Thinking outside of the lake: Can controls on nutrient inputs into Lake Erie benefit stream conservation in its watershed?

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Abstract

Investment in agricultural conservation practices (CPs) to address Lake Erie's re-eutrophication may offer benefits that extend beyond the lake, such as improved habitat conditions for fish communities throughout the watershed. If such conditions are not explicitly considered in Lake Erie nutrient management strategies, however, this opportunity might be missed. Herein, we quantify the potential for common CPs that will be used to meet nutrient management goals for Lake Erie to simultaneously improve stream biological conditions throughout the western Lake Erie basin (WLEB) watershed. To do so, we linked a high-resolution watershed-hydrology model to predictive biological models in a conservation scenario framework. Our modeling simulations showed that the implementation of CPs on farm acres in critical and moderate need of treatment, representing nearly half of the watershed, would be needed to reduce spring/early summer total phosphorus loads from the WLEB watershed to acceptable levels. This widespread CP implementation also would improve potential stream biological conditions in >11,000 km of streams and reduce the percentage of streams where water quality is limiting biological conditions, from 31% to 20%. Despite these improvements, we found that even with additional treatment of acres in low need of CPs, degraded water quality conditions would limit biological conditions in >3,200 stream kilometers. Thus, while we expect CPs to play an important role in mitigating eutrophication problems in the Lake Erie ecosystem, additional strategies and emerging technologies appear necessary to fully reduce water quality limitation throughout the watershed.

Key words: best management practices, SWAT, non-point source pollution, Great Lakes, ecosystem-based management, index of biotic integrity

Introduction

Reducing nutrient inputs from the western Lake Erie basin (WLEB) watershed is integral to reversing Lake Erie's recent re-eutrophication (Ohio EPA, 2010; Ohio EPA, 2013; Scavia et al., 2014; Annex 4, 2015). This large watershed (~26,000 km²) drains a landscape that is >70% agricultural and contains nearly 2 million ha of farmland that is mostly in corn and soybean crop rotations (USDA NRCS, 2011). Multiple changes in local agricultural practices have occurred during the past 30 years, including the type of fertilizer used, the timing of fertilizer application, tillage practices, and increased artificial drainage, the combination of which has increased the potential for nutrient runoff into Lake Erie from the WLEB watershed (Richards et al., 2002; Daloğlu et al., 2012; Smith et al., 2015). When combined with an increasing frequency of single and multi-day severe storms during the winter and spring (Hayhoe et al., 2010) and the widespread nature of legacy loads (Sharpley et al., 2013; Powers et al., 2016), these changes in agricultural practices have contributed to increased loading of highly bioavailable dissolved reactive phosphorus into Lake Erie (Richards et al., 2010; Daloğlu et al., 2012; Scavia et al., 2014). This excess phosphorus loading, in turn, has helped fuel Lake Erie's re-eutrophication (Stumpf et al., 2012; Michalak et al., 2013; Kane et al., 2014; Scavia et al., 2014). Because eutrophication poses a threat to important ecosystem services provided by Lake Erie (Ludsin et al., 2001; Hobbs et al., 2002), reducing phosphorus loading from WLEB tributaries is a management priority (Ohio EPA, 2010; Ohio EPA, 2013; Scavia et al., 2014; Annex 4, 2015).

While efforts to reduce phosphorus loading will benefit Lake Erie, the extent to which these efforts will help improve water quality and biological conditions in the ecologically, culturally, and economically important stream network of the WLEB watershed remains uncertain. This network contains > 20,000 km of streams and rivers that historically supported a

rich diversity of invertebrates and fish (Trautman, 1981; Krebs et al., 2010). The WLEB watershed, much like Lake Erie proper, provides valuable ecosystem services (e.g., drinking water; recreational opportunities such as fishing and canoeing) to residents in Indiana, Michigan, and Ohio. Unfortunately, stream water quality in the watershed also has become degraded during the past century, owing in large part to the same agricultural sediment and nutrient non-point source (NPS) runoff that has degraded Lake Erie (Karr et al., 1985; Ohio EPA, 2014). Thus, reducing agricultural NPS runoff to help clean up Lake Erie may offer an opportunity to improve water quality and biological conditions throughout the WLEB stream network. Because farmers in the area feel a strong sense of responsibility to protect water quality in their local watersheds (Burnett et al., 2015), they might be more willing to adopt voluntary and potentially costly agricultural conservation practices (referred to as CPs hereafter), if they knew that such practices would benefit their local watershed in addition to benefiting downstream Lake Erie. Such adoption, in turn, could lead to a potential “win-win” for user groups of both Lake Erie and its watershed.

At present, however, perceived benefits of targeted phosphorus load reductions for Lake Erie have not included consideration of the possible benefits to the large stream network contained within the WLEB watershed. Thus, the extent to which targeted load reductions to Lake Erie also might improve water quality, biological conditions, and ecosystem services throughout WLEB tributaries remains an important information gap. A better understanding of where and by how much water quality and biological conditions would change throughout the WLEB watershed because of targeted load reductions to Lake Erie also could help prioritize nutrient management strategies.

Because agriculture is the dominant form of land use in the WLEB watershed, one approach to reducing nutrient loading from this watershed is to increase implementation of CPs. These CPs could include erosion control practices such as filter strips and cover crops, as well as nutrient management, which includes altering the rate, timing, amount, and method of fertilizer application. Since the mid-1970s, CPs, in particular erosion control practices such as conservation tillage, have been widely adopted in the WLEB watershed (Richards et al., 2002). These practices appear to have reduced nutrient and suspended sediment concentrations in some Lake Erie tributaries (Richards and Baker, 2002; Richards et al., 2009), and are correlated with recent improvements in stream biological conditions (Miltner, 2015). How effective additional investment in these and other widely adopted CPs would be for meeting Lake Erie nutrient reduction goals remains unknown. Even more uncertain is how additional conservation treatment of cropland would affect stream conditions and the resident aquatic biota within Lake Erie's watershed.

Herein, we provide findings from a coupled physical-biological modeling study that sought to quantify the potential benefits of increasing investment in CPs to stream biological conditions within Lake Erie's watershed. More specifically, we linked an existing high-resolution watershed-hydrology model for the WLEB watershed (Daggupati et al., 2015a) to a predictive statistical model of an Index of Biotic Integrity (IBI) developed from several long-term state-agency datasets to forecast potential benefits of additional investment in CPs. While our simulations were not designed to provide the most cost-effective solutions nor model stream impacts of reducing phosphorus loads to the levels recommended for Lake Erie, several of them more than satisfactorily met the targeted reductions in phosphorus loading to the

lake. Ultimately, we discuss the potential of CPs to simultaneously meet water quality goals in Lake Erie and benefit stream biological conditions within the WLEB watershed.

Methods

Study Area and Species

We focused on the WLEB watershed because it is integral to effective Lake Erie nutrient management (Ohio EPA, 2010; Ohio EPA, 2013; Scavia et al., 2014; Annex 4, 2015). This relatively flat watershed (average slope is $< 2\%$) drains an $\sim 26,000\text{km}^2$ area in portions of Ohio, Indiana, and Michigan (Figure 1). Most of the watershed falls within the Eastern Corn Belt Plains or the Huron/Erie Lake Plains Ecoregions, although a small portion ($< 2\%$) is in the Southern Michigan/Northern Indiana Drift Plains. Historically, this watershed was comprised of a mixture of hardwood forests, wetlands, and prairie, which eventually succumbed to rapid and widespread land clearing, wetland draining, and stream channelization that began during the mid-1800s (Trautman, 1981). Today, $>70\%$ of the watershed is in row-crop agriculture, with patchily distributed urban and forested lands each making up $\sim 12\%$ of the remaining area. Because of this topography and land-use history, most streams in the WLEB watershed are low gradient and slow flowing, carrying heavy nutrient and sediment loads that have negatively impacted native stream biodiversity and Lake Erie (Trautman, 1939; Trautman and Gartman, 1974; Karr et al., 1985; Scavia et al., 2014).

The stream network of the WLEB watershed historically supported a diverse fish fauna (Trautman, 1981). At least 98 native fish species that span a wide range of reproductive (e.g., nest builders, crevice spawners, broadcast spawners), feeding (e.g., detritivores, herbivores, invertivores, piscivores), and habitat (e.g., benthic, pelagic, littoral) guilds have been observed in the watershed. These species have different sensitivities to nutrient and sediment pollution

(Trautman, 1981; Ohio EPA, 1987). In turn, different fish communities occur throughout the WLEB watershed, with their composition likely determined to some degree by the magnitude and intensity of agricultural runoff impacts on water quality. Degraded water quality in this watershed has indeed negatively affected piscivores, herbivores, and insectivores in particular, leading to fish communities dominated by omnivorous species (Karr et al., 1985).

Modeling Stream Water Quality

We simulated sediment and nutrient processes and stream hydrology using the Soil and Water Assessment Tool (SWAT; Arnold et al., 1998). SWAT is a semi-distributed, continuous-time model developed by the United States Department of Agriculture – Agricultural Research Service for large-scale watershed simulation. SWAT is a robust and flexible approach for simulating agricultural effects on hydrologic processes that performs well relative to other watershed models in the WLEB watershed (Gebremariam et al., 2014).

We used SWAT to develop a watershed model (Daggupati et al., 2015a) at the 1:100,000 resolution using the National Hydrography Database Plus Version 2 (NHDPlusV2) dataset (http://www.horizon-systems.com/NHDPlus/NHDPlusV2_home.php). However, because conducting simulations at this resolution was too computationally expensive, we initially calibrated model parameters at a broader watershed resolution (12-digit hydrologic unit code, HUC-12). Afterwards, we transferred those parameters to the NHDPlusV2 model to provide reasonable starting points for parameter values for this finer-resolution model. We further calibrated monthly stream flow, suspended sediment, total phosphorus (TP), and total nitrogen (TN) for the NHDPlusV2 model using five river gauges that had historical data with these attributes: 1) the Raisin River

near Monroe, MI; 2) St. Joseph River near Newville, IN; 3) St. Marys River at Wilshire, OH; 4) Maumee River at Waterville, OH; and 5) Sandusky River near Fremont, OH. Detailed descriptions of the calibration and validation procedure can be found in Daggupati et al. (2015a), but followed general guidelines for SWAT model development (Daggupati et al., 2015b). We chose to focus on percent bias (PBIAS) over other performance measures, such as Nash-Sutcliffe efficient (NSE), because PBIAS measures how well the model captures long-term average conditions, whereas measures such as NSE better assess the ability to capture extreme events (e.g., storm runoff). Because we expected long-term average conditions would have a larger effect on fish communities than extremes, our effort focused on reducing the model's PBIAS.

Predictive Models of Fish Community Health

We used a multi-metric fish community index, the IBI, to assess stream biological condition (Karr, 1981; Karr et al., 1986). Indices of biotic integrity, which compare biotic communities in a given stream reach to those expected in reference conditions (i.e., streams less disturbed by human activity), are commonly used by state and federal management agencies, academic researchers, and conservation organizations as a measure of stream biological condition. To calculate IBI values, we used fish community data collected at numerous stream sites throughout the WLEB (Fig. 1) by the Indiana Department of Environmental Management (n = 18 segments), Michigan Department of Environmental Quality and Michigan Department of Natural Resources (n = 101 segments), and the Ohio Environmental Protection Agency (n = 722 stream segments) during 1990 to 2012 (n = 841 unique stream segments). Fish sampling methods were similar among states, with electro-shocking procedures that varied more within each agency (based on the size of the stream sampled) than among agencies (Ohio EPA, 1987; Michigan DEQ, 1997; Indiana DEM, 2007). Because sampling protocols were designed to comprehensively

evaluate fish communities based on species relative abundances, we assumed they generated accurate samples of the fish community across the basin (Esselman et al., 2013). We rigorously evaluated each dataset to ensure that all collections were indeed community samples, species occurrences accurately reflected their range, and site locations were geographically accurate, similar to the approach used in Esselman et al. (2013). From these fish community data, we calculated the IBI according to Michigan's Procedure 51 (P51; Michigan DEQ, 1997). We rescaled P51 scores to have a minimum of 0 and a maximum of 1, with a higher score indicating a better biological condition.

Fish community samples were spatially linked to an NHDplusV2 stream segment based on latitude and longitude, as well as written descriptions of their location. We assumed a sample was representative of the entire stream segment. In cases where multiple sites were sampled within the same stream segment in the same year, we used the average IBI of those samples to represent the stream segment. For stream segments sampled during multiple years, we used the most recent fish community sample to reflect conditions during our watershed simulation period as closely as possible. This procedure resulted in a varying number of yearly samples through time, although some years had particularly large sample sizes (Fig. A1).

We were particularly interested in understanding how nutrients and suspended sediments affected stream biological conditions. We chose these stressors because they can affect stream biotic communities in multiple ways (e.g., Waters, 1995; Evans-White et al., 2009; Miltner, 2010; Taylor et al., 2014), and a primary approach to mitigate eutrophication in Lake Erie is implementation of CIP to reduce sediment and nutrient runoff from farm fields in the watershed. Because we were uncertain as to whether annual or sub-annual (seasonal) nutrient and sediment concentrations would better predict IBI scores, we included average annual, springtime, and

summertime concentrations as predictors in our models. We focused on spring and summer because we expected agricultural pollution to have its largest impacts during these two eco-hydrological periods. These two periods also reflect different aspects of the seasonal hydrograph and are important to the life-history of most fishes in the WLEB watershed. We defined the spring period as 1 March through 30 June, which encompasses the falling limb in the typical WLEB hydrograph (SCK, unpublished data) and the period when most fishes spawn (Auer, 1982, Ohio Division of Natural Resources, website contains fish reproductive behavior, accessed on 20 Aug 2014: <http://wildlife.ohiodnr.gov/species-and-habitats/species-guide-index/fish>; M. Kibbey, The Ohio State University Museum of Biological Diversity, 2015, personal communication). We defined the summer period as 1 July through 30 September, which covers base-flow conditions and encompasses the growing season of most fishes.

To assess whether stream water quality was limiting stream-fish community health, we used multiple quantile regression to model the relationship between observed IBI scores and water quality attributes generated by our watershed model (i.e., stream discharge and TP, TN, and suspended sediment concentrations). Water quality attributes for each stream segment were derived by determining the annual median concentration (mg/L) for each time period and then calculating the average of these values from the 21-year SWAT simulation (1990 – 2010; Table A1). Thus, our measures of water quality reflect long-term average conditions within a stream segment. We used quantile regression because it can reveal reliable relationships despite not all influential (i.e., limiting) factors being measured, which often is the case with ecological data (Cade and Noon, 2003). We modeled the upper 97th percentile of IBI scores (hereafter referred to as the maximum IBI) in relation to water quality attributes because modeling upper percentiles offers a means to identify limiting relationships (Cade et al., 1999).

We used Akaike's Information Criterion adjusted for small sample size (AIC_c) to identify the best supported model that could reliably predict a maximum IBI score. Because multiple water quality stressors often co-occur and interact to affect stream biota (Townsend et al., 2008; Matthaei et al., 2010; Piggott et al., 2015), we included different additive and interactive effects of water quality stressors in our initial candidate set of models (Table A2). We did not include water quality attributes from multiple time periods (i.e., annual, spring, or summer) in the same model to avoid fitting overly complex models. We also included average stream discharge (L/s) as an additive effect in all models to account for the influence that stream size has on fish communities (Sheldon, 1968; Horwitz, 1978; Angermeier and Schlosser, 1989).

We did not include covariates that were highly correlated ($r \geq |0.7|$; Table A3) in the same model to avoid potential prediction errors associated with multicollinearity (Dormann et al., 2013). As a result, we could not include TN or TP in the same models. Because both TN and TP can degrade stream fish biotic integrity (Miltner and Rankin, 1998; Wang et al., 2007), we felt it was important to evaluate the potential limiting effect of TN and TP. We therefore developed a separate set of candidate models containing TN or TP (Table A2), and selected the best supported model from each candidate set as the model with the lowest AIC_c score (Burnham and Anderson, 1998). We then evaluated the accuracy of the best TN and TP model using k -fold cross-validation ($k = 10$). Because predictions of the maximum IBI from our quantile regression models were expected to be higher than observed values, we adopted assessment statistics from Vaz et al. (2008). For each k -fold training and test dataset, we calculated the Spearman's rank correlation coefficient (r_s) between observed and predicted maximum IBI and the percentage of observed scores that fell below our predictions. We considered the models acceptable, if 1) we

found a statistically significant and positive correlation for each k -fold and 2) at least 97% of the observed values, on average, fell below our predicted value.

We used the best supported and validated TN model and TP model to make separate forecasts of the maximum IBI with a stream segment based on water quality conditions generated from our watershed simulation. We then selected the lowest score from these forecasts to use as the maximum IBI score within a stream segment. This approach assumes that either TN or TP, along with potential interactions with stream discharge and suspended sediment concentration, is limiting stream fish communities in a stream segment. Thus, whichever model predicts the lowest score represents the maximum IBI given the simulated water quality conditions.

We standardized all water quality variables to have a mean of zero and standard deviation of one to place water quality attributes on the same scale. While discharge data were $\log_{10}$ -transformed to achieve linearity, transformations of other water quality variables were not necessary. We logit-transformed observed IBI scores because values were bounded between zero and one. All biological models were developed and analyzed with the *quantreg* package (Koenker, 2015) in the R statistical environment (R Core Team, 2015). We used the *MuMIn* package (Barton, 2015) to calculate model selection statistics.

Conservation Scenarios

We used conservation scenarios developed as part of the USDA's Conservation Effects Assessment Project (CEAP) Cropland National Assessment to examine the potential benefits of increasing investment in CPs for improving stream biological conditions and Lake Erie nutrient management. These scenarios consisted of applying erosion control and nutrient

management CPs at three treatment levels in the WLEB. The erosion control practices included were filter strips, field borders, surface roughening, herbaceous and forest riparian buffers, wind erosion control, cover crops, and residue tillage management. Nutrient management consisted of altering the timing, amount, rate, and/or form of nutrient application.

The CPs were applied to 1) only farm acres in critical need of treatment, 2) farm acres in critical and moderate need of treatment, and 3) all acres. An acre's need for CPs was determined by its level of inherent vulnerability for nutrient and sediment loss and its current level of treatment based on farmer surveys from a subset of the National Resources Inventory (USDA NRCS, 2011). According to these farmer surveys, about 8% (384,160 acres) of the watershed is in critical need of treatment and 40% (1,920,800 acres) is in moderate need of treatment for at least one resource concern (i.e., sediment, phosphorus, or nitrogen loss through surface or subsurface flows; USDA NRCS, 2011). In most cases, several CPs were applied to the same field to address multiple resource concerns (USDA NRCS, 2011). We assumed a CP adoption rate of 80% on the acres in need of treatment and that the "best" option would be chosen on 75% of the treated acres to implicitly account for limitations in CP adoption associated with individual farmer behavior. In addition to these three conservation scenarios, we included a "grassland" scenario in which we replaced all agricultural land with native grasses. This grassland scenario served as a theoretical upper benchmark to assess impacts of agricultural runoff and the effectiveness of CPs.

Assessing the Benefits of Conservation Scenarios

We simulated edge-of-field reductions in agricultural runoff from CP implementation using the Agricultural Policy/Environmental eXtender (APEX) model (Gassman et al., 2009). APEX is

a flexible model capable of simulating a broad array of agricultural management options, including nutrient management, tillage operations, cropping systems, and CPs (Wang et al., 2011). A major advantage of APEX is that spatially explicit relationships in field units allow for realistic and physically-based simulations of CP reductions in surface and subsurface runoff (Wang et al., 2011). Reductions in agricultural runoff were simulated in APEX through alteration of a number of model parameters (e.g., curve number) according to a mixture of empirical and theoretical data (Wang et al., 2011). Reductions at the field-scale were aggregated for an NHDplusV2 catchment and coupled to our watershed model to simulate changes in water quality and phosphorus loads during 1990 to 2010 in each conservation scenario.

We calculated the combined spring/early summer TP loads (1 Feb to 31 July) from four major WLEB tributaries (River Raisin, Maumee River, Portage River, and Sandusky River) to examine the effectiveness of conservation scenarios for meeting Lake Erie nutrient management goals. These nutrient management goals recommend a 40% reduction in TP loads relative to 2008 loads to reduce the likelihood of harmful algal bloom formation in Lake Erie (Ohio EPA, 2013; Annex 4, 2015). However, observed TP loading data were not available for spring/early summer in 2008 for the River Raisin or Portage River (tributary loading data from National Center for Water Quality Research, accessed on 3 March 2016; www.heidelberg.edu/academiclife/distinctive/newqr/data/data). We therefore used a target TP load of 974.39 MT, which represents a 40% reduction from our simulated load for major WLEB tributaries in 2008.

To assess the potential benefits of CP implementation for improving stream biotic integrity, we first forecasted the potential maximum IBI in each stream segment for the three conservation scenarios. We used one-sided paired *t*-tests to determine if the maximum IBI score was greater in

conservation scenarios than in the baseline scenario. We then calculated the amount of stream kilometers in which the maximum IBI improved as our first stream assessment measure. For our second stream assessment measure, we examined the average change in maximum IBI scores that occurred in each scenario to assess the magnitude of improvements in stream fish communities that occurred with additional CP investment. We used one-sided paired *t*-tests to determine if the change in maximum IBI scores continued to increase with increasing CP implementation. To better understand what changes in water quality were responsible for changes in the maximum IBI, we examined correlations between changes in the maximum IBI and changes in water quality attributes across all scenarios.

For our third stream assessment measure, we used different percentiles of the observed fish community data to assess where water quality was limiting fish community conditions. We considered streams where the potential maximum IBI score was below the 70th percentile of the observed data ($IBI < 0.65$) to be “limited” by water quality, those between the 70th and 90th percentiles ($0.65 \leq IBI < 0.80$) to be “moderately limited” by water quality, and those greater than the 90th percentile ($IBI \geq 0.80$) of the observed data to be “not limited” by water quality. We assessed a conservation scenario’s effectiveness by examining how the percentage of the total stream length in each of these categories changed from baseline conditions.

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Results

Watershed Model Performance

We considered watershed model performance acceptable if the PBIAS during model validation was $\pm 25\%$ for stream discharge, $\pm 55\%$ for suspended sediment loads, and $\pm$

70% for TN and TP loads (Moriassi et al., 2007). Based on these performance ratings, our watershed model performed well for all water quality attributes but stream discharge in the River Raisin (Table 1). Although we did not specifically calibrate for NSE or the coefficient of determination (R^2), our watershed model performed reasonably well for the Maumee River and Sandusky River, with NSE and $R^2 > 0.5$ for most parameters (Table 1). Performance was less accurate at other gages based on these measures for stream discharge, and was poor in many cases for other parameters. Thus, our model accurately captured long-term average conditions across the watershed, but performed less well at capturing extreme events. In terms of simulating annual spring/early summer TP loads from WLEB tributaries, the watershed model performed well ($R^2 = 0.70$) and tended to underestimate TP (PBIAS = -15.5) loads from WLEB tributaries (Fig. 2a).

Biological Model Performance

The best-supported TN model for predicting maximum IBI scores in the WLEB watershed included spring discharge, spring suspended sediment concentration, and an interaction between spring TN concentration and spring suspended sediment concentration as predictors (Table 2). The best-supported TP model also included an interaction with suspended sediment concentration, but in this case, annual water quality conditions were selected. Validation statistics suggest that both the TN model and TP model performed well (Table 2). The average r_s for the TN model was 0.52 (range = 0.43 – 0.63) and 0.51 (range = 0.40 – 0.58) for the TP model, with all relationships statistically significant (p – values < 0.001). The average percentage of the observed IBI scores that fell below the predicted values was 97% for the TN model (range = 94–100%) and TP model (range = 93–99%). Overall, these statistics indicated that both

models correctly identified the upper limits in stream biotic integrity (maximum IBI) based on stream discharge and the water quality attributes that we modeled.

Baseline Conditions

Fish community health. According to our classifications of water quality limitation, we found that 31% (6,323 km) of streams were limited, 43% (8,781 km) were moderately limited, and 25% (5,154 km) were not limited by water quality in the baseline scenario (Fig. 2a; Table 3). Thus, if we assume that removing water quality as a limiting factor for all streams represents an ideal goal for stream conservation, water quality appears to be limiting stream fish communities to some degree in ~75% (15,104 km) of WLEB streams.

Lake Erie loads. Inputs of TP into Lake Erie from major WLEB tributaries varied considerably during our 21-year simulation (Fig. 2a). The average spring/early summer TP load from major WLEB tributaries into Lake Erie was estimated as 1,186 metric tons (MT). The Maumee River contributed nearly 74% of this load (873 MT). The next highest contributor was the Sandusky River (195 MT), followed by the River Raisin (66 MT) and the Portage River (51 MT). The combined TP loads from major WLEB tributaries exceeded management targets in 15 of the 21 years.

Potential Benefits of Conservation Scenarios

Stream water quality. The implementation of CPs improved stream water quality throughout the watershed (Table 4). Predicted nutrient and sediment concentrations varied across scenarios, with average in-stream suspended sediment and nutrient concentrations declining as the number of acres treated increased (Table 4). These improvements in water quality were small when only critical acres were treated with CPs (<7% on average). However, across spring and

summer seasons, average reductions of 38% for TN, 45% for TP, and 51% for suspended sediments occurred when all farm acres were treated (Table 4). These reductions were not due to CP effects on river flows, as average stream discharge either increased slightly (<3%) with CP implementation (Critical & Moderate and All scenarios) or declined negligibly (0.02%) relative to baseline conditions (Critical scenario; Table 4).

We also found water quality stressors may increase in some stream segments with CP implementation. These increases occurred in 18% of the watershed on average when only critical farm acres were treated, 5% when critical and moderate acres were treated, and 2% when all farm acre types were treated. The largest increases occurred when only critical farm acres were treated and related to increases during the spring. Changes were generally small, with mean changes of 3, 0.004, 0.09 mg/L for suspended sediments, TP, and TN, respectively. However, large changes did occur in some stream segments; the largest increase in suspended sediment concentration was 79 mg/L, 0.05 mg/L for TP, and 1.04 mg/L for TN.

Fish community health. One-sided paired t -tests showed that improvements in the average maximum IBI score were statistically significant with CP implementation compared to the baseline scenario in our simulations (p -values of all comparisons < 0.001). The length of streams with a predicted increase in their maximum IBI ranged from 5,436 km (27% of the watershed; critical acres treated) to 13,297 km (66% of the watershed; all acre types treated) of the watershed (Fig. 3a). While the average change in the maximum IBI across the watershed was generally small (range = 0.005 to 0.04; Fig. 3b), comparisons of conservation scenarios indicate that increasing CP implementation continued to increase the change in maximum IBI (critical acres vs. critical and moderate acres: $t_{9158} = 46.74$, p -value < 0.001; critical and moderate acres vs. all acres: $t_{9158} = 43.87$, p -value < 0.001). Despite relatively small changes in the maximum

IBI overall, substantial improvements were possible in some stream segments; the largest change in the maximum IBI ranged from 0.21 to 0.36 across the three CP scenarios, with changes in maximum IBI scores positively related to the number of acres treated. Across all scenarios, the change in the maximum IBI was strongly correlated with reductions in TN concentrations ($r_s = -0.60$, $p < 0.001$), and to a lesser degree, by reductions in TP concentrations ($r_s = -0.47$, $p < 0.001$), suspended sediment concentrations ($r_s = -0.37$, $p < 0.001$), and increases in discharge ($r_s = 0.14$, $p < 0.001$).

These changes translated into large areas where water quality was no longer limiting stream biological conditions (Table 3). For instance, our model simulations predicted that the percentage of the WLEB watershed stream kilometers limited by water quality would be reduced to 20% (from 31% under baseline conditions) when all acres types are treated with CPs (Table 3). This represents 2,228 stream kilometers where water quality was no longer limiting biological conditions. Despite CPs resulting in a net improvement in biological conditions, it should be noted that we observed declines in the maximum IBI score in each CP scenario. These declines occurred in 7%, 8%, and 5% of the watershed from our least to most intensive CP scenarios.

Lake Erie loads. Our modeling simulations also indicated that investment in CPs could sufficiently reduce TP loads into Lake Erie to meet loading goals (Fig. 3c). To do so, however, a large additional portion of farm acres would need to be treated. Implementing CPs to only the acres in critical need of treatment (~8% of the watershed) resulted in an average TP load of 1,088 MT, with loads exceeding the target load in 13 out of 21 years. By contrast, applying CPs to acres in critical and moderate need (~48% of the watershed) resulted in an average TP load of 766 MT, with TP loads exceeding the target in only 4 of 21 years. Further benefits were possible

by treating all acre types with CPs; the average TP load dropped to 575 MT and only 2 years exceeded the target load.

Improvements relative to grassland scenario. While improved biological conditions were predicted with CP implementation, even the treatment of all acre types with CPs did not reach the levels simulated in the grassland scenario. While our simulations revealed that the length of streams with improved maximum IBIs was only 1.2- to 3.6-fold higher in the grassland scenario relative to our three CP scenarios (Fig. 3a), the average change (i.e., increase) in maximum IBI was between 1.4- and 8.4-fold higher for the grassland scenario (Fig. 3b). Similarly, the percentage of the WLEB watershed limited by water quality was between 1.4- and 2.6-fold lower in the grassland scenario relative to the three CP scenarios, while the percentage of streams not limited by water quality was between 1.3- and 1.1-fold higher than in the three CP scenarios (Table 3).

Discussion

Our biophysical modeling simulations suggest that CP implementation will need to be widespread to meet nutrient management goals for Lake Erie and improve stream biological conditions. We found that only treating farm acres in critical need of CPs (~8% of the farm acres) resulted in slight reductions in spring/early summer TP loads, with TP loads exceeding the target load ~62% of the time. If a larger portion of farm acres were treated with CPs (e.g., those in critical and moderate need or about ~48% of the farm acres), however, our simulations show that it would be possible to meet nutrient management goals for TP loading in 18 of the 21 years we simulated. Other Great Lakes modeling efforts also have suggested that widespread

implementation of CPs may be needed to reduce nutrient loading (Hobbs et al., 2002; USDA NRCS, 2011; Bosch et al., 2013; Scavia et al., 2016). Similarly, widespread CP implementation was needed to reduce water quality limitation on stream biological conditions. Implementing CPs on farm acres in critical need of treatment improved the maximum IBI in ~27% of the watershed, but the magnitude of these changes were relatively modest compared to more widespread CP implementation. For instance, treating farm acres in critical and moderate need not only improved stream biological conditions in nearly twice as many stream kilometers compared to only treating farm acres in critical need, but the magnitude of these changes was nearly four times as large on average. Both modelling (Einheuser et al., 2012) and empirical (Wang et al., 2002) studies indicate that widespread CP implementation is needed to improve stream biological conditions. Taken together, these studies support our conclusion that CP implementation will need to be widespread to achieve Lake Erie water quality goals and improve stream biological conditions across the WLEB watershed.

While both TP and suspended sediments certainly appear to be affecting fish community health in the WLEB watershed, our modeling suggests reductions in stream TN concentrations would lead to the largest improvement in stream biological conditions. High nitrogen concentrations negatively affect stream fish communities (Miltner and Rankin, 1998; Wang et al. 2007; Miltner 2010); likely because excess nitrogen feeds algal productivity (Dodds et al. 2002; Dodds et al., 2006; Miltner, 2010) which, in turn, alters dissolved oxygen levels in streams (Miltner and Rankin, 1998; Miltner 2010). Excess nitrogen may also alter the quality of food resources (Evans-White et al., 2009) and some forms of nitrogen, such as nitrate, may be toxic to fish at chronically high levels (Camargo et al., 2005). While CP implementation was able to reduce TN concentrations by ~40% when all acres were treated, these reductions, when

combined with other water quality stressors, were unable to remove water quality limitation across the whole watershed.

Along these lines, our modelling suggests that while CPs will improve stream water quality, they are not a panacea. Even if CPs were implemented across the majority of agricultural lands in the watershed (i.e., all farm acre types treated), not all stream fish communities would become free from limitation by NPS pollution. For instance, >3,241 stream kilometers would still be limited by poor water quality in this conservation scenario. We also found that stream biological conditions might actually decrease in some areas, a result observed in a similar study (Einheuser et al., 2012). This may reflect the fact that water quality stressors increased with CP implementation in some stream segments. It is unclear why these increases occurred, but other modelling studies suggest that CP implementation can sometimes increase NPS pollution (Einheuser et al., 2012; Scavia et al., 2016). Widespread implementation of CPs also fell short of the stream biological conditions observed in the grassland scenario, indicating that it is unrealistic to expect CPs to achieve these more “natural” conditions. Thus, additional approaches (e.g., further reducing point sources, urban and suburban runoff, etc.), emerging technologies, and more efficient CP implementation (i.e., optimized placement of CPs) may be necessary to further reduce water quality limitation of stream biological conditions throughout the watershed.

Our modeling exercise was admittedly imperfect and may underestimate the potential effectiveness of CPs for improving water quality. For example, our scenario approach used CPs that are currently in wide use across the WLEB watershed and does not apply the newest (e.g., tile biofilters, two-stage ditches, ditch plugs) or necessarily the most appropriate management options (e.g., wetlands and drainage water management were not included). Farm fields often contain acreage with various inherent vulnerabilities, including some areas that are more prone to

leaching losses and some that are more prone to runoff losses. Accounting for these inherent vulnerabilities through comprehensive conservation planning would potentially allow land managers and decision makers to develop more holistic and effective conservation plans to address specific resource concerns on specific acres with the most appropriate and up to date practices. If done, achieving greater reductions in nutrient and sediment runoff might be possible by employing a more optimized management approach than we simulated in our scenarios.

Our approach also does not consider how continued climate change may affect the region. Climate change is expected to increase Maumee River discharges into Lake Erie during winter and spring, when farmland typically remains fallow and the potential for nutrient runoff is high (Cousino et al., 2015). Forecasted changes in rainfall patterns (e.g., more intense storms) also may reduce the effectiveness of CPs in controlling agricultural runoff (Hall et al., this issue). Research is needed to understand how continued climate change might alter the amount and types of CPs needed to address agricultural NPS. Such information would allow for the development of more effective nutrient management strategies to rehabilitate and protect Lake Erie and the biological communities within its watershed.

Despite these limitations, we feel that our general approach of using a biophysical model to quantify the impact of CPs on water quality within the lake, as well as within its watershed, is valuable for two reasons. First, our modeling indicates that the use of CPs to meet nutrient management goals will lead to a “win-win” for both Lake Erie and its watershed. Agriculturally-driven NPS pollution is diffuse by its nature, with numerous sources contributing unquantified amounts of nutrients and sediments across large areas (Carpenter et al., 1998). Our modeling shows that sufficiently treating this diffuse problem to address downstream concerns also may benefit biological conditions throughout the large stream network of the WLEB watershed.

Second, our modeling approach offers a way to facilitate more holistic and considered conservation planning by showing that management strategies designed to rehabilitate Lake Erie—which can be hundreds of kilometers downstream from some farms (e.g., those in Michigan or the southwestern part of the basin in Ohio)—also can benefit water quality and fish communities in local streams. This knowledge may help motivate farmers to adopt voluntary conservation practices, especially considering that farmers in the WLEB watershed feel a strong sense of responsibility for their local water quality (Burnett et al., 2015).

Conclusions

Our study offers four key insights that are relevant to the management of Lake Erie and other ecosystems suffering from eutrophication driven by agricultural runoff. First, efforts aimed at cleaning up a downstream ecosystem also are likely to benefit water quality and biological communities in local streams in the surrounding watershed. This notion is supported by findings from other watersheds in which fish communities (Wang et al., 2002; Christensen et al., 2012; Miltner, 2015) were shown to benefit from in-stream habitat and water quality associated with CPs. Second, the implementation of CPs likely will need to be widespread within the WLEB watershed to achieve Lake Erie nutrient management and watershed conservation goals. This notion is supported by other, similar studies conducted across the Great Lakes Region, including Lake Erie (Hobbs et al., 2002; USDA NRCS, 2011; Bosch et al., 2013; Einheuser et al., 2012; Scavia et al., 2016). Third, while our modeling suggests that CPs are likely to improve the health of the Lake Erie ecosystem, expectations should be realistic and it is likely that some areas of degraded conditions will persist. For instance, even if CPs were implemented across most of the

watershed, stream biological conditions may still be limited by water quality in the most degraded areas of the watershed. In addition, other factors unrelated to water quality [e.g., invasive species, dispersal barriers, and habitat degradation (e.g., channelization, lack of riparian vegetation)] also likely would limit full recovery (Ohio EPA 1999; Wang et al. 2006). Finally, because farmers can feel a strong sense of responsibility for their local water quality (Burnett et al., 2015), which likely reflects their consideration of local ecosystem services (e.g., fishing and swimming opportunities, availability of safe drinking water), more studies that consider the benefits of CPs to the surrounding stream network—not just the larger downstream ecosystem—are needed. Such knowledge could prove useful in helping promote the value of CPs to farmers and policymakers, especially when they can lead to a “win-win” for far-off water quality management and local biological conservation.

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Table 1. Model validation statistics for the watershed model at the monthly time-step for stream discharge and suspended sediment, total phosphorus (TP), and total nitrogen (TN) loads. We report the coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE), and percent bias (PBIAS), but focused on minimizing PBIAS, which reflects long-term average conditions, during model development. Bold values indicate acceptable model performance based on the PBIAS (Moriassi et. al., 2007).

Station	Stream discharge			Suspended sediment			TP			TN		
	R^2	NSE	PBIAS	R^2	NSE	PBIAS	R^2	NSE	PBIAS	R^2	NSE	PBIAS
River Raisin	0.72	0.43	26%	0.36	0.27	-35%	0.44	-0.96	23%	0.5	0.35	-4%
St. Joseph River	0.78	0.74	-19%	0.26	-0.01	20%	0.26	-0.56	-5%	0.69	-0.64	69%
St. Marys River	0.49	0.43	-25%	0.13	0.13	-19%	0.24	0.07	-9%	0.31	0.27	-21%
Maumee River	0.92	0.88	-14%	0.66	0.66	10%	0.79	0.78	-3%	0.71	0.69	-13%
Sandusky River	0.76	0.75	-7%	0.35	-0.97	35%	0.54	0.38	-1%	0.64	0.57	12%

Table 2. The best supported predictive total nitrogen (TN) and total phosphorus (TP) models of Index of Biotic Integrity scores for fish in the western Lake Erie basin watershed during 1990-2012, based on Akaike's Information Criterion adjusted for small sample size (Table A2). Parameter estimates on the logit-scale are shown for the model intercept, stream discharge (Q), TN, TP, suspended sediments (SS), and interactions between TN and SS (TN x SS) and TP and SS (TP x SS). Model validation statistics shown are the mean (standard deviation) of the Spearman's rank coefficient (r_s) and the percentage of observed values that were below predictions (% below) from the k -fold cross validation. Note that the TP model is for average summer conditions and the TN model is for average spring conditions.

Model	Intercept	Q	TN	TP	SS	TN x SS	TP x SS	r_s	% below
TN	1.63	0.69	-0.41	-	0.16	0.12	-	0.52 (0.06)	97 (2)
TP	1.60	0.66	-	0.08	-0.21	-	0.25	0.51 (0.07)	97 (2)

Table 3. Percentage of the total western Lake Erie Basin stream length that fell within different stream biological categories for the Index of Biotic Integrity (IBI) under baseline conditions, the three conservation scenarios (Critical, Critical & Moderate, All), and the grassland scenario. The mean (s.d.) maximum IBI that occurred based on simulated water quality conditions is also shown. “Acres treated” refers to the type of farm acres treated in each conservation scenario based on their need for conservation treatment. The baseline and grassland conditions are shown for reference, respectively representing average water quality conditions (1990-2010) and the theoretical upper benchmark.

Acres Treated	Average maximum IBI	Limited	Moderately Limited	Not Limited
Baseline	0.71 (0.13)	31	43	25
Critical	0.72 (0.13)	29	45	26
Critical & Moderate	0.74 (0.12)	20	50	30
All	0.75 (0.12)	16	53	31
Grassland	0.76 (0.11)	11	54	35

Table 4. Average water quality parameters for spring and summer discharge, total nitrogen (TN), total phosphorus (TP), and suspended sediment. “Acres treated” refers to the type of farm acres treated in each conservation scenario based on their need for conservation treatment. The baseline and grassland conditions are shown for reference, respectively representing average water quality conditions (1990-2010) and the theoretical upper benchmark.

Acres Treated	Discharge (L/s)		TN (mg/L)		TP (mg/L)		Suspended Sediment (mg/L)	
	Spring	Summer	Spring	Summer	Spring	Summer	Spring	Summer
Baseline	3727	1243	8.75	2.29	0.25	0.16	171.49	99.06
Critical	3726	1248	8.17	2.15	0.23	0.15	157.89	94.01
Critical & Moderate	3770	1256	6.18	1.68	0.16	0.12	113.96	76.21
All	3809	1262	5.4	1.4	0.12	0.1	70.48	55.65
Grassland	3797	1261	1.94	0.68	0.05	0.07	29.24	33.6

Figure Captions

Figure 1. The western Lake Erie basin watershed (IN-MI-OH, USA) contains > 200,000 km of streams that drain a largely agricultural area. Points indicate the approximate locations of fish sample collections during 1990 to 2012 (n = 841).

Figure 2. Modeled baseline conditions (1990-2010) of (a) , and (b) distribution of stream biological conditions, as measured by an Index of Biotic Integrity for fish (max IBI). combined total phosphorus (TP) during spring/early summer from major tributaries in the western Lake Erie basin (WLEB). Observed nutrient loading data are from the National Center for Water Quality Research at Heidelberg University (accessed on 10 Nov 2015: www.heidelberg.edu/academiclife/distinctive/newqr) Totals do not include the contribution of the Portage River because no observed loading data were available from the 1990s.

Figure 3. Potential of agricultural conservation practices (CPs) to improve stream biological conditions and reduce phosphorus loading from the western Lake Erie basin (WLEB) watershed into Lake Erie. (a) Percentage of WLEB streams in which maximum Index of Biotic Integrity (max IBI) score improved, (b) average change in the max IBI score within a stream segment, and (c) combined annual spring/early summer total phosphorus (TP) loading from major WLEB tributaries (dashed line is baseline loading). Boxes span the interquartile range with whiskers extending to the minimum and maximum values of the change in max IBI scores or the annual spring/early summer load from 1990-2010.