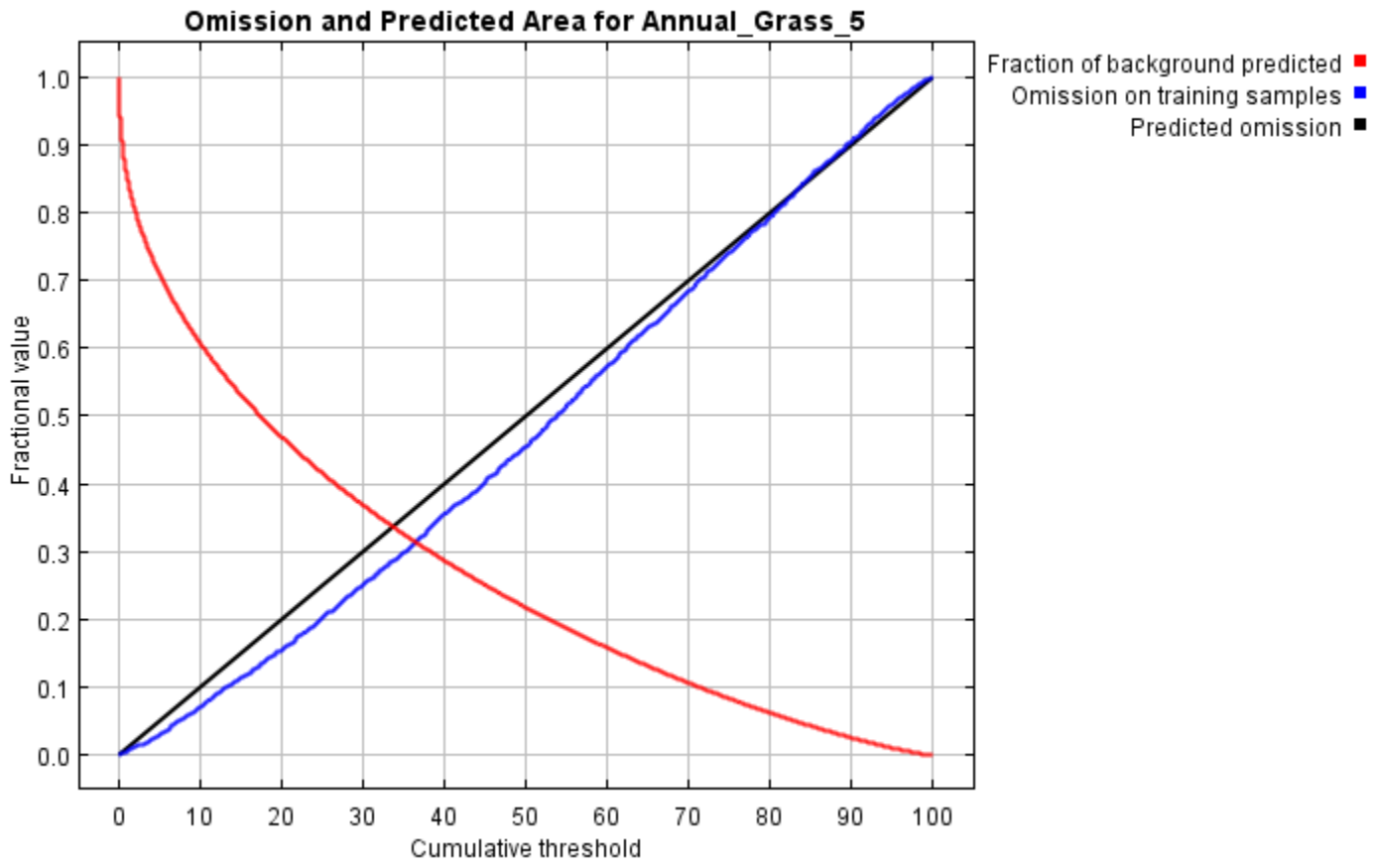
Maxent model for Annual_Grass_5

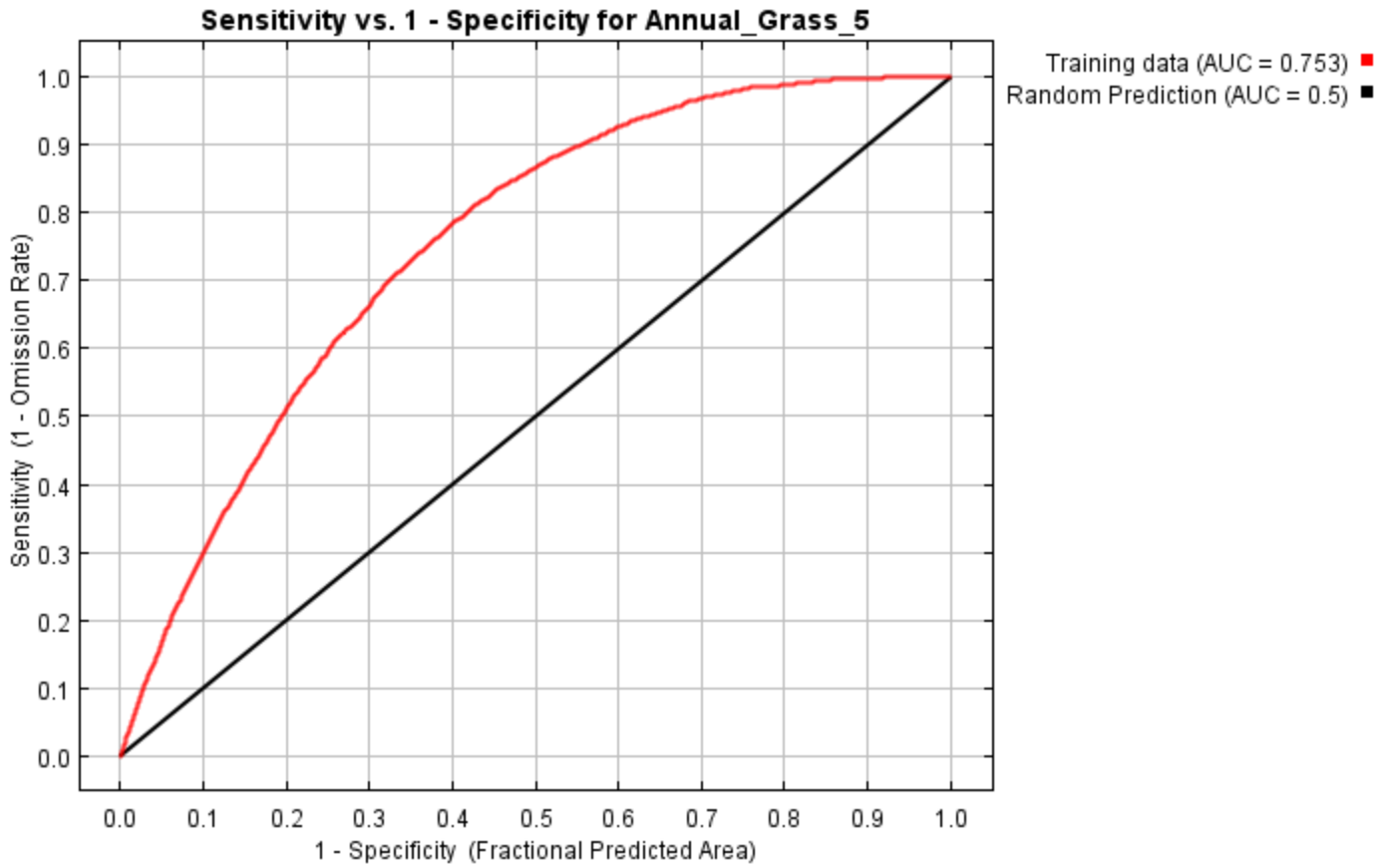
This page contains some analysis of the Maxent model for Annual_Grass_5, created Thu Aug 18 12:42:00 MDT 2011 using Maxent version 3.3.3e. If you would like to do further analyses, the raw data used here is linked to at the end of this page.

Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is is calculated both on the training presence records, and (if test data are used) on the test records. The omission rate should be close to the predicted omission, because of the definition of the cumulative threshold.



The next picture is the receiver operating characteristic (ROC) curve for the same data. Note that the specificity is defined using predicted area, rather than true commission (see the paper by Phillips, Anderson and Schapire cited on the help page for discussion of what this means). This implies that the maximum achievable AUC is less than 1. If test data is drawn from the Maxent distribution itself, then the maximum possible test AUC would be 0.729 rather than 1; in practice the test AUC may exceed this bound.



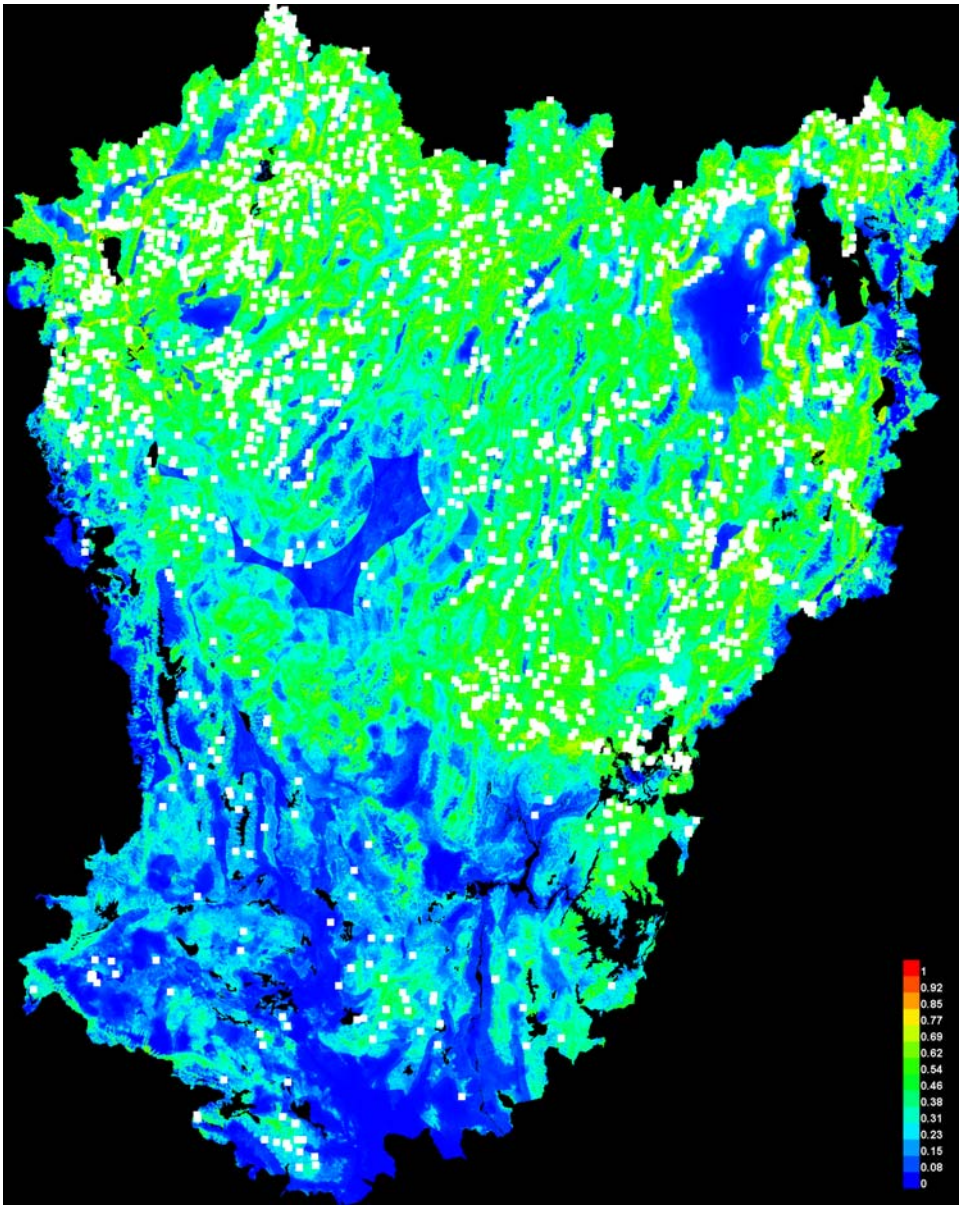
Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that test points are predicted no better than by a random prediction with the same fractional predicted area. The "Balance" threshold minimizes 6 * training omission rate + .04 * cumulative threshold + 1.6 * fractional predicted area.

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.101	Fixed cumulative value 1	0.852	0.007
5.000	0.220	Fixed cumulative value 5	0.709	0.031
10.000	0.291	Fixed cumulative value 10	0.607	0.072
0.006	0.007	Minimum training presence	0.982	0.000
13.082	0.323	10 percentile training presence	0.558	0.100
36.437	0.470	Equal training sensitivity and specificity	0.315	0.315
23.872	0.406	Maximum training sensitivity plus specificity	0.427	0.188
1.235	0.114	Balance training omission, predicted area and threshold value	0.838	0.007

5.256	0.224	Equate entropy of thresholded and original distributions	0.702	0.032

Pictures of the model

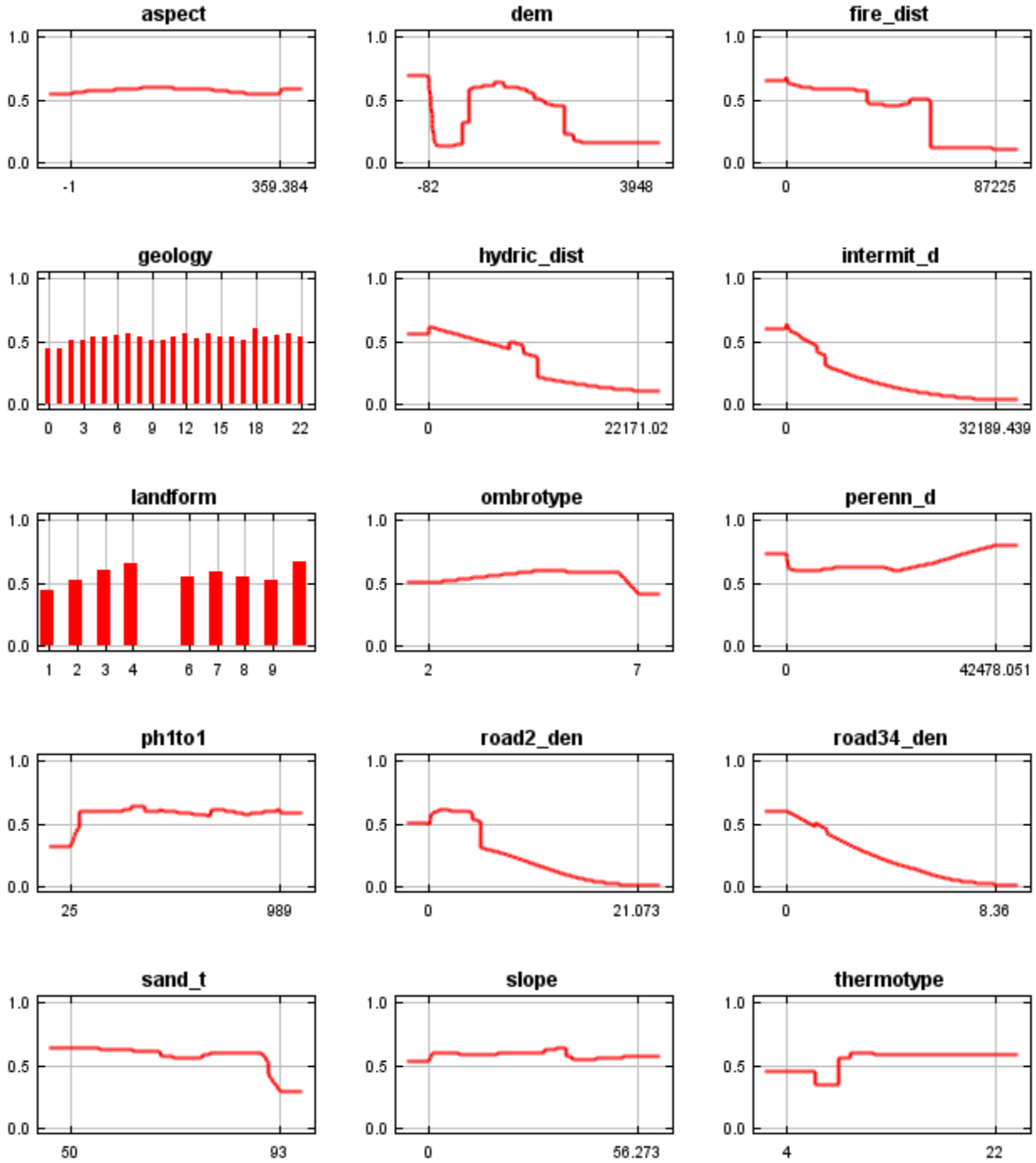
This is a representation of the Maxent model for Annual_Grass_5. Warmer colors show areas with better predicted conditions. White dots show the presence locations used for training, while violet dots show test locations. Click on the image for a full-size version.



(A link to the Explain tool was not made for this model. The model uses product features, while the Explain tool can only be used for additive models.)

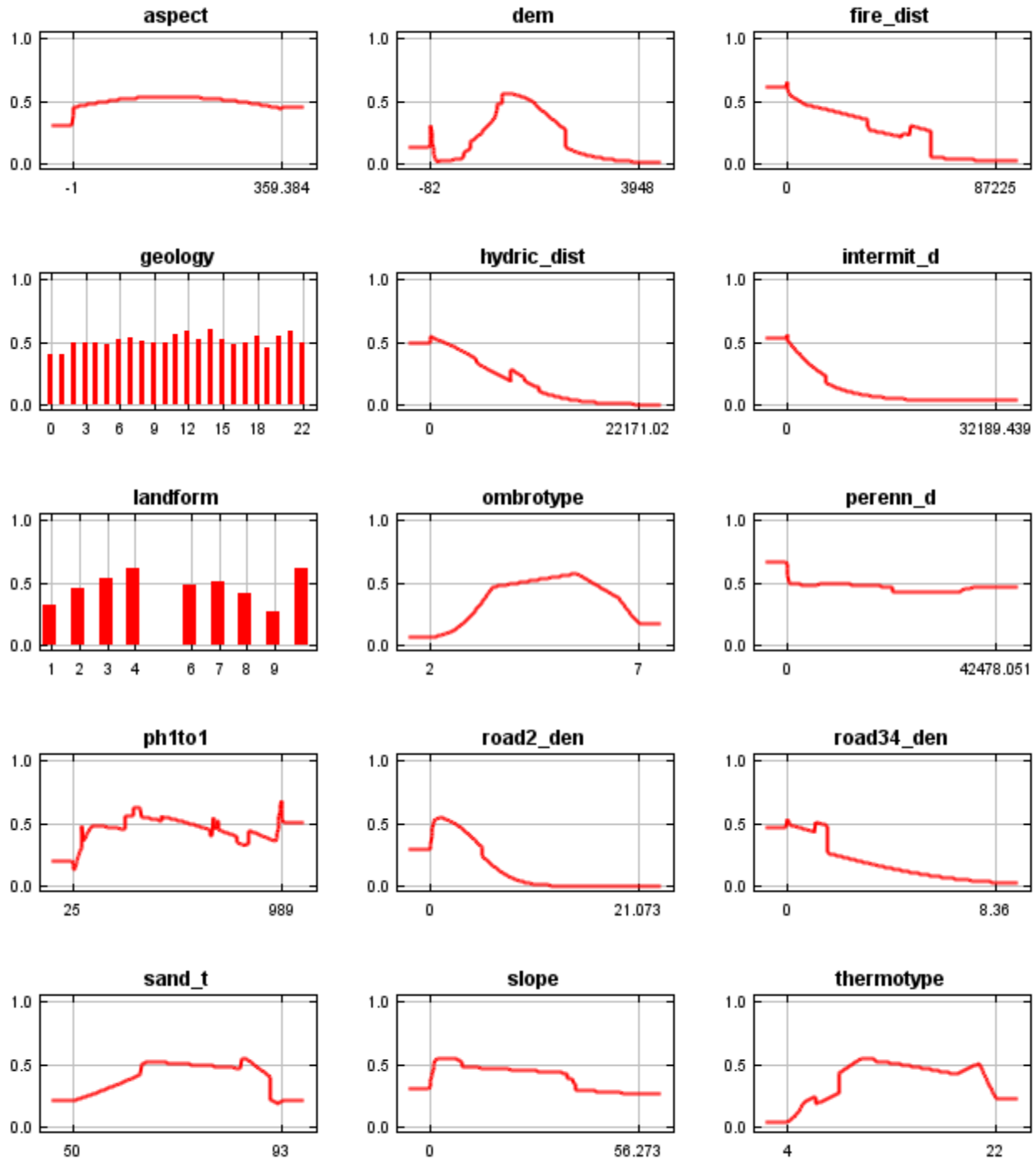
Response curves

These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Click on a response curve to see a larger version. Note that the curves can be hard to interpret if you have strongly correlated variables, as the model may depend on the correlations in ways that are not evident in the curves. In other words, the curves show the marginal effect of changing exactly one variable, whereas the model may take advantage of sets of variables changing together.



In contrast to the above marginal response curves, each of the following curves represents a different model,

namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.



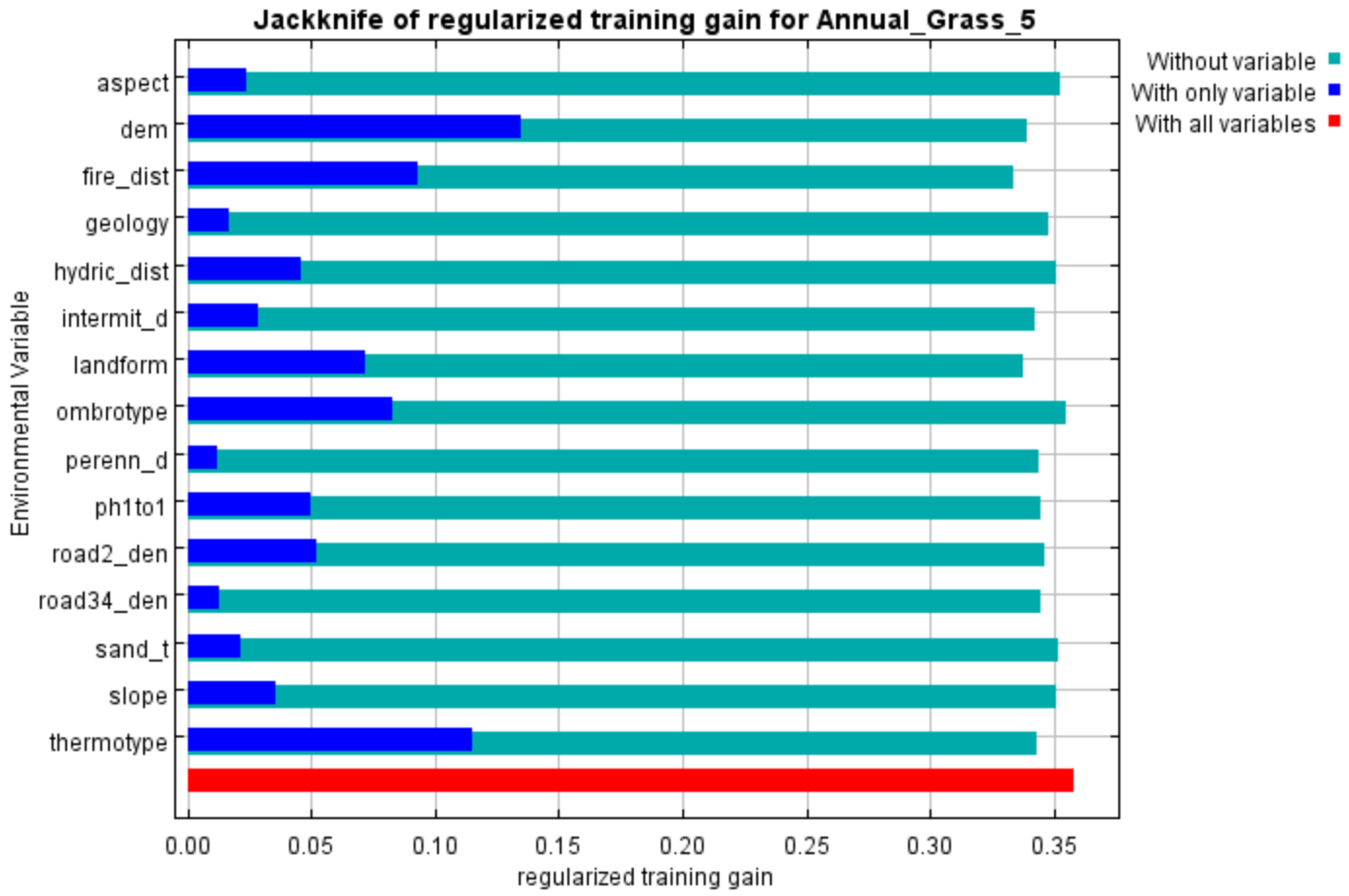
Analysis of variable contributions

The following table gives estimates of relative contributions of the environmental variables to the Maxent

model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from it if the change to the absolute value of lambda is negative. For the second estimate, for each environmental variable in turn, the values of that variable on training presence and background data are randomly permuted. The model is reevaluated on the permuted data, and the resulting drop in training AUC is shown in the table, normalized to percentages. As with the variable jackknife, variable contributions should be interpreted with caution when the predictor variables are correlated.

Variable	Percent contribution	Permutation importance
thermotype	27.5	15.5
landform	16.1	11.3
fire_dist	15.5	11.6
dem	13.7	19.1
road2_den	6.6	7.2
intermit_d	3.3	6.6
geology	3.1	3.5
perenn_d	2.9	4.7
ph1to1	2.6	5.3
slope	2.1	3.1
hydric_dist	1.9	5.2
road34_den	1.8	2.8
sand_t	1.7	2.3
aspect	0.8	1
ombrotype	0.6	0.9

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is dem, which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted is fire_dist, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

The data used in the above analysis is contained in the next links. Please see the Help button for more information on these.
The model applied to the training environmental layers
The coefficients of the model
The omission and predicted area for varying cumulative and raw thresholds
The prediction strength at the training and (optionally) test presence sites
Results for all species modeled in the same Maxent run, with summary statistics and (optionally) jackknife results

Regularized training gain is 0.358, training AUC is 0.753, unregularized training gain is 0.419.
Algorithm terminated after 500 iterations (27 seconds).

The follow settings were used during the run:
2171 presence records used for training.
12170 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used: aspect dem fire_dist geology(categorical) hydric_dist intermit_d landform(categorical) ombrotype perenn_d ph1to1 road2_den road34_den sand_t slope thermotype
Regularization values: linear/quadratic/product: 0.050, categorical: 0.250, threshold: 1.000, hinge: 0.500

Feature types used: product linear quadratic hinge threshold
responsecurves: true
jackknife: true
outputdirectory: D:\Projects\BLM\Invasives\Model\Results
samplesfile: D:\Projects\BLM\Invasives\Model\Training\LF_AnnualGrasses_den.csv
environmentallayers: D:\Projects\BLM\Invasives\Model\Ascii
Command line used:

Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E Annual_Grass_5 responsecurves jackknife outputdirectory=D:\Projects\BLM\Invasives\Model\Results samplesfile=D:\Projects\BLM\Invasives\Model\Training\LF_AnnualGrasses_den.csv environmentallayers=D:\Projects\BLM\Invasives\Model\Ascii -N awc -N kfactor -N road1 -N road2 -N road34 -t geology -t landform