

Acceptance sampling for cost-effective surveillance of emerald ash borer in urban environments

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We develop an acceptance sampling approach for surveillance of the emerald ash borer (EAB), a harmful forest pest, in Winnipeg, Canada. We compare sampling strategies computed with two different management objectives. The first objective maximizes the expected area with detected infestations and the second objective minimizes the expected number of undetected infested trees in sites that were not inspected or where inspection did not find an infestation. The choice of the management objective influences the survey strategy: achieving the first objective involves selecting sites with high infestation rates proximal to the infested area, whereas the second objective requires inspecting sites with both high infestation rates and high host densities. Adding uncertainty prescribes inspecting a larger area with lower sampling rates and extending the surveys to farther distances from the infested locations. If a decision maker wants to minimize the worst-case damage from failed detections, the optimal strategy is to survey more sites with high host densities at farther distances, where EAB arrivals could cause significant damage if not detected quickly. Accounting for the uncertainty addresses possible variation in infestation rates and helps develop a more diversified survey strategy. The approach is generalizable and can support survey programmes for new pest incursions.

Introduction

Surveillance is a critical strategy in reducing the costs of controlling biological invasions. In particular, delimiting surveys serve as a way to uncover the extent of the area invaded by a pest and find established populations before they reach a size that is difficult to eradicate (Ewel *et al.*, 1999; Baker *et al.*, 2009; Leung *et al.*, 2014; Holden *et al.*, 2016). Thus, uncovering the full spatial extent of the invaded area makes eradication and other rapid response measures more effective (Leung *et al.*, 2002; Lodge *et al.*, 2006; Rout *et al.*, 2014; Epanchin-Niell and Liebhold, 2015).

Survey planning for invasive species may be assisted by optimization-based tools (Mehta *et al.*, 2007; Hauser and McCarthy, 2009; Epanchin-Niell *et al.*, 2012; Büyüktaktakın and Haight, 2018). For example, recent work on optimal surveillance strategies for invasions has focused on selection of surveys in spatial (Hester and Cacho, 2012; Horie *et al.*, 2013; Epanchin-Niell *et al.*, 2014; Yemshanov *et al.*, 2015, 2017a) and temporal (Epanchin-Niell *et al.*, 2014; Moore and McCarthy, 2016) domains. Additionally, several studies have explored optimal

survey strategies in combination with pest control activities (Mehta *et al.*, 2007; Hauser and McCarthy, 2009; Homans and Horie, 2011; Epanchin-Niell *et al.*, 2012; Rout *et al.*, 2014; Yemshanov *et al.*, 2017b). Fewer optimization studies have considered particular types of surveillance, such as early detection or delimiting surveys, but see examples in Guillera-Aroita *et al.* (2014) and Surkov *et al.* (2009).

In many cases, delimiting surveys must cover large areas after initial discovery in order to be effective. One of the most common delimiting survey strategies involves maximizing the expected area (or number of sites) with successful detections. Information about the ability of the pest species to spread to uninvaded areas may be unknown, so decision-makers must rely on probabilistic expectations of where and when the pest might enter these areas in order to predict the likely extent of invasion at a point in time (see reviews in Venette *et al.* (2010) and Yemshanov *et al.* (2009)).

Notably, spreading pest populations may damage valuable host resources or impair other economic activities in these areas if they go undetected. However, the probabilistic expectations that managers commonly use to characterize invasion likelihood

do not guarantee a proper account of possible negative outcomes of surveillance actions, such as damage to host resources when detection fails. Statistical quality control methods, such as acceptance sampling (Wetherill and Chiu, 1975), provide better means to account for potential deleterious outcomes of survey decisions (Christensen and Gardner, 2000; Chen et al., 2018). For instance, acceptance sampling has been widely used for quality control in manufacturing, where inspectors accept or reject a lot (i.e. a group of items) based on information obtained from a sample of items inspected in the lot (Schilling and Neubauer, 2009). The technique also plays an important role in public and food safety programmes (Koblinsky and Bertheau, 2005; Starbird, 2005; Whiting et al., 2006; Powell, 2014), human disease control (Christensen and Gardner, 2000) and harmful pest entries with agricultural and plant imports (Venette et al., 2002; Chen et al., 2018).

In acceptance sampling, an inspection plan defines the sample size, the inspection method and the acceptance threshold that sets the decision rule to accept the lot only if the number of defective items in the sample is equal to or less than the threshold. Sampling schemes may be designed to minimize the costs of inspection (Baker et al., 1993; Lattimore et al., 1996) or maintain an acceptable level of risk of overlooking a defective item (Starbird, 2005; Whiting et al., 2006; Yamamura et al., 2016). Often, sampling efforts are constrained by limited budget and personnel (Powell, 2014; Yamamura et al., 2016) and take place in circumstances where many items have to be inspected in a short time. For example, the Canadian Border Security Agency and Canadian Food Inspection Agency regularly conduct inspections of live plant imports from damaging pests at ports of entry (CFIA, 2015; CBSA, 2017).

In this paper, we adapt the acceptance sampling approach to the problem of developing a geographic delimiting survey for an urban forest pest. Our approach is to define the problem as one that is equivalent to the problem of determining an optimal acceptance sampling plan for multiple lots of one commodity that are inspected simultaneously and that is subject to a budget constraint on sampling cost. To do this, we first divide the survey area into a spatial grid of survey sites and consider each site analogous to a lot with items that can be sampled for inspections. The items in this case are the suitable host trees in each site that can be inspected for visible signs of infestation by the pest. A sample of these trees is inspected and if one or more trees is found to contain the pest, the site is declared as infested. Inspecting trees for pests is subject to detection errors which are equivalent to inspection errors in acceptance sampling. However, detection errors for pest sampling methods are usually given as detection rates (i.e. how often is an infested tree successfully detected by a given method). Therefore, we consider the detection rate of each tree inspection method to be analogous to 1 - inspection error in finding the defective items in a sampled lot.

We compare acceptance sampling strategies computed with two different management objectives. The first objective reflects the common surveillance strategy where a manager attempts to minimize the expected number of survey sites with undetected infestations. The second objective reflects a different surveillance strategy where the manager attempts to minimize the expected number of infested trees remaining within the survey area that are either in survey sites that were not

surveyed or in survey sites where inspections did not detect an infestation. Conceptually, this second objective is analogous to minimizing the cost of damage caused by defective items in accepted lots that escape detection during the inspection process. To accomplish the second objective, we apply the formula presented in Chen et al. (2018) to estimate the expected slippage in each survey site, which is defined as the expected number of infested trees in each survey site conditional on the survey failing to detect an infestation, given the number of host trees, the pest detection rate and the infestation rate for a survey site. We propose a linear programming model that allocates the surveillance actions to fulfil the second objective. We then compare the results obtained for the second objective with those from the first objective (i.e. minimizing the expected area with undetected infestations). We then extend the linear programming formulation to find optimal survey strategies when the likelihood of a pest infesting an area is uncertain. We formulate a robust optimization problem (Kouvelis and Yu, 1997) where we represent these uncertain likelihoods of infestation as random variables with a large set of discrete infestation scenarios. We also examine the impact of decision-making perceptions of uncertainty on optimal survey strategies, such as ambiguity-averse behaviour that aspires to avoid worst-case outcomes of survey actions (i.e. failed detections).

We demonstrate the approach using the example of a delimiting survey programme for emerald ash borer (EAB), *Agrilus planipennis* Fairmaire (Coleoptera:Buprestidae), in Winnipeg, Manitoba, Canada, where the pest was first discovered in December 2017 (GoC, 2017). The EAB is native to eastern Asia and poses a major threat to North American ash (*Fraxinus*) trees, all of which are susceptible to attack. Since its initial introduction in Michigan, the insect has caused catastrophic damage in eastern North America (Poland and McCullough, 2006; Kovacs et al., 2010, 2014). Our problem describes a practical case of delimiting surveys that regulatory authorities undertake on a regular basis to uncover the spread of harmful invasive pests that could damage urban and natural forest resources (Reaser et al., 2008).

Methods

We developed a spatial optimization model for surveillance in which we depict uncertainty about the presence of an invader with a set of probabilistic scenarios (see Table 1 for definitions of symbolic notation). Consider an area of J sites that may be infested with a pest. Each site j , $j \in J$, has N_j host trees that may be infested. The manager chooses an inspection intensity m , $m \in M$ for each site j , representing a sample size of n_{jm} trees to inspect for infestation. One of the inspection intensities assumes no inspections (i.e. $n_{jm} = 0$). For each site and inspection intensity, we define a binary decision variable x_{jm} , where $x_{jm} = 1$ if inspection intensity m is selected for site j and $x_{jm} = 0$ otherwise. Only one inspection intensity is allowed for each site. We define e_j as the detection rate (i.e. the probability that an inspection of a tree in site j detects an infestation if it is present). In our case, trees infested with EAB can be detected by sampling branches and inspecting the material for EAB galleries or installing a sticky trap on a tree that attracts emerging adults (see a description of the tree inspection techniques in section 'Case study'). Inspection of a tree at a site j has cost g_j and the total inspection cost is constrained by an upper budget limit B .

Let γ_j be the infestation rate of trees in site j , which denotes the likelihood that a tree in site j is infested. We assume that knowledge of the

Table 1 Summary of the model parameters and decision variables.

Symbol	Parameter/variable name	Description
Sets		
J	Potential 1-km ² survey sites in the managed area j	$j \in J, J = 472$
S	Infestation scenarios s . Each scenario s defines a plausible pattern of infestation likelihoods, γ_{js} in the managed area J	$s \in S, S = 2000$
M	Survey sampling levels m for a site j . Each level m specifies sampling n_{jm} trees at a site j	$m \in M$
Parameters		
B	Survey budget constraint	$B > 0$
N_j	Number of host trees at a site j	$N_j \geq 0$
γ_{js}	Likelihood of that a tree is infested in a site j in a scenario s ($\gamma_{js}N_j$ – expected number of infested trees at a site j in a scenario s)	$\gamma_{js} \in [0; 1]$
e_j	Probability of that inspections of an infested tree at a site j detect the signs of infestation	$e_j \in [0; 1]$
P	Probability of that inspections fail to detect one or more infested trees at a survey site	$P \in [0; 1]$
g_j	Cost of surveying a tree at a site j	$g_j > 0$
n_{jm}	Number of trees inspected at a site j at a survey sampling level m . The sampling level $n_{jm} = 0$ assumes no survey at a site j	$n_{jm} \in [0; N_j]$
E_{jms}	Expected number of infested trees in a site j conditional on an inspection of n_{jm} trees at a sampling level m does not find the infested trees in a scenario s	$E_{jms} \in [0; \gamma_{js}N_j]$
Q	Expected slippage upper bound constraint	$Q > 0$
D_1	Expected number of infested trees at a surveyed site among those that were not inspected	$D_1 \in [0; \gamma_{js}N_j]$
D_2	Expected number of infested trees among those inspected, conditional on the fact that the survey fails the signs of infestation	$D_2 \in [0; \gamma_{js}N_j]$
α	Confidence level that defines the damage value that can be exceeded only in $(1 - \alpha) \cdot 100\%$ of worst pest entry scenarios	0.95
Decision variables		
x_{jm}	Binary selection of a survey at a site j at a sampling level m (i.e. inspecting n_{jm} trees)	$x_{jm} \in \{0, 1\}$
w_s	Problem 1 auxiliary variable for a linearized formulation of minimizing the CVaR	$w_s \geq 0$
v_s	Problem 2 auxiliary variable for a linearized formulation of minimizing the CVaR	$v_s \geq 0$
ζ	Problem 1 auxiliary variable for a linearized formulation of minimizing the CVaR	$\zeta \in \mathfrak{R}$
ξ	Problem 2 auxiliary variable for a linearized formulation of minimizing the CVaR	$\xi \in \mathfrak{R}$

infestation rates γ_j for all $j \in J$ is uncertain. Based on prior knowledge of infestation rates across sites, we define S scenarios of infestation rates. Each scenario $s \in S$ is a vector of infestation rates γ_{js} , for all sites $j, j \in J$, where each element γ_{js} depicts the infestation rate of site j .

PROBLEM 1: Minimizing the expected area of undetected infestations

Consider a survey problem where a manager chooses the number of trees n_{jm} to inspect in each site. If one or more trees in the sample is found to be infested, the site is declared as infested. The survey sites have equal area, so the number of selected sites indicates the area surveyed. The objective is to maximize the expected number of sites that are found to be infested in area J across a set of infestation rate scenarios S , subject to constraints on the inspection budget B , i.e.:

$$z_1 = \max \frac{1}{S} \sum_{s=1}^S \sum_{j=1}^J \sum_{m=1}^M (x_{jm}[1 - (1 - \gamma_{js}e_j)^{n_{jm}}]) \quad (1)$$

s.t.:

$$\sum_{j=1}^J \sum_{m=1}^M x_{jm}n_{jm}g_j \leq B \quad (2)$$

$$\sum_{m=1}^M x_{jm} = 1 \quad \forall j \in J. \quad (3)$$

Constraint (2) sets the inspection budget limit and constraint (3) specifies that only one sample size n_{jm} can be chosen for inspections at each site j . For computational convenience, we reformulate the objective (1) to minimize the expected area of undetected infestations, i.e.:

$$z_1 = \min \frac{1}{S} \sum_{s=1}^S \sum_{j=1}^J \sum_{m=1}^M (x_{jm}[(1 - \gamma_{js}e_j)^{n_{jm}}]). \quad (4)$$

PROBLEM 2: Minimizing expected slippage

In the context of acceptance sampling to inspect shipments of imported plants, [Chen et al. \(2018\)](#) defined expected slippage as the expected number of infested plants in an accepted shipment of live plant imports given shipment size, sample size, infestation rate, and detection rate. In this problem, we define a variable for slippage, E_{jms} , as the expected number of infested trees in site j , sample intensity m , and infestation rate scenario s , given that no trees were found to be infested. Slippage is a function of the number of trees in the site, the number of trees inspected, the infestation rate and the detection rate:

$$E_{jms} = (1 - \gamma_{js}e_j)^{n_{jm}} \left[\gamma_{js}(N_j - n_{jm}) + \frac{1 - e_j}{1 - \gamma_{js}e_j} \gamma_{js}n_{jm} \right] = P\{D_1 + D_2\}. \quad (5)$$

The first term on the right-hand side (P) is the probability that no infested trees were found. Inside the brackets of the second term, D_1 is the expected number of infested trees in the population that were not inspected and D_2 is the expected number of infested trees in the inspected population, conditional on the fact that no infested trees were found. Note that when no trees are inspected in site j , $n_{jm} = 0$ and $E_{jms} = \gamma_{js}N_j$.

Using Equation (5) for expected slippage, we formulate the problem to select a survey intensity for each site to minimize expected slippage across all sites and all scenarios of infestation rates:

$$z_2 = \min \left[\frac{1}{S} \sum_{s=1}^S \sum_{j=1}^J \sum_{m=1}^M x_{jm}E_{jms} \right] \quad (6)$$

s.t.:

constraints (2) and (3).

Note that the expected slippage formula (5) can be also be used to formulate a constraint for problem 1, which sets an upper bound Q on expected slippage:

$$\frac{1}{S} \sum_{s=1}^S \sum_{j=1}^J \sum_{m=1}^M x_{jm} E_{jms} \leq Q. \quad (7)$$

In both problems 1 and 2, the objective value is an average across infestation rate scenarios s which implies that the inspector believes a priori that all infestation rate scenarios are equally likely.

Minimizing the expected worst-case outcomes of survey actions

Variation in the infestation rates in the surveyed sites causes the value of the objective function to vary among the different infestation scenarios. As depicted in Equations (4) and (6), the objective functions z_1 and z_2 minimize the *expected* outcome of the survey actions across all infestation scenarios but do not consider the distribution of outcomes. The right-hand tail of the distribution of outcomes contains the worst cases: for example, a large area of undetected infestations or a large number of infested trees remaining undetected. When faced with the possibility of a worst-case outcome, a risk-averse decision-maker may want to minimize the likelihood of its occurrence. This behaviour represents a general case of ambiguity aversion (Gilboa and Schmeidler, 1989) and has been widely acknowledged as a factor that influences environmental decision-making (Tulloch et al., 2015) and management of biological invasions (Finnoff et al., 2007; Sims and Finnoff, 2013; Springborn, 2014). An ambiguity-averse manager evaluates potential actions in terms of the minimum potential benefit that might emerge from selecting these actions. If the prior information about potential outcomes of invasion is lacking or vague, an ambiguity-averse strategy at least ensures the best of the expected worst possible outcomes.

One approach to minimizing the damage that could be caused by a worst-case outcome is the *minmax* problem (Kouvelis and Yu, 1997), which minimizes the maximum of the distribution of damages. The *min-max* formulation minimizes the damage of the worst outcome but it may not minimize the expected value of the right tail of the damage distribution. Instead, we use percentile-based metrics which offer better control of the expected tail value, such as value-at-risk (Studer, 1997; Jorion, 2006) and conditional tail expectation (CTE) or conditional value-at-risk, (CVaR). Percentile metrics have been widely used to assess extreme losses in finance (e.g. Acerbi and Tasche, 2002; Inui and Kijima, 2005).

In our delimiting survey problem, value-at-risk (VaR_α) is defined, with a confidence level α , $\alpha \in [0;1]$, as the objective function value that is exceeded in $(1 - \alpha) \times 100$ per cent of the scenarios. For a random variable, the conditional value at risk, with a confidence level α , (CVaR_α , or CTE_α) is the conditional mean of the objective function values exceeding VaR_α . For this analysis, we use the conditional value at risk to depict the ambiguity-averse strategy of avoiding the *expected worst-case* outcome in delimiting survey problems 1 and 2, i.e.:

$$z'_1 = \min \left[\text{CVaR}_\alpha \left(\sum_{j=1}^J \sum_{m=1}^M (x_{jm} [(1 - \gamma_{js} e_j)^{\eta_{jm}}]) \right) \right] \text{ for problem 1} \quad (8)$$

and

$$z'_2 = \min \left[\text{CVaR}_\alpha \left(\sum_{j=1}^J \sum_{m=1}^M x_{jm} E_{jms} \right) \right] \text{ for problem 2.} \quad (9)$$

The objective functions z'_1 and z'_2 are linear with respect to decision variables x_{jm} , hence we used a linear formulation of the CVaR

minimization problem for discrete distributions from Rockafellar and Uryasev (2000, 2002). For a discrete set of S scenarios with equal probability of occurrence $1/S$, the CVaR_α , at a confidence level α , can be approximated with an equivalent set of $S + 1$ auxiliary decision variables and $S + 1$ inequality constraints. Problem 1 can be rewritten as:

$$z'_1 = \min \left[\zeta + \frac{1}{S(1 - \alpha)} \sum_{s=1}^S w_s \right] \quad (10)$$

s.t.

$$\sum_{j=1}^J \sum_{m=1}^M (x_{jm} [(1 - \gamma_{js} e_j)^{\eta_{jm}}]) - \zeta \leq w_s \quad \forall s \in S \quad (11)$$

$$w_s \geq 0 \quad \forall s \in S \quad (12)$$

constraints (2) and (3),

and problem 2 can be rewritten as:

$$z'_2 = \min \left[\xi + \frac{1}{S(1 - \alpha)} \sum_{s=1}^S v_s \right] \quad (13)$$

s.t.:

$$\sum_{j=1}^J \sum_{m=1}^M (x_{jm} E_{jms}) - \xi \leq v_s \quad \forall s \in S \quad (14)$$

$$v_s \geq 0 \quad \forall s \in S \quad (15)$$

constraints (2) and (3).

In Equation (11), term $\sum_{j=1}^J \sum_{m=1}^M (x_{jm} [(1 - \gamma_{js} e_j)^{\eta_{jm}}])$ denotes the expected number of undetected infested sites in a scenario s ; In Equation (14), term $\sum_{j=1}^J \sum_{m=1}^M (x_{jm} E_{jms})$ is the expected slippage in a scenario s ; ζ, ξ, v_s and w_s are auxiliary decision variables; and ζ and ξ are members of a set of real numbers.

Case study: delimiting surveys of emerald ash borer (EAB) infestation in Winnipeg, MB

We used the problem formulations that minimized the expected area of undetected infestations and the expected slippage to develop optimal strategies for delimiting surveys of the emerald ash borer (EAB) in Winnipeg, Manitoba, Canada. The insect poses a major threat to North American ash species (Haack et al., 2002; Herms and McCullough, 2014) and has already caused major damage to both urban and natural forests in the eastern US and Canada (Kovacs et al., 2010; McKenney et al., 2012). Long-distance EAB spread has been associated with human activities, primarily with commercial and passenger vehicles that could potentially move firewood or other infested materials (Haack et al., 2006, 2010; Kovacs et al., 2010; Koch et al., 2011; Yemshanov et al., 2015). There is also evidence that the pest can hitchhike on vehicles (Buck and Marshall, 2008). It is difficult to detect new infestations of EAB because the initial attack of the insect occurs at the tops of trees and damage does not become apparent for 2–5 years in some cases, thus new detections usually indicate the presence of already established populations (McCullough et al., 2006; Ryall et al. 2011).

With a detection rate close to 0.7, sampling branches and then peeling their bark to inspect for EAB galleries is the most reliable method to detect EAB, especially during early stages of an outbreak when trees may appear asymptomatic (Ryall et al., 2011; Turgeon et al., 2015). In Canada and the United States, the method has been successfully applied in delimiting surveys following the initial detections of EAB infestation to define the putatively infested area (Ryall, unpublished). To implement the method, a surveyor uses a saw mounted to an

extendable pole to cut two branches from the mid-crown of a suspect tree. A 75 cm section of each branch is then removed and the bark removed to expose any developing EAB larvae.

Another more widely deployed method for EAB survey and detection is the use of sticky traps hung in ash trees that are baited with plant volatiles or plant volatiles and EAB pheromones (Ryall, 2015). In this method, a surveyor uses an extensible pole to hang a single trap at the outer edge of the crown of an ash tree. This trap is baited with slow-release capsules containing either plant volatiles or plant volatiles and EAB pheromones. Adult EAB attracted to the trap are caught in the sticky coating. The surveyor then returns to the trap at some later point, removes it from the tree and counts any EAB that have been trapped. In general, trapping with sticky traps is less expensive on a per-tree basis, but yields lower detection rates (Ryall *et al.*, 2013). Evidence from using sticky traps in previous EAB surveys suggests that the traps tend to capture local insects that are living in or very nearby the 'trap' tree. Possibly, this is because EAB, whilst is an active flier, does not usually disperse far if the tree in which it is feeding is a sufficient host (for oviposition, larval development, etc.).

EAB was first detected in Winnipeg, Manitoba in December 2017 infesting a single green ash tree in the Archwood neighbourhood (GoC, 2017) (Figure 1a). After this initial discovery, the City of Winnipeg and the Province of Manitoba established a delimiting survey programme to determine the full spatial extent of the EAB infestation. The city was divided into 1×1 km survey sites, within some of which, some trees were sampled using the branch sampling method in January and February of 2018 to detect overwintering larvae. In the spring and summer of 2018 additional sites were sampled using sticky traps baited with plant volatiles and the EAB pheromone to detect flying adult beetles. The branch sampling method was primarily used in the neighbourhood immediately surrounding the initial detection, while the traps were deployed throughout the city. Below we briefly describe the parameters used in our optimization models (Table 1).

Likelihoods of EAB spread in urban environment

Our model required an estimate of the expected likelihoods of EAB spreading to locations where the pest has yet to be detected. We assumed that the likelihood of EAB spreading to a new site decreases with distance from a known-infested site. Modelling distance-dependent spread is a common approach to predict spread rates and spatial patterns of biological invasions (Melbourne and Hastings, 2009; Leung *et al.*, 2010) and EAB in particular (BenDor *et al.*, 2006; Kovacs *et al.*, 2010; Prasad *et al.*, 2010; Orlova-Bienkowskaja and Bienkowski, 2018). Since information about the particular behaviour of EAB in Winnipeg was lacking, we estimated the likelihood of spread over distance using historical observations of EAB infestation in Minneapolis–St. Paul (Twin Cities), Minnesota, USA (Fahrner *et al.*, 2017; Osthus, 2017). The EAB outbreak in the Twin Cities is the closest, urban EAB infestation to Winnipeg and so was assumed to act as a reasonable proxy for spread in Winnipeg. Preliminary assessments of the age of recently detected EAB infestations in Winnipeg suggested that the pest entered the area six years ago. Therefore, we used records of EAB from the Twin Cities that documented infestations identified as 6 years old or younger starting from the oldest infestation.

The EAB data for the Twin Cities are a map of infested trees each with an age of infestation. For each infested tree, we estimated the distance from the tree to the known centre of the Twin Cities infestation, which was assumed to be the group of trees with the oldest infestations. We estimated the locations of other non-infested ash trees from municipal tree inventories (City of Minneapolis, 2017; TreeKeeper, 2018) and an urban tree database for St. Paul (used in Koch *et al.*, 2018). We then divided the known-infested area into a grid of 1×1 km sites, and for each site, counted the number of infested and uninfested ash trees.

The spatial resolution of the survey grid was based on the size adopted by city of Winnipeg. To account for spatial uncertainty in our estimates of ash density we repeated the calculations four times after shifting the 1×1 km grid over the known-infested area by ± 500 m in each direction. We have also estimated the proportion of infested ash trees in each site and then, using the total host density estimates and the detection rate values, defined the likelihood of EAB infestation in that site. When estimating the likelihood of infestation in a site we also factored in EAB detection rates based on information gathered during previous survey campaigns in the area (Fahrner *et al.*, 2017; Venette, unpubl. data). We then grouped the sites into 1-km distance classes from the infestation centre and estimated a distribution of EAB infestation likelihoods for each 1-km distance class.

We used the distance-dependent distributions of infestation likelihoods from the Twin Cities to generate infestation scenarios in Winnipeg. As with the Twin Cities, we divided Winnipeg into a grid of 1×1 -km potential survey sites. For each 1-km^2 site j , we estimated the distance to the infested site and, based on that distance, sampled the distribution of infestation likelihood values from the Twin Cities for the corresponding distance class to generate the likelihood of infestation in a particular scenario, s . Using this method we generated a set of 2000 infestation scenarios, which we used as inputs to find optimal solutions to problems 1 and 2. For each site, we also estimated a mean likelihood of infestation from the 2000-scenario set (Figure 1a). The mean values were used as a hypothetical single-scenario case where the rates of EAB spread, and thus the likelihood of infestation, are perceived to be known.

We solved problems 1 and 2 for both the single-scenario case, and the 2000-scenario case in order to see what effect uncertainty had on the results. To solve the single-scenario case we took independent draws from the distribution of infestation likelihoods, solved a single-scenario model for each sample of infestation likelihoods and then averaged the objective function values. Second, we found the optimal solution using the formulation that included 2000 invasion scenarios.

We have also estimated the trade-off between the problem 1 and 2 objectives. We used the problem 1 formulation with the constraint (7) that sets an upper bound Q on the expected slippage value. We evaluated the solutions with different Q values and plotted the trade-off between problem 1 and 2 objectives as a curve (also known as efficiency frontier) in dimensions of the area of undetected infestations and expected slippage.

Estimating the survey costs, detection rates and host tree densities

We estimated the number of ash trees at each survey site in Winnipeg from a municipal inventory of public and private trees (City of Winnipeg, 2018; H. Daudet, City of Winnipeg, Urban For. Br., pers. comm.), which provided information about tree species, ownership and size (Figure 1b). Following the pest survey protocols currently implemented in Winnipeg, inspections only target trees that are between 20 and 60 cm diameter at breast height (dbh). We also used tree size class to adjust the cost of surveying the sites, and so assumed that inspecting trees larger than 60 cm dbh would require doubling the sampling effort to achieve the same detection rate. Trees smaller than 20 cm dbh are not included in Winnipeg surveys and are also too small to be sampled using either sampling method, and so were ignored.

We used evidence from previous survey campaigns in Canada (Hopkin *et al.*, 2004; Ryall *et al.*, 2011, 2013; Turgeon *et al.*, 2015) to determine the likelihood of finding signs of EAB using branch samples and sticky traps. The detection rate for branch sampling was set to 0.7, based on a typical sample of two mid-crown branches from a medium-sized tree (Ryall *et al.*, 2013). The likelihood of a single sticky trap detect-

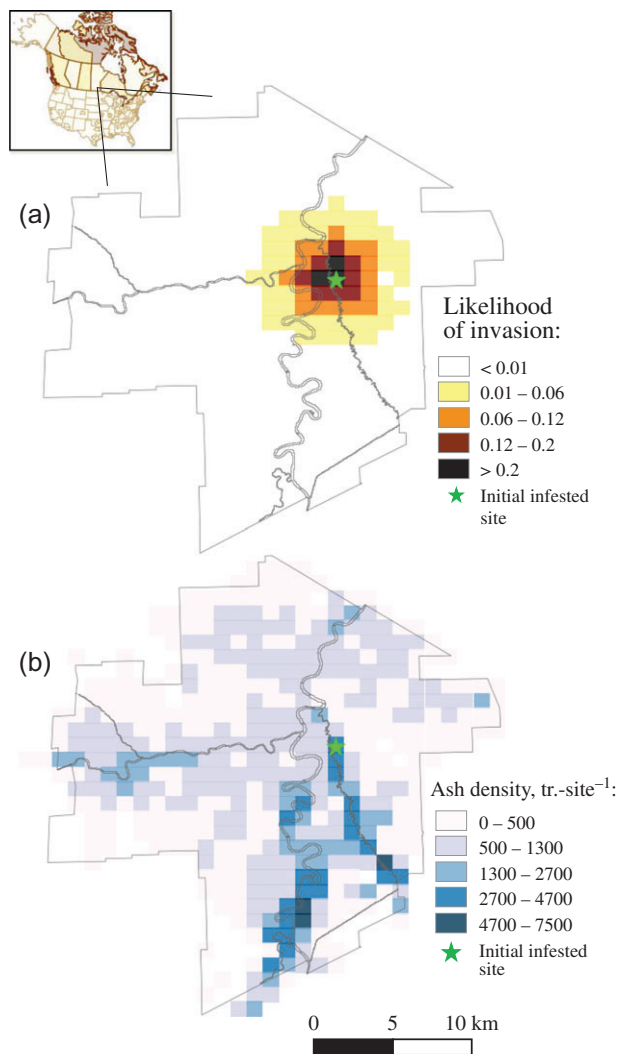


Figure 1 Ash host density in the study area: (a) likelihood of EAB infestation (expected value based on 2000 infestation scenarios); (b) ash host density.

ing the presence of an EAB population was set to 0.5. The specified detection rates were determined for urban EAB populations in southern Ontario, Canada, but should be applicable for Winnipeg given its tree size distribution was typical of other urban areas in Canada. However, we recognize that the effective detection rates may vary depending on tree vigour, the size of the local EAB population, or other unspecified factors. Therefore, we tested alterations whereby the detection rate for each method was adjusted by ± 25 per cent, as well as various detection rate combinations for branch sampling and trapping.

In our objective function formulation, the likelihood of EAB detection was estimated on a per survey site basis (i.e. the likelihood of detecting at least one infested tree in a site). For sites with trapping as the inspection method, this treats the effective area of the placed trap(s) as equivalent to the size of the survey site (i.e. 1 km^2). Experience gained from previous EAB survey campaigns indicates that traps mostly detect insects emerged from the trees in which they are placed or other nearby ash trees. This is because the green ash volatiles and chemicals used to attract EAB are not as strong and long-lasting as sex pheromones for other pests and mostly work at short distances. This was not an issue in

our study because the host trees typically are clustered within a given survey site, such that a large proportion of the trees fall within a single trap's attraction radius.

The cost of tree sampling depends on where trees are located. In Winnipeg, only public trees can be inspected for EAB using traps or branch samples (surveyors are not able to inspect privately owned trees), so we assumed that surveys would target public trees only. However, the likelihoods of EAB infestation in a site were estimated assuming the insect would infest public and private ash trees. The survey costs were calculated using the rates paid to contractors to do branch sampling and trapping in previous EAB surveys in Canada (Cdn $\$25\text{-h}^{-1}$). We identified three broad classes of trees eligible for surveys: medium-sized accessible public (street) trees (20–60 cm dbh), large-sized accessible public trees (>60 cm dbh) and public woodlot, park and riparian zone trees >20 cm dbh. Branch sampling and trapping would target public trees with >20 cm dbh. Sampling trees between 20 and 60 cm dbh would require installing either one sticky trap or sampling two branches. For the purposes of this exercise, we assumed that sampling trees larger than 60 cm dbh would require installing two traps or sampling four branches to achieve the same detection rate. Usually, it takes longer to access woodlot trees, so we assumed the site access and trap setup cost portions for woodlot trees would double.

For trapping, the trap cost was estimated as Cdn $\$24.71$. Sampling procedures include three 15-min visits by a crew of two (for setup, sampling and teardown). Site access costs account for an additional 10 min per visit by the two-person crew. The total trapping cost was estimated as $\$87.21$ for trees between 20 and 60 cm dbh and $\$124.42$ for trees larger than 60 cm dbh.

Branch sampling requires only one site visit. The total cost includes the site access cost by the crew of two (10-min), sampling, bark peeling and branch disposal. Sampling costs were based on estimates from the current survey campaign in Winnipeg (i.e. $\$65$ for a 20–60 cm dbh tree and $\$121.42$ for trees larger than 60 cm dbh, including the site access cost). Peeling the bark from sampled branches was estimated to take 1.11 person-hours per branch and would cost $\$55.60$ for a 20–60 cm dbh tree and $\$111.20$ for a tree larger than 60 cm dbh. Branch disposal included chipping the material and was estimated to take 5 min for the two-person crew ($\$4.17 \text{ branch}^{-1}$). The total cost of branch sampling was estimated as $\$128.90$ for a 20–60 cm dbh tree and $\$249.60$ for trees larger than 60 cm dbh.

We composed problems 1 and 2 in the GAMS environment (GAMS, 2018) and solved with the GUROBI linear programming solver (GUROBI, 2018).

Results

Impact of uncertainty on optimal survey solutions

We compared the optimal solutions between a single-scenario deterministic formulation that used mean likelihoods of infestation and the 2000-scenario formulation (Figures 2 and 3). The single-scenario formulation assumed that the survey manager knows the likelihood of EAB infestation for a particular site. The 2000-scenario solutions assumed that only the approximate range of infestation likelihoods is known for each site.

For both problems 1 and 2, the approach that accounted for uncertainty (2000-scenario solutions, Figure 2c, d) sampled a larger area than the single-scenario approach that assumed the manager had perfect knowledge of the pest distribution (Figure 2a, b). For all solutions (Figure 2), the number of survey sites, the inspection method, and the intensity of survey were all influenced by the survey budget (Figure 3).

For a small budget (i.e. $\$25\,000$), all solutions to both problems selected branch sampling over trapping as the preferred

survey method (Figure 2). In general, the solutions selected branch sampling for the sites around the area of initial detection, with trapping in the peripheral sites. When we incorporated both uncertainty in the pest distribution (Figure 2c, d) and ambiguity aversion (Figure 2e, f) the results showed an increase in the area surveyed but retained the same general pattern of preferring branch sampling over trapping. However, the intensity of survey tended to decrease. For instance, in the presence of uncertainty, more sites were selected but fewer trees were chosen to be inspected (Table 2). We also noted that the allocation of sites tended to track ash density, with higher ash density sites being selected for sampling (e.g. callout 1, Figure 2f highlighting riparian sites with high ash density as seen in Figure 1). Branch sampling was preferred because the lack of funds necessitated the lower sampling rates, and thus placed a premium on the more reliable detection method. Most surveyed sites were within 5 km of the initial infestation, which indicates that

inspections in close proximity to known-infested locations are most cost-efficient.

When a decision-maker aspires to minimize the *expected worst* area of undetected infestations (i.e. the problem 1 objective) given a small budget, the survey sites cover an even greater area and more sites are inspected using the traps instead of branch sampling (Figure 2e). For example, in the solutions with a \$25 000 survey budget, the budget proportion spent on trapping increased from 14 per cent to 53 per cent (Table 2). The reason for using the less reliable but cheaper trapping method is that the cost savings allowed inspections of more trees (i.e. 239 vs. 202 in the 2000-scenario solutions without ambiguity aversion). The ambiguity-averse solutions in problem 2 behaved differently from the solutions in problem 1: the solutions inspected fewer total trees than the ambiguity-neutral 2000-scenario solutions, and the proportion of sites inspected using branch sampling increased (Figure 2f).

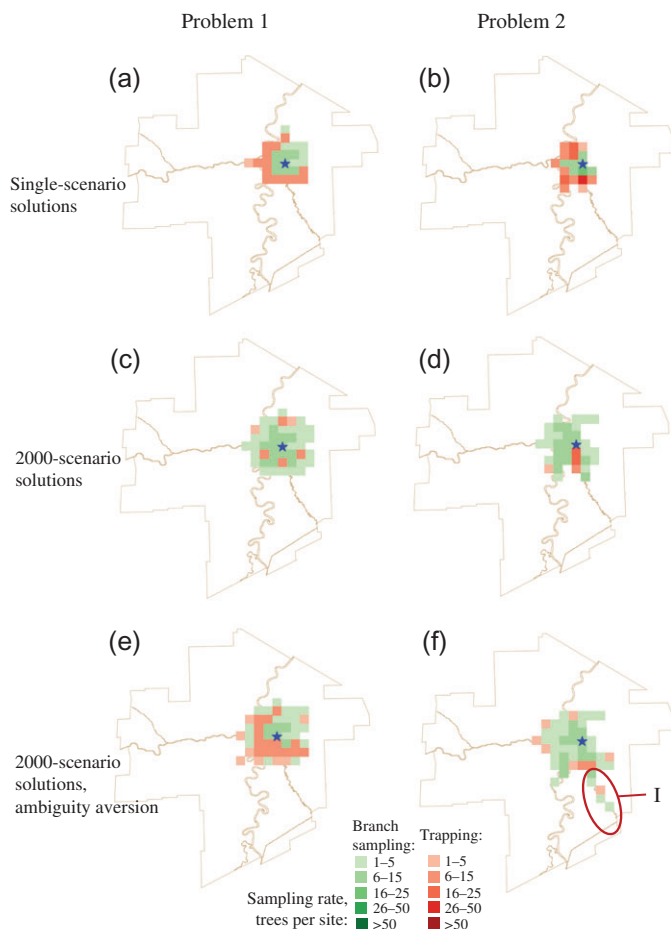


Figure 2 Optimal survey patterns for problem 1 (minimizing the expected area of undetected infestations) and problem 2 (minimizing the expected slippage) solutions with a budget of \$25 000: (a) problem 1, single scenario; (b) problem 2, single scenario; (c) problem 1, 2000 scenarios; (d) problem 2, 2000 scenarios; (e) problem 1, 2000 scenarios, ambiguity aversion; (f) problem 2, 2000 scenarios, ambiguity aversion. Callout I shows the selection of sites in a riparian zone with high host densities at farther distances from the initial infestation.

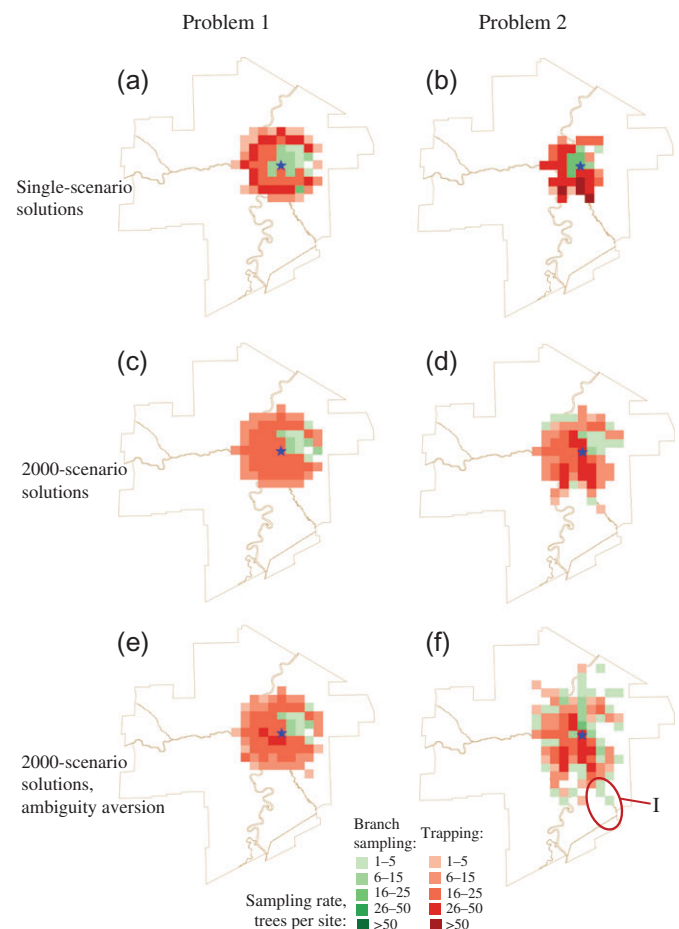


Figure 3 Optimal survey patterns for problem 1 (minimizing the expected area of undetected infestations) and problem 2 (minimizing the expected slippage) solutions, with a budget of \$100 000: (a) problem 1, single scenario; (b) problem 2, single scenario; (c) problem 1, 2000 scenarios; (d) problem 2, 2000 scenarios; (e) problem 1, 2000 scenarios, ambiguity aversion; (f) problem 2, 2000 scenarios, ambiguity aversion. Callout I shows the selection of sites in a riparian zone with high host densities at farther distances from the initial infestation.

For a large budget (\$50 000 and above), the optimal choice of sampling changes. Under this budget, all solutions to both problems selected trapping over branch sampling as the preferred survey method (Figure 3). As with the small budget, the solutions located branch sampling survey sites around the area of initial detection, with trapping in the peripheral sites, however a greater proportion of sites were sampled using traps. When we incorporated both uncertainty in the pest distribution (Figure 3c, d) and ambiguity aversion (Figure 3e, f) the results again revealed an increase in the area surveyed but retained the same general pattern of preferring trapping over branch sampling. The lower cost of trapping enables inspections of more trees, which compensates for the lower detection rate, but ultimately trapping is only cost-effective when the trap density is high (which is only possible when the survey budget is large).

Adding the ambiguity aversion further increased the survey area, although this was more evident in the optimal solutions to Problem 2 (Figure 3e, f). Similar to the large-budget solutions without ambiguity aversion (Figure 3a–d), a significant portion of the budget was spent on surveying sites close to the initial infestation. However, there is always a risk of long-distance low-probability infestations, which, if undetected, could cause significant damages to host trees. So, a portion of the budget was directed toward inspecting sites at farther distances where the likelihood of infestation is low.

Overall, and regardless of budget size, the impact of uncertainty and ambiguity aversion on problem 2 solutions was somewhat similar to their impact on problem 1 solutions, yet with some distinct differences in spatial survey patterns (Figures 2f and 3f). The surveys targeted sites with both high infestation rates and high host densities and applied higher sampling rates than in problem 1 solutions. In general, problem 2 solutions selected survey sites with 30–50 per cent higher host densities than problem 1 solutions (Table 2). Actually, minimizing the expected worst slippage in problem 2 solutions prescribed surveying two distinct groups of sites: sites with high host densities and high infestation rates in close proximity to the infested area and sites with high host densities at far distances where detection failures could cause significant damage to the host resource (Figures 2 and 3, callout I).

Preferred inspection method vs. budget

The choice of trapping vs. branch sampling depended strongly on the size of the survey budget (Figure 4, Table 2). The stacked graphs in Figure 4 show the total areas inspected with a particular sampling rate and survey method for a particular budget level. Colour shades in Figure 4 show the apportionment of the total inspected area among different survey methods and tree sampling rates, with darker colours indicating higher sampling rates. Stacked together, the colour shades show the total inspected area. Figure 4 also shows the areas inspected via trapping and branch sampling for a particular budget level (i.e. yellow-red vs. green-blue shades). Branch sampling was always preferred in small-budget solutions ($\leq \$25\,000$) and trapping is preferred in large-budget solutions ($\geq \$50\,000$). However, the

optimal use of trapping in large-budget solutions is contingent on the use of high sampling rates (i.e. deploying many traps in a survey site) in order to compensate for the lower efficiency of traps. In contrast, branch sampling in most cases was applied with low sampling rates, rarely exceeding 15 trees per site.

Minimizing the undetected infested area vs. expected slippage

Our results indicate a moderate trade-off between strategies that minimize the expected area of undetected infestations (problem 1) and those that minimize the expected slippage (problem 2). The efficiency frontiers in Figure 5 show the trade-off between these strategies. The horizontal portions of the efficiency frontiers indicate that minimizing the expected slippage eventually imposes a significant penalty on the ability to detect infested sites. However, there are substantial distances among the efficiency frontiers for the single-scenario solution and the multi-scenario solutions (Figure 5).

Single-scenario solutions have lower initial expected slippage values and thus will have better capacity to detect infested sites. We expect this pattern because the multi-scenario solutions require surveys of more sites in order to account for uncertainty and the multi-scenario solutions have lower per-site sampling intensities which results in more sites with missed detections. In our single-scenario solutions, the manager knows the likelihood of infestation and so can allocate their budget more efficiently. Adding uncertainty significantly worsens slippage and the number of undetected infestations but also decreases the magnitude of the efficiency frontiers. This indicates the impact of omitting the uncertainty about EAB spread is much greater than differences between the optimal survey strategies for problems 1 and 2. Adding the ambiguity-aversion assumption slightly worsens the trade-off frontier but the penalty is small (Figure 5, dotted lines). This is because the extra portion of sites allocated to long-distance inspections in the ambiguity-averse case is relatively small and most of the budget in both problem 1 and 2 solutions is allocated to sites close to the initially infested area. Differences among the single- and multi-scenario frontiers also suggest that any insights gained from single-scenario solutions with a deterministic depiction of infestation rates may have limited use for survey planning. Typically, managers operate under uncertainty about the likelihood of infestation in a survey site, which is more consistent with the multiple-scenario solutions that yield considerably poorer performance than idealized single-scenario solutions.

Objective function value vs. budget level

Our results allow us to assess the cost-effectiveness of survey efforts. Figure 6 shows the survey budget that is required to meet a desired target with respect to the expected area of undetected infestations (problem 1 objective) and expected slippage (problem 2 objective). All curves in Figure 6 show exponential decay as the budget level increases, indicating diminishing

Table 2 Area surveyed (i.e. number of surveyed sites) and budget proportions allocated to branch sampling and trapping at different survey sampling rates. Results are shown separately for problems 1 and 2 at small (\$25 000) and large (\$100 000) budget levels.

Uncertainty assumptions	1 scenario, deterministic				2000 scenarios, uncertainty				2000 scenarios, uncertainty, ambiguity aversion			
	Number of surveyed sites		Allocated budget proportion		Number of surveyed sites		Allocated budget proportion		Number of surveyed sites		Allocated budget proportion	
Sampling rate	Br. sampl. ¹	Trap.	Br. sampl.	Trap.	Br. sampl.	Trap.	Br. sampl.	Trap.	Br. sampl.	Trap.	Br. sampl.	Trap.
Survey budget \$25 000, Problem 1: Minimizing the expected area of undetected infestations												
1–5 tr.-site ⁻¹	7	1	15%	<1%	27	2	42%	3%	19	8	25%	7%
6–15 tr.-site ⁻¹	8	13	30%	54%	13	4	44%	11%	6	15	22%	45%
16–25 tr.-site ⁻¹	–	–	–	–	–	–	–	–	–	–	–	–
26–50 tr.-site ⁻¹	–	–	–	–	–	–	–	–	–	–	–	–
51–100 tr.-site ⁻¹	–	–	–	–	–	–	–	–	–	–	–	–
Total sites surveyed	15	14	46%	54%	40	6	86%	14%	25	23	47%	53%
Total trees inspected	83	156			162	40			88	151		
Mean host density at the surv.sites, tr.-site ⁻¹	1056	1056			1014	1014			997	997		
Survey budget \$25 000, Problem 2: Minimizing the expected slippage												
1–5 tr.-site ⁻¹	–	2	–	1%	17	1	25%	<1%	27	7	37%	2%
6–15 tr.-site ⁻¹	6	7	33%	24%	14	1	56%	4%	13	2	55%	5%
16–25 tr.-site ⁻¹	1	3	11%	20%	–	2	–	15%	–	–	–	–
26–50 tr.-site ⁻¹	–	1	–	11%	–	–	–	–	–	–	–	–
51–100 tr.-site ⁻¹	–	–	–	–	–	–	–	–	–	–	–	–
Total sites surveyed	7	13	44%	56%	31	4	80%	20%	40	9	92%	8%
Total trees inspected	85	161			156	56			179	22		
Mean host density at the surv.sites, tr.-site ⁻¹	1616	1616			1490	1490			1689	1689		
Survey budget \$100 000, Problem 1: Minimizing the expected area of undetected infestations												
1–5 tr.-site ⁻¹	5	13	3%	4%	6	0	3%	<1%	6	7	3%	2%
6–15 tr.-site ⁻¹	9	8	15%	6%	5	24	8%	21%	4	22	8%	18%
16–25 tr.-site ⁻¹	1	15	2%	32%	–	37	–	69%	–	32	–	62%
26–50 tr.-site ⁻¹	–	16	–	39%	–	–	–	–	–	3	–	7%
51–100 tr.-site ⁻¹	–	–	–	–	–	–	–	–	–	–	–	–
Total sites surveyed	15	52	20%	80%	11	61	11%	89%	10	64	10%	90%
Total trees surveyed	136	917			64	1025			61	1027		
Mean host density at the surv.sites, tr.-site ⁻¹	987	987			1024	1024			1040	1040		
Survey budget \$100 000, Problem 2: Minimizing the expected slippage												
1–5 tr.-site ⁻¹	1	2	<1%	<1%	14	6	5%	2%	32	15	12%	3%
6–15 tr.-site ⁻¹	2	3	3%	3%	2	25	2%	23%	7	21	8%	18%
16–25 tr.-site ⁻¹	5	6	14%	11%	–	15	–	29%	1	14	2%	25%
26–50 tr.-site ⁻¹	–	15	–	49%	–	13	–	40%	–	11	–	32%
51–100 tr.-site ⁻¹	–	4	–	21%	–	–	–	–	–	–	–	–
Total sites surveyed	8	30	17%	83%	16	59	7%	93%	40	61	22%	78%
Total trees inspected	124	953			50	1064			164	893		
Mean host density at the surv.sites, tr.-site ⁻¹	1396	1396			1265	1265			1435	1435		

¹Survey methods: Br.sampl. – branch sampling, Trap. – trapping.

returns, i.e. small-budget surveillance is more cost-effective on a unit cost basis than large-budget surveillance.

We can also compare the solutions that minimized the expected survey outcomes with the ambiguity-averse solutions that minimized the expected worst-case outcomes. As one

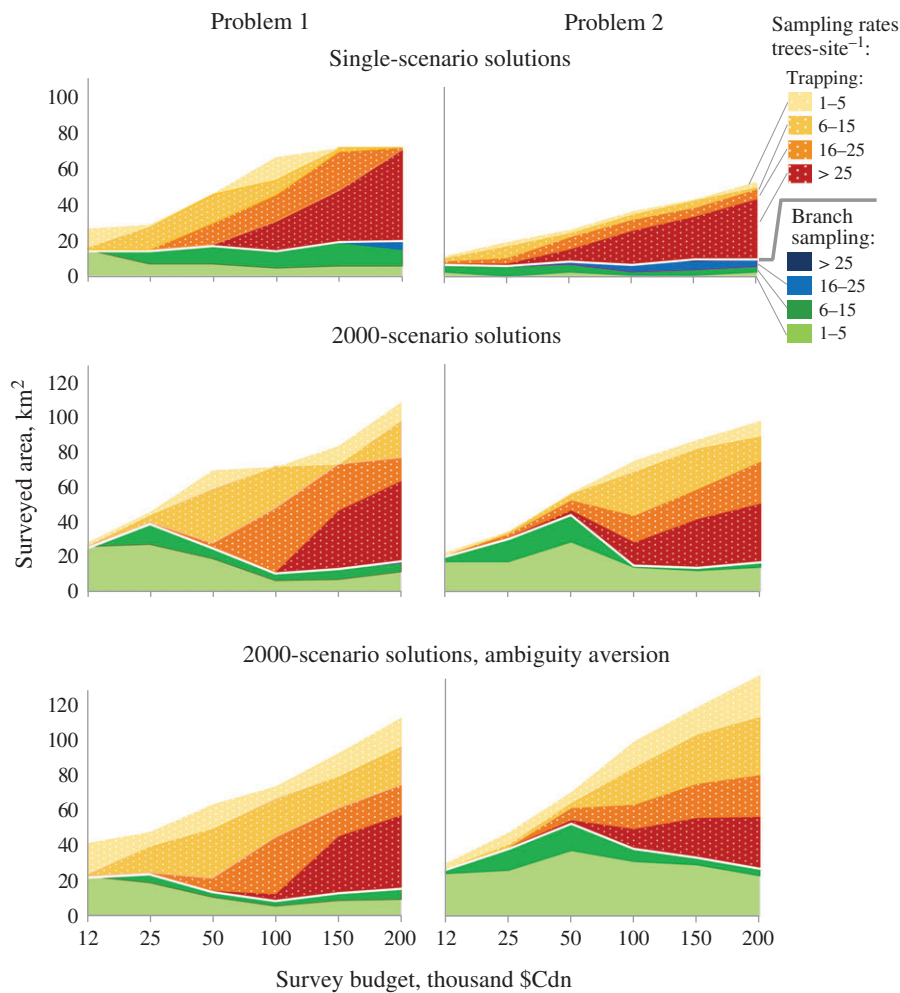


Figure 4 Area surveyed (km^2) with different sampling rates and sampling methods versus the survey budget (\$). X-axis denotes the survey budget, in thousand Canadian dollars, Y-axis denotes the surveyed area, in km^2 . Colours/stacked shades indicate the areas surveyed at a particular sampling rate and survey method for a particular budget limit. Green-blue shades indicate the areas inspected via branch sampling with the sampling rates of 1–5, 6–15, 16–25 and >25 trees-site $^{-1}$. Yellow-red shades indicate the areas inspected via trapping with the sampling rates of 1–5, 6–15, 16–25 and >25 trees-site $^{-1}$. Darker colours indicate higher sampling rates.

would expect, minimizing the worst-case outcome (i.e. the CVaR_α of the undetected infested area in problem 1 and CVaR_α of slippage in problem 2 solutions) imposes a penalty on the expected value (Figure 6). In our case, this penalty was small while the reduction of the worst-case outcomes was significant (Figure 6, callouts I and II). However, the capacity to reduce the worst-case outcomes is limited: further increase of the budget does not lead to a greater net reduction of CVaR_α (Figure 6, arrows). In our case, the reduction of the worst-case outcomes can only be achieved by inspecting sites with a particular range of host densities (i.e. low host densities in problem 1 solutions and very high host densities in problem 2 solutions).

Sensitivity analysis

We estimated the sensitivities of key output metrics to changes in the model parameters (Table 3). Rows in Table 3 denote the input parameters of interest (i.e. survey cost, detection rate,

host density and infestation rate) and columns denote the output metrics. The sensitivity values indicate the relative change of the output metric in response to altering the input parameter by ± 25 per cent. In addition to testing the objective values in problem 1 and 2 solutions, we also examined the sensitivities of other relevant outputs, such as the area surveyed and the number of trees inspected via a particular sampling method.

The problem 1 objective was moderately sensitive to changes in survey costs, detection rates and infestation rates and was insensitive to changes in host densities. The problem 2 objective was most sensitive to changes in host densities followed by changes in infestation rates. This high sensitivity to host densities was expected because the problem 2 solutions targeted sites with higher host densities than the problem 1 solutions, and used higher sampling rates to achieve the same detection success.

At small budget levels, changes in survey costs, detection rates and infestation rates influenced the area and number of trees surveyed via trapping. Decisions to use traps depended on

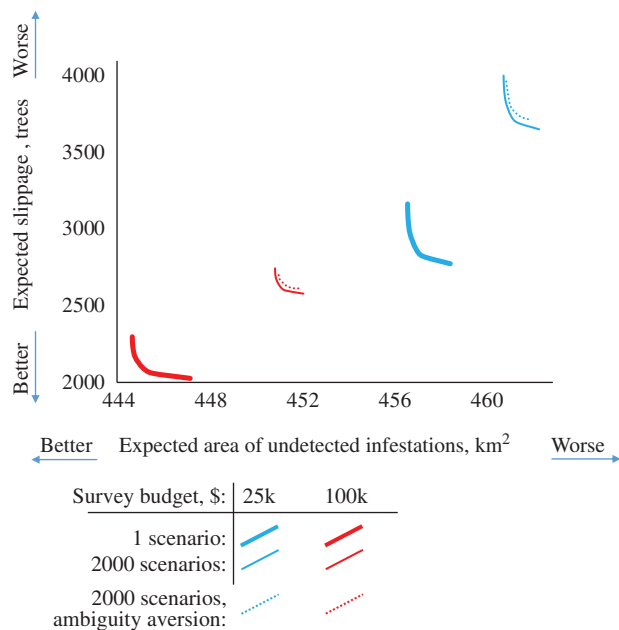


Figure 5 Efficiency frontiers describing the trade-off between the problem 1 and 2 objectives. Curves in bold show the trade-offs between single-scenario solutions, thin lines show the trade-offs between 2000-scenario solutions with the uncertainty assumption and dotted lines show the trade-offs between 2000-scenario solutions with the uncertainty and ambiguity-aversion assumptions.

the detection capacity, infestation rate and the cost of trapping. The use of branch sampling was moderately sensitive to changes in infestation and detection rates but revealed low sensitivity to changes in the survey costs and host densities. Sensitivity of branch sampling to changes in the survey costs as well as the detection and infestation rates increased only in large-budget problem 2 solutions.

Overall, the budget allocation to trapping and branch sampling surveys responded differently to parameter changes in different budget situations. Improving the detection accuracy and decreasing the cost of trapping will have the most impact at small-budget levels. By comparison, branch sampling is less sensitive to budget changes and variations in host density.

Detection rate and the choice of the inspection method

The choice of trapping or branch sampling depends on a combination of the cost and efficiency of each method. We explored the impact of changing the detection efficiency of trapping vs. branch sampling. In addition to our baseline scenario that assumed a detection rate of 0.5 for trapping and 0.7 for branch sampling, we examined solutions with the trap detection rate altered by ± 10 per cent (Figure 7). Colour shades in Figure 4 show the apportionment of the total inspected area among different survey methods and tree sampling rates. Yellow-red shades indicate the area inspected via trapping and green-blue shades show the area inspected via branch sampling. When the detection rate of traps was lowered (i.e. to 0.45), almost all trees were inspected via branch sampling regardless of the budget level (Figure 7a). Increasing the trapping efficiency had the

opposite effect, increasing the proportion surveyed via trapping, but branch sampling was still applied to a small portion of sites (Figure 7c). Branch sampling appears to be the preferred method for sites with a combination of moderate-high infestation rates and low host densities (where detections can be made with low sampling rates). Increasing or decreasing the trapping efficiency has little impact on the total area surveyed irrespective of budget but forced the model to reallocate funds between trapping and branch sampling.

In practical situations, the detection rates for branch sampling and trapping method may vary depending on tree status, age and the severity of infestation (Ryall *et al.*, 2011, 2013; Turgeon *et al.*, 2015). We estimated the detection rate combinations for trapping and branch sampling that cause one sampling method to predominate over the other. This analysis emphasizes the importance of accurate estimation of detection rates for both methods. Figure 8 shows the space of optimal solutions in dimensions of branch sampling and trap detection rate values. Dark and light-shaded regions depict the combinations of trapping and branch sampling rate values that cause one survey method to predominate over the other. For example, all optimal solutions in dark-shaded regions in Figure 8 have branch sampling applied to a larger area than trapping, and all solutions in light-shaded regions have larger areas inspected with traps than via branch sampling. The line that divides regions with a predominance of branch sampling and trapping is a straight line, which indicates that the preference of branch sampling over trapping depends on the ratio between the branch sampling and trap detection rate values. On average, branch sampling is preferred over trapping when its detection rate is 1.45 times greater than the detection rate of traps.

Discussion

Planning delimiting surveys for pests is a balancing act of distributing scarce inspection resources, in many cases across large regions. Managers often have limited understanding of how a pest may spread through the area of interest, which further reduces the efficacy of survey efforts. Our models address these challenges and demonstrate how accounting for this uncertainty about invasion spread could change the optimal survey strategy.

One important aspect of our work is that it focuses on minimizing potentially deleterious outcomes from failed detections. Decision-makers always face the prospect of making ‘false negative’ errors, where inspections fail to find an infestation after surveying a site. False negatives lead to delays with regulation and may eventually prompt decision-makers to neglect or minimize efforts aimed at controlling an invasion, thereby creating the potential for future economic damage (Davidson *et al.* 2015). When the issue of false negatives is overlooked, budget limitations may push survey managers to survey large regions at low sampling rates, resort to less expensive and less reliable detection methods, or adopt both options. Our proposed slippage formulation helps minimize the impacts of false negatives in survey planning decisions. We also demonstrate key differences between a strategy that minimizes slippage and the more common strategy that ignores the issue of false negatives by seeking to minimize the number of undetected infestations. Overall, it appears that accounting for false negatives should

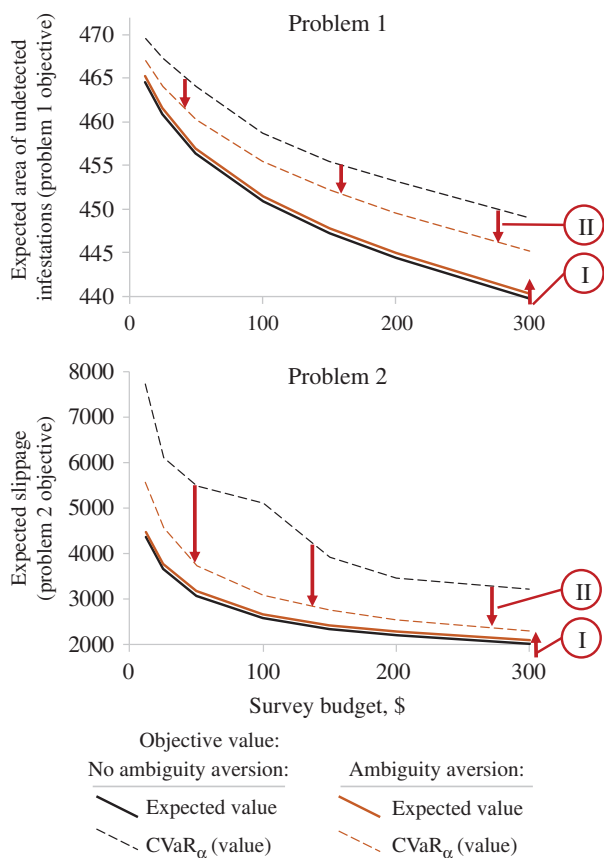


Figure 6 Budget level required to achieve a target objective value in problem 1 and 2 solutions. Callout I indicates a small penalty of the ambiguity aversion on the expected outcome of the survey; callout II shows a significant reduction of CVaR_α compared to the solutions that minimize the expected outcome of survey actions.

assist with more efficient resource allocation in pest management programs. For instance, a well-planned delimiting survey would allow a municipality to allocate pest management tactics (e.g. removals, insecticides) in a targeted manner. This in turn would help detect new pest entries, slow dispersal of the existing infestation and distribute the costs of removal and replacement of damaged host trees over multiple years.

Our expected slippage approach minimized the number of infested trees in sites that are not surveyed or erroneously declared uninfested. This approach could be reformulated into one that attempts to minimize the expected number of sites with failed detections. This formulation would correspond to the acceptance sampling problem that minimizes the expected number of accepted defective lots (Surkov *et al.*, 2009; Powell, 2014). Similar to our expected slippage formulation in problem 2, we expect that these solutions would allocate surveys to sites with high infestation rates, but they should be less dependent on host densities. Along these lines, we compared the behaviour of our problem 2 solutions with the behaviour of an expected slippage model for inspections of live plant imports (Chen *et al.*, 2018). That model found that inspections should be allocated to the largest and dirtiest lots whereas our problem 2 solutions allocated surveys to the sites with the highest host densities

(i.e. the largest lots) and the highest infestation rates proximal to the infested sites (i.e. the ‘dirtiest’ lots). Chen *et al.* (2018) also found that adding uncertainty to their model prompted surveys of additional lots, but at lower sampling rates. When we added uncertainty to our models the solutions behaved similarly by surveying more sites but also at lower sampling rates.

Our results also provide new insights to an ongoing debate regarding the use of trapping versus branch sampling in EAB surveys. The choice of inspection method should always consider the available survey budget and factor in uncertainty about future EAB spread. Note that factors such as the density of infested trees, total number of host trees and the likelihood of infestation (and other parameters defined in Equations (1) and (5)) are likely to influence the selection of the sampling method for a survey site. Additionally, there is a non-linear relationship between the probability of pest detection and the tree sampling rate at a site, and these dependencies behave differently for the trapping and branch sampling methods. Furthermore, the survey allocation patterns and decisions to select particular sampling methods for different sites may be the result of the combinatorial nature of the survey allocation problem. For example, the use of the more reliable but expensive branch sampling method in sites where EAB is more likely to be detected can be offset by using the cheaper but less reliable trapping method in other locations where the likelihood of infestation is lower. This behaviour stems from using the summation over J sites in objective function equations (1) and (5).

The results of our analyses show that when the survey budget is small, low sampling rates are likely to be prescribed. When this occurs, the sampling method with the better detection rate should be used regardless of its cost. Branch sampling can be effective for surveying the two groups of sites: those proximal to the already-infested area that have high likelihoods of infestation, and those sites with low host densities where detections can be made using low sampling rates. The use of traps is only justified when the budget is large enough to support branch sampling inspections of the sites immediately around the initial detection, with sufficient funds remaining to spend on surveying the rest of the area of interest with traps. Trapping is more cost-effective when deployed at moderate and high sampling densities, but the utility of trapping depends on the efficiency of the traps. For example, decreasing trap efficiency by 10 per cent renders traps ineffective in most circumstances and shifts the optimal strategy to branch sampling.

We also found that the switch between sampling methods can be triggered by small changes in sampling efficiency or cost. This is because the model did not incorporate any behavioural inertia or other factors that may influence the preferability or efficacy of a sampling method. In the current formulation, the model always selects the method that yields a higher probability of detection (in problem 1 solutions) or lower slippage value (in problem 2 solutions) for a given combination of model parameters at a survey site.

Impact of ambiguity-averse perceptions on survey strategies

Incorporating uncertainty about how an invading pest will spread changes the optimal survey strategy. The uncertainty

Table 3 Sensitivity of key output metrics to changes in model parameters. The values represent an average relative change in the output value to the parameter change by ± 25 per cent.

Input parameter	Output metric of interest					
	Surveyed area		Number of inspected trees		Objective value	
	Via branch sampling	Via trapping	Via branch sampling	Via trapping	Problem 1 Exp. area of undetected infestations	Problem 2 Expected slippage
Budget = \$25 000						
Problem 1 – minimizing expected number of undetected infested sites						
Survey cost	1.30	8.67	0.88	8.10	0.54	0.25
Detection rate	1.35	9.00	1.44	8.65	0.59	0.28
Host density	0.10	0.67	0.16	1.00	0.01	1.01
Infestation rate	1.15	7.67	1.10	6.50	0.59	0.73
Problem 2 – minimizing expected slippage						
Survey cost	0.52	0.50	0.67	2.71	0.58	0.25
Detection rate	1.16	3.00	0.59	2.43	0.65	0.28
Host density	<0.01	<0.01	<0.01	<0.01	<0.01	1.00
Infestation rate	0.97	2.00	0.29	1.21	0.65	0.73
Budget = \$100 000						
Problem 1 – minimizing expected number of undetected infested sites						
Survey cost	0.91	0.13	1.81	1.15	0.42	0.27
Detection rate	0.73	0.13	1.13	0.10	0.46	0.28
Host density	0.55	0.10	1.44	0.13	<0.01	1.00
Infestation rate	0.73	0.13	1.13	0.10	0.46	0.73
Problem 2 – minimizing expected slippage						
Survey cost	2.50	1.12	5.12	1.42	0.46	0.25
Detection rate	2.88	0.34	5.00	0.35	0.48	0.27
Host density	0.75	0.20	1.00	0.07	<0.01	1.00
Infestation rate	3.25	0.44	5.60	0.39	0.48	0.75

Sensitivity values 1.0 and above are shaded.

Sensitivity values 2.0 and above in bold.

leads to the prescription of surveys across a larger area at lower sampling rates. Accounting for uncertainty addresses possible temporal and spatial variation in infestation rates and helps develop a more diversified survey strategy. When a decision-maker wants to avoid the worst-case outcomes (such as large host losses from failed detections), the optimal strategy is to survey additional sites with high host densities and at farther distances from the infested area where the arrival of the pest would cause significant damage. In our case study of EAB in Winnipeg, the penalty for implementing an ambiguity-averse strategy on the expected survey outcomes was small. Such a small penalty implies that satisfying the preferences of an ambiguity-averse manager does not cause substantial penalties to the pest management objectives of the survey programme and overall makes the survey strategy more robust.

Technical aspects and future work

Our analyses highlight the importance of estimating the likelihoods of pest entries for delimiting survey planning. However, data regarding novel pest entries are seldom available and analysts, at best, can only access records of old infestations in other

geographic regions. In our current formulation, we parameterized the likelihoods of EAB spread from historical records in the Twin Cities area of Minnesota. This area has a slightly warmer climate than Winnipeg. It is possible that the actual rates of EAB spread in Winnipeg could be lower due to a longer (i.e. 2-year) pest development cycle as well as colder winter conditions. Calibrating the EAB spread assumptions would require better understanding of the EAB development cycle in Winnipeg and could be a worthwhile exercise in the future.

Our optimal survey strategies assumed sampling of public trees only due to liability constraints. We recognize that access to private trees would likely change the optimal survey prescriptions, especially in areas with high densities of private trees. Private trees are usually more expensive to inspect due to extra access time. In general, public street trees have the lowest access and inspection costs and tend to be inspected first, especially when a small budget dictates the use of low sampling rates. Although our estimates of the total number of infested and susceptible host trees include trees on both private and public property, the omission of private tree inspections should not impact survey patterns significantly. This is because the public street trees (which not only tend to be inspected first, but are

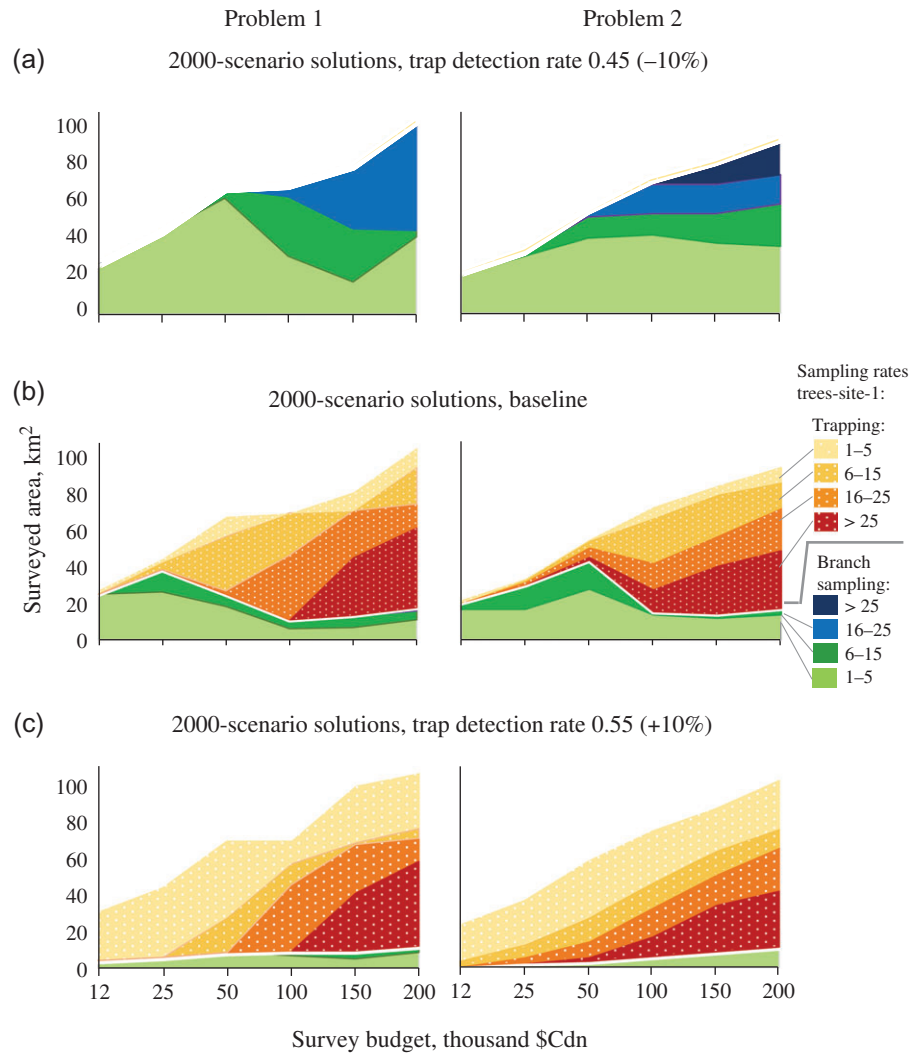


Figure 7 Area surveyed (km^2) with different sampling rates and survey budgets (\$) versus trapping efficiency: (a) alternative solutions with the trap detection rate = 0.45; (b) baseline solutions with the trap detection rate = 0.5; (c) alternative solutions with the trap detection rate = 0.55. X-axis denotes the survey budget, in thousand Canadian dollars, Y-axis denotes the surveyed area, in km^2 . Colours/stacked shades indicate the areas surveyed at a particular sampling rate and survey method for a given budget limit. Green-blue shades indicate the areas inspected via branch sampling at sampling rates of 1–5, 6–15, 16–25 and >25 trees-site $^{-1}$. Yellow-red shades indicate the areas inspected via trapping at sampling rates of 1–5, 6–15, 16–25 and >25 trees-site $^{-1}$. Darker colours indicate higher sampling rates.

present in nearly all survey sites) drive the survey selection process in most cases (i.e. at smaller budget levels), regardless of any private trees on the sites. However, at large budget levels when higher sampling rates can be applied, it may be optimal to inspect trees on private property in addition to public street trees, and so the survey patterns may shift toward inspecting some of the more accessible private trees. In other words, tree inspections on private property become relevant only when the survey budget is large enough that there are sufficient funds left after inspections of public street trees to also inspect notable numbers of private trees. As a practical matter, the impact of the omission of private trees would be more evident if the EAB infestation rates were higher, indicating an advanced stage of an outbreak, but this was not the case in our study where EAB presence was relatively low and mostly confined to a 5-km

radius around the area of initial detection. Nevertheless, given that Winnipeg is not currently planning inspections of private trees, we felt justified in our approach.

Our model considered a fixed size of the survey sites as an exogenous parameter defined prior to optimization. Potentially, the problem could be extended by introducing an additional set of decision variables that specify how the area should be divided into survey sites to maximize the problem objectives 1 and 2. The problem of selecting the optimal size of the survey sites can be formulated as a special case of a redistricting problem (see Kim, 2011) which finds an aggregation of smallest municipal subdivisions into a set of larger units that minimizes the expected area of undetected infestation (or expected slippage value). Note that redistricting problems are often numerically demanding and may only be applicable for small datasets.

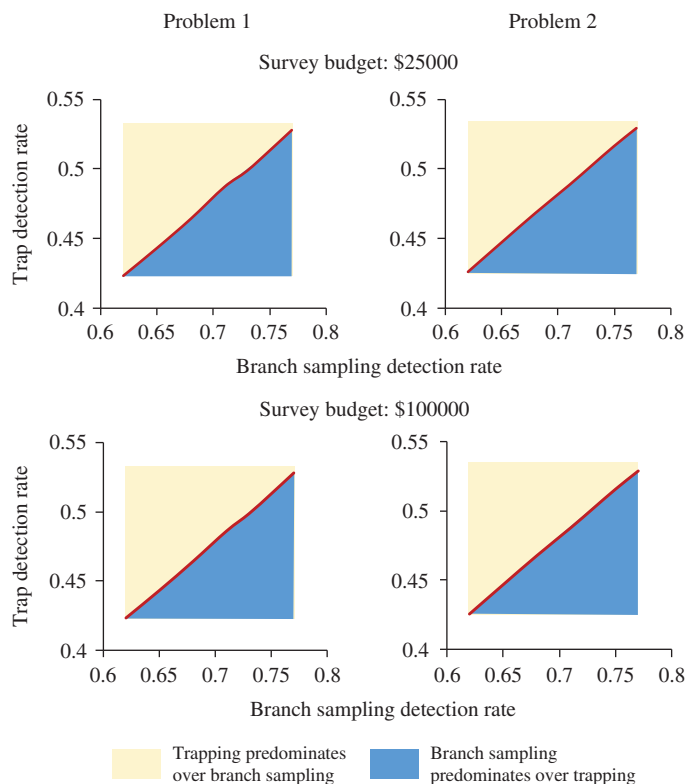


Figure 8 Proportional area allocation to trapping and branch sampling versus their detection rate values. X-axis shows the branch sampling detection rate and Y-axis shows the trap detection rate. The graphs show the combinations of trapping and branch sampling rates that cause one survey method to predominate another in optimal solutions. Red line indicates combinations of trapping and branch sampling detection rate values where the total area surveyed via trapping is equal to the area surveyed via branch sampling. In the optimal solutions below the red line (shaded in dark blue), branch sampling is applied to a larger area than trapping. In the solutions above the red line (shaded in beige) trapping is applied to a larger area than branch sampling.

Because our model is designed as a short-term planning tool for an annual seasonal planning cycle we did not incorporate the update of γ . The model can be re-solved in sequential order after updating the data on infested locations and recalculating the infestation rate values. Potentially, the model could be reformulated as a multi-stage stochastic programming problem but the problem size will make it too big to solve for practical datasets. Reformulating the model as a multi-stage problem could be the focus of future work.

Our model did not consider a sequential strategy for inspecting individual sites (or trees) and did not use information from sampled sites to update knowledge about the infestation probabilities. In practical EAB survey campaigns, the processing of sampled material does not happen immediately after individual tree inspections and often is delayed until such time that enough material has been collected to justify processing. This makes the issue of sequential search less important for EAB, but we note that this aspect could be pertinent in circumstances where there is no delay between sampling and identifying signs of infestation (such as visual tree inspections for signs of Asian

longhorned beetle attack). Nevertheless, we believe non-sequential sampling is a reasonable assumption in the EAB context. Unlike a human disease epidemic, for which there may be frequent status updates, the status of an invasive insect pest such as EAB in an area of concern is usually defined at the end (and less commonly in the middle) of the field season, when the bulk of the surveys have been completed.

For the current study, we only considered survey strategies without follow-up actions to control any established EAB population. Potentially, surveys could be followed by optional removal or treatment of detected infested trees with insecticide and, in some circumstances, removal of all remaining host trees. Adding such management options would likely change optimal survey strategies. This will be the focus of future work.

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Conflict of interest statement

None declared.

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