Forecasting patterns of shifting biodiversity refuges in an increasingly flammable world

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Abstract

In a warming and rapidly changing world, biodiversity is increasingly threatened by more frequent, severe, and larger fires. Variation in the life history attributes and habitat preferences of species mean that they may be affected differently by fire, and hence, decision makers must account for this. Understanding how fire affects the distribution of important areas of habitat and refuges for biodiversity can help guide appropriate conservation and management actions. In 2019-20 Australia suffered widespread and devastating megafires, known as the Black Summer, and the East Gippsland region in state of Victoria was heavily affected. To estimate impacts of the fires on fauna within the region, we used a joint species distribution model fitted to data from 967 camera trap sites to estimate variation in the occurrence for 40 native and invasive animal species. We focused on the influence of the fire regime, lethal control of introduced red foxes (*Vulpes vulpes*), timber harvesting, precipitation, and soil gradients, on wildlife. We then predicted the spatial distribution of each native animal species in the dataset for three time periods: 1) in 2017 prior to the Black Summer megafires, 2) in 2022 following the 2019/2020 wildfires and 3) in 2030. This allowed us to estimate changes in the patterns of occurrence for each species attributable to fire. Finally, we used spatial conservation prioritisation to identify priority conservation areas (‘fire refuges) and identify where potential threats (e.g. invasive species) might co-occur with these areas. We found that fire regime variables, including time since fire and repeat short-interval fires, influence occurrence patterns for ~50% of species and this meant that the megafires influenced predicted occurrence patterns. Half of the mammal species (mostly small and medium-sized ground-dwelling mammals) were positively associated with a topographic wetness index, as were four bird species. Spatial conservation prioritisation also suggested that while there were some shifts in the location of fire havens due to the megafires, some large areas of high-conservation value persisted after fire. These areas were disproportionately likely to be long-unburnt (>= 80 years) with fewer repeat burns, have high fox baiting intensity, and low probabilities of introduced red fox and feral cat (*Felis catus*) occurrence. This suggests maintaining older vegetation in landscapes and managing predation pressure by invasive predators will be important to maintaining the identified high priority refuges. Our study presents a useful approach for guiding fire management before and after large disturbance events, and could be expanded to test the response of species and communities to forecasts of future fire regime scenarios. Predictive approaches such as this study will be essential for managers to understand the possible outcomes of management actions on biodiversity during a time of rapid global change.

Introduction

Fire affects species’ distributions and the community structure of many ecosystems globally (Jones & Tingley 2022). Some plant and animal species are adapted to fire regimes, including the environmental heterogeneity that fire creates (Smith, Bull & Driscoll 2013; Furnas, Goldstein & Figura 2022). However, as fire regimes change, and interact with other threats (Abatzoglou, Williams & Barbero 2019; Keith *et al.* 2022), fire is emerging as a major driver of global extinction risk (Kelly *et al.* 2020; Doherty *et al.* 2024).

Animal species show diverse responses to fire due largely to its impact on habitat resources (Fox 1982). As a result, the availability and location of suitable habitat for animal species may change over time in fire-prone landscapes (Reside *et al.* 2019). This poses a significant challenge for conservation, as species' shifting distributions also change the locations of areas with high conservation value, particularly when other dynamic threats—such as invasive species or human land use (e.g., timber harvesting)—co-occur and interact with fire (Doherty *et al.* 2022). The challenge is magnified by extreme fire events, including megafires (>100,000 ha) and gigafires (>1,000,000 ha), which transform species' distributions across vast areas (Linley *et al.* 2022). Extreme wildfires are becoming common across the globe (Cunningham, Williamson & Bowman 2024), including the 2019 Amazon wildfires, Australia’s 2019/2020 Black Summer wildfires, and 2020 to 2021 California megafires. During such large, intense fires, it is crucial for managers to identify which species are most affected and which areas of the landscape are impacted (Legge *et al.* 2022).

Forecasts are increasingly used in ecology and conservation to guide management (Mouquet *et al.* 2015). Forecasts allow managers to anticipate future conditions, including disturbance, enabling informed decision-making in the face of environmental change (Dietze *et al.* 2018). In ecology, forecasts often link baseline data on species occurrences or abundances across space or time to biophysical or environmental data, and sometimes a management action or disturbance of interest, then project these data to future environmental conditions or possible management scenarios (Penman *et al.* 2015; Briscoe *et al.* 2019; Connell *et al.* 2019). However, robust forecasts require models that are parameterised with robust empirical or field-collected data (Greenville *et al.* 2018). As fire regimes change, there is an increasing need for flexible and adaptive approaches that accurately estimate species’ responses to large disturbances (e.g. megafires) and explicitly link these predictions to guidance for managers.

Our study aims to a) develop a field data-driven framework for forecasting fauna community responses to future fire regimes using baseline data that can be updated as new data are collected post-disturbance, and b) use these forecasts to identify fire havens where managers should focus management effort at a given point in time, including by potentially excluding future fires (e.g. bushfires and/or planning burning) or managing co-occurring threats. We demonstrate our approach by using it to understand how a wildlife assemblage in East Gippsland, Australia, is shaped by fire, and to forecast how species occurrence patterns and areas of high conservation importance were affected by 2019/2020 wildfires. Finally, we evaluate the quality of fire refuges by predicting their vulnerability to six invasive species known to influence food and shelter resources for native species in East Gippsland.

Methods

Study region

Our study focussed on the forests of East Gippsland, Victoria, Australia, an area spanning ~1 million hectares. The study region experiences a temperate climate, with mean annual precipitation ranging of 630–1156 mm (BoM 2020), and is made up of numerous vegetation types, including wet eucalypt forest, mixed eucalypt species foothill forest, coastal heathland, rainforest, and dry woodland (Cheal 2010).

There are a range of forest management practices that occur within our study area. The fire regime in the region is a mix of wildfires and planned burning of a range of severities. Fire return intervals range from <5 years to ~20 years (DELWP 2020b). In East Gippsland, the frequency and severity of fire influences the structure of vegetation, and therefore, habitat for fauna. Timber harvesting has also occurred within State Forests over several decades at a range of intensities, including both clear fell and regrowth thinning. Predation by introduced red foxes (*Vulpes vulpes*) and feral cats (*Felis catus*) is a major threat to native mammals within the study region, and lethal fox control has occurred in the region since the late 1990s, later becoming more extensive through the Southern Ark program (Dexter & Murray 2009).

Camera trapping

To understand the distribution of wildlife species in East Gippsland, we used a large camera trapping dataset collected across 967 sites that spanned the range of vegetation types, fire histories and land tenures (e.g. National Parks and State Forests). Cameras were deployed between June 2016 and June 2017 for a minimum of 30 days to maximise detections. Each camera was baited with a lure staked 1-2 metres in front of the camera. For a full summary of camera site selection procedures, refer to Robley *et al.* (2022). From this camera dataset, we then collated presence-absence data for each of the species detected on the camera traps, with the aim of including in community modelling species that were detected at more than 10 sites.

Covariate development

To understand the drivers of species' distributions in East Gippsland, we developed a series of covariates representing key disturbances and forest management drivers (e.g. fire, timber harvesting and lethal fox control), and biogeographic and habitat variables (e.g. mean annual precipitation, topographic wetness index and soil composition) (Table 1). Because we were interested in predicting species' distributions across the study region and some species in our dataset, such as *Antechinus* spp. have small home ranges (0.5-3 Ha; Lazenby-Cohen & Cockburn 1991), we developed these covariates with pixels at a common resolution of 50 m.

To model species' responses to the fire regime, we developed two fire-related covariates due to their hypothesised effect on vegetation structure, which then influences species occurrence (Swan *et al.* 2015). We use a directed acyclic graph to illustrate the hypothesised causal relationship using a causal model with the key relationships between time since fire, repeat fire, vegetation structure and fauna occurrence (Figure S8.1) (Ferraro, Sanchirico & Smith 2019; Arif & MacNeil 2022). First, for each pixel, we calculated the number of years since it had last burnt (i.e. time since fire) using maps of all past fires (DELWP 2020a). For pixels with no fire history, we arbitrarily assigned the year of last fire as 1900 as large (but unmapped) fires occurred throughout Gippsland in the early 1900s. We also used the fire history data to calculate the mean number of times that pixels within 500 m of each camera site that has been burnt in the 20 years prior to survey. Because the maps of past fires can be inaccurate, particularly for fires that had been mapped without considering satellite imagery (i.e. most fires before the 1990s), we used a burn cover model of south-eastern Victoria to mask out vegetation unlikely to burn in most fires from the mapped fire history, such as gullies and other wet vegetation (Bluff & McCarthy 2018). Using this approach to edit the fire history data produces more accurate estimates of burnt locations within East Gippsland (Lucas Bluff & Luke Smith *pers. comm.*). However, it is important to note that many fires from before ~1970 have not been mapped at all and so fire mapping before this time is incomplete for the East Gippsland region (Bluff 2014). This may bias the fire history dataset, in that the fire mapping may mean that some sites identified as ~100 years post-fire may be closer to ~50 years post-fire.

Timber harvesting is another prominent disturbance within the study region that influences vegetation structure at both the site and landscape-scale (Alexander, Scotts & Loyn 2002). To quantify variation in timber harvesting across the study region, we calculated the proportion of pixels within 500 m of each camera site that were harvested in the 40 years prior to survey using clearfell techniques. Lethal fox control is undertaken throughout the study region by regularly deploying permanent poison bait stations along roadsides, spaced on average every 0.7 km along roads. To quantify the spatial variation in fox baiting intensity, we quantified the density (number of baits per km^2) of poison bait stations within 5 km of each camera site.

As a proxy for landscape-scale variation in resource availability and variation in habitat type, we collated data on the average annual precipitation at each camera site (BoM 2020). To represent local scale variation in resource availability and habitat type, we used the topographic wetness index at each site (Gallant & Austin 2012). The modelled percentage of clay and carbon in the soil at each site was also used to represent variation in habitat types across the study region, as soil type is highly associated vegetation type and structure in the region (Grundy *et al.* 2015).

Finally, before inclusion in further analysis, we assessed whether any pairs of covariates were strongly correlated (using Spearman's correlation test, with a threshold of $r_s > 0.7$). All covariate pairs had correlation coefficients of $r_s < 0.7$ and $r_s > -0.7$.

Table 1: Description of each covariate included in the joint-species distribution modelling framework, and the range and units of their values.

Covariate	Description	Range
Time since fire	The time (years) since each site was last burned by fire of any severity. Where no fires had been mapped, we assigned a year of last fire as 1900 (122 years post-fire).	0 – 122
Mean repeat burn	The average number of times a pixel within 500 m of a site has been burnt in the 20 years prior to survey	0 – 2.11
Bait Intensity	The density of fox baiting stations (number per km^2) within 500 m of a site	0 – 20
Harvest prop 40	The proportion of a 500m buffer around each site that has been clear-fell harvested in the 40 years prior to survey.	0 – 0.93
Mean rainfall	The mean annual precipitation at each site (mm per annum)	630.6 – 1156
Topographic wetness index	The topographic wetness index describes the relative wetness of the site, based on how both local and landscape-scale topography (e.g. slope) and placement within a catchment influences water flow (index).	4.95 – 11.26
Clay	The modelled percentage (by mass, 0-0.05 m depth) of soil in a location made up of clay	9.20 – 20.58
Carbon	The modelled percentage (by mass, 0-0.05 m depth) of soil in a location made up of carbon	1.96 – 7.58

Joint-species distribution modelling

To identify the key drivers of the spatial distribution of the East Gippsland fauna community, we used a spatial joint-species distribution model implemented in the R package *Hmsc*—hierarchical modelling of species communities (Ovaskainen *et al.* 2017; Tikhonov *et al.* 2020). Joint-species distribution models (jSDM) simultaneously estimate species' responses to model covariates, as well as correlations between the occurrence patterns of each individual species. The approach implemented by Tikhonov *et al.* (2020) uses a spatial factor dimension reduction approach and a Nearest Neighbour Gaussian Process with 10 nearest neighbours in a Bayesian framework to efficiently deal with large, spatially-autocorrelated datasets (e.g. many sites and species). The environmental variable component of our model included covariates relating to the fire regime, lethal control of red foxes, spatial variation in precipitation and soil characteristics (Table 1 & 2). We also included a spatial component in the model to account for spatial autocorrelation between camera trap locations (Table 2). All covariates were scaled using the base R scale function prior to modelling, and we used uninformative priors.

Table 2: Environmental and spatial model formulae of the joint species distribution model used to estimate species' occurrences across the study region in East Gippsland, Victoria

Model Component	Model Formula
Environmental	~ time since fire + time since fire^2 + mean repeat burn + bait intensity + harvest prop 40 + mean rainfall + topographic wetness index + clay + carbon
Spatial covariates	Easting, Northing

The model was implemented as a spatial factor jSDM using the species' presence-absence data with a probit error distribution and used Markov Chain-Monte Carlo sampling for four chains, with 25,000 iterations each, as well as a burn in of 25,000 iterations. We retained every 100th iteration of each chain, giving a total number of 1000 posterior samples (250 per chain). To ensure model convergence, we ensured the Gelmin-Rubin statistic was below 1.1 for each parameter (Gelman, Hwang & Vehtari 2014) and examined trace plots for all major values to ensure adequate mixing. To evaluate model predictive performance for each species, we report the root mean squared error (RMSE) and the area under the receiver operating curve (AUC) following *k*-fold cross validation with 4 folds, all implemented within the *hmsc* package and framework (Ovaskainen *et al.* 2017; Tikhonov *et al.* 2020).

Spatial prioritisation

To identify the most important locations within the study area for the 40 native species in our study (i.e. excluding invasive species) immediately before and after the Black Summer fires, we used the systematic conservation planning program Zonation (v5) (Moilanen *et al.* 2005). We produced Zonation rank maps using predicted species occurrence probabilities for a) fire histories in 2017 (pre-Black Summer), b) fire histories in 2022 (immediately post-Black Summer), and c) fire histories 10 years post-Black Summer (calculated by adding 8 years to all values in the 2022 fire history map, and assuming no additional fires following 2022). We chose this time horizon as the natural fire return interval in these forests is typically greater than 10 years (Cheal 2010).

Zonation ranks pixels across the study region based on their contribution to the conservation of each individual species in the analysis, determined by the probability of occurrence of each species identified by the joint-species distribution models. The output of a Zonation analysis is a complementarity-based ranking of conservation priority for the entire study region of interest, where the highest-ranking cells have values closer to 1 and lowest ranking cells have values closer to 0. In our prioritisation, we used the 'Core Area Zonation' algorithm which identifies high ranking areas that have a high probability of occurrence for rare species (i.e. species with relatively restricted distributions within the study region being modelled) (Moilanen *et al.* 2014). Therefore, for this algorithm, cells that are relatively less species rich can be ranked highly if they are important for a single species. We did not apply any weightings to any species (e.g. conservation status) for the purposes of our study. As our goal was to rank sites by their relative conservation importance (rather than an explicit management action) immediately before and after the 2019/2020 wildfires (Moilanen *et al.* 2014; Selwood, Cunningham & Mac Nally 2019), we did not consider cost in our Zonation problem formulation.

We defined 'high-ranking locations' as the 20% of the study region with the highest Zonation ranking (i.e. values above 0.8). We used this threshold to identify locations in the study region that were high-ranking before, 1 year after, and 10 years after the 2019/2020 wildfires.

Finally, to provide some general insight into the potential drivers of the 1 year post-fire Zonation ranking beyond the individual species distributions, we built a beta regression model of 10,000 random spatial point samples of the Zonation rank (as rank data are bounded between 0 and 1) and six scaled covariates—time since fire, baiting intensity, mean repeat burn (Table 1) and predictions from the joint-species distribution model for three invasive species of conservation concern in the study region: the red fox, feral cat and sambar deer (*Rusa unicolor*). All covariates were fitted as 3rd order polynomials to account for non-linear relationships with zonation rank. To account for spatial autocorrelation between residuals, we included an auto-covariate calculated from the zonation ranking using the R package spdep (Bivand *et al.* 2015), with a neighbourhood radius of 10,000 cells. The model was fit using the package brms with four chains and 3000 iterations (Bürkner 2017). Model convergence was assessed by interpreting the effective sample size, Rhat values and diagnostic plots (Gelman & Rubin 1992).

Results

Species modelling

Thirty-four native and six invasive species were detected by the camera traps at 20 or more sites across the study region and were therefore eligible for inclusion in our joint-species distribution model. The most frequently detected species were the black wallaby (*Wallabia bicolor*; 747 sites out of 1196) and superb lyrebird (*Menura novaehollandiae*; 580 sites), whereas species such as fallow deer (*Dama dama*) and crimson rosella (*Platycercus elegans*) were detected at less than 25 (~2% of sites) sites (Table S1).

The joint-species distribution model revealed a range of influential drivers of species occurrence patterns across the East Gippsland study region. Time since fire had significant associations with one third of mammal species (Figure S3), and 31% of bird species (Figure S4). For most bird and mammal species, the time since fire relationship was a negative quadratic relationship, with occurrence peaking at intermediate time since fire ages (Figures S3 and S4). For the invasive species in the joint-species distribution model, time since fire was only influential for sambar deer (positive quadratic shape) (Figure S5). Eight mammal and reptile species (e.g. long-footed potoroo *Potorous longipes*, long-nosed bandicoot *Perameles nasuta*, and short-beaked echidna *Tachyglossus aculeatus*) and nine bird species (e.g. wonga pigeon *Leucosarcia melanoleuca*, white-browed scrub-wren *Sericornis frontalis*) were positively associated with fox baiting intensity (Figure S3). Of the native species, only dingoes and spot-tailed quolls were negatively associated with fox baiting intensity, whereas all invasive species, except sambar deer, were negatively associated with fox baiting intensity (Figure S5). Soil clay and carbon content and topographic wetness index were important for >50% of native mammal and reptile species (Figure S3). Soil carbon content influenced more bird species distributions than clay content, and 50% of the bird species modelled were positively associated with topographic wetness index (Figure S4). Three-quarters of native mammal, reptile and bird species modelled were associated with rainfall (Figure S3, S4).

Based on the model coefficients, at least ten native mammals and reptiles, and six bird species, are predicted to have experienced changes in their spatial patterns of occurrence when comparing their modelled distribution at the time of survey (2017) with their forecast distribution (2022 and 2030). For example, the superb lyrebird is forecast to have seen large areas decrease in occurrence probability and other parts increase (Figure 1). For other species predicted decreases in occurrence probability are forecast to be as much as 30% (Figure 2; Bassian thrush). Other species are predicted to have increased in occurrence probability (e.g.

long-nosed bandicoot), in some places by up to 40%. Model fit for each species was generally good, with almost all (45/48) species having an AUC > 0.7 (Table S2).

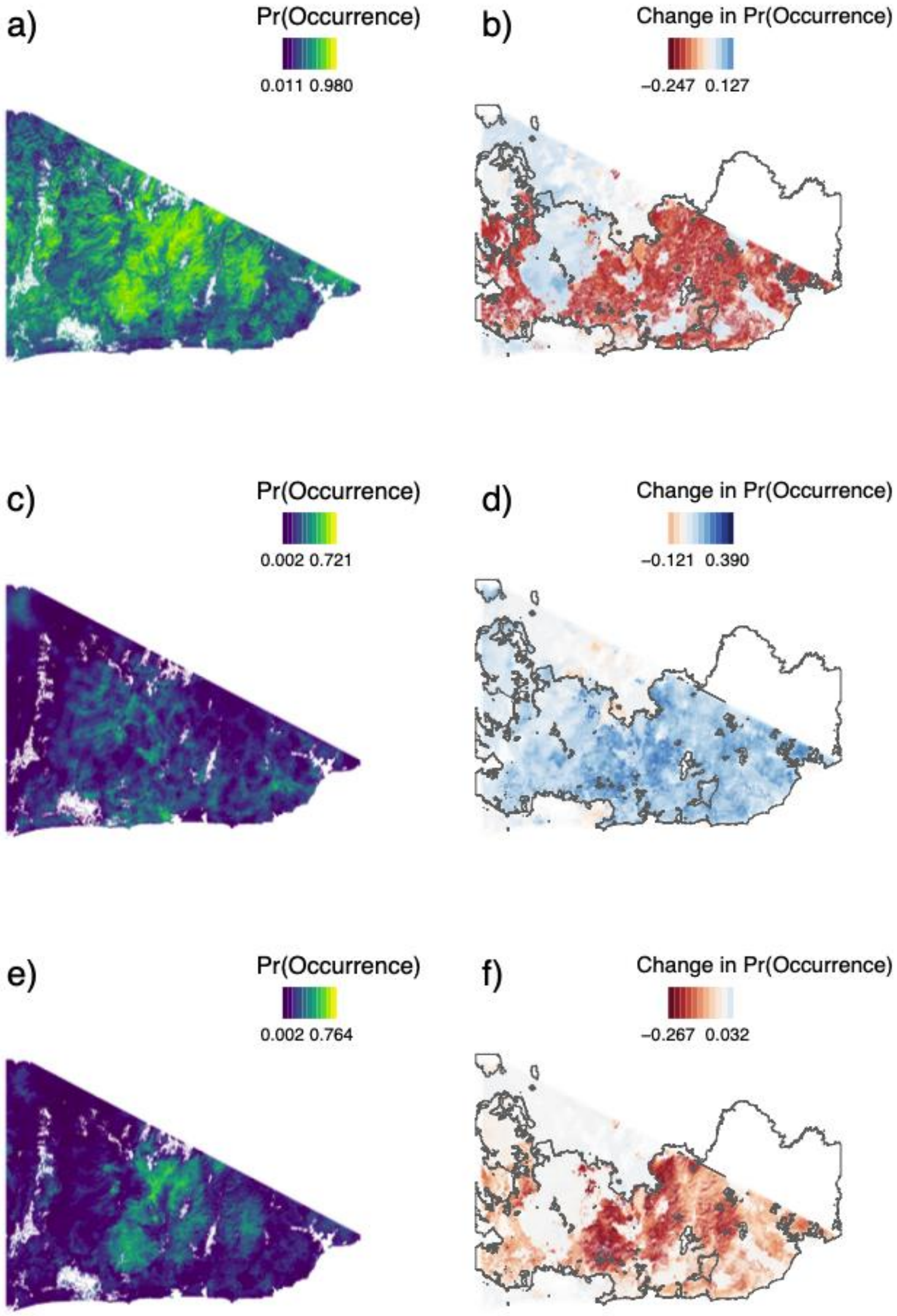

Figure 1: Predicted distributions of probability of occurrence from the joint-species distribution model for the superb lyrebird (*Menura novaehollandiae*) [a, b], the long-nosed bandicoot [c,d] and the Bassian thrush [e,f] for the the year 2017 (pre-Black Summer) and the predicted change in probability of occurrence between 2017 and 2022 (post-Black Summer), respectively.

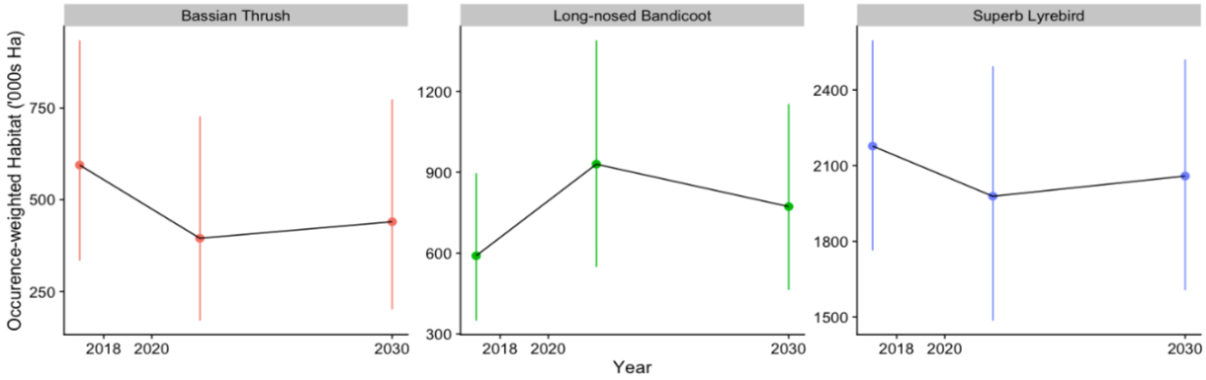

Figure 2: Predicted area of occurrence-weighted habitat (000's of Ha) for three example species, the Bassian thrush, the long-nosed bandicoot and the superb lyrebird (*Menura novaehollandiae*) for the years 2017 (pre-Black Summer), 2022 (post-Black Summer) and 2030.

Spatial prioritisation

Our prioritisations using predictions of 34 native species distributions in both 2017 and 2022 revealed shifts in the distribution of high-ranking habitat for the modelled fauna species following the 2019/2020 Black Summer megafires (Figure 3), demonstrated by the areas that became highly ranked habitat in the 2022 and 2030 scenarios (Figure 3).

Three key areas remained high ranking in both prioritisations—the Errinundra region in the centre of the study region, the Upper Snowy River region in the northwest of the study region, and coastal heathland along the southern coast of the study region (Figure 3). High-ranking locations in the 2017 prioritisation that did not appear in the 2022 prioritisation were scattered throughout the study region, with some larger areas occurring in coastal habitat that was burnt during the 2019/2020 wildfires (Figure 3). Many of the high-ranking locations that only appeared in the 2022 prioritisation were also scattered through the region, aside from a large block of unburnt habitat near the Martins Creek Nature Conservation Reserve in the central west of the study region (Figure 3).

High-ranking locations for native species from the 2022 analysis with current fire history information are more likely to have lower feral cat and red fox occurrence, but higher sambar deer occurrence (Figure 4). Further, high ranking locations are more likely to be long-unburnt, have lower repeat fire and higher fox baiting intensity (Figure 4).

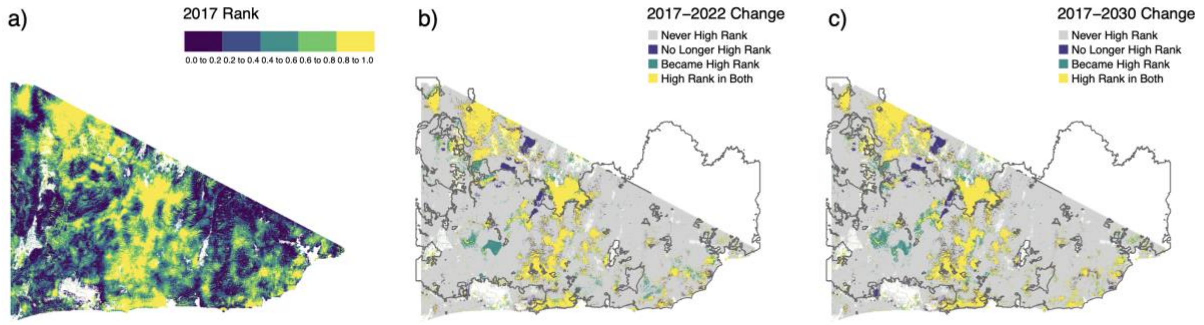

Figure 3: a) Priority rankings from Core Area Zonation analyses using predicted species distributions for the year 2017 (pre-Black Summer) for a fauna community in East Gippsland, Victoria, Australia. Values closer to 1 are relatively higher ranked in terms of conservation importance compared with values closer to 0. Rankings for the 2022 and 2030 scenarios are in Figure S6. Locations of change in the highest ranked (Top 20%) locations by Core Area Zonation between b) 2017 and 2022, and c) 2017 and 2030 for a fauna community in East Gippsland, Victoria, Australia. Yellow locations are within the Top 20% ranking in both 2017 and 2022, green locations became highly ranked in 2022, blue locations were highly ranked in 2017 but not in 2022. Grey locations never occurred in the high ranks for either 2017 or 2022.

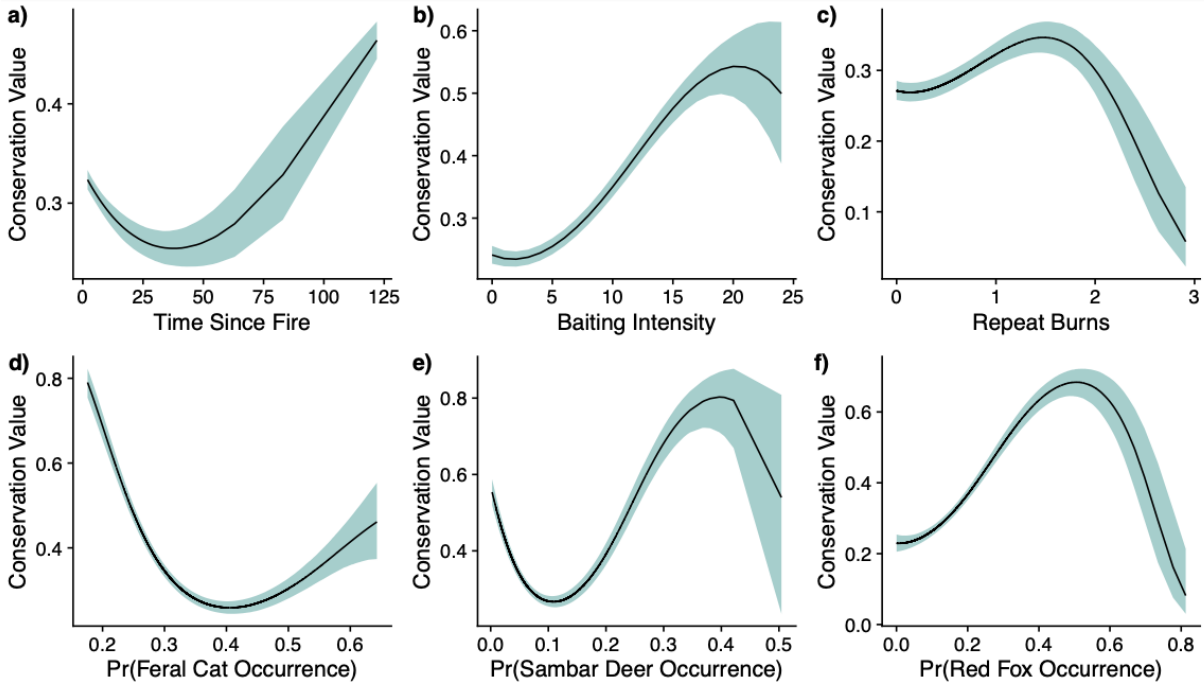

Figure 4: Expected conservation value from the 2022 Zonation analysis against six covariates, including a) time since fire (years), b) baiting intensity, c) repeat burns, d) feral cat occurrence, e) sambar deer occurrence, f) red fox occurrence. Shaded bands represent 95% confidence intervals, and the black line represents the mean predicted relationship.

Discussion

Large, intense fires are become increasingly common across much of the world (Cunningham, Williamson & Bowman 2024). As such, land managers must employ planning approaches that are dynamic, flexible and adaptable to changing conditions (Rhodes *et al.* 2022). Our study provides a framework for using field data and spatial conservation planning to forecast the effects of megafire on individual species and animal communities. To achieve this, we bring together methods developed to forecast species' responses to disturbances such as fire (Connell *et al.* 2019; Verdon & Clarke 2022), and conservation planning approaches that informed the short-term responses to the Australian 2019/2020 wildfires (Geary *et al.* 2021; Ward *et al.* 2022). Our results show that, while a large portion of the study region remained high ranking in the years following the megafires, there was also considerable turnover (i.e. some areas lowering in ranking and some areas increasing in ranking) due to the forecasted changes in species' occurrences.

Species' responses to fires and the overall fire regime are often highly contextual (Nimmo *et al.* 2019) and modelling them often assumes a causal relationship between fire variables and species occurrence, driven by the effect of fire on vegetation structure (Figure S1) (Swan *et al.* 2015). Our model forecasts help to identify species expected to have been positively or negatively affected by the 2019/2020 wildfires as well as their potential recovery trajectories. By explicitly modelling the correlative relationships between species occurrences, fire regime variables (such as time since fire and fire interval), and other environmental factors, our approach enables managers to better understand fine-scale patterns of refuges and provides critical insights for their management. Further, these forecasts can be readily updated with newly collected data from subsequent post-fire surveys (Dietze *et al.* 2018).

Our prioritizations using the species' forecasts revealed that locations of conservation importance following the Black Summer wildfires were more likely to contain vegetation that was over 80 years post-fire and had been burnt less than three times in the previous 20 years. Vegetation older than 80 years is considered mature for several of the vegetation types within this region (Cheal 2010). Therefore, maintaining sufficient vegetation within this age range and reducing fire frequency may be important actions for conserving fauna species in this study, such as the Bassian thrush and superb lyrebird.

Co-occurring threats, such as invasive species, can influence the value of fire refuges (Robinson *et al.* 2013; Reside *et al.* 2019). By jointly modelling occurrence of native species, as well as invasive species that threaten these species, we are also able to identify the invasive species that are likely to co-occur in identified areas of high conservation importance. Our results suggest that feral cats and red foxes were less likely to occur in high-ranking locations after the 2019/2020 wildfires, compared with lower ranking locations. For red foxes, this is likely reflective of decades of lethal fox control that has reduced fox occurrence and abundance in the study region and subsequent increases in the abundance of some native fauna (Dexter & Murray 2009; Robley *et al.* 2022). To maximise the persistence of native species, ensuring that feral cats remain excluded from high-value locations should be a key consideration for managers, under both normal conditions and during post-fire recovery.

The results of our joint-species distribution model also revealed some insights relevant to the management of the fauna community considered in our study. Our results confirm the results of previous studies in the region that fox baiting is negatively associated with fox occurrence, and positively associated with the occurrence of some small and medium-sized mammals (e.g. long-footed potoroo) (Dexter & Murray 2009). It is also worth noting that a negative association between baiting intensity and the probability of dingo and spot-tailed quoll occurrence does not demonstrate a causal relationship. For example, spot-tailed quoll presences were geographically concentrated in the north-west of the study area. While this area has lower baiting intensity for logistical reasons, it is also distinctive across a range of environmental variables beyond the scope of this study. For both bird and mammal species in our analysis, topographic wetness index was an important covariate, suggesting a preference for gullies and other wet areas typically characterised by dense vegetation with favourable microclimates and abundant food resources (Reside *et al.* 2019). As feral cat and feral pig occurrence was also positively associated with wetter areas, this requires management attention as feral pigs are predators of small vertebrates, and can simplify vegetation structure (Bengsen, West & Krull 2017), which may in turn aid feral cat hunting success (McGregor *et al.* 2015).

While our approach has generated some insights into the management of the East Gippsland fauna community following the 2019/2020 wildfires, care is needed when interpreting our results, especially in a management context. Our intention was to demonstrate a method, rather than to develop an accurate management plan. The spatial prioritisation component of our study assumes that each species' relationship with time since fire has been characterised accurately (see Figure S1). As our approach uses a single historical field dataset collected using one survey method (camera trapping) to model correlative relationships, there may be considerable uncertainty in the relationships between some species' occurrences and time since fire, especially when camera traps are not an effective survey method (e.g. arboreal mammals). Further, our analysis only considers 35 mammal and bird species, and one reptile species, for which data were available, and so the identified high-ranking locations are only relevant for these species. Lastly, the severity of the Black Summer megafires were extreme, having been preceded by significant rainfall deficits over three years in East Gippsland (Nolan *et al.* 2020). As our model was parametrised by relating fire history characteristics with species occurrences, forecasting responses to fires outside the historical fire regime will be uncertain.

Rapid and substantial climate and environmental change will require conservation managers to explicitly build flexibility into conservation planning approaches and acknowledge that conservation priorities might need to change in response to large events, such as fires (Rhodes *et al.* 2022), or incursions of invasive species. Our study outlines a dynamic framework for forecasting individual species responses to a range of drivers and identifying how locations of conservation importance shift following a large wildfire. As our approach is easily updateable with new field data and can also be used to forecast individual species and community responses to future fire regimes (sensu Connell *et al.* 2019), it provides land managers with the ability to pre-plan and make decisions before the next fires occur as well as closely manage the identified important refuges in the interim. Two particular future applications are of interest to fire managers: 1) Using scenario analysis to identify areas for protection from future fire or areas that need to be burnt to maintain an appropriate mix of fire age classes in the landscape, and 2) Ensuring important areas are spread geographically throughout the region to maintain species' metapopulations and minimise the risk of losing all important locations during a single large, severe disturbance in the future. This information will be vital to help managers to better prepare biodiversity for a future of climate and disturbance extremes (Wintle, Legge & Woinarski 2020).

Competing Interests

The authors have no competing interests to declare.

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Supplementary Information 1

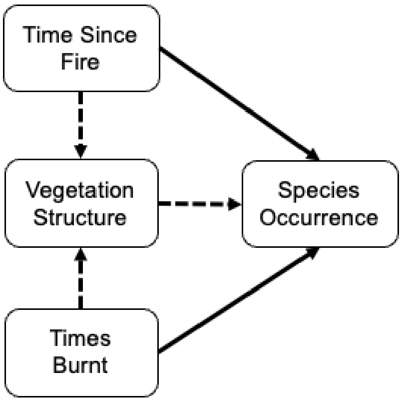

Figure S1: Directed acyclic graph illustrating the hypothesised causal relationship between time-since-fire, vegetation structure and the number of times a site was burnt in this study, and their effects on species occurrence probabilities. Dashed lines indicate hypothesised causal relationships assumed but not explicitly tested in this study, and solid lines indicate the associations tested in this study that are assumed to be representative of the causal relationships.

Table S1: Number of sites each species that was included in the joint-species distribution model was detected. Total number of sites in the analysis was 967.

Species Common Name	**Species Scientific Name**	**Count of Sites Detected**
Black Wallaby	*Wallabia bicolor*	747
Superb Lyrebird	*Menura novaehollandiae*	580
Common Wombat	*Vombatus ursinus*	516
Mountain Brushtail Possum	*Trichosurus cunninghami*	440
Feral Cat	*Felis catus*	371
Common Brushtail Possum	*Trichosurus vulpecula*	344
Long-footed Potoroo	*Potorous longipes*	285
Agile Antechinus	*Antechinus agilis*	242
Grey Shrike-thrush	*Colluricincla harmonica*	228
Lace Monitor	*Varanus varius*	184
Long-nosed Bandicoot	*Perameles nasuta*	184
Bassian Thrush	*Zoothera lunulata*	174
Short-beaked Echidna	*Tachyglossus aculeatus*	167
Wonga Pigeon	*Leucosarcia melanoleuca*	140
Red-necked Wallaby	*Macropus rufogriseus*	128
White-browed Scrubwren	*Sericornis frontalis*	120
Pied Currawong	*Strepera graculina*	116
Eastern Yellow Robin	*Eopsaltria australis*	102
Red Fox	*Vulpes vulpes*	94
Superb Fairy-wren	*Malurus cyaneus*	89
Dusky Antechinus	*Antechinus swainsonii*	88
Sambar Deer	*Rusa unicolor*	86
Pilotbird	*Pycnoptilus floccosus*	70
Dingo	*Canis dingo*	66
Spotted Quail-thrush	*Cinclosoma punctatum*	64
Horse	*Equus ferus caballus*	59

Satin Bowerbird	*Ptilonorhynchus violaceus*	46
White-throated Treecreeper	*Cormobates leucophaea*	45
Eastern Grey Kangaroo	*Macropus giganteus*	44
European Rabbit	*Oryctolagus cuniculus*	43
Laughing Kookaburra	*Dacelo novaeguineae*	43
White-winged Chough	*Corcorax melanorhamphos*	43
Eastern Whipbird	*Psophodes olivaceus*	40
Bush Rat	*Rattus fuscipes*	35
Grey Currawong	*Strepera versicolor*	35
Long-nosed Potoroo	*Potorous tridactylus*	29
Feral Pig	*Sus scrofa*	25
Spot-tailed Quoll	*Dasyurus maculatus*	25
Common Ringtail Possum	*Pseudocheirus peregrinus*	23
Eastern Pygmy-possum	*Cercartetus nanus*	21

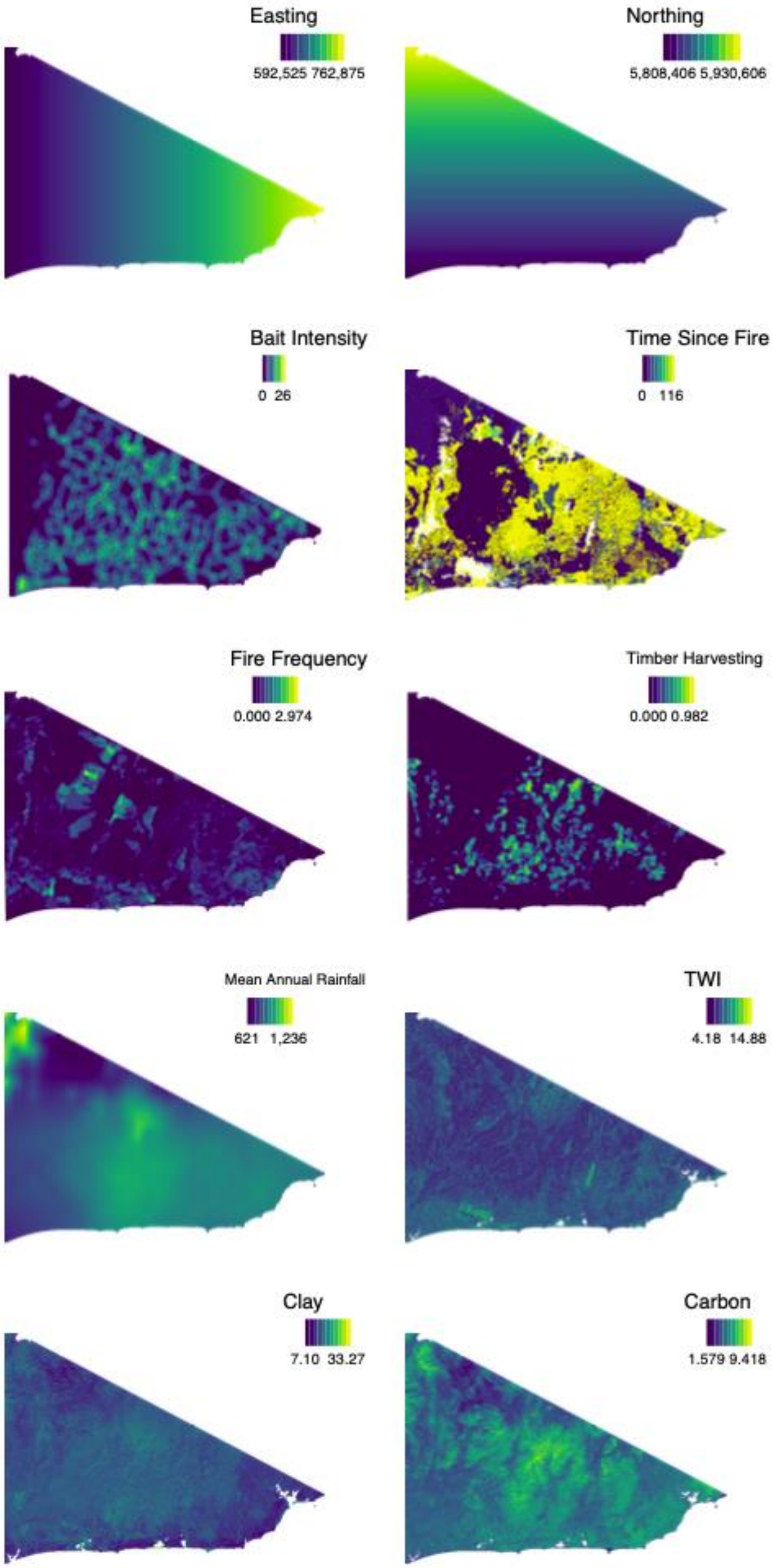

Figure S2: Covariates included in the joint species distribution model used to predict the occurrence of fauna species throughout the study region in East Gippsland, Australia.

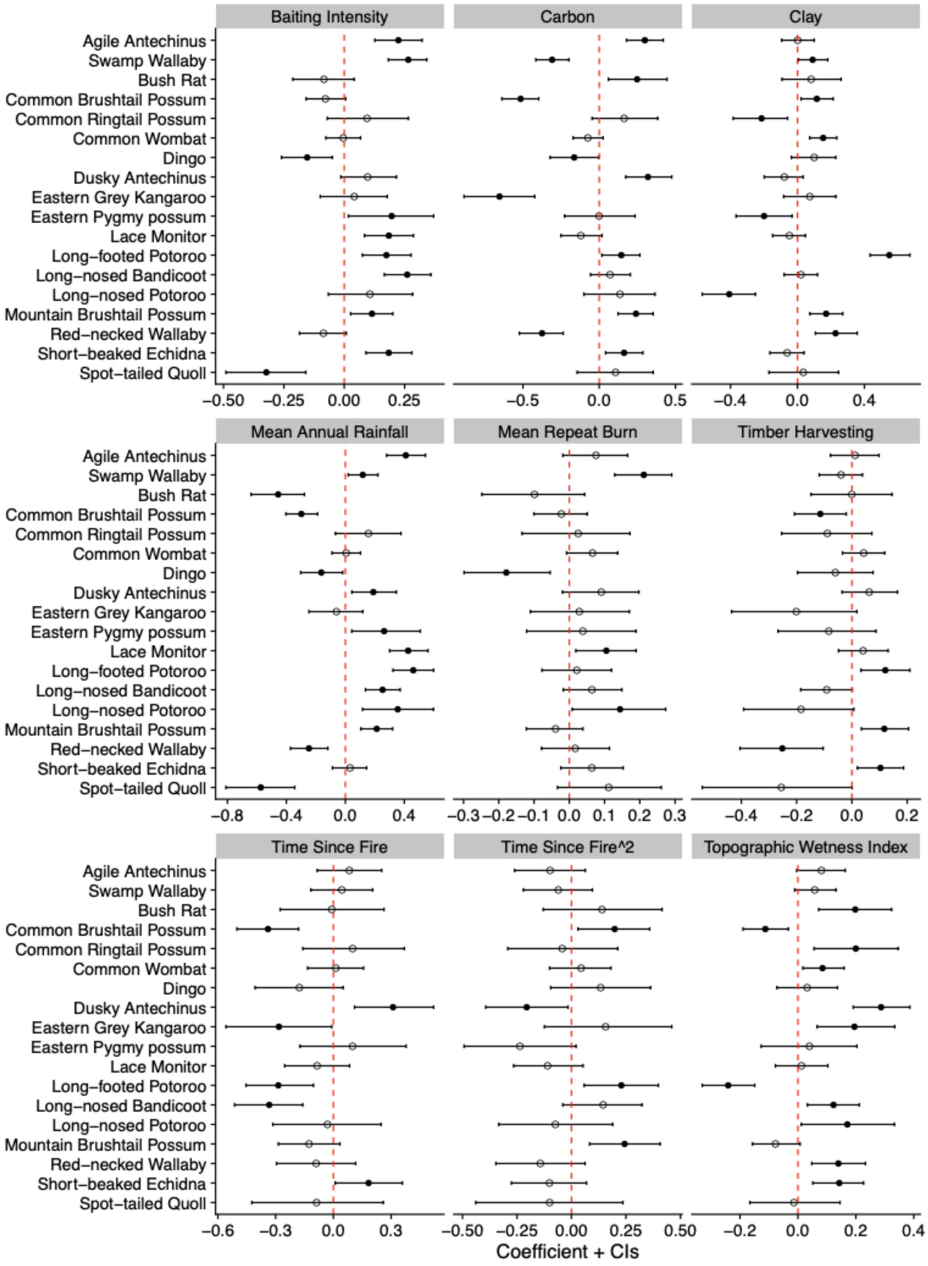

Figure S3: Model coefficients and 90% credible intervals for each native mammal and reptile species and environmental covariate within the joint-species distribution model for the East Gippsland fauna community in Victoria, Australia. Coefficients with closed circles indicate covariates where the credible intervals do not overlap zero, and open circles indicate covariates where the credible intervals do overlap zero.

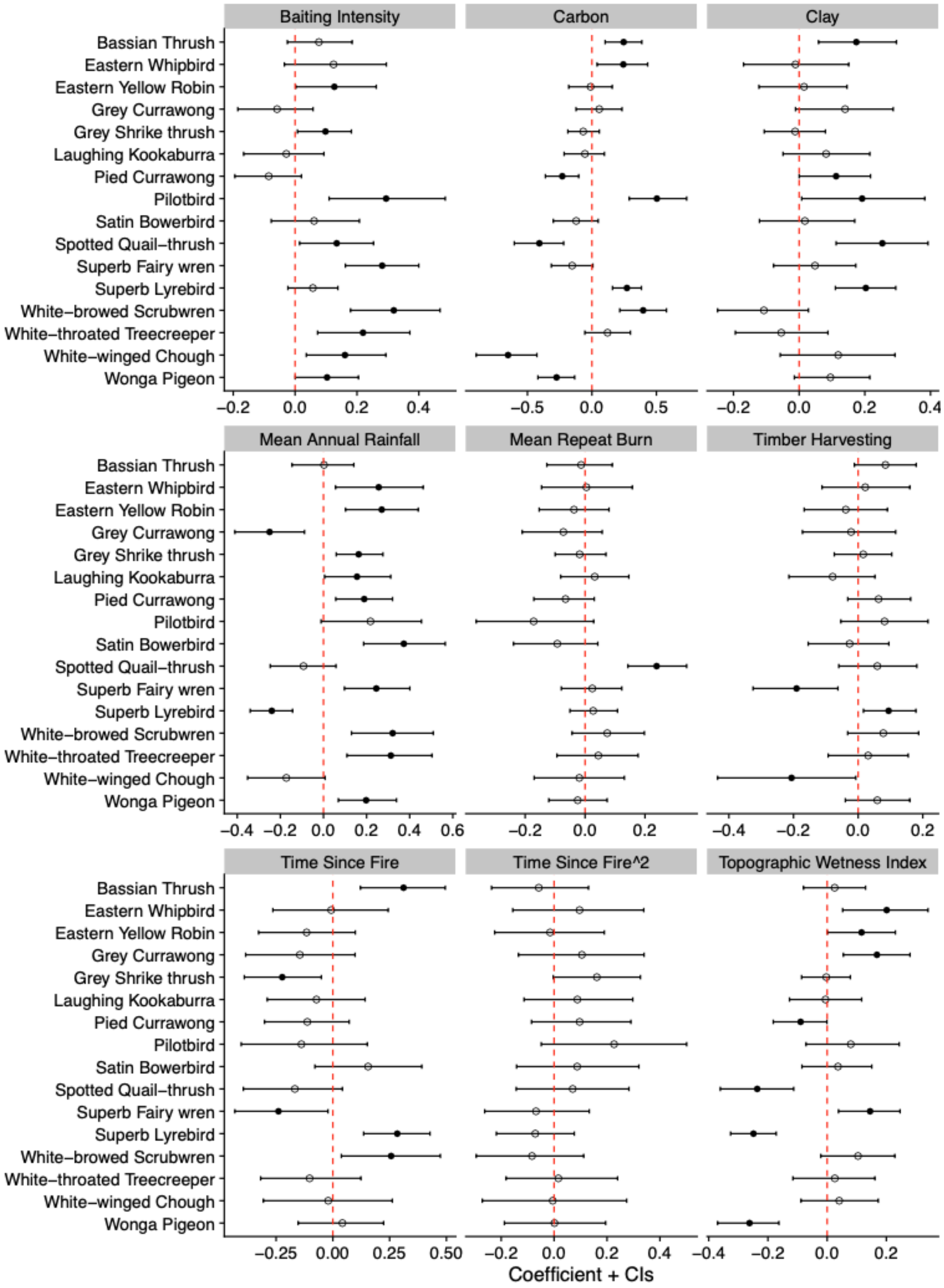

Figure S4: Model coefficients and 90% credible intervals for each native bird species and environmental covariate within the joint-species distribution model for the East Gippsland fauna community in Victoria, Australia. Coefficients with closed circles indicate covariates where the credible intervals do not overlap zero, and open circles indicate covariates where the credible intervals do overlap zero.

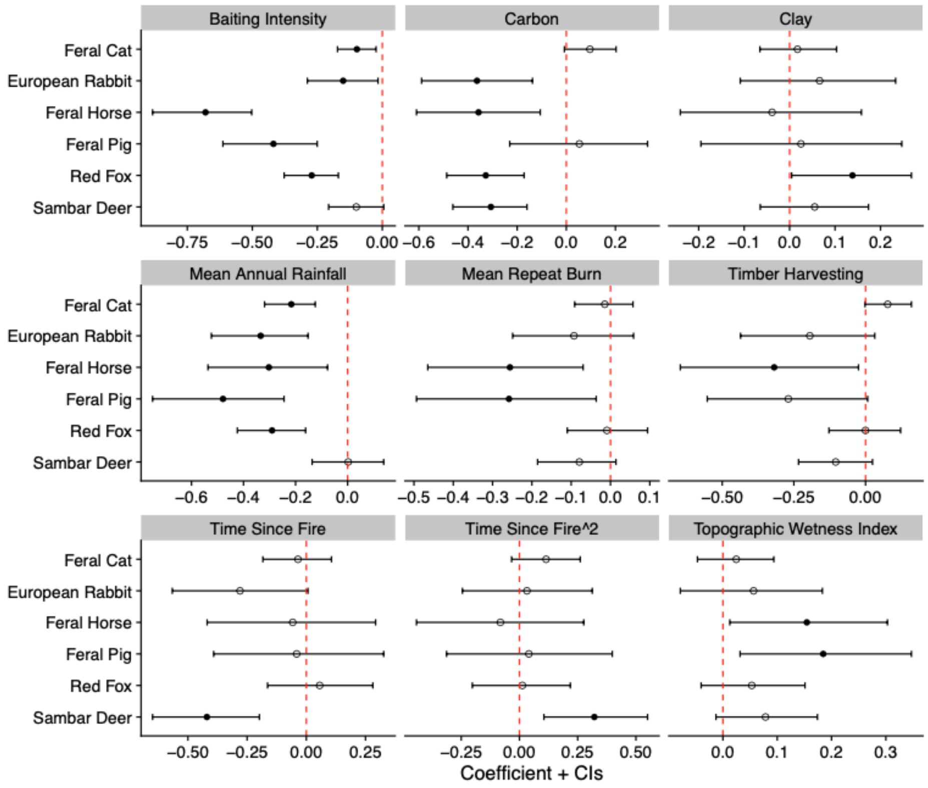

Figure S5: Model coefficients and 90% credible intervals for each invasive species and environmental covariate within the joint-species distribution model for the East Gippsland fauna community in Victoria, Australia. Coefficients with closed circles indicate covariates where the credible intervals do not overlap zero, and open circles indicate covariates where the credible intervals do overlap zero.

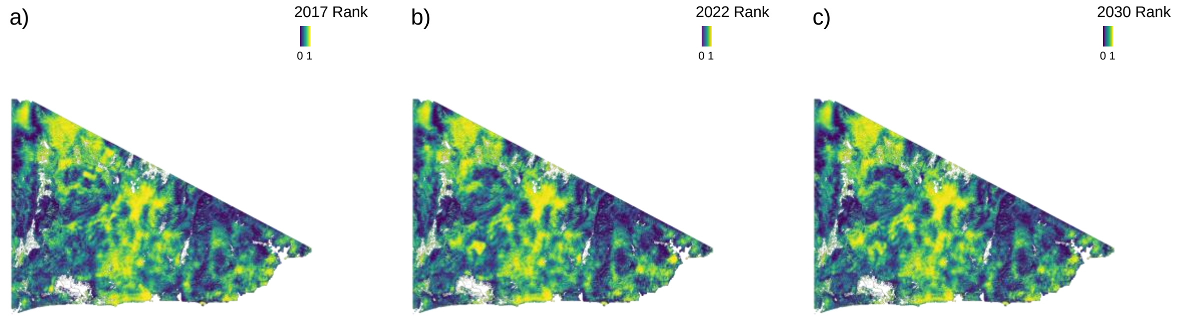

Figure S6: Priority rankings from Core Area Zonation analyses using predicted species distributions for a) the year 2017 (pre-Black Summer), b) the year 2022 (post-Black Summer) and c) 2030 (10 years post-Black Summer) for a fauna community in East Gippsland, Victoria, Australia. Values closer to 1 are relatively higher ranked in terms of conservation importance compared with values closer to 0. Rankings for the 2022 and 2030 scenarios are in Figure S6.

Table S2: Model diagnostics for each species contained within the joint-species distribution model. AUC: Area Under the Curve, RMSE: Root Mean Squared Error, TjurR^2: Tjur R^2.

Species	**AUC**	**RMSE**	**TjurR^2**
Horse	0.98	0.17	0.45
Pilotbird	0.97	0.18	0.34
Pig	0.95	0.14	0.17
Spot-tailed Quoll	0.93	0.15	0.11
Eastern Yellow Robin	0.92	0.25	0.2
White-browed Scrubwren	0.92	0.26	0.25
Eastern Pygmy-possum	0.92	0.14	0.07
European Rabbit	0.91	0.18	0.19
Long-nosed Potoroo	0.91	0.15	0.08
Eastern Grey Kangaroo	0.91	0.18	0.17
White-winged Chough	0.89	0.18	0.16
Eastern Whipbird	0.88	0.18	0.1
Long-footed Potoroo	0.87	0.35	0.31
Bassian Thrush	0.86	0.31	0.22
Red-necked Wallaby	0.86	0.29	0.2
Superb Fairy-wren	0.85	0.25	0.12
Red Fox	0.83	0.27	0.16
Common Brushtail Possum	0.83	0.39	0.29
Satin Bowerbird	0.83	0.2	0.07
Mountain Brushtail Possum	0.82	0.41	0.25
Wonga Pigeon	0.82	0.31	0.11
White-throated Treecreeper	0.81	0.2	0.05
Spotted Quail-thrush	0.79	0.23	0.07
Lace Monitor	0.79	0.35	0.12
Dusky Antechinus	0.79	0.27	0.08
Agile Antechinus	0.78	0.38	0.16
Superb Lyrebird	0.78	0.44	0.2
Bush Rat	0.77	0.18	0.04
Common Ringtail Possum	0.77	0.14	0.02
Dingo	0.76	0.24	0.07
Sambar Deer	0.76	0.27	0.08
Long-nosed Bandicoot	0.76	0.35	0.1
Grey Shrike-thrush	0.75	0.39	0.08
Pied Currawong	0.72	0.3	0.05
Grey Currawong	0.72	0.18	0.02
Short-beaked Echidna	0.72	0.35	0.07
Black Wallaby	0.7	0.45	0.1
Feral Cat	0.68	0.46	0.06
Common Wombat	0.62	0.49	0.03
Laughing Kookaburra	0.61	0.2	0.01

Table S3: Estimated regression coefficients, error and credible intervals from the beta regression model used to explain patterns of conservation value identified in the Zonation analysis. Q2.5 and Q97.5 represent the lower and upper 95% credible intervals, respectively.

	Estimate	Est.Error	Q2.5	Q97.5
Intercept	0.01	0.01	-0.01	0.03
polyCat_s31	-20.93	1.92	-24.66	-17.21
polyCat_s32	25.10	0.97	23.20	27.01
polyCat_s33	-5.01	0.95	-6.84	-3.17
polySambar_s31	0.19	2.57	-4.77	5.11
polySambar_s32	30.37	1.22	28.05	32.82

polySambar_s33	-13.35	1.04	-15.37	-11.38
polyRed.Fox_s31	50.13	3.27	43.67	56.65
polyRed.Fox_s32	-1.73	1.36	-4.38	0.97
polyRed.Fox_s33	-11.84	1.27	-14.26	-9.27
polytsf_s31	17.77	1.05	15.78	19.84
polytsf_s32	12.57	1.17	10.34	14.86
polytsf_s33	-1.59	0.88	-3.33	0.16
polybait_s31	30.52	1.15	28.27	32.75
polybait_s32	9.13	0.93	7.29	10.94
polybait_s33	-5.51	0.83	-7.11	-3.93
polyrepeatburn_s31	6.78	0.88	5.05	8.44
polyrepeatburn_s32	-1.43	0.87	-3.12	0.27
polyrepeatburn_s33	-4.88	1.01	-6.90	-2.93
polyautocov_s31	53.94	1.09	51.86	56.11
polyautocov_s32	-6.49	0.92	-8.27	-4.69
polyautocov_s33	-2.00	0.87	-3.71	-0.30

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