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

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Abstract

Value of information (VOI) analyses reveal the expected benefit of reducing uncertainty. Most ecological VOI analyses focus on population ecology and 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%. Resolving all uncertainty would, on average, increase the final percentage to 42%. 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 be dependent on the number of management options. When the number of management options increased, the value of perfect information increased linearly. However the partial value of perfect information increased at different rates for different model parameters. 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, multiplicative adaptive regression splines, decision theory, monitoring, optimization.

Introduction

Ecosystems are typically managed under uncertainty. Monitoring can reduce uncertainty and facilitate management decisions with greater expected benefits. On the other hand, sometimes it is unclear whether monitoring is necessary (McDonald-Madden et al., 2010). The decision to experiment or monitor 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 the application of VOI to 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) and have been less inclined to tackle more complex 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, are complex and highly parameterized, and often models of communities are continuous rather than discrete (i.e., uncertainty lies in the choices between discrete models as in Runge et al., 2011) making it more difficult to calculate the VOI analytically. Instead, VOI is typically estimated using numerical methods (Yokota and Thompson, 2004).

Study objectives

Management of uncertain systems can benefit from investment in learning about the system itself. But in complex systems with many parameters and multiple state variables changing at different rates, which aspects of the system should we learn about? To answer this question we undertook a VOI analysis using the state and transition models of Czembor et al. (2011). To find the upper bound on the value of information and see if there was any real value in new information we calculated the expected value of perfect information (EVPXI). 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 reduce uncertainty about multiple parameters at once by calculating EVPXI for two parameters of transitions out of each system state and two parameters of transitions for each management strategy. Finally we tested the effect of varying a constraint on action to see what happened to the expected value of information when there were more or less options available to a manager.

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. With this in mind, the value of information is conceptualized in terms of expected value. An expected value is a value a decision analyst may expect, on average, given the outcome of their decision is uncertain. Expected value is value weighted (multiplied) by probability. For example, for two equally likely events resulting in a value of one and two dollars respectively, the expected value will be one and a half dollars.

The expected value *of* information (EVI) extends this idea to uncertain information. In essence, EVI is the difference between the expected value with *new* information (EVWNI) and the expected value with *original* information (EVWOI). The expected value of information can come in a number forms depending on the form of new information. Regardless of form, all variants of VOI analyses assume decisions are being made optimally. That is, the decision analyst considers value to arise from taking actions that maximize the their 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 VOI 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). We refer to these and other related methods collectively, as EVI. 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 in 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). EVPXI is the value of knowing the exact value of one or more (but not all) parameters in a model.

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). To calculate EVWOI (working from the inside of the equation out) first average over the initial uncertainty and then take the action which maximizes value. Whereas for the EVWPI the opposite is true. First choose the action that maximizes value and only then, average this value over the initial 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:

$$\text{EVPXI}_\text{i} = \text{EVWPXI}_\text{i} - \text{EVWOI},$$

where,

$$\text{EVWPXI}_\text{i} = Mean_{s_i}\{Max_a[Mean_{s_c}(Value)]\}.$$

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.

In the following work we apply the above calculations of EVPI and EVPXI to a case study on Box Ironbark Forests and Woodland to ascertain whether and how the addition of new information may improve the outcome of their management.

Box Ironbark Forest and Woodland management

The Box Ironbark Forest and Woodland (BIFAW) region covers approximately 250,000ha 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: the 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' (hereby '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, parameterized 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, including the states most desired by land-managers, low-density mature woodland and high-density mature woodland. The models included three management scenarios, no management/natural disturbance only (NM), a scenario of limited harvest/firewood removal (HF), and thinning (ET). In 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 a set of experts as the initial state of uncertainty.

Methods

Decision problem

The fundamental objective of the BIFAW region managers are 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 or low-density) 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, allow limited harvest/firewood removal and thinning.

Therefore, for the following analyses, the optimization steps have the objective of maximizing the proportion of the BIFAW in either low-density or high-density mature woodland. Also, for the analyses that follow, we place the constraint that only 20% of the BIFAW can be 'thinned' (managers use the ET option) as a larger proportion seems infeasible. However, we also test this constraint by varying the allowable proportion of thinning from 10 to 100% (see below).

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.).

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 modeled BIFAW landscape in four vegetation states after 150 years. 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 was 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. And it is the distribution of these 375 estimates that constitutes the initial uncertainty of the decision model in this case study. These estimates can be thought of as 375 alternative scenarios for the trajectory of the BIFAW over the next 150 years. This is much like how a climate model may produce multiple alternative trajectories of the climate into the future under different warming scenarios.

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. 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 3.2.3 (R Core Team, 2015) with the MARS models fit using the software package ‘earth’ version 4.4.4 (Milborrow. Derived from mda:mars by T. Hastie and R. Tibshirani., 2013).

Calculating EVI

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 same as the original simulated output of Czembor et al. (2011) averaged over the 100 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 new 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 paramters 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_j : $Mean_{s_i}\{Max_a[Mean_{s_c}(Value)]\}$.

Using the algorithm above we calculated the EVPXI for all 169 transition probabilities. Using the same algorithm we then calculated the EVPXI for pairs of parameters simultaneously. First we took the top two most valuable transition probabilities that transition away from each of the four woodland states and calculated their simultaneous EVPXI. Then we did the same for the top pair of of parameters for each management strategy. With these results we can see which state or management strategy it would be most beneficial to focus on for learning.

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 in the position of the two left-most vertices in Figure 1. We recalculated EVI for a maximum allowable amount of thinning from 10 to 100% in increments of 10%.

Results

EVWOI

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 an amount of 20%, 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 2).

EVPXI

Of the 169 transition probabilities most, but not all, had zero or negligible EVPXI (i.e., $\text{EVWXI}_i \approx \text{EVWOI}$). Figure 2 (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 3 shows the effect of changing the allowable amount of thinning of the BIFAW from 10 to 100% on EVPI and the most valuable parameter (according to the EVPXI analysis above) for each management action.

Note that while both increase linearly as the constraint is lifted those parameters unrelated to the ET remain the same despite the change in the feasible region.

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 or 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 low-density regrowth 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 found variability in the EVPXI for parameters of the BIFAW system. Those with the greatest expected value of information were often those with uncertainty to which the system was most sensitive, but not always. Similarly, Moore and Runge (2012) found that the main drivers of willow invasion were not necessarily the same as those that there was most value in learning about. In their case, while fire frequency was a driver of invasion, it was willow tree seed dispersal that had the greatest value of information. These results highlight that for optimal decision making it is not enough to simply identify those aspects of the system to which objectives are most sensitive. In the context of decision making, the expected value of information is a better measure of sensitivity than a simple sensitivity analysis because it can distinguish between decision-critical uncertainty and mere uncertainty (Felli and Hazen, 2014).

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.

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 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 necessarily reflect 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 (if that option is on the table) 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

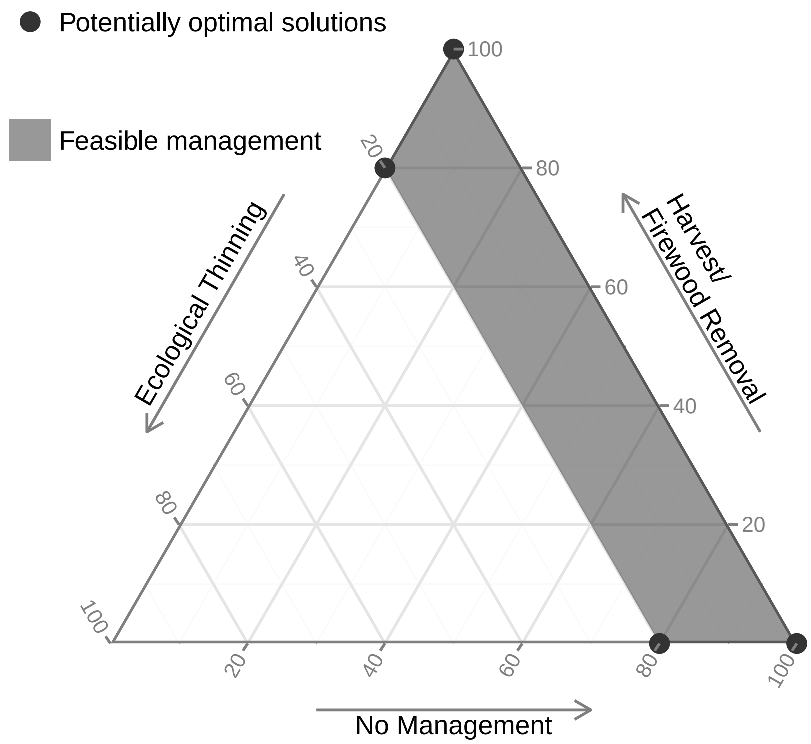
Potentially optimal solutions
Feasible management
Ecological Thinning
Harvest/
Firewood Removal
No Management
100
80
60
40
20

Figure 1

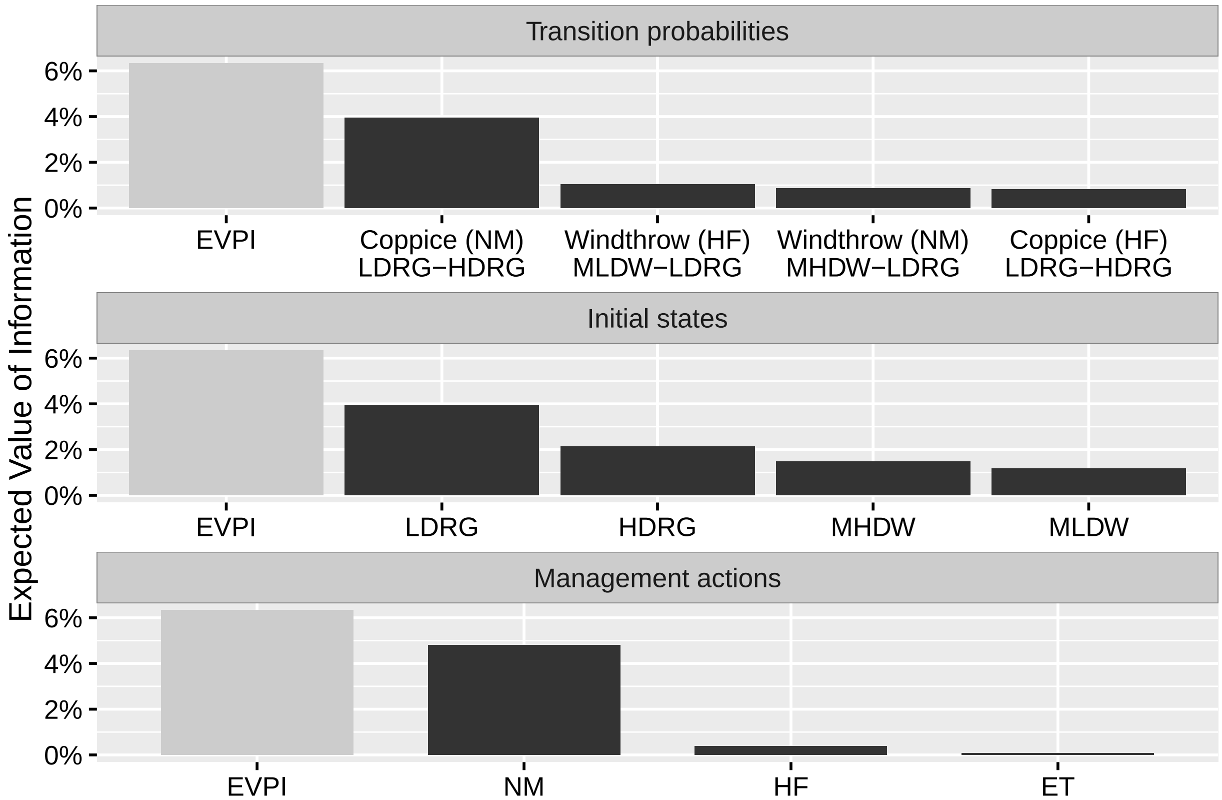
Transition probabilities
6%
4%
2%
0%
EVPI
Coppice (NM) LDRG−HDRG
Windthrow (HF) MLDW−LDRG
Windthrow (NM) MHDW−LDRG
Coppice (HF) LDRG−HDRG
Initial states
6%
4%
2%
0%
EVPI
LDRG
HDRG
MHDW
MLDW
Management actions
6%
4%
2%
0%
EVPI
NM
HF
ET
Expected Value of Information

Figure 2

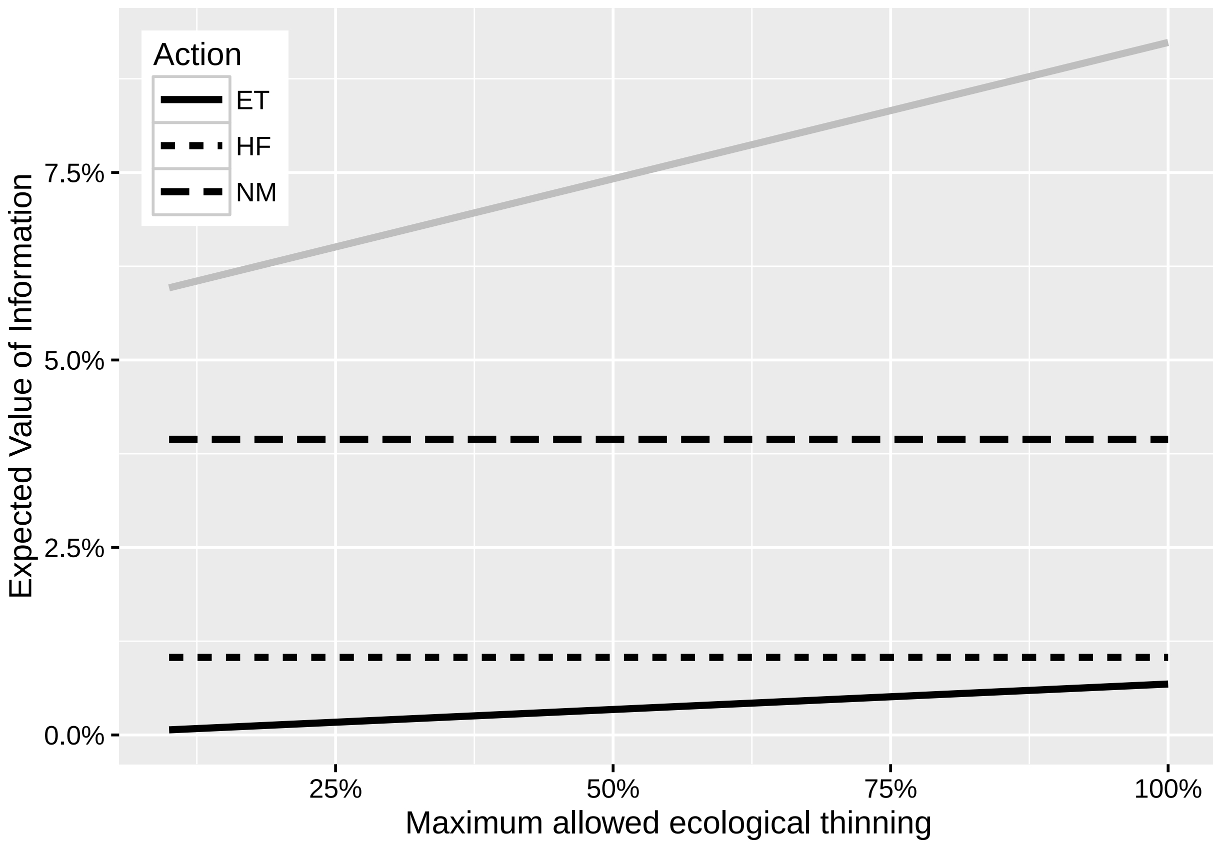
Action
ET
HF
NM
7.5%
5.0%
2.5%
0.0%
Expected Value of Information
25%
50%
75%
100%
Maximum allowed ecological thinning

Figure 3