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Recovery
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Use of models to distinguish places of lesser and greater importance for species persistence

Technical guidance and policy discussion

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Cover image: Long-nosed potoroo. Image: Kristian Golding, CC BY NC 2.0, Flickr

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Executive summary

We define important habitat as that which, if removed, would lead to a material increase in extinction risk for a threatened species. Operationally, application of the concept will vary from species to species according to the availability of knowledge. Here we illustrate how important habitat can be consistently identified in a regulatory setting where our knowledge:

- is restricted to environmental variables that underpin better quality habitat,
- additionally includes good understanding of the species' ecology.

We illustrate how to delineate important habitat in these circumstances using three case study species – Greater glider, Growling grass frog, and Long-footed potoroo; and three modelling approaches – Spatially explicit population viability analysis (PVA), metapopulation modelling and habitat suitability models (HSM). For each species and each technique we illustrate how risk curves can be used to inform regulation aimed at protection of important habitat. The different modelling approaches vary in their relevance and rigour. Spatially explicit PVA and metapopulation modelling is more informative than HSMs but are currently unavailable for many species.

Thresholds for defining important habitat may be conditioned by the conservation status of the species and the risk tolerance of regulators. We outline a proposed regulatory framework that incentivises a transition to methods of greater rigour and relevance. Should habitat protection be given greater regulatory emphasis, thresholds can be informed by an exploration of net social benefit via formal cost-benefit analysis, alongside risk curves prepared using the methods described in this report.

1. Introduction

Conservation management relies on information about the current and future distributions of threatened species and habitats. There is a need for credible modelling approaches that can be consistently applied across the many species of concern, including those with limited data.

This report provides two contributions to the management of threatened species habitat. The spine of the report deals with the technical challenge of how to characterise risk stemming from habitat loss. The solutions offered provide a robust and pragmatic basis for policy response, no matter what form that response may take.

The second contribution is more speculative. We provide an outline of a regulatory framework that utilises and extends insights from technical analyses. The framework and accompanying policy commentary should not be interpreted as recommendations for adoption. Rather, we hope these elements will provide a foundation for discussion and maturation of what is a difficult area of environmental regulation.

Regulatory context

The Environment Protection and Biodiversity Conservation Act 1999 provides a register of *critical habitat*, the application of which is largely confined to Commonwealth land. In the preparation of conservation advice and recovery plans, policy-makers may invoke the concept of *habitat critical* as a means of emphasising protective measures for areas deemed especially important to a threatened species. In neither context is there a formal, repeatable method for identifying critical habitat or habitat critical.

Irrespective of the policy or statutory mechanism invoked, there is a generic challenge in distinguishing habitat of lesser and greater importance in a way that offers transparency and repeatability. The question of whether or not loss of some specified parcel of habitat will lead to harm arises routinely (directly or indirectly) in development proposals, both in the context of individual approvals and strategic assessments. It is reasonable for regulators and decision-makers to ask what the change in risk will be with and without the development and its accompanying loss of habitat. Where the proposed development coincides with the last or near-last known population of a species the exposure to additional risk is abundantly clear. But there will be many settings in which the immediate and direct consequences of loss of a small portion of a species habitat or distribution will be slight. Over several or many decisions the cumulative adverse impact of incremental loss of habitat could be very substantial. Our view is that the current regulatory setting offers little insulation against the risk of piecemeal cumulative loss of habitat. This report proposes an approach to habitat protection that can guard against the cumulative consequences of incremental habitat loss.

The loss of habitat is an environmental stressor, just as contaminants in soil, air and water are environmental stressors. The scientific discipline underpinning environmental regulation of contaminants is ecotoxicology, where the cornerstone is laboratory testing of toxicity on test organisms and the reporting of results as dose-response curves. The response of interest is typically mortality, or some sub-lethal effect, at increasing exposures, doses or contaminant concentrations (Figure 1). The regulatory framework for any individual contaminant, including the issuing of licences to pollute, spins on the laboratory-based specification of a dose or concentration beyond which the contaminant causes material harm (Suter 1993).

The mirror image of the standard dose-response curve is created if we use survivorship rather than mortality on the y-axis. The analogous descriptor of risk for conservation outcomes is species persistence, or more formally, the expected minimum population size (McCarthy and Thompson 2001) derived from a 'laboratory' based ecological model. Instead of dose or concentration on the x-axis, we might be interested in how population viability changes with incremental increase in environmental stress stemming from progressive loss of habitat (Figure 2). The resulting 'dose-response' curve for habitat loss can be used to inform regulatory thresholds. We note that in this context, a permit to clear habitat is analogous to a licence to pollute. Permits or licenses can be issued only to the point where harm may materialise, and no further.

Here we define habitat of greater importance as that which, if removed, would lead to material *change in risk* as we progressively move from removal of *lower to higher quality habitat*. In Section 2 we describe and illustrate how dose response curves for habitat loss can be prepared. In section 3 we revisit the regulatory context.

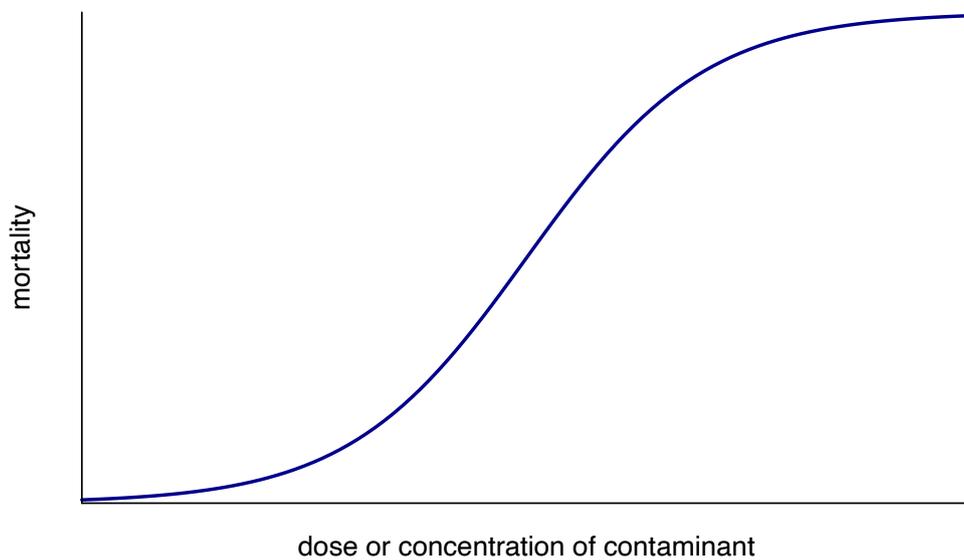


Figure 1. Stylised classic sigmoidal dose response curve used to describe the impact of progressively higher doses or concentrations of a contaminant in the environment.



Figure 2. Conceptual basis for habitat protection based on a 'dose-response' curve describing change in extinction risk with increasing stress from loss of habitat. Two nominal regulatory thresholds are indicated. The yellow threshold is set where the slope of the response begins to steepen. The red might represent a threshold beyond the need to retain habitat is a near necessity for species survival.

2. The technical challenge of characterising risk stemming from habitat loss

In an ideal world we would possess clairvoyance and see with perfect clarity the consequences of habitat loss under various scenarios (Howard 2007). The nearest thing we have to such insight is spatially-explicit population viability analysis (PVA), where the output is a directly relevant statement of risk over a specified time horizon, but PVA can be demanding with respect to information and time. In some settings, metapopulation modelling will offer a more efficient approach with little or no loss of clarity or predictive performance. But the demands of metapopulation modelling, while less than that of PVA, are not trivial.

There are few species for which a PVA or metapopulation model has been done. We might therefore need to use tools offering less clarity, but reasonable insight. Habitat suitability models (HSM), including Maxent, boosted regression trees, and logistic regression, among others, provide understanding of important correlates and their spatial distribution. Although they offer only partial and tangential insight into risk, they are readily available for many threatened species.

This report explores these three modelling tools in the context of discerning habitat or sites of lesser and greater importance. We illustrate their use with three threatened species. Specifically:

- Greater glider application in PVA, where the output is a descriptor of extinction risk of direct interest - expected minimum population size (McCarthy and Thompson 2001).
- Growling grass frog application in metapopulation modelling, where the output, minimum number of occupied sites, is a close proxy for extinction risk.
- Long-footed potoroo application in habitat suitability modelling, where the descriptor of risk is quality adjusted habitat, a relatively distal and coarse proxy for risk.

2.1 Population viability analysis

Approach

Spatially explicit PVA models link habitat suitability with other demographic (e.g. dispersal, vital rates) and landscape (e.g. clearing, climate) processes to simulate species persistence in space and time (Figure 3). Data on initial abundances of species – either observed/surveyed or simulated – is required. Augmenting correlative HSM with population dynamics is not a new practice (see Akçakaya et al, 2004; Keith et al, 2008), and has been demonstrated to produce better forecasts of species distributions (Fordham et al, 2018). PVA can be a useful extension to correlative HSM as they use predictions of occurrence or abundance as inputs to simulations. Manually combining model frameworks for all of the components required in PVA (e.g. dispersal, growth, density dependence, biotic interactions) is possible (Merow et al, 2016), but software has been created to assist analysts to organise input data, streamline computations, and visualise results. Visintin et al (2020) have developed spatially explicit PVA software that is freely available, highly customisable, and computationally efficient called STEPS.

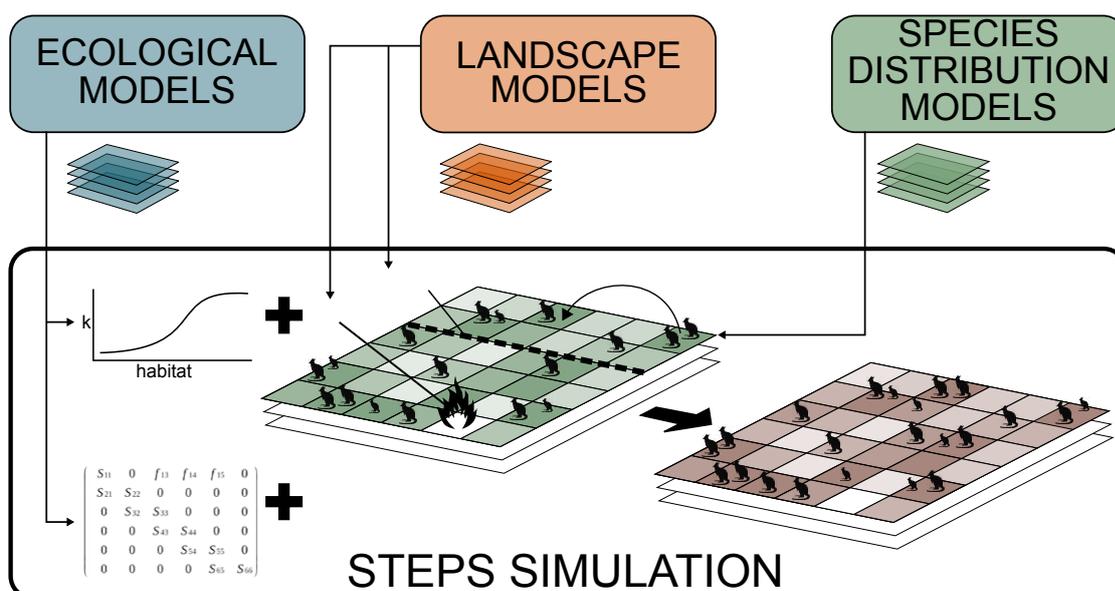


Figure 3. Spatially-explicit PVA modelling enables integration of spatial products from other modelling software, including climate, landscape, physiological and disturbance information to simulate changes in species abundance through space and time. These simulations require a habitat suitability layer, some initial abundances – either from existing data or simulated, and some information on vital rates (survival and fecundity) and dispersal characteristics for a species. Figure taken from Visintin et al (2020).

Example application: greater glider

Greater gliders (*Petauroides volans*) are a large (900-1700 grams), arboreal possum capable of extended aerial travel and are found in forests along the east coast of Australia. Greater gliders (hereafter 'gliders') are vulnerable to environmental change because they have slow life history characteristics, low thermoregulatory capacity and their dispersal is limited by the presence of tree canopy (Taylor et al, 2007). They also have specialist habitat requirements including large tree hollows (and therefore mature forests) for nesting and nitrogen-rich leaves from specific eucalypt species for suitable forage (Wagner et al, 2021). They were recently listed as "vulnerable" under Australia's EPBC Act (Commonwealth of Australia, 1999) based on data showing population declines (Lindenmayer and Sato, 2018) and loss of habitat. Gliders face the cumulative impacts of a range of threats including habitat loss, fire and climate change (Wagner et al, 2021).

We performed spatially-explicit population simulations for gliders across the southern part of their range in the states of New South Wales and Victoria for a projected time horizon of 30 years (to year 2050). Our model included a small amount of environmental stochasticity, density dependence in the vital rates, fire affected survival, predation, demographic stochasticity, dispersal based on available carrying capacity and landscape quality, habitat modification by fires, and was spatially organised by raster grids at a resolution of 1000m x 1000m.

Predicted habitat suitability for the entire range came from a boosted regression tree model used to fit environmental data to glider occurrences and projected to future climate conditions. Original predictions were at 250m x 250m resolution and were confined to the southeast boundary for one of the newly classified three species of greater glider per recent work (McGregor et al., 2020). Only grid cells that could potentially contain populations of gliders were included – i.e. areas where gliders were known to be absent were excluded from the analysis. Known observations of gliders were plotted over the predictions and indicated plausible values. We predicted habitat suitability to all future years in the simulation time horizon based on climate projection data from the Australian Commonwealth Scientific and Industrial Research Organisation (CSIRO – see Clarke et al, 2011) and then aggregated the spatial grids to our simulation resolution of 1000m x 1000m (Figure 4).

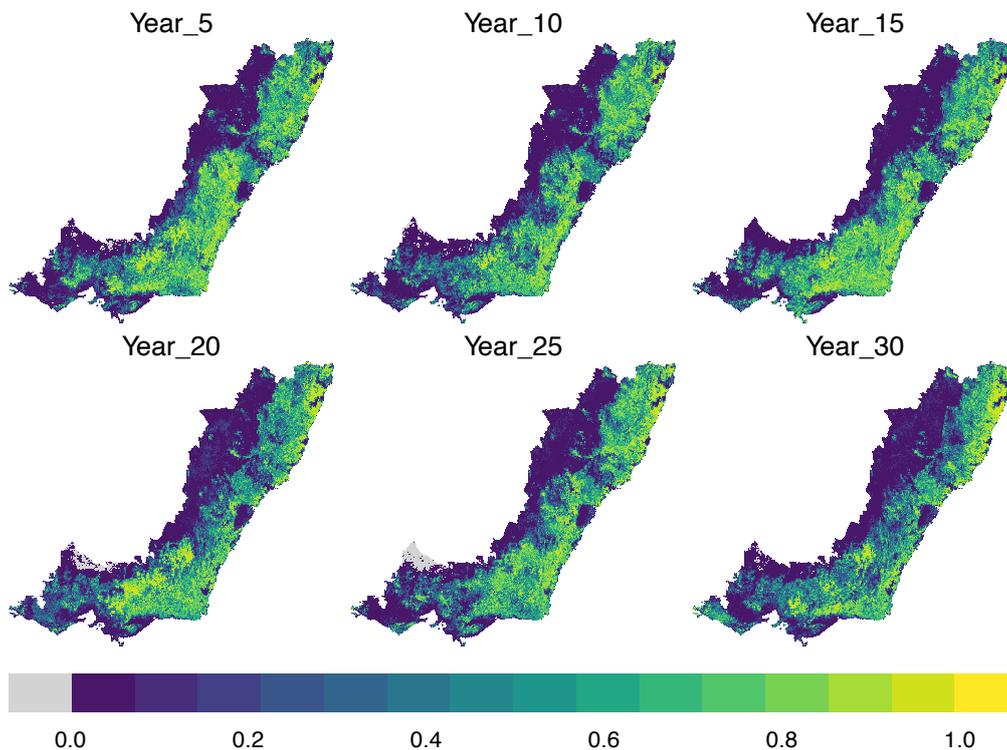


Figure 4. Predicted distribution of relative suitable habitat across the study area for select years. Zero indicates unsuitable habitat, with an increase in quality of habitat indicated by a scale from zero to one (one being the best habitat).

A maximum number of individuals per grid cell is based on one female per ha (Henry, S.R., 1984) or 100 individuals per grid cell in the absolute best habitat. The relationship between habitat suitability and carrying capacity (k) was controlled by a logistic function that allowed more individuals in higher quality habitat at a greater rate than in lower quality habitat (Figure 5).

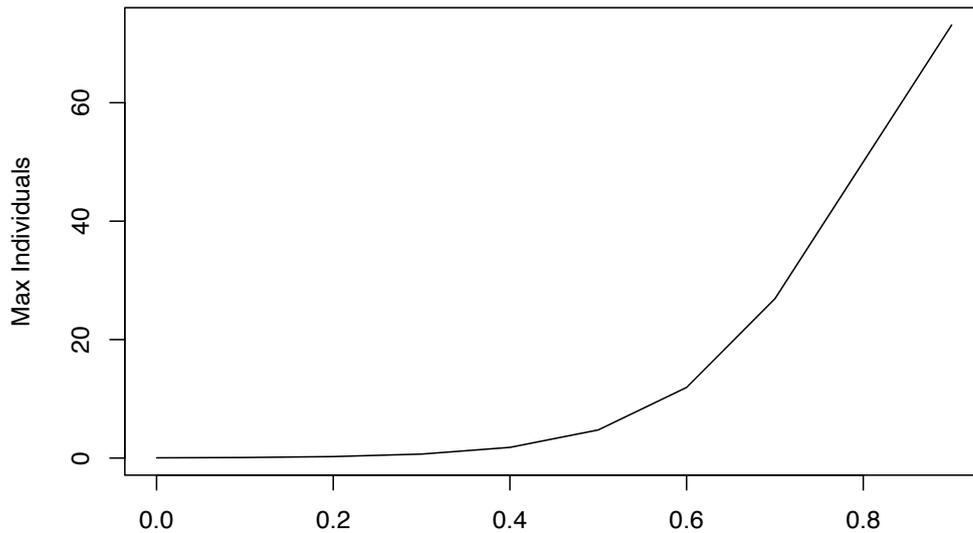


Figure 5. Relationship between habitat quality and the maximum number of individuals allowed to be in an area (i.e. carrying capacity). Note, this relationship can take several forms and is best determined by using empirical data.

Vital rates of survival and fecundity were defined in a single-sex, multi-stage transition matrix and the life-stages were classified as newborns, juveniles and adults. The transition matrix was based on a female-only, post-breeding, age-based model adapted from Possingham (1994) with an intrinsic rate of change (λ) of 1.05. All values were randomly adjusted within all simulations to represent environmental stochasticity. Demographic stochasticity was also present in all simulations.

Initial populations were allocated according to habitat suitability in each cell. Populations began at a fraction of their theoretical carrying capacity in cells that were randomly assigned as "occupied" based on Bernoulli trials in each cell where the probability was the habitat suitability value. This was to allow glider populations to increase in the absence of all threats and density-limiting factors. It was also used to approximate a total population size across the range that was closer to an expectation of between 250,000 and 300,000 individuals. Each simulation began with approximately 280,000 individuals. The proportions of abundance for each life stage in each cell were based on the stable age distributions calculated from the transition matrix (Figure 6).

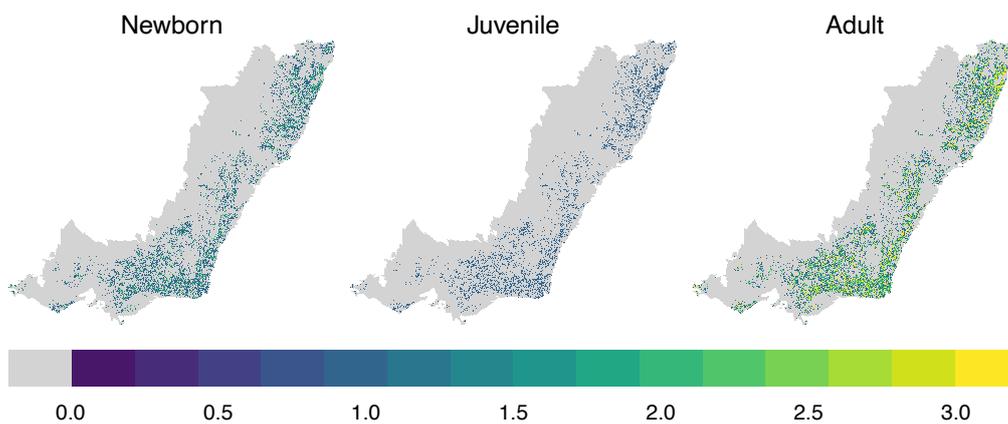


Figure 6. Distributions of initial populations for each life-stage across the study area used for all simulations. Zero (light gray) indicates no individuals in a grid cell. Note: initial populations were rounded whole integers (e.g. 1, 2, 3, etc).

Movements around the landscape were controlled by carrying capacity and habitat suitability and only juveniles and adults dispersed. The proportions of gliders that dispersed from populations were controlled by the relationship to carrying capacity – i.e. the maximum number of individuals. More gliders dispersed as populations approached their respective carrying capacities - up to 80% of a population dispersing for juveniles and 20% of a population dispersing for adults. Movements were based on cellular automaton (individuals moved according to logical rule sets). Individuals were allowed to move up to a maximum number of cells - zero for newborns, two for juveniles, and one for adults. Directions were randomly selected, however, weighted more favourably based on good habitat and/or available space.

We explicitly included a background rate of predation in our simulations. We reduced the population of gliders due to predation by owls throughout the simulations (based loosely on Kavanagh, 1988). In each timestep of the simulation, we calculated the total area of good habitat for gliders in which owls may predate. We then determined the total pairs of owls that could be supported in the good glider habitat (based on Soderquist, 2007). We assumed foraging every night of the year and that this would reduce only the juvenile populations that were targeted by 20%.

The 2020 bushfires were included in our simulation and based on fire severity maps for Victoria and New South Wales. We also simulated hypothetical fires across the study area for the entire simulation period (since having no fires would be unrealistic). To do so, we examined the history of fire extent and frequency across the landscape to determine a plausible trajectory. Once a trajectory was established, we used a function that randomly burned the landscape to match the intended total hectares burnt for each year in the simulated trajectory. The number of individual fires for each year was randomly selected between one and the 95th percentile of total historic annual fires and the total hectares burnt was randomly allocated to each individual fire (Figure 7). Note that since we did not have good data on the intensities of historic fires, we burnt the landscape at a fine scale (250m x 250m) and then coarsened to the simulation resolution which summed the number of burnt cells (between zero and four) and then divided by the total cells (four).

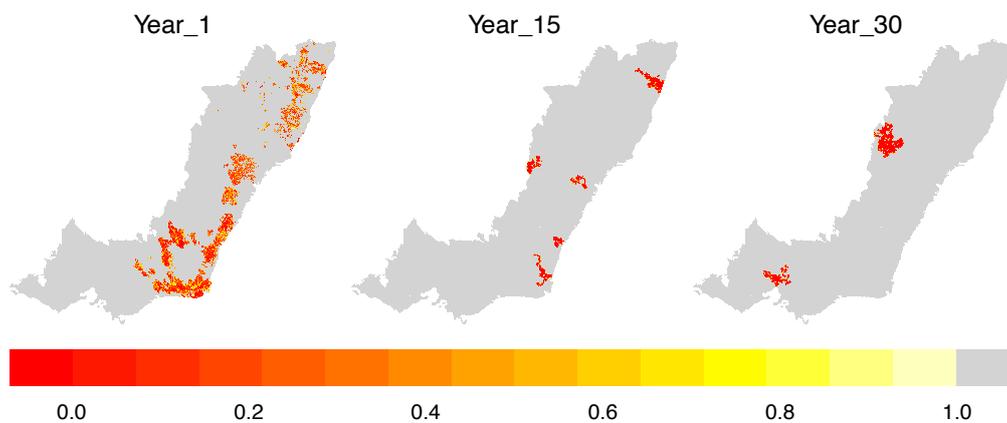


Figure 7. Predicted distribution of fire across the study area for select years. One indicates no fires with a decrease in fire severity indicated by a scale from one to zero (with zero being the most intensive fires). Simulation year one (2020) contains actual recorded fires whereas the remaining years contain simulated fires based on historic records.

We ran a baseline simulation and four additional simulations where we removed habitat below thresholds based on the 35%, 55%, 75%, and 95% quantiles of the initial habitat suitability values. This was done to test the outcomes of protecting the top 5%, 25%, 45%, and 65% of identified habitat (e.g. Figure 8). Each simulation was replicated 20 times to allow stochastic (random) effects to propagate through the projections and we recorded the expected minimum populations (McCarthy and Thompson, 2001), which were used to compare the effects of reducing habitat to each of the quantile thresholds.

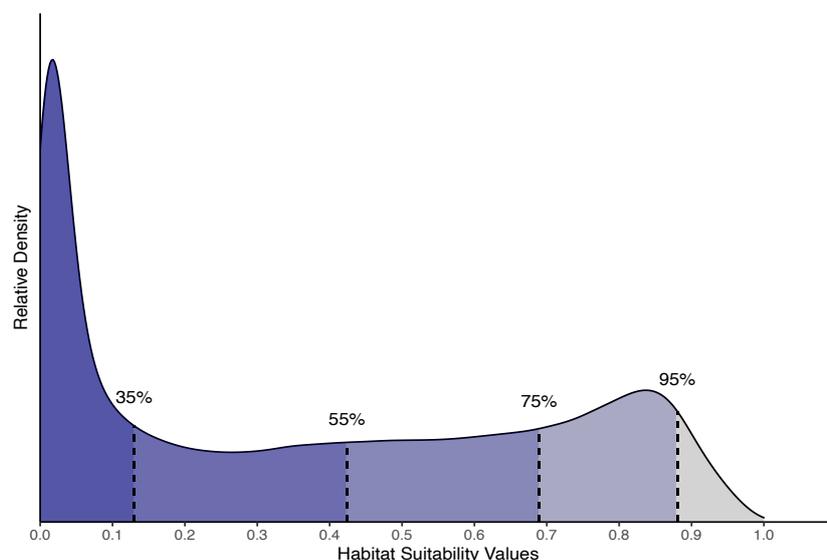


Figure 8. Density distribution of all non-zero initial habitat suitability values. Quantiles were selected to capture all of the values within 35%, 55%, 75%, and 95% of the area under the density curve (dashed lines). Each dashed line indicated includes all of the habitat suitability values to the left of the line and its threshold value is identified where the line intersects the x-axis.

Risk characterisation

The risk curve shown in Figure 9 plots expected minimum population size against progressive removal of habitat from lowest quality to highest. Moving from left to right, the points on the plot represent loss of 0%, 35%, 55% and 75%, 95%, and 100% of the non-zero suitable habitat, by area.

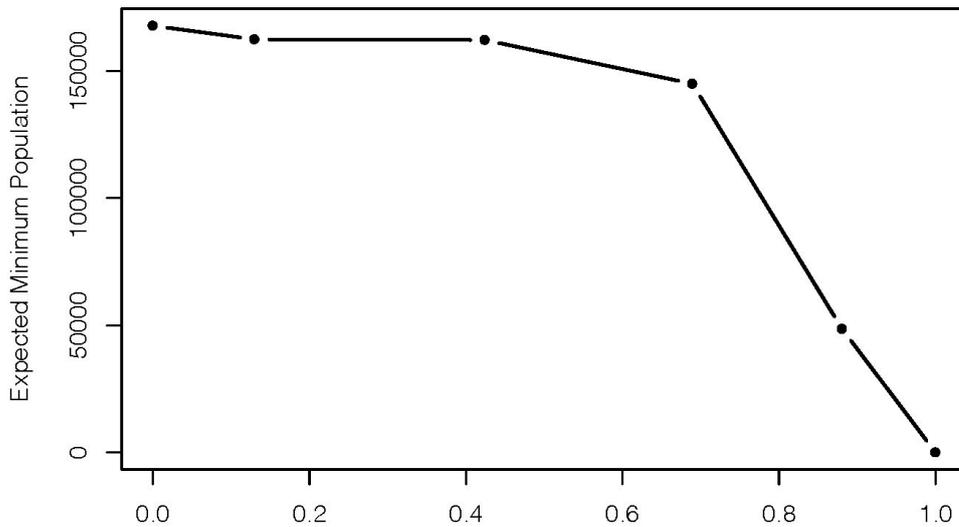


Figure 9. Risk curve describing the impact of habitat loss, progressing from least suitable to most suitable, on Greater glider.

Risk doesn't materially change until about 75% of the least suitable habitat is lost. This outcome may be surprising. How can it be that loss of some habitat, even if it is of lesser quality, makes no difference (or next to no difference) for a threatened species? Sometimes habitat availability isn't a limiting factor, and sometimes even when it is a limiting factor, the modest carrying capacity of lesser habitat makes negligible difference to outcomes. For some species there is no reasonable prospect of extant populations being able to disperse and access faraway habitat. We note that the dispersal capabilities of Greater glider over a 30 year time horizon are reasonably modest.

2.2 Metapopulation model

Approach

Metapopulation models determine the likelihood of discrete populations persisting through time by incorporating information about site characteristics (e.g. size, quality) and the connections between them (Hanski, 1994). Like spatially-explicit PVA, metapopulation models consider dispersal dynamics and population viability, be it at the patch (or site) level. These models differ from spatially-explicit PVA by implicitly assuming internal population dynamics such as survival/fecundity, density dependence, and individual-based actions.

Example application: growling grass frog

We model growling grass frog (GGF) populations in a small, fragmented landscape in Victoria. The GGF is federally listed as vulnerable under the EPBC Act and is threatened by habitat modification and climate change. As a large (>100mm in length) frog, the GGF relies on healthy matrices of terrestrial and aquatic habitats for shelter and breeding. Dispersal between sites is crucial for the GGF and urbanisation is a prime threat to movement.

The metapopulation model we demonstrate here was originally developed by Geoff Heard and the methods are fully described in Heard et al (2013) and Rose et al (2016). The metapopulation was comprised of 222 population sites in the north of the greater Melbourne metropolitan area. Site presence and absence records from the last survey round conducted in 2016/2017 indicated that 207 out of 222 sites were still present (i.e. not destroyed or modified). In the model, occupancy was fitted to three site characteristics; effective size of site (i.e. area moderated by hydrological features), proportion cover of aquatic vegetation, and type of wetland (lentic or lotic). The model also considered connectivity between the populations based on size, distance, and urban barriers.

Using the fitted parameters of the model, we simulated the probability of site persistence over thirty years beginning with site occupancy data (recorded in 2016/2017) to set initial occupancies. Sites which were found to be no longer present in the latest surveys were excluded from the analysis. Fifty eight out of 207 sites were initially occupied (a prevalence of 0.28).

We ran 500 replicates of a baseline simulation to determine the mean probabilities of persistence for all sites. The probability of site persistence is determined by environmental characteristics of a site and can be considered an analogue to habitat suitability. We then ran additional simulations where we removed sites, again below thresholds based on the 35%, 55%, 75%, and 95% quantiles of the mean probabilities of site persistence in the baseline simulation (Figure 10). For each simulation, we recorded the mean minimum number of occupied sites.

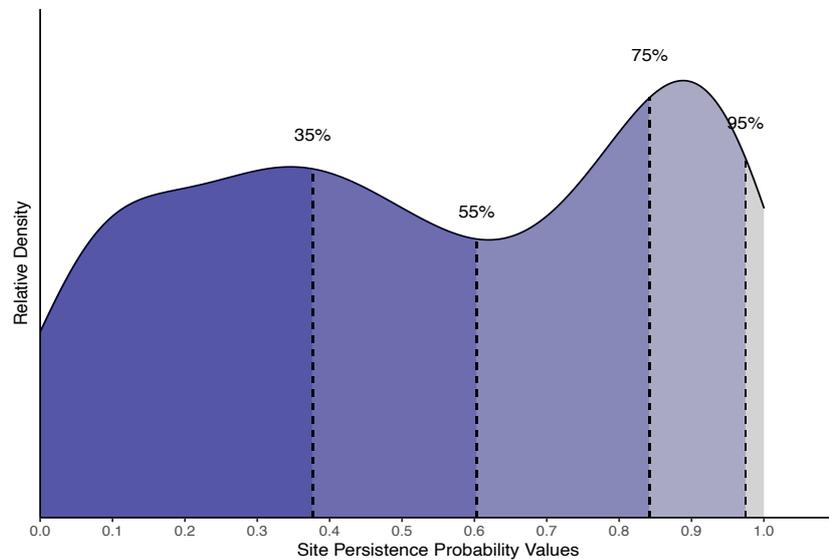


Figure 10. Density distribution of all non-zero site persistence probability values. Quantiles were selected to capture all of the values within 35%, 55%, 75%, and 95% of the area under the density curve (dashed lines). Each dashed line indicated includes all of the persistence probability values to the left of the line and its threshold value is identified where the line intersects the x-axis.

Risk characterisation

The 'dose-response' risk curve for the impact of habitat loss on GGF is qualitatively different to that of Greater Glider. The mean minimum number of sites materially declines (i.e. extinction risk increases) even with loss of the least suitable 35% area of habitat.

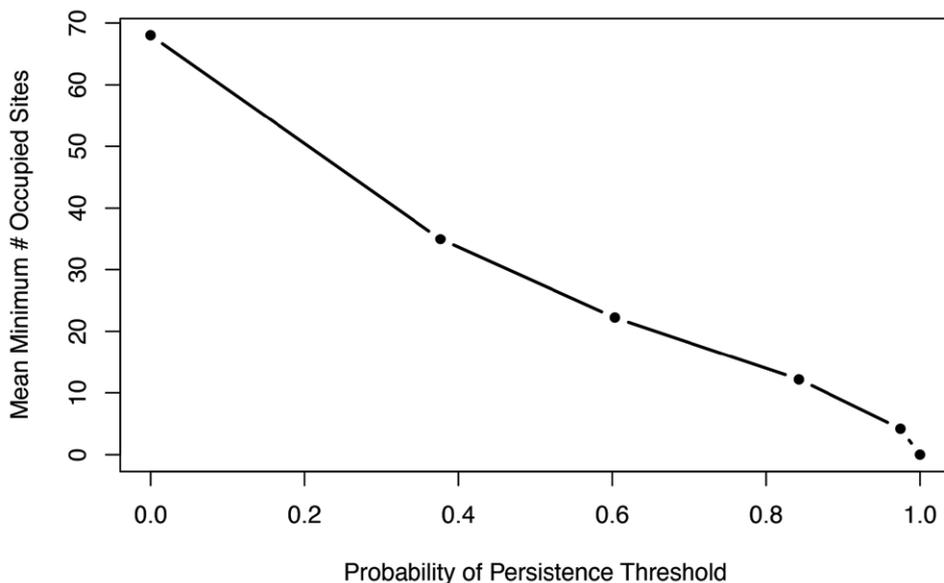


Figure 11. Risk curve describing the impact of habitat loss, progressing from least suitable to most suitable, on Growling grass frog. Note that probability of persistence in the context of metapopulation modelling is an attribute describing habitat quality.

2.3 Habitat suitability models

Approach

Habitat suitability modelling (HSM) has been commonly used to predict potential impacts of environmental change and management on biodiversity, and is still one of the fastest growing technical disciplines in science (Guisan et al., 2013). In its simplest form, correlative HSM relates field observations of species to information about the environment.

Example application: long-footed potoroo

We analysed suitable habitat for the long-footed potoroo (LFP) in its limited Victorian range. The LFP is listed as endangered globally, federally, and locally under the IUCN (1994) criteria, the Commonwealth Environment Protection and Biodiversity Conservation Act 1999, the Victorian Flora and Fauna Guarantee Act 1988, and the New South Wales Threatened Species Conservation Act 1995. As a "critical weight range" mammal, major threats include feral predators and habitat loss/modification. The LFP occurs in small colonies and primarily feeds on fungi.

We obtained a spatial grid of static predicted habitat suitability values (cell resolution of 225m x 225m) from the Victorian Department of the Environment, Land, Water & Planning (DELWP). Note that the 2019/2020 bushfires were not considered when these predictions of habitat suitability were first made (Figure 12).

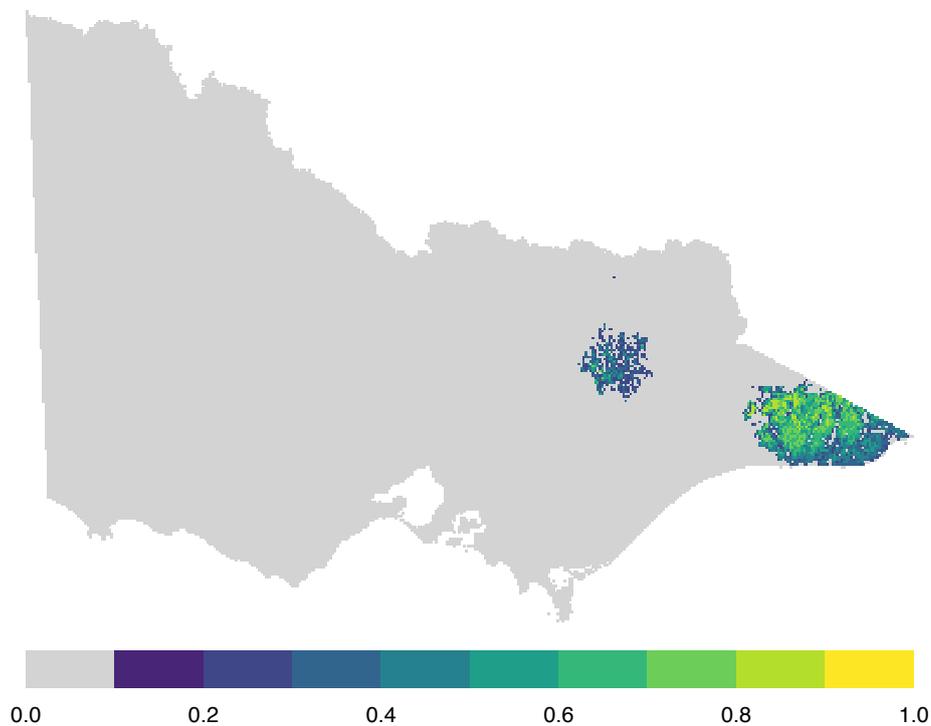


Figure 12. Predicted distribution of relative suitable habitat across the study area for the potoroo. Zero indicates unsuitable habitat with an increase in quality of habitat indicated by a scale from zero to one (one being the best habitat).

We determined thresholds from habitat suitability values that fell within the 35%, 55%, 75%, and 95% quantiles (Figure 13). For each threshold, we calculated "quality adjusted habitat" by summing all of the cell values above the threshold. That is, a grid cell with habitat suitability of 0.8 contributes four times that of another cell with a suitability of 0.2 in the calculation of quality adjusted habitat.



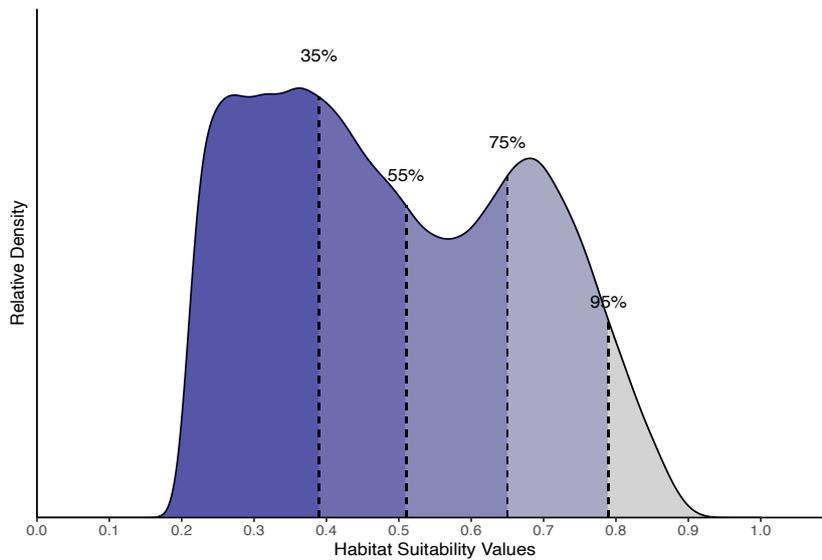


Figure 13. Density distribution of all non-zero initial habitat suitability values. Quantiles were selected to capture all of the values within 35%, 55%, 75%, and 95% of the area under the density curve (dashed lines). Each dashed line indicated includes all of the habitat suitability values to the left of the line and its threshold value is identified where the line intersects the x-axis.

Risk characterisation

The shape of the risk curve shown in Figure 14 is somewhere in between those prepared for Greater glider and Growling grass frog. For the potoroo, the curve declines non-trivially with the loss of 35% of the habitat of least quality, but not as substantially as the frog (Figure 11). Our coarse proxy for risk – quality adjusted habitat – changes rapidly between a loss of 35% and 95%.

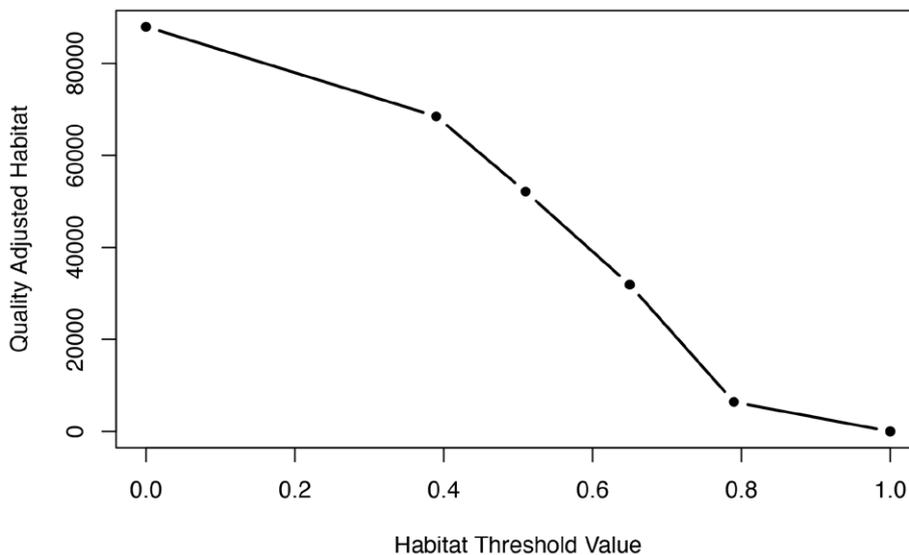


Figure 14. Risk curve describing the impact of habitat loss, progressing from least suitable to most suitable, on Long-footed potoroo.

The analysis can be extended to incorporate home range characteristics of species if data exists to support it. For example, male potoroos have recorded home ranges of between 15 and 60 hectares (Green et al, 1998). Since our habitat suitability predictions are at a resolution of 225m x 225m - or roughly five hectares - we consider nine contiguous cells (3 x 3) to support a home range. Counting the number of contiguous grid cells around a given cell and within the habitat suitability threshold, we can further refine important habitat for each threshold. We do this by multiplying the thresholded habitat suitability values by the number of contiguous cells - rescaled to be between zero and one. Outcomes for the potoroo are shown in Figure 15. In this case, the home range refinement has made little difference to the risk curve and inferences of material change in risk, except that the magnitude of quality adjusted habitat at any level of habitat loss is somewhat less in Figure 15 than the corresponding level in Figure 14.

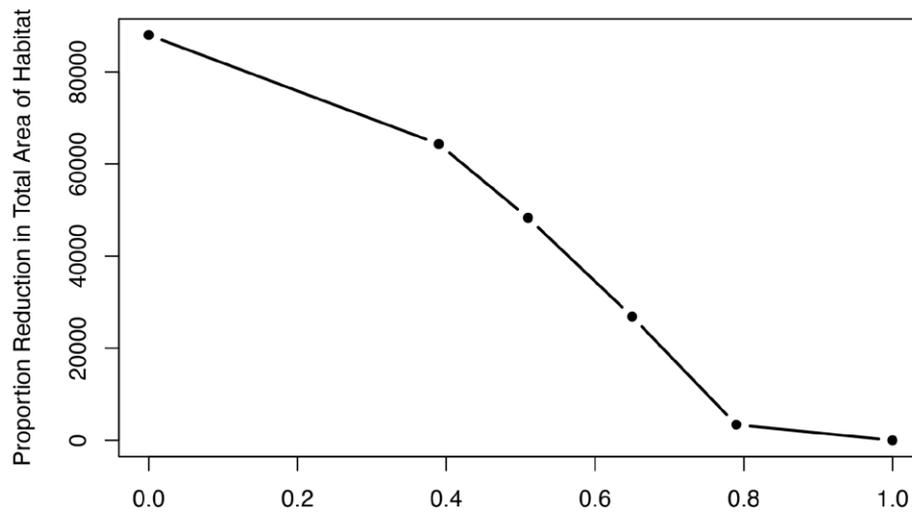


Figure 15. Risk curve describing the impact of habitat loss on Long-footed potoroo after accounting for home range.

2.4 Discussion

In deciding on an approach to characterising risk, regulators often need to balance rigour and practicality. Fischhoff et al. (1981) propose a set of criteria for assessing alternative approaches to acceptable risk, against which we have rated the three modelling methods used in this report (Table 1). We regard PVA as the most comprehensive approach because of its capacity to capture ecological detail and to explicitly describe population status spatially and in a way that relates directly to extinction risk. We rate metapopulation modelling almost as high on comprehensiveness. We rate habitat suitability very low. Its main limitation is that, for many species, its ecologically naïve outputs will imply the desirability of protecting areas of relatively high habitat suitability which may never be available to extant populations.

Table 1: Ratings of alternative approaches to assessing acceptable risk of habitat loss against the criteria described by Fischhoff et al. (1981).

Criterion	Population viability analysis	Metapopulation modelling	Habitat suitability modelling
Comprehensive	10	9	2
Logically sound	9	9	8
Practical	7	8	9
Open to evaluation	8	8	8
Politically acceptable	7	7	7
Compatible with institutions	5	5	8
Conducive to learning	9	9	9

Simplicity drives the popularity of HSM in global change analyses. However, the limitations of HSM approaches in predicting change are well-recognised. For example, HSM does not account for dynamics such as dispersal or density-dependence (Briscoe et al., 2016), neglects to integrate ecological theory (Guisan & Thuiller, 2005), fails to model underlying drivers of occupancy (Guillera-Arroita et al., 2015), and is subject to naïve statistical assumptions (Dormann, 2007).

On the other hand, HSM is highly practical and compatible with institutions. That is, many conservation agencies already have the technical capacity to undertake HSM or have access to good quality model outputs. Although PVA and metapopulation modelling has been less accessible to date, we believe the availability of free software (Visintin et al. 2020) and ecological data (at least for a subset of vertebrates and vascular plants), and the growing technical competencies of many organisations, will enable broader uptake over the next five years or so.

In contrast to correlative HSM methods, PVA and metapopulation modelling methods consider causal processes explicitly in the modelling. Bringing population dynamics into our models had an important influence on projected outcomes for the Greater glider; impacts that may not be captured in an analysis based solely on correlative HSMs. Including stochasticity in the model projections provided different expectations of future population size. Our stochasticity parameterisation was based on plausible variation in parameter values under changing environments, and so provides useful characterisation of future risks that should be incorporated in land management and conservation decision making. The inflation of risks of extremely low population sizes or even local extinction in stochastic systems is well documented (McCarthy and Thompson 2001) but is crucial to consider when avoiding extinction is an organisation’s mandate.

Our simulations were based on regular grids that spatially organised our input data and set the operational framework for a PVA STEPS simulation. Because our framework used several different models and sources of input data, we were limited in the choice of modelling resolution. Grid cell size does, in fact, have an influence on population outcomes in a spatially-explicit simulation – especially when effects of demographic stochasticity (e.g. Allee effects) are included. This is because species attributes such as range size and activity patterns, and density dependence mechanisms, are explicitly represented in the modelling. We could have chosen a cell size that was closer to the observed 1.5 ha (~125m x ~125m grid cell) mean home range of Greater gliders (Norton, 1988) but this would have amplified the effect of demographic stochasticity (the random fates of individuals) by only allowing a maximum of two animals in each grid cell. However, despite our larger cell sizes, the populations showed some initial decreases due to demographic stochasticity. Given a reasonably small area, analysts may opt to run several comparative simulations at different cell (i.e. patch) sizes.

Simulation results are influenced by where initial populations are placed in the landscape, especially if grid cell sizes do not allow adequate dispersal around the landscape. Given our coarser resolution of 1000m by 1000m and the limited home range size of the glider, dispersal was very limited and thus populations were more affected by local density dependence and habitat modifications. This should be considered by analysts when selecting the optimal simulation parameters or interpreting simulation results.

3. Revisiting the regulatory setting

Incentivising rigour and clarity

In the face of ongoing habitat loss, there is a pressing regulatory need to distinguish areas of lesser and greater importance systematically and coherently for threatened species. Clearly, spatially explicit PVA and metapopulation modelling are the best approaches for doing so, but there will be a considerable lag in their routine development and deployment. In the short term, HSM is the most readily available tool, albeit one that offers only partial insight into the implications of habitat loss for extinction risk.

We propose the introduction of a regulatory framework that makes use of HSMs in the short term, but incentivises a transition to PVA and metapopulation modelling over the medium term. Regulatory thresholds for acceptable habitat loss using HSMs may be more conservative than those for PVA or metapopulation modelling, acknowledging the deficiencies and uncertainties of HSMs and the need for precaution. For example, let’s say we were to develop a regulatory framework that includes two tiers of protection for a threatened species’ habitat:

Tier 1 - areas of highly important habitat where protection is the clear objective.

Tier 2 - areas of lesser but significant importance, where protection measures are less (e.g. a premium is paid on offsets).

Regulatory thresholds for the placement of these tiers may vary according to conservation stratus. For example, if a HSM was the basis for regulation we may have a schedule with the thresholds shown in Table 2A. If a PVA or metapopulation model is available, thresholds could be less conservative (Table 2B, Figure 16).

Table 2A. Notional regulatory thresholds for the protection of a threatened species’ habitat where a habitat suitability model is used to discern habitat of lesser and greater importance.

Criterion	Critically endangered, CR	Endangered, EN	Vulnerable, VU
Tier 1	Best 65% by area	Best 45%	Best 25%
Tier 2	Remaining 35%	Next best 20%	Next best 20%

Table 2B. Notional regulatory thresholds for the protection of a threatened species' habitat where a spatially explicit PVA or metapopulation model is used to discern habitat of lesser and greater importance.

Criterion	Critically endangered, CR	Endangered, EN	Vulnerable, VU
Tier 1	Area required to maintain 80% of expected minimum population (EMP), (or expected minimum number of occupied sites, EMNOS), over 30 years	Area required to maintain 60% of EMP/EMNOS	Area required to maintain 40% of EMP/EMNOS
Tier 2	Additional area required to maintain 95% of EMP/EMNOS over 30 years	Additional area required to maintain 80% of EMP/EMNOS	Additional area required to maintain 60% of EMP/EMNOS

The idea is to incentivise proponents of projects or development to undertake peer reviewed PVAs or metapopulation models via avoidance of the relatively higher costs of risk aversion embedded in thresholds associated with HSMs.

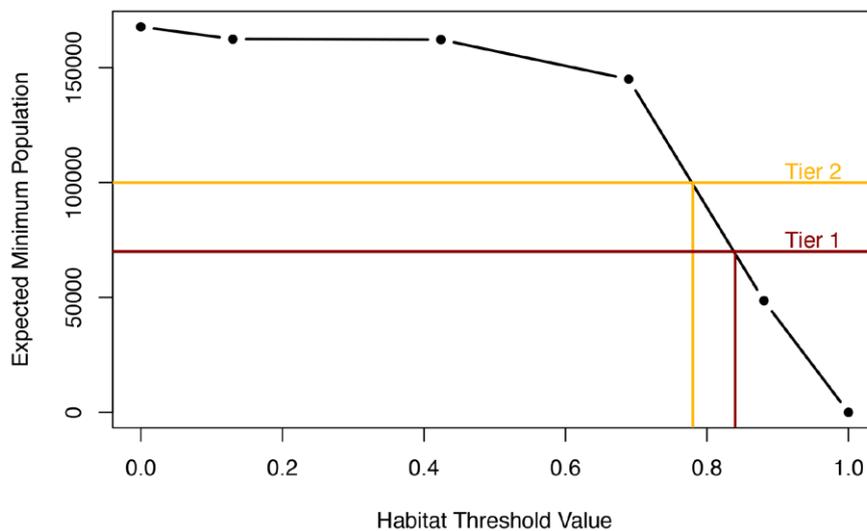


Figure 16: Application of the notional thresholds in Table 2B to the risk curve prepared for the Greater glider using a spatially explicit PVA. Areas of habitat with suitability greater than 0.84 would be protected under Tier 1 arrangements. Areas with suitability between 0.78 and 0.84 would be protected under Tier 2 restrictions.

Reviewing regulatory thresholds

Under the framework proposed here, thresholds for Tier 1 and Tier 2 protections for any individual listed species could be reviewed:

- after 10 - 20 years by administrative default, or
- when outcomes of credible population models become available, or
- when understanding of extinction risk substantially changes, as a consequence of fire, disease or other catastrophic event.

Example - review after a catastrophic events

Here we illustrate review for the potoroo example where a HSM was used. But the approach can be used for circumstances where a PVA or metapopulation model is available.

The HSM potoroo example in Section 2.3 did not account for any known major changes to habitat. If we have recent disturbance data on hand, such as the 2020 bushfires, we can incorporate this information. To illustrate how this data can be included, we multiplied the bushfire data - based on fire severity maps for Victoria - with the potoroo habitat suitability map to provide adjusted habitat suitability values (Figures 17 and 18).

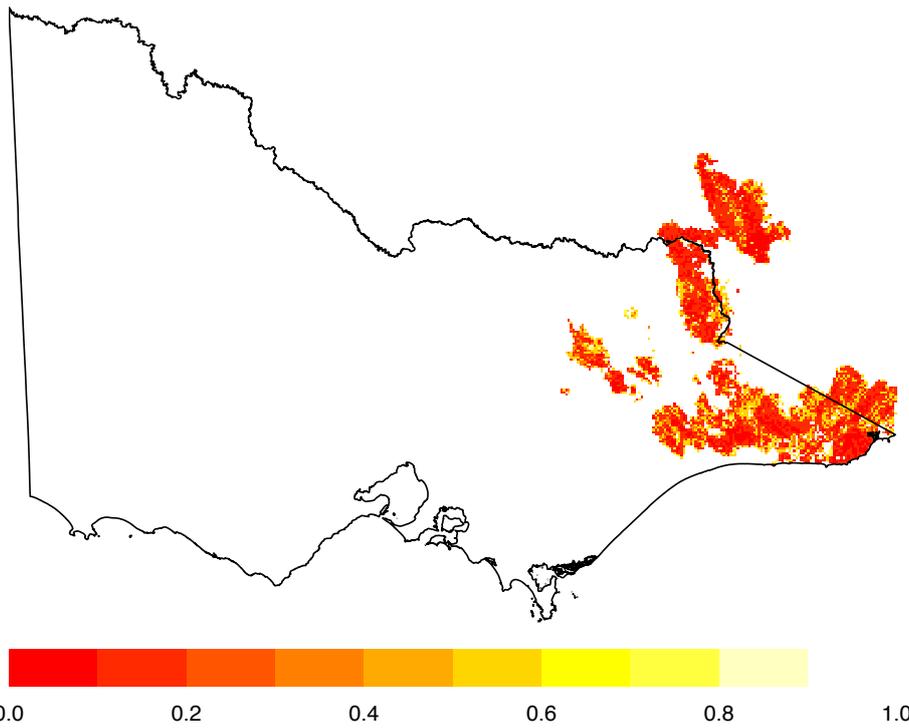


Figure 17. Recorded bushfires across the study area for 2019/2020. One indicates no fires with a decrease in fire severity indicated by a scale from one to zero (being the most intensive fires).

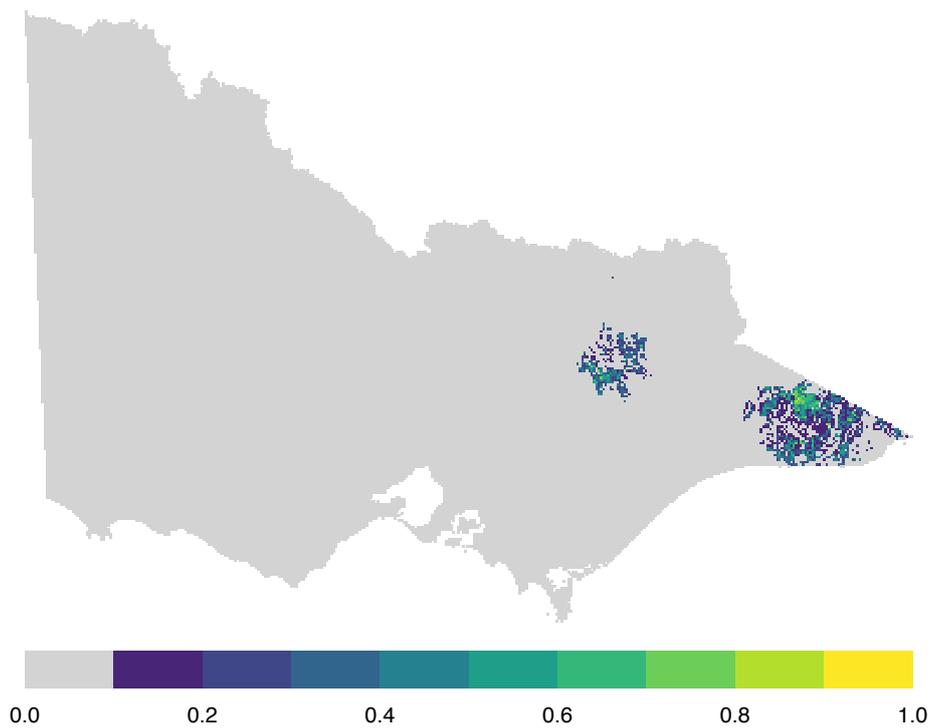


Figure 18. Modified distribution of relative suitable habitat across the study area for the potoroo. Zero indicates unsuitable habitat with an increase in quality of habitat indicated by a scale from zero to one (one being the best habitat).

From the modified predictions, we determined thresholds from habitat suitability values that fall within the 35%, 55%, 75%, and 95% quantiles (Figure 19). As with the previous example, for each threshold, we calculated “quality adjusted habitat” by summing all cell values above the threshold.

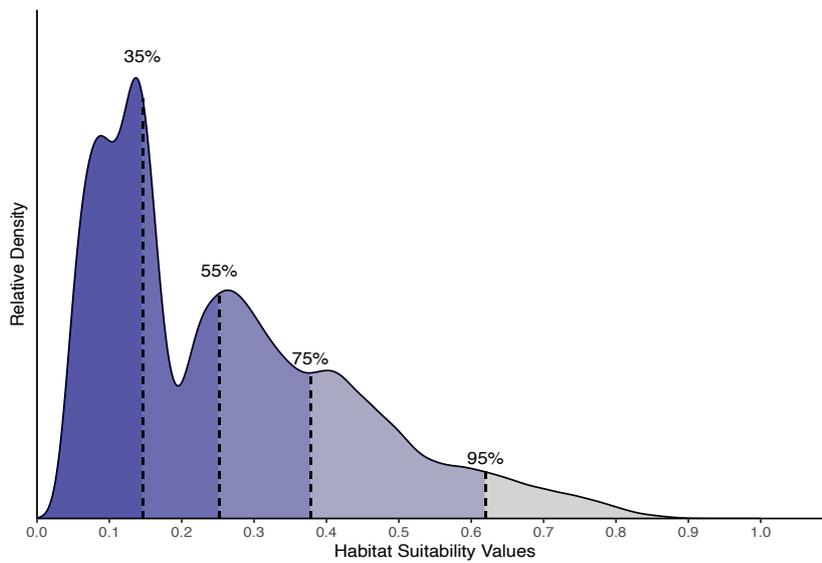


Figure 19. Density distribution of all non-zero initial habitat suitability values. Quantiles were selected to capture all values within 35%, 55%, 75%, and 95% of the area under the density curve (dashed lines). Each dashed line indicated includes all habitat suitability values to the left of the line and its threshold value is identified where the line intersects the x-axis.

For the potoroo, the effect of the 2019/20 fires was a loss of more than 50% of its habitat, by area. This magnitude of loss would likely qualify the species for a change in conservation status from vulnerable to endangered under rule A2 of the IUCN criteria (IUCN 2012).

Prior to the 2019/20 fires, Tier 1 habitat for the *vulnerable* potoroo under our proposed framework is the 25% of highest suitable habitat, with Tier 2 habitat comprising the next 20% (Table 2A). These thresholds and accompanying maps are shown in Figure 20a. Post-fire, and with change in status to *endangered*, the thresholds change to the best 45% for Tier 1 and the next best 20% for Tier 2 (Table 2A, Figure 20b).

We note that the shape of the post-fire risk curve in Figure 20b is very different to the pre-fire curve shown in Figure 20a. Post-fire, any further loss of habitat (even of low quality) may lead to harm, as indicated by the relatively steep decline in quality adjusted habitat. Greater clarity on the extent to which further loss of low suitability habitat may add to extinction risk can only be ascertained through a spatially explicit PVA or metapopulation model.



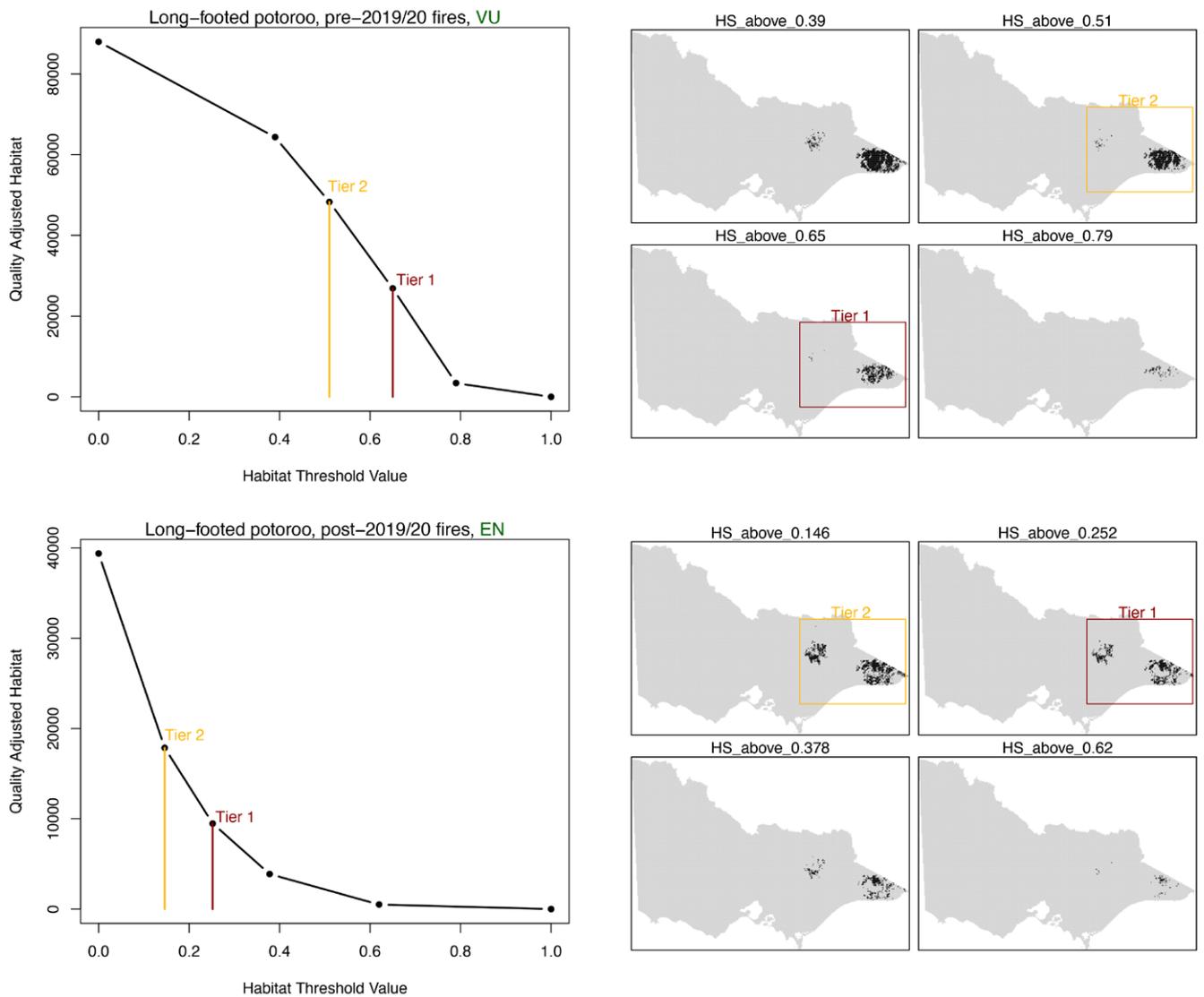


Figure 20. Nominal regulatory thresholds for Long-footed potoroo (a) pre-fire, and (b) post-fire. See text for details.

Concluding remarks

This report has shown how risk curves describing the impact of habitat loss on threatened species can be prepared using PVAs, metapopulation models, or HSMs. The choice of approach to risk characterisation involves trade-offs in clarity, information needs, and error. Here we have suggested there may be an opportunity to transition from the lesser rigour and relevance of HSMs to population modelling through a regulatory framework that incentivises improved risk characterisation through a relatively greater emphasis on precaution and risk aversion in the placement of thresholds for HSMs.

The current regulatory framework for the designation of critical habitat relies on Ministerial discretion (section 207A of the EPBC Act 1999). Our view is that this mode of decision-making is appropriate and consistent with the limited scope of critical habitat under current statute. But if the use of protection measures for important habitat is to be broadened and elevated, along the lines proposed in this report, there will be a need for wider social and economic assessment of benefits and costs. Key elements of any benefit-cost analysis potentially undertaken as part of a regulation impact statement (Commonwealth of Australia 2021) would be preparation of risk curves described in this report and an understanding of the opportunity costs of habitat protection at various candidate thresholds.

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