

**An Integrated Social and Ecological Model: Impacts of Agricultural Conservation Practices on  
Water Quality**

**by**

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*To my family with deepest gratitude  
for their love and continuous support*

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## **List of Abbreviations**

<b>ABM</b>	Agent-based model
<b>BMP</b>	Best Management Practice
<b>CRP</b>	Conservation Reserve Program
<b>DRP</b>	Dissolved Reactive Phosphorus
<b>EPA</b>	Environmental Protection Agency
<b>GLWQA</b>	Great Lakes Water Quality Agreement
<b>HRU</b>	Hydrologic Response Unit
<b>NASS</b>	National Agricultural Statistics Service
<b>NSE</b>	Nash-Sutcliffe Efficiency
<b>ODD</b>	Overview, Design concepts, and Details
<b>P</b>	Phosphorus
<b>PBIAS</b>	Percent Bias
<b>SES</b>	Social-ecological System
<b>SUFI2</b>	Sequential Uncertainty Fitting
<b>SWAT</b>	Soil and Water Assessment Tool
<b>TP</b>	Total Phosphorus
<b>US</b>	United States
<b>USDA</b>	United States Department of Agriculture
<b>WRP</b>	Wetland Reserve Program



## **Abstract**

Most phosphorus loading to Lake Erie is now attributable to agricultural non-point sources; hence a better understanding of the factors that affect the ecosystem health is crucial. Decisions farmers make regarding the adoption of conservation practices are inherently dynamic, affected by changes in social, economic and environmental conditions, whereas the water quality models used to assess policy interventions lack this dynamic social component. To bridge this gap, this dissertation presents three necessary steps to evaluate the impacts of farmers' adoption of conservation practices on water quality using a coupled natural and human systems modeling approach. The necessary steps are: 1) water quality modeling of the Sandusky watershed, Ohio using Soil and Water Assessment Tool (SWAT), 2) development of a farmer typology of conservation practice adoption among Corn Belt farmers and building an agent-based model (ABM) for adoption of conservation practices using the farmer typology, and 3) coupling the ABM with the water quality model to understand impacts of conservation practice adoption on water quality. In Chapter 2, SWAT is used for the Sandusky basin for 1970-2010 to simulate nutrient loading, particularly focusing on dissolved reactive phosphorus (DRP). The results indicate that recent increased storm events, interacting with changes in fertilizer application timing and rate, as well as management practices that increase soil stratification at the soil surface, appear to increase DRP runoff. In Chapter 3, the broad literature review on conservation practices adoption by Corn Belt farmers consistently identify four policy-relevant farmer characteristics, namely farm size, land tenure arrangements, source of income and information networks. In an examination of

these characteristics, four broad farmer types emerged: traditional, supplementary, business-oriented, and non-operator farmers. To study the dynamic social component of farmers on water quality, an ABM of conservation practice adoption by farmers using the farmer typology is built. In Chapter 4, the results of ABM are used as input for water quality models to explore the linkages between social and biophysical processes within this coupled system. This linked modeling framework highlights the importance of non-operator owners and the influence of crop revenue insurance in lieu of commodity payments on farmers' adoption decisions.

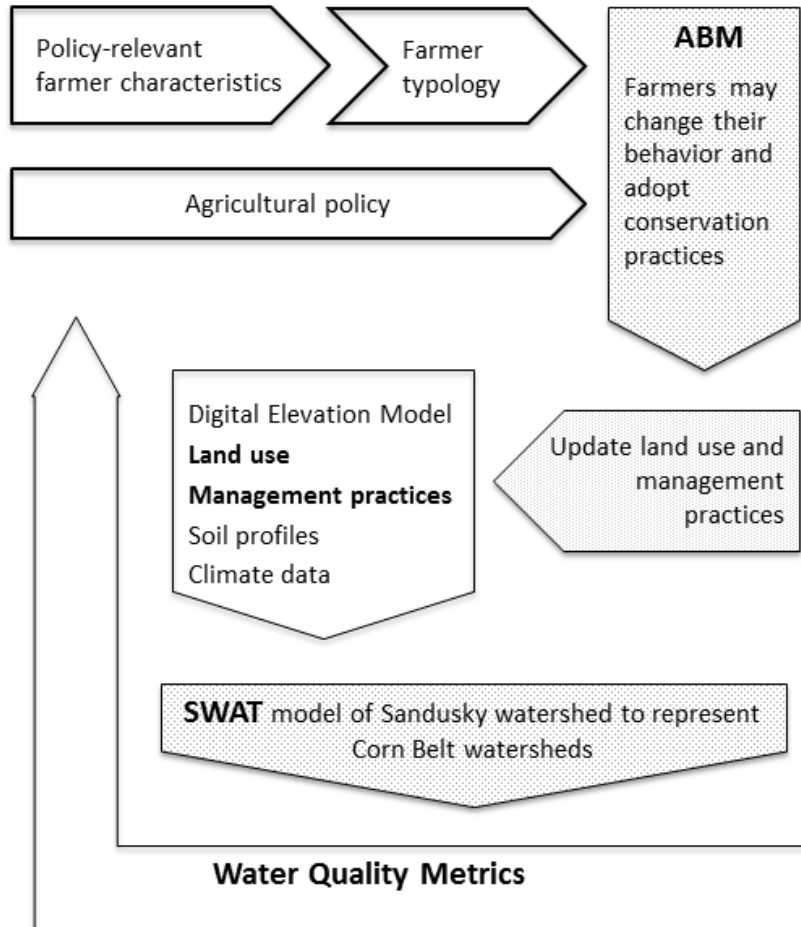
# Chapter 1: Introduction

The progress of human societies has been highly dependent on agriculture, the expansion and intensification of which parallel the growth of the human population and its footprint. However, the ecosystems upon which agriculture depends are constrained. According to the Food, Agriculture, Conservation and Trade Act of 2008, enhancing the quality of the environment and resource base is a key agricultural sustainability goal. Therefore, to move toward sustainability, we must employ policies that provide benefits at different scales and preserve the integrity of existing resources. The adoption of conservation practices is regarded as an effective strategy to enhance water quality and improve agricultural sustainability by increasing system resilience (NRC, 2010). The central objective of this dissertation is to contribute to agricultural sustainability by understanding and optimizing the relationships among water quality, agro-environmental policy, and farmer adoption of conservation practices. This research examines the social-ecological system using a social model (Agent-based model, ABM) and a biophysically based watershed model (Soil and Water Assessment Tool, SWAT) to study farmer responses to agro-environmental policies of the United States, as well as the impacts of those responses on water quality.

Agriculture is a major consideration in discussions of water resources sustainability as it can negatively affect water quality and quantity across a landscape wider than the agricultural production area. In fact, nutrient pollution from agriculture is the leading cause of water quality impairment in lakes, estuaries, and rivers (EPA, 1998). More specifically, important indicators

of nutrient pollution - high river concentrations of nitrogen and phosphorus - are correlated with inputs from application of fertilizers and manure from livestock wastes (Boyer et al., 2002; Galloway et al., 2004; Ribaudo and Smith, 2000).

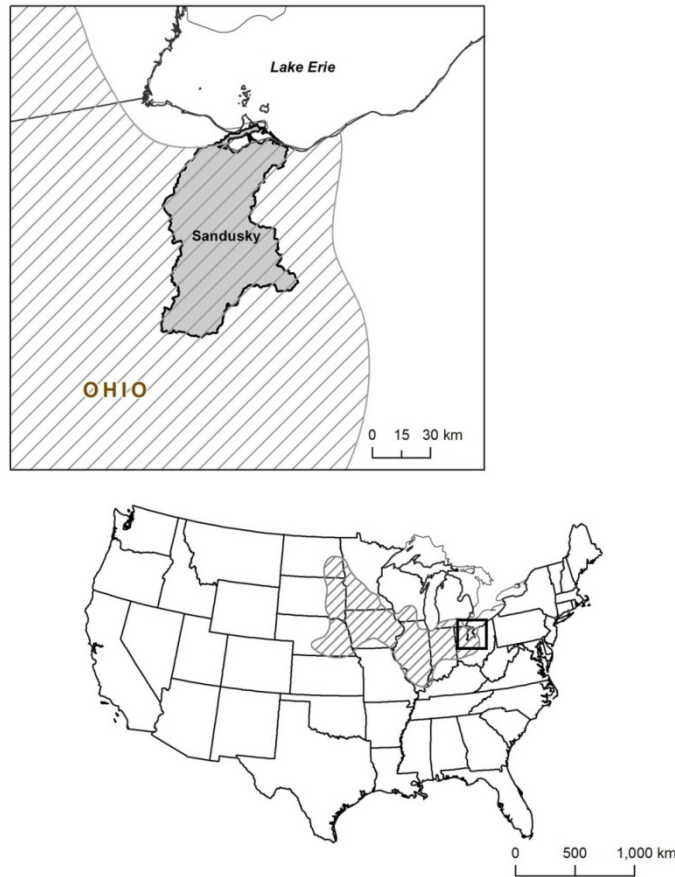
To mitigate the damage to ecosystem services, policies have focused on a range of solutions and institutions, including the development and implementation of conservation practices intended to alleviate negative impacts on water resources. To study the effectiveness of these solutions, Veldkamp and Verburg (2004) highlighted the need for coupling models that incorporate dynamic feedbacks between social and biophysical systems. This research responds to that need by examining this coupled human and natural system using an agent-based model (ABM) and a biophysically based water quality model (SWAT) to investigate how farmer characteristics might interact with the combination of conservation practices to explain the effects of adoption on water quality (Figure 1-1).



**Figure 1-1: Coupled human and natural system of farmers’ adoption of conservation practices and effects on water quality.**

The study area is an intensively cultivated watershed of Lake Erie, namely the Sandusky watershed in Ohio (Figure 1-2). Lake Erie is the 11th-largest freshwater lake in the world and the southernmost, shallowest, warmest, and most biologically productive of the five Great Lakes (Myers et al., 2000). Historically, Lake Erie has been subject to significant cultural eutrophication from excessive phosphorus loading, primarily from agricultural runoff and point source discharges (Dolan and McGunagle, 2005; Dolan and Chapra, 2012); however, non-point sources, particularly agriculture, are the major current causes of pollution in Lake Erie (Forster et

al., 2000; Dolan and McGunagle, 2005). In response to concerns about the consequences of eutrophication, the governments of the US and Canada, largely through the support of the Great Lakes Water Quality Agreement (GLWQA, 1978), implemented a program of phosphorus load reduction that was unique worldwide (DePinto et al., 1986). The program led to a combination of point and nonpoint phosphorus load reductions that achieved the target load, prompting a response in the lake that was rapid, profound, and similar to that predicted by models (Makarewicz, 1993). Despite decades of a successful nutrient control program, serious symptoms of eutrophication persist in Lake Erie. Importantly, in recent years, unexpected increases in oxygen depletion and hypoxia have renewed policy attention on nutrient control. Hypoxia has severely impacted commercial and sport fisheries with cascading effects throughout the aquatic and coastal food webs (Carpenter et al., 2008). Because most phosphorus loading to Lake Erie now comes from agricultural non-point sources, causing hypoxia, it is important that we gain a better understanding of the agricultural factors that affect the health of the ecosystem.



**Figure 1-2: Map of the geographic setting farmer types, showing the Corn Belt (dashed) and the Sandusky Watershed, Ohio.**

Chapter 2 focuses on building the water quality model of the Sandusky watershed in the Lake Erie basin using SWAT to simulate nutrient loadings, as indicators of water quality impacts (Figure 1-2). SWAT is an integrated hydrologic and biogeochemical water quality model that is particularly well suited for exploring the impacts of land management and conservation practices and for evaluating the effectiveness of policy alternatives (Arabi et al., 2007).

The highly cultivated watersheds like the Sandusky, are major sources of non-point source pollution in Lake Erie (Hawley et al., 2006). As Lake Erie is a phosphorus limited aquatic system, for the water quality model, the emphasis is on phosphorus simulations. Therefore, I

build a process-based model of surface and groundwater hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, and pesticides that can simulate the effects of climate and land use changes on nutrient and sediment delivery from watersheds. The primary objective is to understand potential factors contributing to the dissolved reactive phosphorus (DRP) increase in Lake Erie watersheds, especially in the Sandusky watershed in Ohio. The long term DRP trend change is particularly important in Lake Erie watersheds, as DRP is the form of phosphorus that is 100% bioavailable for plant growth and therefore influential on harmful algal bloom formation. In this study, the extensive observed water quality data set is obtained from Heidelberg University in Ohio and used for calibrating and validating the model. With the advantage of the extensive observed data availability, the modeling period is 1974-2010, which is an exceptionally long simulation period in water quality modeling. Results show that there are numerous factors causing the increase in the observed DRP loading and concentration after mid-1990s, such as fertilizer application rates and timing, adoption of conservation practices and climate change.

Chapter 2 indicates that land management decisions play a critical role in nutrient management from agricultural landscapes. These decisions that farmers make regarding the adoption of conservation practices are inherently dynamic, affected by changes in social, economic and environmental conditions, whereas the water quality models used to assess policy interventions lack the dynamic social component of farmers' decisions. To represent the heterogeneity of farmers, Chapter 3 presents a classification of farmers into types according to policy-relevant farmer characteristics for use in agent-based models (ABM) that supports the development of targeted conservation policies aimed at reducing water-quality degradation. To develop this typology, I conducted a broad review of the literature on conservation practices and



their adoption by farmers in the Corn Belt region (Figure 1-2), with farmers defined as owners or renters of land on which cash crops such as corn, soybean and winter wheat are grown. This literature synthesis revealed that farm size, land tenure arrangements and source of income could be the policy-relevant farmer characteristics that influence farmers' decision-making processes regarding conservation practices. By examining these policy-relevant farmer characteristics, four broad types of farmers emerged: (1) Traditional, (2) Supplementary, (3) Business-oriented, (4) Non-operator farmers. I operationalized these farmer types for use in ABMs, which tend to be most useful when constructed with the fewest characteristics (Axelrod, 1997). Farmer typologies have been developed for US farmers based on farm sales and operator occupations to understand the factors that influence decisions regarding conservation practices (Briggeman et al., 2007; Hoppe et al., 2007; Lambert et al., 2007). However, none of the US agricultural typologies serve as the basis for an ABM.

In Chapter 3, I also use this typology to develop an ABM that can be used to examine alternative approaches to targeting conservation policy in Corn Belt agroecosystems. ABMs are computer-based models that can represent decentralized decision-making and interactions of heterogeneous social agents on multiple scales. The feature that distinguishes ABMs from other simulation techniques is that the former are constructed in a "bottom-up" manner by defining the model at the level of individual actors and their interactions with each other and with the environment. The ABM generates agent behavior as agents use the already defined rules to determine which other agents to interact with, what to do when they interact, and how to interact with the environment. This flexibility allows the ABMs to be used to study systems on many scales, and to integrate the parts into a coherent whole. Moreover, because the ABMs are computational models, they are formal, unambiguous, and thus, replicable and testable. Such

models have previously been applied to agricultural systems (Happe et al., 2008), and have been shown to yield valuable information about responses to changes in policies governing complex systems like those in watersheds.

The farmer typology formulated in Chapter 3 after a thorough review and synthesis of the literature on adoption of conservation practices by Corn Belt farmers is used to populate the agents in the ABM. This model investigates relationships between adopter and non-adopter farmers of conservation practices because ABMs can model individual agents with distinct decision-making patterns and behaviors. Farmer typology informs the ABM about how different factors such as available resources and knowledge of incentives and regulations mediate decisions about land use and applied conservation practices on rural properties. The ABM is designed to study the adoption behavior of the farmers and the results are used as input to the SWAT model to explore the effects of the adoption patterns on water quality. I employed this ABM under changing tenure dynamics and agricultural policies such as subsidized crop revenue insurance as proposed for the next Farm Bill, and found it to be a useful method to represent the dynamic social component in coupled social and biophysical process models. The outcomes of the ABM developed with these farmer types are used as input for water quality models to explore the linkages between social and biophysical processes within this coupled system. Moreover, the development of a farmer typology and subsequent construction of an ABM capable of representing the heterogeneity of US farmers in their adoption of conservation practices support the effective tailoring of agricultural policy to reduce sediment and nutrient runoff from agricultural land.

In Chapter 4, I create coupled social-environmental models of agricultural watersheds with attention to spatial patterns, socio-economic drivers of farmers' conservation practice adoption,

and their water quality impacts. This requires the integration of analytical methods across the natural and social sciences, including water quality modeling and decision and policy analysis. For decision and policy analysis, I use the ABM developed in Chapter 3 and for estimating water quality impacts I use the SWAT model built in Chapter 2. In this study, farmers' reactions to policies intended to affect adoption of conservation practices and their attitudes towards adoption are critical determinants of the spatial distribution of these practices, and therefore, to water quality outcome. By understanding and modeling the interactions among adopters and non-adopters and simultaneously analyzing the effects of these interactions on water quality, I build the knowledge necessary to evaluate the water quality results from alternative policies related to conservation investments. This study constitutes an important step in understanding the effects of different policy approaches on the adoption of conservation practices and their impacts on downstream water quality. By comparing different agro-environmental policies, I provide a timely assessment of the differences among and benefits of alternative policy options. Further, by integrating this knowledge with the linked agent-based and watershed models, I provide a quantitative tool for evaluating alternative policy options.

To summarize, this dissertation develops a farmer typology, constructs an ABM capable of representing the heterogeneity of US farmers in their adoption of conservation practices, and integrates farmer decisions into water quality models to support the effective tailoring of agricultural policy to reduce sediment and nutrient runoff from agricultural land.

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## **Chapter 2: Evaluating causes of trends in long-term dissolved reactive phosphorus loads to Lake Erie**

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### **Abstract**

Renewed harmful algal blooms and hypoxia in Lake Erie have drawn significant attention to phosphorus loads, particularly increased dissolved reactive phosphorus (DRP) from highly agricultural watersheds. We use the Soil and Water Assessment Tool (SWAT) to model DRP in the agriculture-dominated Sandusky watershed for 1970-2010 to explore potential reasons for the recent increased DRP load from Lake Erie watersheds. We demonstrate that recent increased storm events, interacting with changes in fertilizer application timing and rate, as well as management practices that increase soil stratification and phosphorus accumulation at the soil surface, appear to drive the increasing DRP trend after the mid-1990s. This study is the first long-term, detailed analysis of DRP load estimation using SWAT.

## **1. Introduction**

In the 1960s and 1970s, Lake Erie experienced significant cultural eutrophication from excessive phosphorus loading from both agricultural runoff and point source discharges (Dolan and McGunagle, 2005). Responding to concerns about the consequences of eutrophication in the 1970s, the governments of the US and Canada, largely through the Great Lakes Water Quality Agreement implemented a program of phosphorus load reduction (International Joint Commission, 1978). The initial approach of reducing point-source loads alone was not adequate to achieve target loads set by the Agreement (Richards, 1985), so subsequently a combination of point and non-point phosphorus load reductions was used (Makarewicz, 1993). This combination of load reductions led to achieving the target load of 11,000 metric tonnes per year in most years with weather influencing year-to-year variability in non-point source loads. The response of the lake was rapid and profound with reduced algal biomass and reduction of low oxygen conditions in the central basin. With reductions in point source loads, in recent decades, non-point sources, particularly from agriculture, have become dominant sources of phosphorus (Forster et al., 2000).

In the 1980s and 1990s, the main conservation policy goal for limiting non-point source pollution was to reduce sediment runoff and the phosphorus attached to sediments; therefore most conservation efforts focused on erosion reduction (Ohio EPA, 2010). These efforts, following implementation of the Great Lakes Water Quality Agreement, resulted in reductions in suspended solids and particulate phosphorus in Lake Erie tributaries, especially under low flow conditions compared to high flow conditions in spring (Richards, et al., 2009). However, despite decades of improvements in nutrient control, there have been unexpected recent increases in harmful algal blooms and poor water clarity in the western basin, and summer hypoxia (low

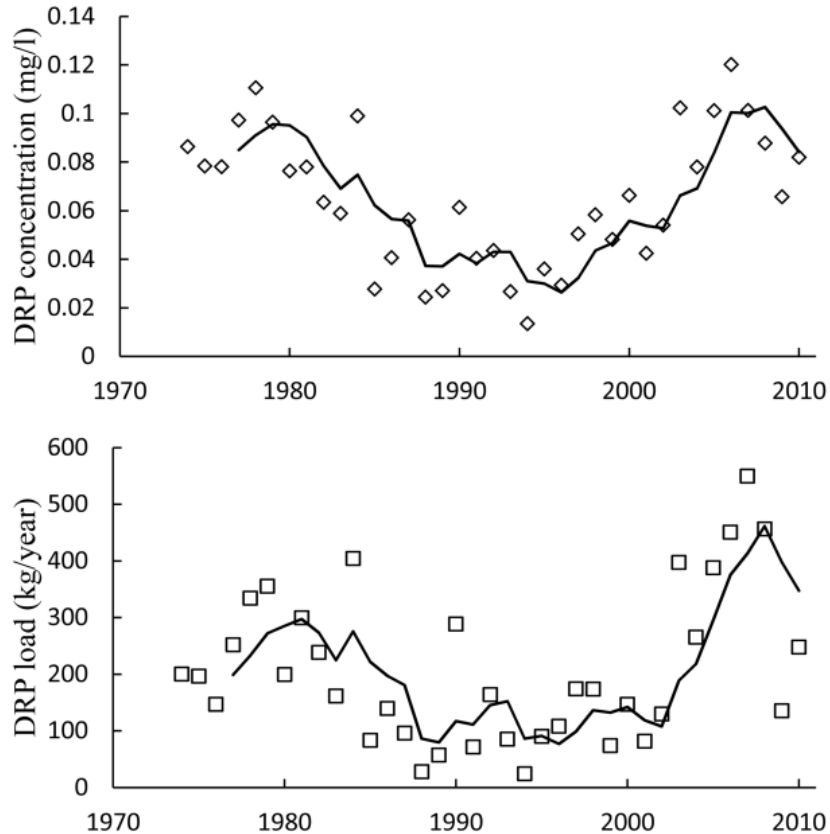
oxygen) in the hypolimnion of the central basin (Hawley et al., 2006). Because of their significant potential impact on food web interactions and fisheries (Vanderploeg et al., 2009), this has brought renewed policy attention on nutrient control.

While the Great Lakes Water Quality Agreement (International Joint Commission, 1978) focused on total phosphorus (TP) as the water quality parameter by which Lake Erie eutrophication is to be managed, recent research indicates that dissolved reactive phosphorus (DRP) is of great importance because it is highly bioavailable (Richards, 2006; Valderploeg et al., 2009). The National Center for Water Quality Research (NCWQR) at Heidelberg University has monitored stream flow and water quality daily from 1975 to the present revealing a perplexing trend in DRP loads, where this highly bioavailable form of phosphorus declined through the early 1990s, but then increased since the mid-1990s (Heidelberg University, 2012). This trend is observed in the agricultural tributaries of Lake Erie (Maumee and Sandusky) (Richards, 2006) and is particularly significant in the Sandusky watershed (Figures 2-1 and 2-2). Moreover, the rate of oxygen depletion in the central Lake Erie basin is strongly correlated with DRP load since the mid-1990s (Rucinski et al., 2010). It is important to note that, even though DRP load trends can be affected by trends in flow, similar trends are reported for DRP river concentration, indicating that changes in the loads of DRP are not solely a function of changes in hydrology (Richards, 2006; Richards et al., 2009).





**Figure 2-1: Locator map of the Sandusky watershed, Ohio**



**Figure 2-2: Observed mean annual dissolved reactive phosphorus (DRP) load and concentration in the Sandusky River, OH (1974-2010) with a moving 4-year average trendline.**

Herein, we use the Soil and Water Assessment Tool (SWAT) to explore the role of several potential causes of the recent increases in DRP loading suggested by the Ohio P Task Force (Ohio EPA, 2010): 1) changes in fertilizer application rates; 2) widespread adoption of no-till and conservation tillage practices after the mid-1990s; 3) stratification of phosphorus (P) in the soil surface layer; and 4) changes in rainfall patterns. We focus on the Sandusky watershed because it is representative of the other agriculturally dominated watersheds, has extensive (daily) flow and water quality data, and is small enough to allow SWAT to be applied at farm scale resolution. Our approach is to fully calibrate and evaluate the model to 40 years of observations and then explore the impact of hypothetical management and weather scenarios on DRP loading.

## **1.1 Study Area**

The Sandusky watershed, located in northwest Ohio, is a 3926 km<sup>2</sup> watershed (Figure 2-1) that drains into Lake Erie. The dominant land use is agriculture (77%), where farmers specialize in corn, soybean, and winter wheat rotations, with minor livestock production. Daily discharge as well as sediment, TP, and DRP loads are provided by NCWQR at Heidelberg University for the simulation time period (Heidelberg University, 2012).

## **2. Methods**

SWAT is a continuous-time, integrated, watershed-scale hydrologic and water quality model that runs at a daily time-step (Gassman et al., 2007). It is a process-based model of weather, surface hydrology, sedimentation, soil temperature, crop growth, nutrients, pesticides, and groundwater that can simulate the effects of climate and agricultural management changes on nutrient and sediment delivery from watersheds (Arnold et al., 1998).

SWAT is considered suitable for simulating long-term impacts of agricultural best management practices (BMPs) (Arabi et al., 2008) and land management measures on water, sediment, and agricultural nutrient loss from large, complex watersheds with varying soils, land use, and management measures (Arnold and Fohrer, 2005). SWAT simulates the transformation and movement of nitrogen and phosphorus in several organic and inorganic pools (Neitsch et al., 2011), where nutrient losses from soil occur through crop uptake, surface runoff, and eroded sediment (Jha et al., 2004).

SWAT is a semi-distributed model with the hydrologic response unit (HRU), representing unique combinations of land cover, soil type, and slope, as the fundamental computational unit. Runoff flow, sediment, and nutrient loads are calculated separately for each HRU and summed to determine total load contribution from subwatersheds (Neitsch et al., 2011). We employed the

model at a spatial scale such that the average HRU size corresponds to the average farm size in the Sandusky basin (105 hectares) (USDA, 2009), resulting in 147 subbasins and 959 HRUs. Bosch et al. (2011) used SWAT to simulate tributary sediment and nutrient loading from six watersheds draining into Lake Erie, including the Sandusky, *albeit* at a much coarser physical scale and shorter time period. Their simulation period was 1998 to 2005, and thus not sufficient to capture the significant changes in DRP load, especially during the early and mid-1990s. So, we extended the modeling period to calibrate and evaluate the model with the extensive daily-observed flow and water quality data from 1974 to 2010 for stream discharge and sediment, total phosphorus (TP), and DRP loads (Heidelberg University, 2012).

We calibrated the model for 1991-2010 and evaluated it for 1974-1990, with 1970-1973 as spin-up years using daily flow discharge, sediment, TP, and DRP loads. We used the extensive empirical data of high quality (10918 data points for 1975 to 2010, i.e., on average 303 data points for each year for 36 years). We used the Sequential Uncertainty Fitting (SUFI2) method (Abbaspour et al., 2007), a stochastic procedure, and additional manual calibration to first calibrate for flow and then for sediment, TP, and DRP loads. Table 2-1 shows flow and DRP parameters with their ranges for the sensitivity analysis and calibrated values. Model performance (Tables 2-2 and 2-3) was considered satisfactory for use in this study based on the coefficient of determination ( $R^2$ ), Nash-Sutcliffe efficiency (NSE), and percent bias (PBIAS), based on criteria developed by Moriasi et al. (2007).

Parameter	Min	Max	Rank		Calibrated Value	Definition
			Flow	DRP		
ESCO	0	1	1		0.99	Soil evaporation compensation factor
REVAPMN	0	500	2		278.50	Threshold depth of water in the shallow aquifer for percolation to the deep aquifer (mm H2O)
CN2	35	98	3		86.97	Initial SCS runoff curve number for moisture condition
SMFMX	0	10	4		4.52	Melt factor for snow on June 21 (mm H2O/°C-day)
SOL_AWC	0	1	5		0.02	Available water capacity of the soil layer (mm H2O/mm soil)
EPCO	0	1	6		0.12	Plant uptake compensation factor
SOL_K	0	2000	7		571.33	Saturated hydraulic conductivity (mm/hr)
SMTMP	-5	5	8		2.37	Threshold temperature for snowmelt (°C)
GW_DELAY	0	500	9		204.83	Groundwater delay time (days)
SFTMP	-5	5	10		3.93	Snowfall temperature (°C)
SMFMN	0	10	11		8.55	Melt factor for snow on December 21 (mm H2O/°C-day)
CANMX	0	100	12		15.57	Maximum canopy storage (mm H2O)
TIMP	0	1	13		0.60	Snow pack temperature lag factor
CH_K2	-0.01	500	14		39.82	Effective hydraulic conductivity in main channel alluvium (mm/hr)
SURLAG	0.05	24	15	4	10.44	Surface runoff lag coefficient
CH_N2	-0.01	0.3	16		0.02	Manning's "n" value
ALPHA_BF	0	1	17		0.98	Baseflow recession constant
PHOSKD	100	400		1	292.63	Phosphorus soil

PSP	0.01	0.7	2	0.44	partitioning coefficient
P_UPDIS	0	100	3	20.00	Phosphorus sorption coefficient
PPERCO	10	17.5	5	5.48	Phosphorus uptake distribution parameter
					Phosphorus percolation coefficient

**Table 2-1: Sensitivity analysis results for flow and DRP parameters.**

		Observed mean (m <sup>3</sup> /s)	Simulated mean (m <sup>3</sup> /s)	R <sup>2</sup>	NSE	PBIAS (%)
Calibration (1991-2010)	Daily	34.8	31.2	0.55	0.54	9.79
	Monthly	35.8	31.9	0.74	0.72	10.96
	Annual	35.8	31.9	0.77	0.61	10.83
Evaluation (1974-1990)	Daily	33.8	30.4	0.50	0.49	9.91
	Monthly	34.1	30.6	0.65	0.63	10.25
	Annual	33.9	30.6	0.74	0.59	9.67

**Table 2-2: Calibration and evaluation results for daily stream discharge (m<sup>3</sup>/s). Coefficient of determination (R<sup>2</sup>), Nash-Sutcliffe efficiency (NSE), and percent bias (PBIAS) are used to evaluate the model performance. Model simulations for flow are accepted as satisfactory if NSE>0.5 and PBIAS ± 25% (Moriassi et al., 2007).**

		R <sup>2</sup>	NSE	PBIAS (%)
Calibration (1991-2010)	Annual			
	Sed	0.59	0.55	-7.42
	TP	0.62	0.55	-6.41
	DRP	0.71	0.62	-16.52
Evaluation (1974-1990)	OrgP	0.50	0.37	-4.42
	Sed	0.43	0.30	15.71
	TP	0.21	0.11	9.44
	DRP	0.32	0.30	-0.32
	OrgP	0.14	-0.04	11.23

**Table 2-3: Calibration and evaluation results for annual sediment loading (Sed, tons/year), total phosphorus (TP, kg/year), dissolved reactive phosphorus (DRP, kg/year), organic phosphorus (OrgP, kg/year). Coefficient of determination (R<sup>2</sup>), Nash-Sutcliffe efficiency (NSE), and percent bias (PBIAS) are used to evaluate the model performance. Model simulations are accepted as satisfactory if NSE>0.5 and PBIAS ± 55% for sediment and PBIAS ± 70% for nutrients (Moriassi et al., 2007).**

## 2.1 Baseline Scenario

Our baseline scenario uses a realistic representation of trends in weather and agricultural landscape in the Sandusky watershed between 1970 and 2010. Agricultural operations for tillage practices, fertilizer inputs and application timing, and crop choices for the simulation period are generalized from the most common agricultural land management practices in the watershed. In this region, cash-crop agriculture production with rotations of soybean, corn, and winter wheat is widespread. According to Richards et al. (2009), corn acreage in the Sandusky area has not changed significantly, while soybean acreage has increased and winter wheat acreage has decreased since the 1970s. For land cover types other than agriculture, such as residential, industrial, pasture, forest, and wetlands, we constructed operation schedules based on the most common management practices.

Because fertilizer application is the largest input of both nitrogen and phosphorus in the agricultural watersheds of Lake Erie (Han et al., 2011), the amount of phosphorus application is a key management consideration, and these rates have changed over the simulation period in the Sandusky watershed (Ruddy et al., 2006). In our baseline scenario, we used watershed-scale nutrient budgets constructed for the Lake Erie watersheds to represent temporal variation in application rates (Han et al., 2012). Trends in the Sandusky show higher fertilizer application rates in the 1970s, and after a reduction in the 1990s, an increase during the past decade.

The baseline scenario also reflects changes in the long-term adoption rates of no-till and conservation tillage. Agricultural land under conservation tillage has at least 30% of crop residue from the previous year on the soil surface, and under no-till practices crops are planted with no soil disturbance in the crop residue of the previous year (Ohio EPA, 2010). These practices were minimally adopted in the early 1980s and approached nearly 50% by the mid-1990s (Forster et

al., 2000; Richards and Baker, 2002; Richards et al., 2009). This increase is due to the Great Lakes Water Quality Agreement which promoted best management practices that reduce sediment runoff from agricultural fields (i.e., conservation tillage and no-till practices), that resulted in reductions in flow-adjusted concentrations of suspended solids and particulate phosphorus in Lake Erie tributaries (Richards, 2006; Richards et al., 2009). However, under no-till practices, phosphorus can accumulate in the soil surface layer because crop residue and surface P are not mixed into the soil column (Beauchemin and Simard, 2000; Kleinman et al., 2011; Sharpley, 2003). Moreover, no-till practices can increase soil stratification and accumulation of residual fertilizer P at the top of the soil profile and potentially intensify DRP runoff (Kleinman et al., 2011). In fact, widespread adoption of no-till and conservation tillage practices corresponds in time with the increased DRP loading after the mid-1990s. In addition to no-till and conservation tillage practices (Kleinman et al., 2011), fertilizer application exceeding crop needs (Bennett et al., 2001) and surface application (broadcasting) of P fertilizer and manure (Richards, 1985) have also lead to an increase in P accumulation in the soil surface layer and to a higher likelihood of P runoff from agricultural fields (Allen et al., 2006; Carpenter, 2005).

SWAT incorporates certain agricultural management practices such as tillage practices, fertilizer input and time of application, and a number of model parameters governing phosphorus generation and transformation in different P pools. After investigating the governing equations and mechanisms for P transformation and generation, both Radcliffe et al. (2009) and Vadas and White (2010) suggest that certain model parameters should be modified to reflect soil types and soil test phosphorus levels. For example, model parameters such as the P soil partitioning coefficient (PHOSKD), P availability index (PSP), initial labile P concentration (SOL\_SOLP),

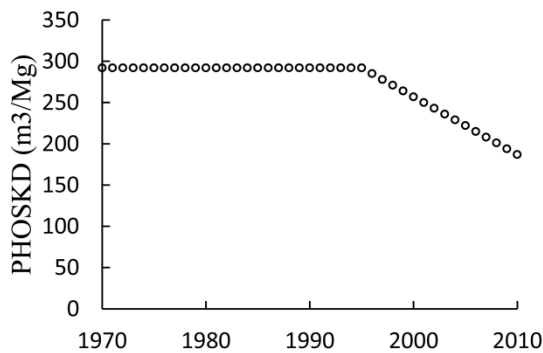


and organic P concentration (SOL\_ORGP) in the surface soil layer should be determined by soil types and can be estimated using soil test phosphorus values and soil properties. Radcliffe et al. (2009) suggest that the P availability index (PSP) – rate of exchange between the inorganic labile P and active P pools in soils, should be spatially dynamic and calculated using the soil P concentration, clay content, and organic C content. Using the suggested methodology by Radcliffe et al. (2009), we calculated the area-weighted average of PSP for the entire Sandusky watershed for the simulation period.

Based on our sensitivity analyses, PHOSKD is the most sensitive parameter for calibrating to DRP observations (Table 2-1). Because the standard version of SWAT is not capable of representing some of the mechanisms responsible for soil stratification and accumulation of P at the soil surface layer, we used the P soil partitioning coefficient (PHOSKD) - the ratio of the soluble phosphorus concentration in the soil surface layer to the concentration in surface runoff (Neitsch et al., 2011) - as a proxy representing the vulnerability of P to runoff from the soil surface layer. Increased adoption of no-till and conservation tillage after 1995, coupled with surface application of fertilizers, increased soil stratification and accumulation of P at the soil surface layer. Low values of PHOSKD allow more P runoff and therefore decreasing PHOSKD after the mid-1990s reflects this increased susceptibility of P runoff due to soil P stratification (Figure 2-3).

Loss of DRP from watersheds is likely to be correlated strongly with storm events (Sharpley et al., 2008) and therefore weather patterns may have influenced trends in DRP runoff from agricultural land (Ohio EPA, 2010). Fertilizer application time, relative to weather patterns, therefore is another potential factor driving increased DRP yields. Traditionally, farmers apply fertilizer before planting crops, usually in spring. However, economic and practical incentives

such as lower fertilizer prices and labor and equipment availability motivate farmers for fall application (Ohio EPA, 2010). The runoff potential of nutrients, especially DRP, is higher in fall because the ground is bare and plant roots are not available or deep enough for nutrient uptake (Richards, 1985). However, because fertilizer sales are reported on an annual basis, there is no accurate method to determine month of application. Therefore, for our baseline scenario we relied on previously conducted surveys with the farmers in the area (EPA, 2008; Napier and Bridges, 2002) and informal conversation with the extension agents to determine the percentage of spring vs. fall application over the 40 year simulation period. Within the dominant crop rotations, winter wheat always has fall fertilizer application. In early 1980s, corn farmers started broadcasting fertilizers in the fall after harvesting soybean. The transition to fall application started slowly but increased rapidly as farm size increased. Currently, many large farmers choose fall broadcasting; however, there appears to be a more recent trend back to spring application.



**Figure 2-3: Time-dependent P soil partitioning coefficient, PHOSKD ( $\text{m}^3/\text{Mg}$ ) as a proxy to reflect the impact of soil stratification and P accumulation at the soil surface layer.**

### **3. Results**

#### **3.1 Baseline Scenario**

While we evaluated the model adequacy against daily, monthly, and annual measurements, we use 4-year running averages in our scenario analysis because we are more interested in exploring the long-term trends in DRP loads than in studying year-to-year fluctuations (Figure 2-4a). The baseline scenario has satisfactory model statistics for flow discharge, sediment, TP, and DRP loads (Tables 2-2 and 2-3) and is in accordance with the long-term DRP trends.

#### **3.2 Fertilizer Application Rate Scenario**

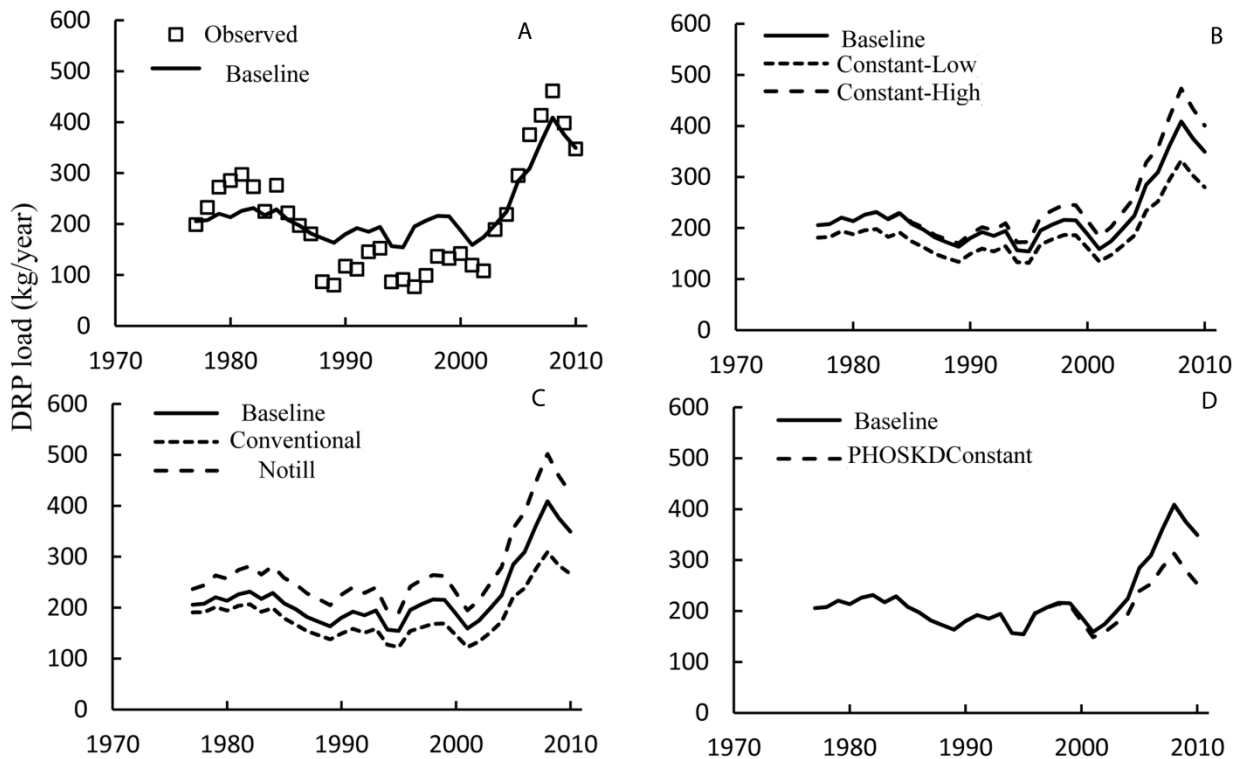
The baseline scenario includes a variable fertilizer application rate that decreases in the mid-1980s and then increases in the early 2000s. To understand whether the pattern driving the DRP trend is due to changes in fertilizer application rates, we generated hypothetical scenarios that kept application rates at constant high (1970s) and low (mid-1990s) values (Figure 2-4b). From this analysis, it is clear that fertilizer input influences the magnitude of DRP load but does not appear to be the major factor responsible for the long-term DRP trend.

#### **3.3 Tillage Practices Scenario**

Our baseline scenario used documented historical adoption trends of conservation tillage and no-till practices. We compared those results with two scenarios, one where all agricultural land was under no-till practices and another under conventional tillage. The simulation results indicate that agricultural land under no-till practices yield consistently more DRP compared to the baseline or conventional tillage scenarios (Figure 2-4c), and that the shift from conventional to no-till appears to contribute to the overall trend because the baseline simulation mimics the 100% conventional tillage curve in early years and the 100% no-till curve in later years.

### 3.4 P Accumulation in the Soil Surface Layer

To represent the accumulation of soil P in the soil surface layer in the baseline scenario, we varied the P soil partitioning coefficient (PHOSKD) after 1995 (Figure 2-3) to reflect the impact of adoption of no-till practices and surface application of fertilizers. To test the sensitivity of the model to that effect, we ran a scenario holding PHOSKD constant at the calibrated value equal to  $292 \text{ m}^3/\text{Mg}$ . In this scenario, DRP load is lower through the early 2000s, unlike the baseline loads, suggesting that soil stratification and buildup at the soil surface layer is a significant driver in long-term DRP runoff (Figure 2-4d).



**Figure 2-4: Comparison of mean annual DRP (kg/year) load under the baseline scenario and (a) the observed DRP loads, hypothetical scenarios of (b) constant fertilizer application rate, (c) tillage practices, and (d) without soil stratification. All trends are represented with a moving 4-year average trendline.**

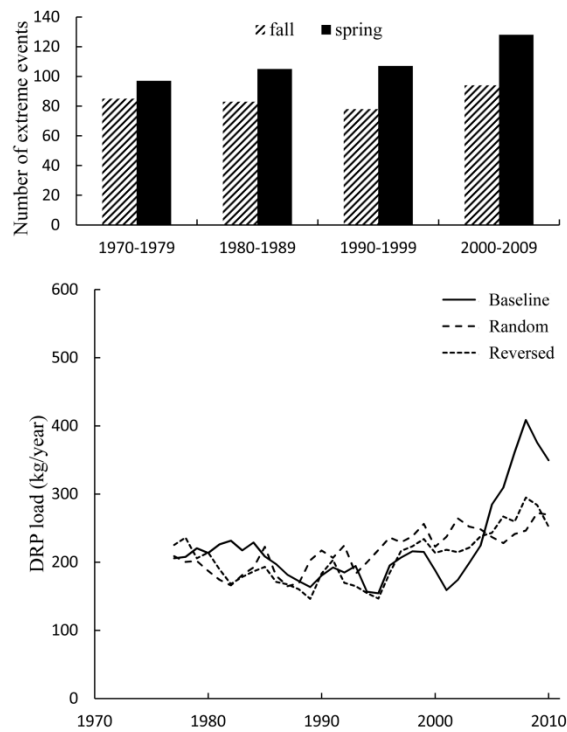
### 3.6 Weather

We evaluated precipitation patterns for the simulation period (1970-2010) to see if the frequency of extreme events in the study area changed during the spring and fall fertilizer seasons. We defined extreme events as events with precipitation magnitude above the 85<sup>th</sup> percentile for the period of record (1970-2009). The frequency of these extreme events during the first three decades was relatively stable in fall and increased in spring (Figure 2-5a). It is also clear that the frequency increased more dramatically in both spring and fall fertilizer seasons in the last decade, shortening the fertilizer application window and perhaps increasing the potential for enhanced runoff.

The baseline scenario incorporated daily rainfall, minimum and maximum air temperature, wind speed, relative humidity, and solar radiation for the simulation period (1970-2010). To explore the impact of weather trends, including storm intensity, on the long-term trend in DRP load, we ran two scenarios; one with randomized weather input and one with “reversed weather”. In both cases, we retained the within-year variability, but modified the orders in which the years were applied. For the random weather case, we ran 10 simulations with weather years randomized; and show results for a representative simulation. For the “reversed weather” simulation, we switched 2010 weather with 1970, 2009 weather with 1971, etc.

Randomizing weather produced the expected result of flattening the trend, (Figure 2-5b and data not shown) indicating that weather is an important factor in explaining the observed year-to-year variation in DRP loading. In addition, the “reversed weather” case revealed an interesting potential interaction effect with land-cover and land-management. While the reversed weather patterns did appear to produce somewhat higher loads in the 1970s and similar loads through the early 2000s, the most dramatic effect was in the latter years (Figure 2-5b). Apparently, the

conditions on the land in the earlier decades, particularly in the 1970s when there was mostly conventional tillage and spring fertilizer application, made runoff less vulnerable to higher-frequency storms that were employed in the “reversed weather” scenario.



**Figure 2-5: Frequency of extreme events (above 85<sup>th</sup> percentile) in the spring and fall fertilizer season where x-axis denotes decades and comparison of mean annual DRP (kg/year) load under the baseline scenario with observed weather pattern and the hypothetical scenario with reversed and random weather patterns. All trends are represented with a moving 4-year average trendline.**

#### 4. Discussion

The somewhat perplexing trend of increased DRP loading from the Sandusky watershed since the 1990s has attracted significant policy attention. To better understand the impacts of land management (i.e., fertilizer application management and adoption of no-till and conservation tillage,) and weather patterns on DRP loading, we compared realistic representations of the agricultural landscape with hypothetical scenarios.

The baseline scenario, with the most representative agricultural operations for fertilizer inputs and application timing, tillage practices, and crop choices for the simulation period (1970-2010), matched the observed loads of sediment and various forms of P well. Our focus was on the long-term DRP loading trend, and our baseline scenario captured the long-term trend well (Figure 2-4a).

To understand the impact of each potential driver of the long-term DRP load trend, we generated hypothetical scenarios. Keeping the fertilizer application rate constant at high 1970s and low mid-1990s values suggested that, while the input rate influences the magnitude of DRP runoff, it does not appear to be the major factor in shaping the long-term DRP trend. However, if application rates during the 40-year period were held at 15% lower than today's rate, then today's load of DRP would be 25% lower (Figure 2-4b).

Similar to fertilizer inputs, changes in tillage practices influenced the magnitude of DRP runoff and appear to have had some influence on the overall temporal DRP pattern. However, since the SWAT model does not include all of the impacts of no-till practices and surface application of fertilizers in the soil surface layer P accumulation and stratification, we modified the phosphorus soil partitioning coefficient (PHOSKD). This allowed us to better represent P accumulation in the soil surface layer due to adoption of no-till and conservation practices and broadcasting fertilizers in the baseline scenario. When PHOSKD values are kept constant, the trend in the load is lower through the early 2000s, but still increases after 2005, signaling the importance of other possible mechanisms, such as the impact of weather.

Precipitation frequency and intensity influence the loss of nutrients following fertilizer application to agricultural fields. Applying fertilizer before storm events increases runoff, and fertilizer applied in fall would have longer exposure to precipitation and therefore to runoff

(Smith et al., 2007). Analyzing the precipitation data for the Sandusky watershed indicates that recent spring and fall fertilizer seasons have had more extreme events compared to previous decades. Similarly, analysis of Midwestern storm events indicate increased number of large storms in the last decade (Saunders et al., 2012). Our hypothetical scenarios investigating the impact of weather on DRP loading by randomizing as well as reversing the precipitation record showed that the interaction of more storms with changes in agricultural practices adopted in the recent decades -- particularly in the mid-1990s (increase in no-till and broadcast fall fertilizer application) -- have likely led to the observed increase in DRP loads.

While these analyses are important in evaluating the potential causes of long-term DRP loading changes from the highly cultivated agricultural watersheds of the Lake Erie, it is important to note that the SWAT model does not allow for the inclusion of other possibly important hydrological mechanisms such as the formation of ephemeral gullies. Moreover, when evaluating the impact of tillage systems on DRP runoff we need to note that rotational tillage, where the fields are tilled every other year instead of continuous no-till practices seem to be an increasingly common practice in the study area. More research is needed on the impacts of rotational tillage on DRP runoff. Stratified soil P tests, detailed farmer surveys regarding fertilizer application times, and inclusion of more processes in SWAT to better represent soil stratification and P accumulation would lead to better informed modeling efforts. For example, fertilizer application time was not included as a separate scenario in our analyses due to SWAT limitations. To evaluate the impact of fertilizer application timing, we would have to keep the fertilizer application date the same throughout the simulation period which could result in the unrealistic fertilizer application during precipitation events. With this limitation, the outcome of



the hypothetical fertilizer application date scenario would depend on the frequency of having a precipitation event on the randomly selected date, which would be biased.

Evaluation of the scenarios demonstrated the importance of P stratification in soil surface layer and increased frequency of storm events observed in the last decade in the recent rise of DRP exported from western Lake Erie tributaries. Climate projections for the Midwest region indicate trends toward even more intense and frequent storms during the spring and winter seasons (Hayhoe et al., 2010). Therefore, attention to actions that remediate nutrient, especially DRP, runoff from the agricultural landscape during such storms is needed.

Our model results emphasize the need to focus on agricultural practices and their impact on water quality. For instance, broadcasting fertilizer on bare ground in fall results in unincorporated nutrient accumulation that is vulnerable to runoff until spring. Moreover, according to Kleinman et al. (2011), broadcasting P fertilizer onto no-till or conservation tillage fields results in higher DRP runoff. Therefore, to reduce P accumulation in the soil surface layer, incorporation of fertilizer especially under no-till practices is highly encouraged. As promoted by the fertilizer industry and the USDA under the Nutrient Stewardship program (IFA, 2009), adjustments in agricultural management practices to achieve the right rate, time, and place of fertilizer application can attain reduction in DRP runoff from agricultural landscapes.

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## **Chapter 3: Adoption of conservation practices: An agent-based modeling typology of farmer characteristics**

*In review: Daloğlu, I., Nassauer, J.I., Riolo, R.L., Scavia, D. Adoption of conservation practices: An agent-based modeling typology of farmer characteristics. *Agricultural Systems**

### **Abstract**

Farmers' decisions about adopting conservation practices are inherently dynamic, affected by changes in environmental, economic, and social conditions, including interactions with other farmers. Water quality models used to assess agricultural policy interventions, such as the Soil and Water Assessment Tool (SWAT), lack the dynamic social component of farmer's decisions. While agent-based models (ABM) can represent and explore these decision dynamics, there are only a few studies that link ABMs to water quality models that can simulate environmental outcomes of farmer decisions. Linking ABMs and SWAT could advance the development of targeted conservation policies. Toward this aim, we developed a typology of Corn Belt farmers based on characteristics relevant to their land management decisions applicable in SWAT. Then, based on this typology we developed an ABM to better understand the emergent land management decisions of the farmers. To identify these characteristics, we reviewed the literature on farmer adoption of conservation practices and found land tenure arrangements, farm size, source of income, and information networks were most consistently identified as characteristics that influence conservation practice decision-making. Employing these

characteristics, we identified four types of farmers to populate the ABM that will be linked to SWAT: (1) “Traditional”: farmers with small operations relying primarily on on-farm income; (2) “Supplementary”: farmers with small operations relying primarily on off-farm income; (3) “Business-oriented”: farmers with larger operations relying primarily on on-farm income and well connected to information networks; (4) “Non-operator”: absentee or investor farmland owners with limited connections to local information networks. We used this typology to develop a conceptual framework for an ABM that can be used to examine alternative approaches to targeting conservation policy in Corn Belt agroecosystems. We employed this ABM under changing tenure dynamics and agricultural policies such as subsidized crop insurance as proposed for the next Farm Bill, and found it to be a useful method to represent the dynamic social component in coupled social and biophysical process models.

**Keywords:** ABM—agroecosystem—water quality—agricultural policy—SWAT—farm bill

## **1. Introduction**

Agriculture continues to be a major contributor to water pollution, soil degradation, climate change, and biodiversity loss. The highly cultivated watersheds of the Corn Belt are major sources of non-point source pollution (Nassauer et al. 2007; National Research Council 2010; Mississippi River/Gulf of Mexico Watershed Nutrient Task Force 2008). Agricultural runoff is often the cause of algal blooms, poor water clarity, and summer hypoxia (low oxygen) in the Gulf of Mexico (Ribaud and Johansson 2006), Lake Erie (Hawley et al. 2006), and elsewhere (Committee on Environment and Natural Resources 2010). Hypoxia has severely impacted commercial and sport fisheries, with trophic cascades affecting aquatic and coastal food webs (Carpenter et al. 2008).

Federal policy strongly affects the management choices of American farmers and thus the landscape characteristics and water quality of farms and downstream ecosystems. Farmers are defined in this analysis as owners or renters of farmland where cash crops are grown. The US Farm Bill, which is renewed approximately every five years, is the federal policy that most directly affects agricultural land use and practice. Since the 1930s, the Farm Bill has included specific soil and water conservation programs, as well as support for production of certain crops (Nassauer and Kling 2007). Yet, Farm Bill support for crop production has substantially and consistently outweighed incentives for conservation (Doering et al. 2007).

Recent changes proposed for the Farm Bill include replacement of direct payments for crop production with subsidized crop insurance that acts as an income safety net that may affect management decisions, especially for risk-averse farmers. Currently, farmers can choose between two insurance policies, crop yield and revenue insurance, and USDA provides subsidized insurance premiums for these risk management programs (Coble and Barnett 2013).

Crop yield insurance protects farmers from income effects of reduction in agricultural yield due to weather and other factors, whereas revenue insurance protects farmers' income from both market fluctuations and yield changes.

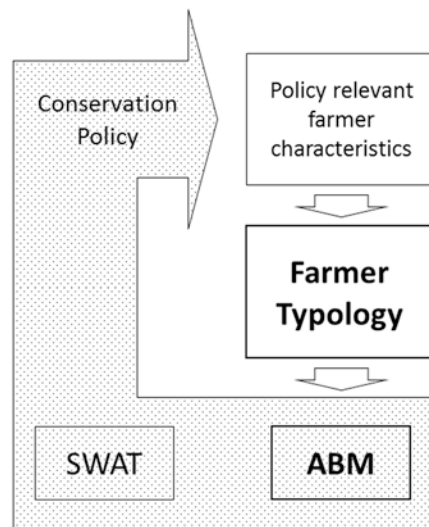
Developing more effective agricultural policies necessitates a better understanding of the motivations and underlying socio-economic circumstances of farmers (National Research Council 2010). However, these attributes are not homogenous or static among farmers responding to conservation policies.

The relationship between farmers' decisions about adoption of conservation practices and water quality outcomes is part of a complex coupled human and natural system and, as such, coupled social-biophysical models can be valuable tools for better targeting federal investments (Jackson-Smith et al. 2010). Such approaches can incorporate farmer decisions in exploring whether or not substantial changes in water quality can be expected as a result of specific policy interventions. Knowledge of the socio-economic factors that influence farmers' conservation-related decisions is essential for the construction of such a model.

Typologies have been suggested (Kostrowicki 1977; Duvernoy 2000; Valbuena et al. 2008) as a means to effectively represent the heterogeneity of farmers' motivations and socio-economic circumstances related to conservation behavior. This is particularly relevant because typologies are key components of agent-based models (ABMs), computational methods that model decentralized decision-making in a given heterogeneous system to predict emergent characteristics. Implementation of a farmer typology in an ABM can demonstrate the impacts of changing land tenure dynamics and proposed risk management programs in US agricultural policy on adoption of conservation practices. This paper describes the basis for a farmer typology developed for use in an ABM designed to be linked with the Soil and Water



Assessment Tool (SWAT), a river basin scale water quality model, developed and maintained by the US Department of Agriculture to assess the water quality benefits of conservation practices (Gassman et al. 2007; Osmond 2010). We used this ABM to compare how different land tenure dynamics and policy interventions may affect spatial patterns of adoption of conservation practices, and ultimately use it in the linked model to compare their impacts on downstream water quality (Figure 3-1).



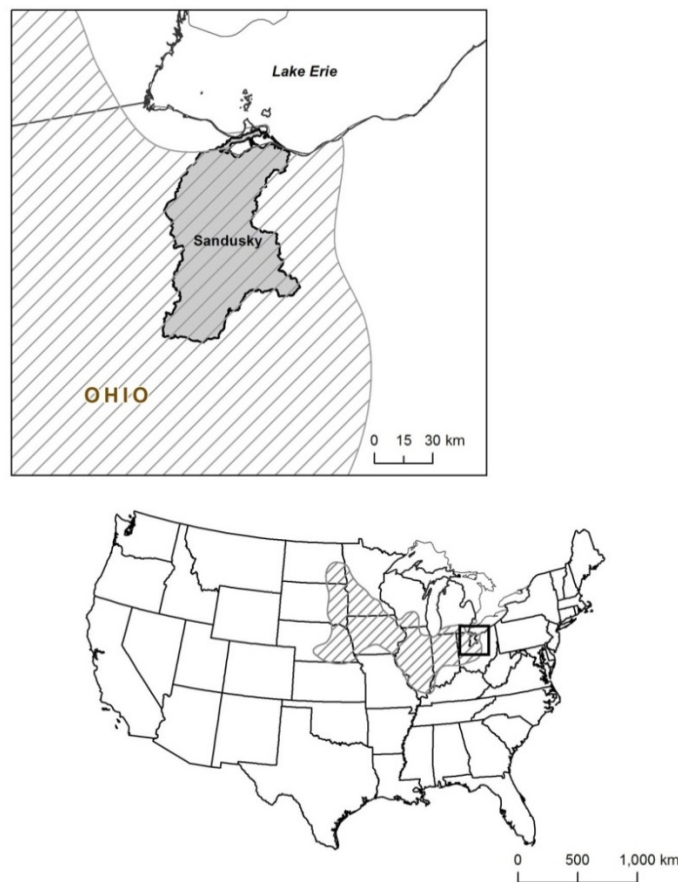
**Figure 3-1: Using a farmer typology in a coupled human and natural system of farmers’ adoption of conservation practices and effects on water quality. We constructed our farmer typology using farmer characteristics relevant to adoption of conservation practices that are applicable in SWAT models and we implemented this typology in an ABM.**

### **1.1. Geographic Setting of Farmer Types**

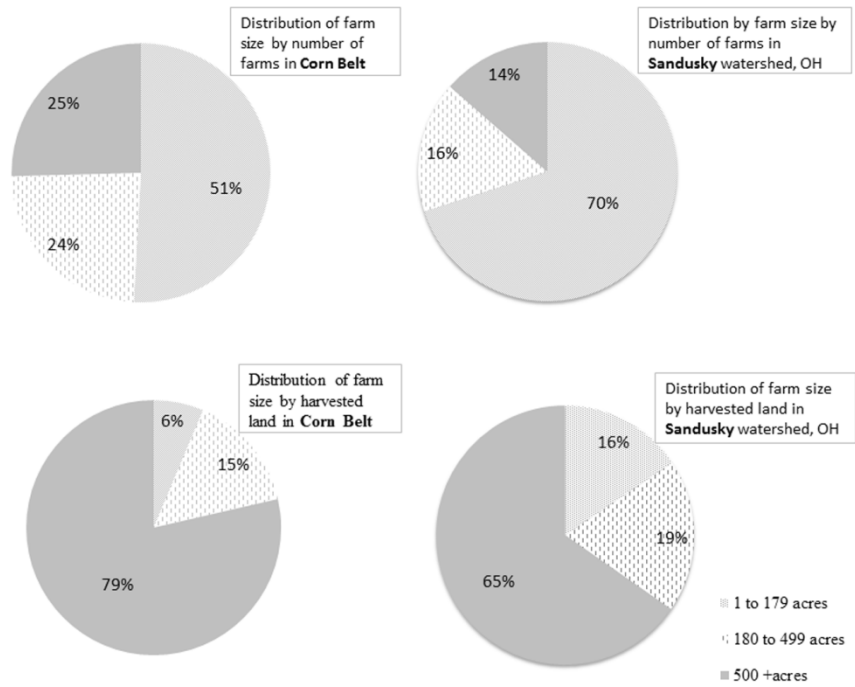
Our study site, the Sandusky Watershed, Ohio drains into Lake Erie (Figure 3-2), and is typical of the Corn Belt, which occupies portions of the states of Ohio, Indiana, Illinois, Iowa, Minnesota, Michigan, Missouri, Nebraska, and South Dakota. Consequently, we developed a policy-relevant farmer typology by reviewing and synthesizing the literature on the adoption of conservation practices by farmers in the Corn Belt. The highly cultivated watersheds of the Corn

Belt are major sources of non-point source pollution in Lake Erie (Hawley et al. 2006), as well as the Mississippi River and its tributaries (Ribaud and Johansson, 2006).

Farmers specialize in cash-crop (corn, soybean) production, with livestock production less common (USDA 2009). In the Sandusky Watershed, like much of the Corn Belt, most farmers rent at least some of the land they farm, and about half declare their primary occupation to be non-farming (Table 3-1). While most farms in the Corn Belt and the Sandusky Watershed are small (less than 180 acres), large farms (more than 500 acres) make up a much larger proportion of the total area harvested and large-scale, commercial farms dominate the landscape (Figure 3-3).



**Figure 3-2: Map of the geographic setting of farmer types, showing the Corn Belt (dashed) and the Sandusky Watershed, OH.**



**Figure 3-3: Distribution of farm size in the Corn Belt and the Sandusky watershed (OH) by number of farms and harvested land. Source: USDA (2009)**

	Corn Belt		Sandusky, OH					
	farms	acres	owned	rented	farms	acres	owned	rented
Full owner	50.9%	16.6%	43.0%	63.9%	50.4%	14.8%	35.6%	60.6%
Part owner	39.9%	72.4%			43.0%	77.0%		
Tenant	9.2%	8.8%			8.6%	8.7%		
<b>Primary occupation</b>								
Farming	47.9%				44.6%			
Other	52.1%				55.4%			
<b>Gender</b>								
Male	89.2%	95.3%			91.4%	96.5%		
Female	10.8%	4.7%			8.6%	3.5%		
<b>Principal operator</b>								
worked days off, any	63.70%				65.6%			
>200 days	36.30%				34.4%			
<b>Used conservation practices</b>								
	34.10%				46.3%			

**Table 3-1: Characteristics of farmers in the Corn Belt and the Sandusky Watershed, OH. Source: USDA (2009).**

## **1.2. Farmer Characteristics**

Among the many factors that influence farmers' decisions regarding conservation practices, we focus on farmer characteristics most immediately relevant to conservation practices affecting water quality and applicable in SWAT. Many empirical studies have been conducted to describe the relationship between the adoption of conservation practices and farmer-specific variables such as age, education, land tenure, and farm size. Some emphasize attitudes and motivations (Lynne et al. 1988; Ryan et al. 2003), and some emphasize other social, economic and structural variables (Nowak 1983; Tosakana et al. 2010; Napier et al. 2000; Napier and Bridges 2002; Lemke et al. 2010). Unfortunately, no one variable has been identified as universally influencing the diffusion and adoption of conservation practices. Knowler and Bradshaw (2007) reviewed empirical studies from around the world in an attempt to identify such a universal variable; however, they were unable to do so due to differences in geography, relevant agricultural policies and statistical methods employed by the different studies reviewed. Similarly, after reviewing 55 US studies on the adoption of best management practices, Prokopy et al. (2008) conclude that there is no single factor that consistently affects decisions. Although a number of studies have found farm income to be an important consideration, that alone cannot explain the adoption decisions of a farmer under every circumstance (Chouinard et al. 2008). Camboni and Napier (1993) conclude that adoption decisions are generally more influenced by structural variables such as farm size, income source, farm specialty, debt-to-asset ratio and participation in government programs than by personal variables such as environmental problem awareness, farming experience and education.

For a typology to be used in an ABM, which requires simplicity to explore dynamic interactions among agents (Axelrod 1997), we selected a minimum number of widely studied

farmer characteristics that would be relevant to the conservation practices intended to affect water quality. As such, we eliminated variables such as education, age, attitudes/motivations, environmental awareness, and farming experience that generally have been found to be less relevant to these practices.

## **2. Methods**

### **2.1. Agent-based Models**

ABMs are computer-based models that can be used to represent decentralized decision-making and interactions of heterogeneous social agents on multiple scales. ABMs consist of one or more types of agents (e.g., different types of farmers), as well as an environment in which these agents are embedded. The models are useful for running computational experiments to assist in reasoning about systems that are inherently dynamic and uncertain (Bankes 1993). That is, ABMs are not prescriptive, and their purpose is not to predict the system outcome, but rather to identify relationships among agents and particular variables as well as how these relationships affect system behavior. Because ABMs are computational models, they are formal, unambiguous, and thus, replicable and testable (Miller and Page 2007). They are powerful tools for modeling coupled human and natural systems (Liu et al. 2007; An 2011).

Agent definitions can include various characteristics, preferences, memories of recent events and social connections, abilities to carry out particular behaviors, decision-making rules, heuristics, and other mechanisms to generate individual agent responses to inputs from other agents and from the environment. ABMs can also include social networks of various kinds that define interaction topologies based on group memberships, business contacts and common information sources (Lopez-Pindato 2008; Kuandykov and Sokolov 2010). They can

demonstrate the dynamics of agent behavior, as agents use rules to determine which other agents to interact with, how to interact with them, and how to interact with the environment.

The ‘bottom-up’ nature of ABMs– defining the model at the level of individual decision makers (agents) and their interactions with each other and with the environment – differentiates them from other simulation techniques (Gilbert 2008). Because ABMs can capture spatial interactions among agents, they can reflect robustly the diffusion of information in social networks (Baerenklau 2005; Happe et al. 2008; Kaufman et al. 2009) making them especially well-suited to model how heterogeneous farmer characteristics affect spatial patterns of adoption decisions.

An ABM is most informative when it is comprised of a small number of variables that allow for better transparency and a deeper level of understanding (Axelrod 1997). Therefore, we aimed for parsimony in developing the farmer typology to be linked with SWAT.

## **2.2. Typology Studies**

Building a typology based on empirical literature can present potential limitations if they are oversimplified in an ABM. In that case model implications may be more theoretical than policy-relevant (Valbuena et al. 2008). In his seminal study, Kostrowicki (1977) argues that the variables selected for the construction of typologies are more important than the classification technique applied. Valbuena et al. (2008) highlight the importance of choosing variables that reflect the socio-economic situation and context of decision makers.

To test the effects of policy-relevant characteristics of farmer decisions, the typology developed should be focused on bringing insight to responses to policy. Because farmer typologies have often been tested using survey data from a specific locality (e.g., Kraft et al. 1989; Bohnet et al. 2011), their conclusions may not be broadly applicable. To address this

limitation, we sought a simple, synthetic set of policy-relevant farmer characteristics to be employed in a more generally applicable ABM.

Farmer typologies developed in the Netherlands (Valbuena et al. 2008), Chile (Carmona et al. 2010), Greece (Daskalopolou and Petrou 2005) Argentina (Duvernoy 2000), and Australia (Bohnet et al. 2011), as well as the United States (Hoppe et al. 2007; Briggeman et al. 2007; Lambert et al. 2007) have been useful when program managers and policy makers have been able to differentiate between landowners with different land-management motivations and management capacities that influence their behavior (Emtage et al. 2007). The geographic scale of such studies varies from continental (Andersen et al. 2006; Terluin et al. 2010) to national and regional. For example, Hoppe et al. (2007) categorized US farmers based on farm sales and operator occupations, using the results of the Agricultural Resource Management Survey (ARMS) administered by the National Agricultural Statistical Services (NASS) to understand the factors that influence decisions regarding conservation practices. Lambert et al. (2007) used this same typology in another national study employing random utility regressions to examine which farmer characteristics promote the adoption of conservation practices; they found that farmers are heterogeneous in their response to conservation policy depending on their characteristics. Another example of a national farmer typology is a characterization of US farm households based on household economic theory (Briggeman et al. 2007). Typologies developed to characterize farmers within a region include Kraft et al. (1989), who constructed a typology to study southern Illinois farmers' goals and views on soil conservation. However, none of the typologies constructed for US farmers have been developed for use as the basis for an ABM.

Farmers are diverse in their structural characteristics related to conservation decisions. This diversity, coupled with the assumption that conservation practice adoption is guided by

economic rationality, has been suggested as the reason for errors in conventional farm-level models of US agricultural policy (Nowak 1987; Nowak and Cabot 2004). As Happe et al. (2008) point out, failure to consider farmer diversity and interaction among farmers in designing agricultural policies often leads to program failure. ABMs can fill this gap by demonstrating the effects of diversity and interactions.

### 3. Results and Discussion

We identified four policy-relevant farmer characteristics that are consistent throughout the literature related to conservation decisions of Corn Belt farmers: land tenure arrangements, farm size, income source, and information networks. Because we used this typology to populate an ABM that will be linked to SWAT, the capabilities of SWAT were decisive in constructing the parsimonious typology. Therefore, we categorized these conservation practices in three broad, SWAT-applicable categories: “non-structural”, “structural”, and “land retirement” practices (Table 3-2).

<b>Conservation Practice Categories</b>	<b>Conservation Practices</b>	<b>Economic and Environmental Benefits</b>
Non-structural	Conservation tillage, no-till	Reduces soil erosion from both water and wind, increases organic matter and enhances water quality. Reduces labor, saves time and fuel, reduces machine wear
Structural	Filter strips, grassed waterways	Enhances water quality by trapping soil particles, nutrients and pesticides; improves water infiltration; enhances wildlife habitat. Eligible for cost-share programs
Land retirement	Conservation Reserve Program (CRP), Wetlands Reserve Program (WRP)	Plants long-term, resource-conserving covers. Reduces soil erosion from highly erodible lands (HEL), restores wetlands. Enhances water quality and wildlife.

**Table 3-2: Conservation practice categories applicable in SWAT models.**



### 3.1. Land Tenure Arrangements

Tenure arrangements indicate the extent of ownership and control of farmland, which can directly affect adoption of conservation practices. In this analysis we have three land tenure arrangements for defining farmer types: full owner, part owner, and non-operator owner (Table 3-3). With full ownership, the farmer owns all of the land in operation, whereas part owners own only a portion of the operated land with the remainder rented from others. ‘Non-operator owners’ rent out all of the land and do not operate any farmland themselves. Non-operator owners may include both ‘absentee landowners’, individuals who live outside the county where they own farmland but who may be or have been involved in farming (Petrzelka et al. 2009), as well as ‘investors’, non-operator owners who describe themselves as never having farmed and who may not necessarily live outside the county where they own farmland (Nassauer et al., 2011).

*Farmer types*

<i>Policy-relevant farmer characteristics</i>	Traditional	Supplementary	Business-oriented	Non-operator owners
Land Tenure	Full owner	Full/Part owner	Part owner	Non-operator owner
Farm Size	Small	Small	Medium to Large	N/A
Primary Source of Income	On-farm	Off-farm	On-farm	Off-farm
Information Networks	Moderately connected	Moderately connected	Most connected	Least connected

**Table 3-3: Farmer types constructed by using policy-relevant farmer characteristics.**

In general, US agriculture has undergone a steady decline in full ownership and a rise in part and non-operator ownership (Wunderlich 1993; Duffy 2008). This rapidly growing proportion of non-operators, both absentee landowners and investors, deserves focused attention. The

ARMS database reflects how this phenomenon has affected the Corn Belt, as represented by the Sandusky Watershed (Table 3-1). There, only 14.8% of the total farmland acreage is owned by full owners, compared to 27.4% owned by part owners, 46.7% rented by part owners, and 8.7% rented by tenants who rent all the land they farm and own no farmland. In other words, more than half of the land farmed in the Sandusky watershed is owned by someone other than the operator. While it is possible that some of those owners are farmers who simply choose not to operate some of their land, it is reasonable to assume that non-operators own land rented by others.

Most empirical research concludes that operators control decisions regarding production and adoption of conservation practices on farmland owned by non-operators (Constance et al. 1996; Soule et al. 2000; Arbuckle 2010). However, with growing proportions of farmland owned by non-operators, current policy and future expectations that Corn Belt farmers generally own the land they farm may change as well, and non-operators may have more influence on decisions.

While conventional wisdom suggests that owner-operated land is better preserved and managed because renters generally have no long-term stake in the environmental quality and sustainability of the land they rent, actual experience is mixed (Prokopy et al. 2008; Petzelka et al. 2009; Nassauer et al. 2011; Fuglie 1999; Bultena and Hoiberg 1983). Soule et al. (2000) suggest that the relationship between tenure arrangements and adoption of conservation practices varies with the type of practice in question. For example, renters are more likely to adopt practices that are profitable in the short term, such as non-structural practices, whereas owners are more likely to adopt practices that have long-term implications and require capital investment, such as installing structural practices, which include filter strips and grassed waterways (Soule et al. 2000; Caswell et al. 2001).

Recently, studies have highlighted the need to study the growth of subgroups of non-operator owners, like absentee landowners and investors. Absentee landowners generally have not been involved in land management decisions, deferring to their renters (Duffy 2008; Petrzelka et al. 2011; Petrzelka et al. 2012, Petrzelka et al. 2009; Soule et al. 2008; Wells and Eells 2011). On the other hand, in a study of 549 Iowa farmers (Nassauer et al., 2011), 54.5% of investors (farmland owners who described themselves as never having farmed) stated that they made daily decisions regarding farm operations. Compared with operators, investors were notably more likely to adopt certain structural and non-structural practices that enhance environmental quality. The study concluded that investors' limited experience with management requirements of some conservation practices could explain their positive attitudes toward these practices. Petrzelka et al. (2011) found that those absentee landowners who did participate in land management decisions favored adopting conservation practices more than their renters.

A review of the literature reveals that enrollment in land retirement programs is less prevalent among absentee landowners than operator landowners. Petrzelka et al. (2009) report that absentee landowners lag operator landowners by 64% in land retirement program enrollment in the Great Lakes Basin. In contrast, Nassauer et al. (2011) found investors to have higher land retirement program enrollment rates compared with active farmers across Iowa. While non-operator owners presently tend to leave production and conservation decisions to their renters, who tend to make decisions that support short-term profitability, our ABM simulates a hypothetical future scenario in which non-operators are more involved in management decisions (Section 3.6)

### **3.2. Size of Farm (owned and rented land)**

Farm size, or acres of harvested cropland, varies across the US (see, for example, Hoppe et al. 2007), and has been one of the most-explored variables in adoption studies (Rahm and Huffman 1984; Nowak 1987; Belknap and Saupe 1988; Caswell et al. 2001; Napier et al. 2000). For example, Hoppe et al. (2007) reveal that large-scale farms with annual sales of \$250,000 or more accounted for only 10 percent of US farms but 75 percent of production value in 2004. Farm size reflects both economic and social aspects of farming, and operators of small and large farms respond differently to policy and market changes (Prokopy et al. 2008). Therefore, we identified operators of small farms as a distinct category (Table 3-3). After reviewing 55 studies conducted in the US, Prokopy et al. (2008) conclude that farm size is positively correlated with the adoption of conservation practices more often than it is negatively correlated (i.e. Belknap and Saupe 1988; Caswell et al. 2001; Bultena and Hoiberg 1983; Gould et al. 1989; Soule et al. 2000; Napier et al. 2000). In general, operators of larger farms are assumed to be more willing to invest in new technologies and adopt conservation practices, because the overall benefits of adoption increase for large farms (Knowler and Bradshaw 2007). However, the relationship between farm size and adoption of conservation practices may vary with the particular conservation practice employed (Table 3-2).

Data collected from 371 farmers in east Ohio show that the area farmed influences farmers' decisions to adopt conservation tillage, filter strips, and grassed waterways (Camboni and Napier 1993). Lee and Steward (1983) conclude that small farm size may impede adoption of non-structural practices such as conservation tillage and no-till practices, and Fuglie (1999) suggests that operators of larger farms are more likely to adopt no-till practices. Based on the 2001 USDA ARMS data, Lambert et al. (2007) conclude that adoption of non-structural practices is

unaffected by production scale, but that production scale as well as implementation costs become significant when farmers need to invest in more costly structural practices.

The influence of farm size on the adoption of conservation practices can be explained in a number of ways. For example, operators of large farms may adopt structural practices such as filter strips and grassed waterways because they have the ability to spread installation or equipment costs over a large area, lowering the per-acre cost of adopting new technologies and conservation practices (Lambert et al. 2007). The risks of adopting new technologies and conservation practices also can be spread with larger farms (Lichtenberg 2004). However, land retirement programs such as the Conservation Reserve Program (CRP) and Wetland Reserve Program (WRP) have been adopted at higher rates among small farmers (Lambert et al. 2007) because these programs reduce farmers' labor and time requirements. In general small farms are more likely to have full owners, whereas large farms are more likely to be partly owned or fully rented. Our ABM simulations reflect this notion by allowing farmers to have varying farm sizes. In the model, through time, as farmers age, they either sell their land to other farmers or become non-operators by renting their land to others, reflecting the increasing percentage of large scale farms and non-operators as time progresses (Section 3.6).

### **3.3. Source of Income**

Farmer income affects most decisions, including those regarding conservation practices because the adoption of which can require financial investment and can reduce short-term profitability (Caswell et al. 2001). To understand the role of income generated from farm and off-farm sources, source of income is generally categorized by measuring off-farm employment in terms of number of days the primary farm operator works off the farm for wages or a salary (National Agricultural Statistics Service, NASS), percentage of income from off-farm sources

(Nowak 1987; Loftus and Kraft 2003), and primary occupation of farm operators (Petrzelka et al. 2009). Our typology characterizes farmer types by on-farm and off-farm income because these categories may relate to conservation adoption decisions (Table 3-3).

A significant proportion of Corn Belt farmers have income from off-farm sources, which may be used to stabilize and/or increase household income (Napier and Camboni 1993; Loftus and Kraft 2003; Briggeman et al. 2007). According to an econometric model built by Mishra and Goodwin (1997) and validated with survey results from 300 Kansas farmers, off-farm income is positively correlated with lowered risk and variability for farmer incomes. For this reason, off-farm income sources are appealing to risk-averse farmers. A study by Fernandez-Cornejo et al. (2007) shows that in 2004, more than half of US farm operators worked off the farm and more than 80% of total farm household income was earned from off-farm sources. Similarly, the US Agricultural Census for 2007 shows that 55.4% of farmers in the Sandusky Watershed had a primary occupation other than farming (Table 1). Dependence on off-farm income differs with the size of the managed farmland. While small farm households receive a significant portion of their income from off-farm sources (Hoppe et al. 2007), large farm households tend to be more dependent on farm income (Nehring et al. 2005). Households with greater dependence on farm income may feel pressure to maximize short-term profits from their land (Caswell et al. 2001; Fernandez-Cornejo et al. 2007).

Debt-to-asset ratio, the degree of financial leverage used in farmland operations, also affects motives to maximize profits as it affects farmers' risk aversion. A number of studies have argued that high debt-to-asset ratios will increase risk aversion and prevent farmers from investing in conservation practices (Belknap and Saupe 1988; Ervin and Ervin 1982). Certain studies also show a positive correlation between off-farm income and the adoption of conservation practices

(Fuglie 1999; Nowak 1987; Loftus and Kraft 2003). This suggests that farmers with greater off-farm income have greater financial flexibility and stability. Both farmers who depend on farm-generated income (Napier et al. 2000) and farmers who have supplementary income (Gould et al. 1989) have been found to adopt non-structural conservation practices (Table 3-2). However, based on interviews with more than 1,000 farmers in Ohio, Iowa and Minnesota, Napier et al. (2000) find that farmers with higher reported gross income from farm sources have higher rates of adoption of structural conservation practices. Farmers with higher off-farm income have higher enrollment rates in land retirement programs such as the CRP and WRP, perhaps because they have limited time available for farming (Hoppe et al. 2007). In general, off-farm income provides financial flexibility to smaller farms, whereas larger farms whose operators may rely primarily on farm income may feel they have less flexibility to choose practices that reduce short-term profits.

In our ABM simulations, source of income and risk management are important variables. In the model, farmers fall into different farmer types depending on the percentage of on-farm income and adopt different conservation practices under changing agricultural policies. For example, farmers that have off-farm income are assigned a higher tendency to enroll in land-retirement programs (Section 3.6).

Proposed changes in the US Farm Bill to promote crop insurance would have significant impacts on farmers' risk management and consequently on their adoption decisions. Risk management programs such as substantially increased premium subsidies for crop insurance tend to encourage production and stabilize farm-generated income. Previous research indicates higher adoption rates for risky conservation practices when crop insurance is purchased (Bosch and Pease, 2000). Farmers may perceive non-structural practices (conservation tillage and no-till) as

risky in terms of their possible yield reduction; therefore with the safety net provided by crop insurance, farmers would be incentivized to adopt practices that they perceive could reduce yield (Bosch and Pease, 2000). Because crop insurance is based on production area, we would expect farmers to be discouraged from adopting structural practices which reduce the insurable production area. In fact, Goodwin and Smith (2003) raise concerns about possible decrease in CRP enrollment with the revenue protection provided by crop insurance because it may promote production. Numerous studies indicate increased nutrient management and application of less fertilizer with enrollment in crop insurance (Goodwin and Smith, 2003, Babcock and Hennessy, 1996; Smith and Goodwin, 1996; Sheriff, 2005).

In our ABM, we simulate hypothetical future scenarios in which farmers buy subsidized crop insurance. However, heterogeneity among farmer types becomes less relevant with a crop insurance program because it motivates farmers to increase production area regardless of their type. In our ABM simulations, farmers are assumed to have revenue crop insurance at the 75% coverage level and make conservation decisions considering their future expectations for crop yields and prices, and these expectations change by farmer type (see Section 3.6 and Appendix A).

### **3.4. Information Networks**

Studies of the adoption of conservation practices have long recognized information as influential. Information channels include media, observation of other farmers' fields and practices, and communication with other farmers and extension agents (Rahm and Huffman 1984; Belknap and Saupe 1988; Lemke et al. 2010). Access to various information networks is a crucial variable in our typology because ABMs can effectively explore the dynamics of information dissemination through spatial as well as social networks.



Information is crucial when decisions are made about conservation practices because the adoption of conservation practices is a complex process that requires trial and evaluation. In addition to extant knowledge, personal contacts influence the adoption process and significant relevant information and experience flows through networks (Nowak 1987; Lemke et al. 2010).

Farmers need information that will allow them to estimate the costs and benefits of available alternatives. One reason for non-adoption of a new technology is uncertainty about the outcomes of adoption. Autant-Bernard et al. (2007) suggest that networks of adopters and non-adopters or potential adopters are the foremost mechanisms for reducing this uncertainty, and that frequent contact among adopters and non-adopters deepen relationships and promote information exchange. They suggest that geography is crucial in the diffusion process, providing an environment for the transmission of knowledge, experience, and technology.

In agriculture, the physical proximity of adopters is considered to affect the decision-making process (Hagerstrand 1967), and the ‘neighborhood effect’ has been studied extensively (Baerenklau 2005; Case 1992). Farmers are known to update their decision-making strategies by using their prior experience and by observing what their neighbors have done (Saltiel et al. 1994). As Rogers (2003) states, direct observation of what others have done is very important in adoption decisions and can provide potential adopters with persuasive information about the nature of conservation practices and their potential outcomes. Imitation of neighbors’ practices can be understood as a strategy to compensate for lack of knowledge (Belknap and Saupe 1988).

In addition to spatial proximity and neighborhood observation, other information networks provide channels through which farmers can obtain information on conservation practices and new technologies. For example, Loftus and Kraft (2003) found that farmers who paid frequent visits to a National Resources Conservation Service (NRCS) office obtained more information

on filter strips and had higher rates of adoption of this practice. Similarly, Tucker and Napier (2002) discovered that farmers who had greater access to information networks and education programs were more aware of the non-economic benefits of conservation practices and had higher adoption rates. In addition, Prokopy et al. (2008) showed that access to social networks is one of the most influential variables influencing adoption. They also found that not all farmers are exposed to information at the same level. In other words, there is a variation in the level of network 'connectedness' among farmers, which ultimately affects the patterns of conservation practice adoption in a given locale. Similarly, Petzelka et al. (2009) showed that financial constraints did not significantly affect decision-making for absentee landowners in the Great Lakes Basin, but that lack of communication and information networks did.

Social ties to the renter also lead to greater participation in decision-making by non-operator landowners. Stronger social ties are indicated by more continuous rental years, longer periods of having known the renter, and longer lease lengths. Moreover, previous research has shown that as the spatial distance between the landowner and the renter increases, the frequency of communication decreases (Arbuckle, 2010). Petzelka et al. (2011) point out that renters communicate differently with absentee landowners than with non-operators that live within the county. Namely, absentee landowners are not as connected as local farmers to information networks, which may hinder the ability of absentee landowners to access information, including information on conservation practices. Similarly, when explaining the gap between high interest in conservation practice but low participation, Petzelka et al. (2009) suggest lack of communication between absentee landowners and natural resource agencies as well. Since the percentage of both types of non-operators continues to increase, we used the ABM to investigate

the potential impacts of land tenure change and non-operators' network connectedness on management decision and consequently on the landscape.

In our ABM simulations, we define two types of information networks, spatial and social. The spatial network is based on the immediate geographic connections, whereas the social network represents social ties that a farmer may have (see Appendix A). While non-operators currently have lower network connectedness, our ABM simulates a hypothetical future scenario in which both absentee landowners and investors have higher network connectedness (Section 3.6). This is based on the assumption that the natural resource agencies will reach out more to the non-operators and provide information about existing practice and policies. In these hypothetical scenarios, investors who could live in the county where they own farmland are more connected to both the spatial and social networks that consists of both other farmers and natural resource agencies, whereas absentee landowners who tend to not live in the same county where they own farmland are only connected to the social networks of natural resource agencies. Because network connectedness is influential on adoption decisions, this difference affects how investors and absentee owners make management decisions

### **3.5. Farmer Typology**

Using the farmer characteristics described above, we constructed a simple mutually exclusive four-part typology for our ABM (Table 3-3):

#### *3.5.1. Traditional Farmers*

Farmers of this type are full owners of small farms (less than 180 acres or 73 hectares), operating only the land they own. Farming is their primary occupation, and they depend primarily on income generated from farm production. Both operator and spouse spend a

significant amount of time working on the farm (Briggeman et al. 2007). They are attentive to financial concerns, but they also value preserving their rural lifestyle (Kraft et al. 1989).

In general, smaller farms are associated with lower farm income. Therefore, traditional farmers require a longer time period to pay off conservation investments (Caswell et al. 2001), and this could discourage adoption of practices that require a high initial investment and a relatively longer pay-off period. Consequently, structural conservation practices such as grassed waterways and filter strips may have lower adoption rates among traditional farmers. However, traditional farmers have the highest enrollment rates in land retirement programs such as CRP and WRP (Hoppe et al. 2007). Both the secure income and low labor requirements of land retirement programs may make them attractive to traditional farmers, who also favor non-structural practices such as conservation tillage that reduce overall labor requirements (Hoppe et al. 2007, Napier 2009).

### *3.5.2. Supplementary Farmers*

Supplementary farmers have small farms (less than 180 acres) and substantial off-farm income. They may be retired or part-time farmers whose off-farm income sources may include part-time or full-time jobs. These farmers do not depend solely on earnings generated from farming activities, and this substantially affects their management and conservation decisions. In addition, unlike traditional farmers, supplementary farmers may rent or own the farmland they operate, although most own all the land they farm.

Supplementary farmers favor adopting non-structural practices such as conservation and no-till, because these practices are less costly and less labor intensive (Gould et al. 1989; Fernandez-Cordejo et al. 2007). As they earn most household income from off-farm sources, supplementary farmers are more willing to use conservation practices that reduce the area that must be

cultivated for example filter strips (Loftus and Kraft, 2003; Lynch et al. 2002). Supplementary farmers also have high enrollment rates in land retirement programs such as CRP and WRP (Hoppe et al. 2007) that are not labor intensive and provide a secure income source.

### 3.5.3. *Business-oriented Farmers*

Business-oriented farmers operate at least 180 acres and most likely rent at least part of the land they farm. They are highly dependent upon farm income since farming is their primary occupation (Hoppe et al. 2007). Fernandez-Cordejo et al. (2007) found an inverse relationship between off-farm income and farm size measured with gross annual sales, showing operators with large operations to be less dependent on off-farm income sources. Business-oriented farmers are also less dependent upon conservation payments, but more dependent upon commodity-related federal programs such as agricultural disaster payments and direct payments (Hoppe et al. 2007; USDA, 2011).

Because business-oriented farmers focus more on farm yield and profitability, they tend to concentrate on high-value cash grains and hence adopt management intensive conservation practices that increase short-term returns from production. Compared with other types of farmers, business-oriented farmers are more likely to adopt conservation tillage and, because of their focus on farm production they are also more likely to adopt structural practices (grassed waterways, filter strips) (Bultena and Hoiberg 1983; Lambert et al. 2007). Considering that they are more motivated by short-term profits than traditional and supplementary farmers, business-oriented farmers' decisions about whether to enroll land in the CRP and WRP may be limited by their need for land for production.

#### 3.5.4. *Non-operator Owners*

Non-operators are owners of the land, but they are not the primary day-to-day decision makers regarding production and management. Non-operator owners include absentee landowners and investors. Absentee landowners own the agricultural property but do not reside on or operate it, they tend to live in urban areas, away from their farmland (Petrzelka et al. 2011), whereas investors describe themselves as never having farmed, but may live on or near their farmland (Nassauer et al. 2011). Petrzelka et al. (2009) find that nearly half of the owners of farmland in the Great Lakes Basin do not operate the land that they own. They also show that 603 absentee landowners in the survey sample owned relatively small farms (100-285 acres). In a survey sample of 549 Iowa farmers, Nassauer et al. (2011) observed that Iowa farmland investors owned farms similar in area to those of other farmers. Petrzelka et al. (2009) also state that less than half of the household income of absentee landowners in the Great Lakes Basin was generated from farmland, and Constance et al. (1996) show that absentee landowners tend to depend less on farm income than local non-operator landowners.

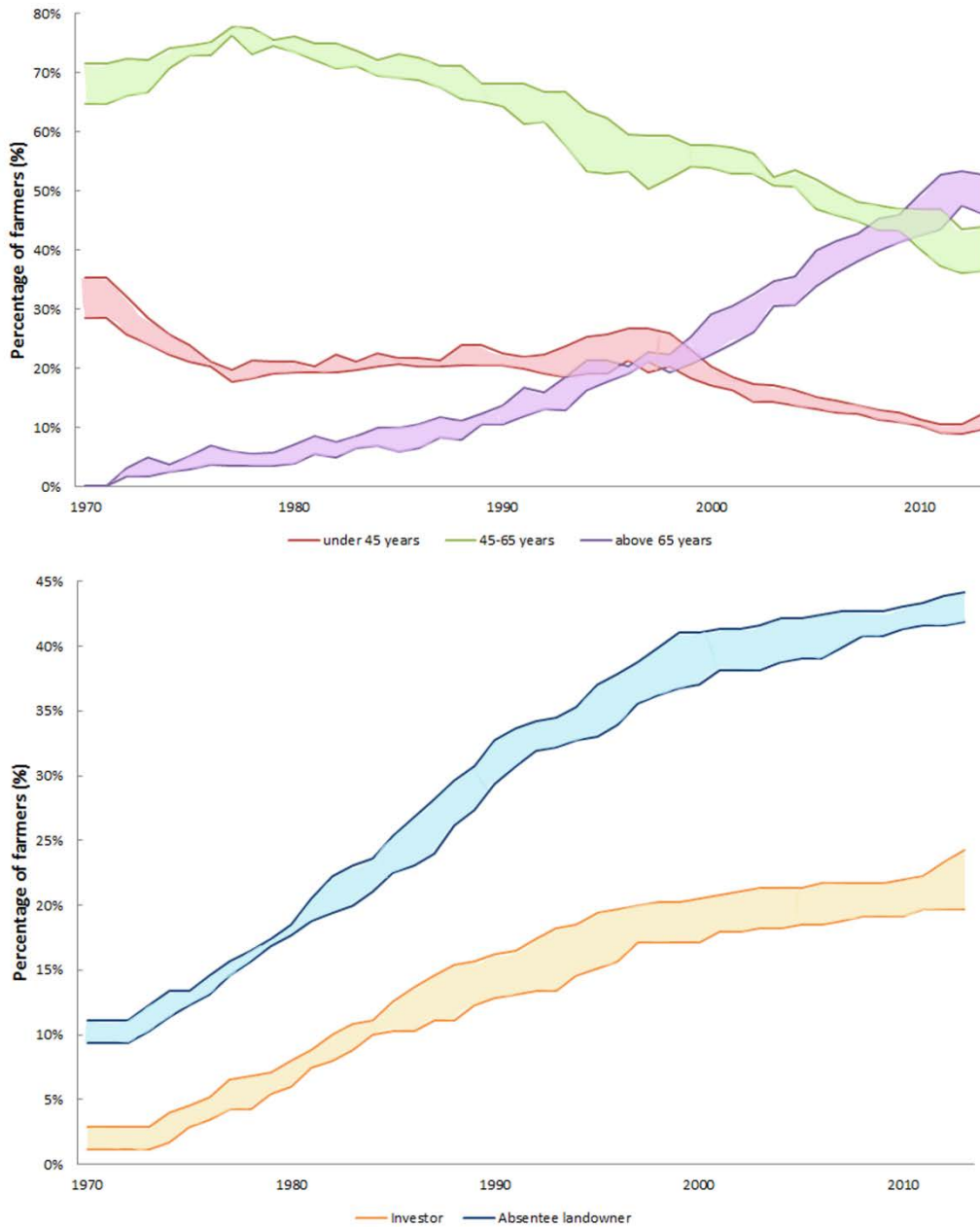
As absentee landowners live out of the county, and investors describe themselves as never having farmed, both groups may be less connected to local information networks and less aware of environmental problems and government programs, compared with operator landowners. Therefore, Petrzelka et al. (2009) found that absentee landowners lag behind operator landowners in adoption of land retirement programs (CRP and WRP). However, Nassauer et al. (2011) found that Iowa farm investors reported higher CRP and WRP enrollment rates than other Iowa farmers. Owners may be more likely to adopt structural practices because these practices require capital investment (Soule et al. 2000; Caswell et al. 2001). Nassauer et al. (2011) note that, compared to active farmers, investors are more positively inclined to adopt certain structural

practices and Pertzilka et al. (2009) underline the positive attitudes of absentee landowners to certain conservation practices and their benefits,

### **3.6. ABM Results**

We used the above farmer typology to populate ABM agents to investigate the impacts of changing land tenure dynamics and agricultural policy such as subsidized crop insurance as a risk management program on farmers' conservation decisions. To apportion the farmer attributes, such as farm size, land tenure, and source of income, we used county scale NASS survey data and national agricultural census data collected every 5 years by USDA. However because these data are not available to the public at a scale representing individual farms, the ABM represents farms as cells on a two-dimensional grid in a stylized model. The model is run with annual steps for 40 years (1970-2010). Model details are explained in Appendix A using the ODD protocol (Grimm et al., 2006; Grimm et al., 2010).

Our farmer typology represents the heterogeneity of farmers in the region. To better represent the socio-economic condition during the simulation period, we embedded key temporal trends in the model, such as the decline in full ownership of small production areas and an increase in large production areas and non-operator ownership (Wunderlich 1993; Duffy 2008). We first tested the model against documented socio-economic trends observed in the region such as increasing average age of farmers (Figure 3-4A) (USDA 2009). Because the model is applied to investigate the impact of changing land tenure dynamics, we used it to confirm the model findings on growing number of non-operators (absentee and investors) (Figure 3-4B) who may make conservation decisions differently (Wunderlich 1993; Duffy 2008; Petrzilka et al. 2009; Nassauer et al. 2011). The main results from the ABM can simply be listed as follows:

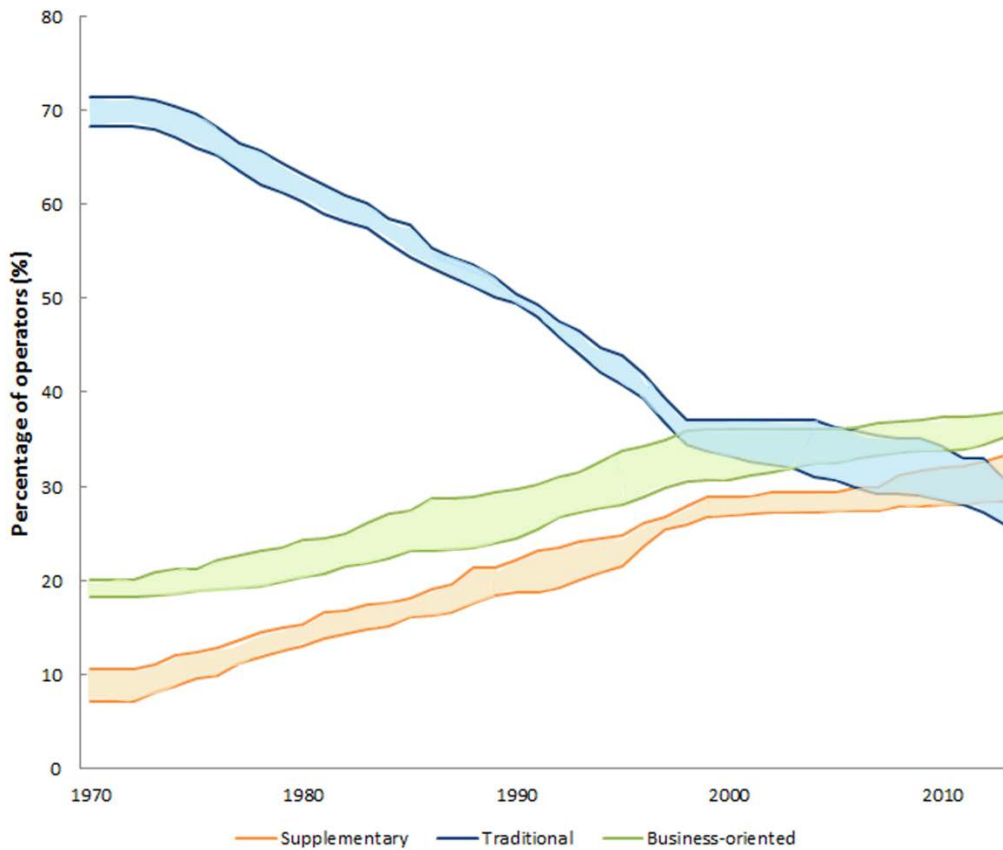


**Figure 3-4: (A) Average age distribution for farmer agents indicates that farmer population is aging. (B) Percentage of non-operators (absentee landowners and investors) is increasing for the simulation period (1970-2010). 25 ABM simulation runs fall between two lines of the same color.**

*Percentage of business-oriented and supplementary farmers increase, while traditional farmers decrease through time: In the model, some farmers change their types as they age. For*



example, after age 65 some of the traditional farmers leave farming and become non-operator owners by renting their land to business-oriented or supplementary farmers or they sell their land. Over time during the simulations, this results in an increase in business-oriented and supplementary farmers and a concomitant decrease in small traditional farmers (Figure 3-5). It also demonstrates the rapidly growing proportion of the non-operators (Figure 3-4B).



**Figure 3-5: Proportion of farmer types during the simulation period (1970-2010). Percentage of small traditional farmers decreases, whereas large business-oriented farmers and small supplementary farmers increase. 25 ABM simulation runs fall between two lines of the same color.**

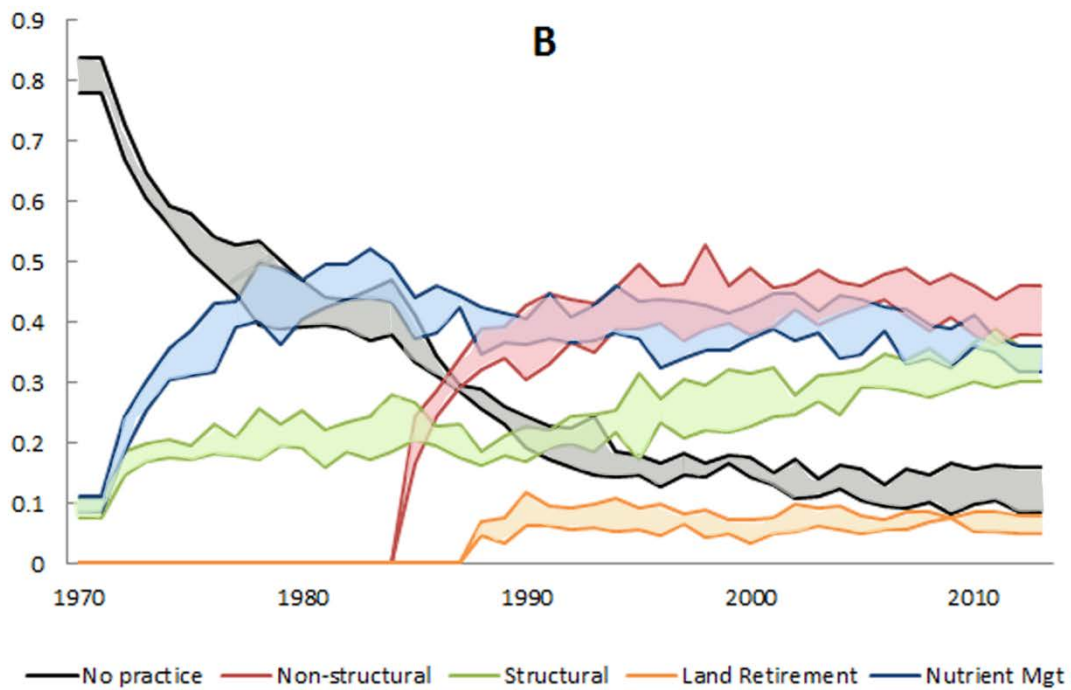
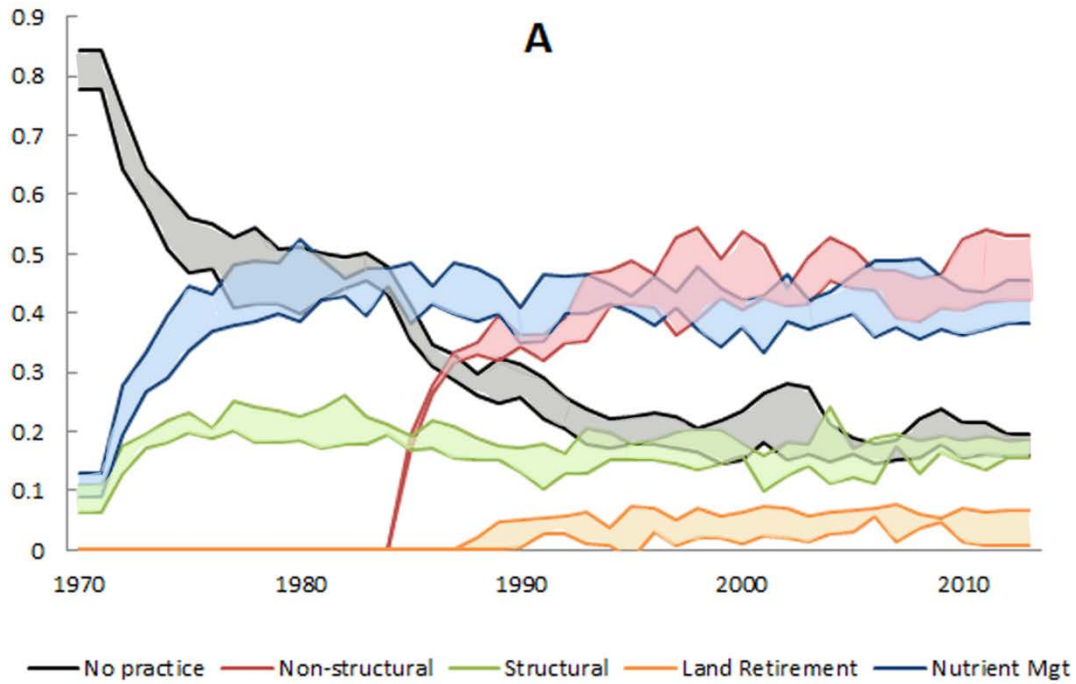
*Farmer population becomes more connected mostly due to increasing business-oriented farmers:* Connectedness to the information network is another dynamic component of our model. In our farmer typology, different farmer types have varying connectedness to information networks, both spatial and social. In our ABM, business-oriented farmers have more connections

compared to traditional and supplementary farmers. Non-operator owners are initially not connected to the spatial and social networks because they do not live in the county in which they own land, or they do not have a farming background. In the scenario when non-operators are involved in decision-making, investors are connected to the spatial network, but with a smaller number of connections when compared to the operator types. In addition, we assume that non-operators are connected to natural resource agencies if they are decision makers. As the percentage of business-oriented farmers and non-operators increases with time, the social network structure also changes. Increasing percentage of business-oriented farmers that take active role in decision-making implies a more connected farmer society.

*Adoption of structural conservation practices increase parallel to the increasing role of non-operator owners in decision-making:* Following the farmer typology, the model associates different agent types with different tendencies to make certain management decisions.

We used the ABM to explore the potential impacts of non-operator involvement in management decisions because certain conservation practices require financial investment and thus owner involvement. Because non-operators (absentee landowners and investors) have more positive attitude towards certain conservation practices (Nassauer et al., 2011, Petrzelka et al., 2012), their increased involvement resulted in an increase in adoption of conservation practices, especially structural practices like filter strips (Figure 3-6A and B). At the same time, farmer awareness of conservation practices is fundamental in adoption decisions. Therefore growing numbers of non-operators, who are not well connected to information networks, also discourages adoption of some practices. As noted by Nassauer et al. (2011) and confirmed by our model results, the agricultural landscape can change profoundly with the growth in the proportions of

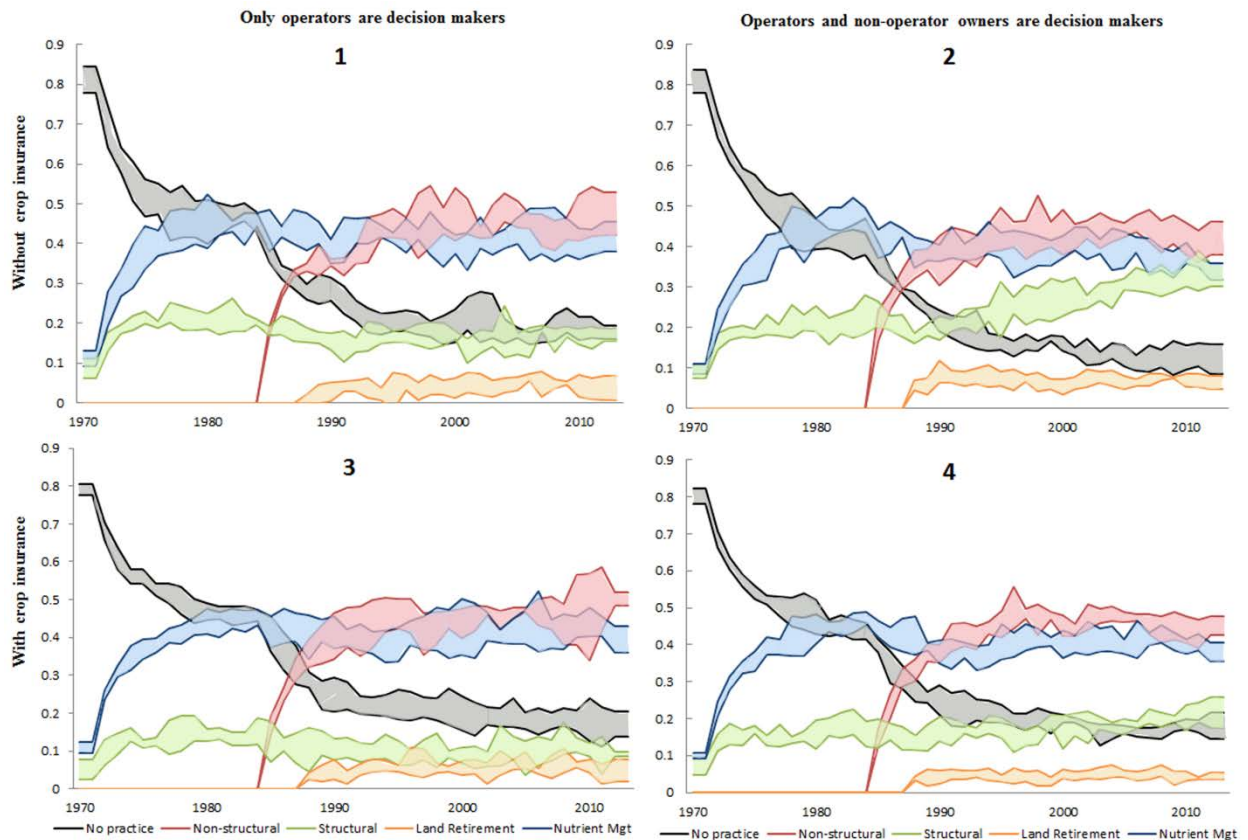
non-operators, especially investors who have limited farming background but positive attitude towards conservation practices (Figure 3-6A and B).



**Figure 3-6: Conservation practice adoption distribution for the simulation period (1970-2010) when traditional, supplementary and business-oriented farmer agents are the decision makers (A) and when non-operators (absentee landowners and investors) are involved in decision-making as well (B). Increased involvement of non-operators results in an increase in adoption of conservation practices, especially structural practices like filter strips. 25 ABM simulation runs fall between two lines of the same color.**

*Introduction of subsidized crop insurance results in increased non-structural practice adoption but decreased structural practice adoption and land retirement program enrollment:*

We also used the ABM to investigate the potential impact of subsidized crop insurance, specifically revenue insurance on management decisions of farmers. With revenue insurance in place, farmers have a safety net that protects them from fluctuations in both market prices and crop yields. The crop insurance policy scenario leads to a homogenous response at the landscape since risk management programs tend to promote production across all farmer types. Our model results are consistent with studies (Bosch and Pease 2000; Goodwin and Smith 2003; Babcock and Hennessy, 1996; Smith and Goodwin, 1996; Sheriff, 2005) showing a decrease in CRP enrollment and structural practice adoption, but an increase in non-structural practice adoption such as no-till systems and nutrient management plans with revenue insurance (Figure 3-7).



**Figure 3-7: Comparison of conservation practice adoption rates under the revenue crop insurance and non-operator involvement scenarios. Increased adoption of structural practices when non-operators are involved in decision-making (Panel 1 and 2). When revenue crop insurance is provided in both cases when operators (Panel 3) and non-operators (Panel 4) are decision makers, structural practice adoption and CRP enrollment decreases whereas nutrient management plan implementation increases. 25 ABM simulation runs fall between two lines of the same color.**

#### 4. Conclusion

Farmer typologies are critical for representing diversity in farmers' decision-making characteristics and mechanisms in social models designed to aid policies targeting specific conservation practices. Different policy interventions for promoting conservation practices that reduce sediment and nutrient runoff may appeal to different farmer types. The typology presented here, based on a synthesis of the adoption literature and the identification of policy-relevant farmer characteristics (land tenure arrangements, size of farm, source of income, and

information networks), comprises a heuristic set of four mutually exclusive types that differs from the existing USDA farmer typology (Hoppe et al. 2007; Lambert et al. 2007) in that it includes a previously non-differentiated but important group, non-operator owners. Moreover, the selection of only policy-relevant characteristics to represent the diversity of Corn Belt farmer adoption ensured the classification was parsimonious, as required by ABMs. Incorporating this farmer typology and associated heterogeneity into a larger coupled human and natural system model in which ABMs are linked with water quality models such as SWAT will help inform the assessment of impacts of policy interventions. Using the ABM populated by this typology makes it possible to simplify and represent the diversity of Corn Belt farmers with regards to their land management decisions. The ABM results are in line with the documented socio-economic trends of the Corn Belt and adoption statistics of the modeled conservation practices.

Considerable changes in the structure of US agriculture and the global socio-economic situation over the past decade have had a profound impact on soil and water conservation policies and programs. Grain prices have increased continuously (Napier 2009) and are likely to continue to do so, leading to increased rental rates (Secchi et al. 2008). In response to high grain prices, farmers have attempted to maximize production by taking land out of conservation, thereby jeopardizing previous conservation efforts (Napier 2009; Cox et al. 2011). If farmers, especially business-oriented farmers, continue to opt for maximization of profits, more set-aside land can be expected to be brought back into production, thereby increasing soil erosion rates and again raising water quality issues in places where previous policies had achieved some environmental quality progress.

The farmer typology described above demonstrates how different farmer types may be drawn to different conservation practices and policies depending on the relative importance of tenure

arrangement, production size, income source, and information networks. Not only do traditional and supplementary farmers have the highest enrollment rates in land-retirement programs such as the CRP and WRP, they are also connected to the landscape and behave as ‘citizens of the land’. Non-operators, including both absentee landowners and investors, can also be expected to have an increasing influence on conservation outcomes as they own increasing amounts of farmland. This increased influence makes the land management and conservation decisions to be less predictable from a social modelers’ point of view due to the limited number of studies focusing on non-operator owners. This group generally has had only limited involvement in on-farm decision-making in the past. However, as more and even most farmland begins to be owned by non-operators, their involvement may change, and surveys indicate their willingness to adopt conservation practices.

In the hypothetical future scenarios, where we model increased involvement of non-operators in management decisions, we observe higher adoption rates for structural practices such as filter strips. This potential change in management decisions highlight the importance of land tenure change and require further attention on non-operators. Using the ABM as a tool to investigate the impacts of subsidized risk management programs leads to an important policy insight. In our simulations, subsidized crop insurance programs lead to a homogenous landscape in terms of management decisions. As these programs promote production, we observe a reduction in CRP enrollment and structural practice adoption.

The typology presented here, based on characteristics relevant to the adoption of conservation practices by Corn Belt grain farmers, and ABM results obtained using this typology should enable policy makers to better assess the allocation of conservation program payments and potential impacts of agricultural policy on landscape. Since this typology is operationalized



for use in our ABMs that will be linked to SWAT, we focused on conservation practices applicable in SWAT and categorized them as non-structural, structural and land retirement. However, from prior studies we know that SWAT is sensitive to management practices such as fertilizer management especially application time and rate (Daloğlu et al. 2012). The adoption literature is not rich with empirical data about fertilizer management. Thus, to build better-informed linked models to investigate the impact of farmer behavior on water quality, there is a need for improved field data on fertilizer management and for these data to be linked to farmer characteristics.

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# **Chapter 4: An Integrated Social and Ecological Modeling Framework - Impacts of Agricultural Conservation Practices on Water Quality**

## **Abstract**

We present a new modeling framework that synthesizes social, economic, and ecological aspects of landscape change under different agricultural policy scenarios. The social-ecological system modeling framework evaluates how different policies, land management preferences, and land ownership affect landscape pattern and subsequently downstream water quality. To model this system, we link a stylized agent-based model (ABM) of farmers' conservation practice adoption decisions with a watershed model, the Soil and Water Assessment Tool (SWAT) to simulate the influence of changing land tenure dynamics and the crop revenue insurance in lieu of commodity payments on water quality over 41 years (1970-2010) for a predominantly agricultural watershed of Lake Erie. Results show that non-operator owner involvement in land management decisions yields the highest reduction in sediment and nutrient loads, and crop revenue insurance produces a homogeneous conservation landscape and a slight increase in sediment and nutrient loads. However, linking conservation compliance to crop insurance and strengthening and expanding conservation compliance provisions could reduce nutrient loads.

## **1. Introduction**

US agricultural policy strongly impacts the land use and land management decisions of farmers, especially in predominantly agricultural landscapes. Due its link to agriculture, policies often indirectly, but profoundly, impact water quality (Broussard et al., 2012). An overall goal of conservation policies with regard to water quality is to reduce sediment and nutrient loss from the agricultural landscapes by promoting nutrient efficiency and managing nutrient and sediment runoff via conservation practices (Sharpley et al., 1994). Thus, detailed studies of the connections between the US agricultural policies and the water quality in estuaries, rivers, and lakes can help policymakers provide appropriate incentives for controlling agricultural pollution.

High surface water concentrations of nitrogen and phosphorus, which are important drivers of nutrient pollution, are correlated with inputs from fertilizers used for crops (Boyer et al., 2002; Galloway et al., 2004; Goolsby, 1999; Howarth et al., 1996; Ribaudo and Smith, 2000), and these nutrient loads can accelerate eutrophication of receiving marine and freshwaters. Although increases in the loadings of organic matter and nutrients from land has persisted with contributions from industrial development and land conversion, Great Lakes and coastal eutrophication did not emerge as a serious problem until the 1950s and 1960s. The current increase in eutrophication is attributed to the intensification in agricultural production and concomitant soil erosion and nutrient runoff from non-point sources (Boesch and Brinsfield, 2000). To address these issues, conservation practices, such as conservation tillage, filter strips, land retirement, and nutrient management -- the focus of this research -- are employed to mitigate sediment and non-point source nutrient delivery. Moreover, adoption of conservation practices is regarded as a strategy to enhance water quality and improve sustainability in agricultural production by increasing the resilience of the systems (NRC, 2010).

In this study, we explore linkages between human and environmental systems and the implications of these linkages for policy makers. Our framework is one of a social-ecological system (SES) that combines decisions and actions of human actors with ecological responses to these actions in a reciprocal feedback system. These social-ecological systems are affected by multi-dimensional and complex relationships of causal variables arising from the biophysical, institutional, infrastructural, demographic, economic, and socio-political contexts. Hence, SES are also considered complex adaptive systems that exhibit emergent properties -- unique properties not belonging to human or natural systems separately but emerging from the interactions between them (Janssen, 1998; Monticino et al., 2007; Parket et al., 2003; Rammel et al., 2007; Levin et al., 2012). The success or failure of management depends on the extent to which the complexities of SESs are considered (Liu et al., 2007). Even so, in complex systems - such as the one we investigate here - unforeseeable and undesirable consequences can result if the biophysical and human systems are not examined together; highlighting the need for coupled modeling that incorporates dynamic feedback between the social and biophysical model components (Veldkamp and Verburg 2004; Levin et al., 2012).

In this study, we introduce a modeling framework designed to investigate the SES consisting of agricultural policy, farmer land management choices, and water quality through investigation of the impact of plausible future scenarios on farmer adoption of conservation practices intended to enhance water quality. For this purpose, this framework links a social, agent-based model (ABM) to study farmer adoption of conservation practices with a biophysical water quality model, the Soil and Water Assessment Tool (SWAT). The framework defines farmers as owners or renters of farmland on which cash crops are grown. Moreover, farmers make decisions about land management based on policy scenarios involving economic, institutional, and

environmental information. This framework incorporates the heterogeneity and complexity of Corn Belt farmers by defining a farmer typology (Daloğlu et al., in review) in the ABM that simulates farmer decisions. The farmer typology represents the relevant heterogeneity of Corn Belt farmers in terms of their tendency towards adoption of conservation practices.

The focal point of this study is to investigate the impact of plausible future scenarios on this SES. The impact is quantified at the watershed scale by modeling the change in water quality metrics -- the bioavailable dissolved reactive phosphorus (DRP) and total phosphorus (TP). SWAT incorporates land management decisions with soil properties, climate information, and land topography to estimate water quality metrics (Arnold et al., 1998).

Few water quality models represent farmer decisions regarding land management and conservation practice adoption dynamically. Instead most provide ideal conservation practices and locations with a goal of minimizing pollutant loading. For example, genetic algorithms have been used to optimize the cost of adoption and pollutant reduction from the landscape (Maringanti et al., 2008; Rabotyagov et al., 2010; Arabi et al., 2006). Another widely used method is representing farmer decisions through surveys that inform conservation practice adoption rates and spatial locations (Turpin et al., 2005; Saleh et al., 2007). However, these models lack dynamic interactions among farmers and their responses to policy changes. One exception is coupling ABM and SWAT to represent adoption of second-generation biofuel crop and farmers' response to markets and policy (Ng et al., 2011).

## **2. The Modeling Framework**

The study area is the Sandusky watershed of Lake Erie, which represents a typical watershed of the Corn Belt region (Figure 4-1). Historically, Lake Erie has been subject to significant eutrophication from excessive phosphorus loading, primarily from agricultural runoff and point

source discharges (Dolan and Chapra, 2012; Dolan and McGunagle, 2005); however, non-point sources, particularly agriculture, are currently the major causes of nutrient pollution to Lake Erie (Forster et al., 2000). Agricultural runoff has resulted in algal blooms, poor water clarity, and summer hypoxia (low oxygen) (Hawley et al., 2006) that can impact commercial and sport fisheries, recreation, and drinking water throughout many aquatic and coastal systems (Carpenter et al., 2008). To address these issues and remediate Lake Erie eutrophication, effective adoption of conservation practices and enterprises will be essential.

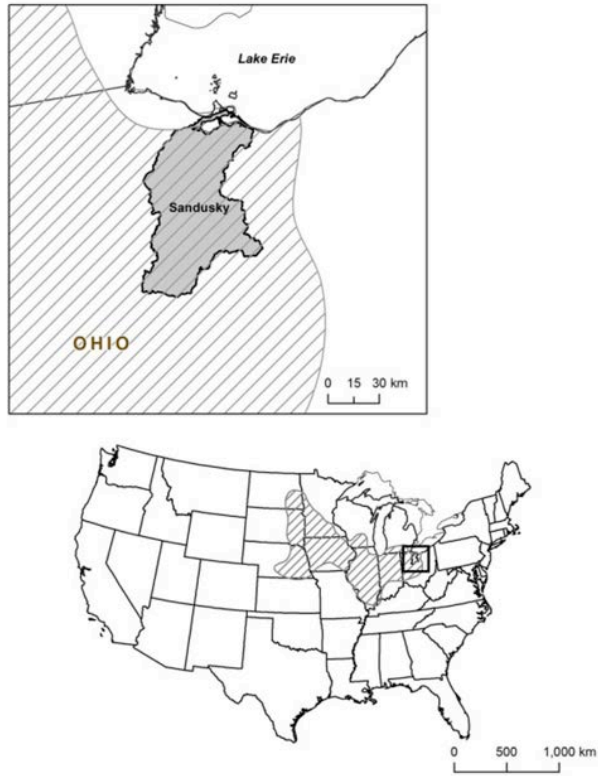
The modeling framework<sup>1</sup> consists of several components including the landscape, agents (farmers, in a typology that represents their heterogeneity), conservation practice adoption, and the ecosystem response to changes in the land management (sediment, DRP, and TP loading), all of which were derived from previous studies (Figure 4-2). The farmer typology for adoption of conservation practices (Daloğlu et al., in review) represents the heterogeneity among Corn Belt farmers and provides the necessary pillar for the design of the ABM. An existing, fully calibrated SWAT model of the Sandusky watershed (Daloğlu et al., 2012) is used to simulate nutrient loadings as indicators of water quality. With this linked ABM-SWAT framework, we investigate how policy and farmer characteristics might drive selection of conservation practices and, in turn, their effects on water quality.

Agent-based models are constructed at the individual decision-making level, hence farmer (agent) behavior and decisions are modeled typologically (see Section 2.2). We use this modeling framework to investigate plausible future scenarios of US agricultural structure and policy. We explore the changes in US agricultural structure specifically in land tenure dynamics (see Section 2.3) and influence of crop revenue insurance on farmers' conservation practice

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<sup>1</sup> The ABM is implemented in Java using Repast J agent-based libraries within the Eclipse integrated environment and linked to SWAT using the MatLab programming language.

adoption decisions (see Section 2.4) as plausible future scenarios. The benefit of following this approach is that the exploration of different plausible scenarios helps us explain certain policy initiatives affect adoption of conservation practices and their effects on water quality, consequently, suggests policy insights. Farmer agents of different types make adoption decisions every year on the basis of their decision algorithm (see Section 2.6). If these decisions include the adoption of conservation practices, the landscape is altered, which eventually changes the land management strategy (see Section 2.5). The output from the ABM is used to examine plausible future scenarios for modifying and reflecting the changes in adopted conservation practices (see Section 2.7). Hence, the updated land management map is the crucial input for the corresponding SWAT model, where the farmer behavior is transferred to the watershed model (see Section 2.8) (Figure 4-2). To understand the impacts of these plausible future scenarios, we focus on sediment and phosphorus runoff from the landscape over a 41 year period (1970-2010) (see Section 3). The linked models also respond to the priorities of the Lake Erie Management Plan – 2008 (LaMP), which identified nutrient (especially phosphorus) management as the basin’s top priority and therefore seeks to develop a nutrient management strategy for Lake Erie.



**Figure 4-1: Locator map for the Sandusky Watershed, Ohio. The study watershed is representative of the Corn Belt watersheds.**

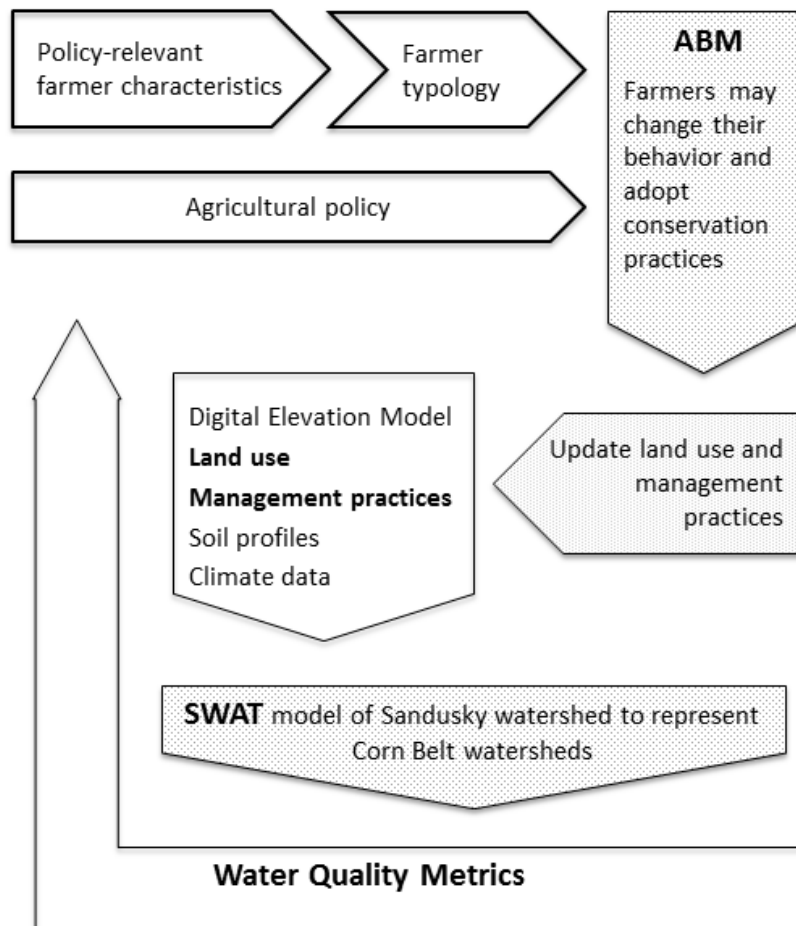


Figure 4-2: The coupled human and natural system of an agricultural landscape in the Corn Belt

## 2.1. The Model Landscape

The model landscape consists of a two-dimensional grid space, built within the ABM, abstractly representing the agricultural landscape of the Sandusky watershed. Because the ABM is linked with SWAT, the specifics of the water quality model are taken into consideration during the ABM setup phase. SWAT uses hydrologic response units (HRU) as fundamental computational units. Runoff flow, sediment, and nutrient loads are calculated separately for each individual HRU and then summed to determine the total load contribution from each subwatershed (Neitsch et al., 2011). Land management decisions are represented at the HRU



scale; therefore SWAT was implemented so that the average HRU size corresponds to the average farm size in the Sandusky basin (Daloğlu et al., 2012). This strategy resulted in 147 subbasins and 351 agricultural HRUs based on the average farm size in the basin (258 acres) (USDA, 2009). Therefore, 351 farmers are represented as agents in the ABM.

## **2.2. Agents as Farmers**

Farmers have exceptionally diverse characteristics, particularly with regard to their farm size, land tenure, education, age, sources of income, and socioeconomic attributes. To represent the heterogeneity of farmers in the Corn Belt region in the ABM, we employ a farmer typology (Table 4-1, Daloğlu et al., in review) based on an extensive literature review and previous surveys conducted in this watershed region to avoid survey fatigue (Porter, 2004). Because ABMs require simplicity (Axelrod, 1997), like others (Valbuena et al., 2008; Robinson et al., 2012) our typology represents the diversity and heterogeneity among agents in simple terms.

Due to limited data, representation of the exact location of farms and long-term management decisions is not possible. To produce a more generalizable result, we chose to represent the study area in a stylized model. The ABM is therefore an abstraction, but one based on and nourished by long-term socio-economic trends of the Corn Belt region and when data are available for the Sandusky basin where dominantly cash crops such as corn, soybean, and winter wheat are grown. Model details are explained in Appendix A using the ODD protocol (Grimm et al., 2006; Grimm et al., 2010).

Building on the previously built farmer typology we have four farmer types: traditional, supplementary, business-oriented, and non-operator owners (Daloğlu et al., in review). This typology represents the relevant heterogeneity of Corn Belt farmers in terms of their adoption of conservation practices (Table 4-1).

Farmer Type	Properties	Land Management Attitudes
<b>Traditional</b>	Full-owner, small operations, dependent on on-farm income, moderately connected to information networks	<ul style="list-style-type: none"> <li>- favor non-structural practices because of potential reduction in labor requirements</li> <li>- financial investment requirement leads to lower adoption rates for structural practices</li> <li>- secure income provided by land retirement programs is appealing</li> </ul>
<b>Supplementary</b>	Full/Part-owner, small operations, has off-farm income, moderately connected to information networks	<ul style="list-style-type: none"> <li>- favor non-structural practices because of potential reduction in labor requirements</li> <li>- substantial off-farm income leads to higher adoption rates for structural practices.</li> <li>- secure income provided by land retirement programs is appealing</li> </ul>
<b>Business-oriented</b>	Part-owner, medium to large operations, dependent on on-farm income, highly connected to information networks	<ul style="list-style-type: none"> <li>- favor non-structural practices because of potential reduction in labor requirements</li> <li>- long-term plans and dependence on soil quality leads to higher structural practice adoption</li> <li>- focused on profitability, leading to low enrollment rates in land retirement programs</li> </ul>
<p><b>Non-operator owner</b>  <i>Absentee landowners:</i> own the land but do not reside on or operate it (Petzelka et al., 2011)  <i>Investors:</i> describe themselves as never having farmed (Nassauer et al., 2011).  Mutually exclusive subtypes.</p>	Non-operator owner, medium to large operations, has off-farm income, least connected to information networks	<ul style="list-style-type: none"> <li>- have less control on land management strategies but positive attitudes toward conservation practices</li> </ul>

**Table 4-1: Farmer typology (from Daloğlu et al., in review)**

### **2.3. Land Tenure Changes in the Model**

US agriculture has undergone critical changes in land tenure dynamics, especially the continuous increase in non-operator ownership followed by an increase in part ownership or full renting (Wunderlich 1993; Duffy 2008). Our study site, the Sandusky watershed, followed national trends in land tenure dynamics, especially in relation to increased non-operator ownership (Daloğlu et al., *in review*). The impact of this increase on land management strategies has been studied in the Corn Belt region (Soule et al., 2000; Petzelka et al. 2009; Nassauer et al. 2011, Petzelka et al., 2011). Structural practices are appealing to non-operators (Nassauer et al., 2011; Petzelka et al., 2009). Among absentee landowners, land retirement enrollment is lower in the Great Lakes Basin (Petzelka et al., 2011). However, Nassauer et al., (2011) found investors have higher land retirement enrollment rates in a survey of 549 Iowa farmers.

Because the percentage of both absentee landowners and investors continues to increase, further emphasis is given to the relationship between operators and their non-operator owners concerning conservation decisions. This is important because nearly half of Corn Belt farmers live outside of the county in which they own the land (Petzelka et al. 2009). We define these non-operator owners as absentee landowners (Petzelka et al. 2009) and previous research has shown that as the spatial distance between landowner and tenant increases, the frequency of communication decreases (Arbuckle, 2010). We use our framework to investigate the impact of changing land tenure dynamics on conservation practice adoption and subsequent water quality impacts by modeling increased involvement of non-operator owners in conservation decisions. In our simulations, when non-operator owners are involved in the decision-making, we assume the rate of involvement to increase from 0% to eventually reach 50% at the end of the simulation.

#### **2.4. Changes in Agricultural Policy in the Model: Crop Revenue Insurance**

The governance systems and institutions play a role in social-ecological systems. For example, in this linked system, the rights, rules, and decision-making mechanisms that guide farmers' actions may have destructive or constructive impacts on the biophysical system. At the same time, governance systems also provide mechanisms, such as insurance and financial subsidies that can help alleviate the negative impacts of biophysical changes on human systems (Kotchen and Young, 2007).

Current agricultural policies offer numerous incentives for farmers to adopt conservation practices; however, other drivers, including policy incentives, frequently outweigh these, resulting in a patchwork of adoption that is not sufficiently effective in improving water quality (Doering, 2007). Current Farm Bill discussions include replacement of commodity payments such as direct payments with subsidized crop insurance. Providing subsidized crop insurance to US farmers started in 1930 with Dust Bowl and Great Depression and participation levels increased in 1980s with the involvement of private insurance industry. In 1985, with the introduction of conservation compliance, participation in subsidized crop insurance programs required refraining from draining wetlands and implementing a conservation plan when farming highly erodible lands. Conservation compliance requires a basic level of conservation as a condition for farmer eligibility for agricultural programs, which can be categorized as a voluntary, incentive-based policy instrument. However, in the 1996 Farm Bill, in an effort to encourage more farmers to purchase crop insurance, crop insurance was removed from compliance requirements (Smith and Glauber, 1997).

Since 1996, conservation compliance has been tied to commodity payments such as direct payments. Direct payments were a central component of commodity payments, offered to

farmers regardless of crop prices and whether farmers have planted crops. However, because of the high cost of emergency disaster payments each year, the current Farm Bill suggests replacement of direct payments with subsidized crop insurance. Currently, farmers can choose between two insurance policies, crop yield or revenue insurance, where USDA provides subsidies for two-thirds of the cost of farmers' premium (Coble and Barnett 2013). Crop yield insurance protects farmers from income effects of reduction in agricultural yield due to weather and other factors, whereas revenue insurance protects farmers' income from both market fluctuations and yield changes, and indirectly encouraged farmers to increase their production area.

In light of these discussions, evaluation of crop insurance as a plausible future scenario is timely and policy-relevant. The federal crop insurance program can be viewed as a risk management tool that provides farmers a safety net. The importance of risk management cannot be ignored, indeed uncertainty and risk associated with adoption of new practices is one reason for non-adoption. Risk-averse farmers may be reluctant to accept voluntary risks associated with conservation practices even if there is a probability of increase in expected returns (Bosch and Pease, 2000). Moreover, with the observed variability in weather patterns, farming has become increasingly risky in the last decade. To evaluate potential impacts of crop insurance replacing commodity payments, we concentrate on revenue insurance, which is protecting farmers' income from both market fluctuations and yield changes (Coble and Barnett 2013).

Numerous studies have investigated the role of risk aversion in adoption of non-structural practices (conservation tillage and no till) and have consistently found a negative relationship between risk aversion and practice adoption (Belknap and Saupe, 1993; Bultena and Hoiberg, 1983; Ervin and Ervin, 1982). Similarly, when farmers consider implementing a nutrient

management plan (fertilizer reduction), they generally assume increased yield uncertainty. Providing revenue insurance for farmers reduces the risks involved with nutrient management plan implementation and non-structural practice adoption (Bosch and Pease, 2000). However, interestingly several studies have highlighted drawbacks to crop insurance. For example, a moral hazard can result if farmers use crop insurance as an incentive to under fertilize their crops in order to receive indemnities (Sheriff 2005). Goodwin and Smith (2003) also raised concerns about crop insurance and other disaster relief programs discouraging land retirement. Another criticism is the potential of supporting an increase in production on erodible land (Griffin, 1996; Keeton et al. 2002; Goodwin and Vandever 2000). Our previous modeling efforts indicate that regardless of farmer type, crop revenue insurance promotes increased production, which results in a more homogenous conservation landscape (Daloğlu et al., *in review*).

## **2.5. Conservation Practices**

We define land management change as driven by the adoption of four conservation practices and government programs that are widely used and could be represented in SWAT (Table 4-2). In the model, farmers can adopt combinations of conservation practices to control pollution source (nutrient management), trap soil before it reaches water bodies (structural practices, i.e., filter strips), promote long-term conservation covers (land retirement, i.e., Conservation Reserve Program-CRP), and reduce soil disturbance (non-structural practices, i.e., conservation tillage and no-till). Farmers' annual adoption decisions are then explored under different plausible future scenarios (see Section 2.7).

US agricultural programs generally allow farmers to choose which programs to participate in and have flexibility in selecting conservation practices that fit their climate, soils, and, most importantly, management skills (Bernstein et al., 2004). So, in our model, adoption of structural,

non-structural practices, nutrient management plans, and enrollment in land retirement is voluntary. Each farmer determines whether to participate in land retirement or adopt certain practices depending on policy incentives and the farmer's overall objectives. Land retirement programs such as Conservation Reserve Program (CRP) generally remove land from agricultural production for a long period (at least 10 years) or, in some cases, permanently. Structural practices are eligible for cost-share; farmers receive 50% of the implementation cost from the federal government as an economic incentive and are required to make multi-year commitments. When farmers receive economic incentives for structural practice adoption and land retirement enrollment, non-compliance to these programs and practices before the contract ends is accompanied by penalties (Claassen, 2012). Because non-structural practice adoption and enrollment in nutrient management plans do not provide economic incentives, non-compliance to these practices do not entail penalties in the model.

In this model, farmers consider the expected utility of adoption decisions influenced by profit generated by agricultural production, their intrinsic attributed, and their neighbor' adoption decisions. Because land retirement contracts and structural practices require multi-year commitments, whereas adoption of non-structural practices and nutrient management plans are made annually, these decisions have temporal consequences, and therefore in the model, farmers' participation is dynamic.

The conservation practices available to farmers have been implemented and promoted widely; however, few field studies have examined their effectiveness. (Easton et al., 2008; Makarewicz, 2009; Lemke et al., 2011; Cullum et al., 2006; Gitau et al., 2005). The existing field studies measuring the effectiveness of these conservation practices report a wide range of results (Gitau et al., 2005). This lack of consistent results is likely related to the fact that the

effectiveness of these practices depends on the landscape properties, implementation location and implementation extend. With this perspective in mind, in this framework, the effect of farmers’ adoption of conservation practices on water quality outcome depends in part on the spatial distribution of these practices across a watershed.

<b>Conservation Practice Categories</b>	<b>Conservation Practices</b>	<b>Economic and Environmental Benefits</b>
Non-structural	Conservation tillage, no-till	Reduces soil erosion from both water and wind, increases organic matter and enhances water quality. Reduces labor, saves time and fuel, reduces machine wear
Structural	Filter strips, grassed waterways	Enhances water quality by trapping soil particles, nutrients and pesticides; improves water infiltration; enhances wildlife habitat. Eligible for cost-share programs
Land retirement	Conservation Reserve Program (CRP), Wetlands Reserve Program (WRP)	Plants long-term, resource conserving covers. Reduces soil erosion from highly erodible lands (HEL), restores wetlands. Enhances water quality and wildlife.
Nutrient management	Reducing fertilizer application rate	Reduces nutrient application on agricultural landscape and eventually reduces nutrient runoff.

**Table 4-2: Conservation practice categories applicable in SWAT models (modified and adapted from Daloğlu et al., *in review*).**

## **2.6. Conservation Practice Adoption Decisions in the Model**

This model addresses the critical information gap in effectively and efficiently employing conservation programs: understanding why some farmers do not adopt conservation practices and understanding how to affect spatial relationships among farmers who do and do not adopt with a special emphasis on their heterogeneity. In the model, at each annual time step, every



farmer decides on a land management strategy for conservation practice adoption (Table 4-2). The decision-making algorithm includes income generated from government programs and agricultural production, influence of the farmers' neighbors, and farmers' intrinsic attributes (details in Appendix A). Farmers can choose to adopt none or a combination of available practices.

Depending on farmers' agricultural profit generated, preferences, and on the actions of the neighbors, farmers react differently to the same agricultural policies. Every farmer in the model uses the same decision algorithm but with different parameters based on the heterogeneity of preferences. A critical variable in the model is whether owners or operators make adoption decisions. Most empirical research concludes that operators control decisions regarding production and adoption of conservation practices on farmland owned by non-operators (Arbuckle, 2010; Constance et al., 1996; Soule et al., 2000); however, we also investigate the possible impact of the growing proportions of farmland owned by non-operators and their influence on adoption decisions (see Sections 2.3 and 2.4).

In the ABM, farmers calculate their agricultural profit generated from production and collect financial incentives provided by enrollment in government programs. For agricultural profit, farmers use Bayesian inference for expectation formation of price and yield in the form of a probability distribution. We represent farmer heterogeneity by setting different parameters for Bayesian updating for different farmer types. For example, traditional farmers have more stable price and yield expectations and business-oriented farmers are better following the fluctuations in the market because we assume that they are more connected to the information networks. Farmers' perceptions of crop prices and yields change from year to year. At the beginning of

each year, farmers use publicly available price and yield information and their experiences and characteristics of their type to form future price and yield expectations.

Farmers also observe their social and spatial network and evaluate which practices their neighbors adopt. Non-operators (absentee landowners and investors) are initially not connected to the information networks, whereas operators (traditional, supplementary and business-oriented farmers) are connected to both spatial and social networks. Business-oriented farmers have higher network connectedness compared to traditional and supplementary farmers (Daloğlu et al., *in review*). Farmers' intrinsic environmental attitudes toward each available conservation practice, as reflected in their type (Table 4-1), also influence their adoption decisions. Once all information is gathered, farmers use their decision algorithm to decide which conservation practice to adopt (see Appendix A).

## **2.7. Plausible Future Scenarios**

The primary goal of this modeling framework is to understand farmer adoption of conservation practices and subsequent impacts on water quality under plausible future scenarios. For this purpose, we constructed four plausible future scenarios intended to form a bridge between the science of land management and policy development (Table 4-3). At the same time, these scenarios are intended to be prospective and informative rather than projective or prescriptive of the future (Nassauer and Corry, 2004). We use these scenarios to evaluate simulated land management patterns and determine possible water quality implications. Our integrated method, linking a social model with a biophysical model contributes to the growing body of research on social-ecological systems.

		NON-OPERATOR INVOLVEMENT	
		NO	YES
CROP REVENUE INSURANCE	NO	1 <i>Baseline</i> Simplified representation of existing land tenure and policy context	2 <i>Non-operator owners involvement</i> Increased non-operator involvement in land management decisions
	YES	3 <i>Crop revenue insurance</i> Only operators are decision makers and crop revenue insurance is available as a risk management tool Available to all operators as a risk management tool	4 <i>Crop revenue insurance with non-operator owner involvement</i> Both operators and non-operators owners are decision makers and crop revenue insurance is available as a risk management tool

**Table 4-3: Land management strategies tested under different agricultural policy and structure scenarios**

The *Baseline scenario* (1) represents a simplified version of existing land tenure where operators (traditional, supplementary and business-oriented farmers) are responsible for conservation practice adoption decisions and non-operator owners have no involvement in production and conservation decisions. In this scenario existing crop insurance programs are not represented and crop revenue insurance is not offered in lieu of commodity payments.

The *Non-operator owner involvement scenario* (2) simulates the potential impact of non-operator owners being more involved in decisions about conservation practice adoption. This premise follows recent research that demonstrated positive attitudes of non-operator owners for certain conservation practices (Petrzelka et al., 2009; Nassauer et al., 2011). In this scenario, we assume natural resource agencies and NGOs reach out to non-operator owners and effectively inform them about existing and available conservation practices (Table 4-4).

The *Crop revenue insurance scenario* (3) follows the latest US Farm Bill discussions about providing federally subsidized crop revenue insurance rather than commodity production

subsidies. This scenario does not assume that conservation compliance is required for land to be eligible for crop revenue insurance. In this scenario, only operators are decision makers and they purchase crop revenue insurance at 75% coverage level for all the land that they manage including the rented land. Crop revenue insurance provides an accessible risk management tool to operators and at the same time encourages an increased production area (Table 4-4).

The *Crop revenue insurance with non-operator owner involvement scenario* (4) presents the plausible changes both in land tenure and policy by assuming non-operators owners as active decision makers when crop revenue insurance is offered in lieu of commodity payments. Crop revenue insurance provides a safety net and indirectly motivates both operators and non-operator owners to increase their production area (Table 4-4).

	Assumptions in the model
Non-operator owner involvement	<ul style="list-style-type: none"> <li>- When non-operator owners are involved in the decision-making, the rate of involvement increases from 0% to eventually reach 50% at the end of the simulation</li> <li>- Absentee landowners are only connected to social network but not to the spatial network because they live out of the county that they own</li> <li>- Investors are connected both to the spatial and social network</li> </ul>
Crop revenue insurance	<ul style="list-style-type: none"> <li>- Farmers buy subsidized crop revenue insurance premium with 75% coverage level</li> <li>- Buying crop revenue insurance changes farmers' land management preferences</li> <li>- Both non-operator owners and operators buy crop revenue insurance for both the land they own and rent.</li> <li>- Conservation compliance is not linked to crop revenue insurance</li> <li>- Rental rates of non-operator owners' reflect the revenue risk reduction represented by crop revenue insurance</li> </ul>

**Table 4-4: Assumptions embedded in scenario simulations**

## **2.8. Water Quality Model - SWAT**

The Soil and Water Assessment Tool (SWAT) is a distributed and spatially explicit continuous-time water quality model at the scale of river basins or watersheds. This model

divides watersheds into subbasins with hydrologic response units (HRU) that represent areas with common land cover, management, and slope and soil properties (Arnold et al. 1998). It is a process-based model of surface hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, pesticides, and groundwater that can simulate the effects of climate and land use changes on nutrient and sediment delivery from watersheds (Arnold et al., 1998) that is used widely for evaluating and predicting impacts of conservation practices (Arabi et al., 2008).

SWAT models have been developed and applied for Lake Erie watersheds to predict potential impacts of conservation practice adoption on water quality (Bosch et al. 2011). More recent SWAT applications indicate that more aggressive strategies than currently employed are needed to substantially reduce nutrient and sediment delivery (Bosch et al. (a, in review), especially under anticipated future climates (Bosch et al. (b, in review).

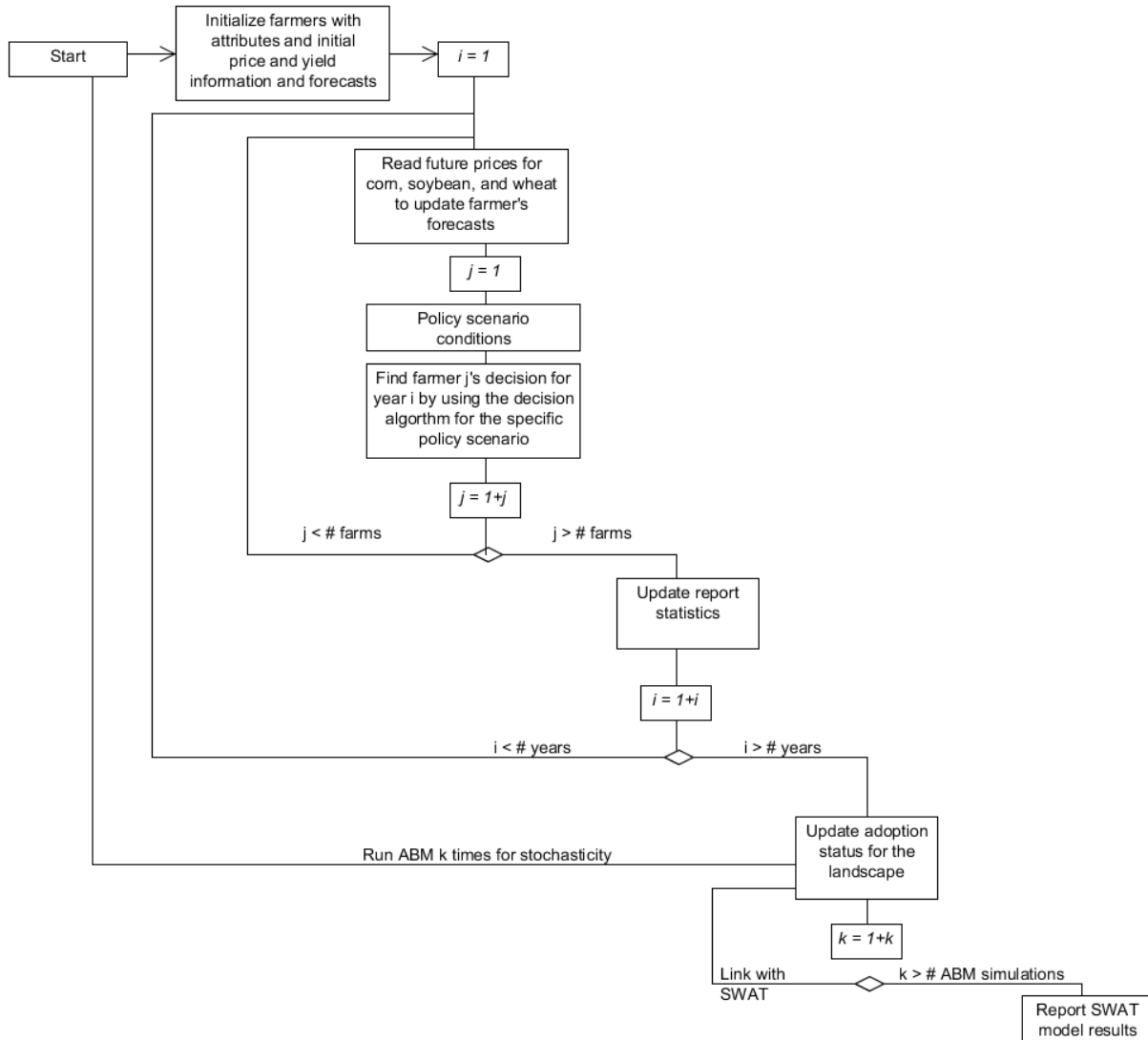
For this study, we used an existing, higher spatial resolution SWAT model developed for the Sandusky watershed (Daloğlu et al., 2012). The model is employed at a spatial scale in which the smallest computational unit of SWAT, average HRU size, corresponds to the average farm size in the Sandusky basin (258 acres; USDA, 2009). The model was calibrated and validated with extensive daily observed flow and water quality data for the simulation period (1970-2010) and can be used for future scenario testing. Our previous modeling efforts indicated the importance of farmer management decisions on nutrient delivery especially on DRP runoff (Daloğlu et al., 2012).

### **3. Modeling Framework: Water Quality Impacts of Land Management Strategies**

This modeling framework is used to evaluate the impacts of farm-scale decisions at the watershed scale, a scale large enough to be policy-relevant, and thus relevant to plausible future scenarios. The diagram in Figure 4-3 gives the process overview and scheduling of the modeling

framework. Because model parameters are sampled from distributions for decision-making algorithms, each scenario consists of 25 runs. For each run, farmers update their adoption decisions annually under plausible future scenarios such as changes in the land tenure or policy.

During the simulation phase, farmers of different types adopt conservation practices based on a behavioral model consisting of their agricultural profit generated from production, their preferences towards conservation practices, and the adoption decisions of their neighbors and other farmers in their social network. After farmers decide whether to adopt a specific conservation practice or not, the results lead to an update of the landscape. We link ABM output to SWAT and report water quality model output as the average of the 25 SWAT runs for the 41-year simulation period (1970-2010) (Figures 4-9 to 4-11).



**Figure 4-3: Process overview and scheduling for the modeling framework**

### 3.1. Linking ABM with SWAT

Once all farmer adoption status is updated, the ABM output in the abstract grid file provides the adoption status for every farmer in every period and is used to make the necessary updates in relevant input files of SWAT in the Sandusky watershed file. Abstract grid cell characteristics are assigned to Sandusky watershed locations by the smallest computational unit of SWAT, hydrologic response units, HRUs. SWAT is then run for the whole simulation period (1970-

2010) to provide water quality metrics such as sediment and phosphorus loads. The input files for SWAT are all in ASCII text format, making it easy to interface with the ABM and this linkage is supported with the MatLab programming language.

For each year, farmers' decisions regarding conservation practice adoption are used to modify several SWAT input files. For example, if a farmer adopts non-structural practices such as no-till instead of conventional tillage, the land management input file (.mgt) in SWAT is modified to reflect this change. Similarly, if a farmer adopts structural practices such as filter strips, the operations input file (.ops) is updated with a filter strip of 10 m width. Because farmers receive economic incentives to adopt structural practices, their continued use of filter strips is expected. For enrollment in land retirement programs, we change the land cover type in the input file (.mgt) to be one of the perennial covers such as big bluestem without fertilizer application. Once a farmer enrolls in land retirement programs, adherence to the contract is mandatory for at least 10 years as a requirement of the program. If a farmer adopts nutrient management plan, then a 20% reduction in fertilizer application rate is assumed. This change is also reflected in the management input file of SWAT (.mgt).

The decision algorithm used by our farmers includes social and spatial networks which influence their adoption decisions. Throughout the simulation period, farmers are programmed to observe their neighbors and the conservation practices they adopt. Therefore, in our model, the process of conservation practice adoption has the necessary spatial component and shows variance in each simulation. For the purposes of illustration, we reported the average load reductions from numerous simulations but also included the variability in error bars (Figures 4-9 and 4-10). Due to the stochasticity built-in the model, in each ABM initialization, different farmer types are assigned to each farmer, which results in different decision-making



characteristics. Each ABM run result has different spatial locations for conservation practices. The initial spatial distribution of farmer types affects the social and spatial network structure and has thus an impact on the final spatial distribution of adopted practices. For example, if a farmer located in the downstream part of the watershed adopts a conservation practice, its impact on water quality would be different than adopting a practice in the upstream part of the watershed. To eliminate this initial condition bias, we perform numerous ABM runs and link those to SWAT, which yields differences in water quality metrics as well; hence the bars demonstrate this impact of the different implementation locations of the conservation practices.

### **3.2. Impact of Land Tenure Change**

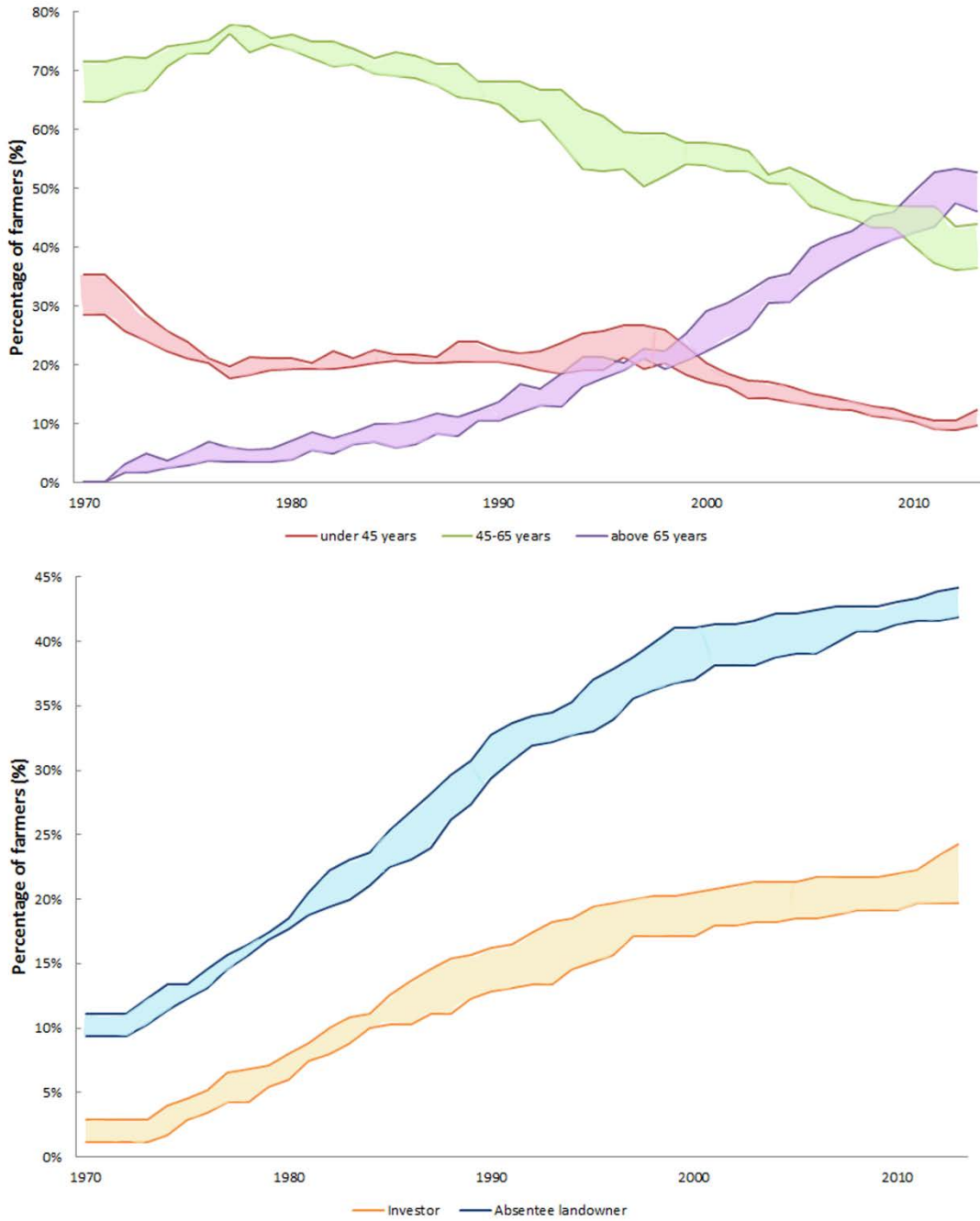
US agriculture has undergone a structural change of land tenure with a decline in full-ownership and an increase in non-operator ownership and large scale operations (Wunderlich 1993; Duffy 2008). In this context, in particular, the role of the understudied group of landowners, non-operator owners, in land management decisions deserves more attention (Nassauer et al., 2011; Petrzelka et al., 2009) and our farmer typology includes a separate category for them. In our ABM, we assume that traditional farmers after age 65, switch to be non-operator owners or sell their land to business-oriented or supplementary farmers which leads to an increase in the percentage of business-oriented farmers who own large scale productions and supplementary farmers who own small operations, and a decrease in traditional farmers who own the land that they farm (Figure 4-4A). We assume supplementary and business-oriented farmers to not change their types as they age. In addition, this change in landownership also leads to an increase in the percentage of non-operator owners (absentee landowners and investors) among the farmer population (Figure 4-4B) and the production area under their control (Figure 4-5) (Appendix A for details). These model results are validated with observed trends

(Appendix A; Wunderlich, 1993; Blandford and Hill, 2006; Duffy, 2008; USDA, 2009). Because ABM results denote the adoption status for a given farmer in every period, taking averages of multiple simulations is not possible. For that reason, in Figures 4-4 to 4-8, 25 ABM simulation runs are represented between two lines of the same color.

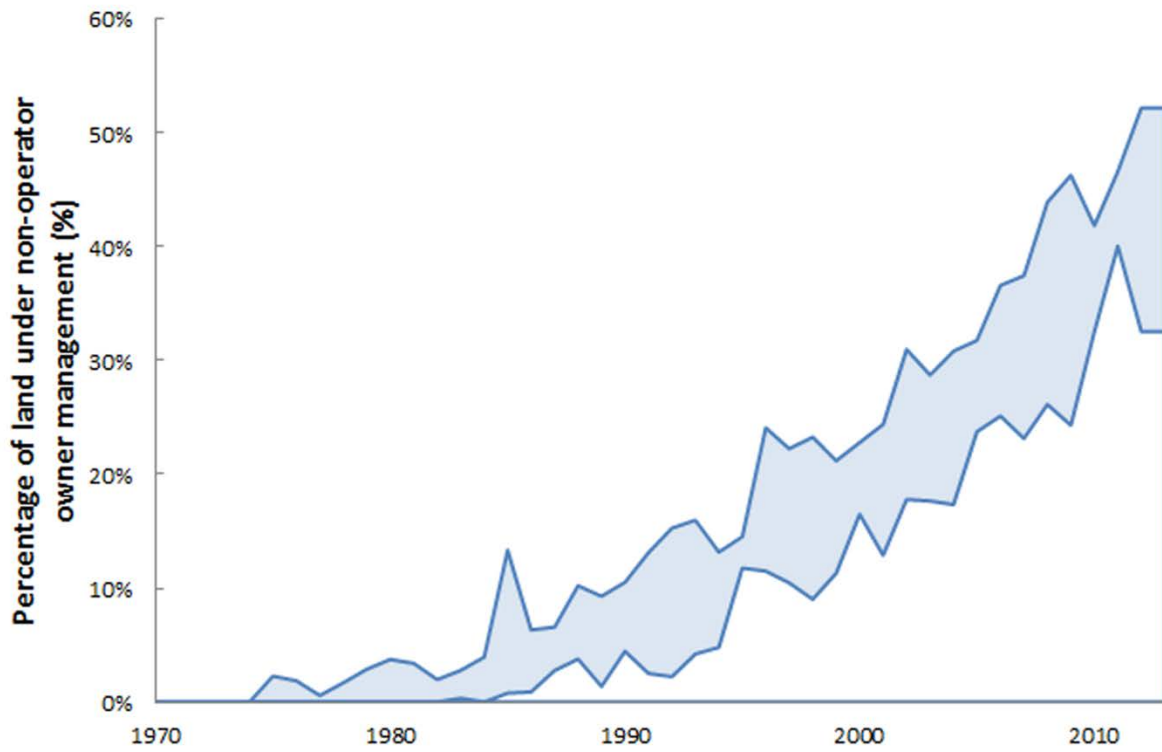
According to our farmer typology, different farmer types have different tendencies to make certain adoption decisions. Therefore, as the composition of the farmer types in the population changes, the emergent adoption pattern of conservation practices evolves. For example, in the scenario where the non-operator owners are not involved with decision-making and crop revenue insurance is not available (Scenario 1), the percentage of farmers who adopt nutrient management and structural practices show a significant increase, with a more pronounced increase in nutrient management adoption (Figure 4-6). Because non-structural practices, such as no-till technologies had not yet been developed until the mid-1980s, those practices were not present in the model for the first 15 years of the simulation run. However, in the mid-1980s non-structural practices became available and the composition of the farmer population evolved, leading to a significant increase in the percentage of farmers who adopt these practices over the next 10 years. Land retirement, on the other hand, had very limited implementation, due mostly to the requirement for enrolled land to be retired for 10 years, with penalties for noncompliance (Figure 4-6A and 4-10). In scenario 2, when non-operator owners take an active role in decisions, they have higher adoption rates for structural practices and land retirement (Figure 4-6 and 4-8).

Comparing scenarios 1 and 2 illustrates the water quality impacts of the plausible future when non-operator owners take an active role in land management decisions in the absence of crop revenue insurance (Table 4-3). In Scenario 2, we assume that at the end of the simulation

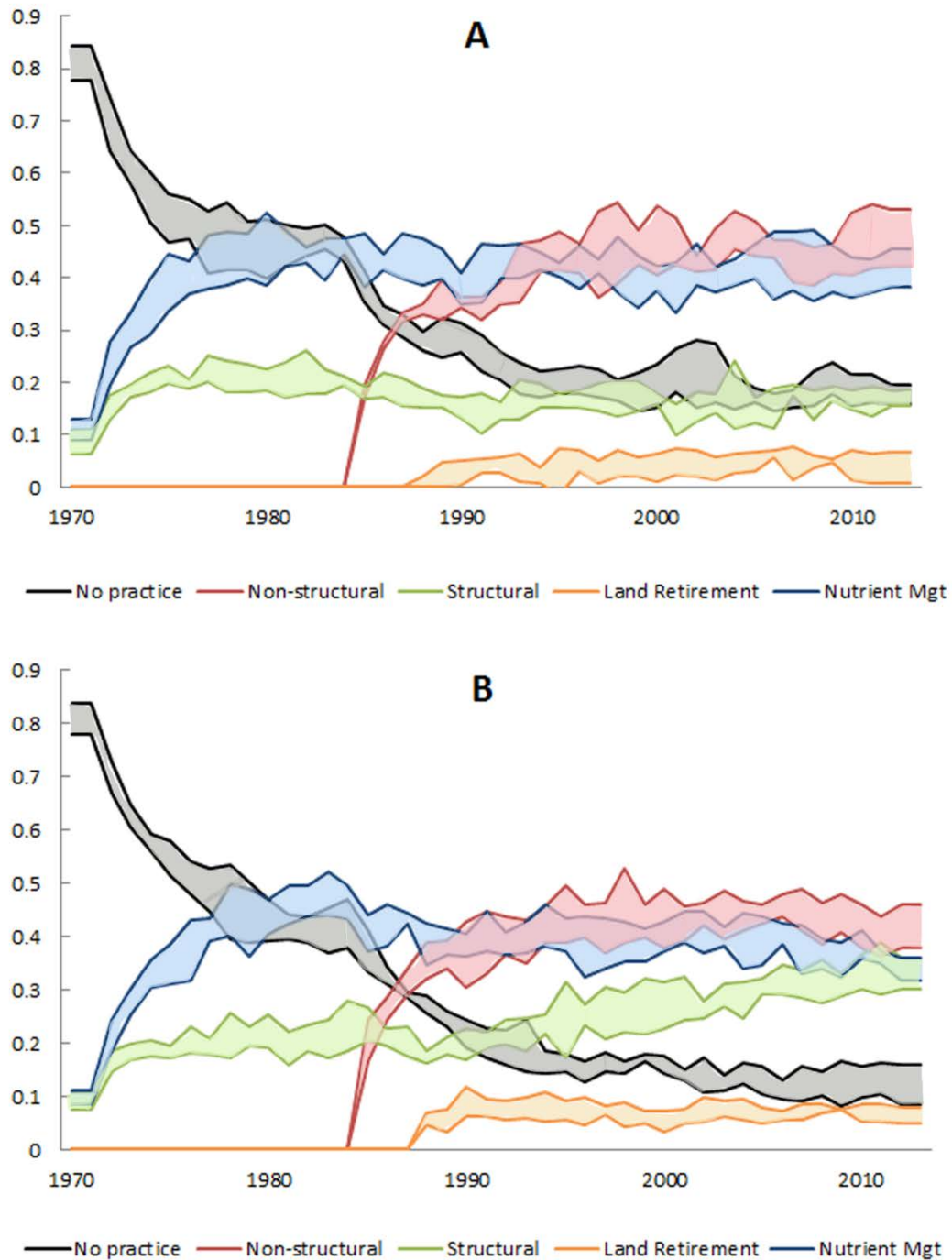
period 50% of the non-operator owners are the decision makers for conservation practice adoption (Table 4-4). The impact of the positive attitudes of non-operator owners for conservation practices and higher adoption rates for structural practices and enrollment in land retirement programs is reflected in lower TP loads (Figures 4-8, 4-9, and 4-11). That is, the non-operator owners' involvement in decision-making increases the adoption of conservation practices that are more effective in mitigating nutrient runoff from agricultural landscape. Results for sediment, organic P (OrgP), and DRP load are similar, with the improvement more pronounced for sediment load because non-operator owners favor structural practices, which are more effective in reducing the sediment load.



**Figure 4-4: Percentage of farmer types in the total farmer population (A), percentage of non-operator owners in the total farmer population throughout the simulation period. 25 ABM simulation runs fall between two lines of the same color.**



**Figure 4-5: Percentage of land under non-operator owners' control increases. 25 ABM simulation runs fall between two lines of the same color.**

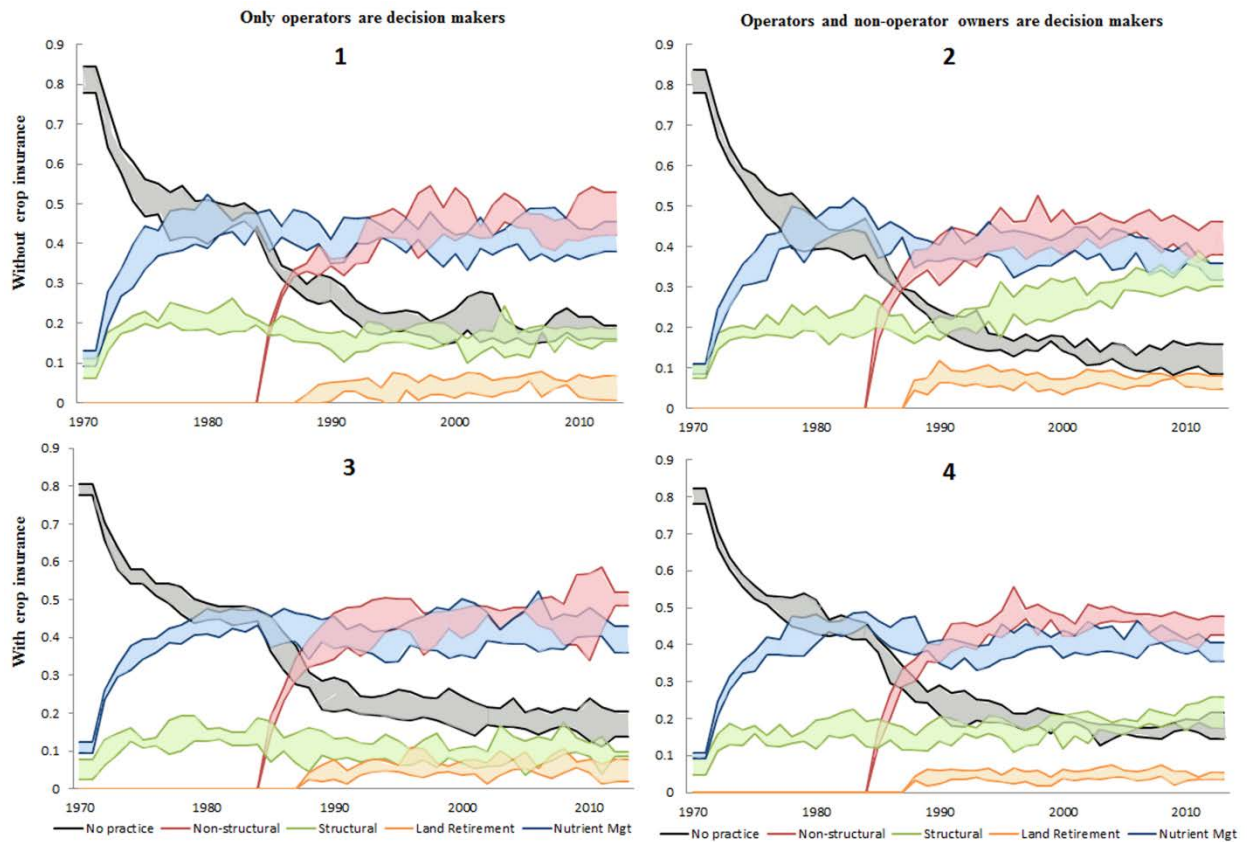


**Figure 4-6: Scenario 1- Conservation practice adoption distribution for the simulation period (1970-2010) when traditional, supplementary and business-oriented farmers are the decision makers (A) and Scenario 2 - when non-operator owners (absentee landowners and investors) are also involved in decision-making (B).**

**Increased involvement of non-operator owners results in an increase in the adoption of conservation practices, especially structural practices like filter strips. 25 ABM simulation runs fall between two lines of the same color.**

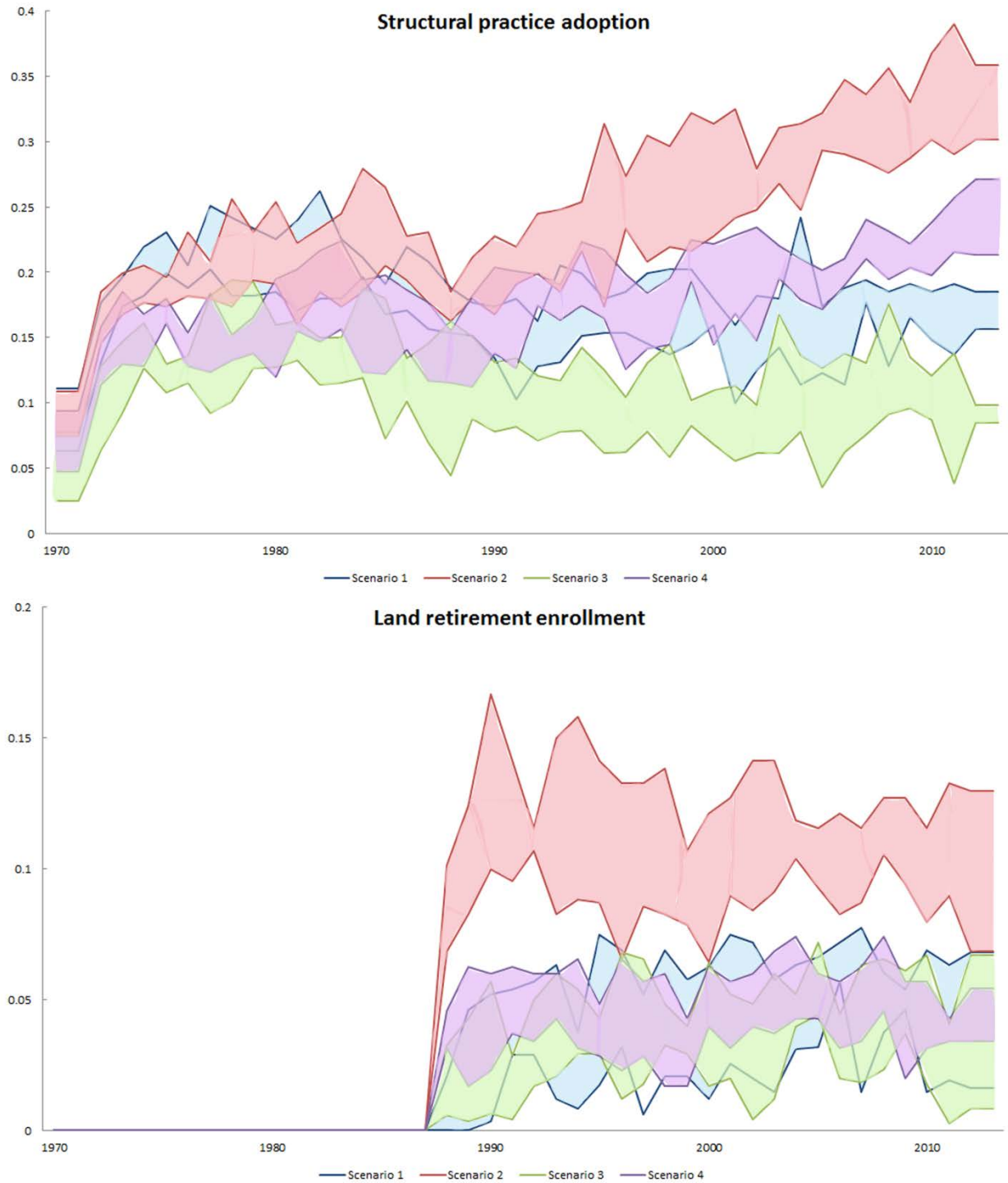
### **3.3. Impact of Agricultural Policy Change**

Proposed changes to the US Farm Bill suggest replacing commodity payments with subsidized crop revenue insurance premiums to create stronger incentives for farmers to enroll in crop revenue insurance. In our simulations, conservation compliance is not required for crop revenue insurance enrollment. The effects of such supports can be seen by comparing Scenarios 1 and 3 (Table 4-3). Crop revenue insurance protects farmers from both market and crop yield fluctuations and because crop revenue insurance payments depend on production area, farmers are indirectly encouraged to increase their production area. Under this scenario, nutrient management plans and non-structural practices increase, with a more prevalent rise in nutrient management, and a steep increase in adoption of non-structural practices when these practices become available (Figure 4-7). The ABM results also indicate a decrease in land retirement and land allocated to structural practices regardless of the non-operator owner involvement (Scenarios 3 & 4) which leads to a more homogenous conservation landscape, in the absence of conservation compliance (Figure 4-7). When subsidized crop revenue insurance is available, average TP, OrgP, DRP, and sediment loads are higher (Figures 4-9 and 4-11), due mainly to the reduction in structural practices and land retirement.



**Figure 4-7: Comparison of conservation practice adoption rates under the plausible scenarios such as crop revenue insurance and non-operator owner involvement in decision-making. Scenario 1: Only operators are decision makers with the support of crop revenue insurance. Scenario 2: Both operators and non-operator owners take active role adoption decisions. Scenario 3: Crop revenue insurance is offered in lieu of commodity payments to operators. Scenario 4: Crop revenue insurance is offered in lieu of commodity payments to both operators and non-operator owners who are active decision makers. When crop revenue insurance premiums are subsidized, structural practice adoption and land retirement enrollment rates decrease both for operators and non-operator owners whereas enrollment in nutrient management plans increase. 25 ABM simulation runs fall between two lines of the same color.**





**Figure 4-8: Structural practice adoption and land retirement enrollment show significant variability for different scenarios. When non-operator owners are active decision makers, structural practices have high adoption rates (Scenarios 2 and 4). Land retirement enrollment is highest when non-operator owners are active decision makers and crop revenue insurance is not offered to replace commodity payments as a risk management program (Scenario 2). 25 ABM simulation runs fall between two lines of the same color.**

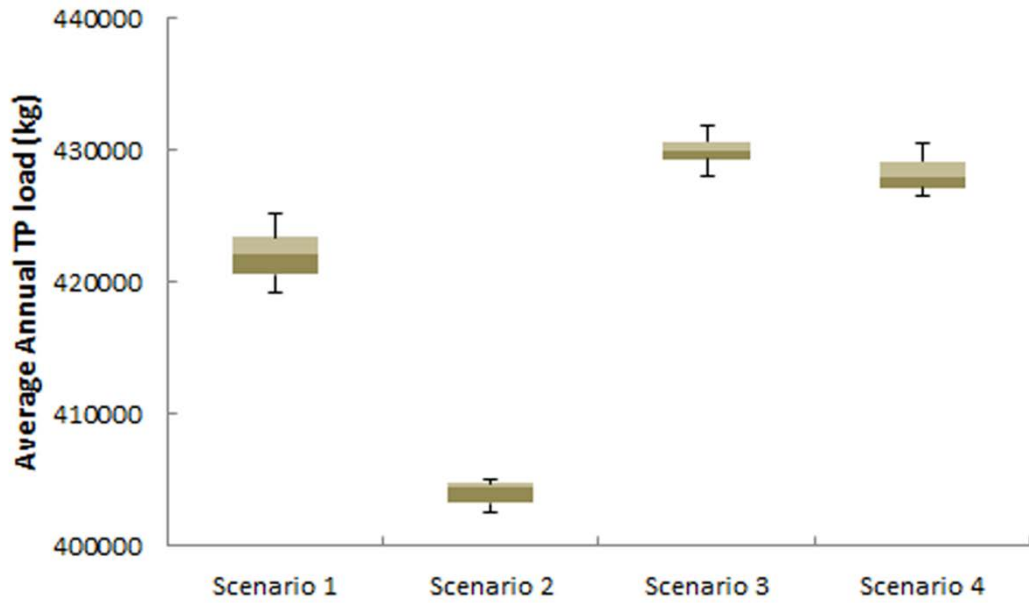


Figure 4-9: Comparison of average annual total phosphorus (TP) load in kilograms for Scenarios 1-4 representing the average of 25 ABM simulations linked to SWAT.

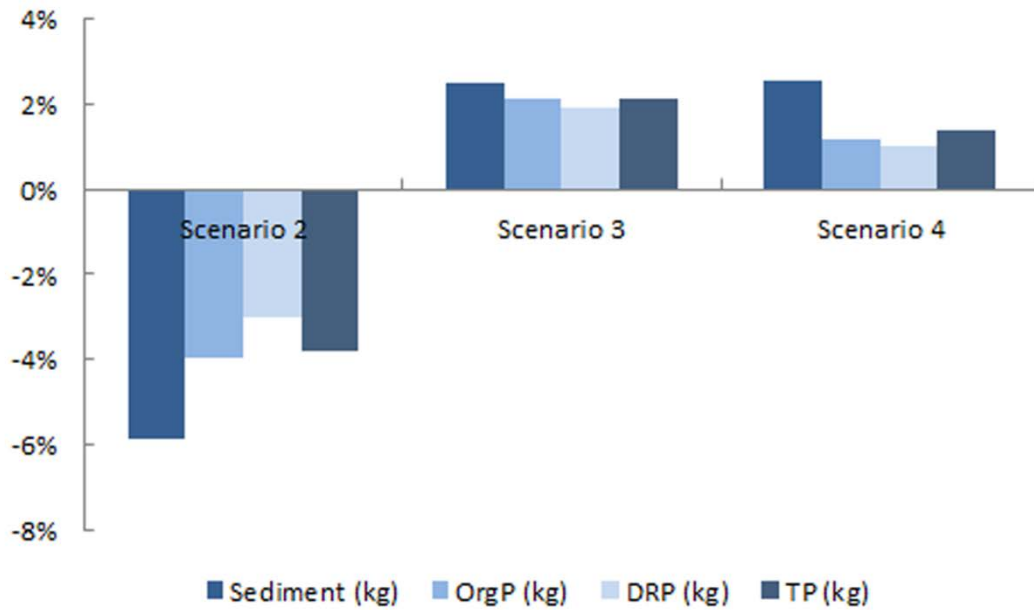


Figure 4-10: Comparing scenarios with Scenario 1 in terms of sediment, organic phosphorus (OrgP), dissolved reactive phosphorus (DRP), and total phosphorus (TP) loads, representing the average of 25 ABM simulations linked to SWAT.

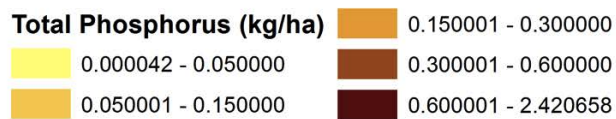
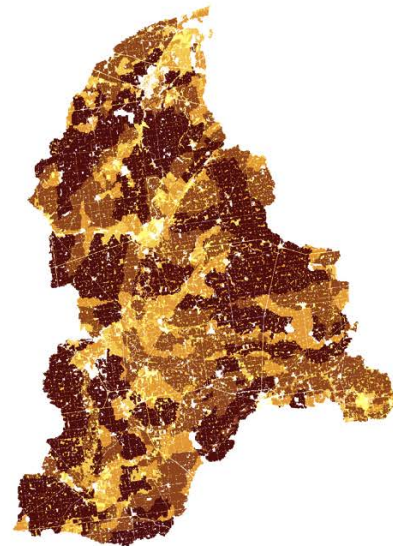
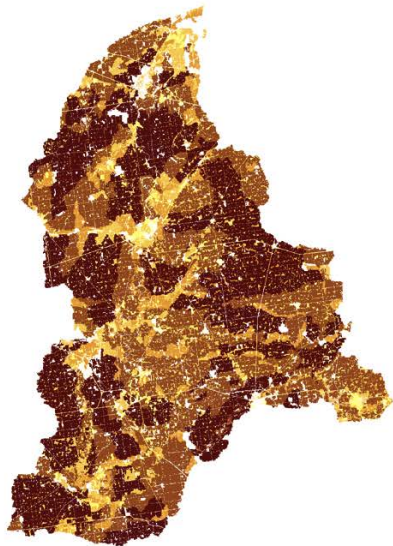
1. Baseline Scenario: Operators are decision makers

2. Owners Involvement Scenario: Operators and non-operators are decision makers



3. Crop Insurance Scenario: Operators are decision makers when crop insurance is available

4. Crop Insurance with Owner Involvement Scenario: Operators and non-operators are decision makers when crop insurance is available



**Figure 4-11: Spatial representation of average total phosphorus yield (1970-2010). Owner involvement results in lower TP yield (Scenario 2), whereas introduction of subsidized crop revenue insurance results in higher TP yields regardless of non-operator owner involvement**

### **3.4. Modifications in Agricultural Policy in the Model: Closing the SES loop**

In the modeling framework, to evaluate the impact of agricultural policy change, we build plausible scenarios that follow the latest US Farm Bill discussions of providing federally subsidized crop revenue insurance rather than commodity production subsidies (Scenario 3). In our simulations, we assume that conservation compliance is not tied to crop revenue insurance. The linked model results suggest slightly higher TP, OrgP, DRP, and sediment yields (Figure 4-9). This increase in water quality metrics compared to the baseline (Scenario 1) is attributed to the reduction in structural practice and land retirement enrollment (Figure 4-10).

To model a complete SES where social and environmental systems have a reciprocal feedback system, we add a policy modification step. Once the policies are modified, farmers have a new set of incentives, sanctions, and regulations to observe. For this purpose, as a plausible policy modification, we linked conservation compliance to crop revenue insurance. Moreover, we utilize our framework to evaluate different conservation compliance definitions. Currently, conservation compliance requires farmers to refrain from draining wetlands and implement a conservation plan when farming highly erodible lands. For simulation purposes, we treat Sandusky watershed as a critical source area and require every farmer to implement a conservation plan for crop revenue insurance participation.

Residue management is an important and effective method of achieving conservation compliance requirements and most farmers implement non-structural practices (i.e., conservation tillage or no-till systems) to reduce sediment erosion. However, conservation compliance has been critiqued for its narrow focus on erosion control. In fact, nutrient runoff from agricultural landscape is a significant cause of water quality impairment (Boyer et al.,

2002; Galloway et al., 2004; Ribaudo and Smith, 2000) but an indirect focus of conservation compliance. For example, non-structural practices are promoted for erosion control but could lead to increased DRP runoff (Daloğlu et al., 2012; Kleinman et al., 2011).

There have been discussions of strengthening and expanding conservation compliance requirements (American Farmland Trust, 2011; Cox et al., 2011; Perez, 2007). In our framework, we tested three conservation compliance definitions where farmers can (a) either choose non-structural or structural practices; (b) adopt non-structural; (c) implement structural practices to qualify conservation compliance requirements and be eligible for subsidized crop revenue insurance programs (Table 4-5).

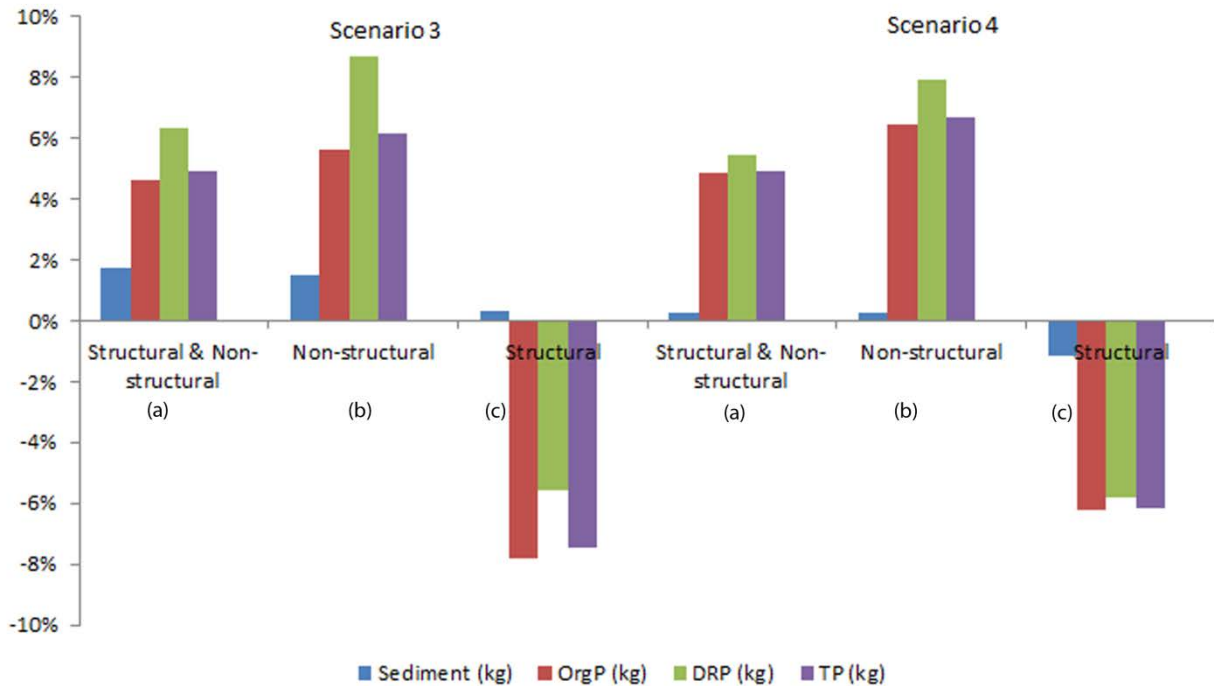
<i>Required Conservation Practice</i>	<i>Definition of Conservation Compliance in the model</i>
(a) Either non-structural or structural practices	Choose between non-structural and structural practice practices
(b) Non-structural practices	Adopt no-till practices, focus on erosion control
(c) Structural practices	Implement filter strips, focus on water quality

**Table 4-5: Different definitions of conservation compliance**

Linked model results indicate the effectiveness of structural practices in reducing nutrient delivery from agricultural landscape (Figure 4-12). The current definition of conservation compliance requires farmers to implement necessary practices to control soil erosion. With the conservation compliance, the monitoring and enforcement of compliance deserves attention. As Government Accountability Office (GAO, 2003) emphasized, the compliance enforcement needs updating and upgrading in regulations and monitoring. Part of the problem arises as Natural Resources Conservation Services (NRCS) is both the enforcement agency and working with farmers to implement the practices as well. Non-compliance can result in determination of the farmer as ineligible for any government payment and require

farmer to pay back current and prior year's payments (Stubbs, 2012). However, NRCS provides numerous reasons for farmers to overturn a violation.

In our models, we assume farmers show 100% adherence to conservation compliance and choose from non-structural or structural practices to fulfill conservation compliance requirements. Because of mostly economic reasons, they choose non-structural practices to qualify for conservation compliance. We observe higher nutrient runoff, especially the bioavailable DRP when farmers choose non-structural practices as conservation compliance requirements. However, investigating different conservation compliance definitions is promising. If conservation compliance requirements are expanded to include nutrient management as a focus and promote structural practices to trap nutrients before reaching to water bodies, our models indicate significant reductions in nutrient runoff (Figure 4-12).



**Figure 4-12: Change in water quality metrics when conservation compliance is linked to crop revenue insurance programs as a requirement. In Scenario 3 only operators and in Scenario 4 both operators and owners are decision makers; crop revenue insurance is available in lieu of commodity payments. Conservation compliance requires adoption of (a) either non-structural or structural practices; (b) non-structural or (c) structural practices.**

## 4. Discussion

### 4.1. Policy Implications of this Framework

This framework provides a powerful tool to explore the impacts of plausible futures such as changes in the agricultural land tenure and policy on adoption of conservation practices. Our model distinguishes between nutrient management plans to reduce fertilizer applications, non-structural practices such as conservation and no-till, structural practices such as filter strips to trap soil particles and nutrients, and land retirement programs. Importantly, this model shows that changes in land tenure and crop insurance policy affect adoption of these practices, altering the agricultural landscape and affecting water quality metrics.

By investigating the water quality impacts of four plausible scenarios, we demonstrate the importance of the understudied non-operator owners and the possible effects of new policies for crop revenue insurance. Our results indicate maximum load reductions, especially sediment load reductions, occur when non-operator owners are involved in the decision-making process and when crop revenue insurance is not offered in lieu of commodity payments (Scenario 2). This improvement is mainly attributed to the increase in the percentage of farmers who favor structural practices, which are more effective in reducing sediment and nutrient load. The linked model results also point to a positive influence of non-operator owner involvement and highlight the importance of devising innovative policy changes to reach out and inform non-operator owners about the existing water quality problems, possible solutions, and their role in implementing them.

Unlike the Scenario 2, if subsidized crop revenue insurance is promoted as a risk management program, in the absence of conservation compliance, this indirectly incentivizes farmers, regardless of their type, to increase production area, even including areas that are highly erodible or wetlands. This then results in a homogenous conservation landscape, which yields slightly higher loads (Scenarios 3 and 4) because of a decrease in structural practice adoption and land retirement enrollment. To discourage farmers from farming highly erodible land and draining wetlands, a main target for conservation compliance, eligibility for crop revenue insurance premiums could be tied to conservation compliance. Coupling conservation with the crop revenue insurance program is critical, as has been shown in a recent analysis in Iowa revealing that the rate of erosion from productive agricultural land to be higher than the sustainable rate (Cox et al., 2011). Our model results demonstrate that structural practices are effective, which suggest that modifying the definition of conservation compliance to require



structural practices as well as non-structural practices are promising approaches to improve water quality. A recent survey of Iowa farmers reveals support for expanding conservation compliance requirements to include nutrient management as well as erosion control (Arbuckle, 2013).

Moreover, because structural practices are visible from satellite images, enforcement of conservation compliance would require fewer NRCS personnel and less federal budget.

Our analyses show only modest load reduction (1-6%) under the plausible future scenarios, which is comparable to other relevant applications of SWAT which assume feasible levels of implementation (Arabi et al., 2008; Lee et al., 2010; Tuppad et al., 2013, Bosch et al., in review). The adoption rates of conservation practices are also consistent with the observations (Bosch and Pease 2000; Goodwin and Smith 2003; Babcock and Hennessy, 1996; Smith and Goodwin, 1996; Sheriff, 2005; Wunderlich 1993; Duffy 2008; Petzelka et al. 2009; Nassauer et al. 2011) and feasible levels of implementation used by other SWAT models (Bosch et al., a (in review), Arabi et al., 2008; Tuppad et al., 2010). Even though our results provide an important starting point for the comparison of different plausible scenarios, considering the modest differences in water quality metrics between different scenarios, they still point to the need for innovative policy scenarios to promote adoption of conservation practices and highlight the need for further discussions on attaching conservation compliance to crop revenue insurance and definition of conservation compliance requirements. Indeed, previous SWAT models implemented in the Lake Erie Basin indicate up to 30-40% yield reduction effectiveness with significantly increased adoption rates (Bosch et al., a, in review).

In this framework we chose to model water quality impacts with retroactive modeling, because our existing watershed model was calibrated and validated for 1970-2010. In future work, a valuable test would be to implement this framework in prospective modeling with the

inclusion of possible climate change scenarios. The use of future climate projections could possibly increase the uncertainty in the linked model results but still be informative for adaptation efforts (Bosch et al. (b, in review)).

#### **4.2. Challenges of Linking Agent-based Models with Biophysical Models**

This framework is designed to investigate the impact of alternative policy approaches and changing land tenure dynamics on farmer adoption of conservation practices intended to increase the water quality. For this purpose, we chose to link SWAT with ABM for farmer adoption of conservation practices. Because SWAT is a river basin scale water quality model developed to assess the water quality benefits of conservation practices (Gassman et al. 2007; Osmond 2010), linking it with ABM aligns with the purpose of our framework.

For this framework, we chose a loose integration method which uses the state variables from one model as a driving variable in the other model (Antle et al., 2001). In Figure 4-2, the ABM determines the land management pattern for the Sandusky watershed and SWAT estimates water quality metrics as a function of the updated land management pattern. One of the disadvantages of using loosely coupled models is the computational overhead associated extracting output files and modifying input files. We used MatLab programming language to link ABM output and modify necessary SWAT input files. Single SWAT run including the modification of input files for 41 years (1970-2010) averaged about 55 minutes when run on quad-core Windows machine. Because of the stochasticity built in the model, we performed 25 simulations and reported the averages of these runs for water quality metrics, which resulted in approximately 1,375 minutes or 0.95 days.

In this framework, we aimed to represent the farm-scale decision making regarding conservation practice adoption. However, due to limited data, representation of the exact location

of farms and long-term management decisions is not possible. Therefore, we constructed an abstract ABM without the spatial representation of decision making process which could affect the farmers' conservation decisions because soil properties and slope of their land are not influential in their adoption decisions.

The capabilities of SWAT were the determining factor for the scale of the linked model. We developed a fine-scale SWAT model to match the average farm size in the Sandusky basin (Daloğlu et al., 2012). However, SWAT is not developed on grid cells and the smallest computational unit of SWAT, hydrologic response units (HRU) cannot be manually delineated which complicates the representation of farm level decision making.

Linking social and biophysical models for social-ecological system representation is profoundly valuable, especially in evaluating plausible policy scenarios. While the recent land use and land change research has contributed to this endeavor, this study goes one step further by linking a widely used water quality model to ABM to better represent the dynamic interactions of farmers.

## **5. Conclusion**

This study introduces a modeling framework designed to investigate the impact of plausible future scenarios such as changes in agricultural land tenure and crop insurance policy on farmer adoption of conservation practices intended to improve water quality. This framework focuses on an agricultural watershed in the Corn Belt with attention to spatial patterns and socio-economic drivers of farmers' conservation practice adoption. The key model elements are factors that influence remediation of eutrophication in downstream waters. Hence, with this framework we investigated both the interactions among farmers and the emergent impacts of those interactions on the ecosystem.

This framework is novel in linking an ABM of farmers' conservation practice decisions and a water quality model investigating the impact of conservation practices. It can serve as a powerful tool in policy analysis as it represents the effects of farm level decision-making on a watershed scale agricultural landscape. In the framework, farmer heterogeneity is represented by the farmer types that populate agents (Daloğlu et al., in review) in the ABM that then generates conservation practice adoption patterns that, in turn, are employed as input to the water quality model (Daloğlu et al., 2012).

This framework analyzes how water quality is affected in future scenarios for conservation practices at the farm scale of the Sandusky watershed. Four plausible future scenarios are investigated, which focus on the involvement of owners in the decision-making of the farm and crop revenue insurance as a risk management program in lieu of commodity payments. These scenarios are plausible given that they are built upon recent discussions on crop revenue insurance policies and documented increase of non-operator owners. The investigation of plausible scenarios reveals the significance of non-operator owners and their potential impact on the agricultural landscape and consequently on water quality. The highest nutrient and sediment reduction is achieved when non-operator owners had active role in conservation decisions. On the contrary, model results indicate a possible increase in nutrient and sediment loads with subsidized crop revenue insurance, in the absence of cross compliance with conservation, with an emphasis on increasing production area. The model results also suggest expanding the conservation compliance requirements to include nutrient management focused practices such as structural practices.

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## **Chapter 5: Conclusion**

The three chapters of this dissertation build the framework to study and model one of the highly cultivated agricultural watersheds of the Lake Erie, the Sandusky watershed, as a social-ecological system. Renewed harmful algal blooms and hypoxia in Lake Erie have drawn significant attention to phosphorus loads, particularly increased dissolved reactive phosphorus (DRP) from highly agricultural watersheds. Chapter 2 builds the SWAT model to estimate dissolved reactive phosphorus (DRP) in the agriculture-dominated Sandusky watershed for 1970-2010 to explore potential reasons for the increased DRP load from Lake Erie watersheds. Chapter 3 develops a farmer typology based on a synthesis of the adoption literature and the identification of policy-relevant farmer characteristics, and uses this typology to populate an agent-based model (ABM) to simulate adoption of conservation practices. Chapter 4 introduces the modeling framework designed to investigate the impact of plausible future scenarios such as changes in the land tenure and policy on the farmers' adoption of conservation practices intended to increase the water quality using. This framework is novel in linking an agent-based model (ABM) of farmers' conservation practice decisions (Chapter 3) and a water quality model investigating the impact of conservation practices (Chapter 2).

### **Renewed Eutrophication Causes in Lake Erie**

Renewed harmful algal blooms and hypoxia in Lake Erie have drawn significant attention to phosphorus loads, particularly increased dissolved reactive phosphorus (DRP) from highly agricultural watersheds. Chapter 2 investigates the potential reasons for increased DRP trends

using SWAT which explores the role of several potential causes of the recent increases in DRP loading suggested by the Ohio P Task Force (Ohio EPA, 2010): 1) changes in fertilizer application rates; 2) widespread adoption of no-till and conservation tillage practices after the mid-1990s; 3) stratification of phosphorus (P) in the upper layer of the soil; 4) increased fall fertilizer application since the mid-1990s; and 5) changes in rainfall patterns.

To better understand the impact of land management and weather patterns on DRP loading, hypothetical scenarios are generated and then compared with the realistic representation of the agricultural landscape (baseline scenario). Hypothetical scenarios represent extreme cases such as high and low fertilizer application rates, full adoption of no-till and conventional tillage, representation of phosphorus accumulation at soil surface layer, and synthetic weather patterns.

The comparisons of these hypothetical scenarios with the baseline scenario emphasize the need to focus on agricultural practices and their impact on water quality. The results demonstrated the importance of P stratification in soil surface layer caused by no-till practices and increased frequency of storm events observed in the last decade in the recent rise of DRP exported the agricultural landscape.

### **Farmer Diversity and Conservation Practice Adoption**

To model farmer adoption of conservation practices, Chapter 3 first develops a farmer typology to represent the heterogeneity of Corn Belt farmers relevant to conservation practice adoption and then uses this typology to populate agents in the agent-based model (ABM) that models the adoption decision under different policy scenarios.

Typologies have been suggested as effective tools to represent the heterogeneity of farmers' motivations and socio-economic circumstances related to conservation behavior (Kostrowicki 1977; Duvernoy 2000; Valbuena et al. 2008). After synthesizing the adoption literature four

policy-relevant farmer characteristics are identified, namely land tenure arrangements, size of farm, source of income, and information networks. These farmer characteristics comprise a heuristic set of four mutually exclusive types: traditional, supplementary, business-oriented farmers, and non-operator owners. Since this typology is operationalized for use in our ABMs that will be linked to SWAT, conservation practices applicable in SWAT are categorized as non-structural (no till and conservation tillage), structural (filter strips), and land retirement (Conservation Reserve Program, CRP).

The analysis of farmer typology demonstrates how different farmer types may be drawn to different conservation practices and policies depending on the relative importance of tenure arrangement, production size, income source, and information networks. Traditional and supplementary farmers have high adoption rates for non-structural practices and land retirement programs, whereas business-oriented farmers focus on profitability and has lower adoption rates of land retirement programs. An understudied group of non-operator owners (absentee landowners and investors) have limited involvement in land management decisions; however surveys indicate their willingness to adopt conservation practices. In addition, more and even most farmland begins to be owned by non-operator owners.

The farmer types populate the agents in the ABM and the ABM results are in line with the documented socio-economic trends of the Corn Belt and adoption statistics of the modeled conservation practices. Chapter 3 also investigates the impact of future plausible scenarios on adoption patterns such as increased involvement of non-operator owners in management decisions and subsidized crop revenue insurance as a risk management program. The model results indicate higher adoption rates for structural practices such as filter strips with increased

involvement of non-operator owners in management decisions and lower adoption rates for land retirement programs and structural practices with subsidized crop revenue insurance.

### **Impacts of Conservation Practice Adoption on Water Quality**

The relationship between farmers' decisions about adoption of conservation practices and water quality outcomes is part of a complex social-ecological system. Farmers' decisions about adopting conservation practices are inherently dynamic, affected by changes in environmental, economic, and social conditions, including interactions with other farmers. Water quality models used to assess agricultural policy interventions, such as the SWAT, lack the dynamic social component of farmer's decisions. Therefore, the framework introduced in Chapter 4 combines and synthesizes previously developed SWAT model in Chapter 2 and the farmer typology and ABM in Chapter 3. This framework provides a powerful and novel tool to explore the impacts of the plausible future scenarios such as changes in the land tenure and policy on land management strategies.

The focus of this framework is to analyze how water quality is affected in future plausible scenarios for conservation practices at the farm scale of the Sandusky watershed. Four plausible future scenarios are investigated, which focus on the involvement of owners in the decision-making of the farm and subsidized crop revenue insurance as a risk management program. The investigation of plausible scenarios reveals the significance of non-operator owners and their potential impact on the agricultural landscape and consequently on water quality. The highest nutrient and sediment reduction is achieved when non-operator owners had active role in conservation decisions. On the contrary, model results indicate a possible increase in nutrient and sediment loads with the subsidized crop revenue insurance, in the absence of conservation compliance, with an emphasis on increasing production area. This increase is mainly due to the

decrease in land retirement program enrollment and structural practice adoption, leading to a homogenous conservation landscape. The linked model results underline the importance of conservation compliance which discourages farmers from farming highly erodible land and draining wetlands.

### **Future Work**

This framework is novel and powerful in modeling the social-ecological system of farmer decision-making and consequent water quality impacts of conservation practices in a predominantly agricultural watershed, the Sandusky watershed OH. Because of data limitation, the ABM is a stylized representation of the watershed; it will be a worthy area for future work to implement a similar framework with empirical field data collected with decision makers.

In this framework water quality impacts are retroactively modeled, because in Chapter 2, SWAT model was calibrated and validated for 1970-2010. In future work, a valuable test would be to implement this framework in prospective modeling with the inclusion of possible climate change scenarios. The use of future climate projections could possibly increase the uncertainty in the linked model results but still be informative for adaptation efforts.

### **References**

Ohio Environmental Protection Agency (EPA), 2010. Ohio Lake Erie Phosphorus Task Force Final Report 2010, Columbus, OH.

# **Appendix A: Model parameters for the agent-based model of farmer adoption of conservation practices**

The following sections present the model used in this study following the ODD (Overview, Design concepts and Details) protocol (Grimm et al. 2006; Grimm et al., 2010).

## **Purpose**

This model is designed to investigate the impact of alternative policy approaches and changing land tenure dynamics on farmer adoption of conservation practices intended to increase the water quality.

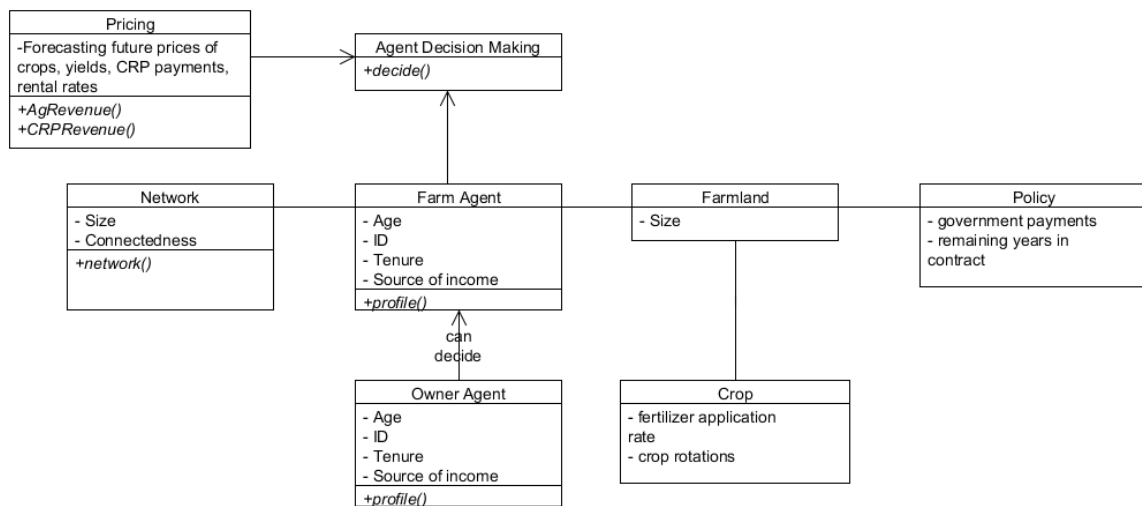
## **State variables and scales**

The modeled environment consists of a two-dimensional grid space representing the abstract agricultural landscape of the Sandusky watershed. The ABM is coupled with a water quality model; therefore the specifics of the water quality model are taken into consideration during the setup phase of the ABM. For a better match with the water quality model, there are 351 farmers in the ABM. The model is run for annual steps of 41 years (1970-2010).

In the model, every farmer owns a farm and each has utility functions with bounded rationality. The farmers specialize in cash-crops such as corn, soybean or winter wheat. They have cash earnings from crop production or from enrollment in government programs. The farmers have different land areas, crop yields, and future crop price and yield expectations. The



farmers also maintain network connections to other farmers and government agencies with varying strengths. In most ABMs, agents are defined by their spatial location (Brown et al. 2005); however, in this model the farmer agents do not change their location as time progresses. A farmer's location on the grid determines the spatial neighbors of that farmer. Some of the farmer attributes do not change during the simulations, such as the percentage of income derived from farming and connectedness to the network. However, as farmers age in every simulation run, some of them change their types. For example, after age 65 some of the traditional farmers leave the farming business and switch to be non-operator owners, or sell/rent their land to business-oriented or supplementary farmers. We assume supplementary and business-oriented farmers to not change their types as they age. Figure A-1 shows the class diagram of the model.



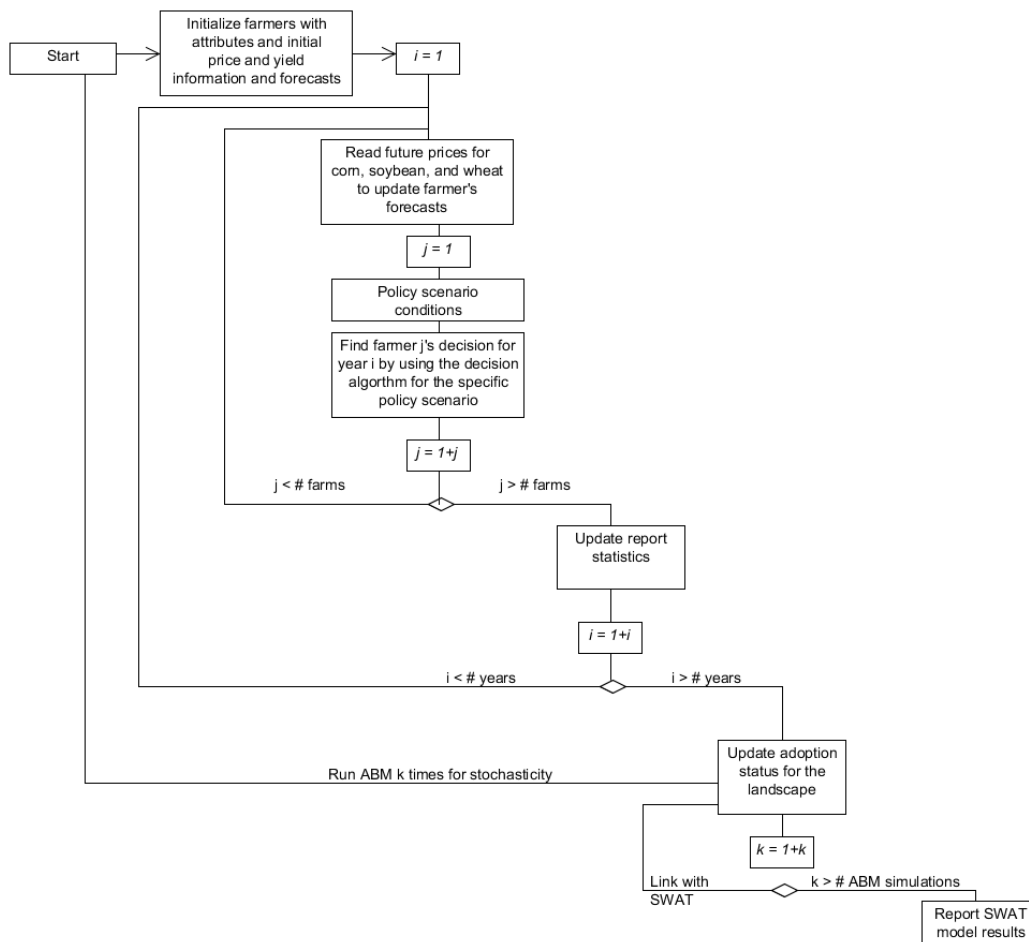
**Figure A-1: Class diagram of the ABM model**

### Process overview and scheduling

The diagram in Figure A-2 gives the process overview and scheduling of the model. For each simulation, farmers annually update their adoption decisions under the influence of agricultural policy, changing land tenure dynamics, their preferences, and their neighbors' decisions. The

agent loop is equally important as the landscape update, which is the key mechanism that affects the water quality component of the coupled system (Figure A-2).

During the simulation phase, each farmer agent is provided with a behavioral model that guides the decision-making process. With the behavioral model and farmer attributes, the farmer agents decide whether to adopt a specific conservation practice or not. The results from the farmer agent decision update the management landscape.



**Figure A-2: Process overview and scheduling for a model run.**

The decision-making algorithm consists of inputs from profit generated from the agricultural activity, enrollment in government programs, the farmer preferences for conservation practices

depending on farmer type, and sometimes information from their spatial neighbors and other farmers in their social network. Every agent in the model uses the same decision algorithm with different parameters due to the heterogeneity of agents' preferences. Depending on their tenure arrangements, decision makers could either be the owner or the tenant. Because of this flexibility, this model is also used to investigate the possible impact of growing proportions of farmland owned by non-operator owners and their influence on conservation decisions.

### **Design Concepts**

- **Emergence:** The agricultural landscape of conservation practices emerge from the individual decisions of farmers which are informed by their economic activities, social and spatial networks, preferences, and policies that they follow.
- **Adaptation:** Farmers adapt and update their decisions depending on price and yield expectations for future years. Depending on their types, farmers have differing network connectivity which influences their conservation decisions. Farmers update their conservation practice adoption decisions by interacting and observing other farmers and due to changes in the agri-environmental policies and markets.
- **Prediction:** Farmers have expectations for future yields, crop prices, and rental rates offered for land retirement programs by using the historic information. Farmers use these forecasts for their adoption decisions every year.
- **Sensing:** Farmers know their production yields every year and their profit from that year's production. Farmers also know whether their neighbors, both in their spatial and social networks, adopted a practice.
- **Interaction:** Farmers interact to exchange information on adoption of conservation practices. Every farmer type has varying network strength and connectivity.

- **Stochasticity:** The model has stochasticity built in several ways. Conservation practice selection decision is stochastic, as the farmers are most likely to select the highest ranked practice. However, as the farmers are not modeled as purely rational decision makers, the highest ranking conservation practice is not always chosen. Moreover, to better represent the decision environment, the submodels also have stochastic parameters to represent the uncertainty and variability observed in nature. By using the agent decision-making algorithm over the model run of 41 years, each agent has a sequence of conservation practices adopted and resultant landscape changes.
- **Collectives:** Farmers are connected in two ways. In the spatial networks, farmers are connected to their immediate spatial neighbors. In social networks, farmers are connected to other farmers with varying strengths and connectivity. Network connections allow farmers to observe whether other farmers in their network have adopted a conservation practice.
- **Observation:** The model produces the conservation adoption patterns at the end of each simulation.
- **Learning:** Bayesian inference used for updating price and yield expectations of farmers is a form of learning.

### **Initialization**

At the beginning of each model simulation, 351 farmers are created to represent the total of approximately 7500 farmers in the Sandusky watershed. Because the ABM is linked to SWAT, properties of SWAT are decisive. In SWAT, there are 351 agricultural hydrologic response units (HRU), smallest computation components; therefore in ABM we have 351 agents. The initial

agent characteristics are given in Table A-1. The farmer typology built in Chapter 3 informs the farmer preferences for conservation practices typologically.

The agricultural structure of the study area is defined by the number of farmers and their production areas. The parameters defining each farmer such as age, ownership of the land, percentage of income generated by agricultural activity, and land tenure arrangements are assigned from a normal distribution within a range that is informed by regional statistics provided by National Agricultural Statistics Service (NASS). Then, each farmer agent is associated with its appropriate type (Table A-2).

Property	Meaning	The Model
Reactive	Responds to changes in the environment	Yes
Autonomous	Have control over its own actions	Yes
Temporally continuous	Continuous agent behavior	Yes
Communicative	Communicates with other agents	Yes
Mobile	Changes location from one to another	No
Flexible/Learning	Actions are not scripted, can change	Yes
Character	Believable personality with emotions	No
Interactive physically	Decisions affect other agents	Yes
Interactive socially	Decisions affect other agents	Yes
Goal oriented	Responsive to the environment	Yes

**Table A-1: Farmer agent properties**

*Farmer types*

<i>Policy-relevant farmer characteristics</i>	Traditional	Supplementary	Business-oriented	Non-operator owners
Land Tenure	Full owner	Full/Part owner	Part owner	Non-operator owner
Farm Size	Small	Small	Medium to Large	N/A
Primary Source of Income	On-farm	Off-farm	On-farm	Off-farm
Information Networks	Moderately connected	Moderately connected	Most connected	Least connected

**Table A-2: Farmer types constructed by using policy-relevant farmer characteristics.**

**Input**

In every simulation run, the model reflects changes in the political and economic environment such as changes in agricultural policy and crop prices.

**Submodels**

Farmers are autonomous decision makers regarding conservation practice adoption. Below are the sub-model explanations that control farmers' adoption decisions. The algorithm includes subcomponents that model the profitability of the farm business, influence of farmer preferences, and connectedness of the farmers, both socially and spatially. A special attention is given to agricultural profit calculations and the social connectedness of the agents, as they play significant roles in agents' decision-making.

At each time step, which can be interpreted as a year, every farmer makes decisions regarding conservation practice adoption. Farmers can choose to adopt none or a combination of the practices. The practices available to farmers tackle the non-point source pollution by controlling the pollution source (nutrient management), trapping the soil particles before they reach water bodies (structural practices, i.e, filter strips), promoting long-term conservation

covers (land retirement, CRP), and reducing soil disturbance (non-structural practices, i.e., conservation tillage and no-till systems) (Table A-3).

Farmers' adoption decisions have temporal consequences. That is, if a farmer enrolls in land retirement programs and signs a CRP contract, the commitment is a multi-year commitment, where in case of contract breach a penalty has to be paid. Similarly, adoption of structural practices such as filter strips requires a multi-year commitment as well because farmers receive economic incentives from the government. Adoption decisions of non-structural practices and nutrient management plans, however, are made on a yearly basis, and do not entail a penalty. In this model, we assume every farmer to be eligible for land retirement enrollment and every farmer who adopts structural practices to be eligible for 50% cost share incentive provided by the government.

Adoption of structural and non-structural practices, land retirement enrollment, and participation in nutrient management plans are voluntary decisions. Each farmer determines whether to enroll in land retirement programs (such as Conservation Reserve Program, CRP), to adopt certain conservation practices, or choose not to adopt any practice, depending on their farm's overall objective. The overall objective is a combination of multiple objectives that include the profitability of the business, attitudes towards different conservation practices depending on farmer type, and influences of the spatial and social network. These objectives, each represented by a specific function, are combined in a single function that represents the overall utility of the farmer (Equation A.1).

Every period, the overall utility to a farmer for every conservation practice adoption option (e.g., no conservation practice at all, single conservation practice adoption or a combination of

conservation practices) is calculated. The list of conservation practices and their combinations are given in Table A-3.

<i>i</i>	Conservation practice
0	None
1	Non-structural practices (no-till)
2	Structural practices (filter strips)
3	Land retirement programs (Conservation Reserve Program, CRP)
4	Nutrient management plans
5	Non-structural practices (no-till) & Structural practices (filter strips)
6	Non-structural practices (no-till) & Nutrient management plans
7	Structural practices (filter strips) & Nutrient management plans
8	Non-structural practices (no-till) & Structural practices (filter strips) & Nutrient management plans

**Table A-3: Available conservation practices and their combinations to farmers.**

The decision algorithm combines all of the available information to the farmer and integrates for the adoption decision. This mechanism includes the profit generated from agricultural production, availability of government programs and policies, influence of the farmers' neighbors and farmers' intrinsic attributes. These are all combined within a utility function,  $F_{\text{decide}}(i)$  for the conservation practice combination  $i$  and farmer  $j$ , which is a combination of 4 sub-functions (Equation A.1).

Once the farmer calculates utility of each conservation practice, the values of utility are transformed into choice probability using logit model. Logit framework allows us to incorporate both uncertainty in decision-making and the bounded rationality of the farmers as it assigns probabilities to different options, where the probability of an inferior option could be non-zero (Equation A.2).

$$F_{\text{decide}}(i,j) = \beta_1 F_{\text{econ}}(i,j) + \beta_2 F_{\text{profile}}(i,j) + \beta_3 F_{\text{social}}(i,j) + \beta_4 F_{\text{spatial}}(i,j) \quad (\text{A.1})$$



$$\text{Selection\_probability}(i,j) = e^{F_{\text{decide}}(i,j)} / \sum e^{F_{\text{decide}}(i,j)} \quad (\text{A.2})$$

In every period, for every farmer ( $j$ ),  $F_{\text{decide}}(i,j)$  is calculated for all possible combinations of the conservation practices ( $i$ ). In this function  $F_{\text{econ}}(i,j)$  represents the agricultural profit generated with production,  $F_{\text{profile}}(i,j)$ , the intrinsic attributes of the farmer towards the given conservation practice combination, which is determined by its type,  $F_{\text{social}}(i,j)$ , the influence of the farmer's social network and  $F_{\text{spatial}}(i,j)$ , the influence of the spatial network, i.e. the farmer's neighbors.  $F_{\text{social}}(i,j)$  and  $F_{\text{spatial}}(i,j)$  are also influenced by the farmer typology. The weights ( $\beta$ ) for each component are informed by the farmer typology and determined using a matrix method (Appendix B). One of the important modeling choices that incorporate the differences between the different farmer types is the assignment of the weights ( $\beta$ ). These weights are assigned in such a way that the farmer types whose income source is solely farming, and the types with profit maximizing mindset (i.e., business-oriented farmers) put more emphasis to  $F_{\text{econ}}(i,j)$ , while farmers with more connection to the landscape (i.e., traditional farmers) put more emphasis on  $F_{\text{profile}}(i,j)$ . Because non-operators do not live in the county in which they own land, or they do not have a farming background, they are not connected to the information networks have no b values for  $F_{\text{spatial}}$  and  $F_{\text{social}}$ . More details on each component of the  $F_{\text{decide}}(i,j)$  function is given in subsequent sections.

### 1. *Agricultural Profit Dynamics, $F_{\text{econ}}(i,j)$*

Farmers generate revenue by enrolling in land retirement programs and allocating land to the CRP or by crop production. If the farmer enrolls in land retirement programs, a fixed payment depending on the farm size and CRP rental rate is paid at the beginning of each year the farmer allocates land for retirement programs. There will be no further agricultural revenue generated from production for the farmer in that case, and that payment will be equal to  $F_{\text{econ}}(i)$ . Otherwise,

the farmer's expected earning is calculated using the farm size, the price and yield of the crop that the farmer expects to get, governmental support for enrolling agricultural programs, and costs associated with production and conservation practice adoption. Single period profit function of a farmer producing a single crop is written below in two forms representing policy scenarios of crop revenue insurance and without crop revenue insurance. In our models, the commodity payments such as direct payments are not represented explicitly.

$$F_{econ}(i,j) = p(A-F)Y(z) + gF + rA - c \quad (A.3)$$

without crop revenue insurance program

$$F_{econ}(i,j) = p(A-F)Y(\lambda, z) + gF + rA - c - \pi(\lambda) \quad (A.4)$$

with crop revenue insurance program

where  $F_{econ}(i,j)$  is profit,  $p$  is farmer's expected crop price (corn, soybean or winter wheat),  $A$  is the production area (acres),  $Y$  is the farm's expected effective yield per acre,  $g$  denotes per acre economic incentive associated with structural practice adoption,  $F$  is total land allocated for structural practices,  $r$  is the CRP per acre payment to the farmer,  $z$  is a measure of fertilizer input on the farm,  $c$  is the total cost of production including cost of conservation practice adoption,  $\pi$  is the per acre premium rate for crop revenue insurance, and  $\lambda$  is the level of insurance purchased. In this model we assume 75% coverage level for revenue insurance.

Agricultural crop production generates revenue (market price multiplied by production size and expected yield). Agricultural profit dynamics also include government payments (such as payments to incentivize structural practice adoption), insurance indemnities if enrolled in crop revenue insurance program, and cost production including maintenance, input, and labor costs as well. To represent the agricultural production cost, a current farm budgeting model developed by

Ohio and Iowa State Universities is adopted and adjusted to previous years using historic consumer price index.

Practices that farmers adopt influence the size of the production area and expected yield; therefore they affect the expected agricultural profit. For example, when a farmer implements structural practices, the size of the filter strip is subtracted from the total size of the farm. Moreover, with nutrient management plans the expected yield decreases. Therefore,  $F_{econ}$  value for each conservation practice available in Table A-3 is calculated separately.

Expected Price and Yield: Expected prices and yield values heavily influence the resulting farm profit. These parameters are based on previous year's price and yield values and updated by each farmer influenced by their farmer type.

In the model, for actual crop yields and prices historical values are used (available at <http://usda.mannlib.cornell.edu> and <http://www.farmdoc.illinois.edu>). In any given time, based on the actual previous crop yields and prices, farmers use Bayesian inference to form price and yield expectations. While a farmer's yield expectation is in the form of a point prediction, a probability distribution is formed for crop prices by taking the price expectation as the mean. Bayesian inference is a statistical approach used to update farmer's existing expectations against observed values of crop price and yield. The Bayesian inference allows farmers to be connected to agricultural markets and at the same time 'learn' with experience. Moreover, with Bayesian inference, we can represent the heterogeneity of farmers by setting different parameters for updating their priors for crop prices and yields depending on the farmer type. For example, traditional farmers are more anchored so that realization of outliers do not affect their expectations much while business-oriented farmers are better at following the fluctuations in the market.

Bayesian inference algorithm is implemented every year, hence farmers' perceptions for crop prices and yields change annually. At the beginning of each year, farmers use publicly available price and yield information from the previous year, their experiences and personalities to form future price and yield expectations.

2. *Intrinsic typology attributes,  $F_{profile}(i,j)$*

Farmer typology developed in Chapter 3 informs  $F_{profile}$  values for each farmer type and conservation practice.  $F_{profile}(i,j)$  lets farmers to adopt economically infeasible practices because of their attitudes and preferences such as being a good citizen of the environment (Table A-4). The synthesis of the adoption literature supports the  $F_{profile}$  values, which change for every practice and every farmer type. In other words,  $F_{profile}$  is the variable representing the socio-economic attributes of the agents including the source of income, impact of farm size and land tenure arrangements in adoption decisions (Table A-5).

Farmer Type	Land Management Attitudes
<b>Traditional</b>	<ul style="list-style-type: none"> <li>- favor non-structural practices because of potential reduction in labor requirements → high <math>F_{\text{profile}}</math> values</li> <li>- financial investment requirement leads to lower adoption rates for structural practices → low <math>F_{\text{profile}}</math> values</li> <li>- secure income provided by land retirement programs is appealing → high <math>F_{\text{profile}}</math> values</li> </ul>
<b>Supplementary</b>	<ul style="list-style-type: none"> <li>- favor non-structural practices because of potential reduction in labor requirements → high <math>F_{\text{profile}}</math> values</li> <li>- substantial off-farm income leads to higher adoption rates for structural practices → high <math>F_{\text{profile}}</math> values</li> <li>- secure income provided by land retirement programs is appealing → high <math>F_{\text{profile}}</math> values</li> </ul>
<b>Business-oriented</b>	<ul style="list-style-type: none"> <li>- favor non-structural practices because of potential reduction in labor requirements → high <math>F_{\text{profile}}</math> values</li> <li>- long-term plans and dependence on soil quality leads to higher structural practice adoption → high <math>F_{\text{profile}}</math> values</li> <li>- focused on profitability, leading to low enrollment rates in land retirement programs → low <math>F_{\text{profile}}</math> values</li> </ul>
<p><b>Non-operator owner</b>  <i>Absentee landowners:</i> own the land but do not reside on or operate it (Petzelka et al., 2011)  <i>Investors:</i> describe themselves as never having farmed (Nassauer et al., 2011).  Mutually exclusive subtypes.</p>	<ul style="list-style-type: none"> <li>- favor non-structural and structural practices because of potential contribution to increased water quality → high <math>F_{\text{profile}}</math> values</li> <li>- absentee landowners favor land retirement programs → high <math>F_{\text{profile}}</math> values</li> <li>- investors have lower enrollment rates for land retirement programs → low <math>F_{\text{profile}}</math> values</li> </ul>

**Table A-4: Farmer typology and its influence on  $F_{\text{profile}}$  values**

The  $F_{\text{profile}}$  value for each farmer type and conservation practice is determined using prioritization matrix method and the synthesis of the adoption literature (Table A-4, Chapter 3).

The prioritization matrix, also known as criteria matrix, provides a way of sorting a diverse set of

items into an order of importance. It also enables their relative importance to be identified deriving a numerical value of the importance of each variable.

$i$	$F_{\text{profile}}$				
	Traditional	Supplementary	Business-oriented	Investor	Absentee Landowner
0	0.90	0.36	0.28	0.00	0.00
1	0.68	0.49	0.74	1.00	1.00
2	0.00	0.06	0.20	0.37	0.60
3	1.00	1.00	0.00	0.48	0.17
4	0.43	0.17	0.43	0.13	0.12
5	0.10	0.22	0.36	0.55	0.72
6	0.51	0.17	1.00	0.30	0.31
7	0.08	0.17	0.28	0.55	0.62
8	0.07	0	0.31	0.86	0.63

**Table A-5:  $F_{\text{profile}}$  values**

### 3. Social and spatial network, $F_{\text{social}}(i,j)$ and $F_{\text{spatial}}(i,j)$

To represent interactions between agents, there are several artificial social network structures such as lattice, small-world, scale-free and random networks. As little to no data is available for the historical and current social network structure of the farmers we chose to rely on artificial network structures. After a comparison of widely used social network structures, Hamill and Gilbert (2009) suggest a simple but at the same time sociologically realistic network structure. To represent the varying network connectedness of agents displayed in the farmer typology, the social network suggested by Hamill and Gilbert (2009) is suitable.

Hamill and Gilbert (2009) base their network structure on the analogy of social circles. In the social network, agents are permitted to have links with other agents who can reciprocate. The agent population is divided into two circles with small and large social reaches. Hamill and Gilbert (2009) network structure allows representing individuals who are more connected than

rest of the population by placing them in the social circle that has larger social reach. When the social reach is larger, the size of the personal network would be larger as well. In our model, business-oriented agents are located in a social circle that has larger social reach than supplementary and traditional farmer agents which results in increased number of connections for business-oriented farmers (Chapter 3). Hamill and Gilbert's (2009) network structure also allows us to connect business-oriented farmers more to other business-oriented farmers. Non-operator owners (investors and absentee landowners) are initially not connected to the social network. However, to demonstrate the potential impacts of information networks on non-operator owner decision, we simulate a scenario that assumes absentee landowners connect to the social network whereas investors connect to both spatial and social networks as they live close to the farmland that they own. Through the information networks (spatial and social networks), farmers observe their neighbors' adoption decisions.

Both  $F_{\text{spatial}}(i,j)$  and  $F_{\text{social}}(i,j)$  are calculated for every farmer for every possible conservation practice given in Table A-2.  $F_{\text{spatial}}$  represents the percentage of Moore neighbors (the eight cells surrounding a central cell on a two-dimensional square lattice) adopting a certain conservation practice. Moore neighbors of a farmer comprise the immediate eight spatial neighbors that every farmer has, except the farmers on the edge of two-dimension grid space.

$$F_{\text{spatial}}(i,j) = \text{Neighbors}(i,j) / \sum \text{Neighbors}(i,j) \quad (\text{A.5})$$

where  $\text{Neighbors}(i)$  is the number of Moore neighbors that adopted the conservation practice combination  $i$ . That is,  $F_{\text{spatial}}(i)$  is a measure of popularity of conservation practice combination  $i$  in the immediate neighborhood of the given farmer. Higher the popularity of a conservation practice in spatial sense, higher the probability of the farmer adopting that conservation practice.

$F_{\text{social}}$  represents the percentage of neighbors adopting a certain conservation practice. Similarly,  $F_{\text{social}}$  is calculated for every possible conservation practice listed in Table A-3. Connectedness in the social network is not uniform among the farmers. The number of connections of a farmer depends on its type. Moreover, among the farmers of a given type, the number of connections may differ, representing the heterogeneity of the farmers within the same type. However, the variation in the number of connections among the farmers of the same type is smaller than the variation between farmers of different types. For example, business-oriented farmers have higher number of social connections than the other farmers on average, while the connections of the business-oriented farmers are mostly to other business-oriented farmers. Traditional and supplementary farmers have lower number of connections. In a similar manner as  $F_{\text{spatial}}(i,j)$ ,  $F_{\text{social}}(i,j)$  measures the popularity of the conservation practice combination  $i$  among the parts of the social network that are connected to the given farmer.  $F_{\text{social}}(i,j)$  can be written as follows:

$$F_{\text{social}}(i,j) = \frac{\text{Network}(i,j)}{\sum \text{Network}(i,j)} \quad (\text{A.6})$$

where  $\text{Network}(i,j)$  is the number of farmers that selected the conservation practice adoption  $i$  within the farmer  $j$ 's social network.

Non-operator owners (investors and absentee landowners) are not initially connected to spatial and social networks. Therefore, initially they have no influence of information networks on their conservation adoption decisions. When increased involvement of non-operator owners in decision-making is simulated in Chapters 3 and 4, absentee-landowners are only connected to the social network and investors are connected to both spatial and social networks. For non-operator owners, social networks are assumed to be NGOs and government agencies leading to a positive influence (Table A-6).



<i>i</i> , conservation practices	Investor	Absentee landowner	
	F <sub>social</sub>	F <sub>spatial</sub>	F <sub>social</sub>
0, none	0	0	0
1, non-structural	1	0	1
2, structural	1	0	1
3, land retirement	1	0	1
4, nutrient mgt plans	1	0	1
5, non-structural & structural	1	0	1
6, non-structural & nutrient mgt	1	0	1
7, structural & nutrient mgt	1	0	1

**Table A-6: When non-operator owners (investors and absentee-landowners) have active roles in conservation decisions, they are connected to the information networks. F<sub>spatial</sub> values for investors are calculated using Equation A.5**

### Policy Scenarios

We simulated four scenarios intended to form a bridge between the science of land management and policy development (Table A-7). The primary goal of these plausible policy scenarios is to be prospective and informative rather than projective or prescriptive of the future (Nassauer and Corry, 2004).

		NON-OPERATOR INVOLVEMENT	
		NO	YES
CROP REVENUE INSURANCE	NO	1 <i>Baseline</i> Simplified representation of existing land tenure and policy context	2 <i>Non-operator owners involvement</i> Increased non-operator involvement in land management decisions
	YES	3 <i>Crop revenue insurance</i> Only operators are decision makers and crop revenue insurance is available as a risk management tool Available to all operators as a risk management tool	4 <i>Crop revenue insurance with non-operator owner involvement</i> Both operators and non-operators owners are decision makers and crop revenue insurance is available as a risk management tool

**Table A-7: Land management strategies tested under different agricultural policy and structure scenarios**

The *Baseline scenario* (1) represents a simplified version of existing land tenure where operators (traditional, supplementary and business-oriented farmers) are responsible for conservation practice adoption decisions and non-operator owners have no involvement in production and conservation decisions. In this scenario existing crop insurance programs are not represented and crop revenue insurance is not offered in lieu of commodity payments.

The *Non-operator owner involvement scenario* (2) simulates the potential impact of non-operator owners being more involved in decisions about conservation practice adoption. This premise follows recent research that demonstrated positive attitudes of non-operator owners for certain conservation practices (Petrzelka et al., 2009; Nassauer et al., 2011). In this scenario, we assume natural resource agencies and NGOs reach out to non-operator owners and effectively inform them about existing and available conservation practices.

The *Crop revenue insurance scenario* (3) follows the latest US Farm Bill discussions about providing federally subsidized crop revenue insurance rather than commodity production subsidies. This scenario does not assume that conservation compliance is required for land to be eligible for crop revenue insurance. In this scenario, only operators are decision makers and they purchase crop revenue insurance at 75% coverage level for all the land that they manage including the rented land. Crop revenue insurance provides an accessible risk management tool to operators and at the same time encourages an increased production area.

The *Crop revenue insurance with non-operator owner involvement scenario* (4) presents the plausible changes both in land tenure and policy by assuming non-operators owners as active decision makers when crop revenue insurance is offered in lieu of commodity payments. Crop revenue insurance provides a safety net and indirectly motivates both operators and non-operator owners to increase their production area.

Certain model parameters are changed depending on the policy scenario being investigated. Appendix B has initial model parameter values and how we change these values for different scenarios.

### **Verification and Validation**

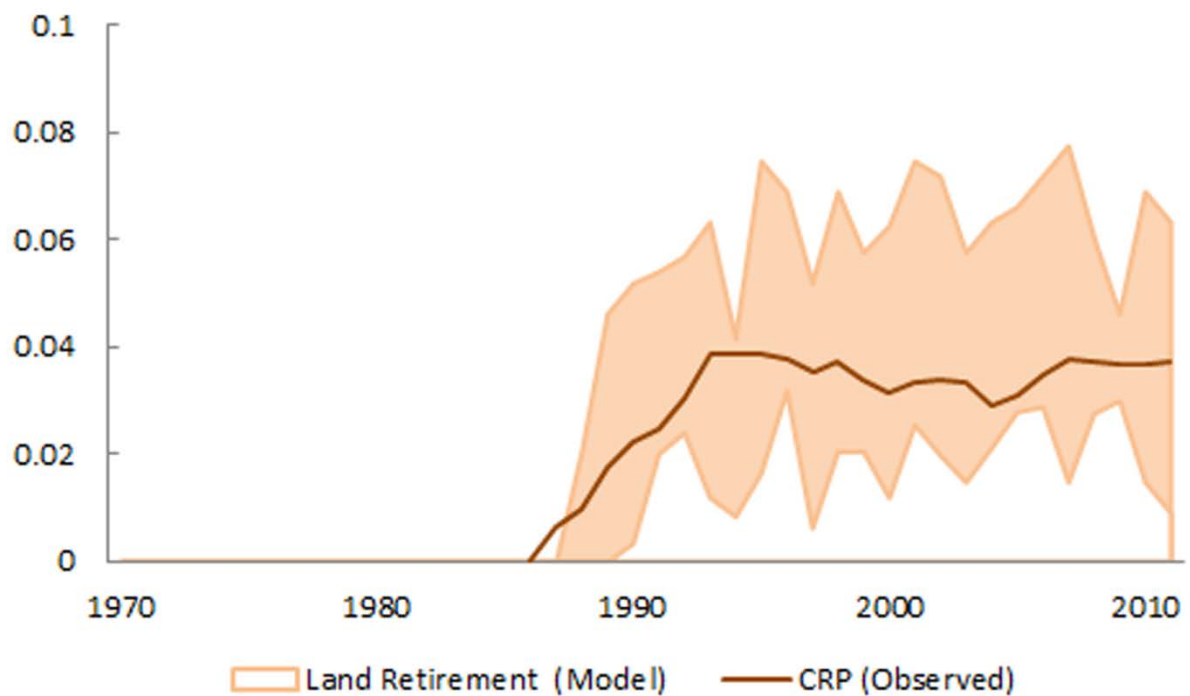
ABMs are informative rather than predictive and useful in investigating plausible scenarios and their potential consequences. Model verification and validation are important steps that contribute to the validity of the developed ABM. Model verification is the process of determining whether the software implementation correctly represent model processes (Ormerod and Rosewell, 2009). As the ABMs are powerful in illustrating the phenomena of emergence, it is particularly difficult to determine whether an unexpected result is due to an error in the model implementation and execution (Galan et al., 2009). Therefore the verification stage of the model is particularly important. For the verification of the model, where the general aim is to make sure that the model does not have programming errors, we built the model in several levels with increasing complexity following unit testing approach (Linck and Frohlick, 2003) (Figure A-3). The unit testing approach suggests writing some test code to exercise the program simultaneously writing the complete model code. The purpose is to construct the model in small, self-contained units and check the results and make sure they align with expected results.

<b>Level 1</b> <b>Isolated World</b>
- Developer creates owners, operators, and farmland 1 a) Farmers give adoption decisions using only profit generated from agricultural production (F econ). 1 b) Farmers add the influence of policy relevant characteristics to their decisions (F profile).
<b>Level 2</b> <b>Information Networks</b>
- Developer creates owners, operators, and farmland - Spatial and social networks - Farmers give adoption decisions with the influence of profit generated from agricultural production (F econ) and policy-relevant farmer characteristics (F profile) 2 a) Influence of spatial networks is added (F spatial) 2 b) Influence of social networks is added (F social)
<b>Level 3</b> <b>Information Networks + Policy and Land Tenure Changes</b>
- Developer creates owners, operators, and farmland - Spatial and social networks - Agricultural policy and land tenure dynamics change to represent plausible future scenarios - Farmers give adoption decisions with the influence of profit generated from agricultural production (F econ), policy-relevant farmer characteristics (F profile), and information networks (F spatial and F social) 3 a) Non-operators are involved in the decision making process and are connected to information networks 3 b) Crop revenue insurance is offered as a risk management tool.

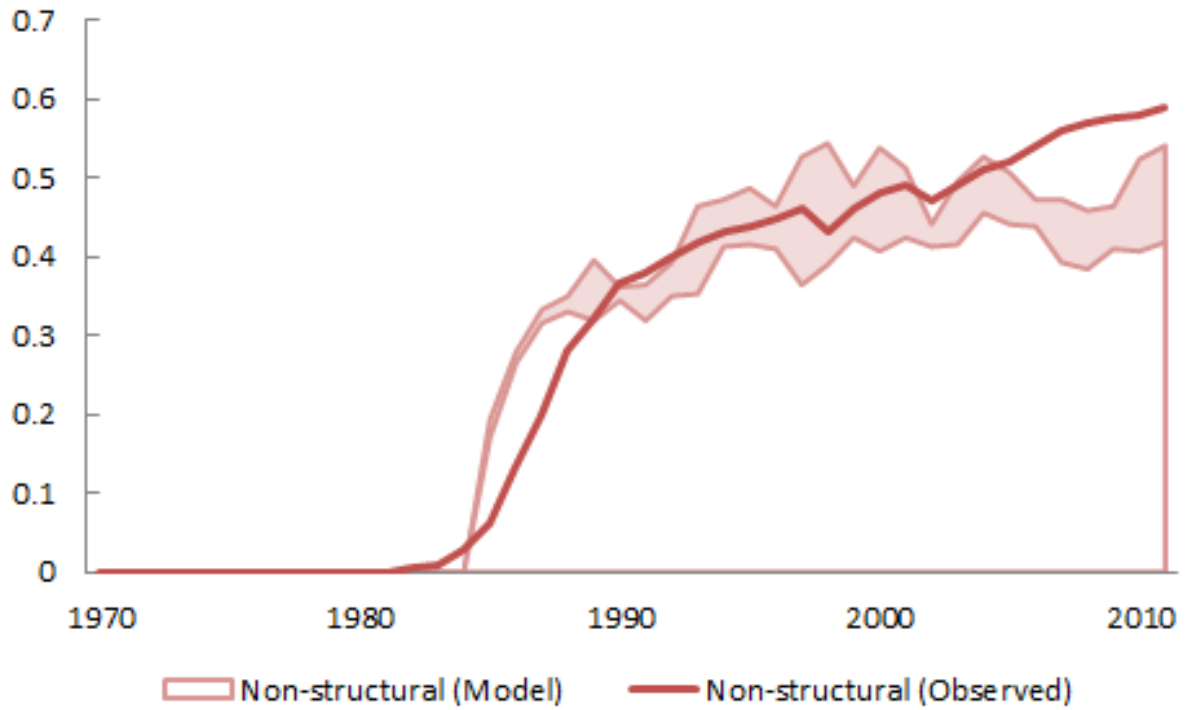
**Figure A-3: Levels of ABM as a verification tool**

Model validation is the process of assessing the degree of which the model is accurately representing the real world interactions and dynamics (Ormerod and Rosewell, 2009). The ABM

is populated using the farmer typology described in Chapter 3. For the farmer typology we synthesized the literature of conservation practice adoption. Therefore, for model validation we used the documented trends in the Corn Belt. Synthesis of numerous studies conducted in the Corn Belt provides spatially and temporally generalizable trends to compare and validate model results. Comparison of documented adoption rates for non-structural practices (CTIC, 2012) and enrollment rates for land retirement programs such as CRP (USDA, 2013) are within the simulated adoption rates (Figures A-4 and A-5). For structural practices, we refer to empirical studies conducted in Ohio, which indicate 20-25% adoption rates similar to ABM results (Napier et al., 2000; Napier and Bridges, 2003).



**Figure A-4: Observed and simulated enrollment rates for land retirement programs such as Conservation Reserve Program, CRP in Sandusky watershed, OH (USDA, 2013). 25 ABM simulation runs fall between two lines of the same color.**



**Figure A-5: Observed and simulated adoption rates for non-structural practices such as conservation tillage and no-till in Sandusky watershed, OH (CTIC, 2012). 25 ABM simulation runs fall between two lines of the same color.**

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**Appendix B: Model parameters for the agent-based model of  
farmer adoption of conservation practices**



<b>Name</b>	<b>Parameter description</b>	<b>Value</b>
<i>percentBus</i>	percentage of business-oriented farmers	0.1
<i>percentSuppl</i>	percentage of supplementary farmers	0.2
<i>percentTrad</i>	percentage of traditional farmers	0.7
<i>initialAdopted0</i>	percentage of farmers that adopted none of the practices	0.8
<i>initialAdopted1</i>	percentage of farmers that adopted non-structural practices	0.0
<i>initialAdopted2</i>	percentage of farmers that adopted structural practices	0.1
<i>initialAdopted3</i>	percentage of farmers that enrolled in land retirement programs	0.0
<i>initialAdopted4</i>	percentage of farmers that adopted nutrient management plan	0.1
<i>initialAdopted5</i>	percentage of farmers that adopted non-structural and structural practices	0.0
<i>initialAdopted6</i>	percentage of farmers that adopted non-structural practices and nutrient management plan	0.0
<i>initialAdopted7</i>	percentage of farmers that adopted structural practices and nutrient management plan	0.0
<i>ownerInterference</i>	percentage of non-operator owners initially giving decisions	0.0
<i>ownerMaxInterference</i>	percentage of non-operator owners giving decisions at the end of the simulation	0.8
<i>farmerAgeToLeave</i>	age at which traditional farmers consider leaving business	65
<i>farmerProbToLeave</i>	probability that traditional farmers leave business	0.8
<i>farmerProbNonoperator</i>	probability that traditional farmers leaving the business become non-operator owners	0.6
<i>farmerProbAbsentee</i>	probability that traditional farmers leaving the business become absentee landowners.	0.6
<i>ciLevel</i>	level of crop revenue insurance coverage	0.8
<i>simpleCiPlusMinusBus</i>	level of business farmers' uncertainty about their price expectation	0.3
<i>simpleCiPlusMinusTrad</i>	level of traditional farmers' uncertainty about their price expectation	0.4
<i>simpleCiPlusMinusSupp</i>	level of supplementary farmers' uncertainty about their price expectation	0.3

**Table B-1: Initial model parameters**

Farmer type	Name	Parameter description	Value (without crop revenue insurance)	Value (with crop revenue insurance)
Traditional	$\beta_1$	weight of agricultural profit on decision algorithm	0.34	0.30
	$\beta_2$	weight of farmer profile on decision algorithm	0.40	0.52
	$\beta_3$	weight of social network on decision algorithm	0.09	0.05
	$\beta_4$	weight of spatial network on decision algorithm	0.17	0.13
Supplementary	$\beta_1$	weight of agricultural profit on decision algorithm	0.27	0.23
	$\beta_2$	weight of farmer profile on decision algorithm	0.46	0.58
	$\beta_3$	weight of social network on decision algorithm	0.17	0.13
	$\beta_4$	weight of spatial network on decision algorithm	0.10	0.06
Business-oriented	$\beta_1$	weight of agricultural profit on decision algorithm	0.49	0.45
	$\beta_2$	weight of farmer profile on decision algorithm	0.19	0.31
	$\beta_3$	weight of social network on decision algorithm	0.24	0.20
	$\beta_4$	weight of spatial network on decision algorithm	0.08	0.04
Absentee landowners	$\beta_1$	weight of agricultural profit on decision algorithm	0.09	0.05
	$\beta_2$	weight of farmer profile on decision algorithm	0.61	0.69
	$\beta_3$	weight of social network on decision algorithm	0.30	0.26
	$\beta_4$	weight of spatial network on decision algorithm	0.00	0.00
Investor	$\beta_1$	weight of agricultural profit on decision algorithm	0.08	0.04
	$\beta_2$	weight of farmer profile on decision	0.45	0.57

		algorithm		
	$\beta_3$	weight of social network on decision algorithm	0.29	0.25
	$\beta_4$	weight of spatial network on decision algorithm	0.18	0.14
Traditional	Fprofile <sub>0</sub>	farmer attributes for adopting none of the practices	0.90	1.00
	Fprofile <sub>1</sub>	farmer attributes for adopting non-structural practices	0.68	0.96
	Fprofile <sub>2</sub>	farmer attributes for adopting structural practices	0.00	0.02
	Fprofile <sub>3</sub>	farmer attributes for adopting land retirement programs	1.00	0.00
	Fprofile <sub>4</sub>	farmer attributes for adopting nutrient management plans	0.43	0.35
	Fprofile <sub>5</sub>	farmer attributes for adopting both non-structural and structural practices	0.10	0.10
	Fprofile <sub>6</sub>	farmer attributes for adopting both non-structural practices and nutrient management plans	0.51	0.42
	Fprofile <sub>7</sub>	farmer attributes for adopting both structural practices and nutrient management plans	0.08	0.07
Supplementary	Fprofile <sub>0</sub>	farmer attributes for adopting none of the practices	0.36	0.48
	Fprofile <sub>1</sub>	farmer attributes for adopting non-structural practices	0.49	1.00
	Fprofile <sub>2</sub>	farmer attributes for adopting structural practices	0.06	0.08
	Fprofile <sub>3</sub>	farmer attributes for adopting land retirement programs	1.00	0.00
	Fprofile <sub>4</sub>	farmer attributes for adopting nutrient management plans	0.17	0.77
	Fprofile <sub>5</sub>	farmer attributes for adopting both non-structural and structural practices	0.22	0.06
	Fprofile <sub>6</sub>	farmer attributes for adopting both non-structural practices and nutrient management plans	0.17	0.82

	Fprofile <sub>7</sub>	farmer attributes for adopting both structural practices and nutrient management plans	0.17	0.09
Business-oriented	Fprofile <sub>0</sub>	farmer attributes for adopting none of the practices	0.28	0.50
	Fprofile <sub>1</sub>	farmer attributes for adopting non-structural practices	0.74	0.65
	Fprofile <sub>2</sub>	farmer attributes for adopting structural practices	0.20	0.03
	Fprofile <sub>3</sub>	farmer attributes for adopting land retirement programs	0.00	0.00
	Fprofile <sub>4</sub>	farmer attributes for adopting nutrient management plans	0.43	1.00
	Fprofile <sub>5</sub>	farmer attributes for adopting both non-structural and structural practices	0.36	0.08
	Fprofile <sub>6</sub>	farmer attributes for adopting both non-structural practices and nutrient management plans	1.00	0.66
	Fprofile <sub>7</sub>	farmer attributes for adopting both structural practices and nutrient management plans	0.28	0.08
	Absentee landowner	Fprofile <sub>0</sub>	farmer attributes for adopting none of the practices	0.00
Fprofile <sub>1</sub>		farmer attributes for adopting non-structural practices	1.00	0.74
Fprofile <sub>2</sub>		farmer attributes for adopting structural practices	0.60	0.02
Fprofile <sub>3</sub>		farmer attributes for adopting land retirement programs	0.17	0.00
Fprofile <sub>4</sub>		farmer attributes for adopting nutrient management plans	0.12	0.49
Fprofile <sub>5</sub>		farmer attributes for adopting both non-structural and structural practices	0.72	0.03
Fprofile <sub>6</sub>		farmer attributes for adopting both non-structural practices and nutrient management plans	0.31	1.00
Fprofile <sub>7</sub>		farmer attributes for adopting both structural practices and nutrient management plans	0.62	0.02

Investor	Fprofile <sub>0</sub>	farmer attributes for adopting none of the practices	0.00	0.38
	Fprofile <sub>1</sub>	farmer attributes for adopting non-structural practices	1.00	0.74
	Fprofile <sub>2</sub>	farmer attributes for adopting structural practices	0.37	0.02
	Fprofile <sub>3</sub>	farmer attributes for adopting land retirement programs	0.48	0.00
	Fprofile <sub>4</sub>	farmer attributes for adopting nutrient management plans	0.13	0.49
	Fprofile <sub>5</sub>	farmer attributes for adopting both non-structural and structural practices	0.55	0.03
	Fprofile <sub>6</sub>	farmer attributes for adopting both non-structural practices and nutrient management plans	0.30	1.00
	Fprofile <sub>7</sub>	farmer attributes for adopting both structural practices and nutrient management plans	0.55	0.02

**Table B-2: Model parameters comparison for crop revenue insurance scenario.**