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ARTICLE

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What state of the world are we in? Targeted monitoring to detect transitions in vegetation restoration projects

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Abstract

Monitoring vegetation restoration is challenging because monitoring is costly, requires long-term funding, and involves monitoring multiple vegetation variables that are often not linked back to learning about progress toward objectives. There is a clear need for the development of targeted monitoring programs that focus on a reduced set of variables that are tied to specific restoration objectives. In this paper, we present a method to progress the development of a targeted monitoring program, using a pre-existing state-and-transition model. We (1) use field data to validate an expert-derived classification of woodland vegetation states; (2) use these data to identify which variable(s) help differentiate woodland states; and (3) identify the target threshold (for the variable) that signifies if the desired transition has been achieved. The measured vegetation variables from each site in this study were good predictors of the different states. We show that by measuring only a few of these variables, it is possible to assign the vegetation state for a collection of sites, and monitor if and when a transition to another state has occurred. For this ecosystem and state-and-transition models, out of nine vegetation variables considered, the density of immature trees and percentage of exotic understory vegetation cover were the variables most frequently specified as effective to define a threshold or transition. We synthesize findings by presenting a decision tree that provides practical guidance for the development of targeted monitoring strategies for woodland vegetation.

KEYWORDS
monitoring, restoration, state-and-transition model, thresholds, woodlands

INTRODUCTION

Many land management organizations have a mission to conserve biodiversity. The protection and restoration of native vegetation is a key focus of biodiversity management programs, to protect native flora in its own right, and as a source of food and shelter for fauna. Managers have expectations about how the site or landscape will respond over time when they are enacting management, and the subsequent outcomes and benefits provided. These hypotheses about cause and effect may not be explicitly defined, but represent the justification for the choice of management applied (Rumpff et al., 2011). Decisions are implemented, and monitoring is often used to better understand how the system is changing in response to management to improve decisions, as well as to report on the outcomes of management investment.

A common problem associated with monitoring the results of vegetation restoration management is that the objectives of management programs (if specified) are often difficult to conceptualize and measure (Nichols & Williams, 2006; Parkes et al., 2003; Yoccoz et al., 2001). Defining biologically relevant performance measures that can reliably inform a manager about whether efforts result in the desired outcomes is not an easy task (Di Stefano, 2003; Legg & Nagy, 2006). For example, a common objective is to improve the condition of native vegetation. But how does one define condition? By definition, vegetation condition is a value judgment defined by a combination of variables, which differentially respond to environmental perturbations and management interventions (McCarthy et al., 2004). As an added complication, "vegetation condition" can reasonably be defined in many ways depending on the biodiversity, production, or aesthetic or social values underpinning management (Backstrom et al., 2018; Keith & Gorrod, 2006; Seastedt et al., 2008).

In vegetation management, a common approach is to monitor multiple structural, compositional, and functional attributes of the system, then either combine these variables into a univariate measure of "condition" (Parkes et al., 2003), or monitor and report on change in the individual attributes. The univariate option can result in difficulties in understanding what the measure actually represents, and an unnecessary loss of clarity (McCarthy et al., 2004), such that it can be difficult to examine whether and how investment in management actions has actually resulted in change (McCarthy et al., 2004; Sato & Lindenmayer, 2021). Reporting on change in individual variables can provide more clarity in this regard but, if multiple variables are responding differently, it can be hard to understand and communicate how the condition of the site is changing as a whole. A tension exists between integrating multiple attributes into a "holistic" view of condition, or leaving the individual attributes disaggregated.

The design and interpretation of condition monitoring may be helped by developing a system model that explicitly captures the cause-and-effect hypotheses that guide decisions, including the assumptions and uncertainty around how individual variables change over time in relation to management and other drivers (e.g., environmental, landscape context; Lindenmayer & Likens, 2010). System models are a key focus of adaptive management programs (Lindenmayer & Likens, 2009), and can be empirically validated or updated with monitoring data over time (Rumpff et al., 2011). They can lead to (qualitative or quantitative) predictions, guiding management decisions that go beyond educated guesses (Keddy, 1992; Rumpff et al., 2011).

State-and-transition models (STMs) are a relatively common form of system model utilized in vegetation management (Bestelmeyer et al., 2017; Stringham et al., 2007; Westoby et al., 1989). These models provide an explicit platform to formalize and communicate knowledge and beliefs about multiple, distinct states of vegetation in a landscape, with various pathways of change (Bestelmeyer et al., 2017; Westoby et al., 2007). States are defined according to single or multiple vegetation variables, so it is easy to understand the broad appeal of STMs as support tools for decision-making. The development of these models in a participatory setting can promote a shared understanding and justification of the decision context, vegetation dynamics, and choice of management interventions (Bestelmeyer et al., 2010). For instance, an explicit model can be used to discuss and define management objectives (i.e., for a site, what is the target state?), the management interventions and funds that are required to achieve the specified objective (Bestelmeyer et al., 2017), and to identify where uncertainty exists in the system (Rumpff et al., 2011).

In addition to providing a framework for modeling vegetation condition, STMs can also help to formulate a more targeted monitoring strategy. For instance, a manager may define the starting state and identify a desired state (the objective), then identify particular vegetation condition variables (e.g., weed cover) that, without intervention, are impeding a transition to the desired state. Presumably, if a manager has identified the threshold for that vegetation variable that defines the two states, one could monitor progress toward that threshold to know whether the desired change had been achieved at a site. Monitoring data would then simultaneously evaluate the model and the effect of the management intervention. Yet choosing what to monitor may not be that simple. There may be some uncertainty around system dynamics, such that the combination of environmental conditions and intervention may result in some unexpected or even perverse transition to a different state. The question then remains, what would one monitor, given that there may be multiple pathways of change and different time frames over which change occurs?

Given that monitoring is expensive, time consuming, and often not linked back to learning about progress toward objectives (Addison et al., 2016; Field et al., 2007; Lindenmayer & Likens, 2009; Thomas et al., 2018; Wintle et al., 2010), there is potentially great value in using STMs to both model vegetation states that reflect condition and generate a reduced set of variables to underpin a targeted monitoring strategy. In this paper, we present a method to progress the development of a targeted monitoring program, using STMs. Using a pre-existing state-and-transition model, we (1) use field data to validate an expert-derived classification of woodland vegetation states; (2) use these data to identify which variable(s) help differentiate woodland vegetation states; and (3) identify the target threshold (for the variable) that signifies when focal transitions have occurred. We discuss the limitations of the approach and provide a guide to the necessary steps for developing a targeted monitoring strategy. The development of STMs provides a practical approach to explicitly structuring hypotheses about system dynamics that underpin management decisions. We extend this thinking to provide an intuitive and accessible way to work toward a targeted monitoring program.

METHODS

The state-and-transition model: Defining the states

This method relies upon having a predefined STM for vegetation attributes or condition for the system at hand, and here we build upon an existing model described in Rumpff et al. (2011). The development of STMs to guide management is covered in more detail elsewhere (e.g., please refer to Bestelmeyer et al., 2010, 2017), but here we briefly summarize the model used in this study.

The STM was developed for the grassy woodland communities of central Victoria, on the northern slopes and plains of the Great Dividing Range. The woodlands are dominated by *Eucalyptus* species, primarily the box species (e.g., *E. microcarpa*, *E. albens*, *E. goniocalyx*, *E. melliodora*), as well as yellow gum (*E. leucoxylon*), and sometimes red gum (*E. camaldulensis*, *E. blakelyi*). The understory is variably dominated by grasses or shrubs, with a wide range of native herbaceous species, particularly within less disturbed areas. The states and transitions that describe the woodland communities were defined by a group of experts, with expertise in woodland ecology and natural resource management. The states included: Reference, Simplified, Oldfield, Thicket, Native pasture, Exotic pasture and Derived (Rumpff et al., 2011; Figure 1). Experts initially described states qualitatively in terms of their structure and composition, using vegetation variables that best characterized each state and are commonly used in condition assessments (Gibbons & Freudenberger, 2006; Noss, 1990; Parkes et al., 2003; Rumpff et al., 2011). Experts then quantitatively described each state according to the expected range for each vegetation "state" variable (e.g., % weed cover; please refer to Rumpff et al., 2011).

Validating the states: Site identification and assignment of state

We presented the conceptual model and the qualitative and quantitative descriptions (Figure 1) of the woodland states from Rumpff et al. (2011) to five land managers in our study area, the Goulburn and Broken River catchments in Victoria, Australia. We asked land managers to identify multiple examples of sites for each state in their landscape. We aimed to have equivalent numbers of sites per vegetation state, even though they were not equally represented within the landscape. For the Reference state, we sought further input from three additional land managers as there are few examples of intact high-quality woodland in this landscape. In total, 85 sites was identified (Appendix S1).

A small team of researchers visited each of the 85 identified sites and each researcher qualitatively assigned the site to a state using state descriptions and photographs accompanying the conceptual model. In addition to the assessment from land managers, at least two researchers assessed each site to provide a coarse understanding of whether perceptions of vegetation states varied between individuals. There was high agreement between the assignment of state to site by the researchers, with 91% of sites classified identically, and corresponding with the managers assignment of states. The greatest uncertainty was in the differentiation of Simplified from Oldfield states (accounting for 50% of "uncertain" site classifications).

We also used data from vegetation condition assessments of 40 sites from the same study area, collected by researchers from the Australian National University (ANU). The ANU sites were independently assigned states by two individuals involved in collecting the data. The field researchers were given the same general criteria for differentiating each state as the Victorian managers.

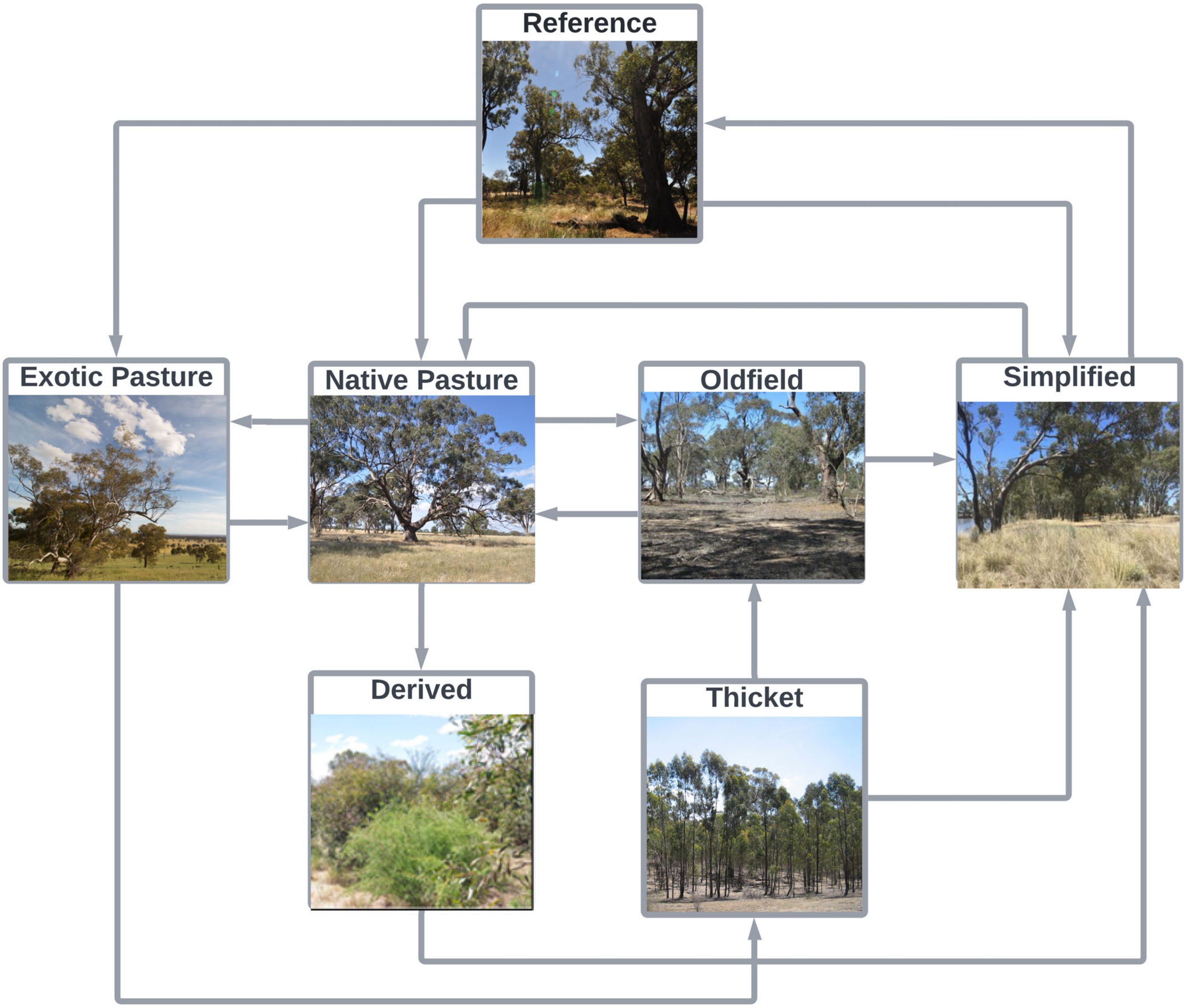

FIGURE 1 State-and-transition model for nonriparian woodlands and a brief description of the woodland states shown to experts, modified from Rumpff et al., 2011. **Reference:** Sites that are largely intact in terms of structural and species diversity, with a low cover of exotic species. Sites that have been little altered since European settlement fall into this category, but the reference state does not necessarily have to represent pre-European vegetation condition. **Simplified:** Sites may have a relatively intact understory, overstory, or midstory structure, but one or more of these strata is likely to be simplified. Species richness may be high, but unlikely to reach that of reference levels. An example of this state is vegetation that has been intermittently grazed at low intensity and/or moderately cleared in the past. **Oldfield:** Sites with a simplified overstory structure, low species richness (of the understory and midstory), but may have a moderate to high cover of shrubs. A typical example includes sites that have been previously cleared and intensively grazed, but then abandoned from grazing and left to recover without management intervention. **Native pasture:** Sites with a simplified overstory, and a low cover and richness of both the midstory and understory. The cover of weeds may be low-moderate. Such sites will typically include those that have been cleared and grazed at a high frequency and intensity, but without the addition of fertilizer. **Exotic pasture:** Sites with an understory composed almost entirely of exotic species, a simplified overstory, and no midstory. Such sites will have been fertilized and sown with an exotic understory. **Thicket:** Sites with a dense regrowth of overstory species, and a relatively low cover/richness of the understory and midstory component. For instance, sites may have had a change in land-use (e.g., removal of grazing or logging) and climatic conditions that were favorable for natural regeneration of woody species. **Derived:** Sites that have low understory species richness, and a low to mid cover of weed, understory, and overstory species. The cover and richness of the midstory can range from low to high. This state represents sites that have been replanted with multiple life-forms for the purpose of enhancing biodiversity.

The two researchers were in perfect agreement for the 40 ANU sites. This brought the total number of sites to 125, with a minimum of seven sites in the Reference state and maximum of 32 sites in the Simplified state (Appendix S1).

Validating the states: Field collection

Field data were collected for all 125 sites by the two separate groups of researchers between October 2011 and February 2013. Sites spanned a range of states for each group and were surveyed using equivalent survey approaches outlined in Appendix S1. Data were collected for each of the nine state indicator vegetation variables described in Rumpff et al. (2011) at all sites. The nine variables defined the overstory (tree density in different size classes), midstory (shrub cover and recruitment density) and understory (cover and diversity) vegetation components of the community (Appendix S1). Data were collected in quadrat areas and along line transects in both survey approaches. Given the equivalent ecosystems and data collection methods, we combined the two datasets for analysis. Stem density and species richness data were calibrated so that all relevant variables from both groups had an equivalent spatial scale (Appendices S1 and S2).

Transitions between states

Each state was considered by the group of experts to be likely to transition to one or more alternative states, as described in the STM conceptual model (Figure 1, Table 1). This was not an exhaustive list of the possible transitions, but rather a list of the transitions commonly observed in the landscape. Although all possible transitions could be evaluated, there was little value in investigating very unlikely transitions, such as those from more degraded states to the ideal Reference state. Additionally, the experts suggested the probable primary drivers of each transitional change, including damaging processes, such as tree clearing, livestock grazing, and fertilization, and restorative processes, such as revegetation, weed control, and destocking. The list of likely transitions and their primary drivers are given in Table 1.

TABLE 1 The most likely transitions between states from the conceptual model (from Rumpff et al., 2011), to be tested in this paper.

Initial state	Transition state	Suggested drivers of change (Rumpff et al., 2011)
Reference	Exotic pasture	Major clearing (overstory and midstory), fertilization, sowing
	Native pasture	Major clearing (overstory and midstory)
	Simplified	Clearing of midstory or overstory, grazing by domestic stock
Simplified	Native pasture	Clearing of midstory and overstory, grazing by domestic stock
	Reference	Active rehabilitation (planting or direct seeding), weed control, native, and pest herbivore control, destocking, and time
Oldfield	Native pasture	Destocking
	Simplified	Active rehabilitation (planting), time
Native pasture	Exotic pasture	Fertilization, sowing
	Thicket	Destocking and “good” rainfall year
	Oldfield	Removal of grazing and fencing
	Derived	Destocking, soil preparation, weed control, active rehabilitation (planting or direct seeding)
Exotic pasture	Native pasture	Cease fertilization, time
	Thicket	Destocking and “good” rainfall year, or mass direct seeding of *Eucalyptus* species with soil disturbance and a “good” rainfall year
Thicket	Oldfield	Natural or manual thinning, poor native seed bank
	Simplified	Manual thinning when native soil seed bank present, and/or active rehabilitation (planting or direct seeding)
Derived	Simplified	Weed control, active rehabilitation (planting or direct seeding), time

Data analysis

Data analyses were conducted to directly address three questions relating to the STM: (1) How valid are the expert-derived woodland vegetation states when tested with field data? (2) What are the variables that differentiate states? (3) What variable(s) and value threshold(s) define a transition from one state to another? The first two questions were addressed using decision tree models, whereas the third was achieved through logistic regression. All analyses were performed using the statistical software package R version 3.6.0 (R Core Team, 2020).

Evaluating the visual classification of states using classification trees

We used classification trees to conduct categorical assignment of sites to individual classes (De'Ath & Fabricius, 2000). These methods are effective for this type of analysis as they make no assumptions about the distribution of variables and are not overly compromised by nonlinear relationships (De'Ath & Fabricius, 2000). We developed an all-site classification tree with the entire dataset of sites and vegetation variables for illustrative purposes only, to see whether the expert-derived STM states are consistent when quantitatively validated with field data in this successive data partitioning process. This model shows the measured vegetation variables that successively partition the entire set of sites into a specified number of groups (states) (Appendix S3). A classification tree model using all sites involves successive partitions that only use a subset of the total sites that is, does not use all the data relating to each state transition. Although there may be benefits to this all-state synthesis, the successive nature of the model with imperfect partitioning means that this approach does not fully discriminate any two particular states. An alternative approach that maximizes the use of all data within each state for determining a set of specific monitoring variables is to make separate models for each pair of states that are targeted for monitoring transitions. For this reason, our set of classification trees used subsets of the data to look at each target pair of states that corresponded to probable thresholds that discriminate states (Table 2).

In constructing the classification trees, we specified the "formula" as a linear model in which the response variable was the assigned state. The predictor variables were the various vegetation state variables measured at each site that reflect the state definitions, their transitions and drivers (Figure 2, Table 1). A stepwise approach termed recursive partitioning was used to sequentially divide splits (branches) until some point of resolution of a group, using the *rpart* statistical package (Therneau & Atkinson, 2019) within R. Within the *rpart* function, the "method" argument in all cases was set as "class," whereas the "control" argument was used to specify the number of splits within the tree to reflect the number of possible states in the set. The most useful variables for differentiating between two states can then be identified and ranked using the paired classification trees (De'Ath & Fabricius, 2000). Additionally, this process also indicates how effectively this top ranked variable splits the sites (e.g., 10 out of 12 sites were split based on this single variable). This can be used to assess how well the classes mapped on to the predefined assignment of state (i.e., the model is not predetermined to split into the different states). However, this only speaks to the top ranked variable and would only be useful if only a single variable was going to be used to monitor state transitions.

Logistic regression: Evaluating thresholds and uncertainty for monitoring

Although classification trees can provide a quantitative estimate of the threshold value of a variable that splits two groups, explicitly examining the uncertainty around this threshold was more easily achieved through logistic regression. Logistic regression maintains input state assignment, whereas classification trees can reallocate states into new groups based on the data. This means that the ranking of classification trees may not align with a ranking of the most certain logistic regression thresholds, but this is not considered a conflict as the outcomes of both tools can be used together to inform monitoring or management decisions. Exploring uncertainty will inform our confidence that a transition has occurred, because values near the threshold are weak indications of a transition. Although all thresholds will be uncertain, some will be more uncertain than others and these will be less reliable indicators of transition. However, it is difficult to determine an ideal or unacceptable level of uncertainty because it depends on the relative suitability of alternative variables and the risk attitude of the manager. For each pair of states (i.e., possible initial to transition states; Table 1) we produced logistic regression models for the three best-performing variables from the classification tree (paired) models and calculated and examined the uncertainty around the threshold.

Logistic regression models were fitted with the *glm* function in R (R Core Team, 2020), with the binomial "family" and logit "link." Models were fitted on transformed response variable data to improve normality; square-root transformations were used for all percentages and a subset of the count data (densities and richness). In general, count data with relatively clear thresholds (little data overlap between states) produced better fitting models with log transformations, whereas square-root transformations performed better for uncertain thresholds. Once fitted, the *predict* function was used to estimate the value (with 95% confidence interval) of the vegetation variable when the state was exactly 0.5, that is, halfway between the two state binary values. Predictions

TABLE 2 The top three variables across the full set of classification trees for all unique combinations presented in the expert-derived conceptual model (STM).

State transition		Model rank of variables for each state pair		
From	**To**	**1**	**2**	**3**
Reference	Exotic pasture	Density of immature trees (Stem.to30)	Exotic understory cover (Perc_ex_us)	Density tree recruits (REGEN_T_ha)
	Native pasture	Density of immature trees (Stem.to30)	Density tree recruits (REGEN_T_ha)	Native shrub cover (Perc_nat_shrub)
	Simplified	Native shrub cover (Perc_nat_shrub)	Density shrub recruits (REGEN_SH_ha)	Density of immature trees (Stem.to30)
Simplified	Native pasture	Density of immature trees (Stem.to30)	Native understory richness (RICH_natund)	Density tree recruits (REGEN_T_ha)
	Reference	As in reference to simplified		
Oldfield	Native pasture	Density of immature trees (Stem.to30)	Density tree recruits (REGEN_T_ha)	Density of mature trees (STEM.50plus_ha)
	Simplified	Density of mature trees (STEM.50plus_ha)	Exotic understory cover (Perc_ex_us)	Native shrub richness (RICH_natmid)
Native pasture	Exotic pasture	Native understory cover (Perc_nat_us)	Exotic understory cover (Perc_ex_us)	Native understory cover (RICH_natund)
	Thicket	Density of immature trees (Stem.to30)	Density tree recruits (REGEN_T_ha)	Exotic understory cover (Perc_ex_us)
	Derived	Native shrub richness (RICH_natmid)	Native shrub cover (Perc_nat_shrub)	Density shrub recruits (REGEN_SH_ha)
	Oldfield	As in Oldfield to Native pasture		
Exotic pasture	Native pasture	As in Native pasture to Exotic pasture		
	Thicket	Exotic understory cover (Perc_ex_us)	Density of immature trees (Stem.to30)	Native shrub cover (Perc_nat_shrub)
Thicket	Oldfield	Exotic understory cover (Perc_ex_us)	Density of immature trees (Stem.to30)	Density of mature trees (STEM.50plus_ha)
	Simplified	Density of immature trees (Stem.to30)	Native shrub cover (Perc_nat_shrub)	Exotic understory cover (Perc_ex_us)
Derived	Simplified	Density shrub recruits (REGEN_SH_ha)	Native shrub richness (RICH_natmid)	Native understory richness (RICH_natund)

Note: Transitions are two-way, that is, reference to simplified is equivalent to simplified to reference, so duplications are not repeated in the table.
Abbreviation: STM, state-and-transition models.

with log transformation were made on the link scale to identify the 0.5 threshold and then back-transformed for plotting. This provides a threshold value that discriminates between the two states.

RESULTS

The seven different states identified in the STM varied considerably in the values of the measured vegetation variables (Figure 2). Native understory cover, shrub richness, and understory richness varied substantially within states, but less so between states. Other variables, like stem density, midstory (shrub) cover and recruitment had greater between-state variation, predominantly due to high values in one of the states (Figure 2). The raw data demonstrated that some states have clearly distinguishing variables (e.g., Thickets are characterized by high stem density, and Derived states by high levels of shrub cover and richness).

Classification trees

The paired classification models were run for all pairs of states with corresponding probable transitions specified in the original STM conceptual model (Figure 1). These trees display the top ranked variable used to split

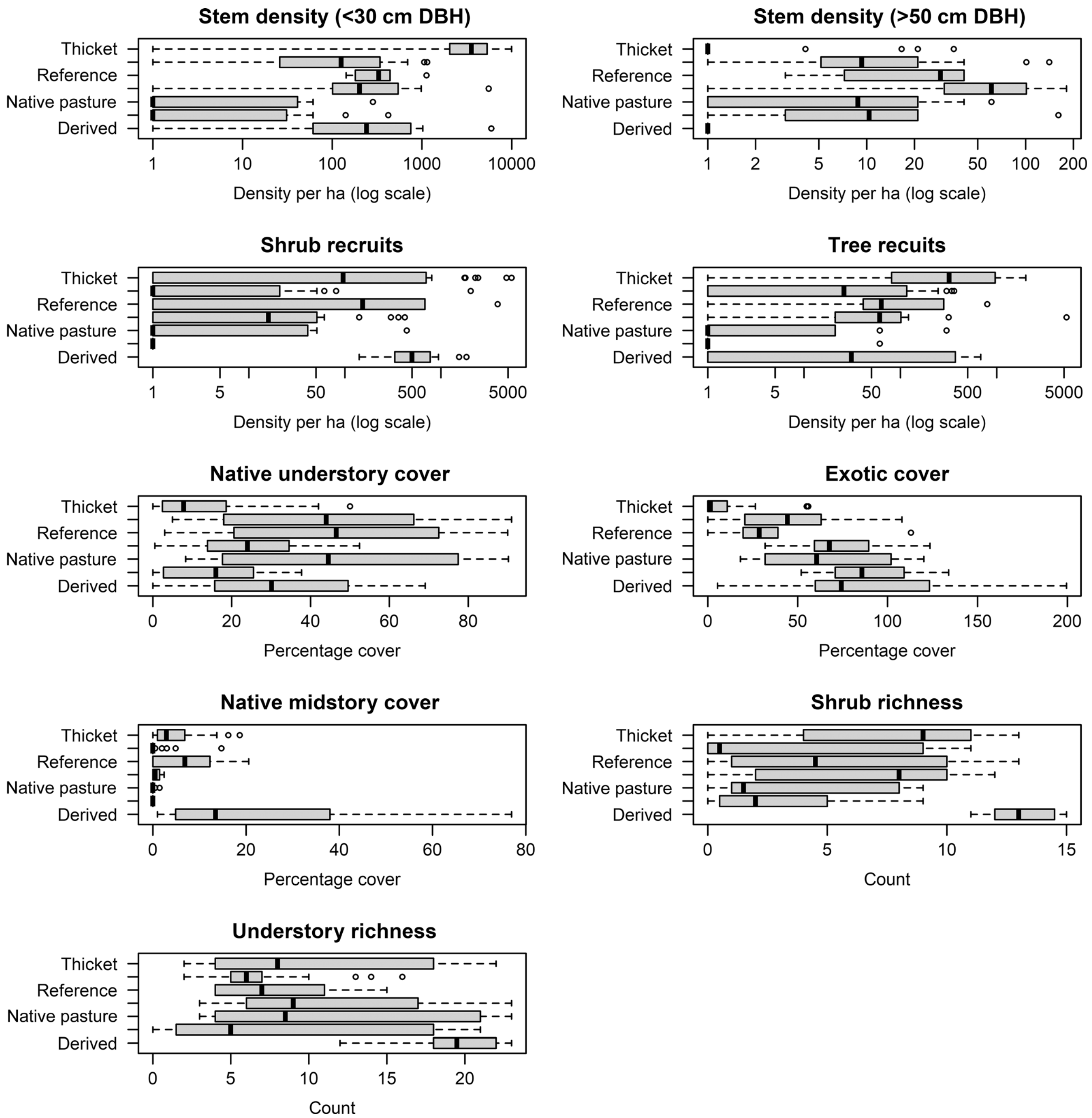

FIGURE 2 Boxplots representing raw data across both the Australian National University (ANU) and University of Melbourne (UM) datasets across each of the vegetation states. Tree and shrub densities are plotted on the log 10 scale to aid visual comparisons, so a constant (1) was added to all values for plotting. Center lines indicate median values, boxes indicate the interquartile range and whiskers extend to no more than 1.5 times the interquartile range from the box. Percentage cover values are summed across individual species, so totals can exceed 100% when species overlap.

between two groups, a threshold value indicating the value of the variable that best splits two states as well as an indication of effectiveness of correctly differentiating between states, as exemplified in Figure 3. The "Native pasture" and "Exotic pasture" states have similar stem densities, woody recruits and midstory cover (Figure 2), but the cover of native understory vegetation appears to be the most important differentiating variable at a 34% threshold (Figure 3). If native understory cover alone were to be used to differentiate between these states it would correctly identify 10 out of 14 sites (71% correct) and six out of seven native pasture sites (81% correct). The "Oldfield" and "Simplified" states differ most in their density of mature trees in the paired models with a

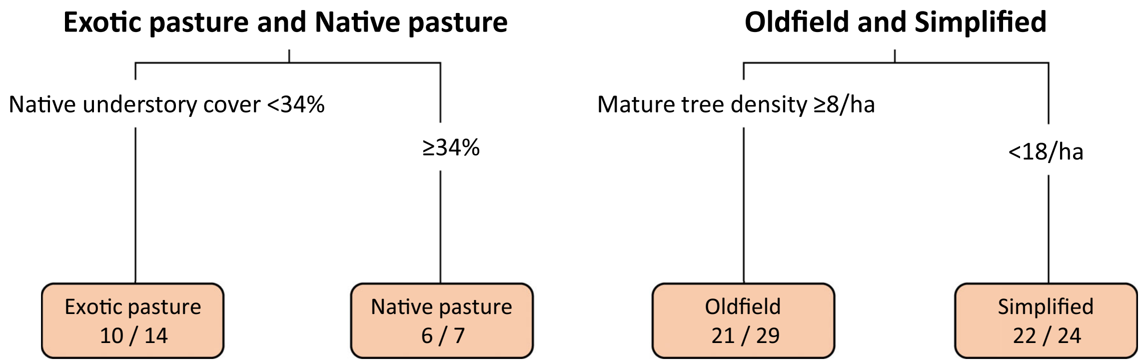

FIGURE 3 A graphical representation of two classification trees for paired states: Exotic pasture and Native pasture (left), and Oldfield and Simplified (right). The trees were generated by hierarchical partitioning of 21 sites using vegetation variables. The percentage cover of native understory was the best variable to distinguish between Native pasture and Exotic pasture states, at a threshold of 34% cover. Whereas a mature tree density threshold of 18/ha was the best for distinguishing Oldfield and Simplified states. Values within each group refer to the number of sites reflecting the label and the total number of sites in that group.

threshold of 18 stems per hectare. If this variable alone was used to differentiate these two states, then Oldfield sites would be correctly identified 72% of the time and Simplified states 92% of the time (Figure 3).

The three most highly ranked vegetation variables defining the difference between each state pair are recorded in Table 2. The threshold value for each variable is included in Appendix S4. Of the most highly ranked variables across all-state pairs, the density of immature trees (Stem.to 30) was most frequently reported (in nine out of 13 unique transitions). The percentage cover of exotic understory was the second most frequently listed (in seven out of 13 unique transitions) followed by density of tree recruits and native shrub cover (both five of 13). Native understory richness, density of mature trees, density of shrub recruits and the richness of native shrubs generally indicated uncertain transitions and occurred in three out of 13 unique transitions. Native understory cover was the least frequently listed (in one out of 13 unique transitions).

Logistic regression

The top three ranked variables determined by the classification trees for each pair of states were modeled using logistic regression via a generalized linear model with a binary variable for states to calculate a threshold value, and the uncertainty (95% CI intervals) around the threshold. Three common vegetation states and their probable transitions are shown in Figure 4. These transitions represent moving in a perceived negative direction (due to a decline in condition) from a "Reference" state to a "Simplified" state (Cunningham et al., 2008), a positive direction moving from a "Derived" state to a "Simplified" state and a potentially problematic transition from "Native pasture" to "Thicket" (Jones et al., 2015). The reference to simplified transition is uncertain and relatively inaccurate, due to the small and inconsistent differences between vegetation variables within these states. Detecting this transition is therefore likely to be difficult and require accurate data from multiple variables. In contrast, the Derived and Simplified states have clearly different data distributions of multiple vegetation variables, and therefore precise and more certain thresholds. This would be a much simpler and more reliable transition to detect. The Native pasture and Thicket states have moderate transitions with high uncertainty at low tree densities but high certainty at high densities. Once states are clearly defined with specific ranges of vegetation variables, a manager could use these results to monitor specific site changes and get an early indication of likely or problematic transitions. The full results for each pair of states is presented in Appendix S4.

Examples of thresholds with low and high uncertainty are shown in Figure 5. The width of the confidence interval and the percentage deviance explained of the logistic regression (Appendix S4) are effective indicators of uncertainty around a threshold. Variables that provide clear thresholds with narrow confidence intervals are optimal for indicators of change in state. When states can be confidently discriminated by a vegetation variable, that variable may be sufficient to detect changes alone, but when variables provide unconfident thresholds, multiple variables may be required to indicate state changes. For example, for a transition between "Thicket" and "Oldfield" states, the variable exotic understory cover may be a useful monitoring variable on its own (Figure 5), as the width of

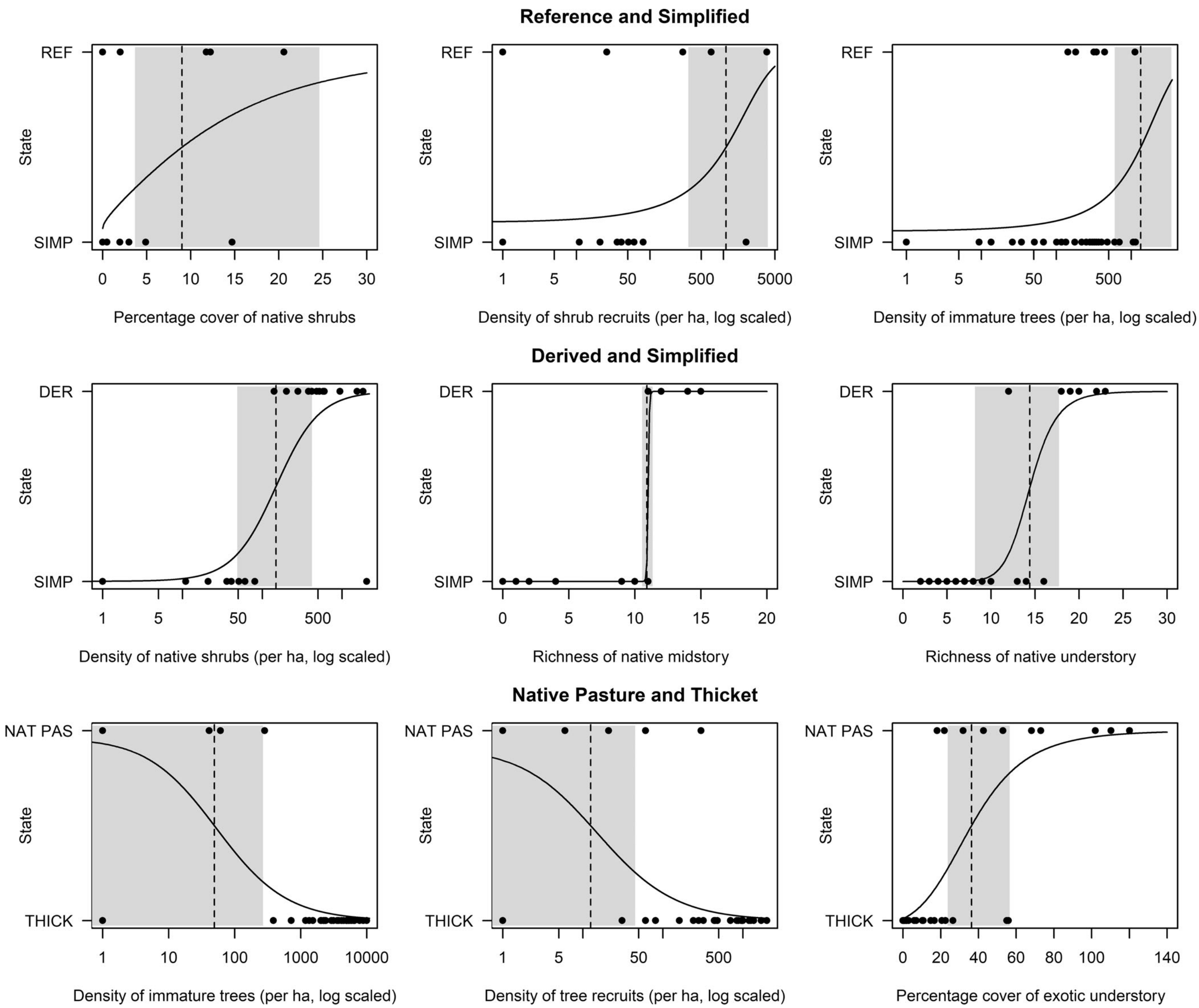

FIGURE 4 An example of three transitions that occur in our study region. Each transition shows the top three ranked vegetation variables (identified by the classification tree analysis) that would be most useful for monitoring these transitions. Solid black lines are the likelihood of a site being in one of two states given the value of a vegetation variable. Black circles indicate measured values at a site (one circle per site). The dashed black line occurs at the 0.5 probability and shaded areas represent 95% CI or uncertainty around threshold values. Densities of trees and shrubs have been log scaled for clarity, so a constant (1) was added to all values for plotting.

the confidence interval around the threshold (37.8% cover) is narrow relative to the range of values and overlapping data distributions (26.9%–47.7%, 79% Dev. Exp., $p = 0.0024$). In comparison, for a transition between "Reference" and "Simplified" states the percentage cover of native shrubs is unlikely to be a useful monitoring variable on its own as the width of the confidence interval around the threshold (9%) is wide (3.6%–24.7%, 23% Dev. Exp., $p = 0.012$) (Figure 5).

It is more likely to be a change in state will be detected when monitoring variables with more certain thresholds, whereas monitoring very large changes may still be insufficient to conclude a state change when the thresholds are uncertain. For example, monitoring a change in exotic understory cover of 35% at a hypothetical site is enough to be confident of a transition between Oldfield and Thicket (Figure 5) because this change is large enough to clearly cross over the threshold and its confidence interval (open circle change from 20% to 55%). However, a change of only 20% (change from 20% to 40%) suggests a state change with low confidence. In contrast, when monitoring the cover of native shrubs at a Simplified state, one is unlikely to be confident in detecting a transition to a Reference site even if the magnitude of the change is as large as 13% (more than 10 times the initial estimate; Figure 5).

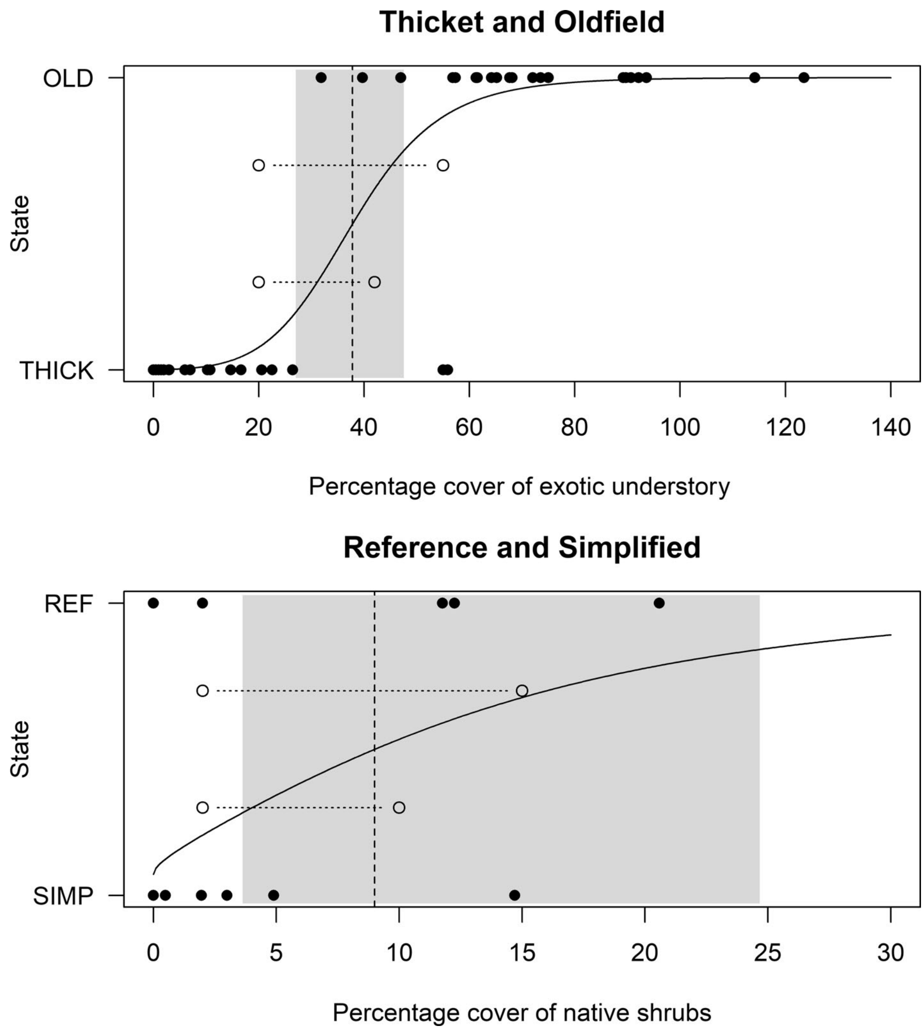

FIGURE 5 A linear model prediction (solid black line) of the likelihood of a site being in one of two states given the value of a vegetation variable. Black circles indicate measured values at a site (one circle per site). The dashed black line occurs at the 0.5 probability, that is, the threshold of likelihood between states, with the gray area showing the 95% confidence interval of this prediction. The open circles and dotted lines indicate changes in value at a hypothetical site, representing examples of clear (Thicket and Oldfield: spanning the threshold uncertainty) and less certain (threshold uncertainty range not crossed) transitions were based on these vegetation variables and different levels of certainty of threshold values.

In only one case there was no overlap between the values of a variable between two different states, that is, the data could be split perfectly into two separate groups (Appendix S4). In two other cases, the data did not overlap apart from one equal value. These include transitions between: "Native pasture" and "Derived" (with native shrub richness), "Exotic pasture" to "Thicket" (with % cover native shrubs) and "Derived" to "Simplified" (with native shrub richness; Figure 4) respectively. These represent the best-case scenario for the use of a variable to define a transition.

DISCUSSION

This study provides good justification for, and demonstrates the development of, targeted monitoring strategies for woodland vegetation. Landscape scale decision-making is a focus in some ecosystems (Bestelmeyer et al., 2011; Steele et al., 2012) and STMs are useful in capturing complex ecological dynamics (Rumpff et al., 2011). However, having measurable targets and monitoring to detect a specific directional change at the site level is often a requirement of useful monitoring programs (Nichols & Williams, 2006). The measured vegetation variables from each woodland site in this study were good predictors of the different vegetation states as previously defined by experts (Rumpff et al., 2011). We demonstrate an effective approach to quantifying transition thresholds and their uncertainty. Importantly, we have shown that by measuring only a few of these variables, it is possible to assign a collection of sites into a vegetation state corresponding with perceptions of condition, and to monitor if and when a transition to another state has occurred.

Of the nine vegetation variables measured across all sites, the density of immature trees and percentage of exotic understory vegetation cover were the most reliable variables to define a threshold or transition between two woodland states. Despite being listed as the most frequently important indicator of a transition, immature stem densities typically had uncertain threshold values and would therefore only be the most practical indicators on their own when the magnitude of change was large. Although the requirement of a large change is not ideal, mass recruitment events are common within these landscapes and high densities of immature trees can occur quickly (Jones et al., 2015). Although the percentage cover of native vegetation is a frequently monitored vegetation variable in Australia (Parkes et al., 2003), it was the least commonly listed as an important variable to define transitions in these woodlands. Similarly, species richness is a commonly recorded variable but was a relatively uncertain indicator of transition in this ecosystem, given the objective of differentiating between vegetation states. However, these variables may be important conservation attributes for other management objectives.

The paired classification approach displays the highest ranked variable for differentiating between sites as well as other useful variables. For any monitoring strategy we would advocate for monitoring at least two of the ranked variables, and this is for several reasons. First, in few cases could a single variable distinguish between states perfectly, nor would we expect this to be the case given the complex nature of ecological systems. Second, the vegetation variables can be measured in different ways that might be more or less prone to measurement error. For example, a threshold for native shrub cover may have narrow confidence intervals (e.g., 2% CI width in Thicket to Simplified) but if visual assessment of cover is being used to monitor this variable, measurement error may be larger compared with this (McCarthy et al., 2004). A narrow confidence interval around the richness of native shrub species (e.g., a one species difference in Derived to Simplified) may be less prone to measurement error, depending on detectability (Kéry & Schmidt, 2008). Third, attention needs to be given to the time frame over which change is monitored. Reporting achievement of a transition may be best demonstrated with a more dynamic variable (i.e., percentage exotic understory cover compared with development of mature trees), but this depends on the time frame of the monitoring given the objectives of the monitoring program. Last, this analysis has only been carried out using two data sets and, whereas those involved in this study could visually assign states to vegetation relatively reliably, larger or more validation data sets may be required to avoid or reduce misclassification errors. In all cases, erring on the side of caution with the choice of variable(s) is wise. A practical next step would be to test how applicable the identified vegetation variables are in signifying transitions across a range of similar vegetation types in Australia.

How to identify targeted monitoring variables, using the state-and-transition model approach

The decision tree in Figure 6 is intended to aid in developing a targeted monitoring strategy at a site level, using the process outlined in this paper. We assume the process of developing the state-and-transition model, data collection, and analysis (as per this paper) is complete (for guidance please refer to Bestelmeyer et al., 2017; Rumpff et al., 2011). The first stage in developing a monitoring strategy based on the state-and-transition model is to determine the objectives for management (Field et al., 2007). This may relate to the landscape level, and/or at the level of a site. At a landscape level, managers first need to identify the objectives for the landscape (i.e., how much of landscape should be in state X vs. Y, by time Z?). This decision depends on the area and distribution of states in the landscape, and what resources are available. Then, at a site level, the objective relates to what state is desired, over what time frame.

In the decision tree (Figure 6) the diamond shapes indicate questions that should be asked at each site, whereas the rectangular shapes indicate the subsequent processes required to develop the monitoring strategy. Important decision triggers include whether the user has, or can identify, the starting state at a site. We recommend that more than one person assesses the starting state, as uncertainty and variation between observers can have implications for which monitoring variables are used to assess condition and change over time.

The next important decision trigger is determining how much uncertainty is tolerable in the selection of monitoring variables. This requires the user to examine the uncertainty around the threshold for each monitoring variable. We have demonstrated a threshold point at which the model is most uncertain about state (i.e., a 50/50 chance of being in either state) but this threshold definition might not always be the most appropriate decision threshold. Instead, the user may wish to specify a different tolerance to uncertainty (Figure 6). We recognize this is an important consideration (Rumpff et al., 2012), but is outside the scope for this paper.

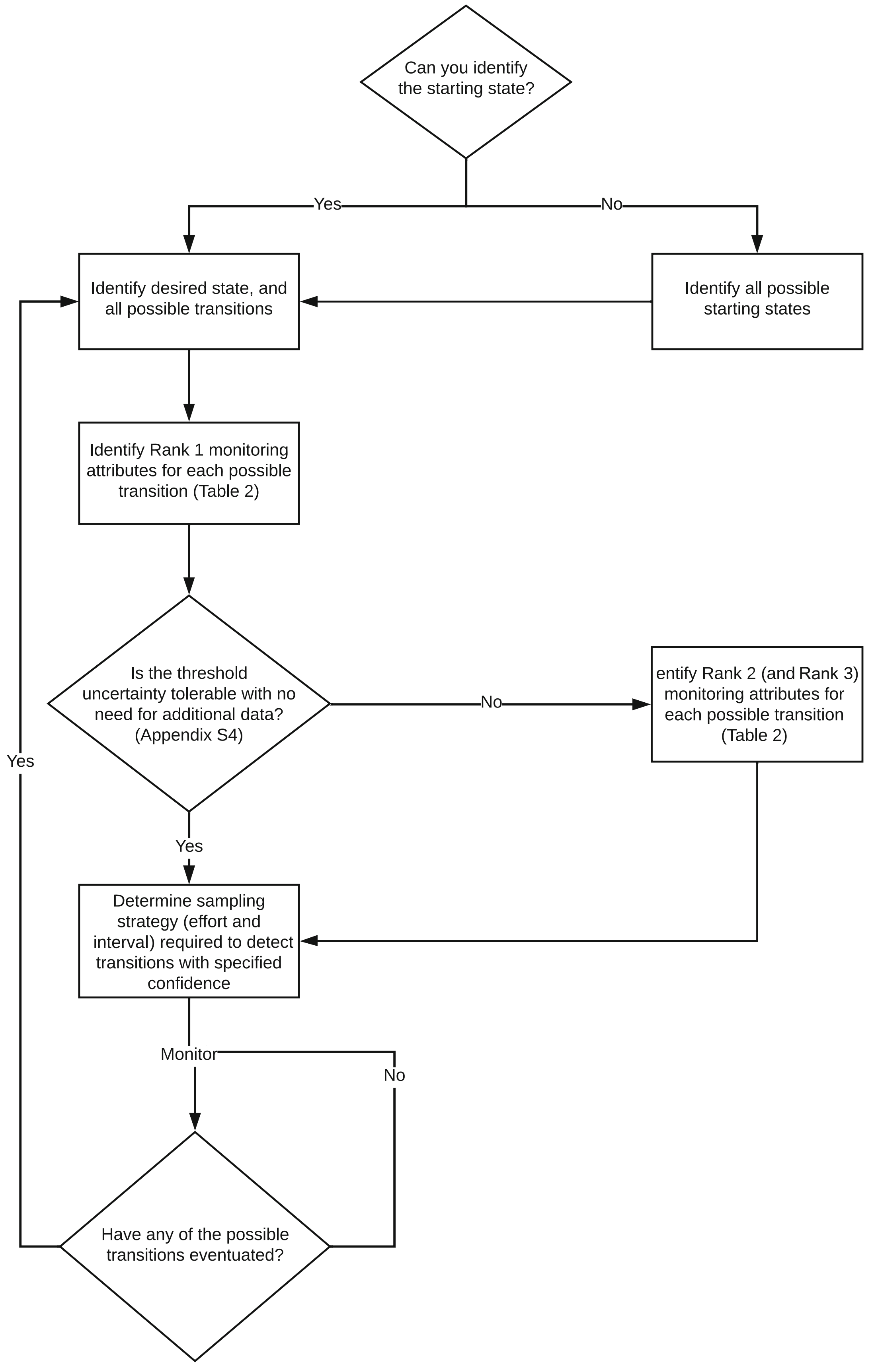

FIGURE 6 Decision tree indicating how to identify targeted monitoring variables given the knowledge of starting states, transitions, monitoring attributes, and tolerance of uncertainty.

Even if the bounds of uncertainty are adequate, it may be prudent to monitor more than one variable to be more certain of a transition (if it occurs), or if the user wants to include a short-term monitoring variable (e.g., recruitment) in addition to a longer term variable (e.g., tree density) in their strategy. Alternatively, when monitoring a variable and the site lies within the bounds of uncertainty (i.e., the 95% CI), the user might want to consider monitoring another variable if greater certainty about the assignment of state is needed (Appendix S4). Of course, other variables may be collected for other purposes at the same time, but here we are focusing on the minimum number of variables to measure to reliably detect state transitions.

The next decision point requires the user to reconsider how confident they want to be that a transition has occurred, or is occurring. That will influence the sampling design as greater confidence requires greater sample size, or reduced variability, or both. A power analysis approach may be helpful in determining monitoring parameters (or for methods for more complex systems please refer to Thomas et al., 2018), but with a key component being the manager's preferred level of confidence in a true state change. Typically, sample size is what one manipulates, as natural variability is less controllable, except by sampling methods of greater or lesser precision. This depends on the available sampling budget and how it needs to be allocated over space and time. Last, when the desired state is reached (or maintained), a manager has to decide whether to set a new objective, and how much monitoring is required to detect whether the desired state is maintained. We use a feedback loop to indicate when a decision needs to be made, rather than to imply that a site is monitored in perpetuity.

Summary

In contrast with surveillance monitoring that can be useful for discovering "unknown unknowns" (Wintle et al., 2010), managers and decision makers require targeted monitoring programs that focus on a reduced set of variables that are tied to specific restoration objectives. In this paper, we provide an example of testing whether a targeted monitoring program can be developed for woodland vegetation in southeast Australia. We use STMs as the framework for specifying site objectives, identifying a reduced set of monitoring variables to help distinguish between states, and identifying thresholds (with uncertainty) that provide monitoring targets that are linked to objectives. Our findings indicate that measured vegetation variables from each site in this study were good predictors of the different vegetation states, and there are a few variables that can be commonly used as monitoring variables distinguishing among multiple states. This approach, although developed for one ecosystem only, is a promising step toward developing more targeted and efficient monitoring protocols that can support learning about change over time for vegetation restoration projects when specific objectives have been identified.

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CONFLICT OF INTEREST

There are no conflicts of interest associated with the publication of this manuscript.

DATA AVAILABILITY STATEMENT

Data and code (Jones et al., 2022) are available in the Open Science Framework at https://doi.org/10.17605/OSF.IO/5XA9P.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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