Accounting for Complementarity to Maximize Monitoring Power for Species Management

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Running head: Complementary monitoring indicators

Keywords: indicator species, surrogacy, uncertainty, network theory, resource allocation, 1080 fox baiting, critical weight range mammals, *Vulpes vulpes*, Western Australia

Type of article: Contributed Paper, Conservation Biology

Abstract

To choose among conservation actions that may benefit many species, managers need to monitor the consequences of those actions. Decisions about which species to monitor from a suite of different species being managed are hindered by natural variability in populations and uncertainty in several factors: the ability of the monitoring to detect a change, the likelihood of the management action being successful for a species, and how representative species are of one another. However, the literature provides little guidance about how to account for these uncertainties when deciding which species to monitor to determine whether the management actions are delivering outcomes. We devised an approach that applies decision science and selects the best complementary suite of species to monitor to meet specific conservation objectives. We created an index for indicator selection that accounts for the likelihood of successfully detecting a real trend due to a management action and whether that signal provides information about other species. We illustrated the benefit of our approach by analyzing a monitoring program for invasive predator management aimed at recovering 14 native Australian mammals of conservation concern. Our method selected the species that provided more monitoring power at lower cost relative to the current strategy and traditional approaches that consider only a subset of the important considerations. Our benefit function accounted for natural variability in species growth rates, uncertainty in the responses of species to the prescribed action, and how well species represent others. Monitoring programs that ignore uncertainty, likelihood of detecting change, and complementarity between species will be more costly and less efficient and may waste funding that could otherwise be used for management.

Introduction

Monitoring programs are crucial for learning about and detecting changes in systems, evaluating the success of management actions or policies, and understanding the effects of perturbations or disturbances (Nichols & Williams 2006; Lindenmayer & Likens 2009). However, monitoring costs money. Limited resources and time mean that not everything can be monitored and decisions need to be made about how, where, and what to monitor (McDonald-Madden et al. 2010; Possingham et al. 2012). To deal with this problem, many authors have suggested monitoring just one or a few indicator species rather than many species (Caro & O'Doherty 1999; Rice & Rochet 2005; Regan et al. 2008). The vast literature on indicators often ignores one of the basic motivations for their use – provision of cost-effective information on whether an action is working. Using network theory and decision science, we devised a new way to combine the benefits, costs, and uncertainties inherent in selecting species to monitor in a method that selects the best set of indicator species.

Selection of indicator species that are surrogates for the responses of other species is one way to allocate resources to monitoring species that provide the most useful information for the least cost, especially when the target species for management are cryptic or more costly to monitor (Caro 2010; Tulloch et al. 2011). Here, we were concerned with situations where several species are co-managed with one kind of action. In general, previous research on indicator selection focused on either species surrogacy (capacity of 1 or 2 species to provide information about other species [Rodrigues & Brooks 2007; Halme et al. 2009; Cushman et al. 2010]), species detectability [Quinn et al. 2011], or the ability of the indicators to detect trends (in the environment, or in response to management [Trenkel & Rochet 2009]). Only a few studies have accounted for costs of monitoring alternative indicators (Pannell & Glenn 2000; Kurtz et al. 2001; Rice & Rochet 2005). To date, no indicator-selection frameworks have combined all these components and accounted for complementarity between species.

Complementarity in reserve selection ensures that areas selected for conservation complement those already selected (Margules et al. 1988; Justus & Sarkar 2002). In the case of indicator selection, the principle of complementarity allows one to choose different species, each of which provides information (e.g., on behavioral ecology, habitat use, or responses to management) on other species, by measuring the extent to which one species contributes unrepresented values to an existing set of species.

There are 2 kinds of errors one can make when choosing indicators: thinking an action is working when it is not (type I error) and believing an action is not working when it is (type II error). Each has consequences (Field et al. 2004), which may differ depending on the system change one is trying to monitor and the number or characteristics of species being represented by the indicator(s). In a threatened species management context, thinking an action is working when it is not could lead to the loss of a species because we fail to take further action (Field et al. 2004). Alternatively, one may manage the system, fail to detect the benefit to the indicator species, and stop management prematurely.

Decision makers need a repeatable and systematic way to select a set of indicator species to monitor, to ensure changes are detected when they occur, and to reduce the chance of management errors. Variability in dynamic systems means it is not always clear how populations will change over time, which leads to uncertainty when deciding what, when, and how to monitor (Magurran et al. 2010; Wilson et al. 2011b). The ability to detect a change may differ depending on how long a population has been monitored or how long ago an action took place (Gerber et al. 2005; Magurran et al. 2010). Outcomes of actions may also be uncertain and thus make it difficult to predict whether a population is likely to increase or decline. These uncertainties lead to an inability to articulate clear objectives for a monitoring program (Legg & Nagy 2006) and make it difficult to interpret whether monitoring results reflect the true status of the system (e.g., whether management has been successful). Previous prioritization approaches to indicator selection generally used a scoring or ranking method (e.g., Rice &

Rochet 2005; Tulloch et al. 2011), which in its simplest form does not take into account uncertainty or complementarity (Justus & Sarkar 2002; Margules & Sarkar 2007). Using real time-series data to characterize population variability over time, we built on previous indicator prioritization work to investigate the effects of different forms of uncertainty (Ives et al. 2003; Wilson et al. 2011a).

We solved the problem of selecting a complementary set of indicators that will detect a response to management, and demonstrated an example of candidate mammal species for monitoring the management of an invasive-predator (European red fox [*Vulpes vulpes*]) in Australia (Burbidge & Manly 2002). Finally, we compared our approach to finding optimal monitoring indicators with traditional methods of indicator selection.

Methods

Our new decision-science approach to cost-effective monitoring consisted of 6 steps: (1) define monitoring objectives and constraints; (2) list candidate indicators and calculate costs of monitoring each; (3) define data underlying species responses to management and determine likelihood of detecting a trend; (4) determine surrogacy value; (5) Combine information on trend detection and surrogacy to calculate monitoring benefits; and (6) solve optimization problems (Fig. 1).

Defining objectives and constraints

To optimally allocate resources among monitoring projects, it is important to clearly define the monitoring objectives and constraints, which might include resource limitations, and acceptable levels of risk (Possingham et al. 2001). Our objective was to design an optimal monitoring program for determining the effectiveness of a management action. We sought the best set of indicator species to monitor that would maximize the likelihood of detecting a meaningful change in the target species for a given budget. Species to be monitored (i.e., indicator species) and species that are in need of conservation (i.e., target species) can be the same. We used 2 groups of target species: all mammals in the system that we believe are affected by the management action and only the mammals listed as threatened.

Listing candidate indicators and calculating costs

Candidate indicators are species that decision makers wish to monitor to measure the effectiveness of their actions (Supporting Information). We used the method outlined in Tulloch et al. (2011) to calculate the individual cost (c) of monitoring species i over time T, assuming a discount rate of γ (Gerber et al. 2005):

$$c_i = \sum_{t=1}^{T} \gamma^{t-1} c_{it}, \tag{1}$$

where c_{it} is the cost of monitoring species i in year t. We defined the cumulative cost of monitoring a set of Z species ($C[Z]$) as the sum of the individual monitoring costs (Supporting Information).

Defining underlying data

Determining likelihood of detecting a trend

We defined the likelihood of detecting a real trend for each species as the difference between the likelihood of change in managed and unmanaged populations (Tulloch et al. 2011). This value depends on the magnitude of the response that we deemed significant (x), variability in count data (σ_n) and direction of the response to the action in the past (i.e., overall trend [$\bar{\mu}_n$]), and amount of empirical data that documents a response (i.e., length of the data set [n]). Using time-series data for managed populations, we derived the likelihood of detecting a trend for positive and negative growth rates (Supporting Information):

$$P_i\ (\mu > x) = 1 - P_i\ (\mu \leq x) \qquad \text{and} \tag{2}$$

$$P_i\ (\mu \leq x) = \Phi\ [(x - \bar{\mu}_n / (\sigma_n / \sqrt{n})], \tag{3}$$

where P_i ($\mu > x$) is the probability that the observed growth rate (μ) is greater than a given growth rate threshold (x), P_i ($\mu \leq x$) is the probability that μ is $\leq x$, Φ is the cumulative distribution function of the standard normal, and x can be any target growth rate set by the user. We refer to the likelihood of detecting a trend under management for each species as $P_i\,(x)$. Similarly, using time-series data for unmanaged populations, we derived the probability $P_{oi}\,(x)$ of species i increasing in population size faster than x if that action had not occurred. Hence the likelihood of detecting a real trend is $P_i\,(x) - P_{oi}\,(x)$.

Determining surrogacy value

We defined s_{ij} to be the amount of information that indicator species i provides on target species j. Previous researchers have used a range of methods to account for the information that makes a species a good surrogate for others, including area-by-feature scoring matrices (Margules et al. 2002), predictive modeling of species-level or community-level distributions (Ferrier et al. 2002; Ferrier et al. 2007), similarity or cluster analyses of abundance and distribution patterns (Halme et al. 2009; Cushman et al. 2010), and expert opinion (Tulloch et al. 2011). Our method requires the surrogacy measure take a value that ranges from zero to one. If the surrogacy measure is zero, then a change in species i does not imply a likely change in species j. If the surrogacy measure is close to one, then a change in species i means species i is a good surrogate for species j. We calculated the surrogacy value as the product of 3 attributes that reflect the similarity between the species: behavioral ecology, threat level, and habitat use overlap (Supporting Information). Other combining operators are possible, but the product operator results in a surrogacy value that is highest when the values of all 3 similarity indices are high.

Calculating monitoring benefits

We defined the benefit of monitoring a single indicator species as the likelihood of successfully detecting a response for a given action combined with how well it represents a given target. We calculated a benefit (B_{ij} [x]) that represents the value of monitoring indicator i for target j given x:

$$B_{ij}(x) = [P_i(x) - P_{oi}(x)] \times P_i(x)P_j(x) \times s_{ij}. \qquad . \tag{4}$$

The value produced by calculating $P_i\,(x) - P_{oi}\,(x)$ is the likelihood of successfully detecting a trend due to management as defined by the underlying data. The second part of the equation represents the interaction between species i and j. A value of $P_i\,(x)P_j(x)$ close to one means both species have a high likelihood of response under management, whereas s_{ij} tells one how much species i may inform one about species j. Because P_i, P_j, $P_i(x) - P_{io}(x)$, and s_{ij} all take values from zero to one, the value of $B_{ij}\,(x)$ is also a value between zero and one; higher values of $B_i\,(x)$ indicate greater benefits to species j of monitoring species i. The benefit of monitoring i for j is equal to the benefit of monitoring j for i only when the chance of detecting a real trend due to management is equal for both species, for example, $P_i(x) - P_{io}(x) = P_j(x) - P_{jo}(x)$. When $P_i\,(x) - P_{oi}\,(x)$ is $>P_j\,(x) - P_{oj}\,(x)$, the benefit of monitoring i for j is greater than the benefit of monitoring j for i. We represented the benefit of monitoring a species for another as a benefit network (Fig. 2).

We used 2 scenarios to calculate the monitoring benefits of a set of species Z. First, we defined a set benefit function (BS[x,Z]) that maximizes the complementary-monitoring benefits of Z for all target species and had a given growth rate x. For this benefit function we assumed overlapping benefits (i.e., all indicator species in set Z contribute in the same way to inform management success on the target species (Supporting Information). In this case, one should only account for species i that contribute the most to a target species j:

$$\mathrm{BS}(x, Z) = \sum_{j=1}^{m} \max_{\mathrm{i} \in \mathrm{Z}} B_{ij}(x). \qquad . \tag{5}$$

Second, we explored the effects of uncertainty in species complementarity by using an alternative way to calculate the benefit of monitoring a set of species (BU[x,Z]). For this method we assumed all species in set Z contribute in different random ways (nonoverlapping or overlapping) to the total benefits. In this case, we summed rather than maximized the benefit values for each species selected:

$$\mathrm{BU}(x, Z) = \sum_{j=1}^{m} \{1 - \prod_{i \in \mathrm{Z}} [1 - B_{ij}(x)]\}. \tag{6}$$

The BU(x,Z) represents a risk-averse approach in which it is uncertain whether the benefits are complementary and all the information for each species is included.

Solving the optimization problems

The optimization problem is to find the best set of species to maximize monitoring objectives under budget constraints. We calculated the solutions with traditional approaches we based on trend detection only or surrogacy only. We compared these solutions with solutions that combined trend detection and surrogacy.

The best set of species Z (formally defined as Z*) determined on the basis of trend detection only corresponded to the set that maximized the chance of detecting a real trend within a given budget, formally

$$Z^*(x) \ = \mathrm{argmax}_Z \ \ \sum_{\mathrm{i} \in Z} \ [P_i(x) - P_{oi}(x)] \ \text{ s.t. } C(Z) \leq budget, \tag{7}$$

where argmax_Z returns the set of species Z*(x) for which the function is maximized.

With surrogacy data alone, Z* is the set that maximizes the surrogacy value of each species for a given budget, formally

$$Z^* \ = \mathrm{argmax}_Z \ \ \sum_{j=1}^{m} \max_{\mathrm{i} \in \mathrm{Z}} s_{ij} \ \text{ s.t. } C(Z) \leq budget. \tag{8}$$

With a combination of trend detection and surrogacy, Z^* maximizes monitoring power for a given budget (Supporting Information), formally

$$Z^*(x) = \mathrm{argmax}_{Z,}\ \mathrm{BS}(x, Z) \quad \text{s.t. } C(Z) \leq budget, \tag{9}$$

where BS(x,Z) is a benefit set function that maximizes the complementary monitoring benefits of a set of species Z for all target species and a given growth rate x. We explored the effects of uncertainty in species complementarity with the risk-averse benefit function BU(x,Z) instead of BS(x,Z).

Example of selecting species for monitoring invasive predator control in south-western Australia

To illustrate the method (Fig. 1), we applied our approach to a case study of monitoring management of invasive foxes in Western Australia. The European red fox costs over $400 million/year to control (Reddiex et al. 2004). (All monetary units are Australian dollars.) Poison baits containing sodium monofluoroacetate (1080) are laid to reduce fox numbers in areas of high conservation significance, in particular where mammals in the critical weight range (between 35 and 5500g [Burbidge & McKenzie 1989]) occur. A growing body of literature describes the responses of a range of threatened species to fox management (Kinnear et al. 2002; Orell 2004; Saunders et al. 2010), but high monitoring costs mean that despite calls for a whole-community approach (Glen et al. 2009), it is rare for all species to be funded for monitoring. Managers need to identify which species are likely to be the most informative indicators with which to evaluate the effectiveness of their fox management within their budget constraints.

The candidate indicator species were 14 mammals from south-western Australia (Supporting Information). We parameterized Eqs. 2 and 3 by setting the target growth rate threshold x at 0%, 1%, 3%, 6%, and 10% for positive responses and at 0, –1%, –3%, –6% and –10% for negative responses. For species with no time-series data, we collated information from time-series data for other species with a similar weight range or life history (see Supporting Information for other methods when time-series were not available). To calculate the behavioral-ecology similarity index, we used a combination of similarity in microhabitat use (whether or not a species is ground dwelling, arboreal, or shelters in burrows or an aboveground nest) and similarity in body size (Burbidge & McKenzie 1989). The threat-similarity matrix listed the major threat classifications identified by the International Union for Conservation of Nature (2001, 2008) for the candidate indicator species (urbanization, agriculture, persecution, fire, and invasive species). Thus, we assumed species sharing the same threats respond in similar ways. The habitat-similarity index was a measure of how much 2 species share the same habitat (Supporting Information).

We identified the set of indicator species that maximized the monitoring benefit for all 14 target mammal species and the 6 threatened target species in the list of candidate indicator species. We also calculated the benefits of monitoring the set of species that are currently monitored at a broad scale in southwestern Australia and compared the benefits and costs of monitoring these species with the solutions from our approach. Finally, we conducted sensitivity analyses to test the underlying variables within our benefit function and to test the results of the optimization problems under different budgets. The MATLAB code is in Supporting Information.

Results

Trend detection with no surrogacy

The average trend in candidate indicator species under management ranged from a decline in abundance of 27% per year (western ringtail possum) to an increase in abundance of 25% per year (western quoll) (Supporting Information). Scientific names are provided in Table 1. When foxes were managed, the probability that the observed growth rate for each species was >0 ranged from 13% (woylie) to almost 100% for 3 species (Table 1). With no management of foxes, the probability that the observed growth rate of each species was >0 ranged from almost 0% (tammar wallaby) to >80% (woylie and honey possum) (Supporting Information). Incorporating the probability of increase with no management of foxes resulted in values for the likelihood of detecting a real trend due to management ($P_i - P_{oi}$) that were significantly different from values that only accounted for the probability of increase when foxes were managed ($t = 2.65$, d.f. = 26, $p = 0.01$) (Supporting Information). As expected the likelihood of detecting an increase in growth rate decreased with increased target growth rate thresholds x (7 species) (Supporting Information). The species with the greatest trends were the numbat, southern brown bandicoot, and dibbler.

For a budget of $100,000 and a growth-rate threshold of $0 > x > 1\%$, the top suite of species selected for trend detection alone were the western brush wallaby, tammar wallaby, and dibbler (cost $82,528). The western brushtail possum replaced the dibbler for a target growth rate of $x > 10\%$ (cost $75,409). With negative target growth rates ($-10\% < x < 0$), the woylie and western ringtail possum were selected (Table 1). Solutions that were based on only the probability of increase when foxes were managed without accounting for the likelihood of a trend in unmanaged populations contained different species for some target growth rates and were regularly more expensive (Supporting Information).

Surrogacy with no trend detection

The minimum multiplied surrogacy value s_{ij} between any pair of species was 0 (between the western ringtail possum and western brushtail possum), and the maximum was 1.00 (between the western mouse and numbat) (Supporting Information). The top surrogates selected as a suite of indicators under a budget of $100,000 were the southern brown bandicoot, western brushtail possum, and western mouse (cost $99,894). Each combining operator selected different species. Average surrogacy values resulted in selection of the tammar wallaby, western mouse, and bush rat (cost \$96,318); maximum values selected the tammar wallaby, western brush wallaby, and red-tailed phascogale (cost \$96,352); and minimum values selected the western brush wallaby, western brushtail possum, and numbat (cost \$76,113).

Combination of surrogacy and trend detection

When using our approach to maximize the benefit of monitoring by combining surrogacy and trend information, the selected set of species differed from those selected by just surrogacy or just trend information. For a budget of \$100,000 and an objective of maximizing the likelihood of monitoring an increase in population growth for all species (using BS[x,Z] in Eq. 9) (Figs. 3a & 4a), our selected species were similar to those for monitoring just the likelihood of response (western brushtail possum replaced the dibbler for a target growth rate of $x > 3\%$), and we no longer monitored the western ringtail possum for growth rates of $x < -3\%$ (Fig. 3). When we adjusted the monitoring objective to consider only indicators that represented the trends of threatened species, the selected set changed; the western brush wallaby dropped out of the indicator species group for all positive growth rate thresholds and the western quoll was added to the group for a target growth rate of $x > 10\%$ (Table 1 & Figs. 3b & 4).

Using the risk-averse benefit metric $BU(x,Z)$ (Eq. 9), we selected similar species to those selected with the maximum benefit metric $BS(x,Z)$ (Eq. 9, Fig. 3). For negative growth rates, we always monitored 2 species, the woylie and western ringtail possum, except for growth rates of $0.1 < x \leq 0.06$, for which we replaced the western ringtail possum with the southern brown bandicoot. The results for targeting threatened species with the risk-averse approach were similar to those for all species; the western quoll substituted the western brushtail possum for growth rates of $x < 6\%$.

For \$200,000 up to 7 species could be monitored. Using the maximum benefit metric ($BS[(x,Z])$ in equation Eq. 9), we selected different species for detection of different positive growth rates. For negative target growth rates, we selected the same 2 species as for a budget of $100,000. Using the risk-averse approach ($BU[x,Z]$ in Eq. 9), the species selected differed on the basis of target growth rate for positive and negative target growth rates (Supporting Information).

The comparison of objectives showed that combining surrogacy and likelihood of response always resulted in the highest benefit for detecting an increase or decrease compared with using just surrogacy or just likelihood of response, and almost always had the lowest cost (Table 2). This cost was considerably lower than the cost of monitoring the currently selected species (southern brown bandicoot, western quoll, woylie, and western brushtail possum). Changing the surrogacy classification resulted in changes to the best set of species to monitor for maximizing the benefit (Supporting Information).

Discussion

Monitoring the success or failure of management actions is important for learning about species dynamics, auditing conservation programs or policies, accounting for efficient spending of funding, and driving adaptive management decisions (Nichols & Williams 2006; Possingham et al. 2012). Deciding what, when, where, and how to monitor is difficult, particularly when the outcomes of actions are not certain (Williams 2001). Limited funding means one needs to choose species as surrogates or indicators for others. Past research on indicator selection has ignored the varying costs of monitoring different species, and has failed to account for uncertainties such as the likelihood of species responding to management, ability to detect real rather than spurious trends in populations, and how well one species represents another. Our new framework incorporates all these components in a transparent benefit function and can be used as a model for decision makers to select a set of species for monitoring that provides the most reliable information on the responses of other species that cannot all be monitored due to funding constraints (Fig. 1).

The first step in designing and implementing an effective monitoring program is to set realistic objectives and determine targets for population responses that are measureable and representative of the system (Legg & Nagy 2006; Lindenmayer & Likens 2009). We set clear objectives for species recovery during invasive predator control, which included positive and negative target growth rates. We the likelihood of detecting a response to management changes depended on the desired direction and magnitude of the response (Supporting Information). Sensitivity analyses showed that the level of knowledge available for a species (here the length of the monitoring data set) also altered the likelihood of detecting a trend and the subsequent value of the species for monitoring (Supporting Information). Monitoring objectives with too short a time frame or that do not account for the likelihood of positive and negative responses may result in more costly strategies that prioritize the wrong species for monitoring (Supporting Information). For our candidate species, we suggest that at least 5-10 years of monitoring is required for the best chance of detecting a real versus spurious effect of management. The choice of target growth rate depends on how risk averse managers are. A lower growth-rate threshold may result in a higher likelihood of a type I error (due to low growth-rate thresholds several species may decline or increase [Supporting Information]), whereas a higher growth-rate threshold may result in a higher chance of a type II error occurring (where managers are trying to detect too large a change and miss smaller changes).These findings highlight the importance of clearly stated goals an targets that reflect the level of knowledge of the system and the monitoring program constraints (e.g., acceptable level of risk or uncertainty [Supporting Information]).

We argue that a cost-effective indicator should be responsive (with low variability in growth rates over time [Hilty & Merenlender 2000]), representative (i.e., have high surrogacy), complementary to the indicator already chosen, and cheap. Previous approaches have dealt only with responsiveness and surrogacy, usually separately (but see Tulloch et al. 2011). The quantitative benefit function that we developed is flexible for multiple scenarios and types of data (Supporting Information) but still able to account for responsiveness and representation. In particular, our benefit function accounts for species that do not represent others on the basis of surrogacy information, and that are unlikely to respond to an action in the expected way (e.g., species likely to decline when others are expected to increase). Combining information on surrogacy and trend detection instead of treating these factors separately changes the species selected for monitoring (Table 2). Our benefit function is an improvement on the traditional methods of indicator selection because it allows one to select sets of complementary species for prioritization. Our results support previous findings that prioritization methods that account for complementarity are more efficient than ad hoc approaches (Pressey & Tully 1994) and ranking methods (Pressey & Nicholls 1989), the traditional approaches to indicator selection (Landres et al. 1988; Rice & Rochet 2005). Sensitivity analyses allowed us to explore the robustness of sets selected under different surrogacy scenarios. The value of monitoring different combinations of species depended on several factors (Fig. 4), but some species were always selected regardless of the surrogacy classification or the way benefit values were combined. These species could be considered more reliable than others that are selected only on the basis of one surrogacy classification or 1 of the 2 set benefit functions (Fig. 3 & Supporting Information).

Our new benefit function showed that the species monitored in our case study were not the most representative, cheapest, or most informative indicators of the responses of species to invasive-predator management (Table 2). Our indicator-selection approach translated to more information and less cost. Only 2 of the 4 species that are now actually monitored in our study area were represented in our best sets (western brushtail possum and woylie) (Table 2). The species not selected were either too variable in their expected response (southern brown bandicoot) (Supporting Information) or had a high likelihood of showing a response in the absence of management (western quoll) (Supporting Information), findings that indicated the species may be reacting to factors other than the management action in question. The two species selected most frequently for detecting an increase under fox management (Fig. 3 & Supporting Information) were the tammar and western brush wallabies that, although rare, are not listed as threatened (IUCN 2009), but they have low variability and high growth rates when managed (Supporting Information). The dibbler was also frequently selected as an indicator (Figs. 3 & 4). This species is highly threatened and found in few locations, but its high certainty of response to management meant it was often selected over other species with higher surrogacy values (Supporting Information).

Monitoring choices should be driven by clear objectives, cost, and knowledge of uncertainty. Indicator species provide managers with a systematic, cost-effective, and repeatable way to measure and monitor the outcomes of conservation actions, which can feed into decisions for adaptive management (Caro & O'Doherty 1999). We developed a new decision-science framework to select indicators that maximize the benefit of monitoring complementary sets of species and account for natural variability in species growth rates, uncertainty in the responses of species to the prescribed action, and how well species represent others (Fig. 1). If costs and species complementarity are not incorporated into the planning process, decisions could be costly and inefficient, uninformative species might be monitored, with potential negative consequences for management. Many actions will not benefit all species – for invasive-predator management, we found a likelihood of negative effects on some species (Table 1). In these cases, we recommend a risk-averse strategy of selecting the set of species that maximizes the expected benefit of detecting any change (negative or positive) that informs actions relevant to most species. By setting measurable objectives and targets with a realistic time frame for monitoring and by exploring uncertainty before monitoring takes place, it will be easier to adaptively manage and monitor populations and audit investment decisions during and after monitoring programs. This framework can be used to design optimal monitoring strategies that can detect trends in population growth in spite of the variability and levels of uncertainty inherent in the system, which will enhance the utility and transparency of monitoring programs in the future.

Acknowledgments

This research was conducted with funding from the Australian Government's National Environmental Research Program and the Australian Research Council Centre of Excellence for Environmental Decisions, an Australian Research Council Linkage Grant (A.T.) and an Australian Research Council Federation Fellowship (H.P.). We thank K. Wilson, H. Wilson, V. Tulloch and T. Martin for comments on earlier drafts and Peter Orell, the Western Australian Department of Environment and Conservation, Australian Wildlife Conservancy, Bush Heritage, Nick Dexter, and Katherine Moseby for the use of unpublished data.

Supporting Information

Detail explaining the methodology behind deriving the likelihood of detecting a real trend (Appendix S1), calculating monitoring costs (Appendix S2) and calculating surrogacy values (Appendix S3) for each species are available online. Also available online are the link to the MATLAB code and illustrations of outputs from the optimization approach (Appendix S4), the results of sensitivity analyses (Appendix S5) and further descriptions of the two benefit metrics (Appendix S6). The authors are solely responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author.

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Table 1. Likelihood of an increase or decrease under management (P_i [0]) compared with the likelihood of detecting a real trend ($P_i [x] – P_{oi} [x]$) for target growth rates (x) of 0% and 10%.

		Increasing growth rate			Decreasing growth rate		
Species no.	Species	P_i (0)	P_i (0) – P_{oi} (0)	P_i (10%) – P_{oi} (10%)	P_i (0)	P_i (0) – P_{oi} (0)	P_i (−10%) – P_{oi}(−10%)
1	Tammar wallaby, *Macropus eugenii*	0.99*	0.99*	0.89*	0.01	0	0
2	Western brush wallaby, *Macropus Irma*	1.00*	0.99*	1.00*	0.00	0	0
3	Western quoll, *Dasyurus geoffroii*	1.00*	0.34	0.44	0.00	0	0
4	Dibbler, *Parantechinus apicalis*	0.85	0.79*	0.55	0.15	0	0
5	Red-tailed phascogale, *Phascogale calura*	0.57	0.57	0.45	0.43	0	0
6	Southern brown bandicoot, *Isoodon obesulus*	0.99	0.53	0	0.01	0	0.05
7	Woylie, *Bettongia penicillata*	0.13	0	0	0.87*	0.71*	0.62*
8	Western brushtail possum, *Trichosurus vulpecula*	1.00	0.49	0.60*	0.00	0	0
9	Numbat, *Myrmecobius fasciatus*	0.65	0.51	0.20	0.35	0	0
10	Western ringtail possum, *Pseudocheirus occidentalis*	0.39	0	0	0.61*	0.04*	0.21*
11	Western mouse, *Pseudomys occidentalis*	0.72	0.30	0.27	0.28	0	0
12	Echidna, *Tachyglossus aculeatus*	0.50	0.14	0.29	0.50	0	0
13	Bush rat, *Rattus fuscipes*	0.52	0.20	0.12	0.48	0	0
14	Honey possum, *Tarsipes rostratus*	0.87	0.05	0.41	0.13	0	0
	Monitoring cost (Australian dollars)	96,352	82,528	75,409	79,297	79,297	79,297

* Sets of species selected under a budget of $100,000 and only accommodating trend detection.

Table 2. Comparison of the best indicator sets of species selected under a budget of AU$100,000 and to detect an increase of at least 6% growth rate annually and a decline of at least 6% for all target species and for threatened target species (see also Fig. 4).

	All target species			Threatened species		
Monitoring objective and method of calculation[a]	best set (Z) of species[b]	benefit $\mathrm{BS}(x, Z)$	cost (AU$)	best set (Z) of species	benefit $\mathrm{BS}(x, Z)$	cost (AU$)
Objective 1						
increase $x > 0.06$						
Method						
just trend: P_i and P_{oi}	1 2 4	4.44	82,527	4 5	0.74	78,334
just trend: P_i only	1 2 3	4.38	96,352	3 4	1.01	78,334
just surrogacy	6 8 11	1.97	99,894	4 9 10	0.73	91,313
best indicator	1 2 8	4.68	75,409	1 4	1.18	57,391
currently monitored	3 6 7 8	2.55	156,461	3 6 7 8	0.86	156,461
Objective 2						
decrease $x < -0.06$						
Method						
just trend: P_i and P_{oi}	7 10	2.33	79,297	7 10	1.33	79,297
just trend: P_i only	6 7	2.31	85,246	7 10	1.33	79,297
just surrogacy	6 8 11	0.47	99,894	4 9 10	0.14	91,313
best indicator	7 10	2.33	79,297	7 10	1.33	79,297
currently monitored	3 6 7 8	2.31	156,461	3 6 7 8	1.31	156,461
Combined best set of objectives 1 and 2	1 2 7 8 10	7.01	154,706	1 4 7 10	2.51	136,688

[a] Variables: x, given growth rate threshold; P_i, likelihood of detecting a trend with fox management for each species; P_{oi}, likelihood of detecting a trend without fox management for each species; Z, set of species; BS(x, Z), maximum benefit function (Equation 9).

[b] Species names provided in Table 1.

Figure legends

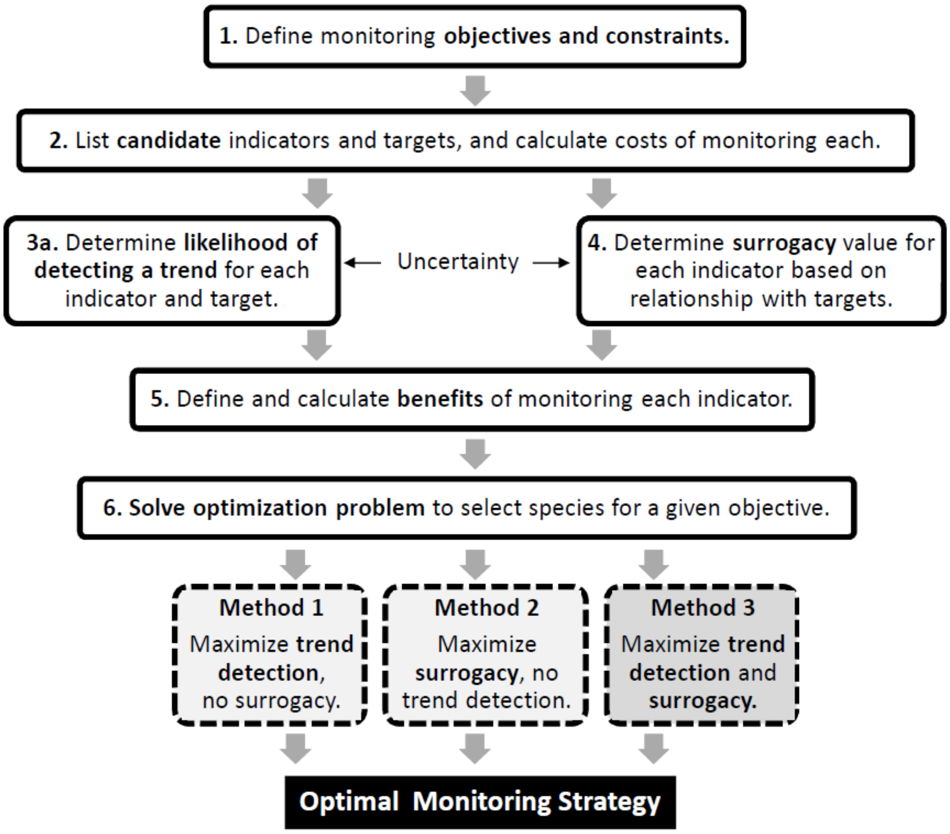

Figure 1.

Decision framework for selecting indicator species to monitor given multiple species, species' responses to management, and monitoring objectives. Methods 1 and 2 represent traditional approaches to selecting species to monitor. Method 3 is our new approach.

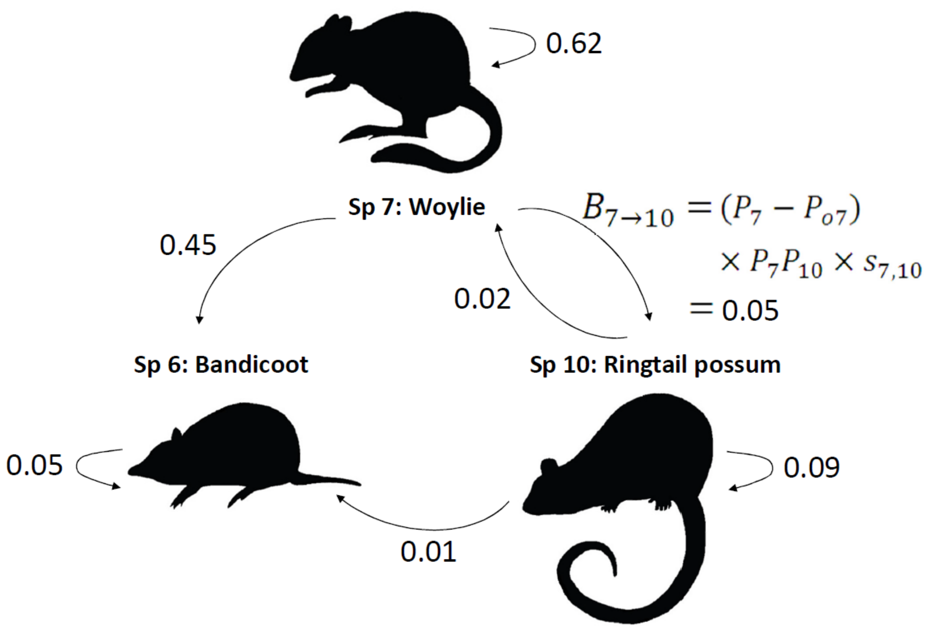

Figure 2. Benefit network for 3 species, where species are nodes and arrows are the species' monitoring benefits (*B*). The benefit of monitoring indicator species (*i*) 7 (woylie) for target species (*j*) 10 (western ringtail possum) is shown as $B_{i\to j}$; s_{ij} is the surrogacy value of species *i* for species *j*; P_i and P_j are the likelihood of detecting a trend under management for species *i* and *j* respectively, and P_{oi} is the likelihood of detecting a trend when species *i* is not managed. In this case, the benefit of monitoring the woylie to inform one of a trend in the ringtail possum is 0.05. We assume a significant decline rate is 10% . The bandicoot has no arrows leading to another species and thus has a monitoring benefit of zero for detecting a response of 10%.

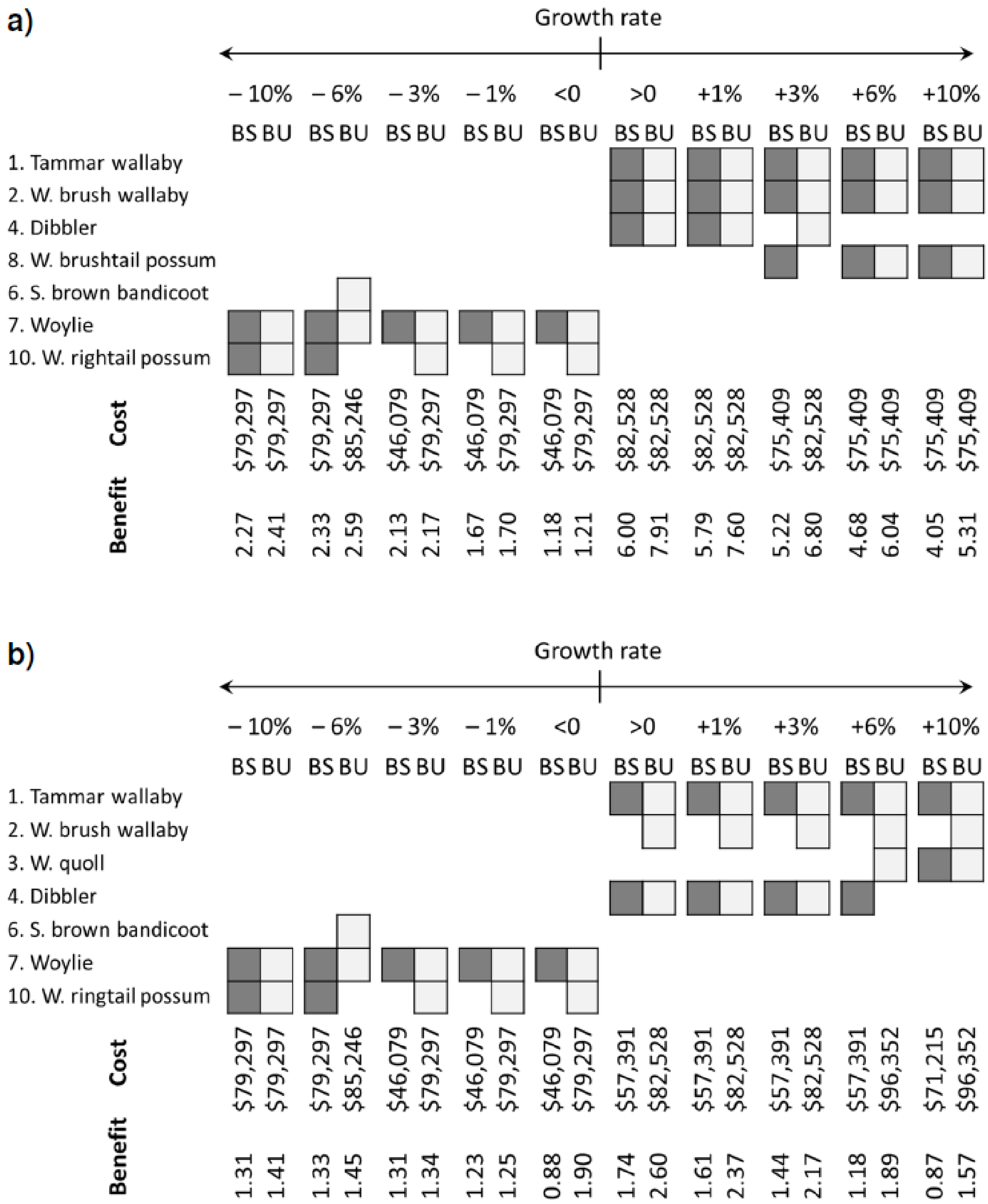

Figure 3. Best set of species to monitor under a range of growth rates for a budget of AU$100,000 for (a) all target species and (b) threatened target species only. Equations 5 and 6 are used to derive benefit values of $\mathrm{BS}(x, Z)$ (dark grey) and $\mathrm{BU}(x, Z)$ (light grey) respectively (BS, maximum benefit metric; BU, risk-averse benefit metric) Eq. 9 is used to solve the optimization (see also Fig. 4). The boxes represent whether or not that species was chosen on the basis of a given metric. For example, in (a) on the basis of a maximum benefit metric that assumes overlapping benefits (BS[x,Z]) and to detect a positive growth rate of 6%, the tammar wallaby, western brush wallaby, and western brushtail possum are selected at a cost of $75,409. On the basis of a risk-averse metric (BU[x,Z]) that assumes nonoverlapping benefits, this species set changes to tammar wallaby, western brush wallaby, and dibbler at a cost of $82,528.

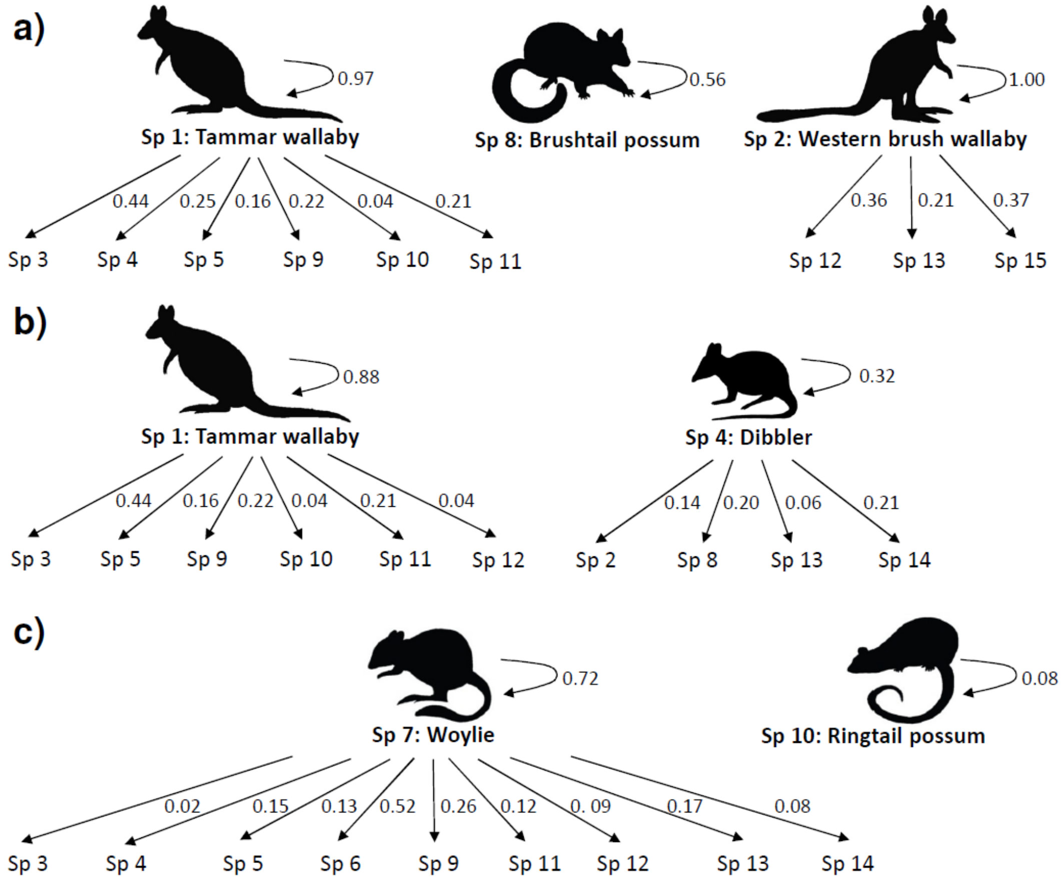

Figure 4. The sets (Z) of species selected for monitoring under a given annual budget of AU$100,000 that maximize the summed benefits for detecting (a) an increase of 6% annually, (b) an increase of 6% annually in threatened species only, and (c) a decline of 6% annually (Eq. 5 used to derive edge values of BS[x,Z]). For example, in (c) species 7 (woylie) informs managers of changes in 9 species, and species 10 (western ringtail possum) informs managers of changes only in itself.