Payment for Best Management Practices and Downstream Water Quality: A Spatially Integrated Economic-Hydrological Model of the Lake Erie Water Basin

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Abstract:

Agricultural nutrient runoff, especially phosphorus, from the Maumee River watershed entering Lake Erie, has led to frequent and severe water quality crises, including harmful algal blooms (HABs) and hypoxia in Lake Erie, and the 2014 Toledo water crisis (Lake Erie LaMP 2011; Scavia et al. 2014; Stumpf et al. 2012). To address these growing concerns, U.S. and Canada adopted the Great Lakes Water Quality Agreement (GLWQA) with the target to reduce total phosphorus (TP) and dissolved reactive phosphorus (DRP) entering affected areas of Lake Erie by 40 percent based on 2008 loading levels. Despite international and regional efforts, there lacks systematic evaluation of the efficacy and cost-effectiveness of the current and alternative nutrient management policies in reducing nutrient runoffs. In this paper, we use an integrated

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assessment model (IAM) that explicitly link a micro-level farmer decision making model with a process-based hydrological watershed model for the Maumee River watershed in the western Lake Erie water basin.

Our model explicitly incorporates the micro-level farmer decision making at the field level to capture the realistic responses to policy incentives using a survey data consisting over 1,800 randomly sampled corn and soybean farmers within the Maumee River watershed, which is the largest tributary in the western Lake Erie basin and the largest source of nutrient loadings into the lake. We consider several market-based policies designed to incentivize targeted desired field-level nutrient management practices that have been identified by a previous hydrological modeling assessment to be the most effective at reducing nutrient runoff from agricultural fields: subsurface placement of fertilizer, cover crops, and phosphorus (P) rate reductions. The model allows us to evaluate the efficiency of alternative nutrient management policies designed to achieve reductions in nutrient loadings to Lake Erie via these best management practices. Specifically, we investigate uniform and targeted cost-share payments, standalone fertilizer taxes, and a coupled policy that combines fertilizer tax and cost-share payments. With this integrated model, we are able to not only compare the behavioral change in farmers' agricultural management decisions with aggregate nutrient loading change in Lake Eire, but also to establish policy tradeoff frontier which evaluates each policy via its nutrient runoff reduction and associated costs.

The most striking result is that, despite a significant increase in adoption rate or decrease in fertilizer rate in response to these various market-based policies, the corresponding water quality improvements achieved by any single policy are modest, reducing TP and DRP by 5-10%

at the most. We conclude that a combination of policies are needed to effectively achieve the policy goal.

Key Words: Integrated Economic-Ecological Model; water quality; Agri-environmental policy; Conservation Practice; Nutrient Management

JEL Codes: H23, Q51, Q52, Q53

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1. Introduction

Excessive nutrient runoff from agricultural production contributes to freshwater eutrophication and coastal hypoxia across the United States and globally, including the Great Lakes, Gulf of Mexico, Baltic Sea in Europe, and Lake Taihu in China. In 2011, a harmful algal bloom (HAB) of unprecedented size and severity occurred in the western basin of Lake Erie (Michalak et al. 2013). The Lake Erie watershed is the most populous of all the Great Lakes and such events pose significant risks to ecosystem services provided by this vital lake, including recreation opportunities, public health, and safe drinking water. As an example, in 2014, the algal toxins in Lake Erie disrupted the water services in the city of Toledo, Ohio resulting in millions of residents being left without safe drinking water for two or more days (Raymond 2015).

To address the agricultural nutrient pollution problem, substantial efforts have been made at the federal and state levels to promote adoption of best management practices (BMP) through voluntary payments for conservation programs. At the international level, the Great Lakes Water Quality Agreement (GLWQA), committed to by both the United States and Canada, adopted targets to reduce total phosphorus (TP) and dissolved reactive phosphorus (DRP) entering affected areas of Lake Erie by 40% based on 2008 loading levels (GLWQA, US EPA). At the national level, spending on federally funded conservation programs is projected to be over $5.5 billion annually, or about $15 per acre per year, during the five-year life of the 2014 Farm Bill. At the state level, Ohio Governor John Kasich quickly responded to the Toledo incident, signing Ohio Senate Bill 1 in early 2015, which requires nutrient management plans for all producers, prohibits manure or fertilizer application on frozen grounds as well as 24 hours before a storm

forecast, and encourages injecting or incorporating fertilizer or manure application into the ground. Despite these efforts, a 2015 Lake Erie HAB was even larger and more severe than the HAB recorded in 2011 (Stumpf et al. 2016).

A key feature of these federal and state programs is that they are largely voluntary programs: producers opt to participate and receive a cost-share payment, which is often a uniform payment, that compensates them for their additional costs and effort. In 2018, Ohio Senate Bill 299 provided $23.5 million for soil and water conservation districts (SWCD) located in the Western Lake Erie Basin (WLEB) for nutrient management programs. Economists have long argued that a uniform payment design may not yield water quality improvements at lowest cost (Ferraro and Kiss 2002; Duke et al. 2013; Duke et al. 2014; Jack et al. 2008); however, many of the studies are pilot-scale or in experimental settings. Despite its prevalence, there remains a significant lack of empirical evidence of the cost-effectiveness of these conservation adoption policies in terms of their downstream water quality impacts (Garnache al. 2016). Furthermore, there is a lack of understanding about the realistic efficiency gains across the watershed from targeting and hybrid policies (i.e., linking fertilizer tax with payment for BMPs). This is because hydrologic models by themselves cannot account for behavioral motivations or economic costs and therefore simply assume full or random adoption of BMPs (e.g., Scavia et al. 2016).

Studies of farmers' adoption of conservation practices have shown that farmers respond to policy incentives, especially monetary incentives (Cary and Wilkinson 1997; Pretty et al. 2001; Blackstock et al. 2010), and adoption costs (e.g., Sheriff 2005; Kurkalova et al. 2006) in nutrient application decisions. Some studies find that farmers' socioeconomic and demographic

characteristics are important in driving the adoption of conservation practices (Featherstone and Goodwin 1993; Norris and Batie 1987). A few recent studies also reveal that behavioral preference heterogeneity, including environmental stewardship and perceived efficacy of the policy, are important factors in explaining the diversity of responses of farmers to incentive-based programs (Howard and Roe 2013; Wilson, et al. 2014; Zhang 2015; Zhang et al. 2016; Burnett et al. 2018). However, most models focus on only on the socio-economic aspects of agricultural management decisions and use highly stylized representations of the hydrological processes (e.g., Babcock et al. 1997; Laukkanen and Nauges 2014; Rabotyagov et al. 2014;) or vice versa, use simplified economic and behavioral assumptions with more sophisticated models of geo-physical or hydrological process in the watershed (e.g., Ando and Mallory 2012; Scavia et al. 2016; Scavia et al. 2017).

Our paper fills a policy evaluation gap by developing a spatially integrated assessment model. To our best knowledge, our paper is the first integrated assessment model that links socio-economic characteristics of individual farmers and their heterogeneous field characteristics with the hydrological process model (Soil and Water Assessment Tool, SWAT) to evaluate the cost-effectiveness of agri-environmental policies. By considering socio-economic and behavioral attributes together, we are able to examine the relative magnitude of a behavioral change relative to a change in an economic incentive in terms of how each affect nutrient runoff reductions. By integrating with SWAT, we can simulate the aggregate outcomes from different policy scenarios that stem from the choice behavior at an individual scale. Our integrated model allows us to assess the efficiency of market-based alternative nutrient management policies: uniform and targeted cost-share payments, standalone fertilizer taxes, and a coupled policy that combines

fertilizer tax and cost-share payments. We explicitly examine the adoption of three working land conservation practices: subsurface phosphorus fertilizer placement, cover crops, and phosphorus fertilizer application rate reductions.

Our spatially-articulated integrated assessment model links a model of BMP adoption, which incorporates adoption costs and individual farmer's socio-economic characteristics from survey data, with a hydrological process model (SWAT). In so doing, we incorporate management decisions, geophysical data, as well as other climate information as inputs to assess the efficiency of different policy scenarios. Based on the survey of individual farmer and their fields, we derive field-level specific adoption costs of BMPs that reveals the heterogeneity in socio-economic and spatial characteristics. We use an ordered logit model to analyze and predict farmers' adoption decisions under different BMP cost share scenarios, a fertilizer demand model to analyze and predict farmers' fertilizer application rate decisions, and link the economic behavior model with SWAT to analyze their impacts on Lake Erie water quality.

We apply this model to the largest Great Lake watershed- the Maumee River watershed- which contributes the largest volume of sediment and nutrient loadings into Lake Erie, leading to excessive HABs and other water quality problems (Reutter et al. 2011). This watershed has significant influence on the lake—although it contributes less than 5% of water flow into Lake Erie, it contributes almost 80% of nitrogen and phosphorus loadings entering Lake Erie (Ohio Lake Erie Phosphorus Task Force 2013; Scavia et al. 2014).

Data on farmers' economic, behavioral, and land characteristics come from a 2014 comprehensive survey of 2,324 farmer respondents in the Maumee Watershed of the Western Lake Erie Basin with extensive questions on farmers' field-level choices of multiple land

management practices in 2013, demographics, and risk attitudes of farmers, as well as farm- and field-level spatial characteristics. In particular, we focus on three salient conservation practices that have been shown to be critical and cost-effective in reducing nutrient runoff (Gildow et al. 2016; Mahler 2001; Scavia et al. 2014)—subsurface placement of fertilizer under the soil surface (via banding or in-furrow with seed), planting cover crops after fall harvest, and reduction in phosphorus application rates. In addition, we also examine the combination of cost-share payments with tax policies that would affect both BMP adoption and the rate of P fertilizer application.

Our main results reveal that payments for BMPs alone, from subsurface placement, cover crops, or P rate reductions, achieve only modest reductions in nutrient loadings to Lake Erie. Specifically we find that subsurface placement can generate up to a 0.8% of reduction TP and 2.3% reduction of DRP; cover crops leads to 4.6% of TP and 1.8% of DRP reduction; P rate reduction leads to 2.4% of TP and 2.3% of DRP reduction. These preliminary results suggest that a combination of multiple policies are needed to affect more substantial reductions in TP and DRP loadings, and that the overall economic costs of these policies may be substantially higher than the current level of spending on voluntary programs. In addition, it shows that it is naive to assume to large increases in conservation practice adoption would necessarily translate into proportionate nutrient reduction outcomes. While spatial targeting is likely to be more cost effective, we have not yet run the SWAT simulations to assess the effectiveness of spatial policies nor have we yet explored combinations of various policies. Finally, these results are also limited as we have not yet run the models multiple times to reduce the uncertainty from randomness.

Despite these current limitations, our model represents an important advance in the design of integrated assessment models by incorporating multiple sources of behavioral, economic and physical heterogeneity, and accounting for these sources of variation in farmer decision making and responses to market-based policies. In so doing, our work demonstrates the potential gains in more realistic representations of farmers' heterogeneous responses to policies. Given the reliance of agri-environmental policies on voluntary incentives, such an approach is necessary to identify the most efficient mix of policies, including assessing the potential inefficiencies from uniform policies that fail to account for these sources of heterogeneity and evaluating the conditions under which spatial targeting policies are justified.

2. Study Area and Data

The Maumee River watershed of the western Lake Erie water basin is a HUC-6 watershed spanning four million acres across three states (northwestern Ohio, northeastern Indiana, and southern Michigan) and is the largest source of phosphorus loadings into Lake Erie (Scavia et al. 2014) (Figure 1). The Maumee River watershed has 85% of its four million acres in agricultural production—more than 10,000 corn and soybean farms and an additional 2,000 livestock farms. Despite the presence of urban landscapes, estimates show that 85% of phosphorus loadings in the Maumee River watershed come from agricultural fertilizer and manure application (Scavia et al. 2017). As a result, the nutrient management practices of conventional row-crop farmers in this geographic area are of significant interest in improving water quality in Lake Erie.

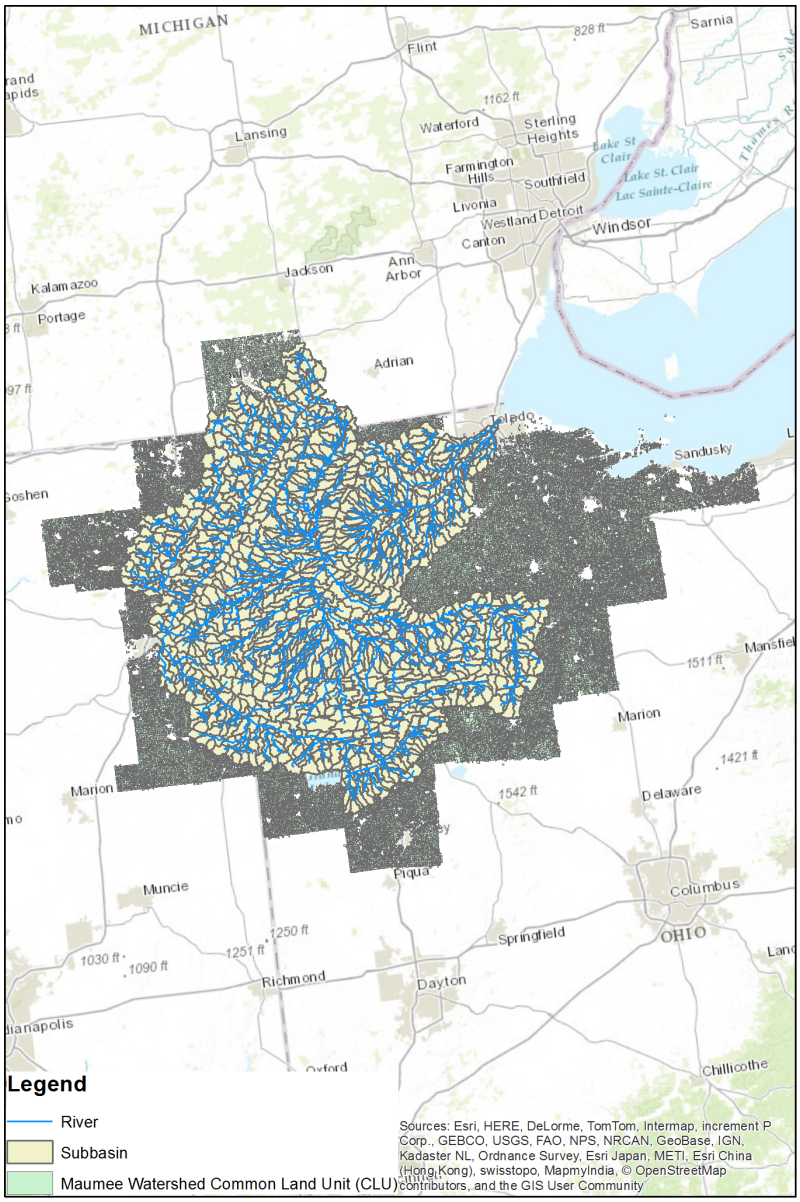

Figure 1. Maumee River watershed map.

As part of an NSF-funded coupled natural-human systems project (Martin et al. 2011; Zhang et al. 2016; Zhang 2015), we conducted a representative mail survey of 7,500 farmers in the western Lake Erie basin on their field, farm, and operator characteristics from February to April, 2014. We also solicited field-specific responses on crop choices, fertilizer application, and other nutrient management practices in 2013. The addresses of all farmers in the Maumee River watershed were provided by a private vendor, pulled from lists of farmers receiving government payments, and from farming magazine subscription rolls. The two-round survey was conducted following Dillman's Tailored Design method (Dillman 2011). The total set of mailings included an announcement letter, a survey packet, a reminder letter, and a replacement packet for non-responders. Respondents received a $1 bill in the mailings as an incentive to increase the response rate. Several months before the initial mailings of the survey it was pilot tested using farmers recruited by local extension professionals.

A total of 3,234 surveys were initially returned, of these 438 were no longer farming and another 32 did not answer the crop management questions. In total, we obtained 2,324 valid survey responses, yielding a response rate of 37%. Of these, 1,213 respondents did not provide answers to either fertilizer rate or price questions or certain field or operator characteristics. Table 2 shows the summary statistics for the farmer survey, including crop and nutrient application rates, output and input prices, field characteristics, farm characteristics, and operator characteristics. A comparison between our data and the Census of Agriculture data for counties in the Maumee River watershed reveals that our sample is skewed toward large farms with high gross sales and farmers who additionally earn off-farm income.[i] Most of the variables in Table 2 are intuitive; however, we want to highlight one group of variables—the interaction terms

between the normalized phosphorus fertilizer prices and the four variables that control for heterogeneous responses due to different soil quality and familiarity with 4R Nutrient Stewardship.[ii] The sample was stratified based on farm size to ensure the representation of farmers managing the largest proportion of acreage (as opposed to representing the population of farmers). The sample was divided by farms 50–249 acres (15%), 250–499 acres (13%), 500–999 acres (22%), 1000–1999 acres (31%), and 2000+ acres (19%). The final sample closely matched census data for farms over 50 acres (with approximately 28% of the respondents in the under 500 category, 22% in the 500–999 category, and 50% in the 1000+ category). The census reports 34%, 24%, and 40% in each category, respectively. The average farm size is larger than that of the 2012 Census of Agriculture for counties in this watershed, but larger farms also have more potential to impact the water quality in Lake Erie (Zhang et al 2016). A descriptive report on this survey can be found online at the project website at http://ohioseagrant.osu.edu/archive/maumeebay/ and in Burnett et al. (2015). More descriptions on this survey can also be found in Zhang (2015) and Zhang et al. (2016).

In the survey we ask farmers whether they have adopted a specific BMP, where 0 = not adopted and 1 = adopted, and report the summary statistics in Table 1. Following Zhang et al. (2016), we construct our dependent variable using the non-adopters' self-expressed attitudes towards future BMP adoption, ranging from 0 (will never adopt), 1 (unlikely to adopt), 2 (likely to adopt), to 3 (will definitely adopt). We combine the already adopted farmers into this variable by assigning the adopted decisions 4 (have already adopted). We consider farmers responding 3 or 4 as having a probability of adopting the conservation practice in the next year.

In this study, we focus on three conservation practices identified by multiple models as critical and effective in reducing nutrient runoff from the Maumee River watershed—subsurface placement of fertilizer under the soil surface via banding or in-furrow with seed (referred to as subsurface placement); planting cover crops after fall harvest (referred as cover crops); and a reduction in the phosphorus commercial fertilizer application rate (referred as P rate reduction)(Gildow et al. 2016; Scavia et al. 2014, Scavia et al. 2017). Among the methods to reduce nutrient runoff, subsurface placement of fertilizer and fertilizer incorporation after broadcast can not only improve fertilizer efficiency (Kelley and Sweeney 2005; Mengel, Nelson, and Huber 1982; Randall and Hoeft 1988), but also reduce nutrient runoff (Gildow et al. 2016; Mahler 2001; Mengel, Nelson and Huber 1982; Timmons, Burwell, Holt, 1973). In particular, hydrological simulations using the SWAT model reveal that full watershed adoption of fertilizer subsurface placement reduces spring DRP and TP loadings by 42% and 27%, respectively, when compared to baseline levels, which is more effective than changing the timing of fertilizer application (Gildow et al. 2016).

We included the socio-psychological, socio-economic, and field-level spatial characteristics as the explanatory variables (Table 1) as established by previous studies (Huang et al. 2000; Kurkalova et al. 2006; Sheriff 2005; Zhang et al. 2016). The social-psychological characteristics include perceived efficacy, perception of control, risk attitude, and farmer identity, which quantitatively measures farmers' productivity-oriented versus conservationist inclinations (Arbuckle 2013; McGuire et al. 2013, 2015; Burton 2004). In particular, Farmer identity (farmer_identity) is the difference between the conservationist values and the productionist values, which could range from -4 (greatest identity as productionist) to 4 (greatest identity as

conservationist). For subsurface placement and cover crops, we have a well-established perceived efficacy measures (efficacy_placement, and efficacy_covercrop) represent the farmers' belief in the effectiveness of subsurface placement application of fertilizer or cover crops at reducing nutrient loss, ranging from 0 (not at all) to 4 (to a great extent). This psychological factor has been found to be a major driver of farmers' adoption choices of fertilizer timing (Burnett et al. 2018; Zhang et al. 2016) so we expect a higher perceived efficacy of a particular conservation practice in reducing soil loss will lead to higher adoption rate of phosphorus placement or cover crops. Additional socio-psychological measure include perception of control (perception_control) which represents the farmer's perceived control over nutrient loss, ranging from 0 (no control) to 6 (complete control). Risk attitude (risk_mean) represents the farmer's willingness to take risks on a scale from 0 (not willing to take risks) to 10 (very willing to take risks).

For socio-economic characteristics, we have the farmer's age and annual gross income for the 2013 production year (farm_income), which can range from 1 (<$50,000), 2 ($50,000 – $99,999), 3($100,000 – $249,999), 4 ($250,000 – $499,999), to 5 (>$500,000). For field-level characteristics, we included the acreage of the field, soil quality (low, medium, or high), slope (0 – 2%, 2 – 5%, 5 – 10%, >10%, not sure), and whether or not the farm is rented. We also calculated a farmer- and practice-specific adoption cost for each practice using farmers' stated expenditures on nutrient inputs, machinery, labor and other things as well as farm or regional level input prices. We provided more details on how this variable was constructed in the next section.

Table 1. Variable Description and Summary Statistics

Variable	Description	Mean	Std. Dev.	Min	Max
Farmer choice					
Adopt_place	The attitude of adopting subsurface placement	2.648	1.250	0 (will never adopt)	4(have already adopted)
	Distribution of attitude	category	Number of respondents	percentage	
		0	54	2.55	
		1	408	19.30	
		2	604	28.57	
		3	211	9.98	
		4	837	39.59	
Adopt_cover	The attitude of adopting cover crops	1.956	1.131	0 (will never adopt)	4(have already adopted)
	Distribution of attitude	category	Number of respondents	percentage	
		0	89	4.19	
		1	766	36.08	
		2	791	37.26	
		3	104	4.90	
		4	373	17.57	
Socio-psychological characteristics					
Efficacy_placement	Perceived effectiveness of a dopting subsurface placeme nt	2.588	.973	0 (‘not at all’)	4(‘to a great extent’)

Efficacy_cover	Perceived effectiveness of a dopting cover crops	2.558	1.006	0 (‘not at all’)	4(‘to a great extent’)
Perception_control	Farmers’ perception of control over the farm	3.486	1.015	0 (‘no control’)	6 (‘complete control’)
Risk_mean	Risk attitude	5.167	2.089	0 (not willing to take risks)	10(very willing to take risks)
Farmer_identity	Farmer identity	1.2883	0.837	-1.257 (greatest identity as productionist)	4(greatest identity as conservationist)
Socio-economic characteristics					
Age	Age (years)	58.158	11.868	17	85
Farm_income	annual gross farm Income (2013 dollars)	3.046	1.330	1(<$50,000)	5 (>$500,000)
Field-level characteristics					
field_acre	Acreage of the field	51.647	49.130	5	650
Soil_quality	Soil quality of the field	2.022	.821	1 (“low”)	3 (“high”)
Slope	Slope of the field	2.130	1.434	1 (0-2%)	5 (not sure)
field_rent	=1 if field is rented	.359	.480	0 (not rent)	1 (rent)

3. Methods

3.1 Construction of Field-level Production Cost

We calculate the total costs of managing the farm for each respondent based on their specific responses in the survey. In particular, each farmer was asked to allocate all their fields into high, medium, and low productivity categories based on corn and soybean yield ranges, and then instructed to pick one field from a randomly selected quality class, e.g., pick one field among all high-productivity fields that they operate. For this particular field, the farmer provided various field-specific expenditures that we used to construct the field-level production cost (see Appendix A for sample questions on these expenditures). These responses include field-specific seeding rate and seeding cost, manure quantity, type, and unit price, fertilizer application quantity, type, and unit price, per-acre expenditures on herbicide, Federal Crop Insurance program, as well as whether the fields are cash rented from other farmers. The respondents also provided agricultural production details on corn drying, machinery usage and repairs, fuel usage, labor and management conditions, which were converted into dollar-based expenditures using the statewide custom rates and standard production costs based on the 2012 Ohio State University Production Cost and Custom Rate survey (Ward, 2012).

3.2 Predicting Field-level Adoption Cost of Conversation Practice

One unique explanatory variable is the field-level adoption cost of specific conservation practices. For each practice, fertilizer subsurface placement or cover crops, we run a separate

OLS regression of the field-level total production cost, as described in section 3.1, on field-level physical characteristics (field size, soil quality, rent status), management practice decisions (BMP adoption), and field operator's demographic characteristics (age). This regression allows us to separate the adoption cost for each conservation practice at the field level from its total production cost and allow for heterogeneity in this cost across fields and operators. We include two interaction terms between this already adoption dummy with one operator's demographic characteristic, age in particular, and one field-level characteristic, proxied by field size. Previous literature has demonstrated that adoption cost will vary by both operator and field characteristics (Traoré, Landry, and Amara, 1998; Prokopy et al. 2008). We use the age of the operator and field size as two proxies for this heterogeneity. We represent the field size in both acreage and acreage bins[6] and find robust results. In particular, we estimate the following two regressions for phosphorus fertilizer subsurface placement and cover crop adoption separately.

$$\begin{aligned} \textit{Field level total production cost} \\ &= \alpha * \mathrm{X}_{\mathrm{field}} + \beta * \mathrm{X}_{\mathrm{operater}} + \gamma_1 * \text{already adopted subsurface placement} + \gamma_2 \\ &* \text{already adopted subsurface placement} * \text{age} + \gamma_3 \\ &* \text{already adopted subsurface placement} * \text{acreage} + \gamma_4 \\ &* \text{adopted any BMP other than subsurface placement} + \varepsilon \end{aligned} \qquad \text{Eq. [1]}$$

[6] 150 acres each bin

$$Field\ level\ total\ production\ cost$$

$$= \zeta * \mathrm{X}_{\mathrm{field}} + \eta * \mathrm{X}_{\mathrm{operater}} + \theta_1 * \text{already adopted cover crops} + \theta_2 * \text{already adopted cover crops} * \text{age} + \theta_3 * \text{already adopted covercrops} * \text{acreage} + \theta_4 * \text{adopted any BMP other than cover crops} + \varepsilon \qquad \text{Eq. [2]}$$

where $\mathrm{X}_{\mathrm{field}}$ includes field size, soil quality, whether the field is rented (0/1), and whether the field has adopted any BMP other than subsurface placement (0/1), and $\mathrm{X}_{\mathrm{operater}}$ includes the age of the farmer. In particular, as explained earlier, we included a binary variable "already adopted." which equals to one when the farmer has already adopted the BMP of interest on this specific field. We also controlled for the adoption of other BMPs than the one of our interest, which include: grid soil sampling with variable rate, delaying broadcasting when the forecast predicts a 50% or more chance of at least 1 inch of total rainfall in the next 12 hours, managing field water levels with drainage management systems, avoiding winter or frozen ground surface application of phosphorus, avoiding fall application of phosphorus, determining rates based on regular soil testing once within the rotation (or every 3 years), following soil test trends to maintain the agronomic range for phosphorus in the soil (15 to 30 ppm), and requiring a 4R certification program for private applicators.

In practice, the adoption dummy variable and these two interaction variables allow us to derive field-specific adoption costs after estimating these two aforementioned regressions:

$$\text{Field level predicted adoption cost for field i for subsurface placement} = \widehat{\gamma}_1 * \text{already adopted subsurface placement} + \widehat{\gamma}_2 * \text{already adopted subsurface placement} * \text{age\_i} + \widehat{\gamma}_3 * \text{already adopted subsurface placement} * \text{field size\_i} \quad \text{Eq. [3]}$$

$$\text{Field level predicted adoption cost for field i for cover crops} = \widehat{\theta}_1 * \text{already adopted cover crops} + \widehat{\theta}_2 * \text{already adopted cover crops} * \text{age}_i + \widehat{\theta}_3 * \text{already adopted cover crops} * \text{field size}_i \quad \text{Eq. [4]}$$

where $\widehat{\gamma_0}, \widehat{\gamma_1}, \widehat{\gamma_2}, \widehat{\gamma_3}, \widehat{\theta_0}, \widehat{\theta_1}, \widehat{\theta_2}, and\ \widehat{\theta_3}$ are coefficients estimated from Eq. [1] and Eq. [2].

These regressions naturally suggest that in our study, the adoption costs for BMPs vary not only by the intrinsic features of BMP adoption ($\widehat{\gamma_0}, \widehat{\gamma_1}, \widehat{\theta_0},$ and $\widehat{\theta_1}$), but also varies across different fields and farmers due to heterogeneous age/experience and spatially-varying field characteristics. We expect $\widehat{\gamma_1} and\ \widehat{\theta_1}$ to be postitive representing an increase in production cost in general due to BMP adoption, but $\widehat{\gamma_2}$ and $\widehat{\theta_2}$ to be negative meaning that more experienced operators could adopt these practices in a marginally more cost-effective manner. $\widehat{\gamma_3}$ and $\widehat{\theta_3}$ can be positive or negative depending on the particular BMP because some larger fields have lower per acre costs due to economies of scale, while some other larger fields require different technology or crops that potentially increase per acre costs.

3.3 BMP Adoption Model Incorporating (Changes in) Adoption Costs

We use an ordered logit model to estimate the effect of each characteristic on the adoption choice of BMPs (subsurface placement and cover crops) and predict the future likelihood of adoption under different policy incentive programs. We use the ordered logit model following Zhang et al. (2016) because the dependent variable is ordinal and categorical, and estimate the model using the "ologit" command via Stata 15 as follows:

$$\text{adoption decision} = \beta_0 \text{ field level adoption cost} + \beta_1 \text{ farmer specific charactertistics} + \beta_2 \text{ field specific characteritics} + \varepsilon \qquad \text{Eq. [5]}$$

where the dependent variable is future adoption decisions of BMPs, which ranges from 0 (will never adopt), 1 (unlikely to adopt), 2 (likely to adopt), 3 (will definitely adopt), to 4 (already adopted). The practice-specific field level predicted adoption cost is included as an explanatory variable. Other farmer specific characteristics include their perceived efficacy of the BMP, mean risk level, identity as a farmer, perception of control, age, and farm income (Table 1). The field specific characteristics include acreage of the field, soil quality, slope, and whether or not the field is rented. We include spatial fixed effects and cluster standard errors at the county level to control for unobserved spatial heterogeneity and heteroskedastic errors, which effectively controls for spatial dependence.

In the future likelihood prediction model, we examine policy payment scenarios that range from $1 to $80 per acre, which reduce farmers' adoption costs therefore affect their adoption decisions. The midpoint of this range is analogous to the USDA NRCS Environmental

Quality Incentives Program payment for enhanced nutrient management with deep placement, which is $42.99/acre[7]. Under each scenario with payment subsidy, we predict the probability of one's BMP adoption decisions fall into categories 2 (likely to adopt), 3 (will definitely adopt), and 4 (already adopted) after the ordered logit model using the "predict" command via Stata 15. We interpret the probabilities as a set of rules that govern the behavior of BMP adoption in the near future following Lewis and Plantinga (2007). For example, if the probability is 0.4 for a farmer to be in categories 2 to 4, then the farmer will adopt subsurface placement or cover crops 40% of the time if the choice situation is repeated enough times. To simulate this situation, we generate a random number from uniform distribution U [0, 1] and compare the predicted probability of adoption with this random number. If the predicted probability is larger than the random number, then we assume the farmer will adopt the BMP; otherwise, we assume the farmer will not adopt. We add up the land acres that are predicted to be operated by future adopters and divide it by the total field acreage from the survey sample in a given county. This generates the predicted land share of each BMP for each scenario at a county level. We use this predicted share as a means of integrating these farmer land management predictions with the hydrological model, as explained below.

3.4 Fertilizer Demand Model

[7] https://www.nrcs.usda.gov/wps/PA_NRCSConsumption/download?cid=nrcseprd423686&ext=xlsx

To evaluate the effects of a fertilizer tax policy on commercial phosphorus fertilizer application rates, we estimated a fertilizer demand model. This reduced form model is in spirit similar to the model presented at length in Zhang (2015). In particular, in addition to relying on just the fertilizer application rates in response to current prices, we constructed a reduced-form panel data model using phosphorus application rates under the actual and two hypothetical price scenarios, and identify the mean elasticity of phosphorus fertilizer demand. This elasticity could be interpreted as the "sufficient statistic" argued by Chetty (2008) that could be identified using reduced-form studies and then used to simulated policy changes and welfare effects.

Our farmer survey is based on their crop and nutrient management choices in 2013, so it is based on data from a single year and a relatively small region. There is some variation in the fertilizer prices paid among the farmers; however, it may not provide enough variation to reveal the farmers' true demand elasticity of phosphorous fertilizers: over the past decade, the average U.S. phosphorus price index ranges from $300/ton to $900/ton. As a result, in addition to one question about the farmers' actual fertilizer application rate and fertilizer price paid, we added two hypothetical questions to induce farmers' responses under alternative phosphorus fertilizer price scenarios. Specifically, we ask "if commercial phosphorus fertilizer prices had been $X/ton, what rate of P would you have applied on this field for this most recent crop? _____ lbs/acre", in which X could be 200, 250, 300, 350, 450, 500, 550, 750, 800, 850, and 900. With these two hypothetical questions on phosphorus rate and prices in addition to the question on the

observed levels, we now have a short panel of three choices and thus could formulate a panel data fixed effects model:

$$x_{iPlt} = \kappa_{Pl0} + \gamma_{Pl0} * \overline{r_{iPlt}} + \theta_{il} \qquad t = 1,2,3 \qquad \text{Eq. [6]}$$

where θ_{il} is individual fixed effects, $\overline{r_{iPlt}}$ is the normalized phosphorus fertilizer prices adjusted by fertilizer types, x_{iPlt} denotes the fertilizer application rate by farmer i for each crop and fertilization frequency choice l, κ_{Pl0} is the intercept denoting the baseline application rate, and t represents the three fertilizer price scenarios – one actual and two hypothetical.

The actual estimation is a two-stage process, first we model the choices in the first stage as a combination of crop and phosphorus application frequency choices, which include five distinct choices denoted by L: corn and single year application (corn-single, cs), corn and multi-year application (corn-multi, cm), soybean and single year application (soybean-single, ss), soybean and multi-year application (soybean-multi, sm) and other crop choices (other, o). This is modeled as a multinomial logit model and more details could be found in Zhang (2015). In the second stage, for each crop and fertilization frequency choice l, we could estimate the key parameter of interest $\widehat{\gamma_{Pl0}}$ – the mean coefficient for phosphorus fertilizer prices without heterogeneity, and this estimated parameter implies a mean elasticity of phosphorus fertilizer demand, and then will be used to simulate the effects of fertilizer tax policy or a policy that couples fertilizer taxes with payments for conservation practices.

3.5 Hydrologic Model – Soil and Water Assessment Tool (SWAT) Model

SWAT is a basin-scale model that has been continuously developed over the past 30 years by the Agricultural Research Service (ARS) in the United States Department of Agriculture (USDA) (Arnold et al., 1998; Arnold and Fohrer 2005; Gassman et al. 2007). It is widely used to predict the impact of regional management practices on nutrient transport, agricultural chemical yields to support the analysis of total maximum daily loads (TMDL) (Borah et al. 2006), and a wide range of water use and water quality applications (Abbaspour et al. 2007; Gassman et al. 2007). SWAT incorporates a wide variety of data, including topography, land use/cover, types of vegetation, soil, climate, and curve number (which predicts direct runoff or infiltration from rainfall excess) as well as assumptions about farmer decisions including land management, -such as fertilizer and pesticide application and crop choice- and crop growth and tile drainage (Arnold et al. 1998; Green et al. 2006; Shang et al. 2012). It models stream flow and the transport of various nutrients to evaluate the change of non-point source pollution and other biogeochemical processes associated with nutrients. The SWAT models have been extensively utilized to analyze how land use, agricultural management practices, and climate change affect water quality in Lake Erie (e.g., Bosch et al. 2011, 2013, 2014; Gildow et al. 2016; Michalak et al. 2013). Multiple SWAT models in the western Lake Erie basin have established land use and management scenarios to achieve the 40% nutrient reduction goal (Gildow et al. 2016; Scavia et al. 2017). However, these biophysical studies assume large-scale or random adoption of conservation practices without linking the physical process model with economic behavior assessing actual adoption by farmers, which makes it hard to predict the practicality and

efficiency of the scenarios. Following Scavia et al. (2017), we use the spatially-explicit SWAT model to simulate the hydrology and nutrient cycling of the Maumee River watershed under different policy and management scenarios (Aloysius et al. 2019, and Gildow et al. 2016).

Water quality indicators are generated using model outputs from the SWAT model developed for the Maumee River watershed (Aloysius et al., 2019). Building on Gebremariam et al. (2014) and Gildow et al. (2016), we delineate 1482 sub-basins within the drainage area of the Maumee River watershed, and further divide them into 9494 Hydrological Response Units (HRUs) based on spatial features in land use, soils, and topography. Agricultural practices, including crop rotations, fertilizer applications, tillage practices, subsurface drainage, and other BMPs were incorporated in the model (at HRU-level) in consultation with the USDA-ARS, the Ohio State University Agriculture Extension personnel, and farmer surveys conducted in the western Lake Erie region (Burnett et al. 2015; Gebremariam et al. 2014; Gildow et al. 2016). Water quality data (stream flow, suspended solids - SS, total phosphorus - TP and soluble reactive phosphorus - SRP, nitrate-nitrogen – NO_3 and total Kjendahl nitrogen - TKN) measured at the Waterville River gaging station were obtained from the National Center for Water Quality Research at Heidelberg University for 1986–2015 (Baker et al. 2014). These daily forcings are used to set up the model to calibrate and validate runoff, sediment fluxes, and total and soluble reactive phosphorus fluxes during the historical period. To link the economic results with SWAT, we randomly allocate the areas of adoption to HRUs within each county and make sure the total adopted area matches the land share as explained in the following section 3.6.

3.6 Linking the BMP Adoption and Hydrologic Models

The BMP adoption model generates predictions of near-term BMP adoption decisions at the field level for a given set of farmer and field characteristics for each policy scenario. Linking these predictions with SWAT requires that we assign a spatial location to the land management decisions, so that the changes in total land area for each BMP under a given scenario is represented in SWAT. We do this for each policy scenario as follows. First, we assume that the predicted county-level land share of a given BMP, calculated as described in section 3.3, holds at a smaller spatial subbasin level. We then randomly assign BMP adoption to each HRU within a subbasin, using the predicted share of land acres as a constraint, so that the total share of land allocated to a given BMP corresponds to the predicted share at both subbasin and county level. There are 1,480 subbasins in the watershed, which means on average each subbasin has about 2,266 acres of agricultural land. There are two sources of uncertainty in our model: the probability of BMP adoption at a field level, which determines the predicted share of land under a given BMP, and the allocation of BMP land acres to a specific HRU. For each policy scenario, we account for both sources of uncertainty by repeating these predictions multiple times[8], which generates a predicted range of water quality impacts for each scenario.

4. Results

[8] Due to the limitation of time, we haven't

Based on the survey, about 51% of the field area in the Maumee River watershed already adopted subsurface placement and 20% had adopted cover crops at the time of the survey, which is the baseline scenario without policy interventions (Table 2).

Table 2. Summary of Current Adoption Rates among Counties

State	Already adopted subsurface placement			Already adopted cover crops		
	Mean	Std. dev.	Freq.	Mean	Std. dev.	Freq.
IN	.461	.100	5	.140	.084	5
MI	.522	.107	2	.247	.071	2
OH	.526	.184	15	.209	.118	15
Total	51.08%	.161	22	19.65%	.110	22

4.1 Predicting Field-level Adoption Cost of Conversation Practice

As explained in section 3.2, we estimate Eq. [1] to predict field-level adoption costs of subsurface placement. Table 3 shows that on average the cost of adopting any BMP other than subsurface placement is $24 per acre. Larger farms and better soil quality induce higher production cost, which may be interpreted as higher investment on the farm. Rented land also incur higher associated costs. As explained before, our approach allows us to dissect the farm-specific adoption cost of BMP based on farmer demographic characteristics (represented by farmer's age) and farm-level physical characteristics (represented by field size). As predicted, we find $\widehat{\gamma_1}$ to be positive, showing there is additional cost of adopting subsurface placement. $\widehat{\gamma_2}$ and $\widehat{\gamma_3}$ are both negative, indicating that farmer experience and economy of scale reduces the per acre adoption cost. For those who adopted subsurface placement, the adoption cost decreases

by \$1 ($\widehat{\gamma_2}$) with one-year increase in farmer's age and one-acre increase in field size decreases the adoption costs by about 28 cents ($\widehat{\gamma_3}$). Based on these estimates, we uncover the field- and farmer-specific subsurface placement adoption cost following Eq. [3]:

$$subsuface\ placement\ adoption\ cost = 102.3464 - 1.0503 * age - 0.2828 * field\ acreage \qquad Eq.[6]$$

We set the lower bound of adoption cost at 0 and replace those below 0 as 0 because it is unrealistic to assume a negative adoption cost, which accounts for less than the lowest 5% tail of the distribution. The average estimated per acre subsurface placement adoption cost is \$24.32 based on average farmer characteristics and field-level characteristics, which is in line with BMP adoption cost, and different federal or state cost-share programs. Generally, subsurface placement is \$12–\$15 more per acre than broadcast phosphorus application, where broadcasting costs \$4.10 – \$15.20 per acre depending on the fertilizer type. For non-adopters, we assume their costs are higher and use the 75th percentile (\$100.07/acre) of the adoption cost distribution as the proxy.

Table 3. Subsurface Placement Adoption Cost Estimates

Variable	Total cost	
	Field acreage	Field acreage bins
Other_BMP	23.7767***	25.6974***
	(7.228)	(7.253)
Field_acre	0.2821***	
	(0.058)	
Field_size_bin_dummy		32.3665**
		(12.677)
Age	-0.2244	-0.2329

	(0.212)	(0.213)
Soil_quality	27.6678***	28.4730***
	(3.446)	(3.460)
Field_rent	14.1109**	14.4501**
	(6.013)	(6.039)
Already_placement($\widehat{\gamma_0}$)	102.3464***	127.7725***
	(26.584)	(33.620)
Already_placement*age ($\widehat{\gamma_1}$)	-1.0503**	-1.0638**
	(0.440)	(0.442)
Already_placement*field acreage($\widehat{\gamma_2}$)	-0.2828***	
	(0.058)	
Already_placement* Field_size_bin_dummy ($\widehat{\gamma_2}$)		-37.0227*
		(20.424)
Constant	242.5131***	218.3774***
	(62.212)	(64.200)
Fixed effect	County level	County level
Observations	2,324	2,324

The results for cover crops resemble that for subsurface placement (Table 4), and similarly, wee uncover the field- and farmer-specific cover crop adoption cost following Eq. [4]:

$$cover\ crop\ adoption\ cost = 38.8825 - 1.0555 * age + 0.2957 * field\ acreage \qquad Eq.[7]$$

As expected, we find $\widehat{\theta_1}$ to be positive, showing the additional cost of adopting cover crops. We find $\widehat{\theta_2}$ to be negative, indicating one year of experience reduces the adoption costs by about $1. Here we find adoption cost increases with field size, which could be explained by the different types of cover crops or different technology chosen due to the field size. Using this proxies, we find that the average per acre adoption cost for cover crops is $31.70, which is in the

range of USDA-NRCS payments ($28.71/acre to $34.76/acre).[9] Again, for non-adopters, we assume their costs are higher and use the 75th percentile ($36.60/acre) as a proxy for their adoption costs.

Table 4. Cover Crops Adoption Cost Estimates

Variable	Total cost	
	Farm acreage	Farm acreage bins
Other_BMP	38.3383***	38.4771***
	()	(6.87)
Field_acre	-0.0007	
	(.002)	
Field_size_bin_dummy		21.3790*
		-11.072
Age	-0.3167	-0.3396*
	(0.198)	(0.198)
Soil_quality	27.5982***	27.9594***
	(3.488)	(3.486)
Field_rent	13.6962**	13.7392**
	(6.077)	(6.083)
Already_cover_crop($\widehat{\theta_0}$)	38.8825	73.2262
	(36.938)	(44.877)
Already_cover_crop*age ($\widehat{\theta_1}$)	-1.0555*	-1.1383*
	-0.614	-0.613
Already_cover_crop*acreage($\widehat{\theta_2}$)	0.2957**	
	-0.13	
Already_cover_crop* Field_size_bin_dummy		-14.4433
		-44.877
Constant	272.0461***	246.7916***
	-61.978	-63.363
Fixed effect	County level	County level
Observations	2,324	2,324

4.2 Impacts of BMP Payments on Adoption Choices

[9] https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/stelprdb1082778.pdf

This field and farmer specific adoption cost is then used as an explanatory variable to estimate effects of socio-psychological, socio-economic, and field-level spatial characteristics on the adoption choice. Regression results from ordered logit models are odds ratios, but we translate results to exponentiated coefficients estimates for easier understanding in Table 5. A higher adoption cost for subsurface placement or cover crops is hypothesized to lead to a lower probability of adopting these practices. Results confirm this: a $10 increase in the adoption costs for fertilizer subsurface placement leads to a 22.2% decrease in the likelihood of likely adopting this practice in the future. Comparatively, a $10 increase in field-level adoption cost for cover crops results in a 49.6% decrease in the future likelihood of adopting cover crops. One factor that consistently affects farmers' adoption decisions is the perceived efficacy of their conservation practices in reducing nutrient runoff. It has a large positive impact on adoption decisions – a one unit increase in the perceived efficacy indicator almost doubles the likelihood of future adoption -- which confirms what Zhang et al. (2016) found. Other characteristics do not have consistently significant impact on farmer's adoption decision; age and farm income have opposite impacts on the adoption of subsurface placement and cover crops. These results could be explained by the intrinsic differences between these two BMPs and emphasize the heterogeneity among BMPs as well as farmers and fields. The finding is consistent with Zhang et al. (2016).

Table 5. Ordered Logit Model Estimates of Conservation Practice Adoptions

Variables	Adopt subsurface placement	Adopt cover crops
Socio-demographic characteristics		
Perceived_efficacy_of_subsurface_placement	0.7608***	
	(0.063)	
Perceived_efficacy_of_cover_crops		0.9018***
		(0.058)
Perception_control	0.0566	0.0631
	(0.057)	(0.051)
Risk_mean	0.0177	0.0177
	(0.028)	(0.025)
Farmer_identiy	-0.0037	0.1857***
	(0.068)	(0.063)
Socio-economic characteristics		
Age	0.0057*	-0.0080**
	(0.003)	(0.003)
Farm_income	-0.1199***	0.1126***
	(0.045)	(0.042)
Field-level spatial characteristics		
Subsurface_placement_cost	-0.0225***	
	(0.003)	
Cover_crops_cost		-0.0496***
		(0.009)
Field_acre	0.0001	0.0008
	(0.001)	(0.001)
Soil_quality	0.0601	0.0053
	(0.068)	(0.061)
Slope	-0.0484	-0.0209
	(0.039)	(0.036)
Field_rent	0.0561	0.0427
	(0.119)	(0.109)
Fixed effect	County level	County level
Observations	1,796	1,801

We aggregate the predicted adoption land share at county level for each payment scenario and present the average adoption rates (Figure 2 and Figure 3), which are measured in acres: adoption rate = total acreage of adoption agricultural land / total acreage of agricultural land. We see that with $1/acre to $80/acre payment, the adoption rate of subsurface placement can increase from 47% to 65% (up to 39% increase given then 47% adoption baseline). For cover crops, the adoption rate can increase from 21% to 62%, which is almost a 200% increase from baseline. County-specific predicted adoption rates for all policy scenarios are available upon request.

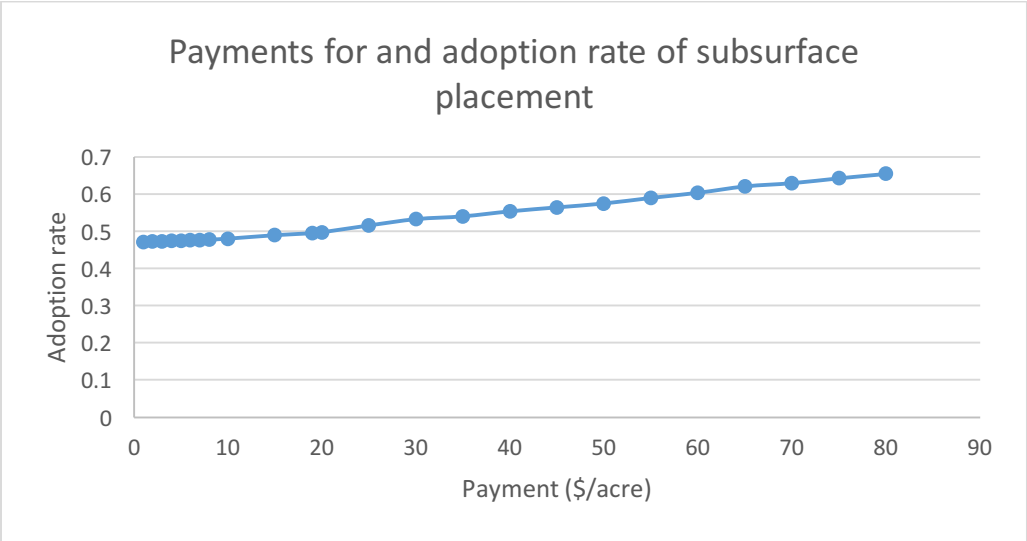

Figure 2 Subsurface placement adoption rate under various uniform cost share payments

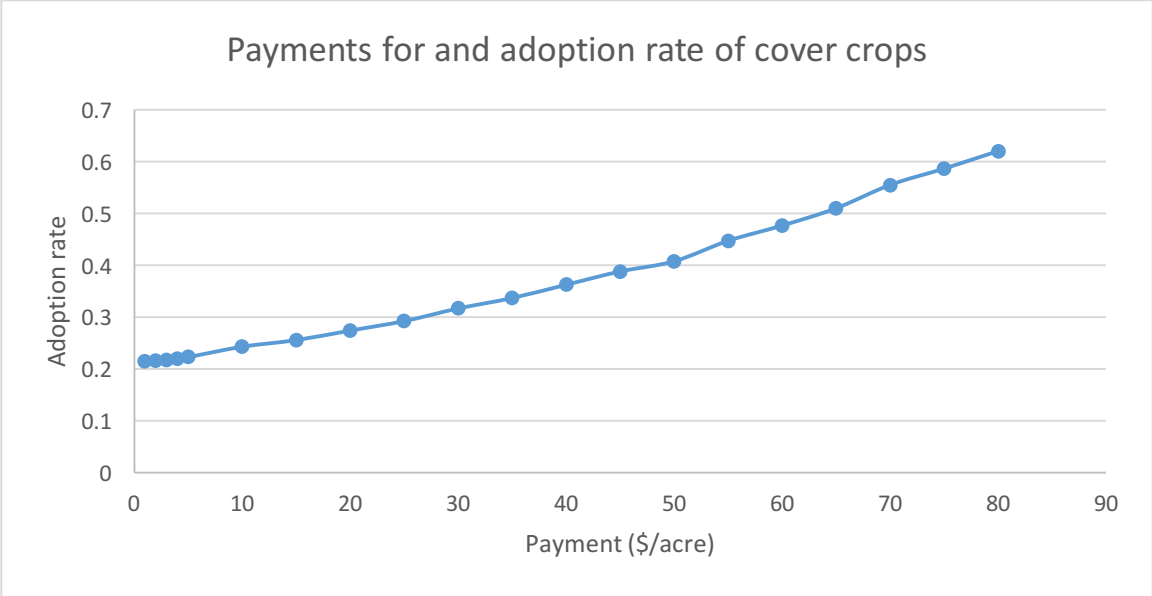

Figure 3 Cover crops adoption rate under various uniform cost share payments

4.3 Uncovering Water Quality Impacts of BMP Payments through Linkage with SWAT Model

To link the adoption prediction results under different policy scenarios with SWAT, we randomly allocate conservation practice adoption within each county across 9,494 Hydrological Response Units (HRU) while maintaining the predicted adoption rate changes for each county. That is, for each county we predict the county level adoption rate, which shows the percentage of agricultural land that adopts certain BMP, we first allocate the adoption rate into each subbasins then randomly allocate to HRUs within each subbasin. The percentage adoption rate is maintained at subbasin and county level to match the predictions. The HRUs are the smallest

spatial units at which the hydrologists can identify the nutrient flow. The simulation generates monthly TP and DRP runoff from 2005 to 2015 (with 2000 to 2004 as the configuration years) and we calculate the yearly spring (March to July) load. The GLWQA (2016) set the target to reduce spring P loads by 40% from their 2008 levels, which leads to 860 metric tons (MT) of TP and 186 MT of DRP. In Figure 4 and 5 we show the annual spring TP and DRP loads under different BMP policy scenarios with DRP on the secondary axis. We see that with higher payments both TP and DRP decrease, but not enough to reach the GLWQA goal. For example, Figure 4 reveal that an increase from $20/acre to $40/acre in terms of uniform cost-share payments for subsurface place would lead to about 2.5 MT of TP and 1.2 MT of DRP, respectively.

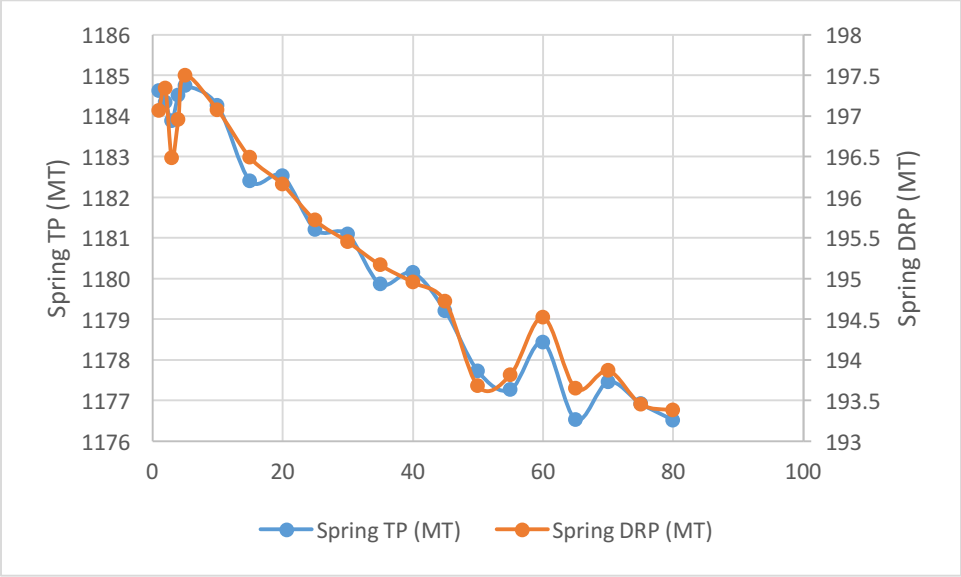

Figure 4 TP and DRP annual spring loads under different uniform subsurface placement payments

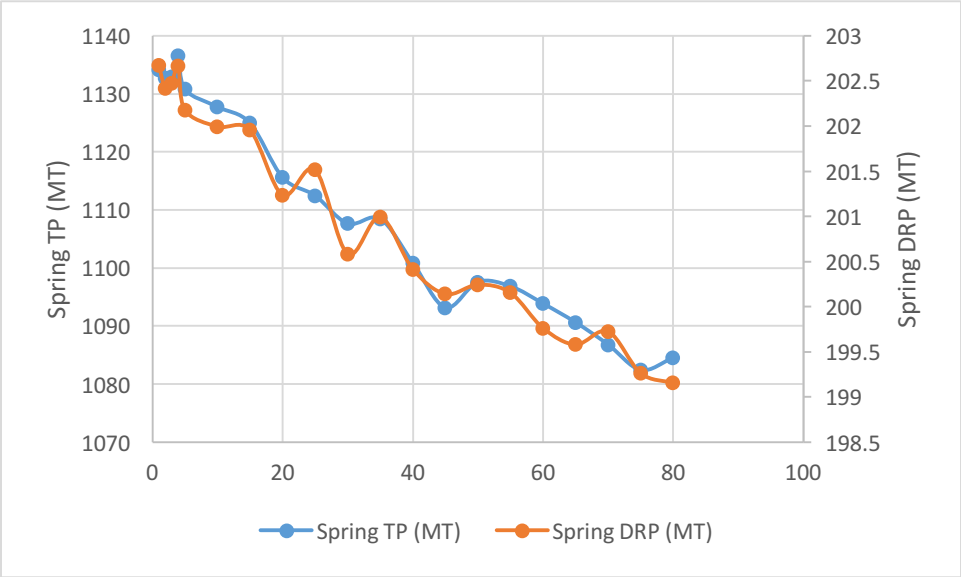

Figure 5 TP and DRP annual spring loads under different uniform cover crops payments

We compare the simulation outcomes with the baseline (simulation with current landscape and management practice) to calculate the percentage reduction in phosphorus runoff with the total cost of each payment programs to get the cost-benefit frontier (Figures 6 and 7). In particular, for each uniform payment scenario, we are able to contrast the predicted improvements in environmental outcomes through reduced nutrient runoffs with the total simulated costs of these cost-share programs. The total payment costs (per acre payment * total adoption acreage) increase at an increasing pace because of the increased adoption acreages with higher payments. We see that the phosphorus runoff reduction plateaued at around $45 to 50 per acre policy for both DRP and TP. This also coincides with NRCS EQIP payment for enhanced nutrient management with deep placement, which is $42.99 per acre.

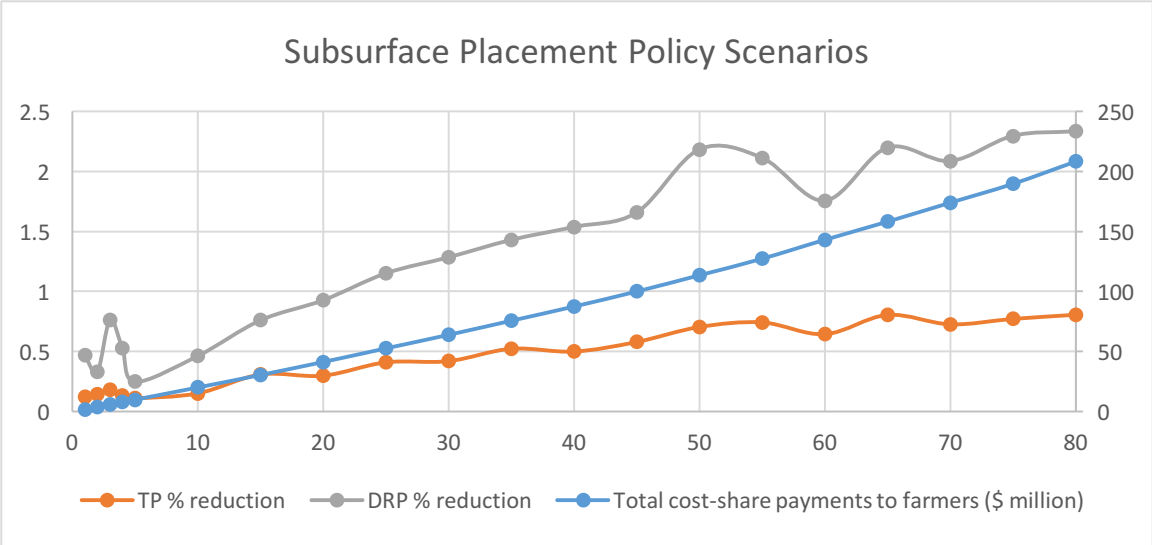

Figure 6 Cost-benefit frontier for uniform subsurface placement payments

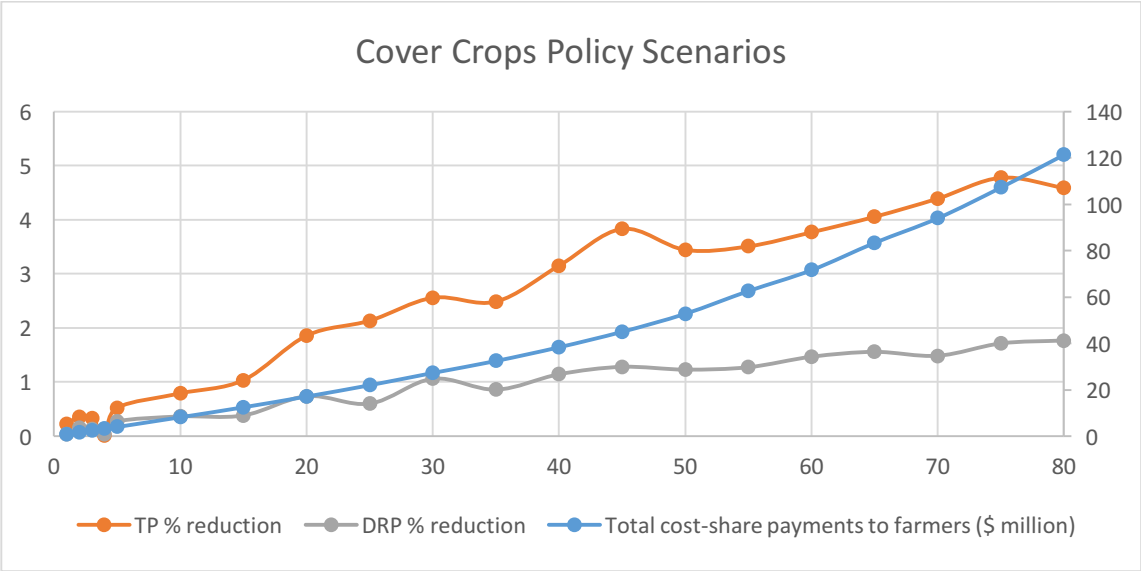

Figure 7 Cost-benefit frontier for uniform cover crops payments

4.4 Uncovering Water Quality Impacts of Fertilizer Tax through Linkage with SWAT Model

We also explore how fertilizer tax influences farmers' decisions and leads to P rate reduction, and how that is translated into water quality outcomes. Table 6 reports the results for the reduced-form panel data analysis shown in Eq. [6]. This model is estimated separately for each crop and fertilization frequency choices. The mean estimated elasticity of phosphorus fertilizer demand is derived from the coefficient for *p_price _norm*, which is the estimated $\widehat{\gamma_{Pl0}}$ in Eq. [6], while holding all other variables constant at means. On average, the derived elasticity of phosphorus fertilizer demand ranges from -0.264 to -0.488. For example, there is a 2.64% reduction in phosphorus fertilizer rate given a 10% fertilizer price increase for corn fields with single-year fertilization. These estimates are similar to previous estimates of elasticity of fertilizer demand (Griliches 1959; Pitt 1983), which ranges from -0.20 to -0.95. A comparison of the elasticity across different fertilization frequency choices reveals that fields with multi-year fertilization application have a significantly higher elasticity of phosphorus demand than fields with single-year application. This makes sense because farmers are more likely to over-apply nutrients under multi-year applications and could make flexible changes facing input price shocks. To evaluate the stableness of our elasticity estimate, panel (II) only uses responses from these two hypothetical fertilizer application rates questions and assess the effects of potential "hypothetical bias" on the estimated coefficient in phosphorus fertilizer prices. The implied

elasticities are very similar with the main specification except for the corn with multi-year applications, which is also within the range of previous estimates from the literature[10].

Table 6 Estimated elasticity of phosphorus fertilizer demand from reduced-form panel regressions

	corn single	corn multi	soybean single	soybean multi
Linear panel fixed effects model				
Actual and hypothetical phosphorus price	-0.4376*	-0.5634***	-0.4104***	-0.8462***
	(0.2259)	(0.1689)	(0.1111)	(0.2325)
Intercept	115.89***	112.47***	109.52***	148.71***
	(12.77)	(9.43)	(6.186)	(13.39)
Number of observations	1752	1097	603	405
Implied mean elasticity	-0.2714*	-0.388***	-0.2638***	-0.4876***
Implied average P reduction (lbs/ac) for a 10% price increase	-2.474*	-3.146***	-2.286***	-4.874*
Linear panel fixed effects model – Hypothetical questions only				
Hypothetical phosphorus price	-0.4682***	-0.3616***	-0.3561***	-0.8307***
	(0.1554)	(0.1063)	(0.1012)	(0.2620)
Intercept	124.65***	100.82***	112.63***	155.93
	(8.71)	(5.84)	(5.559)	(14.990)
Number of observations	1168	731	402	270
Implied mean elasticity	-0.2665***	-0.2456***	-0.2101***	-0.4383***
Implied average P reduction (lbs/ac) for a 10% price increase	-2.623***	-1.988***	-1.956***	-4.752***
Average actual phosphorus application rate (lbs/ac)	106.22	123.95	109.35	112.03

[10] first-stage crop and fertilization frequency choices are shown in Appendix B

Linking the model estimation with SWAT, we simulate 5 different scenarios, 10%, 20%, 30%, 40%, and 50% tax on phosphorus fertilizer, which leads to 1.23% to 6.15% decrease in the fertilizer input and 0.42% to 2.34% reduction in TP and 0.51% to 2.82% reduction in DRP In Figure 8 and Figure 9, we compare the amount of tax revenue with percentage reduction in TP and DRP.

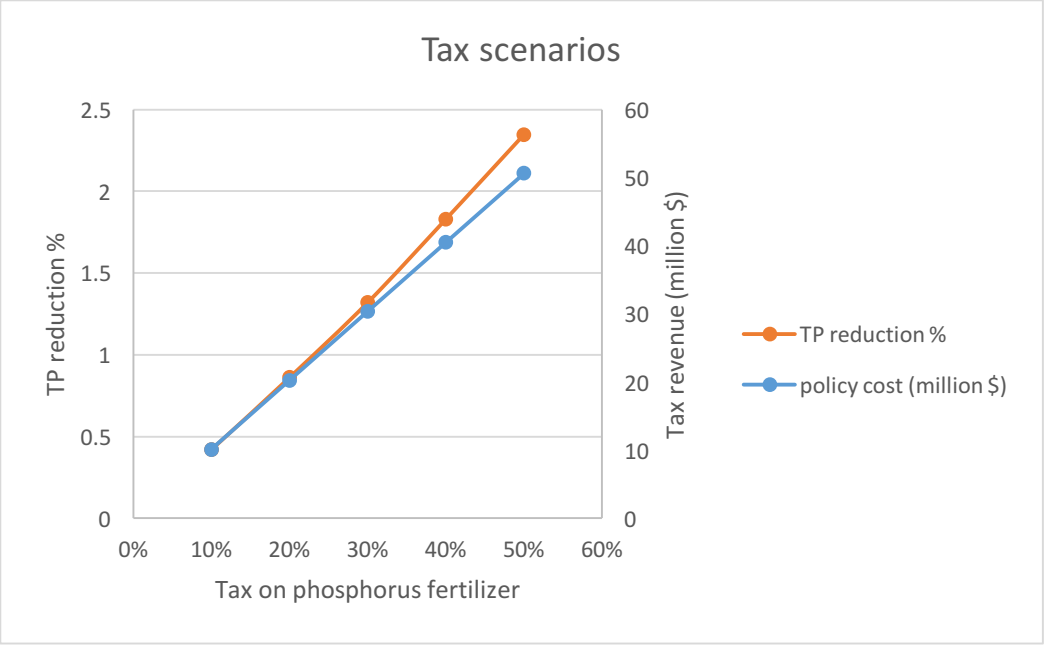

Figure 8 Percentage of TP reduction and total tax revenue under various tax increase

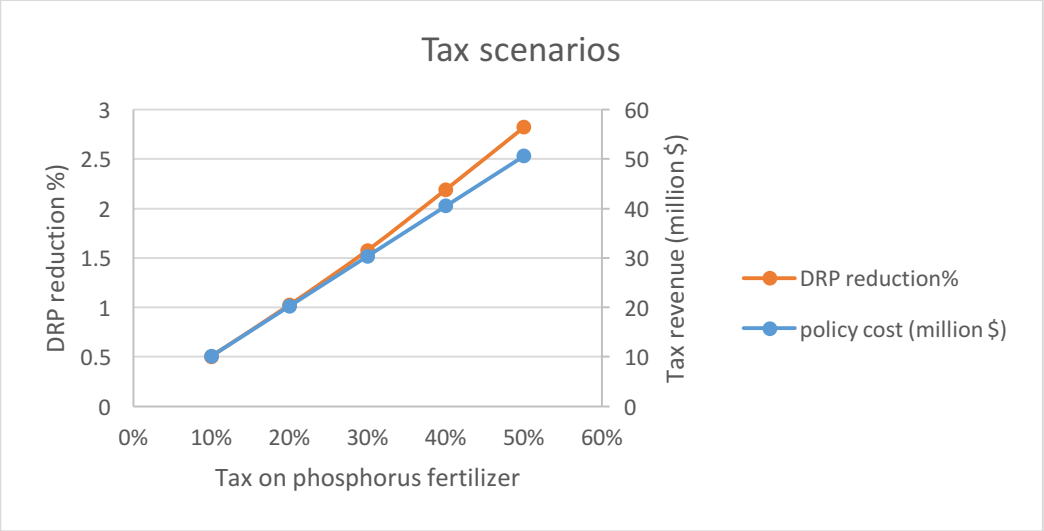

Figure 9 Percentage of DRP reduction and total tax revenue under various tax increase

4.5 Combination of Tax and Cost-share Payments

From section 4.3 and 4.4 we see that any one single practice is not enough to achieve the 40% reduction goal in Lake Erie. We propose an innovative way to link the two different types of policies increase effectiveness, which is to use the tax revenue as subsidy for BMP payments. Based on the survey, on average farmers spend $30.22/acre on phosphorus fertilizer. We estimate the fertilizer demand change in response to taxes and aggregate for the whole watershed to calculate the total tax revenue (Table 7).

Table 7 Combinations of tax and cost-share payments

Tax (%)	Total revenue (million dollars)	Matching payment for subsurface placement ($/acre)	matching payment for cover crops ($/acre)
10	10.09	6	12
20	20.09	11	22
30	30.00	19	29
40	39.80	24	35
50	49.48	28	41

For each level of tax revenue, we find the most efficient way of using it as cost-share payment, i.e. the level that leads to highest adoption rate (Table 7). For example, the 10% fertilizer tax will collect 10.09 million dollars, if used for payment for subsurface placement, it can pay $6/acre which leads to 47.55% of adoption. Similarly, if budget is used for cover crops

payment, it can pay $12/acre which leads to about 24.6% of adoption. Note that the current adoption rate is lower for cover crops, which requires higher payment to increase[11].

5. Discussion and Conclusion

5.1 Robustness Check

Due to the randomness in interpreting the future adoption probability (Lewis and Plantinga 2007), and the randomness in assigning economic model outputs to HRUs, we will run the economic models 30 times and SWAT 10 times for robustness check[12].

5.2 Hotspot Targeting

Due to the spatial heterogeneity in both farmers' socio-economic and socio-behavioral characteristics and field-specific characteristics, each field exhibit different contribution to the nutrient runoff and therefore has different impact on the water quality in Lake Erie. We test our hypothesis, that, by targeting at the nutrient runoff "hotspot,"– spatial areas with higher runoff potentials due to higher erodibility– we can achieve reductions more cost-effectively.

Based on Scavia et al. 2016, we identify the counties that contribute most to both TP and DRP runoff in the Maumee River watershed (Auglaize, Henry, and Putnam in Ohio, Adams, Allen, and Steuben in Indiana, and Hillsdale and Lenawee in Michigan) as the nutrient runoff

[11] We are also simulating these outcomes using SWAT, but haven't got the results yet.

[12] Due to the limit of time, we haven't finished all the simulations yet.

hotspot[13]. The runoff hotspot counties have a total of 1,537,826.49 acres, which accounts for 37.22% of the total area in the watershed. In this analysis, we assume all other counties continue with their current agricultural management decisions while these hotspot counties are eligible to receive BMP payment if farmers choose to adopt certain BMP. Similar to Section 4, we will run the payment scenarios for payments ranging from $1 to $80 for subsurface placement and cover crops respectively and report the results here[14].

5.3 Educational Programs

In additional to the technological and economic difficulties in BMP adoption, farmers also have to overcome the behavioral barrier of their own perception of BMP effectiveness as shown from the survey that some farmers are not convinced that the proposed BMPs are feasible to implement or likely to be effective (Wilson et al. 2018; Wilson et al. 2019; Zhang et al. 2016). To explore more cost-effective ways to improve water quality, we also examine the socio-behavioral aspect of farmer decisions. In addition to BMP subsidy and fertilizer tax, the government could also consider promoting educational programs to increase farmers' confidence and belief in the effectiveness of BMPs.

[13] The counties that contribute most to the TP runoff are: Allen, Auglaize, Henry, and Putnam in Ohio; Adams, Allen, De Kalb, Noble, and Steuben in Indiana; and, Hillsdale and Lenawee in Michigan. The counties that contribute most to the DRP runoff are: Auglaize, Hardin, Henry, Mercer, Paulding, Putnam, Van Wert, and Williams in Ohio; Adams, Allen, and Steuben in Indiana; and, Hillsdale and Lenawee in Michigan (Scavia et al. 2016).

[14] Due to the limit of time, we haven't finished the simulations yet.

Table 8 Predicted Adoption Rate under Overall and Hotspot Targeting Policies

County	Payments to all farmers	Payments only to farmers in hotspot watersheds
Adams-IN	0.6806	0.7083
Allen-OH	0.6260	0.6183
Allen-IN	0.7500	0.7692
Auglaize-OH	0.7778	0.8205
De Kalb-IN	0.6418	0.5970
Defiance-OH	0.7018	0.6930
Fulton-OH	0.6635	0.6635
Hancock-OH	0.6917	0.6750
Hardin-OH	0.7179	0.7051
Henry-OH	0.7045	0.7424
Hillsdale-MI	0.7209	0.7209
Lenawee-MI	0.7500	0.7500
Lucas-OH	0.8929	0.8214
Mercer-OH	0.6886	0.6826
Noble-IN	0.6909	0.6909
Paulding-OH	0.6712	0.6575
Putnam-OH	0.7022	0.7111
Shelby-OH	0.6176	0.6176
Steuben-IN	0.8636	0.9091
Van Wert-OH	0.6381	0.6000
Williams-OH	0.5889	0.5889
Wood-OH	0.7013	0.6948
Overall average	0.7037	0.7017
Hotspot county average	0.7437	0.7665

The potential pathways of increasing farmer perceived efficacy include outreach and educational programs to encourage voluntary adoptions, but more research need to be

done to see the effectiveness of such programs (Wilson et al. 2019). In this paper, we make a simplified assumption that the cost to increase perceived efficacy is roughly correlated with the percentage increase and the area of agricultural land. We consider two scenarios under the same budget: (*a*) increasing the perceived efficacy of subsurface placement for every farmer by 10%; and, (*b*) increasing the perceived efficacy of subsurface placement for every farmer in the nutrient runoff hotspot counties by 26.86% (10%/37.22%). We use the updated information to predict farmers' decisions based on the ordered logit model, and repeat the process from the section 4. As shown in Table 8, the adoption rates of hotspot counties are higher than average. The overall average adoption rate in the first scenario is slightly higher than in the second, but the adoption rate in nutrient runoff hotspot counties are much higher under the second scenario. We follow the previously explained method to randomly assign county adoption to HRUs within that county, and run SWAT to simulate the impact on water quality in Lake Erie.

Results (Table 9) show both TP and DRP are lower under the second policy scenario. By targeting the nutrient runoff hotspots, we are increasing the cost-effectivenss of policies that aim to increase farmers' perceived efficacy. The first scenario generates outcome similar to the $5 to $10 per acre payments for subsurface placement, which is equivalent to 10 to 20 million dollars in total cost share payments to farmers. The second scenario generates outcomes that are similar to those under a payment of $15 to $20 per acre, which is equivalent to a 30 to 40 million dollar expenditure in total cost share

payments to farmers. Thus, a targeted campaign that yields a greater increase in the perceived efficacy of farmers living in these hotspot counties generates greater water quality benefits and could potentially save costs compared to the cost-share programs, depending on the actual costs of educational programs. This analysis provides a solid foundation for future cost-benefit analysis to choose among different educational programs.

Table 9 Annual spring P loads outcome

	Spring TP load (MT)	Spring DRP load (MT)
Policy scenario 1: overall increase	1184.29	196.97
Policy scenario 2: hotspot targeting	1182.40	196.21

5.2 Contributions

Harmful Algal Blooms (HABs) have been worsening (e.g. density and surface area) since the 1990s in Lake Erie, with the five worst blooms on record all occurring since 2011 (Kane et al. 2014; NOAA 2017; Wilson et al. 2019). This work provides an interdisciplinary collaboration to examine various policies and programs to look for more cost-effective ways to achieve the phosphorus reduction goal in Lake Erie. We combine economic analysis on farmers' behaviors with a hydrologic model of the fate and transport of nutrients to generate comprehensive understanding of the human-natural system.

This work captures the complex system from farmers' decisions to water quality change in Lake Erie and highlights the importance of heterogeneity among farmers' socio-economic and

socio-behavioral characteristics in addition to the field-level spatial characteristics. We use heterogeneous adoption costs, socio-economic, socio-behavioral, and farm-level physical characteristics to predict farmers' adoption decisions under different policy scenarios including uniform and targeted cost-share payments, fertilizer tax, their interactions, hotspot targeting, and educational programs. We then link the economic outcomes with hydrologic model to simulate water quality outcomes in Lake Erie. Results show that no single practice is enough to meet the 40% reduction goal, which provides the strong argument for combinations of policies. Importantly our results also reveal that it is naive to assume that a significant increase in adoption of a particular suite of conservation practices would necessarily lead to a proportionate water quality improvements or nutrient runoff reductions. Rather, our results show that the nutrient runoff reduction is much more modest for either the standalone policy or the combination policy when compared to the outcomes in conservation practice adoptions. This in particular demonstrated the importance of the use of an integrated assessment model that incorporates both economic outcomes and ecological impacts, as opposed to examining the economic effects of conservation practice adoption alone.

We can also increase the cost-effectiveness by targeting the nutrient runoff hotspot counties, either with payment programs, or educational programs to increase farmers' perceived efficacy of BMPs. Future research are needed to explore the interactions between policies and test for additionality problem of different policies and programs. In particular, we will examine the heterogeneity of the nutrient reduction effects explicitly considering the field and farmer

heterogeneity in the integrated assessment model, and compare the relative cost-effectiveness of the nutrient reduction policies with alternative policies such as the educational campaign aiming to improve the perceived effective of conservation practices. More research is also needed to further link the nutrient reduction with economic valuation of downstream water quality benefits due to these environmental improvements in the Lake Erie watershed.

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Appendix A. Sample question from the farmer survey regarding management costs

- What plant population did you plant on this field for this most recent crop?

Quantity: _____ seeds/acre
Price: _____ $/10,000 seeds

- Did you apply manure on this field for this most recent crop?
  ☐ No
  ☐ Yes →source of manure (check all that apply)
    ☐ Dairy ☐ Swine ☐ Poultry
    Quantity: _____ lbs/acre
    Price: _____ $/lb

- Considering all fertilizers on this field for this most recent crop, how much phosphorus and nitrogen was applied and what was the price you paid? *(Please write '0' if none was applied)*

	Phosphorus	Nitrogen
Rate (lbs/acre):	_____	_____
Price ($/ton):	_____	_____
Form (P):	☐ MAP ☐ DAP ☐ APP	
Form (N):	☐ Urea ☐ UAN ☐ NH3	

- How much in total did you spend on herbicide, insecticide, and fungicide for this field last year? Please select the **costs per acre** that best approximate your situation with this field.

  ☐ $10 ☐ $15 ☐ $20 ☐ $30

  ☐ $40 ☐ $50 ☐ $60 ☐ $80

- Is this field covered by any Federal Crop Insurance program?
  ☐ No ☐ Yes

- Do you rent this field?

☐ No

☐ Yes→ Who is primarily responsible for nutrient management decisions? *(Check one)*

☐ Me alone

☐ Primarily me, with landlord input

☐ Equally me and my landlord

☐ Primarily my landlord, with my input

☐ My landlord alone

☐ Other_____

→What is your rental agreement with your landlord? *(Check all that apply)*

☐ Rent for cash

☐ Rent for a share of crop

- Tell us more about the machinery and equipment you used on this field last year:

Horsepower of your largest tractor_____

Horsepower of combine harvester _____

Number of rows in planter _____

For more details, please refer to the descriptive report about the survey on this website: http://ohioseagrant.osu.edu/archive/maumeebay/

Appendix B.

Appendix Table 1 shows the results for the first-stage crop and fertilization frequency choices. Relative to other crop choices, fields with a larger size and better soil quality have a higher probability of choosing corn or soybean. Farmers currently enrolled in crop insurance program[iii] or with higher farm income are more likely to grow corn, while farmers who rent a field have a higher probability to choose soybean. Many other characteristics do not have statistically significant effects, suggesting that farmers in our study region may follow a historic crop rotation pattern as evidenced by the significance for previous crop dummy. We still model crop choice in the first stage because according to agronomists phosphorus applications depend more on crop choice on a particular year[iv] and the effect of crop rotation is at least in part accounted for by including the previous crop dummy and modeling the fertilization frequency in the first stage as well.

Table 1 First stage multinomial logit model of crop and fertilizer application frequency choices

	Corn single	Corn multi	Soybean single	Soybean multi
Previous Crop Choices				
2012 crop is corn	2.2336**	1.7330**	4.0188***	4.0946***
	(0.7992)	(0.8173)	(0.8241)	(0.8624)
2012 crop is soybean	0.0079	-0.0990	-0.3574	-0.6500
	(0.3576)	(0.3777)	(0.4245)	(0.5250)
Input and Output Prices				
P fertilizer price	-4.05E-05	0.0001	-0.0011	0.0022
	(0.0012)	(0.0013)	(0.0014)	(0.0018)
N fertilizer price	0.0011*	0.0015***	-0.0026***	-0.0009
	(0.0005)	(0.0005)	(0.0007)	(0.0007)
Corn price 2012	-0.0015	0.0002	-0.0025	-0.0010
	(0.0020)	(0.0021)	(0.0021)	(0.0024)
Soybean price 2012	0.0016	0.0007	0.0030**	0.0011
	(0.0011)	(0.0012)	(0.0015)	(0.0014)
Field Characteristics				

Poor soil	-0.9097**	-1.1490	-0.6979*	-0.8304*
	(0.3629)	(0.3815)	(0.4029)	(0.4446)
Top soil	0.5194	0.4437	-0.1799	0.1756
	(0.4229)	(0.4352)	(0.4694)	(0.5036)
Precipitation	0.0012	-0.0806	0.0006	0.0428
	(0.0770)	(0.0892)	(0.0977)	(0.0892)
Field acres	0.0208***	0.0200***	0.0167**	0.0182**
	(0.0070)	(0.0070)	(0.0074)	(0.0074)
Distance to Lake Erie	2.56E-06	6.58E-06	3.95E-06	2.84E-06
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Slope	0.0863	-0.0131	0.0061	-0.0306
	(0.1173)	(0.1255)	(0.1300)	(0.1459)
Soil texture is clay	-0.5975*	-0.1392	0.2179	0.5949
	(0.3402)	(0.3528)	(0.3764)	(0.4126)
Soil texture is sand	0.2450	1.0549	0.3793	-0.5422
	(1.1616)	(1.1666)	(1.3038)	(1.5717)
Field is rented	0.1359	0.3494	0.8272**	0.8047**
	(0.3401)	(0.3527)	(0.3784)	(0.4105)
Farmer Characteristics				
Age	-0.0003	0.0057	-0.0012	-0.0045
	(0.0137)	(0.0154)	(0.0157)	(0.0175)
Familiar with 4R Nutrient Stewardship	-0.1302	-0.1719	-0.2491*	-0.3317**
	(0.1251)	(0.1301)	(0.1419)	(0.1545)
More risk loving	-0.0858	-0.0046	-0.0070	-0.1384*
	(0.0645)	(0.0679)	(0.0730)	(0.0793)
Education	-0.1017	0.0996	0.0107	-0.0316
	(0.1076)	(0.1115)	(0.1212)	(0.1360)
Years of farming experience	-0.0003	-0.0050	-0.0075	-0.0065
	(0.0069)	(0.0094)	(0.0082)	(0.0093)
Female operator	10.618	11.111	10.87	12.147
	(412.83)	(412.83)	(412.83)	(412.83)
Farm income	0.3632**	0.3884**	0.2139	0.3322*
	(0.1609)	(0.1676)	(0.1809)	(0.1926)
Farm Characteristics				
Has crop insurance	0.7918**	0.8517**	0.5870	0.4722
	(0.3154)	(0.3354)	(0.3576)	(0.4034)
Farm acres	-0.0002	-0.0001	-0.0002	3.38E-06
	(0.0002)	(0.0002)	(0.0003)	(0.0003)

% corn in farm acres	0.1374	0.1579	-3.481***	-0.4756
	(0.3073)	(0.3162)	(0.7182)	(0.4962)
Intercept	-0.8430	-0.7509	-0.9311	-3.6794
	(2.5433)	(2.8446)	(3.2373)	(3.1296)
# Observations	707	368	248	135
Log-likelihood		-1194.24		
Pseudo R^2		0.1917		

Grouped Endnotes

[i] While this may suggest that our sample is not statistically representative of all 18,116 farms in the Maumee River watershed, the 2012 Census of Agriculture data also shows that over 80% of all cropland in Ohio and Indiana are located on farms with at least 180 acres and over half of the acreage is on farms with at least 500 acres (U.S. Department of Agriculture 2012b). As larger farms manage a greater relative proportion of cultivated lands in the Corn Belt (Lambert et al., 2007), they also have a disproportionate potential to impact environmental quality through adoption or non-adoption of conservation practices. In fact, in the western Lake Erie basin, almost 65% of the cropland is managed by farmers with operations of at least 500 acres, while those with operations under 50 acres manage less than 3% of the total acreage (U.S. Department of Agriculture 2012b). Since the focus of our paper is farmers' water-quality-related management choices, it seems appropriate to focus on the larger farms, or the farmers who manage proportionally more acreage in the watershed, which is more important from both a behavioral and a water quality control perspective (Zhang et al. 2016).

[ii] 4R refers to using the Right Source of nutrients at the Right Rate and Right Time in the Right Place.

[iii] The contemporary crop insurance participation might be endogenous, and thus we ran two robustness checks using county-level yield protection insurance rates in 2012 or historical farmers' loss ratios as instruments and the results are qualitatively similar.

[iv] For example, phosphorus application rates for soybean fields and corn fields both in corn-soybean rotation could have different phosphorus application rates.