The value of information for woodland management: updating a state and transition model

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Abstract

Value of information (VOI) analyses reveals the expected benefit of reducing uncertainty to a decision maker. Most ecological VOI analyses have focused on population ecology using discrete expressions of uncertainty, rarely addressing complex community models or models with continuous uncertainty. We performed VOI analyses for a complex state and transition model of Box-Ironbark Forest and Woodland management with continuous parameter uncertainty. With three management alternatives (limited harvest/firewood removal, ecological thinning and no management), managing the system optimally (for 150 years) with the original information, would on average, increase the amount of forest in a desirable state from 19 to 35% (a 6 percentage point increase). Resolving all uncertainty would, on average, increase the final percentage to 42% (a 13 percentage point increase). In other words, after resolving all uncertainty, we would expect to more than double the performance from management. However, only resolving the uncertainty for a single parameter was worth almost two-thirds the value of resolving all uncertainty. We found the VOI to depend on the number of management options, increasing as the management flexibility increased. Our analyses show it is more cost-effective to monitor low-density regrowth forest than other states, and more cost-effective to experiment with the no management alternative than the other management alternatives. Importantly, the most cost-effective strategies did not include either the most desired forest states, nor the least understood management strategy, ecological thinning. This implies that managers cannot just rely on intuition to tell them where the most value of information will lie, as critical uncertainties in a complex system are sometimes cryptic.

Keywords: Box-Ironbark, multivariate adaptive regression splines, decision theory, monitoring, optimization.

Introduction

Ecosystems are typically managed with uncertainty. Reducing uncertainty (through monitoring, experiments, or other research) can facilitate management decisions with greater expected benefits. On the other hand, sometimes reducing uncertainty is not warranted (McDonald-Madden et al., 2010). The decision to gather information at all, is only rational if the expected benefit when making a decision with new information outweighs the cost of learning. Determining the value of information facilitates calculating this benefit (Raiffa and Schlaifer, 1968).

Value of information (VOI) theory is a set of decision theoretic tools that have previously been applied to decision problems in economics, medicine, engineering and other domains (Dakins, 1999; Yokota and Thompson, 2004; Claxton, 2008; Wu and Zheng, 2013). With the VOI toolset, a decision analyst can assess what to monitor, how much to monitor and even whether monitoring is justified at all.

Compared with other fields, such as operations research and medicine, ecology and natural resource management have been slower to adopt VOI analyses for decision making, although recently, some examples have appeared in the literature (e.g., Polasky and Solow, 2001; Moore et al., 2011; Runge et al., 2011; Runting et al., 2013). Most examples have focused on evaluating VOI for models with discrete expressions of model uncertainty (e.g., Moore and Runge, 2012). Furthermore, ecological decision problem solvers have tended to focus on models of population dynamics (Runge et al., 2011; Canessa et al., 2015; Johnson et al., 2014; Maxwell et al., 2015) rather than community and/or ecosystem-level models. This is an important gap in our understanding, as much effort and resources are expended on ecosystem management.

One reason why communities and ecosystems have rarely been the focus of VOI analyses is that community or ecosystem models do not lend themselves easily to VOI analysis. Ecosystem models, such as state and transition models, exhibit complex nonlinear dynamics, have many parameters (multidimensional), and their critical uncertainties are often continuous (rather than discrete), making it difficult to calculate the VOI analytically.

An approach to dealing with multidimensional continuous uncertainty and avoid having to contend with the complex integral calculus needed to perform a VOI analytically, is to simplify the problem by representing the uncertainty with a set of discrete values. Here we introduce a case study on VOI for a complex, high-dimensional model with underlying continuous uncertainty represented by sets of discrete parameter values. For the present analysis we purposely avoid the issue of non-linear temporal dynamics and only set out to address the problems of high-dimensionality and continuous uncertainty, leaving this third potential source of complexity for another forum.

In the work that follows we briefly introduce our motivating example of Box Ironbark Forest and Woodland (BIFAW) management and revisit the state transition models of this system built by Czembor and Vesk (2009). We then provide the reader with some introductory material on VOI analyses and its variants, before applying these techniques to our case study and demonstrate how some of the inherent complexities can be addressed by discretising the uncertainty and applying stepwise algorithms that negate the need for complex integral calculus.

Box Ironbark Forest and Woodland management

The BIFAW region covers approximately 250,000 ha of central Victoria, Australia. The BIFAW are plant communities that occur on low-fertility soils and in a semi-arid to temperate climate. Much of the pre-European stands of BIFAW were cleared for agriculture and gold mining. Most of the current extent is highly fragmented regrowth. These regrowth stands are typically missing key ecosystem components such as large, hollow-bearing trees and a diverse understory shrub layer. Tree species found in BIFAW include Grey Box (*Eucalyptus microcarpa*), Red Box (*E. polyanthemos*), Long Leaf Box (*E. goniocalyx*), Yellow Box (*E. melliodora*), Red Ironbark (*E. tricarpa*), Red Stringybark (*E. macrorhyncha*) and Yellow Gum (*E. leucoxylon*). The BIFAW supports important habitat for three Victorian-listed threatened taxa: Brush-tailed Phascogale (*Phascogale tapoatafa*), Powerful Owl (*Ninox strenua*) and Regent Honeyeater (*Xanthomyza phrygia*) (Tzaros, 2005). The latter is also a federally listed endangered species. Regent Honeyeaters are threatened because they rely on large trees for foraging and nesting (Menkhorst et al., 1999).

In 1996 the state government of Victoria commissioned an investigation into an appropriate system for the protection and management of BIFAW. As a direct result, over 200,000 ha of BIFAW were gazetted as national park and other protected areas. The report recommended a program of ecological thinning be undertaken as part of an ecological management strategy to assist the development of a forest structure ultimately dominated by large diameter trees in the new parks and reserves (Environment Conservation Council, 2001; Pigott et al., 2009). Ecological thinning is the active reduction of stem density to improve forest health, while retaining some fallen timber to improve habitat for plants and animals (Cunningham et al., 2009). In 2003 the body in charge of BIFAW park management, Parks Victoria, established an ecological thinning trial. The aim of the trial was to investigate whether ecological thinning could be used to restore structural diversity of habitat types and the functioning and persistence of key communities and species populations (Pigott et al., 2010).

State and transition models of Box Ironbark Forest and Woodland

Czembor and Vesk (2009) built a suite of simulation models of BIFAW dynamics with parameters estimated through expert elicitation using methods adapted from Morgan and Henrion (1990). Their BIFAW state and transition models predict the proportions of a model landscape in four states: high-density regrowth (HDRG), low-density regrowth (LDRG), and the two states most desired by land-managers, mature high-density woodland (MHDW), and mature low-density woodland (MLDW). The models included three management options, no management/natural disturbance only (NM), limited harvest/firewood removal (HF), and ecological thinning (ET). Briefly, the models predict the state of the landscape through time by applying a transition matrix that differs according to the management action applied (see methods, Czembor and Vesk, 2009; Czembor et al., 2011, for more information).

We make the simplifying assumption that the dynamics of the system are linear with respect to the actions taken. That is, they lack interactions that make the outcome of one action depend on the application of any other action. In effect, there were separate models for each of the actions, one model that predicted the dynamics (changes in state through time) of the BIFAW when NM was applied, one model for HF and one for ET. While a more complex model that included the extra layer of dynamism and included non-linear relationships between combinations of actions and outcome may have produced more realistic results, the simplification was necessary to facilitate the expert elicitation used to parameterise the models.

Uncertainty in Box Ironbark Forest and Woodland models

Analyzing the variation among models which included three components of uncertainty, Czembor et al. (2011) found that between-expert uncertainty was the greatest contributor to total model uncertainty, followed by imperfect individual expert knowledge, then system stochasticity. In the case presented here we treated the opinions of the experts as the initial state of uncertainty—the original information.

Uncertainty in state and transition model parameters can be represented by a continuous multidimensional (where the dimensions are the different model parameters) probability distribution. However, the elicitation process used by Czembor et al, yields an approximation of such a distribution in the form of multiple discrete estimates of each parameter (in this case, 375 estimates per parameter) that represents the underlying continuous expression of uncertainty. With the discrete estimates of the parameter values we can summarise the continuous parameter space, in much the same way as a histogram of samples represents some underlying probability distribution.

Decision problem

The fundamental objective of the BIFAW region managers is to ensure the persistence of key, functioning communities and species populations of the region. Managers have determined that the means of achieving these objectives is to maximize the proportion of the landscape in a mature woodland (either high, MHDW, or low-density, MLDW) state which supports key habitat components such as hollow bearing trees and a diverse shrubby understory. They have three management actions available to achieve this objective: no management/allow natural disturbance only (NM), allow limited harvest/firewood removal (HF) and thinning (ET). Importantly for the models of Czembor et al, the actions are applied initially and only once, then the models track the state transitions of the modelled BIFAW units (spatially implicit cells) through time.

The objective is to maximize the proportion of the BIFAW in either low-density or high-density mature woodland in the long term (t = 150 yr), by finding the optimal management action to apply initially. To represent the practical limitations on the resources available for management, we placed a constraint that only 20% of the BIFAW can be thinned. However, we also test the effect of applying this constraint by varying the allowable proportion of thinning from 10 to 100%.

The case study, as outlined here, falls in class of problems known as linear optimizations. As such, the solutions to the objective maximization will always lie on one of the vertices of the feasible region of management. In other words, the action that maximizes the objective will be be either 100% NM, 100% HF, 20% ET and 80% NM or 20% ET and 80% HF (or the equivalent proportions when the constraint on ET is different; Figure 1.). Here it is important to not that if the additional dynamic complexity of between action interaction had been modelled (as discussed above) then this assumption of linearity could not be made and any combination of actions may potentially be optimal.

Calculating the value of information

A value of information analysis can be used to assess the benefit of reducing epistemic uncertainty before making a decision. A decision analyst cannot know, in advance, what information they will gain if they seek to learn before taking action. The expected value *of* information (EVI) is the difference between the expected value with *new* information (EVWNI) and the expected value with *original* information (EVWOI). The EVI can come in a number forms depending on the form of new information. Regardless of form, all variants of EVI analyses assume decisions are being made optimally. That is, the decision analyst considers value to arise from taking actions that maximize the expected value given the original or new information. To do so, the decision analyst requires a model that can be used to predict the outcomes of possible future decisions. In calculating EVI, the analyst will use such a model to predict decision outcomes using the original or new information as their model inputs.

As noted above, value of information can take multiple forms. Here we deal with two forms: the expected value of perfect information (EVPI) and the partial expected value of perfect information (EVPXI). Where X in this case indicates the component of information that will be known perfectly. Here we will briefly outline the general form of an EVI analysis in terms of EVPI and EVPXI. For a more detailed description of the derivation of EVI and its variants, see the seminal text of Raiffa and Schlaifer (1968) and for more recent treatments see Yokota and Thompson (2004) and Williams et al. (2012).

The expected value of perfect information (EVPI) quantifies the expected performance gain if all uncertainty is resolved prior to taking action (Raiffa and Schlaifer, 1968). The EVPI is the upper bound of expected performance improvement and can identify the amount of resources worth investing to resolve uncertainty (Runge et al., 2011). While EVPI provides a value for complete reduction of uncertainty, EVPXI can quantify the performance gain if uncertainty is only partially resolved (Ades et al., 2004).

Again, the EVI is the difference between the EVWNI and the EVWOI. When the new information is perfect (i.e., the analyst's model will have all uncertainty eliminated) then it follows that:

$$\text{EVPI} = \text{EVWPI} - \text{EVWOI},$$

where EVWPI is the expected value *with* perfect information.

To calculate the expected values EVWPI and EVWOI, like any expected value, the analyst will work out the value they expect to see on average when taking the most optimal, or maximizing actions. More formally:

$$\text{EVWOI} = Max_a[Mean_s(Value)]$$

and

$$\text{EVWPI} = Mean_s[Max_a(Value)].$$

Where a indicates the actions available and s indicates the initial uncertainty or the state space (the world of possible scenarios that could lead an action to generate some value). As you can see, both the equations for EVWPI and EVWOI are similar. The key difference is the order of maximization (optimizing) and averaging (taking the mean over the uncertainty). Calculating the EVPXI requires a similar yet more complicated approach. For a model with multiple parameters, to calculate the EVPXI for the i^{th} parameter(s) of interest is expressed formally as:

$$\mathrm{EVPXI_i} = \mathrm{EVWPXI_i} - \mathrm{EVWOI},$$

where,

$$\mathrm{EVWPXI_i} = Mean_{s_i}\{Max_a[Mean_{s_c}(Value)]\}.$$

Here c represents the rest of the parameters in the model with uncertainty, s. Partial perfect information requires an additional averaging-over step, where value is averaged over the c^{th} not-of-interest parameters, then maximization occurs, before finally averaging over the initial uncertainty of the parameter(s) of interest takes place.

Study objectives

In the following work we apply the above calculations of EVPI and EVPXI to the BIFAW model to ascertain whether and how the addition of new information may improve the outcome of their management. To find the upper bound on the value of information we calculated the expected value of perfect information (EVPI) for the BIFAW model. We then calculated the the partial value of perfect information (EVPXI) for all transition probabilities to determine which parameters have the greatest value for learning. We also analysed a set of sampling strategies that resolved the uncertainty for multiple parameters simultaneously by calculating EVPXI for two parameters of transitions out of each system state, and two parameters of transitions for each management action (see methods section for further details). Finally we tested the effect of varying a constraint on action to see what happened to the expected value of information when the options available to a manager changed.

Methods

Predicting the outcome of management under uncertainty

The system model we used to make predictions of BIFAW management decision outcomes were multivariate adaptive regression splines (MARS) (Friedman, 1991), a regression modelling technique, fit to the output data from the state and transition models of Czembor et al. (2011). We chose to represent the state and transitions using MARS rather than run further state and transition models as the latter would be computationally infeasible given the large number of repeated model runs needed for the analyses.

The state and transition models predicted the proportion of the modelled BIFAW landscape in four vegetation states after 150 years. Again, the four states in the models were high-density regrowth (HDRG), low-density regrowth (LDRG), high-density mature woodland (HDMW), and low-density mature woodland (MLDW). The transition probabilities among these states for each of the three management actions were parameterized by five experts (Czembor and Vesk, 2009). Transition probabilities were elicited for a set of causal agents. The set of transition probabilities were different for each of the three management scenario (see Table 1 in Czembor and Vesk, 2009). Combining transition types, management scenarios, and causal agents, there were 169 different transition probability parameters elicited from each of the five experts. There were other parameter types included in the state and transition models, but for simplicity we focus solely on the transition probabilities.

The expert elicitation resulted in 375 separate estimates of each transition probability. Where for each of the 5 experts there were 75 separate estimates of each of the parameters that together represented the within expert uncertainty in transition probabilities. The distribution of the 375 estimates constitutes the initial uncertainty of the decision model in this case study as each of the 375 estimates is equally likely (see figure 2 for an example of the distribution of uncertainty for a single parameter). These estimates can be thought of as 375 alternative scenarios for the trajectory of the BIFAW over the next 150 years (much like how a climate model may produce multiple alternative trajectories of the climate into the future under different warming scenarios). Here the parameter estimates are somewhat correlated, but only between experts as there is no correlation in the parameter estimates (75 for each expert) of individual experts.

Czembor et al. (2011) used the 375 estimate sets as alternative parameterizations to simulate BIFAW forest dynamics with the state and transition modelling software package, Vegetation Dynamics Development Tool (VDDT) (ESSA Technologies Ltd., 2007) running the model ten times for each scenario. Here, we took the output from their simulations and fit MARS models for each management action separately. Again, it was only possible to approximate the state and transition models with a fast regression method as the models of each action were fitted independently and therefore where linear with respect to the application of the actions. Had the extra complexity of the additional layer of dynamism been included, then using MARS to approximate the STM models may not have been appropriate. For each of the MARS models the response ($n = 375 \times 10 = 3750$) was the proportion of the model landscape in the two mature woodland states combined. The predictors were the model parameters (including but not limited to the transition probabilities).

All analyses were done using the statistical computing language R version 3.3.2 (R Core Team, 2016) with the MARS models fit (see R code provided in supplement for the specific model parameters used) using the software package 'earth' version 4.4.7 (Milborrow. Derived from mda:mars by T. Hastie and R. Tibshirani., 2013).

Calculating the Value of Information

EVPI

To calculate EVPI we applied equations 1, 2, and 3 to the outcomes of BIFAW management predicted by MARS models for each of the 375 alternative expert-derived parameterizations (which is equivalent to the original simulated output of Czembor et al. (2011) averaged over the 10 model runs). These data can be transformed into a 375 by 4 matrix where cells hold the predicted proportion of the landscape in a mature state, with the rows representing alternative input parameter sets and columns representing the potentially optimal solutions as in Figure 1. This matrix can then be used to both calculate EVWOI and EVWPI and by extension EVPI.

To calculate the EVWOI we first average across the rows (down the columns) to ascertain the expected value of each potentially optimal solution. Then choose the solution with the maximum value and this will be the EVWOI. Calculating EVWPI requires the opposite approach. First we work with each row individually and choose the column that maximizes the value as if we knew with certainty that the particular parameter set, associated with a given row, was correct. After we have maximized the value of each of the 375 alternative scenarios, only then do we take the average of these, which will be the EVWPI. Again the EVPI is simply the difference between these values.

EVPXI

EVPXI requires a slightly more complicated algorithm. The EVWOI in equation 4, which is used to calculate EVPXI can be calculated as above. However, calculating the EVWPXI for the i^{th} parameter(s) requires the double looping algorithm which we outline in the pseudo-code in Box 1.

Box 1: Calculating EVWPXI$_i$

To calculate EVPXI for any given parameter or parameters of interest, which we will denote as the i^{th} parameter(s), we apply the following algorithm to the 375 alternative parameterizations of the 169 parameters.

For each alternative parameterization, p, from 1 to 375.

Step 1. Set parameter(s) i to parameter estimate(s) p_i.

For each each alternative parameterization, p', from 1 to 375.

Step 2. Set parameter(s) c to parameter estimate(s) p'_c.

Step 3. Predict the proportion of BIFAW in a mature state with the parameters set in steps 1 and 2.

Step 4. Record the values of each potentially optimal management strategy: $Value$.

Repeat steps 2 to 4 above for each alternative parameterization p'.

end loop

Step 5. Average the results of step 4 across each alternative parameterization p': $Mean_{s_c}(Value)$.

Step 6. Record the maximum average value from step 5: $Max_a[Mean_{s_c}(Value)]$.

Repeat all steps above for each alternative parameterization p.

end loop

Average the result of step 6 across each alternative parameterization p: $Mean_{s_i}\{Max_a[Mean_{s_c}(Value)]\}$.

Using the algorithm above we calculated the EVPXI for all 169 parameters. Using the same algorithm we then calculated the EVPXI for pairs of parameters simultaneously, such that the i^{th} parameter was now two parameters instead of one. First we took the top two most valuable transition probabilities that transition away from each of the four states and calculated their joint EVPXI. Then we did the same for the top pair of parameters for each management action. With these results we can see which state or management action it would be most beneficial to focus learning on.

Finally we recalculated the EVPI and EVPXI for all transition probabilities, this time varying the constraint on the amount of ET management allowable. This has the effect of changing the size of the feasible management region and changing the position of the two left-most vertices in Figure 1. We recalculated the EVI for a maximum allowable amount of thinning from 10 to 100% in increments of 10%.

Results

MARS approximation of the state transition model

The MARS models had good fit to the STM output data. The average cross-validated (ten-fold) R^2 was at least 93% for each of the three MARS models.

EVWOI: Optimal management in the face of uncertainty

With the original information elicited from the five experts, the optimal decision would be to put 100% of the BIFAW under the NM option regardless of the constraint applied to the ET option. Given the optimal decision is made with the original information, managers would expect, on average, to see approximately 35% of the BIFAW in a mature state after 150 years. This represents a land area of 88,462 ha, a 40,962 ha increase over the initial amount (47,500 ha, 19%) estimated by the five experts.

EVPI

If the managers of the BIFAW had perfect knowledge and could at most, thin 20% of landscape, they would expect on average to see 42% mature woodland after 150 years (which is an EVWPI of 104,276 ha). This means that the EVPI is 6% or 15,814 ha (Figure 3). For managers, this area of mature woodland represents the upper limit on what resources they should be willing to spend on improving their models of BIFAW dynamics. If the resources necessary were worth more than this amount of mature woodland to them then it would be irrational to seek to reduce the uncertainty.

In calculating EVPI the 100% NM solution was optimal 45% of the time, while the 100% HF solution was only optimal 23% of the time. Of the solutions including 20% ET, the solution including 80% NM and the solution including 80% HF, were optimal 24% and 8% respectively.

EVPXI

Of the 169 transition probabilities, most but not all, had zero or negligible EVPXI (i.e., $\text{EVWXI}_i \approx \text{EVWOI}$). Figure 3 (top panel) shows the top four most valuable parameters, while remaining parameters had EVPI $<$%1. Notably, one parameter (the probability of woodland transitioning from a low-density to a high density regrowth state, due to coppicing of tree stems, when the BIFAW is left unmanaged) was 4%. To managers, this means if they could completely resolve the uncertainty in this parameter alone, they would expect to manage the BIFAW so much more optimally that on average, they would see 9,857 ha more mature woodland in 150 years than if they managed the forest under their initial level of uncertainty.

EVI when constraint on management changes

Figure 4 shows the effect of changing the allowable amount of thinning of the BIFAW from 10 to 100%, that is, altering the constraint on the ET management option. The figure indicates that EVPI and the EVPXI of the most valuable transition probability parameter (according to the analyses in the preceding section) associated with ET increase linear as the constraint on ET is relaxed. The EVPXI of the parameters associated with other management options, in contrast, are invariant with respect to the constraint.

Discussion

The most important implication of these analyses for managers, is that the most cost-effective strategies did not include either the most desired states (mature low-density or high-density woodlands), nor what would be thought of as the least understood management strategy (thinning). As such, managers cannot just rely on intuition to tell them where the most value of information is. Critical uncertainties (those uncertainties that affect decision making) in a complex system might be not be the most variable, or the uncertainties to which outcomes are most sensitive.

We have identified those aspects of the BIFAW system model that have the greatest value for learning. If monitoring was targeted at the most valuable parameter according to the EVPXI, rather than a random parameter or even the most uncertain parameter, then the expected performance of a subsequent decision would be greater by up to 9,857 hectares of mature woodland, given the number of management options and constraint we used here, which is an average of 66 hectares per year.

We have also shown that if learning is targeted at subsets of the system, so as to update multiple parameters simultaneously, then some system states and management options would be better foci than others. This is because the uncertainty of some parameter sets is more critical to management decisions than others. Managers would be wiser to focus monitoring on areas subject to management under the HF scenario rather than ET or NM options, because learning by reducing the uncertainty in the parameters associated with those latter options would not change the decision about which management option to use as much, on average, if their uncertainty was reduced. Also, if managers chose only to monitor one system state, then learning about transitions from the LDRG state would see greater expected benefit than the other three states.

However, the value of information depends on the number and range of management options. In other words, the options available to manager can drive the value of information. The greater the number and range of management options, the greater the value of information, because the more options you have the more potential there is for learning which option is the best. Taken to an extreme, if you have only one option (i.e., no decision to make) then learning would be pointless and the value of information would be zero. In the present case, when more thinning was permitted, EVPI and the EVPXI of the parameter predicting a transition after thinning increased linearly, whereas the EVPXI of parameters not associated with thinning did not change at all (Fig 3).

We caution that, to some degree, the results we obtained for our analyses may in part be driven by limitations in the STM models, fit previous to the current work. Lacking the non-linear dynamics of action level interactions, and fitting separate models for each management action, may have led to different optimal decisions and therefore different expected values of information than if more complex and potentially more realistic approach had been taken initially. Nevertheless, a key advance we have made in this work is to formulate a process for calculating VOI for complex models with continuous expressions of uncertainty. For such models the state space is too large to make analytical integration feasible for the VOI analyses and numerical methods must be used instead.

However, such an approach can be computationally expensive with models such as state and transition models, as it is prohibitively resource-consuming to refit a complex model repeatedly. To overcome this, we represented the state and transition model with an efficient regression method (MARS) and use the output from this in our calculations of the EVI. The method we present can be used a template for VOI analyses of complex models with continuous expressions of uncertainty. Again, had a more complex STM simulation been applied initially, the MARS approximation step we used may not have been as successful.

The analyses we performed required us to make assumptions regarding the monitoring to update the parameters in the model. For monitoring to take place in the manner described, vegetation states must be able to easily be determined in the field. In addition they must be identifiable to a degree of accuracy that they can be distinguished from one another, so that a transition between states is evident and recordable after revisits occurring in a short space of time. States must not only themselves be identifiable, but the surveyor must also be able to tell that a unit of vegetation has been in a state for the required period of time, for a specific transition to occur, and that any transition that does occur has occurred due to a specific causal agent. For some transition probabilities this set of assumptions seems plausible. For instance, the transition from low to high-density regrowth due to coppicing may be simple to identify and record, whereas recognizing that a unit of vegetation remained as low-density regrowth because of combination of drought and mistletoe may be far more difficult. This problem arises because state-transition models are only supposed to represent vegetation dynamics on average and do not necessarily reflect directly observable phenomenon.

In summary we would recommend a value of information analyses be performed to inform monitoring and even decide whether it should take place at all. We have shown that it can be used to identify which parts of a complex model system are most valuable to address. Here, given the assumptions we have outlined above, managers should focus scarce monitoring resources first on the harvest management option and the low-density regrowth states. Here we have demonstrated how to overcome the challenges of implementing a VOI analysis for a complex, continuous model.

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List of Figures

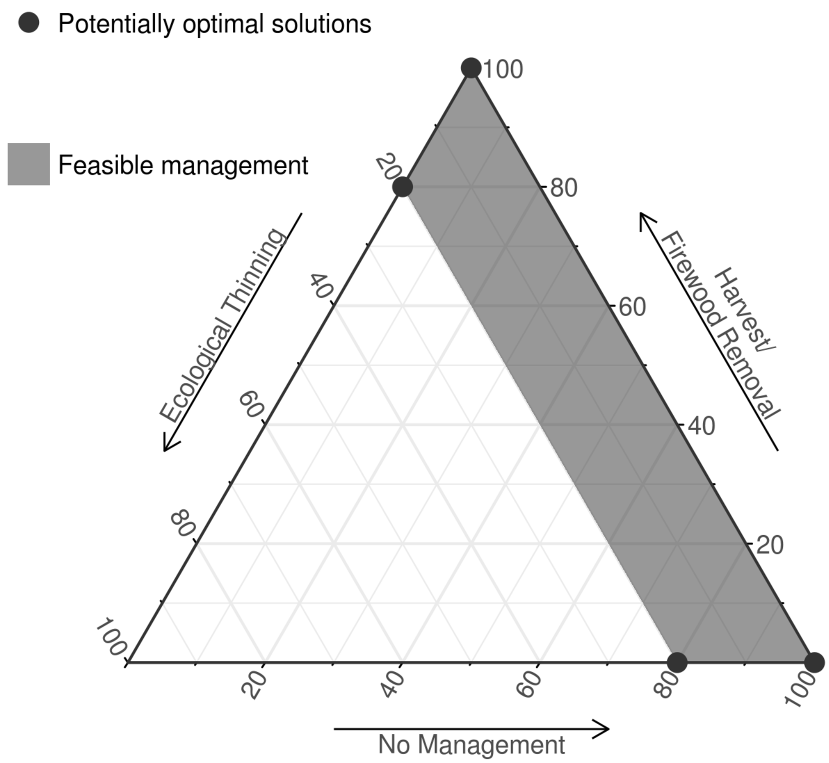
Potentially optimal solutions
Feasible management
Ecological Thinning
Harvest/
Firewood Removal
No Management
100
80
60
40
20
20
40
60
80
100
20
40
60
80
100

Figure 1

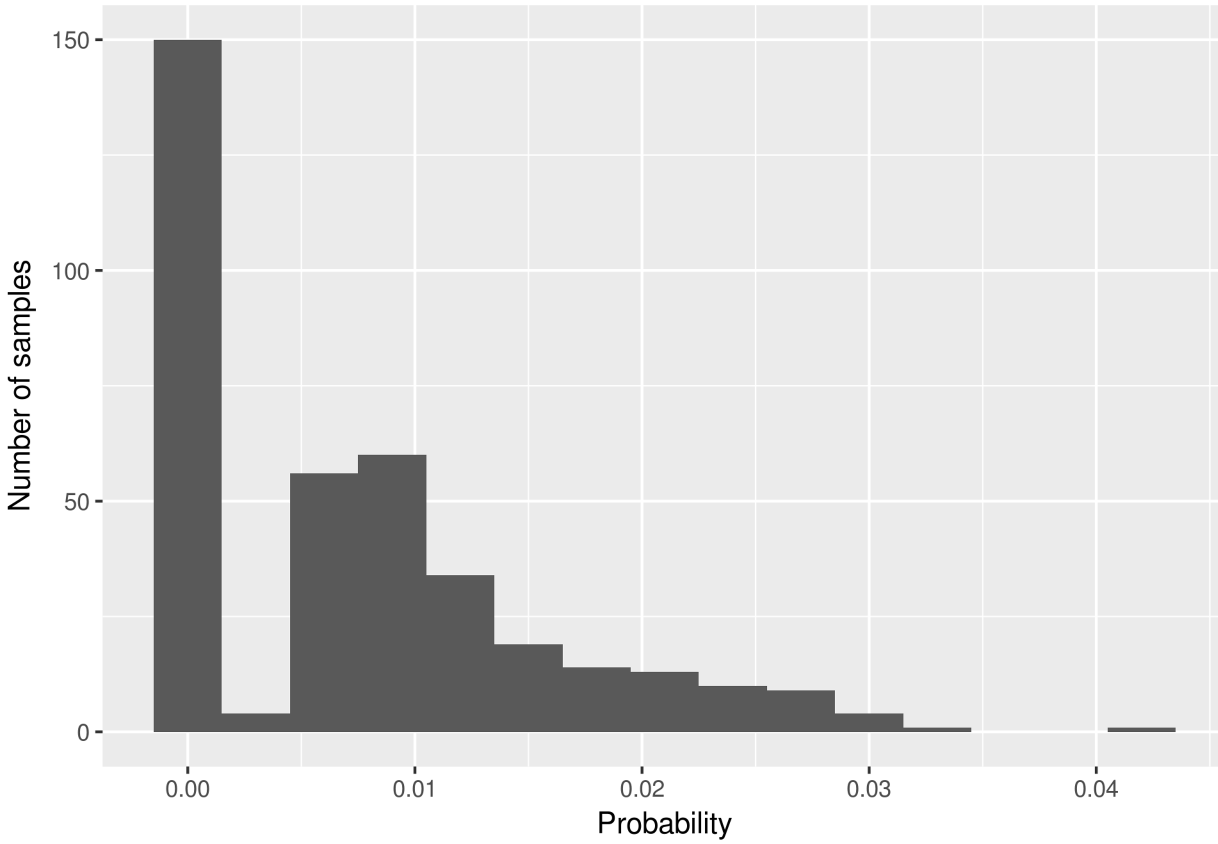
150
100
50
0
Number of samples
0.00
0.01
0.02
0.03
0.04
Probability

Figure 2

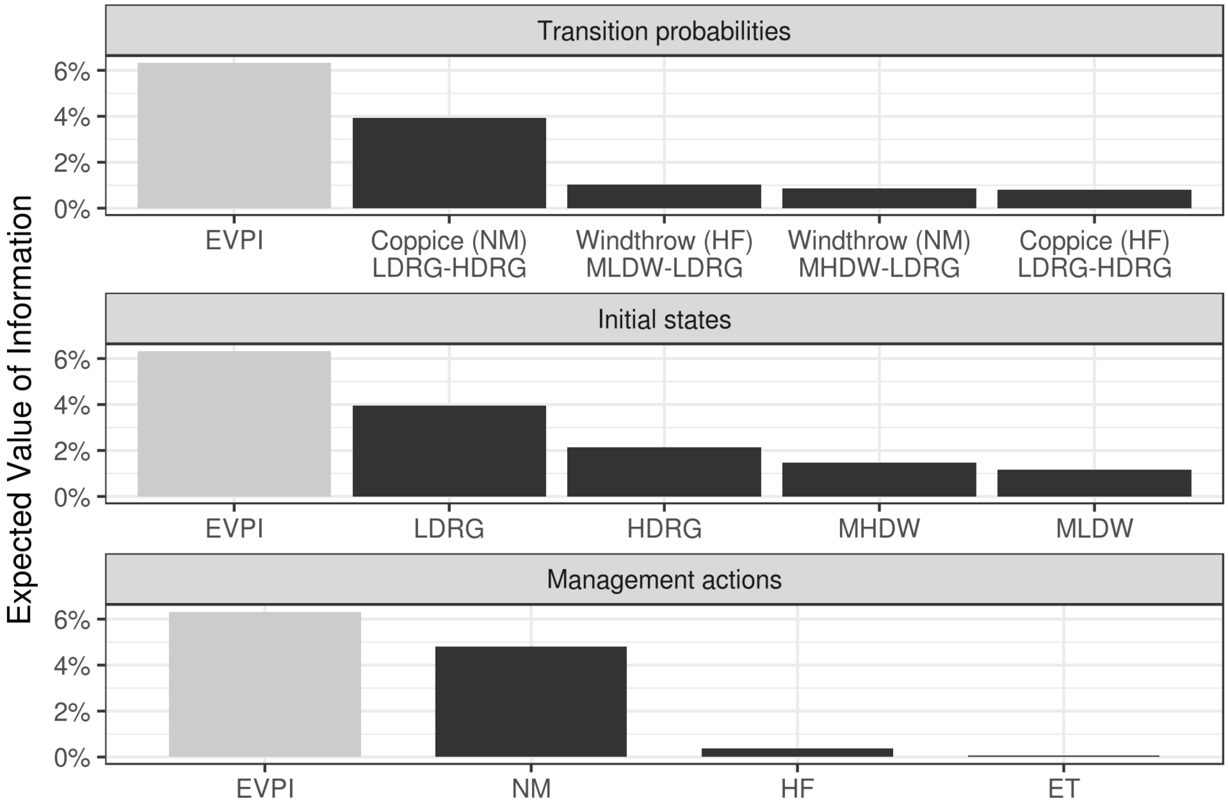
Expected Value of Information
Transition probabilities
6%
4%
2%
0%
EVPI
Coppice (NM)
LDRG-HDRG
Windthrow (HF)
MLDW-LDRG
Windthrow (NM)
MHDW-LDRG
Coppice (HF)
LDRG-HDRG
Initial states
6%
4%
2%
0%
EVPI
LDRG
HDRG
MHDW
MLDW
Management actions
6%
4%
2%
0%
EVPI
NM
HF
ET

Figure 3

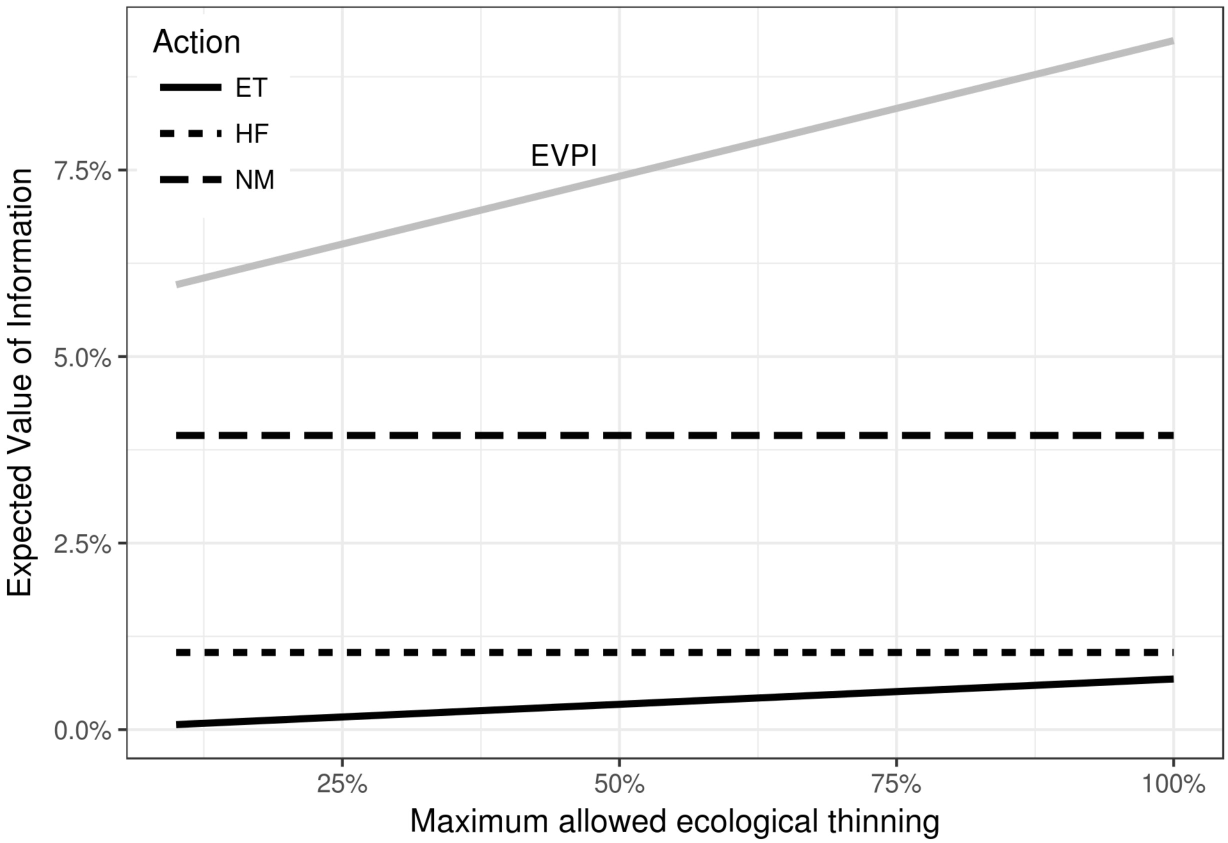
Action
ET
HF
NM
EVPI
7.5%
5.0%
2.5%
0.0%
Expected Value of Information
25%
50%
75%
100%
Maximum allowed ecological thinning

Figure 4