

ARTICLE

Optimal allocation of resources among general and species-specific tools for plant pest biosecurity surveillance

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Abstract

This paper proposes a surveillance model for plant pests that can optimally allocate resources among survey tools with varying properties. While some survey tools are highly specific for the detection of a single pest species, others are more generalized. There is considerable variation in the cost and sensitivity of these tools, but there are no guidelines or frameworks for identifying which tools are most cost-effective when used in surveillance programs that target the detection of newly invaded populations. To address this gap, we applied our model to design a trapping surveillance program in New Zealand for bark- and wood-boring insects, some of the most serious forest pests worldwide. Our findings show that exclusively utilizing generalized traps (GTs) proves to be highly cost-effective across a wide range of scenarios, particularly when they are capable of capturing all pest species. Implementing surveillance programs that only employ specialized traps (ST) is cost-effective only when these traps can detect highly damaging pests. However, even in such cases, they significantly lag in cost-effectiveness compared to GT-only programs due to their restricted coverage. When both GTs and STs are used in an integrated

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surveillance program, the total expected cost (TEC) generally diminishes when compared to programs relying on a single type of trap. However, this relative reduction in TEC is only marginally larger than that achieved with GT-only programs, as long as highly damaging species can be detected by GTs. The proportion of STs among the optimal required traps fluctuates based on several factors, including the relative pricing of GTs and STs, pest arrival rates, potential damage, and, more prominently, the coverage capacity of GTs. Our analysis suggests that deploying GTs extensively across landscapes appears to be more cost-effective in areas with either very high or very low levels of relative risk density, potential damage, and arrival rate. Finally, STs are less likely to be required when the pests that are detected by those tools have a higher likelihood of successful eradication because delaying detection becomes less costly for these species.

KEYWORDS

bark- and wood-boring insects, general traps, optimal surveillance, plant pest, specialized traps, survey tools

INTRODUCTION

As part of national biosecurity programs, many countries allocate considerable resources to preborder and border measures to prevent the accidental introduction of potentially damaging nonnative species (Hulme, 2011). Preborder biosecurity encompasses preventive measures targeting populations before they reach the border. These measures include prohibitions on the importation of specific plants or commodities, certifications verifying that imported materials are free of prohibited organisms, and phytosanitary treatments (Nahrung et al., 2023). On the other hand, border biosecurity entails inspection, detection tools, phytosanitary measures, and diagnostics to identify invasive species (Nahrung et al., 2023). However, certain invasion pathways are challenging to control. As a result, even with comprehensive border biosecurity measures, some new species may still arrive and establish.

In this context, effective surveillance, paired with eradication, becomes pivotal in national biosecurity programs. These actions are integral to postborder biosecurity, which also includes containment and pest management (Nahrung et al., 2023). The coupling of surveillance with eradication is also termed “early detection, rapid response” (Reaser et al., 2020). The classic strategy applied in these programs is to survey broad areas to detect and delimit new nascent populations in order to locate them for extirpation (Liebhold et al., 2016; van Havre & Whittle, 2015; Westbrooks, 2004). Conducting large-scale surveillance programs can be cumbersome and expensive. Thus, careful planning of such efforts can significantly influence their cost-effectiveness (Epanchin-Niell, 2017; Kean et al., 2015).

Many studies have been conducted to search for biosecurity surveillance design strategies that achieve improved economic efficiency. Some studies have focused on the development of specific tools such as remote sensing (Rocchini et al., 2015), molecular detection (Simmons et al., 2016), and semiochemical traps (Poland & Rassati, 2019) that provide increased sensitivity for the detection of individual species across large landscapes. Other studies have recognized an inherent trade-off in the allocation of resources between spending on survey and eradication versus methods devised for allocation between these actions (Bogich et al., 2008; Horie et al., 2013). Several studies have focused on the spatial allocation of surveillance intensity across landscapes to optimize invasive species detection and eradication (Epanchin-Niell et al., 2012; Hauser & McCarthy, 2009; Hester & Cacho, 2012; Kompas et al., 2016; Nguyen et al., 2021).

Another fundamental challenge in devising efficient surveillance/eradication strategies lies in the integration of surveillance programs among multiple species. In many cases, separate surveillance programs exist for individual target species within the same region, but combining these efforts into a single coordinated program could result in greater efficiency (Epanchin-Niell et al., 2014; Jarrad et al., 2011). This integration is challenging in part because different invading species may vary in their habitat requirements, invasion pathways, and impacts. Moreover, the detectability of different species can vary across survey methods. For example, various types of traps are typically used in surveillance programs that target insect pest species. Some types of traps are baited with lures

that can survey multiple species (Brockerhoff et al., 2006; Kerr et al., 2017; Rabaglia et al., 2019). Compounds such as α -pinene and ethanol are attractive to a variety of bark- and wood-boring insects and can be used to simultaneously survey for a large number of species (Miller & Rabaglia, 2009; Sweeney et al., 2007). However, some of these same species may also be attracted to highly species-specific pheromones and can be used in traps to only detect individual species (Meier et al., 2016; Miller & Borden, 2000). Designing a unified surveillance program for detecting multiple invasive species poses challenges in resource allocation between highly specialized versus generalized survey methods.

Across countries, the implementation of surveillance programs varies significantly. European Union member countries, for instance, primarily use specialized survey tools, as they are mandated to survey a number of regulated pests. Generic traps are typically employed when no species-specific traps exist for a target (e.g., an unidentified pheromone) or for optional generic surveillance. This requirement likely arises from the presumption of predictability regarding which species will establish or be especially damaging. However, predicting such occurrences is challenging, and most species invasions are unexpected. Likely because of this, other countries prefer using more generic traps. Examples include the EDRR program in the United States (Rabaglia et al., 2019) and trap networks in New Zealand (Brockerhoff et al., 2006) and Italy (Rassati et al., 2015). Yet, tools that assist policymakers in determining whether to adopt species-specific traps, generic traps, or a blended approach to surveillance are scarcely existent.

In this light, we propose a model for optimizing the allocation of resources among species-specific and generalized survey tools for the surveillance and eradication of invading species. We ask whether species-specific survey tools are required given the prevalent use of the generalized ones (e.g., Brockerhoff et al., 2006; Rabaglia et al., 2019) and, if required, what the optimal combination would be. The model presented here optimizes total net benefits, accounting for both surveillance costs and discounted impacts anticipated following species establishment. We demonstrate the applicability of this optimization approach for the surveillance of bark- and wood-boring insects, which is typically accomplished using networks of attractant-baited traps (Brockerhoff et al., 2006; Rassati et al., 2015). In some programs, these traps are baited with host compounds (e.g., ethanol and α -pinene) that are attractive to a range of bark- or wood-boring insect species (Rabaglia et al., 2019). Alternatively, higher-sensitivity species-specific lures are available for some species, and these are used for species-specific surveillance programs. We apply our optimization model to the previously developed analysis by Epanchin-Niell et al. (2014)

for the optimal allocation of resources for surveillance (i.e., postborder survey) for the presence of populations of bark- and wood-boring insects in New Zealand. Specifically, the insects are Scolytinae (bark and ambrosia beetles), Cerambycidae (longhorn beetles), and Siricidae (woodwasps). Our work differs from existing literature in that it provides an optimization framework that simultaneously optimizes the allocation of different survey tools (i.e., types of trap in this case) used for the surveillance of multiple target species.

THE MODEL

Our model considers two trade-offs in surveillance against pests simultaneously. The first one is the choice between early and late detection. Here, a decision needs to be made as to how much to spend on detecting pests early so that eradication can be implemented to prevent further loss or damage. The second trade-off is the choice between different kinds of surveillance devices (i.e., traps). Some devices can detect one or a small number of pests with high sensitivity, while others attract a broader range of species, but at the expense of sensitivity.

We formalize our model in a way that facilitates the use of expert opinions. The reason is that estimating biological and economic parameters from data, especially those involved with uncertainty, is a challenging and ongoing task. Thus, we chose functional forms that minimize the required parameters without compromising the model's rigor and practical purpose when possible. Mathematics is expressed in the formula that is best suited with an intuitive explanation of parameters and the accompanying technical assumptions.

We first explain the notation and define the time horizon. We then delineate the modeling components for a single pest. Finally, we extend this framework to multipest-multitrap settings and describe some decision-making problems that this framework can address.

NOTATION AND TIME HORIZON

In the model description, we use uppercase letters for numerical parameters and lowercase letters for functions, subscripts, and superscripts. We use superscripts to distinguish categories of variables, such as types of costs or probabilities. On the other hand, we use subscripts to index variables in different sets, such as a set of time, a set of pests, or a set of traps. The mathematics is specified in such a way that all numerical parameters have nonnegative values unless indicated otherwise.

Time in the model is discrete (i.e., $t = 0, 1, 2, \dots$). Traps are established at time $t = 0$, and the project spans over T years, from $t = 1$ to $t = T$.

SINGLE-PEST SETTING

Dynamics of pest population

We largely follow Epanchin-Niell et al. (2014) in modeling the dynamics of pest species invasion. In particular, we denote by $x(s, t)$ the number of isolated populations that are s years old at time t , that is, the populations established at time $t - s$ that have remained undetected since then. We further denote by $p^{\text{det}}(s, D)$ the detection probability given trap density D , which could be a vector if there is more than one type of trap, and the age of the population s . The dynamics of undetected populations can be formalized as follows:

$$x(1, t+1) = b(t) \text{ with } t = 0, 1, \dots, T-1, \quad (1)$$

$$x(s, t+1) = x(s-1, t) [1 - p^{\text{det}}(s-1, D)] \text{ with } s = 2, \dots, S^{\text{max}} \text{ and } t = 0, 1, \dots, T-1, \quad (2)$$

where $b(t)$ is the arrival rate at time t , and S^{max} is the maximum age of a population. To this end, the number, location, and spatial extent of pest populations at any point in time are unknown prior to detection.

Likewise, the dynamics of detected population $z(s, t)$ can be formalized in the form

$$z(1, t+1) = 0 \text{ with } t = 0, 1, \dots, T-1, \quad (3)$$

$$z(s, t+1) = [z(s-1, t) + x(s-1, t) \times p^{\text{det}}(s-1, D)] \times [1 - \text{erad}(s-1)p^{\text{er}}(s-1)] \text{ with } s = 2, \dots, T \text{ and } t = 0, 1, \dots, T-1, \quad (4)$$

where $\text{erad}(s)$ is a dummy variable that takes a value of 1 when it is optimal to eradicate a population of age s and a value of zero otherwise; $p^{\text{er}}(s)$ is the probability that an eradication campaign will be successful if it is chosen to occur.

Pest spread

Following Epanchin-Niell et al. (2014), we assume that a pest population occupies an increasingly large circular area over time, and its spread follows a sigmoid function that allows for an initially accelerating rate of radial population range growth that eventually asymptotes at a rate g .

Under this assumption, the annual change in the radius of a population is given by $gs^m/(h^m + s^m)$, 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 $h = 10$, following Epanchin-Niell et al. (2014).

Eradication cost

We denote by $c^e(s)$ the cost of eradicating a population of age s . A function that presents $c^e(s)$ needs to have two mathematical properties, (1) $c^e(s) \geq 0$ and (2) $\frac{\partial c^e(s)}{\partial s} > 0$. These properties ensure that the eradication cost will be nonnegative and will rise as a population area increases. Many mathematical equations have these two properties, including

$$c^e(s) = C^{e0} \times a(s)^{C^e}, \quad (5)$$

where C^{e0} is a positive constant, $a(s)$ is the size of the population at age s , C^e is the elasticity of the eradication cost with respect to the population area, or if the population area increases by 1%, the eradication cost will increase by C^e percent.

Probability of eradication success

Should eradication be chosen, the probability of success would either decrease or stay the same with the size of a population, $a(s)$, and, thus, the age s . In light of this assumption, the probability of successful eradication $p^{\text{er}}(s)$ needs to satisfy the two properties including (1) $p^{\text{er}}(s) \in [0, 1]$ and (2) $\frac{\partial p^{\text{er}}(s)}{\partial s} \leq 0$.

We choose a commonly used logit model that uses the cumulative density function of the logistic distribution

$$p^{\text{er}}(s) = \frac{e^w}{(1 + e^w)}, \text{ where } w = \beta_0 + \beta_1 \ln(a(s)), \quad (6)$$

of which β_1 should be negative to satisfy the two preceding assumptions.

Pest population damage

We assume that there is no damage if there is no population. On the other hand, the damage increases with population size. Bearing this in mind, a function representing the annual damage $c^d(s)$ needs to satisfy the two

properties $c^d(0) = 0$ and $\frac{\partial c^d(s)}{\partial s} > 0$. The most intuitive and simplest function satisfying these properties is probably in the form

$$c^d(s) = C^d \times a(s), \quad (7)$$

where C^d is the damage per hectare caused by the pest population.

Following Epanchin-Niell et al. (2014), the population damage will accumulate until it is successfully eradicated or it reaches its maximum age of an infestation, beyond which the damage stays constant. Thus, c^{noer} , the cumulative damage of a population of age s if it remains noneradicated, can be calculated as the present value of all future damage as follows:

$$c^{\text{noer}}(s) = \sum_{t=1}^{S^{\text{max}}-s} \frac{c^d(s+t)}{(1+\Gamma)^t}, \quad (8)$$

where Γ is an interest rate.

When to eradicate?

A decision to eradicate a detected population needs to consider a trade-off. Eradication, if successful, will prevent cumulative damage, $c^{\text{noer}}(s)$. However, it will incur an up-front cost, $c^e(s)$, and the probability of successful eradication, $p^{\text{er}}(s)$, may be less than one. Thus, eradication should be chosen when the expected avoided cumulative damage is greater than the cost, in the form

$$\text{erad}(s) = 1. [c^e(s) < p^{\text{er}}(s) \times c^{\text{noer}}(s)], \quad (9)$$

where the Boolean function $1.()$ returns a value of 1 if the eradication cost is less than the avoided damage, and zero otherwise.

MULTIPEST–MULTITRAP DESIGN AND DETECTION PROBABILITY

Design of trapping programs for multiple pests

Suppose there are M types of trapping devices (indexed as $m = 1 \dots M$) and N pests (indexed as $n = 1 \dots N$). We denote by S_{mn} the sensitivity of type- m trap to type- n pest or the probability that trap m will detect a population of pest n when the pest is located in its neighborhood. Trap m is considered a generalized trap (GT) if $S_{mn} > 0$ for all

or most $n \in \{1 \dots N\}$. On the other hand, it is considered species-specific if $S_{mn} > 0$ with only one or a few $n \in \{1 \dots N\}$.

We denote by A the area of the pest surveillance region and by D_m the density of trap m . Assuming a spatially random distribution of pest population establishments, the detection probability in Equation (2) can be extended to reflect the multipest–multitrap setting as follows:

$$p_n^{\text{det}}(s, D) = 1 - \prod_{m=1}^M \left[\left(1 - S_{mn} \min\left(\frac{a_n(s)}{A}, 1\right) \right)^{D_m A} \right], \quad (10)$$

where a subscript n is added to refer to the pest type.

Cost of trapping programs

The cost of a trapping program is twofold. The first cost is the cost of establishing a trapping program:

$$C^{\text{start}}(D) = C^{\text{start-prog-oh}} + \sum_{m=1}^M [C_m^{\text{start-trap-oh}} \times 1.(D_m > 0) + C_m^{\text{start-trap}} D_m A], \quad (11)$$

where $C^{\text{start-prog-oh}}$ is the overhead cost of the whole program, which does not depend on how many types of trap will be used (e.g., the cost of a program management unit does not normally vary with the trap quantity); $C_m^{\text{start-trap-oh}}$ is the overhead cost of a type- m trap subprogram, if any, which is incurred only if decision makers choose to use the type- m trap (i.e., when $D_m > 0$); and $C_m^{\text{start-trap}}$ is the marginal cost of using each type- m trap, which will vary with the type- m trap quantity.

The second cost is the ongoing monitoring and maintenance cost of a trap:

$$C^{\text{og}}(D, t) = C^{\text{og-prog-oh}}(t) + \sum_{m=1}^M [C_m^{\text{og-trap-oh}}(t) \times 1.(D_m > 0) + C_m^{\text{og-trap}}(t) D_m A], \quad (12)$$

where $C^{\text{og-prog-oh}}(t)$ is the annual overhead cost of the whole trapping program, $C_m^{\text{og-trap-oh}}(t)$ is the annual overhead cost of the type- m trap subprogram if any, and $C_m^{\text{og-trap}}$ is the marginal cost of monitoring and maintaining each trap.

Total expected cost

The total expected cost $TEC(D)$, which depends on the trapping density, has four components:

$$\begin{aligned}
 TEC(D) = & \underbrace{C^{\text{start}}(D)}_{\text{start-up cost}} + \underbrace{\sum_{t=1}^T \frac{C^{\text{og}}(D, t)}{(1+\Gamma)^t}}_{\text{on-going cost}} \\
 & + \underbrace{\sum_{t=1}^T \sum_{n=1}^N \sum_{s=1}^{S_{\max}} \frac{[x_n(s, t) + z_n(s, t)] c_n^d(s)}{(1+\Gamma)^t}}_{\text{cumulative damage}} \\
 & + \underbrace{\sum_{t=1}^T \sum_{n=1}^N \sum_{s=1}^{S_{\max}} \frac{x_n(s, t) p_n^{\text{det}}(s, D) \text{erad}_n(s) c_n^e(s)}{(1+\Gamma)^t}}_{\text{cumulative eradication cost}} \\
 & + \underbrace{\sum_{n=1}^N \sum_{s=1}^{S_{\max}} \frac{c_n^{\text{noer}}(s) [x_n(s, T+1) + z_n(s, T+1)]}{(1+\Gamma)^{T+1}}}_{\text{residual cost}}, \quad (13)
 \end{aligned}$$

where the first two terms represent, respectively, the startup and ongoing costs of the surveillance program; the third and fourth terms capture, respectively, the damage and eradication cost, while the final term, “residual” cost, covers all damage after the program ends (i.e., at time T) for a particular period. It is worth noting that all costs are in present value and summed up over time, pest, and population ages.

The decision-making problem

The decision-making problem is to choose the density of all trap types, that is, $D \equiv [D_1, D_2, \dots, D_m]$, so that the total expected cost of a surveillance program is minimized:

$$\min_{D \geq 0} TEC(D). \quad (14)$$

We solved this problem using a nonlinear programming solver (i.e., `fmincon`) in MATLAB version R2020a.

EMPIRICAL APPLICATION: MODEL PARAMETERIZATION

We apply our model to design an optimal network of traps to detect invasions of bark- and wood-boring insect species in New Zealand. These insects complete their larval development in the bark, phloem, or xylem of living or recently dead woody plants

(Dodds et al., 2023; Lieutier et al., 2004). Prominent taxa include Scolytinae, Cerambycidae, Buprestidae, Siricidae, and others. Our model parameters can be classified under four categories: general, pest-related, trapping cost, and trap sensitivity parameters. All values discussed in this application are in 2011 US dollars, unless otherwise specified.

General parameters

The baseline values of the general parameters and their ranges for sensitivity analysis are presented in Appendix S1: Table S1. We consider a 30-year time horizon for the surveillance program and an annual interest rate of 5%.

The surveillance program covers four New Zealand port regions: Auckland, Tauranga, Wellington, and Christchurch. Together, these regions receive approximately 90% of the trade volume that poses the greatest risk for invasions of bark- or wood-boring insects (Epanchin-Niell et al., 2014). The trapping program discussed in this paper predominantly targets 20% of the urban areas in these regions, which we estimate would detect about 80% of future invaders. This assumption is made based on the widespread understanding that high-risk sites are typically clustered around ports, including industrial and commercial zones where imports are unloaded. Hence, we anticipate these regions to experience a higher concentration of new invasions in the future. The percentage pertaining to areas and invaders considered here is anchored in the findings of Epanchin-Niell et al. (2014). We direct readers to their work for a comprehensive sensitivity analysis of this assumption. In our paper, we accept this assumption as a base premise and focus our investigation on determining the optimal allocation of various trap types within a trapping program.

Pest-related parameters

Appendix S2 presents the pest-related parameter values, with a summary provided in Section S1, Table S1. In the baseline, the arrival rate is 0.065 introductions per year, which is based on historical data from 1980 to 2011 for New Zealand (Epanchin-Niell et al., 2014). Considering the potential substantial uncertainty surrounding this rate (Haack et al., 2014, 2022), the subsection *Empirical application: Model results* examines how variations in this rate might impact our results. Following the approach used by Epanchin-Niell et al. (2014), we allocated this rate proportionally to the flow of trade that is likely to use wood packing material—the most probable

introduction pathway of wood-boring beetles—across four surveillance sites. Thus, Auckland, Christchurch, Tauranga, and Wellington account for 48.7%, 9.3%, 23.0%, and 8.1% of the introduction risk, respectively. With areas of 217, 90, 33.6, and 88.8 km², the corresponding shares of risk per square kilometer are 0.23%, 0.10%, 0.68%, and 0.09%. Consequently, Tauranga, the smallest region, is also the riskiest in terms of relative risk density. The relative risk density here is about three times that of Auckland and seven times greater than that of the other two regions.

We consider nine potential species classes, classified based on two features: damage and trap responsiveness, with each feature having three subclasses (Appendix S2: Section S1, Table S2). We choose to delineate invasive species based on their classes rather than as specific species because it is difficult to know which bark- or wood-boring insect species are most likely to establish in the future. We assume that the features of damage and trap responsiveness are pair-wise independent. That is, the proportion in each species class is the product of its proportions of each damage and trap responsiveness subclass.

The damage caused by a species can be low, medium, or high. We assume the baseline corresponding species distribution based on these damage levels is 70%, 20%, and 10%, respectively. Our assumption is based on evidence from Aukema et al. (2011) for wood borers, which suggests that the smallest fraction of new species causes the most extensive damage, while most species cause low damage, and a smaller proportion causes medium damage.

The harvest value is estimated to be USD 103.12/ha/year. This estimation is based on New Zealand's annual forest land harvest value of USD 1154 million (Epanchin-Niell et al., 2014), and its total forest land area is 11.19 million ha (Landcare Research New Zealand Ltd, 2020). Following Epanchin-Niell et al. (2014), we assume a 5-year delay before damage begins accruing in a newly invaded forest to account for initially low population densities. Following this delay, damage increases linearly in those areas over the next 5 years to reach their maximum reduction in harvest value in the 10th year following the arrival of the invader. Maximum reductions in harvest value continue until the maximum age of the population, $S_{\max}$, or until the population is eradicated. We assume low-, medium-, and high-damage pests cause 1%, 10%, and 50% of the total possible damage, respectively.

Likewise, there are three subclasses in trap responsiveness. A species can be trapped by (1) GTs, but not specialized traps (STs) (labeled as GT species), (2) GTs and STs (ST species), or (3) not detected by any trap types (NT species). This classification is motivated by the fact

that most species respond to GTs, while species that could be detected using specialist lures (STs) could also be targeted by generalist lures. In the sensitivity analysis presented in the subsection *Empirical application: Model results*, we explore scenarios where ST species are exclusively trapped by STs and the rarer scenario where there are NT species in a population.

For the baseline, we assume that only 5% of species are ST species, all of which are highly damaging. This assumption takes into account the fact that species-specific tools are only available for certain target species, and these tend to be developed for species posing the most significant risk of severe damage. It is worth noting that we later explore another scenario in the subsection *Empirical application: Model results*, where this 5% of ST species are evenly distributed across all damage levels.

In practice, multiple types of specific traps may be used concurrently and are capable of attracting one or several species. As long as they share the same attributes—namely, their trapping coverage, cost, and sensitivity—they are considered to be the same type from the model's perspective. Due to a lack of comprehensive data on the sensitivity and cross-sensitivity ranges of various potential STs, we have restricted our focus to one specific trap type in our application, despite our model's capacity to consider multiple trap types. We categorize all species that respond exclusively to that trap type as ST species. Although we acknowledge that the context of our application is not perfect, we firmly believe that the insights derived remain invaluable.

In every scenario, we assume that all low- and medium-damage species spread at a rate of 20 km/year, while high-damage species spread at a rate of 30 km/year. This assumption is based on the study by Epanchin-Niell et al. (2014), where it was determined that slower invading species spread at a rate of 10 km/year, while faster ones can disperse up to 50 km/year. Following Epanchin-Niell et al. (2014), we also assume that the maximum age of an infestation, denoted by $S_{\max}$, is 75 years. We direct readers to Epanchin-Niell et al. (2014) for a sensitivity analysis of these parameters. The maximum size of an infestation is determined by the total area that provides suitable habitat for wood-boring beetles, based on the land cover database for New Zealand (Appendix S2: Section S1, Table S4).

Finally, both the eradication cost and the maximum probability of successful eradication are functions of population range areas. Their function coefficients are estimated based on empirical evidence from Brockerhoff et al. (2010) and Epanchin-Niell et al. (2014) (see our Appendix S2B,C for more details). We assume that the coefficients are the same for all species classes.

Trapping cost parameters

In the baseline, we assume the costs of GTs and STs are the same. These costs include all expenses detailed in Equations (11) and (12). The annual fixed cost of the whole trapping program is USD 25,000 as in Epanchin-Niell et al. (2014). The cost of adding a trap of both types depends on the trap density, ranging from USD 328 to USD 633 (Appendix S3). For the purpose of sensitivity analysis, we accommodate a 50% increase in the cost associated with setting up each type of trap relative to the baseline. The implications of these cost adjustments on the TEC of a trapping program are discussed in the subsection *Empirical application: Model results*.

Trap sensitivity (or insect-capture) parameters

GTs and STs vary not only by the range of species they can trap and their associated cost but also by their efficiency at trapping or trap sensitivity. Under our baseline assumptions, we assign trap sensitivities of 80% to STs and 15% to GTs. We evaluate the influence of these assumptions on TEC of a trapping program by exploring two additional scenarios: one where the ST sensitivity increases to 90%, and another where the GT sensitivity decreases to 10%. These scenarios are discussed in the subsection *Empirical application: Model results*. In the interest of thoroughness and covering a broad range of potential parameter values, we provide in Appendix S4: Figure S1 additional results illustrating how the TEC and the proportion of STs required in integrated programs are impacted when the sensitivity of STs is varied from 30% to 90%.

It is important to acknowledge the complexity involved in determining the parameter values of trap sensitivity. In the absence of more concrete data, we rely on a Poisson model of insect capture proposed by Turchin and Odendaal (1996) for the southern pine beetle. Their research established that a multifunnel trap baited with frontalinal and turpentine for southern pine beetle has an effective sampling area (ESA) of ~0.1 ha. The ESA is defined as the area by which the trap catch must be divided to estimate the population density (Turchin & Odendaal, 1996). To quantify the trap sensitivity, we used the formula “ $1 - \exp(-\min(\text{ESA}, \text{occupied area}) \times \text{mean population density within the occupied area})$ ” as suggested by Kean (2015) and adopted by Epanchin-Niell et al. (2014). Notably, Epanchin-Niell et al. (2014) applied this formula and the ESA of ~0.1 ha to justify a trap sensitivity of 60%, implying an initial population density of about 9.2 beetles/ha. The sensitivity range of 30%–90%

corresponds to 3.3–21.5 trappable beetles/hectare for this combination of target species and trap type.

Empirical application: Model results

This section presents evidence of when an integrated trapping surveillance program is required and optimal combinations of GTs and STs. Our discussion centers around the impact of establishing a trapping program compared with the case of “do nothing” and the effect of possibly using a single trap type versus a combination of them. The section starts with a discussion of the baseline results, followed by an analysis of the changes when key model parameters vary.

Baseline

Recall that under a “do nothing” strategy, TEC simply equals the total expected damage in the absence of pest eradication. On the other hand, the TEC under a trapping strategy has various components (Equation 13). Here, we only present TECs and their most significant expected cost components for brevity, namely, damage and trapping costs. The eradication cost is negligible in our model since eradication happens only when its benefit exceeds its cost (Equation 9). Results for the baseline scenarios are in italics (Table 1).

From the table we observe that setting up a trapping program is economically efficient in all four sites. Single-trap-type surveillance programs using only STs cost 63%–68% of the TEC in the case of “do nothing,” while programs using only GTs are even more economically efficient, costing only 11%–26% of the baseline’s TECs. The use of integrated survey tools only marginally reduces TECs compared with GT-only programs. Although including STs in GT-only programs always reduces TECs, it can either increase or decrease the total number of traps at optimal. Trapping costs under these programs range from 33% to 47% of the TEC.

Moreover, Table 1 reveals significant differences in trap density among the four sites. For programs that use only GTs, Tauranga requires about 700 traps/km², while Auckland requires only 317 traps/km², and Wellington and Christchurch require just 100 traps/km². Similar heterogeneity in trap density is observed for programs that use only STs and those that include both STs and GTs. These results suggest that the regions’ relative risk densities are positively related to their optimal trap densities. Here, we use the term “risk” synonymously with the annual rate or likelihood of pest introduction.

TABLE 1 Baseline and impact of changes in annual arrival rate (*b*) of invasive species.

Arrival rate	Trapping programming	Total expected cost (USD million)	Damage (USD millionAU)	Trap cost (USD million)	Traps required (traps)	Trap density (traps/km ²)
(a) Auckland (share of risk/km ² = 0.22%)						
<i>b</i> = 0.18						
	Doing nothing	12,400	12,400			
	GT only	1482	752	729	144,348	665
	ST only	7775	7592	183	36,133	166
	GT and ST	1448	768	680		
	GT				121,156	558
	ST				13,417	62
	ST share				0.10	
<i>Baseline</i> (<i>b</i> = 0.065)						
	<i>Doing nothing</i>	<i>4478</i>	<i>4478</i>			
	<i>GT only</i>	<i>858</i>	<i>509</i>	<i>348</i>	<i>68,850</i>	<i>317</i>
	<i>ST only</i>	<i>2900</i>	<i>2782</i>	<i>118</i>	<i>23,336</i>	<i>107</i>
	<i>GT and ST</i>	<i>811</i>	<i>512</i>	<i>300</i>		
	<i>GT</i>				<i>44,132</i>	<i>203</i>
	<i>ST</i>				<i>15,061</i>	<i>69</i>
	<i>ST share</i>				<i>0.25</i>	
<i>b</i> = 0.0325						
	Doing nothing	2239	2239			
	GT only	541	392	148	29,227	135
	ST only	1497	1423	75	14,660	67
	GT and ST	516	343	173		
	GT				23,820	110
	ST				10,194	47
	ST share				0.30	
(b) Tauranga (share of risk/km ² = 0.68%)						
<i>b</i> = 0.18						
	Doing nothing	5856	5856			
	GT only	411	227	184	36,273	1080
	ST only	3605	3565	40	7786	232
	GT and ST	409	230	179		
	GT				33,875	1008
	ST				1436	43
	ST share				0.04	
<i>Baseline</i> (<i>b</i> = 0.065)						
	<i>Doing nothing</i>	<i>2115</i>	<i>2115</i>			
	<i>GT only</i>	<i>241</i>	<i>122</i>	<i>119</i>	<i>23,490</i>	<i>699</i>
	<i>ST only</i>	<i>1324</i>	<i>1294</i>	<i>30</i>	<i>5779</i>	<i>172</i>
	<i>GT and ST</i>	<i>237</i>	<i>125</i>	<i>112</i>		
	<i>GT</i>				<i>19,981</i>	<i>595</i>
	<i>ST</i>				<i>2034</i>	<i>61</i>
	<i>ST share</i>				<i>0.09</i>	

(Continues)

TABLE 1 (Continued)

Arrival rate	Trapping programming	Total expected cost (USD million)	Damage (USD millionAU)	Trap cost (USD million)	Traps required (traps)	Trap density (traps/km ²)
<i>b</i> = 0.0325						
	Doing nothing	1057	1057			
	GT only	169	90	78	15,413	459
	ST only	675	652	23	4430	132
	GT and ST	163	92	70		
	GT				11,432	340
	ST				2287	68
	ST share				0.17	
(c) Christchurch (share of risk/km ² = 0.1%)						
<i>b</i> = 0.18						
	Doing nothing	2368	2368			
	GT only	409	228	182	35,846	398
	ST only	1520	1464	56	10,936	122
	GT and ST	391	232	159		
	GT				25,019	278
	ST				6245	69
	ST share				0.20	
<i>Baseline</i> (<i>b</i> = 0.065)						
	<i>Doing nothing</i>	<i>855</i>	<i>855</i>			
	<i>GT only</i>	<i>211</i>	<i>154</i>	<i>57</i>	<i>11,167</i>	<i>124</i>
	<i>ST only</i>	<i>575</i>	<i>545</i>	<i>29</i>	<i>5652</i>	<i>63</i>
	<i>GT and ST</i>	<i>203</i>	<i>135</i>	<i>68</i>		
	<i>GT</i>				<i>9389</i>	<i>104</i>
	<i>ST</i>				<i>3892</i>	<i>43</i>
	<i>ST share</i>				<i>0.29</i>	
<i>b</i> = 0.0325						
	Doing nothing	428	428			
	GT only	127	92	36	6943	77
	ST only	297	285	11	2119	24
	GT and ST	127	88	39		
	GT				6484	72
	ST				1000	11
	ST share				0.13	
(d) Wellington (share of risk/km ² = 0.09%)						
<i>b</i> = 0.18						
	Doing nothing	2062	2062			
	GT only	376	216	160	31,661	357
	ST only	1330	1278	52	10,151	114
	GT and ST	358	219	138		
	GT				21,072	237
	ST				6200	70
	ST share				0.23	

TABLE 1 (Continued)

Arrival rate	Trapping programming	Total expected cost (USD million)	Damage (USD millionAU)	Trap cost (USD million)	Traps required (traps)	Trap density (traps/km ²)
<i>Baseline ($b = 0.065$)</i>						
	<i>Doing nothing</i>	745	745			
	<i>GT only</i>	190	140	50	9875	111
	<i>ST only</i>	504	478	26	4939	56
	<i>GT and ST</i>	184	123	61		
	<i>GT</i>				8616	97
	<i>ST</i>				3324	37
	<i>ST share</i>				0.28	
<i>$b = 0.0325$</i>						
	Doing nothing	372	372			
	GT only	115	82	33	6423	72
	ST only	260	251	9	1690	19
	GT and ST	115	79	36		
	GT				5954	67
	ST				1000	11
	ST share				0.14	

Note: “GT only” denotes a trapping program that uses only generalized traps; “GT and ST” denotes a trapping program that potentially uses both generalized and specialized traps. The baseline results are in italics. All costs and damage are rounded to the nearest million USD.

Abbreviations: GT, generalized trap; ST, specialized trap.

Finally, we observe an inverse relationship between the risk density and the share of STs at optimal levels. For example, Tauranga has the lowest optimal share of STs with only 9%, followed by Auckland with 25%, while the other two regions optimally include 28%–29% of total traps as ST in their integrated survey programs. These results suggest that it is more economically efficient to blanket landscapes with GTs in high-risk areas due to GTs’ extensive coverage.

Impact of changes in annual countrywide arrival rate of invasive species

We began by analyzing the impact of the upper and lower bounds of the annual countrywide arrival rate, 0.0325 and 0.18, respectively (Table 1).

Across regions, costs move in line with arrival rates. We also observed a positive correlation between the arrival rate and the optimal number of traps in single-trap-type programs, as well as between the arrival rate and the optimal number of GTs in integrated programs.

However, for STs in integrated programs, the results are more complex. We found no consistent relationship between the arrival rate and the numbers or shares of STs within regions. For example, in Auckland, the optimal number of STs decreased when the arrival rate either

increased or decreased. On the other hand, in Tauranga, the area with the highest risk, the optimal number of STs was negatively related to the arrival rate, while in the other two regions it was positively associated with the arrival rate.

To gain a better understanding of this relationship, we increased the level of granularity of our analysis. We focused on the relationship between the arrival rate and the share of STs in integrated programs, divided the range of arrival rates ([0.18–0.032]) into 12 small steps, and obtained the model outcome for each of them.

Figure 1 reveals three key findings. First, the share of STs is hump-shaped with respect to the arrival rate in Auckland, Christchurch, and Wellington. The share increases when the rate increases, reaches its peak, and then falls. The similarity in the lines for Christchurch and Wellington suggests that the relative risk density strongly influences this relationship. In Auckland, the share reaches its peak much faster than those of less risky regions, while there is no peak in Tauranga. These results confirm the baseline findings that it is not economically efficient to use STs in areas where the risk of pest entry is either too high or too low.

Second, trapping surveillance programs become more cost-effective as the arrival rate increases, particularly for integrated and GT-only programs. The proportions of TECs relative to those under the “do nothing” scenario decrease from 0.7 to 0.6 for ST-only programs and from

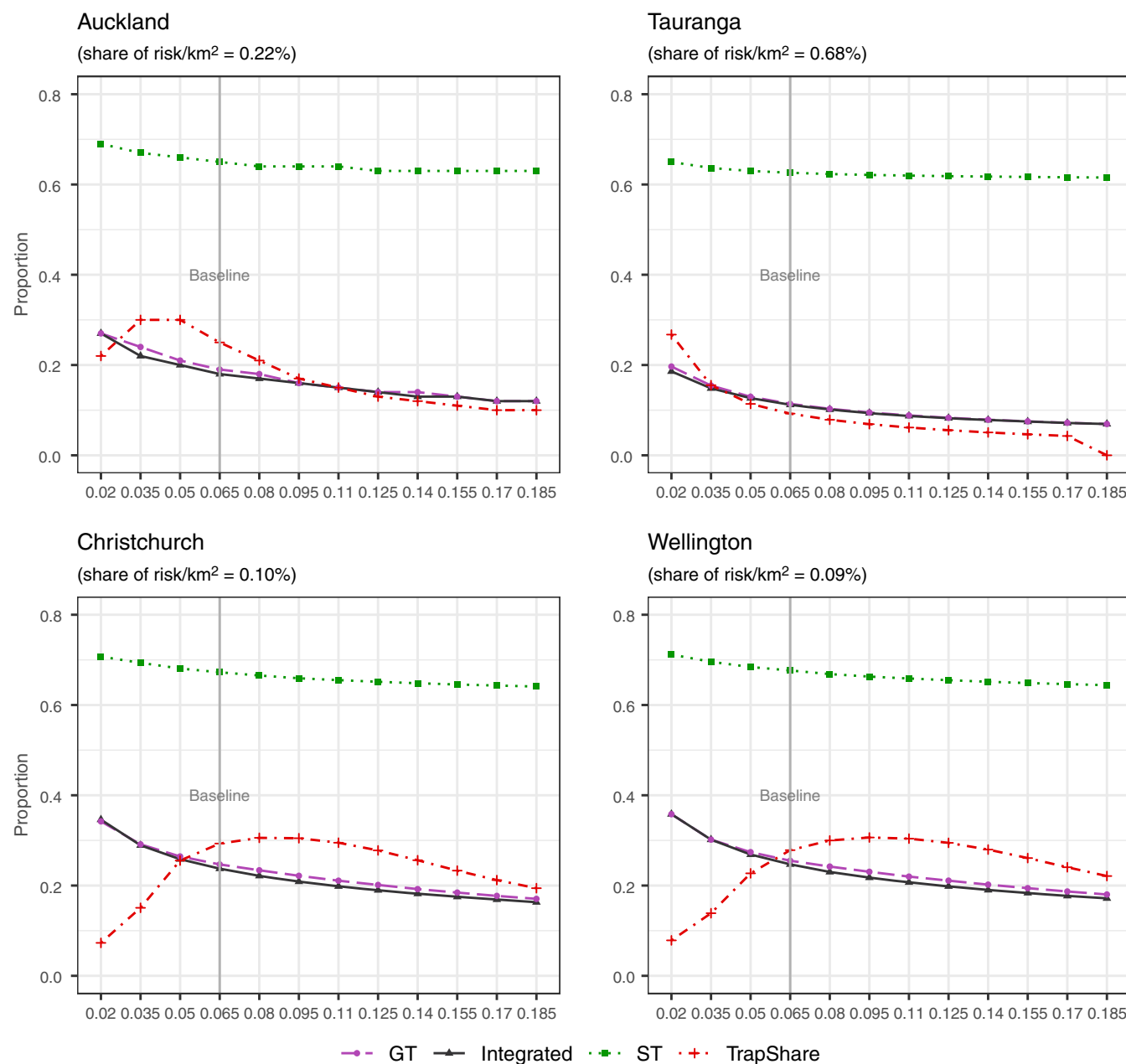


FIGURE 1 Total expected costs (TEC) under different trapping programs relative to corresponding TEC under a “do nothing” scenario and the share of STs in the required traps of integrated programs as the arrival rate varies. GT, GT-only surveillance programs; ST, ST-only surveillance programs; integrated, GT- and ST-integrated programs; and TrapShare, share of STs in total required traps of an integrated trapping program. Each point in red dashed-dotted line represents the share of STs in the total required traps of an integrated trapping program for each value of arrival rate. Meanwhile, each point on the other three lines represents the corresponding shares of the TEC of a corresponding trapping program compared to that under “do nothing.” The vertical bar represents the baseline scenario. The min and max of the horizontal axis represents roughly the upper and lower bounds of the arrival rate.

0.3 to 0.1 for other programs as the arrival rate increases from the lower to upper bound.

Lastly, the benefit of using STs diminishes as the arrival rate increases. This is seen in the widening gap between the loci of proportions for the ST-only program and those of the other two programs as the arrival rate increases. This finding underscores the need to use GTs in high-risk settings.

Impact of changes in damage density

The financial cost of damage per hectare (i.e., damage density) has a significant impact on the need for a surveillance program. In the extreme case where damage density is zero, no surveillance program is necessary. To examine the impact of changes in damage

density, we analyzed a range of 0.5 to 1.5 times the baseline damage density and divided it into 11 small steps. We obtained model outcomes for each step to determine the impact on the TECs of surveillance programs.

Figure 2 shows two key insights. First, the cost savings of trapping programs relative to the “do nothing” scenario increase as damage density increases, particularly for integrated and GT-only programs. Second, there is a hump-shaped curvature in the share of STs in the

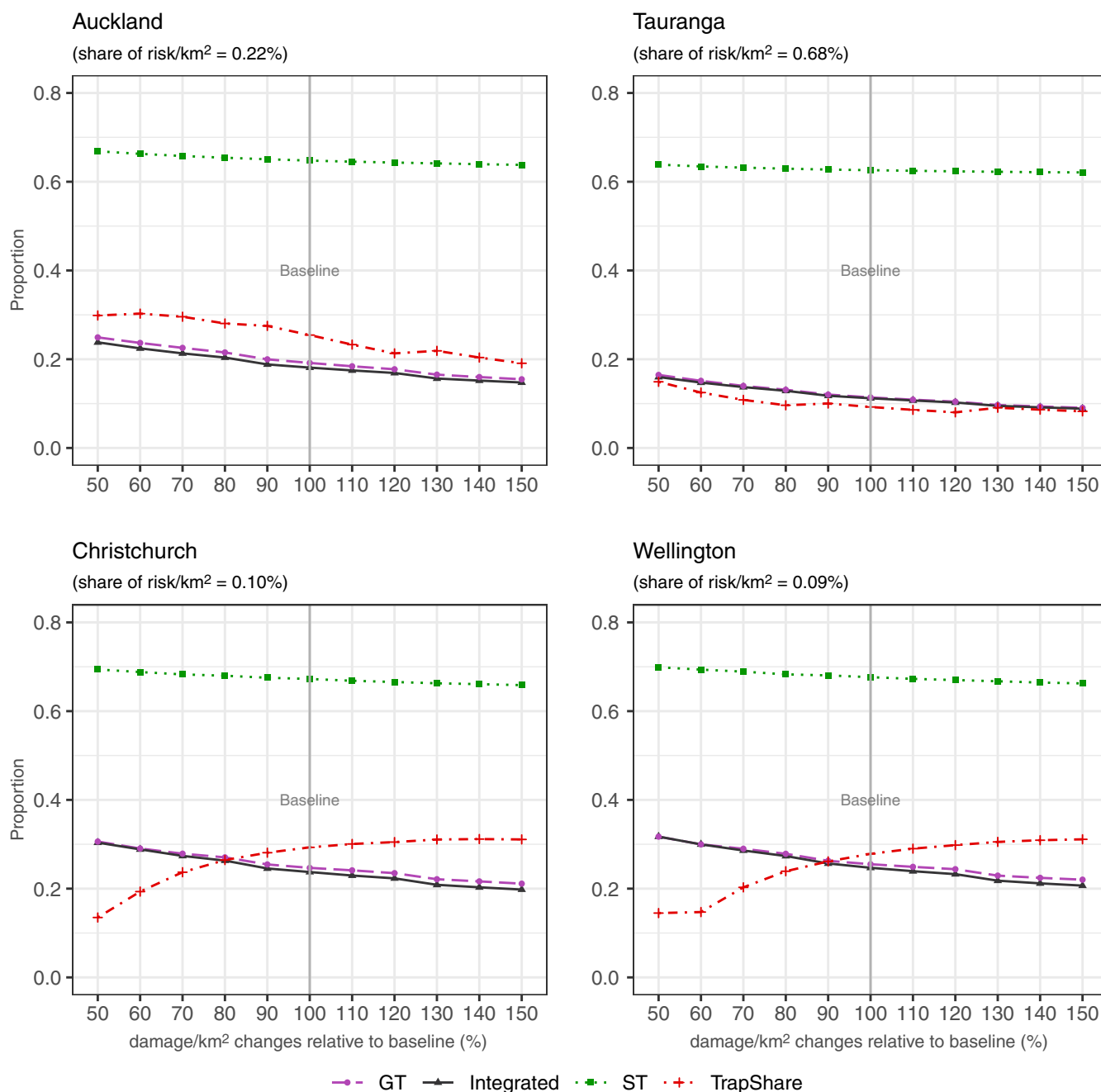


FIGURE 2 Total expected costs (TEC) under different trapping programs relative to corresponding TEC under “do nothing” and ST shares in the required traps of integrated programs as the damage per square kilometer varies. GT, GT-only surveillance programs; ST, ST-only surveillance programs; integrated, GT- and ST-integrated programs; and TrapShare, share of STs in total required traps of an integrated trapping program. Each point in the red dashed-dotted line represents the share of STs in the total required traps of an integrated trapping program for each level of damage per square kilometer relative to baseline. Meanwhile, each point on the other three lines represents the corresponding shares of the TEC of a corresponding trapping program compared to that under “do nothing.” The vertical bar represents the baseline scenario. Moving to the left of the horizontal axis, the damage per square kilometer gradually reduces to the level of 50% of baseline, and moving to the right, the damage per square kilometer increases gradually to the level of 150% of baseline.

total required traps, as can be inferred from the positive relationship between the share of STs and damage density in areas at low risk, such as Christchurch and Wellington, and the corresponding inverse relationship in Tauranga and Auckland, which are regions at high risk. These results suggest the use of GTs when damage density is very low or very high.

Impact of changes in trapping costs

In this subsection, we explore how the cost of STs and GTs affects the TEC of a trapping program. It is reasonable to assume that STs are more expensive than GTs due to factors such as the need for a special lure and lack of economies of scale as they can be used just for one or a tiny number of species (Rabaglia et al., 2019). However, the wide coverage of GTs also implies that the bycatch in those traps can be much higher than that in STs, resulting in higher labor costs for sorting out invasive species. To investigate this, we simulated scenarios where each type of trap's cost was increased by 50% compared to the baseline.

Table 2 presents the results of the simulations. We observed that TECs increased when trap costs increased, particularly for GTs. This increase was likely due to the fact that fewer traps were used at optimal, leading to greater damage. Additionally, as the cost of one trap type increased, demand for that type fell while demand for the other type increased, due to changes in their “relative” prices.

It is worth noting that the absolute change in TEC resulting from the shift in the trapping cost of GTs was much larger than that of STs due to their more extensive use. While STs are substitutable for only a small share of species, GTs can be fully interchangeable with STs. Therefore, their impact is more significant.

Impact of changes in range of species that traps can capture

The range of species that each trap type can capture is anticipated to significantly influence model outcomes. To explore this impact, we evaluated three scenarios.

In the first scenario, we distributed the 5% of species that STs can capture across all damage levels, rather than isolating them to the highly damaging subgroup as in the baseline (Table 3). Across all sites, the TEC of ST-only programs rose considerably, a 50% increase compared to the baseline values. This significant increase was primarily caused by the rise in damage since fewer high-damage

pests could then be captured by STs. Consequently, the benefits of STs are outweighed by their costs, rendering their use no longer optimal in integrated programs.

In the second scenario, we assume that GTs cannot capture ST insects (Table 3). Predictably, the results of ST-only programs remained the same compared with those of the baseline as nothing changed over STs. However, there was a marked shift in GT-only programs. Specifically, the TEC in Tauranga, the riskiest region, more than quadrupled, while the TEC in Auckland, the second riskiest region, almost tripled. In the remaining regions, the TEC more than doubled. The bulk of this increase in TEC is attributed to the heightened damage caused by pests that GTs can no longer lure in this scenario. In integrated programs, there is a marginal increase in TEC, ranging from 4% to 7%, thanks to the optimization of the use of trap types. To this effect, we observed the proportion of STs used escalated significantly—nearly threefold in Tauranga and about 1.5-fold in other regions. This suggests that even minor changes in the species range captured by GTs can lead to substantial shifts in their demand within optimal integrated programs.

In our third scenario, we reduced GT coverage by 20%, meaning that 20% of the pest population, distributed across all damage levels, could not be trapped (i.e., the NT species). As expected, the results of single-trap-type programs that use only STs were the same as those in the baseline, since nothing changed in this scenario. However, the impact of programs that use GTs was significant. Specifically, TECs under those programs increased by 65%–165%, with the magnitude of the impact positively correlated with the region's relative risk density. These additional costs are mainly due to increased damage when it is impossible to trap some pests. In parallel, the number of required GTs and their densities were reduced across regions by 11%–34%, while the relative use of STs increased proportionally with regional relative risk densities (Table 4). Specifically, the share of STs almost doubled in Tauranga and increased by 50% in Auckland and 20% in the other regions. Thus, a reduction in GT coverage not only increased TECs but also reduced the number of GTs while increasing the number of STs required at optimal numbers due to the change in their relative effectiveness in catching pests.

Impact of changes in probability of successfully eradicating ST species

The probability of successfully eradicating pests may have a significant impact on the deployment of traps. In

TABLE 2 Impact of changes in trap costs.

Trap cost	Trapping programming	Total expected cost (USD million)	Damage (USD million)	Trap cost (USD million)	Traps required (traps)	Trap density (traps/km ²)
(a) Auckland (share of risk/km ² = 0.22%) higher						
ST cost 50%						
	Doing nothing	4478	4478			
	GT only	858	509	348	68,850	317
	ST only	2952	2814	139	18,259	84
	GT and ST	841	514	327		
	GT				51,772	238
	ST				8552	39
	ST share				0.14	
<i>Baseline</i>						
	<i>Doing nothing</i>	<i>4478</i>	<i>4478</i>			
	<i>GT only</i>	<i>858</i>	<i>509</i>	<i>348</i>	<i>68,850</i>	<i>317</i>
	<i>ST only</i>	<i>2900</i>	<i>2782</i>	<i>118</i>	<i>23,336</i>	<i>107</i>
	<i>GT and ST</i>	<i>811</i>	<i>512</i>	<i>300</i>		
	<i>GT</i>				<i>44,132</i>	<i>203</i>
	<i>ST</i>				<i>15,061</i>	<i>69</i>
	<i>ST share</i>				<i>0.25</i>	
GT cost 50% higher						
	Doing nothing	4478	4478			
	GT only	993	677	316	41,638	192
	ST only	2900	2782	118	23,336	107
	GT and ST	897	595	301		
	GT				27,527	127
	ST				18,174	84
	ST share				0.40	
(b) Tauranga (share of risk/km ² = 0.68%)						
ST cost 50% higher						
	Doing nothing	2115	2115			
	GT only	241	122	119	23,490	699
	ST only	1337	1299	38	4989	148
	GT and ST	240	124	117		
	GT				21,420	638
	ST				1000	30
	ST share				0.04	
<i>Baseline</i>						
	<i>Doing nothing</i>	<i>2115</i>	<i>2115</i>			
	<i>GT only</i>	<i>241</i>	<i>122</i>	<i>119</i>	<i>23,490</i>	<i>699</i>
	<i>ST only</i>	<i>1324</i>	<i>1294</i>	<i>30</i>	<i>5779</i>	<i>172</i>
	<i>GT and ST</i>	<i>237</i>	<i>125</i>	<i>112</i>		
	<i>GT</i>				<i>19,981</i>	<i>595</i>
	<i>ST</i>				<i>2034</i>	<i>61</i>
	<i>ST share</i>				<i>0.09</i>	

(Continues)

TABLE 2 (Continued)

Trap cost	Trapping programming	Total expected cost (USD million)	Damage (USD million)	Trap cost (USD million)	Traps required (traps)	Trap density (traps/km ²)
GT cost 50% higher						
	Doing nothing	2115	2115			
	GT only	294	152	142	18,720	557
	ST only	1324	1294	30	5779	172
	GT and ST	279	156	123		
	GT				14,005	417
	ST				3154	94
	ST share				0.18	
(c) Christchurch (share of risk/km ² = 0.1%)						
ST cost 50% higher						
	Doing nothing	855	855			
	GT only	211	154	57	11,167	124
	ST only	586	558	28	3553	39
	GT and ST	210	145	65		
	GT				10,130	113
	ST				1653	18
	ST share				0.14	
Baseline						
	Doing nothing	855	855			
	GT only	211	154	57	11,167	124
	ST only	575	545	29	5652	63
	GT and ST	203	135	68		
	GT				9389	104
	ST				3892	43
	ST share				0.29	
GT cost 50% higher						
	Doing nothing	855	855			
	GT only	235	172	63	8192	91
	ST only	575	545	29	5652	63
	GT and ST	223	146	77		
	GT				7229	80
	ST				4297	48
	ST share				0.37	
(d) Wellington (share of risk/km ² = 0.09%)						
ST cost 50% higher						
	Doing nothing	745	745			
	GT only	190	140	50	9875	111
	ST only	513	491	22	2870	32
	GT and ST	190	133	56		
	GT				9252	104
	ST				1135	13
	ST share				0.11	

TABLE 2 (Continued)

Trap cost	Trapping programming	Total expected cost (USD million)	Damage (USD million)	Trap cost (USD million)	Traps required (traps)	Trap density (traps/km ²)
<i>Baseline</i>						
	<i>Doing nothing</i>	745	745			
	<i>GT only</i>	190	140	50	9875	111
	<i>ST only</i>	504	478	26	4939	56
	<i>GT and ST</i>	184	123	61		
	<i>GT</i>				8616	97
	<i>ST</i>				3324	37
	<i>ST share</i>				0.28	
GT cost 50% higher						
	Doing nothing	745	745			
	GT only	212	154	57	7497	84
	ST only	504	478	26	4939	56
	GT and ST	203	133	70		
	GT				6700	75
	ST				3683	41
	ST share				0.35	

Note: “GT only” denotes a trapping program that uses only generalized traps; “GT and ST” denotes a trapping program that potentially uses both generalized and specialized traps. The baseline results are in italics. All costs and damage are rounded to the nearest million USD.

Abbreviations: GT, generalized trap; ST, specialized trap.

TABLE 3 Impact of changes in range of species that traps can capture.

Trap capture range	Trapping programming	Total expected cost (USD million)	Damage (USD million)	Trap cost (USD million)	Traps required (traps)	Trap density (traps/km ²)
(a) Auckland (share of risk/km ² = 0.22%)						
ST species evenly distributed						
	Doing nothing	4478	4478			
	GT only	858	509	348	68,850	317
	ST only	4318	4301	18	3404	16
	GT and ST	858	509	348		
	GT				68,850	317
	ST				0	0
	ST share				0.00	
<i>Baseline</i>						
	<i>Doing nothing</i>	4478	4478			
	<i>GT only</i>	858	509	348	68,850	317
	<i>ST only</i>	2900	2782	118	23,336	107
	<i>GT and ST</i>	811	512	300		
	<i>GT</i>				44,132	203
	<i>ST</i>				15,061	69
	<i>ST share</i>				0.25	

(Continues)

TABLE 3 (Continued)

Trap capture range	Trapping programming cost (USD million)	Total expected cost (USD million)	Damage (USD million)	Trap cost (USD million)	Traps required (traps)	Trap density (traps/km ²)
GT and STs mutually exclusive						
Doing nothing		4478	4478			
GT only		2426	2250	176	34,757	160
ST only		2900	2782	118	23,336	107
GT and ST		848	554	294		
GT					34,757	160
ST					23,336	107
ST share					0.40	
(b) Tauranga (share of risk/km ² = 0.68%)						
ST species evenly distributed						
Doing nothing		2115	2115			
GT only		241	122	119	23,490	699
ST only		2032	2023	9	1577	47
GT and ST		241	122	119		
GT					23,490	699
ST					0	0
ST share					0.00	
<i>Baseline</i>						
<i>Doing nothing</i>		<i>2115</i>	<i>2115</i>			
<i>GT only</i>		<i>241</i>	<i>122</i>	<i>119</i>	<i>23,490</i>	<i>699</i>
<i>ST only</i>		<i>1324</i>	<i>1294</i>	<i>30</i>	<i>5779</i>	<i>172</i>
<i>GT and ST</i>		<i>237</i>	<i>125</i>	<i>112</i>		
<i>GT</i>					<i>19,981</i>	<i>595</i>
<i>ST</i>					<i>2034</i>	<i>61</i>
<i>ST share</i>					<i>0.09</i>	
GT and STs mutually exclusive						
Doing nothing		2115	2115			
GT only		1046	958	88	17,359	517
ST only		1324	1294	30	5779	172
GT and ST		254	137	118		
GT					17,359	517
ST					5779	172
ST share					0.25	
(c) Christchurch (share of risk/km ² = 0.1%)						
ST species evenly distributed						
Doing nothing		855	855			
GT only		211	154	57	11,167	124
ST only		828	823	6	1000	11
GT and ST		211	154	57		
GT					11,167	124
ST					0	0
ST share					0.00	

TABLE 3 (Continued)

Trap capture range	Trapping programming cost (USD million)	Total expected cost (USD million)	Damage (USD million)	Trap cost (USD million)	Traps required (traps)	Trap density (traps/km ²)
<i>Baseline</i>						
<i>Doing nothing</i>		855	855			
<i>GT only</i>		211	154	57	11,167	124
<i>ST only</i>		575	545	29	5652	63
<i>GT and ST</i>		203	135	68		
<i>GT</i>					9389	104
<i>ST</i>					3892	43
<i>ST share</i>					0.29	
GT and STs mutually exclusive						
Doing nothing		855	855			
GT only		492	449	43	8339	93
ST only		575	545	29	5652	63
GT and ST		211	140	71		
GT					8339	93
ST					5652	63
ST share					0.40	
(d) Wellington (share of risk/km ² = 0.09%)						
ST species evenly distributed						
Doing nothing		745	745			
GT only		190	140	50	9875	111
ST only		722	717	5	957	11
GT and ST		190	140	50		
GT					9875	111
ST					0	0
ST share					0.00	
<i>Baseline</i>						
<i>Doing nothing</i>		745	745			
<i>GT only</i>		190	140	50	9875	111
<i>ST only</i>		504	478	26	4939	56
<i>GT and ST</i>		184	123	61		
<i>GT</i>					8616	97
<i>ST</i>					3324	37
<i>ST share</i>					0.28	
GT and STs mutually exclusive						
Doing nothing		745	745			
GT only		433	394	39	7696	87
ST only		504	478	26	4939	56
GT and ST		192	127	65		
GT					7696	87
ST					4939	56
ST share					0.39	

Note: "GT only" denotes a trapping program that uses only generalized traps; "GT and ST" denotes a trapping program that potentially uses both generalized and specialized traps. The baseline results are in italics. All costs and damage are rounded to nearest million USD. Abbreviations: GT, generalized trap; ST, specialized trap.

TABLE 4 Impact of species that cannot be trapped and changes in ST species eradication probability.

TD and STSEP	Trapping programming	Total expected cost (USD million)	Damage (USD million)	Trap cost (USD million)	Traps required (traps)	Trap density (traps/km ²)
(a) Auckland (share of risk/km ² = 0.22%)						
Percentage NT						
	Doing nothing	4478	4478			
	GT only	1643	1374	269	53,166	245
	ST only	2900	2782	118	23,336	107
	GT and ST	1562	1323	239		
	GT				29,260	135
	ST				17,849	82
	ST share				0.38	
<i>Baseline</i>						
	<i>Doing nothing</i>	<i>4478</i>	<i>4478</i>			
	<i>GT only</i>	<i>858</i>	<i>509</i>	<i>348</i>	<i>68,850</i>	<i>317</i>
	<i>ST only</i>	<i>2900</i>	<i>2782</i>	<i>118</i>	<i>23,336</i>	<i>107</i>
	<i>GT and ST</i>	<i>811</i>	<i>512</i>	<i>300</i>		
	<i>GT</i>				<i>44,132</i>	<i>203</i>
	<i>ST</i>				<i>15,061</i>	<i>69</i>
	<i>ST share</i>				<i>0.25</i>	
ST species eradication probability 50% higher						
	Doing nothing	4478	4478			
	GT only	759	513	246	48,574	224
	ST only	2845	2782	64	12,477	57
	GT and ST	756	511	245		
	GT				44,132	203
	ST				4202	19
	ST share				0.09	
(b) Tauranga (share of risk/km ² = 0.68%)						
Percentage NT						
	Doing nothing	2115	2115			
	GT only	638	533	106	20,848	620
	ST only	1324	1294	30	5779	172
	GT and ST	627	537	90		
	GT				14,723	438
	ST				3019	90
	ST share				0.17	
<i>Baseline</i>						
	<i>Doing nothing</i>	<i>2115</i>	<i>2115</i>			
	<i>GT only</i>	<i>241</i>	<i>122</i>	<i>119</i>	<i>23,490</i>	<i>699</i>
	<i>ST only</i>	<i>1324</i>	<i>1294</i>	<i>30</i>	<i>5779</i>	<i>172</i>
	<i>GT and ST</i>	<i>237</i>	<i>125</i>	<i>112</i>		
	<i>GT</i>				<i>19,981</i>	<i>595</i>

TABLE 4 (Continued)

TD and STSEP	Trapping programming	Total expected cost (USD million)	Damage (USD million)	Trap cost (USD million)	Traps required (traps)	Trap density (traps/km ²)
ST species eradication probability 50% higher	ST				2034	61
	ST share				0.09	
	Doing nothing	2115	2115			
	GT only	228	124	104	20,427	608
	ST only	1315	1294	21	4099	122
	GT and ST	228	124	104		
	GT				20,427	608
	ST				0	0
	ST share				0.00	

(c) Christchurch (share of risk/km² = 0.1%)

Percentage NT

Doing nothing	855	855				
GT only	350	303	47	9274	103	
ST only	575	545	29	5652	63	
GT and ST	340	279	61			
GT				7777	86	
ST				4194	47	
ST share				0.35		

Baseline

Doing nothing	855	855				
GT only	211	154	57	11,167	124	
ST only	575	545	29	5652	63	
GT and ST	203	135	68			
GT				9389	104	
ST				3892	43	
ST share				0.29		

ST species eradication probability 50% higher

Doing nothing	855	855				
GT only	180	132	48	9400	104	
ST only	552	542	10	1774	20	
GT and ST	180	132	48			
GT				9400	104	
ST				0	0	
ST share				0.00		

(d) Wellington (share of risk/km² = 0.09%)

Percentage NT

Doing nothing	745	745				
GT only	311	268	43	8389	94	

(Continues)

TABLE 4 (Continued)

TD and STSEP	Trapping programming	Total expected cost (USD million)	Damage (USD million)	Trap cost (USD million)	Traps required (traps)	Trap density (traps/km ²)
<i>Baseline</i>	ST only	504	478	26	4939	56
	GT and ST	303	247	55		
	GT				7212	81
	ST				3587	40
	ST share				0.33	
	<i>Doing nothing</i>	<i>745</i>	<i>745</i>			
	<i>GT only</i>	<i>190</i>	<i>140</i>	<i>50</i>	<i>9875</i>	<i>111</i>
	<i>ST only</i>	<i>504</i>	<i>478</i>	<i>26</i>	<i>4939</i>	<i>56</i>
	<i>GT and ST</i>	<i>184</i>	<i>123</i>	<i>61</i>		
	<i>GT</i>				<i>8616</i>	<i>97</i>
	<i>ST</i>				<i>3324</i>	<i>37</i>
	<i>ST share</i>				<i>0.28</i>	
	ST species eradication probability 50% higher					
	Doing nothing	745	745			
	GT only	162	118	44	8603	97
	ST only	482	473	9	1600	18
	GT and ST	162	118	44		
	GT				8603	97
	ST				0	0
	ST share				0.00	

Note: "GT only" denotes a trapping program that uses only generalized traps; "GT and ST" denotes a trapping program that potentially uses both generalized and specialized traps. The baseline results are in italics. All costs and damages are rounded to the nearest million USD.

Abbreviations: GT, generalized trap; ST, specialized trap; STSEP, ST Species Eradication Probability; TD trap detectability.

this context, we focus only on highly damaging species that STs can catch. We increased the likelihood of successful eradication by 50% compared to the baseline scenario. As shown in Table 4, TECs decreased in all regions, but using STs is no longer economically efficient in any area except Auckland. This result may seem counterintuitive at first, but it makes sense because, in this scenario, the detection of ST species was not affected, and it was easier to eradicate them than in the baseline scenario. Consequently, delaying detection is less costly for ST species in this scenario, reducing the benefits of trapping for them.

Impact of changes in trap sensitivity

The efficiency of a specific type of trap in capturing particular species, referred to as trap sensitivity, can influence the traps' allocation and, ultimately, the economic

outcomes of the pest management program. In this study, we examined the impact of this variable through two different scenarios. In the first scenario, we enhanced the sensitivity of STs from 80% to 90%. In the second scenario, we decreased the sensitivity of GTs from 15% to 10%.

As expected, increasing ST sensitivity and decreasing GT sensitivity resulted in lower and higher TECs, respectively (Table 5). However, the impact on the share of STs was more nuanced. We observed a uniform increase in ST shares across all regions as ST sensitivity increased. In contrast, when GT sensitivity decreased, ST shares increased in high-risk areas, namely, Auckland and Tauranga, but marginally decreased in low-risk areas, namely, Christchurch and Wellington. These results highlight two important implications. First, there is a substitution effect between the two trap types, and second, the use of GTs is less sensitive to their detectability in low-risk regions.

TABLE 5 Impact of changes in trap sensitivity.

Sensitivity	Trapping programming	Total expected cost (USD million)	Damage (USD million)	Trap cost (USD million)	Traps required (traps)	Trap density (traps/km ²)
(a) Auckland (share of risk/km ² = 0.22%)						
ST 10% higher sensitivity						
	Doing nothing	4478	4478			
	GT only	858	509	348	68,850	317
	ST only	2887	2775	112	22,055	102
	GT and ST	803	510	292		
	GT				42,742	197
	ST				14,931	69
	ST share				0.26	
<i>Baseline</i>						
	<i>Doing nothing</i>	<i>4478</i>	<i>4478</i>			
	<i>GT only</i>	<i>858</i>	<i>509</i>	<i>348</i>	<i>68,850</i>	<i>317</i>
	<i>ST only</i>	<i>2900</i>	<i>2782</i>	<i>118</i>	<i>23,336</i>	<i>107</i>
	<i>GT and ST</i>	<i>811</i>	<i>512</i>	<i>300</i>		
	<i>GT</i>				<i>44,132</i>	<i>203</i>
	<i>ST</i>				<i>15,061</i>	<i>69</i>
	<i>ST share</i>				<i>0.25</i>	
GT 5% lower sensitivity						
	Doing nothing	4478	4478			
	GT only	993	677	316	62,458	288
	ST only	2900	2782	118	23,336	107
	GT and ST	897	595	301		
	GT				41,292	190
	ST				18,174	84
	ST share				0.31	
(b) Tauranga (share of risk/km ² = 0.68%)						
ST 10% higher sensitivity						
	Doing nothing	2115	2115			
	GT only	241	122	119	23,490	699
	ST only	1320	1293	28	5342	159
	GT and ST	235	125	111		
	GT				19,658	585
	ST				2066	61
	ST share				0.10	
<i>Baseline</i>						
	<i>Doing nothing</i>	<i>2115</i>	<i>2115</i>			
	<i>GT only</i>	<i>241</i>	<i>122</i>	<i>119</i>	<i>23,490</i>	<i>699</i>
	<i>ST only</i>	<i>1324</i>	<i>1294</i>	<i>30</i>	<i>5779</i>	<i>172</i>
	<i>GT and ST</i>	<i>237</i>	<i>125</i>	<i>112</i>		
	<i>GT</i>				<i>19,981</i>	<i>595</i>
	<i>ST</i>				<i>2034</i>	<i>61</i>
	<i>ST share</i>				<i>0.09</i>	

(Continues)

TABLE 5 (Continued)

Sensitivity	Trapping programming	Total expected cost (USD million)	Damage (USD million)	Trap cost (USD million)	Traps required (traps)	Trap density (traps/km ²)
GT 5% lower sensitivity						
	Doing nothing	2115	2115			
	GT only	294	152	142	28,080	836
	ST only	1324	1294	30	5779	172
	GT and ST	279	156	123		
	GT				21,007	625
	ST				3154	94
	T share				0.13	
(c) Christchurch (share of risk/km ² = 0.1%)						
ST 10% higher sensitivity						
	Doing nothing	855	855			
	GT only	211	154	57	11,167	124
	ST only	571	542	29	5567	62
	GT and ST	200	133	68		
	GT				9248	103
	ST				4026	45
	ST share				0.30	
<i>Baseline</i>						
	<i>Doing nothing</i>	<i>855</i>	<i>855</i>			
	<i>GT only</i>	<i>211</i>	<i>154</i>	<i>57</i>	<i>11,167</i>	<i>124</i>
	<i>ST only</i>	<i>575</i>	<i>545</i>	<i>29</i>	<i>5652</i>	<i>63</i>
	<i>GT and ST</i>	<i>203</i>	<i>135</i>	<i>68</i>		
	<i>GT</i>				<i>9389</i>	<i>104</i>
	<i>ST</i>				<i>3892</i>	<i>43</i>
	<i>ST share</i>				<i>0.29</i>	
GT 5% lower sensitivity						
	Doing nothing	855	855			
	GT only	235	172	63	12,289	137
	ST only	575	545	29	5652	63
	GT and ST	223	146	77		
	GT				10,845	121
	ST				4297	48
	ST share				0.28	
(d) Wellington (share of risk/km ² = 0.09%)						
ST 10% higher sensitivity						
	Doing nothing	745	745			
	GT only	190	140	50	9875	111
	ST only	501	475	25	4926	55
	GT and ST	182	121	61		
	GT				8494	96
	ST				3510	40
	ST share				0.29	

TABLE 5 (Continued)

Sensitivity	Trapping programming	Total expected cost (USD million)	Damage (USD million)	Trap cost (USD million)	Traps required (traps)	Trap density (traps/km ²)
<i>Baseline</i>						
	<i>Doing nothing</i>	745	745			
	<i>GT only</i>	190	140	50	9875	111
	<i>ST only</i>	504	478	26	4939	56
	<i>GT and ST</i>	184	123	61		
	<i>GT</i>				8616	97
	<i>ST</i>				3324	37
	<i>ST share</i>				0.28	
GT 5% lower sensitivity						
	Doing nothing	745	745			
	GT only	212	154	57	11,246	127
	ST only	504	478	26	4939	56
	GT and ST	203	133	70		
	GT				10,051	113
	ST				3683	41
	ST share				0.27	

Note: “GT only” denotes a trapping program that uses only generalized traps; “GT and ST” denotes a trapping program that potentially uses both generalized and specialized traps. The baseline results are in italics. All costs and damage are rounded to the nearest million USD.

Abbreviations: GT, generalized trap; ST, specialized trap.

Lastly, we investigated how the model results fluctuated with a broader variation in ST sensitivity, ranging from 30% to 90%. Appendix S4: Figure S1 illustrates the impact on TEC and the proportion of STs required in integrated programs. Within the baseline scenario, where GTs can capture all species detectable by STs, albeit with lower sensitivity, STs must demonstrate high effectiveness to be included in integrated programs. Indeed, in the riskiest region, Tauranga, STs necessitate a sensitivity of 45% or higher to be considered, and even at a 90% sensitivity level, their share does not exceed 10% of the total traps required. In contrast, in other regions, STs necessitate a comparable level of sensitivity to be included, potentially constituting up to 30% of the total traps in integrated schemes.

DISCUSSION

Surveillance is used for several purposes in national surveillance programs (Kalaris et al., 2014). However, its most important objective is to detect newly founded populations early enough to facilitate their eradication (Kean et al., 2015). Two approaches to surveillance are often recognized: passive surveillance, which utilizes

existing information (e.g., data mining from biodiversity samples or citizen observations), and directed surveillance, which applies methods (e.g., traps, molecular sensors) that target individual species or groups of species (Anderson et al., 2017). In this paper, we focus on directed surveillance and explore its optimization for use in detecting plant pests.

Due to the high cost of implementing national surveillance systems and their importance to the success of biosecurity programs, there are major incentives in designing these systems to be cost effective. Several approaches have been taken in the optimization of surveillance systems (Koch et al., 2020). One approach has been to identify optimal strategies that minimize surveillance expenditures while simultaneously minimizing damage that occurs when surveillance fails (e.g., Holden et al., 2016; Yemshanov et al., 2019). Other approaches to surveillance optimization, such as those adopted here, minimize surveillance costs along with eradication costs (e.g., Epanchin-Niell et al., 2012; Hauser & McCarthy, 2009; Kompas et al., 2023).

While early efforts to identify optimal surveillance strategies relied on several simplifying assumptions to keep the problem tractable, recent work has been able to account for more realistic complexities that make this work more applicable. These complexities have included

accounting for uncertainty in underlying biological parameters (Horie et al., 2013), accounting for spatial variation in detection costs (Moore & McCarthy, 2016), and accounting for travel routes to surveillance locations (Yemshanov et al., 2020). Only a few studies have attempted to optimize surveillance programs that focus on the detection of multiple species (Epanchin-Niell et al., 2014; Jarrad et al., 2011). But to date there have been no published attempts, to the best of our knowledge, to optimize surveillance for multiple species by allocating surveillance effort among various types of detection tools, even though practical implementation of surveillance often demands the selection of tools (e.g., traps) of varying specificity and cost (Poland & Rassati, 2019).

In this study, we investigated whether using a combination of trap types that differed in their specificity for detecting species could enhance the efficiency of invasive surveillance programs. We explored the trade-offs among the use of different trap types by applying a bioeconomic surveillance model to manage bark- and wood-boring insect species in New Zealand. These species are among the most serious groups of forest pests worldwide (Aukema et al., 2011; Lieutier et al., 2004), and they vary substantially in their detectability by different lures and survey methods. Our findings illustrate the context dependence of their complementarity and substitutability, with the relative importance of each trap type depending on the attributes of the traps and the invasion contexts.

We found that the wide deployment of GTs is economically justified—even if they are generally less sensitive than STs—because GTs detect a wider range of species. However, the inclusion of STs is optimal across most of the contexts that we explored because of their greater sensitivity for detecting more damaging species.

The relative efficiency of STs, however, is quite dependent on their cost and sensitivity compared to GTs and, predominantly, the coverage capacity of GTs. The lower sensitivity or higher costs of a particular type of trap tend to reduce that type's relative use but can increase overall trapping investments. Thus, the relative price and detectability between the two trap types will, by and large, determine their optimal combination. But the marginal impact of the change caused by GTs on model outcomes is expected to be much more significant due to their extensive coverage. Furthermore, high arrival rates by invasive species generally make it more economical to blanket landscapes with GTs as they can detect a broader range of species. Finally, the higher the chance of successfully eradicating insects that specialized tools can catch, the less likely the tools will be required because delaying detection becomes less costly for these species.

One limitation of our analysis is that we only considered two categories of surveillance tools, but in reality, there may be a larger array of tools available. This would obviously make the selection of an optimal mixture of surveillance tools more complex. While many scolytine species utilize species-specific compounds for chemical communication, other species share certain compounds, and in some cases a single compound or blend of compounds may be attractive to multiple species (Raffa et al., 2015). For example, most North American *Ips* species are attracted to the blend of compounds used by the European spruce bark beetle, *Ips typographus*, for aggregation (Rabaglia et al., 2019). Also, in some cases, it is possible to utilize a single trap that is baited with multiple lures, each highly specific for multiple pests (Chase et al., 2018; Moir et al., 2022). This may represent a situation intermediate between the GT and ST methods considered here. Furthermore, our analysis assumed that there was no trend of association between the availability of specialized traps for a given species and the cost of the impact of a species. In reality, this often may not be the case because research on semiochemicals and trapping technologies often focuses on high-impact species. When pests are anticipated to have lower impacts, highly specific attractants may not be available.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

All data and statistical code (Nguyen et al., 2023) are available from the Open Science Framework at <https://osf.io/38scx/>. Data used for this research were obtained from published and publicly available sources as listed in Appendices S2 and S3.

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REFERENCES

- Anderson, C., S. Low-Choy, P. Whittle, S. Taylor, C. Gambley, L. Smith, P. Gillespie, H. Löcker, R. Davis, and B. Dominiak. 2017. "Australian Plant Biosecurity Surveillance Systems." *Crop Protection* 100: 8–20.
- Aukema, J. E., B. Leung, K. Kovacs, C. Chivers, K. O. Britton, J. Englin, S. J. Frankel, et al. 2011. "Economic Impacts of Non-native Forest Insects in the Continental United States." *PLoS One* 6(9): e24587.
- Bogich, T. L., A. M. Liebhold, and K. Shea. 2008. "To Sample or Eradicate? A Cost Minimization Model for Monitoring and Managing an Invasive Species." *Journal of Applied Ecology* 45(4): 1134–42.
- Brockerhoff, E. G., D. C. Jones, M. O. Kimberley, D. M. Suckling, and T. Donaldson. 2006. "Nationwide Survey for Invasive Wood-Boring and Bark Beetles (Coleoptera) Using Traps Baited with Pheromones and Kairomones." *Forest Ecology and Management* 228(1–3): 234–240.
- Brockerhoff, E. G., A. M. Liebhold, B. Richardson, and D. M. Suckling. 2010. "Eradication of Invasive Forest Insects: Concepts, Methods, Costs and Benefits." *New Zealand Journal of Forestry Science* 40(suppl): S117–S135.
- Chase, K. D., L. D. Stringer, R. C. Butler, A. M. Liebhold, D. R. Miller, P. W. Shearer, and E. G. Brockerhoff. 2018. "Multiple-Lure Surveillance Trapping for *IPS* Bark Beetles, *Monochamus* Longhorn Beetles, and *Halyomorpha halys* (Hemiptera: Pentatomidae)." *Journal of Economic Entomology* 111(5): 2255–63.
- Dodds, K. J., J. Sweeney, and J. D. Allison. 2023. "Woodborers in Forest Stands." In *Forest Entomology and Pathology*, Vol. 1: Entomology, edited by D. Allison, T. D. Paine, B. Slippers, and M. J. Wingfield, 361–415. Cham: Springer International Publishing.
- Epanchin-Niell, R. S. 2017. "Economics of Invasive Species Policy and Management." *Biological Invasions* 19(11): 3333–54.
- Epanchin-Niell, R. S., E. G. Brockerhoff, J. M. Kean, and J. A. Turner. 2014. "Designing Cost-Efficient Surveillance for Early Detection and Control of Multiple Biological Invaders." *Ecological Applications* 24(6): 1258–74.
- Epanchin-Niell, R. S., R. G. Haight, L. Berec, J. M. Kean, and A. M. Liebhold. 2012. "Optimal Surveillance and Eradication of Invasive Species in Heterogeneous Landscapes." *Ecology Letters* 15(8): 803–812.
- Haack, R. A., K. O. Britton, E. G. Brockerhoff, J. F. Cavey, L. J. Garrett, M. Kimberley, F. Lowenstein, et al. 2014. "Effectiveness of the International Phytosanitary Standard ISPM No. 15 on Reducing Wood Borer Infestation Rates in Wood Packaging Material Entering the United States." *PLoS One* 9(5): e96611.
- Haack, R. A., J. A. Hardin, B. P. Caton, and T. R. Petrice. 2022. "Wood Borer Detection Rates on Wood Packaging Materials Entering the United States during Different Phases of ISPM 15 Implementation and Regulatory Changes." *Frontiers in Forests and Global Change* 5: 1069117.
- Hauser, C. E., and M. A. McCarthy. 2009. "Streamlining 'Search and Destroy': Cost-Effective Surveillance for Invasive Species Management." *Ecology Letters* 12(7): 683–692.
- Hester, S., and O. Cacho. 2012. "Optimization of Search Strategies in Managing Biological Invasions: A Simulation Approach." *Human and Ecological Risk Assessment: An International Journal* 18(1): 181–199.
- Holden, M. H., J. P. Nyrop, and S. P. Ellner. 2016. "The Economic Benefit of Time-Varying Surveillance Effort for Invasive Species Management." *Journal of Applied Ecology* 53(3): 712–721.
- Horie, T., R. G. Haight, F. R. Homans, and R. C. Venette. 2013. "Optimal Strategies for the Surveillance and Control of Forest Pathogens: A Case Study with Oak Wilt." *Ecological Economics* 86: 78–85.
- Hulme, P. E. 2011. "Biosecurity: The Changing Face of Invasion Biology." In *Fifty Years of Invasion Ecology: The Legacy of Charles Elton*, edited by D. M. Richardson, 301–314. Chichester, West Sussex, UK: John Wiley & Sons Ltd.
- Jarrad, F. C., S. Barrett, J. Murray, R. Stoklosa, P. Whittle, and K. Mengersen. 2011. "Ecological Aspects of Biosecurity Surveillance Design for the Detection of Multiple Invasive Animal Species." *Biological Invasions* 13(4): 803–818.
- Kalaris, T., D. Fieselmann, R. Magarey, M. Colunga-Garcia, A. Roda, D. Hardie, N. Cogger, N. Hammond, P. T. Martin, and P. Whittle. 2014. "The Role of Surveillance Methods and Technologies in Plant Biosecurity." In *The Handbook of Plant Biosecurity: Principles and Practices for the Identification, Containment and Control of Organisms that Threaten Agriculture and the Environment Globally*, edited by G. Gordh and S. McKirdy, 309–337. New York: Springer.
- Kean, J. 2015. "The Effective Sampling Area of Traps: Estimation and Application." In *The Plant Protection Data Toolbox*, edited by R. Beresford, K. J. Froud, J. M. Kean, and S. P. Worner, 67–76. Christchurch, New Zealand: New Zealand Plant Protection Society Incorporated.
- Kean, J. M., G. M. Burnip, and A. Pathan. 2015. "Detection Survey Design for Decision Making during Biosecurity Incursions." In *Biosecurity Surveillance: Quantitative Approaches* 238–250. Wallingford: CABI.
- Kerr, J. L., D. Kelly, M. K.-F. Bader, and E. G. Brockerhoff. 2017. "Olfactory Cues, Visual Cues, and Semiochemical Diversity Interact during Host Location by Invasive Forest Beetles." *Journal of Chemical Ecology* 43: 17–25.
- Koch, F. H., D. Yemshanov, R. G. Haight, C. J. MacQuarrie, N. Liu, R. Venette, and K. Ryall. 2020. "Optimal Invasive Species Surveillance in the Real World: Practical Advances from Research." *Emerging Topics in Life Sciences* 4(5): 513–520.
- Kompas, T., L. Chu, S. McKirdy, M. Thomas, and J. Van Der Merwe. 2023. "Optimal Post-Border Surveillance against Invasive Pests to Protect a Valuable Nature Reserve and Island Asset." *Ecological Economics* 208: 107789.
- Kompas, T., L. Chu, and H. T. M. Nguyen. 2016. "A Practical Optimal Surveillance Policy for Invasive Weeds: An Application to Hawkweed in Australia." *Ecological Economics* 130: 156–165.

- Landcare Research New Zealand Ltd. 2020. "LCDB v5.0 - Land Cover Database version 5.0, Mainland New Zealand." <https://iris.scinfo.org.nz/layer/104400-lcdb-v50-land-cover-database-version-50-mainland-new-zealand/>.
- Liebholt, A. M., L. Berec, E. G. Brockhoff, R. S. Epanchin-Niell, A. Hastings, D. A. Herms, J. M. Kean, et al. 2016. "Eradication of Invading Insect Populations: From Concepts to Applications." *Annual Review of Entomology* 61: 335–352.
- Lieutier, F., K. R. Day, A. Battisti, J.-C. Grégoire, and H. F. Evans. 2004. *Bark and Wood Boring Insects in Living Trees in Europe: A Synthesis*. Dordrecht: Kluwer Academic Publishers.
- Meier, L. R., Y. Zou, J. G. Millar, J. A. Mongold-Diers, and L. M. Hanks. 2016. "Synergism between Enantiomers Creates Species-Specific Pheromone Blends and Minimizes Cross-Attraction for Two Species of Cerambycid Beetles." *Journal of Chemical Ecology* 42: 1181–92.
- Miller, D. R., and J. H. Borden. 2000. "Dose-Dependent and Species-Specific Responses of Pine Bark Beetles (Coleoptera: Scolytidae) to Monoterpenes in Association with Pheromones." *The Canadian Entomologist* 132(2): 183–195.
- Miller, D. R., and R. J. Rabaglia. 2009. "Ethanol and Alpha-Pinene: Attractant Kairomones for Bark and Ambrosia Beetles in the Southeastern US." *Journal of Chemical Ecology* 35: 435–448.
- Moir, M. L., L. Croeser, D. Telfer, C. Fenner, and R. McCauley. 2022. "Value-Adding in Biosecurity Surveillance and Monitoring: Testing Colour and Non-target Semiochemical Lures on Psylloidea and Pentatomoidea." *Journal of Applied Entomology* 146: 1333–42.
- Moore, A. L., and M. A. McCarthy. 2016. "Optimizing Ecological Survey Effort over Space and Time." *Methods in Ecology and Evolution* 7(8): 891–99.
- Nahrung, H. F., A. M. Liebhold, E. G. Brockhoff, and D. Rassati. 2023. "Forest Insect Biosecurity: Processes, Patterns, Predictions, Pitfalls." *Annual Review of Entomology* 68: 211–229.
- Nguyen, H.-T.-M., L. Chu, and T. Kompas. 2023. "Optimal Allocation of Resources Among General and Species-Specific Tools for Plant Pest Biosecurity Surveillance." Open Science Framework. Dataset. <https://osf.io/38scx/>.
- Nguyen, H.-T.-M., P. V. Ha, and T. Kompas. 2021. "Optimal Surveillance against Bioinvasions: A Sample Average Approximation Method Applied to an Agent-Based Spread Model." *Ecological Applications* 31: e02449.
- Poland, T. M., and D. Rassati. 2019. "Improved Biosecurity Surveillance of Non-native Forest Insects: A Review of Current Methods." *Journal of Pest Science* 92(1): 37–49.
- Rabaglia, R. J., A. I. Cognato, E. R. Hoebeke, C. W. Johnson, J. R. LaBonte, M. E. Carter, and J. J. Vlach. 2019. "Early Detection and Rapid Response: A 10-Year Summary of the USDA Forest Service Program of Surveillance for Non-native Bark and Ambrosia Beetles." *American Entomologist* 65(1): 29–42.
- Raffa, K. F., J.-C. Grégoire, and B. S. Lindgren. 2015. "Natural History and Ecology of Bark Beetles." In *Bark Beetles: Biology and Ecology of Native and Invasive Species*, edited by F. Vega and R. Hofstetter, 1–40. London: Academic Press.
- Rassati, D., M. Faccoli, E. Petrucco Toffolo, A. Battisti, and L. Marini. 2015. "Improving the Early Detection of Alien Wood-Boring Beetles in Ports and Surrounding Forests." *Journal of Applied Ecology* 52(1): 50–58.
- Reaser, J. K., S. W. Burgiel, J. Kirkey, K. A. Brantley, S. D. Veatch, and J. Burgos-Rodríguez. 2020. "The Early Detection of and Rapid Response (EDRR) to Invasive Species: A Conceptual Framework and Federal Capacities Assessment." *Biological Invasions* 22(1): 1–19.
- Rocchini, D., V. Andreo, M. Förster, C. X. Garzon-Lopez, A. P. Gutierrez, T. W. Gillespie, H. C. Hauffe, et al. 2015. "Potential of Remote Sensing to Predict Species Invasions: A Modelling Perspective." *Progress in Physical Geography* 39(3): 283–309.
- Simmons, M., A. Tucker, W. L. Chadderton, C. L. Jerde, and A. R. Mahon. 2016. "Active and Passive Environmental DNA Surveillance of Aquatic Invasive Species." *Canadian Journal of Fisheries and Aquatic Sciences* 73(1): 76–83.
- Sweeney, J., P. de Groot, L. Humble, L. MacDonald, J. Price, T. Mokrzycki, and J. M. Gutowski. 2007. "Detection of Wood-Boring Species in Semiochemical-Baited Traps." In *Alien Invasive Species and International Trade*, edited by H. Evans and T. Oszako, 139–144. Warsaw: Forest Research Institute.
- Turchin, P., and F. J. Odendaal. 1996. "Measuring the Effective Sampling Area of a Pheromone Trap for Monitoring Population Density of Southern Pine Beetle (Coleoptera: Scolytidae)." *Environmental Entomology* 25(3): 582–88.
- van Havre, Z., and P. Whittle. 2015. "Designing Surveillance for Emergency Response." In *Biosecurity Surveillance: Quantitative Approaches* 123–133. Wallingford: CAB International.
- Westbrooks, R. G. 2004. "New Approaches for Early Detection and Rapid Response to Invasive Plants in the United States." *Weed Technology* 18(sp1): 1468–71.
- Yemshanov, D., R. G. Haight, F. H. Koch, R. C. Venette, T. Swystun, R. E. Fournier, M. Marcotte, Y. Chen, and J. J. Turgeon. 2019. "Optimizing Surveillance Strategies for Early Detection of Invasive Alien Species." *Ecological Economics* 162: 87–99.
- Yemshanov, D., R. G. Haight, C. J. MacQuarrie, F. H. Koch, N. Liu, R. Venette, and K. Ryall. 2020. "Optimal Planning of Multi-Day Invasive Species Surveillance Campaigns." *Ecological Solutions and Evidence* 1(2): e12029.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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