

Variable selection

Variable selection - general considerations

1. Ecological Framework / conceptual considerations

- What aspects of the environment should be important and why?
- Mechanistic explanation of predictors
- Direct vs. indirect
 - Avoid indirect unless:
 - study area is small
 - goal is a highly accurate model in that region only
 - No plans to project elsewhere

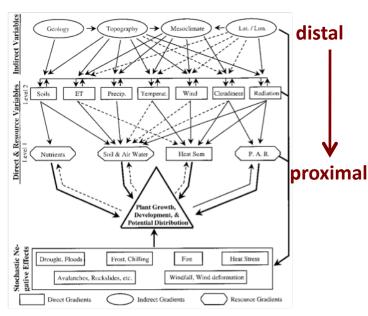


Fig. 3. Example of a conceptual model of relationships between resources, direct and indirect environmental gradients (see e.g. Austin and Smith, 1989), and their influence on growth, performance, and geographical distribution of vascular plants and vegetation.

Guisan & Zimmermann

Variable selection - general considerations

- Direct vs. indirect
 - Try to use direct, especially if:
 - Goal is to understand spatial patterns / drivers of distribution
 - Projecting to new places / times

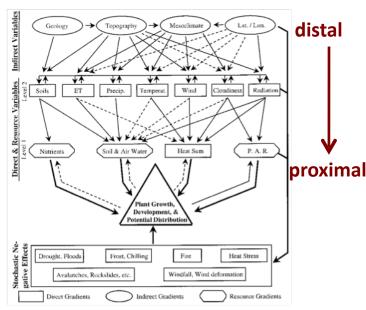


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Variable selection - general considerations

2. Data considerations

- Resolution and extent
 - What matches the occurrence data and the known distribution of the species?
 - Do not truncate using political boundaries
- Scope of available predictors

3. Model considerations

Categorical data?

Geology

Topography

Mesoclimate

Lat. / Lon.

distal

Plant Growth,

Development, &

Potential Distribution

Potential Distribution

Process

Avalanches, Rockslides, etc.

Windfall, Wind deformation

Direct Gradients

Indirect Gradients

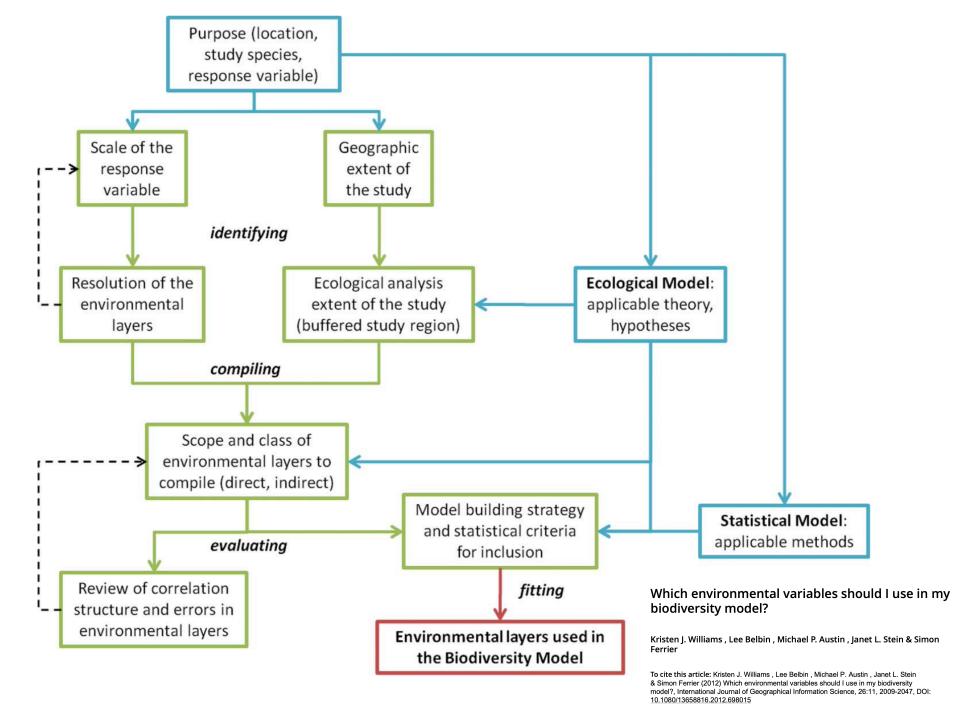
Resource Gradients

Fig. 3. Example of a conceptual model of relationships between resources, direct and indirect environmental gradients (see e.g. Austin and Smith, 1989), and their influence on growth, performance, and geographical distribution of vascular plants and vascular plants.

Guisan & Zimmermann

just because we can make a raster at a fine resolution, doesn't mean that it is accurate

categorical data will drive the algorithms available to you



- Highly correlated variables will cause problems
 - Statistical inference
 - Interpretation
- Climate variables tend to be highly correlated
- Need to assess issues and remove problematic variables

- 160 - 140 - 120 - 100 - 80 - 200 - 150 - 100 - 50 320 280 240 200 - 400 - 300 - 200 - 25 - 20 - 15 - 10 - 5

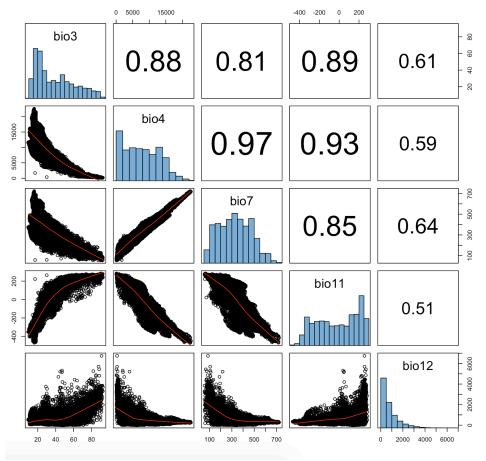
variance inflation factor used in the homework

- Visualization
 - Pairwise correlations / plots
 - ▶ Remove if >0.7-0.8
 - May hide hidden structure

pick the variable to keep that is physiologically easier to understand

'ecospat.cor.plot'

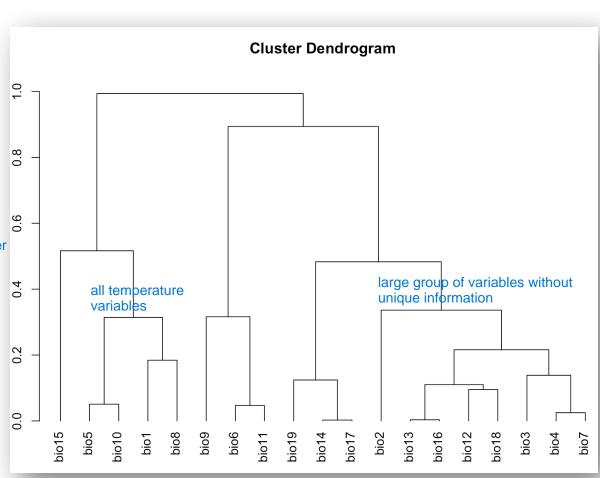
in ecospat package



this is a univariate comparison that only compares pairs of variables at a time univariate approaches can hide multicollinearity

- Visualization
 - Determine correlations
 - Cluster
 - Plot dendrogram

variables that tend to be correlated with one another tend to group



- Variance Inflation Factor(VIF) best way to do it
 - Measures extent to which variance in a regression increases due to collinearity compared to when uncorrelated variables are used
- Values > 10 (~20 maybe) problematic
- 'vif' and related commands in 'usdm' package

normally it's one variable that's multicollinear with all the other variables VIFStep goes through this process sequentially removing the variables eith

```
highest collinearity | library(usdm) | vif(data[,4:8]) | Variables | VIF | UIF | UIF
```

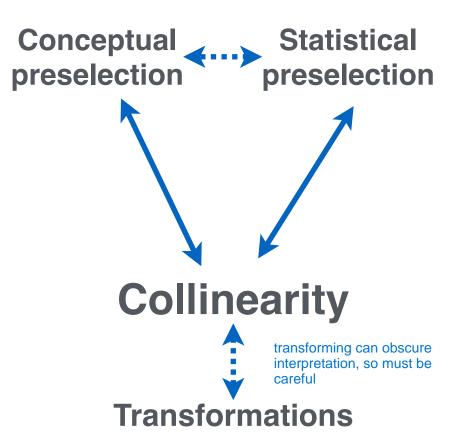
VIF score > 10 is problematic but can specify any variable

if using machine learning, these approaches are pretty insensitive to multicollinearity but the interpretation of importance is sensitive to multicollinearity

in machine learning, if you do a permutation test to see variable importance and which is driving the pattern, if there is collinearity the other variables will just stand in for the permuted variable, making it more difficult to see the impact of the permutation

Variable selection - summary

- Use conceptual preselection to the extent possible
 - What is important from:
 - Literature
 - Experiments
 - Expert knowledge
 - What can be removed from the outset as unimportant?
- Use statistical preselection
 - Methods like GBM
- Check correlations using VIF
- Blindly using all 19 bioclim variables not a good idea



Variable selection - summary

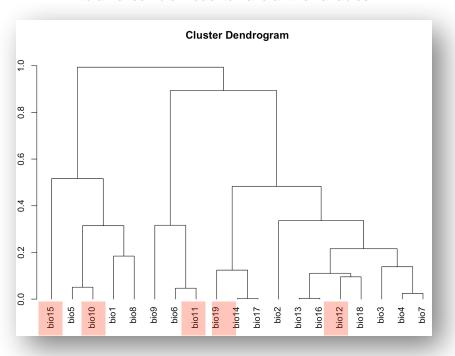
how many variables should you use for parametric models (ie. GLM, GAM)? You should have at least ten occurrence points per predictor variable -- this rule is not for machine learning: can use as many as you want

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ie if you have 20 points, only use 2 predictors

for rare species, people fit models with only 2-3 variables to avoid breaking the rule and then they combine the models into an ensemble model to have all the variables



Questions?