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## CliMond: global high-resolution historical and future scenario climate surfaces for bioclimatic modelling

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### Summary

1. Gridded climatologies have become an indispensable component of bioclimatic modelling, with a range of applications spanning conservation and pest management. Such globally conformal data sets of historical and future scenario climate surfaces are required to model species potential ranges under current and future climate scenarios.

2. We developed a set of interpolated climate surfaces at 10' and 30' resolution for global land areas excluding Antarctica. Input data for the baseline climatology were gathered from the WorldClim and CRU CL1-0 and CL2-0 data sets. A set of future climate scenarios were generated at 10' resolution. For each of the historical and future scenario data sets, the full set of 35 Bioclim variables was generated. Climate variables (including relative humidity at 0900 and 1500 hours) were also generated in CLIMEX format. The Köppen–Geiger climate classification scheme was applied to the 10' hybrid climatology as a tool for visualizing climatic patterns and as an aid for specifying absence or background data for correlative modelling applications.

3. We tested the data set using a correlative model (MAXENT) addressing conservation biology concerns for a rare Australian shrub, and a mechanistic niche model (CLIMEX) to map climate suitability for two invasive species. In all cases, the underlying climatology appeared to behave in a robust manner.

4. This global climate data set has the advantage over the WorldClim data set of including humidity data and an additional 16 Bioclim variables. Compared with the CRU CL2-0 data set, the hybrid 10' data set includes improved precipitation estimates as well as projected climate for two global climate models running relevant greenhouse gas emission scenarios.

5. For many bioclimatic modelling purposes, there is an operational attraction to having a globally conformal historical climatology and future climate scenarios for the assessments of potential climate change impacts. Our data set is known as 'CliMond' and is available for free download from <http://www.climond.org>.

**Key-words:** Bioclim, biosecurity, climate change, climatology, CLIMEX, conservation biology, CRU, invasion ecology, MAXENT, niche model, pest risk assessment, species distribution model, WorldClim

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### Introduction

Climate is the primary factor constraining the potential distribution of many organisms (Andrewartha & Birch 1984; Woodward & Long 1988). As such, climatic data sets have long underpinned efforts to describe species' native distribution (Fitzpatrick & Nix 1970) for addressing conservation-based questions (e.g. Graham *et al.* 2004; Chefaoui, Hortal, &

Lobo 2005; Guisan & Thuiller 2005). Climatic variables have also been used to model the potential distribution of invasive alien species to better understand weed and pest risk (Baker *et al.* 2000; Kriticos & Randall 2001; Vaclavik & Meentemeyer 2009; Venette *et al.* 2010) and to aid in biological control programmes (Julien, Skarratt, & Maywald 1995; Robertson, Kriticos, & Zachariades 2008). To model the potential distribution of species over multiple continents, a globally conformal data set is a critical requirement.

The earliest computer-based potential distribution models relied upon point location data sets (Sutherst & Maywald 1985) or spatially gridded climatologies over a limited spatial region (e.g. Booth *et al.* 1987). Following the development of sophisticated spatial interpolation routines such as thin-plate splines (Hutchinson & Gessler 1994) and more powerful personal computers, bioclimatic modellers rapidly adopted spatially gridded global climatologies. Subsequently, the globally conformal CRU CL1.0 (New, Hulme, & Jones 1999) and WorldClim (Hijmans *et al.* 2005) data sets (Table 1) have become popular among correlative and mechanistic niche modellers alike. Despite concerns that 30' might represent the spatial resolution limit at which climate data might be reliably estimated (New, Hulme, & Jones 1999; Daly 2006), there has been a strong drive to develop finer scale data sets (New *et al.* 2002; Hijmans *et al.* 2005).

The WorldClim data set is valued for its fine (10') or very fine (30'') spatial resolution. The CRU CL1.0 data set (30' resolution) is attractive because when compared with station data it contains few apparent anomalies (D. J. Kriticos, pers. obs.) and it includes vapour pressure and other variables that can be used to estimate potential evapotranspiration to drive soil moisture submodels. In choosing between these data sets, modellers have to assess whether their desire for finer spatial resolution outweighs their need for variables relating to atmospheric or soil moisture balance. The WorldClim data set includes the 19 core Bioclim variables (Busby 1991; described in full in Table S1 Supporting information) derived from

monthly averages of daily minimum and maximum temperatures and monthly total precipitation. These variables appear to satisfy the requirements of most regression-based species distribution modelling efforts.

However, more process-oriented modelling approaches such as CLIMEX (Sutherst & Maywald 1985; Sutherst, Maywald, & Kriticos 2007), infection models (Magarey, Sutton, & Thayer 2005) and mechanistic ecophysiological models (Kearney *et al.* 2008) rely upon estimates of atmospheric moisture as an index of the saturation pressure deficit and hence the drying potential of the atmosphere. Atmospheric moisture affects phenomena such as the soil moisture balance that is critical for plant growth and survival, dew point duration, which can affect plant pathogen infection rates, and desiccation potential for amphibians. The extended list of 35 Bioclim variables (Table S1; Hutchinson *et al.* 2009) includes derived variables that rely upon potential evapotranspiration, indicating that some species distribution models developed using Bioclim also required indications of atmospheric moisture characteristics to model the species ranges. While the CRU CL2.0 data set (New *et al.* 2002) is available at 10' resolution and includes relative humidity data, it contains many anomalies in the rainfall data, which do not correspond satisfactorily with station data or plausible extrapolations (D. J. Kriticos, pers. obs.). Moreover, the CRU CL 2.0 data set does not include future climate scenario layers, which are becoming an increasingly important component of bioclimatic modelling in an era of rapid global change.

In an effort to understand the climatic component of global change, climate classification systems, such as Köppen–Geiger (Köppen 1936) and Klimadiagramms (von Walter & Leith 1960), are experiencing a resurgence in popularity as modellers seek to understand bioclimatic patterns in global climates. For example, there is a growing appreciation of the sensitivity of correlative species distribution models such as MAXENT, ecological niche factor analysis (ENFA) and logistic regression to the manner in which the pseudo-absence or background data

**Table 1.** Characteristics of climatologies discussed in this paper

Data set	Nominal time period	Spatial resolution	Primary variables (monthly averages)*	Source and description
WorldClim	1950–2000	30'', 2.5', 5' and 10'	prec, tmin, tmax, tmp	Hijmans <i>et al.</i> (2005)
CRU CL1.0	1990–1961	30'	prec, wet, tmp, tmin†, tmax‡, dtr, vap, spe‡, cld, wnd, frs§, rad†	New, Hulme, & Jones (1999)
CRU CL2.0	1990–1961	10'	prec, wet, tmp, dtr, rh, ssh, frs, wnd	New <i>et al.</i> (2002)

\*cld: cloud cover (%); dtr: diurnal temperature range (°C); frs: number of days with ground frost per month (days); prec: precipitation (mm month<sup>-1</sup>); rad: radiation; rh: average relative humidity; ssh: sunshine hours as percentage of day length; tmax: maximum temperature (°C); tmin: minimum temperature (°C); tmp: average temperature (°C); Vap: vapour pressure (hPa); Wet: wet day frequency(days); wnd: 10 m wind speed (ms<sup>-1</sup>).

†Not included in the original CRU release but now available from the IPCC Data Distribution Centre ([http://www.ipcc-data.org/obs/get\\_30yr\\_means.html](http://www.ipcc-data.org/obs/get_30yr_means.html)).

‡Listed on the CRU website (<http://www.cru.uea.ac.uk/cru/data/hrq>) but variable is undescribed and has no known download location.

§Listed as available on the CRU website (<http://www.cru.uea.ac.uk/cru/data/hrq>) and in New, Hulme, & Jones (1999), but now only available through the CRU TS 2.1 data set ([http://www.ipcc-data.org/obs/cru\\_ts2\\_1.html](http://www.ipcc-data.org/obs/cru_ts2_1.html)).

are specified (Chefaoui & Lobo 2008; VanDerWal *et al.* 2009). A recent novel approach has been to use the Köppen–Geiger zonation to specify a background or pseudo-absence data around the known presence points for these models (Webber *et al.* 2011).

Mechanistic modelling approaches can be costly and time consuming, which is a strong incentive to avoid developing an elaborate model for pest risk assessments (PRA) if it is unnecessary. Climatic zonations can be used as a first approximation to assess the climatic similarity between the region the pest occupies, or is creating economic damage, to the PRA area. While the Köppen–Geiger climate classification has been recently updated and digitized for GIS applications, it is only available globally at a 30' spatial resolution based on a gridded climatology (Kottek *et al.* 2006), or at a finer resolution, but relying on climatologies that were interpolated without the benefit of altitude as a temperature covariate (Peel, Finlayson, & McMahon 2007).

The purpose of this paper is to describe the development and testing of a fine-scale global data set uniquely tailored for use in species bioclimatic modelling, including correlative and process-based mechanistic models. The 10' gridded data set includes a hybrid historical data set, a set of future climate scenarios from two global climate models (GCMs) for a range of time periods in the twenty-first century and the Köppen–Geiger climate classification constructed using the same climatologies developed elsewhere. We demonstrate the use of the climatologies with a correlative model for a rare and threatened species and two previously published mechanistic models for invasive species. The combined data set has been named *CliMond*, derived from the French *climat mondial*, meaning 'world climate', recognizing the global coverage of the data set.

## Materials and methods

### HISTORICAL CLIMATE DATA SOURCES

Monthly historical climatological data centred on 1975 at 10' spatial resolution were downloaded from the WorldClim (<http://www.worldclim.org/current>) and CRU CL2.0 (<http://www.cru.uea.ac.uk/cru/data/hrg/tmc> and [http://www.ipcc-data.org/obs/get\\_30yr\\_means.html](http://www.ipcc-data.org/obs/get_30yr_means.html)) websites. From WorldClim, minimum ( $T_{mn}$ ) and maximum ( $T_{mx}$ ) monthly temperature, monthly total precipitation (Prec) and altitude were downloaded in ESRI grid format. From the CRU, mean relative humidity ( $RH_m$ ) was downloaded in ASCII format. The data sets were imported into ArcGIS 9.3 to create a hybrid historical data set based on the minimum and maximum temperatures and

the precipitation data from WorldClim, and  $RH_m$  values from the CRU data set.

For each of the 10' historical and future climate data sets (described elsewhere), the full list of 35 Bioclim variables was calculated based on published algorithms (Hutchinson *et al.* 2009; Table S1) on a weekly basis (rather than monthly as is performed for WorldClim). The commonly available 19 'core' Bioclim variables (Bio 10–Bio 19) require only  $T_{mn}$ ,  $T_{mx}$  and Prec for their calculation (Table S1). The remaining 16 Bioclim variables making up the extended list of 35 variables (Hutchinson *et al.* 2009; Table S1) also require radiation (Bio20–Bio27) and a water-balance soil moisture index (Bio28–Bio35) for their derivation (Hutchinson *et al.* 2009). To calculate the eight derived Bioclim radiation variables, monthly values for radiation (Rad) gridded to 30' for 1961–1990 from the CRU CL1.0 data set (Table 1) were downloaded from the Intergovernmental Panel on Climate Change (IPCC) Data Distribution Centre. Because this data set excludes small offshore islands and some coastal regions, we extended the surface by 2° using an inverse distance weighting interpolation. For more remote islands not covered by this interpolation, we generated radiation values using the mean output of two GCMs (CSIRO-MK3.0 and MIROC-H; Table 2). The final 30' surface was interpolated to 10' resolution using an inverse distance weighted method in ArcGIS 9.3. To generate the eight soil moisture index Bioclim variables, DYMEX (Maywald *et al.* 2007) was used to construct a single-bucket soil moisture model driven by the CLIMEX-formatted data described elsewhere. The single-bucket soil moisture model interrelated monthly climate variables to estimate weekly values of relative soil moisture availability scaled from zero (oven dry) to one (field capacity), with values greater than one possible, representing excess moisture above field capacity. These weekly values of the soil moisture index were used to calculate the eight soil moisture index Bioclim variables (Bio28–Bio35). All of the 35 Bioclim data sets are made available for download in ASCII grid and ESRII grid format.

CLIMEX requires monthly values of  $T_{mn}$ ,  $T_{mx}$  and Prec and also requires monthly values for relative humidity at 0900 hours ( $RH_{0900}$ ) and 1500 hours ( $RH_{1500}$ ) as a means of estimating how conducive the air is to evaporation from the land surface, as an input into a single-bucket soil moisture model.

Relative humidity at 0900 and 1500 was estimated as follows (Unwin 1980 and see Appendix S1, Supporting information for a worked example):

$$RH(\%) = e \times 100 / e_{s(T)} \quad \text{eqn 1}$$

where  $e$  is the vapour pressure, and  $e_{s(T)}$  is the saturated vapour pressure at the corresponding air temperature  $T$ .

The temperature at 0900 ( $T_{0900}$ ) and 1500 ( $T_{1500}$ ) was estimated from the daily temperature range DTR,  $T_{mx}$  and  $T_{mn}$  using the following empirical relationships:

**Table 2.** Characteristics of the two global climate models used for generating future climate scenario data

Originating group, Country	Model	Approximate horizontal grid spacing (°)*	Warming (°C)†
CSIRO, Australia	CSIRO-MK3.0	1.9 × 1.9	2.11
Centre for Climate Research, Japan	MIROC-H	1.1 × 1.1	4.31

\*Information sourced from Randall *et al.* (2007).

†Global mean warming generated by the model over the twenty-first century for the A1B scenario. Information sourced from Hennessey & Colman (2007).

$$T_{0900} = T_{mn} + 0.39 \times \text{DTR} \quad \text{eqn 2}$$

$$T_{1500} = T_{mx} - 0.116 \times \text{DTR} \quad \text{eqn 3}$$

where  $\text{DTR} = T_{mx} - T_{mn}$ .

Following Mitchell *et al.* (2004), the saturated vapour pressure  $e_s$  (hPa) at air temperature  $T$  ( $^{\circ}\text{C}$ ) was calculated using the Magnus equation:

$$e_s = 6 \cdot 107 \exp\left(\frac{17.38T}{239 + T}\right), \text{ where } T_w \geq 0 \quad \text{eqn 4}$$

$$e_s = 6 \cdot 107 \exp\left(\frac{22.44T}{272.4 + T}\right), \text{ where } T_w < 0 \quad \text{eqn 5}$$

Again, following Mitchell *et al.* (2004), the wet-bulb temperature ( $T_w$ ) was estimated from dew point temperature ( $T_d$ ), using an empirical relationship for which daily minimum temperature is used as a proxy:

$$T_w = \frac{3T_d + 2T}{5} \quad \text{eqn 6}$$

Together with the temperature and precipitation data at 10', these relative humidity data were transformed into the CLIMEX .loc and .met file formats.

Historical climatological data at 30' (half degree) spatial resolution were downloaded from the CRU CL1.0 ([http://www.cru.uea.ac.uk/cru/data/hrq/cru05/cru05\\_intro.html](http://www.cru.uea.ac.uk/cru/data/hrq/cru05/cru05_intro.html) and [http://www.ipcc-data.org/obs/get\\_30yr\\_means.html](http://www.ipcc-data.org/obs/get_30yr_means.html); New, Hulme, & Jones 1999) websites in ASCII format. The climate variables were monthly mean values from 1961–1990 of average daily temperature, daily temperature range and relative humidity, and average monthly totals of precipitation. Relative humidity values for 0900 and 1500 hours were estimated using the procedures described by Kriticos *et al.* (2007). These 30' resolution data were then transformed into the CLIMEX .loc and .met file formats.

## ELEVATION

The elevation data sets provided with the WorldClim and CRU data sets were derived through different processes and show significant differences (data not shown). The elevation data provided with the WorldClim data set were derived from the Shuttle Radar Topography Mission (<http://srtm.csi.cgiar.org>). Those provided with the CRU data set were derived from the GLOBE 1 km data set (NGDC 2000). Because elevation strongly affects temperature through the adiabatic lapse rate, the elevation and corresponding temperature data from the WorldClim data set are packaged together in CliMond.

## FUTURE CLIMATE PROJECTIONS

### Greenhouse gas emission scenarios

The IPCC produced a set of forty emission scenarios for future global emissions of greenhouse gases and sulphate aerosols, the so-called SRES scenarios (Special Report on Emissions Scenarios; Nakićenović & Swart 2000). Each scenario is consistent with a storyline based on a set of plausible assumptions about global demographic, economic and technological factors likely to influence future emissions. They selected a representative subset of six 'marker' and two 'illustra-

tive' scenarios, which range from the B1 scenario in which greenhouse gas emissions diminish rapidly, to the A1FI scenario, in which fossil fuels continue to be used intensively. Since then, Rahmstorf *et al.* (2007) showed that projections from GCMs had underestimated recent global temperature and sea level trends. More recently, Manning *et al.* (2010) illustrated that since 2000, carbon dioxide emissions owing to fossil fuel use are consistent with the most extreme of the SRES scenarios. These observations, combined with continued failures to agree on legally binding global reductions in greenhouse gas emissions, suggest that the conservative emission scenarios are no longer plausible. As such, we elected to include only the 'A' family SRES emission scenarios in the CliMond data set. Projections of future climate for 2030, 2050, 2070 and 2080 were generated for the A1B and A2 scenarios for emissions of greenhouse gases and sulphate aerosols.

### Global climate models

For both the 10' and 30' resolution data sets, climate projections were generated from three GCMs from which output was available from the World Climate Research Programme's (WCRP) Coupled Model Intercomparison Project phase 3 (CMIP3) multimodel data set (Meehl *et al.* 2007; Table 2). These exemplar models were selected from 23 GCMs for which the data set includes output based on three criteria. Firstly, monthly averages of daily maximum and minimum temperatures, precipitation, mean sea level pressure and specific humidity were available for these three models. The availability of data for these variables allowed the calculation of input data for CLIMEX as well as the extended list of 35 Bioclim variables. Secondly, the models have relatively small horizontal grid spacing (less than  $2^{\circ} \times 2^{\circ}$  over Australia). Thirdly, according to a listing of GCM skill scores provided by Hennessy & Colman (2007), they perform well relative to other GCMs in terms of representing basic aspects of the observed climate at a regional scale. The Hennessy & Colman (2007) skill scores describe GCM skill at reproducing observed patterns of seasonal average climate over Australia, a region with a range of tropical, arid and temperate climate regimes. We note that, though it seems reasonable to suppose that a low score may correspond to an unreliable simulation of future regional climate conditions, there is no guarantee that the Hennessy & Colman (2007) scores are relevant to the simulation of future regional climate changes across the globe. However, a full assessment of the relevance of different measures of GCM skill to such changes is potentially a large undertaking and is beyond the scope of this paper. The three GCMs that best met the selection criteria were as follows: CSIRO-MK3.0 (CSIRO, Australia), NCAR – CCSM (National Centre for Atmospheric Research, USA) and MIROC-H (Centre for Climate Research, Japan; Table 2). However, during processing, it was discovered that there were some concerning errors in the NCAR data set in arid regions, and it was removed from further processing.

### Climate change surfaces

For each of the two GCMs, extracts were taken from transient forcing simulations of future climate from the CMIP3 data base (Meehl *et al.* 2007) and worldwide surfaces of change per  $^{\circ}\text{C}$  of global warming at 30' were developed. In case of the 30' data set, the change surfaces were interpolated from the native model resolution to 30' resolution using a bilinear interpolation routine. In case of the 10' gridded data, the change surfaces were further interpolated from 30' to 10' using an inverse distance weighted method using ArcGIS 9.3. The change surfaces are relatively smooth as most of the topographic effect in future climate layers is contained in the baseline climatology,

and so this simple interpolation method is appropriate. In some locations where historical monthly precipitation values were zero or near zero, some of the downloaded GCM change surfaces included no data values (assigned a value of 1e9; Fig. S1). Future precipitation values affected by these change surfaces were manually assigned historical precipitation values as the change in projected precipitation with climate change was interpreted to be negligible.

For each model grid box, a change per °C of global warming ( $\Delta$ ) was calculated by linear regression of values of the variable of interest against global average temperature (Whetton *et al.* 2005). For some variables (precipitation and specific humidity), changes were expressed as percentage changes relative to the model climate for 1961–1990 ( $\Delta\%$ ). The resultant changes per °C of global warming were rescaled by a given amount of global warming to produce a pattern of change that would apply for a given future time period and global warming scenario (Whetton *et al.* 2005).

Global warming estimates consistent with those given by the IPCC’s Fourth Assessment Report for warming between the 1980–1999 and 2090–2099 periods (IPCC 2007) were calculated for the A1B and A2 scenarios for warming between 1961–1990, the period of our baseline climatology, and each of 2030, 2050, 2070 and 2080 (Table 3). Hennessy & Colman (2007) provide estimates of warming between 1980–1999 and 2030, 2050 and 2070 that are consistent with IPCC (2007). Estimates of warming between 1980–1999 and 2080 were obtained by fitting a second-order polynomial to the Hennessy & Colman (2007) values for 2050 and 2070 and the IPCC (2007) value for 2090–2099 (taken as corresponding to the year 2095; Cher Page, pers. comm.). Estimates relative to 1961–1990 were then derived from these by adding an adjustment to account for warming between 1961–1990 and 1980–1999. An adjustment of approximately 0.18 °C was estimated from a linear trend analysis of each of the three time series of observed global average temperatures used in the IPCC’s Fourth Assessment Report (from the Climatic Research Unit/United Kingdom Meteorological Office (CRU/UKMO), National Climatic Data Center (NCDC) and Goddard Institute for Space Studies (GISS) data sets; IPCC 2007).

In this study, climate variable values for future scenarios were estimated using the best estimate values of global warming (GW) as follows for temperature and mean sea level pressure:

$$x_{imgsy} = c_{im} + \Delta_{img} \times GW_{sy} \tag{eqn 7}$$

and for precipitation and specific humidity:

$$x_{imgsy} = c_{im} + \frac{\Delta_{img} \times GW_{sy} \times c_{im}}{100} \tag{eqn 8}$$

where  $x$  is the value of a given variable at a particular grid box ( $i$ ) for a period centred on a particular month ( $m$ ) and year ( $y$ ) using the GCM ( $g$ ) for the SRES scenario ( $s$ ).  $x$  is calculated from the observed

**Table 3.** Global warming best estimates (°C) relative to 1961–1990 for 2030, 2050, 2070 and 2080 and SRES scenarios A2 and A1B

Year	SRES emission scenario	
	A1B	A2
2030	1.08	0.98
2050	1.71	1.58
2070	2.31	2.43
2080	2.59	2.88

climatological mean from 1961–1990 from either the 10’ hybrid data set or the 30’ CRU CL1.0 data set ( $c$ ), the best estimates values of GW and the change per °C of global warming ( $\Delta$ ) or the percentage of change per °C of global warming ( $\Delta\%$ ) from the GCM ( $g$ ) for the SRES scenario ( $s$ ).

Data pertaining to changes in relative humidity at 0900 and 1500 were not available from the CMIP3 data base for either of the GCMs. Projections of relative humidity at 0900 ( $RH_{0900}$ ) and 1500 hours ( $RH_{1500}$ ) were estimated from available daily maximum and minimum temperatures ( $T_{mx}$  and  $T_{mn}$ ), mean temperature ( $T_{av}$ ), vapour pressure (vap), mean sea level pressure (psl), specific humidity (huss) and elevation ( $z$ ) data (Meehl *et al.* 2007) through the following process.

Monthly mean surface pressure (ps) for 1961–1990 was calculated for each grid box ( $i$ ) and month ( $m$ ) for the CRU 10’ data set using the method described by Allen *et al.* (1998; Annex 3, Atmospheric Pressure):

$$ps_{im} = psl_{im} \times \left(1 - \frac{6.5 \times 10^{-3} \times z_i}{T_{av_{im}}}\right)^{\left(\frac{9.806}{6.5 \times 10^{-3} \times 287}\right)} \tag{eqn 9}$$

[Correction added after online publication 25 Aug 2011:  $e$  replaced by  $\times 10$ ]

Monthly mean specific humidity (huss) for 1961–1990 was calculated for a given grid box ( $i$ ) and month ( $m$ ) (Rosenberg, Blad, & Verma 1990):

$$huss_{im} = \frac{0.622 \times vap_{im}}{ps_{im} - 0.378 \times vap_{im}} \tag{eqn 10}$$

Projected values of monthly mean psl, huss,  $T_{av}$ ,  $T_{mx}$  and  $T_{mn}$  were calculated for a given grid box ( $i$ ), month ( $m$ ), year ( $y$ ), GCM ( $g$ ) and SRES scenario ( $s$ ) using eqns 7 and 8.

Projected values of monthly mean ps were calculated using projected values of psl and  $T_{av}$ :

$$ps_{imgsy} = psl_{imgsy} \times \left(1 - \frac{6.5 \times 10^{-3} \times z_i}{T_{av_{imgsy}}}\right)^{\left(\frac{9.806}{6.5 \times 10^{-3} \times 287}\right)} \tag{eqn 11}$$

[Correction added after online publication 25 Aug 2011:  $e$  replaced by  $\times 10$ ]

Projected values of monthly mean vap were calculated using projected values of ps and huss:

$$vap_{imgsy} = \frac{ps_{imgsy} \times huss_{imgsy}}{0.622 + 0.378 \times huss_{imgsy}} \tag{eqn 12}$$

Following the method described by Kriticos *et al.* (2007), projected values of monthly mean temperature at 0900 ( $T_{0900}$ ) and 1500 hours ( $T_{1500}$ ) were calculated from  $T_{mx}$  and  $T_{mn}$  (eqns 2 and 3) and projected values of relative humidity at 0900 ( $RH_{0900}$ ) and 1500 hours ( $RH_{1500}$ ) were calculated from vap,  $T_{mn}$ ,  $T_{0900}$  and  $T_{1500}$  for a given grid box ( $i$ ), month ( $m$ ), year ( $y$ ), GCM ( $g$ ) and SRES scenario ( $s$ ).

#### KÖPPEN–GEIGER CLIMATE CLASSIFICATION

There are a variety of Köppen–Geiger climate classification schemes reflecting various attempts to improve the classification (Wilcock 1968). The algorithm adopted here for calculating the Köppen–Geiger climate classification generally follows that of Peel, Finlayson, & McMahon (2007), who followed Köppen’s last publication on his classification system in the Köppen–Geiger Handbook (Köppen 1936). There were three points of departure from (Köppen 1936): (i)

we followed Russell (1931) and used the temperature of the coldest month  $>0^{\circ}\text{C}$ , rather than  $>-3^{\circ}\text{C}$  as used by Köppen (1936) to define the boundary between the temperate (C) and cold (D) climates; (ii) we followed Peel, Finlayson, & McMahon (2007) in using a 70% precipitation criteria for distinguishing the B climates; and (iii) we followed the approach of Peel, Finlayson, & McMahon (2007) in making the subclasses 's', 'w' and 'f' mutually exclusive. Unlike Peel, Finlayson, & McMahon (2007), we applied the classification algorithm to gridded climate surfaces rather than kriging the classified climate stations. Applying the algorithm to gridded climate data resulted in class boundaries that respected topo-climatic patterns more obviously than the excessively smooth polygons of Peel, Finlayson, & McMahon (2007). This also meant that we did not have to apply the altitude-based approximation utilized by Peel, Finlayson, & McMahon (2007) for Greenland and allowed the climates on the smaller islands that were excluded from the Peel, Finlayson, & McMahon (2007) data set to be classified.

#### DEMONSTRATING THE CLIMOND DATA SETS

To demonstrate the value of the different resolution climate data sets, the CliMond historical data set (CM10\_1975H\_V1) was used to run one correlative and two mechanistic bioclimatic models spanning Mediterranean, temperate and tropical climate zones. Firstly, to demonstrate the use of the Bioclim variables and Köppen–Geiger surface components of the CliMond data set, we used MAXENT (V3.2.2), a regression-based species distribution model (Phillips & Dudík 2008), applying the model exploration tools described by Elith, Kearney, & Phillips (2010), particularly multivariate environmental similarity surfaces (MESS) via maps and projection overlays. A conservation biology 'identification of additional suitable climatic regions' scenario was modelled for *Banksia cuneata* A.S.George (Proteaceae), an endangered shrub with a highly restricted native distribution in south-west Western Australia (Broadhurst & Coates 2004). Distribution data for *B. cuneata* populations were obtained from NatureMap (Department of Environment and Conservation 2007–2011). The MAXENT model of *B. cuneata* was constructed, interpreted and displayed following the methods by Webber *et al.* (2011) with the following exceptions: (i) five Bioclim variables (Bio04, Bio10, Bio11, Bio18 and Bio19) from the CliMond 10' data set were chosen *a priori* based on the main ecological factors thought to define the Mediterranean climate in which *B. cuneata* is found, (ii) a lower threshold of 0.1 was set for climatic suitability, (iii) using the CliMond 10' Köppen–Geiger data set, class polygons that contained *B. cuneata* distribution records were joined and buffered by 10' (using ArcGIS 9.3) to define an ecologically relevant background for the MAXENT model. The resulting model was projected into Australia with the CliMond 10' historical climatology (CM10\_1975H\_V1). We use the *B. cuneata* model as an example only and recognize that alternative nonclimatic variables may provide more ecologically relevant projections for a species with such a restricted range (Yates *et al.* 2010).

Secondly, two previously published mechanistic niche models of invasive species: a temperate tussock grass *Nassella trichotoma* (Nees) Hack. ex Arechav. (Poaceae: Stipae) (Kriticos *et al.* 2004) and a tropical cattle tick *Rhipicephalus microplus* (Canestrini) (Acarina: Ixodidae; syn. *Boophilus microplus*) (Sutherst & Maywald 1985; Sutherst & Bourne 2009) were used to demonstrate the CLIMEX component of the CliMond data set. In addition to the historical data set (CM10\_1975H\_V1), models for both species were also run using (i) the CliMond projections of climate in 2080 under the A2 emission scenario generated by the CSIRO-MK3.0 GCM (CM10\_2080\_A2\_CS\_V1), (ii) a Food and Agriculture Organization (FAO)-derived

climate station data set and (iii) a 30' gridded climatology from the CRU (New, Hulme, & Jones 1999). The latter two data sets are distributed with CLIMEX V3 (Sutherst, Maywald, & Kriticos 2007) and represent standard tools for pest risk assessment modelling.

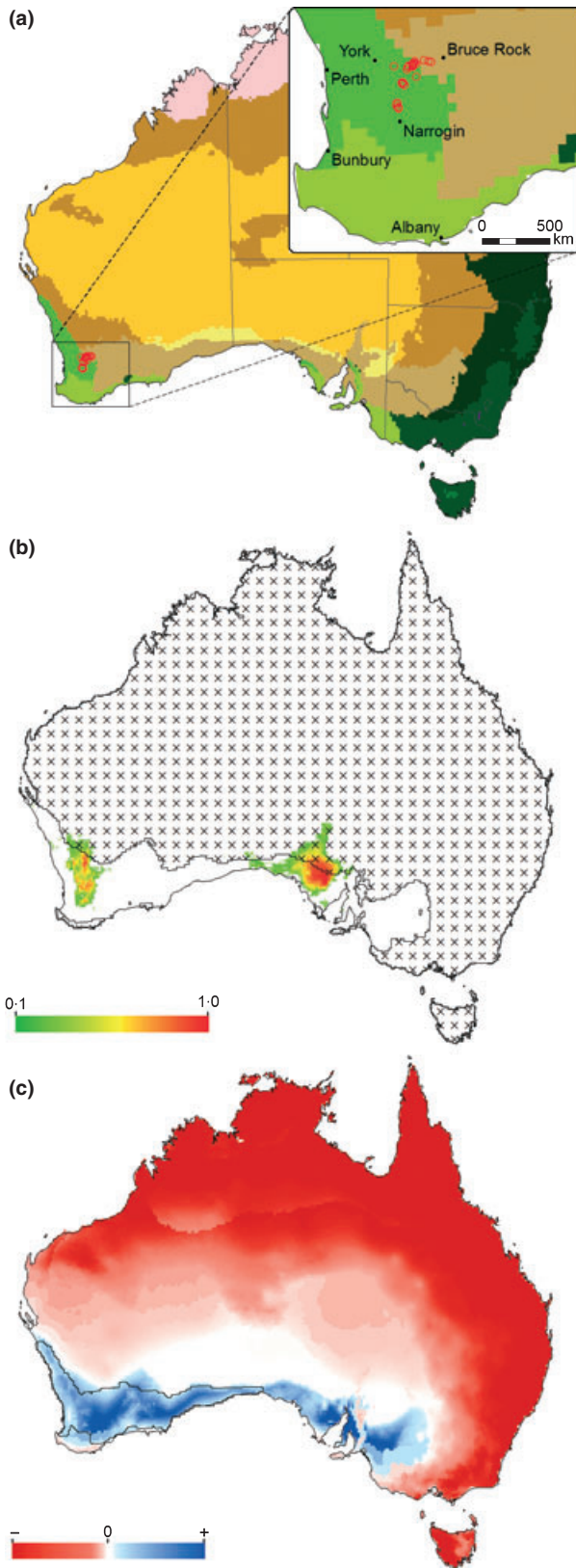
## Results and discussion

There are two paradigms in bioclimatic modelling as follows: correlative approaches that have origins in conservation biology, such as characterizing regions that share similarities with species known distributions, and mechanistic approaches that were developed for invasion ecology to study species in novel regions (Sutherst & Bourne 2009). While the methodological challenges faced by modellers attempting to inform biodiversity conservation and invasion biology are sometimes contrasted (e.g. valuing omission and commission errors differently; Lobo, Jiménez-Valverde, & Real 2008), they share the need for reliable climatological data sets at suitable spatial precision and accuracy. The CliMond data sets can be applied to both correlative and mechanistic modelling applications, and they are available for free download from <http://www.climond.org>.

#### CORRELATIVE MODELLING

When applied to a conservation biology scenario for *Banksia cuneata* using the correlative model MAXENT, the CliMond historical and Köppen–Geiger data sets (the latter to define the model background) produced results that matched the known distribution points well (Fig. 1) and had excellent predictive ability as measured by the area under the receiver operator characteristic curve for the test model (AUC = 0.952). Within the region of projection interpolation (i.e. areas with a positive MESS map value; MESS+; Fig. 1c), two other regions of climatic suitability were identified as follows: one around Koorda, c. 150 km north of the known distribution, and one north of the Eyre Peninsula in South Australia. The former region appears biologically plausible as an area for searching for undiscovered populations or for carefully considered managed relocation. The latter region straddles the MESS+ region and a region of MESS- projection extrapolation (i.e. outside of the range of climates in the training data set, with a negative MESS map value), indicating that additional caution is required when interpreting these projections. Given the open-ended response curves that would influence the model in this region (Fig. S2), we suggest that the region of projected suitable climatic on the Eyre Peninsula needs further research before it could be considered as a possible site for managed relocation.

For correlative species distribution models, the 10' climatology affords the modeller the opportunity to identify marginally climatically suitable locations and appears to support model projections that are ecologically meaningful (Fig. 1). Following the method outlined by Webber *et al.* (2011), the Köppen–Geiger data sets are intended to be used to assist modellers to define the background landscape or pseudo-absences for species distribution models. The definition of the background



**Fig. 1.** Climate suitability for *Banksia cuneata* modelled using MAXENT with the CliMond hybrid historical data set 10' grid showing (a) Köppen–Geiger classes (see Fig. 2 for class definitions) and the distribution data of known populations (red circles), (b) projected climatic suitability and (c) multivariate environmental similarity surface (MESS) maps and the background training domain (black outline) for the model. Blue MESS regions indicate positive values (i.e. climatic parameters within the bounds of the reference set), while the hashed overlay (b) or red MESS regions (c) indicate MESS- areas (i.e. at least one climatic parameter has a value outside the range of the reference set; novel projection climates).

as a means of identifying climatic regions that are ‘ecologically realistic’ or based on an ‘understanding of how far the focal species could have dispersed’. This data set is also suitable for use as a basis for an initial assessment of climate similarity, and by inference, pest risk.

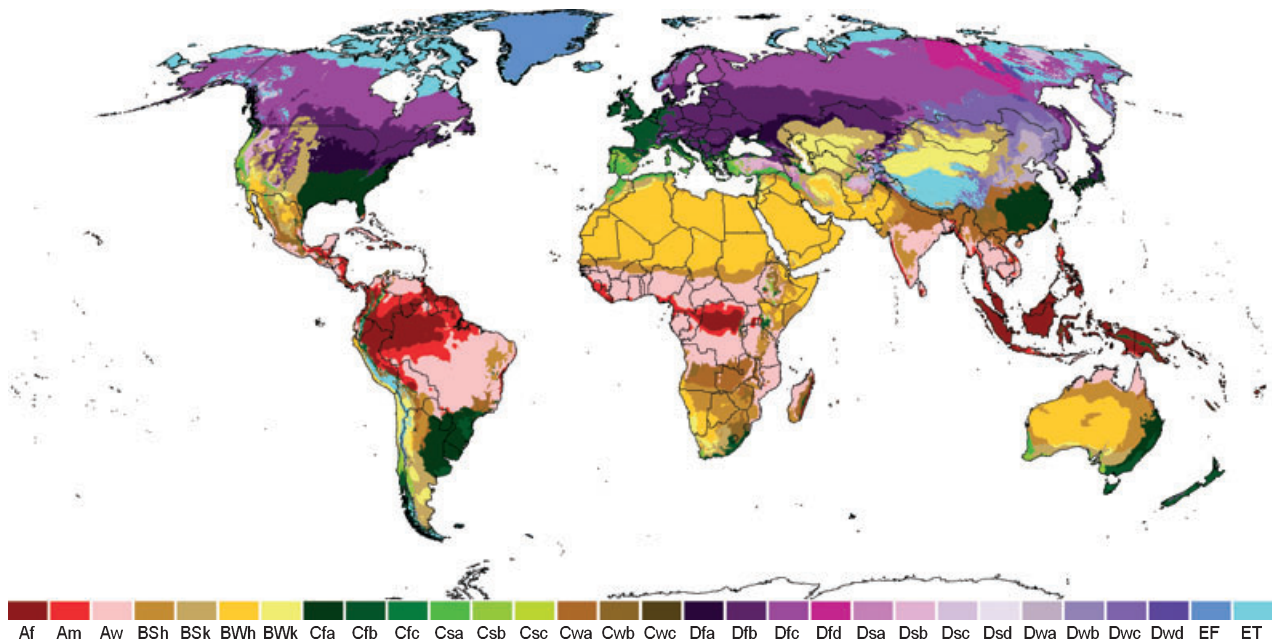
#### MECHANISTIC NICHE MODELLING

When applied in an invasion ecology setting using the CLIMEX mechanistic niche model, the CliMond data for historical and future climate scenarios performed in a robust manner. Models for serrated tussock, *Nassella trichotoma*, (Fig. 3) and the bovine tick, *Rhipicephalus microplus*, (Fig. 4) projected at a world scale using the 10' CliMond historical data set, produced finer scale, but broadly similar results to the 30' historical data set for each species (see Supporting information for CLIMEX parameters, Sutherst & Maywald 1985; Kriticos *et al.* 2004). The two examples demonstrate the CliMond data applicability in both tropical and temperate environments. Both are a considerable advance over the distribution determined by climate stations (Figs 3a and 4a), enabling model projections into areas where stations are lacking (compare inserts in Figs 3 and 4). Moreover, the finer resolution of 10' captures some of the subtlety in the station data while maintaining the overall pattern of the 30' analysis. Both models show broadly consistent trends expected with climate change (Figs 3d and 4d), that is, poleward movement for projected future climatic suitability relative to the historical distribution, demonstrating the potential for CliMond for use in climate change scenario analyses. For mechanistic niche modelling, the 10' climate data sets afford the CLIMEX modeller more precision in fitting points than the previously available 30' data set from the CRU (565 801 vs. 67 420 points). CliMond represents the first freely available future climate scenarios available in CLIMEX format, and the historical data set represents an improvement in quality over the 10' CRU CL2.0 data set distributed previously with CLIMEX.

#### LIMITATIONS IN CURRENT AND FUTURE GLOBAL CLIMATOLOGIES

In developing the CliMond data sets, we have identified five areas where modellers need to be aware of data limitations or where further data development is required. Firstly, when fitting models to climatological data, the spatial precision of the

for MAXENT and absences for models such as ENFA and generalized linear models is a highly sensitive and arbitrary process (VanDerWal *et al.* 2009; Elith *et al.* 2011). Following the guidelines of Elith *et al.* (2011) for defining a background for MAXENT, we provide the Köppen–Geiger data set (Fig. 2)



**Fig. 2.** Köppen–Geiger classification of CliMond hybrid historical data set 10' grid. See Köppen (1936) for a detailed account of each class. A high-resolution image of this figure is available for separate download in the Supporting information.

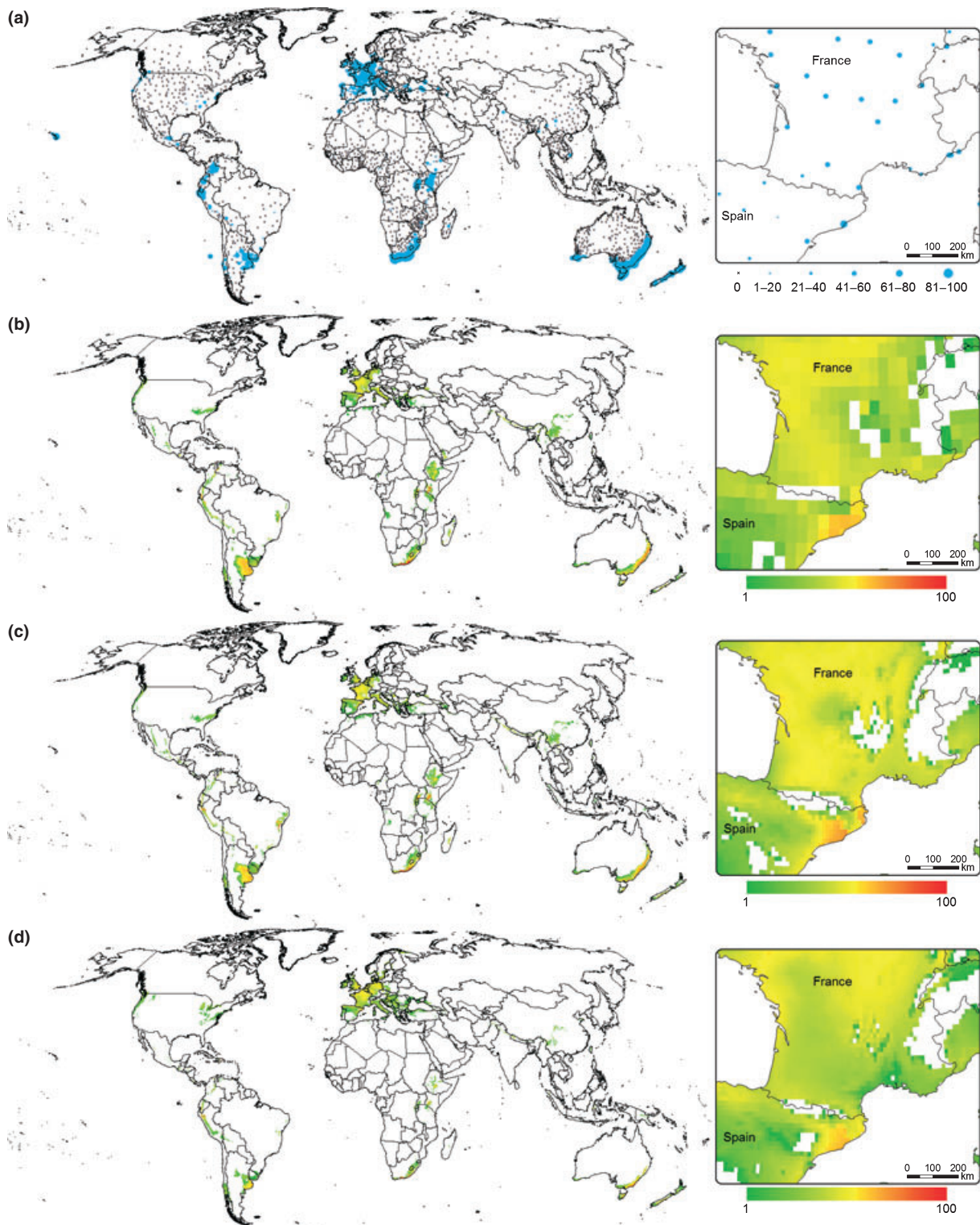
data can affect the model parameterization, as can the source and treatment of the foundation climatological data (Kriticos & Leriche 2010). For CLIMEX models, this will affect the stress parameters, which are closely related to the geographic range of the species. In contrast, the fitted growth parameters, which are best informed by phenological observations or observed responses to climate variables, are relatively immune to the source of climatological data. The spatial pattern of the calculated annual growth index ( $GI_A$ ) will likely be relatively unaffected by the spatial precision of meteorological data.

Secondly, we recognize that the 10' and 30' data sets presented here have slightly different derivations. Any comparison between models run with these two data sets may include undesirable artefacts because of inconsistencies between the originating data sets. While these inconsistencies indicate a degree of uncertainty in these data sets, they are an undesirable feature for many applications. To avoid these problems, a 30' data set derived by resampling the 10' climatology is presently being developed.

Thirdly, for both correlative species distribution and mechanistic niche modelling, it is important that the climatological data are concurrent with the species geographical distribution data used to fit the models. A cardinal assumption of correlative modelling is that the species is at equilibrium with its climatic environment (Panetta & Mitchell 1991). Under a rapidly changing climate regime, such as with anthropogenic climate change, it will be necessary to update periodically the baseline climatology so that inductive models can more correctly infer climate suitability from species distribution records in areas of recent range expansion. Both the WorldClim and CRU (and, therefore, the CliMond) historical data sets are centred on 1975. Given the rate of increase in temperatures

since 1975 (Rahmstorf *et al.* 2007) and the observed shifts in species distributions (Parmesan *et al.* 1999), there is clearly a pressing need to update global climatologies to support operational and scientific research for both biosecurity and conservation biology purposes.

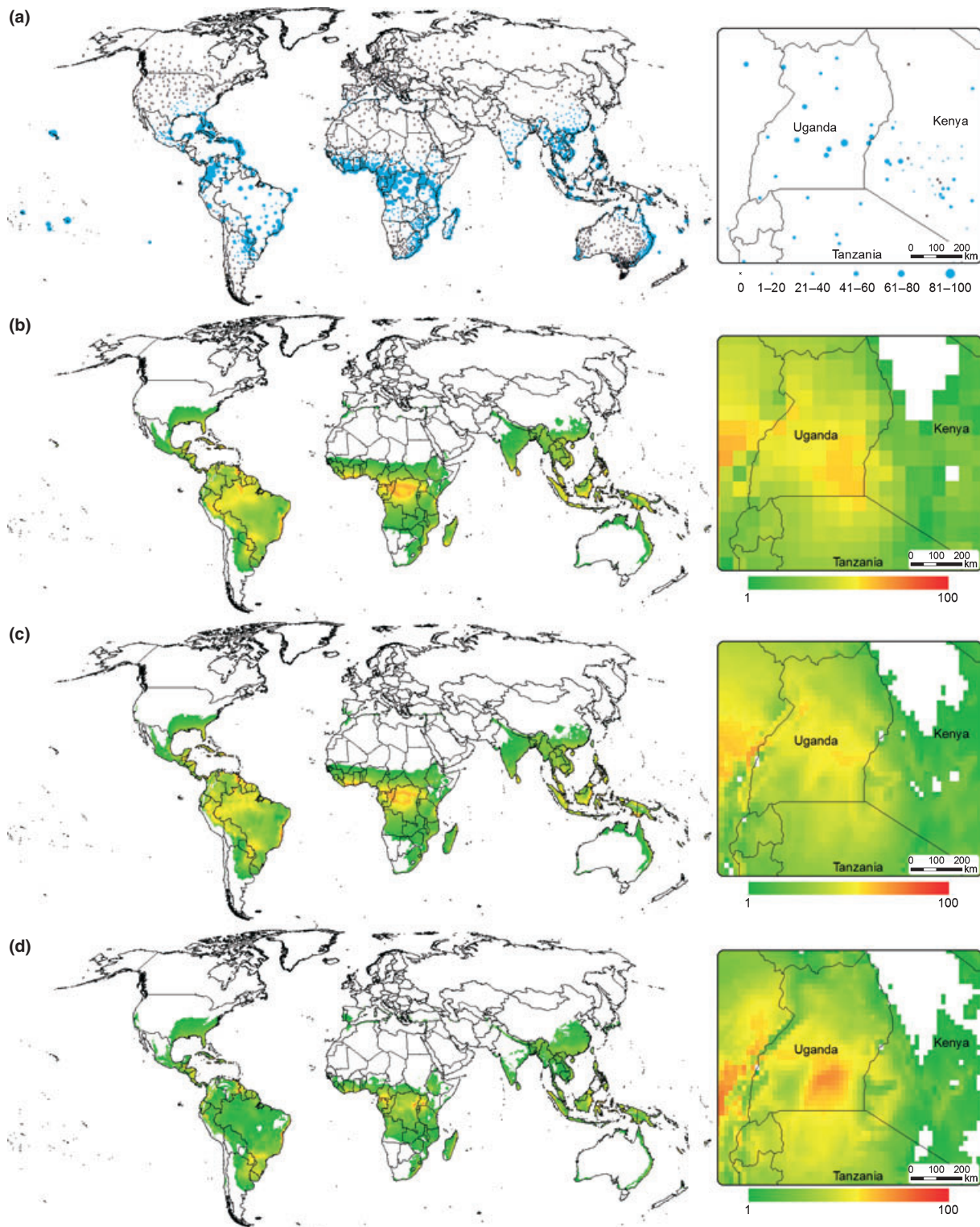
Fourthly, the utility of climate data sets at a finer resolution than 30' has been questioned as being excessively precise (New, Hulme, & Jones 1999; Daly 2006). While we are sympathetic to this caution, it is clear that the added precision in moving from 30' to 10' is capable of highlighting areas of limited extent with interesting pest threat or conservation values, particularly where they fall in regions of dissected topography (Kriticos & Leriche 2010). Such geographic outliers can often be inordinately important in both conservation biology and biosecurity domains. Although the notion of applying data from a modelled future climate scenario to a potentially excessively precise climatology may seem like adding another floor onto a house of cards, it is nonetheless operationally attractive. The widespread popularity of the WorldClim data set at both 10' and 30'' resolutions indicates that despite cautions regarding excessive precision, and the tendency to equate resolution with realism (Daly 2006), these data sets are being widely employed. Similarly, applications of the future climate scenarios are also popular in the recent literature. Perhaps, a logical compromise is to develop a bioclimatic model using a fine-scale grid and then aggregate the results to a coarser grid that better represents the spatial accuracy of the data using a suitable method, such as the maximum climate suitability value of the finer-scale cells or an area-weighted mean. In topographically dissected regions that are marginally suitable, this method could identify risks that might otherwise be overlooked using only a coarse spatial data set and yet not indicate the location of that risk in an excessively precise manner.



**Fig. 3.** Climate suitability for *Nassella trichotoma* modelled with CLIMEX using (a) CLIMEX FAO-derived station data, (b) CRU 1961–1990 30' climate grid (New, Hulme, & Jones 1999), (c) CliMond hybrid historical 10' grid data set, (d) CliMond hybrid historical data set modified using data from the CSIRO Mk 3 global climate model (GCM) running the A2 SRES emission scenario and pattern-scaled to 2080. A high-resolution image of this figure is available for separate download in the Supporting information.

Lastly, there is significant uncertainty regarding the future climate scenarios (Moss & Schneider 2000). The bioclimatic modelling results for future climates illustrated here can be used in conjunction with the results for the recent period as indicat-

ing the possible direction and magnitude of changes in climatic suitability to be expected sometime this century or the next. The uncertainties in future climate change arise through uncertainties associated with future greenhouse gas and sulphate aer-



**Fig. 4.** Climate suitability for *Rhipicephalus microplus* modelled with CLIMEX using (a) CLIMEX FAO-derived station data, (b) CRU 1961–1990 30' climate grid (New, Hulme, & Jones 1999), (c) CliMond hybrid historical 10' grid data set, (d) CliMond hybrid historical data set modified using data from the CSIRO Mk 3 global climate model (GCM) running the A2 SRES emission scenario and pattern-scaled to 2080. A high-resolution image of this figure is available for separate download in the Supporting information.

osol emissions, the sensitivity of the global mean temperature to these emissions and the response of local climate conditions to global warming. While our inclusion in CliMond of data from two GCMs goes a very small way to sampling the latter

source of uncertainty, and the inclusion of data for both the SRES A1B and A2 scenarios partially samples the uncertainty associated with future emissions, we have not attempted to explore all types of uncertainty in their entirety. The included

data should be interpreted as describing a small number of future climate scenarios that lie within a population of plausible scenarios not described by the data set. However, the methodology described by this paper could, in principle, be employed to add more scenarios to the CliMond data set based on different emission scenarios, global warming estimates or GCMs.

## Conclusion

The hybrid CliMond data set represents an improvement on existing global climate data sets available for bioclimatic modelling. It is a pragmatic compromise that addresses some of the deficiencies in the currently available products. It is neither the finest resolution data set available (WorldClim) nor does it include the most primary variables (CRU CL2.0). However, it does include the most Bioclim variables, and because the baseline data and future climate scenarios in CliMond share a conformational spatial and climatological framework, their combined use is made far easier and more reproducible because of consistent downscaling of the GCM data. By creating a global climatological data set featuring the extended set of 35 derived Bioclim variables, we are increasing the options for correlative modellers to identify range-limiting variables that are more relevant to organisms that are limited by radiation or moisture availability (e.g. plants). By building the CLIMEX-formatted data based on exactly the same climatology as the Bioclim variables, we have removed one impediment to model intercomparisons between correlative species distribution models on the one hand and CLIMEX mechanistic niche models on the other (e.g. Webber *et al.* 2011). Bioclimatic species models have become an essential tool for answering many questions concerning conservation biology and invasion ecology in a rapidly changing global environment. The CliMond data set has the capacity to provide core functionality to a broad range of these models.

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## References

Allen, R.G., Pereira, L.S., Raes, D. & Smith, M. (1998) *Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements*. FAO, Rome, 300 pp.

Andrewartha, H.G. & Birch, L.C. (1984) *The Ecological Web: More on the Distribution and Abundance of Animals*. University of Chicago Press, Chicago.

Baker, R.H.A., Sansford, C.E., Jarvis, C.H., Cannon, R.J.C., MacLeod, A. & Walters, K.F.A. (2000) The role of climatic mapping in predicting the potential geographical distribution of non-indigenous pests under current and future climates. *Agriculture, Ecosystems and Environment*, **82**, 57–71.

Booth, T.H., Nix, H.A., Hutchinson, M.F. & Busby, J.R. (1987) Grid Matching: a new method for homoclimate analysis. *Agricultural and Forest Meteorology*, **39**, 241–255.

Broadhurst, L.M. & Coates, D.J. (2004) Genetic divergence among and diversity within two rare *Banksia* species and their common close relative in the subgenus *Isostylis* R.Br. (Proteaceae). *Conservation Genetics*, **5**, 837–846.

Busby, J.R. (1991) BIOCLIM - a bioclimatic analysis and prediction tool. *Plant Protection Quarterly*, **6**, 8–9.

Chefaoui, R.M., Hortal, J. & Lobo, J.M. (2005) Potential distribution modelling, niche characterization and conservation status assessment using GIS tools: a case study of Iberian *Copris* species. *Biological Conservation*, **122**, 327–338.

Chefaoui, R.M. & Lobo, J.M. (2008) Assessing the effects of pseudo-absences on predictive distribution model performance. *Ecological Modelling*, **210**, 478–486.

Daly, C. (2006) Guidelines for assessing the suitability of spatial climate data sets. *International Journal of Climatology*, **26**, 707–721.

Department of Environment and Conservation (2007–2011) *NatureMap: Mapping Western Australia's Biodiversity*. Department of Environment and Conservation, Western Australia.

Elith, J., Kearney, M. & Phillips, S. (2010) The art of modelling range-shifting species. *Methods in Ecology and Evolution*, **1**, 330–342.

Elith, J., Phillips, S.J., Hastie, T., Dudik, M., Chee, Y.E. & Yates, C.J. (2011) A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions*, **17**, 43–57.

Fitzpatrick, E.A. & Nix, H.A. (1970) The climatic factor in Australian grasslands. *Australian Grasslands* (ed R. Milton Moore), pp. 3–26. Australian National University Press, Canberra.

Graham, C.H., Ferrier, S., Huettman, F., Moritz, C. & Peterson, A.T. (2004) New developments in museum-based informatics and applications in biodiversity analysis. *Trends in Ecology & Evolution*, **19**, 497–503.

Guisan, A. & Thuiller, W. (2005) Predicting species distribution: offering more than simple habitat models. *Ecology Letters*, **8**, 993–1009.

Hennessy, K.J. & Colman, R. (2007) Global climate change projections. *Climate change in Australia - Technical Report 2007* (eds K.B. Pearce, P.N. Holper, M. Hopkins, W.J. Bouma, P.H. Whetton, K.J. Hennessy & S.B. Power), pp. 148. CSIRO, Melbourne, Australia.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G. & Jarvis, A. (2005) Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology*, **25**, 1965–1978.

Hutchinson, M.F. & Gessler, P.E. (1994) Splines - more than just a smooth interpolator. *Geoderma*, **62**, 45–67.

Hutchinson, M., Xu, T., Houlder, D., Nix, H. & McMahon, J. (2009) *ANUCLIM 6.0 User's Guide*. Australian National University, Fenner School of Environment and Society, Canberra.

IPCC (2007) Climate Change 2007: The Physical Science Basis. *Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (eds S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor & H.L. Miller), pp. 996. Cambridge University Press, Cambridge, UK and New York, NY, USA.

Julien, M.H., Skarratt, B. & Maywald, G.F. (1995) Potential geographical distribution of alligator weed and its biological control by *Agasicles hygrophila*. *Journal of Aquatic Plant Management*, **33**, 55–60.

Kearney, M., Phillips, B.L., Tracy, C.R., Christian, K.A., Betts, G. & Porter, W.P. (2008) Modelling species distributions without using species distributions: the cane toad in Australia under current and future climates. *Ecography*, **31**, 423–434.

Köppen, W.P. (1936) Das Geographische System der Klimate [The geographical system of the climate]. *Handbuch der Klimatologie* (eds W. Köppen & R. Geiger), pp. 44. Gebrüder Bornträger, Berlin.

Kottek, M., Grieser, J., Beck, C., Rudolf, B. & Rubel, F. (2006) World map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift*, **15**, 259–263.

Kriticos, D.J. & Leriche, A. (2010) The effects of spatial data precision on fitting and projecting species niche models. *Ecography*, **33**, 115–127.

Kriticos, D.J. & Randall, R.P. (2001) A comparison of systems to analyse potential weed distributions. *Weed Risk Assessment* (eds R.H. Groves, F.D. Panetta & J.G. Virtue), pp. 61–79. CSIRO Publishing, Melbourne, Australia.

Kriticos, D.J., Lamoureaux, S., Bourdôt, G.W. & Pettit, W. (2004) Nassella tussock: current and potential distributions in New Zealand. *New Zealand Plant Protection*, **57**, 81–88.

Kriticos, D.J., Potter, K.J., Alexander, N., Gibb, A.R. & Suckling, D.M. (2007) Using a pheromone lure survey to establish the native and potential distribution of an invasive lepidopteran, *Uraba lugens*. *Journal of Applied Ecology*, **44**, 853–863.

Lobo, J.M., Jiménez-Valverde, A. & Real, R. (2008) AUC: a misleading measure of the performance of predictive distribution models. *Global Ecology and Biogeography*, **17**, 145–151.

- Magarey, R.D., Sutton, T.B. & Thayer, C.L. (2005) A simple generic infection model for foliar fungal plant pathogens. *Phytopathology*, **95**, 92–100.
- Manning, M.R., Edmonds, J., Emori, S., Grubler, A., Hibbard, K., Joos, F., Kainuma, M., Keeling, R.F., Kram, T., Manning, A.C., Meinshausen, M., Moss, R., Nakicenovic, N., Riahi, K., Rose, S.K., Smith, S., Swart, R. & van Vuuren, D.P. (2010) Misrepresentation of the IPCC CO<sub>2</sub> emission scenarios. *Nature Geoscience*, **3**, 376–377.
- Maywald, G.F., Kriticos, D.J., Sutherst, R.W. & Bottomley, W. (2007) *Dymex Model Builder Version 3: User's Guide*. Hearne Publishing, Melbourne.
- Meehl, G.A., Covey, C., Delworth, T., Latif, M., McAvaney, B., Mitchell, J.F.B., Stouffer, R.J. & Taylor, K.E. (2007) The WCRP CMIP3 multimodel dataset: a new era in climate change research. *Bulletin of the American Meteorological Society*, **88**, 1383–1394.
- Mitchell, T.D., Carter, T.R., Jones, P.D., Hulme, M. & New, M. (2004) *A comprehensive set of climate scenarios for Europe and the globe: the observed record (1900–2000) and 16 scenarios (2000–2100)*. University of East Anglia, Norwich, UK, pp. 30.
- Moss, R.H. & Schneider, S.H. (2000) Uncertainties in the IPCC TAR: recommendations to lead authors for more consistent assessment and reporting. *Guidance Papers on the Cross Cutting Issues of the Third Assessment Report of the IPCC* (eds R. Pachauri, T. Taniguchi & K. Tanaka), pp. 33–51. World Meteorological Organization, Geneva.
- Nakićenović, N. & Swart, R. (2000) *Special Report on Emissions Scenarios. A Special Report of Working Group III of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge and New York, USA.
- New, M., Hulme, M. & Jones, P. (1999) Representing twentieth-century space-time climate variability. Part I: Development of a 1961–90 mean monthly terrestrial climatology. *Journal of Climate*, **12**, 829–856.
- New, M., Lister, D., Hulme, M. & Makin, I. (2002) A high-resolution data set of surface climate over global land areas. *Climate Research*, **21**, 1–25.
- NGDC (2000) *Global Land One-kilometer Base Elevation (GLOBE) Digital Elevation Data: Version 1.0*. URL: <http://www.ngdc.noaa.gov/mgg/topo/globe.html>.
- Panetta, F.D. & Mitchell, N.D. (1991) Homocline analysis and the prediction of weediness. *Weed Research*, **31**, 273–284.
- Parnesan, C., Ryrholm, N., Stefanescu, C., Hill, J.K., Thomas, C.D., Descimon, H., Huntley, B., Kaila, L., Kullberg, J., Tammaru, T., Tennent, W.J., Thomas, J.A. & Warren, M. (1999) Poleward shifts in geographical ranges of butterfly species associated with regional warming. *Nature*, **399**, 579–583.
- Peel, M.C., Finlayson, B. & McMahon, T. (2007) Updated world map of the Köppen–Geiger climate classification. *Hydrology and Earth System Sciences*, **11**, 1633–1644.
- Phillips, S.J. & Dudík, M. (2008) Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. *Ecography*, **31**, 161–175.
- Rahmstorf, S., Cazenave, A., Church, J.A., Hansen, J.E., Keeling, R.F., Parker, D.E. & Somerville, R.C.J. (2007) Recent climate observations compared to projections. *Science*, **316**, 709.
- Randall, D.A., Wood, R.A., Bony, S., Colman, R., Fichefet, T., Fyfe, J., Kattsov, V., Pitman, A., Shukla, J., Srinivasan, J., Stouffer, R.J., Sumi, A. & Taylor, K.E. (2007) Climate models and their evaluation. *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (eds S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor & H.L. Miller), pp. 590–662. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- Robertson, M.P., Kriticos, D.J. & Zachariades, C. (2008) Climate matching techniques to narrow the search for biological control agents. *Biological Control*, **46**, 442–452.
- Rosenberg, N.J., Bland, B.L. & Verma, S.B. (1990) *Microclimate*. John Wiley & Sons, New York.
- Russell, R.J. (1931) Dry climates of the United States: I climatic map. *University of California, Publications in Geography*, **5**, 1–41.
- Sutherst, R.W. & Bourne, A.S. (2009) Modelling non-equilibrium distributions of invasive species: a tale of two modelling paradigms. *Biological Invasions*, **11**, 1231–1237.
- Sutherst, R.W. & Maywald, G.F. (1985) A computerised system for matching climates in ecology. *Agriculture, Ecosystems and Environment*, **13**, 281–299.
- Sutherst, R.W., Maywald, G.F. & Kriticos, D.J. (2007) *CLIMEX Version 3: User's Guide*. Hearne Scientific Software Pty Ltd, <http://www.Hearne.com.au>.
- Unwin, D.M. (1980) *Microclimate Measurement for Ecologists*. Academic Press, London.
- Vaclavik, T. & Meentemeyer, R.K. (2009) Invasive species distribution modeling (iSDM): are absence data and dispersal constraints needed to predict actual distributions? *Ecological Modelling*, **220**, 3248–3258.
- VanDerWal, J., Shoo, L.P., Graham, C. & Williams, S.E. (2009) Selecting pseudo-absence data for presence-only distribution modeling: how far should you stray from what you know? *Ecological Modelling*, **220**, 589–594.
- Venette, R.C., Kriticos, D.J., Magarey, R., Koch, F., Baker, R.H.A., Worner, S., Gómez, N.N., McKenney, D., Dobsberger, E., Yemshanov, D., De Barro, P., Hutchison, W.D., Fowler, G., Kalaris, T. & Pedlar, J. (2010) Pest risk maps for invasive alien species: a roadmap for improvement. *BioScience*, **80**, 349–362.
- von Walter, H.B. & Leith, H. (1960) *Klimadiagramm-Weltatlas*. VEB Gustav Fischer Verlag, Jena.
- Webber, B.L., Yates, C.J., Le Maitre, D.C., Scott, J.K., Kriticos, D.J., Ota, N., McNeill, A., Le Roux, J.J. & Midgley, G.F. (2011) Modelling horses for novel climate courses: insights from projecting potential distributions of native and alien Australian acacias with correlative and mechanistic models. *Diversity and Distributions*. DOI: 10.1111/j.1472-4642.2011.00811.x.
- Whetton, P.H., McInnes, K.L., Jones, R.N., Hennessy, K.J., Suppiah, R., Page, C.M., Bathols, J.M. & Durack, P. (2005) *Australian Climate Change Projections for Impact Assessment and Policy Application: A Review*. CSIRO Marine and Atmospheric Research, Melbourne, Australia, pp. 33.
- Wilcock, A.A. (1968) Köppen after fifty years. *Annals of the Association of American Geographers*, **58**, 12–28.
- Woodward, F.I. & Long, S.P. (1988) Temperature and the distribution of plant species. *Plants and Temperature, Symposium of the Society for Experimental Biology*. Company of Biologists, Cambridge.
- Yates, C.J., McNeill, A., Elith, J. & Midgley, G.F. (2010) Assessing the impacts of climate change and land transformation on *Banksia* in the South West Australian Floristic Region. *Diversity and Distributions*, **16**, 187–201.

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## Supporting Information

Additional Supporting Information may be found in the online version of this article.

**Appendix S1.** Worked example of calculating relative humidity estimates for the 10' hybrid dataset.

**Fig. S1.** Locations of grid cells in the CSIRO Mk3 global climate model dataset where precipitation values were given 'no data' values of 1e9 for July (a), August (b) and September (c).

**Fig. S2.** Species response curves to Bioclim variables generated by correlative MAXENT modelling for *Banksia cuneata*.

**Table S1.** Description of Bioclim variables and an indication of the climate variables used in their calculation.

**Table S2.** CLIMEX Compare Locations model parameter values used in the niche models for *Nassella trichotoma* (Kriticos et al. 2004) and *Rhipicephalus microplus* (Sutherst & Bourne 2009).

**Table S3.** Technical terms defined.

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