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

H. Bashari [a,*], C. Smith [b], O.J.H. Bosch [b]

[a] *Department of Natural Resources, Isfahan University of Technology, Isfahan, Iran*
[b] *School of Natural and Rural Systems Management, The University of Queensland, Gatton, QLD 4343, Australia*

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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

* Corresponding author. Tel.: +98 261 3410169/9127474208.
*E-mail address:* H_bashari2001@yahoo.com (H. Bashari).

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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