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Research article

Enhancing monitoring to promote early detection and eradication of invasive species

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Ecological niche models are often used to predict the distribution of invasive species before or after they have been detected in new regions. Such models should also be used to guide surveys to promote the early detection and eradication of invasive species. Here we propose a practical framework that seamlessly uses ecological niche models to develop sampling routes that promote detection of invasive species. Our framework uses habitat suitability predictions and occurrence data on incursion populations to generate potential survey sites, which are then prioritized for sampling based on their size and suitability. The generated survey route is then displayed on an open street map platform. Our framework was developed into the '*enmRoute*' R package and a user-friendly website to facilitate its application, and we validated our framework with a case study. We show that integrating ecological niche models with human transport routes promotes identification of survey sites that are predicted to collect more individuals and have a greater potential for species detection than traditional sampling approaches. Our framework may help industries, invasion biologists, and regulators develop economical and efficient survey programs for invasive pest monitoring that make eradication programs more attainable.

Keywords: Ecological niche model, habitat suitability, incursion population, invasive species, monitoring, species distribution model

Introduction

Invasive species can damage ecosystems and affect human health and productivity (Seebens et al. 2021). Globally, invasive species are estimated to have cost nearly $1.3 trillion worldwide (2017 dollars) over the past few decades in management efforts and damage, and the cost of damage is estimated at nearly 13 times higher than management (Diagne et al. 2021). Invasive species become particularly problematic when they overcome genetic bottlenecks and humans miss the window when the species is not widely established and eradication is feasible (Sakai et al. 2001). Early detection

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and eradication of invasive species, which rely on predicting where the species may establish and eliminating incursion populations, are key for more efficient allocation of resources in targeted survey and control efforts (Reaser et al. 2020).

Ecological niche models are popular tools to predict areas of habitat suitability for invasive species, and integration of niche suitability predictions into surveys represents an active area of research (Guillera-Arroita et al. 2015, Camac et al. 2021, Jamieson et al. 2022). For example, the platform *edmaps* in R predicts areas of establishment and prioritizes surveillance sites (Camac et al. 2021). However, efforts to survey for invasive species should not only be informed by habitat suitability models, especially if some sites with high suitability are unavailable for monitoring or would be too expensive to monitor; similarly, low suitability sites may be appropriate to survey if they are located near areas of high human transport (Huang et al. 2012, Cassey et al. 2018). This has led to a need to integrate habitat suitability models with human dispersal corridors and transport systems to inform invasive species surveys (Jamieson et al. 2022).

To overcome limitations associated with use of habitat suitability maps to guide surveys, models should consider tradeoffs between odds of species detection and any logistical constraints (Hanson et al. 2023). Such constraints may include distance between sites, or site availability, as isolated sites may incur disproportionately high costs (Hanson et al. 2023). These considerations require integrating habitat suitability and social geographical information system models, along with a platform to deliver information and allow managers to easily plan field surveys despite logistical constraints. Here, we propose such a framework that integrates ecological niche model predictions with data on transport systems to guide invasive species surveys.

Our framework has four main steps: 1) buffer incursion populations to identify survey sites, 2) convert suitability predictions into patches to identify additional sites, 3) prioritize survey sites based on suitability and size, and 4) build a survey route. Our framework uses a conventional heuristic algorithm (Chvatal 1979) and can be implemented using the '*enmRoute*' R package (www.r-project.org, https://github.com/gpzhu/enmRoute) or on the web (www.losorio.shinyapps.io/enmroute). As case studies, we implement our framework for northern giant hornet *Vespa mandarinia*, an invasive species in the Pacific Northwest US and Canada, and brown marmorated stink bug *Halyomorpha halys*, a species that has spread across North America. We show that our framework may improve the efficacy of invasive species surveys by increasing odds of detection while limiting logistical costs associated with travel; our framework can also be used post hoc to assess the effectiveness of prior surveys and adjust from year-to-year.

Material and methods

Our framework is implemented in the 'enmRoute' package (Fig. 1). First, candidate survey sites are assembled from occurrence data on incursion populations and habitat suitability models. The logistics of surveying these sites are then determined by linking habitat suitability predictions with data on human transport pathways (i.e. roads) to generate a survey route. Our framework requires that a habitat suitability model has been created for a species in question, whereas the inclusion of incursion populations is optional and depends on whether the invasive species has been established in survey areas. The most common method to create a habitat suitability model is to relate occurrence records to environmental variables (Peterson et al. 2011, Araújo et al. 2019) (Supporting information). Ecological niche models are often used in invasion risk assessment because model development packages have been created that can be readily used to identify areas of potential establishment (Peterson et al. 2011, Araújo et al. 2019). We detail each step in the sections to follow, and then show how the framework is implemented with two case studies: 1) one to develop a survey for early detection of a newly discovered invasive species and 2) one to evaluate a nationwide monitoring network for a widespread invader.

Generating candidate patches

Candidate survey patches are assembled from data on incursion populations and from the habitat suitability predictions. The establishment of incursion populations in introduced areas is usually followed by population expansion, and these locations are sources of potential invasive spread. First, if the user has incursion population data available, candidate survey patches are attained by drawing buffers around known occurrence records of the incursion populations. Users should choose a buffer size based on the known dispersal capacity of the species in question and/or the ability of humans to transport the species over long distances. For species without an incursion history, a user may also fit habitat suitability models using more relevant predictors (e.g. human transport networks or human footprint) so as to approach a realized distribution of the species in question for the purposes of planning a field survey (Jiménez-Valverde et al. 2011).

Additional potential survey sites are identified from ecological niche model predictions. Individual pixels that are deemed suitable or unsuitable for a species are determined using a binary threshold (Peterson et al. 2008). One such threshold is the minimum training threshold, where the lowest habitat suitability value associated with an occurrence record is the threshold. Another is the 10th training threshold, where the lowest 10% of habitat suitability values that are associated with known occurrence records are considered to not reflect suitable habitat (Peterson et al. 2008). While there are many thresholds that can be based on data, a user can also select a 'fixed threshold' based on an arbitrary habitat suitability value (Liu et al. 2013).

After a threshold is chosen, the package converts a raster of binary predictions to polygons to generate candidate patches, which are a set of spatially explicit shapes that represent suitable areas where species can survive and develop. In habitat suitability predictions, adjacent pixels often have similar suitability values due to spatial autocorrelation

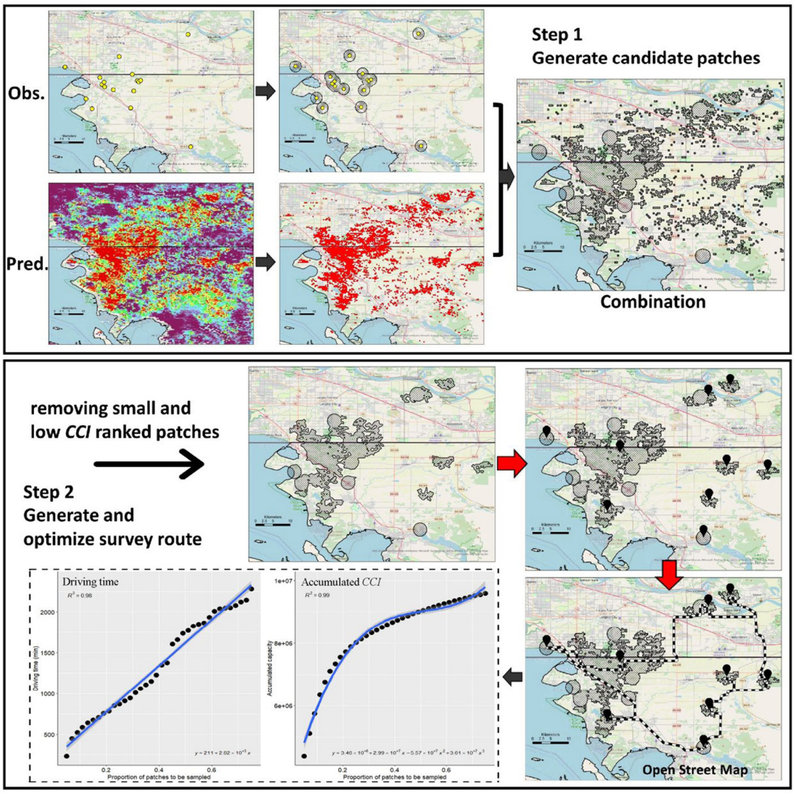

Figure 1. Schematic overview of the survey framework with example based on *V. mandarinia*. The arrows indicate data flows and outputs. First, candidate survey polygon patches are assembled by buffering incursion population distributions and from habitat suitability models. Habitat suitability predictions are changed into binary predictions and transformed into polygons (step 1). Candidate polygon patches are then prioritized by removing small and low CCI ranked patches, and the centroids of remaining candidate polygons are used to generate the optimal survey route (step 2). Iterations of the procedure in red arrows can assess the relationship (panel in dashed line) between survey time, accumulated CCI, and the number of patches sampled, which can be used to determine how many and which patches should be used in a survey network given available time and resources. [Correction added on 5 December 2024, after first online publication: Figure 1 was replaced with new version.]

(Tobler 1970). Given a binary threshold, pixels with similar values are spatially clustered, creating patches of variable shape, size and suitability. From a practical perspective, the choice of threshold impacts the size, shape and geographic distributions of these candidate patches. More sparse and small patches occur with high thresholds, but patch connectedness decreases, while lower thresholds result in larger and more connected patches, although these patches may incur greater survey costs. We further detail how the threshold affects the size and shape of patches in the Supporting information.

As the basis for creating the survey routes, potential polygons that are suitable for sampling from both buffering of incursion populations and habitat suitability predictions are combined into a single dataset. When a niche model-based polygon patch overlaps or shares a boundary with the buffering of an incursion population, we merge them together to form a single polygon using the dissolve function. The combined polygon patches are then used to identify potential sites for including in a survey to maximize detection of the invasive species (step 1 in Fig. 1).

Prioritizing candidate survey patches

When monitoring for an invasive species, the survey area may be restricted by administrative boundaries (e.g. state lines), or a route may be designed based on a start point with a maximum survey time (isochrones) or distance (isodistances). Sampling is also limited by available time, financial resources, or other logistical challenges like labor availability or site accessibility. To address these limitations, our framework uses habitat suitability predictions as well as the known distribution of incursion populations in a survey area to identify potential survey sites (Fig. 1).

In regional niche model predictions, some candidate survey patches may have high suitability and medium size (patch 1 in Fig. 2), and others have medium suitability but large size (patch 2 in Fig. 2). In addition, some high suitability patches are far from a starting point, whereas others are close but have lower suitability. Our framework uses a heuristic algorithm to prioritize candidate patches based on size, suitability and isolation distance using two procedures. First, some patches may be too small to host an invasive population, and we eliminate these patches (e.g. with a single pixel). For example, areas to support the minimum viable population (Wang et al. 2019) would be different among invasive species, those patches that could not support a viable introduced population were omitted in planning field surveys.

Second, we recognize the benefit of larger and higher suitability patches with a carrying capacity (Hui 2006) that ranks the suitability of a patch for sampling while accounting for size and suitability. The carrying capacity index (CCI) was calculated as total grid cell (i) estimated suitability values (Si) within a unique patch:

$$\mathrm{CCI} = \sum_{i=1}^{N} \mathrm{Si}$$

Patches with higher CCI values should be able to host more suitable habitat for individuals than those with lower CCI values and are thus more valuable for survey, we subset and priorize the patches by selecting high CCI ranked patches, which are then used to search for survey routes. Total survey expense (T_S) can then be calculated based on survey time and expense spent in these high ranked patches (t_p), as well as expenses driving between these patches (t_d):

$$T_S = t_p + t_d$$

Driving time would be closely related to distance between centroids of these high ranked patches, where inner patch survey expenses may vary based on the method(s) used to sample the invasive species as well as the average patch size. With a lower binary threshold, patches will be larger and likely more expensive to sample, but there will be fewer patches. Invasive species that are easy to sample and identify would also tend to have lower in-patch survey expenses (relative to driving expenses), while species that are difficult to sample and/or identify would tend to have high in-patch survey expenses compared to driving expenses (Reznick et al. 2002).

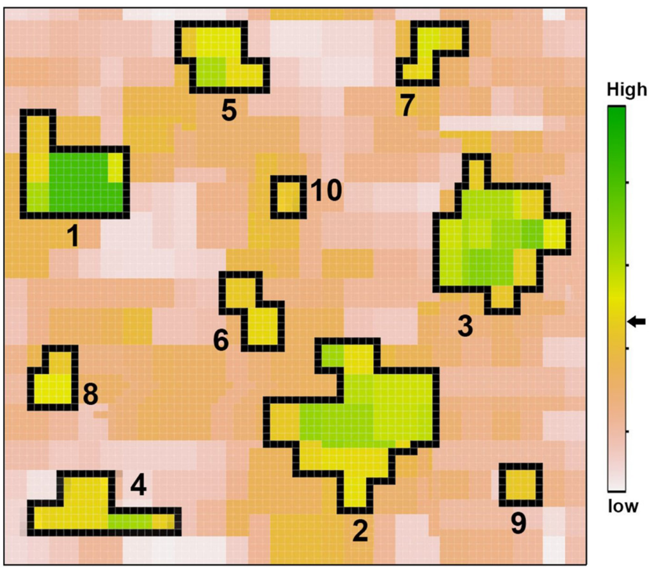

Figure 2. Illustration of polygon carrying capacity. Regional binary predictions are converted into polygons and the carrying capacity index (CCI) is used to rank polygons (i.e. 1–10 in bold line). Notice that patch 2 has medium suitability and large size, but ranks second to patch 1, which has a relatively small size but high suitability. The arrow on the suitability bar indicates threshold used to generate binary prediction.

Generating survey routes

We used the conventional heuristic algorithm (Chvatal 1979) to develop a survey plan for a given budget, aiming to maximize detection of earlier introduced populations while minimizing travel time. Specifically, we estimate the relationship between the expected number and size of survey patches and sampling expenses, via iteratively selecting candidate sites to generate survey plans and compare their expenses; this approach allows our platform to aid invasive species managers design their sample scheme for a given budget. However, for a true optimization, managers must have a detailed understanding of how within-patch sampling expenses varies based on survey site size and shape, and how within-patch expenses compare to driving expenses. If sampling expenses do not vary based on patch size (for example with a species where a certain number of traps are used regardless of patch size), the optimization will promote a higher CCI value with a given amount of travel time. However, when sampling expenses vary based on patch size, the true optimization will depend on how total survey expenses vary based on accumulated CCI. In either way, rather than selecting random sites/patches for planning survey in an expected survey area, our framework offers an approach to determine where to survey that can promote detection given a desired survey time or expense and other known logistical constraints.

Centroids of each prioritized candidate patch are used to calculate survey routes; we use the 'osrm' R package (www.r-project.org, www.project-osrm.org) to search for the shortest potential route and to calculate the driving time, incorporated into the OpenStreetMap platform (www.openstreetmap.org). This platform relies on open data to make it customizable. The 'osrm' package offers a routing service based on OpenStreetMap data, which allows the computation of distances (travel time and kilometric distance) between these centroid points and searches for the shortest route (Giraud 2022).

Running iterations of the above procedure (i.e. red arrows in Fig. 1) by randomizing the prioritized polygon patches can assess the relationship between survey expenses (i.e. inter patch driving time plus accumulated inner patch survey expense) and the number of patches to sample (i.e. dashed line panel in Fig. 1). For example, if many patches can be assembled (e.g. > 100), the first survey scheme would be generated by taking the top 10% of CCI ranked patches, and the next scheme would be iteratively generated by including the following high ranked patches (i.e. 20% to 100% in increments of 10%). Users may also iteratively drop patches if assembled candidate patches are insufficient to generate survey route. The functional relationship between survey expenses and patches to be sampled can also be estimated (i.e. dashed line panel in Fig. 1), which could help field managers or conservation professionals determine how many and which patches should be used in surveys given available time and resources.

Choosing patches - Pareto curve

To help users choose parameters for 'enmRoute', scatter diagrams of accumulated CCI against driving time generated in the heuristic search were plotted and regressed. The line (i.e. Pareto curve) that was fit to these scatter points is used to estimate patch capacity or size based on driving time (Lotov and Miettinen 2008). We predict that accumulated *CCI* will be positively correlated with driving distance as it represents more patches to be surveyed. We also predict that the shape of Pareto curves will vary across landscapes based on the size and shape of candidate patches and their connectedness. For example, given the same accumulated CCI, a landscape with more connected candidate patches would be expected to have a higher slope in the fitted Pareto curve than landscapes with more fragmented patches that are distributed far from each other. By assessing the Pareto curves, we were able to test relationships between survey expenses and number of patches to be sampled for *V. mandarinia* in Washington State, and for *H. halys* surveyed in three US States. We hypothesized slopes of Pareto curves for *V. mandarinia* would be higher than for *H. halys* as *V. mandarinia* has less variability in habitat suitability (over a smaller region) than *H. halys* (Zhu et al. 2020, Gutiérrez-Illán et al. 2022).

Case studies

We implemented our framework with data for two invasive species of considerable ecological and economic impact (Supporting information). We first show how our platform could be used for the northern giant hornet, *V. mandarinia*, which was first detected in North America in 2020. *Vespa mandarinia* has only been detected across three counties of Washington State in the USA (Zhu et al. 2020) and provided a model case to test our framework for a species where early detection and eradication is a high priority. For this case study, a habitat suitability model was fit in Maxent with introduced records (Muscarella et al. 2014, Araújo et al. 2019; Supporting information). Model outputs were converted to binary predictions using a 10th training presence threshold (Pearson et al. 2007). This threshold is highly conservative, it assumes 10% of the occurrence records with the lowest modelled suitability occurred in locations that are not representative of the species overall habitat (Peterson et al. 2008). The habitat suitability prediction of *V. mandarinia* in Washington State, and the parameters and R script that were used for running 'enmRoute' for *V. mandarinia* are available in our 'enmRoute' readme document.

Our second case study used brown marmorated stink bug *H. halys*, which has risen from an unknown species to a pest of national concern in North America and Europe over the past decade (Abram et al. 2020). We used *H. halys* to demonstrate and validate that our framework could be employed for promoting selection of sites to collect a maximum number of individuals for a given number of survey sites compared to routes designed without ecological niche models. To monitor spread of this species, a standardized monitoring network was established in 17 states from 2017 to 2020 (Acebes-Doria et al. 2020, Illán et al. 2022). We used data from states that had extensive sampling in the western US: Washington, California and Utah, for validating survey routes from our heuristic algorithm. In each state, H. halys were sampled with sticky panel traps baited with lures spaced at 50 m intervals and collected every two weeks. We standardized the counts for modeling analyses as average *H. halys* adults per trap per week (Illán et al. 2022).

We hypothesized more *H. halys* would be collected along routes with greater accumulated CCI. For surveys in Washington, California and Utah, we transformed habitat suitability models into binary predictions using different thresholds (Washington = 0.8, California = 0.8, Utah = 0.3). The habitat suitability predictions of *H. halys* in Washington, California and Utah States along with the parameters and R script that were used for running below 'enmRoute' are available at: https://doi.org/10.17605/OSF.IO/5R8PZ. After models were built, we also removed patches < 5 km^2 given that brown marmorated stink bug cannot establish in areas without considerable host resources over such a large area (Baguette and Stevens 2013). These thresholds were also used to create a landscape with around 20 suitable patches in each state. We then generated a survey route based on the 20 centroids of high CCI ranked patches (red and white line in Fig. 3b), which were obtained by removing low ranked and small patches after using binary thresholds to classify model predictions in each state. We quantified the relationship between survey expenses and the number of patches to be sampled in these high ranked 20 patches using linear regression.

To validate models, we generated 500 pseudo-survey routes (Fig. 3) that each contained a random selection of 20 sites from a particular state (Washington, California, Utah). The number of *H. halys* individuals collected in each route was calculated, together with the driving time and habitat suitability values accumulated in these 20 sites. We used 3D plots to show relationships between number of individual *H. halys* collected in these 20 sampling sites with the accumulated suitability values and the driving distance; we then calculated the Spearman correlation to test the relationships. We hypothesize that brown marmorated stink bugs are most abundant in areas predicted to have high suitability, and the closer of sampling sites to high suitable area the more individuals would be collected.

Results

Case study of *Vespa mandarinia*

Our survey route for *V. mandarinia* was demonstrated using our framework (Fig. 1). A total of 2517 candidate patches were assembled, including 12 from the 1 km buffering of introduced distributions and the rest from niche models. Many single pixel-based patches were generated; we de-prioritized patches < 5 km^2, a minimum areas requirement for a viable insect population (Baguette and Stevens 2013), this resulted in 31 remaining patches. We calculated CCI to rank the 31 patches and discarded the lowest 11, which left 20 high suitability patches (Fig. 1). We chose these values to demonstrate the step-by-step procedure, while another user might choose not to discard any patches or to vary the number of patches. Finally, centroids of the high CCI patches were used to design a survey route (Fig. 1) that is predicted to generate the highest probability of species detection for a number of sites. Our approach identifies the relationship between survey expenses (i.e. driving time) with accumulated CCI and the number of patches to be sampled (panel in dashed line, Fig. 1). For example, a least squares regression line shows a steady increase of driving time over patches to be sampled, whereas a third order polynomial was best to describe accumulated CCI increase. Equations relating driving time to CCI can determine how many and which survey patches should be used in monitoring network given available time and resources (panel in dashed line, Fig. 1). The Pareto curve that was fitted with second order polynomial regression line describes the relationship between the accumulated CCI and driving time well ($R^2 = 0.96$; Fig. 4a), which could be used to estimate the possible area or patch capacity covered using a particular driving time budget.

Case study of *Halyomorpha halys*

In Washington State, we found a positive and significant Spearman correlation between the estimated *H. halys* collected and accumulated habitat suitability ($\rho = 0.18$) in our 500 pseudo-survey routes (Fig. 3a); this shows our survey route would have collected more individuals than random surveys. This trend was even stronger in Utah, where surveys with greater habitat suitability values were estimated to collect

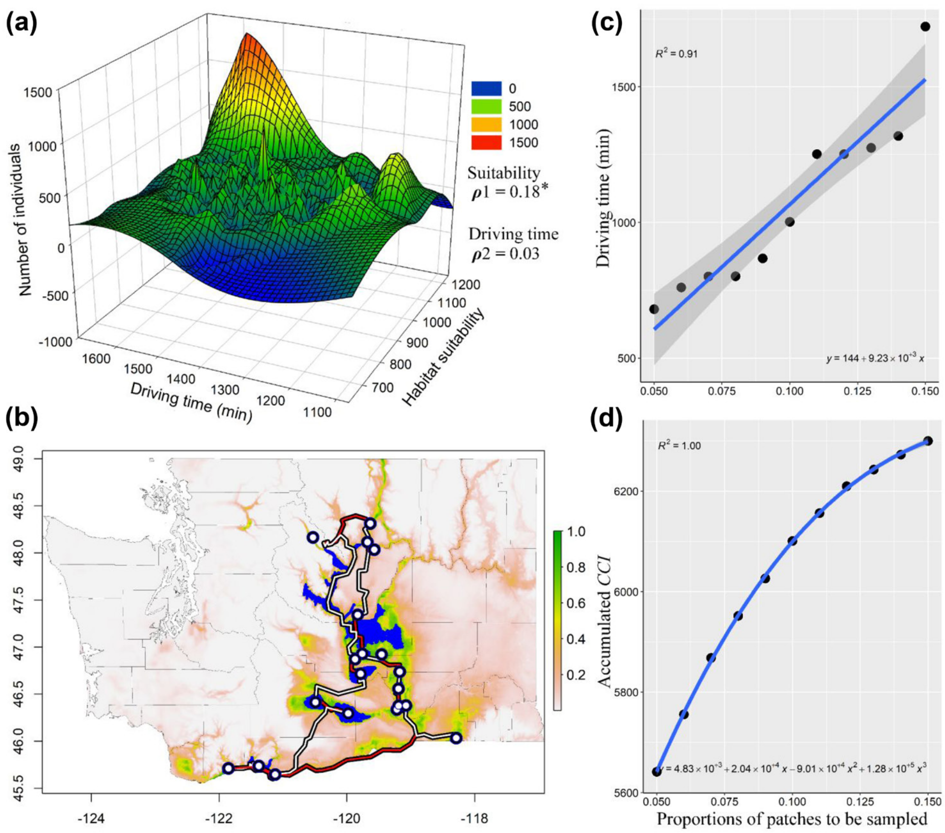

Figure 3. Validation of model survey route for *H. halys* in Washington State, USA. (a) A 3D plot showing number of individual *H. halys* collected in 20 sampling sites in Washington State against accumulated habitat suitability and driving distance. The ρ denotes the Spearman correlation between total *H. halys* collection with accumulated suitability and driving times in these 20 sampling sites (* - significant $p < 0.05$ relationship). (b) A survey route (black and red line) was generated by the platform using 20 patches (blue areas) from habitat suitability model predictions. (c, d) Relationships between survey expenses (inter patch driving time and the accumulated inner patch survey expense), which is scaled with accumulated CCI and the number of patches to be sampled to determine how many and which patches should be used in a survey network given available time and resources.

significantly more individuals than surveys with lower habitat suitability ($\rho = 0.30$) (Supporting information). However, correlation between *H. halys* collected and habitat suitability were marginally negative (but insignificant) in California ($\rho = -0.09$) (Supporting information). The correlation between *H. halys* collected and driving time was marginally significant in each state (Fig. 3, Supporting information).

In Washington State, a least squares regression line shows a steady increase of driving time over patches sampled ($R^2 = 0.91$), whereas a third order polynomial described accumulated CCI with more driving or sample sites ($R^2 = 1$). Similar results were found in Utah and California, where a least squares regression line indicated a steady increase of driving time over patches to be sampled, and a third order polynomial regression described accumulated CCI increase (R^2 values > 0.87). In each case, these equations determined how many and which patches should be used in survey network given available time and resources (Fig. 3, Supporting information). These equations could also aid managers understand relationships between driving time, number of sites, and estimated captures. Managers may increase the number of sites, or increase driving time, based on the shape of the curves and their desired sampling outcome(s). The Pareto curves fitted with second order polynomial regression line also describe well the relationship between the accumulated CCI and driving time for *H. halys* surveying in Washington ($R^2 = 0.93$; Fig. 4b), California ($R^2 = 0.98$; Fig. 4c) and Utah ($R^2 = 0.94$; Fig. 4d) states.

Discussion

Our 'enmRoute' platform seamlessly integrates readily available habitat suitability predictions into planning field surveys. Our platform uses heuristics to develop a survey plan for a known extent and is agnostic to the method used to generate habitat suitability predictions. The platform uses driving time and conventional heuristic algorithms to develop field surveys, allowing users to account for the size, shape, and suitability of potential habitat patches in planning surveys that also minimize driving time and expenses. In our case studies, we found that the accumulated carrying capacity and driving time were highly correlated, but the Pareto curves varied between *V. mandarinia* and *H. halys*, and among *H. halys* in Washington, California and Utah States (Fig. 4). When the Pareto curves are fitted with polynomial regression, they can be used to choose patch size based on a total expected driving time (Fig. 4). We note that the patches are based on binary niche models, and their size is closely connected with the threshold used in binarization of suitability prediction: a conservative threshold would generate large patches whereas

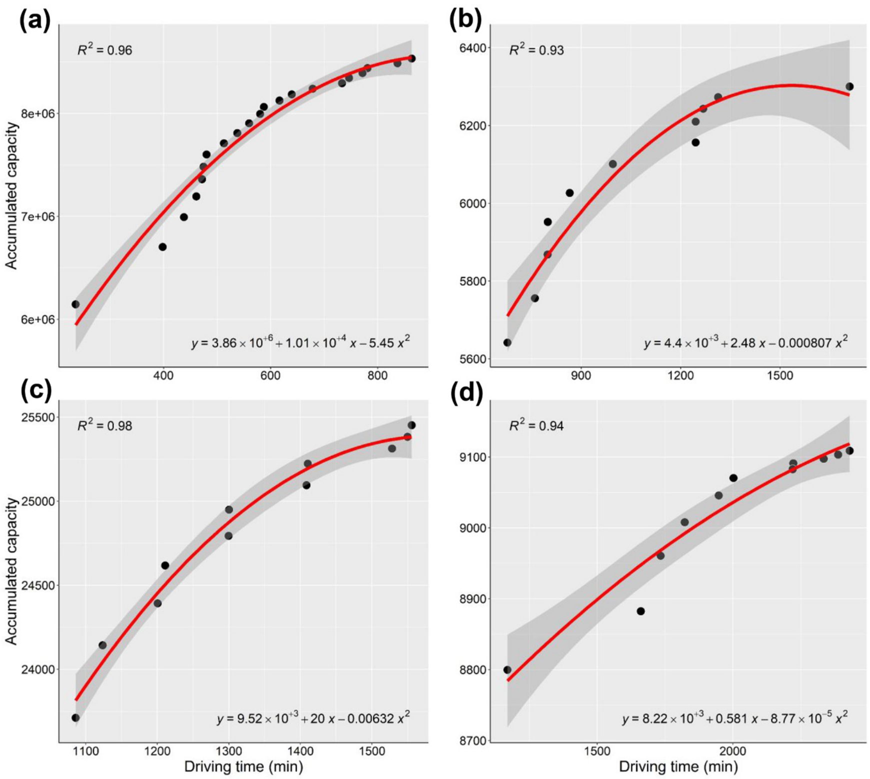

Figure 4. Scatterplots of accumulated carrying capacity against driving times (Pareto curves). The random sites in the 20 prioritized sampling patches were iteratively selected to develop sampling routes for *V. mandarinia* in Washington (a), and *H. halys* in Washington (b), California (c) and Utah (d) States, their corresponding driving time and accumulated carrying capacity were assembled and were plotted. The second order polynomial lines describe well the regression of the accumulated carrying capacity against driving time.

a less conservative threshold would produce small patches (Supporting information).

Our survey route framework may be customized to meet additional logistical criteria for particular species. For example, the conservative threshold (e.g. minimum training threshold or 5th training threshold) to convert niche model suitability predictions into binary values (suitable or not) might generate large patches. Large patches would increase internal driving time (i.e. within patch), which could make our approach ineffective, as we used the centroid to generate routes. It may be more effective to employ a less conservative threshold under this scenario (e.g. 10th training threshold), which could generate many higher suitable patches that were isolated or far away from each other. In addition, the proposed sampling sites or patches could be manually removed or added if, for example, a proposed site is on private land. Field managers often have information on additional regional conditions that should be considered in generating survey routes for particular species. Lastly, in CCI calculation, users may also put more weight on incursion population related patches than patches that were generated from niche model predictions, as invasive source populations would more likely disperse into adjacent areas.

Our framework may also address regulatory standards for pests of quarantine concern, where international standards have specified surveillance and trapping requirements (e.g. International Standard for Phytosanitary Measures, ISPM 2018). The types of regulatory pest survey activities that our framework could address include 1) detection: conducted in an area to determine if pests are present (or absent), and 2) monitoring: surveys to verify dynamics of a pest population. For the purposes of detection, larger patches with higher suitability might be prioritized to increase odds of capturing a rare invader; for monitoring variable patches of differing suitability may be chosen to study variability in the pest population across landscapes. By using our system, overall costs could be reduced by allowing scientists, regulators and policy makers to develop survey routes that minimize costs while promoting species detection. Our framework could also be used for surveys of rare native species for conservation purposes. The application of our framework requires coordination between spatial analysts and pest managers given the interdisciplinary nature of the approach to combine models and field surveys.

Our study fills a methodological gap between niche model predictions and application for practical management of invasive species by developing a framework that uses suitability predictions to generate survey routes that promote detection of invaders. Given that many invasive species are well monitored, especially as they spread beyond initial incursion zones (e.g. *H. halys*), our framework could also be used for evaluating monitoring networks by searching for optimal surveys based on particular sampling aims. We believe our framework may improve efficiency and cost-effectiveness and could be extensively adopted in invasive species management. Moreover, surveys of pests are commonly used in agroecosystems to assess the regional risk to farmers (Wohleb et al. 2021), and our approach might be widely applicable to agricultural pests. 'enmRoute' would also work for rare species and other biodiversity monitoring but be better in road accessible areas, as it requires human transport pathways to find the shortest route. Overall, this framework can be tested and applied to more case studies in invasive species, agriculture and biodiversity monitoring to refine the approach and expand its implementation.

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Author contributions

Gengping Zhu: Conceptualization (equal); Data curation (equal); Formal analysis (equal); Methodology (equal); Resources (equal); Software (equal); Validation (equal); Visualization (equal); Writing - original draft (equal); Writing - review and editing (equal). **Luis Osorio-Olvera:** (olvera) Methodology (equal); Software (equal). **Vera Pfeiffer:** Validation (equal); Visualization (equal); Writing - review and editing (equal) **Javier Gutierrez Illan:** Resources (equal); Writing - review and editing (equal). **Lisa G. Neven**: Conceptualization (equal); Data curation (equal); Funding acquisition (equal); Investigation (equal); Methodology (equal); Project administration (equal); Resources (equal). **David W. Crowder:** Conceptualization (equal); Data curation (equal); Funding acquisition (equal); Investigation (equal); Methodology (equal); Project administration (equal); Resources (equal); Supervision (equal); Writing - review and editing (equal)

Transparent peer review

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Data availability statement

Data are available from the Dryad Digital Repository: https://doi.org/10.5061/dryad.7pvmcvf3k (Zhu et al. 2024).

Supporting information

The Supporting information associated with this article is available with the online version.

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