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Optimizing wetland restoration to improve water quality at a regional scale

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Abstract

Excessive phosphorus (P) export to aquatic ecosystems can lead to impaired water quality. There is a growing interest among watershed managers in using restored wetlands to retain P from agricultural landscapes and improve water quality. We develop a novel framework for prioritizing wetland restoration at a regional scale. The framework uses an ecosystem service model and an optimization algorithm that maximizes P reduction for given levels of restoration cost. Applying our framework in the Lake Champlain Basin, we find that wetland restoration can reduce P export by 2.6% for a budget of \$50 M and 5.1% for a budget of \$200 M. Sensitivity analysis shows that using finer spatial resolution data for P sources results in twice the P reduction benefits at a similar cost by capturing hot-spots on the landscape. We identify 890 wetlands that occur in more than 75% of all optimal scenarios and represent priorities for restoration. Most of these wetlands are smaller than 7 ha with contributing area less than 100 ha and are located within 200 m of streams. Our approach provides a simple yet robust tool for targeting restoration efforts at regional scales and is readily adaptable to other restoration strategies.

1. Introduction

Eutrophication is a problem in many regions around the world, resulting in locally important water quality problems (Carpenter 2005) and the degradation of ecosystem services worth Billions annually the US (Dodds *et al* 2009). Eutrophication in freshwater systems has been attributed to excessive phosphorus (P) export from agriculturally-dominated landscapes (Carpenter 2005, Schindler *et al* 2016). The cost of reducing P export from uplands to waterbodies can be substantial, so there is a need for effective management frameworks to mitigate excessive P export in water bodies worldwide (Conley *et al* 2009).

State and non-profit organizations are beginning to deploy nature-based solutions such as wetlands and floodplains to mitigate P export in freshwater bodies (Bertule *et al* 2014, Liquete *et al* 2016, Thorslund *et al* 2017). Here, the underlying assumption is that the natural form and functions of restored wetlands will retain nutrients and improve water quality (see, Thorslund *et al* 2017). Despite the range of ecosystem services provided by wetlands (Zedler 2003, Watson *et al* 2016) and ongoing wetland restoration efforts, wetland areas have been declining globally due to anthropogenic alterations (Moreno-Mateos *et al* 2012, Serran *et al* 2018). It is increasingly important to manage and restore wetlands for supporting biodiversity and human benefits, including water quality issues.

Studies have long recommended using wetlands to retain nutrients for improving water quality (see, Van der Valk and Jolly 1992, Mitsch and Day 2006).

Subsequently, these studies also point to the challenges in determining the effectiveness of wetland restoration at large spatial scales and identifying optimal places for restoration to maximize water quality benefits at a given cost. However, to address these research needs, limited attempts have been made to develop robust wetland prioritization frameworks based on P retention benefits and restoration costs at the watershed scale (Newbold 2005, Dai *et al* 2016). Using a GIS-based fuzzy stochastic algorithm, Dai *et al* (2016) demonstrated the potential of prioritizing topography derived wetlands in retaining P and N in a watershed (~600 km^2) of China. Initially, Newbold (2005) showed the application of a simple heuristic-based prioritization approach based on N retention capacity and restoration cost of wetlands in select watersheds of California, USA. These studies were limited in the scope, particularly regarding the choice of rather simple prioritization tools, spatial scale (<1000 km^2), or the physical wetland characteristics considered. Studies have rarely employed formal optimization techniques that account for costs and analyze common physical attributes of priority wetlands to advance a general understanding needed for practitioners and decision-makers elsewhere. Given that wetland restoration is conducted worldwide, there is a need for robust yet straightforward approaches that can be adapted by stakeholders globally to prioritize wetlands.

This work provides a novel framework to advance wetland restoration efforts based on their P retention services and restoration cost at a regional scale. We evaluate tradeoffs between P reduction and restoration cost, and identify wetlands and related spatial properties that are effective in retaining P. We test this framework in the Vermont (USA) portion of Lake Champlain Basin, which has been experiencing episodic eutrophication due to excessive P export from the contributing watersheds (Ghebremichael *et al* 2010, Zia *et al* 2016, Isles *et al* 2017). To explore the potential role of nature-based interventions in improving the water quality of the lake, we combine a database of potential wetland sites, a widely used ecosystem service model, and an optimization algorithm. Our overarching goal is to provide a decision-making tool based on commonly used datasets, which could be useful for wetland managers anywhere to visualize a range of optimal restoration solutions under the budgetary constraints.

2. Methods

2.1. Study site

The framework was tested in the Lake Champlain Basin that drains 23000 km^2 (figure S1 is available online: stacks.iop.org/ERL/14/064006/mmedia) of the US (Vermont, New York) and Canada (Quebec) and comes under the jurisdiction of the Boundary Waters Treaty between both countries (IJC International Joint Commission 2018). Lake Champlain serves as a major source of drinking water for more than 200 K people and contributes substantially to the local economy (Voigt *et al* 2015). Our focus was on the Vermont portion of the Lake Champlain Basin, covering 56% of the basin area, where the US Environmental Protection Agency (EPA) has set a Total Maximum Daily Load target of 34% reduction in P export from agricultural lands and other sources to Lake Champlain (EPA Environmental Protection Agency 2016). The state of Vermont and non-profits aim to meet some proportion of this P Total Maximum Daily Load target by restoring wetlands in the Lake Champlain Basin. In 2017, nearly $23 M in state funds have been dedicated to supporting the implementation of management interventions to meet clean water targets (VCWI Vermont Clean Water Initiative 2018). Here onward we refer to the Vermont-portion of the Lake Champlain basin simply as the Lake Champlain Basin.

2.2. Modeling framework

We used the nutrient delivery ratio (NDR) module provided in the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model to simulate P retention services of wetlands. We coupled this model with an optimization algorithm to find a range of optimal solutions that might meet the budgetary constraints of stakeholders (figure S2). Restoration managers provided feedback on the modeling framework and desired outputs to help refine their restoration needs and improve the suitability of the work for the broad community of decision makers. We solicited feedback over ten times during the two-year project.

2.2.1. Simulating P retention services of wetlands

Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) is an open-source modeling environment, widely used for scenario-based modeling and assessment of ecosystem services (e.g. nutrient retention) given changes in land uses (Nelson *et al* 2009, Hamel *et al* 2017, Redhead *et al* 2018, Sharp *et al* 2018). The Nutrient Delivery Ratio (NDR) is a spatially distributed InVEST module that quantifies the relative fraction of a nutrient retained and transported from uplands to the stream network. In brief, NDR simulates the delivery ratio of P to a given pixel as a function of landscape connectivity to the stream and retention efficiency along the flow path. In the model, connectivity depends on the upslope contributing area, slope gradient, position along stream network and, whereas retention efficiency depends on the land use class, associated contributing area and retention coefficients (table S1). Inputs to the NDR model include a digital elevation model, land use land cover, runoff proxy raster, and biophysical parameters including, critical length, threshold flow accumulation, Borselli K values, and retention efficiencies of landcover types (table S1; Sharp *et al* 2018). The model output is provided as an NDR raster. The digital elevation model and land cover datasets (Homer *et al* 2015) were obtained at 30 m spatial resolution from the United States Geological Survey. The runoff proxy raster was acquired from the seasonal water yield module of InVEST developed for the state of Vermont by Watson *et al* (2019). Details regarding biophysical parameters can be gleaned from Sharp *et al* (2018). Briefly, critical length was set to the resolution of the land cover raster (30 m), Borselli *K* value was set to 4, and the threshold flow accumulation value was set to 1000 (Sharp *et al* 2018).

To estimate P export, we multiplied the NDR raster with a P source raster derived from EPA's P model used in establishing Total Maximum Daily Load requirements for the Lake Champlain Basin (EPA Environmental Protection Agency 2015). The EPA's P model was fully calibrated and validated for more than a dozen stream gauges using 20 years of P data (EPA Environmental Protection Agency 2015). The P source raster spanned the Lake Champlain Basin at the spatial resolution of National Hydrography Dataset plus scale and watersheds ranging in size from 100–70000 ha. Due to the large computational time and to facilitate efficient convergence of optimal solutions, we constrained the optimization space to high P (>75th percentile) source areas. It is worth noting that because of the availability of fully validated P source raster from EPA's model, we simply used InVEST's NDR to estimate the differential in P retained due to change in landuse.

To simulate the influence of P retention services of wetlands, we conducted scenario-based modeling using the NDR module and the state of Vermont's wetland database with 3606 potential wetland sites (VANR Vermont Agency of Natural Resources 2007) varying in size (1–300 ha), contributing area (1–24000 ha) and distance from a stream (1–850 m). Each scenario involved a three-step process of raster calculations within the model. Firstly, we ran the model for the baseline land cover and estimated the NDR and the corresponding P export. Secondly, we used an optimization algorithm (see section 2.2.2) to stochastically select wetlands from the database to update the baseline land cover and to estimate NDR and the corresponding P export for the new scenario. Finally, we calculated the change in P export from the baseline at the watershed scale.

We estimated the restoration costs associated with each scenario, data provided by the Vermont field office of the United States Department of Agriculture's Natural Resources Conservation Service. We defined wetland restoration cost as the cost of purchasing land easements, which in turn are based on market-based land values that vary with soil type and region within the state (NRCS Natural Resources Conservation Service 2017). For simplicity, we do not include the costs of active restoration or site management, which are likely minor compared to easement costs. The restoration costs of wetlands ranged from \$4839 to \$2258 808 with a median of \$21 250. Restoration data can be requested from the local United States Department of Agriculture's offices. For regions outside the United States, wetland managers may use local property values as the restoration cost. To be consistent with other input rasters, restoration costs and wetland polygons were converted into rasters with a spatial resolution of 30 m.

2.2.2. Genetic algorithm optimization

A genetic algorithm is a heuristic search technique based on the concept of evolution, where solutions iteratively evolve through mutation, crossover, and selection to converge on a set of optimal solutions (e.g. Eiben and Smith 2003). Genetic algorithms have been used widely in solving complex water quality problems where a large decision space is queried for identifying optimal spatial locations to employ management practices (Arabi *et al* 2006, Maringanti *et al* 2009). Wrapping a genetic algorithm around the spatially explicit InVEST model allowed us to account for spatial dependencies in prioritizing P retention services of wetlands at a watershed scale.

We used a computationally efficient multi-objective genetic algorithm to find a set of Pareto optimal restoration solutions. We define Pareto optimal solutions as those that maximize P reductions (i.e. Objective function 1) for a given level of restoration cost (i.e. Objective function 2). Outputs from the multi-objective genetic algorithm were used to analyze tradeoffs between P reductions and costs. Such multi-objective spatial optimization approaches are common when solving conservation problems at regional scales (Kennedy *et al* 2016, Gourevitch *et al* 2016). We implemented the genetic algorithm using the Distributed Evolutionary Algorithms in Python package in Python version 2.7 (Fortin *et al* 2012). Table S2 summarizes the genetic algorithm parameters and operators used in the modeling framework. The objective functions were run iteratively for 150 generations.

We conducted a sensitivity analysis on the spatial resolution of the P source raster and the major InVEST model parameters, including critical length, threshold flow accumulation, and Borselli *K* values. The sensitivity analysis was conducted for the Missisquoi basin (figure S1), one of the major sub-basins (>1000 Km^2) of the Lake Champlain Basin, where a spatially intensive, fully calibrated and validated P model was available from Winchell *et al* (2015). The Missisquoi basin model predicts P source areas ranging from 0 to 19 kg ha^{-1}, based on spatially distributed soil P data and calibrated to river loads as described in Winchell *et al* (2015). The EPA's Lake Champlain basin model was similarly developed and calibrated from basin-wide soils data and calibrated to river stations, but P source areas have been rescaled to a coarser resolution

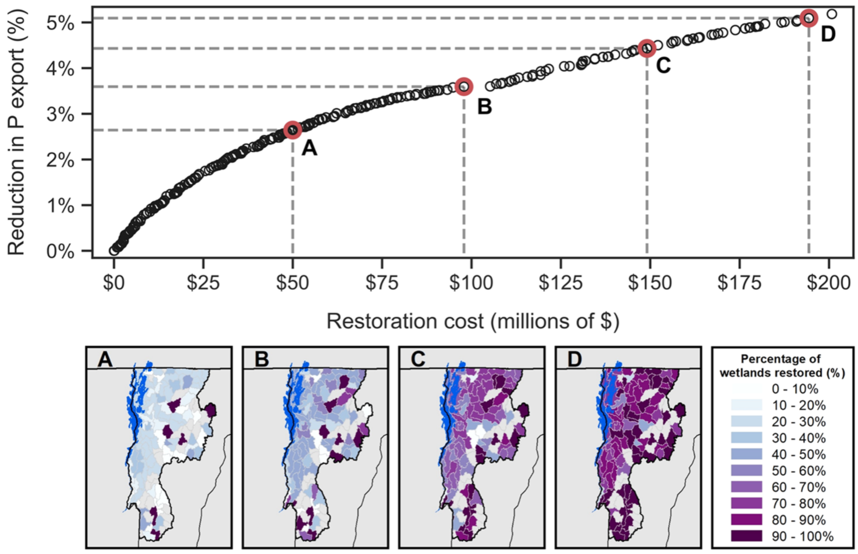

Figure 1. Tradeoff curve showing a range of optimal restorations solutions (i.e. set of wetlands) to mitigate P loading at minimal cost in the Lake Champlain Basin, Vermont. Points represent maximum reductions in phosphorus export for a range of restoration budgets. Maps on the bottom panel correspond to points A–D in the tradeoff curve. Point D involves restoration of >90% of wetlands in the basin (equivalent to 1.1% of watershed area) at relatively high cost, while point A involves restoration of < 30% of wetlands in the basin (equivalent to 0.02% of watershed area), at relatively low cost.

of the National Hydrography Dataset plus scale, with P source values ranging from 0–2 kg ha^{-1}. Sensitivity analysis of the biophysical parameters was conducted by increasing and decreasing the default parameter values by more than two-fold. For instance, the default Borselli K value varied from 4 to 2 and 6. The critical length was varied from 30 m (default) to 60 m and 90 m; and the threshold flow accumulation was varied from 1000 (default) to 500 and 2000.

2.2.3. Irreplaceability index

We developed an 'irreplaceability' index to compare the importance of wetlands in achieving our restoration objectives. We defined the irreplaceability of a given wetland as the frequency of its occurrence across all Pareto optimal solutions. For instance, a wetland with an irreplaceability index of 0.5 is one that was optimally selected in 50% of optimal genetic algorithm solutions. To investigate whether highly irreplaceable wetlands may be predicted from easily measurable characteristics, we summarized a set of observable variables including, wetland size, distance from a stream, contributing area, and related percentage of land use for wetlands with high (>0.75) and low (<0.75) irreplaceability. The selection of the top quartile (>0.75) of the irreplaceable wetlands is arbitrary, but it provided a large enough sample size of the most optimal wetlands to test their statistical distributions. Further, a Wilcoxon-Rank Sum was used to test if medians of wetland characteristics are significantly different between wetlands of high and low irreplaceability values.

3. Results

Our findings revealed that wetland restoration in the Lake Champlain Basin could reduce P export over baseline by 2.6% for a budget of $50 M (scenario A) and 5.1% for a budget of $200 M (Scenario D; figure 1). The tradeoff curve provided optimal solutions (i.e. sets of wetlands) for restoring 0.5% (scenario A) to 2% (scenario D) of the watershed area of the Lake Champlain. The flattening of the curve from scenarios A to D illustrates diminishing marginal P reductions as costs and the area restored increased (figure 1). The watershed area restored in scenario D corresponded to 3489 wetlands out of the potential 3606 total wetland sites. For these four select scenarios, median wetland size, associated contributing area, and distance from stream were approximately 3 ha, 14 ha, and 129 m, respectively. Lastly, these wetlands were downgradient from pasture (median = 31%) and cultivated (median = 6%) lands.

Overall, the irreplaceability index varied from 0.007–0.97, indicating that some wetlands were selected in as few as 0.7% and others in as many as 97% of all optimal solutions (figure 2). There were about 890 wetlands in the top quartile (>0.75) of the irreplaceable wetlands, most were smaller than 7 ha with a contributing area of less than 100 ha and within 200 m from the stream (figure 3). Among these wetlands, only ~ 20% were larger than 7 ha or had a contributing area greater than 100 ha. The medians of wetland size and distance from stream were significantly different between wetlands of high irreplaceability and wetlands of low irreplaceability (Wilcoxon, $p < 0.05$; figure 3).

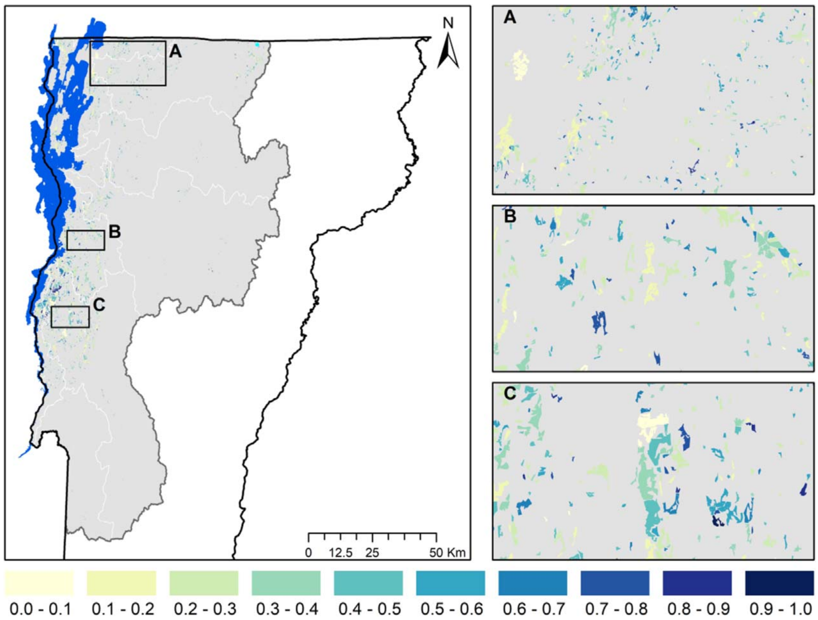

Figure 2. Irreplaceability of wetlands in the Vermont portion of Lake Champlain Basin. Irreplaceable wetlands occur in the majority of optimal scenarios, and are robust priorities for restoration efforts to reduce phosphorus export. Panels to the right correspond to three black rectangles in the map at left.

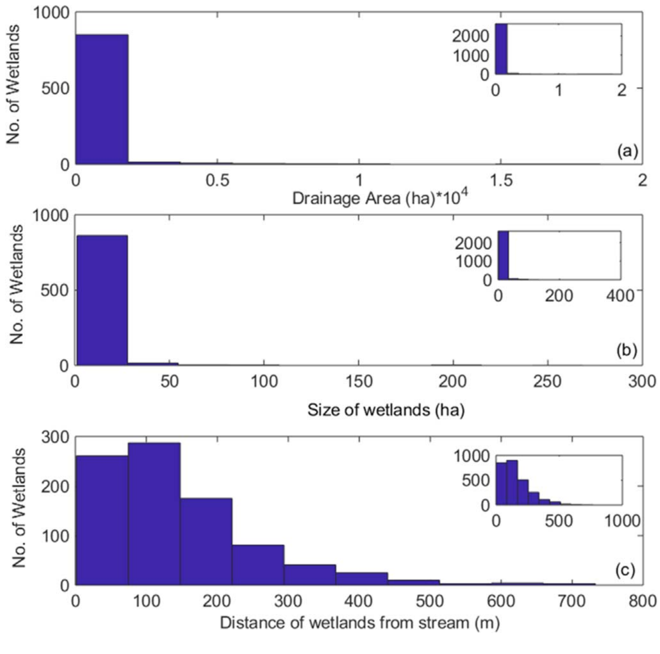

Figure 3. Spatial characteristics of wetlands: (a) contributing area, (b) size, and (c) distance from the nearest stream, with high and low irreplaceability (inset).

Importantly, replacing basin-wide P source data with finer resolution data from the Missisquoi basin resulted in a two-fold increase in our estimates of P reduction for the same restoration cost, compared to using basin-wide data for Missisquoi (figure 4). Finer resolution P data also resulted in a greater marginal P reduction with an increasing number of wetlands restored, compared to the low-resolution P data. On the contrary, varying the InVEST biophysical parameters had minimal influence on the optimal solutions for the range of values tested in our sensitivity analysis (figure 4). The lack of model sensitivity to biophysical parameters may be because outcomes were expressed as a change from the baseline condition rather than absolute values.

4. Discussion

Our framework enabled us to quantify P retention services for 3606 wetlands and the potential efficacy of

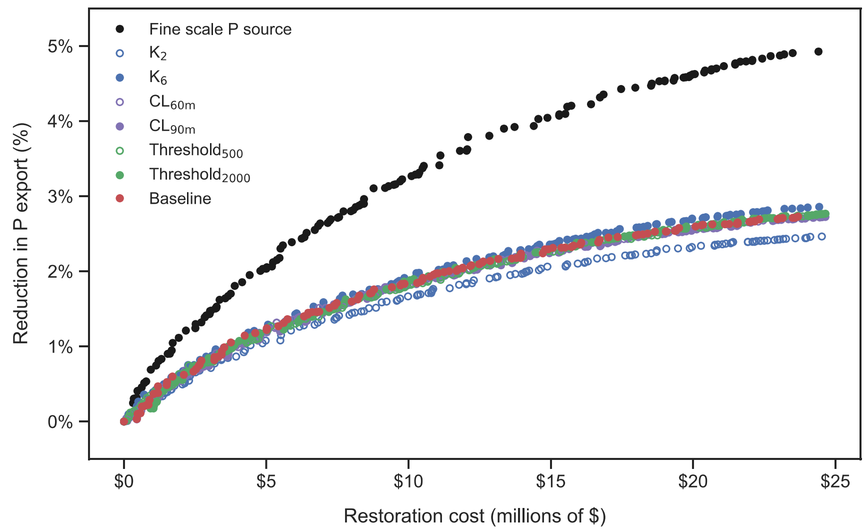

Figure 4. Sensitivity of the optimal solutions to the spatial resolution of P source data and InVEST model parameters for the Missisquoi basin, a major sub-basin of Lake Champlain Basin. Black symbols represent optimal solutions using fine-scale data on P loading (Winchell *et al* 2015). All other symbols represent coarse-scale data on P loading that we used basin wide. At this coarse scale, we varied other InVEST parameters: threshold flow accumulation at 500 ($Threshold_{500}$) and 2000 ($Threshold_{2000}$), critical length at 60 m (CL_{60}) and 90 m (CL_{90}), Borselli constant (K) at 2 (K_2) and 6 (K_6) and Baseline model ($K = 4$, Threshold $= 1000$, Critical length $= 30$ m, and National Hydrography Dataset plus scale low P resolution P source data). See Sharp *et al* (2018) for descriptions of these parameters in the InVEST model.

wetlands as nature-based solutions to improve water quality in agricultural landscapes. Irreplaceability values identify a robust set of priority wetlands that are important restoration targets across a range of budgets. Wetlands with high irreplaceability values (>0.75) highlight physical characteristics that tend to be associated with cost-effective P retention services.

Our results suggest that reductions in P export of 2.6%–5.1% are achievable from restoring wetlands at a cost ranging from \$50–\$200 M in the Lake Champlain Bain (figure 1). It is important to note that the sensitivity analyses, conducted on one of the sub-basins of Lake Champlain, with finer resolution P source data suggests that P reductions may be twice as large as demonstrated here (figure 4). The greater reduction in P values are likely because higher resolution data are able to capture fine scale 'hotspots' of P loading, which are averaged out and obscured by data at coarser spatial resolutions (figure 4). Further, the steeper slope of the Pareto curve for high-resolution P data indicates greater marginal returns to increasing the budget and restoring more wetlands. By using the coarse data that are available at the Lake Champlain basin scale, we may have underestimated P retention by a factor of two or more. Wetlands may be substantially more effective than our results indicate.

In general, studies have long discussed the potential impacts of wetland restoration in reducing nutrient export at a watershed scale (Mitsch and Gosselink 2000, Verhoeven *et al* 2006). However, there has been less emphasis on the economic feasibility of the wetland restoration (Widney *et al* 2018). Wang and Mitsch (1998) reported 5%–67% reduction in P while restoring to 1%–15% of the watershed area, whereas Verhoeven *et al* (2006) reported 30% reduction in N export while restoring 2%–7% of the watershed area. However, most of these studies did not consider prioritization and restoration cost in the analysis; therefore, the economic feasibility of achieving higher nutrient reductions more effectively due to restoration could not be evaluated. Our P reduction estimates are in the range reported by Wang and Mitsch (1998); but our estimates are conservative due to smaller restoration area, use of low retention efficiency for wetlands, and coarser resolution of P data that missed P hot-spots in the Lake Champlain Basin (figure 4). Overall, these results suggest that wetland restoration has the potential to contribute to reaching the Total Maximum Daily Load target for P established by EPA (EPA Environmental Protection Agency 2016). While the costs of wetland restoration are substantial, wetlands provide a range of valuable ecosystem services (e.g. flood attenuation, biodiversity, carbon storage) that we did not evaluate here. So, the total benefits of wetland restoration are surely underestimated in this analysis. However, if these other suite of ecosystem services are to be considered, we expect that the benefits provided by wetlands will outweigh the restoration costs.

Wetlands with high irreplaceability are likely to be part of any optimal solution, no matter the available budget. We found these wetlands to be smaller in size or are nearby streams, compared to wetlands of lower irreplaceability. These results indicate that smaller wetlands, if well-located, can be equally or more important than the larger wetlands in retaining P. Our results support those of recent studies showing that P retention capacity is substantially higher for smaller wetlands (Cohen and Brown 2007, Cheng and

Basu 2017) and that the position of wetlands along streams exerts strong control over their nutrient retention capacity (Hansen *et al* 2018). These approach can provide a simple heuristic for identifying wetlands, likely to be important in retaining P, based on readily available landscape characteristics at a large spatial scale. Given the coarse data resolution and simple models used in our analysis, results for individual wetlands should be interpreted with caution. Wetlands with high irreplaceability scores may not be viable candidates for actual restoration, for practical or other reasons. Nevertheless, combining broad optimizations and site-specific knowledge can help decision-makers decide where on the landscape to restore wetlands to regulate water quality.

We show that restoring wetlands can be an important part of retaining nutrients and improving water quality. Tradeoff curves based on optimizations represent a powerful tool to help regulatory agencies, nonprofits, and landowners explore benefits from a range of restoration scenarios. This work reported here has resulted in a close collaboration among scientists and restoration managers and decision-makers and further contributes to growing research in translational ecology (Enquist *et al* 2017). That said, two enhancements to this decision support tool would expand its utility for managers. First, the irreplaceability values estimated for wetlands could be combined with maps of other wetland co-benefits to prioritize conservation based on multiple ecosystem services (e.g. biodiversity, flood-attenuation). Second, irreplaceability maps can complement other nutrient control measures, e.g. channel, soil, and crop management strategies (Schoumans *et al* 2014) to meet large P reduction goals more effectively.

We recognize that important limits to the long-term efficacy of wetland restoration are not explored in this study. The nutrient retention capacity of wetlands may decrease over time (Land *et al* 2016), and increases in local nutrient export may affect the overall biodiversity of wetlands themselves (Brinson and Malvárez 2002). Because of these effects, watershed managers need to carefully evaluate all potential consequences of restoring wetlands now and in the near future.

5. Conclusions

We demonstrated the viability of wetland restoration as a management tool to mitigate the P export, which may lead to the improvement of water quality at the regional scale. The tradeoff curves highlighted the range of marginal benefits that wetlands may provide multiple stakeholder and decision makers. The irreplaceability index highlighted the most efficient wetlands that can be prioritized and restored; and the associated landscape properties can help restore wetlands for decision makers here and elsewhere. The spatial prioritization framework proposed here can be adapted for other nutrients, ecosystem services, or restoration goals.

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