and phosphorous loadings, 3% reduction in nutrient concentrations, a 1.5 bu/ac increase in corn yield, no change in soy yields, and a cost of $3 /ac in the set of BMPs implemented at their observed adoption rates.

5.2.3 Nutrient Management Results

ITEEPGAM was tested to isolate a fertilizer reduction amount that nutrient management (switching application timing from fall to spring) could supplement without a reduction in yield (Scenario 1). The results from the universal fertilizer stress tests from the previous section were used to set farmer agents' anticipated yield effect on corn yields ($Y_{BMP\ NAME}$) when considering the paired nutrient management and reduction in fertilizer. Fertilizer reductions were assessed from 2.5% to 35% within the BMP baseline configuration (as a choice among the three BMPs for this study). Reductions resulted in gains for soybean farmers who adopted during their MAP application rotation, but immediately resulted in losses for corn farmers. The first three fertilizer reductions resulted in similar adoption rates as the BMP baseline (Table 5.7). Adoption rates initially rose due to the profitability for soybean farmers, but decreased because of steep losses for corn plantings (Figures 5.12 – 5.14).

Table 5.4: Nutrient Management Results (Scenario 1)

Nutrient Management Scenarios with fertilizer reductions 2005-2012						
Fertilizer Modification	2.5% Decrease		5% Decrease		7.5% Decrease	
Adoption Rate	11% RCC, NM 56%, 4% DWM		12% RCC, 58% NM, 3% DWM		11% RCC, 59% NM, 3% DWM	
	Change From No BMP Baseline					
	Amount	%	Amount	%	Amount	%
Avg Annual N Load	-53298 kg	-8.7%	-67062 kg	-10.4%	-81850 kg	-12.2%
Avg Annual P Load	-699 kg	-3.12%	-687 kg	-3.0%	-620 kg	-2.6%
Avg Annual N Conc	-0.45 mg/L	-8.6%	-0.55 mg/L	-10.2%	-0.66 mg/L	-12%
Avg Annual P Conc	-0.01 mg/L	-3%	-0.01 mg/L	-2.8%	-0.01 mg/L	-2.4%
Avg Annual Water Yield	-0.61 mm	-.15%	-0.86 mm	-.22%	-1.03 mm	-.27%
Avg Annual Corn Yield	+.26 bu/ac	+.16%	-1.05 bu/ac	-.65%	-2.45 bu/ac	-1.5%
Avg Annual Soy Yield	Unch.	Unch.	Unch.	Unch.	Unch.	Unch.
Avg Annual Corn Return	-6.06 $/ac	-9.23%	-10.2 $/ac	-15.6%	-14.4 $/ac	-22%
Avg Annual Soy Return	-3.06 $/ac	-6.32%	-2.57 $/ac	-5.3%	-1.71 $/ac	-3.54%

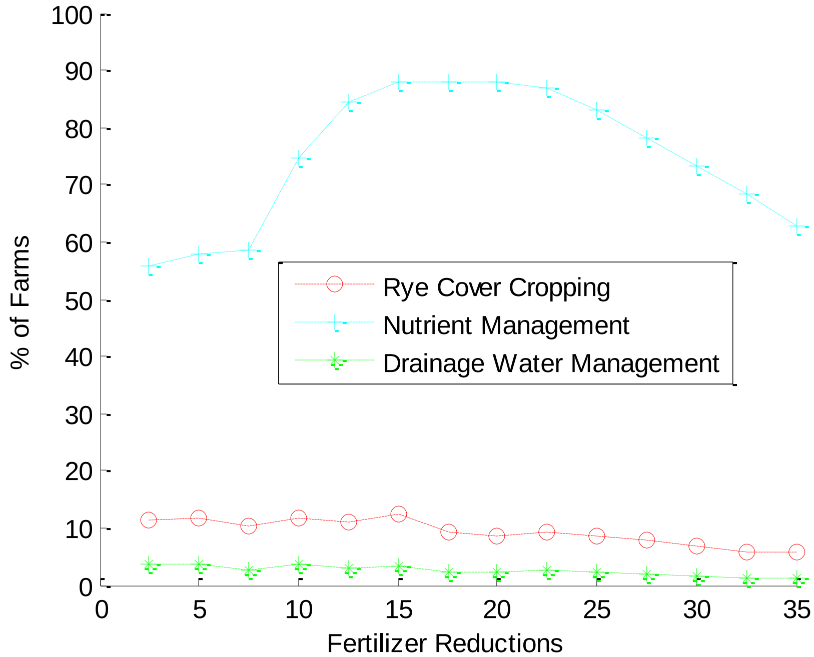

Figure 5.12: ITEEPGAM (Scenario 1) Adoption Rates for Nutrient Management with Fertilizer Reductions

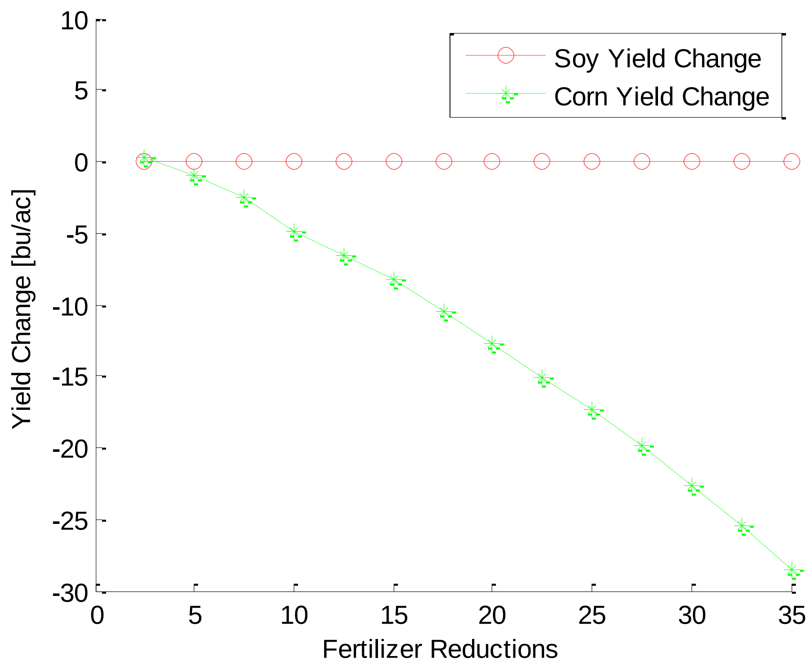

Figure 5.13: ITEEPGAM (Scenario 1) Change in Crop Yields (From No-BMP Baseline) for Nutrient Management with Fertilizer Reductions

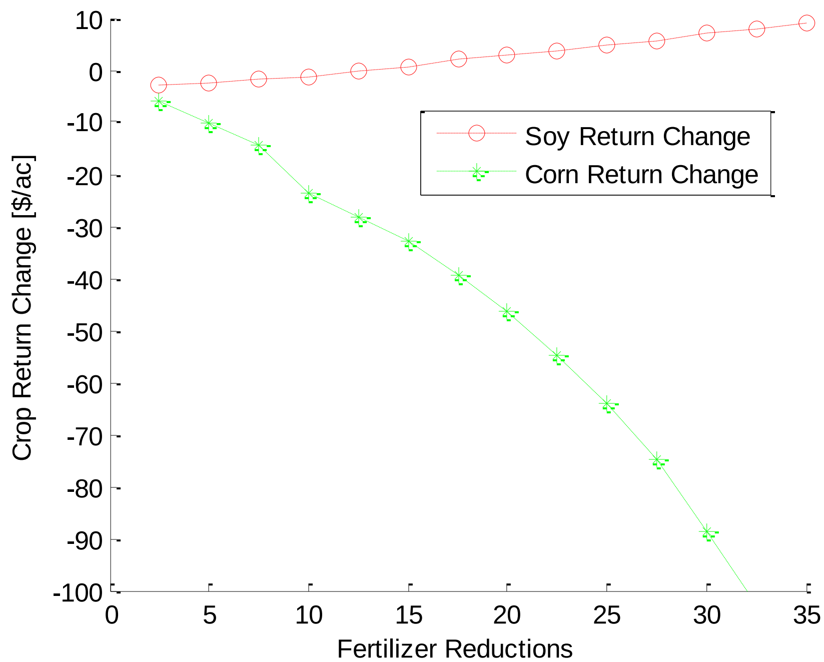

Figure 5.14: ITEEPGAM (Scenario 1) Change in Crop Returns (From No-BMP Baseline) for Nutrient Management with Fertilizer Reductions

5.2.3.1 Nutrient Management Discussion

ITEEPGAM was only calibrated for average adoption rates across all corn and soybean plantings with respect to the available survey results (Upper Salt Fork Project Survey Report and Status Update, 2011). Nutrient Management adoption rates between corn and soybean plantings were not considered for the analysis. In the case of nutrient management, the different prospects between corn and soybean plantings drove adoption rates. Adoption rates for paired nutrient management and fertilizer reductions initially increased with larger fertilizer reductions. Soybean plantings saw greater returns and no effect on yield for all fertilizer reductions. Only when fertilizer reductions exceeded 20%, did economic loss for corn plantings discourage adoption. This result was not considered practical, as farmers absorbing losses greater than $10 an acre resulted in a greater than 10% loss in revenue, thus making adoption unrealistic. .The impractical behavior was also a consequence of ITEEPGAM using yields and not revenues to assess the farmer opinions of BMPs, as detailed in the in Chapter 4. In addition, nutrient management was calibrated with a high initial perception in the study watershed to achieve an adoption rate of 56%: reflecting a high farmer opinion of the practice. The high initial BMP perception overcame the economic disincentive of fertilizer reductions in these scenarios. This negative feedback loop was not immediately strong enough to discourage adoption, but adoption rates eventually reacted to economic disincentives.

Due to the relatively high adoption rates, it was possible to consider near universal adoption of nutrient management across the whole watershed. A paired nutrient management and fertilizer reduction of 20% resulted in an adoption rate of 88% and a corn yield reduction of 12.7 bu/acre (7.5%). In the universal fertilizer reduction analysis, a 20% reduction in fertilizer resulted in a corn yield reduction of 10.3%. Therefore, switching application timing to spring over the whole watershed could mitigate some of the anticipated yield losses associated with fertilizer reductions. In addition, the reduction in observed nitrogen load at the outlet correlated with fertilization reductions: a fertilizer reduction of 2.5% resulted in an additional 1.6% reduction in load at the outlet, and a fertilizer reduction of 5% resulted in an additional 3.3% reduction in load at the watershed outlet.

5.2.4 Winter Cover Cropping Results

Similar to nutrient management coupled with fertilizer reductions, ITEEPGAM was tested to isolate a fertilizer reduction amount that winter cover cropping (rye plantings) could supplement without a reduction in yield (Scenario 2). The results from the universal fertilizer stress tests were used again to set farmer agents' anticipated yield effect on corn yields ($Y_{BMP\ NAME}$) when considering the paired winter cover cropping and reduction in fertilizer. Corn yields were not significantly affected with a reduction less than 10% (Table 5.8).

Table 5.5: Winter Cover Cropping Results (Scenario 2)

Winter Cover Cropping (Rye) Scenarios with fertilizer reductions 2005-2012						
Fertilizer Modification	10% Decrease		12.5% Decrease		15% Decrease	
Adoption Rate	15% RCC, 56% NM, 4% DWM		15% RCC, 57% NM, 3% DWM		17% RCC, 59% NM, 4% DWM	
	Change From No BMP					
	Amount	%	Amount	%	Amount	%
Avg Annual N Load	-51981 kg	-8.5%	-54854 kg	-8.9%	-59743 kg	-9.44%
Avg Annual P Load	-954.9 kg	-4.2%	-953.01 kg	-4.09%	-1097 kg	-4.83%
Avg Annual N Conc	-0.44 mg/L	-8.28%	-0.46 mg/L	-8.67%	-0.49 mg/L	-9.17%
Avg Annual P Conc	-0.01 mg/L	-4%	-0.01 mg/L	-3.9%	-0.01 mg/L	-4.5%
Avg Annual Water Yield	-0.84 mm	-0.22%	-0.86 mm	-0.22%	-1.15 mm	-0.3%
Avg Annual Corn Yield	+0.51 bu/ac	+0.31%	+0.28 bu/ac	+0.17%	-0.24 bu/ac	-0.15%
Avg Annual Soy Yield	Unch.	Unch.	Unch.	Unch.	Unch.	Unch.
Avg Annual Corn Return	-5.2 $/ac	-7.26%	-5.76 $/ac	-8.78%	-7.26 $/ac	-11.1%
Avg Annual Soy Return	-3.59 $/ac	-7.42%	-3.5 $/ac	-7.23%	-3.49 $/ac	-7.21%
Avg Annual Cost Share	$208,390		$204,390		$231,780	

Soybean yields and returns were not affected; corn yields and returns were adversely affected with reductions beyond 15% (Figures 5.15 – 5.17).

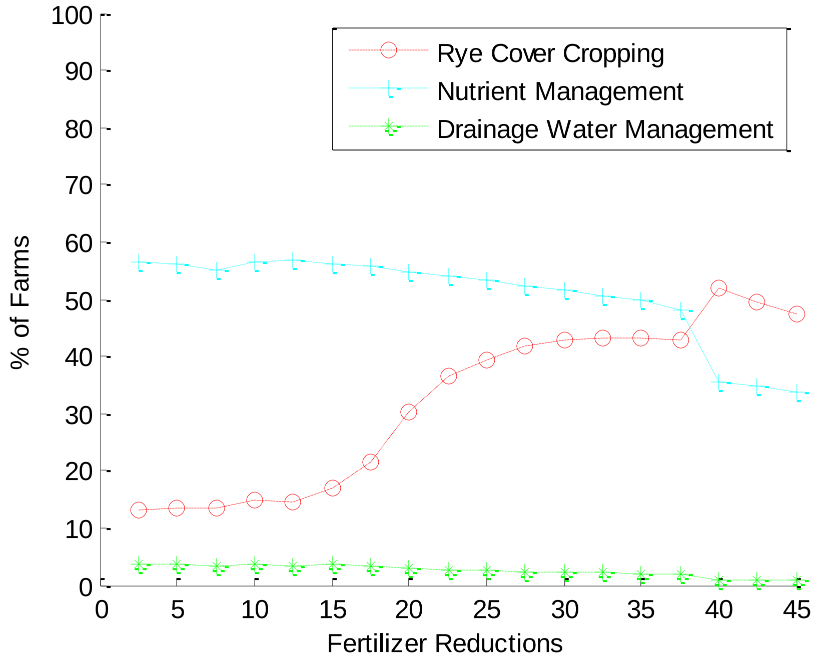

Figure 5.15: ITEEPGAM (Scenario 2) Adoption Rates for Winter Cover Cropping with Fertilizer Reductions

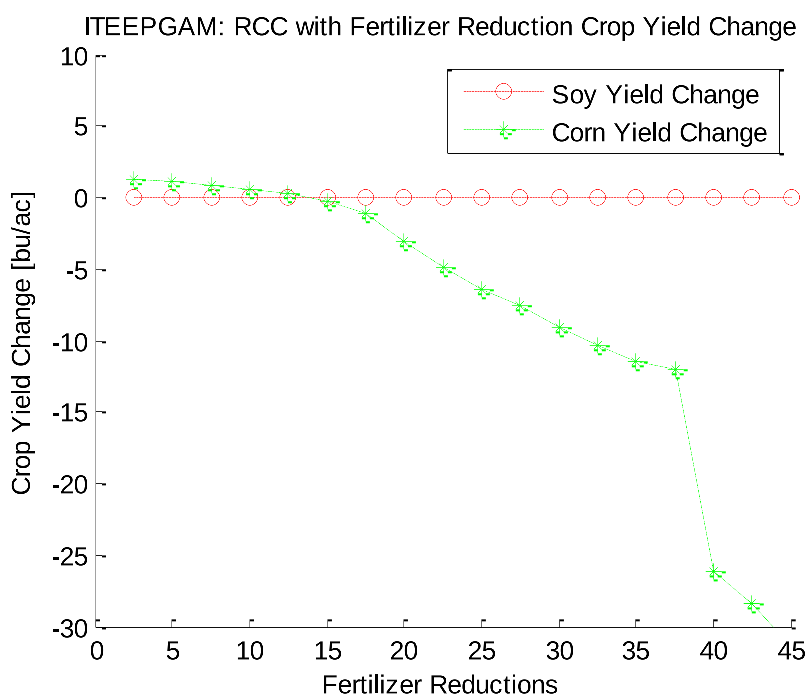

Figure 5.16: ITEEPGAM (Scenario 2) Change in Crop Yields (From No-BMP Baseline) Winter Cover Cropping with Fertilizer Reductions

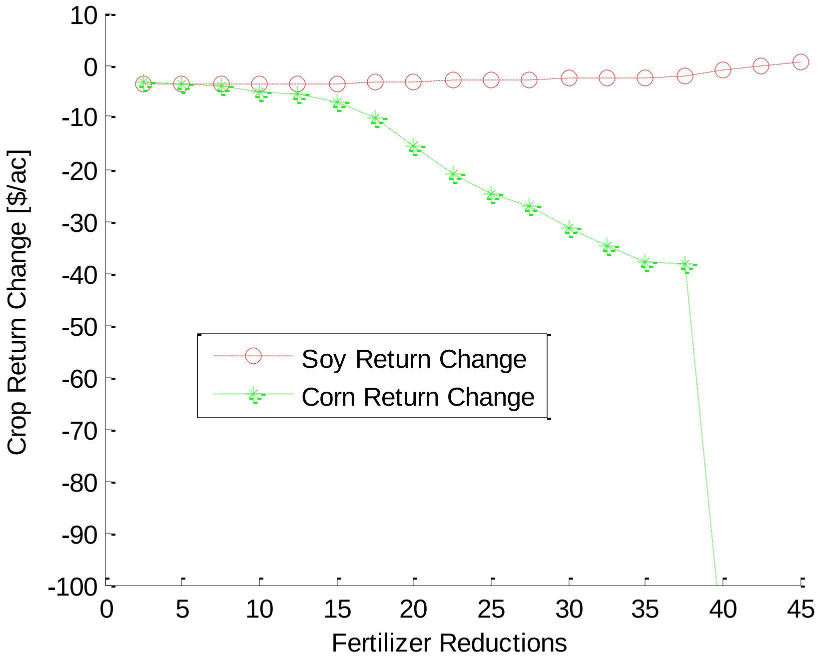

Figure 5.17: ITEEPGAM (Scenario 2) Change in Crop Returns (From No-BMP Baseline) Winter Cover Cropping with Fertilizer Reductions

5.2.4.1 Winter Cover Cropping Discussion

ITEEPGAM showed that winter cover cropping could meet crop nutrient demands when coupled with fertilizer reductions. Yield reductions were less than 1% with fertilizer reductions up to 12.5%, while observed nutrient loads at the outlet were reduced by an additional 2%. As with nutrient management, ITEEPGAM unrealistically predicted increased adoption even with economic disincentives with fertilizer reductions beyond 15%. And for smaller fertilizer reductions that resulted in environmental gains without yield effects, ITEEPGAM did not predict larger adoption rates. However, since cover cropping was not well-established (11%), fertilizer reductions did not increase significantly before crop returns became unrealistic (17% of farmers cover cropping with a 15% reduction in fertilizer and 10% reduction in corn returns). A less-established practice like cover cropping did not immediately produce increased adoption even with reduction in nutrient loads and concentrations. This behavior illustrates the persistent effect of BMP perceptions despite economic incentives (the counter effect of high perceptions despite economic disincentives as in the case of nutrient management).

5.2.5 BMP Cost Share Schemes

Varied cost share amounts for the three BMPs (Scenario 3) were tested to identify cost-effective policy changes. The purpose of varying cost share amount with each BMP scenario was to simulate the effects of governmental cost share programs on the BMP adoption rates, agricultural yields and returns, and environmental integrity over the watershed. Results showed that offsetting BMP costs for farmers steadily improved environmental outcomes, yields, and returns (Figures 5.18 – 5.22). Specifically, offsetting the cost of all BMPs entirely resulted in 10-fold increase in drainage management adoption (Table 5.9).

Table 5.6: Cost Share Results (Scenario 3)

Selected Cost Share Scenarios 2005-2012						
Cost Share	$X_{RCC} = 50\%, X_{NM} = 25\%, X_{DWM} = 25\%$		$X_{RCC} = 90\%, X_{NM} = 90\%, X_{DWM} = 90\%$		$X_{RCC} = 100\%, X_{NM} = 100\%, X_{DWM} = 100\%$	
Adoption Rate	12% RCC, 58% NM, 5% DWM		18% RCC, 75% NM, 12% DWM		18% RCC, 75% NM, 43% DWM	
	Change From No-BMP Baseline					
	Amount	%	Amount	%	Amount	%
Avg Annual N Load	-41991 kg	-7.51%	-58090 kg	-9.66%	-52598 kg	-8.2%
Avg Annual P Load	-685 kg	-4.2%	-1097 kg	-4.76%	-1158 kg	-5.4%
Avg Annual N Conc	-0.37 mg/L	-7.34%	-.5 mg/L	-9.59%	-0.47 mg/L	-8.61%
Avg Annual P Conc	-0.01 mg/L	-3%	-0.01 mg/L	-4.7%	-0.01 mg/L	-5%
Avg Annual Water Yield	-0.32 mm	-0.07%	-0.41 mm	-0.06%	+1.15 mm	+0.5%
Avg Annual Corn Yield	+1.59 bu/ac	+0.97%	+2.46 bu/ac	+1.50%	+2.56 bu/ac	+1.56 %
Avg Annual Soy Yield	Unch.	Unch.	Unch.	Unch.	Unch.	Unch.
Avg Annual Corn Return	-0.58 $/ac	-0.89%	+9.48 $/ac	+14.46%	+11.64 $/ac	+17.7 %
Avg Annual Soy Return	-3.22 $/ac	-6.66%	-0.79 $/ac	-1.64%	-0.26 $/ac	-0.54%
Avg Annual Cost Share	$257,980		$921,450		$1,022,200	

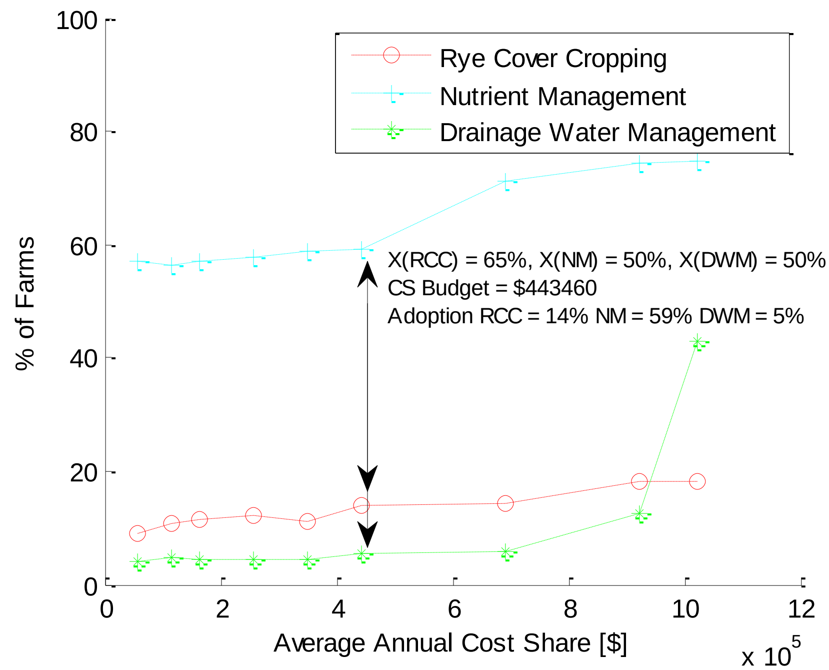

Figure 5.18: ITEEPGAM Adoption Rates for Cost Share Scenarios (Scenario 3)

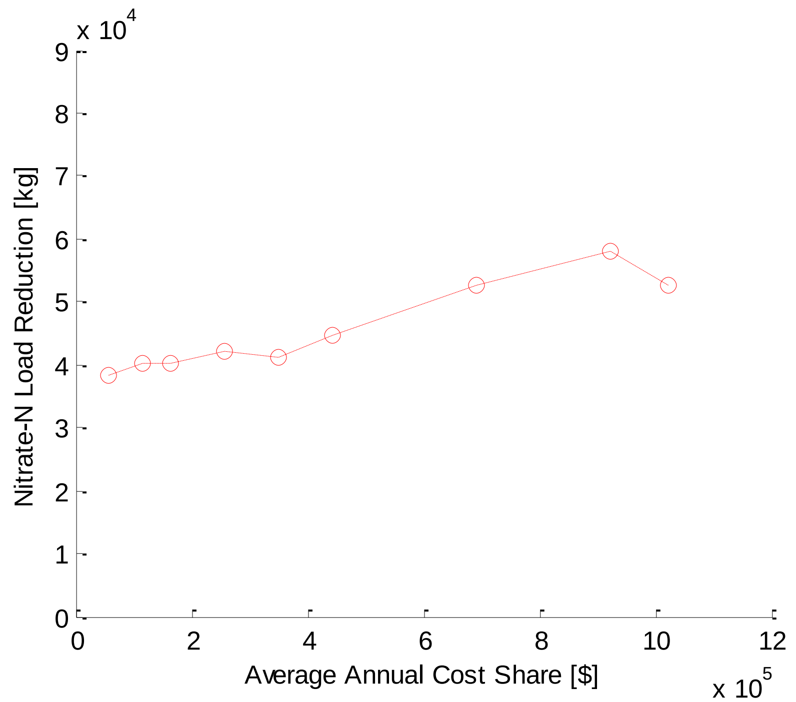

Figure 5.19: ITEEPGAM Nitrate-N load reduction for Cost Share Scenarios (Scenario 3)

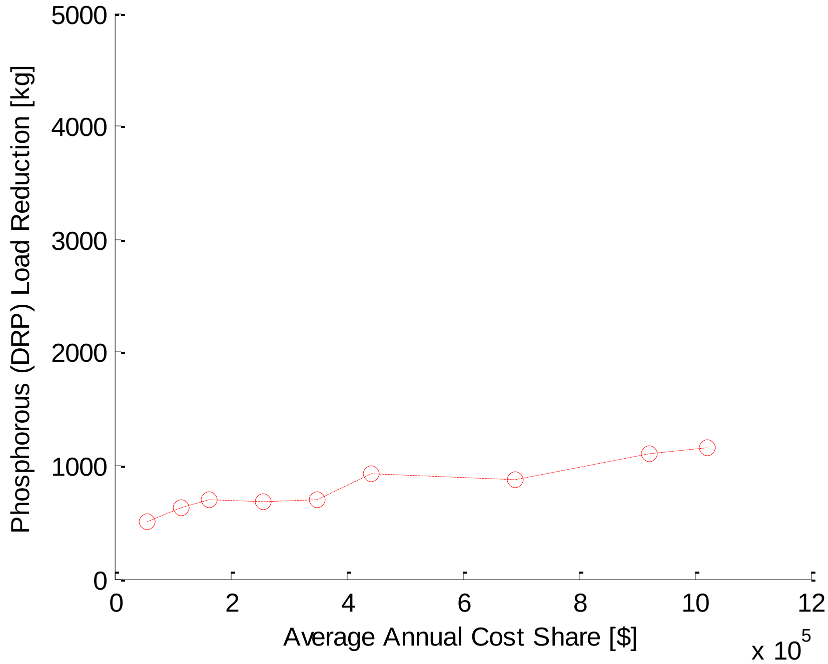

Figure 5.20: ITEEPGAM Phosphorous load reduction for Cost Share Scenarios (Scenario 3)

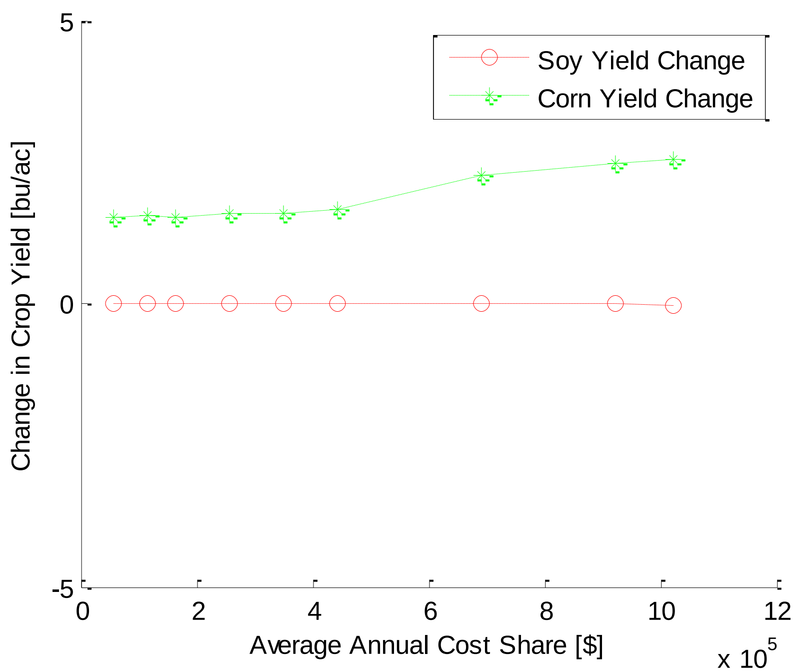

Figure 5.21: ITEEPGAM Change in Crop Yields for Cost Share Scenarios (Scenario 3)

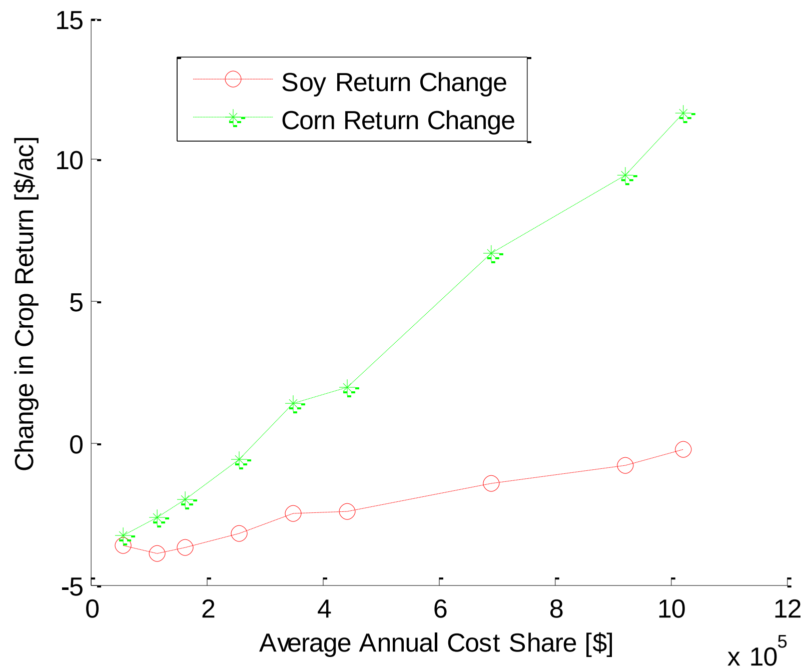

Figure 5.22: ITEEPGAM Change in Crop Returns for Cost Share Scenarios (Scenario 3)

5.2.5.1 Cost Share Discussion

Offsetting the cost of each BMP correlated with a slight increase in adoption up to a threshold (18% for RCC, 75% for NM, and 43% for DWM). Figure 5.18 shows that varying the cost share between 0% and 65% didn't increase adoption rates appreciably: NM, RCC, and DWM adoption rates increased by 3%, 2%, and 1% respectively. Adoption rates increased and plateaued at threshold rates with cost shares above 65%. In the case of completely offsetting the cost of all BMPs (100% cost share), while DWM adoption increased 10-fold. NM was already well-established (a majority of farmers), and potential adoption gains were already achieved with a 65% cost-share as Figure 5.18 shows. DWM presented farmers with a free (no expense to the farmer) perceived yield boost (2%) in the case of a complete cost-share and incentivized farmers to adopt up to the 43% threshold. Additionally, increasing DWM adoption up the threshold 43% increased water yields, higher crop yields, lowered nitrogen reductions, and increased phosphorous reductions. This would indicate that large-scale adoption of DWM (adoption schemes greater than 43%) may not lead to environmental gains. As described in Chapter 3, the SWAT implementation of DWM enforced one setup and static timing of water table management (fixed dates, fixed drain depth, irrespective of weather events) across the entire geographic region. Applying this homogenous DWM scheme to a watershed may not be appropriate.

5.2.6 Incentive Results

Varying incentives with respect to environmental outcomes (a threshold for nutrient concentrations, and subsidy amount provided for farmers beyond that threshold) were tested to identify cost-effective policy changes (Scenario 4). As Chapter 4 details, incentive schemes were enforced in tandem: simultaneously setting thresholds for nitrogen and phosphorous concentrations and then scaling up rates. The schedule of thresholds and rates was designed to simulate different potential sizes of government budgets and the effect on adoption rates, nutrient loads, and farmer revenues. Incentives were scaled for perceived effectiveness of a BMP and added to the revenue of an adopting farmer, as discussed in Chapter 4. Supplementing income for farmers always improved returns, but only increased adoption and environmental benefit before plateauing (Figures 5.23 – 5.27). RCC showed the most potential for adoption gains using incentive schemes.

Table 5.7: Incentive Results (Scenario 4)

Selected Incentive Scenarios 2005-2012						
Incentives	$N_{INC\ CONC} = 5\frac{mg}{l}$ $N_{INC\ RATE} = \$1500000$ $P_{INC\ CONC} = 0.025\frac{mg}{l}$ $P_{INC\ RATE} = \$15000000$		$N_{INC\ CONC} = 5\frac{mg}{l}$ $N_{INC\ RATE} = \$3000000$ $P_{INC\ CONC} = 0.025\frac{mg}{l}$ $P_{INC\ RATE} = \$30000000$		$N_{INC\ CONC} = 7\frac{mg}{l}$ $N_{INC\ RATE} = \$2000000$ $P_{INC\ CONC} = 0.075\frac{mg}{l}$ $P_{INC\ RATE} = \$20000000$	
Adoption Rate	45% RCC, 70% NM, 7% DWM		75% RCC, 75% NM, 18% DWM		29% RCC, 69% NM, 4% DWM	
	Change From No-BMP Baseline					
	Amount	%	Amount	%	Amount	%
Avg Annual N Load	-63400 kg	-10.25%	-75942 kg	-11.85%	-48468 kg	-8.93%
Avg Annual P Load	-3897.5 kg	-13.03%	-5542.5 kg	-22.2%	-1323 kg	-7.65%
Avg Annual N Conc	-0.49 mg/L	-9.46%	-0.56 mg/L	-10.7%	-0.42 mg/L	-8.48%
Avg Annual P Conc	-0.03 mg/L	-12.3%	-0.04 mg/L	-21.1%	-0.01 mg/L	-5%
Avg Annual Water Yield	-3.51 mm	-0.9%	-5.04 mm	-1.29%	-1.77 mm	-0.5%
Avg Annual Corn Yield	+1.76 bu/ac	+1.07%	+2.02 bu/ac	+1.24%	+1.60 bu/ac	+0.98%
Avg Annual Soy Yield	Unch.	Unch.	Unch.	Unch.	Unch.	Unch.
Avg Annual Corn Return	+6.08 $/ac	+9.27%	+24.55 $/ac	+37.43%	+0.51 $/ac	+0.77%
Avg Annual Soy Return	+3.87 $/ac	+8%	+22.8 $/ac	+47%	-1.36 $/ac	-2.82%
Avg Incentive Budget	$1,096,600		$3,051,300		$457,980	

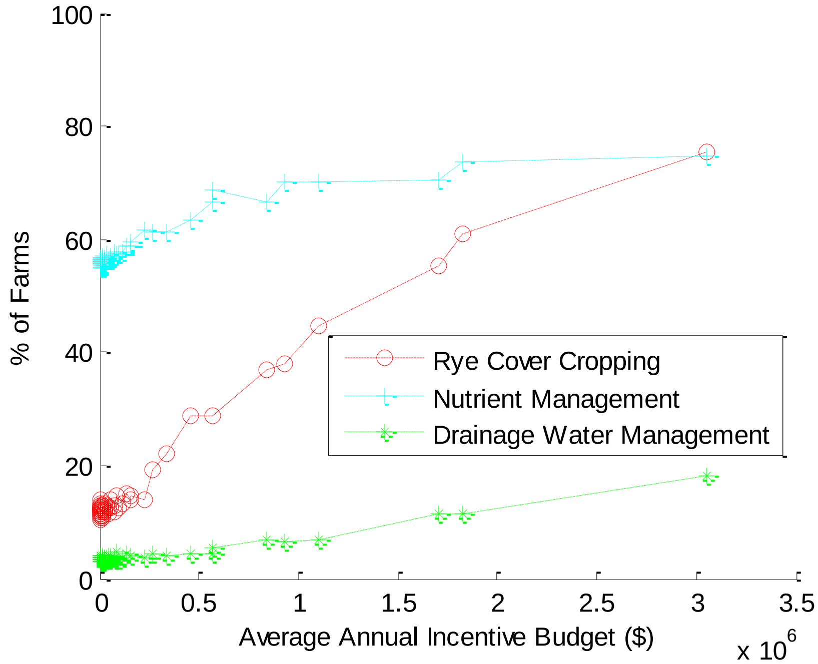

Figure 5.23: ITEEPGAM Adoption Rates for Incentive Scenarios (Scenario 4)

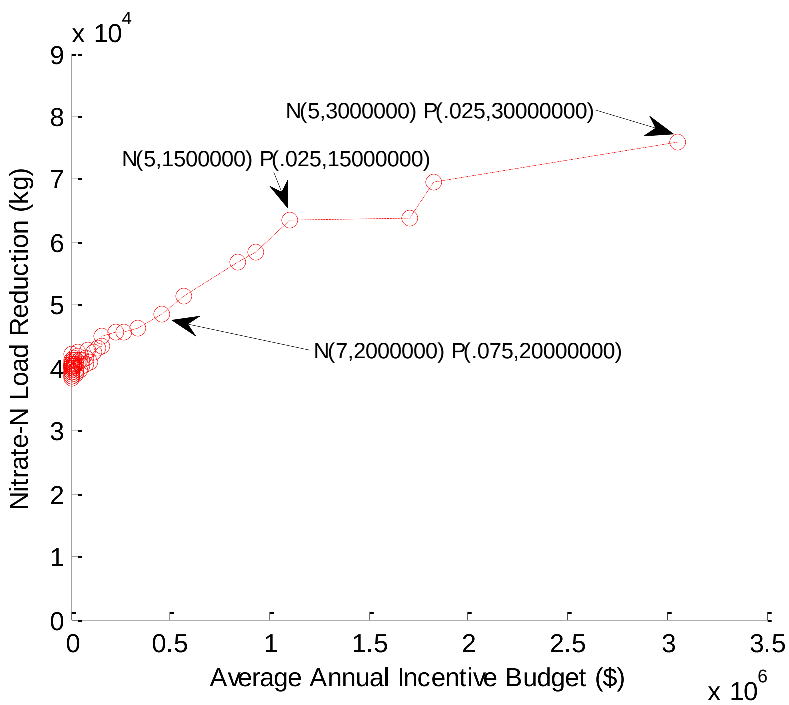

Figure 5.24: ITEEPGAM Nitrate-N Load Reduction for Incentive Scenarios (Scenario 4)

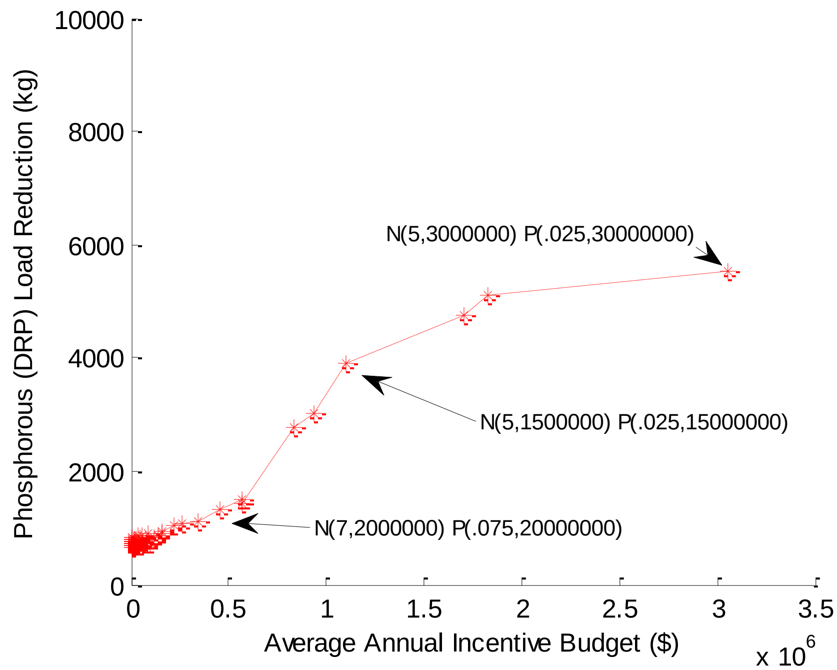

Figure 5.25: ITEEPGAM Phosphorous Load Reduction for Incentive Scenarios (Scenario 4)

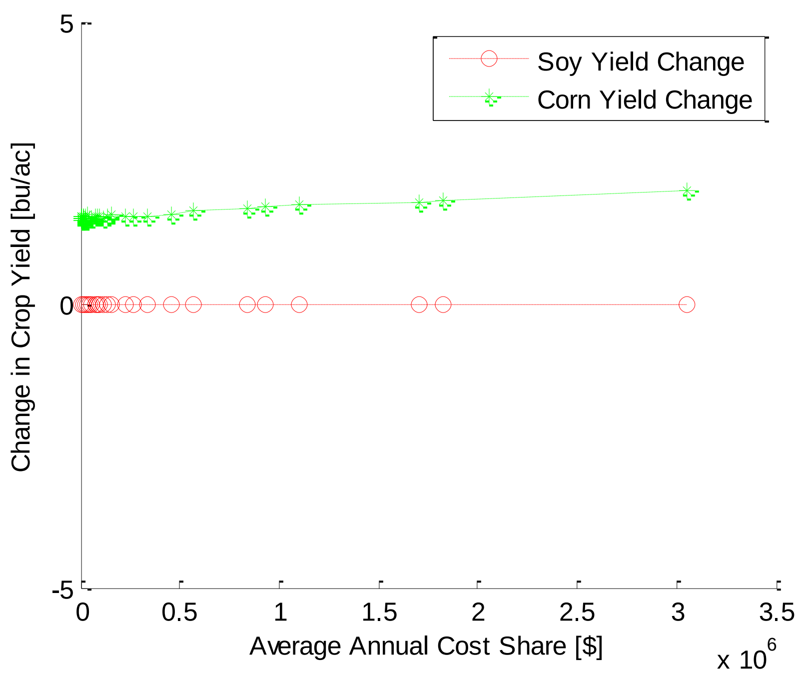

Figure 5.26: ITEEPGAM Change in Crop Yields for Incentive Scenarios (Scenario 4)

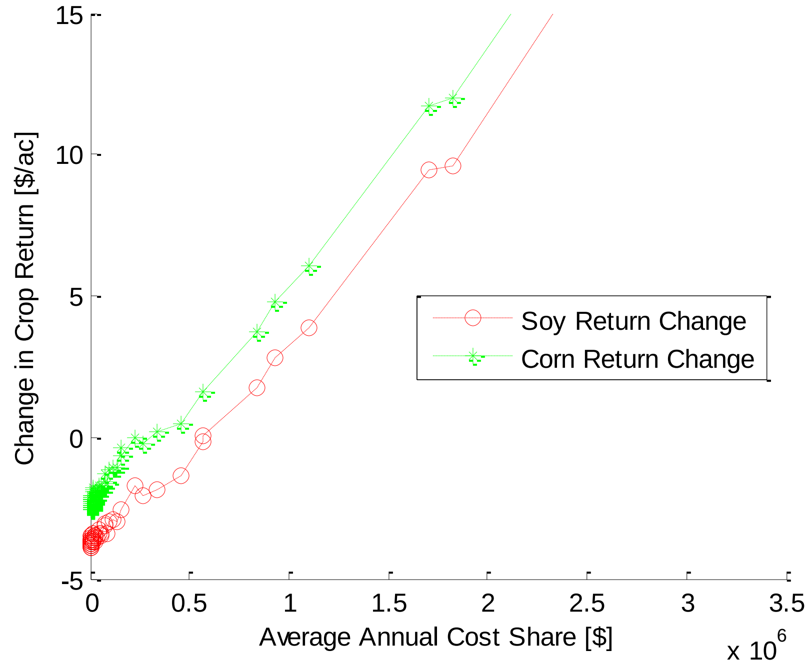

Figure 5.27: ITEEPGAM Change in Crop Returns for Incentive Scenarios (Scenario 4)

5.2.6.1 Incentive Results Discussion

Incentive schemes showed a steady improved yields, returns, and environmental gains In addition, the results identified practical thresholds and rates for implementing an incentive scheme. A $1,000,000 incentive budget increased farmer returns 10%, increased adoption rates (an additional 12% for NM, 32% for RCC, and 3% of famers for DWM), and increased nutrient reductions (an additional 3% for nitrogen, and 10% of loads for phosphorous). Figure 5.27 shows how incentive schemes uniformly increase farmer returns, while Figures 5.24 and 5.25 show how environmental gains plateau with payments above $1,000,000.

RCC adoption rates were affected most significantly with increasing incentive amounts. This contrasts with cost-share policy, where DWM saw the greatest gains. This result could be due to the fact that incentive schemes rewarded farmer agents based on the perceived effectiveness of installed BMPs, whereas cost-shares just offset the upfront cost. As detailed in Chapter 4, RCC was perceived to reduce nutrient loads more than DWM. In addition, farmers perceived a yield increase associated with DWM. The yield increase combined with a cost-share promoted DWM over RCC, while incentives promoted the greater perceived BMP effectiveness for RCC.

5.2.7 Tax Results

Varying tax levels with respect to environmental outcomes (a threshold for nutrient concentrations, and tax enforced for farmers beyond that threshold) were tested to identify cost-effective policy changes (Scenario 5). In the same fashion as incentives, as Chapter 4 detailed, tax schemes were enforced in tandem: simultaneously setting thresholds for nitrogen and phosphorous concentrations and then scaling up rates. A schedule of thresholds and rates was designed to simulate different potential tax amounts and their effect on environmental and economic performance. Taxes were applied in proportion to the size of a farmers land across the watershed. Farmers could reduce the mandatory tax, scaled by the perceived effectiveness of a BMP, by adopting BMPs as discussed in Chapter 4. Taxing farmers did result in environmental benefit up to a point ($500,000), but beyond that tax amount, adoption, and therefore environmental benefit, decreased (Figures 5.28 – 5.32). Crops returns were immediately adversely affected; even a small tax was not sufficiently offset by farmer economic gains (Table 5.8).

Table 5.8: Tax Results (Scenario 5)

Selected Tax Scenarios 2005-2012						
Incentives	$N_{TAX\ CONC} = 6\frac{mg}{l}$ $N_{TAX\ RATE} = \$250000$ $P_{TAX\ CONC} = 0.05\frac{mg}{l}$ $P_{TAX\ RATE} = \$2500000$		$N_{TAX\ CONC} = 9\frac{mg}{l}$ $N_{TAX\ RATE} = \$2000000$ $P_{TAX\ CONC} = 0.15\frac{mg}{l}$ $P_{TAX\ RATE} = \$20000000$		$N_{TAX\ CONC} = 9\frac{mg}{l}$ $N_{TAX\ RATE} = \$3000000$ $P_{TAX\ CONC} = 0.15\frac{mg}{l}$ $P_{TAX\ RATE} = \$30000000$	
Adoption Rate	35% RCC, 62% NM, 2% DWM		42% RCC, 58% NM, 3% DWM		36% RCC, 46% NM, 2% DWM	
	Change From No-BMP Baseline					
	Amount	%	Amount	%	Amount	%
Avg Annual N Load	-57375 kg	-8.82%	-57053 kg	-8.87%	-49384 kg	-7.27%
Avg Annual P Load	-2784.1 kg	-8.69%	-3136.8 kg	-8.13%	-2949.6 kg	-9.78%
Avg Annual N Conc	-0.44 mg/L	-8.27%	-0.43 mg/L	-8.3%	-0.37 mg/L	-6.69%
Avg Annual P Conc	-0.02 mg/L	-8.15%	-0.02 mg/L	-10.32%	-0.02 mg/L	-9.24%
Avg Annual Water Yield	-2.52 mm	-0.62%	-3.29 mm	-0.8%	-2.69 mm	-0.62%
Avg Annual Corn Yield	+1.92 bu/ac	+1.17%	+1.79 bu/ac	+1.09%	+1.69 bu/ac	+1.03%
Avg Annual Soy Yield	Unch.	Unch.	Unch.	Unch.	Unch.	Unch.
Avg Annual Corn Return	-11.74 $/ac	-17.89%	-14.02 $/ac	-21.37%	-15.3 $/ac	-23.4%
Avg Annual Soy Return	-11.72 $/ac	-24.23%	-12.3 $/ac	-25.42%	-14.78 $/ac	-30.55%
Avg Tax Budget	$429,610		$446,600		$760,360	

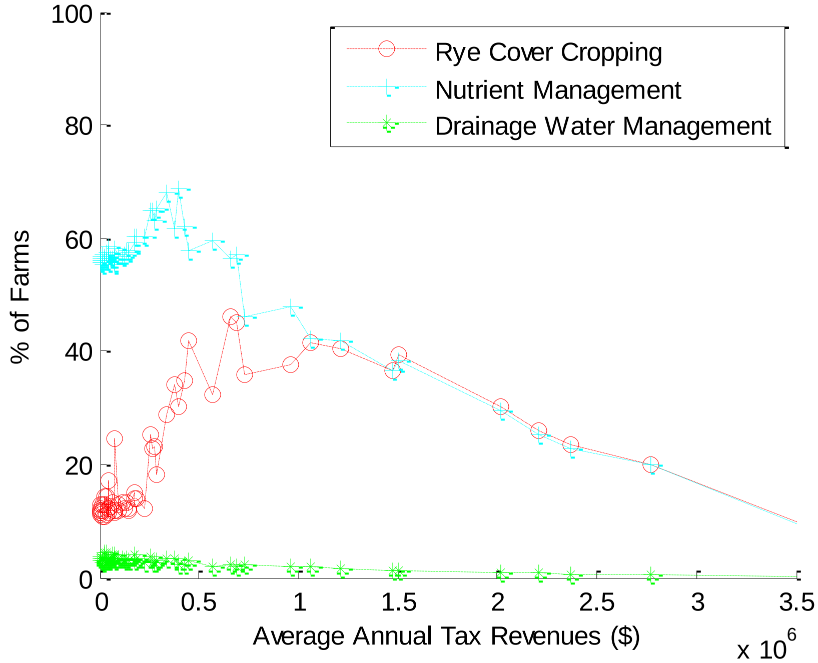

Figure 5.28: ITEEPGAM Adoption Rates for Tax Scenarios (Scenario 5)

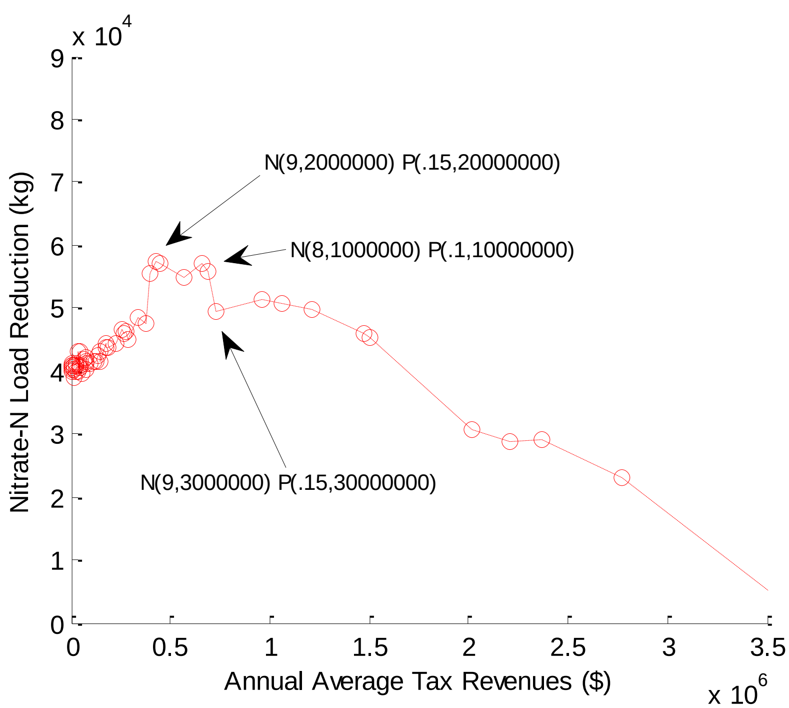

Figure 5.29: ITEEPGAM Nitrate-N Load Reduction for Tax Scenarios (Scenario 5)

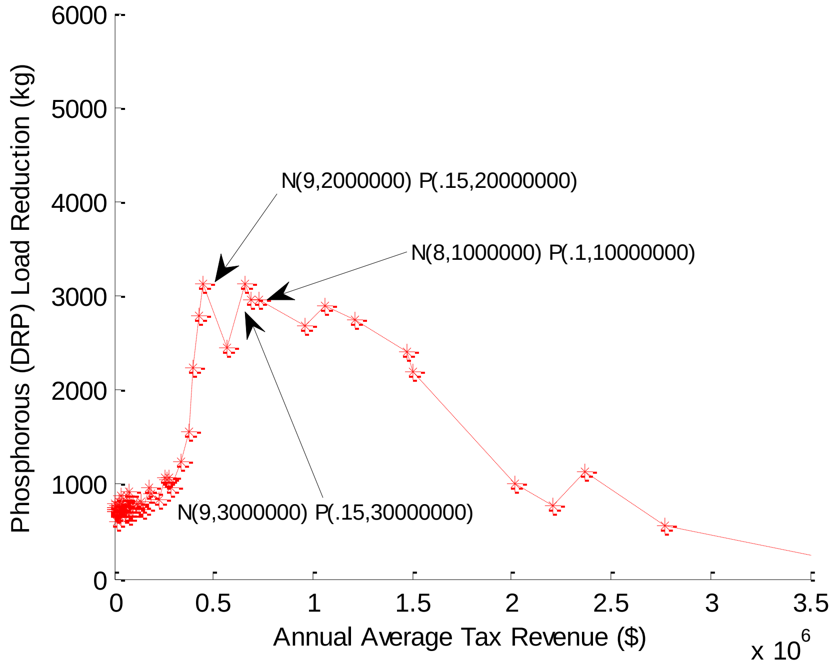

Figure 5.30: ITEEPGAM Phosphorous Load Reduction for Tax Scenarios (Scenario 5)

Figure 5.31: ITEEPGAM Change in Crop Yields for Tax Scenarios (Scenario 5)

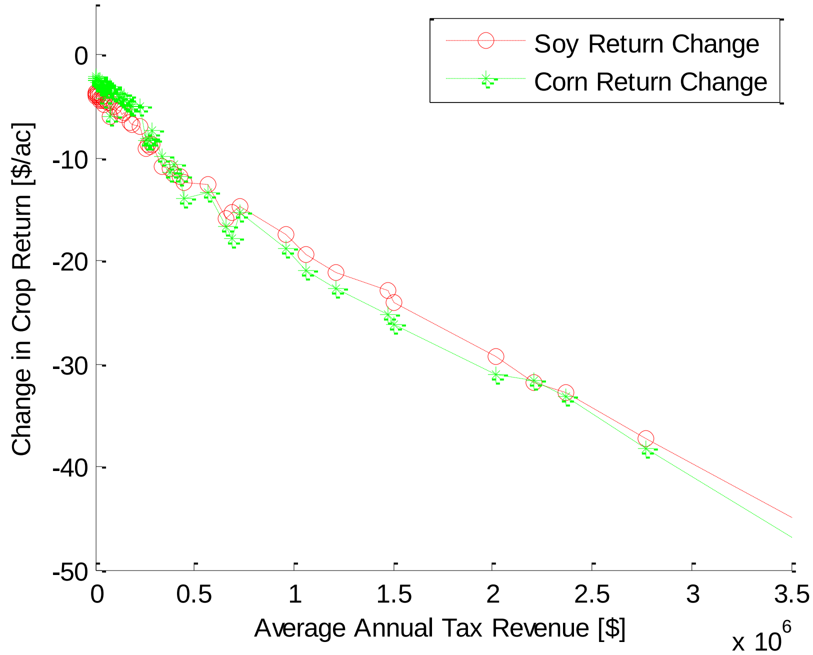

Figure 5.32: ITEEPGAM Change in Crop Returns for Tax Scenarios (Scenario 5)

5.2.7.1 Tax Results Discussion

Enforcing a mandatory tax did encourage adoption and improve environmental gains but only up to a threshold ($500,000), before becoming purely punitive without encouraging additional adoption. Further, tax schemes with revenues greater than $400,000 resulted in farmer economic losses greater than 10%, rendering them impractical. Greater establishment (NM) and more perceived effectiveness (RCC) in BMPs were more responsive to tax enforcement (additional 10% of farmers adopting NM, and an addition 30% of farmers adopting RCC). By linking tax burdens to effectiveness, as with incentives, taxes promoted RCC over other BMPs.

5.3 Results Summary

This chapter presented the results and discussion of a schedule of scenarios evaluated using ITEEPGAM to form conclusions about economic and environmental performance of BMPs and policy measures. A baseline scenario calibrated with observed BMP adoption was used to establish economic and environmental benchmarks. For the baseline, ITEEPGAM attributed 7.1% and 3.3% reduction in average annual nitrogen and phosphorous loads, and 3.6% and 7.8% reductions in corn and soybean returns for baseline adoption rates of 56%, 12%, and 4% of farmers for nutrient management, rye cover cropping and drainage water management, respectively. In addition, uniform fertilizer reductions and increases (without BMPs) were applied across the watershed study area and yields responded in a similar quadratic fashion but with a lower maximum yield than established in geographically similar studies (Hollinger & Angel, 2009; Hu et al., 2007). The results of the fertilizer scenarios were used to set farmer expectations for yield changes in scenarios coupling fertilizer reductions with BMPs.

Fertilizer reductions paired with nutrient management (switching application timing from fall to spring) resulted in crop yield losses with the smallest fertilizer reductions (2.5%). The yield losses became unsustainable after 5% fertilizer reductions (losses in returns exceeding 10%). The nutrient management results identified necessary future work in modeling to allow soybean farmers to consider fertilizer reductions (farmers were biased towards adopting reductions) and using purely yields (not returns) for economic decision-making. High adoption rates did show that nutrient management with fertilizer reductions did mitigate 1.5% of the yield loss predicted by the universal fertilizer reduction scenarios (all farms experiencing fertilizer reductions).

Fertilizer reductions paired with cover cropping were also assessed for economic and environmental tradeoffs. Yield reductions were less than 1% with fertilizer reductions up to 12.5%, while observed nutrient loads at the outlet were reduced by an additional 2%. While paired nutrient management was promoted despite results for crop yield losses, paired cover cropping was not adopted quickly despite economic and environmental performance. The initial perceptions of NM and RCC, with NM being well perceived, explain pairing results.

Tax and incentive schemes promoted adoption up to a point. Incentive schemes beyond a $1,000,000 budget merely supplemented farmer incomes beyond a 10% increase, while environmental gains plateaued. Tax schemes became purely punitive above a $400,000 budget, but did encourage adoption up to that threshold. Both incentive and tax schemes identified thresholds and rates that could be valuable information for policy makers when developing target budgets.

CHAPTER 6

CONCLUSION

6.1 Introduction

This study coupled a natural systems and a human systems model to form the Integrated Tool for Economic, Environmental, and Policy Goals in Agricultural Management (ITEEPGAM). ITEEPGAM was then applied to the Upper Salt Fork Watershed in East-Central Illinois to identify cost-effective and environmentally beneficial best management practices and community policies. ITEEPGAM successfully modeled environmental outcomes (nitrogen loads, phosphorous loads, and crop yield), economic metrics (farm revenues), and BMP adoption rates with utilizing available sources from government agencies (USDA-NASS, 2012; USGS, 2012), extension resources for the study area (Upper Salt Fork Project Report and Status Update, 2011; Hollinger & Angel, 2009; Urbana-Champaign Sanitary District & UIUC-NRES, 2013), previous field studies (Gentry et al., 2007; Gentry et al., 2009) and simulation studies (Bekele et al., 2011; Hu et al., 2007; Ng et al., 2010). The model was calibrated for observed adoption rates for the three BMPs considered in the study (nutrient management, rye cover cropping and drainage water management) and for behavioral characteristics of area farmers (environmental, economic, and social). The baseline calibrated model for observed adoption rates model results attributed a 7% reduction in nutrient loads, a 1.5% increase in corn yields, at $3 / acre cost to the BMPs at their observed adoption rates in the watershed. The results for the observed adoption rates served as a baseline to perform an analysis of several scenarios. The scenarios were designed to compare changes in the best management practices paired with fertilizer amounts, cost share levels, incentive payments, and taxes. This chapter summarizes the results and discusses the implications of the study for modeling of coupled systems and agricultural management.

6.2 Summary

Pairing nutrient management (switching application timing from fall to spring) with fertilizer reductions mitigated simulated nutrient loads at the outlet, but at too burdensome an economic cost. For a 5% reduction in fertilizer paired with nutrient management, adoption rates remained unchanged (58%), nitrogen loads decreased by an additional 3.4% of totals, but at a cost of $7 / acre. Nutrient management adoption rates increased with large fertilizer reductions despite the economic losses. The increasing adoption rates were deemed impractical as farmer absorbed the losses in order to adopt. Increasing adoption rates were also a consequence of some of the decisions made in model development. Soybean farmers adopted by reducing their phosphorous fertilizer (MAP) in the nutrient management scenarios and did not observe a yield reduction, which led to larger adoption rates. In addition, model development included an initial perception for farmers of each BMP. Nutrient management was calibrated to be well-established (56%) in the watershed as described in survey results (Upper Salt Fork Project Report and Status Update, 2011). Consequently, farmers were initialized to have a positive opinion of the practice, which persisted beyond large economic disincentives (more than 10% reduction in revenues).

An analysis of rye cover cropping coupled with fertilizer reductions identified potential environmental gains while the mitigating economic losses associated with fertilizer reductions. The simulations showed that farmers were amenable to a fertilizer reductions of 10% coupled with cover cropping. An additional 4% of farmers adopted, nutrient load reductions improved by an additional 1.5% of totals, with an average yield loss of 1% and a corn revenue decrease of $2 / acre.

Scenarios were also tested to identify potential community policy strategies and their effect on adoption, environmental gains, and economic outcomes. Cost shares -- off-setting of BMP costs by the community -- showed that the community must offset more than 50% of the cost to see an increase in adoption, and completely offsetting BMP costs by not be appropriate as farmer incomes continue to rise without an environmental benefit. Increasing cost shares increased adoption by promoting the least expensive available BMP, with a 10-fold increase in adoption for drainage water management (DWM). Further, increasing cost share amounts beyond 90% did not improve environmental outcomes because BMP installations were not effective when more installations were generically adopted across the watershed area. In addition, completely off-setting BMP costs also indicated that a percentage of farmers were not open to adoption regardless of economic incentives. Even with cost-free management options, owners perceived that their environmental goals had been met and additional adoption did not occur.

Simulating incentive and tax policy identified potential nutrient thresholds, rates, and budgets and their effect on adoption, environmental benefit, and farmer revenues. An incentive payment rate of $1,500,000 per mg/L above 5 mg/L for nitrogen loads and $15,000,000 per mg/L above 0.025 mg/L for phosphorous loads could add an additional 34%, 14%, and 3% of farmers adopting RCC, NM, and DWM respectively. This incentive scheme resulted in an average annual $1,000,000 payment to farmers, and prevented an additional 3% of nitrogen and 7% of phosphorous totals at the outlet, and increased returns by $9 an acre for corn farmers and $6 an acre for soybean farmers. Incentive payments beyond $1,000,000 saw diminishing environmental returns and unnecessarily supplemented farmer returns.

Simulating tax budgets identified an efficient average annual budget of $400,000, which could be implemented with nitrogen tax rate of $250,000 per mg/L above threshold of 6 mg/L and a phosphorous tax rate of $2,500,000 per mg/L above threshold of 0.05 mg/L (alternatively, $2,000,000 per mg/L and 9 mg/L for nitrogen and $20,000,000 per mg/L and 0.15 mg/L for phosphorous). Tax schemes immediately resulted in farmer losses, and beyond an annual tax budget of $400,000 were purely punitive and discouraged adoption because farming became uneconomical. The results showed that tax schemes could deliver an additional nitrogen load reduction of 2% and phosphorous load reduction of 5% at a cost of $8 an acre.

6.3 Implications

The results lead to important conclusions about modeling and forecasting outcomes of agricultural management. Most significantly, natural systems and human systems phenomenon can be satisfactorily modeled and analyzed for potentially greater environmental and economic gains. Natural systems outcomes in this study -- nitrogen, phosphorous, flow, and crop yields -- were all modeled satisfactorily using SWAT with respect to accuracy benchmarks established in previous studies (Hu et al., 2007; Moriasi et al., 2012; Ng et al., 2010). Human systems outcomes in this study -- farming revenues, adoption rates, and farmer profiles -- were modeled successfully with respect to empirical results from extension resources and previous studies (UIUC-ACES, 2003-2012).

Several implications for agricultural management could be drawn from the results. The study identified rye cover cropping coupled with small fertilizer reductions with the greatest potential for preserving economic performance and improving environmental gains while maintaining adoption rates. BMP incentives presented the most cost-effective return for designing community policy, but were not suitable to increase beyond $1,000,000 as incentives could supplement farmer returns without environmental benefit. This was a result of extending nutrient management and drainage water management uniformly across the watershed did not categorically lead to environmental gains. In the case of nutrient management paired with fertilization reductions, it could only offset very small fertilizer reductions and was therefore not economical. Cost shares were effective at increasing adoption, but only to a threshold of adopters. Finally, small tax schemes could promote adoption and generate revenue for communities.

While the coupled model (ITEEPGAM) results relating environmental outcomes to farmer economic performance posed hypotheticals, and were unique to the group of BMPs and the Upper Salt Fork River watershed in Illinois, they could be assessed in the context of other studies. The results show that potential for BMP adoption and environmental gains were lower for this study than other coupled BMP studies discussed in Chapter 2. Optimal placement of filter strips, grassed waterways, and constructed wetlands in the Mackinaw River watershed in Illinois using SWAT resulted in nitrogen and phosphorous load reductions of 25 to 35% with expenditures of $75,000 (Bekele et al., 2011). However, the analysis only considered the economic tradeoffs in placing BMPs. In the Silver Creek watershed in Southern Illinois, the optimal placement of detention ponds, filter strips, stabilization structures, terraces, and grassed waterways to reduce nitrogen and phosphorous loadings by 20% cost $1,000,000 (Kaini et al., 2012). The lower potential for environmental gains (8%-10% reductions in nitrogen and phosphorous) in this study reflected the smaller set of BMPs considered, an incorporation of an agent-based model as opposed to an optimization analysis. The USDA-CEAP report identified that targeting critical locations for BMP installation as the most effective way for improving environmental gains (USDA - NRCS, 2011). But watersheds cannot be simply papered over with BMP installations. Farmers in this study were adapting to their unique profile and priorities, and not according to economic optimal strategies.

Integrating farmer profiles in this study did not optimize the layout of BMP installations, but addressed significant factors with how farmers adopt. An analysis must also address societal, economic motivations of stakeholders to assess the adoption and effectiveness of conservation (Nowak & Korsching, 1998). The lower potential for gains highlights the need to incorporate of diverse farmers, their motivations, and values. This study showed that these values could drive farmer decision-making, even when presented with economic incentive or disincentive. Ng et al. (2011) identified the importance farmer profiles in forecasting adopting carbon trading, miscanthus planting, and conservation tillage in the Salt Creek watershed in Illinois. Adoption rates ranged from 0% to 40% for miscanthus planting depending on the sociability, time horizon, and risk-aversion of farmers.

Ng et al. (2011) also discussed the lack of empirical results to verify such hypothetical farmer profiles and resultant adoption rates. Similarly, this study's scenario analysis could not be verified with observed results. In addition, the availability and resolution of empirical observations in developing farmer profiles could have led to greater insights in behavior. This study incorporated survey results from a single available year to calibrate adoption rates. How and when adoption rates changed through time would have led to more robust results. Further, geographic and hydrological boundaries were used to define farmer land parcels when does not accurately represent human land ownership. Additional considerations regarding information about human decision-making must recognize that some information is not public, is proprietary and may not be verifiable. For instance, this study generically calibrated farmer revenues, while not focusing on the returns of an individual farmer, as that information was proprietary to a farm operation. Even management decisions like when soybeans were planted, and when DWM was performed and water table height were uniformly implemented across the area. Yet optimal

DWM spacing, depth, and timing varies spatially with topography and soil and temporally with weather events and soil moisture (Luo et al., 2010). These management decisions were uniformly simulated across farmer agents, years, and weather event events. Further, precise DWM operations would have been proprietary to an individual farmer in practice. A similar resolution and availability of management information affected the modeling practicality. Nutrient management measures were defined as switching application timing from a month after harvest to two weeks prior to planting. Again the practice was applied uniformly across adopters, years, and weather events. Randall et al. (2005) illustrated how switching from fall to spring can lead to lead yield variability in loads and yields with climatic variation. For this study, precise fertilizer timing and application amounts in the watershed would have been proprietary and had to be generalized for modeling purposes.

The results also identified several scenario that fell into the modeling adage of "garbage in, garbage out". In this study, it was evident that enforcing fertilizer reductions beyond 15% was impractical for farmers. This study identified levels where farmers' economic returns became untenable. Beyond that level, this study's model design facilitated increasing adoption. The economic logic of farmers could be modified, but, more significantly, it questions whether universal fertilizer reductions are acceptable options in agricultural management. A farmer would not jeopardize their business to adopt a management option.

Beyond modeling considerations, empirical information needs and availability, and conclusions about effective agricultural management, the study quantified the cost and performance of potential community strategies in agricultural management. Developing ways to model farmer economic performance, environmental gains with respect to community budgets could useful for policy makers. The model could serve as a tool in the debate over funding programs and initiatives. Of particular importance is realistic estimates of environmental gains for a quantifiable investment.

CHAPTER 7

FUTURE WORK

7.1 Introduction

This paper presented the formulation and application of a coupled human and natural systems model: the Integrated Tool for Economic, Environmental and Policy Goals in Agricultural Management (ITEEPGAM). ITEEPGAM was applied to the Upper Salt Fork Watershed in East-Central Illinois to identify strategies in agricultural management and policy that promoted economic and environmental gains. The study incorporated publicly available topography (Illinois Natural Resources Geospatial Data Clearinghouse, 2012), climatic (Illinois State Water Survey, 2012), land cover (USGS, 2012), sewage treatment loading (Environmental Protection Agency, 2012), and typical agricultural management (Hollinger & Angel, 2009) information to model observed adoption rates for three best management practices (BMPs) (winter cover cropping, nutrient management, and drainage water management) (Upper Salt Fork Project Report and Status Update, 2011), nutrient loadings (nitrogen and phosphorous) (UCSD & UIUC-NRES Biochemistry Group, 2013), crop yields (USDA-NASS, 2012), and farmer revenues (UIUC-ACES, 2012). ITEEPGAM was then tested with a schedule of scenarios to assess the performance of paired fertilizer reduction and BMPs, tax, incentive, and cost share schemes. The results of the scenario analysis identified levels of fertilizer reductions that BMPs might supplement without an effect on yields, along with thresholds for effective cost shares, incentives, and taxes. This section explores the considerations for future development of ITEEPGAM planned and potential areas to expand its capabilities. These areas and capabilities include: expanding the geographic region and types of land-use, incorporating greater stakeholder diversity and profiles of agent behavior, facilitating flexible management strategies, delineating accurate farm boundaries and cropping patterns, adopting the model for changes in source information resolution and availability, extending the simulation time period, expanding the geographic region and types of land-use, facilitating variable management implementations among farmers, building a portable and versatile version of the tool for public use, facilitating weather/climatic scenario testing, and adjusting the model for contemporary government and community decision-making with respect to agricultural production. This chapter discusses each area in sections.

7.2 Future work

This explores ways to expand the capabilities of ITEEPGAM and issues to consider in applying the tool to future study areas.

7.2.1 Expanding the Study Area

This study targeted a 328 km^2 agricultural watershed in East-Central Illinois. The area of the watershed was determined by the automatic hydrologic delineation routine in SWAT (Srinivasan, 2009). The study area served the purposes of this study, however, in future applications, ITEEPGAM will be applied to watersheds in different and larger geographies that will span cities, states, government jurisdictions, and diverse land-uses. The eventual goal is to utilize ITEEPGAM to model the Hypoxia in the Gulf of Mexico for the entire Mississippi River Basin. ITEEPGAM is only a small piece in that larger puzzle right now. This pie-in-the-sky goal is a formidable undertaking that will take decades and many man hours, but is not without precedent. The USDA assessment of the CEAP (Conservation Effectiveness Assessment Program) in the Upper Mississippi River Basin modeled nutrient loads with respect to management for the 81 million acres and 278,687 farms in the region (USDA-NRCS, 2012).

Applying ITEEPGAM to larger and more diverse watersheds will require expanding the natural-systems and human-systems model to account for the variety of land-use, management, industries, economies, and community institutions impacting water quality in the Gulf of Mexico.

7.2.2 Larger Set of Farmers and Stakeholders

Applying ITEEPGAM to different watersheds will entail more diversity in agricultural producers, management, and institutions. ITEEPGAM was developed for corn and soybean farmers, and a hypothetical 'community' institution. Different watersheds and larger areas will require adopting ITEEPGAM for additional farmer profiles and stakeholders. For example, the UVa Bay Game, an agent-based model simulation to explore strategies to improve water quality in the Chesapeake Bay included the watermen, real estate developers, livestock and crop farmers, and congressional policy makers as agents (Learmonth et al., 2011). Similarly, future applications of ITEEPGAM in the Mississippi River Basin will require identifying stakeholders ranging from suburban Chicago homeowners to Mississippi River longshoremen, and developing agents, parameterizing their behavior profiles, and implementing logic for integration in to ITEEPGAM.

7.2.3 More Comprehensive Set of BMPs

This study assessed the effect of three BMPs (nutrient management, winter cover cropping, and drainage water management) in the Upper Salt Fork Watershed. These three BMPs were selected based on management choices confronting a typical corn and soybean farmer in the study area (Upper Salt Fork Project Report and Status Update, 2011), UIUC extension resources for these practices (Cooke, 2011; Hollinger & Angel, 2009), and constraints of the natural systems model (SWAT) (Neitsch et al., 2009) used in developing ITEEPGAM. The set of three

BMPs was not a comprehensive list of available management strategies for area farmers. The survey of farmers (Upper Salt Fork Project Report and Status Update, 2011) used to calibrate adoption rates in this study found that farmers in the study area were adopting a variety of other BMPs: grassed waterways, filter strips, saturated lateral riparian buffers, precision application technologies, field terraces, wetland restoration, land retirement, and bioreactors. Adding functionality to model additional BMPs into ITEEPGAM will give a more comprehensive of assess of management in this study area, but also improve ITEEPGAM's robustness in applications to varied watersheds in geography and management (Sections 7.2.1 and 7.2.2). This study included preliminary attempts have been made to include saturated lateral riparian buffers and biofilters into ITEEPGAM as documented in Appendix A. Future development of ITEEPGAM to include these management options will need to be built or utilize functionality in the natural systems component, SWAT. Appendix A documents some of the limitations in modeling feasible BMPs for area farmers with SWAT in this analysis. SWAT treats wetland and filter strip processes as 'overland' processes, which are not subject to tile drainage routines (Neitsch, 2009). In this study, 80% of total water yield was modeled as tile-drained. In order to model saturated lateral buffers, wetlands, and bioreactors accurately, the SWAT tile-drained component must be routed through the BMP routine within SWAT. Customizing SWAT routines may be part of ITEEPGAM's future development, or included in future official releases of SWAT.

7.2.4 Dynamic Farm Management

This study modeled the logistics of agricultural management (planting date, harvest date, fertilizer application dates) statically along with the implementation of BMPs (drainage system design, table management operations, planting dates, fertilizer timings). In practice, farmers manage their operations dynamically and make adjustments in real-time. While this study highlighted that the precise date and technique used in operation may be proprietary, not available, or observed, ITEEPGAM will be expanded to include time windows over which farmers may perform operations and include some logic with respect to weather events. In addition, the 2012 crop year exposed the need to account for catastrophic weather events and disaster planning to accurately forecast farmer yields. ITEEPGAM was not developed to account for farmers forgoing planting or deserting fields as happens in extreme drought and flooding. These implications were evident the context of agricultural decision-making this study, and will become more relevant with the inclusion of diverse stakeholders in larger areas and their responses to rare events like natural disasters.

7.2.5 Accurate Farm and Crop Areas

The delineation of the watershed was performed with respect to the hydrologic properties of the watershed as outlined in the ArcSWAT manual (Srinivasan, 2009). The delineation procedure produced Hydrologic Response Units (HRUs) to partition the watershed into like areas for inputting management options using SWAT configuration files as detailed in Chapter 3. The HRU partitioning was used to parcel land to farmer agents in this study. In reality, farm boundaries cut across soil types, elevation changes, and hydrologic regions. Future applications of ITEEPGAM will need to include functionality that can assign land parcels to agents realistically. Those land parcels could also be considered in characterizing agent behavior, i.e. knowledge of existing BMPs for that specific land parcel, or public domain tax and ownership information. Further, ITEEPGAM was calibrated using cropping patterns that were assigned on a percentage of farmers planting, not using accurate locations of crop decisions within the watershed. Including realistic land parcels and an accurate accounting of planting decisions made on the parcel will lead to a more comprehensive representation of farmers.

7.2.6 Updating Model Input Data

This study also commented on the availability of information, resolution, and its influence on modeling objectives. ITEEPGAM will be updated for additional information and improvements in resolution as it becomes available. Resolution and availability of information may change over time. For example, the USGS announced the discontinuation of 375 stream gages recording surface water information as a request of federal legislation mandating budget cuts in 2012 (USGS, 2013) (available at http://streamstatsags.cr.usgs.gov/ThreatenedGages/ThreatenedGages.html). The streamflow gauge used in this study will not be affected, but the environmental observations used to calibrate and assess the performance of the model is subject to change and will need to be updated. In addition, the model's predictive power will be assessed each year for the metrics discussed through the study: nutrient loads, yields, returns, adoption rates. Of particular importance for this study was adoption rates. The study took one isolated observed point from a survey of BMP adoption in the study area. It will be insightful to test the model's power in predicting adoption rates over time as more survey results becomes available.

7.2.7 Length and Interval of Simulation

This study assessed the average response of yields, adoption rates, and nutrient loads over an 8 year period.   Future applications will assess longer term performance of the model over decades with weather simulations. In addition, the resolution of model will be focused on individual years to explore the effect of past weather events on model performance.

7.2.8 Adopting ITEEPGAM For Public Use

All required sources and SWAT are freely available over the internet. The code for ITEEPGAM and supporting files are available on a UIUC server with proper credentials through the ABE department and Dr. Luis Rodriguez at: "https://bfp-ebi.age.uiuc.edu/svn/Projects/ITEEPGAM/". A single scenario with customizable inputs in the user interface can be run by invoking MainGUI.m. The schedule of scenarios performed in this project can be run by invoking MainScenarios.m. Output from MainScenarios.m is saved to the CSVOutput folder (output specific to this project is located in CSVOutput) and can be tabulated for display by invoking RunCompiler.m. Running these files requires a license of Matlab; this study utilized an academic license of Matlab. Matlab must be purchased from Mathworks in order to run ITEEPGAM. Future implementations of ITEEPGAM will be developed using freely available software or programs for public use.

7.2.9 Incorporating Contemporary Impacts and Issues

As a natural and human systems model, future work with ITEEPGAM will focus on improving the robustness and accuracy of its modeling capabilities. To sufficiently model more diverse, larger, and varied watersheds for economic and environment goals in the future, ITEEPGAM will be need to be updated for relevant changes the behavior of stakeholders and land management issues. In the context of this study, three issues that were abstracted in the formulation of the ITEEPGAM that will be updated in the future included: the advent of agricultural technology, changing farmer revenues, costs, and marketing, and government policy.

ITEEPGAM, via relying on the natural-systems model, SWAT, did not account for long-term changes in farm yields. UIUC extension reports that corn and soybean yields exhibited linear trend increases since 1960s due to good weather, improving management, and the advent of new technologies (Tannua et al., 2008). Whereas in ITEEPGAM, there was no difference in technology or method of planting and harvesting between years. For example, inputting the same weather observations and simply changing the years to 1975-1982 would produce the same yields for the simulation period 2005-2012. Future versions of ITEEPGAM will need to address agricultural technologies, changes in the efficiency of management and their effect on yields. Similar potential solutions for BMP modeling needs, future versions of SWAT may address these issues.

In addition, ITEEPGAM abstracted the economics of typical corn and soybean farmers in Central Illinois according to UIUC FarmDoc (UIUC-ACES, 2012) averages and did not account for differences in marketing strategies. In practice, every farmer had a unique set of costs and received different prices for their grain through varied marketing strategies. Further, ITEEPGAM did not itemize labor, power, rent, and insurance costs, which fluctuate over time. Future applications of ITEEPGAM will focus on improving the accuracy, resolution, and progression over time of observations used to develop agent profiles.

ITEEPGAM implementation of a 'community' agent also abstracted the role and identity of government and societal institutions that impact agricultural production and stakeholder behavior. The abstraction will be expanded upon in future applications of ITEEPGAM to account for specific watersheds and more diversity in relevant institutions. In addition, specifics of laws, regulations, and programs impacting stakeholders like farmers will be explored, particularly as they evolve over time. For example, one abstraction used in ITEEPGAM was average UIUC-FarmDoc crop insurance payments for Central Illinois farmers (UIUC-ACES, 2012). The level of these payments are determined by the U.S. Farm Bill every five years. The debate over the 2012 version of the bill illustrates the considerations for future ITEEPGAM applications. The debate included efforts to curb federal spending in the form of these payments, and government aid for a profitable industry was drawing bipartisan criticism (Crop Insurers' $14 Billion Some See as Money Laundering, 2013). A scheduled 2012 Farm Bill was not passed in the year of 2012 and the 2008 version was extended (Taxpayers Turn U.S. Farmers Into Fat Cats With Subsidies, 2013). ITEEPGAM could be used in the future to simulate practical policy outcomes like the differences between the two legislative outcomes for a U.S. Federal Government agent, as opposed the 'community' agent abstraction.

Finally, ITEEPGAM will be used for simulating climate change with respect to environmental and economic performance of land management. The Intergovernmental Panel on Climate Change (IPCC) estimates worldwide impacts of climate change and has developed weather models to forecast temperature, precipitation, and variability over time for different levels of carbon emissions (Parry et al., 2007). Various climate scenarios will be analyzed using ITEEPGAM.

7.3 Conclusion

Future work based on this study and the development of ITEEPGAM will focus on improving model robustness, applying the analysis to larger and more diverse areas, and integrating more realistic representations of agents and their behavior. A major area of development will be extending ITEEPGAM to perform forecasting and account for changes in complex systems over time.

REFERENCES

Abbaspour, K. C., Johnson, A., & Van Genuchten, M. T. (2004). Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure. Vadose Zone Journal, 3(4), 1340-1352.

Aero-Metric. (2008). LIDAR airborne GPS/IMU and ground checkpoint survey report for U.S. Army Corps of Engineers St Louis district: Champaign, Grundy, Kane, and McHenry counties, Illinois No. Aero-Metric Project No. 1-080208). Wisconsin: Aero-Metric.

Agricultural Systems Research Unit. (2009). RZWQM - root zone water quality model. Fort Collins, CO: USDA-ARS.

Ale, S., Bowling, L. C., Brouder, S. M., Frankenberger, J. R., & Youssef, M. A. (2009). Simulated effect of drainage water management operational strategy on hydrology and crop yield for drummer soil in the midwestern United States. Agricultural Water Management, 96(4), 653-665.

Alexander, R. B., Smith, R. A., Schwarz, G. E., Boyer, E. W., Nolan, J. V., & Brakebill, J. W. (2008). Differences in phosphorus and nitrogen delivery to the Gulf of Mexico from the Mississippi River basin. Environmental Science & Technology, 42(3), 822-830.

Arabi, M., Frankenberger, J. R., Engel, B. A., & Arnold, J. G. (2008). Representation of agricultural conservation practices with SWAT. Hydrological Processes, 22(16), 3042-3055.

Arnold, J. G. (1996). Estimating hydrologic budgets for three Illinois watersheds. Journal of Hydrology, 176(1-4), 57.

Baker, J. L., David, M. B., Lemke, D. W., & Jaynes, D. B. (2008). Understanding nutrient fate and transport, including the importance of hydrology in determining field losses, and potential implications for management systems to reduce those losses. Upper Mississippi River Subbasin Hypoxia Nutrient Committee Final Report: Gulf Hypoxia and Local Water Quality Concerns Workshop, American Society of Agricultural and Biological Engineers, St. Joseph, MI. pp. 1-17.

Baker, J. L., & Johnson, H. P. (1981). Nitrate-nitrogen in tile drainage as affected by fertilization. Journal of Environmental Quality, 10, 519-522.

Bakhsh, A., Kanwar, R. S., Jaynes, D. B., Colvin, T. S., & Ahuja, L. R. (2001). Simulating effects of variable nitrogen application rates on corn yields and NO3-N losses in subsurface drain water. Transactions of the ASAE, 44(2), 269-276.

Bekele, E. G., Lian, Y., & Demissie, M. (February 2011). Development and application of coupled-optimization-watershed models for selection and placement of best management practices in the Mackinaw River watershed. Illinois State Water Survey, Institute of Natural

Resource Sustainability, University of Illinois at Urbana-Champaign: The Nature Conservancy.

Berger, T. (2001). Agent-based spatial models applied to agriculture: A simulation tool for technology diffusion resource use changes and policy analysis. Agricultural Economics, 25, 245-260.

Bicknell, B. R., Imhoff, J. C., Kittle Jr., J. L., Jobes, T. H., & Donigian Jr., A. S. (2001). Hydrological simulation program - fortran: HSFP version 12 user's manual. Athens, GA: U.S. Environmental Protection Agency.

Black, P. E. (1991). Watershed hydrology Prentice Hall Advanced Reference Series.

Blooming horrible: Nutrient pollution is a growing problem all along the Mississippi. (2012, June 23). The Economist.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. Proceedings of the National Academy of Sciences of the United States of America, 99(3), 7280-7287.

Bone, C., Dragicevic, S., & White, R. (2011). Modeling-in-the-middle: Bridging the gap between agent-based modeling and multi-objective decision-making for land use change. International Journal of Geographical Information Science, 25(5), 717-737.

Borah, D. K., Yagow, G., Saleh, A., Barnes, P. L., Rosenthal, W., Krug, E. C., et al. (2006). Sediment and nutrient modeling for TMDL development and implementation. Transactions of the ASABE, 49(4), 967-986.

Borchers, B., Baker, T., Erickson, B., & Gloy, B. (2011). When to purchase fertilizer: A comparison of fall and spring prices. West Lafayette, IN: Center for Commercial Agriculture.

Bracmort, K. S., Arabi, M., Frankenberger, J. R., Engel, B. A., & Arnold, J. G. (2006). Modeling long-term water quality impacts of structural BMPs. Transactions of the ASAE, 49(2), 367-384.

Brodt, S., Klonsky, K., & Tourte, L. (2006). Farmer goals and management styles: Implications for advancing biologically based agriculture. Agricultural Systems, 89(1), 90-105.

Bulletin 811 optimum crop productivity ratings for Illinois soils (2000). Urbana, IL: University of Illinois College of Agricultural, Consumer and Environmental Sciences Office of Research.

Butler, G. B., & Srivastava, P. (2007). An Alabama BMP database for evaluating water quality impacts of alternative management practices. Applied Engineering in Agriculture, 23(6), 727-736.

Burkart, M. R., & James, D. E. (1999). Agricultural-nitrogen contributions to hypoxia in the Gulf of Mexico. Journal of Environmental Quality, 28(3), 850-859.

Castella, J. C., Tran Ngoc Trung, & Boissau, S. (2005). Participatory Simulation of land-use changes in the northern mountains of Vietnam: The combined use of an agent-based model, a role-playing game, and a geographic information system. Ecology and Society, 10(1), 27.

CES (Cooperative Extension Service). (1987). Iowa drainage guide. Special Report (Revised)

Chaplot, V. (2005). Impact of DEM mesh size and soil map scale on SWAT runoff, sediment, and NO3-N loads predictions. Journal of Hydrology, 312, 207-222.

Chaubey, I., Cotter, A. S., & Soerens, T. S. (2005). Effect of data resolution on SWAT output uncertainty. Hydrological Processes, 19, 621-628.

Cirillo, R. (2006). Evaluating the potential impact of transmission constraints on the operation of a competitive electricity market in Illinois No. ANL-06/16. Argonne, IL: Argonne National Laboratory.

Claasen, R. (2009). Cost-effective conservation programs: The role of economics. Journal of Soil and Water Conservation, 64(2), 53A-54A.

Colvin, T. S. (1990). Automated weighing and moisture sampling for a field-plot combine. Applied Engineering in Agriculture, 6(6), 713-714.

Condor Team. (2013). Condor version 6.8.7 manual. 2013, from http://www.cs.wisc.edu/condor/manual/v6.8.7/index.html

Cooke, R. A., Doheny, A. M., & Hirschi, M. C. (2001). Bioreactors for edge of field treatment of tile outflow No. ASAE Paper No. 01-20182001. St. Joseph, MI: ASAE.

Cooke, R. A. (2011). Illinois drainage guide. Retrieved 4/4, 2012, from http://www.wq.illinois.edu/DG/DrainageGuide.html

Corson, M. S., Rotz, C. A., Skinner, R., & Sanderson, M. A. (2007). Adaption and evaluation of the integrated farm system model to simulate temperate multiple-species pastures. Agricultural Systems, 94(2), 502-508.

Cotter, A. S., Chaubey, I., Costello, T. A., Soerens, T. S., & Nelson, M. A. (2003). Water quality model output uncertainty as affected by spatial resolution of input data. Journal of the American Water Resources Association, 39(4), 977-986.

Crawford, C. (2008). Lidar solutions in ArcGIS. Retrieved 12/27, 2012, from http://blogs.esri.com/esri/arcgis/2008/11/06/lidar-solutions-in-arcgis_part-1-assessing-lidar-coverage-and-sample-density/

Czapar, G. (November 9, 2012).

David, M. B., Gentry, L. E., Kovacic, D. A., & Smith, K. M. (1997). N balance in and export from an agricultural watershed. Journal of Environmental Quality, 26, 1038-1048.

David, M. B., Gentry, L. E., Starks, K. M., & Cooke, R. A. (2003). Stream transport of herbicides and metabolites in a tile drained, agricultural watershed. Journal of Environmental Quality, 32, 1790-1801.

David, M. B., Del Grosso, S. J., Hu, X., Marshall, E. P., McIssac, G. F., Parton, W. J. (2008). Modeling denitrification in a tile-drained, corn and soybean agroecosystem of Illinois, USA. Biogeochemistry, 93(1-2), 7-30.

David, M. B., Drinkwater, L. E., & McIsaac, G. F. (2010). Sources of nitrate yields in the Mississippi River basin. Journal of Environmental Quality, 39, 1657-1667.

David, M., Flint, C., Czapar, G., & Cooke, R. (2011). Tile drainage modifications to reduce nitrate losses in an agricultural watershed: Integration of biophysical and social sciences with extension and education. National Institute of Food and Agriculture, U.S. Department of Agriculture, National Integrated Water Quality Program.

Department of Agricultural and Consumer Economics. (2012). Revenue and costs for corn, soybeans, wheat, and double-crop soybeans, actual for 2005 through 2011, projected for 2012. Champaign, IL: University of Illinois.

Di Luzio, M., Arnold, J. G., & Srinivasan, R. (2005). Effect of GIS data quality on small watershed streamflow and sediment simulations. Hydrological Processes, 19, 629-650.

Economic Research Service, United States Department of Agriculture. (2007). Structure and finances of U.S. farms, family farm report, 2007 edition No. EIB-24 USDA.

Environmental Protection Agency. (2012a). Enforcement and compliance history online. Retrieved February, 2012, from http://www.epa-echo.gov/echo/compliance_report_water_icp.html

Environmental Protection Agency. (2012b). Permit compliance system (PCS) and integrated compliance information system (ICIS). Retrieved February, 2012, from http://www.epa.gov/enviro/facts/pcs-icis/index.html

ESRI. (2012). ArcGIS desktop: Release 10.1. Redlands, CA: Environmental Systems Research Institute.

European Commision. (2013). Agriculture and rural development farm accounting data network. Retrieved 1/30, 2013, from http://ec.europa.eu/agriculture/rica/

Feyereisen, G. W., Wilson, B. N., Sands, G. R., Strock, J. S., & Porter, P. M. (2006). Potential for a rye cover crop to reduce nitrate loss in southwestern Minnesota. Agronomy Journal, 98, 1416-1426.

Fox, R. H., Kern, J. M., & Piekielek, W. P. (1986). Nitrogen fertilizer source, and method and time of application effects on no-till corn yields and nitrogen uptake. Agronomy Journal, 78, 741-746.

Frankenberger, J., Kladivko, E., Sands, G., Jaynes, D., Fausey, N., Helmers, M., et al. (2006). Questions and answers about drainage water management for the midwest No. WQ-44. West Lafeyette, IN: University of Purdue Extension.

Gassman, P. W., Reyes, M. R., Green, C. H., & Arnold, J. G. (2007). The soil and water assessment tool: Historical development, applications, and future research directions. Transactions of the ASABE, 50(4), 1211-1250.

Gentry, L. E., David, M. B., Below, F. E., Royer, T. V., & McIsaac, G. F. (2009). Nitrogen mass balance of a tile-drained agricultural watershed in east-central Illinois. Journal of Environmental Quality, 38, 1841-1847.

Gentry, L. E., David, M. B., Royer, T. V., Mitchell, C. A., & Starks, K. M. (2007). Phosphorus transport pathways to streams in tile-drained agricultural watersheds. Journal of Environmental Quality, 36, 408-415.

Gilbert, N. (2007). Agent based models. London: Sage.

Gitau, M. W., Chaubey, I., Gbur, E., Pennington, J. H., & Gorham, B. (2010). Impacts of land-use change and best management practice implementation in a conservation effects assessment project watershed: Northwest Arkansas. Journal of Soil and Water Conservation, 65(6), 353-368.

Gitau, M. W., Chiang, L., Sayeed, M., & Chaubey, I. (2011). Watershed modeling using large-scale distributed computing in condor and the soil and water assessment tool model. Simulation: Transactions of the Society for Modeling and Simulation International, 88(3), 365-380.

Grassland Soil and Water Research Laboratory. (2013). Potential heat unit program. 2012, from http://swat.tamu.edu/software/potential-heat-unit-program/

Green, C. H., Tomer, M. D., Di Luzio, M., & Arnold, J. G. (2006). Hydrologic evaluation of the soil and water assessment tool for a large tile-drained watershed in Iowa. Transactions of the ASABE, 49, 2413-2422.

Happe, K., Kellermann, K., & Balman, A. (2006). Agent-based analysis of agricultural policies: An illustration of the agricultural policy simulator AgriPoliS, its adaption, and behavior. Ecology and Society, 11(1), 49.

Hoag, D., Luloff, A. E., & Osmond, D. L. (2012). Lessons learned from the NIFA-CEAP: How farmers and ranchers make decisions on conservation practices. Raleigh, NC: NC State University.

Hollinger, S. E., & Angel, J. R. (2009). Illinois agronomy handbook (24th ed.). Champaign, IL: University of Illinois Extension.

Hu, X., McIsaac, G. F., David, M. B., & Louwers, C. A. L. (2007). Modeling river nitrate export from an east-central Illinois watershed using SWAT. Journal of Environmental Quality, 36, 996-1007.

Illinois Department of Agriculture. (2010). Fertilizer tonnage report summaries: County totals. Springfield, IL: Illinois Department of Agriculture.

Illinois Office of United States Department of Agriculture National Agricultural Statistics Service. (2005-2011). Illinois county estimates USDA-NASS.

Illinois Natural Resources Geospatial Data Clearinghouse. (Illinois Height Modernization: Digital Elevation Data). Illinois height modernization: Digital elevation data. Retrieved July, 2011, from http://www.isgs.uiuc.edu/nsdihome/webdocs/ilhmp/data.html

Illinois Society of Professional Farm Managers and Rural Appraisers. (2012). Illinois farmland values & lease trends 2012. Menomonee Falls, WI: Illinois Society of Professional Farm Managers and Rural Appraiser.

Illinois State Water Survey. (2012). Illinois state water survey - climatologist data. Retrieved March, 2012, from http://www.isws.Illinois.edu/data/climatedb/

InterContinental Exchange. (2013). Chicago climate exchange (CCX). Retrieved 1/30, 2013, from https://www.theice.com/ccx.jhtml

Iowa Learning Farms, & Practical Farmers of Iowa. (June 2011). Cover crops: Frequently asked questions. Ames, Iowa: Iowa Learning Farms.

Jantz, C. A., Goetz, S. J., Donato, D., & Claggett, P. (2010). Designing and implementing a regional urban modeling system using the SLEUTH cellular urban model. Computers, Environment and Urban Systems, 34(1), 1-16.

Jaynes, D. B., Dinnes, D. L., Meek, D. W., Karlen, D. L., Cambardella, C. A., & Colvin, T. S. (2004). Using the late spring nitrate test to reduce nitrate loss within a watershed. Journal of Environmental Quality, 33(2), 669-677.

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., et al. (2003). The DSSAT cropping system model. European Journal of Agronomy, 18, 235-265.

Kaini, P., Artita, K., & Nicklow, J. W. (2012). Optimizing structural best management practices using SWAT and genetic algorithm to improve water quality goals. Water Resources Management, 26, 1827-1845.

Kalita, P. K., Cooke, R. A., Anderson, S. M., Hirschi, M. C., & Mitchell, J. K. (2007). Subsurface drainage and water quality: The Illinois experience. Transactions of the ASABE, 50(5), 1651-1656.

Kannan, N., Jeong, J., & Srinivasan, R. (2011). Hydrologic modeling of a canal-irrigated agricultural watershed with irrigation best management practices: Case study. Journal of Hydrologic Engineering, 16, 746-757.

Kanta, L., & Zechman, E. M. (2010). An agent-based modeling approach to evaluate the impact of conservation practices on water resources sustainability. World Environmental and Water Resources Congress 2012, 4253-4259.

Kaspar, T. C., Jaynes, D. B., Parkin, T. B., & Moorman, T. B. (2007). Rye cover crop and gamagrass strip effects on NO3 concentration and load in tile drainage. Journal of Environmental Quality, 36(5), 1503-1511.

Keith, G., Norvell, S., Jones, R., Maguire, C., Osei, E., Saleh, A., et al. (2000). CEEOT-LP modeling for the upper maquoketa river watershed, iowa No. PR0003). Tarleton State University, Stephenville, Texas: Texas Institute for Applied Environmental Research.

Lambert, D., Sullivan, P., Claassen, R., & Foreman, L. (2006). Conservation-compatible practices and programs: Who participates? No. 14 USDA-ERS.

Lant, C., Loftus, T., Kraft, S., & Bennett, D. (2001). Land use dynamics in a southern Illinois watershed. Environmental Management, 28, 325-340.

Le, Q. B., Park, S. J., & Vlek, P. L. G. (submitted for publication). Household typologies and socio-ecological determinants for their land-use choices in Vietnam forest margins: Implications for empirical multi-agent modeling. Submitted to Journal of Land use Science.

Le, Q. B., Park, S. J., Vlek, P. L. G., & Cremers, A. B. (2008). Land-use dynamic simulator (LUDAS): A multi-agent system model for simulating spatio-temporal dynamics of coupled human-landscape system. Structure and theoretical specification. Ecological Informatics, 3, 135-153.

Learmonth, G., Smith, D. E., Sherman, W. H., White, M. A., & Plank, J. (2011). A practical approach to the complex problem of environmental sustainability: The UVa bay game. The Innovation Journal: The Public Sector Innovation Journal, 16(1), 1-1-8.

Li, L., Malone, R. W., Ma, L., Kaspar, T. C., Jaynes, D. B., Saseendran, S. A., et al. (2008). Winter cover crop effects on nitrate leaching in subsurface drainage as simulated by RZWQM-DSSAT. Transactions of the ASABE, 51(5), 1575-1583.

Limnotech. (2007). DRAFT TMDL salt fork vermilion river watershed. Ann Arbor, Michigan: Limnotech.

Logsdon, S. D., Kaspar, T. C., Meek, D. W., & Prueger, J. H. (2002). Nitrate leaching as influenced by cover crops in large soil monoliths. Agronomy Journal, 94, 807-814.

Luo, W., Sands, G. R., Youssef, M., Strock, J. S., Song, I., & Canelon, D. (2010). Modeling the impact of alternative drainage practices in the northern corn-belt with DRAINMOD-NII. Agricultural Water Management, 97(3), 389-398.

Lynch, D.J. (2013, September 9). Taxpayers Turn U.S. Farmers Into Fat Cats With Subsidies. Bloomberg.

Lynch, D.J., Bjerga, A. (2013, September 18). Safety Net for Crops Means $14 Billion Tab for Taxpayers. Bloomberg.

Ma, L., Ahuja, L. R., Ascough II, J. C., Shaffer, M. J., Rojas, K. W., Malone, R. W., et al. (2001). Integrating system modeling with field research in agriculture: Applications of root zone water quality (RZWQM). Advances in Agronomy, 71, 233-292.

Ma, L., Malone, R. W., Heilman, P., Jaynes, D. B., Ahuja, L. R., Saseendran, S. A., et al. (2007). RZWQM simulated effects of crop rotation, tillage, and controlled drainage on crop yield and nitrate-N loss in drain flow. Geoderma, 140(3), 260-271.

Matthews, R. B., Gilbert, N. G., Roach, A., Polhill, J. G., & Gotts, N. M. (2007). Agent-based land-use models: A review of applications. Landscape Ecology, 22, 1447-1459.

McDonnell, R. A. (2008). Challenges for integrated water resources management: How do we provide the knowledge to support truly integrated thinking. International Journal of Water Resources Development, 24(1), 131-143.

McFarland, A., & Hauck, L. (1995). Livestock and the environment: Scientific underpinnings for policy analysis. Stephenville, Texas: Texas Institute for Applied Environmental Research: Tarleton State University.

McIsaac, G. F., & Hu, X. (2004a). Net N input and riverine N export from Illinois agricultural watersheds with and without extensive tile drainage. Biogeochemistry, 70, 251-271.

McIsaac, G. F., & Hu, X. (2004b). Relating net N input in the Mississippi River basin to nitrate flux in the lower Mississippi River: A comparison of approaches. Biogeochemistry, 70, 251-271.

Mississippi River/Gulf of Mexico Watershed Nutrient Task Force. (2008). Gulf hypoxia action plan 2008 for reducing, mitigating, and controlling hypoxia in the northern Gulf of Mexico and improving water quality in the Mississippi River basin. Washington, D.C.: Mississippi River/Gulf of Mexico Watershed Nutrient Task Force.

Mitchell, J. K., Banasik, M. C., Hirschi, M. C., Cooke, R. A. C., & Kalita, P. (2001). There is not always surface runoff and sediment transport. Soil Erosion Research for the 21st Century, Proc. Int. Symp. Honolulu, HI. pp. 575-578.

Mitchell, J. K., McIsaac, G. F., Walker, S. E., & Hirschi, M. C. (2000). Nitrate in river and subsurface drainage flows from an east central Illinois watershed. Transactions of the ASAE, 43, 337-342.

Mock, K. J., & Testa, J. W. (2007). An agent-based model of predator-prey relationships between transient killer whales and other marine mammals. Anchorage, AK: University of Alaska Anchorage.

Monteith, J. L. (1965). Evaporation and environment. In G. E. Fogg (Ed.), The state and movement of water in living organisms (19th ed., pp. 205-234). NY: Academic Press, Inc.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Binger, R. L., Harmel, R. D., & Veith, T. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Transactions of the ASABE, 50(3), 885-900.

Moriasi, D. N., Arnold, J. G., Vazquez-Amabile, G. G., Engel, B. A., & Rossi, C. G. (2009). Incorporation of a new shallow water table depth algorithm into SWAT2005. Transactions of the ASABE, 52(3), 771-784.

Moriasi, D. N., & Starks, P. J. (2009). Spatial resolution effect of precipitation data on SWAT calibration and performance: Implications for CEAP. Transactions of the ASABE, 52(4), 1171-1180.

Moriasi, D. N., & Starks, P. J. (2010). Effects of the resolution of soil dataset and precipitation dataset on SWAT2005 streamflow calibration parameters and simulation acccuracy. Journal of Soil and Water Conservation, 65(2), 63-78.

Moriasi, D. N., Rossi, C. G., Arnold, J. G., & Tomer, M. D. (2012). Evaluating hydrology of the soil and water assessment tool (SWAT) with new tile drain equations. Journal of Soil and Water Conservation, 6(67), 513-524.

Muchnik, E., Errazuriz, F., & Dominguez, I. (1996). Lmpacto de la asociación de chile al mercorsur en el sector agrícola y agroindustrial No. Documento de Trabajo No. 253)Universidad Católica de Chile.

Nafziger, E. D., Fernandez, F. G., Adee, E., Dunker, R. E., Ebelhar, S. A., & Paul, L. E. (2010). Assessing variability in corn response to N rate: Soil residual effects following 10 years of trials. Illinois Fertilizer Conference Proceedings, Peoria, IL. 15-26.

Nair, S. S., K.W. King, J.D. Witter, B.L. Sohngen, & N.R. Fausey. (2011). Importance of crop yield in calibrating watershed water quality simulation tools. Journal of the American Water Resources Association, 47(6), 1285-1298.

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models: Part 1. A discussion of principles. Journal of Hydrology, 10(3), 282-290.

National Climate Data Center. (2012). Daily surface data. Retrieved February, 2012, from http://gis.ncdc.noaa.gov/map/daily/

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., & Williams, J. R. (2009). Soil and water assessment total, theoretical documentation version 2009. Temple, Texas: Grassland, Soil and Water Research Laboratory - Agriculture Research Service.

Neitsch, S. L., Arnold, J. G., Haney, E. B., Kiniry, J. R., & Williams, J. R. (2011). Soil and water assessment tool Input/Output File documenation version 2009. Texas Water Resources Institute Technical Report no. 365.

Neitsch, S. L., Arnold, J. G., Haney, E. B., Kiniry, J. R., & Williams, J. R. (2013). Soil and water assessment tool Input/Output File documenation version 2012. Texas Water Resources Institute Technical Report no. 439.

Nejadhashemi, A., Smith, C., Williams, J., Douglas-Mankin, K., & Golden, B. (2011). An analysis of sedimentation reduction strategies for Tuttle Creek Lake. 2008 - 2011 FINAL PROGRESS REPORT. Kansas Water Resources Competitive Grants Program.

Ng, T. L., Eheart, J. W., & Cai, X. M. (2010). Comparative calibration of a complex hydrologic model by stochastic methods GLUE and PEST. Transactions of the ASABE, 53(6), 1773-1773-1786.

Ng, T. L., Eheart, J. W., Cai, X., & Braden, J. B. (2011). An agent-based model of farmer decision-making and water quality impacts at the watershed scale under markets for carbon allowances and a second-generation biofuel crop. Water Resources Research, 47(W09519).

NOAA. (2012). National climatic data center. 2012, from http://www.ncdc.noaa.gov/

Nowak, P., Korsching, P. (1998). The human dimension of soil and water conservation: A historical and methodological perspective. In Pierce, F.J., Frye, W.W. (Ed.), Advances in Soil and Water Conservation (pp. 159-184).

NRCS-USDA. (2012). EQIP cost share practices -Illinois NRCS. Retrieved 11/27, 2012, from http://www.il.nrcs.usda.gov/programs/eqip/cspractices.html

O'Brien, D. M., & Duncan, S. R. (2011). Cost-return budgets in northeast Kansas No. Publication #MF-570-573). Manhattan, Kansas: Kansas State Research and Extension.

Ohio Agricultural Research and Development Center. (2012). OARDC weather system. 2012, from http://www.oardc.ohio-state.edu/newweather/

Ohlmer, B., Olson, K., & Brehmer, B. (1998). Understanding farmers' decision making process and improving managerial assistance. Agricultural Economics, 18(3), 273-290.

Osei, E., Gassman, P.W., & Saleh, A. (2000). Livestock and the environment: Economic and environmental modeling using CEEOT. No. PR0002. Stephenville, Texas: Tarleton State University, Texas Institute for Applied Environmental Research.

Pannell, D. J. (2006). Understanding and promoting adoption of conservation practices by rural landholders. Australian Journal of Experimental Agriculture, 46(11), 1407.

Parajuli, P. B., Mankin, K. R., & Barnes, P. L. (2008). Applicability of targeting vegetative filter strips to abate fecal bacteria and sediment yield using SWAT. Agricultural Water Management, 95(10), 1189-1200.

Parry, M.L., Canziani, O.F., Palutikof, J.P., van der Linden, P.J., and Hanson, C.E. (eds). Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, 2007. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Pennington, J. H., Steele, M. A., Teague, K. A., Kurz, B., Gbur, E., Popp, J., et al. (2008). Breaking ground: A cooperative approach to collecting information on conservation practices from an initially uncooperative population. Journal of Soil and Water Conservation, 63(6), 208A-2011A.

Rabalais, N. N., Turner, R. E., & American Geophysical Union. (2001). Coastal hypoxia: Consequences for living resources and ecosystems. Washington, D.C.: American Geophysical Union.

Rabalais, N. N., Turner, R. E., & Jr., W. J. W. (2002). Gulf of Mexico hypoxia, a.k.a. "the Dead Zone". Annual Review of Ecology and Systematics, 33, pp. 235-263.

Rains, T. H., & Miranda, R. M. (2002). Simulation of flow and water quality of the Arroyo Colorado, Texas basin. 1989-99 No. Rep. No. 02-04110. Austin, TX: USGS, Water Resources Investigations.

Randall, G. W., & Vetsch, J. A. (2005). Corn production on a subsurface-drained mollisol as affected by fall versus spring application of nitrogen and nitrapyrin. Agronomy Journal, 97, 472-478.

Robinson, T. R., Brown, D. G., Parker, D. C., Schreinemachers, P., Janssen, M. A., Huigen, M., et al. (2007). Comparison of empirical methods for building agent-based models in land use science. Journal of Land use Science, 2(1), 31-55.

Rosenthal, W. D., Harman, W. L., Wang, E., & Sheng, B. (2001). Arroyo colorado river sedimentation: An investigation of range and cropland management practices to reduce erosion. No. 01-32. Temple, Texas: Blackland Research Center.

Rotz, C. A., Kleinman, P. J., Dell, C. J., Veith, T. L., & Beegle, D. B. (2011). Environmental and economic comparisons of manure application methods in farming systems. Journal of Environmental Quality, 40(2), 438-448.

Rotz, C. A., Corson, M. S., Chianese, D. S., Montes, F., Hafner, S. D., & Coiner, C. U. (2012). The integrated farm system model reference manual version 3.6. University Park, Penn: Agricultural Research Service United States Department of Agriculture.

Rouholahnejad, E., Abbaspour, K. C., Vejdani, M., Srinivasan, R., Schulin, R., & Lehmann, A. (2012). A parallelization framework for calibration of hydrological models. Environmental Modelling & Software, 31(0), 28-36.

Royer, T. V., David, M. B., & Gentry, L. E. (2006). Timing of riverine export of nitrate and phosphorus from agricultural watershed in Illinois: Implication for reducing nutrient loading to the Mississippi River. Environmental Science & Technology, (40), 4126-4131.

Saleh, A., Arnold, J. G., Gassman, P. W., Hauck, L. W., Rosenthal, W. D., & MacFarland, A. M. S. (2000). Application of SWAT for the upper north bosque river watershed. Transactions of the ASABE, 43(5), 1077-1087.

Saleh, A., Osei, E., D.B., J., B., D., & Arnold, J. G. (2007). Economic and environmental impacts of LSNT and cover crops for nitrate-nitrogen reduction in Walnut Creek watershed, Iowa, using FEM and enhanced SWAT models. Transactions of the ASABE, 50(4), 1251-1251-1259.

Schilling, K. E., & Helmers, M. (2008). Effects of subsurface drainage tiles on streamflow in iowa agricultural watersheds: Exploratory hydrograph analysis. Hydological Processes, 22, 4497-4497-4506.

Sengupta, R., Lant, C., Kraft, S. E., Beaulieu, J., Peterson, W., & Loftus, T. (2005). Modeling enrollment in the conservation reserve program by using agents within spatial decision support systems: An example from southern Illinois. Environment and Planning B; Planning and Design, 32, 821-834.

Shaw, E. M. (1994). Hydrology in practice (Third ed.). London, U.K.: Chapman & Hall.

Sheshukov, A., Daggupati, P., Lee, M., & Douglas-Mankin, K. (2009). ArcMap tool for pre-processing SSURGO soil database for ArcSWAT. 5th International SWAT Conference.

Shoemaker, L., Dai, T., & Koenig, J. (2005). TMDL model evaluation and research needs No. EPA/600/R-05/149. Cincinnati, OH: U.S. Environmental Protection Agency.

Singer, J. W., Malone, R. W., Jaynes, D. B., & Ma, L. (2011). Cover crop effects on nitrogen load in tile drainage from Walnut Creek Iowa using root zone water quality (RZWQ) model. Agricultural Water Management, 98(10), 1622-1628.

Singh, J., Knapp, H. V., Arnold, J. G., & Demissie, M. (2005). Hydrological modeling of the Iroquois River watershed using HSPF and SWAT1. JAWRA Journal of the American Water Resources Association, 41(2), 343-360.

Singh, K. P., Broeren, S. M., King, R. B., & Pubentz, M. L. (1987). Basinwide flow and aquatic habitat assessment model for the Middle Fork and Salt Fork of the Vermillion River, Wabash basin No. 428). Champaign, IL: Illinois State Water Survey Division, University of Illinois Urbana - Champaign.

Skaggs, R. W. (1980). Methods for design and evaluation of drainage-water management systems for soils with high water tables. DRAINMOD reference report. Transactions of the ASAE, 21(3), 522-528.

Srinivasan, R. (2009). ArcSWAT: ArcGIS interface for soil and water assessment tool (SWAT). College Station, Texas: Blackland Research and Extension Center and Spatial Sciences Laboratory Texas A&M University.

Srinivasan, R., Zhang, X., & Arnold, J. G. (2010). SWAT ungauged: Hydrological budget and crop yield predictions in the upper Mississippi River basin. Transactions of the ASABE, 53(5).

St. John, L., & Ogle, D. (October 2008). Vegetative filter or buffer strips. Aberdeen, Idaho: USDA-NRCS.

Sustainable Agriculture Network. (2007). Managing cover crops profitably. Beltsvile, MD: Sustainable Agricultural Network.

Tannura, M. A., S. H. Irwin, and D. L. Good. “Weather, Technology, and Corn and Soybean Yields in the U.S. Corn Belt.” Marketing and Outlook Research Report 2008-01, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, February 2008. [http://www.farmdoc.uiuc.edu/marketing/morr/morr_archive.html]

TeraGrid. (2013). TeraGrid., 2013, from http://www.teragrid.org

Texas Water Development Board (TWDB). (2005). Water conservation best management practices (BMP) guide for agriculture in Texas No. Rep. 362). Austin, TX: Water Conservation Implementation Task Force.

Thorp, K. R., Youssef, M. A., Jaynes, D. B., Malone, R. W., & Ma, L. (2009). DRAINMOD-N II: Evaluated for an agricultural systems in Iowa and compared to RZWQM-DSSAT. Transactions of the ASABE, 52(5), 1557-1573.

U.S. Department of Agriculture, Natural Resources Conservation Service. (2007). 2003 natural resources inventory. Washington, D.C.

U.S. Environmental Protection Agency. Clean Water Act, 33 U.S.C. 1251 (1972).

U.S. Environmental Protection Agency. (2009). National water quality inventory: Report to congress. 2004 reporting cycle No. EPA 841-R-08-001.

University of Illinois at Urbana-Champaign (UIUC) College of Agricultural, Consumer and Environmental Sciences (ACES). (2003-2012). Farm economics facts and opinions (FEFO) archive. Urbana, IL: UIUC ACES FarmDOC.

Upper Salt Fork Project Report and Status Update. (2011). Champaign, IL: University of Illinois Champaign County Soil and Water Conservation District.

Urbana-Champaign Sanitary District (UCSD) & University of Illinois at Urbana-Champaign (UIUC) Department of Natural Resources & Environmental Sciences (NRES) Biogeochemistry Group. (2013). Salt fork river watershed water quality monitoring subcommittee. Retrieved 2/26, 2013, from http://saltfork.nres.uiuc.edu/water_quality.html

USDA. (2006). Conservation and the environment.

USDA. (2009). 2007 census of agriculture No. AC-07-A-51.

USDA-FSA. (2004). Conservation reserve program overview. CRP: Planning for the future. Washington, D.C.: U.S. Department of Agriculture, Farm Service Agency.

USDA-FSA. (2013). Conservation programs. Retrieved 1/29, 2013, from http://www.fsa.usda.gov/FSA/webapp?area=home&subject=copr&topic=rns

USDA-NASS. (2009). 2007 census of agriculture. Washington, D.C.: United States Department of Agriculture.

USDA-NASS. (2012). National agricultural statistics service. 2012, from http://www.nass.usda.gov/

USDA-NASS. (2013). Cropland data layer. Retrieved 1/2013, 2013, from http://www.nass.usda.gov/research/Cropland/SARS1a.htm

USDA-NRCS. (2011a). Assessment of the effects of conservation practices on conservation effects assessment project (CEAP) cultivated cropland in the great lakes region.

USDA-NRCS. (2011b). Soil Survey Geographic (SSURGO) Database). Soil survey geographic (SSURGO) database. Retrieved July, 2011, from http://soils.usda.gov/survey/geography/ssurgo/

USDA-NRCS. (2012a). Assessment of the effects of conservation practices on cultivated cropland in the Missouri River basin.

USDA-NRCS. (2012b). Assessment of the effects of conservation practices on cultivated cropland in the upper Mississippi River basin. Conservation Effects Assessment Project.

USDA-NRCS. (2012c). Environmental quality incentive program NRCS Illinois.

USDA-NRCS. (2012d). Iowa environmental quality incentives program (EQIP) list of eligible practices and payment schedule FY2012. USDA - NRCS.

USDA-NRCS. (2012e). U.S. general soil map, 2012, from http://websoilsurvey.nrcs.usda.gov

USDA-NRCS. (2013). Soil data mart - U.S. general soil map. Retrieved 1/29, 2013, from http://soildatamart.nrcs.usda.gov/USDGSM.aspx

USGS. (2012a). National elevation dataset, 2012, from http://ned.usgs.gov/

USGS. (2012b). National hydrography data set, 2012, from http://nhd.usgs.gov/

USGS. (2012c). National water information system: Web interface. 2012, from http://waterdata.usgs.gov/nwis/rt

USGS. (2012d). Seamless data warehouse. Retrieved July, 2011, from http://seamless.usgs.gov/index.php

USGS. (2013). National water information system: Web interface, 2013. From http://streamstatsags.cr.usgs.gov/ThreatenedGages/ThreatenedGages.html

USGS-NLCD. (2012). National land cover institute, 2012, from http://landcover.usgs.gov/usgslandcover.php

van Ittersum, M. K., Ewert, F., Heckelei, T., Wery, J., Olsson, J. A., Andersen, E., et al. (2008). Integrated assessment of agricultural systems - A component-based framework for the European Union (SEAMLESS). Agricultural Systems, 96, 150-165.

Vendrell, P. F., Nelson, M. A., Cash, L. W., Steele, K. F., McNew, R. W., & Murdock, J. F. (1997). Continuation of the Illinois River water quality monitoring of Moores Creek (Non-Point Source Final Report No. Publication No. MSC-213 Arkansas Water Resources Center.

Vetsch, J. A., & Randall, G. W. (2004). Corn production as affected by nitrogen application timing and tillage. Agronomy Journal, 96, 502-509.

Villamil, M. B., Bollero, G. A., Darmody, R. G., Simmons, F. W., & Bullock, D. G. (2006). No-till Corn/Soybean systems including winter cover crops. Soil Science Society of America, 70(6), 1936-1944.

Vitosh, M. L., Johnson, J. W., & Mengel, D. B. (1995). Tri-state fertilizer recommendations for corn, soybeans, wheat and alfalfa No. Extension Bulletin E-2567 Michigan State University Extension.

Walter, G. (1997). Images of success: How Illinois farmers define the successful farmer. Rural Society, 62, 48-68.

Walter, T., Dosskey, M., Khanna, M., Miller, J., Tomer, M. D., & Wiens, J. (2007). The science of targeting within landscapes and watersheds to improve conservation effectiveness. In M. Schnepf, & C. Cox (Eds.), Managing landscaping for environmental quality: Strengthening the science base (pp. 63-63-89). Ankeny, IA.: Soil and Water Conservation Society.

Winstanley, D., Angel, J. A., Changnon, S. A., Knapp, H. V., Kunkel, K. E., Palecki, M. A., et al. (2006). The water cycle and water budgets in Illinois: A framework for drought and water-supply planning No. I/EM 2006-02. Champaign, IL: Illinois State Water Survey.

Wortmann, C. S. (2008). Targeting of watershed management practices for water quality protection. No. RP195. University of Nebraska-Lincoln: USDA-ARS.

Yeh, P. J., Irizarry, M., & Eltahir, E. A. B. (1998). Hydroclimatology of Illinois: A comparison of monthly evaporation estimates based on atmospheric water balance and soil water balance. Journal of Geophysical Research, 103(D16), 19823-19837.

Zellner, M. L. (2007). Generating policies for sustainable water use in complex scenarios: An integrated land-use and water-use model of Monroe County, Michigan. Environment and Planning B: Planning and Design, 34(4), 664-686.

Zhou, J., Liu, Y., Guo, H., & He, D. (2012). Combining the SWAT model with sequential uncertainty fitting algorithm for streamflow prediction and uncertainty analysis for the lake dianchi basin, China. Hydrological Processes, 1085-1099.

APPENDIX A – CONSIDERATIONS FOR ADDITIONAL BMPs

A.1 Introduction

This Appendix documents an initial attempt to use the existing SWAT routines to model saturated buffer strips and bioreactors in ITEEPGAM. Saturated buffer strips and bioreactors could potentially be added to the suite of BMPs that farmer agents consider in ITEEPGAM in future development. However, in both cases, current SWAT functionally does not route tile-drained flow through the modeled BMP. The calibration sequence and results in this Appendix were limited to overland (non tile-drained) flow. The goal of these BMPs would be to intercept tile-drained flow for this study. Consequently, these BMPs were not considered in the study.

A.1.1 Bioreactors

Bioreactors are large water filters that intercept water leaching from a field. A bioreactor is a structure attached to the outlet of conventional drainage piping and filled with a carbon food source for bacterial populations (Christianson et al., 2012). These microorganisms denitrify water as it leaves the field and before the water enters the stream network (Schipper et al., 2010). Researchers at the University of Illinois have documented the performance, costs, and installation of bioreactors in and around the study area (Cooke, 2011). UIUC extension recommends installations targeting between 40% and 75% nitrate removal performance (Cooke et al., In Preparation). They do not require any modification to existing practices, do require taking any land out of production, and can be designed so they do not affect drainage effectiveness (Cooke et al., 2001).

A.1.2 Bioreactor model setup

Bioreactors provide a carbon source for denitrifying bacteria to treat outflow from a field before it enters the receiving waterbody. Researchers at UIUC are quantifying the amount of nitrate removed by bioreactors in typical installations on Midwestern farms (Cooke et al., In Preparation; Cooke et al., 2001). Cooke et al. (In Preparation) observed and modeled the denitification rates in bioreactors in nearby East-Central Illinois. As Figure A.1 shows, Cooke characterized a nitrate load reduction for a loading density for area bioreactor installations.

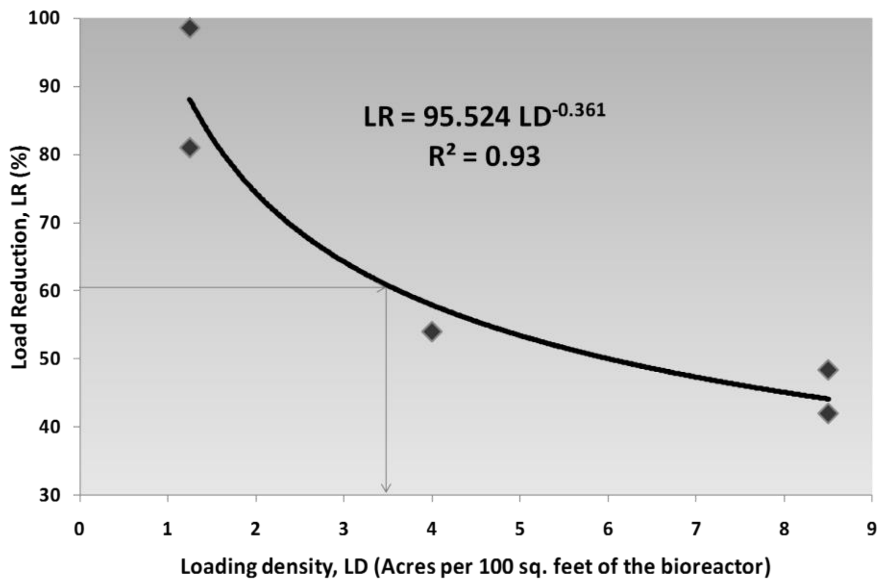

Figure A.1: Biofilter Load Reduction vs Loading Density (R. A. Cooke et al., In Preparation)

The SWAT model does not have a built-in capacity to simulate the effect of bioreactors on outflow. However, SWAT does have the ability to simulate wetlands. Kovacic et al. (2006) studied two constructed wetlands of sizes .16 ha (W1) and .41 ha (W2) and observed nitrate load reductions of 42% (W1) and 31% (W2) with loading densities 7.8 (W1) and 23.7 (W2) in Bloomington, IL. Kovacic et al.'s (2006) reduction rates for the wetland are within 6% of the reduction rates predicted by Cooke's bioreactor load reduction curve. Based on the similarities between the performance of bioreactors and wetlands, this study devised a bioreactor representation by finding an appropriate set of SWAT wetland parameters to mimic observed nitrate load reductions in field bioreactors.

This study calibrated the existing wetland configuration files (.pnd) in SWAT to mimic this loading curve. This study considered a range of feasible wetland sizes (area = WET_NSA = WET_MXSA), nitrogen settling rates (NSETLW1=NSETLW2), and areas draining into the wetlands to achieve a similar curve. The average depth and maximum depths of the wetland were set to .5 m (WET_NVOL) and a full depth of 1 m (WET_MXVOL). These depths were derived from the design of the two constructed wetlands studied by Kovacic et al. (2006).

The calibrated values the wetland size and nitrogen settling rates were determined by finding the minimal mean squared error for the nitrogen reduction generated by SWAT for 20 HRUs relative to the rate predicted by Cooke et al. (In Preparation) That mean squared error for selected loading densities between 1 and 25 (1.1, 1.75, 3, 5, 7, 11, 15, 18, 23, 30, 40) was 40.78. The equivalent wetland size GKEW (Graham Kent Equivalent Wetland) was set as .41 ha and a nitrogen settling rate of 2.87 m/year. Figure A.2 shows the load reductions for the 20 HRUs for the selected wetland size, and settling rate.

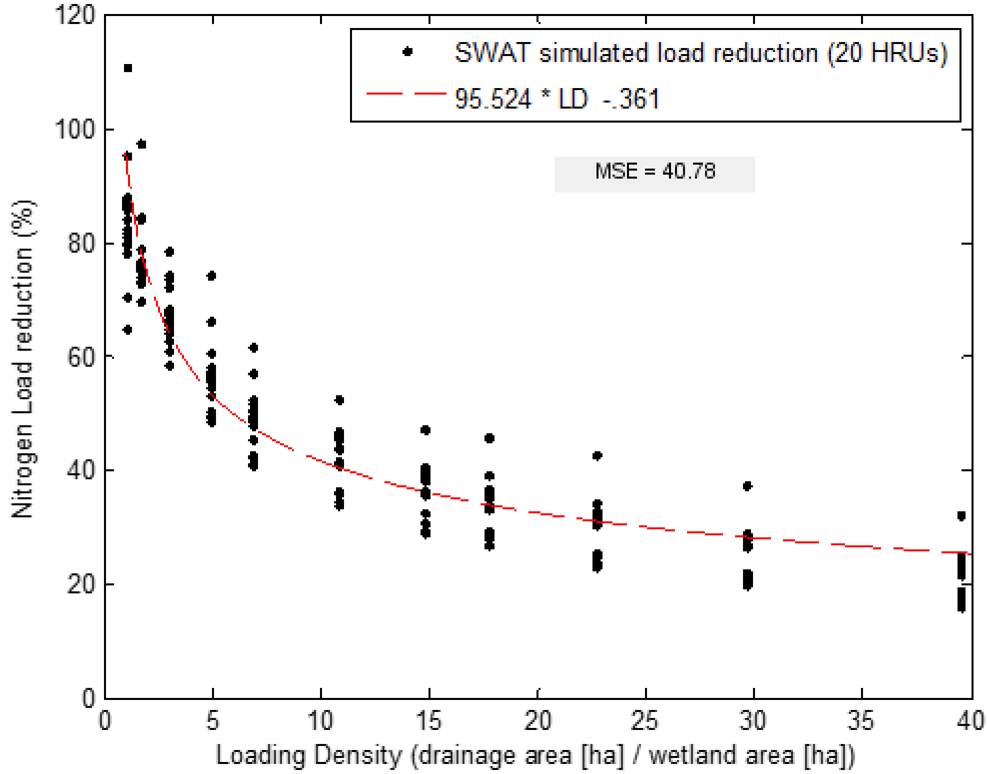

Figure A.2: Nitrogen Load Reduction (%) vs Loading Density: SWAT Simulated Wetland Routine Calibration HRUs

The proposed wetland size and settling rate was then applied to 20 HRUs not used in the calibration. The result was a MSE of 70.68 as shown in Figure A.3.

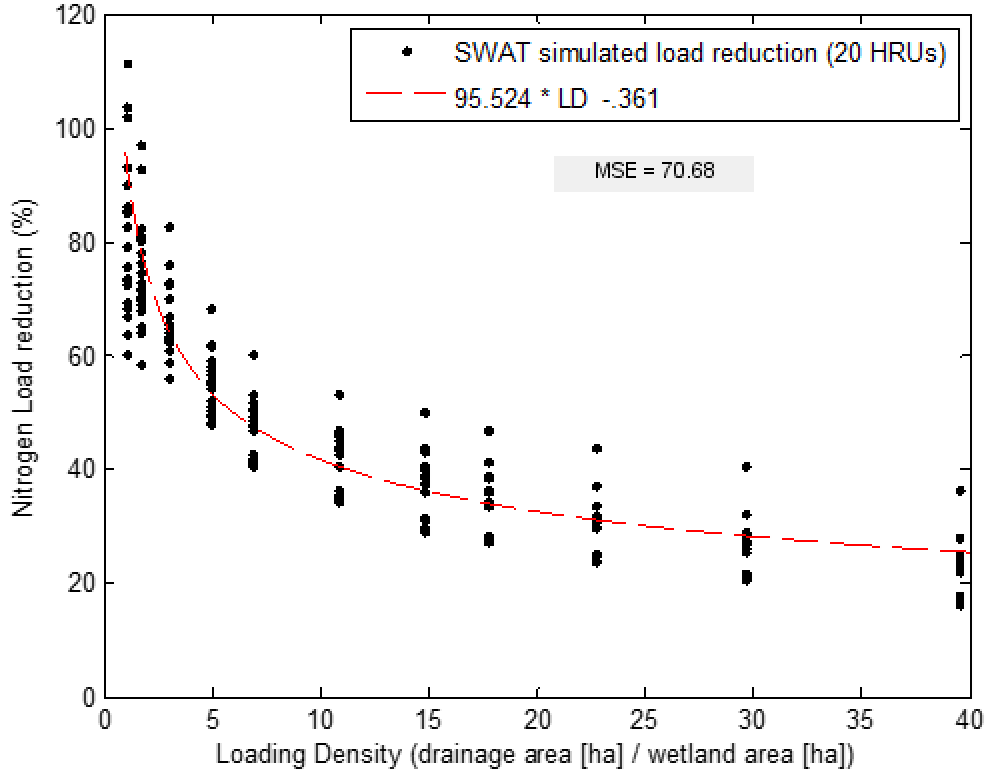

Figure A.3: Nitrogen Load Reduction (%) vs Loading Density: SWAT Simulated Wetland Routine Validation HRUs

The modeled load reductions sufficiently characterized the bioreactor curve. However, there were variations between HRUs. The load reductions greater than 100% result from the use of HRU sizes much greater than the drainage area. The drainage area used for calculating load reduction for lower loading densities was much less than the total HRU. Yet, in order to calculate a load reduction, the total nitrate load for the entire wetland must be used. The SWAT output files do not partition the flows into wetland and non-wetland. Therefore, to calculate the load reduction for a drainage area smaller than the HRU (Equation A.1):

$$Load\ Reduction = \frac{1}{fraction\ of\ HRU\ draining\ through\ wetland}\left(N_{no\ wetland} - N_{wetland}\right) \qquad A.1$$

As a result, the load reduction for the drainage area is extrapolated through the entire HRU area. This will not affect the simulated nitrogen reduction in the simulation because SWAT will only route the considered fraction of drainage area through the wetland. It is only a consideration in the formation of the GKEW.

To incorporate the wetland routine in the simulation, a maximum bioreactor size and target range of load reductions were considered. Based on those constraints, producers consider loading densities to install bioreactors based on user-inputted parameters. In a simulation, a user would consider a bioreactor size and anticipated load reduction. Farmers then consider the associated drainage area (field for that installation).

Farmers also consider multiple bioreactor installations within their land parcel. However, one land parcel (HRU) is discretized into one outlet point in the SWAT model. For that reason the GKEW was extrapolated to larger sizes to perform nitrate reductions like multiple bioreactors. The extrapolation was performed by finding the equivalent reduction rate for the drainage areas associated with multiple bioreactors. A 50% reduction rate was chosen, along with 20 HRUs, and wetland sizes for each drainage area. The wetland sizes were tested for twice, three times, four times, and so on, up to 20 times the drainage area for an equivalent wetland size that resulted average 50% nitrate reduction across the HRUs. The equivalent wetland sizes are shown in Table A.1. The wetland sizes were not just a linear extrapolation of wetland sizes, i.e. a smaller wetland than 15 times the .41 ha was sufficient for modeling 15 bioreactors. Figure A.4 shows how wetland sizes smaller than a linear extrapolation were sufficient for modeling an equivalent reduction rate.

Table A.1: Calibration For Multiple Bioreactor Installations

Number of Bioreactors	Drainage Area [ha] (50% reduction)	Wetland size [ha] for 50% average reduction
1	2.46	0.41
2	4.92	0.8
3	7.38	1.19
4	9.84	1.58
5	12.3	1.975
6	14.76	2.375
7	17.22	2.755
8	19.68	3.165
9	22.14	3.56
10	24.6	3.97
11	27.06	4.35
12	29.52	4.725
13	31.98	5.145
14	34.44	5.55
15	36.9	5.945
16	39.36	6.3175
17	41.82	6.72
18	44.28	7.12
19	46.74	7.5225
20	49.2	7.9275
25	61.5	9.89
30	73.8	11.87
35	86.1	13.835
40	98.4	15.815
50	123	19.795

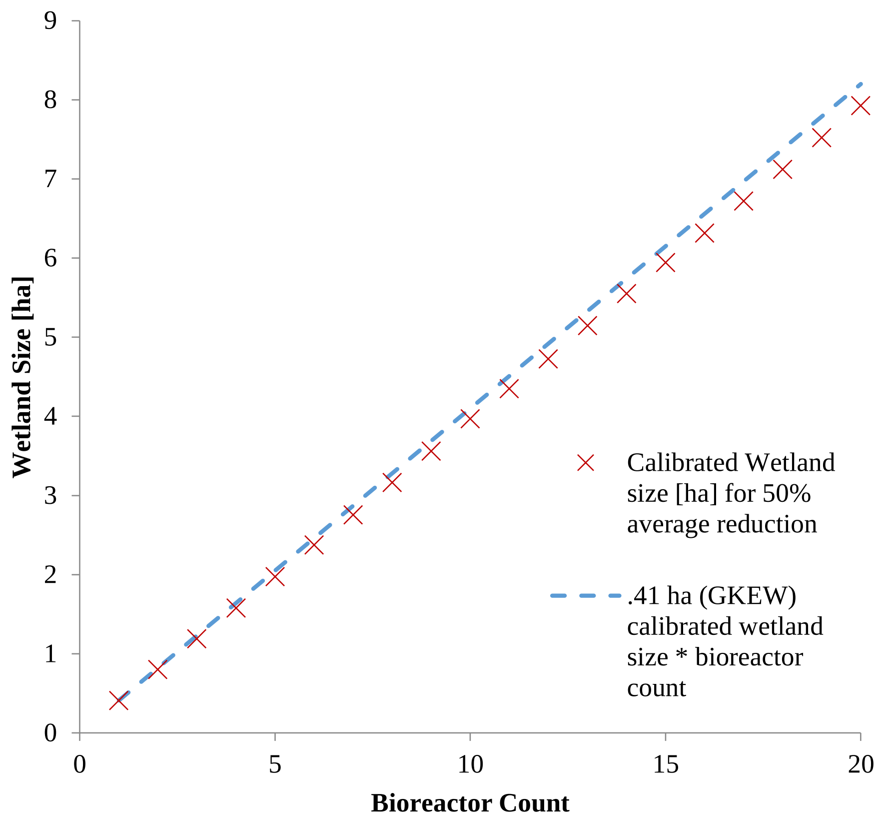

Figure A.4: Equivalent Wetland Sizes for Multiple Bioreactors

After the calibration procedure, the wetland sizes were validated with 20 different HRUs for 10 loading densities and a mean squared error calculation was performed for each wetland size. The mean squared error was less than 65 for all wetland sizes. The validation for 10 bioreactors and 20 bioreactors are shown in Figures A.5 and A.6 respectively.

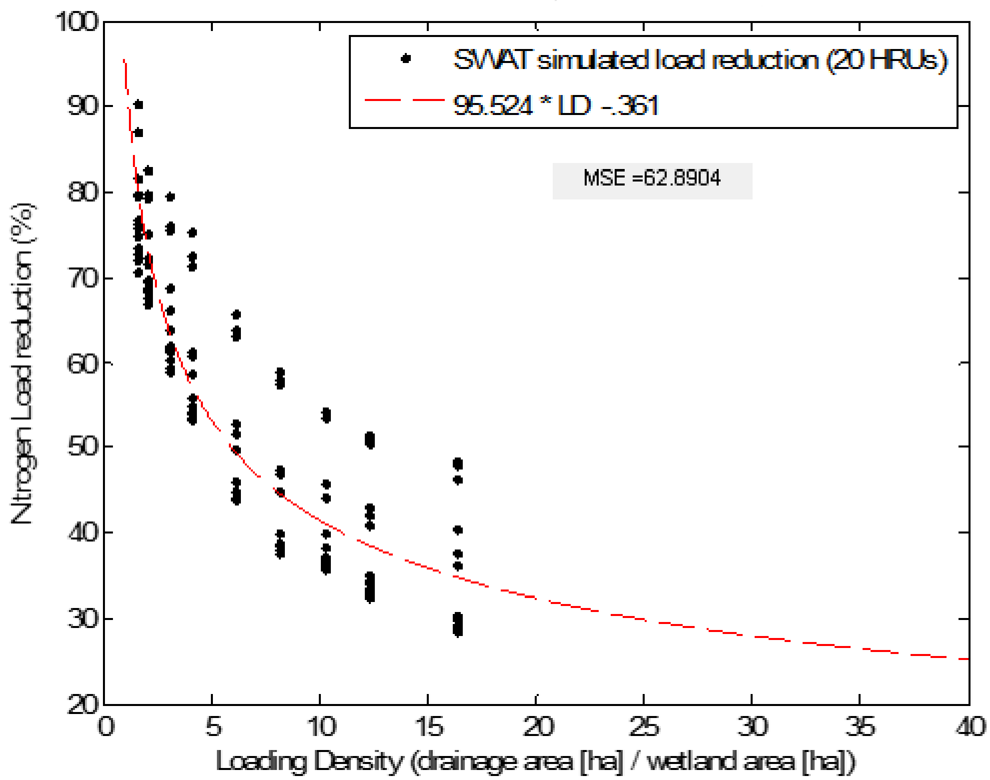

Figure A.5: Nitrogen Load Reduction (%) vs Loading Density: validation for 10 bioreactors represented by 3.97 ha wetland

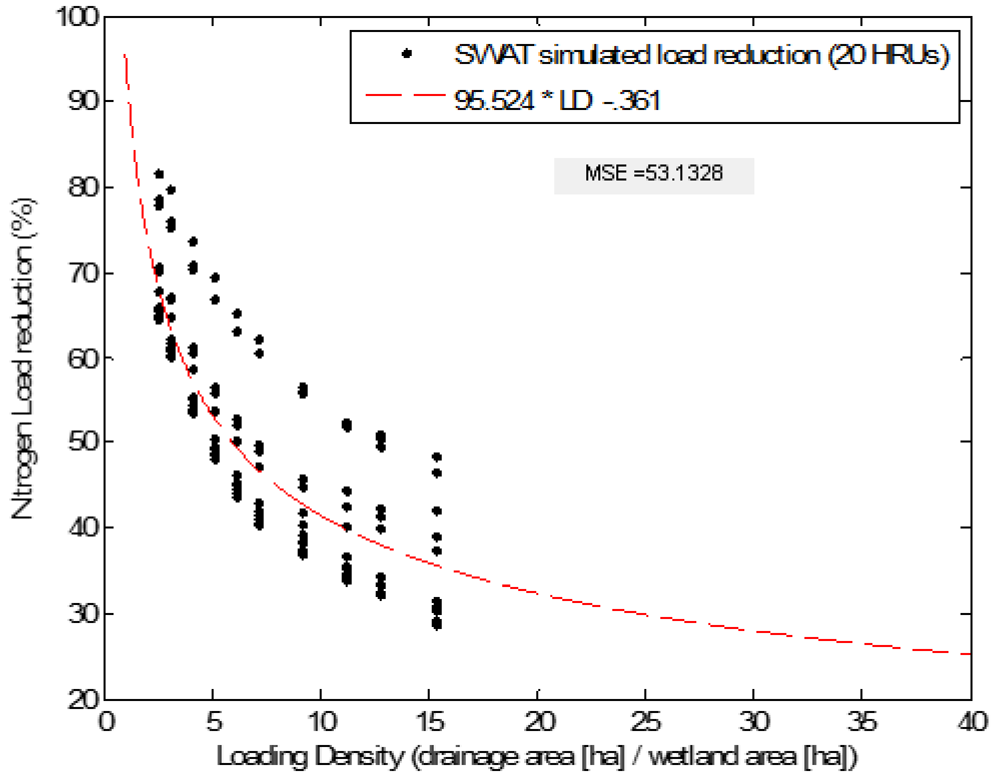

Figure A.6: Nitrogen Load Reduction (%) vs Loading Density: validation for 20 bioreactors represented by a 7.9275 ha wetland

A.2 Other BMPs

A.2.1 Saturated lateral buffer strips

Buffer strips are another edge-of-field best management practice available to Central Illinois farmers. Vegetative filter strips, or buffer strips, are areas of herbaceous perennial vegetation, usually grass, planted and managed to intercept sediment, nutrients, pesticides and other contaminants in runoff water before the runoff can enter water bodies (St. John & Ogle, 2008). Filter strips have been shown to reduce nitrate leaching completely, with most performance ranging between 25% and 75% (Natural Resources Conservation Service (NRCS), 1999; White & Arnold, 2009). With respect to phosphorus, filter strips have been shown to reduce loadings by 27% to 96% (Lee et. al, 2000). Filter strips do affect yield by taking filter strip area out of production.

A.2.2 Saturated lateral buffer strips model setup

Filter strips are another edge-of-field strategy to intercept outflow and allow for infiltration and denitrification before it enters the waterway. Filter strips were simulated using the built-in SWAT parameters (.ops, .mgt). The SWAT filter strip routine provides a width (FITLER_W) and drainage area to filter size ratio FITLER_RATIO) parameter to simulate filter strips. White & Arnold (White & Arnold, 2009) documented the studies used to design the SWAT routine. White & Arnold compiled 22 studies which investigated the effect of filter strips on sediment, flow, and nutrients. The physical studies provided the basis for the SWAT routine's performance using a loading ratio and filter strip size to determine nutrient reductions. Figure A.7 shows a summary of the 22 studies with redundant points removed and an interpolated loading curve. This loading curve was used in the logic to determine the drainage area for a targeted effectiveness in a producers' installation.

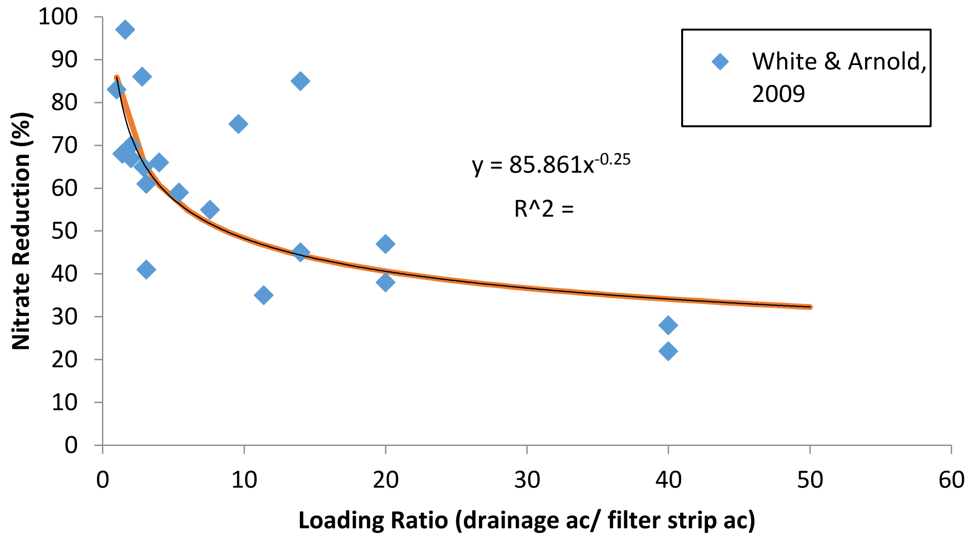

Figure A.7: Filter strip effectiveness and simulated load curve (White & Arnold, 2009)

Helmers et al. (2008) summarized loading ratios and filter sizes and concluded that a loading ratio greater than 20:1 can be expected under most field conditions. The NRCS (1999) standard states that drainage ratios should range from 50:1 to 70:1. The NRCS also recommends filter strips of 20 feet to 40 feet (6 meters to 12 meters) with loading ratios greater than 50:1 requiring a larger width. The size of the filter strip (FILTER_W) is a user-inputted variable within these ranges for simulation.

A.2.3 Future BMP work

This study proposes to utilize the procedure outlined in this Appendix with future functionality for routing tile-drained flow through bioreactors and filter strips.