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Analysis

A Stochastic Economic Framework for Partitioning Biosecurity Surveillance Resources

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ABSTRACT

Effective biosecurity systems are important for protecting trade and the environment from the introduction of exotic pests and diseases, particularly as the movement of goods and people increases worldwide. But systems are complex and the optimal division of resources between biosecurity operations is difficult to determine. In this paper we formulate tractable, stochastic, bio-economic models to guide the optimisation of cost-efficiency in decisions concerning biosecurity operations. In particular, to guide a tradeoff between effort afforded to preventing the introduction of pests and diseases, and post-border surveillance, although the approach has general relevance. The models offer a practical means of optimising resource partitioning, designed to transfer easily between disparate settings and a range of pest-types, and to enable the incorporation of uncertainty. For highly complex problems, tractable frameworks are not always available or efficient. However, using an application to Asian gypsy moth trapping and reference to applications in the literature, we demonstrate that the proposed approach is relevant, is straightforward to apply, and provides a comprehensive analysis for decision-makers.

1. Introduction

Biosecurity systems are implemented world-wide to protect trade and the environment, while also facilitating the movement of goods and people. Efficient operations are particularly important to countries such as Australia, which currently remain free from many exotic pests and pathogens; however, effective biosecurity processes are expensive and logistically difficult. There is a need for accessible quantitative approaches that address the cost-efficiency of resourcing different operations, and which are designed to guide policy decisions in the face of increasing costs, much uncertainty and the rapidly increasing volume of incoming goods and travellers (Mastin et al., 2019).

There is a continuous low-level risk of new pest and disease introductions from source countries with arriving goods and the movement of people (Chapman et al., 2017). Available resources can be allocated to measures that reduce the frequency of pest arrivals, such as the education of arriving passengers and inspections at the border, or allocated to post-border operations, such as surveillance aimed at the early detection of newly established pests and diseases. In this paper we formulate a tractable, stochastic, economic framework that allows an optimal assessment of resource partitioning between pest-arrival prevention measures and post-border operations. Our purpose is to provide a practical means of partitioning resources so as to minimise costs, but one that can also incorporate uncertainty into decision-making and can be applied in disparate settings and across a range of different pest-types and scenarios. By choosing to formulate closed-form distributions for total costs rather than relying on simulations, our models are simple to apply, are easily transferable between applications and, when parameter estimates are poor or unavailable as is common in biosecurity applications, their potential influence on results can be easily interpreted for decision-makers.

A number of stochastic economic models in ecology and biosecurity have appeared in the recent literature, with a variety of purposes including the optimal partitioning of expenditure between prevention and surveillance. Management decisions are typically determined using expected values without the incorporation of uncertainty (Anderson et al., 2017; Gormley et al., 2016; Kompas et al., 2018; Moore et al., 2010; Regan et al., 2006) and, except for some simple scenarios (in (Moore et al., 2010; Regan et al., 2006), for example), most rely on simulation results (Anderson et al., 2017; Gormley et al., 2016; Kompas et al., 2018; Ramsey et al., 2011), or solutions using Markov decision theory (Moore et al., 2010; Regan et al., 2006). Several studies propose large-scale spatial simulation models with high data requirements ((Gormley et al., 2016; Kompas et al., 2018), for example), with some modelling approaches taking monetary discounting into account (Kompas et al., 2018; Regan et al., 2006). The biosecurity system

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modelled in this paper is conceptually similar, with the same purpose and optimisation criteria of cost minimisation. Our approach, however, differs fundamentally. We provide closed-form solutions to the stochastic models, which are fast and simple to apply, and which are highly relevant to this class of problems and associated policy decisions.

We formulate a full distribution for the total costs of a general biosecurity system through time, providing explicit expressions for the mean and variance. The biology of the pest or disease underpins results through functions that relate surveillance effort to pest-arrival probabilities, and to eradication costs and probabilities, making use of pest-specific detectability and growth characteristics. The distribution constructed incorporates many of the features in the models referenced above, including both border and post-border biosecurity operations, switching between response strategies, and the option to include monetary discounting. Pest-arrivals are considered as independent stochastic events, with alternative arrival distributions easily accommodated in order to generalise applicability to the diverse range of pests and diseases. And the success of sequential eradication programs is modelled using a distribution that depends on pest-type and present-value surveillance expenditure. A key difference between our approach and many of those referenced above is that, in the event eradication fails, a single long-term management cost replaces the cost of further prevention and surveillance measures, so as not to count the costs of a long-term incursion of the same pest more than once.

The cost-distribution we construct is formulated using the standard properties of discrete mixed-distributions and conditioning, while also accounting for present-value costs through time. The model is not spatially explicit, focussing on newly arrived pests and diseases and their early detection rather than details of their spatial spread — for which further assumptions and greater complexity are required. We have not taken a decision-theory approach to optimisation, considering rather the cost-efficiency of partitioning general biosecurity activities as in (Anderson et al., 2017; Gormley et al., 2016; Kompas et al., 2018; Moore et al., 2010; Ramsey et al., 2011; Regan et al., 2006). The explicit model proposed has comparable, or greater, complexity than many of those cited, is suited to a number of those studies and, by design, results from spatial modelling (when available) can be integrated easily — as we show in an example application.

To demonstrate how the framework performs, we optimise the trapping-grid spacing for Asian gypsy moth in Australia. The moth is not currently established, although there is a continuous low-level risk of its introduction, despite pre-border and border measures, and an incursion has the potential to devastate the Australian forest industry — as has occurred elsewhere (Sharov, 2004). Results show that the explicit model is easy to apply and can replace the need for simulations, providing a more comprehensive analysis.

In Section 2 we formulate stochastic models for a variety of biosecurity systems. We then consider some optimal surveillance strategies (Section 3), demonstrate how the model performs with a cost-minimisation application (Section 4) and discuss some advantages and limitations of the proposed approach for more general application (Section 5).

2. The Model Framework

Fig. 1 provides a schematic diagram for the framework we formulate. For a single pest/pathogen species, we assume a continuous low-level risk of arrival and model this as a stochastic process, with alternative distributions easily accommodated. Arrivals from source countries often occur in 'clumps' and, in order to avoid double-counting the long-term consequences of several arrivals in a short time, we limit the number of incursions in a time-interval to one. Thus we cost a single incursion for the species during that interval although alternatives are easily substituted. Prevention measures implemented pre-border, or at the border, reduce the number of pests and pathogens that arrive in any time interval, with the probability of arrival depending on pest-type

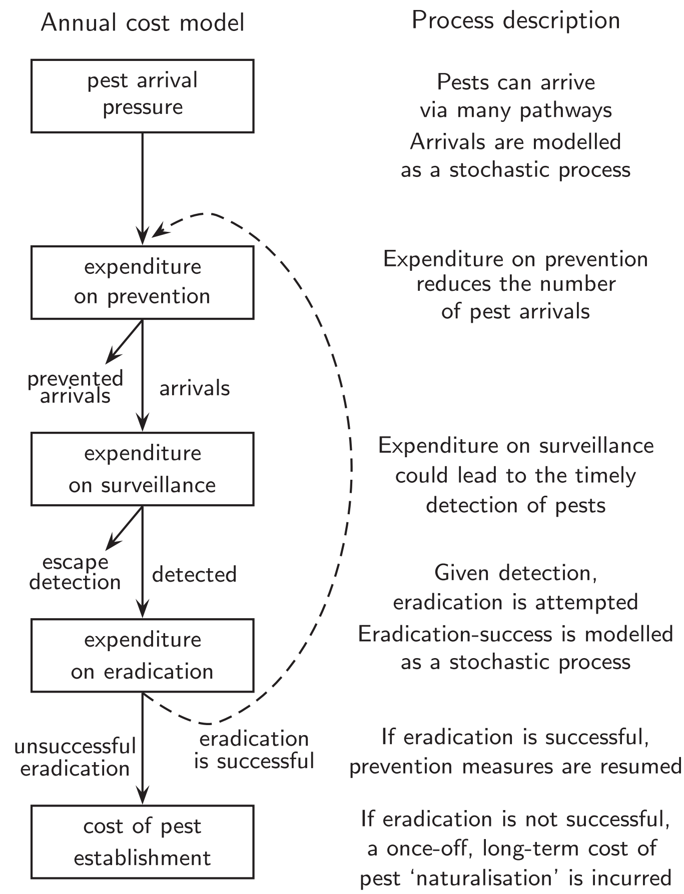

Fig. 1. Schematic diagram for the bio-economic model.

and declining with increasing expenditure on prevention. In the case post-border surveillance is undertaken, the pest or pathogen may be detected early, in which case eradication is more likely to succeed and eradication costs are reduced. How expenditure relates to pest-arrival rates, early detection, eradication costs and the probability of eradication success, depend explicitly on the pest-type and associated spread mechanisms, and the framework is designed to accommodate alternative relationships and disparate data availability. Eradication programs are not always successful and, in the event of failure, it is assumed that prevention and surveillance measures cease and a long-term cost of 'living with' this pest is incurred — that is, the cost of its naturalisation. The stochastic economic framework we formulate takes the present-value costs of each component into account, as well a shift in strategy when eradication fails, with both the pest-arrival process and success of eradication programs treated as independent, discrete stochastic processes. We apply this modular structure of the consequences of each arrival to take advantage of repeated, identical processes to construct our framework, and then incorporate a distribution of times between arrivals to link them. Frameworks applied in, for example, (Anderson et al., 2017; Kompas et al., 2018; Moore et al., 2010), are conceptually similar in many respects; however, here we formulate the economic distributions explicitly and establish analytical results that provide clear advantages for analysis.

The stochastic framework is developed in stages so that economic models are formulated for a number of different scenarios, including the case without surveillance effort which provides a baseline for comparison. Table 1 defines the notation, variables and parameters used.

Table 1
Random variables, parameters and notation.

Symbol	Description
$\mathbf{E}$	Expected value
$\mathbf{P}$	Probability
$\Phi_X(s)$	Probability generating function for generic random variable X
T	Discrete random variable for the time of an arrival-and-establishment event
T_k	Discrete random variable for the time of the k^{th} arrival-and-establishment event, starting from the time of the $k-1^{\text{th}}$ (previous) arrival-and-establishment event — a random variable for the inter-arrival time between the $k-1^{\text{th}}$ and the k^{th} arrivals
E	Event that an arrived pest is successfully eradicated — complement $\overline{E}$
E_k	Event that the k^{th} pest arrival is successfully eradicated — complement $\overline{E}_k$
$\overline{E}^{(k)}$	Event that the k^{th} pest arrival is the first for which eradication is unsuccessful
C_L	Once-off total cost of 'living with' an arrived pest given eradication was unsuccessful — equivalently, the cost of naturalisation
C_E	Total cost of implementing an eradication program
c_p	Annual cost of border or pre-border prevention measures
c_s	Annual cost of post-border surveillance measures — c_s^* optimal value
p_0	Probability a pest arrives and establishes in any randomly selected year
p	Probability a pest arrives and establishes in any randomly selected year, when prevention measures are in place ($0 \le p \le p_0$)
$\delta, \hat{\delta}$	Monetary discount rate ($0 < \delta$); $\hat{\delta} = 1/(1+\delta)$
γ	Search sensitivity for the inspection of arriving containers/ships
k	Calibration constant relating prevention measures to pest-arrival probability
TC	Random variable for total present-value costs for the full model
TC_0	Random variable for total present-value costs for the baseline model
TC_p	Random variable for total present-value costs for the single-incursion model
N	Number of years under consideration
B	Limited annual budget available for prevention and surveillance measures
$f_1(c_p), \hat{f}_1(c_p)$	Functions relating expenditure on prevention to a reduction in p
$f_2(c_s)$	Function relating expenditure on surveillance to a reduction in C_E
$f_3(c_s)$	Function relating expenditure on surveillance to an increase in $\mathbf{P}(E)$

2.1. Baseline Stochastic Cost-Model for a Single Incursion

Consider a single species that could arrive from overseas. Let p_0 be the probability that a pest or pathogen arrives and establishes in a given year t (which could be determined from a Poisson arrival process (Becker, 2015); Appendix E), assuming that, at most, a single incursion can occur each year. We construct a stochastic model for the associated present-value costs.

Let T be a discrete random variable for the time (year) of the first pest-arrival. In the case arrival times are geometrically distributed (although alternatives could be substituted), the probability mass function and probability generating function are, respectively, for $t = 1, 2, \ldots,$

$$T \sim \text{Geometric}(p_0), \;\; \mathbf{P}(T=t) = p_0(1-p_0)^{t-1}, \;\; \Phi_T(s) = \frac{p_0 s}{1-(1-p_0)s}. \tag{1}$$

The interpretation of the geometric distribution applied here is that the pest arrives in year $T = t$ with probability p_0, and does not arrive in any of the previous $t-1$ years with cumulative probability $(1-p_0)^{t-1}$.

Let C_L be the estimated long-term cost of naturalisation if an eradication program fails, let $\delta > 0$ be the annual, monetary discount rate, and let TC_0 be the total present-value cost over time. It follows that, given an arrival at $T = t$, the probability mass for total present-value costs is

$$\mathbf{P}\left(TC_0 = \frac{C_L}{(1+\delta)^t}\right) = \mathbf{P}(T=t) = p_0(1-p_0)^{t-1}, \tag{2}$$

so that the total expected present-value cost, which takes all possible pest-arrival times into account, is

$$\mathbf{E}(TC_0) = \sum_{t=1}^{\infty} C_L\left(\frac{1}{1+\delta}\right)^t \mathbf{P}(T=t) = C_L\,\Phi_T\left(\frac{1}{1+\delta}\right). \tag{3}$$

The distribution for T (geometric distribution in Eq. (1) or an alternative) can now be substituted into Eq. (3) using its generating function $\Phi_T(s)$. The associated variance is (Appendix A.1)

$$\begin{aligned}\text{Var}(TC_0) &= \mathbf{E}[(TC_0 - \mathbf{E}(TC_0))^2] \\ &= C_L^2\left(\Phi_T\left(\left(\frac{1}{1+\delta}\right)^2\right) - \left(\Phi_T\left(\frac{1}{1+\delta}\right)\right)^2\right).\end{aligned} \tag{4}$$

By construction, this cost-distribution is not necessarily symmetrical, and is valid for a range of pest-arrival distributions.

2.2. Stochastic Cost-Model for a Single Incursion Including Prevention Measures

Suppose now that arrival-prevention measures are implemented pre-border or at the border with an annual cost of c_p. We assume that prevention measures reduce the annual probability of arrival from p_0 to p, where $0 \le p \le p_0$ and p is an explicit function of both the arrival probability without prevention (p_0) and expenditure on prevention measures (c_p). Probability mass associated with total costs, notated TC_p, is then

$$\mathbf{P}\left(TC_p = \frac{C_L}{(1+\delta)^t} + \sum_{j=1}^{t}\frac{c_p}{(1+\delta)^j}\right) = \mathbf{P}(T=t) = p(1-p)^{t-1} \tag{5}$$

so that the total expected present-value cost becomes (Appendix B.1)

$$\begin{aligned}\mathbf{E}(TC_p) &= \sum_{t=1}^{\infty}\left(\frac{C_L}{(1+\delta)^t} + \sum_{j=1}^{t}\frac{c_p}{(1+\delta)^j}\right)\mathbf{P}(T=t) \\ &= C_L\,\Phi_T\left(\frac{1}{1+\delta}\right) + \frac{c_p}{\delta}\left(1 - \Phi_T\left(\frac{1}{1+\delta}\right)\right).\end{aligned} \tag{6}$$

A distribution for arrival time T can then be incorporated — geometric distribution (Eq. (1)) with p in the place of p_0, or an alternative. Note that, with prevention measures in place and $p < p_0$, $\Phi_T(s)$ in this expression differs from that in Eq. (3). The associated variance is (Appendix A.2)

$$\begin{aligned}\text{Var}(TC_p) &= \mathbf{E}[(TC_p - \mathbf{E}(TC_p))^2] \\ &= \left(C_L - \frac{c_p}{\delta}\right)^2\left(\Phi_T\left(\left(\frac{1}{1+\delta}\right)^2\right) - \left(\Phi_T\left(\frac{1}{1+\delta}\right)\right)^2\right).\end{aligned} \tag{7}$$

2.3. Stochastic Cost-Model for Multiple Incursions Over Time

Consider now a single species, for which there is a continuous risk of an arrival in any given year, and for which there may be multiple incursions over time, although we assume that, at most, a single incursion can occur each year as above. We incorporate prevention measures (pre-border and border) and post-border surveillance costs, as well as all other costs and processes represented in Fig. 1.

Let c_p and c_s be the annual costs of prevention and surveillance, respectively, and let C_E be a once-off cost of eradication. Eradication is assumed successful with probability $\mathbf{P}(E)$, after which prevention and surveillance measures are resumed. In the case eradication fails, with probability $\mathbf{P}(\overline{E}) = 1 - \mathbf{P}(E)$, prevention and surveillance are abandoned and a once-off long-term cost C_L of naturalisation is incurred.

Define E_k to be the *event* that eradication of the k^{th} pest-arrival is successful, and $\overline{E}_k$ to be the event that it is not. And let $C \mid E_k$ be the cost, conditional on event E_k. Let TC denote the total cost, and then

$$\begin{aligned}
\mathbf{E}(TC) &= (1-\mathbf{P}(E))C|\overline{E}_1 + \mathbf{P}(E)C|E_1 \\
&= (1-\mathbf{P}(E))C|\overline{E}_1 + \mathbf{P}(E)[(1-\mathbf{P}(E))C \mid \overline{E}_2, E_1 + \mathbf{P}(E)C \mid E_2, E_1] \\
&= (1-\mathbf{P}(E))C|\overline{E}_1 + \mathbf{P}(E)(1-\mathbf{P}(E))C|\overline{E}_2, E_1 \\
&\quad + \mathbf{P}(E)^2[(1-\mathbf{P}(E))C \mid \overline{E}_3, E_2, E_1 + \mathbf{P}(E)C \mid E_3, E_2, E_1] \\
&\quad \vdots \\
&= \sum_{k=1}^{\infty} (C \mid \overline{E}_k, E_{k-1}, \dots, E_1)\mathbf{P}(E)^{k-1}(1-\mathbf{P}(E))
\end{aligned} \tag{8}$$

where the conditional cost is not yet specified. With pest arrivals possible in any year, total expected costs, conditional on the k^{th} pest-arrival being the *first* for which eradication is *unsuccessful*, thus has a geometric distribution. This follows because, in the event an eradication program is unsuccessful, a once-off long-term cost of naturalisation is incurred and there are no further costs.

To incorporate the stochastic nature of pest arrivals we model inter-arrival times. The memoryless property of standard distributions applied to such processes (geometric or exponential distributions, for example) means that the time of future pest-arrival events is independent of the arrival history, in the sense that an arrival in one time interval does not alter the probability of an arrival in the following, or any other, interval. Let T_k be a random variable for the time (year) of the k^{th} pest arrival, measured in years from the time of the previous $k-1^{\text{th}}$ arrival. It follows that, for any two sequential inter-arrival times,

$$\mathbf{P}(T_k \mid T_{k-1}) = \mathbf{P}(T_k). \tag{9}$$

Further, we consider the probability of successfully eradicating a pest that has established to be independent of the time at which that pest arrived, although, if it spreads, this probability will depend on the time between arrival and detection. Then, for all pest arrivals,

$$\sum_t \mathbf{P}(E \mid T_k = t)\mathbf{P}(T_k = t) = \mathbf{P}(E)\sum_t \mathbf{P}(T_k = t) = \mathbf{P}(E). \tag{10}$$

In contrast, present-value costs depend explicitly on time — more specifically, on the year of each arrival event. To establish a distribution for total present-value costs, let $\overline{E}^{(k)}$ denote the event that the k^{th} pest arrival is the first for which eradidation fails, so that $\mathbf{P}(\overline{E}^{(k)}) = \mathbf{P}(\overline{E}_k, E_{k-1}, \dots, E_1)$. Total cost, conditional on $\overline{E}^{(k)}$ and all inter-arrival times T_i, is then given by (see Eq. (8) and Appendix B.2)

$$\begin{aligned}
&TC|\overline{E}^{(k)}, T_k, T_{k-1}, \dots, T_1 \\
&= \frac{c_p + c_s}{\delta} + C_E\left(\left(\frac{1}{1+\delta}\right)^{t_1} + \left(\frac{1}{1+\delta}\right)^{t_1+t_2} + \dots + \left(\frac{1}{1+\delta}\right)^{\sum_{j=1}^{k-1} t_j}\right) \\
&\quad + \left(C_L - \frac{c_p + c_s}{\delta}\right)\left(\frac{1}{1+\delta}\right)^{\sum_{j=1}^{k} t_j}
\end{aligned} \tag{11}$$

where the T_i are independent and identically distributed random variables for pest inter-arrival times with associated probability mass functions (see Eq. (1)), for example). From Eq. (8), the probability mass associated with event $\overline{E}^{(k)}$ is $\mathbf{P}(E)^{k-1}(1 - \mathbf{P}(E))$. Thus, for the system (Fig. 1), Eqs. (8) and (11) fully define a distribution for total present-value costs, with probability mass function

$$\mathbf{P}(TC \mid \overline{E}^{(k)}, T_k, T_{k-1}, \dots, T_1) = \left(\prod_{i=1}^{k} \mathbf{P}(T_i)\right)\mathbf{P}(E)^{k-1}(1-\mathbf{P}(E)), \tag{12}$$

so that (conditional) total costs are geometrically distributed.

To determine the expected total-cost, because inter-arrival times T_i are independent and identically distributed as a result of our chosen modular approach, the conditional expected cost is (from Eqs. (11), (12) and Appendix B.2)

$$\begin{aligned}
&\mathbf{E}(TC \mid \overline{E}^{(k)}) \\
&= \sum_{t_1} \dots \sum_{t_k} (TC \mid \overline{E}^{(k)}, T_k, \dots, T_1)\mathbf{P}(T_k = t_k)\dots\mathbf{P}(T_1 = t_1) \\
&= \frac{c_p + c_s}{\delta} + C_E\Phi_T(\hat{\delta})\left(\frac{1-(\Phi_T(\hat{\delta}))^k}{1-\Phi_T(\hat{\delta})}\right) + \left(C_L - \frac{c_p + c_s}{\delta}\right)(\Phi_T(\hat{\delta}))^k
\end{aligned} \tag{13}$$

where we have set $\hat{\delta} = 1/(1+\delta)$ for reasons of parsimony. The total expected present-value cost is then given by (Appendix B.2)

$$\begin{aligned}
\mathbf{E}(TC) &= \mathbf{E}[\mathbf{E}(TC \mid \overline{E}^{(k)})] \\
&= \frac{\frac{c_p + c_s}{\delta}(1-\Phi_T(\hat{\delta})) + C_E\Phi_T(\hat{\delta}) + C_L(1-\mathbf{P}(E))\Phi_T(\hat{\delta})}{1-\mathbf{P}(E)\Phi_T(\hat{\delta})}.
\end{aligned} \tag{14}$$

We highlight that, by construction, result (14) holds for any arrival distribution with the properties of independence discussed in Eqs. (9)–(10) and thus alternatives are easily accommodated (see Appendix D).

Note that, when surveillance and eradication measures are excluded from the model (c_s, C_E and $\mathbf{P}(E)$ set to zero), expression (14) reduces to Eq. (6), and when prevention measures are also excluded, the expression reduces to Eq. (3). Thus our models are consistent.

The associated variance, taking variation in both inter-arrival times and eradication-success into account, is (Appendix A.3)

$$\mathrm{Var}(TC) = \mathbf{E}[\mathrm{Var}(C \mid \overline{E}^{(k)})] + \mathrm{Var}(\mathbf{E}[C \mid \overline{E}^{(k)}]), \tag{15}$$

where, with $c = c_s + c_p$,

$$\begin{aligned}
\mathrm{Var}(\mathbf{E}[C \mid \overline{E}^{(k)}]) &= \left(C_L - \frac{c}{\delta} - \frac{C_E\Phi_T(\hat{\delta})}{1-\Phi_T(\hat{\delta})}\right)^2 \\
&\quad \times \left[\frac{(1-\mathbf{P}(E))(\Phi_T(\hat{\delta}))^2}{1-\mathbf{P}(E)(\Phi_T(\hat{\delta}))^2} - \left(\frac{(1-\mathbf{P}(E))\Phi_T(\hat{\delta})}{1-\mathbf{P}(E)\Phi_T(\hat{\delta})}\right)^2\right]
\end{aligned}$$

and

$$\begin{aligned}
\mathbf{E}[\mathrm{Var}(C \mid \overline{E}^{(k)})] &= \frac{[\Phi_T(\hat{\delta}^2) - (\Phi_T(\hat{\delta}))^2]}{1-\mathbf{P}(E)\Phi_T(\hat{\delta}^2)}\left[\left(\frac{C_E}{1-\Phi_T(\hat{\delta})}\right)^2\right. \\
&\quad + 2\left(\frac{C_E}{1-\Phi_T(\hat{\delta})}\right)\left(C_L - \frac{c}{\delta} - \frac{C_E\Phi_T(\hat{\delta})}{1-\Phi_T(\hat{\delta})}\right)\frac{1-\mathbf{P}(E)}{(1-\mathbf{P}(E)\Phi_T(\hat{\delta}))} \\
&\quad \left. + \left(C_L - \frac{c}{\delta} - \frac{C_E\Phi_T(\hat{\delta})}{1-\Phi_T(\hat{\delta})}\right)^2\frac{1-\mathbf{P}(E)}{(1-\mathbf{P}(E)(\Phi_T(\hat{\delta}))^2)}\right].
\end{aligned}$$

Note that total variance Eq. (15) reduces to Eq. (7) when surveillance and eradication measures are excluded from the model (c_s, C_E and $\mathbf{P}(E)$ set to zero), and to Eq. (4) when prevention measures are also excluded — as would be expected.

In summary, we have formulated a stochastic economic model that incorporates all costs and processes described in Fig. 1, including a continuous low-level risk of new incusions, and is sufficiently general to be applicable to a variety of cost-efficiency problems. Explicit expressions for the full distribution, the mean and the variance have been established. The distribution for total present-value costs, conditional on the first pest-arrival for which eradication fails and no further annual costs are incurred, has been shown to be geometric, and sufficient flexibility has been built into the framework so that alternative pest-arrival distributions could be substituted. Pest-arrival and eradication-success processes retain independence between sequential events — between inter-arrival times and between sequential eradication successes, respectively. The probability of eradication success ($\mathbf{P}(E)$), while not dependent on arrival time, will be a function of outbreak size at the time of detection, which will depend on surveillance-effort and efficacy; the cost of eradication (C_E) will also be a function of outbreak size, surveillance-effort and efficacy; and the probability of a pest-arrival in any given year (p) will depend on prevention-effort and the efficacy of those measures. And all three functions depend on pest-type. By construction, this economic formulation allows for the substitution of different relationships and/or distributions for $\mathbf{P}(E)$, C_E and inter-arrival times T_i, which can be explored and compared. And where data are available, it is straightforward to incorporate simulation results through these parameters and functions — as we demonstrate in Section 4.

3. An Optimal Economic Strategy

The purpose of the framework is to guide the partitioning of expenditure between prevention and surveillance measures, or between other alternative surveillance scenarios (see Section 4), which minimises total expected present-value costs while also enabling decisions to take uncertainty and stochasticity into account.

3.1. Minimising Expected Costs

The minimisation of total expected costs, using a tradeoff between competing expenses, is often applied to determine an optimal strategy (see, for example, (Anderson et al., 2017; Kompas et al., 2018)). This optimal strategy is straightforward to determine from the above economic framework Eq. (14),

$$\mathbf{E}(TC) = \frac{\frac{c_p + c_s}{\delta}(1 - f_1(c_p)) + f_2(c_s)f_1(c_p) + (1 - f_3(c_s))C_L f_1(c_p)}{1 - f_3(c_s)f_1(c_p)} \tag{16}$$

where $\Phi_T(\hat{\delta}) = f_1(c_p)$ is a function of annual expenditure on prevention (c_p), as well as arrival probability (p_0), and $C_E = f_2(c_s)$ and $\mathbf{P}(E) = f_3(c_s)$ are functions of surveillance expenditure (c_s) and incorporate infestation size at the time of detection. The resulting equation is a function of two variables, c_p and c_s. The optimal expenditure on prevention and surveillance, which results in the minimum total expected cost, can be determined from Eq. (16) using standard calculus (derivatives), noting that solutions may occur on the boundaries of the solution space. An example application to clarify this process is provided in Section 4.

In cases with a fixed annual budget for border and post-border surveillance expenditure combined, denoted B so that $c_p = B - c_s$, total expected cost Eq. (14) becomes (Appendix B.3)

$$\begin{aligned}\mathbf{E}(TC) &= C_L + \frac{\left(\frac{B}{\delta} - C_L\right)\left(1 - \Phi_T\left(\frac{1}{1+\delta}\right)\right) + C_E\Phi_T\left(\frac{1}{1+\delta}\right)}{1 - \mathbf{P}(E)\Phi_T\left(\frac{1}{1+\delta}\right)} \\ &= C_L + \frac{\left(\frac{B}{\delta} - C_L\right)(1 - f_1(B - c_s)) + f_2(c_s)f_1(B - c_s)}{1 - f_3(c_s)f_1(B - c_s)}\end{aligned} \tag{17}$$

noting that $\Phi_T(1/1 + \delta) = f_1(c_p) = f_1(B - c_s)$, $C_E = f_2(c_s)$ and $\mathbf{P}(E) = f_3(c_s)$ are all functions of the single variable c_s. It is straightforward to find the value of c_s which minimises this cost using derivatives. An example application is provided in Section 4.

3.2. Incorporating Uncertainty

The above approach to cost-minimisation considers only expected values, although it is well recognised that appropriate consideration of uncertainty in biosecurity decision-making is important. Explicit algebraic forms for system variance, or stochasticity, have been formulated in this paper for this purpose. There are a number of approaches to optimising resource allocation, which respond to uncertainty using different criteria (Barnes et al., 2019; Bridges, 2004; Prattley et al., 2007; Yemshanov et al., 2017; Yemshanov et al., 2014). It is beyond the scope of this paper to consider the wide variety of response criteria for distinct biosecurity applications and specific priorities. However, an approach conceptually similar to that proposed in (Barnes et al., 2019), which responds to model stochasticity and parameter uncertainty, is relevant to the type of biosecurity problem considered here.

3.3. The Effect of Monetary Discounting on the Optimal Strategy

Monetary discounting transforms future economic effects into present-values, with higher rates attributing less value to future benefits and costs, relative to those current. It is commonly incorporated into optimisation techniques for decision-making; however, it is also well known that appropriate discount rates are difficult to determine and can be highly influential (Clark, 1990; Scheraga and Sussman, 1998). For biosecurity applications, the inclusion of inappropriate discount rates can mean that long-term consequences are trivialised in the decision process (Scheraga and Sussman, 1998). For that reason we provide model formulations for extreme cases so that a complete understanding of how the chosen discount rate might affect decisions can be determined.

For the case without discounting ($\delta = 0$), the cost distribution of Section 2.3 (Eqs. (11)–(14)) is not appropriate because that formulation assumed $\delta > 0$. The appropriate model is (Appendix C)

$$\mathbf{E}(TC) = (c_p + c_s)\frac{(1 - \mathbf{P}(E))\mathbf{E}(T)}{1 - \mathbf{P}(E)\mathbf{E}(T)} + \frac{C_E}{1 - \mathbf{P}(E)} + C_L, \tag{18}$$

noting that Eq. (18) differs from Eq. (14) when $\delta \to 0$ *only* in the first term — as would be expected. In this extreme case, optimal surveillance expenditure is independent of the naturalisation cost C_L. Alternatively, for high discount rates, results can be determined directly from Eq. (14), noting that $\mathbf{E}(TC) \to 0$ as δ increases without bound. An appropriate upper-bound for the discount rate would depend on the application.

4. Application to Asian Gypsy Moth (AGM) Trapping

Australia is currently free from gypsy moth (*Lymantria dispar*), which has been identified as a National Priority Plant Pest (Bloomfield et al., 2018). This moth has the potential to devastate the Australian forest industry, with estimated economic consequences exceeding 1.6 billion dollars (Bloomfield and Arthur, 2019). To avoid an incursion, prevention measures include the inspection of external container surfaces and ships to ensure they are clean with respect to egg masses. Onshore, early-detection trapping programs are focussed near potential points of entry, such as shipping ports, but this surveillance is costly to maintain particularly when the distance between traps is low. We apply our analytical framework to determine optimal (lowest overall expected present-value cost) expenditure on container inspections at the border and post-border trapping programs, taking into account a continuous low-level risk of pest-arrival and establishment, costs of prevention and surveillance strategies, the cost of eradication and the costs incurred if eradication fails.

First we consider a simplified version of the system without prevention measures, as in (Bloomfield and Arthur, 2019), which allows a direct comparison between published simulation results and those using our formulation. We then include expenditure on prevention measures and demonstrate how the surveillance tradeoff can alter the expected outcome.

We model pest arrivals using a sequence of geometrically

Table 2
Estimated annual costs (AU$) for alternative AGM trapping densities (Bloomfield and Arthur, 2019).

Trap-spacing (km)	Annual cost c_s	Trap-spacing (km)	Annual cost c_s
0.5	22,425,000	5	224,000
0.75	9,967,000	6	156,000
1	5,606,000	7	114,000
1.5	2,492,000	8	88,000
2	1,402,000	9	69,000
3	623,000	10	56,000
4	350,000	no traps	0

distributed pest inter-arrival times (Eq. (1)), with the distribution for total-costs defined by Eqs. (11) and (12). Directly from Eq. (14), the expected present-value cost is

$$\mathbf{E}(TC) = \frac{c_p + c_s + pC_E + p(1 - \mathbf{P}(E))C_L}{\delta + p(1 - \mathbf{P}(E))} \qquad (19)$$

where $p = \hat{f}_1(c_p)$, $C_E = f_2(c_s)$ and $\mathbf{P}(E) = f_3(c_s)$. These are functions of annual costs, c_p and c_s, and relate expenditure to the efficacy of prevention measures to reduce pest-arrival rates, and the efficacy of surveillance measures to reduce the cost of eradication programs and increase the probability of success. Discrete values of post-border surveillance, c_s, link to alternative trapping densities (Table 2). For AGM, $\hat{f}_1(c_p)$ is unknown (see below); however, $f_2(c_s)$ and $f_3(c_s)$ have the form (Bloomfield et al., 2018)

$$C_E = f_2(c_s) = \frac{c_2}{1 + e^{a_2 \log_{10}(c_s+1)+d_2}} + b_2,$$
$$\mathbf{P}(E) = f_3(c_s) = \frac{c_3 - b_3}{1 + e^{-a_3 \log_{10}(c_s+1)+d_3}} + b_3, \qquad (20)$$

as illustrated in Fig. 2, noting that a range of costs are aggregated in each function, and that as expenditure on surveillance increases the probability of eradication increases due to early detection. In the limit, this relationship captures the event a pest is never detected; however, the probability is small.

Fig. 3 provides a comparison between the expected values and variances for the case without prevention measures ($c_p = 0$ and fixed p) and with functions Eq. (20) (dashed curves), and those determined from simulations (solid points). The turning point of the curve in Fig. 3(a) (dashed-curve) identifies the minimum expected cost (y-axis) and the associated optimal surveillance expenditure (x-axis). For comparison, the case without surveillance for which $c_s = 0$ (intersection of curve with y-axis in Fig. 3), and also the case without surveillance or response, for which $c_s = 0$, $C_E = 0$ and $\mathbf{P}(E) = 0$ (dash-dotted line), have been included. From an economic perspective, results suggest that, on average, there is considerable advantage in undertaking surveillance (minimum total expected cost (dashed-curve) falls below the cost without surveillance and the 'do nothing' option (dash-dotted line) in Fig. 3(a)). Results are consistent with (Bloomfield and Arthur, 2019).

Annual surveillance expenditure for which the minimum expected total-cost is achieved, denoted $(c_p{}^*, c_s{}^*)$, can be calculated directly from Eq. (19), and satisfies the simultaneous equations

$$c_s = \delta C_L - pC_E - \frac{(f_2'(c_s) + 1/p)(\delta + p(1 - \mathbf{P}(E)))}{f_3'(c_s)} - c_p$$
$$c_p = \delta C_L + \frac{\delta C_E}{1 - \mathbf{P}(E)} + \frac{\delta + p(1 - \mathbf{P}(E))}{\hat{f}_1{}'(c_p)(1 - \mathbf{P}(E)} - c_s, \qquad (21)$$

where f' denotes the first derivative and p is a function of c_p so that both sides of this equation may be functions of c_p and c_s. In the simplifying case $c_p = 0$, minimum surveillance-expenditure $c_s{}^*$ satisfies

$$c_s = \delta C_L - pC_E - \frac{(f_2'(c_s) + 1/p)(\delta + p(1 - \mathbf{P}(E)))}{f_3'(c_s)}, \qquad (22)$$

with p fixed. This minimum is identified in Fig. 3 (dotted line) at $c_s{}^* = 0.75 \times 10^6$ for this example, in agreement with that in (Bloomfield and Arthur, 2019).

It is also straightforward to determine from Eq. (19) how variation in the arrival probability, costs, the probability of eradication and the discount rate affect the outcome — individually or in combination. For example, with respect to the discount rate δ,

$$\frac{d\mathbf{E}(TC)}{d\delta} = -\left(\frac{c_p + c_s + pC_E + p(1 - \mathbf{P}(E))C_L}{(\delta + p(1 - \mathbf{P}(E)))^2}\right) < 0 \qquad (23)$$

provides an explicit rate of decline for total expected costs as δ increases, from which the case without prevention measures is easily deduced.

Fig. 4(a)–(c) illustrates a few simple sensitivity results to show how the proposed approach is consistent with, and extends, the analysis in (Bloomfield and Arthur, 2019). Fig. 4(a) shows that the discount rate has marginal influence on decisions concerning trapping-grid spacing when it is sufficiently large, which is consistent with the scenarios reported in (Bloomfield and Arthur, 2019). In contrast, this figure also reveals that when $\delta < 0.02$ the chosen value of δ has a considerable influence, and that uncertainty in the arrival probability is also influential. Results demonstrate that the response of optimal trap-spacing to variation in a combination of discount rates and arrival probabilities may be highly nonlinear, but is easily determined from Eqs. (22) and

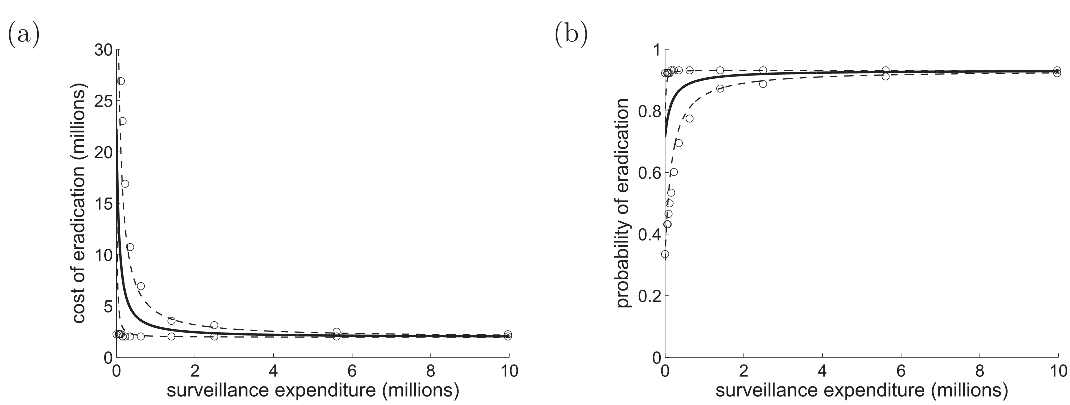

Fig. 2. (a) The cost of eradication, $C_E = f_2(c_s)$, as expenditure on surveillance (x-axis) increases (function Eq. (20)). Open dots identify the 5th and 95th percentiles for the specific trapping densities in Table 2 from (Bloomfield and Arthur, 2019), with dashed curves function approximations. (b) The probability of eradication success, $\mathbf{P}(E) = f_3(c_s)$, as expenditure on surveillance (x-axis) increases (function Eq. (20)). Open dots identify the 5th and 95th percentiles for the specific trapping densities in Table 2 from (Bloomfield and Arthur, 2019), with dashed curves function approximations. Parameter values from (Bloomfield and Arthur, 2019): $c_p = 0$, $p = 1/65$, $\delta = 0.07$, $C_L = 1.6 \times 10^9$ (dollars), for $\mathbf{P}(E)$, $a_3 = 2.39439$, $b_3 = 0.7143211$, $c_3 = 0.9314516$, $d_3 = 12.46908$, and for C_E, $a_2 = 2.514612$, $b_2 = 1.956207$, $c_2 = 20.25718$, $d_2 = -12.14324$.

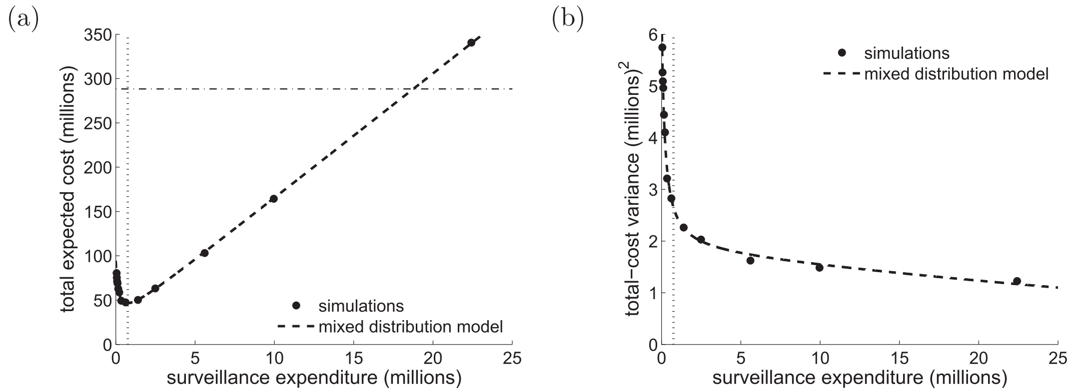

Fig. 3. (a) A comparison between total expected present-value costs defined by Eq. (19) (dashed curve) and using simulations (solid points), as expenditure on surveillance (trap-spacing) increases, assuming functions Eq. (20). The minimum total expected cost and associated optimal surveillance expenditure (dotted line) is identified using Eq. (22), and the dash-dotted line identifies total costs without surveillance or response to an incursion. (b) The same comparison as in (a) but for variance (Eq. (15)). Parameter values from (Bloomfield and Arthur, 2019): $c_p = 0, p = 1/65, \delta = 0.07, C_L = 1.6 \times 10^9$ (dollars). Parameter values for $\mathbf{P}(E)$ and C_E are provided in Fig. 2.

(23). Fig. 4(b) illustrates the nonlinear manner in which the arrival probability influences optimal surveillance expenditure. Arrival events for AGM are rare (Bloomfield and Arthur, 2019; Bloomfield et al., 2018), and this result, which establishes how rare arrival events can influence outcomes, is a key strength of analytical formulations — an attribute often difficult to capture with simulations. Fig. 4(c) illustrates how the optimal trap-spacing is likely to vary with uncertainty in the costs of eradication (C_E) and naturalisation (C_L) — neither of which can be estimated with certainty. For an expected value of C_L (vertical dotted line at 1.6×10^9), results suggest that, at worst, the optimal trap-spacing could approach 2 km, while at best it approaches 5–6 km (see Table 2). Acknowledging that the percentile functions in Fig. 2(b) are rough approximations, results nevertheless demonstrate that variation in the eradication probability and naturalisation costs can be highly influential with a nonlinear response in the optimal trap-spacing.

Determining the probability of 'pest-freedom' does not require the cost model. Probabilities are illustrated in Fig. 4(d) for a fixed value of p, and established by noting that inter-arrival times and the probability of eradication for each arrival are independent processes. An estimate for the probability that, regardless of the number of pest introductions within a fixed number of years N, all incursions are successfully eradicated and the area is 'AGM-free' is (Appendix B.4)

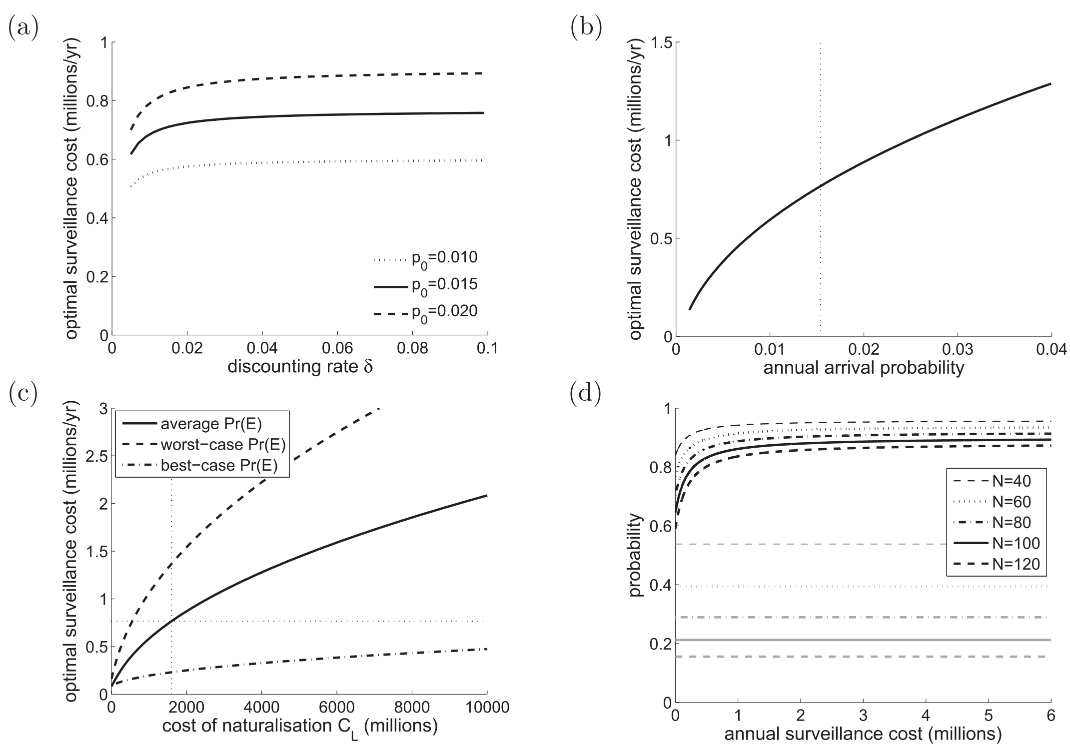

Fig. 4. (a) For a range of plausible discount rates δ (x-axis), optimal trapping expenditure c_s^* (minimum expected present-value costs) is plotted for a variety of annual arrival probabilities p (line-styles). (b) For a range of plausible annual pest-arrival probabilities p (x-axis), optimal surveillance expenditure, c_s^*, is plotted. (c) Curves illustrate variation in the optimal surveillance cost (c_s^*), with variation in the estimated cost of naturalisation C_L (x-axis) and probability of eradication $\mathbf{P}(E)$ (line-styles for the three curves in Fig. 2(b)). Dotted lines identify the case for $C_L = 1.6 \times 10^9$ (dollars). (d) For each time period of N years (line-styles), black curves illustrate the probability that any AGM introductions that may occur during this period are successfully eradicated (Eq. (24)), while grey lines of the same line-style provide the associated probability there are no introductions during this period ($\mathbf{P}(E) = 0$ in Eq. (24)). Parameter values from (Bloomfield and Arthur, 2019) (unless otherwise specified): $c_p = 0, p = 1/65, \delta = 0.07, C_L = 1.6 \times 10^9$ (dollars). Parameter values for $\mathbf{P}(E)$ and C_E are provided in Fig. 2.

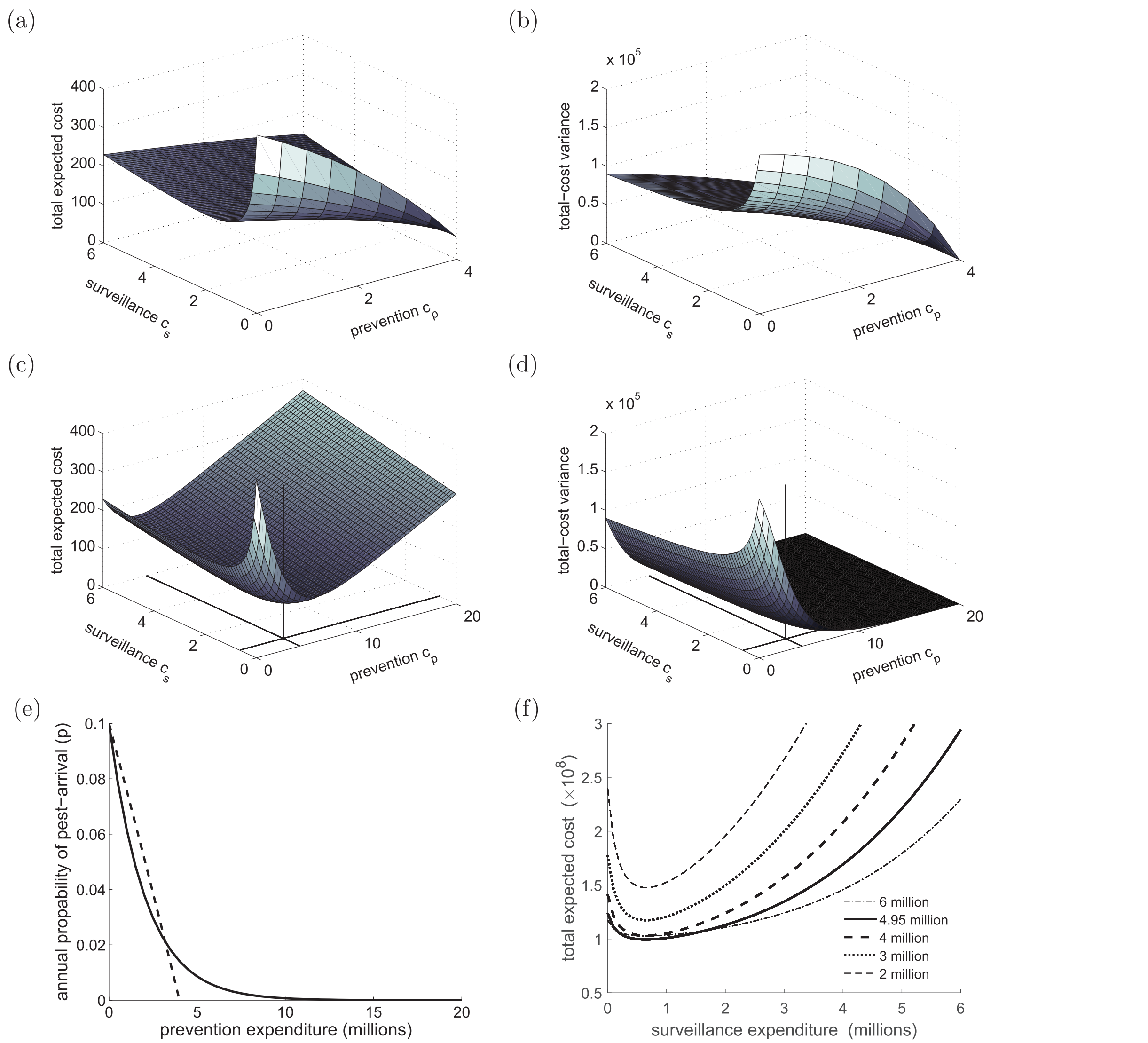

Fig. 5. (a) Surface for the total expected present-value costs using the full model Eq. (19) as expenditure on prevention measures and post-border-surveillance (trap-spacing) vary, assuming the near-linear relationship between expenditure on prevention and the probability of pest-arrivals (dashed curve in (e)). (b) The same comparison as in (a) but for variance (Eq. (15)). (c) Surface for the total expected present-value costs using the full model Eq. (19) as expenditure on prevention measures and post-border-surveillance (trap-spacing) vary, assuming the exponential relationship between expenditure on prevention and the probability of pest-arrivals (solid curve in (e)). Vertical black lines identify the optimal solution. (d) The same comparison as in (d) but for variance (Eq. (15)). In all cases functions Eq. (20) are assumed, and costs given in millions of dollars, with variance given in dollars $\times 10^{12}$. (e) Alternative relationships between expenditure on prevention measures (c_p) and the probability of at least one pest-arrival per year (p): Eq. (26) (solid curve), and a near-linear relationship (dashed curve). (f) Comparison of total expected costs associated with a limited budget (Eq. (17)) for a budget of $B = 6$,4.95,4,3 or 2 million dollars. Results assume the exponential relationship between expenditure on prevention and the probability of pest-arrivals (solid curve in (e)). Parameter values: $p_0 = 0.1$, $\delta = 0.07$, $C_L = 1.6 \times 10^9$ (dollars). Parameter values for $\mathbf{P}(E)$ and C_E are provided in Fig. 2 and $k = 0.5 \times 10^{-6}$ in Eq. (26), or $k = 0.25 \times 10^{-6}$ in the linear case.

$$(1 - p + p\mathbf{P}(E))^N, \tag{24}$$

with $p = \widehat{f_1}(c_p)$ (fixed in this figure) and $\mathbf{P}(E) = f_3(c_s)$. The probability of 'freedom' Eq. (24) clearly declines with the number of years N and with decreasing surveillance effort c_s (Fig. 2(c)). The probability of no arrivals is given by $(1 - p)^N$ (grey lines in Fig. 4(c)), while the case with no trapping is established by setting $c_s = 0$ in Eq. (24) (intersection between curve and y-axis in Fig. 4(d)). For the parameter scenario considered, results suggest that surveillance expenditure above 1 million dollars (approximately) offers little benefit to the probability of 'AGM-free' status, which equates to a trap spacing of 3 or more km (Table 2). Results provide a consistent generalisation for the simulated scenarios in (Bloomfield and Arthur, 2019).

We now incorporate prevention measures, not considered in (Bloomfield and Arthur, 2019). For the example application, it is reasonable to assume that annual expenditure on prevention relates directly to the proportion, ρ, of arriving containers and/or ships searched before entry (RRRA Unit, 2016), so that, approximately, the annual probability of pest-arrival is reduced from p_0 (without prevention measures) to (Appendix E)

$$p = 1 - e^{-(-\ln(1-p_0))(1-\gamma\rho)} = 1 - (1 - p_0)^{(1-\gamma\rho)}, \tag{25}$$

where γ captures the search-sensitivity and ρ is the proportion of containers searched.

For this application the relationship between annual expenditure on prevention (c_p) and arrival probability (p) is unknown. We contrive two plausible associations for illustrative purposes. Following (RRRA Unit, 2016), who suggest a linear relationship for this application, we set $\gamma\rho \approx kc_p$ (dashed curve in Fig. 5(e)). However, because a linear relationship is unlikely we also consider the scenario that an increase in the proportion searched becomes progressively more difficult to achieve with further expenditure — that is, an increase in the proportion searched becomes progressively more expensive (solid curve in Fig. 5(e)). In this case we assume

$$\gamma\rho \approx 1 - e^{-kc_p},$$

so that the relationship between expenditure and annual arrival probability Eq. (25) becomes

$$p = \widehat{f}_1(c_p) = 1 - (1 - p_0)^{e^{-kc_p}}. \tag{26}$$

In both cases, k is a calibration constant.

For the linear relationship, Fig. 5(a)–(b) provides the associated surfaces for expected present-value costs and variance (analogous to Fig. 3). As expected, results demonstrate that the lowest expected cost is achieved on the boundary of the solution space, with, for this example, all expenditure on prevention reducing the probability of an arrival to zero. When the nonlinear relationship Eq. (26) is assumed, Fig. 5(c)–(d) illustrates the associated surfaces, with the minimum total expected cost and associated optimal expenditure on prevention and surveillance identified by the minimum across the surface in Fig. 5(c). In this case a minimum total expected cost ($c_p{}^* = 4.31 \times 10^6$ and $c_s{}^* = 0.64 \times 10^6$ dollars) is established from Eq. (21) and identified by the vertical black lines. Results illustrate a tradeoff between the strategies of prevention and post-border trapping for the full model.

It is common that surveillance budgets are constrained and this can affect optimal results. For a range of fixed budgets (legend), Fig. 5(f) illustrates how total expected costs vary with surveillance expenditure (Eq. (17) with budget B), where the remaining budget is allocated to prevention measures. The solid curve provides the minimum cost in Fig. 5(c), illustrating how both higher and lower expenditures lead to an increase in the expected costs, and that lowering the budget has a nonlinear effect on total costs. For this application, however, trap-spacing for which the minimum expected cost is achieved remains consistent (Table 2). These results can also be deduced from Fig. 5(c) directly, by restricting prevention and surveillance costs, and alternative constraints can be explored similarly using Eqs. (16)–(17).

We do not extend the sensitivity analysis further or interpret these results because data were not available to parameterise the relationship between expenditure on prevention measures and pest-arrival rates. Analysis, however, would follow similarly to that undertaken above for the one dimensional case.

5. Discussion

Ecological systems are highly complex, and the costs and consequences of pest or pathogen infestations extremely difficult to predict. Simulation approaches provide a powerful tool with which to model complexity; however, adequate supporting data are often unavailable or difficult to quantify. Tractable formulations with less complexity can offer a more appropriate analysis under uncertainty, or can complement simulation approaches with the potential to facilitate a more robust interpretation of results — as illustrated in this paper.

The stochastic economic model formulated in this paper offers a tractable framework to guide the partitioning of surveillance resources, which can be adapted to data availability and pest characteristics, and for which the level of complexity equals, or surpasses, many simulation models currently applied to similar problems in the literature. Our framework is constructed for general applicability to a variety of these problems. Such frameworks provide a fast and accessible means of exposing the effect of parameter interactions; they capture the influence of rare stochastic events; alternative cost functions, pest-arrival distributions and surveillance efficiencies are easily incorporated; management strategies can be readily compared; and transferability between applications is straightforward. We also note that the quarantine of regions is comparable to the implementation of border-measures that reduce pest-arrival rates, and thus our framework is also relevant to biosecurity resource partitioning problems of that type (see (Moore et al., 2010), for example). Further, the algebraic expression for variance enables uncertainty to be incorporated into the decision-making process in a systematic way — for example, by combining the framework with concepts of portfolio theory (Barnes et al., 2019).

Greater complexity could be included in the proposed models, such as, a variety of pest types and/or further stochasticity in processes and cost functions. Or included to address specific biosecurity questions. For highly complex systems, however, analytical formulations are not efficient, or even possible to determine in a tractable form — simulations are more appropriate. Nevertheless, for systems with a level of complexity similar to that considered here, algebraic expressions can replace simulations, can be combined with simulation results as in our application, or can be used to validate simulation outcomes that are difficult to test.

Finally, we highlight that national biosecurity decisions are intended to serve the long-term public good, including communities and the environment, while present-value economic approaches maximise cost-efficiency and can be misleading when considered in isolation. In this light, we propose the framework as a versatile means of economic assessment that contributes to one facet of an objective decision-making process.

Declaration of Competing Interest

None

Appendix A. Supplementary Data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2020.106784.

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