

RESEARCH ARTICLE

Optimal planning of multi-day invasive species surveillance campaigns

Denys Yemshanov¹  | Robert G. Haight² | Chris J. K. MacQuarrie¹ | Frank H. Koch³ | Ning Liu¹ | Robert Venette² | Krista Ryall¹

¹ Natural Resources Canada, Canadian Forest Service, Great Lakes Forestry Centre, 1219 Queen Street, Sault Ste Marie, Ontario P6A2E5, Canada

² USDA Forest Service, Northern Research Station, 1992 Folwell Ave, St. Paul, Minnesota 55108, USA

³ USDA Forest Service, Southern Research Station, Eastern Forest Environmental Threat Assessment Center, 3041 East Cornwallis Road, Research Triangle Park, North Carolina 27709, USA

Correspondence

Denys Yemshanov, Natural Resources Canada, Canadian Forest Service, Great Lakes Forestry Centre, Sault Ste. Marie, ON, Canada.
Email: denys.yemshanov@canada.ca

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Abstract

1. Multi-day survey campaigns are critical for timely detection of biological invasions. We propose a new modelling approach that helps allocate survey inspections in a multi-day campaign aimed at detecting the presence of an invasive organism.
2. We adopt a team orienteering problem to plan daily inspections and use an acceptance sampling approach to find an optimal surveillance strategy for emerald ash borer in Winnipeg, Manitoba, Canada. The manager's problem is to select daily routes and determine the optimal number of host trees to inspect with a particular inspection method in each survey location, subject to upper bounds on the survey budget, daily inspection time, and total survey time span.
3. We compare optimal survey strategies computed with two different management objectives. The first problem minimizes the expected number of survey sites (or area) with undetected infestations. The second problem minimizes slippage – the expected number of undetected infested trees in sites that were not surveyed or where the surveys did not find infestation.
4. We also explore the impact of uncertainty about site infestation rates and detection probabilities on the surveillance strategy. Accounting for uncertainty helps address temporal and spatial variation in infestation rates and yields a more robust surveillance strategy. The approach is generalizable and can support delimiting survey programs for biological invasions at various spatial scales.

KEYWORDS

biological invasions, emerald ash borer, multi-day survey campaigns, optimal routing, optimization, pest detection, surveys and sampling

1 | INTRODUCTION

Delimiting surveys are among the most common tools used to monitor biological invasions, but they require costly and coordinated efforts over extended periods of time (Hauser et al., 2016; Leung et al., 2002).

In budget-constrained situations, survey planning has been facilitated by optimization models (Büyüktaktın & Haight, 2018; Epanchin-Niell, Brockerhoff, Kean, & Turner, 2014; Epanchin-Niell, Haight, Berc, Kean, & Liebhold, 2012; Homans & Horie, 2011; Moore & McCarthy, 2016; Yemshanov et al., 2017, 2019a). Several models have been

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TABLE 1 Summary of the model parameters and decision variables

Symbol	Parameter/variable name	Description
<i>Sets:</i>		
N	Sites n, m in a landscape (nodes in a landscape network). First and last sites 1 and N define the main facility location. The first site $n = 1$ defines the start of a daily inspection route and the last site $n = N$ defines the end of a daily inspection route	$n, m \in N, N = 469$ sites
T	Daily inspection routes t scheduled to visit sites n in a landscape N during the survey campaign T and inspect trees for signs of infestation	$t \in T$
S	Infestation scenarios s . Each scenario s defines a plausible pattern of infestation probabilities γ_{ns} for each site n in a landscape N	$s \in S, S = 1$ and $S = 1500$
P	Survey sampling intensity levels p in site n . Each level specifies inspecting q_{np} trees in site n . Minimum sampling intensity level is inspecting one tree	$p \in P, p = 10$ levels (1–10 trees)
<i>Decision variables:</i>		
x_{nmt}	Binary selection of an arc nm connecting sites n and m in daily inspection route t	$x_{nmt} \in \{0, 1\}$
z_{ntp}	Binary selection of a survey intensity level p in site n visited during a daily inspection route t (i.e., inspecting q_{np} trees)	$z_{ntp} \in \{0, 1\}$
u_{mt}, u_{nt}	Auxiliary variables which define the position of nodes n, m in an inspection route t	$u_{mt}, u_{nt} \in [2; N]$
<i>Parameters</i>		
B	Maximum daily inspection and access time limit (working day length)	$B = 450$ min
H_n	Number of host trees in site n	$H_n \geq 0$
γ_{ns}	Probability of that a tree is infested in a site n in a scenario s ($\gamma_{ns}H_n$ is the expected number of infested trees in site n in a scenario s);	$\gamma_{ns} \in [0; 1]$
e_{1n}, e_{2n}	Probability that inspection of an infested tree with detection method 1 (branch sampling) or 2 (trapping) in site n finds signs of infestation	$e_{1n} = 0.7, e_{2n} = 0.5$
q_{np}	Number of trees inspected in a site n at a survey intensity level p	$q_{np} \in [1; 10]$
d_{nm}	Travel time from site n to a neighbouring site m through an arc nm	$d_{nm} > 0$
g_{1np}, g_{2np}	Times required to inspect a sample of q_{np} trees at the intensity level p with detection methods 1 or 2 in site n	$g_{1np} > 0, g_{2np} > 0$
$\theta_{1nsp}, \theta_{2nsp}$	Probabilities of detecting one or more infested trees in survey site n in scenario s after inspecting q_{np} trees with a sampling intensity p using survey methods 1 or 2	$\theta_{1nsp} \in [0; 1]$ $\theta_{2nsp} \in [0; 1]$
$\delta_{1nsp}, \delta_{2nsp}$	Expected number of infested trees in site n on the condition that inspection of a sample of q_{np} trees with survey methods 1 or 2 fails to detect the infested tree(s) in site n in scenario s (expected slippage for inspections of a site n in scenario s with methods 1 and 2)	$\delta_{1nsp} \in [0; \gamma_{ns}H_n]$ $\delta_{2nsp} \in [0; \gamma_{ns}H_n]$
M_t	Number of daily routes that use survey method 1 in a multi-day survey campaign T (The number of daily routes that use the survey method 2 is $T - M_t$)	$0 \leq M_t \leq T$
w_{1t}, w_{2t}	Binary parameters which specify the selected survey method 1 or 2 for a daily route t	$w_{1t}, w_{2t} \in [0; 1],$ $w_{2t} = 1 - w_{1t}$

proposed to assist early detection (Guillera-Arroita, Hauser, & McCarthy, 2014; Surkov, Alfons, Lansink, & Van der Werf, 2009; Yemshanov et al., 2019b), select optional invasion control measures (Hauser & McCarthy, 2009; Rout, Moore, & McCarthy, 2014; Yemshanov et al., 2017b, 2019c) and determine survey logistical details (Gust & Inglis, 2006; Moore, McCarthy, Parris, & Moore, 2014; Pullar, Kingston, & Panetta, 2006). However, few studies have considered multi-day surveillance planning because of the complex accounting for multi-day logistics in the face of personnel working time limits (but see Chades et al., 2011; Mayo, Straka, & Leonard, 2003).

Indeed, planning surveillance in multi-day surveys has to account for many factors, such as the road network, travel costs and sampling densities at inspected sites. Typically, survey managers must make their own judgments on how best to manage the survey logistics, personnel

and time, and default to their experience when designing the survey. This is a sensible approach, but because the multi-day survey problem is so complex, their decisions may fail to include all relevant factors and may not be cost-effective.

The time and cost to access the survey sites often depends on the configuration of the transportation network in the survey area. In geographical transportation networks, such as urban street networks, optimal planning of site inspections can be achieved with route optimization approaches. Several formulations have been proposed to solve optimal routing problems, including the maximum tour collection problem (Butt & Cavalier, 1994), the optimal dispatch (Solomon, 1987; Weigel & Cao, 1999) and the price-collecting Steiner tree problem (Chopra & Rao, 1994). In this study, we propose a new survey planning approach that accounts for optimal routing with common daily

logistical constraints, such as route planning and working time, in multi-day pest surveys. For each day in the surveillance campaign, our model finds a route visiting a sequence of sites and a corresponding set of host tree sampling plans. We adapt a team orienteering problem (Vansteenwegen, Souffriau, & Van Oudheusden, 2011) for the optimal routing model, which we then link with the two common geographical pest surveillance problems previously described in Yemshanov et al. (2019a).

Our first surveillance problem (problem 1) depicts a strategy to minimize the expected number of sites with undetected infestations. Our second problem addresses the issue of failed detections: it minimizes slippage – the expected number of infested trees that remain undetected following the survey – if the survey fails to detect the pest in previously uninvaded locations. We adapt the acceptance sampling concept from statistical quality control methods to account for the potential damage of failed detections. With acceptance sampling, the inspector accepts or rejects a group of items based on information obtained from a subsample of items inspected in the group (Schilling & Neubauer, 2009). We use the acceptance sampling problem formulation from Chen, Epanchin-Niell, and Haight (2018) and Yemshanov et al. (2019a). Thus, our second survey problem minimizes the expected number of infested host trees remaining in the area, which includes the infested trees in sites that were not surveyed and in sites where inspections did not detect an infestation.

We demonstrate the approach using a multi-day survey program for emerald ash borer (EAB), *Agrilus planipennis* Fairmaire (Coleoptera: Buprestidae), in Winnipeg, Canada, where the pest was first discovered in December 2017 (GoC, 2017). EAB is native to eastern Asia and poses a major threat to North American ash (*Fraxinus* spp.) trees, all of which are susceptible to attack. Our problem describes a common case of multi-day surveys that municipalities continue to do in areas with high risk of pest damage.

2 | MATERIALS AND METHODS

2.1 | A multi-day surveillance problem

Consider an area of N sites that may be infested with a tree pest. Each site n has H_n host trees that may be infested. A manager allocates tree inspections in area N to detect signs of infestation. A site n can be surveyed with intensity level p by inspecting a sample of q_{np} trees. We assume that the sample size, q_{np} can be selected from a finite set of sampling intensity levels $p = 1, \dots, P$ with the tree sample sizes q_{n1}, \dots, q_{nP} . The lowest site sample size is inspecting one tree, that is, $q_{n1} = 1$. All of the variables are summarized in Table 1.

Let γ_n be the probability that a tree in site n is infested, and e_n be the probability that inspection of an infested tree in site n detects the presence of the pest. Then, $\gamma_n H_n$ is the expected number of infested trees in site n . Based on prior *uncertain* knowledge about the invader, we depict the probabilities of invasion in the area as a set of S scenarios, where each scenario represents a vector of plausible tree infestation rates γ_{ns} , $s \in S$, across N sites from previously infested areas.

The manager chooses the number of trees to inspect (q_{np}) in each survey site n . If at least one tree in a sample of inspected trees is infested, the site is declared infested. The probability, θ_{nsp} , of detecting one or more infested trees in survey site n in scenario s using the sampling intensity p is:

$$\theta_{nsp} = 1 - (1 - \gamma_{ns} e_n)^{q_{np}}. \quad (1)$$

We also implement an alternative metric – expected slippage – which estimates the expected number of infested trees that remain undetected after the survey. We define this metric using the acceptance sampling formula from Chen et al. (2018) to estimate the expected number of infested trees, δ_{nsp} , in site n in scenario s , after sampling q_{np} trees and finding no signs of infestation, that is:

$$\delta_{nsp} = (1 - \gamma_{ns} e_n)^{q_{np}} \left[\gamma_{ns} (H_n - q_{np}) + \frac{1 - e_n}{1 - \gamma_{ns} e_n} \gamma_{ns} q_{np} \right]. \quad (2)$$

The δ_{nsp} value is termed the ‘expected slippage’ in optimal sampling literature. When no trees are inspected in site n , the expected slippage is equal to the expected number of infested trees, $\delta_{nsp} = \gamma_{ns} H_n$.

In our study, we focus on surveys in urban environment. During the working day, an inspection crew visits several sites in the area to conduct tree surveys. After finishing inspections at one site, the crew moves to another site and so on. Daily inspections fall along a route that starts at the main facility where fleet vehicles are stored and the collected samples are processed. After the inspections, the inspection crew returns to the main facility by the end of the day. We assume that the number of days with the surveys is limited by the duration of the survey campaign, T , and the total time that can be spent on tree inspections in any day t is limited by the working day length, B (7.5 h), which includes time to access the sites, inspect trees and return to the main facility.

To model the daily inspection routes we depict the survey area as a network of N nodes (potential survey sites). Daily surveys are conceptualized as routes through a network of interconnected sites (nodes), where every pair of sites n and m sharing a common boundary is connected by a pair of arcs nm and mn . Survey crews can move between neighbouring nodes n and m in the network N through arcs nm . The daily inspection routes can be depicted as sequences of connected nodes, starting and ending at the main facility. We introduce two surrogate nodes $n = 1$ and $n = N$ to define the starting and ending points of the daily inspection routes. Both nodes 1 and N point to the same main facility from which survey crews depart and to which they return. The other nodes in the network, $n = 2, \dots, N - 1$ define the potential survey sites in area N .

In order to sample trees in the first site during daily inspections, inspectors have to travel to that site from the main facility. There is no need to find the actual route from the main facility to the first inspected site. Instead, one only needs to estimate the total travel time from the main facility to the *first* inspected site in a daily schedule t and the time of return from the *last* inspected site to the main facility. To simplify the problem, we introduce two sets of auxiliary arcs $1n$ and mN . The set of arcs $1n$ connects node 1 (the main facility) to each of the other nodes

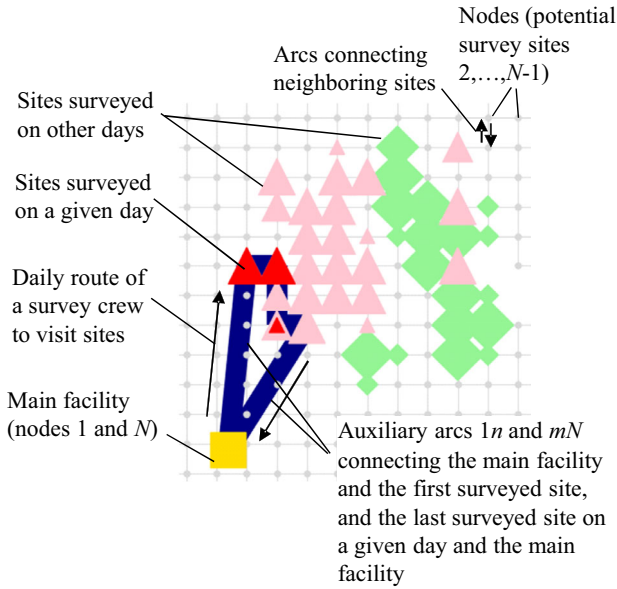


FIGURE 1 Conceptual example of a daily surveillance problem with routing. The area of interest is represented by a network of nodes (potential survey sites) interconnected by arcs. Each day, the survey crew leaves the main facility and follows a route that takes them to a set of survey sites before returning to the facility at the end of the day. Daily route scheduling must account for several practical factors, including site visit times and travel times between them, as well as any site access limitations

$2, \dots, N-1$ and depicts the access from the main facility to each site n as the potential first surveyed site of the day (Figure 1). Likewise, the set mN connects each of the nodes (except node 1) to the main facility (node N) and depicts the return route from each site m as the potential last surveyed site of the day. Each arc in sets $1n$ and mN is assigned the cost and time of getting from the main facility to site n (arc $1n$) and returning from site m back to the main facility (arc mN) (Figure 1). The cost and time to traverse each of these arcs is determined prior to optimization.

A daily survey route t represents a sequence of connected nodes starting in node 1 (the main facility), visiting some survey sites n and returning to node N (the main facility) (Figure 1). For each arc nm connecting an adjacent pair of nodes (potential neighbouring sites) n and m , $n, m \in N$, a binary variable x_{nmt} indicates whether the arc nm was included in the daily inspection route t ($x_{nmt} = 1$ and $x_{nmt} = 0$ otherwise). Traveling from site n to site m along an arc nm takes time d_{nm} . We assume that daily inspection routes may pass through some sites without conducting a survey in order to reach other sites where the risk of invasion is higher.

Inspectors, when accessing site n in route t , may decide to conduct surveys. A binary decision variable z_{ntp} selects the survey of a site n with a sampling intensity p (i.e., inspecting q_{np} trees) in daily route t ($z_{ntp} = 1$, and $z_{ntp} = 0$ for all sampling intensities p at the sites passed through without inspections or not visited). The selection of sampling intensity p in site n is done with respect to the outcomes of all S infestation scenarios; we do not define the scenario-specific sampling intensities because we assume that the inspector knows only the approximate

rate value based on S scenarios. We assume that the inspection of q_{np} trees in site n takes time g_{np} .

We further assume that the manager can select between two inspection methods: inspecting branches of the host tree for signs of pest attack (Ryall, Fidgen, & Turgeon, 2011) or setting up traps in host trees to catch flying adults emerging from the infested trees (Ryall, 2015). It is not possible to mix two survey methods in a daily route because each method is effective in different seasons. Traps are deployed in the summer, when adult insects emerge to mate and lay eggs, and branch sampling is done during the cold season when branches can be collected without leaves. Hence, a daily route t can only be spent on inspections with one particular method. We define the binary parameters w_{1t} and w_{2t} to select the survey method for a daily route t and the parameter M_t , $M_t \in [0; T]$, to set the number of daily routes that use survey method 1 in a survey campaign T . The number of daily routes that used survey method 2 is $T - M_t$. We then set parameters w_{1t} and w_{2t} so that:

$$\begin{cases} w_{1t} = 1 \forall t \leq M_t \\ w_{1t} = 0 \forall M_t < t \leq T \\ w_{2t} = 1 - w_{1t} \\ w_{1t}, w_{2t} \in \{0, 1\} \end{cases} \quad (3)$$

By altering the parameters M_t , w_{1t} and w_{2t} one can explore different proportions of the survey methods to find the most effective solution.

Survey methods 1 and 2 differ in their cost, detection rates, e_{1n} and e_{2n} , and time needed to survey a tree, g_{1np} and g_{2np} . The probability of detecting one or more infested trees in survey site n in scenario s after inspecting q_{np} trees with methods 1 and 2 is:

$$\theta_{1nsp} = 1 - (1 - \gamma_{ns} e_{n1})^{q_{np}} \quad \text{and} \quad \theta_{2nsp} = 1 - (1 - \gamma_{ns} e_{n2})^{q_{np}}. \quad (4)$$

We then formulate our pest survey problem 1 as finding a configuration of T daily inspection routes and tree sampling rates at survey sites that maximizes the expected number of sites with detected infestations across a set of infestation scenarios S , subject to the upper bounds on daily inspection time and the total length of the survey campaign, that is:

$$\max \frac{1}{S} \sum_{s=1}^S \sum_{n=2}^{N-1} \sum_{t=1}^T \sum_{p=1}^P (z_{ntp} (\theta_{1nsp} w_{1t} + \theta_{2nsp} w_{2t})). \quad (5)$$

The objective function (5) is analogous to the problem 1 formulation in Yemshanov et al. (2019b). For consistency with the problem 2 formulation, we reformulate objective (5) as an equivalent minimization problem, that is, minimizing the expected number of survey sites with undetected infestations:

$$\begin{aligned} \min & \frac{1}{S} \sum_{s=1}^S \sum_{n=1}^{N-1} \sum_{t=1}^T \sum_{p=1}^P (z_{ntp} ((1 - \theta_{1nsp}) w_{1t} + (1 - \theta_{2nsp}) w_{2t})) \\ & + \frac{1}{S} \sum_{s=1}^S \sum_{n=2}^{N-1} \left(1 - \sum_{t=1}^T \sum_{p=1}^P z_{ntp} \right). \end{aligned} \quad (6)$$

The first term in Equation (6) denotes the expected number of sites which are surveyed and no infestation is found and the second term denotes the expected number of uninspected sites.

We also investigate our problem 2 that minimizes the expected slippage δ_{nsp} , that is:

$$\min \frac{1}{S} \sum_{s=1}^S \sum_{n=1}^{N-1} \sum_{t=1}^T \sum_{p=1}^P (z_{ntp} (\delta_{1nsp} w_{1t} + \delta_{2nsp} w_{2t})) + \frac{1}{S} \sum_{s=1}^S \sum_{n=2}^{N-1} \left(\gamma_{ns} H_n \left[1 - \sum_{t=1}^T \sum_{p=1}^P z_{ntp} \right] \right). \quad (7)$$

The first term in Equation (7) defines the expected slippage for the surveyed sites. Because the survey selection variable z_{ntp} , when set to 1, only specifies the positive sampling sizes, we need the second term in Equation (7) to define the expected slippage for the unsurveyed sites (i.e., $\gamma_{ns} H_n$). Terms δ_{1nsp} and δ_{2nsp} are based on Equation (2) and denote the expected slippage values for the inspections with survey methods 1 and 2, that is:

$$\delta_{1nsp} = (1 - \gamma_{ns} e_{1n})^{q_{np}} \left[\gamma_{ns} (H_n - q_{np}) + \frac{1 - e_{1n}}{1 - \gamma_{ns} e_{1n}} \gamma_{ns} q_{np} \right] \text{ and} \quad (8)$$

$$\delta_{2nsp} = (1 - \gamma_{ns} e_{2n})^{q_{np}} \left[\gamma_{ns} (H_n - q_{np}) + \frac{1 - e_{2n}}{1 - \gamma_{ns} e_{2n}} \gamma_{ns} q_{np} \right].$$

In order to account for the stochastic nature of the infestation spread, the objective functions (6) and (7) are formulated as a scenario-based robust optimization problem (see the summation over S spread scenarios in (6) and (7)).

Below we define the model constraints for the problem 1 and 2 objectives in (6) and (7), respectively. Constraint (9) ensures that only one sampling intensity level p can be chosen for inspections at a surveyed site n over T daily inspection routes, that is:

$$\sum_{t=1}^T \sum_{p=1}^P z_{ntp} \leq 1 \forall n \in 2, \dots, N-1, t \in T. \quad (9)$$

Constraint (9) ensures that a site n can only be surveyed once during the survey campaign T . The set $n = 2, \dots, N-1$ includes all potential survey sites except the main facility location (sites 1, N).

We adapt the team orienteering problem formulation (Vansteenwegen et al., 2011) to ensure that the inspected sites are visited via a connected route that starts and ends at the main facility. The team orienteering problem (Butt & Cavalier, 1994; Chao, Golden, & Wasil, 1996) determines T routes, each limited by a time B , that maximize the total value collected at the sites visited along the routes. We find a collection of T daily inspection routes that minimizes objectives (6) and (7). Constraints (10–17) ensure the contiguity of the inspection routes and enforce the inspection time limits. Constraints (10) and (11) guarantee that each route starts in node 1 and ends in node N (the main facility):

$$\sum_{m=2}^N x_{1mt} = 1 \forall t \in T \quad (10)$$

$$\sum_{n=1}^{N-1} x_{nNt} = 1 \forall t \in T. \quad (11)$$

Constraint (12) guarantees the connectivity of each route and ensures that each route is a single path, that is, a connected node has no more than one incoming and one outgoing arc:

$$\sum_{n=1}^{N-1} x_{nkt} = \sum_{m=2}^N x_{kmt} \leq 1 \forall k \in 2, \dots, N-1, t \in T. \quad (12)$$

Constraint (13) specifies that tree inspections can only be done at sites that are visited during a daily route t , that is:

$$\sum_{p=1}^P z_{mtp} \leq \sum_{n=1}^{N-1} x_{nmt} \forall m \in 2, \dots, N, t \in T. \quad (13)$$

Constraints (14) and (15), the so-called Miller–Tucker–Zemlin formulation in the traveling salesman problem (Miller, Tucker, & Zemlin, 1960), are used to prevent sub-tours in individual routes t , that is:

$$u_{nt} - u_{mt} + 1 \leq (N-1)(1 - x_{nmt}) \quad \forall n, m \in 2, \dots, N, t \in T, \quad (14)$$

$$2 \leq u_{nt}, u_{mt} \leq N \forall n, m \in 2, \dots, N, t \in T, \quad (15)$$

where u_{nt} , u_{mt} are auxiliary decision variables which define the positions of nodes n and m in a daily inspection route t . Constraint (16) sets the maximum time limit B for a daily inspection route t , that is:

$$\sum_{n=1}^{N-1} \sum_{m=2}^N (x_{nmt} d_{nm}) + \sum_{n=2}^{N-1} \sum_{p=1}^P (z_{ntp} [w_{1t} g_{1np} + w_{2t} g_{2np}]) \leq B \forall t \in T, \quad (16)$$

where d_{nm} is the time to travel along an arc nm between sites n and m and g_{1np} and g_{2np} are times to inspect a sample of q_{np} trees in site n at the intensity level p with survey methods 1 and 2. There is no need for a budget constraint because the cost of the survey is limited by the fixed length of the working day B and the total length of the survey campaign T . A desired budget level is a linear function of the length of the survey campaign T (because hiring the survey crews and renting equipment is done on a daily basis) and can be set by varying the T value.

Constraints (17) and (18) tighten the formulation and force the scheduling of surveys every day t and the survey of at least one site per day over the campaign time span T , that is:

$$\sum_{n=1}^{N-1} \sum_{m=2}^N (x_{nmt} d_{nm}) + \sum_{n=2}^{N-1} \sum_{p=1}^P (z_{ntp} (w_{1t} g_{1np} + w_{2t} g_{2np})) \geq B_{\min} \forall t \in T, \quad (17)$$

$$\sum_{n=2}^{N-1} \sum_{p=1}^P (z_{ntp} (w_{1t} + w_{2t})) \geq 1 \forall t \in T. \quad (18)$$

The minimum time limit B_{\min} includes the maximum time to access a single site from the main facility, inspect trees with the maximum sampling size and return to the main facility. Because the total survey cost is a linear function of the survey campaign length T , same-duration surveys are comparable. Since problems 1 and 2 use different objectives they can only be compared in the dimensions of either objective 1 or

2. To explore the trade-off between minimizing the expected slippage versus minimizing the expected number of sites with undetected infestations, the problems can be combined into a bi-objective formulation. However, we only consider here the endpoints of this trade-off, which is the solution of problems 1 and 2 in Equations (6) and (7).

2.2 | Multi-day surveys planning for EAB infestation in Winnipeg, Canada

We adapted the problem 1 and 2 formulations to develop optimal survey strategies for the EAB in Winnipeg, Canada. EAB has destroyed ash populations in much of the eastern United States and eastern Canada (Herms & McCullough, 2014; Kovacs et al., 2010; McKenney et al., 2012). EAB spread is assisted by vehicular transport (Buck & Marshall, 2008) and movement of infested materials (Haack, Petrice, & Wiedenhoft, 2010; Short et al., 2019). Early detection of EAB is problematic because tree damage does not become visible for at least 2 years, so new finds usually indicate pre-established populations (Poland & McCullough, 2006; Ryall et al., 2011). The two most common methods to detect EAB are sampling branches and then peeling their bark to inspect for EAB galleries or placing sticky traps baited with ash volatiles and EAB pheromones. Branch sampling is the more reliable detection method, especially for detecting infestations in asymptomatic trees (Ryall et al., 2011; Turgeon, Fidgen, Ryall, & Scarr, 2015). The use of sticky traps is less expensive on a per-tree basis but yields a lower detection rate (Ryall, 2015; Ryall, Fidgen, Silk, & Scarr, 2013).

After EAB was first discovered in Winnipeg in December 2017 (GoC, 2017), the City of Winnipeg and the Province of Manitoba established a program to delimit the full extent of the EAB infestation. The city was divided into a grid of 1×1 km sites where some trees were sampled using the branch sampling method and trapping. These surveys found two sites in the city with infested trees (Figure 2a).

2.3 | Estimates of EAB spread

The model parameterization required data describing the spatial distribution of host densities, the estimates of the likelihoods of EAB spread, site-to-site travel times and the survey times, which we describe below. We used a conventional approach to estimate the probabilities of EAB spread to other sites as a function of distance from the infested locations (Kovacs et al., 2010; Leung, Cacho, & Spring, 2010; Prasad et al., 2010). We used historical observations from the urban EAB infestation closest to Winnipeg in Minneapolis–St. Paul, Minnesota, USA (Fahrner, Abrahamson, Venette, & Aukema, 2017; Osthus, 2017) – to predict the distance-dependent probabilities of EAB spread (see details in Yemshanov et al. (2019a)). The pest is believed to have entered the Winnipeg area approximately 7 years ago, so we used the observations of EAB spread in Minneapolis–St. Paul over the same timeframe. We divided the area into a grid of 1×1 km sites, and estimated the proportion of infested ash trees in each site based on municipal tree inventories (City of Minneapolis, 2017; Koch, Ambrose, Yemshanov,

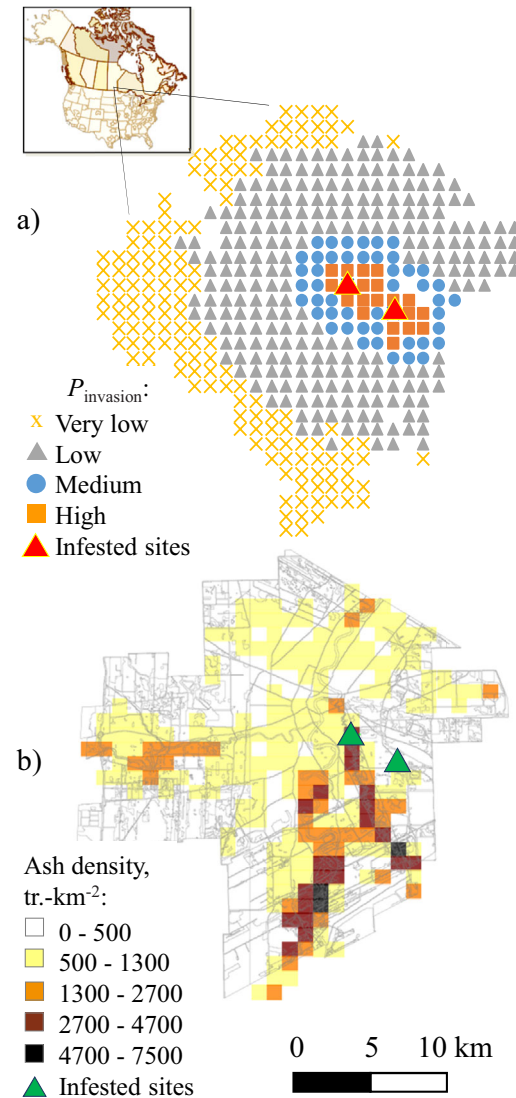


FIGURE 2 (a) Probabilities of EAB infestation in the study area (mean value based on 1500 infestation scenarios); (b) ash host density

Wiseman, & Cowett, 2018; TreeKeeper, 2018) and documented EAB detection rates (Fahrner et al., 2017; Venette, 2019) from the Minneapolis–St. Paul region. From these estimates, we calculated the probabilities of EAB infestation in each site. We compiled these into distributions of invasion probabilities for 1-km distance classes from the closest infested site. Then, for each 1×1 km site in Winnipeg we calculated the distance to the nearest infestation and sampled the distribution of infestation probabilities for the corresponding distance class. We generated 1500 scenarios depicting the universe of plausible invasion outcomes, which we used to find the optimal survey solutions. We also estimated the mean probabilities based on 1500 scenarios (Figure 2a) to explore the survey solutions when the uncertainty about EAB spread is ignored, and compared these mean solutions with the set of individual scenario solutions to identify the impact of the uncertainty assumption.

Additionally, we compared the optimal solutions for the problem 1 and 2 formulations with similar theoretical problem solutions from

Yemshanov et al. (2019a) that did not include optimal routing. Since the theoretical problem formulations factored the access constraints indirectly into the survey cost value, a direct comparison between the theoretical and new model solutions was impossible. Instead, we first solved the new model formulation for a desired survey duration (e.g., 40 days) and found the solution with the optimal allocation of days spent surveying with branch sampling and trapping. We then calculated the total survey cost in the optimal solution using the sampling cost estimates provided below. In turn, we used this total cost as a budget constraint to solve the theoretical problem 1 and 2 formulations (i.e., eqs. 1–6 in Yemshanov et al. (2019a)), so both the theoretical and new model solutions used the same budget levels. Finally, we calculated the expected slippage in problem 2 solutions and the expected number of sites with undetected infestations in problem 1 solutions to compare the survey performance between the theoretical and new model formulations.

2.4 | Inspection times, detection probabilities and host densities

Previous EAB surveys in Canada (Ryall et al., 2011; Turgeon et al., 2015) provided estimates of the detection probabilities when using branch samples versus sticky traps. Sampling two branches in mid-crown from a medium-sized tree yields a detection rate of 0.7 (Ryall et al., 2013). Experience from urban surveys in Ontario suggests that the EAB detection rate with a sticky trap is ≈ 0.5 . However, the effectiveness of traps varies depending on trap placement and density of EAB infestation, so we evaluated solutions with trap detection rates varying from 0.5 to 0.58 to estimate when the use of traps becomes more effective than branch sampling.

We assumed that municipal EAB surveys would target public trees ≥ 20 cm dbh (which is the current practice in Winnipeg). We stratified public trees into three classes: street trees 20–60 cm dbh, large but accessible trees > 60 cm dbh and public trees in woodlots and riparian zones. Sampling trees 20–60 cm dbh would require installing either one sticky trap or sampling two branches and sampling trees larger than 60 cm dbh would require doubling the time and cost to achieve the same detection probability. The site access and trap setup times for woodlot trees were assumed to double that of street trees and accessible trees. We estimated the densities and sizes of host trees from a municipal forest inventory for Winnipeg (City of Winnipeg, 2018; Daudet, 2019) (Figure 2b).

Site access times were assumed to depend on their location and the route followed by the crew. The total access time for a crew of two was estimated to cost \$3.12 per minute for both survey techniques. The total trap setup time for a two-person crew was estimated to take 17 and 24 min for trapping a medium- and large-sized street tree, respectively, and 34 min for a tree in a woodlot or riparian zone. Branch sampling requires only one visit to a survey site but the time to obtain a sample also factors in the bark peeling and branch disposal time, activities that may take place at the main facility. Based on data from the initial EAB delimiting survey in Winnipeg, the access time for a

three-person crew to obtain branches from a medium- and large-sized tree was 25 and 35 min, respectively. We also estimated the trap sampling costs based on experience from this previous survey (i.e., \$71.50 for a 20–60 dbh tree and \$111.50 for trees larger than 60 cm dbh). The total cost of branch sampling was estimated as \$120.60 for a 20–60 cm dbh tree and \$241.80 for trees larger than 60 cm dbh.

We estimated the site-to-site access times for each pair of neighbouring sites from typical driving times using the urban street network data. We computed the driving distances between the sites via the urban survey network, and then converted the distances to driving time by querying Google Maps to determine the approximate driving times between representative locations in the same neighbourhoods in Winnipeg. The model (Yemshanov et al., 2020) was composed in the GAMS environment (GAMS, 2019) and solved with the GUROBI linear programming solver (GUROBI, 2019).

3 | RESULTS

We first examined the optimal solutions from a single-scenario formulation, which used mean spread rate values based on 5 scenarios. This formulation depicts the hypothetical case when a manager 'knows' the infestation value (and so a single scenario is used). We then compared the single-scenario solutions with solutions from a formulation based on 1500 scenarios (Figure 3), which assumed the manager knows only the approximate range of infestation rates for each site. The maps in Figures 3 and 4 show the survey locations and tree inspection densities with a particular method (green cells = branch sampling, red cells = trapping) in optimal solutions. For both short- and long-duration survey campaigns (i.e., $T = 20$ and $T = 40$ days), all solutions prescribed more branch sampling than trapping (Figures 3 and 4). However, the deterministic solutions had more (and mostly peripheral) sites inspected via trapping than the uncertainty solutions.

3.1 | Optimal versus theoretical survey solutions

We compared the survey patterns from the theoretical and new model solutions for budgets equivalent to 20- and 40-day survey campaigns. Among the no-uncertainty (i.e., single-scenario) solutions, the theoretical solutions for problem 1 showed a uniform survey pattern allocated within 5–6 km of the already-infested locations (Figures 3a and 4a). The new model solutions for problem 1, which incorporated routing, surveyed a larger perimeter around the existing infestations but in a clustered fashion by avoiding hard-to-access sites in river valleys (i.e., grey lines in Figures 3b and 4b); instead, most of the selected sites were located in residential or commercial areas with abundant and accessible street trees.

In the theoretical, no-uncertainty solutions to problem 1, trapping (red squares in Figures 3a and 4a) was used regularly to inspect sites farther from the existing infestations and branch sampling (green squares in Figures 3a and 4a) was used to survey sites close to the infestations. In contrast, the problem 1 theoretical solutions that accounted

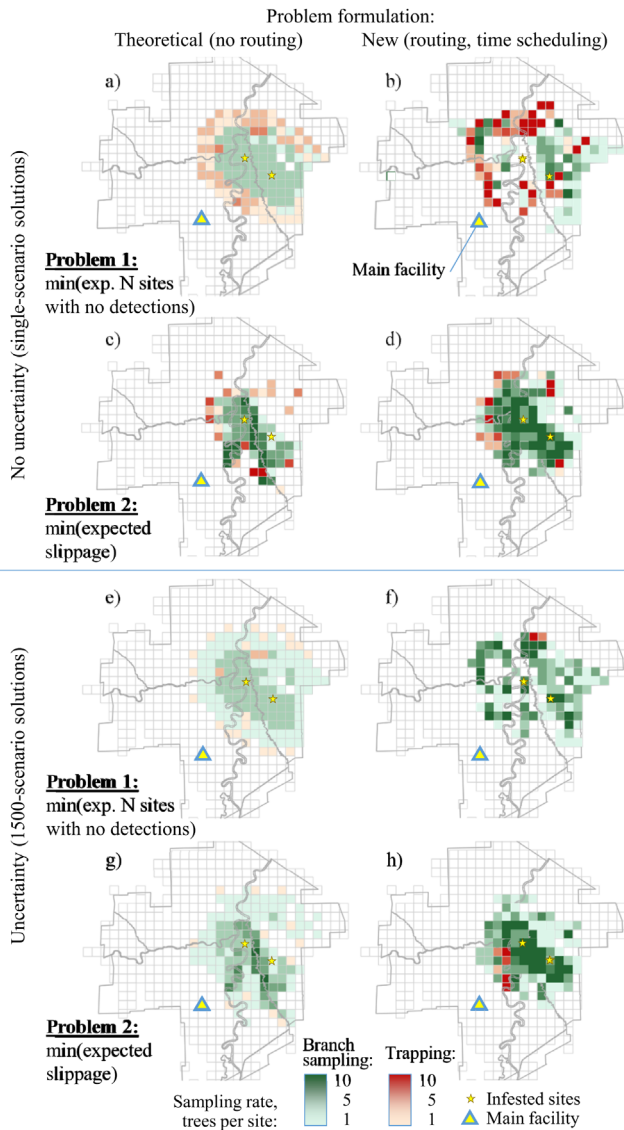


FIGURE 3 Optimal survey patterns for problem 1 (minimizing the expected number of sites with undetected infestations) and problem 2 (minimizing expected slippage) solutions for 40-day survey campaigns (or equivalent budget levels in the theoretical model formulations). The maps show the sampling densities with a particular method in optimal solutions (i.e., cells in green show branch sampling and in red trapping). No-uncertainty (single-scenario) solutions: problem 1, (a) theoretical formulation and (b) new formulation with routing and time constraints; problem 2, (c) theoretical formulation and (d) new formulation. Uncertainty (1500-scenario) solutions: problem 1, (e) theoretical formulation and (f) new formulation; problem 2, (g) theoretical formulation and (h) new formulation

for uncertainty restricted the use of trapping to sporadic inspections of peripheral sites (Figures 3e and 4e). The impact of the uncertainty was similar in the new model solutions, with the use of trapping minimized in favour of branch sampling (Figure 3b vs. 3f, Figure 4b vs. 4f).

Differences between the theoretical and new model formulations for the problem 2 solutions were less dramatic than they were for the problem 1 solutions. With respect to the theoretical solutions to

problem 2, more sites were surveyed in the solutions that accounted for uncertainty, but at lower sampling sizes to compensate for the uncertainty (Figure 3c vs. 3g, Figure 4c vs. 4g). In fact, the problem 2 theoretical solutions that accounted for uncertainty surveyed more sites than in the corresponding uncertainty solutions from the new model (Table 2, Figure 3g vs. 3h). Regardless, the spatial footprint of the survey was similar in all model solutions and tended to prioritize areas with high risk of infestation and high host densities. For example, unlike the problem 1 solutions, which avoided allocating surveys in hard-to-access sites, the problem 2 solutions targeted sites in river valleys, but only if the infestation risk and host density were both high. The solutions for the new model formulation, on average, recommended a sampling size 1.84 times higher and inspected an area 1.7 times smaller than in the theoretical model solutions (Table 2). This was because the new model solutions included routing, and typically the most efficient routes chose sites close to each other and devoted more time to inspecting trees in the selected sites.

3.2 | Survey performance versus the duration of the survey campaign

We examined the optimal solutions for a range of survey durations between 10 and 70 days. For both problems 1 and 2, the objective value (i.e., the expected number of sites with undetected infestations or the expected slippage) began to stabilize after about 50 days (Figure 5). In theory, the relationship between objective value and survey duration should be an exponential decay that follows the law of diminishing returns. However, in our case the curves decayed almost linearly before stabilizing (Figure 5). This behaviour can be explained as follows. At least for the near future, only a small portion of the Winnipeg area is expected to face a moderate or high risk of EAB infestation (Figure 2a). This means that while it may be possible to find new infestations far away from the existing infestations, the chance of this occurring is low. Instead, new infestations are more likely to emerge near the existing infestations, as exemplified by the discovery of the second infestation in Winnipeg in 2018 less than 5 km from the initial infestation (Figure 2).

Including site access and inspection time constraints forces the model to prioritize the sites with the shortest access times, so more trees can be inspected during workday hours. One consequence of this behaviour is the piecewise shape of the curve in Figure 5. Generally, sites with short access and inspection times are located in residential and commercial areas with accessible street trees. The objective value levels off once all sites with short access and inspection times that are within 5–6 km of the already-infested locations are surveyed at the maximum allowed sampling size.

3.3 | Trapping versus branch sampling

Branch sampling was strongly preferred in the uncertainty solutions under both the theoretical and new model formulations (Table 2).

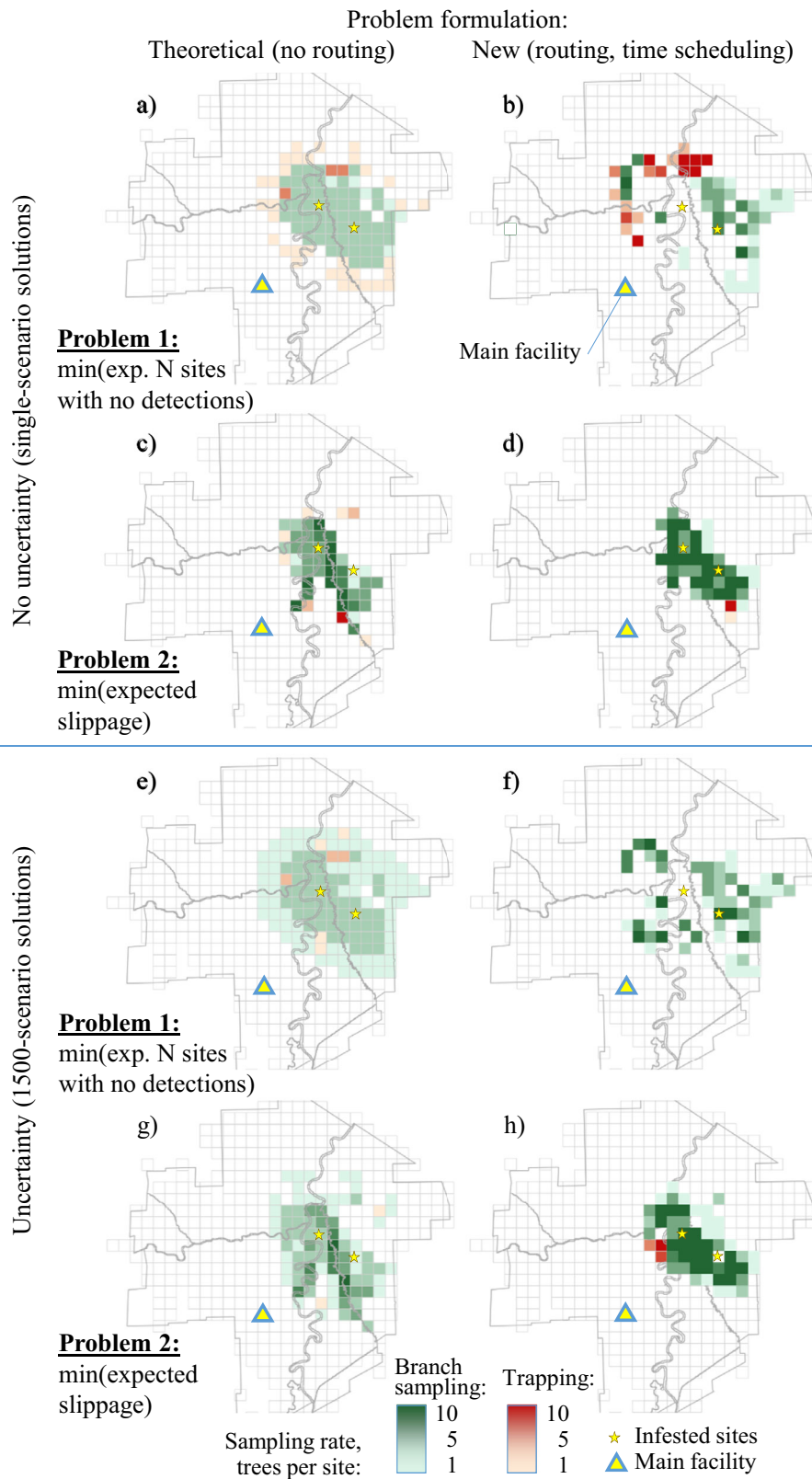


FIGURE 4 Optimal survey patterns for problem 1 (minimizing the expected number of sites with undetected infestations) and problem 2 (minimizing expected slippage) solutions for 20-day survey campaigns (or equivalent budget levels in the theoretical model formulations). The maps show the sampling densities with a particular method in optimal solutions (i.e., cells in green show branch sampling and in red trapping). No-uncertainty (single-scenario) solutions: problem 1, (a) theoretical formulation and (b) new formulation with routing and time constraints; problem 2, (c) theoretical formulation and (d) new formulation. Uncertainty (1500-scenario) solutions: problem 1, (e) theoretical formulation and (f) new formulation; problem 2, (g) theoretical formulation and (h) new formulation

TABLE 2 Objective function values, the number of inspected sites, mean tree sampling densities and the number of inspected trees in theoretical and new problem 1 and 2 solutions with routing and operational daily time constraints

Problem objective	Model formulation	Time span, days	Optimal N days spent on branch sampling	Exp. slippage ES	Exp. N sites with detections	Number of surveyed sites			Number of sampled trees			Sampling size, trees-site ⁻¹		
						Total	Br.sAMPL. Method 1	Trapping Method 2	Total	Br.sAMPL. Method 1	Trapping Method 2	Average	Br.sAMPL. Method 1	Trapping Method 2
Problem 1	New*	20	20	2,4406	14.3	56	56	0	255	—	—	4.6	4.6	—
	Theoretical**	***	***	1,4722	30.3	135	128	7	261	16	16	1.9	1.9	2.3
Problem 2	New	20	20	2,3532	7.6	49	49	0	301	—	—	6.1	6.1	—
	Theoretical	***	***	1,1966	26.2	86	84	2	279	2	2	3.2	3.3	1.0
Problem 1	New	40	39	2,3778	20.0	93	90	3	528	24	24	5.7	5.6	—
	Theoretical	****	****	1,1123	45.3	149	134	15	527	23	23	3.5	3.8	1.5
Problem 2	New	40	39	2,2518	15.4	98	95	3	623	24	24	6.4	6.3	8.0
	Theoretical	****	****	9419	38.2	133	123	10	517	11	11	3.9	4.1	1.1

*The new model formulation with optimal routing and operational time constraints is shown in Equations (3)–(19).

**See the theoretical formulation with a global budget constraint without routing and operational time constraints in (1.1), in Equations (1)–(6).

***The total budget equivalent to a 20-day survey campaign in the new model formulation.

****The total budget equivalent to a 40-day survey campaign in the new model formulation.

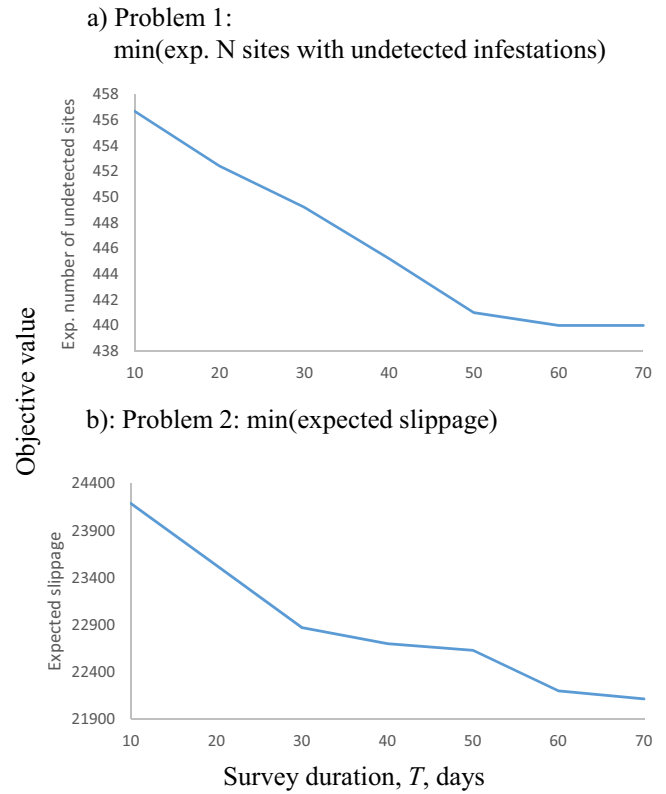


FIGURE 5 Objective value versus survey campaign duration, T : (a) problem 1 (minimizing the expected number of sites with undetected infestations) solutions; (b) problem 2 (minimizing expected slippage) solutions

While trapping is cheaper than branch sampling, it is less reliable. Accounting for site access time and routing makes the use of traps less attractive than branch sampling. This is why trapping was used rarely in the new model solutions and only on the periphery of the survey area, where the probability of infestation is low and where both inspection methods would yield low detection rates.

Indeed, trapping must attain a fairly high detection rate to become the preferred method. In our EAB case, trapping becomes dominant – representing 75% of all sampling – when the trap detection rate exceeds 0.53 in problem 1 solutions and 0.55 in problem 2 solutions (Figure 6). Nevertheless, increasing the detection rate does not allow trapping to completely replace branch sampling in the solutions to problem 2 (Figure 6). This finding emphasizes the value of a reliable estimate of the detection rate for tree inspection methods. In our case, branch sampling is preferred over trapping when its detection rate averages 1.35 times greater than the detection rate of traps.

4 | DISCUSSION

Planning multi-day surveys of biological invasions in geographical environments is challenging because multiple logistical aspects must be factored into the planning process. Our work helps address these challenges and demonstrates how operational time constraints, when

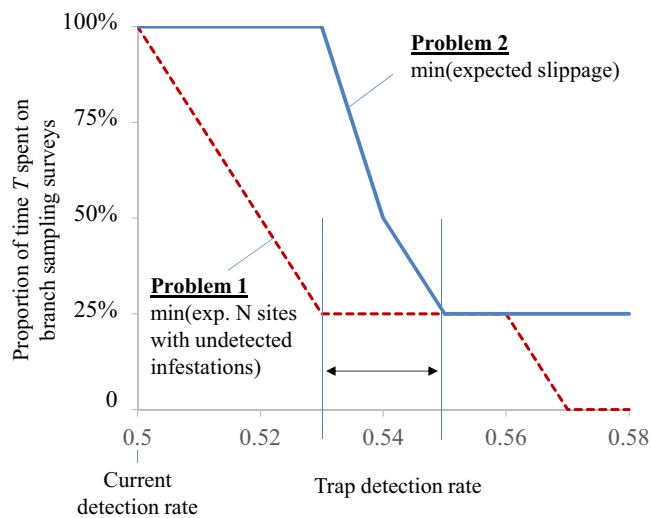


FIGURE 6 Trap detection rate vs. preferred inspection method. Arrow indicates the range of trap detection rates when the use of traps becomes the preferred method. Dashed line indicates the problem 1 (minimizing expected number of sites with undetected infestations) solutions and solid line indicates the problem 2 (minimizing expected slippage) solutions

accounted for in survey planning, typically result in lower – but more realistic survey efficiency than in the theoretical planning case that does not include these details. Our study also confronts the issue of failed detections in operational pest surveys. The prospect of inspections failing to detect an infestation after surveying a site is especially high in multi-day surveys when planners are constrained by daily schedules.

Additionally, our results provide insights regarding the problem of choosing the most appropriate detection method for urban EAB surveys. In our solutions for EAB in Winnipeg, trapping was only cost-effective for surveying peripheral areas far from the existing infestations, while branch sampling was suggested for inspecting all sites with high or moderate infestation risk. Branch sampling also performed better in fixed-time daily surveys. For trapping to be equally effective in multi-day surveys, traps would need to be at least 0.76–0.78 the detection accuracy of branch sampling.

More generally, our findings highlight the importance of accounting for operational and site access constraints in survey planning process. The omission of these details leads to overly optimistic expectations of planned survey actions. Adding these constraints imposes spatial restrictions on the scope and extent of the survey efforts and produces less effective prescriptions than the theoretical prescriptions, which do not account for routing and daily time constraints. Nevertheless, these prescriptions offer more realistic expectations of the survey's outcomes.

With respect to the issue of detection methods for insect pests, traps are often favoured by surveyors for their perceived ease of use. This is because traps are relatively easy to deploy and require less training to operate. By contrast, branch sampling requires training and some specialized equipment to implement and identify the insect of interest.

This effort may dissuade a survey agency from selecting branch sampling, even though it provides a more reliable detection of the insect population. This is confirmed by our results, which show that branch sampling is more effective for detecting EAB near an existing infestation, with traps deployed at a greater distance. However, only a modest potential increase in the efficacy of traps can bring them on par with branch sampling at detecting incipient populations. One advantage of the branch sampling method, not considered here, is that it also provides a direct estimate of population density that can be used to inform management decisions. For EAB, we presently do not know the effective range (i.e., the area sampled) of the traps (but see Parker, Ryall, Aukema, & Silk, 2019) and so cannot infer the density of the population from trap results.

Another finding that surprised us was the relatively minor differences in spatial survey patterns between the problem 2 solutions with the new model configuration and those from the theoretical model, which did not include routing and working time constraints. We believe this is due to the nature of the expected slippage metric in the objective function. Minimizing the expected slippage directs the model to inspect the 'dirtiest' sites, which are those with both the highest host densities and the highest risk of infestation (e.g., in Winnipeg's river valleys and woodlots where failed detections would lead to greater host loss). As a practical matter, prioritizing these 'dirty' sites downplays the importance of the routing and access constraints. By comparison, the problem 1 solutions minimize the expected number of surveyed sites with undetected infestations and so tend to survey a larger area at lower sampling densities. Because as many sites as possible must be inspected within a fixed time limit, site access times must be reduced and so the optimal routing of site visits becomes critical.

More broadly, our model is applicable for planning large-scale surveys and ecological sampling campaigns because it links the optimal routing concept – which helps minimize the travel costs required to inspect a large geographical region – with the determination of the optimal sampling size at each site. Our results show that even in an urban setting where the street network provides a high degree of accessibility, accounting for optimal routing of daily surveys significantly changes the survey pattern and its efficacy. Furthermore, the impact of optimal routing and operational constraints is likely to be much greater for surveys conducted across large regions of interest.

COMPETING INTERESTS

None.

AUTHORS' CONTRIBUTIONS

DY, RGH, CJKM, FHK and RV conceived the ideas and designed methodology; DY, RV and NL collected the data; DY, NL, FHK and KR analyzed the data; DY and RGH developed the model; DY, RGH, CJKM and FHK led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

DATA AVAILABILITY STATEMENT

Data available from the Zenodo Digital Repository at <https://zenodo.org/record/4091551> (Yemshanov et al., 2020).

PEER REVIEW

The peer review history for this article is available at <https://publons.com/publon/10.1002/2688-8319.12029>.

ORCID

Denys Yemshanov  <https://orcid.org/0000-0002-6992-9614>

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