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AIS explorer: Prioritization for watercraft inspections-A decision-support tool for aquatic invasive species management

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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

Invasions of aquatic invasive species have caused significant economic and ecological damage to global aquatic ecosystems. Once an invasive population has established in a new habitat, eradication can be financially and logistically impossible, motivating management strategies to rely heavily upon prevention measures to reduce the introduction and spread. To be productive, on-the-ground management of aquatic invasive species requires effective decision-making surrounding the allocation of limited resources. Watercraft inspections play an important role in managing aquatic invasive species by preventing the overland transport of invasive species between waterbodies and providing education to boaters. In this study, we developed and tested an interactive web-based decision-support tool, *AIS Explorer: Prioritization for Watercraft Inspections*, to guide AIS managers in developing efficient watercraft inspection plans. The decision-support tool is informed by a network-based algorithm that maximized the number of inspected watercraft that move from AIS infested to uninfested lakes within and between counties in Minnesota, USA. It was iteratively built with stakeholder feedback, including consultations with county managers, beta-testing of the web-based application, and workshops to educate and train end-users. The co-development and implementation of data-driven decision support tools demonstrate how interdisciplinary methods can be used to connect science and management to support decision-making. The *AIS Explorer: Prioritization for Watercraft Inspections* application makes optimized research outputs accessible in multiple dynamic forms that maintain pace with discovery of new infestations and local needs. In addition, the decision support tool has supported improved and closer communication between AIS managers and researchers on this topic.

1. Introduction

Invasions of aquatic invasive species (AIS) have led to significant ecological and economic impacts across the world (Meyerson and Reaser, 2003; Perrings et al., 2005; Diagne et al., 2021). In the Laurentian Great Lakes region of North America, AIS are considered one of the most significant threats to the health of the aquatic natural resources (Escobar et al., 2018). The introduction and establishment of AIS in the Great Lakes region have resulted in displaced native species, shifting food webs, and declining water quality, leading to direct management costs to industries and tribal, federal, state, and local agencies, and the public (Strayer, 1999). In response to recent introductions, management programs have been established in the region with the objective of preventing the spread of AIS to new habitats (Vander Zanden et al., 2010).

A common prevention activity includes standardized watercraft

Abbreviations: AIS, aquatic invasive species; MN DNR, Minnesota Department of Natural Resources; ILP, integer linear programming; WIP, watercraft inspection program; PNG, portable network graphic; AWS, Amazon web services; CSV, comma-seperated values; CSS, cascading style sheets; DOW, Division of waters.

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inspections, most often administered at water access sites (e.g., boat ramps), to intercept AIS moved overland via recreational boat movement (Minnesota Department of Natural Resources). Many states conduct watercraft inspections; however, Minnesota's Watercraft Inspection Program (WIP) is one of the largest, conducting ~606,000 inspections in 2020 (Minnesota Department of Natural Resources, 2020). The goal of the WIP is to prevent the spread of AIS through inspection and decontamination efforts (Minnesota Department of Natural Resources). To accomplish this, watercraft inspectors examine water-related equipment for AIS, other aquatic plants, and residual water prior to launching at public access points across the state. In addition to active prevention, the WIP also gathers significant amounts of data through boater surveys of previous and future boating activity. These data can be used to guide future management decisions, including the prioritization for locating watercraft inspectors given limited resources.

Minnesota has capitalized on local-level efforts through the AIS Prevention Aid program, which provides $10 million per year to counties to prevent the introduction and spread of AIS, distributed based on the number of public boat ramps and parking spaces (Minnesota Department of Natural Resources, 2021). The county-level activities are determined by local AIS managers, often in consultation with other stakeholder groups, including non-profit and private organizations and state and federal government agencies. Substantial resources are spent on county-based watercraft inspection programs established through delegation agreements with the Minnesota Department of Natural Resources (MN DNR). In 2019, county-led efforts resulted in approximately 730 inspectors who performed over 385,000 inspections across 40 counties in the state (Minnesota Department of Natural Resources, 2019 a,b,c).

Due to the large number of recreational boats that move across the landscape (~880,000 registered watercraft)(Minnesota Department of Natural Resources, 2019 a,b,c) and lakes throughout Minnesota (11,842 lakes) (Minnesota Department of Natural Resources, 2016), county AIS watercraft inspection programs can be particularly difficult to manage, underscoring the need for decision support tools that transform data into information that can be easily accessed. Previous studies have focused on identifying watercraft inspection locations that maximize the number of boats inspected. For example, Fischer et al. (2021) used a linear integer programming (ILP) approach to find the optimal placement of boat inspectors for roadside inspections, considering zebra and quagga mussels (*Dreissena* spp.) as focal species. Their work expanded upon theoretical AIS management by providing solutions to operational management problems considering different budget constraints. However, the computational cost of the ILP model precludes it from being a feasible approach to exploring different scenarios through an online interactive tool. While there are many AIS online information systems in North America that record, track, and disseminate information on AIS detections (Reaser et al., 2020; Bargeron and Moorhead, 2007; NOAA; USGS; S.E.R. Center; Center) there are still only a few easy to access tools that go beyond recording and mapping AIS occurrences to support managers' decisions surrounding resource allocation (Simpson et al., 2020; U.S. Dept,; U.S. Dept, 2019; U.S. Fish & Wildlife U.S.,; University of Minnesota Natural Resources Institute Saint Louis County M. St, 2021).

Here we developed and implemented a decision support tool informed by a network-based optimization algorithm that maximizes the number of inspections that occur on watercraft that move from AIS infested to uninfested lakes. We tested the algorithm in three counties. Here we present the results of one, Crow Wing County, as a case study, comparing the network-based optimization algorithm to a traditional integer linear optimization approach and AIS managers' decision processes. The network-based optimization algorithm is available through the *Prioritization for Watercraft Inspections* application accessible on the AIS Explorer dashboard (http://www.aisexplorer.umn.edu). This paper discusses the development and testing the application and end-user training that provides Minnesota's AIS managers with a first-of-its-kind support tool for decision-making. Our quantitative approach, application development, and stakeholder engagement methods apply to other geographic locations, invasive species, and pathways in which surveillance is conducted.

2. Methods

2.1. Estimation of boat traffic

A database that included estimated boat traffic between lakes throughout Minnesota was obtained as a comma-separated values file (CSV) from the University of Minnesota Data Repository (Vander Zanden et al., 2010) and previously published by Kao et al., 2021). The estimated network was created from data collected through WIP surveys (n = 1,329,259) by the MN DNR during the open-water seasons from 2014 to 2017 (Kao et al., 2021). The database included the estimated annual number of boat movements to and from each lake greater than ten acres, recorded by its Division of Waters, Soils, and Minerals (DOW) number (Minnesota Conservation Department-Division of Waters Soils and M, 1968). Each lake was assigned to a county if its geographical boundaries were within a county. If a lake was positioned on the border of a neighboring county and had a boat ramp at which a watercraft inspector could be located, the lake was included in each of the counties' analyses.

2.2. Network-based optimization algorithm

We developed a network-based optimization algorithm (Bellingeri et al., 2019; Holme and Saramäki, 2012; Crucitti et al., 2004; Albert et al., 2000) to support the development of the decision support application in RShiny. The network-based algorithm was inspired by an ILP model (Haight et al., 2020), in which the variables of the expression were integers, and the constraints were linear (Graver, 1975). For each county selected in the application, the network-based algorithm considered estimated annual boat movements from infested to uninfested lakes, traveling into, out of, and within the selected county. The infestation status of lakes included in the analysis was based on the MN DNR infested waters list, which lists waterbodies that currently have confirmed infestations of one or more species (Minnesota Department of Natural Resources, 2019a,b,c). The algorithm was based on a weighted and directed network in which lakes were categorized as *nodes*, boat movements between the lakes, as *edges,* and the weight of each edge represented the estimated annual boat movements between lakes. The network was represented by an adjacency matrix a_{ij}. If a connection from node i to j was considered risky, meaning boats moved from an infested to an uninfested, then $a_{ij} = 1$; otherwise, $a_{ij} = 0$. The algorithm used *igraph* (Nepusz and InterJournal, 2006) and *dils* (James and Gary King, 2011) packages in R (R Core Team, 2019). Lakes involved in risky movements, as senders or receivers or both, were ranked based on their strength (weighted degree) (Wasserman and Faust, 1994), or the sum of the number of risky boats they send (out-strength) and the number of risky boats they receive (in-strength) annually (Fig. 1).

For each county, the boater network was filtered to include three types of risky boat movements: 1) those between lakes that resided in the county; 2) risky boat movements from lakes in the county to lakes outside the county; and 3) risky boat movement from lakes outside the county to lakes within the county. We defined the weight w_{ij} of an edge as the annual estimated number of boats moving from node i to j and let be the strength of node i, which is the sum of the numbers of risky boats departing node i for all nodes $j = 1, \ldots, N$, $n \neq i$ and the number of risky boats entering node i from all nodes $j = 1, \ldots, N$, $n \neq j$. The strength was expressed as

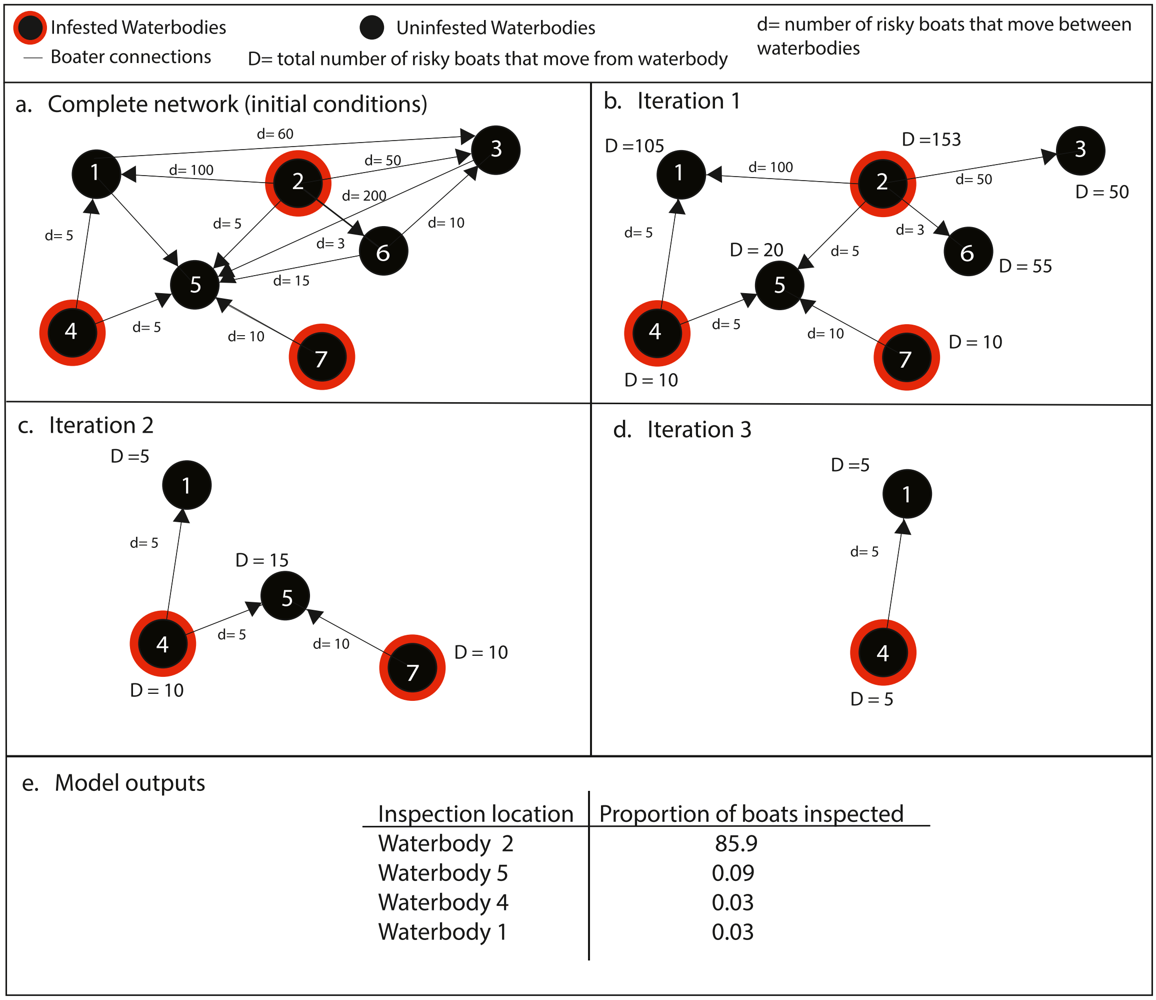

Fig. 1. Overview of the degree-based ranking algorithm considering the spread of one invasive species of interest, for simplicity. (a) The algorithm starts with a boat traffic network describing the movement of boats between waterbodies. (b) The algorithm first filters the movements to include those moving from infested to uninfested waterbodies, or the "risky boats". During the first iteration, the waterbody that is involved in sending or receiving the highest number of risky boats is selected as the top priority location for watercraft inspection. It is then removed from the network along with any waterbodies that were uninfested recipients. (c) For the second iteration, the waterbody involved in the highest number of risky boat movements is selected as the second highest priority for watercraft inspection locations. It is removed from the network. (d) The iterative process continues until eligible waterbodies no longer remain. (e) The model outputs include a list of the waterbodies in descending order and the relative proportion of boats inspected per waterbody.

$$s_i = \sum_{j=1}^{N} a_{ij}w_{ij} + \sum_{j=1}^{N} a_{ji}w_{ji}$$

The lake with the highest strength and thus the highest ranking was recorded and removed from the database (Fig. 1a–b), preventing the boats moving to and from that from being inspected multiple times. The sum of the remaining movements was calculated, and the lakes were iteratively reranked until 100% of the risky boats were removed (Fig. 1c–d). The output of the network algorithm was a list of lakes removed from the edgelist in descending order, representing the order in which inspectors could be deployed to maximize the number of risky boats that are inspected at least once (i.e., at their origin or destination lakes or both), considering that inspection resources are limited. The output also describes the proportion of risky boats inspected per location selection.

2.3. Application development

The *Optimization for Watercraft Inspections* application was developed using the RStudio Shiny package to support accessibility through a web browser without installing specialized software. The network algorithm was coded as an R script and then wrapped into an R function to handle parameters coming from the application.

2.3.1. Application design

The *Optimization for Watercraft Inspections* application was one of two related applications bundled in the AIS Explorer. Therefore, the application logic for this was kept separated using modules, a core feature of R Shiny for separating units of functionality. The network algorithm was not directly included in this module code for the application. By keeping the network algorithm decoupled from the core application logic, it was simple to make changes to the algorithm or application independently so that changes to one did not interfere with the other. This approach also made it simple to access and run the algorithm independently as required, including the automated data pre-processing feature.

JavaScript was used to extend some of the functionality of the application, and Cascading Style Sheets (CSS) was used to provide the layout and styling. The html2canvas JavaScript library was used to produce the map image export functionality. The application was built up using the following functional elements:

- **Reactivity:** Reactivity is one of the key features of the Shiny package that allows for parameters in the user interface to be dynamically adjusted by the user and automatically update the algorithm calculation or outputs as a result. There were two main phases of reactivity for this application. Reactivity for the algorithm computation controlled the input parameters to the algorithm, including the county, selected lakes, and risk species. The post-algorithm reactivity controlled the visualizations of algorithm outputs, including the percentage of boats to inspect and the choice of map/chart displayed adjacent to the output table. The algorithm outputs for each unique combination of selected county and risk species (with no lakes excluded from the analysis) were pre-calculated and cached in the application for faster access.
- **Isolation:** Whenever the network algorithm runs, there is a short wait time before the algorithm outputs are shown in the application. To minimize the effect of this waiting period, the "Run" button on the application sidebar was introduced. With this, the function wrapping the network algorithm, and the variables feeding into the algorithm, were "isolated" from their reactive behavior in this context so that the algorithm would only be triggered if the user clicked this button, instead of triggering every time the input variables to the function changed. The post-algorithm input variables were still reactive without isolation being applied, as adjusting these values simply filtered the algorithm output and did not require the network algorithm to re-run.
- **Downloadable data:** Outputs from the algorithm, including the accompanying map and chart visualizations, were available for download.
- **Default values:** On the initial launch of the application, default parameters for the algorithm are pre-selected in the user interface, the first alphabetical county, no excluded lakes, and the first risk species in the selection. The associated pre-calculated algorithm output is also retrieved for these default values.
- **Automatic updates:** The AIS Explorer stays current on its algorithm outputs using its automatic update feature that retrieves information regarding infestation status based on the DNR Infested Waters List (Minnesota Department of Natural Resources, 2019a,b,c). An automated service checks the status of the DNR Infested Waters List twice daily for changes in the data since the last update. The automated update pipeline is triggered to re-compute the dashboard outputs when a change is detected. These results are stored in an AWS S3 cloud storage bucket, which the application pulls from each night at 12 a.m. CT. This is an important feature enabled to keep the dashboard outputs relevant, especially during the summer and fall seasons, and to support managers in the face of changing conditions.
- **Hosting:** The AIS Explorer is hosted on Amazon Web Services (AWS) in the US East (Ohio, us-east-2) region, on an auto-scaling group which is managed by a load balancer (1 minimum instance, 2 maximum, 1 desired) to spin up extra capacity when CPU usage or concurrent user access is high. Each Elastic Compute Cloud (EC2) instance managed by the scaling group is created at a t2.large specification (2 vCPUs, 8 Gb Memory).

2.4. Stakeholder engagement

2.4.1. Case study-Zebra mussels in Crow Wing County, Minnesota

The application's scope and design were crafted with input from multiple groups of stakeholders, including county AIS program managers, lake association members, water resource managers, and AIS researchers. In the early development phase (2019–2020), four county AIS managers (Crow Wing, Meeker, Ramsey, and Stearns counties) were consulted regarding their program needs, decision-making process, and data collection practices. Crow Wing County was selected as a case study to compare the network-based optimization algorithm to an ILP optimization model described in detail elsewhere (Haight et al., 2020) and to current county-level decision-making.

Crow Wing County is situated in central Minnesota, approximately 100 miles north of the Twin Cities metropolitan region (Fig. 2). It has a population of over 60,000 and covers about 1,000 square miles. Aquatic natural resources play a significant role in the county's history, and its lakes have attracted many permanent and seasonal residents, and tourists. To prevent the introduction and limit the spread of AIS, Crow Wing county has developed inspection, decontamination, treatment, and education programs (Crow Wing County and No, 2019). Zebra mussels were first confirmed in the county in Ossawinnamakee and Pelican Brook in 2003 and subsequently listed as infested in 2004 (Minnesota Department of Natural Resources, 2019a,b,c). The network-based optimization algorithm and ILP comparison presented here focused on preventing the spread of zebra mussels (*Dreissena polymorpha*) using the infestation status of lakes in 2017. We applied the network-based optimization algorithm and ILP to identify the locations for watercraft inspectors to inspect the highest number of boats traveling from infested to uninfested lakes within the county, to the county's lakes from other counties, and from the county's lakes to others within Minnesota.

2.4.2. Beta testing

Early in the application development phase, stakeholders were presented with a basic Shiny version of the algorithm and were asked to provide feedback on development (Haight et al., 2019). As application development progressed to a web-accessible platform, a beta version was released to 14 stakeholders, comprised of AIS program managers, MN DNR staff, lake association members, water resource managers, and AIS researchers, to provide their direct feedback regarding design and functionality. Invited stakeholders were given password-protected access to the application and asked to provide their name, the date of the testing session, operating system, and browser details. Stakeholders were also asked to provide a description of the suggested modification with a screenshot highlighting the referenced application element. Responses to the suggestion were recorded, indicating the adoption or rejection of each suggestion and the method, or supporting reasoning.

2.4.3. Workshops and webinars

AIS Explorer was publicly released in November 2020. Following its release, workshops were held in November 2020 for county-based AIS managers. Invitations to participate in the workshops were extended to 140 AIS managers. The main goals of the workshops were to 1) provide a brief overview of the data and methods used to develop the algorithm, 2) provide training to this key user group to ensure that they were able to effectively use the online dashboard and interpret outputs for their planning purposes, and 3) solicit real-time feedback for future improvements. Likewise, webinars were provided to public audiences (i.e., www.aisdetectors.org) to ensure broad dissemination of the applications.

2.4.4. End-user survey

To provide feedback on the application, AIS managers (county government staff typically housed in water resources departments, environmental services divisions, or local Soil and Water Conservation Districts) (n = 140) were invited via email to participate in an anonymous survey in January 2021. In the survey, participants were asked about their affiliation, experience with AIS management, how they became aware of the application, and if they attended any training workshops. They were also asked about their current AIS management responsibilities, their intentions to use the application for decision-making to guide surveillance and watercraft inspection programs, and to provide feedback to support future development.

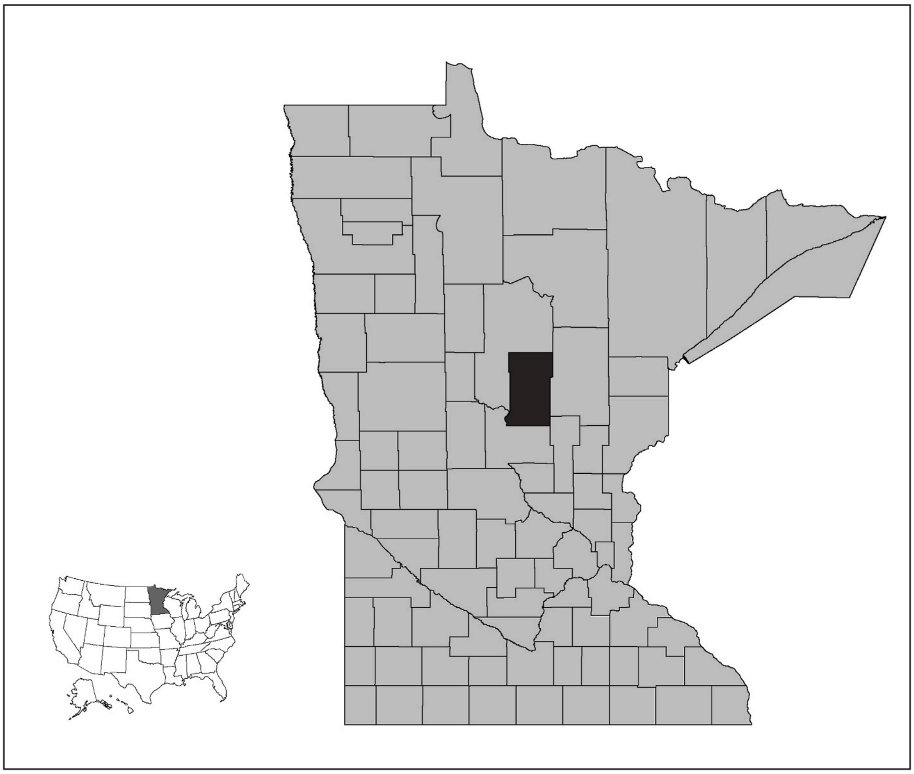

Fig. 2. Crow wing county, Minnesota.

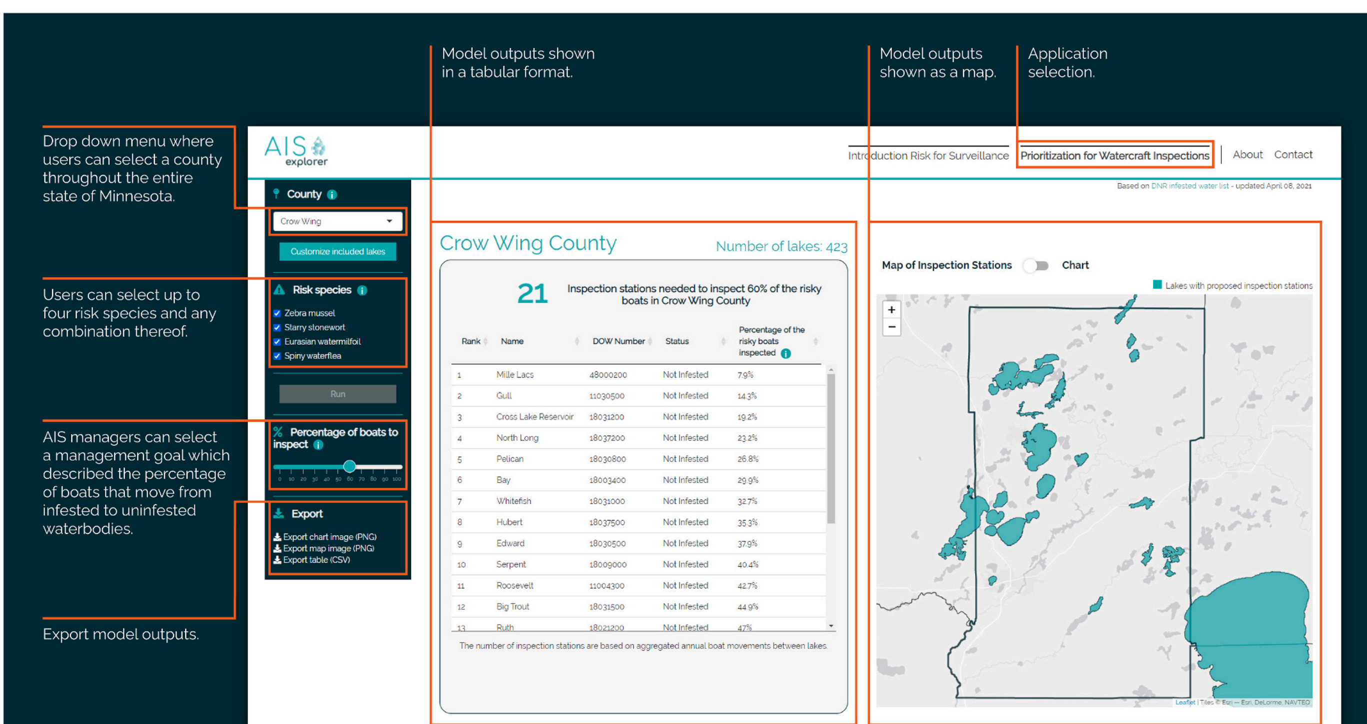

Fig. 3. Depiction of the *AIS Explorer: Prioritization for Watercraft Inspections* application. The user can select the county of interest, risk species, and percentage of boats to inspect; at the bottom of the menu, users can select to export their model outputs in the form of an image (PNG), map image (PNG), or table (CSV).

3. Results

3.1. Application overview and outputs

In the *AIS Explorer: Prioritization for Watercraft Inspection* application (www.AISExplorer.umn.edu), users can select from any of the counties in Minnesota by using a drop-down menu (Fig. 3). Users can choose from four priority AIS known to move through the recreational boating pathway (Johnson et al., 2007; Glisson et al., 2020). Those priority species include zebra mussels, Eurasian watermilfoil (*Myriophyllum spicatum*), spiny water flea (*Bythotrephes longimanus*), and starry stonewort (*Nitellopsis obtuse).* Users can select any combination of these species or can select all four. Once the species of interest are selected, the boater network is then filtered to include risky boat movements, which are boat movements from infested lakes with one or more of the selected species that move to any lake that is not known to be infested with one or more of the selected species. Each selected species is equally important in the analysis, meaning that if a user selects zebra mussels and spiny waterflea as the species of interest, then a boat that moves from a zebra mussel infested lake is considered with equal weight compared to the movement from a spiny waterflea infested lake.

Users can move a slider bar to select a management threshold to determine the number of inspection locations revealed in the tabular output (Fig. 3). This threshold and the number of inspection locations are marked by an intersecting horizontal and vertical line on the chart (Fig. 5). The user can also hover over any point along the curve to see the number of inspection stations required for inspecting the corresponding percentage of boats.

By default, the network-based optimization algorithm considers all lakes involved in risky boat movements in the selected county. However, users can customize the lakes considered in the analyses by using the "Customize included lakes" button (Fig. 4). The selection removes selected lakes from the algorithm, which is appropriate for situations in which there are no public access points, or another agency is responsible for inspections on that lake. Lakes located in multiple counties show up in each county's analysis.

In the app, the algorithm output is revealed as a table listing the locations in ranked order, with the location involved in the highest number of risky movements listed as rank 1 (Fig. 3). The table is exportable as a CSV file (Fig. 3). Outputs can also be observed on a map focused on the county of interest or as a chart that describes the number of risky boats inspected per increase in inspection locations and can help determine the point of diminishing returns (Fig. 5). The map and the chart are downloadable as a portable network graphic (PNG) (Fig. 3).

3.2. Beta testing

Formal feedback was provided by four individuals and the MN DNR as part of the beta testing, with additional early-stage feedback provided by at least six stakeholders. Feedback gathered from this exercise was critical and addressed user functionality issues, and suggested additional info buttons and editorial changes for clarity. Beta testers also identified data visualization errors that were corrected before public release.

3.3. Workshop trainings

Eight workshop sessions were held from November 16th to 20th, 2020. Each session included four to five participants and lasted approximately one and a half hours. The session included a brief overview of the data collection, algorithm development methods, and key features of the application. In total, approximately 37 AIS professionals were trained through the workshops. Most attendees were informed about the workshops through direct email invitation. A few attendees were extended invitations through word-of-mouth by other attendees. The attendees represented 32 county-level AIS programs, one tribal organization, one non-profit/lake association, one state, and one federal organization.

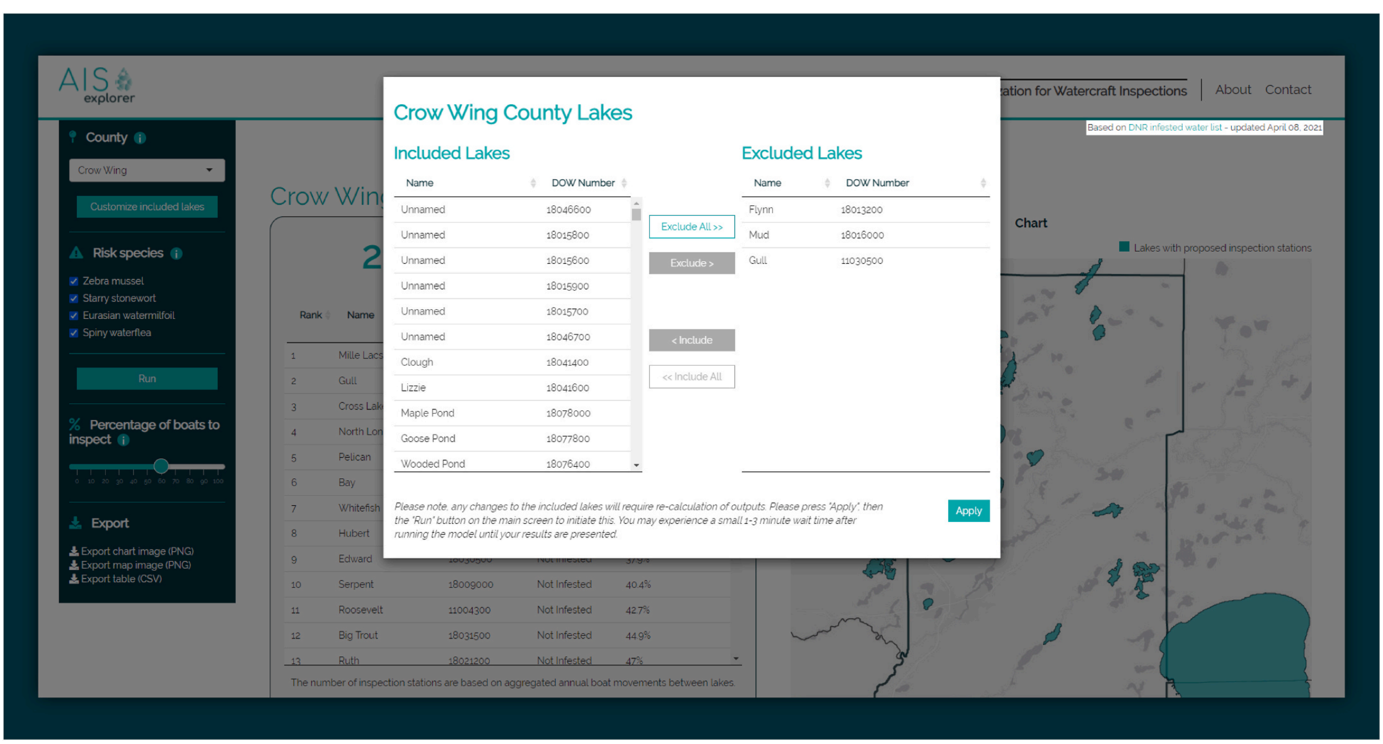

Fig. 4. View of the customizable analysis. Waterbodies can be excluded from the analysis based on lake name and unique Division of Waters Number (DOW Number).

Fig. 5. Model outputs for the *AIS Explorer: Prioritization for Watercraft Inspections* application available through the AIS Explorer dashboard (http://aisexplorer.umn.edu) shown as a table (left) and chart (right) describing the percentage of risky boats inspected by watercraft inspection station. The intersecting horizontal and vertical lines in the chart show the number of inspectors needed to meet a management goal of 60%.

3.4. Survey results

Of the 18 participants responding to the survey, 50% worked for a department within a county government, 55.6% worked for a Soil and Water Conservation District, and 11.1% were volunteers, with three participants serving in multiple roles. The average time spent working in aquatic resource management was 1.9 years (SD = 1.03). Survey participants reported hearing about AIS Explorer through a variety of sources, including local webinars (40.9%), newsletters (18.2%), websites (9.1%), and other means (31.8%). A majority of the respondents attended a workshop offered by the Minnesota Aquatic Invasive Species Center (MAISRC) staff and researchers (72.2%). Sixty-one percent of the respondents (n = 11) had the authority to make decisions surrounding AIS management, including watercraft inspections, while 17% (n = 3) had shared decision making and 11% (n = 2) served as advisors in the process. When asked to rank the likelihood of using the algorithm to inform watercraft inspection placement from 0 to 10 (with 0 representing definitely not and 10 representing definitely yes), 17 respondents revealed a mixed response with a minimum of 0, maximum of 10, and a mean of 6.16 (SD = 2.77). End-users were asked to expand on their intentions to use the application; respondents reported that the data and visualizations were key factors in their decision to use the application in their planning and that a lack of understanding regarding the data and algorithm was a barrier. These barriers highlight the importance of continued training and education surrounding the tool's use and methods, similar to the workshops.

3.5. Case study

During the study period, Crow Wing County had 27 lakes infested with zebra mussels and 132 lakes uninfested with zebra mussels. On average, 8,955 boats traveled from zebra mussel infested lakes to zebra mussel uninfested lakes per year, 22,770 boats traveled from zebra mussel infested lakes in Crow Wing County to zebra mussel to uninfested lakes out of the county within Minnesota per year, and 10,594 boats on average traveled from zebra mussel infested lakes outside of the county within Minnesota, to zebra mussel uninfested lakes in the county per year. According to the network-based optimization algorithm and the ILP, the most effective ranked solution when placing inspectors at 10 locations was six inspectors at infested lakes and four inspectors at uninfested lakes (Table 1). The inspection locations and their respective estimates of inspected risky boats were in agreement on the rankings

Table 1
Results of the network optimization algorithm and integer linear programming model for Crow Wing County, Minnesota based on 2017 infestation status. NOA= network optimization algorithm; ILP= integer linear programming model.

Rank	Lake Name	Infestation status	NOA Cumulative risky boats inspected (%)	ILP Cumulative risky boats inspected (%)
1	Mille Lacs	Infested	23	25
2	Emily	Uninfested	31	32
3	North Long	Infested	39	39
4	Pelican	Infested	44	45
5	Trout	Uninfested	48	50
6	Little Rabbit	Infested	52	53
7	Gull	Infested	56	56
8	Horseshoe	Uninfested	59	60
9	Clamshell	Uninfested	62	63
10	Cross Lake	Infested	65	66

with a two percent difference in the estimated percentage of risky boats inspected at two inspection locations, Mille Lacs and Trout.

4. Discussion

The *AIS Explorer: Prioritization for Watercraft Inspections* application is an interactive web-based interface developed as a decision-support tool for local AIS managers to support prevention activities that aim to slow the spread of AIS through the recreational boating pathway. The intuitive dashboard allows county AIS managers to select a management goal that fits their county's needs and resource availability. The decision support tool was created using a network-based optimization algorithm that allows managers to customize the boat traffic network.

Stakeholder engagement was a critical component of the *AIS Explorer: Prioritization for Watercraft Inspections* application's development, from conception to implementation. The conception of the application began with feedback from AIS county managers who identified an interest in early iterations of our approach but lacked the needed expertise to manipulate and interpret algorithm outputs. During the consultation process, current inspection placement strategies were discussed, and the network data was compared to the empirical data collected within the county. An initial algorithm was constructed using the ILP approach. Then an online platform was constructed using a network-based optimization algorithm to prioritize watercraft inspection locations using a rank and removal process based on a node's degree. When we compared the network algorithm outputs to the ILP outputs for Crow Wing County, we saw that the network-based optimization algorithm and the ILP model agreed about location selection. Minor differences in the estimates of the percentage of boats inspected were likely due to rounding that occurred within the network-based algorithm. Although counties collect their own boat traffic data and have access to the WIP survey results, the estimation of a complete network and construction of optimization algorithms (network or ILP) is challenging and time-consuming. By constructing this decision-support tool with easy-to-read tables, maps, and charts, AIS managers have the synthesized data to make efficient watercraft inspection placements, communicate their decisions to supervisors and local partners, and test different scenarios based on varying levels of inspection resources.

There are two key features of the *AIS Explorer: Prioritization for Watercraft Inspections* application that make it a unique and flexible tool, able to support operational tasks in the dynamic context of AIS infestations. The first is that the application automatically updates on an as-needed basis, incorporating any new infestations listed on the MN DNR Infested Waters list (Minnesota Department of Natural Resources, 2019a,b,c). This is important because new infestations may change a county's watercraft inspection location plan if the infestation occurs within the county or includes risky movements from an infested lake outside the county to lakes within the county. The second critical feature is the customizability of the networks. By being able to remove or add to the network, end-users can create a completely customized list of lakes. This may be of importance when AIS managers are not responsible for inspections at a particular lake or share responsibility with other agencies/organizations.

The risk of recreational boats and their equipment and residual water in the overland spread of AIS has been well established. For example, the recreational boating pathway has been associated with the spread of spiny waterflea, starry stonewort, Eurasian watermilfoil, and zebra and quagga mussels (Johnson et al., 2007; Schwartz et al., 2017; Ashander et al., 2021). Our efforts addressed this risk and to our knowledge presents the first online and publicly available quantitative tool that uses boat traffic data to support decision-making surrounding the allocation of limited resources for watercraft inspections at the county-level. Since conservation occurs in complex socioecological systems that require transparent and defensible decision making, electronic decision-support tools like *AIS Explorer: Prioritization for Watercraft Inspections* are increasingly considered components of invasive species prevention and management (Schwartz et al., 2017). The application presented here supports systematic conservation planning by identifying critical locations for action, supporting structured decision-making by identifying which actions are likely to achieve specific objectives most efficiently, and pointing to how we can best use limited resources to achieve a desired outcome.

Although we used results from a previous study to create the network algorithm and interactive dashboard, the empirical data are only an estimate of boat traffic. In the previous study, the boat traffic network was constructed based on the WIP survey in which boaters were asked to self-report their movements (Minnesota Department of Natural Resources). The previous work incorporated machine learning techniques to overcome gaps in information regarding lakes where inspectors did not gather data or were biased in their inspection effort. While the analysis revealed high sensitivity and specificity, our stakeholder survey results revealed that an understanding of the data and approach remain barriers in its incorporation in management decision making, highlighting the need for continued training and outreach. Another consideration is that we tested the performance of our network algorithm for only three of the counties in the state. For a more robust comparison of the performance of network metrics, such as betweenness and hub and authority scores, compared to ILP optimization over a broader range of conditions, we refer readers to Ashander et al. (2021). They found that a rank and remove method based on a node's strength achieved near-perfect performance relative to ILP when expanding the consideration to the majority of counties in Minnesota for a range of county-level budgets. These performance results add additional support to the use of a heuristic for finding near-optimal solutions in AIS Explorer. However, additional network-based methods directed at solving vertex cover problems, which aim to cover a certain number of edges using the fewest number of nodes (Mkrtchyan et al.), may provide additional insight on identifying near-optimal inspection station locations and should be considered in future work on this topic. Another caveat is that the unit of analysis for the network algorithm is the entire lake, rather than specific water access points, an issue raised by managers if a lake has more than one access point. This presents one example in which manager knowledge coupled with algorithm outputs is useful for lake-level decision-making.

Although the network optimization algorithm generated approximate outputs similar to those of the ILP model, there may be instances in which committing to a lower-ranked (higher priority) node may produce a less optimal solution than the selection of two high ranking (lower priority) nodes. Experience gained through the case studies suggests that this doesn't arise often and is unlikely to have a significant impact when budgets extend beyond a few locations. Despite this potential deviation from optimal, the network optimization algorithm's speed and simplicity enabled the development of the interactive decision support tool that can be produce updated algorithm outputs based on end-user modifications.

Planning and decision support tools, such as the *AIS Explorer: Prioritization for Watercraft Inspections* application, create an opportunity for research to inform practice (, sitting within the "research-implementation space" (Toomey et al., 2017) by making research outputs accessible in multiple dynamic forms that maintain pace with the discovery of new infestations which support communication between local AIS county managers and researchers. It's important to note that knowledge gained through empirical, data-driven, "evidence" is only one factor in the decision-making process (PielkeJr, 2007; Owens, 2012), and practical, social, and institutional constraints, in addition to stakeholder attitudes, beliefs, and intentions, are all critical contributions to decision-making and AIS management.

The development of this application used a collaborative and transdisciplinary approach in which stakeholder participation was facilitated through a co-production process that considered stakeholder needs and perspectives. By creating interactive decision support tools with the input and insight of the local level end-users, natural resource managers can integrate their local-level knowledge and values with technical solutions to optimize their responses and communicate their decision-making process to others. By working with multiple stakeholder groups, we were able to gain an understanding of diverse views and values and were able to develop solutions tailored to a county's specific needs. Although the decision-support tool focused on management at the county level to match the management scale in Minnesota, future updates to the dashboard will include new functionalities to foster collaboration and coordination across counties. Additionally, future work guided by end-user needs will focus on added complexity and realism with new data and provide additional spatial and temporal features.

Credit author statement

Amy C. Kinsley: Conceptualization, Writing, Methodology, Formal Analysis. **Robert G. Haight**: Conceptualization, Methodology, Formal Analysis, Writing. **Nicholas Snellgrove**: Software, Methodology, Writing. **Petra Muellner:** Conceptualization, Writing. **Ulrich Muellner:** Software, Conceptualization, Methodology, Writing. **Meg Duhr:** Resources, Investigation, Writing. **Nicholas B. D. Phelps:** Conceptualization, Supervision, Resources, Writing.

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.

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