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Research article

A bi-level model for state and county aquatic invasive species prevention decisions

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ABSTRACT

Recreational boats are important vectors of spread of aquatic invasive species (AIS) among waterbodies of the United States. To limit AIS spread, state and county agencies fund watercraft inspection and decontamination stations at lake access points. We present a bi-level model for determining how a state planner can efficiently allocate inspection resources to county managers, who independently decide where to locate inspection stations. In our formulation, each county manager determines a set of optimal plans for the locations of inspection stations under various resource constraints. Each plan maximizes inspections of risky boats that may carry AIS from infested to uninfested lakes within the county. Then, the state planner selects the set of county plans (i.e., one plan for each county) that maximizes the number of risky boats inspected throughout the state subject to a statewide resource constraint. We apply the model using information from Minnesota, USA, including the infestation status of 9182 lakes and estimates of annual numbers of boat movements from infested to uninfested lakes. Comparison of solutions of the bi-level model with solutions of a state-level model where a state planner selects lakes for inspection stations statewide shows that when state and county objectives are not aligned, the loss in efficiency at the state-level can be substantial.

1. Introduction

The spread of aquatic invasive species (AIS) among waterbodies of the United States is a major social, environmental, and economic concern (Escobar et al., 2017; Fantle-Lepczyk et al., 2022). The economic costs of zebra mussel (*Dreissena polymorpha*) alone are estimated to range from hundreds of thousands to billions of dollars annually, depending on the scale of the study (Lovell et al., 2006; Fantle-Lepczyk et al., 2022). An important vector of AIS spread is the accidental transport of aquatic organisms on recreational boats as they are moved between waterbodies (Johnson et al., 2001; Vander Zanden and Olden, 2008; Rothlisberger et al., 2010). In response, state and local agencies invest considerable resources on activities to prevent or slow AIS spread, including boat inspections at high priority lakes and outreach campaigns to educate the public (Rothlisberger et al., 2010). In this paper, we address the design of watercraft inspection programs at state and county levels. We aim to advance our understanding of how decision-making associated with bi-level governance may influence effective AIS prevention and further develop optimization models for the design of watercraft inspection programs.

The design of watercraft inspection programs is informed by estimates of boat movements and related AIS establishment. For example, Buchan and Padilla (1999) used results of a boater survey to estimate boat movements between counties in Wisconsin. They found that AIS establishment was most related to long-distance boat movements and recommended that boat inspection and education activities be focused on high-frequency, long-distance boat movement paths. Likewise, Kao et al. (2021) used results of boat inspection surveys to estimate annual numbers of boat movements between lakes in Minnesota. They found that infested lakes on average were connected via boat movement to many more lakes than uninfested lakes and suggested that prevention strategies focus on highly connected, infested lakes. Timar and Phaneuf

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(2009) used data on boaters' trip choices, travel costs, and lake attributes to predict probabilities that boaters will visit different lakes. They also estimated the probability of invasion of each lake as a function of the rate of incoming boats from infested lakes. Because the model of boat movement includes policy actions, the combined models can be used to predict how policy choices influence boater behavior, boat movement pattern and invasion spread. When boater survey information is not available, analysts have used gravity models to predict the numbers of boats that move between pairs of lakes where the force of attraction depends on attributes of the boater population at the source lake, attributes of the destination lake, and the distance between them (Bossenbroek et al., 2001; Leung et al., 2006; Robertson et al., 2020).

Researchers are beginning to incorporate estimates of boat movements directly into optimization models to help design watercraft inspection programs. For example, Fischer et al. (2021) developed an integer programming model to optimize locations and operating times of watercraft inspection stations while accounting for temporal variations in boat movement along routes between sets of infested and uninfested lakes. Their objective was to maximize the number of boat movements that pass at least one inspection station along their routes, subject to a budget constraint. Haight et al. (2021) developed an integer programming model for allocating inspection resources among lakes. That model used species-specific infestation status of lakes and estimates of boat movement between lakes and identified lakes for inspection stations to maximize the number of risky boats inspected, where risky boats are ones that move from infested to uninfested lakes and potentially carry AIS. While integer programming models provide optimal solutions to inspection station location problems, heuristics that rank and select lakes for inspection stations according to network metrics based on risky boat movements provide near-optimal solutions to problems with objectives of maximizing the number of risky boats inspected and have been incorporated into decision support systems (Ashander et al., 2022; Kinsley et al., 2022).

Building on the work of Haight et al. (2021), we address a bi-level planning problem of how a state planner can efficiently allocate inspection resources to county planners, who in turn decide where to locate inspection stations according to their own local objectives. This problem is important because many states use bi-level planning where the state allocates funding and other resources to local organizations to support their plans for watercraft inspections and outreach to boaters. For example, the Minnesota AIS Prevention Aid program allocates $10 million a year to counties to fund activities, such as watercraft inspections, that prevent the introduction and limit the spread of AIS (Minnesota Department of Natural Resources, 2022).

In our bi-level model, we assume that state and county planners have the same information on the infestation status of lakes and estimates of boat movement between lakes. The objective of the state planner is to allocate a fixed amount of inspection resources to the counties to maximize the number of risky boats inspected, where risky boats are ones that move from infested to uninfested lakes throughout the state. Using their resource allocation from the state, each county planner then selects lakes for inspection stations to maximize the number of risky boats inspected within the county. We assume that the county's resource allocation is a number of inspectors and each inspector manages an inspection station at a single lake. There is an important difference between the state and county planners' management objectives: the state planner accounts for risky boat movements between lakes throughout the state, but the county planner only accounts for risky boat movements between lakes within the county and is not concerned about the transmission of AIS to waterbodies outside the county. Because the objectives of the county planners are not consistent with the state planner, both the allocations of the state planner and the decisions of the county planners obtained with the bi-level model may not be efficient from the perspective of the state planner. Using theory of bi-level planning, we develop a framework to estimate the level of this inefficiency. We apply our models using data on lake infestation and boater movement for the state of Minnesota, considering zebra mussels, starry stonewort (*Nitellopsis obtusa*), and Eurasian watermilfoil (*Myriophyllum spicatum*) as focal AIS.

2. Methods

2.1. Data

Both the state and county planners use the same set of information about lakes and boat movements between lakes. We focus our analysis on 9182 lakes in 87 counties in Minnesota (Fig. 1). The lakes are all Type 5 waterbodies, meaning that they are at least 0.04 km^2 (10 acres) in size, contain open water wetlands, including shallow ponds and reservoirs, and provide floodwater detention, wildlife and fish habitat, and recreation, including hunting, fishing and canoeing. While this definition excludes smaller lakes and wetlands, it does include most lakes relevant to recreational boating and risk of AIS movement through this pathway.

We used the infestation status of lakes reported in the MNDNR Infested Waters List, as of May 1, 2019 (Minnesota Department of Natural Resources, 2021). Each lake was classified as infested or uninfested with zebra mussel, starry stonewort, and Eurasian watermilfoil. A total of 471 lakes were infested with one or more these AIS in 49 counties (Fig. 2), with 212 lakes infested with zebra mussel, 14 infested with starry stonewort, and 316 infested with Eurasian watermilfoil.

We used estimates of annual boat movements between lakes. The estimates were based on responses from boaters to questions during the watercraft inspection process and aggregated by the MNDNR for the period 2014–2017. Boaters were asked to recall and identify the previous lake visited and identify the next lake they planned to visit. Using these responses, Kao et al. (2021) employed an extreme gradient boost analysis to estimate the annual number of boats moving between each pair of lakes in the state. They accounted for variation in inspection effort at lakes with inspection stations and extrapolated the survey information to estimate movement between all lakes in MN, including lakes that were not surveyed. Using these estimates, we created a 9182 by 9182 matrix of annual number of boat movements from each source lake (row) to each destination lake (column). The matrix included an estimated 733,901 risky boat movements, where each risky boat is one that moves from a source lake that is infested with one or more AIS to a destination lake that is not infested with one or more of the AIS that are present in the source lake.

2.2. Model overview

Our bi-level model is an example of a two-level hierarchical system in which a higher government unit aims to efficiently allocate resources to lower government units (Cassidy et al., 1971). The higher-level decision maker (leader) controls decision variables $x \in X$, and each lower-level decision maker (follower) controls decision variables $y_i \in Y_i$ where the index i refers to lower government unit i. The leader makes their decision first and the followers make their decision afterward, based on the leader's decision. A general statement of the bi-level problem is (Colson et al., 2007):

$$\max_{x \in X} F(x, y_1, y_2, \ldots, y_n) \text{ subject to : } f(x) \leq 0,$$

where $y_1, y_2, \ldots, y_n$ solve

$$\max_{y_i \in Y_i} G_i(x, y_i) \quad \text{subject to : } g_i(x, y_i) \leq 0 \quad \text{for } i = 1, \ldots, n,$$

F and G_i are the higher- and lower-level decision makers' objective functions and f and g_i are resource constraints. As in a Stackelberg game, the objectives of the upper- and lower-level decision makers may be different (Simaan and Cruz, 1973). The leader makes their decision with anticipation of how the followers will react according to their objective functions. The followers make their decisions taking the leader's

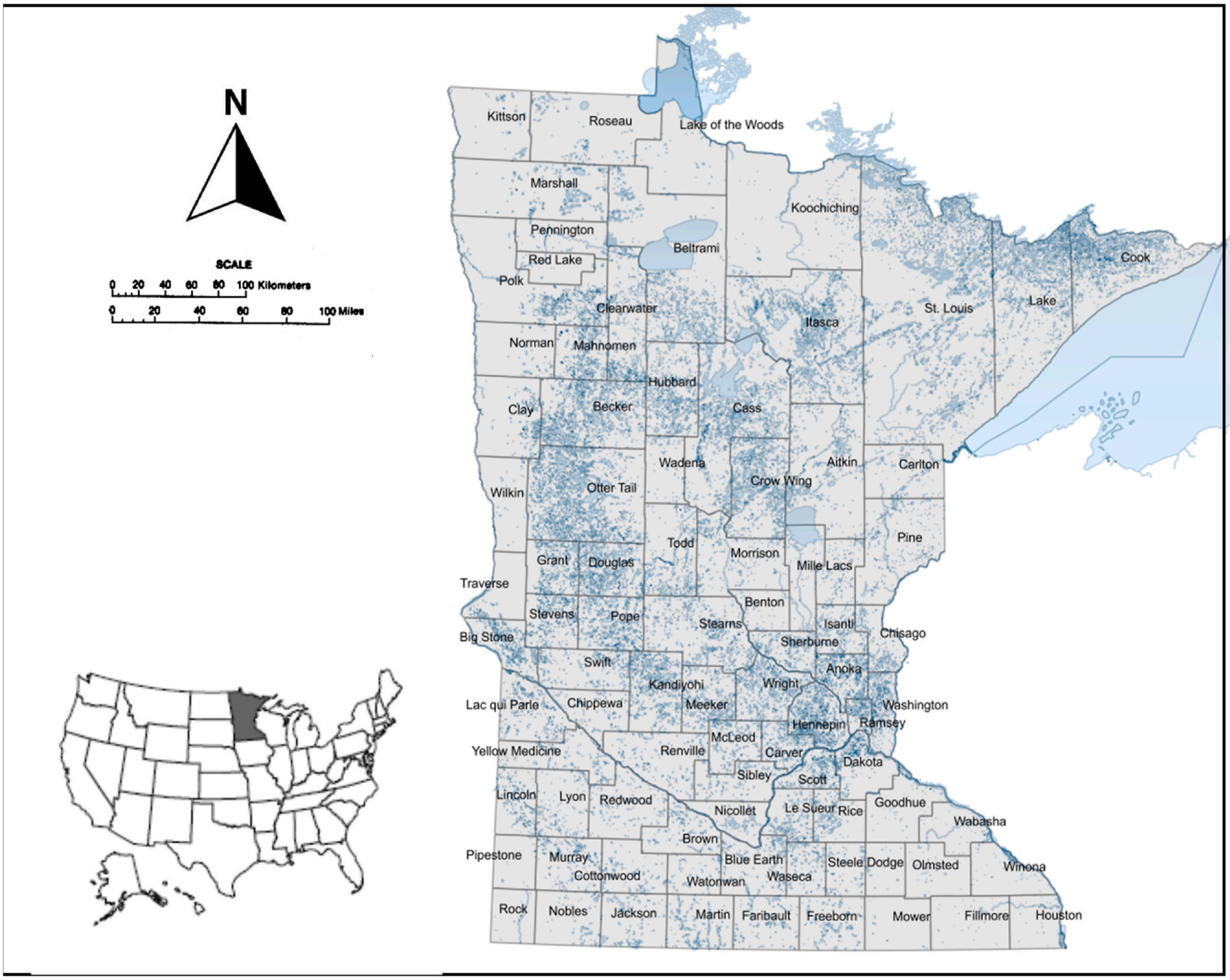

Fig. 1. Map of waterbodies in Minnesota counties.

decision as given and independently of other followers' decisions. This bi-level formulation has been applied to public policy decisions including setting electricity prices and subsidizing energy conservation programs (Hobbs and Nelson, 1992), developing tax credits to encourage biofuel production (Bard et al., 2000), designing road networks for transporting hazardous materials (Kara and Verter, 2004), developing evacuation plans for regional hurricane preparedness (Apivatanagul et al., 2012), and allocating water from reservoirs to various water use sectors (Ahmad et al., 2018).

The allocations found with the bi-level formulation may be inefficient from the perspective of the higher-level planner because the objectives of the lower-level planners may not be consistent with those of the higher-level planner. To estimate the inefficiency, we formulate and solve an optimization problem for the higher-level level planner as follows:

$$\max_{x \in X; y_1, \ldots, y_n} F(x, y_1, y_2, \ldots, y_n) \quad \text{subject to} : \ f(x) \le 0$$

Here, all the decision variables, $x \in X$; $y_1, y_2, \ldots, y_n$, are determined according to the leader's objective function F and constraints $f(x) \le 0$ without regard for the followers' objective functions and constraints. The solution to this problem is used as a baseline for comparison with the solution of the bi-level model, and the difference in the objective function values is an estimate of the inefficiency of the bi-level solution from the perspective of the higher-level planner.

2.3. State-level model

We begin with a description of a state-level model in which a state planner selects lakes for inspection stations statewide to maximize the number of risky boats inspected, where risky boats are ones that move from infested to uninfested lakes throughout the state (Fig. 3). This state-level model follows from the inspection station location problem formulated by Haight et al. (2021) and is used as a baseline for comparing solutions of the bi-level model, which we describe in the next section.

We assume that a state planner uses information about the species-specific infestation status of lakes and estimates of boat movement between lakes. Let I be the set of lakes in the state and w_{ij} be the number of watercraft that move from lake i to lake j, $\forall i,j \in I$. Further, let K be the set of AIS and f_{ik} be a binary parameter for whether or not lake i is infested with species k (i.e., $f_{ik} = 1$ if species k is present in lake i; $f_{ik} = 0$ otherwise). From these infestation parameters, we compute $g_{ij} = \sum_{k \in K} f_{ik}(1 -$

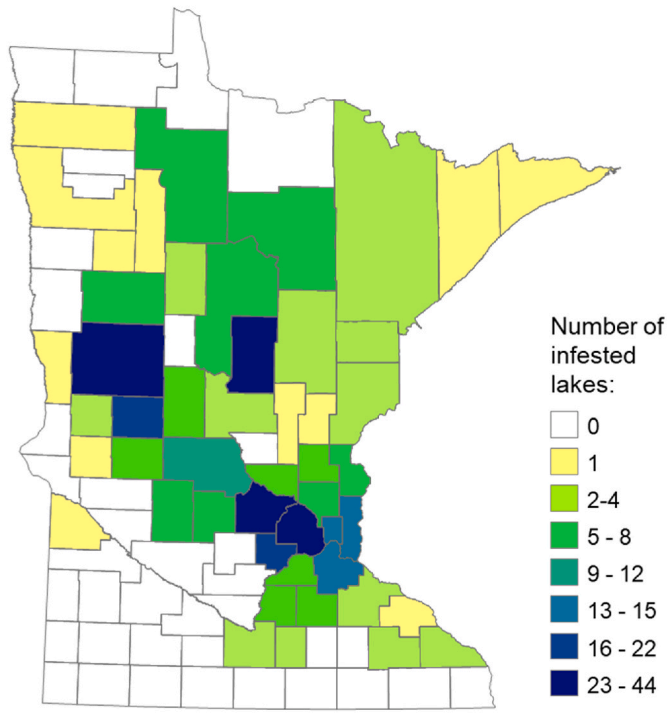

Fig. 2. Number of infested lakes in Minnesota counties.

f_{jk}), which is an integer counter for the number of species that may be moved via watercraft from infested lake i to uninfested lake j. For example, if lake i has three invasive species and lake j has one of those species, then a boat moving from lake i to lake j is at risk of carrying two kinds of invasive species from infested lake i to lake j. We define binary decision variables x_i, $\forall i \in I$, for whether lake i is selected for an inspection station (i.e., $x_i = 1$ if lake i is selected; $x_i = 0$ otherwise). Further, we define binary decision variables y_{ij}, $\forall i,j \in I$, for whether or not risky boats that move from lake i to lake j are inspected at either lake i or lake j or both. Using these definitions, we formulate the following inspection station location problem:

$$\text{Max } Q = \sum_{i \in I} \sum_{j \in I} w_{ij} y_{ij} \tag{1}$$

Subject to:

$$g_{ij} = \sum_{k \in K} f_{ik}\left(1 - f_{jk}\right) \quad \forall i,j \tag{2}$$

$$y_{ij} \le \left(x_i + x_j\right) g_{ij} \quad \forall i,j \tag{3}$$

$$\sum_{i \in I} x_i \le B \tag{4}$$

$$x_i, y_{ij} \in \{0,1\} \quad \forall i,j \tag{5}$$

The objective (1) is to choose lakes for inspection stations, x_i, $\forall i \in I$, to maximize the number of risky boats that are inspected throughout the state, where a risky boat is one that moves from infested lake i to lake j, which is not infested with one or more of the species that are present in lake i. Constraint (2) is the integer counter for the number of species that may be moved via watercraft from infested lake i to uninfested lake j. Constraint (3) defines the value of the 0-1 decision variable y_{ij} for whether risky boats are inspected: $y_{ij} \le 1$ only if one or both of the lakes i or j is selected for inspection (i.e., $x_i + x_j \ge 1$) and lake i is infested with at least one species k that is not present in lake j (i.e., $g_{ij} \ge 1$). Note that, since the objective function maximizes the sum of the products $w_{ij}y_{ij}$, constraint (3) will set as many $y_{ij} = 1$ as possible. Equation (4) is the budget constraint B representing an upper bound on the number of lakes that may be selected for inspection stations statewide. Equation (5) describes the integer restrictions on the decision variables.

2.4. Bi-level model

In contrast to the state-level model, the bi-level model assumes the following two-step decision making process (Fig. 3). First, each county determines a set of optimal plans for inspection station locations under various levels of a resource constraint. We define the resource constraint as an upper bound on the number of lakes that may be selected for inspection stations within the county. Levels of the constraint are set from zero to a maximum equal to the number of lakes within the county and represent alternative levels of support that may be granted to the county by the state planner. Each county plan is optimal in the sense that it identifies lakes for inspection stations that attain the county planner's local objective of maximizing the number of risky boats inspected within the county subject to the resource constraint. At the second step, the state planner selects a set of county plans (one plan for each county) that attains the state-level management objective of maximizing the number of risky boats inspected throughout the state subject to a state-level resource constraint representing an upper bound on the number of lakes that may be selected for inspection stations statewide. This two-step decision-making process represents a type of hierarchical planning in which a state planner selects a set of locally developed plans that they support through grants to local units of government.

2.4.1. County-level problem

Let M be the set of counties and m be an index denoting county m. Let r_{im} be a parameter for whether or not lake i is in county m; $r_{im} \in \{0,1\}$. Let N be the set of budget levels, where each budget level $n \in N$ is an upper bound b_{mn} on the number of lakes that can be selected for inspection stations in county $m \in M$. The budget levels b_{mn} for all $n \in N$ represent alternative levels of support that may be granted to county m in the state-level problem described in the next subsection. We define binary decision variables x_{imn}, $\forall i \in I$, for whether lake i is selected for an inspection station (i.e., $x_{imn} = 1$ if lake i is selected; $x_{imn} = 0$ otherwise) in county m under budget level n. Note that the constraints, $x_{imn} \le r_{im} \forall i \in I$, restrict the selection of lakes to those that occur within county m. We define binary decision variables y_{ij}, $\forall i,j \in I$, for whether risky boats that move from lake i to lake j are inspected at either lake i or lake j or both, where $y_{ij} \in \{0,1\}$. Note that the constraints, $y_{ij} \le r_{jm} \forall i,j$, restrict the counting of risky boats inspected to those that are moving into lakes within county m from inside or outside the county. Using these definitions, we formulate the following inspection station location problem for county m and budget level n:

$$\text{Max } Q_{mn} = \sum_{i \in I} \sum_{j \in I} w_{ij} y_{ij} \tag{6}$$

Subject to:

$$g_{ij} = \sum_{k \in K} f_{ik}\left(1 - f_{jk}\right) \quad \forall i,j \tag{7}$$

$$y_{ij} \le \left(x_{imn} + x_{jmn}\right) g_{ij} \quad \forall i,j \tag{8}$$

$$x_{imn} \le r_{im} \quad \forall i \tag{9}$$

$$y_{ij} \le r_{jm} \quad \forall i,j \tag{10}$$

$$\sum_{i \in I} x_{imn} \le b_{mn} \tag{11}$$

$$x_{imn}, y_{ij} \in \{0,1\} \quad \forall i,j \tag{12}$$

The objective (6) is to choose lakes for inspection stations within county m to maximize the number of risky boats inspected. As we

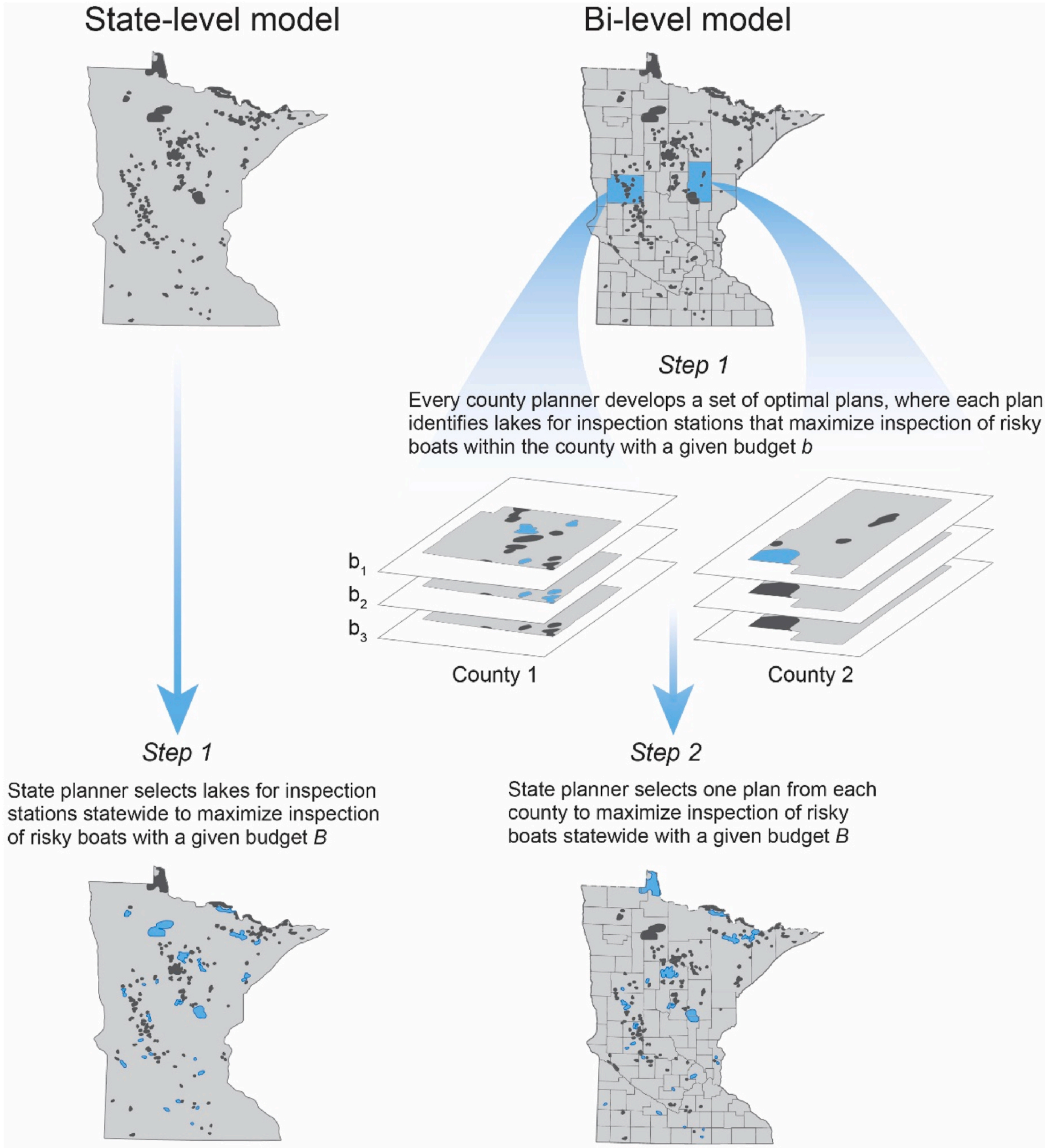

Fig. 3. Processes for solving the state-level and bi-level models of aquatic invasive species planning.

describe with the constraints below, the county planner maximizes the inspection of risky boats that move between lakes within the county and from lakes outside the county to lakes within the county. The county planner is not concerned about the inspection of risky boats that move from lakes within the county to lakes outside the county. Constraint (7) is the integer counter for the number of species that may be moved via watercraft from infested lake *i* to uninfested lake *j*. Constraint (8) defines the value of the 0-1 decision variable y_{ij} for whether risky boats are inspected: $y_{ij} \leq 1$ only if one or both of the lakes *i* or *j* is selected for inspection (i.e., $x_{imn} + x_{jmn} \geq 1$) and lake *i* is infested with at least one species *k* that is not present in lake *j* (i.e., $g_{ij} \geq 1$). Note that, since the objective function maximizes the sum of the products $w_{ij}y_{ij}$, constraint (8) will set as many $y_{ij} = 1$ as possible. Constraint (9) requires that only lakes in county *m* may be selected for inspection stations. Constraint (10) restricts pathways of risky boats that can be counted for inspection to those for boats moving into or within county *m*. In essence, constraint (10) implies that y_{ij} can equal 1 only if the destination lake *j* is in county *m* ($r_{jm} = 1$), while there are no restrictions y_{ij} related to the location of the source lake *i*. Constraint (11) sets the upper limit (i.e., budget) b_{mn} on the number of inspection stations for county *m*. Equation (12) describes the integer restrictions on the decision variables.

2.4.2. *State-level problem*

In the bi-level model, the state planner's problem is to select the set of county plans that best achieves the state planner's management objective, which is to maximize the number of risky boats that are inspected throughout the state subject to a statewide budget constraint on the number of lakes selected. To formulate the state planner's problem, we let $x^*_{imn}, \forall i \in I$, be the optimal solution (i.e., set of lakes selected for inspection stations) for county *m* and budget level *n*, obtained from the county planner's problem defined above. We let z_{mn} be a binary decision variable for whether or not the solution for budget level

n is selected by the state planner for county m. Then, we define the binary variable $v_i = \sum_{m \in M} \sum_{n \in N} x^*_{imn} z_{mn}$ for whether or not lake i is selected, where $v_i = 1$ if $x^*_{imn} z_{mn} = 1$ and $v_i = 0$ otherwise. Then, the optimization problem is:

$$\text{Max } R = \sum_{i \in I} \sum_{j \in I} w_{ij} y_{ij} \tag{13}$$

Subject to:

$$v_i = \sum_{m \in M} \sum_{n \in N} x^*_{imn} z_{mn} \quad \forall i \tag{14}$$

$$\sum_{n \in N} z_{mn} = 1 \quad \forall m \tag{15}$$

$$g_{ij} = \sum_{k \in K} f_{ik} \left(1 - f_{jk}\right) \quad \forall i, j \tag{16}$$

$$y_{ij} \le \left(v_i + v_j\right) g_{ij} \quad \forall i, j \tag{17}$$

$$\sum_{m \in M} \sum_{n \in N} b_{mn} z_{mn} \le B \tag{18}$$

$$z_{mn} \in \{0, 1\} \ \forall m, n; \ v_i \in \{0, 1\} \ \forall i; \ y_{ij} \in \{0, 1\} \ \forall i, j \tag{19}$$

Equation (13) is the objective function to choose the set of county-level plans (one for each county), represented by values of the binary decision variables, $z_{mn}, \forall m \in M, n \in N,$ and associated lakes for inspection stations, $v_i, \forall i \in I,$ to maximize the number of risky boats that are inspected throughout the state. Equation (14) sets the values of the binary lake selection variables, $v_i \forall i \in I,$ according the binary decision variables $z_{mn}, \forall m \in M, n \in N,$ for whether or not the plan for budget level n is selected for county m. Equation (15) requires that only one plan with its associated budget level can be selected for each county m. Equations (16) and (17) are similar to equations (7) and (8) for the county problem. Equation (16) is the integer counter for the number of species that may be moved via watercraft from infested lake i to uninfested lake j, and equation (17) defines the value of the 0–1 variable y_{ij} for whether at-risk boats are inspected moving from lake i to j. Equation (18) is the state-level budget constraint B, representing an upper bound on the number of inspection stations that may be allocated to the counties statewide. Equations (15) and (18) work together to require that only one plan may be selected per county (Equation (15)), and the selected plans must have budgets that in sum are less than the state-level budget constraint B (Equation (18)). Equation (19) is the integer restrictions on the decision variables.

2.5. Analysis

First, we solve the state-level model in which a state planner selects lakes for inspection stations statewide to maximize the number of risky boats inspected. We solved the state-level model with alternative levels of the budget that limits the number of lakes that may be selected for inspection stations statewide, assuming one inspection station per selected lake. Budget levels varied from zero to 100 lakes in increments of 10, 100 to 200 lakes in increments of 20, and 200 to 700 lakes in increments of 100. Each solution of the state-level model shows the optimal location of watercraft inspection stations under the given budget.

Next, we solved the bi-level model in two steps. First, we solved each county-level problem and determined a set of optimal plans for inspection station locations for the county under various levels of a budget constraint that limited the number of lakes that may be selected for inspection stations within the county. Budget levels varied from zero to a maximum equal to the number of lakes within the county with an increment of one. Second, we solved the state-level problem of selecting the set of plans (one plan for each county) that attains the state-level management objective of maximizing the number of risky boats inspected throughout the state subject to a budget constraint representing an upper bound on the number of lakes that may be selected for inspection stations statewide. The statewide budget levels were the same as for the state-level model described above: the state-level budget constraints varied from zero to 100 lakes in increments of 10, 100 to 200 lakes in increments of 20, and 200 to 700 lakes in increments of 100. Each solution of the state-level problem shows the optimal plan selected for each county and associated locations of watercraft inspection stations within the counties.

Finally, using the state-level model as a baseline, we compared the solutions of the state-level model in which a state planner selects lakes for inspection stations statewide with solutions of the bi-level model in which a state planner chooses the optimal set of county-level plans. The solutions of the state-level model and bi-level model are compared according to the number of risky boats that are inspected statewide and the number of lakes that are selected for inspection stations in each county.

We used the General Algebraic Modeling System (GAMS v27.3) to formulate and solve the optimization problems. GAMS is a high-level modeling system for mathematical programming and optimization, consisting of a language compiler and a set of integrated high-performance solvers. We used CPLEX, a solver for the mixed-integer programming problem. The problems proved to be tractable using a consumer-level laptop computer: solutions to each county problem were found in seconds on an HP840G3 Laptop running Windows 10 64-bit operating system.

3. Results

3.1. State-level model

The number of risky boats inspected increases rapidly with the number of lakes selected for inspection but with diminishing returns (Fig. 4). Almost all risky boats are inspected by selecting 400 lakes. This is unsurprising because, with 471 infested lakes, all risky boats could be inspected by selecting each of the infested lakes for inspection stations.

To illustrate how lakes selected for inspection stations are distributed among counties of Minnesota, we map the solution for a budget that allows selection of 400 lakes for inspection stations (Fig. 5). This solution inspects 725,300 risky boats, and lakes are selected in 48 of the 87 counties. The six counties with the most infested lakes (Wright, Crow Wing, Hennepin, Otter Tail, Douglas, and Carver) each have more than 20 lakes selected for inspection stations and account for almost half of the 400 selected lakes (Table 1).

Our previous work on the inspection station location problem (as represented by the state-level model in Equations (1)–(5)) has shown that a ranking and selection of lakes according to their weighted degree (i.e., a network metric based on the numbers of connecting lakes and

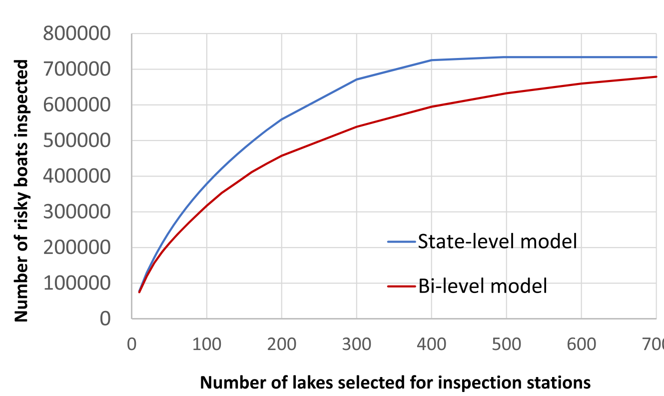

Fig. 4. Number of risky boats inspected versus number of lakes selected for inspection stations.

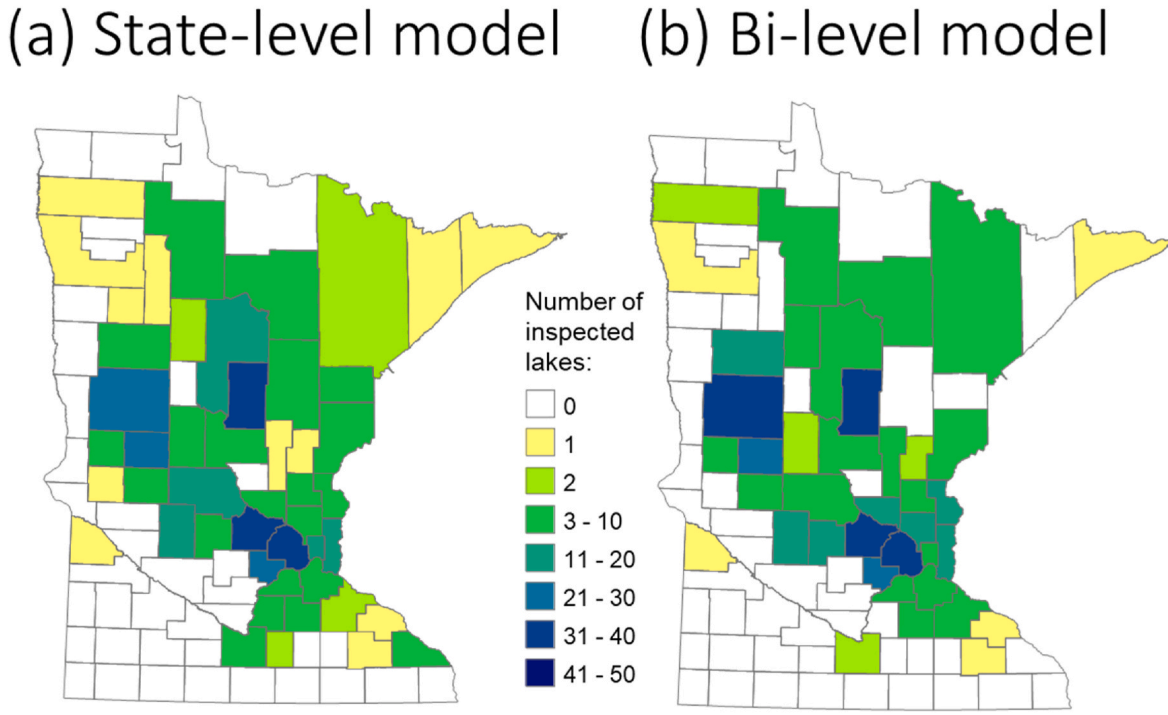

Fig. 5. Number of lakes selected for inspection stations per county in the 400-lake solution of the (a) state-level model and (b) bi-level model.

Table 1
Number of lakes selected in the top six counties of Minnesota in the 400-lake solution of the state-level model and the bi-level model.

County	Number of infested lakes	Number of lakes selected	
		State-level model	Bi-level model
Wright	41	39	38
Crow Wing	39	35	31
Hennepin	44	32	35
Otter Tail	38	30	33
Douglas	27	26	28
Carver	27	21	22

boat movements between connecting lakes) provides near-optimal solutions to the problem of maximizing the number of risky boats inspected subject to an upper bound on the number of lakes selected (Ashander et al., 2022; Kinsley et al., 2022). The optimal solutions obtained from our integer programming model are consistent with the performance of this heuristic in the sense that our optimal solutions are largely composed of lakes with the highest weighted degrees. We computed the weighted degree of each lake in Minnesota. In our case, the weighted degree is the weighted sum of the focal lake's connections to all other lakes where the weights are the numbers of risky boats that move across the connection. We found that 95% of the lakes with the highest weighted degrees were among the set of 400 lakes selected in the optimal solution obtained from the integer programming model (Equations (1)–(5)). The 5% of the top 400 lakes with highest weighted degrees that were not in the optimal solution had large numbers of incoming risky boats from infested lakes that were themselves selected for inspection stations by the optimization model. In these cases, the optimization model determined that inspection resources were more efficiently used at lakes that had lower weighted degrees but more risky boats arriving from infested lakes that had not been selected for inspection stations.

3.2. Bi-level model

The curve showing the number of risky boats inspected statewide in the solutions to the bi-level model increases with the number of lakes selected for inspection stations but lies below the curve for solutions to the state-level model (Fig. 4). The numbers of risky boats inspected in the solutions to the bi-level model are up to 20 percent less than those obtained for solutions to the state-level model. For example, the objective function value of the 400-lake solution of the bi-level problem indicates that 594,885 risky boats were inspected, which is 18 percent less than the number of risky boats inspected (725,300) for the solution to the state-level model. Further, 160 (40 percent) of the lakes that were selected in the 400-lake solution of the bi-level model were different than the lakes selected in the 400-lake solution of the state-level model.

The differences in solutions and objective function values between the bi-level and state-level models result from differences in management objectives of the two models. In the bi-level model, the county planner proposes inspection plans with alternative budget levels to meet the county-level objective of maximizing the number of risky boats inspected within the county. The optimal sets of lakes in those plans include those with the highest numbers of incoming risky boats from both inside and outside the county and outgoing risky boats to lakes within the county. Lakes in the county with high numbers of risky boats departing for uninfested lakes outside the county are of no value in the county planner's objective function and as a result tend not to be included in the optimal solution. When the state planner selects the set of county inspection plans that maximizes risky boat inspections at the state level, the optimal solution may not include inspection stations at infested lakes where many risky boats depart for uninfested lakes across county boundaries because those infested lakes have lower value from the county planner's prospective. For example, Ruth Lake in Crow Wing County is infested with zebra mussel and has 2527 outgoing risky boats. Of those outgoing risky boats, 84 percent (2,134) have destinations in uninfested lakes outside the county and 16 percent (393) have destinations inside the county. As a result, Ruth Lake is not a high priority for selection at the county level, but it is a high priority for selection in the state-level model. Using the bi-level model, the state planner may select only one plan from among the set of optimal plans for Crow Wing County, and because those plans do not include Ruth Lake (for example), the state planner cannot achieve the same level of performance as they can achieve using the state-level model, which accounts for risky boat movements and lake selection statewide regardless of the county jurisdictions.

To show how the lakes selected with the bi-level model are distributed among counties, we display the solution for a budget that allows selection of 400 lakes for inspection stations (Fig. 5). The solution to the bi-level model distributes inspection stations to 400 lakes in 38 counties, ten fewer counties than the solution of the state-level model. The numbers of lakes selected in the six counties with the most infested lakes are similar to the numbers of lakes selected in the state-level model (Table 1).

4. Discussion

We address a bi-level planning problem of how a state planner can efficiently allocate watercraft inspection resources to county managers, who in turn decide where to locate inspection stations according to their own local objectives for slowing the spread of AIS by recreational boaters. This problem is important because many states use bi-level planning to allocate resources to local organizations who design and administer local watercraft inspection plans. The strength of this bi-level model is that it allows county planners to develop plans that meet their local objectives and submit them to the state planner, who selects the best set of plans across counties to meet the statewide objective of slowing the spread of AIS while meeting the statewide budget.

The bi-level planning problem is also important because it is an example of environmental planning where political boundaries do not align with the structure of the ecological system of interest. In our case, an invasion of AIS takes place across multiple county jurisdictions where spread and damage depend on the objectives and actions of multiple county decision makers. When county planners choose prevention activities based only on damages occurring in their own jurisdictions, an externality occurs because their local strategies may underperform from a statewide perspective, leading to increased invasion of the landscape (Wilen, 2007). A state planner who determines the optimal control of a bio-invasion can internalize this diffusion externality and increase total net benefits across jurisdictions (e.g., Kovacs et al., 2014). Accordingly, we formulate and solve a state planner's model of resource allocation to evaluate the performance of solutions obtained with our bi-level model. The strengths of the state-level model are that it accounts for the movement of risky boats throughout the state, and its solutions are the best that can be achieved given the objective of maximizing the inspection of risky boats statewide.

We apply our bi-level and state-level models to analyze AIS prevention decisions for the state of Minnesota, USA. Using solutions from the state-level model as a baseline, we find that solutions of the bi-level model depart from optimal solutions of the state-level model because the county plans were developed with an objective that does not account for the transmission of AIS to waterbodies outside the county. As a result, the objective function values of bi-level solutions were 10–20 percent lower than those obtained with the state-level model. The lower performance of the solutions of the bi-level model relative to the solutions of the state-level model highlights how a state-level grant or aid program that disperses funds to local decision makers to support proposals that meet local objectives may be less efficient compared with a state-level plan designed by a state-level decision maker. The ecological significance of this underperformance is that more risky boats potentially carrying AIS propagules are moving between waterbodies statewide under the bi-level solution.

There may be social benefits of dispersing state funds for locally developed county plans, such as support from local non-government organizations, and these benefits may outweigh the costs of greater movement of risky boats and greater propagule pressure and infestation risk to the remaining uninfested lakes around the state. In this case, the bi-level model could be extended to depict a cost-sharing strategy in which a state planner allocates inspection resources to lakes statewide to supplement the resources granted to support optimal county plans. This combination of statewide and county level allocation of inspection resources might increase efficiency while maintaining the benefits of local AIS prevention initiatives.

Like other integer programming models for allocating watercraft inspection resources to slow the spread of AIS (Fischer et al., 2021; Haight et al., 2021), our models facilitate the detailed analysis of tradeoffs between management objectives and the effects of budget constraints. Further, our integer programming formulations, with thousands of lakes and millions of possible boat movements between lakes, can be solved in seconds or minutes using commercial software on consumer-level computers. This capability enables practical applications of the model at both state and county levels, although software costs and expertise to manipulate the models may limit widespread adoption by individual planners.

There are several ways to improve our formulation to more realistically fit practical AIS management. First, we define risky boats as those that move from infested to uninfested lakes. In practice, state and local planners may have different definitions of "risky" based on boat type, time of day/week/month in which movement occurs, and species of concern. We could adapt our model to handle more stratified definitions of risky boat movement if those data are collected and become available in the future. Second, we assume that the infestation status of lakes is known and that uninfested lakes each have the same likelihood of becoming infested per unit of propagule pressure. We could strengthen the model by introducing uncertainty and calculating the risk of AIS establishment as a function of environmental suitability and propagule pressure. Then, the objective function could be modified to minimize the *expected* number of newly infested lakes. Third, we assume that each lake can have a maximum of one inspection station; however, some lakes have multiple boat access points. In practice, managers select boat access points for inspection stations rather than lakes. In the best possible world where we had a list of access points for each lake and estimates of the numbers of boat movements between access points on different lakes, we could refine the bi-level model to include decision variables for locating inspectors at lake access points. Further, we could include operating costs of one or more inspection stations on each lake, depending on the number of access points, and define the resource constraint as an upper bound on operating cost. Finally, our model is a single-period formulation in the sense that it takes the sets of infested and uninfested lakes as fixed. We could strengthen the model by creating a multi-period, stochastic invasion process based on estimated AIS establishment rates as a function of environmental suitability and propagule pressure. Then, inspection station location decisions could be developed using contingencies of observed patterns of infestation over time.

It is important to note that both our bi-level and state-level models do not entirely match how AIS resource allocations are actually made in Minnesota. Under that Minnesota AIS Prevention Program, the state planner must allocate resources to counties based on the number of public water access points and parking spaces within each county (Minnesota Department of Natural Resources, 2022). County planners then have full discretion to use the funding for activities that prevent the introduction or limit the spread of AIS within the county, including watercraft inspection, boater education, and AIS surveillance. However, these quotas may not be consistent with the actual number of risky boats which may be moved between lakes nor do they account for the possible patterns of infested lakes across the state. In contrast, our bi-level model assumes that each county planner determines a set of optimal plans for inspection station locations under various budget constraints, and in the second step, the state planner selects the set of plans (i.e., one plan for each county) that attains a state-level management objective that takes into a consideration the patterns of infested lakes. The bi-level model's assumption that a state planner has discretion to select county-level watercraft inspection plans for support clearly departs from Minnesota policy. Further, our state-level model assumes that a state planner determines the optimal watercraft inspection plan by selecting lakes for inspection stations statewide. This state-level model clearly departs from Minnesota policy by leaving out county planning entirely. While our bi-level and state-level models represent hypothetical planning problems, their results can be used to inform planners about outcomes associated with changes in boat inspection resource allocation policy. Importantly, the results of our state-level model can be used as a baseline for evaluating existing state policies because solutions of the state-level model are the best that can be achieved given the data at hand and the objective of maximizing the inspection of risky boats statewide.

Credit author statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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