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Analysis

Optimizing surveillance strategies for early detection of invasive alien species

Denys Yemshanov[a,*], Robert G. Haight[b], Frank H. Koch[c], Robert C. Venette[d], Tom Swystun[a], Ronald E. Fournier[a], Mireille Marcotte[e], Yongguang Chen[a], Jean J. Turgeon[a]

[a] *Natural Resources Canada, Canadian Forest Service, Great Lakes Forestry Centre, 1219 Queen Street East, Sault Ste. Marie, ON P6A 2E5, Canada*
[b] *USDA Forest Service, Northern Research Station, 1992 Folwell Ave, St. Paul, MN 55108, USA*
[c] *USDA Forest Service, Southern Research Station, Eastern Forest Environmental Threat Assessment Center, 3041 E. Cornwallis Road, Research Triangle Park, NC 27709, USA*
[d] *USDA Forest Service, Northern Research Station, 1561 Lindig St., St. Paul, MN 55108, USA*
[e] *Canadian Food Inspection Agency, 1400 Merivale Road, Ottawa, ON K1A 0Y9, Canada*

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ABSTRACT

Surveillance programs to detect alien invasive pests seek to find them as soon as possible, but also to minimize the cost of damage from invasion. To examine the trade-offs between these objectives, we developed an economic model that allocates survey sites to minimize either the expected mitigation costs or the expected time until first detection of an invasive alien pest subject to a budget constraint on surveillance costs. We also examined strategies preferred by ambiguity-averse decision makers that minimize the expected and worst-case outcomes of each performance measure. We applied the model to the problem of detecting Asian longhorned beetle (*Anoplophora glabripennis*) in the Greater Toronto Area, Canada, one of the most harmful invasive alien insects in North America. When minimizing expected mitigation costs or expected time to detection, the trade-off between these survey objectives was small. Strategies that minimize the worst-case mitigation costs differed sharply and surveyed sites with high host densities using high sampling intensities whereas strategies that minimize the worst detection times surveyed sites across the entire area using low sampling intensities. Our results suggest that preferences for minimizing mitigation costs or time to detection are more consequential for ambiguity-averse managers than they are for risk-neutral decision-makers.

1. Introduction

Early detection of invasive species populations has long been recognized as a strategy to reduce the impacts of invasive alien species (see Büyüktahtakın and Haight, 2018 for review). The fundamental goal of early detection is to find invasive pest populations before they reach a size that is too difficult to eradicate (Baker et al., 2009; Ewel et al., 1999; Finnoff et al., 2007; Holden et al., 2016; Leung et al., 2012). In addition to increasing the chance of eradication success, early detection soon after establishment makes other rapid response measures (e.g., deployment of biological control) possible and less costly (Epanchin-Niell and Liebhold, 2015; Leung et al., 2002; Lodge et al., 2006; Rout et al., 2014).

Surveillance is fundamental to early detection. Recent work on developing surveillance strategies for invasive species has focused on finding optimal levels of surveillance effort, sometimes in combination with eradication or other control activities (e.g., Chen et al., 2018; Epanchin-Niell et al., 2012; Hauser and McCarthy, 2009; Homans and Horie, 2011; Mehta et al., 2007). Other work has examined optimal survey selection in spatial settings (Hester and Cacho, 2012; Horie et al., 2013; Yemshanov et al., 2015, 2017a) and jointly in both spatial and temporal domains (Epanchin-Niell et al., 2014; Moore and McCarthy, 2016). In these studies, surveillance was undertaken to minimize the expected costs of damage, subject to budgetary constraints on the surveys and/or other aspects of the management response.

The objective of an early detection survey is to uncover the presence of a species of concern in the shortest possible time after it arrives and establishes. This objective has a one-period planning horizon that follows a typical one-year pest survey planning cycle. Often, first detection of a novel harmful pest in a previously uninvaded area triggers a set of response actions aimed to eradicate the pest population or impose

* Corresponding author.
E-mail address: Denys.Yemshanov@canada.ca (D. Yemshanov).

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phytosanitary restrictions to initiate containment actions (CFIA, 2013a, 2014a, 2017, FAO-IPPC, 2010; Guillera-Arroita et al., 2014). These large-scale response actions can only be initiated once the pest's establishment into the area of concern is confirmed.

Timely detection is critical because eradication and containment at earlier stages of an invasion have a substantially higher probability of success (Tobin et al., 2012). In short, early detection surveys that aim to discover the first arrival of a new invader into the area of concern can be thought of as analogous to an alarm system that is designed to detect the first unauthorized entry and trigger the response actions as soon as possible. Therefore, the objective of early detection survey differs from a typical objective of a delimiting survey, which aims to uncover all details about the pest distribution in the area and may continue over longer periods after initial discovery of the invader and regardless of the number of detections in the area. Often delimiting surveys place higher emphasis on sites with high host densities, since they are most vulnerable to having high damages if detection fails. The strategy of minimizing time to first detection does not have the same requirement to consider site vulnerability to high mitigation costs. Instead, quick detection of pest entry is the priority because it allows managers to head off these mitigation costs by applying response measures at earlier stages of an invasion when they are most effective.

To examine the trade-offs between these survey objectives, we developed a spatial optimization model that selects a subset of survey locations to minimize either the expected costs of mitigating the invasion (if the survey fails to detect the pest organism) or the expected time until first detection of the pest in the surveyed area, subject to a budget constraint on surveillance costs. In our study, the mitigation costs amount to the expense of removing and destroying infested and highly susceptible host trees from invaded sites, according to the protocols defined for managing wood-boring pest invasions in urban areas. The probabilities of pest introduction are uncertain and vary across the landscape. We used estimates of these probabilities to develop a large set of probabilistic invasion scenarios that depicted likelihoods of invasion and subsequent damage to suitable hosts. We examined the sensitivities of the survey allocations to changing the management objective (i.e., minimizing expected mitigation costs vs. expected time to first detection) and examined alternative strategies that minimized the expected worst-case costs of each performance measure. We addressed these surveillance problems using the example of an ongoing early detection survey program for Asian longhorned beetle (ALB, *Anoplophora glabripennis*) in the Greater Toronto Area (GTA) of Ontario, Canada to detect the presence of new introductions resulting from the importations of commodities that may carry ALB from its native range.

2. Methods

We have developed a spatial optimization model for surveillance in which uncertainty about the presence of an invader is represented by a set of probabilistic scenarios (see Table 1 for a summary of notation definitions). We subdivided our study area landscape into J contiguous sites. For each site j, there is a population of N_j trees that may host an invasive pest. Individual sites may have different risk of pest attack and require different amounts of tree inspections to detect the signs of infestation. To detect the pest at a site j, we need to estimate the following parameters contributing to a successful detection. For each tree k, $k = 1, \ldots, N_j$ at a site j, we need to know the likelihood that a tree is infested θ_{jk}, the inspection effort v_{jk}, the cost per time unit of inspection c_{jk} and the probability of detecting an outbreak after inspecting a tree if it is present, γ_{jk}. While the true likelihoods of tree infestations are unknown, their relative values can be estimated based on the invader's historical patterns of spread and empirical estimates of infested trees found in surveyed sites during previous surveillance campaigns. We have used these estimates to develop a set of infestation scenarios, S, where each scenario s, $s \in S$, is characterized by probabilities of infestation, θ_{jks}, for all trees $k \in N_j$ and all sites $j \in J$. These scenarios are based on stochastic predictions of the pest's spread through an uninvaded area. We assume each invasion scenario s has an equal probability of occurrence, $1/S$.

The specific objective of our optimization model is to define the amount of inspection effort that must be devoted to each candidate site to minimize either the expected mitigation costs across the area of concern (problem 1) or the inspection effort until first detection of the pest in the targeted area (problem 2). We depict the intensity of inspections at surveillance sites as a number of trees inspected at a site j. We define a set of M tree sampling levels, where each inspection level m, $m \in M$, is characterized by a number of inspected trees, K_m, where $K_m \geq 1$ and $K_m \leq N_j$. We also assume that K_m trees are selected in order of ease of access (i.e., accessible street trees before park and backyard trees). For each site j, the choice of tree sampling level is defined by a set of binary decision variables x_{jm}, for all $m \in M$ and $j \in J$, where each x_{jm} represents whether or not the sampling level m is selected at survey site j. At most, one tree sampling level may be selected for each site:

$$\sum_{m=1}^{M} x_{jm} \leq 1, \forall j \in J \tag{1}$$

Given a solution that the site is not surveyed, $\hat{x}_{jm}$, $m = 1, , , , , M$, then $\sum_{m=1}^{M} \hat{x}_{jm} = 0$.

2.1. Problem 1: minimize expected mitigation costs

Problem 1 minimizes the expected costs to mitigate the invasion from potential pest entries into both surveyed and un-surveyed sites. For simplicity, we estimated the mitigation costs as the number of infested and susceptible host trees that must be removed if the pest establishes in the area. For each surveyed site j under an infestation scenario s, the mitigation cost, if the pest is found, is d_{1js}, which represents the cost of removing and disposing of infested trees. If the pest is not found due to failed detection, we assume the pest continues to spread in the area until it is detected by other means, leading to greater mitigation costs, d_{0js}, where $d_{0js} > d_{1js}$. The mitigation cost d_{0js} represents the cost of removing and disposing of the infested trees once the signs of infestation are detected later by some other means (i.e., accidental detection by the general public), when a greater number of trees will have to be removed to control the infestation. Similarly, we assume that some trees will have to be removed from unsurveyed sites, under the assumption that a portion of the trees across these sites may be infested. Since each scenario s has unique probabilities of infestation for individual trees, θ_{jks}, the mitigation cost at each site j is indexed by scenario s.

Let p_{jms} be the probability of detecting one or more infested trees in a sample of K_m trees in site j under scenario s:

$$p_{jms} = 1 - \prod_{k=1}^{K_m} (1 - \theta_{jks}\gamma_{jk}) \tag{2}$$

Then, the expected mitigation cost value at a surveyed site j under scenario s is:

$$\sum_{m=1}^{M} x_{jm} [p_{jms} d_{1js} + (1 - p_{jms}) d_{0js}] \tag{3}$$

If the site is not surveyed, $\Sigma_{m=1}{}^{M} x_{jm} = 0$, the expected mitigation costs under scenario s is:

$$\left(1 - \sum_{m=1}^{M} x_{jm}\right) d_{0js} \tag{4}$$

Then, problem 1 minimizes the total expected mitigation costs over all sites and scenarios:

Table 1
Summary of the model variables and parameters.

Symbol	Parameter/variable name	Description
Sets:		
j	Potential survey sites in the managed area	$j \in J$, $J = 1180$
s	Stochastic pest entry scenarios	$s \in S$. $S = 1800$
m	Survey intensity levels	$m \in M$, $M = 7$
n,k	Individual trees n,k inspected in a sample of K_m trees at a survey site (auxiliary subscript, used to derive time to first detection t_{jms} and detection probability p_{jms}, see Appendix S1)	$n,k \in K_m$
Parameters		
B	Survey budget	$B > 0$
N_j	Number of host trees at a site j	$N_j \geq 0$
θ_{jks}	Probability of infestation of a tree k in a site j in a scenario s	$\theta_{jks} \in [0; 1]$
γ_{jk}	Pest detection rate for tree k in site j	$\gamma_{jk} \in [0; 1]$
p_{jms}	Probability of detecting one or more infested trees in a sample of K_m trees at a site j in a scenario s	$p_{jms} \in [0;1]$
c_{jk}	The cost of a unit of time to survey tree k in site j	$c_{jk} > 0$
v_{jk}	Time to inspect tree k in site j	$v_{jk} > 0$
t_{jms}	Expected time to first detection in site j using a sample size K_m, under scenario s	$t_{jms} > 0$
d_{1js}	Damage to host at the time of detection at a site j in a scenario s	$d_{1js} \geq 0^{**}$
d_{0js}	Damage to host at a site j in a scenario s when the survey fails to detect the pest	$d_{0js} \geq 0$
K_m	Total number of trees that are inspected at a survey intensity level m	16…600
α	Confidence level that defines the mitigation costs value that can be exceeded only in $(1 - \alpha)_*100\%$ of worst pest entry scenarios	0.9
D	Expected worst-case mitigation cost limit that could be tolerated by decision-maker	$D > 0$
Decision variables:		
x_{jm}	Binary survey selection of a site j	$x_j \in \{0,1\}$
R_{jms}	Binary variable for each scenario s that denotes whether the first detection was made at site j using inspection level m.	$R_{jms} \in [0;1]$

$$\min_{\{x_{jm}\, j \in J\, m \in M\}} \frac{1}{S} \sum_{s=1}^{S} \sum_{j=1}^{J} \left[\sum_{m=1}^{M} (x_{jm} [p_{jms} d_{1js} + (1 - p_{jms}) d_{0js}]) + \left(1 - \sum_{m=1}^{M} x_{jm}\right) d_{0js} \right] \quad (5)$$

subject to an upper bound B on the inspection budget:

$$\sum_{j=1}^{J} \sum_{m=1}^{M} \left(x_{jm} \sum_{k=1}^{K_m} c_{jk} v_{jk} \right) \leq B \quad (6)$$

and the inspection level selection constraint (1).

2.2. Problem 2: minimize time to first detection

The objective of problem 2 is to choose an inspection level for each site to minimize the expected inspection time until first detection of the pest in the area of concern. For each site j, inspection level m, and scenario s, the parameter for the expected time to first detection of an infested tree is t_{jms}. The time to first detection is a statistical expectation of the effort (measured in inspection time units) required to detect the signs of infestation in a sample of inspected trees at a survey site j. The time unit in our model depicts the effort required to inspect a single tree (term v_{jk} in Appendix S1 and Eq. (7)). It can also be expressed in monetary terms as units of inspection effort (where inspecting a single tree equals one unit of effort). Consider an inspection of a sample of k trees in a survey site. Inspection of the first tree takes a unit of time, v_1. After inspecting the first tree, the probability of finding the infestation is $p(v_1)$. Inspection of the next tree takes v_2 and yields the detection probability $p(v_2) \times (1 - p(v_1))$, which is the probability of failing to detect after examining tree 1 but making the detection after inspecting tree 2, etc. The time to first detection after inspecting k trees is a product of the time (or inspection effort) spent on surveying trees 1, …, k and the conditional probabilities of detecting the pest after inspecting the k^{th} tree while failing to detect after surveying all previous trees 1, …, k-1. In short, we estimate the probability mass function for detecting the pest after surveying a k^{th} tree in a sample of inspected trees.

It is possible that the inspections of a sample of k trees may find no infestation, therefore we need to account for the probability of detection failure after inspecting a sample of k trees. Based on a history of past pest outbreaks, new infestations are eventually discovered by accidental means over a longer time, so we depict the "no-detection" conditions in similar time domain and define the "no-detection" effort with a very large time value at a site level, T that greatly exceeds the detection times in sampled trees ($T = 1000$). Thus, the time to first detection metric is not a true estimate of detection time because it factors in the conditional probability that the inspections of tree samples at the survey sites fail to detect an infestation, allowing it to spread until the pest is detected by other means outside of the survey program.

In Appendix S1, we derive a formula for t_{jms} by first defining a discrete random variable for the time before the first detection is made and then calculating its expected value:

$$t_{jms} = \sum_{n=1}^{K_m} \left[\left(\sum_{k=1}^{n} v_{jk} \right) \theta_{jks} \gamma_{jn} \prod_{k=1}^{n-1} (1 - \theta_{jks} \gamma_{jk}) \right] + T \prod_{k=1}^{K_m} (1 - \theta_{jks} \gamma_{jk}) \quad (7)$$

The time to first detection formula (7) has two terms. The first term on the right-hand-side is the statistical expectation of the time (or effort) needed to make the first detection in a sample of inspected trees and the second term is the expectation that the inspections of the sampled trees will fail to detect the pest and it will be detected in time T by other accidental means. For each site j, Eq. (7) computes the unique detection time t_{jms} for each combination of an infestation scenario s and tree sampling rate x_{jm}. For each scenario s, the expected time to first detection is equal to the minimum detection time t_{jms} across the J sites in a scenario s, so the possibility of simultaneous inspections across multiple sites is not considered.

The detection time metric t_{jms} always varies between 0 and T, so it is a relative measure. The closer the time to first detection across all sites j to T, the more likely tree inspections will not find the pest after inspections of surveyed sites. The larger the sample of the inspected trees at a site, the more likely the first detection will be made, so the detection time becomes shorter. Accounting for non-detection is important because it helps depict the conditions when the tree-sampling rate (or the probability of infestation) is low.

To minimize the expected time to first detection, we define a binary variable R_{jms} for each scenario s that denotes whether the first detection was made at a site j using an inspection level m. Binary variable R_{jms} is used to identify the site with shortest detection time in an area J in a scenario s. A detection can be made at site j using inspection level m

only if the site is surveyed at that level, i.e., $R_{jms} \le x_{jm}$. Further, only one detection event across the landscape J is considered shortest in each scenario, i.e.:$\Sigma_{j=1}{}^{J}\Sigma_{m=1}{}^{M}R_{jms} = 1$. We assume that additional detections will not reduce the time to the first detection any further. Then, problem 2 minimizes the expected time to the first detection over all sites and scenarios:

$$\min_{\{x_{jm}\ j\in J\ m\in M\}} \frac{1}{S}\sum_{s=1}^{S}\sum_{j=1}^{J}\sum_{m=1}^{M} t_{jms}R_{jms} \tag{8}$$

subject to the budget constraint (6), inspection level selection constraint (1) and the constraints on the decision variables:

$$R_{jms} \le x_{jm}\ \forall\ s\in S, j\in J, m\in M \tag{9}$$

$$\sum_{j=1}^{J}\sum_{m=1}^{M} R_{jms} = 1\ \forall\ s\in S \tag{10}$$

Note that budget constraint (6) in problem 2 includes both inspection effort v_{jk} and cost per unit of inspection effort c_{jk}. Eq. (6) stipulates that the sum of the inspection cost for each inspected tree (i.e., $c_{jk}v_{jk}$), across all surveyed sites, must be less than or equal to the total budget. Inspections of more trees usually increase the likelihood of finding infested trees and so reduce the time to first detection, so the budget constraint (6) is meaningful for problem 2.

2.3. Minimizing the expected worst-case time to first detection

Uncertainty about which sites the pest invades and how many trees the pest infests causes the expected detection times t_{jms} to vary across infestation scenarios s, $s \in S$. As a result, for any given surveillance plan, the inspection efforts to first detection within the managed area will vary across the scenarios. The objective function in Eq. (8) minimizes the mean time to first detection over all infestation scenarios but does not explicitly consider the longest detection times in the tail of the distribution (which have a small effect on the mean value). As a practical matter, the right-hand tail of the detection time distribution may contain times to first detection close to T values, which indicate non-detection and translate into greater damage to the host and greater mitigation costs.

When faced with a potential detection failure, an uncertainty-averse decision-maker may decide that non-detections are unacceptable even if the probabilities of these events are low and will try to minimize these outcomes at all costs. This behaviour is an example of ambiguity aversion (Gilboa and Schmeidler, 1989). An ambiguity-averse manager evaluates potential actions in terms of the minimum utility that might emerge from selecting these actions. If the prior information about potential outcomes of infestation is lacking, an ambiguity-averse strategy at least ensures the best of the expected worst possible outcomes.

Minimizing the expected longest time to first detection over the infestation scenarios requires controlling the right tail of the distribution of detection times with a percentile metric that characterises the expected tail value (Jorion, 2006; Studer, 1997). In particular, value-at-risk (VaR) and conditional value-at-risk (CVaR) are used in the finance field to evaluate risk of extreme losses (Acerbi and Tasche, 2002; Duffie and Pan, 1997; Inui and Kijima, 2005; Rockafellar and Rockafellar and Uryasev, 2000, 2002). In our detection survey problem, VaR_α is defined, with a confidence level α, $\alpha \in [0,1]$, as the value in the distribution of times to first detection in S scenarios that is exceeded only in $(1-\alpha) \times 100\%$ of the scenarios (see Fig. S2.1 in Appendix S2). In turn, CVaR_α is defined as the expected detection time above VaR_α for confidence level α (Fig. S2.1 in Appendix S2). We use CVaR to depict the ambiguity-averse strategy of avoiding the worst-case outcomes of survey actions, i.e., minimizing the *expected worst-case* time to first detection (and by extension, the *expected worst-case* mitigation costs D), i.e.:

$$\min[\mathrm{CVaR}_\alpha(\text{time to first detection})] \tag{11}$$

s.t.

$$\mathrm{CVaR}_\alpha(\text{mitigation costs}) \le D \tag{12}$$

where D is the expected worst-case mitigation cost level that could be tolerated by a decision-maker. In our scenario-based formulation, the objective function was linear with respect to the decision variables x_{jm} and R_{jms}, so we linearized the CVaR minimization using concepts from Rockafellar and Rockafellar and Uryasev (2000, 2002), as implemented by Yemshanov et al. (2017b) (see Appendix S2).

Table 2 lists basic optimization scenarios, which include the problem 1 and 2 solutions with and without ambiguity aversion assumption. The model was composed in the GAMS environment (GAMS, 2016) and solved with the GUROBI linear programming solver (GUROBI, 2016). We also explored the sensitivity of the objective function values for problems 1 and 2 to relative changes in the model parameter values (see Appendix S3).

2.4. Case study

2.4.1. Early detection of Asian longhorned beetle in the GTA

We applied our optimization models to develop strategies to detect the presence of ALB in the GTA. Several outbreaks of ALB have been found in eastern North America since 1996, when the first population was found in New York, NY USA (Haack et al., 1997; Haack et al., 2010; Shatz et al., 2013; Trotter III and Hull-Sanders, 2015; Turgeon et al., 2015). All of these introductions involved specimens that arrived from China (APHIS, 2005, 2013, 2016; Carter et al., 2009a, 2009b, 2010; Javal et al., 2017). In all these infestations, maple (*Acer* spp.) was ALB's main host. Other good hosts included birch (*Betula* spp.), poplar (*Populus* spp.), elm (*Ulmus* spp.) and willow (*Salix* spp.) (CFIA, 2014b; Lingafelter and Hoebeke, 2002; Smith et al., 2009; Wang et al., 2005; Williams et al., 2004). The first outbreak of ALB in Canada was discovered in the GTA in 2003 (Hopkin et al., 2004). As part of the eradication strategy, a 152-km^2 regulated area was established around the infested area (Carter et al., 2009b; Haack et al., 2010; Smith et al., 2009; Turgeon et al., 2010). Canadian Food Inspection Agency (CFIA) declared this regulated area pest free in 2013 (CFIA, 2013b). Despite successes at eradicating ALB in Canada and in the United States (APHIS, 2015; CFIA, 2013b; Stefan et al., 2014), and the implementation in 2006 of International Standards for Phytosanitary Measures No.15

Table 2
Model scenarios.

Problem formulation	Objective value	Decision-maker's perception of the uncertainty	Objective function
Problem 1	Mitigation cost	Ambiguity-neutral	**Min** (expected mitigation cost) over S infestation scenarios and J survey sites
Problem 1	Mitigation cost	Ambiguity-averse	**Min** (expected *worst* mitigation cost) over S scenarios and J survey sites
Problem 2	Time effort to first detection	Ambiguity-neutral	**Min** (expected time to first detection) over S scenarios and J survey sites
Problem 2	Time effort to first detection	Ambiguity-averse	**Min** (expected *worst* time to first detection) over S scenarios and J survey sites

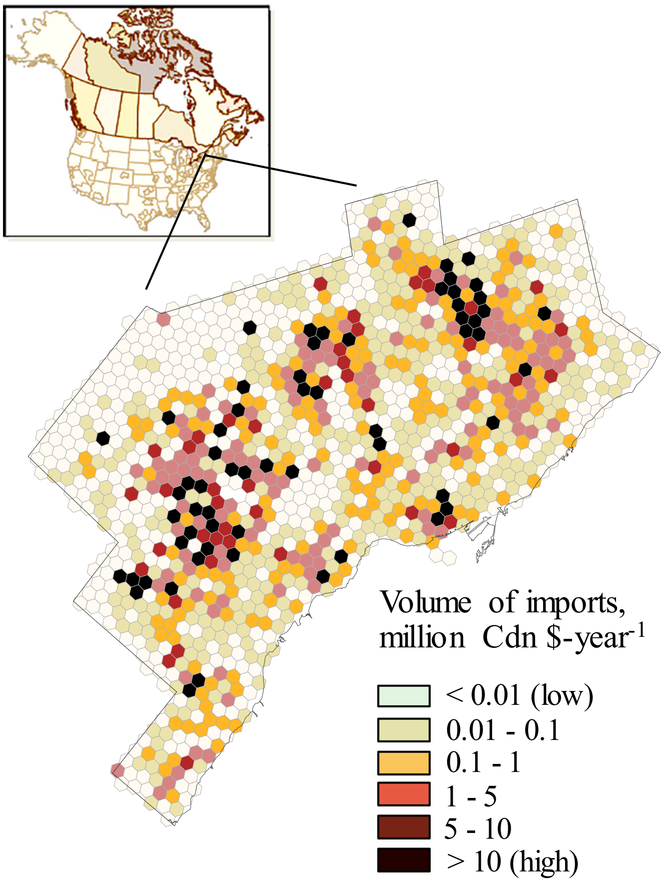

Fig. 1. Hexagonal pattern of survey sites in the Greater Toronto Area and the risk of pest entry (depicted as average volumes of imports of pest-associated commodities to GTA for 2014–2016, Cdn $-year^{-1}).

(ISPM 15) to reduce the risk of introduction of quarantine pests associated with the movement of wood packing materials (FAO-IPPC, 2017), ALB remains a threat in the GTA because the area receives large quantities of imports from countries where ALB is found. The following subsections briefly describe the values of parameters we used in our optimization models (Table 1). We also provide full parameter estimation in Appendix S4.

2.4.2. Sites and inspection levels

The CFIA currently conducts surveys to detect the presence of new ALB populations in the GTA. The survey scheme involves subdividing an area of potentially high risk of ALB arrival into hexagonal cells approximately 146.6 ha in size (Fig. 1) and inspecting 30 trees at each site (Bullas-Appleton et al., 2017). We used this grid of hexagonal cells to define our sites, and defined seven (M = 7) possible inspection levels, K_m, ranging between 15 and 600 trees inspected per survey site.

Our detection time estimation followed the standard protocols adopted by plant biosecurity agencies and municipalities for site surveys involving tree inspections. Due to budget constraints, we assumed that tree inspections at a site are performed sequentially by minimum-size crews. Unlike a disease epidemic, for which there may be frequent status updates, the status of an invasive insect pest such as ALB in an area of concern is usually reassessed on an annual basis, which is consistent with the life cycle of the pest and the deciduous tree hosts.

2.4.3. Likelihoods of ALB entry

We associated potential entries of ALB with imports based on historical data that recorded interceptions of wood-boring pests on different commodity types. We used data on imports of commodities to the GTA for 2014–16 provided by the Canadian Border Security Agency. The data included country of origin, destination, commodity type, and declared value. We considered only commodities that are documented as potential carriers of ALB and similar wood-boring pests (Haack, 2001, 2006; Koch et al., 2011; McCullough et al., 2006; Work et al., 2005). We used the import values as proxies of the likelihoods of ALB

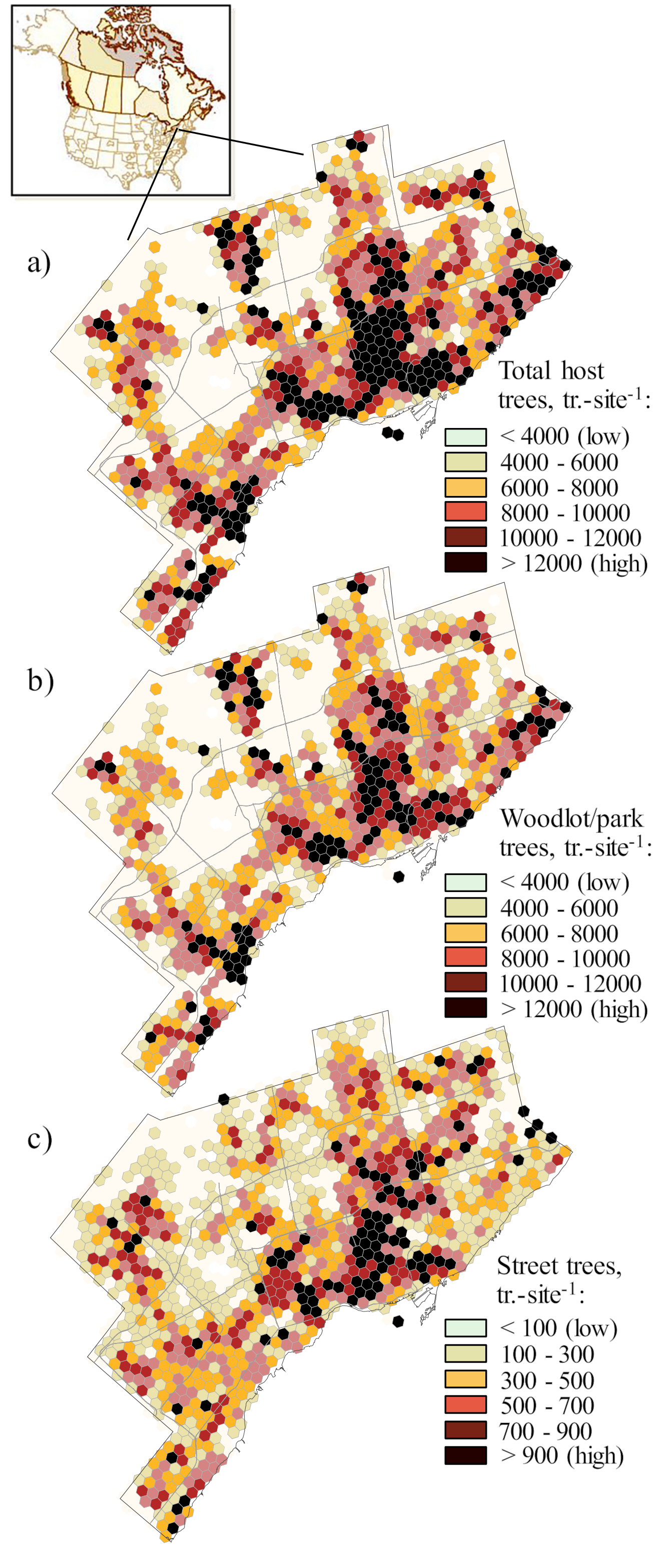

Fig. 2. Host tree density in the study area (ALB host genera only): a) total host tree density; b) woodlot and park tree density; c) street tree density.

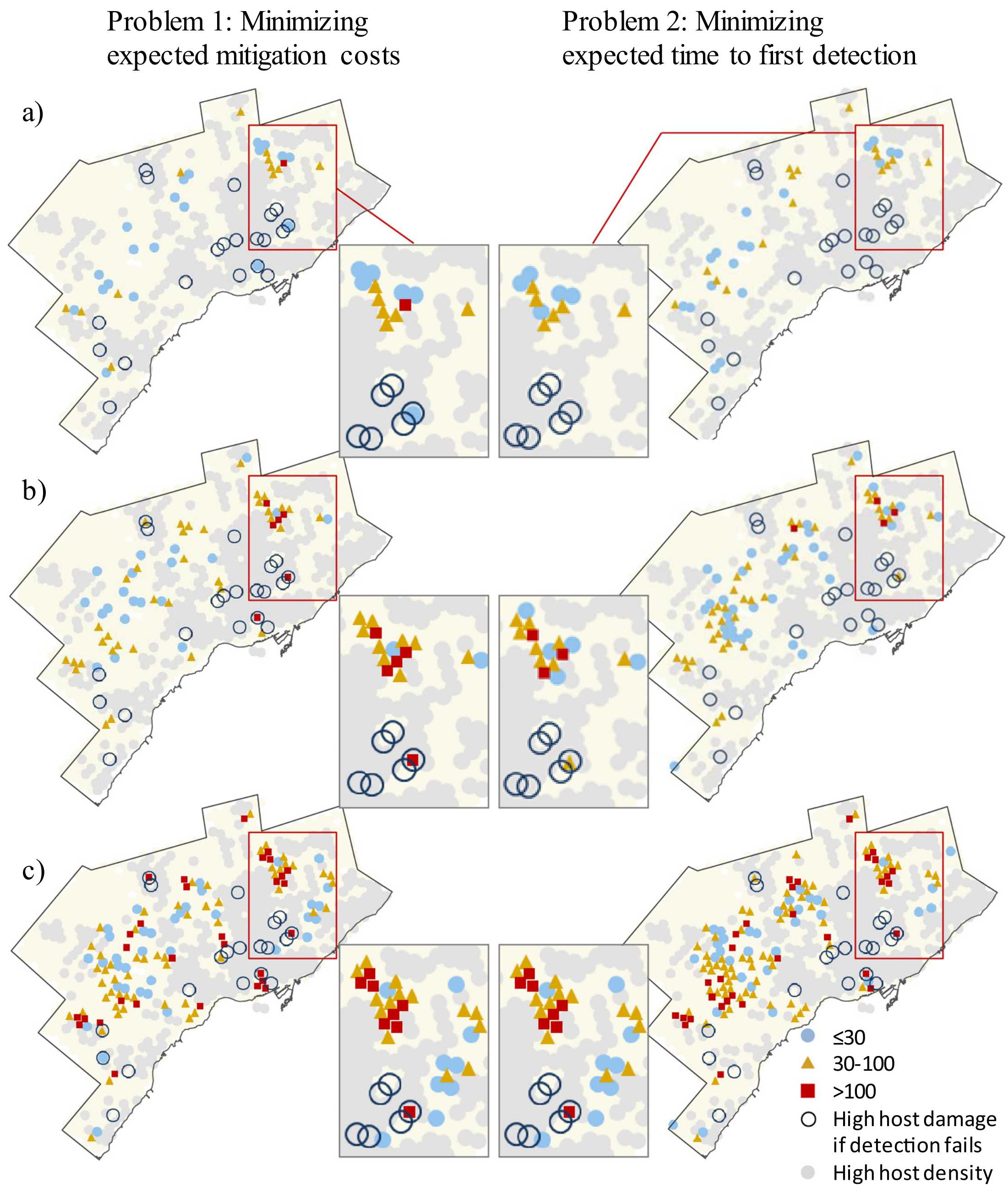

Fig. 3. Survey allocations in problem 1 (minimizing the expected mitigation costs) and problem 2 solutions (minimizing expected time to first detection): a) budget level \$10,000; b) budget level \$30,000; c) budget level \$90,000. Maps show the solutions based on 1800 invasion scenarios. Close-ups highlight a portion of an industrial area in the eastern GTA for problem solutions 1 and 2 (outline rectangle). Areas with high host tree densities are shaded in light grey. Empty circles show the locations with the highest expected mitigation costs if detection fails (or the location is not surveyed). Solid circles, triangles and squares show different inspection rates at the selected survey sites in optimal solution, trees-site^{-1}.

entry at the survey sites (Fig. 1, Appendix S4).

Reports from ALB outbreaks in the GTA and in the eastern USA suggested that infestations generally start at a single entry point (Hull-Sanders et al., 2017; Turgeon et al., 2015). Hence, we assumed that an ALB infestation at a site j represented a population spreading from a single nucleus within a site. This assumption is primarily for computational simplicity and does not preclude infestations occurring (and being detected) in multiple sites. For each scenario s, the number of infested trees in an infested site j was chosen at random from a distribution of infested tree densities recorded in previous surveys in response to the GTA outbreak. Based on records from these surveys, the infested nuclei included between 1 and 40 infested trees with an average of 8.3 trees per nucleus (Turgeon, unpubl. data). We used the distribution of infested trees per nucleus to generate the number of infested trees at ALB entry points in each stochastic scenario s (see Appendix S4).

2.4.4. *Mitigation cost values for successful and failed detections*

We associated the mitigation cost values for successful and failed detections, d_{1js} and d_{0s} respectively, with the number of infested and likely infested host trees requiring removal when the pest is detected via survey (or an undetected infestation is reported by the general public). For successful detections, we assumed the size of the detected nucleus to be roughly similar to the nuclei sizes documented in previous ALB surveys in the GTA. We assumed that the number of trees requiring removal would include the infested trees at the time of detection plus

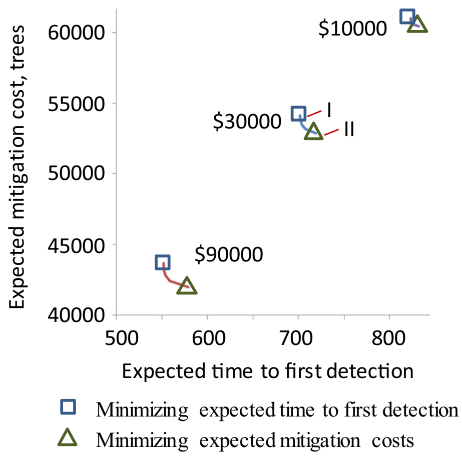

Fig. 4. Trade-off between the expected mitigation costs (in terms of the number of trees requiring removal) and expected time to first detection. Squares (callout I) show optimal solutions for problem 2, which minimizes the expected time to first detection. Triangles (callout II) show the optimal solutions for problem 1, which minimizes the expected mitigation cost value. Labels above the symbols denote the budget limit (B) for the optimal solutions. The coordinates of each point on the curve show the problem 2 objective value (expected time to first detection) and problem 1 objective (expected mitigation costs) set as a constraint.

healthy host trees in a 400-m safety zone around all infested nucleus plus those within the safety zone (as prescribed by CFIA's eradication program (Smith et al., 2009)). We interpreted the number of host trees within that safety zone as the mitigation cost value, d_{1js}, when the pest was detected at a site j.

When detection failed or the site was not surveyed, ALB was expected to spread undetected and build a larger population comparable with the size of unchecked ALB populations observed during the 2003 outbreak in the GTA (i.e., over 646 infested trees). To estimate the mitigation cost values for undetected populations, d_{0js}, at each site, we imposed a spatial spread configuration consistent with infestation patterns during the 2003 GTA outbreak. We then added a 400-m safety buffer to the locations of infested trees (again in keeping with eradication plan) and calculated the total number of host trees that would require removal (see Appendix S4).

2.4.5. *Detection probabilities and host tree densities*

Estimation of mitigation cost values and detection probabilities required spatial information on the number of host trees in the GTA. We predicted the total number of host trees by first estimating the area of tree cover at each survey site j from the SOLRIS (2008) land cover dataset and then converting this area into a number of host trees using tree densities and the host species proportions from the City of Toronto's Every Tree Counts survey (City of Toronto, 2012, 2013). We identified host tree genera using CFIA's list of host species for ALB (CFIA, 2016).

Detection of signs of infestation in urban settings was done via visual tree inspections by trained professionals (Turgeon et al., 2010). The probability of finding signs of attack depends on where a tree is located. Based on experience from previous ALB surveys in the GTA, we identified three broad tree classes: street, backyard and woodlot/park trees (Fig. 2). Street trees were the most accessible and required the shortest inspection times. Inspection of backyard trees takes 2.5 times longer due to limited access. Park and woodlot trees take six times longer to inspect.

For each survey site we estimated the number of street trees using Toronto's street tree database (City of Toronto, 2016). For areas in the GTA but outside of the Toronto municipality, the number of street trees was estimated as a function of the length of the street network and the proportion of a given land cover type in a survey polygon (see Appendix S4). The model explained 92.4% of the variance with cross-validation accuracy 86.7% and was used to map the street tree densities outside of the Toronto city limits (Fig. 2b). We assumed that the number of backyard trees in the GTA was equal to the number of street trees (McKenney et al., 2012). We estimated the number of woodlot trees as the difference between the total number of host trees (described earlier) and the number of street and backyard trees (Fig. 2c).

The detection probability, γ, after inspecting a street or backyard tree was 0.7 (Turgeon et al., 2010). Park and woodlot trees have lower detection rates ($\gamma = 0.4$) because ALB exit holes are located higher in dense stands, making the probability of detecting the pest lower than for street trees.

Survey costs were based on the rates paid to contractors to do street tree inspections in previous ALB surveys, with the average cost of inspecting a street tree $c_{jk}v_{jk}$ = Cdn \$6.83 tr.$^{-1}$. The costs of inspecting backyard and woodlot trees were assumed to be proportional to their inspection times (i.e., 2.5 and 6 times higher respectively). Tree types were also assigned different likelihoods of being infested by ALB. Based on data gathered from previous outbreak in the GTA, we assumed that street and backyard trees are 5.6 and 5.9 times more likely to be infested with ALB than woodlot trees (see Appendix S4).

2.4.6. *Comparing optimal and rule-based survey strategies*

In some circumstances, optimization-based planning of pest surveys is unavailable and the survey design is guided by rules of thumb (Parnell et al., 2015). We compared expected times to detection for four simple rule-based strategies with the detection times in our optimal solutions. Rule-based strategy 1 ranks the sites in the area by the likelihood of pest entry and then the survey starts with inspecting all trees at the site with the highest likelihood of pest entry. After all trees

Table 3
Number of sites surveyed vs. program budget in problem 1 and 2 solutions.

Model	Survey intensity, trees-site^{-1}	Total number of sites surveyed[a] Budget level:			Proportion of sites surveyed, % Budget level:		
		\$10,000	\$30,000	\$90,000	\$10,000	\$30,000	\$90,000
Problem 1:	0–50 (low)	20	20	36	1.7%	1.7%	3.1%
minimize the expected mitigation costs	50–150	12	36	56	1.0%	3.1%	4.7%
	150–300	1	6	20	0.1%	0.5%	1.7%
	300–600 (high)	–	–	10	–	–	0.8%
	Total	33	62	122	2.8%	5.3%	10.3%
Problem 2:	0–50 (low)	18	36	33	1.5%	3.1%	2.8%
Minimize expected time effort to first detection	50–150	16	38	72	1.4%	3.2%	6.1%
	150–300	–	4	29	–	0.3%	2.5%
	300–600 (high)	–	–	3	–	–	0.3%
	Total	34	78	137	2.9%	6.6%	11.6%

[a] The total number of candidate survey sites, J = 1180.

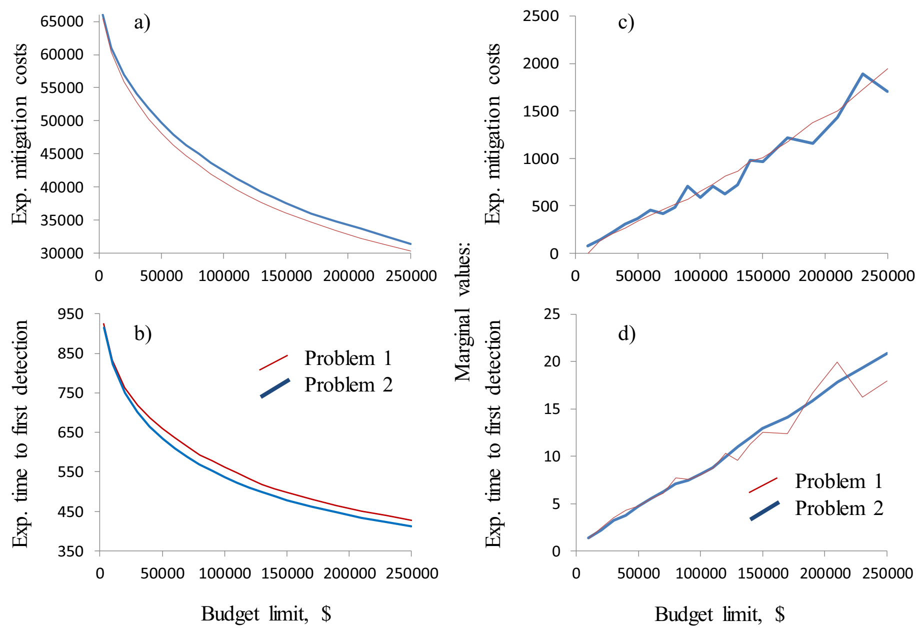

Fig. 5. Budget required to achieve a target expected mitigation cost value or expected time to first detection: a) budget required to reduce the expected mitigation costs below a given target value; b) budget required to reduce the expected time to first detection below a target value; c) marginal expected mitigation costs vs. budget limit; d) marginal expected time to first detection vs. budget limit. Problem 1 minimizes the expected mitigation costs and problem 2 minimizes the expected time to first detection.

at the highest-ranked site are inspected, all trees at the site with the second highest pest entry rank are inspected, and so on until the survey budget is exhausted. Rule-based strategy 2 uses the same site ranking scheme but limits the surveys to inspections of street trees only. Strategies 3 and 4 also use the same site ranking scheme but limit the survey to 90 and 30 street trees per site. The rule-of-thumb solutions used the same input data and detection time calculations as the optimization-based solutions.

3. Results

3.1. Minimizing mitigation costs vs. minimizing time to first detection

Fig. 3 compares the model solutions that minimized expected mitigation costs (problem 1) with those that minimized the expected time to first detection (problem 2). At a broad scale, solutions to problems 1 and 2 concentrated surveillance in the three major industrial and commercial areas in the GTA (Fig. 3 callout I) where the likelihood of ALB introduction is highest (Fig. 1). Both problems called for industrial areas to be surveyed at moderate inspection intensities. These areas are characterized by low host densities (represented mostly by street trees) and high likelihoods of pest introduction because they receive the largest amounts of high-risk imports. This makes industrial and commercial areas prime candidates for surveys. Surveys also tended to avoid sites with high host densities (shaded in light grey in Fig. 3) in parks, woodlots and ravines. High tree density and difficult site access make those sites expensive to survey.

The objective values in the solutions to problems 1 and 2 responded differently to changes in model parameters. In problem 1 solutions that minimized expected mitigation costs, the amount of damage if detection fails was the most influential parameter (Table S3.1 Appendix S3). With respect to problem 2 solutions that minimized the expected time to first detection, pest entry likelihood and the probability of detection were the most influential parameters, followed by the survey cost (Table S3.2 Appendix S3). In general, the spatial configuration of pest entry likelihoods had greater influence on the objective function value than the host density pattern. This implies that the correct estimation of spatial likelihoods of infestation is critical for estimating the optimal survey solutions.

At fine scales, the survey patterns in the problem 1 and 2 solutions showed notable differences (Fig. S5.1 Appendix S5). Problem 1 solutions tended to select sites with high likelihood of pest entry (Fig. 1) and the potential for high host damage (Fig. 3a) if detection fails (to minimize the potential mitigation costs). For example, at larger budget levels, the problem 1 solutions selected some sites in industrial and commercial areas in close proximity to wooded areas (Fig. S5.1b Appendix S5 callout I). These sites are characterized by high probability of pest entry but also high host densities in nearby woodlots. The problem 1 solutions selected these sites because timely detections could avoid significant damage from undetected infestations that otherwise would be incurred given the sites' proximity to these wooded areas. The problem 1 solutions (i.e., at larger budget levels) also selected some sites with very high potential host damage values that derived largely from their high host densities (Fig. S5.1b Appendix S5 callout II). However, sites with high host densities require large numbers of trees to be inspected, which is expensive. Therefore, the problem 1 solutions only called for inspections of a few of these critical sites in wooded areas, although it is worth noting that these sites were not surveyed at all under problem 2. Indeed, at larger budgets the problem 2 solutions selected more sites in core industrial and commercial areas (Fig. S5.1b, c Appendix S5, callout III), where the likelihood of pest entry is high but host tree density is low.

We explored the trade-offs between model objectives under different budget levels and found that the budget level had much greater impact on the expected mitigation costs value and expected detection time than the choice of the model objective. Indeed, the trade-off between problem 1 and 2 solutions for the same budget level is small (Fig. 4, callouts I and II), but the expected mitigation costs and detection time both decline steadily as the budget level increases. This is not surprising for a couple of reasons. Foremost, the budget level determines the total number of trees that can be inspected throughout the survey area; more tree inspections translate to higher detection probabilities and less time to expected first detection – but also to lower expected mitigation costs from failed detections. The small magnitude of the trade-off is explained partially by the contrasting spatial configurations of the mitigation cost values for failed detections and the likelihoods of pest entry. The sites that receive large quantities of imports and thus have high pest entry likelihoods are all located in industrial and commercial areas. Most of these areas have low host densities. A low number of host trees at a site translates to a smaller sample of trees that require inspection to achieve a desired likelihood of detection. Additionally, a low host density at a survey site also

Table 4
Expected times to first detection in optimization-based and rule of thumb survey strategies.

Scenario	Budget $60,000			Budget $90,000		
	Total sites surveyed	Proportion of sites surveyed	Exp. time to first detection	Total sites surveyed	Proportion of sites surveyed	Exp. time to first detection
Rule 1, survey all host trees at a site[a]	1	0.1%	944.1	6	0.5%	935.8
Rule 2, survey all street host trees at a site	42	3.6%	677.4	56	4.7%	631.1
Rule 3, survey 90 street host trees at a site	93	7.9%	649.4	137	11.6%	603.1
Rule 4, survey 30 street host trees at a site	282	23.9%	772.6	316	26.8%	772.2
Optimal solution	108	9.2%	601.2	138	11.7%	552.1

[a] All rule-based strategies 1–4 start from surveying sites with highest risk of invasion and proceed towards surveying sites with low invasion likelihoods.

translates to a lower expected mitigation cost value if detection fails. In short, a combination of high pest entry likelihoods and low host densities makes industrial and commercial areas the best survey candidates in both problems 1 and 2, so the trade-off between the problem solutions is small. The magnitude of the trade-off would be greater if more of the areas that receive high quantities of imports were close to areas with high densities.

The budget level also influenced the number of sites surveyed at high and low inspection intensities. The problem 1 solutions surveyed more sites at high inspection intensity (Table 3). These sites were located in wooded areas with high host densities and so required a high inspection rate to facilitate detection. The problem 2 solutions selected 3–26% more sites for survey than the problem 1 solutions, and generally called for lower inspection rates (50–150 tr.-site^{-1}) in the selected sites.

3.2. Project budget and the expected mitigation cost target

Our results also provide insights on the cost-effectiveness of survey efforts. Fig. 5a shows the survey budget level that is required to achieve a desired target with respect to the expected mitigation costs and Fig. 5b shows the budget level that is required to achieve a desired time to first detection. Both curves in Fig. 5a, b show exponential decay as the budget level increases. In both cases, the marginal mitigation cost values and detection time both increase almost linearly starting from very low budget levels (Fig. 5c, d). This implies that the surveillance at low budget levels uses the budget funds more effectively than high-budget surveys.

3.3. Rule-based vs. optimization-based survey strategies

We compared times to first detection in problem 2 solutions that minimized the expected time to first detection with times to first detection under four rule-based survey strategies (Table 4). For strategy 1, which inspects all trees at survey sites, starting from the site with the highest pest entry risk, the expected detection times were close to worst detection time (i.e., $T = 1000$). If the surveillance budget is low, then under rule-based strategy 1, it may not be possible to inspect more than a few sites. In turn, the expected detection time becomes close to the maximum cutoff time T, when surveillance is assumed to have failed. Inspecting all trees at a survey site implies examining backyard and woodlot trees which have longer access and higher inspection cost than street trees. This is why strategy 1 is less cost-effective than strategies 2–4, which limit inspections to street trees only and reveal shorter detection times. The rule-based strategy 3, which calls for inspection of a small set of street trees at a site, had the closest detection times to the optimal solution for problem 2.

The budget range shown in Table 4 shows a typical range of survey budgets in ALB survey programs in the GTA. At both budget levels, the optimal solutions for problem 2 consistently yielded shorter expected detection times than rule-based solutions. Nevertheless, it appears that prioritizing the surveys by the risk of pest entry is a useful rule-based strategy as long as inspections are limited to a small fixed number of street trees.

3.4. Ambiguity-averse vs. risk neutral survey strategy

We compared the solutions for problems 1 and 2 that minimized the expected values (Fig. 3) with the solutions when minimizing, respectively, the expected worst-case mitigation costs and the longest expected time to first detection (Fig. 6). The survey patterns under these ambiguity-averse strategies differed from the allocations based on the strategies that minimized the expected values. For example, the problem 1 solutions that minimized the expected mitigation costs in Fig. 3 selected survey sites mostly in industrial areas. In contrast, the solutions based on minimizing the worst-case mitigation costs prioritized sites

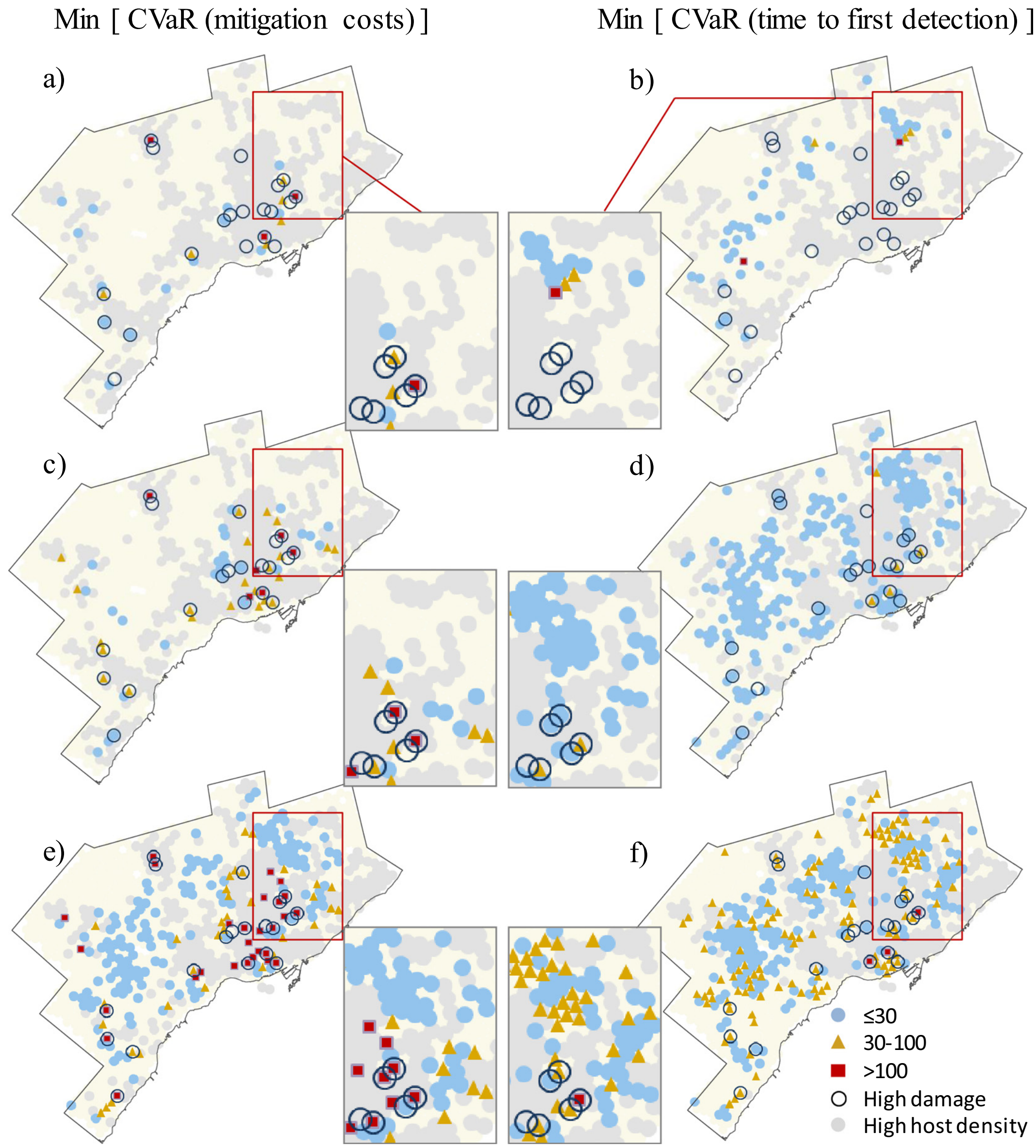

Fig. 6. Survey patterns for risk-averse policies in problems 1 and 2 that minimize either the expected worst-case mitigation costs or the expected worst-case time to first detection: a, c, e) minimizing expected worst-case mitigation costs value, i.e., CVaR of cost values; b, d, f) minimizing expected worst-case time to first detection, i.e., CVaR of detection time. Budget level: a, b) $10,000; c, d) $30,000; e, f) $90,000. Close-ups show an example of an industrial area in the eastern GTA (rectangle outline). Areas with high host tree densities are shaded in light grey. Empty circles show the sites with highest expected mitigation costs when detection fails or the site is not surveyed. Solid circles, triangles and squares show different inspection rates at the selected survey sites in optimal solution, trees-site^{-1}.

with very high host densities near parks and ravines (Fig. 6a, c, e). Moreover, all selected sites in Fig. 6a, c, e that had high host densities were surveyed at high inspection rates. This is because the acceptable detection probability could only be achieved at those sites by inspecting large numbers of trees.

Similarly, the problem 2 solutions that minimized the worst-case time to first detection (Fig. 6b, d, f) revealed different survey patterns than the solutions that minimized the expected detection time (Fig. 3). Almost all selected sites were surveyed at the lowest inspection intensity and were spread widely across entire study area. By comparison, the strategy that minimized the expected time to first detection surveyed fewer sites in major industrial areas, and at higher inspection rates.

The spatial survey configurations in problem 1 and 2 worst-case solutions did not coincide because of the distinct spatial configurations of site attributes that cause the worst-case outcomes in problems 1 and 2. In problem 1, the sites that are likely to experience the most host damage and require significant mitigation costs are characterized by high host densities. Therefore, minimizing worst-case costs requires surveying sites with high host densities. However, making detections at these sites requires high sampling rates, which limits the total number of sites that can be inspected for a given budget level. In problem 2, the range of sites that could have the worst detection times (i.e., non-detection) is much wider. Theoretically, detections could fail at any site, so to constrain the worst detection times in the area as many sites as possible must be surveyed. Because the best chances to make first detection are at sites with high infestation likelihoods but low host densities, lower sampling rates can be used and so more sites can be inspected than in problem 1 solutions.

We also examined the trade-offs between the two worst-case strategies. Fig. 7 shows trade-off curves for the two objectives at three different budget levels. The squares at one end of each curve depict the solutions minimizing the worst-case time to first detection (corresponding to the maps in Fig. 6b, d, f), while the triangles at the other

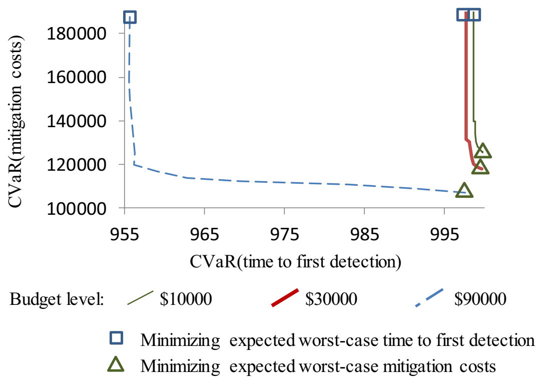

Fig. 7. Trade-off between minimizing the expected worst-case mitigation costs and minimizing the expected worst-case time to first detection. Squares on the trade-off curves correspond to the solutions in survey maps in Fig. 6b, d, f and triangles to the solutions in survey maps in Fig. 6a, c, e. The coordinates of each point on the curve show the problem 2 objective value ($CVaR_{(time\ to\ first\ detection)}$) and problem 1 objective ($CVaR_{(mitigation\ costs)}$) set as a constraint.

end of each curve depict the solutions minimizing the worst-case mitigation costs (corresponding to the maps in Fig. 6a, c, e). The curves indicate that a moderate reduction of the worst-case mitigation costs does not substantially increase the worst-case detection time until a point beyond which the worst-case detection time increases sharply. This abrupt increase is a consequence of changing the survey strategy: The only way to further decrease the expected worst-case mitigation costs beyond that point is to survey sites with high host densities at high inspection rates. This would reduce the budget portion spent on surveying the remainder of the area and so the detection time increases sharply. Fig. 7 suggests that the optimal strategy is to minimize the worst-case detection time with moderate reduction of the worst-case mitigation costs but not minimizing both.

Compared to the solutions based on minimizing the expected outcome, minimizing the worst-case outcomes imposes a penalty on the expected time and expected mitigation cost values (Fig. 8). For example, minimizing the expected detection time does not lead to minimization of the worst-case detection time (Fig. 8a, callout I). Furthermore, minimizing the worst-case detection time actually *increases* the expected detection time, in some cases by > 12% (Fig. 8a, arrows). Note that the expected detection time decays exponentially as the budget increases but the worst-case detection time decreases linearly (Fig. 8a). This implies that the reduction of the worst-case detection time, in relative terms, remains cost-effective when the survey budget increases. A small budget is not sufficient to reduce the worst-case detection time but causes a sharp increase of the expected detection time (Fig. 8a callout II). Effective reduction of the worst-case detection time is only possible when the budget limit exceeds \$32,000. This indicates that an ambiguity-averse strategy may only be feasible when the budget is sufficient to survey a large number of sites. In comparison, the strategy that minimizes the expected time to first detection is most cost-effective at small budget levels (below \$32000) when the surveys yield the greatest marginal reduction of the detection time.

Minimizing the worst-case mitigation costs also imposes a penalty on the expected mitigation cost value, but this penalty is relatively low (Fig. 8b, arrows). As the budget level increases, both the expected and worst-case mitigation cost decline in a similar fashion starting from very small budget levels. This implies that strategies that minimize either the expected or worst-case mitigation costs can be effective at a wide range of budget levels, including small budgets below \$32,000.

4. Discussion

Early detection of invasive alien species is challenging because decision-makers deal with uncertainty about where and when the species might establish in an uninvaded area. Often, the detection efforts are constrained by poor capacity of the surveys to detect the organism and a limited survey budget. Our model helps address these challenges with the objective of detecting the invader in the shortest possible time. The model also provides a mathematical foundation for the logic behind some general pest surveillance practices, and facilitates the identification of optimal early detection strategies for complex spatial cases when the underlying assumptions about an invasive pest are uncertain. We also demonstrate key differences between the time-minimizing detection strategy and surveys that minimize expected mitigation costs across the entire landscape.

Our model is designed as a one-period planning tool but can be applied within a broader response framework. Briefly, there are two overarching outcomes of our model: the pest of interest is detected by the survey program or it is not detected. If it is not detected, then the model can be applied for the next planning cycle and so on until the first detection in the area is made. However, if it is detected, this initiates a new and distinct sequence of response actions, which might include more detailed delimiting surveys and eradication efforts.

Note that the objective of early detection surveys is intrinsically short-term – the surveys aim to detect the fact of new pest entry into an uninvaded area and thereby serve as an alarm system designed to trigger large-scale response actions after detection. In this case, the number of invaded sites that are discovered over the course of the

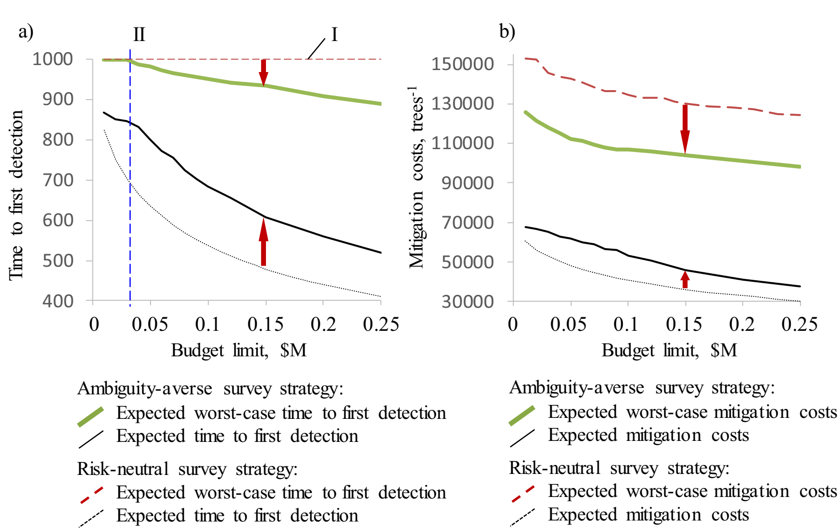

Fig. 8. Budget level vs. the reduction of the expected and worst-case mitigation costs and times to first detection: a) budget level vs. expected and worst-case times to first detection. Ambiguity-averse survey strategy (bold lines) indicates minimizing the expected worst-case time to first detection (CVaR of detection time); risk-neutral strategy (dotted and dashed lines) indicates minimizing the expected time to first detection (the problem 2 solution); b) budget level vs. expected and worst-case mitigation costs. Ambiguity-averse survey strategy (bold lines) indicates minimizing the expected worst-case mitigation costs value (CVaR of cost values); risk-neutral strategy (dotted and dashed lines) indicates minimizing the expected mitigation cost value (the problem 1 solution). Callout I shows that minimizing the expected time to first detection does not minimize the CVaR of detection time. Callout II shows a survey allocation example with the budget level B = \$32,000. Arrows show differences between the expected and worst-case outcomes under risk-neutral (dotted and dashed lines) and risk-averse survey strategies (bold lines).

survey is not critical as long as the pest is detected at some site in the shortest possible time. In focusing on this specific short-term objective, we are able to downplay time-sensitive components such as discounting or pest population growth after arrival.

One important feature in our model is that it factors in failed detections in the calculations of expected mitigation costs in individual scenarios and therefore emphasizes the penalty for not finding the target pest in a particular scenario. This instructs the model to focus on those scenarios that may incur the largest damage from failed detections, so that successful detections in those scenarios would reduce the total mitigation costs. The rationale behind including failed detections is to consider the trade-off between choosing sites with the shortest times to first detection versus sites where successful detections would yield a greater reduction of the cost to mitigate further damage.

In theory, the model might behave differently if the control of mitigation costs was included in the objective function equation. The non-detections at the sites with low host densities would be penalized in favour of selecting the sites with high host densities where the damage to host from non-detection would be high. Incorporating the mitigation costs into the objective function equation would enable assessing integrated management strategies which include both surveys and eradication (such as presented in Yemshanov et al., 2017a, 2017b). This aspect is beyond the scope of this study but could be the focus of future work.

4.1. When is an ambiguity-averse survey strategy preferred?

The problem 1 and 2 solutions both assume that a decision-maker is risk-neutral and thus prefers to minimize the expected outcome. However, these solutions differed sharply from the ambiguity-averse survey strategies that minimized the expected worst-case outcomes. In our case, the right tail of the detection time distribution included the time when infestation is not detected via survey and instead is reported by the general public (i.e., $T = 1000$). Lowering the expected longest detection time implies that the survey could detect the presence of the pest, in the worst case, sooner than the public. So, in practical terms, minimizing the longest detection time can be thought of as an ambiguity-averse survey strategy to find the pest before it is reported by the public.

Having a low tolerance for pest detection failure significantly constrains the spatial options for selecting the surveys. It appears that an ambiguity-averse strategy becomes feasible only when the budget is sufficient to inspect a large number of sites. When the budget is too small, the worst-case detection time cannot be reduced (Fig. 8a callout II). This implies that managers should follow an ambiguity-averse strategy of minimizing the expected longest detection times only if there are enough resources to survey a large area.

4.2. Utility of the optimization-based approach

Our model reveals key trade-offs between early detection strategies with different objectives and decision-making perspectives. It also answers some practical survey questions, such as when it is useful to inspect trees in parks and woodlots. Doing so seems to be ineffective when the survey budget is small. Our findings agree with the current survey protocol in the GTA that mostly targets street trees.

We were also able to compare the performance of our approach to that of a set of rule-based survey strategies. Our comparisons revealed that surveying a fixed number of street trees yields the closest detection times to the optimal solution, but the choice of the number of trees to inspect depends on the budget level and the likelihood of infestation at a particular site. Moreover, while the rule-based strategies may yield acceptable detection times, they do not approach the detection times in the optimal solutions because the trade-offs between the factors that control invasion are not considered.

Some other aspects that have not been addressed in the model may be important in practical applications. In our calculations of time to first detection, we assumed that tree inspections within a site occur in sequential order but did not assume a particular order or a case of multiple simultaneous inspections at different sites. The assumption of simultaneous tree inspections at multiple sites would require finding optimal combinations of inspection sequences at multiple sites, which minimizes time to first detection. This aspect was beyond the scope of the current study and could be the focus of future work.

For the current ALB case study, we limited our mitigation cost estimates to the cost of removing the infested trees as well as healthy host trees in surrounding safety zone. It is possible that other damages, such as decrease in property values or extra costs to local industries, could increase the total cost value. Incorporating these costs would require developing the data that quantify the spatial variation of these damages in the area of interest. This would be an important consideration if, for example, the model was applied to a larger region beyond the city limits where the spread of ALB could cause damage to the commercial timber supply and non-market ecosystem services.

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