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Budgeting and portfolio allocation for biosecurity measures

Tom Kompas, Long Chu, Pham Van Ha and Daniel Spring[†]

This paper presents a practical model for optimally allocating a budget across different biosecurity threats and measures (e.g. prevention or border quarantine, active surveillance for early detection, and containment and eradication measures) to ensure the highest rate of return. Our portfolio model differs from the common principle, which ranks alternative projects by their benefit cost ratios and picks the one that generates the highest average benefit cost ratio. The model we propose, instead, aims to allocate shares of the budget to the species where it is most cost-effective, and consequently determine the optimal scale of the control program for each threat under varying budget constraints. The cost-effectiveness of each block of budget spent on a threat is determined by minimising its expected total cost, including the damages it inflicts, and the control expenditures incurred in preventing or mitigating damages. As an illustration, the model is applied to the optimal allocation of a budget across four of Australia's most dangerous pests and diseases: red imported fire ants; foot-and-mouth disease; papaya fruit fly; and orange hawkweed. The model can readily be extended to consider more species and activities, and more complex settings including cases where detailed spatial and temporal information needs to be considered.

Key words: biosecurity, cost-benefit analysis, invasive pests, portfolio allocation, stochastic programming.

1. Introduction

Biological invasions and pathogens pose a major threat to industry, the environment and human health, causing billions of dollars in damages every year (Pimentel *et al*. 2005; Sinden *et al*. 2005). The cost inflicted by biosecurity threats includes not only economic and environmental damages, but also the control costs incurred in preventing or mitigating their effects. Since resources to address these ever-increasing threats are limited, it is essential that these resources are used efficiently. As a result, public biosecurity agencies face challenging decisions of how best to allocate scarce resources when they attempt to prevent, suppress, and eradicate exotic and established pests and diseases (Perrings *et al*. 2010; Yemshanov *et al*. 2014; Akter *et al*. 2015).

[†] Tom Kompas (e-mail: tom.kompas@unimelb.edu.au), Long Chu, and Pham Van Ha are with the Crawford School of Public Policy, Australian National University, Australian Capital Territory, Australia. Tom Kompas and Daniel Spring are with the Centre of Excellence in Biosecurity Risk Analysis, School of Biosciences and School of Ecosystem and Forest Sciences, University of Melbourne, Melbourne, Victoria, Australia.

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While resource allocation in biosecurity may be approached as a standard portfolio problem (Prattley *et al.* 2007; Yemshanov *et al.* 2014), allocating resources to address biosecurity threats may pose extra challenges. First, policymakers are often faced with a (possibly large) number of threats, and each can be associated with a complicated range of biosecurity measures, namely pre-border, border quarantine, post-border surveillance, and containment and eradication measures. A measure to control or prevent a particular pest or disease probably influences the effectiveness of other measures and the overall cost-effectiveness of the money spent to address that threat. Consequently, a proper portfolio allocation in biosecurity must allocate a budget not only across threats, but also across different measures used to counter each threat. Second, apart from the biological and ecological uncertainty inherent with invasive species, uncertainties that can greatly influence outcomes (Perrings *et al.* 2010), biosecurity measures must often be decided at early stages where data about the many characteristics of the threats are very rough and limited. For this reason, biosecurity portfolio models, ideally, should not be overly demanding in the information required to calibrate them. Third, invasive species are diverse in terms of how they spread, how they cause damages, and how they are controlled. Hence, evaluating the cost-effectiveness across measures and species as well as making them comparable is complicated. Thus, from a practical perspective, models that guide portfolio allocation often need to focus on the common features of biosecurity threats, rather than on the specific characteristics of each invasive species.

This paper presents a practical model, which can help government agencies allocate a biosecurity budget to where it is most cost-efficient. To evaluate cost-effectiveness, we draw on a generic framework, first proposed by Moore *et al.* (2010) for a single species, which focuses only on the most common economic features of biosecurity measures associated with a possible incursion, namely: (i) quarantine measures against the risk of entry; and (ii) surveillance for early detection to counter or avoid losses that go with the spread of a pest or disease over time. We also include two major additions in our extension to a multispecies setting. First, our model includes the costs of failed quarantine and detection, as endogenous variables, by allowing them to vary with a number of fundamental factors such as spread and damage rates and the cost of eradication per unit of an established incursion. Second, we model detection probability as a function of not only of surveillance expenditure, but also the size of the incursion to better reflect the fact that some threats can be detected, for example, by the community or farmers, without active surveillance, although possibly at a later date. Both extensions aim at enhancing the practicality of the model while requiring only a few (albeit indispensable) parameters, which can be collected by policymakers or adopted from relevant sources.

It is important to note that our portfolio model differs from the common principle, which ranks alternative biosecurity measures by their benefit cost ratios (Parris *et al.* 1999) and picks the one that generates the highest average benefit-cost ratio (BCR). This principle is sometimes referred to as 'the winner takes all' principle since projects with the highest average BCRs will be allocated at full scale while others may have no or limited budgets. The result is generally a misallocation of resources since the average BCR of a biosecurity measure can be highly sensitive to its scale or the level of activity. The model we propose, instead, aims to allocate each (small) block of budget to a biosecurity measure where it is most cost-effective, and consequently determine the optimal scale of the control program for each threat with different funding levels or budget constraints. The cost-effectiveness of each block of budget spent on a threat is determined by minimising its expected total cost, including the damages it inflicts and the control expenditures incurred in preventing or mitigating damages. Stochastic programming is used to control for uncertainty in the success of quarantine and surveillance measures as well as in the arrival rate of exotic pests and diseases. The model can be extended to directly incorporate additional information on spatial heterogeneity.

As a pilot study, we apply our model to determine optimal budget allocations among four invasive threats of great significance for Australia, all with location-specific attributes: red imported fire ants (RIFA) in Queensland; orange hawkweed in Victoria; foot-and-mouth disease (FMD) in Victoria; and papaya fruit fly (PFF) in the Torres Strait Islands and Northern Queensland. Two of the species (RIFA and hawkweed) are now largely local surveillance and eradication projects, and the other two threats mostly involve entry prevention and preparedness measures. That said, all four cases potentially require active surveillance for early and ongoing detection, along with the assurance of ultimate pest-free status. While the four threats are diverse and the ecology of each species can be modelled in various ways, with different levels of technical detail and sophistication, they in principle share a common control budget, a budget which must be properly allocated, albeit with budget decisions often made by separate jurisdictions.

2. Approaches to resource allocation for biosecurity in Australia

Invasive pests and diseases pose a major threat to Australia's agricultural industries, environmental assets, and recreational and social activities. Border and postborder biosecurity programs are aimed at minimising the costs of exotic pests and diseases, including the damages they inflict and the control costs incurred in preventing or mitigating damages. Publicly funded biosecurity agencies face challenging decisions as they attempt to prevent, eradicate, and suppress invasions.

Early methods for allocating biosecurity resources in Australia relied heavily on expert assessment of the risks posed by different exotic species. This included the use of scoring methods in which different biosecurity threats were ranked by experts, including scientists and biosecurity managers.

This approach is exemplified by the Australian 'Weed Risk Assessment' system (WRA), which was introduced in 1997 to determine which exotic plant species should be targeted and prevented from entering Australia (Pheloung *et al.* 1999). Under the WRA system, a set of attributes for exotic plant species were identified and assigned weights by experts. These attributes included whether the plants were classified as weeds in other countries and whether they reproduce by vegetative propagation. Applying these weights to attributes produced a ranking of plant species in terms of the risk they posed. Newer risk assessment methods, including applications of multicriteria analysis (MCA), extended this methodology to address concerns with subjective identification and the weighting of pest attributes. In the MCA method, for example, developed to rank weeds in Victoria, weights applied to weed attributes were estimated using the 'Analytic Hierarchy Process' rather than being based solely on expert opinion (Benke *et al.* 2011).

Nevertheless, scoring methods, including the more sophisticated MCA approaches, are not well suited to budget allocation decisions in which choices must be made not only about which biosecurity measures to fund, but also the level of expenditure on each threat and measure. Budget allocation decisions of this type require information on the magnitude of gains and losses from increasing expenditure on some measures, while reducing expenditure on others. This type of information is also not readily considered with MCA methods.

The difficulty in addressing budget allocation problems with scoring methods is further exacerbated by difficulties in avoiding the double-counting of benefits arising from the selection of inappropriate attributes for estimating scores (Dobes and Bennett 2009). Thus, policymakers have looked for more quantitative models, including more sophisticated spread models, that can help determine the costs and benefits of biosecurity threats and measures over time.

Over the past 15 years, significant advances have been made in spread modelling and these models are increasingly being used in combination with economic information to estimate the costs and benefits of biosecurity programs (Andersen *et al.* 2004; Renton and Savage 2015). The typical approach to conducting a benefit cost analysis (BCA) for a specific biosecurity measure is to simulate the spread of a pest or invasive species with and without the biosecurity measure in place. The project's estimated net benefit is calculated as the difference in damages and control costs between the two scenarios. For projects in which eradication is not achieved immediately, future control costs and benefits are converted to present values using a discount rate that typically is specified in government evaluation guidelines (Hafi *et al.* 2014). Discounting of benefits and costs produces an estimate of the project's net present value (NPV), often expressed as a benefit cost ratio (BCR), for a specific level of project funding. Budget allocation methods in which allocations are based on estimated benefits and costs have advantages over methods in which priorities are based on scores estimated with largely qualitative data. This reflects the fact that unlike the previously developed ranking methods for prioritising biosecurity expenditures, BCA-based methods allow for the estimation of the magnitude of differences in key performance indicators among various proposed biosecurity measures and across various threats.

The increased use of BCA in evaluating biosecurity expenditures has been facilitated by advances in methods for predicting invasion outcomes, including the use of Bayesian inference to estimate invasion spread parameters (Schmidt *et al.* 2010; Keith and Spring 2013). These advances have facilitated improvements in the accuracy of spread predictions, which increase the reliability of cost benefit analyses by allowing for improved precision in cost and benefit estimation. Further impetus for the increased use of BCA-based methods in biosecurity planning was provided by advances in non-market valuation methods, which underpin estimates of the environmental and social benefits of pest control (Adams *et al.* 2011; Garcia-Llorente *et al.* 2011). These non-market valuation methods involve structured surveys of households to determine various 'willingness to pay' measures for biosecurity outcomes. Unfortunately, the high cost of achieving sufficient survey responses to accurately estimate benefits, and the time it takes for getting survey outcomes, has proven a serious obstacle. This has led to the use of lower-cost valuation methods, including the benefit-transfer (Wilson and Hoehn 2006) and cost-transfer method (Rossi *et al.* 2004), which have greatly expanded the scope for using BCA-based methods for allocating biosecurity budgets.

However, most applications of BCA in Australia focus on the evaluation of individual biosecurity measures and (even more often) eradication projects, rather than using cost and benefit information to determine how to allocate a biosecurity budget. These single-project evaluations usually also consider only one, or a small number of potential project spending levels, determined in consultation with scientists and biosecurity managers. The initial evaluation of Australia's program to eradicate RIFA, for example, considered only a single proposed level of program funding (Kompas and Che 2001), and the most recent evaluation of that program considered only two proposed funding levels (Hafi *et al.* 2014). This has occurred despite the fact that spread models can be modified to consider many different spread rates and spending levels.

With this in mind, and given the potentially significant impacts of various spending levels for biosecurity measures, it is important that multiple funding levels be considered to avoid misallocations of program budgets. The common practice of evaluating only a single proposed level of biosecurity funding, or a very small number of funding levels, has potentially reduced the efficiency with which Australia's limited biosecurity resources have been used in the past. Indeed, a second potential source of inefficiency is the consideration of individual biosecurity measures, or small groups of proposed eradication projects, in isolation from other measures and threats, ones that compete for limited available resources and may have higher rates of return on expenditure.

3. The portfolio model

In this section, we set out the model for allocating a biosecurity budget across different invasive species (referred to as ‘threats’) and geographical areas. The total cost of each threat consists of four components which are referred to hereafter as damage costs, eradication costs, active surveillance costs, and prevention expenditures. ‘Damages’ are the losses caused by a threat, which grow and accumulate over time as the threat spreads. The damages could be to agriculture, local industry, household welfare or the environment. ‘Eradication’ expenditures include all costs incurred in the removal of known threats, including chemical treatment and monitoring in known areas of infestation, until the disease or pest is contained or eliminated. ‘Surveillance expenditures’ refers to active search measures that ensure early detection of a pest or disease. The main purpose of active surveillance expenditures is to detect new invasions sooner (rather than later or ‘naturally’ in the community) to allow for containment or eradication to take place while the invasion is still small. ‘Prevention expenditures’ includes spending on all measures that reduce the frequency of occurrence, including border and local quarantine, search, the removal of potential threats (including the removal of exotic species that have not yet become established), and containment of existing threats to avoid long-distance dispersal.

Among these four components, only prevention and active surveillance expenditures are largely under the direct control of a budget planner. The loss and eradication components can be influenced via prevention and active surveillance activities, but they also depend on other factors, including invasion attributes such as spread rate, severity of damages, and uncertainty in the prevention and detection processes. The fundamental trade-off faced by the planner is that the loss and eradication components will, on average, be smaller when an increased share of the biosecurity budget is allocated to prevention and surveillance. The model developed here provides a framework for determining the budget shares to assign to prevention and the active surveillance of each threat to minimise the expected total cost arising from the threat. Budget shares are determined with and without an overall budget constraint.

3.1 The economics of biosecurity

We consider N biosecurity threats where entry times of threat n ($n \in \{1, 2 \ldots N\}$) are modelled via a random walk process b_1^n, b_2^n, with b_i^n being the time of the i^{th} entry. The drift, and possibly the variance, of the random walk can be controlled via prevention measures. Increasing the budget share allocated to prevention measures (q^n) will, on average, reduce the frequency of entry or (equivalently) increase the duration of intervals between two consecutive entries. This implies that:

$$b_i^n = b_{i-1}^n + \Phi^n(q^n) + \varepsilon_i^n, \tag{1}$$

where $\frac{\partial \Phi^n}{\partial q^n} > 0$, $\varepsilon_i^n \overset{iid}{\sim} D^n$, where D^n is a random distribution with mean zero and, for the sake of notational simplicity, $b_0^n \equiv 0$.

Conditional on the entry at time b_i^n, threat n spreads at rate r^n and the infestation size at time $t \geq b_i^n$ is:

$$x_i^n(t) = \widetilde{x}^n e^{r^n\left(t - b_i^n\right)}, \tag{2}$$

where $\widetilde{x}^n$ is the size of the initial entry. The larger is an infestation and/or the greater the active surveillance effort, the more likely the threat will be detected. The detection probability function, denoted as p^n (x^n,s^n), with s^n being active surveillance expenditure and x^n being infestation size, when detected, satisfies the following assumptions:

$$\forall (x^n, s^n) : p^n \in [0,1]; \frac{\partial p^n}{\partial s^n} \geq 0; \frac{\partial p^n}{\partial x^n} \geq 0; \forall s^n : p^n(0, s^n) = 0. \tag{3}$$

Conditional on being detected at size x_i^n, threat n will be eradicated at a (current value) cost of C^n per infected unit. Summing over all entries, the expected eradication cost (discounted to time zero with an annual discount rate ρ) is:

$$\begin{aligned} B_e^n &= E\left\{\sum_{i=1}^{\infty} C^n x_i^n e^{-\rho t\left(x_i^n\right)}\right\} = E\left\{\sum_{i=1}^{\infty} C^n \widetilde{x}^n e^{(r^n-\rho)\left(t\left(x_i^n\right)-b_i^n\right)-\rho b_i^n}\right\} \\ &= \sum_{i=1}^{\infty} C^n \widetilde{x}^n E\left\{e^{-\rho b_i^n}\right\} \int_{\widetilde{x}^n}^{\infty} e^{(r^n-\rho)\left[t\left(x_i^n\right)-b_i^n\right]} \frac{\partial p^n\left(x_i^n, s^n\right)}{\partial x_i^n} dx_i^n \\ &= \frac{E\left\{e^{-\rho \varepsilon_i^n}\right\} \times e^{-\rho \Phi^n(q^n)}}{1 - E\left\{e^{-\rho \varepsilon_i^n}\right\} \times e^{-\rho \Phi^n(q^n)}} C^n \widetilde{x}^n \int_{\widetilde{x}^n}^{\infty} e^{(r^n-\rho)\left[t\left(x_i^n\right)-b_i^n\right]} \frac{\partial p^n\left(x_i^n, s^n\right)}{\partial x_i^n} dx_i^n \end{aligned}, \tag{4}$$

where the detection time t (x_i^n) is the inverse function of (2).

Equation (4) shows how eradication cost relates to prevention and active surveillance budgets. The first fraction on the right-hand side of the equation captures two possible effects of prevention, one on the entry frequency and the other on the uncertainty over entry times. The first effect unambiguously specifies that allocating an increased budget share to prevention will reduce the frequency of entry and hence reduce eradication costs. The second effect of prevention is its potential influence on uncertainty over entry times, which can only be calculated with a specific functional form, or distribution, for this type of uncertainty.

The remainder of the right-hand side of Equation (4) captures the effect of active surveillance on eradication cost. The net effect depends on the relative magnitudes of the discount and spread rates. The discount rate reflects the rate at which a bank deposit increases over time. If the spread rate is larger, or equivalently, the eradication expenditure grows at a rate larger than the rate at which a bank deposit increases, a higher active surveillance budget will unambiguously reduce eradication costs. On the other hand, if the spread rate is smaller, early detection and eradication may increase the present value of eradication costs. It is important to note that, in some cases, early detection can be facilitated by low-cost measures such as community engagement programs, or the development of new remote sensing methods that can be applied to multiple invasive species at the same time. It may be worth developing or refining the active surveillance method, even if spread rates of the pests that would be detected with these methods are smaller than the discount rate.

It is also worth noting that a large discount rate and a small spread rate are not sufficient conditions for abandoning efforts to facilitate early detection and eradication, because a cumulative and growing loss from damages that occurs when the threat spreads, which can be substantial, must also be considered (Kompas *et al.* 2016). If we denote d^n and F^n as the annual rate of loss caused by one 'infested unit' and the fixed component of the loss which does not vary with the size of the incursion, then the (expected) loss caused by the threat (summed over all entries and discounted to the present) is:

$$
\begin{aligned}
L^n &= E\left\{\sum_{i=1}^{\infty}\left\{F^n \times e^{-\rho b_i^n} + d^n \int_{b_i^n}^{t\left(x_i^n\right)} x_i^n(t) e^{-\rho t} dt\right\}\right\} \\
&= \sum_{i=1}^{\infty}\left\{E\left\{e^{-\rho b_i^n}\right\} \times \left[F^n + d^n \times \int_{\widetilde{x^n}}^{\infty} \int_0^{t\left(x_i^n\right)-b_i^n} x_i^n(t) e^{-\rho t} dt \frac{\partial p\left(x_i^n, s^n\right)}{\partial x_i^n} dx_i\right]\right\} \\
&= \frac{E\left\{e^{-\rho \varepsilon_i^n}\right\} \times e^{-\rho \Phi^n(q^n)}}{1 - E\left\{e^{-\rho \varepsilon_i^n}\right\} \times e^{-\rho \Phi^n(q^n)}} \left[F^n + d^n \times \int_{\widetilde{x^n}}^{\infty} \int_0^{t\left(x_i^n\right)-b_i^n} x_i^n(t) e^{-\rho t} dt \frac{\partial p\left(x_i^n, s^n\right)}{\partial x_i^n} dx_i^n\right]
\end{aligned}
\quad . \tag{5}
$$

We will use the expected eradication cost in Equation (4) and the expected loss in Equation (5) to determine the expenditures on prevention and active surveillance that minimise the total cost of the biosecurity measure itself, plus the expected eradication cost and losses associated with the invasive pest or disease, or:

$$
\begin{gathered}
\min_{\langle s^n \geq 0, q^n \geq 0\rangle} \sum_{n=1}^{N}\left\{L^n + B_e^n + B_q^n + B_s^n\right\} \\
\text{subject to } (4) - (5) \text{ and } \sum_{n=1}^{N}\{q^n + s^n\} \leq B
\end{gathered}
\quad , \tag{6}
$$

where B is the annual total budget allocated to prevention and active surveillance (of all N threats), and B_q^n and B_s^n are the present values of the expenditures on prevention and active surveillance associated with the annual budgets for prevention q^n and active surveillance s^n, respectively.

3.2 The economics of resource allocation in biosecurity

Depending on the number of threats, problem (6) can be a large optimisation problem since for each value of the overall budget (B) the expenditures for the prevention and active surveillance of all threats must be determined simultaneously. To address this issue, we approach this optimisation in two steps. First, problem (6) is solved without an overall budget constraint. This is equivalent to solving for the prevention and active surveillance expenditures that together minimise the expected total cost of one threat at a time, and then repeating the process for all N threats, or:

$$\begin{array}{c} \min\limits_{\langle s^n \geq 0, q^n \geq 0 \rangle} \left\{ L^n + B_e^n + B_q^n + B_s^n \right\} \\ \text{subject to (4) and (5) for each } n \in \{1, 2 \ldots N\} \end{array} . \tag{7}$$

In the second step, we add the solutions to all of the problems in (7) to obtain the optimal total budget across all species. If the total budget is less than the budget specified in the overall constraint (B), then the solution of (7) will also solve problem (6). Otherwise, the budget for some activities/threats must be reduced to meet the constraint. To solve this, we sequentially remove a small block of budget (e.g. \$1,000) from the activity/measure that has the lowest net additional benefit until the constraint is met. This process ensures that any available (and limited) funds are allocated efficiently.

To calibrate the model numerically, we draw from search theory (Koopman 1980) to specify the detection probability function in Equation (8):

$$\begin{array}{c} p^n\left(x_i^n, s^n\right) = \begin{cases} 0 \text{ if } x_i^n \leq l^n \times \widetilde{x}^n \\ \frac{x_i^n}{\overline{x}^n(s^n)} \text{ if } x_i^n \in \left(l^n \times \widetilde{x}^n, \overline{x}^n(s^n)\right] \\ 1 \text{ if } x_i^n > \overline{x}^n(s^n) \end{cases} \\ \text{with } \overline{x}^n(s^n) \equiv \left(\overline{X}^n - \widetilde{x}^n\right)e^{-\eta^n s^n} + \widetilde{x}^n \end{array} , \tag{8}$$

where $\overline{X}^n$ is the natural detection point (the point where the pest or disease will be detected with 100 per cent probability even without active or any additional passive surveillance), $\overline{x}^n(s^n)$ is the detection point with a given active surveillance effort s^n (the targeted detection point), $l^n = 1$ if threat n has a latent period and 0 otherwise, and $\eta^n > 0$ is a parameter measuring active surveillance effectiveness.

We also specify that uncertainty in the entry times follows a normal distribution, with a variance proportional to the expected entry interval as in Equation (9):

$$D^n \equiv N(0, \mu^n \Phi^n(q^n)) \text{ with } \Phi^n(q^n) = \alpha^n + \beta^n q^n, \tag{9}$$

where α^n is the average interval between two entries without prevention, β^n measures the effectiveness of that intervention, and μ^n is the proportion of the variance of the entry times to the average entry interval.

Given the functional forms in Equations (8) and (9), the expected eradication expenditure in Equation (4) and the expected damage caused by the disease in Equation (5), we can simplify the system to obtain Equations (10) and (11). In the Appendix, we show that an increase in prevention spending will reduce both the expected eradication expenditure and damages, but with diminishing returns.

$$\begin{aligned} B_e^n = {} & \frac{e^{-\rho(\alpha^n+\beta^n q^n)\left(1-\frac{\rho\mu^n}{2}\right)}}{1-e^{-\rho(\alpha^n+\beta^n q^n)\left(1-\frac{\rho\mu^n}{2}\right)}} \times \frac{C^n(\tilde{x}^n)^{\frac{\rho}{r^n}}}{\left(2-\frac{\rho}{r^n}\right)\left(\bar{x}^n(s^n) - l^n \times \tilde{x}^n\right)} \\ & \times \left[\bar{x}^n(s^n)^{2-\frac{\rho}{r^n}} - (\tilde{x}^n)^{2-\frac{\rho}{r^n}}\right]. \end{aligned} \tag{10}$$

$$\begin{aligned} L^n = {} & \frac{e^{-\rho(\alpha^n+\beta^n q^n)\left(1-\frac{\rho\mu^n}{2}\right)}}{1-e^{-\rho(\alpha^n+\beta^n q^n)\left(1-\frac{\rho\mu^n}{2}\right)}} \times \left\{F^n + \frac{\tilde{x}^n d^n}{\left(\bar{x}^n(s^n) - l^n \times \tilde{x}^n\right)(r^n-\rho)}\right. \\ & \left. \times \left[(\tilde{x}^n)^{\frac{\rho-r^n}{r^n}} \frac{r^n}{2r^n-\rho}\left(\bar{x}^n(s^n)^{\frac{2r^n-\rho}{r^n}} - (\tilde{x}^n)^{\frac{2r^n-\rho}{r^n}}\right) - \left(\bar{x}^n(s^n) - \tilde{x}^n\right)\right]\right\}. \end{aligned} \tag{11}$$

4. Application to hawkweed, FMD, RIFA, and PFF in Australia

4.1 Background information on each species

4.1.1 Hawkweed

Invasive hawkweeds are a group of invasive weeds originating from Europe that have become worldwide weeds, causing serious problems in New Zealand, the United States, Canada, and Japan. The biological characteristics of these weeds allow them to survive and grow in various types of habitats and, more importantly, create ecological threats to biodiversity and agricultural production. Hawkweed infestation covers 500,000 hectares (ha) in New Zealand's South Island (Hunter 1991). In Australia, hawkweed has been found in four states (Victoria, New South Wales, ACT, and Tasmania) over a search area of 10,040 ha, with the estimated area of occupancy of 306 ha. It is a particular problem in Victoria. The weed is in its early stage of spread, but can potentially cause large damages over time. For example, Brinkley and Bomford (2002) estimate that 14.3 million ha of agricultural land is in highest risk area for a hawkweed invasion with a production value of \$A1.25 billion. Cunningham *et al.* (2004), using a more targeted approach, estimate the area at risk is 1.2 million ha with a production value of \$A1.77 billion and profit of $A0.3 billion. Climatic changes may contract its range, but much of the Australian Alps, which contain large contiguous tracts of reserves and many endemic species, will continue to remain climatically suitable for hawkweed through to 2,070 (Beaumont *et al.* 2009). The most cost-effective method of hawkweed control is with the use of herbicides applied by spot spraying or wick-wiping to reduce the risk of off-target damage, indicating that the removal of hawkweed is very labour-intensive.

4.1.2 FMD

FMD is one of the most contagious animal diseases, which affects cloven hoofed animals. The FMD virus can survive for an extended period in many parts of the environment and in a recovered animal, as well as spread rapidly via various pathways. The disease produces debilitating effects, including weight loss, decreased milk production, loss in productivity, and high mortality in young animals. FMD also results in significant trade barriers, hence substantial economic losses, to endemic countries. To avoid high potential damages, FMD-free countries have focused on the prevention of FMD. Measures include stringent quarantine at ports of entry and along main pathways. No matter how aggressive those measures are, complete prevention has proven impossible, as demonstrated by ongoing large losses of approximately $US25 billion over the last 15 years in countries which previously were free of FMD (Kompas *et al.* 2017). FMD detection relies primarily on the recognition and reporting of clinical signs; although even when clinical signs exist, FMD can easily be misdiagnosed or confused with other diseases. In terms of active surveillance for FMD, our case study considers only bulk milk testing (BMT) of dairy herds in Victoria (Kompas *et al.* 2017). This test is based on the finding that the milk from FMD incubating cattle may contain an FMD virus for up to 4 days before clinical signs of the disease become evident. The case study also assumes that existing passive surveillance activities for FMD in Victoria continue to operate.

4.1.3 RIFA

RIFA is one of the world's worst invasive species (Lowe *et al.* 2000) with annual control costs and damages in the United States alone ranging from $1 billion (Pimentel *et al.* 2005) to over $6 billion (Lard *et al.* 2006). The species was discovered in Queensland, Australia, in 2001, and an eradication program commenced soon after (Moloney and Vanderwoude 2002). There was significant uncertainty over the initial spread of the pest, with subsequent and large infestations implying a substantial spread may have begun long before eradication efforts commenced. The eradication program originally involved extensive areas of broadcast pesticide application, with much smaller areas actively searched. The recent introduction of a low-cost active surveillance method based on remote sensing will allow for larger areas to be searched in the future (Spring and Cacho 2015; Spring and Kompas 2015).

4.1.4 PFF

There is a permanent, native population of the exotic PFF in the Western Province of Papua New Guinea immediately adjacent to the Torres Strait islands. This poses a serious risk of PFF establishment and spread in the Northern Territory and QLD, areas important in terms of horticulture and agricultural production. Pests move into the Torres Strait by natural means, such as wind currents, and also through human-assisted pathways such as vessel and people movements, and unauthorised foreign fishing activity. Like most tropical fruit fly species, PFF multiplies rapidly and can disperse over large distances. It is capable of establishing in any of the mainland states of Australia. According to the Australia's Department of Agriculture and Water Resources, identifying and assessing the risk of PFF is essential for managing the pest in the Torres Strait before they can establish on the mainland. Early detection of the pest greatly enhances the likelihood that PFF can be eradicated. For over 18 years, the 'Long-term Containment Strategy for Exotic Fruit Flies in the Torres Strait' has been very successful in protecting Australian horticulture from exotic fruit fly pests. Over the past 10 years, there were at least 373 incidences of PFF detected in the Torres Strait Zone, with significant preventive measures in place (Kompas and Che 2009). Currently, active surveillance for PFF is performed through an elaborate 'trap and destroy' program in the Torres Strait Islands and on the mainland of Australia.

4.2 Baseline parameter values

Quantitative information about the possible values of each model parameter is crucial. We draw largely on existing reports for spatial spread and other key parameters. Kompas *et al.* (2016) and Hamilton *et al.* (2015) provide information on hawkweed, while FMD information, including measures for active surveillance and BMT in particular, is taken from Kompas *et al.* (2017). Hafi *et al.* (2014) and Spring and Kompas (2015) provide information to calibrate RIFA parameters, while Kompas *et al.* (2004) and Kompas and Che (2009) provide spatial modelling measures and model context for PFF and its potential pathway through the Torres Strait Islands. We assume there are no correlations among the potential incursions of the four species.

A problem we confronted in calibrating the model is that the four species have different units of measurement. The invasion sizes of hawkweed, RIFA, and PFF are typically measured in terms of hectares, while FMD is measured in terms of the number of infected animals, herds, or farms. Thus, to compare across species, we chose to normalise the infection unit of all species such that the damage (parameter) caused by one unit of 'infestation' is 1,000 dollars. For example, if each hectare of hawkweed causes an environmental damage of \$70 per year, the unit of measurement for a hawkweed infestation will be converted to 1,000/70 = 14.29 ha (so each unit causes \$1,000 damage), the initial incursion of 0.01 hectare will be converted accordingly to

$0.01/14.29 = 7 \times 10^{-4}$ (units), and the eradication cost (\$25 thousand/ha) will be converted to $25 \times 14.29 = \$357.14$ thousand dollars per unit. Likewise, if the loss of each animal infected with FMD is \$250, then one unit of FMD infection is \$1,000/250 = 4 infected animals, and the passive detection threshold for FMD is 10,000 (i.e. \$10 million dollars), corresponding to the assumption that the passive detection threshold is 40,000 animals. Other parameters were converted using the same principle. All parameters are collected in Tables 1–4, including a brief description of the assumptions used to calibrate their values.

4.3 Budgeting for biosecurity measures

Model results for mean responses for the optimal budget are reported in Table 5. The expected total cost of the four species is approximately \$61.4 million a year. Around 45 per cent of this total cost is the spending on prevention and active surveillance which amount to \$27.44 million, of which \$15.85 million is allocated to prevention, and \$11.59 million is for active surveillance. Eradication expenditures, approximately \$5.52 million a year, is the amount of money that should be 'banked' every year or, put differently, it is the optimal annual contingency fund needed to cover eradication costs should incursions occur.

Table 1 Baseline parameter values for hawkweed for each 10,000 ha of 500,000 ha at risk

Symbols	Parameters	Assumptions to calibrate model	Baseline values
ρ	Discount rate	Annual discount rate is 3%	0.03
α	Average entry interval	Average frequency of entry without additional prevention is once every 5 years	5
β	Prevention effectiveness	On average, an \$100,000 increase in the annual prevention budget increases the entry interval by 1 year	0.01
μ	Interval coefficient	The variance in entry time is 10% of the entry interval	0.1
d	(Normalised) damage	The unit of measurement is scaled such that the damage rate is normalised to \$1,000/year/unit	1
r	Spread rate	Average spread rate without intervention: 10% a year	0.1
F	Fixed loss	There is no fixed loss associated with hawkweed	0
C	Eradication cost	Eradication cost (including spraying, manual removal, monitoring, follow-up): \$25,000/hectare	357.14
$\overline{X}$	Natural detection point	Environmental value per hectare: \$70/year; and natural detection point without surveillance: 200 ha	14
$\widetilde{x}$	Initial entry	Initial entry size: 0.01 ha	7×10^{-4}
η	Surveillance effectiveness	An active surveillance budget of \$540,000 can reduce the detection point by 100 times (via a grid surveillance search path)	0.8537
l	Latent period	hawkweed can be detected with surveillance	0

Table 2 Baseline parameter values for FMD

Symbols	Parameters	Assumptions to calibrate model	Baseline values
ρ	Discount rate	Annual discount rate is 3%	0.03
α	Average entry interval	Average frequency of entry without additional prevention is once every 50 years	50
β	Prevention effectiveness	On average, a $1 million increase in the annual prevention budget can increase the entry interval by 1 year	0.001
μ	Interval coefficient	The variance of the uncertainty in the entry time is 10% of the entry interval	0.1
d	(Normalised) damages	The unit of measurement is scaled such that the damage rate is normalised to $1,000/year/unit	1
r	Spread rate	Average spread rate without intervention is 14.8% a day	54.02
F	Fixed loss	Whenever an FMD outbreak occurs, the fixed component of the trade loss is $5.692 billion	5.692×10^6
C	Eradication cost	(i) Average value of an animal is $200, (ii) Culling ratio is 3.74, (iii) Centres cost is $0.475 million per day starting from the first detection day until the last confirmed case plus 90 days surveillance (average break duration is 58 days), (iv) Each infected animal causes $50 productivity loss if not eradicated, (v) Variable trade loss associated with an outbreak of 24 farms is $518 million	0.1378
$\overline{X}$	Natural detection point	(i) FMD can be detected after 23 days after the first infection (ii) Average farm size is 673 animals	6.5012×10^5
$\tilde{x}$	Initial entry	Initial entry is one farm, but the disease cannot be detected during the latent period of 14 days	1.716×10^5
η	Surveillance effectiveness	An annual active surveillance budget of $1.25 million (for the whole Australia) is required to reduce the detection time to 19 days	7.472×10^{-4}
l	Non-detection period	FMD has a period where its presence cannot be detected	1

The result in Table 5 makes it clear that it is not always effective to invest in the full array of biosecurity measures. Prevention measures are cost-effective only for FMD and PFF. Most of the active surveillance expenditures are allocated to RIFA, with much smaller allocations to active surveillance for PFF and hawkweed. Among the four species, FMD has more than half of the total biosecurity budget, where the entire budget allocated to FMD is spent on prevention (i.e. border quarantine), indicating that no money should be spent on active surveillance over and above the passive surveillance system that is already in place. There are three main reasons for this: (i) the arrival rate for FMD is very small, with an expected occurrence of one entry every 50 years; (ii) there are huge fixed costs involved; that is, there are large economic losses from the suspension of international trade once FMD occurs

Table 3 Baseline parameter values for RIFA

Symbols	Parameters	Assumptions to calibrate model	Baseline values
ρ	Discount rate	Annual discount rate is 3%	0.03
α	Average entry interval	Average frequency of entry without prevention is once every 4.5 years	4.5
β	Prevention effectiveness	On average, a \$3 million increase in the annual prevention budget can increase the entry interval by 1 year	3.33×10^{-4}
μ	Interval coefficient	Variance in entry time is 10% of the entry interval	0.1
d	(Normalised) damages	The unit of measurement is scaled such that the damage rate is normalised to \$1,000/year/unit	1
r	Spread rate	Average spread rate without intervention is 10.88%/year	0.1088
F	Fixed loss	There is no fixed loss associated with RIFA	0
C	Eradication cost	The size of invaded area in 2012 is approximately 300,000 ha and the average cost of eradication (including spraying, bait, monitoring, and follow-ups to ensure a successful eradication) is \$3,000 ha	40.9
$\overline{X}$	Natural detection point	Natural detection point without active surveillance is approximated by the annual loss when it was detected in 2001; and the annual loss in 2012 is approximately \$22 million	7.064×10^3
$\tilde{x}$	Initial entry	RIFA may have entered 10 years before detection in 2001	2.515×10^3
η	Surveillance effectiveness	\$6 million annual active surveillance budget can reduce the detection point by 50%	$2.497 \times 10^{-}4$
l	Latent period	RIFA can be detected with surveillance	0

and often regardless of how early an FMD outbreak is detected (although larger outbreaks, postincursion, generally imply a longer time out of market); and (iii) the size of the latent period relative to how early FMD can be detected with active surveillance leaves little to be gained in terms of reducing the number of days for detection, relative to the cost of BMT per unit. PFF is the only species that has both active surveillance for early detection, via a dedicated trapping program, and prevention (i.e. measures in the Torres Strait to protect against flies from passing to mainland Australia) as both are cost-effective at the margin.

We calculate the average BCR of each activity in Table 6. The BCR indicator is evaluated by the ratio of avoided losses to the amount of money spent on each species at the optimal allocation. For example, each dollar spent on surveillance for hawkweed can reduce the expected loss by \$7.63, and each dollar spent on border quarantine for FMD generates a benefit of \$1.40. There are three activities that have a BCR < 1, namely hawkweed prevention, active surveillance for FMD, and RIFA prevention. A BCR less than one means that spending an extra dollar, so to speak, in these three

Table 4 Baseline parameter values for PFF

Symbols	Parameters	Assumptions to calibrate model	Baseline values
ρ	Discount rate	Annual discount rate is 3%	0.03
α	Average entry interval	Average frequency of entry without prevention is once every 2.25 years	2.25
β	Prevention effectiveness	On average, a \$0.5 million annual prevention budget can increase the entry interval by 25 years	0.0455
μ	Interval coefficient	The variance of the uncertainty in the entry time is 100% of the entry interval	1
d	(Normalised) damages	The unit of measurement is scaled such that damage rate is normalised to \$1,000/year/unit	1
r	Spread rate	Spread rate without intervention 63.3% per month (at this rate, PFF in a farm can spread to 2,000 farms in 1 year)	7.596
F	Fixed loss	There is no fixed loss associated with PFF	0
C	Eradication cost	(i) Average farm gate value: \$412,000; (ii) Average loss caused by fruit flies: 20% of the farm gate value; (iii) Cost of eradicating fruit flies (e.g. spraying): \$370/hectare	15
$\overline{X}$	Natural detection point	Natural detection point without any intervention is 80,000 km^2	1.979×10^5
$\widetilde{x}$	Initial entry	Initial entry is 1 farm	82.4
η	Surveillance effectiveness	The detection point can be reduced to 10,000 km^2 with an active surveillance budget (including traps, search, etc.) of \$1 million	0.0021
l	Latent period	PFF can be detected with surveillance	0

Table 5 Optimal annual budget and expected annualised cost (\$1,000 dollars, 2012)

Unit: \$1,000	Biosecurity budget			Eradication expenditure	Minimised total cost
	Total	Prevention	Surveillance		
Hawkweed	1,468	0	1,468	442	1,921
FMD	15,093	15,093	0	282	43,726
RIFA	8,277	0	8,277	4,310	12,688
PFF	2,605	754	1,852	487	3,097
Total	27,443	15,846	11,597	5,521	61,432

(i) Active surveillance does not include existing community engagement and awareness improvement programs in place for FMD; (ii) Eradication expenditure and the minimised total cost are expected values.

activities would, on average, generate less than one dollar in benefit, so they are not cost-effective and have zero budgets, as shown in Table 5.

Finally, we undertake a sensitivity analysis to examine how the results are sensitive to parameter values. In the sensitivity analysis, each parameter is varied from its baseline value by ± 30 per cent. With each of the deviations in parameter values, we recalculate the optimal budget for prevention and surveillance. The four tornado diagrams in Figure 1 illustrate the sensitivity of model solutions to each parameter. For example, if the spread rate of hawkweed were 30 per cent lower than the baseline value (i.e. 7 per cent/year

Table 6 Expected benefit and cost ratios (avoided losses/cost) of biosecurity spending: all monetary values are converted to present values

	Prevention	Active-Surveillance
Hawkweed	0.00	7.63
FMD	1.4	0.14
RIFA	0.35	2.4
PFF	17.77	11.86

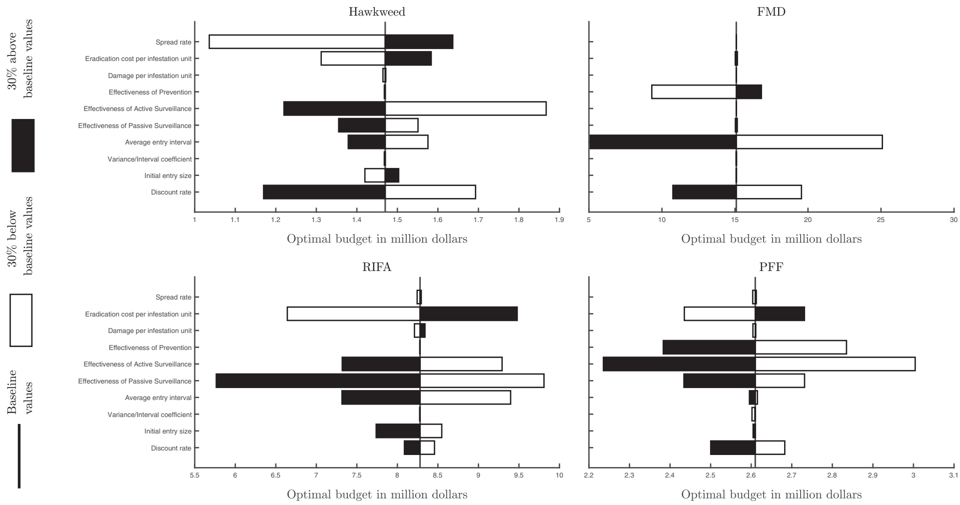

Figure 1 Sensitivity of the optimal budget.

compared to 10 per cent/year), then the optimal budget would reduce to approximately \$1.05 million a year from \$1.468 million; and if the spread rate were 30 per cent above the baseline value (i.e. 13 per cent/year), then the budget would increase to \$1.62 million. Likewise, if the eradication expenditure for one hectare of hawkweed infestation was lower than the baseline value by 30 per cent, then the budget would reduce to around \$1.32 million, while if the cost were 30 per cent higher than the baseline, the budget would increase to \$1.58 million.

The sensitivity analysis indicated in Figure 1 shows that the most influential parameters vary across species. The spread rate, for example, is most important to the budget for hawkweed, which, among the four species, is likely the most difficult to detect naturally by untrained observers or nonexperts, and early detection primarily depends on active surveillance. In addition, the faster the weed spreads, the larger is the budget allocated to surveillance to avoid the normally very substantial cost of eradicating a large infestation. Interestingly, results for FMD, RIFA, and PFF are not very sensitive to their spread rates.

There are a variety of reasons for this. FMD and PFF are fast-spreading threats, so a moderate deviation from their baseline spread rates does not have a substantial impact on model outcomes. Also, RIFA and PFF can often be detected with passive surveillance (i.e. by farmers and non-experts), which means spending money on active surveillance is not the only means for early detection. The spread rate has almost no impact on the budget for FMD because this is the only species where a huge and overriding fixed cost will be incurred, in terms of losses from international trade, if an outbreak occurs, regardless of the spread rate. Of course, post-incursion, bringing the system back to market and controlling the disease through an eradication campaign clearly depend on the spread rate and the size of the initial outbreak.

Eradication expenditures and the damage per unit of infestation have some impact on the optimal budget across the four species but with differing effects. An increase in the eradication expenditure per unit of infestation will increase the biosecurity budget for hawkweed, RIFA, and PFF. However, the eradication expenditure has almost no influence on the optimal budget for FMD, again because of the dominating effect of trade losses.

The damage rate per unit of infestation, however, has a very limited impact on budgets. This is because the economic or environmental damage rate per unit of infestation is usually smaller than eradication expenditures, so a moderate variation in the damage rate does not generate substantial impacts. Hawkweed is a good example of this. Here, one infested hectare requires approximately $25,000 to eradicate while only causing an economic or environmental damage of $70 a year, so when hawkweed is detected and eradicated, on a single hectare, the damage is relatively small compared to eradication expenditures. However, it is important not to jump to the misleading conclusion that small damages can be overlooked to save on eradication expenditures. If eradication is not implemented soon, if not immediately, economic consequences grow exponentially. For example, if the eradication of hawkweed were delayed until the infestation increased from one to 50 hectares, then the cost of containing only this single incursion would be very large, namely $3,500 in damages plus the eradication costs for every additional 5 hectares every year (as the weed spreads at the rate of 10 per cent), which amounts to $125,000, far exceeding the one-off eradication expenditure on a single hectare if the weed were eradicated from the outset.

It is also worth noting that increases in the effectiveness measures of both passive and active surveillance can reduce the budget for hawkweed, RIFA, and PFF, but not for FMD since it is not cost-effective to undertake active surveillance for FMD in the first place, as shown in Table 5. The effectiveness of prevention only has a significant impact on the budget for FMD and PFF because these two species require non-zero budgets for prevention. Finally, the discount rate used to convert all future into present values affects the budget for all species since a high discount rate means smaller future costs when converted to present values, which reduces the cost-effectiveness of spending current dollars to avoid future losses overall.

5. Portfolio allocation under different budget constraints

In this section, we address the question of how much to allocate to each species if the budget available is less than the optimal level. We show that the size of the budget clearly matters in terms of the ranking across pests and biosecurity measures and final allocations. To maximise the rate of return, getting the 'best bang for the buck', so to speak, the constrained budget should be allocated to where it is most cost-effective, at the margin, or in other words, each block of budget (e.g. \$1,000 or \$1 million) should be spent on the activities that reduce the expected loss by the largest amount. When the available biosecurity budget is less than the optimal level (i.e. \$27.44 million a year with baseline parameters), each \$1 million block of this limited budget will reduce expected damages and eradication expenditures by more than \$1 million, thus generating net benefits.

To illustrate this point, we calculate the reduction in the expected loss for each \$1 million budget block in the top panel of Figure 2, where the gap between the solid and broken lines represents the net benefit of biosecurity. In this panel, spending the first \$1 million on biosecurity will reduce expected damages and eradication expenditures by around \$16.5 million, so the net benefit is approximately \$15.5 million, with the second block of budget generating a benefit of around \$10 million, or a net benefit of \$9 million. Additional incremental increases in the budget will generate smaller benefits, that is, diminishing returns, though the net benefit is still positive until the budget reaches the optimal level of \$27.44 million where it is no longer cost-effective to increase spending.

The bottom panel of Figure 2 depicts the optimal allocation with different levels of available budget, and Table 7 provides corresponding numerical values for five levels, in descending order, 25, 20, 15, 10, and 5 million dollars a year. Here, for better accuracy, each block of budget to be allocated is

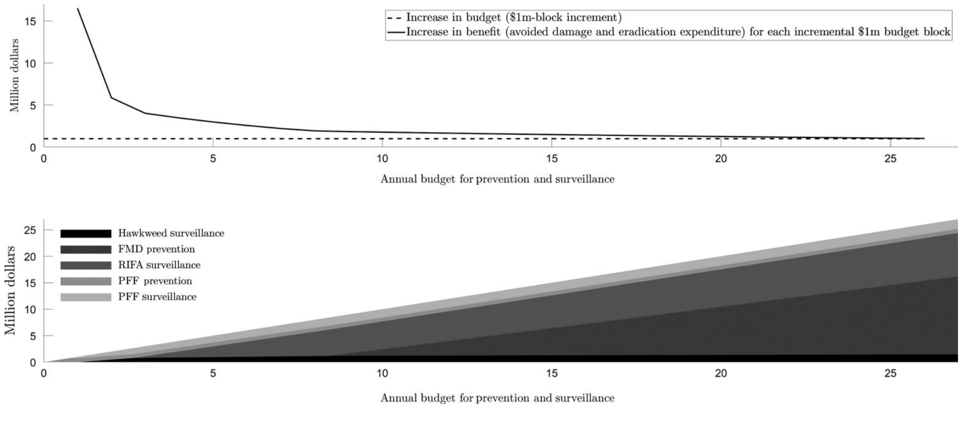

Figure 2 Value for money and optimal allocation under different budget constraints.

Table 7 Optimal allocation at different budget levels (in million dollars)

	Total budget			
	25	20	15	10
Budget allocation				
Hawkweed surveillance	1.43	1.36	1.28	1.2
FMD Prevention	13.11	9.08	5.13	1.22
RIFA Surveillance	7.89	7.07	6.19	5.26
PFF Prevention	0.75	0.75	0.75	0.74
PFF Surveillance	1.82	1.74	1.66	1.58

$1,000. As the figure and the table show, FMD prevention has the largest share when the total budget is 25 or 20 million dollars a year; however, when the total budget is reduced to $15 million, RIFA surveillance is the largest expenditure category. In total, FMD prevention is most sensitive to the available budget, while PFF prevention is the least sensitive. This can be explained by the BCRs in Table 6, which show that, among activities with a positive budget, FMD prevention has the lowest BCR, so spending on this activity will be reduced first when the total budget becomes more constrained. On the other hand, PFF prevention has the highest BCR, so it will be preferred when budgets decrease.

It is important to note that the BCR in Table 6 only measures the average value for money, which may not truly reflect the optimality principle for budget allocations in some situations. Consider a reduction of the budget from $25 to $20 million. This reduction of $5 million is equivalent to 5,000 blocks, each worth $1,000; and if BCR were used as the sole allocation criteria, the 5,000 blocks should be cut only from FMD prevention which has the lowest BCR. However, as Table 7 shows, the budget for FMD prevention reduces by only $4.03 million – equivalent to 4,030 blocks, the budget for hawkweed surveillance reduces by 70 blocks, RIFA loses 820, and PFF loses 180 blocks. In other words, the reduction in the total budget not only affects FMD prevention, with its low BCR, but also reduces the scale of other activities that have higher BCRs. This is because the BCR is only an average measure of the value for money over the entire budget, of which different blocks generate different and usually diminishing returns, as illustrated in the top panel of Figure 2. For this reason, the fact that FMD prevention has a smaller BCR than hawkweed surveillance does not necessarily mean that the return for every block allocated to FMD prevention is smaller than all blocks allocated to hawkweed. In fact, at the budget of $25 million dollars, a few budget blocks of FMD generate higher returns than the 70 final blocks allocated to hawkweed; and hence when the budget is reduced, these 70 final blocks of hawkweed would be affected.

6. Policy implications for budget allocation in biosecurity

Although calibrated to only four species with specific characteristics, the model provides a number of key policy implications and general insights into budget allocation decisions in biosecurity. First, active surveillance is ongoing and incurs an expenditure every year, while its benefit, that is, early detection, if any, can be realised only when an incursion occurs. Active surveillance is usually less cost-effective than prevention if a species has a low probability of incursion. In our calibration, FMD has a zero budget for active surveillance mainly because of an expected occurrence of one entry every 50 years (along with the high cost of the BMT surveillance protocol). This is broadly consistent with Kompas *et al.* (2017), with its finely calibrated spatial analysis.

Second, early detection may be cost-effective even when the economic or environmental damage caused by an invasive pest or disease is far smaller than the expenditure for eradicating it. The reason is that the threat, if not detected, can spread causing eradication expenditures to grow exponentially. In the case of hawkweed, for example, it is effective to spend money on surveillance to detect the weed early even when the expenditure for eradicating one infested hectare is several hundred times larger than the damage.

Third, it may be worth evaluating the cost-effectiveness of different types of surveillance. The model incorporates passive detection thresholds, which reflect the effectiveness of passive surveillance, and the sensitivity analysis shows that passive and active surveillance can usually complement each other. In the case of FMD, passive surveillance can even substitute for active surveillance, pre-incursion, or in lieu of using expensive bulk milk testing (Kompas *et al.* 2017). In our model, existing passive surveillance programs are taken as given. Calculating the cost-effectiveness of these programs, such as community engagement and improved awareness, is a useful exercise that needs addressing in the future. It is also useful to explore different types of active surveillance protocols and to evaluate their cost-effectiveness; for example, surveillance for hawkweed and RIFA can be undertaken individually or jointly by groups of volunteers, trained dogs, and remote sensing (Hamilton *et al.* 2015).

Fourth, the model we propose provides an alternative approach to biosecurity budget allocation, which often, instead, relies on project rankings (Heikkila 2011; Dodd *et al.* 2017), where the key ranking metric is a BCR (Pannell 2015; Pannell and Gibson 2016). Under a BCR ranking, decision-makers typically proceed top-down and set a threshold where projects with higher BCRs get the entire budget they ask for, and projects with lower BCRs receive much less or nothing – an outcome often known as the Noah's Ark solution (Martin 1998; Joseph *et al.* 2009). The BCR ranking approach has clear limitations in achieving the optimal outcome, a point that has been recognised in the literature (e.g., Schwab and Lusztig 1969). The simple reason is that a BCR ranking does not take into account the fact that the value of money for incremental budget blocks usually diminishes as the scale of a project expands. Our model, instead of a simple ranking, optimises outcomes by minimising the net present value of the total cost of biosecurity threats (Hoskins 1974), along with choosing the optimal scale for each of proposed biosecurity measures.

Finally, models used to inform decision makers over budget allocations should take into account the uncertainties that can significantly influence biosecurity decision making (Burgman and Yemshanov 2013). Uncertainties in biosecurity often include unpredictable arrivals and possible failures in detection, which have been incorporated in our model using probability distributions – a common approach to model uncertainty in biosecurity (see Epanchin-Niell 2017). This uncertainty may also include possible failures in eradication, likely for invasive plants like hawkweed, which can be controlled by allowing for adequate eradication expenditures to cover monitoring and follow up during the possible lifespan of the weed's seed bank (Hamilton *et al.* 2015). Uncertainties in parameter values such as spread rates, surveillance and prevention effectiveness, as well as eradication expenditure, can be considered through sensitivity analyses and by investigating how changes in the underlying parameters affect outcomes. Nevertheless, our model does not explicitly control for the uncertainty in knowledge improvements, or updating; for example, lessons from detection failures over time may help improve detectability in the future. This too could be a useful direction for future research, adding a 'learning by doing component' to the model as more data and information about the invasive species becomes available.

7. Concluding remarks

Much recent progress in the quantitative analysis of biological invasions has focused on the prediction and management of individual invasions. There has been less progress on the equally important problem of allocating limited biosecurity funds across multiple species and locations, as well as different biosecurity measures, to maximise the benefits arising from the use of these funds. Misallocations of biosecurity program budgets can lead to missed eradication opportunities and otherwise avoidable damages to valued assets. Methods used previously in Australia to prioritise biosecurity efforts, including methods that determine priorities based on scores estimated with qualitative and quantitative data, are of limited relevance to assisting budget allocation decisions. This reflects the fact that those methods provide little information on the magnitude of gains and losses from reallocating biosecurity program funds between alternative projects.

Information produced by cost-benefit analysis can potentially address the limitations found in scoring methods, depending on how the information is used. However, a commonly proposed budget allocation rule that uses benefit and cost information for a single project, at a given scale, is likely to result in misallocations of biosecurity program budgets. This commonly used rule is to choose those projects with the largest ratio of benefits to costs (the BCR), and to continue choosing additional projects until the budget is exhausted. Unfortunately, this rule is a potential source of substantial inefficiency because the BCR of biosecurity projects can be highly sensitive to the project's scale. Our case studies demonstrate that for some of Australia's most important biosecurity pests and diseases, the BCR ratio can vary by orders of magnitude with plausible changes in biosecurity budgets.

Instead, we developed a budget allocation method that considers these potential changes in project BCRs. The method can implicitly consider a large range of alternative allocations of a biosecurity program's budget among competing activities. The method considers many of the key biological and economic attributes of pests and diseases in order to determine their environmental and economic impacts. We applied the model to find optimal budget allocations among four invasive pests and diseases of great significance for Australia: red imported fire ants; orange hawkweed; foot-and-mouth disease; and papaya fruit fly. One of our main findings was that in the unconstrained budget scenario, it was cost-effective to allocate a substantial share of the optimal active surveillance expenditures to RIFA, with much smaller allocations to active surveillance for PFF and hawkweed. This, in part, reflects the fact that a much larger area is potentially occupied by RIFA infestations, compared to other species. FMD, alternatively, dominates on expenditures for prevention or border quarantine.

Another key finding was that under different budget constrained scenarios, the optimal budget allocation to RIFA and FMD was highly sensitive to the size of the budget. At a low budget, RIFA and FMD would optimally receive a relatively insignificant share of total biosecurity expenditures, but this share increases substantially as the budget increases. This reflects the size of the RIFA management area required for the eradication program to be successful, along with the importance of limiting entry of FMD at the border.

Finally it is important to note that the four programs analysed in our work all fall under different governmental jurisdictions, even though we treat them as being managed under a single or shared budget. In practical terms, this is not the case, at least in Australia, with different states having different budgets and priorities, and this needs to be considered. That said, the model and the approach provides a structured and transparent method for allocating investments across different invasive species or threats and biosecurity activities; investments or allocations that can be scaled according to the available budget. The allocation principle considers which investment has the highest extra net returns, or the highest ratio of the change in benefits to the change in costs or expenditures, and not the (usual) ratio of benefits to costs. In the end, the size of the budget matters to both the priority given to pests and diseases and the appropriate biosecurity measures that are employed.

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Appendix

Here, we show that an increase in prevention spending will reduce both the expected eradication expenditure in Equation (10) and the expenditure for expected damages in Equation (11), but with diminishing returns. Differentiating Equations (10) and (11) with respect to q^n gives:

$$\frac{\partial B_e^n}{\partial q^n} = -\frac{\beta^n \rho\left(1 - \rho\frac{\mu^n}{2}\right)e^{-z}}{\left(1 - e^{-z}\right)^2} U_b < 0. \tag{12}$$

$$\frac{\partial L^n}{\partial q^n} = -\frac{\beta^n \rho\left(1 - \rho\frac{\mu^n}{2}\right)e^{-z}}{\left(1 - e^{-z}\right)^2} U_l < 0, \tag{13}$$

where

$z \equiv \rho(\alpha^n + \beta^n q^n)\left(1 - \rho\frac{\mu^n}{2}\right) U_b \equiv \frac{C^n\left(\widetilde{x}^n\right)^{\frac{\rho}{r^n}}}{\left(2 - \frac{\rho}{r^n}\right)\left[\overline{x}^n(s^n) - l^n \times \widetilde{x}^n\right]}\left[\overline{x}^n(s^n)^{2-\frac{\rho}{r^n}} - \left(\widetilde{x}^n\right)^{2-\frac{\rho}{r^n}}\right]$,

and $U_l \equiv F^n + \frac{\widetilde{x}^n d^n}{\left[\overline{x}^n(s^n) - l^n \times \widetilde{x}^n\right](r^n - \rho)}\left[\left(\widetilde{x}^n\right)^{\frac{\rho - r^n}{r^n}} \frac{r^n}{2r^n - \rho}\left[\overline{x}^n(s^n)^{2-\frac{\rho}{r^n}} - \left(\widetilde{x}^n\right)^{2-\frac{\rho}{r^n}}\right] - \left[\overline{x}^n(s^n) - \widetilde{x}^n\right]\right]$.

Equations (12) and (13) imply that an increase in the spending on prevention will reduce the expected eradication expenditure B_e^n and expected damages L^n.

Further differentiating Equations (12) and (13) with respect to q^n gives:

$$\frac{\partial^2 B_e^n}{(\partial q^n)^2} = \frac{\left[\beta^n \rho\left(1 - \rho\frac{\mu^n}{2}\right)\right]^2 e^{-z}(1+e^{-z})}{(1-e^{-z})^3} U_b > 0. \tag{14}$$

$$\frac{\partial^2 L^n}{(\partial q^n)^2} = \frac{\left[\beta^n \rho\left(1 - \rho\frac{\mu^n}{2}\right)\right]^2 e^{-z}(1+e^{-z})}{(1-e^{-z})^3} U_l > 0. \tag{15}$$

Equations (14) and (15) imply that the impact of prevention spending on expected eradication expenditure and damages diminishes as spending increases.