Machine-learning predictions of annual lake-level recreational boat traffic in Minnesota

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ABSTRACT

Recreational boating provides human health and economic benefits, but can also cause harm through introductions of aquatic invasive species (AIS). Minnesota, USA, has a large number of lakes, an active boating community, and a watercraft inspection program that collects data regarding boat launches at select sites. However, there is currently no direct monitoring system that measures boating activity across the state, requiring the synthesis of boating surveys to estimate boat traffic. We addressed this challenge by predicting lake-level boating traffic for all Minnesota lakes ≥ 10 acres using an XGBoost machine learning algorithm that integrated observed boat launch data and standardized site information. We estimated an average annual launch frequency of 7.14 launches per registered boat, totaling 5.8 million annual launches during 2018 through 2023 boating seasons. During this period ~10% of Minnesota's lakes were monitored. Our model suggests that an average of 7.08% of launched boats were inspected; lakes received an annual mean of 634 boats (SD = 932), and lakes infested with aquatic invasive species received, on average, 1,120 more visits than uninfested lakes. This framework supports ongoing assessment of recreational boating pressure and provides a foundation for understanding boating patterns, invasion risk, and environmental management across large lake networks.

KEYWORDS
(7/7)

1. Aquatic invasive species prevention
2. Recreational boating
3. Boater traffic
4. Lakes
5. Machine Learning
6. Predictive modeling

LIST OF TERMINOLOGY AND ABBREVIATIONS
(alphabetical)

Term or acronym	**Definition**
AIS	Aquatic invasive species
Biofouling	An accumulation of aquatic invasive organisms or plant fragments on aquatic equipment
Boat Traffic	The number of times recreational watercraft have launched at public and private boat launches annually (e.g., annual count of launches, not including outings by shore-stored boats)
Boating season	A typical time window of suitable weather for boating in Minnesota, estimated as 178 days, from May 1 October 28
Case number	DOW-based unique public water access site (PWAS) identifier, also called the subbasin number
DOW	Division of Waters number (e.g., unique lake-level identifier)
Estimated annual traffic	The model input data, which was derived by integrating observed hourly traffic and the parking space key. Estimated lake-level boat rates were effort-adjusted and parking normalized for lakes with records of observed hourly traffic
LGU	Local Government Unit
ML	Machine learning
MN	Minnesota, USA
MN DNR	Minnesota Department of Natural Resources
Observed hourly traffic	Hourly boat inspection rate for public water access sites (PWAS). Derived from a subset of inspected PWAS using MN DNR and LGU inspection logs
Parking space key	Inventory of parking spaces for the PWAS that appeared in observed hourly traffic, keyed to standard MN case-numbers associated uniquely with each PWAS

Predicted traffic (calibrated)	The final M1 model output, calibrated to statewide plausible traffic. This is the predicted number of times recreational watercraft launched at public and private boat launches annually, in which the raw prediction was calibrated to the statewide estimated traffic across 6-years. For lakes with ≥ 1000 observation hours, the "estimated annual traffic" was retained as the calibrated output
Propagule pressure	The size and number of invasive propagules (e.g., aquatic invasive organisms or plant fragments) arriving at a waterbody
PWAS	Public water access site. A location on a public water where boats can be launched and landed by the public
Raw predicted traffic	The intermediate raw model output. The predicted number of times recreational watercraft launched at public and private boat launches annually, without any calibration
Watercraft Inspection	The practice of inspecting a boat upon entry or exit of a waterbody for the presence of AIS. May include additional boater education and decontamination by manual or hot water removal if AIS are found
WIP	Minnesota Watercraft Inspection Program

1. INTRODUCTION

Lakes and rivers provide recreational opportunities that support economies, ecosystems, and human well-being (1). Recreational boating on inland and coastal waters is a popular pastime in North America. Among Americans ≥6 years of age, 47.3 million participated in motorized boating in 2021, with millions more participating in human-powered boating (2). However, a high volume of recreational boats can cause ecological disturbances (3–5), diminish the experiences of other recreators and bystanders (6), and lead to conflicts and unintended consequences (7). Some drivers of recreational activity are understood; perceived quality and safety of the natural environment, availability of recreational infrastructure, and remoteness (8,9). However, uncertainty and gaps remain in understanding how these factors translate into spatial and temporal patterns of recreational boat traffic (1).

Recreational boats have been identified as one of the highest-risk pathways for the overland spread of aquatic invasive species (AIS) (Johnson et al. 2001; Kauano et al. 2017; Kinsley et al. 2024a) (10–12). Zebra mussels (*Dreissena polymorpha*), spiny waterflea (*Bythotrephes longimanus*), and starry stonewort (*Nitellopsis obtusa*) have spread through recreational boater pathways, causing ecological changes that threaten native species and damage infrastructure. Many states mitigate AIS risk through watercraft inspection and decontamination programs (13) that are viewed as essential and effective efforts to prevent the spread of AIS into new locations. However, the success of such programs depends on understanding when and where boats move across the landscape, highlighting the need for accurate, up-to-date estimates of recreational boating traffic.

Managing AIS is a key challenge in the midwestern state of Minnesota, USA, due to its strong recreational boating culture, with over 800,000 registered boats potentially operating on more than 10,000 lakes (14). Minnesota's primary strategy for mitigating AIS risk is through the Minnesota Watercraft Inspection Program (WIP), a statewide collaboration between the Minnesota Department of Natural Resources (MN DNR) and local government units (LGUs) that deploy watercraft inspectors to ~700 lakes each boating season (15). The program is remarkably robust relative to other states (400,000+ inspections annually; 15), but high WIP demand coupled with limited program funding necessitates site prioritization and leaves spatial and temporal gaps in inspections. The allocation of limited AIS prevention resources often relies on boating traffic estimates as a proxy for introduction risk; yet, available estimates are frequently incomplete, outdated, or difficult to access (1,16).

Despite high adoption and demonstrated effectiveness of prevention practices, the recreational boater pathway remains a potential source of AIS spread (14). Over 95% of boaters are reported to follow AIS prevention recommendations (14), and prevention practices are between 56.4% and 84.4% effective in empirical tests (17). However, the continued emergence of new invasions, particularly in lakes with high boating activity, indicates that the residual risk along this pathway persists. Previous work developed a statewide recreational boater network to characterize relative movement among Minnesota lakes (18). However, comprehensive estimates of boat traffic, particularly for sites unmonitored by WIP, are not available. We addressed this gap in knowledge of boating traffic patterns by (1) developing a framework for ongoing estimation of lake-level recreational boating pressure from fragmented monitoring data, and (2) predicting lake-level traffic and calibrating against independent measures of statewide boating activity, incorporating recent WIP data and detailed, within-lake launch information.

2. METHODS

2.1 Overview

We fit an XGBoost regression model to annual estimates of boat traffic for Minnesota lakes (≥ 10 acres; Kao et al. (2021). Annual boat traffic was estimated using inspection data collected through the Minnesota Watercraft Inspection Program (WIP) during the boating season (May 1 to October 28) from 2018 to 2023 (n = 286 lakes). During inspections at public water access sites (PWAS), boats entering and/or exiting the waterbody were examined for AIS, boaters completed a survey, and these data were recorded in a statewide database. We accounted for variability in the effort and spatial distribution of WIP inspectors across PWAS by extrapolating lake-level boat traffic from observed counts at inspected PWAS using parking capacity as a proxy for relative use across sites.

2.2 Lake inclusion criteria

Lakes were included if they appeared in the MN DNR Hydrography Dataset (19), had an 8-digit Division of Waters (DOW) number, were ≥ 10 acres, and met at least one of the following conditions:

1) The lake was included in previous statewide estimates (18), or
2) The lake was confirmed as infested with zebra mussels, starry stonewort, or Eurasian watermilfoil according to the MN DNR Infested Waters List as of February 2024 (20). These AIS are established in MN (20) and known to be translocated through the boater pathway (10,21,22).

2.3 Traffic estimate

Observed hourly traffic

The MN DNR and LGUs independently define WIP implementation details, including schedules, locations, and prioritization. The WIP aims to prevent AIS spread through watercraft inspection, boater education, and hot water decontamination at PWAS. The location and duration of inspection shifts at PWAS (i.e., effort) varied across lakes and, where applicable, across multiple PWAS on the same lake. Consequently, inspection counts required adjustment to account for unequal effort.

Detailed PWAS-level hourly watercraft inspection logs were obtained from MN DNR and five LGUs: Cass, Hennepin, Hubbard, and Ramsey Counties, and the Washington Conservation District (WCD). The LGU reports either contained inspections-per-hour (as was the case for WCD) or sufficient detail to calculate this metric for a subset of lakes. The MN DNR data included hours only and not inspection counts; therefore, inspections per hour were derived by integrating these data with WIP records. We assumed that MN DNR and LGUs did not concurrently inspect the same PWAS on the same day. Accordingly, all inspections recorded on days attributed to MN DNR were allocated to corresponding MN DNR inspection hours. We included only instances with at least one recorded boat inspection and dates within the defined boating season.

Parking space key

We used the number of boat-trailer-accessible parking spaces (hereafter “parking spaces”) as a proxy for relative PWAS popularity on the same lake. This method is consistent with local precedent for allocating prevention funding at the county-level (23). We cross-referenced PWAS names from the Minnesota Public Water Access database (24) with those used in MN DNR and LGU inspection logs. Additional verification was needed because name standardization was inconsistent across databases, and some sites were identified only by vague geographic markers (e.g., "East," "Dam," or "Campground"). An index linking a subset of case numbers to non-standardized PWAS names supplied by the MN DNR served as an additional reference.

When name matching was inconclusive, we used Google Maps (accessed 20 December 2024) to align PWAS names across databases using geographic markers. In the remaining inconclusive cases, we employed a logic-based matching strategy, assuming higher parking capacity corresponded to higher observed hourly boat inspection rates and matched the remaining sites in descending order.

Normalized traffic estimate

We accounted for variable popularity across multiple PWAS on the same lake by integrating the observed hourly traffic with the parking space key. We calculated the mean hourly traffic at each observed PWAS and normalized it by the number of parking spaces to obtain a rate of boats per hour per parking space. This rate was then applied to the total number of trailer parking spaces to estimate lake-level hourly traffic. We extrapolated from hourly to annual traffic by multiplying the lake-level hourly traffic estimate by 12 active hours per day and 178 boating days per season (18). The result under this "parking space assumption" was a parking-normalized, effort-adjusted mean annual traffic estimate for each lake with at least 10 mean inspection hours across observed seasons. Cases with recorded inspection hours and boat counts but 0 PWAS were treated as though they had 1 PWAS and 1 parking space for the purposes of estimating annual traffic. These lakes were inspected at private or unofficial access-sites that were not indicated in the Public Water Access database.

The effect of accounting for variable PWAS popularity was evaluated by calculating an alternative simplified "PWAS assumption" estimate. For this alternative assumption, the mean traffic across observed PWAS was multiplied by the number of PWAS on the lake, assuming that observed PWAS represent traffic at all PWAS on the lake. This calculation was used only to assess the impact of the "parking space assumption" and was not used in downstream modeling.

2.4 Traffic model

Lake attributes

Predictive model feature variables are described in Supplemental Table S1; these included lake attributes related to physical characteristics, accessibility, and surrounding human activity (18). Spatial features were drawn from the Minnesota Hydrography Dataset (19)and supplemented with Public Waters and Basin Delineations (25)when missing.

Predicting lake-level traffic

We implemented an XGBoost regression algorithm (26) using the caret package (27) to predict annual lake-level traffic for all MN lakes ≥ 10 acres. The model was tuned to the estimated annual traffic data using lake attributes as predictive feature variables. We explored a range of hyperparameters (Supplemental Table S2) to select optimal values by running 20 iterations with 90% of the data for training and 10% for testing. Internal 5-fold cross-validation selected the best model based on the lowest mean absolute error (MAE). The best iteration out of 20 was selected using a combination of qualitative and quantitative criteria:

1) Key lakes: Top-ranked lakes aligned with known high-use lakes (18),

2) Traffic distribution: The distribution of traffic predictions was consistent with the shape of the estimated annual traffic distribution and contained few extreme values, and
3) Access and infestation status consistency: All or nearly all zero-traffic lakes lacked PWAS and were not infested with AIS.

We retained the hyperparameter combination from the best iteration and trained 100 replicates on 90% of the data for training and 10% for testing. We predicted lake-level traffic using each final model, resulting in 100 traffic prediction replicates for each lake. Predicted annual boater traffic was then calibrated and averaged as follows.

Prediction calibration with statewide traffic estimate

We calculated a statewide boat traffic estimate to validate and calibrate the predicted traffic. Launch frequencies reported in the 2020 MN DNR Recreational Boating Study (28) and Historical Registration Information (29) were used to estimate the total number of boat launches that occurred at private and public water access sites in 2020 (Supplemental Table S3). Assuming that 2020 was atypical due to disruptions and restrictions related to the COVID-19 pandemic, we calculated the percent change in inspections, relative to 2020, for lakes with reported observation hours in all six years of DNR & LGU hourly WIP data. We calculated the estimated annual traffic for each year by applying the percent change to the 2020 launch frequency and used the mean of all six years for our statewide traffic estimate (Supplemental Table S4).

We implemented a post hoc calibration approach under assumptions about total statewide traffic and the treatment of high-effort lakes (n = 20). This calibration preserved the characteristics we previously established to meet plausibility criteria: relative lake rankings, overall distribution of traffic (Supplemental Figure S1), and low predicted use for lakes uninfested with AIS and with no PWAS (Supplemental Table S5).

We calibrated the predictions by applying a universal scaling factor to all lake-level predictions with one key exception; we retained the effort-adjusted estimated traffic for lakes with ≥ 1000 mean inspection hours as we had high confidence in the estimated annual traffic for these highly observed lakes. We preserved the annual statewide traffic estimate by removing high-confidence lakes' traffic prior to calibration and adding it afterward. Reported values reflect the mean traffic prediction for each lake across 100 calibrated replicates.

2.5 Analyses

Using calibrated traffic predictions across all modeled lakes, differences in predicted traffic between infested and uninfested lakes were evaluated using the Wilcoxon rank sum nonparametric test implemented with the mosaic package (30). Statistics, visualizations, and data preparation were performed using R statistical software version 4.5.1 (31).

3. RESULTS

3.1 Estimated traffic

Reconciliation of MN DNR and LGU hourly WIP logs identified 448 individual PWAS across 334 lakes with records of inspection hours in any year from 2018 to 2023. The parking space key aligned boat-trailer-accessible parking space counts to these PWAS (Supplemental Table S6). After removing PWAS with zero-boat entries (29 PWAS and 21 lakes removed), 419 PWAS across 313 lakes with at least one recorded boat remained. Each of these remaining lakes had between 0 and 24 PWAS (mean = 2.08; SD = 2.72), of which a range of 1 to 8.5 (mean = 1.23; SD = 0.79) PWAS had recorded inspection hours in any year from 2018 to 2023. Each of the 419 PWAS with recorded inspection hours had between 0 and 107 (mean = 15.45; SD = 12.91) parking spaces, and the lake-wide parking spaces were between 0 and 326 (mean = 23.96; SD = 38.67). Boat traffic per PWAS, with recorded inspection hours and at least 1 boat, was between 0.02 and 8.43 (mean = 1.48; SD = 1.18) boats-per-PWAS-per-hour. When adjusted for the number of observed parking spaces, the estimated traffic across lakes ranged from 0.003 to 4.98 boats-per-parking-space-per-hour (mean = 0.18; SD = 0.38).

Using the “parking space assumption” instead of the “PWAS assumption” resulted in estimated traffic differences for 184 lakes cumulatively ranging from 117,119 fewer boats to 10,624 more boats (mean = 3,006 fewer; SD = 9,174) for “parking space assumption” estimates (Figure 1). The “parking space assumption” estimate ranged from 83 to 54,503 boats (mean = 4,669; SD = 5,872), while the “PWAS assumption” estimate ranged from 83 to 171,622 (mean = 7,675; SD = 14,354).

Fig 1 Comparison of estimated annual boater traffic for Minnesota lakes during boating seasons 2018 through 2023 under two alternative assumptions: traffic estimated with the number of public water access sites (PWAS assumption; x), and traffic estimated with the number of parking spaces (parking space assumption; y). The red line references a 1:1 relationship, demonstrating estimated annual traffic for lakes with a single PWAS.

Upon 6-year aggregation, lakes with fewer than 10 mean annual inspection hours were excluded, assuming these to be low-confidence estimates (27 lakes removed). This left 286 lakes that met the minimum observation threshold and were used to fit the traffic model. Estimated annual traffic for these lakes ranged from 83 to 54,503 boats (mean = 4,882; SD = 5,969).

3.2 Predicted traffic

Hyperparameter selection

From 20 iterations of XGBoost with variable hyperparameters, we selected the iteration that most closely met plausibility criteria (see iteration 13 in Supplementary Table S2). The distribution was right-skewed; top-ranked lakes aligned with top-ranked lakes predicted by Kao et al. (2021), and there were zero lakes with zero predicted boats (Supplementary Table S2).

Statewide traffic

Registered boats were estimated to launch an average of 7.14 times (SD 0.51; Supplemental Table S4) annually in Minnesota during boating seasons 2018 to 2023. Of the estimated 5,855,048 (SD = 411,192) boats launched at public and private water access sites, an average of 7.08% (414,277; SD = 46,627) were inspected by the WIP program annually. These inspections took place at between 673 and 704 lakes, depending on the year (Supplementary Table S7).

Predicted traffic

From 100 XGBoost replicates with fixed hyperparameters (Supplementary Table S1), the mean raw prediction was 1,655 (SD = 1,387) annual boats per lake, ranging from 485 to 36,010 boats per lake and 15,276,891 total boats launched annually. After calibrating the model predictions with plausible statewide traffic, the final predicted traffic was, on average, 634 boats (SD = 932) per lake annually, with a median of 471, a minimum of 171, and a maximum of 54,503 (Figure 2). The correlation between observed and predicted annual boats was 0.91 for the raw prediction and 0.83 for the calibrated prediction (Figure 2). A full prediction table for all 9,233 lakes accompanies this text in Supplementary Table S5. The ten lakes with the highest predicted traffic account for 204,556 annual launched boats, which is 3.53% of predicted traffic (Table 1). A heatmap showing spatially explicit traffic distribution is shown in Figure 3.

Table 1. Top 10 lakes with highest predicted recreational boat traffic in Minnesota boating seasons 2018 through 2023.

Traffic rank	DOW	Lake name	County name	Annual traffic (boats)	Percent of statewide annual traffic
1	27013300	Minnetonka	Hennepin County	54,503	0.93 %
2	11020300	Leech	Cass County	39,292	0.67 %
3	48000200	Mille Lacs	Mille Lacs County	26,171	0.45 %
4	11030500	Gull	Cass County	23,316	0.40 %
5	69069400	Rainy	Saint Louis County	11,319	0.19 %
6	69037800	Vermilion	Saint Louis County	11,070	0.19 %
7	16000100	Superior	Cook County	10,751	0.19 %
8	69084500	Kabetogama	Saint Louis County	9,714	0.18 %
9	31053200	Pokegama	Itasca County	9,243	0.17 %
10	69022400	Lac La Croix	Saint Louis County	9,177	0.16 %

Fig 2 Comparison between mean estimated (x) and mean predicted (y) annual boats for raw and calibrated predictions for Minnesota lakes (n = 286) with reported inspection hours during boating season 2018 through 2023. The correlation between estimated and predicted annual boats was 0.91 for the raw model and 0.83 for the calibrated model. The estimate was retained through the calibration step for 20 lakes with high (≥ 1,000) mean inspection hours.

Fig 3 Spatial distribution heat map of mean predicted annual boater traffic for lakes (n = 9,233) in Minnesota during boating seasons 2018 through 2023. Warmer colors signify higher predicted traffic.

The most frequent top predictors of annual boat traffic, summarized from 10 replicates randomly selected from 100, were terms related to lake area, county population size, PWAS per acre, and distance to the nearest highway (Figure 4). Accessibility by PWAS and infestation status alone were consistently of low importance, but predictors that included infested status in combination with other variables (e.g., infest_x_log_acre, infest_x_log_pop) were moderately important to the prediction (Figure 4; Supplementary Table S1).

Fig 4 Important feature variables for annual boater traffic predictions for Minnesota lakes during boating seasons 2018 through 2023, generated using the XGBoost algorithm. Warmer colors were more important for the model predictions, and these trends were consistent across 100 iterations. See Supplementary Table S1 for feature variable definitions.

Inspected lakes (n = 910 inspected in any year 2018 to 2023) made up 9.86% of all modeled lakes and accounted for 1,379,682 predicted annual boats launched (23.50% of predicted boat traffic). Given that we estimate 7.08% of boats are inspected as part of the current WIP, and 23.50% of boats launch at inspected lakes, 16.42% (n=961,398) of boats launch uninspected at lakes identified as priorities for inspection.

Infested lakes had ~3x higher mean and ~2x higher median predicted traffic than uninfested lakes (Figure 5; Wilcoxon rank sum test with continuity correction, W = 586,710, p-value < 0.001). Infested lakes had a mean traffic of 1,681 (SD = 3,215) and 1,100 median (n = 603), compared to uninfested lakes' mean traffic of 561 (SD = 357) and 464 median (n = 8,630). This is 1,120 more boats, on average, per infested lake annually.

Fig 5 Predicted annual boater traffic for Minnesota lakes infested with aquatic invasive species known to be transmitted through the boater pathway (zebra mussels, starry stonewort, or Eurasian watermilfoil; n = 603) and uninfested lakes (n = 8,630) during boating seasons 2018 through 2023.

4. DISCUSSION

Recreational boating is a primary pathway for AIS spread (10,12,32), and estimates of lake-level boating traffic are needed to guide research and management. We developed a framework that combined fragmented monitoring data and independent statewide traffic information to predict lake-level boater traffic that can support decision-making. Applying this framework to Minnesota produced predictions that were consistent with ecological expectations; AIS-infested lakes received higher traffic on average than those without infestations. The majority of boater traffic was concentrated among relatively few lakes and >93% of lakes were predicted to be visited by <1,000 boats per year. This approach advances Minnesota's AIS decision-support tools with up-to-date boat traffic predictions that are anchored in contextually relevant, real-world site information and user activity.

Estimation of PWAS-level boat-traffic rates was necessary because observed PWAS had non-random inspection effort, lakes with multiple PWAS rarely had all sites observed, and PWAS popularity is known to vary on the same lake (Supplemental Figure S2). In Minnesota, the number of boat-trailer-accessible parking spaces at PWAS is one of the criteria used to allocate Minnesota's $10 million annual AIS Prevention Aid to counties as a proxy of risk (23,33). While independent data are not available to validate PWAS-level estimates, by allowing variability among PWAS on the same lake, our estimates are consistent with realistic patterns of use, and we avoid the unrealistic assumption that all PWAS on the same lake receive equal traffic. Our approach assumes that PWAS traffic is constrained by available parking, which has exceptions. In some cases, the formally recognized trailer-accessible parking fails to represent overflow parking, such as informal spaces along the roadside, that could increase boat traffic capacity. Nevertheless, we consider this approach to be a reasonable, replicable approximation of traffic, which can be updated as more representative data are available. Using weighted parking spaces as a proxy for variable PWAS popularity incorporates relevant details that were not addressed in the previous model.

Our annual statewide launch estimate is consistent with other regional estimates. For example, the U.S. Coast Guard's 2018 exposure survey reported that, in Minnesota, 239,000 boats (57.5% of operated boats) were launched an average of 25 times for a total of 5.98 million boat launches (2). We assume the remaining 42.5% would be resident boats on a single lake. While our estimate linked launch frequency to registrations and not the percentage of boats operated, our findings are similar. Although registration data do not perfectly reflect boating activity, they provide a stable and reproducible basis for estimating changes in launch rates over time. Our approach allowed us to generate an independent statewide estimate that can be adjusted for annual variation without requiring additional surveys and boat operation rate inference. The resulting frequency falls within the same general range as other studies that used operated boat counts, suggesting that our approach is a reasonable and practical proxy for estimating statewide boating activity.

The utility of boater traffic predictions extends beyond AIS risk assessment, with implications and applications for ecology, economics, public health and safety, and human well-being. The U.S. Coast Guard, for example, uses boating activity data to estimate exposure risk, calculate boating accident statistics, and update safety plans (2). Fisheries management uses recreational (creel) surveys to estimate fishing pressure and inform harvest limits, develop regulations, and guide management decisions (34). Natural resource managers estimate visitation to public water access sites to prioritize AIS management plans and evaluate infrastructural capacity and facility needs (28). Most estimates, however, do not fully reflect the pattern of recreational boat traffic because they are not directly observed and rely on irregular or limited observational and survey data, leaving gaps in undersampled locations. Consequently, traffic trends can be missed or misinterpreted, even though the effective management of many recreational resources depends on accurate estimates. Continued research could evaluate our traffic predictions with other historically established approaches, such as creel-based estimates of fishing effort.

A major challenge in this study was sampling bias within the WIP data because inspection sites are chosen based on local and state management objectives, rather than a random or representative design. Our estimated hourly traffic shows evidence of the targeted prevention strategies that drive WIP coverage: 70.3% of lakes with estimated hourly traffic were infested with AIS, compared to 6.5% of modeled lakes. Our modeling approach aimed to address the observation bias through predictive machine learning and post hoc validation and calibration; however, predictions should be interpreted with this potential bias in mind. Low-traffic lakes that are rarely or never inspected were not well represented in our data; therefore, there is uncertainty in their traffic prediction. Predictions in these cases are best leveraged in combination with local-level knowledge. Additionally, sampled lakes varied across years, limiting the temporal resolution of model input data. Alternative methods would be needed to explore inter-year variability, such as refining our boat registration-based statewide plausible traffic estimate to a finer resolution and integrating it with boater connectivity patterns from the WIP data. We were unable to predict traffic at the PWAS-level, though this could be useful for local-level prioritization and resource allocation. Of the 1,491 lakes that were accessible by PWAS, 253 (17%) have more than one PWAS. Modeling at the access-site resolution would require more spatially granular observations than were available. Despite data limitations, we are confident that our lake-level predictions contribute a useful representation of boater traffic patterns. Future research should explore boat type within the context of lake popularity and movement patterns to identify subnetworks (e.g., certain boat types use certain lake types), risk factors (e.g., certain boat types are high risk for translocating AIS), and recreational pressure (e.g., fishing boats vs. ski boats) to better inform lake management. However, we expect that sampled lakes underrepresented car-top and non-trailered watercraft because paddlecrafts (e.g., canoes, kayaks) do not require officially designated landing facilities, so can be launched at rarely inspected car-top only PWAS or along shorelines. Thus, their contributions to overall traffic pressures are likely underestimated, a bias that is consistent with other (e.g., New York) watercraft inspection program data (35,36). Predicted boat traffic is a proxy for potential AIS exposure but does not explicitly describe AIS risk. Although boats are a primary risk pathway, boat pressure itself does not capture all pathways and the riskiness of those boats. For example: boat-type and user behavior (37–39); hydrologic connectivity (32); alternative vectors such as private exchange of aquatic equipment, i.e., docks and lifts (40); AIS propagule translocation by wildlife (41); spatial distribution of species and habitat features (42,43); habitat suitability (44); the amount of off-water time between launch events (10); species survival rates (21,22); and intervention effectiveness (17) are among important factors that should be considered, in combination with boat traffic, to understand AIS risk.

The 9,233 lakes that were included in our model were selected to maintain continuity with similar models and relevance for recreational boating and AIS introduction risk. Future studies expanding lake traffic prediction beyond Minnesota may struggle to align lakes across multistate or national databases. Within-state resolution may be a cost of up-scaling, where some lakes may be excluded from the models of larger areas. For example, the DOW and case-number assigning systems are Minnesota-specific, whereas other states have their own unique public waters inventories and categorization systems, and national efforts (e.g., North American Lake and Geoinformatic Observing System; LAGOS) have yet to fully harmonize with local identifiers. Additionally, there is a nationally available database of public and private PWAS (45), but it contains no information on parking spaces or boat traffic. Approaches to modeling lake traffic across geographic and regulatory boundaries will likely encounter issues with missing locales if trying to address both long-distance spread dynamics and local-level management needs. Future studies could explore hybrid approaches by integrating state-based and interregional lake databases, addressing regional approaches and local gaps in AIS management (14,46).

Kao et al. (2021) addressed the challenge of allocating limited resources by using WIP data from 2014 to 2017 to develop a connection network that simulates boat movements between lakes in Minnesota. The foundational study opened several lines of inquiry that have contributed to AIS management in Minnesota by enhancing our understanding of invasion risk (32), developing approaches to optimize and evaluate cost-benefit scenarios for intervention plans (47,48), identifying potential collaboration networks of LGUs (11), and guiding management decisions through publicly available tools (48,49). Our predictions provide comprehensive traffic values beyond those historically sampled and reduce the data gap by incorporating statewide baselines and variable PWAS traffic. Kao et al. (2021) integrated their traffic predictions as a foundation for a predictive boater network implemented through an interactive AIS decision-support dashboard, i.e., www.aisexplorer.umn.edu. Updating Minnesota's boater network with our new traffic predictions to keep management tools current is our next step. The utility and value of our traffic predictions reach beyond immediate AIS risk assessment applications. Traffic predictions can inform decision-making for policy and research in ecology, public health, safety, and human well-being. Our work offers an approach that can be adapted and applied to similar natural resource management challenges beyond Minnesota.

AI DECLARATION

During the preparation of this work, the author(s) used ChatGPT Version 1.2025.224 to improve code efficiency, troubleshoot coding errors, and assist with structuring and organizing text. All content generated using this tool was subsequently reviewed and edited by the author(s), who take full responsibility for the final content of the publication.

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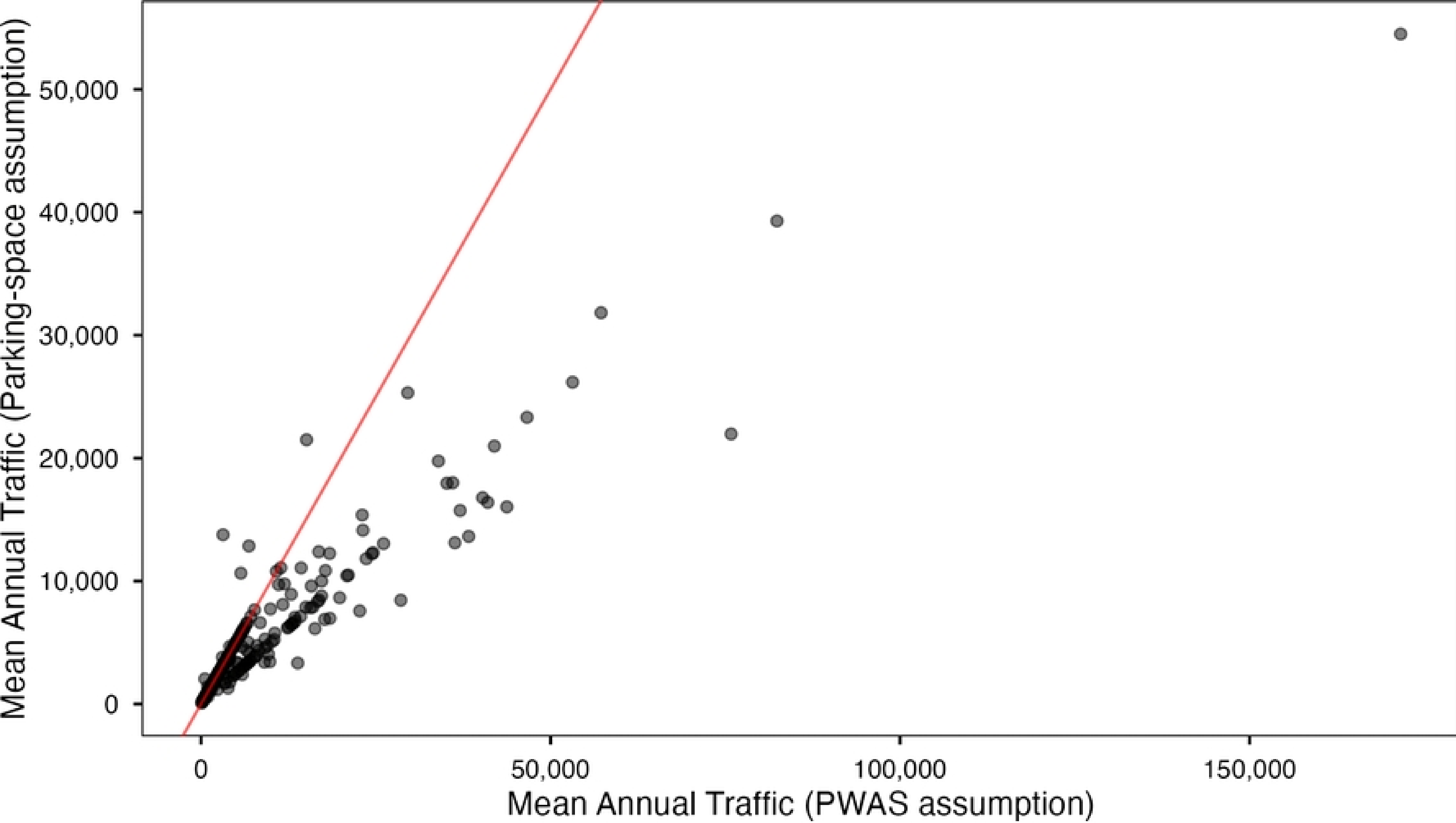
SUPPLEMENTAL INFORMATION (under curation)

Final supplemental information will be available through the Data Repository of the University of Minnesota, https://hdl.handle.net/11299/280750.



Mean Annual Traffic (Parking-space assumption)
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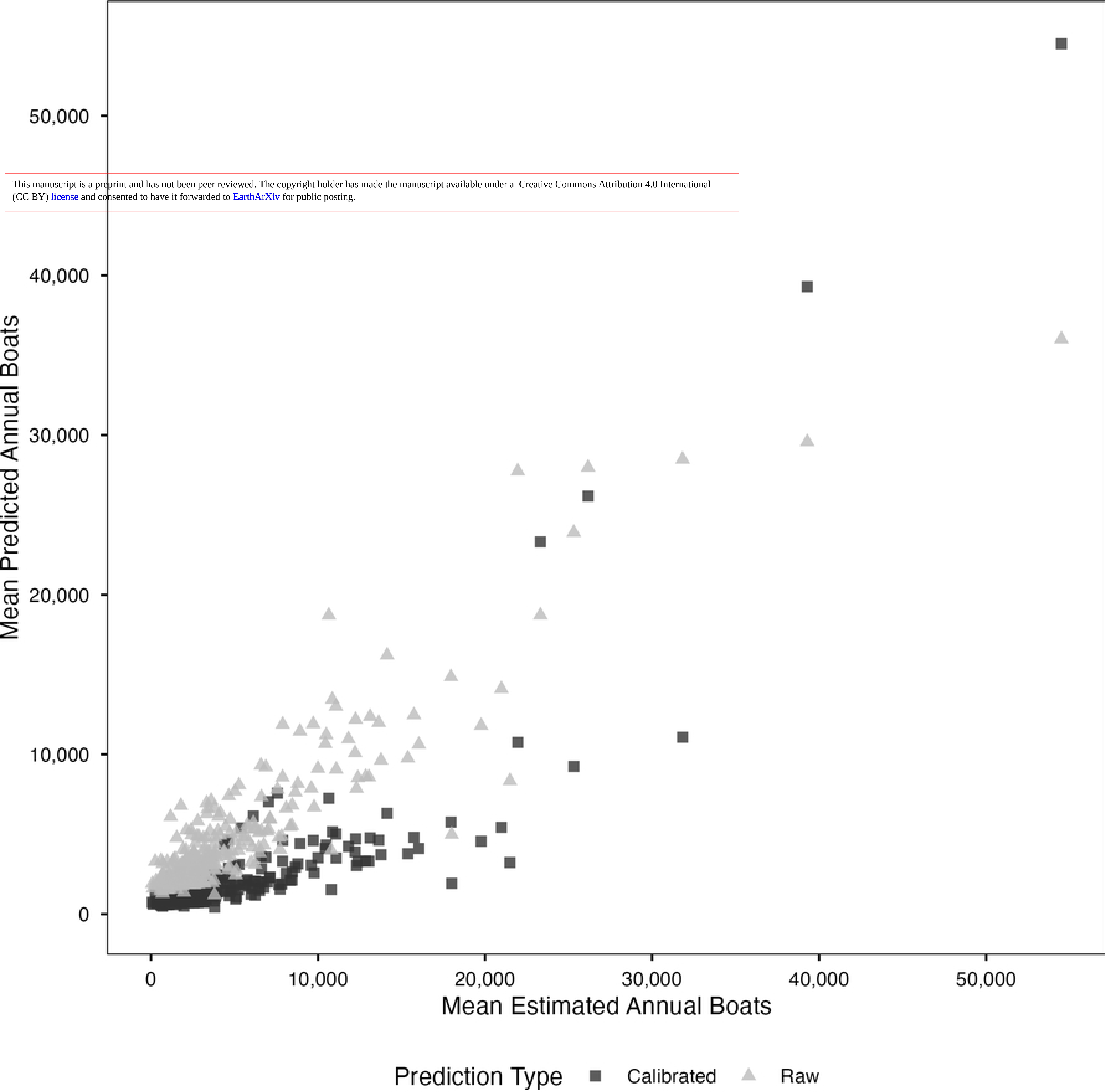
Mean Annual Traffic (PWAS assumption)

Figure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Prediction Type
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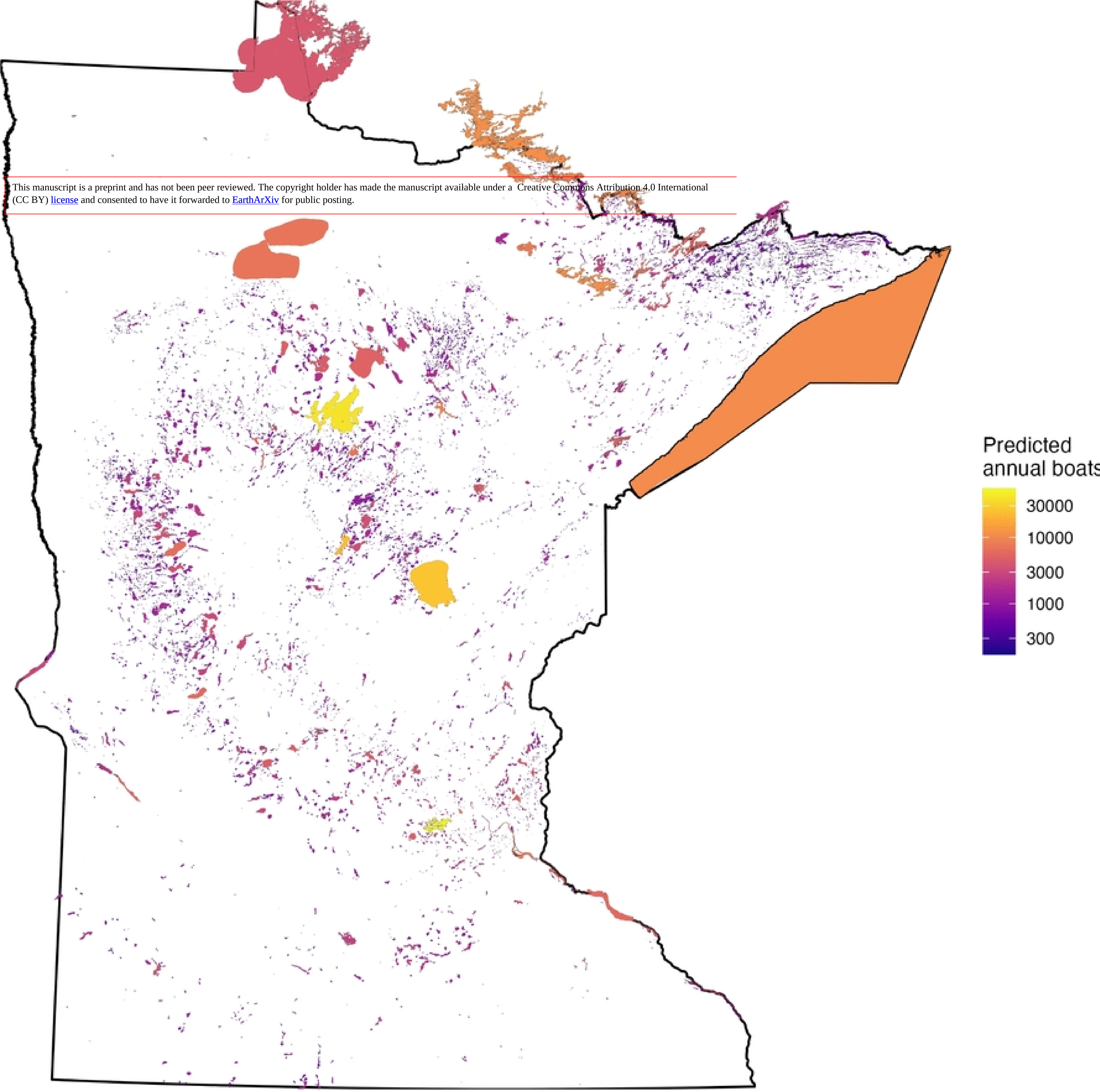

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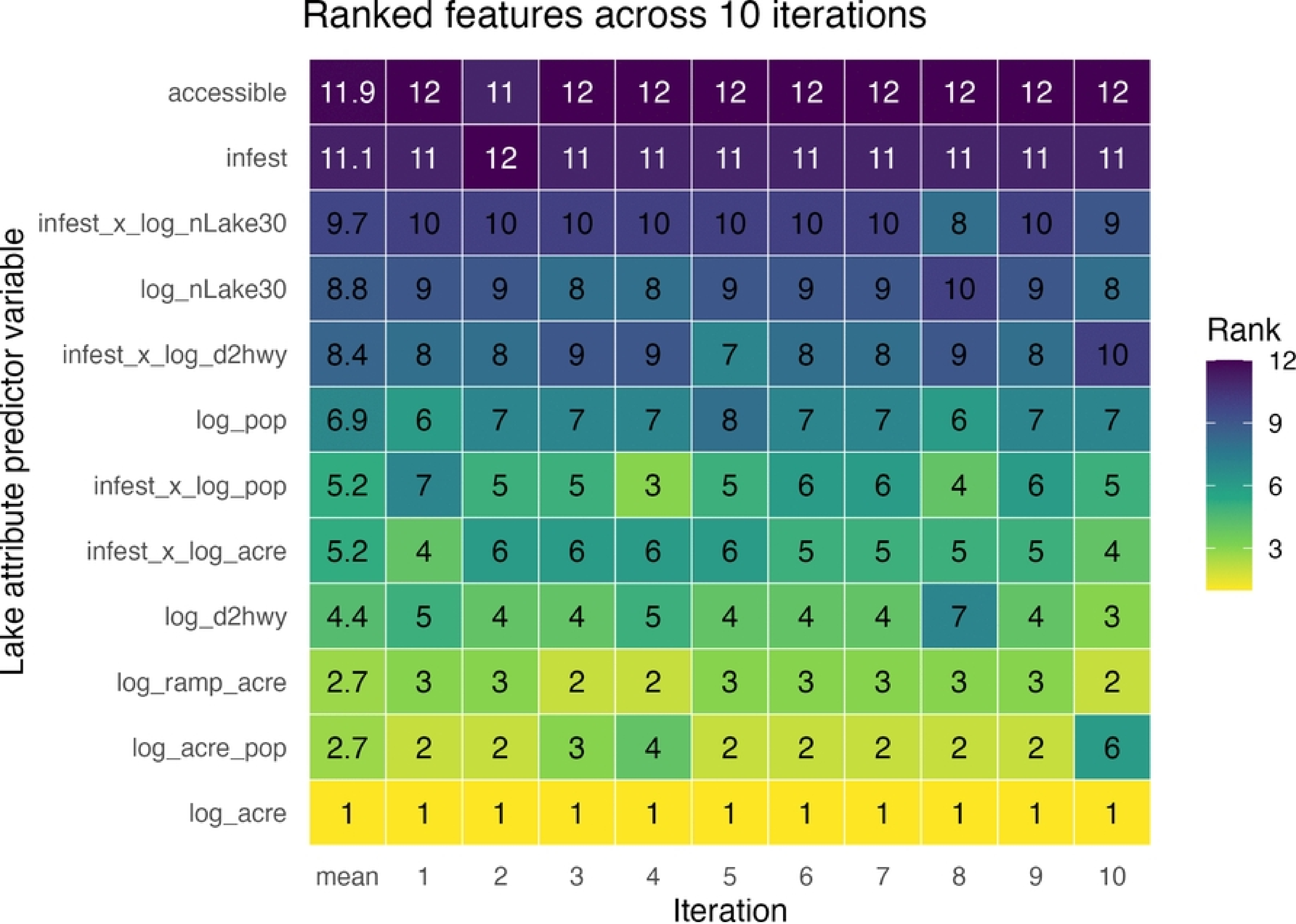
Ranked features across 10 iterations
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log_nLake30 8.8 9 9 8 8 9 9 9 10 9 8
infest_x_log_d2hwy 8.4 8 8 9 9 7 8 8 9 8 10
log_pop 6.9 6 7 7 7 8 7 7 6 7 7
infest_x_log_pop 5.2 7 5 5 3 5 6 6 4 6 5
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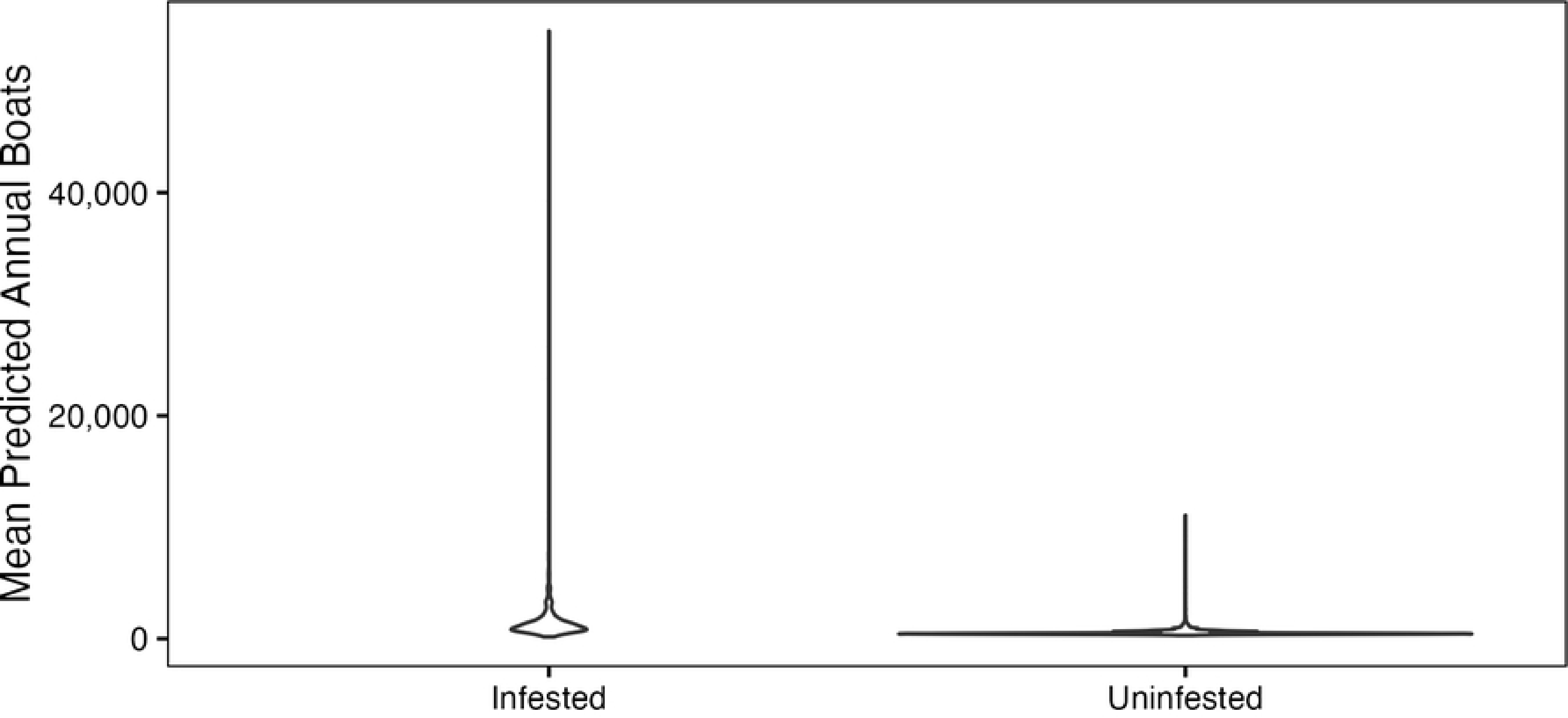
Figure


Mean Predicted Annual Boats
40,000
20,000
0
Infested
Uninfested

Figure