

Research

An integrated social and ecological modeling framework—impacts of agricultural conservation practices on water quality

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ABSTRACT. We present a modeling framework that synthesizes social, economic, and ecological aspects of landscape change to evaluate how different agricultural policy and land tenure scenarios and land management preferences affect landscape pattern and downstream water quality. We linked a stylized agent-based model (ABM) of farmers' conservation practice adoption decisions with a water quality model, the Soil and Water Assessment Tool (SWAT), to simulate the water quality effects of changing land tenure dynamics and different policies for crop revenue insurance in lieu of commodity payments 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 leads to more homogeneous farmer decisions and a slight increase in sediment and nutrient loads unless cross compliance with expanded conservation requirements is implemented.

Key Words: *ABM; agricultural policy; agriculture; conservation practice; integrated modeling; SWAT; water quality*

INTRODUCTION

Agricultural policy in the USA strongly impacts the land use and land management decisions of farmers and indirectly, but profoundly, impacts water quality (Broussard et al. 2012). An overall goal of conservation policies with regard to water quality is to reduce sediment and nutrient load from agricultural landscapes by promoting nutrient efficiency and managing nutrient and sediment runoff through conservation best management practices (Sharpley et al. 1994). Thus, detailed studies of the connections between agricultural policies and water quality can help identify more effective strategies to reduce agricultural pollution.

High surface water concentrations of nitrogen and phosphorus are correlated with inputs from fertilizers used for crops (Ribaud and Smith 2000, Boyer et al. 2002, Galloway et al. 2004). For example, the current resurgence of eutrophication symptoms in the Great Lakes is attributed to the intensification in agricultural production and concomitant soil erosion and nutrient runoff from nonpoint sources (Dolan and Chapra 2012). 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 nonpoint source nutrient delivery, enhance water quality, and improve sustainability in agricultural production by increasing resilience (National Research Council 2010).

The focus of this study is the impact of plausible future policy and land tenure scenarios on the delivery of bioavailable dissolved reactive phosphorus (DRP) and total phosphorus (TP) to Lake Erie by exploring links between human and environmental systems. We describe a social–ecological system (SES) that links farmer decisions and actions to ecological responses in reciprocal feedbacks. Social–ecological systems are affected by complex relationships arising from the biophysical, institutional, infrastructural, demographic, economic, and sociopolitical contexts. Hence, SESs exhibit emergent properties—unique

properties not belonging to human or natural systems separately but emerging from their interactions (Janssen 1998, Monticino et al. 2007, Rammel et al. 2007, Levin et al. 2012). Understanding the complexities of SESs may affect the success or failure of their management (Liu et al. 2007). Unforeseen and undesirable consequences can result if biophysical and human systems are not examined together (Veldkamp and Verburg 2004, Levin et al. 2012).

We describe an SES model to investigate the impact of different plausible future policy and land tenure scenarios on farmer adoption of conservation practices intended to enhance water quality. We link a social agent-based model (ABM) of farmer adoption of conservation practices with a biophysical water quality model, the Soil and Water Assessment Tool (SWAT), which integrates land management decisions with soil properties, climate information, and land topography to estimate water quality metrics (Arnold et al. 1998). We define farmers as owners or renters of land on which cash crops are grown, who make decisions about land management based on policy scenarios involving economic, institutional, and environmental information. This ABM incorporates the heterogeneity and complexity of Corn Belt farmers through a typology (Daloğlu et al. in review) that simulates farmer decisions in terms of their tendency toward adoption of conservation practices.

THE MODELING FRAMEWORK

The study area is the Sandusky watershed of Lake Erie, which represents a typical watershed of the Corn Belt region (Fig. 1). Lake Erie has experienced significant eutrophication because of excessive phosphorus loading, primarily from agricultural runoff and point-source discharges (Dolan and Chapra 2012); however, non-point sources, particularly from agriculture, are currently the major causes of nutrient pollution (Forster 2000). Agricultural runoff has resulted in algal blooms (Michalak et al. 2013), poor water clarity, and summer hypoxia (low oxygen) (Hawley et al. 2006, Zhou et al. 2013, Scavia et al. 2014) that impact fisheries,

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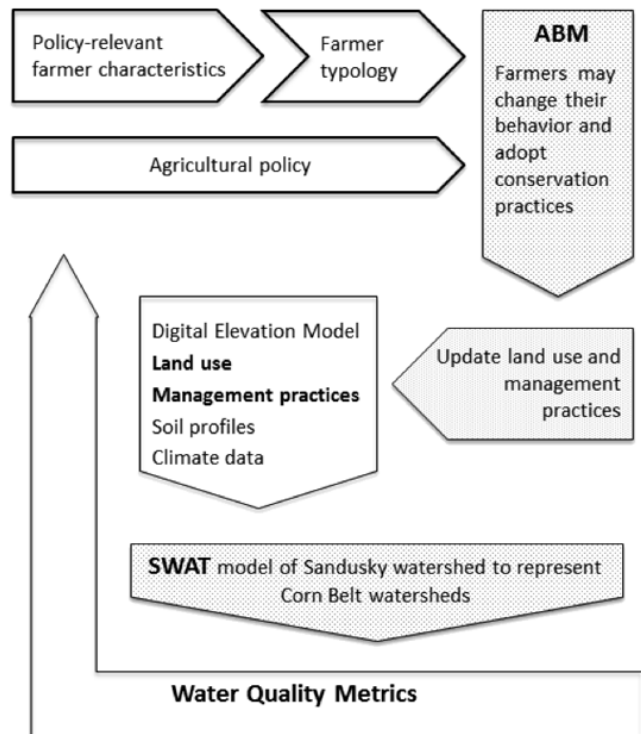
recreation, and drinking water throughout many aquatic and coastal systems (Carpenter 2008). To address these issues, effective adoption of conservation practices is essential.

Fig. 1. Locator map for the Sandusky Watershed, Ohio. The study watershed is representative of Corn Belt watersheds (striped region).



With our linked ABM–SWAT framework, we investigate how policy and farmer characteristics influence conservation practice selection and, in turn, their effects on water quality. The framework—the ABM is implemented in Java using Repast J agent-based libraries within the Eclipse integrated environment and linked to SWAT using MatLab—includes the landscape, agents (farmers, in a typology that represents their heterogeneity), conservation practice adoption, and ecosystem responses (sediment, DRP, and TP loading) to changes in land management (Fig. 2). The farmer typology (Daloğlu et al. 2014) represents the heterogeneity among Corn Belt farmers and provides the necessary pillar for the ABM. An existing fully calibrated and verified SWAT model of the Sandusky watershed (Daloğlu et al. 2012) is used to simulate nutrient load responses.

Fig. 2. The coupled human and natural system of an agricultural landscape in the Corn Belt.



The ABM is constructed at the individual decision-making level, and so we use our farmer typology to represent farmer behavior and decisions. In the model, farmer agents of different types make adoption decisions every year based on decision algorithms. If farmer decisions include the adoption of conservation practices, the landscape is altered, which eventually changes the land management strategy. Through this model, we explore possible changes in the structure of U.S. agriculture through land tenure dynamics and the influence of crop revenue insurance on farmers' conservation practice adoption decisions.

The output from the ABM, in the form of updated land management maps (Fig. 2), is used to examine the impacts of these changes as presented in plausible future scenarios. To understand the impacts of these scenarios, SWAT is used to simulate sediment and phosphorus loss from the landscape over a 41-year period (1970–2010).

The Model Landscape

The model landscape consists of a two-dimensional grid, built within the ABM, abstractly representing the agricultural landscape of the Sandusky watershed. Because the ABM is linked with the SWAT, the specifics of the water quality model are taken into consideration during ABM setup. The SWAT uses hydrologic response units (HRU) as its fundamental computational unit. Runoff flow, sediment, and nutrient loads are calculated separately for each 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;

Table 1. Farmer typology (from Daloğlu et al., unpublished manuscript)

Farmer Type	Land tenure, income and information network properties	Land Management Preferences
Traditional	Full-owner, small operations, dependent on on-farm income, moderately connected to information networks	- favor nonstructural practices because of potential reduction in labor requirements - financial investment requirement leads to lower adoption rates for structural practices - secure income provided by land retirement programs is appealing
Supplementary	Full/Part-owner, small operations, has off-farm income, moderately connected to information networks	- favor nonstructural practices because of potential reduction in labor requirements - substantial off-farm income leads to higher adoption rates for structural practices. - secure income provided by land retirement programs is appealing
Business-oriented	Part-owner, medium to large operations, dependent on on-farm income, highly connected to information networks	- favor nonstructural practices because of potential reduction in labor requirements - long-term plans and dependence on soil quality leads to higher structural practice adoption - focused on profitability, leading to low enrollment rates in land retirement programs
Nonoperator owner	Nonoperator owner, medium to large operations, has off-farm income, least connected to information networks	- have less control on land management strategies but positive attitudes toward conservation practices

we used an HRU size corresponding to the average farm size in the Sandusky basin (258 acres; United States Department of Agriculture (USDA) 2009, Daloğlu et al. 2012). This strategy resulted in 147 subbasins and 351 agricultural HRUs. Therefore, 351 farmers are represented as agents in the ABM.

Agents as Farmers

Farmers are exceptionally diverse, particularly with regard to farm size, land tenure, education, age, sources of income, and socioeconomic attributes. To represent this heterogeneity in the ABM, we used a typology (Table 1; Daloğlu et al. 2014) derived from an extensive literature review and previous surveys conducted in the Corn Belt region. Because ABMs require simplicity (Axelrod 1997), like others (Valbuena et al. 2008, Robinson et al. 2012), our typology represents diversity and heterogeneity in simple terms based on four farmer types: traditional, supplementary, business-oriented, and nonoperator owners (Table 1) (Daloğlu et al. 2014).

Because of limited data, it is not possible to identify exact locations of farms and management decisions. Therefore, we chose to represent the study area in a more stylized model, as described in Appendix 1, using the “overview, design concepts, and details” (ODD) protocol (Grimm et al. 2010).

Conservation Practices

We define land management as driven by four conservation practices and government programs that are widely used and could be represented in SWAT (Table 2). In the model, farmers can adopt combinations of conservation practices to control pollution sources (nutrient management), trap soil and nutrients before they reach 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 (nonstructural practices, i.e., conservation tillage and no-till). Farmers’ annual adoption decisions are then explored under the influence of different future scenarios.

Table 2. Conservation practice categories applicable in SWAT models (modified and adapted from Daloğlu et al., unpublished manuscript).

Conservation Practice Categories	Conservation Practices	Economic and Environmental Benefits
Nonstructural	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)	Plants long-term, resource conserving covers. Reduces soil erosion from highly erodible lands (HEL), restores wetlands. Enhances water quality and wildlife. Annual payment for enrollment.
Nutrient management	Reducing fertilizer application rate	Reduces nutrient application on agricultural landscape and eventually reduces nutrient runoff.

Agricultural programs in the USA generally allow farmers to choose which programs to participate in, with flexibility to select practices that fit their climate, soils, and, most importantly, management skills (Bernstein et al. 2004). So, in our model, adoption of structural practices, nonstructural practices, nutrient management plans, and enrollment in land retirement are voluntary (Table 2). Each farmer determines whether to participate in land retirement or adopt certain practices

depending on policy drivers and the farmer's overall objectives. Land retirement programs such as the CRP generally remove land from agricultural production for a long period (at least 10 years) or, in some cases, permanently, for an annual rental fee. Structural practices are eligible for cost-share where farmers receive 50% of the implementation cost from the federal government as an economic incentive in return for multi-year commitments. When farmers receive economic incentives for structural practice adoption and land retirement enrollment, penalties are levied for noncompliance (Claassen 2012). Because economic incentives are not provided for nonstructural practices and enrollment in nutrient management plans, noncompliance does not incur penalties.

Conservation Practice Adoption Decisions in the Model

This model focuses on helping understand why some farmers adopt conservation practices and others do not, and how spatial relationships among farmers impact those decisions, with special emphasis on their heterogeneity. At each annual time-step in the model, every farmer agent decides on a land management strategy for conservation practice adoption (Table 2). The decision-making algorithm includes net income generated from government programs and agricultural production, the farmers' preferences and land tenure, and influences of their neighbors (summarized below and detailed in Appendix 1).

Every farmer agent in the model uses the same decision algorithm but with different parameters based on the preferences associated with their type. Given these differences, individual agents react differently to the same agricultural policies, including their decision to adopt none or combinations of available practices. A critical variable in the model is land tenure: whether farmers are owners or operators, and 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 nonoperators (Constance et al. 1996, Soule et al. 2000, Arbuckle 2010); however, we also investigate land tenure dynamics, the possible impact of the growing proportion of farmland owned by nonoperators, and their influence on adoption decisions.

In the ABM, farmers calculate their agricultural income generated from production and collect financial incentives by enrolling in government programs. For agricultural income, farmer agents use Bayesian inference for the expected price and yield from a probability distribution. We represent farmer heterogeneity by setting different parameters for Bayesian updating for different farmer types (Table 1). For example, traditional farmers have more stable price and yield expectations, and business-oriented farmers more likely follow fluctuations in the market because we assume they are more connected to information networks. Farmers' perceptions of crop prices and yields change from year to year. Thus, at the beginning of each year, farmer agents use publicly available price and yield information, their experiences, and their type characteristics to form future price and yield expectations.

Farmer agents also use their social and spatial information networks to evaluate which practices their neighbors adopt. In the model, nonoperators are not initially connected to the information networks, whereas operators (traditional, supplementary, and business-oriented farmers) are connected to both spatial and

social networks, and business-oriented farmers have higher network connectedness compared with traditional and supplementary farmers (Daloğlu et al. 2014). As described below, we also test a case in which nonoperator owners increase involvement. Farmer agents' intrinsic environmental attitudes toward each available conservation practice, as reflected by their type (Table 1), also influence their adoption decisions. Based on these variables, the model uses the farmers' decision algorithm to decide which conservation practice to adopt (see Appendix 1).

Land Tenure Changes

Agricultural land tenure in the USA has undergone critical changes; especially through increases in nonoperator ownership followed by increases in part ownership or full renting (Wunderlich 1993, Duffy 2008). Our study site, the Sandusky watershed, followed these national trends, especially in relation to increased nonoperator ownership (Daloğlu et al. 2014). Studies of the impact of these increases in the Corn Belt region have shown that structural practices are appealing to nonoperators (Petzelka et al. 2009, Nassauer et al. 2011). However, nonoperator ownership is not defined consistently across studies. Nearly half of Corn Belt farmers are absentee landowners, defined as owners living more than 50 miles from their land (Petzelka et al. 2009), and land retirement enrollment is lower among absentee landowners compared with other farmers in the Great Lakes Basin (Petzelka et al. 2009). However, Nassauer et al. (2011) found that one type of nonoperator, investors (defined as landowners who have never farmed), has higher land retirement enrollment rates than other Iowa farmers.

We exploit the difference between these two different studies of different, overlapping subsets of nonoperators as we investigate the impact of changing land tenure dynamics on conservation practice adoption and water quality. In our model, we define absentee landowners and investors as mutually exclusive subtypes of nonoperator owners. Over time, our simulations assume increased involvement of nonoperator owners in conservation decisions (from 0% to 50% by the end of the simulation) as they become increasingly connected to information networks over time.

Changes in Agricultural Policy: Crop Revenue Insurance

Current agricultural policies have numerous drivers for farmers to adopt conservation practices; however, policy incentives frequently outweigh these, resulting in a patchwork of adoption that is not sufficiently effective in improving water quality (Doering et al. 2007). Current Farm Bill discussions include replacement of commodity payments with subsidized crop insurance. Starting in 1985, participation in subsidized crop insurance programs required conservation compliance, i.e., refraining from draining wetlands and implementing a whole farm conservation plan to reduce erosion to acceptable levels. However, in the 1996 Farm Bill, the conservation compliance requirement was removed from the insurance program (Smith and Glauber 1997).

Currently, farmers can choose between two insurance policies, crop yield or revenue insurance, where the USDA provides subsidies for two-thirds of the cost of farmers' premiums (Coble and Barnett 2013). Crop yield insurance protects farmers from the income effects of reduced yield due to weather and other factors, whereas revenue insurance protects farmers' income from

both yield changes and market fluctuations and indirectly encourages farmers to increase their production area. To evaluate potential impacts of crop insurance replacing commodity payments, we concentrate on revenue insurance (Coble and Barnett 2013).

Numerous studies have investigated the role of risk aversion in adoption of nonstructural practices (conservation tillage and no till) and have consistently found a negative relationship between risk aversion and practice adoption (Bultena and Hoiberg 1983, Belknap and Saupe 1988). 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 nonstructural practice adoption (Bosch and Pease 2000).

Plausible Future Scenarios

The primary goal of this analysis is to understand the drivers of conservation practice adoption and subsequent water quality impacts under plausible futures. For this purpose, we constructed four scenarios by crossing two policy futures with two assumptions about nonoperator owners (Table 3). These scenarios are intended to be prospective and informative rather than projective or prescriptive of the future (Nassauer and Corry 2004).

Table 3. Land management strategies tested under different agricultural policy and structure scenarios

		Nonoperator Involvement	
		No	Yes
Crop Revenue Insurance	No	1 <i>Baseline</i> Simplified representation of existing land tenure and policy context	2 <i>Nonoperator owners involvement</i> Increased nonoperator 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	4 <i>Crop revenue insurance with nonoperator owner involvement</i> Both operators and nonoperator owners are decision makers and crop revenue insurance is available as a risk management tool

The “Baseline scenario” (1) represents existing land tenure where operators (traditional, supplementary, and business-oriented farmers) are responsible for conservation practice adoption decisions, and nonoperator owners have no involvement in production and conservation decisions. In this scenario, existing crop insurance programs are not included. The “Nonoperator owner involvement scenario” (2) simulates the potential impact of increased involvement of nonoperator owners on the baseline scenario. In this scenario, we assume natural resource agencies and nongovernmental organizations (NGOs) reach out to nonoperator owners and effectively inform them about existing and available conservation practices (Table 4). The “Crop revenue insurance scenario” (3) follows recent U.S. Farm Bill discussions about providing federally subsidized crop revenue insurance

rather than commodity production subsidies. This scenario does not assume conservation compliance is required; however, we do explore the alternative below. Here, we assume only operators are decision makers, that they purchase crop revenue insurance at 75% coverage level for all the land that they manage including the rented land, and that the reduced risk encourages them to increase production area (Table 4). The “Crop revenue insurance with nonoperator owner involvement scenario” (4) explores the impact of increased nonowner involvement on the crop insurance scenario (3). Crop revenue insurance provides a safety net and indirectly motivates both operators and nonoperator owners to increase their production area (Table 4). Cross compliance with conservation programs is also not included in this scenario.

Table 4. Assumptions embedded in scenario simulations

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

Water Quality Model—SWAT

The 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 HRUs that represent areas with common land cover 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 and is used widely for evaluating and predicting impacts of conservation practices (Arabi et al. 2008). Models created using SWAT 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. 2013), especially under anticipated future climates (Bosch et al. 2014).

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 weather and farmer management decisions on nutrient delivery especially on DRP runoff (Daloğlu et al. 2012).

Water Quality Impacts of Land Management Strategies

This modeling framework evaluates impacts of farm-scale decisions at the watershed scale. Farmers update their adoption decisions annually during each 41-year simulation; however, because decision-relevant model parameters are sampled from distributions in the decision-making algorithms, each scenario consists of 25 runs, each representing a sampling from the distribution.

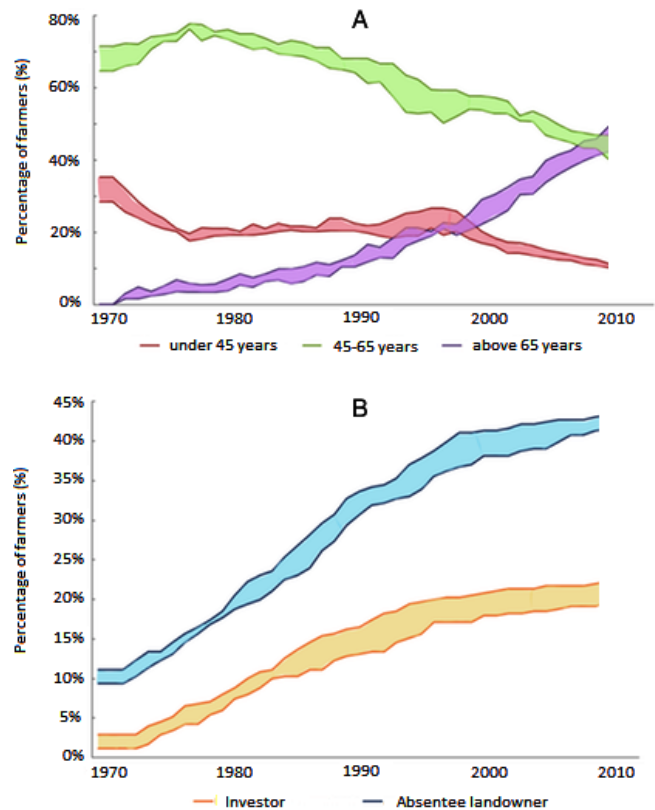
We ran the ABM for the 41-year simulation period (1970–2010) to get the landscape management data for the simulation period. We then used that output from the ABM as input to the SWAT and report water quality model output as the average of the 25 SWAT runs over the simulation period (1970–2010) (Figs. 3, 4). Regarding the linkage of ABM and SWAT, for each year, farmers' decisions on conservation practice adoption are used to modify several SWAT input files. Once information on all farmer adoption statuses 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 the SWAT in the Sandusky watershed file. Abstract grid cell characteristics are assigned to Sandusky watershed locations by the smallest computational unit of the SWAT, HRUs. The 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 the SWAT are all in ASCII text format, making it easy to interface with the ABM, and this link is supported with the MatLab programming language. Because ABM results represent adoption statuses for each individual farmer in every period, it is not appropriate to represent the result as averages across multiple simulations. For that reason, results (Figs. 3, 4) are reported as simulation envelopes that contain the results from all 25 simulations. Appendix 2 has further details on how we link ABM with the SWAT.

RESULTS

Impacts of Land Tenure Change

Model results are consistent with observed trends in land tenure (Appendix 1). For example, U.S. agriculture has undergone a structural change of land tenure with a decline in full ownership and an increase in nonoperator ownership and large-scale operations (Wunderlich 1993, Duffy 2008). To represent this, we assume that, after age 65, traditional farmers switch to be nonoperator owners or sell their land to business-oriented or supplementary farmers. This leads to an increase in the percentage of large business-oriented farms and smaller supplementary farms, at the expense of traditional farms (Fig. 3A). We assume supplementary and business-oriented farmers to not change their types as they age. This obviously also leads to an increase in the

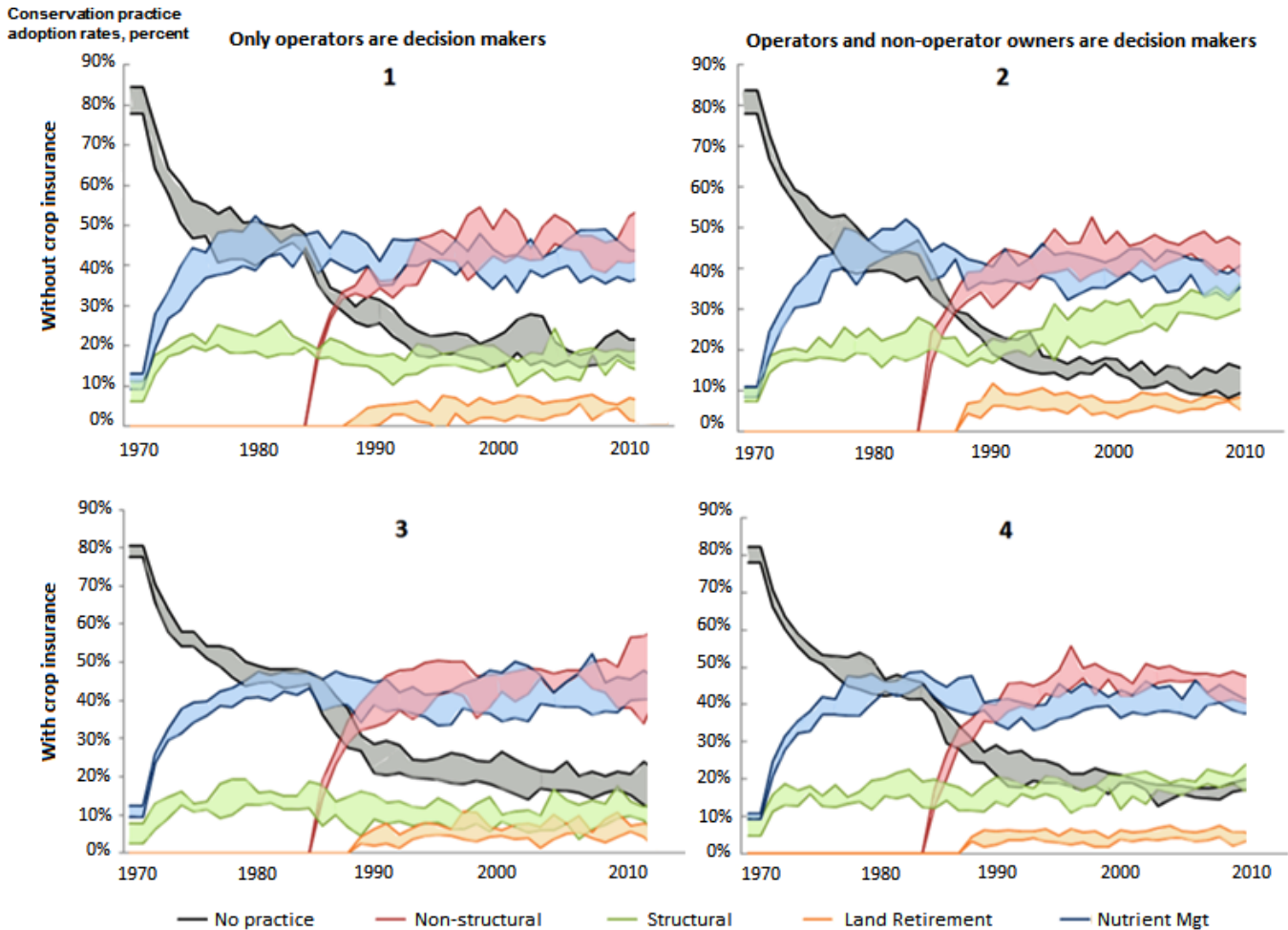
Fig. 3. Percentage of farmer types in the total farmer population (A), percentage of nonoperator owners in the total farmer population throughout the simulation period (B). Twenty-five ABM simulation runs fall between two lines of the same color.



percentage of nonoperator owners among the farmer population (Fig. 3B), as well as production area under their control (Appendix 1 for details).

Because different farmer types have different tendencies toward adoption decisions, as the composition of types changes, the emergent adoption pattern evolves. For example, when nonoperator owners are not involved in decision making and crop revenue insurance is not available (Scenario 1), the percentage of farmers who adopt nutrient management and structural practices shows a significant increase over time, with a more pronounced increase in nutrient management adoption (Fig. 4). Because nonstructural practices, such as no-till technologies were not available until the mid-1980s, these practices were not present in the model until then. Coupled with evolved composition of farmer types, this resulted in a significant increase in adoption over the next 10 years. Land retirement, on the other hand, was minimally adopted, due mostly to the requirement for enrolled land to be retired for 10 years, with penalties for noncompliance (Fig. 4). In Scenario 2, when nonoperator owners take a more active role, they tend to have higher adoption rates for structural

Fig. 4. Comparison of conservation practice adoption rates under the plausible scenarios such as crop revenue insurance and nonoperator owner involvement in decision making. Twenty-five ABM simulation runs fall between two lines of the same color.



practices and land retirement. Average adoption rate for structural practices increased from 17% to 23% when nonoperators are active decision makers (Fig. 4).

Impacts on Water Quality

In Scenario 2, by the end of the simulation period, 50% of the nonoperator owners are the decision makers for conservation practice adoption (Table 4). The positive attitudes of nonoperator owners toward conservation practices results in higher adoption rates for structural practices and enrollment in land retirement programs reducing TP loads (Figs. 5, 6). In Scenario 2, results for sediment, organic P (OrgP), and DRP load are similar, with the improvement more pronounced for sediment because nonoperator owners favor structural practices, which are more effective in reducing the sediment load.

Impacts of Agricultural Policy Change

Options under consideration for the U.S. Farm Bill include replacing commodity payments with subsidized crop revenue insurance premiums to create stronger incentives for farmers to enroll in crop revenue insurance. In these simulations, conservation

Fig. 5. Comparison of average annual total phosphorus (TP) load in kilograms for Scenarios 1–4 representing the average of 25 ABM simulations linked to SWAT. Whiskers show minimum and maximum values, whereas the box shows 25, 50, and 75 percentiles.

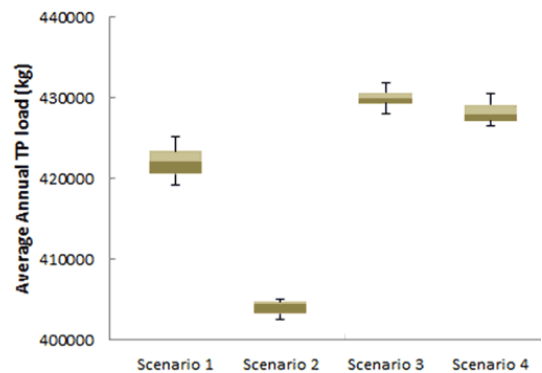
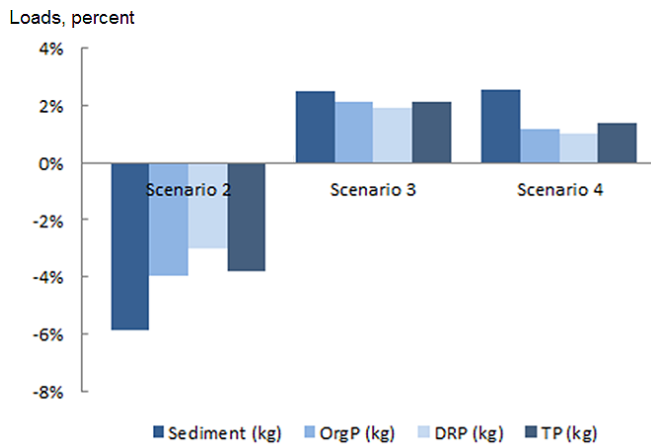


Fig. 6. Comparison of Baseline, Scenario 1, with Scenarios 2, 3, and 4 in terms of sediment, organic phosphorus (OrgP), dissolved reactive phosphorus (DRP), and total phosphorus (TP) loads, representing the average of 25 ABM simulations linked to SWAT.



compliance is not required for crop revenue insurance enrollment. The effects of the insurance program can be seen by comparing Scenarios 1 and 3 (Table 3). The insurance protects farmers from both market and crop yield fluctuations, and because the payments are based on production area, farmers appear encouraged to increase their production area. Under this scenario, nutrient management plans increase, followed by a steep increase in nonstructural practices when these practices become available (Fig. 4). When crop revenue insurance premiums are subsidized, structural practice adoption and land retirement enrollment rates decrease both for operators and nonoperator owners, whereas enrollment in nutrient management plans increase. The ABM results also indicate a decrease in land retirement and structural practices regardless of the nonoperator owner involvement (Scenarios 3 and 4), which leads to a more homogenous conservation landscape (Fig. 4). With subsidized crop revenue insurance, average TP, OrgP, DRP, and sediment loads are higher (Figs. 5, 6), primarily due to the reduction in structural practices and land retirement.

However, a moral hazard can result if farmers use crop insurance as an incentive to underfertilize their crops to receive indemnities (Sheriff 2005) or to introduce practices or enterprises that they might avoid without crop insurance, i.e., planting corn or soybeans where adequate seasonal rainfall is uncertain. 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 (Keeton et al. 2000).

Modifications in Agricultural Policy: Closing the SES Model Loop

In our modeling framework, we built plausible scenarios that follow the latest U.S. Farm Bill discussions of providing federally subsidized crop revenue insurance rather than commodity production subsidies (Scenario 3) and assumed conservation compliance is not tied to crop revenue insurance (Stubbs 2012).

The model results suggest slightly higher TP, OrgP, DRP, and sediment yields (Fig. 6) under this scenario compared with the baseline (Scenario 1), attributed to the reduction in structural practice and land retirement enrollment (Fig. 4).

To close the loop in the SES model where social and environmental systems have reciprocal feedbacks, we add a policy modification step and allow farmer agents to respond to the new set of incentives, sanctions, and regulations. For this purpose, we linked conservation compliance to crop revenue insurance and evaluated different conservation compliance definitions. There have been discussions of strengthening and expanding conservation compliance requirements (Perez 2007, American Farmland Trust 2011, Cox et al. 2011). So, in our framework, we tested three conservation compliance definitions where farmers can; (a) adopt nonstructural practices; (b) implement structural practices; or (c) choose either nonstructural or structural practices (Table 5). Although the U.S. General Accounting Office (GAO 2003) has emphasized that compliance enforcement needs updating and upgrading, we assume 100% adherence to conservation compliance.

We observe higher nutrient runoff; especially the bioavailable DRP when farmers choose nonstructural practices as conservation compliance requirements (Fig. 7), a common practice for economic reasons. However, if conservation compliance requirements are expanded to include nutrient management with a focus on promoting structural practices, linked model results indicate the effectiveness of structural practices in reducing nutrient delivery from agricultural landscapes (Fig. 7).

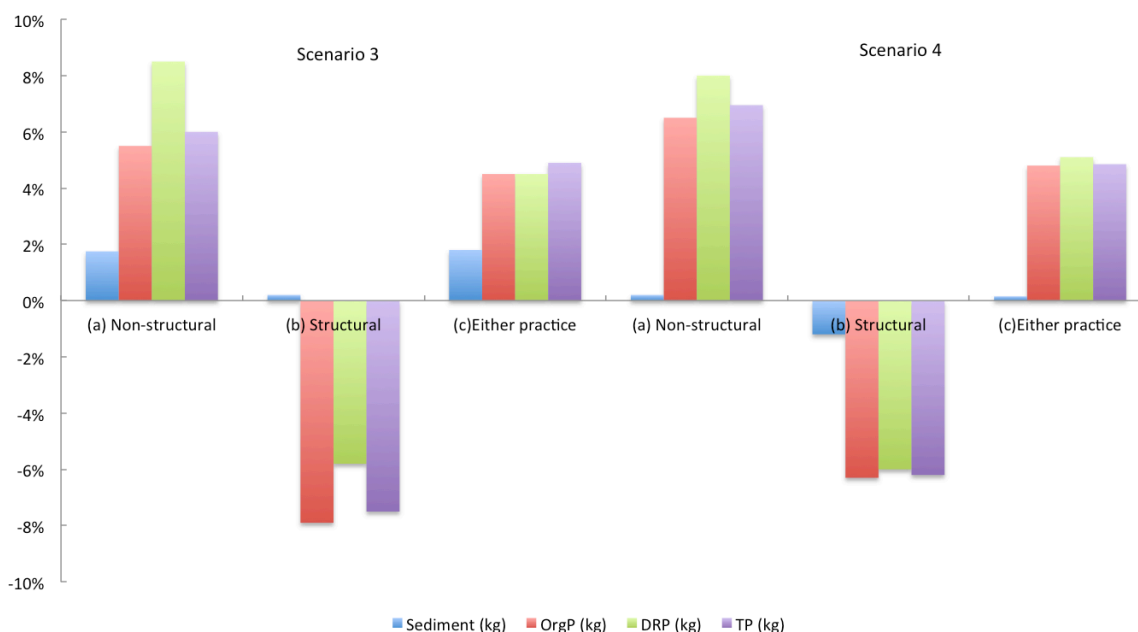
POLICY IMPLICATIONS

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 linked model distinguishes among nutrient management plans that reduce fertilizer application, nonstructural 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.

Sandusky Watershed represents a typical watershed of the Corn Belt region. Therefore, the conclusions of the study are relevant for other Corn Belt watersheds. However, differences in location-specific environmental drivers and processes such as land cover, soil type, and climatic conditions, and their effects on the transformation of N and P need consideration.

By investigating the water quality impacts of four plausible scenarios, we demonstrate the importance of the understudied nonoperator owners and the possible effects of new policies related to crop revenue insurance. Our results indicate maximum load reductions, especially sediment load reductions, occur when nonoperator owners are involved in the decision-making process and when crop revenue insurance is not offered in lieu of commodity payments tied to compliance (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. Our results also point to

Fig. 7. Change in water quality metrics when conservation compliance is linked to crop revenue insurance programs as a requirement.



the positive influence of nonoperator owner involvement and highlight the importance of devising innovative policies to reach out and inform nonoperator owners about the existing water quality problems, possible solutions, and their role in implementing them.

When subsidized crop revenue insurance is promoted as a risk management program, in the absence of conservation compliance, it incentivizes farmers, regardless of type, to increase production area, even including areas that are highly erodible or wetlands. This then results in a more homogenous conservation landscape that yields slightly higher loads (Scenarios 3 and 4) due to a decrease in structural practices and land retirement enrollment. In contrast, our results show that if crop revenue insurance is tied to conservation, particularly structural practices, sediment and nutrient loads decrease. A recent survey of Iowa farmers reveals support for expanding conservation compliance requirements to include nutrient management as well as erosion control (Arbuckle 2010). Moreover, because structural practices are visible by remote sensing, compliance enforcement 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 the SWAT that assume feasible levels of implementation (Arabi et al. 2008, Bosch et al. 2013). The adoption rates of conservation practices are also consistent with the observations (Smith and Goodwin 1996, Bosch and Pease 2000, Goodwin and Smith 2003, Duffy 2008, Petzelka et al. 2009, Nassauer et al. 2011) and feasible levels of implementation used by other SWAT models (Arabi et al. 2008, Bosch et al. 2013). Collectively, these results point to the need for innovative policies that promote greater adoption of conservation practices and for

attaching conservation compliance to crop revenue insurance with perhaps new definitions of conservation compliance. 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. 2013).

Responses to this article can be read online at:
<http://www.ecologyandsociety.org/issues/responses.php/6597>

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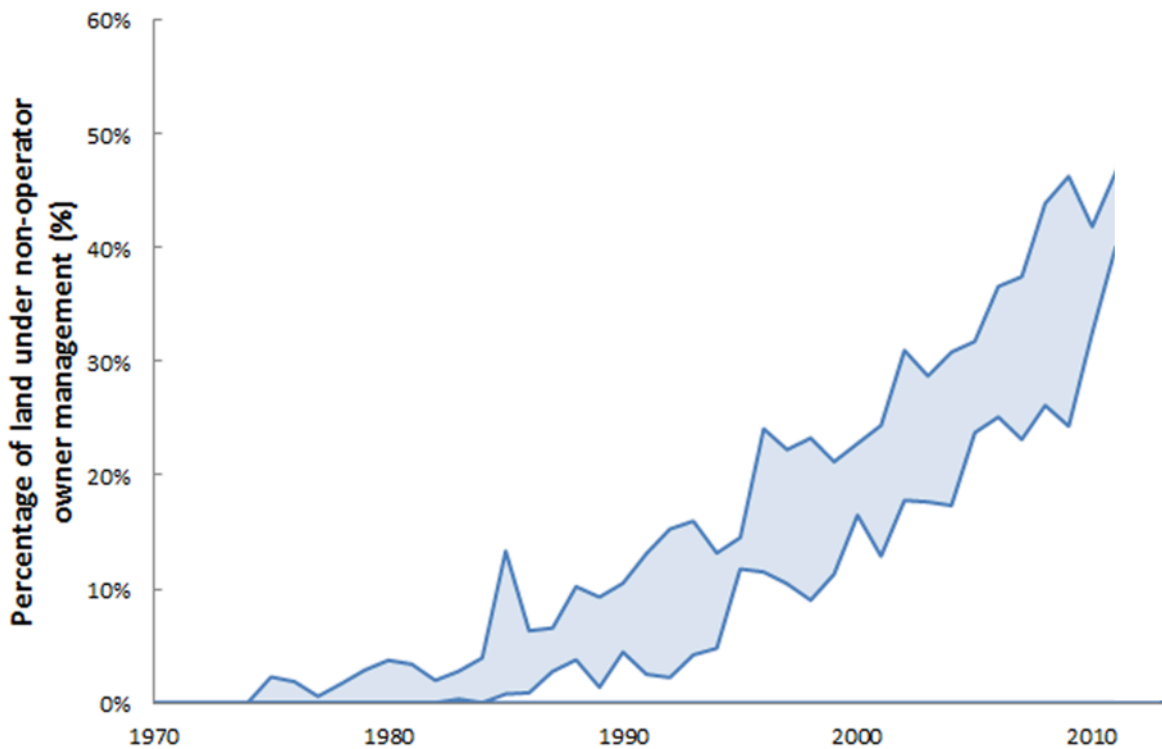
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24 farmers have different land areas, crop yields, and future crop price and yield expectations. The
 25 farmers also maintain network connections to other farmers and government agencies with
 26 varying strengths. In most ABMs, agents are defined by their spatial location (Brown et al.
 27 2005); however, in this model the farmer agents do not change their location as time progresses.
 28 A farmer's location on the grid determines the spatial neighbors of that farmer. Some of the
 29 farmer attributes do not change during the simulations, such as the percentage of income derived
 30 from farming and connectedness to the network. However, as farmers age in every simulation
 31 run, some of them change their types. For example, after age 65 some of the traditional farmers
 32 leave the farming business and switch to be non-operator owners, or sell/rent their land to
 33 business-oriented or supplementary farmers. We assume supplementary and business-oriented
 34 farmers to not change their types as they age. This obviously also leads to an increase in the
 35 percentage of non-operator owners among the farmer population (Figure 3B, main text), as well
 36 as production area under their control (Figure 1-2).



37

38 **Figure 1-2: Percentage of land under non-operator owners' control increases. 25 ABM**
 39 **simulation runs fall between two lines of the same color.**

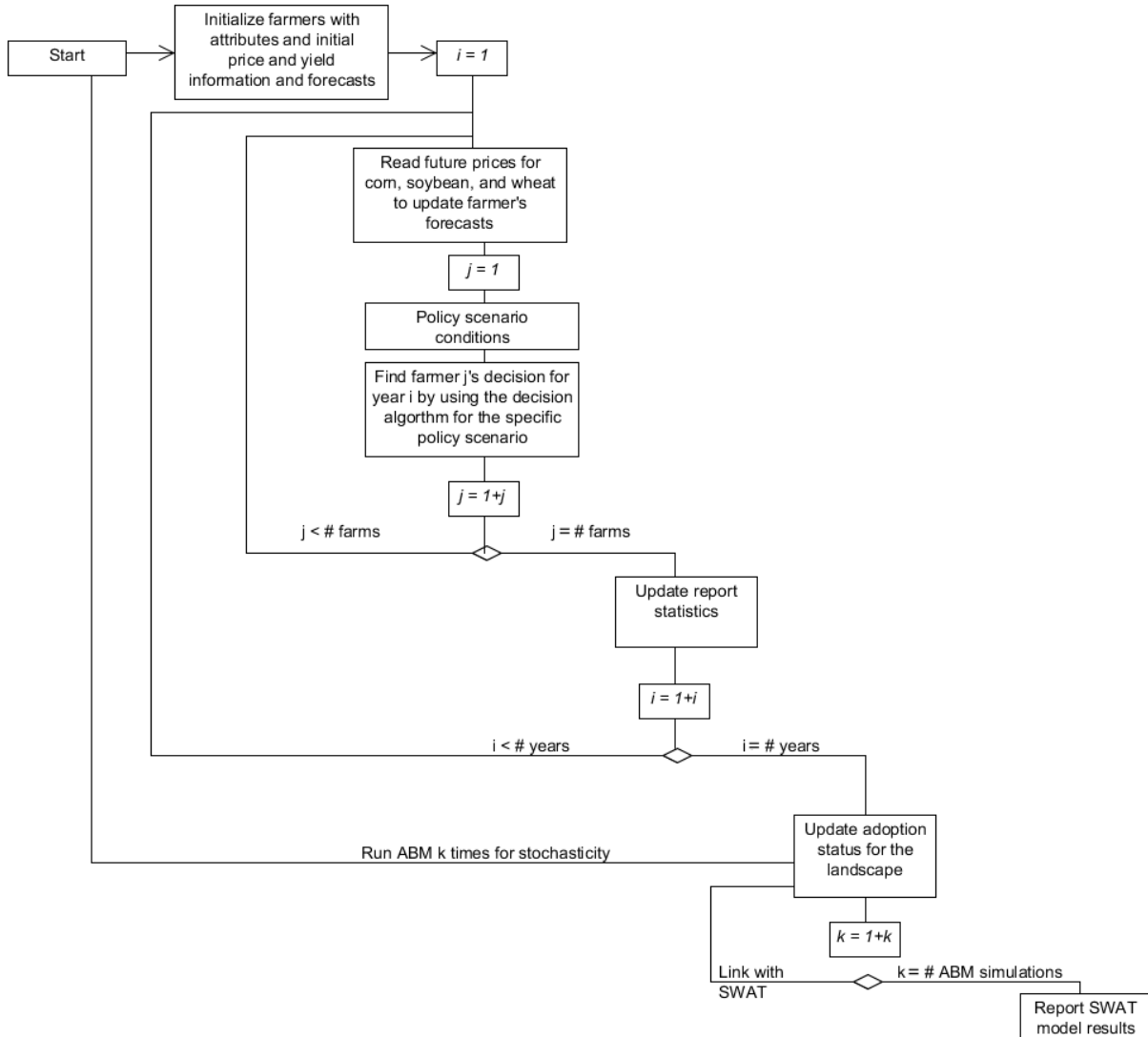
40

41 **Process overview and scheduling**

42 The diagram in Figure 1-3 gives the process overview and scheduling of the model. For each
 43 simulation, farmers annually update their adoption decisions under the influence of agricultural
 44 policy, changing land tenure dynamics, their preferences, and their neighbors' decisions. The

45 agent loop is equally important as the landscape update, which is the key mechanism that affects
 46 the water quality component of the coupled system (Figure 1-3).

47
 48 During the simulation phase, each farmer agent is provided with a behavioral model that
 49 guides the decision-making process. With the behavioral model and farmer attributes, the farmer
 50 agents decide whether to adopt a specific conservation practice or not. The results from the
 51 farmer agent decision update the management landscape.



52

53

Figure 1-3: Process overview and scheduling for a model run.

54 The decision-making algorithm consists of inputs from profit generated from the agricultural
 55 activity, enrollment in government programs, the farmer preferences for conservation practices
 56 depending on farmer type, and sometimes information from their spatial neighbors and other
 57 farmers in their social network. Every agent in the model uses the same decision algorithm with
 58 different parameters due to the heterogeneity of agents' preferences. Depending on their tenure

59 arrangements, decision makers could either be the owner or the tenant. Because of this
60 flexibility, this model is also used to investigate the possible impact of growing proportions of
61 farmland owned by non-operator owners and their influence on conservation decisions.

62 **Design Concepts**

- 63 • **Emergence:** The agricultural landscape of conservation practices emerges from the
64 individual decisions of farmers, which are informed by their economic activities, social
65 and spatial networks, preferences, and policies that they follow.
- 66 • **Adaptation:** Farmers adapt and update their decisions depending on price and yield
67 expectations for future years. Depending on their types, farmers have differing network
68 connectivity, which influences their conservation decisions. Farmers update their
69 conservation practice adoption decisions by interacting and observing other farmers and
70 due to changes in the agri-environmental policies and markets.
- 71 • **Prediction:** Farmers have expectations for future yields, crop prices, and rental rates
72 offered for land retirement programs by using the historic information. Farmers use these
73 forecasts for their adoption decisions every year.
- 74 • **Sensing:** Farmers know their production yields every year and their profit from that
75 year's production. Farmers also know whether their neighbors, both in their spatial and
76 social networks, adopted a practice.
- 77 • **Interaction:** Farmers interact to exchange information on adoption of conservation
78 practices. Every farmer type has varying network strength and connectivity.
- 79 • **Stochasticity:** The model has stochasticity built in several ways. Conservation practice
80 selection decision is stochastic, as the farmers are most likely to select the highest ranked
81 practice. However, as the farmers are not modeled as purely rational decision makers, the
82 highest ranking conservation practice is not always chosen. Moreover, to better represent
83 the decision environment, the submodels also have stochastic parameters to represent the
84 uncertainty and variability observed in nature. By using the agent decision-making
85 algorithm over the model run of 41 years, each agent has a sequence of conservation
86 practices adopted and resultant landscape changes.
- 87 • **Collectives:** Farmers are connected in two ways. In the spatial networks, farmers are
88 connected to their immediate spatial neighbors. In social networks, farmers are connected
89 to other farmers with varying strengths and connectivity. Network connections allow
90 farmers to observe whether other farmers in their network have adopted a conservation
91 practice.
- 92 • **Observation:** The model produces the conservation adoption patterns at the end of each
93 simulation.
- 94 • **Learning:** Bayesian inference used for updating price and yield expectations of farmers
95 is a form of learning.

96 **Initialization**

97 At the beginning of each model simulation, 351 farmers are created to represent the total of
98 approximately 7500 farmers in the Sandusky watershed. Because the ABM is linked to SWAT,
99 properties of SWAT are decisive. In SWAT, there are 351 agricultural HRUs, smallest
100 computation components; therefore in ABM we have 351 agents. The initial agent characteristics
101 are given in Table 1-1. The farmer typology built in Daloğlu et al. (2014) informs the farmer
102 preferences for conservation practices typologically.

103
104
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109

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 1-2).

110

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

111

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

<i>Policy-relevant farmer characteristics</i>	Traditional	Supplement ary	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 1-2: 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.

123

124 At each time step, which can be interpreted as a year, every farmer makes decisions
 125 regarding conservation practice adoption. Farmers can choose to adopt none or a combination of
 126 the practices. The practices available to farmers tackle the non-point source pollution by
 127 controlling the pollution source (nutrient management), trapping the soil particles before they
 128 reach water bodies (structural practices, i.e, filter strips), promoting long-term conservation
 129 covers (land retirement, CRP), and reducing soil disturbance (non-structural practices, i.e.,
 130 conservation tillage and no-till systems) (Table 1-3).

131
 132 Farmers’ adoption decisions have temporal consequences. That is, if a farmer enrolls in land
 133 retirement programs and signs a CRP contract, the commitment is a multi-year commitment,
 134 where in case of contract breach a penalty has to be paid. Similarly, adoption of structural
 135 practices such as filter strips requires a multi-year commitment as well because farmers receive
 136 economic incentives from the government. Adoption decisions of non-structural practices and
 137 nutrient management plans, however, are made on a yearly basis, and do not entail a penalty. In
 138 this model, we assume every farmer to be eligible for land retirement enrollment and every
 139 farmer who adopts structural practices to be eligible for 50% cost share incentive provided by the
 140 government.

141
 142 Adoption of structural and non-structural practices, land retirement enrollment, and
 143 participation in nutrient management plans are voluntary decisions. Each farmer determines
 144 whether to enroll in land retirement programs (such as CRP), to adopt certain conservation
 145 practices, or choose not to adopt any practice, depending on their farm’s overall objective. The
 146 overall objective is a combination of multiple objectives that include the profitability of the
 147 business, attitudes towards different conservation practices depending on farmer type, and
 148 influences of the spatial and social network. These objectives, each represented by a specific
 149 function, are combined in a single function that represents the overall utility of the farmer
 150 (Equation 1.1).

151
 152 Every period, the overall utility to a farmer for every conservation practice adoption option
 153 (e.g., no conservation practice at all, single conservation practice adoption or a combination of
 154 conservation practices) is calculated. The list of conservation practices and their combinations
 155 are given in Table 1-3.

156

<i>i</i>	Conservation practice
0	None
1	Non-structural practices (no-till)
2	Structural practices (filter strips)
3	Land retirement programs (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

157 **Table 1-3: Available conservation practices and their combinations to farmers.**

158 The decision algorithm combines all of the available information to the farmer and integrates
 159 for the adoption decision. This mechanism includes the profit generated from agricultural
 160 production, availability of government programs and policies, influence of the farmers'
 161 neighbors and farmers' intrinsic attributes. These are all combined within a utility function,
 162 $F_{\text{decide}}(i,j)$ for the conservation practice combination i and farmer j , which is a combination of 4
 163 sub-functions (Equation 1.1).

164
 165 Once the farmer calculates utility of each conservation practice, the values of utility are
 166 transformed into choice probability using logit model. Logit framework allows us to incorporate
 167 both uncertainty in decision-making and the bounded rationality of the farmers as it assigns
 168 probabilities to different options, where the probability of an inferior option could be non-zero
 169 (Equation 1.2).

$$171 \quad F_{\text{decide}}(i,j) = b_1 F_{\text{econ}}(i,j) + b_2 F_{\text{profile}}(i,j) + b_3 F_{\text{social}}(i,j) + b_4 F_{\text{spatial}}(i,j) \quad (1.1)$$

$$172 \quad \text{Selection_probability}(i,j) = e^{F_{\text{decide}}(i,j)} / \sum e^{F_{\text{decide}}(i,j)} \quad (1.2)$$

173
 174
 175 In every period, for every farmer (j), $F_{\text{decide}}(i,j)$ is calculated for all possible combinations of
 176 the conservation practices (i). In this function $F_{\text{econ}}(i,j)$ represents the agricultural profit generated
 177 with production, $F_{\text{profile}}(i,j)$, the intrinsic attributes of the farmer towards the given conservation
 178 practice combination, which is determined by its type, $F_{\text{social}}(i,j)$, the influence of the farmer's
 179 social network and $F_{\text{spatial}}(i,j)$, the influence of the spatial network, i.e. the farmer's neighbors.
 180 $F_{\text{social}}(i,j)$ and $F_{\text{spatial}}(i,j)$ are also influenced by the farmer typology. The weights (b) for each
 181 component are informed by the farmer typology and determined using a matrix method
 182 (Appendix C). One of the important modeling choices that incorporate the differences between
 183 the different farmer types is the assignment of the weights (b). These weights are assigned in
 184 such a way that the farmer types whose income source is solely farming, and the types with
 185 profit maximizing mindset (i.e., business-oriented farmers) put more emphasis to $F_{\text{econ}}(i,j)$, while
 186 farmers with more connection to the landscape (i.e., traditional farmers) put more emphasis on
 187 $F_{\text{profile}}(i,j)$. Because non-operators do not live in the county in which they own land, or they do
 188 not have a farming background, they are not connected to the information networks have no b
 189 values for F_{spatial} and F_{social} . More details on each component of the $F_{\text{decide}}(i,j)$ function is given in
 190 subsequent sections.

191 192 *1. Agricultural Profit Dynamics, $F_{\text{econ}}(i,j)$*

193 Farmers generate revenue by enrolling in land retirement programs and allocating land to the
 194 CRP or by crop production. If the farmer enrolls in land retirement programs, a fixed payment
 195 depending on the farm size and CRP rental rate is paid at the beginning of each year the farmer
 196 allocates land for retirement programs. There will be no further agricultural revenue generated
 197 from production for the farmer in that case, and that payment will be equal to $F_{\text{econ}}(i)$. Otherwise,
 198 the farmer's expected earning is calculated using the farm size, the price and yield of the crop
 199 that the farmer expects to get, governmental support for enrolling agricultural programs, and
 200 costs associated with production and conservation practice adoption. Single period profit
 201 function of a farmer producing a single crop is written below in two forms representing policy
 202 scenarios of with crop revenue insurance and without crop revenue insurance. In our models, the
 203 commodity payments such as direct payments are not represented explicitly.

204 $F_{econ}(i,j) = p(A-F)Y(z) + gF + rA - c$ (1.3)
 205 without crop revenue insurance program

206
 207 $F_{econ}(i,j) = p(A-F)Y(l, z) + gF + rA - c - p(l)$ (1.4)
 208 with crop revenue insurance program

209
 210 where $F_{econ}(i,j)$ is profit, p is farmer's expected crop price (corn, soybean or winter wheat), A
 211 is the production area (acres), Y is the farm's expected effective yield per acre, g denotes per acre
 212 economic incentive associated with structural practice adoption, F is total land allocated for
 213 structural practices, r is the CRP per acre payment to the farmer, z is a measure of fertilizer input
 214 on the farm, c is the total cost of production including cost of conservation practice adoption, p is
 215 the per acre premium rate for crop revenue insurance, and l is the level of insurance purchased.
 216 In this model we assume 75% coverage level for revenue insurance.

217
 218 Agricultural crop production generates revenue (market price multiplied by production size
 219 and expected yield). Agricultural profit dynamics also include government payments (such as
 220 payments to incentivize structural practice adoption), insurance indemnities if enrolled in crop
 221 revenue insurance program, and cost production including maintenance, input, and labor costs as
 222 well. To represent the agricultural production cost, a current farm budgeting model developed by
 223 Ohio and Iowa State Universities is adopted and adjusted to previous years using historic
 224 consumer price index.

225
 226 Practices that farmers adopt influence the size of the production area and expected yield;
 227 therefore they affect the expected agricultural profit. For example, when a farmer implements
 228 structural practices, the size of the filter strip is subtracted from the total size of the farm.
 229 Moreover, with nutrient management plans the expected yield decreases. Therefore, F_{econ} value
 230 for each conservation practice available in Table 1-3 is calculated separately.

231
 232 Expected Price and Yield: Expected prices and yield values heavily influence the resulting
 233 farm profit. These parameters are based on previous year's price and yield values and updated by
 234 each farmer influenced by their farmer type.

235
 236 In the model, for actual crop yields and prices historical values are used (available at
 237 <http://usda.mannlib.cornell.edu> and <http://www.farmdoc.illinois.edu>). In any given time, based
 238 on the actual previous crop yields and prices, farmers use Bayesian inference to form price and
 239 yield expectations. While a farmer's yield expectation is in the form of a point prediction, a
 240 probability distribution is formed for crop prices by taking the price expectation as the mean.
 241 Bayesian inference is a statistical approach used to update farmer's existing expectations against
 242 observed values of crop price and yield. The Bayesian inference allows farmers to be connected
 243 to agricultural markets and at the same time 'learn' with experience. Moreover, with Bayesian
 244 inference, we can represent the heterogeneity of farmers by setting different parameters for
 245 updating their priors for crop prices and yields depending on the farmer type. For example,
 246 traditional farmers are more anchored so that realization of outliers do not affect their
 247 expectations much while business-oriented farmers are better at following the fluctuations in the
 248 market.

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

253

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

255 Farmer typology developed informs $F_{profile}$ values for each farmer type and conservation
256 practice (Daloğlu et al. 2014). $F_{profile}(i,j)$ lets farmers to adopt economically infeasible practices
257 because of their attitudes and preferences such as being a good citizen of the environment (Table
258 1-4). The synthesis of the adoption literature supports the $F_{profile}$ values, which change for every
259 practice and every farmer type. In other words, $F_{profile}$ is the variable representing the socio-
260 economic attributes of the agents including the source of income, impact of farm size and land
261 tenure arrangements in adoption decisions (Table 1-5).

Farmer Type	Land Management Attitudes
Traditional	<ul style="list-style-type: none"> - favor non-structural practices because of potential reduction in labor requirements → high $F_{profile}$ values - financial investment requirement leads to lower adoption rates for structural practices → low $F_{profile}$ values - secure income provided by land retirement programs is appealing → high $F_{profile}$ values
Supplementary	<ul style="list-style-type: none"> - favor non-structural practices because of potential reduction in labor requirements → high $F_{profile}$ values - substantial off-farm income leads to higher adoption rates for structural practices → high $F_{profile}$ values - secure income provided by land retirement programs is appealing → high $F_{profile}$ values
Business-oriented	<ul style="list-style-type: none"> - favor non-structural practices because of potential reduction in labor requirements → high $F_{profile}$ values - long-term plans and dependence on soil quality leads to higher structural practice adoption → high $F_{profile}$ values - focused on profitability, leading to low enrollment rates in land retirement programs → low $F_{profile}$ values
<p data-bbox="248 1329 529 1360">Non-operator owner</p> <p data-bbox="188 1367 583 1507"><i>Absentee landowners</i>: own the land but do not reside on or operate it (Petrzelka et al., 2011)</p> <p data-bbox="188 1514 583 1612"><i>Investors</i>: describe themselves as never having farmed (Nassauer et al., 2011).</p> <p data-bbox="196 1619 574 1650">Mutually exclusive subtypes.</p>	<ul style="list-style-type: none"> - favor non-structural and structural practices because of potential contribution to increased water quality → high $F_{profile}$ values - absentee landowners favor land retirement programs → high $F_{profile}$ values - investors have lower enrollment rates for land retirement programs → low $F_{profile}$ values

Table 1-4: Farmer typology and its influence on $F_{profile}$ values (adapted from Daloğlu et al. 2014)

266 The F_{profile} value for each farmer type and conservation practice is determined using
 267 prioritization matrix method and the synthesis of the adoption literature (Table 1-4, Daloğlu et al.
 268 2014). The prioritization matrix, also known as criteria matrix, provides a way of sorting a
 269 diverse set of items into an order of importance. It also enables their relative importance to be
 270 identified deriving a numerical value of the importance of each variable.
 271

i	F_{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

272 **Table 1-5: F_{profile} values**

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

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

281
 282 Hamill and Gilbert (2009) base their network structure on the analogy of social circles. In
 283 the social network, agents are permitted to have links with other agents who can reciprocate. The
 284 agent population is divided into two circles with small and large social reaches. This network
 285 structure allows representing individuals who are more connected than rest of the population by
 286 placing them in the social circle that has larger social reach. When the social reach is larger, the
 287 size of the personal network would be larger as well. In our model, business-oriented agents are
 288 located in a social circle that has larger social reach than supplementary and traditional farmer
 289 agents which results in increased number of connections for business-oriented farmers. This
 290 network structure also allows us to connect business-oriented farmers more to other business-
 291 oriented farmers. Non-operator owners (investors and absentee landowners) are initially not
 292 connected to the social network. However, to demonstrate the potential impacts of information
 293 networks on non-operator owner decision, we simulate a scenario that assumes absentee
 294 landowners connect to the social network whereas investors connect to both spatial and social
 295 networks as they live close to the farmland that they own. Through the information networks
 296 (spatial and social networks), farmers observe their neighbors' adoption decisions.

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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 1-2. F_{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.

$$F_{\text{spatial}}(i,j) = \text{Neighbors}(i,j) / \Sigma \text{Neighbors}(i,j) \quad (1.5)$$

where $\text{Neighbors}(i,j)$ is the number of Moore neighbors that adopted the conservation practice combination j . 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_{social} represents the percentage of neighbors adopting a certain conservation practice. Similarly, F_{social} is calculated for every possible conservation practice listed in Table 1-3. 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:

$$F_{\text{social}}(i,j) = \text{Network}(i,j) / \Sigma \text{Network}(i,j) \quad (1.6)$$

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, 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.

337 **Policy Scenarios**

338 We simulated four scenarios intended to form a bridge between the science of land
 339 management and policy development (Table 1-6). The primary goal of these plausible policy
 340 scenarios is to be prospective and informative rather than projective or prescriptive of the future
 341 (Nassauer and Corry, 2004).
 342

		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	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

343 **Table 1-6: Land management strategies tested under different agricultural policy and**
 344 **structure scenarios**

345 The *Baseline scenario* (1) represents a simplified version of existing land tenure where operators
 346 (traditional, supplementary and business-oriented farmers) are responsible for conservation
 347 practice adoption decisions and non-operator owners have no involvement in production and
 348 conservation decisions. In this scenario existing crop insurance programs are not represented and
 349 crop revenue insurance is not offered in lieu of commodity payments.
 350

351 The *Non-operator owner involvement scenario* (2) simulates the potential impact of non-operator
 352 owners being more involved in decisions about conservation practice adoption. This premise
 353 follows recent research that demonstrated positive attitudes of non-operator owners for certain
 354 conservation practices (Petzelka et al., 2009; Nassauer et al., 2011). In this scenario, we assume
 355 natural resource agencies and NGOs reach out to non-operator owners and effectively inform
 356 them about existing and available conservation practices.
 357

358 The *Crop revenue insurance scenario* (3) follows the latest US Farm Bill discussions about
 359 providing federally subsidized crop revenue insurance rather than commodity production
 360 subsidies. This scenario does not assume that conservation compliance is required for land to be
 361 eligible for crop revenue insurance. In this scenario, only operators are decision makers and they
 362 purchase crop revenue insurance at 75% coverage level for all the land that they manage
 363 including the rented land. Crop revenue insurance provides an accessible risk management tool
 364 to operators and at the same time encourages an increased production area.
 365

366 The *Crop revenue insurance with non-operator owner involvement scenario* (4) presents the
 367 plausible changes both in land tenure and policy by assuming non-operators owners as active
 368 decision makers when crop revenue insurance is offered in lieu of commodity payments. Crop

369 revenue insurance provides a safety net and indirectly motivates both operators and non-operator
370 owners to increase their production area.

371
372 Certain model parameters are changed depending on the policy scenario being investigated.
373 Appendix 3 has initial model parameter values and how we change these values for different
374 scenarios.

375 **Verification and Validation**

376 ABMs are informative rather than predictive and useful in investigating plausible scenarios
377 and their potential consequences. Model verification and validation are important steps that
378 contribute to the validity of the developed ABM. Model verification is the process of
379 determining whether the software implementation correctly represent model processes (Ormerod
380 and Rosewell, 2009). As the ABMs are powerful in illustrating the phenomena of emergence, it
381 is particularly difficult to determine whether an unexpected result is due to an error in the model
382 implementation and execution (Galan et al., 2009). Therefore the verification stage of the model
383 is particularly important. For the verification of the model, where the general aim is to make sure
384 that the model does not have programming errors, we built the model in several levels with
385 increasing complexity following unit testing approach (Linck and Frohlick, 2003) (Figure 1-4).
386 The unit testing approach suggests writing some test code to exercise the program
387 simultaneously writing the complete model code. The purpose is to construct the model in small,
388 self-contained units and check the results and make sure they align with expected results.

Level 1 Isolated World
- 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).
Level 2 Information Networks
- 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)
Level 3 Information Networks + Policy and Land Tenure Changes
- 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.

389

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Figure 1-4: Levels of ABM as a verification tool

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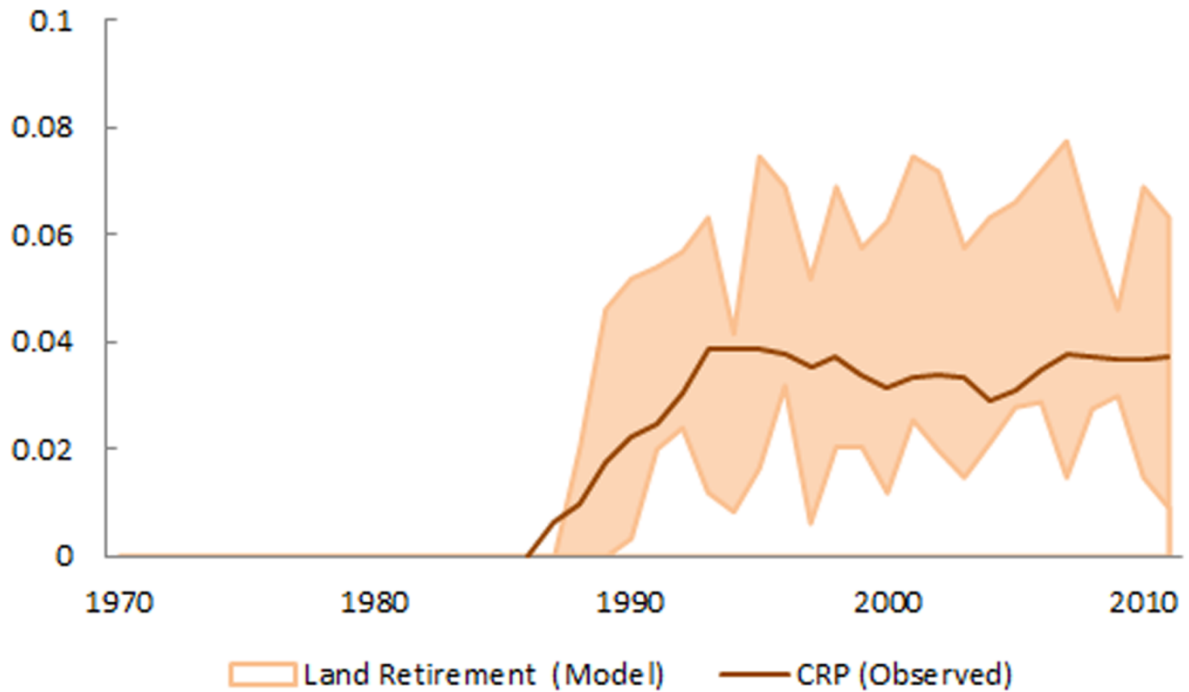
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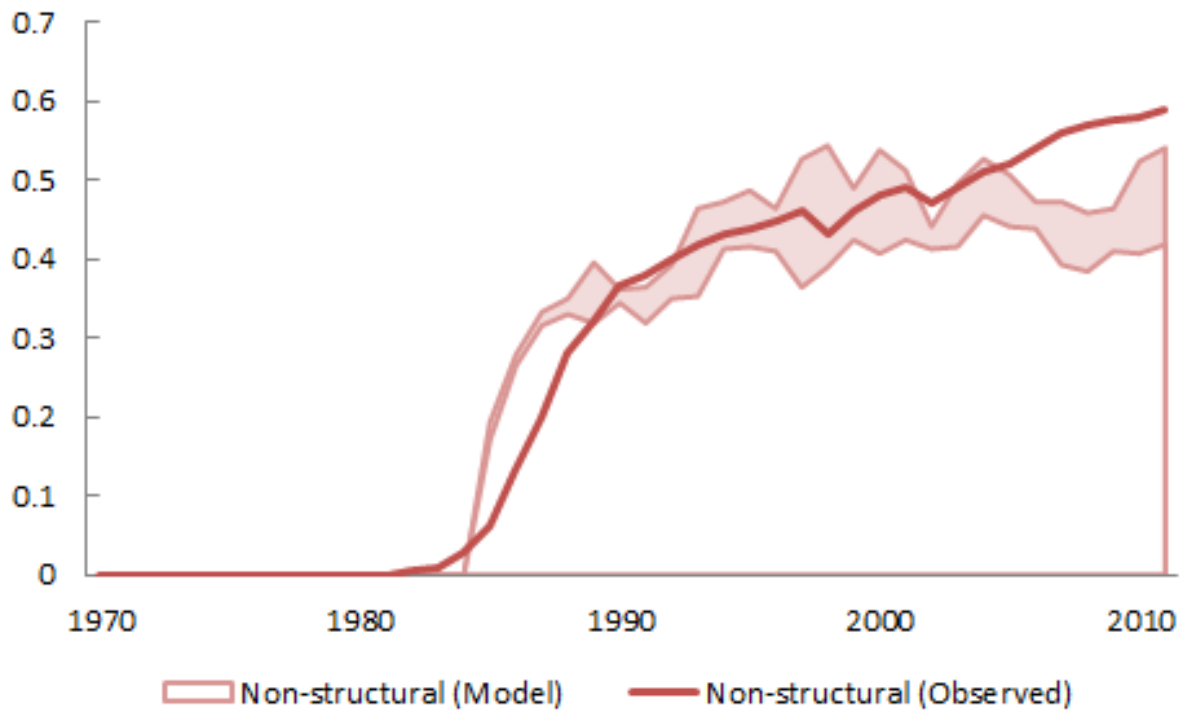
Model validation is the process of assessing the degree of which the model is accurately representing the real world interactions and dynamics (Ormerod and Rosewell, 2009). For the farmer typology, we synthesized the literature of conservation practice adoption (Daloğlu et al., 2014). Therefore, for model validation we used the documented trends in the Corn Belt. Synthesis of numerous studies conducted in the Corn Belt provides spatially and temporally

396 generalizable trends to compare and validate model results. Comparison of documented adoption
397 rates for non-structural practices (CTIC, 2012) and enrollment rates for land retirement programs
398 such as CRP (USDA, 2013) are within the simulated adoption rates (Figures 1-5 and 1-6). For
399 structural practices, we refer to empirical studies conducted in Ohio, which indicate 20-25%
400 adoption rates similar to ABM results (Napier et al., 2000; Napier and Bridges, 2003).



401

402 **Figure 1-5: Observed and simulated enrollment rates for land retirement programs**
403 **such as CRP in Sandusky watershed, OH (USDA, 2013). 25 ABM simulation runs fall**
404 **between two lines of the same color.**



405

406 **Figure 1-6: Observed and simulated adoption rates for non-structural practices such as**
 407 **conservation tillage and no-till in Sandusky watershed, OH (CTIC, 2012). 25 ABM**
 408 **simulation runs fall between two lines of the same color.**

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Appendix 2: 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, 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 5-6, main text). 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.

40 **Challenges of Linking Agent-based Models with Biophysical Models**

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

47
48 For this framework, we chose a loose integration method, which uses the state variables from
49 one model as a driving variable in the other model (Antle et al., 2001). ABM determines the land
50 management pattern for the Sandusky watershed and SWAT estimates water quality metrics as a
51 function of the updated land management pattern. One of the disadvantages of using loosely
52 coupled models is the computational overhead associated extracting output files and modifying
53 input files. We used MatLab programming language to link ABM output and modify necessary
54 SWAT input files. Single SWAT run including the modification of input files for 41 years
55 (1970-2010) averaged about 55 minutes when run on quad-core Windows machine. Because of
56 the stochasticity built in the model, we performed 25 simulations and reported the averages of
57 these runs for water quality metrics, which resulted in approximately 1,375 minutes or 0.95 days.

58
59 In this framework, we aimed to represent the farm-scale decision-making regarding
60 conservation practice adoption. However, due to limited data, representation of the exact location
61 of farms and long-term management decisions is not possible. Therefore, we constructed an
62 abstract ABM without the spatial representation of decision-making process which could affect
63 the farmers' conservation decisions because soil properties and slope of their land are not
64 influential in their adoption decisions.

65
66 The capabilities of SWAT were the determining factor for the scale of the linked model. We
67 developed a fine-scale SWAT model to match the average farm size in the Sandusky basin
68 (Daloğlu et al., 2012). However, SWAT is not developed on grid cells and the smallest
69 computational unit of SWAT, HRU cannot be manually delineated which complicates the
70 representation of farm level decision making.

71
72 Linking social and biophysical models for social-ecological system representation is
73 profoundly valuable, especially in evaluating plausible policy scenarios. While the recent land
74 use and land change research has contributed to this endeavor, this study goes one step further by
75 linking a widely used water quality model to ABM to better represent the dynamic interactions
76 of farmers.

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Appendix 3: Model parameters for the agent-based model of farmer adoption of conservation practices

Name	Parameter description	Value
<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

5

Table 3-1: Initial model parameters

Farmer type	Name	Parameter description	Value (without crop revenue insurance)	Value (with crop revenue insurance)
Traditional	b ₁	weight of agricultural profit on decision algorithm	0.34	0.30
	b ₂	weight of farmer profile on decision algorithm	0.40	0.52
	b ₃	weight of social network on decision algorithm	0.09	0.05
	b ₄	weight of spatial network on decision algorithm	0.17	0.13
Supplementary	b ₁	weight of agricultural profit on decision algorithm	0.27	0.23
	b ₂	weight of farmer profile on decision algorithm	0.46	0.58
	b ₃	weight of social network on decision algorithm	0.17	0.13
	b ₄	weight of spatial network on decision algorithm	0.10	0.06
Business-oriented	b ₁	weight of agricultural profit on decision algorithm	0.49	0.45
	b ₂	weight of farmer profile on decision algorithm	0.19	0.31
	b ₃	weight of social network on decision algorithm	0.24	0.20
	b ₄	weight of spatial network on decision algorithm	0.08	0.04
Absentee landowners	b ₁	weight of agricultural profit on decision algorithm	0.09	0.05
	b ₂	weight of farmer profile on decision algorithm	0.61	0.69
	b ₃	weight of social network on decision algorithm	0.30	0.26

	b ₄	weight of spatial network on decision algorithm	0.00	0.00
Investor	b ₁	weight of agricultural profit on decision algorithm	0.08	0.04
	b ₂	weight of farmer profile on decision algorithm	0.45	0.57
	b ₃	weight of social network on decision algorithm	0.29	0.25
	b ₄	weight of spatial network on decision algorithm	0.18	0.14
Traditional	Fprofile ₀	farmer attributes for adopting none of the practices	0.90	1.00
	Fprofile ₁	farmer attributes for adopting non-structural practices	0.68	0.96
	Fprofile ₂	farmer attributes for adopting structural practices	0.00	0.02
	Fprofile ₃	farmer attributes for adopting land retirement programs	1.00	0.00
	Fprofile ₄	farmer attributes for adopting nutrient management plans	0.43	0.35
	Fprofile ₅	farmer attributes for adopting both non-structural and structural practices	0.10	0.10
	Fprofile ₆	farmer attributes for adopting both non-structural practices and nutrient management plans	0.51	0.42
	Fprofile ₇	farmer attributes for adopting both structural practices and nutrient management plans	0.08	0.07
Supplementary	Fprofile ₀	farmer attributes for adopting none of the practices	0.36	0.48
	Fprofile ₁	farmer attributes for adopting non-structural practices	0.49	1.00
	Fprofile ₂	farmer attributes for adopting structural practices	0.06	0.08
	Fprofile ₃	farmer attributes for adopting land retirement programs	1.00	0.00
	Fprofile ₄	farmer attributes for adopting nutrient management plans	0.17	0.77
	Fprofile ₅	farmer attributes for adopting both non-structural and structural practices	0.22	0.06

	Fprofile ₆	farmer attributes for adopting both non-structural practices and nutrient management plans	0.17	0.82
	Fprofile ₇	farmer attributes for adopting both structural practices and nutrient management plans	0.17	0.09
Business-oriented	Fprofile ₀	farmer attributes for adopting none of the practices	0.28	0.50
	Fprofile ₁	farmer attributes for adopting non-structural practices	0.74	0.65
	Fprofile ₂	farmer attributes for adopting structural practices	0.20	0.03
	Fprofile ₃	farmer attributes for adopting land retirement programs	0.00	0.00
	Fprofile ₄	farmer attributes for adopting nutrient management plans	0.43	1.00
	Fprofile ₅	farmer attributes for adopting both non-structural and structural practices	0.36	0.08
	Fprofile ₆	farmer attributes for adopting both non-structural practices and nutrient management plans	1.00	0.66
	Fprofile ₇	farmer attributes for adopting both structural practices and nutrient management plans	0.28	0.08
Absentee landowner	Fprofile ₀	farmer attributes for adopting none of the practices	0.00	0.38
	Fprofile ₁	farmer attributes for adopting non-structural practices	1.00	0.74
	Fprofile ₂	farmer attributes for adopting structural practices	0.60	0.02
	Fprofile ₃	farmer attributes for adopting land retirement programs	0.17	0.00
	Fprofile ₄	farmer attributes for adopting nutrient management plans	0.12	0.49
	Fprofile ₅	farmer attributes for adopting both non-structural and structural practices	0.72	0.03
	Fprofile ₆	farmer attributes for adopting both non-structural practices and nutrient management plans	0.31	1.00

	Fprofile ₇	farmer attributes for adopting both structural practices and nutrient management plans	0.62	0.02
Investor	Fprofile ₀	farmer attributes for adopting none of the practices	0.00	0.38
	Fprofile ₁	farmer attributes for adopting non-structural practices	1.00	0.74
	Fprofile ₂	farmer attributes for adopting structural practices	0.37	0.02
	Fprofile ₃	farmer attributes for adopting land retirement programs	0.48	0.00
	Fprofile ₄	farmer attributes for adopting nutrient management plans	0.13	0.49
	Fprofile ₅	farmer attributes for adopting both non-structural and structural practices	0.55	0.03
	Fprofile ₆	farmer attributes for adopting both non-structural practices and nutrient management plans	0.30	1.00
	Fprofile ₇	farmer attributes for adopting both structural practices and nutrient management plans	0.55	0.02

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Table 3-2: Model parameters comparison for crop revenue insurance scenario.