

The development of a Bayesian Belief Network as a decision support tool in feral camel removal operations

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Abstract: The removal of feral camels in Australia is complicated by the vast area over which they range, their remoteness and the changing weather conditions that constantly affect their distribution. Decision Support Systems (DSS) provide a framework in which program managers can undertake a more formal assessment of pest removal actions under different conditions, using past data and expert knowledge. The objective of a DSS in pest management is to minimise costs and optimise on-ground effectiveness. In this study we develop a Bayesian Belief Network (BBN) as a component of a camel DSS. BBNs provide a transparent visualisation of the components of the problem, underpinned by probability tables consisting of likelihoods and states in an uncertain environment. They enable managers to interrogate different scenarios, often consisting of incomplete intelligence data, and help seek the best course of action. We describe a novel approach of eliciting data from past camel culling operations into a BBN using a simulation algorithm. The algorithm simulates all aspects of the operation including search patterns, sightability, the time it takes to undertake the operation, fuel costs and camel densities. We verified the output of a range of scenarios from these simulations interactively with a group of experts and then using a wide range of environmental conditions we populated the states and dependencies of the final BBN. Using some hypothetical scenarios we demonstrate the BBN outputs including probabilities associated with a different number of camels removed and the associated costs.

Keywords: *Bayesian Belief Network (BBN), Feral camel removal, Decision Support System (DSS), knowledge elicitation.*

1. INTRODUCTION

Decision Support Systems (DSS) are computer-based algorithms and models that combine decision logic with relevant data to assist in decision making (Crossland 2007). DSSs are widely promoted as a wildlife management tool (Shea et al. 1998). They help find efficiencies in management programs and optimise the return on investment (Maguire 2004; Marinoni et al. 2009). The removal of feral camels in Australia is complicated by the vast area of inland Australia over which they range, their remoteness, and the changing weather conditions that constantly affect their distribution. In this context, a DSS provides a framework in which program managers can undertake a more formal assessment of the costs and benefits of undertaking different actions, using all available data. Here the objective of a DSS in pest management is to minimise costs and optimise on-ground outcomes. Bayesian Belief Networks (BBNs) have also become a popular tool for supporting decision making processes and comparing alternative management options (Farmani et al. 2009). They have been widely used in a range of applications including adaptive management (Nyberg et al. 2006), ecology and resource management (Cain et al. 1999; McCann et al. 2006), population viability (Marcot et al. 2001), ecological predictions including habitat suitability (Marcot et al. 2006; Smith et al. 2007), water quality management (Reckhow 1999), and disease diagnosis (McKendrick et al. 2000). The advantage of BBNs is that the probabilities and dependencies can be based on any or all available information including empirical data, simulation models, scientific information and expert knowledge (Borsuk et al. 2006; Marcot et al. 2001; Martin et al. 2005; Phillips 2005; Raphael et al. 2001).

In this paper we develop a BBN for aerial camel culling operations in South Australia. We start by developing a conceptual model. This basic model eventually forms the structure of a BBN. We then combine expert knowledge and statistical information from the camel culling operations and use a deterministic model *Aerial Culling Planning* (Lethbridge 2011), that can be validated against past culls and enable practitioners to explore future hypothetical scenarios. We then simulate a large range of scenarios into a case file using this tool and populate a BBN using the Netica software (Norsys 1995-2010). Our objective is to provide a DSS that assists NRM managers, who are often provided with incomplete data, to seek the most efficient removal outcome.

2. METHODOLOGY

2.1. Data inputs

Data from the 2010 Simpson Desert and 2011 Great Victoria Desert (GVD) aerial surveys were used to derive camel GIS density raster grids, to be used as camel density input data. The Simpson Desert survey covered an area of 36,820 km² and the Great Victoria Desert survey covered an area of 61,576 km². Both GIS density raster grids were derived using a Kernel Density Estimator (KDE - Silverman 1985). Spatial data relating to culling operations including track lines and culling locations were provided by the Department for Environment, Water and Natural Resources (DEWNR), South Australia. The 2010 Simpson Desert culling operations largely target camel density hotspots identified by the aerial survey. Typically, two helicopters, one kilometre (km) abreast ferry out from fuel towards a hotspot and then break into a grid search pattern that generally moves in a direction back towards the fuel. The grid pattern is 4km x 9km on each side.

2.2. Aerial culling planning tool

Aerial Culling Planning software (Lethbridge 2011) was used to elicit expert knowledge through a workshop process with practitioners by exploring past and hypothetical cull operations. The software's outputs, including total cost and the cost per removed animal can also be validated against past operations. The tool allows the user to select spatial data of likely fuel locations, cull target areas and GIS raster grids of density. The software then calculates how many camels would be seen based on a sightability factor and distance function and lays out an optimal search pattern (similar to Figure 1) over the nominated target areas. It also calculates the total cost, the cost per camel removed and the number fuel drums required at each fuel location. The software also determines when an aircraft needs to return for more fuel. Thus an increase in the number of camels removed in a high-density area will use up more fuel and increase the number ferry trips back to fuel. In Figure 1, the fuel drum locations are green points, the simulated density hotspots used as input data are depicted as a GIS raster grid ranging from pink (the highest density) to pale blue (the lowest density). The thin red polygons are the target cull areas defined by the user.

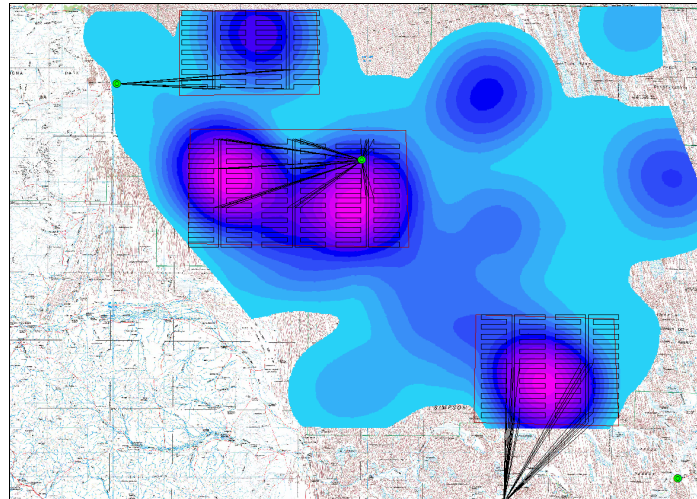


Figure 1. Example output from the *Aerial Culling Planning* software (Lethbridge 2011).

Distance sampling (Buckland et al. 1993) involves collecting distances with count data and modelling observer bias using a probability detection function $g(x)$. Once camels are sighted, the helicopter pilot quickly responds by turning the machine towards the animals to be culled. This obvious change in direction in the GPS track flights enable us to model sightability and the group size of animals shot with the distance from aircraft. Here $g(x)$ is the probability of detecting an object at a particular distance. The detection function usually decreases with increasing distance and $0.0 \leq g(x) \leq 1.0$ (Buckland et al. 1993). Using program *Distance* (Thomas et al. 2009) we modelled a half normal probability detection function for $g(x)$ with distance x . Distance sampling assumes that $g(0) = 1.0$. However, aerial searching undertaken during aerial removal operations, like formal aerial surveys, are negatively biased (Pollock and Kendall 1987; Samuel et al. 1987). In other words, $g(0) \neq 1.0$. This was solved using a Mark Recapture Distance Sampling (MRDS) method, which combines Distance Sampling with a double-count method (Borchers et al. 2006). However, as there is only one shooter and a pilot, we used sightability correction factors from past camel aerial surveys over the same area. The detectability of different group sizes will also vary with distance. Here we used a method that uses group size as an additional covariate.

2.3. Knowledge Elicitation

A workshop was conducted to present and discuss the conceptual model framework, and elicit expert knowledge about the fixed and hourly costs associated with culling operations. However, the statistics we gathered from the data collection during the Simpson 2010 culling operations (aircraft track lines and cull locations/numbers) were also presented in the first half of the workshop. This was to seek a general agreement about the way in which the data was analysed; to ensure there was a sense of ownership of the results by all; and to better familiarise us with how these operations occur. Participants directly involved in culling operations were also present to provide their knowledge. We used this opportunity to seek clarity about any issues we didn't fully understand, and to allow the group to understand and agree with the way in which *Aerial Culling Planning* software (Lethbridge 2011) calculates the costs per-head.

2.4. Bayesian Belief Network

BBNs are graphical probabilistic models that model the dependencies in a knowledge domain (Jensen 1996). They consist of nodes (variables) with directional arrows (or arcs) indicating the dependence between the nodes. There are two main approaches to building a BBN. The first involves manually eliciting knowledge from experts while the second involves automatic learning of the structure and parameters from data (Pourret et al. 2008). Stochastic sampling is another method for building a BBN, where the learning process is based on simulated data (Darwiche 2009, Krieg 2001). Following Cousins et al. (1993), we used *Aerial Culling Planning* software (Lethbridge 2011) to generate 20,000 simulations in a case file to populate each state of each node of our BBN in a Netica (Norsys Software 1995-2010).

3. RESULTS

3.1. Analysis of aerial culling data

Using 2010 aerial culling spatial data of the Simpson Desert we calculated the time per camel to be 22.9 +/- 1.8 Standard Error (SE) seconds. The average search speed of the aircraft was 76.3 +/- 0.14 SE seconds.

The shape of the probability detection function $g(x)$ for a given distance and three example group sizes is shown in Figure 2.

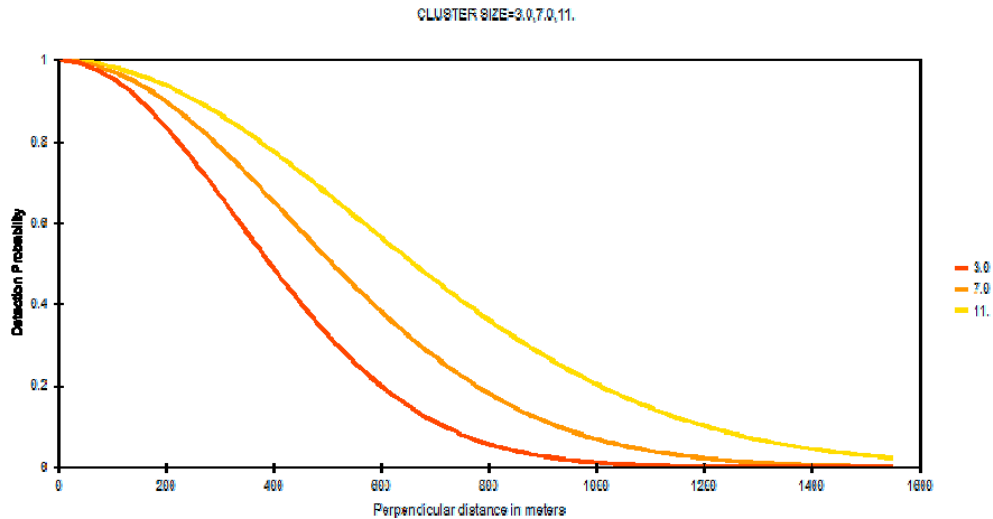


Figure 2. The number of camels seen and their associated sight distance for three group sizes ($\alpha_1=809.6$, $\alpha_1=0.02397$)

3.2. BBN

In Figure 3 a hypothetical example has been provided where the input node states have been selected with certain information (100% bars). Here the cull area is greater than 15,000 km², there are medium level congregations, the average distance between fuel and multiple target areas is 25 – 50 km, the hourly cost is between \$900 and \$1,000 per-hour, fixed costs are between \$30,000 and \$40,000 and observed densities are between 0.6 and 0.8 camels per km². A medium congregation of camels is when the highest density hotspot is between six and twelve times the average density across the whole survey area. The BBN subsequently estimates the number of removals to be between 2500 and 5000 with an 18.8 % probability and 5000 – 1000 removals with an 81.2% probability.

This gives a 93.0% chance that the cost is between \$25 and \$40 per camel and 7.04% chance the cost is between \$40 and \$60 per camel.

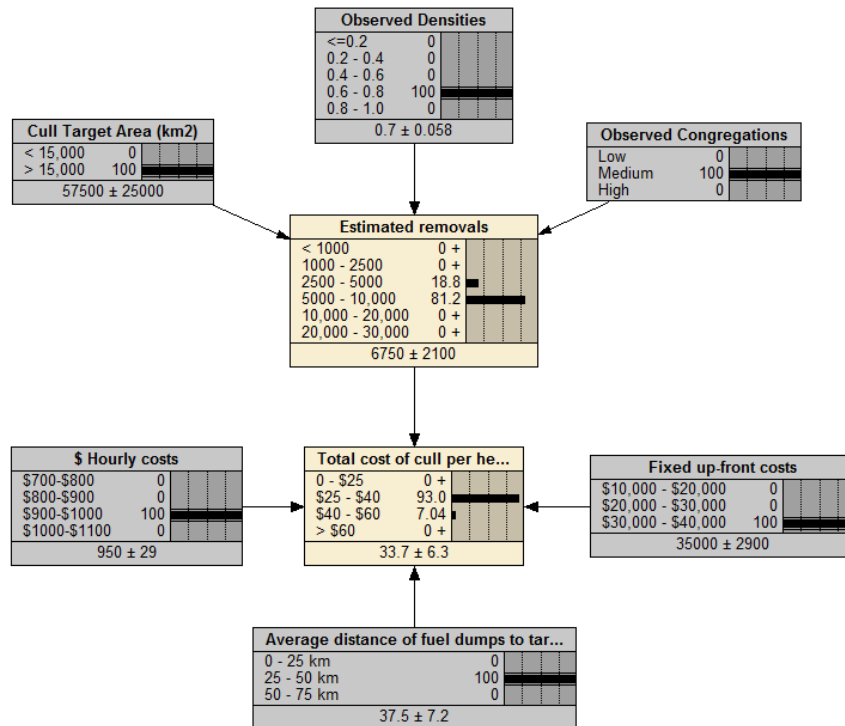


Figure 3. Cost-per-head BBN with hypothetical 'findings' or evidence

We also conducted a sensitivity analysis using Netica (Norsys 1995-2010). Not surprisingly, the total cost of cull per head is most sensitive to knowledge of the observed density of camels (35.7%), after which the remaining inputs offer little contribution (< 5.4%). While we do not suggest the following is a validation of the model, we also compared the BBN results with the actual conditions and costs of undertaking aerial control operations in the Simpson Desert in 2010, when there was an average density of 0.4 camels km². The BBN suggested there was a 42% chance that the cost per head would be \$25 - \$40 per head, a 39.5% chance the cost would be \$40 - \$60 per head and an 18.5% chance the costs would be above \$60 per head. In reality, the cost per head was \$57.

4. DISCUSSION AND CONCLUSIONS

One benefit of BBNs is the ability for them to be refined and evolve with more data over time. To this end our BBN is a work in progress. Further data from actual culling operations also provides a form of validation of the BBN. However, the integration of further case data may also shed light on the range of states required in each node for the BBN to be able to have a wider utility in camel management. Expanding the utility of the BBN may also require the addition of new nodes that depict differences between landscapes and environmental conditions. For example, in more heavily wooded landscapes, camel sightability may change and in more remote landscapes, fuel drums may need to be slung into position by air rather than placed by vehicle.

We were guided by expert opinion in terms of the number of categories (or states) required each node's CPT. We now consider these to be too coarse. For example, our classification of the congregations into high, medium and low were based on the densities recorded in the Simpson Desert. As such, there is a jump in the estimated removals when switching between the medium to high congregations categories. If used elsewhere, it may be necessary to include more classes of congregation. Likewise the cost per head and cull target area node states should be broken down into more categories to allow a more diverse range of scenarios.

Because of the more regular search patterns used in camel operations in desert land systems, we also had the advantage of being able to model camel sightability with distance from the aircraft. This provided *Aerial Culling Planning* software (Lethbridge 2011) with both group-size and distance-dependent parameters that allowed it to estimate the proportion of camels that would have been seen and shot for a given search pattern

grid spacing and these sightability parameters. The search pattern used had a constant grid spacing of four kilometres. However, the *Aerial Culling Planning* software (Lethbridge 2011) also allows this to be varied to explore an optimal search pattern spacing for a given density of camels.

Dörge and Heucke (2003) suggested that greater than two camels per km² can have a serious impact on vegetation. They also noted that camel densities during drought from 0.2 to 1.0 camel per km² have no adverse impact. Unfortunately, despite these figures only being obtained at one site in Australia they have been broadly adopted as a density threshold for camel management. The BBN presented in this study should not be seen as tool to decide when to cull camels. That decision should always be based on the impacts the species is causing and in the context of other grazing pressures (Pople et al. 1998). The tools we present in this study are designed to enable NRM managers to choose between different management options to seek the most efficient outcome, not to decide whether or not to remove camels from the landscape.

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