Stochastic Environmental Research and Risk Assessment
https://doi.org/10.1007/s00477-019-01745-4

ORIGINAL PAPER

Value of information in multiple criteria decision making: an application to forest conservation

Kyle Eyvindson[1,2,3] · Jussi Hakanen[4] · Mikko Mönkkönen[1,3] · Artti Juutinen[5] · Juha Karvanen[6]

Abstract

Developing environmental conservation plans involves assessing trade-offs between the benefits and costs of conservation. The benefits of conservation can be established with ecological inventories or estimated based on previously collected information. Conducting ecological inventories can be costly, and the additional information may not justify these costs. To clarify the value of these inventories, we investigate the multiple criteria value of information associated with the acquisition of improved ecological data. This information can be useful when informing the decision maker to acquire better information. We extend the concept of the value of information to a multiple criteria perspective. We consider value of information for both monetary and biodiversity criteria and do not assume any fixed budget limits. Two illustrative cases are used describe this method of evaluating the multiple criteria value of information. In the first case, we numerically evaluate the multiple criteria value of information for a single forest stand. In the second case, we present a forest planning case with four stands that describes the complex interactions between the decision maker's preference information and the potential inventory options available. These example cases highlight the importance of examining the trade-offs when making conservation decisions. We provide a definition for the multiple criteria value of information and demonstrate the potential application when conservation issues conflict with monetary issues.

Keywords Bayesian decision theory · Conservation planning · Decision analysis · Information updating · Optimization · Simulation · Trade-offs

1 Introduction

Decisions should be made using and acquiring information appropriate to the problem. In a conservation planning setting where decisions need to be made on which potential areas should be protected, the information needed to make decisions can relate to the qualities of the specific potential conservation area, such as the productivity of the area, time since human intervention or the inventory information on specific species in the area. The information needs depend on the specific conservation priorities. When prioritizing conservation needs a wide set of factors may need to be taken into account. This requires a balance between multiple, potentially conflicting conservation and economic issues. These considerations will influence how the conservation problem is structured, and unique data acquisition strategies may best guide the decision making process. In a conservation setting there is a clear trade-off between spending money to conserving larger areas and spending money to ensure the highest quality areas are conserved.

This trade-off between using information currently available, or the acquisition of improved information has been formalized using the value of information (VoI) (Raiffa and Schlaifer 1961; Eidsvik et al. 2015). The VoI is often defined as the amount an individual is willing to pay to be able to make the decision without uncertainty.

✉ Kyle Eyvindson
kyle.j.eyvindson@jyu.fi

1 Department of Biological and Environmental Sciences, University of Jyvaskyla, P.O. Box 35, 40014 Jyvaskyla, Finland

2 Present Address: Natural Resources Institute Finland (Luke), Latokartanonkaari 9, 00790 Helsinki, Finland

3 School of Resource Wisdom, University of Jyväskylä, P.O. Box 35, 40014 Jyvaskyla, Finland

4 Faculty of Information Technology, University of Jyvaskyla, P.O. Box 35 (Agora), 40014 Jyvaskyla, Finland

5 Natural Resources Institute Finland, P.O. Box 4600, 90014 Oulu, Finland

6 Department of Mathematics and Statistics, University of Jyvaskyla, P.O. Box 35 (MaD), 40014 Jyvaskyla, Finland

Published online: 05 November 2019

Alternatively, the VoI can be defined as the willingness of an individual to make decisions with more accurate information. The specific willingness to pay depends on the risk preferences of an individual, with risk averse decision makers willing to pay more for certainty than risk seeking decision makers (Charness et al. 2013). Through the use of a VoI analysis, the value and importance of obtaining new information can be quantified, allowing the trade-off between the costs and benefits to be explored.

The VoI has been shown to be of value in previous environmental planning cases. Canessa et al. (2015) examined the conservation options under certainty, uncertainty and updated uncertainty, and the potential benefit of obtaining new information was described through the VoI. The potential for evaluating the VoI for the specific case of forest management has been reviewed, and the multiple criteria perspective of the VoI has been suggested by Kangas (2010). In the review, Kangas highlights the potential application of Bayesian decision theory (Raiffa and Schlaifer 1961) and Cost-plus-loss analysis (Burkhart et al. 1978), she then describes factors which can impact the VoI (Ketzenberg et al. 2007). While Kangas (2010) highlights the potential of VoI for multiple criteria problems, she also notes a lack of analytical methods to calculate the VoI for multiple criteria.

Related to forest management context, the value of improving forest data has been explored through several frameworks. From a data quality and harvesting decision framework, Kangas et al. (2015) evaluated the VoI for making decisions to harvest a single forest stand (a predefined forested area with relatively homogeneous characteristics). The key idea was to evaluate the differences in VoI between moderately improved data or perfect data, each with different costs. From a forest holding perspective, Eyvindson et al. (2017) used a two-stage stochastic programming framework to identify when the next holding level forest inventory should be conducted. Through a risk preference perspective, Eyvindson and Kangas (2016) evaluated the VoI as a percentage improvement of the objective function (maximizing the expected net present value and while minimizing negative deviations from a targeted periodic value obtained from the forest holding).

In a multiple criteria context, the VoI becomes a trade-off between competing interests. In the presence of multiple conflicting objectives, the optimal solutions are called Pareto optimal which means that none of the criteria values can be improved without impairing at least one of the other criteria values [see e.g. Miettinen (1999)]. Therefore, each Pareto optimal solution represents a trade-off between the criteria and the set of all Pareto optimal solutions is called Pareto front. In a conservation planning perspective this trade-off could be evaluated as the improvement of the ecological benefits and the combination of the costs of both obtaining improved information and the opportunity cost of conservation. These ecological benefits may involve multiple criteria [such as the protection of various species, or ecosystem services (Juutinen and Mönkkönen 2004; Moffett and Sarkar 2006)]. The multi-unit VoI has been explored by Bennett et al. (2018), where they address the importance of considering multiple management units (species, habitat areas) at the same time, with a fixed conservation budget. Their work can be extended to address this trade-off between the cost of information, and value of conservation actions by utilizing preference information from the person making the actual decision. We propose that budgets should be flexible, able to adapt according to the preference information and to the quality of the conservation sites.

The key objective for this research is to develop a semi-analytical method to calculate the multiple criteria VoI. We do this first by utilizing a Bayesian decision framework to identify the trade-off between improving the quality of information and the costs associated with the improvement for a specific stand. We allow the decision maker to freely set her preferences between monetary and biodiversity objectives. In our approach, the decision maker first chooses an initial conservation decision and constructs an indifference curve that describes her preferences. Monte Carlo simulations are carried out to obtain multiple criteria VoI for the possible inventory schemes. The decision maker then chooses the ecological inventory scheme to be followed, which will inform which conservation decisions are made. The approach is first illustrated with a single specified stand and extended to a multi-stand case. We utilize the context of a forest planning case as a representation of land-use/management planning problems. The results highlight how the VoI depends upon the specific characteristics and qualities of the forest stands under consideration.

2 Materials and methods

To clearly detail the process involved in calculating and assessing the multiple criteria VoI, we first apply this method to a simple case where a single conservation area (a forested stand) will be protected or not. We then highlight how the method can be applied to a multi-stand problem, where one or more stands can be protected so that the utility of the decisions is maximized. This is applied to a specific cost-efficiency problem, where the decision maker wishes to maximize the species richness in the set of protected stands while minimizing the costs for conservation (both inventory costs and the opportunity costs to protect a specific stand - later identified simply as the conservation cost). Thus, the criteria are the costs associated with conducting inventories and conservation, and the expected benefits from the conservation efforts. For both cases we utilize explicitly stated preference information from a decision maker. In the single stand case, the preference information relates to the needed conservation value from the stand, while for the multi-stand case we utilize preference information as an indifference curve describing the preferred trade-off between conservation benefits and costs.

2.1 Data

For both cases the data is based on field collected data in forests from the Satakunta region of south western Finland (Juutinen et al. 2009). In that study, multiple aspects of interest to forest conservation were inventoried. To simplify the presentation of the method, we only utilize the inventory information on the number of indicator wood-inhabiting fungi at each stand. Wood-inhabiting fungi species require old-growth forests with a diverse structure of deadwood decomposition, and as a result may be a good indicator of biodiversity of other desired species. Each of the 70 inventoried forest stands in this data set are mature or old-growth forest. The stands were grouped based on their age structure (1: ≤ 80, 2: 81–95, 3: 96–110, 4: > 110 years). We did this to link fairly readily available prior information (age class information) to a distribution of potential outcomes based on this information. The number of used to represent the age classes differed, ranging from 14 to 21 per class. The distribution of the number of indicator wood-inhabiting fungi found in the age class groups is highlighted in Fig. 1. For each age class group, a negative binomial distribution was fitted to the actual data, to provide a modeled representation of the data. For presentation proposes in the single stand case, a Poisson distribution was used of stand 2, as the fitted negative binomial distribution and the Poisson distribution were nearly identical. The costs of conserving and inventorying an example stand for each age class is provided in Table 1. The variations in costs were related to the travel time required to reach the particular stand.

2.2 VoI for conservation of one forest stand

Consider a simplified problem with one stand. The decision maker will first make a decision r on inventorying the stand and then make a decision d on conservation of the stand (both decisions are binary). The conservation and the inventory costs are denoted by b and c, respectively. According to our prior information, Y, the number of species in the stand follows a Poisson distribution with known mean λ. The value Y will be known exactly if the inventory is made. The optimization problem maximizes the combined utility from the conservation cost (U_1) and number of species conserved (U_2). Assuming a risk neutral decision maker, the optimization problem is written as

$$\max_{r,d} \langle U_1(r,d),\ U_2(r,d)\rangle = \max_{r,d}\langle -(bd+rc),\ dY\rangle. \quad (1)$$

The decision maker will define the limit y_0, a threshold number of species conserved, and prefer the conservation if $Y \geq y_0$. If Y is unknown, she will prefer the protection if $\mathrm{E}(Y) \geq y_0$. The utility under the prior information ($r = 0$) is then specified as follows

$$\max_{d} \langle U_1(0,d),\ U_2(0,d)\rangle = \begin{cases} \langle -b, y\rangle, & \text{if } \lambda \geq y_0 \\ \langle 0,0\rangle, & \text{if } \lambda < y_0, \end{cases} \quad (2)$$

where y is the true value of Y. Note that the real benefit is y even in the case she did not conduct the inventory and, therefore we use y instead of $E(Y)$. If decision to conserve the stand ($d = 1$) is made, the true value of U_2 remains unknown to the decision maker, as she did not conduct the inventory.

After the inventory, the decision maker learns that $Y = y$. The utility under the posterior information ($r = 1$) becomes

$$\max_{d} \langle U_1(1,d),\ U_2(1,d)\rangle = \begin{cases} \langle -(b+c), y\rangle, & \text{if } y \geq y_0 \\ \langle -c, 0\rangle, & \text{if } y < y_0. \end{cases} \quad (3)$$

The VoI is the difference of the posterior and prior utility

$$\max_{d} \langle U_1(1,d),\ U_2(1,d)\rangle - \max_{d} \langle U_1(0,d),\ U_2(0,d)\rangle = \begin{cases} \langle -I(y\geq y_0)c + I(y<y_0)(b-c),\ -I(y<y_0)y\rangle, & \text{if } \lambda \geq y_0 \\ \langle -I(y\geq y_0)(b+c) - I(y<y_0)c,\ I(y\geq y_0)y\rangle, & \text{if } \lambda < y_0, \end{cases} \quad (4)$$

where I denotes an indicator function. This provides the decision maker values related to the expected loss/gain in costs or conservation value.

To calculate the expected VoI, we need the cumulative distribution function of the Poisson distribution

$$F(y|\lambda) = e^{-\lambda}\sum_{k=0}^{y}\frac{\lambda^k}{k!}, \quad y = 0,1,2,\ldots. \quad (5)$$

We also need to calculate the expected value of Y on the condition $Y < y_0$

$$\mathrm{E}(Y|Y<y_0,\lambda) = \frac{\sum_{k=0}^{y_0-1} k\frac{\lambda^k e^{-\lambda}}{k!}}{F(y_0-1|\lambda)} = \frac{\lambda F(y_0-2|\lambda)}{F(y_0-1|\lambda)}, \quad (6)$$

and the expected value of Y on the condition $Y \geq y_0$

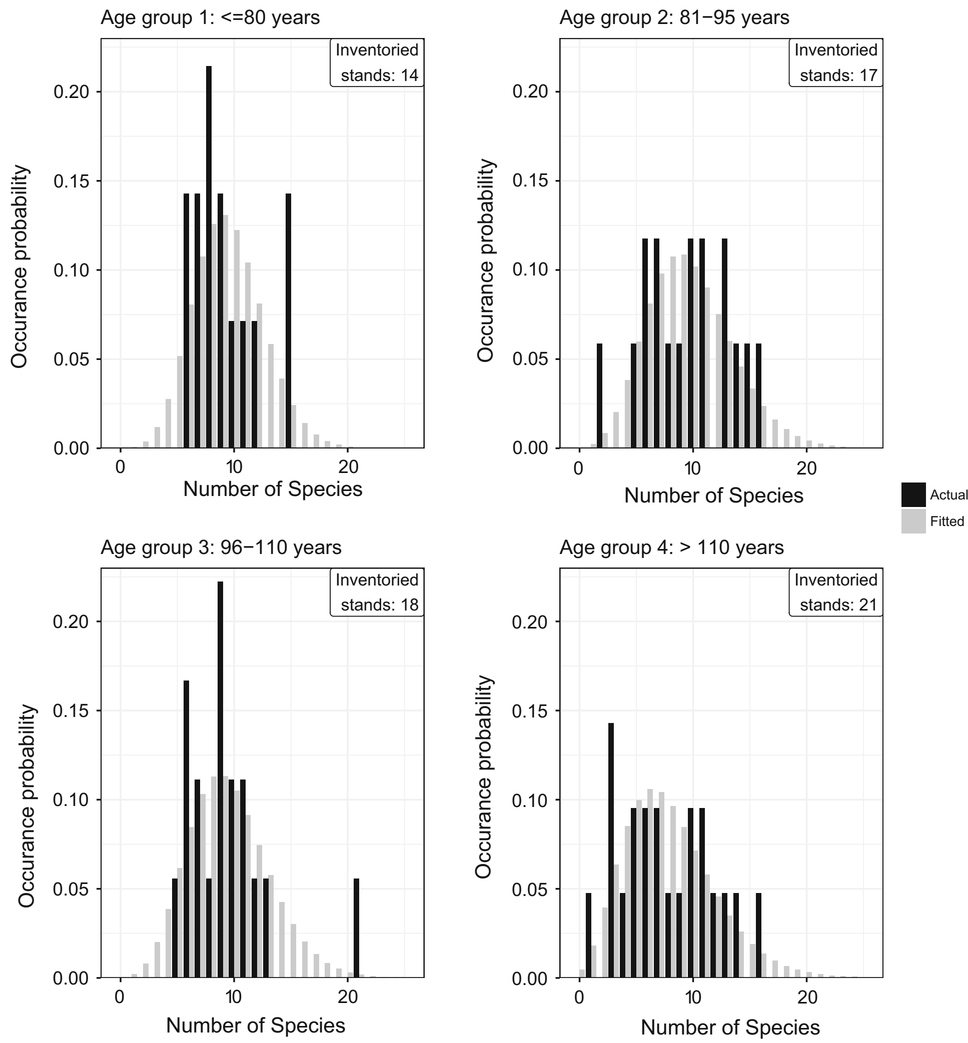

Fig. 1 The distribution of the number of indicator species found for each age structure categorization. A negative binomial distribution model was fitted to the collected data, and both are included to highlight how well the model matches the particular sampled distribution

Table 1 Costs associated with conserving and inventorying a selected stand from each age class. These costs relate to the average conservation cost and inventory cost for those inventoried stands

Costs (in €)	Age class 1	Age class 2	Age class 3	Age class 4
Conservation cost	48,000	66,000	40,200	35,600
Inventory cost	5100	5800	6200	5600

$$\mathrm{E}(Y|Y\geq y_0,\lambda)=\frac{\sum_{k=y_0}^{\infty}k\frac{\lambda^k e^{-\lambda}}{k!}}{1-F(y_0-1|\lambda)}=\frac{\lambda-\lambda F(y_0-2|\lambda)}{1-F(y_0-1|\lambda)}. \tag{7}$$

The expected VoI becomes

$$\begin{aligned}&\mathrm{E}\left(\max_d\langle U_1(1,d),\ U_2(1,d)\rangle-\max_d\ \langle U_1(0,d),\ U_2(0,d)\rangle\right)\\&=\begin{cases}\langle-(1-F(y_0|\lambda))c+F(y_0|\lambda)(b-c),\ -F(y_0|\lambda)\mathrm{E}(Y|Y<y_0,\lambda)\rangle, & \text{if } \lambda\geq y_0\\ \langle-(1-F(y_0|\lambda))(b+c)-F(y_0|\lambda)c,\ (1-F(y_0|\lambda))\mathrm{E}(Y|Y\geq y_0,\lambda)\rangle, & \text{if } \lambda<y_0.\end{cases}\end{aligned} \tag{8}$$

A numerical illustration is presented in Sect. 3.1.

2.3 VoI for conservation of multiple forest stands

For problems larger than a single stand, the complexities increase due to need to include the more complex preference information into the decision problem. With multi-objective problems, there will be no single ’optimal’ solution, rather a set of Pareto optimal solutions. To find a single solution, a human decision maker can provide their preferences to further inform the decision making problem. For the single stand case, the species limit y_0 was used as preference information. For cases with J stands, a species limit approach is not very appropriate as the conservation decision $\mathbf{d} = (d_1, \ldots, d_J)$ is no longer binary (to conserve or not), as we are evaluating the entire set of stands. Now, the conservation decisions are to conserve a particular set of stands, based on the information provided by the most appropriate inventory scheme $\mathbf{r} = (r_1, \ldots, r_J)$. The multiple stand optimization problem remains similar to the single stand case. However, instead of a single value, the preference information associated with this problem is more complex due to interactions between multiple stands/criteria. One way to realize this is to obtain an indifference curve between costs and the sum of indicator species for those stands conserved by asking questions from the decision maker. With multiple stands, the multiobjective formulation remains as maximization between two objective functions presented as

$$\begin{aligned} &\max_{\mathbf{r},\mathbf{d}} \langle U_1(\mathbf{r},\mathbf{d}),\ U_2(\mathbf{r},\mathbf{d})\rangle \\ &\quad = \max_{\mathbf{r},\mathbf{d}} \left\langle -\sum_{j=1}^{J}(b_j d_j + r_j c_j),\ \sum_{j=1}^{J} d_j Y_j \right\rangle. \end{aligned} \tag{9}$$

Here the objective functions of the single stand problem (1) are summed over the J stands under consideration. With this multiobjective formulation we can explore the Pareto front and find implementable decisions (consisting of specific inventory and conservation decisions) by using preference information from a decision maker. This can be done through a variety of approaches, see e.g. Miettinen (1999).

In order to realize this, we identify a procedure with the following steps:

1. Find Pareto optimal conservation decisions based on the prior information, i.e., when no new inventory information is planned to be collected.
2. Let the decision maker identify the most preferred conservation decision from the Pareto optimal decisions found in step 1.
3. Ask preference information from the decision maker related to potential changes in the objective values to obtain the indifference curve.
4. Simulate possible realizations of uncertain inventory data for each inventory scheme.
5. Find Pareto optimal inventory schemes by maximizing the objective in Eq. (10) and visualize them to the decision maker.
6. Ask the decision maker to select the inventory scheme to follow or change her preferences. If the preferences are changed, continue from step 3.
7. Conduct the chosen inventory scheme and ask the decision maker to make the conservation decision based on the data collected in the inventory.

First, Pareto optimal conservation decisions based on available data are identified in step 1. If the number of stands considered is relatively small, all possible decisions can be identified and finding the Pareto optimal ones is a straightforward task. Otherwise, methods of multiobjective optimization are needed to find the Pareto optimal decisions. In step 2, the Pareto optimal conservation decisions found (or a subset of them if a large number is found) are shown to the decision maker who is then asked to identify the most preferred one. Since we here consider only two objective functions (the sum of conservation and inventory costs and the sum of species occurrence), the decisions are easy to visualize just plotting them on a plane with the objectives as coordinates (i.e., as a scatter plot). When more objectives are added, advanced visualization techniques for high dimensional data are required [see e.g. Liu et al. (2014)].

To find a single solution, the objective function presented in (9) requires preference information in steps 2 and 3, highlighting the intentions of the decision maker. An option to elicit the preference information is through direct elicitation. With a series of questions, an indifference curve can be constructed using a method similar to the variable certainty equivalent method (von Winterfeldt and Edwards 1986). The decision maker should be given specific information to allow for contextual orientation to the problem. This can be done by presenting the set of Pareto optimal conservation decisions for the case where no inventory information is planned to be collected (step 1). The decision maker would first be asked to identify the most preferred Pareto optimal conservation decision in step 2. Then in step 3, subsequent questions would aim to identify what kind of conservation decisions would be as good for her as the most preferred one (i.e., specifying preferable trade-offs between objectives). In other words, the decision maker should be able to identify decisions that are equally preferable in terms of conservation benefits and monetary costs. Once enough points are identified, a monotonic spline can be fitted through the solutions to create a continuous curve. The indifference curve is specified by function f that maps cost c to the number of species $f(c)$. The decision maker considers utility $\langle c, f(c)\rangle$ equally preferable to the utility of her initial decision. For a more detailed presentation on the methodology behind preference elicitation for multiple criteria decision making, readers are directed to e.g. Belton and Stewart (2002) or Greco et al. (2016).

After the preferences of the decision maker have been identified, possible realizations of uncertain inventory data are simulated for each inventory scheme in step 4. Then, the Pareto optimal inventory schemes are identified and visualized to the decision maker for further investigation.

From the indifference curve, we can evaluate how the costs of conducting inventories will impact the preferences of the decision maker. Each inventory scheme has a specific associated cost, and the inventory allows for the ability to make a decision to conserve the stand based on the potential realized conservation value. With each inventory scheme, we can evaluate how the added information can change the conservation decisions. If an inventory decision is made, this allows for the possibility to adjust the conservation decision (in step 7) once the 're-alized' conservation benefit is revealed. The objective is then to make decisions which maximizes the positive differences from the indifference curve for the entire distribution of potential outcomes.

To evaluate each of the potential inventory schemes, the following model is used for a predefined inventory option $\mathbf{r}^*$:

$$\max_{\mathbf{d}} \sum_{j=1}^{J} (d_j y_j r_j^* + d_j \mathrm{E}(Y_j)(1 - r_j^*)) - f\left(\sum_{j=1}^{J} (d_j b_j + r_j^* c_j)\right), \tag{10}$$

where f denotes the indifference curve. The objective function in Eq. (10) maximizes the positive distance between the conservation benefit from the actual decision and the corresponding point in the indifference curve f for the specific conservation and inventory cost (which can be interpreted as the VoI). The function f describes the relationship between anticipated costs (conservation and inventory costs) to the number of species conserved. For the specific case when no inventories are conducted, no changes will occur with the conservation decisions. Only when inventories are conducted can the conservation decision change. When all the inventory schemes are evaluated by using (10), the Pareto optimal ones with respect to change in expected costs and number of species conserved are visualized to the decision maker in step 5.

3 Results

3.1 Single stand example

For a numerical illustration, assume the data is similar to group 2 (where the age of the stands is between 81 and 95 years), using a fitted Poisson distribution, with the parameter $\lambda = 9.6$, being the mean number of species in the stand. We used a Poisson distribution due to the ease in how the distribution is mathematically presented. The conservation cost (b) is 66000€, the inventory cost (c) is 5800€, the threshold for the number of species conserved (y_0) is 12. As the expected conservation value is less than 12, the initial decision is not to conserve. We obtain $F(12|\lambda = 9.6) = 0.82788$ and $\mathrm{E}(Y|Y \geq 12, \lambda = 9.6) = 13.6177$. As $\lambda < y_0$, the expected VoI becomes

$$\begin{aligned}
&\langle -(1 - F(y_0|\lambda))(b + c) - F(y_0|\lambda)c;\\
&\quad (1 - F(y_0|\lambda))\mathrm{E}(Y|Y \geq y_0, \lambda)\rangle\\
&\quad = \langle -(1 - 0.82788) \cdot (66000 + 5800)\\
&\quad - 0.82788 \cdot 5800;\ (1 - 0.82788) \cdot 13.6177\rangle\\
&\quad \approx \langle -17{,}159; 2.34\rangle.
\end{aligned} \tag{11}$$

In other words, the expectation for this case is that if we conduct an inventory, the expected cost of the certainty equivalent is 17,159€. This cost reflects the probability for conserving a 'high conservation value' stand. For this case, obtaining additional information will be beneficial when either the cost is low (negative but close to zero) and the expected increase in biodiversity is high, or the financial gain is large and the expected decrease in biodiversity is small. This is value assigned to a risk neutral decision maker where they are indifferent to take the gamble (in this case conduct the inventory and spend money to conserve the stand). On the other side, if we change decisions (from not to conserve to conserve), the increase in the number of species conserved would be greater than 2.

For an alternative numerical example, we can change y_0 so that it falls below the expected value (λ), for this case $y_0 = 7$. We obtain $F(7|\lambda = 9.6) = 0.258$ and $\mathrm{E}(Y|Y < 5, \lambda = 9.6) = 5.11$. As $\lambda > y_0$, the expected VoI becomes

$$\begin{aligned}
&\langle -(1 - F(y_0|\lambda))c + F(y_0|\lambda)(b - c);\ -F(y_0|\lambda)\mathrm{E}(Y|Y < y_0, \lambda)\rangle\\
&\quad = \langle -(1 - 0.258) \cdot 5800 + 0.258 \cdot (66000 - 5800);\ -0.258 \cdot 5.11\rangle\\
&\quad \approx \langle 11{,}228; -1.32\rangle.
\end{aligned} \tag{12}$$

For this case, if we conduct an inventory, the expected savings caused by not conserving the stand when the conservation value is low is 11,228€. This is value assigned to a risk neutral decision maker where they are indifferent to take the gamble (in this case conduct the inventory and save money by not conserving the stand). On the other side, if we change decisions (from conserve to not to conserve), the decrement in the number of species conserved would be greater than 1, due to lost conservation value from 'low value' conservation stands.

From the simple single stand example, the results can be interpreted in a fairly straight forward manner. The decisions to be taken are to conduct an inventory on the stand, and/or to conserve the stand. From the example portrayed in Sect. 2.2, the specific species threshold limits (preference information for the single stand case) were $y_0 = 12$ and $y_0 = 7$. For the first case, if the decision is to conduct no inventory, then the decision will be to not conserve the stand. This decision is made as the expected species richness conserved (λ) is 9.6, which is less than the threshold limit (y_0) of 12. The multiple criteria VoI of conducting an inventory is $\langle -17{,}159; 13.6 \rangle$, as conducting an inventory implies a probability of changing the decision to from not conserve to conserve, the expected cost of the information being 17,159€. The cost represents the probabilistic change in the decision to conserve the stand when the species richness of the stand exceeds the threshold limit (y_0). If the change of conservation is made, then the expected number of additional species conserved is 2.34. For the second case, if the specific threshold limit was $y_0 = 7$, then the initial decision is to conserve the stand. For this case, the multiple criteria VoI of conducting an inventory is $\langle 11{,}228; -1.32 \rangle$ as conducting an inventory implies a probability of changing the decision from conserve to not conserve. The expected cost of the information relates to the cost of the inventory plus the savings from not conserving the stand, and the VoI represents a saving of 11,228€. If the change of conservation is made (to not to conserve the stand), then the decline in the expected number of species conserved would be 1.32.

3.2 Four stand example

The multiple criteria VoI approach is applied to a four stand conservation case study, where the costs of conducting a stand level inventory and the prior information on the conservation benefits relate to the prior information of the stand. As with the one stand example, we consider only one conservation aspect (quantity of indicator polypore species (wood-inhabiting fungi) at the stand) and the monetary cost associated with conducting the inventory and conserving the specific stand. For this case, we use the negative binomial distribution to model all four stands in this case.

Thus, to calculate the expected VoI, we need the cumulative distribution function of the negative binomial distribution:

$$F(y|\alpha, \beta) = \sum_{k=0}^{y} \frac{\Gamma(\alpha + k)}{\Gamma(\alpha)k!} \left(\frac{1}{(1+\beta)}\right)^k \left(\frac{\beta}{(1+\beta)}\right)^k, \quad y = 0, 1, 2, \ldots.$$

To comprehensively compare the set of inventory sampling schemes, we evaluate all possible permutations of inventory and conservation decisions ($16 \cdot 16 = 256$). To aid in comparison, we will focus on the Pareto optimal decisions which relate to the decision maker's specific preferences. All calculations were performed using R, and the script can be found at https://github.com/eyvindson/MultiVoi. The basic premise of the script is the use of a Monte Carlo simulation to evaluate a large number of potential conservation outcomes for the specific inventory methods, and the conservation decisions then relate to the positive distance away from the indifference curve.

In this case, there are several variables and parameters in use. The inventory decision: $\mathbf{r} = (r_1, r_2, r_3, r_4)$, and the conservation decision $\mathbf{d} = (d_1, d_2, d_3, d_4)$ on respectively inventorying and conserving the stands $j = 1, 2, 3, 4$. These decisions are all binary meaning that either we conduct the inventory and/or conserve the stand or not. The stand level protection costs $\mathbf{b} = (b_1, b_2, b_3, b_4)$ and the costs of inventory $\mathbf{c} = (c_1, c_2, c_3, c_4)$ are given in Table 1. According to our prior information, Y_j, the number of species in the stand j follows a discrete distribution obtained from previous inventory data collection. The mean and dispersion depends on the forest stand characteristics. The value Y_j will be known exactly if the inventory is made for stand j. To approximate the distribution of the potential conservation benefits, we generate M observations of random variables $\mathbf{Y} = (Y_1, Y_2, Y_3, Y_4)$. For each generated set of observations, we calculate the Pareto front of the combination of inventory and conservation decisions $(\mathbf{r}, \mathbf{d})$.

Preference information was elicited from an expert decision maker in the field of ecological management. The decision maker was first shown the Pareto optimal conservation decisions when no inventory decisions were taken ($\mathbf{r} = (0, 0, 0, 0)$). The decision maker was then asked to select the most preferred one. Then, follow-up questions identifying potential indifference for costs at specific conservation benefits were asked. When first presented with the task, the decision maker expressed some confusion about how the information would be used. To ease these concerns, we performed the task a second time to allow the decision maker to be comfortable with her preferences. Following the elicitation of the preferences through the variable certainty equivalent method, a monotonic spline was fitted to create a continuous curve.

The expected value results when no inventory decisions were taken are displayed as the numbered points on Fig. 2. The Pareto optimal decisions (those solutions which cannot be improved upon with respect to one objective without a decline in another objective) are shown in black while the dominated ones (those solutions which can be improved upon with respect to one objective without a decline in another objective) are shown in grey. To interpret the labeling of the conservation decisions (and inventory schemes), Table 2 shows an interpretation of the numbered points. The indifference curve is shown on Fig. 2 as dashed, with the stated preference (i.e., preferred conservation decision) indicated by the bold numerical value (C6) and stated indifference points highlighted as black dots along the curve. With this indifference curve we can then

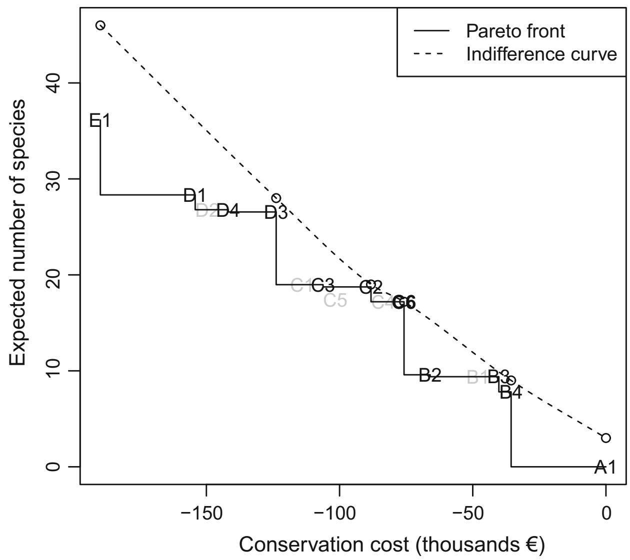

Fig. 2 The outcomes of each of the 16 different conservation decisions (where no stands are inventoried), and the indifference curve provided by the decision maker (dashed line). Numbers in black and grey denote Pareto optimal and dominated outcomes, respectively

explore how data collection (including inventory decisions) can impact and change the conservation decisions.

From the multiple stand example, the preference information has been included as an indifference curve obtained from the decision maker. The impacts of conducting each specific inventory scheme were evaluated for all of the conservation decisions. The impact of conducting the specific inventory scheme were evaluated as the distance from the indifference curve, and the conservation decision with the maximal positive distance was selected as the best option. To present the results we provide visualizations which highlight the interpretation of the decision process. From the preference information portrayed on Fig. 2, calculations to determine the impact of how the inventory schemes influence the decision were performed.

In Fig. 3, the deviations are calculated for each of the 16 inventory schemes highlighting the expected benefit for each scheme. It can be seen that *inventory scheme W4*, i.e., conducting inventory in stand 4, provides the largest shift in the indifference curve. For each of the inventory schemes, the possibility exists that multiple conservation decisions could be taken. This reflects the change in conservation decisions based on the information provided from the conduct of the inventory. In a similar fashion as in the single stand example, the multiple criteria VoI to conduct this inventory scheme is $\langle -11,987; 0.45\rangle$, respectively referencing the increase in the expected costs and increase in the number of species conserved. From Fig. 3, the multiple criteria VoI can be evaluated for each of the inventory schemes, through a comparison to the inventory scheme which performs no additional inventories (scheme V1). None of the inventory schemes cause an increase in costs with a decrease in the number of species (as simply measuring should not change the actual quantity of species present). However by examining the improvement from the indifference curve, only a few inventory schemes relate to a positive shift from the indifference curve, while increasing expected costs. Thus, while positive interpretations can be made from each inventory scheme, it is clear from decision maker's preference perspective only a few inventory schemes dominate.

To examine the impact of utilizing the preferred inventory scheme, a comparison of the individual simulated outcomes is presented in Fig. 4. This figure highlights

Table 2 Explicit labeling of both conservation decision and inventory schemes (where decisions to take conservation or inventory actions or not is respectively represented by 1 or 0)

Conservation decision/inventory scheme	Stand 1	Stand 2	Stand 3	Stand 4
A1/V1	0	0	0	0
B1/W1	1	0	0	0
B2/W2	0	1	0	0
B3/W3	0	0	1	0
B4/W4	0	0	0	1
C1/X1	1	1	0	0
C2/X2	1	0	1	0
C3/X3	0	1	1	0
C4/X4	1	0	0	1
C5/X5	0	1	0	1
C6/X6	0	0	1	1
D1/Y1	1	1	1	0
D2/Y2	1	1	0	1
D3/Y3	1	0	1	1
D4/Y4	0	1	1	1
E1/Z1	1	1	1	1

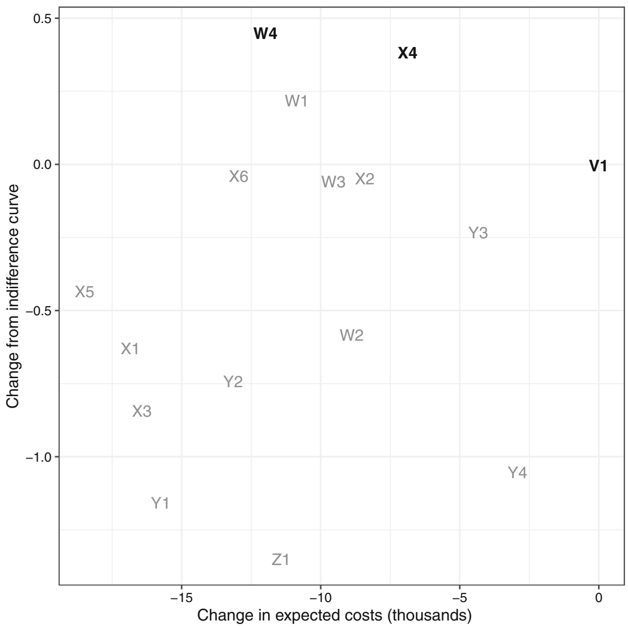

Fig. 3 The expected conservation and inventory costs, and the associated improvement to the indifference curve for each of the 16 inventory decisions. The bold numerical values indicate Pareto optimal inventory schemes. Only the inventory schemes are identified, the specific conservation decisions depend on what the inventory information tells about the conservation value of the stands

the impact of the use of different inventory schemes will have on the specific conservation decision. For the case when no inventories were performed (V1) only a single decision is made, to conserve two stands (C6). For the cases when an inventory was performed (X4 and W4), multiple conservation decisions are possible, as the inventory information prompts changes in the conservation decisions. The indifference curves are included to highlight how the change caused by including inventory information was calculated. For the case V1 (no inventories conducted), the average of the outcomes falls directly on the indifference curve. For the cases X4 and W4, the median outcomes for each conservation decisions fall above or below the indifference curve. As the improvement from the indifference is small (0.45 species), the differences can be difficult to visualize.

Through an examination of the results we can acknowledge the importance and potential to conduct inventories on only a selected number of stands. For instance, Table 3 highlights how the conservation decisions change with the inventory scheme selected. Which stands are inventoried (and resulting in which stands are then conserved) depends on a variety of contextual information. The key elements are the preference information, the costs of the inventory, costs of conservation and the distribution of the conservation benefits. For this case, the preference information was acquired by presenting a baseline of expected conservation benefits at specific costs to the decision maker. Depending on the context of the decision, this method of elicitation may prejudice the decision maker's preferences.

4 Discussion

Being able to understand the importance behind collecting more information enables decision makers to make informed decisions regarding the trade-off between collecting more information and making decisions with the currently available information. Here we examined the trade-off between costs and a single indicator for species of importance to conservation issues. In real world cases, the trade-off will likely involve multiple indicators for biodiversity, where the costs of conducting an inventory may not be easy to compare and understand. For instance, rather than simply examining a single criterion related to conservation, we could have examined multiple criteria of conservation importance, each with its own separate inventory cost (Juutinen and Mönkkönen 2004). For these cases, techniques for visualizing multidimensional improvements may be of more importance. Alternatively, interactive multiobjective optimization methods may be useful in identifying the most appropriate inventory scheme for the specific decision maker (Miettinen et al. 2016).

For this example, we made an explicit assumption that the information we receive after conducting an inventory contains no errors. With this assumption, we are evaluating the maximum potential gain collecting additional information can provide (Birge and Louveaux 2011). This assumption can be relaxed, and we can model the uncertainty of the inventory method used to collect the updated information. If there are multiple potential information sources available at different costs, the assessment could be made for each potential information source or each possible permutation of the information sources. With multiple indicators of interest, multiple potential inventory methods possible and multiple forest stands under consideration, the decision problem can quickly explode, thus the application of some simplifications can be justified for practical reasons.

A key difference between this work and other VoI analyses, is that we have incorporated the cost of acquiring additional information when assessing the VoI (Eidsvik et al. 2015; Kangas 2010). When the costs of acquiring additional information are not included in the analysis, the costs of the data acquisition can be compared to the value provided by the updated information. We have opted to include the inventory costs in the VoI analysis, as the benefit of collecting updated information relates directly to

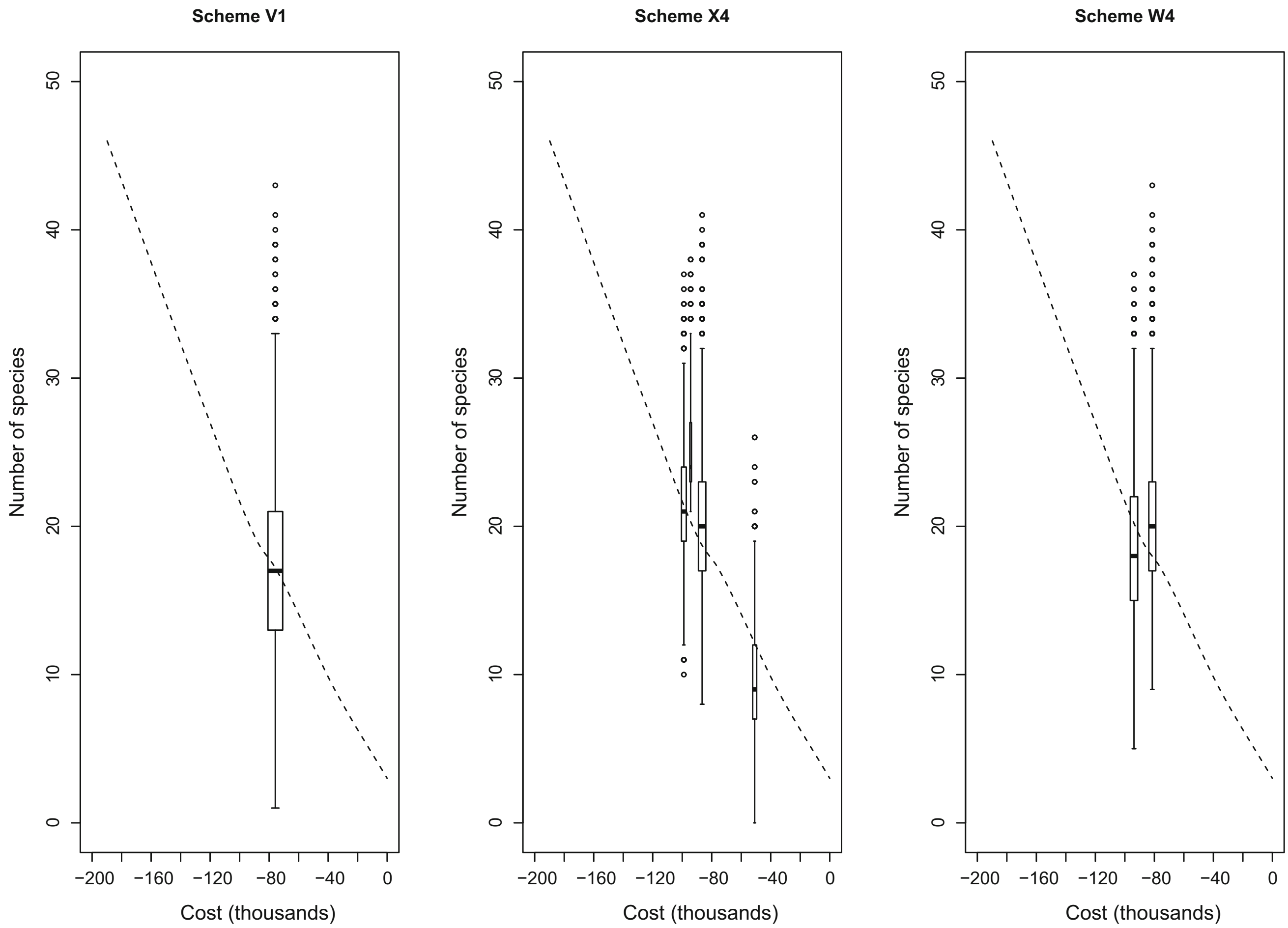

Fig. 4 The conservation decisions for a selection of the inventory schemes. The box plots indicate the range of outcomes for a specific conservation decision. The width of a box plot denotes the probability of the conservation decision to be selected. The schemes which conduct an inventory on multiple stands will have more specific conservation decisions. The dashed line is the indifference curve from the decision maker

the decisions to conserve specific stands or not. Our analysis allows for the comparison between the various inventory schemes, with the natural comparison being the no-inventory case (V1).

Selecting the most appropriate solution for a decision maker will require some form of preference information, which can be elicited in a variety of fashions (Belton and Stewart 2002; Greco et al. 2016). For this case, we connected the preferences of the decision maker to the trade-offs through an indifference curve. In connecting the preference information to the objective functions we made an assumption that the increased costs would require an increase in the required conservation benefit, shifting the indifference curve based on the total inventory costs. We felt this assumption was reasonable, however this assumption may not hold true for all decision makers. For some decision makers, the inventory costs may be subsidized by another party or considered part of a separate budget, limiting the shift to the indifference curve. To examine all potential cases, a parameter (i.e. a real value between 0 and 1) could be included to Eq. (10) which limits the impact of the inventory costs will have on the solution.

For decision makers to place confidence in the data acquisition strategy, the implications of decisions must be understandable. The method that we propose, guides the decision maker to make decisions according to their stated preferences, and the current understanding of the uncertain elements. For the multi-stand case that we presented, the best choice for this particular decision maker is to conduct inventory scheme "W4", which inventories stand 4 and based on the information obtained will conserve stand 3 and in addition either stand 4 or stand 1. As the distribution of potential conservation outcomes is larger for stand 4, if the inventoried value is larger than the expected conservation value of stand 1, the choice will be to conserve stand 4. If a general decision was made to simply acquire updated information, the decision maker would be worse

Table 3 The probability of implementing a specific conservation decision by inventory schemes

	Conservation decision											
	A1	B1	B2	B3	B4	C1	C2	C3	C4	C5	C6	D3
Inventory scheme												
V1	0	0	0	0	0	0	0	0	0	0	100	0
W1	0	0	0	0	0	0	46.4	0	0	0	53.6	0
W2	0	0	0	0	0	0	0	10.1	0	0	89.9	0
W3	0	0	0	0	0	0	0	0	42.8	0	57.2	0
W4	0	0	0	0	0	0	51.5	0	0	0	48.5	0
X1	0	0	0	0	0	1.1	32.3	5.0	0	0	61.6	0
X2	0	0	0	0	17.1	0	20.0	0	19.5	0	43.4	0
X3	0	0	0	0	0	0	0	3.1	28.4	4.9	63.6	0
X4	0	0	0	22.2	0	0	27.2	0	9.3	0	41.3	0
X5	0	0	0	0	0	0	37.3	6.0	0	2.5	54.2	0
X6	0	13.4	0	0	0	0	27.9	0	18.2	0	40.4	0
Y1	0	0	4.4	0	14.7	1.0	18.8	2.5	18.0	0	40.5	0
Y2	0	0	4.3	20.3	0	0.8	23.3	0	9.0	1.5	40.8	0
Y3	7.2	6.2	0	15.0	9.9	0	16.6	0	14.3	0	29.1	1.7
Y4	10.7	0	5.9	24.6	0	0	0	2.9	16.0	1.8	37.8	0
Z1	5.9	9.1	5.6	13.4	8.7	0.5	13.3	1.4	11.5	1.2	27.5	1.6

Proportions (%) of each conservation decisions in the simulations, e.g. on the second row 53.6% of the simulation runs to lead to decision C6 when inventory scheme W1 was applied. For each inventory scheme selected, the probability related to selecting a specific conservation decision changes. Those conservation decisions that were never selected were omitted from the table

off. Figure 3 shows the improved conservation result for a similar expected cost (compare scheme Z1, collecting information from all stands, to scheme W4 information is collected on only 2 stands).

While we used an exhaustive approach to elucidate all possible inventory schemes, for real applications this approach would not be suitable. Rather, the use of optimization methods would be necessary to link decision maker preferences to the modeled problem. For this case, we used the exhaustive method to highlight the interactions between the possible inventory schemes and conservation decisions, but have designed the problem to be solved through optimization. Including additional stands will increase the problem size, and can make the exhaustive approach time consuming, and difficult to understand.

In this analysis we chose to evaluate the a static state, ignoring the potential impact time will have on the conservation value of the different stands. An implicit assumption in the analysis is that for stands can be inventoried prior to conservation. This assumption may not hold, and there is a risk that the stand may be destroyed prior to being inventoried or after being inventoried but not yet conserved. Although a delay to conduct an inventory may not be too long, conservation actions are efficient if directed towards threatened sites. For forest stands threatened with harvesting actions, any delay in conservation could result in felling of the stand.

There are many additional future avenues of research into the potential costs/benefits of improving data quality for conservation needs. While we focused on forest management, any environmental conservation effort could be enhanced by understanding the impacts and potential improvements by collecting additional information. We explored the relatively easy case of measuring the single metric on biodiversity as the sum of the number of species per stand. More informative metrics could be to evaluate the species richness, where biodiversity is measured as the number of different species conserved (Juutinen and Mönkkönen 2004). As biodiversity involves multiple species and species groups, multiple metrics should be simultaneously considered, to address the quantity and diversity of various species or species groups. Ecological information may be spatially correlated, and if estimates on this correlation are available, it should be explicitly considered when evaluating the VoI (Bhattacharjya et al. 2010). Additionally, when considering the ecological value of conservation, the spatial and temporal context of the conservation efforts should also be considered (Fahrig 2017), in addition to the specific stand level conservation value. How a particular forest stand will influence the overall ecological value depends on the context the stand provides. The stand could enlarge a current conservation area, or act as a 'stepping stone' linking habitat areas for different species (Saura et al. 2014). To be applied to a VoI context, the ecological conservation value needs to be stated explicitly. With an accurately defined objective function, optimization tools can be used to evaluate the most appropriate decisions for the specific preferences of a decision maker.

5 Conclusions

Basing conservation decisions on previously acquired data, or using secondary proxies to estimate the conservation potential can be a useful alternative for decision makers. By linking inventory plans to the process of conservation planning, a more efficient use of monetary resources can be expected. While we have shown results for a very small case, the method can be applied to larger, and more realistic cases. Methodological use of the VoI can lead to an improved use of currently available conservation data, guiding the conduct of field work to provide the most value to the decision makers.

Acknowledgements Open access funding provided by University of Jyväskylä (JYU). The authors thank Jo Eidsvik for useful comments. This research was supported by the Academy of Finland (Grant Nos. 311877 and 275329) and is related to the thematic research area DEMO (Decision Analytics utilizing Causal Models and Multiobjective Optimization) of the University of Jyväskylä.

Authors' contributions KE, JH and JK conceived the ideas and designed methodology; MM and AJ collected the data; KE and JK analyzed the data; KE led the writing of the first draft of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

Data accessibility Our data and script to analyze the data available at https://github.com/eyvindson/MultiVoi and available from the JYX repository (https://jyx.jyu.fi).

References

Belton V, Stewart TJ (2002) Multiple criteria decision analysis: an integrated approach. Kluwer, Alphen aan den Rijn

Bennett JR, Maxwell SL, Martin AE, Chades I, Fahrig L (2018) When to monitor and when to act: Value of information theory for multiple management units and limited budgets. J Appl Ecol 55(5):2102–2113

Bhattacharjya D, Eidsvik J, Mukerji T (2010) The value of information in spatial decision making. Math Geosci 42(2):141–163

Birge JR, Louveaux F (2011) Introduction to stochastic programming. Springer, Berlin

Burkhart HE, Stuck RD, Leuschner WA, Reynolds MR (1978) Allocating inventory resources for multiple-use planning. Can J For Res 8(1):100–110

Canessa S, Guillera-Arroita G, Lahoz-Monfort JJ, Southwell DM, Armstrong DP, Chadès I, Lacy RC, Converse SJ (2015) When do we need more data? a primer on calculating the value of information for applied ecologists. Methods Ecol Evol 6(10):1219–1228

Charness G, Gneezy U, Imas A (2013) Experimental methods: eliciting risk preferences. J Econ Behav Organ 87:43–51

Eidsvik J, Mukerji T, Bhattacharjya D (2015) Value of information in the earth sciences. Cambridge University Press, Cambridge

Eyvindson K, Kangas A (2016) Integrating risk preferences in forest harvest scheduling. Ann For Sci 73(2):321–330

Eyvindson KJ, Petty AD, Kangas AS (2017) Determining the appropriate timing of the next forest inventory: incorporating forest owner risk preferences and the uncertainty of forest data quality. Ann For Sci 74(1):2

Fahrig L (2017) Ecological responses to habitat fragmentation per se. Annu Rev Ecol Evol Syst 48:1–23

Greco S, Figueira J, Ehrgott M (2016) Multiple criteria decision analysis—state of the art surveys. Springer, Berlin

Juutinen A, Mönkkönen M (2004) Testing alternative indicators for biodiversity conservation in old-growth boreal forests: ecology and economics. Ecol Econ 50(1):35–48

Juutinen A, Mönkkönen M, Ylisirniö A-L (2009) Does a voluntary conservation program result in a representative protected area network?: The case of finnish privately owned forests. Ecol Econ 68(12):2974–2984

Kangas AS (2010) Value of forest information. Eur J For Res 129(5):863–874

Kangas A, Hartikainen M, Miettinen K (2015) Simultaneous optimization of harvest schedule and data quality. Can J For Res 45(8):1034–1044

Ketzenberg ME, Rosenzweig ED, Marucheck AE, Metters RD (2007) A framework for the value of information in inventory replenishment. Eur J Oper Res 182(3):1230–1250

Liu S, Cui W, Wu Y, Liu M (2014) A survey on information visualization: recent advances and challenges. Vis Comput 30(12):1373–1393

Miettinen K (1999) Nonlinear multiobjective optimization. Kluwer Academic Publishers, Dordrecht

Miettinen K, Hakanen J, Podkopaev D (2016) Interactive nonlinear multiobjective optimization methods. In: Greco S, Ehrgott M, Figueira J (eds) Multiple criteria decision analysis: state of the art surveys, 2nd edn. Springer, New York, pp 931–980

Moffett A, Sarkar S (2006) Incorporating multiple criteria into the design of conservation area networks: a minireview with recommendations. Divers Distrib 12(2):125–137

Raiffa H, Schlaifer R (1961) Applied statistical decision theory. Division of Research, Graduate School of Business Administration, Harvard University, Boston

Saura S, Bodin Ö, Fortin M-J (2014) Editor's choice: Stepping stones are crucial for species' long-distance dispersal and range expansion through habitat networks. J Appl Ecol 51(1):171–182

von Winterfeldt D, Edwards W (1986) Decision analysis and behavioral research. Cambridge University Press, Cambridge, p 624