ACT Government

IDENTIFYING BIODIVERSITY REFUGIA UNDER CLIMATE CHANGE IN THE ACT AND REGION

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Environment Division

Technical Report
June 2019

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Identifying biodiversity refugia under climate change in the ACT and region

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June 2019

ACT Government
Environment, Planning and Sustainable Development

ISBN: 978-1-921117-69-5

This document should be cited as: MacKenzie, J.B., G. Baines, L. Johnston & J. Seddon. 2019. Identifying biodiversity refugia under climate change in the ACT and region. Environment, Planning and Sustainable Development Directorate, ACT Government, Canberra.

http://www.environment.act.gov.au
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Front cover: Ensemble forecast of 2060-2079 climate suitability for *Eucalyptus fastigata* (Brown barrel)

Table of Contents

List of Figures

List of Tables

Executive Summary

Humans are profoundly changing climate and impacting biodiversity around the world. Substantial changes in ecological processes are already visible, including climate impacts on genes, species and ecosystems (Scheffers et al., 2016). Up to half of all known species may already be on the move in response to recent changes in climate (Pecl et al., 2017), and impacts on threatened species are expected to be severe (Pacifici et al., 2017). The planet is undergoing a sixth mass extinction event with urgent action required to avoid grave consequences for human well-being (Diaz et al. 2019).

To help biodiversity adapt to climate change in the ACT and surrounding region, ACT Government established policy commitments under the ACT Nature Conservation Strategy 2013-23 to identify and appropriately manage areas where desirable species are likely to persist under climate change (i.e., biodiversity refugia). Here, plant distribution models are used as criterion to identify local biodiversity refugia under plausible future climate scenarios. These models assess potential climate impacts for regional native plant species (n=151 trees, shrubs and grasses) under near-future (2020-2039) and far-future (2060-2079) climate scenarios proposed by the NSW and ACT Regional Climate Modelling (NARCliM) project. Dominant native plant species, that tend to be data rich and characteristic of local vegetation communities, are the focus of this climate impact assessment in the hope of 'keeping common species common'.

This technical report and the associated 'datapack' provide land managers, researchers and policy makers with the best available evidence of potential climate impacts on local native plant species at the time of publication. The report provides a detailed project methodology, as well as practical guidance on management applications (e.g., revegetation, ecological burns). Current applications by ACT Government include guidance for ecological restoration and fire management on-ground (conservation programs), the design of 'climate-ready' conservation objectives (conservation policy), as well as better understanding of the ecology and vulnerability of desirable species (conservation research). The full 'datapack' (~2Tb) provides full transparency on project inputs and outputs, and is comprised of data (climate projections, species occurrence data, niche models, spatial predictions, tables and analytical zones), maps, and scripts used for modelling and spatial analysis. A lighter module for land management, "Managing Refugia" (~2Gb), excludes models and raster datasets, and clips data to a regional extent, in order to simplify access, storage and distribution. These tools and information products can help conservation practitioners: i) modify planting lists and identify local 'winners' and 'losers' for revegetation programs in light of climate change (e.g., see 'ACT Biodiversity Refugia Atlas.pdf' accompanying Technical Report), and ii) better consider the fire ecology and climate preferences of vegetation communities when prioritising land management interventions (e.g., see Figures 17 - 19).

All models and maps of biodiversity refugia resulting from this project are to be made publicly available and were developed in consultation with stakeholders to support decision making for a range of policy, program and research applications. All models and proposed biodiversity refugia represent working hypotheses, based upon the best available evidence at time of publication. Moving forward, new

observations, ecophysiological experiments and niche models should further test and refine hypotheses about the location and extent of potential biodiversity refugia. It is hoped this project will help stimulate action by regional land managers to better prepare for the threats that climate change poses to regional biodiversity values.

1 Background

Identifying biodiversity refugia – areas that are most likely to remain suitable under climate change for desirable native species – can help fill critical knowledge gaps for conservation policy, conservation programs and conservation research in the region. Information on the location and extent of local biodiversity refugia can inform ecological restoration and fire management on-ground (programs), 'climate-ready' conservation objectives (policy), as well as a better understanding of the ecology and vulnerability of desirable species (research). Regional natural resource management (NRM) investors and land managers need the capability to anticipate and manage on-ground risks for desirable local species. Ideally, a national program could provide up to date and best available climate impacts for all native species at spatial resolutions appropriate for on ground management programs and investment. However, available information on climate change impacts on biodiversity are often too coarse spatially (1-5km resolution) or taxonomically (e.g., broad assemblages or major vegetation subgroups, rather than individual species, etc.) for local on-ground applications. Therefore, ACT Government requires species-specific climate refugia to be identified at a spatial resolution appropriate for local management and planning applications, based upon the best available evidence from regional climate models.

Under the ACT Nature Conservation Strategy 2013-23, ACT Government committed to:

- improve landscape resilience to climate change;
- better understand and manage for climate change impacts; and
- identify, protect and manage potential biodiversity refugia across the region.

The Identifying Biodiversity Refugia project addresses this policy gap by modelling local areas where desirable native species in the ACT and region may persist in the face of climate change. Specific aims of the study are to:

- model and map potential future climate impacts for locally desirable native plant species;
- specify criteria for identifying biodiversity refugia in the region;
- help land managers better understand and effectively manage refugia values; and
- create open access information products to identify biodiversity refugia (i.e., models, maps).

This technical report provides a brief summary of the methodology used to model and summarise climate suitability, as well as product descriptions to assist with end user interpretation.

2 The 'Datapack'

The 'datapack' provided by this project represents the best available compilation of potential climate impacts on regional native plant species in the ACT and surrounding region at the time of publishing. Two versions of the 'datapack' exist – the full version (~2Tb), referred to as "Identifying Refugia", is designed for analysts and modellers, whereas a lighter compact version (~2Gb), referred to as "Managing Refugia", is designed for land managers and conservation practitioners. These 'datapacks' are to be made publicly available for use by any and all regional stakeholders in biodiversity conservation. All spatial data layers were tagged with geospatial metadata in ArcGIS Desktop (ESRI, 2016) using an industry standard format ISO19115 to provide end users with a brief description relating to purpose, methodological basis, and appropriate use. Given the volume of information in the full 'datapack' (~2TB), end users should allocate 3TB or more of data storage to copy the full contents. Questions relating to usage or interpretation may be forwarded to Dr Jason MacKenzie (jasonbmackenzie@gmail.com). To obtain a copy of the 'datapack', the best point of contact is Jen Smits (Jennifer.Smits@act.gov.au) of the Conservation Research Unit in ACT Government.

The high-level structure of the full "Identifying Refugia" 'datapack' is meant to be intuitive, including separating directories for data, maps, reports and scripts (Table 1). 'Data' subdirectories include information relating to climate projections (Section 2.1), species occurrence data (Section 2.2), masking layers for cartography and analysis (Section 2.3), niche models (Section 2.4), spatial predictions (Section 2.5), look up tables and queries (Section 2.6) and analytical zones for reporting (Section 2.7). The 'Maps' subdirectory includes printable maps, symbology layers, and ArcGIS projects. The 'Report' subdirectory includes the Technical Report and associated ACT Biodiversity Atlas. The 'Scripts' subdirectory contains a compilation of core scripts relating to deriving information products. Lastly, the 'Tools' subdirectory contains a set of ArcGIS Toolboxes used in various stages of the project.

Also contained in the full 'datapack' is a compact module, "Managing Refugia", which mirrors the structure of the 'datapack' (Table 1), but is designed to simplify access, storage and distribution. The "Managing Refugia" module clips data to a regional extent (for efficiency) and excludes some content (i.e., rasters). The 'Data' subdirectory contains an ArcGIS file geodatabase, "ManagingRefugia.fgdb', which houses all feature datasets (i.e., predictions, masks, zones) and tables (i.e., occurrence data, look up tables). ArcMap projects (*.mxd) are provided to assist with land management applications relating to revegetation and fire planning. Symbology layers are provided to assist with visualisation. The 'Report', 'Scripts' and 'Tools' subdirectories are identical to the full 'datapack'.

Table 1 *'Datapack' folder structures and contents.*

Information Products	"Identifying Refugia" (i.e., full version = ~2Tb)	"Managing Refugia" (i.e., light Version = ~2Gb)
Data	.../IdentifyingRefugia/Data/	.../ManagingRefugia/Data/
Metadata	.../IdentifyingRefugia/Data/_metadata/	.../ManagingRefugia/Data/_metadata
Climate data	.../IdentifyingRefugia/Data/climate/	[full version only]
Fire Ecology	.../IdentifyingRefugia/Data/vegfire/	.../ManagingRefugia/Data/ManagingRefugia.gdb/IBR_FireEcology/
Masks and Boundaries	.../IdentifyingRefugia/Data/masks/	.../ManagingRefugia/Data/ManagingRefugia.gdb/IBR_Masks*/
Species Distribution Models	.../IdentifyingRefugia/Data/models/	[full version only]
Species Occurrence Data	.../IdentifyingRefugia/Data/occurrence/	.../ManagingRefugia/Data/ManagingRefugia.gdb/IBR_occurrences*
Spatial Predictions	.../IdentifyingRefugia/Data/predictions/	.../ManagingRefugia/Data/ManagingRefugia.gdb/IBR_Predictions*/
Tables	.../IdentifyingRefugia/Data/tables/	.../ManagingRefugia/Data/ManagingRefugia.gdb/IBR_LUT*
Zones	.../IdentifyingRefugia/Data/zones/	.../ManagingRefugia/Data/ManagingRefugia.gdb/IBR_Zones/
Maps & Figures	.../IdentifyingRefugia/Maps/	[full version only]
Technical Report & Biodiversity Atlas	.../IdentifyingRefugia/Report/	.../ManagingRefugia/Report
Scripts	.../IdentifyingRefugia/Scripts/	.../ManagingRefugia/Scripts
ArcGIS Toolboxes	.../IdentifyingRefugia/Tools/	.../ManagingRefugia/Tools

2.1 Climate

The NSW and ACT Regional Climate Modelling (NARCliM) project (Evans et al. 2014) provide the best available climate projections for Southeast Australia (Evans & Ji 2012). All future climates considered are treated as equally plausible in this study, including n=12 near-future (2020-2039) and n=12 far-future (2060-2079) scenarios. NARCliM climate projections were derived from the outputs of four global climate models (GCMs) (Meehl *et al.* 2007) that were dynamically downscaled using 3 different regional climate models (RCMs) (Skamarock et al. 2008). The GCMs assume an IPCC SRES A2 emissions scenario (i.e., "high emissions"; Nakicenovic et al. 2000), and were sourced from Canada (CCCMA CGCM3.1(T47)), Australia (CSIRO-Mk3.0)), Germany (ECHAM5/MPI-OM) and Japan (MIROC3.2(medres)). The three RCMs used (R1, R2 and R3) represent modified configurations of the Weather and Research Forecasting (WRF) RCM (Skamarock et al. 2008). The name and source of NARCliM climate scenarios presented throughout are listed in Table 2.

Table 2 *Standard notation for modelling future climate scenarios.*

Epoch Scenarios	Global Climate Model	Regional Climate Model
future1	CCCMA3.1	R1
future2	CCCMA3.1	R2
future3	CCCMA3.1	R3
future4	CSIRO-MK3.0	R1
future5	CSIRO-MK3.0	R2
future6	CSIRO-MK3.0	R3
future7	ECHAM5	R1
future8	ECHAM5	R2
future9	ECHAM5	R3
future10	MIROC3.2	R1
future11	MIROC3.2	R2
future12	MIROC3.2	R3

To better inform local spatial planning exercises across Southeast Australia, NARCliM climate projections were statistically downscaled from ~10km to ~250m resolution grids (Hutchinson & Xu 2015) using a "delta" change factor downscaling method (Harwood, 2014). From this downscaled climate data, a set of 35 bioclimatic (BIOCLIM) variables (see ANUCLIM User Guide) were derived (Xu & Hutchinson 2011) for each NARCliM epoch, or time period, including a "baseline" climate (1990–2009), as well as multiple (n=12) "near-future" (2020–2039) and (n=12) "far-future" (2060–2079) scenarios. To compliment these standard 35 BIOCLIM variables, two additional predictor variables, atmospheric water deficit (i.e., precipitation – pan evaporation) and aridity index (i.e., precipitation / pan evaporation) were derived for the driest month of each epoch-scenario using downscaled MTHCLIM layers from ANU, following the logic of Williams et al. (2010). These layers are called 'wd.tif' and 'wd_ai.tif' in each climatology provided in the 'datapack' (full version only).

The predictor variables explored in distribution modelling by this project (listed below) are broadly expected to influence the functions and distributions of plant species, including:

- mean diurnal temperature range;
- temperature seasonality (the coefficient of variation of monthly mean temperature);
- maximum temperature of the warmest month;
- minimum temperature of the coldest month;
- precipitation of the wettest month;
- precipitation of the driest month;
- precipitation seasonality (the coefficient of variation of monthly total precipitation); and
- atmospheric water deficit of the driest month.

Levels of correlation observed between predictor variables, shown in Table 3, suggest atmospheric water deficit is closely correlated to maximum temperature of the warmest month. While distribution models were run with and without atmospheric water deficit for exploratory purposes, models and results presented throughout exclude this predictor.

Table 3 *Pairwise correlation coefficients for predictors of distribution models (Pearson Statistics).*

	Diurnal Temperature Range	Temperature Seasonality	Maximum Temperature of Warmest Month	Minimum Temperature of Coldest Month	Maximum Precipitation of Wettest Month	Minimum Precipitation of Driest Month	Precipitation Seasonality	Atmospheric Water Deficit
Diurnal Temperature Range								
Temperature Seasonality	0.707							
Maximum Temperature of Warmest Month	0.750	0.854						
Minimum Temperature of Coldest Month	0.006	0.052	0.509					
Maximum Precipitation of Wettest Month	-0.530	-0.692	-0.638	-0.118				
Minimum Precipitation of Driest Month	-0.644	-0.605	-0.806	-0.491	0.758			
Precipitation Seasonality	0.261	0.063	0.392	0.543	0.196	-0.360		
Atmospheric Water Deficit	-0.619	-0.669	-0.909	-0.619	0.483	0.788	-0.614	

All climate raster data were projected from WGS84 (EPSG: 4326) to GD94 Australian Albers (EPSG: 3577) to ensure equal area of grid cells. The spatial resolution of grid cells was modified from ~250m

to ~275m to minimise resampling, and file formats were converted from floating grids (*.flt) to GeoTIFF (*.tif) to maximise storage efficiency. To simplify integration with other ACT Government datasets, versions of some raster products were projected to GDA94 MGA Zone 55 (EPSG: 28355). Coordinate reference systems defined in R based on proj4 strings from the Spatial Reference website were re-defined manually in ArcGIS to avoid compatibility issues. Manipulation and analyses of raster data were done using the `raster` package (Hijmans 2016) in R (R Core Team 2017). Plotting of summary statistics for climate scenarios (Figures 20-23 of Appendix 2) was done using `ggplot2` (Wickham 2009).

2.2 Occurrences

Species selected for distributional modelling (listed in Appendix 3) include most of the trees, shrubs and grasses that are characteristic of local vegetation communities in the ACT (n=120 species; Armstrong et al. 2013), as well as native plants from surrounding NSW thought to have potential for shifting into the ACT under climate change (n=31 species). Presence-only plant species occurrence data were obtained from multiple repositories, including ACT Government (Conservation Research), NSW Government (BIONET), Canberra Nature Map, Atlas of Living Australia (ALA) and the Global Biodiversity Information Facility (GBIF). Coordinate reference systems of occurrence records were standardised to GD94 Australian Albers (EPSG: 3577) using ArcGIS Desktop version 10.5.1 (ESRI, 2016), then data tables were manipulated in R (R Core Team 2017) using `dplyr` (Hadley et al. 2017) and `tidyverse` (Hadley 2017). Collections were cleansed using data assertions specific to positional accuracy and taxonomic assignment. Only records with high positional accuracy data (i.e., +/- 100m or better), typically derived from GPS coordinates (i.e., date = 2000 to present), were included as model inputs, in order to minimise positional errors between species data and gridded climate data (~275m resolution cells). For record locations provided in geographic coordinate systems (i.e., WGS84, GDA94), latitude and longitude values required precision values ≥ 3 decimal places (i.e., +/- ~100m positional accuracy) to be considered. Naming conventions (e.g., scientific name, species name, canonical name, species codes etc.) were harmonised between collections using a modified version of the GBIF backbone taxonomy. After standardising a core set of fields (i.e., record ID, species, X, Y, positional accuracy, year, source collection), collections were aggregated into a master occurrence dataset. Grid cell IDs across the modelling domain were joined to occurrence data, both to exclude records outside the domain, and to thin duplicate species records within individual grid cells (i.e., resulting in spatially unique records). To ensure ample data for model fitting and evaluation, species selected for modelling (n=151) required ≥ 100 spatially unique occurrence records.

In total, 3,650,120 cleansed plant records were obtained across Southeast Australia, dating from 1950 to present, including 636,161 spatially unique plant occurrences sampled from 161,152 spatially unique locations. Filtering on date (i.e., year ≥ 2000) to rely primarily on GPS-based records as model inputs returned 2,129,259 total plant records, including 330,618 spatially unique species occurrences from 98,083 spatially unique sampling locations.

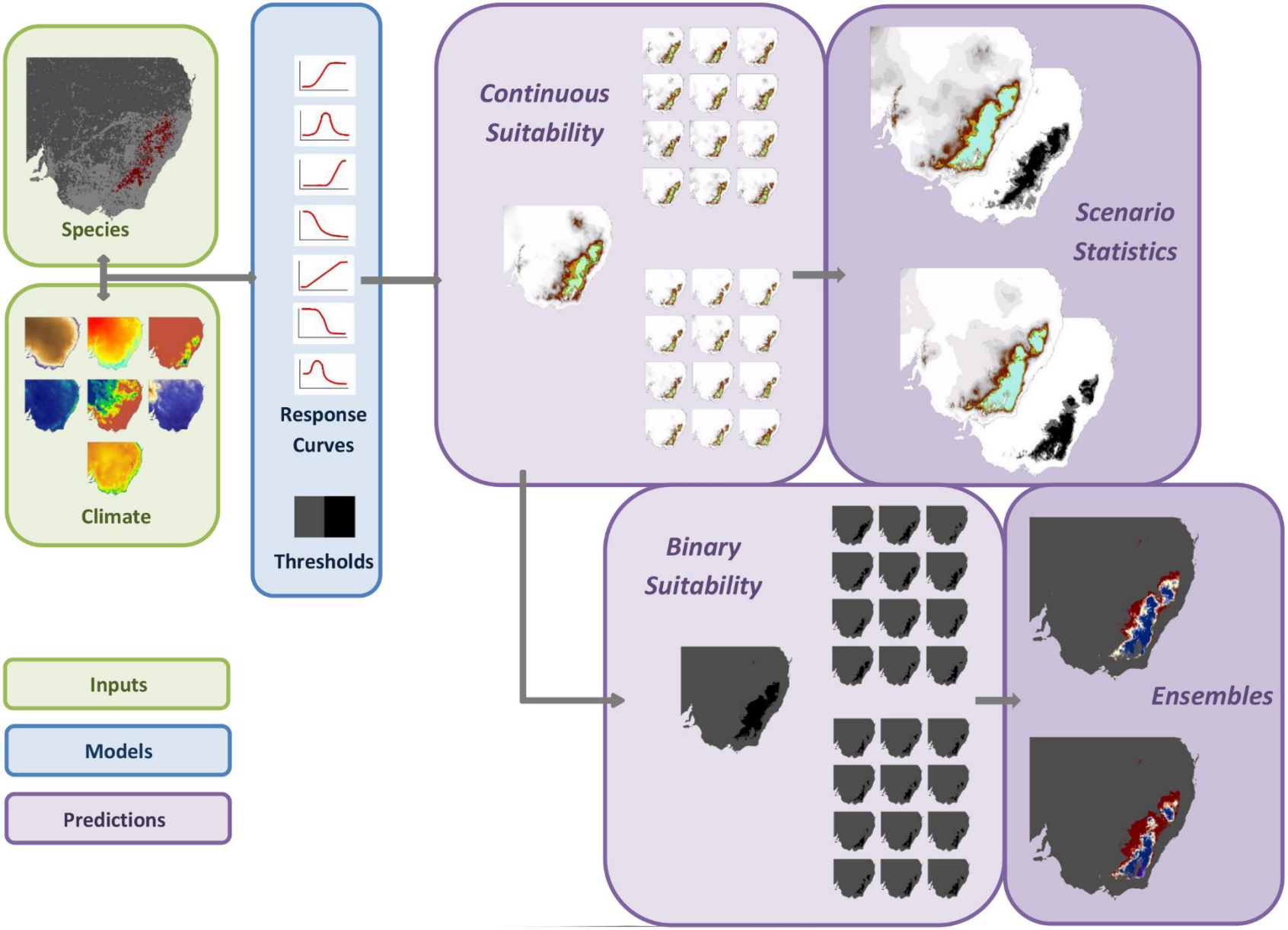
2.3 Masks

Mask layers provided were used to define the boundaries or extents of distribution models (e.g., Southeast Australia) or government jurisdictions (e.g., ACT). Masks derived from Territory wide vegetation mapping provided filters for relevant vegetation communities (i.e., UMC_IDs). Species masks were designed to convey expected areas of local occurrence based upon the association of native plant species with vegetation communities. The look up table for this species-vegetation community association is provided as a look up table (LUT) in the 'datapacks'. For species, both 'inner' and 'outer' masks are provided. 'Inner' masks are primarily for cartography and provide 'holes' where species are expected to occur based on veg mapping. The inverse, 'outer' masks were used for spatial analyses, wherein polygons represent areas of expected occurrence.

2.4 Models

Species distribution models (SDMs), or niche models, generally rely on correlative approaches to infer how species relate to their environment. These SDMs use species occurrence data and associated environmental attributes (e.g., climate, soil, terrain, hydrology) to define species preferences (i.e., "ecological niche"; Grinnell 1917). Once the relationship between a species and its environment is clearly defined (i.e., the "niche model"), then suitability can be projected across space and/or time whenever the appropriate gridded environmental data is available. The modelling approach used to identify biodiversity refugia in this project is consistent with a parallel cross-border initiative funded by NSW Government through the AdaptNSW Biodiversity Node entitled "Where to run or hide: identifying likely climate refugia and corridors to support species range shift" (unpublished). John Baumgartner and Linda Beaumont kindly shared details on their methodology prior to publication, including assistance with coding. A schematic of the modelling workflow used herein is presented in Figure 1.

Figure 1 *Schematic workflow of species distribution models, spatial predictions and summary information products.*



This study modelled climate suitability using Maxent version 3.3.3k (Phillips et al. 2006), a machine learning approach frequently used in species distribution modelling (Elith *et al.* 2011). Maxent has been shown to perform well at predicting species distributions for a wide range of taxa and biomes (Elith et al. 2006). Maxent models were fit and evaluated using `dismo` (Hijmans et al. 2017) in R (R Core Team 2017). Maxent models were fit using mostly default settings; however, hinge and threshold features were disabled to minimise local overfitting of response curves. This study used presence-only occurrence data, rather than structured presence-absence surveys, therefore spatial and environmental biases in species sampling are expected. To help control for this bias in species sampling (used to infer species preferences), a similar bias was applied to background sampling (used to summarise available climate space). Background samples (up to 100,000 per modelled species) were randomly drawn from a pool of grid cells that met TWO criteria: (i) a native plant occurrence record (of any species) was sampled from the grid cell and (ii) the grid cell falls within 200km of a target species record (i.e., a buffered target-group background; Elith & Leathwick 2007; Phillips & Dudik 2008). Code for target-group background sampling was kindly provided by John Baumgartner (personal communication).

Species distribution models were developed using a baseline climate (1990-2009) through 10-fold cross-validation. Occurrence data was randomly divided into five partitions of similar size (i.e., folds), where four folds were used to train models, and the fifth fold was used to test predictive skill. Each fold was used four times for model fitting (i.e., training), and once for model testing (Stone 1974), then the entire process was repeated a second time (i.e., 10-fold), following the approach of Hijmans (2012). Model performance was estimated by calculating the average test AUC (i.e., Area Under the Curve, Receiver Operating Characteristic; Swets 1988) for each of 10 model permutations, then a final mean AUC score was reported in Table 5 of Appendix 3. All cross-validation runs are provided in the full version of the 'datapack'. The final models (presented on throughout and made available in the full version of the 'datapack') were fit using all species occurrence data (i.e., no data withheld for testing) following the recommendation of John Baumgartner (personal communication).

2.5 Predictions

Spatial predictions of species climate suitability are provided in a variety of ‘flavours’ each designed toward a purpose. Schematics of the workflows used to generate these spatial predictions are presented in Figure 1 and Figure 2. Herein, all scenarios within the same epoch are treated as equally plausible, therefore it is most appropriate to consider scenarios in aggregate (i.e., near-futures versus far-futures). Individual scenario-based predictions were combined and summarised into two complimentary sets of management tools, each focusing on a different application – ensemble forecasts (or ‘ensembles’) for scoping revegetation programs, and scenario statistics (or ‘scenarioStats’) for prioritising fire management. Both ensembles and scenario statistic layers simultaneously consider suitability across a wide range of plausible futures. These layers differ in that ensembles attempt to distinguish suitable versus unsuitable areas as discrete categories (i.e., good or

bad outcomes), whereas scenario statistics quantify spatial variation in the suitability of available areas (i.e., high versus low values) without presuming to know what is sufficient for a species to persist.

Logistic predictions

Logistic predictions are the source of all spatial predictions presented or discussed. Logistic predictions provide a continuous measure of suitability for each species, ranging from 0.000 – 1.000, with high values indicating more suitable areas for species. To create logistic predictions, final Maxent models (described above) were projected across space and time on to gridded climate scenarios (Phillips, Anderson & Schapire 2006; Phillips & Dudik 2008). In this project, 25 logistic prediction surfaces were created for each species, by projecting the final Maxent model on to a baseline climate (1990-2009), as well as 12 near-future (2020-2039) and 12 far-future climate scenarios (2060-2079).

Binary predictions

The purpose of binary predictions is to distinguish suitable (value=1) versus unsuitable areas (value=0) for a species under a climate scenario. Binary predictions are derived by applying a species-specific threshold that maximizes training sensitivity plus specificity (Liu et al. 2013, Liu et al. 2016). Here, sensitivity (i.e., the true positive rate) refers to the proportion of occurrence records which are correctly identified as suitable; whereas, specificity (i.e., the true negative rate) refers to the proportion of pseudo-background samples correctly inferred as unsuitable. Scenario-based binary predictions can be scaled and stacked to derive 'ensembles' which simultaneously consider climate impacts across multiple scenarios.

Ensemble forecasts (or 'ensembles')

The purpose of 'ensembles' is to communicate how suitable versus unsuitable areas change over time for a species, including an indication of the support behind conclusions (i.e., levels of model agreement). In order for ensembles to detect changes in suitability over time, and convey levels of model agreement, baseline (*b*) predictions for 1990-2009 were scaled (i.e., *b*100)*, then added to the sum of all future (*f**) scenario predictions (i.e., *b*100 + (f1 + f2 + f3 + f4 + f5 + f6 + f7 + f8 + f9 + f10 + f11 + f12)) for* the near-future epoch (2020-2039). The same process (i.e., *b*100 + (f1 + f2 + f3 + f4 + f5 + f6 + f7 + f8 + f9 + f10 + f11 + f12))* is repeated independently for the far-future epoch (2060-2079). These scaled rasters include values ranging between '0' - '112'. As detailed in Table 4, scaled values (0-112) were reclassified so as to distinguish BOTH changes in categorical responses of species (i.e., 'refugia' = suitable today and in the future, 'losses' = suitability decreases in the future, 'gains' = suitability increases over time, 'uncertain' = suitable today but no future consensus), as well as associated levels of model support (i.e., high = > 80% agreement across scenarios; moderate = > 65% agreement across scenarios). In total, ensembles distinguish seven unique combinations of species responses and levels of model support.

Table 4 *Ensemble forecast values, map labels, model agreement and map interpretation.*

Ensemble Values	Ensemble Labels	Model Agreement	Map Interpretations	Binary Values (scaled sums)
1	Refugia	High	suitable today and in the future, for ≥ 80% scenarios	110-112
2	Losses	High	suitable today but not in the future, for ≥ 80% scenarios	100-102
3	Gains	High	suitable only in the future, for ≥ 80% scenarios	10-12
4	Refugia	Moderate	suitable today and in the future, for > 65% scenarios	108-109
5	osses	Moderate	suitable today but not in the future, for > 65% scenarios	103-104
6	Gains	Moderate	suitable only in the future, for > 65% scenarios	8-9
7	Uncertain	-	suitable today, but no consensus in the future	105-107

Scenario statistics (or 'scenarioStats')

Scenario statistics capture the model mean and variance of a set of scenario-based predictions (Figure 1). Information products derived from 'scenarioStat' layers were designed to provide one of multiple criteria feeding into the prioritisation of ecological burns and fire exclusion areas in the ACT Regional Fire Management Plan (2019-2024). The suite of scenario statistic layers includes a sequence of increasingly targeted climate criteria derived from logistic predictions which can be fed into the spatial prioritisation of fire management interventions. Layer types listed in order of creation are as follows: 'scenarioStats' -> 'AVG' & 'VAR' -> 'UNION' -> 'UMCid' -> 'UMCid_90percentile' -> Intersect' -> 'Climate Priorities'. A schematic workflow of how 'Climate Priorities' are derived from logistic predictions is shown in Figure 2. More detail on how 'Climate Priorities' are derived is described below:

1. 'scenarioStats' rasters include a model mean (band1) and variance (band3) of scenario-based predictions (n=12) for a species and an epoch (i.e., 2020-2039 OR 2060-2079). Rasters extending across Southeast Australia in GD94 Australian Albers (EPSG: 3577) coordinate reference system were clipped to a regional extent and projected to a locally optimised coordinate reference system, GDA94 MGA Zone 55 (EPSG: 28355) prior to converting shapefiles.

2. 'AVG' shapefiles ((i.e., representing scenario means) were derived from projected regional clips of 'scenarioStats' band1 using the ArcPy rasterToPolygons function.

3. 'VAR' shapefiles (i.e., representing scenario variance) were derived from projected regional clips of 'scenarioStats' band3 using the ArcPy rasterToPolygons function.

4. 'UNION' shapefiles were derived with ArcPy as the spatial union of 'AVG' and 'VAR' shapefiles above.

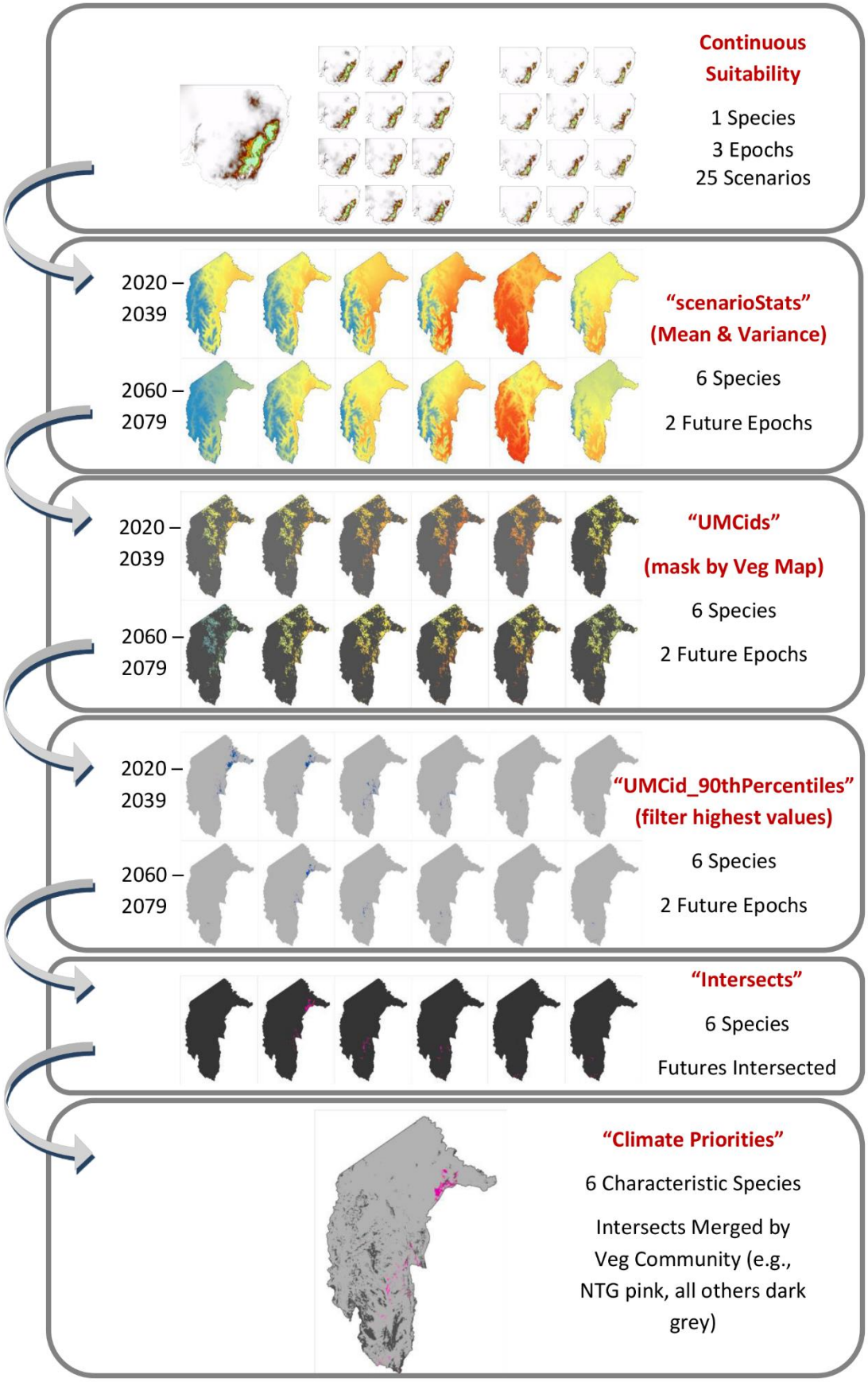
5. 'UMCid' layers, which restrict suitability projections to areas where species are expected to occur today, were derived with ArcPy by masking 'UNION' shapefiles (above) with relevant local vegetation communities from the ACT vegetation map. The look up table used to link plant species and vegetation communities is provided in both 'datapacks'.

6. 'UMCid_90thPercentile' layers, which highlight the most suitable climates for a species in one epoch (i.e., in the near-future OR in the far-future), were derived in R by filtering 'UMCid' polygons for values greater than or equal to 90% of the maximum observed suitability for each species (i.e., 90th percentiles).

7. 'Intersect' layers, which highlight the most suitable climates for a species across all future epochs (i.e., across near-futures AND far-futures), were derived with ArcPy as the spatial intersect of two future 'UMCid_90thPercentile' layers for each species.

8. Finally, 'Climate Priorities' layers, aggregate the most suitable areas (i.e., based upon Intersects above) for all characteristic species of local ACT vegetation communities considered. These 'Climate Priorities' were derived with ArcPy as the spatial merger of 'Intersect' layers for a wide range of characteristic species and vegetation communities. Three variants of the 'Priorities' layers are provided, differing in terms of the number and composition of plant species preferences included. The *100%* layer includes all plant species considered for fire management. The *50%* layer includes only the subset of plant species whose future climate priorities are less than or equal to 50% of the total area available in relevant mapped vegetation communities today. The *25%* layer includes only the subset of plant species whose future climate priorities total less than or equal to 25% of the total area available in relevant mapped vegetation communities today. The *25%* Climate Priority layer provides the basis for Figures 18 - 19.

Figure 2 *Schematic workflow of climate priorities for use in fire management.*



2.6 Tables

Tables provided include look up tables (i.e., LUTs), species occurrence records, climate queries, zonal statistics and descriptive statistics. LUTs are used to list, join, filter, reclassify or label data. Species occurrence records were used to train and test niche models (e.g., to define available versus preferred climate space). Climate queries were used to characterise local climates within the ACT (e.g., biodiversity refugia in Booroomba Rocks described in Section 3.2). Zonal statistics provided help re-interpret potential climate impacts by management themes (i.e., tenure, climate, nature reserves). Descriptive statistics provided assist with evaluating model performance. All tables are provided in both 'datapacks'.

2.7 Zonals

To help land managers interpret climate impacts for characteristic native plant species, ensemble forecasts were summarised using zonal statistics. Zones were defined in 3 complimentary ways to assist different types of end users, based upon: land tenure, climate zones (i.e., local physiography) and reserve complexes (i.e., management units). For each zonal assessment, species ensembles were masked by relevant vegetation communities prior to processing zonal statistics, with the aim of focusing tabular summaries on areas where species are expected to occur today. Land tenure zones include 5 categories: i) nature reserves (as defined on Corporate Geographic Database, or CGD), 2) rural lease (provided by Parks and Conservation Service), 3) national lands (from CGD), remaining Hills Ridges and Buffers (based on Territory Plan), and 'Other' urban areas. Modelled climate zones in the ACT (Cowood et al. 2018) include 4 categories: i) cool and wet, ii) cool, iii) warm and iv) warm & dry. Finally, reserve complexes considered in ACT Government Plans of Management, comprise clusters of individual nature reserves, and include 18 distinct categories (Kate Boyd, personal communication). Mapping of zonal criteria are provided in Figures 3 - 7, and tabular zonal summary statistics are provided in the 'reporting' subdirectory of full 'datapack' tables, or the 'Report' subdirectory of the lighter 'datapack' (Table 1). For each zonal summary, potential future outcomes (i.e., refugia, gains, losses, uncertain) are quantified in terms of total versus percentage of hectares expected for both near-future (2020-2039) and far-future (2060-2079) scenarios.

Figure 3 *Mapping of local vegetation communities used for zonal statistics.*

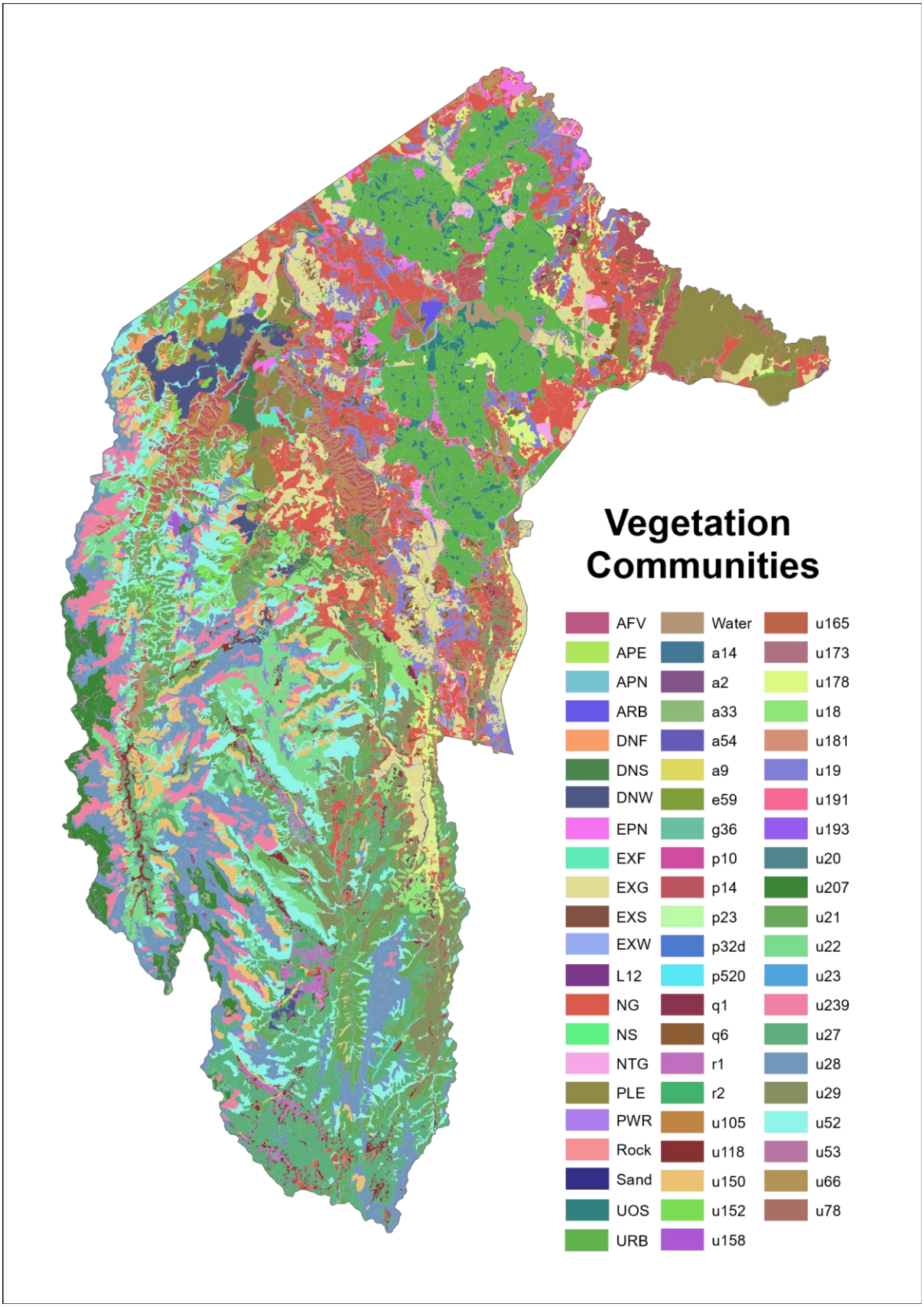


Figure 4 *Mapping of local land tenure categories used for zonal statistics.*

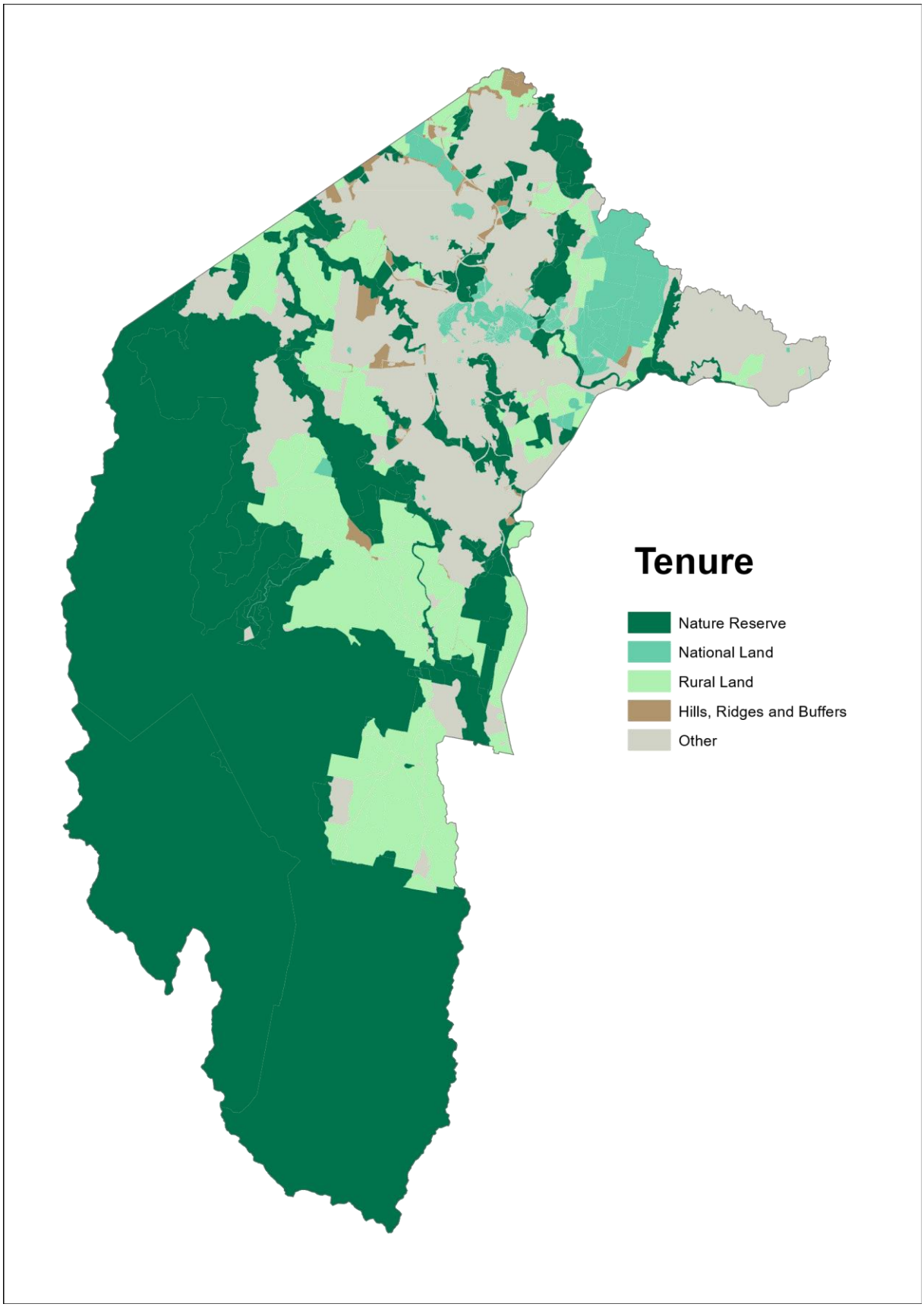


Figure 5 *Mapping of nature reserves complexes used for zonal statistics.*

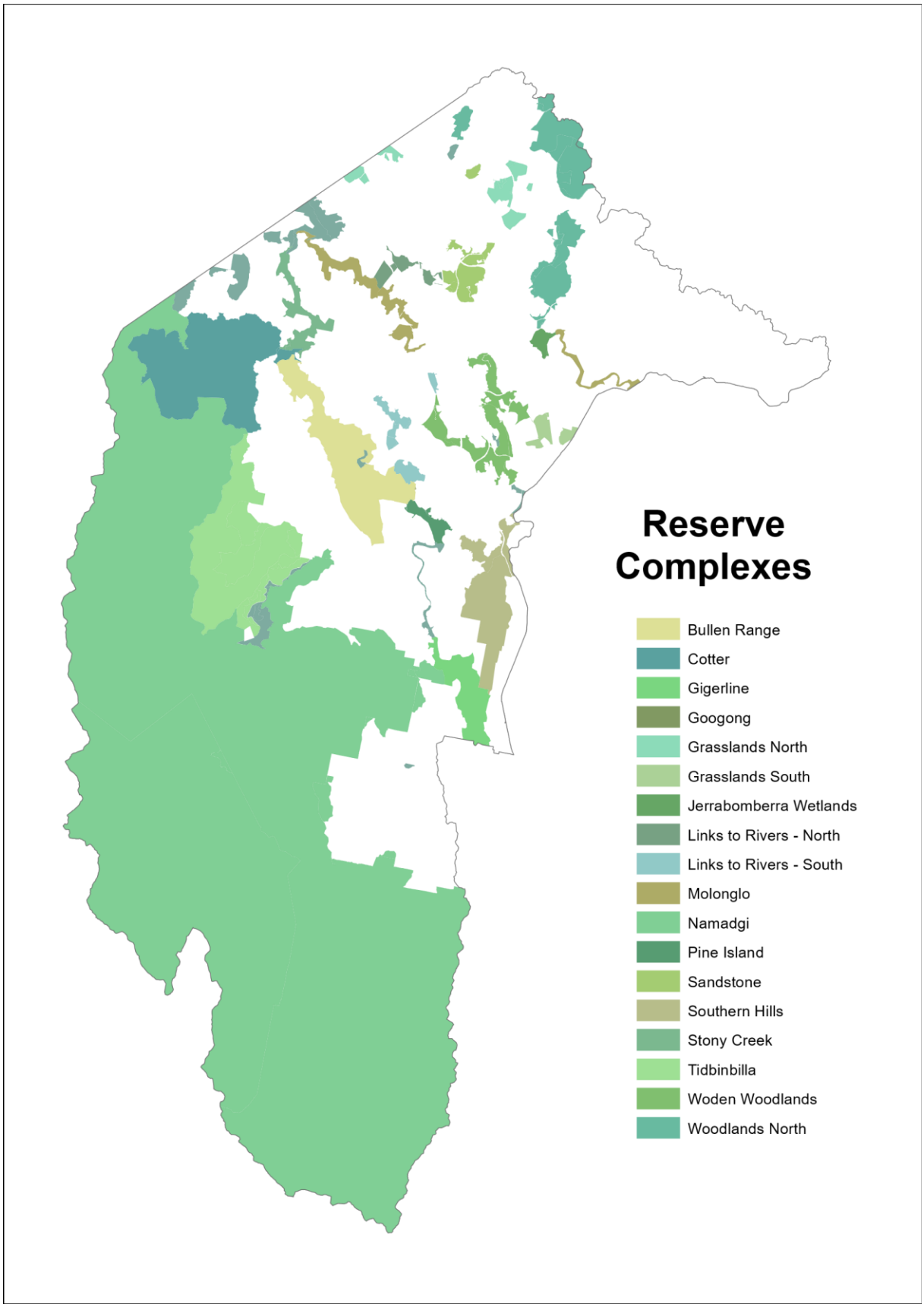
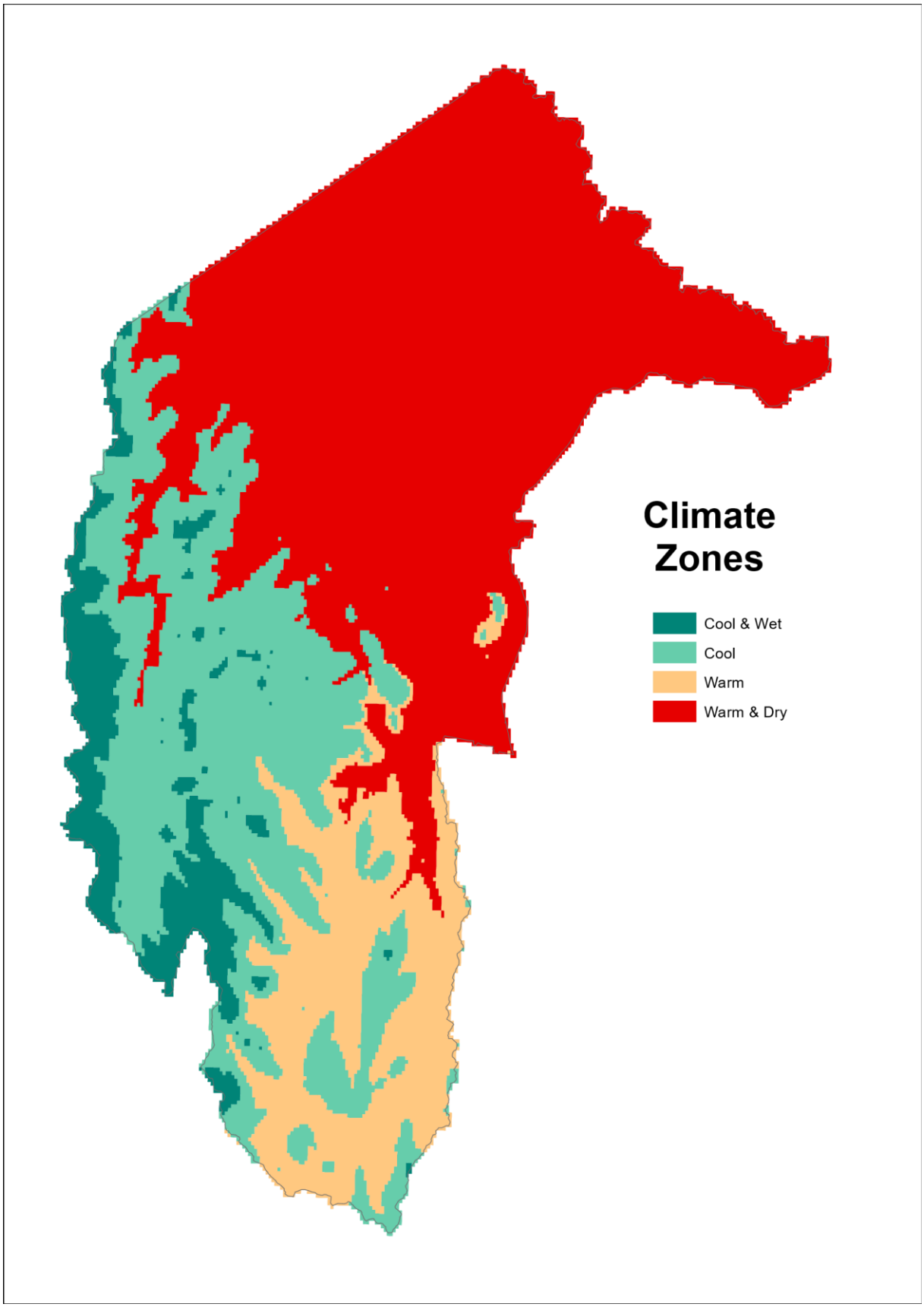


Figure 6 *Mapping of local climate types (by Alie Cowood) used for zonal statistics.*



3 Practical Land Management Applications

Key properties of refugia, which are expected to help species persist under climate change, include the capacity to: "(i) buffer species from climate change, (ii) sustain long-term population viability and evolutionary processes, (iii) minimize the potential for deleterious species interactions, provided that refugia are (iv) available and accessible to species under threat" (Reside et al. 2014). Ideally refugia can offer protection from multiple stressors (e.g., extreme heat, drought, flood, storms, bushfire, etc). Selection of potential climate refugia involves: (i) identifying areas expected to be environmentally stable into the future (i.e., minimal change in relation to temperature and precipitation), and (ii) identifying areas where most biodiversity is expected to persist and additional species may relocate into the future (Reside et al. 2013).

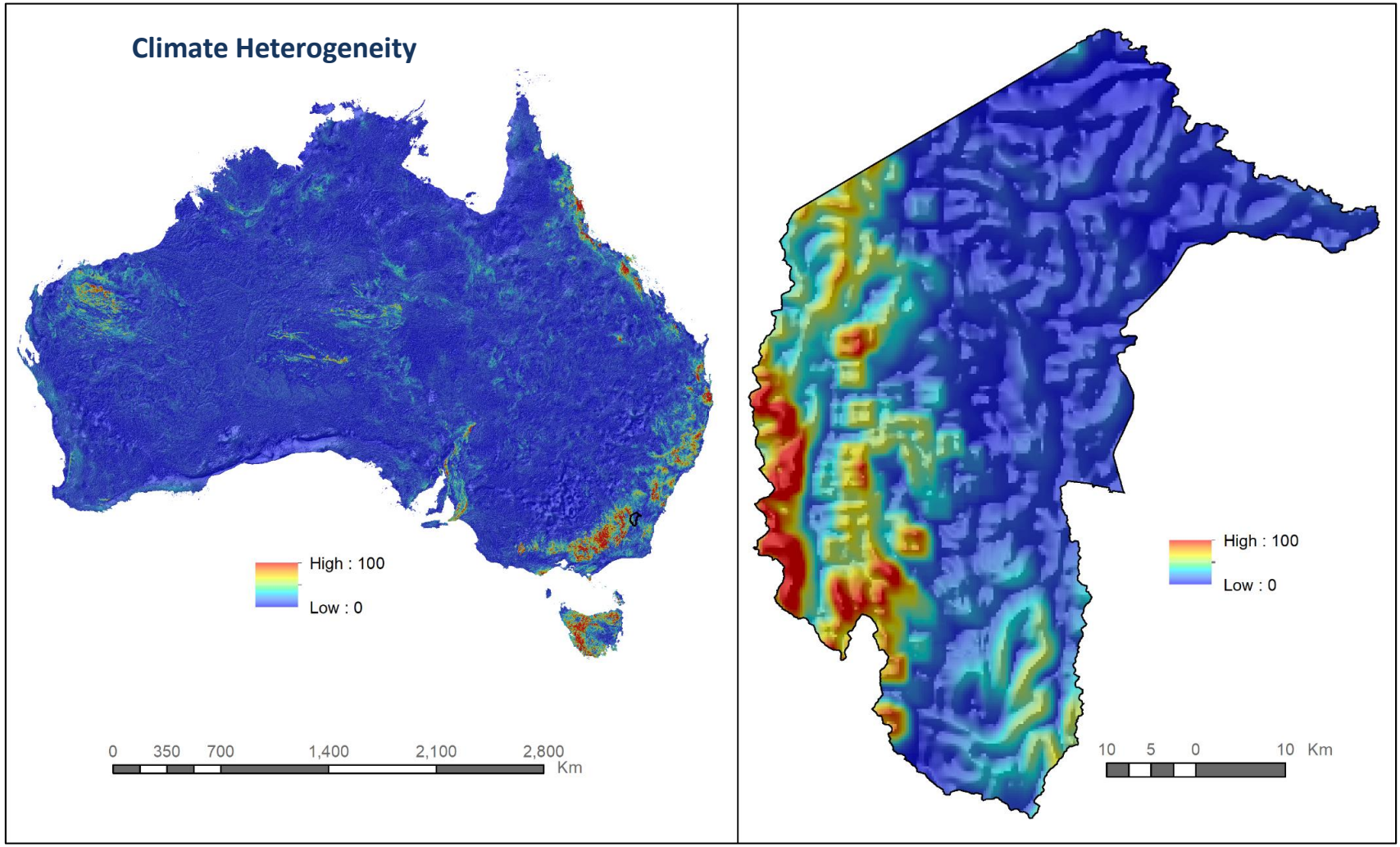
3.1 Climate in the ACT and region

Current climatic zones of the ACT (n=4) largely mirror local physiography and were recently defined, mapped, and described in detail by Cowood et al. (2018; Figure 6). Based upon long-term observations (1910-2011), temperatures in the ACT have been rising since circa 1950, with higher temperatures experienced in more recent decades. Warming is expected to increase significantly in the near-future (2020-2039) as well as the far-future (2060-2079), including more hot days and fewer cold nights (ACT Snapshot). NARCliM projections are in full agreement about temperature rises in the ACT – including annual mean temperatures (not shown), as well as summer highs and winter lows. NARCliM projections suggest total annual rainfall may be similar to current conditions, but the timing of delivery may shift into the future, resulting in less spring rain, and more summer and autumn rains (ACT Snapshot). Descriptive statistics for climate variables restricted to the Australian Capital Territory boundary are presented as boxplots for each epoch & scenario considered (Figures 20-23 of Appendix 2). Most NARCliM scenarios agree that seasonal differences in temperature and/or precipitation are likely to become more noticeable in the future (Figure 21 of Appendix 2).

Enhancing landscape resilience is widely recognised as important for helping biodiversity adapt to climate change (Heller et al. 2009), yet a quantitative measure of landsacpe resilience is frequently not available for conservation planners. Climate heterogeneity represents one component of landscape resilience which can be easily quantified using a sliding window approach to summarise gridded climate data (Brown et al. 2017). Areas with high climate heterogeneity are expected to offer organisms more opportunity to offset large environmental changes by shifting small geographic distances; whereas organisms in areas with low climate heterogeneity may need to shift large geographic distances to offset small environmental changes. Herein, climate heterogeneity (Figure 7) was derived using SDMtoolbox (Brown et al. 2017) for ArcGIS Desktop version 10.5.1 (ESRI, 2016). Climate heterogeneity outputs in the full 'datapack' are based upon 3 focal statistic window sizes (1km x 1km, 2.5km x 2.5km & 5km x 5km). As expected, climate heterogeneity tracks topographic complexity, with higher values in the Alps and lower values in the lowlands. Fortunately, landscapes in the ACT include significant spatial heterogeneity in environmental attributes, as well as steep

environmental gradients, which are both expected to facilitate many species' adaptation to future changes in climate (Dobrowski 2011; Beier et al. 2011; Klausmeyer et al. 2011).

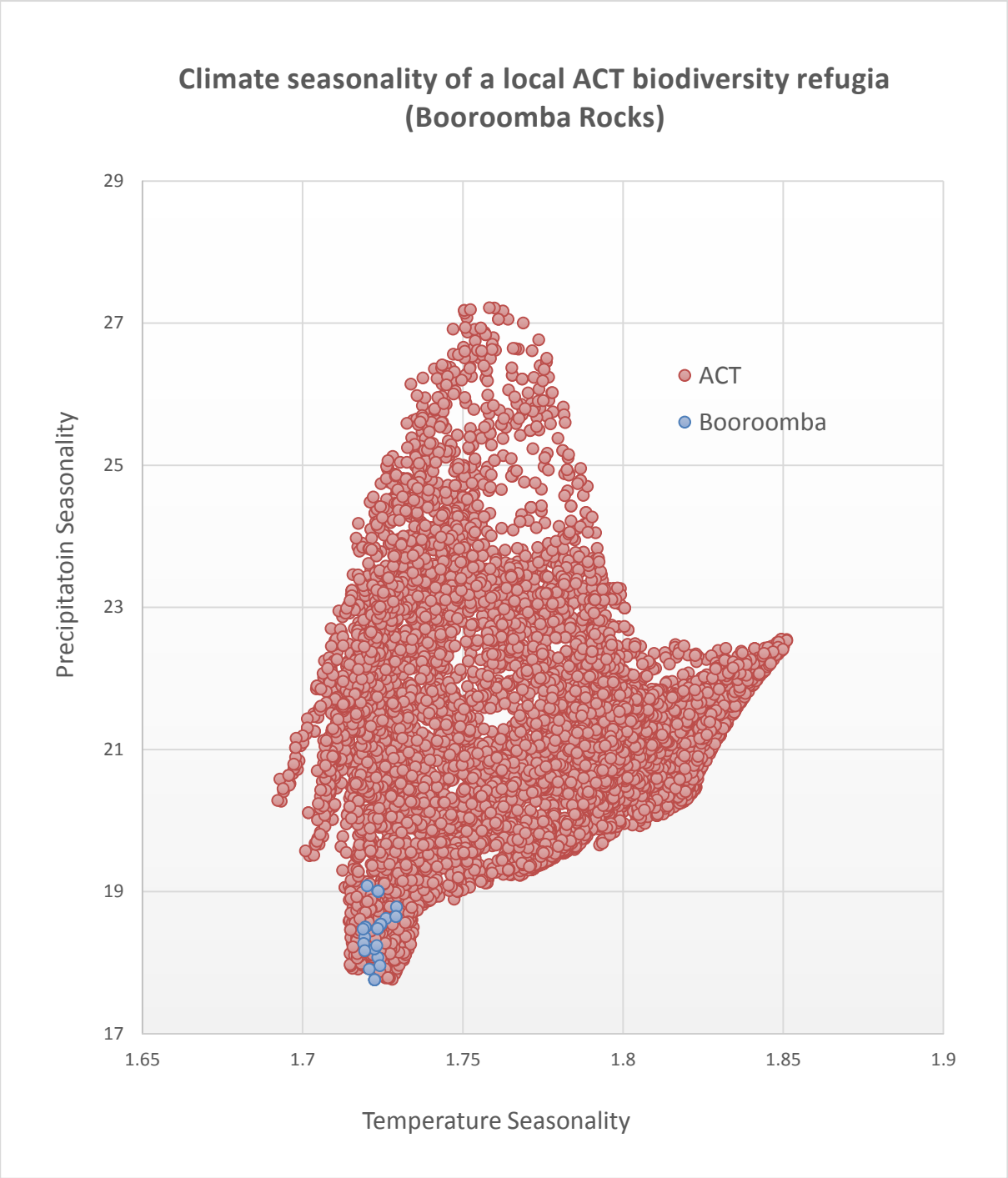
Figure 7 *Climatic heterogeneity shown at continental-scale (left panel) versus local-scale (right panel), derived by summarising NARCliM baseline climate data (1990-2009) with a 2.5km x 2.5km focal statistic sliding window.*



3.2 Existing ACT biodiversity refugia

Existing biodiversity refugia are frequently identified by high levels of native species diversity and/or local endemism (Reside et al. 2013), whereas cryptic refugia can be identified using genetic diversity (Bell et al. 2010; Bell et al. 2011). Booroomba Rocks in Namadgi National Park is an example of a rare plant hotspot in the ACT (Michael Mulvaney, personal communication). Several native plant species are only known from this locality (e.g., *Dampiera fusca*, *Eucalyptus cinerea triplex*, *Logania albiflora*, *Logania granitica*, *Veronica notabilis*). Given the unique floristic qualities of this site, this study explored whether there is any evidence that environmental attributes of Booroomba Rocks may be driving observed species diversity. Baseline NARCliM climate values (1990-2009) were extracted for known rare plant occurrences (obtained from Canberra Nature Map), as well as random points in the Territory (n=10,000). Random points were used to represent available climate space in the Territory which could then be compared to the climate space occupied by rare plants in Booroomba Rocks. A scatterplot of temperature and precipitation seasonality (Figure 8) shows Booroomba Rocks (blue points) is highly atypical for the Territory (red points). Low seasonality at Booroomba Rocks means there are not marked changes in temperature or precipitation patterns between seasons, as compared to the surrounding region. Canonical discriminant analysis (not shown) further emphasises the unique climate space of Booroomba Rocks. One hypothesis is that the stability of temperatures and precipitation across seasons at Booroomba Rocks may be helping to promote and maintain high levels species diversity in plants. Multiple lines of evidence (i.e., floristic diversity, climate seasonality) confirm that Booroomba Rocks is ecologically and evolutionarily significant to the region, and thus should be considered a biodiversity refugia in the ACT. Moving forward, it is important for land managers to consider how existing biodiversity refugia like Booroomba Rocks may be impacted by the rapid climate change underway today.

Figure 8 *Climate seasonality of a local ACT biodiversity refugia (Booroomba Rocks).*



3.3 Interpreting models

The models presented in this project represent the most comprehensive assessment of potential climate impacts on native vegetation in the ACT available at the time of publication. These projections are based on robust theory, extensive field surveys, and the best available climate projections for our region. Nevertheless, this study is just an early step in understanding how climate might affect vegetation in our region, and what actions managers should take in response. Identification of climate refugia should ideally be based upon multiple lines of evidence (e.g., observations, experiments, models), including landscape-based metrics of climate vulnerability (Ackerly et al. 2010; Klausmeyer et al. 2011). There are inherent limitations in species distribution models, including the selection of model inputs (occurrence data, explanatory variables), as well as projecting species responses based solely on this information. It is recommended that these forecasts be used as just one of many tools to predict and prepare for the effects of climate change and to guide the development of strategies and actions to facilitate adaptation by native species and systems. Assumptions built into SDMs that may not be met and therefore limit the applications of SDMs, include: 1) species are in equilibrium with their environments (i.e., all suitable areas are occupied), 2) no biotic interactions limit species distributions (such as competition, predation, and disease), 3) there is no dispersal limitation. Similarly, impacts on distribution associated with land use and/or bushfires are not considered.

Models performance was evaluated using the Area Under the receiver-operator Curve (AUC) statistic (Table 5 of Appendix 3). In this study, species models generally performed well. AUC values for species models were mostly ≥ 0.7, except for a subset of 8 largely widespread species, including: *Carex appressa* (0.654), *Dianella longifolia* (0.655), *Dianella revoluta* (0.519), *Isachne globose* (0.611), *Lomandra filiformis* (0.597), *Lomandra longifolia* (0.519), *Microlaena stipoides* (0.569) and *Themeda triandra* (0.577). Although these AUC values are less than ideal, recent research suggests AUC values are dependent on the type of data used and the distribution of the species. AUC values are frequently lower for widespread species than species with narrow ranges (Hijmans 2012). This outcome presumably relates to generalist species violating the assumption of niche models that species distributions are entirely limited by the predictor variables considered. It is also worth noting that the ranges of some species assessed extend beyond Southeast Australia, such as *Eucalyptus fastigata* in plantations and arboretums around the world (David Bush, personal communication), suggesting that the environmental ranges, physiological tolerances, and adaptive capacities of those species may be underestimated. Alternatively, other models failed to predict suitable areas in the ACT today, despite species being listed as characteristic flora within local vegetation communities (Armstrong et al. 2013), therefore model performance is understood to be poor. Species with poor performing SDMs include: *Acacia melanoxylon*, *Blechnum cartilagineum*, *Blechnum wattsii*, *Casuarina cunninghamiana*, *Cyathea australis*, *Eleocharis sphacelata*, *Goodia lotifolia*, *Imperata cylindrical*, *Leptospermum continentale*, *Phragmites australis*, *Pomaderris aspera*, and *Typha orientalis*.

The most important abiotic drivers influencing distributions vary considerably between species. Nevertheless, on average, minimum temperature of the coldest month (i.e., mean monthly winter low temperatures for the coldest winter month) accounts for 26% of spatial predictions across all species,

followed by diurnal temperature range (i.e., the mean monthly range between daily highs and lows), which accounted for an additional 20% on average. All future NARCliM scenarios predict an increase in winter low temperatures, which likely explains a trend of decreasing suitability for cold-adapted species in the tablelands. Most future scenarios (n=11 of 12) predict increasing diurnal temperature ranges, which presumably translates into a general trend toward warmer nights combined with hotter days than currently observed in the Territory.

3.4 Applying ensembles in revegetation

Revegetation programs are one area of land management where this study provides practical tools to help anticipate and prepare for climate change impacts. This study focuses on assessing climate change impacts in dominant native plant species because: (i) regional conservation practitioners expressed a desire to 'keep common species common' (i.e., to prevent new species from becoming rare and/or listed), (ii) hypotheses about characteristic vegetation dynamics will ultimately inform future wildlife habitat suitability models, and (iii) more information is available on dominant plants to fit and test distribution models. The ACT Biodiversity Refugia Atlas (Appendix 1) accompanying this technical report is specifically designed to clarify where species are local 'winners' and 'losers' under climate change. The Atlas compiles far-future predictions for all modelled species, including panels representing local (i.e., ACT), regional (i.e., Capital Region) and continental (i.e., Southeast Australia) climate change impacts. Spatial predictions for the near-future (2020-2039) are provided in both 'datapacks' (Table 1), however, no raster file formats are included in the lighter 'datapack'. An ArcGIS project (*.mxd) with both sets of layers symbolised is provided for visualisation.

'Ensemble' forecasts are designed to consider the implications of multiple future scenarios simultaneously. To help users visualise and interpret 'ensembles', maps herein rely on colours to distinguish changes in suitability over time and on saturation to convey model support. For example, maps distinguish areas considered suitable today and, in the future, (i.e., refugia=blue), versus areas where suitability is either declining (i.e., losses = red) or increasing over time (i.e., gains = purple). Similarly, predictions based on high support (i.e., dark saturation) mean model agreement is greater than or equal to 80% (i.e., 10 or more of 12 total scenarios), whereas moderate support (i.e., light saturation) means model agreement is greater than 65% (i.e., 8 or 9 of 12 total scenarios). To help users focus on predictions in areas where species are expected to occur today, a set of masks (see Table 1) are provided. Outer masks provide polygons where species are expected to occur (e.g., to be used in spatial analysis, etc.) whereas inner masks (i.e., the inverse) provide holes where species are expected to occur (e.g., to be used in cartography for emphasis). Species masks were created using a locally modified classification schema (Armstrong et al. 2013), where characteristic native plant species are identified for each vegetation community (UMC_IDs).

A subset of contrasting ensemble forecasts are provided in Figures 9 - 16 for the following species: *Austrostipa bigeniculata* (Spear grass), *Eucalyptus blakelyi* (Blakely's red gum), *E. camadulensis* (River red gum), *E. fastigata* (Brown barrel), *E. mannifera* (Brittle gum), *E. pauciflora* (Snow gum), and *Themeda triandra* (Kangaroo grass). In these maps, local projections are masked by relevant vegetation

communities which helps to focus climate impacts on areas of expected occurrence. Ensembles suggest several species may be challenging to maintain in the Territory under climate change, despite widespread distributions today (e.g., see Speargrass in Figure 9, Kangaroo grass in Figure 10, Brown barrel in Figure 11). It should be noted *E. fastigata* provides critical wildlife habitat in upland wet sclerophyll forest, yet it's true ecophysiological limits may be under-represented by only considering Southeast Australia, therefore future research should consider the climate space occupied by plantation cultivars around the globe. Similarly, in urban areas, climate-related heat stress or drought stress may pose significant risks to people if significant numbers of gum trees on streets drop branches (e.g., Brittle gum shown in Figure 12). Ensembles also suggest dieback occurring regionally in *Eucalytpus blakelyi* (i.e., Blakely's red gum, shown in Figure 13) is unlikely to be explained (solely) by climate change. Nevertheless, if this species is locally lost, a regional analogue, *Eucalyptus camaldulensis* (i.e., Red river gum, shown in Figure 14) appears to have increasing suitability in the future. Finally, ensembles suggest *Eucalyptus pauciflora* (i.e., Snow gums, shown in Figure 15) may be lost from many lowland areas, despite widespread persistence in the uplands, and *Eucalyptus delegatensis* (i.e., Alpine ash, shown in Figure 16) may be lost from all, but the most cool and wet sites in the Territory (e.g., Scabby Range).

While it is not surprising the ACT may become inhospitable to some currently common native plant species, other native plants from the surrounding region may invade the ACT under climate change. To help consider the invasion potential into the ACT by natives from the surrounding region, a list of rare plants was modelled (n=31 species) in consultation with local experts (Michael Mulvaney, personal communication). Species occurrence data in the Atlas of Living Australia exhibit clear range limits to the North, East or West of the ACT. While forecasts in this study suggest no clear biogeographic pattern of large-scale migration into the ACT, there is an indication that the ACT may become important for future source populations for some new species under climate change (e.g., *Eucalyptus sieberi*, shown in Appendix 1). Given the ACT may turn out to be important for the persistence of plants which are currently rare in the Territory, it may be worth emphasising these species more often in management programs (e.g., prescribed burns).

Other examples of practical applications for ensembles beyond revegetation initiatives include: i) prioritising investment in areas where conservation values are most likely to persist for a suite of native species; ii) developing modified ('climate-ready') planting lists to facilitate the succession of mature isolated paddock trees in decline, iii) scoping potentially unrealistic EPBC Act policy obligations under climate change; iv) stratifying monitoring programs to track local responses to climate impacts on ground; v) scoping local sites for reintroduction or translocation potential; vi) providing potential climate impacts to inform vulnerability assessments for critical assets.

Figure 9 For *Austrostipa bigeniculata* (Spear grass), an ensemble forecast of climate suitability under multiple future scenarios (2060-2079) shown at three scales – locally restricted to areas of expected occurrence (left), across the Capital Region (bottom right) and throughout Southeast Australia (top right).

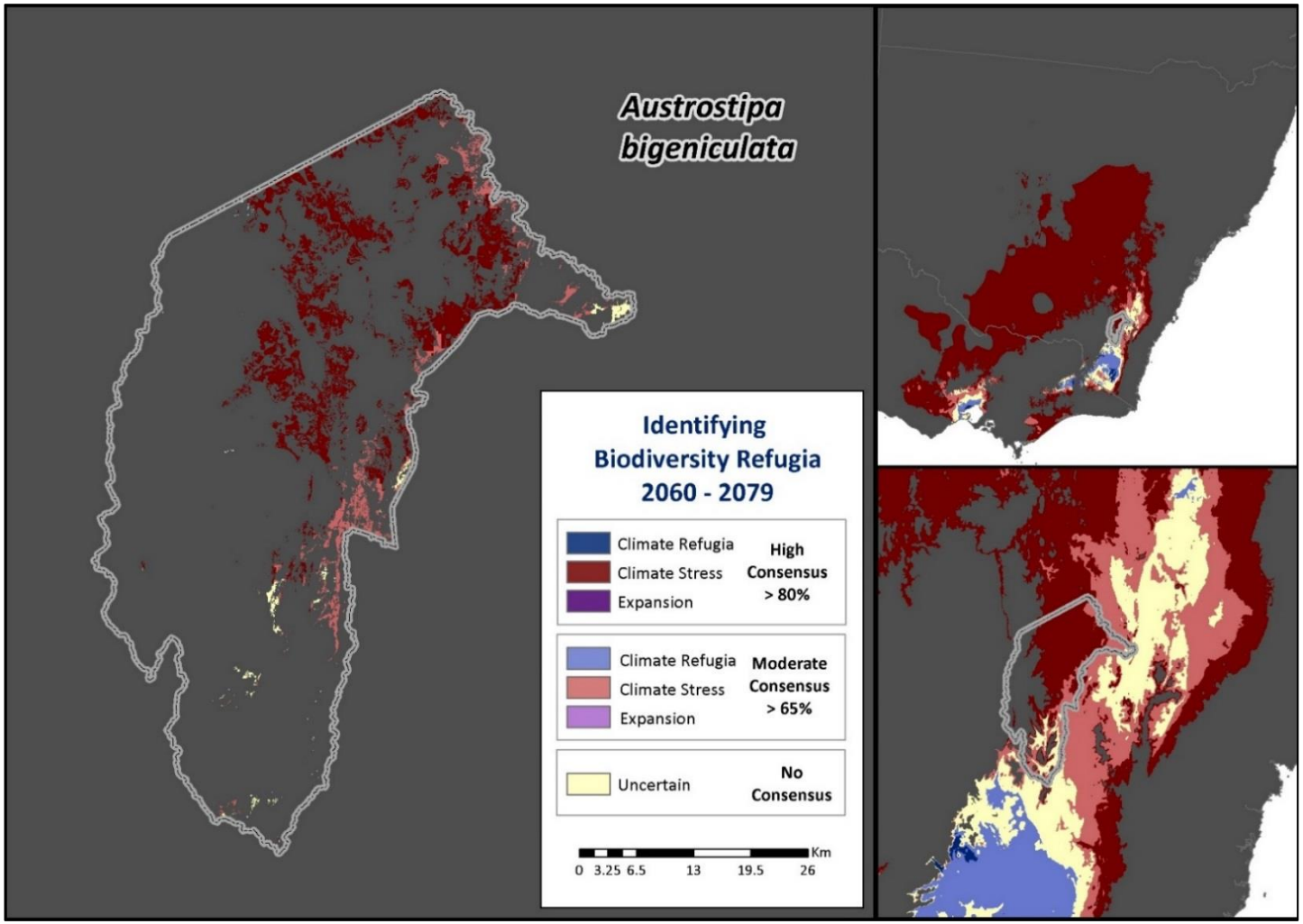


Figure 10 For *Themeda triandra* (Kangaroo grass), an ensemble forecast of climate suitability under multiple future scenarios (2060-2079) shown at three scales – locally restricted to areas of expected occurrence (left), across the Capital Region (bottom right) and throughout Southeast Australia (top right).

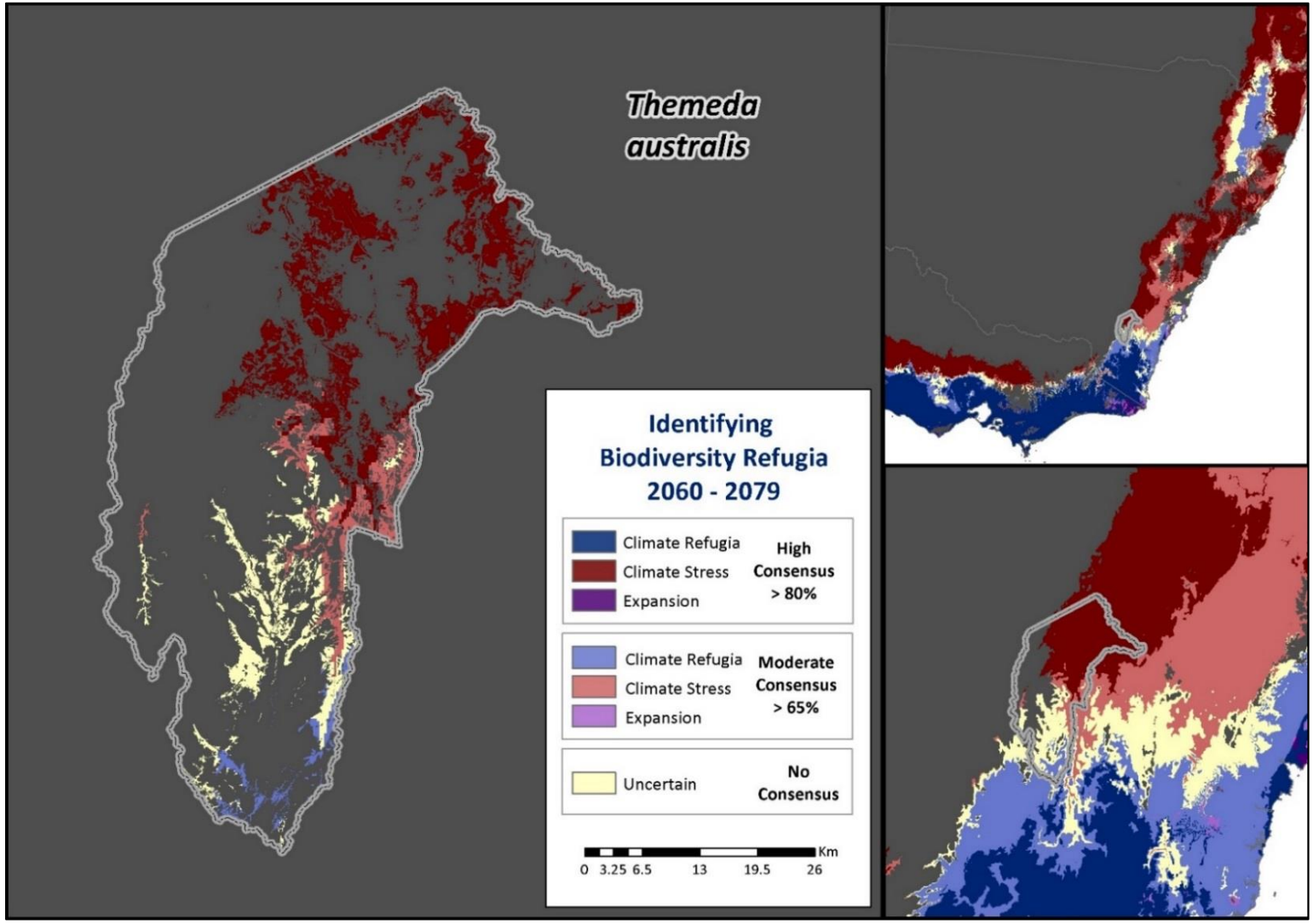


Figure 11 For *Eucalyptus fastigata* (Brown barrel), an ensemble forecast of climate suitability under multiple future scenarios (2060-2079) shown at three scales – locally restricted to areas of expected occurrence (left), across the Capital Region (bottom right) and throughout Southeast Australia (top right).

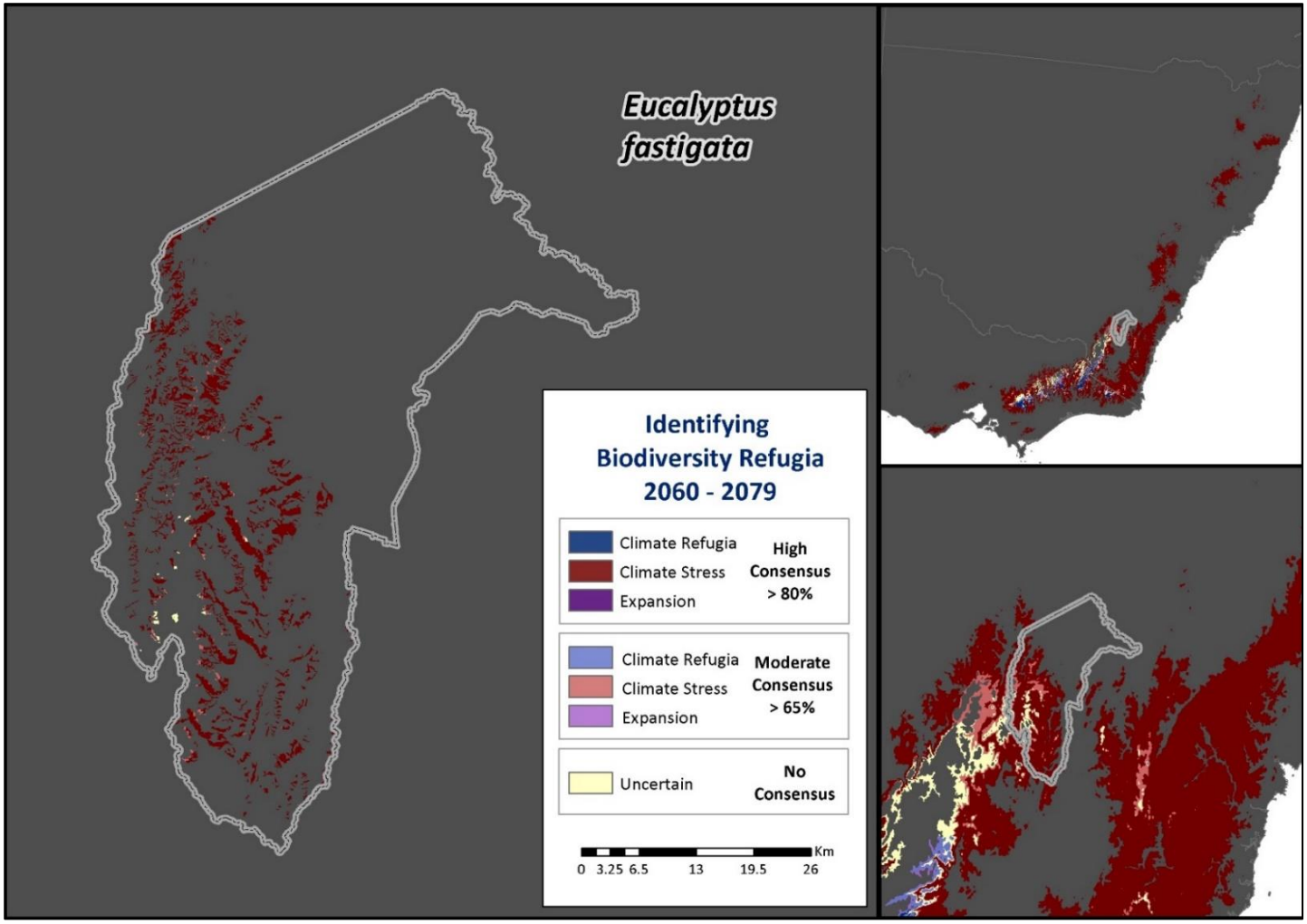


Figure 12 For *Eucalyptus mannifera* (Brittle gum), an ensemble forecast of climate suitability under multiple future scenarios (2060-2079) shown at three scales – locally with urban street tree occurrences as green points (left), across the Capital Region (bottom right) and throughout Southeast Australia (top right).

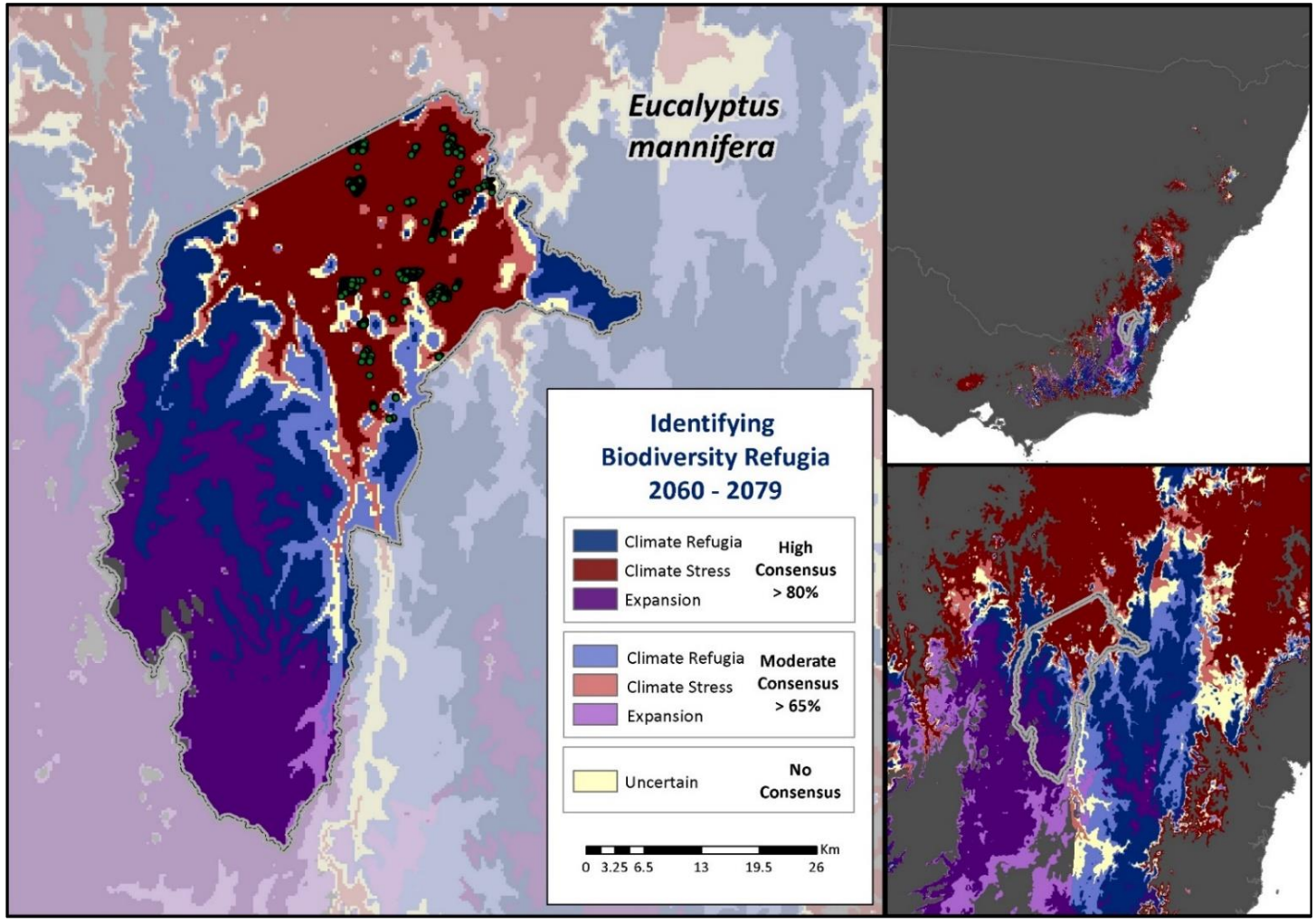


Figure 13 For *Eucalyptus blakelyi* (Blakely's red gum), an ensemble forecast of climate suitability under multiple future scenarios (2060-2079) shown at three scales – locally restricted to areas of expected occurrence (left), across the Capital Region (bottom right) and throughout Southeast Australia (top right).

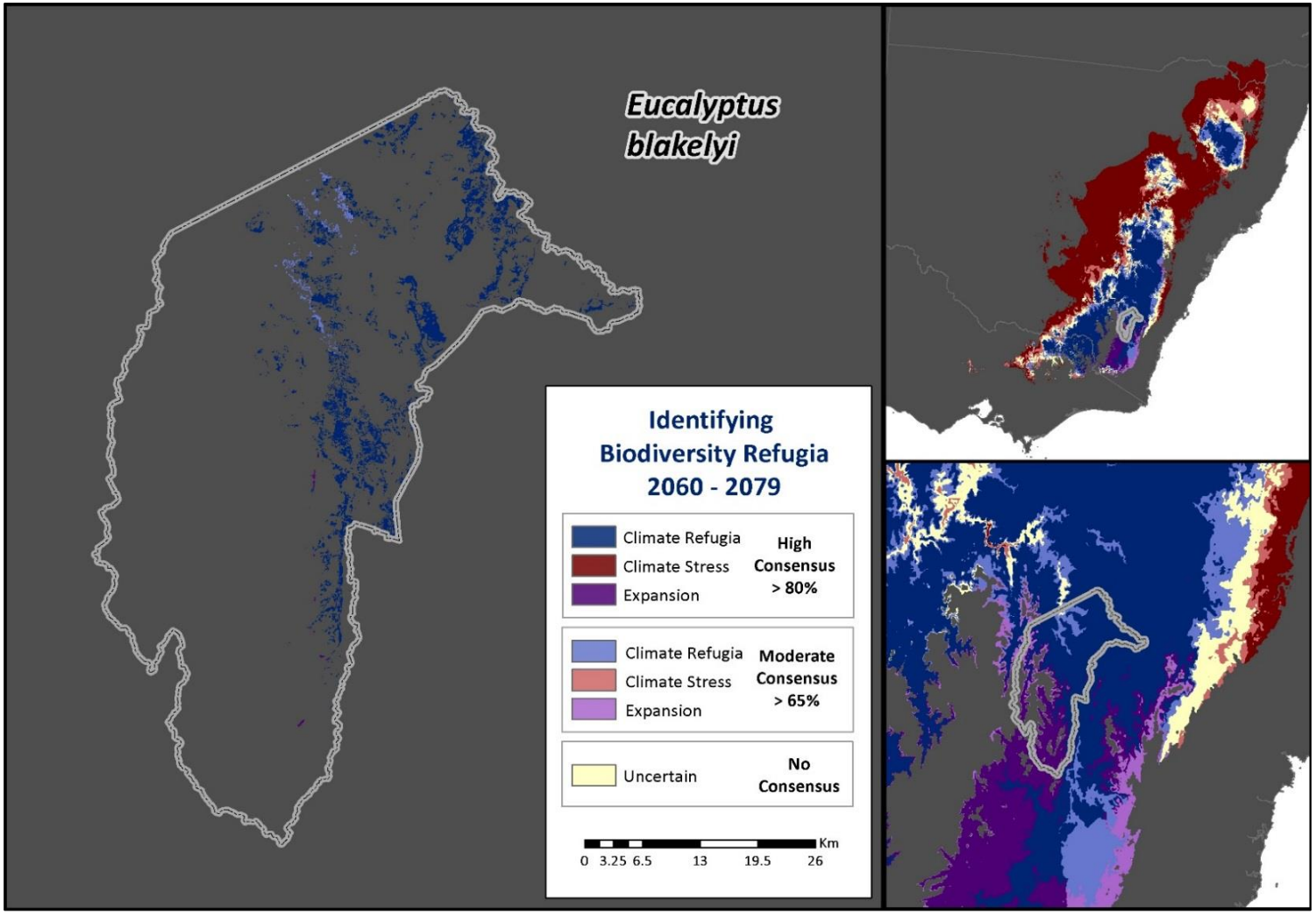


Figure 14 For *Eucalyptus camaldulensis* (River red gum), an ensemble forecast of climate suitability under multiple future scenarios (2060-2079) shown at three scales – locally restricted to areas of expected occurrence (left), across the Capital Region (bottom right) and throughout Southeast Australia (top right).

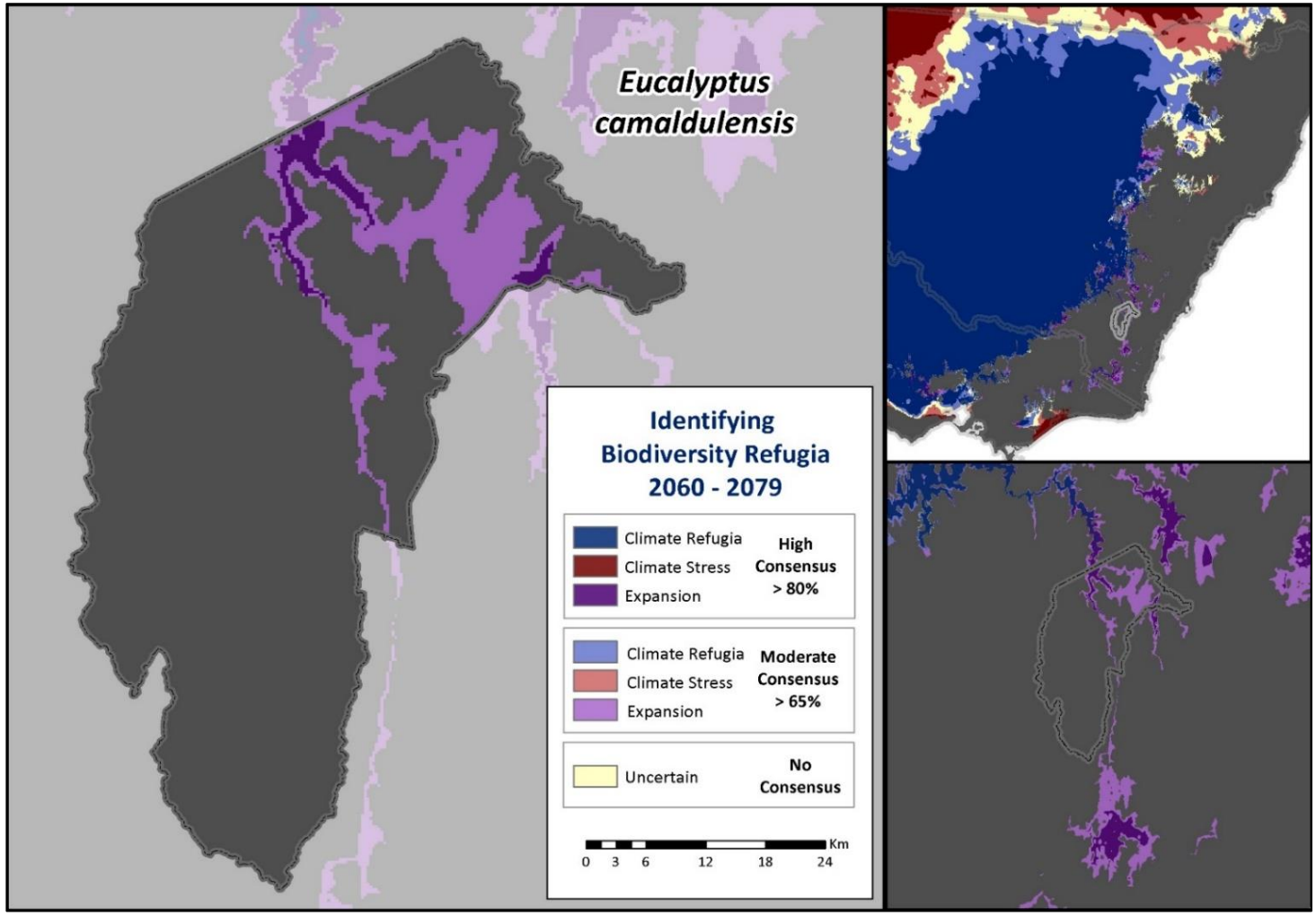


Figure 15 For *Eucalyptus pauciflora* (Snow gum) , an ensemble forecast of climate suitability under multiple future scenarios (2060-2079) shown at three scales – locally restricted to areas of expected occurrence (left), across the Capital Region (bottom right) and throughout Southeast Australia (top right).

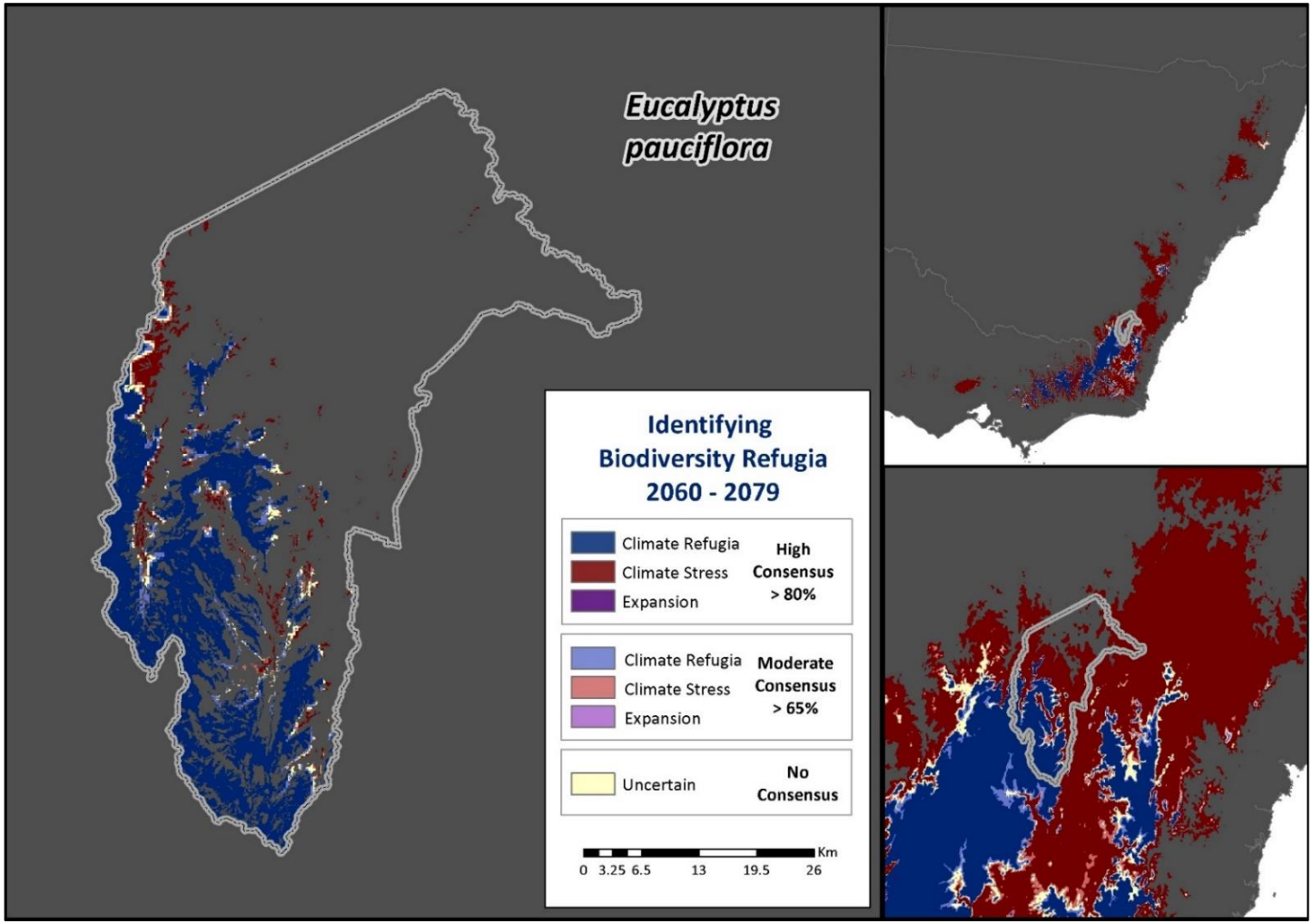
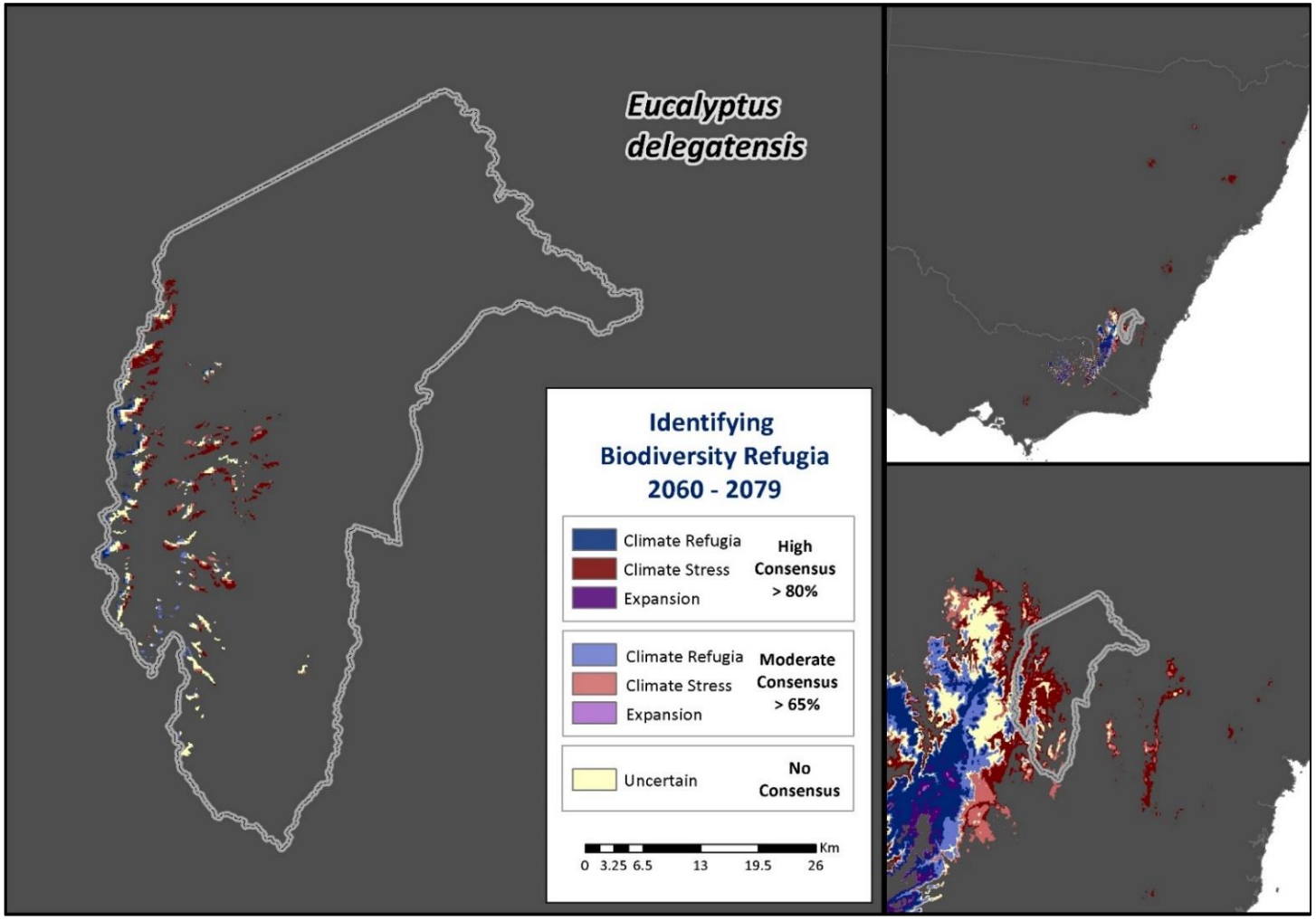


Figure 16 For *Eucalyptus delegatensis* (Alpine ash), an ensemble forecast of climate suitability under multiple future scenarios (2060-2079) shown at three scales – locally restricted to areas of expected occurrence (left), across the Capital Region (bottom right) and throughout Southeast Australia (top right).



3.5 Applying 'scenarioStats' in fire management

The ACT Government is currently updating the next Regional Fire Management Plan (RFMP) 2019-2024, which uses an integrated approach to co-managing fire hazard and biodiversity conservation objectives in order to meet a broad range of land management responsibilities. The RFMP is required to protect assets (both built and natural) from wildfire while maintaining appropriate fire regimes for the conservation of ecological communities and species at the landscape-scale. There are two main objectives of the RFMP. The first objective is to identify a mosaic of burns across the ACT that minimises residual wildfire risk to identified assets and values. The mosaic will be implemented at the landscape-scale (through a range of prescribed burns at varying time intervals over the next 10 years) and at the patch scale (through burns of varying intensity and unburnt areas within each burn block). The second objective is to reduce fuel-driven wildfire risks to human life, property, essential services, agriculture, primary production, biodiversity, cultural heritage, and water catchments.

Updates to the next RFMP 2019-2024 can draw on an exciting range of new spatial and ecological data, allowing ACT Government to jointly explore how changes in fire and climate may maintain or degrade conservation values, today and well into the future. There is a need to spatially classify suitable and unsuitable areas for prescribed burning, based on ecological requirements. With respect to vegetation, mapping of vegetation communities is now available for the entire Territory, and ecological fire thresholds have been derived based on floral and faunal requirements of each community. For example, Tolerable Fire Intervals (TFIs) set a minimum allowable time between burns before which introduction of another fire is expected to degrade biodiversity values in an ecological community. With respect to fire, spatial fire history (post-1900) is mapped allowing for derivation of Time Since last Fire (TSF), Last Fire, and Fire Frequency. Fuel Accumulation Rates are also available to consider for planning prescribed burns and anticipating stochastic wildfire. Combining spatial data on vegetation communities with associated TSF and TFI reveals which areas are under, within or over ecological fire thresholds. Through this project, the process of combining vegetation mapping, TSF and TFI was automated in R (R Core Team 2017) to quickly and easily provide a measure of the 'ecological status' of vegetation communities across the ACT in relation to fire management. Similarly, age class distributions for each vegetation community based on TSF can be incorporated into the planning process and have now been automated in R (R Core Team 2017). Finally, through this project, generation of the 'scenarioStats' prediction surfaces allows for long-term climate suitability to be considered in fire management, alongside more traditional vegetation and fire criteria (described above). For example, identifying areas which are long unburnt, under threshold or future climate refugia, provides a set of spatial priority areas which should be excluded from planned fire, and possibly where strategic burning of buffer areas might serve as protection from unplanned wildfire in the future. Mapped climate priorities proposed for consideration in the RFMP 2019-2014, based on 'Climate Priorities' layers in both 'datapacks', including both potential fire exclusion areas and proposed areas for ecological burns, are presented in Figure 19.

Figure 17 *Current ecological status of ACT vegetation communities in relation to spatial fire histories (Time Since last Fire; TSF) and tolerable fire intervals (TFI).*

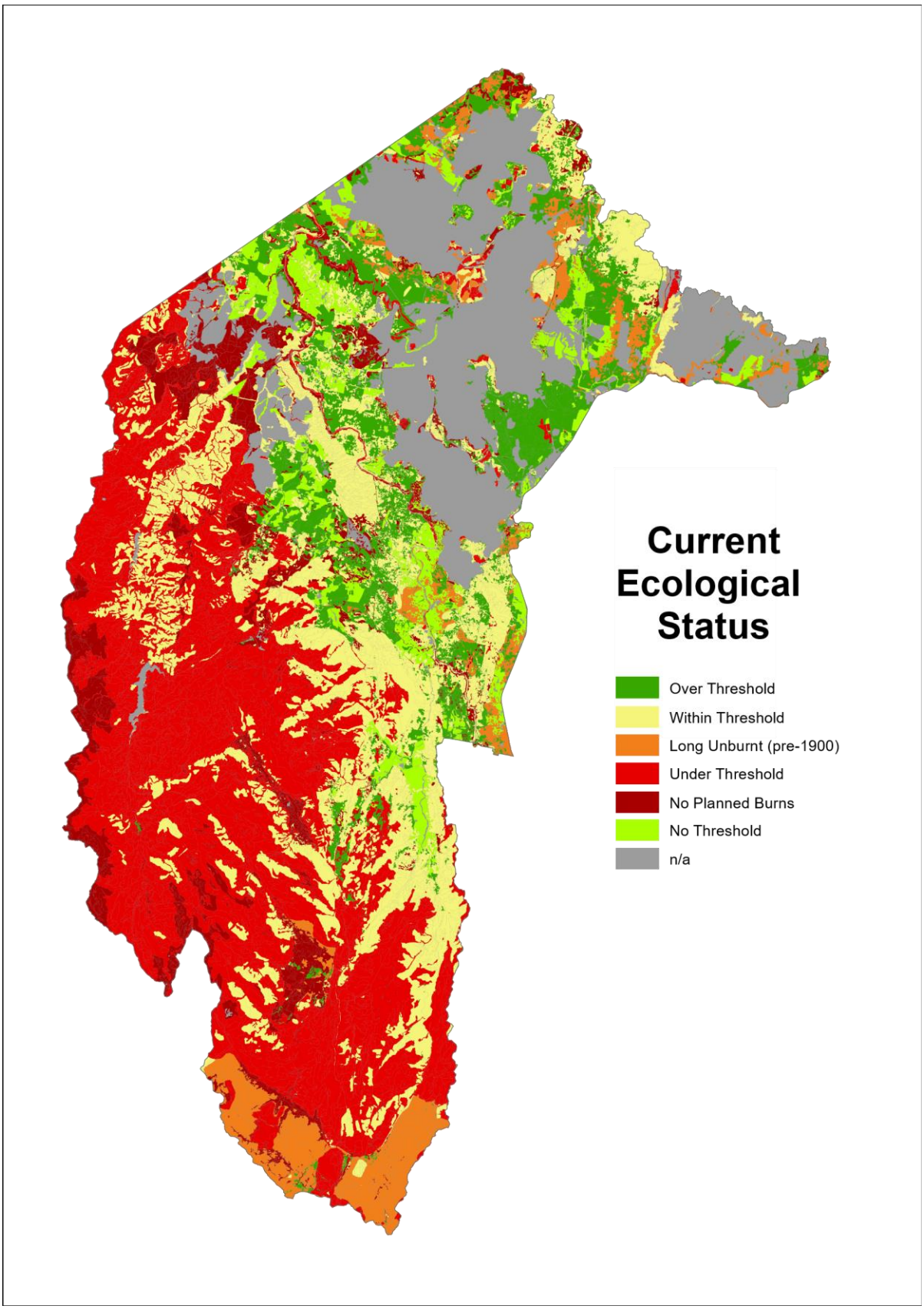


Figure 18 *Future climate priorities for characteristic native plant species based upon where they are expected to occur today and where future climates appear most suitable across all scenarios (i.e., 90th percentiles).*

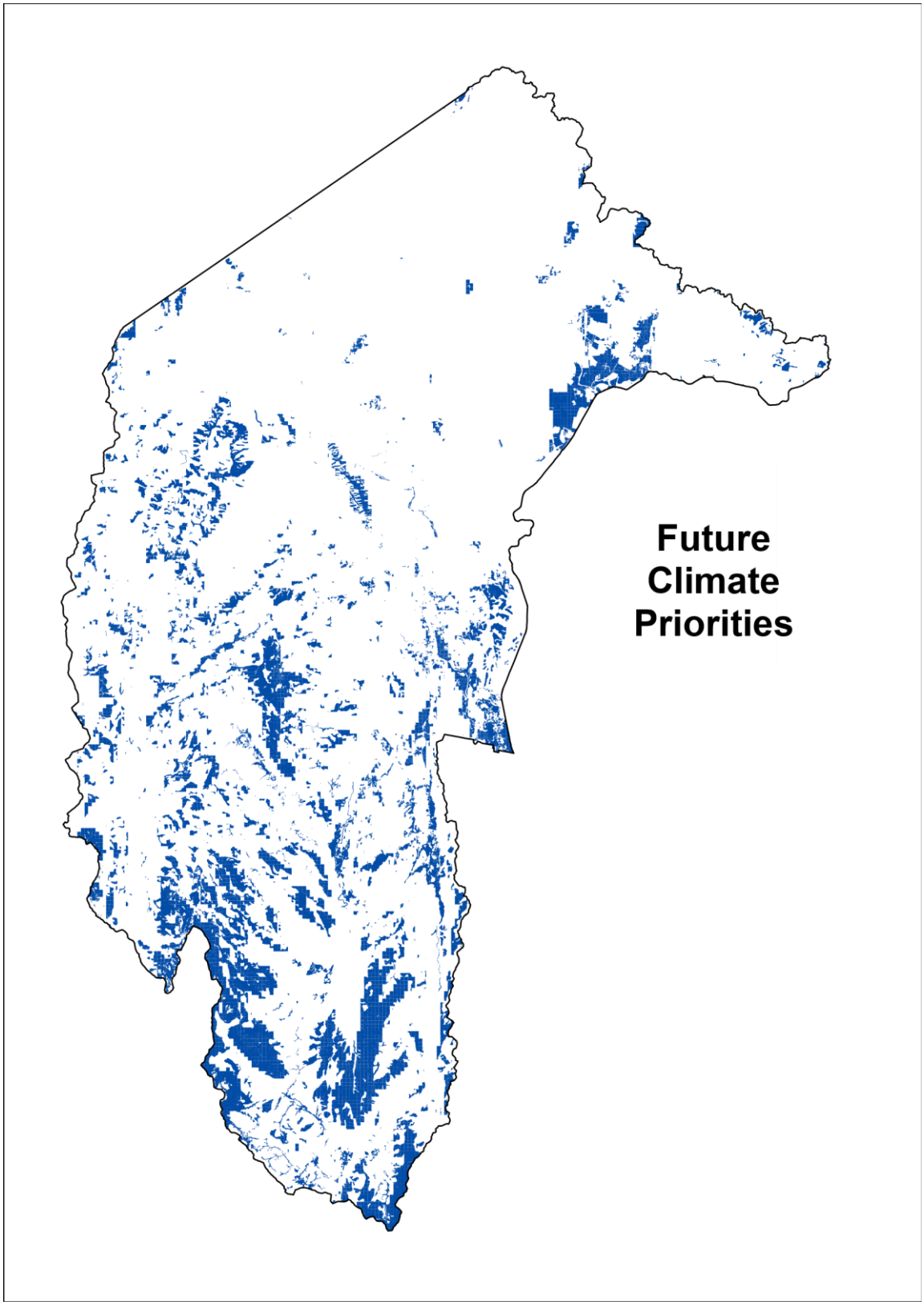
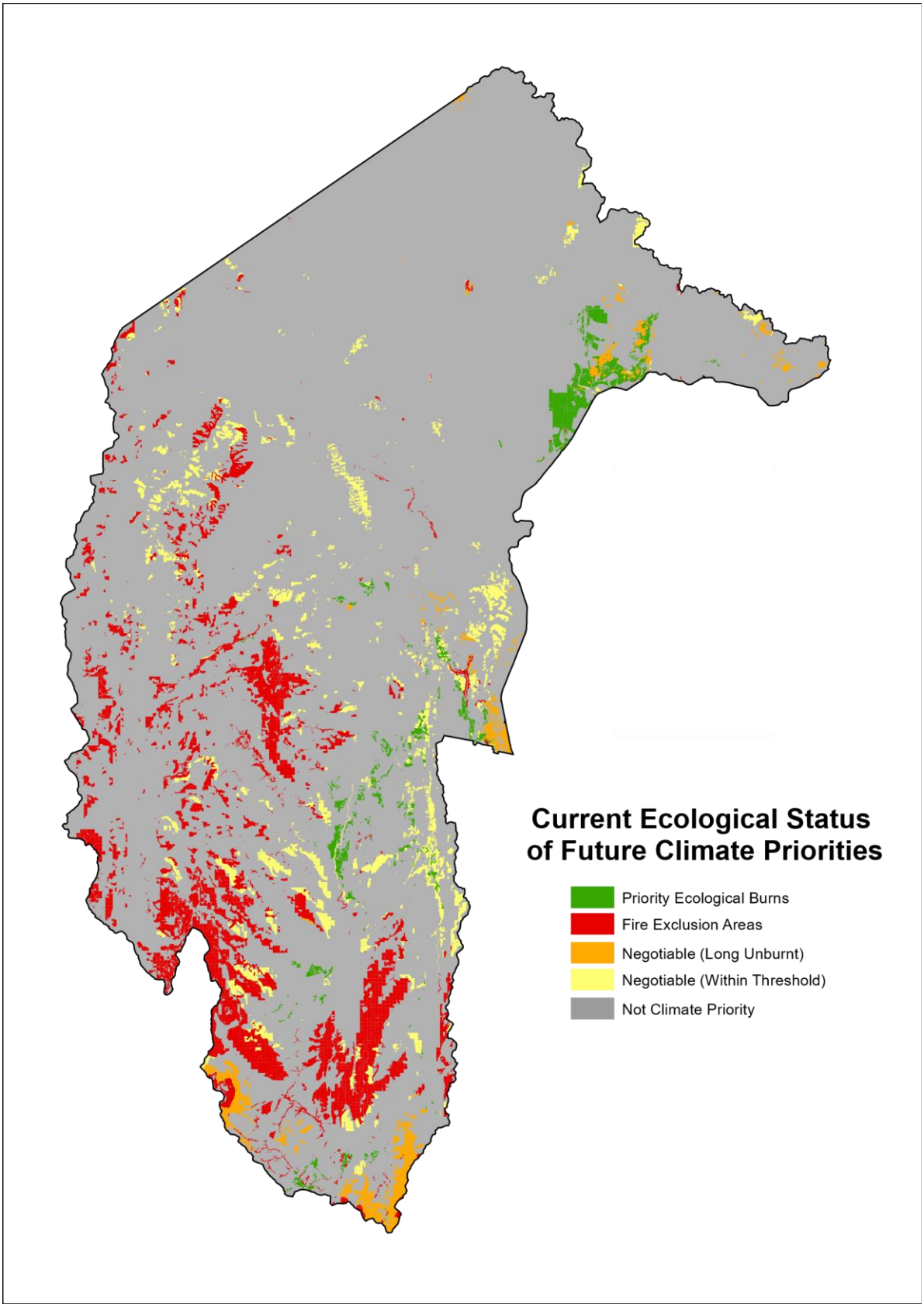


Figure 19 *Management recommendations for prioritising ecological burns and fire exclusion areas derived from the union of current ecological status (Figure 17) and future climate priorities (Figure 18).*



3.6 Applying ensembles in policy development

Evidence (herein) suggests it is unreasonable to expect that all native species occurring within the ACT will be able to persist indefinitely under rapid future changes in climates. Under the Commonwealth's Environmental Protection and Biodiversity Conservation (EPBC) Act, States and Territories are obligated to consider the distributions of threatened species and endangered ecological communities as static entities to be maintained in perpetuity (i.e., no species loss). Given this policy obligation is in direct conflict with best available scientific evidence, new conservation policies need to be developed which aim to preserve existing conservation values, but which also recognise shifting realities on-ground. For example, *Themeda triandra* (Kangaroo grass) is a diagnostic species within Natural Temperate Grasslands (NTG). The NTG are an endangered ecological community and protected under the EPBC Act as a Matter of National Ecological Significance (MNES). Modelling from this project suggests climates are likely to become increasingly unsuitable for maintaining this conservation asset locally, except for small subalpine grassland patches along the southern-most reaches of the Territory (Figure 15). Additional research should be prioritised to improve upon model performance, and our understanding of distribution, for this critical grassland species. Many local threatened species that inhabit NTG (e.g., grassland earless dragon, golden sun moth, northern corroboree frog, legless lizard, superb parrot, etc) are already facing significant conservation threats. It is unclear how the removal of species may impact the structure and function of ecological communities, but theory suggests resilience may drop and potential for ecological invasion will increase. Given the ensuing risks that climate change poses to local flora (and fauna), states and territories may need to negotiate with Commonwealth around more realistic biodiversity conservation policy obligations under climate change.

3.7 Next steps

The most important next step in relation to climate change is transitioning to where we communicate and manage existing and future refugia values to the best of our ability and knowledge. Fortunately, the existing reserve network in the ACT spans over 60% of the Territory and includes significant environmental heterogeneity and steep ecological gradients, which are likely to provide climate refugia for a wide range of native flora (and fauna) in the region. Significant regional investments in maintaining landscape-scale connectivity should also enhance species ability to persist under climate change. Land managers (everywhere) will increasingly be called upon to ensure the survival of viable populations of vulnerable native species, and to facilitate their adaptation to changed conditions. Examples might include protecting vulnerable populations from wildfires, which become more frequent and severe as temperatures rise and soil moisture drops; or planting out species in gaps between existing populations to provide greater likelihood of re-colonisation following major disturbances and greater resilience of the overall population.

Adaptive and effective management approaches under climate change are critical moving forward. One way to approach this would be to convene collaborative workshops and other cooperative efforts among field ecologists, conservation planners and land managers across the region. Additional thought is required to consider how best to protect and maintain existing refugia sites and linkages to facilitate species movement (connectivity) between them as climate continues to change. This could involve: i) assessing the size and location of projected species ranges, characterizing the types of habitat or of assistance that species will need to move amongst suitable areas over time, ii) identifying significant impediments to species movement between core areas, iii) specifying core areas and linkages that would need to be managed or protected to enable species to move to expansion areas, and iv) identifying species and populations that may need to be translocated to new areas. Most or all efforts will require cooperation and active collaboration among regional stakeholders, including local, state and federal agencies, non-profit organizations, and academic researchers.

Locally, there are significant gaps which conservation research can address for land managers in the future: 1) Social values need to be clarified in relation to setting biodiversity conservation objectives (i.e., what are regional stakeholders willing to give up to promote biodiversity conservation); 2) Modelling of local vertebrate responses to changes in vegetation structure is a notable gap; 3) Better estimates of water deficit (a la Harwood 2014) will be critical for anticipating the ecophysiological responses of plants; 4) Assessing changes in the invasion potential of native remnant vegetation will become increasingly more relevant under climate change; 5) The identification of local microrefugia, now possible with LiDAR surveys across the Territory, is potentially one of the most interesting areas of future research; and 6) Identifying freshwater refugia and connectivity corridors between them will be essential for effectively managing precious water catchments under climate change.

4 Acknowledgements

We thank the Commonwealth for funding to support Jason MacKenzie (ACT Government) obtained through the Biodiversity Fund and National Landcare Programs. We thank Nandhini Nagaratnam (ACT Government) for championing the business case for this project. We thank Dr John Baumgartner and Linda Beaumont (Macquarie University), as well as David Freudenberger (Australian National University), Hamish Holewa (Atlas of Living Australia) and David Bush (CSIRO), for input on distribution modelling. We thank Michael Mulvaney (ACT Government) for discussions about the potential for regional native plants to invade the ACT from NSW, as well as identification of historical refugia (e.g., Booroomba Rocks, Pine Island) based on rare plant occurrences. We thank Michael Mulvaney and Jen Smits (ACT Government), as well as James Bibby (NSW OEH), for assistance with occurrence data. We thank Jen Smits for discussions on ArcPY, as well as input on 'datapack' design and compatibility with ACT Government infrastructure. We thank Alie Cowood (University of Canberra) for provision of climate clusters in the ACT used for zonal statistics. We thank Alie Cowood (University of Canberra), Tom Harwood (CSIRO), Danlu Guo (University of Melbourne) and Brendan Choat (University of Western Sydney) for discussions on deriving estimates of atmospheric water deficit and aridity index. We thank Clarissa Barbarosa (ACT Government) for careful review of the manuscript. We also thank the many end users who contributed to discussions about applying project outputs in local conservation, including ACT Government staff from Conservation Research (Margaret Kitchin, Renee Brawata, Tony Corrigan, Mel Snape, Murray Evans, Stacey Taylor, Beth Dunne), Conservation Policy (Johannes Botha, Bindu Johnson, Kathy Tracy), NRM Programs (Tim Wong, Anna van Dugteren, Sally McIntosh), Parks and Conservation Service (Clare McInnes, Kate Boyd, Brett Howland, Richard Milner, Laura Rayner, Chloe Sato, Kristy Gould, Laura Woollcome, Maree Gilbert, Tim Chaseling, Darren Roso, Tom McElroy, Mark Sweaney, Brian Summers, Mirjana Jambrecina, Alexi Williams, Craig Wainwright, John McRae, Stu Jeffress, Nathan Oliver, Brett McNamara and Daniel Iglesias).

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6 Appendix

Appendix 1 ACT Biodiversity Refugia Atlas

Accompanying this report are high resolution maps (300dpi) of ensemble forecasts described in Section 2.5. Maps reveal potential local, regional and sub-continental climate impacts for 151 modelled plant species in a single document named, "Appendix 1- ACT Biodiversity Refugia Atlas.pdf'. The Atlas is a bit large (280Mb), so it is provided separately from the Technical Report. The Atlas is provided in both 'datapacks' (Table 1).

Appendix 2 NARCliM scenario summary statistics for the ACT

Figure 20 *Boxplot of ACT monthly mean diurnal temperature range based upon NARCliM baseline (1990-2009), near-future (2020-2039) and far-future climate scenarios (2060-2079).*

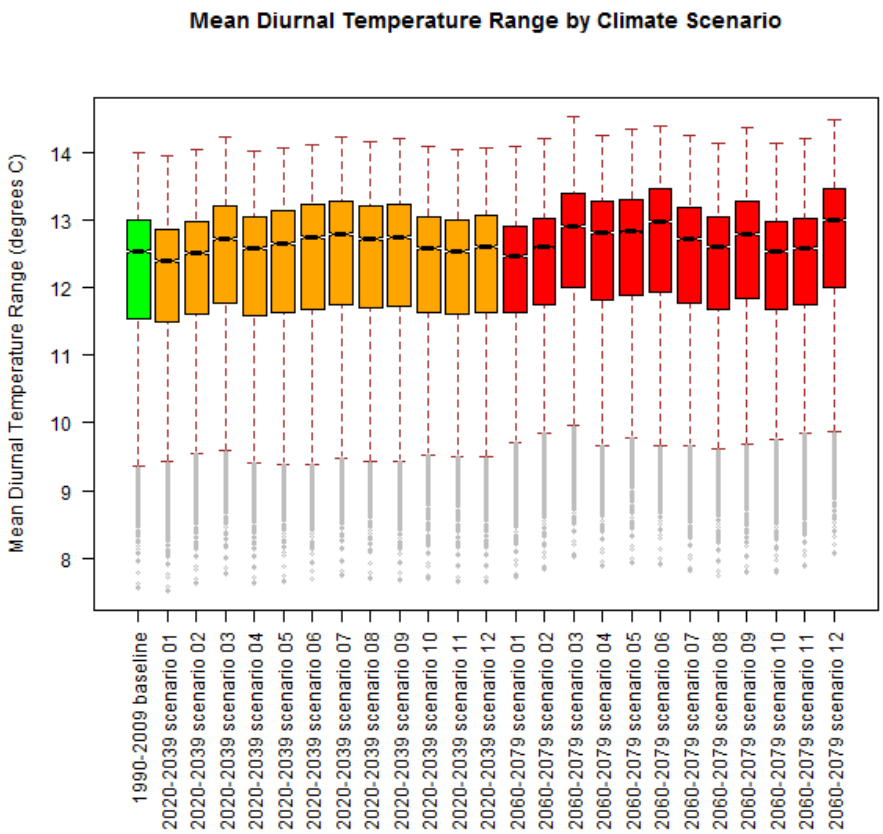


Figure 21 *Boxplots of ACT monthly temperature seasonality (left panel) and precipitation seasonality (right panel) for NARCliM baseline (1990-2009), near-future (2020-2039) and far-future climate scenarios (2060-2079).*

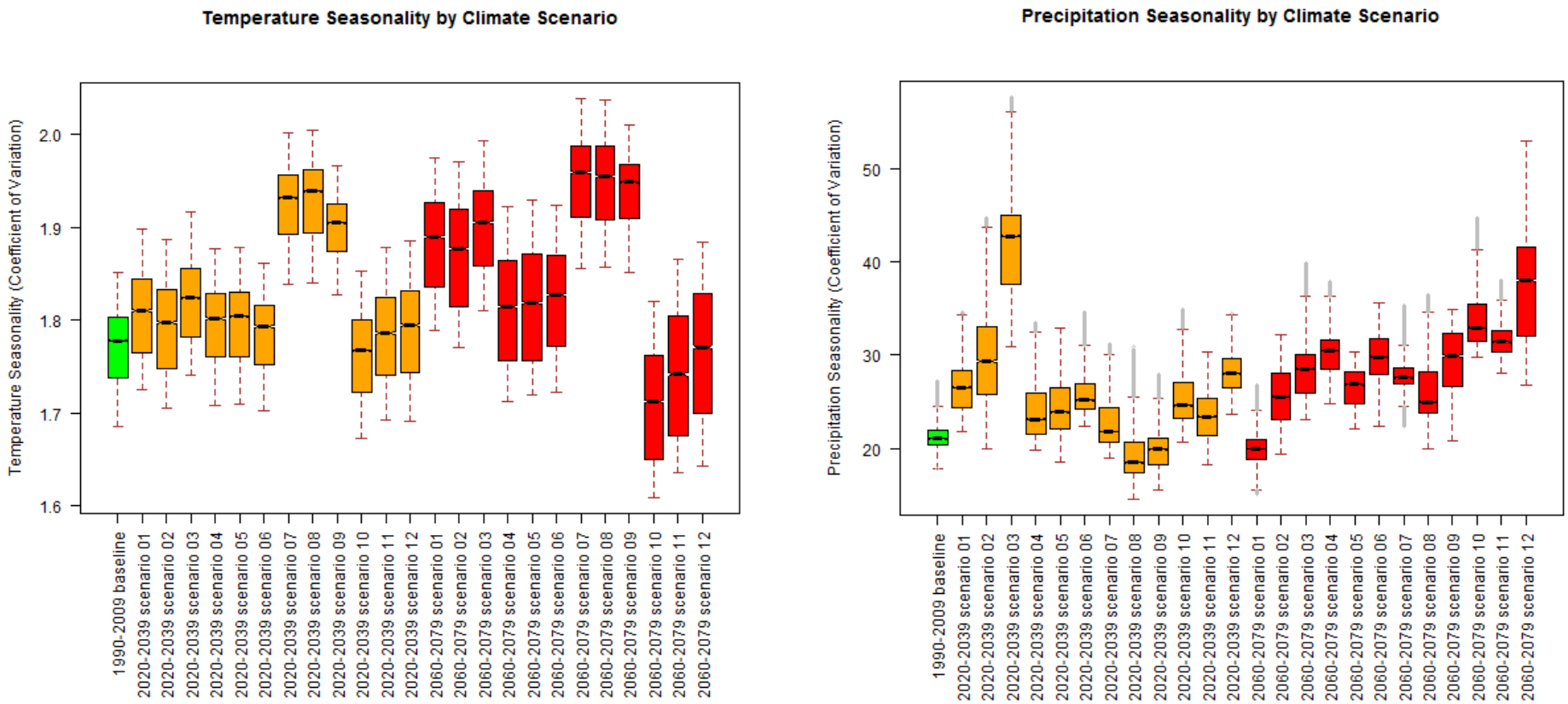


Figure 22 *Boxplots of ACT maximum temperature of the warmest month (left panel) and minimum temperature of the coldest month (right panel) for NARCliM baseline (1990-2009), near-future (2020-2039) and far-future climate scenarios (2060-2079).*

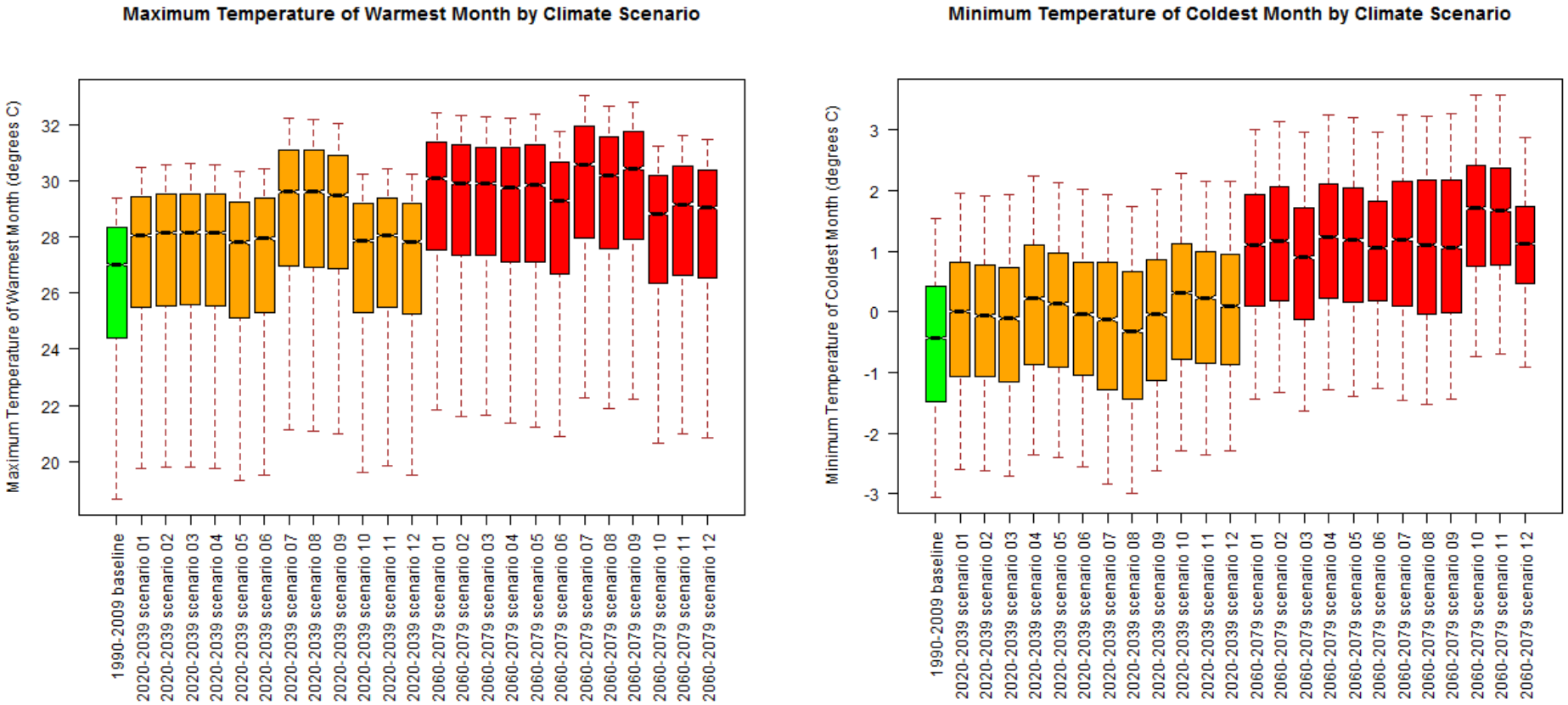
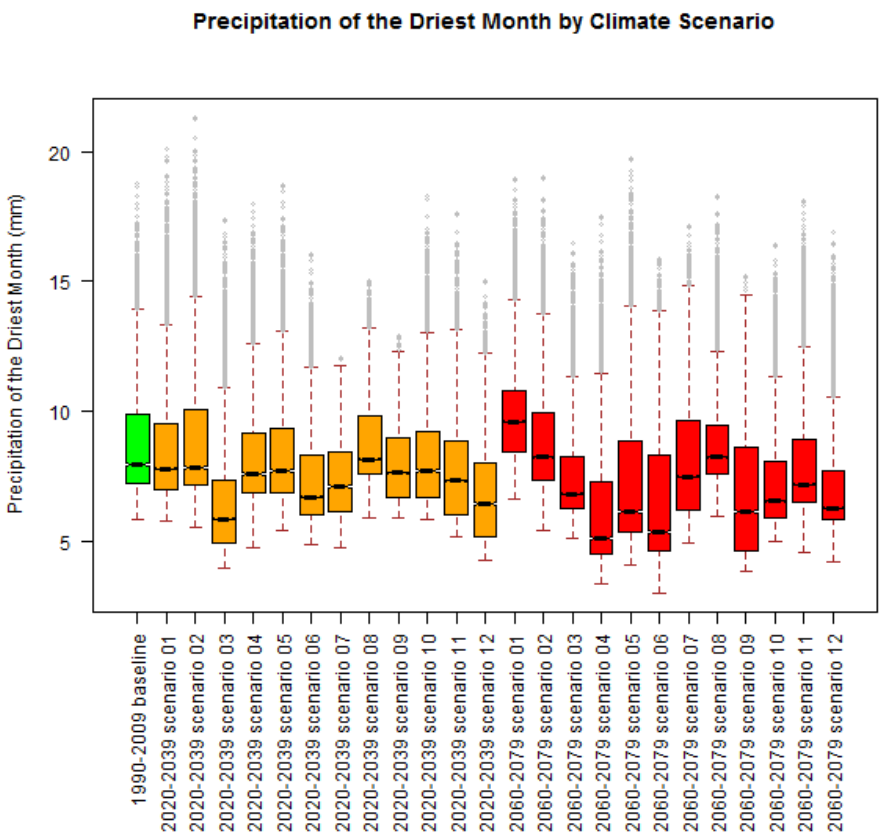
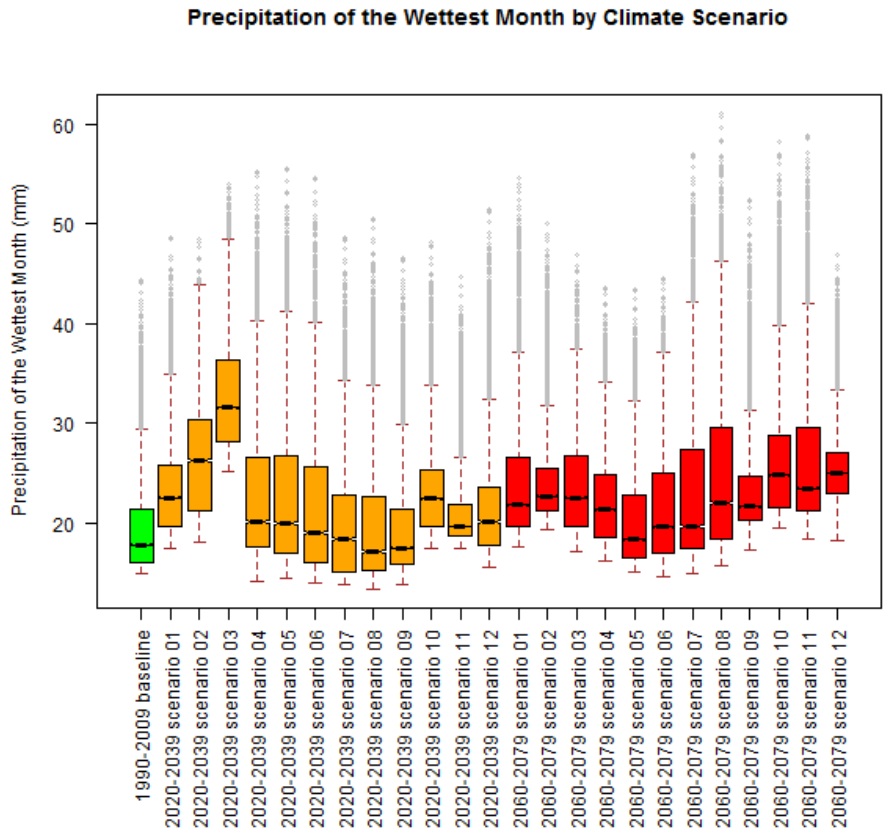


Figure 23 *Boxplots of ACT precipitation of the driest month (left panel) and precipitation of the wettest month (right panel) for NARCliM baseline (1990-2009), near-future (2020-2039) and far-future climate scenarios (2060-2079).*





Appendix 3 Descriptive statistics for species distribution models

Table 5 *Summary statistics of species distribution models (SDMs) relating to occurrence data, explanatory power of predictor variables, model performance, and suitability thresholds.*

Species	Occurrence Records	Background Samples	Diurnal Temperature Range	Temperature Seasonality	Maximum Temperature of Warmest Month	Minimum Temperature of Coldest Month	Maximum Precipitation of Wettest Month	Minimum Precipitation of Driest Month	Precipitation Seasonality	AUC	Suitability Threshold
Acacia dealbata	3941	90833	16	2	12	41	4	7	18	0.848	0.310
Acacia falciformis	1170	86710	6	13	24	43	5	7	3	0.858	0.436
Acacia genistifolia	784	70498	7	10	16	19	28	10	9	0.875	0.352
Acacia implexa	3448	93403	22	9	3	29	12	22	3	0.718	0.595
Acacia melanoxylon	6538	91611	4	29	36	16	6	7	1	0.813	0.496
Acacia obliquinervia	268	65784	33	4	14	41	2	2	2	0.916	0.245
Acacia rubida	550	86901	28	2	3	52	3	8	4	0.877	0.406
Acaena novae-zelandiae	4489	92536	8	4	50	16	13	4	5	0.817	0.363
Allocasuarina verticillata	517	78301	12	3	10	4	28	18	25	0.802	0.533
Anthosachne scabra	5812	97058	8	1	6	38	18	11	18	0.789	0.470
Aristida behriana	821	71816	17	13	16	9	26	12	7	0.915	0.393
Aristida ramosa	4428	92955	50	23	0	3	6	16	2	0.812	0.443
Asperula conferta	4347	97304	19	4	2	55	18	3	0	0.735	0.457
Asperula scoparia	1052	85886	35	2	11	36	5	6	7	0.907	0.276
Austrostipa bigeniculata	1292	83111	10	2	11	8	37	8	25	0.898	0.381
Austrostipa scabra	9994	97720	42	35	1	2	10	6	4	0.810	0.337
Austrostipa verticillata	2059	82387	52	12	11	4	9	9	4	0.902	0.319
Baeckea gunniana	139	34511	19	1	13	27	14	24	2	0.972	0.161
Baumea articulata	346	84845	12	31	5	38	4	7	2	0.882	0.478
Baumea rubiginosa	477	88994	28	21	14	3	9	21	4	0.793	0.539
Bedfordia arborescens	428	41446	7	18	35	24	7	8	1	0.891	0.260
Blechnum cartilagineum	2407	86432	11	32	14	6	25	13	0	0.834	0.313
Blechnum wattsii	388	84272	8	21	36	21	3	10	2	0.871	0.218
Bossiaea foliosa	328	51532	37	3	8	51	1	1	0	0.959	0.235
Bothriochloa macra	4006	95749	34	28	1	16	6	13	1	0.815	0.519
Brachychiton populneus	2901	90302	43	28	1	11	2	14	0	0.828	0.410
Brachyloma daphnoides	3768	93683	29	24	1	26	8	7	4	0.768	0.495
Bursaria spinosa	7170	96673	5	24	3	14	27	20	8	0.701	0.563
Callitris endlicheri	2732	79562	40	27	1	21	3	7	2	0.887	0.326
Calotis anthemoides	160	56480	8	16	0	12	28	5	31	0.872	0.375
Calotis lappulacea	2702	87753	48	31	4	2	4	10	1	0.873	0.331
Calytrix tetragona	2122	95881	16	19	8	4	24	8	22	0.769	0.516
Carex appressa	3320	96661	10	4	40	5	9	18	13	0.654	0.565
Carex gaudichaudiana	597	92036	2	29	24	35	3	3	5	0.823	0.355
Carex tereticaulis	731	71470	19	7	9	12	24	23	5	0.899	0.385
Cassinia aculeata	2300	91510	9	6	28	22	12	6	17	0.832	0.456
Cassinia longifolia	1932	74086	25	8	7	30	8	9	12	0.863	0.397
Cassinia quinquefaria	1609	74650	16	10	1	46	10	8	9	0.876	0.265

Species	Occurrence Records	Background Samples	Diurnal Temperature Range	Temperature Seasonality	Maximum Temperature of Warmest Month	Minimum Temperature of Coldest Month	Maximum Precipitation of Wettest Month	Minimum Precipitation of Driest Month	Precipitation Seasonality	AUC	Suitability Threshold
Casuarina cunninghamiana	1184	76103	53	12	2	4	9	6	14	0.798	0.523
Cheiranthera linearis	330	82583	8	35	8	30	8	4	7	0.943	0.417
Chrysocephalum apiculatum	5148	97998	35	16	1	20	15	9	4	0.759	0.445
C. semipapposum	1727	96884	41	18	4	20	7	5	5	0.761	0.429
Comesperma ericinum	575	84053	27	29	11	5	10	17	1	0.822	0.481
Coprosma hirtella	454	84712	37	4	9	36	1	12	2	0.930	0.265
Coprosma quadrifida	2107	86416	2	24	39	21	2	3	9	0.884	0.274
Coronidium oxylepis	104	67234	17	7	4	31	21	10	10	0.820	0.443
Cyathea australis	1392	86637	11	42	18	16	4	8	0	0.857	0.318
Daviesia mimosoides	754	86876	35	4	7	38	2	5	9	0.915	0.259
Daviesia ulicifolia	2555	95537	13	18	10	7	41	3	8	0.758	0.558
Dianella longifolia	3018	97528	36	9	2	11	16	24	1	0.655	0.623
Dianella revoluta	9834	97387	2	8	8	18	30	26	8	0.694	0.519
Dianella tasmanica	1437	85324	6	6	57	17	5	6	3	0.847	0.436
Dicksonia antarctica	655	83997	3	9	55	21	3	8	2	0.910	0.189
Dodonaea viscosa	4882	98004	44	45	0	1	5	3	1	0.778	0.448
Eleocharis sphacelata	368	95614	7	73	0	1	12	2	5	0.751	0.530
Empodisma minus	1292	86568	28	8	31	2	2	27	2	0.865	0.337
Epacris breviflora	132	75624	33	1	18	39	1	8	1	0.941	0.340
Eucalyptus blakelyi	3429	84979	12	43	1	36	2	5	0	0.874	0.338
Eucalyptus bridgesiana	1662	79045	5	3	1	79	5	4	1	0.904	0.354
Eucalyptus camaldulensis	2156	96666	11	22	18	3	26	15	5	0.868	0.332
Eucalyptus dalrympleana	1197	76896	38	0	7	46	3	5	1	0.951	0.229
Eucalyptus delegatensis	183	29554	33	1	1	44	7	13	0	0.975	0.179
Eucalyptus dives	1291	79247	22	1	4	55	2	3	13	0.924	0.273
Eucalyptus fastigata	499	62988	4	12	35	35	2	3	8	0.939	0.267
Eucalyptus macrorhyncha	2640	91776	4	19	3	64	4	4	2	0.908	0.408
Eucalyptus mannifera	942	59553	3	1	6	80	1	3	6	0.899	0.428
Eucalyptus melliodora	4560	92719	6	32	1	51	2	4	4	0.844	0.494
Eucalyptus nortonii	403	85280	11	17	2	50	2	8	9	0.944	0.289
Eucalyptus pauciflora	1953	86744	41	1	6	45	0	4	3	0.941	0.246
Eucalyptus polyanthemos	1050	68917	4	6	7	57	14	3	9	0.887	0.466
Eucalyptus radiata	1381	84977	16	5	28	37	1	12	2	0.907	0.317
Eucalyptus rossii	1090	66762	1	0	2	68	4	2	23	0.908	0.339
Eucalyptus rubida	1002	84034	39	2	2	40	3	7	7	0.942	0.120
Eucalyptus sieberi	1660	71118	16	12	22	19	5	14	11	0.896	0.302
Eucalyptus stellulata	378	73491	39	3	3	48	2	3	2	0.944	0.147
Eucalyptus viminalis	1572	89291	30	7	10	39	6	6	2	0.882	0.324

Species	Occurrence Records	Background Samples	Diurnal Temperature Range	Temperature Seasonality	Maximum Temperature of Warmest Month	Minimum Temperature of Coldest Month	Maximum Precipitation of Wettest Month	Minimum Precipitation of Driest Month	Precipitation Seasonality	AUC	Suitability Threshold
Exocarpos cupressiformis	3869	95632	5	23	22	11	21	17	1	0.720	0.534
Exocarpos strictus	1605	92808	10	12	14	34	15	8	8	0.750	0.625
Galium leiocarpum	346	82845	3	22	27	25	5	7	11	0.860	0.371
Gleichenia dicarpa	842	82442	26	24	16	6	5	22	2	0.850	0.436
Gleichenia microphylla	308	81172	9	43	32	11	1	2	3	0.872	0.429
Gonocarpus tetragynus	8449	93962	11	3	39	16	14	10	7	0.745	0.496
Goodia lotifolia	206	82095	2	24	31	29	4	5	5	0.897	0.347
Grevillea ramosissima	158	70002	5	21	1	63	1	6	4	0.915	0.313
Hakea microcarpa	405	73060	34	3	13	43	1	5	0	0.919	0.225
Hardenbergia violacea	6632	94399	29	9	3	3	30	23	4	0.717	0.585
Hibbertia obtusifolia	5914	90423	25	8	1	50	3	12	1	0.804	0.406
Hibbertia serpyllifolia	141	68504	19	6	16	17	4	20	18	0.776	0.510
Histiopteris incisa	358	85865	38	36	4	5	3	13	1	0.824	0.335
Hovea montana	171	41361	23	11	10	38	5	12	0	0.980	0.134
Hydrocotyle sibthorpioides	1892	89325	12	14	18	2	20	21	13	0.737	0.558
Imperata cylindrica	5885	90348	20	30	2	4	28	7	8	0.815	0.439
Indigofera australis	2501	94858	12	9	7	41	15	15	0	0.723	0.559
Isachne globosa	191	87154	3	15	14	7	17	14	30	0.697	0.611
Kunzea ericoides	1139	87996	10	16	27	9	5	4	29	0.883	0.532
Kunzea parvifolia	298	87286	5	6	5	70	2	2	11	0.886	0.353
Lepidosperma urophorum	439	68843	10	31	17	20	4	6	13	0.866	0.300
Leptospermum continentale	2519	71217	4	50	24	10	10	1	2	0.881	0.308
Leptospermum grandifolium	250	55973	17	12	16	28	6	20	1	0.932	0.240
Leptospermum lanigerum	155	55510	12	11	19	27	21	5	5	0.910	0.306
Leptospermum myrtifolium	249	52197	32	9	4	50	3	2	0	0.932	0.161
Leptospermum trinervium	2672	70516	7	57	1	18	12	2	3	0.817	0.546
Leucochrysum albicans	551	90217	28	2	7	39	11	3	9	0.900	0.419
Lomandra filiformis	12371	93942	6	6	4	42	16	22	4	0.681	0.597
Lomandra longifolia	14913	93227	16	31	19	3	13	17	2	0.695	0.519
Lomatia myricoides	774	79169	24	6	16	21	4	18	11	0.875	0.286
Melichrus urceolatus	3931	90651	21	24	1	41	3	4	6	0.857	0.319
Microlaena stipoides	16037	95371	10	14	13	20	20	20	2	0.679	0.569
Microsorum pustulatum	238	81437	5	27	31	19	4	11	3	0.927	0.112
Mirbelia oxylobioides	240	53278	40	1	2	38	7	9	3	0.946	0.153
Monotoca scoparia	2920	90667	10	3	54	5	8	17	4	0.742	0.524
Olearia erubescens	549	82177	24	1	31	24	2	13	4	0.934	0.267
Olearia lirata	763	50893	5	52	16	14	2	3	9	0.920	0.328
Olearia megalophylla	174	48882	43	1	3	44	6	3	0	0.963	0.231

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Omphacomeria acerba	124	73067	4	3	29	36	12	8	7	0.809	0.426
Oxylobium ellipticum	276	70006	34	4	14	37	5	3	3	0.968	0.111
Ozothamnus thyrsoideus	149	40671	40	3	2	48	3	1	3	0.945	0.177
Phragmites australis	1905	97413	13	53	3	12	17	0	2	0.780	0.453
Pimelea ligustrina	201	81752	6	5	44	10	14	15	5	0.840	0.293
Poa clivicola	103	48185	33	1	10	47	4	3	2	0.980	0.214
Poa costiniana	233	66202	8	19	12	33	2	25	1	0.988	0.059
Poa helmsii	147	38069	30	7	2	37	9	10	5	0.921	0.241
Poa induta	141	43053	40	3	1	35	3	9	9	0.972	0.162
Poa labillardierei	5204	96730	1	10	52	5	14	9	8	0.758	0.434
Poa sieberiana	10038	94572	30	2	5	56	2	4	1	0.780	0.469
Podolobium alpestre	211	49228	40	3	10	40	4	2	1	0.972	0.181
Polyscias sambucifolia	2742	84923	23	18	7	1	22	20	9	0.807	0.451
Pomaderris aspera	950	73463	3	29	32	19	4	3	10	0.894	0.420
Pteridium esculentum	12837	92156	5	51	29	3	5	7	1	0.750	0.499
Pterostylis curta	151	90167	20	19	4	7	24	19	7	0.730	0.532
Ranunculus inundatus	533	91253	16	19	1	31	10	6	16	0.751	0.644
Ranunculus plebeius	204	81617	9	11	40	5	18	12	5	0.815	0.471
Rubus parvifolius	3411	91104	11	9	35	14	17	11	2	0.748	0.516
Rytidosperma pallidum	4039	91137	17	4	6	50	5	7	10	0.770	0.518
Sida corrugata	3631	97683	31	45	6	3	3	7	4	0.869	0.241
Sorghum leiocladum	993	73489	30	2	1	40	3	3	21	0.840	0.440
Sphaerolobium minus	101	79910	10	33	32	6	4	8	7	0.864	0.378
Stellaria pungens	2272	88255	35	2	10	40	4	4	6	0.879	0.267
Styphelia triflora	997	69498	31	40	5	9	5	6	5	0.819	0.543
Swainsona monticola	105	64990	29	1	16	33	4	14	4	0.899	0.215
Swainsona sericea	257	82828	24	14	12	21	12	9	9	0.925	0.329
Tasmannia lanceolata	176	57049	23	9	19	37	5	6	1	0.929	0.327
Tasmannia xerophila	130	32622	19	6	6	32	8	15	15	0.978	0.134
Thelionema caespitosum	132	83973	7	7	48	8	4	16	10	0.806	0.415
Themeda triandra	13698	97774	12	40	11	7	5	25	0	0.683	0.577
Thesium australe	134	70982	22	16	0	22	16	4	20	0.887	0.405
Todea barbara	295	83543	17	15	6	14	23	21	4	0.820	0.421
Typha orientalis	546	96402	16	10	5	46	18	4	2	0.800	0.550
Viola caleyana	114	73445	6	12	40	18	10	7	8	0.800	0.508
Wahlenbergia planiflora	724	72070	18	26	0	33	5	3	14	0.884	0.318
Zornia dyctiocarpa	450	70451	56	10	0	2	4	6	22	0.828	0.425