Abstract

Many objectives motivate ecological restoration including improving vegetation condition, increasing the range and abundance of threatened species, and improving aggregate measures of biodiversity such as richness and diversity. While ecological models have been used to examine the outcomes of ecological restoration, there are few attempts to develop models to account for multiple, potentially competing objectives. We develop the first predictive model that integrates a vegetation-focused state-and-transition model with species distribution models for birds. We demonstrate how this integrated model can be used to identify effective restoration options for vegetation and bird species under a constrained budget. For example, using a typical agricultural land management scenario from south-eastern Australia, we demonstrate how the optimal management actions for promoting the occurrence of the Brown Treecreeper, an iconic threatened species, may be suboptimal for meeting vegetation condition objectives. This highlights that any 'preferred' management decision depends on the value assigned to the different objectives. An exploration of sensitivity to value weightings highlighted that 'no management' or 'weed control' were most likely to be the best management options to meet multiple objectives in the scenario we explored. We thus illustrate an approach to using the model outputs to explore trade-offs between bird and vegetation objectives. Our approach to exploring management outcomes and trade-offs using integrated modelling and structured decision support approaches has wide application for conservation management problems in which trade-offs exist between competing objectives.

Introduction

The assessment of restoration efforts requires well defined restoration goals that can be measured over space and through time (Miller & Hobbs 2007). However, ecological restoration often has multiple objectives encompassing several ecosystem components, and this can make identifying optimal restoration decisions complicated. In many cases it is assumed that managing for one objective will lead to favourable outcomes for other objectives (Thorpe & Stanley 2011). For example, improving vegetation condition is a common objective in management plans. However, this may be because the condition of vegetation is both fundamentally valued in its own right, and/or because the condition of habitat is assumed to be a proxy, or a means, to achieving outcomes for many plant and animal species (Thomson et al. 2009). Failure to explicitly identify the link between proxy or means objectives and fundamental objectives can hinder efforts to determine the optimal management actions or assess the efficacy of restoration (Keeney 2002).

Even with clear specification of objectives, high uncertainty and a general paucity of information means that the decision making process for restoration implementation is prone to inconsistent approaches and is often poorly justified (Keeney 2002). Predicting the outcomes of restoration actions for multiple objectives is a challenging proposition because ecological systems respond differently to biotic and abiotic factors over space and time (Martin et al. 2012). Modelling expected outcomes can aid the decision making process by ensuring that restoration proceeds logically, consistently and transparently (Starfield & Blelock 1986), such that the assumptions, knowledge gaps and trade-offs underlying the decisions are made clear and can be updated over time (McCann et al. 2006).

Plants and animals are rarely evaluated together in restoration because considering them together is difficult and expertise often divides along taxonomic lines. State-and-transition models are popular frameworks for intuitively depicting the relationship between restoration efforts and vegetation or habitat condition (Bestelmeyer et al. 2004; Rumpff et al. 2011). These models are typically qualitative and use expert opinion in addition to, or in place of, empirical data on responses to restoration. While models of restoration outcomes for fauna are scarce (e.g. Howes et al. 2010), species distribution models (SDMs) have been used to provide quantitative insights into the possible responses of fauna to restoration (e.g. Robinson

2006). State-and-transition models and species distribution models are often seen as alternative, rather than complementary, approaches to examining the efficacy of restoration.

We develop the first example of a predictive model that integrates a vegetation focused state-and-transition model with species distribution models for fauna. We demonstrate our approach with a case study on the box-ironbark woodlands in northern Victoria. This area is managed predominantly by the Goulburn Broken Catchment Management Authority (GBCMA), who list the following biodiversity objectives: 1) improve the quality of 90% of existing (2005) native vegetation by 10% by 2030; and 2) improve outcomes for threatened species (Miles *et al.* 2010). We based faunal objectives on birds because the GBCMA supports several conservation initiatives for birds (Miles et al. 2010; GBCMA 2013). The Goulburn Broken catchment is home to the eastern subspecies of the brown treecreeper (*Climacteris picumnus*), which is classified as near threatened on the Advisory List of Threatened Vertebrate Fauna in Victoria, as well as several species of bird known to be in decline (IUCN 2015), including the white-plumed honeyeater (*Lichenostomus penicillatus*), olive-backed oriole (*Oriolus sagittatus*) and restless flycatcher (*Myiagra inquieta*). Furthermore, the GBCMA states that maintaining species diversity is important because "species provide genetic and other resources that are of inestimable economic value (e.g. tourism, forestry and agriculture), provide indirect benefits to humanity through 'ecosystem services' that are essential to our survival, and are of scientific interest and aesthetic importance" (Miles et al. 2010, p58).

We develop a decision support tool that integrates a quantitative state-and-transition model of vegetation responses to restoration in the Goulburn Broken catchment (Rumpff *et al.* 2011) with species distribution models from the same region (Yen et al. 2011). The integrated model predicts the outcomes of management actions on multiple restoration objectives, and allows us to test the common, but rarely tested, assumption that restoring vegetation condition will improve outcomes for fauna. By demonstrating restoration outcomes for multiple objectives, the model also provides a clear account of any trade-offs among objectives. We present a multicriteria decision analytic approach to exploring trade-offs between multiple objectives using the outputs from the model. This enables decision-makers to transparently explore the relative merits of alternative management strategies that balance outcomes according to stated preferences (weightings) for different objectives.

Materials and methods

Case study area

Our case study was located in the box-ironbark forest and woodlands of northern Victoria, Australia. The area comprises the Victorian Riverina (including the Goulburn Broken Catchment) and experiences hot dry summers and cool, wet winters (average temperatures of 15 to 21°C and 3 to 9°C respectively) with approximately 360- 672mm of rainfall per annum (DEPI 2016). Much of this region has been converted to agricultural lands and the remaining native vegetation is highly fragmented (Bradshaw 2012). Our definition of vegetation condition was based on the cover and richness of the mid- and under-storey vegetation weed cover, stem density and recruitment (Rumpff et al. 2011; Appendix S2), which are commonly used to characterise vegetation condition in Australia (Parkes et al. 2003).

Methodological overview

We developed a combined state-and-transition, species distribution model (ST-SDM) to predict vegetation and faunal (bird) outcomes of restoration in the Goulburn Broken woodlands. This approach considers how restoration influences several major biodiversity measures: vegetation condition, bird species richness, and bird species' occurrences. The state-and-transition model (STM) (Rumpff et al. 2011) predicts changes in vegetation attributes following management interventions, and we linked these predictions of vegetation attributes to species' occupancy probabilities and species richness via a species distribution model (SDM) (Yen et al. 2011). We then used multicriteria decision analysis methods to demonstrate how a single 'best' restoration action might be identified based on the outputs of our combined ST-SDM (Driscoll et al. 2016) (Fig. 1). We describe our general process here; full details of the STM and SDM are in Appendices S2–S5.

State-and-Transition Model

We used a state-and-transition model, constructed as a Bayesian network, to characterise changes in multiple vegetation attributes as a function of management and other environmental variables (Howes et al. 2010; Ticehurst et al. 2011; Rumpff et al. 2011). Bayesian networks are graphical models that depict probabilistic dependencies and comprise nodes that represent variables, and directional links that represent statistical (probabilistic) relationships between nodes (Pearl 1986; McCann et al. 2006). Bayesian networks are well suited to the integration of existing, often diverse, models and complex hypotheses (McCann et al. 2006).

We modified an existing Bayesian network following Rumpff et al. (2011). The original Bayesian network had nodes for vegetation attributes to represent recruitment, richness and cover of the mid and under-storey, weed cover, and immature and mature stem density. To reflect the habitat requirements of the bird species in our case study, we added nodes to reflect percentage tree cover within 500 m of the site, and total understorey cover, which was a composite of nodes for native and exotic understorey cover. In conjunction with nodes describing management actions, site history and environmental conditions, these state variable nodes interact to determine vegetation condition in the future.

Vegetation condition was classified into seven discrete 'states' (reference, simplified, oldfield, derived, thicket, native pasture, and exotic pasture). These states represent different combinations of values at the vegetation attribute nodes (e.g. shrub species richness, mature stem density). As with state variables, additional management actions were integrated into the original model as probabilistic nodes to reflect common management strategies for birds typical for the region (D.R., see Appendix S2 for details on Bayesian network construction). We constructed our Bayesian network model in *Netica* (Norsys 2010) (see Appendix S4 for the *Netica* model file).

Species distribution models

We make static predictions about the vegetation variables associated with bird occupancy and richness by fitting a random forest species distribution model, which uses binary recursive partitioning to assign the response variable to a particular class based on a set of predictor variables, (Breiman 2001). The random forest model makes no *a priori* assumptions about relationships between the predictors and response variables, and can account for complex interactions among predictor variables (Breiman 2001). We fitted random forest models to data on occupancy of birds, with one model for each species (following Yen et al. 2011, code available in Appendix S3).

From the adapted vegetation condition model, we included the number of immature stems per hectare, the number of mature stems per hectare, the number of shrub species, the percentage tree cover within 500m, and the percentage cover of understorey vegetation in a site as predictor variables in the fitted SDMs. We standardized predictor variables to zero mean and unit variance.

We used the percentage reduction in deviance as a measure of model fit. For a regression model with binary outcome, the deviance is $-2\,\Sigma\,[y_i \log(p_i) + (1 - y_i) \log(1 - p_i)]$, where y_i is the observed presence or absence of a given species in site i and p_i is the fitted probability of occurrence of that species in site i. We calculated the null deviance (dev_{null}) from an intercept-only generalized linear model with logit link. We calculated percentage reduction in deviance as (dev_{null} – dev_{rf}) / dev_{null}, where dev_{rf} is the deviance of the fitted random forest model. We recorded the area under the receiver operating characteristic curve (AUC) as an estimate of out-of-sample model predictive performance for occurrence models and used the r^2 value (based on Pearson's r) between observed and predicted species richness to characterise model fit for models of species richness. We fitted random forest models with the random forest package in R (Breiman 2001; Liaw & Wiener 2002) and calculated AUC values using the pROC package (Robin et al. 2011).

Integrated ST-SDM

By using a subset of the state variables from the STM as predictors for birds in the SDM, we were able to develop an integrated model that could predict outcomes for birds as well as vegetation. We used the integrated ST-SDM to predict outcomes under four commonly used management interventions: no action; planting a 20 × 800 m buffer; fencing; weed control; and fencing and weed control. Weed control in this instance was defined as any extensive weed control technique (e.g., a boom sprayer) using residual herbicides (Schirmer & Field 2000; Rumpff et al. 2011).

Our ST-SDM generated predictions for the cover, richness or density of individual vegetation attributes (state variables), and for the probability of a site being in a particular condition state. We also recorded predicted probabilities of occurrence for four species: brown treecreeper, olive-backed oriole, restless flycatcher, and white-plumed honeyeater. We estimated species richness as the total number of species present from a total of 129 species (see Appendix S1). In order to estimate species richness, we summed the number of species modelled to occur at each site, defining a species as present when its predicted probability of occurrence was greater than 0.7. As the results were not substantially different when averaged over a range of thresholds, this cut-off was chosen as achieved the closest correspondence between observed and predicted bird species richness in the training dataset.

Examining vegetation condition as a proxy for faunal outcomes

Bayesian networks contain conditional probability tables that include information on the dependent variables (e.g. bird richness or occurrence) for every combination of states of the predictor variables (e.g. high, medium and low % weed cover). In order to determine whether vegetation condition is a good proxy for bird occurrence and richness, we extracted conditional probability tables from the ST-SDM Bayesian network and found the site(s) with the combination of variables that resulted in the maximum species richness and probability of the four target species (brown treecreeper, white-plumed honeyeater, olive-backed oriole, restless flycatcher) occurring. In cases where not all of the predictor variables strongly influenced occurrence or richness, multiple combinations of predictor variable states yielded the maximum probability of occurrence or species richness. We identified the vegetation condition states that were able to provide vegetation with these characteristics (e.g. which vegetation condition states can have a moderate immature stem density, low mature stem density, very low midstorey richness, very low grass cover and any level of tree cover- as our SDMs results show is preferred by the brown treecreeper). We wanted to determine whether the vegetation condition states which are optimal for bird species occurrence or richness match those considered ‘high’ vegetation condition (i.e. reference or simplified).

Model Validation

We validated our combined ST-SDM using an independent data set from the Goulburn Broken catchment. These data recorded vegetation variables and bird occurrences in 1993 and 2011, which matched the 5–10 year timeframe of our model. A subset of these sites were actively managed, either with a 20 × 800 m planted buffer or with a fence to remove stock.

We used this independent data set to test whether our model reliably predicted vegetation condition, bird species richness, and occurrence of declining bird species under three management interventions: no action, planting buffer vegetation, and fencing. We tested the predictive ability of our SDMs, the STM and, finally our integrated ST-SDM.

To test our bird occurrence SDMs, we calculated the area under the receiver operating curve. We tested the SDM estimates of bird species richness by obtaining an r^2 value for the correspondence between observed and predicted bird species richness.

To test our vegetation condition STM, we input information from our validation dataset about the initial site variables and the management actions undertaken. We compared the vegetation condition post-management according to our validation dataset with the modelled average predicted probability that a site would be classified into each vegetation condition state (e.g. oldfield, exotic pasture, or derived).

To test our ST-SDM, we entered the initial site variables and management actions as before and compared the predicted probability of bird species occurring at sites where the species was observed to occur in the post-management validation data, versus sites where they did not occur. One would expect that a reliable model would predict higher probabilities of occurrence at sites where the species occurred than at sites where the species was absent.

<u>Predictions of restoration effectiveness</u>

To demonstrate how our integrated ST-SDM could support decisions with multiple objectives, we generated model predictions over a 5–10 year period. We assumed restoration was implemented at a site in oldfield condition, stocked continuously with sheep at a low density, which is a typical works site in the study region (Appendix S5). We assumed adequate rainfall at all restoration sites. We focused on three performance measures that reflect the management objectives of the GBCMA: 1) avoid a reduction in vegetation condition (vegetation condition falling into exotic pasture, native pasture, derived, or thicket states); 2) maximise the probability of occurrence for threatened and declining species; and 3) maximise the richness of bird species at the site. We compared the relative costs of restoration actions (Schirmer and Field 2000) as an additional component in the assessment of ‘best’ restoration options.

Multicriteria decision analysis

Different stakeholders will prefer changes in some objectives more than others, and so there may not be a shared ‘preferred’ decision (Keeney 2002). In practice, these values would be elicited from key stakeholders or decision makers. In the absence of elicited weights, we examined the sensitivity of the decision score to weighting.

To facilitate multicriteria decision analysis, we used multi-attribute utility theory (Driscoll et al. 2016). This involved combining model outputs with weights that reflect the relative importance of changes in each of the measurable objectives (bird species richness, brown treecreeper, white-plumed honeyeater, restless flycatcher and olive-backed oriole occurrence, probability of reduced vegetation condition). Each performance measure was scaled such that the worst outcome for that objective was assigned a value of zero and the best outcome was assigned a value of 1.

We used linear additive utility functions to identify the ‘best’ restoration under all possible combinations of weights (Driscoll et al., 2016). We simulated 10,000 random uniform weights for each performance measure, and assigned each performance measure a weighting between 0 (no value) and 1 (most preferred). We present a frequency distribution (Fig. 3) that shows how often the randomly simulated values resulted in each restoration strategy being considered the ‘best’.

Results

Species distribution models

The species distribution models for bird species richness, white-plumed honeyeater, restless flycatcher, olive-backed oriole and brown treecreeper occurrence were integrated with the vegetation condition model. Models for the occurrence of the white-plumed honeyeater, restless flycatcher and olive-backed oriole predicted the training data well with all internal AUC values exceeding 0.7 (table 1). These models also explained a reasonable amount (14-37%) of the deviance in the data. The model for brown treecreeper occurrence predicted and fit the data less well; only explaining 2% of deviance and having an internal AUC of 0.68. Models of species richness fitted the data poorly, with an r^2 value of 0.024 for the relationship between observed and modelled species richness.

[table 1 approximately here]

Vegetation condition as a proxy for fauna

The integrated model (Fig. 2) revealed that the brown treecreeper, olive-backed oriole, restless flycatcher and white-plumed honeyeater have different habitat preferences, particularly when it comes to mature stem density, shrub richness and grass cover. Therefore, the state of vegetation condition that supports the highest species richness and occurrence for these species varies. Oldfield was always a preferred vegetation condition state but species were also variously prevalent in native pasture, exotic pasture, derived and simplified condition states (see Table 2).

[Table 2 approximately here]

Model predictions

Performance measures (occurrence of brown treecreeper, white-plumed honeyeater, olive-backed oriole and restless flycatcher, species richness, and likelihood of reduced vegetation condition) and cost differ under five common restoration strategies (Table 3). It is evident that there is a trade-off between objectives; no single restoration strategy is best for all performance measures. For example, the highest species richness occurs when the site undergoes weed control but this is the worst option for increasing the probability of white-plumed honeyeater occurrence. In contrast, fencing is the best management option for white-plumed honeyeaters but this is quite expensive ($904 per hectare) while the cost of no action is 0 and is only slightly less beneficial.

[Table 3 approximately here]

Model Validation

The SDMs predicted the occurrence of species in the validation dataset reasonably well (table 1), particularly in the case of the white-plumed honeyeater (AUC 0.7) and the olive-backed oriole (AUC 1.0). Bird species richness was predicted poorly, with an r^2 value of 0.0003 between predicted and observed species richness in the validation dataset.

The STM predicted vegetation condition reasonably well under the three management histories: no action, planting a buffer and fencing to remove stock (Table 4). Only three vegetation condition states were observed: oldfield, exotic pasture and derived. The model predicted that sites were likely to fall into one of the three observed vegetation condition states, or into a native pasture condition state. Sites predicted to be in the oldfield condition state had a 0.36 probability of being observed in an oldfield condition state, a 0.45 probability of being observed in an exotic pasture condition state and a 0.34 probability of being observed in a derived condition state.

[table 4 approximately here]

The STM was less able to predict all of the state variables that control vegetation condition and bird species richness and occurrence. r^2 values for the agreement between observed and predicted tree cover, weed cover, native understorey cover and midstorey richness, immature and mature stem density ranged from 0.0003 to 0.08.

The integrated ST-SDM predicted the effect of initial vegetation condition and management actions on bird occurrences and richness poorly. Bird species occurrences were also poorly predicted, with an r^2 value of 0.04 between observed and predicted bird species richness. The integrated ST-SDM predicted that each bird species would occur approximately as frequently in sites where the species were observed as compared with sites where the species did not occur based on our validation dataset. For example, the model predicted probability of restless flycatcher occurrence was 0.44 at sites where it was found in the validation dataset and 0.46 at sites where it was not found in the validation dataset (see appendix S6 for further details).

<u>Multicriteria decision analysis – sensitivity to weighting</u>

When varying randomly simulated weights for each variable (cost, species richness, vegetation condition etc.) to calculate decision scores, we found that no action (43.1%), fencing to remove stock (9.5%), weed control (36.7%) and fencing with weed control (10.7%) were all considered to be optimal management strategies for multiple objectives (Fig. 3). Our analyses also indicated that planting a buffer was never the best sole management action to best meet the management objectives under the time frame (5-10 years) considered in this case-study (i.e. a dominated alternative).

[figure 3 approximately here]

Discussion

Model utility

This study is one of few to use an integrated modelling approach that explicitly models the multiple outcomes sought by managers investing in restoration. We achieved this by integrating two popular modelling techniques in conservation and natural resource management: state-and-transition models and species distribution models. Alone, species distribution models can compare habitat preference among species but do not provide any guidance about how to manage an area given these habitat preferences, taking into account the relative costs and expected outcomes of competing management options. In ecology, state-and-transition models have been predominantly used to predict the response of vegetation to management actions, typically only accounting for objectives focused on vegetation. This precludes analysis of trade-offs when additional objectives exist. By developing a combined ST-SDM we demonstrate a method that can be applied to inform managers about the impacts of restoration actions on multiple objectives that is predisposed to updating as more data becomes available, in the spirit of passive adaptive management (Duncan & Wintle 2008). Teaming integrated model outputs with multicriteria decision analysis can assists managers to identify a preferred restoration strategy, given the expected benefits to multiple objectives arising from candidate restoration options, and the preferences of managers and stakeholders for different outcomes that are embodied in weighting scheme employed within the analysis.

The first key question addressed by our study was whether there are trade-offs between restoration objectives. In our case study, the brown treecreeper preferred sites with lower mature stem density, midstorey richness, and grass cover than the white-plumed honeyeater, indicating likely trade-offs between good outcomes for brown treecreepers and white-plumed honeyeaters when choosing restoration actions (table 2). In the scenario we tested (an oldfield site stocked with a low density of sheep), weed control was the best strategy for brown treecreepers (probability of occurrence, p_{occ} = 0.81) but was the worst strategy for white-plumed honeyeaters (p_{occ} = 0.17) (table 3).

The second key question we address is whether high vegetation condition corresponds to good faunal outcomes. Under the case study tested, the objective of maintaining vegetation condition is best achieved by fencing to remove stock and conducting weed control. However, this is the most expensive option and has poor outcomes for the restless flycatcher, and sub-optimal outcomes for species richness and the occurrence of the other target species (Table 3). The results of our analysis indicate that, at least in the case study presented (a grazed oldfield site within the Goulburn Broken Woodlands), there are trade-offs between preserving species diversity and threatened species, and improving vegetation condition. This may be because, in this case study, the variables associated with high vegetatopmcondition do not strongly determine faunal habitat suitability. However, high levels of degradation in our study area might have led to local extinction of those species with a strong preference for high condition vegetation (such as the turquoise parrot or painted honeyeater), inhibiting our ability to detect a relationship between high condition vegetation and positive faunal outcomes. In any case, it is important to explore the assumption that high condition vegetation will provide the best outcome for fauna, especially if restoring vegetation condition is actually a means objective for the fundamental objective of restoring the habitat suitability for fauna. The ST-SDM framework provided in this study provides the opportunity to undertake such an exploration.

An integrated ST-SDM coupled with multicriteria decision analysis can enable managers to simultaneously predict the effect of restoration strategies on a number of objectives at a site scale and select the restoration strategy that provides the best outcomes given their values. We used this model to explore how preferred restoration strategies might vary when objectives are weighted differently according to different hypothetical stakeholder values. In a real-world context, stakeholders may value changes in a threatened or declining species very highly, while others may be more focussed on enhancing vegetation condition. Our sensitivity to weighting results show that no management strategy was consistently dominant across all objectives in the example we tested, over the time-frame considered (Fig. 3). However, our analysis did highlight an action (planting buffer vegetation) that never provides the best outcomes for objectives (i.e dominated action). Consequently, four strategies may satisfy stakeholder objectives (no action, fencing to remove stock, weed control, and fencing and weed control). The optimal management strategy at any given site will depend on the values of the relevant stakeholders.

Model development and integration

Information about the efficacy of restoration is limited and is usually based on or supplemented by expert opinion due to limited resources for the collection, storage and analysis of monitoring data. An adaptive management framework supported by a quantitative process model can facilitate the integration of existing knowledge with new information to evaluate and improve restoration practices (Duncan & Wintle 2008).

We demonstrate the first stages of adaptive management by validating the model's predictive ability for an independent data set. This validation process identified components of the model that performed poorly, impeding the choice of an optimal course of management. For example, the model predicted vegetation condition reasonably well, but did not predict vegetation state variables or bird outcomes well (table 1, appendix S6). Poor performance in validation tests was not entirely surprising, as the validation data were collected in different years and with different sampling methodologies. Poor model predictions may also be due to the highly non-stationary effects of the millennium drought (Haslem et al. 2015), which affected one of the data collection periods. In addition to possibly changing the relationship between vegetation and bird occurrence (Haslem et al. 2015), the millennium drought may have affected the growth and senescence of vegetation (Fensham & Holman 1999) such that it does not match what is expected in the STM. This may explain why our ST-SDM predicted bird occurrence poorly even though our SDMs performed well for some species (Table 1, Appendix S6). Environmental stochasticity is problematic for all predictive models and it is difficult to compare datasets collected using different years, methods or locations, let alone predict from one to another. We will focus here on the limitations of our methodology, which may have contributed to the poor predictive ability of ST-SDM.

The Rumpff et al. (2011) STM contained eight state (vegetation) variables but not all of these were sampled for Yen et al. (2011) or in the validation dataset. In order to link the STM with the Yen et al. (2011) SDMs, and to validate the model, we restricted the variables used in the SDMs to those that were common to the training and validation data sets and that could reasonably be included in the STM. This resulted in the omission of several variables that are known to predict bird occurrence and richness, including midstorey cover (which was absent in the validation data) and habitat fragmentation (which was absent from the STM and validation data) (Yen et al. 2011; Garrard et al. 2012). The omission of these two variables may account for the model's poor ability to predict bird species richness with r^2 values of 0.024 and 0.0003 for the correlation between predicted and observed bird species richness in the training and validation data respectively. Mismatched variable sets are likely to be problematic whenever models created for different purposes are combined. The integration of state-and-transition models and species distribution models will work best when the data collected for SDMs match the variables in the STM, or vice versa.

Having identified these shortcomings, the integrated model would improve if utilised within an adaptive management framework. This would necessitate the further development of the conceptual model underlying the ST-SDM, in terms of structure and parameterisation, supported by data collection and modelling across a broader range of vegetation variables over a longer period of time. Fortunately, our modelling approach is well suited to iterative and ad-hoc or opportunistic addition of additional data or incorporation of changes in expert knowledge.

Irrespective of the model's current predictive performance, we have illustrated a modelling framework that could be used to quantify expected management outcomes, characterise and explore uncertainty, and examine potential trade-offs among multiple objectives. Our model highlighted the possible pitfalls of assuming that high vegetation condition would mean good outcomes for birds, an important consideration when trying to improve bird richness or occurrence. Ongoing validation and improvement of the model will help to ensure that the assumptions and knowledge gaps influencing decisions are identified and improved over time, providing better management outcomes. To our knowledge, this paper is the first to combine state-and-transition models and species distribution models to predict the impact of restoration strategies on multiple objectives. When paired with multicriteria decision analysis, our model provides a powerful approach to identifying restoration priorities that reconcile empirical evidence and stakeholder preferences for outcomes given competing objectives. Given the broad availability of species distribution models and the possibility of developing state-and-transition models from expert opinion, this modelling approach could be applied to wide variety of contexts to rapidly inform multi-objective management decisions.

Supporting Information

A list of species included in random forest trees to estimate species richness (Appendix S1), details of the integrated model construction and node states (Appendix S2), code used to run random forest trees (Appendix S3), a Netica file containing the full model (Appendix S4), details of the model scenario (Appendix S5) and an analysis of the predictive ability of model components (Appendix S6) are available online. The authors are solely responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author.

Literature Cited

Bestelmeyer BT, Herrick JE, Brown JR, Trujillo DA, Havstad KM. 2004. Land management in the American southwest: a state-and-transition approach to ecosystem complexity. Environmental Management **34**:38–51. Springer New York.

Bradshaw CJA. 2012. Little left to lose: deforestation and forest degradation in Australia since European colonization. Journal of Plant Ecology **5**:109–120.

Breiman L. 2001. Random Forests. Machine Learning **45**:5–32.

Driscoll DA, Bode M, Bradstock RA, Keith DA, Penman TD, Price OF. 2016. Resolving future fire management conflicts using multicriteria decision making. Conservation Biology **30**:196–205.

Duncan DH, Wintle BA. 2008. Towards adaptive management of native vegetation in regional landscapes. Page in C. Pettit, W. Cartwright, I. Bishop, K. Lowell, D. Pullar, and D. Duncan, editors. Landscape analysis and Visusalisation. Springer.

Fensham RJ, Holman JE. 1999. Temporal and spatial patterns in drought-related tree dieback in Australian savanna. Journal of Applied Ecology **36**:1035–1050.

Garrard GE, McCarthy MA, Vesk PA, Radford JQ, Bennett AF. 2012. A predictive model of avian natal dispersal distance provides prior information for investigating response to landscape change. The Journal of Animal Ecology **81**:14–23.

GBCMA. 2013. Goulburn Broken Regional Catchment Strategy 2013-2019. Shepparton.

Haslem A, Nimmo DG, Radford JQ, Bennett AF. 2015. Landscape properties mediate the homogenization of bird assemblages during climatic extremes. Ecology **96**:3165–3174.

Howes AL, Maron M, McAlpine CA. 2010. Bayesian networks and adaptive management of wildlife habitat. Conservation Biology **24**:974–83.

IUCN. 2015. IUCN Red List of Threatened Species. Version 2015-4.

Keeney RL. 2002. Common mistakes in making value trade-offs. Operations Research **50**:935–945.

Liaw A, Wiener M. 2002. Classification and regression by randomForest. R News **2**:18–22. Available from url: http://CRAN.R-project.org.doc/Rnews/.

Martin TG, Burgman MA, Fidler F, Kuhnert PM, Low-Choy S, Mcbride M, Mengersen K. 2012. Eliciting expert knowledge in conservation science. Conservation Biology **26**:29–38.

McCann RK, Marcot BG, Ellis R. 2006. Bayesian belief networks: applications in ecology and natural resource management. Canadian Journal of Forest Research **36**:3053–3063.

Miles C, McLennan R, Keogh V, Stothers K. 2010. Biodiversity strategy for the Goulburn Broken Catchment, Victoria. Shepparton.

Miller JR, Hobbs RJ. 2007. Habitat restoration. Do we know what we’re doing? Restoration Ecology **15**:382–390.

Norsys. 2010. Netica. Norsys Software Corp.

Parkes D, Newell G, Cheal D. 2003. Assessing the quality of native vegetation: The “habitat hectares” approach. Ecological Management & Restoration **4**:S29–S38. Available from http://doi.wiley.com/10.1046/j.1442-8903.4.s.4.x.

Pearl J. 1986. Fusion, propagation, and structuring in belief networks. Artificial Intelligence **29**:241–288.

Robin X, Turck N, Hainard A, Tiberti N, Lisacek F, Sanchez J-C, Müller M. 2011. pROC: an open-source package for R and S+ to analyse and compare ROC curves. Page 77BMC Bioinformatics.

Robinson D. 2006. Is revegetation in the Sheep Pen Creek area, Victoria, improving Grey-crowned Babbler habitat? Ecological Management and Restoration **7**:93–104.

Rumpff L, Duncan DH, Vesk P, Keith D, Wintle B. 2011. State-and-transition modelling for adaptive management of native woodlands. Biological Conservation **144**:1224–1236. Elsevier Ltd.

Schirmer J, Field J. 2000. The cost of revegetation final report. Canberra.

Starfield AM, Blelock AL. 1986. Building Models for Conservation and Wildlife Management. Interaction Book Company, Edina.

Thomson J, Moilanen A, Vesk P, Bennett A. 2009. Where and when to revegetate: a quantitative method for scheduling landscape reconstruction. Ecological Applications **19**:817–28.

Thorpe AS, Stanley AG. 2011. Determining appropriate goals for restoration of imperilled communities and species. Journal of Applied Ecology **48**:275–279.

Ticehurst J., Curtis A, Merritt WS. 2011. Using Bayesian networks to complement conventional analyses to explore landholder management of native vegetation. Environmental Modelling & Software **26**:52–65. Elsevier Ltd.

Yen JDL, Thomson JR, Vesk PA, Mac Nally R. 2011. To what are woodland birds responding? Inference on relative importance of in-site habitat variables using several ensemble habitat modelling techniques. Ecography **34**:946–954.

Tables

Table 1: occurrence model fits and predictive performance based on the training data and validation data

Species	**Internal AUC**	**% Deviance Explained**	**Validation AUC**
white-plumed honeyeater	0.88	37	0.70
brown treecreeper	0.68	2	0.50
olive-backed oriole	0.75	14	1.00
restless flycatcher	0.79	17	0.58

Table 2: Node states for vegetation attributes that maximise bird species occurrence and species richness

	Brown treecreeper	**Olive-backed Oriole**	**Restless Flycatcher**	**White-plumed honeyeater**	**Species richness**
Immature Stem Density (stems/ha)	Moderate (186-548)	Low (0-186)	Moderate (186-548)	Low (0-186)	Moderate (186-548)
Mature Stem Density (stems/ha)	Low (4-6)	High – Very high (12+)	Mid – Very high (6+)	High – Very high (12+)	Very Low (0-4)
Shrub Richness (# species)	Very Low (0-2)	High (10-15)	Very Low (0-2)	High (10-15)	Moderate (3-10)
Grass Cover (%)	Very Low (0-10)	Moderate – Very high (30+)	High – Very high (50+)	Moderate – Very high (30+)	Very Low (0-10)
Tree cover (%)	Any (0-100)	Any (0-100)	Any (0-100)	Any (0-100)	Any (0-100)
Vegetation Condition	Oldfield Native Pasture Derived	Oldfield Native Pasture Simplified Exotic Pasture Derived	Oldfield Native Pasture Exotic Pasture Derived	Oldfield Native Pasture Simplified Exotic Pasture Derived	Oldfield Native Pasture Simplified Derived

Table 3: Outcomes of restoration options at an oldfield site. Reduced condition is the probability of the site moving from oldfield to a lower vegetation condition, species names refer to probability of occurrence, species richness is in number of species, cost is per hectare in AUD

	Species Richness	White-plumed Honeyeater	Brown Treecreeper	Olive-backed Oriole	Restless Flycatcher	Reduced condition	Tree cover (%)	Cost
No Action	0.092	0.316	0.657	0.266	0.589	0.889	9	$0
Buffer	0.092	0.316	0.657	0.266	0.589	0.889	11	$904
Fence	0.091	0.319	0.655	0.266	0.590	0.742	9	$904
Weed Control	0.141	0.170	0.806	0.258	0.466	0.784	9	$178
Fence, Weed control	0.133	0.251	0.759	0.237	0.484	0.498	9	$1,082

Table 4: Comparison of observed vegetation condition with mean predicted vegetation condition. Grey cells indicate that that a vegetation condition was not observed

		Predicted						
		Reference	Oldfield	Native Pasture	Simplified	Exotic Pasture	Thicket	Derived
Observed	Reference							
	Oldfield	0	35.94	6.07	0	43.30	0	14.70
	Native Pasture							
	Simplified							
	Exotic pasture	0	45.39	8.27	0	25.07	0	21.30
	Thicket							
	Derived	0	33.81	11.25	0	27.51	0	25.15

Figure Legends

Fig. 1: Depiction of the methodology used in this study

Fig. 2: The integrated state-and-transition, Species Distribution Model showing the altered nodes in light grey, the new nodes in white and the nodes that remained unchanged from the original STM in dark grey.

Fig. 3: Frequency distribution of best management action under 10,000 simulated weightings for 1) no action, 2) buffer planting, 3) fencing, 4) weed control and 5) fencing and weed control

Figures

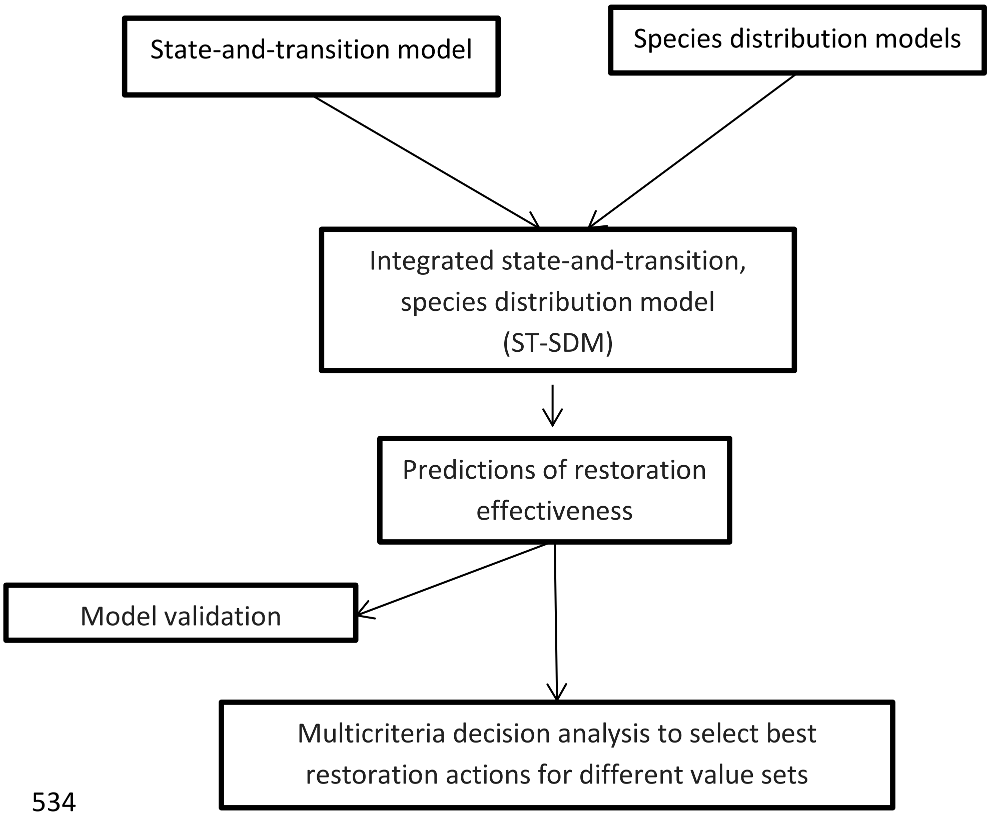
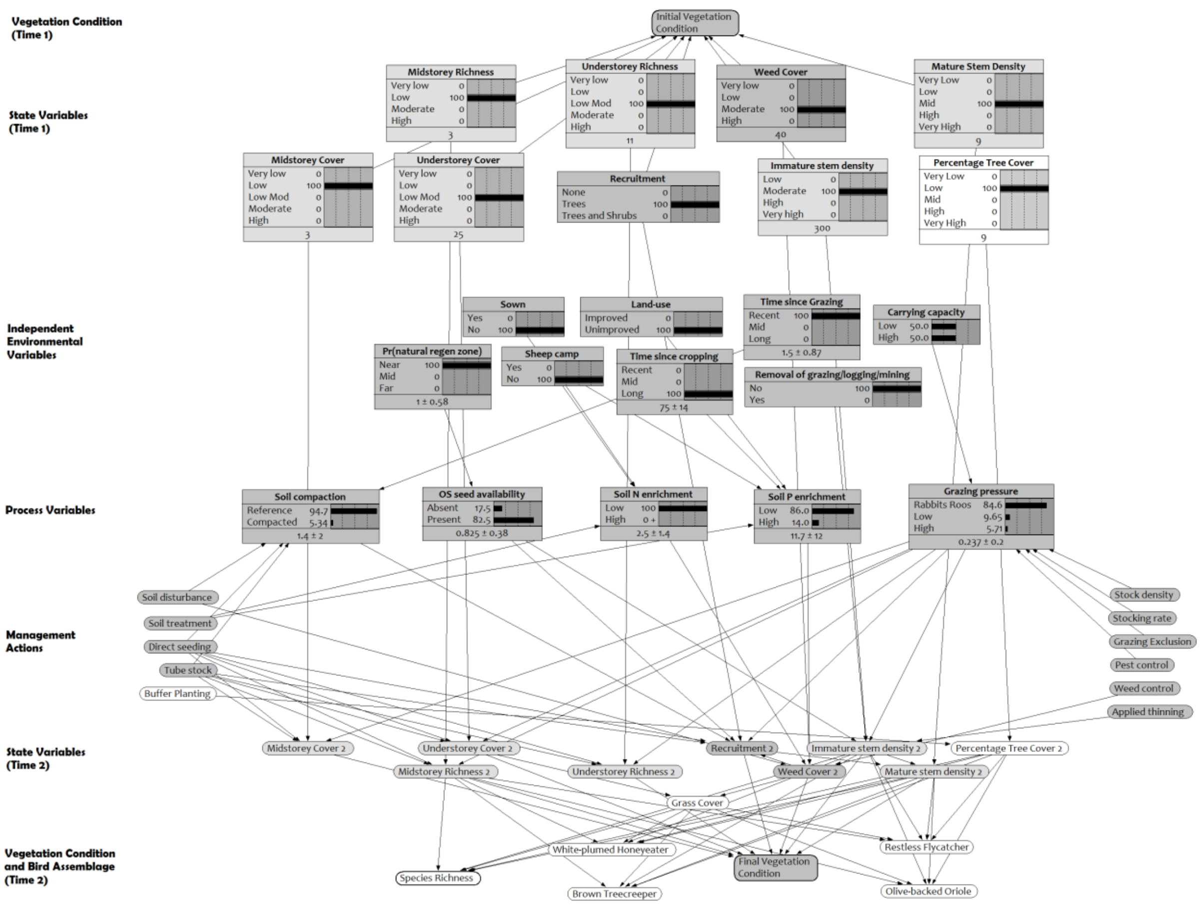


Fig. 1



Vegetation Condition (Time 1)
State Variables (Time 1)
Independent Environmental Variables
Process Variables
Management Actions
State Variables (Time 2)
Vegetation Condition and Bird Assemblage (Time 2)
Initial Vegetation Condition
Midstorey Richness
Understorey Richness
Weed Cover
Mature Stem Density
Midstorey Cover
Understorey Cover
Recruitment
Immature stem density
Percentage Tree Cover
Sown
Land-use
Time since Grazing
Carrying capacity
Pr(natural regen zone)
Sheep camp
Time since cropping
Removal of grazing/logging/mining
Soil compaction
OS seed availability
Soil N enrichment
Soil P enrichment
Grazing pressure
Soil disturbance
Soil treatment
Direct seeding
Tube stock
Buffer Planting
Stock density
Stocking rate
Grazing Exclusion
Pest control
Weed control
Applied thinning
Midstorey Cover 2
Understorey Cover 2
Recruitment 2
Immature stem density 2
Percentage Tree Cover 2
Midstorey Richness 2
Understorey Richness 2
Weed Cover 2
Mature stem density 2
Grass Cover
White-plumed Honeyeater
Restless Flycatcher
Species Richness
Final Vegetation Condition
Brown Treecreeper
Olive-backed Oriole

Fig. 2

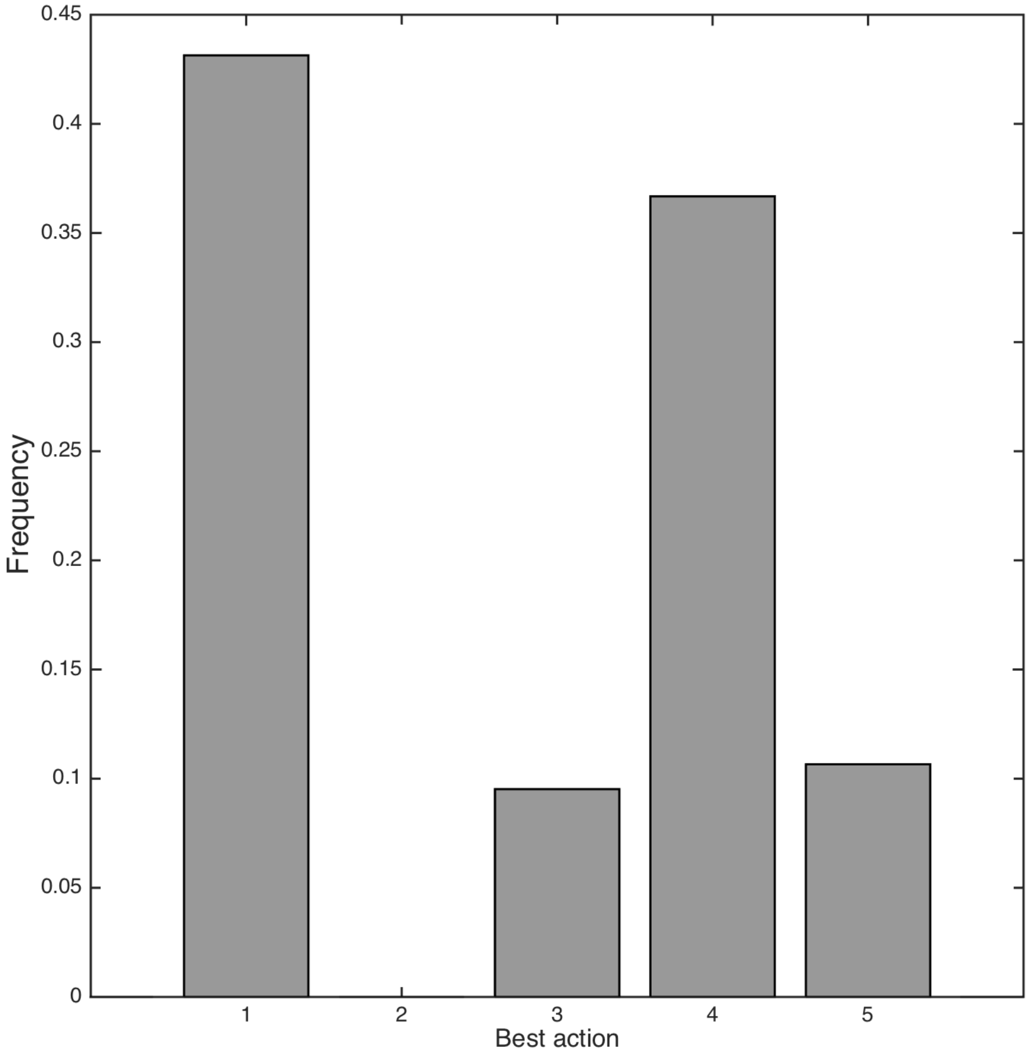


Fig. 3

University Library

A gateway to Melbourne's research publications

Minerva Access is the Institutional Repository of The University of Melbourne

Author/s:
Fraser, H; Rumpff, L; Yen, JDL; Robinson, D; Wintle, BA

Title:
Integrated models to support multiobjective ecological restoration decisions

Date:
2017-12-01

Citation:
Fraser, H., Rumpff, L., Yen, J. D. L., Robinson, D. & Wintle, B. A. (2017). Integrated models to support multiobjective ecological restoration decisions. CONSERVATION BIOLOGY, 31 (6), pp.1418-1427. https://doi.org/10.1111/cobi.12939.

Persistent Link:
http://hdl.handle.net/11343/216796

File Description:
Accepted version