

Supplementary material

Integrating rehabilitation, restoration and conservation for a sustainable jarrah forest future during climate disruption

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Maximum entropy modelling (Phillips *et al.* 2006) version 3.3.3 estimated current and future geographic distribution of *Eucalyptus marginata* and *E. diversicolor* (Fig. 1, main paper) by: (1) modelling climate envelopes for interpolated bioclimatic conditions representative of 1950–2000 (Hijmans *et al.* 2005); (2) projecting potential distributions in SWWA for projected 2070 climate under the IPCC RCP4.5 (Representative Concentration Pathway) climate change severity scenario (CSIRO Mk 3.6 global climate model: Jeffrey *et al.* 2013). Models used five biologically important climate variables (mean temperature wettest quarter, mean temperature warmest quarter, annual precipitation, precipitation seasonality, and precipitation warmest quarter) all at ~1 km resolution. Models had good predictive ability as estimated by area under curve (AUC) against test data (0.77–0.95). The predicted climatic suitability results are logistic suitability values (0–1). Annual precipitation and precipitation seasonality made the largest contributions for *E. marginata*; annual precipitation and precipitation of warmest quarter for *E. diversicolor*. During model generation, by default background environmental data are selected within whole study area extent and these values

compared with species occurrences to differentiate environmental conditions under which a species can potentially occur. We used background data constrained to bioregions in which the species were observed, plus a buffer zone of 50 km. To reduce sampling bias influence due to clusters of *E. marginata* observations near metropolitan Perth, contrasting with sparser sampling elsewhere, observations were spatially rarefied, such that occurrence points were reduced to a single record within a distance of 2 km (Boria *et al.* 2014). For all models generated, the following parameters were altered from default settings: maximum iterations = 5000 with 25% random test percentage and only linear feature types used during model training. Default values were used for remaining model parameters.

References

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