How much is new information worth? Evaluating the financial benefit of resolving management uncertainty.

Authors: Sean L. Maxwell[1,2,*] , Jonathan R. Rhodes[1,2,3], Michael C. Runge[4], Hugh P. Possingham[1,3,5,6], Chooi Fei Ng[1,6,7] and Eve McDonald-Madden[1,2,7]

Affiliations:

[1] ARC Centre of Excellence for Environmental Decisions, The University of Queensland, St Lucia, Queensland 4072, Australia

[2] School of Geography, Planning and Environmental Management, The University of Queensland, St Lucia, Queensland 4072, Australia

[3] NERP Environmental Decisions Hub, The University of Queensland, St Lucia, Queensland 4072, Australia

[4] US Geological Survey, Patuxent Wildlife Research Center, 12100 Beech Forest Road, Laurel, Maryland 20708, United States of America

[5] Imperial College London, Department of Life Sciences, Silwood Park, Ascot SL5 7PY, Berkshire, England, UK

[6] School of Mathematics and Physics, The University of Queensland, St Lucia, Queensland 4072, Australia

[7] CSIRO Ecosystem Sciences, Brisbane, Queensland 4102, Australia.

* Corresponding author

Email: smaxwell@uq.edu.au

Mailing address: Centre for Biodiversity and Conservation Science, School of Biological Sciences, The University of Queensland, St Lucia, Queensland 4072, Australia.

Telephone number: +61 403 477 098

Running title: How much is new information worth?

Word count: 342 (Abstract), 4,967 (Main text), 22 (Acknowledgements), 1,467 (References), 326 (Table and figure legends).

Number of tables and figures: 1 table, 4 figures

Number of references: 54

Summary

1. Conservation decision-makers face a trade-off between spending limited funds on direct management action, or gaining new information in an attempt to improve management performance in the future. Value-of-information analysis can help to resolve this trade-off by evaluating how much management performance could improve if new information was gained. Value-of-information analysis has been used extensively in other disciplines, but there are only a few examples where it has informed conservation planning, none of which have used it to evaluate the financial value of gaining new information.
2. We address this gap by applying value-of-information analysis to the management of a declining koala *Phascolarctos cinereus* population. Decision-makers responsible for managing this population face uncertainty about survival and fecundity rates, and how habitat cover affects mortality threats. The value of gaining new information about these uncertainties was calculated using a deterministic matrix model of the koala population to find the expected population growth rate if koala mortality threats were optimally managed under alternative model hypotheses, which represented the uncertainties faced by koala managers.
3. Gaining new information about survival and fecundity rates and the effect of habitat cover on mortality threats will do little to improve koala management. Across a range of management budgets, no more than 1.7% of the budget should be spent on resolving these uncertainties.
4. The value of information was low because optimal management decisions were not sensitive to the uncertainties we considered. Decisions were instead driven by a substantial difference in the cost efficiency of management actions. The value of information was up to forty times higher when the cost efficiencies of different koala management actions were similar.
5. *Synthesis and applications.* This study evaluates the ecological and financial benefits of gaining new information to inform a conservation problem. We also theoretically demonstrate that the value of reducing uncertainty is highest when it is not clear which management action is the most cost efficient. This study will help expand the use of value-of-information analyses in conservation by providing a more tangible metric by which to evaluate research or monitoring.

Key words: budget, conservation, cost effective, decision, koala, *Phascolarctos cinereus*, Queensland, rule of thumb, strategy, value-of-information analysis.

Introduction

Deciding how to manage species that are under threat requires combining ecological knowledge with knowledge of time constraints, stochastic events, financial budgets, stakeholder perspectives, legal issues and government processes. Combining these components would be relatively straightforward if we knew everything. However, uncertainties surround all environmental management problems (Regan, Colyvan & Burgman 2002), and management decisions that do not account for such uncertainties may be sub-optimal, or in the worst case, ineffective (McDonald-Madden *et al.* 2010b).

A common way to reduce uncertainties about a species or ecosystem being managed is to gain new information. However, not all uncertainties faced by environmental managers are equally important to reduce. The most important uncertainties are those that, when reduced, will encourage a change to a more effective management strategy (e.g. Runting, Wilson & Rhodes 2013). New information is of little management value if it does not change the management strategy implemented in the absence of new knowledge. There are two main reasons why new information may not change a management strategy. The first reason is that monitoring programs do not always adequately consider why, what and how monitoring should be carried out (Yoccoz, Nichols & Boulinier 2001), which can lead to the inability to detect ecologically significant changes (Legg & Nagy 2006), or information that is irrelevant to management decisions (McDonald-Madden *et al.* 2010a). The second reason is that management decisions can be driven by non-ecological factors. For example, managers typically choose actions that are the most cost efficient; where cost efficiency refers to the amount of environmental goods conserved per unit of money spent (Lindsey *et al.* 2005). If new information does not substantially change the cost efficiency of alternative management actions, it is unlikely that the decision made in absence of new information would change. In such cases, new information will not improve management performance (e.g. Lindsey *et al.* 2005).

Allocating resources to gaining new information that does not improve management performance is problematic because investing in information-gain can reduce the resources available for direct management action. Consequently, the decision to invest in gaining new information should be made with an understanding of the associated opportunity costs. The opportunity costs might be other actions that could have resulted in a greater improvement in management performance than investing in information-gain (Grantham *et al.* 2009); for example, restoring habitat, enforcing catch limits, or raising the profile of an endangered species. One approach that directly considers the opportunity costs associated with making a decision is value-of-information analysis (Raiffa & Schlaifer 1961), an approach first developed by economists over half a century ago. This approach has been used extensively in medicine (Yokota & Thompson

2004), engineering (Bratvold, Bickel & Lohne 2009) and land remediation (Dakins *et al.* 1996) to quantify the upper monetary limit worth investing in information-gain before making a management decision. Value-of-information analysis has also been used in fisheries management to quantify the expected increase in fishing yield due to reducing uncertainty about stock abundance (Clark & Kirkwood 1986; Punt & Smith 1999), the stock–recruitment relationship (Kuikka *et al.* 1999; Mäntyniemi *et al.* 2009; Costello *et al.* 2010), and the future demand for stock (Forsberg & Guttormsen 2006).

Despite the apparent benefits of using value-of-information analysis, and the range of uncertainties that can affect conservation outcomes, there are only a few examples outside of fisheries management where this approach has been used to inform conservation planning (Williams, Eaton & Breininger 2011; Moore & Runge 2012; Runge, Converse & Lyons 2011; Runge *et al.* 2011). One of the impediments to broader application is that value-of-information calculations, which are expressed in the units of the decision-maker's performance metric, are not as clear when the performance metric is non-monetary. The performance of a conservation plan is often measured in some ecologically relevant metric, such as likelihood of species persistence (Harris *et al.* 2012). When the value of information is expressed as an expected increase in species persistence from reducing uncertainty, it is difficult to know how much this improvement is worth in financial terms. Translating the ecological benefits of reducing uncertainty surrounding a conservation problem into a financial value would allow managers to better assess the trade-off between information gain and direct management action, and improve the utility of value-of-information analysis for conservation.

In this study we calculate the ecological value of reducing uncertainty surrounding a conservation problem, and translate it into a financial value. Our case study concerns the management of a declining koala *Phascolarctos cinereus* population in south-east Queensland, Australia. We show what koala mortality threats should be made research priorities and how much a decision-maker should be willing to invest in gaining more information about koala survival and fecundity rates, and the effect of habitat cover on koala mortality threats. More generally, we explore the relationship between ecological uncertainty and the cost efficiency of alternative management actions, and theoretically demonstrate that the value of information is highest when it is not clear which management action is the most cost efficient.

Materials and methods

STUDY SPECIES AND SITE

Koalas are tree-dwelling marsupials that inhabit forest, woodland and semi-arid communities dominated by *Eucalyptus* species (Martin & Handasyde 1999). They are endemic to Australia and populations vary geographically in their conservation status. (DSEWPC 2012). The 'Koala Coast' is a 375km^2 region in the south-east Queensland bioregion, which was home to approximately 6200 koalas between the years of 1996 and 1999 (Dique *et al.* 2004). However, intensive urbanisation has since reduced and fragmented the koala habitat in this region. This has led to an increase in koala mortality from vehicle collisions, dog attacks and increased prevalence of potentially stress-related diseases (primarily *Chlamydia psittaci*) (Thompson 2006; DERM 2010). Consequently, the Koala Coast koala population has suffered a 68 percent decline between 1999 and 2010 (DERM 2010), and is now listed as vulnerable under the Environment Protection and Biodiversity Conservation Act and the Nature Conservation Act (DSEWPC 2012).

Managers of this koala population face uncertainty about survival and fecundity rates, and the influence of habitat cover on mortality threats. We used value-of-information analysis to calculate how much management performance could improve if these uncertainties were resolved. The first step of our analysis involved using a decision theory framework to find an optimal management strategy under existing uncertainty (Possingham 2001). The framework included: (1) a management objective, (2) potential management actions, (3) alternative population models of the Koala Coast system to represent the uncertainties faced by koala managers, and (4) an algorithm to find optimal management strategies for different budget levels.

MANAGEMENT OBJECTIVE AND ACTIONS

The management objective for this study was to maximise koala population growth rate in the Koala Coast. To achieve this objective, we simulated a management strategy by allocating a budget between the following management actions: (1) erecting fences, nature bridges and underpasses to prevent vehicle collisions (Caneris & Jones 2004), (2) providing funding for residential enclosures to prevent dog attacks (B. Carter pers. comm.), and (3) restoring habitat, which involves purchasing or restoring koala habitat. Restoring habitat indirectly reduces stress-induced disease-related mortality, while also indirectly reducing vehicle collisions and dog attacks (DEHP 2012). These three actions are currently being implemented in the Koala Coast to varying degrees.

THE POPULATION MODEL

The response of the koala population to a management strategy was modelled using a deterministic age-structured matrix population model (Caswell 2001) of female koalas inhabiting the Koala Coast

(Rhodes *et al.* 2011). To estimate the parameters of this model, two data sets were used: radio-tracking data from 1996 to 2000 (Dique *et al.* 2003; Thompson 2006), and survey data showing population density in 1996 to 1999 (Dique *et al.* 2004), 2005 to 2006 (EPA 2007), and 2008 (DERM 2009). These data provided information on birth rates, survival rates and causes of mortality for female koalas in the population, from which mortality and fecundity rates were estimated to construct the following:

$$\begin{bmatrix} D_{0,t} \\ D_{1,t} \\ D_{2,t} \\ D_{3,t} \end{bmatrix} = \begin{bmatrix} 0 & F_1S_1 & F_2S_2 & F_3S_3 \\ S_0 & 0 & 0 & 0 \\ 0 & S_1 & 0 & 0 \\ 0 & 0 & S_2 & S_3 \end{bmatrix} \times \begin{bmatrix} D_{0,t-1} \\ D_{1,t-1} \\ D_{2,t-1} \\ D_{3,t-1} \end{bmatrix} \qquad \textbf{(1)}$$

where $D_{i,t}$ is the density (individuals per hectare) at time t of age class i (where age class 0 = 0–1 year olds (juveniles), age class 1 = 1–2 year olds (sub-adults 1), age class 2 = 2–3 year olds (sub-adults 2), and age class 3 = 3+ year olds (adults)); S_i is the annual per-capita survival rate for koalas of age class i; and F_i is the annual per-capita birth rate for age class i females (Rhodes *et al.* 2011). The koala population growth rate was obtained by calculating the dominant eigenvalue of the transition matrix (middle matrix) in Equation 1.

The population model included cause-specific mortality rates based on key threats (Ng *et al.* 2014). The mortality probability due to cause k for age class i can be written as:

$$M_{i,k} = C_{i,k} M_i \qquad \textbf{(2)}$$

where $C_{i,k}$ is the probability that, given a mortality event, it arises due to cause k for age class i; and M_i is the unconditional mortality probability for age class i. The causes of mortality present in the region and incorporated into the model are; natural (k = 1), vehicle-related (k = 2), dog-related (k = 3), or disease-related (k = 4). The probability that individual mortality in age class i is due to cause k is related to forest cover as follows:

$$C_{i,k} = \begin{cases} 1 & , \textit{if } i = 0 \textit{ and } k = 1, \\ 0 & , \textit{if } i = 0 \textit{ and } k = 2, 3 \textit{ or } 4, \\ \dfrac{e^{(\gamma_k + \eta_k FOR)}}{\sum_{K=1}^{4} e^{(\gamma_k + \eta_k FOR)}} & , \textit{otherwise} \end{cases} \qquad \textbf{(3)}$$

where, *FOR* is the proportion of forest surrounding a location; γ_k is the intercept for mortality arising from cause k; and η_k is a coefficient for the effect of forest cover (*FOR*) on the mortality due to cause k (see Rhodes *et al.* 2011 for more details). In the absence of other information, we assumed that mortality for dependant juvenile koalas (age class 0) only occurred due to natural causes.

DESCRIBING THE UNCERTAINTIES

This study considered two sources of uncertainty surrounding the Koala Coast koala population. First, we considered structural uncertainty: uncertainty about which koala mortality threats are related to habitat cover. Describing structural uncertainty required exploring the range of possible relationships that could exist between habitat cover and koala mortality threats. To do this, eight alternative structures of the koala population model were built. Each model structure differed in the influence of habitat cover on natural, vehicle-, dog- and disease-related mortalities (Table 1). Deviance Information Criterion was used to calculate model weights for each of the eight model structures (see Rhodes *et al*. 2011 for more details), and were used in the current study to describe structural uncertainty. The second source of uncertainty we considered was parametric uncertainty: uncertainty about koala survival and fecundity rates. Describing parametric uncertainty required considering the range of plausible values for koala survival and fecundity rates in the Koala Coast. Markov Chain Monte Carlo simulation was used to derive a prior distribution of both survival and fecundity rates under each of the eight model structures (see Rhodes *et al.* 2011). The current study randomly drew from these distributions 1000 times to describe parametric uncertainty.

FINDING OPTIMAL MANAGEMENT STRATEGIES

The improvement in koala survival rate due to investment in each of the three management actions has been estimated previously, such that:

$$S_i(x_m)=1-\sum_{k=1}^{4} M_{i,k} f_{i,k.m}(x_m) \qquad \textbf{(4)}$$

where S_i is the survival rate of koalas in age class i after investment (x_m) in action m; $M_{i,k}$ is the probability of koalas in age class i dying due to cause k prior to investment x_m (Equation 2); and the function $f_{i,k,m}(x_m)$ is a return-on-investment equation that describes how mortality due to cause k, for age class i is reduced after investment (x_m) in action m (Ng *et al.* 2014). The return-on-investment equations assumed diminishing marginal returns with increasing levels of investment in each action (Ng *et al.* 2014) (see Appendix for more details). Using Equation 4, we modelled the expected change in koala population growth rate due to management effort. A multidimensional unconstrained nonlinear optimisation algorithm (‘fminsearch’ function in Matlab Version R2012a (Mathworks 1984-2010)) was used to search across different levels of investment in each of the three koala management actions to find the maximum population growth rate possible for a fixed budget.

VALUE-OF-INFORMATION ANALYSIS

The Expected Value of Perfect Information (EVPI) identifies the maximum amount of resources worth investing in resolving uncertainty by estimating the improvement in management performance if you could resolve all specified uncertainty about the system being managed (Clemen 1996; Yokota & Thompson 2004). The expected improvement in koala management performance if all parametric and structural uncertainty was resolved was found by calculating the EVPI:

$$EVPI = E_s\left[\max_a \lambda(a,s)\right] - \max_a E_s\left[\lambda(a,s)\right] \qquad \textbf{(5)}$$

where s is a model of the system, a is the management strategy taken and $\lambda(a,s)$ is the expected population growth rate after taking strategy a under model s (Yokota & Thompson 2004). EVPI was calculated separately for 40 management budgets, increasing in \$5 million increments from \$5 million to \$200 million Australian dollars. The first term in Equation 5 represents the expected management performance if all parametric and structural uncertainty was resolved. We calculated this by finding strategies that led to the maximum expected population growth rate for each of the parameter draws, under each of the eight model structures. The weighted average across models was then calculated to obtain the expected management performance if the uncertainties were resolved. The second term in Equation 5 represents the expected management performance with current levels of information. We calculated this by performing the optimisation once to find a weighted expected population growth rate across all parameter draws, across all model structures.

The Expected Value of Perfect Partial Information (EVPXI) allows the user to isolate components of a source of uncertainty, and then estimate the value of resolving these components individually (Yokota & Thompson 2004). To calculate EVPXI:

$$EVPXI = E_{s_i}\left[\max_a E_{s_i^c}\left[\lambda\left(a,s_i,s_i^c\right)\right]\right] - \max_a E_{s_i,s_i^c}\left[\lambda\left(a,s_i,s_i^c\right)\right] \qquad \textbf{(6)}$$

where s_i is a structural model subset and s_i^c is the complementary set of structural models (Yokota & Thompson 2004). One aim of this study was to quantify how much management performance could improve if structural uncertainty that surrounds koala management in the Koala Coast could be resolved. To do this, we used EVPXI to evaluate the benefits of knowing what koala mortality threats are related to habitat cover, while leaving parametric uncertainty unresolved. Another aim of this study was to identify which component of structural uncertainty is the most valuable to resolve. To calculate EVPXI for this question, model structures were grouped into one of the following categories: habitat cover affects vehicle-related, dog-related, or disease-related mortalities (Table 1). Then, for example, s_i in Equation 6 referred to model structures that assume habitat cover affects vehicle-related mortality, and $\boldsymbol{s}_{\boldsymbol{i}}^{c}$ referred to model structures that assume habitat cover does not affect vehicle-related mortality.

CALCULATING THE FINANCIAL VALUE OF INFORMATION

We converted all improvements in population growth rate due to resolving uncertainty into financial values of information, which showed how much these improvements would cost using direct management action alone. To calculate financial values of information, the optimisation outlined above was reformulated. Instead of finding the strategy that gave the maximum population growth rate for a fixed budget, strategies were optimised to find the minimum budget required to reach a target growth rate in the face of uncertainty. A constrained nonlinear multivariable optimisation algorithm was used to do this (‘fmincon’ function in Matlab Version R2012a (Mathworks 1984-2010)). The target growth rate was initially set to the expected population growth rate with current levels of information, and the minimum budget required to reach that population growth rate was found. The target growth rate was then changed to the expected population growth rate with uncertainty resolved, and the minimum budget required to reach that population growth rate was found. Subtracting the budget required to reach an expected population growth rate under the two information-state scenarios gave the financial value of information.

SENSITIVITY ANALYSIS

Habitat restoration is expensive in the Koala Coast due to the high residential value of land in the region. Preventing vehicle collisions and dog attacks is comparatively very cheap, which makes them much more cost effective than habitat restoration. In fact, reducing vehicle- or dog-related mortality probabilities is 1000 to 10,000 times more cost effective than reducing disease and natural mortality probabilities using habitat restoration (Ng *et al.* 2014). This is not always the case in conservation. Sometimes management actions are similarly cost effective, or it is not known which management action is the most cost effective. To understand how the value of information may respond to such conditions, a sensitivity analysis was carried out on the cost efficiency of the alternative koala management actions. This involved running value-of-information analysis multiple times. For the first run, we used the current cost of habitat restoration in the Koala Coast. For subsequent runs, this cost was divided by 10, 50, 100 to 900 (in increments of 100), 1,000 to 9,000 (in increments of 1,000), & 10,000 to 100,000 (in increments of 10,000). Reducing the cost of habitat restoration in this way allowed us to evaluate the benefits of gaining new information when there was a large difference in the cost efficiency of alternative management actions, and when management actions were similar in their cost efficiency.

Results

In the face of parametric and structural uncertainty, the optimal koala management strategy depended on the budget level (Fig. 1a). For budgets between \$5 million and \$45 million, it was optimal to allocate 88% of the budget to preventing vehicle collisions, 12% of the budget to preventing dog attacks, and nothing to habitat restoration (subplot UC in Fig. 1a). Once the management budget exceeded \$45 million, optimal strategies began to favour increased proportional investment in habitat restoration and reduced proportional investment in preventing vehicle collisions and dog attacks.

A stable population growth rate (a rate at which the population is neither increasing nor decreasing in abundance) is equal to one. A population in decline has a growth rate less than one. The expected Koala Coast koala population growth rate without any investment in management action was 0.93. Optimal management strategies with current levels of information improved this growth rate to 0.955 (± 0.014) with a \$5 million budget, and to 0.98 (± 0.015) with a \$25 million budget. The expected growth rate continued to increase very slowly to 0.983 (± 0.016) as the budget reached \$200 million (Fig. 2). Therefore, the Koala Coast koala population is likely to remain in decline if there is no investment in gaining new information, and \$200 million is optimally allocated between the koala management actions considered in this study.

The resolution of parametric and structural uncertainty had little effect on optimal management strategies (subplots S1 through S8 in Fig. 1a). Resolving these uncertainties increased the expected koala population growth rate, but it remained below one for budgets up to \$200 million. The benefit of resolving uncertainty was greatest when the budget was set at \$5 million, where it increased the expected koala population growth rate by 0.04%. The EVPI declined to a practically non-measurable increase in management performance as the budget increased beyond \$40 million (Fig. 3). The financial value of information showed the maximum amount of resources worth investing in resolving parametric and structural uncertainty remained around \$85,000 for budgets between \$5 million and \$40 million. It then rose sharply and remained at around \$900,000 between budgets of \$55 million and \$200 million (Fig. 3). The financial value of information never exceeded 1.7% of the management budget.

For budgets between \$5 million and \$40 million, resolving only structural uncertainty contributed little to the overall EVPI. Therefore, parametric uncertainty, which accounted for around 97% of the total EVPI, was more valuable to resolve than structural uncertainty in this budget range. As the budget level increased, it became more valuable to resolve structural uncertainty. For budgets of \$50 million and above, the resolution of structural uncertainty accounted for around 70% of the total EVPI, and had a financial value of information of around \$650,000. If a component of structural model uncertainty were to be resolved, it is most valuable to gain new information about how habitat cover affects the probability of koalas dying from disease. For a budget of $50 million, resolving uncertainty about this link accounted for 70% of the total value of resolving all structural uncertainty and carried a financial value of information of $393,000.

Reducing the cost of habitat restoration greatly influenced optimal management strategies. Initially, strategies with and without parametric and structural uncertainty favoured increased proportional investment in habitat restoration at low budget levels as the action became more cost efficient. However, there was substantially greater difference between optimal strategies with and without uncertainty when the cost of habitat restoration was reduced ten thousand fold (Fig. 1b). The differences between management strategies with and without uncertainty were present until the cost of habitat restoration was reduced 100,000 fold, at which point the similarity between strategies with and without uncertainty returned (see Appendix).

The financial value of information had a bell-shaped response to reductions in the cost of habitat restoration (Fig. 4). The value initially increased, with the rate of increase being higher when management budgets were larger. The financial value of information peaked at $27 million (for a budget of $200 million) when habitat restoration was reduced one thousand fold. At this level of reduction, habitat restoration and preventing dog attacks and vehicle collisions were all similarly cost efficient. The financial value of information dropped to around $2.5 million for all budget levels when habitat restoration was reduced one hundred thousand fold, which was similar to the financial value observed when current, non-reduced costs of habitat restoration were considered in the analysis.

Discussion

Value-of-information analysis has been used in fisheries management to show the expected improvement in fisheries yield if management uncertainty was reduced (Forsberg & Guttormsen 2006; Mäntyniemi *et al.* 2009; Costello *et al.* 2010). In this management context, yield can easily be translated into a financial value, which makes the outcomes of value-of-information analysis easy to conceptualise. However, conservation success is usually measured in ecological terms, and the financial value of improving performance based on such metrics is difficult to conceptualise and inescapably subjective. In this study, we develop a method for converting an improvement in an ecologically relevant conservation metric into a financial value by finding the total investment required to achieve a similar improvement in ecological performance. Our approach has the potential to improve the cost efficiency of conservation plans for threatened species or ecosystems.

For budgets below $45 million, it would be inefficient to spend more than $85,000 on resolving parametric and structural uncertainty because the same expected improvement in population growth rate could be achieved by spending $85,000 on direct management action now, without allocating any resources to gaining new information. The financial value of information increased dramatically to $900,000 when budgets exceeded $45 million. This increase coincided with an important change in management strategies – investment in habitat restoration. It was not optimal to invest in habitat restoration when budgets were below $45 million. However, as budgets grew larger, the ecological gains from preventing vehicle collisions and dog attacks declined (a phenomena known as diminished marginal returns), and it became necessary to invest in habitat restoration to continue to drive the population growth rate up. Structural uncertainty was defined using eight different hypotheses about how habitat affects the probability of koala mortality threats. With this in mind, it makes sense that once we begin to invest in habitat restoration it becomes more valuable to know which of these hypotheses most accurately reflects reality.

There is more than one way of reducing the structural uncertainty surrounding Koala Coast koala management. Using Expected Value of Perfect Partial Information we found that it is most valuable to learn about how habitat cover affects the probability of koalas dying from disease. Resolving this link accounted for over 70% of the value of resolving structural uncertainty. Disease is prominent threat for koalas in the Koala Coast and, at this stage, can only be indirectly reduced through habitat restoration (Rhodes *et al.* 2011). Hence, any new research into the Koala Coast koala population should focus on the link between habitat cover and disease-related mortality, or developing new management actions that directly impact disease-related mortality. It may also be valuable to gain new information about uncertainties not explicitly considered in our analysis, such as uncertainties associated with the social willingness to partake in management actions (Knight *et al.* 2011) or uncertainty surrounding the cost of management actions (Salomon *et al*. 2013).

We applied our analysis to a highly studied conservation management problem (Dique *et al.* 2004; Dique *et al.* 2003; Lee *et al.* 2011; Rhodes *et al.* 2011; Ng *et al.* 2014), which may partly explain why the value of information was generally low. These previous studies have led to a good understanding of koala survival and fecundity rates, and the effect of habitat on mortality threats, and hence management decisions were not sensitive to parametric and structural uncertainty. Decisions were instead driven by a substantial difference between the cost efficiency of management actions. In other words, the cost efficiency of habitat restoration was comparatively so bad that resolving uncertainty would not change the decision to invest in preventing vehicle collisions and dog attacks initially, until diminished marginal returns from investment in these actions made it necessary to invest in habitat restoration. This observation is consistent with previous studies that show how the cost efficiency of management actions can drive optimal conservation decisions (Bode *et al.* 2008; Fuller *et al.* 2010). When the cost of habitat restoration was reduced to a level that made it similar to preventing vehicle collisions and dog attacks, management decisions became increasingly sensitive to parametric and structural uncertainty (Fig. 1b) and a substantial increase in the financial value of information was seen (Fig. 4). The management budget influenced the rate at which this increase occurred, with the financial value of information peaking later for lower budgets. An explanation for this is that, when budgets were small, it was not optimal to invest in habitat restoration and a much higher reduction in its cost was needed before it become optimal to include it in management strategies. More generally, our results theoretically demonstrate that it is more valuable to resolve ecological uncertainty when management actions have similar expected levels of cost efficiency in the face of uncertainty, compared to when there is a large difference in the cost efficiency of management actions. This property arises because EVPI is piecewise linear convex as a function of uncertainty, with the junctions occurring where the decision maker is indifferent between two actions (Williams, Eaton & Breininger 2011); thus the maximum EVPI must occur at a point of indifference. Although this result is established in the decision analysis literature, it is a highly relevant observation missing from the applied ecology literature. If nothing else, it serves as a timely reminder to conservation decision-makers that it is important to consider the cost efficiency of alternative management actions when planning monitoring projects.

Several considerations limit the inferences that can be drawn from this study. First, a scenario where perfect information is gained can only ever be hypothetical. For this reason, it is important to remember that results from value-of-information calculations represent the upper bound on any improvement in management performance (Dakins 1999; Yokota & Thompson 2004). Herein lies the potential use of Expected Value of Sample Information (EVSI) analysis, which can estimate the improvement in management performance if a sample of information is gained (Dakins *et al.* 1996;

Ades, Lu & Claxton 2004). The results of EVSI analysis are highly relevant to the decision-making process and future studies demonstrating its use in a conservation management setting would be beneficial. Second, whilst carrying out value-of-information analysis on the Koala Coast system, we ignored the time frame of management actions. For example, preventing dog attacks can potentially be implemented quickly and would be expected to immediately influence koala survival. Conversely, habitat restoration can take years to develop the habitat structure and complexity (Vesk *et al.* 2008) that is needed to increase the survival of threatened tree-dwelling species (Cunningham *et al*. 2007). Just as cost efficiency of management actions influenced the value of information in this study, the time frame of actions may also influence the value of information and there is a clear need to incorporate these time-dependency issues in future studies. Third, we note that our analysis considers only the value of information for the management decision at hand. Information may also be valuable outside the context of the original decision, for example, to similar decisions elsewhere (Nichols & Williams 2006). New information also has the potential to alter management targets, especially if targets prior to gaining new information are too weak or ambitious. Fourth, the population model used in this study assumes no loss in koala habitat into the future (Rhodes *et al.* 2011). Habitat cover in the Koala Coast has been relatively stable in recent years, but intensive urbanisation does threaten koala habitat along the Koala Coast (DERM 2010). Optimal strategies (and hence values of information) might favour increased proportional investment in habitat restoration if current rates of habitat loss and its effect on koala population growth rates were incorporated into the analysis.

The method outlined in this study will help expand the use of value-of-information analyses for conservation problems by providing a more tangible metric by which to evaluate research or monitoring. We also demonstrate that the value of information is higher when the cost efficiency of alternative management actions are similar, which serves as an important reminder for conservation decision-makers. The low value of information illustrated in this koala case study is consistent with previous literature that favours direct management action over gaining new information (Pauly *et al.* 2002; Myers 2003; Field *et al.* 2004). However, conservation problems exist where gaining additional new can dramatically improve management performance (Punt & Smith 1999; Costello *et al.* 2010; Runting, Wilson & Rhodes 2013). These varying results remind us that the value of information is case-specific and that uncertainty can have variable effects on the ability to achieve a management objective. With no blanket conclusions about the value of learning, value-of-information analysis can be used to inform wise conservation investment.

Acknowledgements

This research had funding support from the Australian Research Council Centre of Excellence for Environmental Decisions and the National Environmental Research Program.

Data Accessibility

- Data used to estimate parameters of population model: radio-tracking dataset from 1996 to 2000 (Dique *et al.* 2003; Thompson 2006) and; koala population density and abundance estimates from 1996 to 1999, 2005 to 2006, and 2008 (Dique *et al.* 2004; EPA 2007; DERM 2009).
- Matlab scripts: Dryad requires papers to be accepted before uploading data. If this paper is accepted, we will upload all scripts used in this study to Dryad.

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Tables

Table 1. Description of the eight alternative population model structures used to describe structural uncertainty, which is uncertainty about how habitat affects the probability of koala mortality threats in the Koala Coast. To calculate Expected Value of Perfect Partial Information, model structures were grouped according to whether habitat cover affects vehicle-related (S2, S5, S7 and S8), dog-related (S3, S5, S6 and S7) and disease-related (S4, S6, S7 and S8) mortalities

Model structure	Assumed influence of habitat cover on koala mortality threats
S1	No effect
S2	Reduces vehicle collisions
S3	Reduces dog attacks
S4	Reduces disease
S5	Reduces vehicle collisions and dog attacks
S6	Reduces dog and disease
S7	Reduces vehicle collisions, dog attacks and disease
S8	Reduces vehicle collisions and disease

Figures

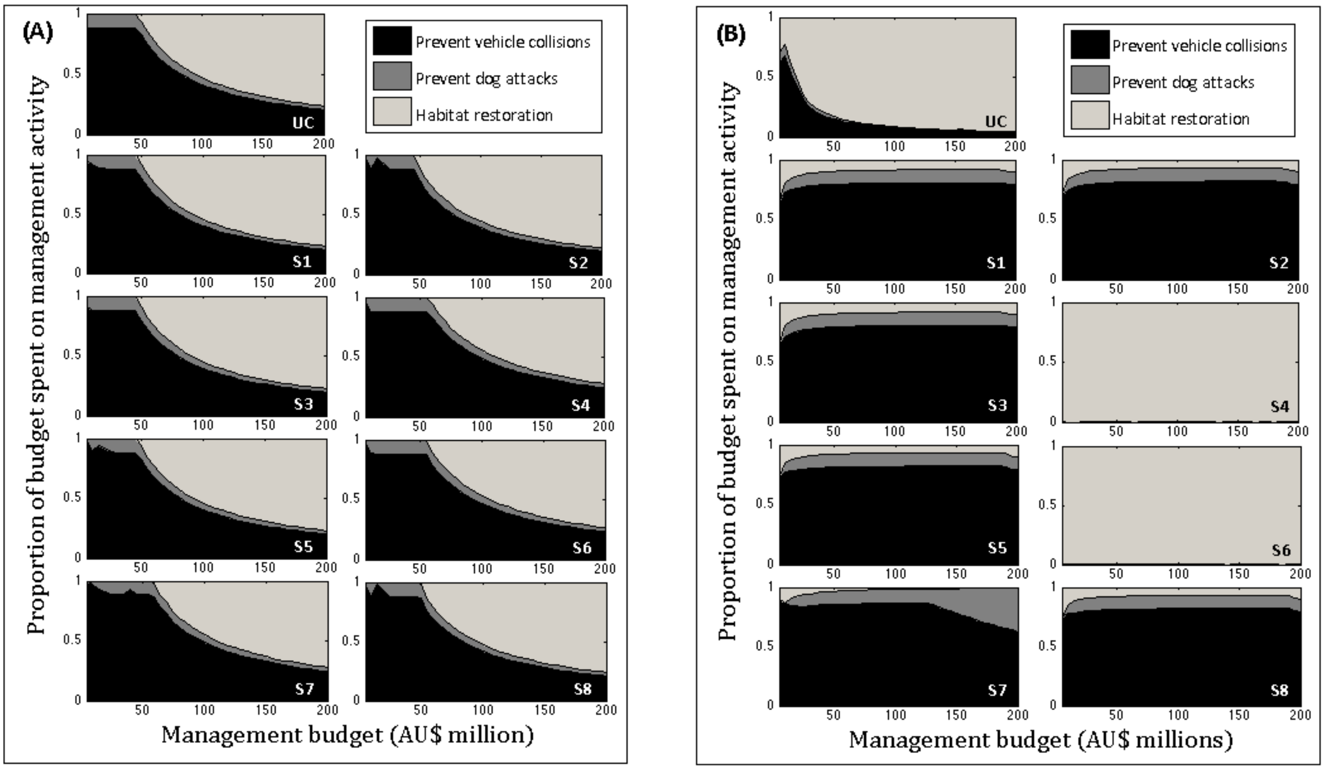


Figure 1. Optimal koala management strategies. Subplots S1 through S8 represent strategies under different model structures, which represent uncertainty about how habitat affects the probability of koala mortality threats. **(a)** Optimal strategies with current costs of habitat restoration in the face of parametric and structural uncertainty (UC), and if these uncertainties were resolved (S1 through S8). **(b)** Optimal koala management strategies with the current cost of habitat restoration divided by 10,000 when parametric and structural uncertainty is present (UC) and resolved (S1 through S8).

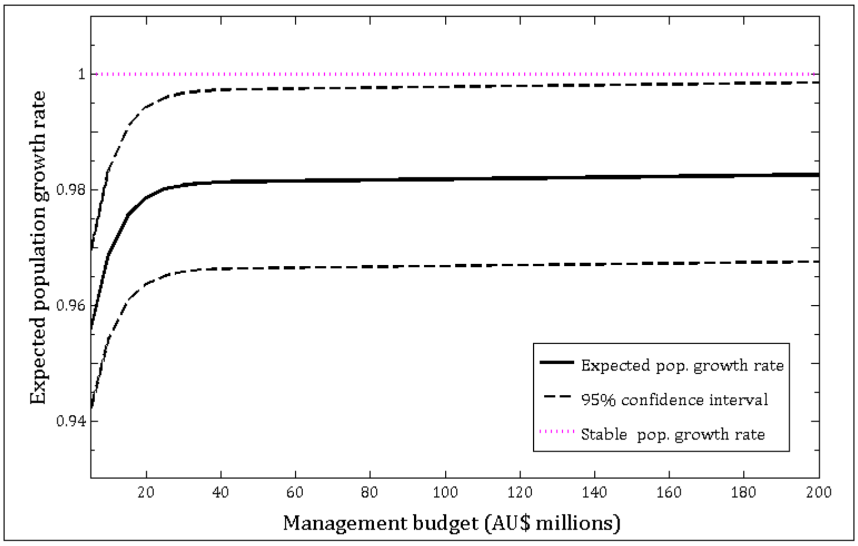
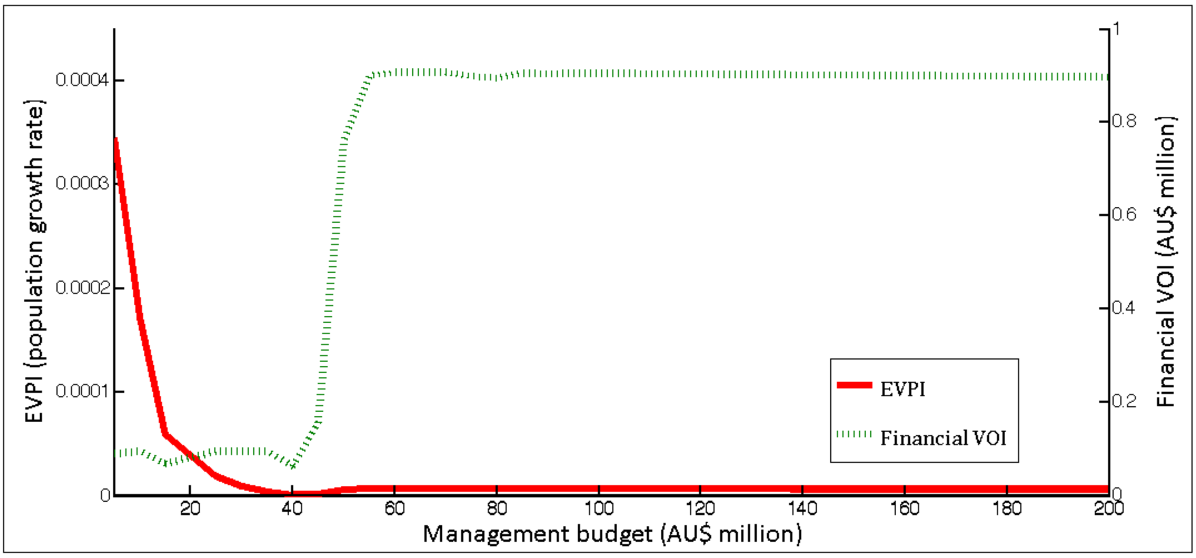


Figure 2. Expected koala population growth rate with current levels of information, using the optimal strategy shown in Fig. 1A (UC). The expected population growth rate is bounded by an upper and lower 95% confidence interval.



axis) represents the expected increase in koala population growth rate if uncertainty about fecundity and survival rates, and the effect of habitat on the probability of mortality threats was resolved. The financial value of information (green line and right y-axis) represents how much this expected increase in population growth rate would cost using management action alone.

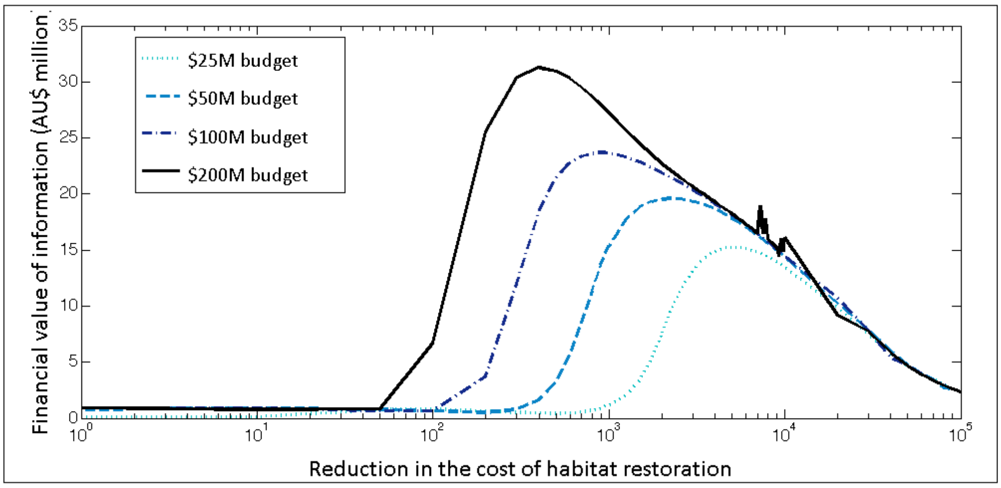


Figure 4. Financial value of information (FVOI) as the cost of habitat restoration is reduced. FVOI represents the maximum amount of money worth investing in new information about koala fecundity and survival rates, and the effect of habitat on the probability of mortality threats. Habitat restoration, and preventing vehicle collisions and dog attacks are similarly cost efficient when the cost of habitat restoration is reduced by 1000 and 10,000 times the current price.