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Optimizing surveillance and management of emerald ash borer in urban environments

Sabah Bushaj[1] | **İ. Esra Büyüktahtakın**[1] | **Denys Yemshanov**[2] | **Robert G. Haight**[3]

[1]Department of Mechanical and Industrial Engineering, New Jersey Institute of Technology, Newark, New Jersey

[2]Natural Resources Canada, Canadian Forest Service, Great Lakes Forestry Centre, Sault Ste. Marie, Ontario, Canada

[3]USDA Forest Service, Northern Research Station, Madison, Wisconsin

Correspondence
İ. Esra Büyüktahtakın, Department of Mechanical and Industrial Engineering, New Jersey Institute of Technology, Newark 07114, NJ.
Email: esratoy@njit.edu

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Abstract

Emerald ash borer (EAB), a wood-boring insect native to Asia, was discovered near Detroit in 2002 and has spread and killed millions of ash trees throughout the eastern United States and Canada. EAB causes severe damage in urban areas where it kills high-value ash trees that shade streets, homes, and parks and costs homeowners and local governments millions of dollars for treatment, removal, and replacement of infested trees. We present a multistage, stochastic, mixed-integer programming model to help decision-makers maximize the public benefits of preserving healthy ash trees in an urban environment. The model allocates resources to surveillance of the ash population and subsequent treatment and removal of infested trees over time. We explore the multistage dynamics of an EAB outbreak with a dispersal mechanism and apply the optimization model to explore surveillance, treatment, and removal options to manage an EAB outbreak in Winnipeg, a city of Manitoba, Canada.

Recommendation to Resource Managers

- Our approach demonstrates that timely detection and early response are critical factors for maximizing the number of healthy trees in urban areas affected by the pest outbreak.

- Treatment of the infested trees is most effective when done at the earliest stage of infestation. Treating asymptomatic trees at the earliest stages of infestation provides higher net benefits than tree removal or no-treatment options.
- Our analysis suggests the use of branch sampling as a more accurate method than the use of sticky traps to detect the infested asymptomatic trees, which enables treating and removing more infested trees at the early stages of infestation.
- Our results also emphasize the importance of allocating a sufficient budget for tree removal to manage emerald ash borer infestations in urban environments. Tree removal becomes a less useful option in small-budget solutions where the optimal policy is to spend most of the budget on treatments.

KEYWORDS

Canada, emerald ash borer, mixed integer programming, stochastic optimization, surveillance, uncertainty

1 | INTRODUCTION

Invasive species are plant, animal, or pest species that are nonnative to a location, and have the tendency to overspread and cause possible damage to the environment, human health, and economy (Ehrenfeld, 2010). The harmful effects of invasive species on agricultural, aquatic, forests, and ecosystems have been studied extensively (DeSantis & Moser, 2013; Gallardo, Clavero, Sánchez, & Vilà, 2016; Koenig, Liebhold, Bonter, Hochachka, & Dickinson, 2013; Paini et al., 2016). The estimated total economic cost from invasive species in the United States alone was expected to exceed $120 billion over 85 years (Pimentel, Zuniga, & Morrison, 2005). The extent of the damage may be an underestimate because many losses caused by invasive species (such as loss of biodiversity, indirect impacts on human health, and loss of ecosystem services) are difficult to estimate in monetary terms (Pejchar & Mooney, 2009).

Management of invasive pests requires substantial resources to locate and control the established pest populations. Once the invader is established in a novel ecosystem, two sets of decisions need to be made on how to survey the area and how to manage the outbreak. By increasing surveillance to detect invasive species, managers may increase their chances of finding a species early at lower population sizes, lessening the extent of damages, and making subsequent control potentially less expensive and more effective. However, detecting invasive species requires costly surveillance, which limits the manager's options to control the infestation when budgets are limited (Mehta, Haight, Homans, Polasky, & Venette, 2007). Optimization-based methods have been widely used to assist with cost-effective resource allocation and address the trade-offs between incurring the costs of damage from invasions versus the costs to manage the outbreaks (Büyüktahtakın & Haight, 2018; Büyüktahtakın, des Bordes, & Kıbış, 2018; Büyüktahtakın, Feng, Frisvold, Szidarovszky, & Olsson, 2011; Epanchin-Niell, Haight, Berec, Kean, & Liebhold, 2012; Hof, 1998; Kovacs, Haight, Mercader, & McCullough, 2014; Mehta et al., 2007; Onal, Akhundov, Büyüktahtakın, Smith, & Houseman, 2019).

In this paper, we present a linear integer programming model that optimizes surveillance and management decisions for controlling a pest outbreak in an urban environment. The model is formulated as a multistage stochastic mixed-integer programming problem (M-SMIP) based on the work of Kıbış et al. (2020). We applied the model to assess the options to manage the infestation of emerald ash borer (EAB) in Winnipeg, a city of Manitoba, Canada. The insect poses a significant threat to North American ash species (Haack & Petrice, 2003; Herms & McCullough, 2014) and has already caused major damage to urban and natural forests in the eastern and central United States and Canada (Kovacs et al., 2010, 2014; 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, 2006; Haack, Hérard, Sun, & Turgeon, 2010; Koch, Yemshanov, Colunga-Garcia, Magarey, & Smith, 2011; Kovacs et al., 2010; Yemshanov, Koch, & Ducey, 2015). There is also evidence that the pest can hitchhike on vehicles (Buck & Marshall, 2008). Timely detection of new EAB infestations is difficult because insect damage is not immediately visible, and as a result, new detections usually indicate the presence of large, established populations that are difficult to control (McCullough, Poland, Anulewicz, & Cappaert, 2009; Ryall, Fidgen, & Turgeon, 2011).

Major economic damage from EAB infestations occurs in cities and populated places where high-value ash trees grow along streets or in parks (Poland & McCullough, 2006). The total cost of the EAB outbreak to property owners and local governments is estimated to be \$10.7 billion in the last decade in the United States (Kovacs et al., 2010) and \$524 million over a 30-year period in Canada (McKenney et al., 2012). Since its discovery, much work has been done to develop management strategies that reduce ash mortality from EAB infestations. Herms and McCullough (2014) proposed various management activities, including surveillance to locate EAB populations at early stages of infestation, treatment of trees with insecticide to protect high-value trees and reduce larval populations, and removal of infested ash trees to slow EAB spread.

Our objective is to determine the optimal location and intensity of ash surveillance, treatment, and removal each year (period) over a 5-year horizon. We consider a budget-constrained problem that maximizes the total benefits of maintaining healthy ash trees in an urban area over a 5-year period minus the penalty associated with the presence of the infested trees. We separate the landscape into 1 km^2 management units (sites). For each unit, we know the number of ash trees and build a scenario tree that depicts a set of possible surveillance and management decisions and accounts for the uncertainty associated with EAB population growth and spread. The scenario tree includes two decisions in each period. The first decision is whether or not surveillance is applied, and the second decision is on the intensity of treatment and removal of the infested trees, depending on the outcome of surveillance. The uncertainty about the tree status after surveillance is depicted with a set of possible infestation outcomes and associated probabilities before a management decision is made. At the beginning of the planning horizon, we describe the ash population in each unit by the number of ash trees at different stages of infestation based on prior knowledge about the infestation. The model then projects changes in the ash population each year based on assumptions about EAB spread within and between units. If surveillance is undertaken, the model estimates the number of infested trees and makes decisions to remove or treat the infested ash trees and then updates the probabilities associated with the expected levels of infestation for the next period.

1.1 | Literature review

Optimization models have been widely used to assist with the surveillance and management of invasive species populations (Baxter & Possingham, 2011; Epanchin-Niell et al., 2012; Mehta et al., 2007). Several studies considered pest control measures that include the removal of infested or susceptible host organisms and applying chemical or biological control treatments to eradicate or slow the invasion (Büyüktahtakın & Haight, 2018; Büyüktahtakın et al., 2011; Hof, 1998). Some studies addressed pest surveillance and control under the assumption of uncertain spread (Horie, Haight, Homans, & Venette, 2013; Yemshanov et al., 2017). These models considered a time domain with only two periods. Onal et al. (2019) present a multi-period simulation-optimization framework to find the optimal search path for locating and controlling the infestation of a biological invader. Kıbış et al. (2020) addressed the problem of joint optimization of surveillance and control decisions with a multistage stochastic mixed-integer programming (MSS-MIP) formulation that extended the time horizon to five stages and applied that model to the management of EAB in Burnsville, Minnesota, USA. MSS-MIP combines the complexity of stochastic programming with a mixed-integer programming model and represents an NP-hard combinatorial problem. Recent developments of multistage MIP solving techniques have been limited (Birge & Louveaux, 2011). Decomposition algorithms are the mainstream methods to tackle two-stage stochastic MIPs. The nonconvex region formed in multistage MIP problems cannot be tackled using direct decomposition. Most solution approaches are based on stage-wise (resource-directive) or scenario-based (price-directive) decomposition. Recent studies in the past decades integrated solution approaches of Stochastic Programming (SP) with discrete optimization methods (IP). For example, Bender's decomposition is applicable to a class of two-stage stochastic problems where the first-stage decisions are mixed-integer, and the recourse decisions are found by solving the linear programming (LP) models (Sen, 2005). Most studies of MSS-MIP problems decomposed them into multiple scenarios and treated each scenario as a separate problem. For example, the study of CarøE and Schultz (1999) treated the solution of the Lagrangian dual as a lower bound of the original problem by relaxing the nonanticipative constraints. Heuristic algorithms were used to provide an upper bound on the dual solution, and branch and bound was used to find a feasible integer solution. Scenario-based decomposition approaches, such as Lagrangian and Dantzig-Wolfe have been shown to be effective in different multistage stochastic integer problems (Lulli & Sen, 2004; Nowak & Römisch, 2000).

In our multistage model, the number of variables, constraints, and scenarios increases exponentially for each additional time period. Therefore, to improve on the solution time and memory, we apply cutting planes and a preprocessing algorithm adapted from Kıbış et al. (2020). These cutting planes helped improve the solution time by a factor of 10+ compared to the standard approach without using cutting planes.

1.2 | Key contributions of the paper

We extend the MSS-MIP formulation of Kıbış et al. (2020) to a study area covering 472 km^2 in the city of Winnipeg, MB, Canada. Our model accounts for the uncertainty about the infestation levels at each site, which is partially resolved by the surveillance decisions.

Our model differs from the study of Kıbış et al. (2020) in the following ways. We depict the temporal dynamics of the infested trees with four infestation levels compared to a five-level model in Kıbış et al. (2020). The first level represents healthy trees, the second level includes asymptomatic infested trees, the third level includes infested trees with visible signs of infestation, and the fourth level represents dead trees.

For each year of the planning horizon, we compute realization probabilities of possible ash infestation outcomes that may be observed via surveillance. Compared to the formulation in Kıbış et al. (2020) that used constant realization probabilities, our probabilities are time-dependent. We present a new heuristic algorithm that dynamically updates the probabilities of the uncertain infestation outcomes based on the outcomes of the previous survey.

To account for EAB spread, we apply a distance-dependent estimation of spread probabilities at four 1-km distance classes from the infested sites, as opposed to the 1-level spread considered in Kıbış et al. (2020). This spread model captures the short-range spread of EAB in urban environments, as suggested by records from previous EAB surveys in Twin Cities, Minnesota (Osthus, 2017).

Based on the experiences from previous EAB survey campaigns, we assume that only a fraction of the trees can be inspected at a site due to cost and personnel constraints. To account for the incomplete survey, we used a surveillance efficiency parameter to depict the percentage of infested trees detected after inspecting a proportion of host trees. The new surveillance-efficiency parameter introduced in our study compensates for the uncertainty of the surveillance outcomes.

We also compared two standard EAB survey methods: applying branch sampling with debarking to detect EAB galleries and placing sticky traps baited with EAB pheromone and ash volatiles to capture EAB adults. We explore the trade-off between the surveillance efficiency and its cost for each survey method over a 5-year planning period.

2 | OPTIMIZATION MODEL

In this section, we present a revised version of the multistage stochastic mixed-integer formulation originally proposed by Kıbış et al. (2020) for the optimal surveillance and control of EAB. This modified formulation improves over the former one by addressing critical issues regarding the surveillance uncertainty as well as the dynamic probabilities of uncertain surveillance outcomes.

2.1 | Problem definition

We formulate the objective of the EAB surveillance and control problem as maximizing the number of uninfested, healthy ash trees in a landscape at the end of the planning period subject to an upper bound on the budget for surveillance and control. Delimiting surveys typically divide the area of concern into a grid of survey sites where a sample of ash trees is inspected at each site. The ash population in each site is divided into healthy trees that are susceptible to infestation and infested trees belonging to three classes (levels): asymptomatic trees, symptomatic trees, and dead trees. Infested trees are the source of EAB spread to susceptible trees in the same site and surrounding sites. Each year, infested trees transition to the next, more severe infestation level, and susceptible trees may become infested through EAB spread within and between neighboring sites. Asymptomatic trees represent the lowest infestation level 1, followed by symptomatic trees with visible signs of infestation (level 2), and if no treatment or removal is applied, trees die (level 3) Figure 1. We assume that decisions to treat the infested trees can be only effective when applied to asymptomatic trees while symptomatic and dead trees may be removed. A time stage in this paper refers to a time period in the stochastic programming model. We set each time period to 1 year because EAB generally has a 1-year life cycle, and ash trees may die after 3–4 years of heavy infestation, although it is difficult to determine the time of first infestation (McCullough & Katovich, 2004). The visual ash tree canopy condition assessment data collected by Flower, Knight, Rebbeck, and Gonzalez-Meler (2013) shows that ash trees progress from one level to the next within 1 year on average. Recent evidence suggests that EAB may switch to a 2-year life cycle in a colder climate (Cappaert, McCullough, Poland, & Siegert, 2005) and in particular, in Winnipeg, so our current assumption depicts a pessimistic view of infestation outcomes.

The number of healthy trees that may be infested at a survey site is uncertain, which requires using a probabilistic depiction of spread. In our case, the number of newly infested trees at a site is a random variable that depends on the number of EAB adults produced at a given site and neighboring sites. Surveillance decisions are critical because they provide information about the infestation, which allows making decisions about ash treatment and removal. Due to the high cost of surveillance, pest surveys limit inspections to a small sample of trees. A partial observation provides limited knowledge about the actual number and location of the infested trees. Because only a portion of all trees is inspected, the actual number of the infested trees after surveillance is unknown, and treatment and removal measures are applied to both infested and healthy trees. We address this uncertainty with a surveillance efficiency parameter that denotes the percentage of infested trees detected after surveillance and serves as a multiplier to adjust the number of detected infested trees that can be treated or removed and update the number of remaining infested trees at a surveyed site.

The progression of tree infestation and an associated sequence of management decisions is shown in Figure 2. In the first period, the actual level of infestation at a survey site is unknown, and management decisions can only be made in the next period, after the site is surveyed. If asymptomatic trees (infestation level 1) are treated in the second period, they become immune to infestation and regain the susceptible tree status in period three. Symptomatic and dead trees at infestation levels 2 and 3 can only be removed. In the third

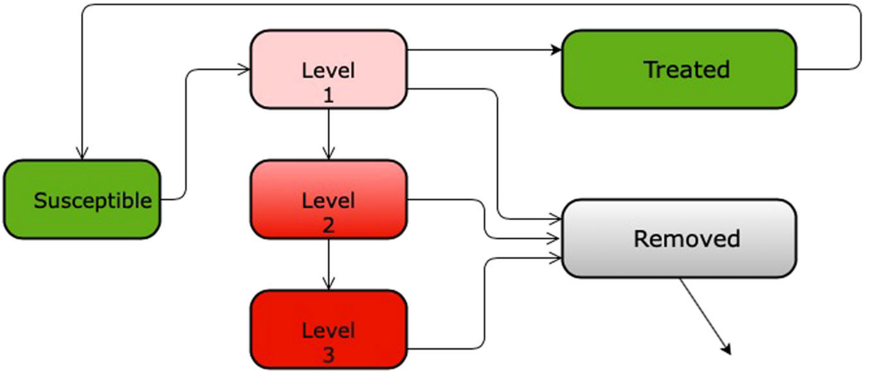

FIGURE 1 Transitions between the infestation levels

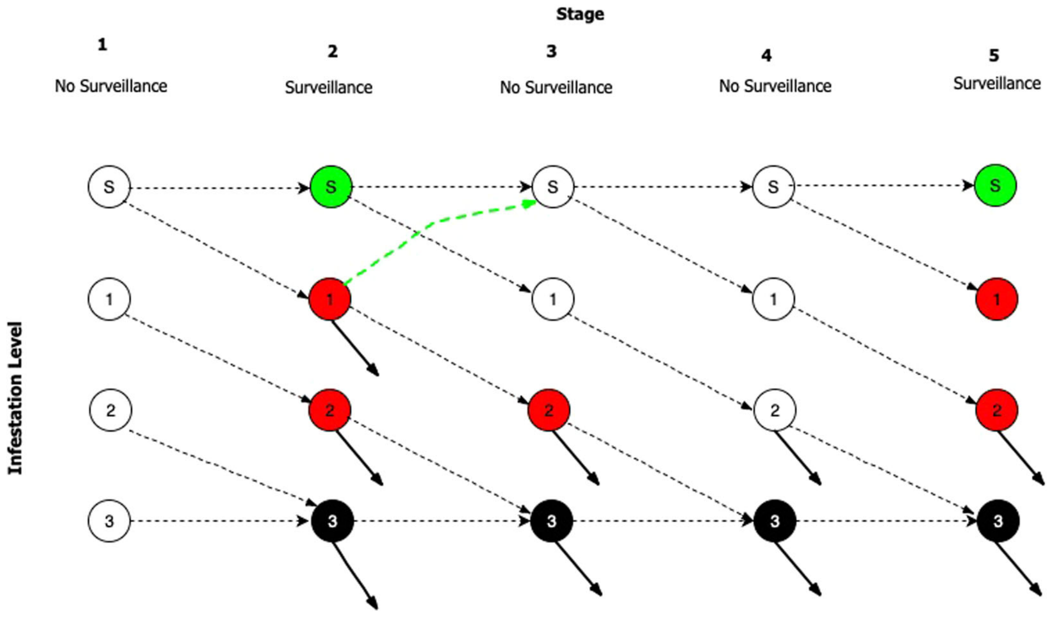

FIGURE 2 An example transition diagram of the ash tree population with over a five-period planning horizon under a particular surveillance regime (i.e., surveys in years 2 and 5 and no surveillance in years 1, 3, and 4). *X*-axis denotes time periods and *y*-axis represents tree infestation levels. Node S denotes the susceptible trees, and nodes 1, 2, and 3 denote the infestation levels 1–3 (asymptomatic, symptomatic, and dead trees). In each stage, uncolored nodes represent the infestation levels for which the actual number of infested trees is unknown because no surveillance was made. Light shaded (green) nodes depict the detected susceptible trees; dark-shaded (red) nodes depict trees at infestation levels 1–3 after surveillance, and black nodes represent the infested dead trees that must be removed. Dashed green lines show the number of treated trees that become temporarily immune to an infestation and are moved to a pool of susceptible trees; dotted lines show the transition in tree infestation level from one period to another; and bold arrows show infested dead trees that are removed (Adapted from Kıbış et al., 2020)

period, no surveillance is applied, and due to the uncertainty in infestation spread, the numbers of susceptible trees and trees at infestation level 1 are expectations based on the outcomes of the survey in the previous period. In period four, no survey is applied, and we only have partial information from period three. In period five, surveillance is applied, which provides an estimated number of trees at each infestation level and allows making decisions on treatment and removal.

2.2 | Scenario tree

Our scenario tree depicts the sequences of possible surveillance decisions and the stochastic infestation outcomes over time and is based on the model of Kıbış et al. (2020). Full details are provided in Appendix A; here we provide only a general description. The scenario tree starts in period one and at each branching progresses through time based on realizations of the uncertain levels of infestation (see example in Figure 3). Two types of nodes in the scenario tree indicate the surveillance (black circles) and no surveillance conditions

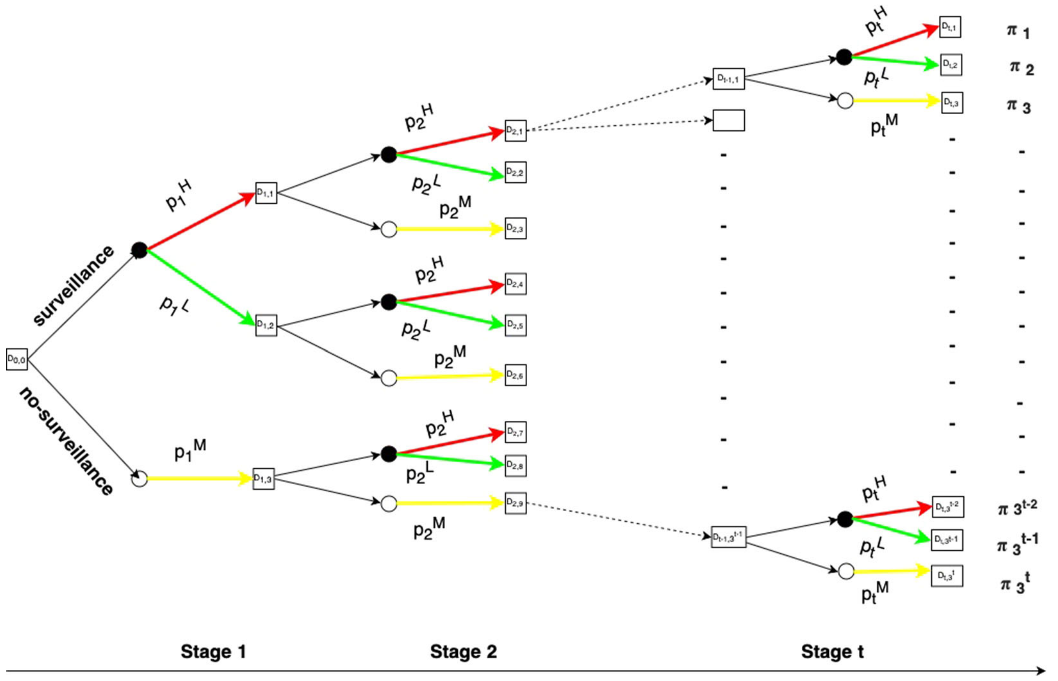

FIGURE 3 Multistage scenario tree. Terms p_t^H and p_t^L denote the realization probabilities of high (H) and low (L) levels of infestation after surveillance; p_t^M denotes a default realization of medium infestation level (M) without surveillance. Black circles represent nodes with decisions after the surveillance; white circles depict nodes without surveillance; arcs leaving black and white circles depict possible realizations of the estimated beliefs about the number of susceptible and infested trees; red arrows depict realizations of high infestation levels; green arrows depict realizations of low infestation levels; yellow arrows depict anticipated levels of infestation without surveillance based on the initial belief. Squares $D_{t,s}$ depict treatment and removal decisions (Adapted from Kıbış et al., 2020)

(empty circles). Square nodes represent treatment or removal decisions. Given the uncertainty about EAB spread, each decision has two possible outcomes: high or low realization of the uncertain level of infestation. The outcome without surveillance (identified by empty circles) yields the expected value of the uncertain infestation level. The notation on each arc, p_t^H, p_t^L, and p_t^M, stands for the probability of detecting the infestation at a high (H) or low (L) levels, or the expected infestation level (M) in the absence of surveillance in period t, producing 3^t scenarios. We assume a medium infestation level as an expected outcome without surveillance and use this level to update the number of infested trees at a given site without surveillance. We obtain an expected level of infestation by explicitly formulating a 4-km radius spread of infestation and spread probabilities from the infested site in the mathematical model. Thus, p_t^M represents this expected infestation level, while p_t^H and p_t^L represent an outcome of surveillance, which is higher or lower than the expected value, respectively. Terms $\pi_1 - \pi_{3t}$ denote the conditional probabilities of a scenario $\omega, \omega \in [1, 2, ..., 3^t]$. This probability is calculated by multiplying the probability of each realization through the whole scenario path and normalizing it over all scenarios, so the sum of the probabilities over all scenarios is equal to 1. An example of a two-stage scenario tree is depicted in Appendix B.

2.3 | Algorithm for scenario tree probability

We computed the expected values of the infestation probabilities for each period in the scenario tree using the uncertain outcomes of spread. Given that the surveillance outcomes are unknown, we assumed equal probabilities for realizations of high and low infestation levels in time period one. We then updated the realization probabilities for future periods based on the outcomes of the surveys done in previous periods. For each scenario in a multistage planning problem, we have calculated the probabilities of infestation with a new heuristic algorithm. This algorithm assigns higher probabilities to reoccurring events and assumes that realizations of infestation outcomes are time-dependent. For example, if a particular realization is observed in time period t, the likelihood of having the same realization in time period $t + 1$ is higher. Appendix C, Algorithm C1, describes the heuristic algorithm and shows a probability calculation example for the three-stage scenario tree depicted in Figure 4.

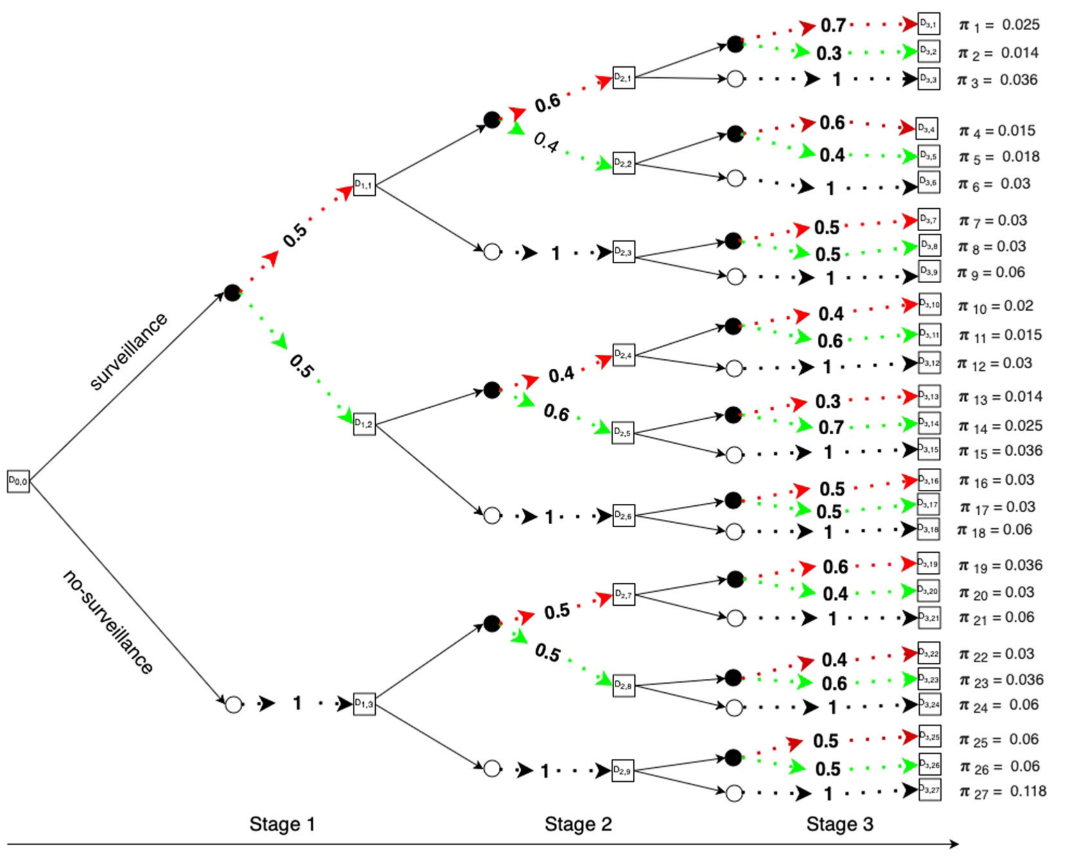

FIGURE 4 Estimating the probabilities of the scenario occurrence for a 3-period example using Algorithm C1. Bold red lines show realizations of high infestation level, dashed green lines show realizations of low infestation level after surveillance, and dotted black lines show realizations of the expected medium infestation level without surveillance. The numbers between lines show the probabilities of a scenario realizations. $\pi_1 - \pi_{3t}$ depict the probabilities for each scenario ω

2.4 | Notation

Sets and indices

Γ	Set of all sites, $\Gamma = \{1, 2, ..., \bar{\Gamma}\}$
K	Set of infestation levels, $K = \{1, 2, 3\}$
T	Set of time periods, $T = \{1, ..., \bar{T}\}$
Ω	Set of scenarios in a scenario tree, $\Omega = \{1, ..., \bar{\Omega}\}$
χ	Set of neighboring layers that a spread can happen from a site i; each layer represents a distance dependent neighbor of site i with similar spread rates
i	Index for site where $i \in \Gamma$
Θ_i^ι	Set of neighboring sites of site i at layer ι
k	Index for infestation level where $k \in K$
t	Index for time period where $t \in T$
j	Index for neighboring sites of site i at layer ι where $j \in \Theta_i^\iota$
ω	Index for a scenario where $\omega \in \Omega$
ι	Index for neighboring layer where $\iota \in \chi$

Parameters

π_ω	Probability for scenario ω
c_1	Cost of surveying (inspecting) a tree
c_2	Cost of treatment
c_3	Cost of removal
α	Monetary value of an uninfested tree
ϑ_k	Penalty value of each infested tree at infestation level k
r_k	Impact rate of each infested tree at infestation level k within a site i, that is, number of new infestations per infested tree at level k
υ	Surveillance efficiency, that is, percent of infested trees that are identified correctly
τ	Discount rate
δ_t	Discount factor at time t which is equal to $\frac{1}{(1+\tau)^t}$
Ψ_ω	Budget for scenario ω
θ_k^ι	Infestation impact of kth-level infested trees in neighboring layer ι belonging to site j
κ	Maximum number of trees surveyed in each site i
γ_i	Number of surveyed trees in site i under surveillance at time t, that is, $\gamma_i = min(N_{i\omega}^t, \kappa)$
$p_{j\to i}^\iota$	Probability of infestation spread from site j to i at neighboring layer ι
$\beta_{ik\omega}^t$	Percentage change in belief of infestation after surveillance for site i, infestation level k, at time t, for scenario ω
$\bar{N}_i$	Initial number of tree population at site i
$\bar{I}_{ik}$	Initial number of infested tree population at each infestation level k, at site i

Binary decision parameters in decision scenario tree

$$x_\omega^t = \begin{cases} 1 & \text{if surveillance is applied at time } t, \text{ for scenario } \omega \\ 0 & \text{otherwise} \end{cases}$$

Decision variables

$N_{i\omega}^t$	Total number of trees at site i, at time t, for scenario ω
$S_{i\omega}^t$	Number of susceptible trees at site i, at time t, for scenario ω

$\tilde{I}^t_{ik\omega}$ Believed number of infested trees at site i, at time t, for infestation level k, for scenario ω before surveillance

$\dddot{I}^t_{ik\omega}$ Transition number of infested trees at site i, at time t, at infestation level k, for scenario ω after surveillance without considering total tree population

$I^t_{ik\omega}$ Estimated number of infested trees at site i, at time t, at infestation level k, for scenario ω after surveillance with considering total tree population

$V^t_{ik\omega}$ Number of treated trees at site i, at time t, at infestation level k, for scenario ω

$R^t_{ik\omega}$ Number of removed trees at site i, at time t, at infestation level k, for scenario ω

$H^t_{i\omega}$ Number of trees surveyed at site i, at time t for scenario ω

$Q^t_{ik\omega}$ Number of infested trees remaining after treatment and removal at site i, at time t, at infestation level k, for scenario ω

Linearization variables

$$u^t_{ik\omega} = \begin{cases} 1, & \text{if transition population is assigned to infestation level } k, \text{ at site } i \text{ at time } t, \\ 0, & \text{otherwise.} \end{cases}$$

2.5 | Mathematical model

$$Max \sum_{\omega\in\Omega} \pi_\omega \left(\sum_{t\in T} \delta_t \sum_{i\in\Gamma} \left(\alpha S^t_{i\omega} - \sum_{k=1}^{n} \vartheta_k I^t_{ik\omega} \right) \right). \tag{1}$$

Subject to:

Initial total population

$$N^1_{i\omega} = \bar{N}_i \quad \forall \ \omega, i. \tag{2}$$

Initial belief of infestation

$$\tilde{I}^1_{ik\omega} = \bar{I}_{ik} \quad \forall \ \omega, i, k. \tag{3}$$

Population constraint

$$N^{t+1}_{i\omega} = N^t_{i\omega} - \sum_{k=1}^{n-2} V^t_{ik\omega} - \sum_{k=1}^{n} R^t_{ik\omega} \quad \forall \ \omega, i, \&, t = 1, \tag{4}$$

$$N^{t+1}_{i\omega} = N^t_{i\omega} - \sum_{k=1}^{n-2} V^t_{ik\omega} - \sum_{k=1}^{n} R^t_{ik\omega} + \sum_{k=1}^{n-2} V^{t-1}_{ik\omega} \quad \forall \ \omega, i, \&, t = 2 \ldots \bar{T} - 1. \tag{5}$$

Transition infestation level

$$\dddot{I}^t_{ik\omega} = \tilde{I}^t_{ik\omega} \left(1 + x^t_\omega \beta^t_{ik\omega} \right) \quad \forall \ \omega, i, t, k. \tag{6}$$

Susceptible (healthy) tree population

$$S_{i\omega}^{t} = N_{i\omega}^{t} - \sum_{k=1}^{n} I_{ik\omega}^{t} \quad \forall \ \omega, i, t. \tag{7}$$

Carrying capacity constraints

$$I_{ik\omega}^{t} \leq N_{i\omega}^{t} - \sum_{d=min(k+1,n)}^{n} I_{id\omega}^{t} \quad \forall \ \omega, i, t, k, \tag{8}$$

$$I_{ik\omega}^{t} \leq \ddot{I}_{ik\omega}^{t} \quad \forall \ \omega, i, t, k, \tag{9}$$

$$\ddot{I}_{ik\omega}^{t} - I_{ik\omega}^{t} \leq \bar{N}_{i}\left(1 - u_{ik\omega}^{t}\right) \quad \forall \ \omega, i, t, k, \tag{10}$$

$$\left(N_{i\omega}^{t} - \sum_{d=min(k+1,n)}^{n} I_{id\omega}^{t}\right) - I_{ik\omega}^{t} \leq \bar{N}_{i} u_{ik\omega}^{t} \quad \forall \ \omega, i, t, k, \tag{11}$$

of treated and removed trees

$$V_{ik\omega}^{t} + R_{ik\omega}^{t} \leq I_{ik\omega}^{t} \sum_{a=max[t-k+1,1]}^{t} x_{\omega}^{a} \quad \forall \ \omega, i, t, k = 1, \tag{12}$$

$$R_{ik\omega}^{t} \leq I_{ik\omega}^{t} \sum_{a=max[t-k+1,1]}^{t} x_{\omega}^{a} \quad \forall \ \omega, i, t \quad k = n-1 \ \& \ n. \tag{13}$$

Believed (expected) number of infested trees

$$\widetilde{I}_{i1\omega}^{t+1} = \sum_{g=1}^{n} Q_{ig\omega}^{t} r_{g} + \sum_{g=1}^{n} \sum_{\iota\in\chi} \sum_{j\in\Theta_{i}^{\iota}} Q_{jg\omega}^{t\iota} \theta_{k}^{\iota} p_{j\rightarrow i}^{l} \quad \forall \ \omega, \ i, \ \iota, \ j \ \& \ t = 1 \ldots \bar{T}-1, \tag{14}$$

$$Q_{ig\omega}^{t\iota} = \begin{cases} I_{ig\omega}^{t\iota} - \upsilon V_{ig\omega}^{t\iota} - \upsilon R_{ig\omega}^{t\iota} & g = 1 \\ I_{ig\omega}^{t\iota} - \upsilon R_{ig\omega}^{t\iota} & g = n-1 \ \& \ n \end{cases} \quad \forall \ \omega, \ i, \ t, \ \iota, \tag{15}$$

$$\widetilde{I}_{ik\omega}^{t+1} = I_{i(k-1)\omega}^{t} - \upsilon V_{i(k-1)\omega}^{t} - \upsilon R_{i(k-1)\omega}^{t} \quad \forall \ \omega, \ i, \ \& \ t = 1 \ldots \bar{T}-1 \ \& \ k = 2, \tag{16}$$

$$\widetilde{I}_{ik\omega}^{t+1} = \left(I_{i(k-1)\omega}^{t} - \upsilon R_{i(k-1)\omega}^{t}\right) + \left(I_{ik\omega}^{t} - \upsilon R_{ik\omega}^{t}\right) \quad \forall \ \omega, \ i, \ \& \ t = 1 \ldots \bar{T}-1 \ \& \ k = n. \tag{17}$$

Budget constraint

$$c_{1} \sum_{t\in T} \sum_{i\in\Gamma} H_{i\omega}^{t} + c_{2} \sum_{t\in T} \sum_{i\in\Gamma} \sum_{k=1}^{n-2} V_{ik\omega}^{t} + c_{3} \sum_{t\in T} \sum_{i\in\Gamma} \sum_{k=1}^{n} R_{ik\omega}^{t} \leq \Psi_{\omega} \quad \forall \ \omega, \ i, \ t, \ k, \tag{18}$$

$$H_{i\omega}^{t} = \gamma_{i} x_{\omega}^{t} \quad \forall \ \omega, \ i, \ k, \quad and \quad t = 1, 2, \ldots, T, \tag{19}$$

$$\gamma_{i} = min\left(N_{i\omega}^{t}, \kappa\right) \quad \forall \ \omega, \ i, \ t. \tag{20}$$

Non-anticipativity constraints

$$\begin{array}{l} N_{i\omega}^t = N_{i\omega'}^t \quad S_{i\omega}^t = S_{i\omega'}^t \quad \tilde{I}_{ik\omega}^t = \tilde{I}_{ik\omega'}^t, \\ I_{ik\omega}^t = I_{ik\omega'}^t \quad I_{ik\omega}^t = I_{ik\omega'}^t \quad V_{ik\omega}^t = V_{ik\omega'}^t, \\ u_{ik\omega}^t = u_{ik\omega'}^t \quad u_{ik\omega}^t = u_{ik\omega'}^t \quad R_{ik\omega}^t = R_{ik\omega'}^t. \end{array} \quad \forall \ \omega = \omega' \in \Omega \text{ such that } \omega_t = \omega_t', \ \forall \ i, \ t, \ k, \tag{21}$$

Nonnegativity and binary restrictions

$$N_{i\omega}^t,\ S_{i\omega}^t,\ I_{ik\omega}^t,\ \tilde{I}_{ik\omega}^t,\ \ddot{I}_{ik\omega}^t,\ V_{ik\omega}^t,\ R_{ik\omega}^t \geq 0 \quad u_{ik\omega}^t \in \{0,1\} \quad \forall \ \omega,\ i,\ k. \tag{22}$$

The objective function of our model, as can be seen in Equation (1), maximizes the expected number of susceptible (healthy) trees in the managed area over the planning horizon minus the penalty associated with the number of asymptomatic and symptomatic infested trees present in the area over a set of plausible infestation scenarios. Equations (2) and (3) initialize the size of host tree population and the expected infestation levels for each site i and scenario ω in the model at time Period 1. Equations (4) and (5) estimate the total size of the ash tree population and its change over time as more infested trees are removed and treated. Based on the expected infestation level and decisions taken at the surveyed sites, we estimate the number of removed or treated trees, which are infested, at a given site i from the total tree population at that site. The treated trees that are removed from the infested tree population will be moved back to the infested population at later periods once they become susceptible after a two-year immunity period.

Equation (6) computes the realizations of infestation scenarios at each level k after the surveillance decisions. We assume that after surveillance, the estimated number of infested trees for each infestation level k is known. Term $\tilde{I}_{ik\omega}^t$ represents the believed expected number of trees infested at a particular level k. If surveillance is applied, the parameter x_ω^t will take a value of 1, and the value of $\tilde{I}_{ik\omega}^t$ will change by $\beta_{ik\omega}^t$, which defines the percent change in the expected level of infestation after the surveillance is performed. Thus Equation (6) estimates the number of infested trees for each infestation level k after surveillance where $\ddot{I}_{ik\omega}^t$ denotes the transition number of the infested trees at each infestation level k, which represents the estimate number without considering the total tree population in a site i.

Equation (7) calculates the number of susceptible (i.e., uninfested and treated) trees. The total population in constraint (7) with Equation (5) also ensure that treated trees are moved back to the infested tree population after their immunization period ends.

We also need an equation to calculate the estimated number of infested trees in a tree population because the number of new infestations is limited by the maximum susceptible tree population that could be infested, that is

$$I_{k\omega}^t = min\left(N_{i\omega}^t - \sum_{d=min(k+1,n)}^{n} I_{id\omega}^t, \ddot{I}_{ik\omega}^t\right). \tag{23}$$

Equation (23) defines the estimated number of infested trees at a survey site i, for each scenario ω, time period t, at infestation level k and implied that the estimated number of infested trees at an infestation level k cannot exceed the total number of healthy trees minus the infested trees at higher infestation levels $(k+1, \ldots, n)$ at a site i. If the remaining size of the healthy tree population exceeds the number of infested trees calculated with Equation (6), the estimated number of trees is set equivalent to the transition number of infested trees that gives the estimated number of trees based on infestation growth equations and realization of the uncertain infestation outcomes after surveillance. Equations (8)–(11) provide an equivalent linearization of the nonlinear carrying capacity constraint (23). Equations (8) and (9) set an upper bound on the estimated number of infested trees and Equations (10) and (11) set a lower bound by using an auxiliary binary decision variable $u_{ik\omega}^{t}$.

Equations (12) and (13) define the upper bound on the number of treated and removed trees. As the infestation spreads, more susceptible trees could become infested. When the budget is too small to treat or remove all detected infested trees immediately, the infestation spreads to other trees in a given site and neighboring sites $j \in \Theta_i^{\iota}$.

Equation (14) defines the expected number of newly infested trees at level $k = 1$ in time period $t + 1$. The term, $Q_{ig\omega}^{t}$, denotes the number of untreated or unremoved trees in time period t in site i and is defined in Equation (15). The parameter υ defines the surveillance efficiency in Equation (15) which is the proportion of infested trees that are detected at a site after surveillance. Term $p_{j\to i}^{\iota}$ in Equation (14) defines the probability of infestation spreading from site j to site i located at the ιth distance class from j. To calculate the infestation spread to a site i we used four distance-dependent spread layers, ι, which cover a 4-km radius from the infested site with 1-km distance intervals. Term Θ_i^{ι} defines the spread rate from the neighboring sites at each distance class ι to a given site i.

Inspecting a small sample of trees allows detecting only a portion of the infested trees and leads to the failure to treat or remove all the infested trees at a survey site. This issue is handled by Equations (16) and (17). The constraint (16) ensures that trees at higher infestation levels ($k > 1$), if not removed or treated, transition to the next infestation level, $k + 1$ at the next time period. Coefficient υ in Equation (16) adjusts the number of removed and treated trees to compensate for the uncertainty of the surveillance outcomes.

Equation (17) states that trees that reach the highest infestation level $k = n$ are considered dead and remain at this level until the end of the planning horizon. We assume that dead trees do not pose an infestation threat but should be removed due to hazard and liability concerns if the budget allows.

The medium extent (M) represents the expected level of infestation in the absence of surveillance based on prior information about the invasion and is calculated in the model using Equations (14)–(17). Because the surveillance selection binary parameter x_{ω}^{t} in Equation (6) becomes 0 under no surveillance, the expected infestation level will not change. When surveillance occurs, the $x_{\omega}^{t} = 1$, and so the expected infestation level will change by $\beta_{ik\omega}^{t}$, (i.e., by +0.4 or −0.2 in realizations of (H) or low (L) infestation levels, respectively).

Equation (18) sets an upper bound on the available budget over the planning horizon in a scenario ω. Treatment and removal decisions depend on the infestation level k. Term $H_{i\omega}^{t}$ denotes the number of inspected trees and is defined in Equation (19). We assume that only a sample of maximum κ trees is inspected at each surveyed site. In Equation (20) γ_i defines the number of surveyed trees, which is the minimum of the total number of trees in site i and sample size κ. Terms $V_{ik\omega}^{t}$ and $R_{ik\omega}^{t}$ denote the number of treated and removed trees, respectively.

Equation (21) lists the nonanticipativity constraints, which ensure that the scenarios with the same history up to a given stage t share the same decisions until that stage. For example, if two scenarios ω' and ω have the same history of infestation and surveillance decisions until period t, that is $\omega_t = \omega_t'$, all decision variables up to stage t should be equal to each other. Finally, Equation (22) defines the nonnegativity constraints on the decision variables and a binary status of the linearization variable, $u_{ik\omega}^{t}$.

3 | MODEL APPLICATION AND DATA

We applied our MSS-MIP model to assess the surveillance and management options for EAB infestation in Winnipeg, MB, Canada. The study area was divided into 1×1-km survey units. We estimated the ash density at each survey site from a municipal tree inventory (Daudet, 2018), which provided information about tree species, ownership, and size (Figure 5). All $ values presented in the case study represent Canadian Dollars (CAD).

We estimated the probabilities of EAB spread from historical records of urban EAB infestation in Twin Cities, Minnesota (Osthus, 2017). As with Winnipeg, we divided the Twin Cities area into a grid of 1×1-km potential survey sites. For each 1-km^2 site j, we estimated the distance to the nearest infested site in a particular year and, based on that

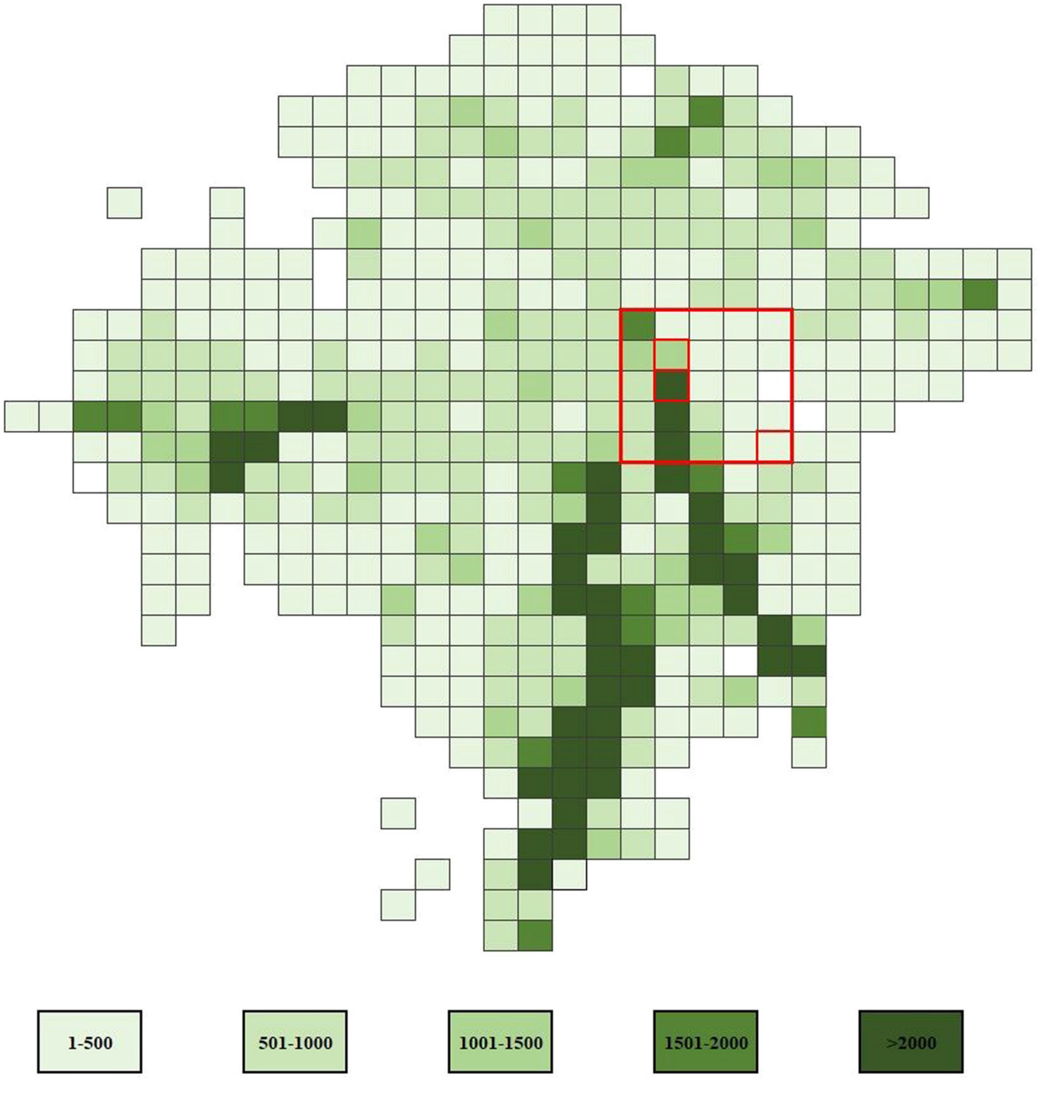

FIGURE 5 Host tree density map for a case study area in Winnipeg, Canada. Square outline delineates the neighborhood area around the current Emerald Ash Borer infestations

distance, estimated the infestation likelihood for a corresponding distance 1-km class. Using a set of distance-dependent infestation probabilities and the locations of the infested sites, we then generated the likelihood of EAB spread for potential survey sites in Winnipeg. When calculating the likelihood of new infestations at a site, we also have taken into account the chance of the infestation spread from the surrounding sites. For each survey site, the model tracked the potential spread of EAB from the neighboring sites at four 1-km distance classes each 1, 2, 3, and 4 km away from the infested site. Distance-dependent probabilities of spread originating from symptomatic infested ash trees were estimated as 0.34 at the infested site, 0.21, 0.12, and 0.05 at the neighboring sites at 2, 3, and 4-km distance while those originating from infested asymptomatic ash trees in 1, 2, 3, and 4-km neighboring sites are 0.2, 0.15, 0.08, and 0.03, respectively. We estimated two sets of distance-dependent probabilities of spread for asymptomatic and symptomatic infested trees. Symptomatic trees have typically more EAB galleries than asymptomatic trees, hence their threat to other susceptible trees was assumed to be higher (Knight et al., 2012). We assumed that dead trees do not produce propagules and have no impact on other susceptible trees. To address the uncertainty about EAB spread, we modeled changes in the anticipated levels of infestation once the surveillance is completed. We assumed that the manager anticipates changes in the infestation levels after surveillance by −20% or +40% from its current level. Each of these two realizations occurs with the probability 0.5 in the first period and then updated dynamically for all other periods using Algorithm C1 as shown in Appendix C. When no surveillance is applied, trees progress to the next infestation level based on the default assumption about the infestation level.

The efficiency of surveillance depends on the choice of the method to detect the signs of EAB attack. In Canada, two common inspection methods used in precious survey campaigns include sampling host tree branches and installing sticky traps (Hopkin, de Groot, & Turgeon, 2004; Ryall et al., 2011, 2013; Turgeon, Fidgen, Ryall, & Scarr, 2016). Sampling branches and peeling their bark to inspect for EAB galleries is the most reliable method to detect EAB (Ryall et al., 2011; Turgeon et al., 2016). The application of sticky traps includes hanging the traps baited with plant volatile and EAB pheromone, followed by one-two checkup visits (Ryall, 2015). Based on the previous EAB survey study (Yemshanov et al., 2019), 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, 2015). The likelihood of a single sticky trap detecting the presence of an EAB population on a tree 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 is typical of other urban areas in Canada. Based on the experiences from past EAB surveys in Ontario, typical sampling rates for branch sampling and trapping rarely exceeded 5–10 trees-km^{-1} due to the high cost of inspections. Hence we consider the scenarios using a fixed sampling rate $\varkappa = 5$ trees-site^{-1}. We used the survey cost estimates from Yemshanov et al. (2019): $87 for installing a sticky trap and $124 to inspect a tree via branch sampling. The monetary value of services provided by a host tree was estimated at $72 (Kıbış et al., 2020). The cost of treating asymptomatic infested trees was estimated at $180, and the cost of removing an infested tree was estimated at $800 (Yemshanov et al., 2019). In the objective function equation, a penalty is assigned to each infested and dead trees. Specifically, the treatment cost is set as the penalty value per each asymptomatic and symptomatic tree, while the removal cost is assigned as the penalty value for each dead tree. We explored the scenarios with the budget limits ranging from $1M to $2M over a 5-year planning horizon. The social discount rate was set to 2%.

4 | RESULTS

Our results reported below describe the general model behavior and present outputs that have practical utility for decision-making, including general indication where and when treatments and or tree removal may be feasible, differences between using trapping and branch sampling methods, and the impacts of survey timing and management actions.

4.1 | Optimal management

4.1.1 | Cost of surveillance, treatment, and removal

We illustrate the general model behavior by showing the solutions for a small area surrounding the infested sites—a 5 × 5 subset of survey sites under a budget of \$2 M (red outline in Figure 5). Since each scenario of the scenario tree has a different combination of the infestation probabilities, management decisions, and budget allocations for surveillance, treatment, and tree removal, we present examples of optimal solutions for four distinct scenarios. For each scenario, we assign an identifier that lists the occurrence of surveillance events and the extent of the detected infestation over a 5-year planning horizon. For example, after surveillance is done, a possible outcome of the survey is the detection of high (H) or low (L) levels of infestation. In the absence of surveys, the expected state of the infestation is a medium extent (M). Our scenarios depict different levels of infestation and the distinct timing of surveillance. For example, a scenario H-H-H-H-H implies that surveillance is done each year, and a high infestation level is detected. Meanwhile, scenario 126 with realization L-L-M-H-H implies that in the first 2 years, surveillance is done, and a low infestation level is detected. Note that H and L only occur under surveillance, and M only occurs under no surveillance. Thus we do not need to provide a specific notation for surveillance decisions to represent scenarios. In the third year, no surveillance is done, so M means we remain truthful to the expected infestation growth calculated by the mathematical model based on the initial belief of the infestation of the manager. Furthermore, in the last 2 years, surveillance is done, and a high realization is encountered. In our case, the scenario with the highest net benefits is scenario 161, which only surveys in the first stage of the problem and has a low infestation realization in the initial stage, as denoted by L-M-M-M-M.

In Figure 6 scenarios H-H-H-H-H and L-L-L-L-L assume the detection of correspondingly high and low infestation levels in all time periods. Scenario H-H-H-L-L assumes the detection of high infestation levels in Periods 1–3 and low infestation levels in Periods 4 and 5, and scenario L-L-L-H-H depicts the opposite survey outcome when low infestation levels are detected in Periods 1–3 and high levels in Periods 4 and 5. The total cost in each scenario varies due to different streams of treatment and removal decisions. Given that the surveys occur every time period, the cost of surveillance is the same for all scenarios. However, the cost of treatment and tree removal depends on the level of the detected infestation. For example, scenario L-L-L-L-L had the lowest total cost because the infestation was detected at a low level and required less treatment and removal efforts. The level of infestation detected early has a higher impact on management actions and their total cost. More budget was allocated in the scenario with the detected high level of infestation in the first two periods than in the scenario with the detected low infestation level in Periods 1–2 (cf. the costs of scenario H-H-H-L-L and scenario L-L-L-H-H in Figure 6).

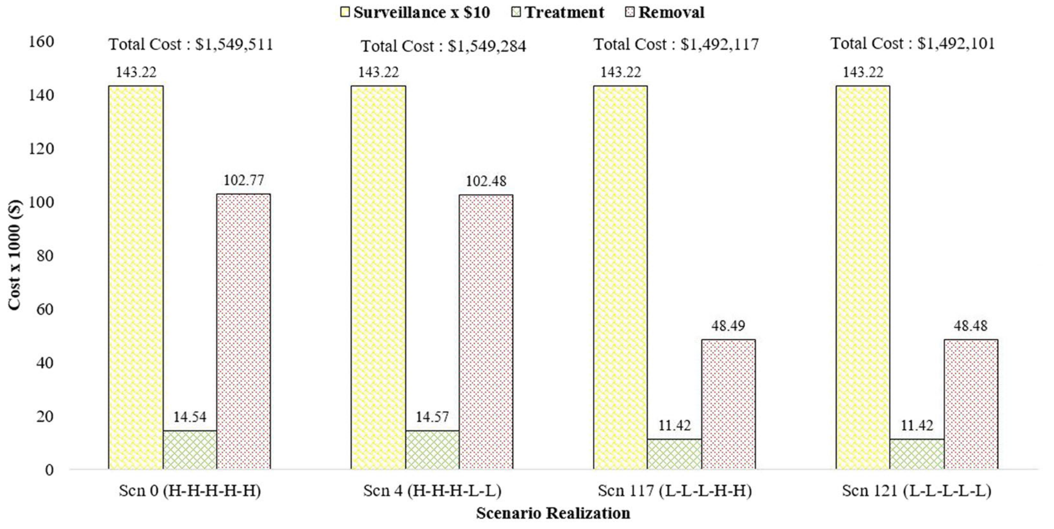

FIGURE 6 Treatment, removal, and surveillance cost for low and high realizations over 5 years for four different scenarios. Scenario 0 is H-H-H-H-H, scenario 4 is H-H-H-L-L, scenario 117 is L-L-L-H-H, and lastly, scenario 121 is L-L-L-L-L, where L and H stand for low and high realization, respectively

4.1.2 | Where to survey, treat, and remove

Most of the applied survey and management actions in optimal solutions have occurred in close proximity to the infested sites; hence we illustrate the model behavior using a 5x5 site area proximate to the infested sites (big red rectangle in Figure 5). Figure 7 shows the number and spatial location of infested, treated, and removed trees for time Periods 1–4 (I–IV) under the worst-case scenario with the high level of infestation detected in all periods (H-H-H-H-H). Specifically, each column corresponds to a time period in increasing order from left to right, while row 1 block represents the number and location of infested trees that are neither treated nor removed (No Action); row 2 block represents the number and location of infested trees that remain after the optimal treatment and removal action (Action); row 3 block represents the number and location of trees that are treated under the optimal action (Treated); and row 4 block represents the number and location of trees that are removed under the optimal action (Removed). When no action is taken, more trees get infested in close proximity to the infested sites, which increases the local rate of spread and the number of infested trees. Timely treatment and tree removal actions help reduce the number of infested trees in close proximity to the infested sites. Most of the treatment occurred in the sites with the detected infested trees in the first two periods (when treatment is the most effective). Tree removal was prescribed roughly in the same selected locations but occurred over Periods 1–4. All treatments and tree removals in Period 1 occurred in the sites with the original infestations. Imperfect detection in the first period required a more aggressive treatment and removal in the following periods to compensate for poor detection accuracy. Our results show that detecting and treating the infested trees as early as possible is the most cost-effective approach but imperfect detection necessitates a larger-scale treatment and tree removal campaign in the following periods.

Figure 8 reports similar results but for scenario L-L-L-L-L when the surveillance detects the low infestation level in each time period. Compared to the worst-case scenario, the detection of

FIGURE 7 Total number of infested trees under no action (No Action), infested trees under optimal action (Action), treated (Treated) and removed (Removed) trees for each period for scenario H-H-H-H-H (high infestation level detected in all periods) over planning Periods 1–4 (I–IV)

the infested trees occurred at shorter distances from the infested sites. Treatment and removal mostly occurred in the currently known infested sites.

We have also compared the impacts of taking no action in four different scenarios, H-H-H-H-H, H-H-L-L-L, L-L-H-H-H, and L-L-L-L-L (1). We define the net benefit summary metric as a difference between the objective function value (which is the total value of healthy and treated trees in a landscape) and the cost of surveillance, treatment, and removal.

The difference between net benefit values for "Action" and "No-Action" scenarios is presented in the fourth column of Table 1, named "Incentive to Act." As Table 1 suggests, optimal management solutions with treatment and tree removal have higher benefits than no-action solutions under all scenarios considered. This result indicates that active treatment and removal options remain cost-effective despite the incurred high survey costs; and taking timely

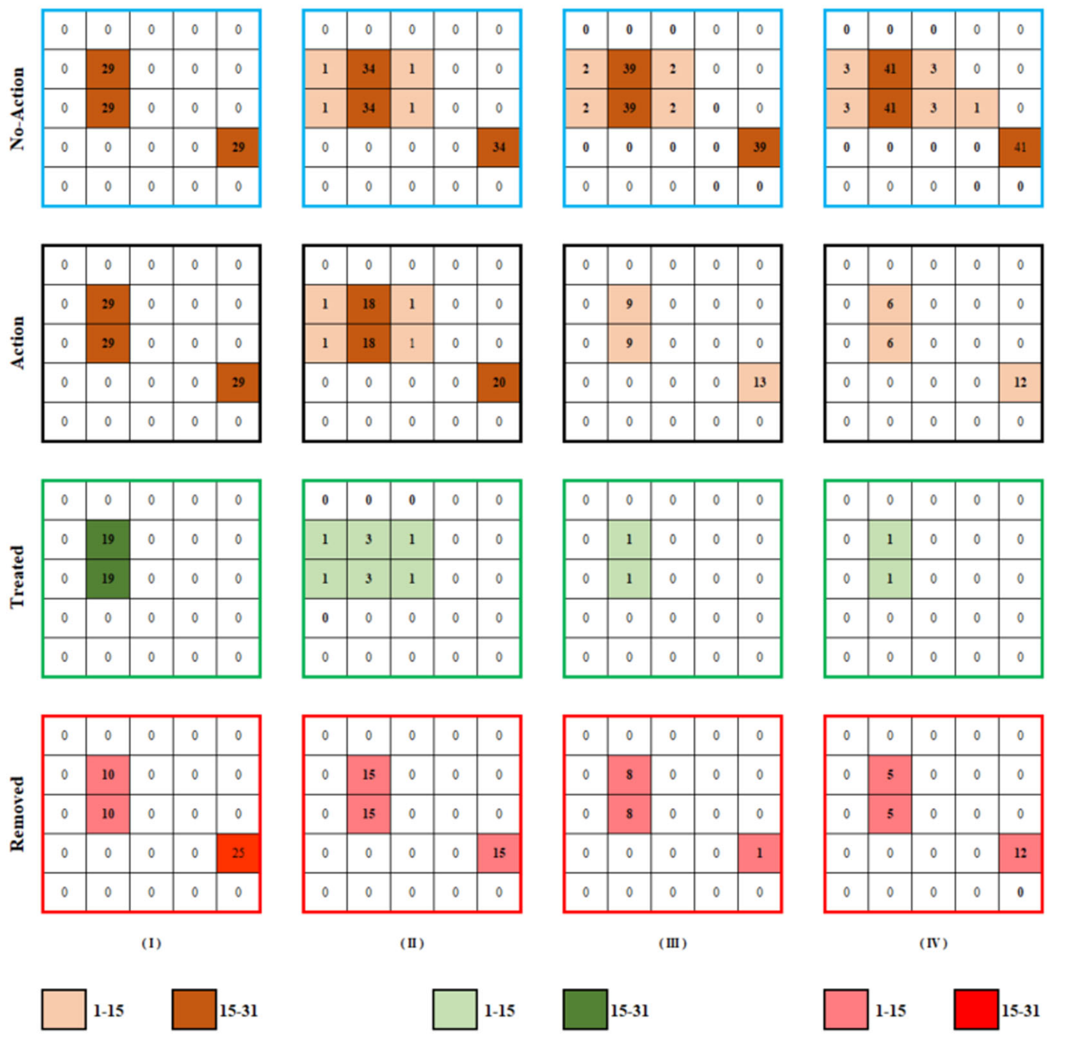

FIGURE 8 Total number of infested trees under no action, infested trees under optimal action, treated, and removed trees for each period for scenario L-L-L-L-L (low infestation level detected in all periods) over planning Periods 1–4 (I–IV)

TABLE 1 Net benefits in the optimal management (action) and no-action solutions for scenario H-H-H-H-H, H-H-L-L-L, L-L-H-H-H, and L-L-L-L-L

Scenario	Action	No Action	Incentive to Act
H-H-H-H-H	$122,258,000	$121,803,800	$454,200
H-H-L-L-L	$122,261,590	$121,841,800	$419,790
L-L-H-H-H	$122,399,610	$122,121,800	$277,810
L-L-L-L-L	$122,400,000	$122,147,800	$252,200

Note: The net benefit is calculated by subtracting the total cost of each scenario from the objective function value of the respective scenario management actions is thus well justified. “Incentive to Act” is higher under the all-high case (H-H-H-H-H) than under the all-low case (L-L-L-L-L). Interestingly, the incentive to act is also much higher under a scenario that starts with a high infestation followed by a low infestation (H-H-L-L-L) than a scenario which starts with a low infestation followed by a high infestation (L-L-L-H-H). This result implies that it is particularly crucial to act in a case where we observe an initially aggressive spread.

4.2 | Effect of surveillance timing on net benefits

Surveillance is crucial in our model, as no action can be taken without surveillance. When no surveillance is performed in a particular time period the infestation continues to spread and causes larger damage. We illustrate the importance of maintaining the surveillance regime by analyzing the optimal solutions with a distinct timing of survey actions. We compare four scenarios, H-M-M-M-M, M-H-M-M-M, M-M-H-M-M, and M-M-M-H-M, which apply the surveys only in time Periods 1, 2, 3, or 4. All scenarios have the same surveillance costs (i.e., 1 year of surveys only). Table 2 indicates that the scenarios with the earliest survey actions have the lowest total treatment and removal cost. This is because early detection leads to a more effective treatment or removal when the infestation is at an early stage. When the surveillance is delayed infestation is allowed to spread to further distances, and more trees get infested and will require treatment or removal. In particular, the efficacy of tree removal action is affected by the timing of surveillance. The sooner the infestation is detected, the less it will cost to remove the infested trees.

The scenario with no survey-delays (H-M-M-M-M) also had the highest net benefits. Overall, the delay in surveillance allows the infestation to spread to a larger area and will necessitate costlier tree removal and treatment actions; hence it is always beneficial to survey and treat the sites as early as possible.

4.3 | Budget allocation and priority of actions

We have solved the problem for the range of budget levels, including $1.45M, $1.5M, $1.55M, and $1.6M. The budget values were set to ensure that they are sufficiently large to cover the high cost of surveillance and apply treatment and removal with the remaining funds from

TABLE 2 Costs of surveillance, treatment, and removal for the scenarios with different timing of the survey actions

Scenario	Survey period	Surveillance cost	Treatment cost	Removal cost	Total cost	Net benefits*
H-M-M-M-M	1 (no-delay)	$286,440	$12,100	$94,520	$393,059	$123,990,000
M-H-M-M-M	2	$286,440	$5,640	$134,000	$462,082	$123,130,000
M-M-H-M-M	3	$286,440	$6,340	$160,680	$453,457	$123,170,000
M-M-M-H-M	4	$286,440	$3,620	$175,660	$465,724	$123,030,000

*The net benefit value is calculated as a difference between the objective value and the total cost of surveys, treatment and tree removal.

surveillance. We also slightly increased a budget from \$1.45 to \$1.6M to show the impact of the budget increases on the optimal treatment and removal when the number of infested trees was initially low. Here, we present optimal solutions for treatment and removal decisions in the worst-case scenario, H-H-H-H-H, with the detected high levels of infestation and the surveillance done in every time period. Figure 9 shows the surveillance, treatment, and removal costs for the worst-case scenario at different budget levels. As expected, we observe an increase in the budget spent on both treatment and removal as we increase the available budget from \$1.45M to \$1.60M. The increase in the budget spent on removal costs is higher than the cost of treatment due to the high cost of removing trees. At the lowest budget, \$1.45M, only a portion of the infested trees in closest proximity to the infested sites can be treated, and also a small number of symptomatic trees can be removed in Period 1. Since the budget is too small to treat or remove all detected infested trees, the infestation continues to spread. At the budget level of \$1.6M, more funds are available for the treatment of asymptomatic trees and the removal of symptomatic and dead trees. Given a small extent of the current EAB infestation in Winnipeg, all the detected infested trees in close proximity to the infested trees can be treated, but only a small portion is feasible to remove due to the high cost of tree removal. The best strategy is to treat the detected infested asymptomatic trees, and if funds permit, remove a portion of symptomatic infested and dead trees in closest proximity to the infested sites.

The budget level affects the timing and the extent of tree removal and treatment actions. Figures 10a,b show the total number of infested, treated, and removed trees over a planning horizon for budget allocations of \$1.5M and \$2M, respectively. In both solutions, treatments of asymptomatic infested trees and removal of symptomatic infested trees help minimize the impact of infestation on a host tree population. Treatments of healthy and asymptomatic trees prevent them from transitioning to a more severe infestation level and so helps reduce the local spread rate in the next time period. Removal of symptomatic infested trees has a higher priority than the removal of dead trees because it reduces the chances of EAB to spread to nearby trees in close proximity to the infested nuclei.

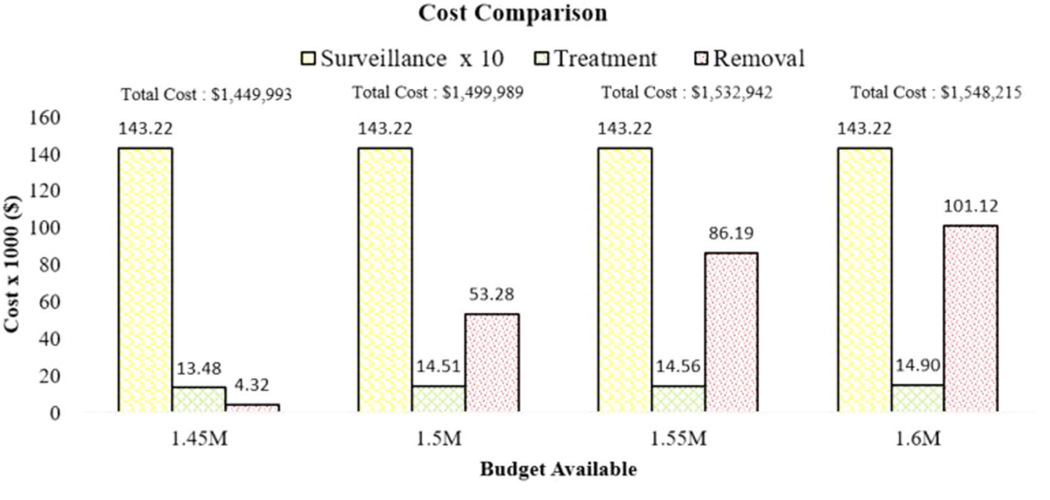

FIGURE 9 Surveillance, treatment, and removal costs for different budget levels under the worst-case scenario H-H-H-H-H with a continuous surveillance over the planning horizon and the detected high level of infestation

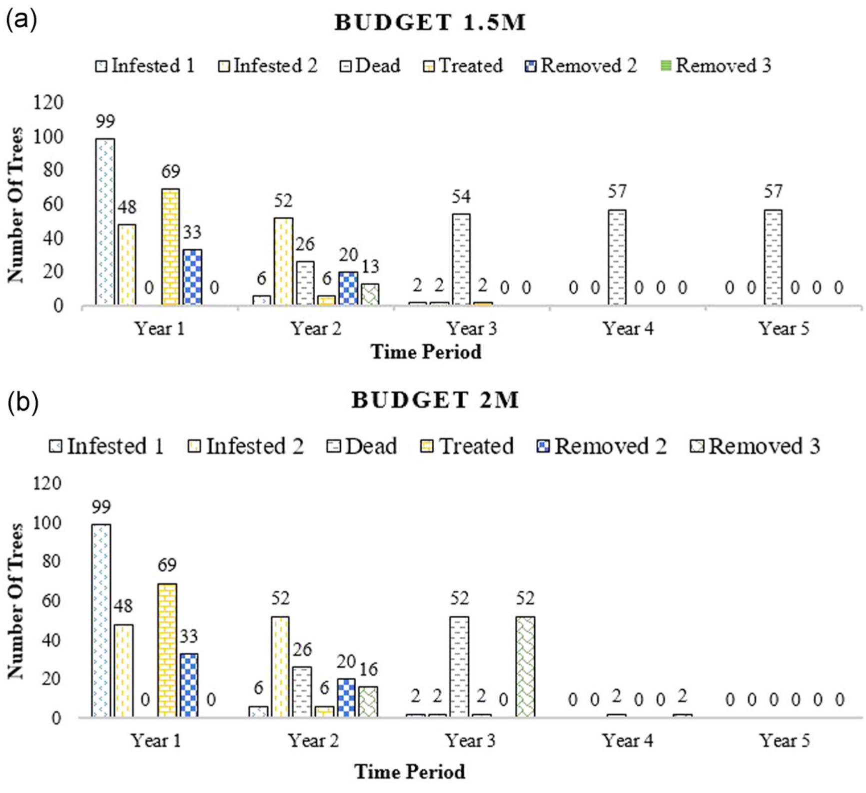

FIGURE 10 Total number of infested, treated, and removed trees over time under scenario 0 with $1.5M (a) and $2M (b) budget

For example, in the scenario with a $1.5M budget, insufficient budget level limited the scope of tree removal actions to a few symptomatic infested trees (Figure 10). Note that the removal of dead trees may be mandatory in an urban setting in some circumstances due to liability or safety concerns, and therefore, may require additional funds to be allocated for mandatory tree removal. Given a small extent of the current EAB infestation in Winnipeg, we did not include mandatory tree removal options, but this could be a focus of future work if the EAB infestation causes widespread tree mortality (like in previous urban EAB outbreaks in Ontario and Michigan). Treatments of asymptomatic trees are only effective in the first three time periods when the infestation is in its early stage. Removal of symptomatic trees becomes most effective in period two and essentially is a more preferred action than the treatment as the number of symptomatic trees increase. Removing dead trees is feasible in Periods 2 and 3 only when there the budget is sufficient to treat the detected asymptomatic and remove the symptomatic trees. No management action is taken for Periods 4 and 5 under a budget of $1.5M because all budget was already spent during time Periods 1, 2, and 3.

4.4 | Is treatment a choice?

We also illustrate the impact of applying the treatments of asymptomatic trees using four distinct scenarios with different infestation level sequences of management decisions. Table 3

TABLE 3 Net benefit values in optimal treatment vs. no-treatment under various scenarios

Scenario	Scenario description	No-treatment net benefits	Optimal treatment net benefits
H-H-H-H-H	1 (no-delay)	$121,994,000	$122,258,000
H-H-L-L-L	2	$122,184,000	$122,262,000
L-L-H-H-H	3	$122,328,000	$122,400,000
L-L-L-L-L	4	$122,335,000	$122,400,000

Note: The net benefit value is calculated as a difference between the objective value and the total cost of surveys, treatment, and tree removal.

shows differences in net benefit values between the solutions with and without treatments in the scenarios having different levels of infestation. The scenarios show distinct infestation profiles with the surveillance done in all time periods. In general, treatments increased the net benefit value in all infestation scenarios.

4.5 | Impact of surveillance efficiency

Surveillance efficiency has a direct impact on the total cost, therefore, also affecting the total net benefits. Here we discuss the trade-off of the surveillance cost and surveillance efficiency.

We have compared the optimal solutions using branch sampling versus the detection with sticky traps in a high-infestation scenario H-H-H-H-H with the surveillance done in all time Periods 1–5. Figure 11 shows that branch sampling yields a higher objective value than using sticky traps because it has a higher detection accuracy and so enables finding and treating more infested asymptomatic trees at early stages. However, branch sampling is a more costly option; hence the total cost portion spent on surveillance is higher (Figure 12). Comparatively, the solutions with sticky traps spend more on treatment and significantly more on removal because sticky traps cannot detect the infestation at early stages. We have also compared the optimal timing of treatment and tree removal actions for the solutions using branch sampling and sticky traps in high-infestation scenario H-H-H-H-H under $2M budget limit. Figure 13 shows the number of infested, treated, and removed trees over time for each of the detection methods. Both methods show a similar number of removed and treated trees in Period 1, but the solutions with branch sampling show that a lower number of trees required treatment and removal in Periods 2 and 3. This is because the higher accuracy of the branch sampling method allows detecting more infested trees at the earliest possible time (Period 1), and so fewer infested trees will need treatment or removal in the following periods. Also, the solutions using sticky traps required more periods of surveys to detect the bulk of the infestation than the solutions with using branch sampling. This is because sticky traps have lower surveillance efficiency. Detecting and subsequently treating or removing fewer trees in a current period leads to a higher infestation rate in the following periods. Our results indicate that while branch sampling has a higher cost, its higher efficiency makes up for the increased cost in terms of reducing the number of trees infested with EAB.

In terms of the net benefits, the surveillance via sticky traps costs less than using branch sampling. However, branch sampling has higher objective value; that is, it enables keeping more uninfested trees in the managed area. The difference in net benefit values is bigger in small-budget solutions than in large-budget solutions (Table 4) because small budgets are

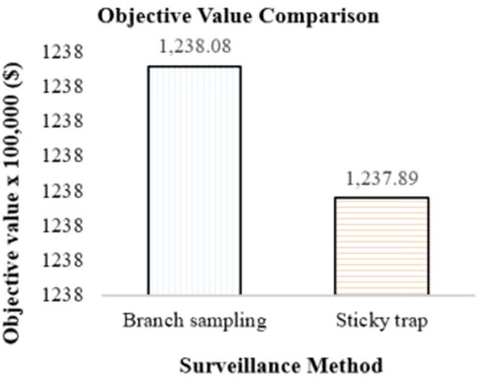

FIGURE 11 Objective function values for scenario 0 (H-H-H-H-H) using branch sampling and sticky trap methods with a $2M budget

insufficient to treat and remove all the detected trees, which essentially renders the survey efforts ineffective.

5 | DISCUSSION AND CONCLUSIONS

Managing pest outbreaks often requires allocating scarce resources between surveillance and control actions (e.g., Epanchin-Niell et al., 2012). Surveillance strategies are usually applied in environments under continual invasion pressure where the number, size, and location of established populations are unknown before detection and change over time depending on population growth, detection, and management. Previous studies simplify this dynamic optimization problem by solving for the optimal long-term equilibrium surveillance effort (Epanchin-Niell et al., 2012) or by considering a time domain with only two periods (Horie et al., 2013; Yemshanov et al., 2017). Kıbış et al. (2020) was the first to address the multiperiod,

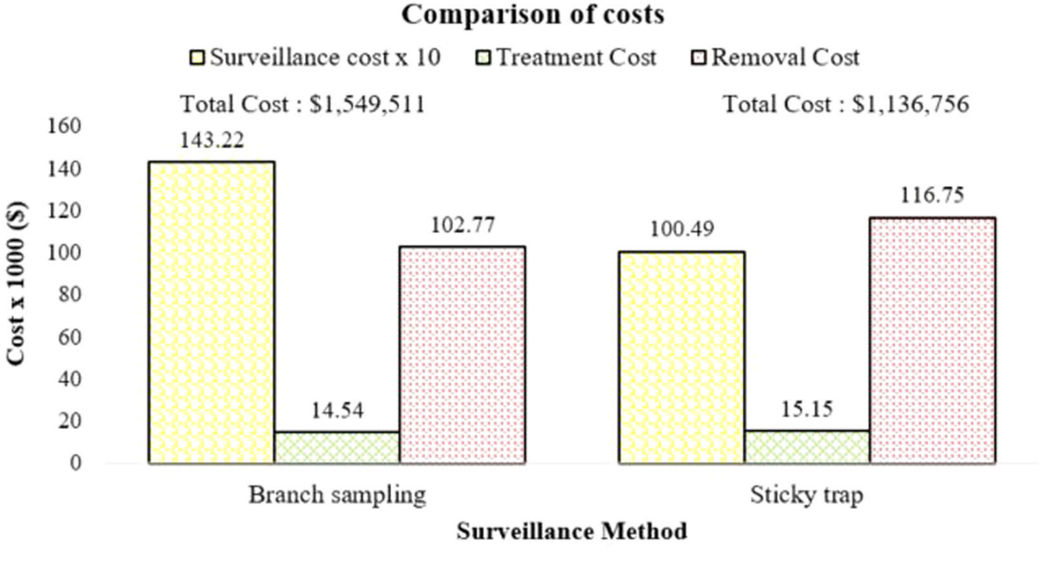

FIGURE 12 Surveillance, treatment, and removal cost comparison between branch sampling and sticky trap methods for scenario 0 (H-H-H-H-H) with $2M budget

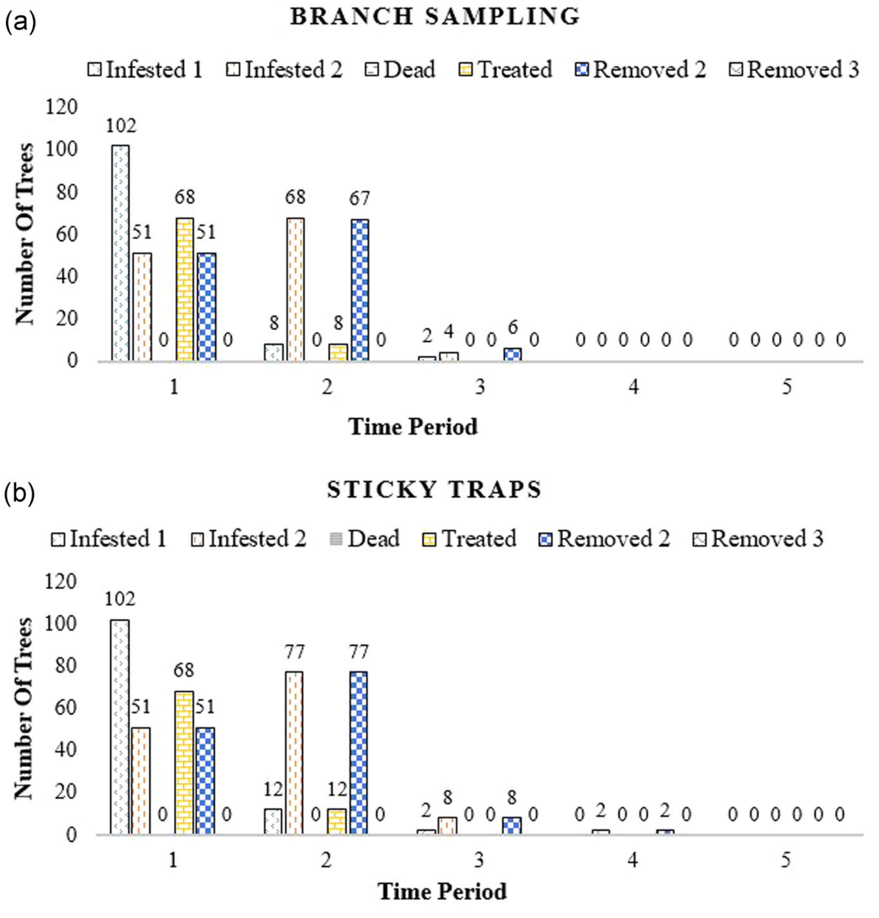

FIGURE 13 Total number of infested, treated, and removed trees over time for scenario 0 with budget \$2M: (a) using branch sampling; (b) using sticky traps

spatial optimization of pest surveillance and control while accounting for stochastic pest dynamics. They formulated and solved a MSS-MIP model with a five-stage time horizon and applied that model to the management of EAB in Burnsville, Minnesota, USA We modified this MSS-MIP model to evaluate surveillance and control strategies for an EAB infestation in Winnipeg, Canada. The model applies surveillance to inform decisions on optional treatment and removal of the infested trees under a limited budget. The sequences of scenario decisions and associated infestation outcomes are integrated into a scenario tree where, for each scenario, the probability of infestation in a given time period is calculated dynamically.

TABLE 4 Net benefit values in the solutions using branch sampling and sticky traps

Surveillance method	\$1.45M	\$1.5M	\$1.75M	\$2M
Branch sampling	\$121,913,000	\$122,055,000	\$122,257,000	\$122,258,000
Sticky traps	\$122,652,000	\$122,652,000	\$122,655,370	\$122,658,020

Note: Net benefits of high-infestation scenario (H-H-H-H-H) with the surveillance applied every period is shown.

Our approach helps address this challenge and demonstrates how accounting for key assumptions about the infestation severity, cost, and spatial patterns of the infestation may affect the scope and timing of control decisions. Our results demonstrate that timely detection and early response actions are key factors in successful control of a pest invasion and a maximization of net benefits of the urban ash trees. This result is consistent with the long-held view that early detection of pests lessens the extent of damage and makes subsequent control less expensive and more effective (see Büyüktahtakın & Haight, 2018, for review). For example (Epanchin-Niell, Brockerhoff, Kean, & Turner, 2014), find that an intensive surveillance program designed to detect invasive wood borers and bark beetles in New Zealand leads to earlier detection, higher likelihood of successful eradication, and lower costs of control and damage, with substantially higher net benefits compared with a program with no surveillance.

The findings also emphasize the importance of treatments of ash trees as early as possible. Treating asymptomatic trees at the earliest stages of invasion provides higher net benefits than tree removal or no-treatment options. However, we show that treatment of the infested trees is only effective when done at the earliest stage of infestation. When the surveillance is delayed, tree removal becomes a more preferred option but would require significantly higher cost to achieve the same level of control. Deterministic models of EAB management in urban landscapes reach similar conclusions. McCullough and Mercader (2012) simulate the effects of treatment and removal strategies and find that annual insecticide treatment of 20% of the ash population can protect 99% of trees after 10 years, and the cumulative costs of treatment are substantially lower than costs of removing dead or severely declining ash trees. Using a spatial-dynamic optimization model, Kovacs et al. (2014) find that strategies with insecticide treatment are superior to ones with only pre-emptive removal because they reduce the number of susceptible trees at a lower cost and protect the benefits of healthy trees.

Our results also provide new insights about the preferred use of trapping versus branch sampling techniques for EAB detection. We found that, in multiyear EAB surveys, the use of branch sampling is advised because it yields better accuracy of detecting the infested asymptomatic trees, and so, when implemented at early stages of infestation, enables treating and removing more infested trees which may help reduce the local rate of spread. Similarly, in an analysis of single-season EAB surveys, Yemshanov et al. (2019) found that branch sampling was preferred over trapping; however, the choice of survey methods depended on the relative detection rates. On average, branch sampling was preferred over trapping when its detection rate of branch sampling was 1.45 times greater than the detection rate of traps.

Another valuable insight from our work is that the level of available budget essentially controls the decisions on treatment or removal of the infested trees. Since tree removal is costly, the extent of tree removal actions depends on the level of the budget available after the surveillance. Our results emphasize the importance of allocating a sufficient budget for tree removal to slow the spread of EAB. Tree removal becomes less important in small-budget solutions where the optimal policy is to spend most of the budget on treatments.

There was no historical data available to parameterize the probabilities of the surveillance outcomes and the possibility of surveillance decisions. In our model, we assume that surveillance is a binary decision variable (not a random variable), which is parametrized in the scenario tree as one if surveillance takes place and zero otherwise. In theory, this assumption could influence the optimal management decisions if the probability of surveillance decisions vary from location to location or over time (which was not assumed in our model).

In our model, only surveyed trees were removed or treated. We have not considered the preventive removal of all trees at a survey site, which is applied in practice to avoid the need to monitor all trees because this strategy has been shown to provide worse solutions compared to the optimization model in the study of Kıbış et al. (2020). Specifically, Kıbış et al. (2020) have performed a comparative analysis of a previous version of our multistage stochastic optimization model with stage removal and monitor-and-remove strategies currently employed by the cities of Minneapolis and Saint Paul for the management of EAB. Their results show that significant benefits are obtained by using the complex multistage stochastic programming model as opposed to the simple approaches currently employed, including preventative removal without surveillance and prophylactic removal of some ash tree population after surveillance.

An ash tree is an invaluable commodity that we should do whatever we can to keep them alive. The expected life span of a white ash tree is 260 years, while it is 120 years for a green ash tree (Home Guides, 2018a). It takes from 16 to 60 years for an ash tree to grow to its full size, depending on species and environmental conditions (Home Guides, 2018b). Thus, the replacement of an ash tree could take tens of years, and its complete removal and replacement are deemed too costly.

Our current model formulation addresses a common situation in managing the established urban pest populations when municipalities strive to keep as many live trees as possible because trees continue to provide numerous social, economic, and ecological benefits (such as providing a habitat for many bird and insect species, producing oxygen, improving soil quality and landscape aesthetic, increasing property values, and reducing noise and pollution (The Tree Council, 2018), which have not been taken into account in this study. For example, in Torbay, England, 95,000 ash trees store 11,400 tons of CO_2 worth \$2.8 million per year. Incorporating such long-term benefits of a healthy ash tree into our model will further justify the need to keep trees alive as long as possible. Thus, unless we have a perfect surveillance with close-to-100% detection rates and the invader is detected in very early stages in a confined area, a preventative removal would be suboptimal, given an objective of maximizing healthy tree population.

The model in its current formulation is not intended to assist decisions on slowing-the-spread or preventive removal of all trees at a survey site, which is applied in practice to avoid the need to monitor all trees. Potentially the model can be reformulated to include the preventive tree removal as an optional strategy by minimizing the total number of infested trees in the area. Preventive host removal can be effective when managers aim to slow the spread of infestation and do not need to protect live trees (as opposed to our formulation), or when the pest can be detected early and reliably and eradicated at moderate costs (such as in the programs aimed to eradicate the infestation of Asian Longhorned Beetle (ALB) in Toronto, Canada (Turgeon, Orr, Grant, Wu, & Gasman, 2015; Yemshanov et al., 2017). The preventive host removal may not be suitable for treatments in urban environments where trees are highly valued, and the city planners strive to keep as many live trees in the city area as possible.

Other potential model applications include cases when a sizable part of the managed area is already infested (and so the preventive eradication is no longer an option) or cases when the pest is detected in a host organism after it is too late to do large-scale preventive measures (which is what we usually observe in the case of an aggressive invader) and management decisions focus on reactive measures, such as treatment of asymptomatic host trees (to keep them alive for a certain period), or removal of the infested trees.

5.1 | Future work

In urban environments, trees perform multiple ecological and social functions and provide various economic and social benefits, which prompts the city planners to maintain and expand the tree population in the urban area. Thus, in our model, the objective function follows the aspiration to keep as many high-valued live trees as possible in the area and maximizes the net health benefits from susceptible trees while penalizing infested and dead trees. Alternatively, some other penalty terms could be considered and the objective reformulated as an invasion control problem that aims to slow the spread or minimize the expected damage from infestation (analogously to problems presented in Büyüktahtakın et al., 2011, Epanchin-Niell et al., 2012, Horie et al., 2013, Rout, Moore, and McCarthy, 2014, Yemshanov et al., 2017). In this case, the goal of treatment and host removal would be to reduce the propagule pressure (or likelihood of spread) from the infested sites to other locations. This would require including the likelihood of spread (or other propagule pressure metric) in the objective function equation. In this case, the amount of the infested and healthy trees at the survey site would influence the likelihood of pest's spread from that site to other locations. Adding the new penalty terms might change the model behavior towards prioritizing preventive measures, which help reduce the rate of spread, such as preventive tree removal over the survey-and-treatment options (similarly to the model behavior described in Yemshanov et al., 2017). Exploring the new objective function formulations aimed to slow or contain the invasion spread could be the focus of future efforts.

Our problem formulation considered multiple time steps when decisions on surveillance and treatment can be reconsidered after decisions made in the previous time step. One possible extension of our model is to add a two-step surveillance before treatment: an initial rapid survey to determine whether any infested trees exist on the site, and a subsequent more detailed survey to find all infested trees in sites with at least one confirmed detection. Introducing the second surveillance stage at each time step to confirm initial detection would require adding another decision step conditional on detecting the pest in the first survey step. This would require complex linearizations (see, e.g., Kıbış & Büyüktahtakın, 2017) to handle decisions conditional on detection and drastically increase the size of the scenario tree, which would make the problem intractable. For example, currently, we have 243 (3^5) scenarios, but a two-step surveillance strategy would increase the number of scenarios to 3,125 (5^5) and further complicate the problem formulation. To keep the size of the two-step survey problem manageable, some other model features are likely to be dropped (such as accounting for distance-dependent dispersal from the infested sites, which is an important model capacity). Adding the second survey stage with decisions conditional on first detection could be the focus of future work.

Slowing the invasion spread is an important strategy to fight against aggressive invaders, such as the EAB. Generic strategies include the removal of small satellite infestations ("nascent foci"), as described by Moody and Mack (1988), and "barrier zone" involving removal of infestations at/near the invasion front (Büyüktahtakın, Feng, & Szidarovszky, 2014, 2015; Sharov & Liebhold, 1998). Although our original model formulation did not consider the slow-the-spread or invasion containment strategies, it can be adapted to plan the response measures aimed to slow or contain the spread of pest invasions. In our model, the impacts of management actions on the rate of spread can be factored in by making the probability of infestation, p_{ji} from site j to other sites i in a distance-dependent spatial layer l a function of the total number of infested trees remaining in site j after treatment and host removal.

The objective function can be modified to prioritize the treatment and host removal that is aimed to minimize the rate of long-distance spread (i.e., the spread to the outermost spatial layers l around the infested site j). In this case, the management actions would prioritize the treatments of the infested sites, which could send propagules to farthest distances. For instance, slowing the long-distance spread could be modeled via prioritizing the treatments of sites that send the propagules with the highest probabilities of spread p_{ji} to the outermost distance layers l in a set χ (i.e., the farthest distances from a given site j).

It is also possible to change the model objective to contain the infestation within a designated area, however, this objective may not be attainable if the pest has a strong capacity for long-distance spread or the budget is insufficient to apply sufficient treatments which stop the spread within a designated area. We have investigated the option of "focused surveillance," which applies surveillance only to a limited area, to reduce the large costs of surveying all sites. This strategy could be further studied for controlling the slow-moving invasive species that does not exhibit significant long-distance dispersal. Reducing the amount of suitable host trees decreases the potential number of individuals that can emerge and spread from a given location to other sites and so controlling the infested, or highly susceptible host density could potentially be to slow the spread of invasion.

In our model, we assumed a fixed tree sampling rate across all surveyed sites. Potentially, the problem could be modified by allowing an optimal selection from a set of predefined sampling rates via an introduction of auxiliary binary variables which select a particular sampling rate value at a survey site (and a linked set of surveillance efficiencies). Selecting an optimal sampling rate at the surveyed sites opens a possibility of incorporating other factors that influence the sampling rate decisions. These factors include the spatial variation of host density, the detection rate for a particular inspection method, and the likelihood of the pest present at a surveyed site. The size and spatial locations of individual host trees may also influence the likelihood of detection and the optimal sampling rate value. Incorporating these aspects will require developing the appropriate data depicting the spatial variation of these factors in urban environments, which could be a future extension of this study.

We acknowledge the risk of failed detection at the infested sites as another potential factor that may affect the optimal sampling decisions. This problem will require making all host treatment and removal decisions conditional on the failure to detect the invasion at the surveyed sites (i.e., failing to detect one or more infested trees after inspecting a sample of trees at a survey site). In Equations (15)–(17), we have incorporated the impact of imperfect detection using a parameter which limits the number of infested trees that are successfully treated or removed based on the detection rate. Another possibility to incorporate the impact of failed detection into the MIP model is to use the techniques from quality control theory, such as estimating the expected slippage value, which in our circumstances denotes the expected number of infested trees in surveyed sites where inspections did not find the signs of infestation although they are actually infested (see, e.g., Chen, Epanchin-Niell, & Haight, 2018 and Yemshanov et al., 2019). However, such a formulation is nonlinear and will require complex linearizations to make them work in a linear programming model, which could be a focus of future efforts.

Further refinements also include an account for long-distance spread assumptions for distances beyond 4 km. These modifications are expected to significantly increase the problem size and its combinatorial complexity and will require new approaches to solve the model for practical cases. Another future direction includes the introduction of coherent risk measures to capture the variability of the random variables in the upcoming stages of the model, enabling the risk-averse decision making of the manager. This will be the focus of our future work.

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AUTHOR CONTRIBUTIONS

S. B. adapted the EAB model of Kibis, Büyüktahtakın, and Haight et al. (2020) and the code for the case of EAB invasion in Canada. Developed the scenario probability algorithm. Performed computational experiments and generated all figures and tables in the manuscript. Wrote the first draft of the paper. E. B. received and led the USDA Forest Service and NSF projects that resulted in this manuscript and funded S. B. Advised all aspects of the paper from methodology to implementation, experimental design, and manuscript writing. Had continuous discussions with D. Y. and B. H. on assumptions, realism of the model, and input data. Revised the manuscript numerous times. D. Y. provided input data as well as insights into the EAB model with Canada application regarding assumptions made and experimental design. Revised the paper critically multiple times. B. H. led the practical component of the USDA Forest Service project. Provided insights into the mathematical model. Revised the manuscript.

ORCID

İ. Esra Büyüktahtakın http://orcid.org/0000-0001-8928-2638
Denys Yemshanov http://orcid.org/0000-0002-6992-9614

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APPENDIX A: GLOSSARY

▹ Infestation layer:	Surrounding neighbors with the same distance from a site
▹ Infestation level:	Classification of the severity of host infestation
▹ Realization:	A specific outcome regarding the degree of uncertain infestation after surveillance
▹ Scenario:	A combination of realizations for each time period and surveillance decisions
▹ Site:	A 1-km^2 area populated by ash trees
▹ Surveillance Efficiency:	The proportion of infested trees that are identified after surveillance
▹ Stage:	A time period in the stochastic scenario tree
▹ Transition:	Change of the host infestation levels from one time period into another
▹ Transition Population:	Estimated population of host trees without taking the maximum host population into account

APPENDIX B: TWO-STAGE EXAMPLE OF POSSIBLE SCENARIOS

Table B1 presents all possible scenarios for a 2-stage problem. As an example of a two-stage problem, at period $t = 1$, we can decide whether to survey or not. If the site is surveyed, two possible infestation levels can be uncovered—a higher than expected (H) or lower than expected infestation (L). If no survey is applied, we assume a default medium infestation level (M) and use this value to compute the probabilities of spread. Thus, at period $t = 1$, three possible realizations are possible, as demonstrated by red, green, and yellow arcs (Table 3). In Period 2, each square node generated at the end of the first period depicts the decisions to survey a site in

TABLE B1 All possible scenarios for a 2-stage formulation

Scenario number	Realization	Surveillance regime
1	H-H	Survey-Survey
2	H-L	Survey-Survey
3	H-M	Survey-Do Not Survey
4	L-H	Survey-Survey
5	L-L	Survey-Survey
6	L-M	Survey-Do Not Survey
7	M-H	Do Not Survey-Survey
8	M-L	Do Not Survey-Survey
9	M-M	Do Not Survey-Do Not Survey

Note: Note each scenario is represented as a combination of the realization and the surveillance regime. Realizations and surveillance decisions are given for each stage consecutively under each scenario.

that period. Similarly, if the site is surveyed, high or low infestation levels can be detected. If no surveillance is performed, we assume a default medium infestation level and use this value to update the probabilities of infestation at the next time period and so on.

APPENDIX C: SCENARIO PROBABILITY ALGORITHM

Algorithm C1 dynamically updates infestation realization probabilities in each period. We start by defining scnProb, which is an array that will hold the probability of encountering a certain infestation realization for a scenario ω at time t, where p_H holding the probability of encountering a high infestation realization and p_L representing a low infestation realization probability. Each realization will be represented by the variable Real, which is either equal to High(H) or Low(L) or Medium(M). We keep track of the probabilities for different infestation realizations at each time stage using variables p_H and p_L. We assign an equal probability for both high and low infestation realizations in the initial time stage. We update the probabilities as we traverse through all the time periods under each scenario. Whenever we encounter a pattern of repeating realizations, we update the probabilities of uncertain outcomes in favor of the repeating event. At the end of the procedure, we obtain a two-dimensional set that lists the occurrence probabilities of infestation realizations at time t for each scenario ω (a *scnProb* array). We then use the function *multiplyList*(ω_i) to multiply all probabilities in array ω_i, which gives the realizations of the infestation for each time t under a specific scenario ω with index $i = 1, ..., 3^t$. Therefore, after we multiply the probabilities in ω_i returning only one probability value for each scenario ω, we use the *normalizeProb*(ω_i) method to normalize the probability of each scenario ω.

Algorithm C1 Calculate probabilities for each scenario

```
Procedure: Probability Distribution
DEFINE sncProb, p_H, p_L
INITIALIZE scnProb = ∅, p_H = 0.5, p_L = 0.5
for each scenario ω ∈ Ω do
  if Real_t is High or Low or Medium then
    append p_H, p_L or 1 , respectively
  end if
  for each Real in time period t ∈ T do
    if Real_t = Real_{t+1} and Real_{t+1} = High then
      p_H+ = 0.1
      p_L− = 0.1
      if Real_t is High or Low or Medium then
        append p_H, p_L or 1 , respectively
      end if
    else if Real_t = Real_{t+1} and Real_{t+1} = Low then
      p_H− = 0.1
      p_L+ = 0.1
      if Real_t is High or Low or Medium then
        append p_H, p_L or 1 , respectively
      end if
    else
      if Real_t is High or Low or Medium then
        append p_H, p_L or 1 , respectively
      end if
    end if
  end for
  Procedure: Scenario Probability
  for each scenario array ω_i, i = 1, . . . , 3^t do
    return multiplyList(ω_i)
  end for
  for each scenario probability ω_i, i = 1, . . . , 3^t do
    return normalizeProbability(ω_i)
  end for
end for
```