

MAKING CONSERVATION DECISIONS UNDER UNCERTAINTY FOR THE PERSISTENCE OF MULTIPLE SPECIES

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Abstract. Population models for multiple species provide one of the few means of assessing the impact of alternative management options on the persistence of biodiversity, but they are inevitably uncertain. Is it possible to use population models in multiple-species conservation planning given the associated uncertainties? We use information-gap decision theory to explore the impact of parameter uncertainty on the conservation decision when planning for the persistence of multiple species. An information-gap approach seeks robust outcomes that are most immune from error. We assess the impact of uncertainty in key model parameters for three species, whose extinction risks under four alternative management scenarios are estimated using a metapopulation model. Three methods are described for making conservation decisions across the species, taking into account uncertainty. We find that decisions based on single species are relatively robust to uncertainty in parameters, although the estimates of extinction risk increase rapidly with uncertainty. When identifying the best conservation decision for the persistence of all species, the methods that rely on the rankings of the management options by each species result in decisions that are similarly robust to uncertainty. Methods that depend on absolute values of extinction risk are sensitive to uncertainty, as small changes in extinction risk can alter the ranking of the alternative scenarios. We discover that it is possible to make robust conservation decisions even when the uncertainties of the multiple-species problem appear overwhelming. However, the decision most robust to uncertainty is likely to differ from the best decision when uncertainty is ignored, illustrating the importance of incorporating uncertainty into the decision-making process.

Key words: conservation planning; information-gap decision theory; metapopulation; multi-criteria decision analysis; multiple-species decision making; population viability analysis; Tumut, New South Wales, Australia; uncertainty.

INTRODUCTION

The ideal conservation planning method would enable decision-makers to measure the effects of landscape-scale management on all species. One of the few ways we have of quantitatively measuring the impacts of management on multiple species is to use population models to predict the extinction probability of each of the species (Possingham et al. 1993, Burgman et al. 2005, Nicholson and Possingham 2006).

Using population models for multiple-species decisions adds further complexities to the decision-making process: uncertainties associated with population models, though rendered open to scrutiny (Burgman and Possingham 2000, McCarthy et al. 2004), are further amplified when modeling many species, and a means of integrating the extinction risks is needed to make a decision across the species. A decision-theoretic framework is required, with defined management goals and

constraints and a measure of performance of the management alternatives, making the process more repeatable, transparent, and capable of dealing with uncertainties (Shea et al. 1998, Guikema and Milke 1999, Drechsler 2004).

An important question when making conservation decisions is how uncertainty in parameters or model structure will change the ultimate decision, given that the absolute values of extinction risk from population models are likely to be inaccurate (Lindenmayer and Possingham 1996, Milner-Gulland et al. 2001, Drechsler et al. 2003, McCarthy et al. 2003). Sensitivity analyses enable modelers to assess the degree of change in the estimate of extinction risk with changes in parameter estimates (McCarthy et al. 1995, Drechsler 2004, Burgman et al. 2005). While no studies have examined the effects of uncertainty in population models on conservation decisions for the persistence of multiple species (Burgman et al. 2005), studies on the impact of uncertainty in single-species management have reached mixed conclusions on the robustness of the relative rankings of management options; some have found rankings to be generally robust to parameter uncertainty (e.g., Possingham et al. 1993, McCarthy et al. 1995, Ralls and Starfield 1995, Lindenmayer and Possingham

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1996, Drechsler et al. 2003), while others have found increasing uncertainty can significantly alter management decisions (e.g., Burgman 2005, Regan et al. 2005, Halpern et al. 2006). Analyses of uncertainty in species-specific fragmentation effects in multi-species reserve design have similarly resulted in altered management decisions (Moilanen and Wintle 2006).

Decision makers may not only wish to know if their decision is sensitive to uncertainty, but how much uncertainty can be permitted before the decision would change. This is the basis of information-gap (info-gap) decision theory, which seeks robust outcomes that are most immune to failure due to uncertainty (Ben-Haim 2001, 2004). Info-gap decision theory provides a means of propagating the impact of uncertainty through the decision-making process. Typically in sensitivity analyses, a probability distribution or range is assigned to parameter values, in which the true value is assumed to lie (Burgman 2005, Regan et al. 2005, Halpern et al. 2006). In info-gap there are no underlying assumptions about parameter distributions; instead, the effects on the decision of an increasing gap between the best-estimate value and possible true values are assessed (Ben-Haim 2004). Info-gap decision theory requires a threshold level of performance to be stated; the management option that meets the performance requirement when great uncertainty exists in the model or data is the most robust (Ben-Haim 2004, Regan et al. 2005, Halpern et al. 2006). For example, the best management option may be one that ensures that a species does not exceed a given risk of extinction under the highest possible level of unfavorable uncertainty. The decision may not minimize the extinction risk when uncertainty is ignored, but it is the option least likely to fail because of uncertainty in model structure or parameter estimates.

Info-gap decision theory has been applied to making conservation decisions for single species (Burgman 2005, Regan et al. 2005, Halpern et al. 2006) and for reserve selection when uncertainty exists in the distributions of multiple species (Moilanen and Wintle 2006, Moilanen et al. 2006). We extend it by examining the effects of uncertainty when making decisions for multiple species based on population models. The use of population models of multiple species to inform conservation decisions requires a structure for integrating the different species and their needs. Measures of persistence for multiple species may be used to inform conservation decisions in a variety of ways, including multi-criteria decision analysis (Drechsler 2004, Sarkar and Garson 2004) and multiple-species utilities (Hof and Raphael 1993, Williams and Araújo 2002, Drechsler 2004, Nicholson and Possingham 2006). In the few studies where the viability of multiple species has been modeled (e.g., Bevers et al. 1995, Williams and Araújo 2002, Carroll et al. 2003, Nicholson et al. 2006), there was no attempt to incorporate uncertainty.

We use information-gap decision theory to incorporate uncertainty into conservation decision-making

processes based on the persistence of multiple species. We estimate the extinction risks of three species under four alternative reserve scenarios of equal size (160 ha), comprising different subsets of patches in a fragmented landscape, using the metapopulation model of Frank and Wissel (2002). The extinction risk of each species is a function of the ecology of the species and the amount and configuration of habitat in the landscape. The best reserve scenario is different for each species, and we seek a method for deciding which configuration to protect for the benefit of all three species when our goal is to minimize the expected loss of species. For each species, a performance requirement is specified, setting a maximum extinction risk that must not be exceeded. Uncertainties in the estimates of key model parameters for each species are propagated into the estimates of extinction risk, and alternative reserve scenarios are ranked in terms of their ability to meet the performance requirements under increasing uncertainty. We then explore three different means of identifying the best reserve scenario across the species, taking into account uncertainty in the estimates of extinction risk:

- 1) The first multiple-species info-gap analysis combines the extinction risks of the three species into one performance measure: the sum of the extinction risks, giving the expected loss of the species. We seek the management option that returns no more than a given expected species loss under the greatest horizon of uncertainty.

- 2) In the second multiple-species info-gap analysis, we keep the extinction risks of the species separate, and seek the management alternative that can ensure that the extinction risk of each species does not exceed its performance requirement under the greatest amount of uncertainty.

- 3) The third method is a multi-criteria decision analysis (Drechsler 2004), using the rank orders of the scenarios generated in the single-species info-gap analyses to derive an overall ranking of the reserve scenarios.

We explore the impacts of uncertainty on conservation decisions based on the persistence of multiple species. We ask how robust the decisions are to uncertainty, and whether it is still possible to make a good decision in the face of the extensive uncertainty associated with the use of population models.

METHODS

To examine the effects of uncertainty when making conservation decisions for multiple species, we require a measure of performance of conservation, a model for uncertainty, and a case study to illustrate how decisions may be made under uncertainty. In this section, we describe the metapopulation model used to estimate the extinction risk of the species, and a case study of three species in a 15-patch forest landscape. We describe the info-gap model used to propagate uncertainty in key model parameters for each of the species, and present alternative methods for including uncertainty when

TABLE 1. Symbols and notation used in the models for the extinction risk of a metapopulation, the info-gap model for uncertainty, and the utility functions.

| Notation | Meaning |
|-----------------------------|---|
| Metapopulation model | |
| $p_k(s)$ | Probability of extinction of species k over 100 years given reserve scenario s |
| $T_k(s)$ | Mean time to extinction of species k given reserve scenario s |
| t | Management time horizon, in this case 100 years |
| n | Number of species under consideration |
| m | Number of patches under consideration |
| M | Number of reserved patches |
| v_{ik} | Extinction rate of species k in patch i |
| c_{ijk} | Colonization rate of species k from patch i to patch j |
| d_{ij} | Distance between patches i and j (km) |
| A_i | Area of patch i (ha) |
| d_k | Mean dispersal distance of species k (km) |
| x_k | Extinction–area exponent for species k |
| γ_k | Emigration rate per unit area of species k |
| ϵ_k | Coefficient for the local extinction rate for species k |
| H_k | Home range size of species k (ha) |
| $E(s)$ | The expected loss of species given reserve scenario s |
| Info-gap model | |
| α | Uncertainty parameter, or horizon of uncertainty; $\alpha = 0$ at the best estimate |
| \tilde{x}_k | Best estimate for parameter x_k for species k , where $\alpha = 0$ |
| $X_k(\alpha, \tilde{x}_k)$ | Set of possible values for x_k |
| $D_k(\alpha, d_k)$ | Set of possible values for d_k |
| R | Performance requirement measured in species loss |
| Indexing | |
| k | Species |
| s | Reserve scenario |
| i, j | Patches |

making conservation decisions for multiple species. The symbols used for all model parameters are summarized in Table 1.

Metapopulation model

The extinction risk of a metapopulation is a function of the location, size and quality of the patches of habitat and the ecology of the species (Hanski 1994). Let the probability of extinction over timeframe t of an established metapopulation of species k , given the patches of habitat in reserve scenario s , be

$$p_k(s) = 1 - e^{-t/T_k(s)} \tag{1}$$

where $T_k(s)$ is the mean time to extinction of the metapopulation of species k in reserve scenario s (Mangel and Tier 1994, Grimm and Wissel 2004). In this study, we use a management timeframe of $t = 100$ years. The mean time to extinction of the metapopulation, $T_k(s)$, is estimated using an approximation formula for a stochastic, time-continuous metapopulation model (Frank and Wissel 2002):

$$T_k(s) \approx T_k^a(s) = \frac{1}{v_{\text{agg}}} \frac{(M-1)!}{M(M-1)^{M-1}} e^{M/z} z^{M-1} \tag{2}$$

with aggregations of the effective colonization ability of

the subpopulations,

$$z = \prod_{i=1}^M \max \left(\sqrt{2}, \sqrt{\left\{ \frac{1}{2} \left[\left(\frac{\sum_{j(\neq i)} c_{ijk}}{v_{ik}} \right)^{-2} + \left(\frac{\sum_{j(\neq i)} c_{jik}}{v_{ik}} \right)^{-2} \right]^{-1} \right\}} \right)^{1/M}$$

and the effective local extinction rate

$$v_{\text{agg}} = \left(\prod_{i=1}^M v_{ik} \right)^{1/M}$$

where M is the number of patches in the metapopulation, in this case the number of reserved patches, v_{ik} is the local extinction rate of species k in patch i , and c_{ijk} is the rate of colonization of species k from patch i to patch j , each described in the sub-models below.

Following Hanski (1994) and Frank (2004), the local extinction rate of species k in patch i , v_{ik} , is a function of area only:

$$v_{ik} = \epsilon_k A_i^{-x_k} \tag{3}$$

where A_i is the area of patch i , ϵ_k a species-specific coefficient relating to minimum patch size, and x_k , the extinction–area exponent, is a species-specific measure of environmental noise in the population, and summa-

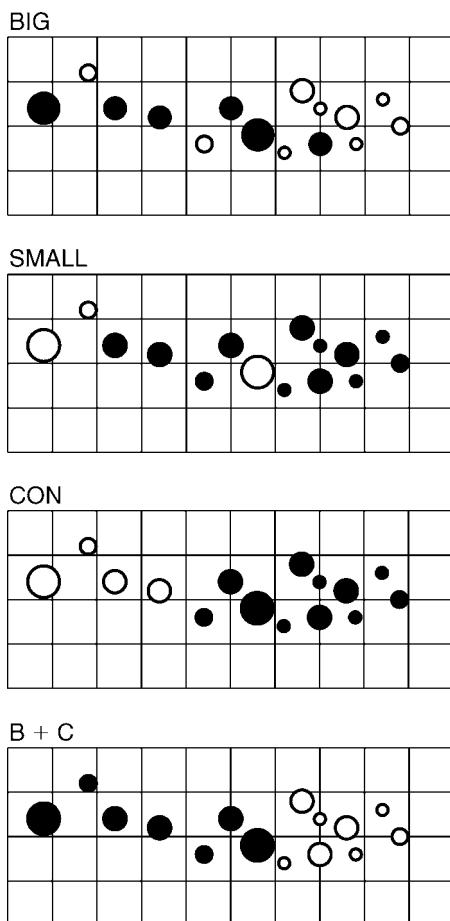


FIG. 1. The 15-patch system and four alternative reserve scenarios of 160 ha, with the reserved patches in black, on a 1-km grid: the Big Reserve scenario (BIG); the Connected scenario (CON); the Small Reserve scenario (SMALL); and the Big and Connected scenario (B + C). The average size and distances between reserves are listed in Table 2.

rizes the environmental conditions and the species' response to them (Hanski 1994, Frank 2004). We assume that extinction is certain when a patch is smaller than the home range required to support a breeding female of species k , H_k , and that the extinction risk of the species in a patch the size of its home range is 99% over 100 years:

$$0.99 = 1 - e^{-100\varepsilon_k H_k^{-x_k}}. \quad (4)$$

The parameter ε_k in Eq. 3 is replaced with a function of home range derived from Eq. 4. The model for the local extinction rate of species k in patch i then becomes

$$v_{ik} = \frac{-\ln(0.01)}{100} \left(\frac{A_i}{H_k} \right)^{-x_k}. \quad (5)$$

We use the "pie-slice" model to estimate the rate at which emigrants of species k from an occupied patch i will colonize an empty patch j for all pairs of patches, where the chance of colonization is proportional to the size and distance of the recipient patch (Possingham et

al. 1994, Possingham and Davies 1995, Etienne and Heesterbeek 2000):

$$c_{ijk} = \gamma_k A_i b e^{-d_{ij}/d_k} \quad (6)$$

where $b = (1/\pi) \arctan(\sqrt{A_j/\pi}/d_{ij})$ for $d_{ij} \geq \sqrt{A_j/\pi}$ and $b = 0.5$ when $d_{ij} < \sqrt{A_j/\pi}$, A_i is the area of patch i , A_j is the area of target patch j , d_{ij} is the center-to-center distance between the two patches, d_k is the mean dispersal distance of species k , and γ_k is the emigration rate per unit area of species k , assumed here to be a function of the number of female juveniles produced per home range size (Possingham and Davies 1995, Etienne 2004, Frank 2004).

The probability of extinction of a metapopulation of species k in reserve system s is therefore a function of the size and spatial arrangement of the reserves and the species-specific parameters for the extinction-area exponent x_k , the mean dispersal distance d_k , the home range size H_k , and emigration rate per unit area γ_k :

$$p_k(s) = p_k(s, x_k, d_k, H_k, \gamma_k).$$

Case study

To illustrate the method for making decisions under uncertainty for the management of multiple species, we use a hypothetical example based on the landscape near Tumut, New South Wales, Australia, comprising remnant patches of eucalypt (*Eucalyptus* spp.) forest surrounded by Monterey pine (*Pinus radiata*) plantations, that has been the subject of many ecological and conservation studies (Lindenmayer et al. 2003). Our model system consists of 15 stylized patches with a total area of 250 ha, with patch sizes ranging from 5 to 40 ha. The objective is to choose between four alternative reserve scenarios that have the same total area of 160 ha (Fig. 1; Table 2), but are based on different theoretical considerations in conservation planning (Etienne and Heesterbeek 2000, Possingham et al. 2001, Westphal et al. 2003):

1) *Big Reserve scenario*.—The largest areas are reserved, placing importance on the size of the patches rather than their spatial configuration, as island-biogeography theory suggests that big reserves are better than small reserves (in the figures referred to as BIG);

2) *Small Reserve scenario*.—As many patches as possible are reserved to spread any risk from catastrophes, resulting in all the smallest patches being selected (SMALL);

3) *Connected scenario*.—The most-connected areas are reserved, as supported by island-biogeography theory, resulting in all the eastern-most patches being selected (CON);

4) *Big + Connected scenario*.—A compromise between high connectivity and maximizing patch size is reached by selecting all the western-most patches up to the budget of 160 ha, including the two largest patches and the patches between them (B + C).

TABLE 2. The four alternative reserve scenarios depicted in Fig. 1, each with a total area of 160 ha.

| Reserve scenario | No. patches | Mean patch size (ha) | Mean distance to other patches (km) |
|------------------|-------------|----------------------|-------------------------------------|
| Big Reserve | 6 | 26.67 | 2.86 |
| Small Reserve | 12 | 13.33 | 2.50 |
| Connected | 11 | 14.55 | 1.84 |
| Big + Connected | 7 | 22.86 | 2.31 |

We modeled three species, all dependent on older forest with numerous hollows for nesting, but with different dispersal abilities, home-range sizes, and responses to environmental stochasticity. Table 3 shows the parameters used and references for each of the species. The mountain brushtail possum, *Trichosurus cunninghamii*, is one of the largest of Australia’s arboreal marsupials, weighing up to 4.5 kg, and feeds on fungi and the leaves of a large range of plant species (McCarthy et al. 2001). It has a home range of approximately 2–6 ha, and good dispersal capabilities (Lindenmayer et al. 1999, McCarthy et al. 2001). The greater glider, *Petaurus volans*, is a specialist folivorous marsupial, weighing up to 1300 g (McCarthy et al. 2001). Its home range is 1–3 ha, with a minimum area of 3 ha required for a breeding female, and it is considered to have limited dispersal capabilities (Lindenmayer et al. 2001, McCarthy et al. 2005). The Red-browed Tree-creeper, *Climateris erythroptis*, feeds on small arthropods gleaned from the bark of trees. Groups hold territories of about 10–20 ha and breed cooperatively, resulting in higher fecundity than the other two species (Noske 1991, McCarthy et al. 2000).

For ease of illustration, we assume that all the species can be found in all patches and that the habitat is equally suitable for each species. However, as some patches are smaller than the home ranges of the Red-browed Tree-creeper (12 ha) or the mountain brushtail possum (6 ha), some of the scenarios include patches that cannot support viable sub-populations of those species, in particular the Small Reserve and Connected scenarios.

Although these species are relatively well known, a great deal of uncertainty exists about most of the parameters for each species. In metapopulation modeling, the most uncertain parameters are usually the extinction–area exponent x_k (Foley 1997) and the mean

dispersal distance d_k (Halpern et al. 2006). The extinction–area exponent x_k may be approximated using estimates of the intrinsic growth rate of a population and its variance (Dennis et al. 1991, Foley 1997, Hanski 1998), requiring a long time series of population abundance (Foley 1994, 1997, Wilcox and Possingham 2002, Frank 2004). Similarly, dispersal parameters can be estimated using patch occupancy and turnover data, and again the amount of data required for accurate estimates is very large (Hanski 1998, Moilanen 1999, Drechsler et al. 2003, ter Braak and Etienne 2003). Frank (2004) argued that the ranking of management options is most likely to be affected by uncertainty in the extinction–area exponent x_k . Given uncertainty in the parameter estimates, is it possible to choose between the four conservation scenarios with any reliability?

We look at how a decision can be affected by uncertainty in the extinction–area exponent x_k and the mean dispersal distance d_k . In order to assess the impact of uncertainty on decisions, we require a model for uncertainty and a framework for analyzing the results.

Info-gap models for parameter uncertainty and decision making

Info-gap decision theory presents a means of assessing the impact of uncertainty in decision making. A novel component of info-gap theory is that uncertainty is unknown and unbounded, rather than assuming probability distributions or ranges for model parameters, making it particularly useful where information is scarce. Info-gap decision theory requires a process model to measure management performance, a performance requirement, a model for uncertainty, and methods for making decisions under uncertainty (Ben-Haim 2001, 2004, Regan et al. 2005).

Performance model and requirement.—The performance of each of the reserve scenarios is measured using the metapopulation model described above to estimate extinction risk. The measure of performance we use is the expected loss of species under reserve system s , $E(s)$. In single-species management, the expected species loss is simply the extinction risk of the species; when dealing with multiple species, the expected loss of species is the sum of extinction risks across the species, giving the expected number of extinctions. The performance requirement, R , is a nominated expected species loss that must not be exceeded or the performance of the reserve scenario would be considered unacceptable.

TABLE 3. The three species modeled and the best estimates for the metapopulation parameters, the performance requirements in extinction risk, and key references for estimating model parameters.

| Species | Parameter | | | | Performance requirements | References |
|---------------------------|------------|-------|-------|-------|--------------------------|--|
| | γ_k | d_k | H_k | x_k | | |
| Greater glider | 0.17 | 0.5 | 3 | 0.87 | 0.13 | Possingham et al. (1994), McCarthy et al. (2001, 2005) |
| Red-browed Tree-creeper | 0.09 | 1 | 12 | 1.20 | 0.19 | Noske (1991), McCarthy et al. (2000) |
| Mountain brushtail possum | 0.04 | 5 | 6 | 1.00 | 0.16 | Lindenmayer et al. (1999), McCarthy et al. (2001) |

Note: For parameter symbol explanation, see Table 1.

Info-gap model for parameter uncertainty.—We use a relatively simple means of modeling uncertainty in this paper, following Regan et al. (2005) and Halpern et al. (2006). Uncertainty in key parameters is modeled as intervals of unknown size around the best estimate values. To illustrate the model of uncertainty used in this paper, and how it propagates into the decision-making process based on extinction risk, we describe the model for uncertainty in the extinction–area exponent x_k ; the same process is used for uncertainty in the mean dispersal distance d_k .

For each species k , we have a best-estimate value of the extinction–area exponent, \tilde{x}_k , based on available data or expert opinion. However, we know that this value is likely to be incorrect, and that there are in fact a range of possible values around the best estimate. The difference between our best estimate and the ‘true’ value is the information gap, or info-gap (Ben-Haim 2004). We model the info-gap as a function of the uncertainty, known as the “horizon of uncertainty,” α . We express the uncertainty in the extinction–area exponent x_k as a fractional deviation from the best-estimate value \tilde{x}_k :

$$\frac{|\tilde{x}_k - x_k|}{\tilde{x}_k} \leq \alpha. \tag{7}$$

Because the extinction–area exponent x_k and the mean dispersal distance d_k cannot take negative values (Cook and Hanski 1995, McCarthy et al. 2005), the lowest value considered for each of the parameters is 0. Therefore the range of possible values for x_k in the set X_k is given by

$$X_k(\alpha, \tilde{x}_k) = \{x_k : \max[0, (1 - \alpha)\tilde{x}_k] \leq x_k \leq (1 + \alpha)\tilde{x}_k\}, \tag{8}$$

$\alpha \geq 0.$

The horizon of uncertainty, α , and thus the size of the info-gap, is unknown (Ben-Haim 2004). The greater our uncertainty, the higher the value of α , and the set $X_k(\alpha, \tilde{x}_k)$ of possible values for the extinction–area exponent x_k becomes more inclusive. Consequently, $X_k(\alpha, \tilde{x}_k)$ is a nested subset of possible values for the extinction–area exponent as the horizon of uncertainty α increases.

The set $X_k(\alpha, \tilde{x}_k)$ of possible values for the extinction–area exponent x_k for the horizon of uncertainty α feeds into the metapopulation model, giving a range of possible values of the extinction risk of the metapopulation of species k in reserve scenario s , $p_k(s, \alpha, \tilde{x}_k)$, also a function of the horizon of uncertainty α . We seek to understand how our decision would change if the best estimates for the parameters were overly optimistic, and so we investigate the effects of parameter values that tend to drive the extinction risk estimate higher. We only consider values that are lower than the best estimates for the extinction–area exponent x_k and mean dispersal distance d_k , respectively reducing the benefit of larger patches and decreasing connectivity among patches. Therefore we model only the values for the extinction–area exponent x_k that lie between the best estimate \tilde{x}_k , where $\alpha = 0$, and $(1 - \alpha)\tilde{x}_k$, where $\alpha > 0$. The lowest

possible value for extinction risk is the best estimate extinction risk, $\tilde{p}_k(s, \tilde{x}_k)$, based on the best estimates for the model parameters.

Info-gap decision theory.—For each reserve scenario, we estimate the set of possible values for performance in expected loss of species, $E(s)$, with increasing uncertainty α in the parameters x_k and d_k . We model the impact of uncertainty in each parameter on the ranking of the reserve scenarios for each species, then for both parameters, x_k and d_k , for each species, then for both parameters across all three species.

The best reserve scenario is that which is most robust to uncertainty: its performance in expected species loss, $E(s)$, meets the performance requirement, R , under the greatest horizon of uncertainty α . The most robust scenario allows the greatest info-gap between our best estimate and the true value, while guaranteeing the specified performance. This is known as a “robust satisficing decision function” (Ben-Haim 2004) and is formally expressed for the expected loss of species, $E(s, x_k)$, with uncertainty in the extinction–area exponent x_k , as

$$\hat{\alpha}(s, R) = \max \left\{ \alpha : \max_{x_k \in X_k(\alpha, \tilde{x}_k)} E(s, x_k) \leq R \right\} \tag{9}$$

where $\hat{\alpha}$ is the largest horizon of uncertainty that can be tolerated while remaining under the performance requirement, R , and is the measure of the robustness of the scenario. The performance requirement acts as a constraint, ensuring that the maximum acceptable expected species loss is not exceeded. For $\alpha = 0.5$, the lowest possible value for the parameter, in this case the extinction–area exponent x_k , is half of the best-estimate value. If the extinction risk of the metapopulation under a given reserve scenario still meets the performance requirement when $\alpha = 0.5$, then the parameter estimate could be wrong by as much as 50% and the outcome would still be acceptable.

When considering uncertainty in multiple parameters concurrently we model identical relative increases in uncertainty (Regan et al. 2005). Therefore when we model uncertainty in the mean dispersal distance d_k and the extinction–area exponent x_k for a species, conditions degrade for both parameters at the same relative rate, and the same value for the horizon of uncertainty α applies. For example, for a horizon of uncertainty $\alpha = 0.5$, the estimate for the extinction–area exponent could be as low as $x_k = \tilde{x}_k(1 - 0.5)$, and for the mean dispersal distance $d_k = \tilde{d}_k(1 - 0.5)$. Similarly, when modeling uncertainty in one or more parameters for all species, we assume the uncertainty in the parameters increase at the same relative rate and horizon of uncertainty, α .

Decisions based on a single species.—In a single-species planning situation, the performance measure is relatively simple: the expected loss of species is the extinction risk of species under consideration, $E(s) = p_k(s)$. We set species-specific performance requirements, R_k , a priori, based on the expected extinction risk of each species if

TABLE 4. Hypothetical preference matrix for one species and four management scenarios, generated by pairwise comparisons between scenarios; the scenario that performs better receives a score of 1, while the less preferred scenario receives 0 (e.g., the boldface 1 shows that the Big Reserve scenario was preferred over the Small Reserve scenario).

| Scenario | Big Reserve | Small Reserve | Connected | Big + Connected |
|-----------------|-------------|---------------|-----------|-----------------|
| Big Reserve | 0 | 1 | 0 | 0 |
| Small Reserve | 0 | 0 | 0 | 1 |
| Connected | 1 | 1 | 0 | 1 |
| Big + Connected | 1 | 0 | 0 | 0 |

the entire area of the fragmented reserve system (160 ha) were amalgamated into a single patch. The equation for the local extinction probability over 100 years for species k in patch i is

$$R_k = 1 - \exp \left[\ln(0.01) \left(\frac{A_i}{H_k} \right)^{-x_k} \right]. \quad (10)$$

Therefore the performance requirement for the greater glider is $R_{gg} = 0.13$, as its extinction risk in a patch of 160 ha is estimated at 13%, given its home range of $H_{gg} = 3$ and extinction–area exponent $x_{gg} = 0.87$. The performance requirement for the mountain brushtail possum is 0.16, and 0.19 for the Red-browed Treecreeper (Table 3).

Decisions based on multiple species: multi-species utility.—In a multiple-species situation, there are several alternative routes for decision making. We can continue with the expected species loss as our performance measure, where the extinction risks of the three species are combined into a single utility value (Nicholson and Possingham 2006). The expected loss of species, or expected number of extinctions, in reserve system s is given by the sum of the extinction risks across the species:

$$E(s) = \sum_{k=1}^n p_k(s). \quad (11)$$

The performance requirement, R , is set a priori to the sum of the performance requirements R_k of each species k , giving an acceptable maximum of 0.48 expected extinctions.

Decisions based on multiple species: multiple constraints.—Alternatively we can keep the extinction risks of each species separate, and ensure that the extinction risk of each species remains under the species-specific performance requirement. Rather than the extinction risk of one species acting as a constraint, we have multiple constraints, as the performance requirement for each species must be met for a scenario to be acceptable. Therefore we seek the reserve scenario s that can tolerate the highest level of uncertainty α , subject to the extinction risks of all n species being lower than the species-specific performance requirements, R_k .

Decisions based on multiple species: multi-criteria decision analysis.—The third multiple-species method we employ is a multi-criteria decision analysis (Drechsler 2004, Moffett and Sarkar 2006). The three species are treated as three separate criteria, and the PROMETHEE method is used to give an overall ranking of the

reserve scenarios (Brans and Mareschal 1990, Drechsler 2004). Pairwise comparisons are made for the four alternative reserve scenarios for each species. The scenario that ranks better receives a score of one point, while the less preferred scenario receives no score. If the two reserve scenarios are equal, neither receives a point. By comparing all the scenarios, a preference matrix can be constructed for each species (Table 4). A total preference matrix is then constructed using the preference matrices for each species. The average of the single species’ preference matrices are taken by adding up the scores for each species and dividing by 3, as we treat all species equally (Drechsler 2004). For example, if the Big Reserve scenario is preferred to the Small Reserve scenario by two of the three species, then its score is 0.667. The sum of each row gives the average number of times that each scenario is preferred, and measures the dominance of a scenario over the other scenarios. The sum of a column gives the average number of times a scenario is beaten; the higher the value, the worse the scenario compared with the others. The average number of times that each scenario is preferred and beaten gives two alternative rank orders for the scenarios, which in some cases may not agree (Drechsler 2004).

In this study we construct two sets of preference matrices: one set where uncertainty is considered and one where it is ignored. When including uncertainty, the rankings of the alternative management scenarios are based on their robustness to uncertainty, using the results from the single-species info-gap analyses. For each species, the reserve scenarios are ranked according to the degree of uncertainty they allow while still meeting the performance requirement. The greater the horizon of uncertainty (α) permitted, the better a scenario ranks. For example, if the Big Reserve scenario is able to meet the performance requirement R_k for species k up to a horizon of uncertainty of $\alpha = 0.4$, and the Small Reserve scenario no longer meets the requirement when $\alpha = 0.2$, the Big Reserve scenario outranks the Small Reserve scenario and receives one point. We construct additional preference matrices based on the ranking of the reserve scenarios assuming no uncertainty. Instead, the rankings and pairwise comparisons are based on the extinction risks of the species calculated using the best-estimate values for the parameters. The single-species preference matrices are constructed in the same fashion, with one point

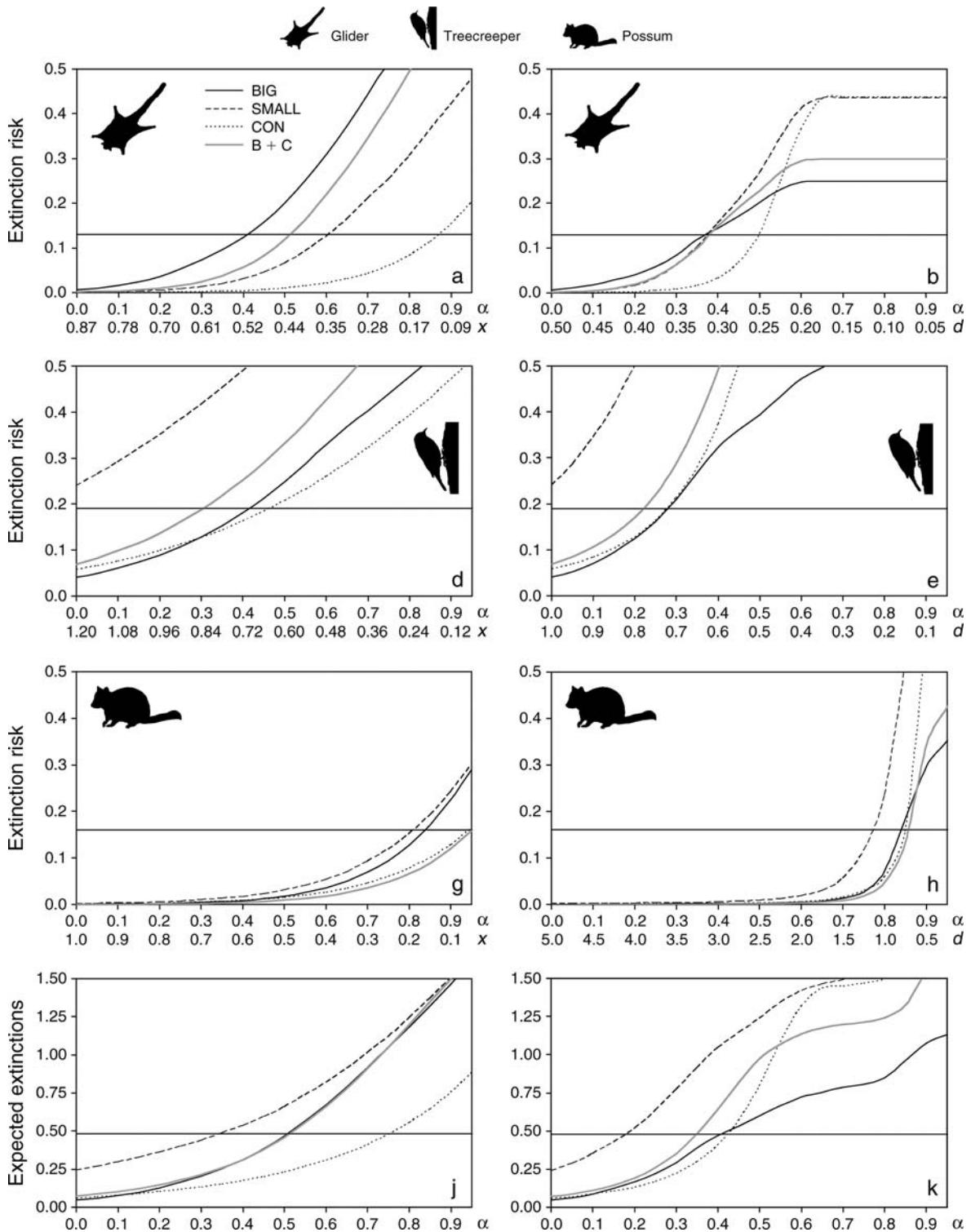


FIG. 2. Info-gap analyses for uncertainty in the extinction–area exponent x_k (panels a, d, g, j [first column]), the mean dispersal distance d_k (in kilometers; panels b, e, h, k [second column]), and both x_k and d_k (panels c, f, i, l [third column]), for each of the species (top three rows of panels) and the multi-species utility (the expected number of extinctions across all three species; bottom row). The upper bound of the set of possible values for expected species loss with increasing uncertainty (α) is shown for each of the alternative reserve scenarios. The performance requirements for each of the species in extinction risk, shown as solid horizontal lines, are $R_{gg} = 0.13$ for the greater glider, $R_{ic} = 0.19$ for the Red-browed Treecreeper, and $R_{bp} = 0.16$ for the mountain brushtail possum; the performance requirement for the expected number of extinctions is 0.48. The most robust scenario is the one that is

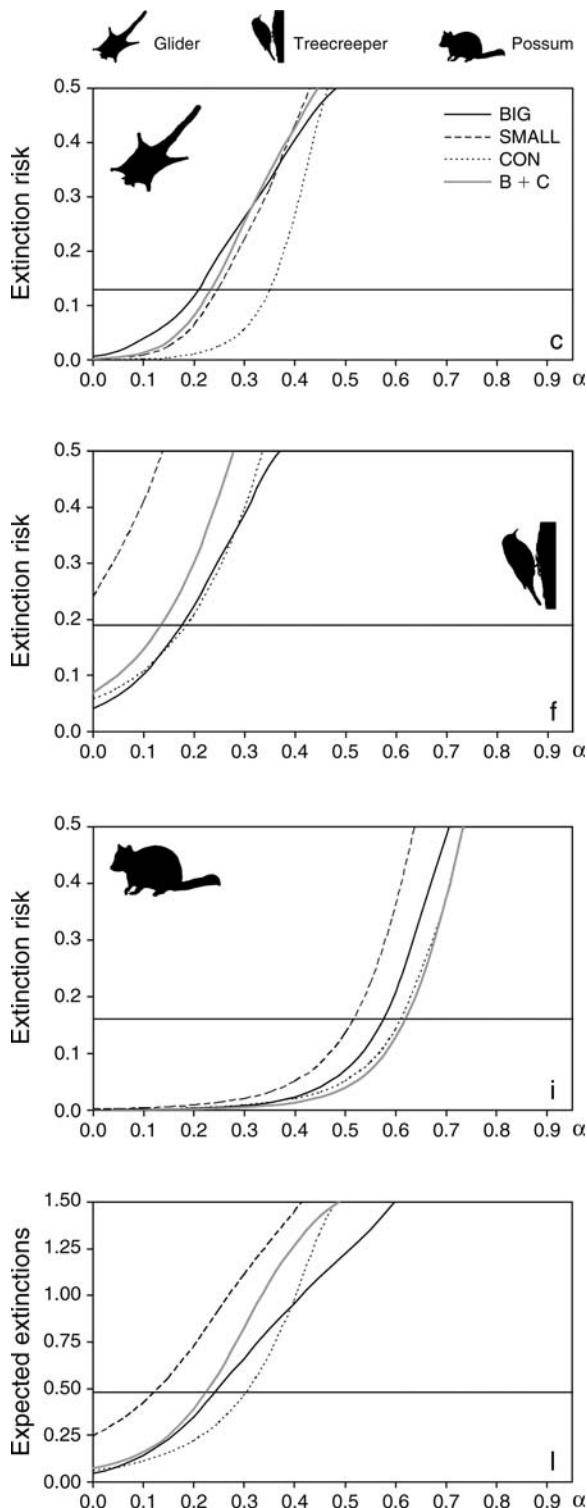


FIG. 2. Continued.

able to meet the performance requirement with the greatest amount of uncertainty α . In the analyses for uncertainty in a single parameter, the x -axis has two sets of unit numbers: values attributed to α (range: 0–1), and, under these, the corresponding values for the parameters d or x that show the lowest possible value for each parameter corresponding to the

allocated to the scenario with a lower extinction risk in pairwise comparisons.

RESULTS

Single-species analyses

For single-species decision making, the ranking of the management scenarios changes little in most cases, even under severe uncertainty (Fig. 2, Table 5). The extinction risks however vary greatly under uncertainty, although the graphs in Fig. 2 show only a limited range of extinction risk for clarity. The strength of preference between scenarios differs among the species. For example, the mountain brushtail possum has low extinction risks under all scenarios up to quite high levels of uncertainty (the best estimates for extinction risk range between 0.024% for the Big and Connected reserve scenario and 0.14% for the Small reserve scenario; Fig. 2g–i). By contrast, for the Red-browed Treecreeper the Small Reserve scenario performs very badly, not even meeting the performance requirement with the best estimate of extinction risk, while the Big Reserve and Connected scenarios remain close together in performance through increasing levels of uncertainty (Fig. 2d–f). The performances of the scenarios for the greater glider, while initially similar, gradually splay out with increasing uncertainty as the best solution becomes more clearly defined (Fig. 2a–c).

Although the ranking of the scenarios for each species is generally insensitive to uncertainty, there is one important change in the rank order of the scenarios: when the estimate for the extinction–area exponent x for the Red-browed Treecreeper is uncertain (Table 5, Fig. 2d). When the horizon of uncertainty α is higher than 0.2, the lowest possible value for the extinction–area exponent x drops below 1, reducing the value of bigger patches. This results in a change in the ranking of reserve scenarios, and the Connected scenario is propelled above the Big Reserve scenario when $\alpha \approx 0.3$. The first and last ranks for the mountain brushtail possum remain stable with uncertainty in the extinction–area exponent x , while the second- and third-ranked scenarios change places when the horizon of uncertainty α is between 0.35 and 0.4, corresponding to an extinction–area exponent x moving below 0.6 (Fig. 2g). There is no change in rank for the greater glider with uncertainty in the extinction–area exponent x (Fig. 2a). It is important to keep in mind that beyond a horizon of uncertainty of about $\alpha = 0.75$, the worst case value of the extinction–area exponent x falls below 0.3

← horizon of uncertainty α . For example, when modeling uncertainty in the extinction–area exponent x for the treecreeper (d), the Big Reserve scenario (BIG) is the optimum under no uncertainty ($\alpha = 0$). When $\alpha \approx 0.3$ and the value for x could be as low as $x = 0.84$, there is a change in rank, as the performance of the Connected scenario is more robust to uncertainty.

TABLE 5. Rankings of the reserve scenarios for each species.

| Reserve scenario | Greater glider | | | | Red-browed Treecreeper | | | | Mountain brushtail possum | | | |
|------------------|----------------|-----|-----|--------|------------------------|-----|-----|--------|---------------------------|-----|-----|--------|
| | Best | x | d | x, d | Best | x | d | x, d | Best | x | d | x, d |
| Big Reserve | 4 | 4 | 4 | 4 | 1 | 2 | 1 | 2 | 2 | 3 | 3 | 3 |
| Small Reserve | 2 | 2 | 3 | 2 | 4† | 4† | 4† | 4† | 4 | 4 | 4 | 4 |
| Connected | 1 | 1 | 1 | 1 | 2 | 1 | 2 | 1 | 3 | 2 | 2 | 2 |
| Big + Connected | 3 | 3 | 2 | 3 | 3 | 3 | 3 | 3 | 1 | 1 | 1 | 1 |

Notes: The ranking of the four reserve scenarios with no parameter uncertainty is shown in the “Best” column for each of the three species; the rankings of the reserve scenarios using the info-gap decision models (illustrated in Fig. 2) for uncertainty in the extinction–area exponent x_k , mean dispersal distance d_k , and both parameters are also shown.

† The extinction risk of the Red-browed Treecreeper under the Small Reserve scenario does not meet the performance requirement even when uncertainty is not considered.

and may be unreasonable. The estimated range of values for the extinction–area exponent x is generally thought to lie between 0.5 and 2.5 (Cook and Hanski 1995), though values outside this range may be possible (McCarthy et al. 2005).

Uncertainty in the mean dispersal distance d_k alters the ranking of scenarios only when the horizon of uncertainty is high, generating extremely low dispersal rates (Fig. 2). In such cases, the patches become effectively isolated and the conservative result is to reserve the biggest patches, giving preference to the Big Reserve scenario. The change in the ranking with increasingly uncertain dispersal is evident in the greater glider (Fig. 2b), the most dispersal-limited species. The glider is favored by several smaller reserves if there is some dispersal; where α is between 0.35 and 0.4, corresponding with mean dispersal distances between 0.325 and 0.3 km, a dispersal threshold is reached and there are several rank changes, although the Connected scenario still performs best; and when there is effectively no dispersal, the Big Reserve scenario is ranked highest (Fig. 2b). There is little impact on scenario rankings for the Red-browed Treecreeper, as the Big Reserve scenario is ranked best under all levels of uncertainty, although the performance of the Big Reserve scenario and the Connected scenario are very similar when the horizon of uncertainty α is between approximately 0.2 and 0.35, corresponding to $0.80 > d > 0.75$ (Fig. 2e). The impact of uncertainty in the mean dispersal distance is negligible on the rankings for the mountain brushtail possum, the best disperser, until the horizon of uncertainty α is above 0.90, which corresponds to a 10-fold overestimate of the best-estimate value for the mean dispersal distance (Fig. 2h).

When we allow for uncertainty in both the mean dispersal distance d and the extinction–area exponent x , the rankings are less robust to uncertainty (Fig. 2c, f, i). For example, the compound uncertainty in both parameters for the greater glider shows the same change in rankings at the dispersal threshold as when considering uncertainty in d alone (at $0.3 < \alpha < 0.4$), but exacerbated by the higher extinction risk with a decreasing value for the extinction–area exponent x (Fig. 2c). For the Red-browed Treecreeper, the change in ranking due to uncertainty in the extinction–area

exponent x where $\alpha \approx 0.3$, corresponding to $x < 1$, combines with the similar performance of the Big Reserve and Connected scenarios where $0.3 < \alpha < 0.4$ (and $0.80 > d > 0.75$). As a result, the Big Reserve scenario and Connected scenario alternate as the highest ranked as uncertainty increases (Fig. 2f). As the Connected scenario outranks the Big Reserve scenario for the interval of the horizon of uncertainty α that coincides with our choice of performance requirement, it is considered the most robust to uncertainty. Thus, the value assigned to the performance requirement can affect the ranking of the scenarios.

Multiple-species analyses

All three multiple-species methods give similar results (Table 6), generally ranking the Connected scenario as the best alternative. The Big Reserve scenario, although in some cases ranked highest, is usually second or third, alternating with the compromise Big + Connected scenario, while the Small Reserves scenario always ranks lowest.

The ranking of the reserve scenarios when using the multiple-species utility appears to be quite sensitive to uncertainty, with the rank order changing several times as the horizon of uncertainty increases (Fig. 2j–l). Note that three of the reserve scenarios perform very similarly from low to moderate levels of uncertainty; the Small Reserve scenario is by far the worst performer until relatively high levels of uncertainty, when other scenarios result in similar expected species loss. As the performance of three of the scenarios is quite similar, changes in scenario rankings result from small fluctuations in the expected species loss, due, for example, to the change in preference to the Connected scenario for Red-browed Treecreeper as the extinction–area exponent x moves below 1. The info-gap results also differ from the best-estimate ranking, with rank changes occurring under a small horizon of uncertainty, $\alpha = 0.1$, even though such sensitivity is not shown by any of the species on their own.

The multiple constraint info-gap method reflects the single-species patterns (Table 6, Fig. 3). The rankings are guided by the species most sensitive to uncertainty: the Red-browed Treecreeper in this case study. Only in one case, when ranking the scenarios with uncertainty in

TABLE 6. Reserve-scenario rankings for multiple species.

| Reserve scenario | Multi-species utility | | | | Multi-constraint | | | | Multi-criteria analysis | | | |
|------------------|-----------------------|-----|-----|--------|------------------|-----|-----|--------|-------------------------|-----|-----|--------|
| | Best | x | d | x, d | Best | x | d | x, d | Best | x | d | x, d |
| Big Reserve | 1 | 3 | 2 | 2 | — | 2 | 1 | 2 | 2 | 3 | 3 | 3 |
| Small Reserve | 4 | 4 | 4 | 4 | — | 4† | 4† | 4† | 4 | 4 | 4 | 4 |
| Connected | 2 | 1 | 1 | 1 | — | 1 | 2 | 1 | 1 | 1 | 1 | 1 |
| Big + Connected | 3 | 2 | 3 | 3 | — | 3 | 3 | 3 | 2 | 2 | 2 | 2 |

Notes: The ranking of the four reserve scenarios with no parameter uncertainty is shown in the “Best” column for each of the three methods for decision making under uncertainty: the info-gap decision model based on the multi-species utility (illustrated in Fig. 2), the multi-constraint info-gap decision model (illustrated in Fig. 3), and the multi-criteria decision analysis. Rankings are also presented for uncertainty in the extinction–area exponent x_k , mean dispersal distance d_k , and both parameters.

† The extinction risk of the Red-browed Treecreeper under the Small Reserve scenario does not meet the performance requirement even when uncertainty is not considered.

the extinction–area exponent x , does the greater glider become the species that guides the decision by tolerating the smallest amount of uncertainty α , placing the Big Reserve scenario second (Fig. 3). However, the overall result is not changed, as the red-browed treecreeper ranks the Big Reserve scenario second regardless. The greater glider and the mountain brushtail possum also occasionally exchange places in the order of species that can tolerate the greatest amount of uncertainty and still meet the performance requirement.

The multi-criteria analysis gives the same ranking of scenarios when uncertainty is ignored and when considering uncertainty in the different parameters (Table 6): the Connected scenario always ranks best, followed by the Big + Connected and Big Reserve scenarios, which tie in second place when uncertainty is ignored; the Small Reserve scenario is always last. The total preference matrix for the multi-criteria analysis across all species is shown in Table 7 for the best-estimate parameter values.

DISCUSSION

In this study we present three alternative methods for making management decisions for the persistence of multiple species that incorporate uncertainty into the decision-making process. This is the first study that explores the impact of gaps in scientific knowledge for the complex conservation problem of planning for multiple species based on population models.

The rankings of the management alternatives for each of the species in this case study are generally robust to uncertainty in parameter values, although predictions of extinction risk vary greatly and are likely to be inaccurate. Our results support previous studies illustrating that uncertain parameter estimates can be useful in decision making based on ranking management options for single species, in particular as the toolbox for dealing with uncertainty expands (e.g., Lindenmayer and Possingham 1996, Drechsler et al. 2003, McCarthy et al. 2003, Halpern et al. 2006). The changes in the rank order of the management actions in the single-species cases could generally be predicted from metapopulation theory. For example, the best reserve system for the Red-browed Treecreeper changes as the extinction–area

exponent x for that species decreases with increasing uncertainty α . This agrees with Frank’s (2002) rule of thumb: where the extinction–area exponent of a species, x , is >1 , patch size is of greater importance than spatial configuration. Our results suggest precautionary rules of thumb for decision making under uncertainty: if managers believe the effects of environmental stochasticity may be large, or catastrophes frequent or severe, connectivity should be favored over patch size. If dispersal is doubtful, the largest areas should be protected: the “metapopulation” may in fact be disjoint populations.

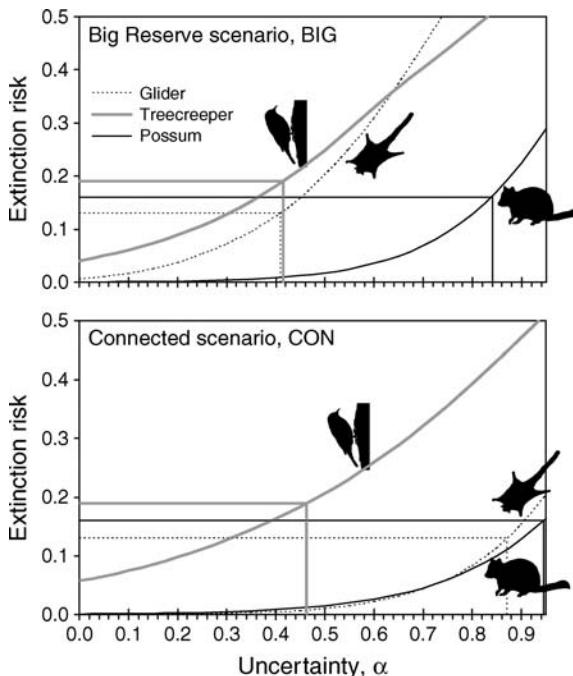


FIG. 3. The multiple constraint info-gap analysis for uncertainty in the extinction–area exponent x , showing the Big Reserve (BIG) scenario and the Connected scenario (CON). The performance requirements for each species are shown in the lines parallel to the x -axis, with their corresponding maximum α values. The Connected scenario is ranked number 1, followed by the Big Reserve scenario in second place.

TABLE 7. Total preference table for the multi-species, multi-criteria decision analysis when uncertainty is not considered and best-estimate parameter values are used.

| Reserve scenario | Big Reserve | Small Reserve | Connected | Big + Connected | Mean no. times preferred (+) |
|---------------------------|-------------|---------------|-----------|-----------------|------------------------------|
| Big Reserve | 0.00 | 0.67 | 0.67 | 0.33 | 1.67 |
| Small Reserve | 0.33 | 0.00 | 0.00 | 0.33 | 0.67 |
| Connected | 0.33 | 1.00 | 0.00 | 0.67 | 2.00 |
| Big + Connected | 0.67 | 0.67 | 0.33 | 0.00 | 1.67 |
| Mean no. times beaten (-) | 1.33 | 2.33 | 1.00 | 1.33 | |

We have demonstrated that uncertain data can be used to make robust decisions for multiple species. The multiple-species methods that rely more heavily on the rankings of the single species, which are quite robust to uncertainty, provide similarly robust decisions, compared with methods that depend on the estimates of extinction risk, which are sensitive to uncertainty. The multi-criteria decision analysis uses only the rankings of the management options from each of the species. As the rankings for each species change relatively little, the overall ranking of the management alternatives across the species is very stable between the best-estimate values and the info-gap analyses of uncertainty in the different parameters.

The multi-constraint info-gap analyses produced similar rankings in the reserve scenarios when including uncertainty in the extinction–area exponent x_k , the mean dispersal distance d_k , and both x_k and d_k across all three species. This is because the results of the multi-constraint analyses largely depend on one species, the red-browed treecreeper. There are several reasons why a species will drive the decision in such a multi-constraint analysis: the species may have the greatest increase in extinction risk with uncertainty in one or more scenarios (such as the red-browed treecreeper, compared with the mountain brushtail possum); the rank order of scenarios may change with increasing uncertainty; or the species' performance requirement may be the most restrictive and intolerant of uncertainty, and thus have low robustness. In this case the performance requirement for the red-browed treecreeper was relatively low because it benefited least from a patchy environment, due to its larger home range size and higher extinction–area exponent x . Therefore the means of setting the performance requirement prejudiced the multi-constraint decision towards the red-browed treecreeper. Had we used alternative criteria for calculating the performance requirement in this study, we may have had different results. This is an issue that we return to below.

The ranking of the reserve scenarios when combining the extinction risks in the multi-species utility is the least robust to uncertainty, with changes in the rank order of scenarios occurring with small (10%) changes in parameter estimates. While the results are not reported here, we performed info-gap analyses using other multi-species utilities, such as the joint probability of no extinctions and adding mean times to extinction, with

similar outcomes. Sensitivity to uncertainty may be a problem in using multiple-species utilities in general, which needs to be weighed against the benefits of such utilities: they provide a readily interpretable and measurable currency, and can be used as an objective in an optimization framework (Hof and Raphael 1993, Williams and Araújo 2002, Nicholson and Possingham 2006), unlike the form of multi-criteria decision analysis used here, which can be used for post hoc ranking only (for a review of multi-criteria methods see Moffett and Sarkar [2006]). More importantly, the use of the multi-species utility allows us to examine the performance of the management options over the entire range of uncertainties. There are multiple rank changes among the top three reserve scenarios (Big Reserve [BIG], Connected [CON] and Big + Connected [B + C]) because they perform similarly. The graphs in Fig. 2 enable us to see the range of uncertainty and parameter values under which the reserve scenarios diverge in performance. The multi-criteria decision analysis we perform does not permit this; in the method used here, the rankings do not differentiate between large or small differences in performance, and any small changes in reserve performance as uncertainty increases are removed at an earlier stage in the decision process.

The sensitivity of the multi-species utility to uncertainty allows us to perceive the dual role of info-gap analysis: firstly, assessing the robustness to uncertainty of the rank order of the management alternatives; and secondly, exploring how much uncertainty can be tolerated and still have the management scenario deliver the desired performance, forcing managers to state the management goal clearly and in a justifiable manner. When the rankings of the management options change, the value attributed to the performance requirement can alter the management decision. For example, when modeling uncertainty in both the extinction–area exponent x and the mean dispersal distance d , the Red-browed Treecreeper ranks the Connected scenario as the best alternative; it permits the greatest horizon of uncertainty α before the extinction risk reaches the performance requirement. Yet the Connected scenario only outranks the Big Reserve scenario for a short horizon of uncertainty α that coincides with the performance requirement. Had the performance requirement been set higher, or lower, the best option would have been the Big Reserve scenario. The performance

requirement needs to be carefully chosen and possibly subjected to a sensitivity analysis. As the aspirations rise (i.e., performance requirement for extinction risk gets smaller), robustness decreases; a trade-off arises between feasibility and aspiration as it gets harder to achieve the aspiration with much certainty (Ben-Haim 2004).

There are many sources of uncertainty other than parameter estimates that we have not dealt with in this paper, but may be incorporated in a similar framework. The choice of modeling framework has been identified as one of the most important sources of uncertainty (Regan et al. 2002, Burgman et al. 2005), which we have not attempted to address here. Model uncertainty may be assessed by comparing performance across a range of alternative models to the model believed to best describe the system, giving an array of discrete measures of performance, as opposed to the continuous range derived when modeling parameter uncertainty (Ben-Haim 2004). We assume that the current model and simplification of population processes, such as minimum patch size, are appropriate, although the applicability of the patch-occupancy or classic metapopulation framework to real populations has been questioned (Baguette 2004, Shreeve et al. 2004). The use of approximation models, such as the formula used in this study (Frank and Wissel 1998, 2002), has been identified as a further class of model uncertainty (Regan et al. 2002). The underlying predictions of species distributions will form another source of uncertainty that may affect decisions (Burgman et al. 2005, Wilson et al. 2005, Moilanen et al. 2006). While adding to uncertainty, additional data such as species distributions and socioeconomic data may also act as constraints, limiting the choices available to the decision maker and potentially making uncertainty in parameters less vital. For example, if species are not found across all areas, their distributions are more likely to determine which areas are selected than the species ability to disperse between them.

What do the results of this study imply for making optimal decisions for the persistence of multiple species? There are two forms of optimal decision making: decisions that are optimal when uncertainty is not considered, such as those generated by reserve selection and other optimization algorithms (Bever et al. 1995, Williams and Araújo 2002, Nicholson et al. 2006); and decisions that are optimal because they are robust to large or varying levels of uncertainty. Decisions based on the best-estimate parameter values that ignore uncertainty are at best risk-neutral and potentially risk-seeking because they may not be robust to uncertainty. Risk-averse managers may prefer a smaller reward with greater certainty, and therefore seek management scenarios that are able to withstand uncertainty (Burgman 2005). Once again, this illustrates the importance of ascertaining and clearly stating the goals of conservation (Guikema and Milke 1999, Nicholson and Possingham 2006), as different strategies may lead to different management outcomes.

We discover that it is possible to make robust conservation decisions even when the uncertainties and complexities of the multiple-species problem appear overwhelming. Rather than ignoring the uncertainty, the key is to acknowledge and incorporate it into the decision process to identify management actions that are robust to uncertainty while still delivering the desired outcomes. We find it comforting that in this case the best management choice is relatively insensitive to the method used to include the uncertainty: the different multiple-species methods return the same ranking among the management alternatives, guiding the management decision in the same way. However, the ultimate decision is likely to differ from the decision when uncertainty is ignored, supporting the importance of considering uncertainty in the decision-making process. Analysis of the gaps in knowledge is particularly important in conservation, where data are inevitably incomplete but decisions need to be made quickly, to ensure transparent, defensible, and honest decision processes.

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