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ANALYSIS

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

Denys Yemshanov [a,*], Robert G. Haight [b], Frank H. Koch [c], Bo Lu [a], Robert Venette [d], Ronald E. Fournier [a], Jean J. Turgeon [a]

[a] Natural Resources Canada, Canadian Forest Service, Great Lakes Forestry Centre, 1219 Queen Street East, Sault Ste. Marie, ON P6A 2E5, Canada
[b] USDA Forest Service, Northern Research Station, 1992 Folwell Ave, St. Paul, MN 55108, United States
[c] USDA Forest Service, Southern Research Station, Eastern Forest Environmental Threat Assessment Center, 3041 Cornwallis Road, Research Triangle Park, NC 27709, USA
[d] USDA Forest Service, Northern Research Station, 1561 Lindig St., St. Paul, MN 55108, USA

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A B S T R A C T

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

* Corresponding author.
E-mail address: Denys.Yemshanov@canada.ca (D. Yemshanov).

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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 $\theta_{1j}, \theta_{2j} \in [0; 1]$ 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.