Ecography

E7085
Pollock, L. J., Morris, W. K. and Vesk, P. A. 2011. The role of functional traits in species distributions revealed through a hierarchical model. – Ecography 34: xxx–xxx.

Supplementary material

Appendix 1 List of *Eucalyptus* species in the Grampians National Park used and a description of environmental variables used in the model.

Code	N. plots	Taxon
ALA	44	*E. alaticaulis* Watson & Ladiges
ARE	43	*E. arenacea* Marginson & Ladiges
ARO	5	*E. aromaphloia* Pryor & J.H.Willis
BAX	173	*E. baxteri* (Benth.) Maiden & Blakely ex J. Black
CAM	37	*E. camaldulensis* Dehnh.
GON	48	*E. goniocalyx* F. Muell. ex Miq.
LEU	3	*E. leucoxylon* F. Muell.
MEL	173	*E. melliodora* Cunn. ex Schauer in W.G.Walpers
OBL	127	*E. obliqua* L'Hér.
OVA	37	*E. ovata* Labill.
PAU	4	*E. pauciflora* subsp. *parvifructa* Rule
RAD	20	*E. radiata* Sieber ex DC.
RUB	10	*E. rubida* Dean & Maiden
SAB	100	*E. sabulosa* K. Rule
SER	25	*E. serraensis* Ladiges & Whiffin
VER	20	*E. verrucata* Ladiges & Whiffin
VIC	11	*E. victoriana* Ladiges & Whiffin
VIM	13	*E. viminalis* subsp. *viminalis* Labill.
CYG	31	*E. viminalis* subsp. *cygnetensis* Boomsma
WIL	83	*E. willisii* subsp. *falciformis* Newnham, Ladiges & Whiffin

Variable	Range	Description
Rockiness	0-95%	Percent cover of rock estimated in 5% increments in field plots

Valley Bottom Flatness	0-6	GIS-derived variable defining flat areas relative to surroundings likely to accumulate sediment (units correspond to % slope e.g. 0.5 = 16% slope, 4.5 = 1% slope, 5.5 = 0.5% slope) (Gallant and Dowling 2003).
Annual Precipitation	555-1348 mm	Sum of monthly precipitation estimated using BIOCLIM based on 20m grid cell Digital Elevation Model (Houlder et al. 2000).
Temperature Seasonality (Coefficient of Variation)	0.136-0.158	Standard deviation of weekly mean temperatures as a percentage of the annual mean temperature from BIOCLIM (Houlder et al. 2000).
Solar Radiation	50-14000 WH/m^2	Amount of incident solar energy based on the visible sky and the sun's position. Derived from Digital Elevation Model in ArcGIS 9.2 Spatial Analyst for the summer solstice (December 22)
Sandiness	0 or 1	Based on soil texture classes from field plots (see Appendix 2)
Loaminess	0 or 1	Based on soil texture classes from field plots (see Appendix 2)

Gallant, J. C. and Dowling, T. I. 2003. A mutliresolution index of valley bottom flatness for mapping depositional areas. — Water Resources Research 39: 1347.

Houlder, D. J. et al. 2000. ANUCLIM User Guide, Version 5.1. Centre for Resource and Environmental Studies, Australian National University.

Appendix 2 Conversion from soil texture categories to 'sandiness' and 'loaminess'

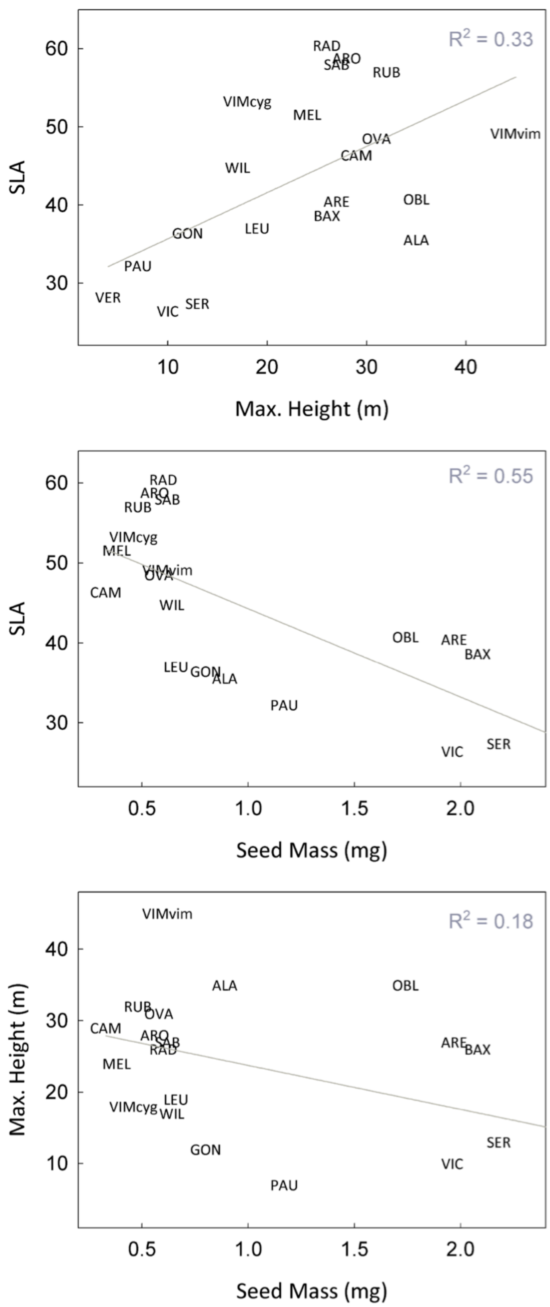
Step 1: We converted soil texture categories into 'sandiness' and 'loaminess' categories according to relative amounts of sand, silt, and clay particles (Table 1). Binary categories aggregate soil textures that have similar physical and chemical properties (water holding capacity, drainage, nutrient content etc.) important for plant growth. Overall, Grampians' soils are toward the sandy end of the spectrum.

Table 1. Representation with binary variables for each soil texture category.

Texture Category	Sandiness	Loaminess
sandy clay	0	0
sandy clay loam	0	0
clay loam	0	1
loam	0	1
silt loam	0	1
silty clay loam	0	1
sandy loam	1	0
loamy sand	1	0

Step 2: We built a boosted regression tree model for estimating 'sandiness' and 'loaminess' based on other environmental variables. We first modelled the probability of occurrence of 'sandiness' and 'loaminess' for each site using environmental variables likely to be associated with soil type such as radiometric data (Th, U, Th:1/K ratio, and total count), geology class, elevation, valley bottom flatness, and topographic wetness. We determined the optimal threshold of probability for predicting binary sandiness and loaminess correctly (i.e. we adjusted the threshold from a probability of 0.50 until the fewest number of incorrect matches between observed and modelled data was reached. The model predicted sandiness correctly for 88% of the sites and loaminess for 96% of the sites. We then used that threshold to assign sandy (1) or non-sandy (0) and loam (1) or non-loam (0) for each site with missing data values (29% of the total sites).

Appendix 3 Trait values for taxa used in the model (median SLA (cm^2/g), median seed mass, and maximum height). Lines are linear regressions on untransformed data and only for indicative purposes (see Appendix 1 for taxon names).



Appendix 4 R code

```
#REQUIRED PACKAGE
library(reshape)  #for melt function
library(lme4)   #for lmer fuction

#DATA

enviro <- read.csv("enviro.csv")   #file with each plot listed in rows and
environmental variable values and species presence/absence for each plot across
columns

traits <- read.csv("TraitsMedianValues.csv") #file with each species in rows
and trait values in columns

PA <- melt(enviro[-c(2:33)],id.vars="PLOTID") #extract presence absence data
colnames(PA)[2:3] <- c("TAXON","PRESENT")

model.data <- merge(PA,enviro[1:33],by='PLOTID',all.x=T)  #merge
presence/absences with environmental data

rm(PA)

model.data <- merge(model.data,traits,by='TAXON',all.x=T) #add species traits

model.covs <- data.frame(PRESENT=model.data$PRESENT,TAXON=model.data$TAXON) #
create dataframe with selected uncorrelated environmental variables

model.covs$Precip <- (log(model.data$PPTann)-
mean(log(model.data$PPTann)))/(2*sd(log(model.data$PPTann))) # Rescale
variables as necessary (e.g. Annual Precipitation logged and centered and
scaled)


order.scaledtraits <-
unique(model.covs[c(2,10:13)])[order(unique(model.covs[c(2)])),] #order scaled
traits
order.scaledtraits$TAXON <- as.character(order.scaledtraits$TAXON)

#MODEL
full.model <- lmer(PRESENT ~ Rock + VBF + Precip + TempVar + SolRad + Sand +
Loam +    #enviro variables
Seedmass:Rock + Seedmass:VBF + Seedmass:Precip + Seedmass:TempVar +
Seedmass:SolRad + Seedmass:Sand + Seedmass:Loam +    #correlation of responses
to traits
SLA:Rock + SLA:VBF + SLA:Precip + SLA:TempVar + SLA:SolRad + SLA:Sand +
SLA:Loam +
Ht:Rock + Ht:VBF + Ht:Precip + Ht:TempVar + Ht:SolRad + Ht:Sand + Ht:Loam +
(1 + Rock + VBF + Precip + TempVar + SolRad + Sand + Loam |TAXON),
#response to enviro variables allowed to vary by taxa
data= model.covs,family=binomial(link=logit),
control=list(maxIter=10000))
```