Hierarchical governance in invasive species survey campaigns

Denys Yemshanov [a,*], Robert G. Haight [b], Chris J.K. MacQuarrie [a], Mackenzie Simpson [a], Frank H. Koch [c], Kathleen Ryan [d], Erin Bullas-Appleton [e]

[a] *Natural Resources Canada, Canadian Forest Service, Great Lakes Forestry Centre, Sault Ste. Marie, ON, Canada*
[b] *USDA Forest Service, Northern Research Station, St. Paul, MN, USA*
[c] *USDA Forest Service, Southern Research Station, Research Triangle Park, NC, USA*
[d] *Silv-Econ Ltd. Newmarket, ON, Canada*
[e] *Canadian Food Inspection Agency, Guelph, ON, Canada*

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ABSTRACT

Large-scale delimiting surveys are critical for detecting pest invasions and often undertaken at different governance levels. In this study, we consider two-level hierarchical planning of surveys of harmful invasive pests including a government agency with a mandate to report the spatial extent of an invasion, and regional governments (counties) concerned about the possible threat of an outbreak. The central agency plans delimiting pest surveys across multiple administrative subdivisions. Counties could participate in these surveys if funds become available. Our goal is to find the optimal levels of cooperation between the central agency and regional governments in the form of the central agency sharing funds with regional governments in a way that benefits both it and the other entities. We propose a Stackelberg game model that finds optimal levels of collaboration between two levels of government in large-scale pest survey campaigns. We apply the model to surveillance of hemlock woolly adelgid, a harmful pest of hemlock trees in Ontario, Canada. Our solutions help anticipate the under-performance of surveys conducted by regional governments because their goals do not fully align with the central agency survey objective. The methodology can be adapted to explore governance hierarchies in other regions and political jurisdictions.

1. Introduction

The spread of invasive species poses major social, environmental and economic concerns in North America and elsewhere (Aukema et al., 2010; Crystal-Ornelas et al., 2021; Zenni et al., 2021; Warziniack et al., 2021). Long-distance spread, facilitated by human activities or in some cases by biota acting as vectors, contributes the most to rapid expansion of novel pest populations across large regions (Siegert et al., 2015; Evans, 2016; Short et al., 2019). As the invaded area becomes larger, timely detection of emerging populations becomes problematic and requires carefully planned deployment of scarce survey resources and personnel.

A delimiting survey is performed to uncover the current extent of an invader's distribution in an area of interest (Ewel et al., 1999; Holden et al., 2016; Leung et al., 2014). Delineating the spatial extent of the invasion makes rapid response measures more effective, which is critical to reduce the damages that could occur if the invasion continued to proceed unchecked (Epanchin-Niell et al., 2012, 2014; Leung et al., 2002; Lodge et al., 2006; Rout et al., 2014). Government agencies tasked with responding to new pest populations can spend considerable resources on delimitation when a pest is detected (Epanchin-Niell et al., 2012). Primarily, national governments are interested in delineating the extent of invasion at a broad geographical scale, to guide the establishment of quarantines or other mitigation measures aimed to prevent or slow the nationwide spread of the pest. In parallel, regional and local governments may undertake similar actions aimed at detecting incursions by the pest within their jurisdictions. These actions are intended to help mitigate possible damages to local economies including negative impacts on property values (Holmes et al., 2010), ecosystem services (Cessna and Nielsen, 2012; Dharmadi et al., 2019) and local wildlife populations (Reay, 2000; Siddig et al., 2016; Degrassi, 2018).

Ideally, surveys for novel pests could be more cost-effective if there

was coordination of the surveys between the central agency responsible for determining the nationwide extent of biological invasions (such as the Canadian Food Inspection Agency) and regional authorities responsible for mitigating the local effects of those invasions. Surveys by regional governments may be more efficient than those performed by the central agency because regional authorities may have better local knowledge (e.g., the local distribution of hosts that are susceptible to a pest) and may be able to survey at a lower cost than the central agency. In this context, the central agency might benefit from collaboration with regional governments via hierarchical planning, where an agency operating at one level of government (i.e., the top level in the hierarchy) uses some of its resources to conduct its own work and distributes the rest of its funds to regional governments, where planners make spending decisions for their administrative areas. In the United States, the Cooperative Agricultural Pest Survey (Cooperative Agricultural Pest Survey (CAPS), 2022) is administered by USDA Animal and Plant Health Inspection Service (APHIS) Plant Protection Quarantine (PPQ) and carried out by US state-level inspectors under guidelines established by the federal agency. The surveys are conducted primarily under USDA funding that is provided through cooperative agreements with state departments of agriculture, universities and other entities. The State of Minnesota's Invasive Species Prevention Aid program uses this approach to allocate approximately US$10 million a year to county governments to prevent the introduction and spread of aquatic invasive species (Minnesota Department of Natural Resources (MDNR), 2020a, 2020b; Haight et al., 2021). In this program, individual counties decide how to use the funds to slow the spread of aquatic invasive species within their own jurisdictions.

In this study, we consider two levels of planning to conduct surveillance for an invasive pest. The first level is that of a government agency with a mandate to report the extent of the pest invasion (central agency hereafter). The central agency needs to allocate its survey inspections for signs of invasion across an entire ecoregion. The second planning level is represented by regional governments (counties hereafter) who are concerned about the extent but also the abundance of the pest within their jurisdictions. Counties may have their own capacity to inspect sites, but only if funds become available.

The goals of inspections implemented by the central agency and counties are distinct. The central agency's goal is to delineate the pest's presence at a coarse resolution of large administrative subdivisions (townships). Briefly, the central agency seeks information on possible presence of the pest in each township. Typically, central agency managers are only interested in knowing which townships have positive detections, as confirming true absences is more challenging due to imperfect detection accuracy and omnipresent possibility of overlooked pest populations. In contrast, the county governments are only concerned with the status of the pest within their administrative areas but want more details about the size of any detected pest populations to guide mitigation and eradication efforts. Thus, the central agency and county survey objectives differ in both the scale of their implementation and the level of ecological detail about the invasive pest.

We consider a scenario where the central agency may conduct surveys using their own inspectors or allocate a portion of their funds to county governments to conduct surveys as a measure to reduce costs and improve efficiency. Our objective is to determine when and where it is economically optimal for the central agency to use their own inspectors versus allocating some survey funds to counties. We propose a bi-level survey planning problem that determines how a central agency could efficiently allocate a portion of funds to regional governments, who then decide where to conduct surveys for the invasive pest within their jurisdictions. We formulate such a strategy as a non-cooperative leader-follower Stackelberg game (Myerson, 2013). A Stackelberg game (Colson et al., 2007; Von Stackelberg, 2010) involves a set of players who move sequentially. The leader moves first, and the other players (the

followers) move after observing the leader's move. Stackelberg games have been applied to investigate the impact of taxing greenhouse gas emissions taxation on remanufacturing (Yenipazarli, 2016), forest product industries (Paradis et al., 2015), allocating funds for fire suppression (Amacher et al., 2006) and for wildlife conservation (Yemshanov et al., 2021). The optimal solution in this study is for the central agency (the leader) to use some funds to do their own inspections and allocate the remainder to counties (the followers), with the anticipation that they will maximize their own objectives while providing the information required by the central agency.

We solve this leader-follower problem using a bi-level optimization. Bi-level optimization is a common approach to solve hierarchical resource allocation problems (Colson et al., 2005), such as finding optimal government policies for biofuel production (Bard et al., 2000), transportation (Brotcorne et al., 2001), biotechnology (Burgard et al., 2003; Ren et al., 2013), energy generation (Arroyo, 2010; Hobbs et al., 2000; Hu and Ralph, 2007) and forestry (Bogle and van Kooten, 2012; Paradis, 2016; Paradis et al., 2015; Ramo and Tahvonen, 2017; Yemshanov et al., 2021; Yue and You, 2014; Zhai et al., 2014). Our bi-level model apportions pest survey resources between a central agency and counties in a spatial setting, by incorporating site inspection costs, pest detection rates and likelihoods of invasion. We applied the model to assist with the planning of optimal survey strategies for hemlock woolly adelgid (HWA, *Adelges tsugae* Annand (Hemiptera: Adelgidae) in Ontario, Canada. HWA is an invasive insect that kills some North American species of hemlock, including the widely distributed eastern hemlock, *Tsuga canadensis* (L.) Carrière. HWA has been spreading in the eastern USA for >50 years (Ellison et al., 2018) and was recently detected in southern Ontario (Canadian Food Inspection Agency (CFIA), 2020).

2. Methods

Below we formulate a bi-level pest survey planning problem for the central agency and county planner. The central agency planner aims to uncover the "big picture" about the extent of the HWA invasion in survey area (southern Ontario), which translates to selecting hemlock sites for inspections to maximize the expected number of townships with positive detections. A county government is also interested in the location of hemlock stands invaded by HWA but may further wish to know the abundance or density of HWA within the stand, information required to take action to mitigate the invasion (e.g., by application of insecticides).

Consider a landscape of J sites with host trees susceptible to pest attack. The landscape is divided into R counties and N townships. Each county r, $r \in R$, includes N_r townships. Each township n, $n \in N$, includes a number of sites with host trees, J_n, which may be invaded by the pest. We consider three levels of territorial units: J sites with host trees susceptible to invasion, some of which can be visited for inspections, N townships and R counties. The number of sites with host trees susceptible to pest attack in county r is J_r. Counties r are the largest subdivisions, townships n are smaller-scale spatial units and inspection sites j are the finest-scale spatial units.

Some sites j in landscape J may be invaded by a pest population. A planner allocates a budget C to inspect the selected sites for signs of the pest. The probability that site j is invaded is p_j and the probability that inspection of site j finds signs of invasion if the invasion is present is e. Therefore, the probability of detecting signs of invasion in site j is $p_j e$. For each site j, we estimate the likelihood of invasion p_j using a pest dispersal model based on prior knowledge of the invader's behaviour and records of its recent spread in neighbouring regions.

We consider two levels of governance to undertake pest surveys in area J: a central agency planner and county planners. When the central agency's planner makes a new detection or becomes aware of an

infestation, they may regulate the area invaded by the pest (e.g., banning the movement of host plants and commodities that might harbour the pest from the invaded area). The central agency has a mandate to produce a delimiting survey of the townships with detected infestations (see Canadian Food Inspection Agency (CFIA), 2020). The central agency can use its own inspectors to survey sites j.

We formulate three pest survey problems for the central agency. Problem 1 describes the scenario when the central agency makes all survey decisions and inspections by itself. In problem 2, the central agency makes all survey decisions but may contract a county to survey some sites if the survey cost using the county's inspectors is lower than the cost of inspections by the central agency's inspectors. Problem 2 assumes that counties follow the central agency's objective. In practice, the central agency cannot control which sites a county's planner decides to inspect nor whether a county decides to do a second survey when it detects the target pest. Furthermore, the county's planner is likely to have differing survey objectives than the central agency's planner. Nevertheless, the solutions to problem 2 provide a theoretical upper bound that can be compared with other formulations. Problem 3 addresses the shortcomings of problem 2 and is formulated as a bi-level model in which the central agency's planner and county planners have different survey objectives and site inspection costs. Problem 3 describes how the central agency's planner can efficiently allocate funds to counties who have autonomy in selecting sites for survey, which is a more realistic scenario than the assumptions in problem 2.

2.1. Problem 1: Central agency planner's pest survey

We first formulate the pest surveillance problem from the central agency planner's perspective. The probability of not detecting an infestation in site j is $1 - p_j e$. Let x_j be a binary decision variable which defines whether site j is inspected by the central agency planner ($x_j = 1$ and $x_j = 0$ otherwise). The probability that the survey does not find an infestation in site j is $1 - x_j p_j e$. The probability that the inspections of sites do not detect infestation in township n is:

$$w_n = \prod_{j=1}^{J_n} \left(1 - p_j e\right)^{x_j} \qquad [1]$$

where set J_n denotes the sites j that are potential candidates for inspections in township n.

The spread of an invasive organism to a particular location is uncertain. We model the uncertainty about the spread with a scenario-based approach. We generate a set of S discrete invasion scenarios where each scenario s depicts a stochastic realization of the organism's spread to a particular site j, with invasion probability p_j. We simulate the detection outcomes via uniform random draws from a set of possible detection outcomes $\{0,1\}$ with probability $p_j e$. In scenario s, the pest can be either detected in invaded site j (i.e., $p_{js} e = 1$) or detection fails (i.e., $p_{is} e = 0$). The probability that the inspections do not find infestations in township n, scenario s is:

$$w_{ns} = \prod_{j=1}^{J_n} \left(1 - p_{js} e\right)^{x_j} \quad \forall \quad s \in S \qquad [2]$$

The central agency's planner aims to uncover the "big picture" about the extent of invasion in landscape J, which translates to maximizing the expected number of townships with positive detections over S invasion scenarios, i.e.:

$$max \frac{1}{S} \sum_{s=1}^{S} \sum_{n=1}^{N} (1 - w_{ns}) \qquad [3]$$

The central agency planner's cost to inspect site j is c_j. The total number of sites that can be inspected is limited by an upper-bound budget C:

$$\sum_{j=1}^{J} c_j x_j \leq C \qquad [4]$$

Eq. [2] is a non-linear function of the decision variables x_j but can be linearized via an approximation (Camm et al., 2002; Arthur et al., 2002) (see Supplement S1). Table 1 lists the model parameters and decision variables.

Table 1
Model parameters and variables.

Symbol	Parameter / variable name	Description
Sets:		
N	Townships	$n \in N$
R	Counties	$r \in R$
J	Sites with host trees susceptible to pest attack	$j \in J$
J_n	Sites with host trees susceptible to pest attack in township n	
J_r	Sites with host trees susceptible to pest attack in county r	
S	Invasion scenarios	$s \in S$
V	Possible candidate budget levels which the central agency planner may devolve to each county r	$v \in V$
I	Central agency inspectors stationed in different geographic locations i	$i \in I$
K	Break points to approximate the interval]0;1] of the probabilities of not detecting an infestation in township n	$k \in K$
Decision variables:		
x_j	Binary indicator of whether site j is inspected by the central agency planner	$x_j \in \{0,1\}$
z_j	Binary indicator of whether site j is inspected by the county planner in the bi-level problem formulation	$z_j \in \{0,1\}$
u_j	Binary indicator of whether site j is inspected by the county planner in the local county planner's problem	$u_j \in \{0,1\}$
f_{ji}	Binary indicator of whether the central agency inspector stationed in location i surveys site j	$f_{ji} \in \{0,1\}$
ω_{rv}	Binary selection indicator of the precomputed optimum (and a corresponding subset of the inspected sites j with $y_{jrv} = 1$) from the set of local county planner's solutions for R counties and V budget levels	$\omega_{rv} \in \{0,1\}$
λ_{nks}	Non-negative decision variable for township n in invasion scenario s, that selects the break point k to approximate the interval]0;1] of the probabilities of not detecting an infestation in township n.	$\lambda_{nks} \geq 0$
w_{ns}	The probability that the inspections in township n do not find infestations in scenario s	$w_{ns} \geq 0$
Parameters		
p_{js}	Likelihood that site j in invaded in scenario s	$p_{js} \in [0;1[$
e	Likelihood that central agency inspector finds signs of attack after inspecting site j	$e \in [0;1[$
e_{local}	Likelihood that county inspector finds signs of attack after inspecting site j	$e_{local} \in]0;1[$
c_j	Cost to visit and inspect a site j by the central agency inspector	$c_j \geq 0$
q_{ji}	Cost to visit and inspect a site j by the central agency inspector stationed in location i	$q_{ji} \geq 0$
C	Survey budget limit for the central agency	$C > 0$
C_r	Total budget available to the local planner in county r	$C_r > 0$
C_{rv}	Discretized levels of funding v which the central agency planner may devolve to each county r, $C_{r1}, ..., C_{rV}$	$0 \leq C_{rv} \leq C$
d_j	Cost to the county planner to inspect site j for signs of pest attack	$d_j \geq 0$
d_{2j}	Cost to the county planner to conduct second survey to estimate the density of the pest population after detecting an infestation in site j	$d_{2j} \geq 0$
y_{jrv}	Binary parameter indicating whether the local inspectors from county r visited site j when the central agency planner allocated the budget portion C_{rv} to the county r at level v	$y_{jrv} \in \{0,1\}$
G	Maximum number of sites that can be inspected in township n	$0 < G \leq J_n$
Q_i	Maximum number of sites that can be surveyed by inspector(s) stationed in location i	$0 < Q_i \leq J$
B_k	The value of kth break point in a set of K break points to approximate the interval]0;1] of the probabilities of not detecting an infestation in township n	$B_k \in]0;1]$

2.2. Problem 2: Central agency planner's pest survey delegating some inspections to counties

In theory, the central agency could use its own inspection resources to conduct surveys. As a cost reduction measure, the central agency may consider partially devolving survey responsibilities for the pest to county governments. Counties may be able to conduct surveys for less cost than the central planner, which would increase the number of sites that can be surveyed, and thus the chances of successful detection. However, since counties are also responsible for managing any infestations they detect, they likely will have other information needs from a survey.

Once a detection is made, county planners must decide how to manage the pest and so, in addition to identifying invaded locations, they need to estimate the size of the pest population in each detected site. This estimation determines whether the population requires a management action, and if so, what action that might be (e.g., remove the infested trees or apply insecticides). When a county receives funds, the county's planner arranges inspections of sites j in the county with susceptible host. The cost to inspect site j in county r is d_j. Compared to the central agency's planner, the county's planner is interested in a fuller characterization of infestations. If a county's inspectors detect an infestation in a survey site, they should then conduct a second, more detailed survey to estimate the size of the pest's population (e.g., MacQuarrie et al., 2021). Thus, a second survey in site j is conditional on detecting the pest presence in j in the first survey. The costs to do the first and second surveys in site j in county r are d_j and d_{2j}. The expected cost of inspecting site j is $d_j + d_{2j}p_j e_{local} = (d_j + d_{2j}) p_j e_{local} + d_j (1 - p_j e_{local})$ without factoring in the uncertainty about invasion spread. Symbol e_{local} denotes the probability that the first survey by a county's inspectors finds signs of infestation. The first term on the right-hand-side of the expected cost equation is the survey cost when the pest is found, which includes the cost of the initial survey plus the cost of the more detailed survey to estimate the size of the pest's population, multiplied by the probability of finding the pest. The second term on the right-hand-side is the cost of the initial survey times the probability of not finding the pest. When factoring in the uncertainty about the pest's spread, the cost of inspecting site j in scenario s is $d_j + d_{2j}p_{js}e_{local}$.

We proceed with formulating the pest survey problem when the central agency's planner allocates a portion of surveys to their inspectors but may devolve some funds to counties to conduct surveys in their jurisdictions. In this scenario, we assume that the central agency's planner directs the county planners as to which sites to inspect. We introduce a binary variable z_j, which identifies sites j surveyed by county inspectors ($z_j = 1$, and $z_j = 0$ if j was inspected by central agency staff or not surveyed). The central agency planner's survey problem with a partial delegation of inspections to county planners (problem 2 hereafter) can be formulated as follows:

Objective [3],

s.t.:

$$w_{ns} = \prod_{j=1}^{J_n} \left[\left(1 - p_{js}e\right)^{x_j} \left(1 - p_{js}e_{local}\right)^{z_j} \right] \quad \forall \ s \in S \qquad [5]$$

$$\sum_{j=1}^{J} c_j x_j + \sum_{j=1}^{J} \left[z_j \left(d_j + d_{2j}p_{js}e_{local}\right) \right] \leq C \ \forall \ s \in S \qquad [6]$$

$$x_j + z_j \leq 1 \quad \forall \ j \in J \qquad [7]$$

As in objective [3], the central agency planner in Problem 2 aims to uncover the "big picture" about the extent of invasion in landscape J, which translates to identifying which sites to inspect (whether by the central agency or the county) to maximize the expected number of townships with positive detections over S invasion scenarios. By solving this problem, we can identify which sites to inspect to maximize the expected number of townships with positive detections (which is the central agency's objective).

Eq. [5] is analogous to eq. [2] and defines the probability that the inspections do not find infestations in township n, scenario s. Eq. [5] is non-linear and was linearized via an approximation (see Supplement S1). We assume that the central agency's inspectors and the county's inspectors may have different proficiency at detecting signs of infestation, so Eq. [5] applies different detection probabilities, e and e_{local}. Constraint [6] defines the project budget and includes the cost of inspections by the central agency and the counties. Note that, because a county's inspection cost is conditional on the probability of infestation in each scenario (p_{js}), we constrain total cost under each scenario s to be less than the budget C. Constraint [7] specifies that site j can be surveyed by either a central agency inspector or a county inspector but not both.

2.3. Problem 3: Bi-level pest surveillance

The most significant difference between the central agency's planner and the counties planners is the type of information they require. A county's planner wants to maximize the estimation of pest population densities in sites where the pest is detected, which is equivalent to maximizing the expected number of sites with second surveys. Since completing a second survey is conditional on detecting the pest in the first survey, the county's objective is equivalent to maximizing the expected number of inspected sites in county r with positive detections, i. e.,:

$$max \frac{1}{S} \sum_{j=1}^{J_r} \left(u_j \sum_{s=1}^{S} p_{js} e_{local} \right) \qquad [8]$$

s.t.:

$$\sum_{j=1}^{J_r} \left(u_j \left[d_j + d_{2j}p_{js}e_{local} \right] \right) \leq C_r \quad \forall \ s \in S \qquad [9]$$

where C_r, $0 \leq C_r \leq C$, is the budget available to the planner in county r and binary variable u_j defines whether site j is visited by the county inspector ($u_j = 1$ and $u_j = 0$ otherwise). The county planner's objective [8] differs from the central agency planner's objective [3], which maximizes the expected number of townships with positive detections. Furthermore, the spatial extent of the county's inspections is limited to sites within the county's borders, J_r. The central agency planner's objective is limited to townships and is therefore coarser than the county planner's objective (i.e., township vs. site level). However, a county can provide a coarser level of detail to the central agency by aggregating the results of their surveys at the township level.

For a county r, the central agency's planner may allocate a portion C_r of their total budget C to that county's planner to inspect sites j for signs of pest presence. County planners, when given the portion of survey funds C_r, conduct site inspections to maximize their own objective [8]. The central agency's planner, when maximizing their survey objective, must anticipate the behaviour of the counties' planners after they receive their budget portions C_r. Note that the central agency planner may decide to use the agency's inspectors in some counties r, in which case $C_r = 0$.

Our formulation of the central agency planner's problem maximizes objective [3] while anticipating that county planners will behave to maximize objective [8]. We solve this problem using backwards induction. We discretize the space of strategies to which the county planners can commit based on different funding levels they may receive from the central agency. Specifically, we discretize all possible levels of funding which the central agency may allocate to each county r to V candidate budget levels, $C_{r1}, …, C_{rV}$. The first step in the bi-level formulation solves the survey problem from each county's perspective for all possible discretized budget levels v, $v \in V$, that county r may receive, including a zero-budget level, $C_{rv} = 0$. Then, based on the optimal survey solutions for each county r at funding level v, we define

the binary parameter y_{jrv}, $y_{jrv} \in \{0,1\}$, for all sites j, indicating whether the county's inspectors visited site j in the solution with the survey budget C_{rv} allocated at level v ($y_{jrv} = 1$ and $y_{jrv} = 0$ otherwise).

In the second step, the central agency's planner devolves a portion of their budget to each county r for pest surveys but may also use the agency's inspectors to survey the sites not visited by the county inspectors. For each county r, a binary variable ω_{rv} selects the precomputed optimum and a corresponding subset of sites j surveyed by the county's inspectors (i.e., with $y_{jrv} = 1$) from the set of the county planner's solutions for R counties and V budget levels including the solutions with zero budget. A set of parameters $C_{r1}, \ldots, C_{rV}$ defines the survey budget levels for a set of solutions for R counties $\times$ V budget levels. Then, the bi-level central agency planner's solution that maximizes the expected number of townships with positive detections can be formulated as follows (problem 3 hereafter):

$$max \frac{1}{S} \sum_{s=1}^{S} \sum_{n=1}^{N} (1 - w_{ns}) \qquad [10]$$

s.t.:

$$w_{ns} = \prod_{j=1}^{J_n} \left[(1 - p_{js}e)^{x_j} (1 - p_{js}e_{local})^{z_j} \right] \quad \forall \ s \in S \qquad [11]$$

$$x_j + z_j \leq 1 \quad \forall \ j \in J \qquad [12]$$

$$z_j = \sum_{r=1}^{R} \sum_{v=1}^{V} \omega_{rv} y_{jrv} \quad \forall \ j \in J \qquad [13]$$

$$\sum_{v=1}^{V} \omega_{rv} = 1 \quad \forall \ r \in R \qquad [14]$$

$$\sum_{j=1}^{J} c_j x_j + \sum_{r=1}^{R} \sum_{v=1}^{V} (\omega_{rv} C_{rv}) \leq C \qquad [15]$$

$$y_{jrv} \in \underset{R,V}{argmax} \left(\frac{1}{S} \sum_{j=1}^{J_r} \left(u_j \sum_{s=1}^{S} p_{js} e_{local} \right), \right.$$
$$\left. s.t. : \sum_{j=1}^{J_r} \left(u_j \left[d_j + d_{2j} p_{js} e_{local} \right] \right) \leq C_r \quad \forall \ s \in S \right) \qquad [16]$$

Objective function [10] is the same as objective [3]. Constraints [11,12] are analogous to constraints [5,7] in problem 2. Constraint [13] restricts the selection of sites surveyed by county inspectors to a configuration prescribed by one of the precomputed county planner's optima. Constraint [14] ensures the selection of the precomputed county planner's solution in county r for one budget level v only. Constraint [15] defines the budget limit for the central agency's planner. Term $\sum_{r=1}^{R} \sum_{v=1}^{V} (\omega_{rv} C_{rv})$ defines the survey budget portions allocated to counties $1, \ldots, R$, and term $\sum_{j=1}^{J} c_j x_j$ defines the central agency's cost to survey the portion of sites using its own inspectors. Eq. [16] summarizes the calculation of a binary parameter y_{jrv}, which stores the locations of the inspected sites j in the precomputed optimal solutions of the county planner's problems for a set of R counties $\times$ V survey budget levels, including the solutions with zero budget.

2.4. Case study

The HWA kills eastern hemlock trees in eastern North America (McClure, 1991) causing ecological and economic damage (Reay, 2000; Holmes et al., 2010; Cessna and Nielsen, 2012; Siddig et al., 2016; Degrassi, 2018; Dharmadi et al., 2019). The insect was first recorded in the eastern USA in 1950 and as of 2020 had spread to 21 U.S. states, the District of Columbia, southwestern Nova Scotia and southern Ontario, Canada (North American Plant Protection Organization (NAPPO), 2012, 2014; Limbu et al., 2018; Ellison et al., 2018; Canadian Food Inspection Agency (CFIA), 2020). Limiting the spread and impact of HWA requires an effective early detection strategy. In southern Ontario, most hemlock

forests at risk of invasion are either privately owned or under the management of regional governments (i.e., counties), conservation authorities, or private entities with leases to operate provincially owned forests (Elliott, 1998; Ontario Ministry of Northern Development, and, Mines, Natural Resources and Forestry (OMNDMNRF), 2021). Therefore, management decisions for HWA will be the responsibility of these smaller, regional governments, whereas initial detection and delineation are the purview of either the Canadian Food Inspection Agency (CFIA, Canada's National Plant Protection Organization) or the Ontario Ministry of Northern Development, Mines, Natural Resources and Forestry (OMNDMNRF), the provincial ministry responsible for forest health.

2.5. Site inspection cost

In Canada, the CFIA conducts surveys to detect the presence of invasive species populations (Canadian Food Inspection Agency (CFIA), 2020). CFIA inspectors are stationed across Ontario in regional offices (inspection stations hereafter). The inspection stations closest to known HWA infestations in Ontario are in St. Catharines, Hamilton, and Guelph, and in the Greater Toronto Area (GTA). For each inspection station, we calculated the costs of accessing survey sites using the times required to travel to the sites from a station. We first divided the area to a hexagonal grid of 1-km^2 sites where each site was considered as a potential survey location j (Fig. 1). We used the CanVec database (NRCan, 2019) to map the presence or absence of roads in each site j. Each site j in the study area was assigned to one of the following land types: rural areas with paved roads, rural areas without paved roads, large cities (GTA and Hamilton) and small cities (other municipalities in southern Ontario). For each land type, we generated multiple queries in Google Maps to estimate the average driving speeds during workdays (i.e., Monday through Friday) and calculated the average driving times per km of travelled distance. Then, for each inspection station i, we calculated the access time to site j by finding the fastest route through a sequence of neighbouring sites between i and j. Each site j was characterized by a "drive-through time" value based on the site's type (i.e., large urban areas, small cities and rural areas with and without paved roads). We then calculated the cost of accessing the site from each inspection station i as the driving time plus the fixed overhead time (0.5 h) times the Cdn$120/h. hourly pay rate. The pay rate value was based on costs for similar services if provided by a privately contracted inspector in Ontario. We used this value to approximate the rate paid by the central agency and counties because personnel costs are difficult to estimate for government agencies (e.g., because of variable rates of pay and benefits among different agencies and levels of government for the same work). The same pay rate was used to estimate the cost of inspections, assuming 45 min for completing the first survey (by county or central agency inspectors), 60 min for the second survey (by county inspectors after detecting the signs of infestation) and 20 min as overhead time. If the site did not have road access, we added 20 min of extra time to access the site based on previous experiences of CFIA inspectors in rural Ontario. The Niagara Peninsula has a dense road network, so access to survey sites was not an issue. The survey costs for county inspectors were calculated in a similar way using the same hourly pay rate. We used the locations of CFIA regional offices to map the inspection stations i in the study area (Fig. 2a). We assumed that county inspectors were stationed in the largest municipality in each county (Fig. 2b).

2.6. HWA detection rates

We used the HWA detection likelihood e, $e_{local} = 0.63$ from MacQuarrie et al. (2021). The detection capacity may vary depending on the inspector's experience and the abundance of hemlock trees in a survey site, hence we tested a range of detection likelihoods between 0.4 and 0.8. We tested different detection rates for county inspectors vs. the baseline detection rate for the central agency's inspectors, $e = 0.63$, and assumed that surveys are performed sequentially by minimum-size crews.
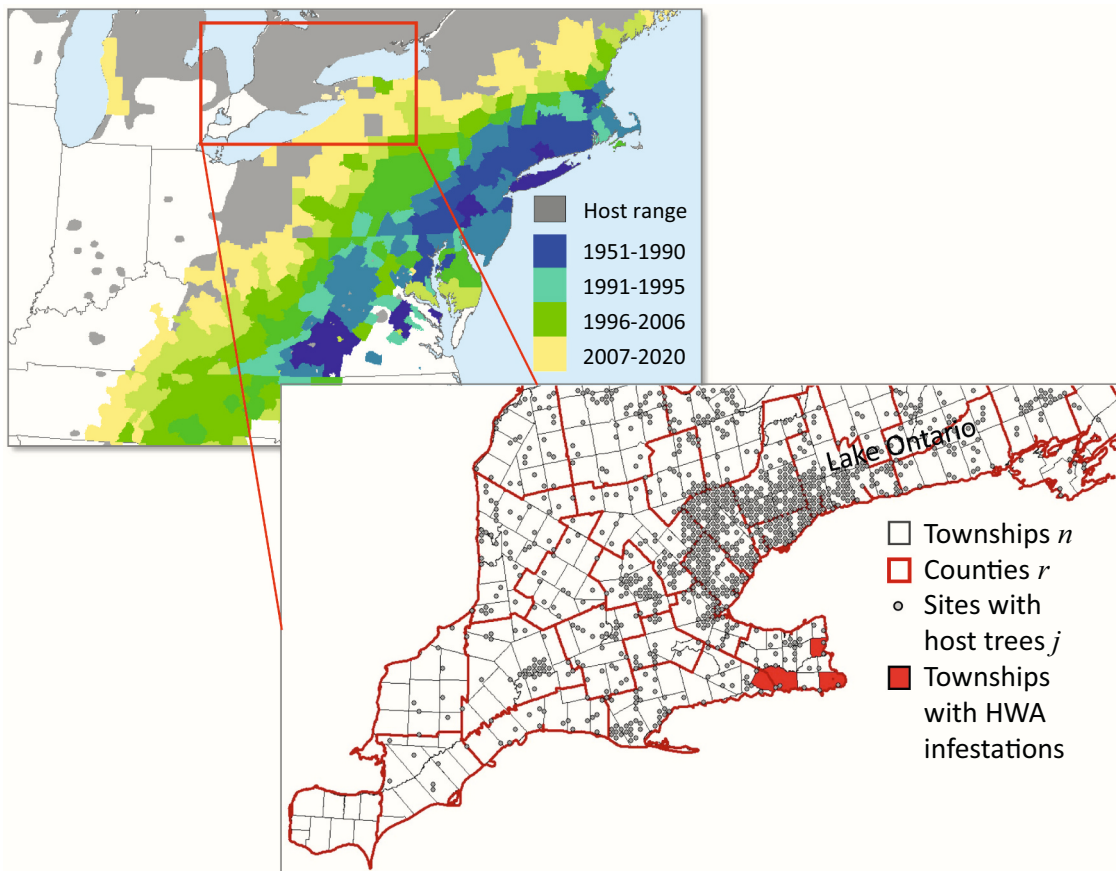
Fig. 1. Study area with counties *R*, townships *N* and candidate survey sites *J* with host resource.
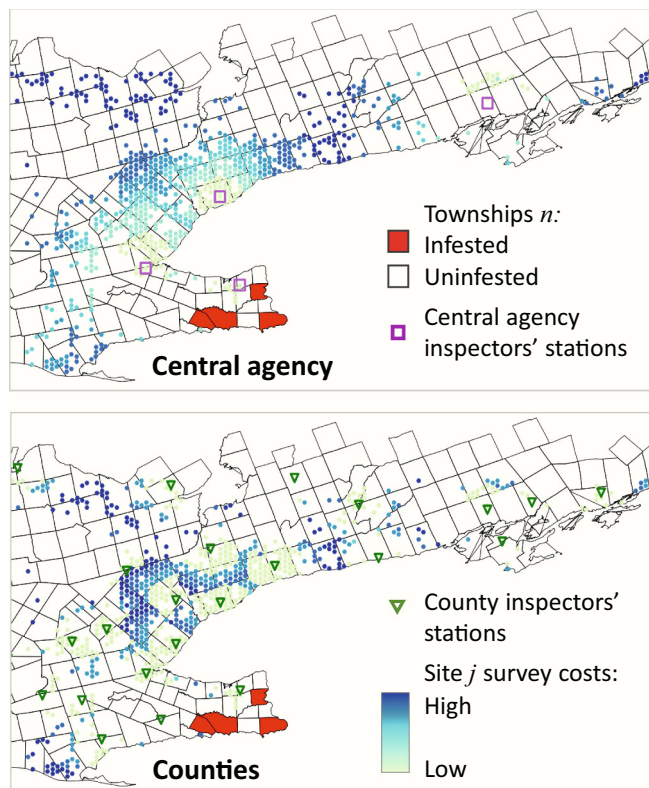

Fig. 2. Survey costs for sites *j* by central agency and county inspectors.

2.7. Likelihoods of HWA spread

We modelled the probability of HWA spread from the invaded locations using the model of Fitzpatrick et al. (2012), which depicts the likelihood of HWA spread as a decaying function of distance using a lognormal distribution function. Using this function, we generated the likelihoods of HWA spread, p_j, for each site in the study area. We also included locations invaded by HWA in the USA that were within 70 km of the Canadian border. Long-distance HWA spread is assisted by migratory birds (Russo et al., 2019), so we used data from Ewert et al. (2012) and Birds Canada (2019) to identify key migration corridors across southern Ontario. The migratory pathways of birds likely to carry HWA (Russo et al., 2019) follow the shorelines of the Great Lakes, so we assumed that the spread paths did not cross Lakes Erie and Ontario. Thus, to calculate the dispersal distances between pairs of uninvaded sites and the nearest invaded site, we used the shortest path algorithm (Dijkstra, 1959) traced over land locations and excluded long-distance dispersal over these two lakes.

We used the likelihoods of HWA spread to generate two groups of models. The no-uncertainty group used a single scenario with actual p_j values in the model equations and assumed that the central agency and county planners knew the probability of invasion in survey sites *j*. For the second group of models, the uncertainty group, we generated 3600 stochastic realizations of invasion scenarios *s* based on p_j values. We solved problems 1-3 for both the single-scenario and 3600-scenario cases to see what effect uncertainty had on the results.

2.8. Host availability

We used a proprietary database of hemlock resources assembled by Silv-econ Ltd. (Newmarket, Ontario) to map the presence of hemlock in

southern Ontario. Hemlock once grew over much of southern Ontario, but its abundance has become much reduced because of the conversion of forests to farmlands and urban areas. The database compiles hemlock presence from provincial records, conservation authorities, municipalities and forest inventories from private lands. Since eastern hemlock is planted as an ornamental tree in urban settings, we assumed the host to be present in municipal areas. We only considered sites with host as potential candidates for surveys. This database may not include all hemlock in southern Ontario and additional data are likely to change the prescribed inspection patterns. However, because the model solutions may be used to guide immediate survey efforts, we felt it was appropriate to include only candidate sites with documented host presence.

2.9. Study scenarios

For the uncertainty and no-uncertainty scenarios, we report the four groups of problem solutions. Problem 1 solves the central agency planner's problem only [2–4], assuming no budget allocation to county planners. Problem 2 (Eqs. [3,5–7]) allows allocation of a portion of funds to county planners but assumes that the county planners would follow the central agency planner's objective. Problem 3 solves a bi-level model [5,7,10–14] that may allocate a portion of funds to county planners and assumes that the central agency planner endogenizes the county planners' differing objectives. We also report a county-only problem 4 where all funds are allocated to county planner problems [8,9] and each county maximizes its own objective.

3. Results

We first examined the optimal solutions for a single-scenario formulation that used invasion likelihoods p_j. This model depicts a hypothetical case when the manager knows the actual invasion likelihood for site j. We compared the single-scenario solutions with solutions based on 3600 stochastic invasion scenarios (Figs. 3 and 4), which assumed the manager knows only the approximate range of invasion outcomes for each site. Figs. 3 and 4 show the solutions for different central agency budgets ($10,000 and $20,000) and the number of sites inspected in each township by the central agency and county inspectors in the solutions for problems 1–4.

Without uncertainty, single-level problem 2 and bi-level problem 3 solutions show minor differences (Figs. 3a,4a). All solutions prescribed surveys in the Niagara Peninsula and near the shores of Lake Ontario, which serves as a corridor for migratory birds. The highest survey site densities were in townships closest to the inspection stations in or near cities (triangles and squares in Figs. 2-4), where invasion risk is moderate or high. For example, inspections by the central agency were allocated to sites with a moderate to high risk of invasion and close to St. Catharines and Hamilton. County inspections were allocated to sites with a low risk of invasion, close to the county inspectors' stations and covered a larger area than the area surveyed by the central agency inspectors. Bi-level model 3 solutions allocated a larger share of surveys to central agency inspectors than single-level model 2 solutions (Table 2). This is because the central agency planner anticipates the underperformance of the county planner and so allocates more surveys to their own inspectors. At small budget levels, the surveys in bi-level problem 3 solutions were less concentrated in major urban areas than in single-level problem 2 solutions and were spread more evenly across rural areas along major pest spread corridors between St. Catharines and Hamilton (Fig. 3 callout I).

In the uncertainty scenarios, both the central agency and county planners allocated inspections over a larger area and more townships as a hedge against the uncertainty of long-distance HWA spread (Figs. 3b,4b). In bi-level model 3 solutions, the central agency's inspectors surveyed more sites and covered a larger area than county inspectors (Table 2). More townships were also inspected at farther distances from already-invaded locations (Fig. 3 callout II). These

locations have low but positive likelihoods of invasion, and inspections of these sites would aim at detecting long-distance HWA spread. The general strategy is for the central agency to use its own resources to survey sites with the high and medium invasion risk that are proximal to the central agency's stations. Sharing the funds with counties is feasible for the inspections of sites located far from known invaded areas but near the county inspectors' stations where the access and inspection costs for county inspectors are lower than the costs for the central agency inspectors (Figs. 3b,4b). Because of travel costs, the distance from an inspector's station to the survey site plays a key role in deciding which party should inspect a particular site.

The apportionment of survey resources between the central agency and counties in the uncertainty scenarios depends on the size of the survey budget. In problem 3 solutions, when budgets were small, the central agency conducted most of the surveys and shared only a small portion of funds with counties (Table 2). It was only when the budget was large enough to inspect all sites with high risk of invasion that a portion of the budget was allocated to county planners. When budgets were large, the central agency used less than half of the budget to conduct their own surveys (Table 2). With that budget, the inspected area was large and covered many counties. Those counties with shorter travel times and lower survey costs within their administrative jurisdictions than the central agency inspectors, therefore these sites were surveyed by county inspectors.

We also explored the trade-offs between problem 1–4 solutions in dimensions of the valuation for the central agency's planner and the county planners (Fig. 5). Central agency-only (problem 2) and county-only (problem 4) solutions depict the endpoints of the trade-off between the survey objectives for the central agency's planner and for the county's planners. Problem 4 had the worst performance in the valuation of the central agency's planner because the objectives of the county's planners differed from that of the central agency's planner. Bi-level problem 3 solutions (empty circles in Fig. 5) fell in between the problem 1 and 2 solutions maximizing the utility for the central agency's planner but also had higher utility for the county's planners than the central agency-only problem 2 solutions. Note that the bi-level problem 3 performed better than problem 1, which did not share survey funds with counties.

The value of the objective function relative to the survey budget level demonstrated the rule of diminishing returns as the survey budget increased (Fig. 6a). The impact of increasing the budget on the success of detecting HWA was greater for small budgets than large budgets. Once the budget was sufficient to inspect all high-risk sites, surveying additional sites at distant sites produced marginal improvements because the probabilities of invasions at those sites were low, as are the likelihoods of detection.

The proportion of the budget allocated to county planners differed in the uncertainty and no-uncertainty solutions (Table 2). In no-uncertainty solutions, when the budget was small, the central agency allocated most of its budget to its inspectors, but a few counties received funds to inspect nearby sites with low access costs. Once the budget was large enough to inspect all high- and moderate-risk sites, the portion allocated to counties increased, stabilizing around 60/40 (Fig. 6b).

Adding uncertainty about HWA spread decreased the budget portion allocated to counties (Table 2). The uncertainty solutions also showed larger differences among the proportions of funds allocated to counties in theoretical problem 2 and bi-level problem 3 solutions (Fig. 6). Note that problem 2 assumed that a county planner, when allocated some survey funds, would strictly follow the central agency planner's objective (i.e., the survey efficiency's theoretical upper bound). Problem 3 was a more realistic assumption that a county's planner would follow their own objectives and so - from the central agency planner's perspective - their inspections would be less efficient. The portion of the budget allocated to counties in problem 3 solutions was lower because the central agency's planner anticipated the underperformance of county inspectors and so used the agency's inspectors to survey high-risk
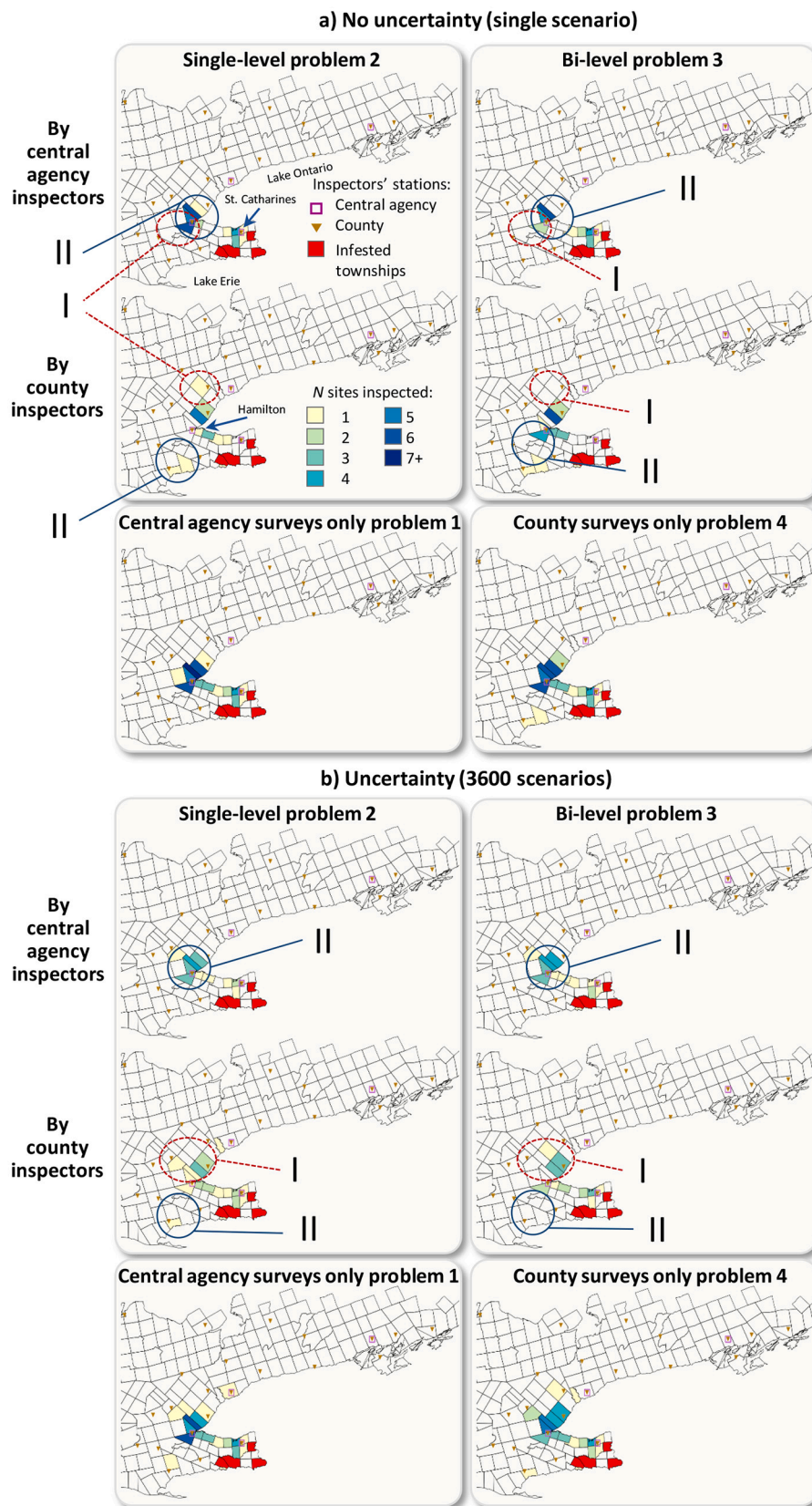
Fig. 3. Spatial survey patterns: the number of sites inspected in townships by the central agency and county inspectors: a) no uncertainty solutions; b) the uncertainty solutions. The survey budget limit C = C\$10000. Callout I (dashed line) highlights key spatial differences between the single level problem 2 and bi-level problem 3 solutions and callout II (solid line) highlights key differences between the no-uncertainty and uncertainty solutions.
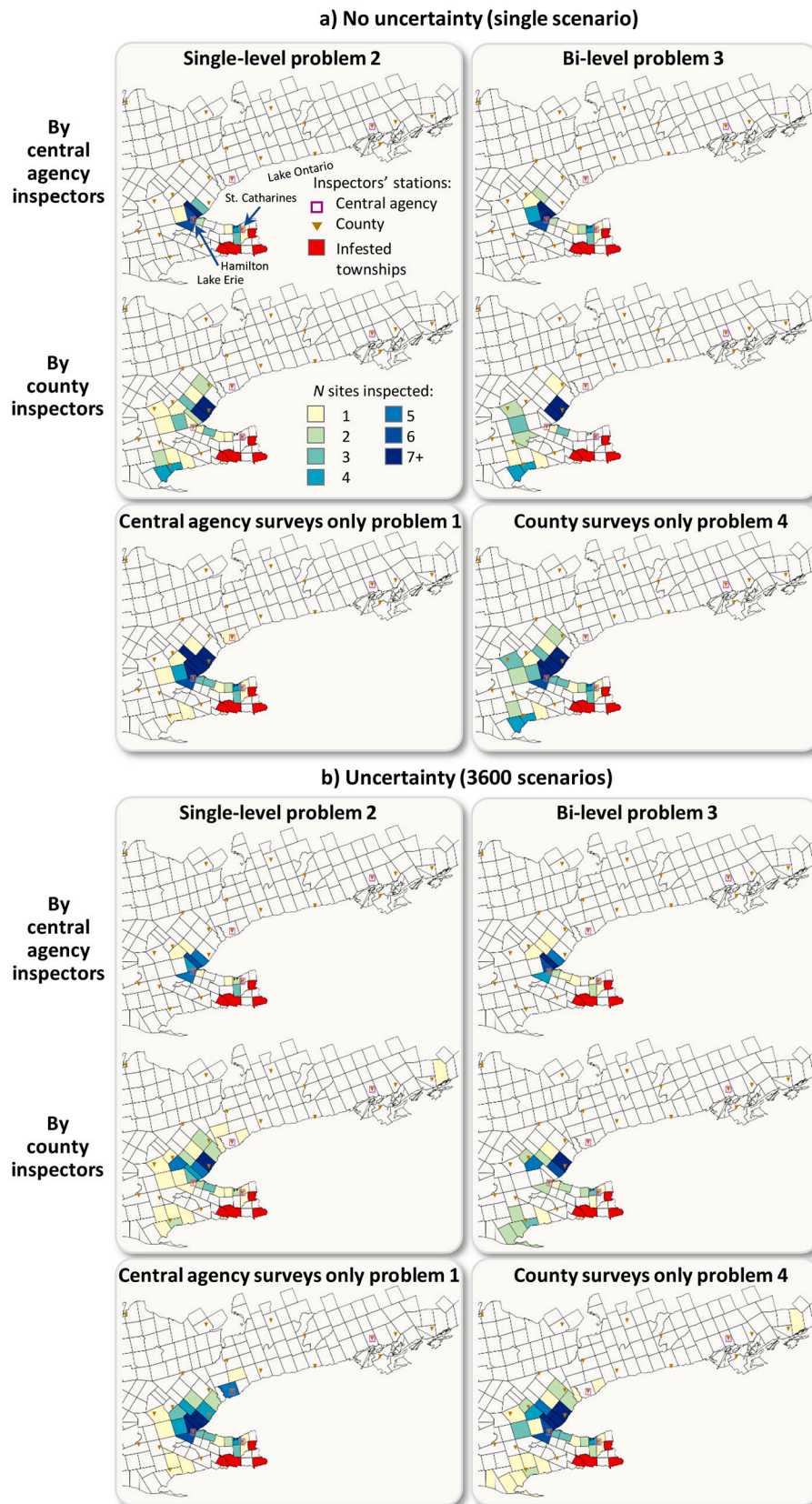
Fig. 4. Spatial survey patterns: the number of sites inspected in townships by central agency and county inspectors: a) no uncertainty solutions; b) the uncertainty solutions. The survey budget limit $C = $ C\$20000.

Table 2
The number of surveyed sites, counties and townships by the central agency and county inspectors and proportion of budget allocated to central agency inspectors in problem 1–4 solutions.

Problem scenario	Survey budget level, $	Uncertainty	Number of sites inspected			Inspections by the central agency		Number of counties inspected			Number of townships inspected		
			By the central agency	By counties	Total	Budget percent	Number of inspectors	By the central agency	By counties	Total	By the central agency	By counties	Total
Problem 1 (single-level)			17	–	17	99%	2	3	–	3	9	–	9
Problem 2 (single-level)		No	10	8	18	53%	1	1	3	4	5	6	11
Problem 3 (bi-level)			12	6	18	65%	1	1	2	3	6	4	10
Problem 4 (counties only)			–	18	18	–	–	–	3	3	–	10	10
Problem 1 (single-level)	4000		18	–	18	100%	2	3	–	3	10	–	10
Problem 2 (single-level)		Yes (3600 scen.)	5	11	16	27%	2	2	3	5	4	9	13
Problem 3 (bi-level)			18	–	18	100%	2	3	–	3	10	–	10
Problem 4 (counties only)			–	16	16	–	–	–	3	3	0	10	10
Problem 1 (single-level)			45	–	45	100%	2	4	–	4	15	–	15
Problem 2 (single-level)		No	30	17	47	64%	2	3	5	8	10	10	20
Problem 3 (bi-level)			24	22	46	52%	2	2	3	5	9	9	18
Problem 4 (counties only)			–	46	46	–	–	–	4	4	–	16	16
Problem 1 (single-level)	10,000		44	–	44	100%	3	6	–	6	18	–	18
Problem 2 (single-level)		Yes (3600 scen.)	20	24	44	44%	2	4	6	10	10	17	27
Problem 3 (bi-level)			23	19	42	52%	2	5	3	8	12	10	22
Problem 4 (counties only)			–	44	44	–	–	–	7	7	–	18	18
Problem 1 (single-level)			85	–	85	100%	3	7	–	7	22	–	22
Problem 2 (single-level)		No	36	58	94	38%	2	3	8	11	11	22	33
Problem 3 (bi-level)			45	48	93	49%	2	4	6	10	13	14	27
Problem 4 (counties only)	20,000		–	94	94	–	–	–	8	8	–	26	26
Problem 1 (single-level)			84	–	84	100%	3	9	–	9	27	–	27
Problem 2 (single-level)		Yes (3600 scen.)	29	61	90	32%	2	4	10	14	10	31	41
Problem 3 (bi-level)			34	50	84	38%	2	4	5	9	13	19	32

Table 2 (*continued*)

Problem scenario	Survey budget level, $	Uncertainty	Number of sites inspected			Inspections by the central agency		Number of counties inspected			Number of townships inspected		
			By the central agency	By counties	Total	Budget percent	Number of inspectors	By the central agency	By counties	Total	By the central agency	By counties	Total
Problem 4 (counties only)			–	89	89	–	–	–	11	11	–	33	33
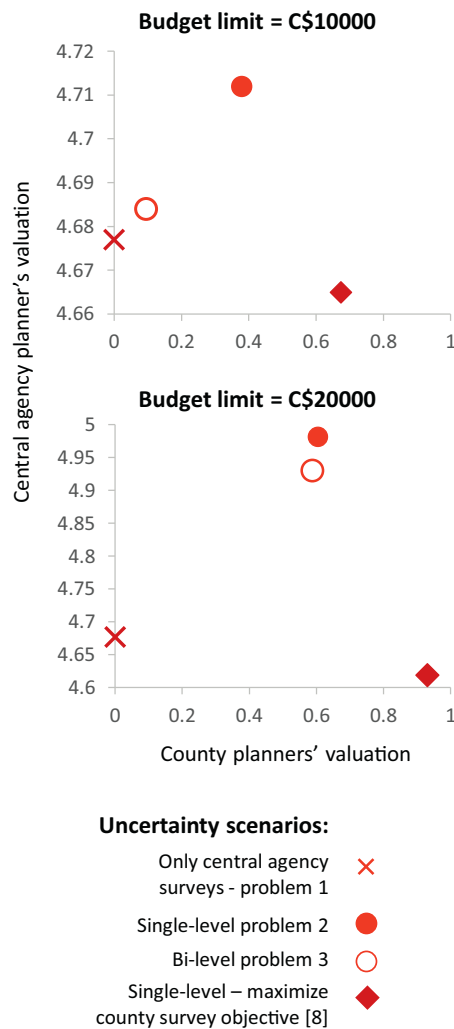
Fig. 5. Problem 1–4 optimal solutions in dimensions of the county planners' valuation (x-axis) and central agency planner's valuation (y-axis).

Fig. 6. a) Central agency planner's objective value (y-axis) vs. the survey budget (x-axis); b) budget proportion allocated to the central agency inspectors (y-axis) vs. the survey budget (x-axis). I – the budget levels when the central agency planner allocates almost entire budget to their own inspectors.

sites. The uncertainty assumption decreased the central agency planner's expectations about successful detections by county inspections. Note that the minimum budget at which the central agency's planner started allocating funds to counties was higher in the uncertainty problem 3 solutions than in no-uncertainty solutions (Fig. 6b callout I). This is because the uncertainty assumption decreased the central agency planner's expectations about successful detections by county inspections.

In single-level problem 2 scenarios, at small budget levels, the budget allocation shifts towards county inspectors before returning to a more even split at larger budget levels (Fig. 6). This is a result of a particular arrangement of the spatial patterns of infestation and the locations of county inspection stations (and the associated site access costs). When
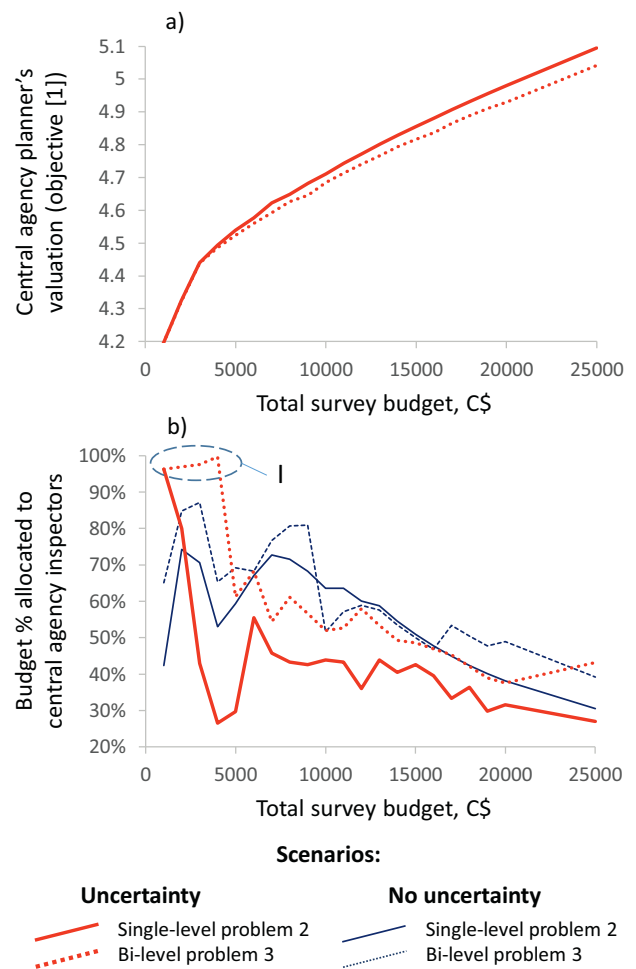
the budget level is small only a few sites can be inspected. At this budget level, the lower survey costs of county inspectors (even with a lower detection rate) translate to a large expected number of inspected sites and higher survey efficiency. At small budget levels, the model picks a few high-risk sites with lower inspection costs for county inspectors than for central agency inspectors. However, this cost advantage only materializes when a small budget forces the central agency planner to select just a few survey locations. Once the budget increases and becomes sufficient to inspect high-risk sites in multiple counties, the cost savings of having the counties inspect these sites are outweighed by the benefits of covering a larger area of high infestation risk with central agency inspections.

3.1. Impact of site inspection costs and pest detection rate

The likelihood of inspections finding signs of pest attack and the cost to access and survey sites influenced the apportionment of funds between the central agency and the counties. Fig. 7 shows the budget portion allocated to the central agency inspectors as a function of the average unit costs of surveys by county inspectors. The no-uncertainty solutions show a sharp increase in the proportion of sites surveyed by the central agency once the unit cost of county inspections exceeded the unit cost of the central agency's inspections. This transition was more gradual in the uncertainty solutions because they captured the uncertainty of predicting long-distance spread of HWA. This spread may lead to infestations and detections over large areas where a county's survey costs tend to be lower than the central agency's costs).

The skill of inspectors at detecting an HWA infestation played an important role in how the budget was divided among the central agency and the counties. Fig. 8 shows the portion of the total budget allocated to the central agency as a function of the detection rate of county inspectors. The no-uncertainty scenarios show a sharp decline in the percentage of sites surveyed by the central agency if their detection rate of their inspectors is lower than that of the county inspectors. This decline is more gradual in the uncertainty solutions (Fig. 8). For example, >20% of surveyed sites were surveyed by the central agency even when the county inspectors' detection rate of was 0.17 more than
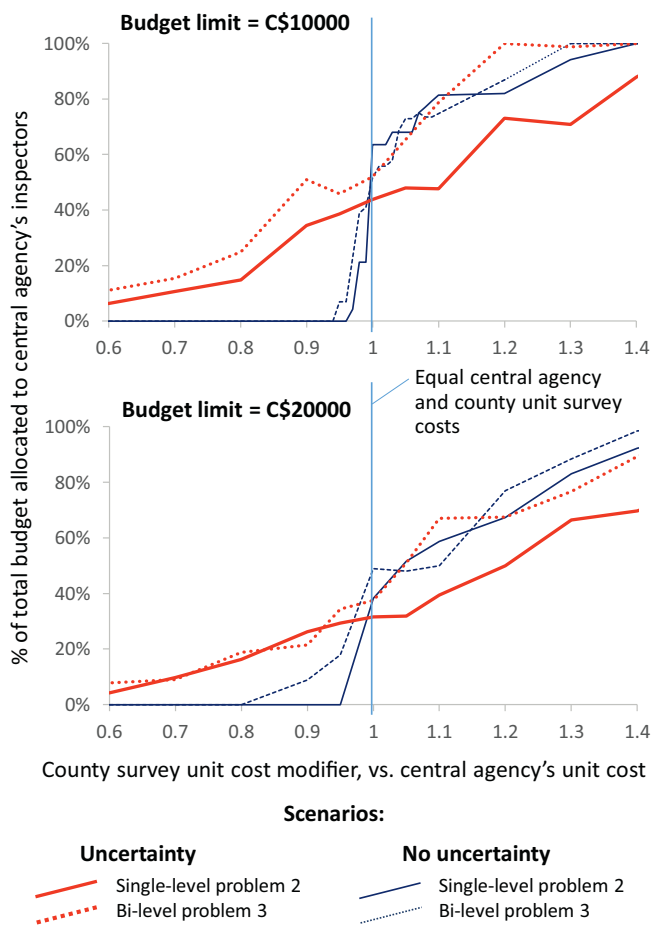
Fig. 8. Budget proportion allocated to the central agency inspectors vs. the detection rate by county inspectors. The x-axis depicts the detection rate of county inspectors, e_{local}. The central agency inspectors' detection rate, e, is set to 0.63 (baseline value). The vertical line shows the point where the detection rates of the central agency and county inspectors are equal.

the central agency inspectors' detection rate.

4. Discussion

We considered a delimiting pest survey planning problem in which a central agency maximized the number of expected detections of an invasive species across a network of administrative units (townships) while devolving a portion of survey funds to regional governments as a measure to reduce the overall survey cost and improve its efficiency. Our approach makes it possible to integrate the aspirations of multiple regional governments acting with little or no coordination (e.g., counties as in this study), into the decisions of a central regulatory agency regarding the hierarchical governance of a pest survey program. Our work helps address two essential questions related to the development of cooperative pest surveys. First, our approach incorporates the likely responses of regional players to a large-scale survey effort and the disparities among the objectives of the central agency aiming to uncover the "big picture" about the invasion and regional governments aiming to understand the size of invader's populations to guide mitigation efforts. Second, we find an effective cost-sharing strategy between a central agency and regional governments that maximizes the performance of the survey campaign. We found that accounting for the anticipated responses of county planners had a moderate impact on how the central agency perceived the efficiency of the survey.

Cost-sharing, where a portion of funds was devolved to counties, had lower efficiency for delimiting surveys of HWA in southern Ontario because the counties' objectives were not fully aligned with that of the

Fig. 7. Budget proportion allocated to the central agency inspectors as a function of the county inspectors' survey unit cost. The x-axis shows the counties' average survey unit cost as a multiplier of the central agency's (baseline) unit cost. A value of 1.0 assumes equal unit costs for the county and central agency inspections. Cost modifier <1 indicates the county survey unit cost is lower than the central agency unit cost and cost modifier >1 indicates the county survey unit cost is higher than the central agency unit cost.
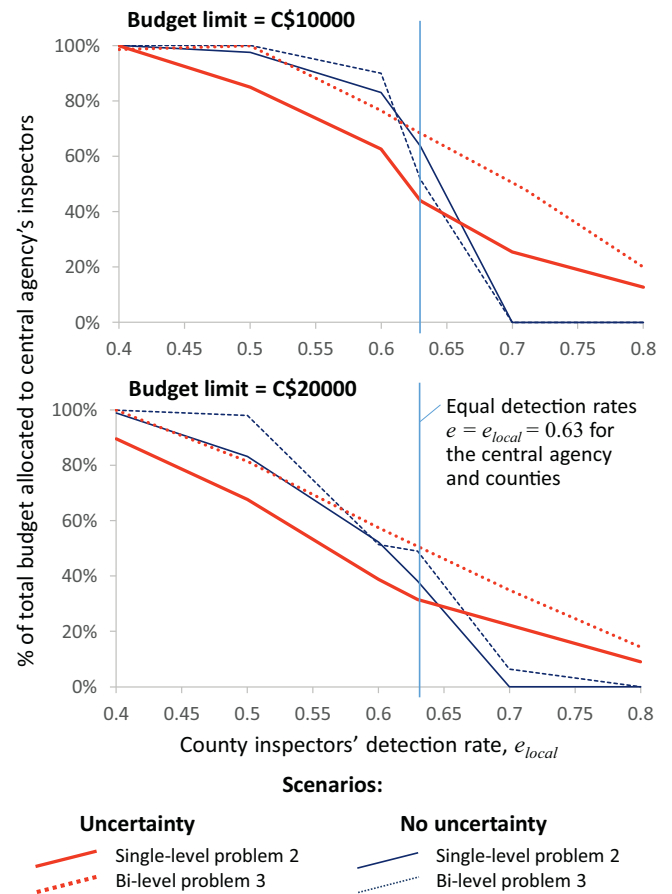
central agency. The budget portion shared with the counties depended on the total survey budget. When the survey budget was small, the central agency allocated almost all its resources to its own inspectors to visit the riskiest sites (Fig. 6). This finding suggests that cooperation with the counties is only feasible when the survey budget is large enough for the central agency to inspect most sites with a high risk of invasion. In turn, a moderate portion of funds can be devolved to counties to inspect sites that are too costly for the central agency to inspect or where the likelihood of the pest invading is low but still possible because of long-distance spread. For example, sites with a high risk of invasion near the central agency's offices were inspected by central agency staff (Figs. 3,4). This aspect is particularly evident in bi-level problem 3 solutions, when most risky sites proximal to St. Catharines were inspected by the central agency (Fig. 4) but sites near Lake Erie, which are far from the central agency's offices, were surveyed by county inspectors.

For many sites in rural settings access time played a critical role in deciding who would conduct the surveys. The bi-level problem 3 solutions allocated a portion of survey funds to counties farther from the known invaded locations, for which the likelihood of invasion was low. The chance of HWA spreading to these areas is small and uncertain, but always positive, so inspections of those regions is a hedging strategy aimed at detecting long-distance spread. The spread rate of HWA compared to that of other invasive forest pests is slow (Evans, 2016), which partially explains the allocation of resources in our optimal solutions. More rapidly spreading pests, such as the emerald ash borer, *Agrilus planipennis* Fairmaire, or spotted lanternfly, *Lycorma delicatula* (White), would have lower uncertainties of long-distance spread, which would result in different outcomes.

The budget portion shared with regional governments is likely to depend on the spatial pattern of the invasion. In our study the area at highest risk of HWA spread is relatively small, with a low hemlock density, and close to regional offices of the central agency. The features made it optimal for the central agency to use its own resources to inspect this area. The cost-sharing strategy could be different if HWA had better long-distance spread capacity, was introduced to Canada in regions with higher abundance of hemlock, or at a site that is farther from the central planner's regional offices. This scenario somewhat describes the situation observed in southern Nova Scotia, where the insect was introduced to a remote area with poor access and fewer possible inspection sites. Initial detection took longer there, resulting in a larger population at the time of this first detection and a relatively rapid rate of spread.

There can be logistical challenges in managing cooperative survey programs. In Canada and the USA some states and provinces have engaged citizen scientists to assist with the detection of new invasive species (e.g., Martel et al., 2021), yet these initial detections still require subsequent inspection by a regulatory body to confirm the detection (Poland and Rassati, 2019). Similar such confirmations by a national regulatory body could be required under a cooperative survey program which would add logistical complexity to the survey program. Furthermore, inspectors conducting surveys for central agencies have more experience, whereas inspections by other jurisdictions may be done by staff with less skill or contracted out to professional pest management companies. In practice, the efficacy of detection can vary immensely across the landscape. Our results suggest that even inspectors with limited experience can still be a better investment for the central agency than apportioning funds to a regional government. Regardless, our results show that under all scenarios there is some utility in allocating funds to regional governments. However, there are often logistical and governance challenges with transferring funds among levels of government. It may take time to negotiate and sign funding agreements, which can delay the initiation of a survey. These delays can be compounded when there are multiple jurisdictions in the region of interest. Our approach assumes that there are no governance issues (and associated extra costs) with apportioning funds from the central agency and counties. In reality, administrative barriers could push the cost of surveys by regional authorities to a level that renders the cost-sharing

option infeasible. If these challenges and cost premiums could be addressed adequately, our approach would facilitate the planning of possible survey campaigns with cooperation between different levels of government.

Notably, our model did not account for other socio-economic factors which are likely to come into play if such cooperation takes place. For example, cost sharing could help motivate regional governments to develop their own pest detection capacity for their management areas. Developing such capacity would also likely reduce the costs of subsequent management efforts for future invasive species, as regional governments with better pest detection capacity are likely better able to react to future invasive threats. Exploring the socio-economic ramifications of possible collaborative practices between federal (or provincial) agencies and regional authorities could be addressed in future research.

Our sensitivity analyses emphasize the importance of estimating the detection capacity of the target pest. A poor detection rate (e.g., due to less experienced inspectors) may render the survey efforts ineffective. In our HWA example, reducing the county inspectors' detection rate from 0.63 to 0.4 (which illustrates a switch from trained to untrained inspectors) severely reduced the share of county inspections in the survey (Fig. 8). Our solutions indicate that the use of untrained inspectors by county planners (or if there is uncertainty regarding their professional qualifications) is likely to dissuade the central agency from the idea of sharing survey resources with regional governments, even though in theory it could improve the efficacy of HWA detection in some counties. The findings also suggest a role for professional pest detection services in the design of surveys. Fig. 8 suggests that when county inspectors are well trained (i.e., have a detection capacity of 0.8 or better) the central agency allocates a significant portion of resources to counties. Realistically, no central agency or county government would be capable of maintaining a staff with that level of dedicated training and proficiency in the detection of a small subset of invasive species. However, professional pest management firms may be able to provide this service, albeit perhaps at a higher cost than the pay rate assumed in this study.

4.1. Methodological aspects

The capacity of our model to analyze combinatorial trade-offs between key biological and economic factors has helped identify critical spatial constraints in the planning of delimiting surveys. Our results indicate that survey allocation is often driven by the interplay between the spatial configurations of important biological and economic drivers (such as infestation likelihoods, inspection costs, site access times and the locations of inspection stations), therefore accounting for this information is critical for identifying optimal pest survey strategies in the target area.

Our bi-level pest survey planning model can potentially be extended in several ways. First, our analysis considers single-species surveys (i.e., HWA). This is a reasonable assumption given the imminent threat of HWA to hemlock in Ontario (Emilson et al., 2018). However, delimiting survey programs may want to include other invasive pests damaging different host species and their spread may be assisted by distinct biological and/or human-mediated means. Our model can be extended to a multi-species formulation to incorporate the host distribution data and dispersal models for multiple pest species and maximize the detection capacity for all these invasive threats. Inspections aimed at detecting multiple invasive threats have become popular (Poland and Rassati, 2019) and have the advantage of reducing survey costs and optimize the use of scarce personnel (Young et al., 2021). Our model could also be enhanced to account for other environmental factors that influence detection capacity and spread, such as the location of tree nurseries, which may receive infested stock and have been implicated in at least one previous HWA introduction to Canada (North American Plant Protection Organization (NAPPO), 2012), or additional survey techniques (MacQuarrie et al., 2021). The inspections of large areas with long

access times could be optimized by incorporating an optimal routing model (Yemshanov et al., 2020) to plan visits to multiple sites. These enhancements would support short-term planning but could be useful when inspection capacity is limited.

Our model is generalizable, but the presented solutions appear highly dependent on the spatial configuration of key model parameters. In this context, our results can be generalized to a pest species with similar dispersal behaviour in comparable spatial surroundings (i.e., in rural, partially urbanized landscapes). However, the key outcomes, such as cost distribution between the central agency and regional governments and the allocated survey patterns, may differ for other pests with contrasting dispersal profiles or in regions with dissimilar spatial patterns with respect to inspection costs, site access times and infestation likelihoods.

Our bi-level optimization approach can be applied to cost-sharing strategies in other governance hierarchies planning invasive species surveillance and management. For example, the approach could help the European Food Safety Authority develop cooperative survey programs in the European Union for EU-wide pest detection efforts by passing some survey responsibilities to the governments of EU member countries. Another potential application is the planning of statewide invasive species surveys in the USA when state governments allocate funds to county governments to conduct surveys, such as invasive species programs managed by the State of Minnesota (Haight et al., 2021; Minnesota Department of Natural Resources (MDNR), 2020a, 2020b). Incorporating these aspects could be the focus of future work.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2022.107551.

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