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Facilitating effective collaboration to prevent aquatic invasive species spread

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A R T I C L E I N F O

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A B S T R A C T

Aquatic invasive species (AIS) threaten ecosystem health, serving as a major challenge for conservation efforts worldwide. Invasive species easily move across jurisdictional boundaries that may each have diverse management approaches, leading to management mosaics in which each manager's actions impact those of neighboring jurisdictions. Here, we investigate the potential impact of collaborations between counties in Minnesota in managing four aquatic invasive species (Eurasian watermilfoil, spiny waterflea, starry stonewort, and zebra mussels), with a focus on evaluating the efficiency of county-led prevention programs. We aimed to identify potential collaboration networks, each representing a group of counties with a relatively high number of potentially infested boats moving between them and describe the connections within those groups using social network analysis. We found that collaboration networks formed by ranking reciprocal connections amongst counties yielded efficiency gains over a non-collaborative or county-focused approach but were still less efficient than a state-wide approach. This study presents an analytical framework for identifying collaborations based on AIS dispersal pathways that may increase the efficiency of inter-jurisdictional prevention efforts.

1. Introduction

Aquatic invasive species (AIS) are a significant threat to the vitality of ecosystems, serving as a major challenge for conservation efforts worldwide. In response, governmental organizations have developed management strategies to mitigate the adverse effects of invasions. However, successful management is challenged by the ability of AIS to remain undetected for long periods in aquatic environments, spreading through both natural and human-mediated pathways (Johnson et al., 2001; García-Berthou et al., 2005). Furthermore, aquatic invasive species easily move across jurisdictions, which may differ in the type, duration, and intensity of management actions (Aslan et al., 2021), leading to a management mosaic impeding overall control efforts (Espanchin-Niell et al., 2012).

Since the 1970s, environmental governance in the United States has largely been "top-down," often using a "command-and-control" approach that specifies, in detail, relevant technologies and procedures to follow (John, 2006; Graham et al., 2019). However, in recent years, a new movement focused on "collaborative conservation" that emphasizes local participation has emerged (Wyborn and Bixler, 2013; Snow, 2001). This movement has sparked questions regarding differences in social and ecological processes that highlight the need to understand their complex interactions (Snow, 2001). This shift has impacted the vision for invasive species management in the country. For example, the 2021–2025 US Department of the Interior's Invasive Species Strategic Plan (U.S. Department of the Interior, 2021) includes the development of cross-jurisdictional collaborations to optimize operations.

Within the United States, Minnesota is a unique example. Here, local governmental units play key roles in AIS prevention and management due to the AIS Prevention Aid, which allocates state funds to counties based on the number of watercraft trailer launches and parking spaces in each county (Minnesota Department of Natural Resources, n.d.). Local governments within the counties are then responsible for administering an AIS program, which generally includes a mix of outreach and education, monitoring, management, and prevention activities. Many counties engage in watercraft inspections as a prevention activity to reduce the risk of overland transport of AIS from infested to uninfested lakes. During an inspection, trained personnel will inspect watercraft for

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AIS and administer a survey requesting information about the boater's previous and future intended trips. The data collected through these surveys have been used to generate boater movement networks between pairs of lakes across the state (Kao et al., 2021) and to develop decision support tools to increase the efficiency of county watercraft inspection plans (Haight et al., 2020; Kinsley et al., 2022).

Recent research on watercraft inspection programs has focused on optimizing locations (Kinsley et al., 2022; Ashander et al., 2021) and operating times of inspections while considering temporal variations in boat movements between lakes (Fischer et al., 2021) and decision-making associated with a bi-level governance structure (Haight et al., 2023). These studies have shown that linear integer programming (ILP) techniques can help evaluate different budget scenarios designed to maximize the number of boats that move from infested to uninfested lakes that receive inspections. In the most relevant work, Haight et al. developed a bi-level optimization model that compared state and county-level governances. In both models, a state planner allocated watercraft inspection resources to county planners, who developed watercraft inspection plans based on their local-level objectives. Their results revealed that the bi-level structure, one in which counties allocate resources based solely on their objectives (only considering the movement of risky boats within its county), resulted in substantial efficiency losses compared to a state-level approach in which the state planner selects lakes for inspection stations throughout the state, ignoring county boundaries.

Building on these efforts, our overarching goal was to assess the impact of collaboration in AIS prevention planning, specifically with respect to identifying the efficient placement of watercraft inspection locations. We investigated the theoretical establishment of collaboration networks between groups of counties to see if this could increase the efficiency of county-led prevention programs aimed at limiting the spread of Eurasian watermilfoil (*Myriophyllum spicatum*), spiny waterflea (*Bythotrephes longimanus*), starry stonewort (*Nitellopsis obtusa*), and zebra mussels (*Dreissena polymorpha*). We sought to identify potential collaboration networks representing groups of counties with a relatively high number of potentially infested boats moving amongst them, which could increase the efficiency of watercraft inspection programs.

2. Methods

2.1. Boater networks

The number of boats that moved between lakes in Minnesota was estimated using a network described in detail elsewhere (Kao et al., 2021). Briefly, the network was generated using survey information from Minnesota's watercraft inspection program (Minnesota Department of Natural Resources, 2024) and a machine learning algorithm that estimated traffic between lakes not directly observed through the inspection program surveys. Each lake in the database was assigned to at least one county in the state, and lakes that extend across multiple counties were assigned to all such counties.

2.2. Collaboration network construction

Our previous work detailed the loss of efficiency at the state-level when county manager's objectives only consider damages to their own jurisdiction (Haight et al., 2023). By only accounting for risky boat movements into and within their county, AIS managers may place inspection locations at lakes where most boats have been inspected in another jurisdiction, thereby introducing redundancy. To identify these instances, we determined potential collaboration networks comprised of counties based on the number of potentially infested boats, or *risky boats*, predicted to move between pairs of counties in the state.

Since there are no external incentives to collaborate, we assumed counties would prefer to collaborate with counties that send relatively high numbers of risky boats into their county. To prevent a scenario where there isn't mutual interest in collaboration or one county would prefer to collaborate with another county, we generated groups of counties comprised of pairs with relatively high reciprocity, described as high numbers of risky boats moving between them. Reciprocity has been shown to have non-trivial effects on network structures and has been identified as a critical real-world component of successful collaborations (Minnesota Department of Natural Resources, 2024) (see Supplementary materials for additional notes).

First, the boater movement network was filtered to include only *risky boats*, i.e., those that move from infested to uninfested lakes. In this regard, a lake was considered infested if it contained at least one of the following: zebra mussels, starry stonewort, Eurasian watermilfoil, or spiny waterflea. A lake's infestation status was determined based on the DNR's 2019 infested waters list (Minnesota Department of Natural Resources, 2019) (Fig. 1). Second, the number of risky boats predicted to move into each county was aggregated and sorted by sending county. To pair counties with the highest potential redundancy in inspections, sending counties were then ranked for each receiving county, where the county sending the highest number of boats received the lowest rank. We constructed a series of networks wherein counties were classified as *nodes* and reciprocal relationships (risky boats moving from one county to another) as *edges*. To establish the reciprocal relationships that served as connections, we ranked counties based on the number of risky boats they sent to each other. The construction of the networks then involved a sequential pairing process. We began by pairing counties that sent the highest number of risky boats to each other. Subsequently, we expanded the pairings to include counties within each other's first ranking (highest number of boats), then those within the second ranking, and so on. The progressive expansion continued until all paired counties were considered. The resulting networks would, therefore, contain sets of counties that are directly and indirectly connected through collaborative pairs. While the ideal group size for any collaboration is difficult to determine, we focused further analyses on collaboration networks that resulted in a relatively small average group size (~5 counties); groups of such size have been shown to create scenarios that foster adaptability and creativity (Sik, 2016; Muric et al., 2019) while using fewer resources needed to maintain the collaboration.

2.3. Decision optimization model

We developed a set of decision optimization models to identify the optimal location of watercraft inspectors in the collaboration networks at different budget levels and governing structures. We ran three variations, which included 1) a statewide model in which there was a single B allocated and used optimally statewide, ignoring all sub-jurisdictional boundaries and following the inspection location problem described by Haight et al. (2023), 2) a "county" model in which B was divided into smaller allotments, b_c, for each county c (here, C = 83 counties) (Haight et al., 2023); and 3) a "collaborations" model in which counties and their budget allotments were pooled into collaborative units.

The boater network was described as $\mathbf{N}_i$, an edge list of rows i (here, $I = 435{,}736$ edges) containing three columns: two identifying the sending lake j (here, $J = 7936$ distinct lakes) and the receiving lake j′, together corresponding via each edge i, and one containing the numbers of risky boats moving from j ➔ j′ annually. $\mathbf{N}_i$ was generated from a larger list, $\mathbf{N}_i$*, containing every lake pair in Minnesota, between which at least an average of one boat is thought to move yearly such that $\mathbf{N}_i$ only contained edges involving movements of *risky* boats.

We let g_{jk} be the binary infestation status of lake j for invasive species k (here, K = 4 species: zebra mussel, Eurasian watermilfoil, spiny water flea, and starry stonewort) such that $g_{jk} = 1$ if lake j is infested with species k and 0 otherwise. A given edge i is considered risky if its corresponding originating lake j is infested with ≥1 species k and can thus spread infestations. Its corresponding receiving lake j′ must also not be infested with at least one of those same species and therefore be

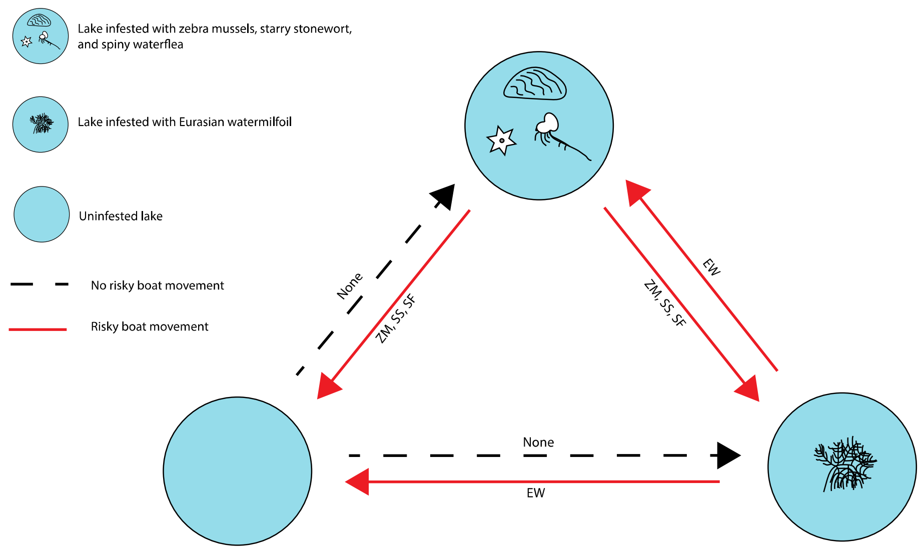

Fig. 1. Hypothetical network depicting connections between lakes with differing infestation statuses. ZM = zebra mussels, EW = Eurasian watermilfoil, SS = starry stonewort, SF = spiny waterflea.

susceptible. We computed the parameter h_i, where $h_i = \sum_k g_{jk}\left(1 - g_{j'k}\right)$, which is the number of species that could potentially be moved between lakes j and j' associated with edge i. If $h_i \geq 1$, edge i was deemed risky (i.e., the potential to spread even one species out of four was sufficient), and only those edges in $\mathbf{N}_i^*$ for which $h_i \geq 1$ were retained in $\mathbf{N}_i$.

Similar to previous studies (Haight et al., 2020; Kinsley et al., 2022; Ashander et al., 2021; Haight et al., 2023) our objective was to maximize, via placement of inspection stations at lakes $j \in J$, the number of risky boats N_i inspected along edges $i \in I$ (See supplementary materials for further details). Next, we defined two binary decision variables, F_j and R_i. $F_j = 1$ if lake j is selected for an inspection station and 0 otherwise; $R_i = 1$ if edge i's risky boats are intercepted by an inspection station at either of its corresponding originating or receiving lakes, j or j′, and 0 otherwise. We assumed inspection stations intercepted all risky boats entering and leaving lakes at which they are placed. Thus, it is sufficient to inspect only *either* lake j or j′ to intercept the risky boats associated with edge j ➔ j′.

We defined the following problem to identify lakes for inspection as

$$max \sum_i R_i N_i \tag{1}$$

Subject to:

$$\sum_j F_j \leq B \tag{2}$$

$$R_i \leq \sum_j F_j v_{ij} \forall i \in \mathrm{I}. \tag{3}$$

Since there are not enough resources to inspect all lakes sending or receiving any risky boats, we prevent the model from inspecting all lakes in J with two constraints. For the first constraint (2), B represents an available state-wide budget for inspection stations such that there is a cap on the number of stations that can be placed.

For constraint (3), v_{ij} are 0–1 parameters with $v_{ij} = 1$ if edge i is associated with lake j (as either an originating or recipient lake) and $v_{ij} = 0$ otherwise. Thus v_{ij} defines which edges correspond to which pairs of lakes. The second constraint prevents an edge i from being deemed as intercepted unless at least one of its corresponding lakes is being inspected.

In variations 2) and 3) of the model, a county c could only place inspection stations at lakes within its borders, which functionally restricted J to a subset, J_c, for each county c (Table 1). This effectively restricted I to a subset, I_c, for each county c such that only edges with recipient lakes within county c were included in I_c. Additionally, counties/collaborations were modeled to have *defensive* and *inward-facing* decision-making when placing inspection stations. While risky boats entering their jurisdiction *did* count towards their objective, risky boats exiting their jurisdiction did *not*. Furthermore, counties/collaborations placed inspectors as though they had no information regarding the placement of inspectors outside of their jurisdiction, and thus, estimates of risky boats entering a county's jurisdiction assumed a lack of inspections outside the county. However, once the set of all lakes J_I being inspected across all counties/collaborations was known, Eqs. (1′–3′) were calculated based on all edges i involving *any* lakes $j \in J_I$. That is, even edges whose boats were not *intentionally* intercepted were nonetheless counted in the outcome.

In variations 2) and 3), we modify the problem to be county-centric. For each county/collaboration network c

$$\max_{i \in I_c} \sum_{i \in I_c} R_i N_i \tag{1′}$$

Subject to:

$$\sum_{j \in J_c} F_j \leq B_c \tag{2′}$$

$$R_i \leq \sum_{j \in J_c} F_j v_{ij} \forall i \in I_c. \tag{3′}$$

Table 1
Overview of the modeling scenarios considered with the decision optimization model.

Scenario	Definition
County	Only lakes within the county were eligible to receive an inspection station. The number of risky boats inspected per lake was calculated by adding all the boat movements that occurred from an infested to an uninfested lake within and into each county.
Collaboration	Lakes within counties involved in collaborations were eligible to receive inspection stations within the collaboration. Lakes in counties not involved in collaborations were considered the same as in the county scenario.
Statewide	Any lake was eligible to receive an inspection station, and placement of these was based on the total number of risky boats that could be inspected there. County boundaries were not considered.

Each county c was allocated a fraction of a statewide budget B equal to the proportion of the AIS Prevention Aid that each county received in 2022 (Minnesota Department of Natural Resources, 2020), B_c, to place inspection stations. However, it could only do so at lakes within its borders; for each county c, we restricted R_i to only edges i with receiving lakes located *within* county c and thus subject to its jurisdiction (Table 1). This functionally restricted J to a subset, J_c, for each county and F to a subset, F_c, for each county's optimization problem (Eq. 1′). The only difference between versions 2 and 3 was that counties involved in a collaboration were recoded to be functionally within the same county when crafting subsets J_c and F_c and by summing their individual B_c terms to build a budget constraint for the collaboration. However, once the set of all lakes J_I being inspected by at least one county/collaboration was known, Eq. (1) was used to calculate the number of risky boats intercepted statewide based on *all* edges i involving *any* lakes $j \in J_I$. Even edges whose boats were not "intentionally" intercepted by the actions of individual counties/collaborations were nonetheless counted in the outcome.

We solved these optimization problems for the three models described above using the Symphony solver with an optimality gap, or the gap between the lower and upper bound, of 1 % and a time limit of 4 h for variation 1) and with an optimality gap of 1.5 % and a time limit of 1 h per county/collaboration for variations 2) and 3). We fit and solved these models within R (R Core Team, 2019) with interfacing between R and Symphony (Harter, 2021) provided by the R packages *ompr* (Schumacher, 2022a), *ROI* (Theußl et al., 2020), *ompr.roi* (Schumacher, 2022b), *Rsymphony* (Harter, 2021), and *ROI.plugin.symphony* (Wincent et al., 2010). We ran each variation for a range of statewide budgets (B) ranging from 10 to 100 in increments of 10, from 100 to 200 in increments of 20, and from 200 to 700 in increments of 100. For variations 2) and 3), jurisdictional allotments (b_c) were allocated as a proportion of the number of agency-managed trailered boat launches within each jurisdiction and the number of parking spaces available at each launch, mirroring the allocation of resources in the AIS Prevention Aid.

While there are 83 counties in Minnesota, four (Dodge, Fillmore, Pipestone, and Rock) do not have any public boat launches. Two additional counties (Houston and Red Lake) are not thought to be sending nor receiving any risky boats to other counties. Other than allotting these counties a b_c in variations 2) and 3), they were otherwise dropped (with their b_c allotments being wasted).

3. Results

3.1. Distribution of AIS at county-level

According to the MN DNR infested waters list of 2019, 212 lakes were listed as infested with zebra mussels, with the highest number of infestations occurring in Otter Tail, Crow Wing, and Douglas counties; 14 lakes were identified as infested with starry stonewort, with the highest number of infestations occurring in Beltrami and Stearns Counties; 316 lakes were identified as infested with Eurasian watermilfoil, with the highest number of infestations occurring in Hennepin, Wright, and Carver Counties; and 37 lakes were identified as infested with spiny waterflea, with the highest number of infestations occurring in Cook and Saint Louis Counties. When assessing the prevalence (number of infested lakes/total number of lakes) of these four AIS, we observed the highest prevalence of zebra mussels in Winona County, starry stonewort in Beltrami, Eurasian watermilfoil in Winona and Carver Counties, and spiny waterflea in Lake of the Woods County (Fig. 2).

3.2. County network construction and descriptions

When considering reciprocal connections formed only by using each county's lowest-ranked sending counties for all four invasive species, a single collaboration network comprised of two counties was observed (Table 2). The networks grew in number and size as we considered

Table 2
Collaboration networks formed between counties in Minnesota when considering risky boat movements for zebra mussels, starry stonewort, Eurasian watermilfoil, and spiny waterflea. The alternative sets of collaboration networks emerged by using reciprocal ranking systems of different depths. For example, in a "ranked reciprocal connection" of level two, reciprocal relationships between two counties were assumed to exist if both counties were amongst each other's lowest two ranked sending counties.

Ranked reciprocal connections	No. of groups	Collaborations	Average group size
1	2	1. Hennepin, Carver	2
2	3	1. Carver, Hennepin, Wright 2. Crow Wing, Cass 3. Ramsey, Washington	2.33
3	2	1. Carver, Hennepin, Wright, Crow Wing, Cass, Stearns 2. Ramsey, Washington, Anoka	4.5
4	2	1. Carver, Hennepin, Wright, Crow Wing, Cass, Stearns, Lake, Cook, Ramsey, Washington, Anoka, Saint Louis 2. Otter Tail, Douglas	7
5	1	1. Anoka, Washington, Ramsey, Hennepin, Stearns, Wright, Carver, Douglas, Otter Tail, Crow Wing, Saint Louis, Cass, Beltrami, Lake, Cook	15

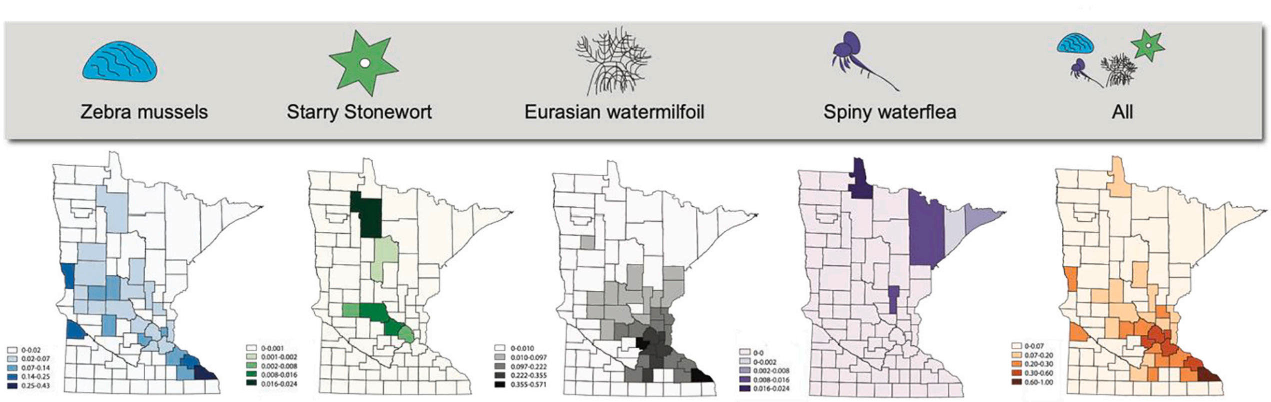

Fig. 2. Prevalence (number of lakes infested/total number of lakes) of zebra mussels, starry stonewort, Eurasian watermilfoil, and spiny waterflea within each county in Minnesota, USA.

sending-county rankings beyond the lowest ranking. In reciprocal connections, including the lowest- and second-lowest sending counties, three collaboration networks were observed, resulting in an average group size of 2.33. As the rankings expanded inclusivity to include the third-lowest sending counties, two collaboration networks were observed, with an average group size of 4.5 (Table 2). Including the fourth-lowest sending counties yielded two collaboration networks with an average group size of 7 and including the fifth-lowest sending counties resulted in one large network of 15 counties (Table 1). The remaining details of the potential collaboration networks are described in Table 1.

We focused additional analyses on collaboration networks that resulted in a relatively small average group size (~5). The two collaboration networks that met this criterion included A) Ramsey, Washington, and Anoka Counties, with Washington County as the central node, and B) Cass, Crow Wing, Hennepin, Carver, Wright, and Stearns Counties, with Crow Wing County serving as the most central node (Fig. 3B, C). In the collaboration networks, each lake's incoming and outgoing out-of-county strength, i.e., the sum of the risky boats moving into or out of each lake, was compared. The strength was heterogeneously distributed across lakes in the collaboration networks. For each lake in counties in Collaboration Network A, the smaller collaboration networks, most of the incoming and outgoing strengths were below 1000 risky boats, with few lakes above 3000 risky boats. In Collaboration Network A, the two largest incoming strengths were observed in lakes in Washington County (White Bear Lake: 5959 risky boats; Forest Lake: 5445 risky boats), and the largest outgoing strength was observed in Anoka County (Coon Lake: 5369 risky boats). For each lake in counties in Collaboration Network B, the strength of one lake was significantly larger than other lakes in the collaboration. The greatest outgoing and incoming strengths were observed in the same lake (Lake Minnetonka: 23,672 incoming risky boats and 11,321 outgoing risky boats; Fig. 4).

When considering the reciprocal relationships formed using "lowest-three" rankings as a function of each individual invasive species in turn, we observed that, for zebra mussels, many potentially risky boats move between Douglas and Otter Tail Counties and between Crow Wing and Cass Counties (Fig. 5A). For Eurasian watermilfoil, we saw many potentially risky boats move between Carver and Hennepin Counties and between Wright and Hennepin Counties (Fig. 5B). The largest out-of-county risky boat movements for starry stonewort occurred between Beltrami and Cass Counties (Fig. 5C) and Lake and Saint Louis Counties for spiny waterflea (Fig. 5D). Considering all four AIS together, the largest between-county risky-boat movements occurred between Cass and Crow Wing Counties, primarily driven by boats potentially moving zebra mussels (Fig. 5E). Collaboration A included 253 lakes and 9579 connections between lakes. Collaboration B comprised 1499 lakes and 164,200 connections between lakes.

3.3. Decision optimization model

For each of the three scenarios, the number of risky boats inspected increased with the number of allotted inspection locations. The statewide model performed better than the collaboration and county models, resulting in more risky boats inspected for each budget level. The maximum number of risky boats inspected was 821,360 for budget levels 500, 600, and 700 in the statewide model. The collaboration scenario yielded more risky boat inspections than the county-based model at every budget level, resulting in the inspection of approximately 658,000 risky boats (65,000 more risky boats than the statewide model at a budget of 400), representing approximately 80 % of all possible risky boats. Although the collaboration scenario outperformed the county-focused scenario, the collaboration and county scenarios yielded fewer risky boat inspections than the statewide model, resulting in approximately 18 and 25 % fewer risky boats inspected, respectively, when 400 inspection stations were allocated (Fig. 6).

The statewide model ran the longest and a solution was found within the time limit for each case with a gap of 0 %.

4. Discussion

Here, we showed that collaboration networks formed by reciprocal boater movements amongst only nine counties could result in gains in efficiency compared to a non-collaborative approach (county scenario), resulting in the inspection of approximately 80 % of the estimated risky boats moving between lakes in the state with 400 inspection stations. However, the collaboration scenario was less efficient than a state-wide approach, resulting in 18 % fewer risky boat inspections. These findings reinforce and build upon previous work that demonstrated a substantial loss in efficiency of watercraft inspection plans in scenarios where state and county objectives are misaligned (Haight et al., 2023). Our results suggest that strategic inter-jurisdictional collaborations could create conditions that preserve some of the benefits of local-level management while mitigating some losses in efficiency from a purely parochial and non-prosocial approach.

By analyzing the movement of risky boats between pairs of counties

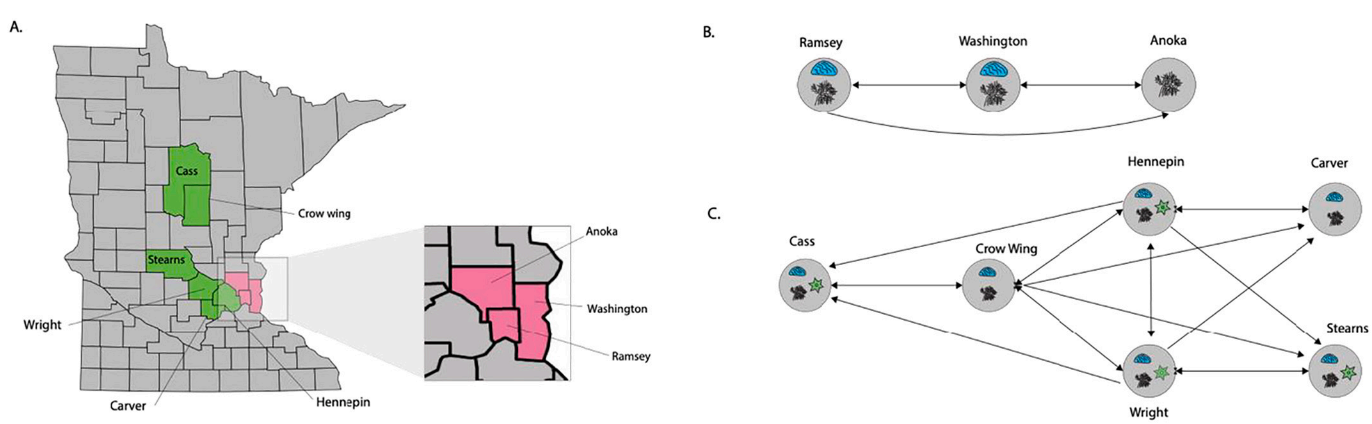

Fig. 3. Counties in Minnesota that were identified as potential watercraft inspection program collaborators when considering the lowest-ranked three sending counties from which risky boats (boats traveling from an infested to uninfested lake) originate. A. Map showing the location of the potential collaborations, comprised of Ramsey, Washington, and Anoka Counties (pink) and Cass, Crow Wing, Stearns, Wright, Carver, and Hennepin Counties (green). B. Networks of potential collaborators, with counties represented as nodes and filled with aquatic invasive species of interest (zebra mussels, starry stonewort, Eurasian watermilfoil, and spiny waterflea) present in each county. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

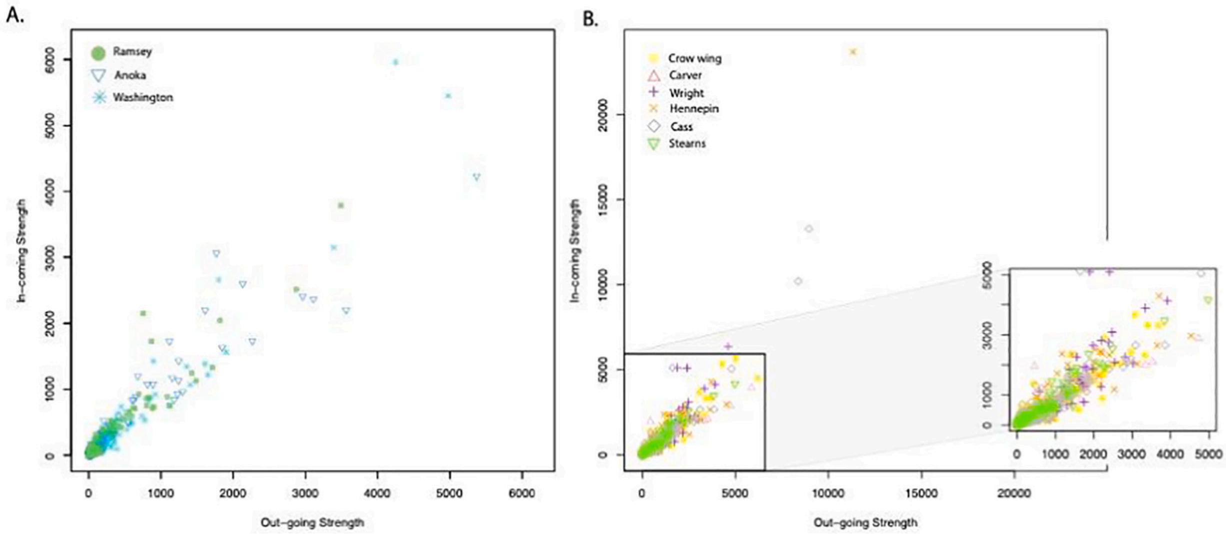

Fig. 4. The in-coming and out-going strength of each lake involved in out-of-county boat movements in the potential collaboration networks when considering the lowest-ranked three sending counties from which risky boats originate. Frame A shows the directional strength of the network involving Ramsey, Washington, and Anoka Counties, and Frame B shows the directional strength of the collaboration network involving Crow Wing, Carver, Wright, Hennepin, Cass, and Stearns Counties in Minnesota, USA.

and focusing on collaboration networks that resulted in a relatively smaller average group size, we identified two potential collaboration networks. One network, Collaboration Network A, included three spatially contiguous counties, Anoka, Ramsey, and Washington Counties, located in the eastern portion of the state (Fig. 3A). This network was formed through boats moving from zebra-mussel-infested lakes in Ramsey and Washington Counties and Eurasian watermilfoil moving between Washington and Anoka Counties (Fig. 5A, B), which may be driven by spatial proximity. Although all three counties in Collaboration Network A have been listed as infested with Eurasian watermilfoil (Minnesota Department of Natural Resources, 2019), more risky boats move between zebra mussel-infested lakes than between Eurasian watermilfoil-infested lakes in Ramsey and Washington Counties (Fig. 5A, B), greatly contributing to risky boat counts resulting in the connection between the two counties. Both counties have large lakes that are infested with zebra mussels. For example, White Bear Lake is a large, popular zebra mussel-infested lake situated on the border of Ramsey and Washington County. Given that it could serve as a source of new infestations for surrounding lakes, this lake could serve as a starting point for a collaboration between the two counties to mitigate the spread of zebra mussels from White Bear Lake to surrounding uninfested lakes.

In Collaboration Network B, all counties had at least one lake listed as infested with zebra mussels and Eurasian watermilfoil, and four of the six counties had at least one lake listed as infested with starry stonewort. Most risky boat movements forming the connection between Cass and Crow Wing Counties are moving from zebra mussel-infested lakes (Fig. 5). Meanwhile, Crow Wing and Hennepin Counties, and Crow Wing and Wright Counties, do not show strong reciprocity for any individual species (Fig. 5), indicating that the sum of multiple species is driving the connections between those pairs of counties. Hennepin and Carver Counties are connected through the high numbers of boats moving from Eurasian watermilfoil- and zebra mussel-infested lakes, and Wright and Stearns Counties are primarily connected through the movement of boats from starry stonewort-infested lakes. Knowing which species influences the number of risky boats moved between counties might help coordinate with organizations oriented towards a specific species. Additionally, having a network based on pathways also supports the development of prevention and surveillance activities that mitigate the risk of multiple species at a time, which may increase the cost-effectiveness of prevention programs.

Once collaboration networks have been identified, the network structure, focused on the county level versus the lake level, could be used to identify counties whose participation may be most beneficial. For example, counties with high strength or betweenness values may be better positioned to engage in resource exchanges or collaborative planning activities due to the higher number of relevant boater movements with the other counties in the collaboration. In our study, we observed that the participation of Washington County in the smaller network and Crow Wing County in the larger network is most likely to benefit the collaboration and may have the most significant influence on forming and maintaining critical components of successful collaborations such as social norms and collective goals (Wincent et al., 2010) due to their higher degree and betweenness values within their networks.

When considering strength, or the number of risky boats moving into and out of each lake, we observed that most lakes within the smaller county collaborations had strength values below 1000, and few lakes had a strength higher than 3000. In the smaller collaboration, White Bear Lake in Washington County had the highest incoming strength, and Coon Lake in Anoka County had the highest outgoing strength. Both lakes are large, popular lakes with a much higher incoming and outgoing strength than most lakes in the collaboration, indicating that they could be useful as sentinel lakes monitored for new invasive species that spread via boater movements and should be considered a high priority for prevention activities. In the larger collaboration network, Lake Minnetonka had a significantly larger strength than other lakes, with an incoming strength >20,000 risky boats per year and an outgoing strength >10,000 boats per year (Fig. 4). All three lakes were listed as infested with Eurasian watermilfoil, and White Bear Lake and Lake Minnetonka were listed as infested with zebra mussels (Minnesota Department of Natural Resources, 2019).

The importance and benefits of collaboration in managing invasive species have been well recognized, particularly surrounding information sharing, monitoring, and management (Reaser et al., 2020; Lubell et al., 2017; Simpson et al., 2009; Delaney et al., 2008; Simpson, 2004). To contribute to the body of knowledge regarding AIS prevention, we compared the optimal placement of watercraft inspectors in 1) state-wide, 2) county-wide, and 3) collaboration models. Using the state-wide model as a baseline, we observed that the county-wide model resulted in up to 25 % fewer risky boat inspections. When we compared these results to the optimal solution for the collaboration model, we saw that the collaboration scenario reduced the number of uninspected boats by 8 % compared to the county-wide model at the point of widest

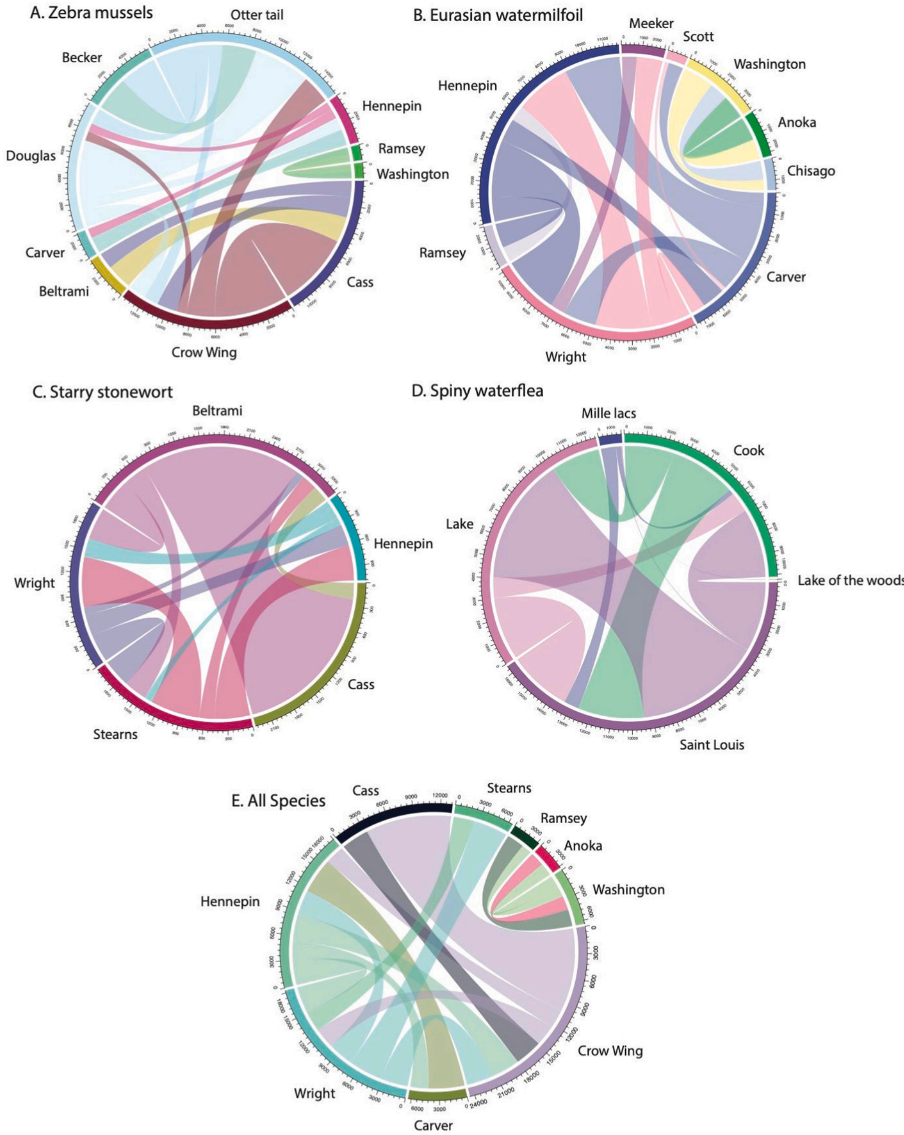

Fig. 5. Chord diagrams depicting reciprocal relationships of boat movements predicted to occur from infested to uninfested lakes traveling between counties in Minnesota, USA. The outer ring corresponds to the county in which the boat in question originates. Thicker bands correspond to higher numbers of risky boats moving between pairs of counties.

difference (Fig. 6B). These results demonstrate the potential benefits of strategic collaboration between counties on watercraft inspection planning and are consistent with our previous work on governance structures and watercraft inspection planning in Minnesota (Haight et al., 2023). In previous work, a statewide model was compared to a bi-level model in which a state planner selected from amongst county plans that were first optimized based on local-level objectives. Both models aimed to maximize the inspection of risky boats subject to resource constraints. The authors found that the bi-level model resulted in the inspection of about 18 % fewer risky boats than the statewide model. This is consistent with the findings presented here, which suggest that the fragmentation of the statewide boater movement network into counties with their own county-focused objectives leads to losses in efficiency when considering the optimized placement of watercraft inspectors. The outputs of this work could motivate managers to share resources (funding, inspectors, information, or other resources) regarding watercraft inspection placement in a way that maximizes their allocation while preserving the benefits of local-level initiatives critical to successful AIS prevention and management.

Proper interpretation of the findings presented here requires a few considerations. First, we used boater networks constructed using empirical data from 2014 to 2017. However, boater movement patterns and infestation statuses could change over time, and the persistence of connections should be evaluated to determine if the reciprocal connections used to form the collaborations are stable. Previous studies have shown that social network metrics, such as loyalty, can be used to assess the validity of retrospective data to derive inferences for managing infectious diseases (Makau et al., 2021). By evaluating the fidelity of boaters to pairs of lakes, researchers and managers could improve prevention activities that aim to educate many unique boaters and determine the stability of network metrics that identify high-risk lakes for prioritization (Haight et al., 2020; Kinsley et al., 2022; Ashander et al., 2021).

An additional point for consideration is that we assumed that counties in the collaboration pooled their resources such that each would contribute inspectors proportionately to the funding they receive through the AIS Prevention Aid. However, counties may allocate substantial portions of their funds to activities other than watercraft inspections or to develop collaborations based on information sharing and paired planning rather than share inspectors. Further, our analyses were

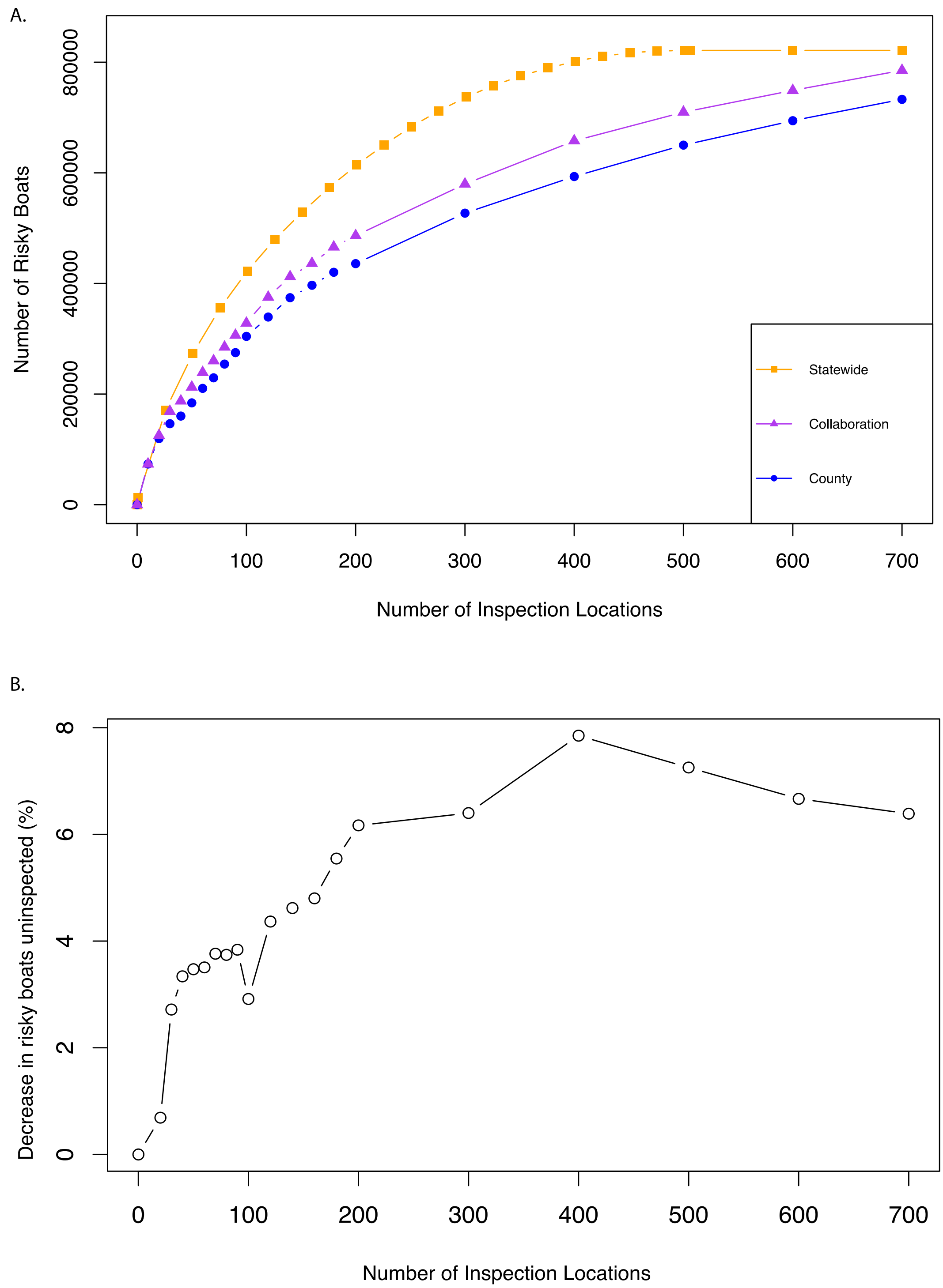

Fig. 6. A. Outputs of the decision optimization model for the statewide, collaboration, and county-level models at a range of statewide budget levels describing the number of inspection station locations that could be distributed (x-axis). Risky boats inspected under a given scenario and budget level are shown on the vertical axis. B. Percentage decrease in uninspected risky boats inspected in the collaboration scenario compared to the county scenario versus the number of inspection locations.

based on the infestation statuses of lakes. These are imperfectly known and likely biased by variation in human density, leading to unequal invasion reporting (Kanankege et al., 2018). Lastly, we made the simplifying assumptions that all lakes would require the same inspection effort and that lakes extending across multiple counties were apportioned to each of those counties. However, lakes have different numbers of access points. These assumptions were made based on the level of detail available in the boater network data, and future studies incorporating the number of different access points and the counties they belong to would strengthen the realism of the modeling approach.

While the involvement of local communities has been identified as critical to invasive species management success (Ford-Thompson et al., 2012), enduring success within collaborations is more likely to arise when there is a win-win situation in which all partners actively work towards a mutually defined goal in which each entity in the collaboration benefits from the success of its partner(s) (Lubell et al., 2017). To increase the likelihood that county managers could identify win-win scenarios, we limited our analysis to counties that send high levels of risky boats to each other. Further, since successful teams tend towards group sizes that are large enough to allow for specialization but small enough to overcome the costs of group work, such as time and money, we limited the group size of the collaboration networks by only considering the lowest three ranked sending counties when building the collaboration networks. However, the results presented here are likely a conservative estimate of the benefits of collaboration and expanding the reciprocal rankings to larger group sizes (Table 2) would likely lead to modeled higher gains. Translating these results into practice requires future studies to measure the costs and benefits of collaboration between counties of different sizes with different budgets, motivations, and local-level objectives. Furthermore, this approach is sensitive to the participation of the counties in the network. If a single county chooses not to participate, it could disproportionately affect the remaining counties and should be considered in the interpretation of the results.

Previous work on network structure and collaborations in other contexts has shown that strategic networks need generalized reciprocity to mitigate risks of opportunism and free-riding when collaboration members do not contribute their fair share of the resources (Marshall, n.d.). However, most clustering or community detection algorithms that identify groups of similar nodes in a network do not account for reciprocity since they were designed for undirected networks (Feuer et al., 2022). Additional algorithms that assess reciprocity and win-win scenarios amongst groups of individuals that optimize collaborations and meet multiple local-level AIS prevention objectives are an exciting area for future research. Moreover, strong social norms encouraging reciprocity are more effective than contractual governance mechanisms but require trust and time to develop (Marshall, n.d.), which should be considered when assessing the costs and benefits of collaborations and should be explored in future research on this topic.

The results of our research can be applied to the prevention and management of additional invasive species at broader spatial scales. For example, network reciprocity in angler and hydrological networks has been considered at the national level (Weir et al., 2022); Weir et al. (2022) identified an "invasion superhighway" spanning across the United States, confirming previous findings that potential dispersal through boater movements is primarily comprised of movements of short distances that nevertheless cross natural and political boundaries. This national-level network could be used to identify collaborations across spatial scales in which key states, counties, and watersheds work together to mitigate the spread of AIS through boat movements.

Collaborative networks have been developed to monitor invasive species and share information regarding prevention and management strategies (Reaser et al., 2020; Lubell et al., 2017; Simpson et al., 2009; Delaney et al., 2008). However, to our knowledge, this was the first study that used aspects of the network's structure to identify collaborative groups to manage AIS strategically. Here, we demonstrate that networks formed by reciprocal boater movements amongst counties could increase the efficiency of watercraft inspection station placement across Minnesota while still providing most of the benefits of a county-led approach. While the collaboration networks we assessed may be effective for managing the spread of invasive species through boater movements, the stability of boater networks and the ability of AIS to spread through alternative pathways is unresolved and is an important focus for future research. Monitoring boater networks and quantifying cost vs. benefits of collaboration in the future may allow managers to use the approach we presented here to align inspection planning more closely with boater movements and invasion dynamics.

CRediT authorship contribution statement

Amy C. Kinsley: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Alex W. Bajcz:** Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Robert G. Haight:** Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Writing – review & editing. **Nicholas B.D. Phelps:** Data curation, Resources, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Amy Kinsley, Alex Bajcz reports financial support was provided by Minnesota Environment and Natural Resources Trust Fund as recommended by the Legislative-Citizen Commission on Minnesota Resources and the Minnesota Aquatic Invasive Species Research Center, and the State of Minnesota. Robert Haight reports financial support was provided by the Northern Research Station, USDA Forest Service.

Data availability

Data is available through the citation provided.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2024.110449.

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