Valuing information for conservation and natural resource management: a review

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Abstract

In conservation and natural resource management, scientist and practitioners have begun to realize the importance of valuing information. Information has a central role to play when it comes to making good decisions that will benefit the environment and satisfy management objectives. But there are limits to benefits from more information. Key questions for practitioners are: how much information is warranted for decision making? What kind of information? And what level of certainty is enough before a decision can be made with confidence in the outcome? These questions arise as the information itself comes at some cost. This cost must be weighed against the value of information for the decision at. Decision theoretic tools aimed at information valuing have existed for over half a century but only relatively recently have begun to appear in the conservation and natural resource management literature. Here, we examine a suite of case studies employing value of information (VOI) analyses to applied ecological decision problems. We have surveyed case studies using VOI analysis in the strict sense and compare and contrast them to less formal methods that also, sometimes inadvertently, put a value on ecological data in the context of decision making. Our aim here, is to provide an overview of the use of VOI in the field to date and to glean generalities. We found that the two strands of information valuing, formal and informal, have their own distinct characteristics and the casual reader of either may get a different picture about the value of information if they were only to engage with one or the other. Formal VOI analyses tend to report a low value of information, while informal methods often report larger values. We conjecture that biases stemming from the way that case studies are performed

and selected may account for this discrepancy. A feature common to both approaches is that the cost of information is rarely calculated or reported. For greater insight into any generalities on information valuing, future work in conservation sciences should place greater emphasis on information cost and converting costs into the same currency as decision objectives.

Introduction

A value of information (VOI) theory was outlined over half a century ago (Raiffa and Schlaifer, 1961). But only relatively recently has it begun to be used within the field of conservation and natural resource management. Here we review the recent literature on valuing information for conservation and natural resource management. We classify information valuing by the type of decisions being made and the type of information being learned. Our literature analysis aims to provide an overview of the use of VOI in the field to date, and to glean generalities from the body of work as a whole. We have attempted to be comprehensive for case studies that employ VOI analysis in the strict sense, save for examples involving fisheries management, where the method has a longer and deeper history (see e.g., Walters, 1986) (and including all examples would be counter-productive). Instead, we have included only a few fisheries management examples that tend to focus more on biodiversity conservation rather than the commercial aspects of fisheries (e.g., Costello et al., 2010). We also include some case studies that employ informal or post-hoc information valuing (e.g., Balmford and Gaston, 1999; Hermoso et al., 2013). We do not claim that these latter examples are by any means an exhaustive list of this study type, as lacking a common language to describe the methods used, informal information valuing studies are difficult to locate in literature databases.

Before addressing the recent history of information valuing for conservation and natural resource management we'll first turn to the origin of the concept and define it in its various forms to a degree necessary to discuss its application. Information, in the context of VOI analyses has no value in and of its self. The value of a piece information arises from its potential to increase the performance of a decision that the particular information pertains to. It is the magnitude of this performance increase that constitutes the value of information. The value of information in this sense, first appeared in mid 20th century via the seminal work of Raiffa and

Schlaifer's Applied Statistical Decision Theory (Raiffa and Schlaifer, 1961). For an introduction to the subject and it's theoretical underpinnings the reader need go no further. The logic of VOI analyses has evolved little since this early work and it is mainly in the algorithms used to calculate it, for its various applications, that advances have been made (Yokota and Thompson, 2004*b*,*a*).

Strictly speaking the *value* of information cannot be foreseen—to do so, a decision would need to be made both with and without the information and the performance compared. Even if it were possible it would not be very useful, as it would not inform the decision maker about the worth of seeking new information prior to decision making. To be useful, the value of information must come in the form of an expected value. An expected value being the performance a decision maker expects to get from a particular action. That expectation being the average of all possible outcomes weighted by their respective probabilities of happening. The value of information is therefore typically encountered as an *expected value* of information (EVI).

Types of VOI

Here we attempt to classify VOI as it has been practised to date in the conservation sciences. Broadly, information valuing falls into two types, informal and formal. The latter is any VOI analyses employing the formal methods outlined by the decision theoretic toolset we discuss further below. But this is by no means the only way to think about, calculate and report the value of information.

Informal VOI

Many authors have undertaken informal VOI analyses, in which they arrive at what is conceptually a calculation of the value of information, even though they don't arrive there by the conventional means. More often than not, these informal value of information analyses take the form of post-hoc comparisons of decision outcomes with different datasets that represent varied levels of uncertainty. The use of informal VOI analyses is particularly prevalent in the field of spatial conservation planning (e.g., Balmford and Gaston, 1999). Most examples of informal VOI fall in this category of decision problem.

Comparisons of data quantity

Some informal VOI analyses compare datasets, or data subsets, with different sample-sizes (e.g., Grantham et al., 2008, 2009; Hermoso et al., 2013). These authors present case-studies in which they evaluate the same decision problem using datasets of varying size or a single dataset that has been subsetted with different sample-sizes in each subset. In these examples, they arrive at a value of information based on the difference in the outcome of decision-making with a smaller dataset compared to a larger dataset. For example, Hermoso et al. (2013) found the performance of reserve system would improve by up to 230% when using their full dataset of fish distributions, compared with any given subsample with a sample size 15% of the sample-size of their full dataset.

Comparisons of data quality

Another type of post-hoc VOI analysis compares data with more qualitative differences. The authors of these studies ascribe the different quality data sources as having greater or less precision and thus producing more or less uncertain predictions for decision making. They then proceed the same way as above and evaluate a single decision problem using the multiple data sources. For example, Stoms et al. (2011) found that using higher quality information in the design of a conservation easement scheme in California, resulted in benefits 20 times greater than using a minimal dataset.

The problem with these types of VOI analysis, typically found in the spatial conservation planning literature, is that in calculating a post-hoc value of information, they are performing the calculation when it is too late. While it is interesting to show, after the fact, that collecting some dataset was worthwhile, it is more important to show that information has some worth prior to it being collected. To a certain extent, these studies may be setting up a straw man.

Active vs. passive adaptive management

There are other examples of informal value of information that don't use a post-hoc approach to value information. By comparing the expected outcomes of active vs passive adaptive management (e.g., Moore and McCarthy, 2010; Baxter and Possingham, 2010) some sense of the value of learning can be gleaned without employing the VOI analysis in the strict sense. We won't explore these ideas further here, other than to note that this line of enquiry is interesting but none-the-less beyond the scope of the present work.

Formal VOI

As alluded to above, in formal value of information analyses the quantity of interest comes in the form of an expected value, the EVI. The EVI comes in different forms but common to all is that they represent the performance increase expected when going from optimal decision making under uncertainty to optimal decision making under less uncertainty (Yokota and Thompson, 2004*a*). The concept doesn't stipulate how much uncertainty there is at either point, just that the latter is less uncertain than the former.

Components of EVI

Being the result of a difference, EVI has two components: the expected value with original information (EVWOI) and the expected value with new information (EVWNI) where,

$$\mathrm{EVI} = \mathrm{EVWNI} - \mathrm{EVWOI} \tag{1}$$

The EVWOI is the component common to all forms of EVI as it the expected value of making a decision under uncertainty without any new information. Calculating EVWOI involves maximizing the expected value of decision making under uncertainty, or more formally,

$$\mathrm{EVWOI} = \max_a \mathrm{E}_s[v(a,s)] \tag{2}$$

where s represents the model describing the uncertainty, and a represents the actions available to the decision maker. Working from the inside out, $v(a, s)$ is the value attained when taking an action, a, when the model state, s, is at particular point in the space of its uncertainty. Then, $\mathrm{E}_s[v(a, s)]$ is the expected value of taking any, a action accounting for the uncertainty in s. And finally, $\max_a \mathrm{E}_s[v(a, s)]$ is the value attained when the action is chosen such that $\mathrm{E}_s[v(a, s)]$ is maximized.

The EVWNI, on the other hand, varies in form, depending on the particular form of EVI being calculated. It is to those different forms of EVI we now turn.

Forms of EVI

EVPI

The most common form of VOI one encounters in the conservation and natural resource management literature is the expected value of perfect information (EVPI) (e.g., Kuikka et al., 1999; Moore et al., 2011). The EVPI is the magnitude of performance improvement if a decision is made with no uncertainty, that is, the decision-maker has perfect knowledge of the outcome of the decision. This is the expected value with perfect information (EVWPI). EVWPI constitutes the new information component of EVPI and thus,

$$\mathrm{EVPI} = \mathrm{EVWPI} - \mathrm{EVWOI} \tag{3}$$

The EVWOI is calculated as above, equation (2), while the EVWPI is defined as,

$$\mathrm{EVWPI} = \mathrm{E}_s[\max_a v(a, s)] \tag{4}$$

Note that the stages of expectation and maximization are reversed in equation (4) compared to equation (2). The EVWPI is thus the expectation of maximized values as opposed to the maximum of expected values. The EVWPI implicitly presupposes that uncertainty has been resolved and takes a weighted average (the expectation) across all the possible values resulting from this presupposition. Taking equations (2) and (4) we arrive at a second definition of EVPI,

$$\text{EVPI} = \text{E}_s[\max_a v(a,s)] - \max_a \text{E}_s[v(a,s)] \tag{5}$$

The EVPI is the upper bound of EVI and for a given decision problem, no other form of EVI can exceed this limit. Therefore, EVPI also reflects an upper limit on what is justifiable to spend on seeking new information to inform a decision (Yokota and Thompson, 2004*a*). In reality, perfect knowledge may be impossible to obtain and the EVPI is employed as a benchmark against which the cost of information must be measured. Failing to pass below this initial cost threshold would mean new information does not need to be considered and decision making should proceed with the information at hand (Runge et al., 2011).

EVPXI

Another commonly encountered form of EVI is the partial expected value of perfect information, also referred to as the expected value of perfect X information (EVPXI) (e.g., Moore and Runge, 2012; Johnson et al., 2014*b*). Here the X refers to a component or part of information about the system model, and so EVPXI refers to the performance increase expected when learning perfectly about that component or part of the whole uncertain system (Yokota and Thompson, 2004*a*). For example, the EXPXI of a decision problem with a system model consisting of multiple uncertain parameters, would be the expected value with knowledge of the exact value of one or more of those parameters, minus the EVWOI. Alternatively, EVPXI can be calculated in situations where there are multiple competing and mutually exclusive models of a system (e.g., Runge et al., 2011). The EVPXI, in such a situation, is the expected increase in performance when ruling one or more of the competing models out. While any given EVPXI will always be less than the EVPI, it isn't necessarily the case that the sum of all EVPXI will equal EVPI (Samson et al., 1989). Formally for a component of the uncertainty (one or more parameters or alternative models), s_j, EVPXI_{s_j} is defined as:

$$\text{EVPXI}_{s_i} = \text{EVWPXI}_{s_i} - \text{EVWOI} \tag{6}$$

Here EVWPXI_{s_i} is the partial expected value with perfect information for the component of uncertainty s_i such that:

$$\text{EVWPXI}_{s_i} = \text{E}_{s_i}[\max_a \text{E}_{s_j}[v(a,s)]] \tag{7}$$

where s_j is the complement of s_i, in other words, the components of uncertainty not captured by s_i.

EVSI & EVSXI

The finest grained and most general forms of VOI are the expected value of sample information (EVSI) (e.g, Runge et al., 2011; Canessa et al., 2015) and the partial expected value of sample information (EVSXI). The value of sample information is among the least encountered forms of VOI yet probably the most useful. The EVSI tells the decision maker the value of reducing uncertainty by some degree; the expected value of a sample of information (Raiffa and Schlaifer, 1961). In contrast to EVPI, which concerns perfect information, the unlikely situation of complete certainty, EVSI only expects an improvement in uncertainty to the degree found when collecting a sample of data that will inform the system model. Where the EVPI gives the upper bound on what should justifiably be spent on learning, EVSI can give the per sample value of information and therefore not only tell the decision maker if new information should be sought, but how much new information and the effort warranted to collect it (Runge et al., 2011). With this in mind, EVPI can be thought of as a special case of EVSI when the sample-size is very large, such that the resulting uncertainty is effectively zero. The EVSXI is to EVSI what EVPXI is to EVPI (Yokota and Thompson, 2004*b*).

Formally EVSI is:

$$\text{EVSI} = \text{EVWSI} - \text{EVWOI} \tag{8}$$

where,

$$\text{EVWSI} = \text{E}_x[\max_a \text{E}_{s|x}[v(a,s)]] \tag{9}$$

the x here, being the sample of information. Calculating EVSI requires a Bayesian preposterior analysis, as one needs to compute posterior distributions for $\text{E}_{s|x}[v(a,s)]]$. It is beyond the scope of the present text to go into this technique in greater detail, but we instead refer the reader to Berger (1985) for a more thorough treatment of the subject.

The expected utility of information

So far we have only discussed the value of information in terms of expected value. Implicitly, expected value only applies to risk-neutral decision making (Hazen and Sounderpandian, 1999). That is, decision making that is indifferent to the relationship between uncertainty and the outcome of the decision. When decision making is optimized to maximize expected value, such as in the case for the forms of VOI outlined above, it does not matter what the relative probability of performing well or poorly is, it is only important to consider the expected (average) outcome given the uncertainty. This is in essence a risk-neutral strategy of decision making (Von Neumann and Morgenstern, 1944). Uncertainty is only important, in the context of risk-neutrality, in order to calculate expected values and does not enter into decision making in any other way. In reality, decision makers are unlikely to be risk-neutral all the time. Risk aversion is a common standpoint when making decisions for conservation, as managers are less willing to risk losses in conservation outcomes, than they are to gamble on potentially unlikely high returns (Tulloch et al., 2015).

Risk-averse decision making (and any risk profile other than neutrality) is sensitive to the relationship between uncertainty and the outcome of the decision. Therefore, uncertainty is more important to the risk-averse decision maker than it is to risk-neutral. And so it follows that EVI is insufficient in it's ability to reveal the worth of new information for non-neutral risk profiles. To account for risk-aversion and other non-neutral risk profiles we must introduce the concept of expected utility. Utility theory recognizes that the desirability of a decision outcome can be sensitive to its probability of happening, depending on how good or bad the outcome is and the unique preferences of the decision maker (Von Neumann and Morgenstern, 1944). If we compare the preference for a particular outcome between a risk-neutral and risk-averse decision maker we would find that while the risk-neutral decision maker's preference for different values increases linearly, the preference for greater values diminishes for the risk-averse decision maker. The quantity describing this preference for different outcomes reflecting different risk-profiles is known as utility. Risk-neutral decision makers have linear utility curves (relationship between utility and value) while risk-aversion leads to a concave (diminishing) utility curve. Convex utility curves indicate risk-seeking behavior that favors high returns in spite of low likelihood of success or high likelihood of failure.

To account for risk and non-linear utility curves, we move from the expected value of information to the expected utility of information (EUI). For a risk neutral decision maker EUI equals EVI (or is at least proportional to it) as the relationship between value and utility is linear. For other risk profiles however, the relationship may yield unexpected results. One might intuit that a risk-averse decision maker would perceive new information as having a greater utility than would a risk-neutral decision maker. As being more sensitive to uncertainty in a decision, one might assume that a risk-averse decision maker prefers to reduce uncertainty over and above a risk-neutral decision maker that is faced with same decision. However, this is not always the case. Indeed, in certain situations, the opposite is a true. Depending on the context, in some cases, a risk-averse decision maker will be less willing to spend resources on new information than would a risk neutral decision maker under same initial level of uncertainty (Eeckhoudt and Godfroid, 2000).

Calculating VOI

It should be clear at this point that calculating the VOI involves knowing two quantities: the value under uncertainty (i.e., the value with original information) and the value with new information (perfect, partial, or sample). It should also be clear, that to calculate these components of the VOI requires two distinct steps, optimization (maximization or minimization) and expectation (prediction, averaging or weighted averaging). In formal VOI analyses these steps are explicit while in the informal branch of the field the steps are often implicit.

In both formal and informal VOI analyses there are many different algorithmic approaches to both these steps.

For optimization, truly optimal algorithms like stochastic dynamic programming (Johnson et al., 2014*a*) can be used. Alternatively, near or approximately optimal methods like greedy algorithms (e.g., Grantham et al., 2009) can be used, as is often the case for spatial conservation planning (Moilanen et al., 2009). Likewise, for calculating expected values, especially for formal VOI analyses, there are multiple methodological approaches. Broadly, these are either analytical, using integral calculus, or numerical, using Monte Carlo and other simulation-based methods to attain approximate solutions.

Empirical examples of VOI

As we allude to above, in our survey of the VOI literature (see Appendix B for full list of case-studies) we found two parallel streams of case-studies in information valuing within the field of conservation and natural resource management. Both begun in the late 90s and early 2000s (e.g., Balmford and Gaston, 1999; Kuikka et al., 1999), and have become more commonplace in the last decade. The first stream is informal, valuing information in a post-hoc manner by reevaluating decision problems with different sample-sizes or different quality datasets and comparing the outcome of each. The second stream is formal, employing the tools of the framework for VOI laid out in the early work of operations research and decision analyses pioneers (e.g., Raiffa and Schlaifer, 1961). Each stream tends to focus on different subfields of conservation and natural resource management, with the first mostly confined to the field of spatial conservation planning (e.g., Balmford and Gaston, 1999; Grantham et al., 2008; Stoms et al., 2011; Runting et al., 2012) and the second commonly addressing population management, in particular fisheries (e.g., Kuikka et al., 1999; Mantyniemi et al., 2009; Costello et al., 2010). The case-studies we surveyed cover a wide-range of conservation decision problems pertaining to many and varied ecological systems. These decision problems encompass a range of spatial and temporal scales from the small scale, 1km^2 (e.g., Perhans et al., 2014) and short-term, 1 year (e.g. Kuikka et al., 1999) to large scale, 10,000,000km^2 (e.g., Balmford and Gaston, 1999) and long-term, 200 years (e.g., Moore and Runge, 2012).

Informal VOI analyses for spatial conservation planning

One of the earliest examples of a VOI-like study in conservation and natural resource management is Balmford and Gaston (1999). These authors contend that the gain in efficiency by using complementarity-based (high information content, low uncertainty) prioritization methods yields cost savings greater than cost of the extra information needed to use the more information-rich methods. Their study marks the beginning of the trend among spatial conservation planning researchers to use informal methods to perform a post-hoc assessment of the value of information. Other such examples that have followed their lead more recently, have included Grantham et al. (2008), Grantham et al. (2009), Stoms et al. (2011), Hermoso et al. (2013), Runting et al. (2012), Hermoso et al. (2014), Lehtomäki et al. (2015), Mazor et al. (2016) and Tulloch et al. (2017).

These examples span a wide range of study systems: country-wide reserve networks (Balmford and Gaston, 1999), the proteaceous flora of the Fynbos biome, South Africa (Grantham et al., 2008, 2009), farmland of the California Central Valley (Stoms et al., 2011), freshwater fish communities of Northern Australia (Hermoso et al., 2013, 2014), coastal wetland ecological communities of South-east Queensland, Australia, boreal forests of southeastern Finland (Lehtomäki et al., 2015), loggerhead turtle (*Caretta caretta*) migration in the Mediterranean Sea (Mazor et al., 2016) and the Kubulau District fishery of Fiji (Tulloch et al., 2017). Notably Polasky and Solow (2001) outlined how VOI might be employed formaly in conservation planning, before efforts to value information began in the field in earnest. However, it appears this early work had little impact and no major efforts to apply their methods to real-world spatial conservation plans have been made since.

Among these examples the objectives are narrow and are typically some variation of either: planning a reserve network (or some related conservation plan) that maximally represents or retains the distribution of some biodiversity feature cost-efficiently; or achieving some target level of protection for a species or set of species for minimal cost. Common to all these case-studies is the use of conservation planning software for the optimization part of the study, when specified, usually one of the software packages Marxan (Ball et al., 2009) or Zonation (Moilanen et al., 2009). Implicitly the actions that the decision maker/conservation planner can take in order to meet their stated objectives is the choice among a set of candidate areas to include in the reserve system or spatial plan.

Other case-studies in informal VOI include Perhans et al. (2014), who found evidence to support the claim of Balmford and Gaston (1999) that comprehensive surveys can yield more efficient conservation planning solutions even at very small scales. And at the opposite end in terms of spatial scale, Nygård et al. (2016) found that the cost of monitoring is easily outweighed by the expected increase in benefit after implementing a program of measures for the Finnish Marine Biodiversity strategy.

Formal VOI analyses

Running parallel to the informal branch of VOI analyses is a set of case-studies that employ VOI in the strict sense that we describe above. Early examples of formal VOI for conservation and natural resource management tend to focus on the management of fisheries (e.g., Walters, 1986; Kuikka et al., 1999, Mantyniemi et al. (2009); Costello et al., 2010). The use of EVI analyses has since become commonplace in this subfield but here we avoid examining the more frequent and recent examples of fisheries VOI as they tend focus on the economic aspects of the field and it would come at the expense of looking at other subfields in more depth.

In the second decade of the 21st century examples of EVI analyses have become more widespread and cover a wider range of problem types in conservation and natural resource management. The subfields it has been applied to include: invasive species control (e.g., Moore et al., 2011; Moore and Runge, 2012) threatened species recovery (e.g., Runge et al., 2011; Canessa et al., 2015; Maxwell et al., 2014) and wildlife harvest management (e.g., Johnson et al., 2014*b*,*a*; Williams and Johnson, 2015; Robinson et al., 2016). Among these more recent examples, there is a bias towards the management of animal populations (Moore et al., 2011; Moore and Runge, 2012, being the only examples dealing with plants). Case-studies surrounding the management of plant and animal communities or the structure and function of ecosystems have so far not been forthcoming.

For formal VOI analyses the decision problem is typically much more well defined than the informal branch, as the framework of EVI analyses demands clearly defined objectives, alternative actions and a model predicting the outcome of the decision. The objectives of formal case-studies typically follow from the subfield of conservation and natural resource management that they are concerned with. For fisheries and wildlife harvest management problems, the objectives are to maximize the harvest (catch, biomass or profits) while maintaining a viable population. When concerned with invasive species, managers aim to eradicate, contain or minimize the losses from the invasive species and maximize the condition of the invaded system. When dealing with threatened species recovery the goals are to maximize the population growth rate of threatened species. Common to almost all the types of decision problem covered above, is that costs of intervention should be minimized.

The types of actions that managers must decide to take, among the formal VOI case studies, fall broadly into two categories. For fisheries management and wildlife harvest problems the predominant action taken is to set a harvest rate or limit (e.g., Kuikka et al., 1999; Mantyniemi et al., 2009; Costello et al., 2010; Johnson et al., 2014*b*; Williams and Johnson, 2015). The second category of actions constitutes a choice among a more discrete set of management strategies. In some instances, the managers must choose the best action and undertake that action alone (e.g., Moore et al., 2011; Runge et al., 2011; Johnson et al., 2014*a*; Canessa et al., 2015; Robinson et al., 2016) while in others the action is to allocate resources (time or budget) among the different strategies (e.g., Moore and Runge, 2012; Maxwell et al., 2014).

Being decisions about populations it should not be a surprise that population models dominate the predictive component of these EVI analyses. In a few cases, the more fine-grained age-structured or state-based stochastic population models (e.g., Kuikka et al., 1999; Costello et al., 2010; Moore and Runge, 2012) are overlooked in favor of more coarse-grained expert-elicited opinions (e.g., Runge et al., 2011; Robinson et al., 2016) to predict the outcome of the actions being chosen by the managers. Broadly, the uncertainty represented by all these system models, which could potentially be reduced with new information, comes in two forms: structural and parametric. Structural uncertainty is where multiple models are proposed and there is uncertainty about which model best predicts the outcome of the decision. Parametric uncertainty occurs, when for a given model structure, there is uncertainty about the value of one or more of the model parameters. Structural and parametric uncertainty are not mutually exclusive. Structural uncertainty is the more common form of uncertainty addressed in EVI analyses for conservation and natural resource management while only a few examples deal with parametric uncertainty (Moore and Runge, 2012; Maxwell et al., 2014; Robinson et al., 2016).

In calculating the EVI for conservation and natural resource management decision problems, case-study authors have used a variety of different tools to perform the optimization step of VOI analyses. When there is a finite and relatively small set of terminal values to calculate (that is, the combinations of alternative model structures and management actions) one can simply calculate them all and then select the combination that maximizes value (e.g., Runge et al., 2011; Johnson et al., 2014*a*; Canessa et al., 2015; Robinson et al., 2016). However if the number of terminal values is too large, (or even infinite, as is the case when the action space or uncertainties are continuous), other more tractable methods must be used. Such methods have included non-exhaustive brute-force searches (Mantyniemi et al., 2009), Monte Carlo simulation (Kuikka et al., 1999; Moore and Runge, 2012), numerical optimization of non-linear simultaneous equations (Moore et al., 2011), multidimensional unconstrained nonlinear optimization (Maxwell et al., 2014) and stochastic dynamic programming (Johnson et al., 2014*b*; Williams and Johnson, 2015).

Of the forms of EVI introduced above, the expected value of perfect information (EVPI) was the most commonly encountered in the conservation and natural resource management literature. All 12 case-studies we found, report EVPI. Less frequently (5 case studies) did authors calculate the partial expected value of perfect information and less frequently still (2 case studies) was the expected value of sample information calculated. We did not find any examples of calculating the partial expected value of sample information or any form of the expected utility of information.

Discussion

In all but one of the cases studies above (Robinson et al., 2016) the authors found that there was some measurable value of information. One might expect this to be the case for two reasons. The first reason being that the necessary conditions for there being a value of information are relatively easily met and the second is that there is probably a publication bias towards case studies that meet these pre-conditions. The conditions for information to have value are that the system is uncertain and that some of aspect of the uncertainty is critical to decision making (Runge et al., 2011). By critical to the decision, we mean that somewhere across the range of the uncertainty the decision-maker would choose to change their action. If the same action was always taken, or the same outcome was always expected, then any uncertainty would not be critical and would be irrelevant to decision making. In such a case, new information has no value. It is understandable that authors would be more likely to present case studies of decision problems that have critical uncertainties (or at least initially thought to be likely to have critical uncertainties) as they would better illustrate a value of information analysis. Yet, demonstrating that sometimes decision problems lack critical uncertainties is important to illustrate also. In calculating the VOI for a multi-criteria decision problem involving white-tailed deer hunting in New York, Robinson et al. (2016) found that the optimal action that the managing agency should take, was the same regardless of the true values of deer survival rates, and the correct model of density dependence. Therefore, in their case, resolving these uncertainties would not have improved the outcome of the decision and their EVPI was 0.

Of the remaining examples that found non-zero values, the magnitude of the EVI covered a wide range. It is difficult to compare the EVI across all the case studies as each has its own distinct objective and therefore different units of measuring value. In some cases the value is expressed in monetary value. But, putting a dollar amount on objectives is relatively rare in the conservation sciences (Edwards and Abivardi, 1998), so cannot easily be used as the common currency with which to compare examples of EVI. An imperfect alternative, putting VOI on a common scale, is to express it as a percentage gain (using the EVWOI, performance under uncertainty, as the starting point). For example, we would consider EVPI as a 5% gain if, in the units of the objective, the value under uncertainty was 20 and the EVPI was 1 (i.e., $1/20 \times 100$). However, not all case-studies begin with a comparable level of uncertainty and expected performance under that uncertainty. For a decision where the initial uncertainty is very high and the expected performance under it low, a relatively small gain when resolving the uncertainty will result in a relatively large percentage increase. Likewise for a decision problem that lacks much uncertainty and where the initial expected performance is high, even large gains in performance from resolving the remaining uncertainty may be diminished when expressed as a percentage. Nevertheless, in the absence of a universal currency in which to present EVI, expressing it as percentage gain seems the most appropriate compromise.

For case-studies employing informal VOI analysis, even considering EVI as percentage gain, it was often difficult to extract a sensible value that could be compared and contrasted with other examples. However, when it was possible to glean such a figure, the value was typically higher than examples found in the formal VOI case-studies and sometimes many orders of magnitude greater (e.g., Stoms et al., 2011; Hermoso et al., 2013; Runting et al., 2012). Collating the EVI in the form of a percentage gain was much easier for the case studies using formal VOI, as it was either reported in those units (e.g., Costello et al., 2010; Moore et al., 2011) or it could be calculated from the reported EVWOI and EVI. In these case studies, the EVPI was typically 0-11% and only in one case (Runge et al., 2011) did it exceed this range and was measured as a 20% performance increase over the expected value under uncertainty. From the point of view of these case study authors, the magnitude of EVI was often considered to be low for formal VOI analyses, in comparison to informal VOI authors. To illustrate, words used to describe the value of information in the formal literature included "low" (e.g., Johnson et al., 2014*b*,*a*; Maxwell et al., 2014) or "modest" (e.g., Moore et al., 2011). When valuing information informally, authors tend to be more positive of about the value and cost-effectiveness of information though sometimes this was qualified that additional information was only useful up to some limit (Grantham et al., 2008, Grantham et al. (2009)).

It may be worth speculating why the two approaches to valuing information seem to differ in the results they find. We think there might be both intrinsic and extrinsic reasons for the discrepancy that sees formal VOI analysts report and perceive low value of information, while the informal branch finds the opposite. Besides the obvious point of difference that each stream of research is using different methods, there is also the fact they are valuing information for very different decision problems. Perhaps there is greater value of information in spatial conservation planning than there is for population management. On the other hand there are compelling reasons to believe that this may not necessarily be the case. Again, something akin to a publication bias may be in effect here. The methods used and case studies chosen by researchers utilizing each branch of VOI analysis may, to some degree, predetermine the value of information that they end up reporting. When using formal VOI analysis, the case studies very often begin with a relatively well understood system. In some cases this may simply be because it is easier to illustrate a new method with an established decision problem. Similarly informal VOI analysis begin from a point of relative information richness having large datasets documenting the distribution of many taxa (e.g., Grantham et al., 2008; Hermoso et al., 2013). At this point, the two approaches go in different directions. Informal VOI analyses look backwards (at least hypothetically) and compare the performance of a spatial plan with fewer or lower quality data. While in the formal branch, VOI analysts look forward and compare the performance of management with the information they have initially, to a hypothetical future where they have more certainty. It is not surprising then, given they both begin from a position of relatively good knowledge, that informal information valuers see great value in having acquired that knowledge, and formal information valuers see relatively less value in acquiring more information.

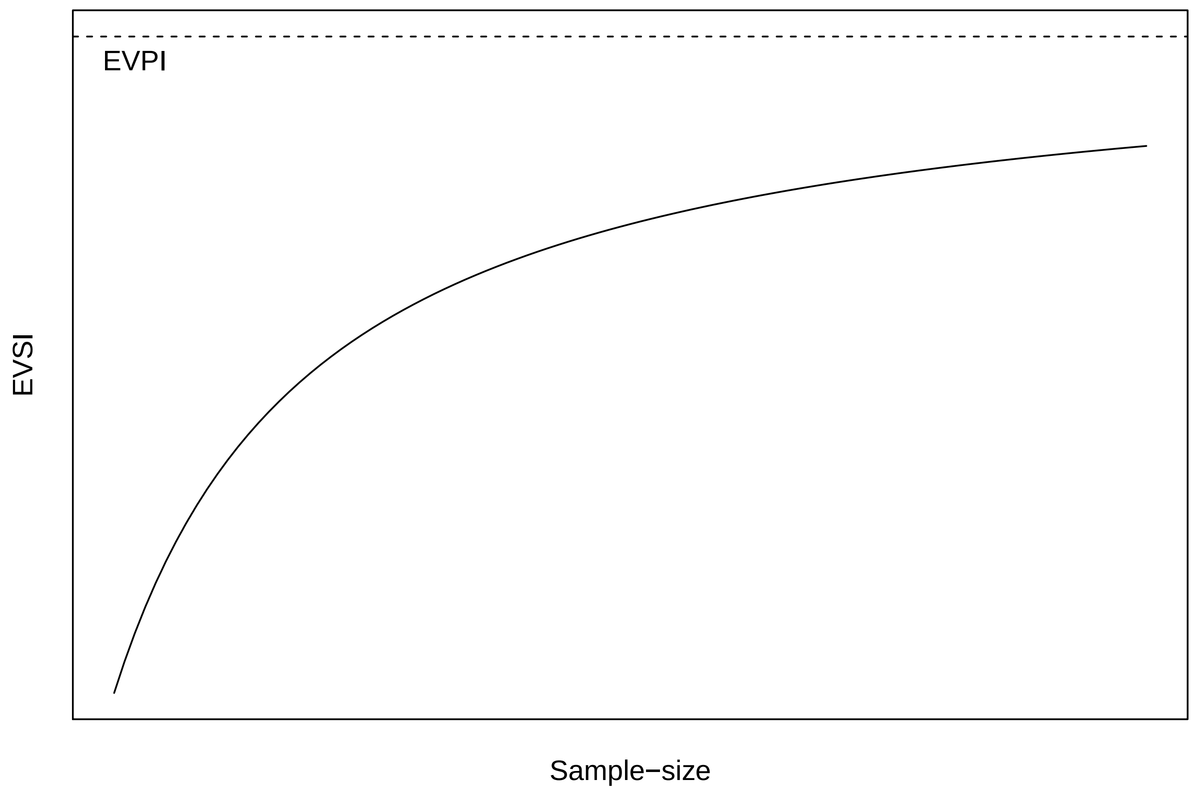

Figure 1: As sample-size increases the expected value of sample information (EVSI) approaches EVPI asymptotically.

The discrepancy between informal and formal information value, and the explanation we provide above, highlights an important point about VOI—that it follows a law of diminishing returns. In other words, the relationship between the amount of information you have and its cumulative value is non-linear. As one approaches perfect information, the upper limit of information value, the relationship asymptotes. The performance gain one would expect when going from a highly uncertain state to a less uncertain state, will be greater than decreasing uncertainty by the same amount, but starting from a state of more complete knowledge. This relationship can be explained graphically if we examine how the EVSI changes as we increase sample-size (1). As sample-size increases the EVSI increases at a diminishing rate such that for very large sample-sizes it approximates EVPI, though it can never exceed it (Raiffa and Schlaifer, 1961).

An important aspect of valuing information is all but missing from the case-studies found in this review—the cost of acquiring new information. For a value of information analysis to be ultimately of use to a decision maker, the value of information must be compared to its cost. Further, the cost and value must measured in the same units. Either the value of information must be converted into the currency with which information cost is being measured (dollars, time, etc.), or the cost must be converted into the units of measurement of the decision objective. Only when this conversion has been performed can a decision maker really know if it is worthwhile collecting any knew information and how much new information to collect. If the cost is equal to, or exceeds the benefit expected from having it, then it should not be collected and decision making should proceed with the current level of uncertainty.

However, at the current time, these final steps in the process of information valuing are missing from the conservation and resource management literature. We found no cases of formal VOI analyses where costs were presented. Only in a few cases was this done in the informal branch. In most cases the cost was not presented in the same units as the value of information (Grantham et al., 2008, 2009; Moore and McCarthy, 2010). The exception being Balmford and Gaston (1999) who found that the cost of information was typically less than 0.7% of the expected performance under uncertainty, while the value of information was at least an order of magnitude larger. Similarly, Nygård et al. (2016), in their assessment of the Finnish marine biodiversity monitoring program, assessed that while the expected benefit of information was 50 to 150 million euros, the cost was only 5.9 million. The lack of information about cost, especially in the formal branch of VOI analyses represents a significant gap in understanding. However, it is understandable that costing information is relatively rare. First, formal VOI analyses propose hypothetical future information collection, the cost of which must be based on assumptions. Second, if the costs can be pinned down at all, they must be converted to the same units as the management objectives (or vice versa). This conversion is fraught, as very often managers are reluctant to express their objectives (e.g., number of individuals of a threatened species protected) in the same units that express their management costs.

An important aspect of VOI analysis to consider is that it only capable of valuing information in the context of the uncertainty characterized by the system model of the decision problem it is applied to. So-called black swans, or unknown unknowns (Wintle et al., 2010), cannot be accounted for in formal VOI analysis (Runge et al., 2011). Relatedly, one cannot completely discount the serendipitous or extrinsic value of information. That is, information doesn't exist in a vacuum, and information collected for the purposes of increasing the performance of a particular decision may be as helpful or even more so, in the context of a completely different decision. These two issues show that to rely on the formal decision theoretic definition of information value alone, may under-value information and that it cannot be the only factor relied on to decide whether information should be collected or not.

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Appendix B: Case studies in VOI for conservation and natural resource management

Table B1: Formal VOI

Case study	Subfield	System	Spatial Scale	Time Scale	Objective	Actions	Model	Uncertainty	Optimization	VOI
Kuikka etal, 1999	Fisheries management	Baltic cod (*Gadus morhua*) fishery	1,600,000 km^2	1yr	Maximize yearly catch and minimize risk of recruitment failure	Choose catch effort	Age-structured stochastic population model	Represented by the probabilities that one of three different recruitment models applies to the fishery dynamics	Monte Carlo simulations	3-7%
Mantyniemi etal, 2009	Fisheries Management	North Sea herring (*Claupea harengus*) fishery	570,000 km^2	20yrs	Maximize fishery profit over 20yrs	Choose catch effort	Bayesian stochastic population model	Alternative model structure: compensatory (Beverton-Holt) or over-compensatory (Ricker) density-dependence in survival of spawned eggs	Non-exhaustive brute-force search	5%
Costello etal, 2010	Fisheries Management	Southern California Bight fishery	11,000 km^2	1yr	Maximise the value of the fishery subject to a conservation weighting	Choose among candidate areas to include in reserve system and/or set a catch limits in candidate areas	Metapopulation model	A set of 8 plausible dispersal kernels for the metapopulation model each kernel is equally likely to be the true kernel	-	0-11%

Moore etal, 2011	Invasive species control	*Acacia paradoxa* invasion of South Africa	3 km^2	20yrs	Minimize costs and losses from invasion	Choose whether to contain, eradicate or take no action	Constant rate of spread from initial infestation to maximum possible extent defined by bioclimatic niche model	The extent of infestation is unknown	Numerical optimisation of non-linear simultaneous equations	8%
Runge etal, 2011	Threatened species recovery	Recruitment dynamics of Eastern migratory whooping crane (*Grus americana*) population	200 km^2	10yrs	Maximise number of breeding pairs, reproductive success, adult survival and condition	Choose among 7 separate management strategies	Expert elicited hypotheses	Each hypothesis weighted according to expert opinion	Calculation of all terminal utilities for each combination of management action and hypothesis	EVPI = 20%, EVPXI = 1-11%
Moore and Runge, 2012	Invasive species control	Grey willow (*Salix cinerea*) invasion of alpine bogs of the Bogong High Plains, Australia	120 km^2	200yrs	Protect the integrity and function of alpine bogs	Allocate effort to control willows among 4 zones	State-based dynamic model	Probability distributions of model parameters	Monte Carlo simulations	EVPI = 0-10%, EVPXI = 0-3.5%
Johnson etal, 2014a	Wildlife harvest management	Dynamics of Svalbard population of Pink-footed Goose (*Anser brachyrhynchus*)	450,000 km^2	1yr	Maintain population size around 60,000 minimizing the probability that population collapses or erupts	Choose harvest rate each year	Stochastic population model	Set of 9 structurally different population models	Stochastic dynamic programming	EVPI = 3-6%, EVPXI = 0-2%
Johnson etal, 2014b	Wildlife harvest management	Dynamics of Webb Wildlife Management Area Population of Northern Bobwhites (*Colinus virginianus*)	30 km^2	1yr	Maximise population growth rate, harvest, feasibility of management while minimizing cost.	10 alternative management strategies with varying combinations of harvest rate, hunting practice, burn scale, food provision and water management	Stochastic population model	4 different hypotheses of what is causing decline in population	Calculation of all terminal utilities for each combination of management action and hypothesis	EVPI = 3.5%, EVPXI = 0-2%

Canessa etal, 2015	Threatened species recovery	Survival of captive-bred and released European pond terrapins (*Emys orbicularis*) in Liguria, Italy.	5,500 km^2	>3yrs	Maximise the survival of released individuals	Release terrapins at either 3, 4 or 5 years of age	Post release mortality rate that may vary by age.	Post release mortality may increase, decrease with age or is invariant	Calculation of all terminal utilities for each combination of management action and hypothesis	EVPI = 6%
Maxwell etal, 2015	Threatened species recovery	Dynamics of southeast Queensland population of Koala (*Phascolarctos cinereus*)	400 km^2	>1yrs	Maximise population growth	Allocate budget to preventing vehicle collisions, preventing dog attacks or restoring habitat	Age-structured population model	Structural uncertainty in the form of 8 different model structures. Parametric uncertainty in the form of probability distributions (represented by Monte Carlo simulations) of survival and fecundity	Multidimensional unconstrained nonlinear optimisations.	EVPI = 0-4%
Williams and Johnson, 2015	Wildlife harvest management	Dynamics of Svalbard population of Pink-footed Goose (*Anser brachyrhynchus*)	450,000 km^2	1yr	Maintain population size around 60,000 minimizing the probability that population collapses or erupts	Choose harvest rate each year	Stochastic population model	Set of 9 structurally different population models	Stochastic dynamic programming	
Robinson etal, 2016	Wildlife harvest management	White-tailed deer (*Odocoileus virginianus*) population dynamics of New York, USA.	140,000 km^2	1yr	Maximise hunting and minimize probability that population exceeds desired size	Six management altenatives: status quo, one buck bag limit, mandatory antler restrictions, partial mandatory antler restrictions, shorter seasons, voluntary restraint	Expert elicited predictions and population growth model	Parametric uncertainty for survival rates for different ages and each sex. Structural uncertainty represented by the inclusion or not of density dependent survival.	Calculation of all terminal utilities for each combination of management action and hypothesis across the range of parametric uncertainty	0%

Table B2: Informal VOI

Case study	Subfield	System	Spatial Scale	Time Scale	Objective	Actions	Model	Uncertainty	Optimization	VOI
Balmford and Gaston, 1999	Spatial conservation planning	Country-wide reserve networks	10,000,000 km^2	> 10yrs	Establish a representative reserve system	Choose among candidate areas to include in reserve system	Assumption that selection rule criteria (intact vegetation, results of biodiversity surveys) predict success of reserve selected	Represented as the information differential between simple selection rules and detailed biodiversity survey data	Unspecified complementarity-based spatial prioritization algorithm	>5%
Grantham etal, 2008	Spatial conservation planning	Proteaceous flora of the Fynbos biome, South Africa	81,000 km^2	10yrs	Maximally represent and retain proteaceous plant distributions in a reserve network	Choose among candidate areas to include in reserve system	Maximum entropy species distribution models of protea species in combination with simulation of vegetation loss and protection over time	Random subsets of complete dataset with sample-sizes ranging from, n = 100 (high uncertainty) to n = 44,000 (low uncertainty) And with the additional information provided by a habitat map.	Maximum gain and minimum loss greedy algorithms with convex square root benefit function (Zonation)	2-24%
Grantham etal, 2009	Spatial conservation planning	Proteaceous flora of the Fynbos biome, South Africa	81,000 km^2	1-10yrs	Maximally represent and retain proteaceous plant distributions in a reserve network	Choose among candidate areas to include in reserve system	Maximum entropy species distribution models of protea species in combination with simulation of vegetation loss and protection over time	Similar to Grantham etal 2008, except instead random subsets, data was subsetted cumulatively through time	Maximum gain and minimum loss greedy algorithms with convex square root benefit function (Zonation)	<10%

Moore and McCarthy, 2010	Ecosystem restoration	Revegetation of Merri Creek Corridor, Melbourne, Australia	400 km^2	20yrs	Maximise the area of successful revegetation over 20yrs/Maximise the number of 5-year periods in which there are at least 3ha of successful revegetation over 20yrs	Allocating resources between planting at high (4000 plants/ha) or low (2000 plants/ha) density	The success of applying either action is stochastic and occurs with some probability unique to each.	The probabilities that taking each action will be successful expressed as beta random variables	Stochastic dynamic programming	-
Stoms etal, 2011	Spatial conservation planning	Farmland of the California Central Valley	6300 km^2	>1yrs	Maximise total benefits of Purchase of Development Rights program	Choose among candidate farms on which to purchase conservation easements	Benefits, Loss and Costs models predicting the payoff of an conservation easements scheme	Different data quality from datasets including, benefits only to benefits and costs and benefits, costs and losses. And minimal, basic, moderate and full information content	Rank farms by cost effectiveness and purchase until budget exhausted	<2000%
Baxter and Possingham, 2011	Invasive species control	Red imported fire ant (Solenopsis invicta) invasion of Australia	300 km^2	0.5 - 20yrs	Minimize density of Red imported fire ants	Choose which sites to search at and eradicate ants and choose whether to not search and just improve map of invasion	Logistic invasive spread model	Searchers are uncertain as to which sites within the invaded region are occupied according to maps of different quality	Stochastic dynamic programming	-
Hermoso etal, 2013	Spatial conservation planning	Freshwater fish distribution of northern Australia	1,200,000 km^2	>10yrs	Minimize cost of set of planning units that protects at least 10% of each species distribution	Choose among candidate areas to include in reserve system	Species distribution models (MARS)	Different data quantities 15 to 85% subsets of full dataset	Spatial prioritisation algorithm (Marxan)	<230%

Runting etal, 2013	Spatial conservation planning	Coastal wetland communities of south-east Queensland, Australia.	600 km^2	100yrs	Maximize the conservation value of purchased planning units	Choose among candidate areas to include in reserve system	Coastal impact model/Sea level rise projection	Combinations of coarse vs fine scale elevation data and a simple vs complex impact model forms a gradient of uncertain predictions	Maximum gain greedy algorithm with core area benefit function (Zonation)	0-300%
Perhans etal, 2014	Timber harvest management	Silvicultural dynamics of Swedish Boreal Forests	0.2 km^2	>4yrs	Maximise the richness of lichen species and maximise the representation and richness of lichen species of conservation concern on retained aspen	Select among candidate aspen trees to retain	Generalised linear models predicting biodiversity value of lichens on retained trees based on tree attributes	4 different datasets used to produce selection criteria of varying uncertainty	Integer linear programming / selecting top ranked trees	-
Hermoso etal, 2015	Spatial conservation planning	Freshwater fish distribution of northern Australia	1,200,000 km^2	>10yrs	Minimize cost of set of planning units that protects at least 10 or 25 or 50% of each species distribution	Choose among candidate areas to include in reserve system	Species distribution models (MARS)	Systematic vs random sampling strategy	Spatial prioritisation algorithm (Marxan)	-
Lehtomäki etal, 2015	Spatial conservation planning	Managed boreal forest of southeastern Finland	14,000 km^2	>4yrs	Maximise the representation of the spatial plan at minimal cost	Choose among candidate areas to include in reserve system	Expert elicited model relating biomass to ecological features of conservation value	Coarse vs fine scaled forest inventory datasets	Maximum gain greedy algorithm with additive benefit function (Zonation)	-
Mazor etal, 2016	Spatial conservation planning	Loggerhead turtle (Caretta caretta) migration in the Mediterranean Sea	2,500,000 km^2	>1yr	Establish a reserve system that represents the entire life-cycle of migrating turtles at minimum cost	Choose among candidate areas to include in reserve system	Assumption that the datasets use represent the migration patterns of the turtles	Four different data-types of decreasing uncertainty: broad distribution, habitat types, mark-recapture data, telemetry data	Spatial prioritisation algorithm (Marxan)	-

Nygård etal, 2016	Ecosystem management	Finnish marine biodiversity	10,000 km^2	6yrs	Maximize the benefit of the program of measures	No management, intermediate management, strict management	-	Three scenarios: No information, indicative information, good information	-	50-151 million euro
Tulloch etal, 2016	Spatial conservation planning	Kubulau District, Fiji, Fishery	260 km^2	>1yr	Minimize the cost of representing 30% of the distribution of biodiversity features	Choose among candidate areas to include in reserve system	Assumption that various datasets represent the biodiversity value of the reserve system	Coarse and fine-scale input data	Spatial prioritisation algorithm (Marxan / MarProb)	-