



## Analysis

## There is no silver bullet: The value of diversification in planning invasive species surveillance



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## ABSTRACT

In this study we demonstrate how the notion of diversification can be used in broad-scale resource allocation for surveillance of invasive species. We consider the problem of short-term surveillance for an invasive species in a geographical environment. We find the optimal allocation of surveillance resources among multiple geographical subdivisions via application of a classical portfolio framework, which allocates investments among multiple financial asset types with uncertain returns in a portfolio that maximizes the performance and, by meeting the desired diversification targets, protects against errors in estimating the portfolio's performance.

We illustrate the approach with a case study that applies a spatial transmission model to assess the risk of spread of the emerald ash borer (EAB), a significant pest in North America, with infested firewood that may be carried by visitors to campground facilities in central Canada. Adding the diversification objective yields an expected survey performance that is comparable with undiversified optimal allocation, but more importantly, makes the geographical distribution of survey priorities less subject to possible errors in the spread rate estimates. Overall, diversification of pest surveillance can be viewed as a viable short-term strategy for hedging against uncertainty in expert- and model-based assessments of pest invasion risk.

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### 1. Introduction

Invasive alien species are a universally recognized problem, causing significant environmental changes and large-scale economic damages worldwide (Hulme et al., 2008; Mack et al., 2000; Meyerson and Reaser, 2003; Perrings et al., 2005). Most introductions of new species have been linked to human activities such as international trade (Costello and McAusland, 2003; Hulme, 2009; Jenkins, 1996; Levine and D'Antonio, 2003), transportation (Paini and Yemshanov, 2012;

Tatem and Hay, 2007) and recreation (Koch et al., 2012). Various post-border surveillance procedures (e.g., Cook and Fraser, 2008; Reaser et al., 2008) have been implemented to detect the arrival of non-native organisms via these and other pathways. For example, in 2007 the United States Department of Agriculture (USDA) allocated \$US 1.2 billion for management of invasive species, with approximately 22% directed toward early detection and rapid response activities (NISC, 2007). A considerable portion of such funding is spent on large-scale pest surveillance programs (Tobin, 2008).

A common objective in surveillance programs aimed at early detection is to gain as much information as possible about the extent of a species' presence in its new environment. Typically, surveillance planning requires some understanding of the species' behavior, such as its capacity to spread to new locations. A variety of models that simulate the invasion process have been used to help with the assessment of species spread (Koch et al., 2009; Pitt et al., 2009; Prasad et al., 2010; Yemshanov et al., 2009). Regardless, knowledge about the behavior of a recently discovered pest in a novel landscape is typically poor, such that any estimates of the organism's spread potential can only be stated in vague probabilistic terms (such as likelihood of spread or the probability of arrival at a specified distance). This further complicates

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the planning of pest surveillance because decisions about allocating resources for the surveys have to be made under substantial uncertainty.

### 1.1. Pest Survey Planning as a Portfolio Valuation Problem

Several methods have been applied to improve the performance of pest surveys, such as identifying surveillance protocols that are robust to uncertainty (Leung et al., 2010; Moffit et al., 2008), applying cost-minimization studies (Sharov and Liebhold, 1998; Hester et al., 2013), assessments of “wait and see” strategies (Sims and Finnoff, 2013) and optimal allocations of search protocols (Epanchin-Niell et al., 2012; Hauser and McCarthy, 2009; Hester and Cacho, 2012; Mehta et al., 2007). In this study we conceptualize the short-term allocation of pest surveillance resources as a portfolio valuation problem. Portfolio theory has been used to allocate investments in financial assets under uncertainty (Elton et al., 2010). In classical portfolio theory, the primary decision problem is to determine the allocation of investments among  $m$  asset types with uncertain returns in a portfolio that maximizes the net returns and protects the investments against volatilities (i.e., the variance of the net return values, which serves as a measure of financial risk). Modern portfolio theory also emphasizes the balancing and diversification of investment assets as measures that reduce the risk of unexpected financial losses (Elton et al., 2010).

While the portfolio allocation problem has been covered extensively in the financial literature, few studies have considered geographical applications of the approach, particularly for tasks such as the surveillance of invasive species (although see Prattley et al., 2007 for similar applications in animal health control). In this study, we consider the general case of survey planning for a recently discovered invasive species in a geographically diverse area that encompasses  $m$  territorial subdivisions. The surveillance objective is to allocate a fixed amount of resources (such as personnel and budget funding) among the  $m$  geographical subdivisions in a way that maximizes the potential to determine the pest's extent in the study area, while also meeting the desired level of geographical diversification as a hedge against potential survey failures (such as misplaced surveys or missed detections) which could be caused by errors in estimating the rate or pattern of the species' spread (i.e., uncertainty in the spread estimates). The estimation of the potential monetary benefits from finding new pest incursions can be problematic for a recently discovered invasive organism, since a key component of this calculation – the organism's anticipated economic impact (such as host losses or mitigation costs) – is generally not well characterized. Therefore, we used a non-monetary metric that describes the estimated potential to find the species of concern in a specific geographical region. We treated the performance metric as analogous to the net returns on investment in financial asset valuation. In the latter context, a decision-maker usually strives for higher return values. With respect to pest surveillance, this translates to the acquisition of more information (i.e., as much as possible) about a species' presence.<sup>7</sup>

### 1.2. Diversification in Pest Surveillance

In financial asset allocation, diversification is considered a useful method to reduce the variance (a measure of financial volatility) of the estimated net returns from an investment portfolio. Typically, a portfolio with higher variance is considered riskier because the likelihood of extreme losses is higher. Portfolios with a relatively large

<sup>7</sup> Many applications of portfolio analysis to non-financial problems, such as assessments of extreme events (Santos and Haines, 2004), veterinary management programs (Galligan and Marsh, 1988), resource allocations for flood protection (Aerts et al., 2008; Zhou et al., 2012) or control of multiple exotic diseases in animal health (Prattley et al., 2007), used non-monetary performance metrics (such as exceedance probabilities or disturbance return intervals; see McInnes et al. (2009) and Zhou et al. (2012)), hence our choice of a non-monetary metric felt justified.

number of asset types may yield lower degrees of financial risk (Luenberger, 1998). The variance of a portfolio can be further decreased when the correlation between the asset types in the portfolio is low or negative (Elton et al., 2010).

In financial asset valuation, risk factors that typically increase the correlation between asset types are generally associated with systematic events that affect all assets in a portfolio, such as general market trends (Elton et al., 2010). However, increasing the proportion of asset types with low or negative correlations improves the stability and reduces the variance of the portfolio given the impacts of these systematic events (Elton et al., 2010). Basically, because asset types with similar (i.e., correlated) behavior fluctuate in value in a similar fashion, a risk-averse decision-maker would find it beneficial to invest in other zero or negatively correlated assets, so that the portfolio's overall value has a lower probability of achieving extreme levels. Increasing diversification also improves the stability of the portfolio in the presence of uncertainty caused by non-systematic events, such as data errors that may distort estimates of the portfolio variance. In our case, diversification of pest surveys is expected to reduce the effects of errors in model-based estimates of the spread of an invasive organism (errors which eventually propagate into the estimates of the expected performance of the survey) and decrease the chance of erroneous selection of survey sites due to incorrect predictions of the pest's pattern of invasion. Errors in allocating surveillance resources are often costly and subsequently imply a penalty. This penalty arises from the trade-off between the desired level of survey performance and tolerated level of uncertainty.

Diversification is also consistent with common decision-making practices for managing outbreaks of invasive pests, where skepticism regarding the accuracy of model-based predictions of spread has caused managers to rely on subjective rules of thumb and allocate surveys in geographical patterns which are more spatially uniform than the model-based spread estimates.

## 2. Material and Methods

### 2.1. A Portfolio-based Model of Geographical Pest Surveillance

Consider a surveillance program for a new invasive pest that covers  $m$  geographical regions. A defined amount of resources is available for the entire program which must be allocated across the  $m$  regions. Each individual region,  $j = 1, \dots, m$ , contains a number of potential surveillance locations, where each location,  $y$ , is characterized by an estimate,  $\xi$ , that depicts the likely outcome if the survey were to be implemented at that location. The distributions of potential survey outcomes ( $\xi$ ) for the survey regions are estimated prior to survey planning with a geographical model of pest invasion that predicts, in probabilistic terms, the expansion of the invasive pest population over the survey period. (Their descriptions will be presented in Sections 2.4, “Model-based Assessment of EAB Spread With Campers”, and 2.5, “Expected Survey Outcome Metric.”).

For each region  $j$ , we constructed the cumulative distribution of the expected survey outcomes from the location-specific  $\xi$  values generated with the invasion model. We then sampled these cumulative distributions at 20 successively increasing percentile points spaced at equal intervals between 0 and 1, so each survey region was characterized by a set,  $I_j$ , of the distribution values  $I_j$  at the sampled percentile points. Since the sampling points were identical for all regions, the size,  $N$ , of set  $I_j$  was the same for all regions, making it possible to directly compare sets  $I_j$  and  $I_i$  for any two regions  $j$  and  $i$ .

A survey of  $m$  geographical regions is conceptually similar to a portfolio of  $m$  assets in financial analysis; essentially, the proportion,  $\omega_j$ , of the total surveillance resource allocated to a particular region  $j$  can be considered analogous to the fraction of investment in a financial portfolio that is allocated to a given asset type  $j$ . For each of our geographical regions, we treated the set  $I_j$  values in the same manner that

a sample of net return values might be utilized to estimate the performance of investment assets.<sup>8</sup> First, we estimated a mean survey performance value,  $\bar{I}_j$ , for each region from its set  $I_j$ . This is comparable to estimating the mean return value of a financial asset type  $j$ . In turn, the mean performance,  $\bar{I}_j$ , of a survey of all  $m$  regions is analogous to the mean return of an  $m$  asset portfolio, and was estimated as the sum of the region-specific  $\bar{I}_j$  values, multiplied by the proportions,  $\omega_j$ , of available resources allocated to these regions in the survey:

$$\bar{I} = \sum_{j=1}^m \omega_j \bar{I}_j \quad \text{where } \sum_{j=1}^m \omega_j = 1 \text{ and } \omega_j \in [0; 1]. \quad (1)$$

We did not consider the possibility of  $\omega_j < 0$ .<sup>9</sup>

The standard deviation of the survey performance values  $I_j$  in a region (cf. asset type)  $j$  was estimated as:

$$\sigma_j = \sqrt{\frac{1}{N} \sum_{k=1}^N (I_{jk} - \bar{I}_j)^2} \quad (2)$$

where  $I_{jk}$  is an element of the set  $I_j$  for region  $j$ ,  $k = 1, \dots, N$ ,  $N$  is the total number of elements in  $I_j$  and  $\bar{I}_j$  is the mean performance value for region  $j$ . Subsequently, the covariance of the survey performance values between any two regions  $j$  and  $i$  was estimated as:

$$\sigma_{ji} = \frac{1}{N} \sum_{k=1}^N (I_{jk} - \bar{I}_j)(I_{ik} - \bar{I}_i) \quad (3)$$

where  $I_{ik}$  and  $I_{jk}$  are expected survey performance values (and elements of vectors  $I_i$  and  $I_j$ ) corresponding to regions  $i$  and  $j$ , respectively, and  $N$  is the number of elements in  $I_i$  and  $I_j$  ( $N$  is the same for all regions). Note that the mean values  $\bar{I}_i$  and  $\bar{I}_j$  are region-specific and therefore do not have sub-index notations. The total variance of the survey (i.e., across all  $m$  regions) was estimated as:

$$V = \sum_{j=1}^m \omega_j \omega_j \sigma_{ji}. \quad (4)$$

A common objective in financial asset valuation is to find a convex frontier of optimal solutions that combine the highest performance ( $\bar{I}$ ) and lowest variance ( $V$ ) (Elton et al., 2010). This is achieved by finding the solutions that minimize the portfolio variance ( $V$ ) for different desired levels of portfolio performance  $\bar{I}$ . We have also added a diversification constraint. Generally, diversification of a portfolio is achieved by minimizing portfolio correlation or adding a portfolio correlation constraint (Zhou et al., 2012). However, a correlation-based metric does not fully capture information about the relationships among portfolio asset types (Kish and Hogan, 2009; Livingston, 2013). Pairwise correlation is sensitive to the shape of the distributions of the asset returns (the survey performance values  $I_j$  in our case) and is not adequate if the distributions deviate from normal. Instead, we used a distance measure of diversification (i.e., the degree of dissimilarity in the allocation of survey resources among  $m$  regions) based on the sum of squared Euclidean distances between the expected survey

performance values ( $I_i$  and  $I_j$ ) of each possible pair of regions,  $i$  and  $j$ , out of the  $m$  regions comprising the survey:

$$D = \sum_{j=1}^m \sum_{\substack{i=1 \\ i \neq j}}^m \omega_j \omega_i d_{ji} \quad (5)$$

where:

$$d_{ji} = \sum_{\substack{k=1 \\ i \neq j}}^N \left[ (I_{jk} - I_{ik})^2 \right], \quad (6)$$

where  $I_{ik}$  and  $I_{jk}$  are survey performance values in (and elements of) sets  $I_i$  and  $I_j$  representing regions  $i$  and  $j$ , respectively, and  $N$  is the number of elements in  $I_i$  and  $I_j$ . The similarity measure ( $d_{ij}$ ) helps find the regions which, while perhaps having relatively high expectations of pest arrival, also have highly dissimilar distributions of the expected invasion outcomes. Obviously, the surveillance of more dissimilar regions in terms of the variation of the predicted survey performance values ( $I_j$ ) would cover more diverse conditions in a landscape and potentially offer more opportunities to detect the pest in unanticipated locations. This is consistent with the basic idea behind financial portfolio diversification, where inclusion of low-correlated assets in a portfolio helps improve the stability of the portfolio returns in uncertain or unforeseen conditions and makes the portfolio less sensitive to errors in estimating the asset variance and expected returns.

We then formulated the survey allocation problem as finding the optimal apportionment of the total surveillance resource among  $m$  geographical regions (represented by a set of the resource fractions,  $\omega_j$ , allocated to each region  $j$ ) that minimizes the portfolio (i.e., survey) variance ( $V$ ) while meeting the desired level of survey performance ( $I^*$ ) and diversification ( $D^*$ ):

$$\begin{cases} \arg \min [V] \\ \omega_j \\ \text{s.t. :} \\ \sum_{j=1}^m \omega_j = 1 \text{ and } \omega_j \in [0; h_{\max}] \\ D^* = D \text{ and } I^* = \bar{I}. \end{cases} \quad (7)$$

Note that we have also added an upper constraint,  $h_{\max}$ , that limits the maximum fraction of the total surveillance resource that can be allocated to any one region. In classical portfolio valuation, the fractions of individual asset types ( $\omega_j$ ) in a portfolio can be changed at extremely small increments from 0 to 1, so optimization may lead to concentrated portfolios that include only a few best-performing and often least-correlated asset types. This can diminish the overall performance of the portfolio if the estimates of the covariance matrix of the return values or net asset returns have errors. This problem is commonly addressed by constraining the maximum number of asset types that can be included in a portfolio (Chang et al., 2000), or by limiting the amount of resources that can be allocated to a single asset type. With respect to surveillance, a positive detection at a survey site typically assumes that a population of the species of interest is present within a certain area around the surveyed location. This area is commonly based on the species' known spread range or local biological spread capacity since the last survey, possibly in conjunction with the effective range of the survey mechanism (e.g., a pheromone trap for an insect pest). As a result, survey locations are typically placed at a certain minimum distance apart, which eventually limits the total amount of survey points that can be allocated to a single region. To keep the problem formulation in general terms, we specified the  $h_{\max}$  value as relative to the equal resource allocation proportion (i.e.,  $1/m$ ) and tested three scenarios with the  $h_{\max}$  constraint exceeding equal resource allocation by two, three and four times ( $h_{\max} = 2/m, 3/m$  and  $4/m$  hereafter).

<sup>8</sup> For consistency with the portfolio valuation literature, we have termed the  $I_j$  values as the expected performance (i.e., the "expected return") of a survey in region  $j$ . Note that our pest invasion model did not include simulation of survey events, so this metric does not indicate whether the pest of interest was actually detected (or not) in region  $j$ .

<sup>9</sup> Negative values of  $\omega_j$  in financial asset valuation indicate *shorting*, the selling of assets that are borrowed from a third party with the intention of buying identical assets back at a later date. Imposing short selling constraints can help prevent extreme positive and negative asset proportions ( $\omega_j$ ) and may lead to modest improvements of portfolio performance (DeMiguel et al., 2009), but the concept does not have an obvious decision-making parallel in our pest surveillance example.

Higher  $h_{\max}$  values offer the possibility of allocating higher resource proportions ( $\omega_j$ ) to fewer regions. In our scenarios, the optimal allocations based on the conditions  $h_{\max} = 2/m$ ,  $3/m$  and  $4/m$  resulted in the assignment of high resource shares to approximately 50%, 38% and 22% of regions, respectively.

We then plotted the sets of optimal allocations in the dimensions of the portfolio variance ( $V$ ) and mean portfolio performance ( $\bar{I}$ ) at different desired levels of diversification ( $D$ ). For each diversification level,  $D$ , we have calculated multiple optimal solutions corresponding to different performance levels ( $\bar{I}$ ). For different desired levels of survey performance, the optimal solutions yielded different values of portfolio variance ( $V$ ). These optimal solutions, when plotted for a given diversification level  $D$  in the dimensions of the  $V$  and  $\bar{I}$  values, delineated a convex frontier. Essentially, this frontier is analogous to a frontier of efficient portfolios in mean–variance space in financial asset allocation. Each point on these frontiers represents an optimal allocation of survey resources for a combination of  $\bar{I}$ ,  $D$  and  $V$  values, and had an associated vector of  $m$  region-specific resource share values  $\omega_j$ . We then mapped these  $\omega_j$  share values in a geographical domain. Given a potentially large amount of geo-referenced outputs (i.e., maps or resource allocations corresponding to each individual point in the convex frontiers), we present only the most prominent examples of the best-performing portfolios for low, moderate and high diversification levels.

## 2.2. Benchmark Allocations of Survey Resources

We also evaluated three allocation approaches that have been regularly used as benchmarks in the financial literature (DeMiguel et al., 2009). The first allocation was based on equal resource distribution among survey regions (i.e.,  $\omega_j = 1/m$ ), while the second defined the resource proportions  $\omega_j$  as proportional to the mean performance values  $\bar{I}_j$ . We also evaluated an equal risk contributions (ERC) portfolio (Maillard et al., 2010). Under this approach, the asset proportions ( $\omega_j$ ) are chosen such that the variance contributions of each asset type to the total portfolio variance are equal (Maillard et al., 2010). The ERC approach may be viewed as a form of variance-minimizing portfolio valuation subject to a constraint of sufficient diversification in terms of the asset type weights (Maillard et al., 2010), and is considered as an intermediate point between the equal asset portfolio ( $1/m$ ) and an unconstrained portfolio that minimizes portfolio variance. The numerical solution for the ERC portfolio was obtained, via a quadratic programming algorithm, by minimizing the Euclidean distance between each asset's (i.e., survey

region) weighted marginal contributions to the total portfolio variance (Maillard et al., 2010):

$$\begin{cases} \omega_j \times \partial_{\omega_j} \sigma(\omega) = \omega_i \times \partial_{\omega_i} \sigma(\omega) \text{ for all regions } i, j = 1, \dots, m, i \neq j \\ \text{s.t.} \\ \sum_{j=1}^m \omega_j = 1 \\ \omega_j \in [0, 1] \end{cases} \quad (8)$$

where  $\partial_{\omega_j} \sigma(\omega) = \frac{\omega_j \sigma_j^2 + \sum_{i \neq j} \omega_j \omega_i \sigma_{ij}}{\sigma(\omega)}$  and  $\sigma(\omega) = \sum_{j=1}^m \sigma_j(\omega)$ .

## 2.3. Case Study Example

We applied a portfolio-based approach to plan the surveillance of spreading populations of the emerald ash borer (EAB), *Agrilus planipennis* Fairmaire (Coleoptera: Buprestidae), in central Canada. Native to eastern Asia, EAB is a major threat to North American ash (*Fraxinus*) tree species, all of which are apparently susceptible to attack. Since its initial introduction near Detroit, MI, it has spread to 22 U.S. states and two Canadian provinces (Fig. 1). The pest has already caused significant damage in eastern North America (Kovacs et al., 2010; Poland and McCullough, 2006). The majority of long-distance EAB transmissions have been associated with human transport, primarily with commercial and passenger vehicles moving firewood or other infested materials (Haack et al., 2002; Koch et al., 2012; Kovacs et al., 2010; Yemshanov et al., 2012). The existing capacity to detect EAB (using traps or other means) remains relatively poor, so new detections usually indicate the presence of already established populations (de Groot et al., 2008; McCullough et al., 2009). Despite significant investment in EAB management efforts – \$32 million by USDA-APHIS alone in 2008 (Kovacs et al., 2010) – timely detection of EAB infestations remains difficult.

Human-mediated movement of EAB with infested firewood that may be carried by visitors to parks and campgrounds is believed to be one of the primary vectors of long-distance spread of the pest in North America. The movement of firewood by campers has been linked to the spread of wood-boring invasive forest pests, specifically including EAB, and camper traffic volume has been recognized as a viable predictor of the human-mediated spread of these pests (Haack et al., 2010; Jacobi et al., 2011; Koch et al., 2012). The geographical extent of our analysis was limited by the range of ash species distribution in Canada and the U.S. (Little, 1971) (Fig. 1), and by the availability of campground



Fig. 1. Areas infested with EAB (as per December 2012) and EAB survey regions ( $j$ ).

reservation data that document the movements of campers. Such data are maintained by provincial ministries of natural resources (MNRs) in Canada, as well as state departments of natural resources (DNRs) in the U.S. In addition, the U.S. National Recreation Reservation Service (US NRRS) maintains an online reservation system at federal campground facilities nationwide. The available information in Canada included data from Quebec, Ontario and Manitoba, and in the U.S., from Minnesota, Michigan and Wisconsin, as well as the reservations stored in the US NRRS dataset (Appendix A, see also Koch et al., 2012). Pest surveys are often planned at the level of administrative jurisdictions, so we used the system of Canadian Consolidated Census divisions (StatCan, 2011) as our survey regions  $j$  (total 138 regions, Fig. 1).

2.4. Model-based Assessment of EAB Spread With Campers

The portfolio model required the estimation of the distributions of the potential survey outcomes in various regions. We evaluated the potential survey outcomes with a geographical invasion model that simulated the potential spread of EAB with campers. The model outputs represented plausible realizations of the human-mediated spread of the pest in the study area. We chose a pathway-based model that projects the spread of an organism via a lattice of vectors connecting a set of nodes (i.e., a network). For networks, the physical distance between nodes may matter less than their degree of connectivity, so the amount of movement along a vector is more important than the vector's length when determining the likelihood of spread (Bodin and Saura, 2010, Moslonka-Lefebvre et al., 2011). The model was based on the frequencies of camper travel to a network of state, provincial and federal campground facilities. These frequencies were estimated from the campground reservation data, which provided visitor origin and destination campground locations, and were modeled as two sets of linked nodes, with the strength of the links defined by the number of campers traveling along them (Appendix A).

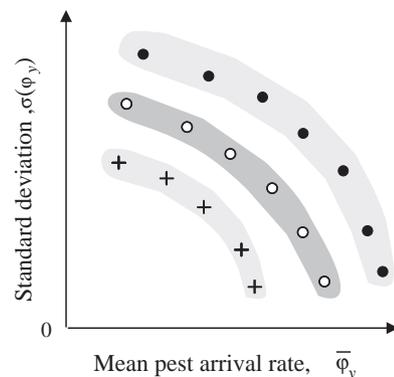
Because symptoms of attack may not be immediately apparent, there is usually a time lag of approximately two years between EAB infestation and detection (Ryall et al., 2011). Although we initialized the invasion model with the distribution of known EAB populations in Canada and the U.S. (USDA APHIS, 2012) as of December 2012 (see Fig. 1), due to this time lag we used campground reservation data for the period between 2009 and 2011, averaged to a 2010 reference year. Notably, our method for addressing the time lag may not have mattered much for the model results; prior to completing the model runs, we examined the year-to-year variation in the campground reservation data and found good consistency between years in terms of major travel patterns (i.e., the most prominent origins and destinations as well as the most heavily traveled pathways in the network). This is not surprising because the local recreational hotspots in central Canada – and the routes that connect them to human population centers – are well known and did not change over that period.

We used the geographical locations of each visitor's origin and destination campgrounds, as well as the total number of visitors along unique "origin–destination" paths, to build a pathway matrix where each element defined the relative rate of camper travel (and by extension, infested firewood movement) from an origin location  $y$  to another location  $z$  (Appendix A). The pathway matrix stored the relative rates of EAB transmission,  $p_{yz}$ , for each pair of locations  $y, z$  in Canada and the U.S. (Appendix A). While we focused our analyses on Canadian provinces only (i.e., Ontario, Quebec and Manitoba), the pathway matrix included cross-border travel to Canadian campgrounds from neighboring U.S. states. We then used the pathway matrix to simulate movements of EAB through the camper travel network from currently infested areas to all other locations in the camper travel network. Based on the stochastic simulations, each geographical location (i.e., a camper travel network node  $y$ ) outside of the areas likely infested with EAB was characterized by a distribution of EAB arrival rates ( $\varphi_y$ ) at that location  $y$ .

2.5. Expected Survey Outcome Metric

Model-based estimates of spread (such as  $\varphi_y$ ) have been regularly used to guide the surveillance of invasive species (Cacho et al., 2010; Hester and Cacho, 2012; Koch et al., 2009; Pitt et al., 2009). For example, locations with high estimated spread rates or high density of the modeled patterns of invasion are often assigned high priority as potential survey sites. Furthermore, if the model forecasts are uncertain, the variation in the predicted spread patterns can still provide useful guidance for an allocation of surveys. In short, it may also be beneficial to visit regions where the predicted uncertainty of the spread estimates is high, so the surveys at those locations could help reduce the variability of the long-distance spread estimates and calibrate the underlying invasion model. Thus, the prime candidate locations to look for a pest may best be represented by a combination of two sets of sites: one with high estimated likelihoods of species arrival, and another with high uncertainty in those estimates. We used this basic idea to calculate our expected survey outcome metric,  $\xi$ .

For each spatial location,  $y$ , within our study area, we generated with the spatial invasion model a distribution of EAB arrival rates  $\varphi_y$ . From these distributions, we estimated for each location  $y$  the mean arrival rate value,  $\bar{\varphi}_y$ , and the standard deviation of the arrival rate,  $\sigma(\varphi_y)$ , as a measure of uncertainty (Fig. 2). We then plotted the individual geographical locations in dimensions of the mean arrival rate ( $\bar{\varphi}_y$ ) and its standard deviation ( $\sigma(\varphi_y)$ ). In the resulting two-dimensional point cloud, locations with some combination of the highest  $\bar{\varphi}_y$  and/or  $\sigma(\varphi_y)$  values were then identified as prime candidates for survey. Clearly, the locations with the highest  $\bar{\varphi}_y$  values can be considered sites where the species is likeliest to be discovered, and surveys of locations with highly uncertain estimates of  $\varphi_y$  could provide opportune (i.e., unexpected but highly useful) knowledge gains about the geographical extent of infestation. In the  $\bar{\varphi}_y - \sigma(\varphi_y)$  point cloud, locations with the highest  $\varphi_y$  and/or  $\sigma(\varphi_y)$  values fall along the cloud's upper outermost convex boundary (Fig. 2). We assigned these points (and their corresponding geographical locations) the highest rank of 1 and then removed them temporarily from the  $\bar{\varphi}_y - \sigma(\varphi_y)$  cloud. Next, another convex boundary (i.e., a new subset of points in the cloud) comprised of the second highest combinations of  $\bar{\varphi}_y$  and  $\sigma(\varphi_y)$  values was found and assigned a performance rank of 2, and so on, until all locations were assigned a rank, 1, 2, ...,  $\nu$ . The ranks denote nested multi-attribute frontiers (Yemshanov et al., 2013) in the dimensions of the  $\bar{\varphi}_y$  and  $\sigma(\varphi_y)$  values. For convenience, we inverted and rescaled the rank values to a



Nested convex frontiers in a  $\bar{\varphi}_y - \sigma(\varphi_y)$  space:

- - frontier 1 (highest rank)
- - frontier 2 (2<sup>nd</sup> highest rank)
- + - frontier 3 (3<sup>rd</sup> highest rank)

Fig. 2. Expected survey outcome metric concept.

[0; 1] range so the highest rescaled ranks, corresponding to the locations where it would be best to survey for EAB, were close to 1 and the lowest to 0 (but note that the rescaling did not change the order relationships within the multi-attribute set). These rescaled ranks became our survey outcome metric,  $\xi$ , and we subsequently composed the cumulative distributions of  $\xi$  to estimate the expected performance values ( $I_j$ ) for each survey region (see Section 2.1) and find optimal allocations of surveillance resources with the portfolio-based technique.

### 3. Results

We first explore the allocations of survey resources in the dimensions of the mean portfolio performance ( $\bar{I}$ ) and the portfolio variance ( $V$ ). We estimated optimal allocations for a range of diversification levels,  $D$ . For each diversification level, the optimal solutions represent points corresponding to different levels of the survey performance ( $\bar{I}$ ) and minimized portfolio variance ( $V$ ). For a given desired level of diversification ( $D$ ), the points constitute the frontier line of optimal solutions in the dimensions of mean performance  $\bar{I}$  and portfolio variance  $V$  (i.e., a mean–variance space, Fig. 3). The frontiers of optimal solutions estimated for multiple diversification levels appear nested when plotted in this mean–variance space (Fig. 3). Note that the differences across the nested frontiers are relative and measured in the dimensions of the survey performance values ( $I_j$ ).

We have also compared the optimal allocations (represented by the frontier lines) with the benchmark scenarios. The benchmark scenarios typically have single solutions and are thus represented by single points in mean–variance space. Fig. 3a–c present the benchmark allocations based on equal resource share (i.e.,  $\omega_j = 1/m$ ), rescaled mean survey performance values ( $\bar{I}_j$ ) and equally-weighted risk contributions (ERC). The positions of the benchmark scenarios in  $\bar{I}$ – $V$  mean–variance spaces relative to the frontier lines of optimal allocations helps better understand the tradeoffs between the scenario objectives (such as desired level of survey performance, diversification and tolerated level of uncertainty) as well as the potential impacts that adding the diversification requirements has on the portfolio performance.

As expected, the allocations based on equal resource shares ( $1/m$ ) and mean survey performance values ( $\bar{I}_j$ ) show low performance, low diversification and relatively high portfolio variance (Fig. 3a–c). Alternatively, the scenarios with the diversification constraint (i.e., the frontier lines) show higher performance and lower variance at low and moderate diversification thresholds. In general, the scenarios with the diversification level below 0.7–0.8 display better performance than the benchmark allocations based on  $1/m$  and  $\bar{I}_j$  criteria. High levels of diversification impose a penalty on the portfolio performance and lead to an increase of the portfolio variance ( $V$ ) above the ERC and  $\bar{I}_j$  benchmark scenarios.

Like the benchmark allocations based on  $1/m$  and  $\bar{I}_j$  values, the ERC allocations exhibited relatively low performance, but with considerably lower variance and levels of diversification. This is not surprising because the ERC allocation method tends to favor low-variance asset types (in our case, survey regions where the estimates of the EAB arrival rate are most certain). The position of the ERC scenario in mean–variance space ( $\bar{I}$ – $V$ ) also points to the minimum level of diversification that can be achieved while meeting or exceeding the performance of the survey in the ERC portfolio. This level is identified by the nearest optimal frontier line above the ERC point in  $\bar{I}$ – $V$  space, e.g., the frontier with the diversification level  $D = 0.9$  in the  $4/m$  scenario (Fig. 3a) or the frontier with the diversification  $D = 0.6$  in the  $2/m$  scenario (Fig. 3c). This aspect is also illustrated in Fig. 3d, which depicts the cross-sections of the frontiers of optimal solutions with the highest performance values (i.e., the points on the right ends of the frontier lines in Fig. 3a–c). In general, the portfolio variance and performance values in the ERC and  $I_j$  allocations were matched or exceeded by the diversification scenarios at low levels of diversification constraint ( $D$ ). Moderately-diversified scenarios

outperform ERC, but usually at the cost of higher portfolio variance (i.e., higher uncertainty).

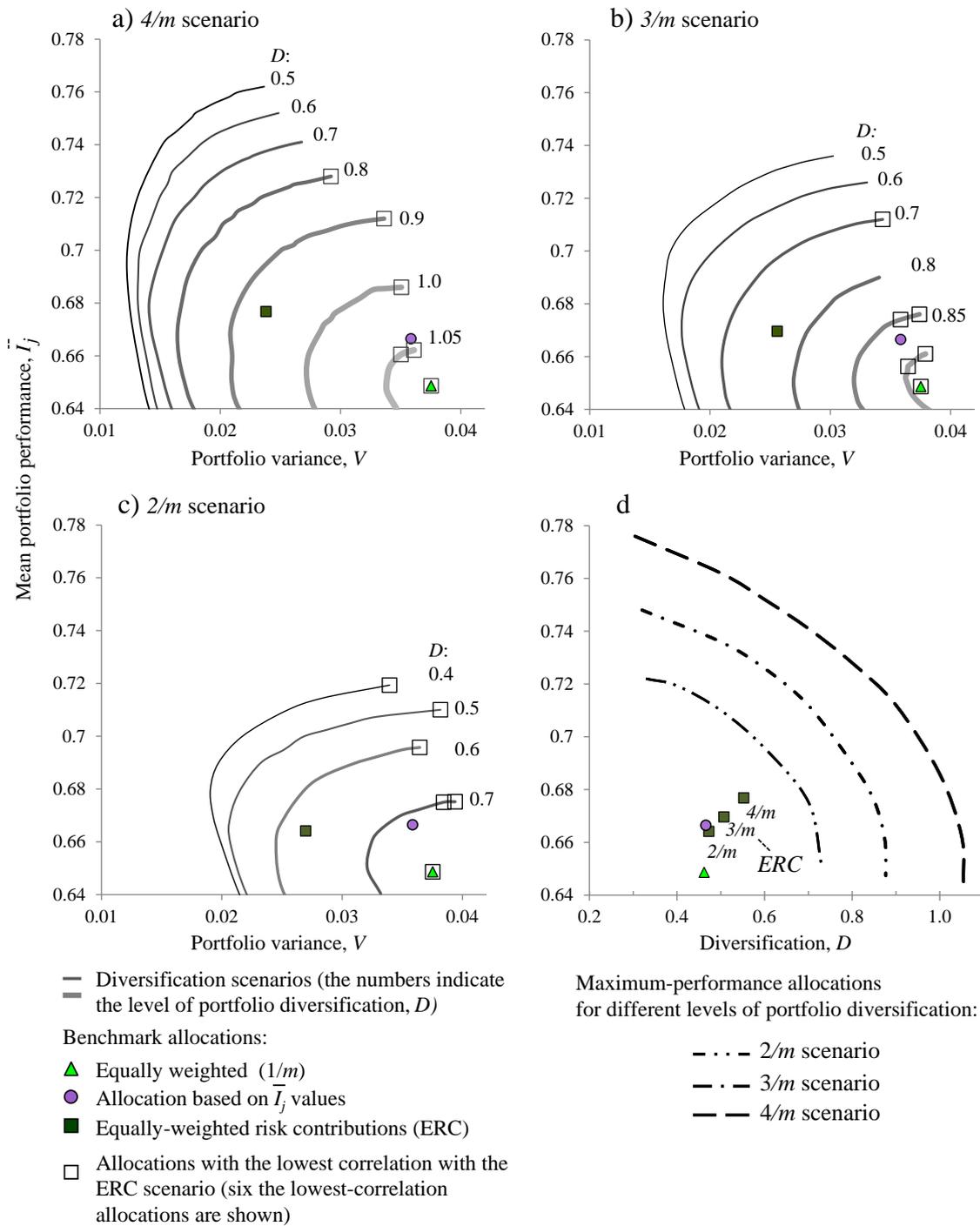
#### 3.1. Geographical Distribution of Survey Resources

Each optimal solution (i.e., a point on the frontier lines in Fig. 3) had an associated vector of resource proportions ( $\omega_j$ ), which could be mapped in a geographical domain. We present the geographical distributions of survey resource proportions ( $\omega_j$ ) for the three illustrative scenarios with high, medium and low levels of portfolio diversification (Fig. 4, Appendix B), as well as map the resource proportions for the ERC and  $\bar{I}_j$  benchmark scenarios (Fig. 5). Compared to the diversification scenarios and ERC allocation, the scenario based on mean performance values ( $\bar{I}_j$ ) exhibited a more even distribution of resource proportions among geographical regions (Fig. 5a). The highest resource proportions ( $\omega_j$ ) were allocated to regions adjacent to areas already infested with EAB, as well as suburban areas around Montreal and Quebec City (QC), both potential hubs of human-assisted movement of EAB. In contrast, the ERC allocation displayed a distinct geographical pattern, with most of the medium and high resource proportions allocated to Quebec (Fig. 5b). This is explained by less diverse camper travel patterns in Quebec versus Ontario, Manitoba and the U.S. Midwest and comparatively lower variance of the campground reservation data from Quebec. Because the ERC allocation tends to pick low-variance asset types, most of the survey resource was allocated to low-variance regions in Quebec. This indirectly highlights a potential drawback of variance-based allocations: because they depend heavily on variance as the sole allocation criterion, they are extremely sensitive to errors in the variance estimates.

Alternatively, the diversification scenarios (Fig. 4, Appendix B) were less influenced by variance and exhibited geographical patterns somewhat similar to the allocation based on  $\bar{I}_j$  values in eastern Canada (Fig. 5). The maps showed three prominent geographical groupings. The first group includes suburban areas near Montreal and Quebec City (QC), as well as portions of the Greater Toronto suburbs (ON) in close proximity to areas already infested with EAB. The second group includes more distant regions in Ontario and Quebec with higher variation of the  $I_j$  values. These areas – such as the Lake Superior coast north of Sault Ste. Marie (ON), areas around Algonquin Park in central Ontario and the “cottage country” north of Barrie (ON) – are characterized by the presence of numerous recreational facilities, which represent potential final destinations for visitors coming from regions already infested with EAB (e.g., southern Ontario and Quebec). The third group of regions with allocated high resource proportions included Winnipeg (MB) and nearby areas in southern Manitoba with low estimated rates of EAB arrival and low to moderate variation of those estimates. Although the threat of EAB arrival is comparatively low in this province, it is nevertheless consistent across its component survey regions due to a low-volume but steady flow of recreational travelers and cross-border visitors from the U.S. Consequently, if implemented in those regions, the survey may lead to unexpected EAB detections, which could be more illuminating than detecting EAB in some parts of southern Ontario or Quebec near existing infestations and could close some important knowledge gaps about the pathways of EAB expansion into western Canada and the U.S.

#### 3.2. Region-specific Performance of the Survey

Three sets of diversification scenarios with the  $h_{\max}$  constraint set to  $2/m$ ,  $3/m$  and  $4/m$  allocated high resource proportions ( $\omega_j$ ) to a different number of regions. The scenarios with  $h_{\max} = 2/m$  assigned high proportions to approximately 66–75 regions, while the scenarios with  $h_{\max} = 3/m$  and  $h_{\max} = 4/m$  allowed higher resource concentrations per region and allocated high resource proportions to approximately 50–55 and 30–33 regions, respectively (Fig. 4, Appendix B). In general, as  $h_{\max}$  increased from  $2/m$  to  $3/m$ , and then from  $3/m$  to  $4/m$ , the

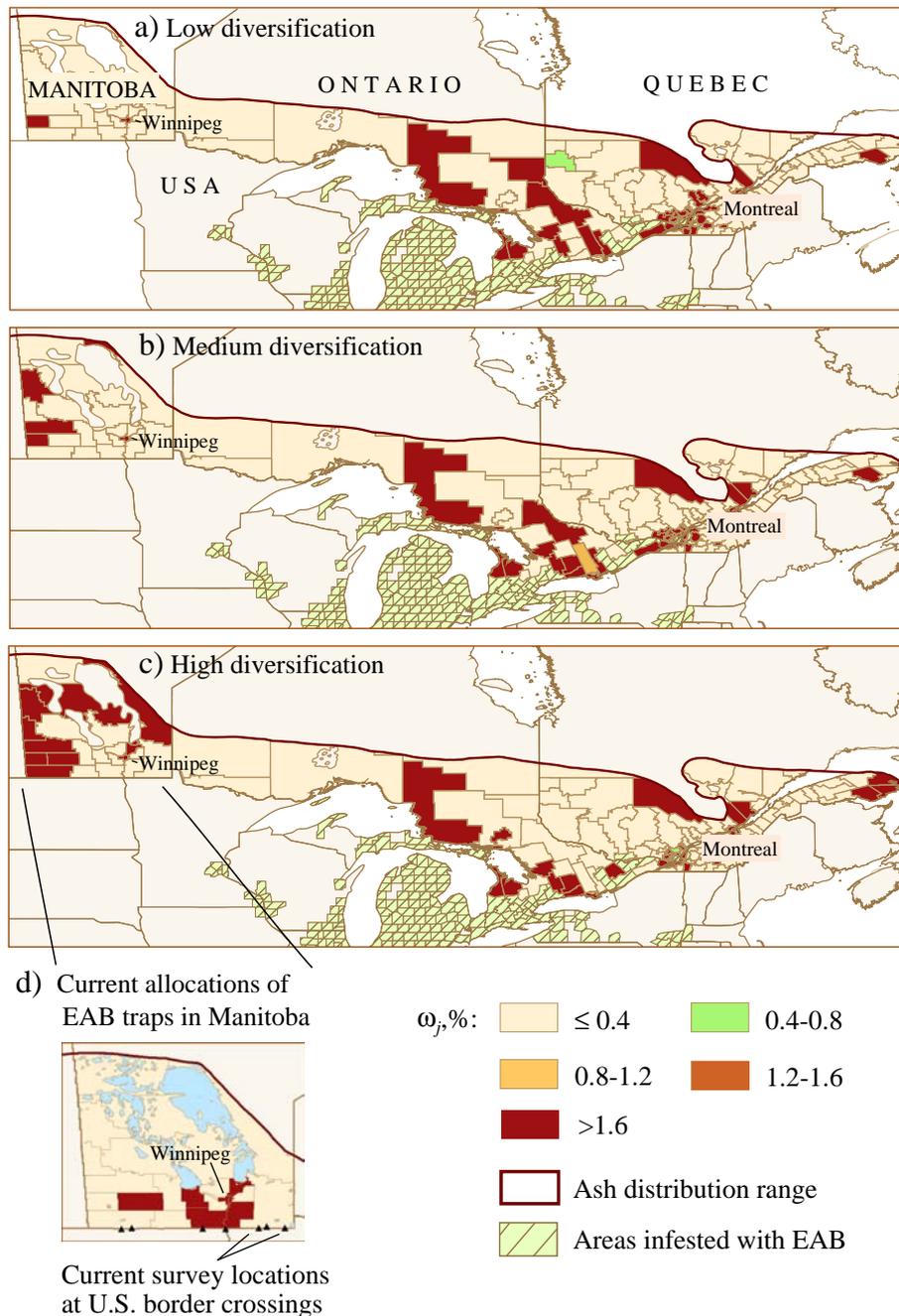


**Fig. 3.** Frontiers of optimal survey allocations in dimensions of mean portfolio performance ( $\bar{I}_j$ ) and portfolio variance ( $V$ ): (a) – 4/m scenarios; (b) – 3/m scenarios; (c) – 2/m scenarios; (d) – cross-sections of best-performing portfolios (the lines connecting the points at the right ends of the optimal frontier lines in Fig. 3a–c) in the dimensions of mean portfolio performance ( $\bar{I}_j$ ) and the desired level of diversification ( $D$ ).

scenarios showed better performance in terms of  $\bar{I}_j$  values, lower portfolio variance and higher possible levels of diversification (Fig. 3a–c). Notably, while the selection of fewer survey regions with increasing  $h_{\max}$  thus led to higher diversification and portfolio performance, it caused only moderate changes in the geographical allocation of high resource proportions (Appendix B).

We also plotted individual survey regions ( $j$ ) as points in the dimensions of the region-specific survey performance value ( $\bar{I}_j$ ) and its standard deviation,  $\sigma(I_j)$  (Fig. 6). The circles in Fig. 6 outline regions with the allocated resource proportions above 0.85% (which is above equal allocation,  $1/m = 0.72\%$ ). The graphs reveal key

differences between the selections of high-priority regions in the diversification scenarios and the benchmark allocations. Unsurprisingly, the allocation based on the mean performance values ( $\bar{I}_j$ ) prioritized regions with high  $\bar{I}_j$  values, while the ERC allocation prioritized regions with low variance (Fig. 6a, b). The diversification scenarios identified high-priority regions in a different fashion: instead of prioritizing only regions with very low variance and/or very high performance, the selected regions tended to be spread evenly along the outer boundary of the mean-variance ( $\bar{I}-V$ ) cloud (Fig. 6c, d, Appendix C). Moreover, in addition to regions with high performance and low variance, the diversification



**Fig. 4.** Geographical distributions of resource proportions ( $\omega_j$ ) under various levels of diversification: (a) –  $3/m$  scenario, low level of diversification ( $D = 0.86$ ); (b) –  $3/m$  scenario, medium level of diversification ( $D = 0.7$ ); (c) –  $3/m$  scenario, high level of diversification ( $D = 0.86$ ); (d) – current (2013) allocations of EAB traps (T. Kimoto, F. Ross, pers. comm.).

scenarios also prioritized medium-variance, low-performing regions at the lower boundary of the  $\bar{I}$ – $V$  cloud. Because these regions are least correlated with the best-performing regions, their inclusion in a survey “portfolio” serves to increase the overall level of diversification with the lowest penalty to the performance levels.

Pairwise correlations between diversification scenarios and the benchmark allocations (Table 1) further emphasize our described findings. The correlations between the benchmark allocations and high diversification scenarios appear to be low. The equal allocation scenario ( $1/m$ ) does not correlate with any other allocation. The ERC scenario is not correlated with high diversification scenarios ( $D_{\text{high}}$ ) and shows moderate correlation with the allocation based on mean performance values ( $\bar{I}_j$ ). In mean-variance space, the scenarios with the lowest correlation between ERC and diversification are allocated along the highest-variance, high diversification region (Fig. 3a–c, lowest-

correlated scenarios are marked empty square symbols), which emphasizes conceptual differences between the ERC and high diversification scenarios. The impact of the  $h_{\text{max}}$  constraint on correlations appears to be moderate: the scenarios with lower  $h_{\text{max}}$  values (i.e., with a resource distribution closer to equal) have generally lower correlations.

#### 4. Discussion

When dealing with new pest incursions over large geographical areas, decision-makers often must choose the best course of action from a set of diverse objectives (such as surveying regions proximal to known infestation versus remote uninvaded locations) in the shortest possible time. The portfolio-based technique helps structure the decision-making process around three key variables: the anticipated performance of the survey, the uncertainty around this anticipated

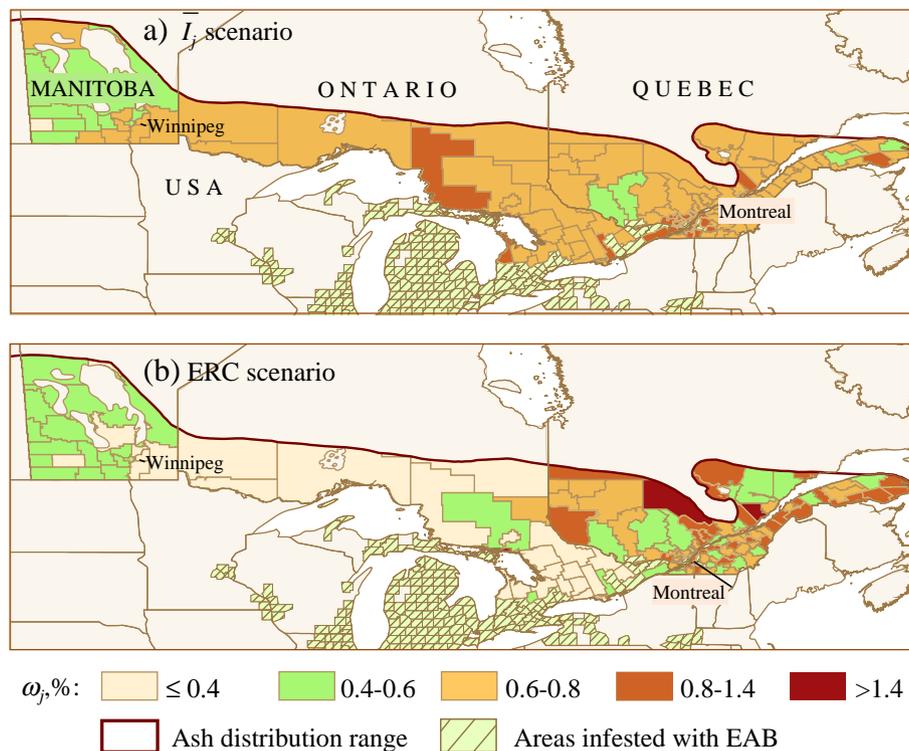


Fig. 5. Geographical distributions of resource proportions ( $\omega_j$ ) in benchmark scenarios: (a) – allocation based on  $\bar{T}_j$  values; (b) – ERC allocation.

performance and the level of geographical diversification of the survey efforts. The latter aspect is especially important in those situations when the geographical extent of the potential survey area is large while the capacity to predict the spread of the pest and assess where the surveillance would be most effective is poor. In such situations, a decision-maker's aspiration to diversify the allocation of surveillance resources across many regions can be viewed as a hedging strategy against potential failures to find the pest as a result of forecasting the spread of invasion. Diversification has important geographical implications because it emphasizes the dissimilarities in organism's spread patterns between individual regions in the survey area and thereby extends the surveillance priorities to regions with low anticipated risk of infestation.

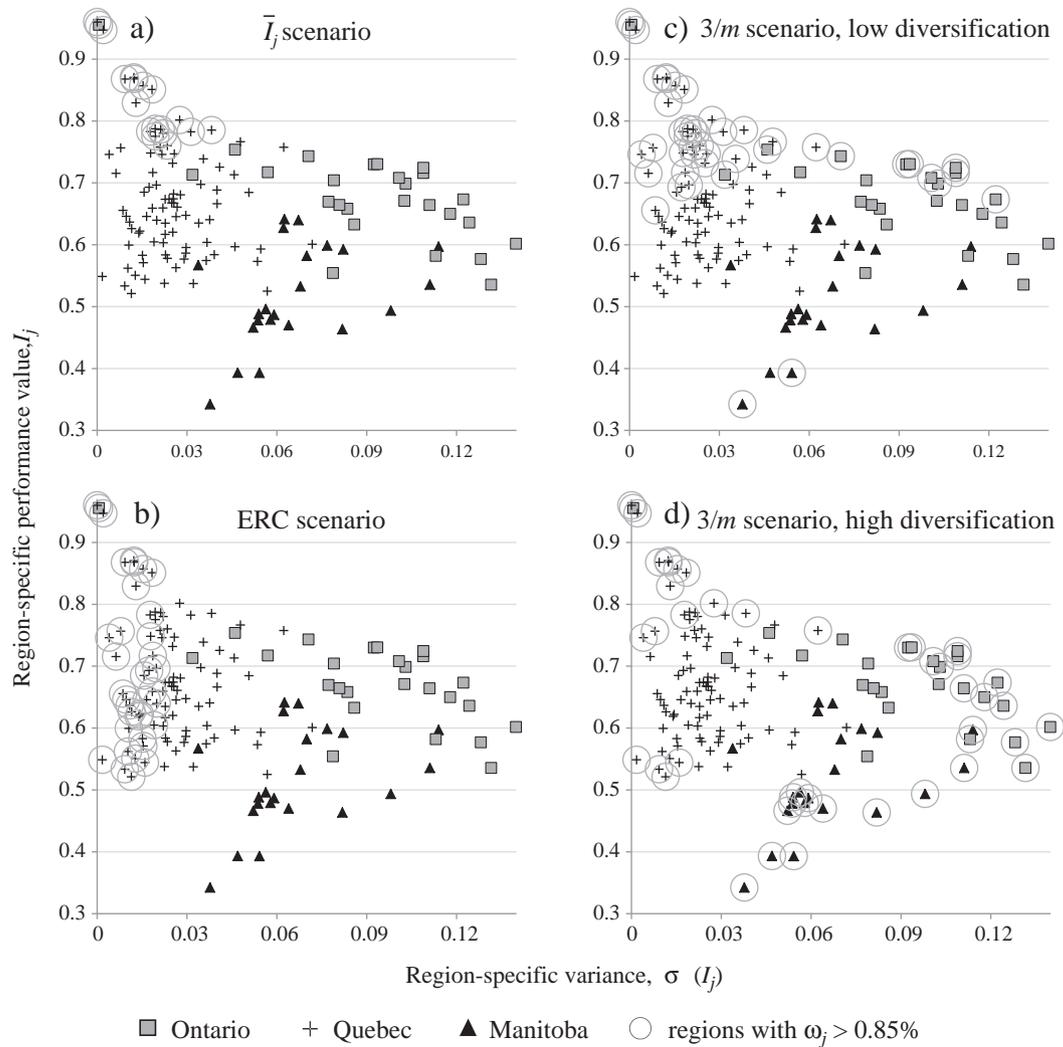
We also compared our diversification scenarios with current survey allocations in Manitoba (established by Canadian Food Inspection Agency and Manitoba Conservation and Water Stewardship). Fig. 4d shows the province's census subdivisions and U.S. border crossings where EAB traps were placed in 2013 (T. Kimoto, F. Ross, pers. comm.). In terms of the census subdivisions, the current trap locations and our diversification scenarios both prioritized Winnipeg (the largest city in Manitoba) and some areas in southwestern Manitoba. The U.S. border crossing locations shown in Fig. 4d indicate where traps have been placed to intercept possible EAB introductions with commercial and passenger transportation from the U.S. Since our pest invasion model did not specifically predict the flows of cross-border commercial or passenger vehicle traffic through these crossing locations, this aspect was not captured in our optimal allocation scenarios, but note that our high diversification scenarios did include regions in southwestern Manitoba near the U.S. border (Fig. 4c, Appendix Bc, f).

In fact, the current abundance of traps in Manitoba, where the risk of EAB arrival is relatively low, provides confirmation that geographical diversification was at least partially considered by pest management professionals when placing the traps. Since we did not know all criteria that influenced the current allocation of traps in central Canada, we did not expect our diversification scenarios to closely match the current trap locations, but rather looked for (and found) general evidence of EAB

surveillance activities in areas, like Manitoba, where the threat of invasion is deemed to be low. Additionally, differences between the current trap allocation and the allocations suggested by our diversification scenarios may help identify areas that have been overlooked by current surveillance efforts. For example, the current trap allocation strongly emphasizes major transportation hubs and populated regions (such as Winnipeg and major border crossings). In contrast, our results, which are based on predictions of EAB spread with campers, provide more detailed stratification of interior areas in central and western Manitoba (i.e., where the majority of recreational destinations is located). Overall, the diversification objective improves the chances of unexpected detections of the pest in areas perceived low risk and therefore helps develop a more informative allocation strategy. Most importantly, it represents a better strategy for early detection because it makes sure to include areas that may be labeled low risk due to errors in the invasion forecasts.

#### 4.1. Benefits of Diversification

Accounting for diversification helps address some technical limitations of the portfolio-based technique. Despite wide recognition in financial literature, mean-variance optimization has a tendency to maximize the impacts of errors in estimating the portfolio performance and its variance (Best and Grauer, 1991; Jobson and Korkie, 1981; Michaud, 1989; Pollak, 2012). For example, errors in underlying data (in our case, model-based pest arrival rates) propagate to the asset type and portfolio variance, which, in turn, shifts the optimal allocation towards lower-variance asset types (Chopra and Ziemba, 1993). In fact, this aspect was evident in the ERC scenario (Fig. 5b), where most of the high resource proportions were allocated to low-variance regions in Quebec. Various regularization techniques have been developed to address this issue, such as resampling techniques (Michaud, 1989; Scherer, 2002), shrinkage estimators of the covariance matrix (DeMiguel et al., 2009; Ledoit and Wolf, 2004; Wang, 2005) or factor analyses to filter out the noise from the covariance matrix (Ledoit and Wolf, 2003; Pollak, 2012). In our study, adding the diversification constraint helped make the optimal allocations less influenced by variance



**Fig. 6.** Resource allocations to individual regions ( $\omega_j$ ) in dimensions of mean performance ( $\bar{I}_j$ ) and its variance ( $\sigma(I_j)$ ): (a) –  $\bar{I}_j$ -based allocation; (b) – ERC allocation. Optimal allocations under the diversification constraint ( $m/3$  scenario is shown): (c) – low diversification ( $D = 0.5$ ); (d) – high diversification ( $D = 0.85$ ). The allocations (c) and (d) depict the best-performing portfolios with the highest  $\bar{I}_j$  values on the right ends of the optimal frontiers in Fig. 3b.

estimation errors because it placed emphasis on general dissimilarities between the survey regions rather than variance estimates. While a constraint requiring minimum levels of diversification has a generally

**Table 1**  
Correlations between the benchmark allocations and high diversification scenario.

$h_{\max}$	Scenario <sup>a</sup>	$\bar{I}_j$	ERC	$D_{\text{high}}$
2/m	1/m	<±0.01	<±0.01	<±0.01
	$\bar{I}_j$		<b>0.41<sup>b</sup></b>	0.28
	ERC			0.07
3/m	1/m	<±0.01	<±0.01	<±0.01
	$\bar{I}_j$		<b>0.40</b>	0.20
	ERC			0.20
4/m	1/m	<±0.01	<±0.01	<±0.01
	$\bar{I}_j$		<b>0.36</b>	0.03
	ERC			0.06

<sup>a</sup> Benchmark allocations:

1/m equal resource allocation;  
 $\bar{I}_j$  allocation based on mean performance values;  
 ERC allocation based on asset types' equal risk contributions;  
 $D_{\text{high}}$  high diversification scenario.

<sup>b</sup> Correlations above 0.3 are marked in bold.

negative impact on the expected performance of a portfolio, the performance of the majority of moderately-diversified survey allocations in our example matched or exceeded the performance of the benchmark allocations based on minimum-variance and equal risk contribution criteria.

Notably, our results did not incorporate spatially explicit factors into our diversification metric, such as proximity to nearby amenities, transportation hubs, populated places or ecological constraints. The implementation of spatial covariates would require proper quantification of the types of economic activities which influence the spread of the pest of interest in a geographical domain, as well as subsequent linkage of these activities to the organism's rate of spread. While including spatial covariates could potentially improve the accuracy of the survey allocations, their estimation would be challenging, as it would require high-resolution metrics of economic activities and the development of econometric models which link these data to the spread rate estimates. The addition of multiple spatial covariates might also require a reformulation of the portfolio model to a multi-objective programming task. Several studies have demonstrated the feasibility of multi-objective approaches in portfolio analysis (Konno et al., 1993; Sealey, 1978). Overall, the addition of multiple decision-making objectives, such as preferred allocations of survey resources to specific locations on the landscape driven by socio-

economic and decision-making considerations, could help accommodate real-life tradeoffs faced by pest management professionals in monitoring and managing alien pest invasions and promote acceptance of the utility of a portfolio-based approach.

## 5. Conclusions

Many areas in biosecurity planning face a problem of balancing the allocation of surveillance resources against the capacity to account for low-probability cases of long-distance pest incursions. The methodology presented in this study provides means to account for a geographical diversification of pest surveillance activities and enables decision-makers to explore the trade-off between the desired level of pest survey performance, tolerated levels of uncertainty, and the degree of geographical diversification of surveillance activities. Overall, the approach is generic and can be a useful tool in managing uncertainties associated with emerging alien invasive threats, especially when knowledge about a new invader is scarce.

Supplementary data to this article can be found online at <http://dx.doi.org/10.1016/j.ecolecon.2014.04.024>.

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