Designing cost-efficient surveillance strategies for early detection of invasive species

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Abstract

Wood borers and bark beetles are among the most serious forest pests worldwide. Many such species have become successful invaders, often causing substantial, costly damages to forests. Here we design and evaluate the cost-efficiency of a trap-based surveillance program for early detection of wood borers and bark beetles at risk of establishing in New Zealand. Though costly, a surveillance program could lead to earlier detection of newly established forest pests, thereby increasing the likelihood of successful eradication and reducing control costs and damages from future invasions. We develop a mechanistic bioeconomic model that relates surveillance intensity (i.e., trap density) and invasion size to probabilities of detection and control; it captures the dynamics of invasive species establishment, spread, and damages to urban and plantation forests. We employ the model to design surveillance programs that provide the greatest net present benefits. Our findings suggest that implementing a surveillance trapping program for invasive wood borers and bark beetles would provide positive net benefits under all scenarios considered. The economically optimal trapping strategy calls for a very high investment in surveillance: about 10,000 traps in each year of the 30-year surveillance program, at a present value cost of US$54 million. This strategy provides a 39% reduction in costs compared with no surveillance, corresponding to an expected net present benefit of approximately US$300 million. Although surveillance may provide the greatest net benefits when implemented at relatively high levels, our findings also show that even low levels of surveillance are worthwhile: the economic benefits from surveillance more than offset the rising costs associated with increasing trapping density. Our results also show that the cost-efficiency of surveillance varies across target regions because of differences in pest introduction and damage accumulation rates across locales, with greater surveillance warranted in areas closer to at-risk high-value resources and in areas that receive more imported goods that serve as an invasion pathway.

Key words: Biological invasions, cost-efficient, detection, eradication, monitoring, pest management, risk management, optimal, search, bioeconomic model

INTRODUCTION

Invasive species cause significant ecological and economic harm to natural and human systems worldwide, affecting biodiversity and ecosystem services, agriculture, industry, and human health and incurring significant expenditures for control (Aukema et al. 2011, Olson 2006, Pimentel et al. 2005). The costs from invasive species introductions are predicted to continue to rise as new invasions occur and spread, facilitated by increasing human travel, trade, and climate change (Simberloff 2000, Liebhold et al. 2012). Resources for reducing invasion damages can be invested at various stages—to prevent new introductions, eradicate established invaders, or reduce the spread or damages from established invaders.

International trade is an important pathway for invasive species introductions, and prevention along this pathway often includes inspection or treatment of imports (Liebhold et al. 2012). However, such efforts cannot effectively prevent all new introductions. When prevention does not succeed, early detection of new invasions can increase the likelihood of control and reduce control costs and damages (Epanchin-Niell and Hastings 2010). However, early detection requires investment in surveillance efforts that can be quite costly, and thus involves inherent economic trade-offs. This trade-off among surveillance costs and invasion costs and damages is inherent to this decision context but rarely is considered explicitly in actual management planning.

Past research on designing cost-efficient surveillance for locating established invaders has taken various approaches, generally focusing on identifying the optimal level of surveillance to implement for locating populations of an invader for which eradication or control, when attempted, is certain (e.g., Mehta et al. 2007, Bogich et al. 2008, Hauser and McCarthy 2009, Homans and Horie 2011, Epanchin-Niell et al. 2012, Horie et al. 2013). Some studies have also considered the optimal location of these efforts (e.g., Cacho and Hester 2011, Hauser and McCarthy 2009, Homans and Horie 2011, Epanchin-Niell et al. 2012, Horie et al. 2013). Each study has relaxed particular assumptions of previous studies to increase the realism and applicability of the modeling approach for designing surveillance programs.

In this study we extend the existing literature on designing cost-effective invasive species surveillance programs in four ways that allow for practical and general application of our approach. First, we consider surveillance efforts that target detection of new populations of multiple pest species simultaneously, rather than considering a single species program. Second, we account for the possibility that eradication may not be feasible or may fail, such that an invasion may continue to spread and cause damages despite the investment in eradication efforts. Third, we assume that managers attempt eradication only if the investment is expected to provide positive net benefits despite the potential for failure. In this way, we account for the endogeneity of the eradication decision in the design of the surveillance system (e.g., Homans and Horie 2011). Fourth, we employ a mechanistic approach to estimating spatially varying damages from invasions based on the likely establishment locations and spread patterns of invaders and the location of susceptible resources across the landscape.

We apply our approach to designing and evaluating the cost-effectiveness of surveillance for wood borers and bark beetles arriving in New Zealand. These species are among the most serious forest pests worldwide, and many have become successful invaders beyond their native range (e.g., Brockerhoff et al. 2006a, Haack 2006, Aukema et al. 2011). Bark beetles can be detected through visual inspections (for the insects themselves or the damage they cause) and approaches that use specific beetle attractant traps to sample species. New Zealand has well-developed forest health and high-risk site surveillance programs that rely on visual insect and damage detection (Stevens 2008), but currently no trap-based surveillance program. Here we develop a novel modeling approach for designing cost-effective surveillance for detecting populations of potential new invaders across multiple regions. We apply the model to evaluate the cost-efficiency of surveillance trapping for early detection of invasive wood borer and bark beetles that may establish in New Zealand.

METHODS

We first introduce a general modeling framework and then parameterize the model to specifically consider surveillance and management of wood borers and bark beetles in New Zealand. We use the model to determine the optimal investment in surveillance, in terms of the numbers and distributions of traps, to minimize the total expected costs of wood borer and bark beetle invasion in New Zealand, including the costs of surveillance, invasion control, and damages.

The model

We begin by developing a model to optimize surveillance for a single location (e.g., a single port region in which invasions may establish) and for a single type of invader (e.g., a single species of wood borer). We then expand the model to consider multiple surveillance locations and multiple potential invaders (e.g., a general suite of wood borer and bark beetle species arriving across multiple port regions). For our application we focus on surveillance using trap samples baited with insect attractants, but surveillance could alternatively employ visual surveys or other sampling techniques at discrete locations. We define surveillance intensity as the density of traps deployed in a region.

Consider a region in which new populations of a nonnative pest are establishing. The rate at which new populations establish is assumed to be constant, but the actual arrival of new populations in that region is random in space and time, such that the number, size, and location of populations in the region at any point in time are unknown prior to detection. We assume that each new population that establishes occupies a circular area that grows radially at a given rate. To find populations, surveillance is conducted annually with traps distributed at random within the specified region and with cost dependent on the number of traps. For each trap that intercepts a circular population, the population may be detected with a probability that depends on the sensitivity of the trap. When a population is detected, eradication can be attempted with some probability of success and a cost that depends on the population's area. If no traps intercept a particular population or if all intercepting traps fail to detect it in a particular year, the population is undetected and continues to grow. Populations also continue to grow if eradication is either not attempted or unsuccessful. Established populations cause damages (e.g., to plantation and urban forests), the magnitude of which depends on the population's location, size, and the time that has passed since its establishment. The choice of whether to attempt eradication of a detected population depends on the expected net benefit of eradication efforts, which depends on the anticipated success of eradication, the anticipated costs of eradication, and the expected damages from the invader if it is not eradicated. We assume that eradication success and costs depend on population area.

This model can be expanded to consider multiple regions and multiple invader types that differ in their anticipated damages and spread rate. The expected long-term costs and damages associated with any surveillance strategy (i.e., trapping density) can be calculated by employing estimates of rates of population establishment and growth, the probabilities of detecting and eradicating populations, the costs of control, and the damages caused by the invasions. In turn, this framework can be used either to determine the long-term trap densities that minimize the total expected costs of surveillance, eradication, and damages over time, or to evaluate the cost-effectiveness of a proposed strategy. The mathematical details of this framework are described next.

Population establishment, growth and detection. We define S as the set of population size (age) classes, $S = \{1,2,\ldots,S_{max}\}$, where we consider damages accrued over the first S_{max} years of an invasion. We define $x^s(t)$ as the expected number of undetected populations of size class $s \in$

S on the landscape at time t and $z^s(t)$ as the expected number of detected populations for which eradication was either unsuccessful or not attempted. If new invaders establish at an average rate b, then the expected number of undetected populations of size class s = 1 at any time t equals b. In each time period, undetected populations of size class s will transition to size class s+1 if undetected. Supposing that the probability of detection of populations of size class s is $p_{detect}(s)$, then a size class model for undetected populations can be specified as

$$\begin{aligned} x^1(t+1) &= b(t) \\ x^s(t+1) &= x^{s-1}(t)(1-p_{detect}(s-1)) \qquad \text{for } s = 2,\ldots,S_{max} \end{aligned} \tag{1}$$

Similarly, in each time period, populations of size class s that have been detected but not eradicated will transition to detected populations of size class s+1 in the next time period. Thus a size class model for extant, detected populations can be specified as

$$\begin{aligned} z^1(t+1) &= 0 \\ z^s(t+1) &= x^{s-1}(t)(p_{detect}(s-1))(1-erad(s-1)*p_{erad}(\mathrm{s}-1)) + z^{s-1}(t) \qquad \text{for } s = 2,\ldots,S_{max} \end{aligned} \tag{2}$$

where $p_{erad}(s)$ is the probability that eradication is successful if attempted, and *erad(s)* indicates whether eradication is attempted when a population of size class s is detected*; erad(s)* equals one if eradication is attempted and zero otherwise. The probability $p_{detect}(s)$ of detecting each population on the landscape increases with surveillance trap density d, population size (measured as areal extent) $a(s)$, and trap sensitivity y, and can be rewritten as $p_{detect}(d,s)$. We define trap sensitivity y as the probability that a trap will detect a population when located within the population's boundaries. If we assume that both trap placement and population establishment are random in space within the region, then the probability that at least one trap will fall within a population and detect that population can be approximated by one minus the zero term of the Poisson distribution with mean $da(s)y$ (Epanchin-Niell et al. 2012). Thus we assume that the probability $p_{detect}(d,s)$ that one or more traps lie within and detect the population equals $1 - \exp(-da(s)y)$ for all populations whose area is less than or equal to the area (A) of the surveyed region, and equals $1 - \exp(-dAy)$ for populations larger than the surveyed region. Note that this approximation relies on the mean being small, as it almost always will be for most biosecurity surveillance systems. Alternatively, a binomial expression can be used, which is slightly more complex and requires greater computational time. We compared results from both approaches and found negligible difference, and thus we present results from the Poisson approximation.

Costs, damages, and identification of optimal surveillance. We assume that surveillance costs $C_s(d, A)$ depend on the density of traps and the area A over which traps are distributed. We assume that the size and damage costs from an invasion depend on the time since its establishment. We define $C_d(s)$ as the total damage costs (e.g., damages to plantation and urban forests) in a single time period from a population of size class s, including the costs of any control efforts to reduce damages.

Following detection, eradication of a population can be attempted at a cost that increases with the population's size, $C_e(a(s))$. The probability of eradication success, $p_{erad}(a(s))$, decreases with the population's size. We assume that eradication will be attempted only if the expected costs and damages from attempting eradication are less than the expected costs of the population remaining on the landscape and continuing to grow. The expected cost of the population remaining on the landscape, $ENPV_{noerad}(s)$, equals the discounted future stream of all costs and damages associated with a population of size class s:

$$ENPV_{noerad}(s) = \sum_{t=0}^{S_{max}-s} \frac{C_d(t+s)}{(1+\delta)^t} \tag{3}$$

where damages are summed across the remaining time periods until the invasion reaches age class S_{max}, accounting for population growth over time and a discount rate δ. Thus, eradication is attempted (i.e., *erad*=1) if

$$C_e\,(a(s))+(1-p_{erad}(a(s))*ENPV_{noerad}\,(s) < ENPV_{noerad}\,(s) \qquad (4)$$

Otherwise eradication is not attempted (i.e., *erad*=0).

The objective of management is to choose a trapping density to minimize the total net present value of expected future costs from surveillance, invasion damages, and control costs. We consider application of a constant surveillance strategy (i.e., a constant trap density) over a fixed time horizon (T) and evaluate the total net present value of costs and damages associated with that strategy, including damages resulting from all populations that establish during the course of the surveillance program or that were present on the landscape (but not yet detected) prior to the start of the program.

We assume that in the absence of surveillance trapping, populations remain undetected for a fixed time horizon, f, at which time they are detected perfectly. We assume that populations were arriving at a background rate prior to the start of the surveillance program. Thus, at the start of the program the expected number of undetected populations already on the landscape equals $x^s(t=1)=b$ for all $s \leq f$ (from Equation 1).

For all time periods of surveillance program implementation, the number of undetected populations of each age class on the landscape can be determined recursively, using Equation 1, with $p_{detect}(s)= p_{detect}(d,s)$. Recognizing that $x^s(t)$ and $z^s(t)$ are also functions of d, they can be written $x^s(t,d)$ and $z^s(t,d)$.

The net present value of total expected costs and damages for a surveillance program lasting *T* years, including the costs and damages associated with all undetected populations at the start of the program and all populations establishing during the program, equals

$$TC(d) = \sum_{t=1}^{T} \begin{pmatrix} C_s(d,A) + \sum_{s=1}^{S_{max}} x^s(t,d) C_d(s) + \sum_{s=1}^{S_{max}} z^s(t,d) C_d(s) \\ + \sum_{s=1}^{S_{max}} x^s(t,d) p_{detect}(d,s) erad(s) C_e(a(s)) \end{pmatrix} (1+\delta)^{1-t} + \frac{ENPV_{noerad}(s)\left(x^s(T+1,d) + z^s(T+1,d)\right)}{(1+\delta)^T} \tag{5}$$

where the terms in the summation are surveillance costs, damages from undetected populations, damages from detected populations, and eradication costs, discounted at a rate δ. The final cost term is the net present value of all populations remaining on the landscape at the end of the surveillance program. To determine the optimal surveillance intensity, we minimize this function with respect to *d*, thereby choosing the trapping density that minimizes the total expected costs of surveillance, eradication, and invasion damages.

Consideration of multiple invaders and regions. We now expand this approach to multiple invaders and invader types by summing the expected costs and damages (Equation 5) across multiple potential invaders that can be detected by the same surveillance mechanisms (e.g., traps). In Equations 1, 2, and 5, $TC(d)$, x, C_d, z, b, p_{detect}, and C_e, each can be indexed by invader type *i*, where $i \in \{1,2,...,I\}$ and *I* is the total number of potential invader types distinguished by a combination of urban and plantation damage intensity and spread rate. In Equation 1, the arrival rate b^i for each invader type is then calculated as the arrival rate *b* for the region multiplied by the probability of a new invader being of type *i*. The total expected cost (Equation 5) of all new invaders over the long term with trapping density *d* thus equals

$$TC(d) = \sum_{i=1}^{I} TC^i(d) \tag{6}$$

We can also optimize surveillance across multiple subregions (e.g., ports). Consider a total survey area composed of N subregions, with each subregion indexed by $n \in \{1,2,..., N\}$. We then choose the optimal sample density d_n for each subregion to minimize the total expected costs and damages (Eqn. 6) across all subregions:

$$\min_{d_n} \sum_{n \in \{1,2,\ldots N\}} TC_n(d_n) \tag{7}$$

where all parameters are indexed by subregion n. If a region-wide budget constrains surveillance efforts, the following constraint applies:

$$\sum_{n \in \{1,2,\ldots N\}} C_{s_n}(d_n, A_n) \leq B \tag{8}$$

where B is the total annual surveillance budget. Optimizing this problem (Equations 7 and 8) finds the distribution and density of trap samples across regions that minimize the total expected costs from surveillance, eradication, and invasion damages, given any budget constraints.

The expected net present benefits of implementing the optimal surveillance program or any other potential surveillance program (as defined by trap densities d_n) relative to doing nothing, is calculated as the difference in total costs (Equation 7) under the specified program and when all d_n=0.

Model parameterization

We apply our approach to designing a trapping surveillance program for bark beetles and wood borers in four major centers of trade in New Zealand: Auckland, Tauranga, Wellington, and Christchurch (Lyttelton) (Figure. 1). These places are the most likely entry points for new wood borers and bark beetles into New Zealand based on trade volume, as described below. We focus on two important types of damages that wood borers and bark beetles cause: damage to plantation forests, since timber export is an important industry for New Zealand, and damage to urban forests and trees, since this can be among the highest damage costs caused by this guild of invasive species (Aukema et al. 2011, Turner et al. 2004).

Application of our model requires information about expected establishment rates of new invaders in the focal regions, the likelihood of different "types" of invaders (as defined by the damages they cause and their spread rate), the chances of detecting and of eradicating populations of different sizes, the costs of surveillance and eradication, and the population spread rates and damage functions. Data for estimating these parameters and functions are quite limited for wood borer and bark beetle invasions in New Zealand, as they are for many systems and invasion management contexts. Thus, parameterizing our model requires making many assumptions that represent our best guesses about the dynamics and characteristics of the system. We therefore test the influence of these uncertain assumptions on the conclusions drawn from our results using sensitivity analyses and by comparing the expected net benefits of surveillance under various assumptions and our baseline parameters.

Parameter estimates for the analysis were obtained from data held in Scion's Forest Biosecurity databases, the Global Eradication and Response Database (GERDA) (Kean et al. 2012), a review of the literature (e.g., Bulman et al. 1999, Liebhold and Tobin 2008, Craighead 2009, Brockerhoff 2009, Haack and Brockerhoff 2011), and experts' input. We describe these estimates next. We use 2011 U.S. dollars as the base currency for our analyses and employ the long-term average exchange rate of 1.0 NZD equalling 0.65 USD as needed (http://www.rbnz.govt.nz/statistics/exandint/B1/data.html).

Potential invader types. We do not know exactly which species of wood borer or bark beetle may establish in New Zealand in the future. Therefore we delineate 18 potential invader types (i.e., I =18), as defined by anticipated damages to urban forests, damages to plantation forests, and spread rate, to represent the potential array of future invaders. Each potential invader type is characterized as causing high, medium, or low damage to plantation and to urban forests, and as slow or fast spreading. We assume that the damage subtypes and spread rate subtypes are independent, such that the probability of each invader type is the product of the probability of each damage subtype (p^U and p^P) and spread rate type (p^s).

The vast majority of new invaders cause low damages, with a smaller proportion causing medium damages, and the smallest fraction causing the largest damages (Aukema et al. 2011). Thus we assume probabilities of 80%, 15%, and 5% for low, medium, and high damages, respectively, for urban and plantation forests. We assume that 50% of new invaders spread quickly (asymptotic rate of spread equals 50 km per year) and 50% spread more slowly (10 km per year). We conduct two sensitivity analyses on the fraction of fast- versus slow-spreading invaders, considering scenarios where 75% of invaders spread slowly and where 25% spread slowly.

Establishment rates. New wood borer and bark beetle species arrive and establish in New Zealand at an average background rate, *b*. Historically, establishments in New Zealand of wood borers and bark beetles occurred at a rate of about 0.4 species per year (i.e., 40 introductions in the past 100 years) (see Table 1 and Figure 3 in Brockerhoff 2009). However, not all of these species would be of concern to New Zealand's plantation forests or urban trees. Furthermore, the rate of wood borer and bark beetle establishments appears to have declined in recent decades. For this analysis, we assume that the recent rate of 0.065 introductions per year is the baseline establishment rate. For sensitivity analyses, we consider establishment rates of 0.18 and 0.032 introductions per year.

Our analyses focus on surveillance trapping within four major trade and urban centers: Auckland, Tauranga, Wellington, and Christchurch (Lyttelton) (Figure 1). Collectively, these receive approximately 90% of the trade volume that poses the greatest risk for invasions of wood borers and bark beetles. We estimate the relative invasion risk across the four focal ports based on the flow of trade that is likely to use wood packing material, which is probably the most common introduction pathway for borers (Haack and Petrice 2009, see also Brockerhoff et al. 2006b). We estimate that 48.7%, 23.0%, 8.1%, and 9.3% of wood borer and bark beetle establishments will occur via introduction into Auckland, Tauranga, Wellington, and Christchurch, respectively, and thus apportion our nationwide estimated invasion establishment rate, *b*, proportionately across the four port regions. We further apportion these establishment rates across the 18 identified invader types based on the probability of each invader type.

Areal extent of regions and proportions of invasion introductions in sampled areas. The total urban areas of Auckland, Tauranga, Wellington, and Christchurch used for our analysis are 1086 km^2, 168 km^2, 444 km^2, and 450 km^2, respectively. For our baseline analysis we assume that trapping efforts are targeted at only 20% of the urban area in each of the four focal regions, thereby focusing surveillance on the highest-risk sites. Furthermore, we assume that 80% of future invaders arriving in a port region establish within that 20% area. The remaining 20% of establishment via each port is not captured by the targeted surveillance system considered here. These values represent the best understanding of the system but are uncertain. For sensitivity analysis we consider four other combinations of trapped area and percentages of establishments occurring within those limited areas. Specifically, we consider trapping of 10% of each port region, which we assume encompasses 60% of establishments; 20% of each port region, encompassing 60% of establishments; 30% of each port region, encompassing 80% of establishments; and 100% of each port region, encompassing 95% of the establishments into those areas.

Cost of surveillance trapping program. The costs of surveillance, C_s, include both fixed and variable costs, where variable costs depend on trap density and the total area surveyed. These costs were estimated using expert opinion. Fixed costs, which include the costs of design, planning and management of the trapping program, data analysis, and writing of reports, are estimated at US$16,250 per year. The estimated per trap variable costs associated with trapping include the costs of traps, attractants, trap deployment and maintenance, sample collection, shipping, and identification; the costs decrease with increasing total trap number and range from US$633 to $328 per trap.

Sensitivity of traps. The sensitivity of traps (y) is the likelihood that a trap will detect a population (i.e., of an invader's being caught and identified as such) when a trap intersects the invader population. This sensitivity is likely to vary across species and is highly uncertain. Thus, we assume a baseline sensitivity of 60% and do a sensitivity analysis for y=30% and y=90%.

Invader population growth. We assume that each invasion begins near a port and spreads radially according to a growth function such that it occupies an increasingly large circular area over time. We model the spatial expansion of populations using a sigmoid function that allows for an initially accelerating rate of radial population growth that eventually asymptotes at a rate g (e.g., Epanchin-Niell et al. 2012). Under this assumption the annual change in the radius of a population is given by $\frac{gs^m}{h^m+s^m}$, where s is the size class (or equivalently the age) of the population, g is the asymptotic radial rate of population growth, m is a shape parameter, and h is the time at which half the asymptotic rate of growth is achieved. We employ a shape parameter m=5 and half time value h=10. We consider h=20 for our sensitivity analyses. We consider two asymptotic radial rates of spread to represent the two potential spread types of invaders: 10 km and 50 km per year.

Damages to plantation forests. We assume that invaders reduce plantation forest harvest values at a location by a proportion that depends on the invader damage type i and how long the invader has been present at the location. Our baseline damage assumptions are maximal harvest value reductions of 1%, 10%, and 50% for low-, medium-, and high-damage plantation pests, respectively. For sensitivity analyses we consider damages of 1%, 5%, and 20% and 1%, 15%, and 75% for low-, medium-, and high-damage plantation forest pests, respectively.

We assume that damages accrue only to forests located within the area occupied by an invader, and thus the amount of forest affected at any given time depends on the age, growth function, and establishment location of the invader, as well as the distribution of plantation forests within New Zealand. New areas of plantation forest are affected over time as an invasive species population spreads. We assume a five-year delay before damages begin accruing in a newly invaded plantation forest, to account for initially low population densities. Following the five-year delay, we assume that damages increase linearly in those areas over the next five years to reach their maximum reduction in harvest value in the tenth year following the arrival of the invader. Maximal reductions in harvest value continue for a fixed time horizon, S_{max}, following the arrival of the invader in New Zealand or until the population is eradicated.

The location and extent of plantation forests within New Zealand were derived from the Land Cover Database 2 (LCDB2) geospatial data (based on 2001–2002 imagery) for New Zealand (Ministry for the Environment 2004). The distribution of plantation forest from these data is illustrated in Figure 1a.

The value of future annual plantation harvests for New Zealand was estimated from forecasts of New Zealand wood availability by region from 2012 to 2040 (e.g., MAF 2009), which suggest a total annual harvest value for New Zealand of approximately US$1,154 million from 2015 onward. We employ this value as our estimate of total annual harvest value in the absence of any new invasions. We assume that this value is distributed in proportion to the area of plantation forest (Figure 1a).

Damages to urban forests. We assume that invaders affect a fraction of urban trees that depends on the invader damage type i and time since invasion arrival at a location. Because there are no data on the distribution and number of urban trees in New Zealand, we follow

Turner et al. (2004) by assuming that 20 million urban trees are distributed proportionally with human population density across New Zealand. We also assume that each tree affected by invasion incurs a one-time average cost of US$2,283, which is an estimated average cost of tree removal and replacement (Turner et al. 2004, Haight et al. 2011) but could capture other damages or control costs.

As with plantation forests, we assume that each invasion begins near a port, grows radially, and causes damage to urban forests within the occupied area. Following invasion arrival at a particular location on the landscape, there is a five-year delay before damages begin to accrue, after which one-fifth of susceptible trees are affected in each of the following five years. Ten years following the arrival of the invader at a location, the damages to urban forest at that location cease because all susceptible trees have been removed and replaced. We assume that a total of 1%, 5%, and 20% of urban trees at any location are susceptible to low-, medium-, and high-damage urban forest pests, respectively. We conduct three sensitivity analyses in which we assume 1%, 2%, and 5%; 1%, 3%, and 10%; and 1%, 10%, and 50%, of trees are susceptible to low-, medium-, and high-damage urban forest pests, respectively.

Eradication cost and probability of successful eradication. Relationships between infested area and the cost and probability of eradication were estimated from values recorded for past eradication programs against wood-boring insects (Kean et al. 2012).

To estimate the costs of eradication, we include only eradications for which costs are known (n=25). The effect of $\log_{10}$(invasion size) on $\log_{10}$(cost) was fitted using linear regression, where costs were measured in millions of 2011 U.S. dollars and area was measured as km^2. We use this estimated cost function as our baseline costs and use the upper and lower confidence interval for the fitted line for sensitivity.

The probability of eradication was estimated from programs whose outcomes are known (n=34). Outcomes were classified as either successful (value 1) or unsuccessful (0). Thirteen of the 34 programs were successful (Kean et al. 2012). The relationship between the log invaded area (km^2) and probability of eradication was estimated by logistic regression. For sensitivity analysis, we employ the upper and lower 95% confidence intervals for predicted success.

Discount rate and time horizons. We use a baseline discount rate equal to 5% and consider 10% and 1% rates for sensitivity analyses. We consider a baseline time horizon, S_{max}, of 75 years over which damages accrue from an invader following its establishment and conduct sensitivity analyses using time horizons of 50 and 100 years. We consider a baseline surveillance program of 30 years but also examine 10 and 50 year programs.

Model application

We evaluate a range of surveillance scenarios using the parameterized modeling framework. Using the baseline parameters, we evaluate the total expected costs and damages under 10 surveillance scenarios. The first 5 scenarios do not optimize trapping across the ports (Equation 6). These scenarios include no trapping (scenario 1) and deployment of four levels of numbers of traps (50, 200, 400, and 1,000 traps) at equal densities across the four ports (scenarios 2–5). The next four scenarios optimize the distribution of a fixed number of traps (50, 200, 400, and 1,000 traps) across the ports, which is equivalent to optimizing under four budget constraints (Equations 7 and 8). The final scenario (scenario 10) identifies the optimal number and distribution of traps across the four ports without any surveillance budget constraints (Equation 7). We evaluate each of the trapping scenarios (scenarios 2–10) against the no-trapping alternative (scenario 1) to identify the expected net benefits from implementing each trapping strategy.

We also conduct parameterization sensitivity analyses by changing one component of the baseline parameterization at a time. For each sensitivity analysis we solve for optimal trapping intensity and expected costs and damages for surveillance scenarios 6–10. We also evaluate the no-trapping alternative (scenario 1). In addition, to see how well the trapping strategies designed as optimal under the baseline parameterization perform if the sensitivity parameterizations are correct, we evaluate the expected costs, damages, and net benefits of implementing the surveillance strategies identified as optimal under the baseline parameterization (scenarios 6–10) when employing the sensitivity analysis parameterizations.

The complexity of the modeling approach prevents derivation of analytical solutions, so we solve for optimal trap densities numerically as a constrained optimization using the "fmincon" solver in Matlab R2010b (The MathWorks, Inc.).

RESULTS AND DISCUSSION

Some background findings

The net present value of expected damages from a potential wood borer or bark beetle that invades New Zealand is shown in Figure 2. The left panel shows the present value of the expected damages from a single pest establishing in each port. Damages across ports vary because of the port locations' differing proximity to plantation and urban forests. The middle panel shows the present value of expected damages from a single pest arriving in New Zealand, where damages associated with arrival in each port are weighted by the likelihood of that port's being the arrival location for the pest. The total expected damages from the arrival of a new pest into New Zealand, if it is not detected and eradicated, is the sum of the four columns. The right panel shows the present value of expected damages associated with pest arrival in a single year, where damages are weighted by the likelihood of pest arrival in each year and port, assuming the baseline establishment rate. The total expected damages from the arrival of pests into New Zealand in a single year, if not detected and eradicated, are the sum of the four columns. These panels do not consider the small probability of arrival outside the main four ports.

Surveillance scenario results

Figure 3 shows how total and component costs and damages vary with trap density for each of four port regions. Surveillance costs increase with trap density, as per definition. Damages to urban and plantation forests decrease with trap density because earlier detection increases the likelihood of eradication by decreasing eradication costs and increasing the probability of success. Expected eradication costs are very low and increase and then decrease with trap density. At low trap densities eradication costs are low because populations are detected too late to be worth eradicating. At moderate trap densities total expected eradication costs are higher because more populations are detected when small enough to make attempted eradication worthwhile. At very high trap densities total eradication costs are lower because populations are smaller and thus less costly to eradicate when detected. The generally convex shape of the total cost curve, which is the sum of the four component costs, reflects the trade-off between surveillance expenditures and damage costs.

Optimal trap density occurs at the minimum of the total cost curve (Figure 3, open blue circle). The optimal trap density is highest for Tauranga, followed by Auckland; Christchurch and Wellington have much lower optimal trap densities (Figure 3, Table 1). The total expected costs and damages are highest for Auckland, followed by Tauranga, with the total expected costs of invasions being much lower for Christchurch and Wellington (Figure 3). The differences across the four regions result from different establishment rates, rates of damage accumulation, and size (i.e., sampling area). For example, Tauranga has the highest optimal trapping density across the four ports even though the annual expected damage from pest establishment is only half that of Auckland, due to lower introduction rates in Tauranga (Figure

2b). The reason for this unintuitive result is that the Tauranga port region is only about one tenth the size of the Auckland region and therefore has about five times more expected damages per unit area, thus warranting a greater density of traps. However, the optimal number of traps is higher in Auckland.

The optimal surveillance strategy calls for a very high investment in traps (just over 10,000 traps deployed annually for 30 years, at a present value cost of US$54 million) (Figure 3, Tables 1 and 2). This strategy provides an expected net present benefit of about US$300 million by reducing the present value of total expected control costs and damages from US$776 million without surveillance trapping to US$476 million with optimal surveillance trapping (Tables 2 and 3). This represents an approximate 39% reduction in expected costs and damages (Table 3).

The expected net present value of benefits from optimally deploying a fixed number of traps across the four port regions is shown in Figure 4. The net benefits increase steeply with initial investments in surveillance, but increase less steeply for surveillance intensity greater than about 4,000 total traps deployed. The maximal expected net benefits are achieved from deploying about 10,000 traps. Deploying more than this number of traps leads to decreasing net benefits, as the marginal costs of additional trapping are greater than the marginal benefits from reduced eradication and damage costs.

Although the optimal trap density provides the greatest expected net benefits, there are substantial net benefits from even low (suboptimal) trapping densities (Figure 4, Table 3). All the surveillance scenarios with fixed numbers of traps (scenarios 2–9) show substantial expected net benefits, ranging from US$69 million to $227 million. The gains from surveillance increase with trap density across the scenarios considered. Within these fixed-trap-number (i.e., budget-constrained) scenarios, the total expected costs and damages are lower when traps are distributed optimally across the port regions rather than at a fixed density (Tables 2 and 3).

For our sensitivity analyses, we find that implementation of a trapping surveillance program is beneficial (i.e., provides positive net benefits) across all parameter specifications evaluated. For all sensitivity analyses, the greatest net benefits arise from deploying more than 1,000 total traps (i.e., more traps than in our highest fixed-effort trapping scenario). The optimal trap densities and total expected costs are most sensitive to the specification of discount rate, with lower discount rates demanding much higher surveillance effort.
The expected net benefits of implementing the surveillance strategies identified as optimal under the baseline parameterization (scenarios 6–10 in Table 1) for each sensitivity analysis parameter specification are positive across all sensitivity analysis parameterizations. Thus, even when accounting for uncertainty in individual model parameters, the surveillance programs identified as optimal in our baseline parameterization are cost-effective.

CONCLUSIONS

Our findings show that implementing a surveillance trapping program for invasive wood borers and bark beetles in New Zealand would be clearly beneficial, for all scenarios considered. The optimal 30-year surveillance strategy is expected to provide a net present benefit (i.e., a net present value savings) of about US$300 million. Sensitivity analyses indicate that our findings of positive net benefits of trap-based surveillance for wood borers and bark beetles in New Zealand are robust to our choice of parameters. In addition, although we did not include potential damages to native forests in our analyses, consideration of these damages would increase the returns from surveillance and increase the optimal surveillance intensity.

Our results indicate that surveillance will provide the greatest net benefits when it is implemented at quite high levels. However, our findings also suggest that even low levels of surveillance are worthwhile. We find that the greatest payoffs from surveillance occur for programs in areas that receive large amounts of imports and in areas where damages will accrue most quickly (because of the proximity to high-value, at-risk resources).

Based on our analyses, we recommend that a trap-based surveillance program for wood borers and bark beetles be implemented in New Zealand. The program's level of surveillance intensity could be scaled to the available funds, and our model can be used to determine the optimal surveillance strategy, in terms of trap numbers and locations, in relation to the funds available, as well as the expected benefits of augmenting funds allocated to surveillance. Future analyses could focus on identifying optimal surveillance efforts outside core establishment areas (i.e., outside the four port regions) and identifying the distribution of trap locations within each region.

Beyond our specific findings of positive net benefits of implementing a trap-based surveillance program for wood borers and bark beetles in New Zealand, this research outlines a framework for designing surveillance programs across a much broader range of contexts. Our approach is applicable across regions and to single or multiple pest species and specific or general suites of species. Parameterization is likely the greatest challenge to its implementation. However, we have illustrated one strategy for parameterizing and implementing the model for an application that addresses a practical and specific management need. Our results also support the general guidance that investments in surveillance are likely to be most cost-effective in areas that receive high amounts of imports and that are near to high-value, at-risk resources.

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Table 1. Numbers of traps and trap density (traps/km^2) for various trapping scenarios using baseline parameters. The first five rows (scenarios 1–5) distribute a fixed number of traps at a constant density across the four sites. The next four rows (scenarios 6–9) optimize the distribution of a fixed number of traps across the four sites. The final row (scenario 10) shows the optimal number and distribution of traps without a budget constraint on total trapping effort.

	Total	Auckland		Tauranga		Wellington		Christchurch	
Trapping scenario	traps	traps	density	traps	density	traps	density	traps	density
No traps	0	0.0	0.00	0.0	0.00	0.0	0.00	0.0	0.00
Equal trap density									
50 traps total	50	25.3	0.12	3.9	0.12	10.3	0.12	10.5	0.12
200 traps total	200	101.1	0.47	15.6	0.47	41.3	0.47	41.9	0.47
400 traps total	400	202.2	0.93	31.3	0.93	82.7	0.93	83.8	0.93
1,000 traps total	1000	505.6	2.33	78.2	2.33	206.7	2.33	209.5	2.33
Optimized trap density									
50 traps total	50	27.4	0.13	19.0	0.57	2.0	0.02	1.6	0.02
200 traps total	200	113.6	0.52	66.3	1.97	10.9	0.12	9.3	0.10
400 traps total	400	251.8	1.16	105.0	3.13	23.0	0.26	20.1	0.22
1,000 traps total	1000	610.0	2.81	219.0	6.52	90.9	1.02	80.1	0.89
Optimal trapping	10185	6811.4	31.36	2149.2	63.96	650.9	7.33	573.5	6.37

Table 2. Total costs and damages for various trapping scenarios using baseline parameters. The first five rows (scenarios 1–5) distribute a fixed number of traps at a constant density across the four sites. The next four rows (scenarios 6–9) optimize the distribution of a fixed number of traps across the four sites. The final row (scenario 10) represents optimal trapping in terms of numbers and distribution of traps in the absence of a budget constraint on trapping.

	Present value of expected costs (millions USD)				
Trapping scenario	Total	Surveillance	Eradication	Urban forest damage	Plantation forest damage
No traps	776.03	0.00	0.62	404.65	370.76
Equal trap density					
50 traps total	706.85	0.73	1.46	365.25	339.41
200 traps total	651.70	1.68	1.00	333.47	315.54
400 traps total	615.24	2.57	0.86	312.32	299.49
1,000 traps total	561.39	5.56	0.70	280.20	274.93
Optimized trap density					
50 traps total	693.94	0.73	1.37	358.84	333.00
200 traps total	634.28	1.68	1.01	324.66	306.93
400 traps total	597.62	2.57	0.85	303.15	291.05
1,000 traps total	549.37	5.56	0.69	273.86	269.25
Optimal trapping	476.36	54.23	0.51	204.80	216.82

Table 3. Return on investment for various trapping scenarios using baseline parameters. The expected net benefits are the difference in total expected costs under the specified trapping scenario relative to no trapping (scenario 1). The percentage reduction in total costs also is relative to no surveillance. The first four rows (scenarios 2–5) distribute a fixed number of traps at a constant density across the four sites. The next four rows (scenarios 6–9) optimize the distribution of a fixed number of traps across the four sites. The final row (scenario 10) shows the optimal number and distribution of traps if there is not a budget constraint on total trapping effort.

	Return on Investment Relative to No Trapping	
Trapping scenario	Expected net benefits (millions USD)	Percentage reduction in total costs (%)
Equal trap density		
50 traps total	69.18	8.9
200 traps total	124.33	16.0
400 traps total	160.79	20.7
1,000 traps total	214.64	27.7
Optimized trap density		
50 traps total	82.09	10.6
200 traps total	141.75	18.3
400 traps total	178.41	23.0
1,000 traps total	226.66	29.2
Optimal trapping	299.67	38.6

Figure Captions

Figure 1. Distribution of a) plantation forest (shaded areas), and b) human population density. Urban trees are assumed to be distributed in proportion to human population density.

Figure 2. Expected damages from pest arrival, by port, if pest is not eradicated. The values are probability-weighted damages across the 18 potential invader types.

Figure 3. Expected management costs as function of trap density, by port. The costs are the net present value of expected costs and damages from a 30-year surveillance program. The dashed lines represent the component management and damage costs, and the solid line is the total cost. Open blue circles indicate optimal trap density, where net present value of total costs is minimized. Open triangles indicate expected costs in the absence of a surveillance trapping program. Note different y-axis scales.

Figure 4. Expected net benefits of trapping, by total number of traps deployed. In the analysis for this figure, the total number of traps (x-axis) is distributed optimally across the four port regions (Equations 7 and 8). The expected net benefits are the difference in total costs and damages with versus without surveillance trapping, and include surveillance costs, eradication costs, and invasion damages. The circle shows the optimal total number of traps.

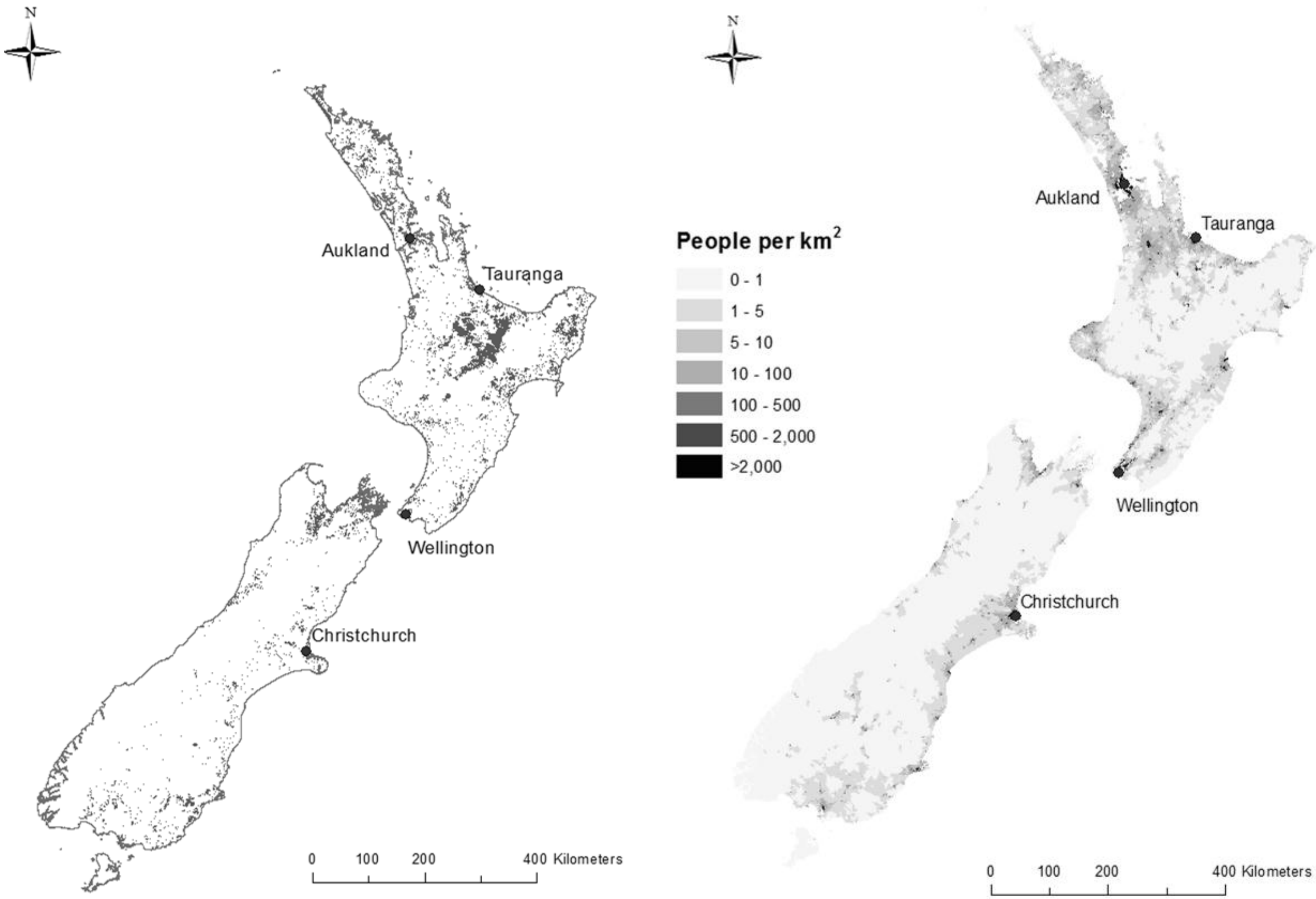
N
Aukland
Tauranga
Wellington
Christchurch
0 100 200 400 Kilometers
People per km2
0 - 1
1 - 5
5 - 10
10 - 100
100 - 500
500 - 2,000
>2,000
N
Aukland
Tauranga
Wellington
Christchurch
0 100 200 400 Kilometers

Figure 1

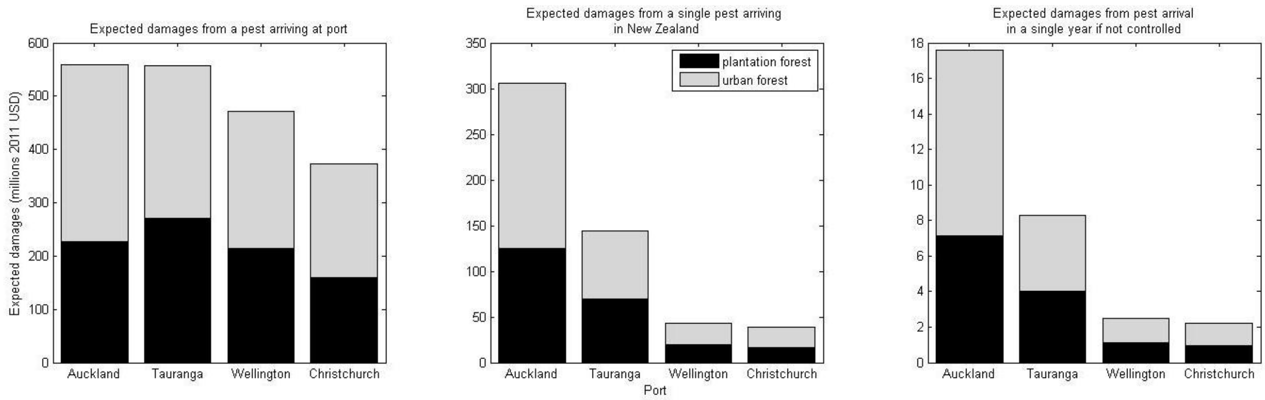
Expected damages from a pest arriving at port
Expected damages (millions 2011 USD)
600
500
400
300
200
100
0
Auckland
Tauranga
Wellington
Christchurch
Expected damages from a single pest arriving in New Zealand
350
300
250
200
150
100
50
0
plantation forest
urban forest
Port
Expected damages from pest arrival in a single year if not controlled
18
16
14
12
10
8
6
4
2
0

Figure 2.

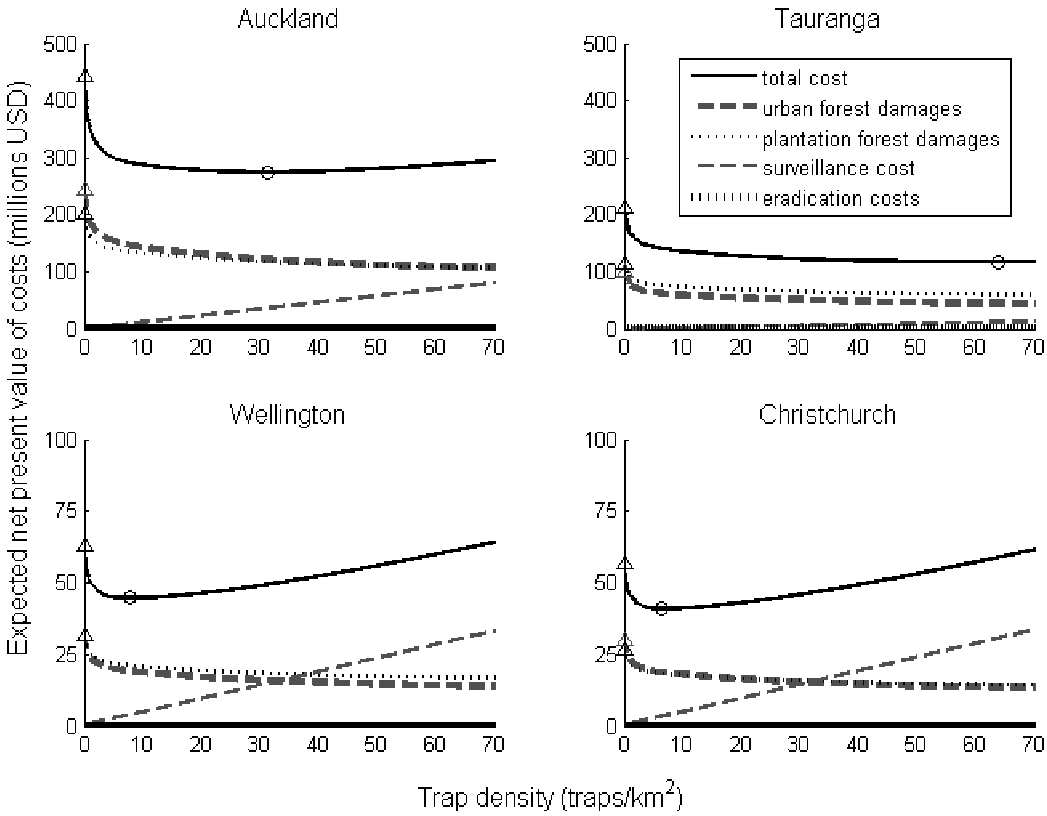
Auckland
Tauranga
Wellington
Christchurch
total cost
urban forest damages
plantation forest damages
surveillance cost
eradication costs
Expected net present value of costs (millions USD)
Trap density (traps/km²)
500
400
300
200
100
0
75
50
25
0
10
20
30
40
50
60
70

Figure 3.

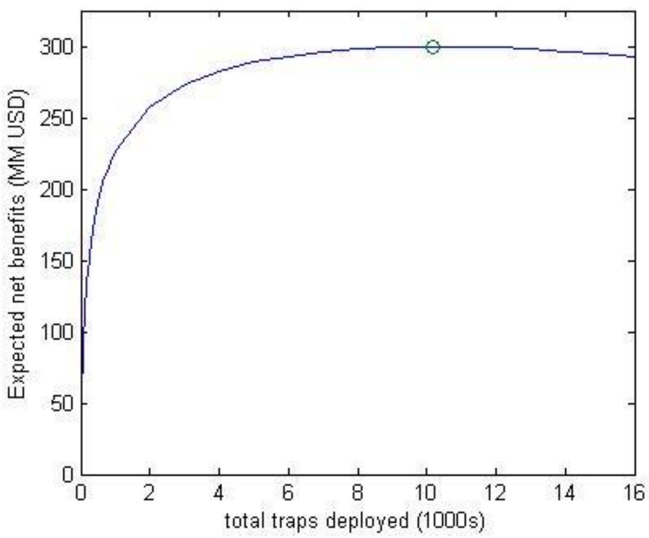
300
250
200
150
100
50
0
Expected net benefits (MM USD)
0
2
4
6
8
10
12
14
16
total traps deployed (1000s)

Figure 4.