Water Research 201 (2021) 117375

Contents lists available at ScienceDirect

Water Research

journal homepage: www.elsevier.com/locate/watres

Evaluating the efficacy of targeting options for conservation practice adoption on watershed-scale phosphorus reductions

Jeffrey B. Kast[a,b,*], Margaret Kalcic[b,c], Robyn Wilson[d], Douglas Jackson-Smith[d], Nicholas Breyfogle[e], Jay Martin[b,f]

[a] Environmental Science Graduate Program, The Ohio State University, 174 18th Ave., Columbus, OH 43210, United States
[b] Department of Food, Agricultural and Biological Engineering, The Ohio State University, 590 Woody Hayes Dr., Columbus, OH 43210, United States
[c] The Translational Data Analytics Institute at Ohio State, 175 Pomerene Hall, 1760 Neil Ave., Columbus, OH 43210, United States
[d] School of Environment and Natural Resources, The Ohio State University, 2021 Coffey Rd., Columbus, OH 43210, United States
[e] Department of History, The Ohio State University, 230 Annie & John Glenn Avenue, Columbus, OH 43210, United States
[f] The Sustainability Institute at Ohio State, 174W. 18th Avenue, Columbus, OH 43210, United States

ARTICLE INFO

Keywords:
Soil and Water Assessment Tool
Conservation identity
Buffer strips
Subsurface nutrient placement

ABSTRACT

Conservation identities of farmers in the Maumee River watershed, derived from farmer surveys, were embedded into a SWAT watershed model. This was done to improve the representation of the heterogeneity among farmers in the decision-making process related to the adoption of conservation practices. Modeled farm operations, created with near field-level Hydrologic Response Units (HRUs) within the SWAT model, were assigned a modeled primary operator. Modeled primary operators held unique conservation identities driven by their spatial location within the watershed. Five pathways of targeting the adoption of subsurface placement of phosphorus and buffer strips to HRUs within the watershed were assessed. Targeting pathways included targeting by HRU-level phosphorus losses, conservation identity of model operators, a hybrid approach combining HRU-level phosphorus losses and conservation identity of the model primary operator managing the HRU, and a proxy measure for random placement throughout the watershed. Targeting the placement of subsurface phosphorus application to all agricultural HRUs resulted in the greatest reduction in total phosphorus losses (32%) versus buffer strips (23%). For both conservation practices, targeting by HRU-level total phosphorus losses resulted in the most efficient rate of phosphorus reduction as measured by the ratio of phosphorus reduction to conservation practice adoption rates. The hybrid targeting approach closely resembled targeting by phosphorus losses, indicating near optimal results can be obtained even when constraining adoption by farmer characteristics. These results indicate that by developing management strategies based on a combination of field-level information and human-operator characteristics, a more efficient use of limited resources can be used while achieving near-maximal environmental benefits as compared to managing environmental outcomes solely based on field-level information.

1. Introduction

Agriculture is a significant source of pollution impairing rivers, lakes, and oceans across the world (Deknock et al., 2019). This non-point source pollution can result in numerous environmental challenges including Harmful Algal Blooms (HABs; Paerl et al., 2018) and hypoxic dead zones (Porter et al., 2015) that cause socioeconomic problems globally (McCrackin et al., 2017). The Laurentian Great Lakes are no exception to these environmental and socioeconomic challenges (Wolf and Klaiber, 2017; Scavia et al., 2017). To lessen the impact agriculture has on nutrient loading to the Laurentian Great Lakes and, in particular, to Lake Erie, which has been affected by HABs of increasing severity since the early 2000s (Stumpf et al., 2016), current policies primarily promote the voluntary adoption of conservation practices (CPs; Holland et al., 2020; Kerr et al., 2016). This approach to watershed management ensures that human decision-makers are instrumental in the adoption and utilization of CPs to improve downstream water quality. However, research conducted on the watershed-scale effectiveness of CPs on reducing nutrient losses does not usually consider these human-actors and their heterogeneous beliefs and attitudes towards conservation

* Corresponding author at: Environmental Science Graduate Program, The Ohio State University, 174 18th Ave., Columbus, OH 43210, United States.
E-mail address: kast.14@osu.edu (J.B. Kast).

https://doi.org/10.1016/j.watres.2021.117375
Received 16 February 2021; Received in revised form 15 June 2021; Accepted 16 June 2021
Available online 19 June 2021

(Evenson et al., 2021; Scavia et al., 2017).

Watershed models are a commonly used tool to assess the impact of agricultural management practices on nutrient runoff at larger scales than an individual agricultural field (Miller et al., 2020; Liu et al., 2017). In the Maumee River watershed (MRW), the largest Lake Erie watershed and the primary driver of HABs in Lake Erie (Stumpf et al., 2016; Maccoux et al., 2016), watershed models have evaluated the nutrient reduction benefits of individual and bundled-practice CPs (Martin et al., 2021; Scavia et al., 2017; Kalcic et al., 2016). Watershed models have been used to highlight how targeting CPs to fields that contribute the greatest amount of nutrients to the watershed outlet can be effective in reducing the impact of agriculture on nutrient and sediment loading (Martin et al., 2021; Parajuli et al., 2008). While this approach highlights variability in biophysical vulnerability, it does not account for the presence of heterogeneous decision-makers across agricultural landscapes. Targeting these hotspots, or critical source areas, in watershed models is generally a function of landscape characteristics such as slope and soil types, with decisions about what and where to implement management practices determined by the modeling team (Martin et al., 2021; Xu et al., 2019; Scavia et al., 2017). Because landowners and farm operators who manage these hotspots are not equally likely to actually implement the necessary practices in the designated locations, these models might over predict the impact of targeting strategies. This limitation suggests that rather than targeting CPs in watershed models solely based on the landscape characteristics, modeling teams could target either (1) By decision-maker characteristics, such as their attitude towards CPs, age, or gross income, or (2) Through a combination of landscape and decision-maker characteristics to simulate, more accurately, the probable spatial adoption of CPs in a watershed.

Many factors influence agricultural producers' beliefs, attitudes, and actions regarding their field-level management decisions (Liu et al., 2018; Ulrich-Schad et al., 2017) leading to heterogeneous decisions made among farmers in a specific region, even when operating in similar economic, political, and ecological contexts (Karali et al., 2013; Chouinard et al., 2008). Farmers in the MRW are no exception to this (Burnett et al., 2018; Zhang et al. 2016). A non-exhaustive list of factors that influence decisions made by farmers in the MRW regarding their land management include a farmer's age, education, experience farming, and conservation identity (Burnett et al., 2018; Liu et al., 2018; Burton, 2014). Conservation identity is a strong indicator of a farmer's willingness to adopt CPs in the present or in the future, and, has been found to be the most predictive characteristics of future adoption for numerous CPs in the MRW (Burnett et al., 2018; Zhang et al., 2016). Farmers who hold greater conservation identities are more likely to adopt CPs than farmers with lower conservation identities. Grounded in identity theory, which indicates that person identities reflect individuals' understanding of themselves as having particular traits and qualities (McGuire et al., 2013), conservation identity is a function of the "good farmer" identity. Rather than an understanding or perception of their individual role or a CP's role in limiting nutrient loss, conservation identity aims to capture how farmers perceive and understand their own role as a farmer and what it means to be a "good farmer." Because identities of farmers are not necessarily linked to the physical characteristics of the fields they manage, targeting CP adoption to this farmer characteristic is a more realistic way of assigning CPs than solely focusing on land characteristics.

The Soil and Water Assessment Tool (SWAT), a common watershed model used in agricultural settings, generally ignores socio-economic factors in its modeling framework (Cools et al., 2011). Integrated modeling frameworks that bridge socio-economic factors and watershed models (Zomorodian et al., 2018; Liu et al., 2015; Yang et al., 2007), have been applied in watersheds around the world (Yazdi and Moridi; 2017; Daloğlu et al., 2014; Cools et al., 2011) including in the MRW (Liu et al., 2020; Wilson et al., 2018). Although integrated modeling allows socio-economic characteristics to be accounted for in watershed models when using SWAT, these models must be externally linked, which leads to a series approach to model integration (Francesconi et al., 2016). In this series approach, socio-economic models are first developed and results from these models are then used to drive inputs for scenario simulations in SWAT.

The goals of this work are to describe an approach to embed the characteristics of human-operators into a calibrated SWAT model and evaluate the potential impact of incorporating characteristics of human-actors in CP targeting simulations. The three objectives of this work are (1) Create modeled farm operations, (2) Assign conservation identities based on a farmer survey to decision-makers of the modeled farm operations, and (3) Compare targeting CP placement based on a combination of field-level phosphorus losses and human-operator conservation identities to solely targeting by field-level phosphorus losses.

2. Methods

2.1. Study area

The MRW (Fig. 1) is the largest contributor of phosphorus to Lake Erie (Maccoux et al., 2016). Row crop agriculture dominates the watershed landscape, with approximately 80% of the land use in row-crop agriculture (Ohio EPA, 2010).

2.2. SWAT model

The Soil and Water Assessment Tool (SWAT, revision 635; modified according to Kalcic et al. (2016)) is a process-based hydrological model that simulates hydrologic and nutrient fluxes within watersheds (Arnold et al., 1998). SWAT has been used in watersheds across the world including within the Great Lakes basins (Martin et al., 2021; Scavia et al., 2017; Muenich et al., 2016). Within the MRW, SWAT has been identified as the most appropriate watershed model among various watershed-modeling frameworks (Gebremarium et al., 2014). A recently developed and validated version of SWAT was used to simulate

Fig. 1. The MRW is approximately 17,000 km^2 in size and spans portions of Indiana, Michigan, and Ohio.

hydrology and nutrient dynamics within the MRW (Apostel et al., 2021; Kast et al., 2021). This SWAT model was satisfactorily calibrated to nutrient and hydrology parameters between 2005 and 2015 at the USGS gauge #04193500, Table 1. Daily water quality and stream flow data used in calibration and validation were obtained from the National Center for Water Quality Research at Heidelberg University (ncwqr.org). Although the model was calibrated and validated at the single gauge, simulation results were compared to Edge-of-Field data of fields located upstream within the watershed. These comparisons showed the model was able to capture the range of water quality results upstream of the watershed outlet (Apostel et al., 2021).

The SWAT model used in this study consists of 24,256 Hydrologic Response Units (HRUs), the smallest spatial discretization in the modeling framework. The mean size of agricultural HRUs (84% of HRUs in the model) is 70.9 ha (175.3 acres), comparable to that of the average farm-field size in Ohio (72.4 ha), Indiana (106.8 ha), and Michigan (82.9 ha; USDA, 2017). For further information of model development, including near field-scale HRU delineation and model calibration and validation see Apostel et al. (2021).

2.3. Creating modeled farm operations and assigning conservation identities to modeled primary operators

2.3.1. Modeled farm operations

Modeled farm operations (MFOs), approximating farm boundaries of farming operations found within the watershed, were created by aggregating agricultural HRUs. HRUs included in each MFO were constrained by the county and model subbasin in which the HRUs were located thus allowing non-adjacent HRUs to be included in a MFO. Each MFO included between one and five HRUs, depending on the size of the operation. Modeled farm operation sizes were stratified within each county according to the percentage of farms in the county between 1 and 179 acres, 180 and 499 acres, 500 and 999 acres, and 1000 or more acres, according to the 2017 Agricultural Census (USDA, 2017; Supplementary Material Table S1).

2.3.2. Assigning conservation identities to modeled primary operators

Each MFO was assigned a modeled primary operator (MPO) who represented the operation's decision-maker on farm management practices. A survey of farmers within the watershed was used to derive characteristics of farmers in the region (Burnett et al., 2018; Zhang et al., 2016). Conservation identity was measured through seven survey items each on a 5-point Likert scale (Supplementary Material Table S5). Respondents were asked to rate the importance of each item on their personal definition of a good farmer from 0 (not at all important) to 4 (very important; Burnett et al., 2018; McGuire et al., 2015; Arbuckle et al., 2013). The average score given to the seven survey items by the respondent was calculated to be the respondent's conservation identity. Survey respondents' conservation identities were grouped by zip code and aggregated to the county level. The maximum, mean, median, and standard deviation of conservation identities among survey respondents were calculated for each county. County-level distributions of conservation identities derived from this process were used to guide assignments of conservation identities to MPOs.

The existing CP use on each MFO per county in the calibrated SWAT model was estimated. Included in this calculation was the use of a cover crop, a grassed waterway, incorporation of nutrients after application, subsurface placement of nutrients, and continuous no-tillage on each HRU within a MFO. A standardized metric of CP adoption was created by dividing the number of CPs present on a MFO by the number of HRUs within the MFO. After standardized metrics of CP adoption were calculated for each model farm operation, model farm operations and their corresponding CP adoption metric value were segregated by county. Within each county, MFOs were ranked from the greatest standardized CP adoption metric to the least. Rankings of standardized CP adoption metrics among the MFOs were used to assign conservation identities of MPOs. Three-levels of conservation identities (weak, moderate, and high) were assigned based on this standardized CP adoption metric and county-level results of conservation identities from the farmer survey (Supplementary Material Tables S2–S4). The qualitative descriptors for the three levels of conservation identities were derived from Burnett et al. (2018). To translate these qualitative categorizations into quantitative values, it was assumed that measured values were equally distributed within each level and constrained by the possible ranges of conservation identities from the farmer survey. Weak conservation identities were assigned a random value between 0.00 and 1.33. Moderate conservation identities were assigned a random value between 1.34 and 2.66. High conservation identities were assigned a value between 2.67 and 4.00. This was completed to link equivalent results of the farmer survey directly to the farmer conservation identities applied to MFOs (i.e., a MFO with an operator holding a conservation identity of 2.5 would be equivalent to a farmer respondent with a conservation identity score of 2.5).

2.4. Targeting CPs to fields

Five alternative targeting approaches were used to apportion two separate CPs, (1) Subsurface placement of inorganic phosphorus

Table 2
Targeting pathways used to apportion subsurface placement (Subsurface P) of inorganic phosphorus fertilizer and buffer strips within the watershed.

Targeting Pathway	Description
Greatest Phosphorus Loading Rate HRUs	The agricultural HRUs with the greatest P runoff were targeted to receive the CP
Least Phosphorus Loading Rate HRUs	The agricultural HRUs with the least P runoff were targeted to receive the CP
Greatest Modeled Primary Operator Conservation Identity HRUs	The agricultural HRUs managed by the modeled primary operators with the greatest Conservation Identity were targeted to receive the CP
Greatest Phosphorus Loading Rate HRUs Managed by Modeled Primary Operators with the Greatest Conservation Identities	The agricultural HRUs with the largest aggregate rank order value were targeted to receive the CP

Table 1
Monthly and daily calibration and validation statistics for the Maumee River SWAT model. All entries met the minimum criteria for 'Satisfactory' performance except monthly and daily sediment PBIAS validation (Apostel et al., 2021).

	Statistic	Metric for Satisfactory Performance	Daily Calibration (2005–2015)	Monthly Calibration (2005–2015)	Daily Validation (2000–2004)	Monthly Validation (2000–2004)
Flow	NSE	>0.5	0.87	0.95	0.82	0.86
	PBIAS	< ±15%	−0.83	−0.88	−10.03	−10.11
Total Phosphorus	NSE	>0.35	0.58	0.52	0.46	0.44
	PBIAS	< ±30%	−3.76	−3.23	−18.53	−18.35
Dissolved Reactive Phosphorus	NSE	>0.35	0.62	0.67	0.63	0.73
	PBIAS	< ±30%	2.03	1.51	−9.89	−10.22
Sediment	NSE	>0.45	0.65	0.75	0.58	0.70
	PBIAS	< ±20%	1.62	2.06	−27.21	−26.09

fertilizer (Subsurface P) and (2) Buffer strips, throughout the watershed (Table 2 and Fig. 2). In each scenario, subsurface placement of inorganic phosphorus fertilizer was simulated by placing 99% of the fertilizer mass below the top 1 cm of soil. Buffer strips were sized at 2% of the field drainage area with 50% being concentrated flow and 25% being fully channelized.

The first targeting approach selected HRUs estimated to have the greatest total phosphorus (TP) loading rates in the baseline calibrated SWAT model, sometimes referred to as "critical source areas" (Evenson et al., 2021; Supplementary Material Fig. S1).The second targeting approach selected HRUs with the least TP loading rates. In these two approaches, agricultural HRUs were rank-ordered from largest to smallest TP discharge rates (Supplementary Material Fig. S2). Rank orders with ties were used when two or more HRUs had similar TP discharge rates. The third targeting approach selected HRUs in MFOs with MPOs that were estimated to have the greatest conservation identities (Supplementary Material Fig. S3). For this targeting approach, conservation identities of MPOs were rank ordered from largest to smallest. Rank orders with ties were used when two or more HRUs managed by MPOs had similar conservation identities. The fourth targeting approach selected HRUs with the greatest TP loading rates that were managed by MPOs with the greatest conservation identities (Supplementary Material Fig. S4). For this targeting approach, each HRU rank order from the first and third targeting approaches were summed. Eleven scenarios that represented increasing adoption rates for each CP were run for each of these targeting approaches. CP adoption ranged from the baseline calibrated model adoption rate to 100% adoption on agricultural HRUs (Supplementary Material Table S6). A one-to-one line was created for each CP from the adoption endpoints, Baseline Adoption and 100% Adoption. This one-to-one line was regarded as a proxy measure of randomly selecting HRUs to receive the CP, a fifth targeting approach. Unlike the previous four targeting approaches, this scenario assumes that results would lie on the one-to-one line between the Baseline Adoption and 100% Adoption scenarios and was not run directly in the SWAT model. This proxy measure represented the average results of thousands of simulations in which different sets of HRUs were randomly selected to receive the CP and was created in place of simulating a random assignment pathway.

3. Results

3.1. Modeled farm operations and modeled primary operator conservation identities

Across the watershed, 17,297 MFOs were created from the 24,256 HRUs in the SWAT model (Supplementary Material Tables S1 and S4). Putnam County, Ohio had the largest number of MFOs while Whitley County, Indiana had the smallest, Table 3. The percentage of MFOs smaller than 180 acres and greater than 1000 acres varied by county with Williams County, Ohio having the largest number of MFOs less than 180 acres and Van Wert County, Ohio having the greatest number of MFOs larger than 1000 acres, Supplementary Material Table S1.

Modeled primary operators in Lucas County, Ohio had the highest average conservation identity while MPOs in Henry County, Ohio had the lowest average conservation identity (Supplementary Material Table S3). Based on the conservation identity categorization presented in Section 2.3, a majority of the MPOs across the watershed were assigned a strong conservation identity (77.8%) while 21.0% and 1.2% of MPOs were assigned moderate and weak conservation identities, respectively (Supplementary Material Table S2).

3.2. Targeting the adoption of subsurface phosphorus applications and buffer strips

Increasing the adoption of Subsurface P to 100% of agricultural HRUs from its adoption rate in the calibrated baseline (8.7%) led to a 31% reduction in March-July TP loads and a 48% reduction in March-July Dissolved Reactive Phosphorus (DRP) loads (Fig. 3). Increasing the adoption of buffer strips to 100% of agricultural HRUs from its adoption rate in the calibrated baseline (31%) led to a 23% reduction in March-July TP loads and a 19% reduction in March-July DRP loads (Fig. 4).

Targeting the adoption of both CPs to the HRUs with the greatest TP loading rates resulted in the highest efficiency (phosphorus reduction/ rate of CP adoption) in achieving phosphorus reductions. As expected, the lowest phosphorus reduction efficiencies were obtained when targeting the adoption of the CPs to the HRUs with the least TP loading rates. Targeting both CPs to the HRUs with the greatest MPO conservation identities resulted in similar phosphorus reduction efficiencies as

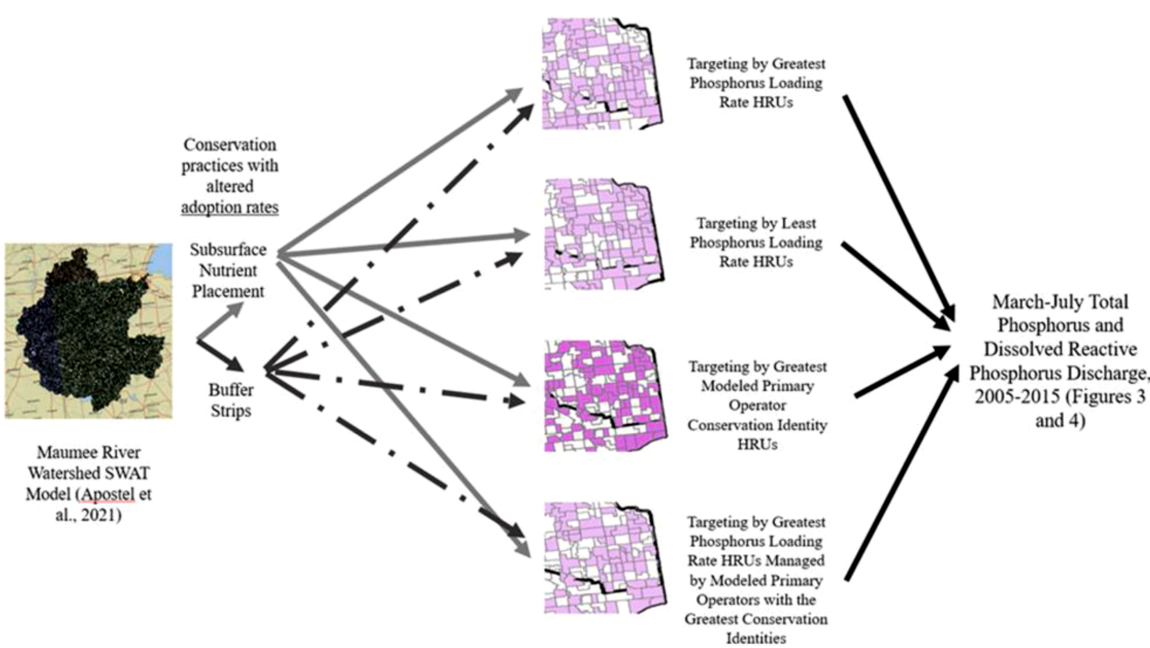

Fig. 2. Conceptual schematic of simulation process.

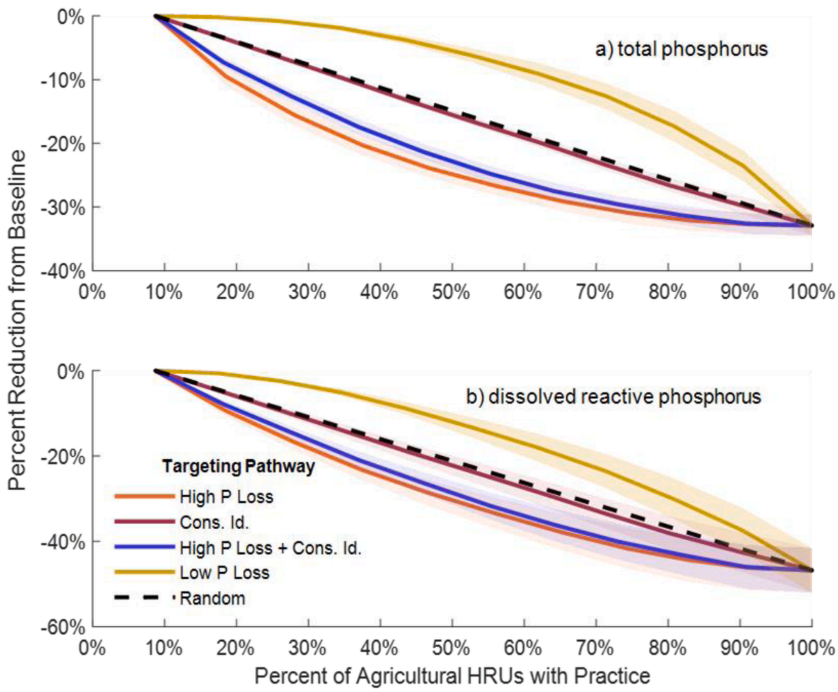

Fig. 3. Reductions of (a) Total phosphorus and (b) Dissolved reactive phosphorus resulting from the adoption of Subsurface P by various targeting pathways. The most efficient phosphorus reduction rates result from the Greatest P Loss pathway, which is likely unattainable because of limited information and farmer participation. Similar phosphorus reduction efficiencies result from targeting the placement of Subsurface P by a combination of field-level information as well as farmer information, which is a more attainable management option. The maximum difference between the Greatest P Loss and Least P Loss targeting pathways is at 54.5% adoption of the CP indicating the adoption rate with the greatest uncertainty related to the effectiveness of the CP on reducing P loads from the watershed model.

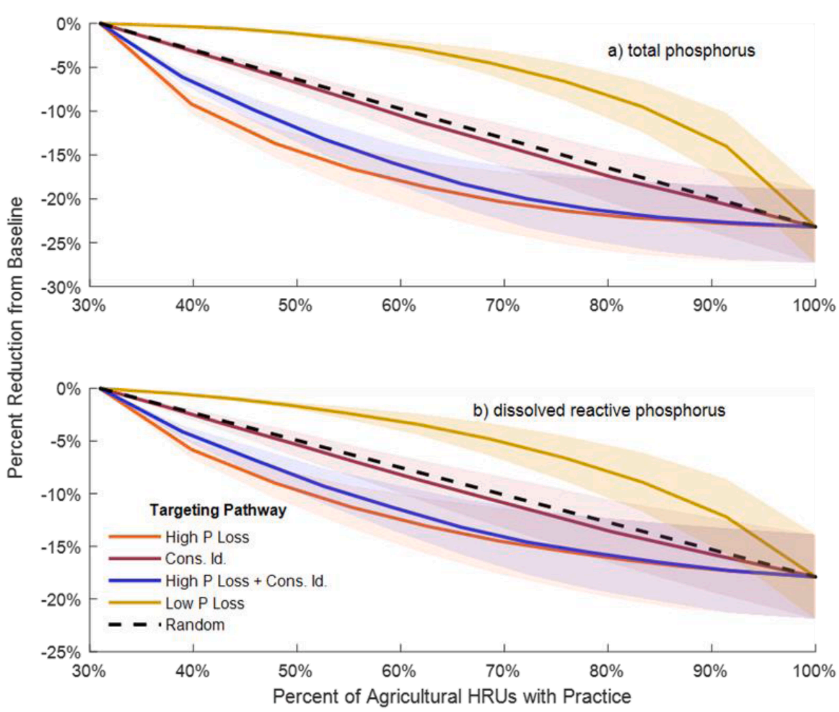

Fig. 4. Reductions of (a) Total phosphorus and (b) Dissolved reactive phosphorus resulting from the adoption of buffer strips by various targeting pathways. Similarly to Subsurface P, achieving phosphorus reduction rates as indicated by the Greatest P Loss pathway may be unattainable and that targeting the placement of buffer strips by a combination of field-level information as well as farmer information achieves similar phosphorus reduction efficiencies. The maximum difference between the Greatest P Loss and Least P Loss targeting pathways is at 65.5% adoption of the CP, indicating the adoption rate with greatest uncertainty related to the effectiveness of the CP on reducing P loads in the watershed model.

randomly selecting HRUs to receive the CPs. Targeting both CPs by combining consideration of HRUs with large phosphorus losses and MPOs with high conservation identities resulted in the second highest efficiency in achieving phosphorus reductions (Figs. 3 and 4). The two most efficient approaches produced the greatest gains in TP and DRP load reduction from the initial increases from baseline adoption. In effect, for the scenario targeting CPs based on high runoff potential, each 1% increase in adoption of Subsurface P from the baseline (8.7%) to 18.5% adoption levels resulted in a decrease of TP loads by 1%. When conservation identities were considered alongside high runoff potential, each 1% increase in adoption of Subsurface P decreased TP loads by 0.77% as adoption rose from 8.7 to 18.2% of agricultural land area. This was expected because initially these practices were applied to fields with the greatest losses and thus where they would realize the greatest reductions. Similar trends were observed for DRP reductions for Subsurface P and for both TP and DRP reductions for buffer strips although the magnitudes of the decreasing phosphorus loading rates differed (Figs. 3 and 4).

3.3. Impacts of watershed-scale CP adoption efficacy in reducing phosphorus losses

3.3.1. Targeting adoption to HRUs with the greatest total phosphorus loading rates compared to other simulated targeting pathways

Since adoption rates of 54.5% for Subsurface P and 65.5% of buffer strips, respectively, resulted in the greatest difference in phosphorus reductions between targeting pathways, this adoption level was used to compare differences due to targeting options (Figs. 3 and 4). Targeting by the least phosphorus loading rates, as compared to targeting by the greatest phosphorus loading rates, resulted in approximately between 10 and 20% more TP and DRP discharged from the watershed. Targeting by the greatest phosphorus loading rates HRUs managed by MPOs with the greatest conservation identities resulted in approximately between 0.5 and 1.5% more TP and DRP discharged from the watershed, as compared to targeting by the greatest phosphorus loading rate HRUs (Fig. 5).

3.3.2. Targeting adoption to HRUs with high total phosphorus loading rates and to high total phosphorus loading rate HRUs managed by modeled primary operators with high conservation identities compared to simulated targeting pathways

The adoption rate of Subsurface P across the watershed with the largest difference in phosphorus reduction between targeting HRUs with the greatest TP losses to those with the greatest TP losses managed by MPOs with the greatest conservation identities (28% adoption of Subsurface P) resulted in TP and DRP losses differing by 2.7% and 1.9%, respectively (Fig. 6). The adoption rate of buffer strips across the watershed with the largest difference in phosphorus reduction between targeting HRUs with the greatest TP losses to those with the greatest TP losses managed by MPOs with the greatest conservation identities (48% adoption of buffer strips) resulted in TP and DRP losses differing by 2.8% and 1.5%, respectively (Fig. 6).

4. Discussion

4.1. Integrating farmer-actors in watershed modeling of agricultural systems

Developing MPOs using results from stakeholder surveys and directly embedding them into a watershed model is a novel approach for integrated modeling analyses. In particular, the approach developed and used in this study is unique for evaluating the efficacy of CP adoption in agriculturally dominated watersheds. This approach allowed for representing over 17,000 unique MPOs. This large number of unique actors, or decision-makers, contrasts with the limited number of actors represented in agent-based models (ABMs) that have been integrated with watershed models. Ng. et al. (2011) integrated an ABM with a SWAT model of the Salt Creek watershed in Central Illinois; however, only 50 farmers were represented in the ABM due to the long computational time needed to run the model. In Ohio's Sandusky Watershed, Daloğlu et al. (2014) grouped the farmer agents into four farmer types that drove parameters influencing their adoption decisions in the ABM. Although this work developed methods to allow for a large number of unique actors a limitation is that these actors could not interact or learn from one another, a benefit common to ABMs of socio-ecological systems (Lippe et al., 2019; Daloğlu et al., 2014; Ng et al., 2011).

While an ABM has not been integrated with a model of the MRW, prior research has coupled economic and farmer behavioral attitudes with watershed models. Liu et al. (2020), focused on coupling a behavioral-economic model with a SWAT model of the MRW to assess how increases in cost-share payments for CP adoption and fertilizer taxes would affect nutrient losses within the watershed by way of increasing CP adoption. Martin et al. (2021) ran scenarios in SWAT models of the MRW guided by results from a survey of farmers in the watershed. Wilson et al. (2018), integrated results from a farmer survey taken within the MRW to a SWAT model of the MRW to assess how changes in farmer efficacies regarding cover crops and subsurface placement of nutrients reduce phosphorus discharge at various adoption levels of filter strips. This work improves upon these prior efforts in the MRW to develop a watershed model that includes socio-behavioral information of farmers in the watershed while also providing a basis to further simulate how socio-behavioral characteristics of farmers in the watershed can affect CP adoption and resulting changes in nutrient discharges, through the addition of MFOs and MPOs.

4.2. Adoption rates of subsurface P and buffer strips and phosphorus discharges

Increasing the adoption of Subsurface P to 100% resulted in 1.3-times and 2.1-times greater TP and DRP reductions from the watershed than by increasing the adoption of buffer strips across the

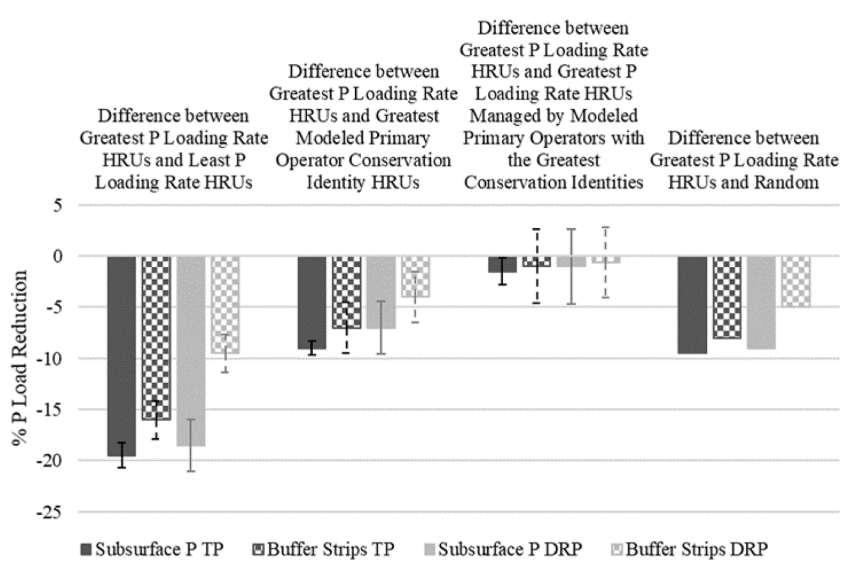

Fig. 5. Percent difference in March-July TP and DRP loads discharged from the watershed through various targeting methods for subsurface placement and buffer strips at adoption rates resulting in maximum differences between the targeting methods (54.5% for subsurface placement and 65.5% for buffer strips). Results from the Greatest Phosphorus Loading Rate HRUs are used as the basis for comparisons.

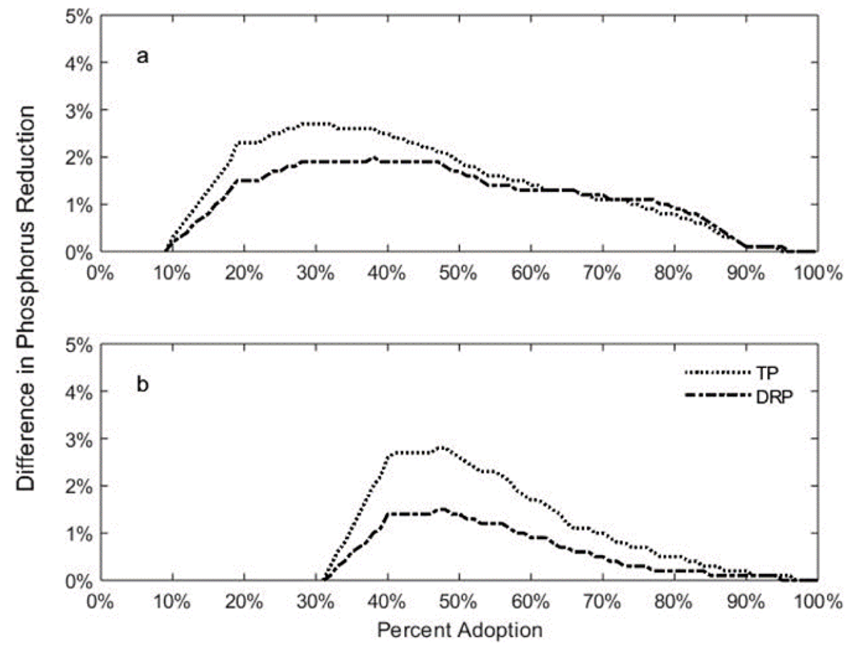

Fig. 6. Differences in TP and DRP losses between targeting HRUs with the greatest TP losses and the HRUs with the greatest TP losses managed by modeled primary operators with the greatest conservation identities for (a) Subsurface P and (b) Buffer strips across the spectrum of BMP adoption rates starting at the baseline level adoption and ending at 100% adoption.

watershed to 100%. Comparing DRP and TP, at 100% adoption of Subsurface P, DRP loss reductions were 1.5 times greater than TP loss reduction. In contrast, DRP loss reduction were 1.2 times less than TP loss reduction at 100% adoption of buffer strip indicating that buffer strips are more effective at reducing TP losses than DRP losses. This result agrees with Roberts et al. (2012) which found that buffer strips affected TP losses more than DRP losses in a variety of locations. Within the MRW, numerous watershed modeling studies have found that placing fertilizer nutrients in the subsurface is the most effective single in-field or edge-of-field practice in reducing nutrient runoff from the watershed at 100% adoption rates (Martin et al., 2021; Scavia et al., 2017). Results from this study confirm this result and show that across a spectrum of adoption rates, subsurface placement of P is more effective at reducing phosphorus discharge than buffer strips. Although subsurface placement of P was the more effective practice at reducing phosphorus discharge from the watershed, buffer strips provide additional environmental benefits that may be of interest to landowners and operators. These additional benefits include reducing soil erosion, providing greater soil moisture contents, and stabilizing ditch and river channels (Cole et al., 2020; Kavian et al., 2018; Borin et al., 2010).

4.3. Effectiveness of targeting CP adoption pathways

As expected, targeting Subsurface P and buffer strips to HRUs with the greatest TP loading rates resulted in greater decreases in TP and DRP discharges from the watershed than randomly applying the CPs across the watershed (Martin et al., 2021; Scavia et al., 2017) and was the most efficient pathway in reducing nutrient losses. Although this pathway was the most efficient pathway in reducing TP and DRP across the watershed, limitations such as a lack of knowledge of the locations of these highest P loss fields in the environment affect the practicality of this approach to watershed management. Targeting the adoption of CPs to HRUs managed by MPOs with high conservation identities and through random selection had similar phosphorus reduction efficiencies. One explanation for these similar phosphorus reduction efficiencies is the little relation between farmers' conservation identity and runoff from their fields. Although farmers' psychological characteristics related to their identity as a farmer affects the practices used on their farms (Burnett et al., 2018; Zhang et al., 2016) they cannot greatly influence the physical features of their landscape (e.g., slope or soil type). Although these two targeting methods showed similar effectiveness in reducing TP and DRP losses, targeting by conservation identity resulted in slightly more advantageous outcomes. This may be due to model development, the linking of conservation identities to model farm operations, and the systematic selection of HRUs with greater amounts of CPs present through the targeting method than through the random adoption process.

4.4. Designing CP adoption programs to improve water quality

Although targeting the adoption of CPs across the watershed by the TP losses from individual fields (HRUs) resulted in the most efficient pathway of reducing TP and DRP losses, economic, social, and political challenges exist in prioritizing these fields to receive CPs. One challenge in targeting CPs to these high phosphorus loss fields is identifying their locations. Although a variety of factors affect phosphorus runoff from agricultural fields such as fertilizer application methods and precipitation (Endale et al., 2019; Hanrahan et al., 2019), field-level characteristics are important in governing nutrient flow dynamics. For example, fields with high soil test phosphorus values have been found to contribute more phosphorus downstream than fields with low soil test phosphorus values (Duncan et al., 2017) indicating they are potential critical source areas of nutrient losses. This field-level data is generally proprietary information, which can lead to a lack of publicly available knowledge of where these high soil-test phosphorus fields are in the landscape. Because federal CP adoption programs are generally designed on a first-come, first-serve basis (Talberth et al., 2015), farmers with fields with the greatest risk of phosphorus loss may not have the chance or may decide to not enroll in a program.

Economic and social-psychological factors contribute to a farmer's willingness to participate in voluntary CP adoption programs (Yeboah et al., 2015; Reimer and Prokopy, 2014). These factors also contribute to the willingness of farmers within the MRW to adopt various CPs to reduce phosphorus discharged to Lake Erie. In this setting, farmers with higher conservation identities are more likely to adopt various CPs (Burnett et al., 2018; Zhang et al., 2016). Thus, within the MRW, TP and

DRP loss reductions due to increasing CP adoption rates likely more closely resemble TP and DRP reduction pathways as indicated when targeting by MPO conservation identities than the most efficient pathway of targeting by high P loss HRUs in the future (Figs. 3 and 4). This likely implies that in agriculturally dominated watersheds more efficient nutrient reduction pathways exist as the amount of phosphorus a field discharges is not the sole factor in a farmer determining whether to adopt a CP to reduce the nutrient discharge. However, if CP adoption programs, whether at the federal, state, or local level, focus on recruiting farmers that have high phosphorus loss fields and who have a strong or high conservation identities similar efficiencies in nutrient reductions can be achieved as by targeting CPs only to the greatest phosphorus loss fields (Figs. 3 and 4). An example of this approach to watershed management at the federal level is the Western Lake Erie Basin Initiative of the United States Department of Agriculture's Natural Resources Conservation Service (USDA-NRCS). Through this initiative, the USDA-NRCS screens applicants for funding through NRCS Environmental Quality Incentives Program (EQIP) with the applicants whose land is fully within the watershed and is vulnerable to nutrient discharge (i.e., higher soil test phosphorus values) being given higher ranking for funding (NRCS, 2016a, 2016b).

4.5. Future work

Although conservation identity has been shown to be a strong predictor of future CP adoption (Burnett et al., 2018) other socio-psychological, demographic, and economic conditions have been found to affect conservation decisions made by farmers (Prokopy et al., 2019; Liu et al., 2018). Using farmer surveys of the MRW, demographic factors such as age and gender and socio-psychological factors such as perceived conservation practice effectiveness at reducing nutrient losses can be linked with MPO conservation identities at the county-level to add further heterogeneity. With these more complete MPOs, an agent-based model can be developed to allow these heterogeneous MPOs to interact and learn from each other. Further, economic analyses on the cost-effectiveness of programs aimed to capture CP adoption trends presented in the targeting pathways can be completed. These economic analyses will provide policy insight for CP adoption programs that are most cost-effective in terms of their ability to reduce phosphorus losses from a watershed.

5. Conclusion

With limited financial resources, it is critical to develop programs that distribute support for CP adoption in ways that generate greater returns in terms of improved water quality. Agricultural CP programs that recruit farmers using dual criteria- targeting the highest phosphorus loading fields as well as those who are most willing to participate in CP programs- can nearly achieve the same phosphorus discharge reduction as programs that focus primarily on placing CPs on fields with the greatest phosphorus loss. An approach that accounts for behavioral factors in responses to program incentives is likely much more realistic than believing that all farmers are equally likely to implement conservation practices on their fields. In the MRW, as in other watersheds, locations of these high phosphorus discharge fields (or high conservation identity farmers) are not always known; however, effective outreach and programming can counteract this gap in knowledge by focusing on farmers who manage fields with higher soil phosphorus values and who hold favorable dispositions towards adopting CPs. This approach is particularly important in efficiently achieving downstream water quality improvement in schemes that rely on the voluntary adoption of CPs, as is the case in the MRW and throughout much of the world.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Support for this work was provided by the National Science Foundation Innovations at the Nexus of Food Energy Water Systems Program (INFEWS 1739909). We thank the anonymous reviewers for their helpful comments on earlier drafts of this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.watres.2021.117375.

References

Apostel, A., Kalcic, M., Dagnew, A., Evenson, G., Kast, J., King, K., Martin, J., Muenich, R.L., Scavia, D., 2021. Simulating internal watershed processes using multiple SWAT models. Sci. Total Environ. 759, 143920 https://doi.org/10.1016/j.scitotenv.2020.143920 https://doi.org/.

Arbuckle, J.G., 2013. Farmer support for extending Conservation Compliance beyond soil erosion: Evidence from Iowa. J. Soil Water Conserv. 68 (2), 99–109.

Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large area hydrologic modeling and assessment part I: model development. JAWRA J. Am. Water Resour. Assoc. 34, 73–89.

Borin, M., Passoni, M., Thiene, M., Tempesta, T., 2010. Multiple functions of buffer strips in farming areas. Eur. J. Agron. 32, 103–111. https://doi.org/10.1016/j.eja.2009.05.003 https://doi.org/.

Burnett, E., Wilson, R.S., Heeren, A., Martin, J., 2018. Farmer adoption of cover crops in the western Lake Erie basin. J. Soil Water Conserv. 73, 143–155. https://doi.org/10.2489/jswc.73.2.143 https://doi.org/.

Burton, R.J.F., 2014. The influence of farmer demographic characteristics on environmental behaviour: a review. J. Environ. Manage. 135, 19–26. https://doi.org/10.1016/j.jenvman.2013.12.005 https://doi.org/.

Chouinard, H., Paterson, T., Wandschneider, P., Ohler, A., 2008. Will farmers trade profits for stewardship? Heterogeneous motivations for farm practice selection. Land Econ 84, 66–82.

Cole, L., Stockan, J., Helliwell, R., 2020. Managing riparian buffer strips to optimise ecosystem services: a review. Agr. Eco. Env. 296, 106891 https://doi.org/10.1016/j.agee.2020.106891 https://doi.org/.

Cools, J., Broekx, S., Vandenberghe, V., Sels, H., Meynaerts, E., Vercaemst, P., Seuntjens, P., Van Hulle, S., Wustenberghs, H., Bauwens, W., Huygens, M., 2011. Coupling a hydrological water quality model and an economic optimization model to set up a cost-effective emission reduction scenario for nitrogen. Environ. Model. Softw. 26, 44–51. https://doi.org/10.1016/j.envsoft.2010.04.017 https://doi.org/.

Daloğlu, I., Nassauer, J.I., Riolo, R., Scavia, D., 2014. An integrated social and ecological modeling framework—impacts of agricultural conservation practices on water quality. Ecol. Soc. 19 https://doi.org/10.5751/ES-06597-190312 https://doi.org/.

Deknock, A., De Troyer, N., Houbraken, M., Dominguez-Granda, L., Nolivos, I., Van Echelpoel, W., Forio, M.A.E., Spanoghe, P., Goethals, P., 2019. Distribution of agricultural pesticides in the freshwater environment of the Guayas river basin (Ecuador). Sci. Total Environ. 646, 996–1008. https://doi.org/10.1016/j.scitotenv.2018.07.185. https://doi.org/.

Duncan, E.W., King, K.W., Williams, M.R., LaBarge, G., Pease, L.A., Smith, D.R., Fausey, N.R., 2017. Linking soil phosphorus to dissolved phosphorus losses in the midwest. Agric. Environ. Lett. 2, 170004 https://doi.org/10.2134/ael2017.02.0004 https://doi.org/.

Endale, D.M., Schomberg, H.H., Truman, C.C., Franklin, D.H., Tazisong, I.A., Jenkins, M. B., Fisher, D.S., 2019. Runoff and nutrient losses from conventional and conservation tillage systems during fixed and variable rate rainfall simulation. J. Soil Water Conserv. 74, 594–612. https://doi.org/10.2489/jswc.74.6.594 https://doi.org/.

Evenson, G.R., Kalcic, M., Wang, Y.C., Robertson, D., Scavia, D., Martin, J., Aloysius, N., Apostel, A., Boles, C., Brooker, M., Confesor, R., Dagnew, A.T., Guo, T., Kast, J., Kujawa, H., Muenich, R.L., Murumkar, A., Redder, T., 2021. Uncertainty in critical source area predictions from watershed-scale hydrologic models. J. Environ. Manag. 279, 111506 https://doi.org/10.1016/j.jenvman.2020.111506 https://doi.org/.

Francesconi, W., Srinivasan, R., Pérez-Miñana, E., Willcock, S.P., Quintero, M., 2016. Using the Soil and Water Assessment Tool (SWAT) to model ecosystem services: a systematic review. J. Hydrol. 535, 625–636. https://doi.org/10.1016/j.jhydrol.2016.01.034 https://doi.org/.

Gebremariam, S., Martin, J., DeMarchi, C., Bosch, N.S., Confesor, R., Ludsin, S., 2014. A comprehensive approach to evaluating watershed models for predicting river flow regimes critical to downstream ecosystem services. Environ. Modell. Soft. 61, 121–134.

Hanrahan, B.R., King, K.W., Williams, M.R., Duncan, E.W., Pease, L.A., LaBarge, G.A., 2019. Nutrient balances influence hydrologic losses of nitrogen and phosphorus

across agricultural fields in northwestern Ohio. Nutr. Cycl. Agroecosyst. 113, 231–245. https://doi.org/10.1007/s10705-019-09981-4 https://doi.org/.
Holland, A., Bennett, D., Secchi, S., 2020. Complying with conservation compliance? An assessment of recent evidence in the US Corn Belt. Environ. Res. Lett. 15, 084035.
Kalcic, M., Kirchhoff, C., Bosch, N., Muenich, R.L., Murray, M., Griffith Gardner, J., Scavia, D., 2016. Engaging stakeholders to define feasible and desireable agricultural conservation in western Lake Erie watersheds. Environ. Sci. Technol. 50, 8135–8145.
Karali, E., Brunner, B., Doherty, R., Hersperger, A., Rounsevell, M., 2013. The effect of farmer attitudes and objectives on the heterogeneity of farm attributes and management in Switzerland. Human Ecol 41, 915–923.
Kast, J.B., Apostel, A.M., Kalcic, M.M., Muenich, R.L., Dagnew, A., Long, C.M., Evenson, G., Martin, J.F., 2021. Source contribution to phosphorus loads from the Maumee River watershed to Lake Erie. J. Environ. Manag. 279, 111803 https://doi.org/10.1016/j.jenvman.2020.111803 https://doi.org/.
Kavian, A., Saleh, I., Habibnejad, M., Brevik, E., Jafarian, Z., Rodrigo-Comino, J., 2018. Effectiveness of vegetative buffer strips at reducing runoff, soil erosion, and nitrate transport during degraded hillslope restoration in northern Iran. Land Degr. Dev. 29, 3194–3203. https://doi.org/10.1002/ldr.3051 https:doi.org/.
Kerr, J.M., DePinto, J.V., McGrath, D., Sowa, S.P., Swinton, S.M., 2016. Sustainable management of great Lakes watersheds dominated by agricultural land use. J. Great Lakes Res. 42, 1252–1259. https://doi.org/10.1016/j.jglr.2016.10.001 https://doi.org/.
Lippe, M., Bithell, M., Gotts, N., Natalini, D., Barbrook-Johnson, P., Giupponi, C., Hallier, M., Hofstede, G.J., Le Page, C., Matthews, R.B., Schlüter, M., Smith, P., Teglio, A., Thellmann, K., 2019. Using agent-based modelling to simulate social-ecological systems across scales. Geoinformatica 23, 269–298. https://doi.org/10.1007/s10707-018-00337-8 https://doi.org/.
Liu, H., Zhang, W., Irwin, E., Kast, J., Aloysius, N., Martin, J., Kalcic, M., 2020. Best management practices and nutrient reduction: an integrated economic-hydrologic model of the Western Lake Erie Basin. Land Econ 96, 510–530. https://10.3368/wple.96.4.510.
Liu, H., Benoit, G., Liu, T., Liu, Y., Guo, H., 2015. An integrated system dynamics model developed for managing lake water quality at the watershed scale. J. Environ. Manag. 155, 11–23. https://doi.org/10.1016/j.jenvman.2015.02.046 https://doi.org/.
Liu, T., Bruins, R.J.F., Heberling, M.T., 2018. Factors influencing farmers' adoption of best management practices: a review and synthesis. Sustainablilty. https://doi.org/10.3390/su10020432 https://doi.org/.
Liu, Y., Engel, B.A., Flanagan, D.C., Gitau, M.W., McMillan, S.K., Chaubey, I., 2017. A review on effectiveness of best management practices in improving hydrology and water quality: needs and opportunities. Sci. Total Environ. 580–593. https://doi.org/10.1016/j.scitotenv.2017.05.212, 601–602https://doi.org/.
Maccoux, M.J., Dove, A., Backus, S.M., Dolan, D.M., 2016. Total and soluble reactive phosphorus loadings to Lake Erie a detailed accounting by year, basin, country, and tributary. J. Great Lakes Res. 42, 1151–1165. https://doi.org/10.1016/j.jglr.2016.08.005 https://doi.org/.
Martin, J.F., Kalcic, M.M., Aloysius, N., Apostel, A.M., Brooker, M.R., Evenson, G., Kast, J.B., Kujawa, H., Murumkar, A., Becker, R., Boles, C., Confesor, R., Dagnew, A., Guo, T., Long, C.M., Muenich, R.L., Scavia, D., Redder, T., Robertson, D.M., Wang, Y. C., 2021. Evaluating management options to reduce Lake Erie algal blooms using an ensemble of watershed models. J. Environ. Manag. 280, 111710 https://doi.org/10.1016/j.jenvman.2020.111710 https://doi.org/.
McCrackin, M.L., Jones, H.P., Jones, P.C., Moreno-Mateos, D., 2017. Recovery of lakes and coastal marine ecosystems from eutrophication: a global meta-analysis. Limnol. Oceanogr. 62, 507–518. https://doi.org/10.1002/lno.10441 https://doi.org/.
McGuire, J., Morton, L.W., Cast, A.D., 2013. Reconstructing the good farmer identity: shifts in farmer identities and farm management practices to improve water quality. Agric. Human Values. https://doi.org/10.1007/s10460-012-9381-y https://doi.org/.
McGuire, J.M., Morton, L.W., Arbuckle Jr, J.G., Cast, A.D., 2015. Farmer identities and responses to the socialbiophysical environment. J. Rural Stud. 39, 145–155.
Miller, M.P., Capel, P.D., García, A.M., Ator, S.W., 2020. Response of nitrogen loading to the Chesapeake Bay to source reduction and land use change scenarios: a SPARROW-informed analysis. J. Am. Water Resour. Assoc. 56, 100–112. https://doi.org/10.1111/1752-1688.12807 https://doi.org/.
Muenich, R.L., Kalcic, M., Scavia, D., 2016. Evaluating the impact of legacy *P* and agricultural conservation practices on nutrient loads from the Maumee River watershed. Environ. Sci. Technol. 50, 8146–8154. https://doi.org/10.1021/acs.est.6b01421 https://doi.org/.
Ng, T.L., Eheart, J.W., Cai, X., Braden, J.B., 2011. An agent-based model of farmer decision-making and water quality impacts at the watershed scale under markets for carbon allowances and a second-generation biofuel crop. Water Resour. Res. 47, 1–17. https://doi.org/10.1029/2011WR010399 https://doi.org/.
NRCS, 2016a. FY16 Western Lake Erie Basin (WLEB) screening tool. Accessed on Nov. 15, 2020. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/null/?cid=nrcs144p2_031032.
NRCS, 2016b. FY16 Western Lake Erie Basin (WLEB) ranking. Accessed on Nov. 15, 2020. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/null/?cid=nrcs144p2_031032.
Ohio EPA, 2010. Ohio Lake Erie phosphorus task force final report.
Paerl, H.W., Otten, T.G., Kudela, R., 2018. Mitigating the expansion of harmful Algal Blooms across the freshwater-to-marine Continuum. Environ. Sci. Technol. 52, 5519–5529. https://doi.org/10.1021/acs.est.7b05950 https://doi.org/.
Parajuli, P.B., Mankin, K.R., Barnes, P.L., 2008. Applicability of targeting vegetative filter strips to abate fecal bacteria and sediment yield using SWAT. Agric. Water Manag. 95, 1189–1200. https://doi.org/10.1016/j.agwat.2008.05.006 https://doi.org/.
Prokopy, L., Floress, K., Arbuckle, J.G., Church, S., Eanes, F., Gao, U., Gramig, B., Ranjan, P., Singh, A., 2019. Adoption of agricultural conservation practices in the United States: evidence from 35 years of quantitative literature. J. Soil Water Conserv. 74, 520–534. https://doi.org/10.2489/jswc.74.5.520 https://doi.org/.
Porter, P.A., Mitchell, R.B., Moore, K.J., 2015. Reducing hypoxia in the Gulf of Mexico: reimagining a more resilient agricultural landscape in the Mississippi River Watershed. J. Soil Water Conserv. 70, 63A–68A. https://doi.org/10.2489/jswc.70.3.63A https://doi.org/.
Reimer, A.P., Prokopy, L.S., 2014. Farmer participation in U.S. Farm bill conservation programs. Environ. Manag. https://doi.org/10.1007/s00267-013-0184-8 https://doi.org/.
Roberts, W.M., Stutter, M.I., Haygarth, P.M., 2012. Phosphorus retention and remobilization in vegetated buffer strips: a review. J. Environ. Qual. 41, 389–399. https://doi.org/10.2134/jeq2010.0543 https://doi.org/.
Scavia, D., Kalcic, M., Muenich, R.L., Read, J., Aloysius, N., Bertani, I., Boles, C., Confesor, R., DePinto, J., Gildow, M., Martin, J., Redder, T., Robertson, D., Sowa, S., Wang, Y.C., Yen, H., 2017. Multiple models guide strategies for agricultural nutrient reductions. Front. Eco. Environ. 15, 126–132.
Stumpf, R.P., Johnson, L.T., Wynne, T.T., Baker, D.B., 2016. Forecasting annual cyanobacterial bloom biomass to inform management decisions in Lake Erie. J. Great Lakes Res. 42, 1174–1183 https://doi.org/10.16/j.jglr.2016.08.006.
Talberth, J., Selman, M., Walker, S., Gray, E., 2015. Pay for performance: optimizing public investments in agricultural best management practices in the Chesapeake Bay watershed. Ecol. Econ. 118, 252–261. https://doi.org/10.1016/j.ecolecon.2015.07.033 https://doi.org/.
Ulrich-Schad, J.D., Garciá De Jalón, S., Babin, N., Pape, A., Prokopy, L.S., 2017. Measuring and understanding agricultural producers' adoption of nutrient best management practices. J. Soil Water Conserv. 72, 506–518. https://doi.org/10.2489/jswc.72.5.506 https://doi.org/.
USDA, 2017. National Agriculture Statistics Survey.
Wilson, R.S., Schlea, D.A., Boles, C.M.W., Redder, T.M., 2018. Using models of farmer behavior to inform eutrophication policy in the Great Lakes. Water Res. https://doi.org/10.1016/j.watres.2018.03.065 https://doi.org/.
Wolf, D., Klaiber, H.A., 2017. Bloom and bust: toxic algae's impact on nearby property values. Ecol. Econ. 135, 209–221. https://doi.org/10.1016/j.ecolecon.2016.12.007 https://doi.org/.
Xu, Y., Bosch, D.J., Wagena, M.B., Collick, A.S., Easton, Z.M., 2019. Meeting water quality goals by spatial targeting of best management practices under climate change. Environ. Manag. 63, 173–184. https://doi.org/10.1007/s00267-018-01133-8 https://doi.org/.
Yang, W., Rousseau, A.N., Boxall, P., 2007. An integrated economic-hydrologic modeling framework for the watershed evaluation of beneficial management practices. J. Soil Water Conserv. 62, 423–432.
Yazdi, J., Moridi, A., 2017. Interactive reservoir-watershed modeling framework for integrated water quality management. Water Resour. Manag. 31, 2105–2125. https://doi.org/10.1007/s11269-017-1627-4 https://doi.org/.
Yeboah, F.K., Lupi, F., Kaplowitz, M.D., 2015. Agricultural landowners' willingness to participate in a filter strip program for watershed protection. Land Use Policy 49, 75–85 https://doi.org/10.1016/j.landusepol.2015.07.016.
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 Lakes Res. 42, 1343–1356. https://doi.org/10.1016/j.jglr.2016.08.007 https://doi.org/.
Zomorodian, M., Lai, S.H., Homayounfar, M., Ibrahim, S., Fatemi, S.E., El-Shafie, A., 2018. The state-of-the-art system dynamics application in integrated water resources modeling. J. Environ. Manage. 227, 294–304. https://doi.org/10.1016/j.jenvman.2018.08.097 https://doi.org/.