Habitat suitability maps for Australian flora and fauna under CMIP6 climate scenarios

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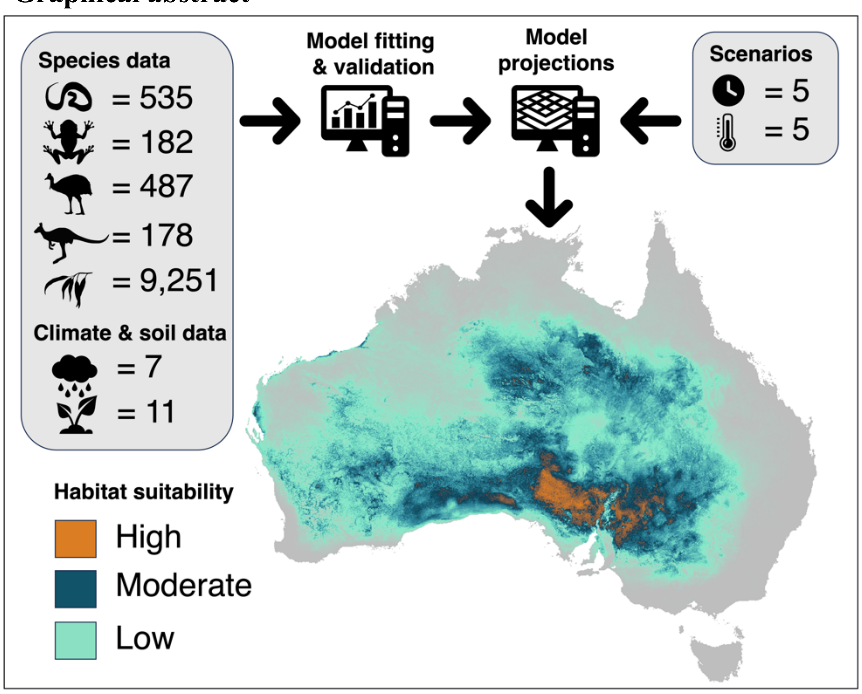
Graphical abstract



Abstract

Background: Spatial information about the location and suitability of areas for native plant and animal species under different climate futures is an important input to land use and conservation planning and management. Australia, renowned for its abundant species diversity and endemism, often relies on modelled data to assess species distributions due to the country's vast size and the challenges associated with conducting on-ground surveys on such a large scale. The objective of this paper is to develop habitat suitability maps for Australian flora and fauna under different climate futures. **Results**: Using MaxEnt, we produced Australia-wide habitat suitability maps under RCP2.6-SSP1, RCP4.5-SSP2, RCP7.0-SSP3 and RCP8.5-SSP5 climate futures for 1,382 terrestrial vertebrates and 9,251 vascular plants vascular plants at 5km^2 for open access. This represents 60% of all Australian mammal species, 77% of amphibian species, 50% of reptile species, 71% of bird species and 44% of vascular plant species. We also include tabular data which includes summaries of total quality-weighted habitat area of species under different climate scenarios and time periods. **Conclusions**: The spatial data supplied can help identify important and sensitive locations for species under various climate futures. Additionally, the supplied tabular data can provide insights into the impacts of climate change on biodiversity in Australia. These habitat suitability maps can be used as input data for landscape and conservation planning or species management, particularly under different climate change scenarios in Australia.

Data Description

Introduction

Rich spatial and temporal information about the effect of climatic and environmental change on species distributions is necessary to ensure robust species management and conservation policy more broadly (Bryan et al., 2014; Hanson et al., 2019; Leclère et al., 2020; Summers et al., 2012). Identifying areas where species occur now, as well as areas which may be suitable in the future, is a crucial aspect of decision making under uncertainty (Summers et al., 2012). The availability of resources for conservation, including financial, staffing and land availability, is limited and exacerbates the challenge of conservation planning during climate change (Hanson et al., 2019). These constraints have sparked the need for more strategic landscape and conservation planning methods, such as spatial prioritization, to identify the most effective conservation solutions (Tulloch et al., 2015). Spatial information on where species are now and where suitable areas may be in the future is the foundation of efficient planning for conservation action, particularly in areas where local conditions are more sensitive to climate change (Summers et al., 2012).

Australia is a hyper-diverse country with high levels of species endemism (Chapman, 2009; Coleman, 2016). Unfortunately, Australia also has some of the highest recorded numbers of contemporary extinctions worldwide and more than 1900 species and ecological communities are under threat (Woinarski et al., 2019; Australian Government Department of Agriculture and the Environment, 2021). Given the extensive and severe range and population declines of many threatened species (Bergstrom et al., 2021; Kearney et al., 2018; Woinarski et al., 2019), many more species are also predicted to have a high risk of extinction in the future (Garnett et al., 2022). To ensure the conservation of Australia's unique biodiversity, identifying and protecting important areas for species such as climate refugia is key to planning for resilience and adaptive capacity (Reside et al., 2014). To fulfill this task, underlying data on species location and the habitat suitability of areas for species under different climate futures is required.

There are many ways to assess suitable areas for species, and one popular approach is to use the maximum entropy method (henceforth, *MaxEnt*). MaxEnt is a niche-based general-purpose machine learning method with a simple and precise mathematical formulation which is particularly well-suited for species distribution modelling with presence-only data (Elith et al., 2006; Phillips et al., 2006). Generating MaxEnt models for individual species at continental scales presents challenges around the processing and storage of large volumes of data. Graham et al. (2019) developed a comprehensive spatial dataset of 1872 terrestrial and freshwater vertebrate species distributions using the Intergovernmental Panel on Climate Change's (IPCC) Coupled Model Intercomparison Project 3 (CMIP3) future climate projections (Meehl et al., 2007) and made them freely available through a web-based portal known as 'CliMAS'. Although the CliMAS models led to many applied outcomes (Maxwell et al., 2019; Ward et al., 2022), the website was retired in 2020, in recognition of the fact that there have been two major updates by the IPCC and the current projections are based on CMIP6. For conservation planning to progress, an improved and enlarged suite of freely available spatial data, based on up-to-date climate projections and extended for a much broader range of species including vascular plants, is needed.

We developed habitat suitability maps for Australian flora and fauna under different climate futures using a MaxEnt approach. We produced freely accessible Australia-wide habitat suitability maps for 1,441 terrestrial vertebrates and 9,251 vascular plants. This represents 60% of all Australian mammal species, 77% of amphibian species, 50% of reptile species, 71% of bird species and 44% of vascular plant species. We fit these models using 7 bioclimatic variables and 11 soil and landscape variables under 4 climate scenarios, 8 General Circulation Models (GCMs) and 1 ensemble average, and 5 time periods. These habitat suitability maps are best used as input data to represent species or biodiversity values for conservation planning and assessment, particularly under climate change in Australia.

Methods

The workflow for this study was adapted from the CliMAS project (Graham et al., 2019) (Figure 1). The first step involved compiling and collecting the input data which consisted of occurrence point data and environmental variables. We then used MaxEnt to fit models of habitat suitability using climate, soil and landscape variables. We used a variable selection procedure which considered the statistical and ecological importance of variables to refine the predictor variables as well as validating the models. We then used the lambda files produced in the model fitting step to project species habitat suitability under future climate scenarios.

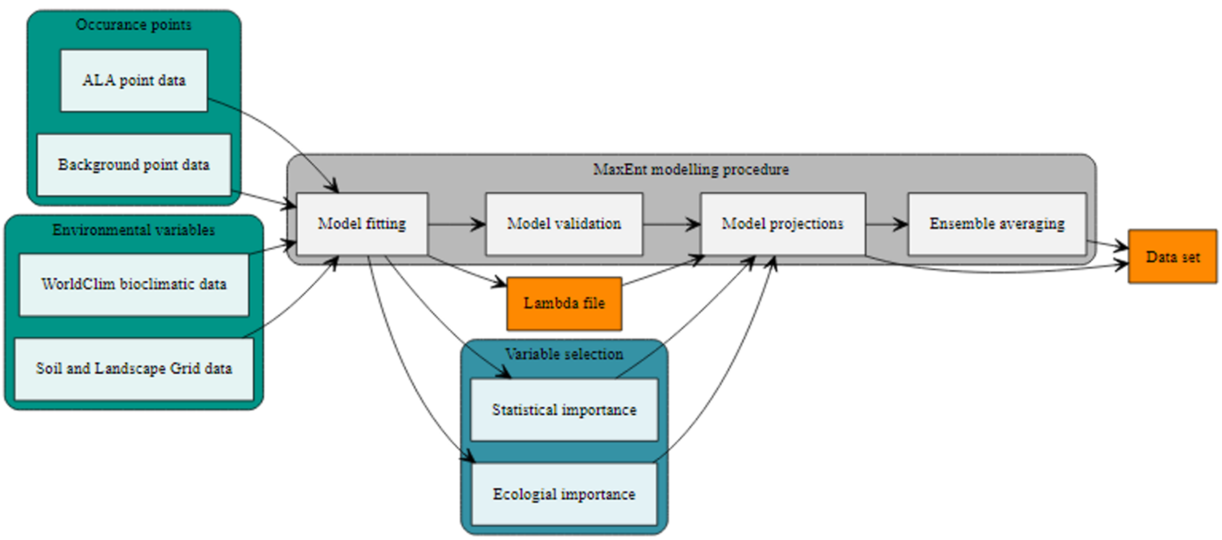


***Figure 1** Workflow of the MaxEnt modelling procedure. Input data is represented as green, variable selection procedure is represented as purple, MaxEnt modelling procedure is represented as grey and the output files are represented as orange.*

Input data

Species occurrence points

Species occurrence records which were used to fit the historical climate models were sourced from the Australian Atlas of Living Australia (ALA) (Atlas of Living Australia, 2012), the Queensland Museum, and CSIRO. Vascular plant occurrence point data were acquired through from the Queensland Museum. Vertebrate species occurrence were records acquired through ALA went through an additional data cleaning process prior to modelling (see Graham et al., 2019). We used the points originally applied in the CliMAS project as of 2012 for vertebrates, and the vascular plant points that were compiled for the CliMAS project but never modelled. Through these sources we obtained occurrence point data for 197 mammals (60% coverage), 523 birds (71% coverage), 530 reptiles (50%), 191 amphibians (77%) and 9,200 vascular plants (44% coverage). Across all species, the median number of occurrence points was 123 and the distribution of the number of occurrence points ranged based on the following quantiles: 0%=1, 25%= 43, 50%= 123, 75%= 410, 100%= 78,503 (Figure 2).

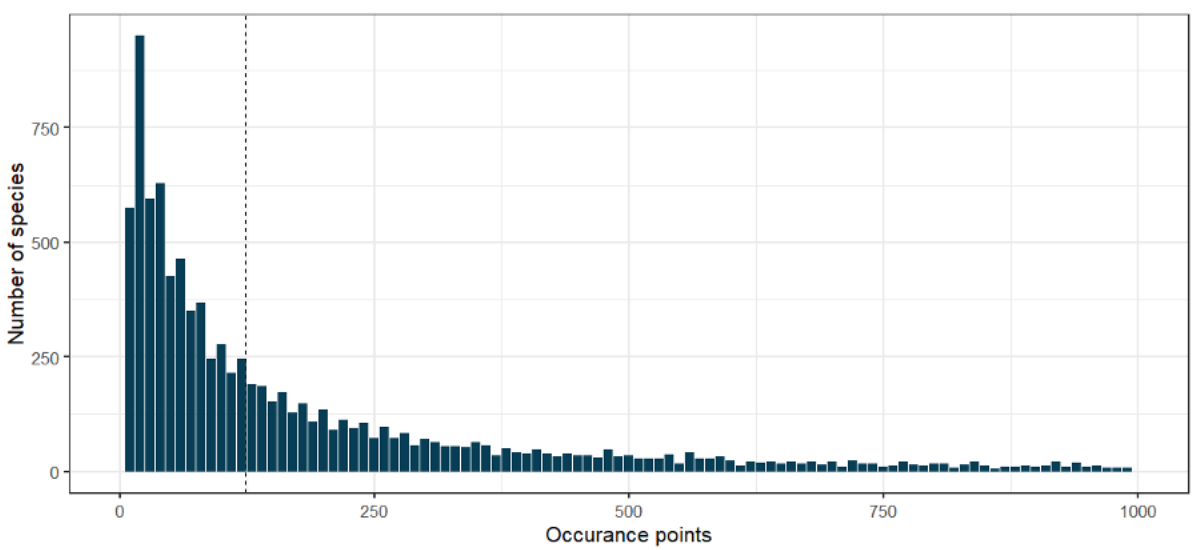


Figure 2 *Distribution of occurrence points (n) for species models.*

MaxEnt uses background sample points as pseudoabsences and recommends the use of target groups in sample selection to help overcome considered spatial biases (Barber et al., 2022; Phillips et al., 2009). To create the target group background files, we combined all occurrence points for all species within a taxonomic group and sampled the background points from this space. Each target group background file contained between 60,000 to 250,000 points depending on the taxonomic group, in which MaxEnt takes a subsample of 10,000 points.

Environmental variables

We used a combination of bioclimatic, soil and landscape variables as predictors to fit the MaxEnt models. For the climate variables, we downloaded spatial data at a $5km^2$ resolution on historical and future CMIP6 modelled bioclimatic variables through the WorldClim database (www.worldclim.org, accessed on the 1st of September 2020). Bioclimatic variables summarise monthly temperature and rainfall values into 19 more biologically meaningful variables (Table 1). Bioclimatic variables were downloaded for eight global climate models (GCMs): BCC-CSM2-MR (Wu et al., 2021), CNRM-CM6-1 (Voldoire et al., 2019), CNRM-ESM2-1 (Séférian et al., 2019), CanESM5 (Swart et al., 2019), GFDL-ESM4 (Krasting et al., 2018), IPSL-CM6A-LR (Boucher et al., 2020), MIROC-ES2L (Hajima et al., 2020), MIROC6 (Tatebe et al., 2018), MRI-ESM2-0 (Yukimoto et al., 2019), for four shared socioeconomic (SSP) (Riahi et al., 2017) and representative concentration pathway (RCP) combinations: RCP2.6-SSP1, RCP4.5-SSP2, RCP7.0-SSP3 and RCP8.5-SSP5 and 5 time-periods (1990, 2030, 2050, 2070 and 2090). As we did not have access to the following two files: IPSL-CM6A-LR SSP2-4.5 2030 and MRI-ESM2-0 SSP5-8.5 2030, we linearly interpolated values. All climate scenarios, bioclimatic variables were clipped to the extent of Australia prior to modelling.

We downloaded 15 environmental variables from the Soil and Landscape Grid of Australia database (https://www.csiro.au/en/research/natural-environment/land/soil-and-landscape-grid-of-australia, accessed on Sep 2021) to use as environmental predictors of habitat suitability. Additionally, we downloaded the Interim Biogeographic Regionalisation for Australia (IBRA) as an indication of the inherent spatial differences in biome across Australia. Soil and landscape variables were clipped and masked to the extent of Australia and scaled to the same resolution as the bioclimatic data (Table 1).

MaxEnt modelling procedure

Model fitting

All habitat suitability models were fit in MaxEnt Version 3.4.1 using the command line. Maxent models were first run with 10 replicates (replicates=10) validated using a cross validation method to train the model and to compute model validation statistics. At this stage, habitat suitability values are calculated as values between 0 and 1 with no threshold applied and were later converted to values between 0 and 100. An example of the full Maxent model specification can be found in the GitHub repository affiliated with this paper. Important outputs of the MaxEnt modelling procedure include a .csv file containing statistical information to inform variable selection and model validation as well as the 'lambdas file', which is a text file containing the regression coefficients or lambdas fit by MaxEnt during modelling.

Variable selection

The variables included in the final MaxEnt model runs were informed by analysing the variable contributions and importance percentages calculated using a full MaxEnt model run, information about variable complexity (Low et al., 2021), as well as ecological knowledge based on several published models of terrestrial vertebrate and vascular plant climate and habitat suitability. The goal of variable selection was to reduce the number of predictor variables from the initial 35 variables chosen as potential environmental predictors to avoid overfitting. Although Maxent is robust to multicollinearity among variables (Feng et al., 2019), including excessive numbers of predictors can affect the model's ability to make inferences outside of the training data.

We reviewed variables included within several Australian biodiversity modelling efforts of terrestrial vertebrates (Graham et al., 2019a), and vascular plants (Butt et al., 2013; Gallagher et al., 2019). We then performed a full MaxEnt model run which included the 35 variables described in the above section, for each species. We reviewed the importance of variables based on the average percent contribution and percent importance values across all species. The percent contribution is a measure of the contribution of each variable towards model fit after each iteration of the MaxEnt model, while the percent importance is a measure of the importance of each variable towards model fit for the final MaxEnt model. We also categorized bioclimatic variables based on complexity and favoured simple variables as they tended to be less correlated with one another (Low et al., 2021).

This combined approach to variable selection resulted in 18 variables which moved through to the model fitting stage (Table 1): 7 bioclimatic variables and 11 soil and landscape variables. All bioclimatic variables selected for this study were included in CliMAS models (Graham et al., 2019) and similar modelling efforts for Australian plants (Gallagher et al., 2019), and all bioclimatic variables with the exception of BIO15 were considered to be simple climate variables (Low et al., 2021) (Table 1). All bioclimatic variables except for BIO05 had high or moderate importance values in the full model. Similarly, we included additional soil and landscape variables (Hageer et al., 2017) based on their use in recent biodiversity models (Gallagher et al., 2019), and we favoured soil and landscape variables that were simpler.

Table 1 *Summary of the bioclimatic, soil and landscape variable selected in the final MaxEnt model.*

Code	Variable Name	Contribution[1]	Importance[2]	Ecological Rationale
Bioclimatic variables				
BIO1	Annual Mean Temperature	8.72	18.21	Influences thermal tolerances of species.
BIO5	Max Temperature of Warmest Month	6.33	9.92	Influences upper thermal tolerances of species through extreme temperatures.
BIO6	Min Temperature of Coldest Month	4.30	8.66	Influences lower thermal tolerances of species through extreme temperatures.
BIO12	Annual Precipitation	8.60	10.81	Average annual rainfall which influences water availability.
BIO13	Precipitation of Wettest Month	17.67	7.77	Maximum rainfall in the wettest month which influences maximum water availability.
BIO14	Precipitation of Driest Month	14.93	8.45	Minimum rainfall in the driest month which influences minimum water availability.
BIO15	Precipitation Seasonality	12.13	13.20	Standard deviation of rainfall in the annually which influences the variation in water availability.
Soil and landscape variables				
AWC	Available Water Capacity	0.94	0.68	The amount of water held by the soil for future use.

BDW	Bulk Density (Whole Earth)	0.89	1.17	Soil's ability to function for structural support, water and nutrient and microbial life movement, and soil aeration.
CLY	Clay	1.04	0.95	Promotes water retention and reduces air circulation in soil.
DES	Depth of Soil	2.00	1.29	Defines the root space and volume of soils available.
ECE	Electroconductivity	3.39	5.21	Movement of nutrients within the soil which influences the availability of soil nutrients.
elev	Elevation	2.37	1.57	Elevation influences soil properties and air pressure.
pHc	pH	5.43	4.30	Affects the amount of nutrients that are water soluble in soil.
slope	Slope Relief	1.81	1.00	Influences soil properties and creates varying microclimates.
SLT	Silt	2.63	2.10	Promotes water retention and creates relatively porous soil conditions.
SND	Sand	1.60	1.60	Promotes water drainage and air circulation in soil.
SOC	Organic Carbon	5.17	3.05	Promotes soil structure by providing a food source for micro-organisms.

Model validation

Once variables were selected, models were re-run, and model performance was assessed based on the area under the curve (AUC, i.e., the area under the receiver operating curve (ROC) curve) and the Boyce index. The AUC is a widely used model validation metric used within the Maxent literature (Merow et al., 2013). The AUC metric measures the predictive accuracy of the model and represents the probability that a randomly selected occurrence point is ranked higher than a randomly selected background point. The Boyce Index is another method that can be used to evaluate model performance and does so assessing the magnitude in which the model predictions differ from random distribution of the observed presences across the prediction gradients (Boyce et al., 2002; Hirzel et al., 2006). The Boyce Index value is represented by the Spearman rank correlation coefficient which assesses the increase in the Orediction/Expected (P/E) plot (Jiménez & Soberón, 2020).

The median AUC across all models was 0.97 and generally, AUC values of 0.7 or below indicates poor performance (Figure 3). We assess that 99.6% (n=10,566) of species have an AUC value above 0.7 AUC, and 0.4% (n=38) of species have an AUC value below the 0.7 threshold (33 birds, 4 vascular plants and 1 mammal). Boyce Index values can vary from −1 to 1 and we find that the median Boyce Index across all models in this study was 0.97 (Figure 3). A Boyce Index closer to 1 indicates that suitability predictions are consistent with the occurrence point distribution, and values of 0.5 or below generally indicate poor performance (Boyce et al., 2002; Hirzel et al., 2006a). We assess that 99.3% (n=10,509) of species have a value over 0.5, 0.65% (n=69) species had a value between 0.5 and 0 and 0.05% (n=5) species had a value below 0 (1 bird and 4 vascular plants).

We have also provided a scatter plot summary of AUC in relation to Boyce Index. Based on the 0.7 threshold for AUC and the 0.5 threshold for the Boyce Index, we find that 98.99% of species meet both thresholds. We find that 0.69% (n= 73) meet the AUC threshold but not the Boyce Index threshold, 0.32% (n= 34) species meet the Boyce Index threshold but not the AUC threshold and 1 species did not meet either threshold (Brown Falcon, *Falco berigora*). Prior to using species data, please ensure you check the AUC and the Boyce Index value which is contained within the species folder within the maxentResults.csv and the boyce_index_score.csv file.

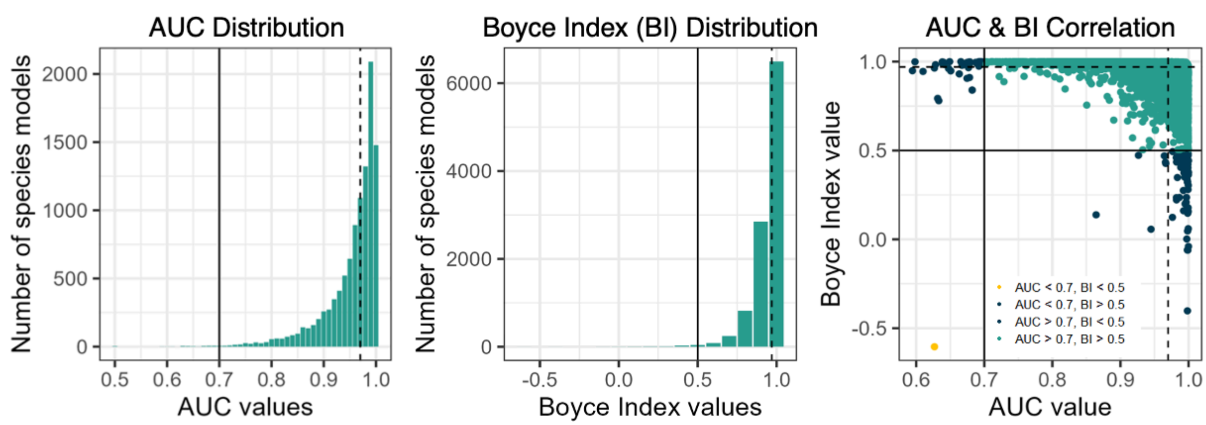


Figure 3 *From left to right the plots are the distribution of AUC values, the distribution of Boyce Index (BI) values and a scatter plot between AUC and BI values for species models. The median AUC and Boyce Index value is represented by a dashed line. On the AUC plot the 0.7 threshold is presented using a solid vertical line. On the BI*

plot the 0.5 threshold is presented using a solid vertical line. These thresholds are also represented by solid lines on the scatter plot.

Model projections

Using the best model selected in the model fitting procedure we projected species-level MaxEnt models under the future climate scenarios RCP2.6-SSP1, RCP4.5-SSP2, RCP7.0-SSP3 and RCP8.5-SSP5, 8 GCMs, for 1 historical time-period (1985) and 4 future time-periods (2030, 2050, 2070, 2090) using the lambda files produced in the model fitting step. Using the predicted habitat suitability data, we then calculated an ensemble average (mean), minimum and maximum habitat suitability (to capture model variance) across 8 GCMs for each species, climate scenario and time-period.

Geospatial calculations

To describe the patterns of habitat suitability across time in an accessible tabular format we calculated the total quality-weighted sum of habitat suitability for each species under different climate scenarios at each time period (Eq 1.). We first adjusted the resolution of the rasters to $1km^2$, therefore the quality-weighted habitat area (*qwHA*) sum corresponds to the 'habitat area' in km^2. For example, if the probable habitat suitability in a cell is equal to 1, the cell is equivalent to $1km^2$, whereas if the probable habitat suitability in a cell is equal to 0.3, the cell is equivalent to $0.3km^2$. Noting that the quality-weighted habitat area is not equivalent to the realised area available for a species given ecological or land use constraints which can both influence habitat availability and suitability for species. The probability of habitat suitability (*p*) was summed across raster cells (*xy*), for each species (*j*), year (*y*) and climate scenario (*c*):

$$qwHA_{jyc} = \sum_{i=1}^{n} p_{jyc,xy} \tag{Eq 1.}$$

To describe how the patterns of habitat suitability may have changed across space under different climate scenarios or years, we summarised raster data for each species in multiple ways. For each taxonomic group (*t*) we calculated changes in habitat suitability (*s*) by subtracting future time periods and climate scenarios (yc) by historical climate niche (p^h). Where positive values indicate areas that increase in suitability in the future and negative values indicate areas that decrease in climate suitability in the future. We provide visual representation of this information in Figure 6, and included the absolute and proportional change in habitat area in the tabular summaries provided for species:

$$s_t^{yc} = p_t^h - p_t^{yc}$$

(Eq 2.)

To spatially identify important areas of climate refugia which was done for Figure 6, we multiplied the historical habitat suitability matrix by the habitat suitability in each future climate scenario and year combination. For each the cell, the probability of habitat suitability values per cell (p), for each species (t), year (y) and climate scenario (c) were multiplied by the future habitat suitability. Cell values were then divided by 100, and the resulting cell value represents climate refugia (r) between 0 to 100.

$$r_t^{yc} = (p_t^h * p_t^{yc})/100$$

(Eq 3.)

Re-use potential

Code availability

For each species, MaxEnt models were run directly from the terminal using java and bash syntax and were ultimately executed using Slurm Workload Manager (SLURM) on a high-performance Linux-based computer cluster. Additional modelling and geospatial analyses were processed using a shell file executed using SLURM on the computer cluster. The scripts used in to generate this data is available in the GitHub repository, (see, https://github.com/CarlaBirdy/MaxEnt-habitat-models).

Dataset

Individual species' maps for historical and future minimum, mean and maximum ensembled habitat suitability, as well as the MaxEnt lambda file and summary reports produced in this study are publicly accessible for download on the open-access companion GigaDB database (Wilkinson et al., 2016). This dataset includes species-level historical (1970-2000 centered on 1990) and the future minimum, mean and maximum habitat suitability projections for 1,382 terrestrial vertebrates (182 amphibians, 487 birds, 178 mammals and 535 reptiles) and 9,251 vascular plants under 4 climate scenarios and 5 time periods, this data equates to 521,017 rasters that are compressed using Lempel–Ziv–Welch (lzw) compression. Additionally, for each species we have included a .csv file which contains the total quality-weighted habitat areas (in km^2) for each species under each different climate scenario and time period. We have also consolidated these tables across all species and included this tabular data. A complete list of the species for which habitat suitability maps were produced can be found in the companion GigaDB database.

Spatial resolution of data

This data is presented at $5km^2$ resolution which is aligned with the climate data used as key inputs to the MaxEnt model. The data can be subsequently downscaled to finer resolutions, however assumptions will have to be made about how habitat suitability is distributed across cells. The current resolution of this data is best utilized to understand general trends across space and time. To demonstrate the resolution, we present the southern cassowary (*Casuarius casuarius*) which is known to occur in the Wet Tropics region of Queensland, Australia. Current suitable areas for the southern cassowary are predicted to occur between Townsville to Cooktown, with an isolated area around the Iron Range (Figure 4). Taking the most severe climate change scenario (RCP8.5 - SSP5), the environmental space for the southern cassowary is predicted to reduce over time around its central habitat in the Atherton Tablelands. The maps for the southern cassowary can be compared with (Graham et al., 2019) for reference.

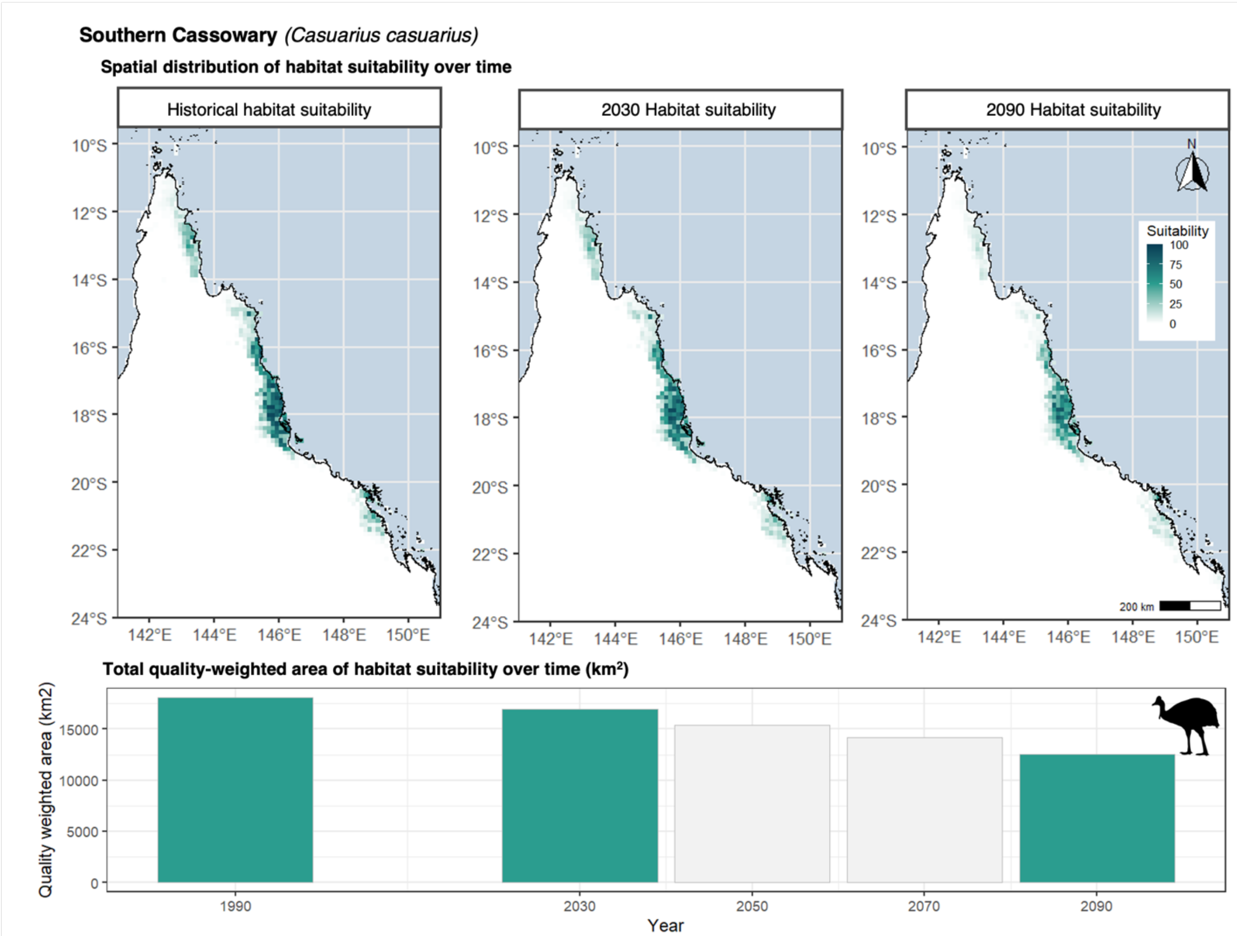


Figure 4 *This habitat suitability distribution is for the Southern Cassowary (Casuarius casuarius) and presents its historical suitability projection historically, in 2030 and in 2090. The graph below represents the total amount of habitat suitability (km^2) available in each time period, green bars correspond to the maps presented (historical, 2030 and 2090).*

Species-level data summary

The dataset includes suitability maps for species under different climate scenarios and time periods using an ensemble average approach. Through the process of ensemble averaging, the minimum and maximum suitability maps were also produced. These maps can be compared to understand the bounds of how climate change may generally impact habitat suitability in the future. The importance of incorporating multiple GCM projections can be seen by the variation among the minimum, mean, and maximum suitability maps (Figure 5). For the common wallaroo (*Macropus robustus*), the differences between the minimum, mean, and maximum suitability maps are most apparent under worsening climate scenarios. Areas across the southern parts of Australia remain suitable across all three suitability maps, compared to areas in the central and northern parts of their range becoming progressively less suitable. These trends are consistent with other macropod modelling studies that also suggest suitability for the common wallaroo will track south as climate scenarios worsen (Ritchie & Bolitho, 2008). The maps for the common wallaroo can also be compared with (Graham et al., 2019) for reference.

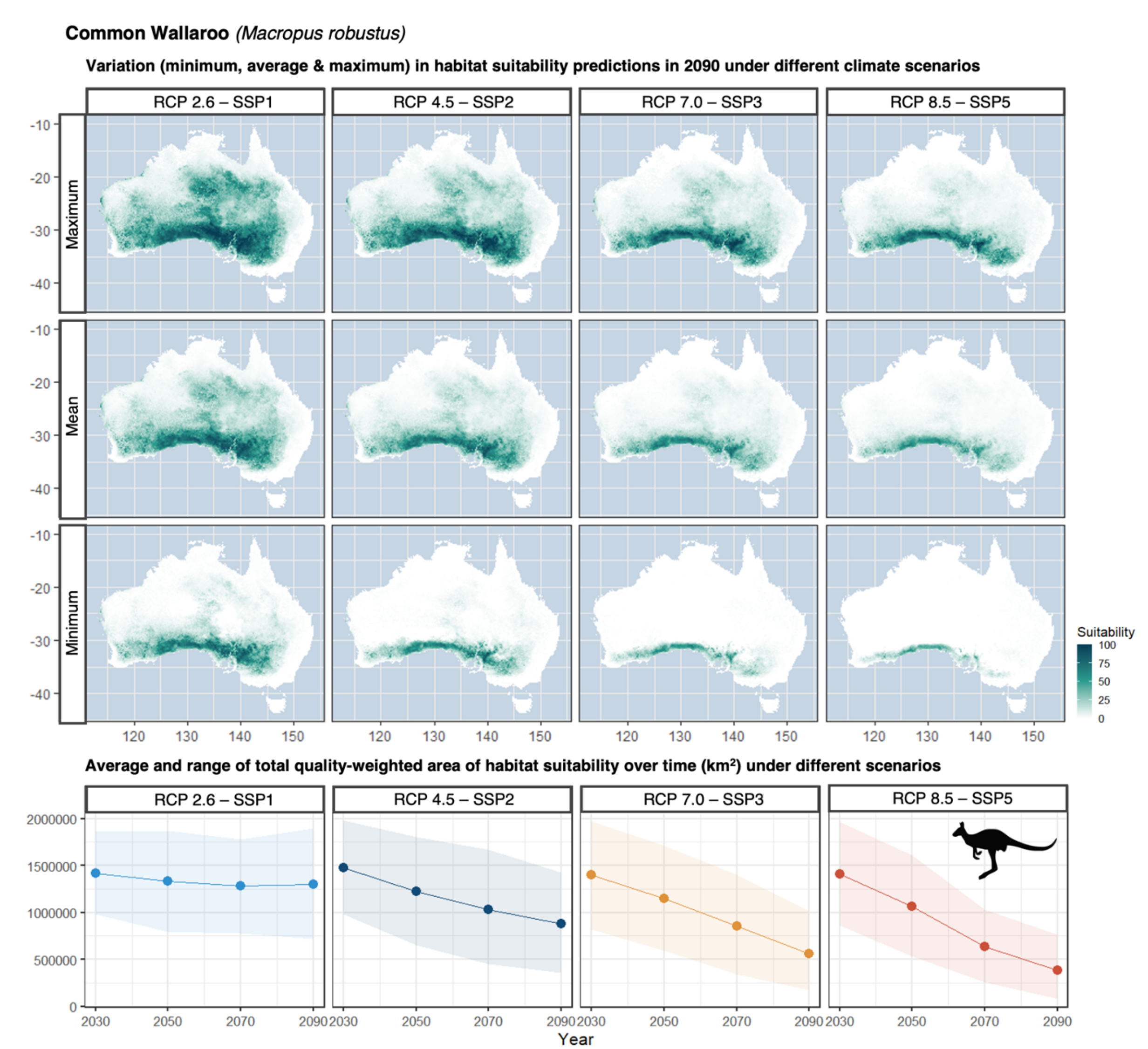


__Figure 5__ These habitat suitability distributions are for the common wallaroo (Macropus robustus) for one historical projection, and four future emission scenarios in the year 2090. The habitat suitability distributions of each row of maps represent the minimum, mean, and maximum habitat suitability projections across GCMs. The line graphs represent the total habitat suitability (km^2) for four future emission scenarios over time. The uncertainty band represents the minimum and maximum amount of habitat suitability across GCMs.

Spatial changes over time

Taking this a step further, geospatial calculations can also be applied to determine the differences between years or climate scenarios. This can be conducted to identify areas of refugia (Equation 3), or the location and magnitude of change between different time periods (Equation 2). To calculate spatial locations of refugia, historical and future suitability maps can be multiplied together to accentuate areas in space that are suitable in both time periods. To calculate spatial changes in habitat suitability through time, historical suitability maps can be subtracted from future suitability maps to spatially accentuate locations that have changed in habitat suitability (i.e., improved in suitability or declined in suitability) across time periods. Using the snow gum (*Eucalyptus pauciflora*) as an example, we find refugia in the alpine region of Australia is predicted to decline for the snow gum under worsening climate scenarios, with declines being most severe in the year 2090 (Figure 6, top). Across all climate scenarios habitat suitability is declining from all areas of the snow gum's range, and we did not identify areas of increases (Figure 6, bottom).

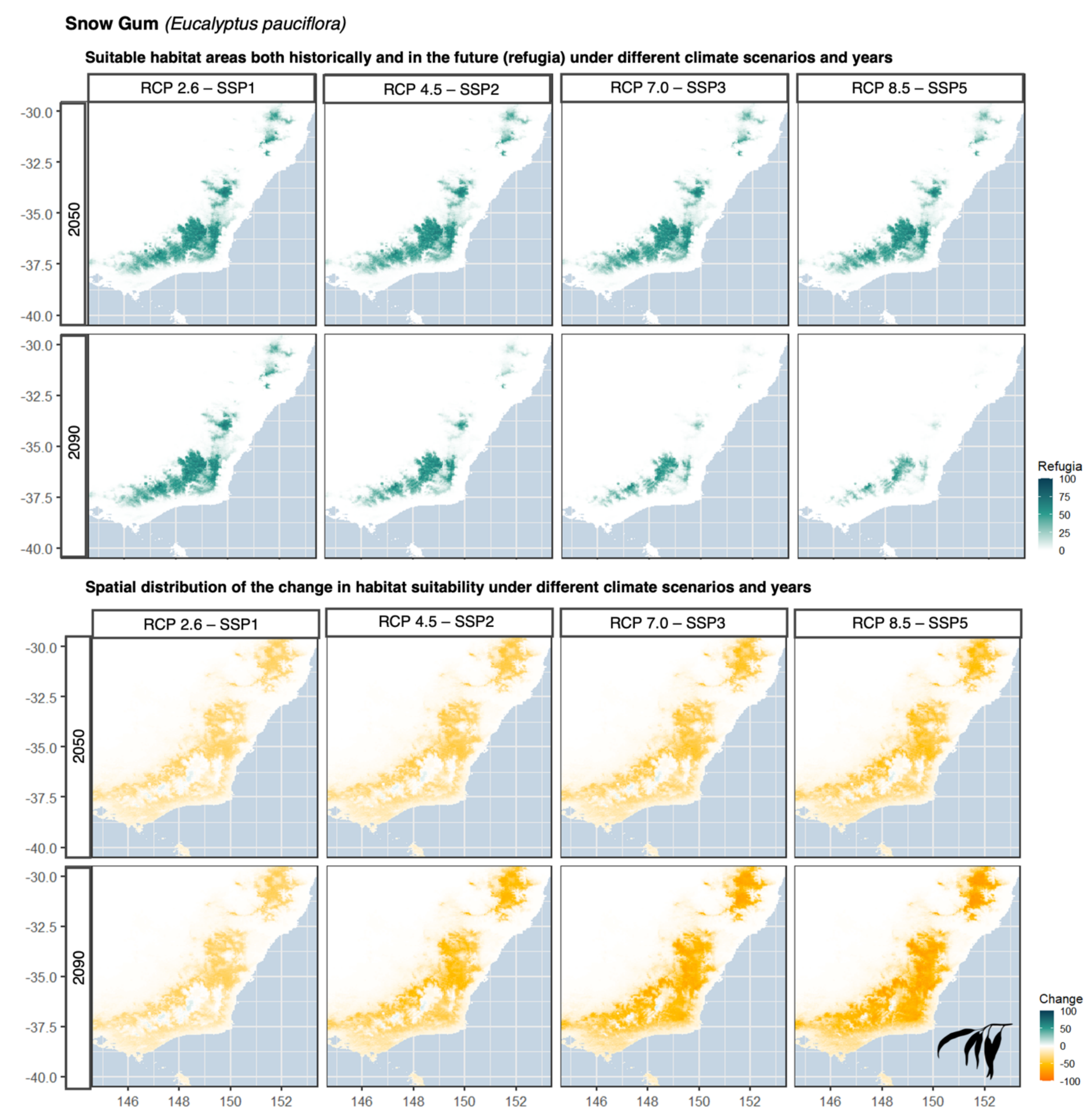


__Figure 6__ Refugia and habitat suitability change maps for snow gum (Eucalyptus pauciflora). The Top Panel present climate change refugia for four future emission scenarios in the years 2050 and 2950. Dark green on the refugia maps represent areas that have high predictive suitability historically as well in future time periods. The Bottom Panel present changes in habitat suitability for four future emission scenarios in the years 2050 and 2090. Orange areas indicate placed that decrease in suitability compared to the previous time period, and green areas indicate areas that improve in suitability. White areas indicate no change in suitability.

Changes in quality-weighted habitat area

The dataset also includes a tabular summary of quality-weighted habitat area in km^2 for each species under different climate scenarios and time periods (Equation 1 and Equation 2). The quality-weighted habitat area values can be analysed and plotted to understand how climate change may impact habitat area for single species or groups of species in the future (Figure 7). When this data is summarised across all species, we can show that in 2030 the distribution of change in habitat area are similar across the four climate scenarios. However, in 2090 the distribution of change in habitat area follows a different pattern across climate scenarios with progressively more species losing progressively more habitat area as climate change worsens (Figure 7).

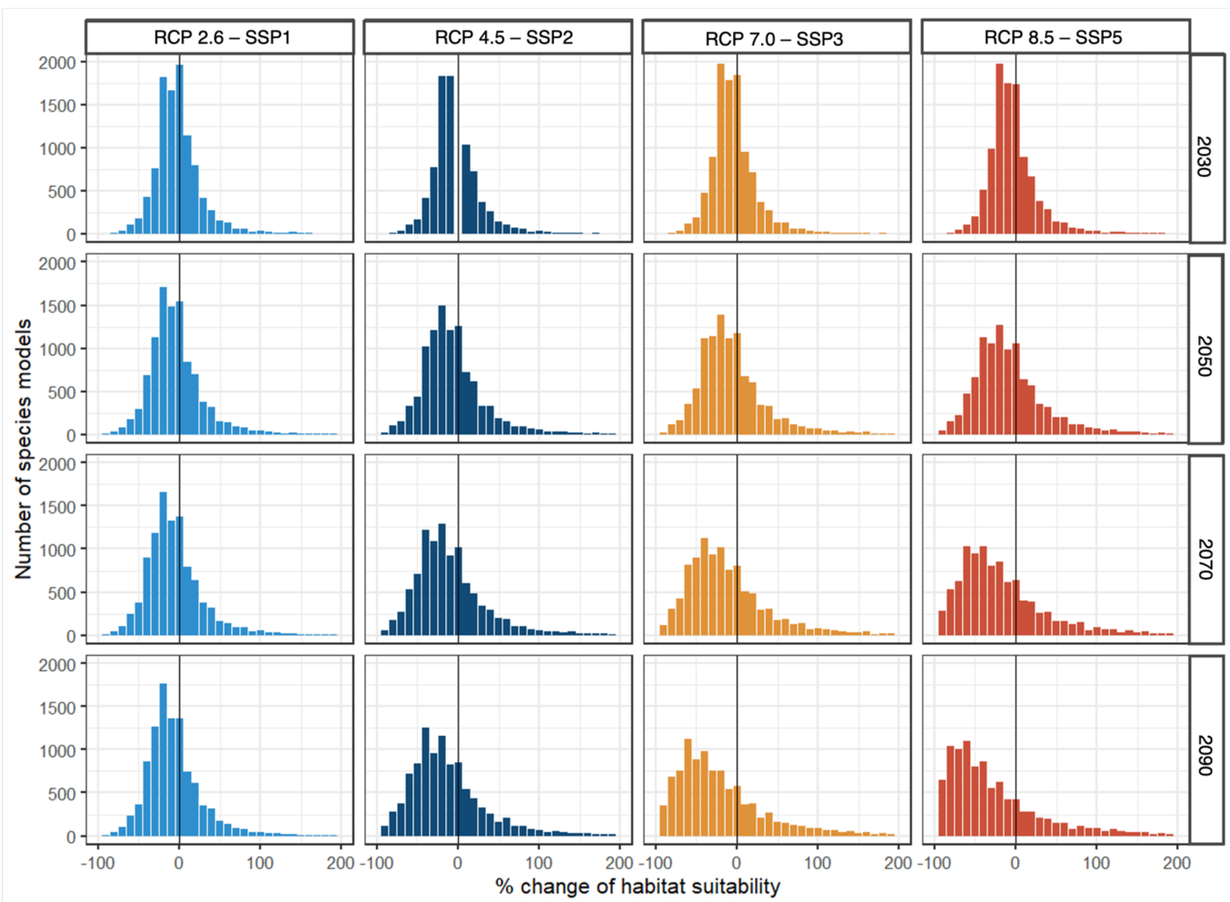


Figure 7 *Histogram of the number of species and their relative change in mean quality weighted habitat area between 1990 and each future time period (2030, 2050, 2070, 2090).*

Discussion

Spatial data on the suitability of areas for species is an important input to guide conservation planning, policy and management. The objective of this paper was to develop habitat suitability maps for Australian flora and fauna under different climate futures using a MaxEnt approach. This data has been developed in a way that is consistent across species and enables users to analyze how different climate futures may impact the habitat suitability for biodiversity more generally across Australia. This data can also be used for species-level analysis and can be a starting point for additional analyses which utilize either geospatial information or tabular information that could take into consideration additional information like land use, conservation actions or species ecology.

Applications for landscape and species conservation

This spatial and tabular dataset is ideal for users that would like to understand how the habitat suitability of areas for species is predicted to change over time or under different climate scenarios. For example, at the landscape level, these habitat suitability maps can be combined into a general biodiversity layer to evaluate how habitat suitability more generally changes over time (Figure 7) or over space and time (Figures 4, 5 and 6) (Hama & Khwarahm, 2023). This data can then be utilized in applications such as spatial prioritisations using such tools as Zonation (Minin et al., 2014) or Marxan (Watts et al., 2009) to guide spatial conservation priorities in Australia (Maxwell et al., 2019; Summers et al., 2012). Therefore, using this data for subsequent analysis can be useful to inform conservation (e.g., where to establish new protected areas), restoration or monitoring plans in areas which are suitable for biodiversity, or are predicted to lose or gain suitable areas for biodiversity.

At the species level, this dataset can be used to support conservation actions for species of interest (e.g., threatened species, iconic species, endemic species). The tabular data can be used to systematically identify species of interest based on the way climate change is anticipated to impact the species. Or could be used to inform processes such as threatened species listing (IUCN, 2022). Spatial information about species could also be useful to compare the long-term suitability of areas for threatened species under climate change to inform present day decision-making and species management (Harley, 2023; Hawke et al., 2020). Could be paired with other types of data to assess the impacts of climate change on species (Eyre et al., 2022). Or could inform boarder scale biodiversity conservation analyses (Engert et al., 2023).

Applications in sustainability and natural capital accounting

Biodiversity forms a foundation of broader sustainability ideals, therefore, to measure progress towards sustainability, conservation or corporate goals spatial data on biodiversity can serve as an important input information to the creation of metrics (Lamb et al., 2009; Watermeyer et al., 2021). Biodiversity indicators like the species richness, or more complex indicators like the Species Threat Abatement and Restoration metric (STAR) (Mair et al., 2021) or the biodiversity intactness index (BII) (Biggs & Scholes, 2005) all draw from species layers as input data. Feeding the habitat suitability maps generated in this study into biodiversity layers and into broader sustainability models or assessments can improve the consideration of biodiversity against other environmental or social values. This may include initiatives such as land use planning, or land use change modelling (Connor et al., 2015; Gao & Bryan, 2017).

Additionally, as many businesses are transitioning towards 'nature positive' the use of biodiversity to monitor business impacts and progress towards nature positive is necessary. The habitat suitability maps generated in this study can be used to represent key species or biodiversity within natural capital within frameworks such as the System of Environmental-Economic (SEEA) framework (UNEP et al., 2015), within sustainability assessments such as 'foot printing' to enhance the biodiversity input data (Halpern et al., 2022; Hoang et al., 2023; Irwin & Geschke, 2023), or within nature-related impact or dependency assessments which inform frameworks like the Taskforce on Nature-Related Financial Disclosures (TNFD) (TNFD, 2023).

Limitations and caveats with the data

When using and interpreting the data contained in this dataset it is important to consider the following limitations and considerations. This dataset presents the habitat suitability of areas for species under different climate scenarios and time periods using a correlative approach. These maps are not distribution maps, rather they present habitat suitability based on climate, soil and landscape characteristics. Due to its $5km^2$ spatial resolution, the data is best for understanding broader spatial trends that can be integrated into spatial planning (Maxwell et al., 2019), rather than more local management such as identifying specific sites for translocation without additional finer detail (Eyre et al., 2022).These maps have not been thresholded, nor do they consider dispersal (Graham et al., 2019), land use (Kapitza et al., 2021), biophysical capacity (Briscoe et al., 2023), or attributes that may be important for species of interest (e.g., NDVI, fire or vegetation structure e.g., (Eyre et al., 2022). There are a multitude of other methods to model suitability and species distributions that have their own use cases and limitations (Briscoe et al., 2016; Elith & Graham, 2009).

The occurrence points used for this analysis were those originally used for the CliMAS work, and the ALA data were passed through an additional rigorous cleaning process for terrestrial vertebrates. This process helped reduce the spatial bias and noise in the occurrence points (Phillips et al., 2009); however, more broadly there are sampling biases that influence the distribution of occurrence points, such as land tenure. To improve on the models, an integrated pathway to ALA into the modelling procedure would be ideal as this would ensure up-to-date input data. However, this can also come with challenges as occurrence data is required to have the same temporal resolution to the historical or current climate data (i.e., 1990 in this study). While we did use target background files to reduce spatial biases (Barber et al., 2022), there may still be limitations of this approach at the taxonomic group level, for example for small ranging species (Breiner et al., 2015). Taxonomic level grouping may still be too broad to adequately capture those species that are highly range restricted and require very specific micro-climate needs, therefore species-specific level grouping may help to overcome this. Background files that are too broad may adequately capture sampling biases or the true relationship between occurrence points and environmental predictors.

MaxEnt models are also prone to overfit but are also less influenced by collinearity than statistical models, we tried mitigating the impacts of overfitting the MaxEnt models by conducting variable selection. In relation to the variables used, we were primarily guided by past efforts that model the suitability of areas across Australia for many species (Butt et al., 2013; Gallagher et al., 2019), however this approach obviously overlooks some variables that can be import to model suitability. For example, we did not consider variables such as the normalized difference vegetation index (NDVI) (Wen et al., 2015), land use (Lentini & Wintle, 2015), weather (Reside et al., 2010), or detailed information about vegetation structure or extreme events like fire (Eyre et al., 2022).Thus, our recommendation is for the users of this data to consider whether the variables used to model habitat suitability in this study is compatible with the species of interest, or whether additional information is required. This will likely be the case if the user is interested in a more fine-scale application of the data, for example at the single species or local level, as this data is best suited for macro-level analyses and applications.

Finally, there is much contention around the best way to assess model performance of Maxent models beyond just the AUC, to approaches like the True Skill Statistic value (TSS), the kappa score and the Boyce Index (Allouche et al., 2006; Hirzel et al., 2006; Jiménez & Soberón, 2020; Valavi et al., 2022). We present the AUC and the Boyce Index and do not consider the thresholds for these indexes prior to creating the habitat suitability projections, therefore the user can assess the model performance for their species on interest when interpreting the data.

Conclusion

To spatially target conservation actions, spatial information about the location and suitability of areas for species is needed. This study provides a comprehensive dataset of predicted habitat suitability under 4 climate futures, while also incorporating the uncertainty across GCMs. We are providing a spatial and tabular data product at the Australian scale and at 5km^2 resolution that can be used to inform research and decision making at local, regional and national scales. This data can be applied within strategic conservation planning approaches and can be used to identify important areas for species consecration (Tulloch et al., 2015). Spatial information about current and future suitable areas for species is a key component of conservation planning, particularly as the impact of climate change on species and biodiversity is uncertain.

Data availability

All spatial and tabular data are freely accessible in the companion GigaDB repository.

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Conflict of interest

The authors declare no conflicts of interest.

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