Report Cover Page

ACERA Project

1002

Title

Time preference and value of information in the context of estimating consequences

Author(s) / Address (es)

Tracy Rout, Australian Centre of Excellence for Risk Analysis
Daniel Spring, Australian Centre for Biodiversity, Monash University
Mike Runge, US Geological Survey
Andrew Robinson, Australian Centre of Excellence for Risk Analysis
Terry Walshe, Australian Centre of Excellence for Risk Analysis

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Final Report

Summary

This report looks at two important dimensions to the characterization of consequences in the context of biosecurity decision-support.

Part A explores time preference. Pests vary in the time over which their impacts are realized. Likewise, stakeholders vary in the time horizons they consider relevant to biosecurity concerns. Agricultural impacts might reasonably be considered over 30 years. Ecologists typically consider environmental impacts over much longer time frames. Part A addresses:

- The conceptual relevance of time preference to biosecurity using monetary benefits and costs associated with the decision of whether or not to invest in preventing invasion of a weed.
- How time preference has been approached in case studies reported in the literature, focussing on contrasts between decision support approaches based on conventional benefit-cost analyses versus those that use a multi-attribute approach. The literature highlights the failure of multi-criteria approaches to address time preference.
- An empirical study that elicited time preferences from biosecurity experts and managers for market and non-market-impacts.
- Problems in dealing with time preference using multi-attribute decision support and a remedy based on normative understanding of weights and their role in articulating trade-offs.

Part B demonstrates the relevance of the economic concept of 'value of information'(VOI), and how biosecurity managers can use VOI analysis to decide whether or not to reduce uncertainty by collecting additional information through monitoring, experimentation, or some other form of research. It explores:

- How some uncertainties may be scientifically interesting to resolve, but ultimately irrelevant to decision-making. VOI analysis provides a rigorous way of assessing the benefits of collecting additional information, and determining whether reducing uncertainty will result in a better decision.
- A prototype model where a manager must choose between eradication or containment of an infestation. Eradication is more cost-effective for smaller infestations, but once the extent reaches a certain size it becomes more cost-effective to contain. When choosing between eradication and containment, how much does knowing the extent of the infestation more exactly improve the outcome of the decision? We calculate the expected value of perfect information (EVPI) about the extent, which provides an upper limit for the value of reducing uncertainty.

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- We then illustrate the approach using the example of red imported fire ant management in south-east Queensland. We calculate the EVPI for three different uncertain variables: the extent of the infestation, the sensitivity (true positive rate) of remote sensing, and the efficacy of baiting. This case study is an illustration only, although with further work it could be developed into a useful support tool.
- Future avenues for research in this area include modelling the time delay associated with research and monitoring, and applying more complex VOI calculations such as the expected value of partial information and the expected value of sample information.

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Time preference and value of information in the context of estimating consequences

ACERA 1002

Improved biosecurity decision-making through better characterization of consequences.

Tracy Rout, Australian Centre of Excellence for Risk Analysis
Daniel Spring, Australian Centre for Biodiversity, Monash University
Mike Runge, US Geological Survey
Andrew Robinson, Australian Centre of Excellence for Risk Analysis
Terry Walshe, Australian Centre of Excellence for Risk Analysis

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Disclaimer

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Executive Summary

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Part A

Time preference in biosecurity decision-making

A 1.0 Introduction

Biosecurity management aims to prevent and mitigate the impact of exotic species and diseases. These impacts can be wide-ranging, and can include decreases in the productivity of agriculture or forestry (Julia et al., 2007; Yemshanov et al., 2009), extinction of native species and communities (Primack, 2006), disruption of ecosystem services (Cook et al., 2007), and effects on human health (Solley et al., 2002). In prioritising species and diseases for quarantine or control action, biosecurity decision-makers must often make tradeoffs between these different types of impacts. To complicate matters further, they must often compare and evaluate outcomes occurring over completely different time frames.

Under all models of decision-making, the future is less important than the present. Formal elicitation of time preference is laborious (Meyer 1976). To illustrate, let's say we expect a stream of consequences over the next four years $\mathbf{x} = (x_1, x_2, x_3, x_4)$. The consequences may be monetary gains, monetary losses, health outcomes, decline in the population size of a threatened native species, or changes in crop yield. To capture an individual decision-maker's time preference we first ask, if x_4 were reduced to zero, what compensating change must be made in x_3 to maintain indifference? That is we ask for a quantity $\hat{x}_3$ such that the decision-maker is indifferent to a choice between two streams

$$(x_1, x_2, x_3, x_4) \text{ and } (x_1, x_2, \hat{x}_3, 0).$$

Suppose the consequences are monetary gains, so that $x_4 > 0$ and $(\hat{x}_3 - x_3) > 0$. Individual decision-makers will have individual choices for investment and consumption over time. Presumably $\hat{x}_3$ depends on x_3 and x_4, but it might also depend on x_1 and x_2. The choice in year 3 need not be the same as the choice in year 2. So next we need to find a quantity $\hat{x}_2$ such that

$$(x_1, x_2, \hat{x}_3, 0) \text{ and } (x_1, \hat{x}_2, 0, 0)$$

are indifferent. And finally we obtain $\hat{x}_1$ such that

$$(x_1, \hat{x}_2, 0, 0) \text{ and } (\hat{x}_1, 0, 0, 0)$$

are indifferent. By transitivity we now have indifference between

$$(x_1, x_2, x_3, x_4) \text{ and } (\hat{x}_1, 0, 0, 0)$$

The quantity $\hat{x}_1$ is the net present value of the stream of consequences (x_1, x_2, x_3, x_4).

Analysts rarely elicit time preferences in such a direct and formal way. Instead, assumptions are made to approximate social time preference. In economics, the discounted utility model (Samuelson, 1937) is the standard for time preference (Frederick et al., 2002). The basic premise of this model is that money available now can be invested in financial markets and gain interest over time. Therefore, just as compounding investments grow exponentially through time, future amounts are discounted exponentially with the time delay before their receipt. The discount rate is chosen based on market interest rates, with the same rate applied to both gains and losses, and to all tradeable goods and services (Hardisty and Weber, 2009). For non-market consequences, the assignment of a rate equivalent to the opportunity cost of investing in financial capital may be a very poor representation of a decision-maker's time preference.

Perhaps unsurprisingly, experiments in behavioural economics and psychology have found that human behaviour does not conform to this rational economic model. The future is less important than the present, but evaluations of future outcomes are driven by more than considerations of market interest rates. For example, people have a strong urge to obtain gains now rather than later (known as 'pure time preference'), independent of any rational reason for doing so (Hardisty and Weber, 2009).

Substantial experimental evidence shows humans and other animals discount the future in a hyperbolic, rather than exponential, pattern (Henderson and Langford 1998, Frederick et al. 2002). For example, when choosing between an immediate (small) food reward and a delayed (larger) reward, laboratory rats and pigeons opt for the delayed reward more frequently than predicted under exponential discounting (Mazur, 1997). A hyperbolic function does not de-value future outcomes as severely as an exponential function with the same discount rate. Some economists have advocated hyperbolic discounting to address concerns around intergenerational equity (Weitzman, 1994). Debate among economists centres on the relative merit of the exponential and hyperbolic functions (Hansen, 2006). Other alternatives, such as the gamma function (Weitzman, 2001) have received far less attention.

Also, people do not discount all outcomes at the same rate—discounting gains at a higher rate than losses, and large outcomes at a lower rate than small outcomes (Chapman, 1996). Experiments have also shown that individuals can apply different discount rates within different ‘domains’, for example, they may discount monetary outcomes at a different rate to health outcomes, with yet another rate for environmental outcomes (Chapman, 1996; Hardisty and Weber, 2009). This ‘domain independence’ has interesting implications for public policy formation.
Many governments now use different discount rates to evaluate projects in different policy areas, but there seems to be no consensus on how these discount rates should be chosen (Zeckhauser and Viscusi, 2008).

Section A2 report outlines the conceptual relevance of time preference to biosecurity using monetary benefits and costs associated with the decision of whether or not to invest in preventing invasion of a weed. Section A3 explores how time preference has been approached in case studies reported in the literature, focussing on contrasts between decision support approaches based on conventional benefit-cost analyses versus those that use a multi-attribute approach. Section A4 reports outcomes of an empirical study that elicited time preferences from biosecurity experts and managers. Finally, Section A5 addresses difficulties in dealing with time preference using multi-attribute decision support and suggests a remedy.

A 2.0 Discounting and its relevance for biosecurity decision-making

To illustrate the important role time plays in decisions about biosecurity management, we consider a scenario of horticultural plant introductions. For an introduced plant to become an invasive weed, it must first become naturalised, that is, it must form self-sustaining populations. Of all plants that are introduced, only some will naturalise, and only some of those naturalised plants will go on to become invasive weeds (Fig. A2.1).

This pathway was examined by Caley et al. (2008) for woody ornamental plants. They combined South Australian nursery data with prior information on naturalisation rates to predict that 18.6% of introduced plants would naturalise (p_n = 0.186), and of these, 44% would go on to become either major or minor invasive weeds (p_w = 0.44). They also found that the mean time to naturalisation was 149 years, with the 95% confidence interval between 130 and 174 years.

For woody ornamental plants, there can therefore be a long delay between the time of introduction, and when the plant begins to cause significant damage. This is illustrated by one of Australia's weeds of national significance—*Lantana camara* was introduced as an ornamental plant in the early 1840s and for decades was considered to be benign. Now widely distributed, it costs the Australian grazing sector more than $104 million per year in lost productivity (Stock et al., 2009).

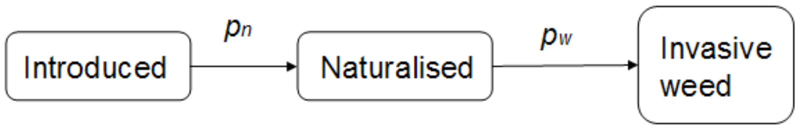

Fig. A2.1. Schematic representing the pathway from plant introduction to weediness. Once a plant is introduced it has probability p_n of becoming naturalised, and once naturalised, it has probability p_w of becoming an invasive weed.

In this example we consider a hypothetical ornamental plant that has recently been introduced to Australia, and is not yet naturalised. This plant has been identified as having an above average chance of naturalisation ($p_n = 0.6$), and of becoming invasive ($p_w = 0.8$). If it does become invasive, it is predicted to cause a loss in agricultural productivity of $500 million (in real dollars) once it spreads to its full extent. For simplicity, we will treat this as a one-off loss occurring at the time of naturalisation, although it would more likely be an annual loss incurred over a number of years. That is, for the sake of conceptual illustration, we make the simplifying assumption that the time stream of consequences is zero up to the point of naturalisation and that we are only interested in costs incurred in the first year of naturalisation.

Imagine there is a management action we could take now to prevent this plant becoming naturalised and invasive, for example, restricting the sale of the plant in nurseries. This management action will cost $1 million in real dollars. The question we pose here is, would it be cost-effective to take this action? That is, should we incur a $1 million loss now, or do nothing with the expectation of a much larger loss in the future?

We can calculate the expected loss caused by our hypothetical plant as the probability that it will become invasive, multiplied by the loss if it does. This gives an expected loss of $240 million. Spending $1 million to prevent a loss of $240 million seems like a cost-effective decision, with a return on investment of 240:1. However, given that the mean time to naturalisation is 149 years, this loss is likely to be incurred far into the future. How this will affect management decisions depends on our attitude to future losses—whether we discount, how we discount, and what discount rate we use.

Under exponential discounting, the standard economic model of time preference, the present value of a future amount is calculated as

$$V = \frac{A}{(1+k)^D}, \qquad \text{(A2.1)}$$

where A is the future value, k is the discount rate, and D is the time delay. The discount rate is usually an annual rate, with D the number of years until the future value is obtained. Time invariant discounting implies impacts in the distant future become very small in terms of their contribution to present (dis)value.

Under hyperbolic discounting, the model best describing many people's inter-temporal choices, the present value of a future amount is calculated as

$$V = \frac{A}{1 + kD}. \qquad \text{(A2.2)}$$

As mentioned in the introduction, a hyperbolic function de-values the future less than an exponential function with the same discount rate (*k*).

This becomes obvious when calculating the present value of the expected damages from our hypothetical plant, which are predicted to occur 149 years into the future (Fig. A2.2). If the decision-maker does not discount future costs (i.e. the discount rate is 0%), the present value of this expected damage is $240 million, which makes prevention extremely cost-effective (Fig. A2.2, Table A2.1). If we apply a very low discount rate of 1%, the present value of the expected damage is $54.5 million under exponential discounting, and $96.4 million under hyperbolic discounting (Fig. A2.2, Table A2.1). While these present values are now quite different, it is still optimal to spend $1 million on prevention under either discount function (Table A2.1).

As the discount rate is increased, the present value of the expected damage diverges under the different discount functions (Fig. A2.2, Table A2.1). This in turn leads to different management prescriptions, depending on which discount function is used (Table A2.1). With a discount rate of 6%, which is around the standard discount rate (), the present value of the expected damage is only $40,704 using exponential discounting. This means it becomes more cost-effective to incur damage in the future than to spend money now on prevention. However, applying the hyperbolic discount function at the same rate means the present value of the expected damage is $24.1 million, and prevention is more cost-effective.

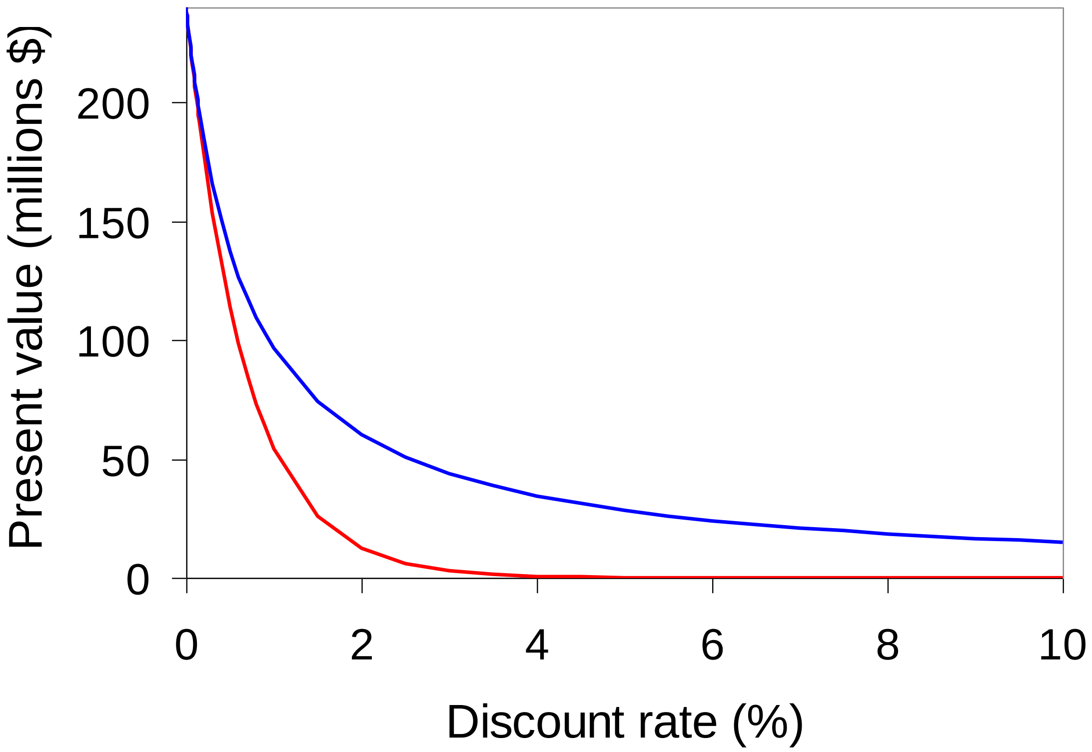

Fig. A2.2. The present value of the damage caused by the hypothetical plant species, discounted over 149 years at different rates and using exponential (red) and hyperbolic (blue) discount functions.

Table A2.1. The present value of the expected damage from our hypothetical plant species under different discount rates and functions, and the implications for cost-effective management.

Discount rate	Discount function	Present value of expected damage, *V*	Most cost-effective management decision
0%	Exponential	$240 million	Prevention
0%	Hyperbolic	$240 million	Prevention
1%	Exponential	$54.5 million	Prevention
1%	Hyperbolic	$96.4 million	Prevention
4%	Exponential	$695,414	Do nothing
4%	Hyperbolic	$34.5 million	Prevention
6%	Exponential	$40,704	Do nothing
6%	Hyperbolic	$24.1 million	Prevention
10%	Exponential	$163	Do nothing
10%	Hyperbolic	$15.1 million	Prevention

This hypothetical scenario illustrates how the choice of discount rate and function can drive economic assessments that inform decision-making. Despite the fact that exponential discounting can drastically de-value outcomes occurring decades into the future, it is used routinely in economic analyses of public policy decisions (Summers and Zeckhauser, 2008).

However, it has been acknowledged that projects undertaken on behalf of society should be subjected to a lower discount rate than private investments (Summers and Zeckhauser, 2008). While the ethical implications of discounting for intergenerational equity and environmental preservation have been identified and discussed, there is no consensus on how to account for this in the selection of discount functions and rates (Summers and Zeckhauser, 2008). For example, The Stern Review (Stern 2006) attracted considerable controversy over its assignment of a 1.4% rate for discounting damages caused by global warming. Nordhaus (2006) argued that this near-zero rate was manifestly inconsistent with the time preference revealed by market indicators.

A 3.0 Treatment of time in biosecurity decision analyses

Given that time preference is an important component of biosecurity decision problems, we conducted a review of the scientific literature to examine how time has been treated in previous analyses of biosecurity management decisions. We began by searching the Institute for Scientific Information (ISI) Web of Science database for journal articles containing the keywords:

- 'invasive species' or 'quarantine' or 'biosecurity', AND
- 'benefit cost' or 'multi-criteria' or 'multi-attribute' or 'multi-objective' or 'prioritisation' or 'decision-making' or 'risk analysis'.

We also searched for alternative spellings of these keywords, including variations without hyphenation. This initial broad search identified 309 candidate articles.

We screened these articles to focus solely on decision analyses for managing invasive animals, plants, and fungi. The alternative options considered in these analyses could be different management actions, or different species or areas on which to focus management resources. We were interested only in analyses that considered the impacts of invasive species, and measured or quantified these impacts in some way. This screening process resulted in a final database of 56 journal articles (see Appendix A1). Of these articles, 22 focused on pre-border management of invasives, 30 on post-border management, and 4 considered management across the biosecurity continuum.

The earliest article was published in 1995, with the majority published after 2006 (Fig. A3.1). We classified articles as either 'economic' analyses, which quantified all the impacts of invasive species as monetary costs or benefits, or 'multi-criteria' analyses, which quantified different types of impacts with different units or attributes, including constructed scales (Keeney and Gregory 2005). Although there was a general increase in the number of biosecurity decision analyses published through the period 1995 to 2010, there was no obvious trend in the ratio of economic to multi-criteria analyses published (Fig. A3.1).

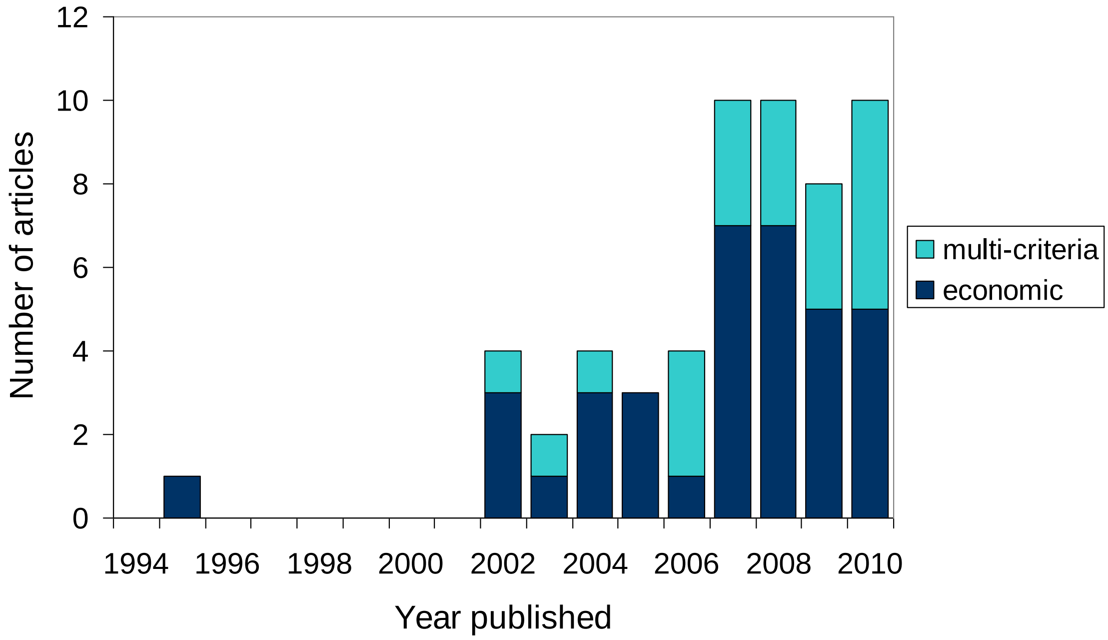

Fig. A3.1. Number of biosecurity decision analyses published 1995 - 2010. Economic analyses quantified all impacts of invasive species as monetary costs or benefits, while multi-criteria analyses quantified different types of impacts with different units.

Of 36 economic analyses, only 4 (11%) included estimates of environmental impacts in their assessment of invasive species damage (Fig. A3.2). An additional 5 analyses (14%) discussed how environmental impacts could be incorporated, but did not quantify them for the case study considered. In contrast, 19 of the 20 multi-criteria analyses quantified environmental impacts (Fig. A3.2).

In the analyses that did not include environmental impacts, it was difficult to determine the reason: while environmental impacts may have simply been ignored or deemed irrelevant to decision making, it is also possible that the particular species considered did not impact on the environment. Either way, our results show that multi-criteria analysis is the preferred method for incorporating environmental impacts within a decision analysis. This is not surprising, given that multi-criteria analysis allows impacts to be expressed in their natural units, for example, the number of bird species affected by invasive vertebrates (Brooke et al., 2007), while economic analyses require environmental impacts to be monetised. Although there are several methods for monetising environmental attributes, they can require substantial work to implement and remain somewhat controversial (see Spangenberg and Settele, 2010 for a critical review of valuation methods).

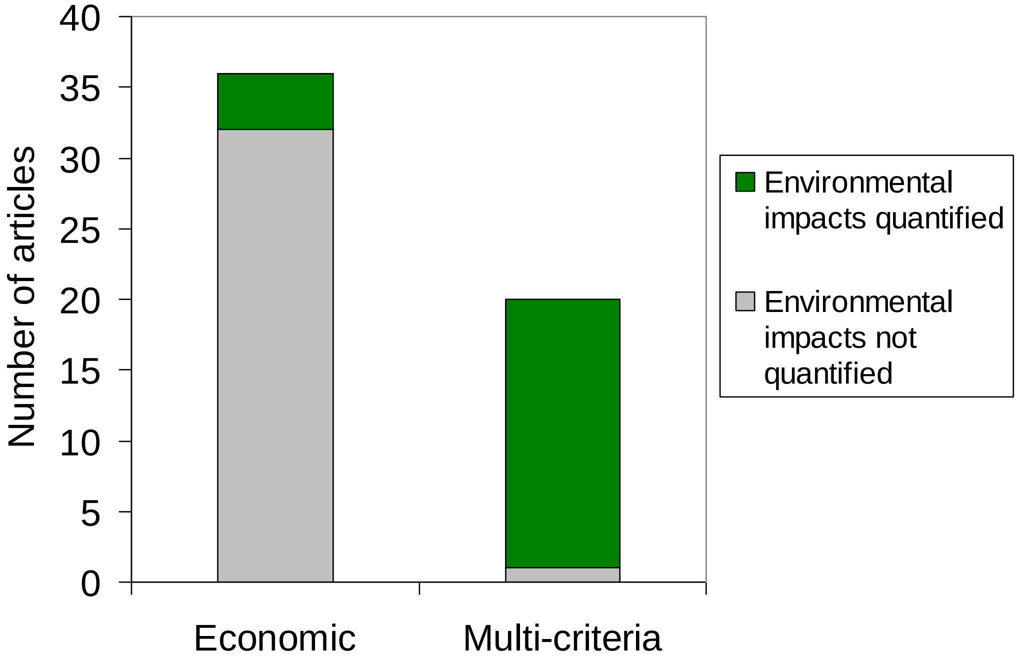

Fig. A3.2. The number of economic and multi-criteria decision analyses that quantified environmental impacts.

The majority of economic analyses incorporated time in some way (Fig. A3.3). Eleven of these did so by specifying a fixed time frame over which they considered the impact of invasive species. For example, Zhang and Swinton (2009) calculated the expected loss in agricultural revenue from an invasive aphid over a period of five years. Over half of the economic analyses (53%) discounted future outcomes (Fig. A3.3). Of these, eleven used exponential discounting, seven did not specify a discount function (although we can assume they used exponential discounting as the standard method), and one tested both exponential and hyperbolic discount functions (Keller et al., 2007). Only one analysis incorporating environmental impacts used a different (lower) discount rate for environmental impacts than for market impacts (Nunes and Markandya, 2008). None of the multi-criteria analyses specified the time frame of impacts, or used any form of discounting (Fig. A3.3).

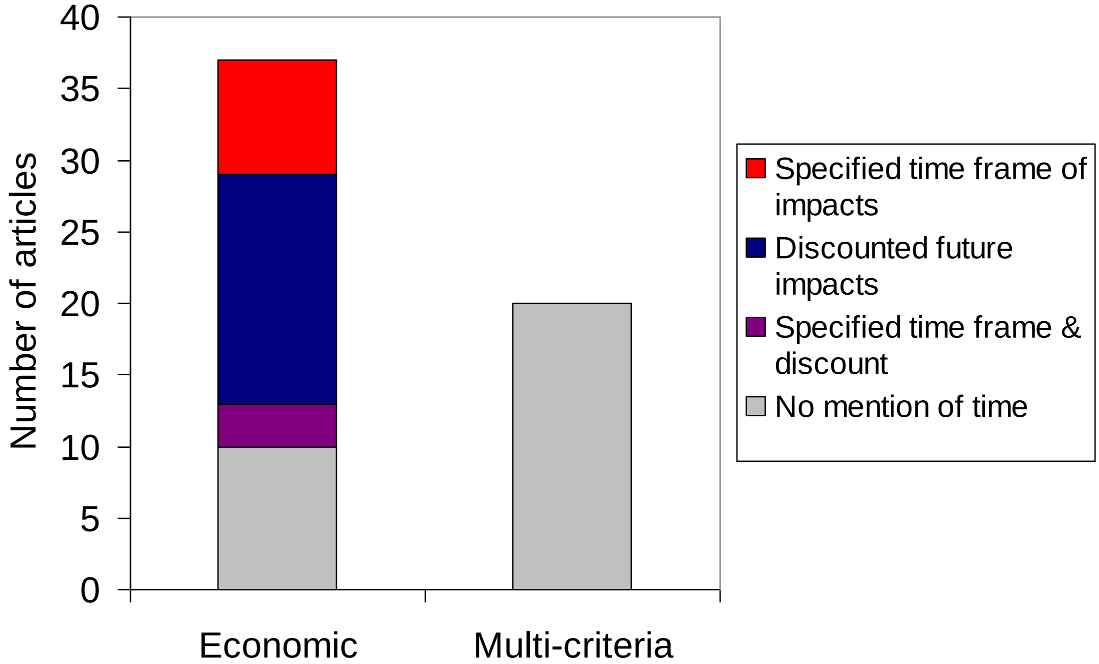

Fig. A3.3. The number of economic and multi-criteria decision analyses to incorporate time, and the method used.

In summary, the literature search provided two key findings:

(i) multi-criteria approaches are much more likely to accommodate non-market impacts than traditional benefit cost analyses; however

(ii) multi-criteria approaches are naïve in their treatment of time preference, commonly ignoring the issue altogether.

A 4.0 Eliciting time preference in multi-attribute problems

Our literature review demonstrated that multi-criteria analysis is the preferred method for biosecurity decisions involving environmental impacts. However, none of these multi-criteria analyses incorporated time preference. To demonstrate how time preferences for non-monetary impacts can be quantified and elicited, we conducted a small survey of biosecurity experts.

A 4.1 Survey methods

We used in-person questionnaires to compare discounting of monetary and environmental outcomes within a biosecurity setting (see Appendix A2). Twenty participants completed the survey while attending a workshop on decision making for biosecurity management. Most participants were employees of state and federal agencies, whose roles involve making decisions about pre- or post-border biosecurity threats. Economists with experience evaluating the cost-effectiveness of biosecurity programmes, and experts in structured decision making also participated.

Participants were presented with two separate questionnaires on subsequent days of the workshop. One questionnaire elicited discount rates for positive outcomes (gains) while the other elicited discount rates for negative outcomes (losses). To minimise anchoring bias the order of these questionnaires was counterbalanced – half of the group was given the gains questionnaire to complete first, while the other half was given the losses questionnaire first. Fifteen participants completed both the gain and loss questionnaires, while five completed only one questionnaire.

Each questionnaire contained two sets of choice questions in counterbalanced order: one set with monetary outcomes, and one set with environmental outcomes. The monetary outcomes were gains or losses in agricultural productivity, specifically to the grains industry. The environmental outcomes were increases or decreases (of more than 10%) in the population levels of a number of native species. Within each set, participants were asked to make 12 choices between an immediate outcome and an outcome of varying magnitude occurring after a delay of 20 years.

This titration procedure was used to find the point at which participants were indifferent between present and future outcomes. The future outcomes tested ranged between 0.8 and 11 times the magnitude of the present outcome. Using the hyperbolic discounting formula (eqn. A2.2) this translates to a range of annual discount rates (k) from -0.01 to 0.5. A positive k means future outcomes are discounted, so the participant prefers gains to occur immediately and losses to be delayed. The larger the value of k, the stronger this preference. A k of zero means the present and future are considered equal, while a negative k means the participant prefers losses to occur immediately and gains to be delayed.

For each set of choice questions, we found the point at which the participant switched from preferring the present outcome to the future outcome. We defined the indifference point as the midpoint between the two values for future outcomes where this switch occurred. We then calculated the participant's annual discount rate k from this midpoint using the hyperbolic discounting formula above. For participants whose preference did not switch, we assigned a discount rate at the limit of the range considered, i.e. either -0.01 or 0.5. This is a conservative approach that may underestimate the magnitude of the participant's true discount rate.

The third question in each questionnaire was a swing weighting question, to gauge how participants weight outcomes occurring in different domains (monetary versus environmental). Participants were presented with two options, each comprised of a monetary outcome and an environmental outcome, both at the extremes of the ranges considered in the choice questions. One option gave the best monetary outcome and worst environmental outcome, and the other gave the worst monetary outcome and best environmental outcome. Participants were asked to rank these options for importance (most favourable or most harmful, depending on whether the outcomes were gains or losses). They were then asked to assign a weight of 100 to the highest-ranked option, and weight the remaining option relative to the highest-ranked option. For example, assigning a weight of 50 to the remaining option would mean it is half as important as the top ranked option (von Winterfeldt and Edwards 1986).

We used the swing weighting responses to obtain participants' point of indifference between immediate outcomes in the two different domains. We refer to these measures as the participants' exchange rates, because they specify the size of the agricultural outcome the participant would be willing to exchange for a particular biodiversity outcome (or vice versa). We used these exchange rates to test whether differences in the perceived magnitude of agricultural and biodiversity outcomes affected the rate at which participants discounted outcomes over time.

A 4.2 Temporal discount rates

We excluded data from one participant whose responses to the choice questions switched back and forth more than once. This exclusion is consistent with the standards of a similar study (Hardisty and Weber, 2009). This left a sample size of n = 15 for the gain questionnaire and n = 18 for the loss questionnaire, with 14 participants completing both questionnaires.

The median annual discount rates for agricultural gains, agricultural losses, and biodiversity gains were very similar, while the median for biodiversity losses was lower (Fig. A4.1). However, this difference was not statistically significant, with large overlap in the 95% confidence intervals around the medians (Fig. A4.1). In all categories, participants gave a wide range of responses (Fig. A4.1). Indeed, for agricultural losses, participants' discount rates covered the full range of possibilities, from -0.01 to 0.5. For biodiversity losses, most participants' discount rates were less than 0.3, with a single outlier of k = 0.5.

There was no evidence of a difference in the discount rates given by participants on different days of the workshop (Fig. A4.2), indicating that participants' responses were not unduly affected by the different activities occurring on each day.

We used data from participants who completed both the gain and loss questionnaires (n = 14) to examine the consistency of individuals' discount rates. Individuals' annual discount rates were significantly linearly correlated across the different categories (Table A4.1). Individuals therefore gave consistent discount rates regardless of valence (gains and losses) or domain (agriculture and biodiversity).

Interestingly, the strongest and most significant linear correlation occurred between discount rates for agricultural gains and biodiversity losses.

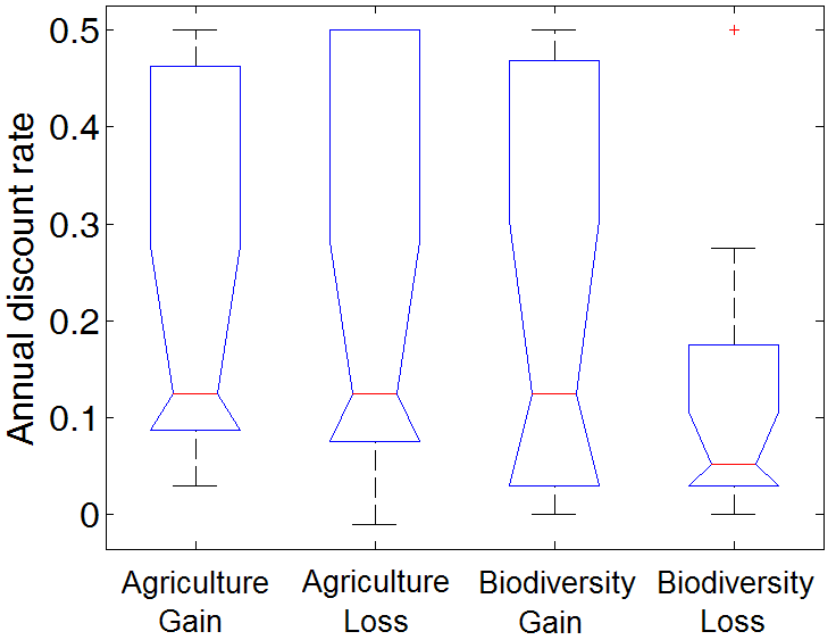

Fig. A4.1. Box and whisker plot of participants' annual discount rates for gains and losses in agriculture and biodiversity. The red lines show the median value, while the blue box shows the inter-quartile range. The notched section of the box around the median shows the 95% confidence interval around the median value. Black whiskers show the range of responses, while red crosses indicate outliers.

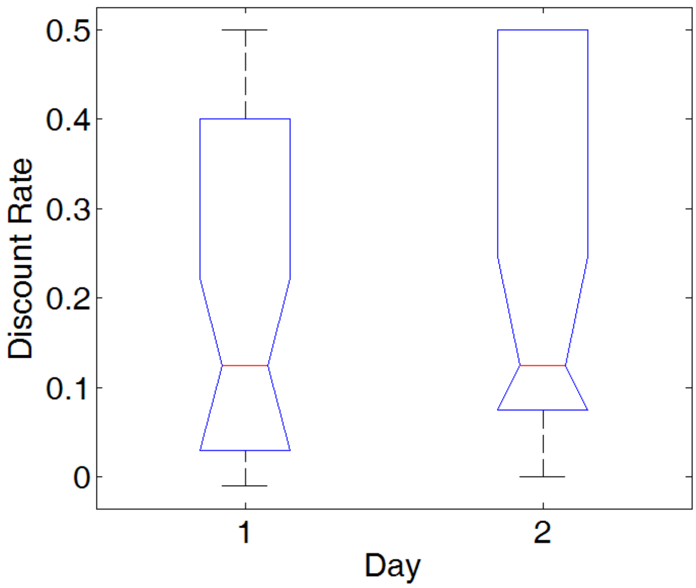

Fig. A4.2. Box and whisker plot of participants' annual discount rates on subsequent days of the workshop. The red lines show the median value, while the blue box shows the inter-quartile range. The notched section of the box around the median shows the 95% confidence interval around the median value. Black whiskers show the range of responses, while red crosses indicate outliers.

Table A4.1. Correlations between individuals' annual discount rates for gains and losses in agriculture and biodiversity

Outcome	Ag Gain	Ag Loss	Bio Gain	Bio Loss
Ag Gain	__			
Ag Loss	0.66*	__		
Bio Gain	0.71**	0.74**	__	
Bio Loss	0.90***	0.74**	0.85***	__

Note: Shows Pearson correlation co-efficient r, with * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$.

A 4.3 Exchange rates

In the swing weighting question, participants were asked to rank and weight two options in order of importance, assigning a weighting of 100 to the most important option (most harmful or most favourable, depending on the questionnaire). Five participants performed the weighting task incorrectly, for example, assigning weights that summed to 100 instead of assigning a weight of 100 to the most important option. Two participants were inconsistent in their ranking and weighting of options. The swing weighting responses of these seven participants were therefore excluded from further analysis. This left a sample size of $n = 13$, with ten participants completing both the gain and loss questionnaires.

The exchange rates express the utility participants experience from biodiversity outcomes relative to agricultural outcomes. Participants with high exchange rates experience more utility for biodiversity than participants with low exchange rates. Participants were willing to exchange between $68,627 and $17 million in extra agricultural productivity for an increase of 10% in the population numbers of a single native species. However, the majority of participants were willing to exchange less than $3.6 million (Fig. A4.3). Participants thought that a decrease of 10% in the population numbers of a native species was equivalent to a loss in agricultural productivity of between $68,627 and $6 million, with the majority again specifying less than $3.6 million (Fig. A4.3). The median exchange rates were not significantly different for gains and losses (Fig. A4.3). Again, there was no evidence that the day on which the questionnaire was taken influenced participants' responses (Fig. A4.4).

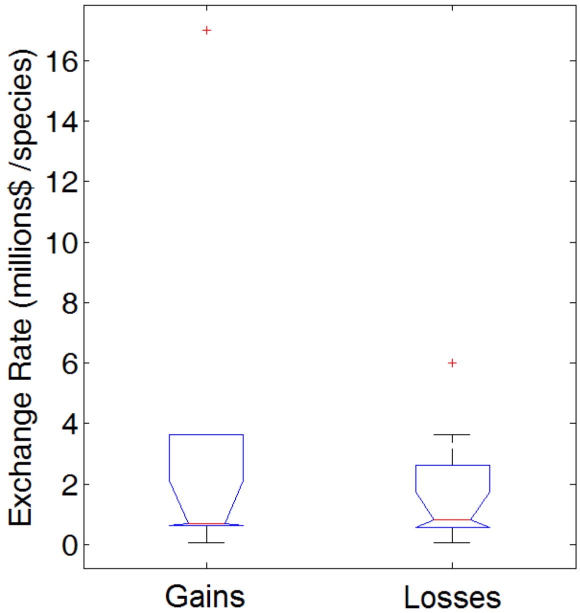

Fig. A4.3. Box and whisker plot of participants' exchange rates between agriculture and biodiversity, for both gains and losses. The exchange rate is expressed as the amount of gained/lost agricultural productivity (in millions of $) participants would be willing to exchange for an increase/decrease of 10% of the population numbers of a native species. The red lines show the median value, while the blue box shows the inter-quartile range. The notched section of the box around the median shows the 95% confidence interval around the median value. Black whiskers show the range of responses, while red crosses indicate outliers.

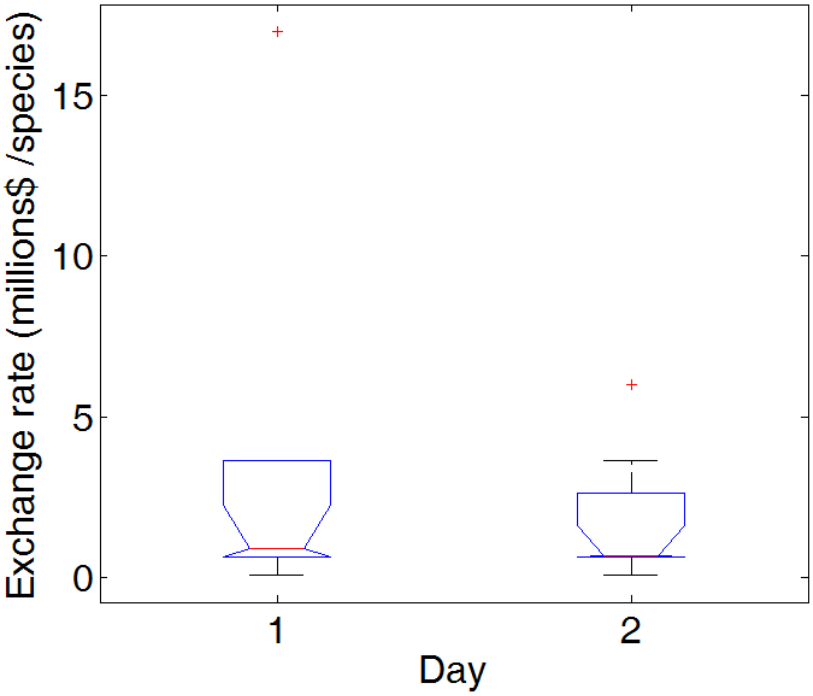

Fig. A4.4. Box and whisker plot of participants' exchange rates on subsequent days of the workshop. The red lines show the median value, while the blue box shows the inter-quartile range. The notched section of the box around the median shows the 95% confidence interval around the median value. Black whiskers show the range of responses, while red crosses indicate outliers.

Of the ten participants that completed the swing weighting questions for both gains and losses, four had the same exchange rate across both valences. The remainder of responses suggest a tendency for lower exchange rates for losses than for gains (Fig. A4.5). This means participants put less emphasis on biodiversity when thinking about lost agricultural productivity and species declines, than when thinking about increased agricultural productivity and increased species population numbers.

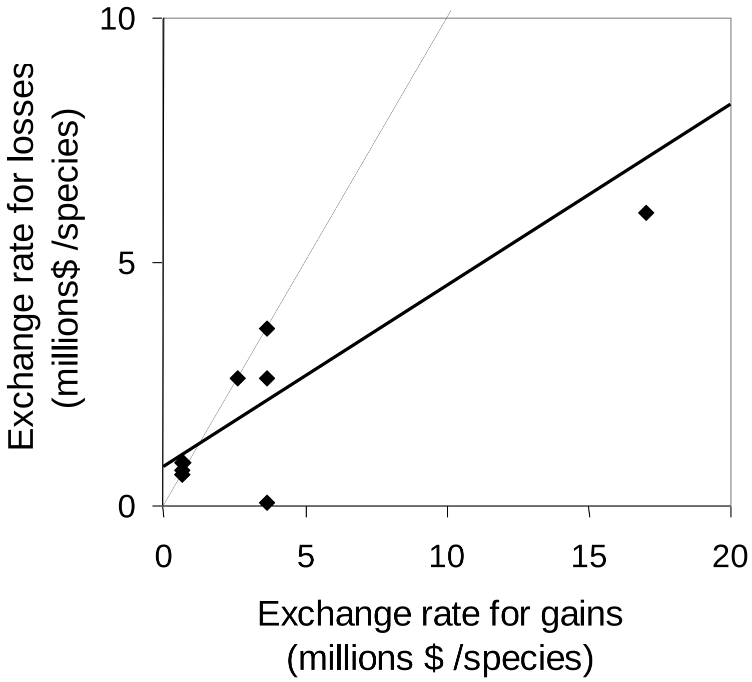

Fig. A4.5. Comparison of individuals' exchange rates for gains and losses. The dotted line marks where exchange rates for gains and losses are equal, while the solid line is a least squares linear regression line (c = 0.7974 [SE 0.3939], m = 0.318 [SE 0.0678]; $F_{1,8}$ =22.01, p = 0.0016, R^2 [adjusted] = 70%). The slope of this regression line is significantly different from a slope of 1 (with $p = 8.11 \times 10^{-6}$).

The 'magnitude effect' describes how people discount larger outcomes at a lower rate than smaller outcomes (Chapman, 1996). If the perceived magnitude of outcomes in different domains affected participants' discount rates in this way, we would expect participants with higher exchange rates (who experience more utility for biodiversity than agriculture) to have lower discount rates for biodiversity than for agriculture. We would therefore expect exchange rates to be negatively correlated with biodiversity discount rates and positively correlated with agriculture discount rates (Chapman, 1996). We in fact found the opposite, that exchange rates were significantly negatively correlated with agriculture discount rates (r = -0.4436, p = 0.034). There was no significant correlation between exchange rates and biodiversity discount rates (r = -0.278, p = 0.199).

A 4.4 Discussion

This study offers a unique perspective on temporal discounting, differing in several ways from previous time preference elicitation studies. Most studies eliciting time preferences have focused on monetary or health decisions for which the outcomes are purely personal, that is, the decision-maker receives or loses a monetary amount, or experiences an increase or decrease in their personal health. The few studies examining time preferences for environmental outcomes (which by definition must be societal outcomes), have compared these to personal monetary or health outcomes (Guyse et al., 2002; Hardisty and Weber, 2009).

In contrast with these previous studies, none of the outcomes in this study are personal; rather they are outcomes that will either be absorbed by others (the grains industry) or by the whole of society. The framing of our questionnaire was therefore unique, in that participants were asked for their preferences not as individuals, but as managers making decisions on behalf of society. Due to the composition of our study group, this was a scenario that most participants were familiar with.

An individual's discount rates tend to be consistent within a single domain (e.g. for all monetary outcomes), but can be quite different between domains. This is known as 'domain independence' (Chapman, 1996). Previous studies found evidence of independence between monetary and health domains (Chapman, 1996; Chapman and Elstein, 1995; Hardisty and Weber, 2009), but no evidence of independence between monetary and environmental domains (Hardisty and Weber, 2009). Our study is consistent with this finding, as we found no difference in individuals' discount rates for monetary and environmental outcomes. It is possible that health outcomes are discounted differently by participants because they elicit a more visceral response than either monetary or environmental outcomes (Hardisty and Weber, 2009).'

We found no difference in discount rates between gains and losses, in either monetary or environmental domains. This is inconsistent with previous studies, which have generally found that discount rates are higher for losses than for gains (Chapman, 1996), for both monetary and environmental outcomes (Hardisty and Weber, 2009). Our results were also inconsistent with previous findings in that we found no evidence of the magnitude effect (that larger outcomes are discounted at a lower rate), and for monetary outcomes we found the opposite. The unique framing of our study is likely to have influenced these results. But interpretation requires caution. It is also likely that our small sample size prevented us from detecting differences if present.

Feedback from participants indicated that the questionnaire was cognitively and emotionally difficult to perform. This may have contributed to the relatively high rate of excluded responses, although this could potentially be mitigated by providing further written and verbal explanation of the questions. Some participants said they felt pressure to provide 'the right' answers, which may mean their responses were not a true indication of their preferences. This reaction could be avoided by delivering the questionnaire in a more anonymous setting, for example as an online survey.

A 5.0 How can we incorporate time preference in multi-attribute decision-support?

The consequences of vertebrate pests include losses to agricultural production and elevated extinction risks for native flora and fauna. McLeod (2004) estimated these consequences for 12 pests, three of which are summarised in Table A5.1 below. Impacts on agricultural production were estimated using annual financial loss. Impact on biodiversity was inferred from the number of affected species listed in threat abatement plans or under the Commonwealth *Environment Protection and Biodiversity Conservation* Act 1999.

The time horizons over which agricultural losses and biodiversity impacts are typically considered vary. Impacts on agricultural production are often characterised over relatively short time horizons, say 30 years, because predictions into the distant future may be irrelevant due to changes in technology, market demand or environmental conditions. The conventions of risk assessment in conservation biology countenance the probability of extinction up to 100 years into the future (IUCN 2001).

Imagine you're asked to allocate a $10M pest control budget for foxes, goats and cats on the basis of the information presented in Table A5.1. You wish to allocate the budget proportional to the magnitude of harm caused by each pest. (Let's say that the technical feasibility and cost-effectiveness of control actions for the three pests are equivalent).

Table A5.1. Estimated agricultural and environmental consequences of three vertebrate pests in the absence of any management intervention. Agricultural losses are aggregated over 30 years (in real dollars). Environmental impacts are estimated over a century. (Adapted from McLeod 2004).

	Agricultural losses	Number of native species extinctions
Foxes	$525 M	34
Goats	$126.9 M	13
Cats	nil	37

The overall harm of a pest needs to combine consequences described in different units (i.e. financial loss and species loss for the example explored here). Foxes clearly cause more harm than goats, but the magnitude of the difference depends on your judgment (on behalf of broader society) of the relative importance of agricultural and environmental impacts. Likewise, the relative and absolute budget allocated to goat and cat control depends on how much emphasis is placed on species loss versus agricultural losses. Multiple attributes that are preferentially independent can be combined using the additive utility model (Keeney and Raiffa 1976),

$$v(x,y) = w_x v_x(x) + w_y v_y(y), \qquad \text{(A5.1)}$$

where v_x and v_y are single attribute utility functions scaled from 0 to 1, and w_x and w_y are attribute weights scaled between 0 and 1 and summing to 1. For our purposes, $v(x, y)$ describes *dis*utility, and we assume that v_x and v_y are linear functions between the best and worst values of X and Y.

Assigning weights is cognitively and emotionally difficult (Luce et al. 1999). The range of within-attribute consequences is critical to the normative interpretation of weights as the point of indifference, or exchange rate between any two attributes (Fischer 1995). Decision-makers frequently fail to understand range sensitivity, leading to arbitrary or meaningless weights (Keeney 2002). The cognitive and emotional demands of the task are made near impossible if consequences are described over different time scales, or if time preference varies across attributes.

The overwhelming response of decision analysts to the problem of time has been to ignore it. The results of the literature search reported in section A3 included the finding that not one of twenty multi-criteria analyses specified the time frame of impacts, or used any form of discounting (Fig. A3.3). In contrast, benefit-cost analyses routinely include discounting. Using our hypothetical budget allocation decision for pest control, here we illustrate the importance of this oversight and suggest a remedy.

A 5.1 The problem of weighting when time is ignored

A decision-maker using multi-criteria methods may be presented with the estimated consequences in Table A5.1 and asked to assign weights to agricultural loss and species loss. Common practice is for no provision of contextual information specifying the time horizon of estimates (Fig A3.3). Let's say after consideration of the information in Table A5.1 weights of 0.8 to agricultural loss and 0.2 to species loss are assigned.

Under the additive model the disutility of the three pests are foxes = 0.98, goats = 0.19 and cats = 0.20, leading to budget allocations of

Fox control	$10M × [0.98/(0.98 + 0.19 + 0.20)] = $7.15M,
Goat control	$10M × [0.19/(0.98 + 0.19 + 0.20)] = $1.39M, and
Cat control	$10M × [0.20/(0.98 + 0.19 + 0.20)] = $1.46M.

How can we interpret these weights? The range of consequences for agricultural loss is $525M – nil = $525M, and for species loss is 37 – 13 = 24 species. Normatively, the four-fold weighting assigned to agricultural loss implies indifference between a loss of $525M and 4 × 24 = 96 species extinctions, or a $5.47M loss per species extinction. Let's say this point of indifference represents the true value judgment of the decision-maker. However, we note that the validity of this interpretation rests critically on an assumption that in assigning weights, the decision-maker interpreted consequences as having no time delay.

Now let's say the information regarding the timing of estimated consequences is made available to the decision-maker. That is, agricultural impacts of foxes and goats are an aggregate of a per annum $17.5M and $4.23M loss, respectively (in real terms) over 30 years. Environmental impacts are expected number of species extinctions over 100 years; and let's say that the timing of extinctions is uniformly distributed over the 100 years (as for agricultural losses over 30 years).

We don't know the decision-maker's time preference (and hence discount rates) for the two attributes, but let's explore the implications of a number of scenarios. One scenario is to say that a real exponential discount rate of 5% for agricultural losses over 30 years is appropriate, broadly consistent with market interest rates. The 100 year time horizon for environmental impacts may invoke a hyperbolic discount rate, with k = 5%. The discounted (net present value) consequences under this scenario are shown in Table A5.2.

Table A5.2. Net present value of agricultural and environmental consequences of three vertebrate pests. Agricultural losses shown in Table A5.1 are discounted exponentially at a rate of 5% over 30 years. Species losses are discounted using a hyperbolic function with k = 5% over 100 years.

	Agricultural losses	Number of native species extinctions
Foxes	$269 M	12.0
Goats	$65 M	4.6
Cats	nil	13.1

Note that the effect of discounting has been to reduce the range of consequences for the two attributes to $269M for agricultural losses and 8.5 for species loss. If we (naively) retain weights of 0.8 for agricultural losses and 0.2 for species loss, there is a change in the implied point of indifference from $5.47M per species to $7.91M per species. That is, the effect of naïve weighting under this scenario is to overvalue species loss and undervalue agricultural loss, leading to misallocation of resources for pest control. Summary results of this discounting scenario together with four others are reported in Table A5.3.

Table A5.3. Five discounting scenarios and their implied point of indifference for weights of 0.8 and 0.2 assigned to agricultural and species loss, respectively. See text for details of Scenario C.

Discounting scenario	Range of net present value		Point of indifference
	Agricultural loss ($M)	Number of native species extinctions	
A. Agriculture: 3% exponential, 30yr Environment: 5% exponential, 100yr	343.0	5	$ 18.0 M per species
B. Agriculture: 5% exponential, 30yr Environment: 5% exponential, 100yr	269.0	5	$ 14.12M per species
C. Agriculture: 5% exponential, 30yr Environment: 5% hyperbolic, 100yr	269.0	9	$ 7.91M per species
D. Agriculture: 6% exponential, 30yr Environment: 3% hyperbolic, 100yr	240.9	11	$ 5.47M per species
E. Agriculture: 7% exponential, 30yr Environment: 1% hyperbolic, 100yr	217.2	17	$ 3.28 M per species

The points of indifference shown in Table A5.3 report a perverse trend. Scenario D is coincidentally equivalent to the 'true' value judgment of a point of indifference of $5.47M per species loss. Greater concern for future species loss (lower discount rates for environment) and less concern for future agricultural losses (higher discount rates for agriculture) seem to imply a lesser monetary point of indifference (Scenario E). That is, if the decision-maker *had* to decide between a loss to agriculture of $3.28M or loss of one species, she would choose randomly. Environmental impact counts for relatively little.

Scenarios A - C imply the exact opposite. Under scenario A, the decision-maker is indifferent to a choice of an $18M loss to agriculture or the loss of one species. The environmental impact appears to be much more important, despite discount rates for species loss being relatively large and rates for agriculture relatively small. These counter-intuitive outcomes arise because of failure to adjust weights in response to reduced ranges in attribute-specific consequences associated with discounting.

A 5.2 Remedying the problem

Fischer (1995) presents the arithmetic needed to adjust weights with a change in the range of attributes. Let's say a decision-maker assigns weights γ_x and γ_y to relatively large ranges of both attributes, bounded by best values denoted X^* and Y^*, and worst values, denoted X^0 and Y^0. The additive utility model is

$$V(x,y) = \gamma_x V_x(x) + \gamma_y V_y(y). \qquad \text{(A5.2)}$$

Discounting leads to a smaller range. Let's denote the bounds of the smaller range x^* and y^*, and x^0 and y^0. The adjusted weights, λ_x and λ_y are,

$$\lambda_x = \frac{\gamma_x \left[V_x(x^*) - V_x(x^0)\right]}{\gamma_x \left[V_x(x^*) - V_x(x^0)\right] + \gamma_y \left[V_y(y^*) - V_y(y^0)\right]}, \text{ and} \qquad \text{(A5.3)}$$

$$\lambda_y = \frac{\gamma_y \left[V_y(y^*) - V_y(y^0)\right]}{\gamma_x \left[V_x(x^*) - V_x(x^0)\right] + \gamma_y \left[V_y(y^*) - V_y(y^0)\right]}. \qquad \text{(A5.4)}$$

Note that the adjusted weights depend on the large range weights, γ_x and γ_y, and on $V_x(x^*) - V_x(x^0)$ and $V_y(y^*) - V_y(y^0)$, the (large range) utility differences between best and worst outcomes on attributes X and Y for the small range context.

Table A5.4 uses these equations A5.3 and A5.4 to calculate adjusted weights for discounted consequences under each of the five time preference scenarios. The effect of the adjustment is to preserve the 'true' value judgment of a point of indifference of a \$5.47M loss to agriculture per species loss. Notice that the adjusted weights for species loss (intuitively) increase as future losses are increasingly emphasised (through lower discount rates).

The budget allocations for the three pests under each of the five discounting scenarios is presented in Table A5.5. Results emphasise the resource implications of naïve weighting, with the budget allocated to cat control ranging from \$0.55M under Scenario A (where future environmental impacts are unimportant) to \$2.04M under Scenario E (where future environmental impacts are of relatively high importance).

Table A5.4. Adjusted weights for five discounting scenarios.

Discounting scenario	Adjusted weight		Point of indifference
	Agricultural loss ($M)	Number of native species extinctions	
A. Agriculture: 3% exponential, 30yr Environment: 5% exponential, 100yr	0.93	0.07	$ 5.47 M per species
B. Agriculture: 5% exponential, 30yr Environment: 5% exponential, 100yr	0.91	0.09	$ 5.47 M per species
C. Agriculture: 5% exponential, 30yr Environment: 5% hyperbolic, 100yr	0.85	0.15	$ 5.47 M per species
D. Agriculture: 6% exponential, 30yr Environment: 3% hyperbolic, 100yr	0.80	0.20	$ 5.47 M per species
E. Agriculture: 7% exponential, 30yr Environment: 1% hyperbolic, 100yr	0.71	0.29	$ 5.47 M per species

Table A5.5. Budget allocations for five discounting scenarios. Note that allocations for Scenario D are identical to the case where time preference is ignored. See text for details.

Pest	Scenario A		Scenario B		Scenario C		Scenario E	
	disutility	budget	disutility	budget	disutility	budget	disutility	budget
foxes	0.99	$7.73M	0.99	$7.62M	0.98	$7.31M	0.96	$6.76M
goats	0.22	$1.72M	0.22	$1.69M	0.21	$1.57M	0.17	$1.20M
cats	0.07	$0.55M	0.09	$0.69M	0.15	$1.12M	0.29	$2.04M

The computations for adjusting weights are not difficult. They could be retrospectively applied to the twenty multi-criteria case studies reported in section A3 for which time preference was completely ignored. Failure to meaningfully address time in multi-attribute decision-support probably reflects a pervasive naivety among analysts on the normative meaning and interpretation of weights (Keeney 2002).

Adjustment is not necessary when weights are elicited using consequences that describe net present value. Of course this requires specification of the form and magnitude of discounting for each criterion or attribute, a challenge which is common to conventional benefit-cost analyses. There is no professional consensus on what discount rate should be used (Harrison 2010). A review of the literature (Portney and Weyant 1999) concludes that 'those looking for guidance on the choice of a discount rate could find justification for a rate at or near zero, as high as 20% and any and all values in between.' Lack of consensus on an appropriate rate for market and non-market consequences is not an excuse for ignoring time preference altogether. Rather, it suggests the need for further empirical research along the lines of the work presented in section A4 of this report.

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BIOSECURITY SURVEY

Biosecurity and environmental management

Thank you for participating in this research project. This questionnaire will ask you to make judgements about the relative importance of different impacts of pests in Australia.

This questionnaire is not a test of your knowledge; rather it is an investigation of your preferences.

- It is requested that you read all the background information before completing each question.
- The survey consists of 3 questions. It should take no longer than 30 minutes to complete.

This is one of two questionnaires in this research project. In order to match up and compare the responses to each questionnaire, we need you to write your name below.

However, **this data will be de-identified**, that is, your name and any identifying information will be removed from your responses, and stored using an anonymous ID number only.

Your responses to this questionnaire will be stored separately from this form.

No identifying information will be kept with any of your responses.

Group results may be published in academic journals and presented at conferences but, again, no individuals will be identified.

Your name: ____

Your signature: ____

Signing above implies that you have read the information on this page and agree that your responses to this survey may be used in this study.

Feel free to ask for clarification about the survey questions or the research aims during the exercise. If you have any further questions please contact either the researcher Tracy Rout (tmrout@unimelb.edu.au) or her supervisor Dr Terry Walshe (twalshe@unimelb.edu.au).

This research has been approved by the Human Ethics Committee of the University of Melbourne (Application No. 0709557.8). If you have any complaints or queries that the have not been answered to your satisfaction, you may contact the Executive Officer, Human Research Ethics, The University of Melbourne, ph: 8344 2073; fax 9347 6739.

Biosecurity and environmental management

- Pest species identified as biosecurity threats vary in the magnitude and type of impacts they are likely to present in the Australian environment. Pest species impact on attributes such as agriculture, biodiversity, and human health.

- Impacts can occur over different time frames for different pest species. Some pest species will establish and spread quickly and have immediate impacts, whereas others will take longer to establish and spread and for their impacts to be felt.

- In addition, the benefits of different programmes to manage invasive species can be realised over different time frames. Some programmes may be able to achieve beneficial outcomes immediately, while others will take longer to achieve beneficial outcomes.

- Resources to mitigate the impact of pests are limited, and implementing any one management programme is likely to present **tradeoffs**, where decision makers must prioritise strategies according to the outcomes they consider to be most important.

- This survey aims to investigate how tradeoffs are affected by the **time frame** of impacts and benefits.

Questionnaire continues next page…

Question 1

As an invasive pest manager, you have a windfall in your management budget and can choose to **fund** one extra invasive pest management programme. You must choose between two programmes of equal cost, that both mitigate the impact of a pest on **agriculture**.

By mitigating this impact, these programmes will increase the productivity of the grains industry. This benefit will occur either **immediately** or after a **delay**.

You will need to indicate which of the two programmes you would choose to fund (Programme A or Programme B) in each of the 12 choice questions below.

1 a) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to grains industry if funded ($ gained)	Benefit will occur	Tick box
Programme A	5 million	Immediately	
Programme B	55 million	In 20 years	

1 b) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to grains industry if funded ($ gained)	Benefit will occur	Tick box
Programme A	5 million	Immediately	
Programme B	4 million	In 20 years	

1 c) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to grains industry if funded ($ gained)	Benefit will occur	Tick box
Programme A	5 million	Immediately	
Programme B	50 million	In 20 years	

Questionnaire continues next page…

1 d) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to grains industry if funded ($ gained)	Benefit will occur	Tick box
Programme A	5 million	Immediately	
Programme B	6 million	In 20 years	

1 e) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to grains industry if funded ($ gained)	Benefit will occur	Tick box
Programme A	5 million	Immediately	
Programme B	45 million	In 20 years	

1 f) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to grains industry if funded ($ gained)	Benefit will occur	Tick box
Programme A	5 million	Immediately	
Programme B	10 million	In 20 years	

1 g) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to grains industry if funded ($ gained)	Benefit will occur	Tick box
Programme A	5 million	Immediately	
Programme B	40 million	In 20 years	

1 h) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to grains industry if funded ($ gained)	Benefit will occur	Tick box
Programme A	5 million	Immediately	
Programme B	15 million	In 20 years	

Questionnaire continues next page…

1 i) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to grains industry if funded ($ gained)	Benefit will occur	Tick box
Programme A	5 million	Immediately	
Programme B	35 million	In 20 years	

1 j) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to grains industry if funded ($ gained)	Benefit will occur	Tick box
Programme A	5 million	Immediately	
Programme B	20 million	In 20 years	

1 k) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to grains industry if funded ($ gained)	Benefit will occur	Tick box
Programme A	5 million	Immediately	
Programme B	30 million	In 20 years	

1 l) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to grains industry if funded ($ gained)	Benefit will occur	Tick box
Programme A	5 million	Immediately	
Programme B	25 million	In 20 years	

Questionnaire continues next page…

Question 2

In this question you must again choose to **fund** one extra invasive pest management programme. You must choose between two programmes of equal cost, that both mitigate the impact of a pest on **biodiversity**.

By mitigating this impact, these programmes will significantly increase (by > 10%) the population numbers of native species. This benefit will occur either **immediately** or after a **delay**.

You will need to indicate which of the two programmes you would choose to fund (Programme A or Programme B) in each of the 12 choice questions below.

2 a) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to biodiversity if funded (# native species to increase)	Benefit will occur	Tick box
Programme A	10	Immediately	
Programme B	110	In 20 years	

2 b) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to biodiversity if funded (# native species to increase)	Benefit will occur	Tick box
Programme A	10	Immediately	
Programme B	8	In 20 years	

2 c) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to biodiversity if funded (# native species to increase)	Benefit will occur	Tick box
Programme A	10	Immediately	
Programme B	100	In 20 years	

Questionnaire continues next page…

2 d) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to biodiversity if funded (# native species to increase)	Benefit will occur	Tick box
Programme A	10	Immediately	
Programme B	12	In 20 years	

2 e) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to biodiversity if funded (# native species to increase)	Benefit will occur	Tick box
Programme A	10	Immediately	
Programme B	90	In 20 years	

2 f) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to biodiversity if funded (# native species to increase)	Benefit will occur	Tick box
Programme A	10	Immediately	
Programme B	20	In 20 years	

2 g) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to biodiversity if funded (# native species to increase)	Benefit will occur	Tick box
Programme A	10	Immediately	
Programme B	80	In 20 years	

2 h) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to biodiversity if funded (# native species to increase)	Benefit will occur	Tick box
Programme A	10	Immediately	
Programme B	30	In 20 years	

Questionnaire continues next page…

2 i) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to biodiversity if funded (# native species to increase)	Benefit will occur	Tick box
Programme A	10	Immediately	
Programme B	70	In 20 years	

2 j) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to biodiversity if funded (# native species to increase)	Benefit will occur	Tick box
Programme A	10	Immediately	
Programme B	40	In 20 years	

2 k) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to biodiversity if funded (# native species to increase)	Benefit will occur	Tick box
Programme A	10	Immediately	
Programme B	60	In 20 years	

2 l) Which programme would you choose to fund? (Please tick the box next to Programme A or B)

	Benefit to biodiversity if funded (# native species to increase)	Benefit will occur	Tick box
Programme A	10	Immediately	
Programme B	50	In 20 years	

Questionnaire continues next page…

Question 3

The table below shows two invasive pest management programmes that have benefits for:

- **agriculture**, increasing the productivity of the grains industry, and
- **biodiversity**, significantly increasing (by >10%) population numbers of native species.

Assume these benefits occur **without delay**, soon after the programmes are implemented.

Your first task is to **RANK** the two programmes in order of priority for funding, with a rank of 1 indicating the most favourable programme, and 2 the least favourable. Write your ranks in the allocated boxes below.

If, for example, you choose Programme A as your number 1 programme, then the increase in gains to the grains industry from $4 million to $55 million matters more to you than the change in number of increasing native species from 8 to 110 species.
If you judge these programmes to be equally favourable, you can rank them both as 1.

	Benefit to grains industry ($ gained)	Benefit to biodiversity (# native species to increase)	RANK	WEIGHT
Programme A	$55 million	8		
Programme B	$4 million	110		

Your next task is to quantify the rankings by assigning weights to the programmes. To do this, begin by **assigning a WEIGHT of 100 to the programme you ranked 1**. You must then judge the **importance of the remaining programme relative to a weight of 100 for the number 1 ranked programme**. Write your weights in the allocated boxes above.

For instance, if you consider the estimated benefit to be half as important as the number 1 ranked programme, give it a weight of 50. The weights you give must be whole numbers less than or equal to 100, but they do not have to add up to any particular value.
Note that if you ranked the programmes as equally favourable, their weights must also be equal.

- This is the end of the questionnaire -

Thankyou for your participation

Part B

Value of information analysis as a decision support tool for biosecurity

B 1.0 Introduction

Invasive species managers operate in unpredictable and imperfectly observable systems and often make decisions in the face of considerable uncertainty (Parma et al., 1998). For example, they may be uncertain about the spatial extent of an invasion, about the efficacy of treatment options, or about various life history characteristics of the species.

In some cases, managers have the option of reducing uncertainty by investing in monitoring or experimentation. However, this often means diverting resources away from on-ground control actions, or delaying actions until the results of research are known. It is therefore important for managers to assess the benefits and costs of collecting this additional information. Some uncertainties, although scientifically interesting to resolve, may not actually affect decision-making. Managers must determine whether investing in collecting additional information will lead to a better management outcome, and if so, how much better?

These questions can be answered using a method known as value of information (VOI) analysis (Raiffa and Schlaifer, 1961). VOI analysis was developed within the theory of information economics and has been applied to decision problems in such diverse fields as medicine (Groot Koerkamp et al., 2008; Singh et al., 2008), health risk management (Yokota and Thompson, 2004a, b), and resource exploration (Eidsvik et al., 2008). It has been recommended particularly as a decision support tool for complex problems with high stakes and large uncertainties (Yokota and Thompson, 2004b).

To be more specific, VOI analysis is useful in situations where:

- a decision must be made, for example, choosing between candidate management actions,
- there is uncertainty in elements of this decision, and
- information can be collected to resolve all or part of this uncertainty.

VOI analysis assesses the benefit of collecting this information, considering the context of the decision to be made.

Assume a manager must choose between several possible management actions, and this choice is affected by an uncertain variable. The simplest type of VOI calculation is the expected value of perfect information (EVPI) (Howard, 1966). This calculates the expected improvement in the outcome of the decision if all uncertainty could be resolved. The equation for the EVPI is:

$$\text{EVPI} = \int_{s\in S}[\max_{a\in A} u(a,s)] f(s)ds - \max_{a\in A}[\int_{s\in S} u(a,s)\, f(s)ds], \qquad \text{(B1.1)}$$

where $f(s)$ is the probability of the uncertain variable taking value s, and $u(a, s)$ is the utility (or 'goodness') of taking action a when the uncertain variable has value s.

The first half of this equation calculates the expected utility with perfect information, assuming that if the decision-maker knew the value s of the uncertain variable, they would choose the action with the highest utility for that particular value. This utility is then multiplied by the probability that the true value is s, and summed for all possible values of s. The second half of the equation describes the scenario under uncertainty, assuming the decision-maker will take the action with the highest expected utility across all possible values of the uncertain variable. In this way, the equation finds the difference in expected utility between the best decision given perfect information, and the best decision under uncertainty. That is, the calculation answers the question, 'what is the difference in the expected outcome of the decision under certainty and uncertainty?'. If the utilities are measured in dollars, then the output of this calculation is the absolute maximum that should be spent on research or monitoring to improve knowledge about this uncertain variable.

In this report we demonstrate how VOI analysis could be used for practical decision-making in biosecurity, focusing on the common post-border decision problem of choosing whether to eradicate or contain an invasion. Throughout this report, we use the value of perfect information to find the maximum amount to invest in reducing uncertainty. We show how the analysis can be tailored to a specific management problem, illustrated with a case study of red imported fire ants in south-east Queensland.

B 2.0 Prototype for a post-border biosecurity decision

Here we develop a prototype VOI analysis for deciding whether to eradicate or contain an existing infestation. We consider the decision as a one-off, irrevocable allocation of resources to either eradication or containment. The expected costs and benefits of either action are a function of the extent of the infestation. From analysis of these costs and benefits we can determine a threshold extent, above which it is optimal to contain, and below which it is optimal to eradicate. Uncertainty in the extent of the infestation induces uncertainty about the optimal decision. In the circumstances we consider, we have the option to learn the extent of infestation precisely before committing our resources. We calculate the expected improvement in management from obtaining that information, allowing us to determine whether it is worth the cost.

B 2.1 The decision model

Let x be the extent of a circular infestation in hectares. If we choose the "contain" action, we will incur an expense that is proportional to the perimeter of infestation, and we will seek to contain the infestation at that extent for the indefinite future. The cost would be spread over the time frame of interest: this might be a fixed time horizon, or else might be viewed as the net present value of annual payments made over an infinite time horizon, either way, the cost is finite. Thus, the cost of containment (Fig. B2.1a) is

$$Cost(C) = c_1 \cdot 2\sqrt{\pi x}\,, \qquad \text{(B2.1)}$$

where c_1 is the long-term cost of containment per 100m of perimeter.

If we choose the "eradicate" action, we incur a large, immediate expense that is proportional to the areal extent of infestation. If the eradication succeeds, the infestation is removed and there are no further costs. If the eradication fails, then the containment cost is incurred and we assume for the sake of simplicity that the infestation remains at the original extent in perpetuity. The probability of failure is an increasing function of the extent of infestation, taking a sigmoid shape (Fig. B2.1b),

$$p(\text{failure}) = \frac{1}{1+e^{-m(x-a)}}\,, \qquad \text{(B2.2)}$$

where a is the area at which the probability of failure is 50%, and m measures how steep the failure curve is near the inflection point. Then, the expected cost of eradication (Fig. B2.1a) is

$$Cost(E) = c_2 x + \frac{2c_1\sqrt{\pi x}}{1+e^{-m\ x-a)}}\,, \qquad \text{(B2.3)}$$

where c_2 is the cost of eradication per hectare, and the second term is the cost of containment times the probability of failure to eradicate.

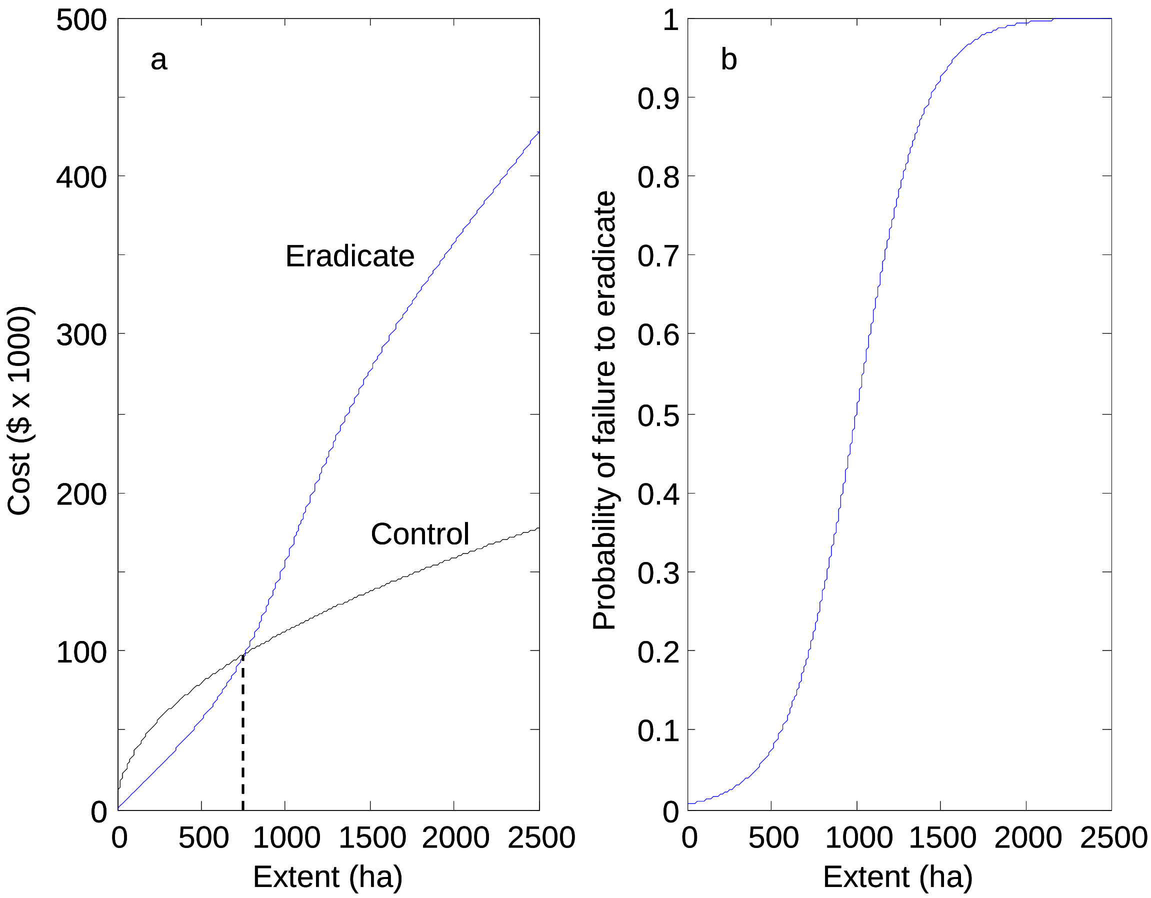

Fig. B2.1. Costs of management actions as a function of extent of infestation. (a) Costs of eradication and containment, where the cost of containment (c_1) is $1000 per 100m of perimeter and the cost of eradication (c_2) is $100 per hectare. The total costs of containment and eradication are equal when the extent of infestation is 753 ha. (b) Probability of failure to eradicate as a function of extent of infestation, where the half-effectiveness area (a) is 1000 ha, and the efficiency slope (m) is 0.005.

In addition to the costs of management, we need to consider the losses associated with the long-term presence of the infestation (due to loss of production, social amenity, etc.). It is reasonable that these losses are proportional to the extent of infestation. If the "contain" action is taken, the long-term extent of infestation is the current extent of infestation, *x*. If the "eradication" action is taken, the long-term extent of infestation is 0 if eradication succeeds, and *x* if eradication fails. Therefore, the expected loss, as a function of the initial extent of infestation, is

$$Loss = \begin{cases} c_3 x & \text{if containment} \\ \dfrac{c_3 x}{1+e^{-m(x-a)}} & \text{if eradication} \end{cases}, \qquad \text{(B2.4)}$$

where c_3 is loss per hectare of infestation (Fig. B2.2a).

The combined losses and costs, *T*, can be found by summing equations B2.1, B2.3, and B2.4,

$$T = \begin{cases} 2c_1\sqrt{\pi x} + c_3 x & \text{if containment} \\ c_2 x + \dfrac{2c_1\sqrt{\pi x} + c_3 x}{1+e^{-m(x-a)}} & \text{if eradication} \end{cases}. \qquad \text{(B2.5)}$$

The objective to minimize the combined losses and costs gives rise to a threshold extent of infestation, *x**, below which it is optimal to attempt eradication, and above which it is optimal to commit to long-term containment (Fig. B2.2b):

$$x^*: 2c_1\sqrt{\pi x^*} + c_3 x^* = c_2 x^* + \frac{2c_1\sqrt{\pi x^*} + c_3 x^*}{1+e^{-m\ x^*-a}}. \qquad \text{(B2.6)}$$

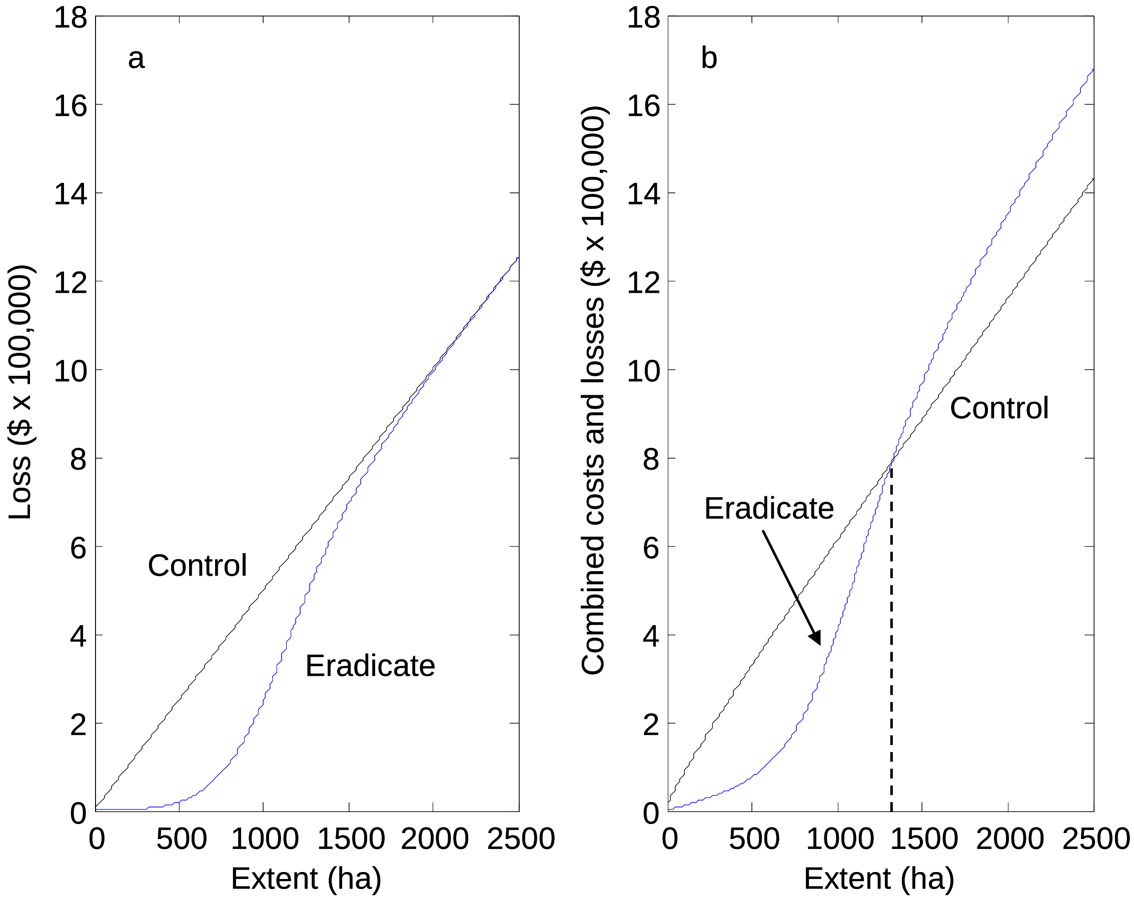

Fig. B2.2. Production and amenity losses (a) combined with management costs (b), as a function of initial extent of infestation, for two management actions. The production and amenity loss rate (c_3) is $500 per hectare. The decision threshold occurs at 1321 ha; if the extent of infestation is less than this, the best course of action is eradication, otherwise, the best course of action is long-term containment. At this level of infestation, the cost of eradication is $239,000 and the cost of containment is $129,000, but eradication is expected to reduce the production and amenity losses more than containment.

B 2.2 Binary uncertainty

Now, suppose that we are uncertain about the extent of infestation, x. This uncertainty about the state of the system may induce uncertainty about which action to take. Further, let us suppose that we could undertake a survey that would allow us to reduce this uncertainty before we had to make the decision (and suppose that the survey could be conducted fast enough so there were no consequences associated with delaying action, other than the cost of the survey). How much would this survey be worth to us?

First, by way of a simple illustration of the value of perfect information, imagine that our uncertainty is binary, that is, the extent is either 750 ha (small) or is 1750 ha (large) (Figure B2.3).

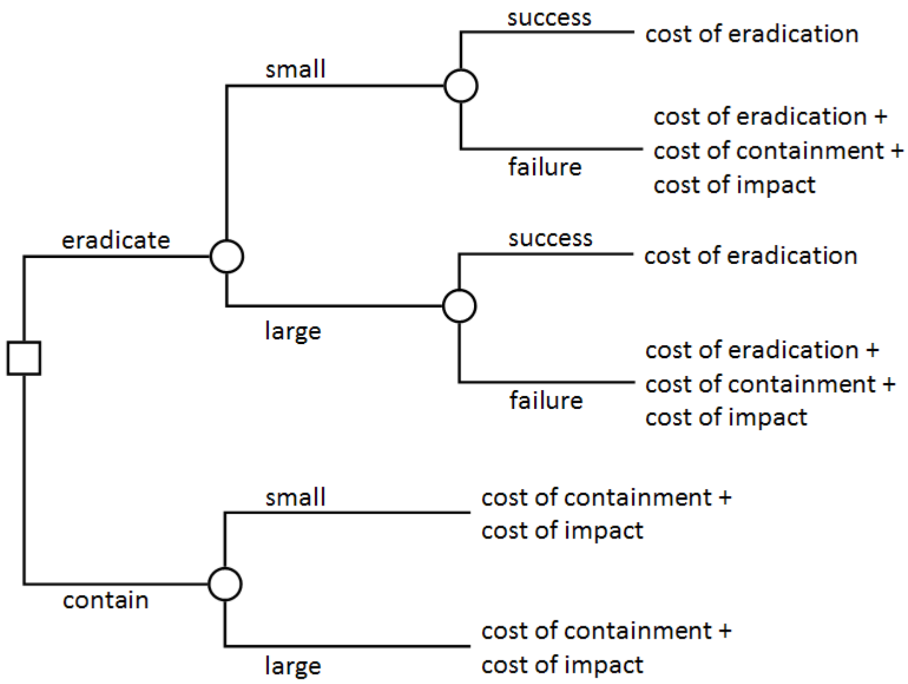

Fig B2.3. A decision tree illustrating the choice between eradication and containment for the scenario with binary uncertainty in the extent of the infestation. The costs of eradication, containment, and impact are greater for large infestations, as given by eqs. B2.1, B2.3 and B2.4. The probability that eradication will fail is also greater for large infestations, as given by eq. B2.2.

A standard analysis of the expected value of information (eq. B2.1) using the parameters given in Figs. B2.1 - B2.3, gives the total costs and losses shown in Table B2.1.

With a prior belief of 0.4 that the extent is "small", the best action to take in the face of uncertainty is to eradicate, because the expected total loss is \$776.9K vs. \$802.8K. If we could resolve that uncertainty ahead of time, we would eradicate if the extent is small (expected loss = \$180.1K), and contain if the extent is large (expected loss = \$1.023 M). Averaging over the prior beliefs that we would discover those states of nature, the expected total loss, provided we can resolve uncertainty first, is \$686.0K. Thus, by reducing uncertainty, we decrease our expected loss by \$90,890. So the expected value of perfect information is \$90,890, and we should be willing to pay up to that amount for the survey that would let us know the extent of the infestation.

Table B2.1. Expected value of perfect information with binary uncertainty in the extent of infestation. The entries are the combined costs and losses associated with each action and the extent of the infestation. The parameters for the cost and loss functions are those given in Figs. B2.1 - B2.3.

	"Small" extent (750 ha) Belief = 0.4	"Large" extent (1750 ha) Belief = 0.6	Weighted average
Action: Contain	\$472,080	\$1,023,300	\$802,810
Action: Eradicate	\$180,130	\$1,174,800	\$776,920
Best	\$180,130	\$1,023,300	\$686,030
EVPI			\$ 90,890

B 2.3 Continuous uncertainty

Next, consider a more realistic situation, and suppose instead that our uncertainty about the extent of infestation is continuous, and can be expressed by a probability distribution, $f(x)$, defined for $0 \leq x < \infty$. For example, our prior belief that the extent is x might be described by a lognormal distribution with mean μ and standard deviation σ,

$$f(x) = \frac{1}{x\sqrt{2\pi\sigma^2}} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}} = \frac{1}{\sigma x}\phi\left(\frac{\ln x - \mu}{\sigma}\right), \tag{B2.7}$$

where $\phi(z)$ is the standard normal probability density function.

The expected cost (EC) of taking the "contain" action is found by integrating the total loss (eq. B2.5) over the range of possible extents, weighted by our prior belief in the extent, that is,

$$\begin{aligned} EC(\text{"contain"}) &= \int_x T(x \mid \text{"contain"}) f(x) dx \\ &= \int_0^\infty \left(c_1\sqrt{\pi x} + c_3 x\right) f(x) dx \end{aligned} . \tag{B2.8}$$

The expected cost of taking the "eradicate" action is found in a similar manner,

$$\begin{aligned} EC(\text{"eradicate"}) &= \int_x T(x \mid \text{"eradicate"}) f(x) dx \\ &= \int_0^\infty \left(c_2 x + \frac{2c_1\sqrt{\pi x} + c_3 x}{1 + e^{-m(x-a)}} \right) f(x) dx \end{aligned} . \tag{B2.9}$$

The best action in the face of uncertainty is the minimum of equations B2.8 and B2.9, that is, the action that minimizes the expected total loss. The expected total loss in the face of uncertainty, EC_u, is

$$EC_u = \min[\int_x T(x\,|\text{"eradicate"})\, f(x)dx,\ \int_x T(x\,|\text{"contain"})\, f(x)dx]\,. \qquad \text{(B2.10)}$$

If we can resolve uncertainty about the extent first, before making the decision, then we would take the "eradicate" action if we find out that x is less than x^*, and the "contain" action if we find out that x is greater than x^*. Thus, prior to collecting that information, the expected cost of the decision under certainty, EC_c, is

$$\begin{aligned} EC_c &= \int_0^{x^*} T(x;\text{"eradicate"})\, f(x)dx + \int_{x^*}^{\infty} (x;\text{"contain"})\, f(x)dx \\ &= \int_0^{x^*} \left(c_2 x + \frac{2c_1\sqrt{\pi x} + c_3 x}{1+e^{-m(x-a)}} \right) f(x)dx + \int_{x^*}^{\infty} \left(c_1\sqrt{\pi x} + c_3 x \right) f(x)dx \end{aligned}, \qquad \text{(B2.11)}$$

and the expected value of information is the difference between the expected cost under uncertainty and the expected cost under certainty,

$$EVPI = EC_u - EC_c\,. \qquad \text{(B2.12)}$$

Consider the set of parameters given above, for which $x^* = 1321$ ha. Suppose that our belief about the extent of infestation can be characterized as a lognormal distribution with $\mu = \ln 1000$ and $\sigma = 0.3$ (Fig. B2.3). When the uncertainty about the extent takes a continuous distribution, the probability that the extent of infestation is less than the decision threshold is 0.823 (Fig. B2.4). In the face of uncertainty, the expected total loss of taking the "contain" action is \$636,154, and the expected total loss of taking the "eradication" action is \$481,526, so the best course of action is eradication, reflecting the weight of evidence that the extent is lower than the decision threshold. But there is a 17.3% risk of making the wrong decision. If the extent of infestation can be determined before the decision is made, the expected total loss is \$465,663. Thus, the expected value of information is \$15,863, which is the maximum we should spend reducing uncertainty in the extent of the invasion.

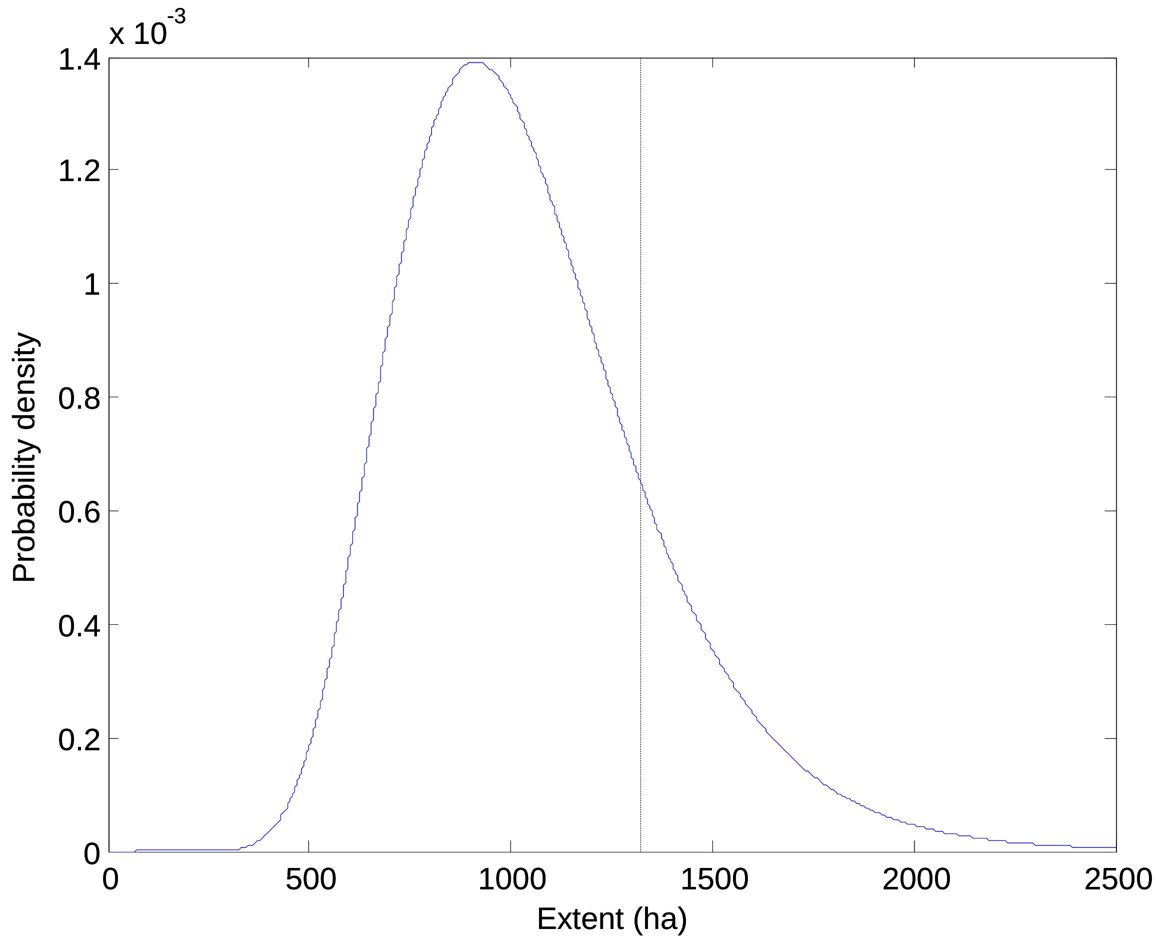

Fig. B2.4. Uncertainty in the extent of infestation, expressed as a log-normal distribution with mean $\mu = \ln(1000)$ and standard deviation $\sigma = 0.3$. The probability that the extent is less than the threshold (x^*) is 0.823.

B 3.0 Tailoring the analysis to a specific management problem

We now illustrate how our prototype VOI analysis can be applied to a specific management situation, using an example of red imported fire ant management in south-east Queensland. Red imported fire ants (*Solenopsis invicta*, hereafter 'fire ants') were first detected in Brisbane in early 2001 (Moloney and Vanderwoude, 2002). Since that time they have been the subject of a major eradication campaign, managed by the Biosecurity Queensland Control Centre (BQCC) (Moloney and Vanderwoude, 2002). One of the world's 100 worst invaders (Lowe et al. 2000), fire ants damage agricultural crops, injure livestock, and affect human health and ecosystems (Moloney and Vanderwoude, 2002). They are a significant pest in the United States, where over 7 billion dollars is spent on control each year (Pimentel et al. 2007).

In the early stages of the Brisbane eradication campaign, fire ants were present at high density within a relatively small area. While eradication efforts successfully reduced population density, occasional long distance dispersal has led to a very large area (approximately 95,000 ha) being occupied at a low density (Telford and Wylie, in preparation). Reflecting these changed circumstances, the focus of management has shifted from intensive surveillance and treatment of a small area, to methods better suited to eradication over a larger area.

This new approach has been informed by quantitative models of fire ant spread under alternative surveillance and control strategies (Schmidt et al. 2010; Spring 2008; Spring et al. 2009, 2010a, 2010b). One of the main findings of modelling research is that if eradication is to be a viable option, new methods will be required to search larger areas at lower cost. Remote sensing technology, which uses an infra-red camera from a helicopter, was identified as a candidate method and recommended for further evaluation. Modelling work indicates there is a threshold level of sensitivity of remote sensing, below which eradication is unlikely to be feasible.

Other cost-effective strategies for containment and eradication are also being considered. One potential strategy is extensive broadbaiting, in which poisoned bait is applied over general areas of infestation. BQCC is currently conducting trials to further evaluate the efficacy of broadbaiting and thereby determine its cost-effectiveness as a containment or eradication method.

To show how VOI analysis can answer practical management questions, we calculate the value of learning about these uncertain variables: the sensitivity of remote sensing and the efficacy of baiting. VOI analysis can tell us how much effort should be expended on research and evaluation of these methods, and if it may be more cost-effective to simply implement these methods despite uncertainty. As in our prototype analysis, we also consider uncertainty about the current spatial extent of the invasion. We intend this VOI analysis to complement recent work by Ward and Kompas (2010), who consider a cost-benefit analysis for fire ant management, and calculate the VOI for resolving uncertainty in the predicted benefits of management.

Although we have attempted to capture the key elements of the fire ant decision problem, our model of fire ant dynamics and management is highly simplified. For this reason the analysis we present here is intended to be an illustration of the decision problem, and not to provide decision support for management. In the discussion section we outline the steps needed to develop this analysis into a practical decision support tool.

B 3.1 Fire ant treatment methods

Several different actions are employed to detect and kill fire ant nests (Table B3.1).
Two kill methods are used: broadbaiting (“baiting”), and nest injection, in which poison is applied directly into detected fire ant nests. Baits contain poison and an attractant, so they are taken back to undetected nests by fire ant workers (Moloney and Vanderwoude, 2002). Baits can be distributed on foot, from all-terrain vehicles, or from the air (Moloney and Vanderwoude, 2002). Experience in North America indicates that baiting is between 80 and 95% effective (Barr et al., 2005), although its efficacy for fire ants in Queensland is uncertain. To be conservative we have used the lower bound of 80% efficacy as the point estimate in our model (Table B3.1). Nest injection is believed to be fully effective in killing fire ant nests (Table B3.1), but can only be applied after a nest is detected.

The most effective detection method is surveying with odour detection dogs, which have close to a 100% nest detection rate (Telford and Wylie, in preparation). To date, 8 dogs have been tested and are routinely used to survey for fire ants (Telford and Wylie, in preparation). This surveillance method is also the most expensive (Table B3.2), because two handlers must accompany the dog, and relatively few hectares can be searched per day. Visual surveillance, where trained BQCC field staff form an evenly-spaced line and move forward uniformly to scan an area for fire ant nests, has an

80% nest detection rate (Telford and Wylie, in preparation). Although it is less effective than canine surveillance, visual surveillance is cheaper per hectare surveyed (Table B3.2).

Remote sensing involves capturing images of a landscape with an infra-red camera from a helicopter, and analysing the images to map the location of fire ant nests (Vogt, 2004). Testing in North America has found this method capable of detecting up to 79% of fire ant nests within an area (Vogt and Wallet, 2008). The technology is currently being developed for application in south-east Queensland, and its efficacy in this setting is currently unknown (Table B3.1). Because large areas can be covered quickly and easily with remote sensing, it is expected to be substantially cheaper per hectare than on-ground surveillance methods when a large area is searched (Table B3.2).

Table B3.1. Efficacy of fire ant nest detection and kill methods

Kill method	Estimated efficacy $\lambda = p$(killing nest)
Nest injection	1 (Grant Telford, *pers. comm.*)
Baiting	Currently uncertain, best estimate is 0.8 (Barr et al., 2005)
Detection method	Estimated sensitivity $\delta = p$(detecting nest | present)
Canine surveys	0.99 (Telford and Wylie, in preparation)
Visual surveys	0.8 (Telford and Wylie, in preparation)
Remote sensing	Currently unknown

Table B3.2. Costs of fire ant nest detection and kill methods

Parameter	Cost per ha	Source
Cost of tracking with dogs + nest injection (/ ha)	$600	Approximate, D. Spring pers. comm.
Cost of visual surveys + nest injection (/ ha)	$366.34	(Telford and Wylie, in preparation)
Cost of remote sensing + nest injection (/ ha)	$223.17	$40 (Telford and Wylie, in preparation) + the cost of injection (estimated as half the cost of visual surveys + nest injection)
Cost of baiting (/ ha)	$70	D. Spring pers. comm.

B 3.2 The decision model

We frame the decision in the same way as the previous section, that is, broadly as a choice between eradication and containment of fire ants. Let x be the extent of the fire ant infestation in hectares, which for simplicity we assume to be roughly circular. If eradication is chosen, a one-off treatment will be applied across the entire extent x, which may or may not be successful in eradicating fire ants. If containment is chosen, treatment will be applied annually to a ring of width b around the outside of the infestation (Fig. B3.1), which we assume will successfully contain the infestation to area x.

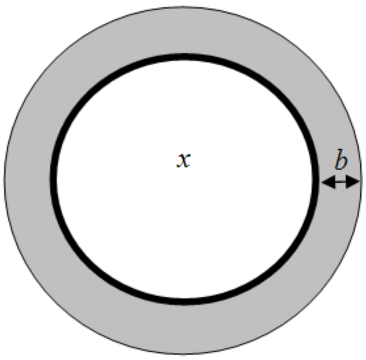

Fig. B3.1. Diagram showing the infestation area x (outlined in bold), and the area in which containment actions are applied (shaded in grey) defined by buffer width b.

The annual cost of containment is then $c\left(\sqrt{\pi x}b + \pi b^2\right)$, where c is the per hectare cost of the treatment applied. Containment will be applied every year from now (t = 0) indefinitely into the future ($t = \infty$). Using standard exponential discounting, the net present cost of containment is therefore

$$Cost(C) = \sum_{t=0}^{\infty} \frac{c\left(\sqrt{\pi x}b + \pi b^2\right)}{(1+j)^t} \qquad \text{(B3.1)}$$

where j is the annual discount rate. Throughout this section we use a discount rate of j = 5%. Eradication is a one-off management expenditure, but if eradication fails we assume containment must then be enacted. The cost of eradication is therefore

$$Cost(E) = cx + (1 - p(\text{success}))Cost(C) \qquad \text{(B3.2)}$$

where p(success) is the probability that eradication will be successful.

The probability that eradication will be successful, and that containment will eliminate all nests within the treatment buffer, depends on the combination of detection and kill actions used as part of the eradication or containment strategy. A strategy may comprise a number of dog surveys, visual surveys, remote sensing surveys and rounds of baiting. Assuming these actions are independent, the probability an individual nest will survive treatment is:

$$p(\text{survive}) = (1-\delta_{dogs})^{n_{dogs}}(1-\delta_{visual})^{n_{visual}}(1-\delta_{remote})^{n_{remote}}(1-\lambda_{bait})^{n_{bait}} \qquad \text{(B3.3)}$$

where δ_y is the sensitivity of detection method y, n_y is the number of surveys with method y, λ_{bait} is the probability the nest will be killed with bait, and n_{bait} is the number of rounds of bait applied.

We assume the nests have a uniform density γ across the extent, which means the total number of nests is given by γx. The probability all nests within the treatment area will be killed is then:

$$p(\text{success}) = (1 - p(\text{survive}))^{\gamma z} \qquad \text{(B3.4)}$$

where z is the treatment area, which is

$$z = \begin{cases} \sqrt{\pi x}b + \pi b^2 & \text{if containment} \\ x & \text{if eradication} \end{cases}. \qquad \text{(B3.5)}$$

Throughout this analysis we assume a fire ant density in the treated area of $\gamma = 1$ nest / ha.

Along with the cost of managing fire ants, there will be losses incurred as a result of fire ant presence. We assume this impact is proportional to the area occupied. If containment is chosen, the long-term extent of the infestation will remain at the current extent *x*. If eradication is chosen, the long-term extent of the infestation will be zero if eradication is successful, and *x* if eradication fails. The expected loss caused by the long-term presence of fire ants is therefore given by:

$$Loss = \begin{cases} \sum_{t=0}^{\infty} \frac{c_i x}{(1+j)^t} & \text{if containment} \\ (1 - p(\text{success}) \sum_{t=0}^{\infty} \frac{c_i x}{(1+j)^t} & \text{if eradication} \end{cases} \qquad \text{(B3.6)}$$

where c_i is the per hectare annual cost of impact, and *j* is the annual discount rate. For simplicity, we assume that the impact losses and costs of management are discounted at the same exponential rate.

A recent cost-benefit analysis estimated the potential loss due to the long-term presence of fire ants in south-east Queensland to be as much as $43 billion (Antony et al., 2009). We simplified the method applied in that analysis (see Appendix B1) to derive an annual cost of fire ant impact of $1031.48 / ha. As in Antony et al. (2009), this includes the costs of ongoing private treatment of fire ant infested areas, the health care costs associated with fire ant stings, and the impact of fire ants on ecosystem services.

The combined total cost and loss of each action, *T*, can thus be found by summing equations B3.1, B3.2 and B3.6:

$$T = \begin{cases} \sum_{t=0}^{\infty} \frac{c\left(\sqrt{\pi x}\, b + \pi b^2\right) + c_i x}{(1+j)^t} & \text{if containment} \\ cx + (1 - p(\text{success}) \sum_{t=0}^{\infty} \frac{c\left(\sqrt{\pi x}\, b + \pi b^2\right) + c_i x}{(1+j)^t} & \text{if eradication} \end{cases} . \qquad \text{(B3.7)}$$

If all model parameters are certain, the most cost-effective management strategy is the one with the lowest total cost, as given by eqn. B3.7 above. We will now examine how different management strategies perform under uncertainty in three model parameters: the extent of the infestation, the sensitivity of remote sensing, and the efficacy of baiting. We use value of information analysis to calculate the expected improvement in the outcome of decisions from resolving those uncertainties.

B 3.3 Uncertainty in the extent of the infestation

We investigate one uncertain parameter at a time, starting with the extent of the infestation, which is estimated as 95,000 ha (Telford and Wylie, in preparation). To confine our uncertainty to a single variable, we consider only management strategies involving detection and kill methods with a known efficacy.

We compare two management strategies:

- a containment strategy applied to a buffer around the perimeter of the infestation, involving 2 canine surveys and 2 visual surveys per year and injection of detected nests with poison, and
- an eradication strategy applied over the entire extent of the infestation, involving 2 canine surveys and 1 visual survey, and injection of detected nests with poison.

These strategies were chosen to provide an interesting conceptual model, and are not based on current practice—the predominant treatment currently applied within the eradication project is a combination of visual surveys and baiting (C. Jennings, pers. comm.). For the containment strategy, the intensive combination of canine and visual surveys is necessary to give a high probability of eliminating all nests within the containment buffer (Fig B3.2), consistent with the model assumption that containment is successful in maintaining the infestation at its current extent.

Given the cost estimates in Table B3.2, the containment strategy will cost $1932.68 per hectare per year, while the eradication strategy will cost $1566.34 per hectare over a larger area. However, the total cost of each strategy includes the cost of management as well as the costs of fire ant impact (eq. B3.7). The most cost-effective strategy to take depends on the extent of the infestation (Fig. B3.3). Eradication is optimal for an infestation size of up to 135,849 ha, while containment is optimal if the infestation is any larger (Fig. B3.3).

Given that the extent of the infestation affects which strategy is the most cost-effective, we next consider how uncertainty about the extent affects decision-making.

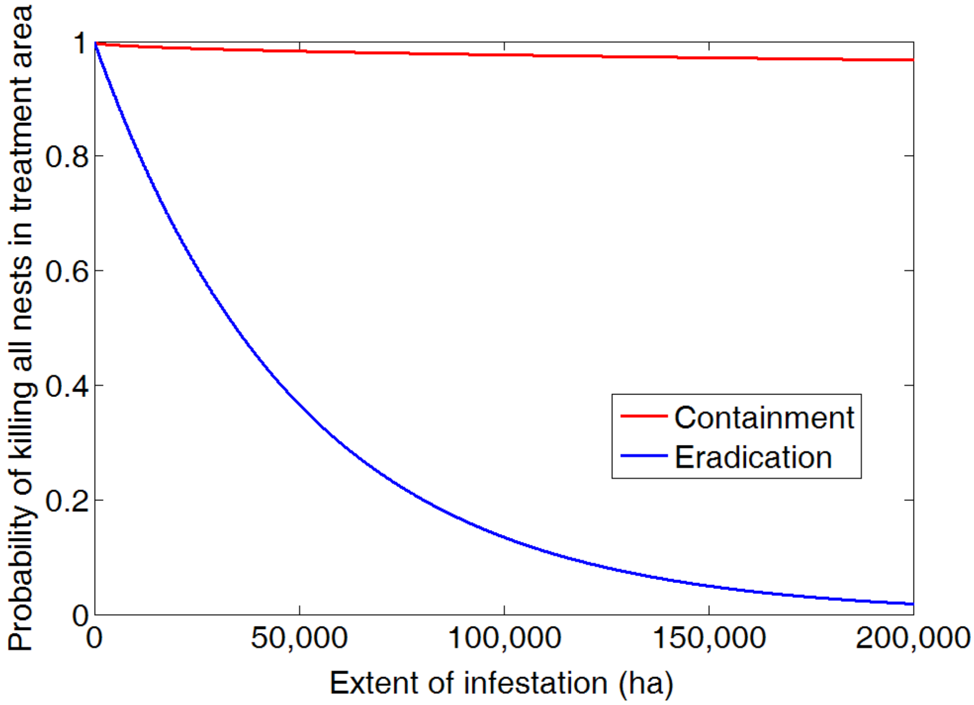

Fig B3.2. The probability of killing all fire ant nests within the treated area under different management strategies, and for different infestation extents. The treatment area is either the containment buffer (containment), or the entire extent (eradication). The probabilities are calculated with eq. B3.4, using the parameter estimates in Table B3.1.

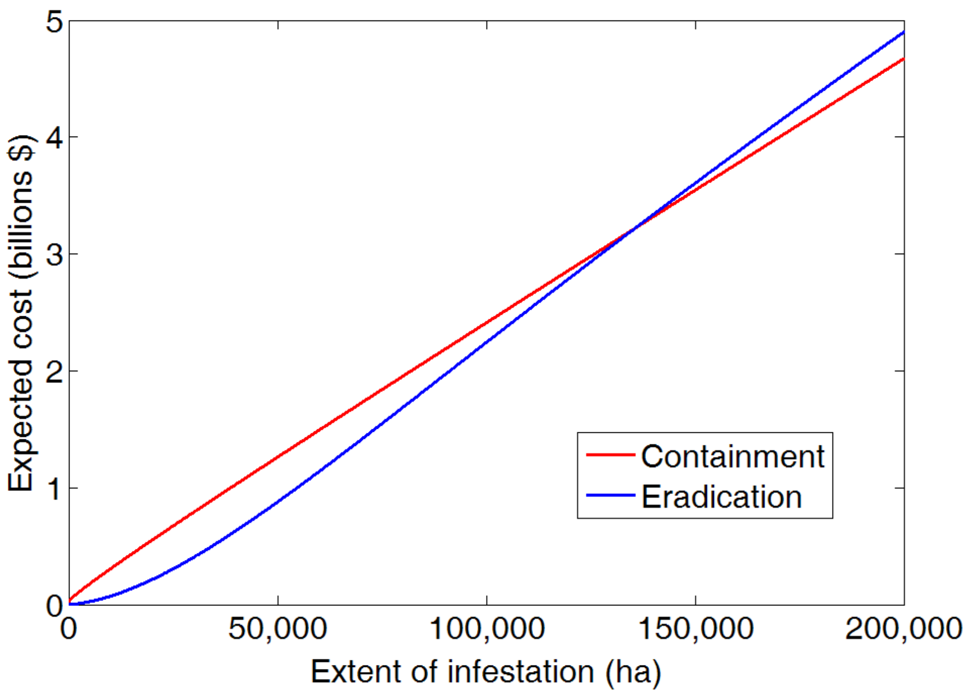

Fig. B3.3. The total expected cost of different management strategies for different extents of the fire ant infestation, calculated with eq. B3.7.

To calculate the value of resolving uncertainty about the extent, we first describe this uncertainty with a lognormal distribution:

$$f(x) = \frac{1}{x\sqrt{2\pi\sigma^2}} e^{\frac{-(\ln x - \mu)^2}{2\sigma^2}} . \qquad \text{(B3.8)}$$

We use a mean μ = ln(96000) and standard deviation σ = 0.1 to give a distribution where the most likely value (mode) is approximately x = 95,000 ha (Fig. B3.4).

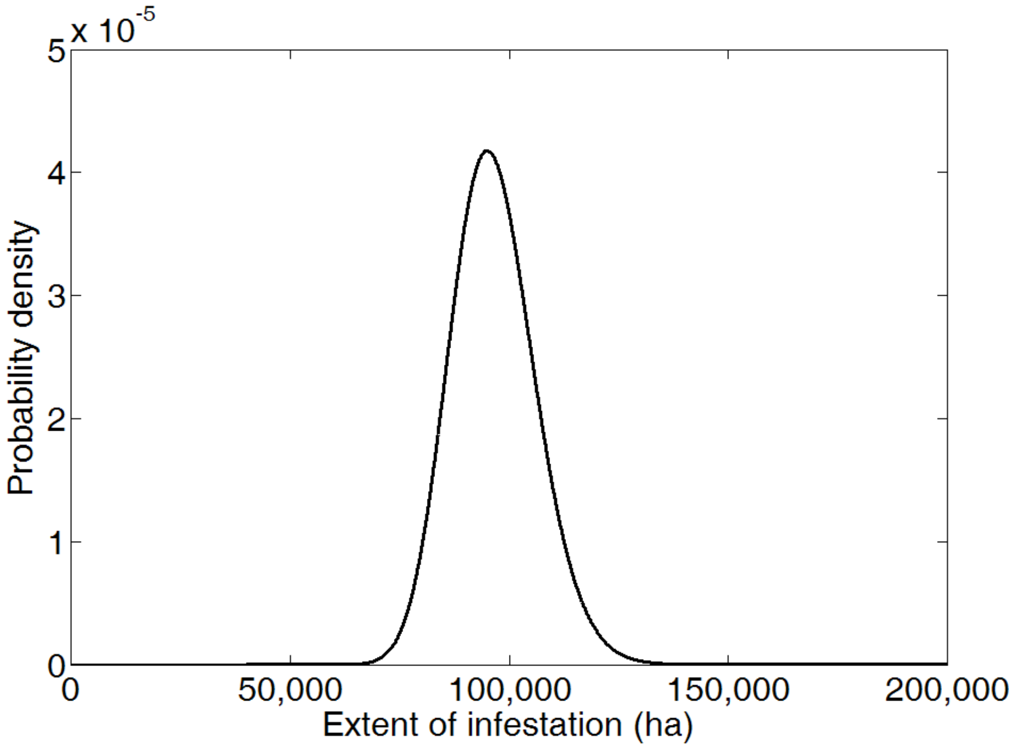

Fig. B3.4. The lognormal probability distribution (eq. B3.8) expressing uncertainty in the extent of the RIFA infestation. The mean μ = ln(96000), and the standard deviation σ = 0.1.

The expected cost of each management strategy can be found by integrating the total cost (eq. B3.7) across the range of possible extents, weighted by our prior belief that each is the true extent (eq. B3.8):

$$\begin{aligned} EC(\text{containment}) &= \int_0^{x_{\max}} T(x \mid \text{containment}) f(x) dx \\ EC(\text{eradication}) &= \int_0^{x_{\max}} T(x \mid \text{eradication}) f(x) dx \end{aligned} . \qquad \text{(B3.9)}$$

To be consistent with Antony et al. (2009), the largest possible extent we consider is x_{max} = 2.7 million ha.

The best strategy in the face of uncertainty is the strategy that minimises the total expected cost given the prior distribution for the uncertain variable. That is, if Fig. B3.4 represents our belief about the likelihood of different infestation sizes, we should choose the strategy with the lowest expected cost across these possible extents. Taking this best strategy, the expected cost under uncertainty is:

$$EC_u = \min \left\{ EC(\text{containment}), EC(\text{eradication}) \right\}, \qquad \text{(B3.10)}$$

where the expected costs are given by eq. B3.9. The best strategy under uncertainty is eradication, with an expected cost of \$2.1391 billion.

If we could find out what the true extent was before making our decision, we would choose the strategy with the lowest expected cost for that particular extent. That means we would choose eradication if we knew the extent was up to x^* = 135,849 ha, and containment if we knew the extent was more than 135,849 ha. Prior to collecting information about the extent, the expected cost of the decision is:

$$EC_c = \int_0^{x^*} T(x \mid \text{eradication}) f(x) dx + \int_{x^*}^{x_{\max}} T(x \mid \text{containment}) f(x) dx, \qquad \text{(B3.11)}$$

which is also equal to \$2.1391 billion.

The expected value of perfect information about the extent is the difference between the expected cost under uncertainty and the expected cost under certainty, i.e.

$$EVPI(x) = EC_u - EC_c, \qquad \text{(B3.12)}$$

which in this case is only \$3856.90. While perfect information about the extent of the infestation is not likely to be possible, this puts an upper limit on the amount that should be spent acquiring information about the extent.

Why is information about the extent worth so little, when our analysis shows the choice of strategy depends on the extent? According to our prior belief distribution (Fig. B3.4), it is quite unlikely that the infestation is large enough for containment to be the most cost-effective strategy. Thus, even though the extent is uncertain, the choice of strategy is not, which means resolving uncertainty will not improve the outcome of the decision substantially.

B 3.4 Uncertainty in the sensitivity of remote sensing

We now explore the value of learning about the sensitivity of remote sensing, another uncertain parameter in this model. To do this we compare three possible management strategies. In addition to the containment and eradication strategies considered previously, we add a new eradication strategy with 2 canine surveys and 2 remote sensing surveys, where detected nests are injected with poison. Given the cost estimates in Table B3.2, this new strategy will cost \$1646.34 per hectare (compared to \$1932.68/ha/yr for containment, and \$1566.34/ha for the original eradication strategy). Again, these three management strategies are chosen for illustrative purposes and do not reflect current or intended future practice.

The total expected cost calculations show that the cost-effectiveness of including remote sensing in an eradication strategy depends on its sensitivity (Fig. B3.5). The eradication strategy with remote sensing is optimal if the sensitivity of remote sensing is greater than 0.56. Otherwise, the original eradication strategy is more cost-effective. Note that these calculations are for an infestation extent of x = 95,000 ha.

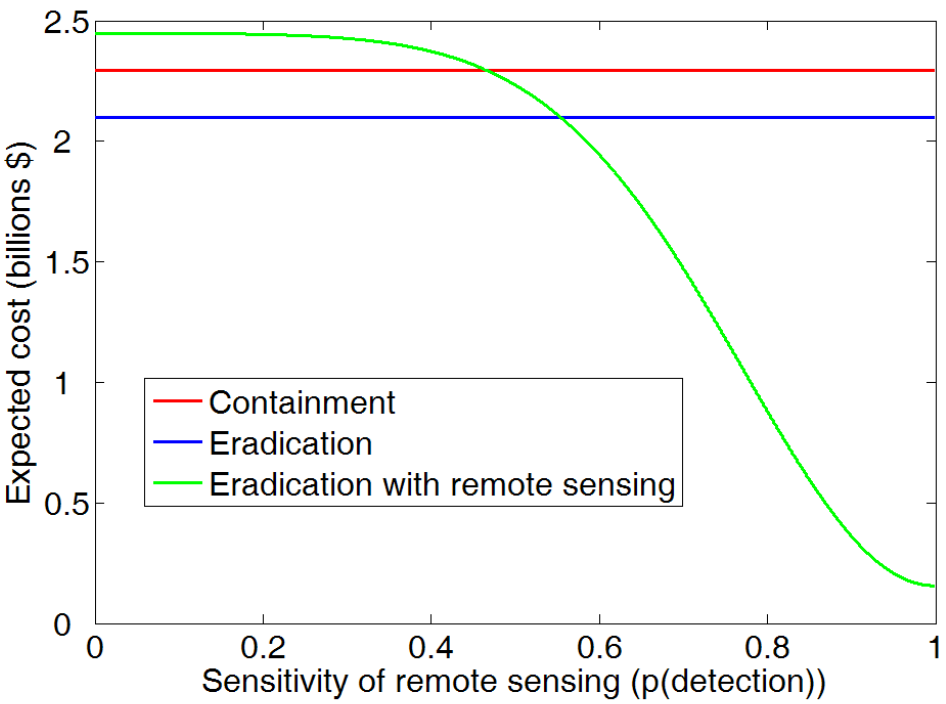

Fig. B3.5. The total expected cost of different management strategies for different values of the sensitivity of remote sensing, calculated with eq. B3.7.

Previous analyses of remote sensing found that eradication using this technology is feasible at much lower levels of sensitivity than 0.56 (Spring et al. 2009, 2010a, 2010b). Although feasibility and cost-effectiveness are not equivalent measures, differences in the fire ant models may have led to differences in the results of these analyses. In particular, this analysis has several simplifying assumptions, for example, that fire ant nests are uniformly distributed across the infestation extent.

To calculate the expected value of information, we start by describing our uncertainty in the sensitivity of remote sensing, using a beta distribution:

$$f(\delta_{remote}) = \frac{\delta_{remote}^{\alpha-1}(1-\delta_{remote})^{\beta-1}}{B(\alpha,\beta)}, \qquad \text{(B3.13)}$$

where α and β are shape parameters, and $B(\alpha, \beta)$ is the beta function:

$$B(\alpha,\beta) = \int_0^1 u^{\alpha-1}(1-u)^{\beta-1}du\,. \qquad \text{(B3.14)}$$

The beta distribution is defined on the interval (0,1) and is thus a suitable and commonly-used distribution for describing probabilities. To reflect the ongoing development of remote sensing technology and the subsequent high level of uncertainty involved, we use an uninformative prior distribution with shape parameters $\alpha = 1$ and $\beta = 1$, (Fig. B3.6).

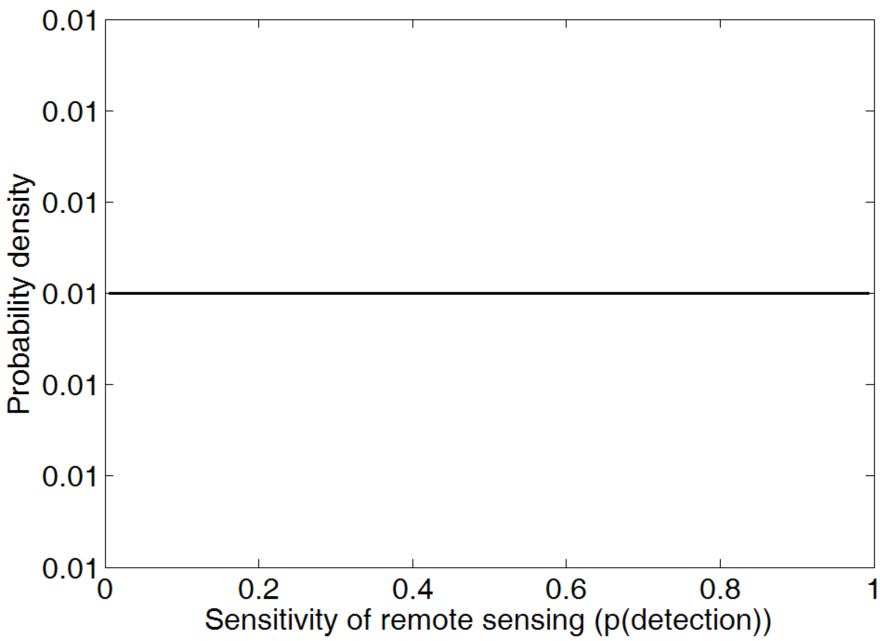

Fig. B3.6. The beta probability distribution (eq. B3.13) expressing uncertainty in the sensitivity of remote sensing. The shape parameters $\alpha = 1$ and $\beta = 1$, equivalent to a uniform distribution over the interval [0,1].

Again, the expected cost of each management strategy can be found by integrating the total cost (eq. B3.7) across the range of the uncertain variable, weighted by our prior belief that each value is the true value (eq. B3.13):

$$\begin{aligned}
EC(\text{containment}) &= \int_0^1 T(\delta_{remote} \mid \text{containment})\, f(\delta_{remote})\, d\delta_{remote} \\
EC(\text{eradication}) &= \int_0^1 T(\delta_{remote} \mid \text{eradication})\, f(\delta_{remote})\, d\delta_{remote} \\
EC(\text{erad w/ remote sensing}) &= \int_0^1 T(\delta_{remote} \mid \text{erad w/ remote sensing})\, f(\delta_{remote})\, d\delta_{remote}
\end{aligned} \qquad \text{(B3.15)}$$

The best strategy in the face of uncertainty is the strategy that minimises the total expected cost, given the prior probability distribution, i.e.

$$EC_u = \min\left\{EC(\text{containment}), EC(\text{eradication}), EC(\text{erad w/ remote sensing})\right\}. \qquad \text{(B3.16)}$$

In this case the best strategy under uncertainty is the original eradication strategy, with an expected cost of \$1.7896 billion.

Under certainty, we would choose eradication with remote sensing if the sensitivity of remote sensing is greater than δ^*_{remote} = 0.56, and the original eradication strategy if the sensitivity is 0.56 or lower. The expected cost of the decision under certainty is:

$$\begin{aligned}
EC_c = &\int_0^{\delta^*_{remote}} T(\delta_{remote} \mid \text{eradication})\, f(\delta_{remote})\, d\delta_{remote} + \\
&\int_{\delta^*_{remote}}^1 T(\delta_{remote} \mid \text{erad w/ remote sensing})\, f(\delta_{remote})\, d\delta_{remote}
\end{aligned}, \qquad \text{(B3.17)}$$

which equals \$1.6296 billion.

The expected value of perfect information is the difference between the expected cost under uncertainty and the expected cost under certainty:

$$EVPI(\delta_{remote}) = EC_u - EC_c, \qquad \text{(B3.18)}$$

which is \$159.96 million. The value of perfect information is substantial in this case because we assume so little is known about the sensitivity of remote sensing, and this assumed ignorance is likely to affect the outcome of the decision, especially given the large difference in the expected cost of the two eradication strategies when the sensitivity of remote sensing is high (Figure B3.5).

B 3.5 Uncertainty in bait efficacy

The third uncertain parameter in this model is the efficacy of baiting undetected fire ant nests. To calculate the value of learning about this parameter we again compare the original containment and eradication strategies with a new eradication strategy, this time involving 2 canine surveys (where found nests are injected with poison) and 4 rounds of baiting. This new eradication strategy will cost \$1480 per hectare, compared to \$1932.68/ha/yr for containment, and \$1566.34/ha for the original eradication strategy. Again, these three management strategies are chosen purely for illustrative purposes.

The eradication strategy with baiting is the most cost-effective strategy if the efficacy of baiting is 0.33 or greater (Fig. B3.7). For values below this, the original eradication strategy is optimal. This outcome is consistent with the findings of previous modelling which found that "aggressive containment" using extensive baiting can be an effective eradication strategy when combined with high-sensitivity visual surveillance (Spring et al. 2010b). Note again that these calculations are for an infestation extent of x = 95,000 ha.

We again use a beta distribution to describe uncertainty in this probability:

$$f(\lambda_{bait}) = \frac{\lambda_{bait}^{\alpha-1}(1-\lambda_{bait})^{\beta-1}}{B(\alpha,\beta)} . \qquad \text{(B3.19)}$$

Our intuition about the efficacy of baiting is stronger than that of remote sensing, but still be substantially uncertain. We use shape parameters α = 5 and β = 2 to give an asymmetric distribution with a mode $((\alpha - 1)/(\alpha + \beta - 2))$ of 0.8 (Fig. B3.8), which is the current best estimate of bait efficacy.

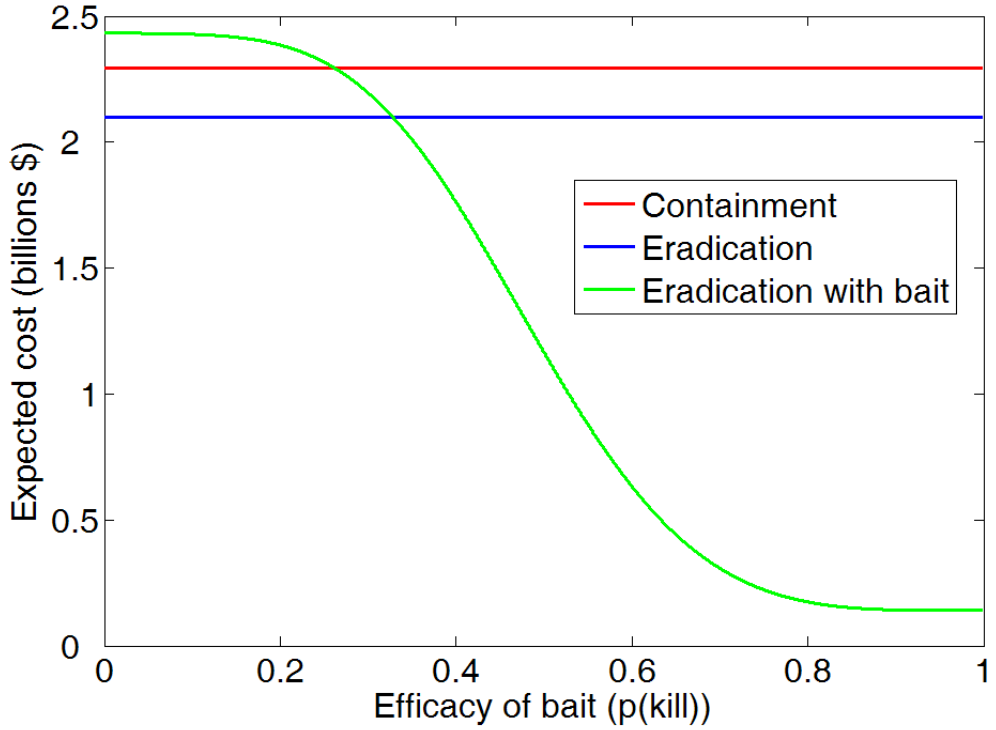

Fig. B3.7. The total expected cost of different management strategies for different values of the efficacy of baiting, calculated with eq. B3.7.

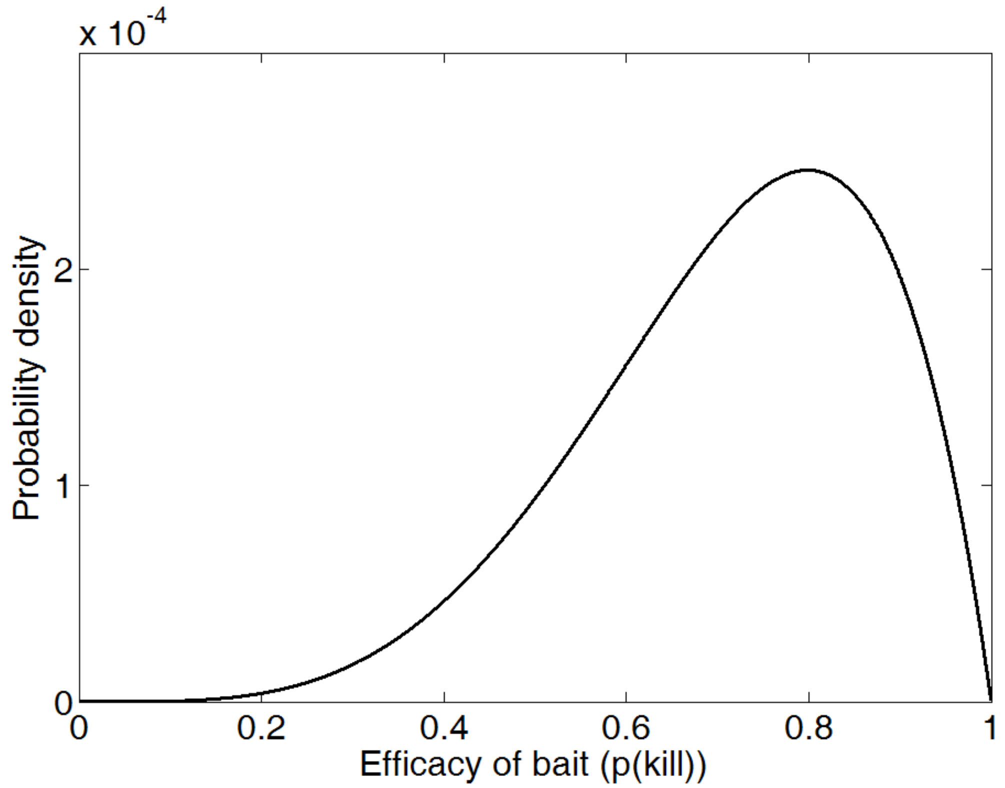

Fig. B3.8. The beta probability distribution (eq. B3.19) expressing uncertainty in the efficacy of baiting. The shape parameters $\alpha = 5$ and $\beta = 2$.

The expected cost of each management strategy is found by integrating the total cost (eq. B3.7) across the range of the uncertain variable, weighted by our prior belief that each value is the true value (eq. B3.19):

$$\begin{aligned} EC(\text{containment}) &= \int_0^1 T(\lambda_{bait} \mid \text{containment}) f(\lambda_{bait}) d\lambda_{bait} \\ EC(\text{eradication}) &= \int_0^1 T(\lambda_{bait} \mid \text{eradication}) f(\lambda_{bait}) d\lambda_{bait} \quad . \\ EC(\text{erad w/ bait}) &= \int_0^1 T(\lambda_{bait} \mid \text{erad w/ bait}) f(\lambda_{bait}) d\lambda_{bait} \end{aligned} \tag{B3.20}$$

Again, the best strategy in the face of uncertainty is the strategy that minimises the total expected loss given the prior probability distribution, which makes the expected cost under uncertainty:

$$EC_u = \min \left\{ EC(\text{containment}), EC(\text{eradication}), EC(\text{erad w/ bait}) \right\}. \tag{B3.21}$$

The best strategy under uncertainty is eradication with baiting, which has an expected cost of \$478.44 million.

Under certainty, we would choose the original eradication strategy if the bait efficacy is less than λ^*_{bait} = 0.33, and eradication with baiting if the bait efficacy is 0.33 or greater. The expected cost of the decision under certainty is:

$$\begin{aligned} EC_c = \; & \int_0^{\lambda^*_{bait}} T(\lambda_{bait} \mid \text{eradication}) f(\lambda_{bait}) d\lambda_{bait} + \\ & \int_{\lambda^*_{bait}}^1 T(\lambda_{bait} \mid \text{erad w/ bait}) f(\lambda_{bait}) d\lambda_{bait} \end{aligned}, \tag{B3.22}$$

which equals \$475.88 million.

The expected value of perfect information is the difference between the expected cost under uncertainty and the expected cost under certainty:

$$EVPI(\lambda_{bait}) = EC_u - EC_c, \tag{B3.23}$$

which is \$2,558,500. Again the value of information is quite substantial here because there is a large difference in the expected cost of the two eradication strategies when bait efficacy is high. However, the value of information is not as large as for the sensitivity of remote sensing, because our prior distribution for the efficacy of baiting is more informative.

B 4.0 Discussion and future directions

This report provides an introduction to value of information analysis, in particular the expected value of perfect information, and describes how this analysis can be useful for biosecurity decision-making. VOI analysis enables managers to identify which uncertainties affect the outcome of management decisions, thus allowing them to prioritise investment in research and monitoring. An EVPI calculation requires:

- clearly defined alternative actions
- a description of uncertainty, whether as discrete probabilities or a continuous probability distribution, and
- predictions of how alternative actions perform under different possible values of the uncertain variable.

Predictions and their associated uncertainties should use the best available techniques in modelling and elicitation of expert judgment (Spiers-Bridge et al., 2010) The output of this calculation, the expected value of perfect information, is the amount by which resolving all uncertainty is expected to improve the decision outcome. This provides managers with an upper limit on the amount that should be spent on research or monitoring to reduce their uncertainty.

While our models capture the basic elements of the "eradicate or contain" decision problem, further work is needed to increase their realism. We employed a simple model of pest distribution and spread involving uniform occupancy over a circular area. There is an obvious need for more sophisticated estimates of costs and benefits when pest distributions are distinctly patchy. We have identified one important element of the decision that is not yet accounted for: reducing uncertainty through research or monitoring takes time and delays decisions, and this delay has an opportunity cost.

While our fire ant case study demonstrates the flexibility of VOI analysis, we stress again that it is primarily a conceptual model and embodies strong simplifying assumptions about fire ant biology. Those simplifying assumptions may have a substantial effect on the choice of management strategy and on decisions regarding research and monitoring to reduce uncertainty. However, our model could provide a basis for the development of a practical decision support tool, provided there is further work to:

- refine the fire ant decision problem, identifying realistic alternative management strategies and key uncertainties,
- elicit realistic probability distributions for key uncertain parameters, and
- use the best available science to inform spatially explicit predictions of management success.

These steps are essential to develop a practical value of information analysis for fire ants that makes use of current science and knowledge, and is consistent with the needs of managers.

In this report we have focused on the expected value of perfect information (EVPI), which gives an upper bound on the value of any reduction in uncertainty. Other types of VOI calculations can deal with more nuanced measures of information value. For example, when a decision involves multiple sources of uncertainty, the expected value of partial information can be used to assess the relative importance of resolving the uncertainty from each source. For two uncertain variables *x* and *y*, the EVPI about variable *x* is:

$$\begin{aligned}\text{EVPXI} = & \int_{x\in X}[\max_{a\in A} u(a,x,y)\, f(y\mid x)dy]f(x)dx \\ & -\max_{a\in A}[\int_{y\in Y}\int_{x\in X} u(a,x,y)\, f(x,y)dxdy]\end{aligned}, \qquad \text{(B4.1)}$$

where $u(a, x, y)$ is the utility of action *a* given *x* and *y*, $f(y \mid x)$ is the prior conditional probability of *y* given *x*, $f(x)$ is the prior probability of *x* and $f(x, y)$ is the prior joint distribution of *x* and *y*.

This equation has a similar form to the EVPI equation, in that it calculates the difference in expected utility between the best decision with perfect information about variable *x* (given uncertainty in variable *y*), and the best decision given uncertainty in both *x* and *y*. In section B3 of this report we performed three separate EVPI calculations for three uncertain variables, each considering different candidate management options. By simultaneously incorporating the uncertainty around multiple variables, the expected value of partial information gives a more accurate measure of the relative importance of resolving uncertainty in each variable, and would enable simultaneous consideration of all possible management options. However, the need for joint probability distributions of the uncertain parameters creates an added complexity, both in specifying these distributions and in performing the subsequent calculations. The complexity of these calculations is beyond the scope of this report.

Obtaining perfect information is impossible for many systems, thus the decision-maker must instead rely on imperfect sample information that reduces but does not eliminate uncertainty. Failure to recognise sampling error associated with underpowered studies leads to overconfidence and the misallocation of resources (Burgman, 2005). The expected value of sample information (EVSI) is calculated as:

$$\text{EVSI} = \int_{t \in T} \max_{a \in A} [\int_{s \in S} u(a,s) p(s \mid t) ds] h(t) dt - \max_{a \in A} [\int_{s \in S} u(a,s) f(s) ds] \text{,(B4.2)}$$

where *t* is the possible sample information that could be collected about the uncertain variable *s*, *p*(*s* | *t*) is the posterior probability of *s* given sample information *t*, and *h*(*t*) is the predictive density of *t*. It is also possible to calculate the expected value of partial sample information to assess the relative merit of reducing uncertainty from different sources. Although the value of sample information is a more realistic measure for real systems, the elements of this calculation can be difficult to define and the calculation itself difficult to solve, limiting its application.

In summary, although VOI analysis is an established and extensively used decision support tool, it is not currently widely applied within the field of biosecuity management. This report provides a first step in increasing the use of VOI analysis for biosecurity decision support, demonstrating its potential utility, and outlining several directions for future research and application.

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Appendix B1 Calculating the per hectare cost of fire ant impact

The analysis by Antony et al. (2009) is dynamic, predicting the increase in impacts of fire ants as they would spread over time if left unmanaged. We adapted this analysis to obtain a static per-hectare cost of fire ant impact.

Antony et al. (2009) assumed that 60% of affected households in 2008 would pay to treat fire ants on their property, and that 100% of affected agricultural land, parks and recreational land, and schools would be treated. Out of the total land mass of 2,624,828 ha considered by the analysis, approximately 130,000 ha was residential land in 2008, 793,241 ha was agricultural land, approximately 14,000 ha was parkland, and 7152 ha was school land (Antony et al., 2009). This means that approximately 5% of the land considered was residential, and 31% was either agricultural, parkland or school land.

We assume that the area occupied by fire ants under the containment strategy is covered by each land type at these proportions, and that the fire ants will be at an intermediate density within the containment area, i.e. 5 nests per hectare. The annual per-hectare cost of treatment at this density is $298.50 (Antony et al. 2009). The average per hectare treatment cost is therefore:
Treatment cost = 0.6*0.05*298.5 + 1*0.31*298.5 = $101.49 /ha/year.

Antony et al. assume that untreated dwellings (40% of total residential land) incur health care costs due to fire ant stings, and that these costs are equal to half the cost of treating the dwellings. Given an intermediate density of fire ants, the average per hectare health care cost is therefore:
Health care cost = 0.4*0.05*0.5*298.5 = $2.99 /ha/year.

The ecosystem service loss for an intermediate ("common") density of fire ants is $927 (Table 4, Antony et al. (2009)). Thus, the total per-hectare cost of impact is:
c_i = 101.49 + 2.99 + 927 = $1031.48 /ha/year.