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To Be Or Not to Be? Variable selection can change the projected fate of a threatened species under future climate

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Key words: *climate change, Maxent, restoration, species distribution models.*

Summary

Species distribution models (SDMs) are commonly used to project future changes in the geographic ranges of species, to estimate extinction rates and to plan biodiversity conservation. However, these models can produce a range of results depending on how they are parameterized, and over-reliance on a single model may lead to overconfidence in maps of future distributions. The choice of predictor variable can have a greater influence on projected future habitat than the range of climate models used. We demonstrate this in the case of the Ptunarra Brown Butterfly, a species listed as vulnerable in Tasmania, Australia. We use the Maxent model to develop future projections for this species based on three variable sets; all 35 commonly used so-called 'bioclimatic' variables, a subset of these based on expert knowledge, and a set of monthly climate variables relevant to the species' primary activity period. We used a dynamically downscaled regional climate model based on three global climate models. Depending on the choice of variable set, the species is projected either to experience very little contraction of habitat or to come close to extinction by the end of the century due to lack of suitable climate. The different conclusions could have important consequences for conservation planning and management, including the perceived viability of habitat restoration. The output of SDMs should therefore be used to define the range of possible trajectories a species may be on, and ongoing monitoring used to inform management as changes occur.

Introduction

Species distribution models (SDMs) are one of the most important tools currently available to assess the potential impacts of climate change on species (Wiens *et al.* 2009). They enable changes in the climatic suitability of habitat over time to be mapped, identifying areas of future vulnerability, restrictions or shifts in the distribution of species. These maps provide a basis for species recovery plans, among other management actions needed to aid the recovery of a species listed as threatened.

Correlative SDMs are based on the statistical relationship between environmental or climatic variables and the current, observed distribution of a species. Assuming that this relationship remains unchanged, the future distribution of the species can then be projected to future climatic conditions. When applied in this way, however, the models are projecting to unsampled and potentially novel future climates. There is therefore no way to validate or refute these projections, yet planners and land managers are dependent on such models to inform decisions about ongoing conservation.

Several studies have assessed the uncertainty associated with SDMs under future climate conditions and have shown that the results can be affected by the climatic variables used to define the current climatic envelope (Beaumont *et al.* 2005; Austin & Van Niel 2011; Synes & Osborne 2011) as well as the climate model or emissions scenario used (Bradley & Wilcove 2009; Bradley *et al.* 2009).

The objective of this article is to illustrate the importance of variable selection when developing models of future species distributions, and the implications for conservation planning and management. We use an example from Tasmania, the Ptunarra Brown Butterfly (*Oreixenica ptunarra*), which is listed as vulnerable under the Tasmanian Threatened Species Protection Act 1995. Habitat restoration and translocation of butterflies have been identified as potential management options in previous recovery plans for the Ptunarra Brown Butterfly (Bell 1999). The location of translocated populations should be informed by maps of future climatic conditions, because colony establishment and persistence will depend on the suitability of the climate, and boosting population numbers in habitat that is projected to become climatically unsuitable in future may not be considered feasible.

Methods

The Maxent model (Phillips *et al.* 2006) was used to project the distribution of suitable climate for the Ptunarra Brown Butterfly under current and future climate conditions. We used Maxent because it is widely used in government agencies and universities, and has been shown to perform well in comparison with several other models (Elith & Leathwick 2009). Presence data were downloaded from the online database Atlas of Living Australia (http://collections.ala.org.au/), and 212 unique observations from 1950s to 2007 were used.

Current climate surfaces (1976–2005) were obtained from ANUCLIM version 6.1 (Xu & Hutchinson 2011), based on the 0.01° (~1 km) Digital Elevation Model for Australia (Hutchinson *et al.* 2008). Climate change grids for T_{max}, T_{min}, precipitation and pan evaporation were calculated relative to the ANUCLIM baseline, for the future period 2070–2099, under the A2 emissions scenario, based on the output of three dynamically downscaled climate models (ECHAM5/MPI-OM, GFDL-CM2.0 and MIROC3.2 (medres)). Downscaling was carried out by the Climate Futures for Tasmania project using CSIRO's Conformal Cubic Atmospheric Model (CCAM). Details of the modelling can be found in Corney *et al.* (2010), and the modelled projections are available through the Tasmanian Partnership for Advanced Computing (TPAC) portal (https://dl.tpac.org.au/tpacportal/). ANUCLIM was used to generate monthly mean data and the 35 commonly used bioclimatic variables at finer scale resolution for the current and future periods.

Three Maxent models were run based on different sets of predictor variables:

1. Model 1: monthly climate variables, chosen to reflect biologically important climatic conditions during the active period of the adult stage, as well as changes in annual conditions: March minimum temperature; April minimum temperature; Annual minimum temperature; Radiation with Rainfall April; and Annual Rainfall.
2. Model 2: all bioclimatic variables (see Table 1 for list).
3. Model 3: a subset of bioclimatic variables, chosen based on knowledge of the species' life cycle: Minimum Temperature of Coldest Period, Mean Temperature of Driest Quarter; and Radiation of Coldest Quarter.

Table 1. **The 35 bioclimatic variables commonly used in species distribution modelling**

BIO1	Annual Mean Temperature
BIO2	Mean Diurnal Range (Mean(period max–min))
BIO3*	Isothermality (BIO2/BIO7)
BIO4	Temperature Seasonality (ANUCLIM Coefficient of Variation; BIOCLIM standard deviation)
BIO5	Max Temperature of Warmest Period
BIO6	Min Temperature of Coldest Period
BIO7	Temperature Annual Range (BIO5-BIO6)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO10	Mean Temperature of Warmest Quarter
BIO11	Mean Temperature of Coldest Quarter
BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Period
BIO14	Precipitation of Driest Period
BIO15	Precipitation Seasonality(Coefficient of Variation)
BIO16	Precipitation of Wettest Quarter
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter
BIO20	Annual Mean Radiation
BIO21	Highest Period Radiation
BIO22	Lowest Period Radiation
BIO23	Radiation Seasonality (Coefficient of Variation)
BIO24	Radiation of Wettest Quarter
BIO25	Radiation of Driest Quarter
BIO26	Radiation of Warmest Quarter
BIO27	Radiation of Coldest Quarter
BIO28	Annual Mean Moisture Index
BIO29	Highest Period Moisture Index
BIO30	Lowest Period Moisture Index
BIO31**	Moisture Index Seasonality (Coefficient of Variation)
BIO32	Mean Moisture Index of Highest Quarter MI
BIO33	Mean Moisture Index of Lowest Quarter MI
BIO34	Mean Moisture Index of Warmest Quarter
BIO35	Mean Moisture Index of Coldest Quarter

*Bio3 (isothermality) is the evenness of temperature over the course of a year, or a quantification of how large the day-to-night temperature oscillation is in comparison to the summer-to-winter oscillation. **Bio31, the coefficient of variation of the moisture index, was not used, because there was a large area in western Tasmania that could not be calculated due to standard deviation values of zero.

All three of these models are plausible models, typical of those commonly used to project future species distributions. We used the default values for all parameters (e.g. regularization) in Maxent, with fifteen replicate runs calculated by cross-validation. Model performance was assessed using the area under the receiver operating curve (AUC), the corrected Akaike information criteria (AICc) and the Bayesian information criteria (BIC), calculated using the program ENMTools (Warren *et al.* 2010). These tests can be used as an objective measure of model performance and provide some guidance where there are large differences between the models. The degree to which novel climate conditions are being encountered is assessed with the multivariate similarity surface (MESS) from Maxent. The MESS shows how similar each point is in future projections to conditions seen during model training.

Results

The projected fate of the species varies depending on which variable set is used as input to the species distribution model (Fig. 1). In one model (Model 3), the butterfly is projected to come close to extinction by the end of the century, while another model (Model 1) suggests that the butterfly may persist until the end of the century, with little contraction of climatically suitable habitat. The variability between Maxent output based on the different climate models is less than that due to different data models (i.e. variable choice) (Fig. 1).

Based on the statistical selection process, Model 3 (subset of bioclimatic variables) performed the best in terms of the AICc and BIC (4115.9 and 4296.4, respectively) but did not have the highest AUC score (0.947). Model 2 (all bioclimatic variables) had the highest AUC value (0.966), and better represented the current distribution (Fig. 1), but had values of AICc of 4568.3 and BIC of 4474.3. These higher values are likely a result of the large number of variables included, which can lead to overfitting of the model. Model 1 (monthly variables) had a slightly lower AICc value than Model 2, and a similar BIC value, but the lowest AUC (AICc = 4311.2; BIC = 4472.3; AUC = 0.938). However, this model had no negative values in the multivariate similarity surface (MESS), while Models 2 and 3 had substantial areas in which one or more environmental variables were outside the range present in the training data, suggesting that projections in those areas should be treated with caution.

The variables identified as important in determining the distribution were as follows:

1. Model 1: April minimum temperature (46%); Radiation with Rainfall April (22%); March minimum temperature (16%); Annual Rainfall (12%); Annual minimum temperature (4%).
2. Model 2: Mean Temperature of Driest Quarter (33%); Minimum Temperature of Coldest Period (28%); Radiation of Warmest Quarter (7.7%); Radiation Seasonality (7%); Highest Period Radiation (5%); Radiation of Coldest Quarter (3%).
3. Model 3: Mean Temperature of Driest Quarter (42%); Minimum Temperature of Coldest Period; and Radiation of Coldest Quarter (19%).

Discussion

The effective conservation of threatened and vulnerable species into the future requires some knowledge of where climatically suitable habitat is likely to persist under changing climatic conditions. However, species distribution models do not always deliver the level of certainty required to inform the ongoing management of populations and habitats. In the present example, a range of very different potential futures was produced, from near extinction to expansion of climatically suitable area, depending on the species distribution model used.

More uncertainty resulted from different variables being included in the SDM than the range in climate models, yet there is no objective method to determine which variables should be included in Maxent models. The initial choice of variable, in Maxent as well as other SDMs, is always to a certain extent subjective. Expert opinion may help in choosing the most relevant variables, but often very little biological information is known about the species. In these cases, there are a range of diagnostics available, including checking how well the current distribution is represented by the model, statistical assessment of model performance and considering the extent to which the model is attempting to project into novel climatic conditions. Statistical methods alone are not sufficient to accept or reject a model, because they provide an objective measure of internal model performance, not a measure of ecological validity. An accurate representation of the current distribution is also no guarantee that the future distribution will be accurate, because the relationship between the climatic variables and the distribution of the species may change.

Effective planning and conservation management within such uncertainty require ongoing monitoring of populations, to track changes as they occur, and adaptive management. Importantly, it requires an understanding of the SDMs. Rather than rejecting their application, the output of SDMs can be used to define the range of possible trajectories the species may be on. A range of species distribution models can be considered to represent the range of plausible outcomes, just as a range of climate models and emission scenarios represent the range of plausible climate futures.

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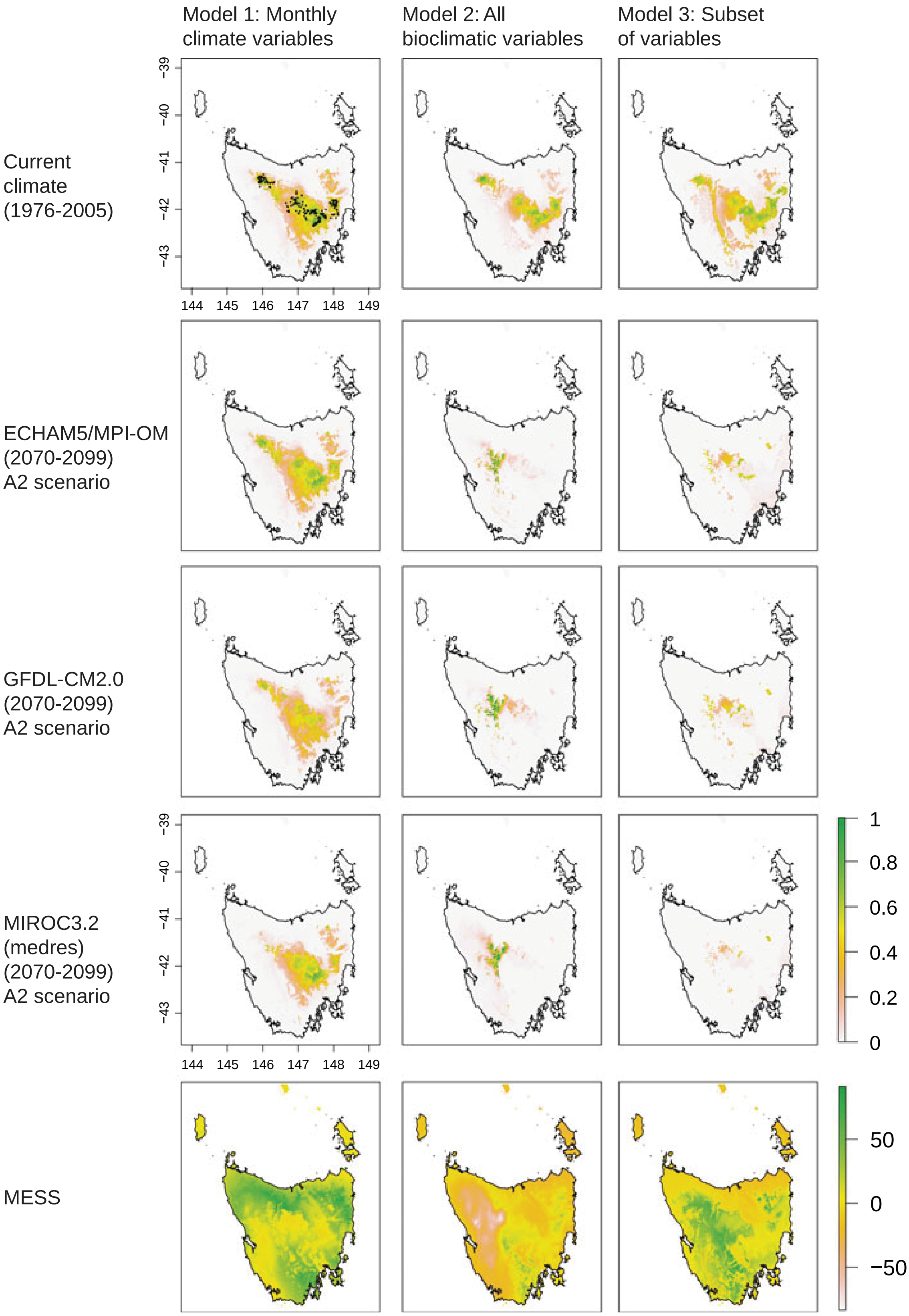

Figure 1. Probability of occurrence for the Ptunarra Brown Butterfly (1= highly suitable, 0= unsuitable), based on three different Maxent models. Current distribution map for Model 1 shows locality points (dots) from Atlas of Living Australia. MESS maps are given for one model (ECHAM5/MPI-OM). Negative values in the MESS maps indicate novel conditions.

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Monitoring *Epacris muelleri* on unreachable cliffs in the Western Blue Mountains, Australia

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Key words: *Blue Mountains, cliff survey, nonpermanent plots, observer bias, sample design.*

Summary

Accurate, repeatable estimates of population densities are often desired for vegetation monitoring. However, conventional transect and quadrat field sampling methods are not always applicable to plants such as the rare shrub *Epacris muelleri* Sond., growing on largely inaccessible cliffs and rock faces. *E. muelleri* is an ericaceous shrub restricted to the Blue Mountains region in New South Wales, which is to be monitored to detect potential effects of underground coal mining. In this manuscript, we evaluated observer error associated with density estimates to assess suitability of applying the timed-meander method to this species. The results indicate that a visual search method using binoculars can generate repeatable results among observers with very different experience levels. However, there is a large margin of error in estimating density when there are many plants growing in close association or overlapping on a cliff. Nonetheless, with a strict set of protocols and further evaluation, this method shows promise as a rapid yet robust method for carrying out repeatable surveys for quantifying changes in the population.

Introduction

Rare and threatened plant species are central to many long-term monitoring programs. However, rare species that are sparsely distributed or clumped across the landscape provide additional challenges to existing sampling approaches which are generally designed to detect common species (e.g. simple random sampling). Subsequently, numerous methods have been proposed to record data on exotic, rare or endangered plant species, such as strip adaptive clustering (Abrahamson *et al.* 2011), adaptive line transects (Pollard *et al.* 2002) and timed-meander (Goff *et al.* 1982). Nevertheless, current methods assume that individual plants are reachable. In this study, we tested whether a set of simple search protocols (underpinning the timed-meander method) could provide a feasible method to monitor the impacts of underground coal mining on *Epacris muelleri* growing on largely unreachable cliffs in the Western Blue Mountains, Australia. This could also be applied to longwall coal mining (a key threatening process in New South Wales; NSW Scientific Committee 2005), a widely used mining technique in other areas.

