NATURAL RESOURCES CANADA - INVENTIVE BY NATURE

OPTIMAL CONTROL OF BIOLOGICAL INVASIONS WITH ERADICATION SUCCESS BENCHMARKS AND MANAGEMENT OF THE RISK OF UNCERTAIN PROGRAM COSTS

Denys Yemshanov[1], Robert Haight[2], Frank Koch[3], Robert Venette[2],
Kala Studens[1], Jean Turgeon[1], Ron Fournier[1],

Denys.Yemshanov@canada.ca

[1]NRCan, Canadian Forest Service, Great Lakes Forestry Centre, Sault Ste. Marie, ON
[2]USDA Forest Service, Northern Research Station, St. Paul, MN
[3]USDA Forest Service, Southern Research Station, Research Triangle Park, NC

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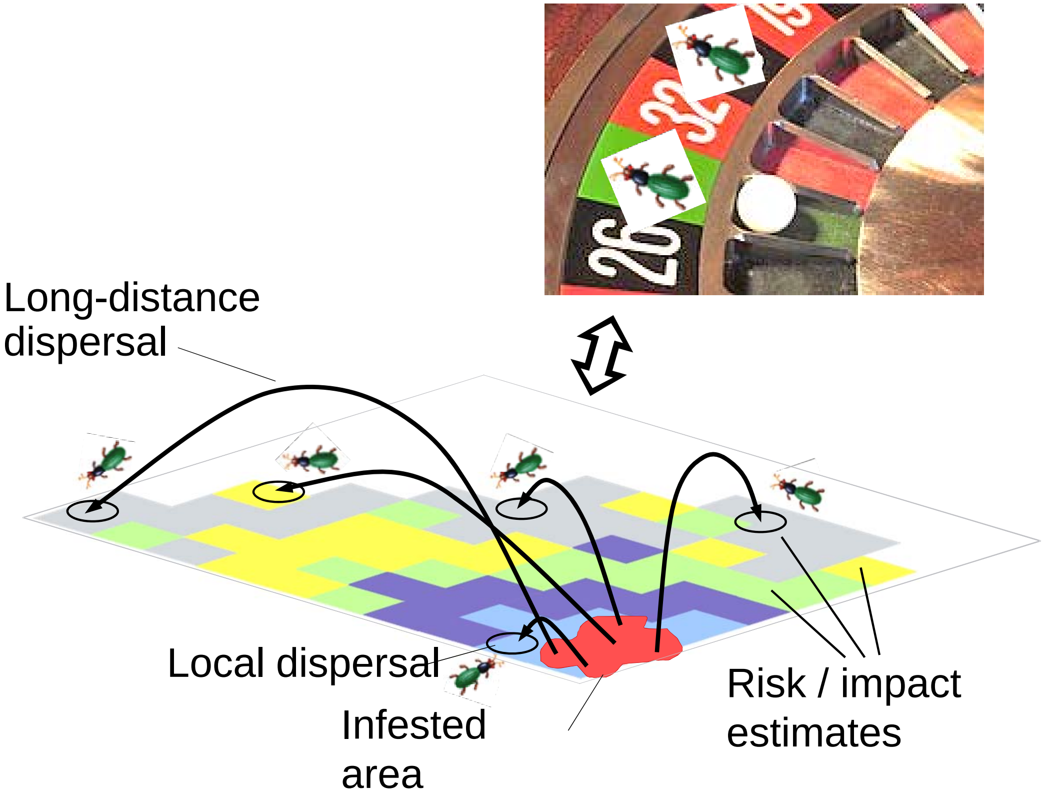
Revisiting basic principles



- Planning the surveillance of uncertain pest outbreaks is analogous to making a wager against uncertain odds

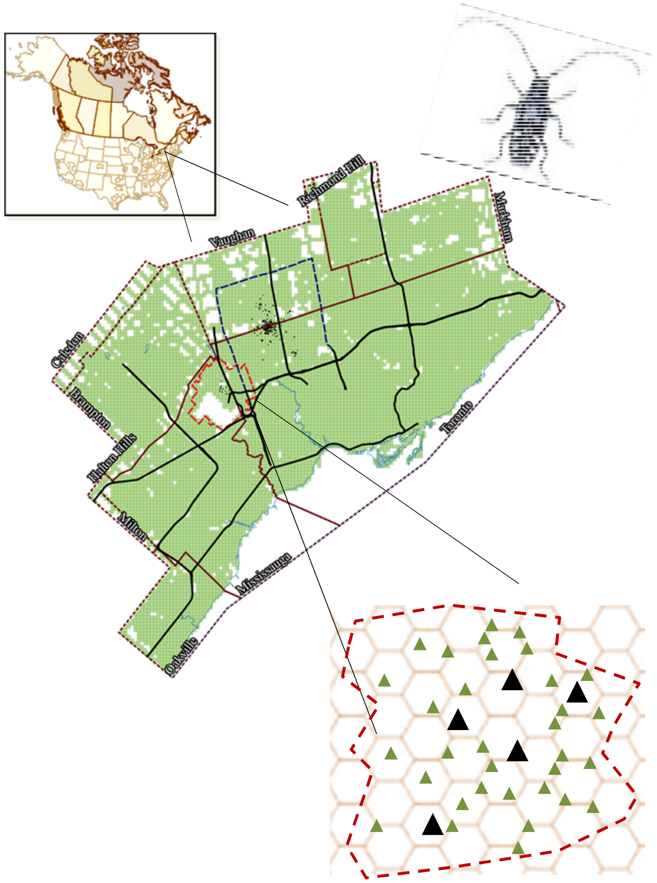
- Information about spread defines the bounds of the uncertainty about the pest of concern (i.e. "known unknowns")

- The size of the budget determines the total number of "bets" a decision-maker can place against the odds of finding the pest of interest in the managed area

Surveillance planning under uncertainty can be achieved with a special class of robust optimization models that incorporate the uncertainty by representing it as a large set of plausible scenarios

These models help examine how the uncertain predictions of future spread may change the survey decisions at the present time

The problem: Managing Asian longhorned beetle outbreak in Greater Toronto Area (GTA), ON



▲ Trees that are infested or likely to be infested

– – Managed area where eradication (tree removal) may be required

⬡ Survey sites

Asian longhorned beetle (ALB)

Management goal is to eradicate ALB in the managed area *J* with a desired probability of success *d*

Tree removal is the only viable eradication method

The future spread of ALB in the area *J* is uncertain but can be depicted by a set of spread scenarios, *S*

The probability of eradication success *d*, must be achieved for a minimum proportion of the scenarios *p*

Manager's objective: Minimize the expected program cost in the area *J* over *S* scenarios given these conditions

Scenario-based pest management model: Basic formulation

$$\tau = \min \frac{1}{S} \sum_{s=1}^{S} \sum_{j=1}^{J} \left(\beta N_j c_j x_j + t_j R_{js} \right)$$

[1] Minimize the expected cost

$$\text{s.t.: } R_{js} \geq N_j \beta \gamma \theta_{js} x_j \quad \forall\ s \in S, j \in J$$

[2] Remove all detected infested trees

$$R_{js} \leq N_j x_j \quad \forall\ s \in S, j \in J$$

[3] Number of removed trees cannot exceed the number of trees at a site

$$\prod_{j=1}^{J} \left[(1 - \theta_{js}[(1-\beta\gamma)/(1-\beta\gamma\theta_{js})])^{(N_j - R_{js})} \right] \geq d \quad \forall\ s \in S$$

[4] Eradication must succeed in all scenarios with probability *d*

Decision variables:

x_j binary survey selection variable at a site j, $x_j \in \{0;1\}$, $j = 1,\ldots,J$

R_{js} number of removed trees at a surveyed site j in a scenario s, $s = 1,\ldots,S$

Parameters:

c_j, t_j per-tree surveillance and tree removal costs

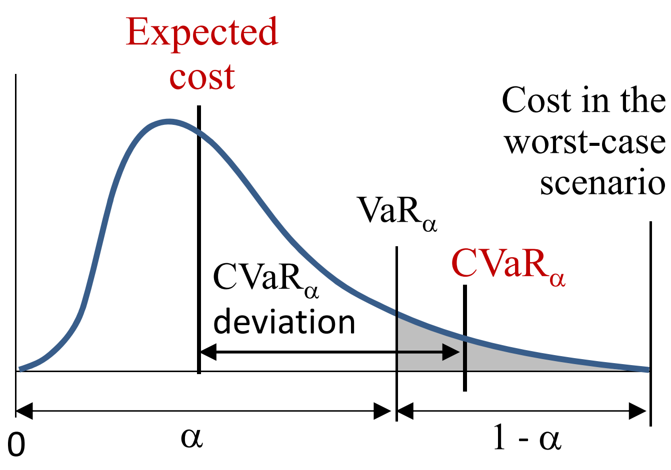
θ_{1js} proportions of infested trees at a surveyed site j in a scenario s

N_j the number of host trees per survey site j (16-ha hexagonal blocks)

β proportion of a site that is surveyed

γ pest detection rate by inspecting a tree

Minimizing the pest management cost under uncertainty



Distribution of the program costs

Minimizing the expected cost does not guarantee a cost decrease in worst-case scenarios –

A better idea is to minimize both, the expected cost and the cost in worst scenarios

Conditional Value-at-Risk (CVaR)[*]

- For a confidence level α, CVaR$_\alpha$ is the expected value of the distribution over $(1 - \alpha)\times 100\%$ of worst scenarios
- Minimizing CVaR controls the worst-case costs
- We minimize both, the weighted average[**] of the **expected cost** and the **CVaR** $_\alpha$ i.e.:

$$\min[(\mathrm{CVaR}_\alpha(\mathrm{cost})) * F + \mathrm{Exp.\ cost} * (1 - F)]$$

where F is a weighting coefficient, $F \in [0;1]$

[*] Acerbi and Tasche 2002; Rockafellar and Uryasev 2000, 2002
[**] Zadeh 1963

Imposing the safety margin and controlling the cost in the worst scenarios

$$\min[F(\mathrm{CVaR}_\alpha)+(1-F)\tau]$$

[1] Minimize the weighted average of the expected cost and the CVaR$_\alpha$ of the cost distribution

where $\tau=\frac{1}{S}\sum_{s=1}^{S}\sum_{j=1}^{J}\left(\beta N_j c_j x_j + t_j R_{js}\right)$ and CVaR$_\alpha$ = $\left(\zeta+\frac{1}{S(1-\alpha)}\sum_{s=1}^{S} w_s\right)$

s.t.:

$$\sum_{j=1}^{J}\left(\beta N_j c_j x_j + t_j R_{js}\right)-\zeta \le w_s,\ w_s \ge 0 \quad \forall\ s\in S$$

[2] A set of auxiliary variables, w_s, ζ and constraints that define the CVaR$_\alpha$*

$$R_{js} \ge N_j \beta\gamma\theta_{js} x_j \qquad \forall\ s\in S, j\in J$$

[4] Remove all detected infested trees

$$R_{js} \le N_j x_j \qquad \forall\ s\in S, j\in J$$

[5] Number of removed trees cannot exceed the number of trees at a site

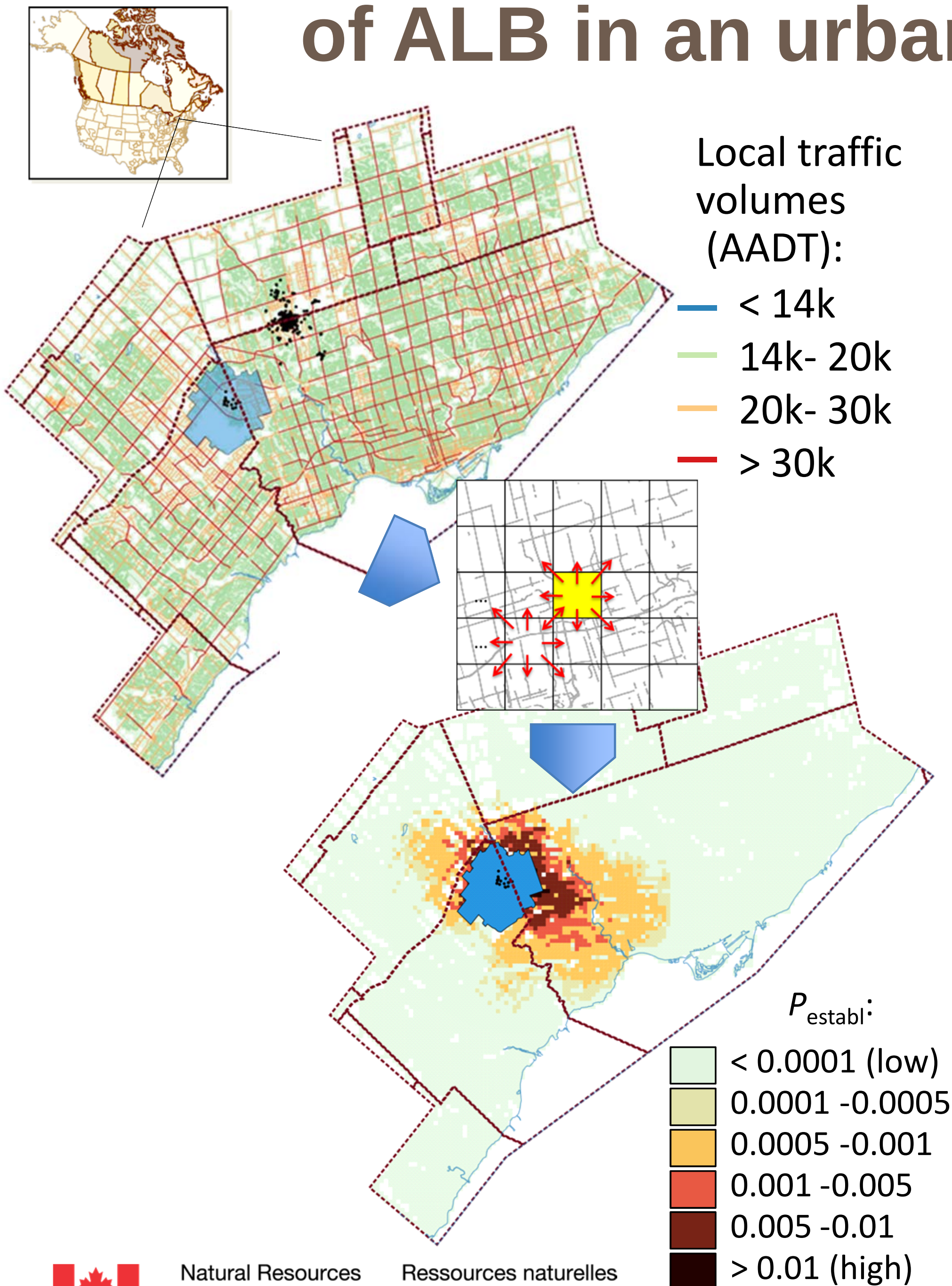
$$\sum_{j=1}^{J}\Big[(N_j-R_{js})\ln(1-\theta_{js}[(1-\beta\gamma)/(1-\beta\gamma\theta_{js})])\Big] \ge g_s \ln(d)+(1-g_s)\ln(d_0) \quad \forall\ s\in S, d_0=10^{-64}, g_s\in\{0,1\}$$

$$\sum_{s=1}^{S}(g_s)\ge pS$$

[6,7] Eradication must succeed in a minimum proportion, *p* of *S* scenarios with a probability *d*

*See a linear formulation of the CVaR in Rockafellar and Uryasev (2000, 2002)

Assessing the human-mediated spread of ALB in an urban setting



ALB's biological spread rate is slow (<300 m/yr.*) but the species may hitchhike on slow-moving vehicles, similar to other pests**

This points to local vehicle traffic volumes as a predictor of ALB spread in urban environments

The TrafficMetrix*** dataset shows the interpolated traffic volumes for Greater Toronto

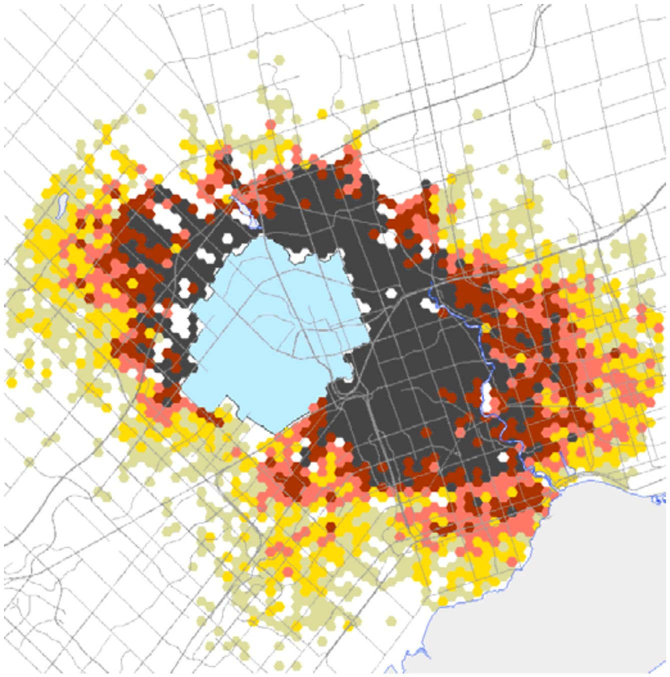
The traffic data and ALB spread model were calibrated to match the spread rates prior to the eradication campaign

Generated 6000 spread scenarios from the areas likely infested with ALB

* Favaro et al. 2015; Trotter and Hull-Sanders 2015
**Buck and Marshall 2008
***Tetrad 2014, Cook and Downing 2013)

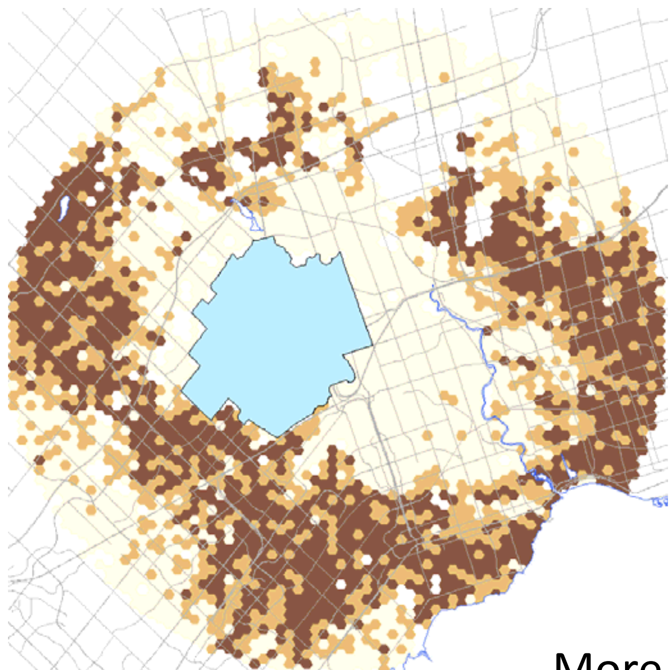
Results: Assessing the optimality gap

Survey allocations,
400 spread scenarios,
mean of 20 replicates, $\bar{x}_j$:



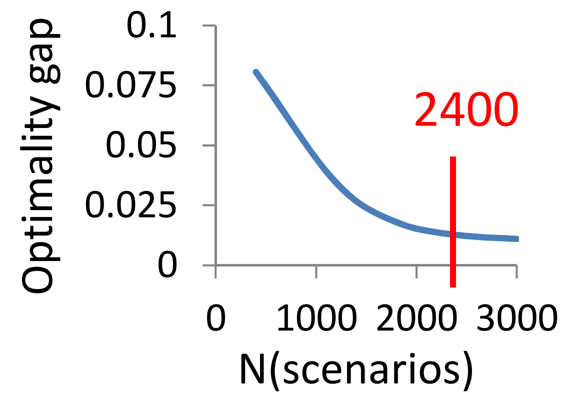
$\bar{x}_j$:
- 0.1 - 0.25
- 0.25-0.45
- 0.45-0.85
- 0.85-1

Differences in survey allocations, 2400 vs. 400 scenarios, $\bar{x}_{j\,2400} - \bar{x}_{j\,400}$:



$\bar{x}_{j\,2400} - \bar{x}_{j\,400}$:
- < 0.2
- 0.2-0.4
- > 0.4

Optimality gap*:

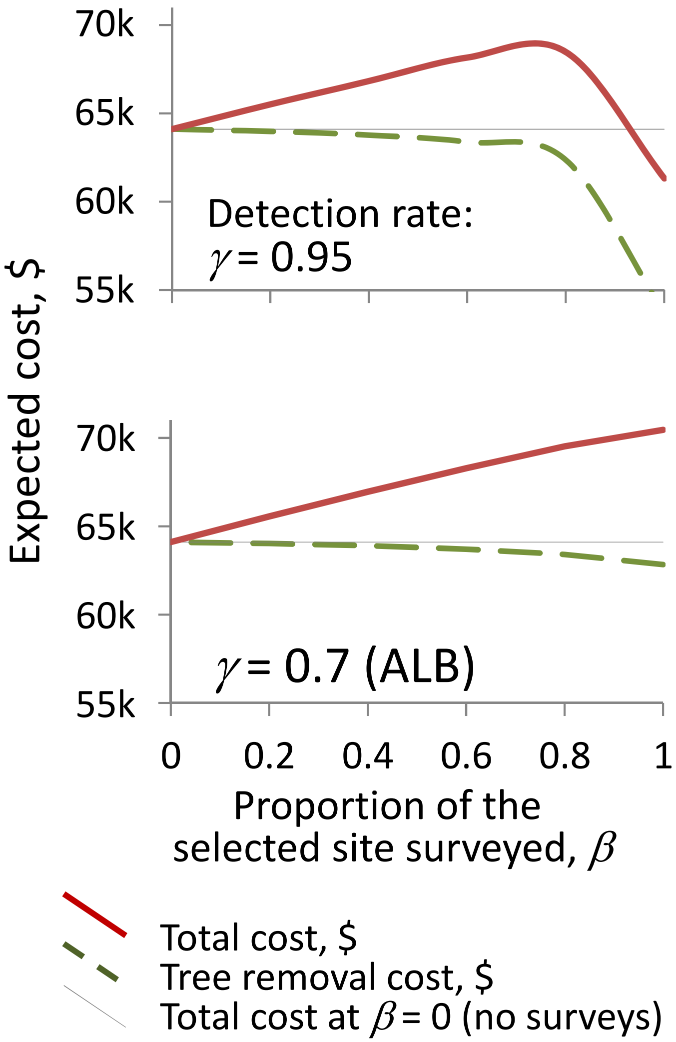


More uncertainty =>
More spread scenarios =>
More sites to survey at long distances

* The optimality gap is ***(U – L)/ U*** (Mak et al. 1999; Lee et al. 2013), where: ***L*** is the lower bound average is obtained by solving the objective functions for 20 replicates with *S* scenarios; ***U*** is the upper bound as a number of invaded and susceptible trees remaining at surveyed sites using the set of 6000 scenarios.

Optimal management policies

Total cost vs. the proportion of a site that is surveyed, β:
(Example with total area 80 ha, *d* = 0.95)



The delineation surveys gain information that help reduce the number of trees to remove but add cost

At some point, cost of surveys outweighs benefits of reducing the tree removal cost

Two optimal management policies:

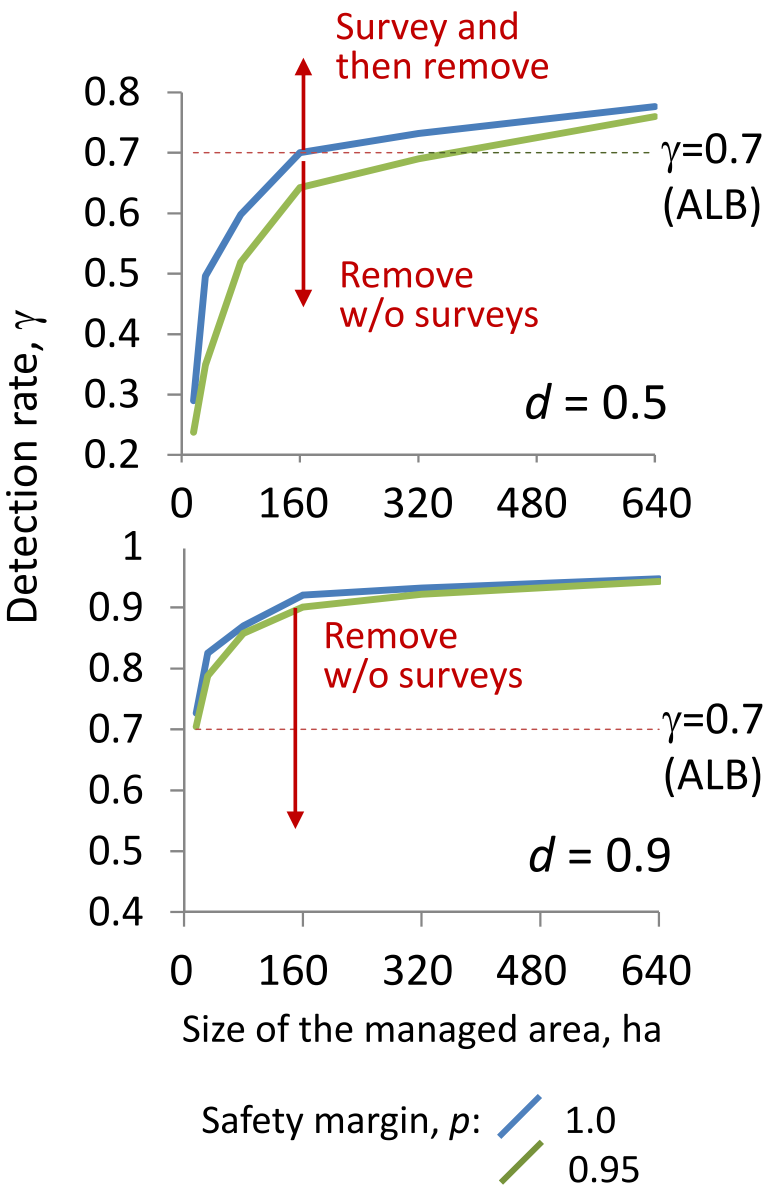
- Survey the area with 100% coverage and remove trees based on the surveys' outcomes

- Pre-emptive tree removal without the surveys

We explore the policy choice in the model parameter space:

- Detection rate γ
- Size of the managed area, J
- Probability of successful eradication, d
- Infestation rate, θ_{js}
- Host density, N_j

Impact of the size of the managed area and the safety margin, *p*



The survey-and-remove policy is likely to be feasible at:

- Lower eradication success thresholds, *d*
- Smaller area sizes, *J*
- Higher detection rates, γ

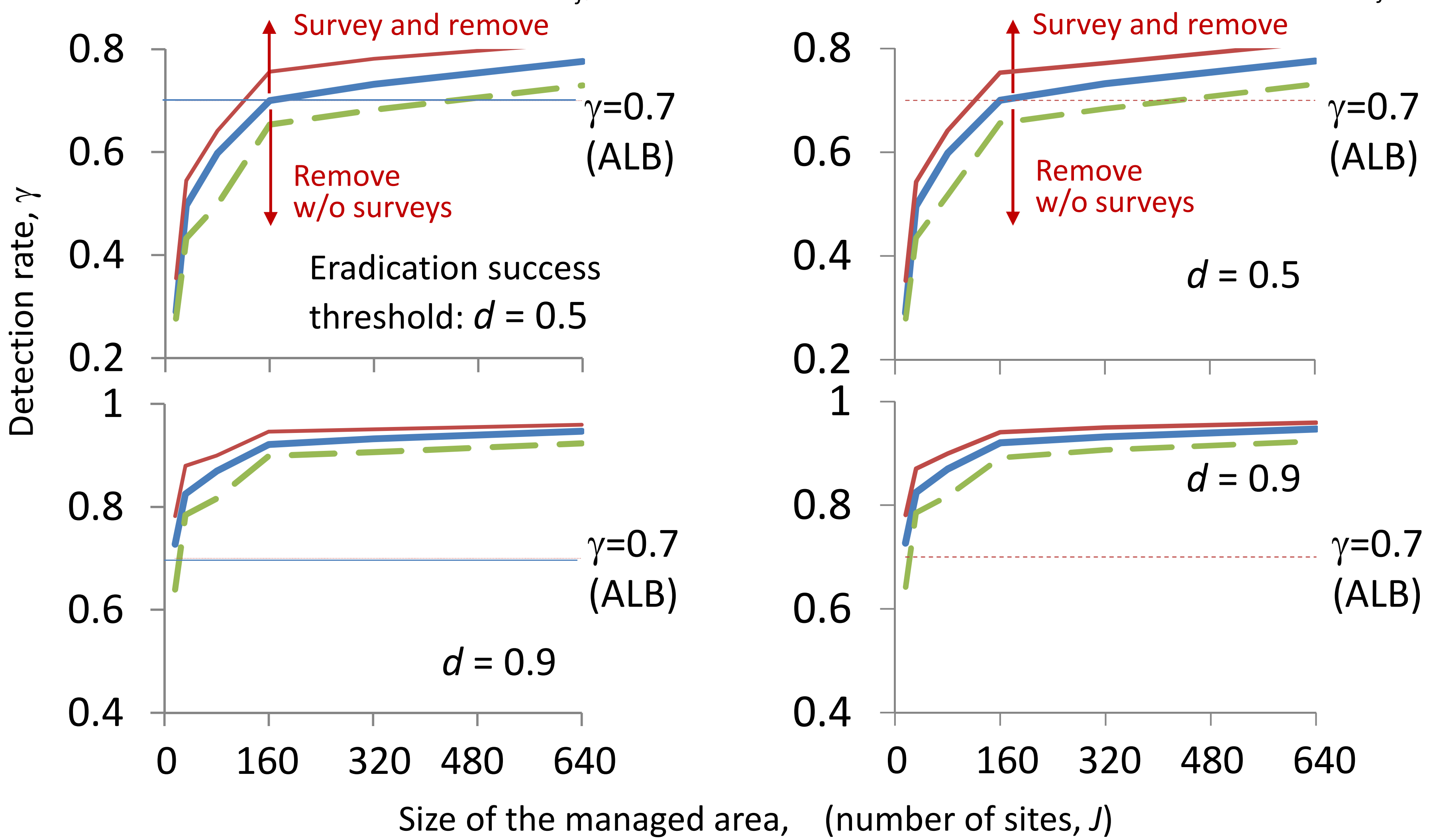
For ALB (γ = 0.7), relaxing the safety margin to *p* = 0.95 does not change the optimal policy when the eradication success threshold is high (*d* = 0.9)

For lower success thresholds (e.g., *d* = 0.5), lower safety margin increases the area where the survey-and-remove policy is optimal

Impact of changing the expected infestation rate, θ_{js} and host tree density, N_j

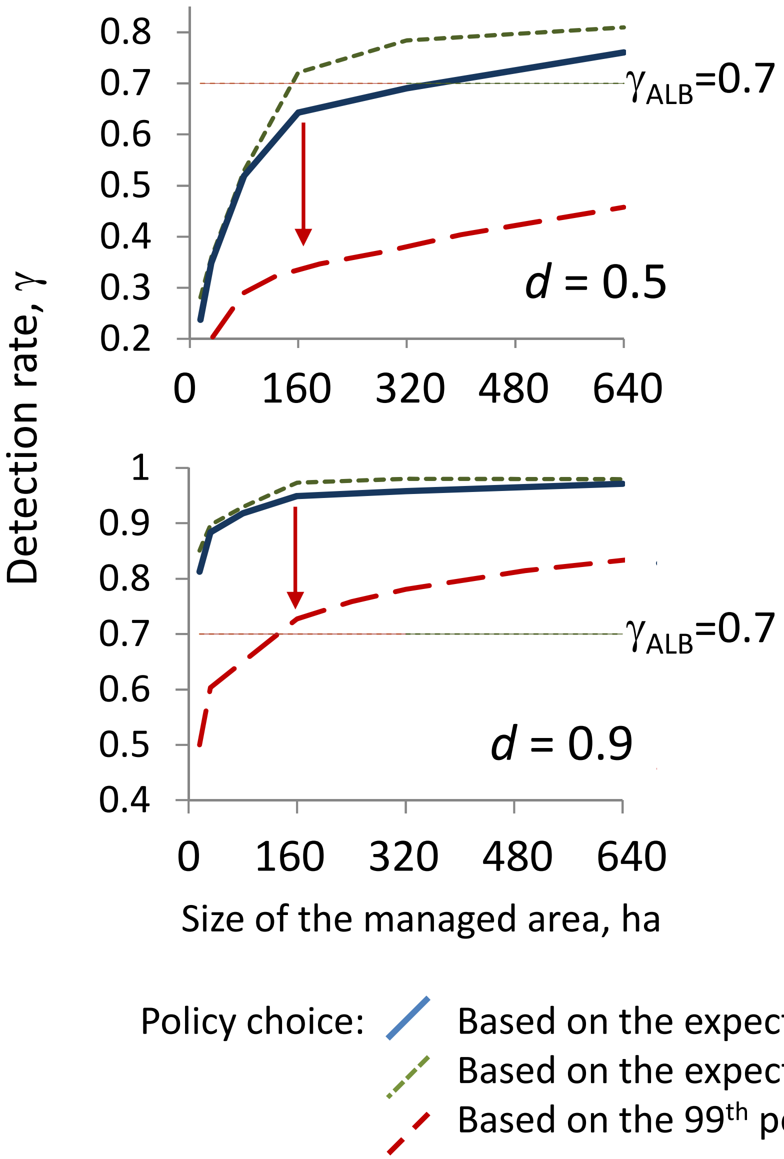
Changing the infestation rate, θ_{js} :

Changing the host tree density, N_j :



Baseline θ_{js} — 0.67*θ_{js} — 1.33*θ_{js} — Baseline N_j — 0.67*N_j — 1.33*N_j

Controlling the cost in the worst scenarios



CVaR does not affect the "remove-only" policy because the only way to decrease the cost in the worst scenarios is to survey more sites

Controlling the cost of worst-case scenarios increases the expected costs and makes the survey-and-remove policy less attractive

However, when manager's wants to prevent worst-case scenarios (so that the policy choice is based on upper cost percentile), survey-and-remove policy may be a better option

It all depends on how manager perceives risk

Insights for decision-making

Our model incorporates the uncertainty about the outcomes of invasion thus helps create robust, risk-averse solutions

Finds the best management strategy, by combining four decision-making constraints:

- The aspirational eradication success target
- Expected rates of pest invasion and pest detection
- The size and spatial extent of the managed area
- Safety margin that defines decision-maker's aversion to uncertainty about the attainment of the risk

For ALB eradication case, delimiting surveys after the initial detection are feasible only when the size of the managed area is small or the pest detection rate is high, otherwise, pre-emptive tree removal should be preferred

The approach is generalizable and can be applied to other species and geographic regions

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