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RESEARCH ARTICLE

Optimising fire and predator management for conservation

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Abstract

1. Interactions between threatening processes compound and accelerate biodiversity decline. Conservation managers need to understand how co-occurring threats interact and account for such interactions when prioritising when, where and how to manage landscapes to recover declining species.
2. Using the Upper Warren region in south-western Australia as a case study, we develop a framework for identifying optimal fire age classes while also considering predation by introduced red foxes (*Vulpes vulpes*)—two co-occurring processes affecting the recovery of a threatened faunal community (woylie *Bettongia penicillata*, chuditch *Dasyurus geoffroii*, quenda *Isoodon fusciventor* and numbat *Myrmecobius fasciatus*). We fitted a multi-species relative abundance model to a dataset from 548 camera trap sites and tested for associations between each species' relative abundance, fox baiting intensity and time since fire. We then used linear programming optimisation to identify the optimal distribution of time since fire values across the study region that maximises the abundance of four focal species under alternative fox baiting intensity and fire severity scenarios.
3. Fire and baiting both influenced the relative abundance of the four species in our study, with fox baiting intensity having a positive association with woylie relative abundance.
4. The optimal distribution of time since fire values across the study region varied with the intensity of fox baiting. The importance of older fire ages increased in some locations when fox baiting intensity was high, but these results were highly uncertain and varied spatially. High fox baiting intensities combined with optimal fire age distributions also led to a higher relative abundance of three focal species overall, namely woylie, quenda and numbat.
5. *Synthesis and Applications*. Our study demonstrates an end-to-end framework for using field data to derive optimal fire regimes for biodiversity in a way that explicitly acknowledges uncertainty and remains useful for conservation decisions.

Approaches such as these are essential for managing ecosystems with compounding threats to biodiversity.

KEYWORDS
fire, interacting threats, invasive predators, optimal fire regimes, threatened species

1 | INTRODUCTION

Many species are declining because of multiple threatening processes acting on them and the ecosystems on which they depend (Bellard et al., 2015; Lu et al., 2020). These threats rarely occur independently; instead, many interact or compound one another (Kimmel et al., 2022; Legge et al., 2019). To develop optimal management practices, it is necessary to understand how co-occurring threats interact and then account for such interactions when prioritising when, where and how to manage landscapes to recover declining species. Although management plans (hereafter, prioritisations) should, ideally, account for threat interactions to guide management of declining species (Tulloch et al., 2018), such detailed prioritisations depend on extensive datasets that can be challenging to obtain and analyse. As such, previous studies have attempted to simplify prioritisations by focusing on managing individual threats to declining species (Chalifour et al., 2022; Ward et al., 2022). However, better outcomes for biodiversity can be achieved by explicitly accounting for threat interactions and the complexity of management problems in prioritisations (Auerbach et al., 2015).

Fire is one of the most widespread agents of disturbance across the planet (Kelly et al., 2020). A goal of land management in fire-prone regions is to manage fire in a way that enhances biodiversity (Jones & Tingley, 2022). This can be challenging because species vary in their responses to fire (Whelan et al., 2002). For example, some species are most abundant soon after fire, while others peak at various stages of post-fire succession (Hale et al., 2016). There is also variability in fire characteristics, such as fire severity (Furnas et al., 2022), which itself can result in contrasting responses by co-occurring species (Smucker et al., 2005). To help managers balance the contrasting needs of different species, prioritisations need to identify combinations of actions to implement in different places that will create a variety of fire ages and severities that will benefit each species and, in turn, maximise overall biodiversity (Jones & Tingley, 2022; Kelly et al., 2015; Tulloch et al., 2016).

Invasive predators are major drivers of species' declines and extinctions (Doherty et al., 2016), including in many fire-prone landscapes across the world, ranging from deserts and savannas to woodlands and wet forests (Geary et al., 2020). Fire-induced changes in habitat structure can both strengthen and weaken the impacts of predators on their prey (Doherty et al., 2022; Ganz et al., 2022). For example, increased rates of predation post-fire may reduce population sizes in recently burned areas, potentially slowing post-fire recovery (Hradsky et al., 2017; Morris et al., 2011; Whitehead et al., 2018). Fire and predator management often occur in the same landscapes, but planning and implementation of these actions usually occur in isolation, despite numerous calls for greater integration of these two management actions (Doherty et al., 2015; Hradsky, 2020; Wintle et al., 2020).

In this study, we aimed to understand how threat interactions could affect species' relative abundances and therefore, conservation priorities, and how this knowledge could be used to inform management. Specifically, we focused on understanding how the optimal fire regime for species' relative abundance can be influenced by the management of co-occurring threats, in this case invasive predator management (Figure 1). To achieve this, we used a camera trapping dataset from the Upper Warren region of south-western Australia and fitted a multi-species relative abundance model to characterise the interactive effects of the fire regime and invasive predator management on a threatened mammal community. We then used predictions from this model to develop prioritisations for optimal fire management under alternate predator management scenarios, building on existing approaches for identifying optimal conservation actions (Auerbach et al., 2015; Thomson et al., 2020). Our findings highlight the importance of explicitly accounting for multiple, interacting threats in conservation decision making, and illustrate an approach for identifying opportunities for further integrating fire and predator management in fire-prone ecosystems across the world.

2 | METHODS

2.1 | Study region

Our study was conducted in the jarrah forests of the Upper Warren region in south-western Australia (−34.21, 116.45). The region is typified by eucalypt forests and woodlands, with jarrah *Eucalyptus marginata* and marri *Corymbia calophylla* the dominant tree species. The region has a Mediterranean-type climate and experiences average annual rainfall of 650 mm in the north-east and 1000 mm in the south-west (BoM, 2020). Approximately 20% of the region is freehold land that is mostly cleared of native vegetation and used for agriculture and plantation forestry. These areas were not included in this study, focussing instead on Crown land vested with and managed by the Government of Western Australia, which retains its natural ecosystems. Roughly two thirds of the Crown land is managed as National Park or Nature Reserve, the remainder being State Forest (Department of Environment and Conservation, 2012). Fire, consisting of both wildfires and planned burns, is the dominant disturbance in the natural ecosystems of the region (Boer et al., 2009).

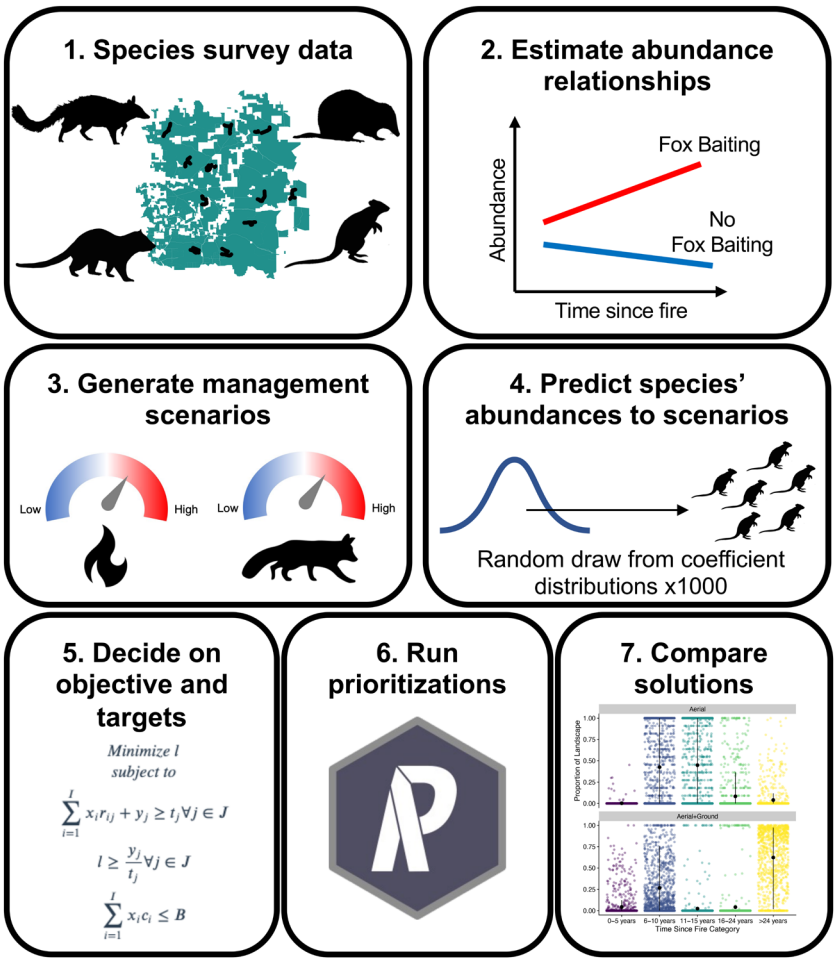

FIGURE 1 Modelling framework of the workflow used to identify optimal fire age distributions under alternate baiting intensities for focal species used in this study.

Native timber harvesting on Crown land ceased in 2024 after more than 100 years of active forestry in the Upper Warren region. Since 1975, the region has undergone lethal control of the invasive red fox *Vulpes vulpes* to reduce predation pressure on native species, including marsupials such as the woylie *Bettongia penicillata*, chuditch *Dasyurus geoffroii*, quenda *Isoodon fusciventor* and numbat *Myrmecobius fasciatus* (Wayne et al., 2017). Fox control has consisted of aerial (since 1997) and ground baiting using 1080 (sodium fluoroacetate) poison baits, which has varied in frequency and intensity over space and time. Feral cats *Felis catus* are also a major invasive predator in the region, but control is less common due to the limitations of existing tools.

2.2 | Camera trapping

We used a large-scale dataset derived from camera trap monitoring at 11 transects across the study region (a subset of sites from Wayne et al., 2024). This dataset enabled us to characterise the interrelationships between the mammal community, the fire regime, and fox management in the region. Each 5-km transect had 50 camera traps, each spaced 100 m apart and 5–20 m from unsealed vehicle tracks used for management. Cameras were deployed for 28–30 days within the period October 2016 to October 2017, with two transects surveyed at any given time. Two cameras were excluded from the dataset as they failed prematurely. The cameras used were either Reconyx HC600 or PC900, and were attached to a 45 cm peg or tree 20–30 cm off the ground and oriented approximately south-facing. Cameras were programmed to take 10 images per trigger, with no quiet period between triggers. *Eradicat*® baits (small, dried meat sausages designed to be attractive to feral cats) were placed 1.5 m in front of each camera and replenished or replaced on four subsequent occasions at 4- to 7-day intervals. Images captured by the cameras were tagged to species level to develop daily detection histories with counts of the number of independent detections at a camera per day for each species. Independent detections were defined as detections of the same species on the same camera that occurred at least 1 h apart. Camera trapping was conducted under the approval of the DBCA Animal Ethics Committee (#2016/04).

2.3 | Covariate compilation

We developed a directed acyclic graph to describe the influence of the fire regime and fox baiting on the abundance of the species in this study (Figure S1). This graph captured the relationships between important fire, fox baiting and habitat (rainfall and site wetness) covariates and each species of interest. We developed two fire-related

covariates, namely time since the last fire (years) at each camera site and the proportion of a 500-m buffer around each camera that had burnt severely in the 6 years prior to survey. We used a 500-m buffer, reflecting the approximate average movement range of individual animals across the target species, as demonstrated by previous studies in the same study system (Geary et al., 2023). We used 6 years as the threshold as the current fire management policy is to have 45% of the landscape less than 6 years post-fire, and 6 years post-fire represents a key threshold in bushfire risk management (Howard et al., 2020). Time since fire was calculated using fire history polygons (Department of Biodiversity Conservation and Attractions, 2021) and fire severity was sourced from a government fire severity database for the region (Table 1; DBCA *unpublished data*), which was developed using the method of Densmore et al. (2023).

To quantify variation in fox baiting effort in the region, we used a spatially explicit fox baiting intensity measure that represented the average number of baits deployed per km^2 within 400 m of each camera site across the study region in the 3 years prior to survey (Table 1; Geary et al. (2022)). We used a 400-m buffer to capture any boundary effects in baiting intensity, particularly where sites were close to private–public land tenure boundaries. To describe regional scale gradients in species abundance driven by annual precipitation, we included mean annual rainfall as a covariate (BoM, 2020). As a proxy for local-scale variation in site wetness and resource availability, we also included topographic wetness index as a covariate (Gallant & Austin, 2012). Before inclusion in further data analysis, we assessed whether any pairs of covariates were strongly correlated (using Spearman's correlation test, with a threshold of $r_s > 0.7$). We initially included easting and northing as covariates to account for possible spatial autocorrelation and variation in detections; however, they were strongly correlated with mean annual rainfall. Therefore, we chose to include mean annual rainfall in the final model as it is more ecologically meaningful. Maps of each covariate are shown in Figure S2.

TABLE 1 Description and data source of the covariates used in the multi-species abundance model.

Covariate	Description
Mean annual rainfall	The mean annual precipitation at each site (mm per annum)
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)
Fox baiting intensity	The average intensity of fox baiting (deployed baits per km^2) at each site (400 m buffer) for the 3 years prior to survey. We used a 3-year time window to capture short-term variation in bait deployments
Time since fire	The time (years) since each site was last burned by fire of any severity
Severe fire	The proportion of a 500-m buffer around each site that had burnt at high severity in the 6 years prior to survey
Julian date	The Julian date that each camera trap was deployed, to account for variation in the time of year each site was surveyed and seasonal variation in the detectability of species

2.4 | Relative abundance modelling

We used the hierarchical multi-species abundance model based on the Royle-Nichols model (Royle & Nichols, 2003) to characterise the responses of the Upper Warren mammal community to the fire regime, predator baiting and other environmental covariates. To account for potential correlations between site-scale relative abundances for each species, we added random site effects comprising a multivariate normal distribution for each species, such that correlation coefficients between species site relative abundances that account for species' responses to model covariates can be estimated (Kery & Royle, 2020; Yamaura et al., 2012). This approach is advantageous because it can be used to understand the influence of each covariate on the relative abundance of each species, while explicitly accounting for both imperfect detection in the underlying camera trap data and correlations between the relative abundance of each species within the faunal community (Kery & Royle, 2020).

To fit our model, we built 28-day detection histories for four native mammal species and the red fox, each of which had at least 50 independent detections and the camera trap design was an appropriate survey method (Table S1). To fit the relative abundance model, our detection histories were filled with presences and absences for each species at each site on each sampling occasion.

Our multi-species models aimed to estimate the relative abundance (N) of each species k at site i, and so modelled the state process model for relative abundance of species k at site using a Poisson distribution (Equation 1) and a detection process model (Equation 2) for each species at each site on sampling occasion j, where C is the observed count (number of independent detections), P is the detection probability for each species at each site on each sampling occasion, conditional on the probability that an individual is detected (p) and the abundance of the species at a site (N).

$$N_{i,k} = \text{Poisson}\left(\lambda_{i,k}\right) \quad (1)$$

$$C_{i,j,k} = \text{Bernoulli}\left(P_{i,j,k}\right) \quad (2)$$

$$P_{i,j,k} = 1 - \left(1 - p_{i,j,k}\right)^{N_{i,k}}$$

We modelled the detection process using only one covariate—the Julian date at which the camera trap was deployed, to account for differences in when each transect was sampled over the 12 months as well as seasonal variation in detectability for each species—and an intercept (Equation 3). As our dates go across

multiple years, we transformed Julian date to radians due to it being a circular statistic. We modelled the latent state of abundance λ for each species at each site as a function of mean annual rainfall (β_1), topographic wetness index (β_2), baiting intensity (β_3), time since fire (β_4), an interaction between baiting intensity and time since fire (β_5) and severe fire (β_6) (Equation 4). The abundance model also included a random site effect η explaining the association between the relative abundance of each species, which is specified as a variance–covariance matrix describing the correlations of abundance between each pair of species (Equation 5). These species associations may represent interactions between species or, more likely, correlations with unmodelled environmental covariates (Blanchet et al., 2020).

$$\text{logit}(P_{i,j,k}) = \alpha_{0,k} + \alpha_{1,k} \times \text{date}_i \quad (3)$$

$$\log(\lambda_{i,k}) = \beta_{0,k} + \beta_{1,k} \times X_i + \beta_{n,k} \times X_i + \eta_{i,k} \quad (4)$$

$$\eta_{i,k} = MVN\left(0, \sum\right) \quad (5)$$

where $\sum$ is a species-by-species variance–covariance matrix of random site residuals with dimensions of $k \times k$.

Because we were uncertain of the most appropriate form of the relationship between time-since-fire and each species' abundance (i.e. linear vs. some other form), we used model selection to compare four different forms. We tested a linear, square-root transformed quadratic and spline with two knots and identified the 'best' model according to the widely applicable information criterion (WAIC) value (Vehtari et al., 2017), where the model with the lowest value was identified as the best model and used in the subsequent steps of our analysis.

For our models, all covariates were scaled and centred. All statistical analyses were conducted in R (R Core Development Team, 2020). We fit the multi-species abundance models using a Bayesian Markov Chain Monte Carlo approach using the R package Nimble (de Valpine et al., 2021). To fit each model, we conducted sampling using three chains for 400,000 iterations each with a burn in of 100,000 and retained every 300th value, leaving 1000 iterations per chain for inference. We used uninformative normal priors for all values. We assessed model convergence by visually inspecting trace plots and ensuring the Gelman-Rubin statistic for each of the model parameters was close to 1 (Gelman & Rubin, 1992).

To assess how well the best model fit the observation data, we used posterior predictive checks and Bayesian *p*-values of the site abundance predictions for each species (Gelman et al., 1996), and calculated the mean absolute and relative error of the abundance predictions. The results of these checks are outlined in the Supporting Information and Figure S4.

2.5 | Identifying optimal fire histories

We used a systematic conservation planning approach to identify strategies that best manage both fire and predators for native species recovery (Margules & Pressey, 2000). Briefly, systematic conservation planning involves using conservation objectives to formulate an optimisation problem, and then using algorithms to solve the problem and identify management strategies (Margules & Pressey, 2000). Our objective was to find the transect-scale composition of fire age classes that resulted in the greatest abundance of each of the four focal native species (woylie, chuditch, quenda and numbat), depending on the intensity of fox baiting implemented. This objective is in line with conservation management objectives in the area as fire management decisions are informed by local-scale information (Wayne, 2018). Optimal time-since-fire values will be dependent on which species occur at that site. Because the distribution of each species in our analysis is not uniform across the landscape, optimal time-since-fire values will be dependent on how site-level factors (e.g. topographic position, annual rainfall) influence the relative abundance of each species at each site; for each scenario we evaluated all possible transect-specific time since fire values (0–33 years post-fire; because this was the range of time-since-fire values surveyed with cameras), meaning in each prioritisation there were 33 possible management options (i.e. 33 different zones) to evaluate at each transect (i.e. planning unit) (Table 2).

To understand the influence of different baiting intensity and fire severity values on the prioritisation results, we used an optimisation analysis to identify the composition of time-since-fire age classes at each transect that maximised the abundance of the focal species in our study, for six scenarios that encompassed alternative fox baiting intensity and fire severity values (Table 2). To achieve this, we used our abundance model to predict species' relative abundances for all time since fire values (i.e. management options) at each site (i.e. planning unit) by specifying model covariate values for each of the six scenarios and summing the site abundances to the transect-scale for a given time since fire value (Table 2). The scenarios were chosen to reflect the actual range of fox baiting intensities applied in the study region (mean: 65.93, range sampled: 3.24–168.60) and the range of the proportions of

TABLE 2 Fox baiting intensity (baits per km^2) and fire severity (proportion of site burnt severely in last 6 years) values used to create the six scenarios to identify optimal fire regimes to maximise the abundance of the target species.

Scenario	Baiting intensity	Fire severity
1	Low (5 baits per km^2)	Low (0.2)
2	Moderate (59 baits per km^2; equivalent to quarterly aerial baiting only)	Low (0.2)
3	High (150 baits per km^2; e.g. quarterly aerial plus monthly ground baiting)	Low (0.2)
4	Low (5 baits per km^2)	High (0.5)
5	Moderate (59 baits per km^2; equivalent to quarterly aerial baiting only)	High (0.5)
6	High (150 baits per km^2; e.g. quarterly aerial plus monthly ground baiting)	High (0.5)

sites burnt severely in the last 6 years sampled in the region (mean: 0.12, range sampled: 0–0.90).

Our problem formulation was a multi-zone, budget limited version of the reserve selection problem (see Supporting Information 5 for mathematical formulation). Briefly, our formulation considered a set of transects and a set of fire ages (time since fires) for each transect (0–33 years post-fire, termed management options) that could be implemented in different parts of each transect that affect the local abundance of each species within each transect. To ensure that the optimal solution balanced the potential needs of each species considered in the analysis, we measured the conservation benefit of a solution according to the lowest species' abundance given the solution, scaled according to the greatest possible abundance for that species (the 90th percentile of each species' model estimated regional-scale relative abundance in each scenario). This effectively meant that the optimal solution considered trade-offs between each species and ensured each species had sufficient suitable habitat, according to our targets. These considerations are foundational to effective conservation decisions (Brown et al., 2015). The problems were formulated using the *prioritizr* R package (Hanson et al., 2017) with the minimum largest shortfall objective, and solved to optimality using the Gurobi software (version 9.0.3) (Gurobi Optimization, 2023).

The modelled relationships between our focal species and the fire regime variables had a degree of uncertainty, which could potentially affect the reliability of the predicted outcomes of our prioritisations. To account for such uncertainty, we generated, for each scenario, 1000 predictions of each species' relative abundance by sampling from the posterior draws of the model coefficients and found the optimal fire age classes for each prediction. We present the full distribution of optimal fire ages and outcomes for species for each fire and baiting scenario, but group the results into fire age classes for visualisation purposes. Once the optimal fire age classes are identified for each scenario and planning unit, the proposed management action is dependent on how far the 'current' fire age distribution is from the optimal solution. For example, if the current fire age distribution is overall older than the optimal distribution (i.e. a higher proportion of recently burnt vegetation is more optimal), then the management action is to undertake prescribed burns in a manner that moves the age class distribution closer to optimal.

3 | RESULTS

The most commonly detected species included in our community abundance model included woylie and chuditch (Table S1). Foxes were detected at 65 of 548 sites (~12%) over the course of the survey period (Table S1). While feral cats prey on species in our study such as woylie, quenda and chuditch, we did not detect them at sufficient sites (<20 sites) to allow inclusion in our community abundance model.

3.1 | Abundance model

The covariates included in our model all had some effect on species' abundances. Fox baiting intensity was positively associated with woylie relative abundance (Figures 2 and 3) and had a negative interaction with time since fire on fox relative abundance. Time since fire had a negative association with red fox, woylie and numbat abundance (Figures 2 and 3). The proportion of the landscape around each site that had been burnt severely within the previous 6 years was negatively associated with the abundance of most species (e.g. woylie, numbat, quenda and chuditch) (Figure 2). Chuditch, numbat, quenda and woylie relative abundances were higher in areas with lower rainfall (Figure 2), whereas woylie, quenda and red fox had higher relative abundances in areas with high topographic

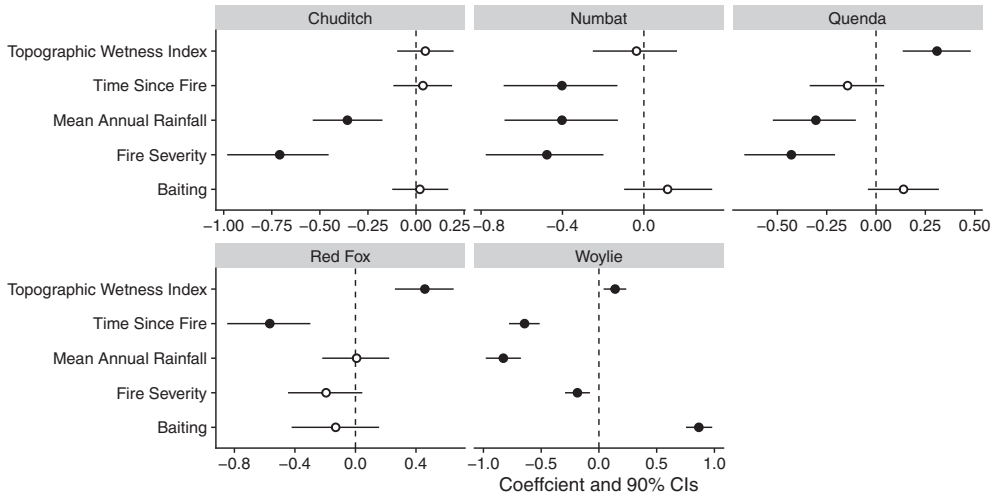

FIGURE 2 Coefficients and 90% credible intervals for covariates explaining the abundance of selected mammal species from the Upper Warren fauna community, Western Australia. Black circles indicate covariates where the credible intervals do not overlap zero and open circles indicate covariates where the credible intervals do overlap zero.

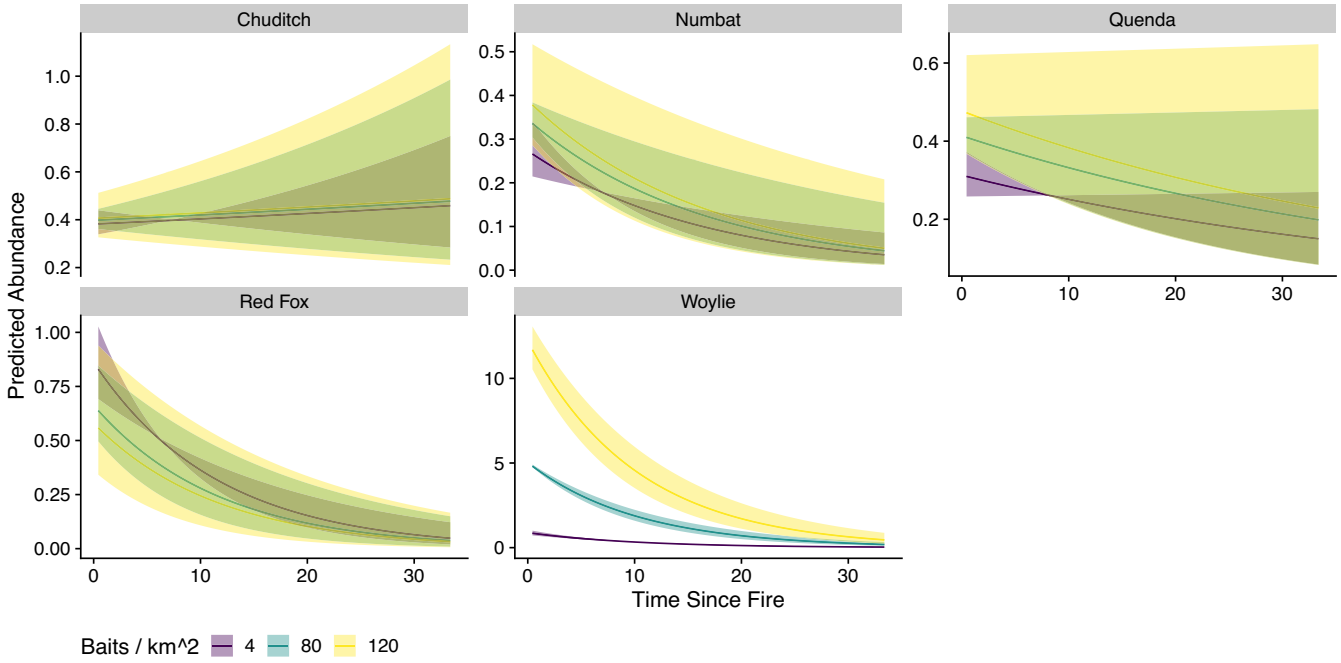

FIGURE 3 Predicted relationship between the relative abundance of each species and time-since-fire (years) under low, medium and high fox baiting intensities. Shaded bands represent 80% credible intervals. Levels of baiting represent low intensity of baiting (4 baits per km^2), medium-intensity baiting (80 baits per km^2) and high-intensity baiting (120 baits per km^2).

wetness (Figure 2). In terms of associations between species, most native species had positive associations with each other (Figure S5). Foxes also had more negative than positive associations with other species, with a negative association found between red fox abundance and quenda and woylie abundance (Figure S5).

Woylie relative abundance was negatively associated with increasing time since fire at high fox baiting intensities, but at lower fox baiting intensities the effect of time since fire on woylie abundance was less pronounced (Figure 3). The relationship between numbat relative abundance and time since fire was similar to woylies (Figure 3). We also found minimal association between fox relative abundance and time since fire at low fox baiting intensities, but a negative association at higher fox baiting intensities (Figure 3). Other species, such as chuditch and quenda, had similar associations with time since fire irrespective of the level of fox baiting intensity (Figure 3). While fire variables were influential for most species, baiting intensity had a relatively stronger association (larger effect size) on the relative abundance of woylie and numbats in our study. Model uncertainty was generally highest for each species at time since fire values >24 years post-fire, where the 80% credible intervals were widest (Figure 3).

3.2 | Optimal fire ages

We found that prioritisations generated to maximise the abundance of the focal species had different compositions of fire ages, depending on the intensity of fox baiting implemented. This variation was also expected to result in different abundance levels for each of the species, due to differences in the optimal fire age compositions and baiting intensities. For all baiting intensities, and with a low proportion of the landscape burnt at high severity, the prioritisations are dominated by fire ages between 6 and 10 years post-fire, however the proportional allocation of these ages is uncertain (Figure 4). At high baiting intensities (e.g., aerial baiting plus ground baiting), and a low proportion of the landscape burnt at high severity, the optimal distribution of fire ages had an increasing amount of older fire ages (>24 years post-fire) at the study region-scale (Figure 4), with some variation of this trend across different sites within the region (Figure 5). The 6–10 years post-fire age class was generally more important in the north and east of the study region compared with the west of the study region (Figure 5).

In terms of outcomes for species, the high baiting intensity scenario resulted in the highest abundances for quenda and woylie (i.e. the CIs did not overlap between scenarios) (Figure 6). There was no difference across the baiting scenarios for chuditch abundance (i.e. the CIs overlapped between scenarios) (Figure 6). Generally, the low fire severity scenario resulted in higher abundances of species (Figure 6a) compared with the high fire severity scenario (Figure 6b), however, the trends reported are consistent regardless of what proportion of the landscape has been burnt severely.

4 | DISCUSSION

Managing the key threats to species' populations in an integrated manner is important, especially when these threats interact. We

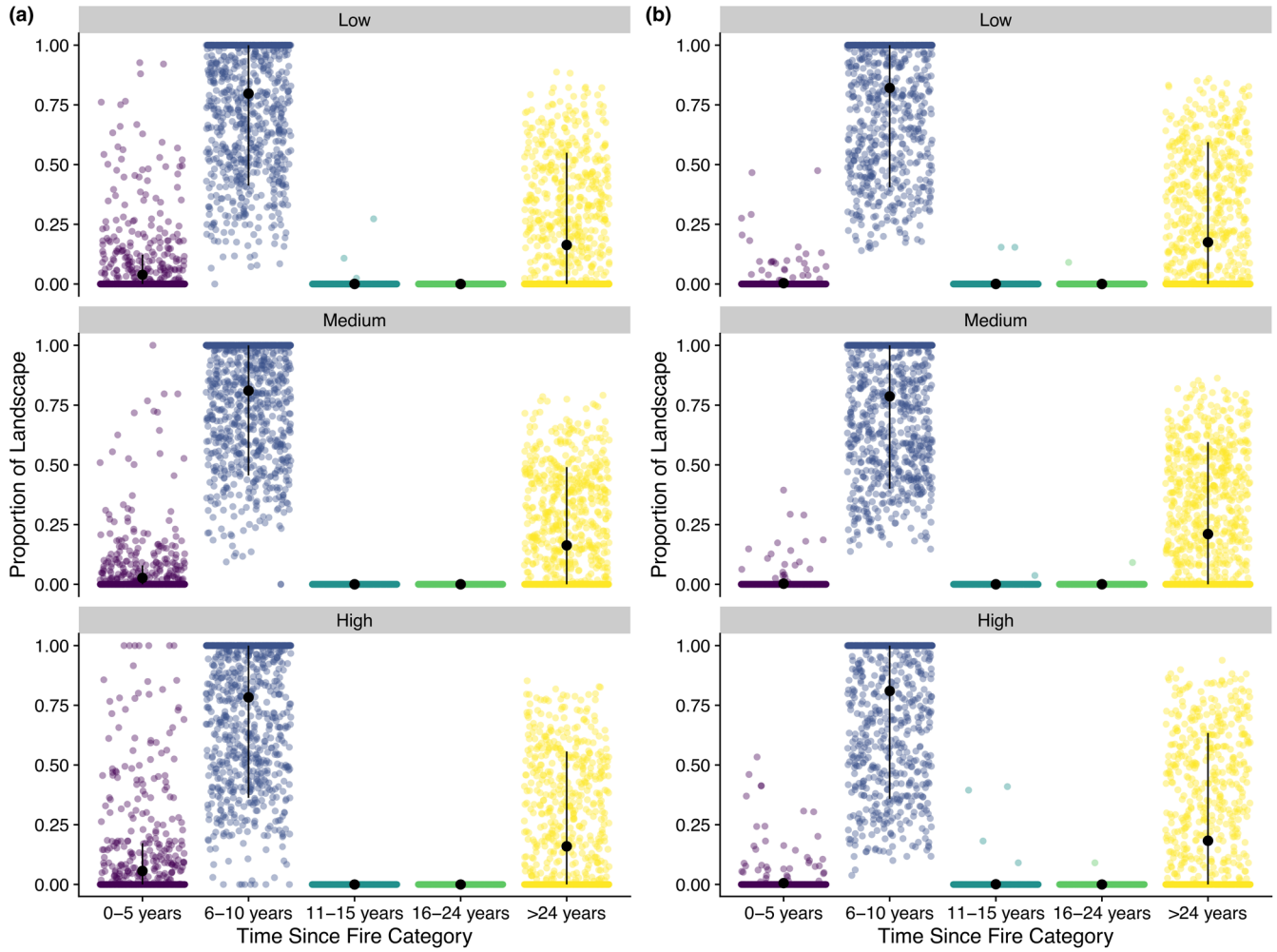

FIGURE 4 Optimisation results for the Upper Warren region that maximise the abundance of the species of interest under three alternative fox baiting intensities (low, medium and high) and at (a) 20% and (b) 50% of the landscape burnt severely in the past 6 years, represented in terms of the optimal proportion of each fire age class across the study region under each scenario. Coloured points represent the proportion of each fire age class from each individual optimisation run. Black points and lines represent the mean, 10th percentile and 90th percentile expected optimal proportion of each fire age class of the 1000 optimisation runs.

have outlined an end-to-end approach for identifying the best management regimes for multiple species subject to interacting drivers of species abundance at a landscape scale. Our results shine a light on the need to consider co-occurring threats and disturbance processes when designing and implementing management strategies for biodiversity conservation. In our demonstration of our framework, we found that the optimal mix of fire age classes was dominated by the 6–10 years post-fire class, and had an increasing amount of long-unburnt (24 years post-fire) vegetation in scenarios with high- compared to low-intensity fox baiting. Only low proportions of the youngest age class (0–5 years post-fire) featured in the optimal mix of fire age classes. By characterising the uncertainty associated with these trends, we were able to show that the application of an optimisation framework to decision problems featuring interacting threats can yield useful information, despite considerable uncertainty. Our approach demonstrates that considering both the potential interacting factors and uncertainty in the effect of management levers on the species of interest are essential steps in managing biodiversity.

We found that the abundance of several native mammals (woylie and numbat) was higher in areas with higher fox baiting intensity, and red fox abundance was higher in areas with low fox baiting intensity that were >10 years post-fire. Given that these associations are the intended outcome of lethal fox baiting (Geary et al., 2022; Wayne et al., 2017), it highlights the conservation benefit of lethal fox control in this region. Although fire regime variables—such as time since fire and landscape-scale severe fire—influenced the abundance of most species in our analysis, baiting intensity had a stronger effect on the abundance of woylies. The proportion of the landscape burnt severely within 6 years of the camera surveys had a negative association with the abundance of all native species. In our demonstration analysis, we found that the optimal distribution of fire age classes for the species in our study was dependent on the level of lethal fox management occurring. However, as the results from this study are based on a single year of camera trapping and are uncertain, the ecological associations should be interpreted with caution. The influence of these interactions on the outcomes of management

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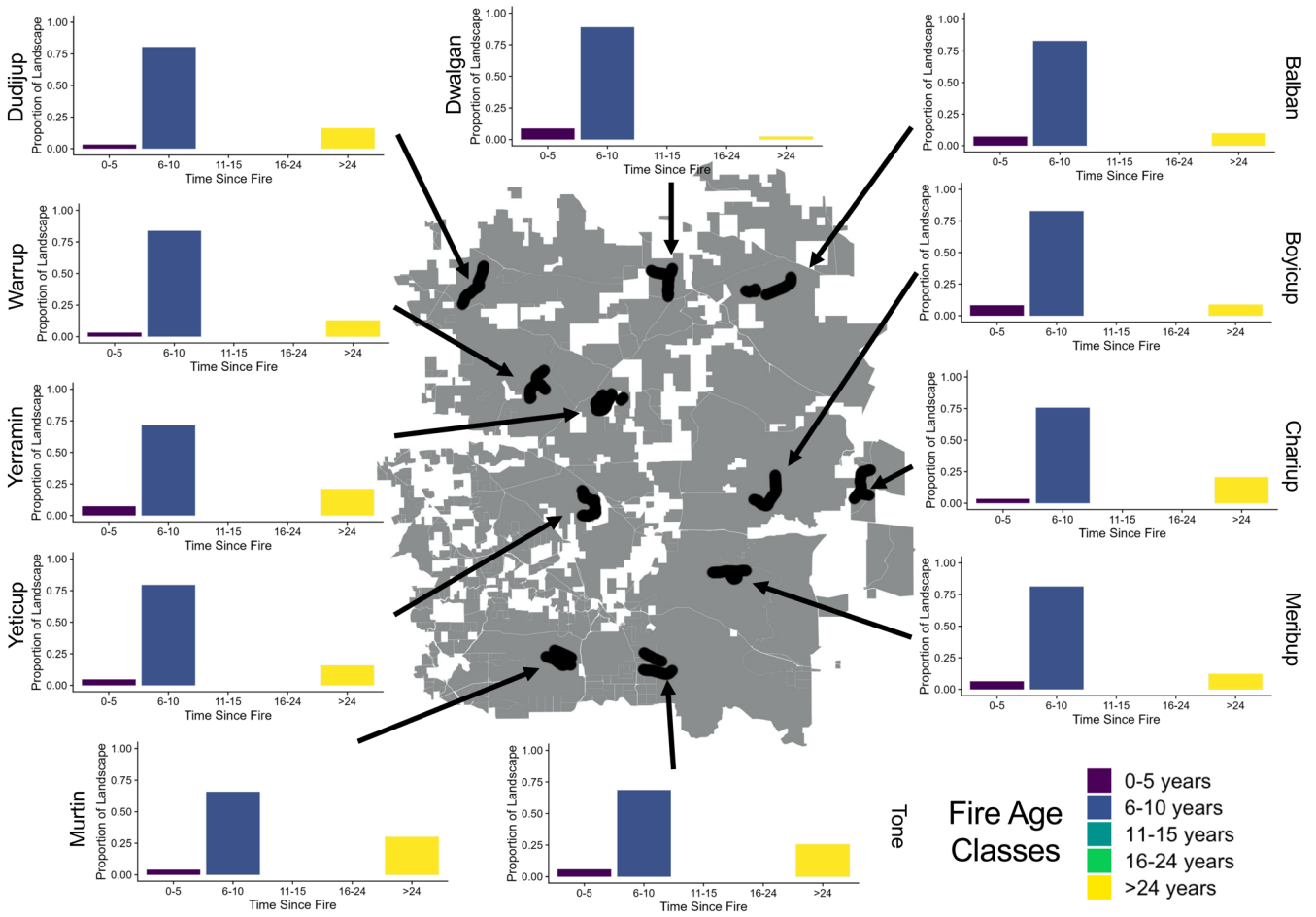

FIGURE 5 Transect-scale optimisation results for the Upper Warren region that maximise the abundance of the species of interest under a high fox baiting intensity scenario and at 20% of the landscape burnt severely in the past 6 years, represented in terms of the optimal proportion of each fire age class across the study region under each scenario. See Figure S6 for comparison across fox baiting intensity scenarios and quantification of uncertainty in optimisation outcomes.

reinforces calls for jointly managing invasive predators and disturbances like fire (Doherty et al., 2015).

By providing fire histories across landscapes, our demonstration prioritisations give managers clear goal posts to aim for with fire management while maintaining flexibility in how these goals can be reached. Our prioritisations also emphasise the need for fire management to be tailored to the specific management context (e.g. baiting intensity), geographic location and current conditions (e.g. how far the landscape is from the optimal fire age distribution). This is because these aspects can influence how species respond to the fire regime and, in turn, alter conservation outcomes. By understanding how the effects of management actions play out in different locations, managers can assess possible trade-offs and conflicts that might occur between species and locations. For example, we found that under a high baiting intensity, the abundance of some species (woylie) is higher in younger fire ages than older fire ages. This is consistent with previous studies that have demonstrated geographic variation in species' responses to fire (Nimmo et al., 2014), and our results suggest that co-occurring threats (e.g. predation by invasive predators) may contribute to such variation. Both changing fire regimes (Kelly et al., 2023) and invasive predators (Doherty et al., 2016) are having large impacts on biodiversity globally, and these drivers of extinction interact in locations across the world. Therefore, managers need approaches that can help disentangle these complex interactions and identify an acceptable path forward.

Our study provides two key advances for identifying optimal fire age distributions. First, by allowing model uncertainty to propagate through to the optimisation analyses, our study demonstrates that the optimal fire age distribution is uncertain, irrespective of the intensity of fox baiting. Communicating the effect of uncertainty on potential decisions is an essential step in building practical models (Addison et al., 2013), particularly as it allows managers to pinpoint where further data collection may be required. In our case study, the largest model uncertainty related to fauna abundances in vegetation >24 years post-fire, thus more certain estimates of species' abundances in long unburnt vegetation could be a logical focus of further monitoring. Further, rainfall and topography can shape species' relationships with time since fire and we did not explicitly consider these effects in this study (Connell et al., 2022; Verdon et al., 2019), which may have also contributed to our model's uncertainties. Second, by

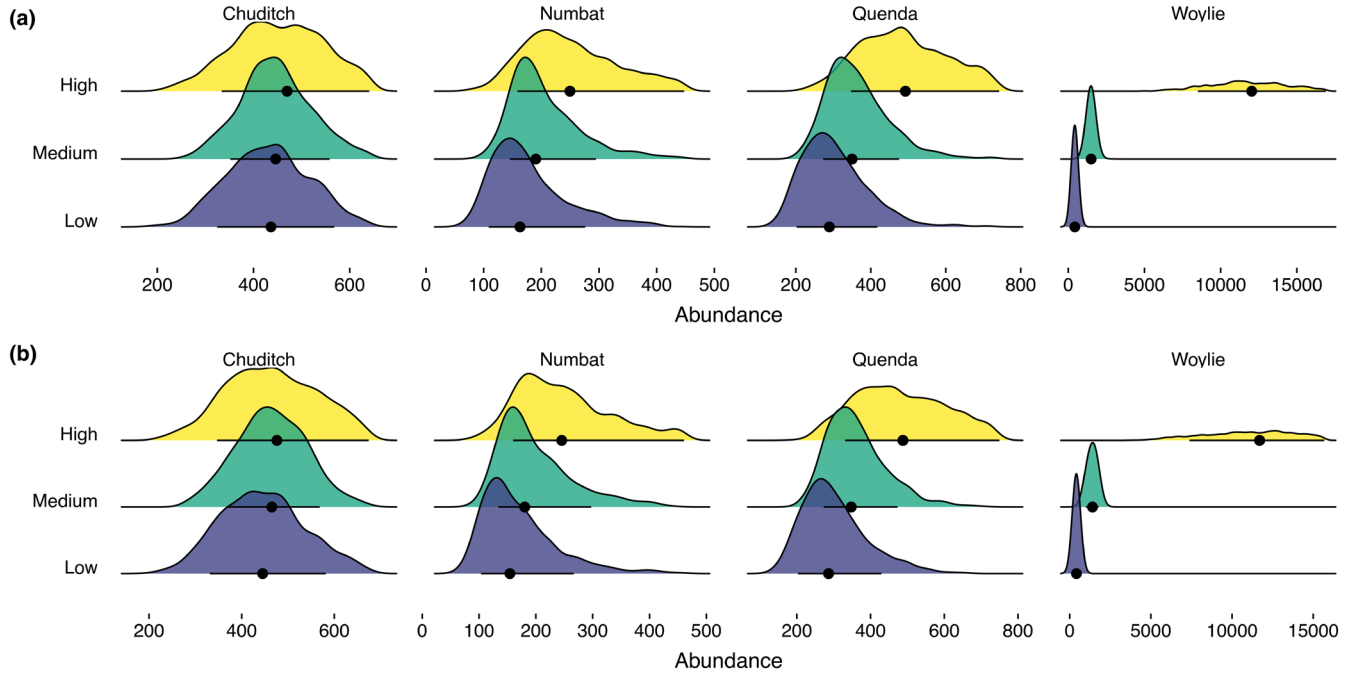

FIGURE 6 Distributions of outcomes of optimisation scenarios for three fox baiting intensities (High, Medium and Low) for the four focal species: chuditch, numbat, quenda and woylie, considered in the analysis, represented in terms of the overall (regional scale) predicted abundance for each species achieved by the optimal distribution of fire ages. Results shown are for the fire severity scenario (a) 20% and (b) 50% of the landscape burnt severely in the past 6 years. Black points and lines represent the mean, 10th percentile and 90th percentile expected overall abundance and for each species.

identifying local optimal fire age distributions and summarising them at the regional scale, our results demonstrate how our approach can provide advice to land managers at multiple spatial scales. Recent studies have shown how the co-occurrence patterns of species can influence where fire management conflicts between species may or may not occur (Verdon & Clarke, 2022). Spatially explicit information from studies such as ours can help fire managers better target actions such as prescribed burning so that bushfire risk can be reduced while also maximising the availability of suitable habitat for multiple species. Future studies could also incorporate simulations of future fire regimes so that trade-offs between prescribed burning and reduced bushfire risks can be appropriately evaluated in the context of biodiversity conservation.

Our study takes advantage of a broadscale, snapshot dataset to develop an end-to-end approach for identifying optimal management strategies for fire and red foxes. Therefore, our results are based on field-collected data on individual species abundances and so the associations observed in our study can only be taken as correlations, rather than conclusive evidence of species interactions or management effectiveness. Further, feral cats are likely to be a major predator for medium-sized mammals in this region (Wayne et al., 2017; Woolley et al., 2019). There was insufficient data in our study to account for feral cat responses, but there is some evidence that feral cat activity is higher in areas with more intense fox baiting (Geary et al., 2022). Cat control is more labour intensive and requires different methods (e.g. different bait types) to fox control (Lohr & Algar, 2020). Our results can therefore help guide fire and fox management priorities across space, but we caution that controlling only a single predator (foxes) without managing the other (cats) could result in perverse outcomes (Marlow et al., 2015; Rees et al., 2023). Structured and robust/unbiased survey data that adequately sample fauna abundances across the full range of fire ages, fire severity, fox baiting intensities and cat activity, in an analysis framework that accounts for the major drivers of species' abundances will reduce uncertainty and further refine the response curves shown here. This is best done using a well-designed experimental approach that accounts for the key factors of interest and their interactions (Foster et al., 2016), such as stratified sampling across spatial and temporal threat gradients (e.g. fragmentation, rainfall decline; Geary et al., 2023). Structured survey data would also allow for our modelling framework to be fully spatially explicit (e.g. considering species' distributions across the whole landscape), which would be an important advance on this study. Value of information analyses could also help design a sampling program that ensures the most influential uncertainties are addressed first (Bal et al., 2018).

In this study, we chose to maximise the abundance for a community of species found in the study region. Our approach allows for the consideration of complementarity—a fundamental principle in conservation planning (Margules & Pressey, 2000)—which is critical for identifying solutions that balance the needs of all species considered. Other taxa with different needs could be incorporated into our approach if monitoring data were available, as could differential weights for species of particular conservation importance. Objectives such as identifying the optimal fire regime that minimises

wildfire risk or species' extinction risk are also possible but not explored here. Similarly, constraints can be applied so that there is a minimum amount of an age class at each site so that the optimal solutions reflect policy conditions or operational constraints (e.g. needing to have some of the landscape in the age classes intervening the optimal age classes). Our approach gives managers optimal fire age class distributions to aim for while also allowing flexibility in how to achieve them, which is necessary given the stochastic nature of fire and factors that limit the implementation of fire management actions (e.g. fire weather conditions, bushfire occurrence). Other specifications of the targets, objective functions and candidate actions (e.g. other characterisations of fire and predator management, incorporation of the effects of fire severity) would likely influence which fire ages are identified as optimal. Further, there are numerous other biodiversity indicators that could be used when designing the objective function for the optimisation. The optimal distribution of fuel ages is often sensitive to the indicator used (Giljohann et al., 2015) and the species included (Giljohann et al., 2018). Therefore, careful consideration of how the overall biodiversity objective is specified (i.e. which species are included, and how they are measured) will be required for this approach to provide robust decision support to land managers.

5 | CONCLUSION

Understanding the consequences of potentially interacting management actions, such as fire and lethal fox control, on outcomes for biodiversity is crucial for managing ecosystems in the Anthropocene (Bergstrom et al., 2021). Here, we have illustrated how fire and predator management can interact, and we developed an approach for understanding how these factors may affect the optimal fire management at both the regional and local scales. Our results emphasise the importance of considering local context and accounting for other drivers of spatial and temporal variation in species abundances when designing fire management strategies.

AUTHOR CONTRIBUTIONS

William L. Geary, Ayesha I.T. Tulloch, Tim S. Doherty, Dale G. Nimmo, Euan G. Ritchie, Jeffrey O. Hanson, Marika A. Maxwell and Adrian F. Wayne conceived the ideas and designed the methodology. Marika A. Maxwell and Adrian F. Wayne collected the data. William L. Geary analysed the data. William L. Geary led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to declare.

DATA AVAILABILITY STATEMENT

Data and code available from the Dryad Digital Repository: https://doi.org/10.5061/dryad.b8gtht7s3 (Geary et al., 2025).

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REFERENCES

Addison, P. F., Rumpff, L., Bau, S. S., Carey, J. M., Chee, Y. E., Jarrad, F. C., McBride, M. F., & Burgman, M. A. (2013). Practical solutions for making models indispensable in conservation decision-making. *Diversity and Distributions*, *19*, 490–502.

Auerbach, N. A., Wilson, K. A., Tulloch, A. I. T., Rhodes, J. R., Hanson, J. O., & Possingham, H. P. (2015). Effects of threat management interactions on conservation priorities. *Conservation Biology*, *29*, 1626–1635.

Bal, P., Tulloch, A. I., Chadès, I., Carwardine, J., McDonald-Madden, E., & Rhodes, J. R. (2018). Quantifying the value of monitoring species in multi-species, multi-threat systems. *Methods in Ecology and Evolution*, *9*, 1706–1717.

Bellard, C., Leclerc, C., & Courchamp, F. (2015). Combined impacts of global changes on biodiversity across the USA. *Scientific Reports*, *5*, 11828.

Bergstrom, D. M., Wienecke, B. C., van den Hoff, J., Hughes, L., Lindenmayer, D. B., Ainsworth, T. D., Baker, C. M., Bland, L., Bowman, D. M., & Brooks, S. T. (2021). Combating ecosystem collapse from the tropics to the Antarctic. *Global Change Biology*, *27*, 1692–1703.

Blanchet, F. G., Cazelles, K., & Gravel, D. (2020). Co-occurrence is not evidence of ecological interactions. *Ecology Letters*, *23*, 1050–1063.

Boer, M. M., Sadler, R. J., Wittkuhn, R. S., McCaw, L., & Grierson, P. F. (2009). Long-term impacts of prescribed burning on regional extent and incidence of wildfires—Evidence from 50 years of active fire management in SW Australian forests. *Forest Ecology and Management*, *259*, 132–142.

BoM. (2020). Bureau of Meteorology. Commonwealth Government of Australia.

Brown, C. J., Bode, M., Venter, O., Barnes, M. D., McGowan, J., Runge, C. A., Watson, J. E. M., & Possingham, H. P. (2015). Effective conservation requires clear objectives and prioritizing actions, not places or species. *Proceedings of the National Academy of Sciences*, *112*, E4342.

Chalifour, L., Holt, C., Camaclang, A. E., Bradford, M. J., Dixon, R., Finn, R. J., Hemming, V., Hinch, S. G., Levings, C. D., & MacDuffee, M. (2022). Identifying a pathway towards recovery for depleted wild Pacific salmon populations in a large watershed under multiple stressors. *Journal of Applied Ecology*, *59*, 2212–2226.

Connell, J., Hall, M. A., Nimmo, D. G., Watson, S. J., & Clarke, M. F. (2022). Fire, drought and flooding rains: The effect of climatic extremes on bird species' responses to time since fire. *Diversity and Distributions*, *28*, 417–438.

de Valpine, P., Paciorek, C., Turek, D., Michaud, N., Anderson-Bergman, C., Obermeyer, F., Wehrhahn Cortes, C., Rodrìguez, A., Temple Lang, D., & Paganin, S. (2021). NIMBLE: MCMC, particle filtering, and programmable hierarchical modeling. R Package Version 0.11, 1.

Densmore, V., van Dongen, R., Ong, R., & Harris, B. (2023). OzCBI: The composite burn index adapted to assess fire severity and key fauna habitat features in Australian ecosystems. *Australian Forestry*, *86*, 1–21.

Department of Biodiversity Conservation and Attractions. (2021). *DBCA fire history (DBCA-060)*. Department of Biodiversity Conservation and Attractions.

Department of Environment and Conservation. (2012). *Perup management plan 2012*. Department of Environment and Conservation.

Doherty, T. S., Dickman, C. R., Nimmo, D. G., & Ritchie, E. G. (2015). Multiple threats, or multiplying the threats? Interactions between invasive predators and other ecological disturbances. *Biological Conservation*, *190*, 60–68.

Doherty, T. S., Geary, W. L., Jolly, C. J., Macdonald, K., Miritis, V., Watchorn, D. J., Cherry, M. J., Conner, L. M., Legge, S. M., Ritchie, E. G., Stawski, C., & Dickman, C. R. (2022). Fire as a driver and mediator of predator-prey interactions. *Biological Reviews*, *97*, 1539–1558.

Doherty, T. S., Glen, A. S., Nimmo, D. G., Ritchie, E. G., & Dickman, C. R. (2016). Invasive predators and global biodiversity loss. *Proceedings of the National Academy of Sciences*, *113*, 11261–11265.

Foster, C. N., Sato, C. F., Lindenmayer, D. B., & Barton, P. S. (2016). Integrating theory into disturbance interaction experiments to better inform ecosystem management. *Global Change Biology*, *22*, 1325–1335.

Furnas, B. J., Goldstein, B. R., & Figura, P. J. (2022). Intermediate fire severity diversity promotes richness of forest carnivores in California. *Diversity and Distributions*, *28*, 493–505.

Gallant, J., & Austin, J. (2012). Topographic Wetness Index derived from 1" SRTM DEM-H. v2. (ed. CSIRO).

Ganz, T. R., DeVivo, M. T., Kertson, B. N., Roussin, T., Satterfield, L., Wirsing, A. J., & Prugh, L. R. (2022). Interactive effects of wildfires, season, and predator activity shape mule deer movements. *Journal of Animal Ecology*, *91*, 2273–2288.

Geary, W., Wayne, A., Tulloch, A., Ritchie, E., Maxwell, M., & Doherty, T. (2022). Fox and cat responses to fox baiting intensity, rainfall and prey abundance in the upper Warren, Western Australia. *Wildlife Research*, *50*, 201–211.

Geary, W. L., Doherty, T. S., Nimmo, D. G., Tulloch, A., & Ritchie, E. G. (2020). Predator responses to fire: A global systematic review and meta-analysis. *Journal of Animal Ecology*, *89*, 955–971.

Geary, W. L., Tulloch, A. I. T., Ritchie, E. G., Doherty, T. S., Nimmo, D. G., Maxwell, M. A., & Wayne, A. F. (2023). Identifying historical and future global change drivers that place species recovery at risk. *Global Change Biology*, *29*, 2953–2967.

Geary, W. L., Tulloch, A. I. T., Ritchie, E. G., Doherty, T. S., Nimmo, D. G., Maxwell, M. A., & Wayne, A. F. (2025). Data from: Optimising fire and predator management for conservation. *Dryad Digital Repository*. https://doi.org/10.5061/dryad.b8gtht7s3

Gelman, A., Meng, X.-L., & Stern, H. (1996). Posterior predictive assessment of model fitness via realized discrepancies. *Statistica Sinica*, *6*, 733–760.

Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science*, *7*, 457–472.

Giljohann, K., McCarthy, M., Kelly, L., & Regan, T. (2015). Choice of biodiversity index drives optimal fire management decisions. *Ecological Applications*, *25*, 264–277.

Giljohann, K. M., Kelly, L. T., Connell, J., Clarke, M. F., Clarke, R. H., Regan, T. J., & McCarthy, M. A. (2018). Assessing the sensitivity of biodiversity indices used to inform fire management. *Journal of Applied Ecology*, *55*, 461–471.

Gurobi Optimization. (2023). Gurobi Optimizer Reference Manual.

Hale, S., Nimmo, D. G., Cooke, R., Holland, G., James, S., Stevens, M., De Bondi, N., Woods, R., Castle, M., Campbell, K., Senior, K., Cassidy, S., Duffy, R., Holmes, B., & White, J. G. (2016). Fire and climatic extremes shape mammal distributions in a fire-prone landscape. *Diversity and Distributions*, *22*, 1127–1138.

Hanson, J. O., Schuster, R., Morrell, N., Strimas-Mackey, M., Watts, M., Arcese, P., Bennett, J., & Possingham, H. (2017). prioritizr: Systematic conservation prioritization in R. *R package version*, 3.

Howard, T., Burrows, N., Smith, T., Daniel, G., & McCaw, L. (2020). A framework for prioritising prescribed burning on public land in Western Australia. *International Journal of Wildland Fire*, *29*, 314–325.

Hradsky, B. (2020). Conserving Australia's threatened native mammals in predator-invaded, fire-prone landscapes. *Wildlife Research*, *47*, 1–15.

Hradsky, B., Mildwaters, C., Ritchie, E., Christie, F., & Di Stefano, J. (2017). Invasive predator and native prey responses to a prescribed forest fire. *Journal of Mammalogy*, *98*, 835–847.

Jones, G. M., & Tingley, M. W. (2022). Pyrodiversity and biodiversity: A history, synthesis, and outlook. *Diversity and Distributions*, *28*, 386–403.

Kelly, L. T., Bennett, A. F., Clarke, M. F., & McCarthy, M. A. (2015). Optimal fire histories for biodiversity conservation. *Conservation Biology*, *29*, 473–481.

Kelly, L. T., Fletcher, M.-S., Menor, I. O., Pellegrini, A. F. A., Plumanns-Pouton, E. S., Pons, P., Williamson, G. J., & Bowman, D. M. J. S. (2023). Understanding fire regimes for a better Anthropocene. *Annual Review of Environment and Resources*, *48*, 207–235.

Kelly, L. T., Giljohann, K. M., Duane, A., Aquilué, N., Archibald, S., Batllori, E., Bennett, A. F., Buckland, S. T., Canelles, Q., Clarke, M. F., Fortin, M.-J., Hermoso, V., Herrando, S., Keane, R. E., Lake, F. K., McCarthy, M. A., Morán-Ordóñez, A., Parr, C. L., Pausas, J. G., … Brotons, L. (2020). Fire and biodiversity in the Anthropocene. *Science*, *370*, eabb0355.

Kery, M., & Royle, J. A. (2020). *Applied hierarchical modeling in ecology: Analysis of distribution, abundance and species richness in R and BUGS: Volume 2: Dynamic and advanced models*. Academic Press.

Kimmel, K., Clark, M., & Tilman, D. (2022). Impact of multiple small and persistent threats on extinction risk. *Conservation Biology*, *36*, e13901.

Legge, S., Smith, J. G., James, A., Tuft, K. D., Webb, T., & Woinarski, J. C. Z. (2019). Interactions among threats affect conservation management outcomes: Livestock grazing removes the benefits of fire management for small mammals in Australian tropical savannas. *Conservation Science and Practice*, *1*, e52.

Lohr, C. A., & Algar, D. (2020). Managing feral cats through an adaptive framework in an arid landscape. *Science of the Total Environment*, *720*, 137631.

Lu, Y., Yang, Y., Sun, B., Yuan, J., Yu, M., Stenseth, N. C., Bullock, J. M., & Obersteiner, M. (2020). Spatial variation in biodiversity loss across China under multiple environmental stressors. *Science Advances*, *6*, eabd0952.

Margules, C. R., & Pressey, R. L. (2000). Systematic conservation planning. *Nature*, *405*, 243–253.

Marlow, N. J., Thomas, N. D., Williams, A. A., Macmahon, B., Lawson, J., Hitchen, Y., Angus, J., & Berry, O. (2015). Cats (*Felis catus*) are more abundant and are the dominant predator of woylies (*Bettongia penicillata*) after sustained fox (*Vulpes vulpes*) control. *Australian Journal of Zoology*, *63*, 18–27.

Morris, G., Hostetler, J. A., Oli, M. K., & Conner, L. M. (2011). Effects of predation, fire, and supplemental feeding on populations of two species of Peromyscus mice. *Journal of Mammalogy*, *92*, 934–944.

Nimmo, D. G., Kelly, L. T., Farnsworth, L. M., Watson, S. J., & Bennett, A. F. (2014). Why do some species have geographically varying responses to fire history? *Ecography*, *37*, 805–813.

R Core Development Team. (2020). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing.

Rees, M. W., Pascoe, J. H., Le Pla, M., Robley, A., Birnbaum, E. K., Wintle, B. A., & Hradsky, B. A. (2023). Mesopredator release among invasive predators: Controlling red foxes can increase feral cat density and alter their behaviour. *Journal of Applied Ecology*, *60*, 1100–1114.

Royle, J. A., & Nichols, J. D. (2003). Estimating abundance from repeated presence–absence data or point counts. *Ecology*, *84*, 777–790.

Smucker, K. M., Hutto, R. L., & Steele, B. M. (2005). Changes in bird abundance after wildfire: Importance of fire severity and time since fire. *Ecological Applications*, *15*, 1535–1549.

Thomson, J., Regan, T. J., Hollings, T., Amos, N., Geary, W. L., Parkes, D., Hauser, C. E., & White, M. (2020). Spatial conservation action planning in heterogenous landscapes. *Biological Conservation*, *250*, 108735.

Tulloch, A. I. T., Chadès, I., & Lindenmayer, D. B. (2018). Species co-occurrence analysis predicts management outcomes for multiple threats. *Nature Ecology & Evolution*, *2*, 465–474.

Tulloch, A. I. T., Pichancourt, J. B., Gosper, C. R., Sanders, A., & Chadès, I. (2016). Fire management strategies to maintain species population processes in a fragmented landscape of fire-interval extremes. *Ecological Applications*, *26*, 2175–2189.

Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing*, *27*, 1413–1432.

Verdon, S. J., & Clarke, M. F. (2022). Can fire-age mosaics really deal with conflicting needs of species? A study using population hotspots of multiple threatened birds. *Journal of Applied Ecology*, *59*, 2128–2141.

Verdon, S. J., Watson, S. J., & Clarke, M. F. (2019). Modeling variability in the fire response of an endangered bird to improve fire-management. *Ecological Applications*, *29*, e01980.

Ward, M., Carwardine, J., Watson, J. E., Pintor, A., Stuart, S., Possingham, H. P., Rhodes, J. R., Carey, A. R., Auerbach, N., & Reside, A. (2022). How to prioritize species recovery after a megafire. *Conservation Biology*, *36*, e13936.

Wayne, A. (2018). Insights from multi-species mammal monitoring programs in the upper Warren, Western Australia. In *Monitoring threatened species and ecological communities* (pp. 179–192). CSIRO Publishing.

Wayne, A. F., Maxwell, M. A., Ward, C. G., & Quinn, J. (2024). Feral cat control: Improving Eradicat® bait efficiency and effectiveness for fauna conservation in the Southern Jarrah Forest, Western Australia. *Wildlife Research*, *51*, WR24073. https://doi.org/10.1071/WR24073.

Wayne, A. F., Maxwell, M. A., Ward, C. G., Wayne, J. C., Vellios, C. V., & Wilson, I. J. (2017). Recoveries and cascading declines of native mammals associated with control of an introduced predator. *Journal of Mammalogy*, *98*, 489–501.

Whelan, R. J., Rodgerson, L., Dickman, C. R., & Sutherland, E. (2002). Critical life cycles of plants and animals: Developing a process-based understanding of population changes in fire-prone landscapes. In R. A. Bradstock, J. E. Williams, & M. A. Gill (Eds.), *Flammable Australia: The fire regimes and biodiversity of a continent* (pp. 94–124). Cambridge University Press.

Whitehead, T., Vernes, K., Goosem, M., & Abell, S. E. (2018). Invasive predators represent the greatest extinction threat to the endangered northern bettong (*Bettongia tropica*). *Wildlife Research*, *45*, 208–219.

Wintle, B. A., Legge, S., & Woinarski, J. C. Z. (2020). After the megafires: What next for Australian wildlife? *Trends in Ecology & Evolution*, *35*, 753–757.

Woolley, L. A., Geyle, H. M., Murphy, B. P., Legge, S. M., Palmer, R., Dickman, C. R., Augusteyn, J., Comer, S., Doherty, T. S., & Eager, C. (2019). Introduced cats *Felis catus* eating a continental fauna: Inventory and traits of Australian mammal species killed. *Mammal Review*, *49*, 354–368.

Yamaura, Y., Royle, J. A., Shimada, N., Asanuma, S., Sato, T., Taki, H., & Makino, S.i. (2012). Biodiversity of man-made open habitats in an underused country: A class of multispecies abundance models for count data. *Biodiversity and Conservation*, *21*, 1365–1380.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Table S1: Species included in the multi-species abundance model, the number of independent detections and the number and number of sites each species was detected across the study region.

Figure S1. Directed acyclic graph outlining the expected causal relationships captured in the multi species abundance model used to make the predictions.

Figure S2. Maps of the covariates used in the community abundance model and their variation across the study region, including (a) time since fire, (b) proportion of the surrounding landscape (500 m buffer) severely burnt within 6 years, (c) fox baiting intensity, (d) mean annual rainfall and (e) topographic wetness index.

Figure S3. Distribution of sampling sites across time since fire values and baiting intensities used to fit the abundance models.

Table S2. Mean estimates of the detection probabilities taken from our abundance model for each species, with the lower and upper 95% credible intervals.

Table S3. Mean coefficient estimates and 95% credible intervals from the detection component of our abundance model for each species and each variable in the model (the model intercept, and Julian date transformed to radians).

Figure S4. Visualisation of the posterior predictive checks of our abundance model, comparing the χ^2 discrepancy based on the simulated and observed abundances for each MCMC iteration.

Figure S5. Correlations between the abundance of each species after accounting for patterns of association with the environmental predictors in the community abundance model.

Figure S6. Transect-scale optimisation results for the Upper Warren region that maximise the abundance of the species of interest under three alternative fox baiting intensities and at 50% of the landscape burnt severely in the previous 6 years, (a) Low, (b) Medium and (c) High fox baiting intensity, represented in terms of the optimal proportion of each fire age class across the study region under each scenario.

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