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Modelling the distribution of a key habitat feature to guide future on-ground habitat assessment for an endangered specialist songbird

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Abstract Species distribution models (SDMs) are often used during the planning stage of reintroduction programmes to model species' occurrence with the aim of selecting potential release sites. However, for many endangered species, only a low number of records are available, leading to models with low accuracy. When planning reintroductions for rare species, an alternative approach may be to model surrogate species that are more abundant or easier to locate. Here, we modelled the distribution of white gum (*Eucalyptus viminalis*), the preferred food tree of the forty-spotted pardalote (*Pardalotus quadragintus*), a rare songbird for which reintroduction has been proposed. Using boosted regression trees, we modelled white gum distribution under current and future climate conditions with the aim of identifying areas of high probability of occurrence that later can be used to plan on ground habitat assessments for reintroductions. Our model show areas with high probability of white gum occurrence outside its currently mapped distribution, indicating that there may be opportunities for reintroduction of pardalotes beyond their current range. Predictions of future climate scenarios showed climate space shifts, not only with some decrease but also with substantial increase in the probability of suitability for occurrence under some scenarios. Our spatial predictions for white gum may be used to design a survey to ground-truth our model and undertake a comprehensive habitat assessment for other habitat features forty-spotted pardalotes need to persist. The approach used in our study may be used for other highly specialized species, not only in the context of reintroduction planning but also in the general management of data-poor specialist species that depend on a more common resource.

Key words: climate change, conservation planning, conservation translocation, endangered species, specialist species, species distribution models.

INTRODUCTION

Conservation translocations (i.e. the intentional movement of individuals to restore populations) are increasingly used in attempts to recover populations of threatened species with the aim to establish self-sustaining populations (IUCN/SSC 2013; Seddon *et al.* 2014). However, reintroductions generally have low success rates, and insufficient knowledge about habitat quality at the release site is a major source of failure (Griffith *et al.* 1989; Wolf *et al.* 1998; Osborne & Seddon 2012; Taylor *et al.* 2017). Low success due to habitat quality is attributed to the complexity of defining what constitutes habitat for a species. This is because habitat is a complex interaction of physical and biotic components, including food, shelter, competitors and predators (Armstrong & Seddon 2008; Osborne & Seddon 2012). Consequently, habitat for reintroductions should be assessed as a species-specific set of resources and environmental conditions that enable a population to persist (Hall *et al.* 1997; Armstrong & Seddon 2008; Stadtmann & Seddon 2020). This also includes considering climate change, because areas suitable for reintroduction today may be unsuitable in the future (Seddon 2010; Osborne & Seddon 2012). Therefore,

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the selection of sites for reintroduction requires careful planning, and species distribution models (SDMs) are a good starting point to address this uncertainty (Osborne & Seddon 2012).

SDMs are often used in reintroduction programmes to help identify sites where there is high chance of meeting a species' needs (e.g. Martínez-Meyer *et al.* 2006; Kalle *et al.* 2017; Maes *et al.* 2019). However, for many endangered species, the low number of records available may lead to inaccurate or inadequate models for conservation planning (Wisz *et al.* 2008). Further, for species that have undergone substantial decline, they might no longer occupy the core of their former distribution, therefore what few locations exist on extant populations might not fully reveal the best habitat conditions (e.g. Kuemmerle *et al.* 2012). When planning reintroductions for rare species, an alternative approach may be to model surrogate species that are more abundant or easier to locate. Selecting surrogates may be relatively straightforward in the case of habitat specialists that, for example might depend on co-occurrence with a small number of other species for food or shelter (Futuyma & Moreno 1988; Devictor *et al.* 2010). A key side benefit of such an approach is that modelling key resources of specialist species under future climate scenarios can inform future conservation planning even for rare species that may be difficult to model on their own (Hannah *et al.* 2002). Later, model predictions can be validated (i.e. ground-truthing model predictions) and used to guide fieldwork for a comprehensive assessment of other habitat aspects required to support the species (e.g. Draper *et al.* 2019). Thus, waste can be avoided by allocating scarce conservation resources to areas that have potential to be occupied by the target species, avoiding focusing on irrelevant locations.

Here, we use the approach of modelling the distribution of the food tree of a rare and declining specialist songbird to evaluate current and future habitat suitability. The endangered forty-spotted pardalote, *Pardalotus quadragintus*, is a small songbird endemic to the island state of Tasmania, Australia. Due to ongoing habitat degradation, wildfire, low nesting site availability, competitors and parasites, pardalotes that were once widely distributed in forests where white gums were present across eastern Tasmania now mainly occur on two offshore islands (Bruny and Maria; Appendix S1; Threatened Species Section 2006; Edworthy *et al.* 2019; Webb *et al.* 2019). Forty-spotted pardalotes forage primarily on white gum *Eucalyptus viminalis*, and local occurrence within their island refuges is governed by the presence of white gums. They are foliage gleaners that forage for arthropods, lerps (crystallized honeydew produced by psyllids) and *manna* (sugary exudates produced by white gums; Woinarski & Bulman 1985). *Manna* is an important food item for forty-spotted pardalotes' nestlings (and possibly adults), constituting 84.2% of their diet (Case & Edworthy 2016). Although many Australian birds feed on manna, forty-spotted pardalotes are the only reported species able to mine *manna* from white gums with their elongated bill tips (Case & Edworthy 2016).

Conservation translocation has been proposed to create insurance populations on the main island of Tasmania (Webb *et al.* 2019)l, but there is no information on habitat availability and quality to inform planning of reintroduction trials. Because of their restricted contemporary distribution and low number of historical records, SDMs based on sparse pardalote occurrence records may have high uncertainty (i.e. result in models with low predictive power), thus using outputs to guide management decisions as misleading. In contrast, there are many more records available on the occurrence of white gum across Tasmania. Given the close association between pardalotes and their food tree, we capitalize on this relationship to develop an SDM of this key habitat feature that can be used to guide on ground habitat assessments. Using boosted regression trees (Elith *et al.* 2008) we model the distribution of white gum under current and future climate scenarios to identify areas where pardalotes' food trees are more likely to occur and investigate possible future shifts in its distribution to inform conservation planning. We compare the previously known extent of white gum with our SDM predictions, and then account for the severe impacts of deforestation across Tasmania in our interpretation of habitat availability for pardalotes. We show that available vegetation mapping underestimates the probability of white gum occurrence, and that there is a large area of potential pardalote habitat on mainland Tasmania available for future conservation efforts. We discuss our results in the context of how our models may be used to guide the next steps in the process of identifying potential sites for forty-spotted pardalotes' translocation trials.

METHODS

Species data

We collated presence and absence records of white gum across Tasmania using data from three different sources: (1) data collected by the authors during other field surveys (Alves et al., 2019; Webb *et al.* 2014); (2) data made available by Sustainable Timber Tasmania (STT; presence and absence data collected at 7234 vegetation plots across Tasmania between 1990 and 2019); and (3) data downloaded from the Natural Values Atlas (www.naturalvaluesatlas.tas.gov.au, accessed 28 October 2019). Data were cleaned to ensure records were recent (i.e. since 1990), accurate (i.e. accuracy was <100 m) and unique (i.e. one record within

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each 250 m spatial grid cell). Two morphologically similar trees (*E. dalrympleana* and *E. rubida*) occur at altitudes between 200 m and 600 m, making the distinction between white gum and these species complex (Williams & Potts 1996). However, we retained presence records of white gums at this altitudinal range but acknowledge some records might be inaccurate due to species mis-identification. The final data set combined comprises 10 837 records across Tasmania, and white gums occurred at 3761 of them (i.e. a prevalence of approximately 35%).

Environmental data for current climate

We used 24 variables to model the distribution of white gum (Table 1). We chose climatic variables based on their importance for the distribution of other *Eucalyptus* spp. (e.g. Austin *et al.* 1997), and the distinct patterns of rainfall between the east and west coast of Tasmania (Grose *et al.* 2010). We also used topographic and soil variables, which are important for the distribution of eucalypt species and known to improve prediction power of SDMs for plants (Austin & Van Niel 2011; Dubuis *et al.* 2013). Bioclimatic predictors were derived using a 250 m digital elevation model (DEM; Geoscience Australia 2008) in ANUCLIM version 6.1 (Xu & Hutchinson, 2011). We also used the DEM to calculate topographic predictors (i.e. aspect and slope) using the package 'raster' v. 3.5–2 in R (Hijmans 2021; R Core Team 2021). We obtained soil layers from the CSIRO database (Kidd *et al.* 2014; Viscarra Rossel *et al.* 2015) with a cell size of three arc seconds (90 m) and aggregated to 250 m cell to align with the other rasters. The soil layers were available for six depth slices (0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm, 60–100 cm and

Table 1. Summary statistics for the environmental variables used to model white gum distribution using boosted regression trees. Values represent minimum, maximum and mean for each predictor. Bioclimatic variables were extracted from ANUCLIM version 6.1

Variable	Description	Mean and range
Bioclimatic predictors		
BIO01	Annual mean temperature (°C)	10.5, 3–14.1
BIO04	Temperature Seasonality (standard deviation *100)	1.1, 0.7–1.3
BIO05	Max temperature of warmest period	20.7, 12.5–24.7
BIO12	Annual precipitation (mm)	1308, 442–3400
BIO14	Precipitation of driest period (mm)	14, 5–40
Soil predictors		
Bulk density (5–15 cm)	Bulk Density of the whole soil (fine and coarse texture fractions; Mg/m3) between 5 and 15 cm depth	0.85, 0.2–1.3
Bulk density (30–60 m)	Bulk Density of the whole soil (fine and coarse texture fractions; Mg/m^3) between 30 and 60 cm depth	1.1, 0.6–1.3
Coarse fragments (5–15 cm)	Coarse Fragments product (particles >2 mm in diameter; %) between 5 and 15 cm depth	4.1, 0–54
Coarse fragments (30–60 cm)	Coarse Fragments product (particles >2 mm in diameter; %) between 30 and 60 cm depth	6.1, 0–55
Clay (5–15 cm)	Clay content (%) between 5 and 15 cm depth	20, 0.01–54
Clay (30–60 cm)	Clay content (%) between 30 and 60 cm depth	31, 0–64.2
Sand (5–15 cm)	Sand content (%) between 5 and 15 cm depth	59, 10.3–98
Sand (30–60 cm)	Sand content (%) between 30 and 60 cm depth	47, 9.2–98
Silt (5–15 cm)	Silt content (%) between 5 and 15 cm depth	22, 0–69
Silt (30–60 cm)	Silt content (%)	23, 0–71
Organic carbon (5–15 cm)	Mass fraction of carbon by weight in the <2 mm soil material (%) between 5 and 15 cm depth	10.4, 0.06–70
Organic carbon (30–60 cm)	Mass fraction of carbon by weight in the <2 mm soil material (%) between 30 and 60 cm depth	1.3, 0.002–14.7
pH (5–15 cm)	pH units (1:5 soil/water paste) between 5 and 15 cm depth	5.3, 3.8–8
AWC (5–15 cm)	Available water capacity (%) between 5 and 15 cm depth	15.5, 10.4–23.3
NTO (5–15 cm)	Mass fraction of total nitrogen in the soil by weight (%) between 5 and 15 cm depth	0.3, 0.05–0.68
PTO (5–15 cm)	Mass fraction of total phosphorus in the soil by weight (%) between 5 and 15 cm depth	0.04, 0.01–0.2
Soil class	Soil classification in 13 classes: (2) Calcarosols, (3) Chromosols, (4) Dermosols, (5) Ferrosols, (6) Hydrosols, (7) Kandosols, (8) Kurosols, (9) Organosols, (10) Podosols, (11) Rudosols, (12) Sodosols, (13) Tenosols, (14) Vertosols	NA
Topographic predictors		
Aspect	Derived from the digital elevation model (°)	177, 0–360
Slope	Derived from the digital elevation model (°)	6.3, 0–55

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100–200 cm), but in most cases they were highly correlated, so we only kept uncorrelated depths (Table 1).

Environmental data for climate scenarios

To project our model of white gum distribution to future climate scenarios, we downloaded gridded projected change data for temperature (minimum and maximum) and precipitation from 'Climate change in Australia' (www.climatechangeinaustralia.gov.au). These gridded data sets are derived from the output of global climate models (GCMs) from the Coupled Model Intercomparison Project 5 (CMIP5) and represent the projected future change in the modelled climate from a 1986–2005 baseline. We obtained change data for 20-year periods centred at the years 2050, 2070 and 2090 for two of four Representative Concentration Pathway (RCP) scenarios. We chose a high (RCP8.5) and a low (RCP4.5) emission scenario to capture the range of emissions uncertainty (van Vuuren *et al.* 2011). To select the models, we used the online climate future tool available at 'Climate change in Australia', which accounts for the whole range of CMIP5 global models, representing the full range of possible projections. Using the Climate Futures Framework (Whetton *et al.* 2012), we selected models representing the 'cooler and wetter', 'hotter and drier' and 'maximum consensus' scenario based on the ranking done as the result of a multivariate statistical goodness of fit test. 'Cooler and wetter' represents a climate future with the greatest increase (or least decrease) in rainfall and the least increase in temperature and 'hotter and drier' a climate future with the largest decrease (or least increase) in rainfall and the greatest increase in temperature. We selected the models GISS-E2-R-CC ('maximum consensus'), IPSL-CM5B-LR ('cooler and wetter' scenario) and HadGEM2-ES ('hotter and drier'). Climate change grids have coarse resolution (spatial resolution: $1 \times 1°$ for GISS-E2-R-CC; $3.7 \times 1.9°$ for IPSL-CM5B-LR; $1.9 \times 1.2°$ for HadGEM2-ES). Therefore, to derive the same bioclimatic variables used to model current distribution, we supplied the gridded climate change projections to the interpolation software ANUCLIM (Xu & Hutchinson 2013) as monthly additive changes for temperature and monthly percentage changes for rainfall. ANUCLIM applies biquadratic spline interpolation to the supplied gridded climate change to downscale climate change grids to the resolution of the input DEM (250 m in our case) and generate bioclimatic variables under different climate scenarios (Appendix S2; Xu & Hutchinson 2013).

Statistical analysis

We modelled the presence/absence of white gum in relation to environmental data using boosted regression trees (Elith *et al.* 2008). We carried out analyses using R version 4.0.2 and the 'dismo' R package version 1.1–4 (Hijmans *et al.* 2017; R Core Team 2021). The white gum data set (presence/absence) was randomly divided into training data (75%, $N = 8127$; 2804 presence and 5323 absence records) that we used for model fitting, and testing data (25%, $N = 2710$; 1753 presence and 957 absence records) to assess model performance. We explored boosted regression trees with varying values for tree complexity ($tc = 1,2,3,5,7,10$), learning rate ($lr = 0.1$, 0.05, 0.01, 0.005, 0.001, 0.0005) and bag fraction ($bg = 0.5$ and 0.75), and used cross-validation to choose the best performing model (i.e. model with lowest deviance; $tc = 10$, $lr = 0.01$, $bg = 0.5$; Elith *et al.* 2008). We also used the area under the receiver operating curve to assess the model discriminatory ability (Fielding & Bell 1997). Area under the receiver operating curve values near 1 represent models with good discriminatory ability, that is any randomly chosen presence record will have a higher predicted probability of occurrence, when compared to a randomly selected absence record.

Predictions were made using the final model by summing predictions from all trees and multiplying them by the learning rate (Elith *et al.* 2008). We assessed uncertainty of predictions using a bootstrap resample of the training data and refitting the best fitting model 999 times, and used the 0.025 and the 0.975 quantiles to create 95% confidence intervals of the uncertainty (e.g. Miller *et al.* 2019). We predicted for future climate scenarios with bioclimatic variables under future climate and kept soil and topographic predictors the same. To better visualize the spatial distribution of changes in the climate space, we performed simple raster algebra using the predictions for current and future climate scenarios (i.e. subtracting a future climate scenario from the current climate predicted probability). Negative values in the map represent decreased probability, positive values represent increased probability and zero represents no changes in the probability of occurrence in relation to the current climate (Fig. 5). The rasters with spatial prediction were created using package 'raster' (Hijmans 2021) and the spatial prediction was plotted using package 'tmap' (Tennekes 2018). To contextualize our model predictions, we overlay the current and historical distribution of forty-spotted pardalotes (Brown 1986). We also overlay the human-modified land and the current mapped white gum forest according to the Tasmanian vegetation mapping (TASVEG 4.0; Department of Primary Industries, Parks, Water and Environment, 2020).

RESULTS

Predictors' contribution and model performance

The 24 predictors used to model the distribution of white gum are summarized in Table 1, and the top 12 in terms of their contribution to boosted regression tree model fit are shown in Figure 1 and Table 2 (see Appendix S4 for contribution of all predictors). The most influential predictors were precipitation of driest period (BIO14, 32.3%) and annual rainfall (BIO12, 10.1%). Overall, the distribution of white gum increased with decreased precipitation

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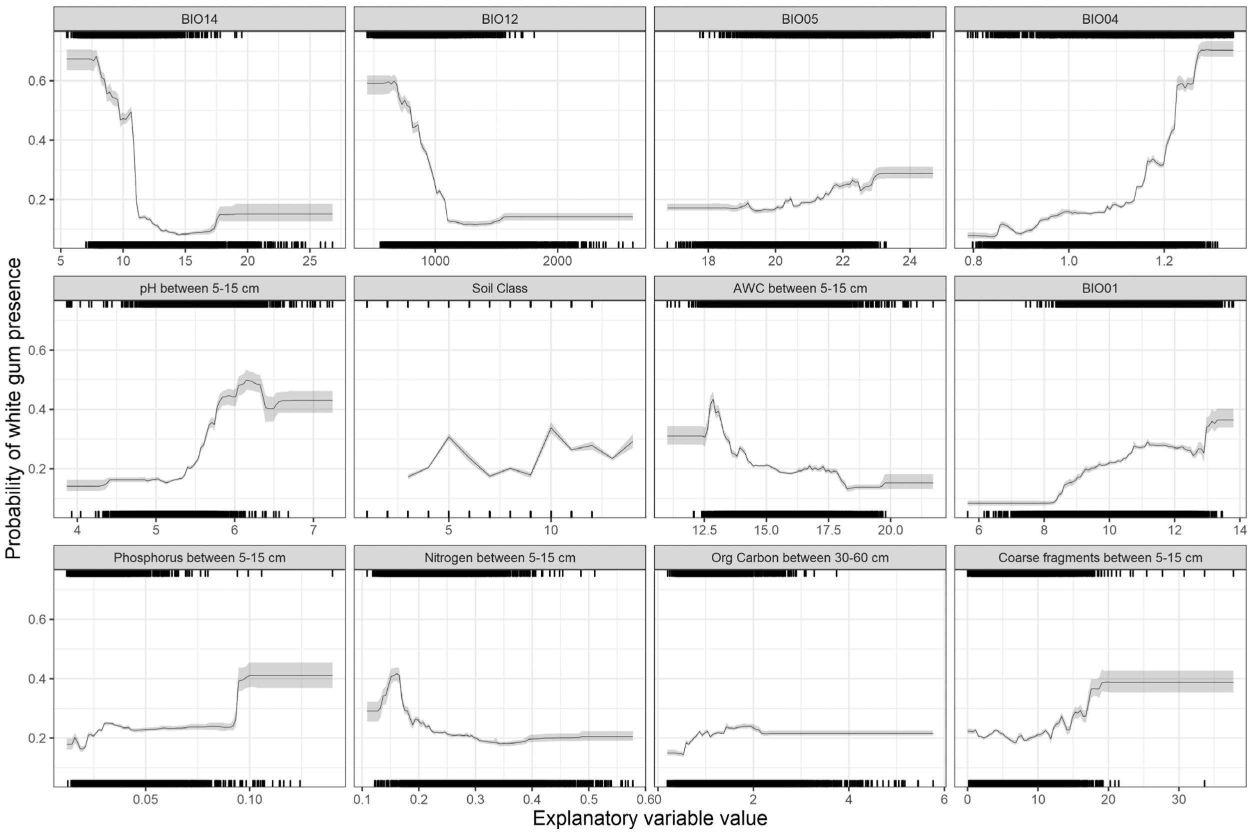

Fig. 1. Marginal effects for the top 12 explanatory variables in the boosted regression tree for current climate (grey shaded area represents 95% CI). The distributions of observed white gum presences (top) and absences (bottom) are indicated by the rug plot on each panel (black marks along the x-axis). Plot with all variables included in the model is presented in supplementary material (Appendix S5).

Table 2. Relative contribution (%) of the top 12 explanatory variables in the boosted regression tree model for distribution of white gum

Explanatory variable	Relative contribution (%)
BIO14 (Precipitation of driest period)	32.2
BIO12 (annual precipitation)	10.1
BIO05 (Max temperature of warmest period)	6.5
BIO04 (Temperature Seasonality)	6.3
pH (5–15 cm)	5.7
Soil class	4.1
Available water capacity (5–15 cm)	3.2
BIO01 (annual mean temperature)	3.1
PT (Total phosphorus; 5–15 cm)	2.6
NT (Total nitrogen; 5–15 cm)	2.4
Organic carbon (30–60 cm)	2.1
Coarse fragments (5–15 cm)	2.1

(Fig. 1). Other bioclimatic and some soil variables also contributed to the model, but their contribution was less than 10% (Table 2). Predictive performance of the model was very good (Area under the receiver operating curve on testing data: 0.95), with very high predicted probabilities for observed presence records, and very low predicted probabilities for observed absence with little overlap (uncertainty) between the two (Fig. 2).

Current and future spatial distribution

Spatial predicted probability of white gum occurrence and associated prediction uncertainty are presented in Figure 3. The spatial distribution predicted in our model shows large areas of high probability of white gum occurrence outside known areas (Fig. 4, panel c). Predicted probability under the climate scenarios we investigated are presented in supplementary materials (Appendix S5), and changes in probability in relation to current climate (i.e. shifts in distribution) are presented in Figure 5. Some loss can be observed in the probability distribution (represented as negative values), particularly for the ‘cooler and wetter scenario’, however, substantial ‘gain’ (represented by positive values) was predicted for both maximum consensus and ‘hotter and drier’ (Fig. 5).

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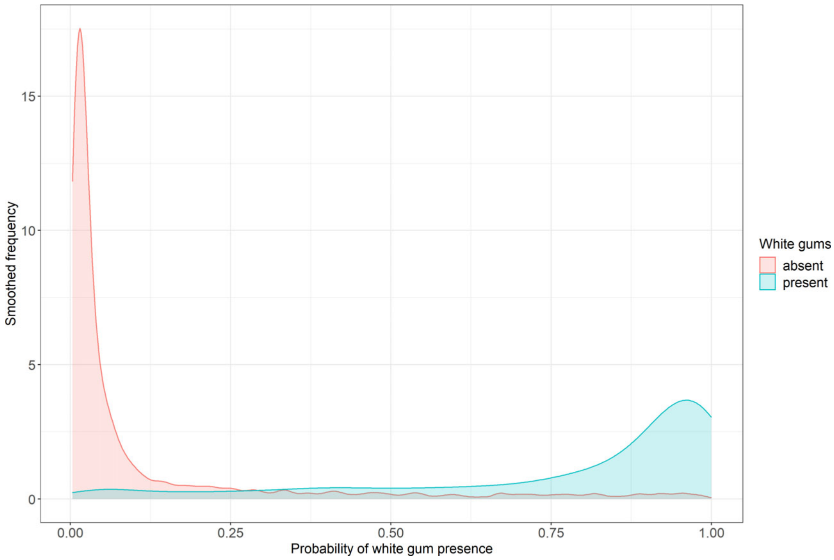

Fig. 2. Predictive performance of the boosted regression tree model evaluated using 25% of the records retained for model testing (N = 2710; 1753 presence and 957 absence records). The x-axis shows the predicted probability of white gum presence, grouped according to whether white gum was present (shaded blue) or absent (shaded red). The y-axis is the smoothed frequency of observations.

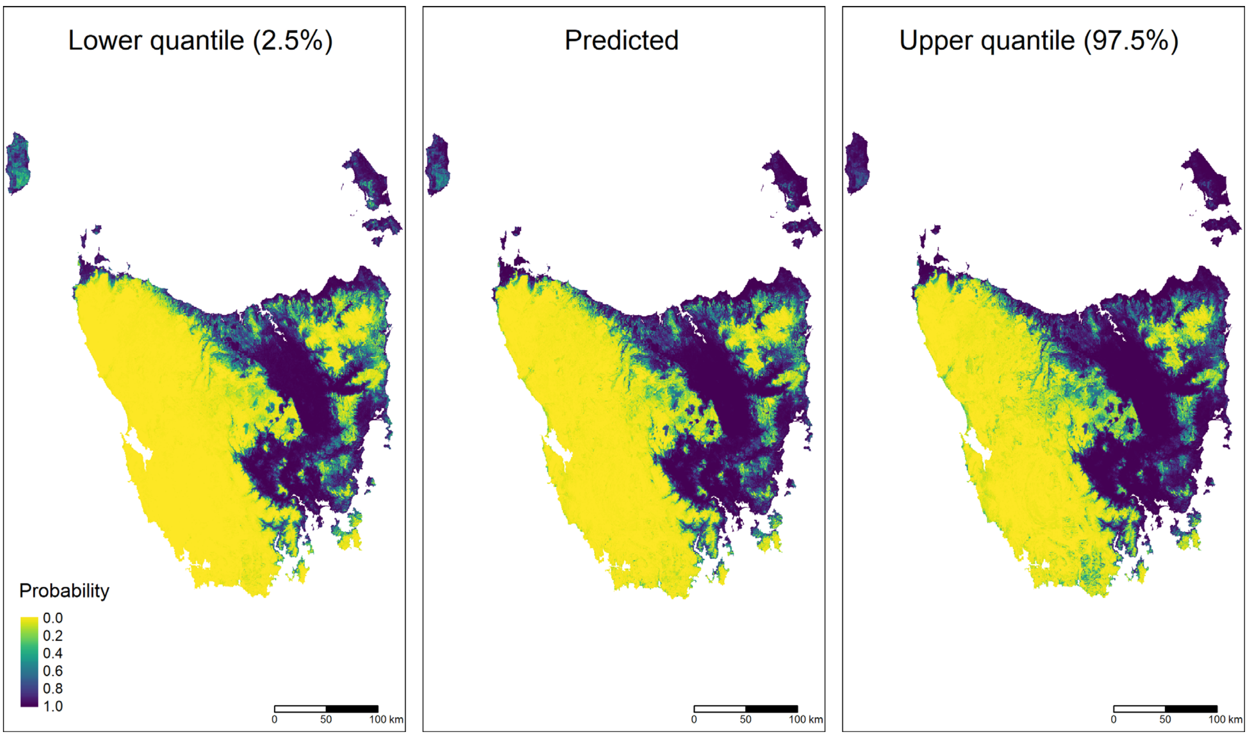

Fig. 3. Predicted probability of white gum occurrence and associated prediction uncertainty (95% confidence intervals).

DISCUSSION

In this study, we created a predictive map for the distribution of white gum, a key food tree of the endangered forty-spotted pardalote. Our model predicted high probability of white gum occurrence across a larger area than its currently mapped distribution. This result is consistent with the known distribution of white gum (Williams & Potts 1996), which occurs in drier lowland coastal and inland areas of northern, eastern and southern Tasmania. Although some loss in the climate space was predicted across the future climate scenarios, the models predicted substantial gain for the maximum consensus and hotter/drier scenario. Our model provides a hopeful indication that, assuming habitat restoration can be achieved at

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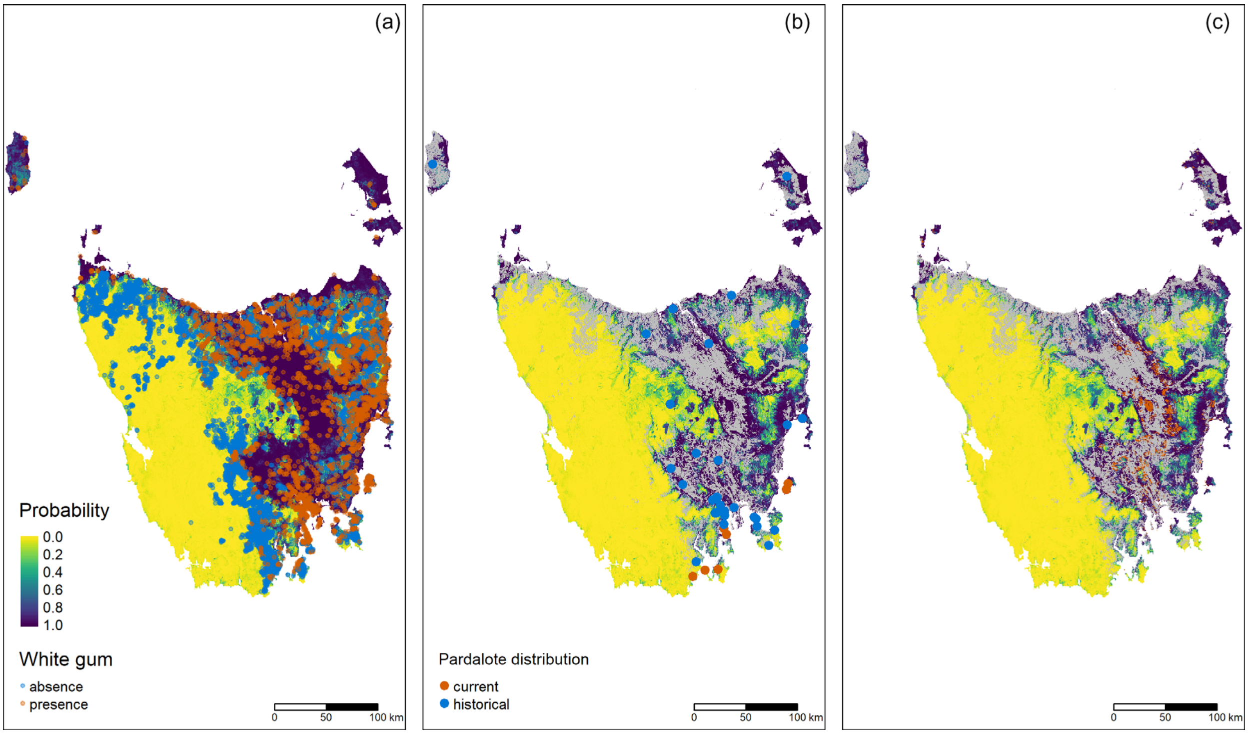

Fig. 4. Predicted probability distribution of white gum across Tasmania: (a) blue (absence) and orange (presence) dots represent raw data used for modelling; (b) grey areas represent human-modified land, and dots represent current (orange) and historical (blue; historical records obtained from Table 1, Brown 1986) distribution of pardalotes; (c) human-modified land (grey) and mapped areas of white gum according to TASVEG (orange), showing that our model predicted areas of high probability outside of known white gum forest. Predicted probability of white gum occurrence for historical and current distribution of forty-spotted pardalotes (b) are presented in supplementary material (Appendix S3).

ecologically relevant spatial scales and time frames, there may be opportunities for reintroduction of pardalotes beyond their current range. Our models also predicted high probability of white gum occurrence in forested areas, showing the need to validate predictions to confirm the presence of white gums and potentially identify sites suitable for reintroduction trials. These predictions are the first step in the complex task of selecting sites for reintroductions and can be used to guide future habitat assessments for translocation trials for forty-spotted pardalotes.

Predicted white gum distribution

Bioclimatic variables were the most important for predicting the presence of white gums. These results are in line with distribution models for other *Eucalyptus* species (e.g. Austin & Van Niel 2011; Butt *et al.* 2013), including white gum on mainland Australia (Adams-Hosking *et al.* 2012). The two key predictors were aspects of precipitation (precipitation of the driest period and annual precipitation), reflecting the distinct pattern of rainfall between the wet west and the drier east coast of Tasmania where white gums are more likely to occur. The spatial distribution predicted in our model shows vast areas of high probability of occurrence in the Midlands and northern coastal hinterlands where white gum was known to have historically occurred as the dominant species in alluvial valleys (Williams & Potts 1996). European colonizers extensively deforested these areas (and land clearing is ongoing in the region), and these regions contain historical records of pardalotes. Based on our results, these locations remain bioclimatically suitable for white gums; however there remain many threats to pardalotes that have not been addressed, for example land clearing and presence of competitors. Thus, despite their bioclimatic suitability for white gums, extensive restoration is required to make the midlands and northern coast regions potential candidates for translocations of pardalotes. Unfortunately, the spatial extent and severity of land degradation in these regions means that large areas may never become suitable, highlighting the importance of protecting remaining forests and woodlands in these areas. However, beyond the midlands other forested areas came up with high probability of white

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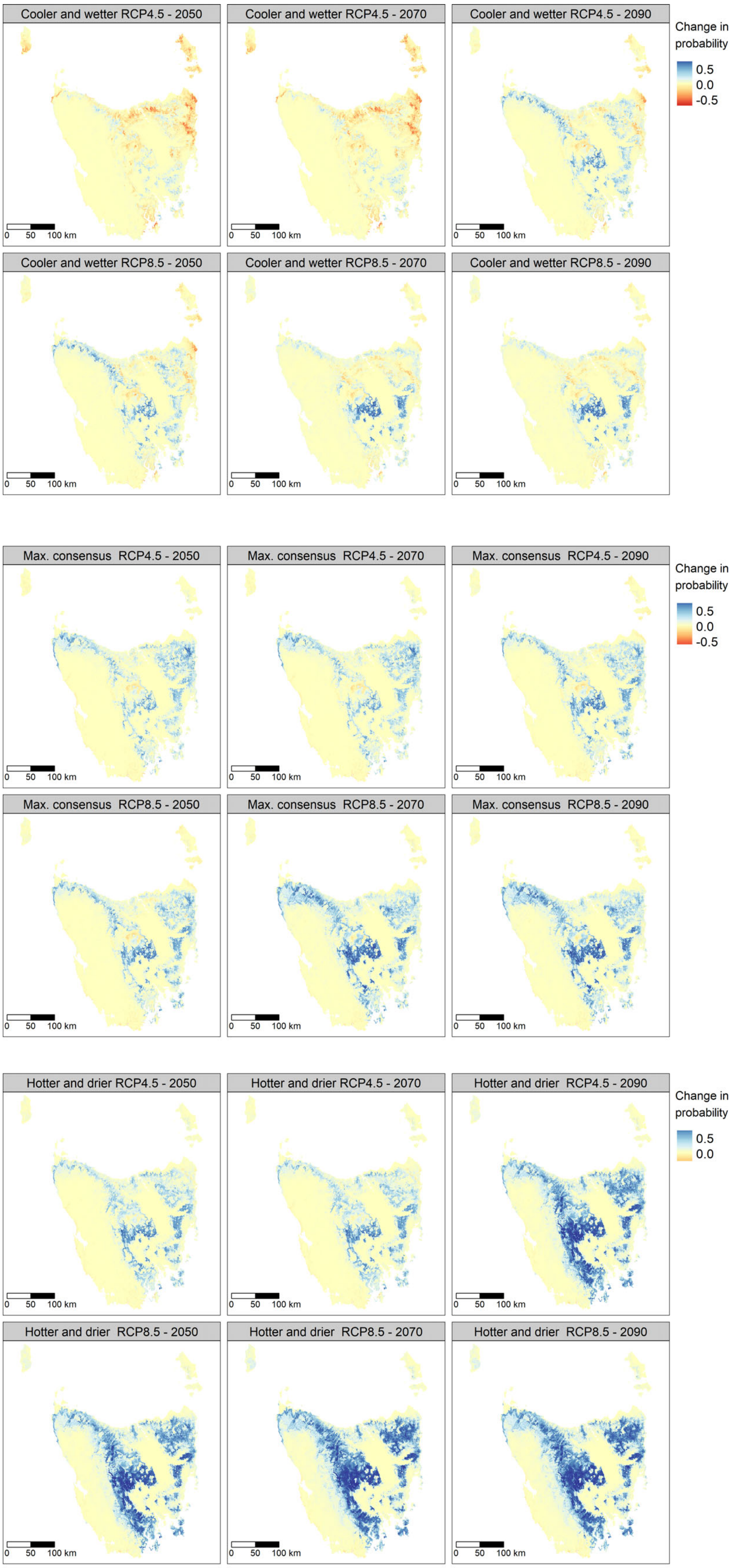

Fig. 5. Change in probability under the climate scenarios we investigated. These maps were created using raster algebra, that is subtracting future climate predicted probability from the current climate predicted probability. Therefore, negative values represent decreased probability in relation to current climate predictions ('loss') at a cell pixel and positive values represent increase probability of occurrence ('gain'); zero represent no change in relation to predictions for the current climate.

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gum occurrence warranting field validation of model predictions with the aim to locate potential reintroduction sites.

Distribution under future climate scenarios

Predictions for the future climate scenarios show more gain than loss in suitability for white gum, at least for some of the scenarios we investigated. This is not surprising as it reflects the patterns of rainfall across Tasmania. Given that white gums are restricted to the drier east coast of Tasmania, the 'cooler and wetter scenario' predicts more rainfall and therefore 'loss' in the climate space while the 'hotter and drier scenario' predicts less rainfall and therefore 'gain' in the climate space, particularly towards the wetter western Tasmania. Although predictions for the cooler/wetter scenarios (particularly for RCP4.5 in 2050 and 2070) show decrease in probability of occurrence for some areas, we acknowledge the limitations of correlative models and interpret these results with caution (Pacifici *et al.* 2015; Butt *et al.* 2016). Correlative models rely on information of a species' realized niche (the environments where a species is found), as opposed to the fundamental niche (the environments where a species can be found; Wiens *et al.* 2019), and therefore we do not have biotic information to predict whether white gum may be able to adapt to an environment with increased rainfall. Nonetheless, our results are consistent with predictions for other *Eucalyptus* species in temperate Australia (Butt *et al.* 2013). Many *Eucalyptus* species are facing climate stress with predictions showing large distributional shifts (e.g. Butt *et al.* 2013; González-Orozco *et al.* 2016), particularly in species in the 'desert and open woodland' climate region (Butt *et al.* 2013). However, predictions for temperate Australia do not show substantial loss in climate space, particularly for Tasmania (Butt *et al.* 2013). This pattern reflects the less pronounced climatic changes projected for Tasmania (evident in the small variability in the bioclimatic variables) when compared to Australian mainland and global average changes (Grose *et al.* 2010). This is due in part to the influence of the Southern Ocean, which stores excess heat, moderating projected changes (Grose *et al.* 2010). Nonetheless, we recognize that the bioclimatic variables used in our models reflect changes in climatic means and do not account for extreme climatic events, which are expected to increase (Meehl *et al.* 2007), or change in variability. Climatic influences such as the El Niño-Southern Oscillation (ENSO) and the Southern Annular Mode (SAM) drive substantial variability in precipitation and drought risk over Tasmania (Mariani & Fletcher 2016; Delage & Power 2020), and prolonged drought can cause forest dieback (Calder & Kirkpatrick 2008; Anderegg *et al.* 2013). The length and intensity of droughts and frequency of extreme fire weather is likely to increase (Timmermann *et al.* 2018; Harris & Lucas 2019; Wang *et al.* 2019; Delage & Power 2020; Kirono *et al.* 2020). White gums are highly vulnerable to dieback in stressed growing conditions (e.g. Ross & Brack 2015) and thus are more likely to be negatively impacted by these extreme climatic events.

Implications for forty-spotted pardalotes

Our models show areas of potential white gum occurrence outside the mapping available for the species. This supports observations made by the authors during fieldwork across Tasmania where subdominant white gum occurrence in forest/woodland canopies is not included in available vegetation mapping. This is encouraging as more areas may be available for further habitat assessment. With regard to future translocation planning, we propose using our spatial prediction to first design a survey to validate model predictions, that is the ground-truth stage. Where presence of white gums is confirmed, surveys for extant forty-spotted pardalotes should be undertaken. Although the current distribution of forty-spotted pardalotes is assumed to be known, systematic surveys to look for extant populations beyond known populations have not been conducted. Forty-spotted pardalotes were recently re-discovered in a small patch of habitat in Southport, on the Tasmanian mainland where the species was last recorded >120 years ago (Webb *et al.* 2019). Given these small, cryptic birds are less vocal in areas where they occur in low density (probably to avoid aggressive competitors, e.g. striated pardalotes; Woinarski & Rounsevell 1983; Alves, 2016, pers. obs), and shelter in tree cavities in inclement weather, it is reasonable to believe they may be easily overlooked during non-targeted surveys.

CONCLUSIONS

Funding for conservation is scarce, and modelling techniques can be a useful way to guide where to concentrate on ground efforts in reintroduction programmes. Previous reintroduction projects have extensively used SDMs to model the distribution of the species target, but the number of records available for modelling are often too small because the species is rare, elusive or suffered substantial decline and their current distribution do not represent their fundamental niche. Moreover, conservation planning

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for specialist species should consider key habitat features, particularly under a changing climate because specialists are more limited by their habitat requirements and less able to shift their distribution (e.g. Adams-Hosking *et al.* 2012). Here, we took advantage of the specialized diet of pardalotes and modelled the distribution of its key food source. This approach may be used for other highly specialized species, not only in context of reintroduction planning but also in the general management of data-poor specialist species that depend on a more common food source.

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AUTHOR CONTRIBUTIONS

Fernanda Alves: Conceptualization (lead); data curation (lead); formal analysis (lead); funding acquisition (lead); investigation (lead); methodology (equal); project administration (lead); writing – original draft (lead). **Joanne M Potts:** Formal analysis (supporting); methodology (equal); writing – review and editing (supporting). **Vanessa Round:** Data curation (supporting); writing – review and editing (supporting). **Dejan Stojanovic:** Supervision (supporting); writing – review and editing (supporting). **Matthew H Webb:** Data curation (supporting); writing – review and editing (supporting). **Robert Heinsohn:** Supervision (supporting); writing – review and editing (supporting). **Naomi Langmore:** Supervision (supporting); writing – review and editing (supporting).

DATA AVAILABILITY STATEMENT

Part of the data that support the findings of this study are available in the public domain Natural Value Atlas at www.naturalvaluesatlas.tas.gov.au. A large proportion of the data are available from Sustainable Timber Tasmania. Restrictions apply to the availability of these data, which were used under license for this study.

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SUPPORTING INFORMATION

Additional supporting information may/can be found online in the supporting information tab for this article.

Appendix S1. Current and known historical distribution of forty-spotted pardalote across Tasmania, showing mapped white gum dominated forest (pardalote's preferred food tree) within remaining forest cover according to TASVEG 4.0 (Department of Primary Industries, Parks, Water and Environment, 2020)

Appendix S2. Summary statistics for the environmental variables used to predict white gum distribution for different climate scenarios.

Appendix S3. Predicted probability of white gum occurrence for historical and current distribution of forty-spotted pardalotes.

Appendix S4. Marginal effects for each explanatory variable in the boosted regression tree (grey shaded area represents 95% CI).

Appendix S5. Spatial predicted probability of white gum distribution for current and future climate scenarios.

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