Accommodating uncertainty in grazing land condition assessment using Bayesian Belief Networks

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1. Introduction

Rangelands are semi-natural landscapes, an important global resource that covers more than 47 percent of the land area of Earth (332 million hectares) (Tueller, 1998). They have been used for many purposes (e.g. grazing, bee industry, hunting, mining and tourism). Rangeland ecosystems are highly variable in terms of their biophysical components such as rainfall and soil type (Gross et al., 2003 & 2006). The primary production of grasses can vary up to 10 times from year to year (Kelly & Walker, 1976). In addition, there are often clear conflicts in the multiple objectives of rangeland use and management (e.g. production and conservation).

Land managers and technical assistance specialists require a system for assessing rangeland condition in order to know where to focus management efforts and for a better understanding of ecosystem processes (Karfs et al., 2009). The assessment of the present condition of the land and monitoring of relevant and meaningful changes are essential for preventing land degradation (Liu, 2009). Range assessment is also essential to evaluate the effectiveness of implemented management practices and to identify the ecological problems in rangelands before its condition becomes seriously degraded (Manske, 2004).

Several key obstacles emerge when considering rangeland condition, namely, 1) no single entity can handle all aspects of rangeland condition and 2) rangeland condition varies in time and space (Bellamy & Lowes, 1999). This introduces uncertainty into rangeland management and therefore assessment tools. Although researchers have developed sophisticated methods of assessing rangeland condition, it is not easy to accommodate the uncertainty associated with the indicators used. Almost all of the rangeland condition assessment tools available at present use deterministic or 'hard' criteria to assess condition against a set of indicators, which does not represent the true variability or uncertainty associated with condition assessment. We believe Bayesian belief Networks (BBNs) (Jensen, 2001) provide a tool that can help solve this problem.

2. Bayesian Belief Networks

In the late 1980s, BBNs were introduced to accommodate uncertainty in the modeling of complex systems (Pearl, 1988). BBNs provide a probabilistic and dynamic representation of the relationships between variables using conditional probability (Jensen, 1996). They consist of qualitative and associated quantitative parts. The qualitative part is a directed graph (cause and effect diagram) with a set of nodes representing relationships between the variables under study. The quantitative part is a set of conditional probabilities that explain the strength of the dependences between variables represented.

BBNs have two main functions that make them valuable assessment tools. The first is a scenario, or what if, analysis where particular states of input nodes are selected to reveal the probability of outcomes occurring (Figure 1a). The second is diagnostic analysis where particular states of outcomes are selected to reveal the probability of inputs occurring (Figure 1b).

Some other key aspects of BBNs that make them attractive assessment tools are:

- They are graphical, which facilitates communication about systems behavior among managers;
- They are updatable, meaning that their conditional probabilities can be updated over time using monitoring records. Thus, nodes, states and relationships can be modified as new knowledge about the system becomes available;
- They provide an integrative framework that combines qualitative and quantitative knowledge, plus probabilities obtained from monitoring, experiential knowledge and outputs from other models.

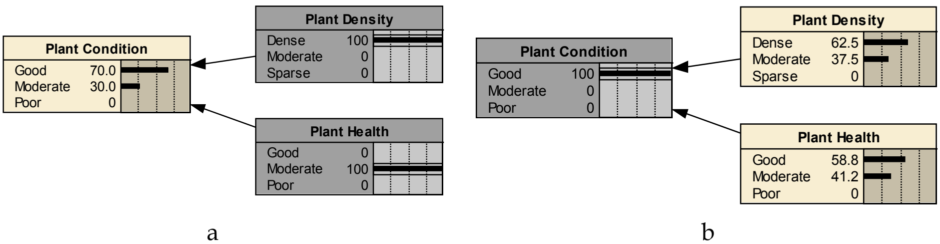

Fig. 1. A BBN used in (a) Predictive mode, (b) Diagnostic mode.

3. Stocktake

Stocktake is a Decision Support System (DSS) for paddock-scale grazing land condition monitoring and management (Department of Primary Industries and Fisheries, 2004). It has been developed and used recently in Australian pastures to assist land managers to assess grazing land condition, long term carrying capacity and calculate short-term forage budgets. It is designed to be applied to different land types and can be used in the broad scale assessment of grazing land condition. The simplicity and repeatability of Stocktake assists managers to assess grazing land condition based on a ABCD grazing land condition scoring framework by using indicators such as pasture composition, tree density, weeds and soil erosion (Chilcott et al., 2003) and relates grazing land condition to grass growth potential for different land types. This enables land managers to evaluate the effect that suboptimal grazing land condition will have on long-term carrying capacity. The forage budgeting component of this DSS provides a tool for land managers to regulate stock numbers according to seasonal forage supply.

Grazing land condition in Stocktake is comprised of three components including pasture condition, soil condition and woodland condition. Grazing land condition directly influences the ecosystem functioning, biodiversity and long term carrying capacity. It is affected by long term paddock management and its rate of change is slow over a number of seasons or years. The pasture condition component of grazing land condition indicates the capacity of the pasture to capture and transfer solar energy into edible components for livestock, capture rainfall and to preserve soil condition and nutrient cycling. Pasture condition depends on the presence of 3P grasses (perennial, palatable and productive grasses), crown cover and health of 3P grasses, species diversity and weed infestation. Soil condition indicates the soil capacity to capture rainfall, cycle and store nutrients, habitat for seed germination, support for the growth of seedlings and to resist erosion. Woodland condition indicates the ability of vegetation to regulate ground water and cycle nutrients (Department of Primary Industries and Fisheries, 2004).

The data requirements for assessing grazing land condition using Stocktake are limited to qualitative data that is very easy to collect. Large amounts of these data, including photos are recorded and stored for future reference. Although this DSS can assist land managers to plan, implement and monitor a grazing land management strategy for the whole property, it lacks the capability of assessing the effect of different grazing management plans on grazing land condition. It also does not incorporate uncertainty inherent in rangeland ecosystems in the assessment of grazing land condition or carrying capacity. In the following section, we demonstrate how BBNs can be used to change the Stocktake monitoring procedure into a predictive DSS.

4. The Grazing Land Condition Model

The development of a grazing land condition model consisted of two main steps: (a) conceptual model development, and (b) converting the conceptual model into a predictive grazing land condition model (Figure 2).

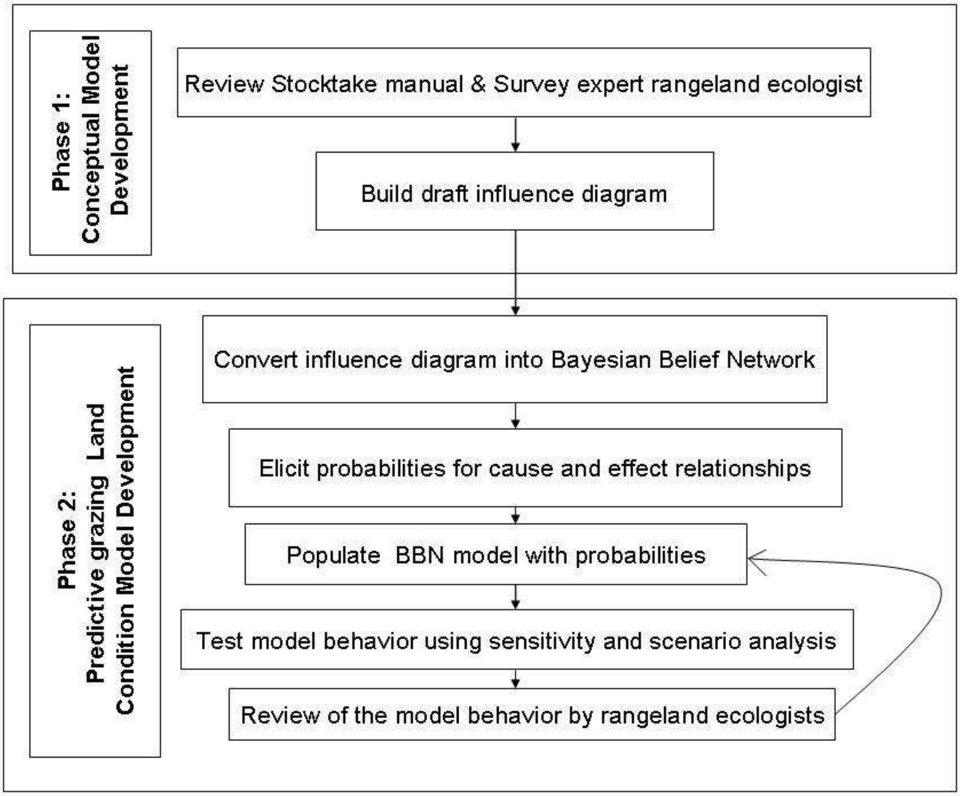

Fig. 2. Steps used to build a predictive grazing land condition model.

4.1. Conceptual Model Development

The purpose of conceptual model development was to build an influence diagram capturing the key variables believed to influence grazing land condition within the Stocktake land condition assessment approach. First, we reviewed the Stocktake manual, followed by a meeting held with an expert of the CSIRO who had expertise in grazing land condition assessment. We used the information from the manual and the meeting to build a draft influence diagram. The influence diagram (Fig.3) contained: (a) key environmental variables believed to influence pasture condition (b) key environmental variables believed to influence soil condition, and (c) key woodland variables believed to influence woodland condition. The draft influence diagram was reviewed by the grazing land condition expert and the influence diagram altered based on the feedback received.

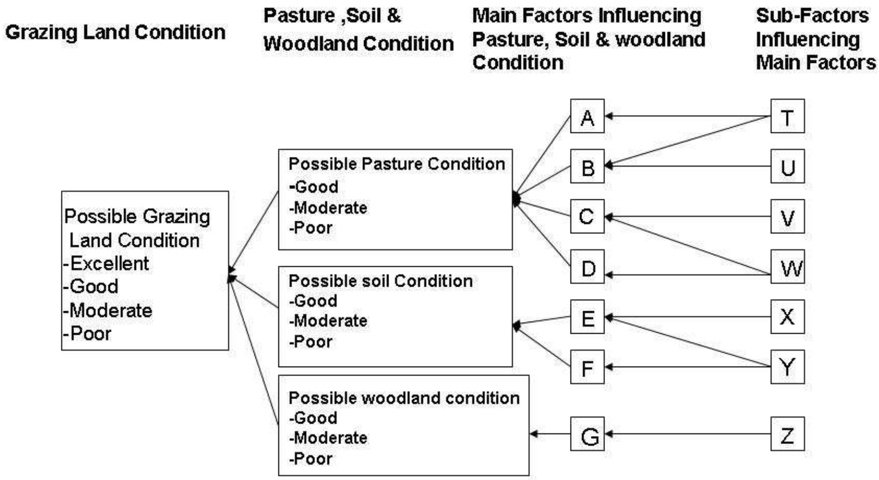

Fig. 3. Framework used to construct an influence diagram for grazing land condition model.

Next, states were defined for each node in the influence diagram. Figure 4 shows the completed influence diagram for Ironbark-Spotted Gum Woodland in south-east Queensland, Australia. Table 1 lists the states and the definitions for each node in the influence diagram.

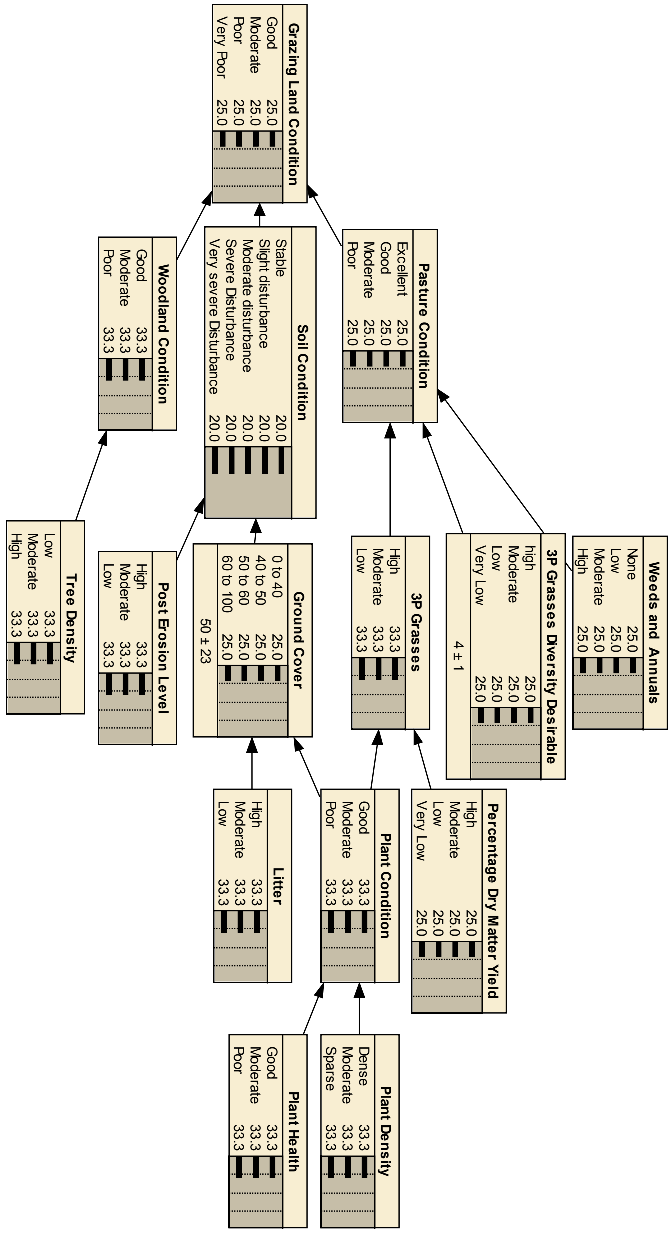

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Fig. 4. Influence diagram for Bayesian grazing condition model.

Node	Definition and classes
Grazing Land Condition	This node represents the overall pasture, soil and woodland condition and represents the efficiency of ecosystem functioning. Grazing land condition is slow to change and it is an indicator of long term safe carrying capacity. Good: good coverage of perennial grasses, little bare ground, few weeds, no woodland thickening. Moderate: some decline of perennial grasses, soil condition and thickening in density of woody plants. Poor: general decline of perennial grasses and past erosion and obvious thickening in density of woody plants. Very Poor: general lack of perennial grasses, severe erosion, thickets of woody plants cover most of the area.
Pasture Condition	This node represents the status of perennial, palatable and productive grasses (3P grasses) , species diversity and weed infestation. Excellent: good coverage of 3P grasses, few weeds Good: some decline of 3P grasses and increase in less favoured species. Moderate: general decline in 3P grasses, large amounts of less favoured species Poor: general lack of 3P grasses.
Soil Condition	This node represents the soil health in terms of capacity of soil to absorb and store rainfall, resist erosion, nutrient cycling, and habitat for seed germination. Stable: good soil surface condition and no signe of erosion and soil movement. Slight Disturbance: some decline in soil condition, some signe of post erosion and increased surface runoff. Moderate Disturbance: obvious signe of past erosion (sheet or rill erosion), and high current erosion susceptibility. Plant pedestalling occurring, gravel and stone pavements common. Severe Disturbance: high erosion level (rill or gully erosion), bedrock at the surface. Very Severe Disturbance: severe erosion or scalding, gully erosion more than 15 mm deep.
Three P Grasses	This node represents the status of perennial, palatable and productive grasses. High: good coverage of 3P grasses. Moderate: some decline of 3P grasses. Low: general decline or lack of 3P grasses
3P Grasses Diversity Desirable	This node represents if a variety of the native species with high grazing value are dominant. High: pasture consists of more than 5 desirable species. Moderate: pasture consists of 3 to 5 desirable species. Low: pasture consists of 2 to 3 desirable species. Very Low: pasture consists of one or less desirable species.
Weeds	This node represents how much of the pasture are covered by unpalatable, invader and in some cases poisonous species. Weeds have direct influence on the paddock productivity. None: there are not any weeds in the pasture. Low: few weeds and no significant infestations. Moderate: there are large amounts of weeds. High: weeds are dominant and infested heavily.

Node	Definition and classes
Ground Cover	This node represents how much of the soil surface is protected against rain. It includes vegetation cover, leaf litter, dung, sticks or rocks. 0 to 4o: this percentage of ground is covered by vegetation cover, leaf litter, dung, sticks or rocks. 40 to 50: this percentage of ground is covered by vegetation cover, leaf litter, dung, sticks or rocks. 50 to 60: this percentage of ground is covered by vegetation cover, leaf litter, dung, sticks or rocks. 60 to 100: this percentage of ground is covered by vegetation cover, leaf litter, dung, sticks or rocks.
Post Erosion Level	This node represents the status of erosion in the past. High: there are obvious and severe erosion signs. Moderate: there are some erosion signs. Low: there are few erosion signs.
Percentage Dry Matter Yield	This node represents how much of the pasture yield is comprised by 3P grasses. High: 3P grasses comprise 80% or more of pasture yield. Moderate: 3P grasses comprise 60 to 80% of pasture yield. Low: 3P grasses comprise 10 to 60% of pasture yield. Very Low: 3P grasses comprise less than 10% of pasture yield.
Plant Condition	This node represents the status of plants in terms of their crown cover and healthiness. Good: plants are dense and healthy. Moderate: moderate density and some plants dead. Poor: sparse and many plants dead.
Plant Density	This node represents the number of individual plants in a given area. Dense: the crowns of 3P grasses are not sparse and there is not bare ground in-between. Moderate: the crowns of 3P grasses are not dense and there is some bare ground in-between. Sparse: the crowns of 3P grasses are sparse and there is much bare ground in-between.
Plant Health	This node represents the healthiness status of 3P grasses. Good: the 3P grasses are healthy and they are not diseased, discoloured or poor growth. Moderate: some of the 3P grasses are healthy and some are diseased, discoloured or dead. Poor: many of 3P grasses are unhealthy, diseased, discoloured or dead.
Litter	This node indicates if there are litter between the tussocks of grasses. High: little bare ground and much litter in-between. Moderate: some bare ground and litter in-between. Poor: much bare ground and low litter in-between.

Table 1. Definition for nodes and their classes in the land condition model, adapted from Department of Primary Industries and Fisheries, 2004)

4.2. Eliciting probabilities for the model

Conditional Probability Tables (CPTs) characterize the relationships between nodes within a BBN (Bashari et al., 2009). To produce a predictive model, the CPTs in the grazing land condition model influence diagram were populated using subjective probability estimates obtained from the expert who participated in building the influence diagram. It was necessary to elicit subjective probability estimates because measured probabilities were not available and can only be obtained from long-term studies.

A CPT calculator developed by Cain (2001) was used in the probability elicitation process to maintain logical consistency in the estimated probabilities. It also reduced the number of probabilities that had to be elicited from the expert to populate the BBN. The CPT calculator works by reducing a CPT to the minimum number of scenarios for which probabilities need to be estimated. These scenarios allow the CPT calculator to determine the relative influence of each factor on the probability of outcomes. Once probabilities for these scenarios are elicited, the calculator checks for logical consistency and then interpolates probabilities for all scenarios in the CPT.

To illustrate, the shaded lines in Table 2 represent the reduced CPT for the node "Plant Condition", which has two input nodes; plant density and plant health. In the reduced CPT, (a) the first line represents the best-case scenario where all of the parent nodes of "plant condition" are in the best state, (b) the last line represents the worst-case scenario where all of the parent nodes of "plant condition" are in the worst state, and (c) the remaining shaded lines represent scenarios where only one parent node is not in the best state. Probabilities for the shaded lines are elicited from an expert, after which the CPT calculator interpolates probabilities for the full CPT (Table2). For parentless nodes in the grazing land condition influence diagram (for example, the "plant density", "plant health" "litter" and "Tree density" and " Post erosion level") uniform probability distributions were specified for their CPTs (each state was given equal probability).

Factors influencing Plant Condition		Probability of Plant Condition (%)		
Plant Density	Plant Health	Good	Moderate	Poor
Dense	Good	100	0	0
Dense	Moderate	70	30	0
Dense	Poor	0	50	50
Moderate	Good	60	40	0
Moderate	Moderate	42	58	0
Moderate	Poor	0	50	50
Sparse	Good	0	40	60
Sparse	Moderate	0	30	70
Sparse	Poor	0	0	100

Table 2. The full probability table for "plant condition" interpolated using the CPT calculator (the scenarios for which probabilities were elicited are highlighted).

4.3.Testing Model Behavior

To test the behavior of the completed grazing land condition model, and to highlight any inconsistencies, a sensitivity analysis was performed and the results compared with the expectations of rangeland scientists (Table 3). The measure of sensitivity used was entropy reduction (Marcot, 2006)

Table 3. Sensitivity of grazing land condition to the key environmental variables (variables are listed in order of influence on grazing land condition from most to least influential)

Node	Entropy reduction
Pasture condition	0.923
3P grasses	0.5061
Soil condition	0.2622
Plant condition	0.2522
Ground cover	0.2272
Plant density	0.09224
Percentage dry matter	0.08194
Plant health	0.06302
Weeds and annuals	0.02942
Post erosion level	0.01361
3P grasses diversity desirable	0.005579
Litter	0.00366
Woodland condition	0.0007306
Tree density	0.0006092

Sensitivity is calculated as the degree of entropy reduction I, which is the expected difference in information bits H between variable Q with q states and findings variable F with f states, after (Marcot, 2006):

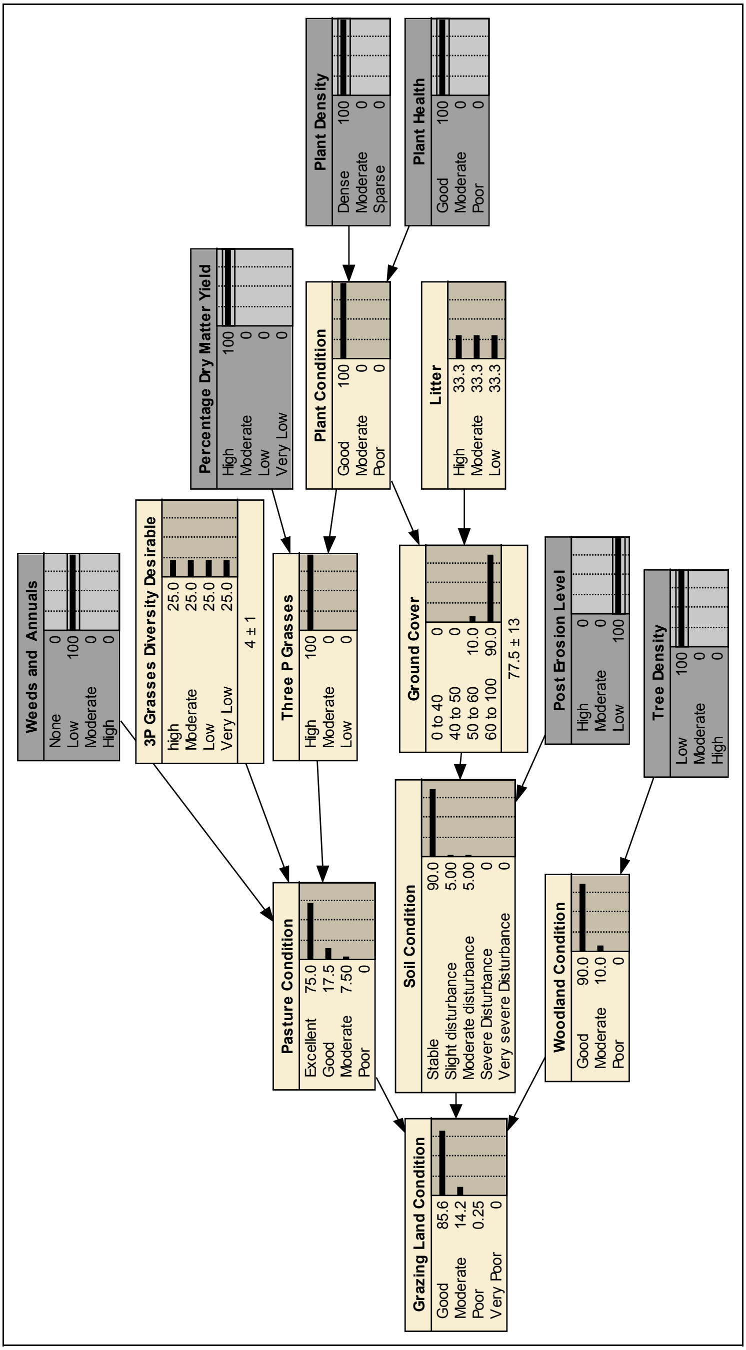
$$I = H(Q) - H(Q \mid F) = \sum_q \sum_f \frac{P(q,f)\log_2[P(q,f)]}{P(q)P(f)}$$

The sensitivity analysis revealed that pasture condition was the most influential factor on grazing land condition, followed by 3P grasses (which directly influences pasture condition). Species composition in most grassland ecosystems has proved to be a good indicator of ecosystem processes (Heady, 1975). Soil and plant condition had similar influence on grazing land condition.

BBN models have the ability to provide rangeland managers with decision support through their analytic capabilities. As mentioned before, two main types of analysis can be performed using a BBN, (a) prediction, and (b) diagnosis. Predictive analysis can be used to answer "what if" questions and diagnostic analysis can be used to answer "how" questions.

Figure 5 is an example of the grazing land condition model used for predictions. Here, the selected states of input nodes (outer boxes) represent a scenario for a site. In Figure 5a, the model shows that, under the selected scenario, the chance of this site being in good condition is high (85.6%). Also there is 75% chance of the site having excellent pasture condition. The model also indicates the probable causes for this condition, that is, good plant condition (100%) and high 3P grasses (100%). These causes were also highlighted by sensitivity analysis as being influential on grazing land condition (Table 3).

Besides answering "what if" questions, the BBN grazing land condition model can also help to answer "how" questions. For example, how might grazing land condition fall in a poor state? Figure 5b is an example of the grazing condition model being used to answer this question using diagnosis. The model shows that it is most likely if pasture condition is poor and soil condition is severely disturbed, and in turn, low abundance of 3P grasses.


Weeds and Annuals
None 0
Low 100
Moderate 0
High 0
3P Grasses Diversity Desirable
high 25.0
Moderate 25.0
Low 25.0
Very Low 25.0
4 ± 1
Percentage Dry Matter Yield
High 100
Moderate 0
Low 0
Very Low 0
Plant Density
Dense 100
Moderate 0
Sparse 0
Plant Health
Good 100
Moderate 0
Poor 0
Plant Condition
Good 100
Moderate 0
Poor 0
Litter
High 33.3
Moderate 33.3
Low 33.3
Three P Grasses
High 100
Moderate 0
Low 0
Ground Cover
0 to 40 0
40 to 50 0
50 to 60 10.0
60 to 100 90.0
77.5 ± 13
Post Erosion Level
High 0
Moderate 0
Low 100
Tree Density
Low 100
Moderate 0
High 0
Pasture Condition
Excellent 75.0
Good 17.5
Moderate 7.50
Poor 0
Soil Condition
Stable 90.0
Slight disturbance 5.00
Moderate disturbance 5.00
Severe Disturbance 0
Very severe Disturbance 0
Woodland Condition
Good 90.0
Moderate 10.0
Poor 0
Grazing Land Condition
Good 85.6
Moderate 14.2
Poor 0.25
Very Poor 0

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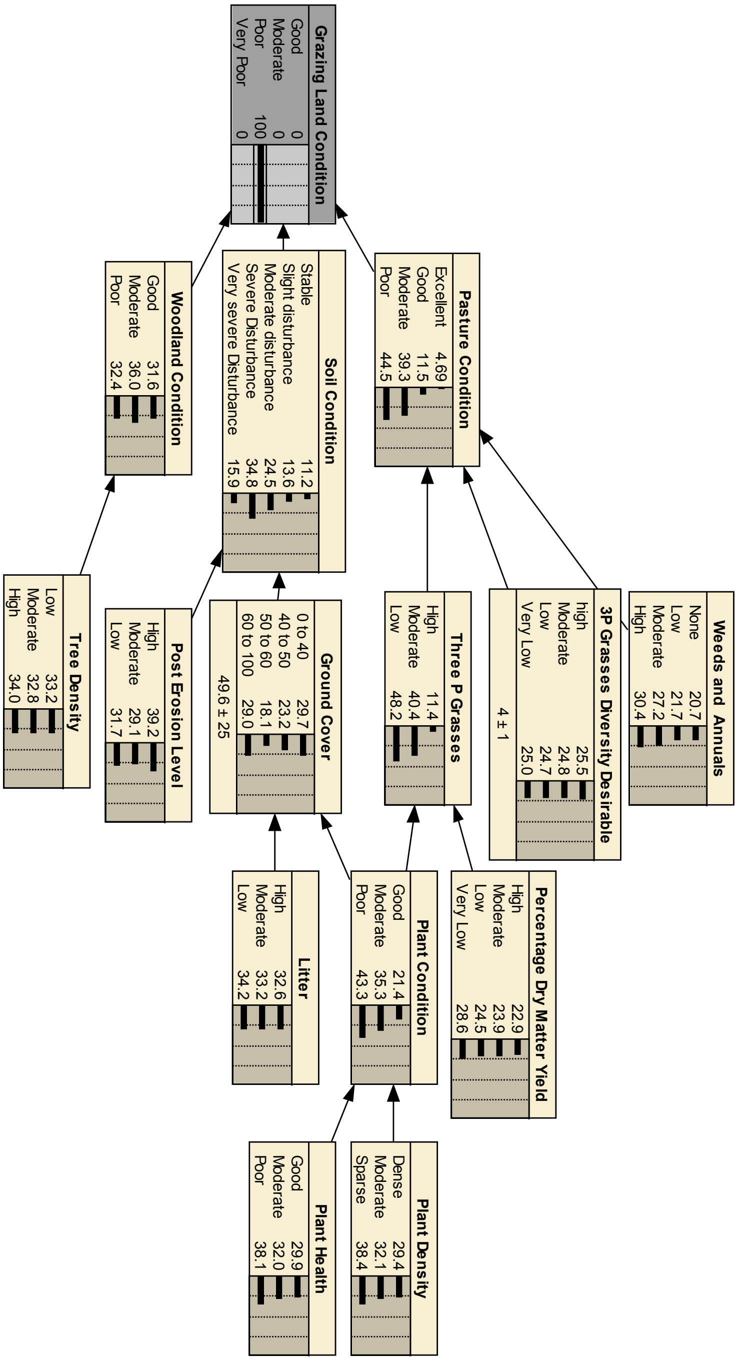

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Fig. 5. Using the Bayesian belief network for diagnosis.

5. Conclusion

Most methods for assessing rangeland condition are deterministic. Stocktake is a local-level monitoring tool that is flexible, adaptive and easy to use by local land users for monitoring and documenting changes in grazing land condition in order to guide and support management responses accordingly. Integration of a condition assessment tool, such as Stocktake, with BBN allows for the construction of cause and effect models and allows uncertainty to be explicitly incorporated into condition assessment. The predictive and diagnostic capabilities of BBNs have the potential to provide valuable information to rangeland managers by allowing them to conduct scenario analysis. The simplicity of the approach, the graphical nature of the models and their scenario analysis capabilities also facilitates the communication of rangeland condition dynamics with land managers.

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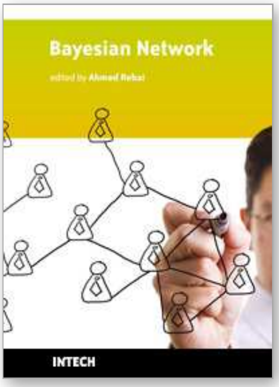

Bayesian Network

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Bayesian networks are a very general and powerful tool that can be used for a large number of problems involving uncertainty: reasoning, learning, planning and perception. They provide a language that supports efficient algorithms for the automatic construction of expert systems in several different contexts. The range of applications of Bayesian networks currently extends over almost all fields including engineering, biology and medicine, information and communication technologies and finance. This book is a collection of original contributions to the methodology and applications of Bayesian networks. It contains recent developments in the field and illustrates, on a sample of applications, the power of Bayesian networks in dealing the modeling of complex systems. Readers that are not familiar with this tool, but have some technical background, will find in this book all necessary theoretical and practical information on how to use and implement Bayesian networks in their own work. There is no doubt that this book constitutes a valuable resource for engineers, researchers, students and all those who are interested in discovering and experiencing the potential of this major tool of the century.