Ecological Economics 133 (2017) 86–98

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

ANALYSIS

Robust Surveillance and Control of Invasive Species Using a Scenario Optimization Approach

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ARTICLE INFO

Article history:
Received 22 April 2016
Received in revised form 2 September 2016
Accepted 25 November 2016
Available online xxxx

Keywords:
Asian longhorned beetle
Uncertainty
Scenario-based model
Mixed integer programming
Robust optimization
Human-mediated spread

ABSTRACT

Uncertainty about future outcomes of invasions is a major hurdle in the planning of invasive species management programs. We present a scenario optimization model that incorporates uncertainty about the spread of an invasive species and allocates survey and eradication measures to minimize the number of infested or potentially infested host plants on the landscape. We demonstrate the approach by allocating surveys outside the quarantine area established following the discovery of the Asian longhorned beetle (ALB) in the Greater Toronto Area (GTA), Ontario, Canada. We use historical data on ALB spread to generate a set of invasion scenarios that characterizes the uncertainty of the pest's extent in the GTA. We then use these scenarios to find allocations of surveys and tree removals aimed at managing the spread of the pest in the GTA. It is optimal to spend approximately one-fifth of the budget on surveys and the rest on tree removal. Optimal solutions do not always select sites with the greatest propagule pressure, but in some cases focus on sites with moderate likelihoods of ALB arrival and low host densities. Our approach is generalizable and helps support decisions regarding control of invasive species when knowledge about a species' spread is uncertain.

1. Introduction

Human-assisted introductions of invasive alien species have resulted in extensive ecological and economic impacts worldwide (Meyerson and Reaser, 2003; Perrings et al., 2005; Hulme et al., 2008; Pejchar and Mooney, 2009; Aukema et al., 2011). In response to the threat, various surveillance programs (Mehta et al., 2007; Reaser et al., 2008; Davidovitch et al., 2009; Hauser and McCarthy, 2009; Cacho et al., 2010; Epanchin-Niell et al., 2012) have been implemented to detect arrivals of non-native species, ideally before they become established in novel locations. In North America and elsewhere, significant resources have also been devoted to large-scale programs to prevent or mitigate damages from the most harmful of these species (Olson and Roy, 2005; Kim et al., 2006; Bogich et al., 2008; Tobin, 2008; Pyšek and Richardson, 2010). For example, in 2007 the United States Department of Agriculture (USDA) allocated $US 1.2 billion for management of invasive pest species, with approximately 22% directed towards early detection and rapid response activities (NISC, 2007).

Deciding where and how to deploy scarce response resources in areas that may have been infested with threatening pests is a fundamental challenge for invasive species managers and other biosecurity decision-makers. The difficulties of this decision-making problem are two-fold. Primarily, managers must meet immediate objectives to monitor and manage an invasion given what is currently known about the organism of concern, and must do so within their economic (such as budget) constraints. They must also account for imprecise knowledge and subsequent uncertainty regarding the organism's future distribution and spread (Melbourne and Hastings, 2009). The issue of uncertainty becomes even more critical when a manager must evaluate the need to implement costly eradication measures to stop or slow the spread of invasion (Epanchin-Niell and Hastings, 2010), such as the large-scale removal of host trees in ongoing Asian longhorned beetle (*Anoplophoraglabripennis* (Motschultsky)) quarantine efforts in Canada and the United States (Turgeon et al., 2010; Trotter and Hull-Sanders, 2015).

In the past, economic decisions regarding the deployment of surveillance and control measures under uncertainty have been supported with two broad types of analytical tools. Stochastic simulation models have been used to forecast the spread of invaders (Hester et al., 2010; Hester and Cacho, 2012; Rafoss, 2003; Yemshanov et al., 2009) and to

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http://dx.doi.org/10.1016/j.ecolecon.2016.11.018
0921-8009/

estimate the bounds of uncertainty on those forecasts (Carrasco et al., 2010; Koch et al., 2009). Concurrently, resource allocation models based on optimization have been used to develop cost-effective surveillance and control strategies in temporal and geographical domains (Cacho et al., 2010; Haight and Polasky, 2010; Hauser and McCarthy, 2009; Epanchin-Niell et al., 2012, 2014, Epanchin-Niell and Liebhold, 2015; Mehta et al., 2007; Sims and Finnof, 2013; Yemshanov et al., 2014). While invasion spread forecasts are commonly rendered in a stochastic setting, resource allocation models based on optimization require deterministic parameters to achieve specific management objectives. Resource allocation under uncertainty can be achieved with a special class of robust optimization models which incorporate the uncertain parameters as random variables and represent them with a large set of scenarios of possible outcomes (Kouvelis and Yu, 1997). These robust models can use the universe of uncertain spread forecasts and thereby provide better support for economic decisions about managing species invasions under uncertainty. In particular, scenario-based optimization offers the opportunity to examine the notion that uncertain future outcomes of an invasion may change the present-time survey planning strategy, an aspect that has rarely been explored in pest surveillance models (but see the scenario-based model in Horie et al., 2013).

This paper addresses the resource planning problem of managing invasive species under uncertainty by combining a stochastic simulation approach, in which we predict the uncertain spread of a non-native species through a landscape, with a scenario-based optimization model that finds the most cost-effective deployment of survey and eradication measures at a regional scale by evaluating eradication decisions at the level of individual survey sites. We apply our modeling approach to allocate sites for verification surveys of Asian longhorned beetle (ALB) in the Greater Toronto Area (GTA) of Ontario, Canada. ALB was initially discovered in the GTA in 2003 (Smith et al., 2009), and a portion of the GTA is currently under ALB quarantine (Turgeon et al., 2015).

We first use prior knowledge about the spread of ALB in the GTA to develop a pathway-based, stochastic model that simulates the spread of the pest in the area of concern, and then use this model to generate scenarios that depict uncertainty about the future extent and impacts of ALB invasion. Next, we apply these scenarios in our robust optimization model to identify optimal survey and eradication (i.e., host tree removal) strategies with the objective to minimize the number of infested and potentially infested host trees on the landscape subject to budget constraints. Our survey planning model explores the following economic problem. Surveys via host tree inspections of the pest population must be allocated to specific sites in the landscape at the beginning of the planning period in present time, using available knowledge about its general pattern of current and anticipated future spread and current extent in the managed area. Knowledge about where the organism has already spread, or where it may spread in the future, is uncertain. This uncertainty stems from the fact that invasion is a dynamic and stochastic process (Melbourne and Hastings, 2009; Epanchin-Niell and Hastings, 2010). The uninvaded status of sites that are going to be surveyed could change if infested trees are found, however, which currently uninvaded sites will be invaded in the near future is unknown. We represent this uncertainty with a large set of stochastic invasion scenarios. Each scenario is characterized by the proportion of infested trees in each site and describes a plausible invasion outcome.

Our model evaluates two sets of decisions. First, decisions about where to allocate surveys are made before undertaking the surveys. These decisions are based on the expected but uncertain pattern of spread. Sites outside of the quarantine area are then surveyed and a set of stochastic spread scenarios depicts possible current and future infestations at the end of the survey period. Because the outcomes of the survey are uncertain, information about spread is available to decision-makers after the surveys are completed and subsequent eradication decisions depend on the surveys' outcomes. The overall cost of survey and eradication (i.e., tree removals) must be within budget for all spread scenarios. In our model, survey planning is done with respect to the outcomes of all plausible scenarios including the costs of eradication in surveyed sites where an infestation is found. This makes the optimal allocation of survey sites robust to the uncertainty about the pest's spread in the area to be managed. Our modeling concept helps achieve a balance between the costs of surveillance and eradication under a limited project budget and addresses many practical situations when economic decisions to survey or eradicate populations of an invasive species are made under uncertainty regarding how the species may spread in the future.

2. Material and Methods

2.1. Robust Allocation of Survey and Control Efforts

We formulate the model as a mixed integer problem by using concepts from robust optimization (Kouvelis and Yu, 1997; Bertsimas et al., 2011) and by incorporating basic aspects of the scenario-based optimization model in Horie et al. (2013). Consider a landscape composed of J sites, each containing N_j trees suitable for the complete development of the pest it may harbor (see Table 1 for summary of model parameters). A site j, $j=1, \ldots J$, can have a proportion of trees that are infested, θ_{1j}, and a proportion of suitable trees that are in proximity (hereafter referred to as the "proximity zone") to the infested trees and at risk of becoming infested soon, θ_{2j}, which we term proximate host trees. The number of trees in a site j that are infested is $N_j\theta_{1j}$, and the number of proximate trees in site j is $N_j\theta_{2j}$, where θ_{1j}, $\theta_{2j} \in [0;1]$ and $\theta_{1j}+\theta_{2j} \leq 1$. The proportion of trees in the proximity zone, θ_{2j}, is estimated from the number of trees within a specific radius around the nucleus of $N_j\theta_{1j}$ infested trees.

A manager allocates surveys and subsequent eradication actions across a subset of sites in J, with a defined budget level B. In our case, eradication measures are aimed to stop or significantly slow the spread of the pest population. When an infestation is found in a surveyed site j, those measures include removal of all invaded host trees and as many apparently uninfested but potential host trees as possible in the proximity zone that surrounds the infested nucleus. For simplicity, we assume

Table 1
Summary of the model variables and parameters.

Symbol	Parameter/variable name	Description
Parameters:		
j, J	Potential survey sites in a study area	$j \in J$, $J = 3208$
s, S	Stochastic spread scenarios	$s \in S$, $S = 400$
N_j	Number of host trees at a site j	$N_j \geq 0$[a]
θ_{1js}	Proportion of trees at a site j in a scenario s that are infested	$\theta_{1j} \in [0;1]$[b]
θ_{2js}	Proportion of host trees at a site j in a scenario s in a proximity zone that surrounds the nucleus with $N_j\theta_{1js}$ infested trees	$\theta_{2j} \in [0;1]$[b]
B	Total budget	Constraint
$M_{\min}$	Minimum desired reduction in the pest's spread capacity from the surveyed sites	Constraint
C	Fixed survey cost	Constraint
c_1	Tree survey cost	\$6.83 tree^{-1}
c_2	Tree removal cost	\$1000 tree^{-1}
p_j	Probability of the pest to spread to a site j	$p_j \in [0;1]$[a]
q_j	Probability of the pest to spread from an infested site j to other uninfested sites	$q_j \in [0;1]$[a]
p_{jk}	Probability of the pest to spread from a site j to site k	$p_{jk} \in [0;1]$[a]
Decisionvariables:		
x_j	Binary survey selection of a site j	$x_j \in \{0,1\}$[a]
R_{js}	Number of host trees removed at a surveyed site j in a scenario s	$R_{js} \in [0;N_j]$[a]

[a] The parameter value is site-specific.
[b] The parameter value is site and scenario-specific.

that there is a single nucleus encompassing all infested trees at site j. The maximum number of uninfested trees to be removed in the proximity zone has an upper bound of $N_j\theta_{2j}$.

Removal of apparently uninfested trees in proximity to the infested trees is considered necessary because detection rates in pest surveys are typically below 100%, so some infested trees at site j may remain undetected, thereby permitting the invader to spread in the future. This necessitates the creation of a buffer zone around the infested trees that is of sufficient size to reduce the chance such spread will occur (Reaser et al., 2008). We assume that the proximity zone around the nucleus of infested trees at site j is defined by a circle that encompasses proportion θ_{2j} of the host trees.

The number of infested and proximate trees, remaining in a site j after R_j host trees have been removed from site j is:

$$N_j\theta_{1j} + N_j\theta_{2j} - R_j \tag{1}$$

The manager's objective is to select survey sites and tree removal levels in the surveyed sites to minimize the number of infested and proximate host trees remaining in the landscape:

$$\min \sum_{j=1}^{J} \left[N_j\theta_{1j} + N_j\theta_{2j} - R_j\right] \tag{2}$$

$$\text{s.t.} N_j\theta_{1j}\, x_j \le R_j \le \left(N_j\theta_{1j} + N_j\theta_{2j}\right)x_j \tag{3}$$

where x_j is a binary selection variable indicating whether site j is surveyed (i.e., $x_j = 1$) or not ($x_j = 0$). Tree removal only occurs at infested sites that have been surveyed, so $R_j = 0$ for all $x_j = 0$. We assume that all infested and proximate trees are removed at surveyed sites, i.e., $R_j \ge N_j\theta_{1j}x_j$.

The true proportion of infested trees, θ_{1j}, at any site j is unknown, but approximate θ_{1j} values can be estimated based on the pest's expected pattern of spread and the numbers of infested trees detected at other sites during previous survey campaigns. These estimates are uncertain, but their uncertainty can be depicted with a large set of probabilistic scenarios, S, where each site j in an invasion scenario s, $s = 1, \ldots, S$, is characterized by the proportion of infested trees at the site, θ_{1js}, and the proportion of trees in the proximity zone, θ_{2js}. The presence of the pest (i.e., the spread pattern) and the θ_{1js} values can be generated with a stochastic invasion model.

We incorporate the uncertainty about the future spread of invasion by representing the pest management problem as a scenario-based model, i.e.:

$$\tau = \min \frac{1}{S}\sum_{s=1}^{S}\left[\sum_{j=1}^{J}\left(\theta_{1js}N_j + \theta_{2js}N_j - R_{js}\right)\right] \tag{4}$$

$$\text{s.t.}: \theta_{1js}N_j\, x_j \le R_{js} \le \left(\theta_{1js}N_j + \theta_{2s}N_j\right) x_j \quad \forall \quad s \in S,\ j \in J \tag{5}$$

$$\sum_{j=1}^{J} c_1 x_j N_j + \sum_{j=1}^{J} c_2 R_{js} \le B \quad \forall s \in S \tag{6}$$

$$x_j \in \{0; 1\} \quad \forall \quad j \in J, \tag{7}$$

where c_1 and c_2 are per-tree survey and removal costs, and B is the total project budget. The objective function in Eq. (4) minimizes the expected number of infested and proximate trees in a management area of J sites after survey and removal. Eq. (5) ensures that all infested trees in each surveyed site are removed, and that removals are bounded by the number of uninfested trees in the proximity zone at the end of the survey period. Eq. (6) specifies the total budget for surveys and tree removal, which must be met in each scenario. We assume that all trees are examined in each surveyed site j. Decision variables include the selection of survey sites, x_j, and the number of trees to be removed around the invasion nuclei that is detected at the surveyed sites in each scenario, R_{js}.

Without eradication management (i.e., removal of infested and proximate host trees), the pest's capacity to spread from the proximity zone of a site j can be estimated at the end of the survey period, in simple terms, as the sum product of the number of host trees (i.e., potential propagule sources) in the proximity zone and the probability that the pest could spread from site j to elsewhere, q_j, as:

$$\sum_{j=1}^{J}\left(\left(\theta_{1js} + \theta_{2js}\right)N_j q_j\right) \tag{8}$$

After the removal of R_{js} trees, the pest's capacity to produce propagules at site j is reduced by $R_{js}q_j$. Higher $R_{js}q_j$ values cause greater impact on the capacity to spread from j elsewhere. The minimum desired reduction in the pest's spread capacity from all surveyed sites can be specified as:

$$M_D \ge M_{\min}, \tag{9}$$

where

$$M_D = \frac{1}{S}\sum_{s=1}^{S}\left[\sum_{j=1}^{J}\left(R_{j_s}q_j\right)\right] \tag{10}$$

Eqs. (4)–(7), (9) and (10) provide the basic model formulation. Since $R_{js} = 0$ when site j is not surveyed (i.e., $x_j = 0$), the survey selection variable x_j is not needed in Eq. (10). In short, the $M_{\min}$ constraint sets the aspirational target to slow the capacity of the pest to spread from surveyed sites elsewhere over all the invasion scenarios, S. By increasing the $M_{\min}$ value, the model selects sites where removal of susceptible trees yields the largest reduction in the pest's expansion. When the budget for tree removal is insufficient to remove all proximate trees, a higher $M_{\min}$ value focuses more tree removal efforts on sites that are likely to be higher sources of pest propagules, so that the procedure still works effectively as a slow-the-spread measure. Note that the spread capacity can only be reduced at sites that have been surveyed.

2.2. Case Study: Optimal Surveillance and Control for ALB Outbreak in Greater Toronto Area (Ontario, Canada)

2.2.1. Model-based Assessment of ALB Spread in Urban Setting

The first detection of ALB in the Greater Toronto Area (GTA) occurred in September 2003 and a regulated area was established soon after. That regulated area was declared pest free in May 2013. Later that year a small satellite infestation was discovered a few kilometers outside the area that had been regulated between 2003 and 2013 (Turgeon et al., 2015). We applied our model to the case of managing the expansion of this recent discovered satellite infestation of ALB. In addition to the GTA, the insect has been introduced to other cities in the eastern U.S., including New York (NY), Chicago (IL), Jersey City (NJ), Clermont county (OH), Carteret (NJ) and Worcester (MA) (Haack et al., 1997, 2010; Shatz et al., 2013; APHIS, 2013; Trotter and Hull-Sanders, 2015; Meng et al., 2015). All of these are believed to be separate introductions from China (APHIS, 2005; Carter et al., 2009). This beetle has also been introduced in Europe (Maspero et al., 2007; EPPO, 2008; Straw et al., 2015). In all these infestations, maple (*Acer* spp.) is the main host of ALB, but the beetle also attacks birch (*Betula*spp.), poplar (*Populus* spp.), elm (*Ulmus* spp.), willow (*Salix* spp.) and several other tree genera (Lingafelter and Hoebeke, 2002; Williams et al., 2004; Wang et al., 2005; CFIA, 2014; Meng et al., 2015) making it one of the world's most threatening invasive forest pests (Nowak et al., 2001; Haack et al., 2010). Eastern North America is especially vulnerable because of the ubiquity of maple and the abundance of suitable habitat conditions (Peterson and Scachetti-Pereira, 2004). If existing outbreaks are not contained, ALB is expected to impact many industries in North America that utilize these hosts.

Several early detection techniques have been proposed for ALB (Smith and Wu, 2008; Haack et al., 2010; Nehme et al., 2014), but visual inspection of trees for signs of attack is currently the only practical detection method (Turgeon et al., 2010). The area around the existing ALB infestation is characterized by high abundance of suitable trees, with 5th–95th percentile density ranging between 1.7 and 40.7 trees-ha^{-1}. Due to significant costs of intensively inspecting and removing the potential host material, the currently regulated area under quarantine was limited to approximately 46 km^2 (Fig. 1) from which all infested and uninfested proximate host trees were removed between September 2013 and April 2014. The potential for extensive damage and high costs of eradication efforts necessitate the assessment of the risk that ALB has spread beyond the currently quarantined area, as well as a rapid-response plan were this to happen.

ALB is known to have slow natural spread rates (Smith et al., 2001, 2004): 80% of the population at a given site is expected to spread <300 m per year (Favaro et al., 2015). Most recent ALB introductions have been facilitated by humans (Carter et al., 2009). Growing anecdotal evidence suggests that the pest may hitchhike on slow-moving vehicles (Trotter and Hull-Sanders, 2015; Turgeon, pers. obs.), similar to the documented spread of another invasive forest insect, the emerald ash borer (*Agrilusplanipennis* Fairmaire), in urban settings (Buck and Marshall, 2008). In most cities and towns, including the GTA, local road traffic (involving both passenger and commercial vehicles) accounts for a large portion of the area-wide movement of people and goods. Consequently, road traffic has been recognized as a reasonable proxy for a variety of local economic activities (SACTRA, 1999). We used volumes of local road traffic as a measure of activities that could cause human-mediated

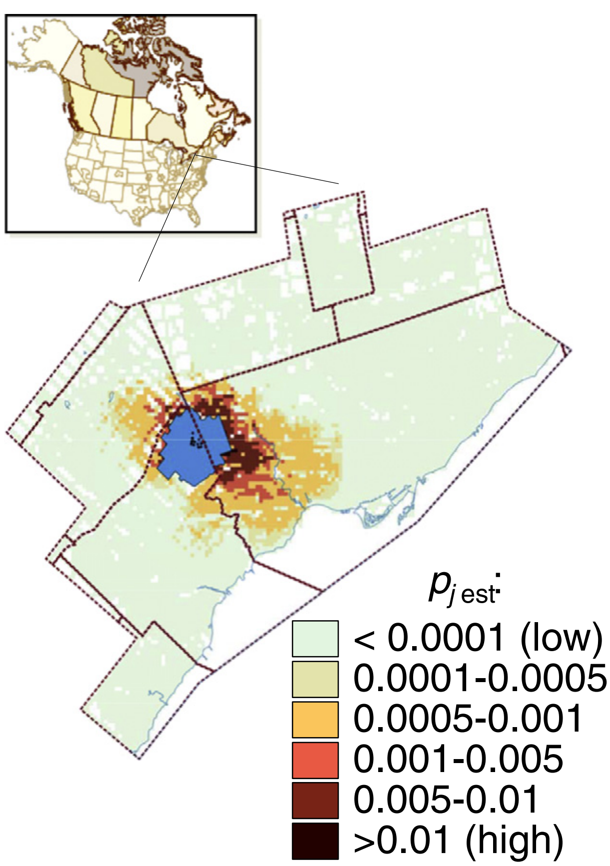

Fig. 1. Study location: Greater Toronto Area (GTA), Ontario, Canada. Map depicts the model-estimated probability, $p_{j\ \mathrm{est.}}$, that ALB will spread to and survive in a site in the GTA outside of the quarantine area (blue zone). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

ALB spread beyond the boundaries of the regulated area. Briefly, we utilized a dataset on local road traffic volumes in the GTA (Tetrad, 2014) that had been linked to the GTA portion of the ESRI Street Map geospatial database (ESRI, 2014, Cook and Downing, 2013) to estimate probabilities of ALB movement from previously invaded locations (see description in Appendix S1). We divided the GTA street network into 400 × 400-meter blocks, each representing a potential survey site, and then used the local traffic volume data to estimate a matrix of probabilities of ALB movement from block to block via the network. This matrix was used to simulate 5×10^6 randomized pathways of ALB spread from sites in the quarantined area. We then adjusted the arrival rates by the suitability of a given site for survival of an ALB population. The suitability value was based on previous detections of the pest during the early stages of the ALB management campaign in the GTA. An ALB population can survive on a few host trees (Turgeon et al., 2015), so the local host density was not used to adjust the establishment rate value. The ALB spread model was calibrated to match the historical spread rate of ALB in the GTA as determined from previous survey campaigns prior to the current eradication campaign (Appendix S1). During the calibration, we first generated expected probabilities of ALB arrival with the spread model (see definition in Appendix S1) and then created new infestations in the study area via uniform random draws against the expected probability values. We next compared the number of generated nuclei with the historical invasion rate prior to the current eradication effort (i.e., 12 new nuclei over the 2004–2007 survey period, Turgeon, unpubl. data) and recalculated the spread matrix by linearly adjusting the spread probability values (the coefficient λ in Eq. (S1), Appendix S1) until the model matched the historical invasion rate.

2.2.2. Parameterizing the Resource Allocation Model

Parameterizing the optimization model required a large set of invasion scenarios. As noted earlier, each scenario had two associated sets of proportions: the proportions of infested trees on invaded sites, θ_{1js}, and the proportion of proximate host trees, θ_{2js}. We generated the scenarios with a two-step process. First, we used our calibrated spread model to estimate the probability of ALB spread to other uninfested sites, p_j, for each site $j$in the area of concern (Fig. 1). For each spread scenario s, we generated a stochastic pattern of invaded sites via random draws against the p_j values. Next, each invaded site j in a scenario s was assigned a number of infested trees that was randomly sampled from an empirical distribution of the number of infested trees. This distribution was based on records of historical ALB detections in the GTA. The proportion of infested trees, θ_{1js}, at a site $j$in a scenario $s$was then found by dividing the number of infested trees sampled from the distribution by N_j, the total number of host trees at site j. We assumed that the invaded trees occupied a single nucleus at site j. Because the size of the survey sites was relatively small and historical rates of ALB spread were low, we felt this was a fair assumption. We then converted the area corresponding to the θ_{1js} proportion of invaded trees at site j to a circle of equivalent area in the center of the 400 × 400-meter survey block. We determined this area based on the average tree density and host tree species proportions reported in the City of Toronto's Every Tree Counts survey (City of Toronto, Parks, Forestry and Recreation, Urban Forestry, 2013), which provided a detailed summary of Toronto's urban forest. To estimate the total number of host trees (N_j) we first estimated the area of tree cover at each survey site j from the SOLRIS (2008) land cover dataset for the GTA. The area of tree cover was then converted into a corresponding number of host trees by multiplying by tree density and the host species proportion.

Having defined the circular area corresponding to the proportion of infested trees, we then added a 200-meter buffer to that area to define the surrounding proximity zone, and recalculated the area of the zone including both infested and proximate trees. The proportion of host trees in the proximity zone, θ_{2js}, was found by dividing the area of the proximity zone by the total area of the survey site. The proportion θ_{2js} depends on the proportion of trees that are infested, θ_{1js}, and the local host density, N_j, hence the values θ_{1js} and θ_{2js} for a site j in a scenario s represent a linked pair. The dependency between the number of infested trees in the nucleus and the average θ_{2js} values can be approximated by a functional relationship (Fig. 2).

In theory, if the number of infested trees is large, the area of the proximity zone may exceed the survey site's total area and the proportion of both infested and uninfested trees, $\theta_{1js}+\theta_{2js}$, may exceed 1. This was not an issue in our case study because the number of infested trees was small based on historical data from the 2003 infestation (i.e., between 1 and 28 trees per site; Turgeon, unpubl. data) and the proximity zone area never exceeded the area of the survey site. The small number of infested trees in each nucleus also explains limited variation in the θ_{2js} values (i.e., between 0.82 and 0.97).

We used the calibrated spread model to generate the probability of the pest's spread from each surveyed site j to other uninfested sites, q_j. Appendix S1 describes the process by which we estimated and calibrated the matrix of spread rates (i.e., probabilities), p_{jk}, from all potential survey sites $j$to other uninfested sites, k, $k \in J$, $k \neq j$. The probability of the pest spreading from a surveyed site j to other uninfested sites was calculated as:

$$q_j = \sum_{j,k=1,k\neq j}^{J} p_{jk} \tag{11}$$

where $0 \leq q_j \leq 1$. We then used the q_j values to evaluate the $M_{\min}$ constraint (Eq. (10)).

We also assessed the practical range of the $M_{\min}$ values by first calculating the M_D value in Eq. (10) in the unconstrained solution, i.e., when $M_{\min}=0$. The M_{D0} value in the unconstrained solution represents a baseline capacity to slow the spread at a given budget level, B. Note that the $M_{\min}$ constraint is only intended to reduce spread capacity from surveyed sites, and does not affect unsurveyed sites. We then solved constrained solutions with $M_{\min}$ values set above M_{D0} by 25% as well as the maximum percentage above M_{D0} that still yields a feasible solution (i.e., around 40–50%). These scenarios depict increasingly higher aspirations to reduce the pest's spread capacity from the surveyed sites.

Additionally, the model required a value for the budget constraint, B, and the costs of survey and tree removal, c_1 and c_2. Because the surveys are conducted in urban sites connected by a dense and accessible street network, we assumed equal survey costs on a per-tree basis. We estimated the survey cost from contractor rates paid to do visual tree

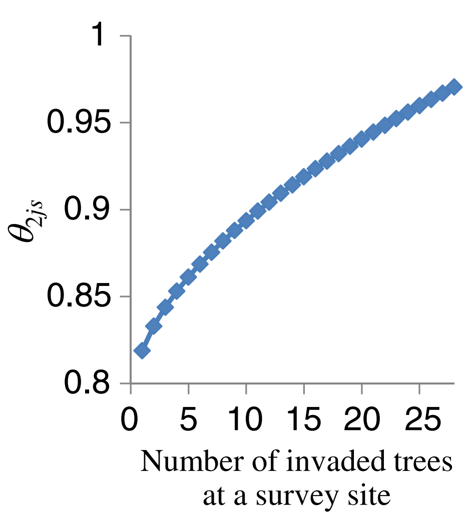

Fig. 2. Average proportion of suitable host trees, θ_{2js}, in the proximity zone around the invaded nucleus of a survey site as a function of the number of infested trees in the nucleus.

inspections in previous ALB survey campaigns. This yielded an average survey cost of \$6.83 per tree. The cost of tree removal was based on current tree disposal costs in the ongoing ALB eradication program and was set at \$1000 per tree. The high cost of tree removal was due to regulatory requirements when disposing of a tree, which require costly chipping operations at designated disposal sites. We evaluated the optimal solutions for project budgets B between \$0.5 M and \$2 M yr^{-1}, which represents the anticipated range in size of the ALB verification survey program outside of the quarantine zone in the GTA.

We also explored the impact of changing the project budget on key survey characteristics, by calculating sensitivity values to the budget changes by plus-minus 10% as:

$$0.5\left|\frac{(w_+-w_0)}{w_0}\Big/\frac{(B_+-B_0)}{B_0}+\frac{(w_--w_0)}{w_0}\Big/\frac{(B_--B_0)}{B_0}\right| \tag{12}$$

where w_0 and B_0 are the baseline survey characteristics and budget constraint values, while w_+, B_+ and w_-, B_- are the survey characteristics and budget values in the solutions with the budget constraint (B) altered by plus and minus 10% from its baseline value B_0. The w values describe the survey characteristics of interest (such as the proportion of trees removed in close proximity to the quarantined area or the number or surveys allocated at long distances).[1] The sensitivity value shows the ratio between the relative change, in absolute terms of the characteristics of interest (such as the proportion of sites surveyed at short distances) and the change of the project budget constraint (B) by $\pm 10\%$.

In addition to solutions with optimal apportionment of survey and tree removal costs, we evaluated solutions with fixed survey costs, by adding the following constraints:

$$\begin{aligned}&\sum_{j=1}^{J} c_1 x_j N_j \leq C \quad \text{for} \quad C<C_{\text{opt}} \quad \text{and}\\&\sum_{j=1}^{J} c_1 x_j N_j \geq C \quad \text{for} \quad C>C_{\text{opt}}\end{aligned} \tag{13}$$

where C_{opt} is the optimal survey budget in the unconstrained solution.

2.2.3. Computing Bounds on the Objective Function Value

Ideally, the optimization model would be supplied with a very large set of invasion scenarios, but the practical number of scenarios is limited by computational capacity. Optimal solutions based on a finite number of random scenarios provide an approximation of the true optimal solution. To better understand how close our model solutions were to the solution with a complete set of scenarios, we estimated the upper and lower bounds on the optimal objective function value using concepts from Mak et al. (1999) and Lee et al. (2013).

The lower bound ($\overline{L}$) was estimated as the mean of the objective function values for the solutions to 25 independent replicate problems with S scenarios. Each replicate used different, non-overlapping sets of stochastic spread scenarios. We then re-used the replicate solutions to compute the upper bound. Specifically, we re-computed the objective function values for a set of 5000 different spread scenarios using the survey allocations from the replicate problems that we calculated for the lower bound. In turn, we estimated the upper bound ($\overline{U}$) as the mean of the objective function values based on those 25 replicate sets. We estimated the optimality gap between the upper and lower bounds as the relative difference between them, i.e.:

$$(\overline{U}-\overline{L})/\overline{U} \tag{14}$$

Table 1 provides a summary of the model parameters and variables. The model was composed in SolverStudio (Mason, 2013) and GAMS

[1] The survey characteristics are for diagnostic purposes and do not represent the model parameters or decision variables.

environments (GAMS, 2015) and solved with GUROBI linear programming solver (GUROBI, 2014). The optimization was terminated once the optimality condition was reached or after a 22-hour time limit.

3. Results

3.1. Assessing the Optimality Gap

We estimated the upper and lower bounds on the objective function value for problem solutions with 50, 100, 200 and 400 spread scenarios (Table 2). The optimality gap values appear to be <2% for problems with 50 or more scenarios. Gaps for the problems with 200 or more scenarios were <1%. The low gap value is a result of the particular formulation of the objective function. Recall that the objective function depicts the number of *remaining* proximate trees at a survey site. When only a small portion of the area of interest (J) is surveyed the number of remaining host trees that could be infested in the area is large. In relative terms, changes in the objective function value at small survey budgets are small and cause the gap value to be low. We believe the result associated with 400 scenarios is close to the unknown optimal solution because the optimality gap is very low (Table 2). The number of spread scenarios also influenced other properties of the surveys (Table S1 in Appendix S2). The solutions with 400 scenarios had no surveys at sites with very low risk of infestation ($p_j < 0.001$) and ten times fewer surveys at distances >4 km from the quarantine area than the solutions with 50 scenarios (Table S1 in Appendix S2). It does not appear that solving problems with >400 scenarios would yield much benefit in terms of precision or accuracy, but would greatly increase computation time.

3.2. Spatial Survey Patterns and the Number of Invasion Scenarios

The number of scenarios, S, affects the spatial patterns of selected survey sites, as evidenced by the survey selection patterns based on the averaging of 25 optimization runs with independent sets of invasion scenarios (Fig. 3). The most commonly selected survey sites (i.e., sites selected for survey in a large percentage of optimization runs) and greatest numbers of removed trees were found close to the northern and eastern portions of the quarantine area, i.e., sites where the arrival of ALB is most likely (Fig. 3, Fig. S1 in Appendix S2). The allocation of surveys at long distances from the quarantine area was less consistent: When the number of scenarios was low (i.e., $S = 50$), the surveys were scattered across large portions of the GTA (Fig. 3a). The spatial allocation of surveys at further distances from the quarantine area appeared to be spatially random (Fig. 3, callout I), which indicates that 50 scenarios were insufficient to characterize long-distance spread properly.

As the number of scenarios increased, surveys at locations away from the quarantine area began to follow the network of main roads closer to the quarantine area (Fig. 3c,d and Fig. S1c, d in Appendix S2). Indeed, the solutions with 400 scenarios revealed two major survey patterns (Fig. 3d and Fig. S1d in Appendix S2): high-risk sites immediately adjacent to the quarantine area (dark-shaded areas in Fig. 3d), but also sites along major streets with heavy local traffic at moderate distances from the quarantine area. At moderate distances, survey selections start to follow a rectilinear grid of the street network (Fig. 3, callout II) and random selections of surveys at long distances (Fig. 3, callout I) disappear. In summary, the map in Fig. 3d suggests that a combination of two distinct strategies is usually the best approach to surveillance: (i) survey the areas with the highest spread rates in proximity to the area under quarantine, but also (ii) allocate a portion of resources to sites at longer distances following major streets and transportation corridors. The proportion of the surveys at long distances should be relatively small compared to the surveys in high-risk areas (i.e., between 4 and 20%). The number of removed trees followed the same pattern, but the hotspots with large numbers of removed trees appeared more compact (Fig. S1d in Appendix S2).

Table 2
Upper and lower bounds on the objective function value for differing numbers of spread scenarios. Mean values of the objective function value for base case with the total program budget $B = \$0.5$ M, computed with sets of 25 independent replicates with increasing numbers of scenarios, $S = 50$, 100, 200 and 400.

Number of spread scenarios, S	Lower bound ($\overline{L}$), 95% confidence interval	Upper bound ($\overline{U}$), 95% confidence interval	Optimality gap*
50	8194.4 ± 96.1	8368.1 ± 12.9	2.08%
100	8224.8 ± 88.7	8351.4 ± 35.4	1.23%
200	8227.9 ± 59.8	8311.5 ± 4.5	1.01%
400	8245.8 ± 35.7	8294.9 ± 3.3	0.06%

* The optimality gap is $(\overline{U}-\overline{L})/\overline{U}$ (Mak et al., 1999).

3.3. Optimal Survey Solutions and the M_{min} Constraint

Penalties from imposing the $M_{\min}$ constraint on the objective function appeared to be minor (Fig. 4): Reducing the pest's spread rate from surveyed sites by 40–50%, by targeting the sites expected to contribute more to future spread, increased the number of remaining host trees only by 0.2–1.5%. The survey pattern shifted from a mix of short- and long-distance surveys (Fig. 4b, callout I) towards high-risk sites near the quarantine area (Fig. 4b, callout II). Tree removal at those sites would have the greatest impact on the pest's expansion.

The sites closest to the quarantine area contribute most to expected future spread because they have the highest probability of ALB establishment. For ALB, the spread rate even when factoring in human-mediated dispersal is slow (i.e., <300 m per year) and the creation of distant nuclei via spread is unlikely, so the sites with the highest likelihood of pest arrival also have the greatest capacity to spread the pest elsewhere.[2] Without the $M_{\min}$ constraint, the model generally selected sites with low host densities (Fig. S2a, b in Appendix S2). Similar behaviour was observed by Horie et al. (2013) for a model of oak wilt disease. Sites with lower host densities were selected because those sites had fewer trees to survey and fewer trees to remove if an infestation was found, thereby lowering the total cost invested in each surveyed site. As a result, more sites could be surveyed across the managed area. Higher $M_{\min}$ values increased the number of surveys and the number of trees removed at sites with high host densities (Fig. S2a, b in Appendix S2). Also, a higher percentage of host trees was removed at the surveyed sites given larger budget levels (Fig. 5a).

Increasing the $M_{\min}$ values forces the model to remove more trees at the sites with high risk of pest arrival, which also have high capacity to spread ALB to other sites. The survey patterns appear to be more compact and located closer to the quarantine area (Fig. 4b). Higher $M_{\min}$ values also resulted in the omission of sites with very low spread rates and led to a small increase in the proportion of the total budget devoted to survey costs, because it costs more to survey sites with high host densities (Fig. 5b). At the same time, more surveys were selected and more trees removed at sites with high pest arrival rates (Fig. S2c, d in Appendix S2), although the total arrival rate at surveyed sites, $\sum^{J}(p_j, x_j)$, declined slightly (Fig. 5c). This happened because the pest arrival rates, p_j, and the spread rates to other uninfested locations, q_j, which are used in the $M_{\min}$ equation are not perfectly correlated.

3.4. Optimal Levels of the Survey Budget

Table 3 shows optimal solutions with unconstrained apportionment of the survey and tree removal costs out of the total project budget. The

[2] For ALB, distant nuclei may also be created by re-introductions with pest-specific imports from the regions of the species' native distribution range. This aspect requires spatially referenced data on imports of pest-associated commodities to GTA and will be a focus of future work.

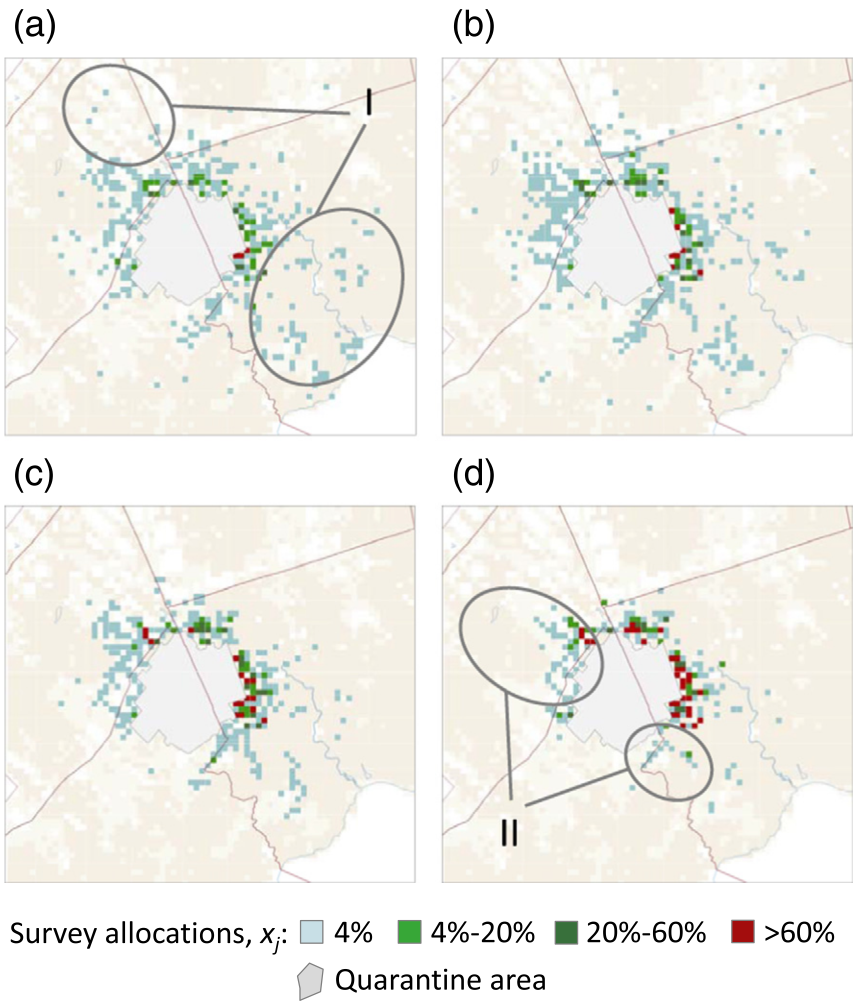

Fig. 3. Survey allocations (i.e., the percentage out of 25 optimization runs in which a site *j* was selected for survey, $x_j = 1$) versus the number of invasion scenarios, *S*: a) 50 scenarios; b) 100 scenarios; c) 200 scenarios; d) 400 scenarios. Callout I shows random survey patterns at long distances from the quarantine area in the solutions with a small number of spread scenarios. Callout II shows rectilinear survey patterns in close proximity to the quarantine area, which appear to follow major streets, in the solutions with a large number of spread scenarios.

three project budget levels (\$0.5-2 M yr.$^{-1}$) presented in Table 3 reflect three hypothetical, but plausible, budget levels for ALB survey and control efforts outside of the quarantine area. At these funding levels, it was optimal to spend approximately one-fifth of the budget on surveys and the rest on tree removal. The low proportion of the total budget devoted to surveys was a result of the high per-tree removal cost, which also limited the number of sites that could be treated. The number of removed trees depended on the project budget and varied between 190 and 390 and between 1267 and 1596 trees, respectively, in baseline scenarios with project budgets of \$0.5 M and \$2 M. Notably, the portion of the project budget devoted to tree removal is large despite the fact that the number of infested trees, as suggested by historical data, is expected to be low (i.e., 12 nuclei on average, between 1 and 28 infested trees each).

Optimal solutions had a sizeable percentage of sites with low host tree density, especially when the project budget was small (Table 3). Basically, surveys and tree removal at low-density sites cost less, which allows for allocating more surveys. Surveying more sites increases the chance of finding infestations, therefore it is optimal, beyond surveying the highest-risk sites, to survey sites with moderate risk of invasion but low host densities.

When the project budget level increased from \$0.5 M to \$2 M, the proportion of surveyed sites with low host densities dropped from 59% to 28%, and so did the proportion of trees removed at sites with high risk of invasion (i.e., from 46% to 35%). Indeed, the proportion of trees removed from all sites – not just the highest-risk ones – near the quarantine area also dropped from 40% to 13%, while the share of surveys at longer distances increased from 21% to 43% (Table 3). This implies that spending significant resources on long-distance surveys is feasible only when the project budget is large. Notably, the budget level did not affect the average percentage of host trees removed at the survey sites (Table 3).

3.5. Survey Budget and the Performance of Pest Management Programs

Our observations of recent efforts to manage the ALB outbreak in the GTA revealed that decisions about survey and eradication measures are usually made at different stages in the overall planning process. In past years, a fixed portion of the program budget has been allocated for surveys at the beginning of the season, whereas decisions to remove trees have depended on the outcomes of surveys. To explore this aspect, we evaluated a range of optimal solutions with fixed survey budgets, *C*, for project budget levels (*B*) ranging from \$0.5 M to \$2 M. By setting a fixed survey cost above the optimal value, we simulated a decision-maker's aspiration to increase the survey area, and thus potentially detect more new infestations, while accepting the reduced ability to remove susceptible trees due to the subsequent shortage of funds for such efforts. Alternatively, fixed survey budgets below the optimal level explored the possible scenario where a decision-maker's capacity to conduct surveys is limited by other unforeseen factors, or he/she anticipates that a large number of tree removals will be necessary. In short,

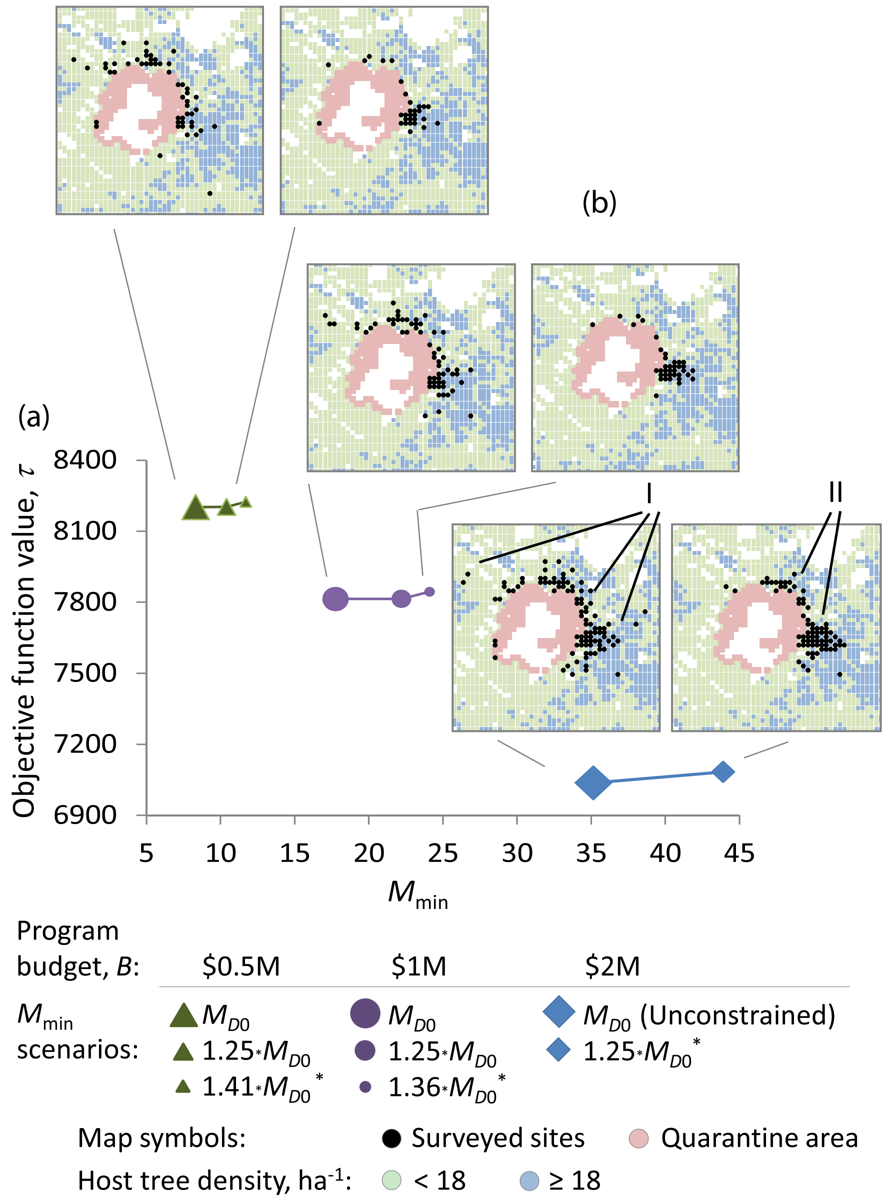

Fig. 4. a) Objective function value τ (the number of suitable host trees remaining at the survey sites) as related to the $M_{\min}$ value at three budget levels. Symbol sizes depict three different M_{min} constraint scenarios: large symbols correspond to unconstrained solutions, M_{D0}, where the $M_{\min}$ constraint was not used; medium symbols correspond to solutions where $M_{\min} = 1.25M_{D0}$; and small symbols correspond to solutions with the maximum $M_{\min}$ value before solution becomes unfeasible. Lower objective function values indicate better solutions. * Feasible solutions with the highest $M_{\min}$ value. b) Examples of spatial patterns of survey selections in solutions with $M_{\min} = M_{D0}$ (unconstrained) and with maximum $M_{\min}$ values. Callout I indicates a mix of short- and long-distance surveys in unconstrained solutions and callout II indicates a shift of the survey pattern towards high-risk sites near the quarantine area in the solution with the $M_{\min}$ constraint.

our results in this context explore the decision-making trade-off between surveying a larger area to increase the chance of detections yet having less resources available for eradication, versus surveying a smaller area but perhaps having a greater chance to disrupt the pest's spread via tree removal.

As expected, deviations from the optimal survey budget worsened the objective function value (Fig. 6a) and decreased the capacity to slow the spread from surveyed sites (Fig. 6b). As the survey budget increased, the proportion of trees removed at the surveyed sites decreased because less funding was available for tree removal (Fig. 6c). The pest arrival rate at surveyed sites generally increased with the survey budget (Fig. 6d) because more high-risk sites (where ALB arrival is most likely) could be visited given a larger survey budget. When the budget share left for tree removal was small (e.g., <60% in the scenarios with B = $0.5 M, Fig. 6d), it was not optimal to survey the high-risk sites at all (Fig. 6d, callout I). Because very few resources were available in this case to treat the high-risk sites (which often have high host densities), removing trees at sites with low host densities became more cost-effective.

Changes in the budget proportion spent on surveys versus tree removal also influenced the spatial patterns of the surveys. When the apportionment between survey and tree removal costs was close to optimal (Fig. S3c in Appendix S2), the surveys were allocated in a two-tiered fashion: The majority targeted high-risk sites near the quarantine area and the rest were assigned to medium-risk, but more distant, sites with low host densities. However, when the share of the total budget devoted to tree removal was below the optimal ratio, it was no longer possible to remove a desired number of trees in the proximity zones at the surveyed sites. Instead, preferential treatment of sites with low host densities was applied (Fig. S3b in Appendix S2). Furthermore, when the tree removal budget was very small, all surveys were allocated to sites with low host densities (Fig. S3a in Appendix S2). The total number of survey sites also increased in this case.

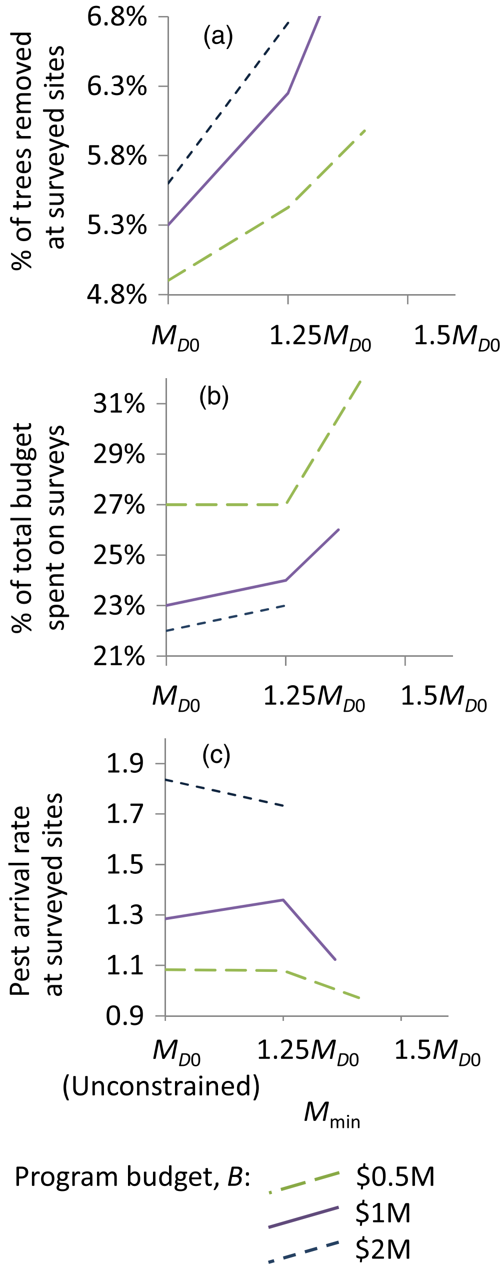

Fig. 5. Optimization model results as related to the M_{min} constraint value: a) proportion of susceptible host trees removed at surveyed sites vs. the M_{min} value; b) the survey cost proportion of the total budget vs. the M_{min} value; c) pest arrival rate, $\sum^{J}(p_j, x_j)$, at surveyed sites vs. the M_{min} value. The M_{D0} value represents the unconstrained solutions where the M_{min} constraint was not used.

When the amount of funds was sufficient for removing the susceptible trees at the surveyed sites, the model selected the highest-risk sites regardless of how many host trees were at those locations (Fig. S3d in Appendix S2). Increasing the survey budget from \$100 k to \$500 k (assuming the same ratio between survey and tree removal costs) did not change the spatial survey patterns (Fig. S3d in Appendix S2). In absolute terms, a larger survey budget increased the proportion of surveys and the number of removed trees at sites with low risk of invasion (Fig. S4a,b in Appendix S2) and decreased the proportion of surveys at high-risk locations (Fig. S4c,d in Appendix S2). As the survey budget increased, more surveys were selected and more trees removed at distant sites (Fig. S4e in Appendix S2).

Table 3
Optimal solutions with unconstrained apportionment of survey and host tree removal costs.

Parameter	Project budget, B		
	\$0.5 M	\$1 M	\$2 M
Survey costs, C (optimal value)	\$109.7 k	\$203.5 k	\$403.9 k
Objective function, τ	8202.3	7813.9	7037.4
% of trees removed at survey sites (average per scenario)	4.9%	5.3%	5.6%
% of surveys at sites with high/low host tree density:			
Low tree density (<100 site^{-1})	58.8%	39.3%	28.1%
High tree density (>300 site^{-1})	7.8%	24.6%	38.5%
Surveys at sites with high risk of ALB invasion ($p_j > 0.03$):			
% of surveyed sites	17.6%	19.7%	15.6%
% of removed trees	46.0%	45.2%	34.7%
Surveys in close proximity (≤400 m) to the quarantine area:			
% of survey sites	27.5%	23.0%	17.7%
% of removed trees	39.6%	16.5%	12.9%
Surveys at long distances (≥1 km) from the quarantine area:			
% of survey sites	37.3%	41.0%	43.8%
% of removed trees	20.6%	27.4%	43.2%

3.6. Sensitivity to Changes in the Project Budget

The survey allocation strategy may also depend on the size of the total project budget. We explored this aspect with a sensitivity analysis of key survey characteristics to budget alterations by ±10% (Table 4). The sensitivity values show the ratio between the relative change in the characteristics of interest (see column 1 in Table 4) and the relative change of the project budget (B) by plus-minus 10%. For example, the sensitivity value 1.0 indicates that the change of the project budget by plus-minus 10% causes the average change in the survey characteristics by 10%. High sensitivity values indicate more abrupt changes in the survey characteristics in response to the project budget deviations from a given level, B. The sensitivities for the percentage of removed host trees and the proportion of survey costs in total budget decreased when the project budget (B) increased (Table 4). A sharp decline in sensitivity was also found for the proportion of surveys at sites with high host densities (Table 4).

For some parameters, the sensitivity values changed drastically once the budget exceeded the \$1 M threshold. In short, an incremental budget increase at a budget level above \$1 M had less impact on the survey characteristics than at budget levels below \$1 M. For example, the sensitivities for the spread capacity, T_{D0}, and the proportion of trees removed at distances above 1 km (Table 4) peaked at $B = \$1$ M and then declined for larger budgets. The sensitivities for the proportion of surveys and the number of trees removed at sites with high host densities declined sharply for budgets below \$1 M and then stayed low for budgets above \$1 M. Overall, this indicates major changes in survey strategy when the project budget exceeds \$1 M. Budgets above \$1 M provide sufficient resources to survey high-risk sites and make the selection of sites with high host densities and at long distances less critical than at small budget levels. Note that budget increases did not yield abrupt changes in the sensitivities for the objective function value; rather, the exhibited increase was gradual and linear (Table 4).

4. Discussion and Conclusions

Forecasts of biological invasions are often uncertain, which makes it difficult to allocate surveillance and management resources effectively (Epanchin-Niell and Hastings, 2010). When the range of possible outcomes of invasion is wide, a robust resource allocation approach that accounts for all plausible invasion scenarios can help decision makers invest scarce resources for surveillance and eradication. Our scenario-based model incorporates the entire distribution of invasion scenarios

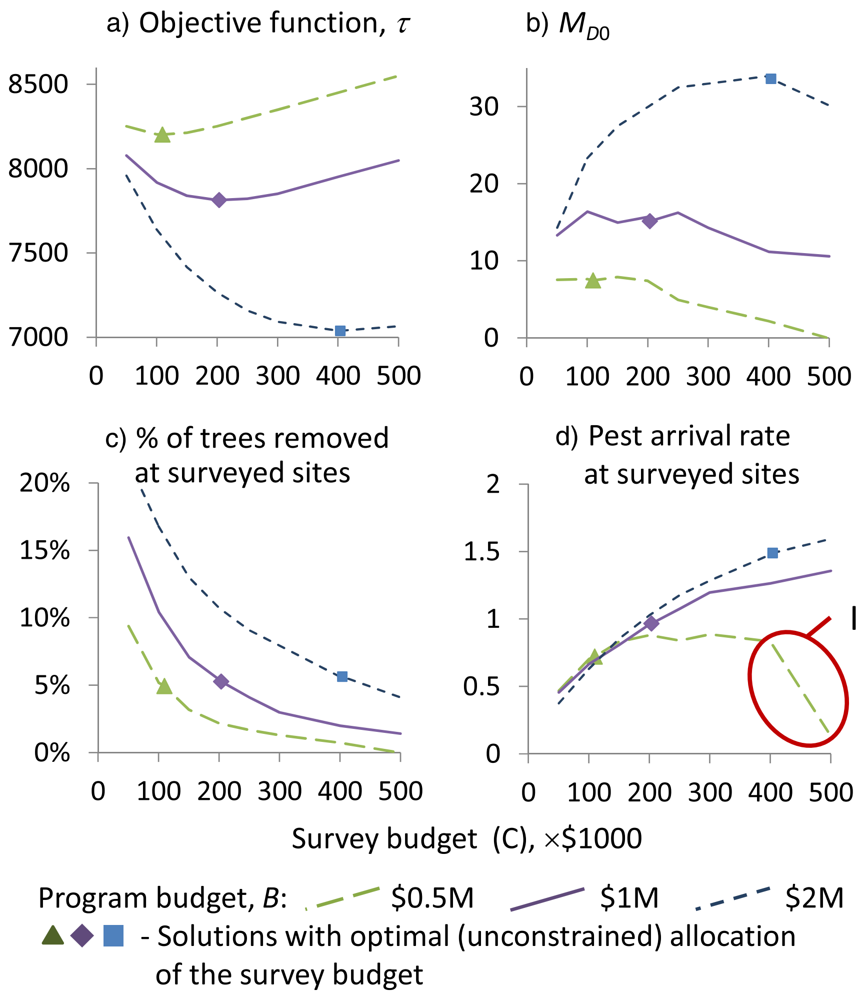

Fig. 6. Key survey selection metrics as related to the survey portion of the budget, C: a) objective function value τ vs. the survey budget; b) M_{D0} metric vs. the survey budget; c) proportion of host trees in the site that are removed vs. the survey budget; d) pest arrival rate, $\sum^{J}(p_j, x_j)$, at the surveyed sites vs. the survey budget. Markers show the unconstrained solutions with optimal apportionments between survey and tree removal costs. Callout I indicates a decrease of the pest arrival rate when the tree removal budget portion is very small.

and creates risk-averse solutions[3] by requiring that investments in surveillance and eradication activities satisfy the budget constraint for all scenarios while minimizing the number of infested and proximate trees remaining.

Our scenario-based approach provides better capacity to factor in uncertainty about spread than a single scenario approach based on the expected probability values. In particular, our approach utilizes estimates of spread made with stochastic models. If we instead used a single scenario approach (i.e., used only the expected spread rate value), the model solutions would generally follow the patterns of the expected probability values. In this case, the optimal strategy would be to allocate surveys starting from the sites with the highest risk of invasion and proceed until the budget is exhausted. However, such a strategy is simplistic because it ignores the uncertainty about where the species is likely to spread. Alternatively, solutions based on a scenario-based approach depict a broader variation of spread and, in turn, allocate a portion of resources to survey sites with lower invasion risk at longer distances. Furthermore, the scenario-based approach provides a good platform for incorporating risk-based objectives that aim to control the degree of variation in the program cost or avoid incurring extreme costs due to uncertainty. The formulation of risk-based constraints can be based on variance or conditional value-at-risk concepts. Such formulations would further improve the robustness of the optimal solutions and would be especially meaningful for risk-averse decision-makers.

[3] This is also an acknowledged property for models based on the robust optimization idea (Kouvelis and Yu, 1997).

4.1. Insights for ALB Management

Our model helps guide general strategies for surveillance of and control of invasive plant pests, including ALB, by combining four basic decision-making aspirations: (i) survey the sites with the highest probabilities of pest arrival; (ii) minimize the expected number of remaining infested and proximate hosts in the managed area; (iii) reduce the capacity of the pest to spread from the surveyed sites to uninvaded areas and (iv) minimize the costs of surveillance and host removal. The first aspiration is captured by using the probabilities of pest arrival, p_j, as random variables to generate the spread scenarios. The second aspiration is depicted by the objective function, τ (Eq. (4)). The third aspiration is captured by the spread capacity constraint, $M_{\min}$ (Eqs. (9), (10)). The final decision-making aspiration is explored in the solutions with a limited budget constraint, B, (Eq. (6)).

For ALB, removal of susceptible host trees from a zone surrounding infested trees has emerged as one of few effective eradication strategies (Haack et al., 2010), which is why the strategy has been adopted in the GTA. Given the impact that broad-scale host removal might have on the available budget, it seemed logical to account for anticipated outcomes of host removal during the survey planning stage. Our formulation provides practical insight into how expected outcomes of pest control

Table 4
Sensitivity values for key survey characteristics. Shaded cells show peak sensitivity values.
The values show the relative change in the survey characteristics (as specified in column 1) in response to changes in the project budget constraint by plus-minus 10% from its defined level, *B*.

Survey characteristics	Project budget (*B*) $M						General trend vs.
	0.25	0.5	1.0	1.5	2.0	2.5	a project budget increase
Objective function value, τ	0.02	0.04	0.10	0.16	0.22	0.28	Linear increase
The survey cost proportion of the total budget, C_{opt}/B	3.35	2.54	1.80	0.99	0.89	0.62	Sharp decline for $B \le$ $1M and very low values for $B >$ $1M
Minimum reduction in the pest's spread capacity from the surveyed sites, M_{D0}	0.77	0.81	1.65	1.04	0.55	0.71	Peaks at B = $1M
Average percent of host trees removed at surveyed sites	0.31	0.66	0.27	0.12	0.05	0.08	General decrease
% of surveys at sites with low host density (<100tr.–site^{-1})	0.44	0.57	1.16	1.30	0.95	1.59	General increase
% of removed trees at sites with low host density (<100tr.–site^{-1})	1.31	1.77	0.87	1.63	1.18	1.59	No clear trend
% of surveys at sites with high host density (>300tr. –site^{-1})	5.51	5.72	0.93	0.51	0.53	0.56	Very high values for $B \le$ $1M and very low values for $B >$ $1M
% of removed trees at sites with high host density (>300tr.–site^{-1})	5.13	4.44	0.79	0.18	0.25	0.11	Very high values for $B \le$ $1M and very low values for $B >$ $1M
% of surveys at close distances to the quarantine area(≤400 m)	0.14	0.39	0.62	2.04	1.15	0.51	Peaks at B = $1.5M
% of surveys at distances > 1 km from the quarantine area	0.56	0.90	0.81	1.10	0.94	0.43	Peak sat B = $1.5M
% of removed trees at close distances to the quarantine area (≤ 400 m)	0.99	0.65	1.04	1 .06	0.94	0.23	No clear trend
% of removed trees at distances > 1 km from the quarantine area	0.44	0.96	2.19	1.34	0.54	0.60	Peaks at B = $1M

actions (such as host removal), combined with managers' aspirations to slow the rate of spread, may alter decisions at this stage. Furthermore, our scenarios with different fixed budgets (Fig. 6, Figs. S3 and S4 in Appendix S2) provide insight into how best to allocate surveys and control measures in the event of an anticipated budget change. The way the surveillance is planned at the present time depends on how much budget is expected to be available for subsequent tree removals. When the eradication budget is anticipated to be large, surveys can target all high-risk sites near the quarantine area. With a moderate eradication budget, it is optimal to extend surveillance beyond these high-risk sites to sites at moderate distances from the quarantine area, and to maximize the survey coverage by selecting sites that can be surveyed and treated at minimum cost.

When the budget is low, it is unfeasible to allocate surveys at long distances from the quarantine area, but instead, it is optimal to survey at closer distances where tree removal for a given budget level can be more effective. However, removal of some of the hosts in the proximity zones of sites adjacent to the quarantine area is insufficient to stop the spread of the pest population. Instead, it is optimal to selectively allocate surveys to sites with very low host densities. Targeting low-density, moderate-risk sites provide better use of the limited budget because, during the eradication phase, removal of the same number of trees at low- versus high-density sites effectively slows the spread over a larger area. As the budget level increases, however, a portion of funds should be set aside to survey sites at long distances because the resources become increasingly sufficient to cover both short-distance, high-risk and long-distance, moderate-risk locations. For example, the sensitivities of the proportion of surveys and percentage of trees removed at distances above 1 km from the quarantine area increase sharply when the project budget exceeds $1 M (Table 4).

Notably, the geographical extent of the surveys (i.e., how far out they extend from the quarantine zone) does not scale down linearly when the program budget decreases. While the budget reduction generally decreases the number of surveys at long distances, it does not eliminate them completely. Effectively, our allocation approach follows a common two-tiered planning strategy when even under strict budget constraints; a portion of the budget is always allocated to search for low-risk incursions at further distances.

Our model was designed to allocate surveys for a single planning period, but it can be applied in a sequential fashion to multiple planning periods. In this case, the outputs from the current period could be used to allocate surveys and control measures for the next period and so on. Alternatively, adding a second planning period to the model itself might improve its capacity to handle longer-term uncertainty. However, this type of multi-period representation would require generating a scenario tree with a very large number of invasion scenarios. While several methods have been proposed to reduce the size of multi-period scenario trees (e.g., Mulvey, 1996; Gulpmar et al., 2004), the number of scenario combinations in a two-period model is likely to be orders of magnitude larger than in a single-period model, and thus would limit the model applications to small datasets only.

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ecolecon.2016.11.018.

References

Animal Plant Health Inspection Service (APHIS), 2005. Asian Longhorned Beetle (*Anoplophoraglabripennis*) Fact Sheet. United States Department of Agriculture, Animal Plant Health Inspection Service (January 2005. Available from http://www.aphis.usda.gov/lpa/pubs/fsheet_faq_notice/fs_phalb.pdf).

Animal Plant Health Inspection Service (APHIS), 2013. Asian Longhorned Beetle Cooperative Eradication Program in Clermont County, Ohio. Available from. http://www.aphis.usda.gov/plant_health/ea/downloads/2013/OHClermontCountyRevised_EA_May_final.pdf.

Aukema, J.E., Leung, B., Kovacs, K., Chives, C., Britton, K.O., Englin, J., Frankel, S.J., Haight, R.G., Holmes, T.P., Liebhold, A.M., McCullough, D.G., Von Holle, B., 2011. Economic impacts of non-native forest insects in the continental United States. PLoS One 6 (9), e24587.

Bertsimas, D., Brown, D.B., Caramanis, C., 2011. Theory and applications of robust optimization. SIAM Rev. 53 (3), 464–501.

Bogich, T.L., Liebhold, A.M., Shea, K., 2008. To sample or eradicate? A cost minimization model for monitoring and managing an invasive species. J. Appl. Ecol. 45 (4), 1134–1142.

Buck, J.H., Marshall, J.M., 2008. Hitchhiking as a secondary dispersal pathway for adult emerald ash borer, *Agrilusplanipennis*. Great Lakes Entomol. 41 (1–2), 197–198.

Cacho, O.J., Spring, D., Hester, S., Mac Nally, R., 2010. Allocating surveillance effort in the management of invasive species: a spatially-explicit model. Environ. Model. Software 25, 444–454.

Carrasco, L.R., Baker, R., MacLeod, A., Knight, J.D., Mumford, J.D., 2010. Optimal and robust control of invasive alien species spreading in homogeneous landscapes. J. R. Soc. Interface 7, 529–540.

Carter, M.E., Smith, M.T., Turgeon, J.J., Harrison, R.G., 2009. Analysis of genetic diversity in an invasive population of Asian longhorned beetles in Ontario, Canada. Can. Entomol. 141, 582–594.

CFIA (Canadian Food Inspection Agency), 2014. Anoplophora glabripennis (Motschulsky) - Asian Longhorned Beetle - Fact Sheet. Available from. http://www.inspection.gc.ca/plants/plant-pests-invasive-species/insects/asian-longhorned-beetle/fact-sheet/eng/1447168284946/1447168408039.

City of Toronto, Parks, Forestry and Recreation, Urban Forestry, 2013e. Every Tree Counts: A Portrait of Toronto's Urban Forest. City of Toronto, Parks, Forestry and Recreation, Toronto, ON (108 pp.

Cook, G., Downing, M., 2013. Traffic Pattern Project Report: Methodology for Interpolating Traffic Count Data to a Road Network. USDA Animal Plant Health Inspection Service, Plant Protection and Quarantine, Centre for Plant Health Science and Technology, Fort Collins, CO (18 pp.

Davidovitch, L., Stoklosa, R., Majer, J., Nietrzeba, A., Whittle, P., Mengerson, K., Ben-Haim, Y., 2009. Info-gap theory and robust design of surveillance for invasive species: the case study of Barrow Island. J. Environ. Manage. 90, 2785–2793.

Epanchin-Niell, R.S., Hastings, A., 2010. Controlling established invaders: integrating economics and spread dynamics to determine optimal management. Ecol. Lett. 13, 528–541.

Epanchin-Niell, R.S., Liebhold, A.M., 2015. Benefits of invasion prevention: effect of time lags, spread rates, and damage persistence. Ecol. Econ. 116, 146–153.

Epanchin-Niell, R.S., Haight, R.G., Berec, L., Kean, J.M., Liebhold, A.M., 2012. Optimal surveillance and eradication of invasive species in heterogeneous landscapes. Ecol. Lett. 15, 803–812.

Epanchin-Niell, R.S., Brockerhoff, E., Kean, J., Turner, J., 2014. Designing cost-efficient surveillance for early-detection and control of multiple invading species. Ecol. Appl. 24, 1258–1274.

EPPO (European and Mediterranean Plant Protection Organization), 2008t. EPPO Reporting Service, No. 5. Available at:. http://archives.eppo.org/EPPOReporting/2008/Rse-0805.pdf.

ESRI, 2014. Street Map Premium for ArcGIS. Available from. http://www.esri.com/data/streetmap.

Favaro, R., Wichmann, L., Ravn, H.P., Faccoli, M., 2015. Spatial spread and infestation risk assessment in the Asian longhorned beetle, *Anoplophoraglabripennis*. Entomol. Exp. Appl. 155 (2), 95–101.

GAMS (GAMS Development Corporation), 2015. General Algebraic Modeling System (GAMS) Release 24.6 (Washington, DC, USA).

Gulpmar, N., Rustem, B., Settergren, R., 2004. Simulation and optimization approaches to scenario tree generation. J. Econ. Dyn. Control 28, 1291–1315.

GUROBI (Gurobi Optimization Inc.), 2014. GUROBI Optimizer Reference Manual. Version 6.0. Available from. https://www.gurobi.com/documentation/6.0/refman.pdf.

Haack, R.A., Law, K.R., Mastro, V.C., Ossenbruggen, H.S., Raimo, B.J., 1997. New York's battle with the Asian longhorned beetle. J. For. 95, 11–15.

Haack, R.A., Heerard, F., Sun, J., Turgeon, J.J., 2010. Managing invasive populations of Asian longhorned beetle and citrus longhorned beetle: a worldwide perspective. Annu. Rev. Entomol. 55, 521–546.

Haight, R.G., Polasky, S., 2010. Optimal control of an invasive species with imperfect information about the level of infestation. Resour. Energy Econ. 32, 519–533.

Hauser, C.E., McCarthy, M.A., 2009. Streamlining 'search and destroy': cost-effective surveillance for invasive species management. Ecol. Lett. 12, 683–692.

Hester, S.M., Cacho, O.J., 2012. Optimization of search strategies in managing biological invasions: a simulation approach. Hum. Ecol. Risk. Assess. 18, 181–199.

Hester, S.M., Brooks, S., Cacho, O.J., Panetta, F.D., 2010. Applying a simulation model to the management of an infestation of *Miconiacalvescens* in the wet tropics of Australia. Weed Res. 50, 269–279.

Horie, T., Haight, R.G., Homans, F., Venette, R.C., 2013. Optimal strategies for the surveillance and control of forest pathogens: a case study with oak wilt. Ecol. Econ. 86 (C), 78–85.

Hulme, P.E., Bacher, S., Kenis, M., Klotz, S., Kuhn, I., Minchin, D., Nentwig, W., Olenin, S., Panov, V., Pergl, J., Pyšek, P., Roques, A., Sol, D., Solarz, W., Vila, M., 2008. Grasping at the routes of biological invasions: a framework for integrating pathways into policy. J. Appl. Ecol. 45, 403–414.

Kim, C.S., Lubowski, R.N., Lewandrowski, J., Eiswerth, M.E., 2006. Prevention or control: optimal government policies for invasive species management. Agric. Resour. Econ. Rev. 35 (1), 29–40.

Koch, F.H., Yemshanov, D., McKenney, D.W., Smith, W.D., 2009. Evaluating critical uncertainty thresholds in a spatial model of forest pest invasion risk. Risk Anal. 29 (9), 1227–1241.

Kouvelis, P., Yu, G., 1997. Robust Discrete Optimization and its Applications. Kluwer Academic Publishers, Norwell, MA.

Lee, Y., Fried, J.S., Albers, H.J., Haight, R.G., 2013. Deploying initial attack resources for wildfire suppression: spatial coordination, budget constraints, and capacity constraints. Can. J. For. Res. 43, 56–65.

Lingafelter, S.W., Hoebeke, E.R., 2002. Revision of Anoplophora (Coleoptera: Cerambycidae). Entomological Society of Washington, Washington.

Mak, W.K., Morton, D.P., Wood, R.K., 1999. Monte Carlo bounding techniques for determining solution quality in stochastic programs. Oper. Res. Lett. 24, 47–56.

Mason, A.J., 2013. SolverStudio: a new tool for better optimisation and simulation modelling in excel. INFORMS Trans. Educ. 14 (1), 45–52.

Maspero, M., Jucker, C., Colombo, M., 2007. First record of *Anoplophoraglabripennis* (Motschulsky) (Coleoptera: Cerambycidae, Lamiinae, Lamiini) in Italy. Boll. Zoologia Agrar. Bachicoltura 39, 161–164.

Mehta, S.V., Haight, R.C., Homans, F.R., Polasky, S., Venette, R.C., 2007. Optimal detection and control strategies for invasive species management. Ecol. Econ. 61, 237–245.

Melbourne, B.A., Hastings, A., 2009. Highly variable spread rates in replicated biological invasions: fundamental limits to predictability. Science 325, 1536–1539.

Meng, P.S., Hoover, K., Keena, M.A., 2015. Asian longhorned beetle (Coleoptera: Cerambycidae), an introduced pest of maple and other hardwood trees in North America and Europe. J. Integr. Pest Manag. 6:4. http://dx.doi.org/10.1093/jipm/pmv003.

Meyerson, L.A., Reaser, J.K., 2003. Bioinvasions, bioterrorism, and biosecurity. Front. Ecol. Environ. 1 (3), 307–314.

Mulvey, J.M., 1996. Generating scenarios for the tower perrin investment system. Interfaces 26, 1–13.

Nehme, M.E., Trotter, R.T., Keena, M.E., McFarland, C., Coop, J., Hull-Sanders, H.M., Meng, P., De Moraes, D.M., Mescher, M.C., Hoover, K., 2014. Development and evaluation of a trapping system for *Anoplophoraglabripennis* (Coleoptera: Cerambycidae) in the United States. Environ. Entomol. 43, 1034–1044.

NISC (National Invasive Species Council), 2007. Fact Sheet: National Invasive Species Council Fiscal Year 2007 Interagency Invasive Species Performance Budget. (online source:). National Invasive Species Council (Available from http://www.invasivespecies.gov/global/org_collab_budget/organizational_budget_performance:based_budget.html).

Nowak, D.J., Pasek, J.E., Sequeira, R.A., Crane, D.E., Mastro, V.C., 2001. Potential effect of *Anoplophoraglabripennis* (Coleoptera: Cerambycidae) on urban trees in the United States. J. Econ. Entomol. 94, 116–122.

Olson, L.J., Roy, S., 2005. On prevention and control of an uncertain biological invasion. Appl. Econ. Perspect. Policy 27 (3), 491–497.

Pejchar, L., Mooney, H.A., 2009. Invasive species, ecosystem services and human well-being. Trends Ecol. Evol. 24, 497–504.

Perrings, C., Dehnen-Schmutz, K., Touza, J., Williamson, M., 2005. How to manage biological invasions under globalization. Trends Ecol. Evol. 20, 212–215.

Peterson, A.T., Scachetti-Pereira, R., 2004. Potential geographic distribution of *Anoplophoraglabripennis* (Coleoptera: Cerambycidae) in North America. Am. Midl. Nat. 151 (1), 170–178.

Pyšek, P., Richardson, D.M., 2010. Invasive species, environmental change and management, and health. Annu. Rev. Env. Resour. 35, 25–55.

Rafoss, T., 2003. Spatial stochastic simulation offers potential as a quantitative method for pest risk analysis. Risk Anal. 23 (4), 651–661.

Reaser, J.K., Meyerson, L.A., Von Holle, B., 2008. Saving camels from straws: how propagule pressure-based prevention policies can reduce the risk of biological invasion. Biol. Invasions 10, 1085–1098.

SACTRA (Standing Advisory Committee for Trunk Road Assessment), 1999e. Transport and the Economy: Full Report (SACTRA). Available from. http://webarchive.nationalarchives.gov.uk/20050301192906/http:/dft.gov.uk/stellent/groups/dft_econappr/documents/pdf/dft_econappr_pdf_022512.pdf.

Shatz, A.J., Rogan, J., Sangermano, F., Ogneva-Himmelberger, Y., Chen, H., 2013. Characterizing the potential distribution of the invasive Asian longhorned beetle (*Anoplophoraglabripennis*) in Worcester County, Massachusetts. Appl. Geogr. 45, 259–268.

Sims, C., Finnof, D., 2013. When is a "wait and see" approach to invasive species justified? Resour. Energy Econ. 35, 235–255.

Smith, M.T., Wu, J.Q., 2008. Asian longhorned beetle: renewed threat to northeastern USA and implications worldwide. Int. Pest Control 50, 311–316.

Smith, M.T., Bancroft, J., Li, G.H., Gao, R.T., Teale, S., 2001. Dispersal of *Anoplophoraglabripennis* (Cerambycidae). Environ. Entomol. 30 (6), 1036–1040.

Smith, M.T., Tobin, P., Bancroft, J.S., Li, G.H., Gao, R.T., 2004. Dispersal and spatiotemporal dynamics of Asian longhorned beetle (Coleoptera: Cerambycidae) in China. Environ. Entomol. 33, 435–442.
Smith, M.T., Turgeon, J.J., De Groot, P., Gasman, B., 2009. Asian longhorned beetle *Anoplophoraglabripennis* (Motschulsky): lessons learned and opportunities to improve the process of eradication and management. Am. Entomol. 55 (1), 21–25.
SOLRIS (Southern Ontario Land Resource Information System), 2008,. Land Use Data. The Ontario Ministry of Natural Resources, Toronto, Ontario.
Straw, N., Fielding, N., Tilbur, C., Williams, D., Inward, D., 2015. Host plant selection and resource utilisation by Asian longhorned beetle *Anoplophoraglabripennis* (Coleoptera: Cerambycidae) in southern England. Forestry 88, 84–95.
Tetrad, 2014. TrafficMetrix Canada. Official website:. http://www.tetrad.com/maps_and_data/canada/traffic/.
Tobin, P.C., 2008. Cost Analysis and Biological Ramifications for Implementing the Gypsy Moth Slow the Spread Program. Gen. Tech. Rep. NRS-37. U.S. Department of Agriculture, Forest Service, Northern Research Station, Newtown Square, PA.
Trotter III, E.T., Hull-Sanders, H.M., 2015. Quantifying dispersal of the Asian longhorned beetle (*Anoplophoraglabripennis*, Coleoptera) with incomplete data and behavioral knowledge. Biol. Invasions http://dx.doi.org/10.1007/s10530-015-0961-9.
Turgeon, J.J., Pedlar, J., de Groot, P., Smith, M.T., Jones, C., Orr, M., Gasman, B., 2010. Density and location of simulated signs of injury affect efficacy of ground surveys for Asian longhorned beetle. Can. Entomol. 142, 80–96.
Turgeon, J.J., Orr, M., Grant, C., Wu, Y., Gasman, B., 2015. Decade-old satellite infestation of *Anoplophoraglabripennis* Motschulsky (Coleoptera: Cerambycidae) found in Ontario, Canada outside regulated area of founder population. Coleopt. Bull. 69, 674–678.
Wang, B., Mastro, V.C., Gao, R.T., 2005. Host range of *Anoplophoraglabripennis*: what we've learned from common-garden experiment data. In: Fosbroke, S.L.C., Gottschalk, K.W. (Eds.), 16th U.S. Department of Agriculture Interagency Research Forum on Gypsy Moth and Other Invasive Species 2005. Newtown Square, PA, USDA Forest Service General Technical Report. NE-GTR-337, p. 89.
Williams, D.W., Lee, H.-P., Kim, I.-K., 2004. Distribution and abundance of *Anoplophoraglabripennis* (Coleoptera: Cerambycidae) in natural *Acer* stands in South Korea. Environ. Entomol. 33, 540–545.
Yemshanov, D., Koch, F.H., McKenney, D.W., Downing, M.C., Sapio, F., 2009. Mapping invasive species risks with stochastic models: a cross-border United States-Canada application for *Sirexnoctilio* Fabricius. Risk Anal. 29, 868–884.
Yemshanov, D., Koch, F.H., Lu, B., Lyons, B.D., Prestemon, J.P., Scarr, T., Koehler, K., 2014. There is no silver bullet: the value of diversification in planning invasive species surveillance. Ecol. Econ. 104, 61–72.