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USING A BAYESIAN BELIEF NETWORK APPROACH TO ASSESS LAND CONDITION IN NATIVE PASTURES, SOUTH-EAST QUEENSLAND, AUSTRALIA

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ABSTRACT

Reliable indicators of rangeland condition enable land managers to understand the ecological dynamics surrounding their management activities and predict the consequences of their actions. However, no indicator is perfect; hence there is a need to accommodate uncertainty in the assessment of rangeland condition. This paper describes the development of a rangeland condition assessment tool for the Ironbark-Spotted Gum woodland of the Lockyer Valley, South-East Queensland, that implements both compositional and functional indicators within a Bayesian Belief Network (BBN) to accommodate uncertainty.

INTRODUCTION

Indicators of rangeland condition change provide valuable information to assist land managers in their decision making. Since ecological processes are often difficult to measure due to their complexity, indicators, such as species presence (and absence), distribution and quantity, are a valuable mechanism for assessing the condition or health of rangeland ecosystems (Scarnecchia 1994).

The management goal, or answering the question "Condition for what?" is the key to deciding which factors should be used to assess rangeland condition. In most cases, changes in status of each factor, relative to its potential within a particular land use will facilitate an assessment of rangeland condition (Wilson and Tupper 1982). Although researchers have developed sophisticated methods of assessing rangeland condition, it is not easy to accommodate the uncertainty associated with the indicators used. Bayesian Belief Networks (BBN) (Jensen 2001) provide a tool that can help solve this problem. They allow for the construction of cause and effect models, and relate variables using conditional probabilities. This allows uncertainty to be explicitly incorporated into models. In this paper, we use vegetation structure and composition indicators of rangeland condition, along with soil function indices, to construct a BBN model for assessing rangeland condition that accommodates indicator uncertainty.

METHOD

Sixty-nine sample plots in Ironbark-Spotted Gum woodland near Gatton, Queensland, were surveyed. These plots were categorised into ungrazed, slightly grazed, moderately grazed and severely grazed sites, covering a grazing gradient. Species frequency and percentage cover were measured at each plot using the Step Point method (Raymond and Love 1957) and Braun-Blanquet method (Braun-Blanquet 1932). A modified pasture condition score sheet of Cosgrove et al. (2001) was used to determine the grazing impact at each plot. Landscape Function Analysis (LFA) was used to characterize each plot in terms of stability, infiltration and nutrient cycling (Tongway and Hindley 2004).

Principal component analysis (PCA) was conducted on species composition and LFA data, to identify correlations with grazing gradient. Indices with a high correlation to grazing gradient were used to construct a BBN model for assessing land condition, using NeticaTM software (Norsys Software Corporation 1998). This involved (a) building an influence diagram showing the relationship between indicators and condition, and (b) populating the influence diagram with probabilities using data from the 69 sample plots to produce a predictive model. To test the behaviour of the completed BBN and highlight any inconsistencies in the model, sensitivity analysis was preformed using the model.

RESULTS AND DISCUSSION

Six plant species were found to be sensitive to the grazing gradient (Table 1). The LFA soil stability index was found to decrease as grazing increased (Figure 1) but infiltration and nutrient cycling indices did not differ significantly ($P < 0.05$) between sites with different grazing levels. It has been argued high grazing pressure decreases infiltration in pastures and this leads to lower productivity as plants are unable to access water (Bennet 1996). However, the results of this study indicate that infiltration does not differ significantly as grazing intensity increases. It suggests that in Sandstone landforms, due to their naturally high infiltration rate, infiltration cannot be regarded as a discriminative indicator of condition.

Table 1: Indicator species and their correlation with grazing gradient

Species	R^2	D	Maximum Measured abundance (%)
Heteropogon contortus	0.9	0.994	68.0
Cynadon dactylon	0.9	0.964	75
Eremochloa bimaculata	0.6	0.769	50
Aristida sp	0.5	0.696	36
Portulaca sp	0.7	0.895	7.0
Chloris gayana	0.5	0.747	44.0

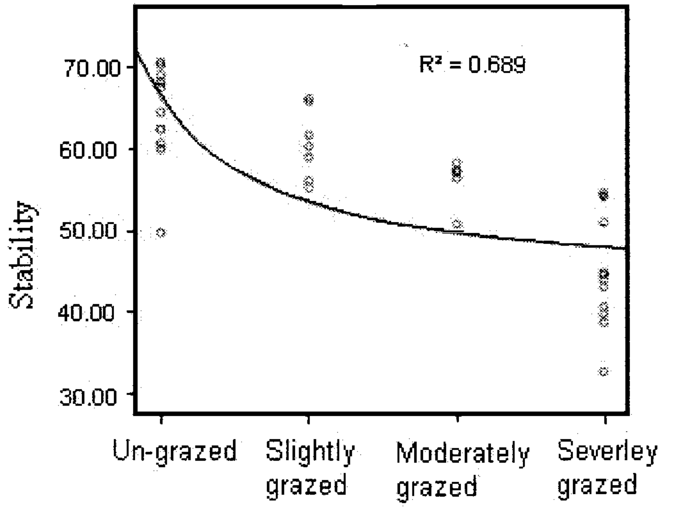


Figure 1: Influence of grazing gradient on soil stability

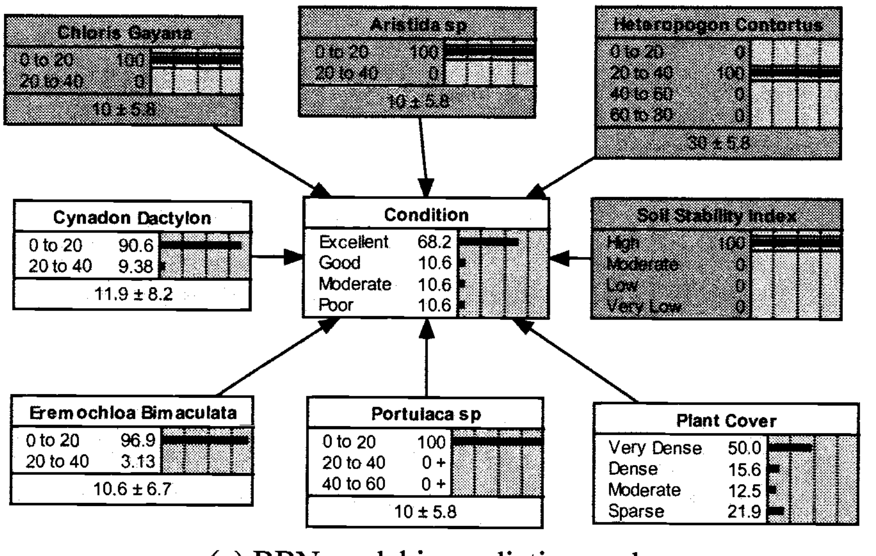
Sensitivity analysis using the BBN model indicated that condition score was most sensitive to soil stability index and the abundance of tall tussock grasses such as *Heteropogon contortus*, and less sensitive to the abundance of annual forbs such as *Portulaca sp* (Table2).

Table 2: Sensitivity analysis for indicators of pasture condition

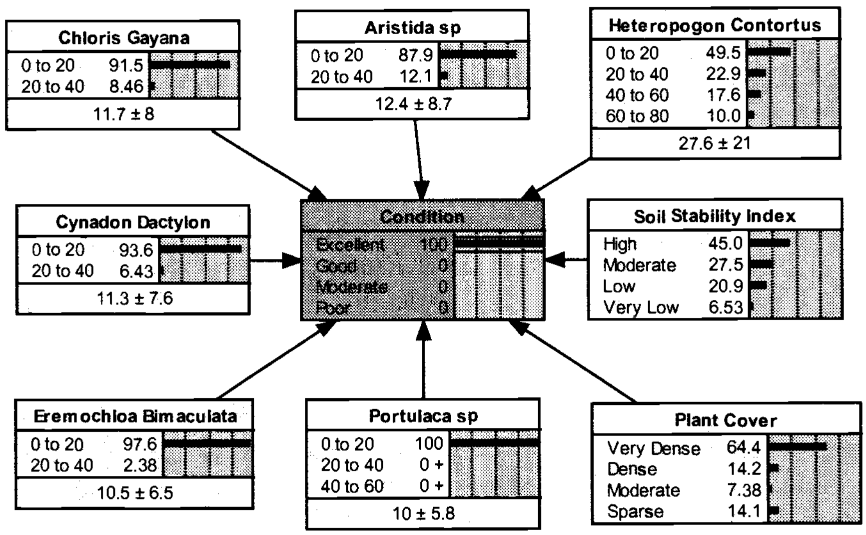
Importance	1	2	3	4	5	6	7	8
Indicators	**Soil Stability index**	**Plant Cover**	***Heteropogon contortus*** Frequency	***Aristida sp*** **Frequency**	*Cynadon dactylon* **Frequency**	*Chloris gayana* **Frequency**	*Eremochloa bimaculata* **Frequency**	*Portulaca sp* **Frequency**

The predictive and diagnostic capabilities of BBNs have the potential to provide valuable information to rangeland managers by allowing them to conduct scenario analysis. Figure 2a is an example of the condition model being used in predictive mode. The selected states of inputs (outer boxes) represent known findings for condition indicators at a site. Those inputs with no select state (eg. Plant Cover) are indicators that have not been measured for the site, so a prior probability is used. The model shows that, under this scenario, the site is most likely to be in excellent condition (68% chance). As findings for more indicators are inserted into the model, the confidence that at site is in a particular condition increases. Figure 2b is an example of the condition model being used in diagnostic mode. The model now shows the likely characteristics of a site for a particular condition outcome. In this example, sites in excellent condition are most likely to have high soil stability, very dense plant cover, and a high abundance of *Heteropogon contortus* compared to other species.

The advantage of using a BBN based tool is that it allows uncertainty in the assessment of condition to be expressed using probability. The simplicity of the approach, the graphical nature of the models and their scenario analysis capabilities also facilitate the communication of land condition dynamics with land managers. The authors of this paper are currently linking a land condition assessment tool to a land management model, which has been developed using a BBN. This will further allow managers to predict the degradation consequences of land management decisions, and identify those management scenarios that are most likely to prevent decline in land condition.



(a) BBN model in predictive mode



(b) BBN model in diagnostic mode

Figure 2: (a) Using the model in predictive mode to assess the likelihood of a condition, and (b) for diagnostic assessment to determine the most likely characteristics of a site under a specific condition

REFERENCES

Bennet, B. (1996). Toward a strategy for sustainable pastures. *CSIRO ECOS.* 87: 26-30.

Braun-Blanquet, J. *Trans* by Cornard, H.S. and Fuller, G.D. (1932). Plant sociology: the study of plant communities. *McGraw-Hill Book Company, Inc*, New York.

Cosgrove, D., Undersander, D. and Cropper, J.B. (2001). Pasture condition score sheet. *USDA-NRCS*, Grazing land Technology Institute.

Jensen, F.V. (2001). Bayesian network and decision graphs. *Springer*, New York.

Norsys Software Corporation. (1998). Netica application user guide. *Norsys Software Corp*, Vancouver, BC, Canada. Available from www.norsys.com.

Raymond, A.E. and Love, R.M. (1957). The step point method of sampling- a practical tool in range research. *Range Management.* 10: 208-12.

Scarnecchia, D.L. (1994). A viewpoint: using multiple variables as indicators in grazing research and management. *Range Management.* 47: 107-11.

Tongway, D. and Hindley, N.L. (2004). Landscape function analysis: procedures for monitoring and assessing landscapes. *CSIRO Sustainable Ecosystem*, Brisbane.

Wilson, A.D. and Tupper, G.J. (1982). Concepts and factors applicable to the measurements of range condition. *Range Management.* 35: 684-9.