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When do we need more data? A primer on calculating the value of information for applied ecologists

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Summary

1. Applied ecologists continually advocate further research, under the assumption that obtaining more information will lead to better decisions. Value of information (VoI) analysis can be used to quantify how additional information may improve management outcomes: despite its potential, this method is still underused in environmental decision-making. We provide a primer on how to calculate the VoI and assess whether reducing uncertainty will change a decision. Our aim is to facilitate the application of VoI by managers who are not familiar with decision-analytic principles and notation, by increasing the technical accessibility of the tool.

2. Calculating the VoI requires explicit formulation of management objectives and actions. Uncertainty must be clearly structured and its effects on management outcomes evaluated. We present two measures of the VoI. The expected value of *perfect* information is a calculation of the expected improvement in management outcomes that would result from access to perfect knowledge. The expected value of *sample* information calculates the improvement in outcomes expected by collecting a given sample of new data.

3. We guide readers through the calculation of VoI using two case studies: (i) testing for disease when managing a frog species and (ii) learning about demographic rates for the reintroduction of an endangered turtle. We illustrate the use of Bayesian updating to incorporate new information.

4. The VoI depends on our current knowledge, the quality of the information collected and the expected outcomes of the available management actions. Collecting information can require significant investments of resources; VoI analysis assists managers in deciding whether these investments are justified.

Key-words: adaptive management, Bayesian pre-posterior analysis, chytridiomycosis, conservation, decision analysis, experimental management, monitoring

Introduction

Our understanding of natural systems is almost invariably limited by their complexity and variability. As a result, uncertainty affects resource management and conservation decisions at every level (Wilson *et al*. 2006; Chadès, Curtis & Martin 2012). It is natural, then, that applied ecologists continually advocate further research, assuming that learning will reduce uncertainty and result in better decisions. However, environmental problems often require immediate decisions with limited time and resources to gather information (Martin *et al*. 2012). The learning process itself may be expensive, and the information collected may be of limited utility. So when is the collection of further information actually warranted?

Value of information (VoI; Schlaifer & Raiffa 1961) can provide a rigorous answer to this question. This method has been applied to health and economic problems (Yokota & Thompson 2004; Bratvold, Bickel & Lohne 2007). A typical example is the decision of whether to adopt widespread screening for certain types of cancer, trading off the benefits of increased screening levels and their economic costs and discomfort for patients (Hassan *et al*. 2009). The environmental management literature is increasingly exploring the concept of VoI (McDonald & Smith 1997; Mäntyniemi *et al*. 2009; Runge, Converse & Lyons 2011; Williams & Johnson 2014). However, as a management tool VoI remains underused, possibly because managers are not familiar with decision-theoretic principles and notation, or because they find the calculations technically challenging. Here, we aim to provide a guide to VoI that is accessible for non-specialist scientists and managers. We first provide formal definitions of the metrics. We then use two examples in the management of endangered species to illustrate the concepts and calculations of two VoI metrics, the expected value of perfect information (EVPI) and of sample information (EVSI). We detail in particular the use of Bayesian

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updating, to illustrate how the learning process in a real-world context influences the VoI.

Definitions

Value of information analysis is a component of decision analysis, the ensemble of theory and methods for rational decision-making under uncertainty (Raiffa 1968). In particular, VoI relies on the concept of the expected outcome of actions. Making a decision implies choosing one of a set of candidate actions to achieve one or more specified objectives. The expected outcomes of each action will be affected by uncertainty about the system. This uncertainty can be represented as alternative hypotheses about the system, each with a given probability of being true (prior belief). Hypotheses might be different conditions of the system (e.g. the number of individuals in a population at a given time), competing models of a system (e.g. the type of density dependence in a population) or competing values for a given parameter of a model (e.g. sampling uncertainty on an estimated survival rate). Hereafter, we use $V(a, s)$ to refer to the *value* (or outcome) of taking action a under state s. These values are measured in units compatible with management objectives (for example, probability of extinction).

The expected value of an action under uncertainty is calculated as:

$$\mathbb{E}_s[V(a,s)] = \sum_{s=1}^{N}\{V(a,s)\cdot p_s\} \qquad \text{eqn 1}$$

where $\mathbb{E}_s$ indicates that the expected value $\mathbb{E}$ is the sum of the possible $V(a, s)$ for action a across the variable s (i.e. across all N states of the system), each weighted by the respective probability p_s of each state s being true. A rational, risk-neutral decision-maker will choose the action with the highest expected value. Non-neutral risk attitudes could be accounted for by measuring the expected utility (perceived benefit) of outcomes instead of their expected value (Von Neumann & Morgenstern 1944). The value of the decision under uncertainty is calculated as:

$$\mathrm{EV}_{\text{uncertainty}} = max_a\mathbb{E}_s[V(a,s)] \qquad \text{eqn 2}$$

where $\max_a$ indicates that the action a with the highest expected value under uncertainty is chosen (the subscript a indicates that the maximum is selected across the variable a, that is, all possible actions).

The VoI represents the difference between the expected management outcomes when a decision is made only on the basis of the prior information, and when new information is gained (Yokota & Thompson 2004). The EVPI is the expected benefit of eliminating uncertainty entirely. Knowing the true state of the system, the optimal action could be identified immediately as the one with the highest value. Therefore, the choice would not be made on the expected value $\mathbb{E}$ under uncertainty, but by choosing the action a with the maximum value V for the known state of the system ($\max_a V(a, s)$). Since the true state is unknown prior to resolving the uncertainty, the *expected* value of a decision made under certainty is as follows:

$$\mathrm{EV}_{\text{certainty}} = \mathbb{E}_s[max_aV(a,s)] = \sum_{s=1}^{N}[\{max_aV(a,s)\}\cdot p_s] \qquad \text{eqn 3}$$

We calculate the value of the best action, conditional on each hypothesis being true, and then calculate the weighted sum of those values, where the weight is the prior belief in the respective hypotheses. EVPI is then calculated as the difference between the expected values under certainty and uncertainty (Raiffa 1968):

$$\begin{aligned}\mathrm{EVPI} &= \mathrm{EV}_{\text{certainty}} - \mathrm{EV}_{\text{uncertainty}}\\ &= \mathbb{E}_s[\max_aV(a,s)] - \max_a\mathbb{E}_s[V(a,s)]\\ &= \sum_{s=1}^{N}[\{\max_aV(a,s)\}\cdot p_s] - \max_a\sum_{s=1}^{N}\{V(a,s)\cdot p_s\}\end{aligned} \qquad \text{eqn 4}$$

The respective positions of $\max_a$ and $\mathbb{E}_s$ in $\mathrm{EV}_{\text{uncertainty}}$ and $\mathrm{EV}_{\text{certainty}}$ highlight how the action with the maximum outcome ($\max_a$) is taken, respectively, before and after uncertainty has been resolved ($\mathbb{E}_s$).

While EVPI provides a useful measure of the maximum possible benefit of resolving uncertainty, in real-world problems achieving perfect information is seldom possible. EVSI calculates the expected improvement in management outcomes that could be obtained by gaining access to a given amount of additional information before making a decision. EVSI is calculated as:

$$\mathrm{EVSI} = \mathbb{E}_x\{max_a\mathbb{E}_{s|x}[V(a,s)]\} - max_a\mathbb{E}_s[V(a,s)] \qquad \text{eqn 5}$$

where x represents the sample information and the first expectation $\mathbb{E}_x\{.\}$ averages over all the possible values that the sample x can take. Note that the second term of eqn 5 is the same as in eqn 4: the expected outcome in the current state of knowledge is the reference term for any formulation of VoI. To calculate EVSI, we perform a Bayesian pre-posterior analysis (Berger 1985). We explain this procedure in detail in the following case studies. Spreadsheets for the calculations are provided as Supporting Information.

Case study 1: VoI for wildlife disease risk assessments

First, we demonstrate the concepts and application of VoI using a simple example: the risk of disease when managing a threatened species. The amphibian chytrid fungus *Batrachochytrium dendrobatidis* has been implicated in the decline and extinction of several amphibian species world-wide (Skerratt *et al.* 2007). In the absence of effective threat removal methods, the management of species threatened by chytrid must account for the risk of disease outbreaks. We consider the hypothetical case of a threatened frog species that occurs in one location within a protected area. We aim to maximise the overall number of individuals of the species within the protected area at the end of a 10-year period. To achieve this objective, we might seek to establish a new population within the protected area by translocating some individuals to a new site. However, we need to consider our management in light of two possible states of the system: whether chytrid is present or

Table 1. Step-by-step calculation of the expected value of perfect information for the frog translocation in Case Study 1. The outcome of each action is expressed as the total number of individuals in the protected area at the end of a 10-year period

		True state at new site		
		Chytrid		No chytrid
Prior belief		0·5		0·5
Decision under uncertainty				
		Predicted outcome (number of individuals)		Expected value under uncertainty (eqn 2)
Action	Translocation	55	135	55 × 0·5 + 135 × 0·5 = 95
	Do nothing	100	100	100 × 0·5 + 100 × 0·5 = 100
Decision under certainty (perfect information)				
	Predicted outcome under certainty (optimal action always chosen)			Expected value under certainty (eqn 3)
Outcome of optimal action	100 (no translocation)	135 (translocation)		100 × 0·5 + 135 × 0·5 = 117·5
		Expected value of perfect information (eqn 4)		117·5–100 = 17·5

absent at the new site. Our prior belief of the fungus being present at the new site is 0·5, reflecting the background infection rate of sites in the region of interest.

For simplicity, we consider two actions: translocating 50 individuals or doing nothing (we could do the calculation for any number of actions). We first need to determine the value V (here the total number of individuals) predicted for each action under each scenario (Table 1). When doing nothing, we expect the existing population to remain at its current size (with a mean expectation of $V = 100$ individuals). When translocating, if chytrid is absent from the new site, then the released individuals will establish and population model predictions indicate that we can expect to have 135 individuals over the whole protected area at year 10, reflecting the high suitability of the new site ($V = 135$). Conversely, if chytrid is present at the new site, the new population will fail to establish. Due to the removal of individuals for the translocation, the existing population will also decrease; we assume that model predictions indicate a total of 55 individuals by year 10 ($V = 55$).

Based on the values of V for each action, and the prior belief in chytrid presence, we can identify the best decision under uncertainty. Using eqn 1, the expected outcome for the translocation is 55 × 0·5 + 135 × 0·5 = 95 individuals. This is less than what is expected if no animals are translocated ($V = 100$ individuals), so the optimal decision under the current state of uncertainty is not to translocate ($EV_{\text{uncertainty}} = 100$).

EXPECTED VALUE OF PERFECT INFORMATION

If we knew that chytrid was absent from the new site, we would choose to translocate, since this action leads to 135 individuals, compared to 100 for no translocation. If chytrid were present, we would do nothing and maintain 100 individuals at the source site. Assuming a method to obtain such perfect information were available, our prior belief suggests a 0·5 chance that it would indicate chytrid presence, and a 0·5 chance that it would indicate its absence. Therefore, making this decision under perfect information has an expected outcome of $EV_{\text{certainty}} = 135 \times 0{\cdot}5 + 100 \times 0{\cdot}5 = 117{\cdot}5$. This is greater than the expected outcome of the optimal action under uncertainty (doing nothing, giving $EV_{\text{uncertainty}} = 100$). Using eqn 4, the expected value of perfect information is EVPI = 117·5–100 = 17·5 individuals. That is, perfect information would lead to an expected gain of 17·5 individuals at the end of the 10 year period (Table 1). But what if, instead of perfect information, we consider the actual process of collecting data?

EXPECTED VALUE OF SAMPLE INFORMATION

We might test for the presence of chytrid in the skin secretions of other amphibians present at the prospective site using quantitative polymerase chain reaction (qPCR). However, the qPCR test for chytrid is imperfect. On the basis of published information (Skerratt *et al.* 2008), we define the mean sensitivity of the standard qPCR for chytrid described by Boyle *et al.* (2004) as 0·73 and its mean specificity as 0·94 (i.e. approximately a 27% chance of a false positive and a 6% chance of a false negative for a single test on a single individual; Table 2).

To evaluate how running such a test might influence our management decisions and outcomes, we need to perform a Bayesian pre-posterior analysis (Berger 1985). For this, we need to consider the possible results of the test (positive or negative) and compute how obtaining either result would change our belief about the system. This can be calculated using Bayes theorem:

$$P(\text{hypothesis}|\text{data}) = \frac{P(\text{data}|\text{hypothesis})\,P(\text{hypothesis})}{P(\text{data})}. \quad \text{eqn 6}$$

For instance, if the test returns positive, we calculate our updated belief about chytrid presence at the new site as

Table 2. Step-by-step calculation of the expected value of sample information for the frog translocation in Case Study 1

Original consequence table (before test)				
		True state at new site		
		Chytrid	No chytrid	
Prior belief		0·5	0·5	
		Predicted outcome (number of individuals)		Expected value under uncertainty
	Translocation	55	135	95
Action	No translocation	100	100	100
Expected test performance				
Test result	$Test^+$	0·73	0·06	
	$Test^-$	0·27	0·94	
Updating prior belief depending on test results				
Test result	Chytrid		No chytrid	
$Test^+$	$P(chytrid\|test^+) = P(test^+\|chytrid) \times P(chytrid)/P(test^+)$ $= 0·73 \times 0·5/0·73 \times 0·5 + 0·06 \times 0·5 = 0·92$		$P(no\ chytrid\|test^+) = 1 - P(chytrid\|test^+) = 1 - 0·92 = 0·08$	
$Test^-$	$P(chytrid\|test^-) = P(test^-\|chytrid) \times P(chytrid)/P(test^-)$ $= 0·27 \times 0·5/0·27 \times 0·5 + 0·94 \times 0·5 = 0·22$		$P(no\ chytrid\|test^-) = 1 - P(chytrid\|test^-) = 1 - 0·21 = 0·78$	
Updated consequence table after test positive				
Updated belief after $test^+$		0·92	0·08	Expected value under uncertainty
Action	Translocation	55	135	$55 \times 0·92 + 135 \times 0·08 = 61·4$
	No translocation	100	100	$100 \times 0·92 + 100 \times 0·08 = 100$
Updated consequence table after test negative				
Updated belief after $test^-$		0·22	0·78	Expected value under uncertainty
Action	Translocation	55	135	$55 \times 0·22 + 135 \times 0·78 = 117·4$
	No translocation	100	100	$100 \times 0·22 + 100 \times 0·78 = 100$
Outcome of optimal action after test result				
	Test positive		Test negative	Expected value under uncertainty
Probability of test result	$0·73 \times 0·5 + 0·06 \times 0·5 = 0·4$		$0·27 \times 0·5 + 0·94 \times 0·5 = 0·6$	
Outcome of optimal action	100 (no translocation)		**117·4** (translocation)	$100 \times 0·4 + 117·4 \times 0·6 = 110·4$
			Expected value of sample information	$110·4 - 100 = 10·4$

$$P(\text{chytrid}|\text{test}^+) = \frac{P(\text{test}^+|\text{chytrid})P(\text{chytrid})}{P(\text{test}^+)}. \qquad \text{eqn 7}$$

The terms of eqn 4 are interpreted as follows. $P(chytrid|test^+)$ is our updated belief after a positive test result (i.e. the probability of chytrid presence, given a positive test). $P(chytrid)$ is our prior belief about the probability of chytrid presence, which we initially assumed to be 0·5. $P(test^+|chytrid)$ is the probability of the test returning positive if chytrid is present, that is, the test sensitivity (0·73). The denominator $P(test^+)$ is the overall probability of observing a positive test result, which includes the probability of a true positive (if chytrid is present and the test correctly detects it) and of a false positive (if chytrid is absent, but the test incorrectly returns positive): $P(test^+) = 0·73 \times 0·5 + 0·06 \times 0·5 = 0·4$. By substituting these values in eqn 7, we obtain that, after a positive test result, our belief about chytrid presence will change from our prior value of 0·5 to $P(chytrid|test^+) = 0·73 \times 0·5/0·4 = 0·92$, and consequently our new belief about chytrid absence will be $P(no\ chytrid|test^+) = 1 - 0·92 = 0·08$. We can similarly apply Bayes theorem to compute updated beliefs assuming a negative test result:

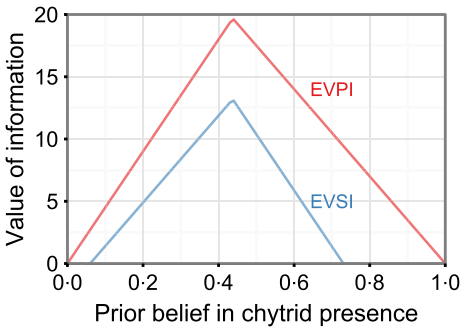

Fig. 1. Relationship between the value of perfect and sample information [expected value of perfect information (EVPI) and expected value of sample information (EVSI), respectively, expressed as the total number of individuals at the end of a 10-year period] and the prior belief that chytrid is present at the destination site for the frog translocation example.

$$P(\text{chytrid}|\text{test}^-) = \frac{P(\text{test}^-|\text{chytrid})P(\text{chytrid})}{P(\text{test}^-)} \qquad \text{eqn 8}$$

Here, $P(\text{test}^-|\text{chytrid})$ = 1 - sensitivity = 0·27 and $P(\text{test}^-)$ is the total probability of a test returning negative, that is the sum of the probabilities of a false negative and of a true negative (0·27 × 0·5 + 0·94 × 0·5 = 0·6). We calculate that our belief will change to $P(\text{chytrid}|\text{test}^-)$ = 0·27 × 0·5/0·6 = 0·22 and thus $P(\text{no chytrid}|\text{test}^-)$ = 0·78 (Table 2).

For each of these two possible sets of new beliefs, we can use eqn 1 to calculate the expected value of translocating or not translocating. If the test returns positive, the expected value of translocating will change to V = 55 × 0·92 + 135 × 0·08 = 61·4 individuals; if it returns negative, it will be V = 55 × 0·22 + 135 × 0·78 = 117·4. The expected outcome for not translocating is not affected by the test result and is thus again V = 100. The optimal decision, then, would be to translocate after a negative test (giving 117·4 individuals), and not to translocate after a positive test (giving 100 individuals). To complete the pre-posterior analysis, we need to weigh these expected values by the overall probability of either test result (including correct and incorrect results, as calculated above). This gives the overall expected value given the test is carried out: 100 × 0·4 + 117·4 × 0·6 = 110·4 (Table 2). Comparing this to the expected value of making the decision without carrying out the test (not translocating, with $EV_{uncertainty}$ = 100), we obtain that the expected value of acquiring the sample information (here testing one individual) is EVSI = 110·4–100 = 10·4 individuals (eqn 5; Table 2). We can also explore VoI for different initial priors (Fig. 1). Information would be most valuable for a prior belief in chytrid presence of 0·43, whereas sample information would have no value if P(chytrid) <0·06 or P(chytrid) >0·74.

Case study 2: VoI for learning about demographic rates

In the previous simplified example, clearly defined uncertainty about the state of the system (the absence or presence of chytrid) was linked to discrete actions (translocation or no translocation). However, applied ecologists will often face less clearly defined structural uncertainty. For example, demographic rates such as survival and fecundity are a common source of uncertainty in the management of threatened species. In this example, we show how VoI can still be applied when learning about demographic rates.

The European pond terrapin *Emys orbicularis* occurs throughout the European continent; however, habitat loss has led to local declines and extinctions (IUCN 2013). In the northern Italian region of Liguria, *E. orbicularis* was considered locally extinct until re-discovery in the 1990s; a captive breeding centre was set up in 2000 to produce individuals for reintroduction (Ottonello *et al.* 2010). As part of a LIFE/EU project (www.lifeemys.eu), three consecutive years of releases will be implemented between 2014 and 2016. The age of individuals released ranges between 3 and 5 years (respectively, the minimum age of release that avoids the high mortality of juveniles in the wild, and the year before the earliest onset of reproduction in this subspecies). Captive-bred turtles can be released as soon as they reach 3 years of age, or held in captivity longer and then released (in numbers that are then smaller than 50 due to mortality) at age four or age five. The decision problem is which age class to release.

The objective is to maximise the survival of released individuals: all other things being equal, greater survival will improve population persistence. The value of the alternative actions can be quantified in terms of the cumulative probability of surviving from 3 to 6 years of age:

$$S_6 = \phi_{3i}\phi_{4i}\phi_{5i} \qquad \text{eqn 9}$$

where ϕ_{ai} describes the survival of individuals of age class a in stage i of the release process: in captivity, in the year after release, or in the wild. This formulation can incorporate differences in captive and wild survival, and the possibility that the survival in the first year after release is affected by post-release effects. Several studies have highlighted reductions in survival following release (Jule, Leaver & Lea 2008; Le Gouar *et al.* 2008). This may reflect adaptation to captive conditions, for example leading to inadequate predator avoidance (Griffin, Blumstein & Evans 2000). Translocated individuals may also be more likely to disperse permanently from the release site (Tweed *et al.* 2003).

Here, we assume that the post-release effect acts only in the first year after release, after which surviving turtles share the survival of wild-born individuals. For individuals released as 4-year-olds, eqn 9 then takes the form $S_6 = \phi_{3c}\phi_{4p}\phi_{5w}$, where survival between 3 and 4 years of age is that of a captive individual (ϕ_{3c}), survival between four and five is that of a newly released individual (ϕ_{4p}) and survival between five and six is that of a 'wild' individual (ϕ_{5w}). For individuals released as 3-year-olds, $S_6 = \phi_{3p}\phi_{4w}\phi_{5w}$; for individuals released as 5-year-olds, $S_6 = \phi_{3c}\phi_{4c}\phi_{5p}$. Since ϕ_{ac} and ϕ_{aw} are known for all ages a, respectively, by observation of captive individuals and by existing information (Canessa, Ottonello & Salvidio 2015; Table 3), the uncertainty affecting the decision is in the post-release survival rates (ϕ_{ap}).

Table 3. Survival rates and expected outcomes for the reintroduction of turtles of different ages. Post-release effect refers to additional mortality in the first year after release. The outcome of each reintroduction strategy is expressed as the cumulative survival of released individuals to 6 years of age

Annual survival of individuals

Age class	Captive	Wild	Post-release effect decreasing with age	Post-release effect increasing with age
3-year-olds	0·9	0·85	0·72	0·68
4-year-olds	0·92	0·90	0·83	0·60
5-year-olds	0·95	0·90	0·86	0·40

Combined survival from 3 to 6 years as outcome of reintroduction strategy

		Post-release effect			
		No change	Decreases with age	Increases with age	Expected value under uncertainty
Prior belief		0·4	0·2	0·4	
Action (age class to release)	3-year-olds	0·689	0·582	0·547	$0{\cdot}689 \times 0{\cdot}4 + 0{\cdot}582 \times 0{\cdot}2 + 0{\cdot}547 \times 0{\cdot}4 = 0{\cdot}611$
	4-year-olds	0·729	0·674	0·484	$0{\cdot}729 \times 0{\cdot}4 + 0{\cdot}674 \times 0{\cdot}2 + 0{\cdot}484 \times 0{\cdot}4 = 0{\cdot}620$
	5-year-olds	0·745	0·710	0·332	$0{\cdot}745 \times 0{\cdot}4 + 0{\cdot}710 \times 0{\cdot}2 + 0{\cdot}332 \times 0{\cdot}4 = 0{\cdot}573$

Decision under certainty (perfect information)

	Predicted outcome under certainty (optimal action always chosen)			
	No change	P-r effect decreases with age	P-r effect increases with age	Expected value under certainty
Outcome of optimal action	0·745 (release 5-year-olds)	0·710 (release 5-year-olds)	0·547 (release 3-year-olds)	$0{\cdot}745 \times 0{\cdot}4 + 0{\cdot}710 \times 0{\cdot}2 + 0{\cdot}547 \times 0{\cdot}4 = 0{\cdot}659$
			Expected value of *perfect* information	0·659–0·620 = 0·039

If there is no post-release effect on survival, the release of 5-year-old turtles is expected to provide the highest survival, since it involves a longer stay in captivity where survival is greater. If survival in the first year after release is reduced compared to wild-born individuals of the same age, its specific effect depends on which age class is most affected. If extra post-release mortality is higher in younger individuals, for example due to greater vulnerability to predation, releases of older turtles may be the best action. Alternatively, the post-release effect may be stronger in older turtles, due to a stronger dispersal instinct or to greater loss of fitness from their longer captive life. In this case, releasing younger individuals may become the best action.

We articulate these three hypotheses about uncertainty as three sets of alternative parameter values within the same model, reflecting the proportional difference between the survival rate of individuals in the first year after release and that of wild individuals of the same age (i.e. $\Delta\phi_a = \phi_{a\mathrm{p}}/\phi_{a\mathrm{w}}$ in eqn 9). We calculate how the value of S_6 for individual actions changes under each hypothesis (Table 3): (i) no post-release effect, with post-release survival equal to that of wild individuals of the same age ($\Delta\phi_a = 0$, i.e. $\phi_{a\mathrm{p}} = \phi_{a\mathrm{w}}$ in eqn 9); (ii) a post-release effect that decreases with age, that is younger individuals have proportionally greater post-release mortality ($\phi_{a\mathrm{p}} < \phi_{a\mathrm{w}}$ and $\Delta\phi_3 > \Delta\phi_4 > \Delta\phi_5$); (iii) a post-release effect that increases with age: older individuals have greater post-release mortality ($\phi_{a\mathrm{p}} < \phi_{a\mathrm{w}}$ in eqn 9, and $\phi_{3\mathrm{p}} < \phi_{4\mathrm{p}} < \phi_{5\mathrm{p}}$). We assume priors of 0·4, 0·2 and 0·4 for the three hypotheses, on the basis of preliminary data analysis of past releases in the area.

EXPECTED VALUE OF PERFECT INFORMATION

Following the procedure described in the previous example, the action with the maximum expected value (EV) of S_6 across all three hypotheses is to release 4-year-old turtles, with $EV_{\mathrm{uncertainty}} = 0{\cdot}620$ (eqn 1–2), whereas the expected value of making the decision under perfect knowledge is $EV_{\mathrm{certainty}} = 0{\cdot}659$ (eqn 3). Therefore, the expected value of acquiring perfect information is an increase of 0·039 in the survival between 3 and 6 years of age (EVPI = 0·039; eqn 4).

EXPECTED VALUE OF SAMPLE INFORMATION

Information about post-release survival could be collected through a trial release, a common approach in reintroductions (Kemp *et al.* 2015). We can release a number of turtles, assess their survival in the first year after release and then update our belief in the hypotheses about post-release survival. However, the observed survival rate will be the result of a stochastic process, and the statistical inference that can be drawn from this observation is limited by the size of the trial release: the smaller the sample, the more uncertain the inference. We assume we

will perfectly observe the fate of each turtle released in the trial (e.g. by use of radiotelemetry). To determine the VoI of a trial release, we again carry out a Bayesian pre-posterior analysis. The formulas we describe in this section are best interpreted through the spreadsheet provided in Appendix S2.

We begin by considering a release of ten 3-year-old turtles. In this case, Bayes theorem can be interpreted as follows:

$$P(\text{hypothesis}|\text{data}) = \frac{P(\text{data}|\text{hypothesis})P(\text{hypothesis})}{P(\text{data})} = \frac{P(N|h)P(h)}{P(N)} \quad \text{eqn 10}$$

where N is the number of individuals released in the trial that would survive after the first year, if hypothesis h were true. Here, we model this number as the result of a binomial process:

$$N|h \sim \text{Bin}(n, \phi_{ap}^{[h]})$$

where n is the number of individuals released of a given age a (here, n = 10 3-year-old turtles) and $\phi_{ap}^{[h]}$ is the predicted post-release survival of those individuals under hypothesis h (Table 3). Hence, the probability of observing a given number of survivors N under hypothesis h is as follows:

$$P(N|h) = \binom{n}{N}\left(\phi_{ap}^{[h]}\right)^{N}\left(1-\phi_{ap}^{[h]}\right)^{n-N} \quad \text{eqn 11}$$

For each value of N between 0 and 10, we have one value of $P(N|h)$ under each hypothesis (that is, three values in total). For example, the probability of observing seven survivors is 0·27 if there is no post-release effect, 0·20 if there is a post-release effect that decreases with age and 0·16 if there is a post-release effect that increases with age (Fig. 2). Since each hypothesis has a given probability $P(h)$ of being true (prior belief), the probability of observing N survivors across all hypotheses is calculated as:

$$P(N) = \sum_{h=1}^{H} P(N|h)P(h) \quad \text{eqn 12}$$

Based on eqns 11–12, we can now apply Bayes theorem (eqn 10) to calculate the belief in each hypothesis after running the experiment and observing a given number of survivors. Every observed number of survivors would lead to a different posterior belief. For example, observing seven survivors would lead to beliefs of 0·5, 0·19 and 0·31 (for post-release effects absent, increasing with age and decreasing with age, respectively). On the basis of the updated belief, we would choose the optimal action under the updated uncertainty (we refer to the uncertainty remaining after the test as 'updated uncertainty' to distinguish it from the initial uncertainty in $EV_{\text{uncertainty}}$). We use eqn 1 to calculate the expected value of a decision: since we have 11 possible outcomes of the trial (0–10 survivors), we have 11 possible sets of posteriors and correspondingly 11 possible expected outcomes of making a decision after the trial.

To calculate the expected value of making a decision over all possible trial results ($\mathbb{E}_x\{.\}$ in eqn 5), we sum the expected values for all possible trial results, weighted by the respective probabilities. We calculate this as follows:

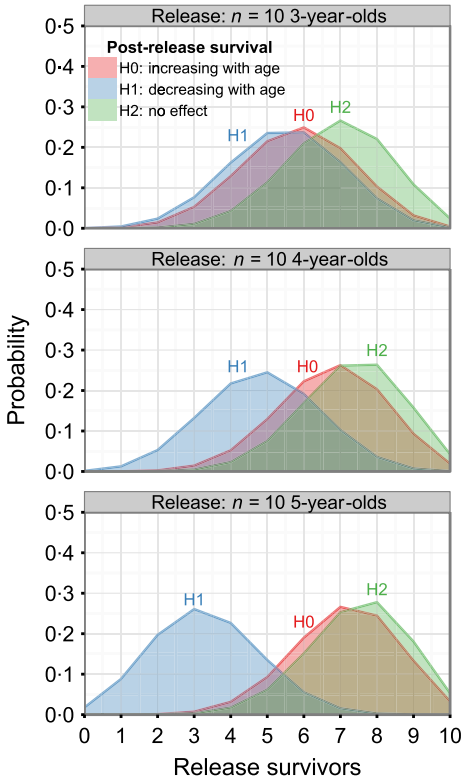

Fig. 2. Probability of observing a given number of survivors 1 year after a release of 10 individuals, under the three hypotheses of how post-release survival changes with age.

$$EV_{\text{uncertainty}}^{\text{updated}} = \sum_{N=1}^{n}\left\{\text{EV}_{\text{uncertainty}}^{[N]}P(N)\right\} \quad \text{eqn 13}$$

where $EV_{\text{uncertainty}}^{[N]}$ is the expected value of making a decision after observing N survivors and $P(N)$ is the probability of observing N survivors (eqn 12).

Here, where the test is to release ten 3-year-old turtles, we obtain a value of $EV_{\text{uncertainty}}^{\text{updated}}$ = 0·622. This is the expected value of our management when the decision is made after running a trial and corresponds to the first term in eqn 5. Since $EV_{\text{uncertainty}}$ before the test (i.e. based on prior beliefs) is 0·620, we obtain that this sample information has an expected value of 0·002 (EVSI = 0·002). We can repeat the procedure for a trial release of ten 4-year-old turtles to obtain $\mathbb{E}_x\{max_a \mathbb{E}_{s|x}[V(a,s)]\}$ = 0·634 and EVSI = 0·014; for a trial release of ten 5-year-old turtles, we obtain EVSI = 0·028. A trial release of 5-year-olds is thus expected to produce greater improvement in management outcomes than trials focusing on 3- or 4-year-olds. We can also explore how EVSI increases for larger trial releases (Fig. 3).

Discussion

Value of information provides the quantitative answer to a fundamental question of applied ecology: when is the collection of further information warranted? Our guided examples highlight the three key determinants of VoI: (i) the initial state of knowledge, (ii) the quality of the information collected (i.e.

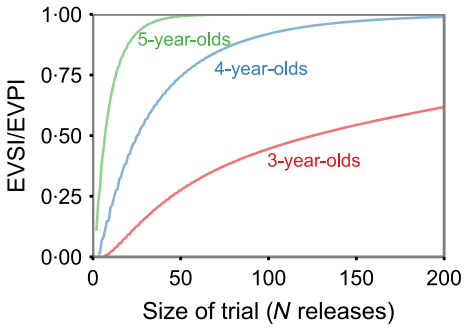

Fig. 3. Increase in the expected value of sample information (EVSI) with increasing numbers of turtles released in the trial. EVSI is expressed as the proportion of the expected value of perfect information (EVPI) calculated for this decision problem (where EVPI = 0·039).

the extent to which it reduces uncertainty) and (iii) the available management actions and their expected outcomes.

Prior beliefs represent our state of knowledge before any additional information is collected and may reflect inference drawn from available data (such as weights assigned to competing models of a system: Maxwell *et al.* 2014), existing literature (including meta-analyses: Ades, Lu & Claxton 2004) or expert judgment (Runge, Converse & Lyons 2011). In general, more informative priors will lead to smaller VoI: the more we already know about the system, the less additional information can be expected to modify our decisions. However, the maximum VoI does not always correspond with the point of maximum uncertainty (e.g. a prior of 0·5 for two competing hypotheses). Rather, the maximum VoI corresponds with the point where the *effects* of uncertainty are greatest, and those effects are defined by both prior beliefs and expected outcomes. In the frog example (Fig. 1), EVSI was >0 only for prior belief in chytrid presence between 0·06 and 0·74: outside this interval, the sample of information considered (a single test with the reported performance) was insufficient to change the optimal action.

Prior information is also important in structuring uncertainty. In the frog example, uncertainty was naturally defined as two states, with chytrid either present or absent. In the turtle example, the choice of our three hypotheses was, to a degree, still arbitrary: we could have specified different hypotheses to explore additional scenarios. However, careful evaluation of prior information allowed us to exclude biologically implausible hypotheses such as extreme differences in survival among individuals of similar age. Additional uncertainty might be incorporated by defining probability distributions for the uncertain parameters, using simulations and numerical integration for the pre-posterior analysis (Ades, Lu & Claxton 2004).

The VoI is also limited by the quality of the information collected. In the frog example, the VoI was influenced by the performance of the diagnostic test: increasing the sample size by testing more individuals might improve the chances of correctly determining the presence or absence of chytrid. The test is already relatively accurate; therefore, EVSI corresponds to a large proportion of the maximum improvement achievable (EVPI; here, EVSI/EVPI = 0·59). For increasing sample sizes, EVSI will approximate EVPI (see also Fig. 3). In this sense, EVPI provides a benchmark for any experimental/monitoring programme under consideration. The value of *partial* perfect information (EVPXI) is a possible formulation of EVPI, representing how much management could improve if we could eliminate or confirm perfectly only one or some of our hypotheses (Runge, Converse & Lyons 2011; Williams & Johnson 2014). Where different learning actions are required to learn about different hypotheses, EVPXI allows for prioritisation of those actions.

From a management perspective focused on the decision problem at hand, if information has no influence over our actions, there is no benefit in collecting it. In the frog example, if we expected the source population to return to its initial size of 100 individuals regardless of the fate of the reintroduced population, the translocation should always be done, and information would have no value (EVPI = EVSI = 0). However, for values of VoI >0 the decision of whether to collect information can become less intuitive, since there is no universal rule to decide whether the VoI is 'high enough'. For example, in the frog translocation problem EVSI suggested a 10% improvement in management outcomes, which may or may not be considered sufficient by the relevant managers to justify the cost of setting up an experimental or monitoring programme.

Information will usually come at a cost, generating a trade-off where the benefits of resolving uncertainty need to be considered against its cost. If the objective is monetary, this trade-off can be addressed directly since VoI itself will be a monetary value (Bratvold, Bickel & Lohne 2007; Maxwell *et al.* 2014). Alternatively, collecting information can represent an opportunity cost, where the resources allocated for learning might have been used for other purposes. Finally, delaying decisions for the time necessary to collect information can affect outcomes, particularly when dealing with diminishing assets such as threatened habitats (Grantham *et al.* 2009) or species (Martin *et al.* 2012). All of these scenarios underscore the fact that VoI is ultimately dependent on management objectives; it is measured in the same units as management objectives and will change as management objectives change.

Lyons *et al.* (2008) noted three reasons for monitoring in a management context: reducing uncertainty about how the system functions, identifying the state of the system for state-dependent decision-making and assessing management success. Information may be required to assess management success even if it has no measurable VoI. However, VoI itself represents the expected improvement in management outcomes expected from collecting additional information and therefore is relevant to uncertainty in either how the system functions, or in the state of the system at a given time and place.

In the frog example, VoI accrues from learning about the state of the system to inform state-dependent decision-making: we want to know whether chytrid is present at a particular site at a particular time, in order to know what to do. In the turtle problem, by contrast, VoI accrues from reducing uncertainty

about how the system functions. In the case of uncertainty about system function, and when decisions are iterated, it is possible to learn from the outcomes of management and use the resulting knowledge to inform future decisions, an approach known as adaptive management (Holling 1978). In this sense, VoI is a necessary condition for adaptive management: if the expected VoI is low, then the use of adaptive management might not be warranted (Williams, Szaro & Shapiro 2009). More generally, constraints make it unlikely that every source of uncertainty can be resolved. In such cases, VoI highlights the key uncertainties which have the greatest effect on our management actions and which can be most effectively reduced, particularly in the partial VoI (EVPXI) formulation (Runge, Converse & Lyons 2011). Research and monitoring can then be focused on these key uncertainties, ensuring a rational and cost-efficient allocation of resources.

Finally, learning can further modify the decision problem. For example, our trial release of turtles could lead to estimates of survival which deviate from the expected values we used to populate the consequence table (e.g. recaptures of released turtles may indicate post-release survival increases with age more markedly than expected). This in turn can modify the expected values of actions from our initial predictions. Again, carefully structuring uncertainty and prior beliefs will assist in addressing these issues. In general, VoI is part of a decision-analytic framework, in which decision-making should be seen as an iterative process, any stage of which can be repeated and revised once the new information is collected (Gregory *et al.* 2012).

In summary, VoI analysis is an intuitively useful tool for applied ecology. Where a desire for additional information is expressed, VoI can assist in determining whether it is actually warranted (which benefit it will provide), where it should be directed (the key uncertainties we should focus on) and how it should be collected (the required study design). We have provided a reference guide for applied ecologists and managers interested in the application of VoI.

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Data accessibility

All data and formulas used for the case studies in this paper are provided in the tables and the Supporting Information spreadsheets.

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Supporting Information

Additional Supporting Information may be found in the online version of this article.

Appendix S1. Spreadsheet for calculating VoI for case study 1.

Appendix S2. Spreadsheet for calculating VoI for case study 2.