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Developing decision support tools for rangeland management by combining state and transition models and Bayesian belief networks

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ABSTRACT

State and transition models provide a simple and versatile way of describing vegetation dynamics in rangelands. However, state and transition models are traditionally descriptive, which has limited their practical application to rangeland management decision support. This paper demonstrates an approach to rangeland management decision support that combines a state and transition model with a Bayesian belief network to provide a relatively simple and updatable rangeland dynamics model that can accommodate uncertainty and be used for scenario, diagnostic, and sensitivity analysis. A state and transition model, developed by the authors for subtropical grassland in south-east Queensland, Australia, is used as an example. From the state and transition model, an influence diagram was built to show the possible transitions among states and the factors influencing each transition. The influence diagram was populated with probabilities to produce a predictive model in the form of a Bayesian belief network. The behaviour of the model was tested using scenario and sensitivity analysis, revealing that selective grazing, grazing pressure, and soil nutrition were believed to influence most transitions, while fire frequency and the frequency of good wet seasons were also important in some transitions. Overall, the integration of a state and transition model with a Bayesian belief network provided a useful way to utilise the knowledge embedded in a state and transition model for predictive purposes. Using a Bayesian belief network in the modelling approach allowed uncertainty and variability to be explicitly accommodated in the modelling process, and expert knowledge to be utilised in model development. The methods used also supported learning from monitoring data, thereby supporting adaptive rangeland management.

1. Introduction

Many decision support tools have been developed by researchers for the purpose of predicting the outcomes of rangeland management decisions (see National Land and Water Resources Audit (2004) for those developed in Australia). However, many of these tools failed to be adopted by rangeland managers. There may be several reasons for this, such as a lack of credibility in, or a perceived lack of usefulness of, decision support tools; a resistance among managers to replace their own decision-making processes, knowledge, and experience with decision support tools; the high cost of developing and maintaining decision support tools (particularly those that are data hungry and computationally intensive); and the need for decision support tools to compete with consultants and advisors who are trusted and socially integrated with managers (Matthews et al., 2005). Efforts to overcome these barriers to adoption have included the testing of models, improving the cost effectiveness of decision support tools (developing low cost, low-data decision support tools), and using participatory methods to build decision support tools (building decision support tools with managers rather than for them) (Lynam, 2001; Smith et al., 2007a).

State and transition models (STMs) have traditionally provided a simple, versatile, and low cost means for developing rangeland dynamics models. They have been used by researchers in many rangeland ecosystems to integrate knowledge about vegetation dynamics and the possible responses of vegetation to management actions and environmental events (Friedel, 1991; Laycock, 1991; Hall et al., 1994; Allen-Diaz and Bartolome, 1998; Phelps and Bosch, 2002). STMs generally describe vegetation dynamics using diagrams that position vegetation states along several axes representing environmental or management gradients (such as grazing pressure). Possible transitions between these vegetation states are represented using arrows, and a table, called a catalogue of transitions, is used to describe the environmental or management conditions under which each transition can occur.

Because of their graphical and descriptive nature, STMs are excellent tools for communicating knowledge about rangeland dynamics between scientists, managers, and policy makers (Ludwig et al., 1996), and for allowing managers to identify

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opportunities (environmental conditions and management options) that may lead to favourable transitions (such as an improvement in pasture composition) or avoid circumstances likely to trigger unfavourable or irreversible transitions (such as pasture degradation, soil erosion, or the invasion of weeds). However, because they are essentially descriptive diagrams, one shortcoming of STMs is their limited predictive capability, which has restricted their practical application in scenario analysis. Another shortcoming of STMs is related to their coarse handling of uncertainty, which in the past has been accommodated using qualitative descriptions of transition probability such as "high", "moderate", and "low" (Orr et al., 1994).

Both predictive ability and the ability to accommodate uncertainty are highly desirable features of any rangeland management decision support tool (Prato, 2005; Pilke, 2001, 2003). While several sophisticated tools have been developed for predictive purposes (National Land and Water Resources Audit, 2004), they have been costly to develop and maintain, data hungry, and difficult to modify or update by non-technical people. An approach to decision support tool development that maintains the advantages of STM models (diagrammatic, low cost, flexible, and suited to participatory development with rangeland managers), while providing predictive capability and accommodating uncertainty, would be attractive to rangeland managers and researchers alike. This could be a step forward in improving the adoption and use of decision support tools in rangeland management generally.

Bayesian belief networks (BBNs) (also knows as belief networks, causal nets, causal probabilistic networks, probabilistic cause effect models, and graphical probability networks) are graphical models consisting of nodes (boxes) and links (arrows) that represent system variables and their cause-and-effect relationships (Jensen, 1996, 2001). BBNs consist of qualitative and associated quantitative parts. The qualitative part is a directed acyclic graph (cause-and-effect diagram made up of nodes and links) while the quantitative part is a set of conditional probabilities that quantify the strength of the dependencies between variables represented in the directed acyclic graph.

BBNs are becoming an increasingly popular modelling tool, particularly in ecology and environmental management, because they are diagrammatic models that have predictive capability and, because they use probabilities to quantify relationships between model variables, they explicitly allow uncertainty and variability to be accommodated in model predictions (McCann et al., 2006; Uusitalo, 2007). Like STMs, they also facilitate the integration of qualitative and quantitative knowledge about system dynamics, and are low cost, flexible, and suited to participatory development with managers (Cain et al., 2003; Smith et al., 2007a, 2005). An added benefit of BBNs is that they are well suited for use in the adaptive management of natural resources (Smith et al., 2007a; Nyberg et al., 2006; Henriksen and Barlebo, 2008) principally because BBNs can learn from monitoring data. This is an advantage in rangeland management because predicting the outcomes of management decisions may be very uncertain due to complex system dynamics, and learning from the outcomes of previously implemented management decisions can, over time, lead to better predictions.

The premise of this paper is that by combining STMs and BBNs, rangeland management decision support tools can be developed that retain the benefits of STMs (such as diagrammatic, low cost, flexible, and suited to participatory development with rangeland managers) whilst providing scenario analysis capabilities, adaptive management capabilities, and the ability to accommodate uncertainty. Decision support tools with these characteristics are likely to be attractive to developing countries in particular, where the data, expertise, and money required to develop and maintain sophisticated process-based simulation models are generally limited.

In this paper, we demonstrate how an STM can be transformed into a predictive decision support tool using a BBN. The STM was developed for subtropical grassland in south-east Queensland, Australia, located 90 km west of Brisbane. The area has a subtropical climate with an average annual rainfall of 800 mm, which is summer dominant (October–March). The native vegetation is Spotted Gum (*Corymbia citriodora*), Narrow-leaf Ironbark (*Eucalyptus crebra*) and Bull Oak (*Casuarina leuhmannii*) with black spear grass (*Heteropogon contortus*) communities (Tothill and Gillies, 1992). The vegetation has been modified by extensive clearing, grazing, and the introduction of exotic pasture species.

2. Methods and results

The development of the decision support tool involved several steps. First, an STM for Ironbark-spotted gum woodland was developed using previously published STMs and statistical analysis of vegetation survey data. Following this, an influence diagram (directed acyclic graph) was built to show the possible transitions and the factors influencing each transition. Next, the influence diagram was converted into a BBN by populating it with probabilities elicited from rangeland scientists to produce a predictive model. The behaviour of the model was tested using scenario and sensitivity analysis. The details of each step are explained further below.

2.1. State and transition modelling

Multivariate analysis (principle component analysis, multidimensional scaling and cluster analysis) of pasture survey data was used to identify indicator species of pasture condition (along an increasing grazing pressure gradient) in cleared Ironbark-spotted gum woodland (Allen-Diaz and Bartolome, 1998). The vegetation survey data were collected from 69 sample plots across the study area with varying grazing pressure history. These data included pasture species composition obtained using the step-point method (Raymond and Love, 1957), landscape function analysis (Tongway and Hindley, 2004) and soil properties (such as texture, colour, pH, electrical conductivity, and organic matter content). The indicator species were used to define pasture states for inclusion in an STM of the rangeland ecosystem.

To identify possible transitions between pasture states and their possible causes, published STMs for similar rangeland ecosystems were reviewed (Orr et al., 1994; McIvor et al., 2005). Two workshops, one with livestock owners and the other with rangeland scientists, were conducted to elicit experiential knowledge of pasture dynamics within the study area. In both workshops, participants were asked to review the vegetation state definitions developed from the multivariate analysis results, as well as possible transitions and causes for transitions identified from previously published STMs. In reviewing transitions and their causes, a simple table was used to record the main factors believed to influence a transition and the sub-factors believed to influence each main factor (Table 1). In this table, the relative order of importance of each main factor to the transition was also recorded (this was used later when testing the behaviour of the model – see Section 2.3), along with the classes of each factor (for example, the classes none, low, moderate, and high for grazing pressure). Finally, the expected time frame over which the transition could occur was recorded.

Fig. 1 contains the completed STM for Ironbark-spotted gum woodland. The model consists of five vegetation states (Table 2) and 17 transitions (Table 3). The vegetation states within the model sit along three axes: palatability, grazing intensity, and soil-nutrient status. For example, palatable tall grasses (PTGs) have

Table 1
Example of a table used in the workshops to record knowledge relating to transitions

Transition: palatable tall grasses to lawn		Time frame: 2–5 years
Main factors influencing transition	Sub factors influencing main factors	Relative importance of main factors to transition
Grazing pressure (none, low, moderate, high)	Stocking rate (low, moderate, high)	1
	Drought (no, yes)	
	Supplements in dry seasons (no, yes)	
Soil nutrition (average, above average)	Accumulation of faeces and urine (none, low, high)	2
	Fertilizer application (none, low, moderate, high)	

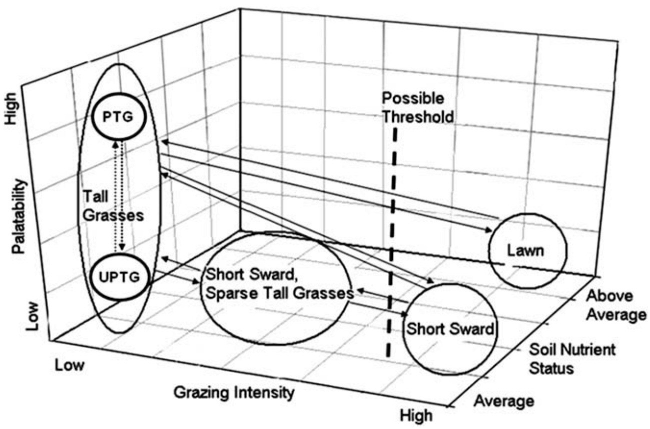

Fig. 1. State and transition model for cleared Ironbark-spotted gum woodland in south-east Queensland, Australia; UPTG, unpalatable tall grasses, PTG, palatable tall grasses. The possible threshold is the point at which the rangeland is unlikely to return to a better state without extreme management intervention.

Table 2
Catalogue of vegetation states for cleared Ironbark-spotted gum woodland in south-east Queensland, Australia

State number	State description	Dominant species composition
I	Palatable tall tussock grasses	*Heteropogon contortus*
		Cymbopogon refractus
		Chloris gayana
		Panicum maximum
		Themeda triandra
II	Unpalatable tall tussock grasses	*Aristida* sp.
		Bothriochloa decipiens
		Melinis repens
		Sporobolus creber
III	Short sward and sparse tall grasses	*Eragrostis sororia*
		Eremochloa bimaculata
		Tall tussock grasses
IV	Short sward	*Eragrostis sororia*
		Fimbristylis dichotoma
		Eremochloa bimaculata
V	Lawn	*Cynodon dactylon*
		Digitaria sp.

high palatability and occur when grazing intensity is low and when soil-nutrient status is average.

2.2. Transforming the STM into a BBN

2.2.1. Converting the STM into an influence diagram

As noted above, BBNs consist of nodes (boxes) that represent system variables (each node has two or more classes), links (arrows) that represent causal relationships, and probabilities that quantify the relationship between nodes.

The graphical component of a BBN is called an influence diagram: this is a directed acyclic graph consisting of nodes and links. Because the graph is acyclic, it cannot contain two-way arrows, cycles, or feedback loops. STMs, on the other hand, generally contain cycles and two-way arrows to show possible transitions between vegetation states. To overcome the incompatibility between STMs and BBN influence diagrams, the framework shown in Fig. 2 was used to construct a directed acyclic influence diagram from the STM. The framework contains a node representing possible initial vegetation states (see possible states node in the first (left-hand) column of Fig. 2), nodes representing possible transitions from each of these states to other states (see second column in Fig. 2), and nodes representing the main factors influencing each of these transitions and their sub-factors (see third and fourth columns in Fig. 2).

Next, classes were defined for each node in the influence diagram. For the transition nodes, their classes were the vegetation states in the STM. For the main factor and sub-factor nodes, classes

Table 3
Catalogue of vegetation transitions for cleared ironbark-spotted gum woodland in the south-east Queensland, Australia

Transition name	Main causes	Probability	Time frame (years)
I, II	Selective grazing (high), grazing pressure (low)	High	2–5
I, III	Selective grazing (high), grazing pressure (moderate)	High	2–5
I, IV	Grazing pressure (high)	High	2–5
I, V	Grazing pressure (high), soil nutrient content (above average)	High	2–5
II, I	Grazing pressure(none), selective grazing (none), fire in time period (frequent)	High	2–10
II, III	Grazing pressure(high), selective grazing (low), fire in time period (infrequent)	High	2–5
II, IV	Grazing pressure (high), fire in time period (frequent)	High	2–5
II, V	Grazing pressure (high), soil nutrient content (above average)	High	2–5
III, I	Grazing pressure (none), selective grazing (none), good season (frequent)	High	2–5
III, II	Selective grazing (moderate), grazing pressure (moderate), good seasons (frequent)	High	2–5
III, IV	Grazing pressure (high), selective grazing (none), good season (infrequent)	High	2–5
IV, I	Grazing pressure (none), good seasons (frequent)	Low	1–10
IV, II	Grazing pressure (low), good seasons (frequent)	Low	1–10
IV, III	Good season (frequent), grazing pressure (none)	Moderate	>5
IV, V	Soil nutrient content (above average), grazing pressure (high)	High	2–5
V, I	Grazing pressure (none), soil nutrition (average), good season (frequent)	Low	>5
V, II	Grazing pressure (none), soil nutrition (average), good season (frequent)	Low	>5

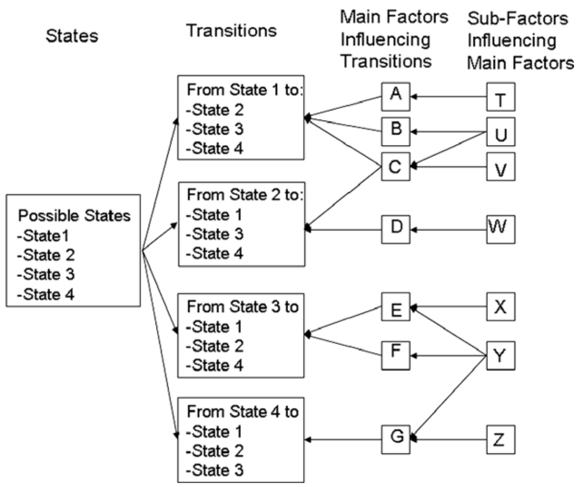

Fig. 2. Framework used to construct an directed acyclic graph from a state and transition model.

were defined in consultation with the rangeland scientists who participated in the STM building workshops. Appendix 1 lists the classes and their definitions for each node in the final model (Fig. 3).

2.2.2. Eliciting probabilities for cause-and-effect relationships

Relationships between nodes within a BBN are defined using conditional probability tables (CPTs). These CPTs store the probabilities of outcomes under particular scenarios and these probabilities allow uncertainty and variability to be accommodated in model predictions. Measured probabilities for vegetation transitions can only be obtained from long-term studies and were not available for the rangeland system examined here. In the absence of measured probabilities, subjective probability estimates were obtained from rangeland scientists. A method similar to the CPT calculator developed by Cain (2001) was used in the probability elicitation process to maintain logical consistency in the estimated probabilities and reduce the number of probabilities that had to be elicited. The method works by reducing a CPT to the minimum number of scenarios for which probabilities need to be estimated. Probabilities for these scenarios are then elicited and used to determine the relative influence of inputs on the probability of outcomes. Probabilities for all scenarios in the CPT are then interpolated.

To illustrate, the shaded lines in Table 4 represent the reduced CPT for the node "from short sward to", which has three input nodes; good seasons in time period, grazing pressure, and soil nutrition (the inputs current state and time frame are not been included in Table 4 in order to simplify the illustration). In the reduced CPT, the first line represents the best-case scenario where all of the input nodes of "from short sward to" are in the best class, meaning that they are most likely to lead to favourable transitions (for example grazing pressure is "none", soil nutrition is "average", and good seasons in time period is "frequent": note that in this rangeland ecosystem, "average" soil nutrition favours transitions to the best vegetation state (palatable tall grasses). Therefore, it is the best class for soil nutrition. "Above average" soil nutrition favours transitions to poorer vegetation states.). The last line in Table 4 represents the worst-case scenario where all of the input nodes of "from short sward to" are in the worst class and most likely to lead to unfavourable transitions. The remaining shaded lines in Table 4 represent scenarios where only one input node is not in the best class. Probabilities for the shaded lines are elicited from experts. Probabilities for the unshaded lines in Table 4 are interpolated from the probabilities elicited for the shaded lines (see Cain

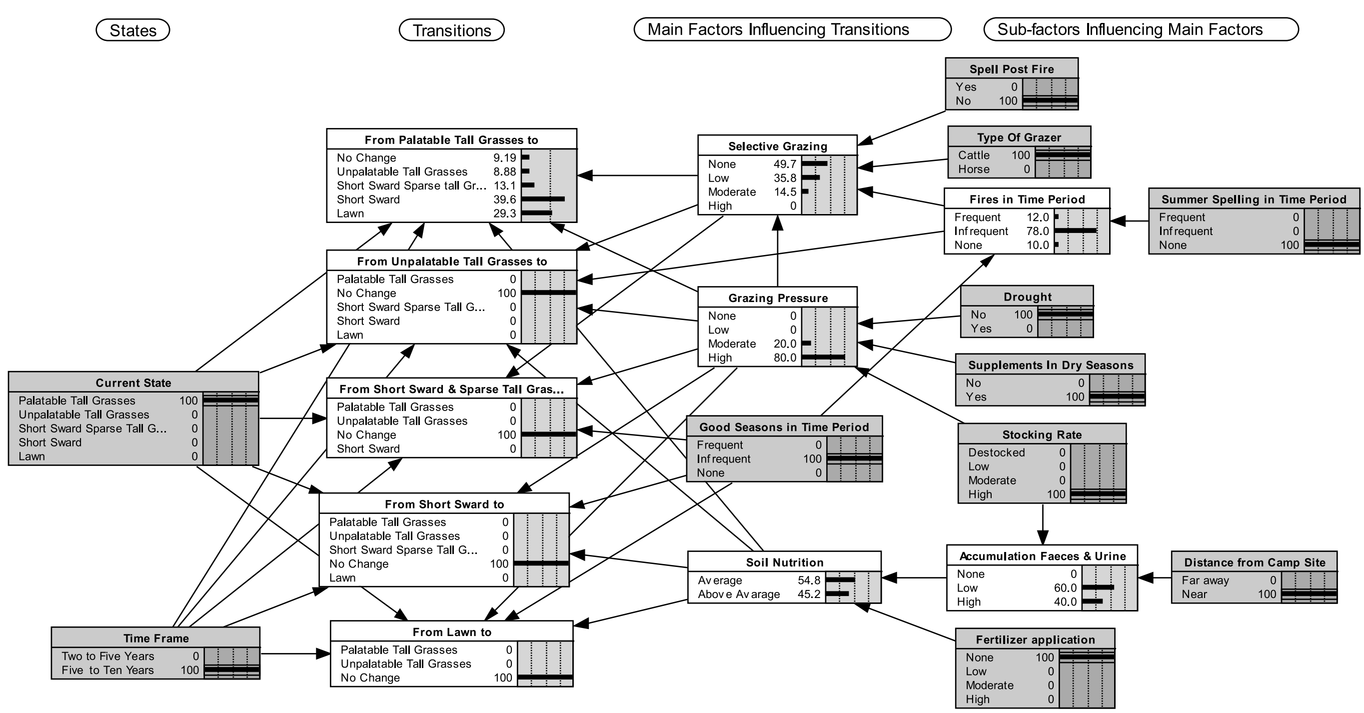

Fig. 3. State and transition model for cleared Ironbark-spotted gum woodland in the form of a Bayesian belief network. In this figure a scenario has been inserted by selecting particular classes for the nodes shaded grey. The scenario shown here is where the current state of pasture is "palatable tall grasses" (hence only transitions from palatable tall grasses are possible), the time frame is "5–10-years", spell post-fire is "no", type of grazer is "cattle", summer spelling in time period is "none", drought is "no", supplements in dry season is "yes", stocking rate is "high", distance from camp site is "near", good seasons in time period is "infrequent" and fertiliser application is "none". Under this scenario the model is predicting that the most likely transition is to "short sward" (39.6% chance).

Table 4
Conditional probability table for the node "from short sward to"

Factors influencing transitions from the state "Short Sward" to another state			Probability of transition to another state (%)				
Grazing pressure	Soil nutrition	Good season in time period	Palatable tall grasses	Unpalatable tall grasses	Short sward sparse tall grasses	No change	Lawn
None	Average	Frequent	25	25	50	0	0
None	Above average	Frequent	10	10	10	60	10
None	Average	Infrequent	10	10	30	50	0
None	Above average	Infrequent	0	0	15	70	15
None	Average	None	0	0	20	80	0
None	Above average	None	0	0	0	80	20
Low	Average	Frequent	25	25	50	0	0
Low	Above average	Frequent	10	10	10	55	15
Low	Average	Infrequent	5	5	10	80	0
Low	Above average	Infrequent	0	0	0	80	20
Low	Average	None	0	0	0	100	0
Low	Above average	None	0	0	0	80	20
Moderate	Average	Frequent	0	25	50	25	0
Moderate	Above average	Frequent	0	0	30	50	20
Moderate	Average	Infrequent	0	20	40	40	0
Moderate	Above average	Infrequent	0	0	35	40	25
Moderate	Average	None	0	0	20	80	0
Moderate	Above average	None	0	0	0	70	30
High	Average	Frequent	0	0	0	100	0
High	Above average	Frequent	0	0	0	70	30
High	Average	Infrequent	0	0	0	100	0
High	Above average	Infrequent	0	0	0	65	35
High	Average	None	0	0	0	100	0
High	Above average	None	0	0	0	50	50

The shaded lines represent scenarios for which probabilities estimates were elicited from rangeland scientists. Probabilities for unshaded lines were interpolated.

(2001) for a detailed explanation of the algorithm used in the interpolation process).

2.3. Testing model behaviour

To test the behaviour of the completed BBN and identify any inconsistencies, a sensitivity analysis was performed and the results presented back for review to the rangeland scientists who had participated previously in the STM building and the probability elicitation process. The sensitivity analysis was performed on each transition node in the BBN by systematically selecting different classes of their input nodes and recording the effect that this had on the probability of transitions. For example, the different classes of "grazing pressure" were selected to test the influence that this had on the transition probabilities in the node "from short sward to" other vegetation states. When grazing pressure was set to "none", the most likely transition was no change from the current short sward state (46.7% probability) and the second most likely transition was to short sward with sparse tall grasses (20.4% probability). Setting grazing pressure to "high" increased the probability of no change to 75%, with a 25% chance that a transition to lawn would occur. This behaviour indicates that changing

Table 5
Sensitivity analysis for transition "from short sward to lawn"

Rank	Input node	Probability (%) of transition to lawn	Difference (% Probability)
1	*Soil nutrition*		
	Average	0	28.5
	Above average	28.5	
2	*Grazing pressure*		
	None	7.08	17.92
	Low	10.8	
	Moderate	14.2	
	High	25	
3	*Good seasons in time period*		
	Frequent	11.6	7.5
	Infrequent	12.2	
	None	19.1	

Input nodes are ranked from most (1) to least (3) influential on the transition.

grazing pressure causes major changes in transition probabilities away from a short sward state.

The results of sensitivity analysis on each transition were summarized into tables similar to Table 5. These tables highlight the relative influence of input nodes on transitions by showing the overall difference in the probability of a transition caused by changing the classes of input nodes (this difference is shown in the difference column in Table 5). Where the results of the sensitivity analysis did not match the expectations of the rangeland scientists (these expectations had been recorded during the development of the STM where the expected relative influence of each main factor on each transition was recorded, see Table 1), the appropriate CPT was adjusted and the sensitivity analysis was performed again.

Table 6 summarizes the results of the final sensitivity analysis for all transitions in the Ironbark-spotted gum woodland BBN (Fig. 3). The sensitivity analysis revealed that selective grazing, grazing pressure, and soil nutrition were believed to influence most transitions, while the fire frequency and the frequency of good wet seasons were also important in some transitions. Grazing pressure was the main driver of 12 transitions, and selective

Table 6
Summary of sensitivity analysis performed on the transition nodes in the cleared Ironbark-spotted gum woodland BBN

Transition		Selective Grazing	Grazing Pressure	Soil Nutrition	Fire in Time Period	Good seasons in Time Period
Palatable tall grasses to:	Unpalatable tall grasses				×	×
	Short sward & sparse tall grass				×	×
	Short sward				×	×
	Lawn				×	×
Unpalatable tall grasses to:	Palatable tall grasses					×
	Short sward & sparse tall grass					×
	Short sward					×
	Lawn					×
Short sward & sparse tall grass to:	Palatable tall grasses			×	×	
	Unpalatable tall grasses			×	×	
	Short sward			×	×	
Short sward to:	Palatable tall grasses	×			×	
	Unpalatable tall grasses	×			×	
	Short sward & sparse tall grass	×			×	
	Lawn	×			×	
Lawn to:	Palatable tall grasses	×			×	
	Unpalatable tall grasses	×			×	

The shading indicates the relative influence of factors on each transition, from most influential (black) to least influential (white). A cross (×) means that this factor had no influence on the transition.

grazing was the main driver of three transitions. Grazing pressure was either the most or the second most important driver of all transitions. Selective grazing was a relatively important driver of transitions to or from unpalatable tall grasses but had no influence on transitions from short sward and lawns to tall grass states.

Soil nutrition was relatively important for transitions to or from lawns but had little to no influence on other transitions. Fire frequency had an affect on some transitions but only through its affect on selective grazing. Low fire frequency increased the likelihood of selective grazing, making transitions to unpalatable tall grasses more likely. This is because, frequent fires tend to homogenise the palatability of pastures, and so low fire frequency leads to a diversity of palatability in pasture, leading to selective grazing. Frequent good seasons were important for transitions from short sward and lawn states to tall grass states.

2.4. Using a combined STM and BBN model for rangeland management decision support

A combined STM and BBN model has the ability to provide rangeland managers with decision support through its analytic capabilities. The three main types of analysis that can be performed are prediction, diagnosis, and sensitivity analysis. Sensitivity analysis was described in Section 2.3 so examples of predictive and diagnostic analysis are given here.

Predictive analysis can be used to answer 'what if' questions by selecting classes for inputs and using the model to predict the probability of transitions, as shown in Fig. 4. In the example, the selected classes of input nodes represent a 'what if' scenario for a site and the model predicts that the chance of transition away from palatable tall grass to lawn is relatively high (64%) within a 5–10-year timeframe (note that the class '5–10-years' is selected

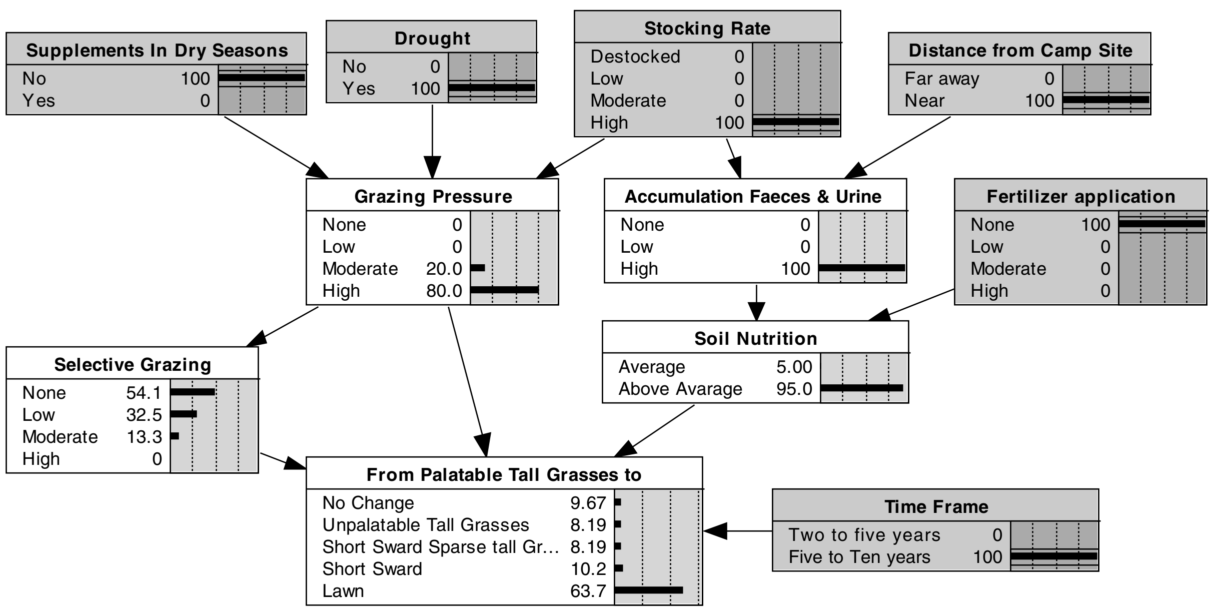

Fig. 4. Using the Bayesian belief network for prediction (shaded nodes represent the selected scenario).

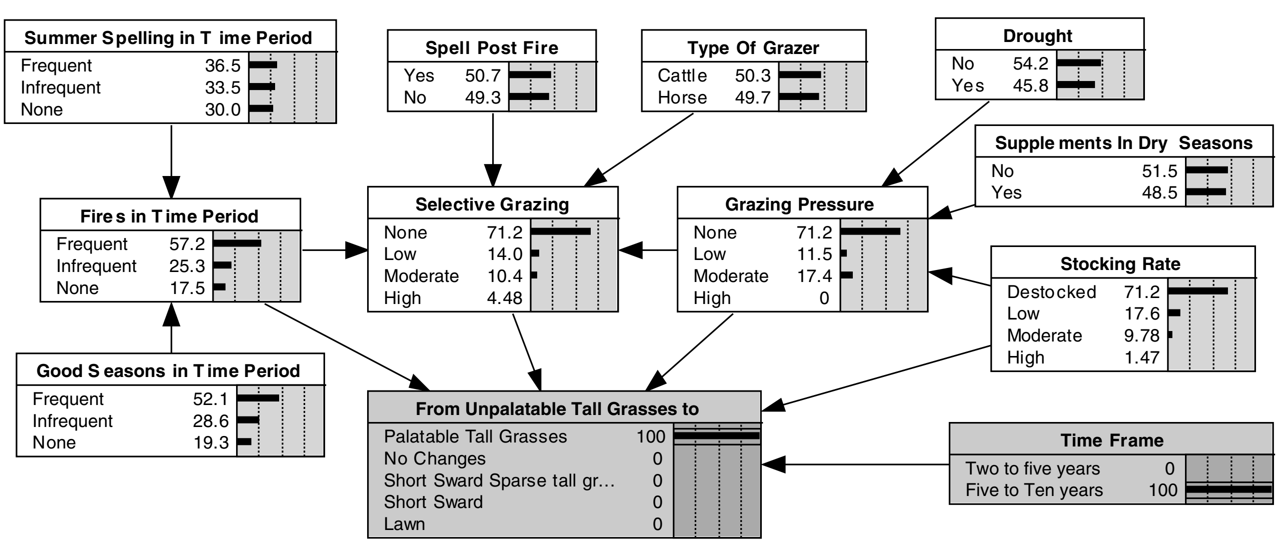

Fig. 5. Using the Bayesian belief network for diagnosis (shaded nodes represent the selected scenario).

in the time frame node). The model also indicates the probable causes for this transition:high grazing pressure (80% chance) and above-average soil nutrition (95% chance).

Diagnostic analysis can be used to answer 'how' questions by selecting a desired outcome and using the model to identify the scenario that is most likely to lead to that outcome, as shown in Fig. 5. In this example, the model is used to identify how a land manager might shift pasture from an unpalatable tall grass state to a palatable tall grass state within a 5–10-year time frame (note that the class '5–10-years' is selected in the time frame node). The model shows that this transition is most likely if grazing pressure and selective grazing are absent (see the selective grazing and grazing pressure nodes), and this is most likely where destocking is applied (see the stocking rate node). The model also shows that frequent fires are important for achieving low to no selective grazing (see the fires in time period node), and in turn, good seasons are important for achieving frequent fires (see the good seasons in time period node).

3. Discussion

3.1. Pasture dynamics in cleared Ironbark-spotted gum woodland

The combined STM and BBN model developed in this paper revealed that grazing pressure is the main factor driving almost all pasture transitions in the cleared Ironbark-spotted gum woodland ecosystem studied. Stocking rate had the greatest influence on grazing pressure, but drought and the use of dry-season supplements magnified the influence of stocking rate. This finding is supported by Walker (1995), who also suggested that stocking rate is the most important variable in grazing management. If the stocking rate is not in balance with available forage, regardless of other grazing management practices (timing, distribution, and type of livestock), grazing management objectives will probably not be met.

Selective grazing was highlighted by the model as an important factor in transitions from or to unpalatable tall grasses. It is one of the key factors influencing the vegetation composition in grasslands (Ksiksi et al., 2005) and covers items such as diet selection, landscape selection, and bite selection (Senft et al., 1987). Selective grazing has a significant effect on the competitive interactions of plants and the structure and function of ecosystems (Archer and Smeins, 1991; Belsky, 1992) as it creates gaps in the pasture, allowing unpalatable tall grasses such as *Aristida* sp. and *Bothriochloa deciepiens* to establish. Drought can accelerate this gap creation because it reduces the seed set of favourable grasses such as *H. contortus*, which can also accelerate the establishment of exotic pasture species (Ash and Ksiksi, 1999). Selective grazing can be reduced using frequent fire to homogenise the palatability of pasture and spelling post-fire to allow palatable species such as *H. contortus* to establish. The importance of selective grazing, as highlighted by the model, suggests that more research is needed to clarify the exact effect of selective grazing on rangeland vegetation dynamics and its condition.

Occurrence of good seasons and bad seasons (drought) were two unmanageable factors that had an influence on vegetation state via their direct impact on grazing pressure and fire frequency. This indicates that drought and climate change are likely to have a big impact on the state of rangelands, particularly where stocking rates and spelling regimes are not managed appropriately.

Soil nutrition was another environmental variable that could be affected by grazing management. It is considered by McIvor et al. (2005) to be an important factor in transitions from any state to lawns. Land managers can adjust soil nutrition by changing the stocking rate and by locating watering points to minimize the accumulation of faeces and urine at any one site. The implementation of some form of grazing system such as rotational grazing can help to distribute evenly the impact of animals through all parts of a paddock (Johnston et al., 2005).

3.2. Use of the combined STM and BBN model for adaptive management in rangelands

Adaptive management refers to the process of using management outcomes to continuously modify or adapt management practice (Janssen et al., 2000; Sabine et al., 2004; Morghan et al., 2006). It is a process of "learning by doing" whereby management objectives are set and management plans developed using current knowledge of the management system (which can be in the form of a model). Actions are implemented and monitored. Monitoring results are then used to evaluate management success and modify management objectives or plans where necessary.

Adaptive management is particularly important for rangeland management because rangelands are complex systems in which the outcomes of management decisions are often difficult to predict. While the importance of adaptive management in rangeland management has been stated frequently in the literature, very few tools to support it have been provided. Hence, rangeland management tools are needed that not only capture the uncertainty associated with rangeland dynamics, but also support adaptive management by being updatable using monitoring data (Ringold et al., 1996). A combined STM and BBN model has potential to provide such a tool because BBNs can learn from monitoring data. Put simply, the probability tables within BBNs can be updated iteratively by importing monitoring results. This is called incorporating 'case data' (or data from previous cases) into the model.

A demonstration of this model-updating process is not possible here because empirical data for transitions in the rangeland ecosystem studies are not available. Hypothetically, however, the process would work by monitoring the vegetation state of a rangeland at many sites, and simultaneously monitoring the main factors and sub-factors stated in the model as influencing vegetation state transitions (such as grazing pressure, fire frequency, etc.). The result of monitoring would be a record describing prior vegetation state, management actions implemented, and the occurrence of environmental events, and any vegetation state transitions that occurred. The model could then learn from these data by adjusting conditional probabilities to reflect real-word observations. Hence, a combined STM and BBN model could provide a tool for evaluating the likely influence of previous management actions and environmental scenarios on vegetation state, as well as a predictive tool for planning future rangeland management actions.

3.3. The modelling approach

This paper has shown how rangeland dynamics can be modelled by combining STMs and BBNs. It captures the advantages of both STMs and BBNs to provide decision support tools that (a) are simple graphical models describing rangeland vegetation change in relation to management actions and environmental events (e.g. drought), (b) can be used for scenario and diagnostic analysis to answer "what if" and "how" questions, (c) can be applied in areas where empirical data are scarce by utilizing experiential knowledge, (d) can utilise empirical data where available, (e) can accommodate uncertainty, and (f) show promise in being able to support adaptive management.

There are significant criticisms in the literature of both the STM and the BBN modelling approaches. STMs have been criticised for being "event-driven" models of vegetation dynamics (Watson et al., 1996) in which transitions are a result of infrequent and unpredictable events such as drought, fire, favourable climatic periods, or sustained management (Stafford-Smith and Pickup, 1993). In rangelands, vegetation change is often gradual and there is a separation in time between management actions and outcomes (Stafford-Smith, 1996). STMs cannot model this gradual change in the way that temporal simulation models can.

As is the case with STMs, BBNs also have limitations when it comes to temporal modelling. This is because they are acyclic models (Coupe and Van der Gaag, 2002) that predict the aggregate outcomes of management or events for a specified time period, such as one year or 10 years. Changes within this time period are not modelled. Other limitations of BBNs relate to the size of the probability tables and the influence of model structure on model behaviour. Nodes in a BBN with several input nodes have large conditional probability tables containing many scenarios. Often there are insufficient data available to populate such large probability tables and gaps have to be filled in using expert opinion.

The difficulties in populating large probability tables meant that when constructing the cleared Ironbark-spotted gum woodland BBN, it was necessary to summarize the many factors that influenced transitions into a few nodes with as few classes as possible. Hence, the BBN modelling approach has similar limitations to other modelling approaches, in that all possible factors that may contribute to outcomes cannot be accommodated.

Although databases, scientific literature, and other models (see Koivusalo et al. (2005) for an example) can be used to determine the probabilities of transitions in a combined STM and BBN model, this study indicates that the knowledge and practical experience of experts are often the only available sources of data. There are many knowledge gaps in the science of vegetation dynamics and sometimes the available knowledge is not rich enough to allow for reliable assessments of transition probabilities. An additional difficulty is that published experimental results rarely match the conditional probabilities required for a BBN (Druzdzel and Van der Gaag, 1995).

When the probabilities within a model are based mainly on expert opinion, the limits of human judgment become important and the reliability of the probabilities comes into question. The elicitation of probabilities still remains a difficult task, and in some cases is a major obstacle to model building (Druzdzel and Van der Gaag, 1995; Jensen, 1995; Renooij, 2001). Research in experimental psychology has shown that probability elicitation is subject to bias if experts are simply asked to provide a numerical probability (Kahneman et al., 1982) because there are numerous possible scenarios and these need to be compared to estimate probabilities. A well-structured elicitation process is required (Fenton, 1998) that will include selecting the right group of experts and implementing a sound method for probability elicitation. In this study, a method similar to the CPT calculator developed by Cain (2001) was used to provide a structured probability elicitation process. In addition, the results of model behaviour (obtained through sensitivity analysis) were returned to the experts for review. This approach has been recommended by other researchers as "an antecedent conditions check" that significantly increases the reliability of model behaviour (Edwards, 1998). BBNs can quite easily accommodate multiple opinions about conditional probabilities, which can assist in testing the sensitivity of a model to variation in probability estimates. Areas of the model where variation in probability estimates has a relatively large influence on model predictions are those that warrant further investigation and refinement, until the cost of obtaining more accurate probabilities outweighs their benefit (Coupe et al., 2000).

The biophysical, economic, and social aspects of rangelands in which land managers work are complex and it is impossible to account for all this complexity in a decision support tool. Hence, experience and human judgement will remain important. In the current paradigm of using decision support tools, the focus is less on "recommendations" and more on "facilitation of decision-making" (McCown, 2002). In addition, decision support tools are not needed in all situations, nor do they need to be directly accessed by decision-makers. They are most beneficial in situations where managers need to integrate a variety of data and information in order to evaluate alternatives. In many situations, land managers do not have the facility to directly access or use decision support tools. The key issue is not whether they use decision support tools directly; it is the coordination of people, data, models, and tools to provide rangeland management answers in a convenient, timely, and cost-effective manner.

Integrating STMs and BBNs can provide a cost-effective way of bringing together people, knowledge, and data for rangeland management decision-making. First, both STMs and BBNs are well suited for use in participatory modelling in which scientist and land managers can communicate and collaborate in decision support tool development (see Smith et al. (2005, 2007a, b) for examples of the application of BBNs in participatory modelling). Second, no specialist programming expertise is required to develop, maintain, or update models, as easy-to-use BBN software already exists and is widely available (some free of charge). Third, because BBNs can utilise a range of information sources in model development (such as expert opinion, empirical data, and output from other models), they offer a predictive modelling framework that is flexible enough to integrate a range of available information, both quantitative and qualitative. This is particularly useful in situations where empirical data are scarce or patchy and where expert opinion must be relied upon to fill data gaps. Fourth, because the probability tables within BBNs can be updated from observations or monitoring records, the modelling approach is well suited to adaptive management.

4. Conclusion

This paper demonstrates how STMs and BBNs can be combined to develop rangeland management decision support tools that capture the advantages of STMs (graphical, low cost, suited to participatory development with land managers) and BBNs (ability to accommodate uncertainty, utilise a range of information sources, and provide for scenario, diagnostic, and sensitivity analysis). Although, the approach seems to be a promising way to provide rangeland managers with decision support, one key drawback is that it is reliant on subjective expert knowledge and is therefore subject to bias. The lack of empirical data on vegetation transitions makes the use of human judgment necessary. However, because BBNs are able to incorporate updated probabilities from monitoring data, subjective probability estimates can be modified over time as empirical data becomes available. This also makes the approach well suited to adaptive management.

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Appendix 1

Definitions for nodes and their classes in the cleared Ironbark-spotted gum woodland Bayesian belief network (Fig. 3)

Node	Definition and classes
Current state	This node represents possible vegetation states that can occur at the site of interest Palatable tall grasses: perennial palatable tall tussock grasses such as *Heteropogon contortus*, high soil stability Unpalatable tall grasses: perennial unpalatable tussock grasses such as *Aristida* sp. and *Bothriochloa decipiens*, erosion moderate to high Short sward and sparse tall grass: short grasses such as *Eragrostis sororia* interspersed with tall tussock grasses, erosion moderate to high Short sward: short grasses such as *Eragrostis sororia*, erosion moderate to low Lawn: very stable and resistant to disturbances such as grazing and trampling, includes species such as *Cynadon dactylon*
Timeframe	This node represent periods of time over which transitions may occur at the site of interest 2–5-years 5–10-years
From palatable tall grasses to	This node represents transitions away from palatable tall grasses to another vegetation state at the site of interest No change: vegetation remains in the palatable tall grass state Unpalatable tall grasses: vegetations moves to the unpalatable tall grass state Short sward and sparse tall grass: vegetations moves to the short sward and sparse tall grass state Short sward: vegetations moves to the short sward state Lawn: vegetations moves to the lawn state
From unpalatable tall grasses to	This node represents transitions away from unpalatable tall grasses to another vegetation state at the site of interest Palatable tall grasses: vegetations moves to the palatable tall grass state No change: vegetation remains in the unpalatable tall grass state Short sward and sparse tall grass: vegetations moves to the short sward and sparse tall grass state Short sward: vegetations moves to the short sward state Lawn: vegetations moves to the lawn state
From short sward and sparse tall grasses to	This node represents transitions away from short sward and sparse tall grasses to another vegetation state at the site of interest Palatable tall grasses: vegetations moves to the palatable tall grass state Unpalatable tall grasses: vegetations moves to the unpalatable tall grass state No change: vegetation remains in the short sward and sparse tall grass state Short Sward: vegetations moves to the short sward state
From short sward to	This node represents transitions away from short sward to another vegetation state at the site of interest Palatable tall grasses: vegetations moves to the palatable tall grass state Unpalatable tall grasses: vegetations moves to the unpalatable tall grass state Short sward and sparse tall grass: vegetations moves to the short sward and sparse tall grass state No change: vegetation remains in the short sward state Lawn: vegetations moves to the lawn state
From lawn to	This node represents transitions away from lawn to another vegetation state at the site of interest Palatable tall grasses: vegetations moves to the palatable tall grass state Unpalatable tall grasses: moves to the unpalatable tall grass state No change: vegetation remains in the lawn state
Selective grazing	This node represents the selectivity of grazing at the site of interest. Selective grazing mostly occurs in large continuously grazed pastures where stock preferentially eat the most palatable species None: plant composition is consistent and uniform and contains palatable species (this situation is rare) Low: there are many uniform palatable species available in the pasture but some unpalatable ones are present Moderate: palatable species are patchy in the pasture High: palatable species are rare and hidden among unpalatable species in the pasture
Grazing pressure	This node represents the balance between how much grazing animals eat and how fast the pasture grows at the site of interest (grazing pressure = rate of removal of pasture/rate of supply of pasture) None: grazing pressure of 0 Low: supply of pasture is much more than the rate of removal of pasture (grazing pressure $\ll 1$) Moderate: supply of pasture is more than the rate of removal of pasture (grazing pressure <1) High: supply of pasture is equal to or less than the rate of removal of pasture (grazing pressure $\geqslant 1$)
Soil nutrition	This node represents the soil nutritional status at the site of interest. In the case study area, above average soil nutrition had an effect on transitions to lawn state so there are two states for soil nutrition, average and above average. Below average soil nutrition was not considered to be an important factor in any transitions in the case study area. Therefore this class of soil nutrition was not included in the model Average: 50–200 kg N per ha per annum Above average: more than 200 kg N per ha per annum

(*continued on next page*)

Appendix 1 (*continued*)

Node	Definition and classes
Fertiliser application	This node represents the level of fertiliser application at the site of interest (fertiliser = 10% nitrogen, 3.4% phosphorus, 6.4% potassium) None: no fertiliser Low: less than 50 kg N per annum plus other nutrients Moderate: 50–150 kg N per ha per annum plus other nutrients High: more than 150 kg N per ha per annum plus other nutrients
Accumulation faeces and urine	This node represents the level of faeces and urine accumulation caused by cattle at the site of interest None: there is no faeces and urine from stock in the pasture Low: the accumulation of faeces and urine exists in the pasture but it is not considerable (<3% of the soil cover) High: there is a considerable amount of faeces and urine in the pasture (>3% of the soil cover)
Distance from campsite	This node represents the distance of the site of interest from a campsite, which is a site where cattle congregate. Campsites are usually watering points Far away: more than 500 m from a campsite Near: less than 500 m from a campsite
Stocking rate	This node represents the number of hectares per beast Destocked: no stock present Low: 1 beast per 6–8 ha Moderate: 1 beast per 4–6 ha High: more than 1 beast per 4 ha
Supplement in dry season	This node classes whether or not cattle are fed supplements in the dry season. Supplementary feeding tends to allow land managers to maintain cattle numbers in dry timesNo: no feed supplements fed in the dry seasonYes: feed supplements fed in the dry season
Drought	This node classes whether or not drought is present at the site of interest. Drought occurs when rainfall lies above the lowest five per cent of recorded rainfall but below the lowest 10 percent for the period in question No: drought is absent Yes: drought is present
Good seasons in time period	This node represents the frequency of good seasons at the site of interest within the time period of interest. A good season is defined as a wet season with more that average rainfall. Frequent: 3 of 5 years or 7 of 10 years with more than average rainfall Infrequent: 1–2 of 5 years or 1–6 of 10 years with more than average rainfall None: no years with more than average rainfall in the time period
Fires in time period	This node represents the frequency of fires at the site of interest within the time period of interest Frequent: fire occurs in 3 of 5 years or 7 of 10 years Infrequent: fire occurs 1–2 of 5 years or 1–6 of 10 years None: fire occurs 0 of 5 years or 0 of 10 years
Type of grazer	This node represents the type of animal grazing at the site of interest Cattle Horse
Post-fire spelling	This node classes whether or not the pasture at the site of interest is spelt for at least 10 days after burning or until the grass is 10 cm high: Yes: post-fire spelling occurs No: post-fire spelling does not occur
Summer spelling in time period	This node represents the frequency of summer spelling of pasture at the site of interest within the time period of interest Frequent: pasture spelled in 3 of 5 years or 7 of 10 years Infrequent: pasture spelled 1–2 of 5 years or 1–6 of 10 years None: pasture spelled 0 of 5 years or 0 of 10 years

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