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Using models of farmer behavior to inform eutrophication policy in the Great Lakes

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ABSTRACT

To address the management of eutrophication in aquatic systems, the behavioral mechanisms that drive change at the individual level must be considered when designing policy interventions. This analysis identifies the beliefs that are critical to behavioral change, and explores the likelihood that farmers will adopt two management practices believed to be critical to reducing nutrient loading to recommended levels in Lake Erie. We find that there is potential for farmers to adopt key infield practices needed to reduce nutrient inputs. And further, that increased adoption of such practices is possible by increasing the perceived efficacy of the majority of farmers who are motivated to take action. Integrating these findings with physical models of nutrient movement indicates that adoption of these practices in combination with edge of field practices can attain phosphorus reduction targets for the lake. Future research should focus on measuring the effectiveness of education and outreach programs aimed at engaging farmers and promoting adoption of recommended practices. Such programs may only be effective if they are successfully building farmer confidence in their ability to implement the practices (i.e., perceived self efficacy) and increasing farmer's belief in the effectiveness of the practices at reducing nutrient loss and improving local water quality (i.e., perceived response efficacy).

1. Introduction

Eutrophication of aquatic systems is a significant challenge across the globe (Brooks et al., 2016; Johnk et al., 2008; Brookes and Carey, 2011). From Lake Erie to the Gulf of Mexico to the Baltic Sea, aquatic systems, and the people who rely on them, have suffered from excessive nutrient loading. Nutrient loading in marine systems is caused primarily by nitrogen, and leads to hypoxia. Eutrophication in freshwater systems is caused primarily by phosphorus, and leads to harmful algal blooms that restrict recreational opportunities, change the taste and odor of local water supplies, and pose a public health threat through an increase in toxic microcystin (Bejankiwar et al., 2013).

Managing eutrophication will require significant changes in farmer behavior as eutrophication is often driven by non-point source pollution from agricultural lands (i.e., phosphorus and nitrogen from fertilizer applications). Key to addressing this challenge is knowing 1) what behaviors or management practices need to change, 2) the probability of those changes occurring in response to different policy interventions, and 3) the impact of such changes on the downstream ecological system. This requires an integrated modeling approach that collectively addresses potential changes in farmer behavior and resulting changes in nutrient inputs into tributaries and the lakes as a result of changing land management decisions.

Recent studies in the Great Lakes have provided insight into the practices that need to be implemented to help meet the 40% reduction targets set for lakes like Lake Erie, and thus provide insight into the farmer behaviors that need to change (Keitzer et al., 2016; Natural Resoures Conservation Service, 2016; Scavia et al., 2017). However, these studies have not addressed the likelihood that a sufficient number of farmers will change their behavior to achieve the desired levels of implementation suggested by these watershed and lake ecosystem models. There are many factors that can affect a farmer's decision to adopt recommended management practices. Generally speaking, behavioral theories that aim to explain why one might change their behavior in response to a potential threat suggest that the individual must first perceive a threat (i.e., high perceived risk or personal concern), and that they

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must then believe there are effective actions available to reduce the risk (i.e., high perceived efficacy) (Floyd et al., 2000; Armitage and Conner, 2001). Prior evidence from the western Lake Erie basin suggests that farmers are highly motivated to reduce nutrient loss on their farm (Wilson et al., 2014; Prokup et al., 2017). This motivation stems from concern about a variety of perceived threats or problems, including the impact of nutrient loss on water quality, as well as the economic costs of nutrient loss to the farm and concern about future regulation (Prokup et al., 2017). According to behavioral theories, these concerned and motivated farmers must then evaluate the suite of actions available to them, in order to identify what practices they can successfully implement on their farm to reduce nutrient loss. Prior evidence from western Lake Erie also suggests that farmers' perception of their ability to successfully implement recommended practices (i.e., perceived self efficacy or confidence), and their perception of how successful each practice will be at mitigating the risks (i.e., perceived response efficacy or perceived effectiveness of the behavior), is highly variable and particularly low for those who have not yet adopted the recommended practices (Prokup et al., 2017; Zhang et al., 2016; Burnett et al. 2018).

These prior findings suggest that farmers do not lack the motivation to act, rather they lack the appropriate levels of perceived efficacy to take action. Specifically, they may lack the confidence in their ability to use recommended practices on their farm (i.e., self efficacy), and/or the ability of such practices to effectively solve the identified problem (i.e., response efficacy). We might expect that only farmers with high levels of perceived efficacy are using the recommended practices. According to previous research (see Markowitz, 2013 for a review), these individuals are likely those with positive past experience with the practice, who have the resources to innovate (i.e., more education, older, a tolerance for risk), who are not limited by external factors (i.e., low farm income), and who likely have higher levels of specific knowledge about the recommended behavior.

Herein we assess the probability of farmers in the western Lake Erie basin adopting two in-field practices that have been identified as important to reducing nutrient inputs into the lake (Scavia et al., 2017). Specifically, we identify what factors influence the likelihood of adopting these two practices (focusing on concern and perceived efficacy), and the degree to which phosphorus loading would decrease given increased levels of adoption in response to these factors. We pose the following overarching research questions: What is the likelihood that farmers in the western Lake Erie basin will adopt cover crops and subsurface application of fertilizer? What set of beliefs are most likely to influence the likelihood of adoption? And to what extent would changing these beliefs actually increase adoption and reduce nutrient loading to recommended levels? Our results provide insight into the likely impact of targeted outreach and education on phosphorus loading in the downstream system by examining the extent to which changing critical beliefs may increase adoption of recommended practices and improve water quality.

2. Materials and methods

2.1. Study context

The location of this study was the western Lake Erie Basin (WLEB) watersheds (see Fig. 1). This includes a total of 10 HUC-8 watershed boundaries spanning much of northwestern Ohio and extending into southern Michigan and eastern Indiana. Lake Erie is the most biologically and economically productive of the Great Lakes; however, this productivity is increasingly threatened by Harmful Algal Blooms (HABs) (Ohio Lake Erie Phosphorus Task Force, 2013). While phosphorus can enter the lake through a variety of sources and take multiple forms, the primary source is dissolved reactive or soluble phosphorus from non-point sources entering the lake through the Maumee River (Ohio Lake Erie Phosphorus Task Force, 2013). In the western basin, nonpoint sources from the agroecosystem are estimated to contribute over 80% of the annual total phosphorus load driving harmful algal blooms (Ohio Lake Erie Phosphorus Task Force, 2013).

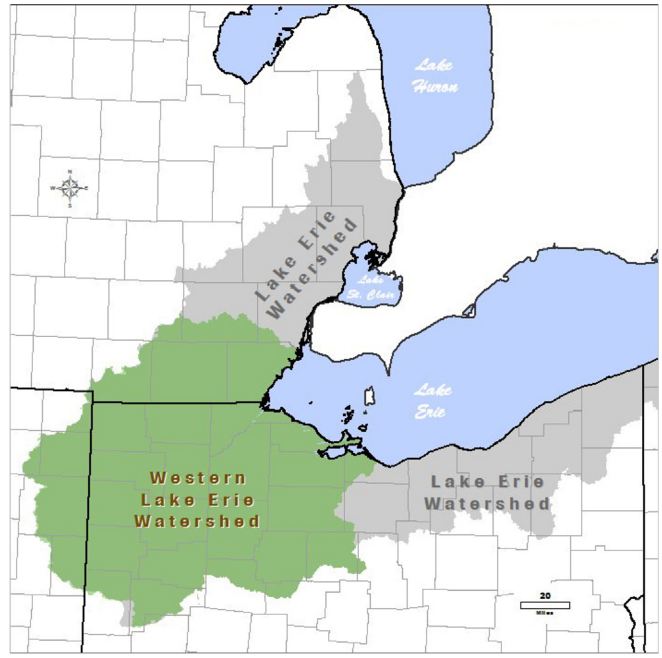

Fig. 1. Map of the study area in green (Source: The Fertilizer Institute at 4rcertified.org).

In many ways, the current issues with HABs in Lake Erie are a climate adaptation problem, or a function of current agricultural management practices not being sufficient given changes in the physical climate system (Bosch et al., 2014; Michalak, 2013). Current nutrient application and retention practices may need to improve or increase given the increased frequency of spring storm events, and warmer lake temperatures in the summer (Ohio Lake Erie Phosphorus Task Force, 2013). The Great Lakes Water Quality Agreement (GLWQA) Nutrients Annex Subcommittee recommends a 40% phosphorus load reduction in the Maumee river (from 2008 values) to reduce the frequency and severity of HABs (Annex 4 Objectives and Targets Task Team, 2015). Furthermore, recent physical models of the watershed indicate that such a reduction is possible with the increased adoption of particular practices across the watershed (e.g., in-field practices like cover crops and subsurface placement, as well as edge-of-field practices like filter strips) (Scavia et al., 2017). In our analysis, we were particularly interested in examining likely farmer adoption of cover crops and subsurface placement. In contrast to filter strips, it is possible that cover crops and subsurface placement provide enough on-farm benefits to justify their adoption without targeted financial investments from the government or other entities to off-set short-term costs. In other words, there is the potential to motivate a voluntary change in behavior by relying solely on cognitive tools or interventions for practices that do not negatively impact farm yields and revenue.

2.2. Survey methods

We conducted a representative mail survey of farm households in the western Lake Erie basin. The survey was developed in 2015, and then pilot tested with two farmer focus groups to assess face validity. The survey draft was then finalized and mailed to farmers between December 2015 and March 2016. Names and mailing addresses for 3273 farmers living in the western Lake Erie basin were obtained from the company Farm Market ID (http://www.farmmarketid.com). The sample was stratified based on farm size to ensure that we could represent the farmers managing the largest proportion of acreage (as opposed to representing the population of farmers[1]). The sample was divided by farms 50-249 acres (15%), 250-499 acres (13%), 500-999 acres (22%), 1000-1999 acres (31%), and 2000 plus 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 plus category). The census reports 34%, 24% and 40% in each category respectively.

Survey implementation followed the Tailored Design Method (Dillman, 2007). Farmers were first sent a postcard informing them that a survey was coming. This postcard also contained a web address for the survey in case they wished to complete the survey online. One week after the postcards were mailed out, potential participants were mailed a paper copy of the survey. A couple of weeks after the first mailing, farmers were mailed a second post card reminding them to complete the survey. Lastly, a second copy of the survey was mailed out to the farmers who had not responded.

2.3. Survey measurement

Respondents were asked to indicate whether or not they used a particular practice on a given representative field (yes/no).[2] The specific wording for the two practices we focus on in this analysis was: 1) Planting cover crops after fall harvest, assuming the weather is favorable; and 2) Subsurface placement of fertilizer (via banding or in-furrow with seed). Respondents were then asked to indicate their plans for the upcoming year on that same field for each practice, selecting from four categories: I will not use it, I am unlikely to use it, I am likely to use it, or I will definitely use it. We created a categorical dependent variable for the analysis with three levels using the measure of intention for the upcoming year. Individuals who reported an intention to definitely use the practice next year were categorized as “Innovators”, while those who reported being likely to use the practice next year became the “Future Adopters”. Finally, those that indicated they will not use it next year, or are unlikely to use it, were categorized as the “Laggards”. Although intentions are not a perfect measure of future behavior, prior meta-analyses suggest that behavioral intentions and actual behavior correlate around 0.50 (Sheeran, 2002), and a medium-to-large change in intention leads to a small-to-medium change in behavior (Webb and Sheeran, 2006). Regardless, we are not assuming intentions perfectly represent future behavior, but rather that they serve as an indicator of a motivated audience who would consider acting in the future given the appropriate amount of behavioral control (Armitage and Conner, 2001; Ajzen, 2002).

Respondents were asked to provide their exact age, and indicate their highest level of education from a selection of categories. For the analysis, the responses were aggregated to represent three categories: those with a high school degree or equivalent, those with some college or an Associate's degree, and those with a Bachelor's or Graduate degree. Respondents were asked to indicate their annual net farm income from a selection of categories. For the analysis, the responses were aggregated to represent four categories: less than \$50,000, \$50,000 to \$99,999, \$100,00 to \$249,999, and \$250,000 or greater. Respondents also indicated the total size of their farm in acres (including both rented and owned land). Finally, we collected data on whether or not the representative field was rented, and what type of tillage practice was being used on that field during the last growing season. For the analysis, the tillage type was aggregated to represent two categories: no-till or other (conventional/conservation tillage).

Respondents were asked to answer a set of questions meant to measure issue attentiveness (as a proxy for awareness and engagement with the issue), nutrient loss concern (as a proxy for perceived risk), perceived efficacy for the particular practice, and perceived barriers associated with the particular practice (see Table 1 for the specific items included in the survey). *Issue attentiveness* was measured by averaging three items capturing to what extent the respondent had heard about several agricultural and environmental issues over the past three years. *Nutrient loss concern* was measured by averaging nine items capturing to what extent the respondent was concerned about nutrient loss. The *perceived efficacy* of each practice was measured by combining three separate measures in the survey that aimed to capture response efficacy at the field and watershed scale, as well as self-efficacy at the field scale. The two measures of response efficacy were averaged and multiplied by the measure of self-efficacy. This score was then divided by 40 to create a normalized score of 0–10 for the analysis, where 0 (no perceived efficacy) and 10 (strong perceived efficacy). The *perceived barriers* for each practice were unique to the practice. For cover crops, respondents were asked to indicate to what extent they disagreed or agreed with four statements. For subsurface placement, respondents responded to two statements. For each practice, the responses were averaged to create a final measure of perceived barriers unique to each practice.

2.4. Survey analyses

We assessed the internal consistency of the proposed scales using Cronbach's alpha. This reliability analysis indicated that the proposed measures were acceptable measures of the intended constructs based on a threshold of 0.700 for acceptability (Kline, 2013). We used exploratory factor analysis to further assess the dimensionality of the proposed measures. For all of the proposed measures except nutrient loss concern, the factor analysis confirmed that the items composed one factor (eigenvalue greater than 1). For nutrient loss, there were two factors or dimensions, with the two items related to concern about regulation and lawsuits forming their own dimension of concern. These two items were pulled out into their own measure of *legal concern*, while the remaining seven items were combined into a measure of *general nutrient loss concern*. For the analysis, all four of the belief measures were recoded into two categories based on a median split so that they could be treated as nominal independent variables in the analysis.

All analyses and results are based on the final sample for analysis using listwise deletion. We used descriptive statistics to summarize the responses for each category of adoption, and one-way ANOVA and chi-square to assess the initial differences between the groups. We then conducted a multinomial logistic regression analysis to assess the impact of farm and farmer characteristics, and relevant beliefs on current and future adoption of the two recommended practices. We ran a separate model for both cover crops and subsurface placement. We then calculated the predicted

[1] This was particularly important as over 50% of the farmers in the basin own small farms covering only 2-3% of the total acreage in the basin.

[2] Respondents were specifically asked to identify a field with a productivity level typical for their farm where a crop was harvested the previous year. They then answered the field management questions with this field in mind.

Table 1
The items used to assess the psychological constructs in the survey and associated reliability statistic for multi-item measures.

Psychological Construct	Measurement Items	Cronbach's Alpha
Issue attentiveness	I have heard about [a]	.759
	Algal blooms in lake Erie	
	4R nutrient stewardship principles	
	Nutrient loss in agriculture	
Nutrient loss concern	How concerned are you about the following issues? [b]	.907
	Nutrient loss occurring on your farm in 2016	
	Your farm contribution to algal blooms in Lake Erie	
	The negative impacts of nutrient loss on Lake Erie	
	The negative impacts of nutrient loss to your farm's profitability	
	Nutrient loss occurring on your farm in 5–10 years	
	Nutrients lost from your farm during a heavy spring rain	
	Your farm's impact on local water quality	
	A lawsuit targeted to farmers because of nutrient loss to Lake Erie	
	Additional government regulation or rules related to nutrients	
Perceived efficacy (cover crops/subsurface placement)		.802/.859
Response efficacy	To what extent can/does …	
	… X[6] reduce phosphorus runoff from your fields? [c]	
	… widespread adoption of X[f] improve water quality in western Lake Erie? [c]	
Self efficacy	How confident are you that you could adopt X[f] on the majority of your fields this upcoming season? [d]	
Perceived barriers	To what extent do you agree/disagree with each statement. [e]	
Cover crops	The profit margins for winter wheat are too small	.785
	Establishing winter cover crops is too difficult due to uncertain planting windows	
	The risks of winter cover crops interfering with spring planting are too great	
	The near-term cost of cover crops is too great for the uncertain long-term payback	
Subsurface placement	The equipment need to inject nutrients into the soil is too costly to purchase	.680
	Alternatives to broadcasting are too slow	

[a] Measured on a scale from 0 (not at all) to 7 (a great deal), where 3 represents a moderate amount.
[b] Measured on a scale from 0 (not at all concerned) to 6 (extremely concerned).
[c] Measured on a scale from 0 (not at all) to 4 (to a great extent).
[d] Measured on a scale from 0 (cannot do it at all) to 100 (absolutely can do it), where 50 = may be able to do it.
[e] Measured on a Likert scale from -2 (strongly disagree) to 2 (strongly agree) where 0 = neither disagree nor agree.
[f] Where "X" indicates the practice being assessed; each item repeated.

probability of adoption given an increase in one key independent variable that was highly predictive of adoption (i.e., perceived efficacy).

2.5. SWAT model analyses

One of the Maumee River watershed SWAT models used in the Scavia et al. (2017) multi-model study was then applied to estimate total phosphorus load reductions associated with adoption level increases predicted by the behavioral models. The baseline representations of cover crops and subsurface placement in the watershed model were adjusted according to the behavioral survey results for adoption of those practices in 2015 (i.e., 14% cover crops and 32% subsurface placement). Model scenarios were then created that combined the predicted cover crop and subsurface placement adoption levels associated with 20%, 40%, 60%, 80%, and 100% increases in perceived efficacy. For each of the iterative increases in perceived efficacy and the baseline case, three different filter strip adoption levels were assumed: estimated current adoption (30%), and increases in adoption to cover an additional 25% and 50% of cropland area. These combinations generated a total of 18 watershed model simulations (i.e., six levels of cover crop and subsurface placement adoption simulated for three levels of filter strip adoption). All management practices were randomly assigned to cropland, as opposed to targeting areas with higher phosphorus export. Filter strips in the baseline scenario were assumed to be of "field border" quality. When generating the updated filter strip placement scenarios, the randomizing function was allowed to select agricultural fields that already had these lower quality filter strips in place as well as fields with no filter strips. Newly placed filter strips were represented with higher treatment efficiencies in the model.

3. Results

3.1. Descriptive results

Of the 3273 farmers who were mailed a survey, 70 addresses were returned unopened as being invalid and 278 farmers contacted us asking to be removed from the study. Another 351 farmers indicated on their survey that they were either no longer farming, or did not plan to farm in the next year. These were also removed from the study. Of the remaining 2574 farmers that we contacted, 748 returned usable surveys accounting for an adjusted response rate of 29.1%.

On average, our farmers were 56 years old (ranging from 19 to 95). Approximately 45% of our sample had a high school education, while 30% had some college, and 25% had a bachelors or graduate degree. The median farm size was 350 owned acres and 500 rented acres (ranging from a combined 50 to 6100 acres). Overall, 26% of the respondents had farms under 500 acres, 24% had farms between 500 and 1000 acres, 30% had farms between 1000 and 2000 acres, and 20% had farms over 2000 acres. In terms of annual farm income, 21% of our final sample had an income under $50,000, 25% between $50,000 and $99,999, 25% between $100,000 and $249,999, and 28% over $250,000. Across our sample, 73% of the representative fields were owned, and the tillage practices ranged from conventional tillage (22%), to conservation tillage (45%) and rotational or continuous no-till (33%).

For the 2015 season, 14% of respondents indicated they used cover crops on their representative field, while 32% reported using some form of subsurface placement. For the 2016 season, 23% of respondents reported an intention to use cover crops on their representative field, while 36% reported an intention to use subsurface placement. Another 30% reported they were *likely* to use subsurface placement in the upcoming year, while 41% reported the same for cover crops. A respective 35% for subsurface placement and 37% for over crops can be considered laggards (reporting that they will never use them, or are unlikely to use the practice in the upcoming year). The mean responses for each of these three categories of respondents across the independent variables of interest are summarized in Tables 2 and 3.

We used a one-way ANOVA and chi-square to assess the initial differences between the groups ($p < .05$). For cover crops, the innovators had significantly higher issue attentiveness than the laggards, while both the innovators and the future adopters had greater general nutrient loss concern than the laggards. The innovators were also significantly more likely to use no-till practices on their chosen field than the other two groups. In terms of perceived efficacy and barriers, all of the groups were significantly different from one another with innovators having the highest perceived efficacy and lowest perceived barriers, followed by the future adopters, and then laggards. For subsurface placement, the innovators had significantly higher issue attentiveness, general nutrient loss concern, and specific legal concern when compared to the future adopters (interestingly the laggards were similar to the innovators). The innovators perceived significantly fewer barriers relative to both other groups, while all of the groups were different in regards to perceived efficacy, with innovators indicating the greatest perceived efficacy, followed by the future adopters and the laggards.

3.2. Regression and SWAT model results

The data met the assumptions for a multinomial logistic regression. Namely, the observations were independent, and there was no evidence of multicollinearity. The Pearson's correlation coefficient did not exceed 0.6 for any pairwise comparisons of the independent variables. Similarly, the tolerance and VIF statistics were acceptable using linear regression as a proxy (i.e., tolerance > 0.2 (Menard, 1995) and average VIF not substantially greater than 1 (Bowerman and O'Connell, 1990)). There were also over 30 cases or survey responses per independent variable in the final model.

3.2.1. What is the likelihood that farmers will adopt subsurface placement? What set of beliefs influence their likelihood of adoption?

For subsurface placement, we found that 328 of our 748 cases were missing at least one of the variables in the analysis. Using listwise deletion that left 420 valid responses for analysis. The final model was statistically significant, $\chi2$ (26, N = 420) = 116.666, p = .000, indicating that the model was able to distinguish between different categories of adoption. The model as a whole explained between 24% (Cox and Snell) and 27% (Nagelkerke) of the variance in adoption. The likelihood ratio tests indicated that there was a significant effect of issue attentiveness ($\chi2$ (2, N = 420) = 9.614, p = .010) and perceived efficacy ($\chi2$ (2, N = 420) = 72.411, p = .000) on the category of adoption. Respondents with high issue attentiveness were 0.54 times more likely to be a laggard (as opposed to a future adopter) (CI for Exp(B) 0.320-0.913). Respondents with high perceived efficacy were 3.895 times more likely to be a future adopter (as opposed to a laggard) (CI for Exp(B) = 2.187−6.937). Although issue attentiveness did not distinguish innovators from laggards, respondents with high perceived efficacy were 10.727 times more likely to be an innovator than a laggard (CI for Exp(B) = 5.929−19.410).

3.2.2. What is the likelihood that farmers will adopt cover crops? What set of beliefs influence their likelihood of adoption?

For cover crops, we found that 322 of our 748 cases were missing at least one of the variables in the analysis. Using listwise deletion that left us with 426 valid responses for analysis. The final model was statistically significant, $\chi2$ (26, N = 426) = 177.96, p = .000, indicating that the model was able to distinguish between different categories of adoption. The model as a whole explained between 34% (Cox and Snell) and 39% (Nagelkerke) of the variance in adoption. The likelihood ratio tests indicated that there was a significant effect of cover crop barriers ($\chi2$ (2, N = 426) = 25.66, p = .000), perceived efficacy ($\chi2$ (2, N = 426) = 53.65, p = .000), using no-till on the field ($\chi2$ (2, N = 426) = 7.72, p = .021), total farm acres ($\chi2$ (2, N = 426) = 5.17, p = .076), and having only a high school education ($\chi2$ (2, N = 426) = 7.43, p = .024) on the category of adoption. Respondents with high perceived barriers were 0.34 times more likely to be a laggard (as opposed to a future adopter) (CI for Exp(B) = 0.202-0.583). Respondents with high perceived efficacy were 3.4 times more likely to be a future adopter (as opposed to a laggard) (CI for Exp(B) = 1.969−5.876). There were several other effects differentiating innovators from laggards, in addition to the two identified for future adopters. Similarly, respondents with high perceived barriers were 0.17 times more likely to be a laggard (as opposed to an innovator) (CI for Exp(B) = 0.079-0.375), while respondents with high perceived efficacy were 14.9 times more likely to be an innovator than a laggard (CI for Exp(B) = 6.645−33.508). In addition, respondents using no-till on their chosen field (as opposed to conventional or conservation tillage) were 2.57 times more likely to be an innovator than a

Table 2
The mean response on the designated scale or percent of individuals in each category of adoption for each of the independent variables used in the model for subsurface placement of fertilizer.

Variable Name	Laggards (n = 146, 35%)	Future Adopters (n = 124, 30%)	Innovators (n = 150, 36%)
Issue attentiveness[a]	4.81	4.57	5.06
Nutrient loss concern[b]	4.22	4.06	4.46
Legal concern[b]	4.97	4.72	5.11
Perceived efficacy[c]	2.78	4.61	6.71
Perceived barriers[d]	.51	.36	.06
Median farmed acres	1100	800	1075
No-till on field	32%	36%	34%
Rented field	26%	27%	27%
Income (250K+)	33%	24%	25%
Age	56	56	57
H.S. education only	48%	45%	40%

[a] Response scale: from 0 (not at all) to 6 (a great deal) where 3 (a moderate amount).
[b] Response scale: from 0 (not at all concerned) to 6 (extremely concerned).
[c] Response scale: from 0 (very weak perceived efficacy) to 10 (very strong perceived efficacy).
[d] Response scale: -2 (strongly disagree), -1 (disagree), 0 (neither disagree nor agree), 1 (agree), 2 (strongly agree.

Table 3
The mean response on the designated scale or percent of individuals in each category of adoption for each of the independent variables used in the model for cover crops.

Variable Name	Laggards (n = 156, 37%)	Future Adopters (n = 174, 41%)	Innovators (n = 96, 23%)
Issue attentiveness[a]	4.62	4.85	5.12
Nutrient loss concern[b]	3.95	4.36	4.56
Legal concern[b]	4.81	4.95	5.12
Perceived efficacy[c]	2.67	5.20	7.73
Perceived barriers[d]	.72	.14	-.47
Median farmed acres	1000	855	1175
No-till on field	23%	34%	50%
Rented field	27%	27%	26%
Income (250K+)	26%	26%	34%
Mean age	56	56	57
H.S. education only	44%	48%	35%

[a] Response scale: from 0 (not at all) to 6 (a great deal) where 3 (a moderate amount).
[b] Response scale: from 0 (not at all concerned) to 6 (extremely concerned).
[c] Response scale: from 0 (very weak perceived efficacy) to 10 (very strong perceived efficacy).
[d] Response scale: -2 (strongly disagree), -1 (disagree), 0 (neither disagree nor agree), 1 (agree), 2 (strongly agree.

laggard (CI for Exp(B) = 1.308–5.048). Respondents with more than a high school education were 2.2 times more likely to be an innovator than a laggard (CI for Exp(B) = 1.138–4.301), while every increase of total farm acreage by 100 acres made respondents 1.04 times more likely to be an innovator than a laggard (CI for Exp(B) = 1.005–1.080).

3.2.3. To what extent would increasing perceived efficacy increase adoption and reduce nutrient loading to recommended levels?

Given the relative importance of perceived efficacy at differentiating between levels of adoption, we then modeled the predicted probability of adoption given incremental increases in perceived efficacy (e.g., 10% increase from baseline measures, 20% increase, etc. up to a 100% increase in perceived efficacy) (Fig. 2a and b).[3] For example, increasing efficacy by 50% for cover crops results in an increase in adoption from 14% at baseline levels to 27%. A similar increase in efficacy for subsurface placement results in an increase from 32% to 51%. We know that 64% of our sample for cover crops and 66% for subsurface placement constitute our motivated or willing audience (i.e., those who reported the potential use of cover crops in the future). According to the predicted probabilities, reaching these levels of adoption would require an increase in efficacy of over 90% for cover crops, and an increase in efficacy of about 80% for subsurface placement. This suggests that on average, to move future adopters to the innovation stage, we would need to raise their perceived efficacy by approximately 2 points for subsurface placement, but approximately 5 points for cover crops on our standardized scale of perceived efficacy from 0 to 10.

Following the approach described in Scavia et al. (2017), the results of the watershed model scenarios were evaluated against the 860 MT March-July Maumee River total phosphorus loading target recommended by the Annex 4 Objectives and Targets Task Team (2015) by averaging model predicted March-July loads for the 2005-2014 period. With no increase in filter strip adoption from baseline conditions, model results suggest that a combined perceived efficacy increase of approximately 70% for both cover crops and subsurface placement may achieve the March-July total phosphorus loading target (Fig. 3). This would correspond with total adoption levels of 34% for cover crops and 60% for subsurface placement, well within the potential for adoption among our motivated or willing audience. As adoption of filter strips increases, the necessary increases in perceived efficacy for cover crops and subsurface placement required to change behavior and achieve the loading target lessens. The combination of 25% additional filters (i.e., for a total of 55% of the fields with filter strips) lessens the need for perceived efficacy increases to 50% (i.e., for a total of 27% of fields in cover crops and 51% in subsurface placement), while 50% additional filters (i.e., for a total of 80% filters) lessens the increased need in perceived efficacy to 20% (i.e., for a total of 18% of the fields in cover crops and 39% in subsurface placement). Both scenarios would result in the loading target being met, on average, according to the watershed model (Fig. 3). It is important to note that meeting the 860 MT total phosphorus loading target on average over the 2005-2014 period does not ensure that the target will be met for each individual year. In fact, model results for the 25% filters plus 60% efficacy increase scenario suggest that phosphorus loads will still exceed the target in five out of the ten years simulated (2008, 2010, 2011, 2013, and 2014). It is also important to note that because these simulations relied on single randomization assignments, load reduction predictions may vary with alternative or multiple randomization assignments.

4. Discussion

An understanding of the behavioral mechanisms driving decision making are critical to solving eutrophication challenges. Our data suggest that cognitive solutions or outreach-based interventions could be an effective means of achieving the recommended 40% reduction in total phosphorus to western Lake Erie. Technological solutions to these challenges often bypass the human behavior at the root of the problem. One such example would be geoengineering to reduce nutrients in aquatic systems, such as adding aluminum, which is perhaps most effective in deep lakes with small watersheds (Mackay et al., 2014). While structural solutions aimed at changing the *real* costs and benefits of a behavior (e.g., economic incentives) are a popular and often effective tool in the agroecosystem, limited funding and the tendency for cost-sharing programs to be a short-term solution leads many practitioners to rely on informational interventions aimed at increasing intrinsic motivation (Deci et al., 1999). These cognitive solutions are designed to educate and inform the target audience, ultimately changing the *perceived* value of costs and benefits over time in an attempt to change behavior.

Our data indicate that farmers in the western Lake Erie basin are highly motivated to adjust their land management practices. From a communication standpoint, we know the only individuals who are likely to adjust their beliefs about a particular issue are those that are currently indifferent or do not have a strong position on the issue at stake (Pomerantz et al., 1995; O'Keefe, 2015). Using that logic to think about behavioral intentions, we might expect that a

[3] Baseline measures for adoption were based on actual past behavior or the use of the practice on the representative field during the past growing season.

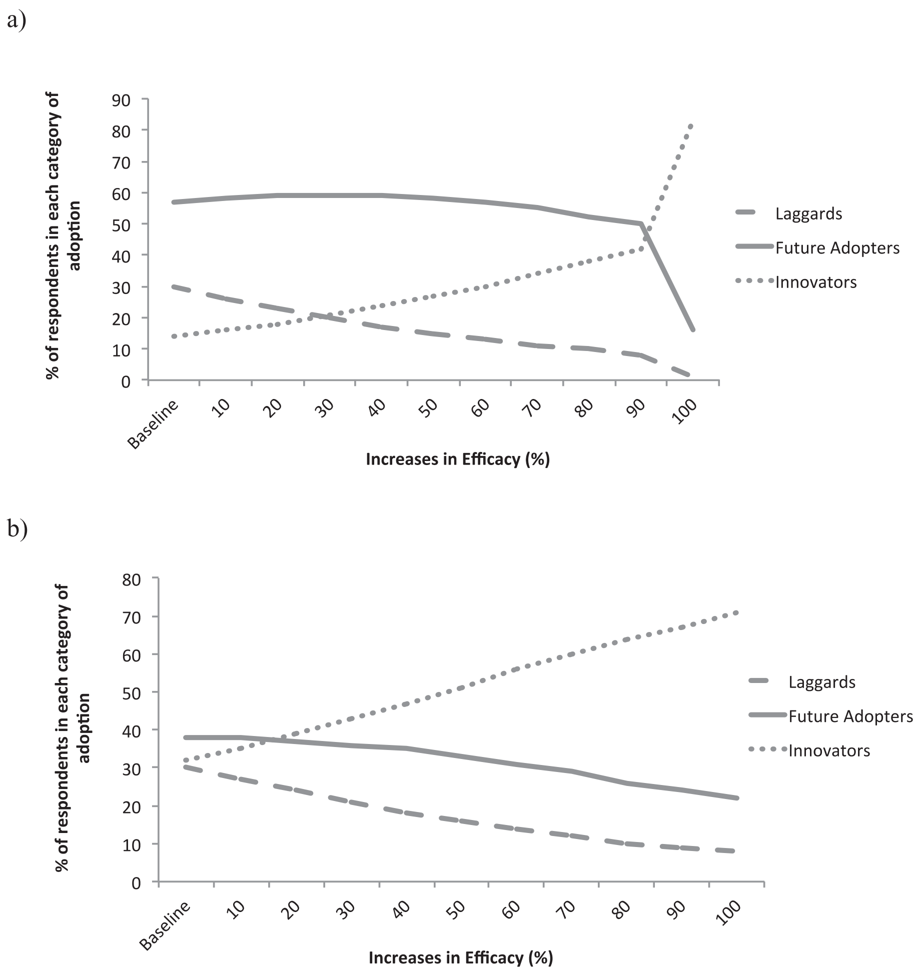

Fig. 2. The predicted probability of adoption as perceived efficacy increases by 10% increments from baseline levels for (a) cover crops and (b) subsurface placement of fertilizer.

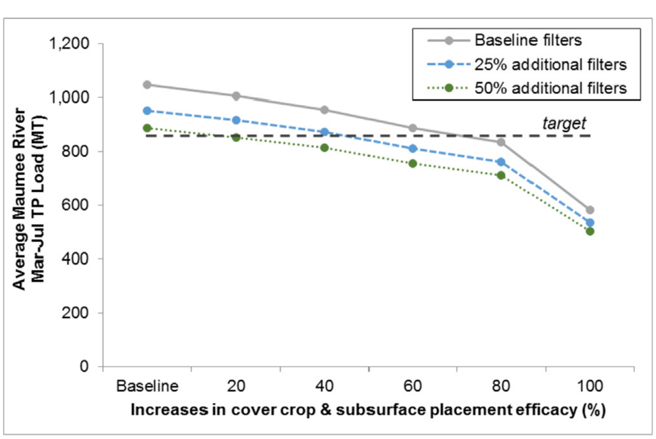

Fig. 3. Maumee River watershed SWAT model predicted average 2005-2014 March-July total phosphorus (TP) load for various increases in perceived cover crop and subsurface placement behavior as a function of increased perceived efficacy and three different filter strip adoption levels relative to the 860 metric ton (MT) target.

cognitive intervention would only be effective for those individuals who are already likely to change their behavior (i.e., the 30 to 40% of individuals for the two recommended practices who have not used the practice yet but report a likelihood of using it in the future). These are individuals who are considering adopting a particular practice, and are most likely to be receptive to efforts meant to inform them about the benefits of the practice in an attempt to motivate a change. Achieving a change among just these motivated individuals appears to go a long way toward meeting phosphorus reduction targets set for Lake Erie.

To engage these individuals, the question then becomes what set of beliefs need to change, and how likely is it that a change in those beliefs might actually result in a change in behavior and an improvement in environmental conditions. As mentioned previously, behavioral theories tend to suggest that the last piece of the puzzle before a behavior change occurs relates to the idea of perceived efficacy and individual agency (Floyd et al., 2000; Armitage and Conner, 2001; Ajzen, 2002). Specifically, that an individual must perceive both an ability and capacity to take action, and that those actions will actually help the individual achieve his or her specific goals. Our results indicate that this idea of perceived efficacy is especially critical to promoting the recommended behaviors, and that increasing perceived efficacy through outreach and education has the potential to meet the phosphorus loading target on average in Lake Erie. This finding is consistent with a recent meta-analysis of the farmer adoption literature that indicates the three best determinants of adoption are access to quality information about recommended practices, financial capacity and being connected to the right social networks (Baumgart-Getz et al., 2012). Increases in the quality of information and one's financial and social capital are likely to reduce many of the relevant barriers, and increase perceived efficacy.

In our study, we measured both the perception that one could perform the behavior (i.e., self-efficacy), as well as the perception that the performed behavior would actually work at multiple scales (i.e., field and watershed level response-efficacy). We found that these two constructs were positively related, that individuals with greater confidence in their ability to take action were also more likely to believe that the recommended actions would work. From a practical standpoint, this indicates that it is a combination of not knowing how to implement a practice *and* not believing it will be effective that seems to inhibit change in the agroecosystem. Although in many ways, the issue of eutrophication in agricultural landscapes is a collective action problem, there are also on-farm benefits of the recommended actions that may be relevant to individual actors. Farmers are not just stymied by a concern that the collective will is lacking to improve water quality in Lake Erie, they are similarly concerned about their own ability to implement the practice and achieve on-farm benefits (e.g., decreased nutrient loss, improved soil health, etc). The relatively low levels of perceived efficacy that we see for the laggards relative to the future adopters, and for the future adopters relative to the innovators, suggest that increasing perceived efficacy is a promising solution to increase adoption and achieve the 40% reduction in total phosphorus.

Taking cover crops as example, the agronomic literature is rather mixed on the effectiveness of the practice. In some cases, cover crops (in combination with a practice like continuous no-till) are believed to be an effective tool for phosphorus retention (Bosch et al., 2014; Kovar et al., 2011). However, contradictory studies suggest that cover crops are an ineffective tool for improving surface water quality (Sharpley and Smith, 1991), partially due to the benefits being so context dependent (Dagel et al., 2014; Duiker and Curran, 2005). Therefore it is not surprising that the perceived efficacy of cover crops is wide-ranging among farmers due to the mixed messages they are receiving about this particular strategy. In addition, cover crops, relative to many other recommended practices, are recognized as particularly complex to manage. This increasing complexity in the decision to use cover crops relative to a practice like subsurface placement results in a higher threshold of efficacy needed to elicit a change in behavior. Specifically, increasing adoption by building perceived efficacy requires twice as large an increase for cover crops as it does for subsurface placement. Generally speaking, this suggests that motivating adoption of subsurface placement, as a means of addressing this complex systems challenge, may be possible through outreach focused on building perceived efficacy. While cover crops may require some combination of efficacy-building and cost-sharing to decrease the real up-front costs and perceived risks associated with adoption.

Previous research indicates that past experience seems to be of particular importance to building perceived efficacy, where prior success with a practice builds efficacy and failures decrease efficacy (Bandura, 2002). As a result, building perceived efficacy among farmers may be as simple as creating low-risk opportunities for individuals to test out a practice at a small scale on their farm. We do see evidence in our data that perceived efficacy and the perceived barriers are inversely correlated, meaning as one perceives the practice specific barriers as more challenging (i.e., too complex, too expensive, too time consuming), their perceived efficacy decreases. This challenge could perhaps be addressed by applying previous research that indicates observing others performing the action can build one's own sense of efficacy and decrease the perceived barriers (Bandura, 1986). This strategy is fairly common in agricultural outreach and education efforts where peer learning is used as a means of educating individuals about conservation practices. Field days and demonstration farms are often used to demonstrate how a practice has been successfully implemented by a peer, with the idea being that this social modeling may encourage adoption among others by increasing the belief that the practice can be successfully adopted on one's own farm (Rogers, 2003).

Although peer-to-peer learning is an effective method for building perceived efficacy, leveraging other effective strategies from behavioral science could enhance such opportunities. For example, we know that one way to decrease perceived uncertainty about a behavior is to acknowledge the uncertainty while demonstrating what is known (Palenchar and Heath, 2007), while allowing participants to engage in group deliberation about the best actions given the uncertainty (Roncoli et al., 2011). Greater opportunities at field days and demonstration events to engage the attendees in discussion about the costs and benefits of the practices, and ways to adapt a specific practice to a particular farming context, could be very valuable. The literature on goal-setting also recommends that a concrete, written plan be in place to ensure that an individual is able to act on their “good intentions” (Locke and Latham, 2002). Ending an outreach event with a planning exercise that helps the attendee map out the steps it will take to implement a particular practice could help each individual realize such a change.

Despite the wealth of knowledge in the behavioral sciences, most of these strategies have not been explicitly identified or evaluated to assess to what extent they can successfully alter behavior in complex systems. Nor has there been serious consideration given to the importance of these behavioral mechanisms in designing policy aimed at achieving ecological outcomes. This study is an attempt to consider those behavioral mechanisms, and assess to what extent the practices that are physically promising as a solution are also behaviorally realistic. Future research should design and evaluate interventions aimed at building perceived efficacy to document how to design education and outreach efforts that will be more effective at removing barriers to change at the individual level and increasing adoption of recommended practices in the agricultural landscape.

5. Conclusions

Using western Lake Erie as a case study for eutrophication policy design, the evidence suggests that behavioral solutions could play an important role in meeting water quality challenges. The in-field management practices that have been identified as important to meeting the 40% reduction target have a high probability of being adopted by the target audience, and in levels that are necessary to meet the target. Furthermore, increasing adoption of these practices among the motivated future adopters may be possible by building perceived efficacy. Past failures to engage the agricultural community in voluntary adoption of conservation practices may be due less to a lack of motivation and concern, and more a lack of high quality, science-based outreach communicating how to successfully implement the necessary practices. Intersecting the results of the behavioral models with the watershed model provides significant benefits, as it allows for optimizing the application of limited resources (budget and time) across BMP implementation and cognitive solutions to increase adoption rates. Moving forward, it is important to consider the likelihood of recommended practice adoption when designing policy, but it is also critical to demonstrate the effectiveness of the proposed solutions at both a local and watershed scale.

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References

Ajzen, I., 2002. Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. J. Appl. Soc. Psychol. 32 (4), 665–683.
Annex 4 Objectives and Targets Task Team, 2015. Recommended phosphorus loading targets for Lake Erie. In: US EPA and Environment and Climate Change Canada.
Armitage, C.J., Conner, M., 2001. Efficacy of the theory of planned behaviour: a meta-analytic review. Br. J. Soc. Psychol. 40, 471–499.
Bandura, A., 1986. The explanatory and predictive scope of self-efficacy theory. J. Soc. Clin. Psychol. 4 (3), 359–373.
Bandura, A., 2002. Social cognitive theory in cultural context. Appl. Psychol. 51 (2), 269–290.
Baumgart-Getz, A., Prokopy, L.S., Floress, K., 2012. Why farmers adopt best management practice in the United States: a meta-analysis of the adoption literature. J. Environ. Manag. 96 (1), 17–25.
Bejankiwar, R., Benoy, G., Child, M., Demsey, D., Nevin, J., 2013. International Joint Commission Draft Summary Report (Lake Erie Ecosystem Priority): Recommendations to Reduce Nutrient Loadings and Harmful Algal Blooms. The International Joint Commission, Windsor, ON.
Bosch, N.S., Evans, M.A., Scavia, D., Allan, J.D., 2014. Interacting effects of climate change and agricultural BMPs on nutrient runoff entering Lake Erie. J. Great Lake. Res. 40 (3), 581–589.
Bowerman, B.L., O'Connell, R.T., 1990. Linear Statistical Models: an Applied Approach. Duxbury Press.
Brookes, J.D., Carey, C.C., 2011. Resilience to blooms. Science 334 (6052), 46.
Brooks, B.W., Lazorchak, J.M., Howard, M.D.A., Johnson, M.-V.V., Morton, S.L., Perkins, D.A.K., Reavie, E.D., Scott, G.I., Smith, S.A., Steevens, J.A., 2016. Are harmful algal blooms becoming the greatest inland water quality threat to public health and aquatic ecosystems? Environ. Toxicol. Chem. 35 (1), 6–13.
Burnett, E., Wilson, R.S., Heeren, A., 2018. Farmer adoption of cover crops in the western Lake Erie basin. J. Soil Water Conserv. 73 (2), 143–155. https://doi.org/10.2489/jswc.73.2.143.
Dagel, K.J., Osborne, S.L., Schumacher, T.E., 2014. Improving soybean performance in the northern great plains through the use of cover crops. Commun. Soil Sci. Plant Anal. 45 (10), 1369–1384.
Deci, E.L., Koestner, R., Ryan, R.M., 1999. A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation. Psychol. Bull. 125 (6), 627–668.
Dillman, D.A., 2007. Mail and Internet Surveys: the Tailored Design Method. John Wiley & Sons, New York, NY.
Duiker, S.W., Curran, W.S., 2005. Rye cover crop management for corn production in the northern mid-Atlantic region. Agron. J. 97 (5), 1413–1418.
Floyd, D.L., Prentice-Dunn, S., Rogers, R.W., 2000. A meta-analysis of research on protection motivation theory. J. Appl. Soc. Psychol. 30 (2), 407–429.
Johnk, K.D., Huisman, J., Sharples, J., Sommeijer, B., Visser, P.M., Stroom, J.M., 2008. Summer heatwaves promote blooms of harmful cyanobacteria. Global Change Biol. 14 (3), 495–512.
Keitzer, S.C., Ludsin, S.A., Sowa, S.P., Annis, G., Arnold, J.G., Daggupati, P., Froehlich, A.M., Herbert, M.E., Johnson, M.-V.V., Sasson, A.M., 2016. Thinking outside of the lake: can controls on nutrient inputs into Lake Erie benefit stream conservation in its watershed? J. Great Lake. Res. 42 (6), 1322–1331.
Kline, P., 2013. Handbook of Psychological Testing. Routledge, New York, NY.
Kovar, J.L., Moorman, T.B., Singer, J.W., Cambardella, C.A., Tomer, M.D., 2011. Swine manure injection with low-disturbance applicator and cover crops reduce phosphorus losses. J. Environ. Qual. 40, 329–336.
Locke, E.A., Latham, G.P., 2002. Building a practically useful theory of goal setting and task motivation: a 35-year odyssey. Am. Psychol. 57 (9), 705.
Mackay, E.B., Maberly, S.C., Pan, G., Reitzel, K., Bruere, A., Corker, N., Douglas, G., Egemose, S., Hamilton, D., Hatton-Ellis, T., 2014. Geoengineering in lakes: welcome attraction or fatal distraction? Inland Waters 4 (4), 349–356.
Markowitz, E., 2013. Efficacy: a Brief Overview with an Eye towards Implications and Measurement. FrameWorks Institute, Washington, D.C.
Menard, S., 1995. Applied Logistic Regression Analysis. Quantitative Applications in the Social Sciences, vol. 106. Thousand Oaks, London, England.
Michalak, A.M., 2013. Record-setting algal bloom in Lake Erie caused by agricultural and meteorological trends consistent with expected future conditions. Proc. Natl. Acad. Sci. Unit. States Am. 110 (16), 6448–6452.
Natural Resoures Conservation Service, 2016. Effects of Conservation Practice Adoption on Cultivated Cropland Acres in Western Lake Erie Basin, 2003-06 and 2012. 120 pp.
O'Keefe, D.J., 2015. Persuasion: Theory and Research. Sage Publications, Inc, Thousand Oaks, California.
Ohio Lake Erie Phosphorus Task Force, 2013. Ohio Lake Erie Phopshorus Task Force II Final Report, Ohio Department of Agriculture, Ohio Department of Natural Resources. Ohio Environmental Protection Agency, Ohio Lake Erie Commission.
Palenchar, M.J., Heath, R.L., 2007. Strategic risk communication: adding value to society. Publ. Relat. Rev. 33 (2), 120–129.
Pomerantz, E.M., Chaiken, S., Tordesillas, R.S., 1995. Atittude strength and resistance processes. Journal of Personality and Social Pscychology 69 (3), 408–419.
Prokup, A., Wilson, R., Zubko, C., Heeren, A., Roe, B., 2017. 4R Nutrient Stewardship in the Western Lake Erie Basin. The Ohio State University, Columbus, OH.
Rogers, E.M., 2003. Diffusion of Innovations. Free Press, New York, NY.
Roncoli, C., Orlove, B.S., Kabugo, M.R., Waiswa, M.M., 2011. Cultural styles of participation in farmers' discussions of seasonal climate forecasts in Uganda. Agric. Hum. Val. 28 (1), 123–138.
Scavia, D., Kalcic, M., Muenich, R.L., Read, J., Aloysius, N., Bertani, I., Boles, C., Confesor, R., DePinto, J., Gildow, M., Martin, J., 2017. Multiple models guide strategies for agricultural nutrient reductions. Front. Ecol. Environ. 15 (3), 126–132.
Sharpley, A.N., Smith, S.J., 1991. Effects of Cover Crops on Surface Water Quality. Soil and Water Conservation Society, Ankeny, IA, pp. 41–50.
Sheeran, P., 2002. Intention—behavior relations: a conceptual and empirical review. Eur. Rev. Soc. Psychol. 12 (1), 1–36.
Webb, T.L., Sheeran, P., 2006. Does changing behavioral intentions engender behavior change? A meta-analysis of the experimental evidence. Psychol. Bull. 132 (2), 249.
Wilson, R.S., Howard, G., Burnett, E.A., 2014. Improving nutrient mangement practices in agriculture: the role of risk-based beliefs in understanding farmers' attitudes toward taking additional action. Water Resour. Res. 50, 6735–6746.
Zhang, W., Wilson, R.S., Burnett, E., Irwin, E.G., Martin, J.F., 2016. What motivates farmers to apply phosphorus at the “Right” time? Survey evidence from the Western Lake Erie Basin. J. Great Lake. Res. 42 (6), 1343–1356.