available at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/biocon

Using a Bayesian belief network to predict suitable habitat of an endangered mammal – The Julia Creek dunnart (*Sminthopsis douglasi*)

Carl S. Smith[a,1], *Alison L. Howes*[b,2], *Bronwyn Price*[b,*], *Clive A. McAlpine*[b]

[a]*School of Natural and Rural Systems Management, The University of Queensland, Gatton 4343, Australia*
[b]*Centre for Remote Sensing and Spatial Information Science, School of Geography, Planning and Architecture, The University of Queensland, St. Lucia 4072, Australia*

ARTICLE INFO

Article history:
Received 12 February 2007
Received in revised form
14 June 2007
Accepted 29 June 2007

Keywords:
Expert knowledge
Uncertainty
Wildlife management
Mitchell grasslands
Participatory modelling
Conservation

ABSTRACT

Wildlife managers are often required to make important conservation and recovery decisions despite incomplete and uncertain knowledge of the species and ecosystems they manage. Conducting further research to collect more empirical data may reduce that uncertainty. However, a sense of urgency often surrounds threatened or endangered species' management and decisions cannot wait until a definitive understanding of a species' ecology and distribution is obtained. Bayesian belief networks (BBNs) are proving to be valuable and flexible tools for integrating available expert knowledge and empirical data, thus strengthening conservation decisions when empirical data is lacking. We developed a BBN model and linked it to a geographical information system (GIS) to map habitat suitability for the Julia Creek dunnart (*Sminthopsis douglasi*), an endangered ground-dwelling mammal of the Mitchell grasslands of north-west Queensland, Australia. Expert knowledge, supported by field data, was used to determine the probabilistic influence of grazing pressure, density of the invasive shrub prickly acacia (*Acacia nilotica*), land tenure, soil variability and seasonal variability on dunnart habitat suitability. The model was then applied in a GIS to map the likelihood of suitable dunnart habitat. Sensitivity analysis was performed to identify the influence of environmental conditions and management options on habitat suitability. The study provides an example of how expert knowledge and limited empirical data can be combined within a BBN model, and linked to GIS data, to assist in recovery planning of endangered fauna populations.

1. Introduction

Wildlife managers are often required to make important species management decisions in the face of uncertainty. This can be due to a combination of data inaccuracies or gaps, the inherent stochasticity of ecosystems, or a lack of understanding surrounding the relationships between wildlife populations and environmental variables (Salski, 1992; Fieberg and Jenkins, 2005). The uncertainty may be reduced through the collection of comprehensive empirical data and with experimentation (Fieberg and Jenkins, 2005). However, in circumstances where a species is threatened or endangered,

* *Corresponding author*: Tel.: +61 (0)7 3365 3535; fax: +61 (0)7 3365 6899.
E-mail addresses: c.smith2@uq.edu.au (C.S. Smith), b.price@uq.edu.au (B. Price).
[1] Tel.: +61 (0)7 5460 1107; fax: +61 (0)7 5460 1324.
[2] Australian Centre for Sustainable Catchments, University of Southern Queensland, Toowoomba 4350, Australia.
0006-3207/$ - see front matter
doi:10.1016/j.biocon.2007.06.025

managers may not have the luxury of waiting for further scientific study before developing management plans and actions. In these instances, the only available information to base decisions on may be expert knowledge and opinion, along with limited empirical data (Cain, 2001; Martin et al., 2005). Expert knowledge in ecological modelling is a valuable resource that should not be underestimated (Cain, 2001). When combined with field data, it can strengthen results significantly (Martin et al., 2005), and is proving beneficial in decision making where scientific data are limited (Marcot et al., 2001, 2006a; Raphael et al., 2001; Taylor, 2003; Clark, 2005; Martin et al., 2005; Marcot, 2006).

Several studies have demonstrated the utility of Bayesian belief networks (BBNs) (Jensen, 2001) in capturing and integrating expert knowledge and empirical data to model wildlife population distributions and to identify the factors most likely to influence species' occurrence and abundance (Marcot et al., 2001; Raphael et al., 2001; Taylor, 2003; Clark, 2005; Martin et al., 2005). BBNs provide a means for predicting species' occurrence or abundance according to environmental variables and management actions (Clark, 2005; Gelfand et al., 2006). The key advantages are that they can: synthesise existing data with experts' experience; accommodate uncertainty in modelling; be used for scenario analysis; and be rerun with different alternatives and assumptions (Taylor, 2003). They also help to provide an understanding of the sources and implications of uncertainties that exist in both data and expert understanding. Therefore, BBNs can be a useful tool for identifying where further research would lead to the greatest improvements in model confidence (Marcot et al., 2001; Marcot, 2006). However, like any modelling tool (expert or empirically), without rigorous peer review, model updating and calibration with field data to ensure credibility, a BBN is nothing more than a belief system (Marcot et al., 2006b). Given this, a BBN is a tool for organising current thinking and generating testable hypotheses that can be calibrated, validated and updated as new knowledge and data become available.

Until recently, the unique biodiversity of Australia's northern rangelands has received little consideration as it was perceived that these regions were largely undisturbed by intense agriculture and free from widespread loss of native vegetation (Mackey et al., 1998; Woinarski and Fisher, 2003). However, broad scale conversion of native ecosystems to cropping and improved pastures over the past decade, changes in seasonal fire regimes, biological invasions by exotic species, and excessive grazing pressure, have negatively influenced the biodiversity of Australia's northern rangelands (Woinarski and Ash, 2002), including significant declines in small mammal populations (Woinarski et al., 2001; Andersen et al., 2005).

The Julia Creek dunnart (*Sminthopsis douglasi*) is just one example of a rare and little understood mammal species in the northern rangelands whose distributions and abundance is likely to be impacted by European land management practices. It is listed as an endangered species under the Environmental Protection and Biodiversity Conservation Act 1999, the Australia and New Zealand Environment Conservation Council (ANZECC) Threatened Species list, the World Conservation Union (IUCN) Red List of Threatened Animals, the Australian Marsupials and Monotremes Action Plan, and the Queensland Nature Conservation (Wildlife) Regulation Act 1994 (Lundie-Jenkins and Payne, 2000). The species was first documented in 1931 in northwest Queensland, however it was not scientifically recorded until 1979 (Archer, 1979). Between 1931 and 1972, only four specimens had been collected and by the early 1980s it was presumed extinct (Woolley, 1992). Research in 1990 found evidence of the existence of the species from owl and cat remains, and in 1991–1992 live specimens were caught, doubling the known habitat range (Woolley, 1992). Observational evidence from trapping and owl pellets suggests that the Julia Creek dunnart has a restricted distribution and is not abundant at any location within its distribution (Mifsud, 1999).

A number of threatening process are thought to be of significance for the Julia Creek dunnart, including excessive grazing pressures by sheep and cattle, altered fire regimes, predation by foxes (*Vulpes vulpes*) and feral cats (*Felis catus*) and the invasion of the exotic prickly acacia (*Acacia nilotica*) (Lundie-Jenkins and Payne, 2000). A recovery plan to address these threatening processes and to identify suitable habitat has been drafted (Lundie-Jenkins and Payne, 2000). However, there remains limited information on the distribution, abundance and ecology of the Julia Creek dunnart, hindering the application of the recovery plan for the species.

This paper aims to demonstrate, using the Julia Creek dunnart as a case study, how habitat suitability can be modelled at a regional scale (10,000 s km^2) using a BBN model linked to a geographical information system (GIS). Given the limited knowledge on the abundance and distribution of the Julia Creek dunnart, this paper models habitat suitability rather than species' occurrence. The paper applies expert knowledge captured from a small group of experts familiar with the ecology of the study species and the rangeland environments it inhabits to build a BBN to identify potential suitable habitat where the species may occur or where it may be reintroduced in the future. We conducted scenario and sensitivity analysis to demonstrate how the model can be used to assess options for species' management and recovery. The results show that BBNs can spatially model habitat suitability with a moderate level of accuracy.

2. Methods

2.1. *Study species and study area*

The Julia Creek dunnart is a small insectivorous, nocturnal marsupial confined to the cracking clay soils of the Mitchell grasslands of north-west Queensland (Lees, 1999). The species shelters from predation and extreme temperatures in the deep cracks in dry clay soil (Mifsud, 1999). During the wet season or wet years, the clay soils become heavily waterlogged and expand, closing the cracks. During this period, the Mitchell grass (*Astrebla* spp.), along with the new growth of annual grasses and short lived annual forbs, provide adequate shelter for the dunnart (Woolley, 1992).

The Mitchell grasslands form an extensive region (33 million ha) of almost treeless grassland extending in a southeasterly direction for 1500 km from the centre of the Northern Territory, to central-southern Queensland (Phelps and Bosch, 2002). Rainfall across the Mitchell grasslands is highly seasonal with the Australian monsoon delivering high precipitation during summer months of December to March (Gentilli, 1971; Trapper and Hurry, 1993). However, monsoonal rainfall in the region is inter-annually variable with some years significantly wetter than others. *Astrebla* spp. are highly palatable to cattle and sheep, with excessive grazing pressure altering the dynamics of the system through changes in vegetation composition and surface soil characteristics (Orr, 1975; Landsberg et al., 1997; James et al., 1999; Lees, 1999; Phelps, 1999; Pringle and Landsberg, 2004).

In 1926, the Queensland Department of Agriculture recommended planting prickly acacia as shade and fodder for livestock in the region (Cooperative Research Centre for Weed Management, 2003). Prickly acacia is now a weed of national significance (a weed which has high economic, social and environmental costs and is prioritised for national action (Thorp and Lynch, 2000)), occurring throughout the region at varying densities (Lundie-Jenkins and Payne, 2000; Spies and March, 2004). Its extensive root structure prevents the cracking of heavy clay soils and out-competes native pastures, reducing productivity and ground cover significantly (Spies and March, 2004).

An area of the Mitchell grassland containing confirmed sightings of the Julia Creek dunnart was chosen to develop and test a spatial BBN model of suitable habitat. The area consisted of a triangle encompassing the region between Julia Creek (20.66S, 141.74E), Richmond (20.73S, 143.14E), east to Hughenden (20.87S, 144.24E) and south to Winton (22.40S, 143.04E) (Fig. 1).

2.2. Suitability modelling

The habitat suitability modelling process consisted of two main steps: (a) conceptual model development, and (b) converting the conceptual model into a predictive model, following which the predictive model was linked to geographic data to map habitat suitability (Fig. 2).

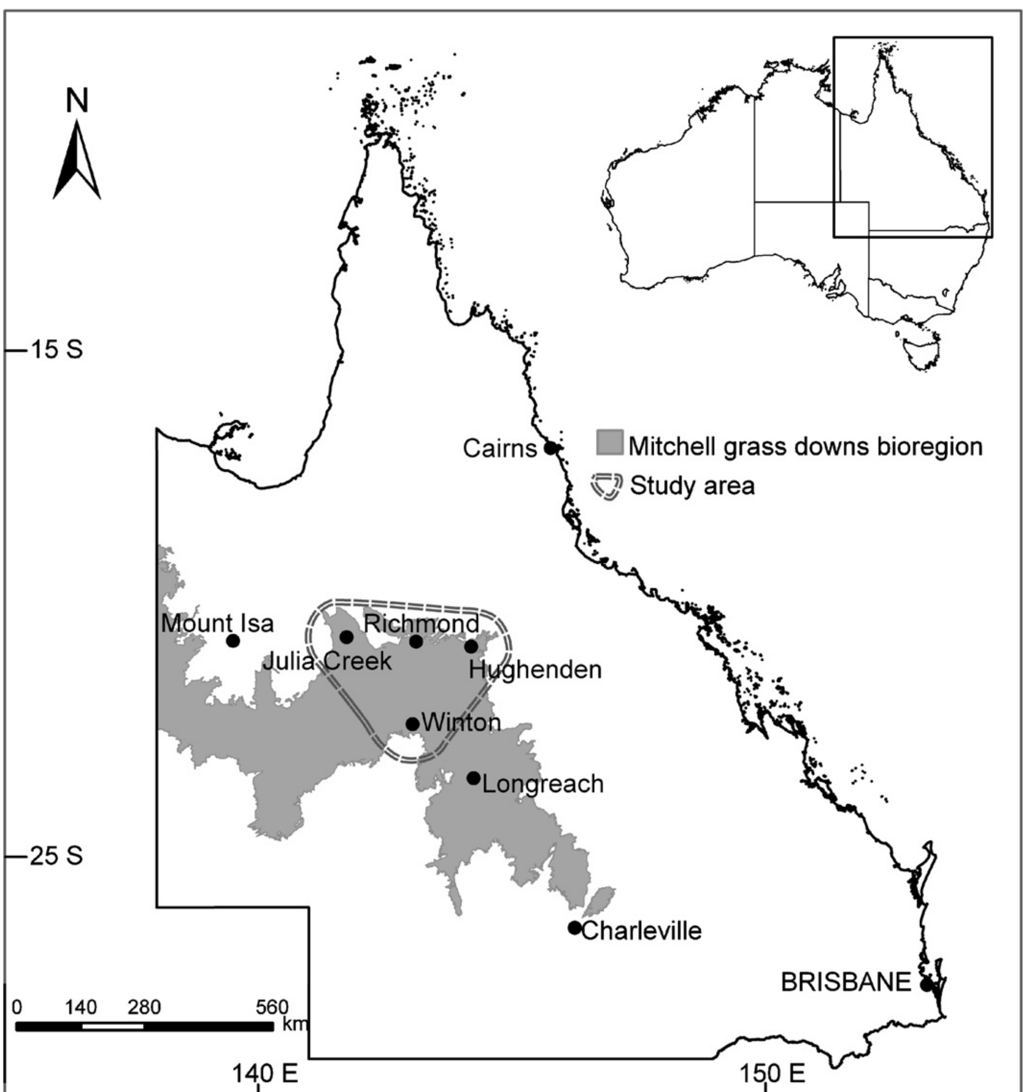

Fig. 1 – Map of the Mitchell grasslands in Queensland. Our study location encompassed the region between Julia Creek, Richmond and Winton. (Map taken from Queensland Parks and Wildlife Service, 2000).

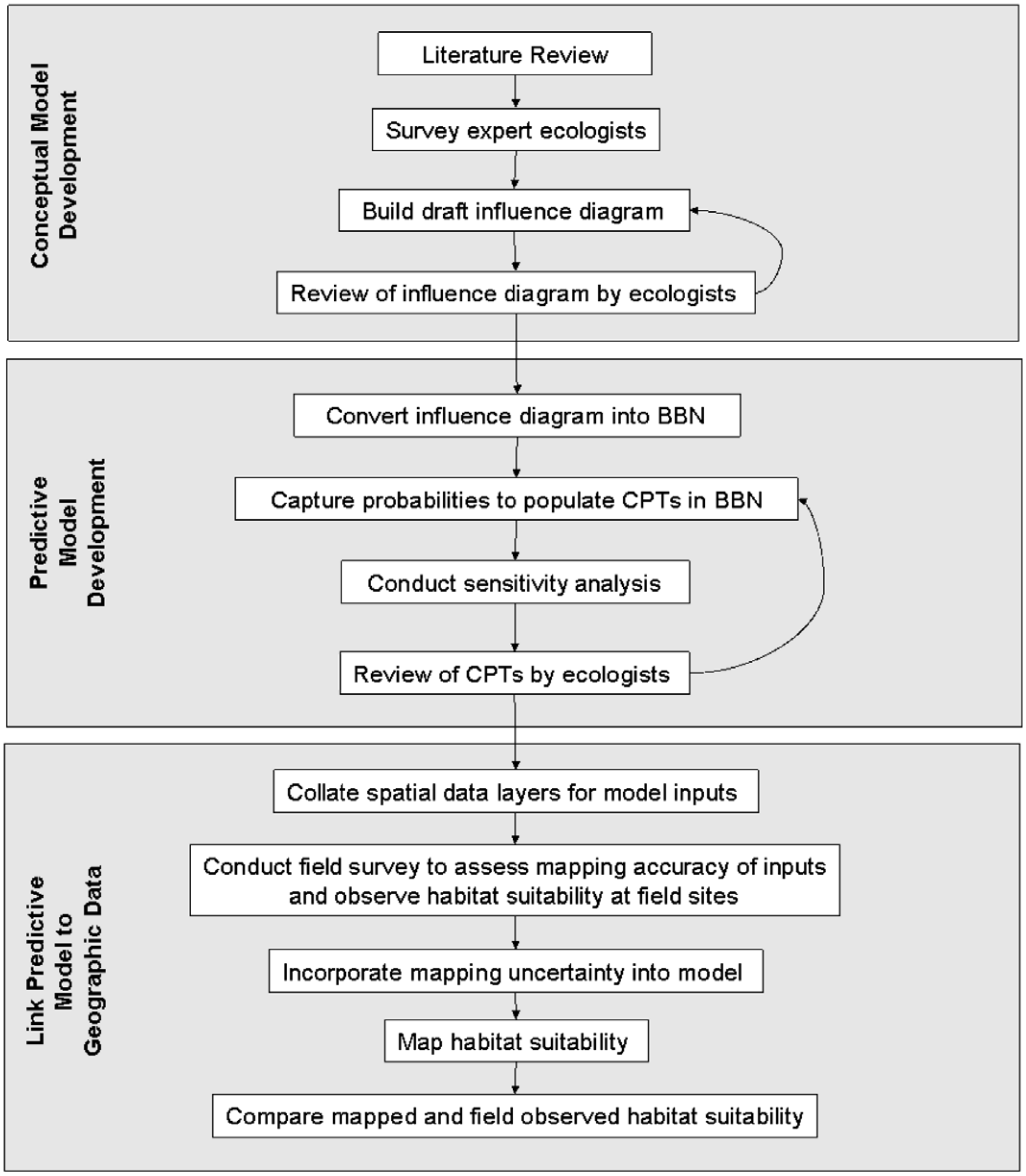

Fig. 2 – Schematic showing the sequential steps used to model and map dunnart habitat suitability.

2.2.1. *Conceptual model development*

The purpose of conceptual model development was to build an influence diagram capturing the key environmental variables believed to influence dunnart habitat suitability. Here habitat implies areas which offer the suitable foraging and shelter resources necessary for mating, dispersal, denning, feeding, and shelter from predators. Habitat suitability is defined based on the presence and quality of these resources in a heterogeneous and dynamic landscape. To identify these variables, a process similar to the Delphi technique was used (Liou, 1992; Clark et al., 2006). First, we conducted a review of the current literature (published literature, theses, and research reports), followed by a meeting held with an expert of the Mitchell grasslands and the Julia Creek dunnart. We used the information from the literature review and the meeting to build a draft influence diagram with a similar structure to that proposed by Marcot et al. (2001). The influence diagram (Fig. 3) contained: (a) Geographic Information System (GIS) variables that can be used as proxies for key environmental variables, (b) key environmental variables believed to influence habitat variables, and (c) habitat variables believed to influence habitat suitability. A survey was then sent to 10 ecologists with expertise in the Mitchell grasslands and the Julia Creek dunnart, in which their opinion of the draft set of habitat variables influencing habitat suitability, and the key environmental variables influencing each habitat variable were obtained. We altered the influence diagram based on the feedback received from these ecologists. The redrafted influence diagram was then returned to two ecologists (leading experts in the ecology of the Julia Creek dunnart) for final review. The review process continued until each of these two ecologists agreed with the influence diagram.

2.2.2. *Predictive model development*

To build a predictive model, the revised influence diagram was converted into a BBN using Netica™ software (Norsys

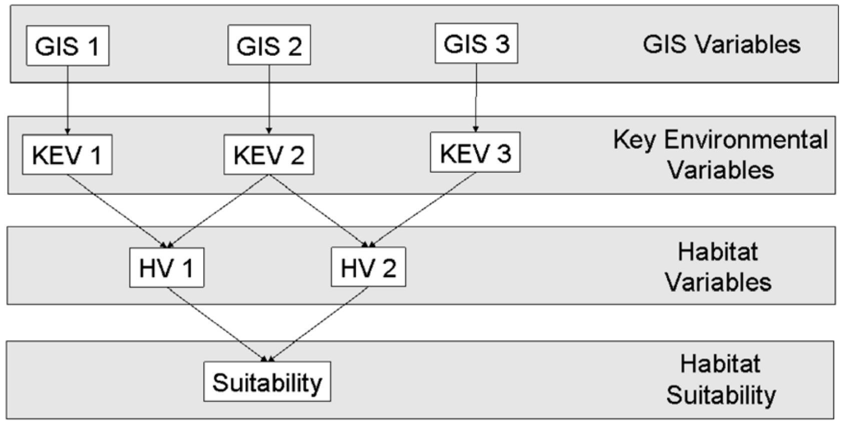

Fig. 3 – Structure used to develop an influence diagram for dunnart habitat suitability (after Marcot et al., 2001).

Software Corporation, 1998). This conversion meant quantifying the relationship between GIS variables and key environmental variables, between key environmental variables and habitat variables, and between habitat variables and habitat suitability. BBNs use conditional probability tables to quantify relationships between nodes (boxes) in an influence diagram. To illustrate, Fig. 4 is a BBN showing the dependence of soil cracks (a habitat variable) on prickly acacia density, rainfall (above or below average rainfall year) and dominant soil type (which are key environmental variables). The probabilities that soil cracks will be 2–3, 1–2 or 0–1 per square metre are stored in the conditional probability table shown in Table 1. The rows in Table 1 are scenarios constructed from different combinations of the input (or parent) nodes to soil cracks.

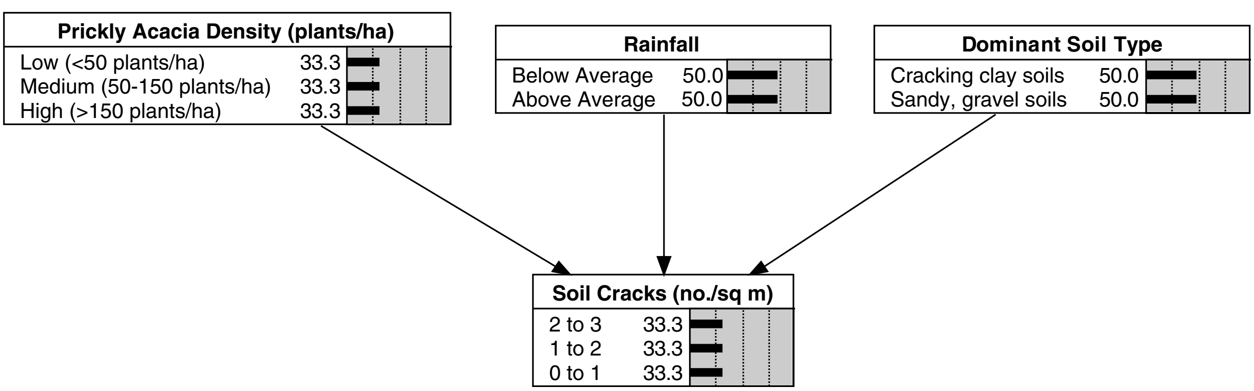

Fig. 4 – Example Bayesian belief network.

Table 1 – Populated conditional probability table for soil cracks node in Fig. 4 (italicised rows are those scenarios for which probabilities are elicited first)

Rainfall	Dominant soil type	Prickly acacia density (plants/ha)	Soil cracks (no./sq m)		
			2–3	1–2	0–1
Below average	*Cracking clay soils*	*Low*	90	10	0
Below average	*Cracking clay soils*	*Medium*	50	50	0
Below average	*Cracking clay soils*	*High*	0	0	100
Below average	*Sandy, gravel soils*	*Low*	0	0	100
Below average	Sandy, gravel soils	Medium	0	0	100
Below average	Sandy, gravel soils	High	0	0	100
Above average	*Cracking clay soils*	*Low*	0	0	100
Above average	Cracking clay soils	Medium	0	0	100
Above average	Cracking clay soils	High	0	0	100
Above average	Sandy, gravel soils	Low	0	0	100
Above average	Sandy, gravel soils	Medium	0	0	100
Above average	*Sandy, gravel soils*	*High*	0	0	100

2.2.2.1. Populating condition probability tables for habitat variable and suitable nodes. Very little empirical data were available to populate the conditional probability tables for habitat variable nodes (which quantify the relationship between key environmental variables and habitat variables) and the habitat suitability node (which quantifies the relationship between habitat variables and habitat suitability) in the dunnart suitability model. Therefore, probability estimates had to be elicited from the expert ecologists who participated in building the original influence diagram. To maintain logical consistency in the elicited probabilities, a procedure similar to that described by Cain (2001) was adopted. Specific scenarios were selected from a conditional probability table. These were: (a) the best-case scenario where all of the parent nodes (input variables) are in the best state; (b) the worst-case scenario where all of the parent nodes are in the worst state, and; (c) scenarios where only one parent node is *not* in the best state. Probabilities were elicited for these scenarios and were then used as reference points for eliciting probabilities for the remaining scenarios in a conditional probability table (see Table 1 for example, where the first row represents that best case scenario for soil cracking and the last row represents the worse case scenario for soil cracking). During the probability elicitation process conditional probability tables were not normalised (that is, 100% probability was not automatically assigned to the best child node state for the best case scenario, and the worst child node state for the worst case scenario). Once complete, each probability table was checked for logical consistency (using Table 1, an example of a logical consistency check would be to check that the probabilities in the 2–3 soil cracks' column are $\leqslant$90% (the probability for the best case scenario) and $\geqslant$0% (the probability for the worse case scenario)).

Sensitivity analysis was then used to check that the relative influence of key environmental variables on habitat variables, of habitat variables on habitat suitability, and of key environmental variables and habitat variables together on habitat suitability met with the expectations of the ecologists involved in the probability elicitation process. Netica's entropy reduction (also called "mutual information") was used as the measure of sensitivity in the analysis. In an iterative process, we revised the conditional probability tables for habitat variables and habitat suitability nodes where the results of sensitivity analysis did not meet the expectations of the ecologists. The sensitivity analysis and conditional probability table revision process continued until the ecologists were satisfied with the relative order of influence of key environmental variables on each habitat variable, of habitat variables on habitat suitability, and of key environmental variables and habitat variables together on habitat suitability.

2.2.2.2. Populating conditional probability tables for key environmental variable nodes. The conditional probability tables for key environmental variables (which quantify the relationship between GIS variables and key environmental variables) show how accurately key environmental variables are represented by their corresponding GIS variables. The conditional probability table shown in Table 2 is an example, which relates prickly acacia density (key environmental variable) to mapped prickly acacia density (GIS variable). Data obtained from a field survey conducted in the study area was used to evaluate the mapping accuracy of the land tenure, prickly acacia density and soil type GIS variables used in the model. This field survey was conducted in late May 2006 and recorded actual land tenure, prickly acacia density and soil type at 100 sites distributed across the study area. The observed data was compared with mapped land tenure, prickly acacia density, and soil type to calculate mapping accuracy percentages for each GIS variable, which were then used to populate the conditional probability tables for key environmental variables in the dunnart suitability model.

Table 2 – Conditional probability table for prickly acacia density (key environmental variable) showing the accuracy of mapped prickly acacia density (GIS variable)

Mapped prickly acacia density	Observed prickly acacia density		
	Low (<50 plants/ha)	Medium (50–150 plants/ha)	High (>150 plants/ha)
Low (<50 plants/ha)	85	9	6
Medium (50–150 plants/ha)	94	0	6
High (>150 plants/ha)	42	29	29

2.2.2.3. Relating GIS variable nodes. GIS variables represent model inputs within the dunnart suitability model structure (Fig. 3). To check for possible relationships between model inputs, maps for all GIS variables were intersected and the combined attribute table used to perform a Chi Square test between all GIS variables. Those GIS variables that were significantly correlated ($P < 0.05$) were linked in the dunnart suitability model. The conditional probability tables relating linked GIS variables were populated using conditional probabilities calculated from the combined GIS variable attribute table (see Table 3 for example, which relates mapped land tenure, distance to water and prickly acacia density GIS variables).

For the parentless GIS variables in the dunnart suitability model, prior probabilities were assigned to their states based on the percentage of the study area covered by each state. For

Table 3 – Conditional probability table showing the relationship between mapped land tenure, distance to water and prickly acacia GIS variables

Mapped land tenure	Distance to water (km)	Mapped prickly acacia density		
		Low (<50 plants/ha)	Medium (50–150 plants/ha)	High (>150 plants/ha)
Reserve	$\geqslant$5	56	14	30
Reserve	0–5	52	13	35
Stock route	$\geqslant$5	65	15	20
Stock route	0–5	58	15	27
Grazing	$\geqslant$5	66	17	17
Grazing	0–5	61	18	21

Table 4 – Spatial data layers used as GIS variables in the dunnart habitat suitability model

GIS variable	Map	Source	Description	Attribute classes applied
Mapped land tenure	Tenure	NRMW	Land use of the Mitchell grasslands	Reserve land Grazing land Stock routes
Distance to water	Distance to water points	Desert channels, NRMW	Distance to water points including dams, weirs, bores and drainage points	0–5 km >5 km
Mapped prickly acacia density	Prickly acacia survey 1999	Desert Channels, NRMW	Prickly acacia density	Low (<50 plants/ha) Medium (50–150 plants/ha) High (>150 plants/ha)
Mapped dominant soil type	Regional ecosystems	Queensland Herbarium	Regional ecosystems of Queensland incorporating soil type data	Cracking clay soils Sandy, gravel soils

NRMW, Queensland Department of Natural Resources, Mines and Water; BOM, Bureau of Meteorology.

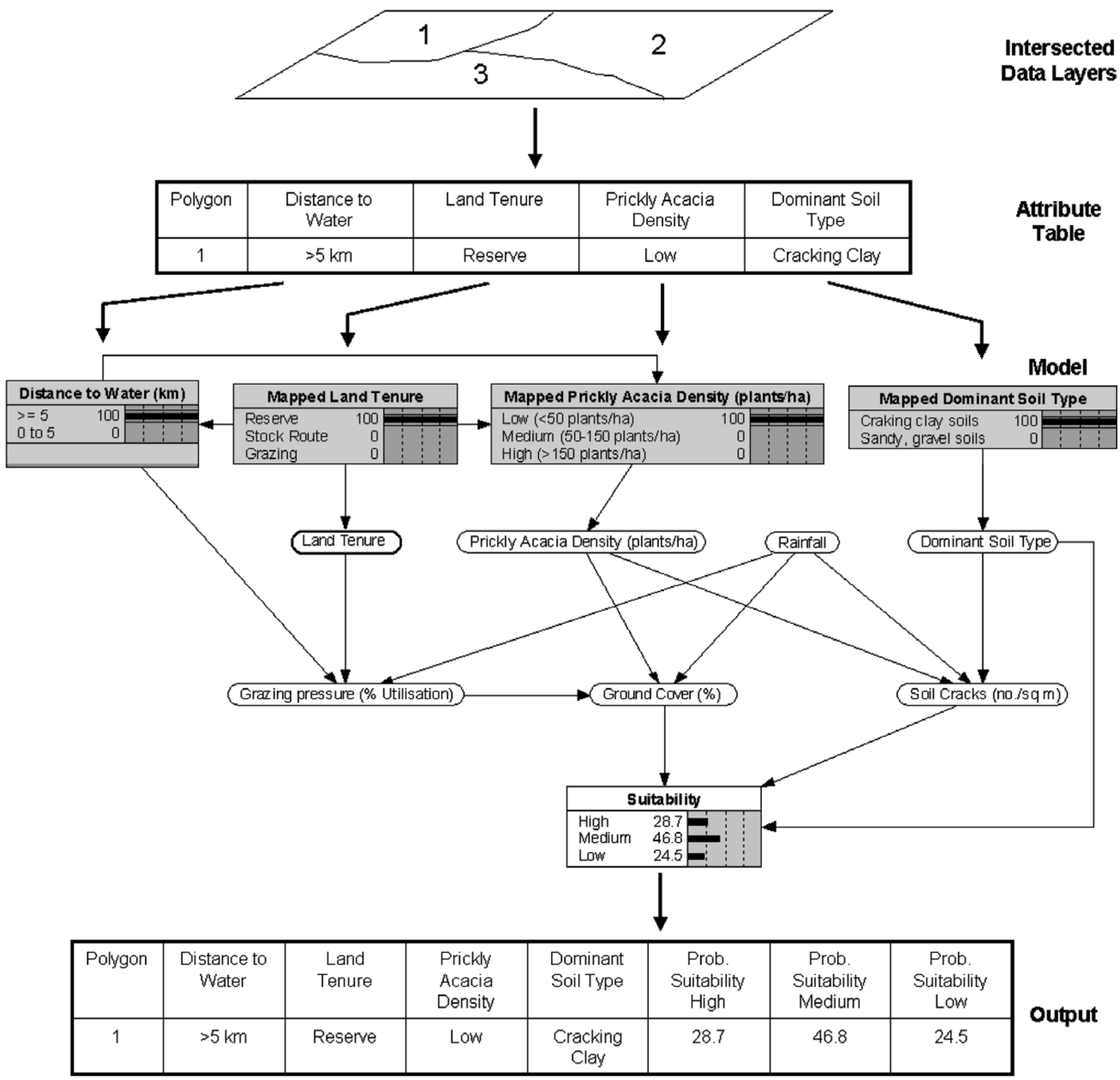

Fig. 5 – Schematic showing the sequential steps used to produce habitat suitability maps.

example, the prior probabilities assigned to the states of the GIS variable ‘mapped land tenure’ were: reserve 2.3%, stock route 5.1% and grazing 92.6%; meaning that 2.3% of the study area was mapped as reserve, 5.1% was mapped as stock route and 92.6% was mapped as grazing. Uniform probabilities were assigned to the input key environmental variable ‘rainfall’ because rainfall was simply used as a switch in the model to produce output for alternative rainfall scenarios (that is, below and above average rainfall year scenarios).

2.3. *Mapping dunnart habitat suitability*

To produce dunnart habitat suitability maps a process similar to that described by Raphael et al. (2001) was used. First, maps representing all GIS variables in the dunnart suitability model (Table 4) were intersected using ArcGIS version 9.1 (Environmental Systems Research Institute, Inc (ESRI)) to form a single GIS data layer. The attribute table of this layer was used to create a case file (of approximately 25,000 rows) in which each row contained the GIS variables for a single polygon in the study area. The case file was run through the dunnart suitability model using the ‘Process Cases’ function in Netica and the probability distribution for the ‘Suitability’ node was output for each case (polygon) (Fig. 5). Two scenarios were processed, a below and above average rainfall year scenario. The suitability outputs obtained for both scenarios were joined back to the attribute table of the GIS data layer and mapped.

2.4. *Accuracy assessment*

Dunnart habitat suitability was determined in the field for the 100 survey sites used to assess the mapping accuracy of the GIS variables used in the dunnart suitability model. Habitat suitability was rated as either low, medium or high for each site based on the habitat variables of each site. For example, sites with low ground cover and non-cracking sandy soils would rate as low suitability.

The habitat suitability ratings collected for sites were used to assess the accuracy of the dunnart habitat suitability maps using the error matrix method (Congalton, 1991; Foody, 2002). The matrix tabulated the value of habitat suitability (low, medium or high) observed for the field sites against the most probable suitability classes predicted by the dunnart suitability model. Accuracy was assessed through the producer’s accuracy: a measure of the probability of a field site being correctly classified (Eq. (1)), and the user’s accuracy (Eq. (2)): a measure of the probability that modelled habitat suitability matches that which can be observed in the field (Congalton, 1991). In addition, an overall accuracy value (Eq. (3)) and the Kappa statistic (Eq. (4)) were calculated. The Kappa statistic is a measure of the difference between the observed accuracy and the accuracy that can be expected by pure chance alone (Lillesand and Kiefer, 1999). Only the suitability map produced for the above average rainfall scenario was assessed for accuracy because the field survey was undertaken following a period of above average autumn rainfall (caused by Cyclone Larry).

$$\text{Producer's accuracy} = \frac{x_{ii}}{x_{+i}}, \tag{1}$$

$$\text{User's accuracy} = \frac{x_{ii}}{x_{i+}}, \tag{2}$$

$$\text{Overall accuracy} = \frac{\sum_{i=1}^{r} x_{ii}}{n} * 100, \tag{3}$$

$$\text{Kappa} = \frac{n\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} * x_{+i})}{n^2 - \sum_{i=1}^{r}(x_{i+} * x_{+i})}, \tag{4}$$

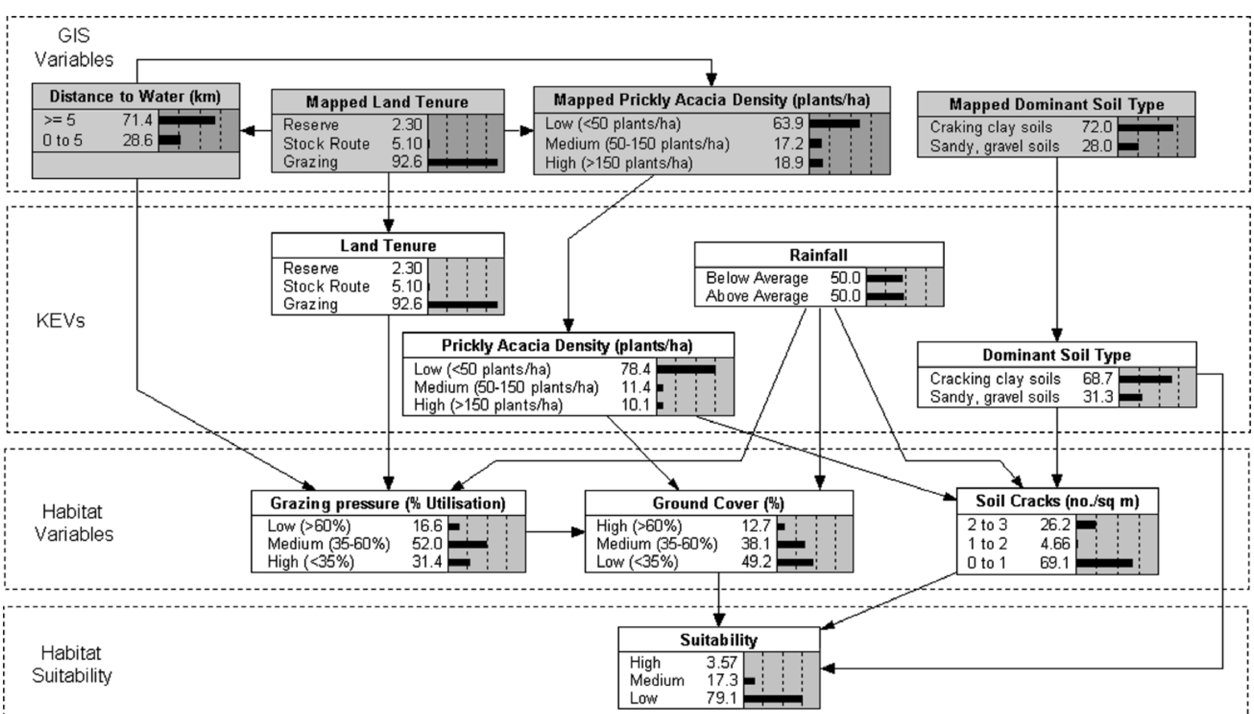

Fig. 6 – Dunnart habitat suitability model.

where r is the number of rows in the error matrix, x_{ii} the number of observations in row i and column i, x_{i+} the total observations in row i, x_{+i} the total observations in column i, and n the total number of observations included in the matrix (Lillesand and Kiefer, 1999; Foody, 2002).

3. Results

3.1. Dunnart habitat suitability model

The complete model for dunnart habitat suitability containing GIS variables, key environmental variables, habitat variables and habitat suitability nodes is shown in Fig. 6 (each node in the model, and their states, is described in Appendix 1). Note that although grazing pressure has been classed as a habitat variable, strictly it is an intermediate node that influences the habitat variable ground cover. The links between GIS variables show that distance to water and mapped prickly acacia density were significantly correlated with mapped land tenure, and that mapped prickly acacia density was significantly correlated with distance to water (Table 5). Sensitivity analysis performed on the model (Table 6) highlights ground cover as the most influential factor on habitat suitability, followed by grazing pressure (which directly influences ground cover), dominant soil type (which directly influences habitat suitability as well as influencing soil cracks) and soil cracks.

The mapping accuracy assessments for the GIS variables revealed that mapped land tenure and mapped dominant soil type had a high accuracy while the mapped prickly acacia density had lower accuracy. The prickly acacia mapping was conducted in 1999, and therefore did not account for recent clearing and chemical treatment programs that have since thinned prickly acacia. In addition, prickly acacia density was mapped at a coarse resolution for entire paddocks or entire properties, which contributed to its lower accuracy.

Table 5 – Significantly correlated GIS variables

GIS variables	n	χ^2	DF	P
Prickly acacia density vs land tenure	17333	147.036	4	0.000
Distance to water vs land tenure	25366	146.569	2	0.000
Prickly acacia density vs distance to water	17333	60.985	2	0.000

Table 6 – Sensitivity of habitat suitability to key environmental variables and habitat variables calculated using entropy reduction (variables are listed in order of influence on habitat suitability from most to least influential)

Node	Entropy reduction
Ground cover	0.18254
Grazing pressure	0.13763
Dominant soil type	0.13055
Soil cracks	0.02800
Rainfall	0.02527
Prickly acacia density	0.02322
Land tenure	0.00921
Distance to water	0.00145

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

3.2. Dunnart habitat suitability maps

Dunnart habitat suitability maps for the below and above average rainfall year scenarios (Fig. 7) show the probability of habitat suitability being low (light areas have a high probability of being unsuitable habitat, while dark areas have a high probability of being suitable habitat). The maps highlight the strong influence of soil type on habitat suitability. The large patches of white to the north east and south west are sandy soils, which have low habitat suitability. Riparian areas are also highlighted as areas of low habitat suitability due to their sandy soils. Conservation reserves are highlighted as areas of high habitat suitability (darkest areas on the maps). On the above average rainfall year scenario map (Fig. 7b), stock routes and road reserves appear as areas with relatively high habitat suitability. On the below average rainfall year scenario map (Fig. 7a) these stock routes and road reserves become less suitable and disappear, while areas close to watering points (white dots) appear and have relatively low habitat suitability due to increased grazing pressure. Square patches of low suitability land also appear in the below average rainfall year scenario (particularly in the northern part of the map). These areas have high prickly acacia density, which not only prevents the soil from cracking in dry years, but also competes with grasses for water, reducing ground cover in dry years.

The overall accuracy of model predictions was 89%, indicating a moderate-high level of discrimination (Table 7). The user's accuracy indicates how likely an area classified to a given habitat suitability will actually represent that suitability on the ground (Lillesand and Kiefer, 1999), and as such is the more useful measure of model accuracy. It shows a high proportion (93%) of low suitability sites were correctly predicted, while only 43% of medium suitability sites and no high suitability sites were correctly predicted. The value of the Kappa statistic for our error matrix is 0.402, suggesting our classification is 40% better than what can be expected from chance alone.

4. Discussion

4.1. Approach

The modelling approach developed in this study is not intended to replace empirical field research or species' distribution and population models. Rather, it provides a means for structuring knowledge of species-habitat relationships so that 'rapid appraisal' of habitat suitability can be conducted. This gives managers a basis for conservation and recovery planning in situations where actions to protect an endangered species have to be taken urgently. It also

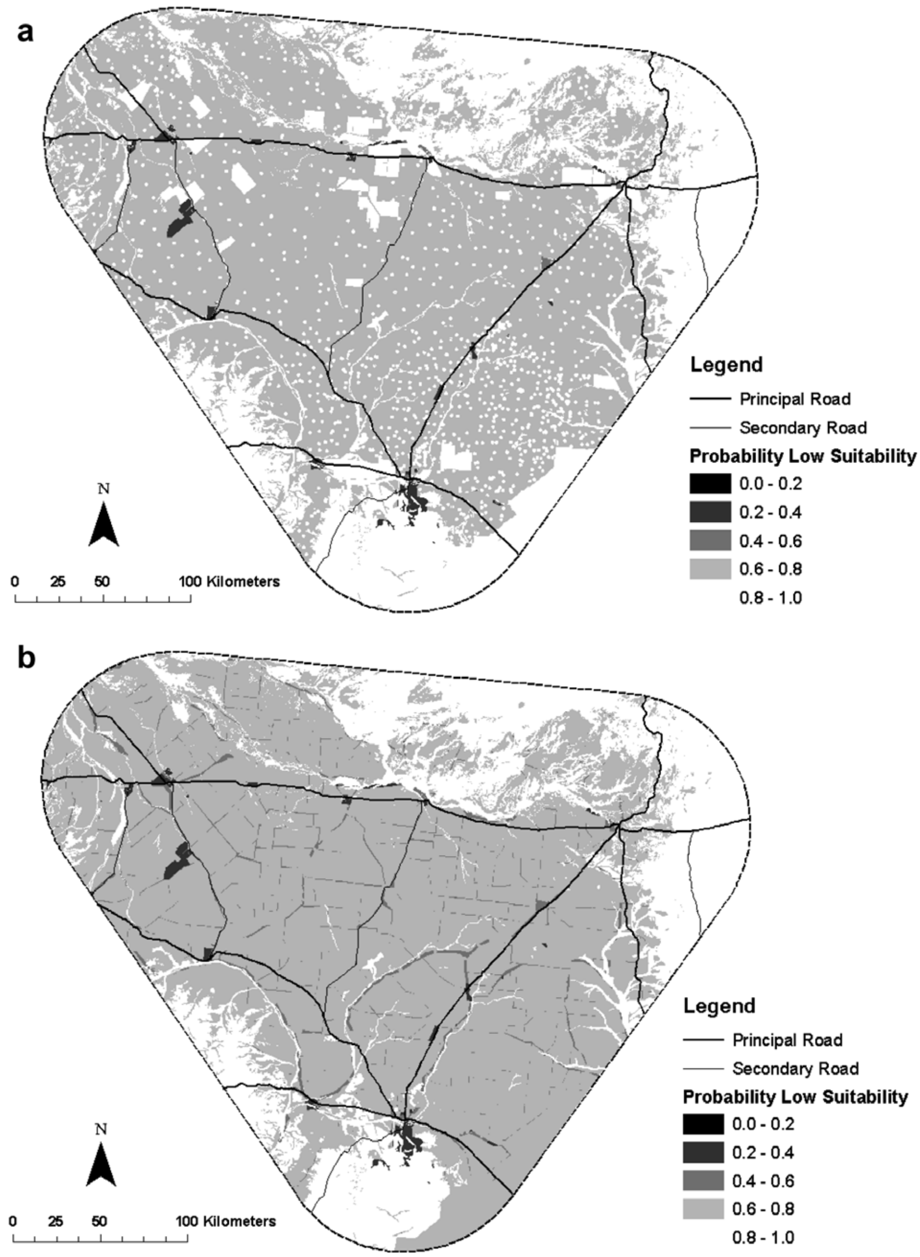

Fig. 7 – Maps showing the probability of low habitat suitability under: (a) below average rainfall year, and (b) above average rainfall year scenarios (light areas represent a high probability that habitat is unsuitable for dunnarts).

Table 7 – Error matrix showing the accuracy of the predicted habitat suitability for the above average rainfall year scenario

Predicted suitability (Model)	Observed suitability (Field)			Row total	User's accuracy
	Low	Medium	High		
Low	86	7	0	93	93%
Medium	1	3	3	7	43%
High	0	0	0	0	n/a
Column total	87	10	3	100	
Producers accuracy	99%	30%	0%		

Overall accuracy, 89%.
Kappa statistic, 0.402.

allows managers to test their hypotheses of species–habitat relationships and provides guidance for future detailed field research (Marcot, 2006). BBNs provide an extremely flexible modelling tool that is well suited to species habitat modelling in data and information poor environments. The ability of these models to combine empirical data with expert judgement, and account for uncertainty in data and knowledge, are distinct advantages. In addition, the scenario and sensitivity analysis capabilities of BBNs allow researchers and managers to identify the critical factors influencing habitat suitability based on available knowledge (Taylor, 2003).

BBNs also provide a 'low cost' means of modelling in that expensive computer programming or modelling expertise are not required to develop and update models. BBNs allow the end users of models to participate in model development, which is ideal for participatory modelling (Lynam, 2001; Smith et al., 2005, in press) and participatory conservation planning, in which the habitat modelling process is not simply a technical exercise, but a conduit for co-learning, knowledge sharing, assumption testing, and the development of a common understanding of a species' conservation requirements among stakeholders (such as conservation planners and land managers). Participatory modelling is particularly important in situations where land manager participation is required to achieve conservation outcomes because participation engenders a sense of shared ownership in the modelling outputs, which is likely to improve the adoption of species' management and recovery plans based on them. In the case of the Julia Creek dunnart, the participation of landholders in voluntary conservation agreements will be critical to improving and maintaining habitat suitability on private, grazed land (Lundie-Jenkins and Payne, 2000). Therefore, the use of a participatory modelling process is particularly appealing.

Spatial distribution models are used extensively in ecological research to explain and predict species' occurrence. Capturing expert knowledge of species' ecology and habitat requirements within a BBN, and linked to a GIS, is a cost-effective alternative to expensive field surveys required for developing species' distribution models. Further, few if any studies have applied distribution models to target where to find a species as a basis for its management and recovery. Such an application is particularly relevant to the Julia Creek dunnart, which requires extensive trapping effort to find in the field and has a limited and patchy distribution over a large region, making field surveys time consuming and expensive (Mifsud, 1999). Our research was conducted on a modest budget of approximately AUD10 000 over a 6 month period. Our focus was on predicting habitat suitability rather than species' occurrence. It is likely that many locations predicted as having moderate habitat suitability may no longer support the Julia Creek dunnart due to historical disturbance pressures, especially historical high grazing pressure, not captured in our model. Given these constraints, the BBN provides a cost-effective tool for prioritising where animals are most likely to occur within its patchy distribution, and hence help guide targeted field surveys for locating this endangered species and monitoring its recovery.

4.2. *Limitations*

A major limitation of the study was the overall accuracy of the model predictions. While the user's accuracy in predicting areas of low habitat suitability was high (93%), the model performed less well for the other categories of habitat suitability. It has been suggested that a minimum of 50 samples per category is necessary for constructing a reliable error matrix (Congalton and Green, 1999; Lillesand and Kiefer, 1999). We were not able to reach this target for medium and highly suitable sites because of the small areas of these types of habitat present in the study area at the time of the survey. This was largely because most of the study area is freehold or leasehold land tenure and was extensively grazed. Even though the region had experienced recent good rains, these rains fell at the end of the growing season and favoured the growth of the annual Flinders grass (*Iseilema* spp.) and ephemeral forbs over the perennial Mitchell grass. Hence, habitat suitability outside of conservation reserves and stock routes was, in general, low. The small sample size of observed medium and high quality habitat, therefore, has resulted in lower model accuracy in predicting medium and high suitability sites.

Marcot (2006) states that the process of building a BBN model must include peer review, reconciliation, testing and updating with unbiased and known site data. The BBN model and accuracy of results produced by our model were limited by the use of expert opinion, the lack of site data and accuracy of the input maps. In particular, the out-of-date and coarse resolution prickly acacia density map had a significant influence on our results. More accurate prickly acacia density mapping, especially at a higher spatial resolution, would have improved our modelling results.

Field data on the actual occurrence of the Julia Creek dunnart is very sparse (Archer, 1979; Mifsud, 1999; Lundie-Jenkins and Payne, 2000). The limited observations indicate that the species is still present at Bladensburg national park and Toorak research station (Julia Creek) and Moorrinya national park southeast of Hughenden, and some small reserves in the Julia Creek, Richmond and Hughenden districts. The BBN model predicted these locations as having relatively high habitat suitability. A strength of the BBN approach lies in its ability to spatially-prioritise new field surveys where animals may still occur, and hence better target conservation efforts.

4.3. *Implications for dunnart conservation*

Within the known habitat range of the Julia Creek dunnart, most of the area was predicted to have low habitat suitability, with similar findings from the field survey. The notable exceptions were in national parks (especially Bladensberg national park), roads reserves, stock routes and Toorak research station. These areas are subject to low grazing pressure from domestic stock (absent from national parks) and in general, have a low density of prickly acacia and watering points. Ground cover and grazing pressure were the most influential factors on habitat suitability, while dominant soil type, rainfall and prickly acacia density were the most influential key environmental variables (Table 6). Our results therefore suggest that maintaining areas of good ground cover on clay soil with low prickly acacia density is vital for dunnart conservation and recovery.

Because areas of medium to high dunnart habitat suitability are now limited to national parks and lightly grazed road reserves and stock routes, there is a strong need to identify and restore suitable habitat areas on private and leasehold grazing land. This idea is supported by the Queensland Environmental Protection Agency's recovery plan for the Julia Creek dunnart, which suggests that voluntary conservation agreements with landholders (such as Land for Wildlife agreements, Natural Resource Management Agreements or Nature Refuge declarations) would assist in conserving populations of the Julia Creek dunnart (Lundie-Jenkins and Payne, 2000). As suggested by Marcot et al. (2006a), demonstrating a working BBN to land managers (such as graziers) would be a very effective communication tool that could help them discern the kinds of sites where rare species may occur and the specific site conditions that are required for conservation or restoration of the species. The BBN model shown here would highlight the need for clearing of prickly acacia and fencing to reduce grazing pressure and maintain ground cover as important habitat restoration measures for the dunnart. These measures, along with the baiting of feral predators (such as cats), are also suggested by Lundie-Jenkins and Payne (2000).

Type I (false positive) and II (false negative) errors can have significant implications for the conservation of rare species (Marcot, 2006). In our study, a Type I error would indicate prediction of high habitat suitability when it is in fact low, and Type II errors represent prediction of low habitat suitability when it is in fact high. Given that our model predicted high habitat suitability only in national parks, stock routes and road reserves, areas that are largely already managed for prickly acacia and where grazing is limited or non-existent, the implications of Type I error for management are minimal. Type II errors represent more significant implications for conservation of the Julia Creek dunnart in that, if areas of highly suitable habitat are assumed to be of low suitability, they may not be targeted in conservation planning. Since areas of low habitat suitability were predicted and observed across the majority of the known range for the Julia Creek dunnart, our management recommendations should also be applied to areas of predicted low habitat suitability outside of national parks and stock routes, thus reducing the implications of Type II error.

4.4. *Further development of the dunnart habitat suitability model*

The model presented in this paper serves as a preliminary peer reviewed model of habitat suitability for the Julia Creek dunnart. It is a 'beta' model under the BBN model development process described by Marcot et al. (2006b). Further steps in model development could include the updating of prior and conditional probabilities in the model using site observation data (also known as 'case' data) and validation testing of the updated model.

In the longer-term as detailed field survey and dunnart restoration activities are implemented, the gathering of 'case' data and model updating can be used as a learning and hypothesis testing activity whereby the outcomes of habitat restoration are used to validate and finetune the knowledge contained within the dunnart habitat model. In other words, an adaptive management cycle (Holling, 1978) can be used as a mechanism for model refinement (Marcot, 2006), and in turn, the model can support the adaptive management cycle by supporting future habitat restoration planning and the review of habitat restoration success. Nyberg et al. (2006) provide a comprehensive explanation of the use of BBNs in adaptive management.

5. Conclusions

Through the combination of empirical data and expert knowledge this study was able to develop a Bayesian belief network, linked to a GIS, to model and map habitat suitability for the endangered Julia Creek dunnart. The results showed that modelled habitat suitability matched well to that recorded in the field. Thus, using a BBN model, areas of high conservation value with respect to dunnart populations have been identified. In particular, management efforts should be addressed towards maintaining areas of low grazing pressure and low prickly acacia density on clay soils to conserve dunnart populations. While the model and modelling results presented in this paper represent the first stages of model development and require further refinement, the BBN modelling approach demonstrates a low cost means for organising current knowledge about rare species habitat requirements and applying this knowledge to the rapid appraisal of habitat suitability. The approach also provides a sound mechanism for communicating understanding of what affects habitat suitability for ground-dwelling native fauna such as the Julia Creek dunnart and provides direction to conservation planning and future fieldwork efforts. As future field work and habitat restoration activities are implemented, new site observations can be used to refine the model, and the updated model used for future restoration planning. Hence the BBN modelling approach is supported by, and supports, adaptive management.

Acknowledgements

We acknowledge the support of the Queensland Environmental Protection Agency and Geoff Lundie-Jenkins in funding the project. Reinhardt Berger assisted with the GIS data preparation and analysis. Thanks also go to the ecologists who provided expert knowledge used in the development of the model. The quality of this manuscript was greatly improved by the comments of two anonymous reviewers.

Appendix 1. Nodes and states used in the dunnart habitat suitability model

Node	Description	States
Mapped land tenure AND land tenure	Reserve land: national park, covenant, easement and reserved land Grazing land: leasehold and freehold grazing land Stock route: land used for grazing but not as regularly as grazing land	Reserve Grazing Stock route
Mapped prickly acacia density AND prickly acacia density (plants/ha)	Heavy infestations of prickly acacia impede the growth of native pastures and prevent the soil from cracking extensively. The states selected for this node were derived from the Prickly Acacia National Case Studies Manual (Spies and March, 2004)	Low: density of less than 50 plants/ha Medium: density of 50–150 plants/ha High: density of more than 150 plants/ha
Rainfall	Julia Creek experiences significant rainfall variation within years (due to its monsoonal climate) and between years. This node represents rainfall variation between years	Below Average: below average annual rainfall Above average: above average annual rainfall
Mapped dominant soil type AND dominant soil type	Deep gray and brown cracking clays, sandy gravel soils, shallow brown clays with hard setting surfaces, and clays with stone cover are the dominant soils in the Julia Creek area (Environmental Protection Agency, 2005). Clay soils contain less than 40% gravel and rocks, and over 60% clay, while sandy gravel soils contain less than 40% clay and over 60% sand or gravel (Mifsud, 1999). The cracking clay soils crack extensively during the dry season	Cracking clay soils Sandy, gravel soils
Distance to water (km)	Grazing pressure and erosion is often heavier around watering points and few grazing locations extend beyond 10 km from water (Foran, 1980; Fusco et al., 1995; Landsberg et al., 1997; James et al., 1999; Ludwig et al., 1999; Landsberg et al., 2003; Ludwig et al., 2004). Watering points also encourage the spread of weeds such as prickly acacia	0–5 km >5 km
Soil cracks (number per square metre)	Cracks form in the clay soils during low rainfall periods. The roots of prickly acacia prevent extensive cracking or clay soils (Mifsud, 1999).	2–3 cracks/sq m 1–2 cracks/sq m 0–1 cracks/sq m
Grazing pressure (%)	The percentage of ground cover left during grazing is an indication of the degree of grazing pressure. Maintaining ground cover at 30% or more is considered a 'safe' grazing pressure (Orr, 1975), however it often less near water points were grazing pressure is highest	Low: >60% of ground cover remains Medium: 35–60% ground cover remains High: <35% ground cover remains
Ground cover (%)	Wet season rain encourages the return of short lived annual forbs, increasing ground cover (Phelps, 1999). *Astrebla* species are capable of regeneration following just 40 mm of rain and rapid growth follows seasonal rains (Orr, 1975). Grazing pressure also influences ground cover, and were grazing pressure is high, ground cover rarely exceeds 70% (expert opinion)	High: >60% ground cover Medium: 35–60% ground cover Low: <35% ground cover
Suitability	Studies have indicated that the most suitable habitat for *S. douglasi* contains extensive cracking soils and adequate ground cover to escape both predation and the hot temperatures	High: areas with high ground cover, extensive cracking soils, limited to no prickly acacia, limited to no grazing pressure Medium: areas with moderate ground cover, presence of cracking soils but also presence of grazing or prickly acacia Low: areas with limited ground cover, absence of cracking soils or presence of prickly acacia or extensive grazing

REFERENCES

Andersen, A.N., Cook, G.D., Corbett, L.K., Douglas, M.M., Eager, R.W., Russell-Smith, J., Setterfield, S.A., Williams, R.J., Woinarski, J.C.Z., 2005. Fire frequency and biodiversity conservation in Australian tropical savannas: implications from the Kapalga fire experiment. Austral Ecology 30, 155–167.

Archer, M., 1979. Two new species of Sminthopsis Thomas (Dasyuridae: Marsupialia) from northern Australia, *S. butleri* and *S. douglasi*. Australian Zoologist 20, 327–345.

Cain, J., 2001. Planning Improvements in Natural Resources Management. Guidelines for Bayesian Networks to Support the Planning and Management of Development Programmes in the Water Sector beyond. Centre for Ecology and Hydrology, Wallingford, UK.
Clark, J.S., 2005. Why environmental scientists are becoming Bayesians. Ecology Letters 8, 2–14.
Clark, K.E., Applegate, J.E., Niles, L.J., Dobkin, D.S., 2006. An objective means of species status assessment: adapting the Delphi technique. Wildlife Society Bulletin 34, 419–425.
Congalton, R.G., 1991. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of the Environment 37, 37–46.
Congalton, R.G., Green, K., 1999. Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. Lewis Publishers, Boca Raton.
Cooperative Research Centre for Weed Management, 2003. Weed Management Guide: Prickly acacia (*Acacia nilotica*), Weeds of National Significance. Commonwealth Department of the Environment and Heritage, Canberra.
Environmental Protection Agency, 2005. Regional EcosystemDescription Database (REDD). Version 5.0, updated December 2005.
Fieberg, J., Jenkins, K.J., 2005. Assessing uncertainty in ecological systems using global sensitivity analyses: a case example of simulated wolf reintroduction effects on elk. Ecological Modelling 187, 259–280.
Foody, G.M., 2002. Status of land cover classification accuracy assessment. Remote Sensing of the Environment 80, 185–201.
Foran, B.D., 1980. Change in range condition with distance from watering point and its implications for field survey. Australian Rangeland Journal 2, 59–66.
Fusco, M., Holechek, J., Tembo, A., Daniel, A., Cardenas, M., 1995. Grazing influences on watering point vegetation in the Chihuahuan desert. Journal of Range Management 48, 32–38.
Gelfand, A.E., Silander, J.A., Wu, S., Latimer, A., Lewis, P.O., Rebelo, A.G., Holder, M., 2006. Explaining species distribution patterns through hierarchical modeling. Bayesian Analysis 1, 41–92.
Gentilli, J., 1971. Climates of Australia and New Zealand. Elsevier, Amsterdam.
Holling, C.S., 1978. Adaptive Environmental Assessment and Management. Wiley, New York.
James, C.D., Landsberg, J., Morton, S.R., 1999. Provision of watering points in the Australian arid zone: a review of effects on biota. Journal of Arid Environments 41, 87–121.
Jensen, F.V., 2001. Bayesian Networks and Decision Graphs. Springer, New York.
Landsberg, J., James, C.D., Morton, S.R., Hobbs, T., Stol, J., Drew, A., Tongway, H., 1997. The effects of artificial sources of water on rangeland biodiversity, Final report to the Biodiversity Convention and Strategy Section of the Biodiversity Group Environment Australia and CSIRO Division of Wildlife and Ecology, Canberra.
Landsberg, J., James, C.D., Morton, S.R., Muller, W.J., Stol, J., 2003. Abundance and composition of plant species along grazing gradients in Australian rangelands. Journal of Applied Ecology 40, 1008–1024.
Lees, N., 1999. *Sminthopsis douglasi*. Environmental Management, Forest Resources. Department of Natural Resources.
Lillesand, T.M., Kiefer, R.W., 1999. Remote Sensing and Image Interpretation, fourth ed. Wiley, New York.
Liou, Y.I., 1992. Collaborative knowledge acquisition. Expert Systems with Applications 5, 1–13.
Ludwig, J., Eager, R.W., Williams, R.J., Lowe, L.M., 1999. Declines in vegetation patches, plant diversity, and grasshopper diversity near cattle watering-points in the Victoria River district, northern Australia. The Rangeland Journal 21, 135–149.
Ludwig, J.A., Tongway, D.J., Bastin, G.N., James, C.D., 2004. Monitoring ecological indicators of rangeland functional integrity and their relation to biodiversity at local to regional scales. Austral Ecology 29, 108–120.
Lundie-Jenkins, G., Payne, A., 2000. Recovery plan for the Julia Creek dunnart (*Sminthopsis douglasi*) 2000–2004. Queensland Parks and Wildlife Service, Brisbane, Australia.
Lynam, T., 2001. Participatory Systems Analysis: An Introductory Guide, Institute of Environmental Studies Special Report. University of Zimbabwe, Harare, Zimbabwe.
Mackey, B.G., Lesslie, R.G., Lindenmayer, D.B., Nix, H.A., 1998. Wilderness and its place in nature conservation in Australia. Pacific Conservation Biology 4, 182–185.
Marcot, B.G., 2006. Characterizing species at risk I: modeling rare species under the Northwest Forest Plan. Ecology and Society 11, 10. online.
Marcot, B.G., Holthausen, R.S., Raphael, M.G., Rowland, M.M., Wisdom, M.J., 2001. Using Bayesian belief networks to evaluate fish and wildlife population viability under land management alternatives from an environmental impact statement. Forest Ecology and Management 153, 29–42.
Marcot, B.G., Hohenlohe, P.A., Morey, S., Holmes, R., Molina, R., Turley, M.C., Huff, M.H., Laurence, J.A., 2006a. Characterizing species at risk II: Using Bayesian belief networks as decision support tools to determine species conservation categories under the Northwest Forest Plan. Ecology and Society 11, 12. online.
Marcot, B.G., Steventon, J.D., Sutherland, G.D., McCann, R.K., 2006b. Guidelines for developing and updating Bayesian belief networks applied to ecological modeling and conservation1. Canadian Journal of Forest Research 36, 3063–3074.
Martin, T.G., Kuhnert, P.M., Mengersen, K., Possingham, H.P., 2005. The power of expert opinion in ecological models using Bayesian methods: Impact of grazing on birds. Ecological Applications 15, 266–280.
Mifsud, G., 1999. Ecology of the Julia Creek dunnart, *Sminthopsis douglasi*, (Marsupialia: Dasyuridae), Masters Thesis. La Trobe University, Bundoora, Victoria, Australia.
Norsys Software Corporation, 1998. Netica™ Application for Belief Networks and Influence Diagrams: User's Guide. Norsys Software Corporation, Vancouver, Canada.
Nyberg, J.B., Marcot, B.G., Sulyma, R., 2006. Using bayesian belied networks in adaptive management. Canadian Journal of Forest Research 36, 3104–3116.
Orr, D.M., 1975. A review of *Astrebla* (Mitchell grass) pastures in Australia. Tropical Grasslands 9, 21–36.
Phelps, D., 1999. Mitchell Grass, Australia's Own Grass, DPI& F Notes. Department of Primary Industries and Fisheries, Longreach.
Phelps, D.G., Bosch, O.J.H., 2002. A quantitative state and transition model for the Mitchell grasslands of central western Queensland. Rangeland Journal 24, 242–267.
Pringle, H.J.R., Landsberg, J., 2004. Predicting the distribution of livestock grazing pressure in rangelands. Austral Ecology 29, 31–39.
Raphael, M.G., Wisdom, M.J., Rowland, M.M., Holthausen, R.S., Wales, B.C., Marcot, B.G., Rich, T.D., 2001. Status and trends of habitats of terrestrial vertebrates in relation to land management in the interior Columbia River Basin. Forest Ecology and Management 153, 29–42.
Salski, A., 1992. Fuzzy knowledge-based models in ecological research. Ecological Modelling 63, 103–112.
Smith, C., Russell, I., King, C., 2005. Rats and rice: Belief network models of rodent control in the rice fields of Cambodia. In: Zerger, A., Argent, R.M. (Eds.), MODSIM 2005 International Congress on Modelling and Simulation. Modelling and Simulation Society of Australia and New Zealand, Melbourne, pp. 449–455.

Smith, C., Felderhof, L., Bosch, O.J.H., in press. Adaptive Management: Making it happen through participatory systems analysis. Systems Research and Behavioral Science.
Spies, P., March, N., 2004. Prickly Acacia National Case Studies Manual: Approaches to the Management of Prickly Acacia (*Acacia nilotica* subsp. *indica*) in Australia. Department of Natural Resources, Mines and Energy, Brisbane.
Taylor, K.J., 2003. Bayesian belief networks: A conceptual approach to assessing risk habitat, Masters Thesis. Utah State University, UT.
Thorp, J.R., Lynch, R., 2000. The Determination of Weeds of National Significance. Weeds Strategy Executive Committee, Launceston.
Trapper, N., Hurry, L., 1993. Australia's Weather Patterns: An Introductory Guide. Dellasta, Mount Waverley, Victoria.
Woinarski, J.C.Z., Ash, A.J., 2002. Responses of vertebrates to pastoralism, military land use and landscape position in an Australian tropical savanna. Austral Ecology 27, 311–323.
Woinarski, J.C.Z., Fisher, A., 2003. Conservation and maintenance of biodiversity in the rangelands. Rangeland Journal 25, 157–171.
Woinarski, J.C.Z., Milne, D.J., Wanganeen, G., 2001. Changes in mammal populations in relatively intact landscapes of Kakadu National Park, Northern Territory, Australia. Austral Ecology 26, 360–370.
Woolley, P.A., 1992. New records of the Julia Creek dunnart, *Sminthopsis douglasi* (Marsupialia, Dasyuridae). Wildlife Research 19, 779–783.