Climate and Fire Scenario Uncertainty Dominate the Evaluation of Options for Conserving the Great Desert Skink

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Abstract
Fire regimes are predicted to change under climate change, with associated impacts on species and ecosystems. However, the magnitude and direction of regime changes are uncertain, as will be species’ responses. For many species, how they respond will determine their medium-long-term viability. We propagate fire regime and species’ response uncertainties through a 50-year viability analysis of the great desert skink, Liopholis kintorei, in central Australia, characterizing fire regime change under three scenarios. Species’ response uncertainty was characterized with three competing models based on fire and habitat variables, fitted to 11 years of occupancy data. We evaluate fire management options for conserving the species, based on their robustness to uncertainty about fire and species’ response. Efforts to minimize the frequency and size of fires provides the most consistent improvements to species’ persistence. We show that disentangling important from unimportant uncertainties enables conservation managers to make more efficient, defensible decisions.

Introduction
The management of threatened species should be based on an understanding of habitat requirements, and the dynamics of that habitat through space and time. However, there are typically large uncertainties in such knowledge, especially in the context of a changing climate that can dramatically influence management effectiveness (Hulme 2005; Kujala et al. 2013). Fire is a fundamental driver of habitat change and uncertainty across many continents (Bond & Keeley 2005), and endemic species have evolved to tolerate or depend on certain broad patterns of fire that occur in their landscapes (Van Wilgen 2009; Bird et al. 2013). Conservation managers can therefore use fire and fire suppression as management tools for achieving conservation outcomes (Edwards et al. 2008). However, wildfire is irreducibly stochastic in its ignition and propagation, and our understanding of fire dynamics is often uncertain. Severe uncertainty about fire is compounded by projected changes in temperature and rainfall, and by an incomplete understanding of species’ fire ecology at both local and regional scales.

Conservation managers should aim to incorporate such uncertainties into the development of conservation strategies for two reasons. First, an explicit characterization of uncertainty allows managers to anticipate a range...
of possible outcomes, avoiding nasty surprises. Second, a quantitative description of uncertainty allows managers to choose actions that will maximize beneficial outcomes.

However, considering all uncertainties is overwhelming and inefficient because some are more important than others. In the context of management decisions, an uncertainty is only important if its resolution would lead to a change in management. Ignoring unimportant uncertainties can be liberating for decision-makers, increasing clarity by reducing apparent complexity. Ignoring important uncertainties, however, generally leads to decisions that are fragile (Ben-Haim 2006), and it is not a priori obvious which uncertainties are important. Explicit uncertainty analyses are not common in the conservation decision-making literature, and even fewer deal with realistic levels of uncertainty for conservation management problems.

Here we consider how to quantify and incorporate uncertainties into fire management decisions for the great desert skink (*Liopholis kintorei*; Stirling & Zeitl 1893), a listed threatened species (IUCN 1996) that occurs in arid central Australia (McAlpin 2001). There is substantial uncertainty about the drivers of apparent population declines, and about how the species will respond to changing climates and fire regimes. *L. kintorei* is expected to experience accelerated declines as increasing fire frequency expands recently burnt habitat that is thought to be unsuitable (Moore et al. 2015a).

Interactions between fire and feral predators may also play a role, as for other small reptiles and mammals in the region (McGregor et al. 2014; Moore et al. 2015b). This uncertainty is compounded by the dynamics of future fire regimes in central Australia (Watterson et al. 2015), which are driven by poorly-understood relationships between temperature, rainfall, plant growth, fuel load, and ignition.

Here, we demonstrate the value of understanding the differential value of multiple sources of uncertainty—both model and scenario uncertainty—when managing threatened species in fire-prone landscapes. The aim of this study is to illustrate how metapopulation modelling, combined with a spatially-explicit fire model, can describe the likely fate of a species under a range of future fire scenarios, and can identify fire management strategies most likely to secure its persistence. We predict the medium-term (50 years) impacts of three different fire regimes on the persistence of *L. kintorei* metapopulation on Newhaven Wildlife Sanctuary, central Australia, under three competing models of species response to fire. Our analysis supports the choice of fire management practices for conserving *L. kintorei* within fire-prone spinifex (*Triodia* spp.) habitat. We provide general insights into the use of metapopulation models for evaluating management options in the face of uncertainty.

### Materials and methods

#### Case study

*L. kintorei* is a large, nocturnal skink found in restricted pockets of arid and semiarid habitat across the central and western deserts of Australia (McAlpin 2001). *L. kintorei* live in family groups, unusually for reptiles, and build extensive burrow systems (McAlpin et al. 2011) which provide some protection from fire and feral predators (Moore et al. 2015a).

The Australian Wildlife Conservancy’s (AWC) Newhaven Wildlife Sanctuary in central Australia is an important stronghold for *L. kintorei*. Securing *L. kintorei* in the sanctuary is a key AWC objective. Newhaven covers 262,000 ha of the Great Sandy Desert Bioregion, 300 km northwest of Alice Springs. Widespread and intense wildfire is a common and integral feature of spinifex (*Triodia* spp.) dominated landscapes (Paltridge 2005) during the extremes of summer, particularly following above average rainfall. AWC have a number of fire-related management objectives, focused on conserving biodiversity through a variety of habitats at various stages of postfire recovery.

#### Habitat models

*L. kintorei* occurrence records consisted of burrow presence/absence data collected over 11 years (2003–2013) through a mixture of survey techniques described in the Supporting Information (S1). Environmental variables of vegetation, geology, and fire history on Newhaven were obtained from AWC along with radiometric data on soil types and geological formations (Minty et al. 2009). Annual fire records were used to calculate time-since-last-fire and number-of-fires over a 44-year period (1970-2013). Modelling was restricted to soft spinifex-dominated (*Triodia pungens* Brown 1810) sandplain habitat, as no *L. kintorei* burrows were found outside this habitat type, despite 11 years of search effort. These data support local knowledge about the specificity of *L. kintorei* to soft spinifex habitats within the study area (D. Moore, personal communication, 2013).

Competing generalized linear models (GLM: McCullagh & Nelder 1989) were fitted and evaluated in R (R Core Team 2015), describing *L. kintorei* presence/absence as a function of environmental variables. Candidate variables were chosen based on ecological relevance (*sensu* Austin 2002). Generalized additive models (Hastie & Tibshirani 1990) and boosted regression trees (Elith et al. 2008) were fitted to investigate the effect of modelling method. Models were evaluated using: (1) AIC (Akaite 1973); (2) deviance explained; and (3) predictive discrimination (ROC curve: Hanley & McNeil 1982).
Estimates of the latter two metrics were obtained through cross-validation (sensu Elith & Graham 2009). All three methods included the same variables in their final models and performed similarly in terms of predictive accuracy (see Supporting Information: S3). GLMs were retained for metapopulation modelling because they can be described with a simple mathematical equation. To propagate uncertainty about species’ response to fire through the modelling process, we retained the three lowest AIC GLMs for the metapopulation analyses.

**Dynamic-landscape metapopulation (DLMP) models**

We used RAMAS Landscape (Akçakaya & Root 2002) to construct a dynamic metapopulation model for *L. kintorei*, run within RAMAS Repeater to facilitate joint analysis of population and landscape stochasticity (Chisholm & Wintle 2007). For a schematic representation of this process, see Gordon et al. (2012).

Fire dynamics in the study region are strongly influenced by variation in vegetation type and structure, and landform (Morton et al. 2011). Vegetation types and geological features were formed into 24 unique land types with varying pyric characteristics that were based on the AWC fire history maps. This increased the realism of fire ignition and spread across the sanctuary. Three different plausible fire scenarios represented the uncertainty about the direction of fire regime changes under climate change: current, “increased,” and “decreased” scenarios (Supporting Information: S3).

Metapopulation model simulations were run for 50 years in annual time steps, which was deemed a sufficient simulation period given the relatively short fire disturbance and recovery cycle at play in the study landscape (mean fire return interval of 15 years, based on fire records). Population parameter estimates used in the DLMP models can be found in the Supporting Information (S3). Carrying capacity (*K*) estimates the number of individuals supported by a patch of suitable habitat, and was defined as a function of habitat suitability and area (Figure 1).

Following Gordon et al. (2012), we calculated the expected minimum population size (EMP), the average of the lowest abundances reached during each replicate population simulation. This metric provides a more robust ranking of scenarios than classic measures such as extinction probability or final population size (McCarthy & Thompson 2001).

**Sensitivity analyses**

Sensitivity analyses provide a means of determining the importance of assumptions and uncertainties in predicting population viability and making management decisions (Gordon et al. 2012). In addition to the fire scenario and habitat model uncertainties, we measured the sensitivity of EMP to plausible uncertainty in population parameters such as fecundity, survival and dispersal distance which were obtained from data, published studies and expert opinion (Supporting Information: S4).

**Results**

**Habitat models**

Vegetation type, topographic elevation, soil properties and fire history drive *L. kintorei* distribution on Newhaven. The three lowest AIC GLMs were congruent in their choice of these variables (Table 1). These three models, which differed subtly but importantly in the fitted functions of the two fire variables, were
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Figure 2

Table 1

The three best performing GLMs, showing the relationship between great desert skink occurrence and habitat variables. AIC is the Aikaike information criterion, "cvROC" indicates the results of the 10-fold cross validation, and ROC is the receiver operating characteristic. Italics highlight differences between models. See Supporting Information: S3 for more details.

| Name | Model | AIC  | Explained deviance (%) | cvROC |
|------|-------|------|------------------------|-------|
| A    | $PA \sim e^2 + f + t + tsf^2 + nf^2$ | 262.53 | 34.73 | 0.85 |
| B    | $PA \sim e^2 + f + t + tsf^2 + nf$ | 267.91 | 32.76 | 0.83 |
| C    | $PA \sim e^2 + f + t + tsf + nf$ | 269.42 | 31.86 | 0.82 |

Model abbreviations are as follows: PA: Presence/Absence, $e$: elevation (m), $f$: ferrous iron content of soil (proportion), $t$: thorium content of soil (proportion), $tsf$: time-since-fire (years), $nf$: number of fires in a 44-year period (years).

chosen to represent uncertainty about $L. kintorei$ local-scale response to fire in the DLMP model simulations. Model A treated both fire variables as quadratic functions, model B fitted only time-since-fire as a quadratic function and number of fires in 44 years as linear, and both fire terms were linear in model C (Table 1). Within the soft spinifex habitat of $L. kintorei$, fire history and geological variables are responsible for the fine scale variation in occupancy (Figure 2).

DLMP model outcomes

Fire scenario had a large impact on the population trajectory, irrespective of which habitat model was assumed to represent species’ response to fine-scale fire history. The EMP of all “increased” fire scenarios was below five individuals, around 1,000 individuals for the current scenario, and up to 22,000 individuals under the “decreased” scenario (Figure 3). Differences in EMP predictions between the habitat models became more pronounced in the “decreased” fire scenario. Across all fire scenarios, model C, which assumes linear fire responses, provides the bleakest outlook for the species.
Figure 3 Expected minimum population size for each combination of habitat model and fire scenario over a 50-year period for the great desert skink. Note the break in the y-axis. Model A has a quadratic relationship between *L. kintorei* occupancy and the two fire history variables, model B a quadratic relationship with time-since-fire and a linear one with number of fires in a 44-year period, and both fire variables are treated as linear in model C.

the mean population trajectories across all models, the "increased" fire scenario lead to decreases in population size, with a large risk of extinction, while the "decreased" fire scenario led to population booms (Figure 4).

**Sensitivity analyses**

Apart from sensitivity to the fire scenario, the EMP was most sensitive to the shape of the carrying capacity function and the choice of $R_{max}$ (Figure 5). Using either linear or logistic functions (Figure 1) of habitat quality to describe variation in $K$ led to dramatic increases in EMP. This response is driven by an increase in the carrying capacity of low/mid quality patches that are excluded when using the exponential function. Due to a lack of empirical data, many DLMPs assume a linear relationship between carrying capacity and habitat quality (Griffiths 2004; Southwell et al. 2008). Our results indicate that this could lead to optimistic predictions.

$R_{max}$ represents the population growth rate in the absence of competition. Our model was moderately sensitive to alternative $R_{max}$ assumptions. A decrease in $R_{max}$ by 15% led to a 75% decrease in EMP. $R_{max}$ is based on maximum observed fecundity and survival rates. Experts’ confidence of fecundity estimates is high (S. McAlpin, personal communication, 2014), though survival rates in the absence of competition are more difficult to estimate. However, because the model wasn’t sensitive to our highest and lowest plausible survival assumptions (Figure 5), this aspect of the $R_{max}$ calculation is not of concern.

**Discussion**

Future fire regimes are the major determinant of *L. kintorei* population viability at Newhaven. In fact, irrespective of the uncertainty surrounding the species’ response to fire (reflected in the competing habitat models we fitted to the survey data), a major increase in fire size and frequency will drive this population to extinction. In quantifying different uncertainties in a management context, we have identified and separated relevant from irrelevant uncertainties. This allows
managers to more effectively allocate limited resources to those uncertainties that can be resolved through further action or research to make a tangible difference to the species. Managers at Newhaven Sanctuary can continue to focus on generating suitable habitat using fire management, rather than characterizing the species’ response to fire history and other habitat variables.

We characterized uncertainty about the species’ response to fire using competing habitat models fitted to 11 years of occupancy data. Thus we can be confident that our key finding about the importance of future fire scenarios is not an artefact of fragile habitat model assumptions. A crucial strength of this study is that we have explored, quantified and effectively discounted an aspect of uncertainty that often goes unaccounted for when modelling to inform conservation management (Southwell et al. 2008). Nonetheless, we have not characterized uncertainty about all key ecological processes relevant to the persistence of L. kintorei. For example, our simulations of fire impacts on habitat did not take account of fine scale variation in fire type and intensity due to weather and fuel loads. Fire

Figure 4 Mean population trajectory over the next 50 years for the great desert skink under three different fire scenarios and three different habitat models. Model A has a quadratic relationship between L. kintorei occupancy and the two fire history variables, model B a quadratic relationship with time-since-fire and a linear one with number of fires in a 44-year period, and both fire variables are treated as linear in model C. Dashed lines show mean minimum and maximum trajectories across all simulations. Y-axes are on a different scale for each fire scenario.
type and intensity are aspects of the fire regime that may have an influence on the survival of *L. kintorei* and the carrying capacity of habitats, but dynamics at this spatial and temporal resolution were beyond the technical dimensions of our simulation models. Additionally, our study did not disentangle uncertainty about the role of introduced and native predators and their interaction with fire regime. We are, therefore, unable to say how sensitive our predictions would be to varying levels of predator control. Recent studies suggest that increased predation risk post-fire, due to a lack of vegetation cover, is a key reason for the high extinction risk to *L. kintorei* under increasing fires (Moore et al. 2015a, 2015b). This response to recent fire history is consistent with studies of other arid zone species (Bolton & Latz 1978; Smith et al. 2012). Feral predators may be an underlying driver of decline, but fine-scale spatial and temporal variation in vegetation structure appears to be important in mediating the persistence of *L. kintorei*, and *this* is governed by fire extent, intensity, and spatial arrangement of fires.

As patches of spinifex begin to form more suitable habitat postfire, recolonization of *L. kintorei* from nearby occupied patches will drive longer term patch occupancy. An increase in the frequency and size of fires reduces landscape connectivity and isolates populations. Under even the most extreme fire scenario simulated here, suitable habitat exists across the sanctuary for the duration of the simulation (Figure S1). However, the relatively low dispersal potential of the species—a maximum of 2 km (McAlpin et al. 2011; Supporting Information: S3)—means that recolonization of suitable but unoccupied patches is too low to maintain metapopulation persistence. This highlights the importance of considering spatial population dynamics in addition to changing habitat availability when predicting the fate of dispersal-limited species. The availability of suitable habitat is not enough to ensure persistence, particularly
when examining future fire regimes, which can increase fragmentation and isolation of suitable habitats.

Although the population trajectory of the “decreased” fire scenarios indicated extremely high numbers of skinks on Newhaven, the models do not explicitly account for increased predator abundances or other constraints that would dampen population growth under reduced fire. We rather interpret this prediction of increasing abundance under decreasing fire as an indication that reducing fires is not a direct threat to L. kintorei persistence. The quadratic relationship between occurrence and time-since-fire in two of the three habitat models (A and B) indicates that long-unburnt habitat is less suitable. However, given the flammability of this environment, too much long-unburnt habitat is unlikely to be a problem.

Management implications

The dominance of fire scenario uncertainty over species’ response uncertainty is a reassuring result for conservation managers, who currently use fire management as a key conservation tool. Management should, where possible, avoid frequent, widespread, hot fires. Fire management—be it fire suppression or prescribed burning—is a well-established tool in central Australian land management (Edwards et al. 2008); one that our analyses reinforce as an essential technique for managing L. kintorei persistence. Moore et al. (2015a) used experimental burns to establish the short-term effects of fire on L. kintorei and make specific fire management recommendations at a fine scale. Our study reinforces these recommendations by clarifying that uncertainty around habitat preferences will not affect management decisions: conservation management efforts for this species should focus on reducing the impacts of fire. This may include suppressing fire at known L. kintorei sites or strategic burning in surrounding areas to form fire breaks.

Suppressing all fire across the landscape, however, is neither possible nor desirable. Our study focuses on a single-species; although many arid-zone species are likely to benefit from decreases in fire frequency and size, our analysis cannot speak to that, and it is unlikely to be a one-size-fits-all solution (Pastro et al. 2014). We acknowledge that our recommendations are strongly L. kintorei-focused, given that Newhaven management objectives concern multiple species.

Feral predators, particularly cats, are a threat to L. kintorei, as they are to reptiles and mammals across the continent (McGregor et al. 2014; Moore et al. 2015b; Woinarski et al. 2015). Feral predation must be considered concurrently to inappropriate fire regimes, as an interacting threat to L. kintorei persistence. However, it is important to note that feral cat management is currently infeasible at a landscape scale with current resources and methods (Denny & Dickman 2010; Department of the Environment 2015). In a practical sense, fire management may be the most effective way of mitigating the effects of feral predators, by making conditions less amenable to their hunting techniques. There is evidence that feral predators forage in more open habitat, such as recently burnt landscapes (McGregor et al. 2014; Doherty et al. 2015); this reinforces the idea that excluding wildfire and strategically burning around patches of known L. kintorei habitat may reduce extinction risk.

Fire management is a prime example of an area of conservation where decision-makers are swamped by uncertainty. Analyses that show a certain type of uncertainty to be largely inconsequential in a particular decision context can save managers time, money and anxiety. For the persistence of L. kintorei, Newhaven managers should invest significantly more effort in using fire to create and maintain large areas of mid-late succession vegetation, than in understanding species’ response to fire and other habitat variables. More broadly, however, by explicitly testing the influence of different sources of uncertainty on species’ persistence, we show that it is possible to liberate conservation practitioners from questions that may not influence management decisions.

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Supporting Information

Additional Supporting Information, including extensive text responding to VMEA’s arguments, as well as the following tables and figures, may be found in the online version of this article at the publisher’s web site:

**Table S1.** The three best performing models for each method, showing the relationship between great desert skink occurrence and habitat variables. “cvROC”
indicates the results of the 10-fold cross validation, AIC is the Akaike information criterion, and ROC is the receiver operating characteristic. Variable names are explained in text above. No standard form is given for BRT models.

**Table S2.** RAMAS Landscape parameter values chosen for fire scenarios. * indicates values constrained by program.

**Table S3.** Metapopulation parameters for modelling the population dynamics of the great desert skink.

**Figure S1.** Partial plots of the relationship between the probability of occupancy and environmental variables included in the final GLM models for *Liopholis kintorei*.

**Figure S2.** Carrying capacity of the landscape through time under the “increased” fire scenario and model A species-fire responses. Solid line represents average over 5000 simulations, and dotted lines represent ±1 standard deviation from the mean. Model A has a quadratic relationship between *Liopholis kintorei* occupancy and the two fire history variables.

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