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Implementing backcasting for conservation: Determining multiple policy pathways for retaining future targets of endangered woodlands in Sydney, Australia

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ABSTRACT

Developing conservation policy is a challenging process, often impeded by a lack of clear objectives and a limited understanding of the pathways to achieve them. Here, the utility of target-based 'backcasting' is demonstrated for developing effective conservation policies. Backcasting encodes social values by requiring a desired future state be selected as a target; it then involves searching for multiple pathways to reach this state from the present. This approach is demonstrated with a case study examining policy options for mitigating impacts from the growth of Sydney on a critically endangered woodland community. A model was developed to predict changes in woodland area over time in response to a range of processes: declines in habitat condition; legal and illegal clearing for development; and the implementation of biodiversity offsets to compensate for clearing. Using a target of retaining 60% of the current woodland distribution in 50 years time, the backcasting analysis involved searching for all combinations of processes that would achieve this target. Results demonstrate how backcasting provides a structured way to explore the trade-offs and robustness of combinations of policy interventions leading to a desirable future. For this case study, the most viable way of achieving the target may be to ensure the offset policy is adequate and enforced. If this was not feasible, the analysis shows that reducing the rate at which habitat is declining in condition would be most important in opening up other policy options. This study provides the first quantitative demonstration of backcasting in a conservation context.

1. Introduction

A pervasive problem in the global attempts to conserve biodiversity is evaluating the extent to which conservation focused policies achieve their goals (Bennear and Coglianese, 2005; Ferraro and Pattanayak, 2006). There are many reasons why this poses such a challenge, including factors internal to the policy development cycle such as poorly defined objectives or a lack of political will for accountability (Ferraro and Pattanayak, 2006). External factors pose an even greater challenge and include the temporal delays between policy interventions and on-ground outcomes, uncertainties in the baseline data from which to measure performance and a lack of resources to monitor outcomes at appropriate temporal and spatial scales (Bull et al., 2014; Bottrill et al., 2011; Griscom et al., 2009).

Together, these factors complicate the policy development cycle and often result in traditional ex-post evaluations of policy outcomes being unfeasible. They also add considerable uncertainty in determining how existing conservation-focused policies should be refined, or how new policies should be structured. A number of approaches have been proposed to help address these issues including scenario analysis, adaptive approaches and resilience thinking (Peterson et al., 2003; Groves and Lempert, 2007; Polasky et al., 2011). Here, it is proposed that 'backcasting' is added to this list as a complementary and under-utilised approach for supporting the development of effective conservation policies.

'Backcasting' has different meanings across fields of science and was first used as an alterative to forecasting in the early 1980s for developing energy policy (Robinson, 1982). However the origins of backcasting go back further to the 1970s when Amory Lovins proposed a 'backwards-looking-analysis' to overcome difficulties in long-term energy forecasting (Robinson, 1982). An interesting aspect of backcasting is that it is an explicitly normative approach in that it involves defining a *desired* future state as a target, and then determining multiple pathways to traverse from the current state to the future state (Dreborg, 1996). It can be thought of as temporally opposite to forecasting, which involves extrapolating current trends and is often used with scenario analysis (Cinq-Mars and Wiken, 2002). One of the strengths of the backcasting approach is that it

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is explicitly based on searching out multiple pathways to meet future objectives, and can thus encourage a broader view of relevant factors, leading to the systematic consideration of options that may not otherwise be considered 'feasible' (Manning et al., 2006).

There have been numerous interpretations of backcasting (Holmberg, 1998; Höjer and Mattsson, 2000; Vergragt, 2005) and although the technique has significant potential in a conservation context, its use to date has been limited and qualitative. These qualitative approaches have proposed using backcasting for planning ambitious restoration projects (Manning et al., 2006), as a tool for participatory scenario planning (Palomo and Montes, 2011) and for determining general incentives for ecosystem conservation (Cinq-Mars and Wiken, 2002).

Here, a quantitative example of target-orientated backcasting (Wangel, 2011) is presented (henceforth referred to as "backcasting") using a case study examining policy development to mitigate biodiversity impacts from the growth of Sydney, Australia. The utility of backcasting is demonstrated in a modelling context by exploring multiple policy options likely to meet future conservation targets for retaining critically endangered woodlands on the Cumberland Plain to the west of Sydney.

2. Methods

2.1. Study area

The Cumberland Plain Shale Woodlands and Shale-Gravel Transition Forest ecological community (henceforth referred to as "CPW") occurs primarily to the west of Sydney, in the state of New South Wales (NSW), Australia. This threatened ecosystem has been extensively cleared for agriculture and urban development. Its pre-1750 coverage was estimated to be 125,450 ha, and now 9% (10,726 ha) of this original area is estimated to remain (State of New South Wales, 2011). Less then 10% of the current CPW extent is represented in formal conservation reserves with the remainder occurring predominantly on private land (State of New South Wales, 2011). As the CPW community is now listed as "critically endangered" under the Australian Government's Environment Protection Biodiversity Conservation (EPBC) Act (Commonwealth of Australia, 2009), actions impacting the community are only subject to approval under specific conditions.

To meet Sydney's projected population growth, expansions of two Urban Growth Centres are planned, which includes the development of areas that will result in clearing significant amounts of CPW over the next 30 years (State of New South Wales, 2010). To compensate this loss, "biodiversity offsets" (Bull et al., 2013) will be implemented inside and outside the Growth Centres, resulting in CPW being protected and managed. The intention behind the offsets is that the gains in ecological condition and the avoided clearing of CPW will "offset" the clearing of CPW for urban development (Gordon et al., 2011). These offsets are required under both NSW state legislation (State of New South Wales, 2010) and the EPBC Act (Commonwealth of Australia, 2012). Additional background is given in Appendix A.

In addition to urbanisation, there are other threats to the remaining CPW. The most significant being legal and illegal clearing of vegetation outside the Growth Centres and the decline in ecological condition of the community due primarily to invasive plant species such as the African Olive and African Love Grass (State of New South Wales, 2011).

2.2. Modelling the change in CPW over time

A model developed to predict changes in CPW extent over time was written in *python* using a new open source modelling framework entitled *Tzar* (Gordon et al., 2013). Construction and parameterisation of the model was undertaken by utilising the expert opinion and data obtained from relevant experts within in two Australian Government Departments: the Environment Assessment and Compliance Division of the Federal Department of the Environment, and the NSW Office of Environment and Heritage. Further details are given in Appendix A.

The model predicts changes in the total area of CPW over time for the next 50 years in one-year time steps and incorporates the development and offset processes. Six land-use categories were used in the model (Table 1), and these categories determined where clearing and offsets could occur and how the condition of the CPW would change. The initial areas of CPW in each land-use category are given in Table A2 of Appendix A.

The scenario modelled here meets requirements for both NSW State legislation and Federal legislation (the EPBC Act). For each parcel developed the EPBC Act allows for half the CPW on the parcel to be cleared, provided an offset comprising twice the area of the cleared CPW is implemented. As the remaining CPW on the parcel can count towards this offset, a parcel with an area A of CPW can have $A/2$ cleared with an offset consisting of $A/2$ retained on the parcel and $A/2$ of CPW protected outside the Growth Centres. The relevant NSW state legislation is the State Environmental Planning Policy (SEPP; State of New South Wales, 2006). Over the next 30 years the SEPP and the EPBC Act together allow 594 ha CPW to be cleared within Growth Centres. The SEPP specifies that 518 ha CPW will be included as offsets within the Growth Centres and an additional 594 ha of CPW need to be implemented outside the Growth Centres to meet the EPBC Act offset requirements.

2.2.1. Modelling declines in CPW condition

Although there are good estimates of the current extent of CPW (NSW Scientific Committee and Simpson, 2008), there is limited information about its current condition or the rate at which its condition is declining. As there is strong evidence (State of New South Wales, 2011) combined with expert opinion that habitat decline is occurring, a habitat decline process was included in the model. Due the lack of information, no assumptions were made about the condition dynamics of any of the CPW apart from the fact that each year a fixed proportion, d, degrades to a level where it is no longer classified as CPW (or where it is not economically viable to restore; Table 2). Apart from the *protected* and *offset* land uses where CPW is assumed to be managed (Table 1), all remaining CPW is subject to this decline. For an area of unmanaged CPW, A, the decline of CPW in time step $t+1$ given by

$$A_{t+1} = A_t - d \times A_t, \quad 0 \leqslant d \leqslant 0.02. \tag{1}$$

Expert estimates of the upper plausible bound of parameter d was 0.02, resulting in a loss of 2% of the unmanaged CPW per year (Table 2). The actual value for d will depend on both the distribution of the current condition of the patches of CPW, as well as the rate at which they are degrading. This approach is effectively modelling the lower tail of the condition distribution, where d determines that rate at which CPW "drops off" from being in low condition to no longer being assumed to be CPW.

2.2.2. Modelling clearing and offsets

The loss of CPW each time step is given by two terms: $A_t^{dev,oGC}$ and $A_t^{dev,iGC}$ representing the area of CPW cleared outside and inside the Growth Centres, respectively. $A_t^{dev,oGC} = c$, which can be expanded to

$$A_t^{dev,oGC} = p \times c + (1 - p) \times c \tag{2}$$

while

Table 1
A description of the landuse categories used to model the change in area of CPW over time.

Landuse category	Description
Protected	Existing conservation reserves, not available for clearing. CPW assumed managed and the habitat condition of CPW occurring here does not decline over time
Secured	Land owned by the Commonwealth Government, not available for clearing. CPW assumed unmanaged and the condition of CPW occurring here does decline
Undevelopable	Land inside the Growth Centres that cannot be cleared or offset (such as flood prone areas). CPW assumed unmanaged and condition of CPW occurring here does decline
Developable/ developed	Land that is available for clearing (unmanaged, CPW condition declines)/has been cleared for development (CPW is removed)
Offsettable/offset	Land that is available for offsets (unmanaged, CPW condition declines)/land that has been used as an offset and the CPW is assumed managed and does not decline in condition

Table 2
Description on the four policy parameters used in the model. The parameter range specifies the upper and lower plausible values estimated by available evidence and/or expert opinion (Table A1, Appendix A). The step size indicates the size of the increment used to iterate over parameter values between the upper and lower plausible bounds.

Parameter name	Symbol	Description	Parameter range	Step size
Degradation rate	d	Yearly proportion of CPW that declines in quality to a level where rehabilitation is considered unviable	0–0.02	0.002
Clearance rate	c	Yearly area of CPW cleared (legally and illegally) outside Growth Centres	20–75 ha/year	5
Proportion of clearing requiring offsets	p	Proportion of CPW outside the Growth Centres that is legally cleared and results in biodiversity offsets	0–1	0.1
Offset multiplier	m	Offset area multiplier required for CPW cleared outside the Growth Centres (e.g. $m = 2$ means that 4 ha of CPW is required to be protected for every 2 ha cleared)	0.5–4	0.5

$$A_t^{dev,iGC} = \begin{cases} 19.8\ \text{ha/year}, & t \leqslant 30\ \text{years} \\ 0, & t > 30\ \text{years} \end{cases}. \tag{3}$$

The 19.8 ha/year in Eq. (3) results in the 518 ha being cleared over 30 years as per the SEPP (see Section 2.2). In Eq. (2), c is the *clearance rate* parameter controlling the area of CWP cleared outside the Growth Centres (Table 2), with p determining the proportion that is legal and $(1 - p) \times c$ representing the area of illegal clearing that does not result in offsets.

The resulting offsets from this clearing are then implemented inside the Growth Centres as

$$A_t^{o,iGC} = \begin{cases} 17.3\ \text{ha/year}, & A_t^{dev,iGC} > 0 \\ 0, & A_t^{dev,iGC} = 0 \end{cases}, \tag{4}$$

and outside the Growth Centres as

$$A_t^{o,oGC} = \begin{cases} m \times p \times c + 19.8\ \text{ha}, & (A_t^{dev,oGC} > 0) \wedge (A_t^{dev,iGC} > 0) \\ m \times p \times c, & (A_t^{dev,oGC} > 0) \wedge (A_t^{dev,iGC} = 0) \\ 19.8\ \text{ha}, & (A_t^{dev,oGC} = 0) \wedge (A_t^{dev,iGC} > 0) \\ 0, & (A_t^{dev,oGC} = 0) \wedge (A_t^{dev,iGC} = 0) \end{cases} \tag{5}$$

where "$\wedge$" represents logical "AND". Thus offsets are only implemented when development can occur. The annual offsets of 17.3 ha and 19.8 ha are fixed requirements from development inside the Growth Centres, m is the offset multiplier (Table 1) and $p \times c$ the proportion of legally cleared CPW outside the Growth Centres.

2.2.3. Full model of change in CPW over time

Using the definitions above, the model describing the change in CPW over time can be expressed as:

$$A_{t=0} = 10726\ \text{ha} \tag{6}$$

$$A_{t+1} = \sum_{i}^{D_t}(A_t^i - d \times A_t^i) + \sum_{j}^{P_t}(A_t^j) - A_t^{dev,iCG} - A_t^{dev,oGC} \tag{7}$$

were Eq. (6) specifies the initial amount of CPW. The first term in Eq. (7) is the loss from decline in habitat condition (Eq. (1)), the second term is the CPW retained and managed (Eqs. (4) and (5), resulting from a land use change from *offsettable* to *offset* and existing *protected* land; Table 2), and the third and fourth terms are the losses of CPW due to clearing (Eqs. (2) and (3), resulting from a land use change from *developable* to *developed*; Table 1). In the first term in Eq. (7), D_t = {*secured*, *undevelopable*, *developable*, *offsettable*} and represents the land uses where CPW can degrade while in the second term P_t = {*protected*, *offset*}, and represents the land uses where CPW is managed. Both D_t and P_t are indexed by time, indicating the area in each of these categories can change over time as specified in Eqs. (2) and (5).

The full specification of the model involves more complex constraints than shown here for Eqs. (2) and (3), and the full constraints are provided in Appendix A (Section A.2.3). This is because clearing and offsetting can only occur if enough CPW is available in the appropriate land uses for both processes. At some point in the simulation the remaining CPW can become "locked up"—all being either lost or protected—at which point no further development and offsetting can occur. If and when this occurs depends on the particular values of the policy parameters.

2.3. Backcasting

The planned clearing within the Growth Centres (and associated offsets) are assumed to be fixed impacts that always occur. The other major threats of condition decline and the legal and illegal clearing of CWP outside the Growth Centres were controlled by the four parameters given above: the *degradation rate* (d), *clearance rate* (c), *proportion of clearing requiring offsets* (p) and the *offset multiplier* (m) (Table 2). As a range of real-world policy interventions could alter the processes represented by these parameters, they are henceforth referred to as the *policy parameters.*

To capture both uncertainty in the current value of the policy parameters d, c, p, m and to explore the impact of a range of future conservation policies, each of the parameters was varied in steps between its plausible maximum and minimum values (Table 2;

see Table A1 in Supplementary Information for further details). The model was then run with every possible parameter value combination. This created an ensemble E, consisting of 11,616 model realizations, with each member, i, of E represented as a function describing the change in CPW over time, and is indexed by the values of each of the four policy parameters used to generate it: $A_t(d_i, c_i, p_i, m_i)$.

To apply the backcasting approach, a future target was defined as $A_{50} \leqslant T$, where A_{50} is the predicted area of CPW remaining in fifty years time, and T is the target area to retain. Selecting an ensemble S which is a subset of E (i.e. $S \subseteq E$) such that for every member j of S,

$$A_{50}(d_j, c_j, p_j, m_j) \geqslant T \quad (8)$$

gives the combinations of input parameter values, and therefore the regions of the 'policy parameter space', predicted to retain at least the target area of CPW.

Even though the ensemble S is a subset of E, it still can contain thousands of members. Thus it is helpful to cluster the members into an operationally useful number of 'policy options', with each corresponding to a different region of the policy parameter space. One useful way of achieving this is via a *classification tree* analysis (Breiman et al., 1984). This builds a 'tree' by splitting the data using simple rules into branch-like segments (nodes), which best predict the value of a discrete dependent variable from a set of independent variables. In this case the dependent variable is binary and represents whether or not the CPW retention target was met and the independent variables are the four policy parameters. As all nodes have mutually exclusive assignment rules, there is a unique 'rule set' associated with each node, which consists of constraints on the values of the policy parameters. This allows the terminal nodes to be considered different policy options. The classification tree analysis was undertaken using the *rpart* package in version 3.1.0 of R (Therneau et al., 2014; R Core Team, 2014) and the R source code for the analysis is provided in Appendix B.

3. Results

Each model realization with one of 11,616 parameter combinations potentially resulted in a different area of CPW remaining. Fig. 1 shows the distribution of the remaining CPW after 50 years for all model realizations as a percentage of the pre-1750 CPW extent. It has a mean of 4.8%, with minimum of 2.8% and a maximum of 7.1%. To illustrate the backcasting approach, a target area of CPW comprising 60% of the current distribution at the fiftieth year was chosen, which corresponds to 5.1% of the estimated original CWP extent. The target is depicted in Fig. 1 as a vertical grey line and there were 4637 parameter combinations that met or exceeded the target. Thus the subset ensemble, S, comprises 4637 members, which corresponds to 40% of the total number in E. Any target could be used for this type of analysis and using a higher (or lower) target resulted in a reduced (or increased) number of policy options compared to the results shown below.

The 4637 members of S comprise the essence of the backcasting approach as they define many different combinations of the policy parameters likely to result in the backcasting target being met. Yet it is a significant challenge to be able to interpret these 4637 members in an operationally useful way. To overcome this, the classification tree analysis was applied using the four policy parameters (d, c, p, m) as the dependant variables. This produces a tree with 12 terminal nodes (Fig. 2), each of which has between two and five splits on the policy parameters. The set of constraints associated with a terminal node can be labelled a "rule set" and the terminal nodes labelled "TRUE" or "FALSE" in Fig. 2 correspond to the rule sets that predominantly meet, or fail to meet the target,

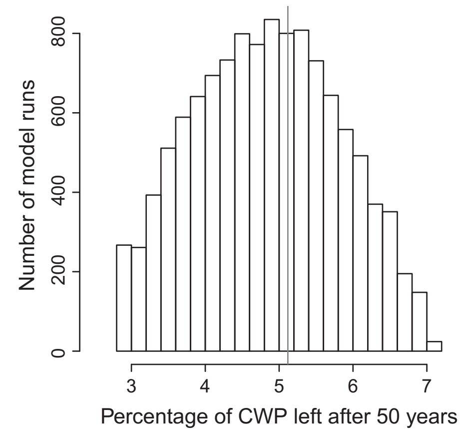

Fig. 1. Histogram summarizing the results of the CPW model. The horizontal axis is the proportion of the estimated original extent of CPW remaining (compared to the pre-1750 CPW estimated extent). The vertical axis shows the proportion of model runs that result in a given proportion of CPW remaining. The grey vertical line represents target used in the backcasting analysis for retaining at least 5.1% of the original CPW extent (60% of the current extent).

respectively. The rule sets associated the six terminal nodes labelled TRUE in Fig. 2 consist of a set of inequalities (such as $0.35 \leqslant p \leqslant 1$), which provide a set of constraints on each of the policy parameters. The full rule sets associated with each of the six policy options are shown in Table 3, which also includes brief descriptions of the policy implications of the rule set.

In the same way as a set of inequalities on two variables defines a rectangle in the two-dimensional plane (e.g. $a \leqslant x \leqslant b; c \leqslant y \leqslant d$ defines a rectangle with width $b-a$, height $d-c$, and area $(b-a)(d-c)$), the set of constraints associated with each rule set defines a four-dimensional rectangle (or technically a 'hyper-rectangular cuboid'). This cuboid exists in a four-dimensional policy space, where the axes of the space are the four policy parameters. Fig. 3 shows three dimensions of this four-dimensional policy space and Fig. 3(a) shows the distribution of all members of ensemble S to which the classification tree analysis is applied. A more intuitive understanding of the resulting rule sets can be obtained by visualising them in three dimensions, along with the constraint on the unshown fourth parameter. This is shown in Fig. 3(b–d) for rule sets 1, 3, 5 and 6 and provides scope for understanding how different policy parameters trade-off against each other in while still allowing for the backcasting target to met.

The 'volume' of each rule set can visualised in three dimensions using this approach (Fig. 3(b–d)) and Table 3 lists the volume associated with each rule set in the four-dimensional policy space. There is considerable variation in the volumes of the rule sets, with rule set 1 (the largest) being 55 times greater then the volume of rule set 6 (the smallest; Table 3). It should be noted that this measure of volume is only useful for comparing rule sets, as the absolute value of the volume depends on the units chosen of the policy parameters.

The accuracy of the classification tree analysis varies for the different rule sets but is generally high. This can be seen in Fig. 2 where the number of results that pass or fail the backcasting target are shown for each terminal node. Table 3 also lists the classification accuracy of each rule set, which varies from over 90% (rule sets 1, 2, 3) down to 68% (rule set 6).

The data and scripts written in R used to create the three figures in this paper are available for download as described in Appendix B.

4. Discussion

This study examined the backcasting approach and explored how it provides a useful methodology for determining multiple

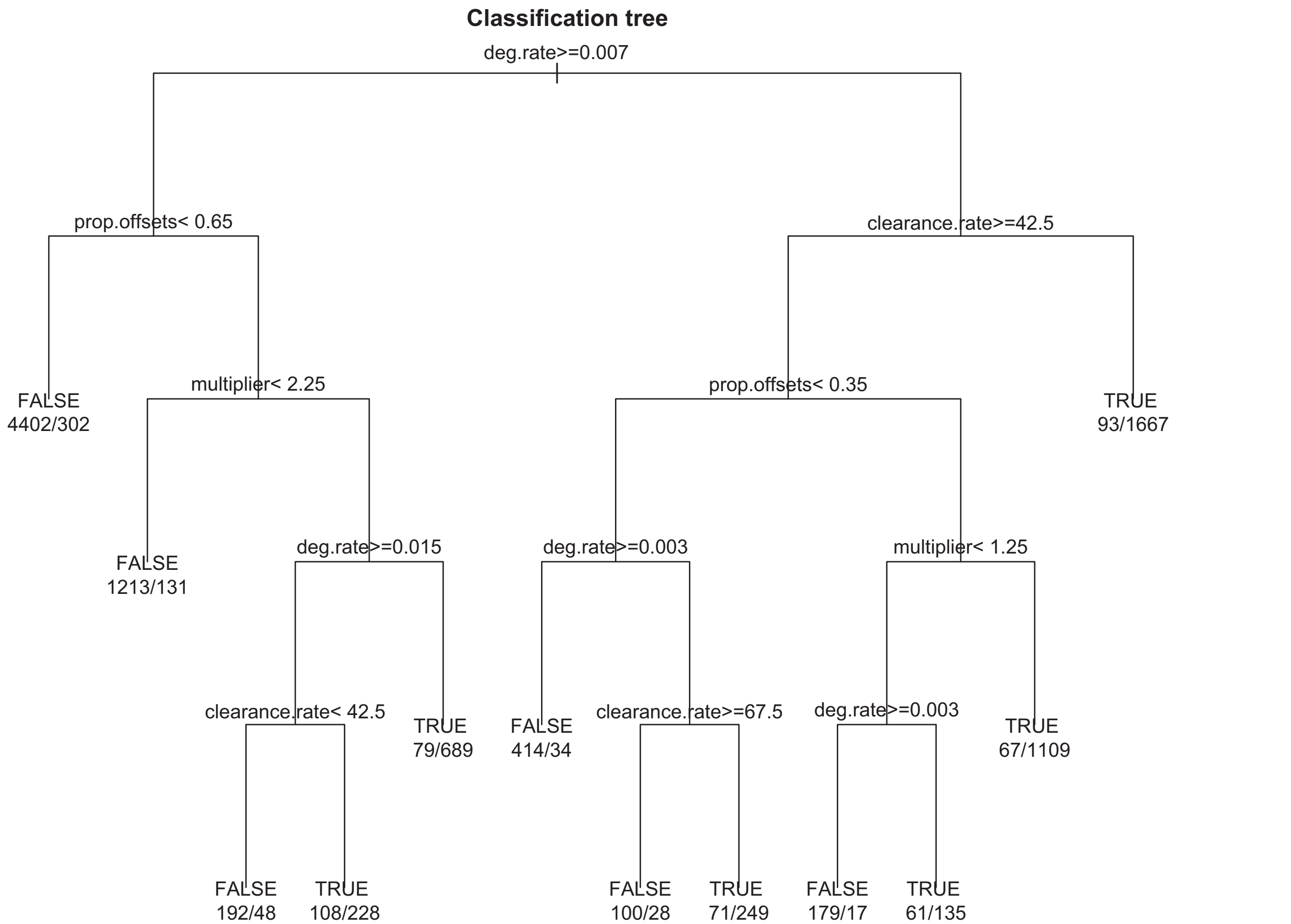

Fig. 2. Results of the classification tree analysis. The inequality rule applied to a single variable is show for each split. The right (left) hand side if each split represents the path taken if the inequality is met (fails). The terminal nodes are labelled either TRUE or FALSE depending on whether the rules leading to that node result in runs predominantly meeting or falling short of the target, respectively. As the classification is not perfect, the number of runs that fail or succeed to meet the TRUE or FALSE status is shown below each node. The first number indicates the number of runs that fail to meet the target and the second represents the number that succeed.

Table 3
The six rule sets associated with each of the policy options from the classification tree analysis (Fig. 2). *prob* is a measure of classification accuracy representing the proportion of parameter combinations consistent with the rule set that meet the backcasting target; *vol* is the volume of the rule set in 4-dimensional policy parameter space; * denotes the upper or lower plausible bound used in the analysis (i.e. no constraint).

Policy option and summary information	Rule set	Description
1 prob = 0.947 vol = 0.55	$^*0 \leqslant d < 0.007$ $^*20 \leqslant c < 42.5$	No constraint on multiplier or the proportion of clearing requiring offsets. The degradation rate must be low and clearance rate has to be in bottom half of range
2 prob = 0.95 vol = 0.41	$^*0 \leqslant d < 0.007$ $42.5 \leqslant c \leqslant 75^*$ $0.35 \leqslant p \leqslant 1^*$ $1.25 \leqslant m \leqslant 4^*$	The degradation rate must be low, the clearance rate can be high but the multiplier needs to be $\geqslant$1.25, and the proportion of clearing having offsets must be $\geqslant$0.35
3 prob = 0.90 vol = 0.27	$0.007 \leqslant d \leqslant 0.015$ $0.65 \leqslant p \leqslant 1^*$ $2.25 \leqslant m \leqslant 4^*$	A higher degradation rate is allowed and there is no constraint on clearance rates. The multiplier must be $\geqslant$2.25 and the proportion of clearing having offsets must be $\geqslant$0.65
4 prob = 0.78 vol = 0.092	$^*0 \leqslant d < 0.003$ $42.5 \leqslant c \leqslant 67.5$ $^*0 \leqslant p < 0.35$	If the degradation rate is kept low (<0.3%) then clearance rate can be medium–high, there is no constraint on the multiplier and the proportion of clearing requiring offsets must be <0.35
5 prob = 0.69 vol = 0.048	$^*0 \leqslant d < 0.003$ $42.5 \leqslant c \leqslant 75^*$ $0.35 \leqslant p \leqslant 1^*$ $^*0.5 \leqslant m < 1.25$	If the degradation rate is kept very low (<0.3%) higher clearance rates allowed with a low multiplier (<1.25), but a greater proportion of clearing requires offsets. (>0.35)
6 prob = 0.68 vol = 0.010	$0.015 \leqslant d \leqslant 0.02^*$ $0.65 \leqslant p \leqslant 1^*$ $2.25 \leqslant m \leqslant 4^*$ $42.5 \leqslant c \leqslant 75^*$	The degradation rate can reach its maximum value of 2% per year with high clearance rates but a high multiplier ($\geqslant$2.25) is needed and the proportion of cleaning requiring offsets must be >0.65

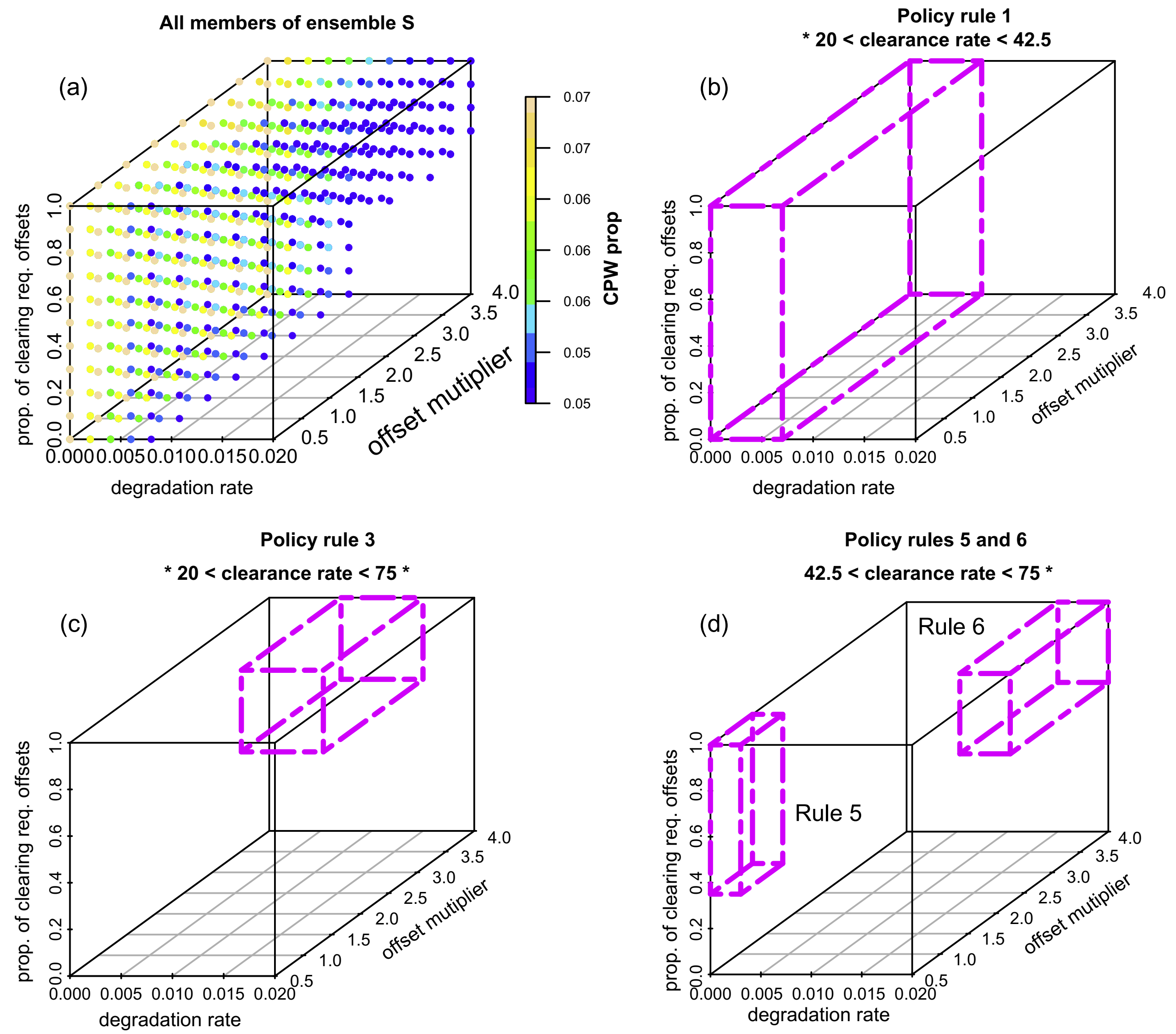

Fig. 3. Policy options resulting from the backcasting analysis. (a) All points in ensemble *S*. Each point represents a combination of parameter values that allow the future target to be met (colour coded by the amount of CPW predicted to remain in 50 years time). (b–d) Depictions of four of the six rule sets obtained using the classification tree analysis. Each rule set defines a 4-dimensional hypercuboid (the constraint on the fourth parameter is shown above the plot) with ∗ denoting no constraint as the maximum/minimal plausible value is used. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

policy options likely to meet future conservation targets. The results presented here provide the first quantitative demonstration of the use of backcasting in a conservation context, examining how this method can be applied to policies aimed at limiting the impact of the growth of Sydney on a critically endangered woodland ecosystem.

The first point to note is that backcasting is a target-based approach, although it differs from more common target-based approaches in conservation (Carwardine et al., 2009) in that the targets are set for a specific point in the future. Target-based approaches are important in that they require explicit measurable objectives to be articulated at the outset of the analysis. This allows the performance of a policy to be tracked relative to its target(s), which is particularly important in a conservation context where policy outcomes are often effectively irreversible. In some cases it may be important to track of the extent to which a policy option might exceed targets, as this could make that option more desirable, or in some cases less preferable if it results in greater negative impacts on some stakeholders. It should also be noted that changing the target results in different rules sets from the classification tree analysis (and therefore different policy options), which should be expected given higher targets provide greater constraints on the viable policy options. The targets in quantitative backcasting also comprise a normative aspect of the analysis as they incorporate societal values. Having this normative component of the analysis limited to the initial target-setting phase provides greater transparency as it is clear how societal values are influencing the analysis.

Once targets have been specified, the results presented here show one way of exploring multiple paths to achieve them, providing a visually compelling analysis of the different combinations of possible policy interventions, and the trade-offs between them. This approach contrasts with the combination of forecasting and scenario analysis, which focuses on extrapolating current trends under multiple scenarios and therefore focusing of the futures that are most likely, rather then those that are most desirable. In some cases, the composition of realistic scenarios producing a desirable future can be difficult to determine, or at worst may not exist. The fact that backcasting is specifically focused on attempting to find these policies or scenarios is one reason why it provides a useful and complementary approach to other methods.

The exploration of different paths to achieve a given future target can encourage policy makers to consider a broader range of policy options when facing a particular conservation challenge (Manning et al., 2006). In this analysis, examining the relative locations of the rectangular cuboids in the policy parameter space (Fig. 3) and the associated rule sets (Table 3), allows a policymaker to obtain a clearer understanding of the different conservation interventions required and the trade-offs between them. For example, in policy option 1, the numerical values listed in Table 3 imply there is no constraint on the *offset multiplier* or the *proportion of clearing requiring offsets*, but the *degradation rate* must be low and the *clearance rate* must be in the lower half of its plausible range. In a policy context, this means there can be more relaxed offsetting requirements and less stringent controls on illegal clearing, provided work is done to limit the declines in condition from invasive species and that the total amount of clearing outside the Growth Centres is not too high. In contrast, policy option 6 allows the *degradation rate* to reach its maximum plausible value with the *clearance rate* in the upper half of its range, but both the *offset multiplier* and the *proportion of clearing requiring offsets* must also be in the upper half of their range. In other words, as long as the offset policy is adequate (large enough multiplier) and strictly enforced (only small amounts of illegal clearing), the CPW targets can be met even with high levels of habitat condition decline and large amounts of clearing outside the Growth Centres. The other policy options shown in Table 3 shows how the policy parameters trade-off between these two extremes. Thus in this situation the backcasting results provide insight into how rigorously a policy would need to be enforced or the extent to which management actions would need to be undertaken.

When examining particular policy options for retaining CPW, the ability of a policymaker to control the processes underlying each of the policy parameters may vary considerably. At one extreme, the policymaker has a high level of control on the value of the offset multiplier (m), as this is part of the offset policy (though it will be subject to political constraints). At the other extreme is the rate at which the CPW is degrading (d) and the illegal clearing rate (given by $(1-p)\times c$) which are characterised by considerable uncertainty regarding the current and future values of d and p. In addition, it may be difficult and expensive to undertake the interventions required to alter these processes. This is due to the expense of controlling invasive species and the difficulties of accessing the CPW, which is mostly on private land. Until better information is available on the rate at which the CPW condition is declining across the study area, policies based on rule sets 3 or 6 may be the most robust choices as they allow higher rates of degradation, but with the trade-off being that offset policies have adequate multipliers and are strictly enforced. This analysis also shows that if such a policy was not feasible, reducing the rate of habitat condition decline would be most important in making multiple policy options available (Table 3). These points highlight the importance of considering both costs and feasibility involved with policy interventions. Cost and feasibility could be incorporated into the analysis in a number of different ways. Most simply this could be done by estimating the cost of feasibility values for each policy option, and then ranking options based on this information. Alternatively, cost could be included as an additional axis in the policy parameter space, requiring the cost of each policy intervention to be determined. This would allow regions of the space be excluded based on budget constraints, limiting the policy options to only those that were financially viable.

Using a classification tree analysis provides a mechanism for grouping the thousands of potential variations in the conservation interventions into broad groups of policy options that can be more easily interpretable by policymakers. In this case study, the 4637 combinations of policy parameters that met the backcasting target were reduced to 6 general policy options by the classification tree. While the classification generally performed well (Table 3), some parameter combinations satisfying the associated rule set may fall short of the CPW target. This is due to the classification tree not producing perfect classification rules; more accurate classifications could likely be obtained, but these would be at the expense of being easily interpretable with simple rule sets. This is not a significant problem as when a given policy option is chosen as being the most feasible, a more detailed classification could be carried out for the corresponding region of parameter space providing a more complex set of constraints relevant to that specific policy option.

Using the "policy parameter space concept" in the backcasting analysis also has a number of useful features and in particular, the volume of the policy space covered by each option provides useful information (Table 3). This is relevant when considering issues of robustness to uncertainty, which includes uncertainty in the current values of the policy parameters as well as how they might change in response to interventions. From this perspective, policy options with a larger volume in parameter space will allow greater variation in parameter values while still meeting the future target, thus providing greater robustness to uncertainty. Another useful criteria for policymakers to consider is the extent to which a given policy choice closes off future options (Lempert and Collins, 2007). Again, considering the volume in the policy space of a given option is a way of addressing this issue, as options with a greater volume allow a greater variation in parameter values, providing more flexibility in how a policy is structured. These considerations could result in excluding policy option 6 due to its small volume in the policy parameter space.

5. Conclusion

Significant challenges remain in developing and implementing conservation policies to halt declines of the natural environment. While backcasting is not a panacea, it provides a useful addition to the conservation policymaker's toolbox, providing a structured way to explore trade-offs between suites of interventions and to identify a multiplicity of pathways to meet desired future targets.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.biocon.2014.10.025.

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