1   **The application of decision support tools and the influence of local data**

2   **in prioritizing barrier removal in lower Michigan, USA**

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11   **Author contributions**

12   K.R. and L.W. conceived of the main idea. H.Y.L. developed the scenarios for analysis. H.Y.L.

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14   manuscript. All authors helped shape this study and contributed essential components during

15   the preparation of this manuscript.

16 **Abstract**

17 Web-based decision support tools (DSTs) can be useful to facilitate decision-making

18 processes for managing complex natural resource systems. However**,** the alignment of DSTs

19 with the objectives in governmental policies or management plans and the influence of limited

20 local data on the outputs of these tools may reduce the use of DSTs by decision makers. In this

21 study, we examined the outcomes of web-based DSTs when different types of local data were

22 incorporated and demonstrated a way to incorporate outputs from multiple DSTs or local

23 inventories to benefit barrier removal decisions. Restoring habitat connectivity in rivers in

24 northwest lower Michigan, USA, was used as a case study due to the abundance of local

25 inventory data and web-based DSTs. We found that, when compared to prioritizations made

26 using local data, some DSTs could produce similar outcomes (in barriers selected, cost, and

27 the benefit for migratory fish) with limited data, but the trade-offs among users' objectives

28 might influence the cost and effectiveness of DSTs' outputs. Improving the ability of DSTs to

29 incorporate objectives consistent with policy and stakeholders' values (e.g., restore certain

30 species or sedimentation control) across management scales can help close the gap between

31 tool recommendations and management decisions while making the barrier removal

32 prioritization process transparent and efficient.

33

34 Keywords: decision support tools, restoring connectivity, barrier removal, prioritization, Great

35 Lakes, sea lamprey

2

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,

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61 Chesapeake Bay, Southeast, and Great Lakes regions, see McKay et al., 2016). Databases

62 included in these tools can help decision-makers gather necessary information, and

63 quantitative models can be used to predict possible outcome scenarios for a decision point

64 (McKay et al., 2016). Therefore, use of DSTs may improve the transparency of

65 decision-making because the tools can provide evidence-based explanations, along with visual

66 aids, to support decisions, and all users can examine the input data, adjust the weights, and

67 reproduce the decision procedure and results (McIntosh et al., 2011).

68

69 Despite advantages of using DSTs, many of these tools are underused by managers and

70 decision makers. Often developers and end-users of these tools differ in the required

71 timeframes and information, expectations, background knowledge, training, and skill sets

72 (Gibson et al., 2017; McIntosh et al., 2011). Some managers may not be aware of existing

73 tools, are wary of real or perceived tool limitations, or are uncomfortable with the tool's

74 assumptions (Addison et al., 2013; van Delden et al., 2011). For example, while many

75 web-based DSTs have been developed to assist managers in selecting the most beneficial sites

76 for connectivity restoration in the Great Lakes Basin (McKay et al., 2016; Moody et al., 2017),

77 most of them have been neither mentioned nor applied in local-scale watershed management

78 plans such as Nonpoint Source program approved watershed management plans in Michigan,

79 USA. Instead, managers often rely on inventory data collected by local watershed groups and

80 management agencies to prioritize barrier removal or mitigation projects (Shook, D. [Grand

81 Traverse Band of Ottawa and Chippewa Indians] and Beyer, A. [Conservation Resource

82 Alliance], personal communication, 2017), or select these projects opportunistically without

83 much, if any, prioritization.

84

85 How DSTs perform given limited data is one of the key factors that influences the use of these

86 tools by managers and decision makers (Gibson et al., 2017). Local inventory data are quite

87 sparse in many regions and can be time-consuming and expensive to collect, and the use of

88 these data may not necessarily change management actions or improve conservation outcomes.

89 For example, the return on investment of survey data decreases rapidly in the conservation of

90 sugarbushes (Proteaceae) in South Africa (Grantham et al., 2008). Similarly, collecting new

91 data about population growth was shown to provide little improvement to koala

92 (*Phascolarctos cinereus*) management in south-east Queensland, Australia (Maxwell et al.,

93 2015). Therefore, comparing the outputs of DSTs given different levels of availability of local

94 data and examining the influence of various types of data on decisions could be valuable. If

95 the value of this local information is low for the decision at hand, the costs related to data

96 collection could be better allocated to other management activities. Furthermore, reviewing

97 data and functions across DSTs and demonstrating possible ways to integrate multiple tools

98 for certain management interests can help managers and decision-makers quickly select

99 suitable tools for their needs and objectives (e.g., an example in Tetzlaff et al., 2013 and

100 Center for Ocean Solutions, 2011). The use of local data extracted from multiple data-driven

101 DSTs provides an opportunity to examine the influence of different levels of data availability

102 on the outputs of model-driven DSTs.

103

104 This study aims to enhance the connection between DST development and management

105 decisions by addressing two main issues that influence the use of DSTs by decision makers: (1)

106 the alignment of DSTs with the objectives and context of policies or management plans, and

107 (2) the performance of DSTs with limited or missing data (Gibson et al., 2017). To accomplish

108 these goals, we conducted a study in which we: (1) reviewed management plans and available

109 web-based DSTs for a case study; (2) examined ways to integrate data and functions across

110   DSTs and created a guide for DST selection according to management context; (3) compared

111   and examined the outputs of a model-driven DST, Fishwerks, given different local data

112   availability; and finally, (4) suggested possible improvements for existing DSTs. The case

113   study was conducted in northwestern lower Michigan (the Fruitbelt region), USA, because this

114   region is included in a number of existing web-based DSTs (see McKay et al., 2016 and

115   Moody et al., 2017) and has relatively comprehensive local inventory data on road-stream

116   crossings collected by local agencies and non-profits that is publicly available on the River

117   Restoration in Northern Michigan website

118   (http://www.northernmichiganstreams.org/rsxinfo.asp). The abundance of existing DSTs and

119   local data provide a unique opportunity to study the influence of data availability on DST

120   outputs and explore the complementarity among DSTs. We also evaluated the influence of

121   information for contradictory objectives (i.e., remove barriers for native species vs. keep

122   barriers for nuisance species). Furthermore, our results can be used to inform managers in

123   regions with limited local inventory data about the sensitivity of model-driven DSTs to local

124   information and the use of data-driven DSTs.

125

126   **Methods**

127   *Case study in northwest lower Michigan*

128   Northwest lower Michigan (Fruitbelt region), USA, is characterized by groundwater-fed

129   cold-water streams that provide critical habitat for native and sport fish populations, such as

130   white sucker (*Catostomus commersonii*), northern pike (*Esox lucius*), walleye (*Sander

131   vitreus*), lake sturgeon (*Acipenser fulvescens*), and salmon and trout (Salmonidae) (Lyons et

132   al., 2009; Peterson et al., 2007; Zorn et al., 2008). This region also supports diverse and

133   productive agriculture, such as blueberry, cherry, apple, and grape production, and forestry.

134 Local watershed management plans have been developed and implemented under the

135 Nonpoint Source (NPS) grant program, which is administered by Michigan Department of

136 Environmental Quality, to protect and restore watersheds in the Fruitbelt region and

137 throughout the state of Michigan (NPS Approved and Pending Watershed Plans, Michigan).

138 As with much of the Great Lakes region, connectivity loss and habitat fragmentation by

139 anthropogenic barriers, such as dams and road-stream crossings, have negatively affected fish

140 populations by blocking migration pathways, reducing the accessibility of critical habitats,

141 degrading habitat quality, and hindering the free movement of materials and energy in the

142 ecosystem (Dodd et al., 2003; Januchowski-Hartley et al., 2013; Porto et al., 1999). Since

143 2015, federal, state, tribal, municipal, and non-government partners have worked together as

144 the Tribal Stream and Michigan Fruitbelt Collaborative to reduce sedimentation and improve

145 aquatic organism passage in the region. Typically, projects that focus on culvert replacement

146 are prioritized after structures are assessed using the Great Lakes Road Stream Crossing

147 Inventory Instructions protocol (2011). Although there is continued interest in restoring

148 connectivity through barrier removal projects across the Great Lakes Basin, evaluating the

149 complex trade-offs between ecological and societal values in the decision-making process is

150 challenging. For any single barrier, the potential ecological consequences of removal could be

151 both positive (via native species and nutrient/energy flows; Dudgeon et al., 2006; Maavara et

152 al., 2015) and negative (via invaders and pathogens; McLaughlin et al., 2013 and Zheng and

153 Hobbs, 2013). Furthermore, decision makers must also consider implications for human safety

154 and recreation (Moody et al. 2017). In the Great Lakes Basin, more than 60 barriers have been

155 constructed or modified to suppress the spread of sea lamprey (*Petromyzon marinus*), and

156 hundreds built for other purposes function as blocking structures critical to controlling sea

157 lamprey (Lavis et al., 2003). Removing barriers may increase sea lamprey populations if

158 suitable spawning and rearing habitats exist upstream of barriers, and the Great Lakes Fishery

159 Commission anticipates that newly infested habitat would require an increased budget to

160 retain sea lamprey control in Great Lakes tributaries (Jensen and Jones, 2017; Mullett and

161 Sullivan, 2016).

162

163 *Policy and management plans review*

164 We reviewed one state act (Michigan Natural Resources and Environmental Protection Act

165 1994 PA 451) and 13 local watershed management plans (Betsie River, Lake Charlevoix,

166 Cheboygan River/Lower Black River, Glen Lake/Crystal River, Grand Traverse Bay, Greater

167 Bear, Lake Leelanau, Little Traverse Bay, Little Manistee, Long Lake, Mullett Lake, Platte

168 River, Upper Manistee River; Fig. 1) to identify objectives relevant to barrier removal for our

169 case study. Surface waters of the State of Michigan are protected by Water Quality Standards

170 for specific designated uses, such as supporting cold- or warm-water fisheries, indigenous

171 aquatic life, and wildlife (R323.1100 of Part 4, Part 31 of the Michigan Natural Resources and

172 Environmental Protection Act, 1994 PA 451). Because most socio-economically and

173 ecologically important fish species are affected by barriers in the Fruitbelt region

174 (Januchowski-Hartley et al., 2013; Moody et al., 2017), barrier removal projects can be used

175 to help achieve some designated uses in the Environmental Protection Act. All 13 watershed

176 management plans within the study area recognized road-stream crossings as critical sites for

177 sedimentation control, and most plans mentioned the effects of poorly-designed road-stream

178 crossings and dams on river connectivity. According to the Great Lakes Road Stream Crossing

179 Inventory Instructions protocol (USFS 2011), both erosion and fish passage issues can be used

180 to prioritize road-stream crossings for upgrade. Besides these management plans, several

181 barriers are operated by the US Fish and Wildlife Service (USFWS) and Fisheries and Oceans

182 Canada (DFO), as contract agents of the Great Lakes Fishery Commission, to control sea

183 lamprey populations. Based on our findings, we included objectives (and measures of these

184 objectives) related to cold- and warm-water fish, indigenous aquatic species and wildlife,

185 invasive sea lamprey, barrier passability, and erosion when considering barrier prioritization.

186

187 *Decision support tools selection*

188 Eight web-based DSTs were identified from the literature (McKay et al., 2016; Moody et al.,

189 2017) and environmental management websites (see Table 1), in which they provided: (1)

190 policy and management plan-relevant data and spatial information on barriers; and/or (2)

191 optimization models, for prioritizing barrier removal in the Fruitbelt region. The High Impact

192 Targeting tool focuses on sedimentation; FishVis, FishTail, and the Fish Habitat Decision

193 Support Tool focus on biological, environmental, and some socio-economic factors; and the

194 Sea Lamprey Control Map, Geospatial Fisheries Information network, Fishwerks and

195 OptiPass focus more directly on river connectivity (Table 1). Among all DSTs evaluated, only

196 Fishwerks and OptiPass had optimization modelling functions for prioritizing barrier removal

197 projects, and only Fishwerks could perform optimization modelling and display the results

198 online without input data from users (Table 1). Seven out of eight DSTs are region-specific

199 tools that cover a geological range from the entire US, part of the US, to part of Canada.

200 OptiPass is the only tool that can be applied to any watershed, depending on input data (Table

201 1). We built a decision guide to facilitate DST selection by decision makers according to

202 policy context and the functionality of DSTs (Fig. 2). One model-driven tool, Fishwerks was

203 chosen for the following scenario analyses to examine the outcomes of DSTs with limited

204 data. Fishwerks was used because less user-provided input data are required, and it is built

205 specifically for the Great Lakes basin with the same basic optimization algorithm (mixed

206 integer linear programming) as in OptiPass. Other data-driven tools, including FishVis,

207 FishTail, and Sea Lamprey Control Map were then used as sources of different local data, as

208 described in the next section.

209

Decision support tool evaluation

211   We examined outcomes of barrier prioritization under different local data availability by

212   comparing results (effectiveness and cost) among a set of simulated scenarios (Table 2).

213   Scenarios were selected according to the objectives from reviewed policy and management

214   plans, such as prioritizing barrier removals to benefit cold- and warm-water fishes and other

215   indigenous aquatic species while considering invasive sea lamprey control. Specifically,

216   barriers were prioritized to maximize habitat connections for fish with different thermal

217   preferences (i.e., cool-, cold-, and warm-water fish; extracted from FishVis), or to maximize

218   the connections between riverine habitats with high water quality or low land-based

219   disturbances (extracted from FishTail). We also considered the cost of applying lampricide to

220   kill sea lamprey larvae in newly-opened streams or keeping all barriers that are important for

221   sea lamprey control intact. The estimated annual lampricide application cost for every stream

222   reach was extracted from Fishwerks (Table 2), and was estimated usng variables including

223   lake basins, reach length, and watershed drainage area to incorporate both costs for chemical

224   lampricide and staff time (Steeves, M. [Fisheries and Oceans Canada] personal

225   communication, 2015). We chose to focus on sea lamprey invasions because many

226   stakeholders in the region consider this as a significant negative effect of terminal barrier

227   removal (McLaughlin et al., 2013). Furthermore, we included predictions of future species

228   distributions to prioritize barriers for removal under possible future climate conditions because

229   species distribution shifts by climate change may reduce the effectiveness of current

230   management actions in the Great Lakes region (Collingsworth et al., 2017; Lynch et al., 2015).

231   Predicted distributions of cool-, cold-, and warm-water fish in the mid and late 21st century

232   throughout the Fruitbelt region were downloaded from FishVis (Table 2).

233

234   First, we ran the optimization model within Fishwerks (scenario code: N, no local information;

235   "base scenario" hereafter), which maximizes total accessibility-weighted upstream habitat for

236   migratory fish under a given budget, to produce a portfolio of removals (Moody et al., 2017;

237   Neeson et al., 2015). The accessibility-weighted upstream habitat was calculated as river

238   length (potential habitat) times the product of all downstream barriers' passability (Neeson et

239   al., 2015). The passability for barriers, which is included as part of the Fishwerks package,

240   was defined as the proportion of fish able to pass through a barrier from downstream (Moody

241   et al., 2017; Neeson et al., 2015). Three levels of passability for each barrier can be found in

242   Fishwerks to represent the effect of barriers on fish with weak, moderate, or strong swimming

243   ability (Moody et al., 2017). For simplicity, the passability for moderate swimmers was used

244   in this study.

245

246   Then, we incorporated additional local information (described in detail below), extracted from

247   other DSTs, to weight upstream habitat and produce other portfolios of barriers prioritized for

248   removal. Additional local information included projected species distribution in the late-20th,

249   mid-21st, and late-21st century for three thermal guilds (1961–2000: cold-water species, Cd1;

250   cool-water species, Cl1; warm-water species, W1; 2046–2065: cold-water species, Cd2;

251   cool-water species, Cl2; warm-water species, W2; and 2081–2100: cold-water species, Cd3;

252   cool-water species, Cl3; warm-water species, W3). Future climate conditions were estimated

253   from 13 general circulation models under the A1B emissions scenario (FishVis: Stewart et al.,

254   2016a). Other local habitat condition data included a water quality index (Q) that represented

255   water quality impairments weighted by the response of the fish community (FishTail: Daniel

256   et al., 2017); indices for local land-use (Lul) and cumulative land-use (Luc), including urban

257   and agricultural land-use, and percent impervious surface cover (FishTail: Daniel et al., 2017);

258   and terminal barriers that block sea lamprey migration (Lam), which were extracted from Sea

259   Lamprey Control Map (http://data.glfc.org/). Projected species distribution data were

260   downloaded from the US Geological Survey database (FishTail: Daniel et al., 2017; FishVis:

261   Stewart et al., 2016b). Then, these variables were normalized to a zero to one scale and used to

262   weight the original accessibility-weighted habitat in the Fishwerks optimization model. In the

263   normalized scale, zero represented the absence of certain species or the worst habitat condition

264   projected while one represented the presence of certain species or the best habitat condition

265   projected. In these scenarios, the optimization model maximized total upstream habitat,

266   weighted by both local information and accessibility. Finally, for the sea lamprey blocking

267   scenario (Lam), we prioritized barriers similar to the base scenario (N) but excluded all

268   terminal barriers that blocked sea lamprey migration from Lake Michigan. In total, 14

269   scenarios were analyzed, as shown in Table 2. Budgets of $2.0, 2.5, and 3.0 million U.S.

270   Dollars (USD) were used to run optimization models because this is the range of funds

271   available to the Michigan Tribal Stream and Fruitbelt Collaborative for barrier removal

272   projects in the study region.

273

274   We ran optimizations in a research version of Fishwerks (available online:

275   https://neos-server.org/neos/solvers/application:Fishwerks/csv.html) that allowed us to

276   incorporate custom barrier inventory data with additional local information. This is different

277   from the current online version of Fishwerks, which can only optimize barrier removals with

278   built-in river length data.

279

280   The influence of local information was assessed by comparing the effectiveness, cost, and

281   simulated suite of barriers selected among barrier removal scenarios that were prioritized with

282   or without local information. Effectiveness ("habitat gain", hereafter) represents predicted

283   habitat gain in kilometers, weighted by different biological and habitat condition indices

284   (Table 3), including: (1) the percentage gain of river length (effectiveness code: Len); (2)

285   cold-water habitat (Cdh); (3) cool-water habitat (Clh); (4) warm-water habitat (Wh); (5)

286 quality habitat (Qh); (6) quality local land-use habitat (Llh); and (7) quality cumulative

287 land-use habitat gain (Lch). We calculated total habitat gain and compared the differences in

288 seven types of effectiveness (as described above) among 14 scenarios. For instance, given a

289 budget, which scenario might produce more habitat gain for cold-water species (Cdh)? A

290 second variable, cost, represents the estimated cost for removing barriers and applying

291 lampricide after removal (Table 3). Although the total cost for removing barriers across

292 scenarios will be similar under given budget limits, we identified different barriers selected by

293 base scenario (N) and each one of the other scenarios and calculated the cost of these barriers.

294 For example, if two barriers selected by the scenario with additional water quality (Q)

295 information were not selected by the scenario without local information (N), the difference in

296 cost between these two scenarios will be the sum of these two barriers. Finally, we compared

297 selected barriers among scenarios by examining: (1) the spatial distribution of selected

298 barriers; (2) selection frequency of each barrier; and (3) the percentage of barriers that were

299 repeatedly selected by both the scenario without local information (N) and each one of the

300 other scenarios.

301

302 **Results**

303 *Differences in the cost, locations, and number of barriers*

304 The selected portfolios of barriers were similar regardless of the input of additional local

305 information for 13 out of 14 scenarios, with the sea lamprey blocking scenario (Lam) as the

306 one exception (Figs. 3 & 4). Selected barriers were scattered throughout the study area for

307 most scenarios, with 20 barriers selected in seven or more scenarios as important barriers to be

308 removed (Fig. 3a). The differences in selected barriers between the base scenario (N) and

309 scenarios using additional information, such as cold-water species distribution (including

310 distribution shift by climate change: Cd1–3), water quality (Q) or land-use indices (Lul & Luc)

14

311   were relatively small (> 75% overlap of selected barriers with < $0.75 million USD cost

312   differences). Adding local information for cool-water and warm-water species (Cl1–3 & W1–

313   3) resulted in moderate differences in barriers chosen, compared to the base scenario (25–75%

314   overlap with around $1–2 million USD cost differences; Fig. 4). If all important barriers for

315   blocking sea lamprey migration were left intact (Lam), selected barriers were concentrated in

316   a few watersheds, especially in small tributaries around Lake Charlevoix and the lower

317   Manistee River (Fig. 3b). Less than 6% of barriers were selected in both the base scenario and

318   the sea lamprey blocking scenario, and the differences in cost were around $4–6 million USD

319   (Fig. 4). Increasing the budget could increase the number of barriers selected (scenarios except

320   Lam: 9–13 barriers given $2 million USD, 14–18 barriers given $2.5 million USD, and 18–26

321   barriers given $3 million USD), however, three to four times more barriers were selected

322   under the sea lamprey blocking scenario (Lam) than other scenarios across budgets (49

323   barriers given $2 million USD, 59 barriers given $2.5 million USD, and 67 given $3 million

324   USD).

325

326   *Differences in habitat gain (effectiveness) and cost of lampricide*

327   1. Among scenarios (excluding climate change)

328   Although the gain in target habitat was optimized in every scenario, the gain in other habitats

329   varied among scenarios (Fig. 5). For example, while the cold-water fish scenario (Cd)

330   produced the highest effectiveness for cold-water habitat (Cdh) and the warm-water fish

331   scenario (W) produced the largest connected warm-water habitat (Wh) among all scenarios,

332   the effectiveness for other habitats (e.g., the gain of quality local land-use habitat, Llh) were

333   also different between these two scenarios. In general, the gain in all habitat types was similar,

334   with 110–160% habitat gain among most scenarios like the base, cold-water fish, water quality,

335   local land-use, and cumulative land-use scenarios, but the habitat gains were around 10 – 25%

336 lower in cold-water and warm-water fish scenarios. The smallest habitat gain for all types of

337 habitats was found in the sea lamprey blocking scenario (Lam, < 20% habitat gain; Fig. 5).

338 Estimated costs for lampricide were similar among most scenarios, except for the cool-water

339 and warm-water fish scenarios. Lampricide cost was not considered for the sea lamprey

340 blocking scenario because all downstream barriers that block sea lamprey migration remained

341 in place.

342

343 2. The effectiveness under climate change

344 Overall, the amount of target habitat for all thermal guilds (cold-water, cool-water, and

345 warm-water species) increased (or remained the same) in the mid-21st century but was

346 followed by a 20–30% decrease in the late-21st century. Incorporating climate change and

347 species distribution data produced the greatest gain in target habitat, because the model

348 maximized accessible habitats while accounting for predicted climate conditions, but the

349 contribution of these sources of information varied among years, habitats, and budgets. For

350 example, the incorporation of climate change and species distribution information yielded a

351 set of barrier removals that would result in 20% more cool-water habitats under the $2 million

352 USD budget in the late-21st century, relative to the base scenario (N); there was no or little

353 benefit from including these sources of information when prioritizing for cool-water habitats

354 under the same budget in the middle of 21st century or under a $2.5 million USD budget in the

355 end of 21st century. Interestingly, although the improvement produced from the addition of

356 climate change data (i.e., the differences between solid and dashed lines in Fig. 6) increased

357 through time, the differences between using both climate change and species distribution data

358 (solid lines) and using no local data at all (dotted lines) declined by the end of the 21st century

359 (Fig. 6).

360

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

386   substantially improved the results from DSTs for sea turtle conservation plans (Mazor et al.,

387   2016), and the cost-effectiveness of coastal wetland protection plans can be increased with

388   high-resolution elevation data (Runting et al., 2013). Our results indicated that maintaining sea

389   lamprey barriers produced low effectiveness in connectivity restoration, around 7 times less

390   than other scenarios, and required the removal of a large number of barriers, around 4 times

391   more than other scenarios. Furthermore, an additional $1 to 3 million USD cost might be

392   required to apply lampricide on newly-connected streams to control the sea lamprey

393   population if sea lamprey barriers were removed. Although the estimated cost in this study

394   may only represent the worst case because it assumed that every newly-opened stream

395   segment contains suitable spawning and rearing habitats for sea lamprey, the strong trade-off

396   between restoring native fish populations and controlling sea lamprey may come from the

397   overlapping distribution between native fish and sea lamprey (Milt et al., 2018). This last point

398   highlights the need for DSTs that can integrate multiple objectives (e.g., migratory fish

399   passage and invasive species control) that can be used as an aid when evaluating the trade-offs

400   for decision-making in barrier prioritization (Hermoso et al., 2015).

401

402   While the sea lamprey scenario in this study focused on maintaining the cost of lampricide

403   application similar to status quo, which means keeping all terminal barriers intact, other

404   scenarios could be used to examine the trade-off between restoring native fish and controlling

405   alien species. For example, managers may want to know the effectiveness of barrier removal

406   when an additional budget has been assigned to cover the lampricide cost, in addition to the

407   barrier removal budget. Another scenario is to prioritize barriers when an overall budget is

408   required to be spent on both barrier removals and lampricide applications. By incorporating

409   potential lampricide expenses into prioritization, these scenarios have the ability to open up

410   more upstream habitats for native fish, as compared to the sea lamprey scenario in this study.

411   These scenarios can also be analyzed within the current version of Fishwerks. However, under

412   current management scheme, budgets for removing barriers are usually managed and provided

413   by agencies (i.e., federal, state, tribal, municipal, and non-government organizations) that

414   differ from the agency in charge of applying lampricide (i.e., Great Lakes Fishery

415   Commission). Studies that evaluate the effectiveness and trade-offs of these scenarios could be

416   beneficial to future management because coordinating efforts and cost-sharing strategies may

417   improve the return-on-investment of barrier removal prioritization (Neeson et al., 2018, 2015).

418

419   As expected, incorporating predicted species distribution data under climate change can

420   increase effectiveness of barrier removal up to 20%, but this improvement varied with time,

421   fish thermal guilds, and budget, and lacked a general pattern. Interestingly, percentage habitat

422   gain from barrier removals changed through time, with a pattern different from predicted

423   species distribution change. For example, effectiveness of barrier removal for warm-water

424   species increased a small amount then reduced about 30% in the late 21st century under \$2

425   million USD budget while previous studies and the DST we used, FishVis, suggest a gradual

426   expansion of warm-water habitats across the Great Lakes Basin with a changing climate

427   (Collingsworth et al., 2017; Melles et al., 2015; Stewart et al., 2016a). In general, water

428   temperature becomes warmer in reaches close to river mouths (Zorn et al., 2008). Therefore,

429   the predicted increase of warm-water habitats might mainly occur in downstream reaches,

430   which are less affected by barriers, compared to upstream cold-water habitats. Nevertheless,

431   the spatial distribution of cold groundwater inflow also plays an important role in determining

432   stream temperature (Zorn et al., 2008), thus influencing the effectiveness of barrier removal

433   for fishes with different temperature preferences. Besides possible changes in the community

434   composition of native fish, climate change may also influence the distribution of nuisance

435   species (Melles et al., 2015). Therefore, although uncertainties in climate models and fish

436 thermal guilds' responses make predicting the influence of climate change on barrier

437 prioritization difficult, incorporating climate change into DSTs can improve the flexibility of

438 management plans and mechanisms for risk assessment (Lynch et al., 2015; Melles et al.,

439 2015).

440

441 Other methods and DSTs, besides the Fishwerks optimization model, can be used to prioritize

442 removal projects, such as scoring and ranking (e.g., Chesapeake Fish Passage Prioritization,

443 web-based DST, Martin and Apse, 2013) and graph theoretic frameworks (e.g., Conefor,

444 standalone software, Saura and Torné, 2009). However, scoring and ranking methods are

445 incapable of fully accounting for the cumulative effects within barrier networks, and graph

446 theoretic frameworks do not produce a recommended removal list (King and O'Hanley, 2016).

447 While managers and stakeholders within the Great Lakes region can use Fishwerks without

448 the input of additional data, users in other places might need to rely on more commonly-used

449 scoring and ranking methods or optimization models requiring user input data. For example,

450 regional DSTs with local environmental, ecological, and connectivity data using scoring and

451 ranking methods have been developed for watersheds in the Northeast US, Chesapeake Bay,

452 and Southeast US (reviewed in McKay et al., 2016). One DST reviewed in this study,

453 OptiPass, is a standalone software with an optimization model that can be applied to any

454 watershed given user input data, such as the location, cost, and passability of candidate

455 barriers and flowlines (O'Hanley, 2015).

456

457 Factors that may improve the use of existing barrier prioritization methods and DSTs by

458 managers and stakeholders, such as prioritizing barrier removal for resident species, ensuring

459 the data are up-to-date, and incorporating socio-economic and political variables, have been

460 discussed in previous studies (King and O'Hanley, 2016; McKay et al., 2016; Moody et al.,

461 2017). Currently available software may be unattractive to managers because of the inability

462 to easily incorporate local, additional, or high-resolution data (e.g. Fishwerks) or because of

463 the requirement to input all analysis data (e.g. OptiPass). In addition, sedimentation control

464 was a key management objective in many local watershed plans that we reviewed, but we

465 found that neither regional barrier prioritization projects nor DSTs explicitly considered this

466 key variable. In the study region, watershed managers often prioritize road-stream crossings

467 for upgrade according to the risk of sedimentation rather than their impact on river

468 connectivity (Shook, D. [Grand Traverse Band of Ottawa and Chippewa Indians] and Beyer,

469 A. [Conservation Resource Alliance], personal communication, 2017). The use of

470 sedimentation information could be because most road-stream crossings, which are usually

471 treated as a source of sedimentation, are managed by local authorities, whereas the effect of

472 dams, generally assessed as barriers for connectivity, is addressed at a regional or national

473 scale (Neeson et al., 2015). Increasing the functionality and flexibility of web-based barrier

474 prioritization DSTs to incorporate data other than the built-in database might lead to greater

475 use by managers. For example, local managers in the Fruitbelt region would like to

476 incorporate socio-economic factors such as the willingness of stakeholders to remove certain

477 barriers or erosion risk into the cost function in prioritization modelling if data are available

478 (Shook, D. and Beyer, A., personal communication, 2017). Improving the communication

479 between tool developers and users during the development of DSTs could help developers

480 understand the needs of users and thus allow for incorporating policy and management

481 plan-relevant information into DSTs or increasing the flexibility of models.

482

483 While the improvement of the database and modelling ability can enhance the usefulness of

484 DSTs, it is important to note that the main purpose of DSTs is to support and facilitate, not to

485 replace, the decision-making process (Power and Sharda, 2009). River restoration plans

486   usually involve multiple stakeholders with competing interests, and some variables and

487   objectives may be difficult to quantify and incorporate into DSTs (Langford and Shaw, 2014;

488   McKay et al., 2016). The incorporation of local interests and opinions is especially important

489   for small dam removal because many decisions are strongly influenced by the willingness of

490   local stakeholders and communities instead of ecological or economic impact (Fox et al.,

491   2016). The use of decision analysis, such as structured decision making and adaptive

492   management, which is increasingly being applied to wildlife management and conservation

493   issues (e.g., Gregory and Long, 2009; Robinson et al., 2016), provides a promising way to

494   incorporate diverse interests and objectives into the decision-making process to reduce

495   possible conflicts. A key challenge for DSTs is to generate predicted effectiveness after

496   removal for comparing the trade-offs among scenarios, which is an important step in decision

497   analysis (Gregory et al., 2012). Predicted effectiveness can be the amount of habitat gain for

498   target fish species as in this study, or even potential changes in the target fish population if

499   demographic data and population models are available (e.g., Jensen and Jones, 2017; Zheng

500   and Hobbs, 2013). In addition, incorporating the tools of strategic foresight (e.g., scenario

501   planning; Cook et al., 2014) to a decision analytic framework can help users to explicitly

502   evaluate the uncertainties related to future conditions, such as climate change (Schwartz et al.,

503   2017).

504

505   Although we tried to enhance the connection between existing web-based DSTs and

506   on-the-ground management by addressing the issues in Gibson et al. (2017), other factors may

507   influence the uptake of DSTs by managers and stakeholders. Combining information from

508   multiple DSTs might make managers less likely to use these tools, especially if they need to

509   spend time reformatting and integrating data from different sources (Gibson et al., 2017).

510   While all DSTs we reviewed can be applied on regional or local scales, we found that many

511   local decision makers and stakeholders were not aware they existed. Furthermore, some policy

512   makers prefer subjective judgements from experts rather than quantified outcomes from

513   mathematical models (Addison et al., 2013). Continuous communication between DST

514   developers and potential users is necessary if these tools will be relevant (Gibson et al., 2017;

515   McIntosh et al., 2011). In addition, user training and support are also important factors

516   influencing the willingness of managers and stakeholders to use the tool (Díez and McIntosh,

517   2009). Ultimately, it is critical to build trust between both developers and end-users to

518   enhance the usefulness of these tools (Díez and McIntosh, 2009).

519

520   **Conclusions**

521   We demonstrated a way to guide the use of existing web-based DSTs for managers and

522   stakeholders according to objectives derived from policy/management plans. Our results

523   suggest that although some DSTs could produce outcomes that were insensitive to some local

524   data, the trade-offs among user defined objectives (e.g., cold-water species vs. warm-water

525   species or invasive species) might influence the effectiveness of DSTs or change the set of

526   barriers selected for removal. Overall, regional DSTs have the ability to aid local decisions

527   about barrier prioritization by providing important biological, environmental, and

528   socio-economic data and/or, modelling functions, especially if used as a tool within a larger

529   decision-making framework, such as decision analysis. Therefore, the development and

530   maintenance of regional DSTs could facilitate both local and regional decision-making

531   processes. Possible improvements for existing barrier removal prioritization DSTs include

532   increasing model flexibility, dealing with sedimentation issues, incorporating other

533   socio-economic factors, and improving the communication and training between tool

534   developer and users. As the development of DSTs is growing, we hope to mitigate the gap

535   between these useful tools and management actions.

536

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734

735 Table 1. Decision support tools that we evaluated to facilitate barrier prioritization in

736 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

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739 Table 2. Fourteen scenarios analyzed for comparing modelling outcomes (effectiveness and

740 cost) given different local data input.

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

741 * Habitat size is the upstream river length (km) of a particular barrier. **Accessibility is calculated as the product

742 of the passability rating of a particular barrier and all downstream barriers. ***Cumulative represents a combined

743 index that includes the disturbances in local and all upstream catchments (see Esselman et al., 2011).

744

745   Table 3. A description of effectiveness and cost used to compare the outcomes of fourteen

746   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

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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

774 conditions, for budgets of $2.0, 2.5, and 3.0 million USD. Scenario: N: base scenario, Cd:

775 cold-water species, Cl: cool-water species, W: warm-water species, Q: water quality, Lul:

776 land-use (local), Luc: land-use (cumulative), Lam: sea lamprey blocking. Habitat: Cdh:

777 cold-water habitat, Clh: cool-water habitat, Len: river length, Lch: quality cumulative land-use

778 habitat, Llh: quality local land-use habitat, Qh: quality habitat, Wh: warm-water habitat.
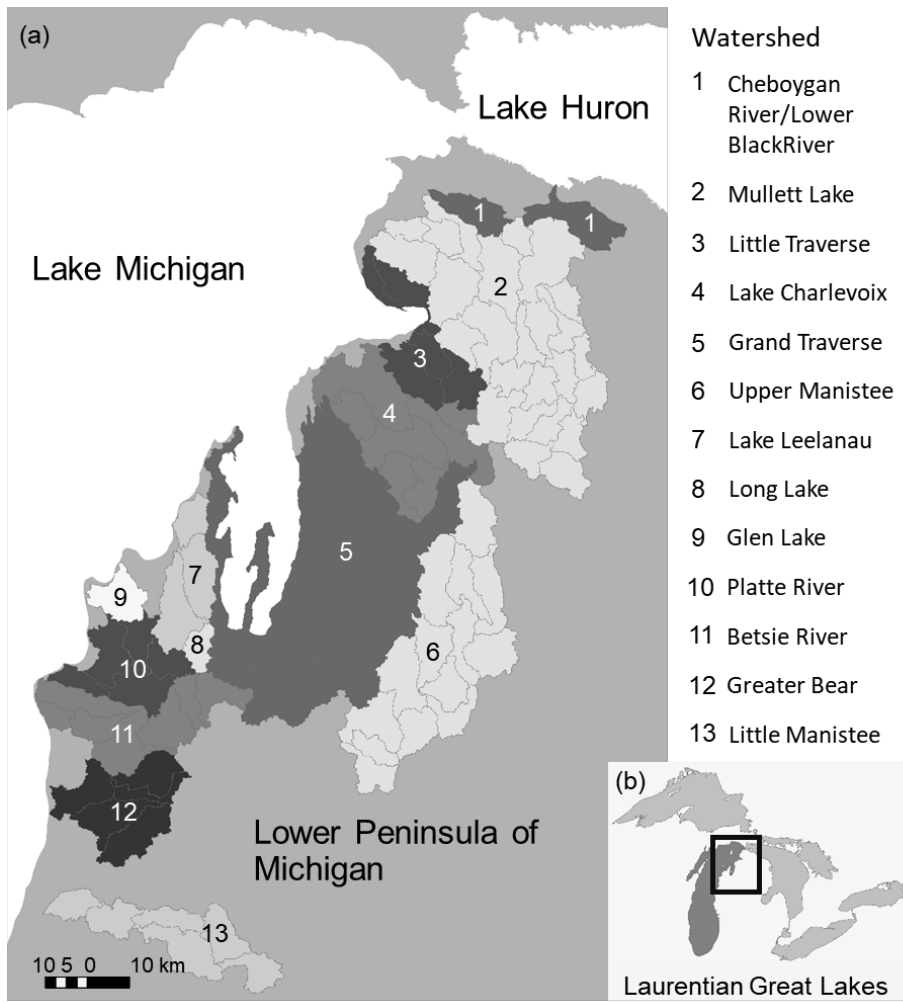
779

780 Fig. 6 The percent gain of quality- and accessibility-weighted habitat among scenarios in

781 late-20th (1961–2000), mid-21st (2046–2065), and late-21st century (2081–2100) at budgets

782 of $2.0, 2.5, and 3.0 million USD for cold-water habitat (circle), cool-water habitat (triangle),

783 warm-water habitat (square), and river length (cross). Results are presented for scenarios

784 including climate change and species distribution information (solid line), without climate

785 change but with species distribution information (dashed line), and without climate change

786 and species distribution information (dotted line).

787

788 Fig. 7 Recommendations (light grey boxes) of using existing DSTs in the steps of barrier

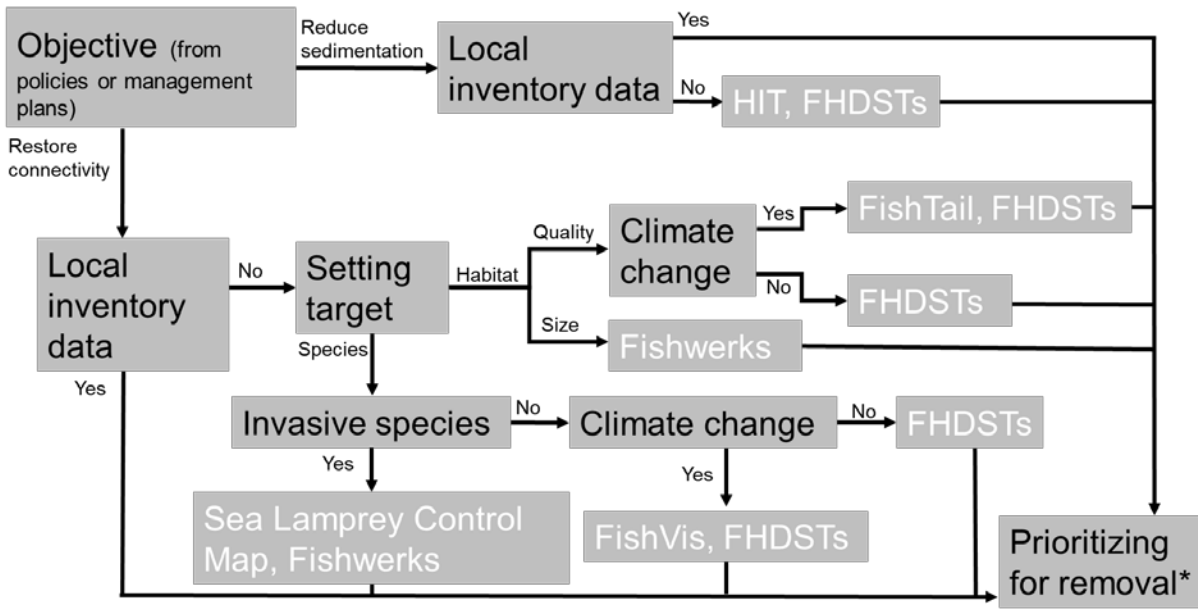789 removal prioritization protocol (dark grey boxes) that were proposed by McKay et al., (2016).

790

791   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

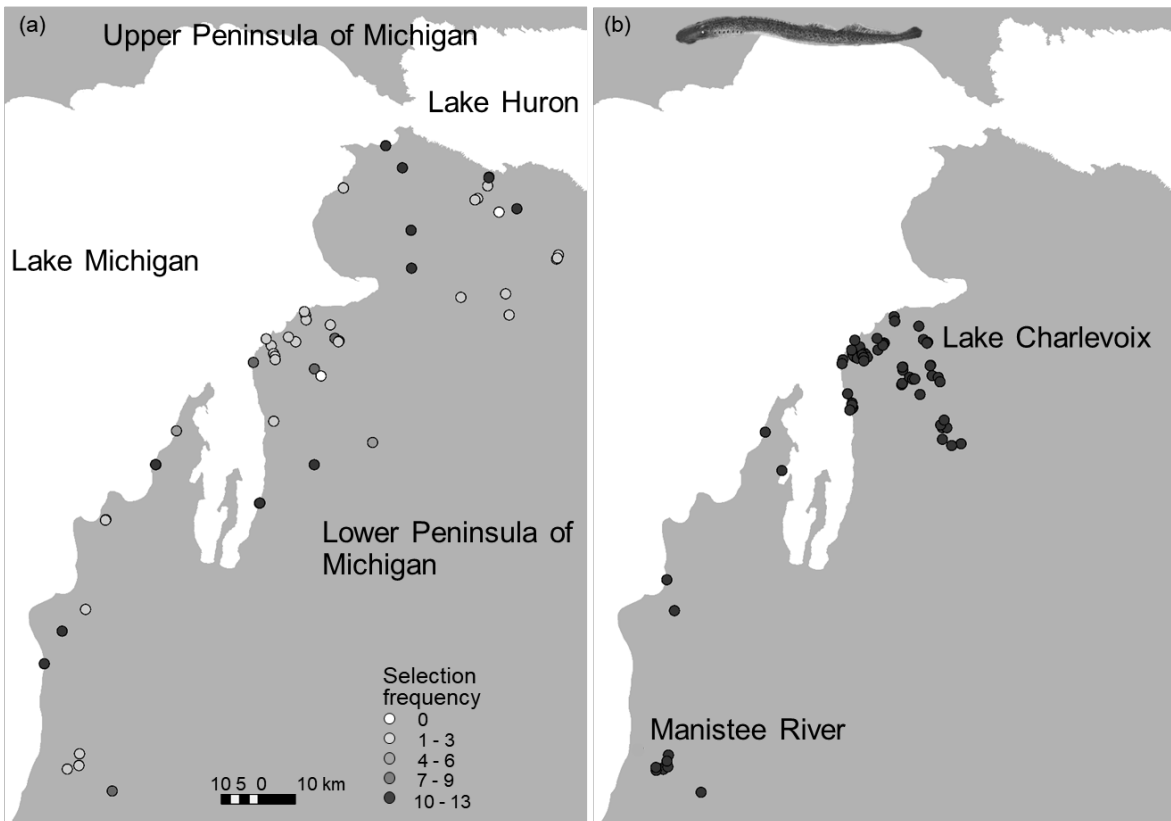13 Little Manistee

(b)

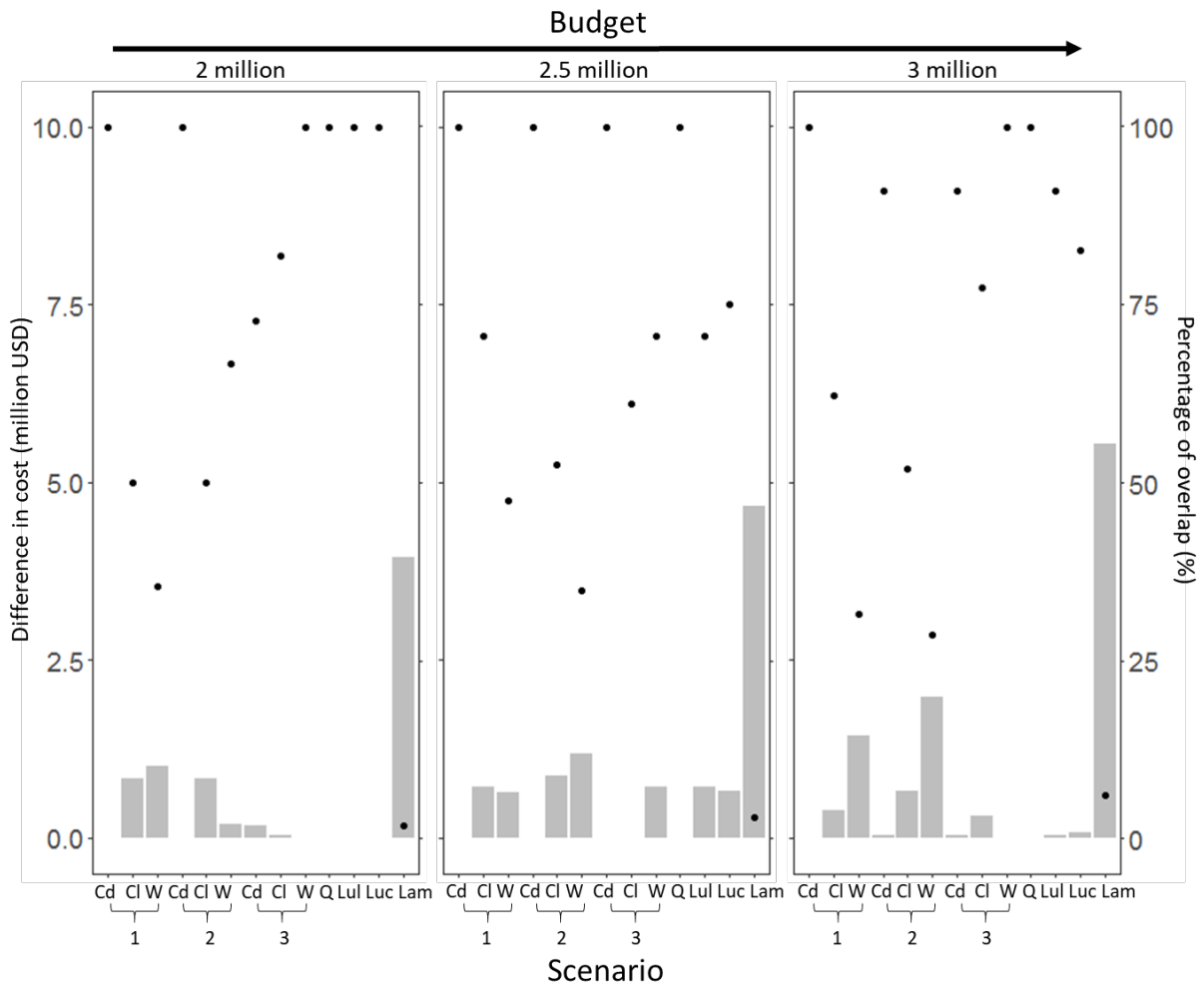Laurentian Great Lakes

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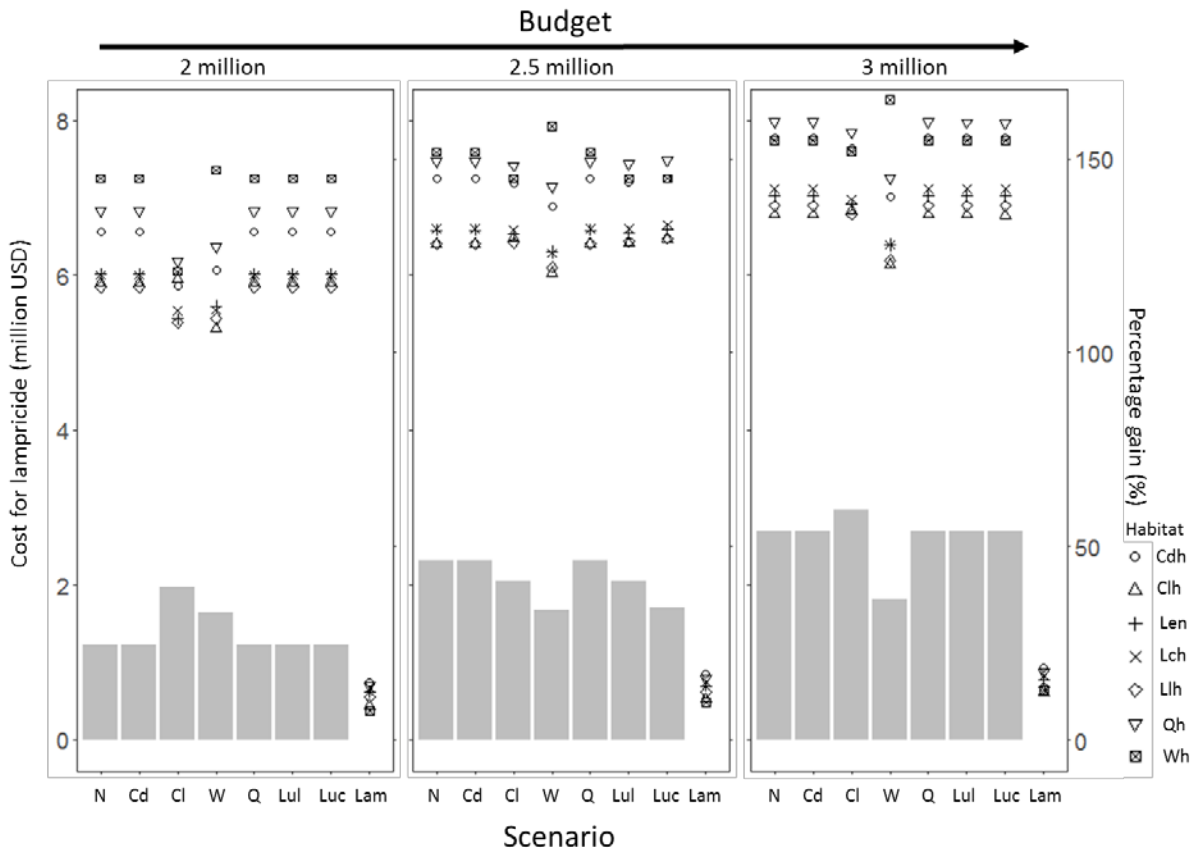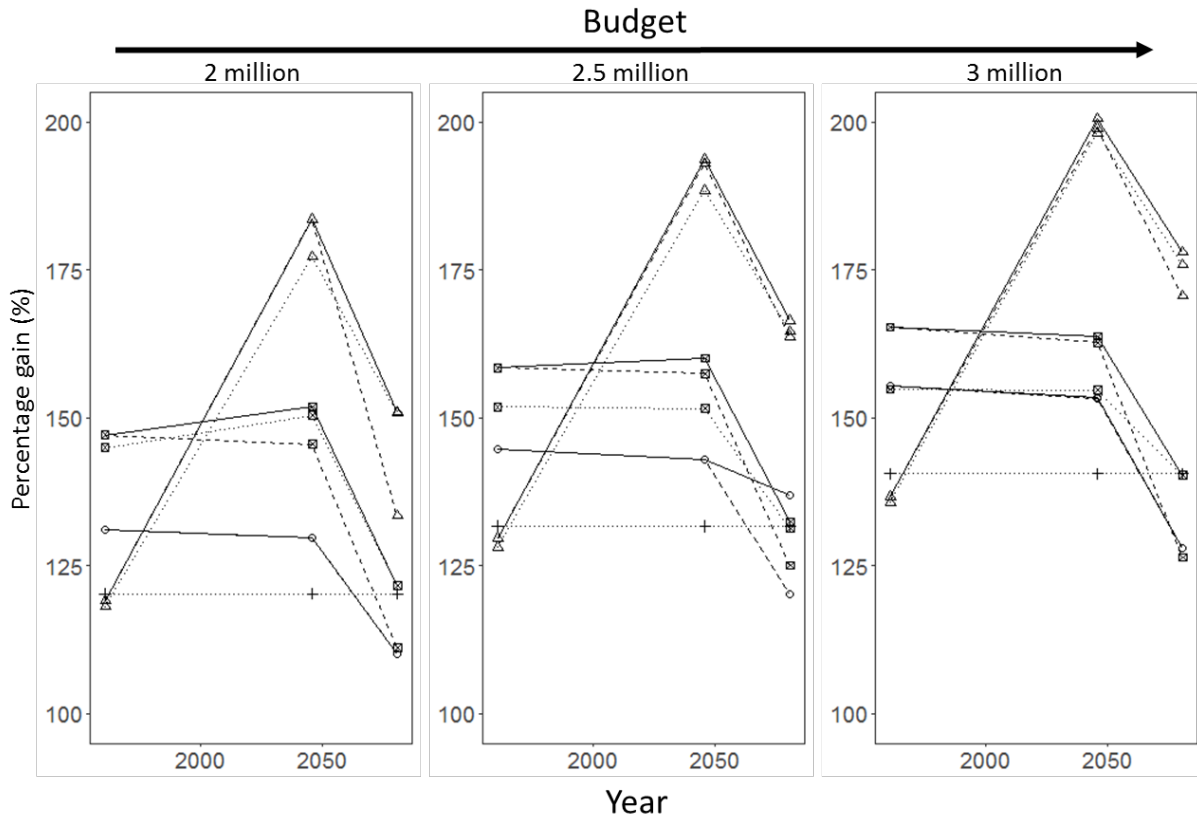793   Fig. 2

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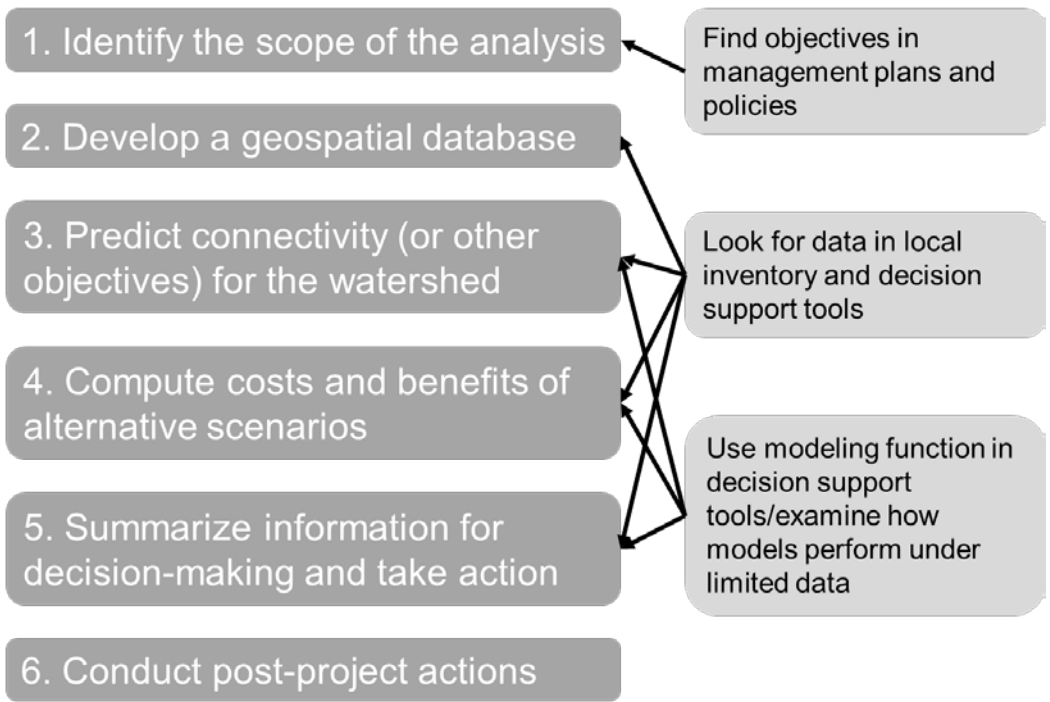796   Fig. 3

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808   Fig. 7

1. Identify the scope of the analysis

Find objectives in management plans and policies

2. Develop a geospatial database

3. Predict connectivity (or other objectives) for the watershed

Look for data in local inventory and decision support tools

4. Compute costs and benefits of alternative scenarios

5. Summarize information for decision-making and take action

Use modeling function in decision support tools/examine how models perform under limited data

6. Conduct post-project actions

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