The application of decision support tools and the influence of local data in prioritizing barrier removal in lower Michigan, USA

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Declarations of interest: none

Author contributions

K.R. and L.W. conceived of the main idea. H.Y.L. developed the scenarios for analysis. H.Y.L. and A.M. performed the computations and analysis. H.Y.L. took the lead in writing the manuscript. All authors helped shape this study and contributed essential components during the preparation of this manuscript.

Abstract

Web-based decision support tools (DSTs) can be useful to facilitate decision-making processes for managing complex natural resource systems. However**,** the alignment of DSTs with the objectives in governmental policies or management plans and the influence of limited local data on the outputs of these tools may reduce the use of DSTs by decision makers. In this study, we examined the outcomes of web-based DSTs when different types of local data were incorporated and demonstrated a way to incorporate outputs from multiple DSTs or local inventories to benefit barrier removal decisions. Restoring habitat connectivity in rivers in northwest lower Michigan, USA, was used as a case study due to the abundance of local inventory data and web-based DSTs. We found that, when compared to prioritizations made using local data, some DSTs could produce similar outcomes (in barriers selected, cost, and the benefit for migratory fish) with limited data, but the trade-offs among users' objectives might influence the cost and effectiveness of DSTs' outputs. Improving the ability of DSTs to incorporate objectives consistent with policy and stakeholders' values (e.g., restore certain species or sedimentation control) across management scales can help close the gap between tool recommendations and management decisions while making the barrier removal prioritization process transparent and efficient.

Keywords: decision support tools, restoring connectivity, barrier removal, prioritization, Great Lakes, sea lamprey

Introduction

Tools are needed to facilitate decision making for managing complex natural systems (Matthies et al., 2007; McIntosh et al., 2011). In river restoration and watershed management, removal of barriers to restore river connectivity has become a major focus (Kemp and O'Hanley, 2010; McKay et al., 2016) because connectivity loss and habitat fragmentation have threatened biodiversity and ecosystem services (Dudgeon et al., 2006; Saunders et al., 2015). Although removal of barriers, such as dams and road-stream crossings, can help to restore native fish populations (Bednarek, 2001; Evans et al., 2015), the decision of which barrier(s) to remove can be difficult for many reasons, including the cost and effort required (Neeson et al., 2015; Zheng and Hobbs, 2013). In addition, removing barriers may have negative effects on local ecosystems by increasing accessibility to habitats for invasive species (Hermoso et al., 2015; McLaughlin et al., 2013). These projects usually require considering multiple and sometimes competing values and objectives from managers and stakeholders (McKay et al., 2016; Zheng and Hobbs, 2013). Tools that can incorporate both benefit and costs of removal projects, reveal trade-offs among alternatives, and visualize the results can facilitate the decision-making process in prioritizing barrier removals (McKay et al., 2016).

Decision support tools (DSTs) are interactive, computer-based platforms that can be used to help facilitate environmental decision making (Gibson et al., 2017; McIntosh et al., 2011; Power and Sharda, 2009). Many of these tools are web-based, allowing for users to overcome the constraint of limited local resources (e.g., time, data, and communication) and increasing the accessibility to managers and stakeholders ("web-based DSTs": Choi et al., 2005; Shim et al., 2002). For example, web-based DSTs have been developed to provide biological, environmental, and socio-economic data, aquatic connectivity estimates, and quantitative models to support barrier removal prioritization across the US (e.g., for the Northeast, Chesapeake Bay, Southeast, and Great Lakes regions, see McKay et al., 2016). Databases included in these tools can help decision-makers gather necessary information, and quantitative models can be used to predict possible outcome scenarios for a decision point (McKay et al., 2016). Therefore, use of DSTs may improve the transparency of decision-making because the tools can provide evidence-based explanations, along with visual aids, to support decisions, and all users can examine the input data, adjust the weights, and reproduce the decision procedure and results (McIntosh et al., 2011).

Despite advantages of using DSTs, many of these tools are underused by managers and decision makers. Often developers and end-users of these tools differ in the required timeframes and information, expectations, background knowledge, training, and skill sets (Gibson et al., 2017; McIntosh et al., 2011). Some managers may not be aware of existing tools, are wary of real or perceived tool limitations, or are uncomfortable with the tool's assumptions (Addison et al., 2013; van Delden et al., 2011). For example, while many web-based DSTs have been developed to assist managers in selecting the most beneficial sites for connectivity restoration in the Great Lakes Basin (McKay et al., 2016; Moody et al., 2017), most of them have been neither mentioned nor applied in local-scale watershed management plans such as Nonpoint Source program approved watershed management plans in Michigan, USA. Instead, managers often rely on inventory data collected by local watershed groups and management agencies to prioritize barrier removal or mitigation projects (Shook, D. [Grand Traverse Band of Ottawa and Chippewa Indians] and Beyer, A. [Conservation Resource Alliance], personal communication, 2017), or select these projects opportunistically without much, if any, prioritization.

How DSTs perform given limited data is one of the key factors that influences the use of these tools by managers and decision makers (Gibson et al., 2017). Local inventory data are quite sparse in many regions and can be time-consuming and expensive to collect, and the use of these data may not necessarily change management actions or improve conservation outcomes. For example, the return on investment of survey data decreases rapidly in the conservation of sugarbushes (Proteaceae) in South Africa (Grantham et al., 2008). Similarly, collecting new data about population growth was shown to provide little improvement to koala (*Phascolarctos cinereus*) management in south-east Queensland, Australia (Maxwell et al., 2015). Therefore, comparing the outputs of DSTs given different levels of availability of local data and examining the influence of various types of data on decisions could be valuable. If the value of this local information is low for the decision at hand, the costs related to data collection could be better allocated to other management activities. Furthermore, reviewing data and functions across DSTs and demonstrating possible ways to integrate multiple tools for certain management interests can help managers and decision-makers quickly select suitable tools for their needs and objectives (e.g., an example in Tetzlaff et al., 2013 and Center for Ocean Solutions, 2011). The use of local data extracted from multiple data-driven DSTs provides an opportunity to examine the influence of different levels of data availability on the outputs of model-driven DSTs.

This study aims to enhance the connection between DST development and management decisions by addressing two main issues that influence the use of DSTs by decision makers: (1) the alignment of DSTs with the objectives and context of policies or management plans, and (2) the performance of DSTs with limited or missing data (Gibson et al., 2017). To accomplish these goals, we conducted a study in which we: (1) reviewed management plans and available web-based DSTs for a case study; (2) examined ways to integrate data and functions across

DSTs and created a guide for DST selection according to management context; (3) compared and examined the outputs of a model-driven DST, Fishwerks, given different local data availability; and finally, (4) suggested possible improvements for existing DSTs. The case study was conducted in northwestern lower Michigan (the Fruitbelt region), USA, because this region is included in a number of existing web-based DSTs (see McKay et al., 2016 and Moody et al., 2017) and has relatively comprehensive local inventory data on road-stream crossings collected by local agencies and non-profits that is publicly available on the River Restoration in Northern Michigan website (http://www.northernmichiganstreams.org/rsxinfo.asp). The abundance of existing DSTs and local data provide a unique opportunity to study the influence of data availability on DST outputs and explore the complementarity among DSTs. We also evaluated the influence of information for contradictory objectives (i.e., remove barriers for native species vs. keep barriers for nuisance species). Furthermore, our results can be used to inform managers in regions with limited local inventory data about the sensitivity of model-driven DSTs to local information and the use of data-driven DSTs.

Methods

Case study in northwest lower Michigan

Northwest lower Michigan (Fruitbelt region), USA, is characterized by groundwater-fed cold-water streams that provide critical habitat for native and sport fish populations, such as white sucker (*Catostomus commersonii*), northern pike (*Esox lucius*), walleye (*Sander vitreus*), lake sturgeon (*Acipenser fulvescens*), and salmon and trout (Salmonidae) (Lyons et al., 2009; Peterson et al., 2007; Zorn et al., 2008). This region also supports diverse and productive agriculture, such as blueberry, cherry, apple, and grape production, and forestry.

Local watershed management plans have been developed and implemented under the Nonpoint Source (NPS) grant program, which is administered by Michigan Department of Environmental Quality, to protect and restore watersheds in the Fruitbelt region and throughout the state of Michigan (NPS Approved and Pending Watershed Plans, Michigan). As with much of the Great Lakes region, connectivity loss and habitat fragmentation by anthropogenic barriers, such as dams and road-stream crossings, have negatively affected fish populations by blocking migration pathways, reducing the accessibility of critical habitats, degrading habitat quality, and hindering the free movement of materials and energy in the ecosystem (Dodd et al., 2003; Januchowski-Hartley et al., 2013; Porto et al., 1999). Since 2015, federal, state, tribal, municipal, and non-government partners have worked together as the Tribal Stream and Michigan Fruitbelt Collaborative to reduce sedimentation and improve aquatic organism passage in the region. Typically, projects that focus on culvert replacement are prioritized after structures are assessed using the Great Lakes Road Stream Crossing Inventory Instructions protocol (2011). Although there is continued interest in restoring connectivity through barrier removal projects across the Great Lakes Basin, evaluating the complex trade-offs between ecological and societal values in the decision-making process is challenging. For any single barrier, the potential ecological consequences of removal could be both positive (via native species and nutrient/energy flows; Dudgeon et al., 2006; Maavara et al., 2015) and negative (via invaders and pathogens; McLaughlin et al., 2013 and Zheng and Hobbs, 2013). Furthermore, decision makers must also consider implications for human safety and recreation (Moody et al. 2017). In the Great Lakes Basin, more than 60 barriers have been constructed or modified to suppress the spread of sea lamprey (*Petromyzon marinus*), and hundreds built for other purposes function as blocking structures critical to controlling sea lamprey (Lavis et al., 2003). Removing barriers may increase sea lamprey populations if suitable spawning and rearing habitats exist upstream of barriers, and the Great Lakes Fishery Commission anticipates that newly infested habitat would require an increased budget to retain sea lamprey control in Great Lakes tributaries (Jensen and Jones, 2017; Mullett and Sullivan, 2016).

Policy and management plans review

We reviewed one state act (Michigan Natural Resources and Environmental Protection Act 1994 PA 451) and 13 local watershed management plans (Betsie River, Lake Charlevoix, Cheboygan River/Lower Black River, Glen Lake/Crystal River, Grand Traverse Bay, Greater Bear, Lake Leelanau, Little Traverse Bay, Little Manistee, Long Lake, Mullett Lake, Platte River, Upper Manistee River; Fig. 1) to identify objectives relevant to barrier removal for our case study. Surface waters of the State of Michigan are protected by Water Quality Standards for specific designated uses, such as supporting cold- or warm-water fisheries, indigenous aquatic life, and wildlife (R323.1100 of Part 4, Part 31 of the Michigan Natural Resources and Environmental Protection Act, 1994 PA 451). Because most socio-economically and ecologically important fish species are affected by barriers in the Fruitbelt region (Januchowski-Hartley et al., 2013; Moody et al., 2017), barrier removal projects can be used to help achieve some designated uses in the Environmental Protection Act. All 13 watershed management plans within the study area recognized road-stream crossings as critical sites for sedimentation control, and most plans mentioned the effects of poorly-designed road-stream crossings and dams on river connectivity. According to the Great Lakes Road Stream Crossing Inventory Instructions protocol (USFS 2011), both erosion and fish passage issues can be used to prioritize road-stream crossings for upgrade. Besides these management plans, several barriers are operated by the US Fish and Wildlife Service (USFWS) and Fisheries and Oceans Canada (DFO), as contract agents of the Great Lakes Fishery Commission, to control sea lamprey populations. Based on our findings, we included objectives (and measures of these objectives) related to cold- and warm-water fish, indigenous aquatic species and wildlife, invasive sea lamprey, barrier passability, and erosion when considering barrier prioritization.

Decision support tools selection

Eight web-based DSTs were identified from the literature (McKay et al., 2016; Moody et al., 2017) and environmental management websites (see Table 1), in which they provided: (1) policy and management plan-relevant data and spatial information on barriers; and/or (2) optimization models, for prioritizing barrier removal in the Fruitbelt region. The High Impact Targeting tool focuses on sedimentation; FishVis, FishTail, and the Fish Habitat Decision Support Tool focus on biological, environmental, and some socio-economic factors; and the Sea Lamprey Control Map, Geospatial Fisheries Information network, Fishwerks and OptiPass focus more directly on river connectivity (Table 1). Among all DSTs evaluated, only Fishwerks and OptiPass had optimization modelling functions for prioritizing barrier removal projects, and only Fishwerks could perform optimization modelling and display the results online without input data from users (Table 1). Seven out of eight DSTs are region-specific tools that cover a geological range from the entire US, part of the US, to part of Canada. OptiPass is the only tool that can be applied to any watershed, depending on input data (Table 1). We built a decision guide to facilitate DST selection by decision makers according to policy context and the functionality of DSTs (Fig. 2). One model-driven tool, Fishwerks was chosen for the following scenario analyses to examine the outcomes of DSTs with limited data. Fishwerks was used because less user-provided input data are required, and it is built specifically for the Great Lakes basin with the same basic optimization algorithm (mixed integer linear programming) as in OptiPass. Other data-driven tools, including FishVis, FishTail, and Sea Lamprey Control Map were then used as sources of different local data, as described in the next section.

Decision support tool evaluation

We examined outcomes of barrier prioritization under different local data availability by comparing results (effectiveness and cost) among a set of simulated scenarios (Table 2). Scenarios were selected according to the objectives from reviewed policy and management plans, such as prioritizing barrier removals to benefit cold- and warm-water fishes and other indigenous aquatic species while considering invasive sea lamprey control. Specifically, barriers were prioritized to maximize habitat connections for fish with different thermal preferences (i.e., cool-, cold-, and warm-water fish; extracted from FishVis), or to maximize the connections between riverine habitats with high water quality or low land-based disturbances (extracted from FishTail). We also considered the cost of applying lampricide to kill sea lamprey larvae in newly-opened streams or keeping all barriers that are important for sea lamprey control intact. The estimated annual lampricide application cost for every stream reach was extracted from Fishwerks (Table 2), and was estimated usng variables including lake basins, reach length, and watershed drainage area to incorporate both costs for chemical lampricide and staff time (Steeves, M. [Fisheries and Oceans Canada] personal communication, 2015). We chose to focus on sea lamprey invasions because many stakeholders in the region consider this as a significant negative effect of terminal barrier removal (McLaughlin et al., 2013). Furthermore, we included predictions of future species distributions to prioritize barriers for removal under possible future climate conditions because species distribution shifts by climate change may reduce the effectiveness of current management actions in the Great Lakes region (Collingsworth et al., 2017; Lynch et al., 2015). Predicted distributions of cool-, cold-, and warm-water fish in the mid and late 21st century throughout the Fruitbelt region were downloaded from FishVis (Table 2).

First, we ran the optimization model within Fishwerks (scenario code: N, no local information; “base scenario” hereafter), which maximizes total accessibility-weighted upstream habitat for migratory fish under a given budget, to produce a portfolio of removals (Moody et al., 2017; Neeson et al., 2015). The accessibility-weighted upstream habitat was calculated as river length (potential habitat) times the product of all downstream barriers’ passability (Neeson et al., 2015). The passability for barriers, which is included as part of the Fishwerks package, was defined as the proportion of fish able to pass through a barrier from downstream (Moody et al., 2017; Neeson et al., 2015). Three levels of passability for each barrier can be found in Fishwerks to represent the effect of barriers on fish with weak, moderate, or strong swimming ability (Moody et al., 2017). For simplicity, the passability for moderate swimmers was used in this study.

Then, we incorporated additional local information (described in detail below), extracted from other DSTs, to weight upstream habitat and produce other portfolios of barriers prioritized for removal. Additional local information included projected species distribution in the late-20th, mid-21st, and late-21st century for three thermal guilds (1961–2000: cold-water species, Cd1; cool-water species, Cl1; warm-water species, W1; 2046–2065: cold-water species, Cd2; cool-water species, Cl2; warm-water species, W2; and 2081–2100: cold-water species, Cd3; cool-water species, Cl3; warm-water species, W3). Future climate conditions were estimated from 13 general circulation models under the A1B emissions scenario (FishVis: Stewart et al., 2016a). Other local habitat condition data included a water quality index (Q) that represented water quality impairments weighted by the response of the fish community (FishTail: Daniel et al., 2017); indices for local land-use (Lul) and cumulative land-use (Luc), including urban and agricultural land-use, and percent impervious surface cover (FishTail: Daniel et al., 2017); and terminal barriers that block sea lamprey migration (Lam), which were extracted from Sea Lamprey Control Map (http://data.glfc.org/). Projected species distribution data were downloaded from the US Geological Survey database (FishTail: Daniel et al., 2017; FishVis: Stewart et al., 2016b). Then, these variables were normalized to a zero to one scale and used to weight the original accessibility-weighted habitat in the Fishwerks optimization model. In the normalized scale, zero represented the absence of certain species or the worst habitat condition projected while one represented the presence of certain species or the best habitat condition projected. In these scenarios, the optimization model maximized total upstream habitat, weighted by both local information and accessibility. Finally, for the sea lamprey blocking scenario (Lam), we prioritized barriers similar to the base scenario (N) but excluded all terminal barriers that blocked sea lamprey migration from Lake Michigan. In total, 14 scenarios were analyzed, as shown in Table 2. Budgets of $2.0, 2.5, and 3.0 million U.S. Dollars (USD) were used to run optimization models because this is the range of funds available to the Michigan Tribal Stream and Fruitbelt Collaborative for barrier removal projects in the study region.

We ran optimizations in a research version of Fishwerks (available online: https://neos-server.org/neos/solvers/application:Fishwerks/csv.html) that allowed us to incorporate custom barrier inventory data with additional local information. This is different from the current online version of Fishwerks, which can only optimize barrier removals with built-in river length data.

The influence of local information was assessed by comparing the effectiveness, cost, and simulated suite of barriers selected among barrier removal scenarios that were prioritized with or without local information. Effectiveness (“habitat gain”, hereafter) represents predicted habitat gain in kilometers, weighted by different biological and habitat condition indices (Table 3), including: (1) the percentage gain of river length (effectiveness code: Len); (2) cold-water habitat (Cdh); (3) cool-water habitat (Clh); (4) warm-water habitat (Wh); (5)

quality habitat (Qh); (6) quality local land-use habitat (Llh); and (7) quality cumulative land-use habitat gain (Lch). We calculated total habitat gain and compared the differences in seven types of effectiveness (as described above) among 14 scenarios. For instance, given a budget, which scenario might produce more habitat gain for cold-water species (Cdh)? A second variable, cost, represents the estimated cost for removing barriers and applying lampricide after removal (Table 3). Although the total cost for removing barriers across scenarios will be similar under given budget limits, we identified different barriers selected by base scenario (N) and each one of the other scenarios and calculated the cost of these barriers. For example, if two barriers selected by the scenario with additional water quality (Q) information were not selected by the scenario without local information (N), the difference in cost between these two scenarios will be the sum of these two barriers. Finally, we compared selected barriers among scenarios by examining: (1) the spatial distribution of selected barriers; (2) selection frequency of each barrier; and (3) the percentage of barriers that were repeatedly selected by both the scenario without local information (N) and each one of the other scenarios.

Results

Differences in the cost, locations, and number of barriers

The selected portfolios of barriers were similar regardless of the input of additional local information for 13 out of 14 scenarios, with the sea lamprey blocking scenario (Lam) as the one exception (Figs. 3 & 4). Selected barriers were scattered throughout the study area for most scenarios, with 20 barriers selected in seven or more scenarios as important barriers to be removed (Fig. 3a). The differences in selected barriers between the base scenario (N) and scenarios using additional information, such as cold-water species distribution (including distribution shift by climate change: Cd1–3), water quality (Q) or land-use indices (Lul & Luc) were relatively small (> 75% overlap of selected barriers with < $0.75 million USD cost differences). Adding local information for cool-water and warm-water species (Cl1–3 & W1–3) resulted in moderate differences in barriers chosen, compared to the base scenario (25–75% overlap with around $1–2 million USD cost differences; Fig. 4). If all important barriers for blocking sea lamprey migration were left intact (Lam), selected barriers were concentrated in a few watersheds, especially in small tributaries around Lake Charlevoix and the lower Manistee River (Fig. 3b). Less than 6% of barriers were selected in both the base scenario and the sea lamprey blocking scenario, and the differences in cost were around $4–6 million USD (Fig. 4). Increasing the budget could increase the number of barriers selected (scenarios except Lam: 9–13 barriers given $2 million USD, 14–18 barriers given $2.5 million USD, and 18–26 barriers given $3 million USD), however, three to four times more barriers were selected under the sea lamprey blocking scenario (Lam) than other scenarios across budgets (49 barriers given $2 million USD, 59 barriers given $2.5 million USD, and 67 given $3 million USD).

Differences in habitat gain (effectiveness) and cost of lampricide

1. Among scenarios (excluding climate change)

Although the gain in target habitat was optimized in every scenario, the gain in other habitats varied among scenarios (Fig. 5). For example, while the cold-water fish scenario (Cd) produced the highest effectiveness for cold-water habitat (Cdh) and the warm-water fish scenario (W) produced the largest connected warm-water habitat (Wh) among all scenarios, the effectiveness for other habitats (e.g., the gain of quality local land-use habitat, Llh) were also different between these two scenarios. In general, the gain in all habitat types was similar, with 110–160% habitat gain among most scenarios like the base, cold-water fish, water quality, local land-use, and cumulative land-use scenarios, but the habitat gains were around 10 – 25%

lower in cold-water and warm-water fish scenarios. The smallest habitat gain for all types of habitats was found in the sea lamprey blocking scenario (Lam, < 20% habitat gain; Fig. 5). Estimated costs for lampricide were similar among most scenarios, except for the cool-water and warm-water fish scenarios. Lampricide cost was not considered for the sea lamprey blocking scenario because all downstream barriers that block sea lamprey migration remained in place.

2. The effectiveness under climate change

Overall, the amount of target habitat for all thermal guilds (cold-water, cool-water, and warm-water species) increased (or remained the same) in the mid-21^{st} century but was followed by a 20–30% decrease in the late-21^{st} century. Incorporating climate change and species distribution data produced the greatest gain in target habitat, because the model maximized accessible habitats while accounting for predicted climate conditions, but the contribution of these sources of information varied among years, habitats, and budgets. For example, the incorporation of climate change and species distribution information yielded a set of barrier removals that would result in 20% more cool-water habitats under the $2 million USD budget in the late-21^{st} century, relative to the base scenario (N); there was no or little benefit from including these sources of information when prioritizing for cool-water habitats under the same budget in the middle of 21^{st} century or under a $2.5 million USD budget in the end of 21^{st} century. Interestingly, although the improvement produced from the addition of climate change data (i.e., the differences between solid and dashed lines in Fig. 6) increased through time, the differences between using both climate change and species distribution data (solid lines) and using no local data at all (dotted lines) declined by the end of the 21^{st} century (Fig. 6).

Discussion

In this study, we showed existing DSTs could be used to address two main issues that hinder the use of these tools by managers: (1) the alignment of DSTs with the objectives and context of a policy, and (2) the ability of DSTs to perform despite limited data (Gibson et al., 2017). We also demonstrated how eight web-based DSTs with different data and functionality can be used to inform decision making for prioritizing barrier removal projects (Figs. 2). While no single DST covered all objectives in policy and management plans, information or data could be extracted from existing data-driven DSTs (e.g., FishVis, FishTail, Fish Habitat Decision Support Tool) or local inventories. Then, decision makers and managers can prioritize barrier removal projects through model-driven DSTs (e.g., OptiPass, Fishwerks) or manually (e.g., scoring and ranking, not shown in this study but see Martin and Apse, 2013). We further built a general guide (Fig. 7) to indicate ways to use existing DSTs in the protocol for barrier prioritization proposed by McKay et al. (2016).

The improvement from the input of additional local information could be minor for barrier prioritization, however, caution is needed when applying regional DSTs to a local management area where the distributions of biodiversity and human disturbances are heterogeneous in fine scale. In general, information about homogeneously- and widely-distributed species (e.g., cold-water fish in our study area), habitat types, or disturbances (e.g., water quality index) may contribute less to the outcome, but trade-offs in effectiveness may occur if an objective is to optimize rare species (e.g., warm-water species in study area) or control nuisance species (McLaughlin et al., 2013). Although some studies have found that the resolution of regional DSTs might be too coarse for local management planning (Runting et al., 2013), river length, the variable optimized in Fishwerks, appears less sensitive to the input of additional local information. On the contrary, telemetry tracking data substantially improved the results from DSTs for sea turtle conservation plans (Mazor et al., 2016), and the cost-effectiveness of coastal wetland protection plans can be increased with high-resolution elevation data (Runting et al., 2013). Our results indicated that maintaining sea lamprey barriers produced low effectiveness in connectivity restoration, around 7 times less than other scenarios, and required the removal of a large number of barriers, around 4 times more than other scenarios. Furthermore, an additional $1 to 3 million USD cost might be required to apply lampricide on newly-connected streams to control the sea lamprey population if sea lamprey barriers were removed. Although the estimated cost in this study may only represent the worst case because it assumed that every newly-opened stream segment contains suitable spawning and rearing habitats for sea lamprey, the strong trade-off between restoring native fish populations and controlling sea lamprey may come from the overlapping distribution between native fish and sea lamprey (Milt et al., 2018). This last point highlights the need for DSTs that can integrate multiple objectives (e.g., migratory fish passage and invasive species control) that can be used as an aid when evaluating the trade-offs for decision-making in barrier prioritization (Hermoso et al., 2015).

While the sea lamprey scenario in this study focused on maintaining the cost of lampricide application similar to status quo, which means keeping all terminal barriers intact, other scenarios could be used to examine the trade-off between restoring native fish and controlling alien species. For example, managers may want to know the effectiveness of barrier removal when an additional budget has been assigned to cover the lampricide cost, in addition to the barrier removal budget. Another scenario is to prioritize barriers when an overall budget is required to be spent on both barrier removals and lampricide applications. By incorporating potential lampricide expenses into prioritization, these scenarios have the ability to open up more upstream habitats for native fish, as compared to the sea lamprey scenario in this study.

These scenarios can also be analyzed within the current version of Fishwerks. However, under current management scheme, budgets for removing barriers are usually managed and provided by agencies (i.e., federal, state, tribal, municipal, and non-government organizations) that differ from the agency in charge of applying lampricide (i.e., Great Lakes Fishery Commission). Studies that evaluate the effectiveness and trade-offs of these scenarios could be beneficial to future management because coordinating efforts and cost-sharing strategies may improve the return-on-investment of barrier removal prioritization (Neeson et al., 2018, 2015).

As expected, incorporating predicted species distribution data under climate change can increase effectiveness of barrier removal up to 20%, but this improvement varied with time, fish thermal guilds, and budget, and lacked a general pattern. Interestingly, percentage habitat gain from barrier removals changed through time, with a pattern different from predicted species distribution change. For example, effectiveness of barrier removal for warm-water species increased a small amount then reduced about 30% in the late 21st century under $2 million USD budget while previous studies and the DST we used, FishVis, suggest a gradual expansion of warm-water habitats across the Great Lakes Basin with a changing climate (Collingsworth et al., 2017; Melles et al., 2015; Stewart et al., 2016a). In general, water temperature becomes warmer in reaches close to river mouths (Zorn et al., 2008). Therefore, the predicted increase of warm-water habitats might mainly occur in downstream reaches, which are less affected by barriers, compared to upstream cold-water habitats. Nevertheless, the spatial distribution of cold groundwater inflow also plays an important role in determining stream temperature (Zorn et al., 2008), thus influencing the effectiveness of barrier removal for fishes with different temperature preferences. Besides possible changes in the community composition of native fish, climate change may also influence the distribution of nuisance species (Melles et al., 2015). Therefore, although uncertainties in climate models and fish thermal guilds' responses make predicting the influence of climate change on barrier prioritization difficult, incorporating climate change into DSTs can improve the flexibility of management plans and mechanisms for risk assessment (Lynch et al., 2015; Melles et al., 2015).

Other methods and DSTs, besides the Fishwerks optimization model, can be used to prioritize removal projects, such as scoring and ranking (e.g., Chesapeake Fish Passage Prioritization, web-based DST, Martin and Apse, 2013) and graph theoretic frameworks (e.g., Conefor, standalone software, Saura and Torné, 2009). However, scoring and ranking methods are incapable of fully accounting for the cumulative effects within barrier networks, and graph theoretic frameworks do not produce a recommended removal list (King and O'Hanley, 2016). While managers and stakeholders within the Great Lakes region can use Fishwerks without the input of additional data, users in other places might need to rely on more commonly-used scoring and ranking methods or optimization models requiring user input data. For example, regional DSTs with local environmental, ecological, and connectivity data using scoring and ranking methods have been developed for watersheds in the Northeast US, Chesapeake Bay, and Southeast US (reviewed in McKay et al., 2016). One DST reviewed in this study, OptiPass, is a standalone software with an optimization model that can be applied to any watershed given user input data, such as the location, cost, and passability of candidate barriers and flowlines (O'Hanley, 2015).

Factors that may improve the use of existing barrier prioritization methods and DSTs by managers and stakeholders, such as prioritizing barrier removal for resident species, ensuring the data are up-to-date, and incorporating socio-economic and political variables, have been discussed in previous studies (King and O'Hanley, 2016; McKay et al., 2016; Moody et al., 2017). Currently available software may be unattractive to managers because of the inability to easily incorporate local, additional, or high-resolution data (e.g. Fishwerks) or because of the requirement to input all analysis data (e.g. OptiPass). In addition, sedimentation control was a key management objective in many local watershed plans that we reviewed, but we found that neither regional barrier prioritization projects nor DSTs explicitly considered this key variable. In the study region, watershed managers often prioritize road-stream crossings for upgrade according to the risk of sedimentation rather than their impact on river connectivity (Shook, D. [Grand Traverse Band of Ottawa and Chippewa Indians] and Beyer, A. [Conservation Resource Alliance], personal communication, 2017). The use of sedimentation information could be because most road-stream crossings, which are usually treated as a source of sedimentation, are managed by local authorities, whereas the effect of dams, generally assessed as barriers for connectivity, is addressed at a regional or national scale (Neeson et al., 2015). Increasing the functionality and flexibility of web-based barrier prioritization DSTs to incorporate data other than the built-in database might lead to greater use by managers. For example, local managers in the Fruitbelt region would like to incorporate socio-economic factors such as the willingness of stakeholders to remove certain barriers or erosion risk into the cost function in prioritization modelling if data are available (Shook, D. and Beyer, A., personal communication, 2017). Improving the communication between tool developers and users during the development of DSTs could help developers understand the needs of users and thus allow for incorporating policy and management plan-relevant information into DSTs or increasing the flexibility of models.

While the improvement of the database and modelling ability can enhance the usefulness of DSTs, it is important to note that the main purpose of DSTs is to support and facilitate, not to replace, the decision-making process (Power and Sharda, 2009). River restoration plans usually involve multiple stakeholders with competing interests, and some variables and objectives may be difficult to quantify and incorporate into DSTs (Langford and Shaw, 2014; McKay et al., 2016). The incorporation of local interests and opinions is especially important for small dam removal because many decisions are strongly influenced by the willingness of local stakeholders and communities instead of ecological or economic impact (Fox et al., 2016). The use of decision analysis, such as structured decision making and adaptive management, which is increasingly being applied to wildlife management and conservation issues (e.g., Gregory and Long, 2009; Robinson et al., 2016), provides a promising way to incorporate diverse interests and objectives into the decision-making process to reduce possible conflicts. A key challenge for DSTs is to generate predicted effectiveness after removal for comparing the trade-offs among scenarios, which is an important step in decision analysis (Gregory et al., 2012). Predicted effectiveness can be the amount of habitat gain for target fish species as in this study, or even potential changes in the target fish population if demographic data and population models are available (e.g., Jensen and Jones, 2017; Zheng and Hobbs, 2013). In addition, incorporating the tools of strategic foresight (e.g., scenario planning; Cook et al., 2014) to a decision analytic framework can help users to explicitly evaluate the uncertainties related to future conditions, such as climate change (Schwartz et al., 2017).

Although we tried to enhance the connection between existing web-based DSTs and on-the-ground management by addressing the issues in Gibson et al. (2017), other factors may influence the uptake of DSTs by managers and stakeholders. Combining information from multiple DSTs might make managers less likely to use these tools, especially if they need to spend time reformatting and integrating data from different sources (Gibson et al., 2017). While all DSTs we reviewed can be applied on regional or local scales, we found that many local decision makers and stakeholders were not aware they existed. Furthermore, some policy makers prefer subjective judgements from experts rather than quantified outcomes from mathematical models (Addison et al., 2013). Continuous communication between DST developers and potential users is necessary if these tools will be relevant (Gibson et al., 2017; McIntosh et al., 2011). In addition, user training and support are also important factors influencing the willingness of managers and stakeholders to use the tool (Díez and McIntosh, 2009). Ultimately, it is critical to build trust between both developers and end-users to enhance the usefulness of these tools (Díez and McIntosh, 2009).

Conclusions

We demonstrated a way to guide the use of existing web-based DSTs for managers and stakeholders according to objectives derived from policy/management plans. Our results suggest that although some DSTs could produce outcomes that were insensitive to some local data, the trade-offs among user defined objectives (e.g., cold-water species vs. warm-water species or invasive species) might influence the effectiveness of DSTs or change the set of barriers selected for removal. Overall, regional DSTs have the ability to aid local decisions about barrier prioritization by providing important biological, environmental, and socio-economic data and/or, modelling functions, especially if used as a tool within a larger decision-making framework, such as decision analysis. Therefore, the development and maintenance of regional DSTs could facilitate both local and regional decision-making processes. Possible improvements for existing barrier removal prioritization DSTs include increasing model flexibility, dealing with sedimentation issues, incorporating other socio-economic factors, and improving the communication and training between tool developer and users. As the development of DSTs is growing, we hope to mitigate the gap between these useful tools and management actions.

Acknowledgements

Funding: this work was supported by the Upper Midwest and Great Lakes Landscape Conservation Cooperative. This project was supported by the USDA National Institute of Food and Agriculture, Hatch project 1012487. We thank M. Khoury for early contributions to this proposal, and D. Shook and A. Beyer for providing useful information and context for barrier removal in the Fruitbelt region. Two anonymous reviewers provided helpful feedback for the manuscript. This is contribution no. XXX of the Quantitative Fisheries Center, Michigan State University.

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Table 1. Decision support tools that we evaluated to facilitate barrier prioritization in Michigan’s Fruitbelt region.

Tool name	Tool type	Tool description, link, and spatial extent
FishVis	Web-based map (data-driven)	Display the distributions of 13 fish species (4 warm-water, 5 cool-water, and 4 cold-water species) under current and future climate conditions (Stewart et al., 2016a) (https://ccviewer.wim.usgs.gov/FishVis/#); US Great Lakes Basin, part of the Upper Mississippi River Basin (Minnesota and Wisconsin), and part of the Mid-Atlantic Basin (New York)
FishTail	Web-based map (data-driven)	Display the current and future condition of stream habitat under human disturbances and climate change (Daniel et al., 2017) (https://ccviewer.wim.usgs.gov/fishtail/#); US Northeast and Midwest region
High Impact Targeting	Interactive map (data-driven)	Display erosion risk and sediment loading, and evaluate the cost-benefits of best management practices (http://www.iwr.msu.edu/hit2/); US Great Lakes Basin
Sea Lamprey Control Map	Interactive map (data-driven)	Display existing barriers, sea lamprey infestation extent and lampricide treatment history, and effects of building or removing barriers on the accessibility of upstream habitat for sea lamprey (http://data.glfc.org/); Canada and US Great Lakes Basin
Geospatial Fisheries Information Network	Interactive map (data-driven)	Display existing barriers and show their effects on accessibility of upstream habitat for migratory species (https://ecos.fws.gov/geofin/); US watersheds
Fish Habitat Decision Support Tool	Interactive map with analytical functions (data-driven)	Display and analyze a variety of biological, environmental, and socio-economic spatial data (http://www.fishhabitattool.org/home.html); US Northeast and Midwest region
Fishwerks	Interactive map with optimization functions (model-driven)	Display existing barriers and optimize barrier removal projects under a given budget (Moody et al., 2017) (https://greatlakesconnectivity.org/); Canada and US Great Lakes Basin
OptiPass	Standalone software (model-driven)	Optimize barrier removal projects, but without map visualization capabilities. Requires user to download and run the model with user provided input data (O’Hanley, 2015) (https://greatlakesinform.org/decision-tools/573); depends on

input data

Table 2. Fourteen scenarios analyzed for comparing modelling outcomes (effectiveness and cost) given different local data input.

Scenario (code)	Target for optimization model to maximize	Source DST
No local information/base scenario (N)	(habitat size*) × (accessibility**)	Fishwerks
Cold-water fish distribution in the late-20th century (Cd1)	(habitat size) × (accessibility) × (predicted occurrence of cold-water fish in 1961–2000)	Fishwerks, FishVis
Cool-water fish distribution in the late-20th century (Cl1)	(habitat size) × (accessibility) × (predicted occurrence of cool-water fish in 1961–2000)	Fishwerks, FishVis
Warm-water fish distribution in the late-20th century (W1)	(habitat size) × (accessibility) × (predicted occurrence of cool-water fish in 1961–2000)	Fishwerks, FishVis
Cold-water fish distribution in the mid-21st century (Cd2)	(habitat size) × (accessibility) × (predicted occurrence of cold-water fish in 2046–2065)	Fishwerks, FishVis
Cool-water fish distribution in the mid-21st century (Cl2)	(habitat size) × (accessibility) × (predicted occurrence of cool-water fish in 2046–2065)	Fishwerks, FishVis
Warm-water fish distribution in the mid-21st century (W2)	(habitat size) × (accessibility) × (predicted occurrence of warm-water fish in 2046–2065)	Fishwerks, FishVis
Cold-water fish distribution in the late-21st century (Cd3)	(habitat size) × (accessibility) × (predicted occurrence of cold-water fish in 2081–2100)	Fishwerks, FishVis
Cool-water fish distribution in the late-21st century (Cl3)	(habitat size) × (accessibility) × (predicted occurrence of cool-water fish in 2081–2100)	Fishwerks, FishVis
Warm-water fish distribution in the late-21st century (W3)	(habitat size) × (accessibility) × (predicted occurrence of warm-water fish in 2081–2100)	Fishwerks, FishVis
Water quality (Q)	(habitat size) × (accessibility) × (water quality index)	Fishwerks, FishTail
Local land-use (Lul)	(habitat size) × (accessibility) × (local land-use index)	Fishwerks, FishTail
Cumulative land-use*** (Luc)	(habitat size) × (accessibility) × (cumulative land-use index***)	Fishwerks, FishTail
Lamprey blocking (Lam)	(habitat size) × (accessibility); similar to base scenario but keep all critical sea lamprey barriers intact	Fishwerks, Sea Lamprey Control Map

* Habitat size is the upstream river length (km) of a particular barrier. **Accessibility is calculated as the product of the passability rating of a particular barrier and all downstream barriers. ***Cumulative represents a combined index that includes the disturbances in local and all upstream catchments (see Esselman et al., 2011).

Table 3. A description of effectiveness and cost used to compare the outcomes of fourteen barrier prioritization scenarios.

	Name (code)	**Description: calculation**
Effectiveness	Habitat (river length) gain (Len)	The increase of accessibility-weighted habitat size, $\Delta\sum_{i=1}^{I}(habitat\ \ size_i)\times(accessibility_i)$, where I = all river segments/potential habitats in study area, after the removal of selected barriers
	Cold-water habitat gain (Cdh)	The increase of accessibility- and cold-water fish distribution weighted habitat size, $\Delta\sum_{i=1}^{I}(habitat\ \ size_i)\times(accessibility_i)\times(predicted\ \ occurrence\ \ of\ \ cold\text{-}water\ \ fish_i)$, the removal of selected barriers
	Cool-water habitat gain (Clh)	The increase of accessibility- and cool-water fish distribution weighted habitat size, $\Delta\sum_{i=1}^{I}(habitat\ \ size_i)\times(accessibility_i)\times(predicted\ \ occurrence\ \ of\ \ cool\text{-}water\ \ fish_i)$, after the removal of selected barriers
	Warm-water habitat gain (Wh)	The increase of accessibility- and warm-water fish distribution weighted habitat size, $\Delta\sum_{i=1}^{I}(habitat\ \ size_i)\times(accessibility_i)\times(predicted\ \ occurrence\ \ of\ \ warm\text{-}water\ \ fish_i)$, after the removal of selected barriers
	Quality habitat gain (Qh)	The increase of accessibility- and water quality index-weighted habitat size, $\Delta\sum_{i=1}^{I}(habitat\ \ size_i)\times(accessibility_i)\times(water\ \ quality\ \ index_i)$, after the removal of selected barriers
	Quality local land-use habitat gain (Llh)	The increase of accessibility- and local land-use index-weighted habitat size, $\Delta\sum_{i=1}^{I}(habitat\ \ size_i)\times(accessibility_i)\times(local\ \ land\text{-}use\ \ index_i)$, after the removal of selected barriers
	Quality cumulative land-use habitat gain (Lch)	The increase of accessibility- and cumulative land-use index-weighted habitat size, $\Delta\sum_{i=1}^{I}(habitat\ \ size_i)\times(accessibility_i)\times(cumulative\ \ land\text{-}use\ \ index_i)$, after the removal of selected barriers
Cost	Cost for removing barrier	Estimated cost for dam removal or culvert upgrade, details in Neeson et al. (2015)
	Cost for lampricide	Estimated cost for applying lampricide after barrier removal, details in the metadata document of Fishwerks

Figure captions

Fig. 1 The location and name of local watershed management plans that were reviewed in this study (a). The black box in (b) indicates the location and range of the case study area (a) in the Laurentian Great Lakes region.

Fig. 2 Flowchart for choosing DSTs based on objectives and data availability. HIT: High Impact Targeting, FHDST: Fish Habitat Decision Support Tool. *Although the prioritization can be done manually (e.g., scoring and ranking method) with local inventory data input, users can also use model-driven DSTs such as OptiPass or Fishwerks to help optimize removal projects.

Fig. 3 The location and selection frequency of barriers selected by optimization models given a $3 million USD budget in (a) the base scenario and 12 scenarios that incorporated local information, and (b) the sea lamprey blocking scenario.

Fig. 4 Differences between the costs (bars) and the locations (dots: percent overlap, where 100% represents the same set of barriers was selected by two scenarios and 0% represents none of the selected barriers are the same) of barriers selected by the base scenario and 13 scenarios of local data inclusion (x-axis) under three different budgets in Fishwerks. Cd: cold-water species, Cl: cool-water species, W: warm-water species, Q: water quality, Lul: land-use (local), Luc: land-use (cumulative), Lam: sea lamprey blocking, 1: projected species distribution in 1961–2000, 2: distribution in 2046–2065, 3: distribution in 2081–2100.

Fig. 5 The cost for lampricide (bars) and the effectiveness (percentage gain of quality-accessibility-weighted habitat; symbols) among scenarios under 1961–2000 climate conditions, for budgets of $2.0, 2.5, and 3.0 million USD. Scenario: N: base scenario, Cd: cold-water species, Cl: cool-water species, W: warm-water species, Q: water quality, Lul: land-use (local), Luc: land-use (cumulative), Lam: sea lamprey blocking. Habitat: Cdh: cold-water habitat, Clh: cool-water habitat, Len: river length, Lch: quality cumulative land-use habitat, Llh: quality local land-use habitat, Qh: quality habitat, Wh: warm-water habitat.

Fig. 6 The percent gain of quality- and accessibility-weighted habitat among scenarios in late-20th (1961–2000), mid-21st (2046–2065), and late-21st century (2081–2100) at budgets of $2.0, 2.5, and 3.0 million USD for cold-water habitat (circle), cool-water habitat (triangle), warm-water habitat (square), and river length (cross). Results are presented for scenarios including climate change and species distribution information (solid line), without climate change but with species distribution information (dashed line), and without climate change and species distribution information (dotted line).

Fig. 7 Recommendations (light grey boxes) of using existing DSTs in the steps of barrier removal prioritization protocol (dark grey boxes) that were proposed by McKay et al., (2016).

Fig. 1

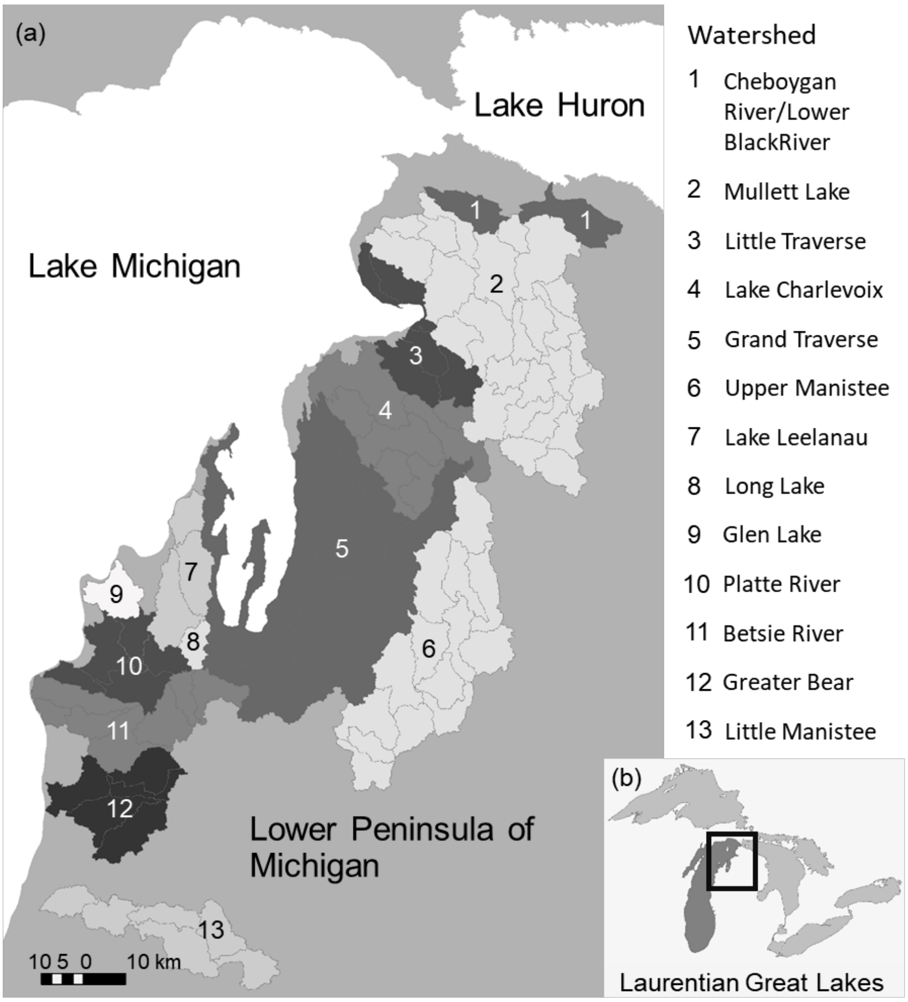
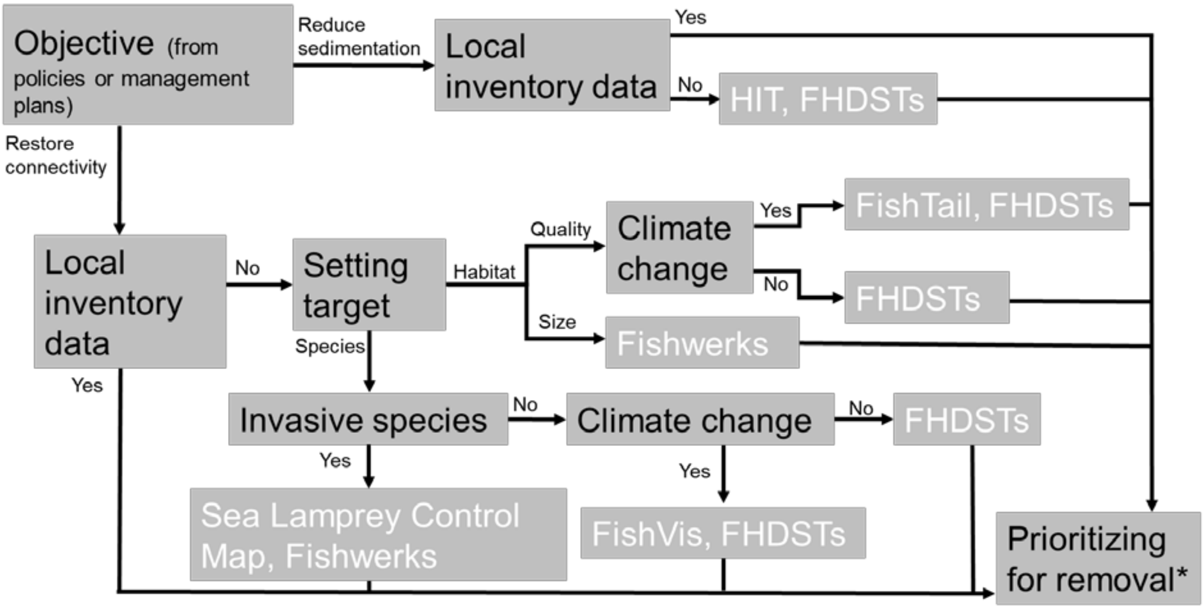

(a)
Lake Huron
Lake Michigan
Lower Peninsula of Michigan
10 5 0 10 km
Watershed
1 Cheboygan River/Lower BlackRiver
2 Mullett Lake
3 Little Traverse
4 Lake Charlevoix
5 Grand Traverse
6 Upper Manistee
7 Lake Leelanau
8 Long Lake
9 Glen Lake
10 Platte River
11 Betsie River
12 Greater Bear
13 Little Manistee
(b)
Laurentian Great Lakes

Fig. 2



Objective (from policies or management plans)
Reduce sedimentation
Local inventory data
Yes
No
HIT, FHDSTs
Restore connectivity
Local inventory data
No
Setting target
Habitat
Quality
Climate change
Yes
FishTail, FHDSTs
No
FHDSTs
Size
Fishwerks
Species
Yes
Invasive species
No
Climate change
No
FHDSTs
Yes
Sea Lamprey Control Map, Fishwerks
Yes
FishVis, FHDSTs
Prioritizing for removal*

Fig. 3

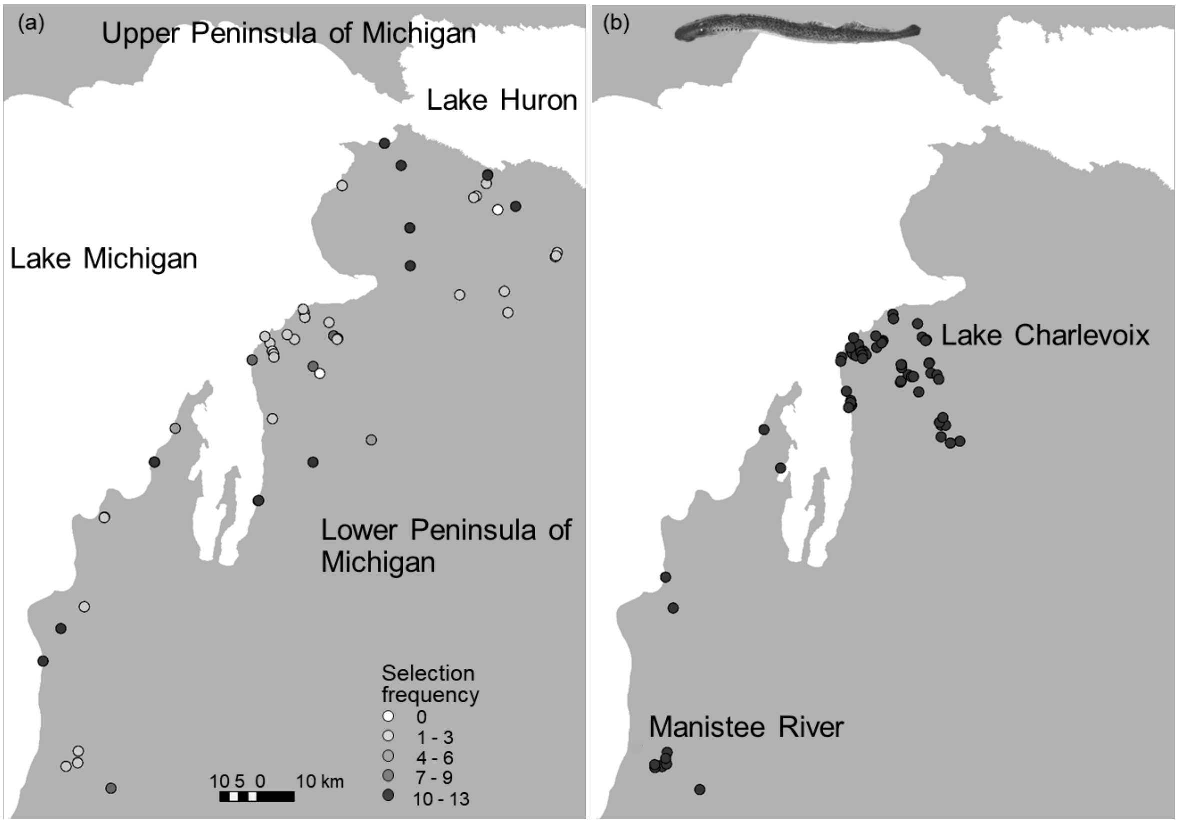
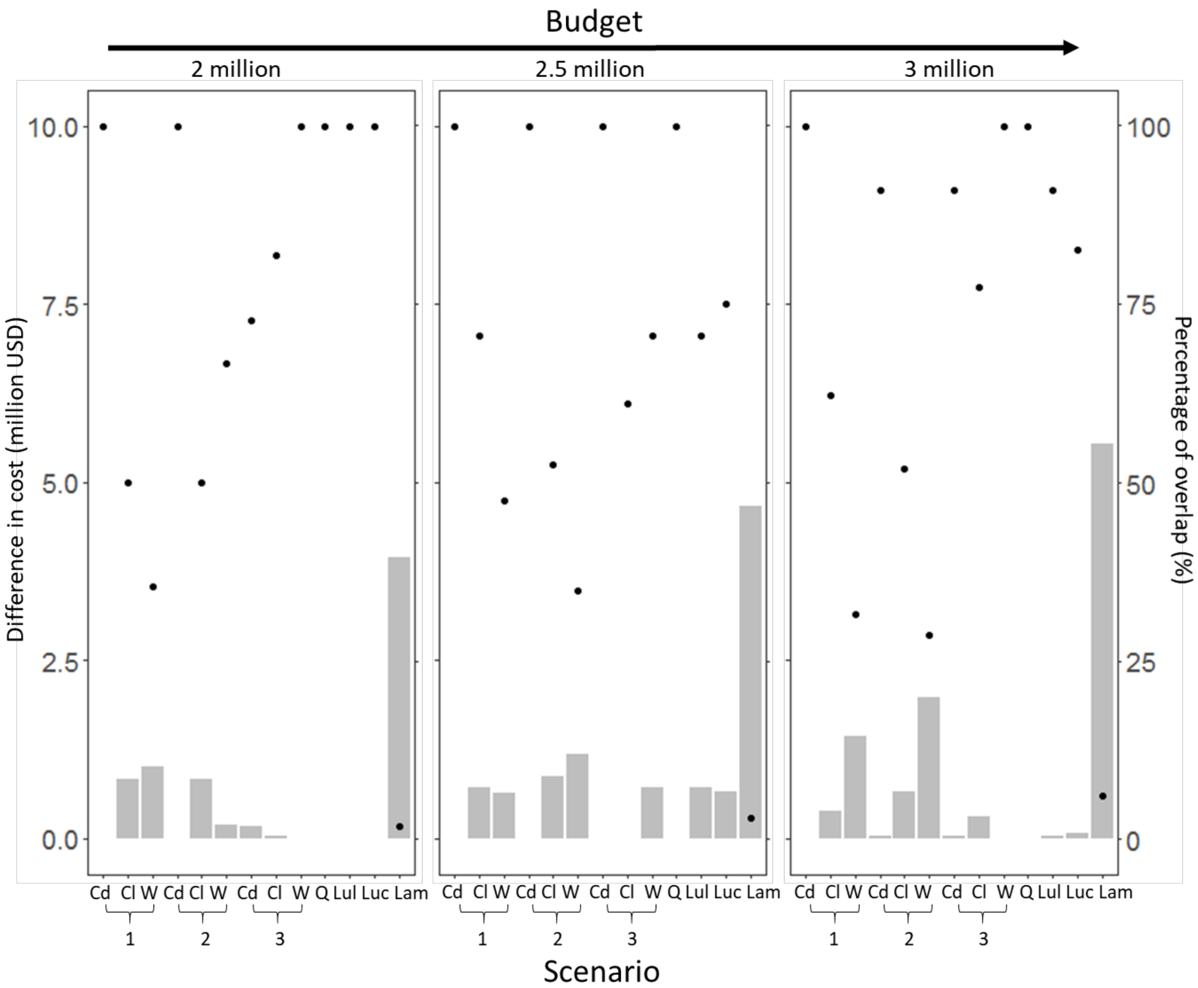
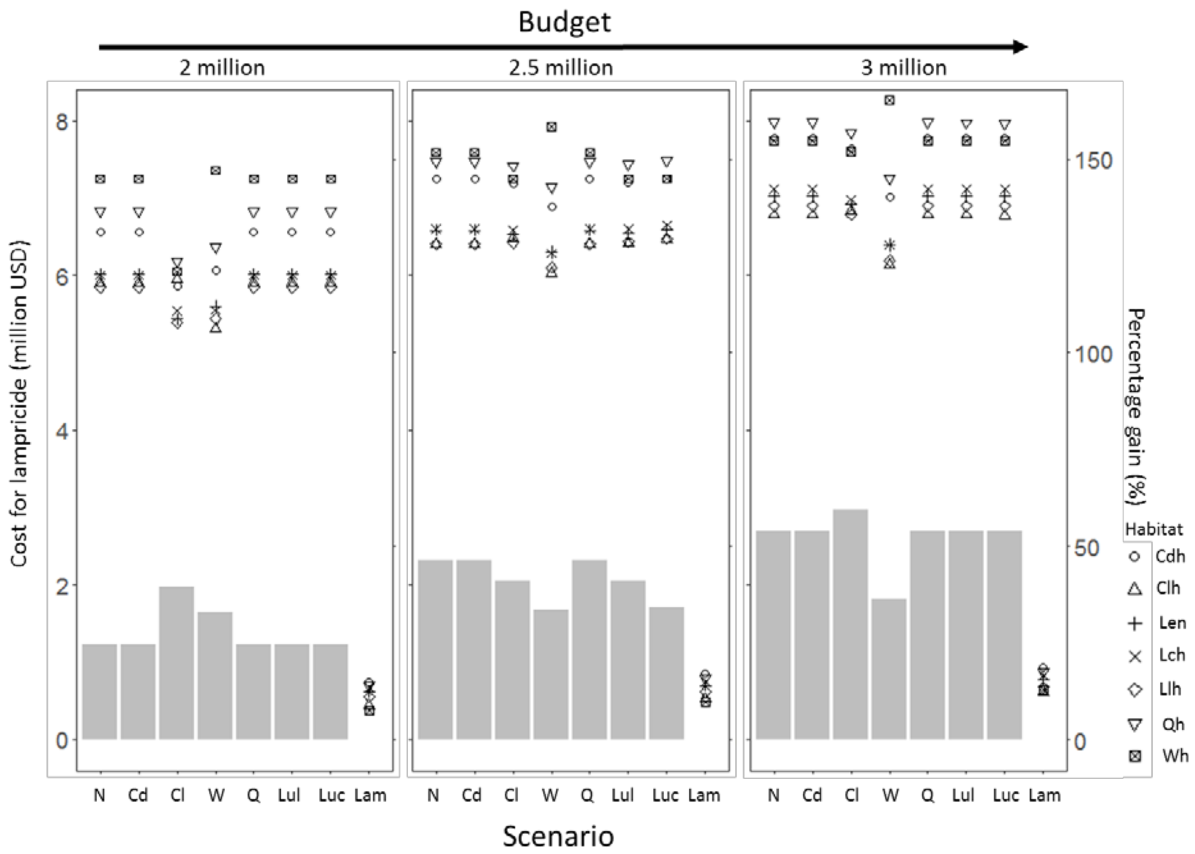

(a)
Upper Peninsula of Michigan
Lake Huron
Lake Michigan
Lower Peninsula of Michigan
Selection frequency
0
1 - 3
4 - 6
7 - 9
10 - 13
10 5 0 10 km
(b)
Lake Charlevoix
Manistee River

Fig. 4


Budget
2 million
2.5 million
3 million
Difference in cost (million USD)
Percentage of overlap (%)
10.0
7.5
5.0
2.5
0.0
100
75
50
25
0
Cd Cl W Cd Cl W Cd Cl W Q Lul Luc Lam
1
2
3
Scenario

802 Fig. 5



803

804

Fig. 6

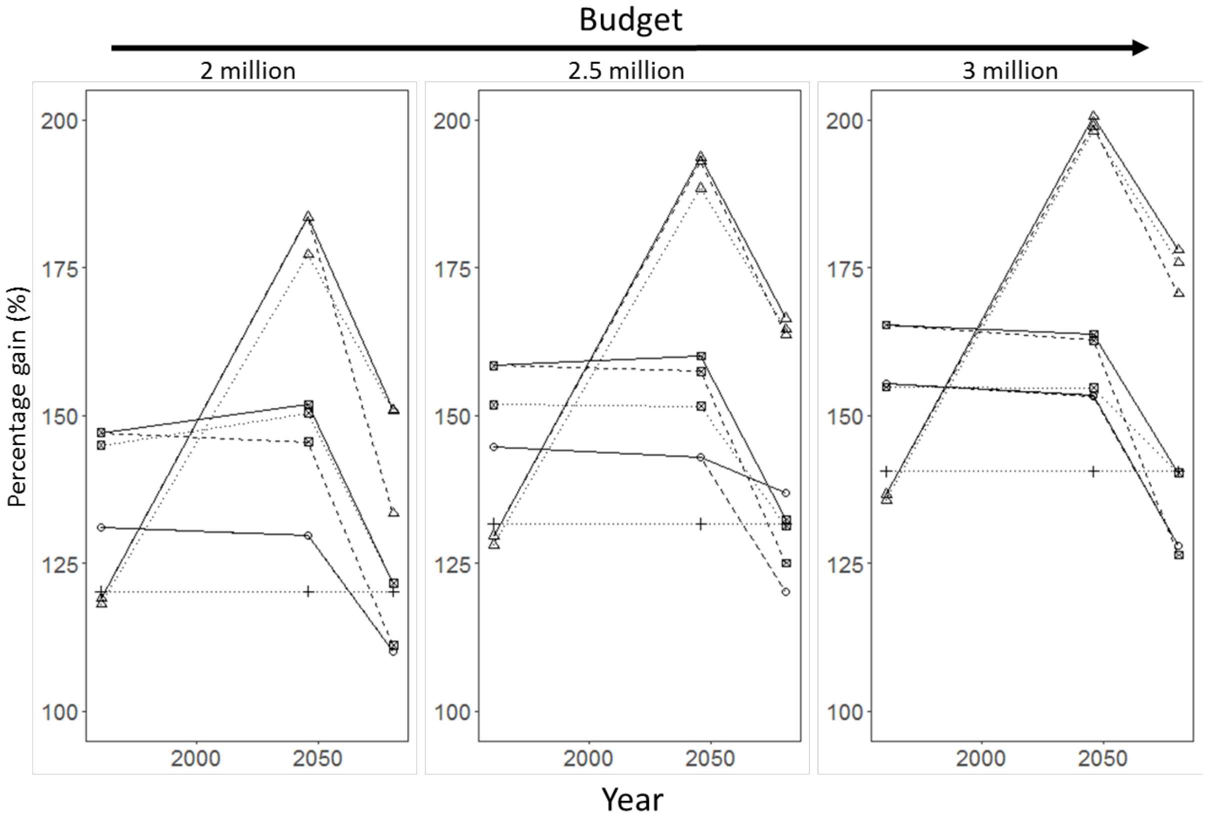
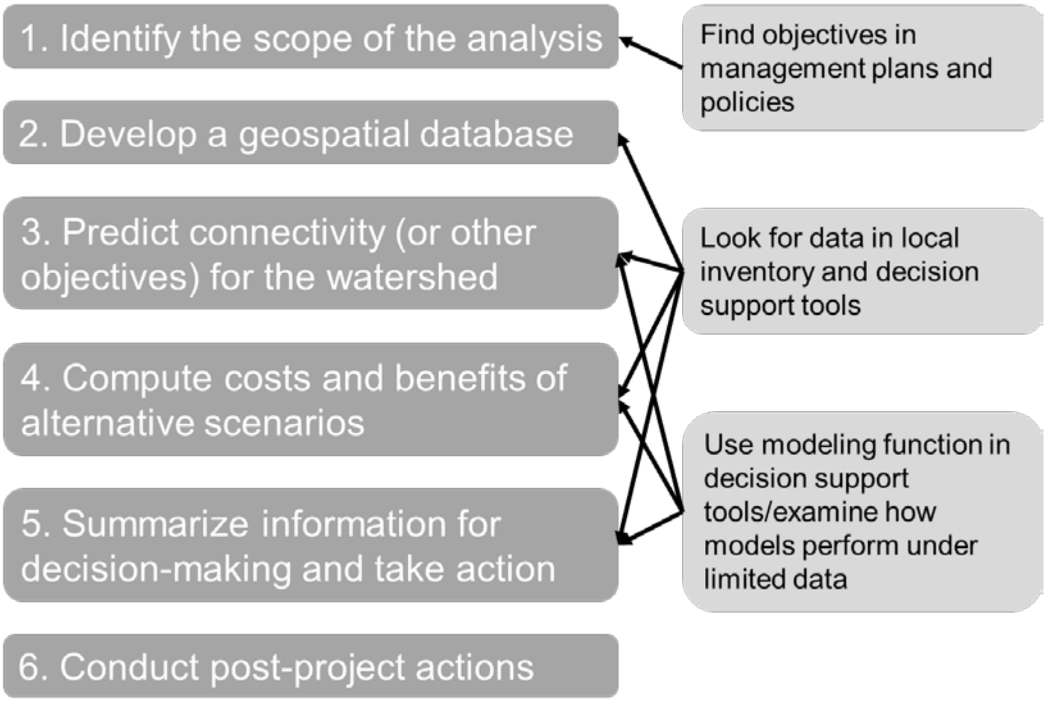

Budget
2 million
2.5 million
3 million
Percentage gain (%)
200
175
150
125
100
2000
2050
Year

Fig. 7


1. Identify the scope of the analysis
2. Develop a geospatial database
3. Predict connectivity (or other objectives) for the watershed
4. Compute costs and benefits of alternative scenarios
5. Summarize information for decision-making and take action
6. Conduct post-project actions
Find objectives in management plans and policies
Look for data in local inventory and decision support tools
Use modeling function in decision support tools/examine how models perform under limited data