Using the Value of Information to improve conservation decision making

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ABSTRACT

Conservation decisions are challenging, not only because they often involve difficult conflicts among outcomes that people value, but because our understanding of the natural world and our effects on it is fraught with uncertainty. Value of Information (VoI) methods provide an

approach for understanding and managing uncertainty from the standpoint of the decision maker. These methods are commonly used in other fields (e.g. economics, public health) and are increasingly used in biodiversity conservation. This decision-analytical approach can identify the best management alternative to select where the effectiveness of interventions is uncertain, and can help to decide when to act and when to delay action until after further research. We review the use of VoI in the environmental domain, reflect on the need for greater uptake of VoI, particularly for strategic conservation planning, and suggest promising areas for new research. We also suggest common reporting standards as a means of increasing the leverage of this powerful tool.

The environmental science, ecology and biodiversity categories of the *Web of Knowledge* were searched using the terms 'Value of Information,' 'Expected Value of Perfect Information,' and the abbreviation 'EVPI.' *Google Scholar* was searched with the same terms, and additionally the terms decision and biology, biodiversity conservation, fish, or ecology. We identified 1225 papers from these searches. Included studies were limited to those that showed an application of VoI in biodiversity conservation rather than simply describing the method. All examples of use of VOI were summarised regarding the application of VoI, the management objectives, the uncertainties, the models used, how the objectives were measured, and the type of VoI.

While the use of VoI appears to be on the increase in biodiversity conservation, the reporting of results is highly variable, which can make it difficult to understand the decision context and which uncertainties were considered. Moreover, it was unclear if, and how, the papers informed management and policy interventions, which is why we suggest a range of reporting standards that would aid the use of VoI.

The use of VoI in conservation settings is at an early stage. There are opportunities for broader applications, not only for species-focussed management problems, but also for setting local or global research priorities for biodiversity conservation, making funding decisions, or designing or improving protected area networks and management. The long-term benefits of applying VoI methods to biodiversity conservation include a more structured and decision-focused allocation of resources to research.

Key words: adaptive management, decision analysis, decision theory, uncertainty, biodiversity, ecology, reporting standards, funding, research prioritisation.

CONTENTS

I. INTRODUCTION

(1) The changing landscape of biodiversity conservation

Our understanding of what constitutes biodiversity [the 'variety of life' (CBD Secretariat, 1992; Watson *et al.*, 1995)] has developed to encompass not only genes, species, and habitats or ecosystems but the variation within them and among all levels, and their inter-relationships. This has led over time to a desire for policy to go beyond the maintenance of species and protection of places. Whilst protecting species and habitats remain key and important conservation objectives, other objectives have emerged that reflect more fully such holistic definitions of biodiversity. These include maintaining genetic variability, evolutionary potential, food webs, ecological networks and the interactions within and among species, and ecosystem resilience and function (Mace, Norris & Fitter, 2012). A significant challenge is presented in both understanding the complex patterns and processes that these components of biodiversity represent and in shaping and implementing policies designed to ensure their maintenance. Amongst the most complex of globally agreed goals for biodiversity are those in the Convention on Biological Diversity's Strategic Plan for Biodiversity 2011–2020 and specifically their constituent Aichi Targets (Leadley *et al.*, 2014), and the environmental goals in the recently adopted Sustainable Development Goals. There are many statutory initiatives to advance the conservation of biodiversity across the globe, but implementation and enforcement of these statutes has been hampered because of the potential regulatory burden they impose and potential for conflict with human activities such as economic development, recreation, and subsistence and sport hunting. As a result, a more nuanced view of biodiversity conservation has emerged, one that recognises the choices and trade-offs implicit in decisions about environmental management.

The political complexity of decisions regarding biodiversity is exacerbated by the remaining uncertainties about the nature of biodiversity and its response to human interventions, to the extent that scientific uncertainty is sometimes used as a pawn during political debates and negotiations. There is a long way to go before the components of biodiversity are fully described, let alone their processes understood or the consequences of disrupting or even losing them are adequately predicted. In the meantime, policy and management decisions are still needed in the absence of such ecological knowledge and thus under substantial uncertainty. This leads to two important questions that are relevant for environmental managers: how should decisions about natural resource management be made in the face of uncertainty, and when is it valuable to reduce the uncertainty before committing to a course of action? The purpose of this review is to consider the literature concerning the second question, while placing it in the context of the first question.

(2) Strengthening scientific input for management and policy

This changing landscape of biodiversity conservation has two important implications for the science that informs or underpins conservation policy. First, decisions about conservation policy are significantly enhanced when what is known about biodiversity is made available to decision makers in a form that they can understand and use (Pullin *et al.*, 2004). There is a significant body of thought and literature concerning how to achieve this, including making literature more available to decision makers, analysing management interventions and other relevant topics through systematic reviews (Pullin & Stewart, 2006; Sutherland *et al.*, 2017), and promoting research that bridges the ‘knowing–doing’ gap (Knight *et al.*, 2008). The diversity of these approaches reflects the large range of contexts in which information on biodiversity, in all its forms, is now sought to inform policy and decision making.

The second implication of the interplay between uncertainty and decisions about biodiversity is the need to identify which uncertainty is most valuable to reduce in order to improve the outcomes of policy or management decisions. The critical issue here is determining which of the sources of uncertainty has the strongest influence on the choice of action. This requires an understanding of the decision context in which knowledge about biodiversity is being used. The question is not whether there is scientific uncertainty and how great it is, but rather, whether the scientific uncertainty impedes the choice of a management action. Here we examine the potential for a formal method called the 'Value of Information' (VoI) to address this question in support of conservation management and policy.

(3) Decision making under uncertainty

Before turning to the topic of the VoI, we first introduce the background on decision making in the face of uncertainty. A summary of terms can be found in Table 1.

(*a*) *Decision analysis*

The field of decision analysis aims to support decision makers by providing insights from a large array of disciplines, including decision theory, cognitive psychology, operations research, economics, and statistics. Based on the work of von Neumann & Morgenstern (1944) and harkening back to work of Nicolas Bernoulli in 1713, the field of decision theory recognises that all decisions have common elements, and searches for rational ways to structure decisions. Decision analysis aims to formalise the decision-making process by using a clear framework that incorporates all aspects that are relevant to making a decision, namely: the decision context (the authority of the decision maker and the environment in which the decision is being made); the objectives that are to be achieved by the decision and how they are measured; the different alternative actions that are under consideration to achieve the objectives; an analysis of the consequences of each action (the prediction of the consequences of each alternative in terms of the objectives is the central means by which scientific information is incorporated into a decision); and methods for navigating various types of trade-offs in choosing an action to implement (Gregory *et al.*, 2012; see Table 1). A diverse set of analytical tools has been developed to aid decision makers, depending on the primary impediments to the decision, including multi-criteria decision analysis (Davies, Bryce & Redpath, 2013), risk analysis (Burgman, 2005), spatial optimisation (Moilanen, Wilson & Possingham, 2009), and VoI (Runge, Converse & Lyons, 2011).

Formal methods of decision analysis have been used extensively for decisions regarding natural resource management (Gregory *et al.*, 2012), wildlife population management (Yokomizo, Couts & Possingham, 2014), fisheries management (Peterson & Evans, 2003), and endangered species management (Gregory & Long, 2009), among other applications. In practice, decision analysis is often used in conjunction with collaborative and participatory facilitation methods, to allow negotiation and dispute resolution (Gregory *et al.*, 2012).

(*b*) *Uncertainty*

Our knowledge of the natural world is extensive, but incomplete. When scientists are asked to make predictions about the outcomes associated with alternative management actions, they should do so with an understanding of the uncertainties that underlie those predictions, where possible. Identifying types of uncertainties can be helpful in determining how to deal with them. It is useful to distinguish three types of uncertainty: linguistic, epistemic, and aleatory. Linguistic uncertainty is any type of uncertainty that is linked to language (vague or ambiguous terms, or terms that are context dependent for example; Regan, Colyvan &

Burgman, 2002), and is often unresolved in conservation decision making (Kujala, Burgman & Moilanen, 2013). Sometimes disputes or confusion arise simply because different people ascribe a different definition to the same term. Epistemic uncertainty arises from limitations in our knowledge of the world and its workings and is often linked to aspects of available data, such as insufficient observations or imprecise measurements, which are often parameters in models used to forecast the effects of management actions. A special case of epistemic uncertainty is structural uncertainty, which refers to uncertainty in the structure of the systems model, or of model form, as opposed to model parameters (Morgan & Small, 1992; Conroy & Peterson, 2013). Both linguistic and epistemic uncertainty are, at least theoretically, reducible uncertainties, that is, with appropriate effort and study, we could resolve the uncertainty (Conroy & Peterson, 2013). The third type of uncertainty, aleatory uncertainty, is irreducible, because it arises from sources that are not possible to know about in advance (Gregory *et al.*, 2012). For example, variation in the weather over the next ten years, and how it will affect a wildlife population relevant to a particular decision, is not something we can know in advance. We can describe its expected mean and variance, but we cannot know the specific temperature and precipitation patterns that will emerge. All three types of uncertainty can be relevant to a decision analysis but they often emerge at different stages of the process. For example, linguistic uncertainty often arises during problem framing or objective setting, whereas epistemic and aleatory uncertainty play a more important role during the prediction of the consequences of the alternative actions.

The first step to grappling with uncertainty in a decision context is simply to acknowledge that uncertainty exists and to identify the potential sources of uncertainty that could affect the prediction of the consequences of the alternative actions. The second step is to estimate the magnitude of the uncertainty. Statistical methods can be used to estimate the magnitude of uncertainty in empirical observations; in other cases, formal methods of expert elicitation

(Martin *et al.*, 2012) can be used. Either way, uncertainty can be expressed as probability distributions associated with the state variables of interest (e.g. population abundance), the parameters of predictive models (e.g. survival or reproductive rates), the underlying alternative hypotheses about how the ecosystem responds to management (e.g. whether the population is limited by habitat or predation), and the efficacy of actions (e.g. fraction of a grassland burned by a prescribed fire). For analysis of empirical data, Bayesian statistical techniques are most useful, because the posterior distributions represent direct statements about the probabilities of values of the parameters in question. For analysis of expert judgment, various elicitation and aggregation methods are available to produce probabilistic summaries. Burgman (2005) discusses the range of methods available for estimating uncertainty in a risk-analysis context.

The third step in grappling with uncertainty is to propagate the uncertainty through the predictions of the consequences. If a model is being used to connect the alternatives to the outcomes, then standard modelling techniques can be used to accomplish this; if not, then again, expert elicitation can be used. The fourth step is the most important – figuring out how to handle the uncertainty in the decision. There are essentially two different paths. Decisions can be made either without resolving uncertainty, or once some of the uncertainty has been resolved. For irreducible uncertainty, only the first choice is available. For reducible uncertainty, both choices are theoretically available, and the question is whether it is worth resolving the uncertainty first. Funders of research may also be interested in prioritisation where there are multiple sources of uncertainty to address. In some instances uncertainty may not be an important consideration, in others, however, uncertainty may play an important role. The next two sections describe the decision analytical tools for evaluating decisions in the face of uncertainty, and evaluating the value of reducing uncertainty.

(*c*) *Decisions in the face of uncertainty*

Many decisions are made in the face of uncertainty, without an attempt to resolve the uncertainty before committing to action; analysis of such decisions is the focus of risk analysis (Burgman, 2005). The essence of such decisions is to choose the alternative action that best manages the risk associated with the uncertain outcomes in a manner that reflects the decision maker's risk tolerance. For a risk-neutral decision maker, the analysis involves calculating the expected outcome for each alternative, with the expectation (the weighted average) taken over all the uncertainty, and choosing the action with the best expected value. The decision maker, however, might not be risk neutral; for instance, they might be much more concerned about the risk of downside losses than the chance of upside gains. If the decision maker is not risk neutral, utility theory (von Neumann & Morgenstern, 1944) is used to express the decision maker's risk tolerance. Both the expected value (risk neutral) and expected utility approaches require a probabilistic expression of uncertainty. There are also approaches to risk analysis and management that do not require uncertainty to be described with probabilities, that instead seek actions that are relatively robust to uncertainty [for example, info-gap decision theory (Ben-Haim, 2006)]. So, there are methods for analysing decisions that are made in the face of uncertainty. But what if there is an opportunity to reduce uncertainty before committing to action – is it worth doing so?

(4) Prioritising research to reduce uncertainty about the things that matter: the Value of Information

From the standpoint of a decision maker, research and monitoring are expensive and time-consuming, and potentially take resources away from management interventions, but hold the promise of providing new information that can guide and improve future management actions. When is new information worth the cost? The VoI addresses this question by helping to focus research and monitoring efforts on uncertainty that impedes choice of an optimal action (Runge *et al.*, 2011). VoI can also be used to identify cases where monitoring or further learning would not improve the management actions (McDonald-Madden *et al.*, 2010).

As an example, if the threats to a declining species are unknown, there is uncertainty around the management action that would best address the decline. In some cases, research may lead to a better understanding of the causes of the decline so the decision maker can choose an appropriate management action. In other cases, research might not affect the choice of action, either because the decision maker cannot address some of the causes of the decline, or because the best action would not change even with more knowledge. The aim of VoI is to establish whether the removal of uncertainty by conducting research or undertaking monitoring would be beneficial. The ability to use VoI to prioritise and choose between different monitoring and research options is particularly useful, but to our knowledge has not become common practice among research-funding agencies or conservation organisations.

VoI was first described by Schlaifer & Raiffa (1961) and has since been used in a wide range of applied disciplines, notably health economics (Yokota & Thompson, 2004; Steuten *et al.*, 2013) and engineering (Zitrou, Bedford & Daneshkhah, 2013). VoI is calculated by determining whether the performance of objectives of a decision could be improved if uncertainty could be resolved before committing to a course of action.

There are several variants of VoI, all of which compare the expected benefit with new information to the expected benefit when the decision is made in the face of uncertainty (Runge *et al.*, 2011). The expected value of perfect information (EVPI) calculates the improvement in performance if all uncertainty is fully resolved, and can be used to establish if research or monitoring is valuable to make effective management decisions. The expected value of partial perfect information (EVPXI or EVPPI) shows the relative value of resolving uncertainty about different hypotheses or different parameters, thus serving as a way to prioritise research questions (Yokomizo *et al.*, 2014). Finally, because reducing uncertainty to zero is likely to be impossible, the expected value of sample information (EVSI) calculates the expected gain in performance from collecting imperfect information rather than for perfect information (Steuten *et al.*, 2013). The expected value of partial sample information (EVXSI) combines the concepts of EVPXI and EVSI. Canessa *et al.* (2015) and Milner-Gulland & Shea (2017) advocate the use of VoI in ecology and also provide explanations and online documentation for ecologists on how it can be calculated (Canessa *et al.*, 2015) and in which contexts it would be useful for addressing uncertainty (Milner- Gulland & Shea, 2017).

II. CALCULATING THE VALUE OF INFORMATION

As the calculations can become complex, we provide here a simplified explanation of how to calculate VoI. A VoI analysis requires that the decision be formally structured (Gregory *et al.*, 2012). First, the decision maker's objectives must be articulated and appropriate performance metrics identified. This is often quite challenging, because it requires critical thought about the aims of management and how the outcomes can be measured. While managers may be able to identify costs of different interventions, estimating benefits for biodiversity conservation is usually more difficult, but there is a growing literature on this topic (Keeney, 2007; Runge & Walshe, 2014). Second, at least two alternative management actions need to be identified that could meet the objectives. Third, the consequences of the alternatives need to be estimated, specifically how effective each alternative will be in meeting the different objectives (Gregory *et al.*, 2012). This is where the evaluation of uncertainty begins. For each action, the uncertainty in achieving the objectives needs to be estimated. Often, this comes in the form of structural uncertainty: different hypotheses about how the system works that result in different predictions of the outcomes associated with each action (see Case Study 3 in Section III.3*c*, for an example). Along with these predictions, the probability of the different hypotheses also needs to be estimated. This information (the objectives, the actions, the consequences, and the estimates of uncertainty) form the basis for a risk analysis, but they also provide the basis for the VoI analysis.

To demonstrate a VoI calculation by example, we consider three different areas that could be purchased, placed in protection, and managed for the benefit of an endangered species. The decision maker has the resources to purchase only one area, and would like to know which one will be of most benefit. The decision maker has indicated that the fundamental objective can be measured using the long-term population size of the endangered species.

There is uncertainty about the ultimate population size of the endangered species that could be supported in the three protected areas, so the population size has been estimated under five different hypotheses about what resource most limits the species, each of which is judged to be equally likely (Table 2). The expected population size across hypotheses is highest for area A with a mean of 1,000, so if we do no further research, area A would be the best option under current knowledge. That is, in the face of uncertainty, a risk-neutral decision maker would choose to acquire area A.

For hypotheses 1 and 5, we estimate that area A has the highest long-term population size, so A is the optimal choice in 40% of the cases. For hypotheses 2 and 3, we estimate that area B would be best, while for hypothesis 4 area C would be best, so there is some uncertainty about the best area in which to invest, depending on which hypothesis is correct. That is, the uncertainty matters to the decision maker. Now we can use VoI to decide whether to select area A now or invest in more research first.

The maximum long-term population size under each hypothesis arises if the decision maker can choose the best action associated with that hypothesis (A for hypothesis 1, B for hypotheses 2 and 3, C for hypothesis 4, and A for hypothesis 5). Taking the mean of the maximum long-term population sizes under each hypothesis, we can calculate the expected value of the maximum long-term population size, which is 1,110. Prior to undertaking research to resolve uncertainty about the true hypothesis, we do not know what we will find out, but we think it is equally likely it will be any one of the five hypotheses. The average of the performance of the best action for each hypothesis tells us the expected value of our decision if we can resolve uncertainty before we commit to action. In comparison, the highest long-term population size under current knowledge is the mean value of A, which is 1,000. The difference is the VoI – we could achieve an expected gain of 110 additional animals in the population if we had perfect knowledge. We assume here that one of the five hypotheses is correct and therefore one of the estimates for long-term population sizes of area A, B, and C under each hypothesis must be correct. The decision maker now knows that reducing uncertainty about the limiting factors would increase the expected outcome by 11% (110 more animals than the 1,000 expected by simply purchasing Area A). Several very difficult questions now arise. First, is research possible that can reduce the uncertainty and identify the limiting factor? This question requires careful consideration of research design. Second, how much would the research cost? A power analysis associated with the research design could help identify the amount of sampling necessary, which could help with estimation of the costs. Third, is the cost of the research worth the gain? Suppose the research would cost $500,000; would the expected gain of 110 individuals of this endangered species be worth that investment? The decision maker needs to weigh this decision, taking into account such things as the importance of this species, the number of other populations that exist, and the other uses to which the funds could be put. This is not a trivial task, but the decision is greatly informed by the transparent analysis of uncertainty, the comparison with the expected outcome in the face of uncertainty, and the estimate of the potential gain. It is now up to the decision maker to decide whether money should be spent on further research, or whether the decision should just be made to protect area A.

III. THE USE OF VoI IN BIODIVERSITY CONSERVATION

(1) Methods

A literature search was undertaken to examine the extent to which the use of VoI in biodiversity conservation has been documented so far. Search criteria were established to identify papers that were written in English and were published in a peer-reviewed journal before the end of July 2017. The *Web of Science* was searched for papers containing the terms “value of information”, “value of perfect information”, or “EVPI” within the environmental science, ecology, and biodiversity conservation categories. To search for grey literature, *Google Scholar* was searched with the following terms: ("value of information" OR "value of perfect information" OR EVPI) AND (biology OR "biodiversity conservation" OR fish OR ecology) AND decision. The term fish was added to ensure that fishing and fisheries papers were included in the search results. Only the first 1,000 matches were examined, however this was deemed sufficient as none were relevant after entry 318. Not all articles found in this way applied VoI in biodiversity conservation, and articles whose research domains were, for example, medicine, meteorology, or economics were excluded. Studies that did not use VoI calculations and studies that advocated the use of VoI but showed no real-world application were also excluded: only studies that incorporated VoI calculations that were applied to biodiversity conservation were selected. We report our search using a PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses; Liberati *et al.*, 2009) flow diagram. Citations of studies meeting the inclusion criteria were searched for further studies, then all studies were summarised with respect to: the application of VoI, management objectives, uncertainties considered and how they were expressed, the predictive modelling used, the performance metric used, and the type of VoI. Papers were further categorised according to the type of uncertainty (structural, parametric – empirical, or parametric – elicited), whether they had single or multiple objectives, whether uncertainty was expressed discretely or continuously, and what type of VoI was used (EVPI, EVPXI, EVSI). We also plotted the number of papers we found and the overall citations over time.

Three papers were chosen as case studies, to illustrate in more detail the decision context, what data sources were used, how VoI was calculated, and whether it made a difference to the decision. They were chosen to represent a range of applications that show clearly how VoI was helpful.

(2) Results

The searches returned 1225 unique references of which 30 met the inclusion criteria, or 2.5% of the total references (Fig. 1). 901 references were excluded because their primary discipline was not biodiversity conservation. 294 were excluded due to no mention of VoI, no real-world application of VoI, or due to duplication of previously identified records.

A range of relevant aspects of the included papers are summarised in Table 3. Single-species management problems were the focus of 18 (60%) of the papers. Of those, the disciplines within which VoI has been used included invasive species management (eight papers: D'Evelyn *et al.*, 2008; Moore *et al.*, 2011; Sahlin *et al.*, 2011; Moore & Runge, 2012; Johnson *et al.*, 2014*b*, 2017; Williams & Johnson, 2015; Post van der Burg *et al.*, 2016) and protected species management (10 papers: Grantham *et al.*, 2009; Runge *et al.*, 2011; Tyre *et al.*, 2011; Williams, Eaton & Breininger, 2011; Smith *et al.*, 2012, 2013; Johnson *et al.*, 2014*a*; Canessa *et al.*, 2015; Maxwell *et al.*, 2015; Cohen *et al.*, 2016). Other papers focused on management of multiple species. Of those, fisheries were the subject of five papers

(Sainsbury, 1991; Costello, Adams & Polasky, 1998; Kuikka *et al.*, 1999; Mäntyniemi *et al.*, 2009; Costello *et al.*, 2010) and the management of ecosystems was also the subject of five papers (Bouma, Kuik & Dekker, 2011; Convertino *et al.*, 2013; Runting, Wilson & Rhodes, 2013; Perhans, Haight & Gustafsson, 2014; Thorne *et al.*, 2015). The use of phylogenetic diversity for deciding which species to protect was used by one study (Hartmann & Andre, 2013) and the sustainable harvest of a species by another (Johnson, Kendall & Dubovsky, 2002).

While there was a range of different objectives considered, there were some common themes, including maximising populations or their growth rates, or having optimal populations (14 papers or 47%), maximising or maintaining harvests (seven papers or 23%) and minimising costs (seven papers or 23%). Many papers listed more than one objective, and further details of objectives that were specific to individual studies can be found in Table 3. The uncertainties considered are also listed (Table 3): six papers (20%) used expert elicitation for estimates of uncertainties, the others used various models.

The type of performance metric, that is, how the achievement of objectives by different management interventions was expressed, was conveyed in a wide variety of ways. Monetary values for costs and benefits were used by 12 papers (40%) (Sainsbury, 1991; Costello *et al*., 1998, 2010; Johnson *et al.*, 2002; D'Evelyn *et al.*, 2008; Mäntyniemi *et al.*, 2009; Bouma *et al.*, 2011; Moore *et al.*, 2011; Moore & Runge, 2012; Runting *et al.*, 2013; Perhans *et al.*, 2014; Post van der Burg *et al.*, 2016). Two papers used monetary values for costs only, and relative benefits that can be achieved at those costs (Maxwell *et al.*, 2015; Convertino *et al.*, 2013). Another eight (27%) papers used a unitless value that reflected a weighted response across multiple objectives (Runge *et al.*, 2011; Smith *et al.*, 2013; Williams *et al.*, 2011; Johnson *et al.*, 2014*a*,*b*, 2017; Thorne *et al.*, 2015; Williams & Johnson, 2015). Other papers used a range of performance metrics, namely cost ratio (Sahlin *et al.*, 2011), probability of survival of different age classes (Canessa *et al.,* 2015), population growth rate in per cent (Cohen *et al.,* 2016), species retention rate at the end of a 20-year simulation period (Grantham *et al.,* 2009), increase in gas extraction while maintaining brook trout (*Salvelinus fontinalis*) populations (Smith *et al.,* 2012), probability of population persisting for 256 years (Tyre *et al.,* 2011), utility function reflecting both yield (kilotons) and risk of falling below critical spawning mass (Kuikka *et al.,* 1999), and proportion of maximum phylogenetic diversity retained (Hartmann & Andre, 2013).

Of the 30 papers found, 19 considered multiple objectives (63%), whereas 11 (37%) considered single objectives (Table 4). 17 papers (57%) were concerned with structural forms of uncertainty and 19 with parametric forms of uncertainty (63%) – six papers considered both forms of uncertainty (20%). While 27 papers used EVPI (90%), 10 used EVPXI (33%), all of which were published since 2011, and six used EVSI (20%). Twelve papers used more than one VoI calculation.

Use of VoI in the field of biodiversity conservation is a recent phenomenon. The number of papers has increased markedly since 2011, with eight papers published before 2011, and 22 papers published since the start of 2011 (Fig. 2). The number of citations has increased steadily and was at 813 at the end of 2017, a mean of 27 citations per paper. Leadership in this arena comes primarily from the USA and Australia: the country of affiliation for first authors was USA for 18 of the papers (60%), Australia for seven (23.3%), and European countries for five (16.7%). 18 papers (60%) had at least one author who worked for the US Department of Interior.

(3) Case studies

All 30 examples found through the literature search undertook a VoI analysis that shed light on whether more information would be valuable to the decision maker, but they varied in the transparency of their presentation, the thoroughness of the uncertainty analysis, and the clarity of the usefulness to the decision maker. Rather than a detailed analysis of the strengths and shortcomings of all 30 cases, we present here three case studies that describe clearly how VoI was used and calculated, represent a range of applications of VoI, and document how VoI informed the decision-making process. These three case studies are exemplary applications of VoI, but each also has a few shortcomings; these shortcomings help identify fruitful areas for improved application. They are also amongst the VoI papers with the highest annual citations.

(*a*) *Case study 1*

Costello *et al.* (2010) used VoI to find an optimal marine protected area network in California, under uncertainty around dispersal of larval fish. Their aim was to design an optimal Marine Protected Areas network for sheephead *Semicossyphus pulcher*, kelp bass *Paralabrax clathratus*, and kelp rockfish *Sebastes atrovirens* to maximise fishery profits whilst ensuring the conservation of the three fish species. They investigated the trade-offs between maximising profits and maximising conservation by changing the weighting of the two objectives across the different scenarios. The authors considered 135 patches of 10 km^2. There was uncertainty around the dispersal of the fish larvae, which affects where the species will be, which is relevant both for fishing these species as well as for protecting them. They used ten different dispersal kernels, of which only eight may accurately represent the real dispersal of fish larvae. The other two were simplified kernels, included to see how incorrect assumptions might affect the outcomes. The management alternatives were based around these kernels: to choose the best possible spatial harvest either under uncertainty or with perfect information, or under the two incorrect dispersal kernels. A stage-structured spatial model as well as an ocean-circulation model were used, and EVPI was calculated.

To maximise profits from fishing, the two incorrect dispersal kernels led to the least profits, while imperfect information led to higher profits and perfect information to the highest profits, for all three species of fish. To maximise the conservation benefits, there was no difference in the value of all three fisheries between the different dispersal kernels. The area in marine protected areas increased with certainty, and was lowest for the two incorrect dispersal kernels. The VoI to maximise profits was 11%.

Two observations about this case study point towards challenges in the application of VoI methods. First, the analysis of uncertainty focused on one aspect of the fish model, the larval dispersal kernels, and did not consider uncertainty in other aspects of the model, such as in the other fish population parameters or in assumptions about the fidelity with which optimal designs are implemented in practice. How comprehensive does the expression of uncertainty need to be? To some extent, the practice of modelling involves judgments about which uncertainties will matter and so which should be explored; these are essentially informal VoI evaluations. There is no guidance yet about how modellers should navigate this question. Second, to generate alternative larval dispersal kernels, Costello *et al.* (2010) used alternative realisations from a stochastic ocean circulation model, but then acknowledge that they assumed those represented fixed dispersal kernels for the purpose of developing an optimal protected area design. Does their set of eight alternative kernels represent the full range of uncertainty for this aspect of their model? Would an alternative ocean circulation model have added to the range of dispersal kernels? We believe this is a valuable open research question – is there a way to evaluate whether a candidate set of models captures the relevant degree of uncertainty for the decision problem at hand?

(*b*) *Case study 2*

Maxwell *et al.* (2015) used VoI to determine the value of more research in choosing the best management intervention for a declining koala *Phascolarctos cinereus* population in Australia. Their objective was to maximise the growth rate of the koala population. Three actions were suggested that could address threats to koalas, and the authors investigated how much should be invested in each action under different budget levels: preventing vehicle collisions by building fences and bridges; preventing dog attacks by building enclosures for dogs; and preventing spread of disease by buying land for conversion to koala habitat, which was also considered to reduce the other two threats. There was uncertainty about how habitat cover affected koala mortality, as well as about the survival and fecundity rates of koalas. These uncertainties were described using eight population models. The optimal strategy (how much of a given budget should be spent on each action) was calculated for various budget levels. EVPI and EVPXI were calculated by determining which uncertainties to reduce under different budget levels to achieve a certain population growth rate, which was then converted into a financial VoI.

The authors found that preventing vehicle collisions was the most cost-effective action at low budget levels but that larger budgets allowed more to be spent on habitat restoration instead, due to the disparity in costs of the different actions. The VoI differed between different budget levels; at budgets below AUS$45 million it was best to resolve the uncertainty around survival and fecundity, whereas at budgets above $45 million it was best to resolve uncertainty around habitat cover. Maxwell *et al.* (2015) made a valuable methodological contribution: even though the management objective was not stated in monetary terms (the objective was to maximise the population growth rate of koalas), the VoI could be converted to a financial value by comparing budget levels that could achieve the same expected population growth rate with and without resolving uncertainty. Interestingly, the VoI was never more than 1.7% of the budget.

Maxwell *et al.* (2015) analysed both structural and parametric uncertainty in a combined analysis, serving as a good example for how others can include both types of uncertainty in a VoI analysis. They found that parametric uncertainty explained around 97% of the EVPI, with structural uncertainty contributing very little, but is this a general result? There has not yet been a comprehensive study to look at how structural and parametric uncertainty contribute to EVPI and whether there are any general patterns that can be inferred.

(*c*) *Case study 3*

A study using expert elicitation was undertaken by Runge *et al.* (2011) who studied the management of a reintroduced whooping crane *Grus americana* population in the USA. At the time of the study, the population was failing to reproduce and so the aim was to enhance the current population under uncertainty around the reasons for low reproductive success. They formulated four objectives to contribute to a self-sustaining population of whooping cranes: provide suitable nest sites; maximise reproduction; maximise survival during the summer months; and improve body condition when the birds leave for their winter quarters. Because quantitative data were not available to evaluate the effectiveness of all proposed actions, they used an expert elicitation process to articulate competing hypotheses for reproductive failure, develop alternative management action, and evaluate the management actions under each hypothesis. Eight hypotheses to explain the pattern of reproductive failure were developed, ranging from nutrient limitation to harassment by black flies. Seven alternative management actions were developed, using the competing hypotheses as motivation. Using formal methods of expert judgment, the experts were then asked to estimate how well each action would address each of the four different objectives, under each hypothesis.

Three variants of VoI (EVPI, EVPXI and EVSI) were calculated with the information provided by the expert panel. Under uncertainty, the best action was meadow restoration, which was thought to address all four objectives best. For three of the four objectives, the VoI was nearly 0, because the best action was the same under most of the hypotheses. But for one objective (maximising the fledging rate), the best action depended on the underlying hypothesis for reproductive failure, thus the VoI was substantial (25.7%). Calculation of the expected value of partial information (EVPXI) revealed that the most important hypotheses to resolve were how parasitic flies and human disturbance affected whooping cranes. In part as a result of this analysis, a controlled experimental study of the effect of parasitic flies on reproduction was undertaken, lending strong support to this hypothesis; in response, management agencies have refocused reintroduction efforts to areas with lower parasitic fly densities.

This study reveals one difficult challenge in estimating uncertainty. The authors considered eight hypotheses against seven alternatives and four objectives, thus, each expert had to estimate 224 values. A panel of experts was used, but uncertainty across experts was not analysed, nor were the experts asked to estimate their internal uncertainty, in part because the sheer magnitude of the elicitation task was already exhausting for the experts. Thus, differences across objectives and hypotheses were evaluated, but differences across and within experts were ignored. In this setting, expert judgement was needed, because empirical data could not inform the full set of questions being asked. But there are not yet methods in the expert judgment literature for eliciting large patterned matrices of responses, while properly estimating within- and among-expert uncertainty and minimising expert fatigue.

IV. DISCUSSION

Natural resource managers have to make decisions despite uncertainty on issues such as rapid species declines, increasing numbers of invasive species, or changes in ecosystems due to land-use change. In many cases, there is an urgency to take action even though the science behind these, and other pressing issues, is generally not fully understood (Tittensor *et al.*, 2014). VoI is a method for evaluating this uncertainty, yet its potential remains relatively unexplored, with only 30 papers so far using it in biodiversity conservation.

The pursuit of a VoI analysis requires a structured approach to decision analysis, which has rewards in its own right (Gregory *et al.*, 2012; Possingham, 2001). Applied biodiversity conservation is about decisions, and the field of decision analysis provides a rich set of tools for helping decision makers navigate the complexities in natural resource-management settings. The consistent use of these methods is emerging in a few conservation organisations around the world, supported by a rapidly expanding literature.

The specific benefit of a VoI analysis is to ascertain whether uncertainty surrounding the effects of management actions should be reduced or not. It is valuable to note that the answer to this question is context specific. There are examples from our review where using VoI showed that uncertainty should be reduced first (Costello *et al.*, 2010; Bouma *et al.*, 2011; Runting *et al.*, 2013), and other examples where it makes little difference to the overall outcomes whether uncertainty is reduced or not (Johnson *et al.*, 2014*a,b*; Maxwell *et al.*, 2015). There are two endeavours where the resolution of uncertainty takes a central role: research design and adaptive management. There is potential to extend the application of VoI to prioritising research topics through the use of EVPXI. This could be used by conservation NGOs or funding agencies to prioritise which projects to fund, or by policy makers to help set national or international conservation and research priorities. VoI can also be used to decide when adaptive management is warranted, as it shows whether resolution of uncertainty will improve the expected outcomes associated with management decisions and, if so, which elements of uncertainty contribute most to that improvement.

Attention to VoI methods in the conservation literature is recent. The first suggestion for using VoI in biodiversity conservation was made by Walters (1986), followed by the earliest paper included in our review (Sainsbury, 1991). Seven more papers on VoI were published in the next 20 years. A turning point appears to have occurred in 2011: 22 of the 30 papers we found were published since then. Because the introduction of VoI methods into the biodiversity conservation literature is fairly recent, the coverage of topics to which it has been applied is incomplete (Table 4). Most of the papers we reviewed focus on EVPI, while the use of EVPXI has increased since 2011. Only six of the 30 papers used EVSI, so its use remains poorly explored. Uncertainty was dealt with in a range of ways: either by using different model structures, by using the same model but with different parameters, or by eliciting uncertainties from experts. A wide range of predictive models has been used for VoI analysis, with many papers using population models, but there is the potential to explore its use with other modelling structures, such as machine-learning methods like Random Forests or Neural Networks.

Our review revealed that although many scientists are talking about VoI methods (hundreds of papers), their use in applied settings is more limited (30 papers) – why is the uptake of VoI so slow? Using VoI in a structured decision-making context is advocated by many in ecology and biodiversity conservation, for example, at the US Department of the Interior (Williams, Szaro & Shapiro, 2009), and recently by the IUCN in their guidelines for species conservation planning (IUCN – SSC Species Conservation Planning Sub-Committee, 2017). It does not appear, however, that these calls have yet resulted in the systematic use of VoI in conservation decision making, with the 30 cases presented herein encompassing the bulk of the applications. The methods are novel enough that applications warrant publication in the peer-reviewed literature. While there is not a mechanism to systematically search the grey literature, during our search we only came across two or three indications of unpublished VoI analyses by conservation decision makers. We have not undertaken an institutional analysis to identify the impediments to faster uptake of these methods, but we suspect that the methods are simply at an early stage of adoption. Widespread introduction to the concept of VoI in the conservation field only occurred in 2011 and conservation agencies are only now deliberately building capacity in decision analysis. The study of organisational change, especially adoption of decision-analysis methods, suggests that it typically takes 15–25 years to achieve widespread adoption of new practices (Spetzler, Winter & Meyer, 2016).

Standardised reporting of VoI analyses might help in the communication and adoption of the methods. The calls for using VoI (Williams *et al*., 2009; IUCN, 2017) ensure there is a clear framework within which VoI can be applied. It also means that reporting standards for VoI analyses can be developed readily (Table 5). These standards include a description of the full decision context, whether a real or hypothetical decision is considered, what the uncertainties are, which type of VoI was used, how the objectives were measured, and the time horizon. As VoI is implemented more widely, these reporting standards can increase the transparency of the VoI calculation. Most of the items we suggest in the reporting standards were listed in the papers we found and have been summarised in Table 3, but for some papers stating the reporting standards explicitly would aid in making the papers easier to understand. Rarely was the decision maker named however, and no paper stated whether the research would be used to inform management.

Our review of the extant literature applying VoI methods suggests a number of fruitful areas for future research and development. First, Tables 3 and 4 reveal a number of gaps in application (e.g. no examples of using EVSI in ecosystem management settings); the continued expansion of VoI methods into all types of conservation decisions, with all system model types, could provide greater guidance for other decision makers. Second, there is a need for guidance about which uncertainties to include in a VoI analysis. That is, how should scientists and decision makers work together to identify the sources of uncertainty to examine, and what are the consequences of leaving out important sources? Third, there are not yet methods for evaluating whether the range of values or range of alternative models used to capture uncertainty adequately does so. Put another way, does uncertainty about the uncertainty matter? Can the usefulness of a VoI analysis be undermined if uncertainty is inadequately captured? This question is perhaps most applicable when uncertainty is expressed as a discrete set of alternative models or parameter sets. Fourth, perhaps to help in developing the guidance for the previous two items, is it possible to identify what types of uncertainty contribute most to EVPI? Is there an important difference between structural and parametric uncertainty? Are there other properties of sources of uncertainty that are associated with greater EVPI? Fifth, there is a need for new methods of expert judgment that are designed to elicit patterned matrices of values, with expression of uncertainty, without exhausting the cognitive resources of experts. For example, a decision setting that involves four possible actions and five alternative models of system response (representing uncertainty) requires elicitation of 20 values, but these values should not be viewed as independent – there are presumably relationships across rows and columns that are part of the expert knowledge. Sixth, and finally, there is a curious pattern in many of the examples we reviewed – EVPI can often be smaller than one might expect. Is this a common occurrence across conservation applications, and if so, why? Is it because the intuitive expectations of a high VoI are biased, or is it because the analysis of uncertainty is too narrow?

Decisions regarding biodiversity conservation, especially in the face of climate and land-use change, are often impeded by uncertainty. Risk-analysis methods can help managers make decisions in the face of uncertainty, and VoI methods can help them decide whether to gather more information before committing to action. The increased use of VoI since 2011 is a positive sign, and its wider implementation will be beneficial for making robust decisions in an uncertain future. To support expanded implementation, there are a number of open research questions regarding how best to conduct VoI analyses.

V. CONCLUSIONS

(1) Formal methods of decision analysis provide tools for making rational conservation decisions in the face of uncertainty, whether those decisions concern management of imperilled species, control of invasive species, establishment and management of protected areas, setting of harvest quotas, or any other of the classes of decisions faced by natural resource-management agencies.

(2) VoI methods allow decision makers to understand the value of resolving uncertainty, and thus provide a way: to evaluate whether more information is needed before taking action; to set a research agenda by ranking the influence of different sources of uncertainty; and to motivate and guide the development of adaptive management.

(3) The increasing use of VoI in biodiversity conservation since 2011 indicates that there are efforts to tie the analysis of uncertainty more explicitly to decision-making contexts. The variety of VoI methods have been explored fairly thoroughly in conservation settings, but there are few examples of the expected value of sample information (EVSI).

(4) While VoI has been extensively promoted as a tool to inform management, it is much less common that is has been implemented for managing conservation issues. For VoI to make a difference, it needs to be used by managers, policy makers and funders, not just scientists. The use of decision analysis and formal VoI could do much to reduce the incoherence of information flow from scientists to practitioners. We postulate that this is a critical missing piece required to bridge the knowing–doing gap.

(5) Common reporting standards to document the use of VoI could be a valuable way to share insights and motivate further application of these methods.

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FIGURES

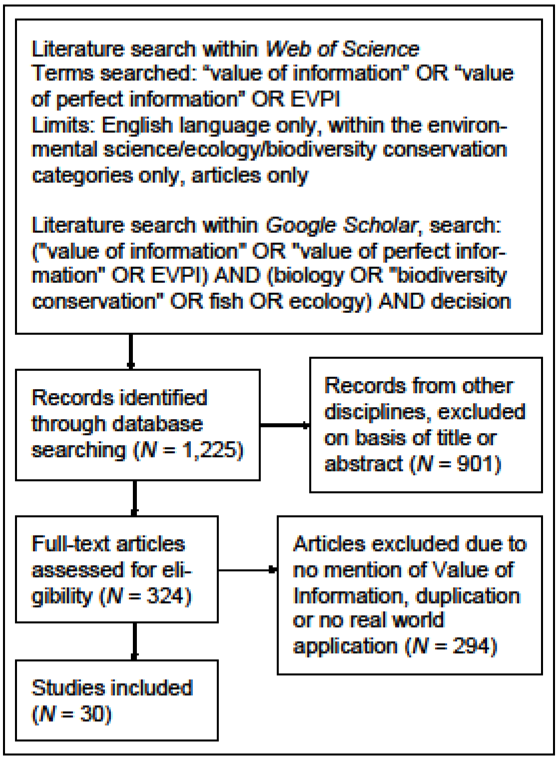

Fig. 1. PRISMA flow diagram (Liberati *et al*., 2009) of results of literature search.

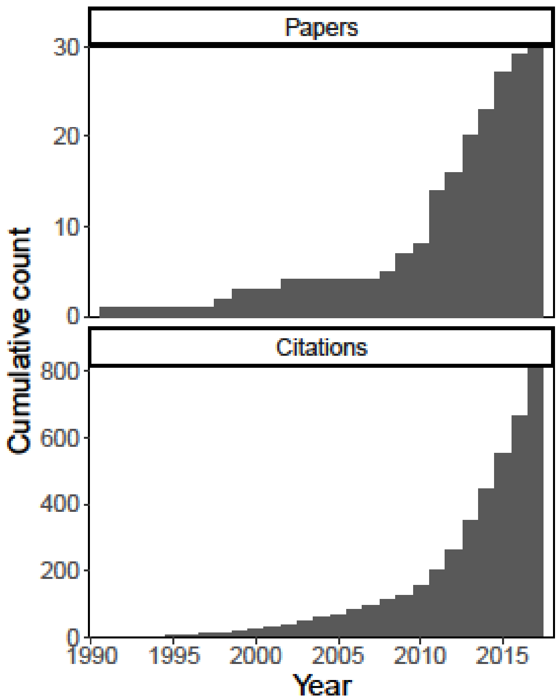

Fig. 2. Cumulative number of applied Value of Information (VoI) papers in biodiversity conservation and their total citations over time. The citations are tallied until the end of 2017.

TABLES

Table 1. Definitions of terms relating to decision making in conservation.

Term	Definition
Decision analysis methodology	
Decision analysis	A broad field that explores both how humans make decisions (descriptive decision analysis) and how they should make decisions (prescriptive or normative decision analysis). Importantly, normative decision analysis provides a framework for decision making that includes the context, the objectives, alternative actions, the consequences of the actions, the uncertainties involved and how learning can be implemented (Gregory *et al.*, 2012).
Decision context	What decision needs to be made and how? Who is the decision maker and what is their authority? What legal, policy, and scientific guidelines form the context for the decision? (Gregory *et al.*, 2012).
Objectives	The fundamental outcomes that the decision maker is pursuing in making the decision. Objectives need to encompass everything that should be achieved by the decision whilst being independent from each other. They can be used to build consensus amongst stakeholders (Gregory *et al.*, 2012).
Alternatives	Set of potential actions under consideration that could achieve the objectives. An alternative may encompass various tasks that will address all objectives, so different alternatives can be comparable. Alternatives need to be distinct from each other (Gregory *et al.*, 2012).
Consequences	The predicted outcomes of the different alternatives relative to the different objectives. Often the consequences show trade-offs between different alternatives (Gregory *et al.*, 2012).
Trade-offs	Competing consequences across objectives, such that improving the outcome associated with one objective requires giving up performance associated with another objective. The challenge to the decision maker is to evaluate consequences of the different alternatives and make a decision on which alternative to implement (Gregory *et al.*, 2012).
Uncertainty terms	
Aleatory uncertainty	Uncertainty arising from inherent variability in random processes. Environmental, demographic, and catastrophic stochasticity are examples (Gregory *et al.*, 2012).
Epistemic uncertainty	Uncertainty arising from the limits of current human knowledge. Often linked to aspects of data, for example lack of data or imprecise measurements (Regan *et al.*, 2002).
Irreducible uncertainty	Uncertainty that cannot be resolved, for example environmental stochasticity (Conroy & Peterson, 2013).
Linguistic uncertainty	Uncertainty linked to language: vague or ambiguous terms, or terms that are context dependent (Regan *et al.*, 2002).

Parametric uncertainty	Special case of epistemic uncertainty: uncertainty about the values of the parameters in a model (Kujala *et al.*, 2013).
Reducible uncertainty	Uncertainty that can be resolved, if enough effort is exerted, for example epistemic or linguistic uncertainty (Conroy & Peterson, 2013).
Structural uncertainty	Special case of epistemic uncertainty: uncertainty around the systems model (Conroy & Peterson, 2013).

Table 2. Long-term population size resulting from choosing areas A, B or C to protect, and maximum long-term population size, as estimated under five different hypotheses, and their means.

Hypothesis	Area A	Area B	Area C	Maximum long-term population size
1	1,250	750	500	A - 1,250
2	1,000	1,250	450	B - 1,250
3	500	750	450	B - 750
4	750	500	800	C - 800
5	1,500	500	300	A - 1,500
Mean	*1,000*	*750*	*500*	*1,110*

Table 3. Summary of 30 papers identified by the literature search for inclusion in this study. EVPC, expected value of perfect choice (analogous to EVPI); EVPI, expected value of perfect information; EVPXI, expected value of partial perfect information; EVSI, expected value of sample information; VoI, Value of Information.

Paper	Paper summary	VoI application	Management objective(s)	Uncertainties considered	How was uncertainty expressed	Predictive model	Net benefit parameter	VoI type
Invasive species papers								
D'Evelyn *et al.* (2008)	To inform management of the invasive brown tree snake *Boiga irregularis* in the USA under uncertainty regarding population size	Establish social costs of invasive species management (control costs and damages) with and without learning about the true population size	Minimise costs of management Minimise damage caused by invasive species	Population size	Continuous – probability distribution for population size	Species population models	$	Simulation comparison of expected value with and without learning
Johnson *et al.* (2014*b*)	Establish management and monitoring options for pink-footed goose *Anser brachyrhynchus* in Western Europe under uncertainty regarding population dynamics to minimise negative effects on farmland and habitats	Choose most appropriate population model for pink-footed goose and whether information on survival or reproduction would be most beneficial	Maintain viable goose populations Minimise losses on agricultural lands and of tundra habitat due to geese Allow goose hunting	Survival and reproductive rates of goose	Discrete – nine different population models considered	Annual life-cycle models	Objective value – relative measure of management performance	EVPI, EVPXI
Johnson *et al.* (2017)	Control of invasive black and white tegu *Salvator merianae* in Florida, a newly introduced species that is increasing rapidly under uncertainty regarding population	Find best management action to control tegu abundance if uncertainty is resolved, and if	Contain tegu population whilst minimising costs	Range of uncertainties of population ecology of tegu, and effectiveness	Continuous – population parameter elicited from experts, replicated to draw	Population matrix model, expert elicitation	Objective function value – combination of weighted management objectives	EVPI, EVPXI

	dynamics	uncertainty remains		of control	distributions, then included in models			
Moore & Runge (2012)	Establish best management strategy for invasive grey sallow willow *Salix cinerea* in Australia despite uncertainty regarding some of its ecological traits and how they can be managed	Establish if further research would enhance management through improving dynamic models at different budget levels	Protect alpine bogs by removing willows Minimise resources used for willow removal	Frequency of fires, population dynamics of willow, effectiveness of management effort	Continuous – effects of actions elicited from experts, then incorporated in the model; discrete - different parameter values used	Expert elicitation, dynamic management model for different budgets	Budget – workdays allocated	EVPI, EVPXI
Moore *et al.* (2011)	Establish which interventions are best for managing *Acacia paradoxa*, an invasive species occurring in South Africa, when its extent is unknown	Establish if more research needed before deciding whether eradication or containment is best for managing *Acacia paradoxa*	Minimise overall cost	Current extent of *Acacia paradoxa*	Continuous - probability distribution for the extent of infestation	Decision model	South African Rand	EVPI, EVPXI
Sahlin *et al.* (2011)	For cultivated introduced marine macroalgae in Europe, establish those that will become invasive and those that will not become invasive to avoid future costs of invasive species while not spending on non-invasive species	Evaluate which species of macroalgae are likely to become invasive so money can be spent on avoiding introductions of such species	Remove populations of species that will become invasive Do not remove populations of species that will not become invasive	Base rate of invasiveness	Continuous – different parameter values in pre-posterior Bayesian analysis	Screening model of species invasiveness	Cost ratio – relative loss of avoiding introduction of species that will not be invasive, and not avoiding introduction of species that will be invasive	EVSI (Bayesian pre-posterior analysis)
Post van der Burg *et*	Find optimal management for two invasive species, leafy spurge *Euphorbia esula* and	Evaluate whether to prioritise one or both invasives and	Maximise native species	A whole range of uncertain	Continuous – probability distributions	State-and-transition	US$ per year with less than 50%	EVPI, EVPXI

al. (2016)	yellow toadflax *Linaria vulgaris*, on private and public lands under different budgets	whether to focus on managing public lands directly or private land indirectly through incentives, under different budgets	populations Minimise costs	values was modelled, see S3 at http://www.fwspubs.org/doi/suppl/10.3996/032015-JFWM-023	for species-specific spread and establishment parameters	model	infestation	
Williams & Johnson (2015)	Inform management of pink-footed goose *Anser brachyrhynchus* in Western Europe despite uncertainty regarding population dynamics over a 50-year time horizon. Establish which aspect of population dynamics would be most beneficial to understand. Data from Johnson *et al.* (2014*b*).	Determine which management option would be best over a 50-year time horizon, looking at different population levels	Maximise sustainable harvest whilst keeping to the population goal	Nine models that differ in the survival and reproductive rates of geese	Discrete – nine different population models considered	Annual cycle models	Objective value – relative measure of management performance	EVPI, EVPXI
Protected species papers								
Canessa *et al.* (2015)	Inform reintroduction strategy for the European pond terrapin *Emys orbicularis* under uncertainty about post-release effect on different age classes	Determine optimal age class at which to release captive terrapins into the wild under uncertainty of post-release effects in different age groups	Maximise survival of terrapins	Uncertainty if post-release effect on terrapins is stable, or increases or decreases with increasing age	Continuous – different parameter values in the model	Population model	Probability of survival of different age classes	EVPI, EVSI
Cohen *et al.* (2016)	Inform management of piping plovers *Charadrius melodus* at nest sites for improved nesting success and adult survival under different	Decide if and in which situations nest exclosures improve breeding success and whether this exceeds	Maximise breeding success Minimise adult	A whole range of uncertain population values was	Continuous – means and confidence intervals identified	Mixed multinomial logistic exposure model, expert	Population growth rate in per cent	EVPI

	predation rates	the effect on adult mortality	mortality	considered, see Materials and Methods in Cohen *et al*. (2016)	through literature or expert elicitation	elicitation		
Grantham *et al.* (2009)	Decide on survey effort to maximise protection of members of the Proteaceae family in South Africa	Choice of six different survey durations or use of a habitat map alone under uncertainty regarding future habitat loss and protection	Maximise protection of Proteaceae	Rate of surveying by volunteers, rate of habitat loss, rate of establishment of newly protected areas	Discrete – habitat suitability of plots; continuous – varying mean rates of habitat loss, habitat protection and volunteer survey hours spent	Maximum entropy model for habitat suitability; minimum loss algorithm and maximum gain algorithm for designation of protected areas	Proteaceae retention rate at the end of 20-year simulation period	EVSI
Johnson *et al.* (2014*a*)	Inform management of a declining population of Northern bobwhite quail *Colinus virginianus* in the USA despite uncertainty regarding population limitations and how management options could address these	Choose which management option would be best and which potential reasons for a decline in Northern bobwhite quail would be most beneficial to study further	Maximise population growth rate and harvest of bobwhites Minimise costs Maximise feasibility of management	Cause of decline of bobwhites	Discrete – hypotheses elicited from experts, then ranked	Expert elicitation, population model	Objective value – calculated with weighted objectives	EVPI, EVPXI
Maxwell *et al.* (2015)	Inform management options for a declining koala *Phascolarctos cinereus* population in Australia despite uncertainty regarding survival and fecundity rates and how habitat affects different threats	Determine if more research is necessary to decide whether habitat restoration or preventing vehicle collisions or dog attacks would be most cost-effective	Maximise koala population growth rate	Survival and fecundity rates	Discrete – eight different structures of the population model; continuous – varying parameter	Deterministic age-structured matrix population model	Relative benefit of actions at different monetary levels in AU$	EVPI, EVPXI

					values			
Runge *et al.* (2011)	Establish which management interventions are best for whooping crane *Grus americana* conservation in the US whilst reasons for low reproduction are unknown	Distinguish between different hypotheses regarding reasons for low productivity as well as possible management actions	Provide suitable nest sites Maximise reproductive success Maximise survival during the breeding season Maximise body condition prior to migration	Cause for reproductive failure	Discrete – hypotheses elicited from experts	Expert elicitation	Multi-criteria scale – relative values of objectives	EVPI, EVSI
Smith *et al.* (2013)	Establish harvest rates in the US for Delaware Bay horseshoe crabs *Limulus polyphemus* with uncertainty regarding its link to red knot *Calidris canutus rufa* abundance	Determine best population model of red knot with and without uncertainty	Maintain crab harvest Ensure red knot recovery	Relationship between horseshoe crab spawning, red knot mass and red knot vital rates	Discrete – three different population models	Species-specific population models	Mean outcome of populations averaged over model weights	EVPI
Smith *et al.* (2012)	Find optimal management to combine extraction of shale gas with maintaining populations of brook trout *Salvelinus fontinalis* under different densities of well pads	Determine level of gas extraction under uncertainty regarding effect of density of well pads on brook trout, and uncertainty around occupancy model	Extract shale gas while maintaining brook trout populations	Well pad density	Discrete – three predictive models; continuous – different well pad densities considered, different model likelihood considered	Urban-type, forestry-type and intermediate type impact models	Increase in gas extraction while maintaining brook trout populations	EVPI

Tyre *et al.* (2011)	Inform stream management for bull trout *Salvelinus confluentus* conservation in north-western USA under uncertainty about migratory behaviour	Choose between four assumptions and a model of bull trout movement	Maintain current distribution Maintain stable/increase in abundance Restore/maintain habitat suitable for all life-history stages Conserve genetic diversity	Mechanisms that determine life-history strategy	Discrete – four different models	Patch network models	Probability of population persisting for 256 years (for demonstration of concept)	EVPI
Williams *et al.* (2011)	Establish optimal habitat management for the recovery of Florida scrub-jay *Aphelocoma coerulescens* despite uncertainty regarding the effect of different habitat management interventions	Find the best option for habitat management under uncertainty of how vegetation will regenerate	Maintain stable scrub jay population	Rate of scrub regeneration, future burning rate after removal of combustibles	Discrete – multiple transition models	Habitat occupancy model	Smallest average loss in objectives	EVPI, EVPXI, EVSI
Ecosystems papers								
Bouma *et al.* (2011)	Potential use of Earth Observation data for Great Barrier Reef protection, used to assess if non-targeted or targeted Water Action Plan would best address sediment discharge	Determine when Earth Observation data has most value: if sediment discharge is an equal issue from all catchments or if there are differences among catchments	Decrease sediment discharge into Great Barrier Reef	Difference in sediment discharge between catchments Cost of pollution abatement	Discrete – differing simulations in model, expert elicitation on data accuracy incorporated as prior belief	Four different simulations for cost minimisation model, expert elicitation	Million AU$/year	EVPI
Convertino *et al.* (2013)	Find optimal interventions and monitoring plans for restoring water flow in the Florida Everglades to meet objectives including	Distinguish between different monitoring efforts (low – medium – high)	Improve ecological conditions whilst minimising	Uncertainty around decisions on restoration alternatives	Discrete – three rainfall scenarios and two soil oxidation	Probabilistic decision network consisting of environmental	Cost in $, benefit is relative utility of management	EVPI - Change in payoff of different monitoring

	biodiversity conservation and flood protection under uncertainty regarding future rainfall and soil oxidation		operational costs	and monitoring as well as climate change	scenarios were modelled	, monitoring and decision sub-models	interventions	plans for one management plan
Perhans *et al.* (2014)	In areas to be clear-cut, find optimal method for selecting trees that are to be conserved with highest biodiversity value, using lichens as indicator species	Decide which method of selecting trees to retain will give most biodiversity benefit	Find trees that would give highest number of lichens Find trees that would give highest number of protected lichens Maximise probability that a protected species is represented	Relationship between different tree attributes and lichens present	Continuous – model averaging of model parameters	Generalised linear model	Swedish krona	EVPI
Runting *et al.* (2013)	Find optimal allocation of resources for conservation areas under uncertainty around sea level rise in coastal South East Queensland	Find optimal allocation of budget towards either research or conservation of coastal areas at different budget levels	Maximise areas for conservation	Future sea-level rise, accuracy of elevation data, budget level	Discrete – different models, coarse/ fine resolution elevation data, different sea-level rise scenarios; continuous – different budget levels	Sea Level Affecting Marshes model or Inundation model	AUS$	EVPXI
Thorne *et al.* (2015)	Find management options robust to different climate change scenarios in the San Francisco Bay area	Decide if and which uncertainty to reduce – storm or marsh resilience	Maximize marsh ecosystem integrity Maximize likelihood of	Frequency and intensity of storms and tidal marsh	Discrete – discrete states in network with conditional	Bayesian network	Relative utility of management under different assumptions on scale from	EVPI

			recovery of California Ridgway's Rail (*Rallus obsoletus obsoletus*) Maximize human benefits from tidal marshes	resilience	probabilities		0 to 100	
Fisheries papers:								
Costello *et al.* (1998)	Find optimal harvest rates of Coho salmon *Oncorhynchus kisutch* under uncertainty around future El Niño events	Choose optimal harvest rate for coho salmon under uncertainty about future El Niño events and if uncertainty can be resolved	Maximize expected net present value of the Coho fishery	Future El Niño occurrences	Discrete; three different states for the annual El Niño phase	Bioeconomic model of Coho salmon fishery	US$	EVPI, EVSI
Costello *et al.* (2010)	Design optimal Marine Protected Areas network for sheephead *Semicossyphus pulcher*, kelp bass *Paralabrax clathratus* and kelp rockfish *Sebastes atrovirens* to maximise fishery profits	Choose location and extent of Marine Protected Areas	Maximise fishery profits whilst ensuring conservation of species	Dispersal of fish larvae	Discrete – 10 different dispersal kernels used	Stage-structured spatial model, ocean circulation model	Net profit of fishing – unitless	EVPI
Kuikka *et al.* (1999)	Management of Baltic cod *Gadus morhua* fisheries in the Baltic Sea	Determine best mesh size for cod fishery	Minimise risk of spawning biomass going below critical levels Maximise yield	Growth rate of cod, recruitment of cod, critical spawning biomass	Discrete – three different models for recruitment	Bayesian influence diagram that combines three different recruitment models	Utility function reflecting both yield (kilotons) and risk of falling below critical spawning mass	EVPI
Mäntyniemi *et al.*	Management of North Sea herring *Clupea harengus*	Determine ideal fishing pressure	Maximise expected profits	Stock–recruitment	Discrete – two stock–	Bayesian probability	Norwegian Krone	EVPI

(2009)	fisheries in the North Sea	under uncertainty around the stock–recruitment relationship	over 20-year period	relationship	recruitment relationships considered	model		
Sainsbury (1991)	Management of a multi-species fishery in north-western Australia of genera *Lethrinus*, *Lutjanus*, *Nemipterus*, *Saurida*	Find optimal management option for fishery by using trap or trawl catch and using adaptive management to incorporate learning into the management process	Maximise value of fisheries	Effect of intra- and interspecific competition as well as habitat on abundance of different fish species	Discrete – four different models; continuous – different parameter values	Population growth models	Million AUS$	EVPI
Other topics								
Hartmann & Andre (2013)	A framework for the use of phylogenetic diversity to inform which species should be protected, and the associated costs and benefits	Distinguish when to use species richness as a measure of biodiversity, and when to use phylogenetic diversity as a better measure	Maximize phylogenetic diversity	Uncertainty in the underlying phylogenetic relationships among a set of species	Continuous – 10,000 samples of possible phylogenetic trees for a set of 20 species	Calculation of phylogenetic diversity, based on the edge lengths for the included species from a phylogenetic tree	Proportion of maximum phylogenetic diversity retained	EVPC
Johnson *et al.* (2002)	Find optimal harvest strategy under uncertainty regarding population processes of mallards *Anas platyrhynchos*	Optimal harvest strategy if accurate population model was known compared to if uncertainty remained	Maximise long-term cumulative harvest	Density dependence and additive or compensatory mortality	Discrete – four population models and their probabilities	Age-structured population models	Harvested mallards/year, converted to $	EVPI

Table 4. Table summarising papers according to the uncertainties and objectives considered and depending on the type of VoI used. EVPI, expected value of perfect information; EVPXI, expected value of partial perfect information; EVSI, expected value of sample information.

	Uncertainty	EVPI	EVPXI	EVSI
Single Objective	Structural	Sainsbury (1991); Costello *et al.* (1998); Johnson *et al.* (2002); Mäntyniemi *et al.* (2009); Bouma *et al.* (2011); Williams *et al.* (2011); Maxwell *et al.* (2015)	Williams *et al.* (2011); Runting *et al.* (2013); Maxwell *et al.* (2015)	Costello *et al.* (1998); Grantham *et al.* (2009); Williams *et al.* (2011)
	Parametric	Sainsbury (1991); Bouma *et al.* (2011); Moore *et al.* (2011); Canessa *et al.* (2015); Maxwell *et al.* (2015)	Moore *et al.* (2011); Runting *et al.* (2013); Maxwell *et al.* (2015)	Grantham *et al.* (2009); Canessa *et al.* (2015)
Multiple Objectives	Structural	Kuikka *et al.* (1999); Costello *et al.* (2010); Tyre *et al.* (2011); Smith *et al.* (2012, 2013); Convertino *et al.* (2013); Johnson *et al.* (2014*b*); Williams & Johnson (2015)	Johnson *et al.* (2014*b*); Williams & Johnson (2015)	
	Parametric	D'Evelyn *et al.* (2008); Runge *et al.* (2011); Moore & Runge (2012); Smith *et al*. (2012); Hartmann & Andre (2013); Johnson *et al.* (2014*a*, 2017); Perhans *et al.* (2014); Thorne *et al.* (2015); Cohen *et al.* (2016); Post van der Burg *et al.* (2016)	Moore & Runge (2012); Johnson *et al.* (2014*a*, 2017); Post van der Burg *et al.* (2016)	Runge *et al.* (2011); Sahlin *et al.* (2011)

Table 5. Suggested reporting standards for the use of Value of Information (VoI) in biodiversity conservation. Adapted from PrOACT (Hammond *et al*., 2015). See also Section I.3. EVPI, expected value of perfect information; EVPXI, expected value of partial perfect information; EVSI, expected value of sample information.

Reporting standard	Description
Problem	What is the problem or the decision to be made? Is it a real-world decision to be made?
Objectives	What objectives are considered to ensure delivery of the decision?
Alternatives	Which alternative actions are proposed to meet objectives?
Consequences	What are the consequences of different alternatives? How have they been estimated?
Trade-offs	What are the trade-offs of the alternative actions?
Uncertainty	What are the key uncertainties? Are they structural or parametric? Are they discrete or continuous? How have they been dealt with?
Type of VoI	EVPI, EVPXI or EVSI
Performance metric	The performance metric needs to be stated and fully explained. Ideally this would have a financial value too, to make the analysis more useful for managers, and to

	enable synthesising of different studies in the future.
Decision makers	State whether the research is undertaken on behalf of a decision maker and whether they are planning on implementing the findings.
Time horizon	State time horizon. If the VoI shows that more research is necessary, and therefore there is a need for adaptive management, a timeframe should be given when the information will be re-assessed. State how long intervention implementation will take.