Evaluating Natural Resource Management Strategies Under Parameter Uncertainty: an Outranking Approach Applied to Koala Conservation

[1, 2, 5] **Rhodes, J. R.**, [1, 2] **C. A. McAlpine**, [3] **D. Lunney, and** [4] **J. Callaghan**

[1] School of Geography, Planning and Architecture, The University of Queensland, Brisbane, QLD 4072, Australia, [2] The Ecology Centre, The University of Queensland, Brisbane, QLD 4072, Australia, [3] New South Wales Department of Environment and Conservation, PO Box 1967, Hurstville, NSW 2220, Australia, [4] Australian Koala Foundation, GPO Box 2659, Brisbane, QLD 4001, Australia, [5] present address: CSIRO Marine and Atmospheric Research, GPO Box 1538, Hobart, TAS 7001, Australia, e-mail: jonathan.rhodes@csiro.au.

Keywords: *Conservation; Decision analysis; Habitat protection; Individual-based model; Koala; Outranking approach; Parameter uncertainty; Spatially explicit model.*

EXTENDED ABSTRACT

Spatially explicit population models are widely used to assess wildlife management strategies that involve landscape change. However, predictions from these models can be highly uncertain due to parameter uncertainty. Therefore, if these models are to be used to reliably inform wildlife management, it is important that we incorporate parameter uncertainty into decision making processes. Where we are predominantly interested in obtaining a rank order of management strategies, outranking approaches to decision analysis may be particularly appropriate. These methods attempt to determine the ranking of alternative strategies only in terms of their pair-wise preference relationships across different criteria (e.g., different parameter values). Under uncertainty they can allow the robustness of a ranking to parameter uncertainty to be assessed.

In this paper we demonstrate an outranking approach for a decision problem in which we evaluate a range of alternative koala (*Phascolartos cinereus* Goldfuss) habitat protection strategies for a population in New South Wales, Australia. The management aim was to minimise the risk of population decline and we used a spatially explicit koala population model to predict the risk of decline. We assumed habitat loss in conjunction with four alternative habitat protection strategies, defined as: (1) 'baseline' – protect no additional habitat, (2) 'protect unfragmented' – protect an additional 260 ha of unfragmented habitat, (3) 'protect fragmented' – protect an additional 260 ha of fragmented habitat, and (4) 'protect highly fragmented' – protect an additional 260 ha of highly fragmented habitat. For two different levels of dog attack mortality (one high and one low) we drew 100 random parameter sets for the population model from distributions describing our parameter uncertainty. For each parameter combination, under each of the alternative habitat protection strategies, we estimated the risk of decline (as measured by the simulated expected minimum population size). We then ranked the strategies using the PROMETHEE outranking approach, which, as applied here, constructs a ranking based on pair-wise comparisons between strategies across different parameter combinations. As a comparison, we also ranked the strategies simply according to the means of the expected minimum population sizes.

The ranking achieved based on the means of the expected minimum population sizes, for both levels of dog attack mortality, was: protect unfragmented $\succ$ protect fragmented $\succ$ protect highly fragmented ~ baseline, where $\succ$ means 'is preferred to' and ~ means 'is indifferent to'. However, differences were small and not significantly different from each other. The outranking approach essentially gave the same overall ranking, but indicated that the ranking was highly robust to parameter uncertainty when dog attack mortality was low, but somewhat less robust when dog attack mortality was high. Therefore, at least with low dog attack mortality, the strategy ranking was robust to parameter uncertainty, even though the absolute risk of decline was highly variable.

The outranking approach was found to provide important information about the robustness of management strategy rankings to parameter uncertainty. This was not apparent in the more traditional approach of simply comparing the mean expected minimum population sizes. In many areas of natural resource management the sensitivity of management strategy rankings to uncertainty is a key concern, for which the application of outranking approaches are particularly appropriate.

1. INTRODUCTION

Spatially explicit population models provide a powerful tool for assessing wildlife responses to changes in landscape structure (Wiegand et al. 1999, With and King 1999). Therefore, these types of models are often used to assess wildlife management strategies that involve landscape change (Lindenmayer and Possingham 1996, McCarthy and Lindenmayer 1999). However, despite some ongoing debate, it is generally accepted that predictions from spatially explicit population models can be highly uncertain due to the propagation of errors in parameter estimates (Conroy et al. 1995, Wennergren et al. 1995, Ruckelshaus et al. 1997, Beissinger and Westphal 1998). Further, parameters for spatially explicit models cannot always be easily estimated from existing data (Dunning et al. 1995), leading to greater uncertainty in parameter estimates than for simpler models with fewer parameters. Therefore, if spatially explicit population models are to be used to reliably inform wildlife management, it is important that we incorporate parameter uncertainty into decision making processes.

Traditionally, parameter uncertainty has been dealt with using sensitivity analysis (Burgman et al. 1993). However, a preferable approach is to explicitly incorporate parameter uncertainty into model predictions. This can be achieved by a Monte Carlo approach, whereby model predictions are obtained for a large number of parameter sets drawn from probability distributions that describe parameter uncertainty (Wade 2002). This allows model predictions to then be summarised as probability distributions that explicitly include parameter uncertainty.

Under different management strategies, the expected values (or expected utilities) can be calculated from the model predictions and then used to rank the strategies, based on some objective(s). A key assumption of this approach is that, for a given management strategy, poor probabilistic outcomes are in some way compensated for by good probabilistic outcomes. However, if the aim is to determine a rank order of management strategies, in addition to determining how the strategies perform relative to each other on average, we are also interested in how sensitive the ranking is to parameter uncertainty. Outranking approaches to decision analysis are particularly useful in this case because they attempt to determine the ranking of alternative strategies only in terms of their pair-wise preference relationships across different criteria (in this case different parameter values). Importantly, outranking methods make no assumptions about compensation between different criteria (Stewart 1992).

In this paper we demonstrate the outranking approach for a decision problem in which we evaluated a range of alternative koala habitat protection strategies. The management aim was to minimise the risk of decline of a koala population in New South Wales, Australia and we used a spatially explicit koala population model to predict the risk of decline. We show that the outranking approach provides information on how robust strategy rankings are to parameter uncertainty that is not apparent using an expected utility approach.

2. METHODS

2.1. Study Area

The study area was situated within the Port Stephens Local Government Area, New South Wales, approximately 150 km north of Sydney. Port Stephens contains one of the most significant koala populations in New South Wales, but the population is threatened by habitat destruction, vehicle collision mortality and dog attacks (Port Stephens Council 2001).

2.2. Population Model

We used a spatially explicit population model to simulate the dynamics of the koala population in the study area (Rhodes 2005). Landscape structure was incorporated by explicitly linking the model to the spatial distribution of koala habitat, main roads and barriers to movement (Lunney et al. 1998, Rhodes 2005, Rhodes et al. 2005). In this application, the population model had 24 parameters that we estimated from empirical data collected from the study area and from the literature.

The population model was individual-based and included reproduction, survival and dispersal / habitat selection processes. Each koala's location and home range size was explicitly defined on the landscape. Home range size was dependent on the amount of good quality habitat in the vicinity of each koala (determined by two parameters: a_{hr} and b_{hr}) and home ranges were allowed to overlap. Annual adult reproductive rates were dependent on the proportion of good quality habitat in each koala's home range (determined by one parameter: h_{thresh}) and the extent of overlap with other koalas' home ranges (determined by two parameters: f_0 and α), thus introducing a form of density-dependence. We also allowed reproductive rates to vary stochastically. Natural survival rates were constant, but different for dependent young and adults (determined by two parameters: S_J and $S_A^{(n)}$). Survival rates due to dog attacks were constant (determined by one parameter: $S_A^{(d)}$). Survival rates due to traffic collisions depended upon the density of roads and traffic volume in each koala's home range (determined by four parameters: a_r, b_r, c_r and d_r). For the dispersal / habitat selection processes we employed a directionally-biased correlated random walk model (determined by seven parameters: λ_{steps}, σ_{turn}, $w_{primsec}$, w_{marg}, w_{other}, w_{clear}, d_{max}). Dispersing koalas were also subjected to additional mortality risk if they crossed a road and this risk depended on the traffic volume (determined by three parameters: W, L, v). For a full description of the population model and parameter values see Rhodes (2005).

2.3. Parameter Uncertainty

For 16 of the parameters we were able to estimate either sampling distributions, based on normal approximations, or empirical distributions derived from Monte Carlo simulations (Rhodes 2005). These distributions were assumed to represent our uncertainty about those parameter values. Although sampling distributions are not strictly the same as parameter distributions, we believed they were sufficiently close to Bayesian posterior distributions with an uninformative prior for our purposes (Wade 2000). We did not consider uncertainty in the remaining parameters because we were able to estimate their uncertainty distributions.

2.4. Management Strategies and Simulations

We considered four alternative habitat protection strategies. However, mortality due to dog attacks was estimated to account for around half of total adult mortality in this koala population. This meant that the population was predicted to go rapidly and deterministically extinct, regardless of the amount of habitat in the landscape. This suggests that management strategies are required that combine both habitat protection and reductions in dog attack mortality. Therefore, the habitat protection strategies were considered in combination with either a 50% or 100% reduction in dog attack mortality. Achieving a 100%, or even a 50%, reduction in dog attack mortality may be difficult in reality. However, our aim was to gain a general understanding of the importance of dog attack mortality for the outcome of alternative habitat protection strategies, rather than to prescribe specific reductions in dog attack mortality. For all habitat protection strategies, land zoned as environmental protection (Port Stephens Council 2000) was assumed to be protected from clearing, but each strategy differed in which additional habitat it protected. The strategies were defined as: (1) 'baseline' – protect no additional habitat, (2) 'protect unfragmented' – protect an additional 260 ha of unfragmented habitat, (3) 'protect fragmented' – protect an additional 260 ha of fragmented habitat, and (4) 'protect highly fragmented' – protect an additional 260 ha of highly fragmented habitat.

From the parameter uncertainty distributions we drew 100 random parameter sets. Then, for each parameter set, we simulated 100 replicates of the dynamics of the population under each dog attack mortality rate and the four different habitat protection strategies. We ran each simulation for 100 years and then assumed a linear 50% loss of unprotected vegetation cover over the next 100 years. The pattern of vegetation loss was assumed to be spatially correlated and was simulated by a mid-point displacement fractal algorithm, with fractal dimension 2.9 (Saupe 1988). For each separate parameter set we then calculated, from the 100 replicates, the expected minimum population size during the 100 year period of habitat loss. The expected minimum population size provided an index of the expected risk of decline of the population (McCarthy and Thompson 2001).

2.5. Decision Analysis

The starting point of any decision analysis is to define the management objective(s). In our case we assumed that the objective was to minimise the risk of decline in the koala population. That is, a strategy with a high expected minimum population size was better than a strategy with a low expected minimum population size. We then applied the PROMETHEE outranking method, as described by Drechsler et al. (2003), to determine a rank order for the alternative habitat protection strategies under parameter uncertainty for both levels of dog attack mortality.

The PROMETHEE outranking approach for multiple criteria decision analysis is based on pair-wise comparisons between alternative strategies (Brans and Mareschal 2005). Consider the multi-criteria problem

$$\max\{g_1(a), g_2(a), ..., g_k(a) \mid a \in A\}, \tag{1}$$

where A is a finite set of alternative management strategies and $\{g_1(\ ), ..., g_k(\ )\}$ is a set of evaluation criteria. We can then define preference functions, $P_j(a,b)$, for each criterion, j, for management strategy a over b as

$$P_j(a,b) = F_j\left(g_j(a) - g_j(b)\right) \quad \forall a,b \in A, \qquad (2)$$

where $0 \le P_j(a, b) \le 1$ and $F_j(\ )$ is a monotonically increasing function. If $\{w_1, w_2, ..., w_k\}$ are then a set of weights of the relative importance of the evaluation criteria, then the degree to which a is preferred to b, $\pi(a, b)$, known as the aggregated preference index, is defined as

$$\pi(a,b) = \sum_{j=1}^{k} P_j(a,b) w_j, \qquad (3)$$

where $\sum_{j=1}^{k} w_j = 1$. The value, $\pi(a, b)$, is a weighted sum of the preferences for a over b across all criteria. A value of $\pi(a, b)$ close to zero indicates a weak global preference for a over b and a value of $\pi(a, b)$ close to one indicates a strong global preference for a over b.

Now, if there are n alternative management strategies in A, then the positive outranking flow for strategy a is

$$\phi^+(a) = \frac{1}{n-1} \sum_{x \in A} \pi(a,x), \qquad (4)$$

and the negative outranking flow for strategy a is

$$\phi^-(a) = \frac{1}{n-1} \sum_{x \in A} \pi(x,a). \qquad (5)$$

The positive outranking flow, $\phi^+(\ )$, is a measure of the extent to which a outranks all the other management strategies (high values are better then low values), while the negative outranking flow, $\phi^-(\ )$, is a measure of how a is outranked by all the other management strategies (low values are better than high values). Either of these measures can be used to provide a partial ranking, but preferences according to the positive outranking flow can conflict with preferences according to the negative outranking flow, leading to incomparabilities. However, we can also form a complete ranking based on the net outranking flow, defined as

$$\phi(a) = \phi^+(a) - \phi^-(a). \qquad (6)$$

Here, the higher the net outranking flow, $\phi(\ )$, the better the management strategy.

Following Drechsler et al. (2003) we treated each parameter combination as a separate evaluation criterion. Since each parameter combination was a random draw from a probability distribution, we assigned them each equal weight, i.e. $w_j = 0.01$. A preference function, $P_j(a, b)$ was then defined so that, under parameter combination j, $P_j(a, b)$ equalled one if the expected minimum population size for strategy a was greater then strategy b and zero otherwise (Figure 3, for alternative preference functions see Brans and Mareschal 2005). We then calculated partial and complete rankings for the habitat protection strategies using the PROMETHEE method described above, for both levels of dog attack mortality. As a comparison, we also ranked the habitat protection strategies based simply on the means of their expected minimum population sizes. This is essentially an expected utility approach assuming utility is equal to the expected minimum population size.

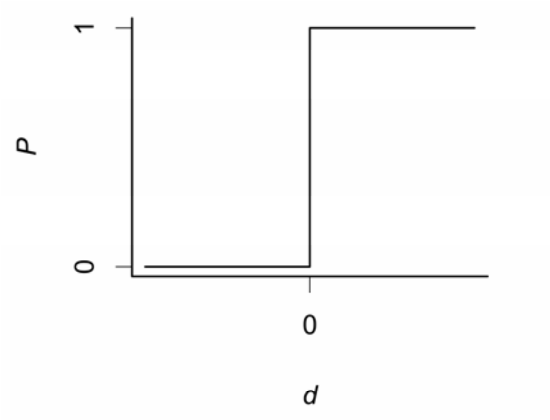

Figure 3. The preference function used in the decision analysis. P is the preference function for strategy a over b and d is the difference in expected minimum population sizes between the two strategies.

3. RESULTS

The ranking obtained from the means of the expected minimum population sizes, for both dog attack mortality rates, was: protect unfragmented $\succ$ protect fragmented $\succ$ protect highly fragmented $\sim$ baseline, where $\succ$ means 'is preferred to' and $\sim$ means 'is indifferent to' (Table 1). However, differences were small and not significantly different from each other (paired t-tests, df = 99, $p > 0.05$).

For the outranking approach, with a 50% reduction in dog attack mortality, the complete ranking was the same as indicated by the means of the expected minimum population sizes (Table 2). However, with a 100% reduction in dog attack mortality, the protect highly fragmented strategy was preferred to the baseline strategy (Table 3).

Table 1. Means and standard errors (in parentheses) of the expected minimum population sizes (expressed as a proportion of the mean population size just prior to the start of the habitat loss).

Dog attack mortality	Habitat protection strategy *			
	B	U	F	HF
50% reduction	0.28 (0.29)	0.30 (0.31)	0.29 (0.30)	0.28 (0.29)
Ranking	3=	1	2	3=
100% reduction	0.56 (0.24)	0.60 (0.25)	0.58 (0.25)	0.56 (0.24)
Ranking	3=	1	2	3=

* B = baseline, U = protect unfragmented, F = protect fragmented, and HF = protect highly fragmented.

Table 2. Matrix of the aggregated preference indices, $\pi(\ )$, negative outranking flows, $\phi^{-}(\ )$, positive outranking flows, $\phi^{+}(\ )$, and net outranking flows, $\phi(\ )$, with a 50% reduction in dog attack mortality.

Habitat protection strategy *	Habitat protection strategy *				$\phi^{+}(\ )$
	B	U	F	HF	
B	0	0.20	0.25	0.32	0.26
U	0.51	0	0.56	0.56	0.54
F	0.45	0.15	0	0.50	0.36
HF	0.41	0.16	0.21	0	0.26
$\phi^{-}(\ )$	0.46	0.17	0.34	0.46	
$\phi(\ )$	-0.20	0.37	0.02	-0.20	
Complete ranking	3=	1	2	3=	

* B = baseline, U = protect unfragmented, F = protect fragmented, and HF = protect highly fragmented.

With a 50% reduction in dog attack mortality there was considerable conflict in habitat protection strategy preferences across different parameter values. Although the protect unfragmented strategy was ranked as the best overall, it was only preferred to the any of the other strategies just over 50% of the time (Table 2). In fact, the aggregated preference indices indicated considerable conflict, and indifference, in preferences for all pair-wise comparisons, especially between the baseline and protect highly fragmented strategies (Table 2). However, with a 100% reduction in dog attack mortality there was far less conflict in the habitat protection strategy preferences across different parameter values. In this case, the protect unfragmented strategy was preferred to any of the other strategies around 90% of the time and was clearly the best strategy (Table 3). Also, the aggregated preference indices for all pair-wise comparisons revealed strong preferences for one of the strategies over the other (Table 3). Therefore, the habitat protection strategy ranking, with a 100% reduction in dog attack mortality, was far more robust to parameter uncertainty than with only a 50% reduction in dog attack mortality.

Table 3. Matrix of the aggregated preference indices, $\pi(\ )$, negative outranking flows, $\phi^{-}(\ )$, positive outranking flows, $\phi^{+}(\ )$, and net outranking flows, $\phi(\ )$, with a 100% reduction in dog attack mortality.

Habitat protection strategy *	Habitat protection strategy *				$\phi^{+}(\ )$
	B	U	F	HF	
B	0	0.04	0.10	0.24	0.13
U	0.91	0	0.88	0.91	0.90
F	0.85	0.06	0	0.86	0.59
HF	0.71	0.05	0.10	0	0.29
$\phi^{-}(\ )$	0.82	0.05	0.36	0.67	
$\phi(\ )$	-0.69	0.85	0.49	-0.38	
Complete ranking	4	1	2	3	

* B = baseline, U = protect unfragmented, F = protect fragmented, and HF = protect highly fragmented.

4. DISCUSSION

4.1. Dealing with Uncertainty

A thorough consideration of uncertainty is crucial if we want to make robust decisions for wildlife management and conservation (Regan et al. 2002). Not only is it important that we adequately characterise uncertainty in model predictions, but also that uncertainty is appropriately accounted for in decision making. The outranking approach demonstrated in this paper provides a straight forward and transparent means of incorporating parameter uncertainty into a decision analysis. Its strength is that it makes no assumption about compensation between the outcomes for different parameter values and allows the robustness of management strategy rankings to parameter uncertainty to be assessed.

In our application to koala conservation we were mainly concerned with obtaining a qualitative ranking for the alternative habitat protection strategies. The outranking approach was well suited in this case because it allowed us to directly assess how robust rankings were to parameter uncertainty. We found that rankings were robust to parameter uncertainty with no dog attack mortality, but far less robust with dog attack mortality at 50% of its estimated value. In contrast, the standard errors of the mean expected minimum population sizes (Table 1) revealed large variations in the absolute risk of decline due to parameter uncertainty. This made it difficult to distinguish alternative strategies from each other, based on the mean expected minimum population sizes, for both dog attack mortality rates. At least in the case of no dog attack mortality, the outranking approach showed the ranking to be robust to parameter uncertainty, even though absolute predictions varied substantially. Drechsler et al. (2003) show a similar result using a metapopulation model for the Glanville fritillary butterfly (*Melitaea cinxia*) in Finland. These findings also support the hypothesis that management strategy rankings derived from population models tend to be far more robust to uncertainty than absolute model predictions (McCarthy et al. 2003).

4.2. Implications for Koala Conservation

When the dog attack mortality rate was only reduced by 50%, the difference between the alternative habitat protection strategies was smaller than when dog attack mortality was reduced by 100%. Further, the absolute risk of decline was much higher with a 50% than a 100% reduction in dog attack mortality. This is a consequence of the high sensitivity of the risk of decline to adult mortality. Essentially, the habitat protection strategies were found to be far less effective when dog attack mortality was high than when it was low. Under high dog attack mortality it did not really matter which habitats were protected because, for a large number of parameter combinations the population went deterministically extinct. The implications of this are that, where anthropogenic influences have substantially elevated koala mortality rates, management strategies that both protect habitat and reduce mortality rates are likely to be required.

The conflict in strategy rankings, even with dog attack mortality reduced to 50% of its estimated value, indicates that, unless dog attack mortality is reduced substantially, it is difficult to rank the alternative habitat protection strategies. To obtain a more robust ranking we would need to reduce the amount of uncertainty in the parameter estimates by collecting more data. Therefore, the decision analysis approach described in this paper can also help to guide future monitoring and data collection within a decision making context.

4.3. Limitations and Future Research

Although we accounted for parameter uncertainty in the decision analysis, we were unable to characterise uncertainty distributions for some parameters. Therefore, we almost certainly underestimated the amount of uncertainty in our model predictions due to parameter uncertainty. Hence, developing methods that account for parameter uncertainty in decision analyses when it is difficult to define parameter distributions is an important area for future research. Methods such as probability bounds analysis may provide a useful way forward in this respect, at least for some models (Ferson and Hajagos 2004).

A further limitation of the approach we used in this paper was that we only dealt with one management objective; to minimise the risk of decline. However, in many situations we will have multiple management objectives, or criteria, as well as prediction uncertainty. In these cases, a slightly different approach will be required. Outranking approaches for stochastic data have been developed that may deal with this problem, but this remains an active area of research (Martel and Matarazzo 2005).

5. CONCLUSIONS

Decision analysis methods that deal with uncertainty are central to robust decision making in natural resource management. In this paper we have shown that, when we are primarily interested in ranking management strategies, outranking approaches are useful methods for dealing with parameter uncertainty.

6. ACKNOWLEDGEMENTS

This research was funded by the Australian Research Council (Australian Postgraduate Award Industry to JRR), the Australian Koala Foundation and the Foundation for National Parks and Wildlife.

7. REFERENCES

Beissinger, S. R. and M. I. Westphal (1998), On the use of demographic models of population viability in endangered species management, *Journal of Wildlife Management*, 62, 821-841.

Brans, J. P. and B. Mareschal (2005), PROMETHEE methods, in Figueira, J., S. Greco, and M. Ehrgott (editors), *Multiple criteria decision analysis: state of the art surveys*, Springer, New York, USA, 163-195.

Burgman, M. A., S. Ferson, and H. R. Akçakaya (1993), *Risk assessment in conservation biology*,

Chapman & Hall, London, UK.
Conroy, M. J., Y. Cohen, F. C. James, Y. G. Matsinos, and B. A. Maurer (1995), Parameter estimation, reliability, and model improvement for spatially explicit models of animal populations, *Ecological Applications*, 5, 17-19.
Drechsler, M., K. Frank, I. Hanski, R. B. O'Hara, and C. Wissel (2003), Ranking metapopulation extinction risk: from patterns in data to conservation management decisions, *Ecological Applications*, 13, 990-998.
Dunning, J. B., D. J. Stewart, B. J. Danielson, B. R. Noon, T. L. Root, R. H. Lamberson, and E. E. Stevens (1995), Spatially explicit population-models: current forms and future uses, *Ecological Applications*, 5, 3-11.
Ferson, S. and J. G. Hajagos (2004), Arithmetic with uncertain numbers: rigorous and (often) best possible answers, *Reliability Engineering & System Safety*, 85, 135-152.
Lindenmayer, D. B. and H. P. Possingham (1996), Ranking conservation and timber management options for Leadbeater's possum in southeastern Australia using population viability analysis, *Conservation Biology*, 10 , 235-251.
Lunney, D., S. Phillips, J. Callaghan, and D. Coburn (1998), Determining the distribution of koala habitat across a shire as a basis for conservation: a case study from Port Stephens, New South Wales, *Pacific Conservation Biology*, 4, 186-196.
Martel, J. M. and B. Matarazzo (2005), Other outranking approaches, in Figueira, J., S. Greco, and M. Ehrgott (editors), *Multiple criteria decision analysis: state of the art surveys*, Springer, New York, USA, 197-262.
McCarthy, M. A., S. J. Andelman, and H. P. Possingham (2003), Reliability of relative predictions in population viability analysis, *Conservation Biology*, 17, 982-989.
McCarthy, M. A. and D. B. Lindenmayer (1999), Incorporating metapopulation dynamics of greater gliders into reserve design in disturbed landscapes, *Ecology*, 80, 651-667.
McCarthy, M. A. and C. Thompson (2001), Expected minimum population size as a measure of threat, *Animal Conservation*, 4, 351-355.
Port Stephens Council (2000), *Local environmental plan*, Port Stephens Council, Raymond Terrace, Australia.
Port Stephens Council (2001), *Port Stephens Council comprehensive koala plan of management. Part 1: the CKPoM*, Port Stephens Council, Raymond Terrace, Australia.
Regan, H. M., M. Colyvan, and M. A. Burgman (2002), A taxonomy and treatment of uncertainty for ecology and conservation biology, *Ecological Applications*, 12, 618-628.
Rhodes, J. R. (2005), *The ecology, management and monitoring of wildlife populations in fragmented landscapes: a koala case study*, PhD thesis, The University of Queensland, Brisbane, Australia.
Rhodes, J. R., C. A. McAlpine, D. Lunney, and H. P. Possingham (2005), A spatially explicit habitat selection model incorporating home range behavior, *Ecology*, 86, 1199-1205.
Ruckelshaus, M., C. Hartway, and P. Kareiva (1997), Assessing the data requirements of spatially explicit dispersal models, *Conservation Biology*, 11, 1298-1306.
Saupe, D. (1988), Algorithms for random fractals, in Peitgen, H. and D. Saupe (editors), *The science of fractal images*, Springer-Verlag, New York, USA, 71-136.
Stewart, T. J. (1992), A critical survey on the status of multiple criteria decision making theory and practice, *OMEGA International Journal of Management Science*, 20, 569-586.
Wade, P. R. (2000), Bayesian methods in conservation biology, *Conservation Biology*, 14, 1308-1316.
Wade, P. R. (2002), Bayesian population viability analysis, in Beissinger, S. R. and D. R. McCullough (editors), *Population viability analysis*, University of Chicago Press, Chicago, USA, 213-238.
Wennergren, U., M. Ruckelshaus, and P. Kareiva (1995), The promise and limitations of spatial models in conservation biology, *Oikos*, 74, 349-356.
Wiegand, T., K. A. Moloney, J. Naves, and F. Knauer (1999), Finding the missing link between landscape structure and population dynamics: a spatially explicit perspective, *American Naturalist*, 154, 605-627.
With, K. A. and A. W. King (1999), Extinction thresholds for species in fractal landscapes, *Conservation Biology*, 13, 314-326.