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Combining Structured Decision Making and Value-of-Information Analyses to Identify Robust Management Strategies

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Abstract: *Structured decision making and value-of-information analyses can be used to identify robust management strategies even when uncertainty about the response of the system to management is high. We used these methods in a case study of management of the non-native invasive species gray sallow willow (*Salix cinerea*) in alpine Australia. Establishment of this species is facilitated by wildfire. Managers are charged with developing a management strategy despite extensive uncertainty regarding the frequency of fires, the willow's demography, and the effectiveness of management actions. We worked with managers in Victoria to conduct a formal decision analysis. We used a dynamic model to identify the best management strategy for a range of budgets. We evaluated the robustness of the strategies to uncertainty with value-of-information analyses. Results of the value-of-information analysis indicated that reducing uncertainty would not change which management strategy was identified as the best unless budgets increased substantially. This outcome suggests there would be little value in implementing adaptive management for the problem we analyzed. The value-of-information analyses also highlighted that the main driver of gray sallow willow invasion (i.e., fire frequency) is not necessarily the same factor that is most important for decision making (i.e., willow seed dispersal distance). Value of-information analyses enables managers to better target monitoring and research efforts toward factors critical to making the decision and to assess the need for adaptive management.*

Keywords: adaptive management, decision model, gray sallow willow, non-native invasive species, *Salix cinerea*

Combinación de Toma de Decisiones Estructurada y Análisis del Valor de la Información para Identificar Estrategias de Manejo Robustas

Resumen: *La toma de decisiones estructurada y el análisis del valor de la información pueden ser utilizados para identificar estrategias de manejo robustas aun cuando la incertidumbre sobre la respuesta del sistema al manejo es alta. Utilizamos estos métodos en un estudio de caso del manejo de la especie exótica invasora* Salix cinerea *en Australia alpina. El establecimiento de esta especie fue facilitada por incendios. Los manejadores son responsables del desarrollo de una estrategia de manejo no obstante la gran incertidumbre relacionada con la frecuencia de incendios, la demografía de* S. cinerea *y la efectividad de las acciones de manejo. Trabajamos con manejadores en Victoria para llevar a cabo un análisis de decisiones formal. Utilizamos un modelo dinámico para identificar la mejor estrategia para una gama de presupuestos. Evaluamos la robustez de las estrategias a la incertidumbre con análisis del valor de la información. Los resultados del análisis del valor de la información indicaron que la reducción de la incertidumbre no cambiaría la estrategia de manejo*

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identificada como la mejor a menos que los presupuestos incrementaran sustancialmente. Este resultado sugiere que la implementación de manejo adaptativo tendría poco valor para el problema que analizamos. El análisis del valor de la información también destacó que el factor principal de la invasión de S. cinerea *(i.e., frecuencia de incendios) no necesariamente es el mismo factor más importante para la toma de decisiones (i.e., distancia de dispersión de semillas). El análisis del valor de información posibilita a los manejadores a realizar un mejor monitoreo y esfuerzos de investigación enfocada a factores críticos para la toma de decisiones y para evaluar la necesidad de implementar manejo adaptativo.*

Palabras Clave: especies exóticas invasoras, manejo adaptativo, modelo de decisiones, *Salix cinerea*

Introduction

Decision-analysis techniques, such as structured decision making (Goodwin & Wright 2009) and adaptive management (Holling 1978; Walters 1986), provide useful frameworks for making difficult decisions and have often been proposed for the transparent, repeatable, and efficient management of ecosystems and natural resources (Shea & NCEAS Working Group on Population Management 1998; Nichols et al. 2007; Martin et al. 2009). In addition to facilitating good decision making, this approach increases understanding of the decision to be made and provides the foundation for ongoing dialogue among affected parties (Gregory & Keeney 2002).

There is often substantial uncertainty associated with conservation decisions, which makes it difficult to identify a strategy that offers the highest probability of achieving the desired objectives. Explicitly recognizing uncertainty and accounting for it in a decision analysis is critical to achieving the objectives. A particularly difficult issue is identifying when investing in learning—research or monitoring that will reduce uncertainty—is worthwhile, given that learning will most likely take resources away from and delay implementation of on-the-ground management actions. How can one decide whether it is worth investing in learning before making a decision?

A related question, for recurrent decisions, is whether adaptive management is warranted. Adaptive management couples monitoring with conservation action and allows learning that accrues from early actions to influence and improve later actions (Runge 2011). There are several schools of thought about adaptive management that differ substantially in the type of uncertainty they address (McFadden et al. 2011). The decision-analytic school focuses on uncertainty that can be explicitly articulated a priori and evaluates whether reduction of that uncertainty will improve management. The resilience-experimentalist school seeks to address not only uncertainty that can be articulated, but also uncertainty that cannot be articulated in advance and to design monitoring and management responses that can adapt to unanticipated events (Wintle et al. 2010). The decision-analytic school asks whether any uncertainty impedes the decision and then on the basis of the answer to this question determines whether adaptive management is warranted. From the perspective of the resilience-experimentalist school it is more difficult to prove in advance that adaptive management is warranted because it is challenging to evaluate quantitatively the importance of uncertainty that cannot be identified. Following the decision-analytic school, we focused on uncertainty that can be identified and used the decision-analytic framework to determine whether adaptive management is warranted.

Analysis of the expected value of information is used to evaluate whether uncertainty is important in making a decision (Yokota & Thompson 2004; Runge et al. 2011; Williams et al. 2011). Expected value of information is a well-established decision analytical tool. It has been used extensively in making medical decisions and in the design and evaluation of clinical trials (Felli & Hazen 1998; Yokota & Thompson 2004; Claxton 2008) and has been applied recently to analyses of environmental decision making (Ritchie et al. 2004; Hauser & Possingham 2008; Mantyniemi et al. 2009) and conservation problems (Polasky & Solow 2001; Moore et al. 2011; Runge et al. 2011).

The expected value of perfect information (EVPI), the most basic calculation of value of information, measures the increase in expected performance (degree to which objective is met) if one were able to resolve all uncertainty before making the decision (Yokota & Thompson 2004; Runge et al. 2011). The EVPI provides an upper bound on the improvement in performance expected as the result of resolving uncertainty and can be used to identify the level of resources (time or money) that is worth investing in resolving uncertainty (Dakins 1999; Yokota & Thompson 2004). Expected value of partial information enables analysis of how resolving different components of uncertainty affect the decision and so facilitates targeted learning to reduce uncertainty (Yokota & Thompson 2004; Runge et al. 2011).

We used structured decision making and value-of-information analyses to identify optimal resource allocations among alternative management strategies when there is substantial uncertainty regarding both the ecology of the system and the effectiveness of management alternatives. We used the control of a non-native invasive willow (*Salix cinerea*) in alpine Australia as a case study. Controlling willow in this region is challenging because invasion is facilitated by wildfire, the frequency of which is difficult to predict in this region, and understanding of the population dynamics of willows in alpine Australia is poor.

Methods

Study Species and Area

The Bogong High Plains is one of Australia's largest contiguous alpine and subalpine areas, constituting approximately 120 km^2 of treeless vegetation (Williams 1992). It includes approximately 1700 ha of alpine bogs and associated fens (hereon bogs), which are listed as endangered under the Australian Government Environment Protection and Biodiversity Conservation Act of 1999. Parks Victoria, the agency responsible for management of the Bogong High Plains, considers the invasion by gray sallow willow one of the main threats to persistence of the bogs. Effects of willow in Australia include reduction of water availability (these willows use large amounts of water compared with native species), displacement of native vegetation, and disruption of aquatic nutrient regimes (Holland-Clift & Davies 2007). The probability that willows will colonize bogs is affected by disturbance, particularly fire (McDougall 2007). In 2003, a severe wildfire burned $\sim$ 50% of the Bogong High Plains (Williams et al. 2008) and widespread establishment of willow seedlings followed.

Gray sallow willow is a multistemmed dioecious shrub willow native to Europe. It is considered one of the most invasive willows introduced to Australia. It is one of the few *Salix* species able to produce seed in Australia and can inhabit a wider variety of environments than other introduced willows (Cremer 2003; Holland-Clift & Davies 2007). It is the only willow known to have colonized Australia's alpine regions (McDougall et al. 2005). The species reproduces predominantly by seed and does not form a persistent seed bank. Seeds are wind dispersed and spread rates suggest seeds can disperse tens of kilometers (Cremer 2003). The species is also able to regenerate after fire (Karrenberg & Suter 2003).

Parks Victoria wished to identify a practical and effective long-term strategy to eradicate (or minimize) willow in bogs on the Bogong High Plains. The key decision to be made was the proportion of resources to allocate to management of existing populations of willow in bogs and to source populations of willow that may serve as sources of colonists in the future. Reducing the size of source populations may be important because the frequency of fires (and hence probability of willow establishment) is expected to increase as climate changes (Hennessy et al. 2005). There is also substantial uncertainty regarding the demographics of gray sallow willow populations and the source of the current invasion. Given this uncertainty, the management agency wished to decide where to focus control effort and whether the management strategy could be improved through learning.

Problem Framing

We worked with managers to elicit the problem context (Fig. 1; step I), objectives of management and corresponding measures of management performance (step II), candidate actions (step III), and how these actions might affect the system (step IV). We used this information to build a dynamic model that described the system and the effect of different management actions (step IV). The model included a feedback loop to ensure the management agency was satisfied that the model accurately described the problem they had defined. We used the model to identify the best management actions taking uncertainty into account (step V). We reported the results of our analyses to the management agency and they subsequently made a decision (step VI).

This framework also can be used for adaptive management if the decision is recurrent and the structured-decision process identifies critical uncertainties that, if resolved, have the potential to improve the management decision. If such uncertainties are identified, a plan for learning can be developed as part of step V, incorporated in the monitoring regime (step VI), and used to update knowledge and repeat the analysis (step VII).

Dynamic Model

We constructed a state-based dynamic model that described the ecosystem and allowed us to analyze the potential effect of management interventions (Fig. 2 & Supporting Information). Three variables described the state of the bogs (Table 1): area of bogs that were in satisfactory condition, defined here as no willows or $<$100 willow seedlings/ha (S); area occupied by $\geq$100 seedlings/ha or any density of juveniles (O); and bog contained mature willows capable of producing seeds (M). Only 2 of these variables need be monitored because the total must sum to the area of bogs. Three additional state variables described the potential for surrounding areas to contribute to the seed rain in the bogs (Table 1 & Supporting information): area containing seed-producing willow in the Bogong High Plains reaches (W, area within 10 m of a watercourse or 5 m of open water, excluding bog), area containing seed-producing willow in the high reaches (H, area within 10 m of a watercourse $<$2 km from the Bogong High Plains with a slope $>$20°), and area containing seed-producing willow in low reaches (L, area within 10 m of a watercourse $<$10 km from the Bogong High Plains, excluding area classified as high reaches).

The area of bogs that changed from satisfactory to occupied in a single growing season (September–April) depended on the size of the seed rain and the time since last fire. This change represented germination and establishment of willows in the bogs and was described by the

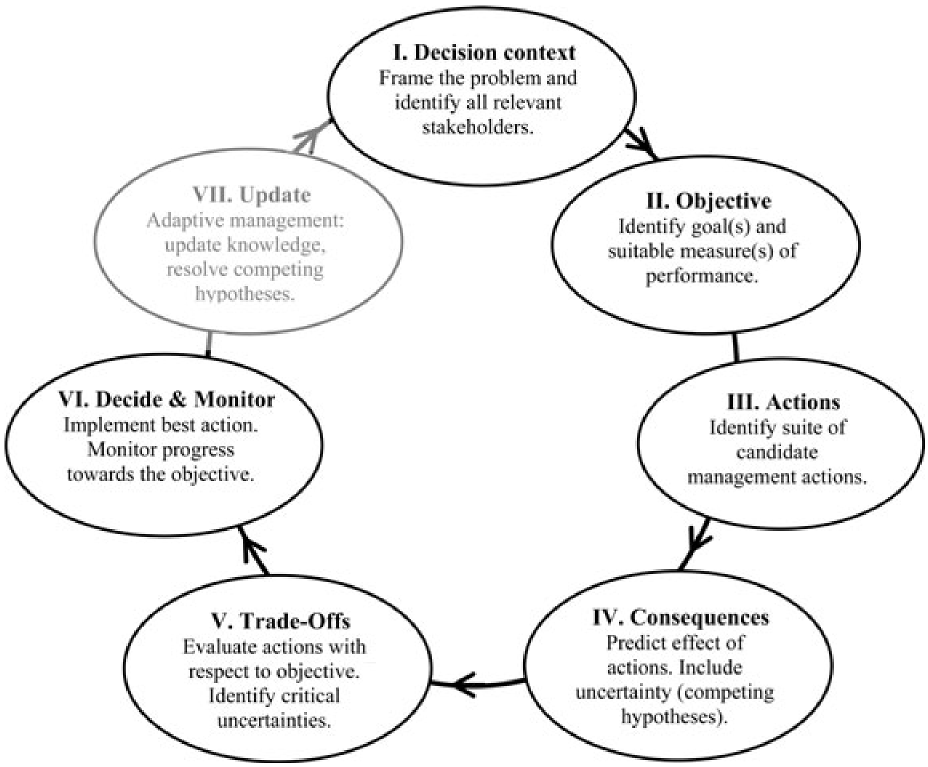

Figure 1. Outline of the key steps undertaken during a structured decision process. Steps I–III and step VI are values-based steps determined by the decision makers. Step IV and V (and VII if required) are science-based steps.

germination function $g(R,T_f)$, where R is the seed rain and T_f is the number of years since the last fire (details in Supporting Information). We assumed germination decreased as time since fire and vegetation cover increased (Table 1, fire parameters). Seed rain was the total number of seeds produced by all possible sources (Table 1, dispersal parameters): mature individuals in bogs (γ_M), in 3 management zones (Bogong High Plains reaches (γ_W), and in high (γ_H) and low (γ_L) reaches and a small contribution from an unidentified external source that we assumed could never be managed (γ_E). The number of seeds contributing to the seed rain differed for the different sources as a function of their proximity to the bogs. We assumed the seed rain fell evenly across all bogs.

The rate at which occupied area changed to mature (i.e., produces flowers) depended on fire frequency and maturation rate and was specified by the maturation function $h(T_f)$, where T_f is the number of years since the last fire and h is the proportion of individuals that mature in each time step (details in Supporting Information). We assumed willows within bogs reached maturity at a constant rate with the exception that fire resets the age of all individuals to zero.

The model also described spread of willows within and between willow-management zones (Table 1, spread parameters). The area of each willow-management zone occupied by mature willows depended on whether the source zone and any source zones that were farther away from the bogs were occupied. We assumed the area of seed-producing willow in any of the 3 source zones increased over time following a logistic function. We used a logistic function because it allowed us to represent typical patterns of colonization (Shigesada & Kawasaki 1997) and was analytically tractable. We also modeled spread from the outer to the inner management zones with a logistic function, but we did not include spread from inner to outer management zones. We assumed that each year there was a small increase in the area occupied in each zone due to immigration from an unidentified source that could not be managed.

Management strategies described the proportion of the budget allocated to control in each of the 4 management zones. We assumed the allocation was constant over time. We considered a discrete set of possible allocations: all possible combinations of 0%–100% of the budget allocated to each zone in increments of 20% for a total of 57 possible allocation strategies, including the special case of no expenditure in any zone. The extent to which controlling willows in any of the zones reduced the area occupied depended on the cost of management and the treatment effectiveness within that zone (Table 1, control parameters). The cost of control and its effectiveness differed among zones.

We represented model uncertainty as uncertainty in the parameter values and the initial conditions of the 6 state variables. We estimated the parameters of the model on the basis of a combination of data and expert knowledge (Supporting Information). The distribution of any given parameter reflected the source of the data and the degree of uncertainty associated with estimation of the parameter (Table 1). For example, there is little information on distances of willow dispersal or

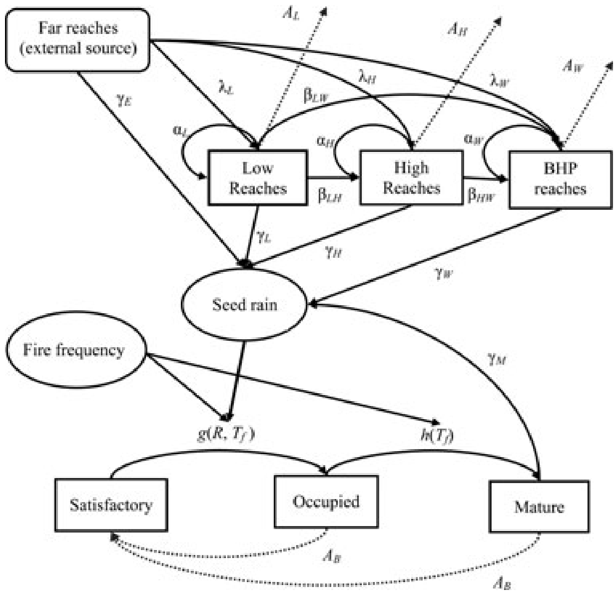

Figure 2. The key processes and links in the dynamic model for predicting gray sallow willow status on the Bogong High Plains (BHP) (Australia) and surrounding reaches (A_L, A_H, *and* A_W, *reduction in area occupied by willows due to control in the low, high, and Bogong High Plains reaches respectively;* A_B, *decrease in area of willows in the bogs due to control; remaining parameters described in Table 1; satisfactory, area of bogs unoccupied or with <100 willow seedlings/ha; occupied, area of bogs occupied by juvenile willows and seedlings (>100/ha); mature, area of bogs occupied by mature willows and seedling and juveniles).*

fire frequency. Hence, the distributions for these parameters were extremely broad, with dispersal parameters ranging over 4 orders of magnitude and average fire frequency ranging from 5 to 100 years. We based estimates of the costs and effectiveness of control on data collected December–March in 2007–2008 and 2008–2009.

To assess the effect of uncertainty on the decision, we ran the model 10,000 times with different parameter values and initial conditions selected from the relevant distribution (Table 1). For each model run, we calculated the average performance (number of years when 90% of the area of the bogs was in a satisfactory state) across the 10,000 runs of all 57 of the possible allocation strategies. The optimal allocation strategy was that which yielded the greatest average performance. We repeated the entire set of calculations for 13 budget levels ranging from 50 to 3000 work days (1 work day = 8 h including travel time and breaks). Current budgets are for 250–500 work days/year. These budgets rarely provide sufficient resources to control all willows in a single year. For example, it would require 2500–7500 work days to treat (i.e., find plants, remove stems, and apply herbicide to stumps) juvenile willows in all bogs and between 25,000 and 74,000 work days to treat the entire lower reaches.

Sensitivity Analyses

We conducted a sensitivity analysis to identify which parameters had the greatest influence on expected performance of management and a linear regression of expected performance against each parameter for all combinations of allocation strategy and budget. We recorded the R^2 statistic for each budget and allocation strategy as our measure of importance (i.e., the proportion of variation in expected performance explained by the parameter). For each parameter and allocations strategy, we calculated R^2 for the 13 budget levels. We identified focal parameters as those parameters that had R^2 values ≥ 0.05 for at least one allocation strategy and budget level.

Value-of-Information Analyses

We calculated the expected value of information to determine the effect of uncertainty on the decision. We calculated the EVPI as

$$\mathrm{EVPI} = E_s[\max_a \mathrm{Perf}(a, s)] - \max_a E_s[\mathrm{Perf}(a, s)], \quad (1)$$

where a is the management strategy (allocation of control effort to each of the 4 zones), s is a model of the system (i.e., a set of parameter values), E_s is the expected value (average) over the s models of the values in the square brackets, and Perf(a,s) is the performance associated with taking action a under model s. We calculated EVPI by recording the performance of every strategy for each of the 10,000 sets of parameters. For each parameter set, we identified the performance of the best strategy for the particular case and then averaged the 10,000 values to estimate the expected performance with perfect information (the first term in Eq. 1). The difference between this value and the expected performance given the optimal strategy (performs best on average) was the EVPI.

We also calculated the partial value of perfect information to examine the relative effect of learning about specific parameters, such as fire frequency or willow dispersal distance (Yokota & Thompson 2004). Partial value of perfect information measures the increase in expected performance if uncertainty associated with a specific process or parameter (e.g., fire frequency) is resolved and thus can be used to target learning toward processes for which reducing the uncertainty regarding the process will result in the greatest reduction in uncertainty about which management strategy is best. We calculated the contribution of certainty of values of the focal parameters (identified in the sensitivity analyses as having $R^2 \geq 0.05$) to expected performance. We ran 1000 simulations to predict the performance for 2 values of each of the 8 focal parameters in all 256 possible combinations (Supporting Information). We chose the remaining

Table 1. Parameter definitions and values used in the dynamic model used to conduct the decision analysis and calculate the expected value of perfect information.

Parameter	*Definition*	*Value*[a]
Total area of management zones		
K_L	total area of low reaches (ha)	7771
K_H	total area of high reaches (ha)	827
K_W	total area of Bogong High Plains reaches (ha)	515
K_B	total area of bogs (ha)	1701
State variables		
O	area of bogs occupied by seedling and juvenile willows (ha)	$\sim$ U(0, K_B)
M	area of bogs occupied by mature willows and seedling and juveniles (ha)	$\sim$ U(0, K_B–O)
S	area of bogs unoccupied or with < 100 willow seedlings per ha (ha)	K_B–(O+M)
W	area of Bogong High Plains reaches with source populations (ha)	$\sim$ U(0, K_W)
H	area of high reaches with source populations (ha)	$\sim$ U(0, K_H)
L	area of low reaches with source populations (ha)	$\sim$ U(0, K_L)
Fire parameters		
μ_T	mean time between fires (years)	$\sim$ U(5,100)
λ_T	bog cover recovery rate after fire (years)[b]	$\sim$ triangle(2,15,7)
Spread parameters (vary over 2 orders of magnitude)		
λ_L	rate of increase of low reaches due to dispersal from external sources (ha/year)	10 ^ $\sim$ U(−4, −2)
λ_H	rate of increase of high reaches due to dispersal from external sources (ha/year)	10 ^ $\sim$ U(−5, −3)
λ_L	rate of increase of Bogong High Plains reaches due to dispersal from external sources (ha/year)	10 ^ $\sim$ U(−6, −4)
α_L	rate of increase of low reaches due to dispersal within low reaches (ha/year)	10 ^ $\sim$ U(−2.3, −0.3)
α_H	rate of increase of high reaches due to dispersal within high reaches (ha/year)	10 ^ $\sim$ U(−2.3, −0.3)
α_W	rate of increase of Bogong High Plains reaches due to dispersal within Bogong High Plains reaches (ha/year)	10 ^ $\sim$ U(−2.3, −0.3)
β_{LH}	rate increase due to dispersal from low to high reaches (ha/year)	10 ^ $\sim$ U(−2.3, −0.3)
β_{LW}	rate increase due to dispersal from low to Bogong High Plains reaches (ha/year)	10 ^ $\sim$ U(−3.3, −1.3)
β_{HW}	rate increase due to dispersal from high to Bogong High Plains reaches (ha/year)	10 ^ $\sim$ U(−2.3, −0.3)
Dispersal parameters (vary over 4 orders of magnitude)		
γ_E	contribution to seed rain from sources external to management (seeds/ha)	10 ^ $\sim$ U(−8, −4)
γ_L	contribution to seed rain from low reaches (seeds/ha)	10 ^ $\sim$ U(−5, −1)
γ_H	contribution to seed rain from high reaches (seeds/ha)	10 ^ $\sim$ U(−4, 0)
γ_W	contribution to seed rain from Bogong High Plains reaches (seeds/ha)	10 ^ $\sim$ U(−3.6, 0.4)
γ_M	contribution to seed rain from mature bogs (seeds/ha)	10 ^ $\sim$ U(−3.6, 0.4)
Establishment and growth parameters		
b_{1R}	effect of bog cover on willow establishment (ha/seed)	$\sim$ U(0.1,0.5)
b_{2R}	mean seed rain for willow establishment (seeds/ha)	$\sim$ U(0,50)
b_{1M}	willow maturity function parameter (1/year)	$\sim$ U(0.5,2.5)
b_{2M}	mean age of willows at maturity (years)	$\sim$ triangular(2,10,6)
Control parameters		
c_L	cost of treating 1 ha of willows in low reaches (work days/ha)	$\sim$ U(3.17,9.51)
c_H	cost of treating 1 ha of willows in high reaches (work days/ha)	$\sim$ U(3.17,9.51)*5
c_W	cost of treating 1 ha of willows in Bogong High Plains reaches (work days/ha)	$\sim$ U(3.17,9.51)
c_O	cost of treating 1 ha of juvenile willows in bogs (work days/ha)	$\sim$ U(1.44, 4.32)
c_M	cost of treating 1 ha of mature and juvenile willows in bogs (work days/ha)	$\sim$ U(3.17,9.51)
δ_L	treatment effectiveness in low reaches (work days/ha)	$\sim$ beta(65,27.7)
δ_H	treatment effectiveness in high reaches (work days/ha)	$\sim$ beta(65,27.7)
δ_W	treatment effectiveness in Bogong High Plains reaches (work days/ha)	$\sim$ beta(65,27.7)
δ_O	treatment effectiveness for juveniles in bogs (work days/ha)	$\sim$ beta(3.56,1.87)
δ_M	treatment effectiveness for mature and juveniles in bogs (work days/ha)	$\sim$ beta(65,27.7)
Management variables (do not vary)		
Time horizon	number of years for which management is optimized	200
Target	management target – proportion of bog area in satisfactory condition	0.9
Budget	annual budget available for management (work days)	50–3000

[a] *Drawn from an underlying probability distribution for each of the 10,000 simulations: U, uniform distribution; beta, beta distribution; triangular, triangular distribution. Dispersal parameters are from uniform distributions on a logarithmic scale.*
[b] *Time taken for bog to return to prefire cover.*

parameters from the distributions described previously (Table 1). We calculated the partial value of perfect information as

$$\begin{aligned}\mathrm{EVPXI} = E_{s_i}[\max_a E_{s_i^c}[\mathrm{Perf}(a, s_i, s_i^c)]] \\ - \max_a E_{s_i, s_i^c}[\mathrm{Perf}(a, s_i, s_i^c)],\end{aligned} \quad (2)$$

where s_i is a subset of the models and s_i^c is its complement. In the case study, s_i is the set of focal parameters that are resolved and s_i^c is the set of parameters that remain uncertain. We also considered all pairwise interactions between the 8 focal parameters by calculating the contribution that knowledge of 2 of the parameters at a time contributed to expected performance.

Results

Problem Framing

The managers identified 2 primary objectives: protect the integrity and function of alpine bogs on the Bogong High Plains through reduction of gray sallow willow and minimize resources allocated to reducing abundance of willow in alpine bogs. The objective was to protect the bogs rather than the more general protection of vegetation on the Bogong High Plains. Managers were unable to make a quantitative link between bog condition and willow abundance and so the decision analysis focused on reducing willow abundance in bogs (a means objective) as a proxy for improving bog condition (a fundamental objective).

Managers developed 2 measures of performance associated with the 2 objectives: expected number of years over the next 200 years for which at least 90% of the area of bogs is in satisfactory condition (<100 seedlings/ha) and number of work days/year allocated to willow-reduction activities.

Managers identified direct control of willows as the major management action available to them, and the question was where this effort should be allocated. They identified 4 zones in which willow control could be carried out: bogs, Bogong High Plains reaches, high reaches, and low reaches (Table 1). These zones were identified on the basis of differences in their perceived ability to contribute willow seed to bogs through wind dispersal and the ease and cost of willow control. There was no natural boundary to define the extent of the low reaches. A 10-km radius around the Bogong High Plains was identified as the extent of the low reaches because this area included the majority of past control effort undertaken to minimize seed rain onto the Bogong High Plains and was a likely limit on where further control effort would be applied in the future.

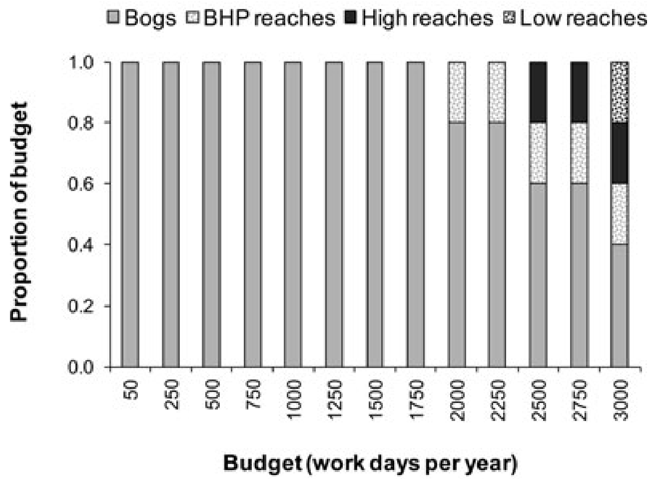

Figure 3. Optimal allocation of willow-control effort across the 4 management zones to maximize expected performance for 13 budget levels (bogs, alpine bogs on the Bogong High Plains; BHP reaches, areas within 10 m of a watercourse or 5 m of open water on the Bogong High Plains, excluding bogs; high reaches, areas within 10 m of a watercourse within 2 km of the Bogong High Plains with slope >20°; low reaches, areas within 10 m of a watercourse within a 10-km radius of the Bogong High Plains, excluding high reaches).

Decision Model

The optimal allocation of management effort among the 4 management zones depended on the budget. The optimal strategy was to allocate all available effort to the bogs until the budget exceeded 2000 work days/year (Fig. 3). Once budgets reached this limit the optimal strategy included the allocation of some effort to eliminate potential source populations. Effort was allocated to the closest populations (Bogong High Plains reaches) first and then to more distant reaches as the budget increased.

As the resources invested in management increased so did expected performance, but the relation was nonlinear and showed diminishing returns (gain in expected performance) as budgets increased (Fig. 4). The model predicted that on the basis of current investment levels the condition of the bogs would be satisfactory in approximately 80 (40%) of the next 200 years (Fig. 4). The broad 90% quantiles indicated substantial uncertainty in the effectiveness of management associated with uncertainty in the model parameters. For example, an investment of 500 work days could result in complete failure (no years in satisfactory condition) or could be highly effective (condition satisfactory in 92.5% of years), depending on the values of the parameters. The greatest efficiency (improvement in bog condition for dollar spent)

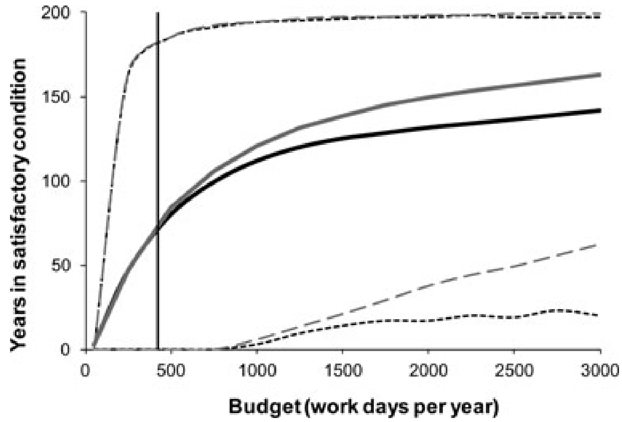

Figure 4. Expected performance of the optimal management strategy with and without perfect information (solid black line, expected performance of the optimal strategy in controlling willow given current knowledge [10,000 parameter combinations equally weighted]; dashed black lines, 90% quantiles; solid gray line, expected performance of the optimal strategy in controlling willow if parameter values are known before allocating effort (indicates how much performance could be improved if information were perfect); difference between the lines, expected value of perfect information; dashed gray lines, 90% quantiles for perfect information; vertical line, resources allocated to control of willow in 2008–2009).

would occur if about 1000 work days were invested, although it was still uncertain that the objective could be achieved.

Sensitivity and Value-of-Information Analyses

Overall R^2 values were small, indicating that no single parameter explained the majority of the variation in performance. Eight focal parameters had an R^2 value ≥ 0.05 for at least one allocation strategy and budget level (Supporting Information). Expected performance was most sensitive to changes in fire frequency. This sensitivity explained approximately 3 times more variance than any other parameter, and management was more likely to succeed when fires were infrequent. Other parameters that had a lesser effect on expected performance were the recovery rate of the bogs after burning and the seed dispersal rates from the 3 source areas. For large budgets, mean seed rain for willow establishment was also correlated with expected performance. For small budgets, expected performance was also affected by the cost of controlling mature willows in bogs and the initial area in satisfactory condition.

Calculation of EVPI for willow management indicated that for small budgets, resolving uncertainty in the parameters did not increase expected performance (Fig. 4). Thus, the optimal allocation was the same irrespective of the parameter values. As budgets increased, value of information increased. These increases indicated the optimal allocation depended on the parameter values; thus, reducing uncertainty could improve expected performance. The EVPI was greatest when budgets were large (2500–3000 work days), indicating that learning about the parameters could potentially improve expected performance by 10%.

Partial value-of-information analyses showed that for large budgets, resolving uncertainty regarding the contribution of the reaches to the seed rain resulted in the largest increase in expected performance (2%–3.5% increase in performance [Supporting information]). The remaining parameters we examined had negligible expected value of partial information values (<0.1%) for all budgets. There was little evidence of interactions between the different parameters. Knowing the value of 2 parameters did not improve performance beyond that associated with knowledge of the 2 parameters separately.

Discussion

We identified clear and robust recommendations regarding the most effective long-term strategy for managing colonization of bogs by a non-native willow in Australia. The first priority is to manage willow populations in the bogs and to allocate effort elsewhere only when budgets are large. Although the optimal management strategy is intuitive, it does not address the cause of the willow invasion. Addressing the cause is not feasible with the resources available.

The structured decision-making process clarified that the management objective was to protect the threatened bog communities rather than control willows across the region. The decision analysis emphasized the need to focus control effort on the threatened bogs, which has resulted in a reduction of effort allocated to treating sources of willow (previously 60% of effort) and a policy of treating sources as close to the bogs as possible. Clarifying objectives and identifying performance measures also resulted in the development of a monitoring program to track changes in willow abundance over time.

The value-of-information analyses revealed that learning about the system is unlikely to improve the ability to manage willows unless current budgets are increased substantially. The increase in performance if information is perfect is negligible for small to medium budgets because the same strategy (treat bogs) is optimal across wide parameter ranges. When budgets are large, resolving uncertainty could improve expected performance because how control effort should be allocated depends on the parameter values. For large budgets, reducing uncertainty regarding dispersal distance is most important—the greater the dispersal distance, the more effort should be allocated to the source populations.

Our case study highlights that the processes important in regulating the system (fire frequency) are not necessarily the most important to the decision (seed dispersal). This is because management interventions are not available to mitigate wildfire. We would expect similar results for other systems regulated by large disturbance events, including wildfires, storms, and floods, if the key driver (or its effect) is beyond the control of management. Value-of-information analyses are useful because they guard against investment in research on processes that, although important drivers of the system, may have little effect on the management decision. Calculating the EVPI allows one to evaluate how information will inform the decision (Runge et al. 2011) and ensures that maximum value is gained from the investment.

Although value-of-information analyses are useful for identifying critical uncertainties, the results are sensitive to the objective function used in the analyses and the range of management actions considered (Hauser & Possingham 2008; Letson et al. 2009; Mantyniemi et al. 2009). Value-of-information analyses are also sensitive to the model used to describe the system and to the description of uncertainty (e.g., probability distribution used). Hence, conclusions may change if one substantially alters the model or the parameter distributions (Mantyniemi et al. 2009; Runge et al. 2011).

Although the most effective management strategy was clear, the substantial uncertainty about the effectiveness of the strategy poses challenges in deciding how much effort to allocate to willow management. The needed budget depends on the objective of management and the level of performance required. The considerable uncertainty in the expected performance (even when the optimal management strategy is implemented) indicated there were situations where any of the proposed management interventions would fail. This uncertainty makes it difficult to justify budget allocations to willow management when there are competing demands for resources. Improving understanding of fire frequency, bog recovery rates, and dispersal from source populations would contribute most to informing decisions about budget allocation to willow.

Adaptive management is warranted when decisions are recurrent (hence, learning can be applied to subsequent decisions) and uncertainty impedes the decision (i.e., there is a high value of information) (Williams et al. 2011). The problem of choosing a management strategy for controlling willow is indeed recurrent; the management agency can revisit this decision annually. However, our EVPI analyses showed there were no critical uncertainties that impeded this decision. Thus, adaptive management of resource allocation among willow-management zones was not needed, at least at current budget levels. We recognize this challenges the common wisdom in conservation biology that adaptive management is a normative concept (Callicott et al. 1999). But recognizing that staff and fiscal resources are scarce, an investment in adaptive management is only warranted when the benefits of improved information offset the costs of acquiring it. In a decision context, information is only valuable if it helps distinguish among possible courses of action. In this case, the best control strategy was not affected by the uncertainties we investigated, so adaptive management to address these uncertainties was not warranted.

Two caveats should be considered, however. First, the value of information is specific to the context of a decision, so adaptive management may be warranted for a different decision regarding willow management. For example, a structured decision-making process to address allocation of management effort among a suite of non-native invasive plant species is also underway. This process may well need to be adaptive because the uncertainty of the effectiveness of willow control could affect the optimal budget allocation. Second, adaptive management is sometimes advocated as a way to discover and respond to unanticipated events. Perhaps there are other uncertainties, which did not occur to either us or managers, that may affect the choice of a control strategy for willows. Should a monitoring program be implemented to detect these unanticipated events and how much should be invested in such a monitoring program? These questions cannot be answered logically because the degree of investment depends on the nature of the uncertainties, which, by definition, cannot be articulated. We believe the way to approach this situation is to work harder to define possible uncertainties and then analyze the expected value of information associated with them. Emphasis on monitoring for unanticpated events is an alluring path to overinvestment in monitoring.

As with any model, the results of our analyses reflect assumptions about how the system works. Three assumptions may have affected our results. First, we assumed that seed from source populations was equally likely to reach the bogs from any direction. However, there are strong prevailing winds at the time of seed release, and some managers believe source populations to the northwest of the Bogong High Plains contribute most to the seed rain. We reran the analyses under the assumption that the potential area of seed source from low and high reaches was one-quarter of the total considered. The pattern remained the same, but allocation of control effort to source populations occurred at lower budget levels (Supporting Information).

Second, our model was spatially implicit and did not examine how effort should be targeted within each of the 4 management zones. Allocation of effort across the Bogong High Plains (bogs and Bogong High Plains reaches) has been addressed in a separate model (Giljohann et al. 2011).

Third, we assumed allocation was constant regardless of the state of the system (e.g., time since fire, area colonized). We expected that the development of state-dependent management strategies would be a clear next step in refining the strategy. However, the robustness of the optimal strategy and the very low value of information suggest to us that there is little room for improvement in management performance because resources to treat the source populations are not currently available. Doing a full analyses of state-dependent strategies (e.g., using stochastic dynamic programming) would be a substantial computational challenge and require a large amount of research effort. We have experimented with some sensible state-dependent strategies that show there is little prospect for improvement given current budget levels (Supporting Information).

Decision analyses are being increasingly applied to conservation decisions (e.g., Szymanski et al. 2009; Walshe & Slade 2009; Blomquist et al. 2010). The step from analyses to implementation is often the slowest, so it is useful to reflect on the circumstances that facilitated the implementation by managers of this particular example. In part, we believe it was because the simplicity of the solution led to very clear recommendations. The workshop also engaged managers in the processes of modeling and analyses. The managers trusted the results of the model because the model reflected the problem defined in the workshop. Despite enthusiasm from managers, it took approximately 18 months for the results to be fully integrated into the management process. Although managers started to allocate increased effort in bogs in the 6 months following dissemination of the workshop results, it was not until the second control season (December 2011 to March 2012) that all control effort was allocated to bogs. We suspect the unappealing nature of the solution—focusing on effects rather than causes—contributed to the delay. Subsequent discussion with managers revealed that uptake of the decision was initially slow because the managers had to discuss the results with the analysts and consider how the results affected their annual management decisions.

Structured decision making and value-of-information analyses can be applied to making any decision. To encourage uptake, we recommend continued and ongoing face-to-face communication to discuss the analyses with managers.

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Supporting Information

Description of the dynamic model used in the analyses (Appendix S1), methods used to estimate model parameters (Appendix S2), additional details associated with sensitivity analysis and partial value of information analysis (Appendix S3), and details of analysis of alternative scenarios (Appendix S4) are available online. The authors are responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author.

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