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When to monitor and when to act: Value of information theory for multiple management units and limited budgets

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Abstract

1. The question of when to monitor and when to act is fundamental to applied ecology and notoriously difficult to answer. Value of information (VOI) theory holds great promise to help answer this question for many management problems. However, VOI theory in applied ecology has only been demonstrated in single-decision problems and has lacked explicit links between monitoring and management costs.
2. Here, we present an extension of VOI theory for solving multi-unit decisions of whether to monitor before managing, while explicitly accounting for monitoring costs. Our formulation helps to choose the optimal monitoring/management strategy among groups of management units (e.g. species, habitat patches) and can be used to examine the benefits of partial and repeat monitoring.
3. To demonstrate our approach, we use case-simulated studies of single-species protection that must choose among potential habitat areas, and classification and management of multiple species threatened with extinction. We provide spreadsheets and code to illustrate the calculations and facilitate application. Our case studies demonstrate the utility of predicting the number of units with a given outcome for problems with probabilities of discrete states and the efficiency of having a flexible approach to manage according to monitoring outcomes.
4. *Synthesis and applications*. The decision to act or gather more information can have serious consequences for management. No decision, including the decision to monitor, is risk-free. Our multi-unit expansion of Value of Information theory can reduce the risk in monitoring/acting decisions for many applied ecology problems. While our approach cannot account for the potential value of discovering previously unknown threats or ecological processes via monitoring programmes, it can provide quantitative guidance on whether to monitor before acting, and which monitoring/management actions are most likely to meet management objectives.

KEYWORDS
decision theory, habitat protection, management strategy, monitoring, multiple management units, optimization, threatened species, value of information

1 | INTRODUCTION

The question of how much information is needed to inform management is central to applied ecology. Information from monitoring is often vital to effective decision making. Unfortunately, many management decisions are made based on inadequate information (Sutherland, Pullin, Dolman, & Knight, 2004), which can lead to inefficient or counterproductive choices (Cook, Hockings, & Carter, 2010). Monitoring, particularly if it is conducted over long time periods, has also led to the discovery of important environmental stressors (e.g. Lindenmayer et al., 2012; Wintle, Runge, & Bekessy, 2010).

However, monitoring costs money and time, both of which can be in short supply. Monitoring instead of managing can also be a way of avoiding difficult but necessary decisions (Nichols & Williams, 2006). Indeed, there are cases of threatened species being monitored continuously until they are extinct (Lindenmayer, Piggott, & Wintle, 2013; Martin et al., 2012). Information gathering, beyond what is necessary to make an effective decision, risks dissipating resources that could have been used for management, and missing critical windows of opportunity (Chadès et al., 2008; Martin et al., 2012; McDonald-Madden et al., 2010).

Value of information (VOI) theory provides an important tool to choose monitoring strategies. By explicitly modelling the value gained by monitoring, VOI theory can be used to determine whether additional information would be useful for a specific management question. The utility of VOI theory has been demonstrated for invasive species management (Hauser & McCarthy, 2009; Moore & Runge, 2012), disease control (Shea, Tildesley, Runge, Fonnesbeck, & Ferrari, 2014), threatened species management (Canessa et al., 2015; Maxwell et al., 2015; Runge, Converse, & Lyons, 2011; Williams & Johnson, 2015), and conservation reserve selection (Mazor, Beger, McGowan, Possingham, & Kark, 2016; Runting, Wilson, & Rhodes, 2013). These applications of VOI suggest that decisions involving a combination of monitoring and management should first assess the value of monitoring strategies.

Despite the applicability of VOI to decision making, there are two key limitations of conventional VOI used in applied ecology. The first limitation is that VOI theory has not been fully developed for multi-unit management, which occurs when managing multiple species or multiple habitat patches. In the decision theory literature, multi-unit problems have recently been explored (Bickel & Zan, 2009; Keisler, 2004; Zan & Bickel, 2013), but with either strict assumptions of identical unit costs, or simulation to examine the influence of relaxed assumptions, rather than generalized theory that is broadly applicable. In applied ecology, VOI theory has only been presented for problems involving decisions for single management units or single decisions applied to grouped sets of management units (e.g. all species or habitat patches in a study), rather than individual decisions among management units (e.g. which species to monitor vs. manage, which habitats to monitor vs. manage). This limitation makes VOI difficult to implement for many real-world problems in applied ecology.

The second limitation is that when monitoring results and financial or time costs are not explicitly related, VOI cannot directly answer the question of when to monitor and when to act. For example, a VOI exercise may suggest value in monitoring, but if the monitoring is expensive or the timeframe for successful management is limited, this value may be diminished or negated. This limitation is closely related to the first limitation, because budgets are often insufficient to manage all units and must be carefully allocated among them (e.g. Joseph, Maloney, & Possingham, 2009; Wilson, Carwardine, & Possingham, 2009).

Recently, several authors have attempted to overcome the challenge of explicitly considering monitoring costs in VOI analysis for problems in applied ecology. Maxwell et al. (2015) calculated the financial value of perfect information for a conservation problem by estimating the cost of optimal population management with current information and with uncertainties resolved. Mazor et al. (2016) used systematic reserve selection software to infer that intensive monitoring information provided better reserve selection outcomes than more extensive information. Shea et al. (2014) used financial VOI to infer whether a monitoring strategy would be worthwhile. Although these approaches provide important advances for quantifying the value of monitoring, they did not explicitly incorporate monitoring costs, nor determine the trade-off between monitoring and management costs.

Here, we present an extension of VOI theory for solving problems of monitoring versus action across multiple management units, while explicitly considering the cost of monitoring. In doing so, we link VOI theory with decision theory for optimal management. We also show that where decisions for management units are based on probabilities of discrete states (e.g. "is species X present in unit Y"), we can calculate the expected number of units with a given state and make decisions to monitor or act more efficiently than using aggregated single-decision VOI calculations. The theory presented is general, and we show how it can be used to understand risk in decision making when there is uncertainty in data. Using these calculations, we can explore a wide range of questions, including trade-offs between monitoring effort and cost, and the benefits of partial or repeat monitoring. We demonstrate potential applications using two simple, simulated case studies of threatened species conservation.

2 | MATERIALS AND METHODS

2.1 | Formulation

VOI analysis addresses the question of whether information to reduce uncertainty about a problem is worth gathering. Across multiple management units, it can be used to address whether additional information would be useful for more efficient management, given limited budgets (Keisler, 2004; Zan & Bickel, 2013). To calculate VOI across multiple management units that explicitly accounts for costs, we require estimates of the following (Table 1): (1) cost of management actions; (2) prior probabilities for states of the units (these can be non-informative priors); (3) expected values of our management actions (i.e. the estimated benefit of actions, given possible states of the management units); (4) monitoring accuracy; and (5) monitoring cost. Monitoring cost can be financial, and thus restrict management options, or can be incurred via impacts on management goals, such as when delays due to monitoring reduce management efficacy.

Estimates of these parameters can contain considerable uncertainty. However, such estimates are commonly used in setting

TABLE 1 Terms of equations

Symbol	Term
$\mathbb{E}$	Expected value of a management action
s	State of a management unit
A	Set of all possible management actions for a given state s
a	Individual management action
x	Binary decision variable identifying whether an action is taken
P_s	Prior probability of a state s
$V(a, s)$	Value of a management action for a state s
y	Monitoring result
U	Number of management units (e.g. habitats, species)
B	Budget
c	Cost of an individual management action

conservation priorities (e.g. Ball, Possingham, & Watts, 2009; Bennett et al., 2014; Joseph et al., 2009; McCarthy et al., 2010), and indeed are implicit in every conservation decision regarding monitoring versus acting. With estimates of these parameters, we can relate monitoring and management costs and use these to calculate trade-offs between monitoring first versus acting on current information. As shown below, we can also explore plausible ranges for parameter estimates, to determine the ranges of conditions in which we would decide to monitor before acting.

Below, we briefly describe conventional single-decision VOI theory, using modified terminology of Canessa et al. (2015), outlined in Table 1. We then present a VOI formulation for decisions across multiple management units that accounts for both monitoring and management costs. We provide a full mathematical formulation in Appendix S1, and step-by-step walkthroughs for the case studies in Appendices S2–S4.

2.2 | VOI for a single management unit

According to VOI theory, one can quantify the expected value of a given action on a scale compatible with the management objectives, for example, the 50-year probability of extinction, or population size. The value of the action depends on the true state of the management unit(s), for example, whether the species is present or absent in a given habitat patch. However, there is uncertainty about which state the management unit is in.

The expected value of an action a_i under uncertainty can be calculated as follows:

$$\mathbb{E}\left[V(a_i, s)\right] = \sum_{s \in S} \left\{V(a_i, s) \cdot P_s\right\} \quad (1)$$

This is the sum of all possible values for the action a_i for all states s of the management unit, with each value weighted by its respective probability of the state s being true.

The expected value of the best management action under uncertainty can be calculated as follows:

$$\mathrm{EV}_{\mathrm{uncertainty}} = \max_{a_i \in A} \mathbb{E}_s[V\left(a_i, s\right)]. \quad (2a)$$

This is the maximum expected value from Equation 1 among all potential management actions. The same equation can be formulated as a decision problem by introducing a binary decision variable x_i identifying whether action a_i is implemented:

$$\mathrm{EV}_{\mathrm{uncertainty}} = \max_{x_i} \sum_{i=1}^{|A|} x_i \mathbb{E}_s\left[V\left(a_i, s\right)\right]. \quad (2b)$$

The standard formulation used herein assumes a single management action can be taken for a unit $\sum_{i=1}^{|A|} x_i \leq 1$ and represents the expected value of the management action one would logically take with current information.

Although absolute certainty rarely exists in environmental decision making, the expected value of the best management action under certainty, which is calculated as follows, is nonetheless useful for comparing with the expected value of sampling or monitoring information:

$$\mathrm{EV}_{\mathrm{certainty}} = \mathbb{E}_s[\max_{a_i \in A} V\left(a_i, s\right)] = \sum_{s \in S} p(s) \max_{a_i \in A} V\left(a_i, s\right). \quad (3a)$$

This is the sum of all the best management actions for all the possible states of the management unit, weighted by the probabilities of each state being true. This differs from the expected value of the best management action under uncertainty in that it sums across all possible states (instead of taking the single best management action with uncertainty). Thus, it is always equal to or greater than the expected value of the best management action under uncertainty.

The expected value under certainty can also be formulated as a decision problem:

$$\mathrm{EV}_{\mathrm{certainty}} = \max_{x_i^s} \sum_{s \in S} \sum_{i=1}^{|A|} p(s)\, x_i^s V\left(a_i, s\right). \quad (3b)$$

where the decision variable x_i^s identifies which action a_i to implement for each possible state s.

The difference between the expected value of the best management action under certainty and uncertainty is termed the expected value of perfect information (EVPI) and is calculated as follows:

$$\mathrm{EVPI} = \mathrm{EV}_{\mathrm{certainty}} - \mathrm{EV}_{\mathrm{uncertainty}} \quad (4)$$

Monitoring will typically improve upon current information and increase the expected value of the best management action. Specifically, monitoring will change our belief about the probability of each state s being true. In VOI, probabilities for each state s being true are estimated for each possible monitoring result using Bayes Theorem, that is, *probability(state s|result y) = probability(result y|state s) × prior probability (state s)/probability(result y)* (Raiffa, 1968). The expected value of the best management action when information from monitoring (y) is incorporated is as follows:

$$\mathrm{EV}_{\mathrm{monitoring}} = \mathbb{E}\left\{\max_{a_i \in A} \mathbb{E}_{|y}[V(a_i, s)]\right\}. \quad (5a)$$

The expected value after monitoring information can also be formulated as a decision problem:

$$\mathrm{EV}_{\mathrm{monitoring}} = \max_{x_i^y} \sum_{y \in Y} p(y) \sum_{i=1}^{|A|} x_i^y \sum_{s \in S} V(a_i, s)\, p(s|y) \tag{5b}$$

where x_i^y identifies the action a_i to implement for each possible monitoring result y. This is the expected value of the best management action for each monitoring result y, weighted by probabilities of obtaining the monitoring results.

The expected value of monitoring information (frequently termed the expected value of sampling information, EVSI, in the VOI literature) is the difference between the expected value of the best management action after monitoring and the expected value of the best management action under uncertainty (i.e. before monitoring):

$$\mathrm{EVSI} = \mathrm{EV}_{\mathrm{monitoring}} - \mathrm{EV}_{\mathrm{uncertainty}} \tag{6}$$

2.3 | VOI across multiple management units with a limited budget

There are two key differences in calculation between VOI across multiple management units and conventional VOI. The first is that VOI across multiple management units allocates decisions among individual units, providing the flexibility to maximize our best *overall* values among units by ranking and summing expected values for management decisions within a budget, as opposed to choosing among general strategies presented as a single-decision problem (Bickel & Zan, 2009; Zan & Bickel, 2013). This flexibility has important implications. For example, if we are deciding whether to protect a single habitat patch, our optimal decision may be to protect even after monitoring does not confirm the presence of our species of interest (because there is a diminished, but non-zero posterior probability it is present). But if we are deciding which of a set of habitat patches to protect, we may only protect patches where we actually found the species.

The second difference from conventional VOI is that for problems involving probabilities of discrete states, prior probabilities can be used to estimate the number (or fraction) of management units with a given state, using the linearity of expectation property of random variables, that is, $\mathbb{E}(X+Y) = \mathbb{E}(X) + \mathbb{E}(Y)$. This allows us to allocate management or monitoring decisions among units to maximize the summed expected values among units, within a given budget. If our budget was unlimited, we would calculate expected value of the best decisions given current, perfect or monitoring information for all management actions, and our expected values would simply be the summed results of conventional VOI equations across all management units. In the far more likely scenario of a limited budget, we can calculate the expected value of decisions across management units and choose the optimal set of decisions that maximizes the summed expected value, subject to our budget.

The expected value of the optimal group of management actions under uncertainty is as follows:

$$\mathrm{EV}^{*U}_{\mathrm{uncertainty}|B} = \max_{x_i^j} \sum_{j=1}^{|U|} \sum_{i=1}^{|A^j|} x_i^j \sum_{s \in S^j} p(s)\, V(a_i^j, s)\,. \tag{7}$$

This is the maximum (subject to the budget B) of the summed expected values of management actions among units under uncertainty (Equation 1), where A_j is the suite of available actions for unit j, and x_i^j is a decision variable which identifies which action a_i^j to implement for a given unit j (see Appendix S1 for details).

Equation 7 can be formulated as a knapsack problem, whereby a decision maker with limited capacity must choose among management options to maximize value. Knapsack problems have a long history in optimization research, and many algorithms to solve them have been proposed (see Kellerer, Pferschy, & Pisinger, 2004; Martello & Toth, 1990 for detailed reviews). In applied ecology, examples of the knapsack problem include setting priorities for managing species (e.g. Bennett et al., 2014; Joseph et al., 2009) and managing threats to biodiversity (e.g. Carwardine et al., 2014). Finding an exact solution to a knapsack problem can be challenging and require considerable computer resources, especially when investments and returns are strongly correlated and the number of potential actions and management units is large (Pisinger, 2005). However, heuristics can be used to find approximate solutions. One well-known approximation first proposed by Dantzig (1957) is to rank potential actions among management units by the expected cost-effectiveness of management based on current knowledge (i.e. expected value of decision under uncertainty/action cost), and choose units sequentially according to rank, with the goal of managing the units with the greatest summed expected value. In conservation, this approach has formed the basis of prioritization protocols for threatened species (e.g. Bennett et al., 2014; Government of New South Wales, 2013; Joseph et al., 2009), and an analogous technique has been used for reserve selection (Moilanen, 2007). Although this approach can be less efficient than more complex approaches (Kellerer et al., 2004), particularly when costs of actions are large compared to the overall budget, it is intuitive and easy to illustrate. We use it in our case studies, but note that our methods are compatible with other techniques. We also note that individually suboptimal actions may sometimes be optimal for multi-unit problems (see Appendix S1 for details). In the simple case where the cost of management for all units is equal (e.g. if we are trying to allocate equal-sized predator exclosures among habitats), costs can be normalized to one, and the expected cost-effectiveness of management in a unit is simply the expected value of the chosen management action under uncertainty for that unit.

2.4 | Expected value of optimal group of management actions under certainty

Among multiple management units, the expected value of the optimal group of management actions under certainty can be calculated as follows:

$$\mathrm{EV}^{*U}_{\mathrm{certainty}|B} = \max_{x_i^{s,j}} \sum_{j=1}^{|U|} \sum_{s \in S^j} \sum_{i=1}^{|A^j|} p(s)\, x_i^{s,j} V(a_i^j, s) \tag{8}$$

This is the maximum, subject to the budget B, of the summed probabilities of possible states s for each unit, multiplied by the values of actions a_i^j among all units for each possible state. For discrete probability distributions, we can use prior probabilities among all management units to predict the expected number (or fraction) of units with a given state using the linearity of expected values property for random variables. We can then calculate the expected values of potential management decisions for units with the predicted states and calculate the expected value of the optimal group of management actions among units that can fit within our budget.

The EVPI is calculated with Equation 4, using expected values of the optimal group of management actions for perfect versus current information for multiple management units. Again, when management costs are equal among units, the expected cost-effectiveness for a unit is simply the expected value of the chosen management action for a given unit.

The expected value of the optimal group of management actions after monitoring is calculated as follows:

$$\mathrm{EV}^{*U}_{\mathrm{monitoring}|B} = \max_{x^j_{iy}} \sum_{j=1}^{|U|} \sum_{y \in Y^j} p(y) \sum_{i=1}^{|A^j|} x^j_{iy} \sum_{s \in S} V\left(a^j_i, s\right) p(s|y) \quad (9)$$

This is the maximum, subject to the budget B, of the summed expected values of actions a^j_i among all units j after monitoring. Specifically, it is the maximum (subject to budget) summed value among all units, of the probability of result y, multiplied the value of action a^j_i given state s, weighted by the probability $p|s$ of state s given result y. For probabilities of discrete states, probabilities of obtaining a result y can be used to calculate the expected number or fraction of units with each outcome, and monitoring accuracy can be incorporated into the expected value of a management action given the monitoring outcome, as per Equations 5a and 5b. As with Equation 8, $\mathrm{EV}_{\mathrm{monitoring}}$ is maximized by allocating the budget to management actions among the units that yield the highest summed expected values. The expected value of monitoring information is calculated using Equation 6, but using results for multiple management units.

2.5 | Explicitly considering cost of monitoring

To account for monitoring cost via the budget, we calculate the expected values using the net budget after subtracting monitoring costs. It is also possible to account for the cost of monitoring in a single-decision context, by removing any potential management actions that cannot be afforded if monitoring costs reduce the management budget. In contrast, the cost of delays caused by monitoring can be directly incorporated into the expected value of management actions, as we illustrate in Case Study 2.

2.6 | Case Study 1—Habitat protection for threatened plant conservation

In this case study, a conservation agency is initiating a programme to protect occurrences of a threatened plant species on private land, by arranging 20-year stewardship agreements. Although we use simulated parameters to simplify illustration of our method, we endeavoured to make them as realistic as possible, using approximate costs of surveys, taxes and land agreements from farmland in southern Ontario, Canada.

As part of stewardship agreements, the agency will pay landowners the equivalent of 20 years of taxes in exchange for protecting 1 ha parcels of private land. Table S1 provides details of cost calculations. Briefly, the estimated survey cost is \$500 per parcel, and the cost of the 20-year stewardship programme is \$5,000 per parcel. The agency has a total budget of \$40,000 for this programme, which is sufficient to protect eight parcels if all funds are used for stewardship agreements and none for surveys.

The agency is considering 20 parcels potentially containing the species (Table S1). For 10 of the parcels, the probability of occurrence is estimated as *c.* 0.5, due to recorded occurrence in an outdated survey. The remaining 10 parcels have estimated probabilities of occurrence of *c.* 0.1, based on habitat suitability only. The agency wants to know if it should survey the parcels before deciding which ones to protect, or if it should arrange protection without monitoring. For simplicity, we measure value of a management action $V(a,s)$ as conserved occurrences of the threatened species; $V(a,s) = 1$ if a parcel in which the species occurs is protected. No other management action contributes to species persistence; thus, the other management actions (not protecting a parcel, or protecting a parcel where the species does not occur) have $V(a,s) = 0$.

We evaluate whether the agency should survey the parcels before deciding which ones to protect, using both conventional VOI and VOI for multiple management units. We present detailed calculations for a detection probability of 0.8 with no false positives, and parcels with an estimated prior probability of occurrence of 0.5. We provide worksheets with additional calculations in Appendix S2, including calculations for 0.1 probability of occurrence, and alternative scenarios including monitoring only a subset of parcels, different management costs for some parcels and repeat surveys. These spreadsheets are intended to further demonstrate the flexibility of our approach and to facilitate understanding of the calculations.

To illustrate the influence of variation in survey accuracy estimates, we calculate VOI across a realistic range of survey detection probability from 0.05 to 0.95 (e.g. Chen, Kéry, Plattner, Ma, & Gardner, 2013; Chen, Kéry, Zhang, & Ma, 2009). We also explore the influence of variation in monitoring costs. While our estimate of \$500 per 1-ha area is compatible with current consultant rates for single surveys, other monitoring options (e.g. free citizen science or more expensive, intensive programmes) might be available. Thus, we simulate monitoring programme costs across a range from \$0 to \$1,500 per parcel.

2.7 | Case Study 2—Classification and management of species threatened with extinction

A conservation agency wishes to prioritize management of species based on extinction risk. Here, we consider the "cost" of monitoring as the probability that an endangered species will go extinct during monitoring and assume that the financial cost of monitoring is separate from the management funding pool.

In this case study, there are three threat categories, "endangered," "threatened" and "not threatened" based on estimated extinction risk. After initial population monitoring, 20 species have been classified as "threatened"; however, there is considerable uncertainty as to whether the classification is accurate. The agency believes that there is a 50% probability that the classification is accurate, a 25% probability that extinction risk has been underestimated such that the category "threatened" is too low (i.e. a species classed as "threatened" is really "endangered"), and a 25% probability the category "threatened" is too high (i.e. a species classed as "threatened" is really "not threatened"). This means that we expect approximately 5 of these 20 species to be endangered, 10 to be threatened and 5 to be not threatened.

The agency has the budget to undertake long-term management for 17 of its 20 "threatened" species. It can either act now or choose to undertake a second round of monitoring to better understand their threat status. However, it estimates that during the time it takes to monitor, each endangered species will have a 10% probability of going extinct. In this round of monitoring, there is again a 50% probability that risk is correctly estimated for a given threat category, a 25% probability that risk is underestimated for a given category, and a 25% probability that risk is overestimated for a given category. However, for species assigned to the category "endangered," any overestimate of risk would still assign them to this category; thus, there is a 75% probability of correctly assigning this category. Likewise, for species assigned to the category "not threatened," there is no lower category, so there is a 75% chance of correctly assigning these species.

Because the agency wants to manage species with the greatest threat, its value structure for management is as follows: for managing an endangered species, the value is 2; for managing a threatened species, the value is 1; for managing a non-threatened species, the value is 0. The agency wants to maximize the summed value among managed species. In Appendix S3, we present an alternative value structure with negative (penalty) values for management of non-threatened species and non-management of threatened and endangered species.

TABLE 2 Prior probabilities and values for parcels with 0.5 probability of occurrence in Case Study 1

	Present	Absent	Expected value under uncertainty
Prior probability	0.5	0.5	
Values of actions			
"Protect"	1	0	1 × 0.5 + 0 × 0.5 = 0.5
"Do not Protect"	0	0	0 × 0.5 + 0 × 0.5 = 0

3 | RESULTS

3.1 | Case Study 1—Habitat protection: Conventional single-decision VOI

The expected value of protecting a parcel with 0.5 prior probability of occurrence and current information (Equations 2a and 2b) is the sum of the values for the action "protect" when the species is present or absent, weighted by the probability of each state, which is (1 × 0.5) + (0 × 0.5) = 0.5 (Table 2). The expected value of not protecting a parcel, similarly calculated, equals 0. Thus, the best management action in this case is "protect" and its expected value with current information is 0.5.

In our case, there is only a value for protecting an occurrence. Thus, the expected value of the best management action under certainty, which is the sum of the values of the best management actions for any state of the management unit, weighted by the probability of each state, is 0.5 + 0 = 0.5, and the EVPI (Equation 4) is 0.

If the parcel is monitored and the species is found, the probability of occurrence is 1 because there are no false positives, whereas if the species is not found, the updated probability of occurrence is (probability not found|present) × (prior probability)/(probability not found) = 0.17 (Table 3). The probabilities of obtaining the results "found" and "not found," based on prior probabilities, are 0.4 and 0.6 respectively (Table 3). The expected value of protection after the species is "found" in a parcel equals 1. However, even if the species is not found in a parcel, the expected value of protecting that parcel is 0.17 due to the possibility of a non-detection error.

For monitored parcels with 0.5 prior probability of occurrence, the expected value of the decision after monitoring is thus (1 × 0.4) + (0.17 × 0.6) = 0.5, and the expected value of monitoring information (Equation 6) is 0. This result is logical, since the best decision for a single parcel only is to "protect" with or without monitoring.

3.1.1 | Habitat protection: VOI across multiple management units with a limited budget

Using current information, the expected value of protecting parcels with 0.5 probability is 0.5 (Equations 2a and 2b). The expected value of protecting parcels with 0.1 probability is 0.1. Protecting the

TABLE 3 Monitoring accuracy and updated beliefs for Case Study 1 parcels with 0.5 prior probability of occurrence, assuming 0.8 probability of detection and no false positives

	Present	Absent	Probability of result
Expected accuracy of monitoring			
Found	0.8	0	0.5 × 0.8 + 0.5 × 0 = 0.4
Not found	0.2	1	0.5 × 0.2 + 0.5 × 1 = 0.6
Updated belief after monitoring			
Found	1	0	
Not found	0.2 × 0.5/ (0.2 × 0.5 + 1 × 0.5) = 0.17	1 − 0.17 = 0.83	

parcels with 0.5 probability is more cost-effective, and the best strategy is to protect as many of these as possible. Our expected value of the optimal group of management actions using current information is our predicted number of occurrences conserved: 0.5 × 8 = 4. With perfect information, we would expect to find 0.5 × 10 + 0.1 × 10 = 6 parcels with occurrences on average. The EVPI (Equation 4), given that we could afford to protect all six expected occurrences, is thus 6 − 4 = 2.

If we monitored before protecting, we would predict the outcomes outlined in Table 4, that is, our monitoring would find, on average, 4.8 occurrences and fail to find 1.2 occurrences. Our top-ranked management options would be to protect parcels where the focal species was found, which would lead to 4.8 expected occurrences (Table 4).

If monitoring had no cost, we would have sufficient resources to protect eight parcels, including the expected 4.8 parcels with found occurrences (our two best ranked outcomes), plus 3.2 of the next most cost-effective parcels we can afford, which in this case are those with 0.5 prior probability, and no found occurrence. However, the cost of monitoring ($10,000) would sacrifice protection of two parcels, leaving resources for protecting the predicted 4.8 found occurrences, and an additional 1.2 parcels from the next-ranked outcome (Table 4). Thus, the expected value of the optimal group of management actions would be 4.8 + 1.2 × 0.17 = 5 occurrences, and the expected value of monitoring information, once the monitoring budget is considered, is 5 − 4 = 1. In other words, we would expect to protect an additional parcel that currently houses the focal species if we were to monitor, even though we would have to sacrifice protecting two parcels. Thus, the agency would justifiably spend the $10,000 cost of the monitoring programme. Note how the VOI across parcels with our limited budget leads to a different decision (monitor first) than if we had extrapolated conventional VOI to any eight parcels.

3.1.2 | Sensitivity to parameter variation

When we calculate VOI across a realistic range of survey detection probability from 0.05 to 0.95, we can see that the expected value of monitoring information is negative when detectability falls below 0.5 (Figure 1a). Thus, in this case if the species cannot be detected with >50% probability when present, it is better to act on existing information rather than monitor all parcels. When we calculate VOI across a range of monitoring programme costs from $0 to $1,500 per parcel, we see that VOI is negative for monitoring costs >$1,000 per parcel (Figure 1b).

3.2 | Case Study 2—Classification of threatened species: Single-decision VOI

Using Equation 1, the expected value of managing a species currently classified as "threatened" with current information is (probability it is endangered × value if endangered) + (probability it is threatened × value if threatened) + (probability it is not threatened × value

TABLE 4 Expected values and cost-effectiveness ranks of protection, across the four possible survey results for parcels in Case Study 1. Since the cost of protecting each parcel is the same, the cost of protecting each parcel is normalized to one and the expected cost-effectiveness of a management action is the value of the action itself (expressed in number of protected occurrences)

Prior probability of occurrence	Found in survey?	Expected value of protecting, given this result	Expected value of decision to protect (single parcel)	Ranking by expected cost-effectiveness (value of protecting/cost)	Expected value among parcels (value of protecting × number of parcels with this prior)
0.5	Y	1.00	0.4	1 (tie)	4
0.1	Y	1.00	0.08	1 (tie)	0.8
0.5	N	0.17	0.1	2	1
0.1	N	0.02	0.02	3	0.2
Predicted total occurrences found					4 + 0.8 = 4.8
Predicted total occurrences not found					1 + 0.2 = 1.2

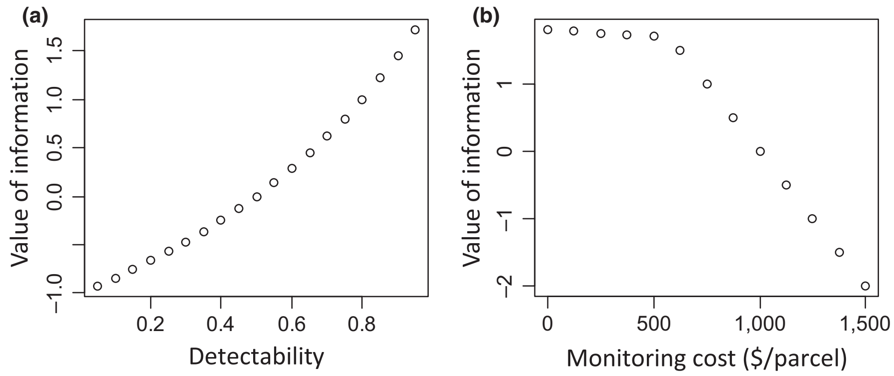

FIGURE 1 (a) Expected value of monitoring information in Case Study 1, across a range of detectability for the focal species; (b) expected value of monitoring information in Case Study 1, across a range of monitoring costs

if not threatened), which is 0.25 × 2 + 0.5 × 1 + 0.25 × 0 = 1. The expected value of not managing is zero. Since there is no value for the decision to not manage, the EVPI is the same as the expected value of current information.

The expected value of monitoring information calculations are shown in Tables 5 and 6. In this case, we are accounting for the probability that our monitored species may be "endangered," and if so may go extinct during the course of monitoring (Table 6). We then subtract this from the expected value of the decision with monitoring information, with the result being 0.95. Using Equation 6, the expected value of monitoring information is 0.95−1 = −0.05, which would lead to the decision "do not monitor."

3.2.1 | VOI across multiple management units

The expected value of the optimal group of management actions under uncertainty is simply the summed expected value of the best management actions with current information for the 17 species we can manage, 1 × 17 = 17. For the EVPI, we assume we would manage up to 17 species with the greatest threat. We would manage the five expected endangered and 10 expected threatened species for a total value of 5 × 2 + 10 × 1 = 20, and an EVPI of 20−17 = 3.

When calculating the expected value of monitoring information, we must account for the potential extinction of endangered species (10% probability per species) while monitoring. Based on the prior

TABLE 5 Case Study 2 probability of results after monitoring species currently classified as "threatened"

Classification	Probability one category too low	Probability correct	Probability one category too high	Probability of classification after monitoring
Endangered	0	0.75	0.25	0.75 × 0.25 + 0.25 × 0.5 = 0.3125
Threatened	0.25	0.5	0.25	0.25 × 0.25 + 0.5 × 0.5 + 0.25 × 0.25 = 0.375
Not threatened	0.25	0.75	0	0.25 × 0.5 + 0.75 × 0.25 = 0.3125

TABLE 6 Expected value of monitoring information for single decision in Case Study 2. Full calculation for updated belief of "endangered" after monitoring result "endangered" is shown

Endangered	Threatened	Not threatened	Expected value if managed
Updated beliefs after monitoring result "endangered"			
(prob result "endangered"|endangered)/(prob result "endangered") = (0.75 × 0.25)/(0.75 × 0.25 + 0.25 × 0.5) = 0.6	0.4	0	2 × 0.6 + 1 × 0.4 = 1.6
Updated beliefs after monitoring result "threatened"			
0.167	0.67	0.167	2 × 0.167 + 1 × 0.67 + 0 × 0.167 = 1
Updated beliefs after monitoring result "not threatened"			
0	0.4	0.6	1 × 0.4 + 0 × 0.6 = 0.4
Expected value of best management action with monitoring if no extinction risk during monitoring			0.3125 × 1.6 + 0.375 × 1 + 0.3125 × 0.4 = 1
Expected value of best management action with monitoring including extinction risk during monitoring			0.3125 × 1.6 + 0.375 × 1 + 0.3125 × 0.4 − (0.1 × 0.25 × 2) = 0.95

probability of 0.1 that we will lose an endangered species during the course of monitoring and the prior expectation of five endangered species, we would expect to lose 0.5 species on average. Taking this into account, our calculation of the expected value of the optimal group of management actions after monitoring is presented in Table 7. The expected value of monitoring information is 18.2–17 = 1.2. Since the expected value of monitoring information is positive, the agency would be justified in monitoring before acting, despite the risk of extinction while monitoring is taking place. This contrasts with the single-decision VOI that suggests monitoring would not be recommended.

4 | DISCUSSION

Value of information theory can help to guide monitoring, by explicitly estimating the expected value of management actions before and after monitoring. However, two key limitations of VOI in applied ecology have been its application within a single-decision framework, rather than over multiple decisions across management units, and the lack of explicit consideration of monitoring costs. In the broader literature, VOI for multi-unit problems has been explored, but with simplified parameters (e.g. perfect information; Keisler, 2004), equal costs among all units (Zan & Bickel, 2013), or via simulation to explore non-equal costs or non-identical probabilities (Zan & Bickel, 2013). Our application is more general and explicitly links monitoring costs to non-monetary value measurements (e.g. number of species or sites conserved).

In addition, we also demonstrate a crucial property of VOI across multiple management units for probabilities of discrete states: prior probabilities can be summed among units, to estimate the expected number of units corresponding to each potential result. This gives the flexibility and realism of allowing different monitoring or management decisions among units (even with the same prior probabilities), to maximize expected value. To our knowledge, this property of VOI has not previously been recognized. Previous applications (Bickel & Zan, 2009; Keisler, 2004; Soares et al., 2012; Zan & Bickel, 2013) have calculated VOI based on summed individual expected values among units.

This property has important implications. As we have shown in our case studies, calculating VOI across multiple units can increase the expected value of monitoring information compared to a single-decision case, because it can allow estimation of the expected number of units with each possible monitoring result, and the choice of management among units to maximize total expected values. We note, however, that this property is applicable to decisions involving discrete states (e.g. presence/absence of a species, threat categories), while problems involving continuous distributions (e.g. expected amount of a particular habitat among patches), and non-independence among units or value objectives require further exploration. For example, in cases where sampled units from a single population lead to increased accumulated knowledge to improve a model (e.g. Soares et al., 2012), extrapolation of probabilities across

TABLE 7 Expected value of actions after monitoring for Case Study 2

Monitoring result	Expected number of species with this result across 20 species	Expected value of managing one species	Ranking by expected cost-effectiveness (exp. value of managing/cost)	Total expected value	Total expected value managed	Leftover budget after each result category managed
"Endangered"	0.3125 × 20 − 0.1 × 5 = 5.75[a]	1.6	1	5.75 × 1.6 = 9.2	9.2	17 − 5.75 = 11.25
"Threatened"	7.5	1	2	7.5 × 1 = 7.5	7.5	11.25 − 7.5 = 3.75
"Not threatened"	6.25	0.4	3	6.25 × .4 = 2.5	3.75 × 0.4 = 1.5	0
			Total expected value		9.2 + 7.5 + 1.5 = 18.2	

[a]This calculation accounts for the predicted rate of extinction during monitoring.

units will not be applicable and simulation-based approaches may be necessary.

Multiple-unit decisions with limited budgets are very common in applied ecology. For example, spatial resource management allocations often consider many management units (e.g. Leathwick, Moilanen, Ferrier, & Julian, 2010; Wilson, McBride, Bode, & Possingham, 2006), and threatened species conservation programmes typically rank species based on priorities (e.g. International Union for Conservation of Nature and Natural Resources (IUCN), 2017; Joseph et al., 2009). Even the more quantitative approaches to these issues are often based on limited data, because time and financial resources are scarce. These limitations are frequently acknowledged, and caution is urged in implementing recommendations where parameters are uncertain (e.g. Game & Grantham, 2008; Moilanen et al., 2014).

Various quantitative methods of addressing uncertainty in decision making have been implemented for conservation problems, including sensitivity analysis to examine the influence of input parameters (e.g. Ardron, Possingham, & Klein, 2008), assigning greater weight to more certain data or outcomes (Moilanen et al., 2014; Tulloch et al., 2013), and using either upper or lower bounds of uncertainty estimates as the basis for decisions (Moilanen et al., 2014).

Multi-unit VOI analysis provides a distinct and complementary approach to addressing uncertainty in multi-unit problems, through examining the potential utility of new information in making more efficient decisions. By calculating the expected value of monitoring information across management units and explicitly linking monitoring and management costs, agencies can better partition their budgets to reducing uncertainty versus immediate action.

Exploring the influence of uncertainty in parameter estimates on VOI can also be highly informative in targeting monitoring to reduce the most influential uncertainties, or determining the plausible ranges of parameters for which monitoring is worthwhile. For example, in Case Study 1, the management agency could use information regarding detectability (e.g. is the species easily recognizable or is it cryptic?), as well as the expected thoroughness of surveys (Chen et al., 2009, 2013; McCarthy et al., 2013) to help determine whether to monitor first or protect without monitoring. Likewise, if monitoring costs are uncertain but can be estimated within a reasonable range, VOI could be calculated across this range. It is important to note that the results of our artificial case study analyses are particular to the parameters we chose. For example, thresholds for positive VOI we identified for monitoring accuracy and cost in Case Study 1 cannot be applied to other studies, and sensitivity should be evaluated on a case-by-case basis. More complex consideration of uncertainty across multiple variables could assign probability distributions to these variables and use sensitivity analysis to assign a probability that a given strategy (e.g. monitor first) is optimal.

Another potential limitation of VOI theory is its perceived complexity (Canessa et al., 2015). This is a potential problem with decision-theoretic or evidence-based approaches in general (Possingham, Ball, & Andelman, 2000; Pullin & Knight, 2005). Managers have limited time and must have expertise in several aspects of decision making, so there is a tendency to use experience-based information in decision making (Cook et al., 2010; Pullin & Knight, 2005). We hope that by illustrating our methods using multiple formats (including customizable spreadsheets and code in the Supporting information that detail calculation steps), that we can diminish this barrier.

Both individual and multi-unit VOI theory are also limited in their ability to account for uncertainties. Although the potential influence of uncertainties in VOI input parameters can be examined using simulation across reasonable ranges of parameter estimates, VOI theory can only resolve questions around so-called known unknowns (e.g. survey accuracy) and cannot account for surprise results that often occur during monitoring programmes (Doak et al., 2008; Wintle et al., 2010). While decisions to monitor must be carefully considered in light of limited resources (Lindenmayer et al., 2013; McDonald-Madden et al., 2010), the benefits of long-term monitoring for finding new threats and solutions cannot be discounted, especially when programmes are sufficiently adaptable to incorporate new information into monitoring protocols (Lindenmayer & Likens, 2010).

A final consideration is that VOI theory generally calculates *expected* values of information, based on probabilities. This uses the implicit assumption of risk neutrality. The actual states of a system or results of monitoring may be different from those that are expected, and the actual values of decisions can be affected accordingly. Such uncertainties may be uncomfortable for conservation and resource management agencies, which appear to be generally risk averse (Tulloch et al., 2015). Explorations of relationships between the degree of risk aversion and single-decision VOI suggest nonlinear relationships that are highly dependent on input parameters (Eeckhoudt & Godfroid, 2000; Hilton, 1981; Willinger, 1989). Intuitively, a strategy of repeated monitoring can improve certainty before acting. However, given that monitoring can have substantial financial costs, and can also lead to missed management opportunities, the decision to monitor is not risk-free. The extension of VOI theory we have presented can provide an objective framework for making justifiable decisions on when to monitor and when to act in many management scenarios.

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AUTHORS' CONTRIBUTIONS

J.R.B. conceived the ideas, designed the methodology and led the writing of the manuscript. S.L.M. helped conceive the ideas and design the methodology and case studies. A.E.M. and L.F. helped design the methodology and case studies. I.C. and B.G. helped with mathematical formulation and designing the methodology;

I.C. wrote the optimization formulation. All authors contributed critically to the drafts and gave final approval for publication.

DATA ACCESSIBILITY

Data for this paper are simulated. Code for generating and analysing data is available from the Dryad Digital Repository https://doi.org/10.5061/dryad.r464h5d (Bennett et al., 2018). Spreadsheets for analysing data are also provided as Supporting information.

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