
APPENDIX 2 – MODEL REPORTS

CONTENTS

Overview	2
Sheep Frog (<i>Hypopachus variolosus</i>)	3
Lesser Prairie-chicken (<i>Tympanuchus pallidicinctus</i>)	12
Piping Plover (<i>Charadrius melodus</i>).....	23
Black-capped Vireo (<i>Vireo atricapilla</i>).....	34
Bachman’s Sparrow (<i>Aimophila aestivalis</i>).....	44
Black-tailed Prairie Dog (<i>Cynomys ludovicianus</i>)	53
Texas Kangaroo Rat (<i>Dipodomys elator</i>).....	65
Swift Fox (<i>Vulpes velox</i>).....	75
Kit Fox (<i>Vulpes macrotis</i>).....	85
Black Bear, Western TX Population (<i>Ursus americanus</i>).....	95
Black Bear, Eastern TX Population (<i>Ursus americanus</i>)	108
Ocelot (<i>Leopardus pardalis</i>)	117
Texas Tortoise (<i>Gopherus berlandieri</i>)	127
Reticulate Collared Lizard (<i>Crotaphytus reticulatus</i>).....	137
Spot-tailed Earless Lizard (<i>Holbrookia lacerata</i>)	147
Texas Horned Lizard (<i>Phrynosoma cornutum</i>).....	158
Texas Indigo Snake (<i>Drymarchon melanurus erebennus</i>)	168
Louisiana Pine Snake (<i>Pituophis ruthveni</i>).....	179
Texas Prairie Dawn (<i>Hymenoxys texana</i>).....	188
Threeflower Broomweed (<i>Thurovia triflora</i>)	197
Zapata Bladderpod (<i>Physaria thamnophila</i>).....	206
Bracted Twistflower (<i>Streptanthus bracteatus</i>)	215
Tobusch Fishhook Cactus (<i>Sclerocactus brevihamatus</i> ssp. <i>tobuschii</i>).....	225
Texabama Croton (<i>Croton alabamensis</i> var. <i>texensis</i>)	235
Johnston’s Frankenia (<i>Frankenia johnstonii</i>)	244
Chihuahua Balloon-vine (<i>Cardiospermum dissectum</i>).....	253
Navasota Ladies’-tresses (<i>Spiranthes parksii</i>)	262

OVERVIEW

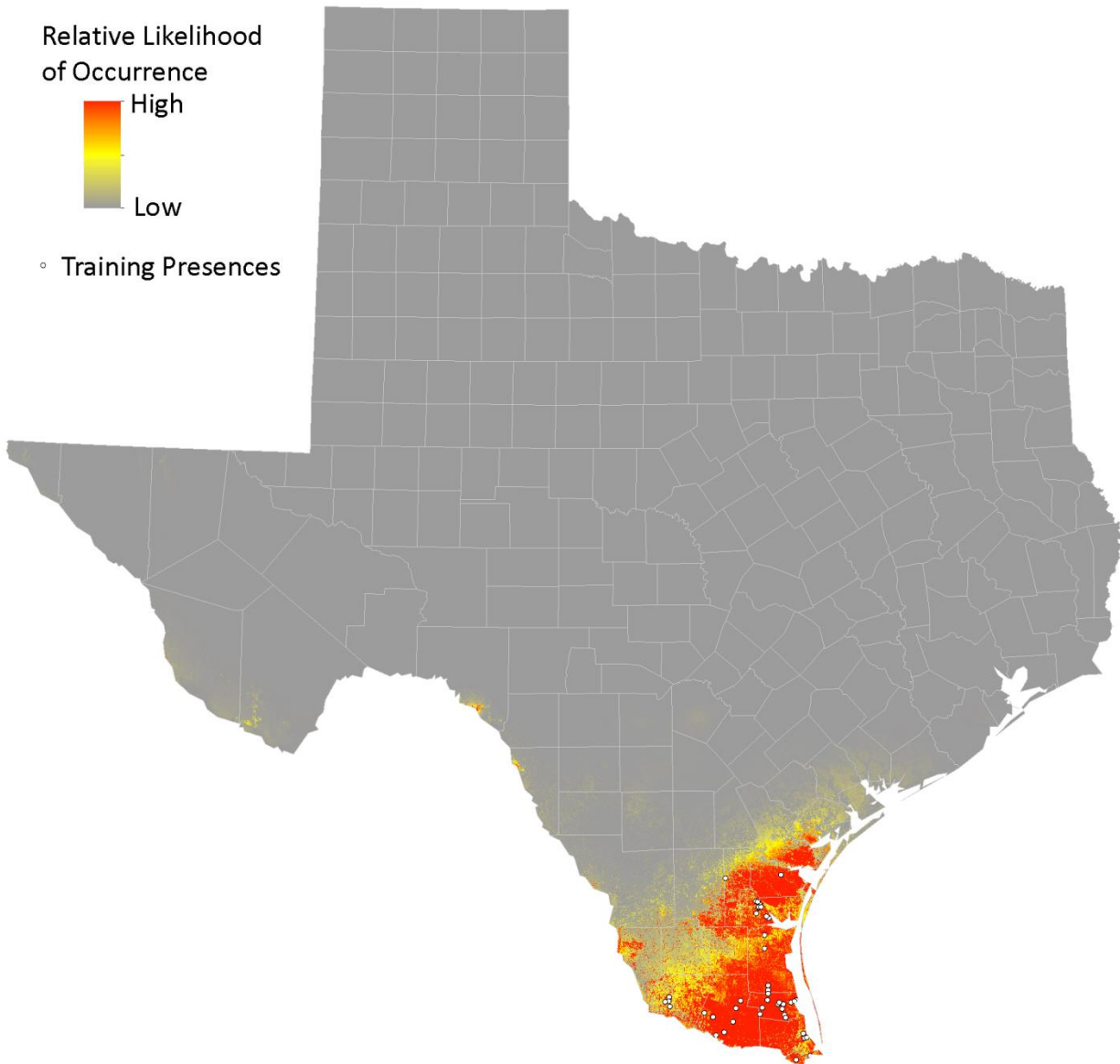
This appendix contains summaries of the final model output for each taxon. In addition to the standard Maxent output describing model quality and variable relationships, there are maps of the logistic-format (i.e., relative likelihood) model output and of a raster representing the standard deviation of the logistic output across cross-validation runs. Logistic output can be interpreted as relative suitability for occupancy by the taxon. The standard deviation raster provides a map of model uncertainty. Areas with higher values in the standard deviation surface are those where the logistic output from the cross-validation replicate runs was the most variable, and, thus, where model uncertainty is the highest. Refer to the HTML files provided with the project dataset for more detailed pictures of responses to specific variables, and clickable links to additional model output. Appendix 1 provides detailed information about the predictor data layers used to generate all models.

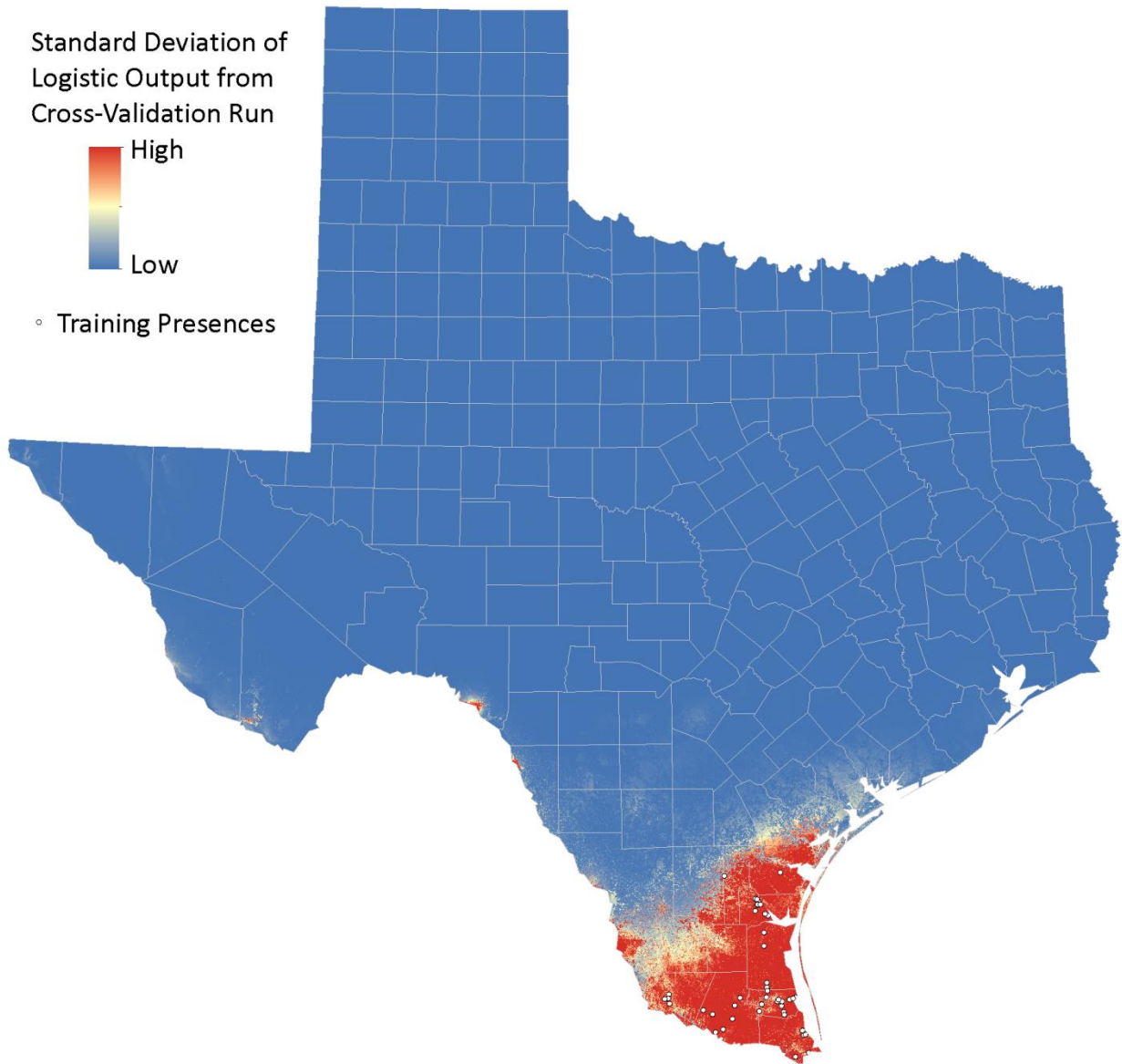
Sheep Frog (*Hypopachus variolosus*)

Species ELCODE: AAABE02010

Date: August 13, 2013

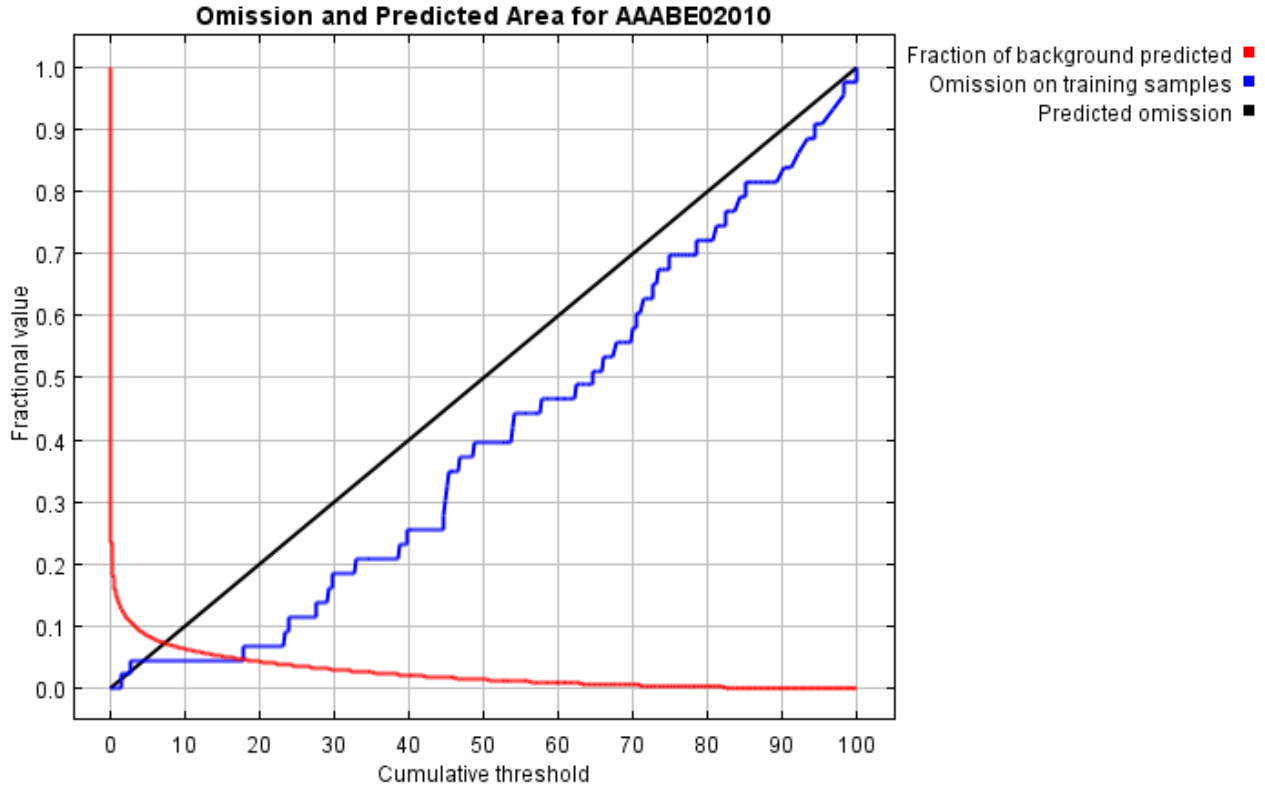
Maxent version: 3.3.3k



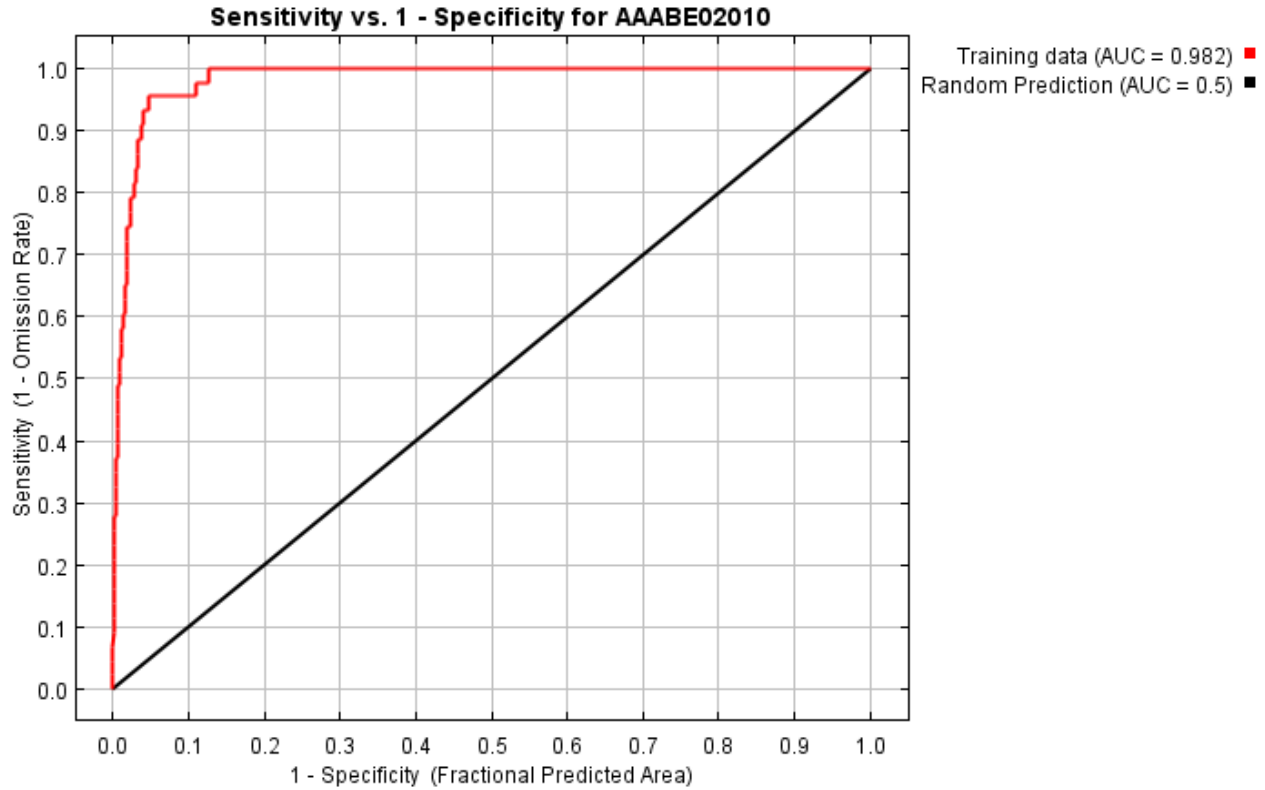


Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.973 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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

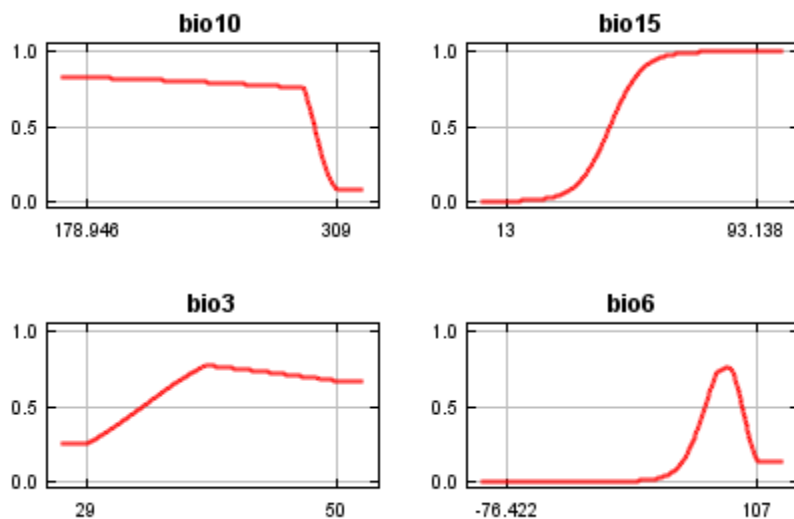
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.018	Fixed cumulative value 1	0.142	0.000
5.000	0.088	Fixed cumulative value 5	0.086	0.047
10.000	0.190	Fixed cumulative value 10	0.064	0.047
1.519	0.028	Minimum training presence	0.127	0.000
23.794	0.338	10 percentile training presence	0.038	0.093

Appendix 2 – Model Reports

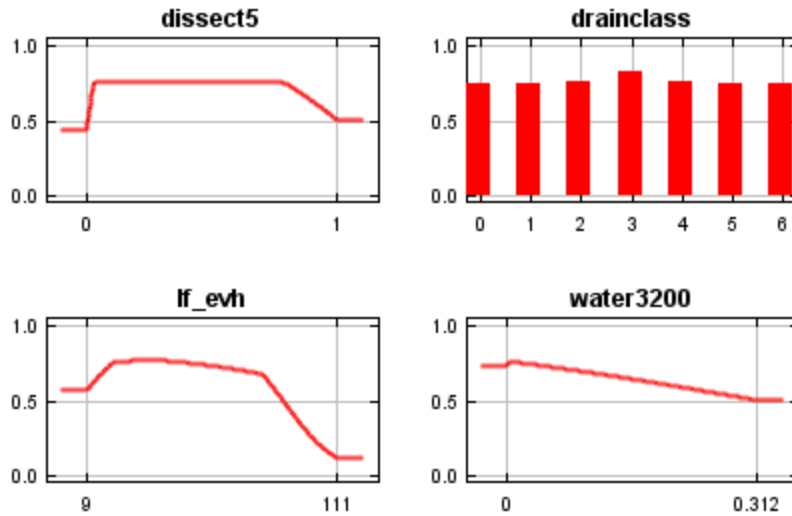
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
17.818	0.281	Equal training sensitivity and specificity	0.047	0.047
17.818	0.281	Maximum training sensitivity plus specificity	0.047	0.047
1.413	0.026	Balance training omission, predicted area and threshold value	0.130	0.000
9.332	0.181	Equate entropy of thresholded and original distributions	0.066	0.047

Response curves

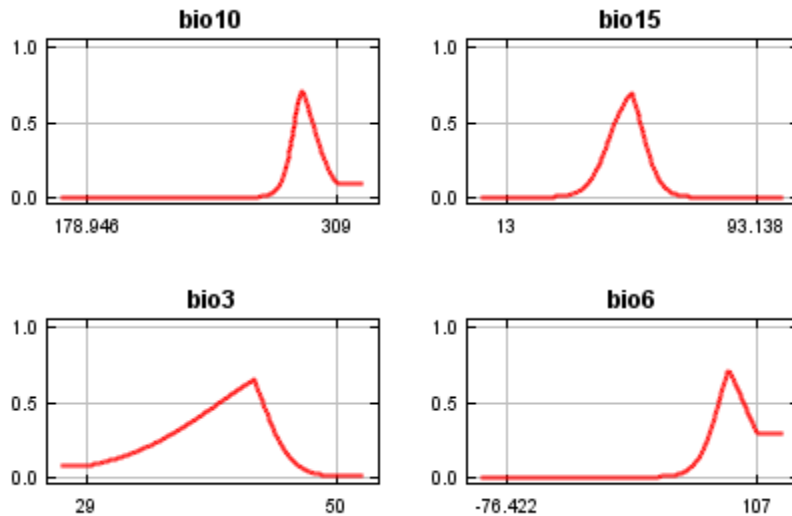
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Click on a response curve to see a larger version. Note 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



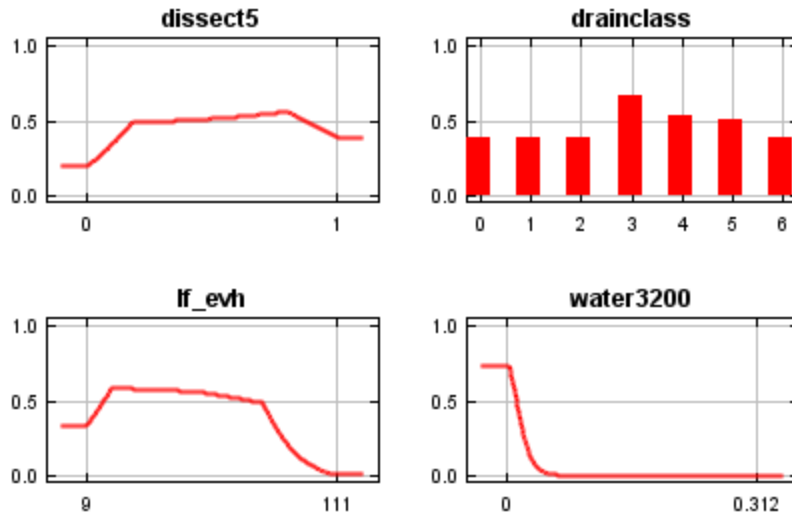
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports

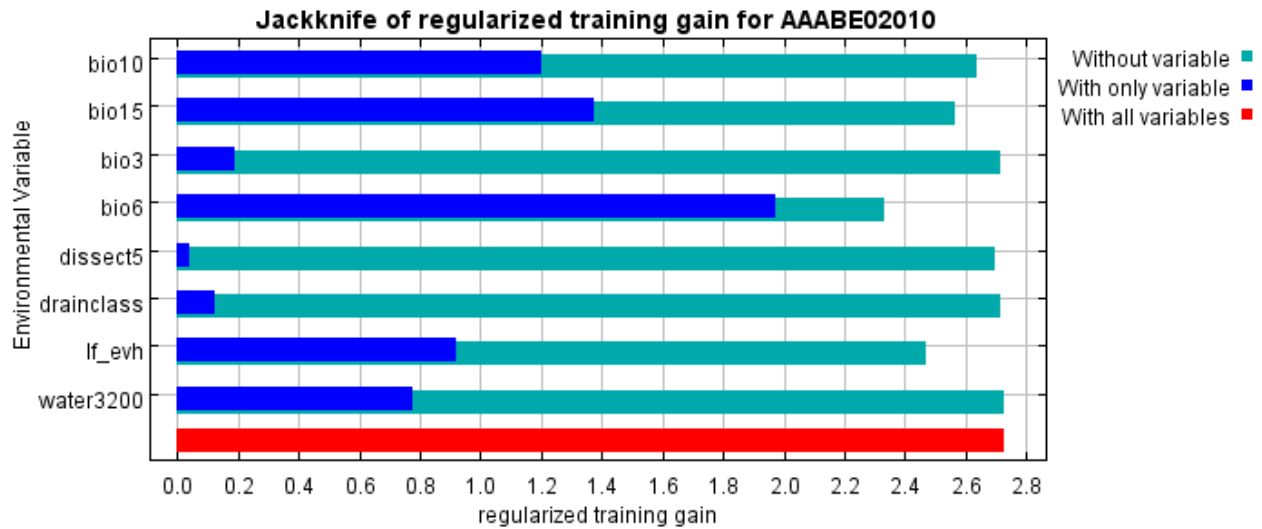


Analysis of variable contributions

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
bio6	49.3	64.9
lf_evh	25	5.5
bio15	18	26.1
drainclass	2.2	0.2
bio3	1.9	0.5
dissect5	1.6	0.7
bio10	1.3	2
water3200	0.7	0

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio6, 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 bio6, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 2.727, training AUC is 0.982, unregularized training gain is 3.065. Algorithm terminated after 500 iterations (4 seconds).

The follow settings were used during the run:

43 presence records used for training.
 7402 points used to determine the Maxent distribution (background points and presence points).
 Environmental layers used: bio10 bio15 bio3 bio6 dissect5 drainclass(categorical) lf_evh water3200
 Regularization values: linear/quadratic/product: 0.213, categorical: 0.250, threshold: 1.570, hinge: 0.500
 Feature types used: linear quadratic hinge
 responsecurves: true
 pictures: false
 jackknife: true
 outputfiletype: bil
 outputdirectory: F:\MODELING\TXNDD_SDM\MAXENT_OUT\AAABE02010\RUN_4
 projectionlayers: F:\MODELING\TXNDD_SDM\MAXENT_IN\PROB
 samplesfile: F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
 environmentalayers:
 F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV

Appendix 2 – Model Reports

writeclampgrid: false
writemess: false
writebackgroundpredictions: true
writeplotdata: true
Command line used: dontwriteclampgrid

Command line to repeat this species model:

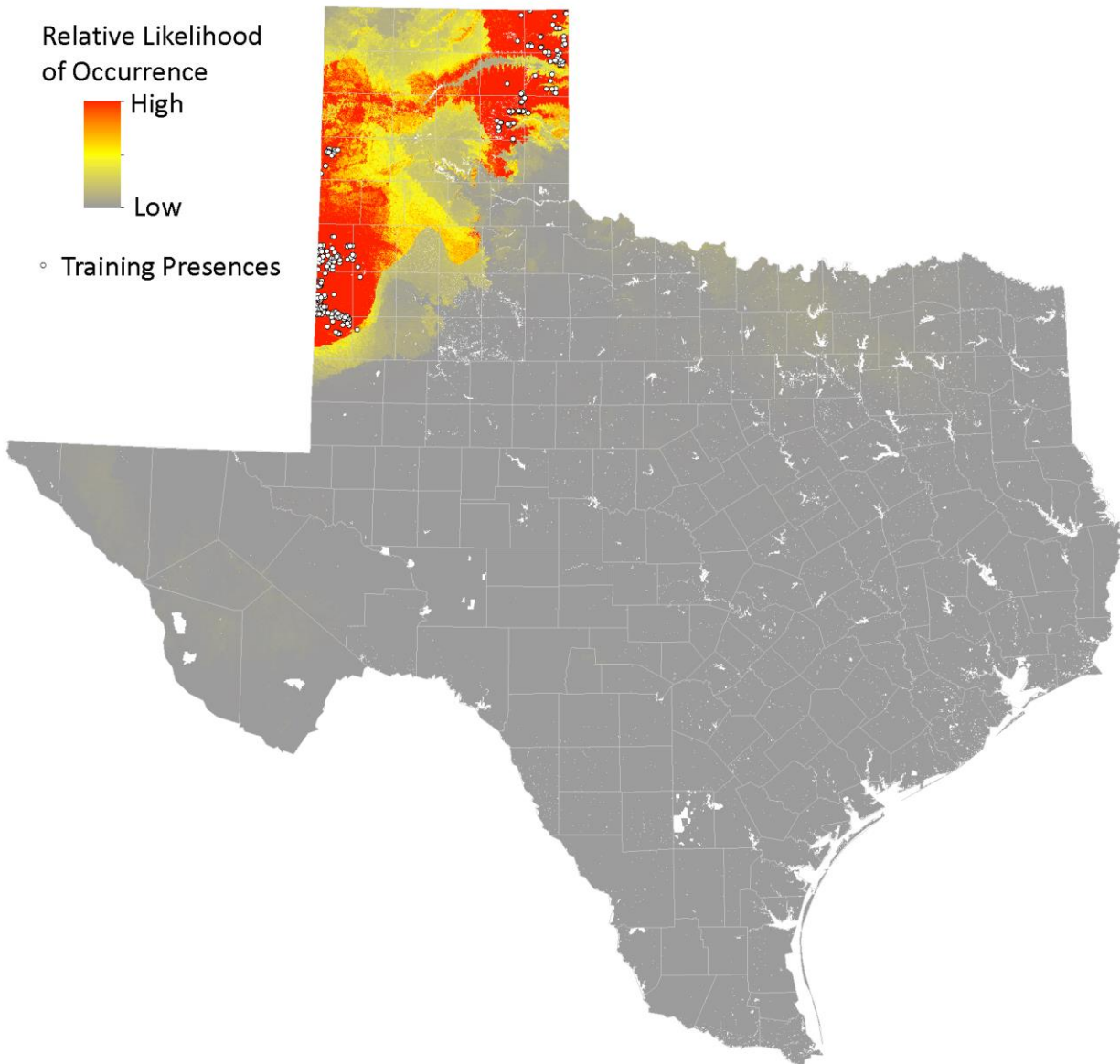
```
java density.MaxEnt nowarnings noprefixes -E "" -E AAABE02010 responsecurves nopictures  
jackknife outputfiletype=bil  
outputdirectory=F:\MODELING\TXNDD_SDM\MAXENT_OUT\AAABE02010\RUN_4  
projectionlayers=F:\MODELING\TXNDD_SDM\MAXENT_IN\PROB  
samplesfile=F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\BACKGROU  
ND.CSV nowriteclampgrid nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -  
N aglands -N allwatdist -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N  
avoid12800 -N avoid1600 -N avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14  
-N bio16 -N bio17 -N bio18 -N bio19 -N bio2 -N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N  
curve10 -N curve5 -N d2foredge -N d2wsl -N dissect10 -N hydgroup -N ksats -N lf_forstcc -N  
lfherbcc -N lfshrubcc -N ned -N nlcdcanopy -N percclay -N percscand -N percscilt -N radld -N slope -N  
soilec -N soilph -N vrm10 -N vrm5 -N water1600 -N water300 -t drainclass
```

Lesser Prairie-chicken (*Tympanuchus pallidicinctus*)

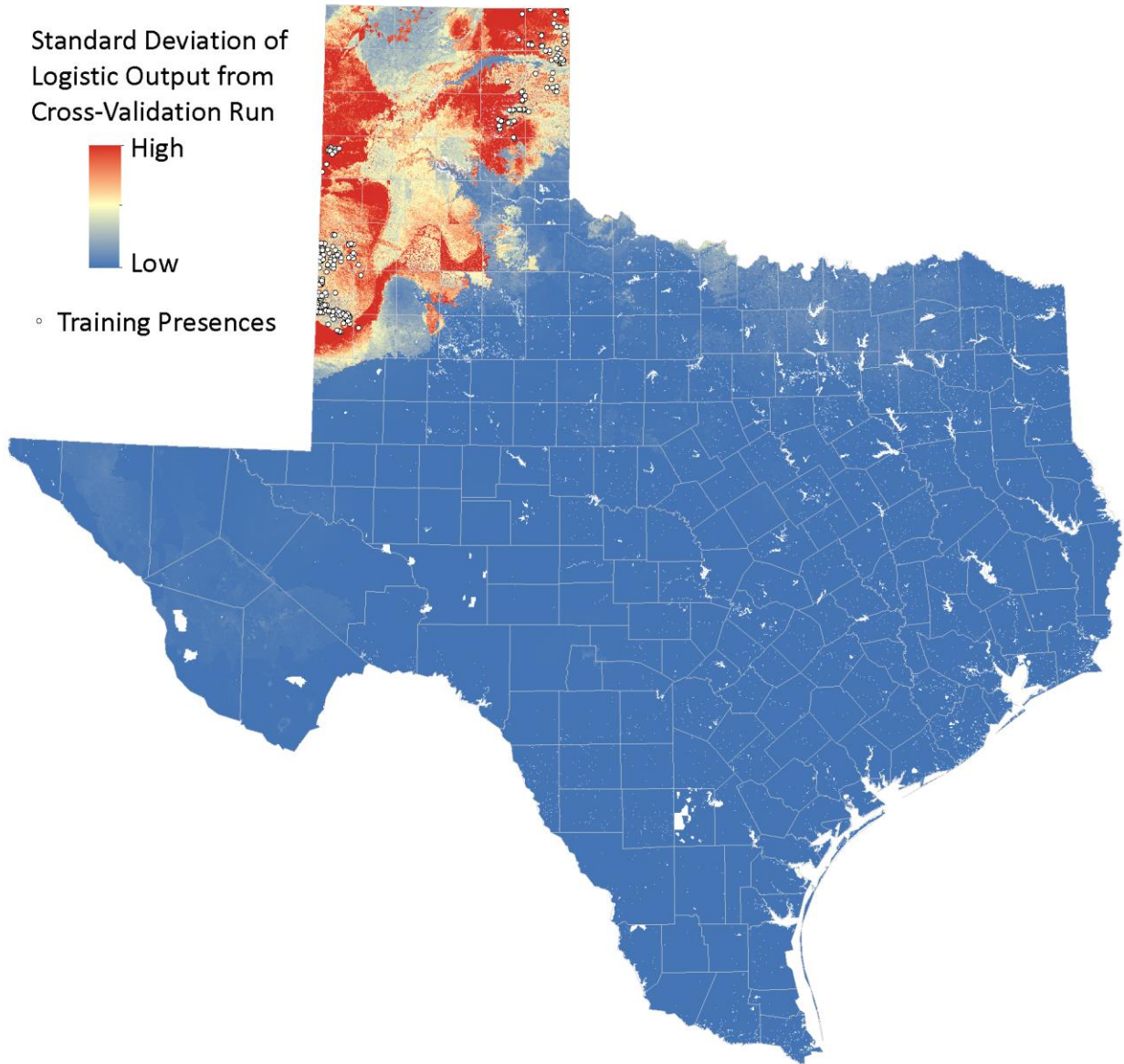
ELCODE: ABNLC13020

Date: August 15, 2013

Maxent version: 3.3.3k

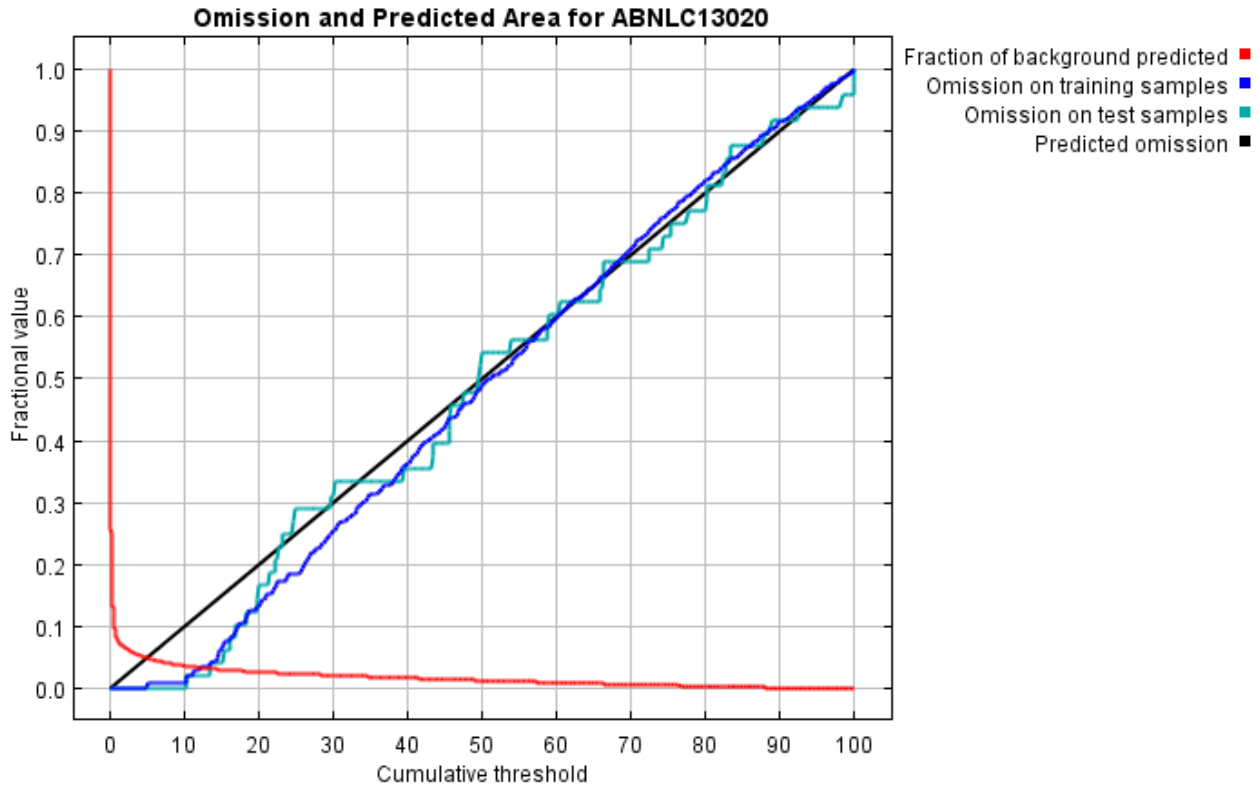


Appendix 2 – Model Reports



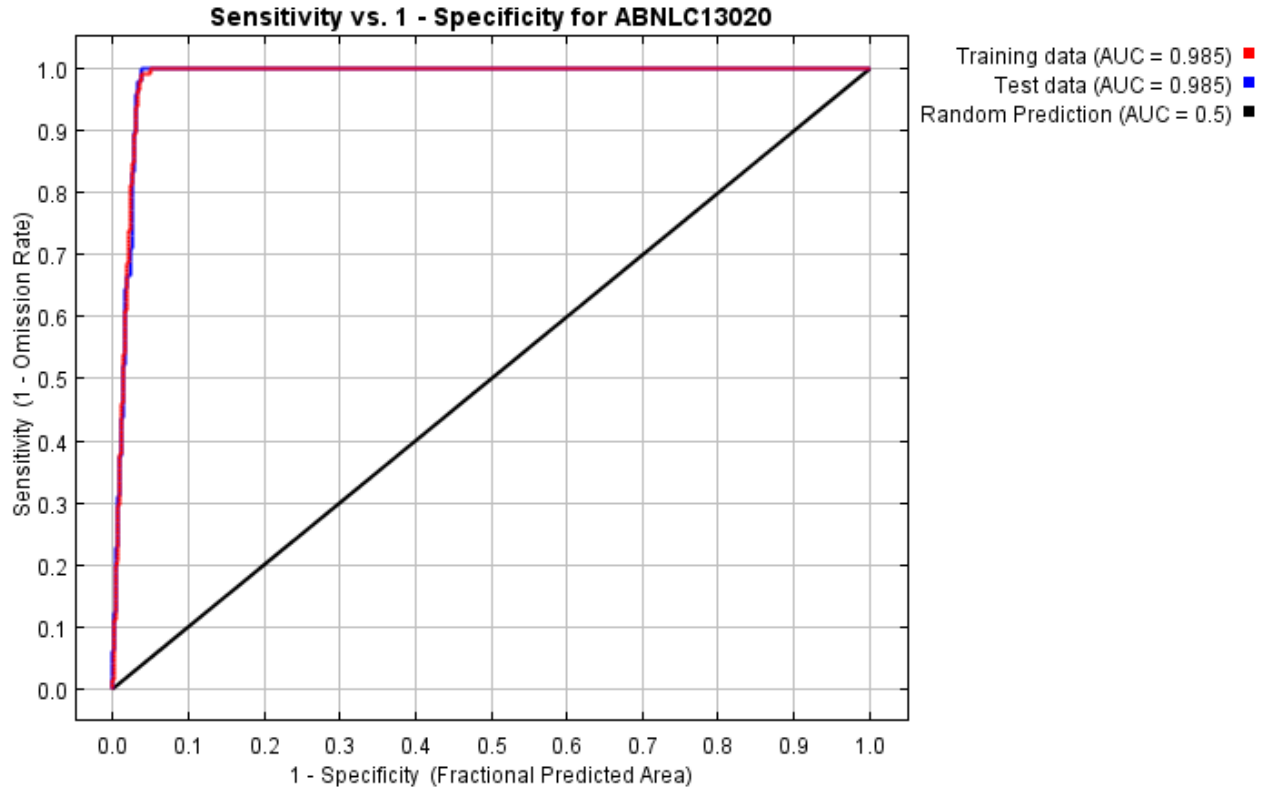
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.981 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
1.000	0.023	Fixed cumulative value 1	0.078	0.000	0.000	0E0
5.000	0.114	Fixed cumulative value 5	0.050	0.010	0.000	0E0
10.000	0.235	Fixed cumulative value 10	0.037	0.010	0.000	0E0

Appendix 2 – Model Reports

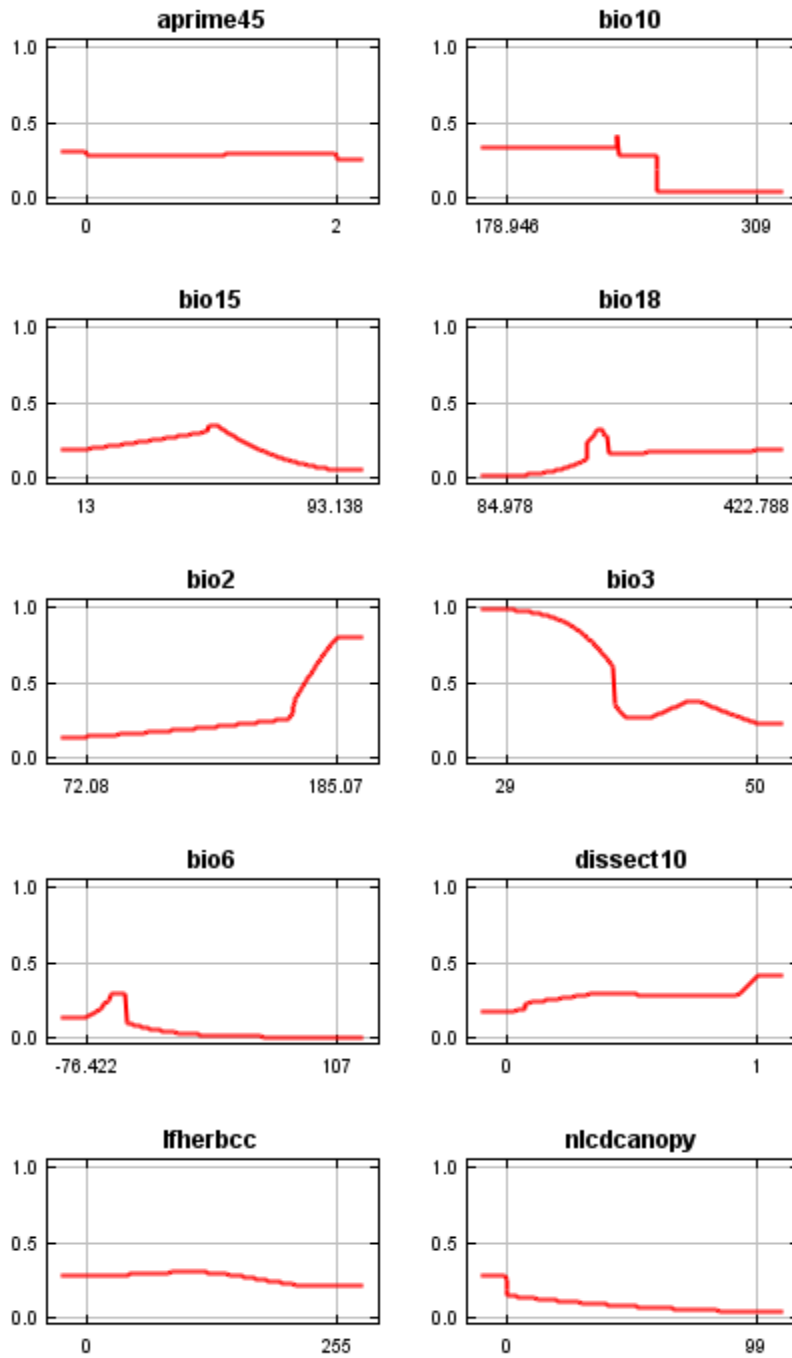
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
4.861	0.110	Minimum training presence	0.050	0.000	0.000	0E0
17.028	0.383	10 percentile training presence	0.030	0.097	0.104	0E0
12.087	0.282	Equal training sensitivity and specificity	0.035	0.036	0.021	0E0
10.129	0.236	Maximum training sensitivity plus specificity	0.037	0.010	0.000	0E0
13.523	0.317	Equal test sensitivity and specificity	0.033	0.036	0.042	0E0
10.215	0.238	Maximum test sensitivity plus specificity	0.037	0.015	0.000	0E0
0.970	0.019	Balance training omission, predicted area and threshold value	0.078	0.000	0.000	0E0
5.366	0.121	Equate entropy of thresholded and original distributions	0.049	0.010	0.000	0E0

Response curves

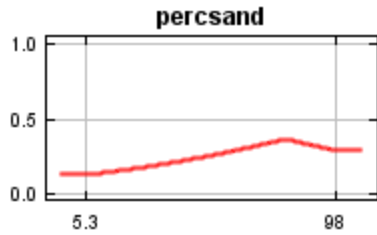
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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

Appendix 2 – Model Reports

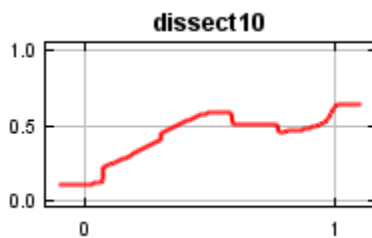
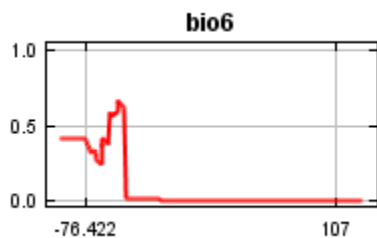
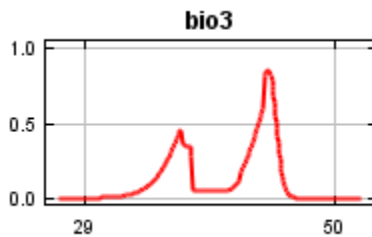
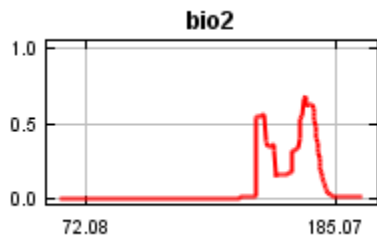
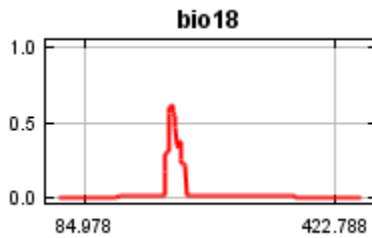
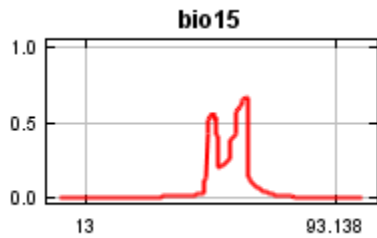
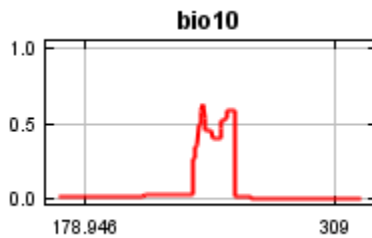
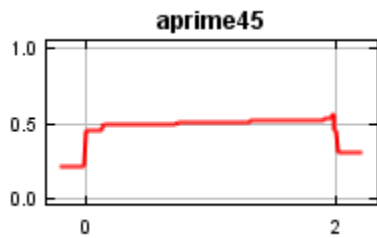
changing exactly one variable, whereas the model may take advantage of sets of variables changing together. See Appendix 1 for detailed explanations of all environmental predictor layers.



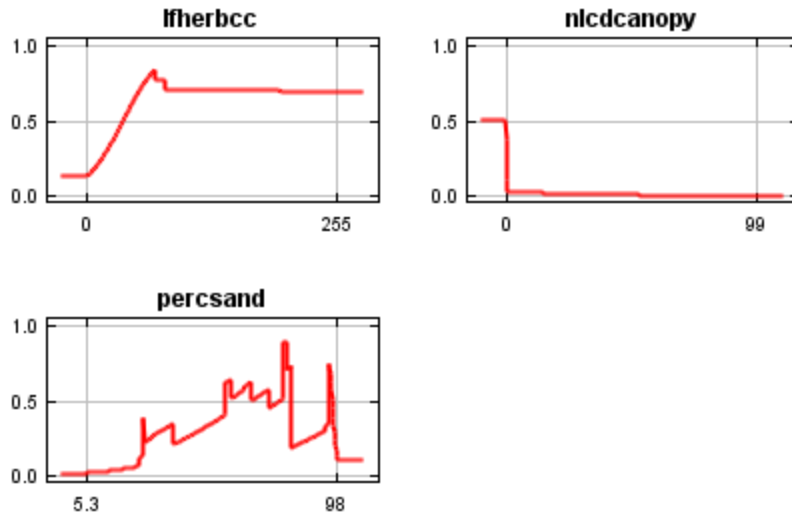
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



Analysis of variable contributions

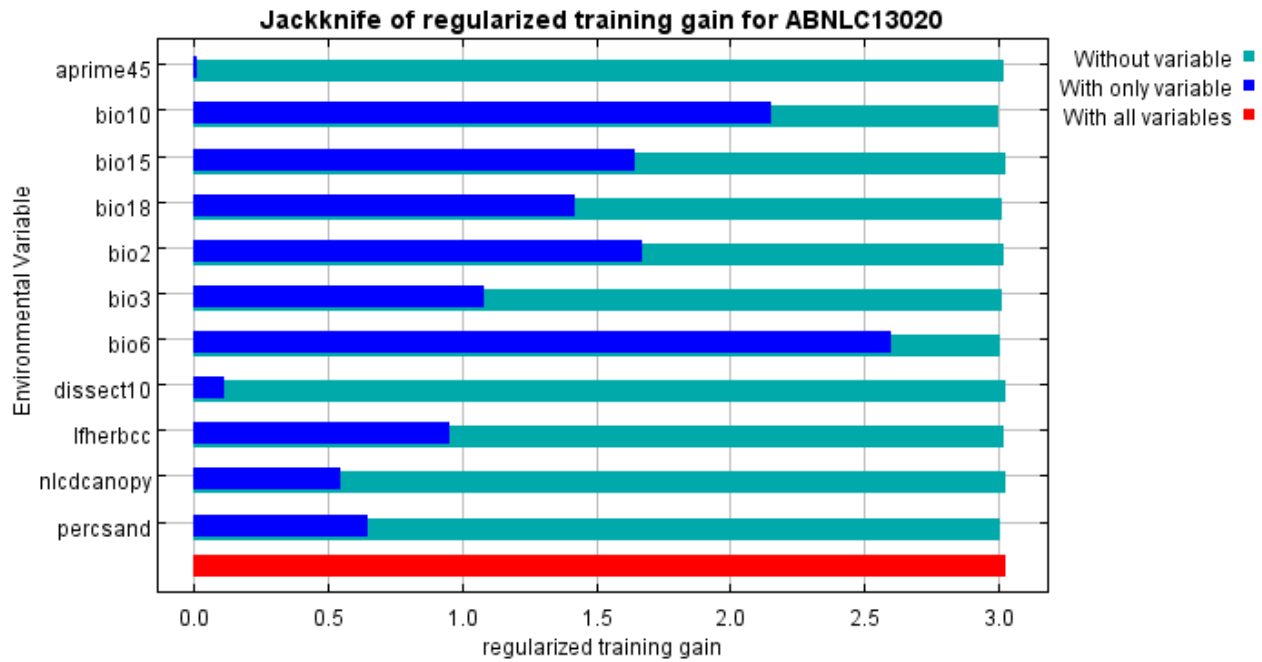
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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
bio6	75.4	38.9
percsand	6.6	3.9
bio10	5.9	11.5
bio3	5.1	15.4
bio2	2.6	4.3
bio18	2.6	10.2
nlcdcanopy	1.1	9.4
dissect10	0.3	0.9

Appendix 2 – Model Reports

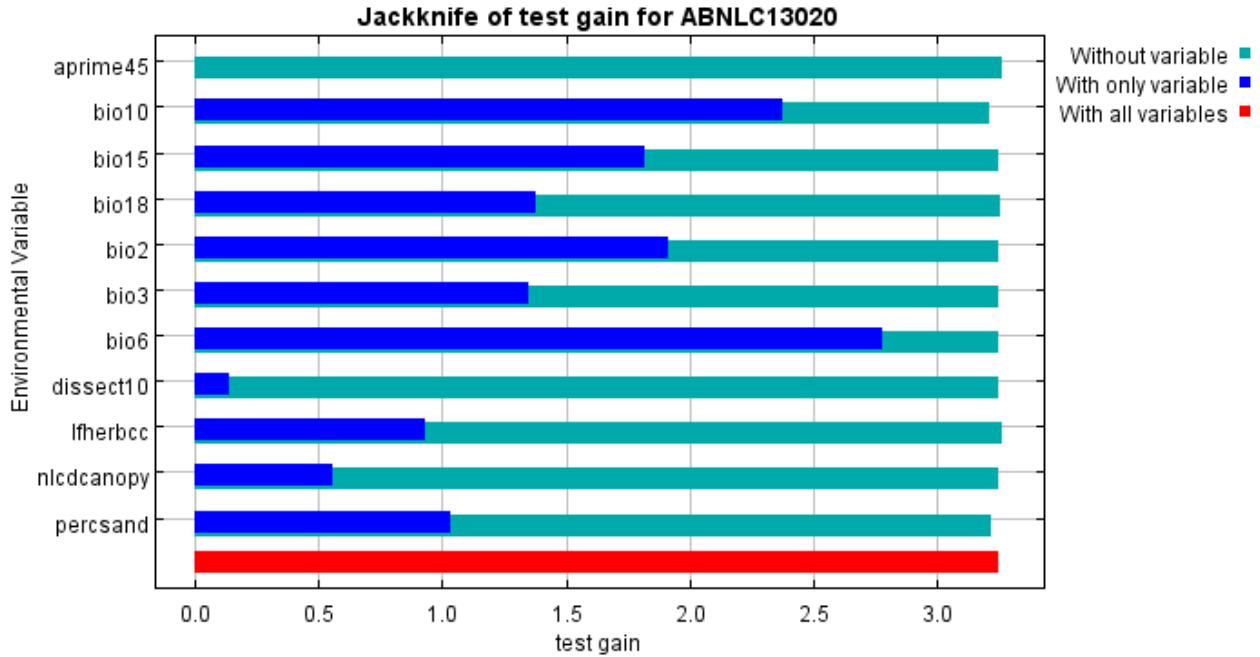
Variable	Percent contribution	Permutation importance
bio15	0.2	3.3
aprime45	0.1	1.2
lfherbcc	0.1	1.1

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio6, 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 bio10, which therefore appears to have the most information that isn't present in the other variables.

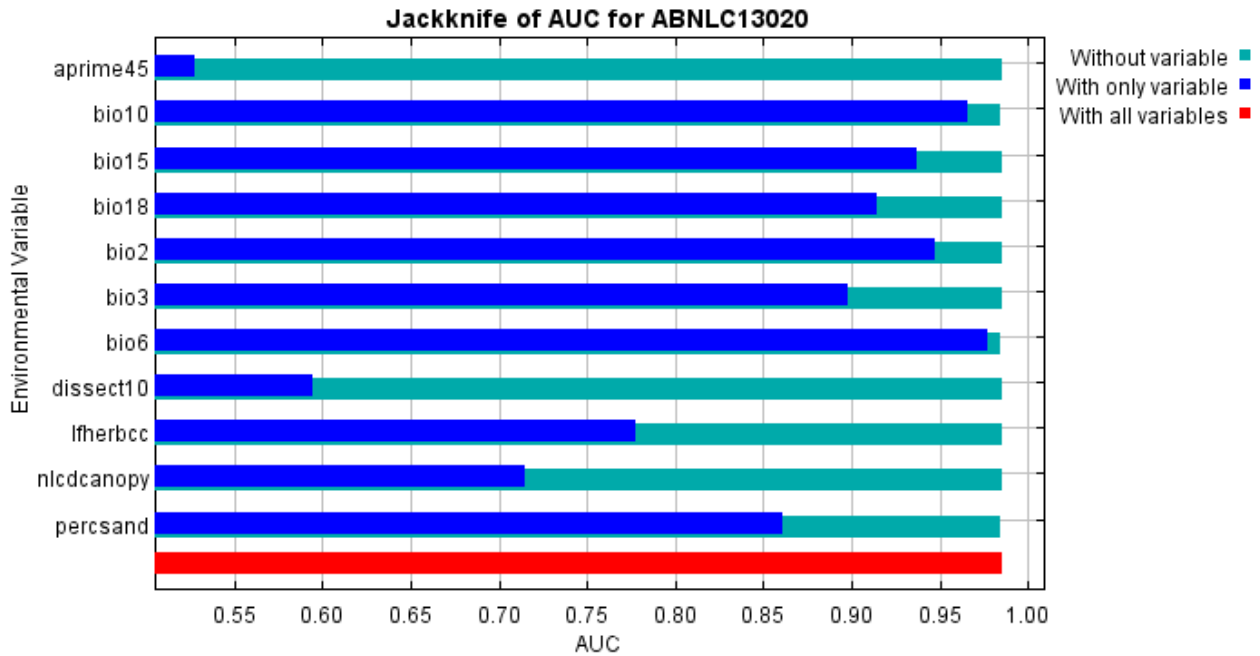


The next picture shows the same jackknife test, using test gain instead of training gain. Note that conclusions about which variables are most important can change, now that we're looking at test data.

Appendix 2 – Model Reports



Lastly, we have the same jackknife test, using AUC on test data.



Raw data outputs and control parameters

Regularized training gain is 3.028, training AUC is 0.985, unregularized training gain is 3.222. Unregularized test gain is 3.246.

Appendix 2 – Model Reports

Test AUC is 0.985, standard deviation is 0.002 (calculated as in DeLong, DeLong & Clarke-Pearson 1988, equation 2).

Algorithm terminated after 500 iterations (34 seconds).

The follow settings were used during the run:

195 presence records used for training, 48 for testing.

7533 points used to determine the Maxent distribution (background points and presence points).

Environmental layers used (all continuous): aprime45 bio10 bio15 bio18 bio2 bio3 bio6 dissect10 lfherbcc nlcdcanopy percсанд

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

pictures: false

jackknife: true

outputfiletype: bil

outputdirectory: F:\MAXENT_OUT\ABNLC13020\RUN_3

projectionlayers: F:\MAXENT_IN\PROB

samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV

environmentallayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV

writeclampgrid: false

writemess: false

randomtestpoints: 20

writebackgroundpredictions: true

writeplotdata: true

Command line used: dontwriteclampgrid

Command line to repeat this species model:

```
java density.MaxEnt nowarnings noprefixes -E "" -E ABNLC13020 responsecurves nopictures
```

```
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\ABNLC13020\RUN_3
```

```
projectionlayers=F:\MAXENT_IN\PROB
```

```
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
```

```
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid
```

```
nowritemess randomtestpoints=20 writebackgroundpredictions writeplotdata -N UNIQUE_ID -N
```

```
aglands -N allwatdist -N aprime135 -N aprime180 -N aprime90 -N avoid -N avoid12800 -N
```

```
avoid1600 -N avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N
```

```
bio17 -N bio19 -N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N
```

```
d2wls1 -N dissect5 -N drainclass -N hydgroup -N ksats -N lf_evh -N lf_forstcc -N lfshrubcc -N ned -N
```

```
percclay -N percslilt -N radld -N slope -N soilec -N soilph -N vrm10 -N vrm5 -N water1600 -N
```

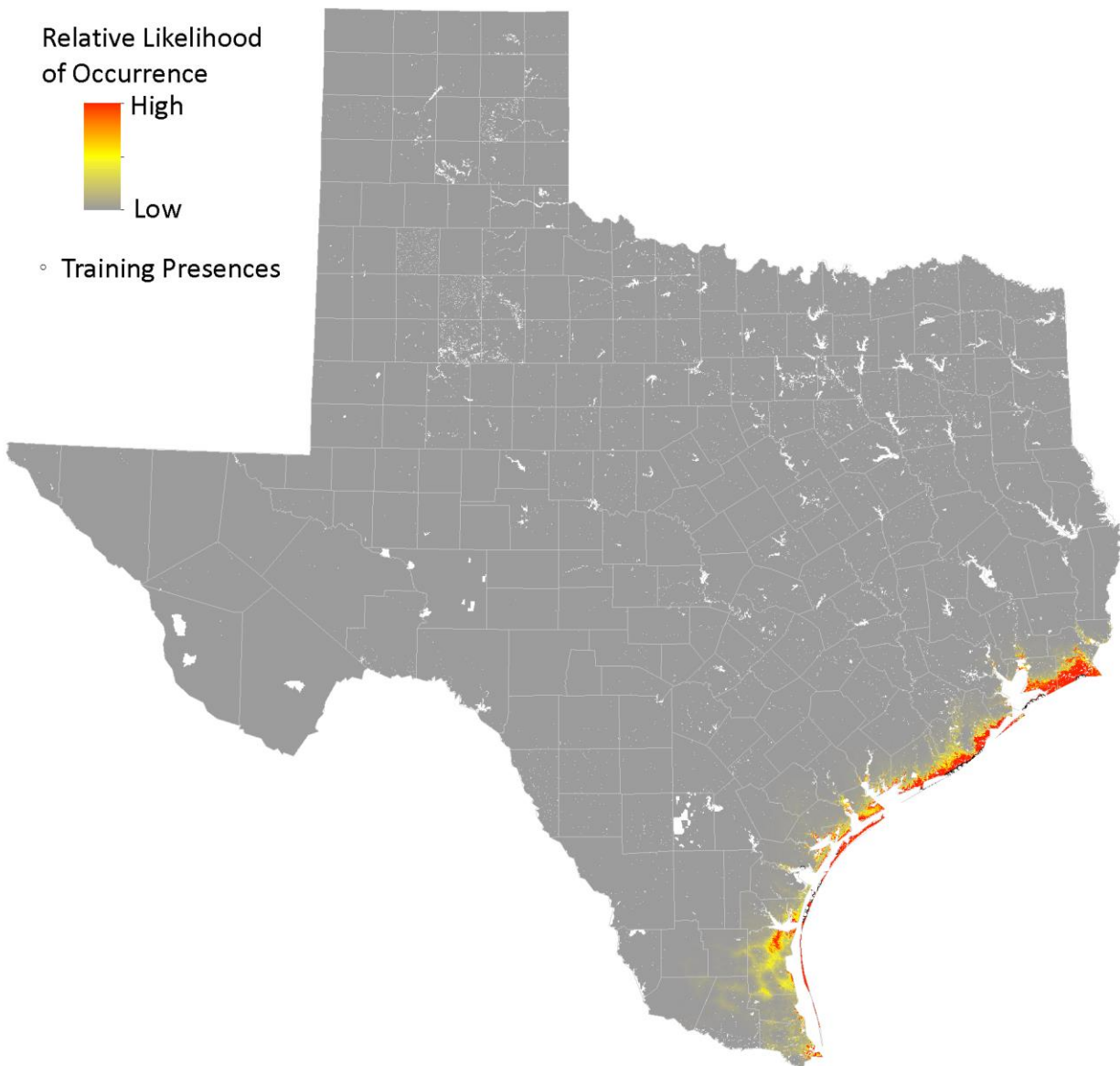
```
water300 -N water3200
```

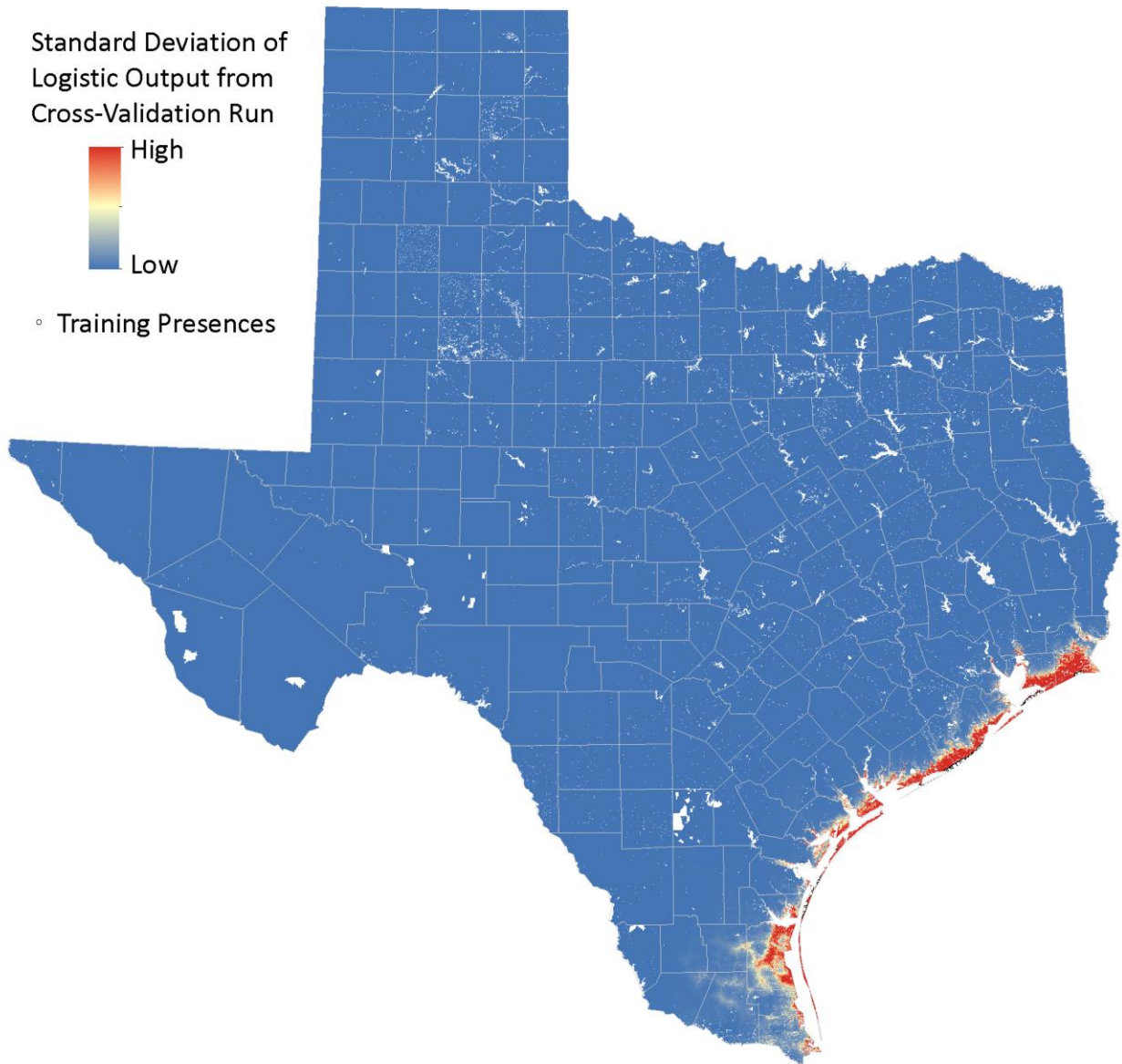
Piping Plover (*Charadrius melodus*)

ELCODE: ABNNB03070

Date: August 14, 2013

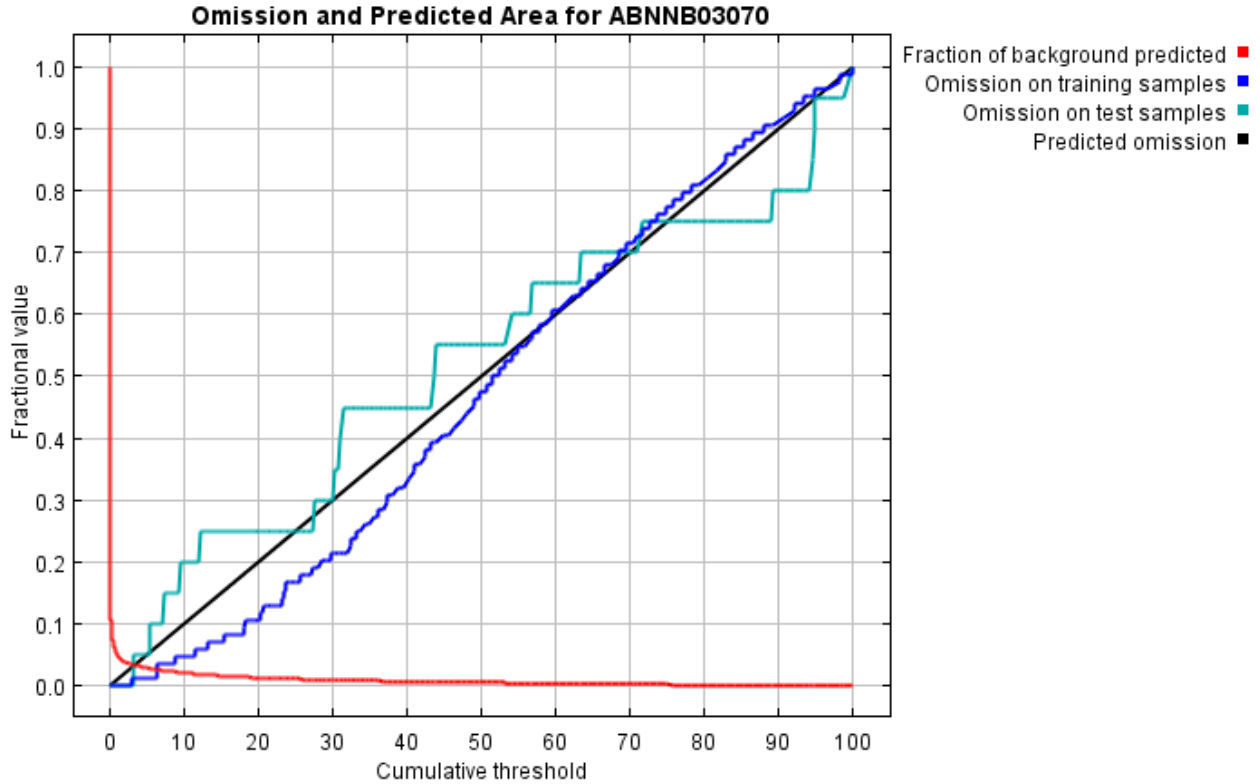
Maxent version: 3.3.3k





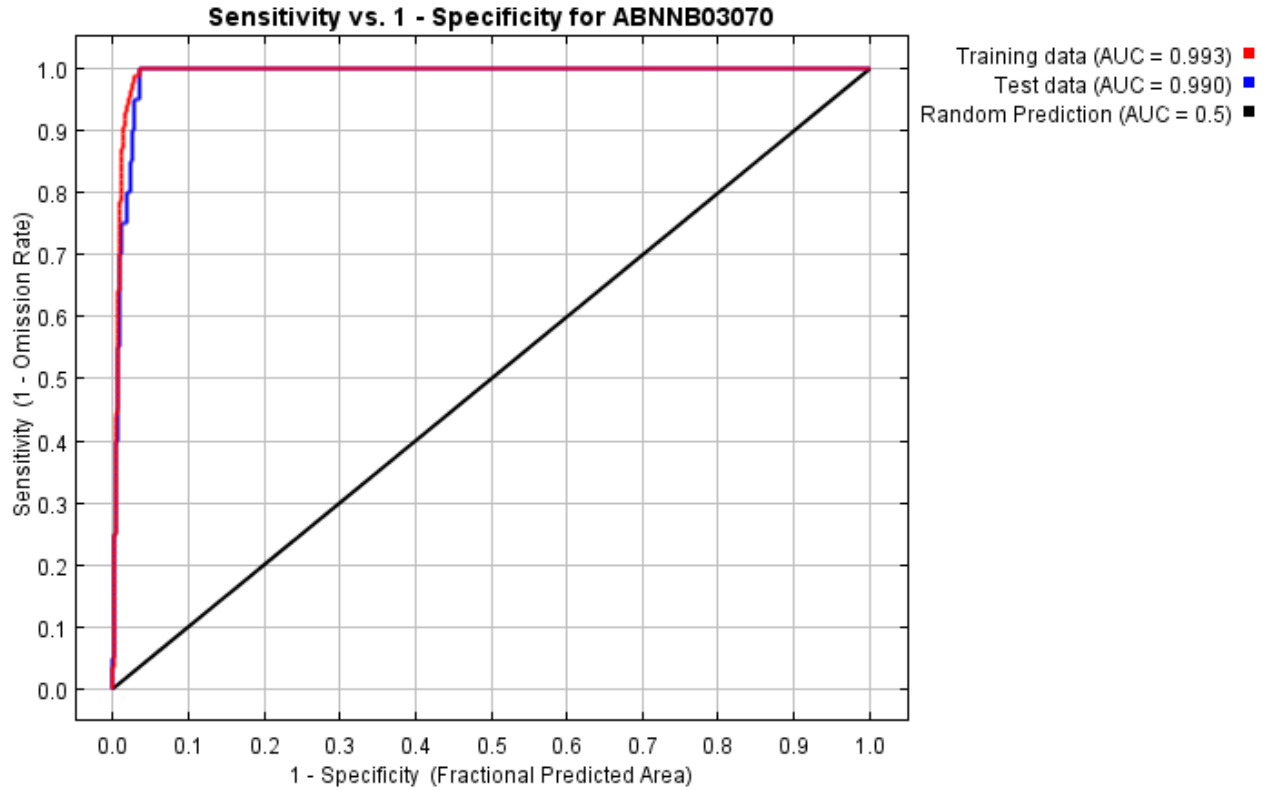
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.990 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
1.000	0.012	Fixed cumulative value 1	0.049	0.000	0.000	6.846E-27
5.000	0.100	Fixed cumulative value 5	0.030	0.012	0.050	1.649E-28
10.000	0.174	Fixed cumulative value 10	0.022	0.048	0.200	1.072E-23
2.991	0.062	Minimum training	0.035	0.000	0.000	7.745E-

Appendix 2 – Model Reports

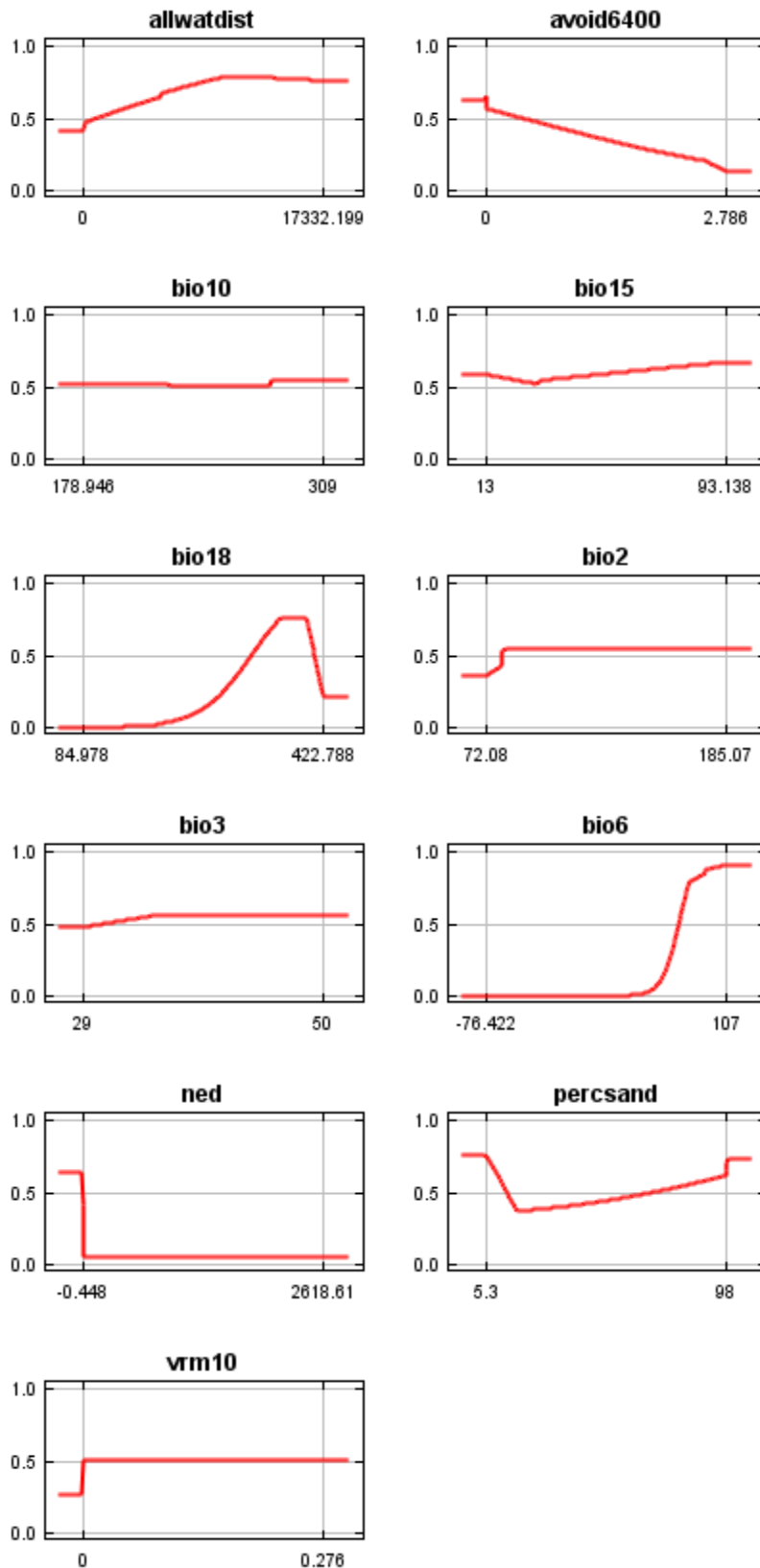
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
		presence				30
18.156	0.293	10 percentile training presence	0.015	0.095	0.250	4.612E-24
6.345	0.120	Equal training sensitivity and specificity	0.027	0.024	0.100	9.255E-27
2.991	0.062	Maximum training sensitivity plus specificity	0.035	0.000	0.000	7.745E-30
3.270	0.072	Equal test sensitivity and specificity	0.034	0.012	0.050	2.548E-27
3.236	0.071	Maximum test sensitivity plus specificity	0.034	0.012	0.000	4.487E-30
0.890	0.010	Balance training omission, predicted area and threshold value	0.052	0.000	0.000	1.889E-26
7.837	0.143	Equate entropy of thresholded and original distributions	0.025	0.036	0.150	4.454E-25

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. 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

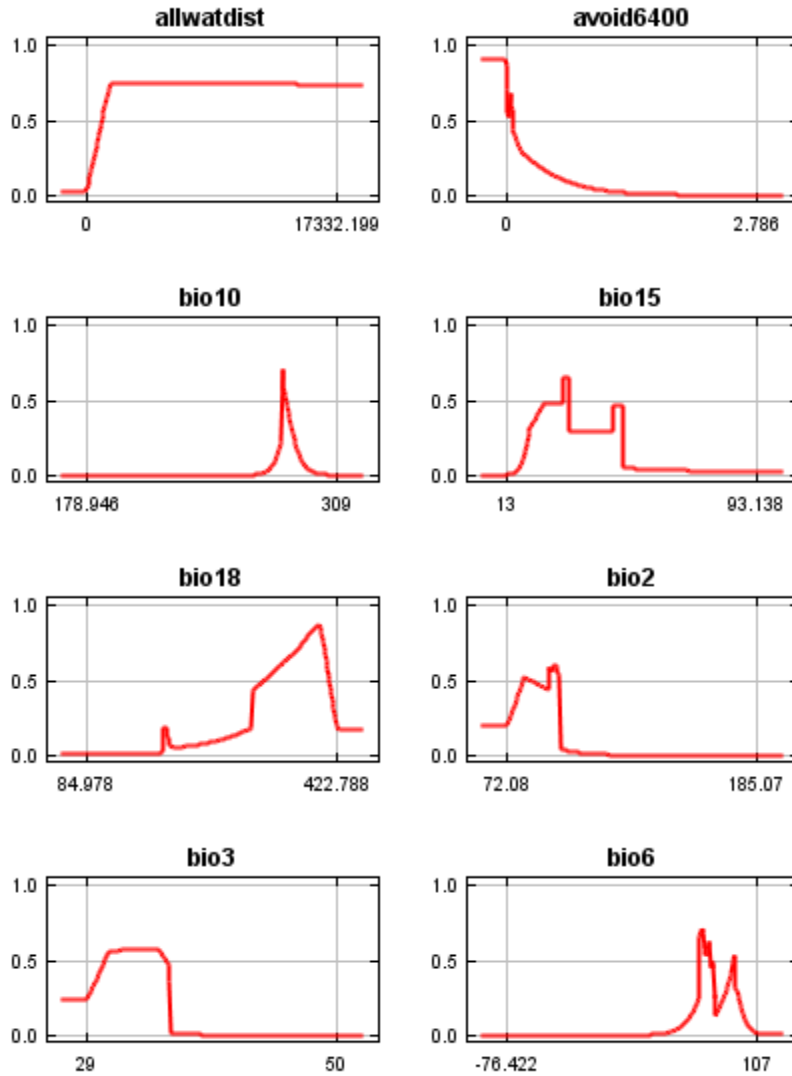
Appendix 2 – Model Reports

together. See Appendix 1 for detailed explanations of all environmental predictor layers.

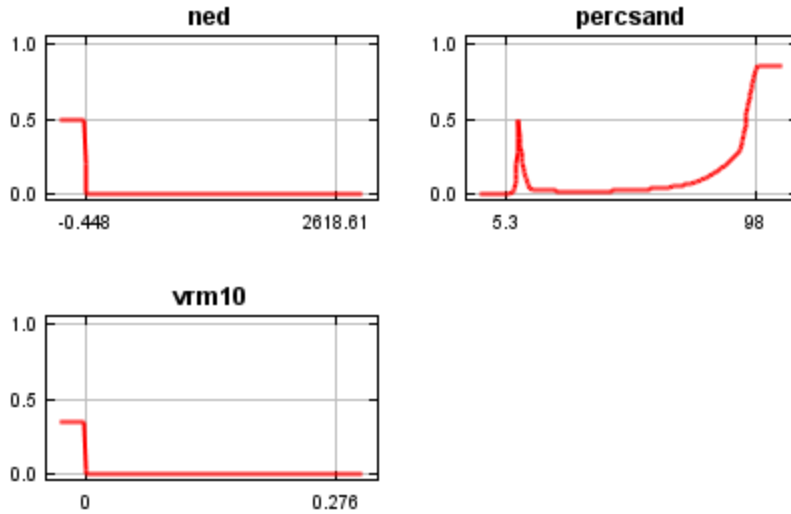


Appendix 2 – Model Reports

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.



Appendix 2 – Model Reports



Analysis of variable contributions

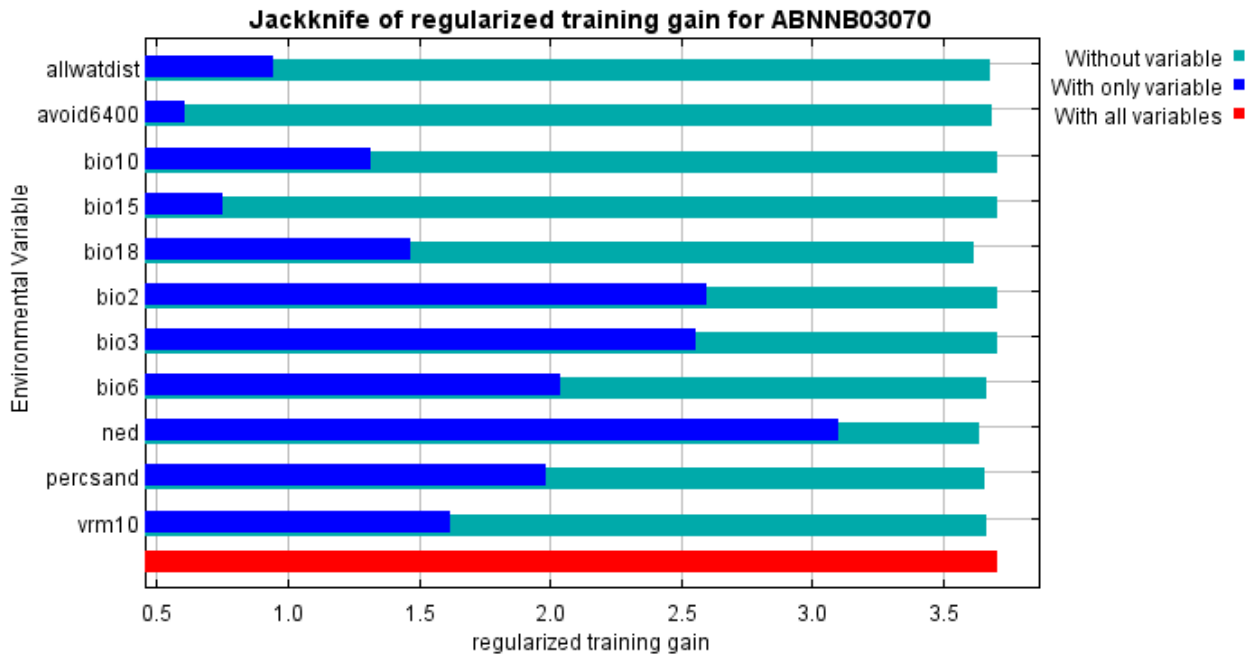
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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
ned	59.2	1.6
bio3	17.3	0
bio2	6.3	0.1
bio18	5.3	15.7
percsand	4.8	0.6
vrml0	3.4	0.1
bio10	1.7	0
allwatdist	0.6	0.6

Appendix 2 – Model Reports

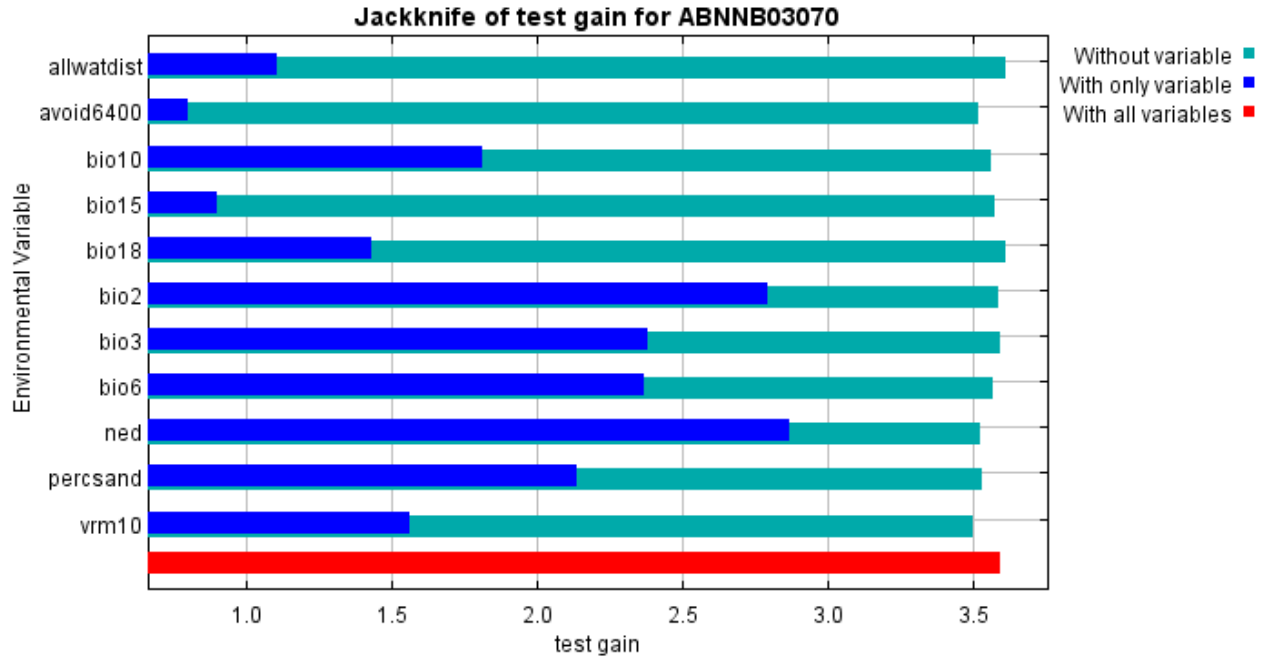
Variable	Percent contribution	Permutation importance
bio15	0.5	0.1
bio6	0.5	80.8
avoid6400	0.3	0.3

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is ned, 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 bio18, which therefore appears to have the most information that isn't present in the other variables.

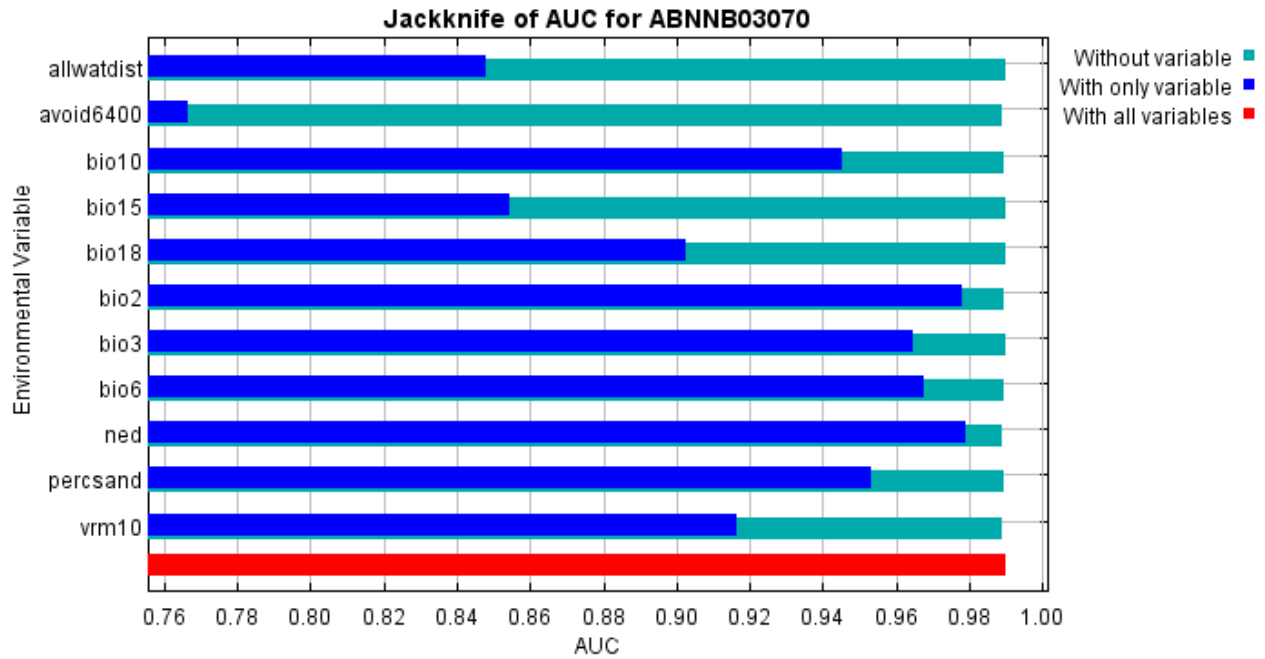


The next picture shows the same jackknife test, using test gain instead of training gain. Note that conclusions about which variables are most important can change, now that we're looking at test data.

Appendix 2 – Model Reports



Lastly, we have the same jackknife test, using AUC on test data.



Raw data outputs and control parameters

Appendix 2 – Model Reports

Regularized training gain is 3.707, training AUC is 0.993, unregularized training gain is 3.911.

Unregularized test gain is 3.592.

Test AUC is 0.990, standard deviation is 0.002 (calculated as in DeLong, DeLong & Clarke-Pearson 1988, equation 2).

Algorithm terminated after 500 iterations (35 seconds).

The follow settings were used during the run:

84 presence records used for training, 20 for testing.

7422 points used to determine the Maxent distribution (background points and presence points).

Environmental layers used (all continuous): allwatdist avoid6400 bio10 bio15 bio18 bio2 bio3 bio6
ned percsand vrm10

Regularization values: linear/quadratic/product: 0.164, categorical: 0.250, threshold: 1.160, hinge:
0.500

Feature types used: product linear quadratic hinge threshold

responsecurves: true

pictures: false

jackknife: true

outputfiletype: bil

outputdirectory: F:\MAXENT_OUT\ABNNB03070\RUN_3

projectionlayers: F:\MAXENT_IN\PROB

samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV

environmentallayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV

writeclampgrid: false

writemess: false

randomtestpoints: 20

writebackgroundpredictions: true

writeplotdata: true

Command line used: dontwriteclampgrid

Command line to repeat this species model:

```
java density.MaxEnt nowarnings noprefixes -E "" -E ABNNB03070 responsecurves nopictures
```

```
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\ABNNB03070\RUN_3
```

```
projectionlayers=F:\MAXENT_IN\PROB
```

```
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
```

```
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid
```

```
nowritemess randomtestpoints=20 writebackgroundpredictions writeplotdata -N UNIQUE_ID -N
```

```
aglands -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N avoid12800 -N
```

```
avoid1600 -N avoid3200 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio19 -
```

```
N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foreedge -N d2wsl -N
```

```
dissect10 -N dissect5 -N drainclass -N hydgroup -N ksats -N lf_evh -N lf_forstcc -N lfherbcc -N
```

```
lfshrubcc -N nlcdcanopy -N percclay -N percsilt -N radld -N slope -N soilec -N soilph -N vrm5 -N
```

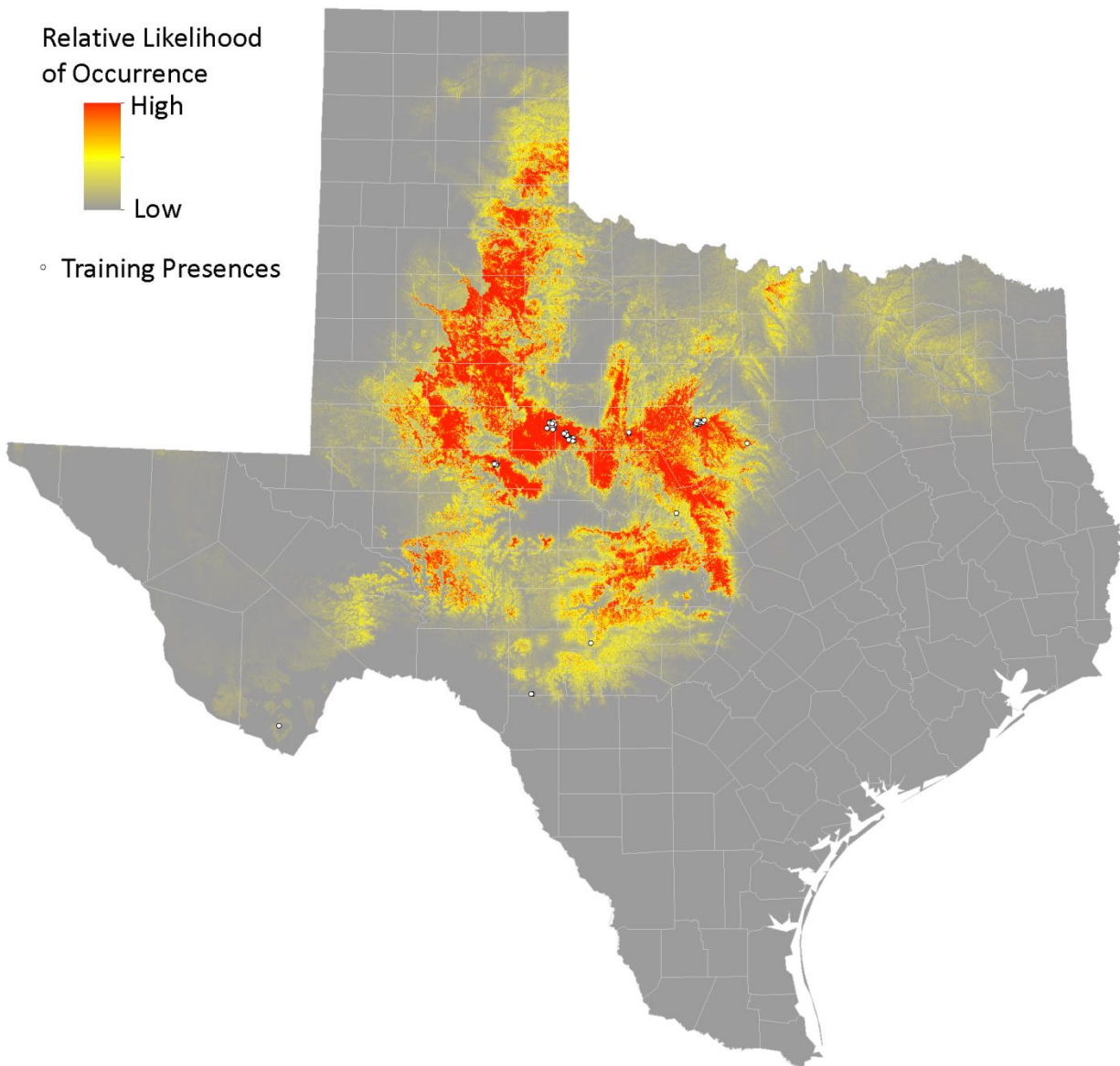
```
water1600 -N water300 -N water3200
```

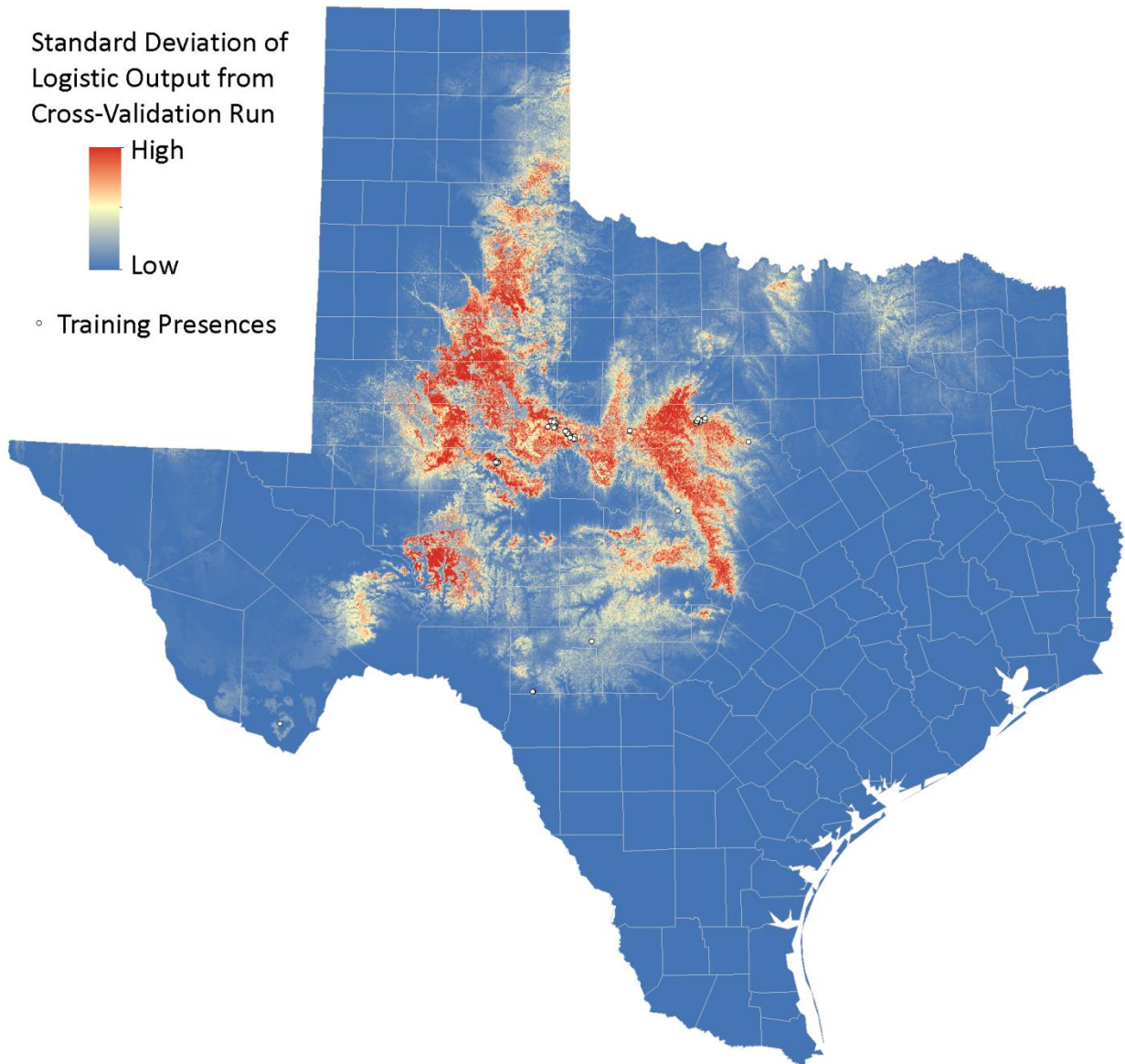
Black-capped Vireo (*Vireo atricapilla*)

ELCODE: APBPW01120

Date: August 13, 2013

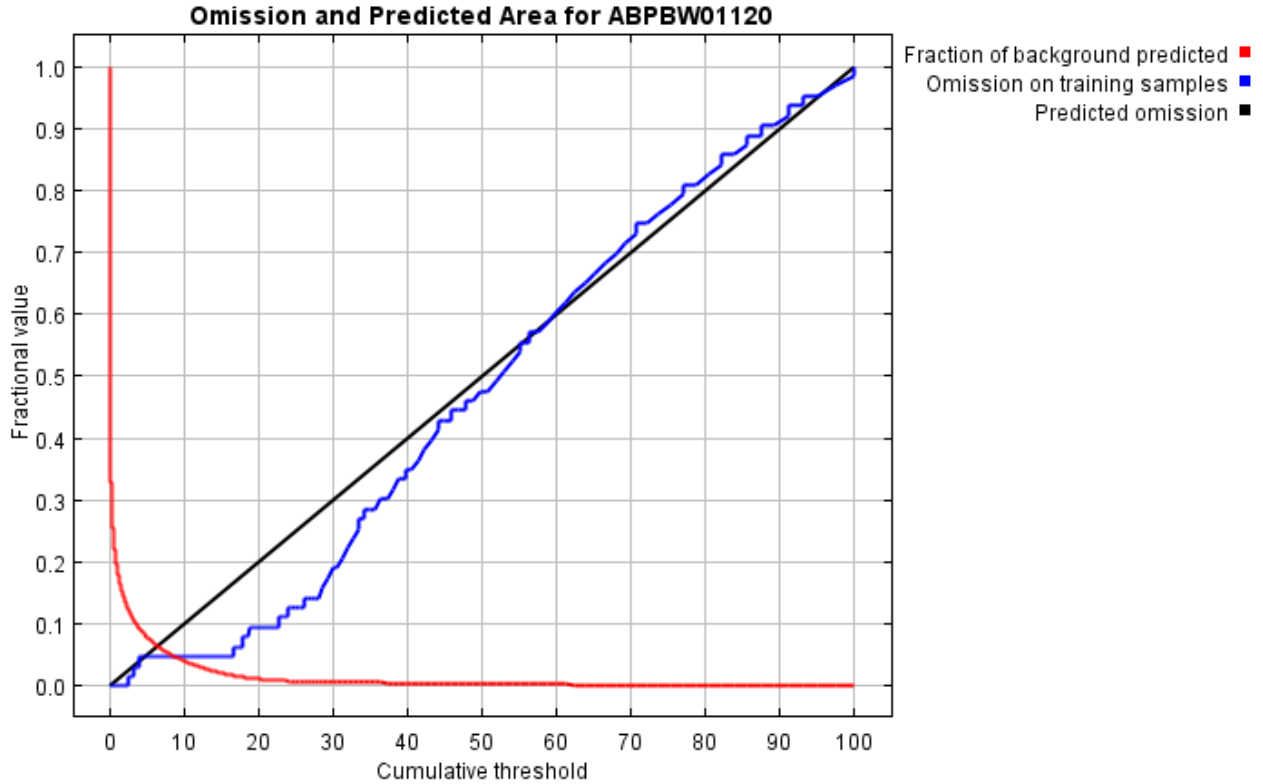
Maxent version: 3.3.3k





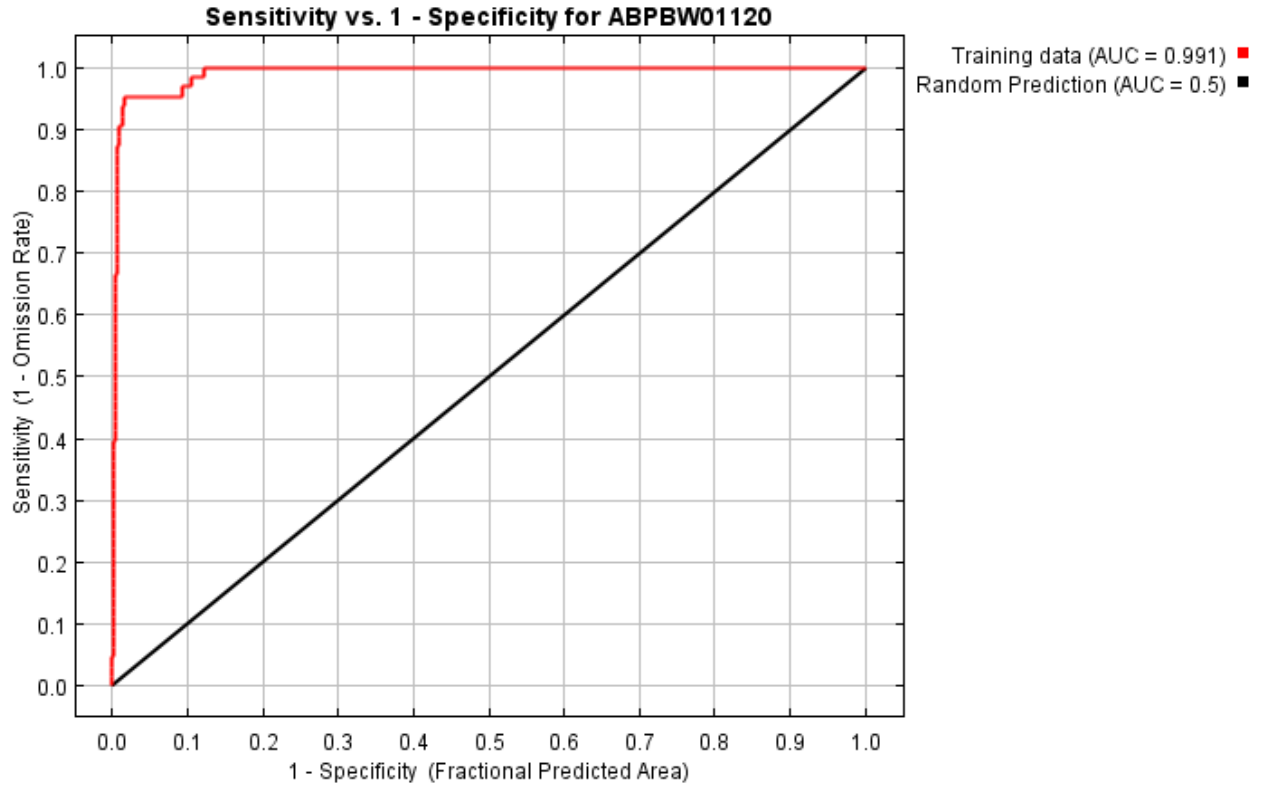
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.983 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

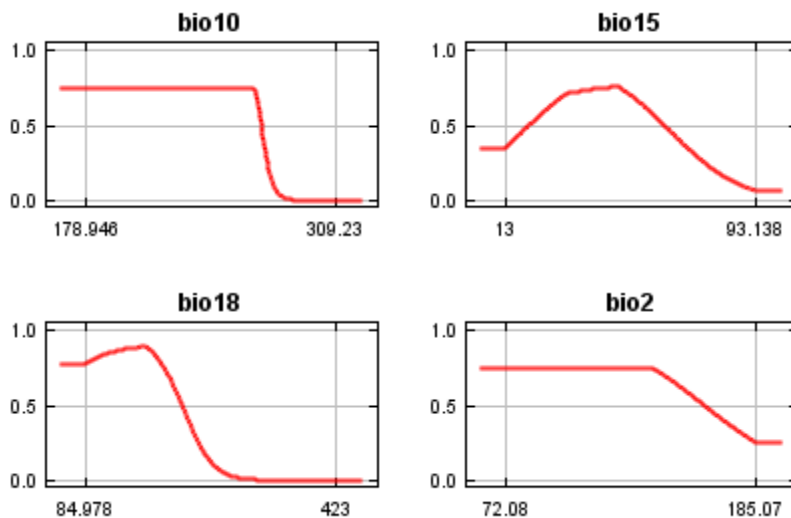
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.003	Fixed cumulative value 1	0.186	0.000
5.000	0.020	Fixed cumulative value 5	0.079	0.048
10.000	0.045	Fixed cumulative value 10	0.040	0.048
2.531	0.009	Minimum training presence	0.122	0.000
22.608	0.251	10 percentile training presence	0.009	0.095

Appendix 2 – Model Reports

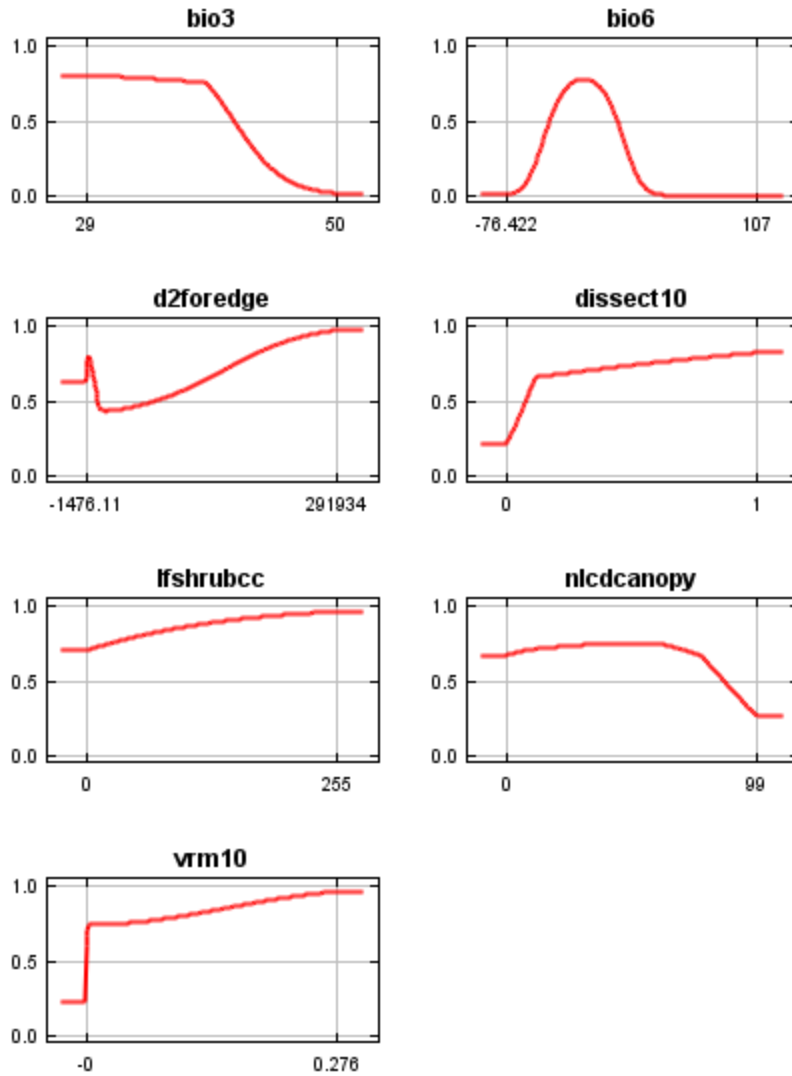
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
8.705	0.040	Equal training sensitivity and specificity	0.048	0.048
16.648	0.104	Maximum training sensitivity plus specificity	0.017	0.048
2.531	0.009	Balance training omission, predicted area and threshold value	0.122	0.000
13.963	0.068	Equate entropy of thresholded and original distributions	0.024	0.048

Response curves

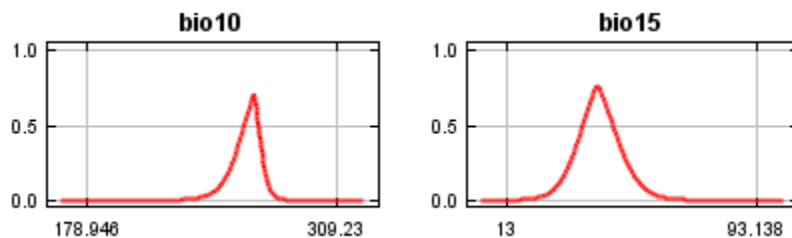
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



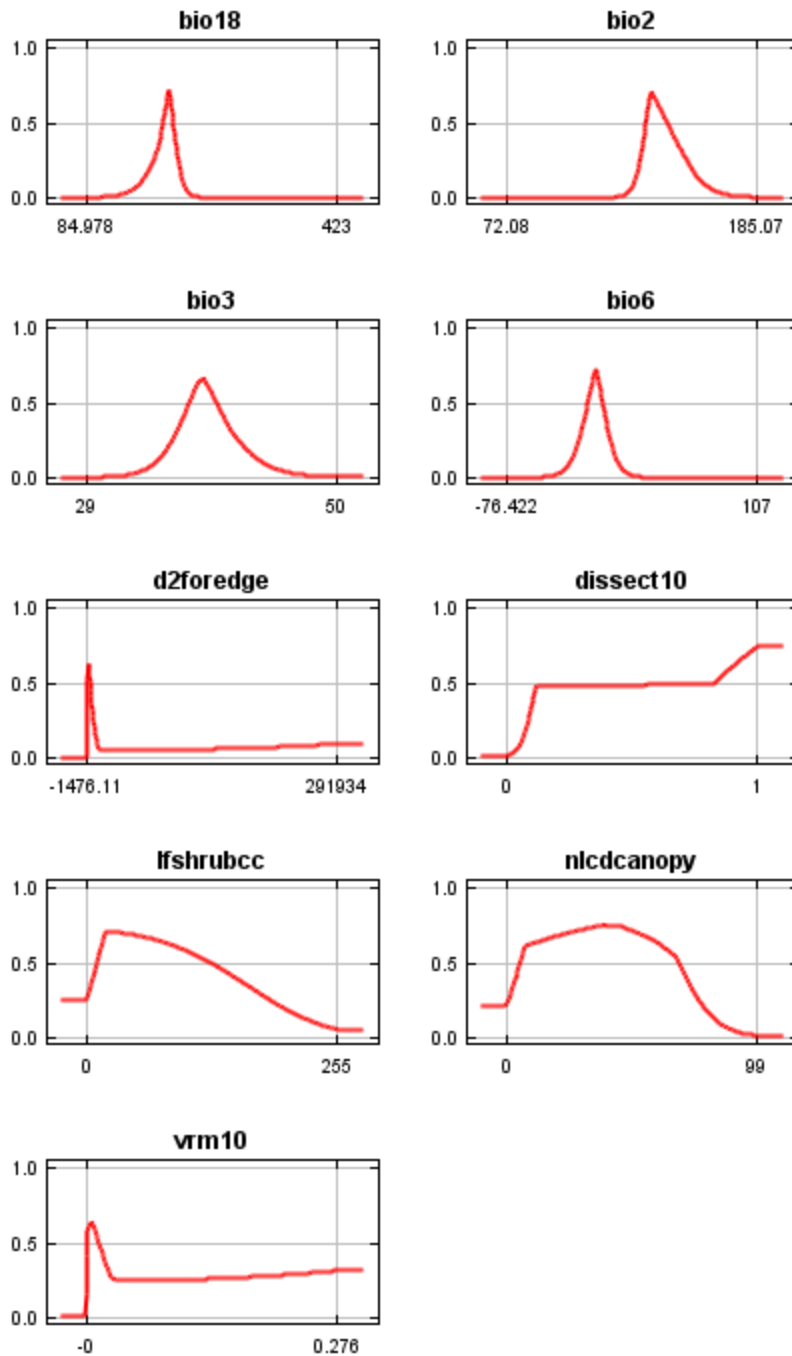
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



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

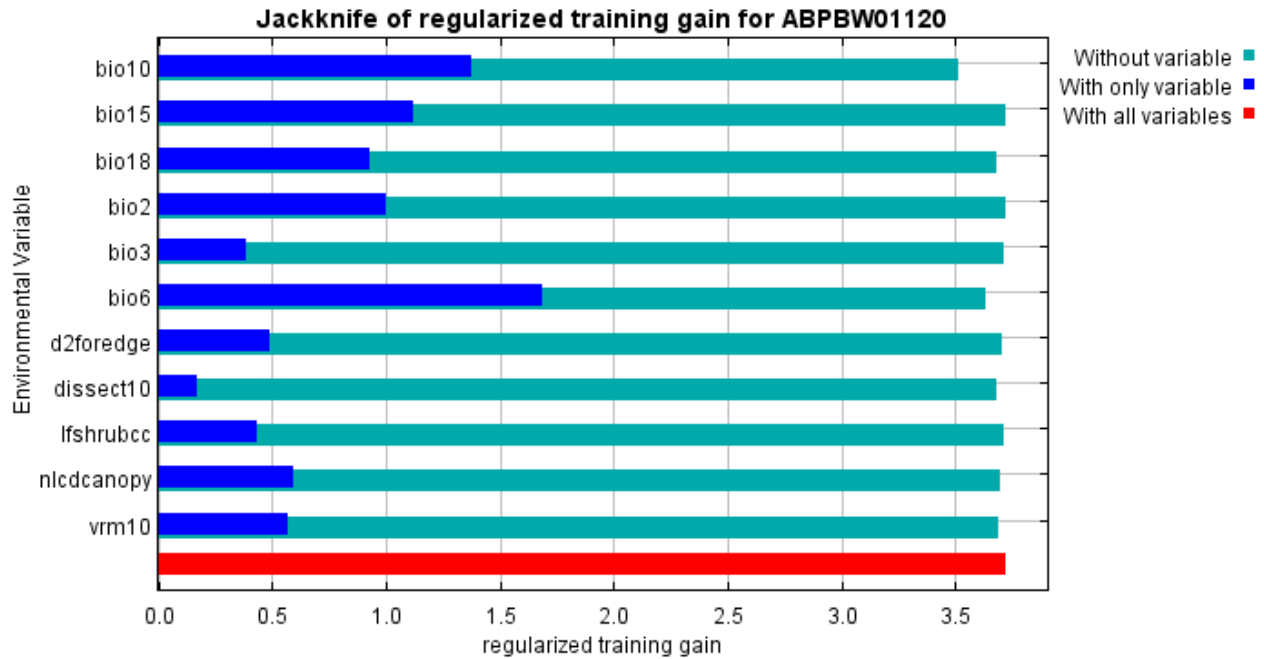
Appendix 2 – Model Reports

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
bio6	24.4	52.9
bio15	16.2	1.4
bio10	15	22.6
d2foredge	11.7	0.9
lfshrubcc	9.4	0.2
bio3	7.3	7.3
vrml0	7	0.5
nlcdcanopy	4.2	0.5
dissect10	4.1	0.3
bio18	0.7	12.5
bio2	0	0.7

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio6, 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 bio10, which therefore appears to have the most information that isn't present in the other variables.

Appendix 2 – Model Reports



Raw data outputs and control parameters

Regularized training gain is 3.723, training AUC is 0.991, unregularized training gain is 4.106.
Algorithm terminated after 500 iterations (7 seconds).

The follow settings were used during the run:

63 presence records used for training.

8680 points used to determine the Maxent distribution (background points and presence points).

Environmental layers used (all continuous): bio10 bio15 bio18 bio2 bio3 bio6 d2foredge dissect10 lfshrubcc nlcdcanopy vrm10

Regularization values: linear/quadratic/product: 0.156, categorical: 0.250, threshold: 1.370, hinge: 0.500

Feature types used: linear quadratic hinge

responsecurves: true

pictures: false

jackknife: true

outputfiletype: bil

outputdirectory: F:\MODELING\TXNDD_SDM\MAXENT_OUT\ABPBW01120\RUN_4

projectionlayers: F:\MODELING\TXNDD_SDM\MAXENT_IN\PROB

samplesfile: F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV

environmentallayers:

F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV

writeclampgrid: false

writemess: false

writebackgroundpredictions: true

Appendix 2 – Model Reports

writeplotdata: true

Command line used: dontwriteclampgrid

Command line to repeat this species model:

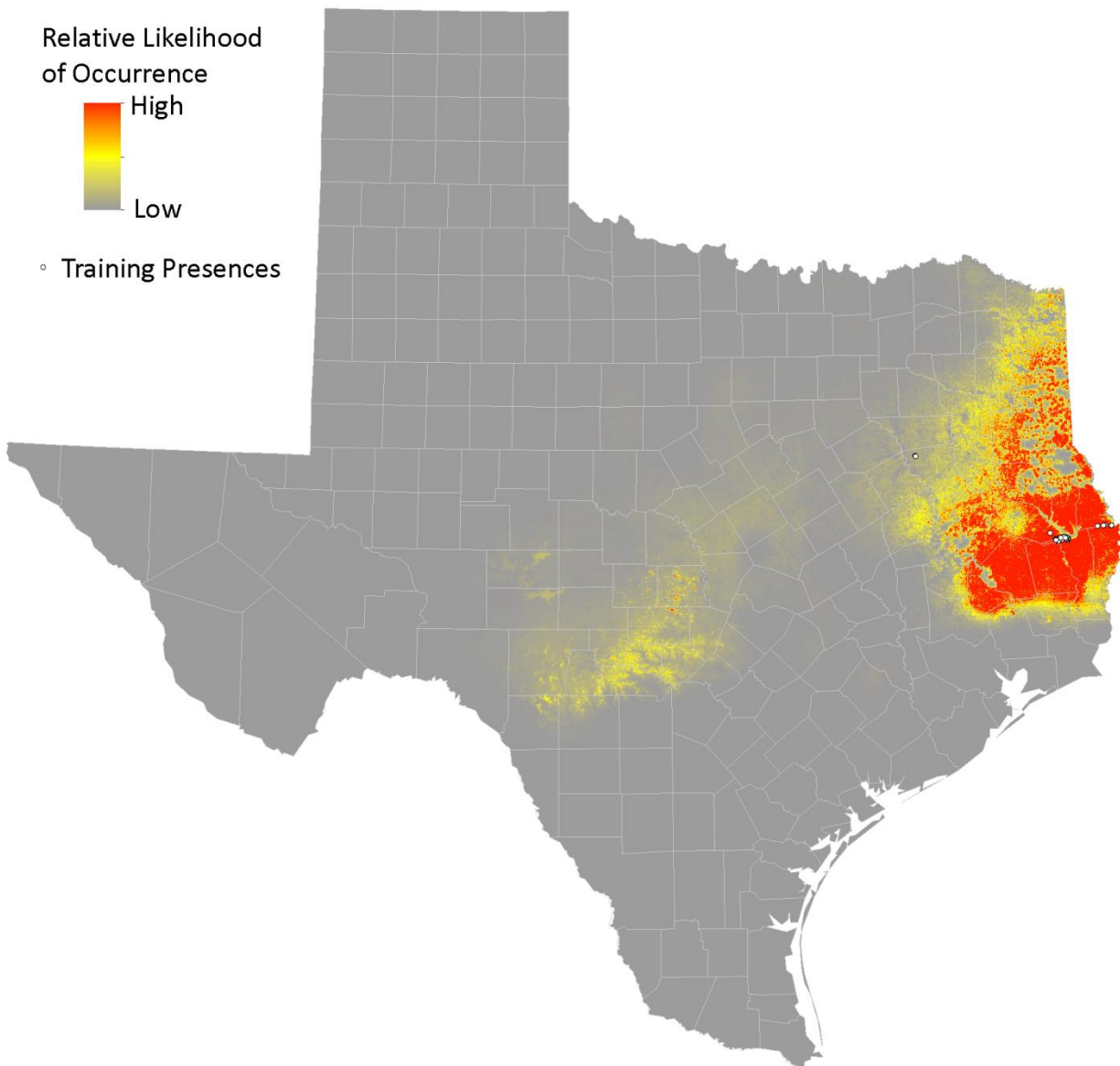
```
java density.MaxEnt nowarnings noprefixes -E "" -E ABPBW01120 responsecurves nopictures
jackknife outputfiletype=bil
outputdirectory=F:\MODELING\TXNDD_SDM\MAXENT_OUT\ABPBW01120\RUN_4
projectionlayers=F:\MODELING\TXNDD_SDM\MAXENT_IN\PROB
samplesfile=F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
environmentallayers=F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\BACKGROU
ND.CSV nowriteclampgrid nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -
N aglands -N allwatdist -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N
avoid12800 -N avoid1600 -N avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14
-N bio16 -N bio17 -N bio19 -N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N
d2wsl -N dissect5 -N drainclass -N hydgroup -N ksats -N lf_evh -N lf_forstcc -N lfherbcc -N ned -N
percclay -N percscand -N percstilt -N radld -N slope -N soilec -N soilph -N vrm5 -N water1600 -N
water300 -N water3200
```

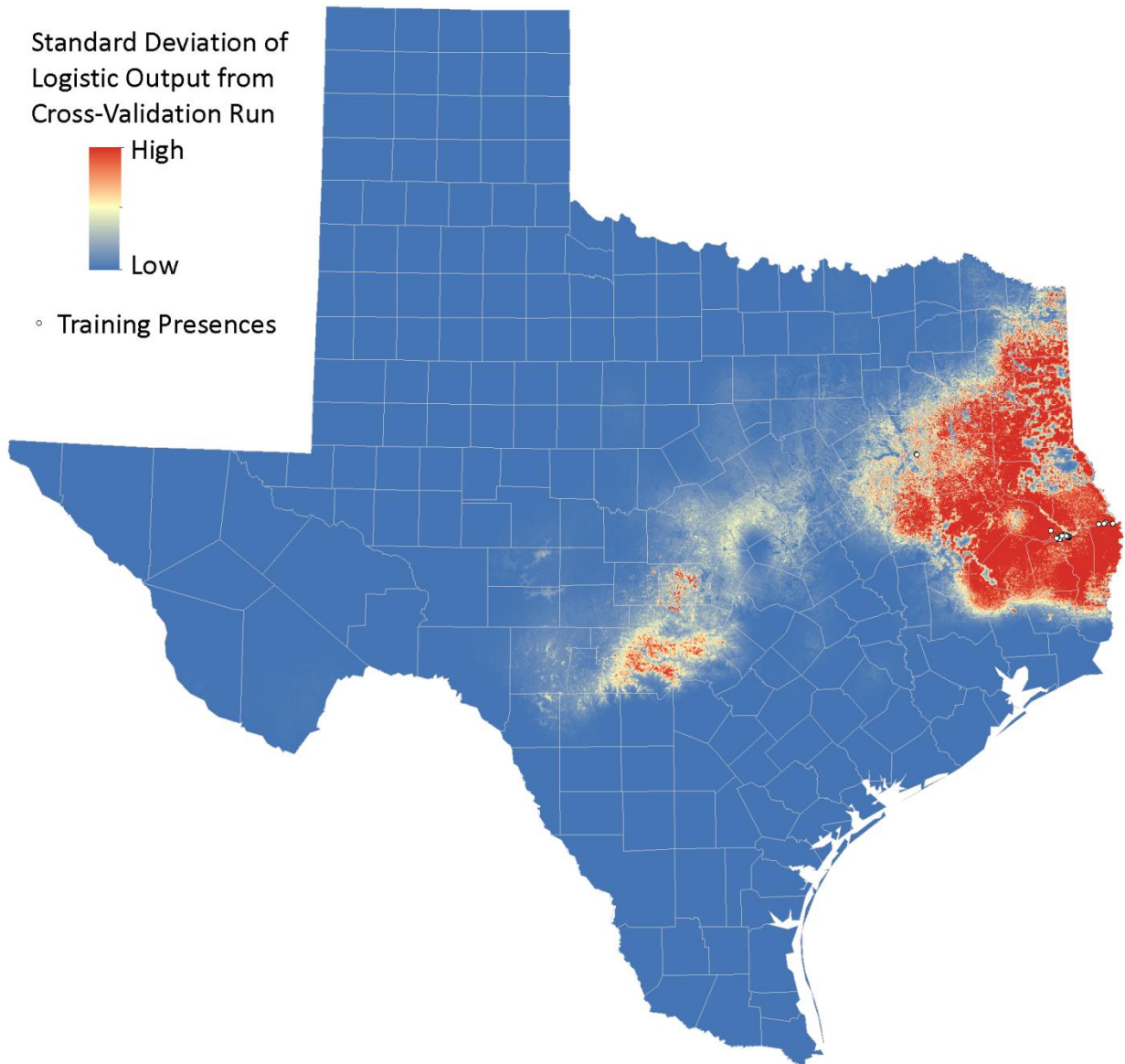
Bachman's Sparrow (*Aimophila aestivalis*)

ELCODE: ABPBX91050

Date: August 15, 2013

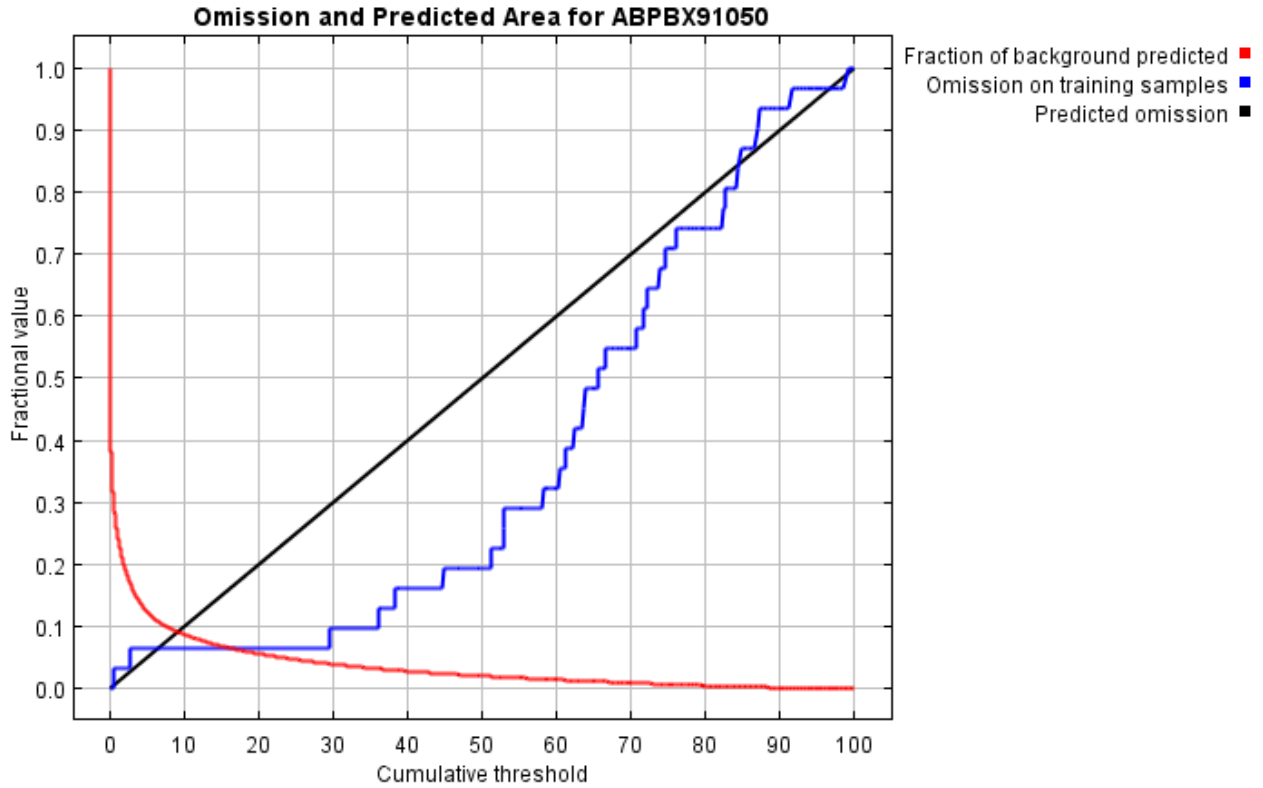
Maxent version: 3.3.3k





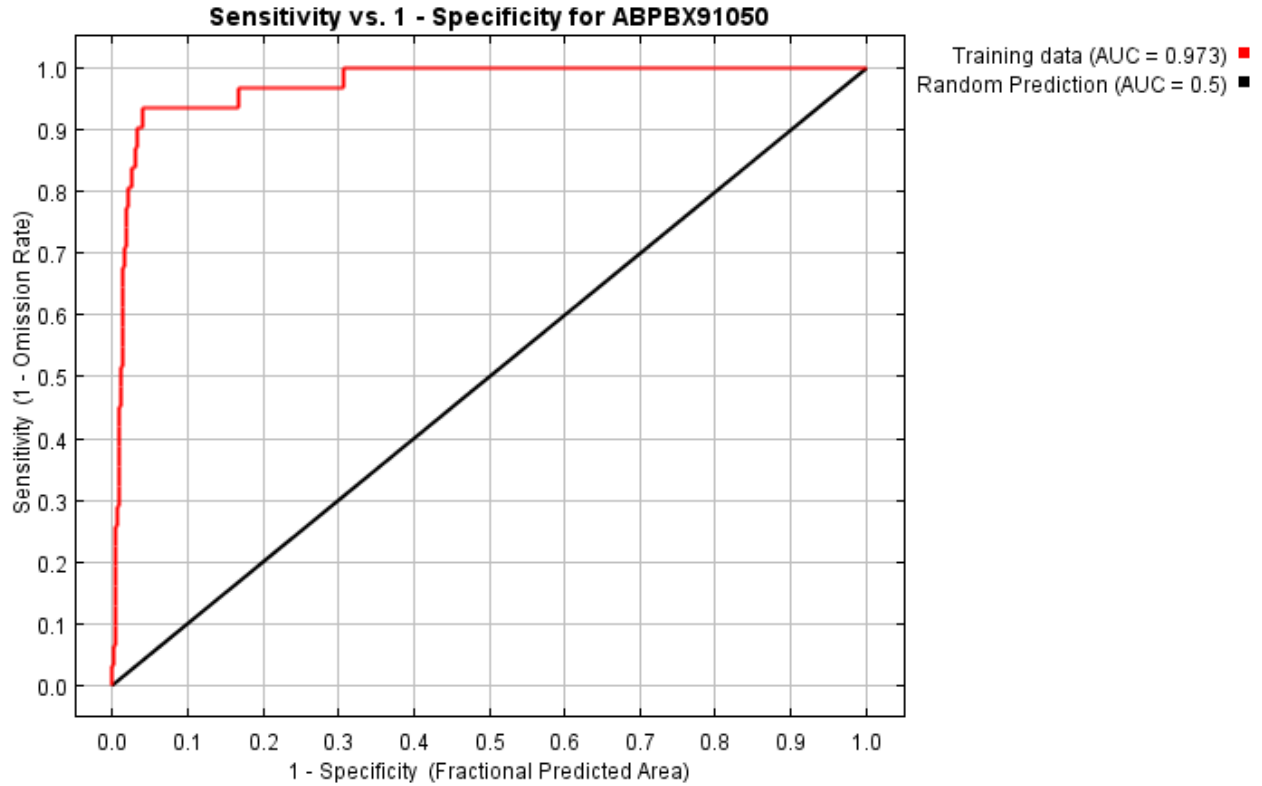
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.962 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

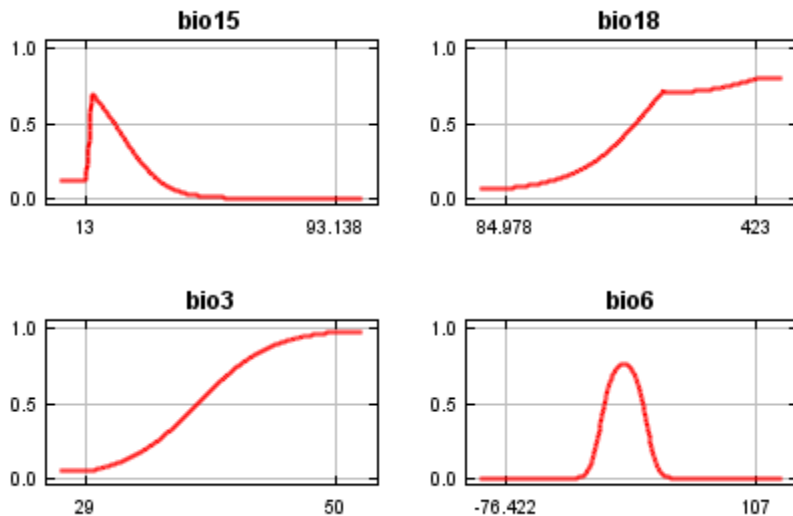
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.012	Fixed cumulative value 1	0.248	0.032
5.000	0.069	Fixed cumulative value 5	0.124	0.065
10.000	0.174	Fixed cumulative value 10	0.087	0.065
0.421	0.006	Minimum training presence	0.308	0.000
35.983	0.468	10 percentile training presence	0.033	0.097

Appendix 2 – Model Reports

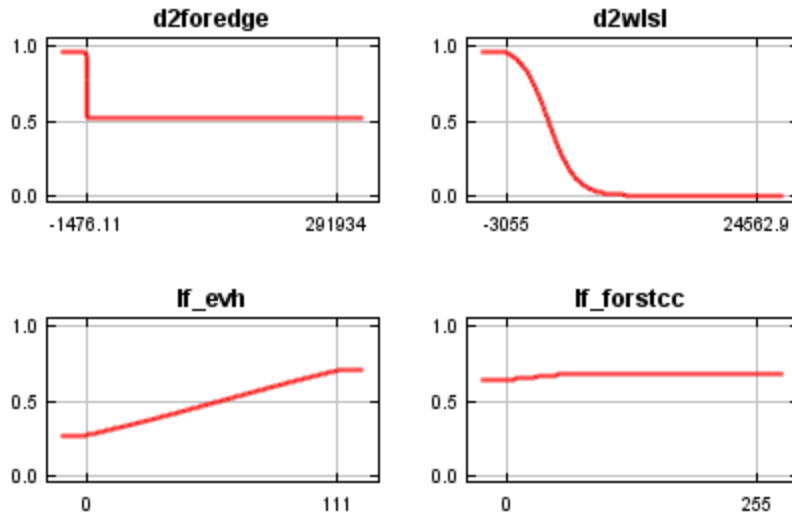
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
16.654	0.264	Equal training sensitivity and specificity	0.065	0.065
29.506	0.411	Maximum training sensitivity plus specificity	0.040	0.065
0.421	0.006	Balance training omission, predicted area and threshold value	0.308	0.000
8.330	0.147	Equate entropy of thresholded and original distributions	0.096	0.065

Response curves

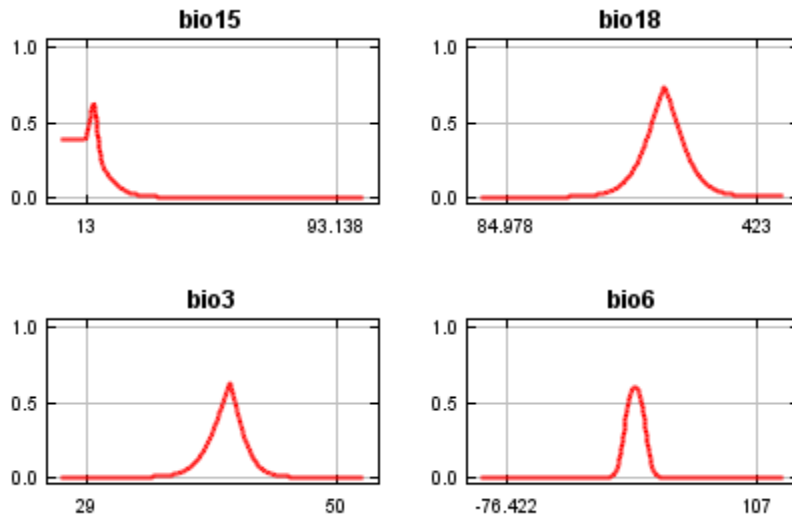
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



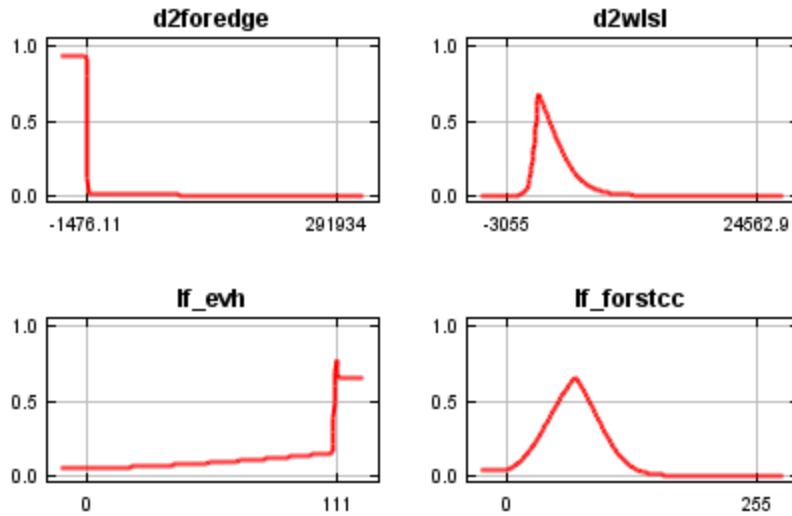
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



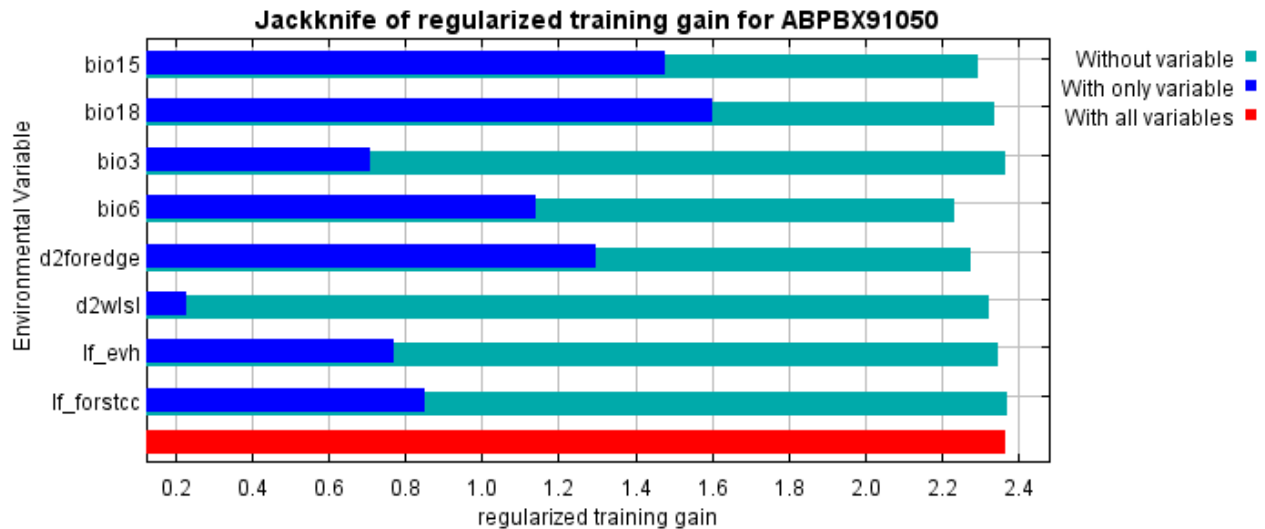
Analysis of variable contributions

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
bio15	50.3	33.8
bio18	16.1	6.2
lf_forstcc	13.5	0
bio6	6.6	47.5
d2foredge	5.9	1.2
lf_evh	5.1	0.9
d2wsl	1.8	4.6
bio3	0.7	5.8

Appendix 2 – Model Reports

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio18, 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 bio6, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 2.365, training AUC is 0.973, unregularized training gain is 2.703. Algorithm terminated after 500 iterations (19 seconds).

The follow settings were used during the run:

31 presence records used for training.
8649 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): bio15 bio18 bio3 bio6 d2foredge d2wsl lf_evh lf_forstcc
Regularization values: linear/quadratic/product: 0.247, categorical: 0.250, threshold: 1.690, hinge: 0.500
Feature types used: linear quadratic hinge
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MAXENT_OUT\APBPX91050\RUN_3
projectionlayers: F:\MAXENT_IN\PROB
samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
environmentallayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV
writeclampgrid: false
writemess: false

Appendix 2 – Model Reports

writebackgroundpredictions: true
writeplotdata: true
Command line used: dontwriteclampgrid

Command line to repeat this species model:

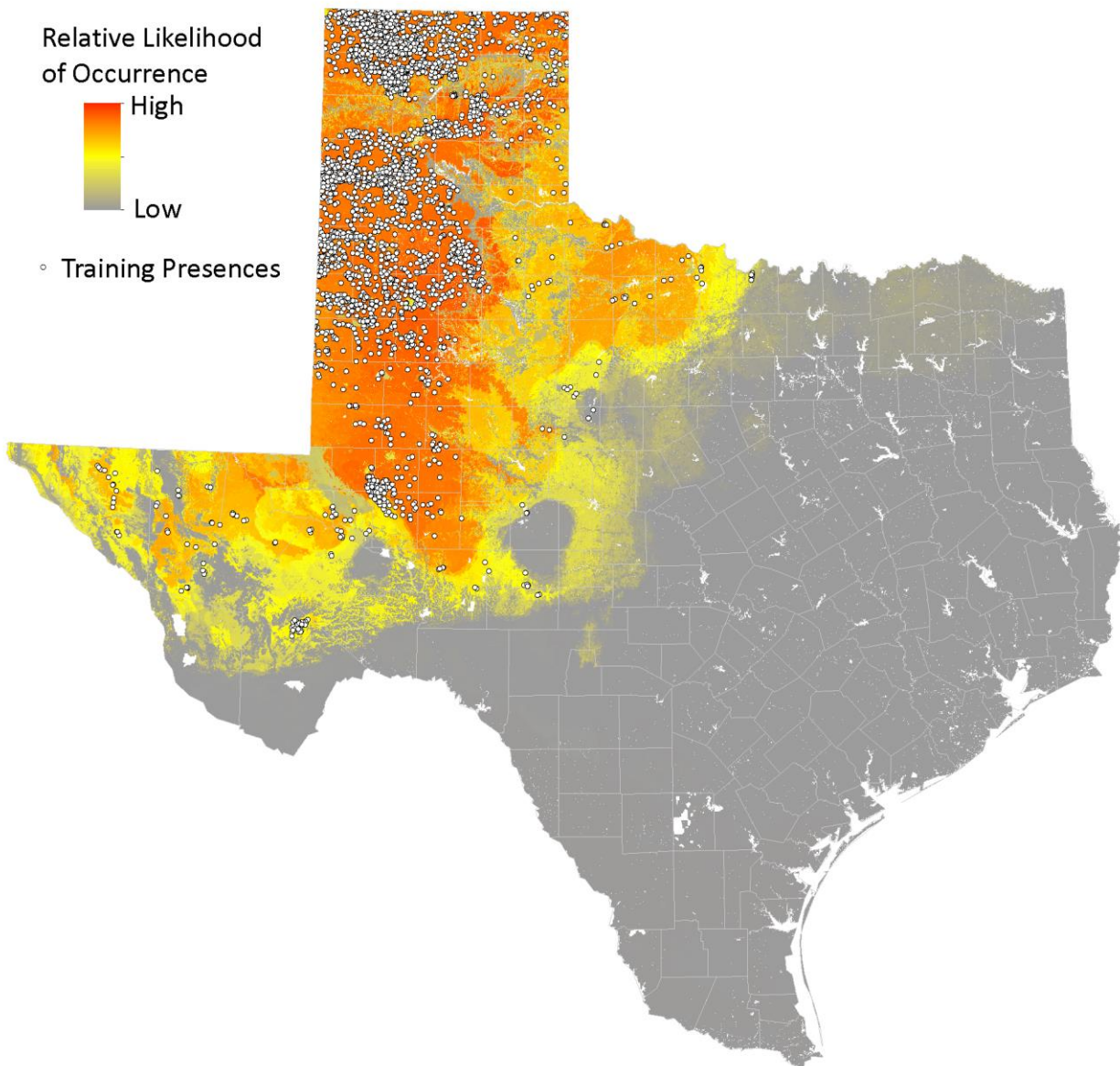
```
java density.MaxEnt nowarnings noprefixes -E "" -E ABPBX91050 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\APBPX91050\RUN_3  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -N aglands -N allwatdist -N  
aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N avoid12800 -N avoid1600 -N  
avoid3200 -N avoid6400 -N bio1 -N bio10 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -  
N bio19 -N bio2 -N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N dissect10 -N  
dissect5 -N drainclass -N hydgroup -N ksats -N lfherbcc -N lfshrubcc -N ned -N nlcdcanopy -N  
percclay -N percscand -N percstilt -N radld -N slope -N soilec -N soilph -N vrm10 -N vrm5 -N  
water1600 -N water300 -N water3200
```

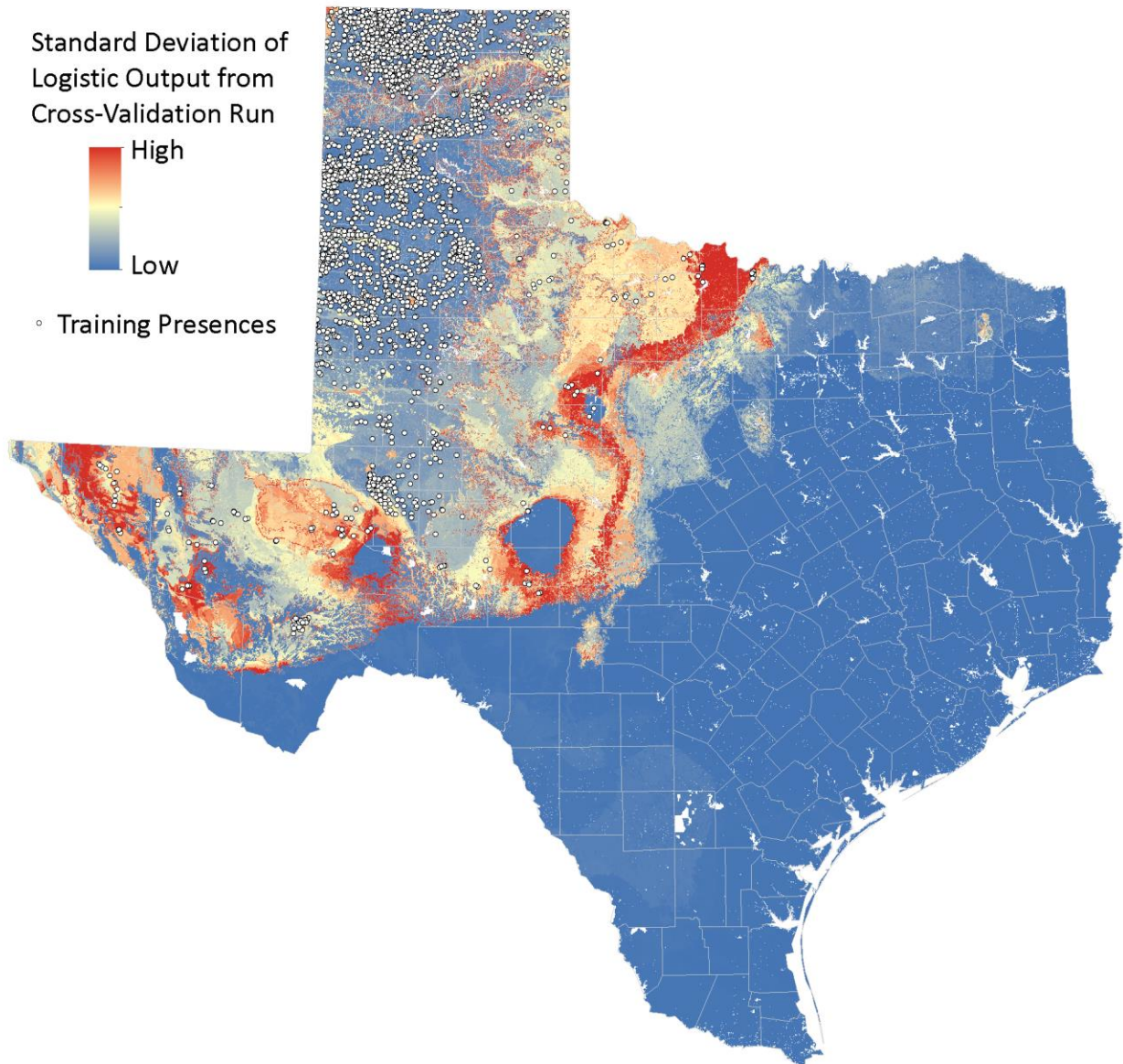

Black-tailed Prairie Dog (*Cynomys ludovicianus*)

ELCODE: AMAFB06010

Date: August 09, 2013

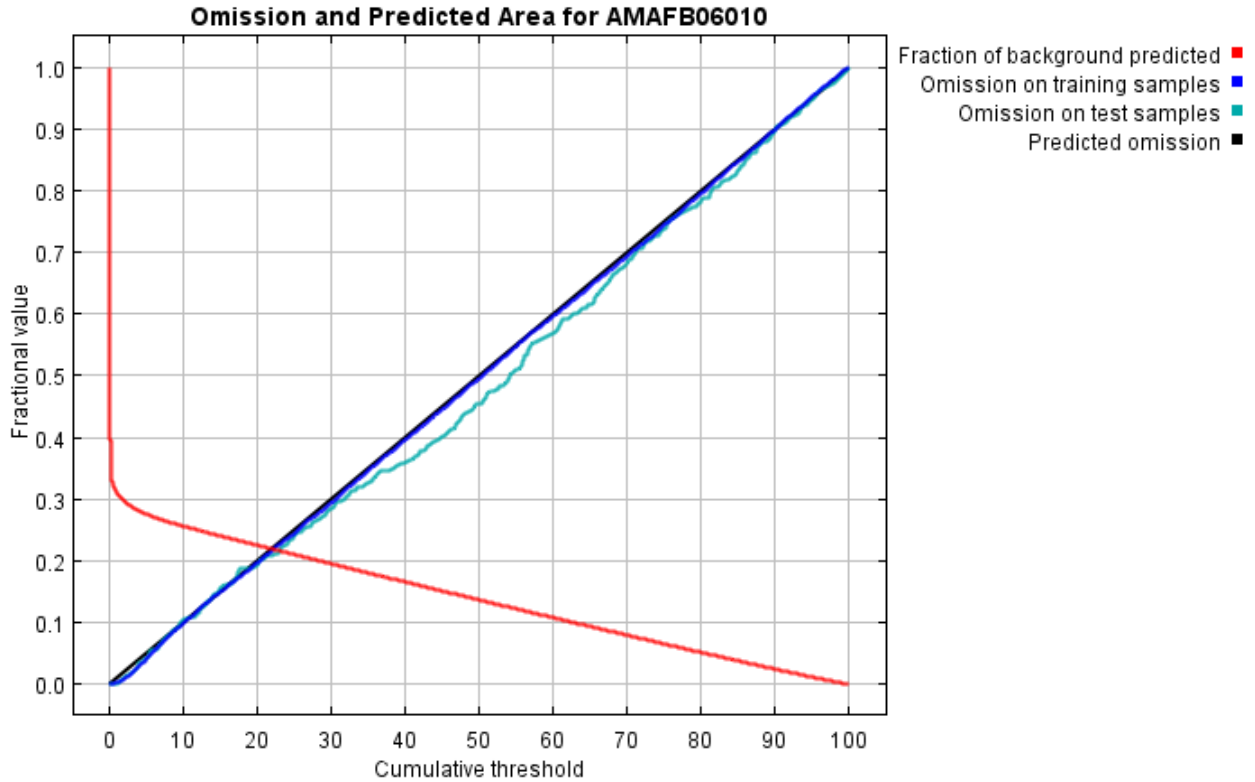
Maxent version: 3.3.3k





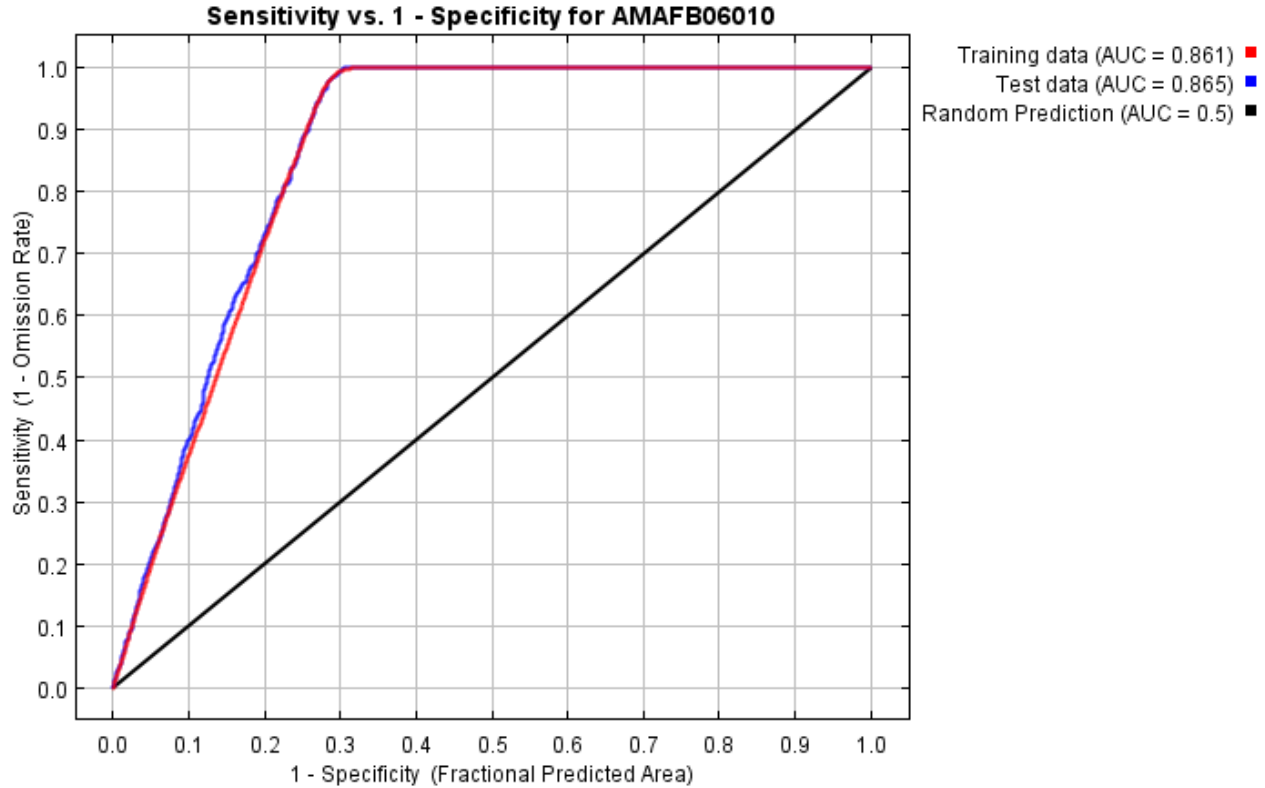
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.860 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
1.000	0.145	Fixed cumulative value 1	0.310	0.003	0.002	0E0
5.000	0.388	Fixed cumulative value 5	0.276	0.041	0.043	0E0
10.000	0.486	Fixed cumulative value 10	0.257	0.100	0.104	0E0

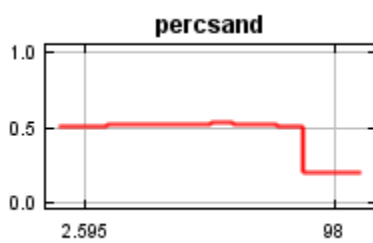
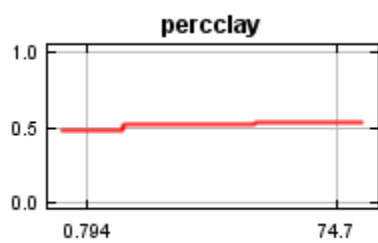
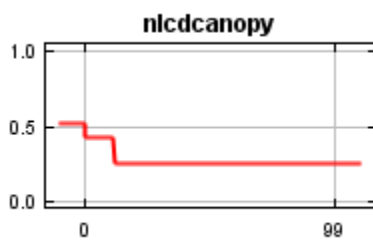
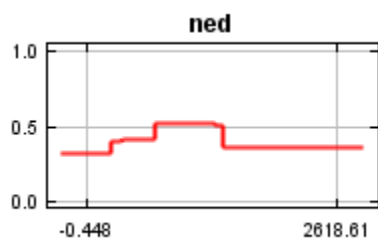
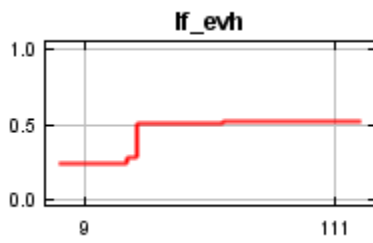
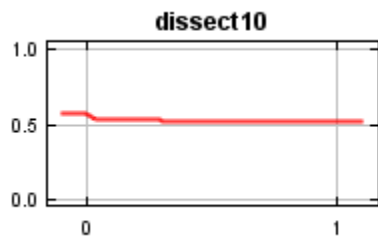
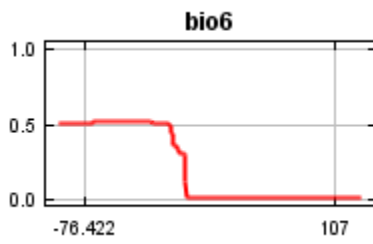
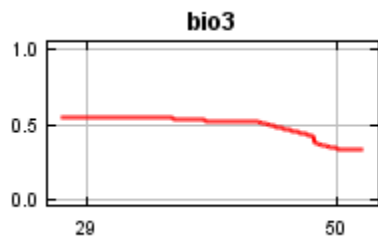
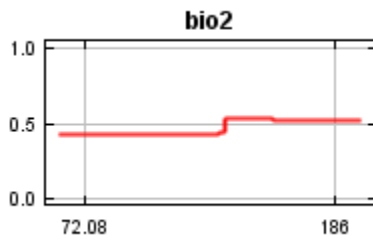
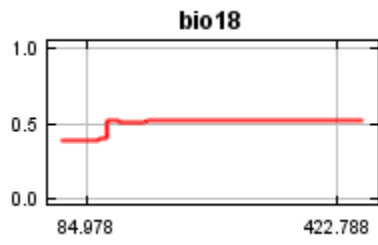
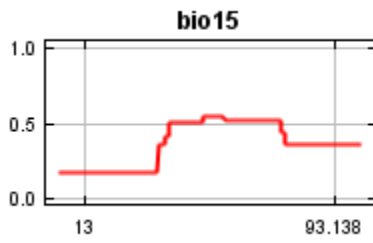
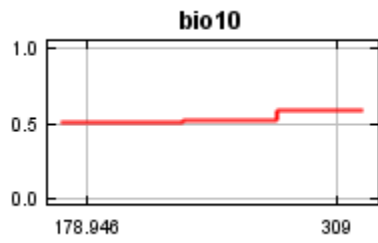
Appendix 2 – Model Reports

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
0.148	0.006	Minimum training presence	0.379	0.000	0.000	0E0
10.061	0.486	10 percentile training presence	0.256	0.100	0.107	0E0
22.182	0.508	Equal training sensitivity and specificity	0.219	0.219	0.209	0E0
2.545	0.268	Maximum training sensitivity plus specificity	0.292	0.013	0.015	0E0
22.963	0.509	Equal test sensitivity and specificity	0.217	0.226	0.216	0E0
2.688	0.275	Maximum test sensitivity plus specificity	0.291	0.015	0.015	0E0
0.406	0.052	Balance training omission, predicted area and threshold value	0.326	0.001	0.000	0E0
0.940	0.141	Equate entropy of thresholded and original distributions	0.311	0.003	0.002	0E0

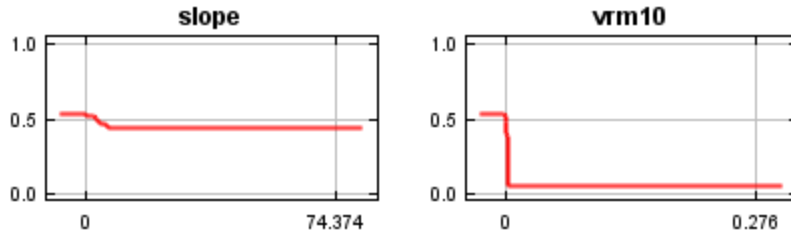
Response curves

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. 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. See Appendix 1 for detailed explanations of all environmental predictor layers.

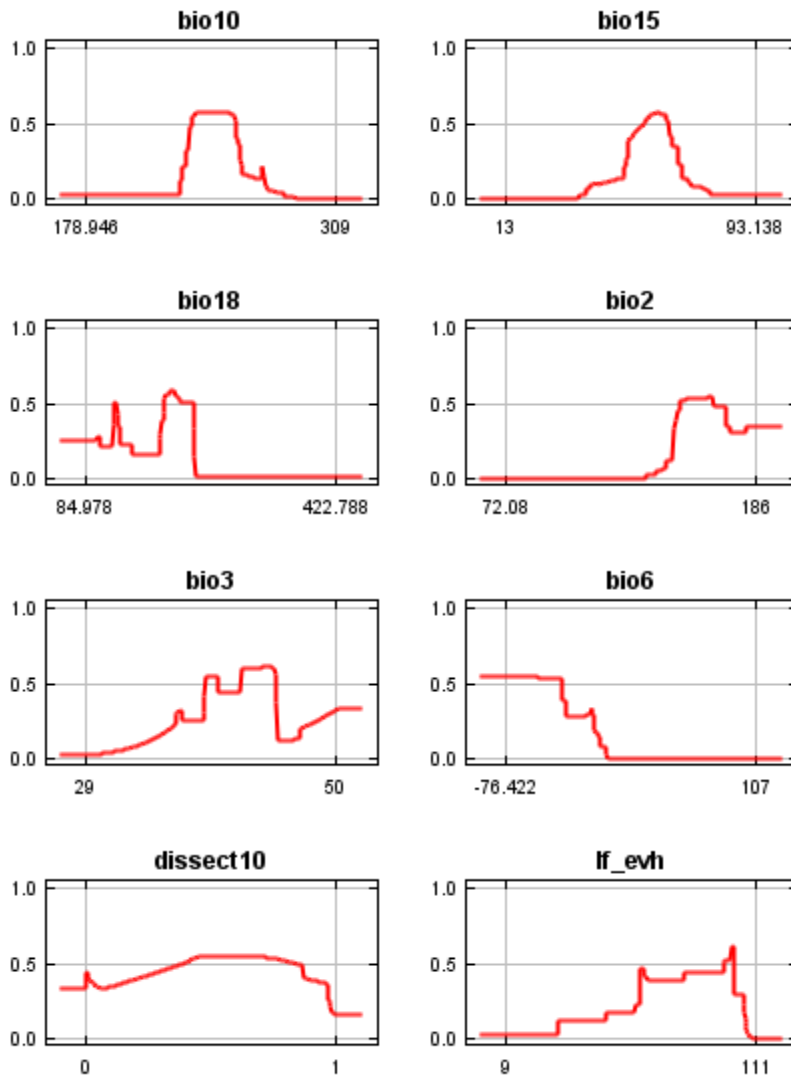
Appendix 2 – Model Reports



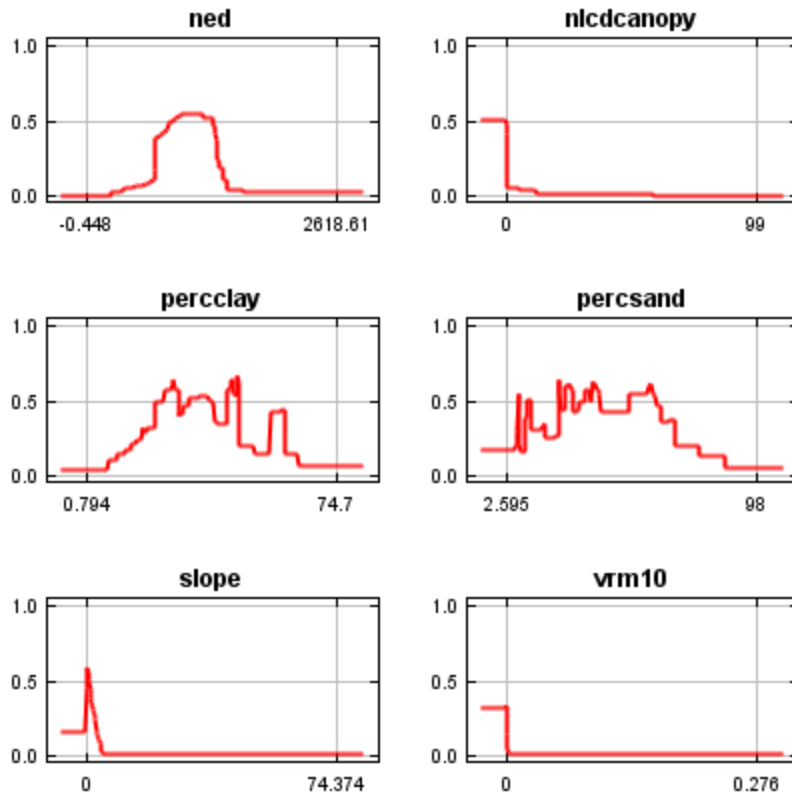
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



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.

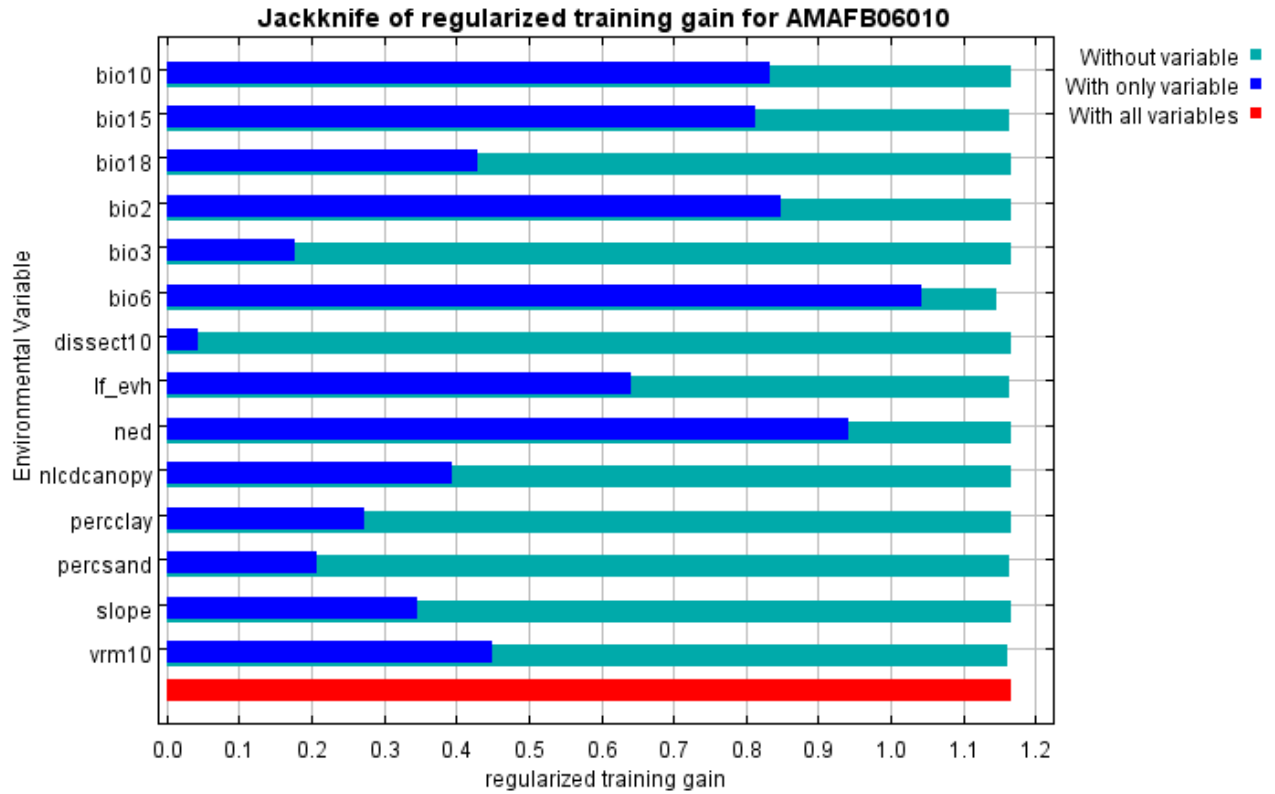
Variable	Percent contribution	Permutation importance
bio6	78	70.7
vrm10	10.2	10.1
bio2	5.5	1.7
nlcdcanopy	1.3	2.6

Appendix 2 – Model Reports

Variable	Percent contribution	Permutation importance
percclay	0.9	0.9
percsand	0.8	1.2
ned	0.8	2.6
bio10	0.7	1.2
bio3	0.6	0.8
bio15	0.6	5
lf_evh	0.5	1.7
slope	0.1	1
bio18	0.1	0.5
dissect10	0	0.1

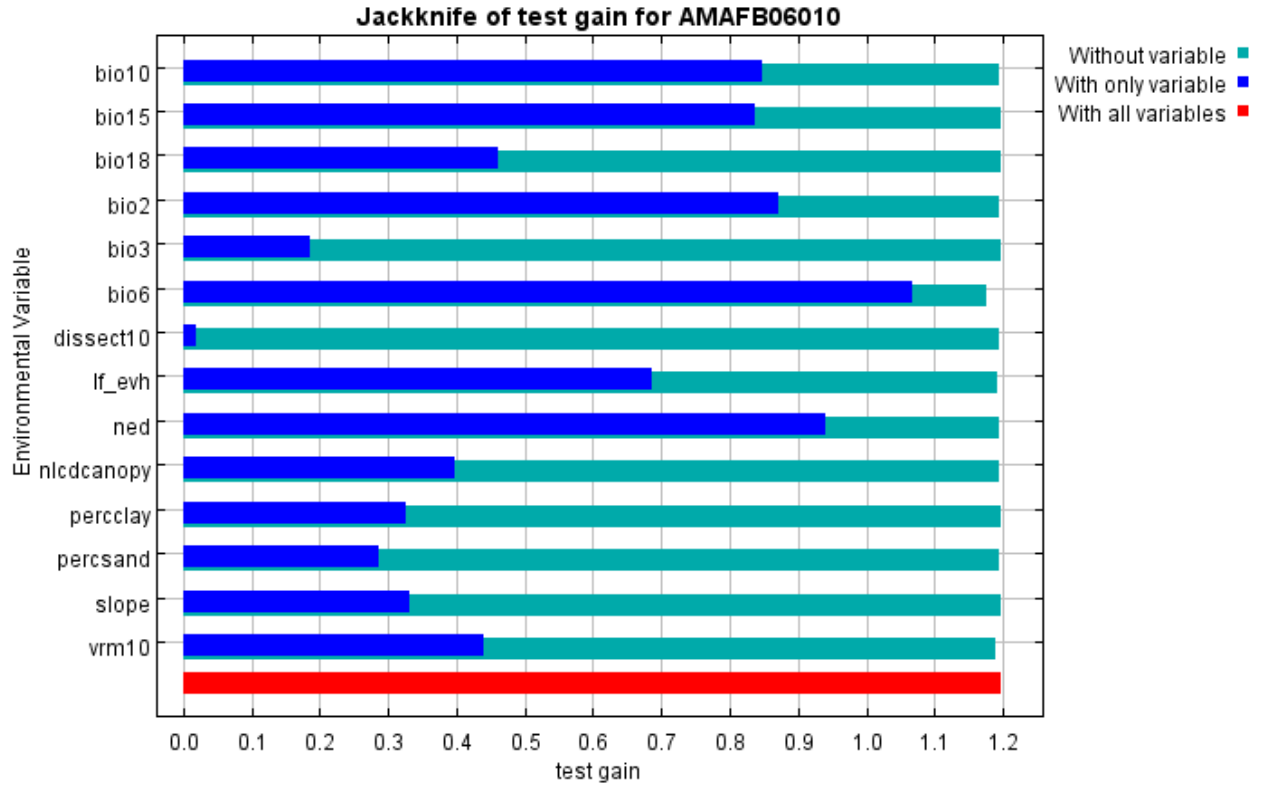
The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio6, which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted is bio6, which therefore appears to have the most information that isn't present in the other variables.

Appendix 2 – Model Reports

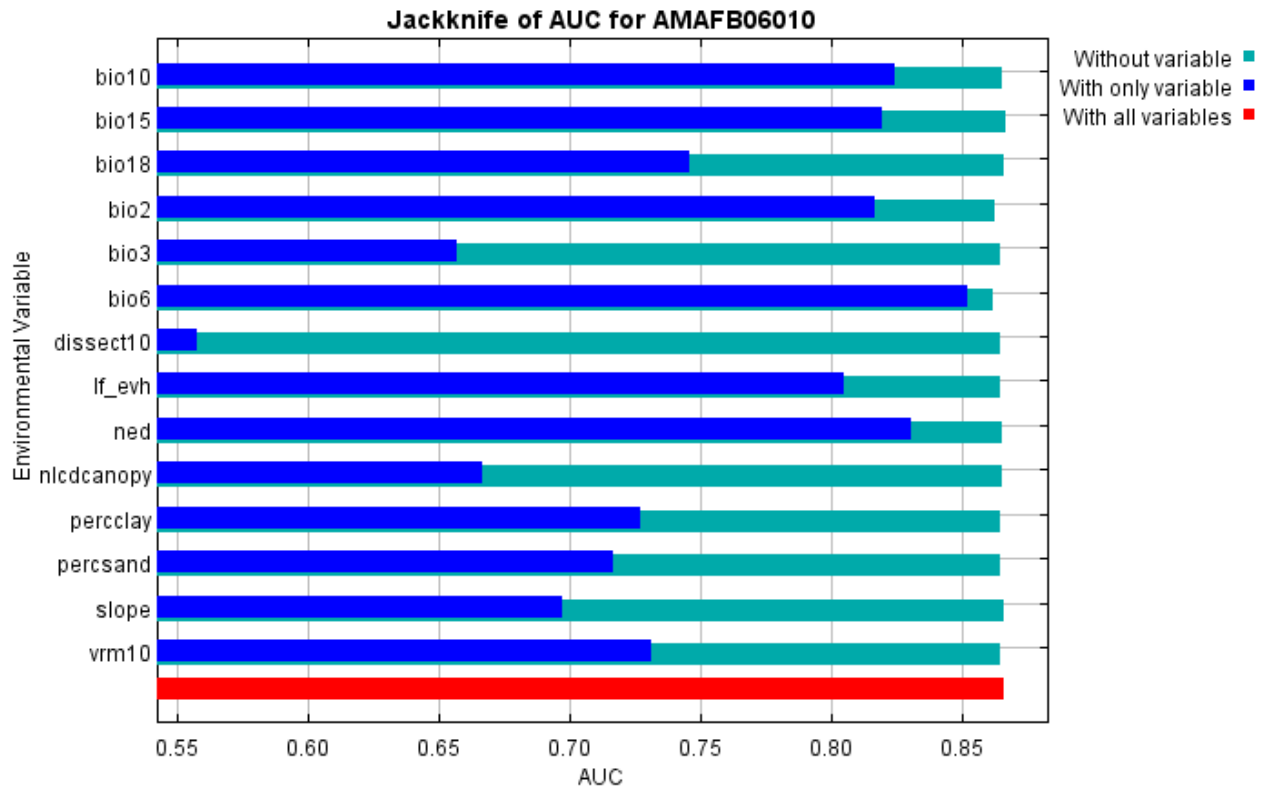


The next picture shows the same jackknife test, using test gain instead of training gain. Note that conclusions about which variables are most important can change, now that we're looking at test data.

Appendix 2 – Model Reports



Lastly, we have the same jackknife test, using AUC on test data.



Raw data outputs and control parameters

Regularized training gain is 1.167, training AUC is 0.861, unregularized training gain is 1.193.

Unregularized test gain is 1.197.

Test AUC is 0.865, standard deviation is 0.004 (calculated as in DeLong, DeLong & Clarke-Pearson 1988, equation 2).

Algorithm converged after 380 iterations (10 seconds).

The follow settings were used during the run:

2355 presence records used for training, 588 for testing.

9692 points used to determine the Maxent distribution (background points and presence points).

Environmental layers used (all continuous): bio10 bio15 bio18 bio2 bio3 bio6 dissect10 lf_evh ned nlcdcanopy percclay percсанд slope vrm10

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

pictures: false

jackknife: true

outputfiletype: bil

outputdirectory: F:\MODELING\TXNDD_SDM\MAXENT_OUT\AMAFB06010\RUN_5

projectionlayers: F:\MODELING\TXNDD_SDM\MAXENT_IN\PROB

samplesfile: F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV

environmentallayers:

F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV

writeclampgrid: false

randomtestpoints: 20

writeplotdata: true

threads: 3

Command line used: dontwriteclampgrid

Command line to repeat this species model:

```
java density.MaxEnt nowarnings noprefixes -E "" -E AMAFB06010 responsecurves nopictures
```

```
jackknife outputfiletype=bil
```

```
outputdirectory=F:\MODELING\TXNDD_SDM\MAXENT_OUT\AMAFB06010\RUN_5
```

```
projectionlayers=F:\MODELING\TXNDD_SDM\MAXENT_IN\PROB
```

```
samplesfile=F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
```

```
environmentallayers=F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\BACKGROU
```

```
ND.CSV nowriteclampgrid randomtestpoints=20 writeplotdata threads=3 -N UNIQUE_ID -N aglands
```

```
-N allwatdist -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N avoid12800 -N
```

```
avoid1600 -N avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N
```

```
bio17 -N bio19 -N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N
```

```
d2wsl -N dissect5 -N drainclass -N hydgroup -N ksats -N lf_forstcc -N lfherbcc -N lfshrubcc -N
```

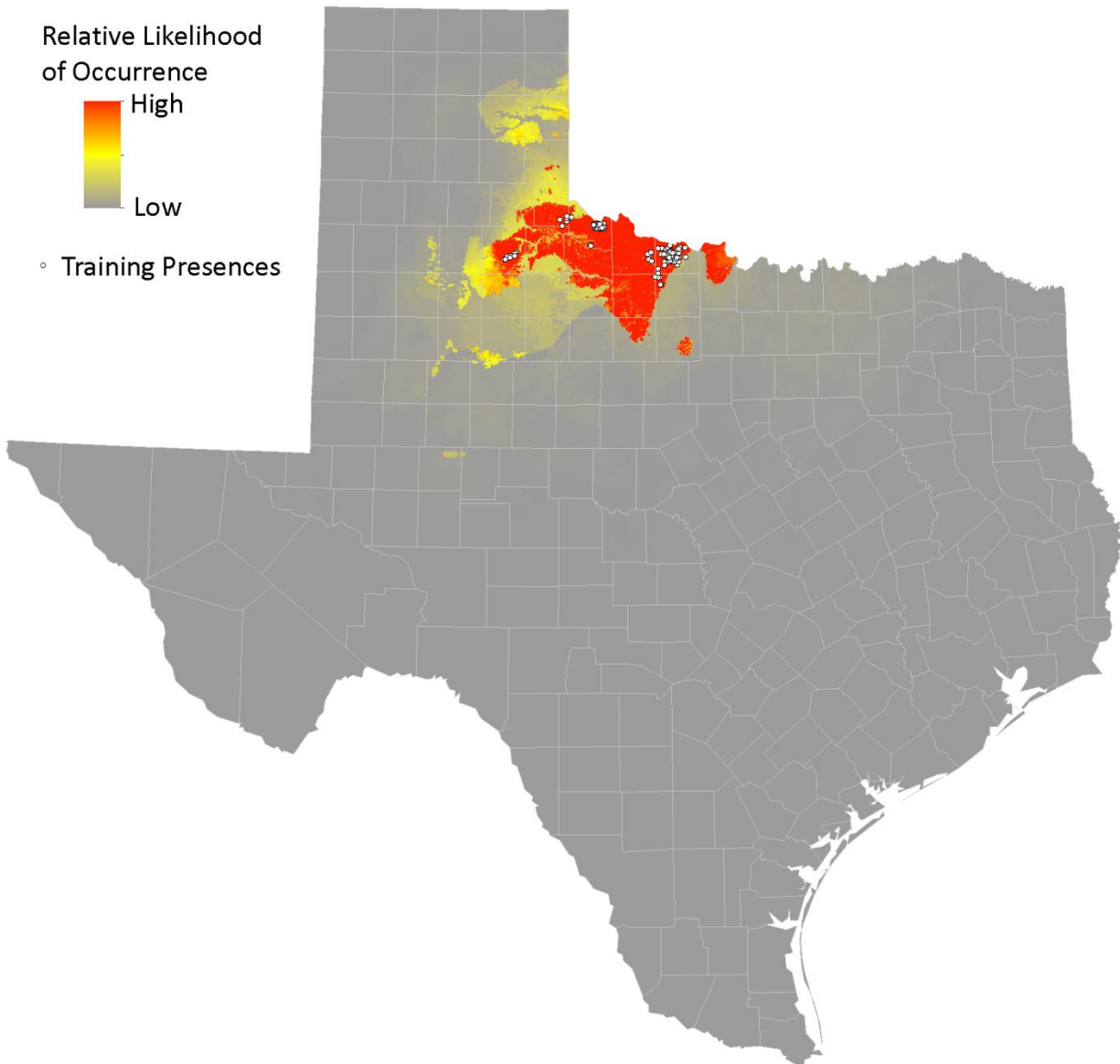
```
percsilt -N radld -N soilec -N soilph -N vrm5 -N water1600 -N water300 -N water3200
```

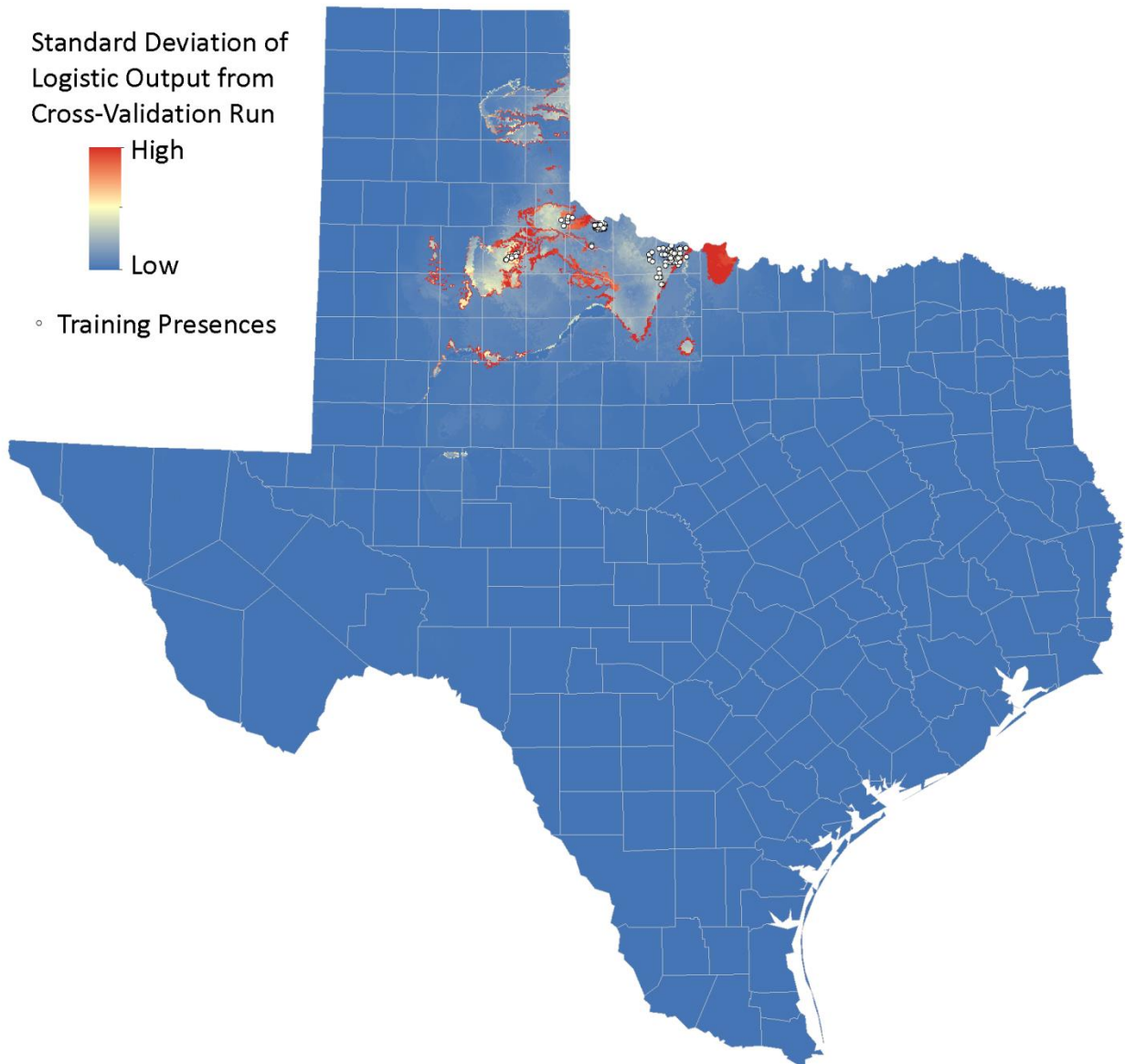
Texas Kangaroo Rat (*Dipodomys elator*)

ELCODE: AMAFD03120

Date: August 15, 2013

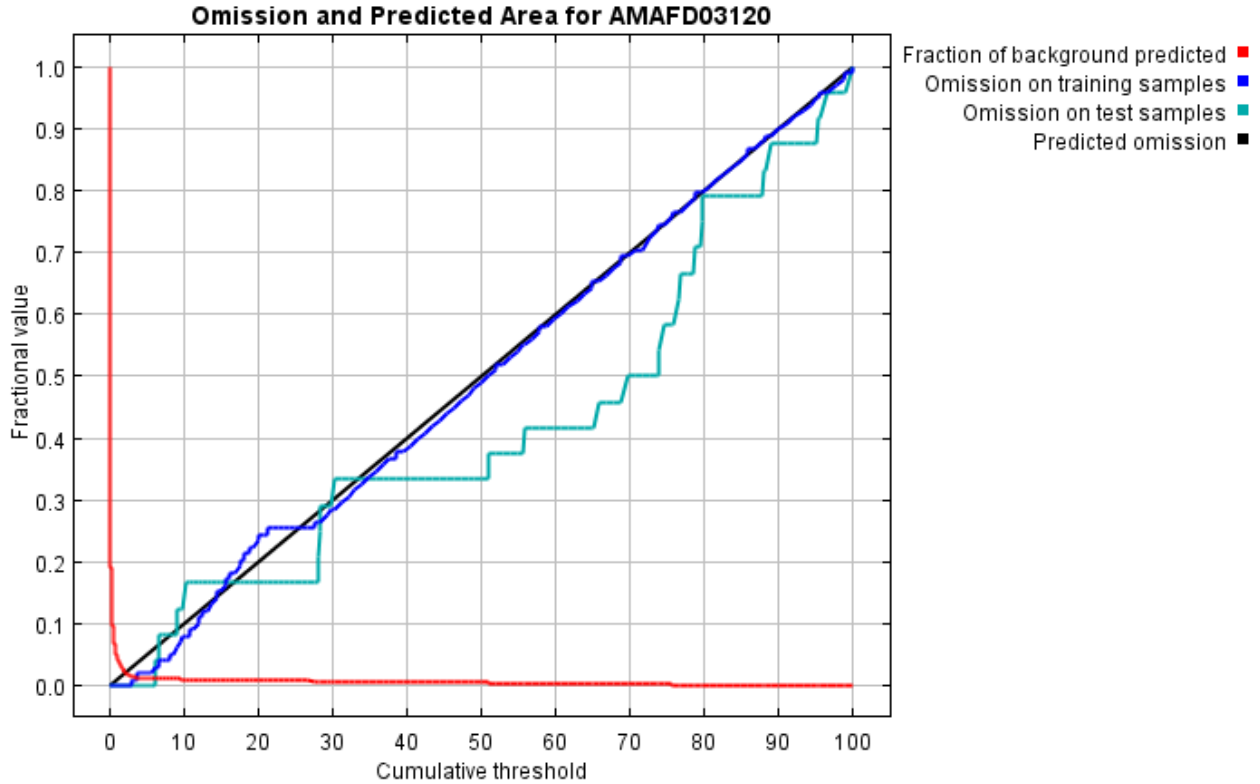
Maxent version: 3.3.3k



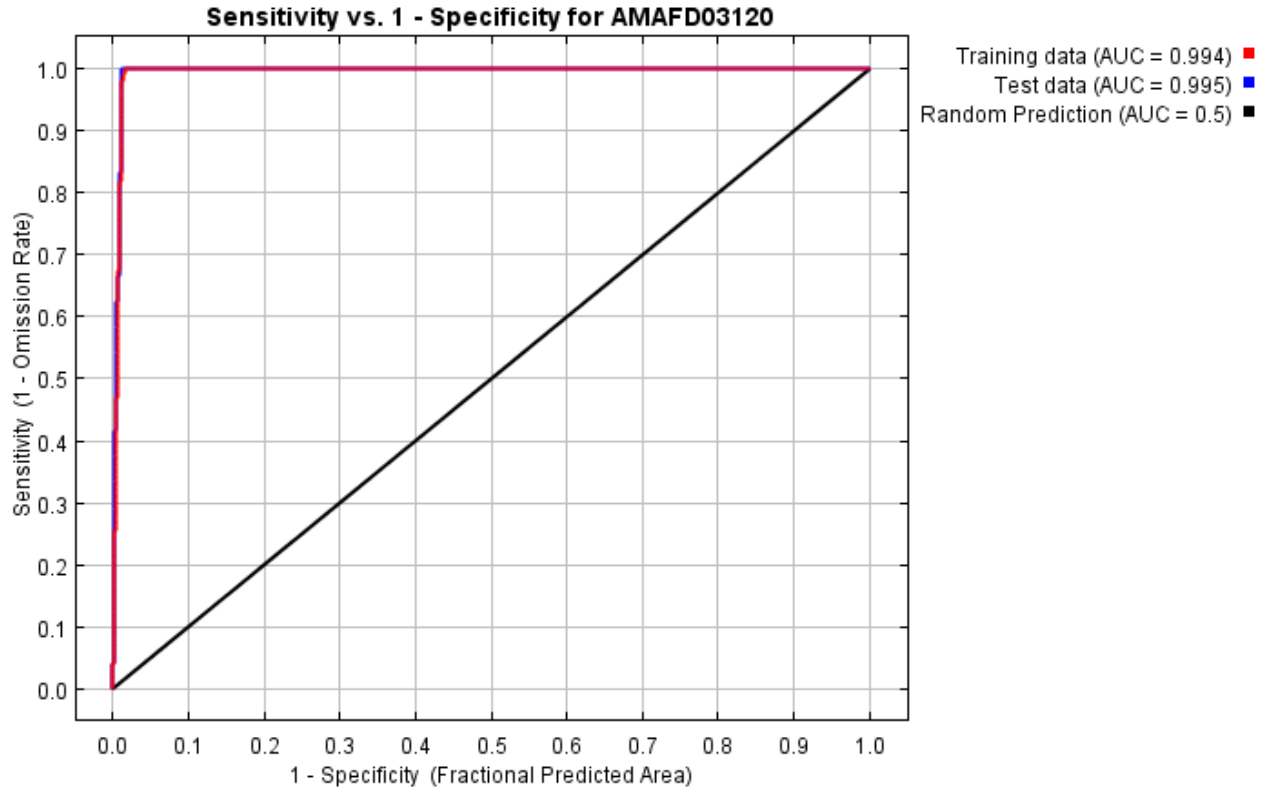


Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.992 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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
1.000	0.004	Fixed cumulative value 1	0.045	0.000	0.000	5.589E-33
5.000	0.210	Fixed cumulative value 5	0.013	0.020	0.000	3.61E-46
10.000	0.434	Fixed cumulative value 10	0.011	0.082	0.167	1.427E-35

Appendix 2 – Model Reports

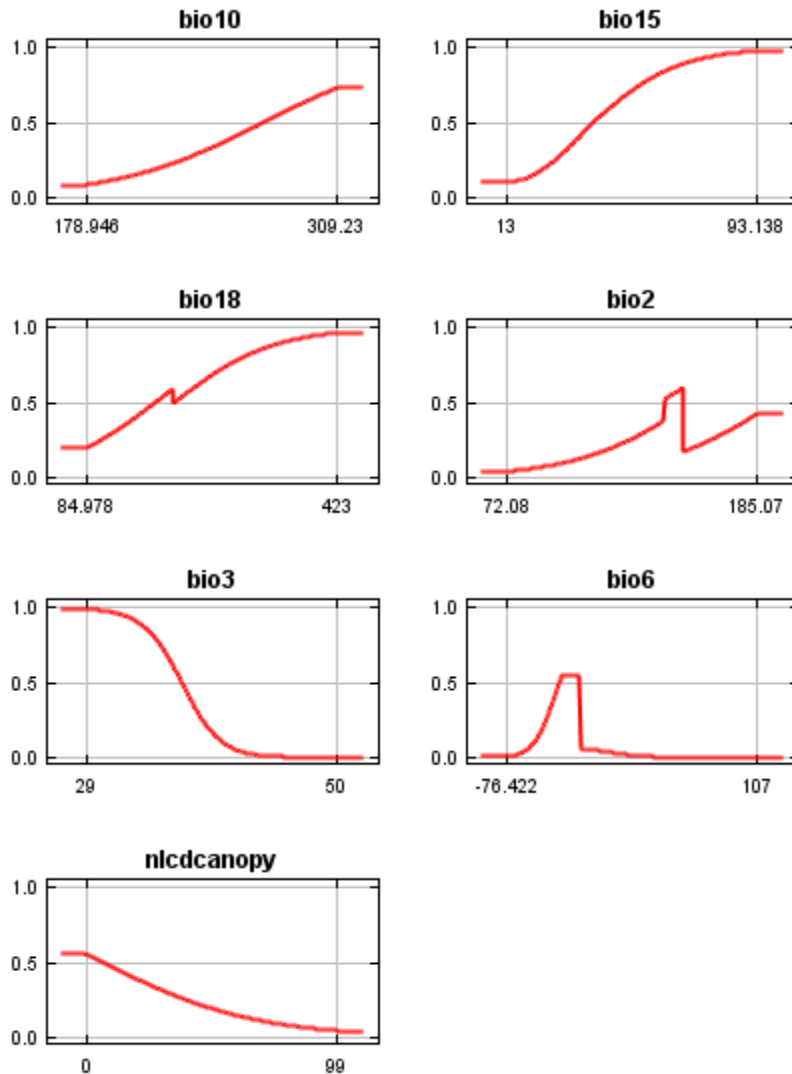
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
2.974	0.036	Minimum training presence	0.015	0.000	0.000	2.672E-44
11.287	0.446	10 percentile training presence	0.011	0.092	0.167	7.769E-36
3.598	0.119	Equal training sensitivity and specificity	0.014	0.010	0.000	3.42E-45
2.974	0.036	Maximum training sensitivity plus specificity	0.015	0.000	0.000	2.672E-44
5.729	0.236	Equal test sensitivity and specificity	0.012	0.020	0.000	1.508E-46
5.729	0.236	Maximum test sensitivity plus specificity	0.012	0.020	0.000	1.508E-46
1.222	0.006	Balance training omission, predicted area and threshold value	0.039	0.000	0.000	1.262E-34
2.874	0.032	Equate entropy of thresholded and original distributions	0.016	0.000	0.000	5.413E-44

Response curves

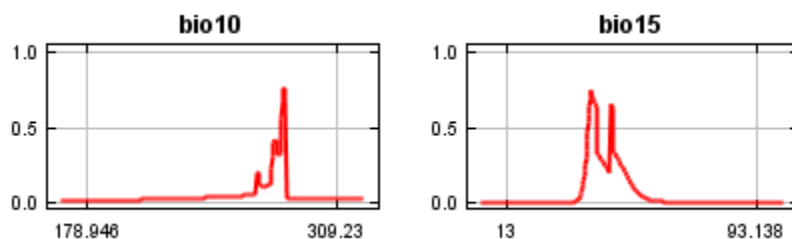
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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

Appendix 2 – Model Reports

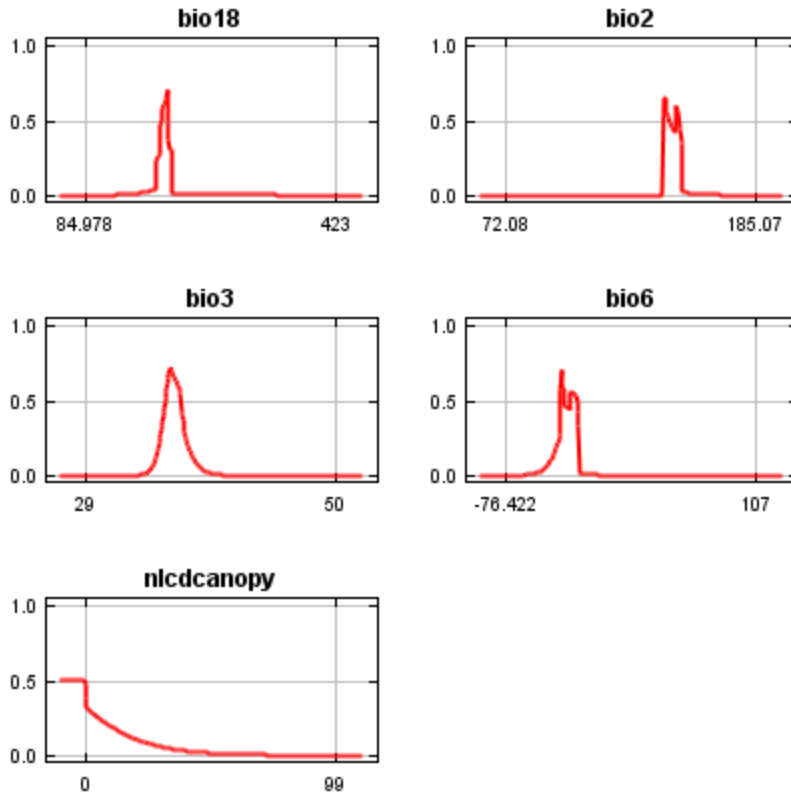
changing exactly one variable, whereas the model may take advantage of sets of variables changing together. See Appendix 1 for detailed explanations of all environmental predictor layers.



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.



Appendix 2 – Model Reports



Analysis of variable contributions

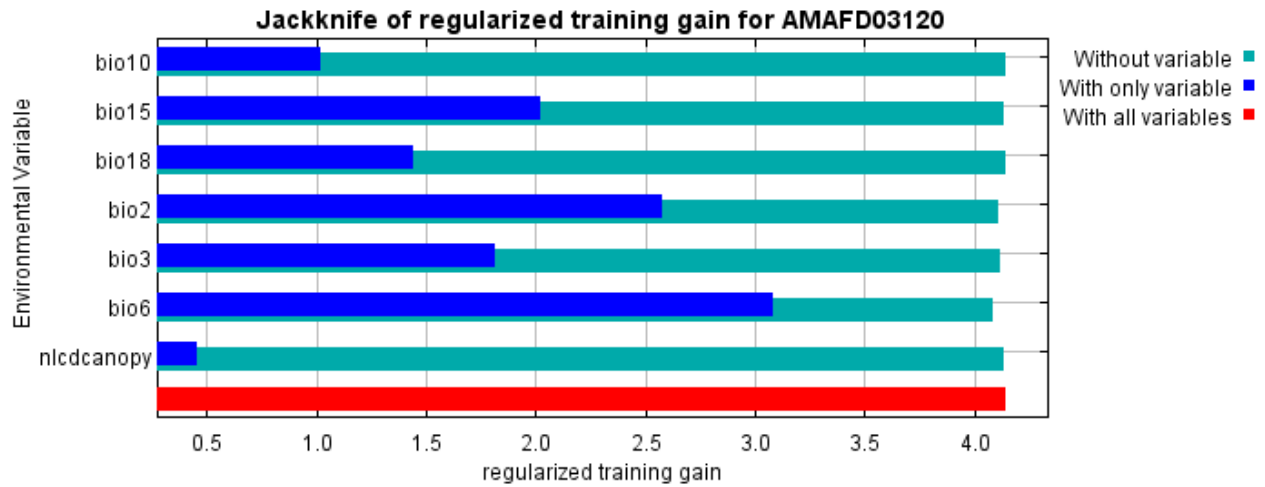
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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
bio6	59.4	82.7
bio3	21.4	15
bio10	13	0.2
bio2	5.5	0.4

Appendix 2 – Model Reports

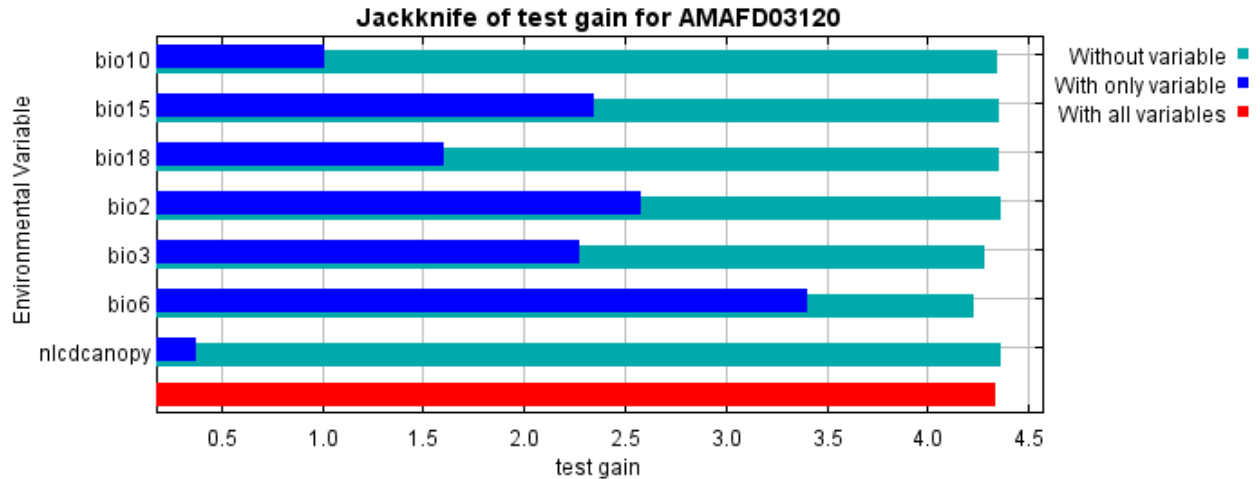
Variable	Percent contribution	Permutation importance
nlcdcanopy	0.5	0.3
bio15	0.2	1.3
bio18	0.1	0.2

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio6, 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 bio6, which therefore appears to have the most information that isn't present in the other variables.

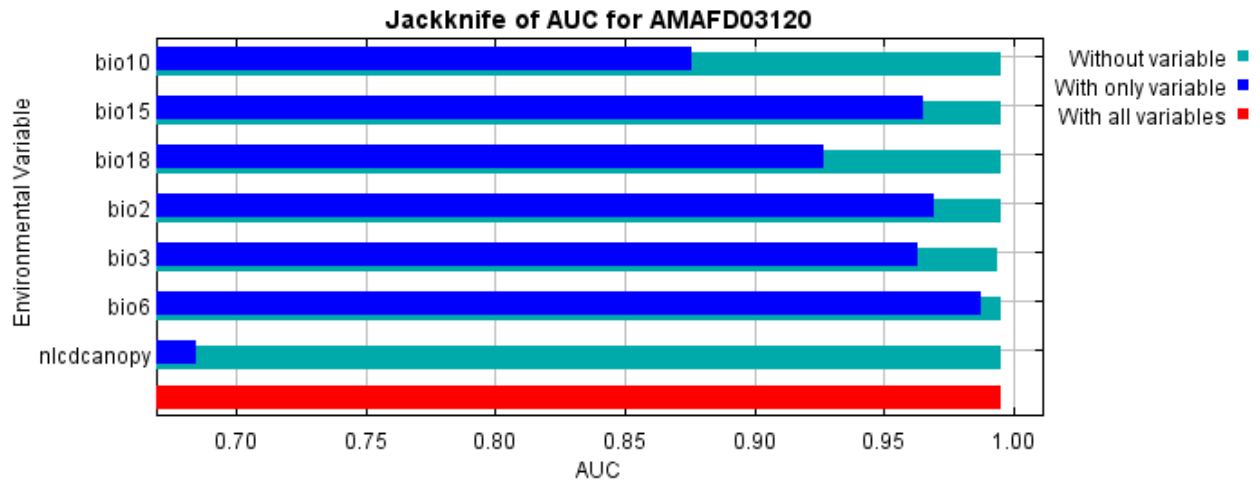


The next picture shows the same jackknife test, using test gain instead of training gain. Note that conclusions about which variables are most important can change, now that we're looking at test data.

Appendix 2 – Model Reports



Lastly, we have the same jackknife test, using AUC on test data.



Raw data outputs and control parameters

Regularized training gain is 4.145, training AUC is 0.994, unregularized training gain is 4.262.

Unregularized test gain is 4.338.

Test AUC is 0.995, standard deviation is 0.001 (calculated as in DeLong, DeLong & Clarke-Pearson 1988, equation 2).

Algorithm terminated after 500 iterations (22 seconds).

The follow settings were used during the run:

98 presence records used for training, 24 for testing.

8763 points used to determine the Maxent distribution (background points and presence points).

Environmental layers used (all continuous): bio10 bio15 bio18 bio2 bio3 bio6 nlcdcanopy

Regularization values: linear/quadratic/product: 0.064, categorical: 0.250, threshold: 1.020, hinge: 0.500

Feature types used: product linear quadratic hinge threshold

Appendix 2 – Model Reports

responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MAXENT_OUT\AMAFD03120\RUN_5
projectionlayers: F:\MAXENT_IN\PROB
samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
environmentallayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV
writeclampgrid: false
writemess: false
randomtestpoints: 20
writebackgroundpredictions: true
writeplotdata: true
Command line used: dontwriteclampgrid

Command line to repeat this species model:

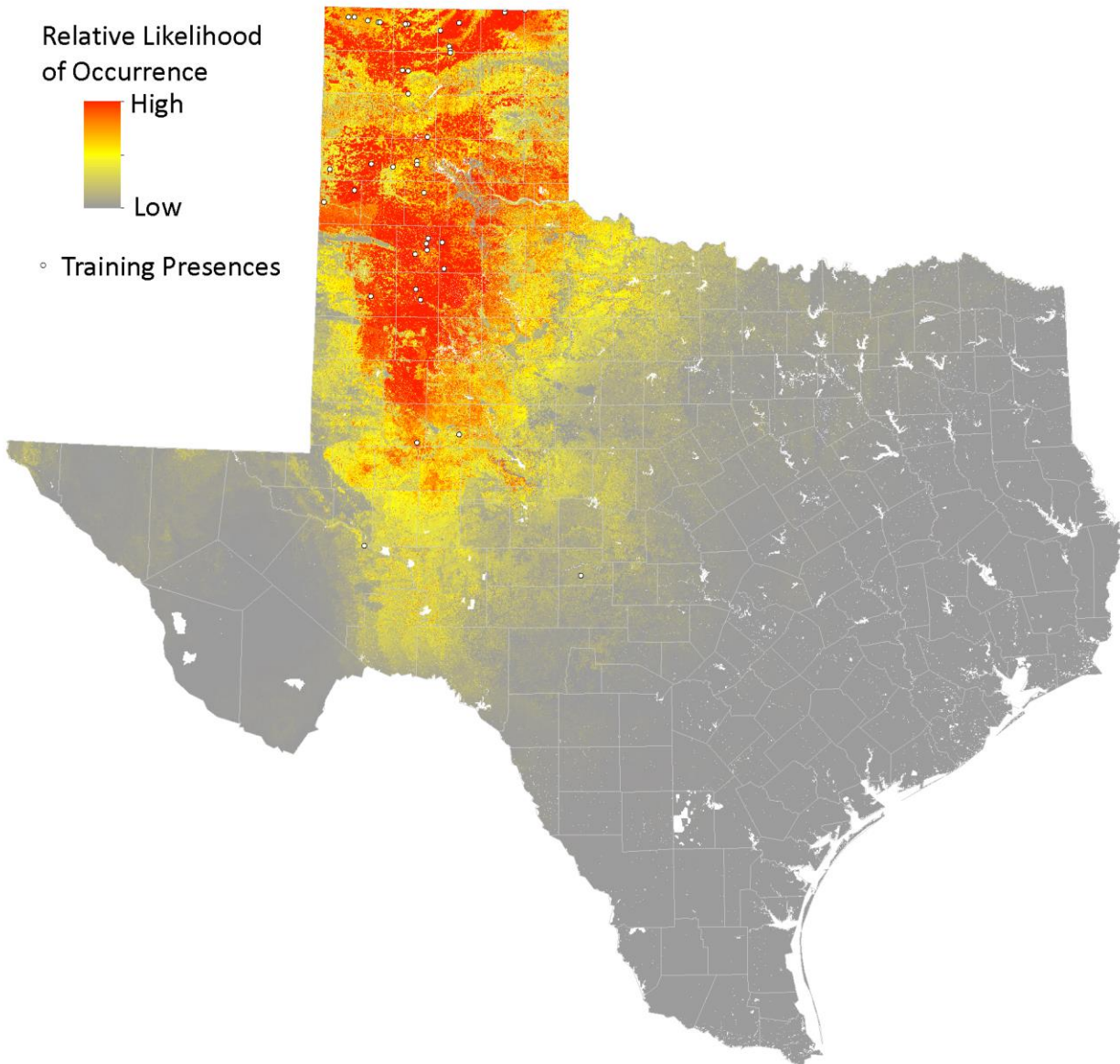
```
java density.MaxEnt nowarnings noprefixes -E "" -E AMAFD03120 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\AMAFD03120\RUN_5  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
nowritemess randomtestpoints=20 writebackgroundpredictions writeplotdata -N UNIQUE_ID -N  
aglands -N allwatdist -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N  
avoid12800 -N avoid1600 -N avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14  
-N bio16 -N bio17 -N bio19 -N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N  
d2foredge -N d2wsl -N dissect10 -N dissect5 -N drainclass -N hydgroup -N ksat -N lf_evh -N  
lf_forstcc -N lfherbcc -N lfshrubcc -N ned -N percclay -N percsand -N percsilt -N radld -N slope -N  
soilec -N soilph -N vrm10 -N vrm5 -N water1600 -N water300 -N water3200
```

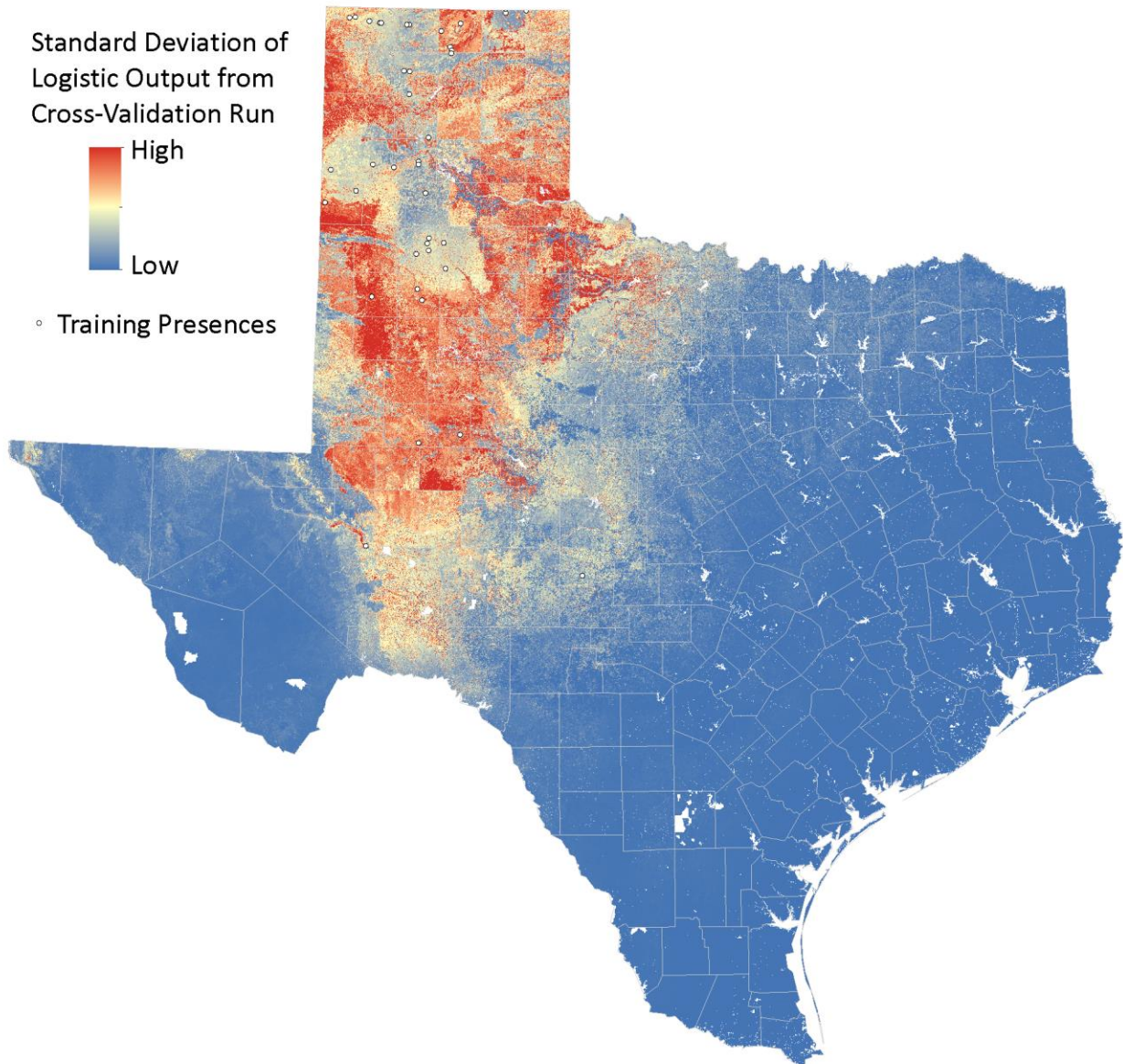
Swift Fox (*Vulpes velox*)

ELCODE: AMAJA03030

Date: August 14, 2013

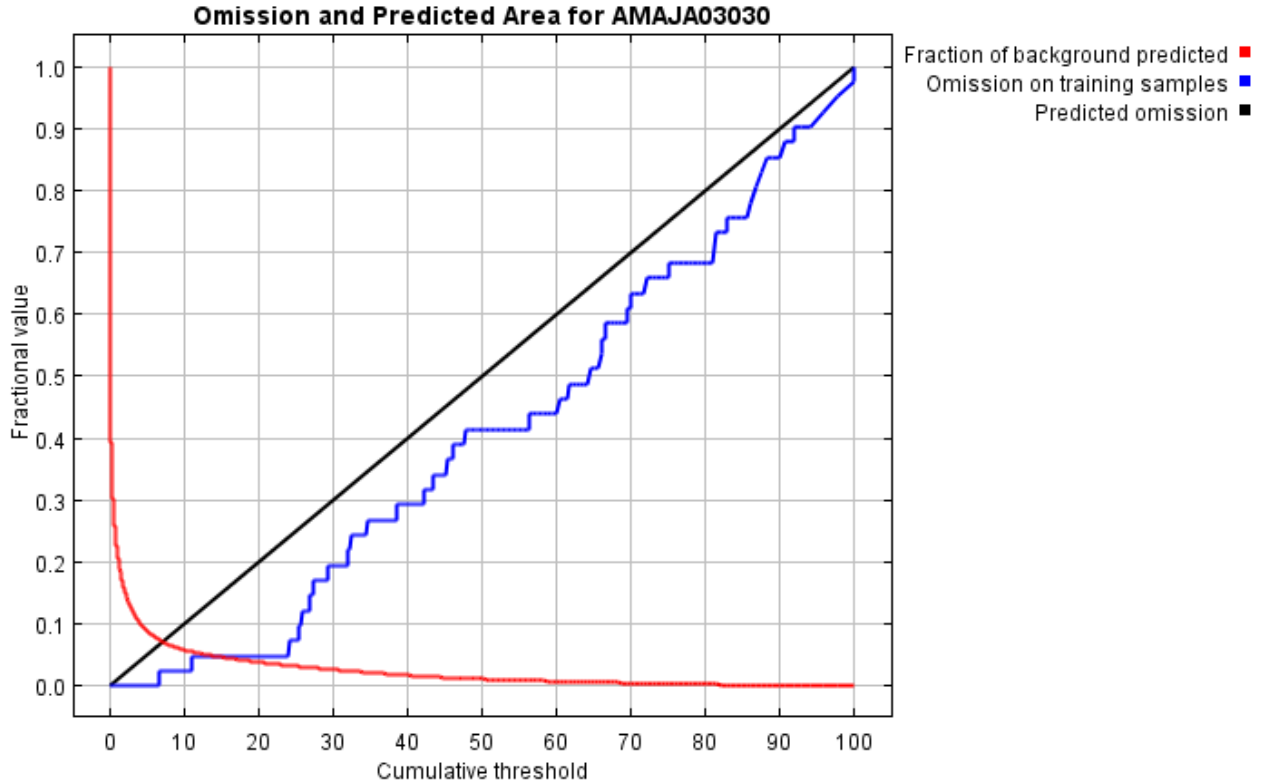
Maxent version: 3.3.3k





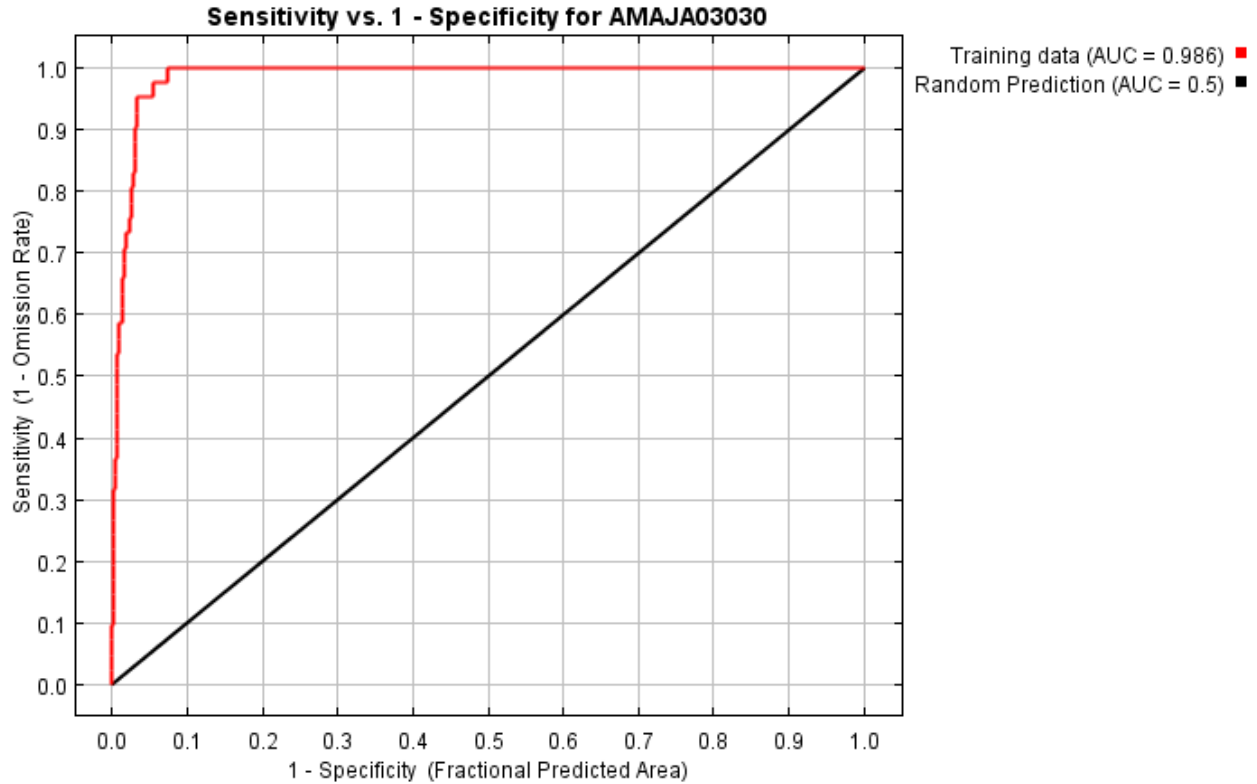
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.972 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

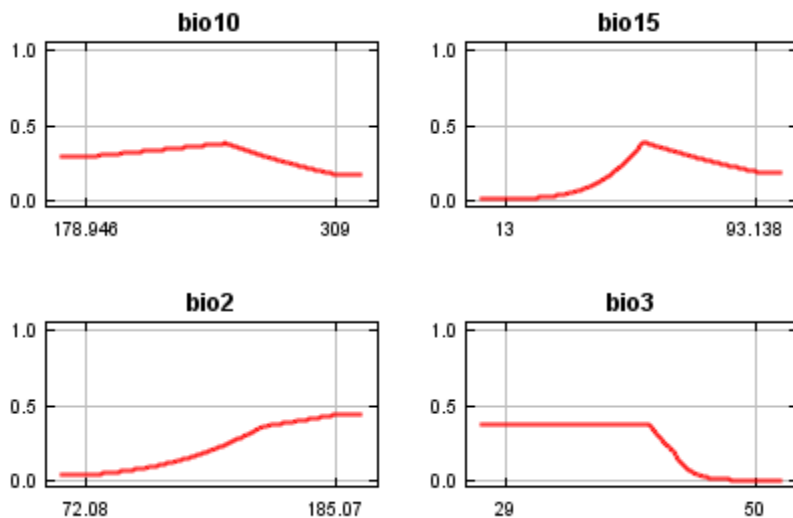
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.007	Fixed cumulative value 1	0.213	0.000
5.000	0.054	Fixed cumulative value 5	0.089	0.000
10.000	0.162	Fixed cumulative value 10	0.058	0.024
6.635	0.081	Minimum training presence	0.075	0.000
25.634	0.352	10 percentile training presence	0.031	0.098

Appendix 2 – Model Reports

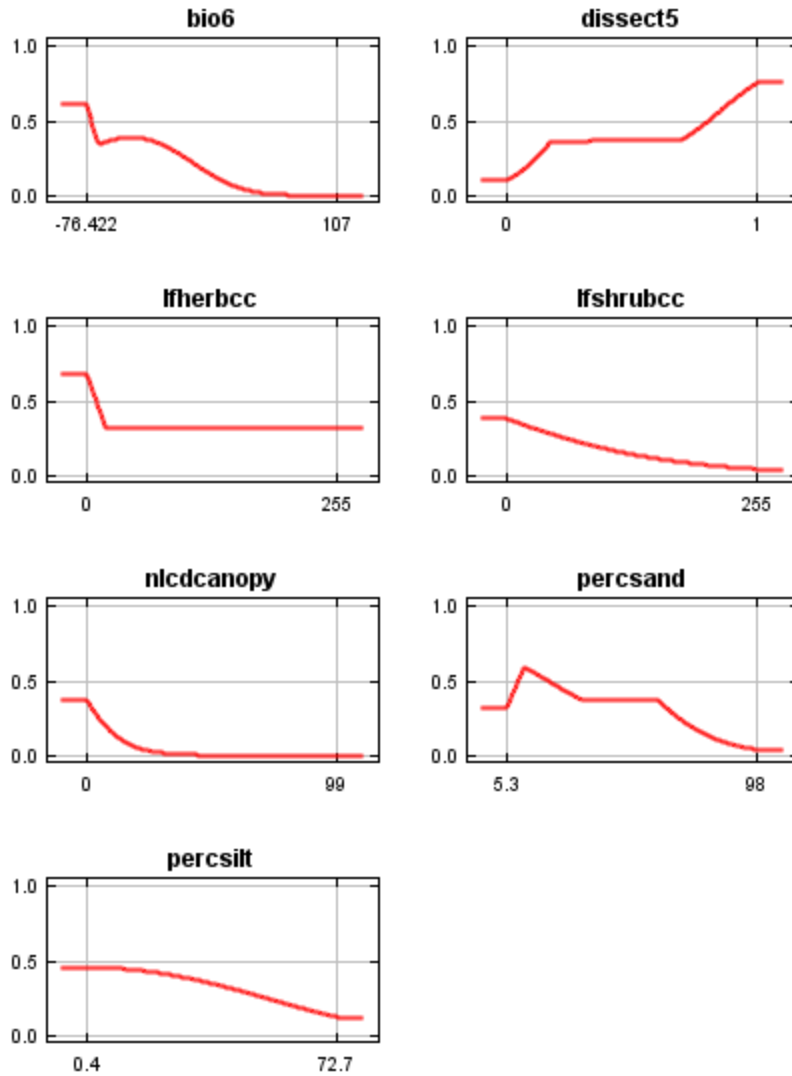
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
14.026	0.231	Equal training sensitivity and specificity	0.049	0.049
6.635	0.081	Maximum training sensitivity plus specificity	0.075	0.000
2.844	0.024	Balance training omission, predicted area and threshold value	0.125	0.000
9.233	0.141	Equate entropy of thresholded and original distributions	0.061	0.024

Response curves

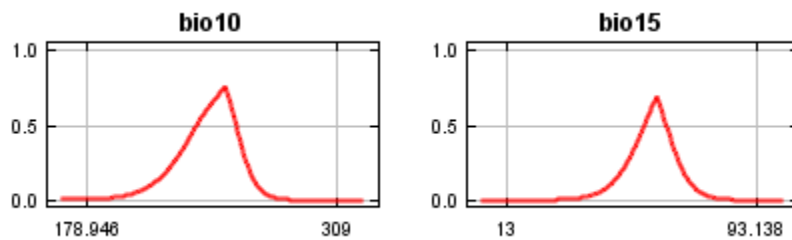
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



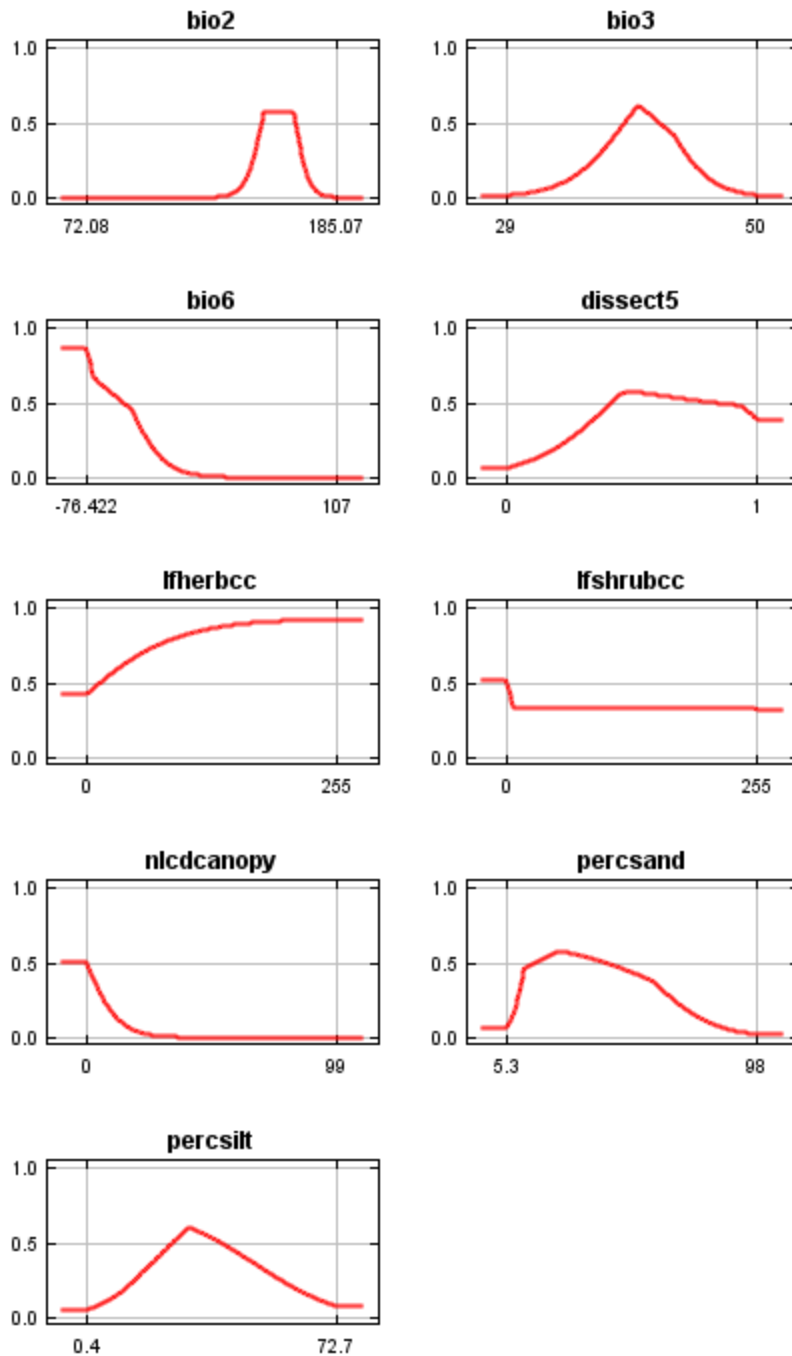
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



Analysis of variable contributions

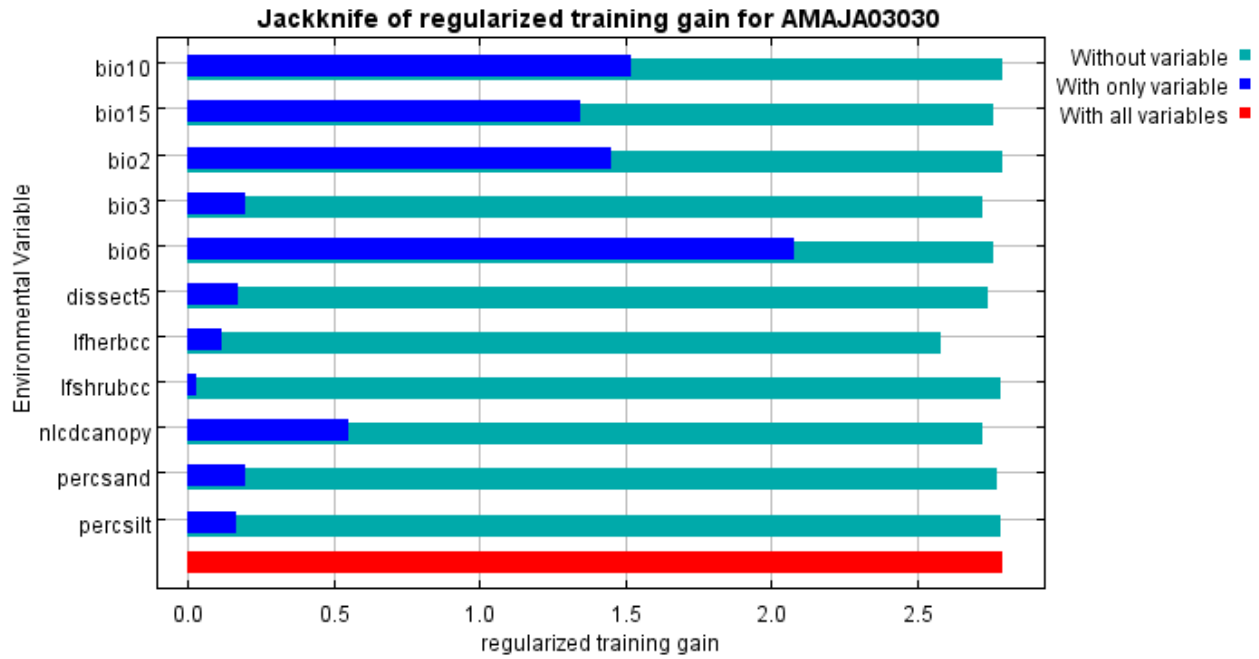
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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

Appendix 2 – Model Reports

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
bio6	69.1	17.4
nlcdcanopy	9.4	59.1
lfherbcc	6.8	2.3
bio3	6	8.4
bio15	4	9.7
dissect5	1.8	0.5
percsand	1.5	1.5
percsilt	0.8	0.1
lfshrubcc	0.2	0
bio10	0.2	0
bio2	0	1

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio6, 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 lfherbcc, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 2.793, training AUC is 0.986, unregularized training gain is 3.198. Algorithm terminated after 500 iterations (24 seconds).

The follow settings were used during the run:

41 presence records used for training.
 7369 points used to determine the Maxent distribution (background points and presence points).
 Environmental layers used (all continuous): bio10 bio15 bio2 bio3 bio6 dissect5 lfherbcc lfshrubcc nlcdcanopy perssand perssilt
 Regularization values: linear/quadratic/product: 0.219, categorical: 0.250, threshold: 1.590, hinge: 0.500
 Feature types used: linear quadratic hinge
 responsecurves: true
 pictures: false
 jackknife: true
 outputfiletype: bil
 outputdirectory: F:\MAXENT_OUT\AMAJA03030\RUN_4
 projectionlayers: F:\MAXENT_IN\PROB
 samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
 environmentalayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV
 writeclampgrid: false
 writemess: false
 writebackgroundpredictions: true
 writeplotdata: true
 Command line used: dontwriteclampgrid

Command line to repeat this species model:

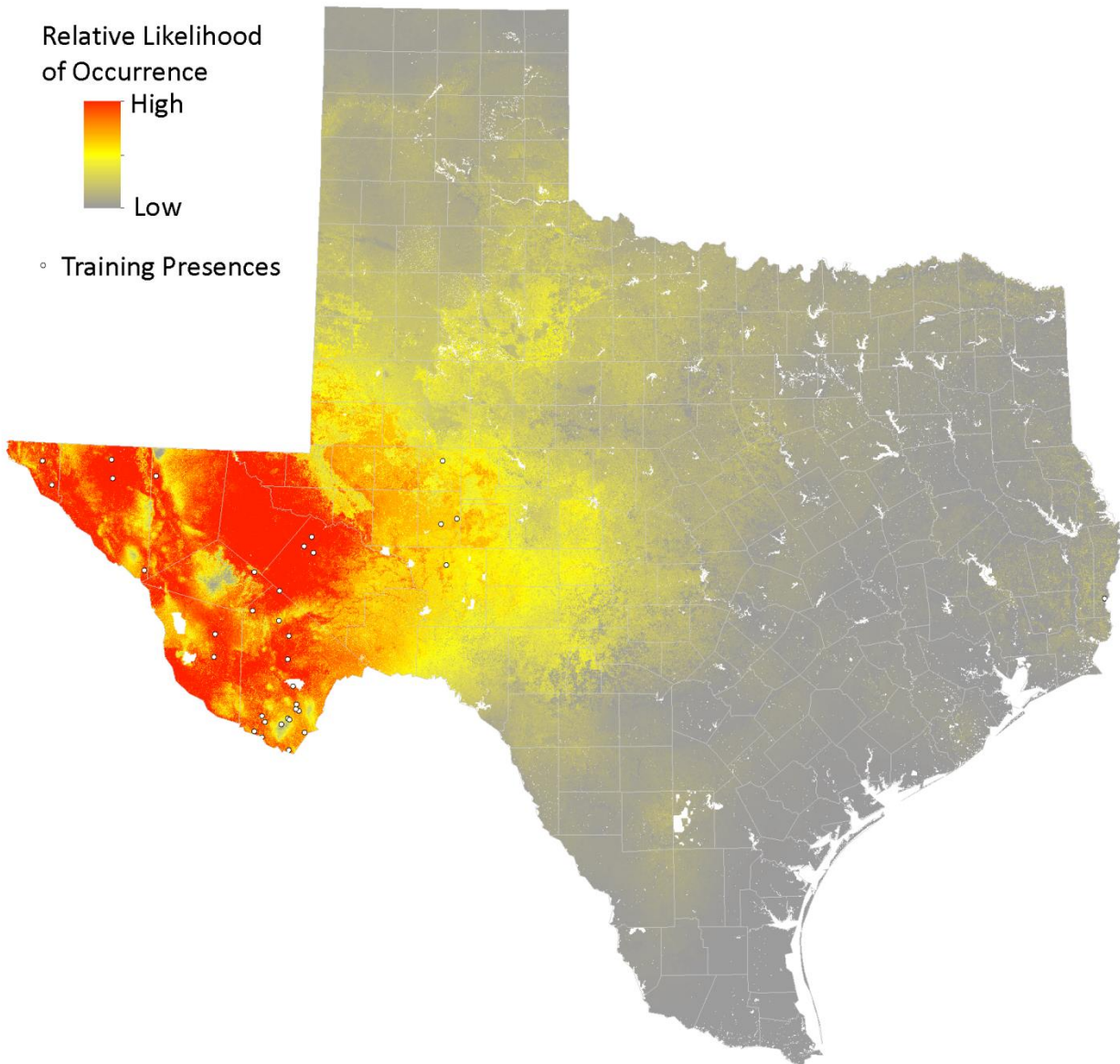
```
java density.MaxEnt nowarnings noprefixes -E "" -E AMAJA03030 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\AMAJA03030\RUN_4  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -N aglands -N allwatdist -N  
aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N avoid12800 -N avoid1600 -N  
avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio18 -  
N bio19 -N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N d2wsl  
-N dissect10 -N drainclass -N hydgroup -N ksat -N lf_evh -N lf_forstcc -N ned -N percclay -N radld -N  
slope -N soilec -N soilph -N vrm10 -N vrm5 -N water1600 -N water300 -N water3200
```

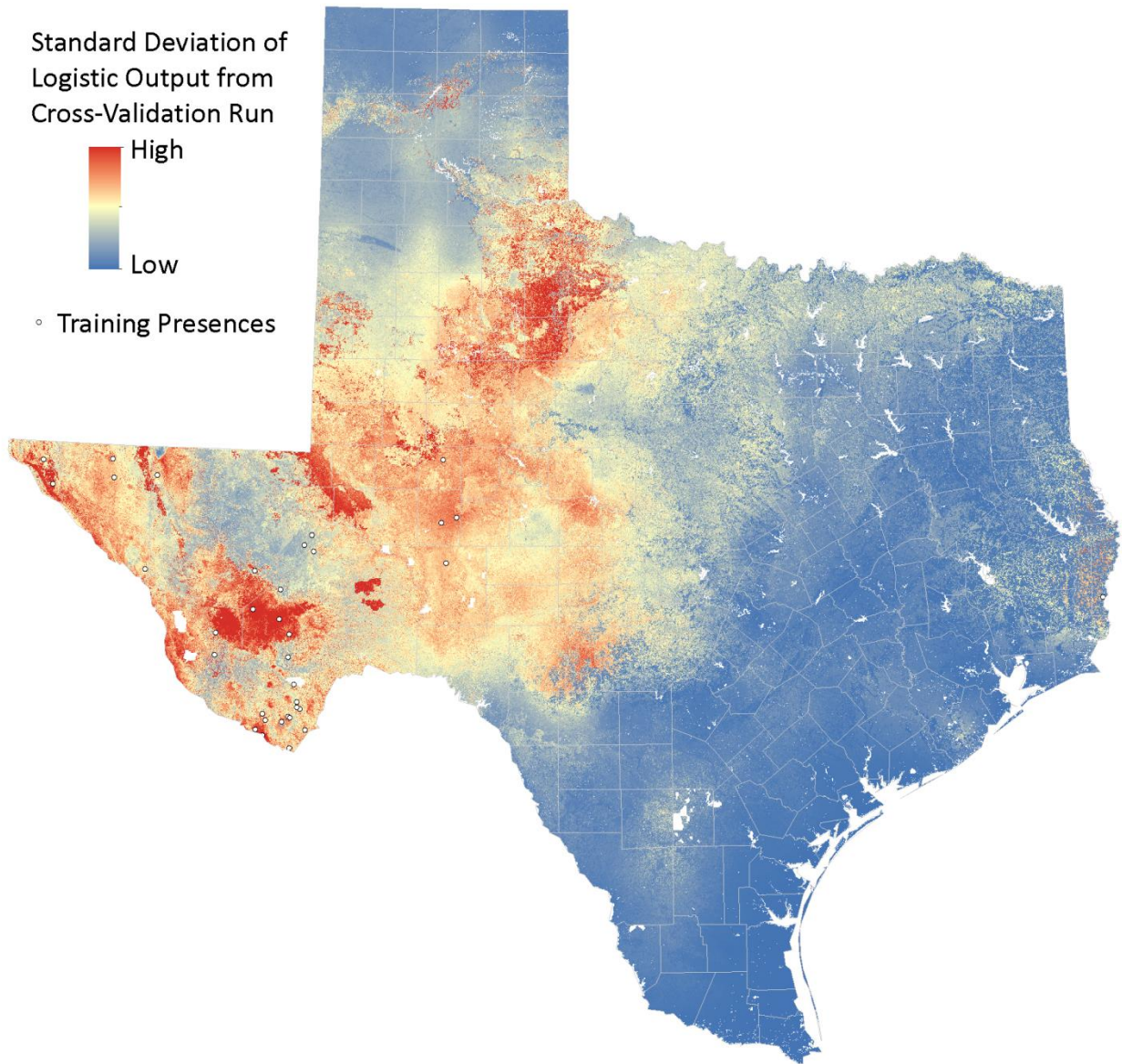

Kit Fox (*Vulpes macrotis*)

ELCODE: AMAJA03040

Date: August 14, 2013

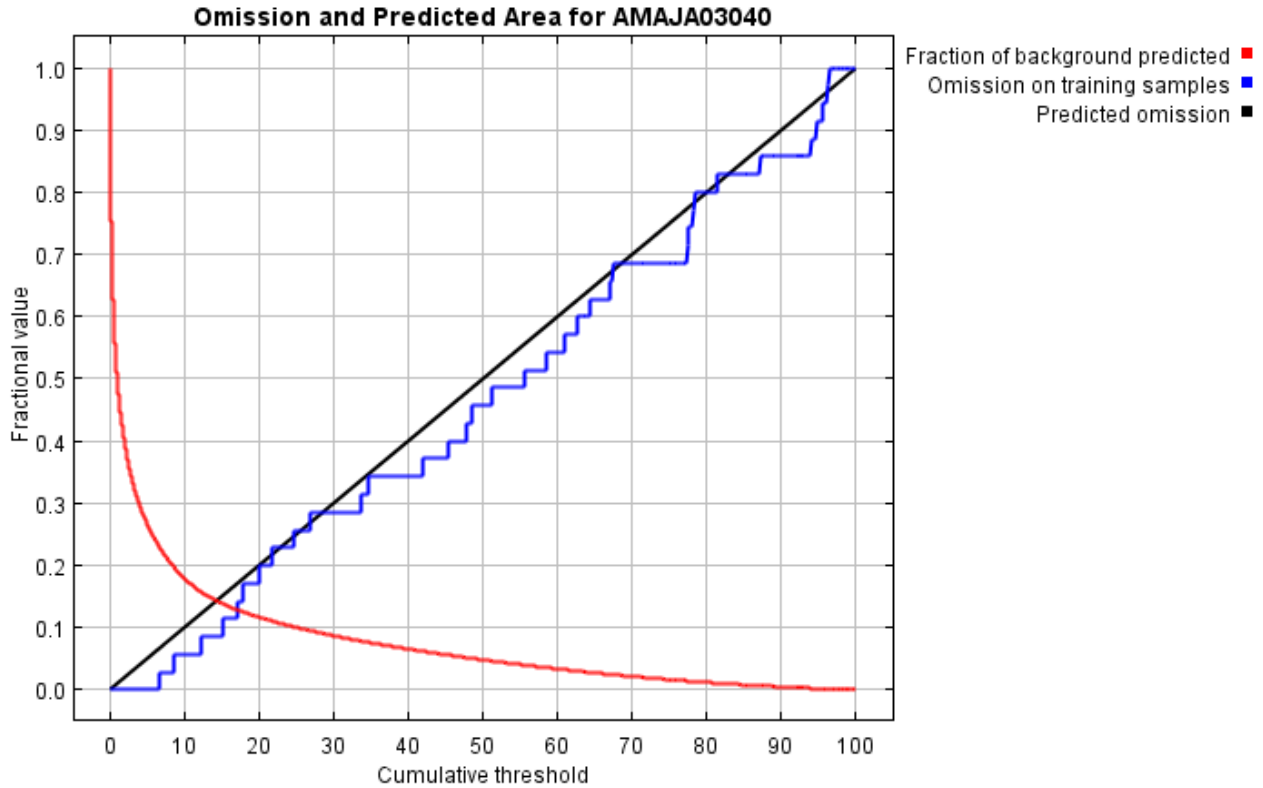
Maxent version: 3.3.3k





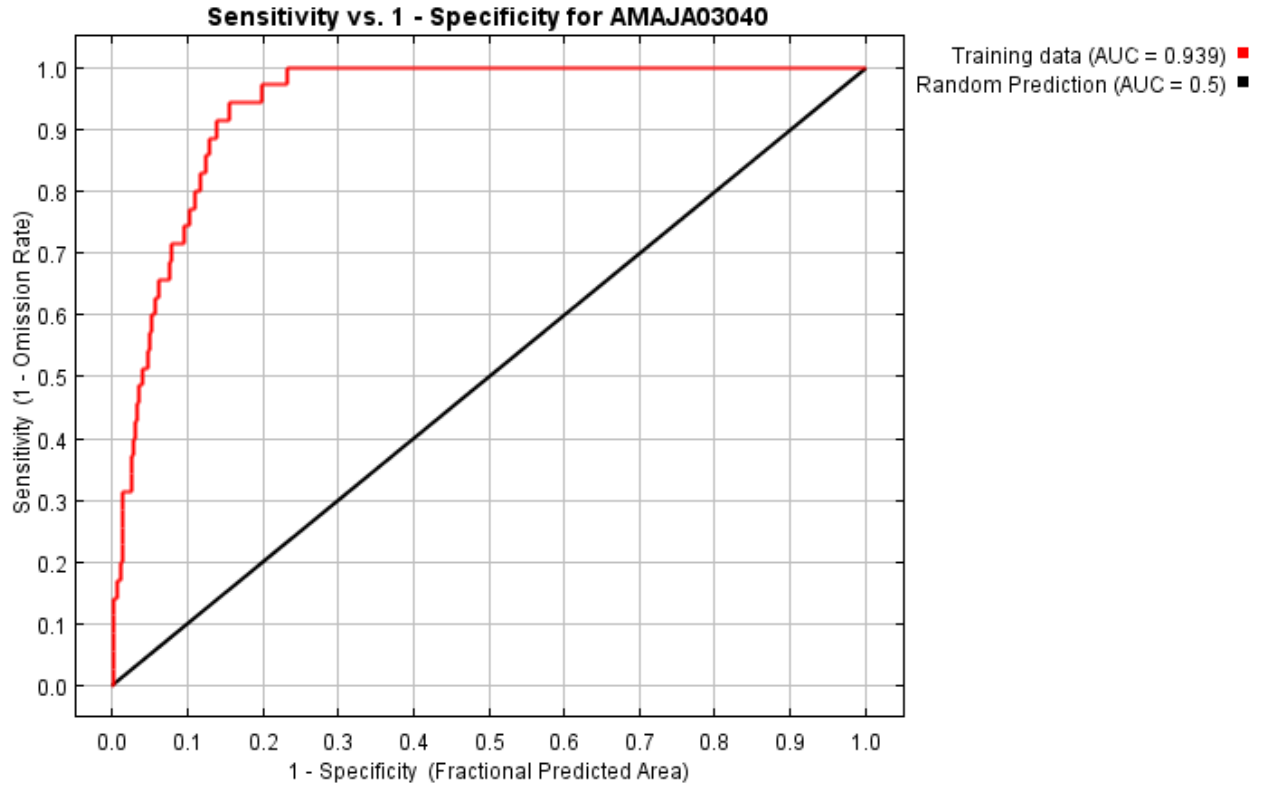
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.921 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

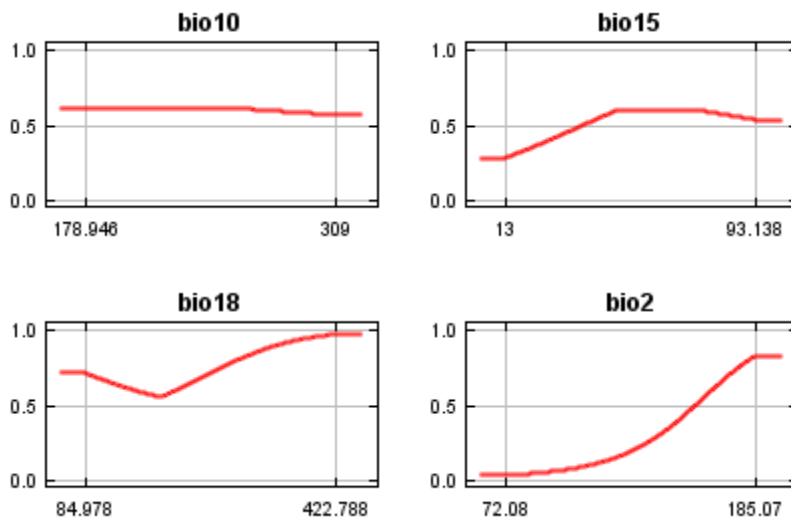
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.014	Fixed cumulative value 1	0.488	0.000
5.000	0.074	Fixed cumulative value 5	0.266	0.000
10.000	0.151	Fixed cumulative value 10	0.179	0.057
6.464	0.092	Minimum training presence	0.232	0.000
15.081	0.267	10 percentile training presence	0.138	0.086

Appendix 2 – Model Reports

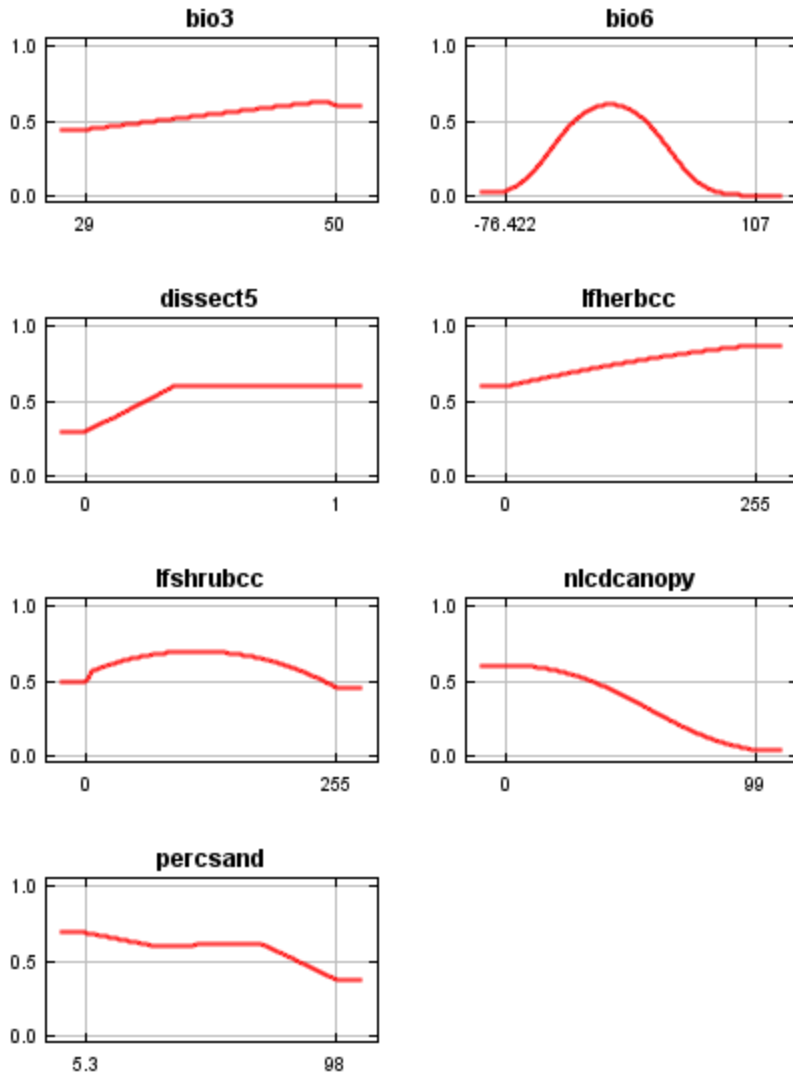
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
17.139	0.315	Equal training sensitivity and specificity	0.128	0.114
12.266	0.208	Maximum training sensitivity plus specificity	0.157	0.057
5.132	0.075	Balance training omission, predicted area and threshold value	0.262	0.000
8.095	0.119	Equate entropy of thresholded and original distributions	0.204	0.029

Response curves

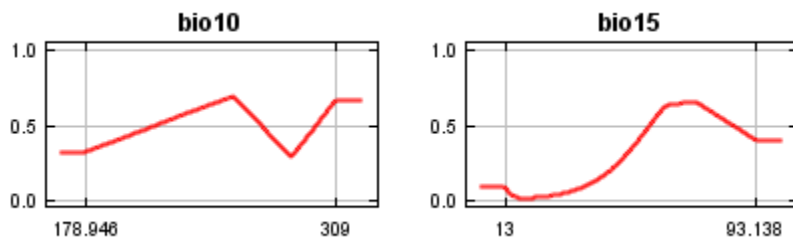
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



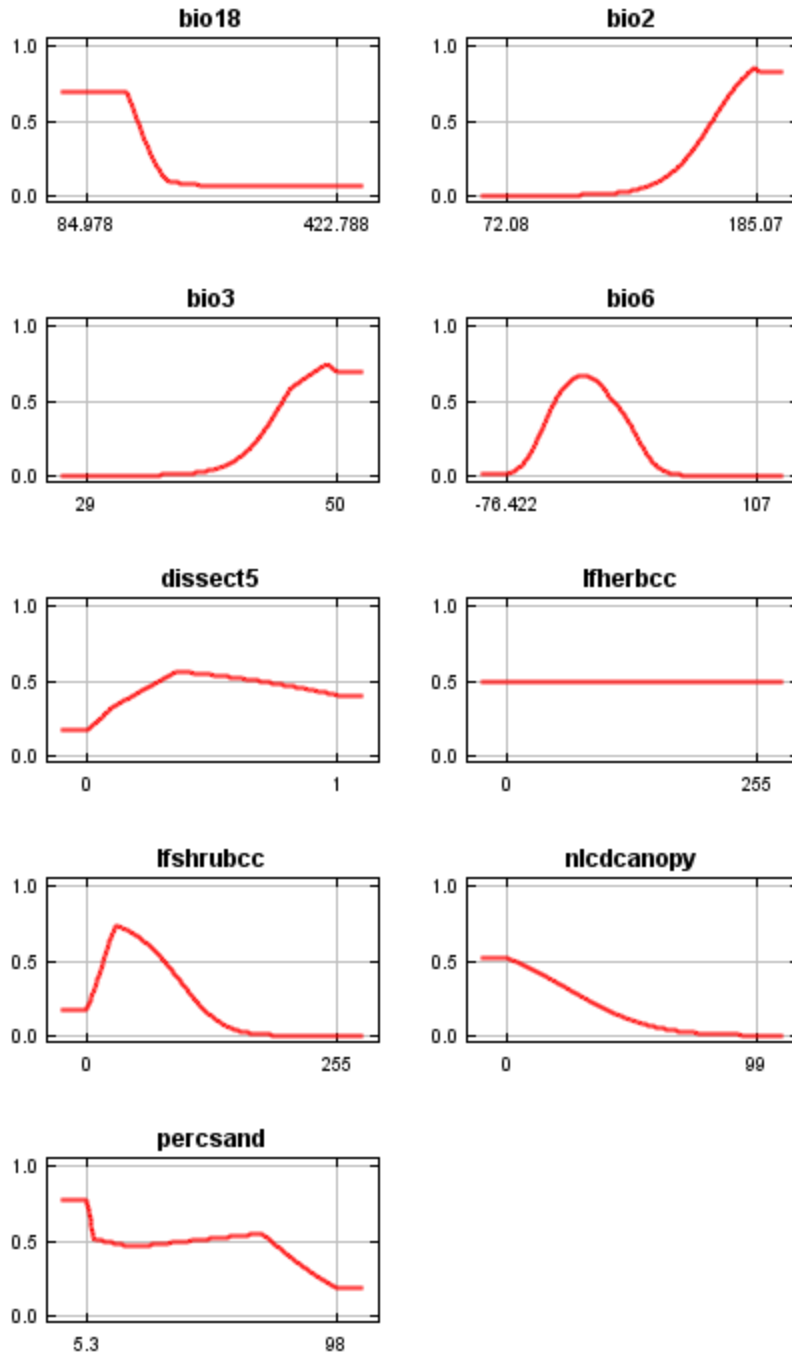
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



Analysis of variable contributions

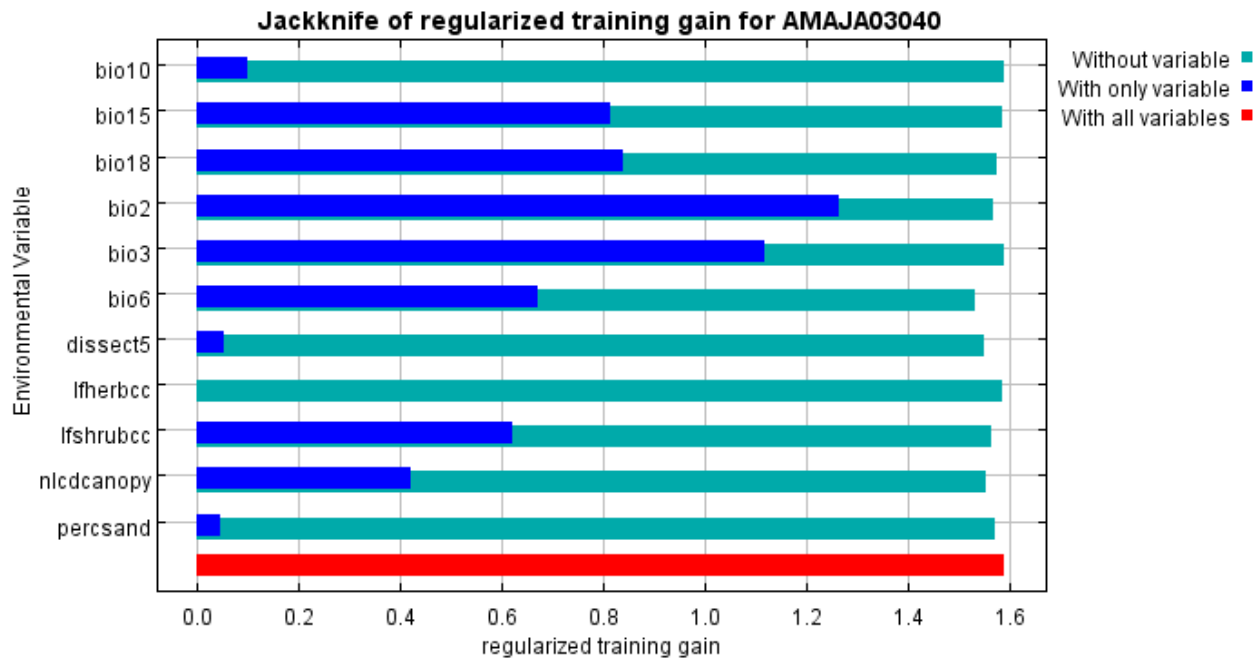
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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

Appendix 2 – Model Reports

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
bio2	45.6	39.4
lfshrubcc	17	0.6
bio3	11.1	0
nlcdcanopy	7.2	18.3
bio6	6.9	22.7
bio15	5.5	3.6
bio18	2.5	9.3
dissect5	2.4	2.9
percsand	1.7	1.9
lfherbcc	0.1	1.4
bio10	0.1	0

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio2, 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 bio6, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 1.591, training AUC is 0.939, unregularized training gain is 1.787. Algorithm terminated after 500 iterations (25 seconds).

The follow settings were used during the run:

35 presence records used for training.
 7372 points used to determine the Maxent distribution (background points and presence points).
 Environmental layers used (all continuous): bio10 bio15 bio18 bio2 bio3 bio6 dissect5 lfherbcc lfshrubcc nlcdcanopy persand
 Regularization values: linear/quadratic/product: 0.236, categorical: 0.250, threshold: 1.650, hinge: 0.500
 Feature types used: linear quadratic hinge
 responsecurves: true
 pictures: false
 jackknife: true
 outputfiletype: bil
 outputdirectory: F:\MAXENT_OUT\AMAJA03040\RUN_4
 projectionlayers: F:\MAXENT_IN\PROB
 samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
 environmentlayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV
 writeclampgrid: false
 writemess: false
 writebackgroundpredictions: true
 writeplotdata: true
 Command line used: dontwriteclampgrid

Command line to repeat this species model:

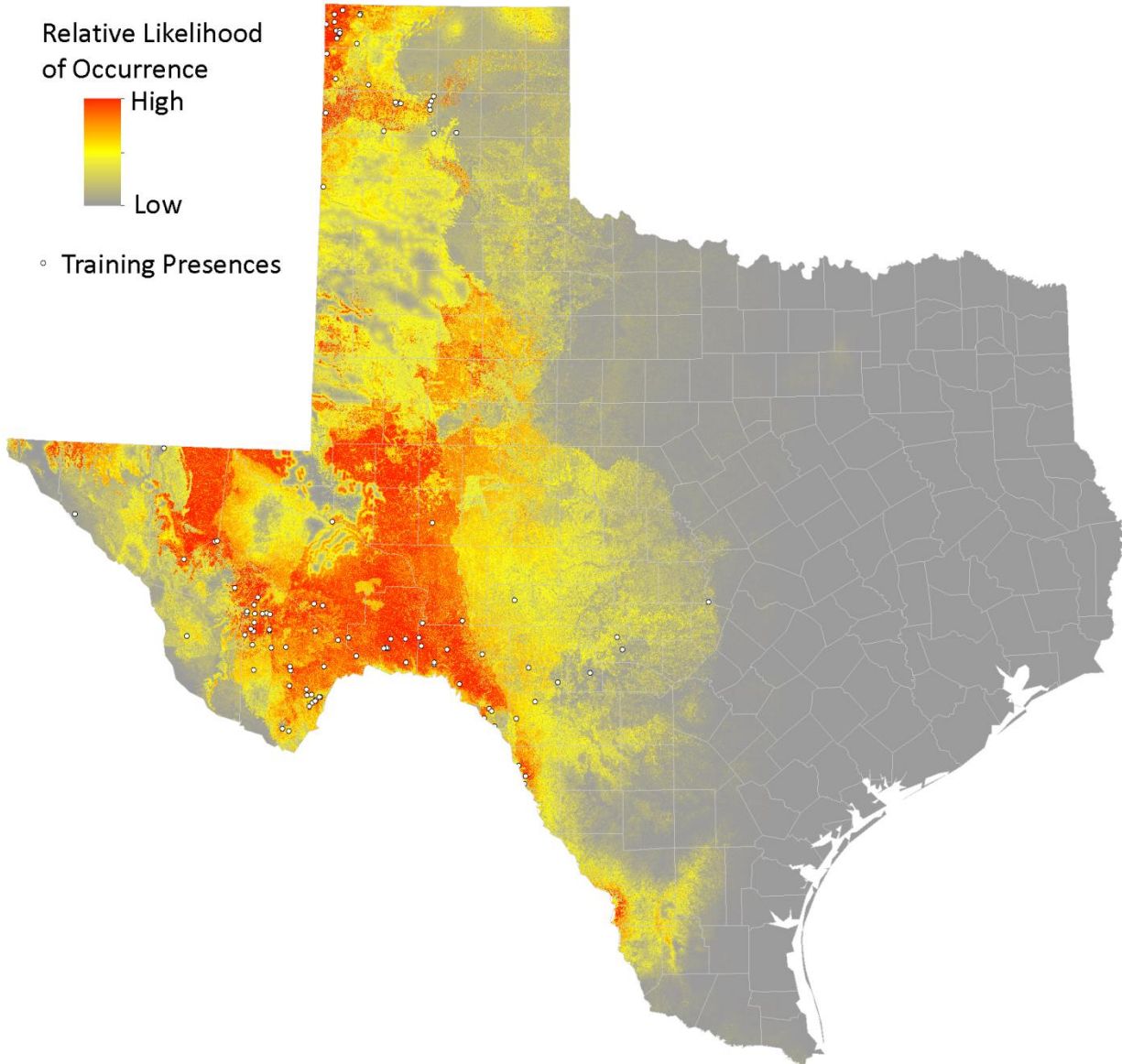
```
java density.MaxEnt nowarnings noprefixes -E "" -E AMAJA03040 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\AMAJA03040\RUN_4  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -N aglands -N allwatdist -N  
aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N avoid12800 -N avoid1600 -N  
avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio19 -  
N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N d2wsl -N  
dissect10 -N drainclass -N hydgroup -N ksat -N lf_evh -N lf_forstcc -N ned -N percclay -N percslit -N  
radld -N slope -N soilec -N soilph -N vrm10 -N vrm5 -N water1600 -N water300 -N water3200
```

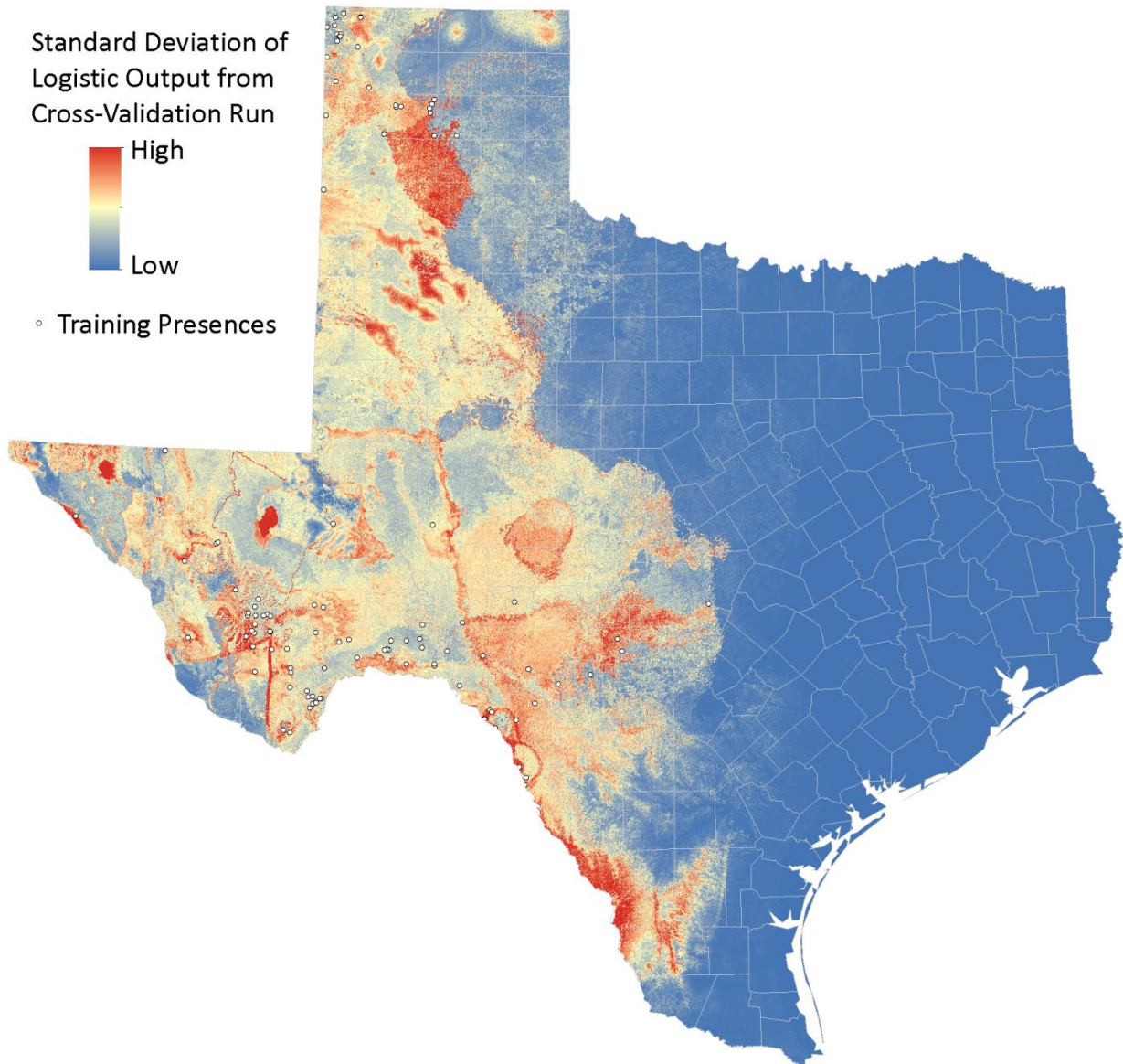
Black Bear, Western TX Population (*Ursus americanus*)

ELCODE: AMAJB0101W

Date: August 20, 2013

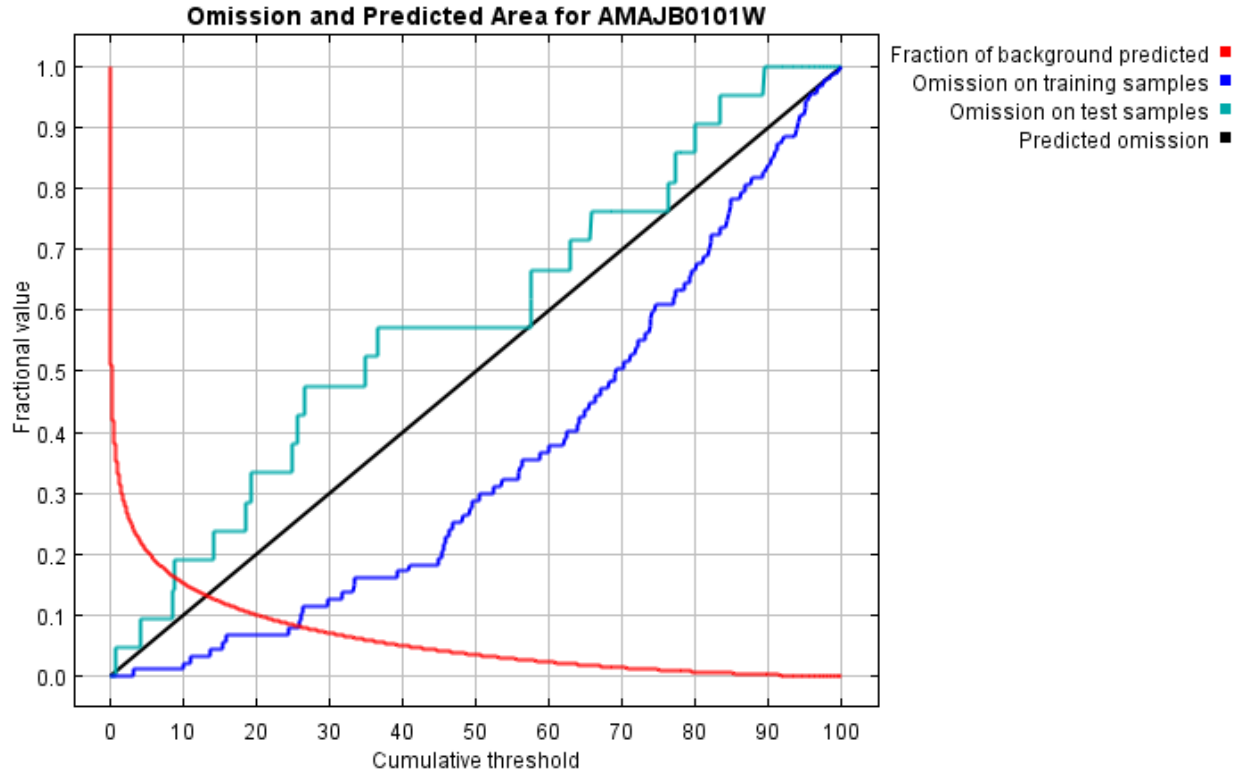
Maxent version: 3.3.3k





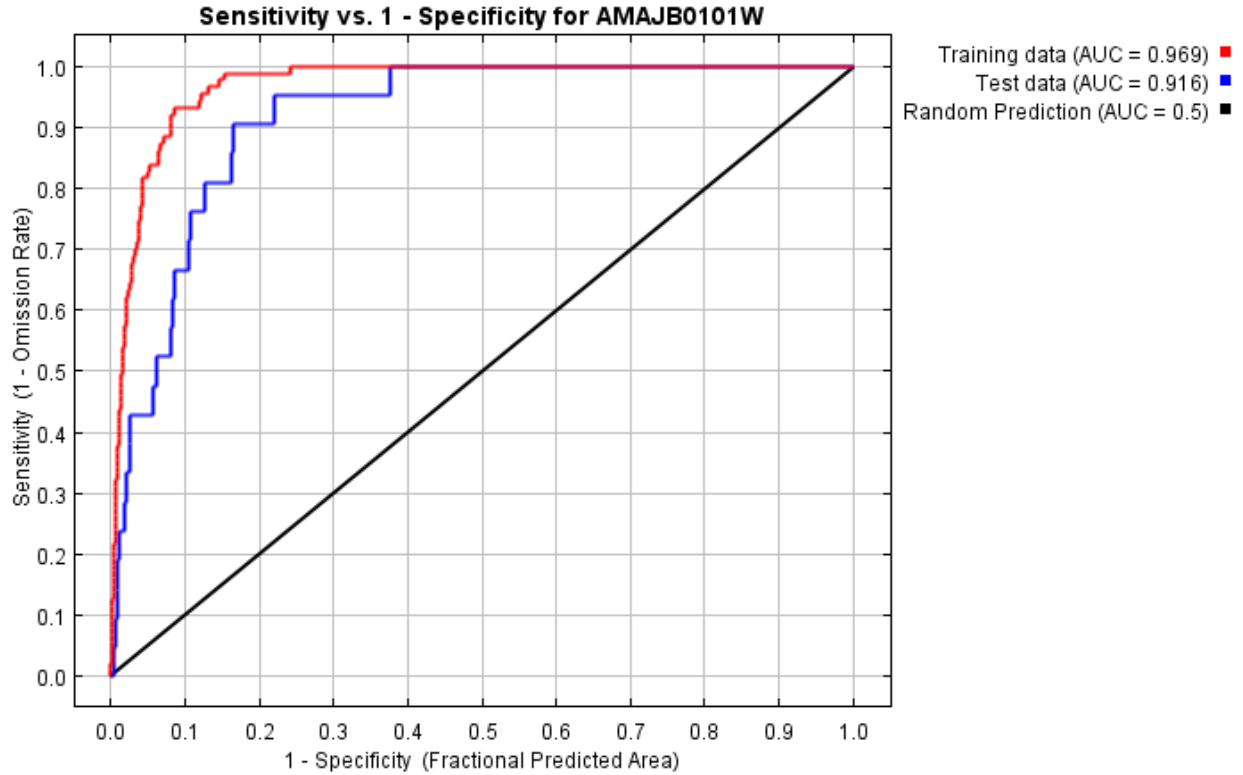
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.938 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
1.000	0.019	Fixed cumulative value 1	0.340	0.000	0.048	6.064E-9
5.000	0.093	Fixed cumulative value 5	0.206	0.011	0.095	1.259E-11
10.000	0.175	Fixed cumulative value 10	0.153	0.023	0.190	4.378E-11
3.178	0.058	Minimum training presence	0.242	0.000	0.048	7.626E-12

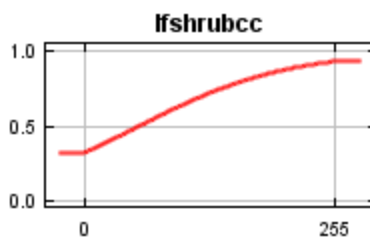
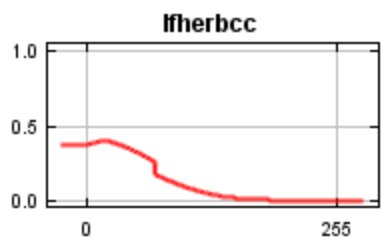
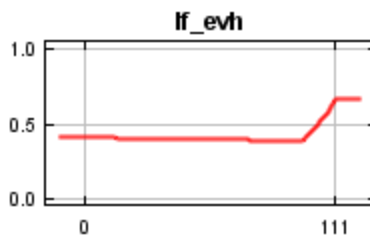
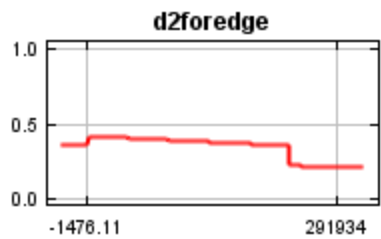
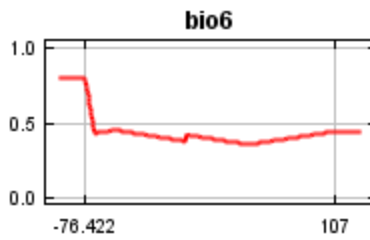
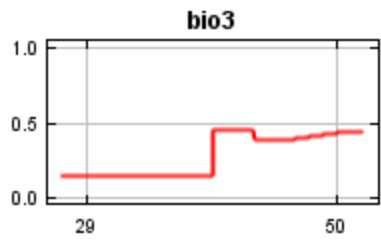
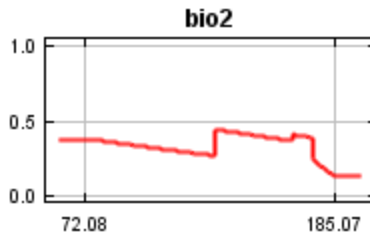
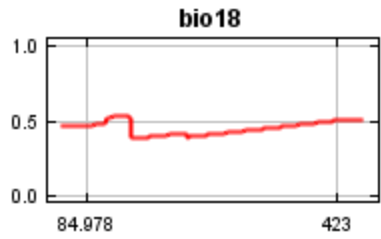
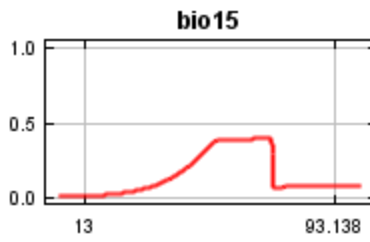
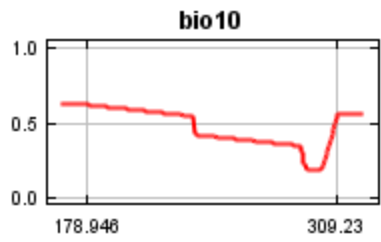
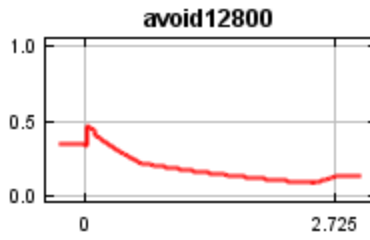
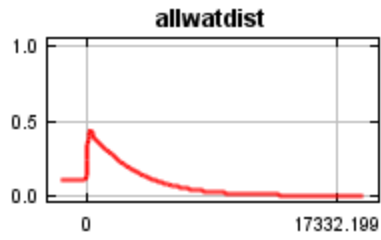
Appendix 2 – Model Reports

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
26.023	0.362	10 percentile training presence	0.082	0.092	0.429	1.281E-8
25.941	0.361	Equal training sensitivity and specificity	0.082	0.080	0.429	1.344E-8
24.445	0.344	Maximum training sensitivity plus specificity	0.086	0.069	0.333	8.328E-11
8.765	0.151	Equal test sensitivity and specificity	0.163	0.011	0.143	5.312E-12
8.448	0.148	Maximum test sensitivity plus specificity	0.166	0.011	0.095	2.265E-13
3.178	0.058	Balance training omission, predicted area and threshold value	0.242	0.000	0.048	7.626E-12
9.145	0.158	Equate entropy of thresholded and original distributions	0.160	0.011	0.190	8.987E-11

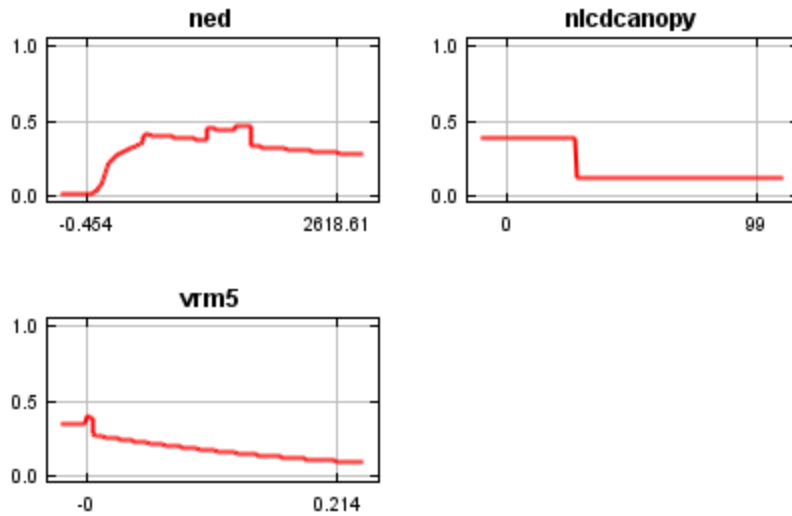
Response curves

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. 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.

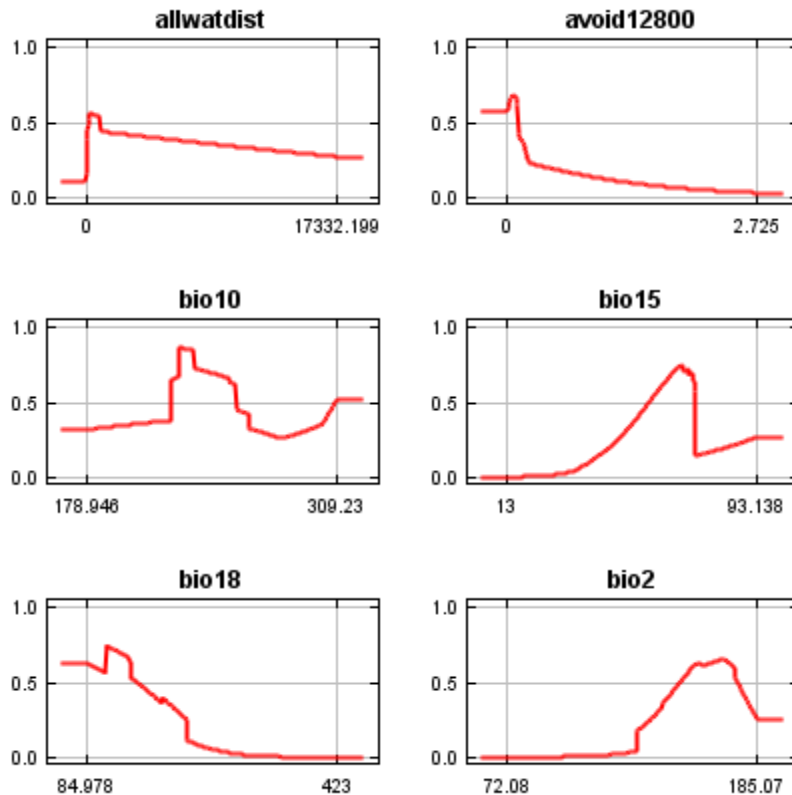
Appendix 2 – Model Reports



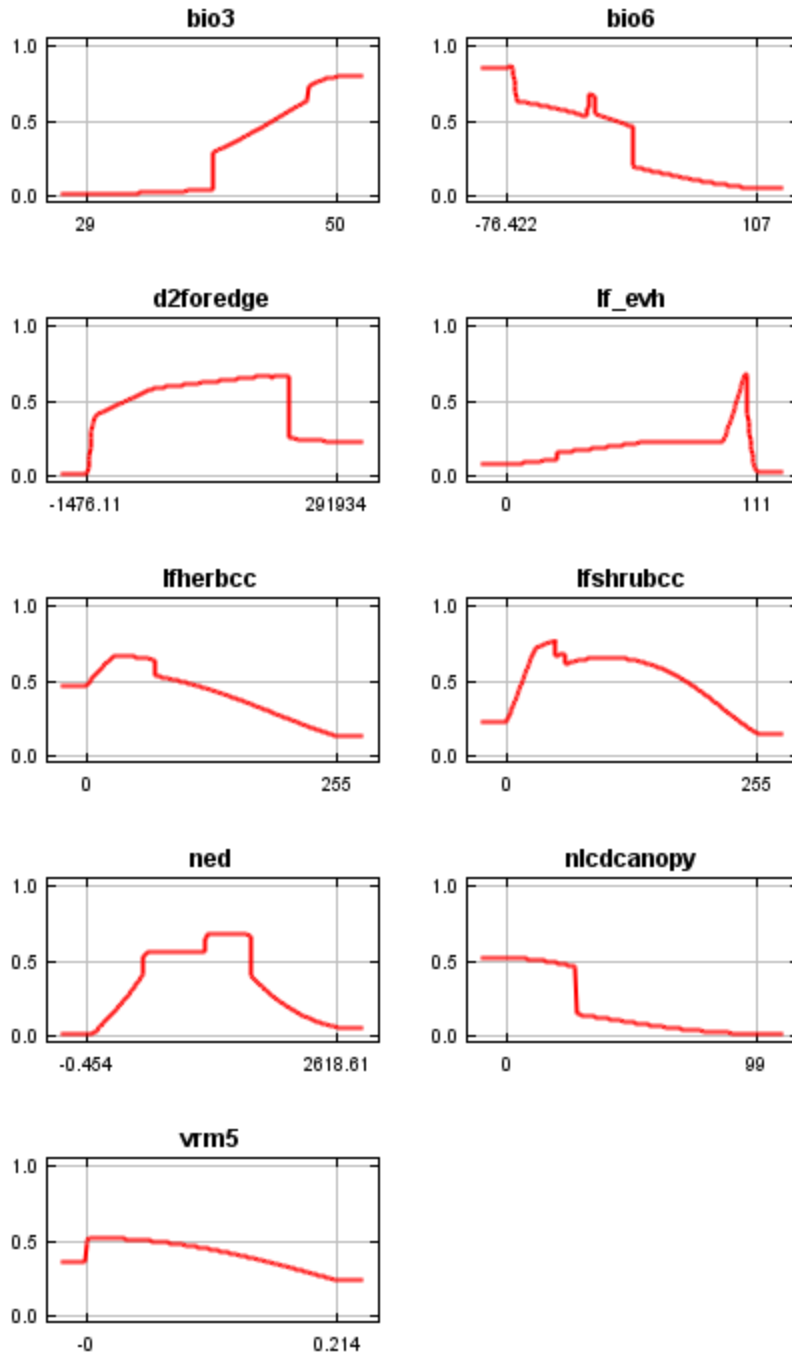
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



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

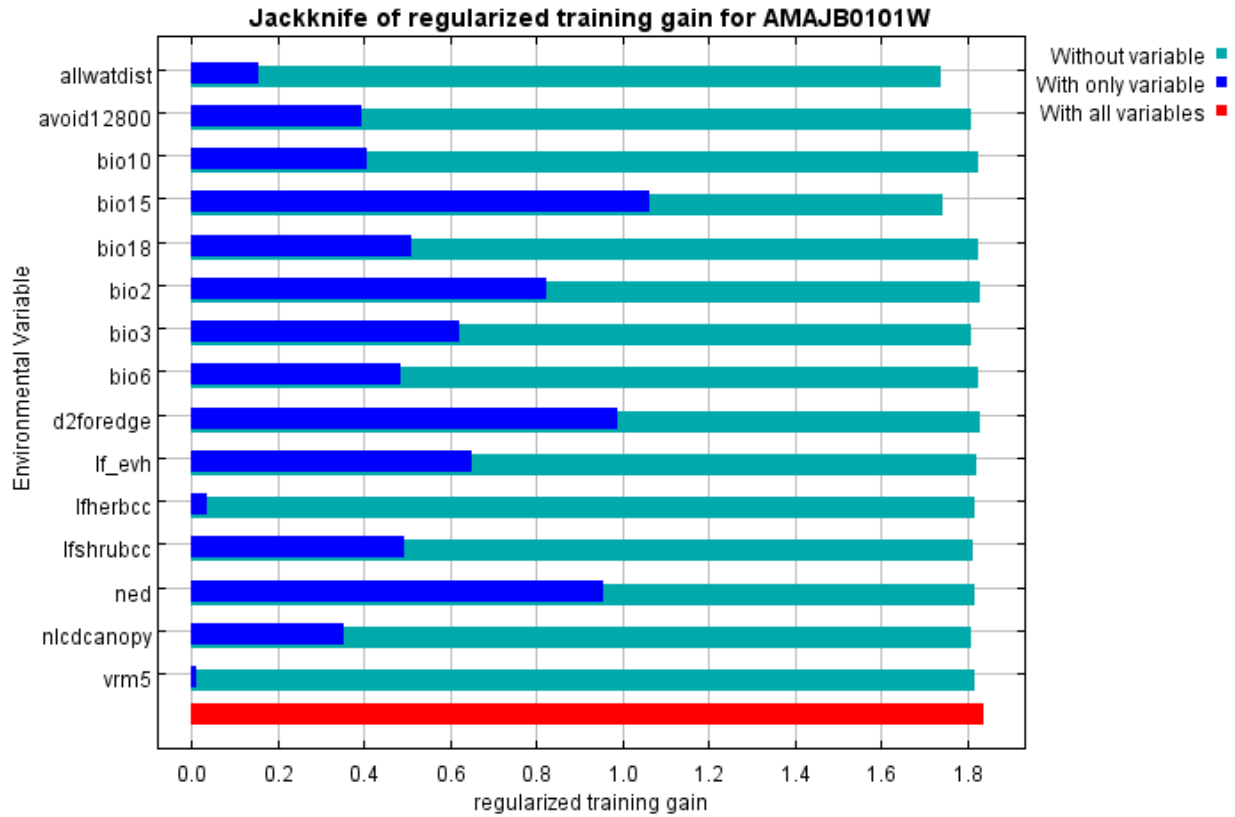
Appendix 2 – Model Reports

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.

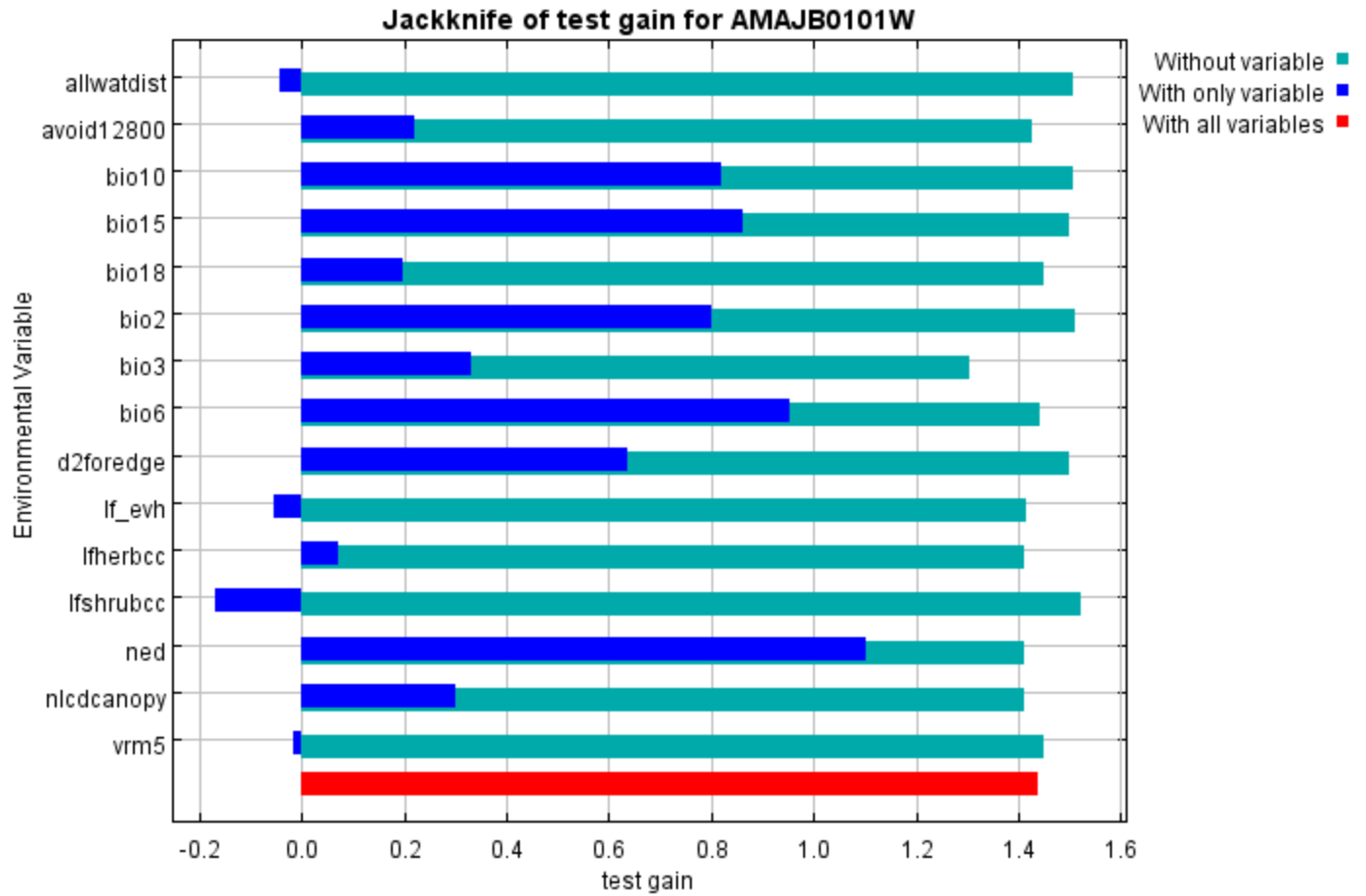
Variable	Percent contribution	Permutation importance
d2foredge	24.7	2.9
ned	19.3	31.3
bio15	17.2	28
bio2	8.1	1.7
allwatdist	6.9	5.2
nlcdcanopy	4.7	6.4
bio3	4.6	5.3
lf_evh	3.4	1.8
bio10	3.1	3.3
lfshrubcc	2	2.1
avoid12800	1.7	4.8
bio18	1.4	1.1
vrn5	1.1	3.1
bio6	0.9	1
lfherbcc	0.8	2

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio15, 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 allwatdist, which therefore appears to have the most information that isn't present in the other variables.

Appendix 2 – Model Reports

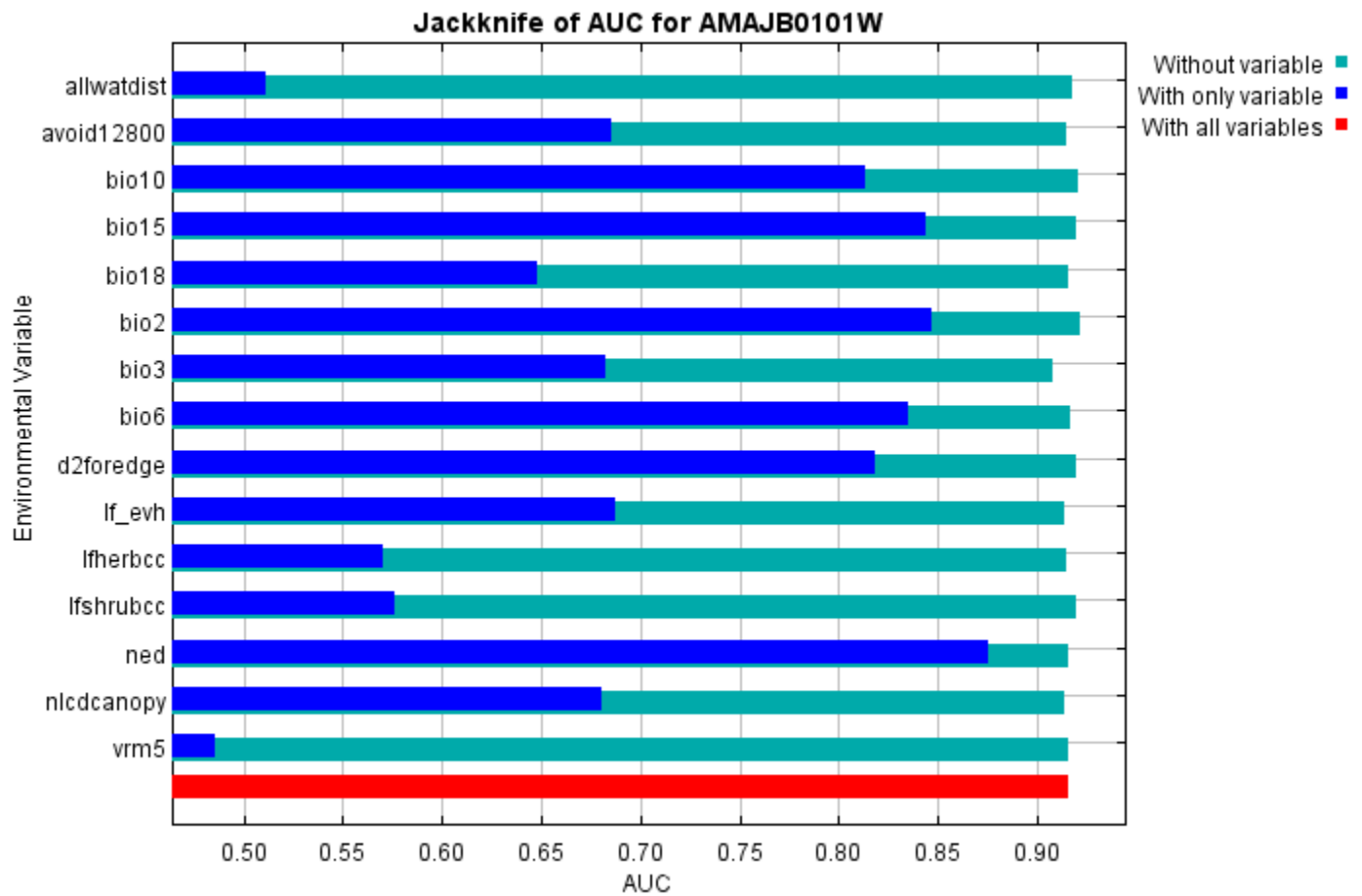


The next picture shows the same jackknife test, using test gain instead of training gain. Note that conclusions about which variables are most important can change, now that we're looking at test data.



Appendix 2 – Model Reports

Lastly, we have the same jackknife test, using AUC on test data.



Raw data outputs and control parameters

Regularized training gain is 1.839, training AUC is 0.969, unregularized training gain is 2.378.

Unregularized test gain is 1.439.

Test AUC is 0.916, standard deviation is 0.019 (calculated as in DeLong, DeLong & Clarke-Pearson 1988, equation 2).

Algorithm terminated after 500 iterations (11 seconds).

The follow settings were used during the run:

87 presence records used for training, 21 for testing.

8705 points used to determine the Maxent distribution (background points and presence points).

Environmental layers used (all continuous): allwatdist avoid12800 bio10 bio15 bio18 bio2 bio3

bio6 d2foredge lf_evh lfherbcc lfshrubcc ned nlcdcanopy vrn5

Regularization values: linear/quadratic/product: 0.143, categorical: 0.250, threshold: 1.130, hinge: 0.500

Feature types used: product linear quadratic hinge threshold

responsecurves: true

pictures: false

Appendix 2 – Model Reports

jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\TXNDD_SDM\MAXENT_OUT\AMAJB0101W\RUN_4
projectionlayers: F:\MODELING\TXNDD_SDM\MAXENT_IN\PROB
samplesfile: F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
environmentallayers:
F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV
askoverwrite: false
writeclampgrid: false
writemess: false
randomtestpoints: 20
writebackgroundpredictions: true
writeplotdata: true
threads: 6
Command line used: dontwriteclampgrid

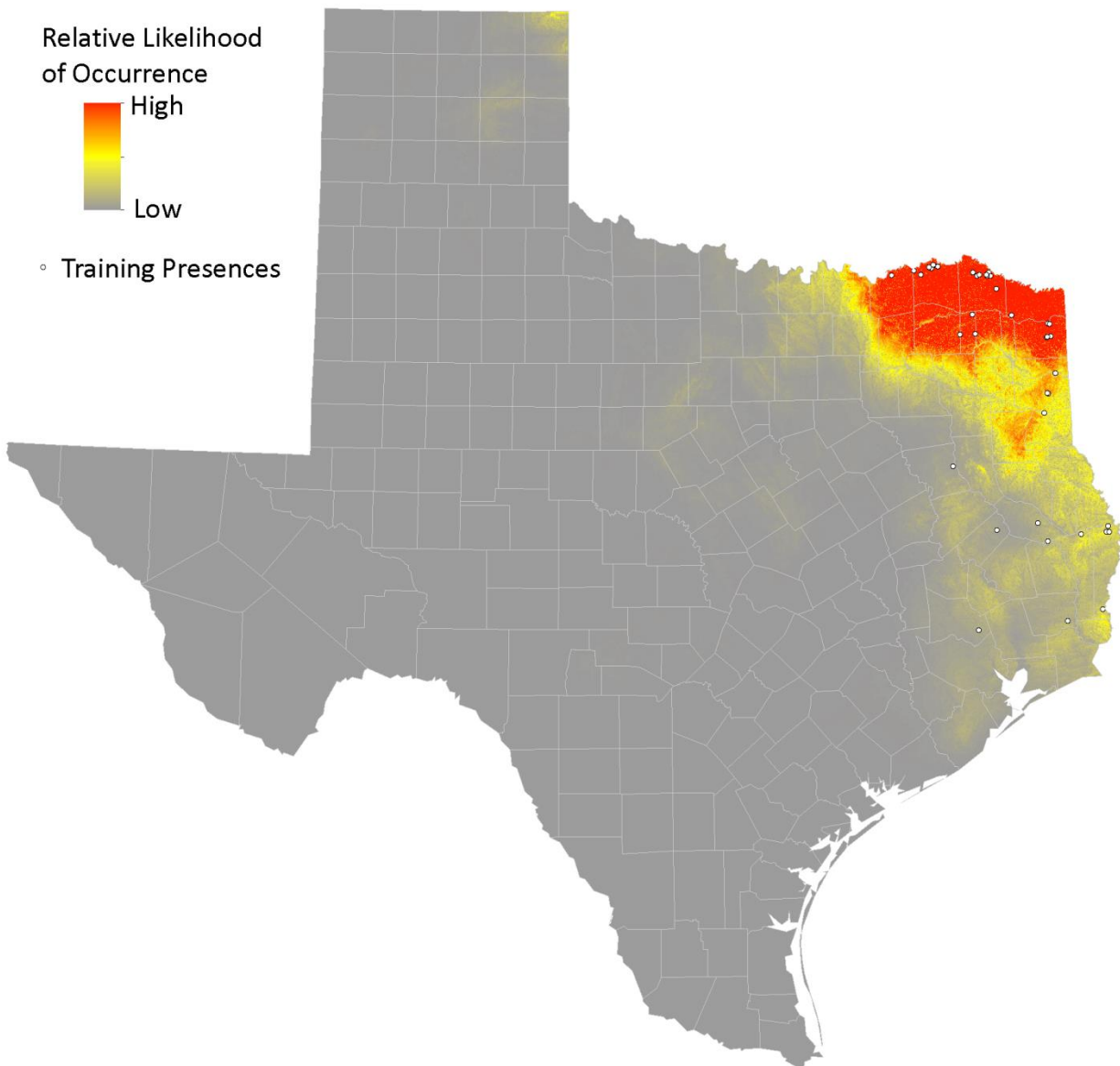
Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E
AMAJB0101W responsecurves nopictures jackknife outputfiletype=bil
outputdirectory=F:\MODELING\TXNDD_SDM\MAXENT_OUT\AMAJB0101W\RUN_4
projectionlayers=F:\MODELING\TXNDD_SDM\MAXENT_IN\PROB
samplesfile=F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
environmentallayers=F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\BACKGROU
ND.CSV noaskoverwrite nowriteclampgrid nowritemess randomtestpoints=20
writebackgroundpredictions writeplotdata threads=6 -N UNIQUE_ID -N aglands -N aprime135 -N
aprime180 -N aprime45 -N aprime90 -N avoid -N avoid1600 -N avoid3200 -N avoid6400 -N bio1 -N
bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio19 -N bio4 -N bio5 -N bio7 -N bio8 -N
bio9 -N cti -N curve10 -N curve5 -N d2wsl -N dissect10 -N dissect5 -N drainclass -N hydgroup -N
ksat -N lf_forstcc -N percclay -N percsand -N percstilt -N radld -N slope -N soilec -N soilph -N vrm10 -
N water1600 -N water300 -N water3200

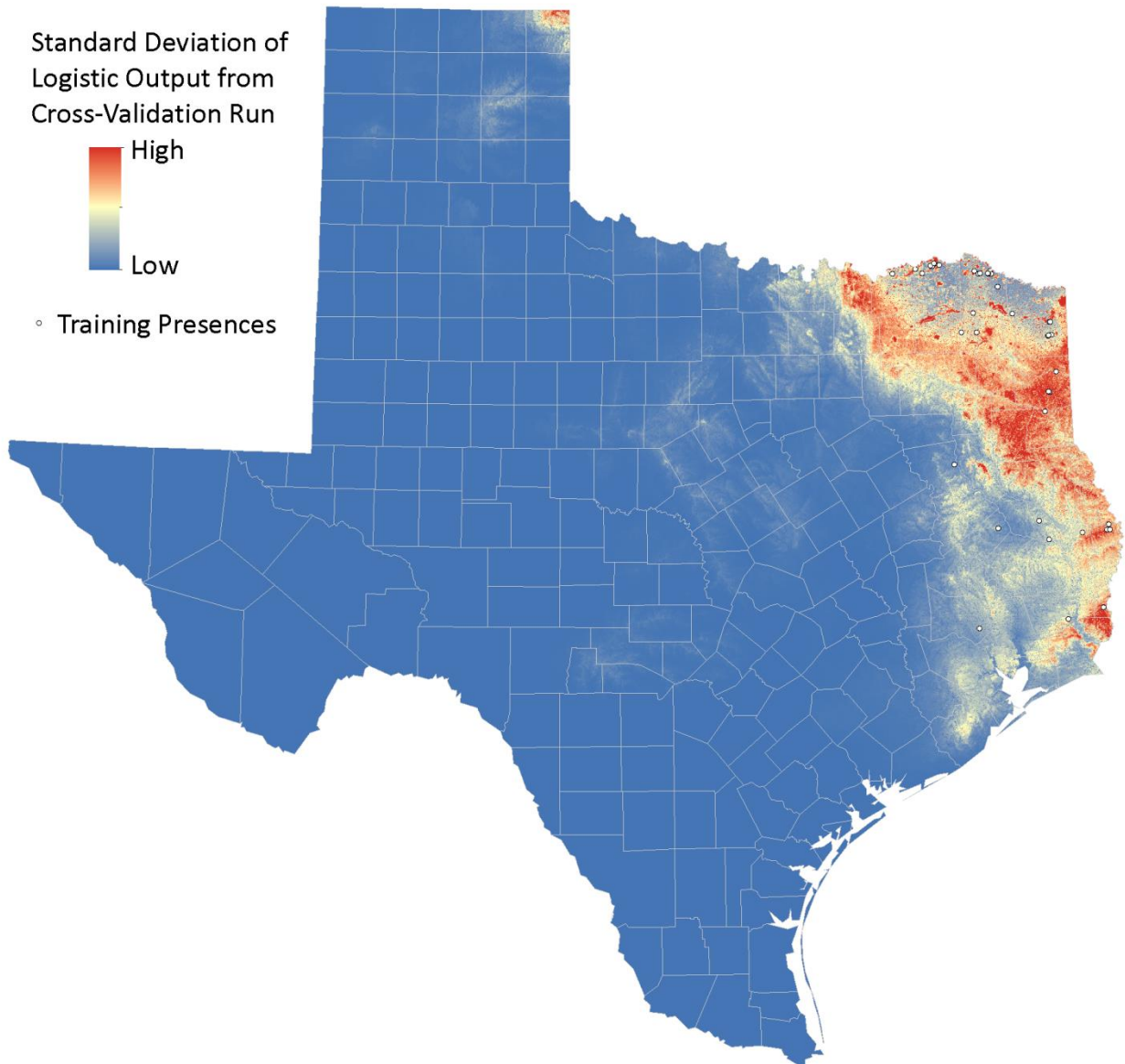
Black Bear, Eastern TX Population (*Ursus americanus*)

ELCODE: AMAJB0101E

Date: August 20, 2013

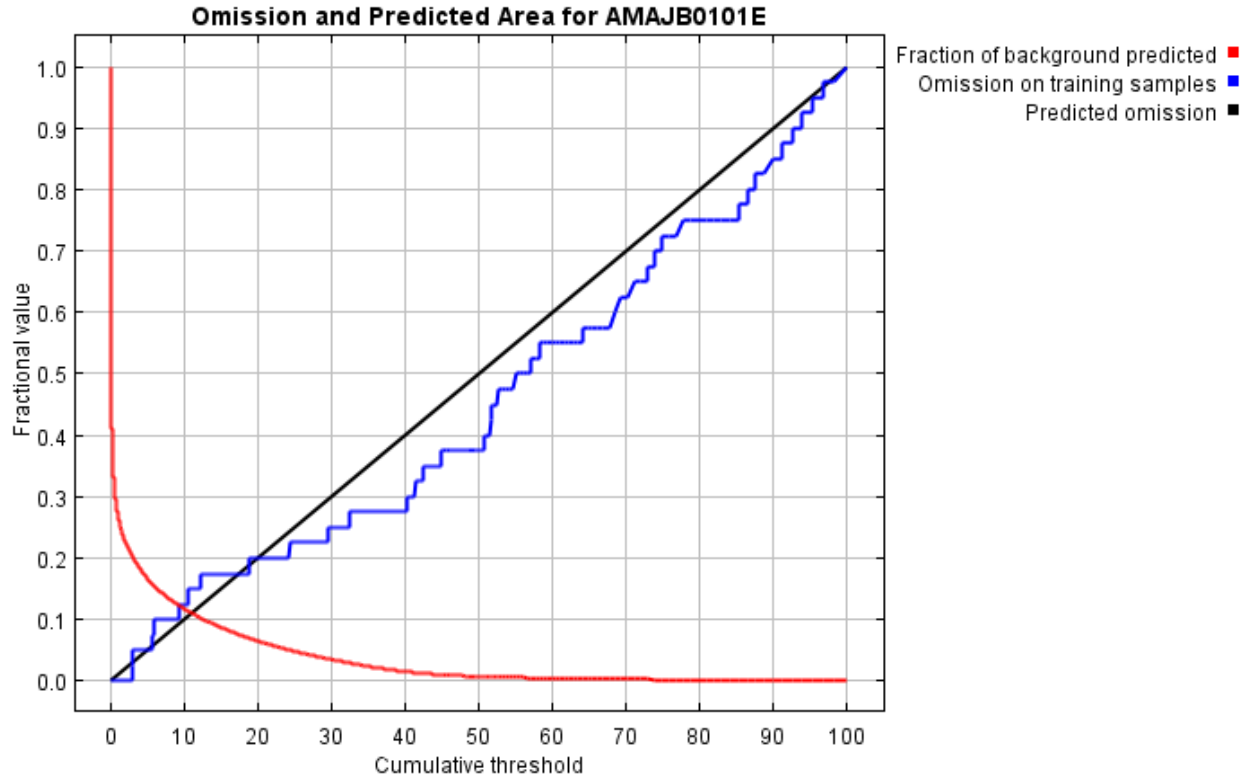
Maxent version: 3.3.3k





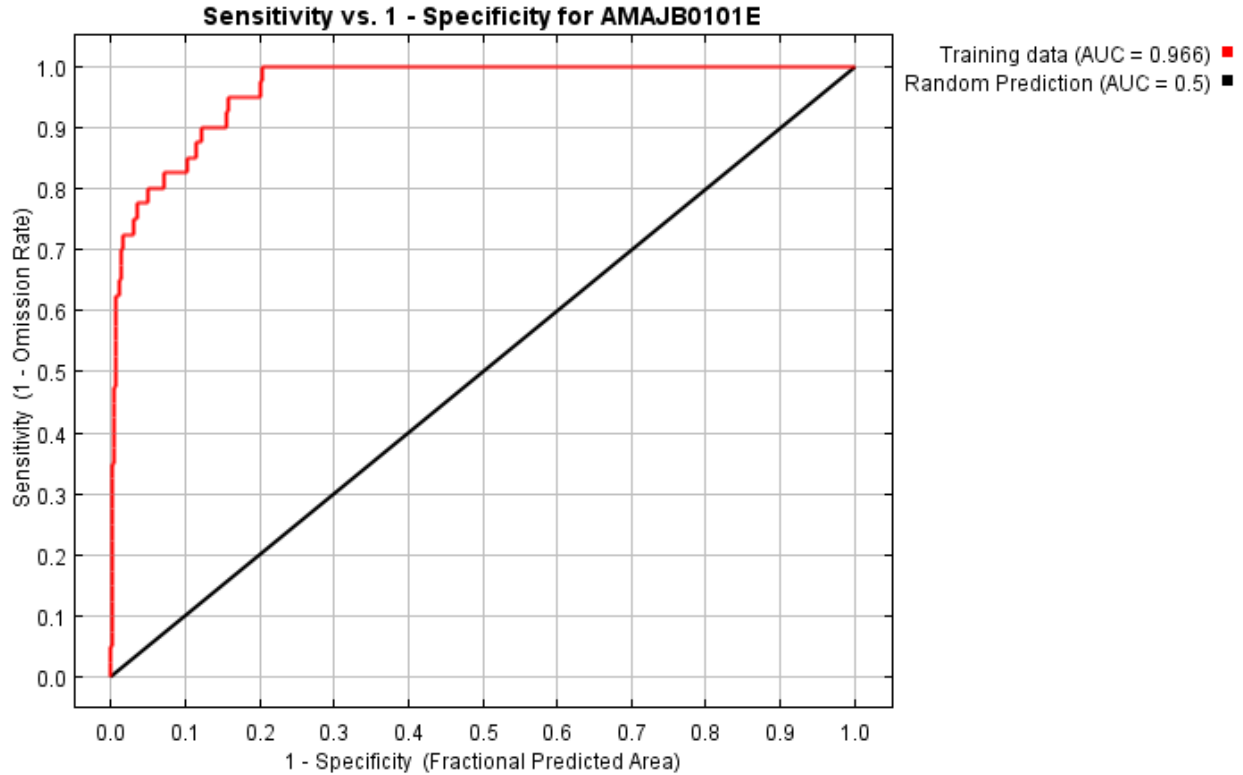
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.961 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

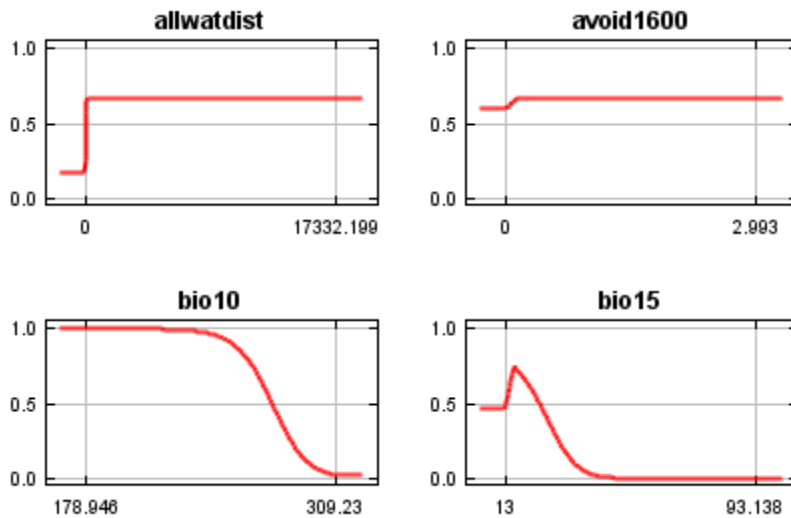
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.010	Fixed cumulative value 1	0.267	0.000
5.000	0.046	Fixed cumulative value 5	0.166	0.050
10.000	0.084	Fixed cumulative value 10	0.117	0.125
2.928	0.030	Minimum training presence	0.203	0.000
9.336	0.079	10 percentile training presence	0.122	0.100

Appendix 2 – Model Reports

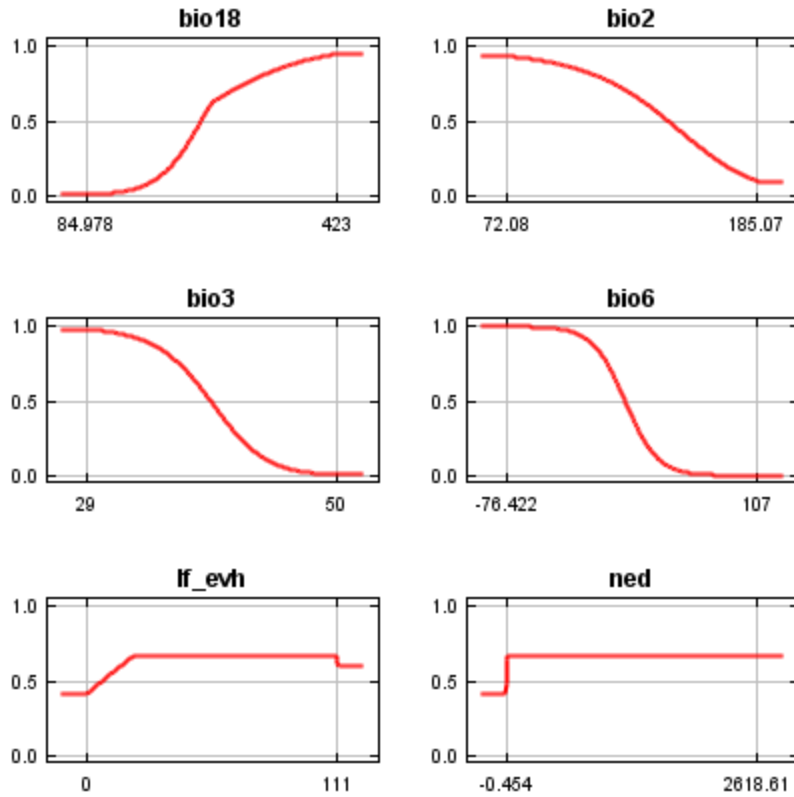
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
9.336	0.079	Equal training sensitivity and specificity	0.122	0.125
2.928	0.030	Maximum training sensitivity plus specificity	0.203	0.000
2.357	0.026	Balance training omission, predicted area and threshold value	0.216	0.000
19.635	0.147	Equate entropy of thresholded and original distributions	0.067	0.200

Response curves

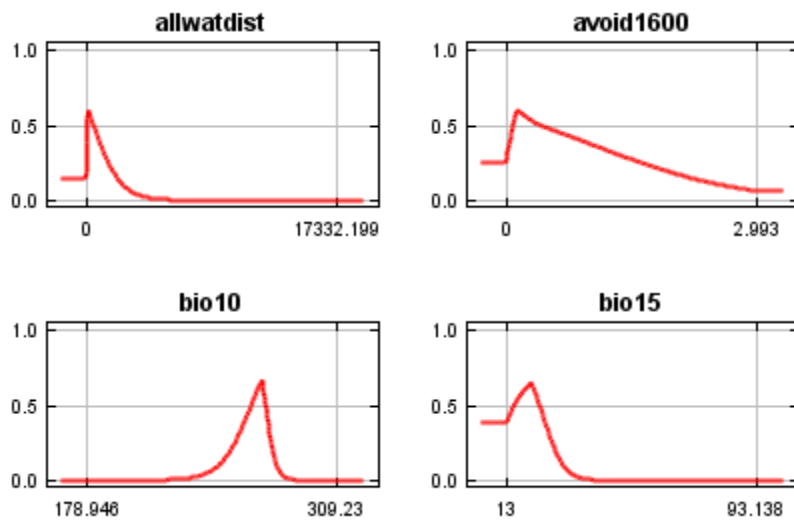
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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.



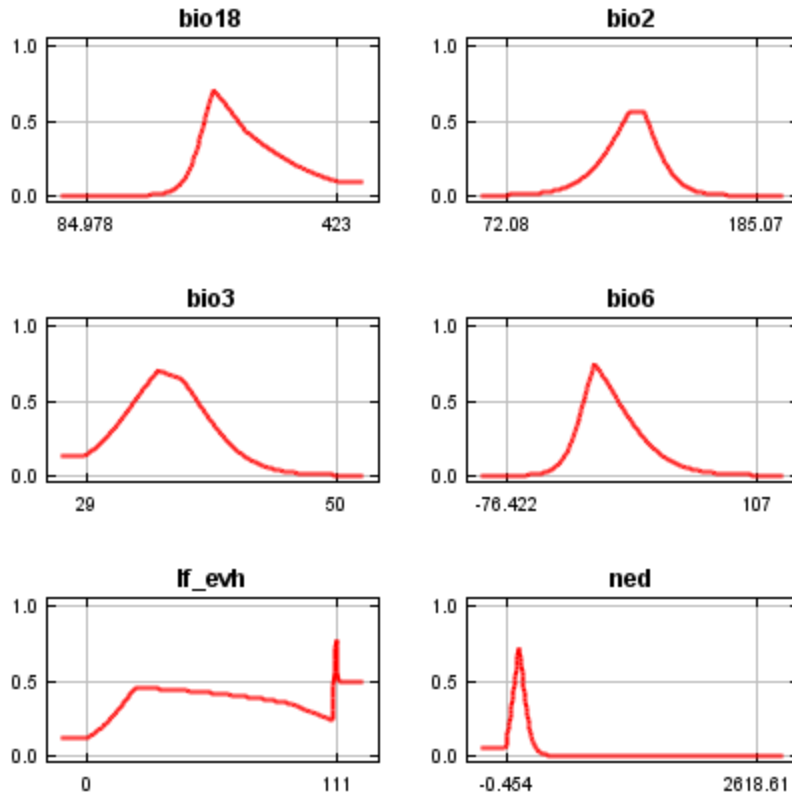
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



Analysis of variable contributions

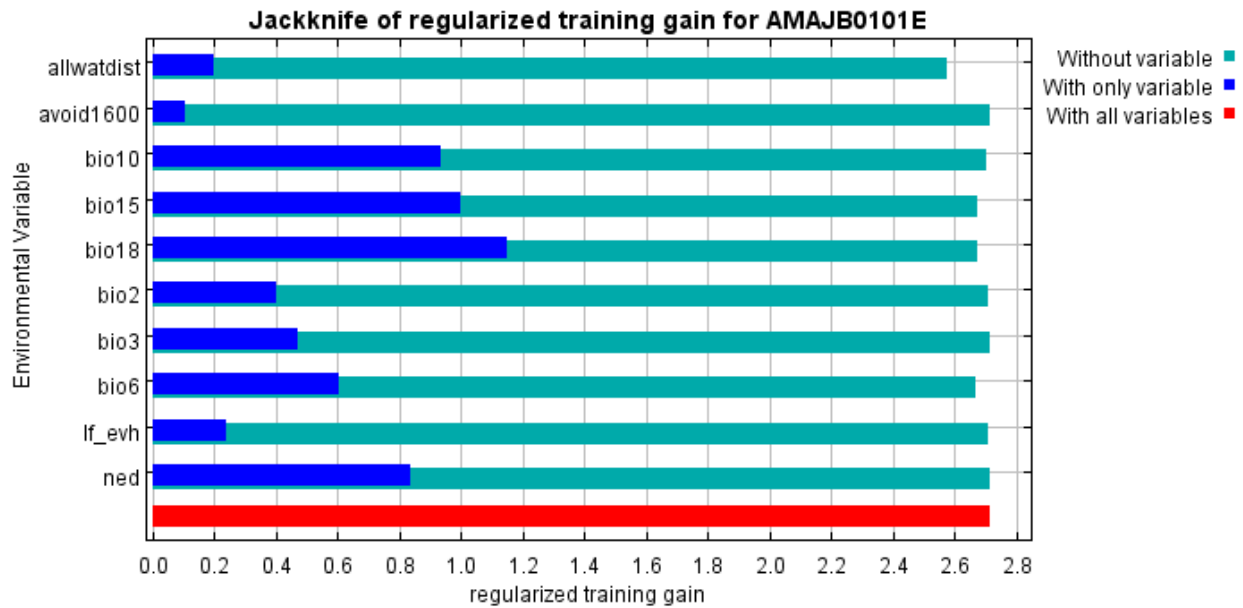
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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
bio18	26.2	11.6
bio6	25.6	22.2
bio15	23.2	48.6
bio3	14.4	4.3

Appendix 2 – Model Reports

Variable	Percent contribution	Permutation importance
allwatdist	5	2
ned	3.7	0.4
bio10	0.9	9.4
lf_evh	0.7	0
avoid1600	0.3	0.1
bio2	0.1	1.3

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio18, 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 allwatdist, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 2.713, training AUC is 0.966, unregularized training gain is 2.983. Algorithm terminated after 500 iterations (6 seconds).

The follow settings were used during the run:
40 presence records used for training.

Appendix 2 – Model Reports

8703 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): allwatdist avoid1600 bio10 bio15 bio18 bio2 bio3 bio6
lf_evh ned

Regularization values: linear/quadratic/product: 0.221, categorical: 0.250, threshold: 1.600, hinge:
0.500

Feature types used: linear quadratic hinge

responsecurves: true

pictures: false

jackknife: true

outputfiletype: bil

outputdirectory: F:\MODELING\TXNDD_SDM\MAXENT_OUT\AMAJB0101E\RUN_3

projectionlayers: F:\MODELING\TXNDD_SDM\MAXENT_IN\PROB

samplesfile: F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV

environmentallayers:

F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV

writeclampgrid: false

writemess: false

writebackgroundpredictions: true

writeplotdata: true

threads: 6

Command line used: dontwriteclampgrid

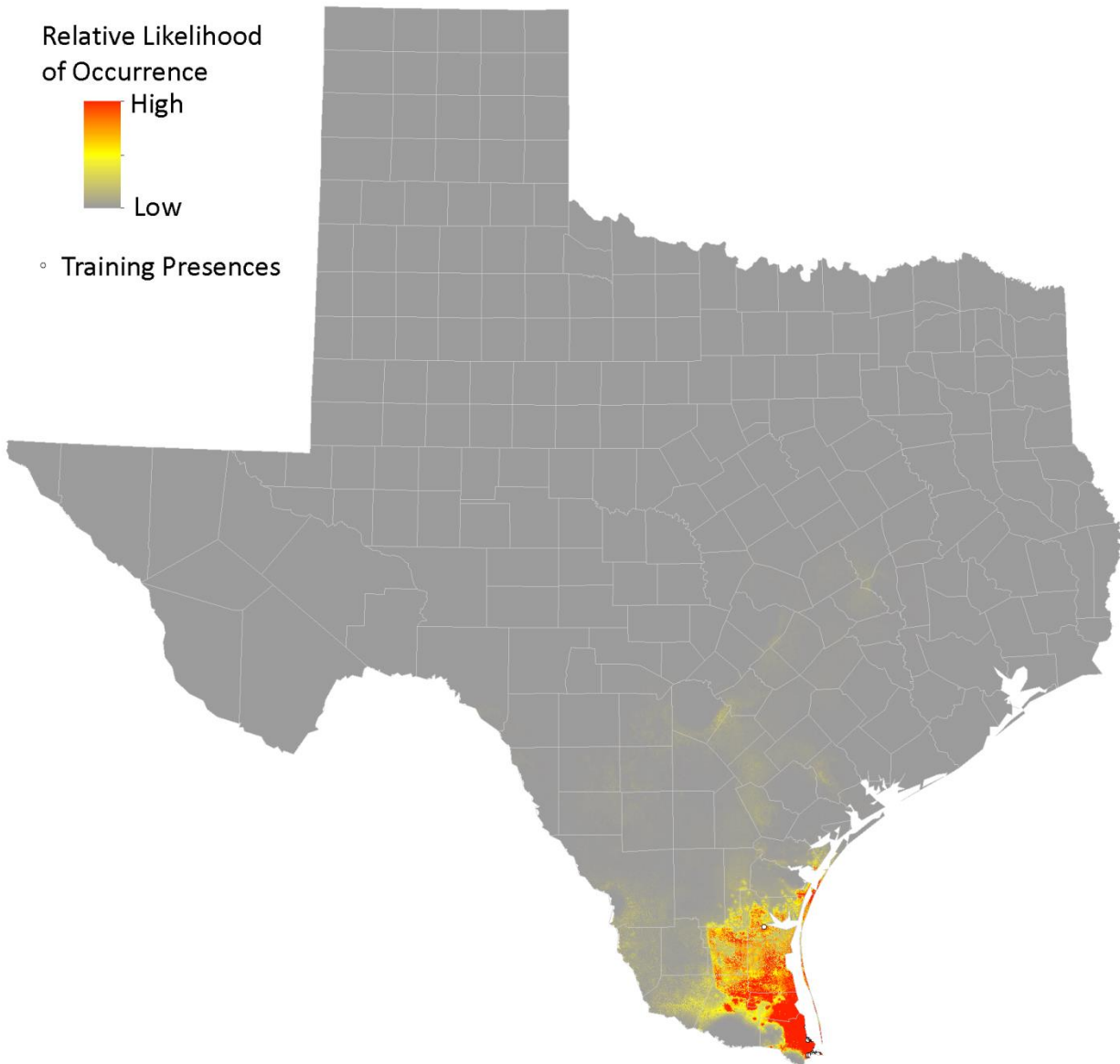
Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E
AMAJB0101E responsecurves nopictures jackknife outputfiletype=bil
outputdirectory=F:\MODELING\TXNDD_SDM\MAXENT_OUT\AMAJB0101E\RUN_3
projectionlayers=F:\MODELING\TXNDD_SDM\MAXENT_IN\PROB
samplesfile=F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
environmentallayers=F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\BACKGROU
ND.CSV nowriteclampgrid nowritemess writebackgroundpredictions writeplotdata threads=6 -N
UNIQUE_ID -N aglands -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N
avoid12800 -N avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N
bio17 -N bio19 -N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N
d2wsl -N dissect10 -N dissect5 -N drainclass -N hydgroup -N ksat -N lf_forstcc -N lfherbcc -N
lfshrubcc -N nlcdcanopy -N percclay -N percscand -N percstilt -N radld -N slope -N soilec -N soilph -N
vrm10 -N vrm5 -N water1600 -N water300 -N water3200

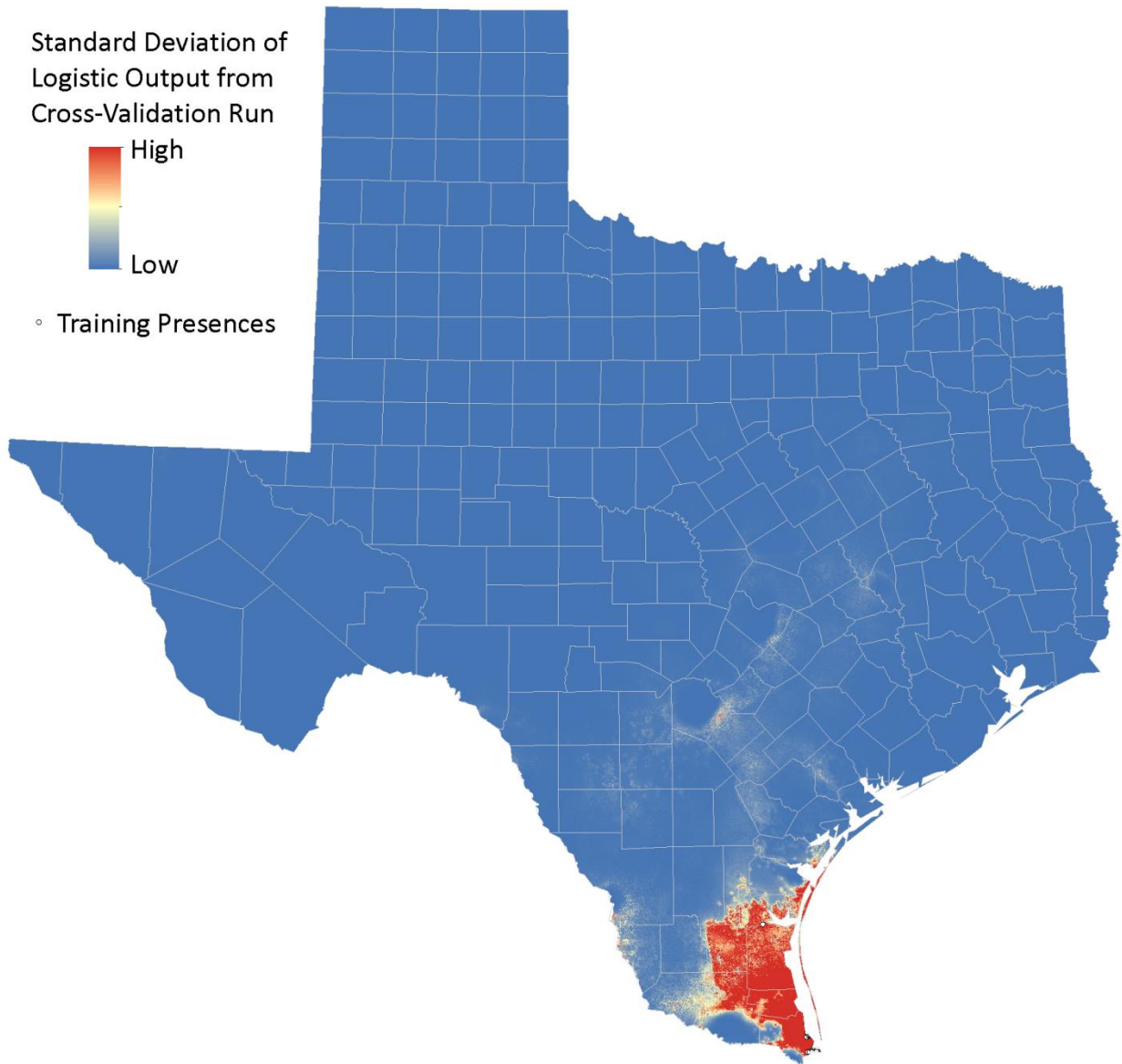
Ocelot (*Leopardus pardalis*)

ELCODE: AMAJH05010

Date: August 15, 2013

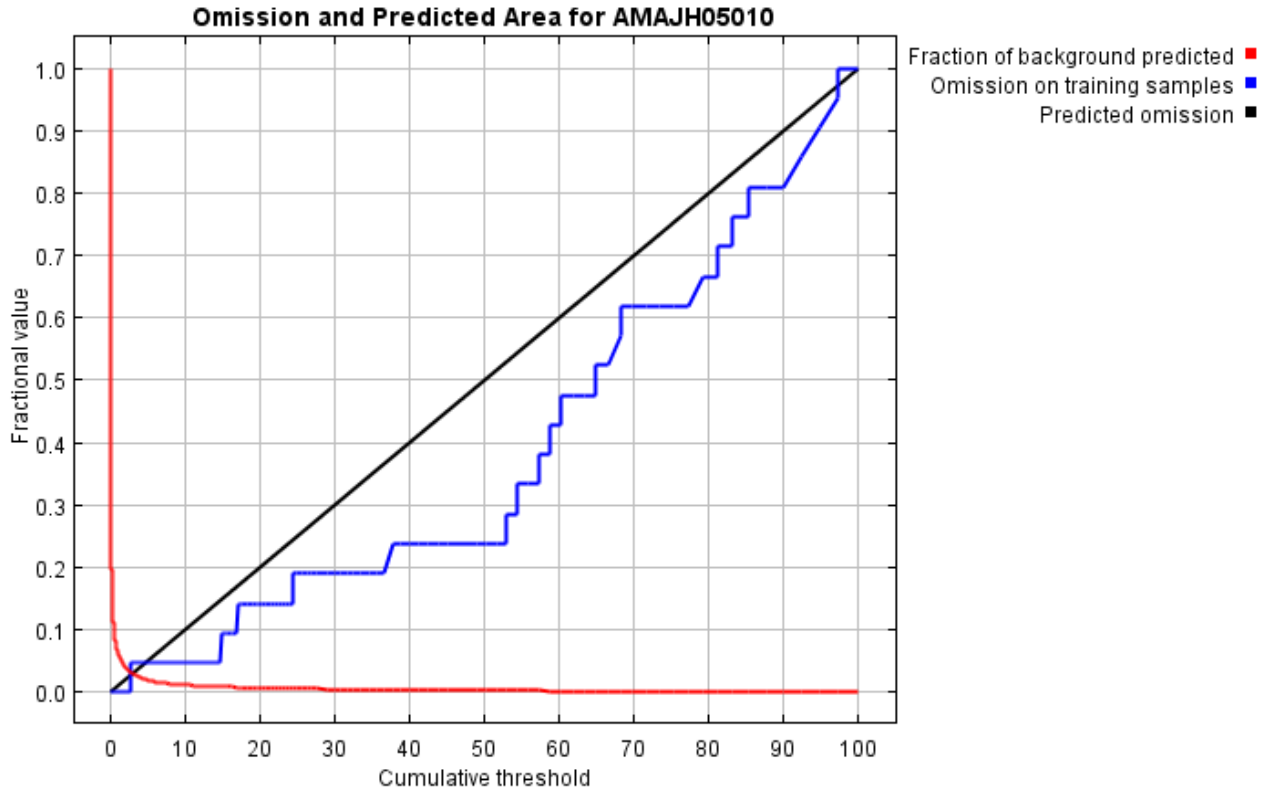
Maxent version: 3.3.3k





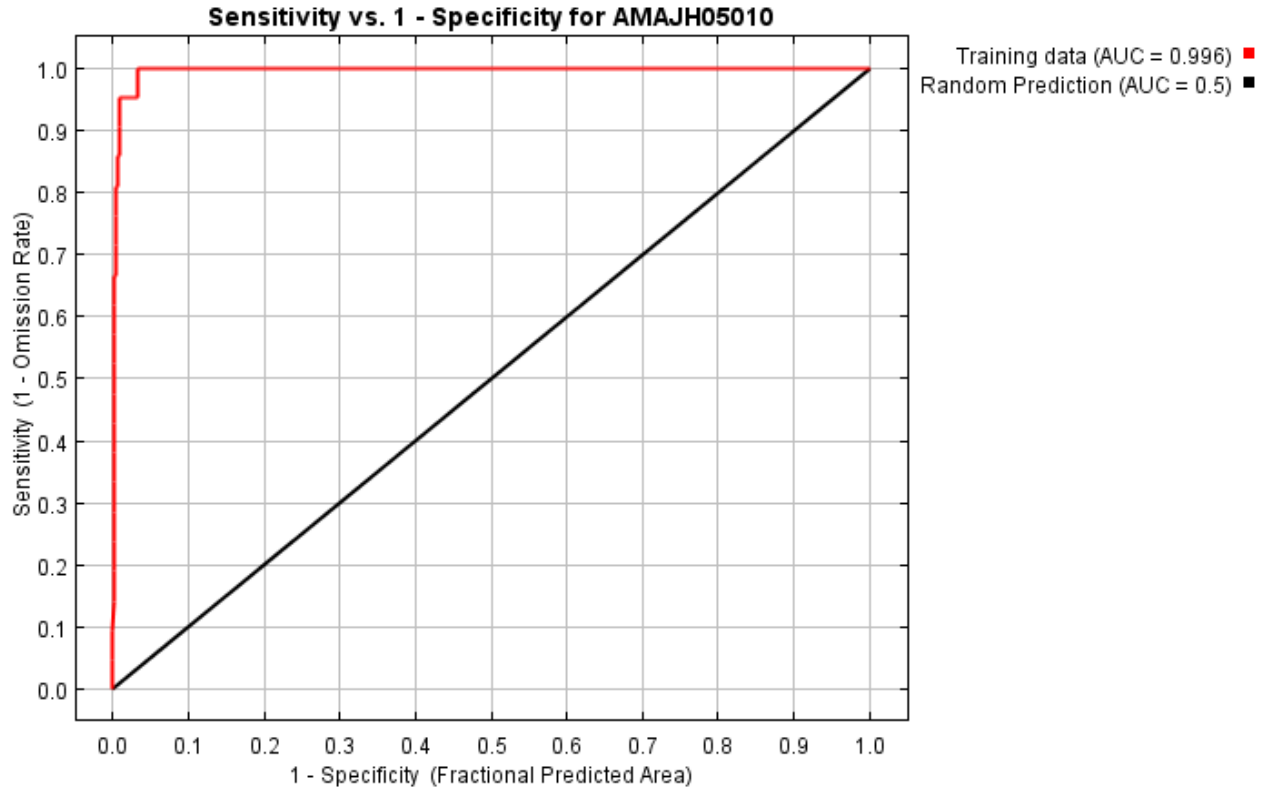
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.992 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

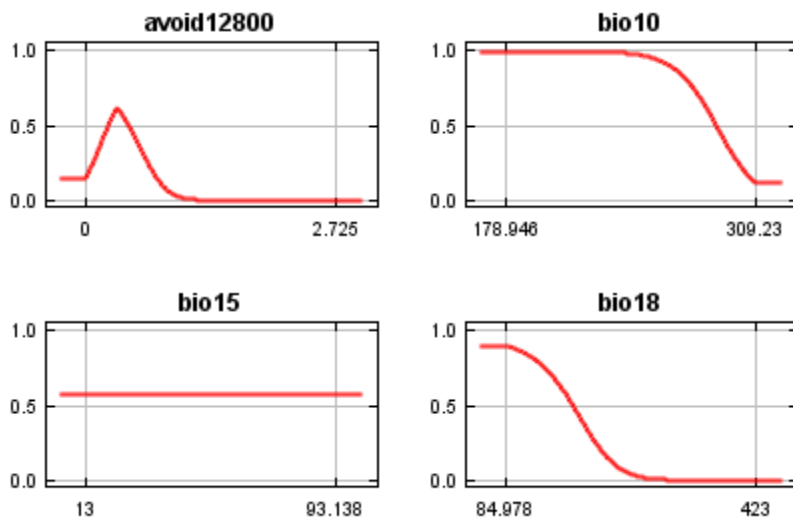
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.004	Fixed cumulative value 1	0.064	0.000
5.000	0.044	Fixed cumulative value 5	0.019	0.048
10.000	0.161	Fixed cumulative value 10	0.012	0.048
2.664	0.016	Minimum training presence	0.033	0.000
16.719	0.261	10 percentile training presence	0.008	0.095

Appendix 2 – Model Reports

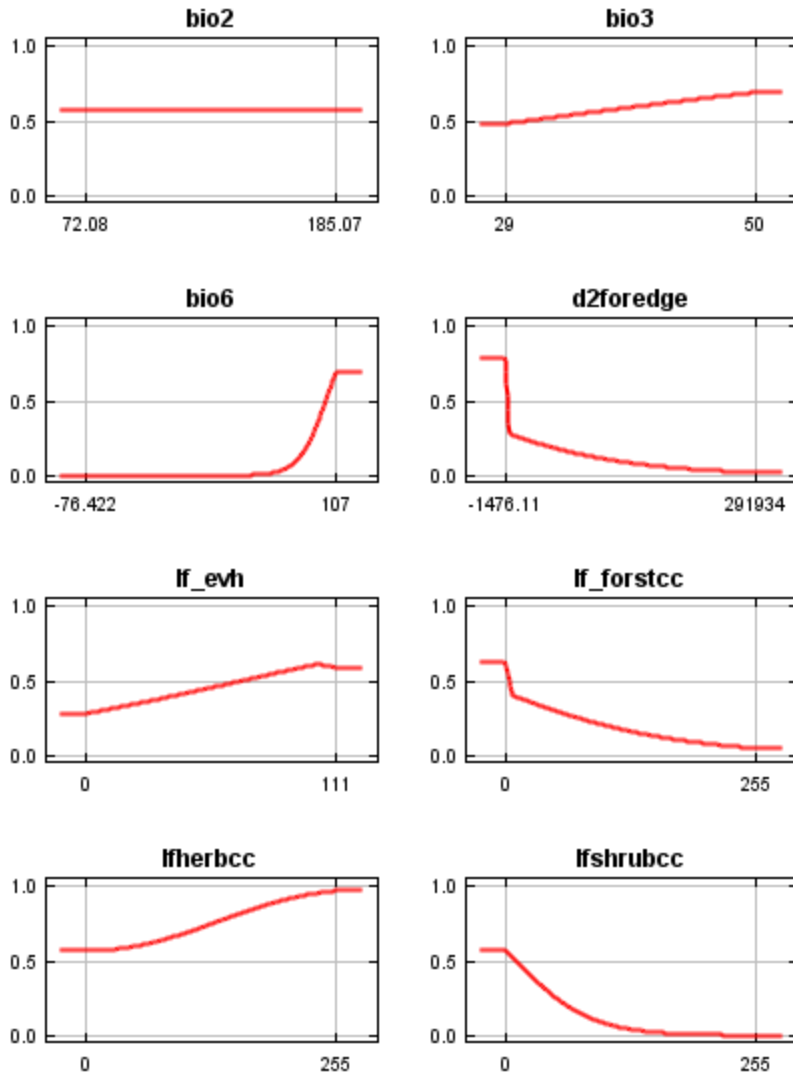
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
2.664	0.016	Equal training sensitivity and specificity	0.033	0.048
2.664	0.016	Maximum training sensitivity plus specificity	0.033	0.000
1.372	0.006	Balance training omission, predicted area and threshold value	0.052	0.000
7.695	0.101	Equate entropy of thresholded and original distributions	0.014	0.048

Response curves

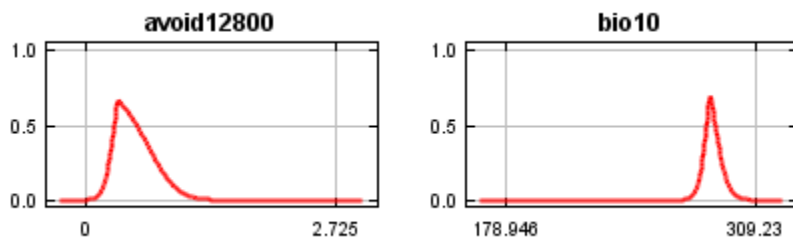
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



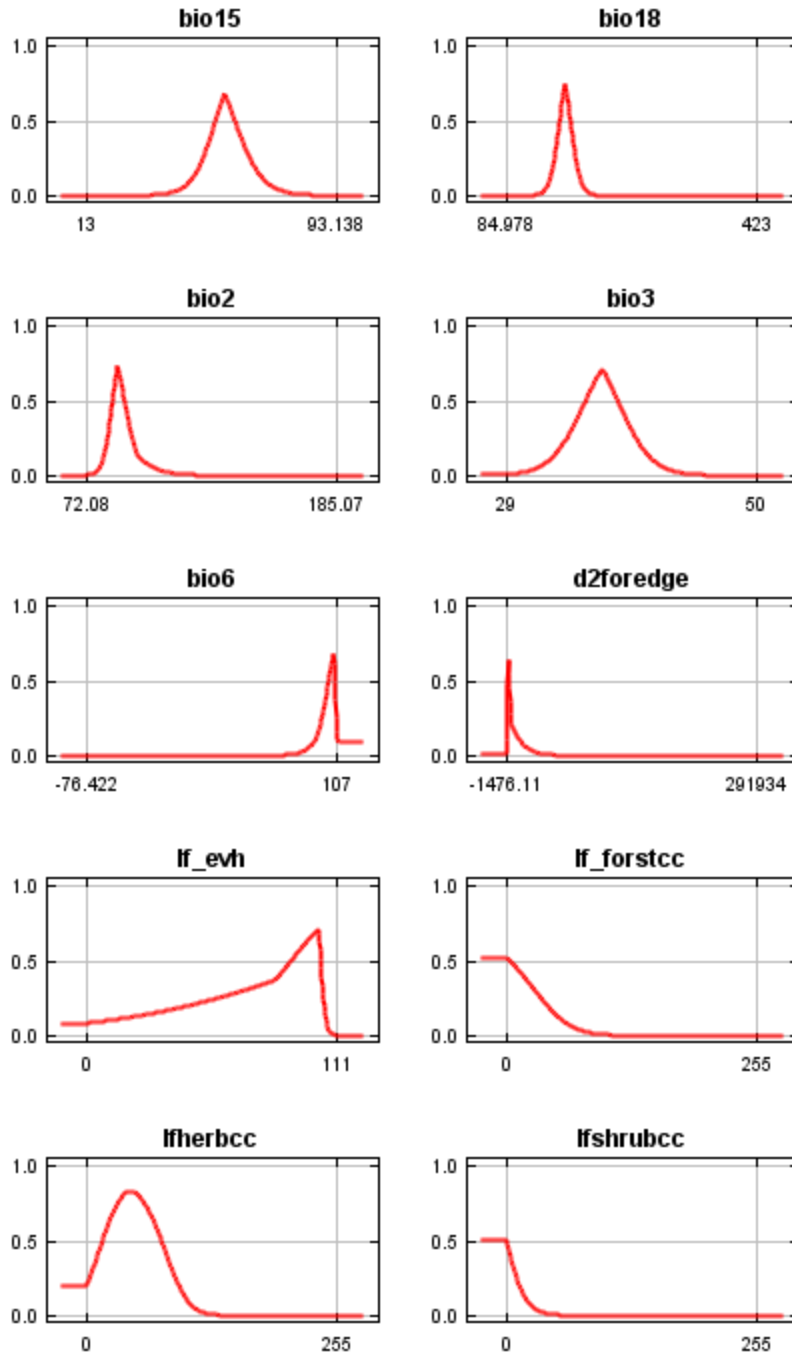
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



Analysis of variable contributions

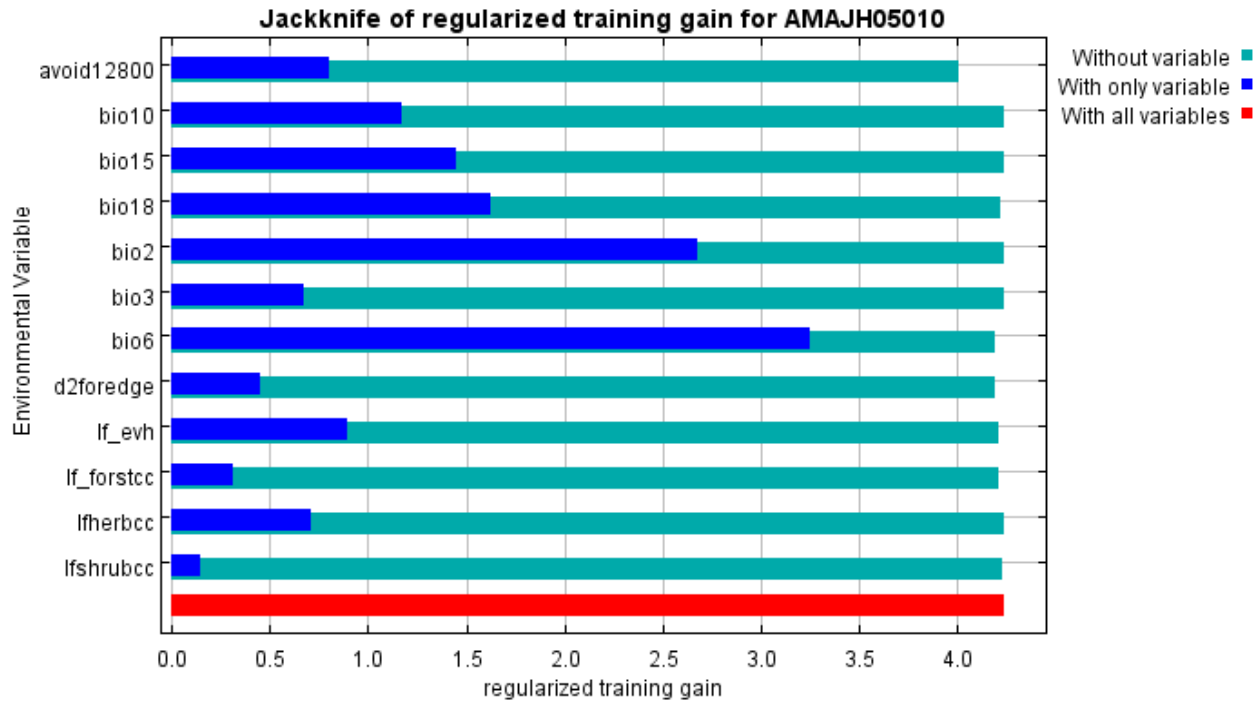
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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

Appendix 2 – Model Reports

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
bio6	72.7	75.5
bio2	8.2	0
avoid12800	6.8	13.9
lfherbcc	5.7	0
lf_evh	2.5	0
d2foredge	1.3	2
lf_forstcc	1.1	0.3
bio15	0.8	0
bio18	0.5	5.9
lfshrubcc	0.4	1.5
bio10	0	0.8
bio3	0	0.1

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio6, 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 avoid12800, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 4.241, training AUC is 0.996, unregularized training gain is 4.558. Algorithm converged after 480 iterations (28 seconds).

The follow settings were used during the run:

21 presence records used for training.
 8639 points used to determine the Maxent distribution (background points and presence points).
 Environmental layers used (all continuous): avoid12800 bio10 bio15 bio18 bio2 bio3 bio6
 d2foredge lf_evh lf_forstcc lfherbcc lfshrubcc
 Regularization values: linear/quadratic/product: 0.423, categorical: 0.250, threshold: 1.790, hinge:
 0.500
 Feature types used: linear quadratic hinge
 responsecurves: true
 pictures: false
 jackknife: true
 outputfiletype: bil
 outputdirectory: F:\MAXENT_OUT\AMAJH05010\RUN_3
 projectionlayers: F:\MAXENT_IN\PROB
 samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
 environmentalayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV
 writeclampgrid: false
 writemess: false
 writebackgroundpredictions: true
 writeplotdata: true

Appendix 2 – Model Reports

Command line used: dontwriteclampgrid

Command line to repeat this species model:

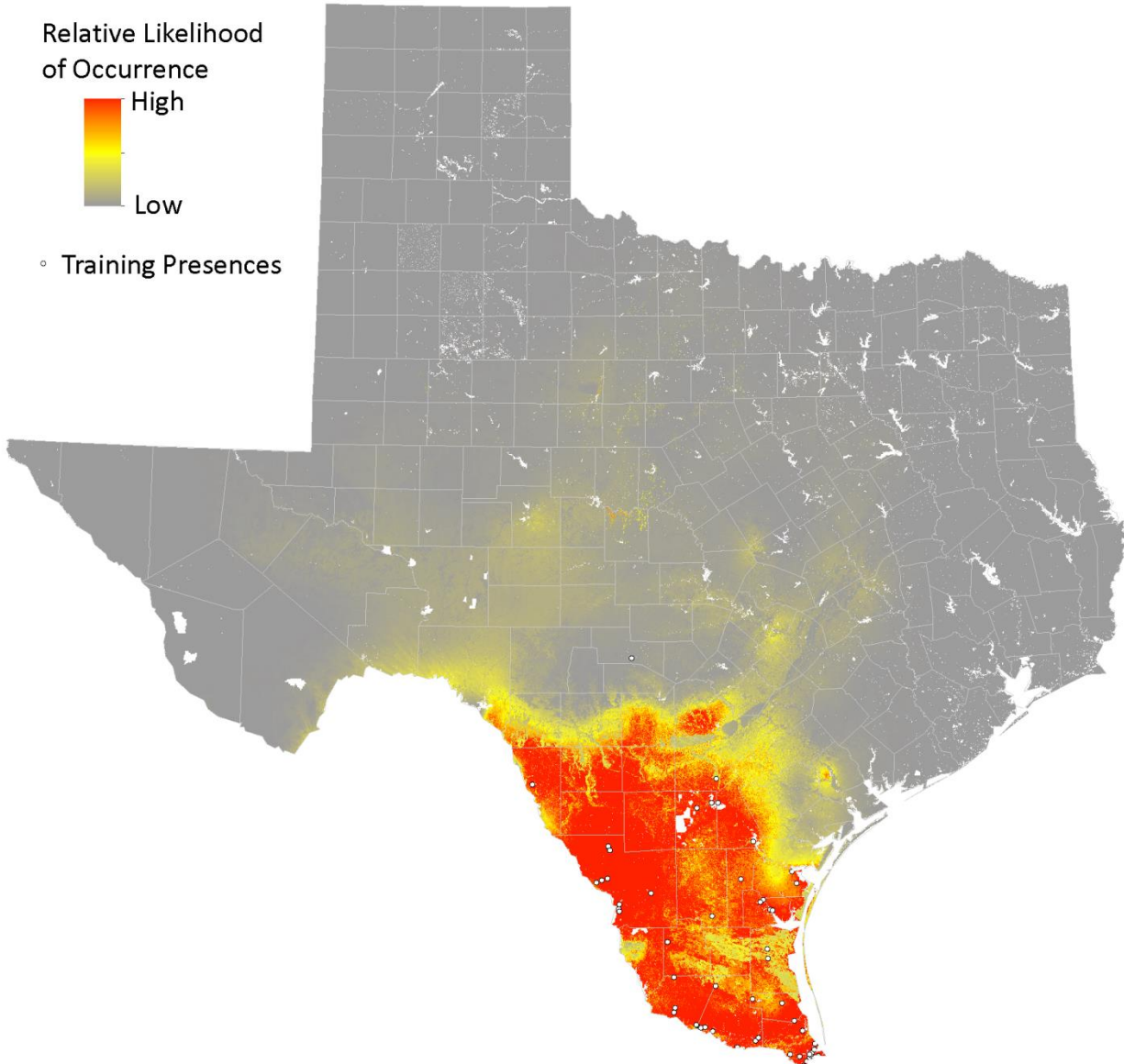
```
java density.MaxEnt nowarnings noprefixes -E "" -E AMAJH05010 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\AMAJH05010\RUN_3  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -N aglands -N allwatdist -N  
aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N avoid1600 -N avoid3200 -N  
avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio19 -N bio4 -N bio5  
-N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2wsl -N dissect10 -N dissect5 -N drainclass  
-N hydgroup -N ksat -N ned -N nlcdcanopy -N percclay -N percsand -N percsilt -N radld -N slope -N  
soilec -N soilph -N vrm10 -N vrm5 -N water1600 -N water300 -N water3200
```

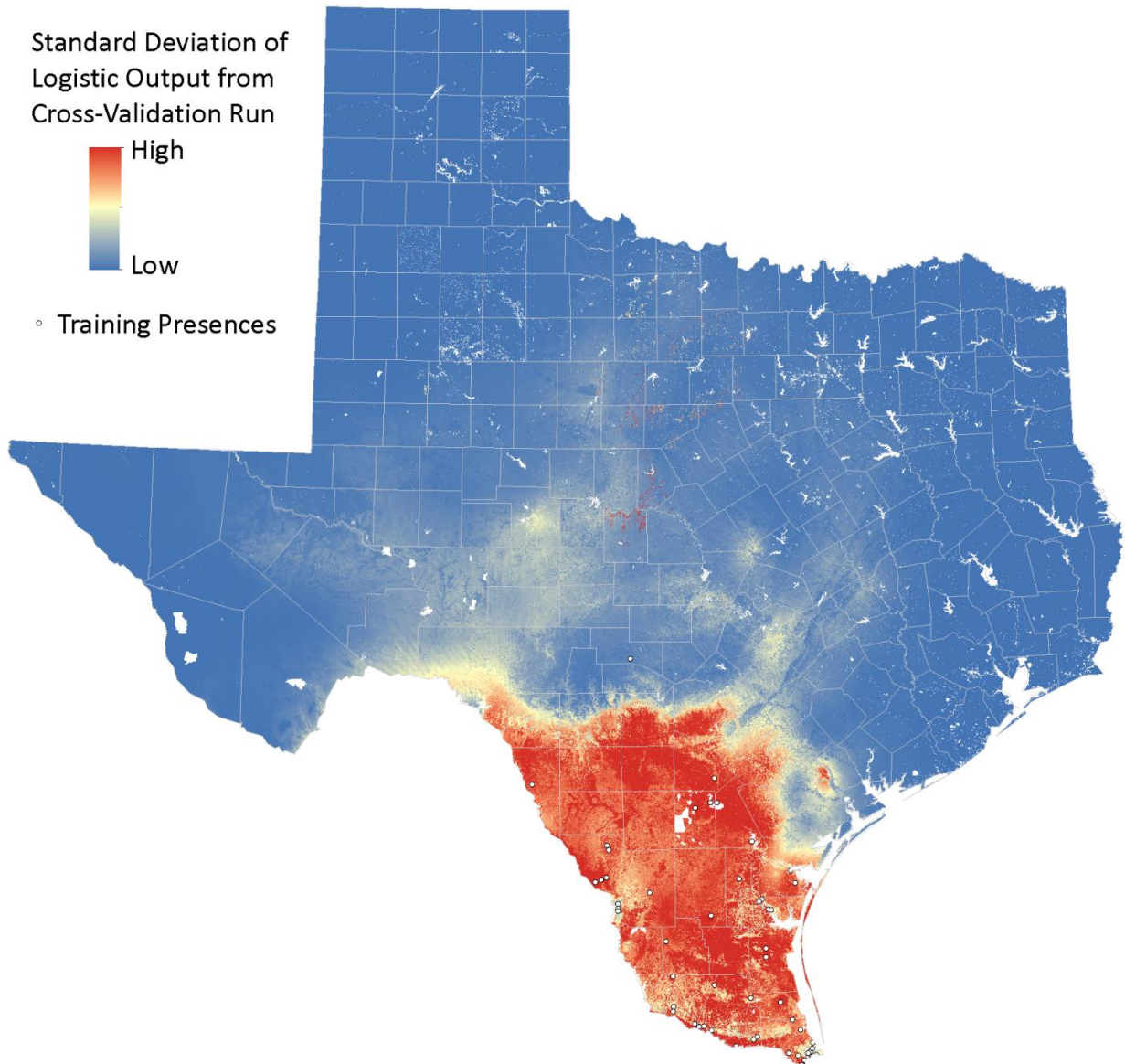
Texas Tortoise (*Gopherus berlandieri*)

ELCODE: ARAAF01020

Date: August 15, 2013

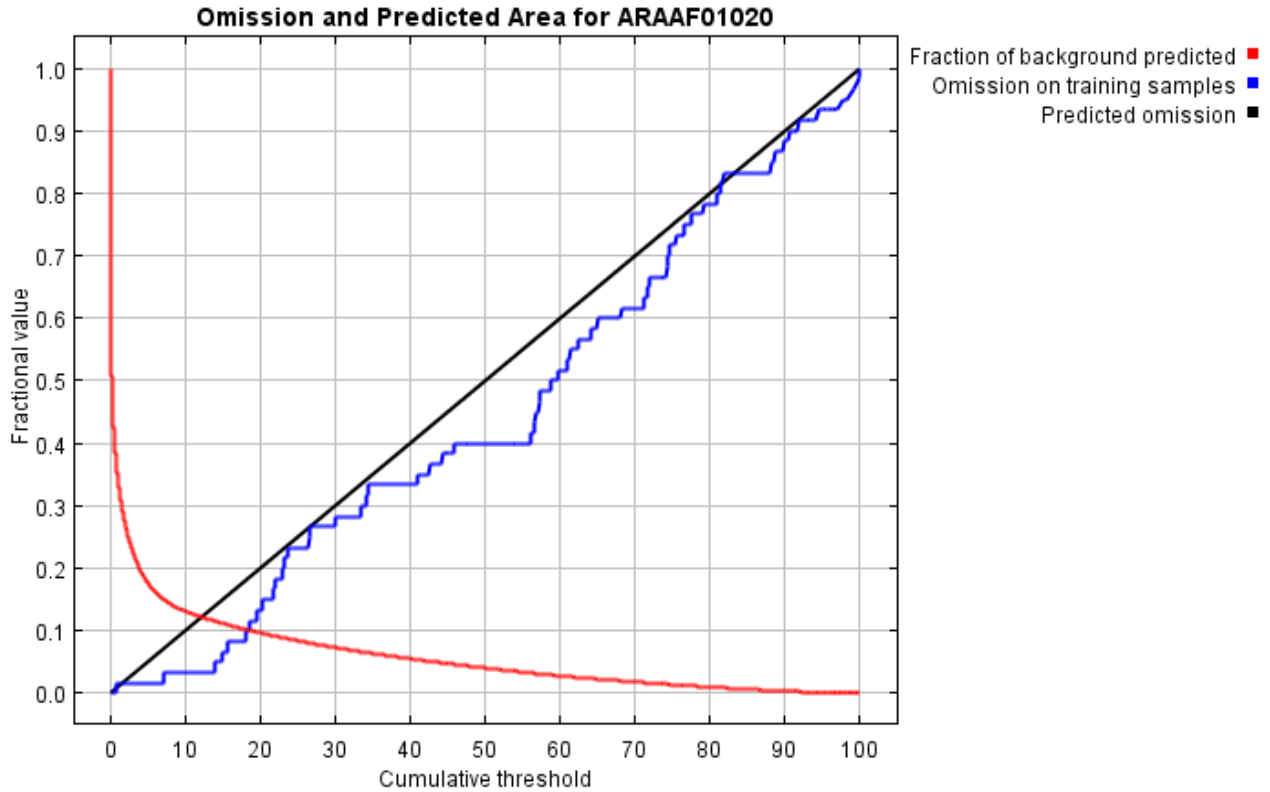
Maxent version: 3.3.3k





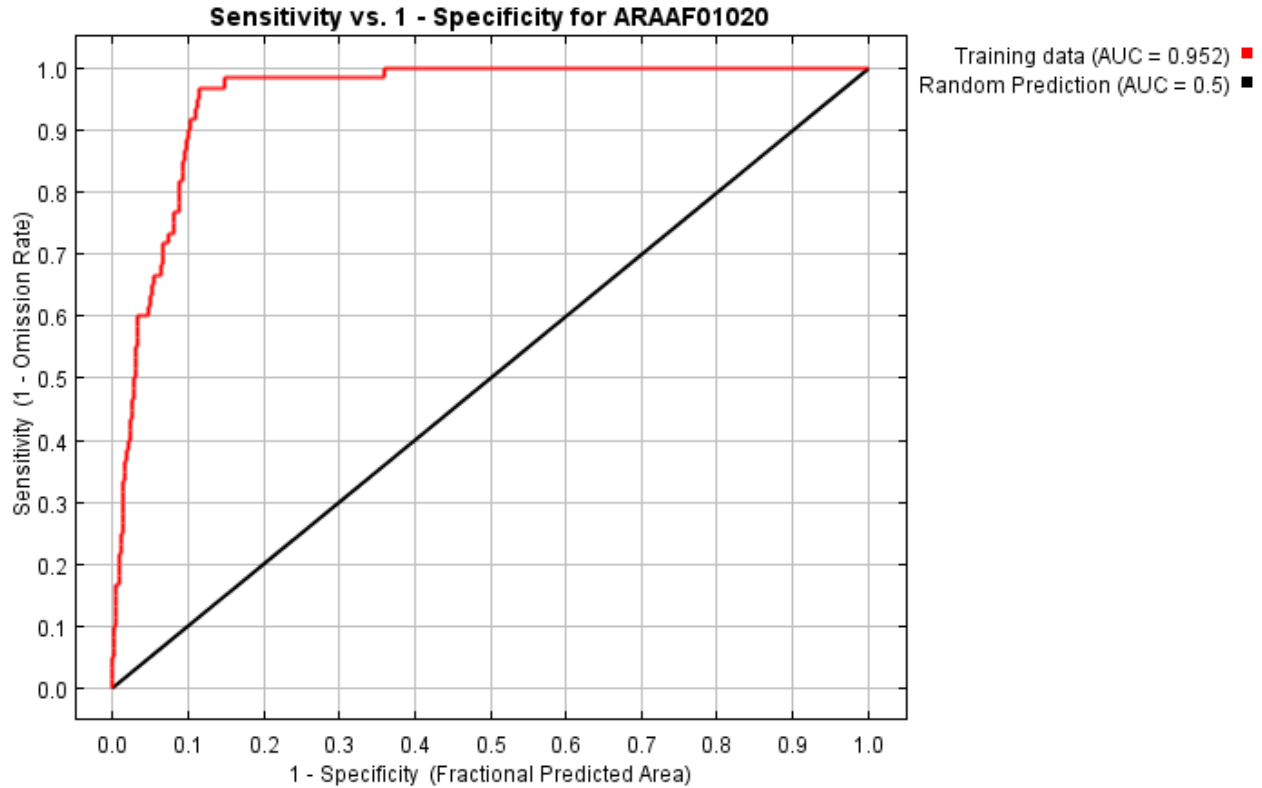
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.939 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

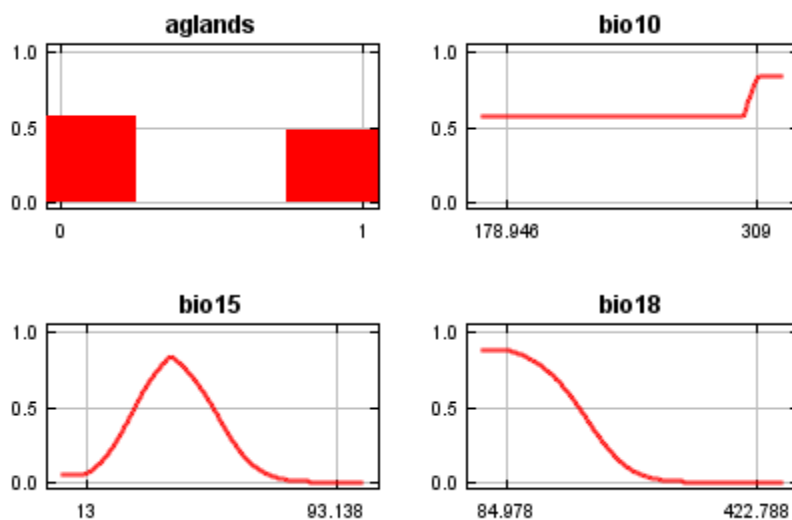
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.016	Fixed cumulative value 1	0.338	0.017
5.000	0.086	Fixed cumulative value 5	0.176	0.017
10.000	0.245	Fixed cumulative value 10	0.131	0.033
0.794	0.013	Minimum training presence	0.359	0.000
18.536	0.352	10 percentile training presence	0.101	0.100

Appendix 2 – Model Reports

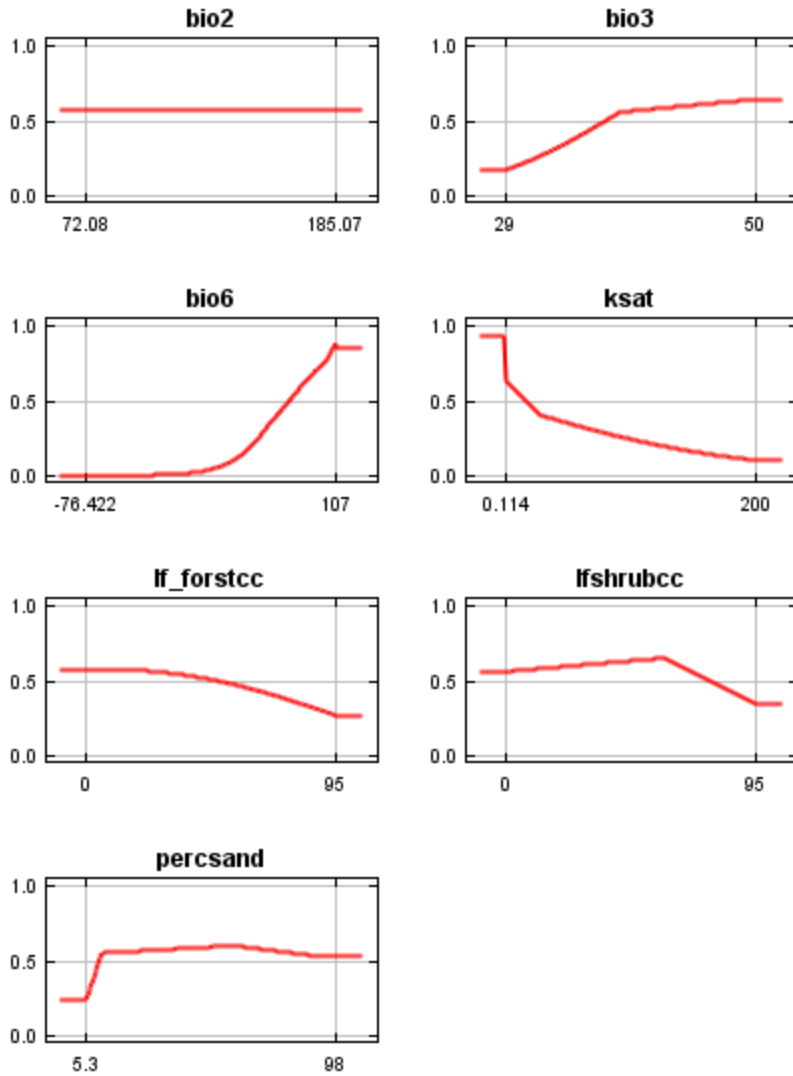
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
18.536	0.352	Equal training sensitivity and specificity	0.101	0.100
13.969	0.314	Maximum training sensitivity plus specificity	0.115	0.033
3.893	0.059	Balance training omission, predicted area and threshold value	0.199	0.017
6.413	0.127	Equate entropy of thresholded and original distributions	0.157	0.017

Response curves

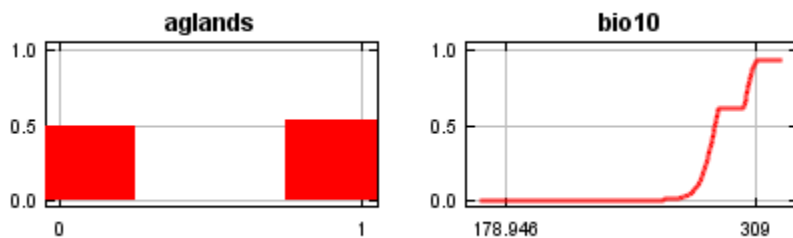
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



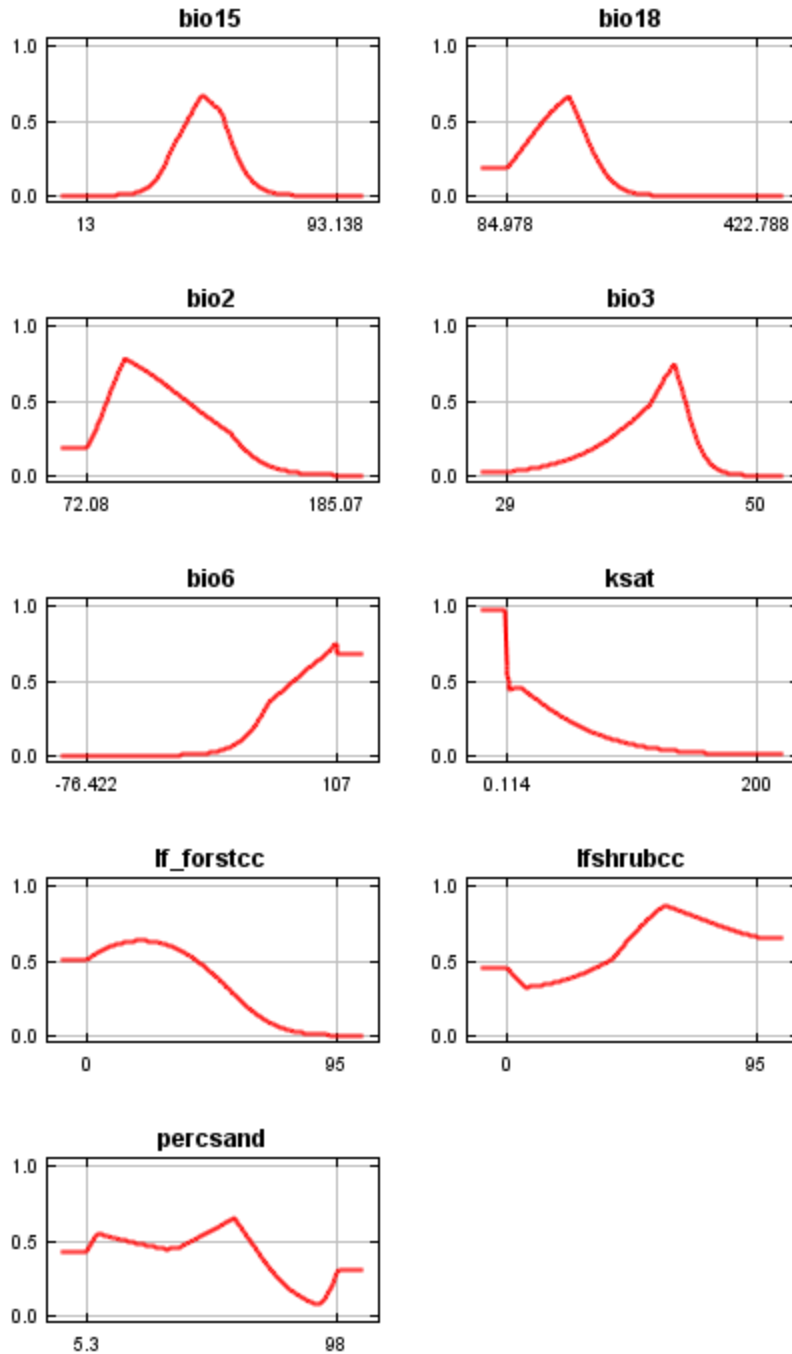
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



Analysis of variable contributions

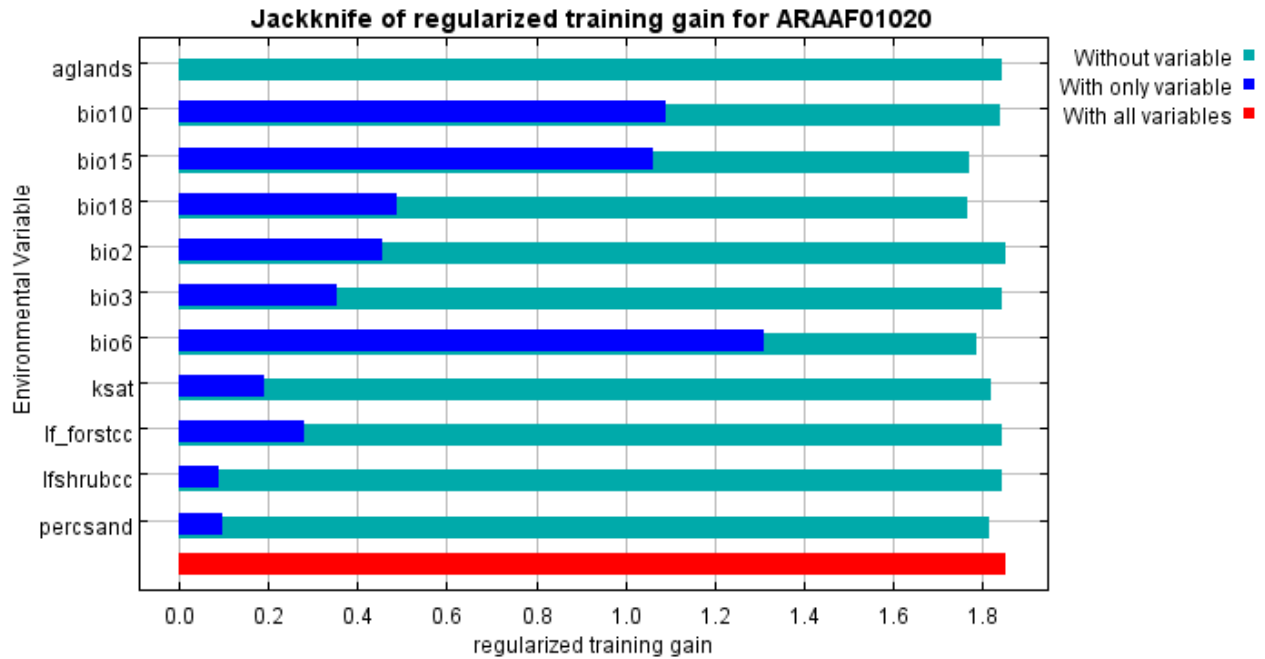
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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

Appendix 2 – Model Reports

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
bio6	65.9	53.7
bio15	20.3	14.6
ksat	4.2	2.9
percsand	3.3	1.7
bio18	3.1	24.3
bio3	1.2	0.5
bio2	0.6	0
aglands	0.6	0
lf_forstcc	0.4	1.8
lfshrubcc	0.3	0.4
bio10	0	0.2

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio6, 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 bio18, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 1.852, training AUC is 0.952, unregularized training gain is 2.073. Algorithm converged after 440 iterations (18 seconds).

The follow settings were used during the run:

60 presence records used for training.
 7393 points used to determine the Maxent distribution (background points and presence points).
 Environmental layers used: aglands(categorical) bio10 bio15 bio18 bio2 bio3 bio6 ksat lf_forstcc lfshrubcc perssand
 Regularization values: linear/quadratic/product: 0.164, categorical: 0.250, threshold: 1.400, hinge: 0.500
 Feature types used: linear quadratic hinge
 responsecurves: true
 pictures: false
 jackknife: true
 outputfiletype: bil
 outputdirectory: F:\MAXENT_OUT\ARAAF01020\RUN_4
 projectionlayers: F:\MAXENT_IN\PROB
 samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
 environmentallayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV
 writeclampgrid: false
 writemess: false
 writebackgroundpredictions: true
 writeplotdata: true
 Command line used: dontwriteclampgrid

Command line to repeat this species model:

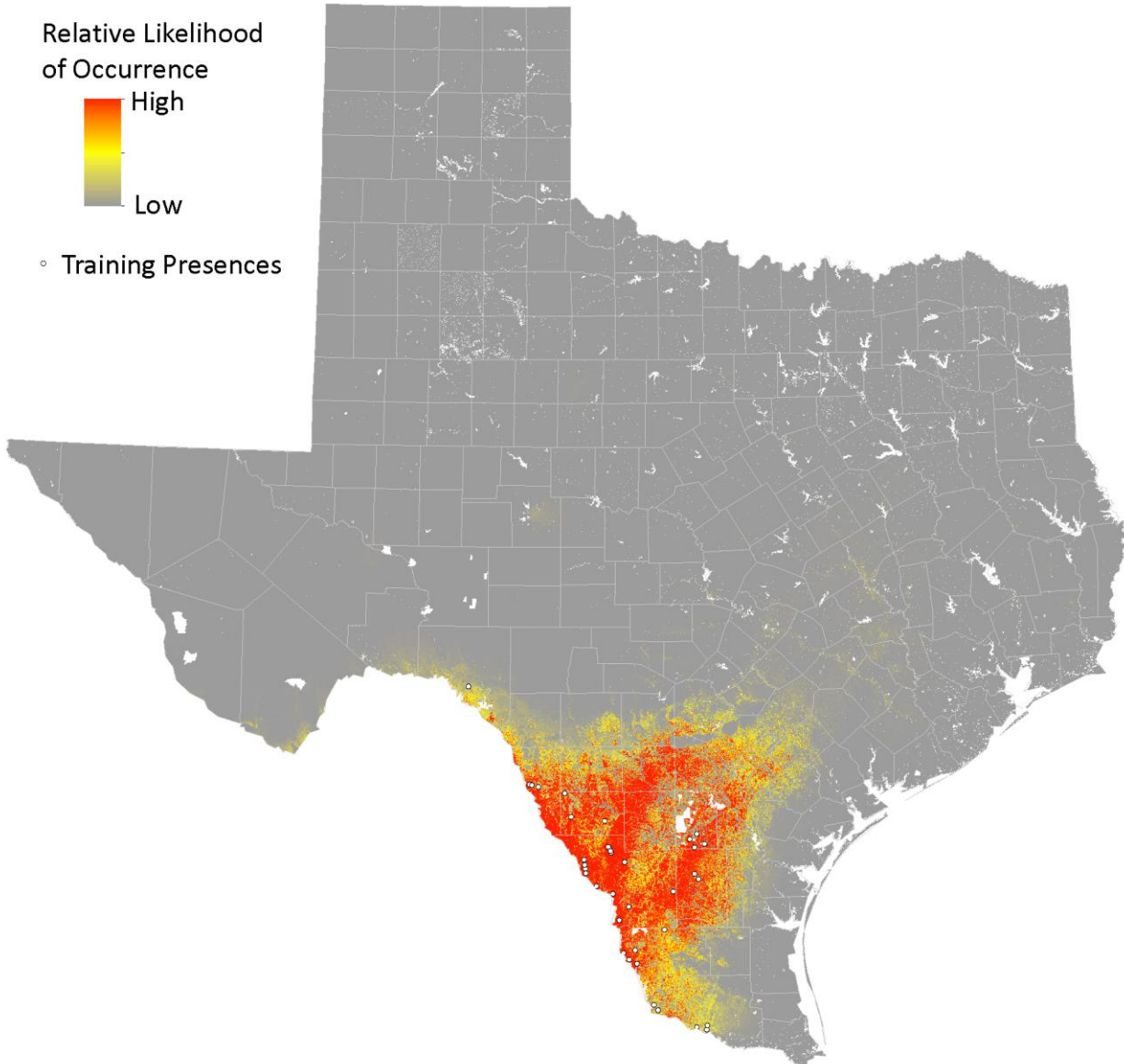
```
java density.MaxEnt nowarnings noprefixes -E "" -E ARAAF01020 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\ARAAF01020\RUN_4  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -N allwatdist -N aprime135  
-N aprime180 -N aprime45 -N aprime90 -N avoid -N avoid12800 -N avoid1600 -N avoid3200 -N  
avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio19 -N bio4 -N bio5  
-N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N d2wsl -N dissect10 -N dissect5  
-N drainclass -N hydgroup -N lf_evh -N lfherbcc -N ned -N nlcdcanopy -N percclay -N percsilt -N  
radld -N slope -N soilec -N soilph -N vrm10 -N vrm5 -N water1600 -N water300 -N water3200 -t  
aglands
```

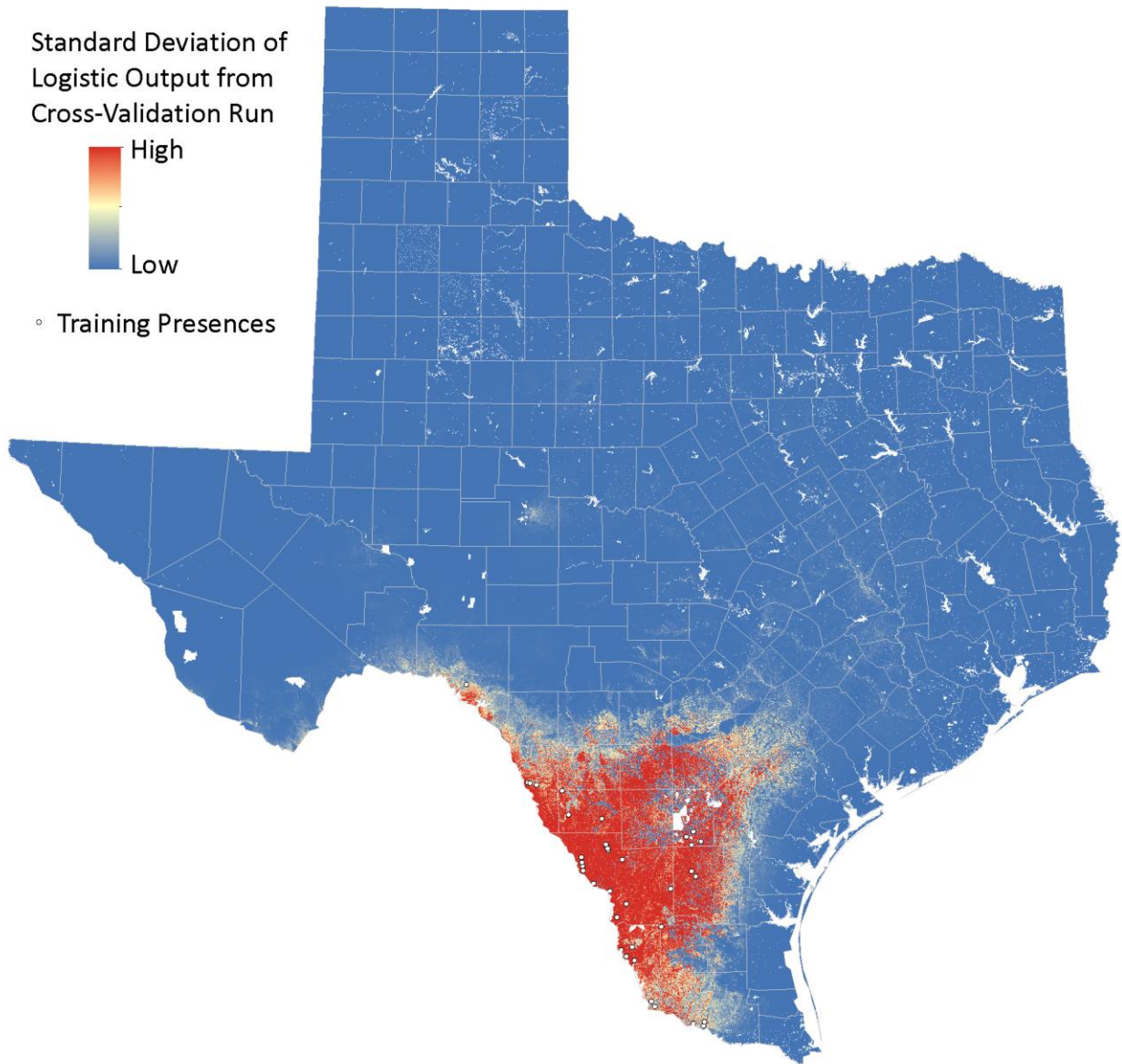
Reticulate Collared Lizard (*Crotaphytus reticulatus*)

ELCODE: ARACF04040

Date: August 14, 2013

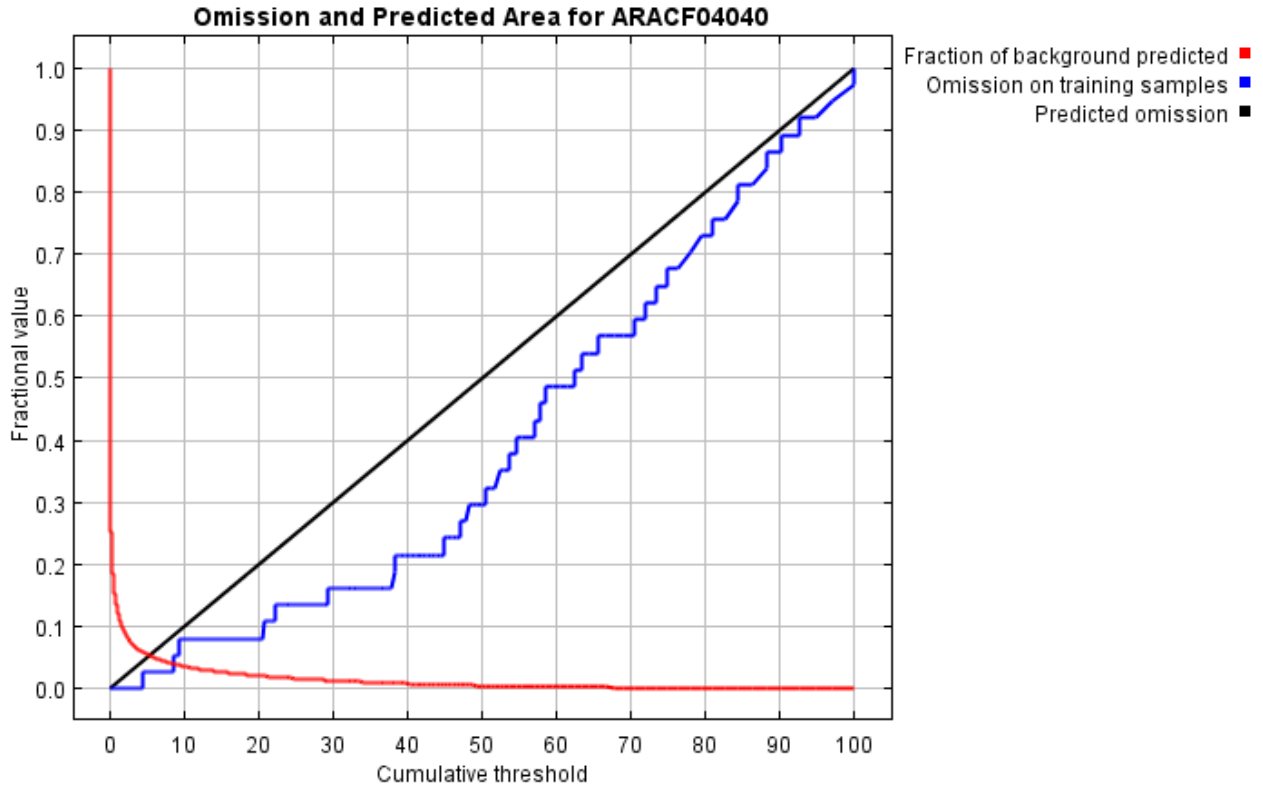
Maxent version: 3.3.3k





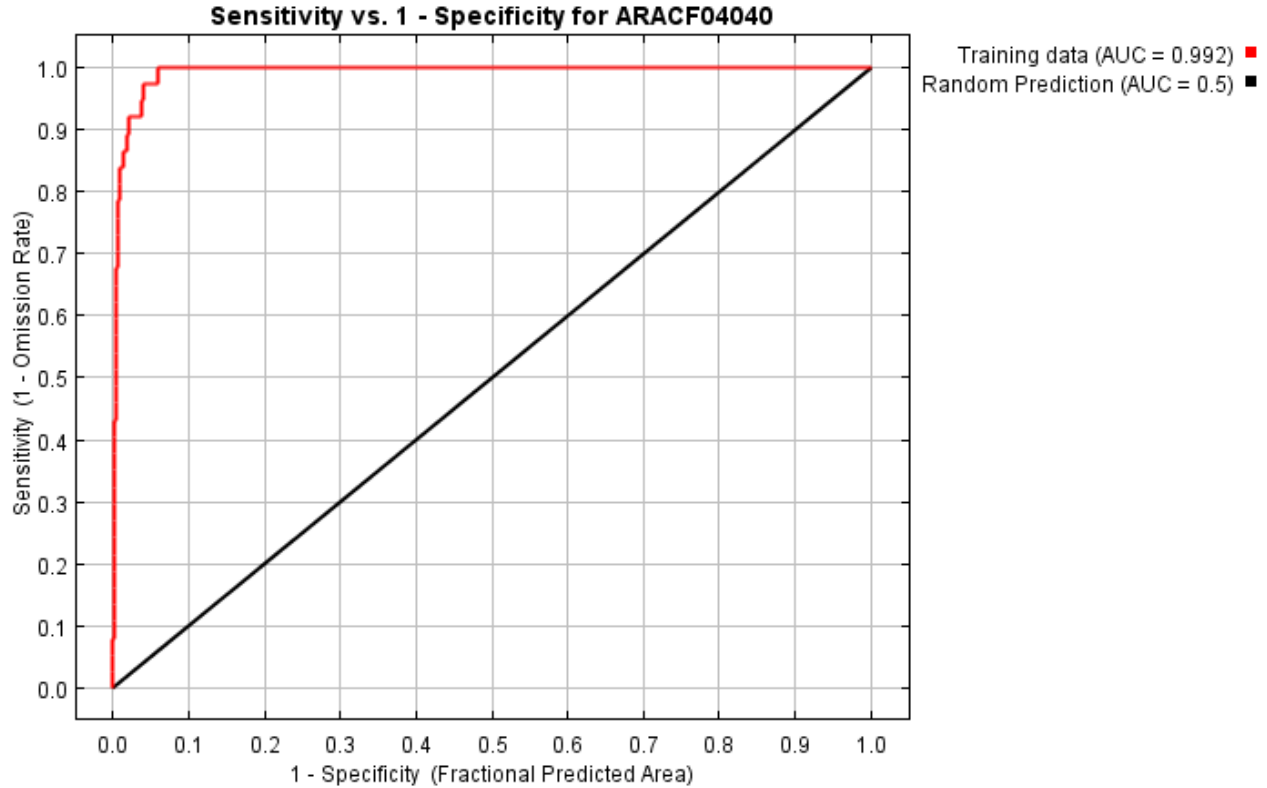
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.983 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

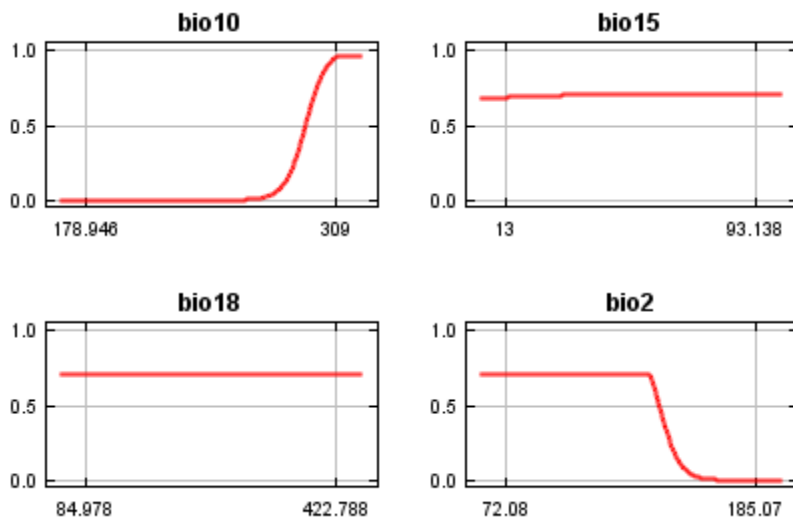
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.006	Fixed cumulative value 1	0.125	0.000
5.000	0.052	Fixed cumulative value 5	0.055	0.027
10.000	0.115	Fixed cumulative value 10	0.036	0.081
4.424	0.046	Minimum training presence	0.059	0.000
20.511	0.248	10 percentile training presence	0.021	0.081

Appendix 2 – Model Reports

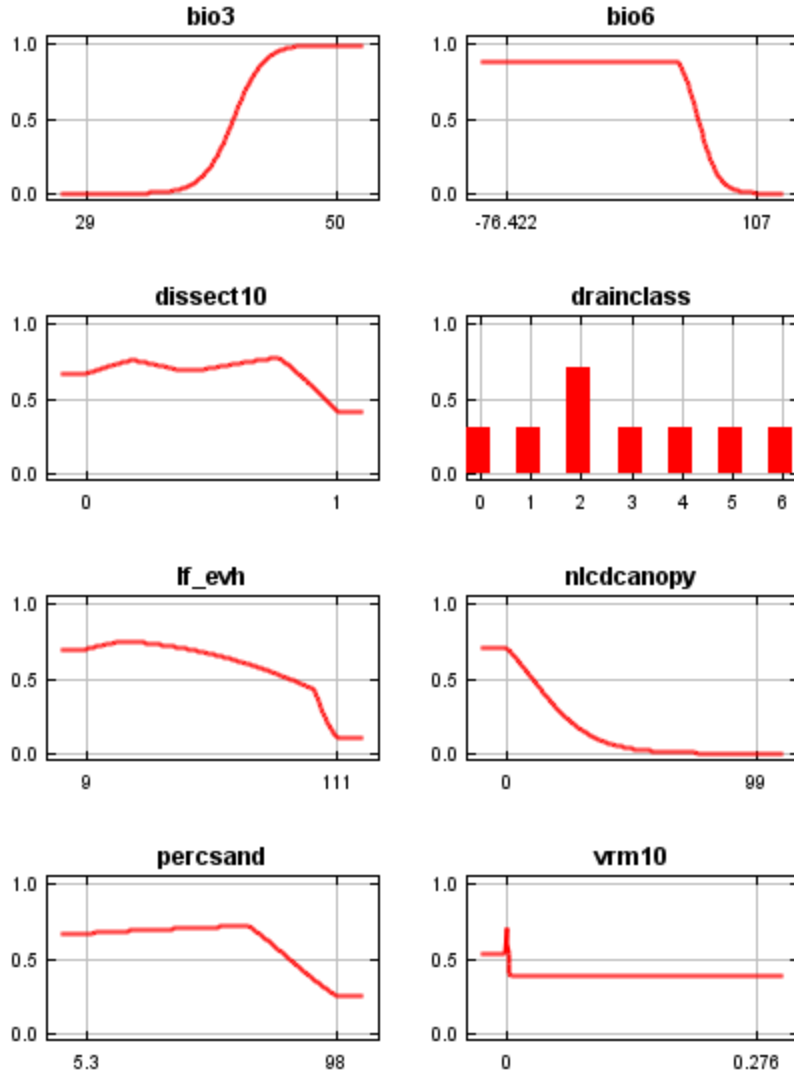
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
8.496	0.097	Equal training sensitivity and specificity	0.040	0.027
4.424	0.046	Maximum training sensitivity plus specificity	0.059	0.000
1.879	0.013	Balance training omission, predicted area and threshold value	0.092	0.000
11.911	0.147	Equate entropy of thresholded and original distributions	0.032	0.081

Response curves

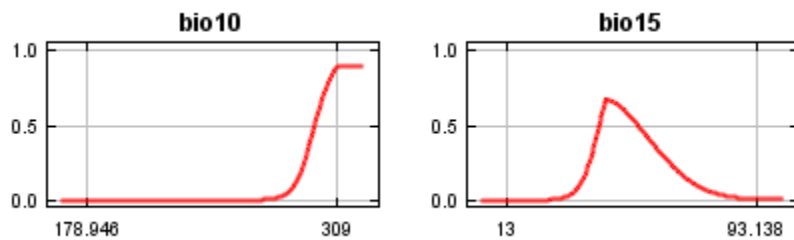
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



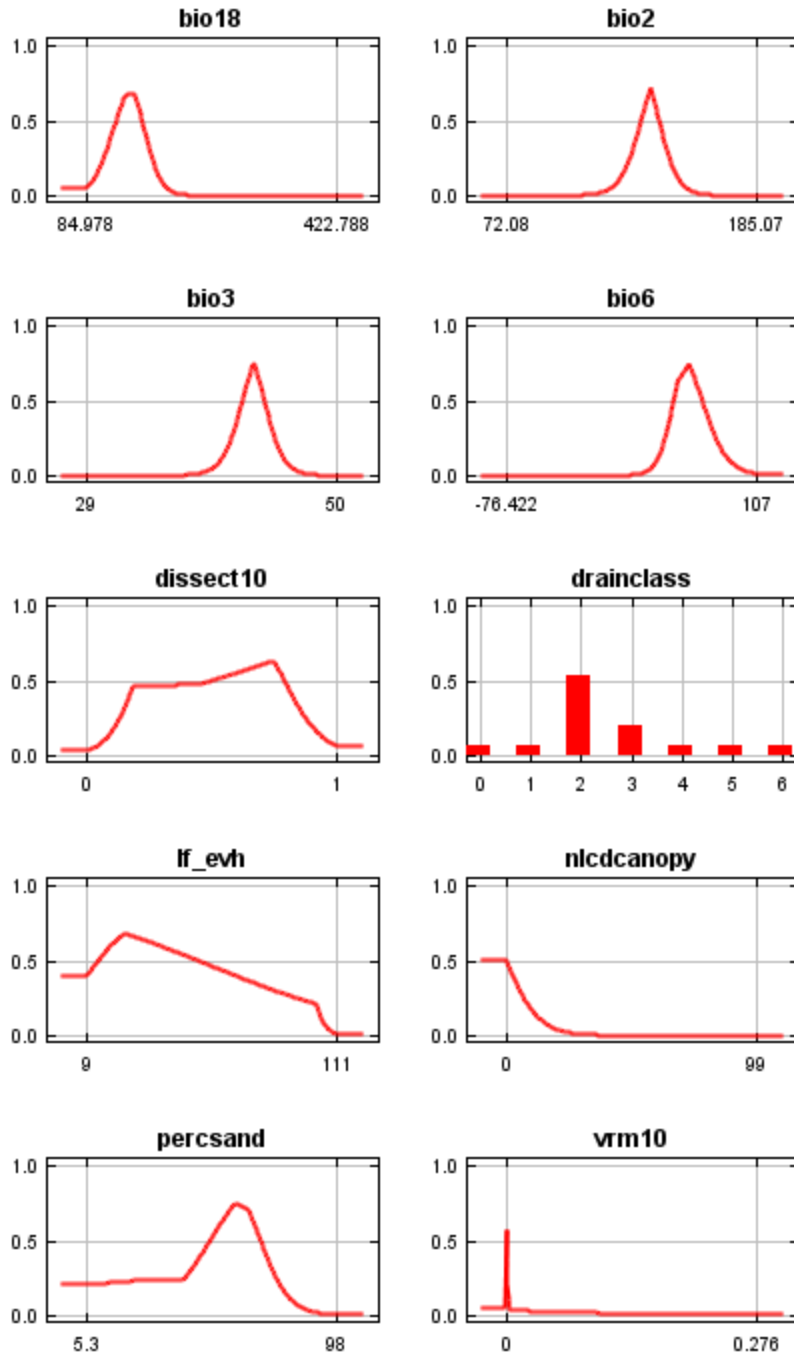
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



Analysis of variable contributions

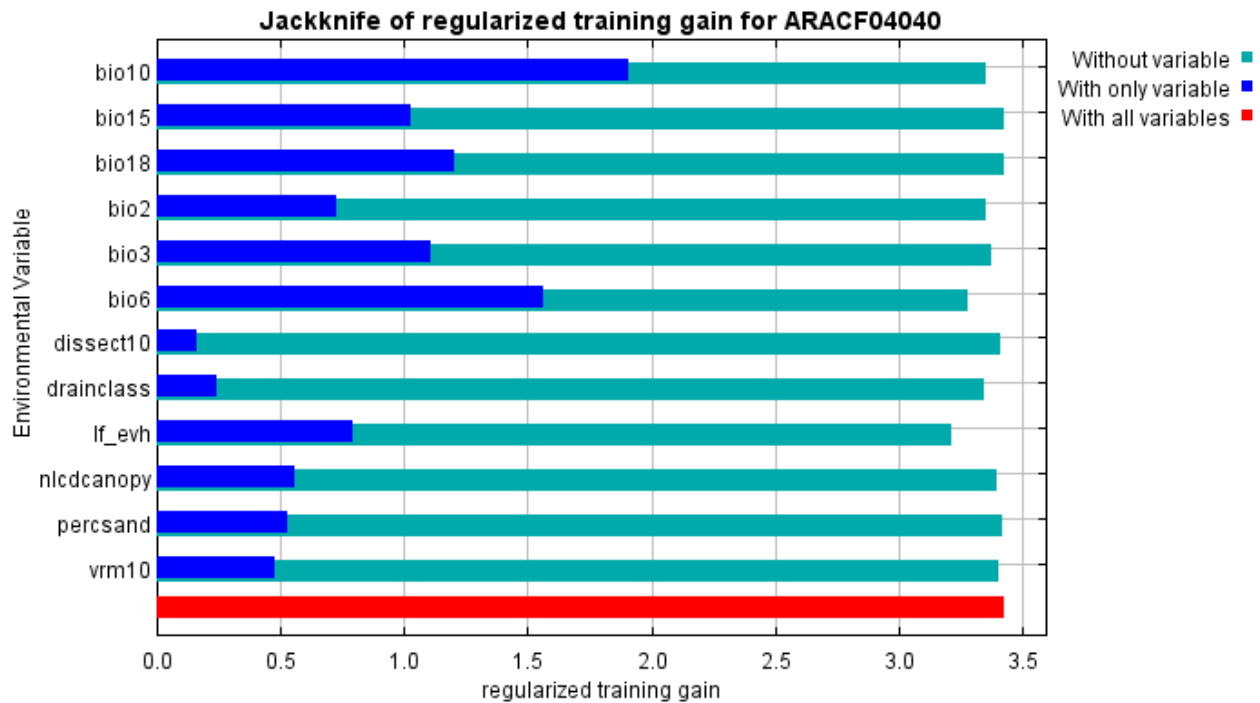
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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

Appendix 2 – Model Reports

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
bio10	41.3	27.5
bio6	14	6.5
lf_evh	12.7	4.1
nlcdcanopy	10.8	25.8
bio2	8.3	15
drainclass	5.3	1.4
bio15	3.1	0
vrml0	2.1	0.6
bio3	0.9	18.6
dissect10	0.6	0.3
percsand	0.6	0.3
bio18	0.3	0

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio10, 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 lf_evh, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 3.431, training AUC is 0.992, unregularized training gain is 3.882. Algorithm terminated after 500 iterations (27 seconds).

The follow settings were used during the run:

37 presence records used for training.
 7370 points used to determine the Maxent distribution (background points and presence points).
 Environmental layers used: bio10 bio15 bio18 bio2 bio3 bio6 dissect10 drainclass(categorical) lf_evh nlcdcanopy percsand vrml0
 Regularization values: linear/quadratic/product: 0.230, categorical: 0.250, threshold: 1.630, hinge: 0.500
 Feature types used: linear quadratic hinge
 responsecurves: true
 pictures: false
 jackknife: true
 outputfiletype: bil
 outputdirectory: F:\MAXENT_OUT\ARACF04040\RUN_4
 projectionlayers: F:\MAXENT_IN\PROB
 samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
 environmentalayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV
 writeclampgrid: false
 writemess: false
 writebackgroundpredictions: true
 writeplotdata: true

Appendix 2 – Model Reports

Command line used: dontwriteclampgrid

Command line to repeat this species model:

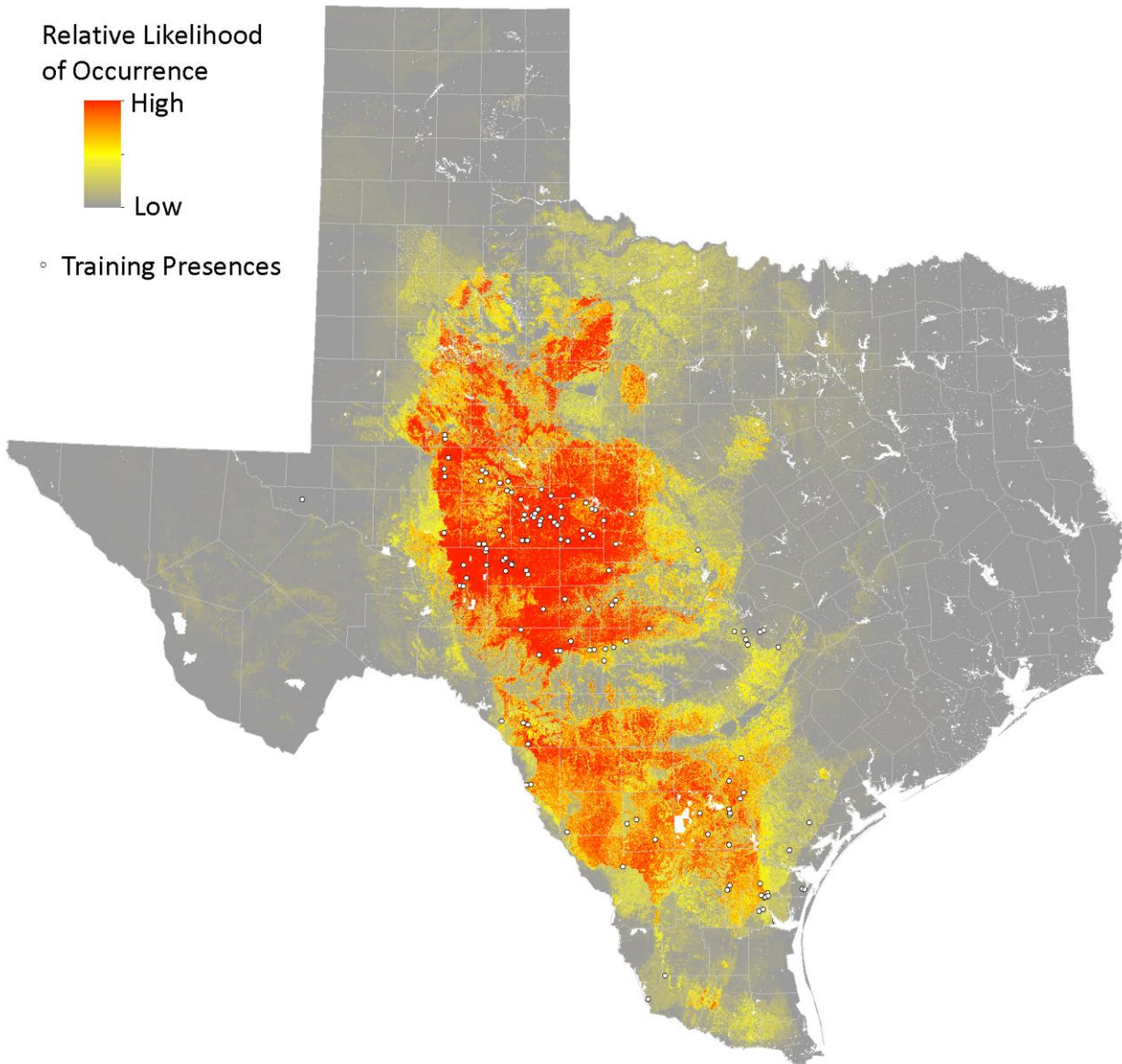
```
java density.MaxEnt nowarnings noprefixes -E "" -E ARACF04040 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\ARACF04040\RUN_4  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -N aglands -N allwatdist -N  
aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N avoid12800 -N avoid1600 -N  
avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio19 -  
N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N d2wsls1 -N  
dissect5 -N hydgroup -N ksats -N lf_forstcc -N lfherbcc -N lfshrubcc -N ned -N percclay -N percsilt -N  
radld -N slope -N soilec -N soilph -N vrm5 -N water1600 -N water300 -N water3200 -t drainclass
```

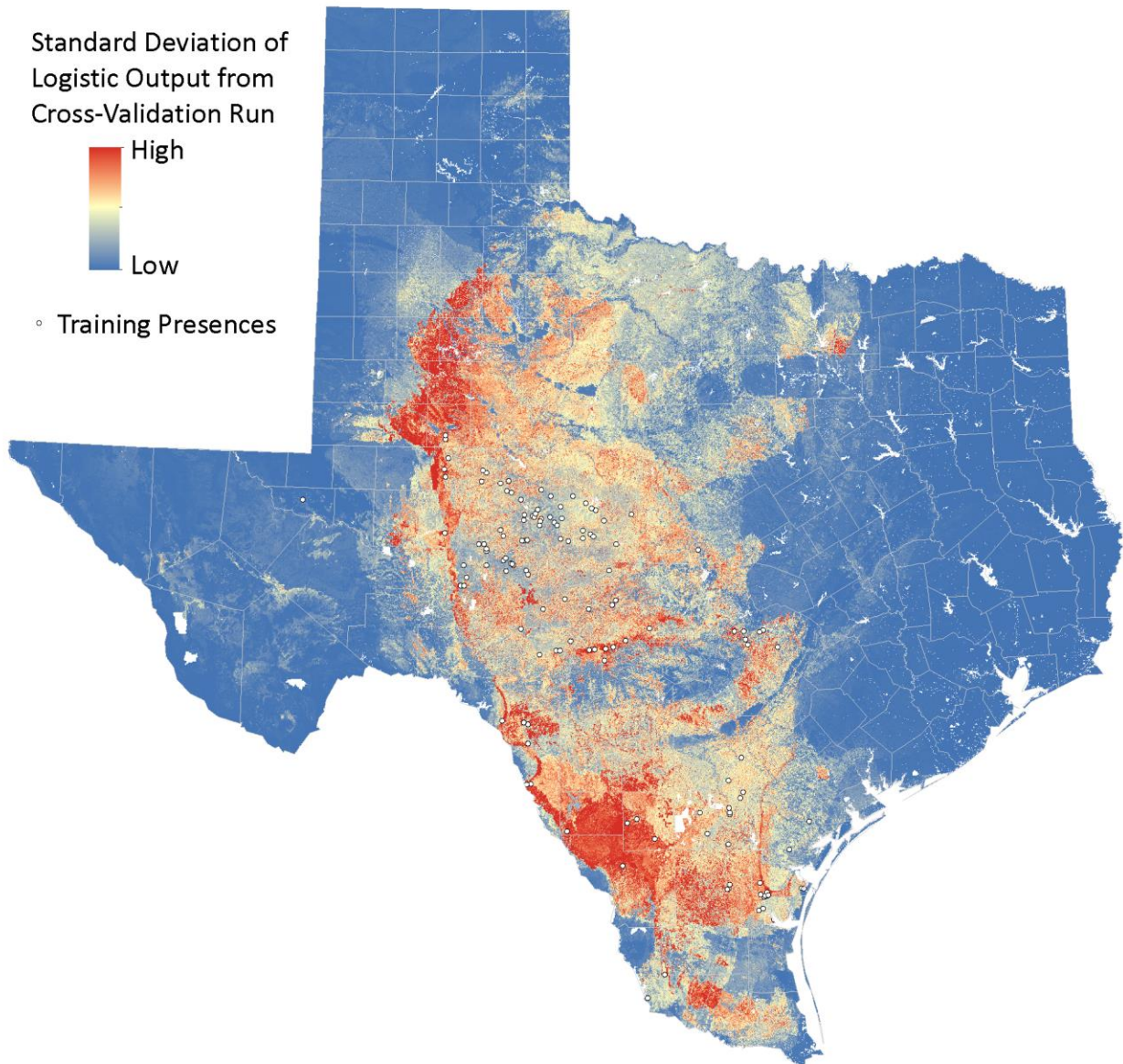
Spot-tailed Earless Lizard (*Holbrookia lacerata*)

ELCODE: ARACF08010

Date: August 14, 2013

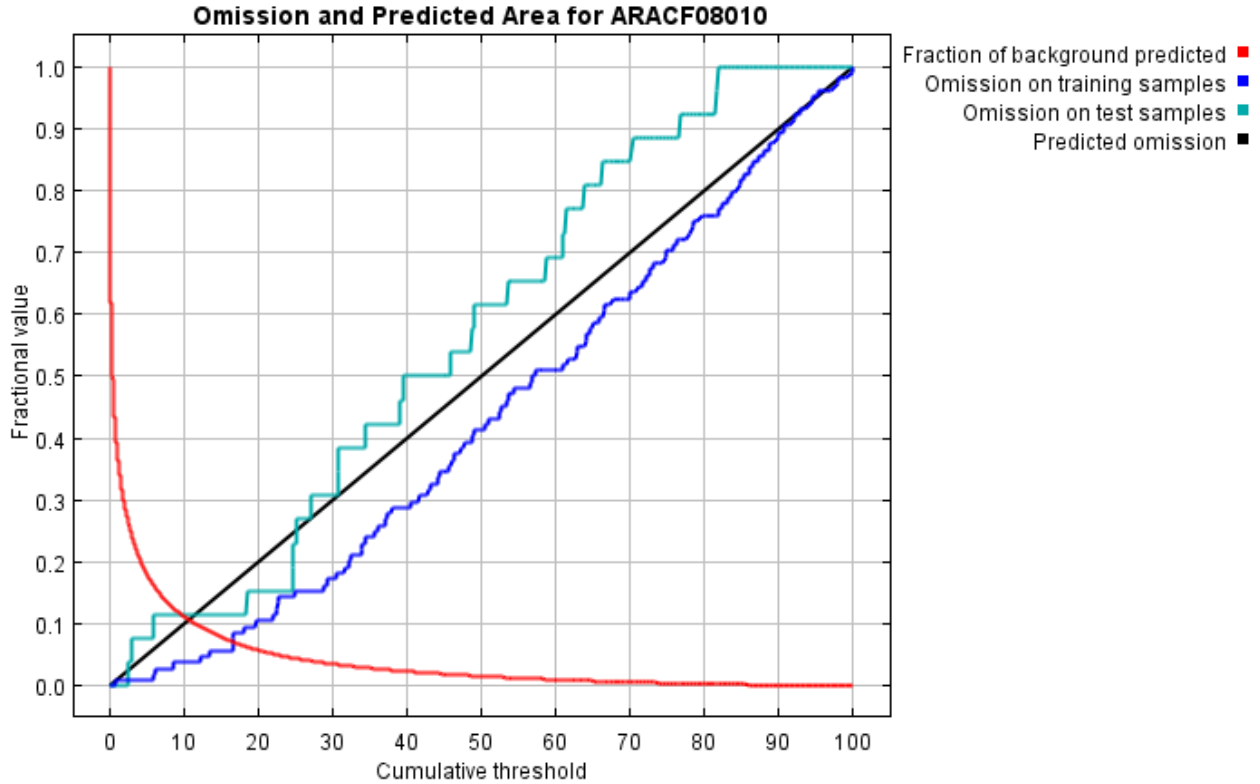
Maxent version: 3.3.3k





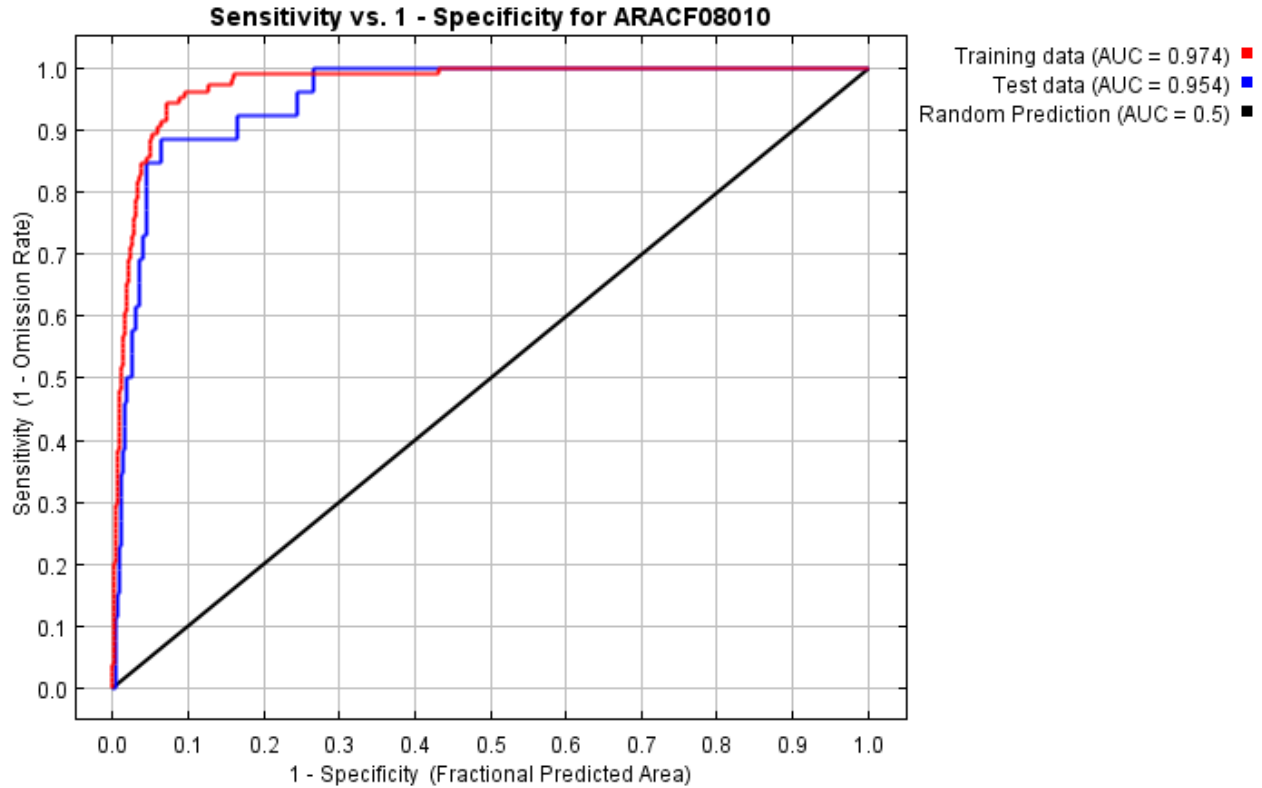
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.956 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
1.000	0.008	Fixed cumulative value 1	0.375	0.010	0.000	2.405E-11
5.000	0.042	Fixed cumulative value 5	0.180	0.010	0.077	2.955E-23
10.000	0.103	Fixed cumulative value 10	0.112	0.038	0.115	4.857E-36

Appendix 2 – Model Reports

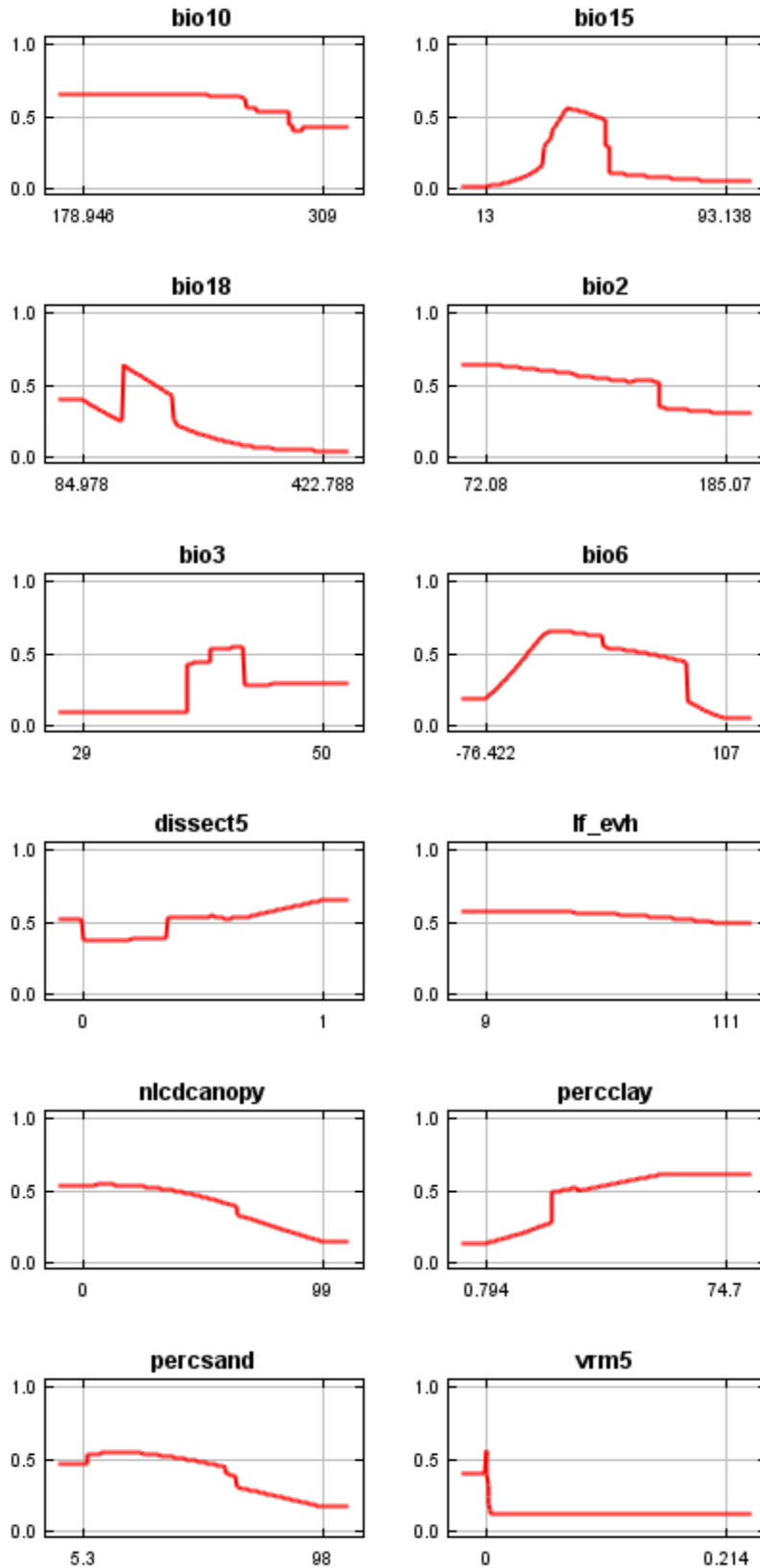
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
0.626	0.005	Minimum training presence	0.432	0.000	0.000	2.58E-9
19.619	0.220	10 percentile training presence	0.059	0.096	0.154	0E0
16.545	0.168	Equal training sensitivity and specificity	0.072	0.067	0.115	2.433E-58
16.488	0.167	Maximum training sensitivity plus specificity	0.072	0.058	0.115	3.174E-58
9.641	0.096	Equal test sensitivity and specificity	0.115	0.038	0.115	6.214E-35
18.409	0.196	Maximum test sensitivity plus specificity	0.064	0.096	0.115	0E0
4.615	0.037	Balance training omission, predicted area and threshold value	0.189	0.010	0.077	5.721E-22
12.286	0.126	Equate entropy of thresholded and original distributions	0.096	0.048	0.115	6.038E-43

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. 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

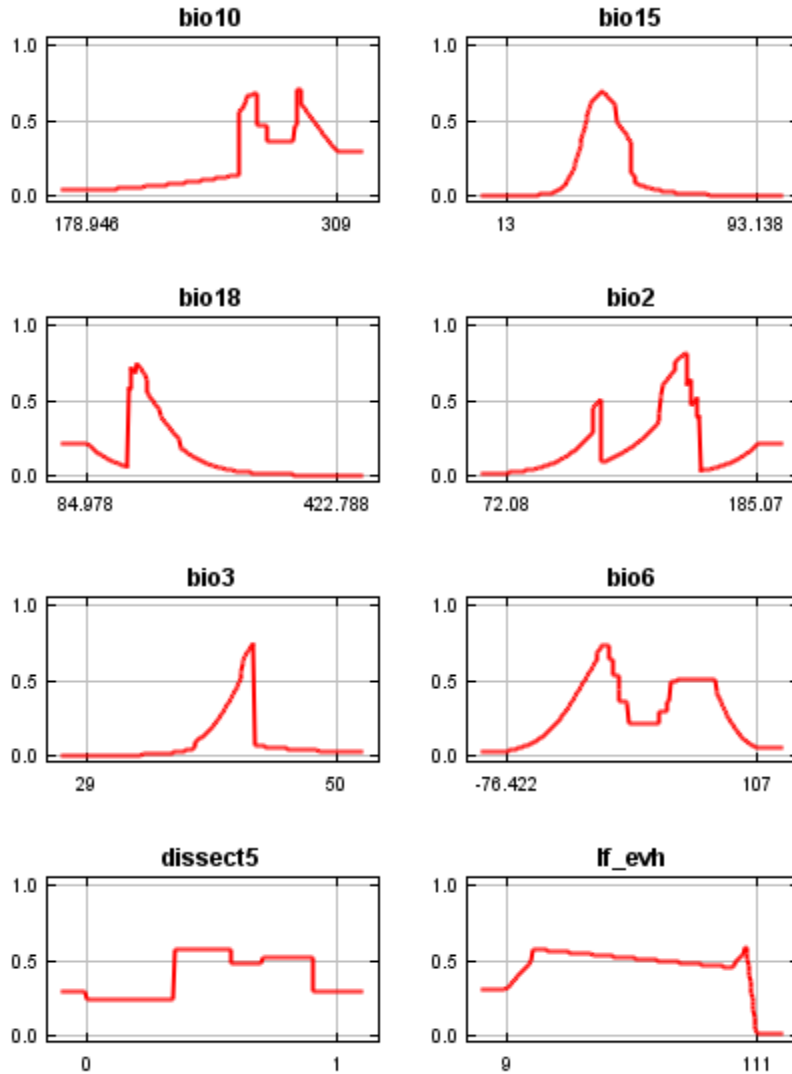
Appendix 2 – Model Reports

together. See Appendix 1 for detailed explanations of all environmental predictor layers.

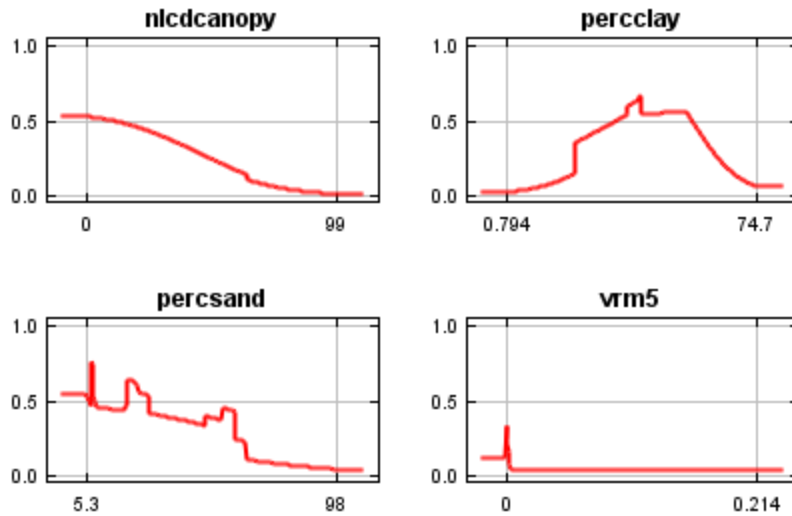


Appendix 2 – Model Reports

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.



Appendix 2 – Model Reports



Analysis of variable contributions

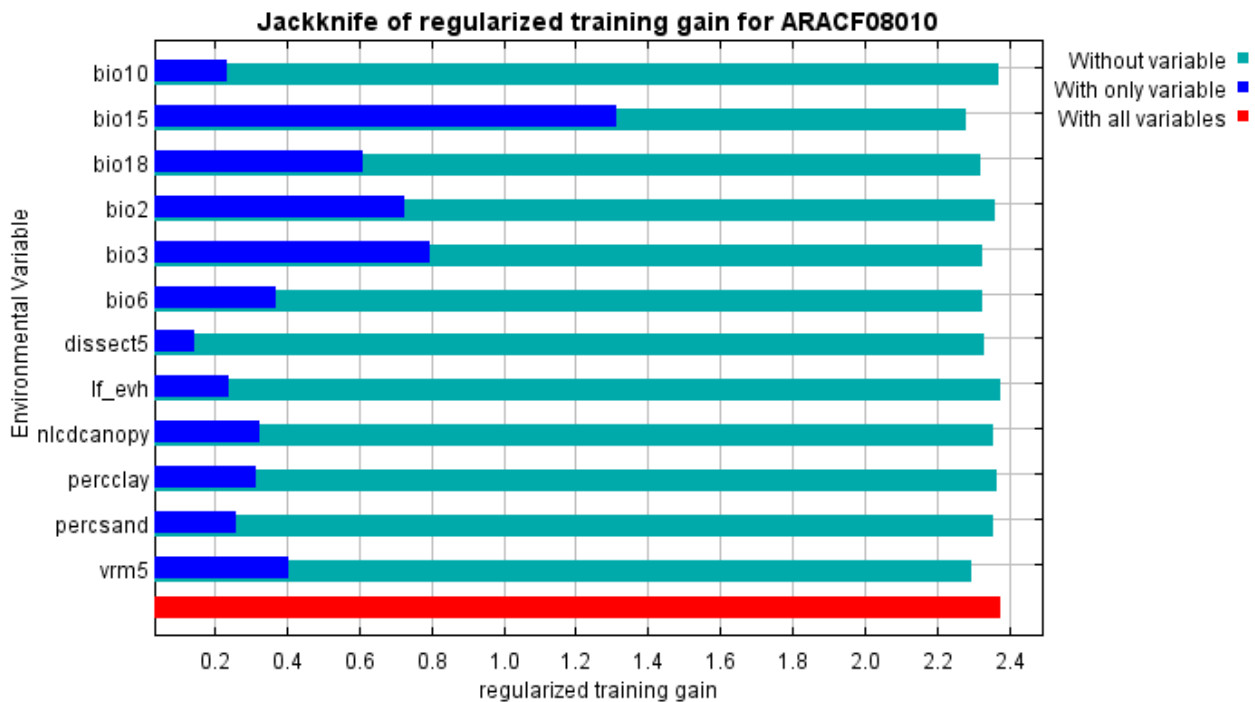
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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
bio15	40.6	21.6
vrm5	11.8	13.8
bio3	9.3	16.3
bio18	8.9	8.4
percclay	8.3	5.8
bio2	6.8	2
bio6	5.1	17.6
nlcdcanopy	3.6	6.1

Appendix 2 – Model Reports

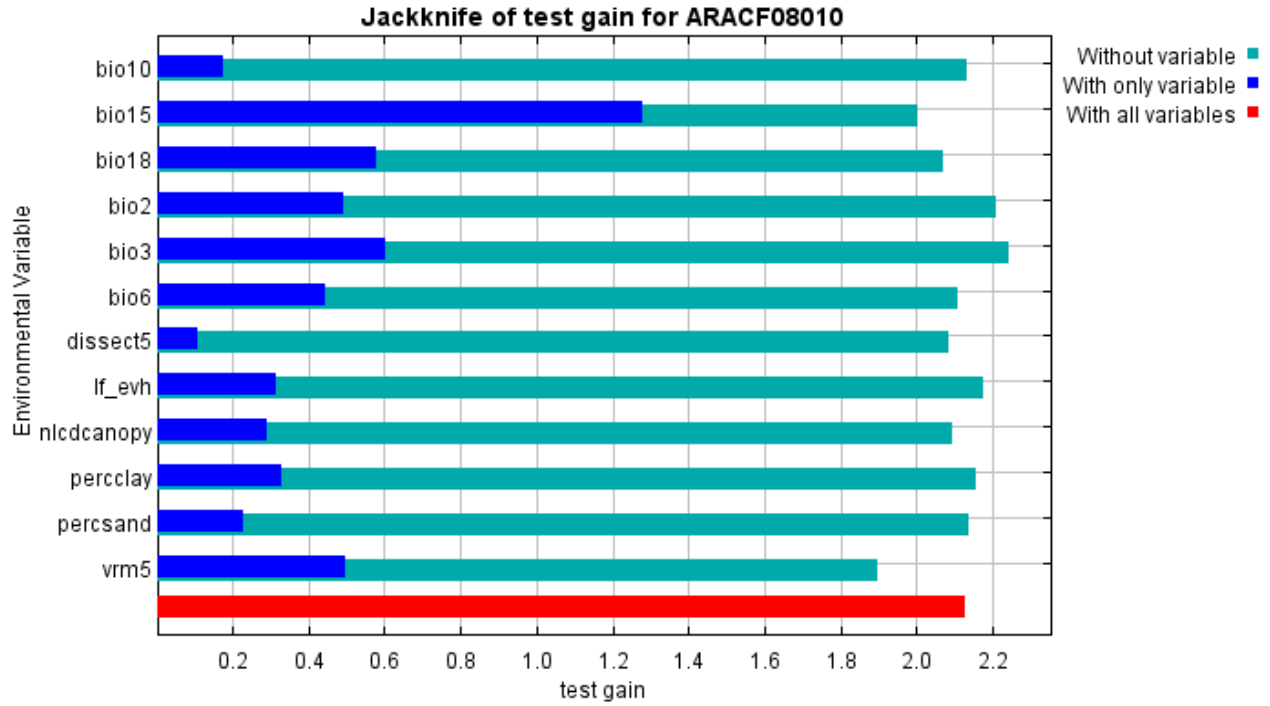
Variable	Percent contribution	Permutation importance
dissect5	3.2	2.6
bio10	1.3	1.3
percsand	0.6	4.2
lf_evh	0.4	0.4

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio15, 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 bio15, which therefore appears to have the most information that isn't present in the other variables.

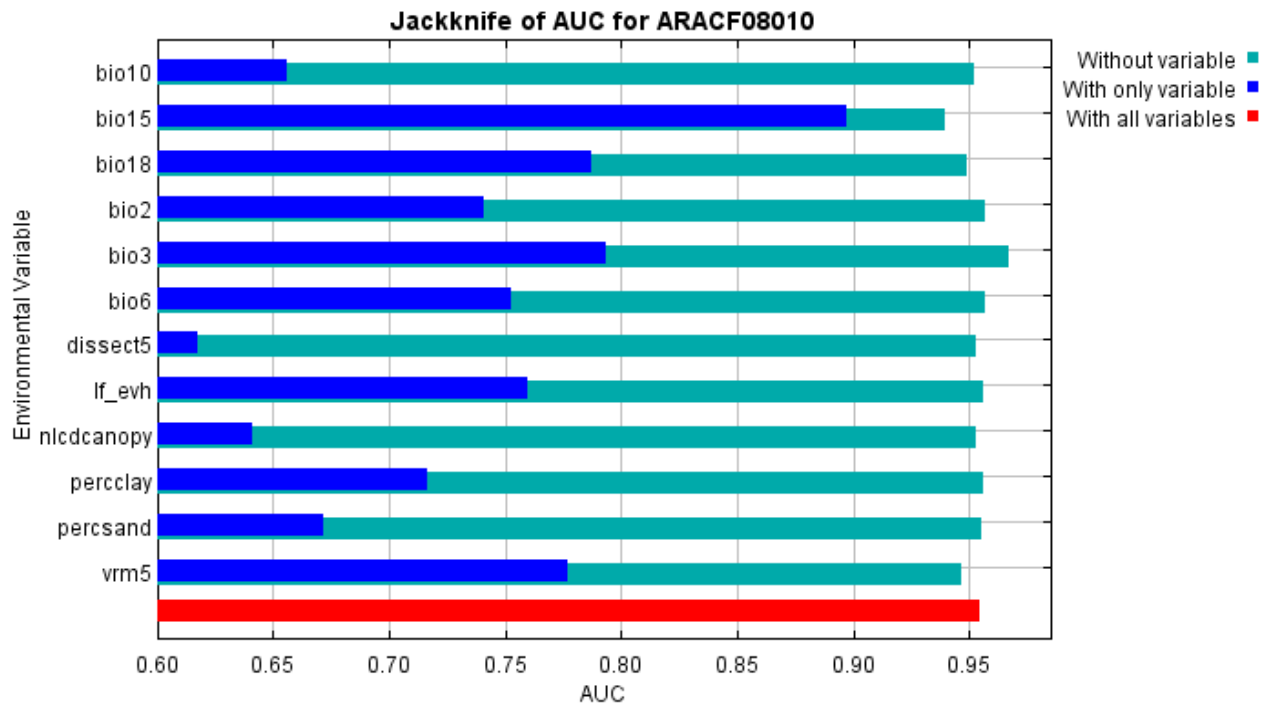


The next picture shows the same jackknife test, using test gain instead of training gain. Note that conclusions about which variables are most important can change, now that we're looking at test data.

Appendix 2 – Model Reports



Lastly, we have the same jackknife test, using AUC on test data.



Raw data outputs and control parameters

Appendix 2 – Model Reports

Regularized training gain is 2.374, training AUC is 0.974, unregularized training gain is 2.740.

Unregularized test gain is 2.127.

Test AUC is 0.954, standard deviation is 0.013 (calculated as in DeLong, DeLong & Clarke-Pearson 1988, equation 2).

Algorithm terminated after 500 iterations (8 seconds).

The follow settings were used during the run:

104 presence records used for training, 26 for testing.

7442 points used to determine the Maxent distribution (background points and presence points).

Environmental layers used (all continuous): bio10 bio15 bio18 bio2 bio3 bio6 dissect5 lf_evh
nlcdcanopy percclay percsand vrm5

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

pictures: false

jackknife: true

outputfiletype: bil

outputdirectory: F:\MODELING\TXNDD_SDM\MAXENT_OUT\ARACF08010\RUN_3

projectionlayers: F:\MODELING\TXNDD_SDM\MAXENT_IN\PROB

samplesfile: F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV

environmentallayers:

F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV

writeclampgrid: false

writemess: false

randomtestpoints: 20

writebackgroundpredictions: true

writeplotdata: true

Command line used: dontwriteclampgrid

Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E

ARACF08010 responsecurves nopictures jackknife outputfiletype=bil

outputdirectory=F:\MODELING\TXNDD_SDM\MAXENT_OUT\ARACF08010\RUN_3

projectionlayers=F:\MODELING\TXNDD_SDM\MAXENT_IN\PROB

samplesfile=F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV

environmentallayers=F:\MODELING\TXNDD_SDM\MAXENT_IN\OCCURRENCE_DATA\BACKGROU

ND.CSV nowriteclampgrid nowritemess randomtestpoints=20 writebackgroundpredictions

writeplotdata -N UNIQUE_ID -N aglands -N allwatdist -N aprime135 -N aprime180 -N aprime45 -N

aprime90 -N avoid -N avoid12800 -N avoid1600 -N avoid3200 -N avoid6400 -N bio1 -N bio11 -N

bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio19 -N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -

N curve10 -N curve5 -N d2foredge -N d2wsl -N dissect10 -N drainclass -N hydgroup -N ksats -N

lf_forstcc -N lfherbcc -N lfshrubcc -N ned -N percsl -N radld -N slope -N soilec -N soilph -N vrm10 -

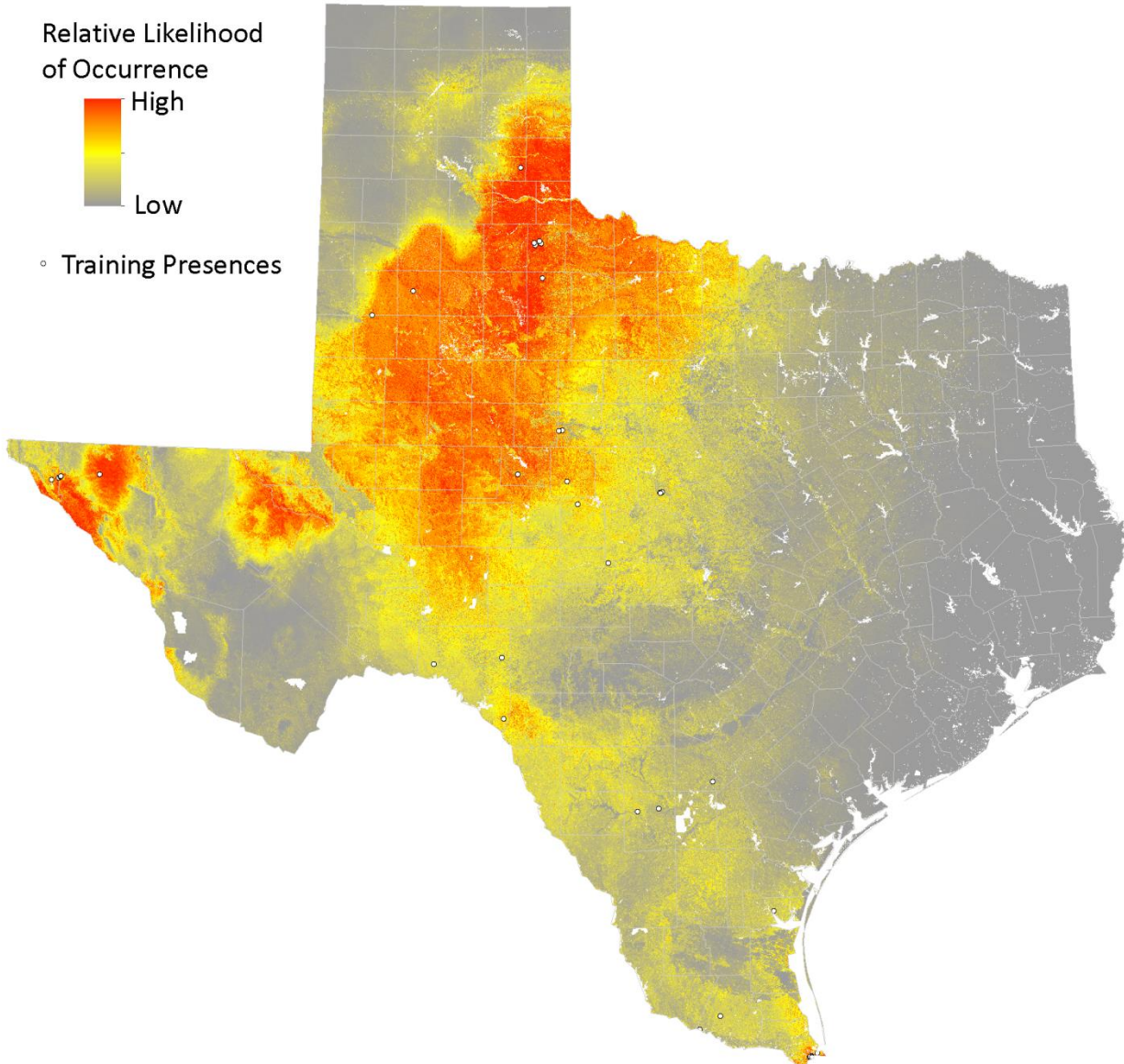
N water1600 -N water300 -N water3200

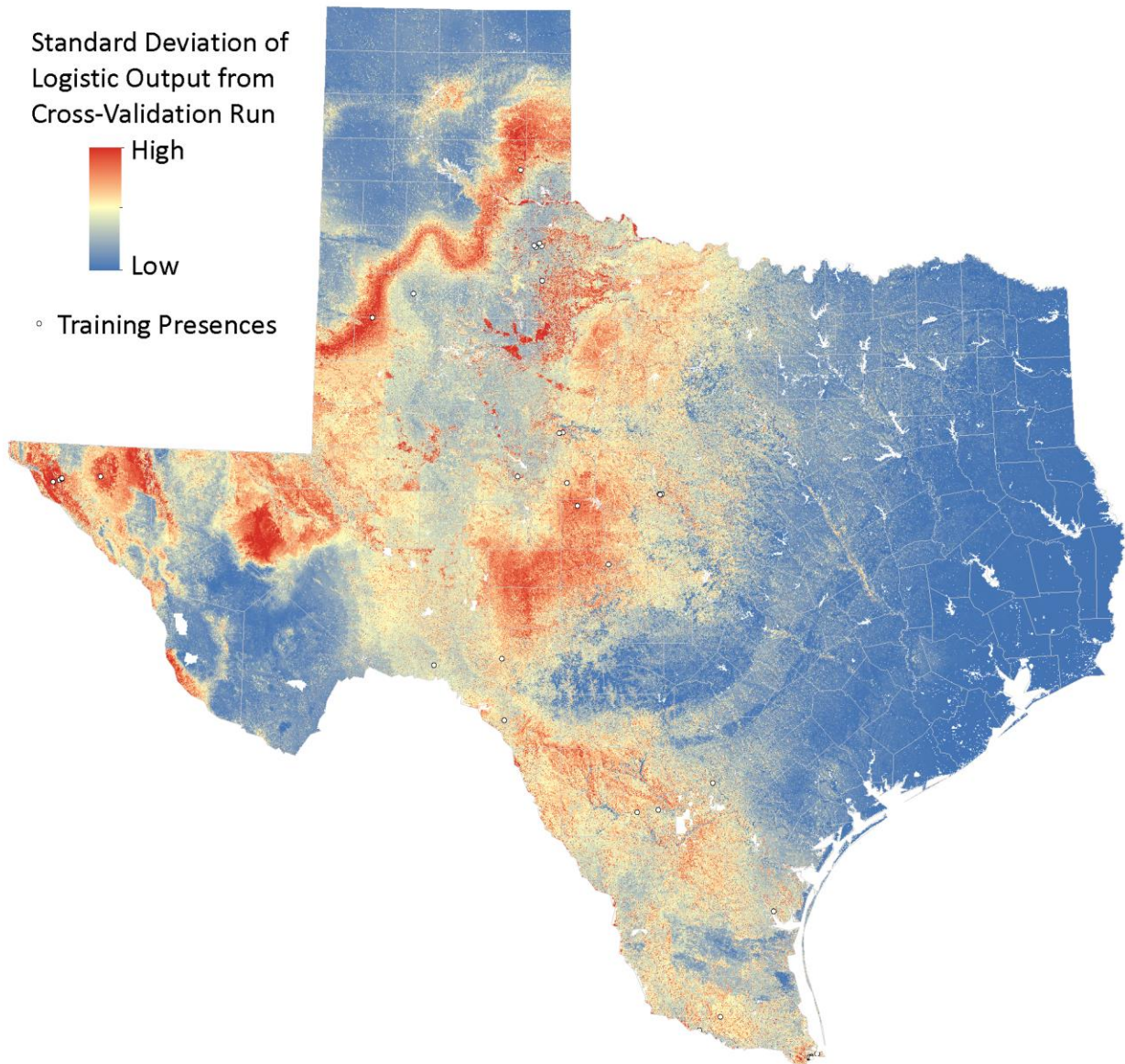
Texas Horned Lizard (*Phrynosoma cornutum*)

ELCODE: ARACF12010

Date: August 14, 2013

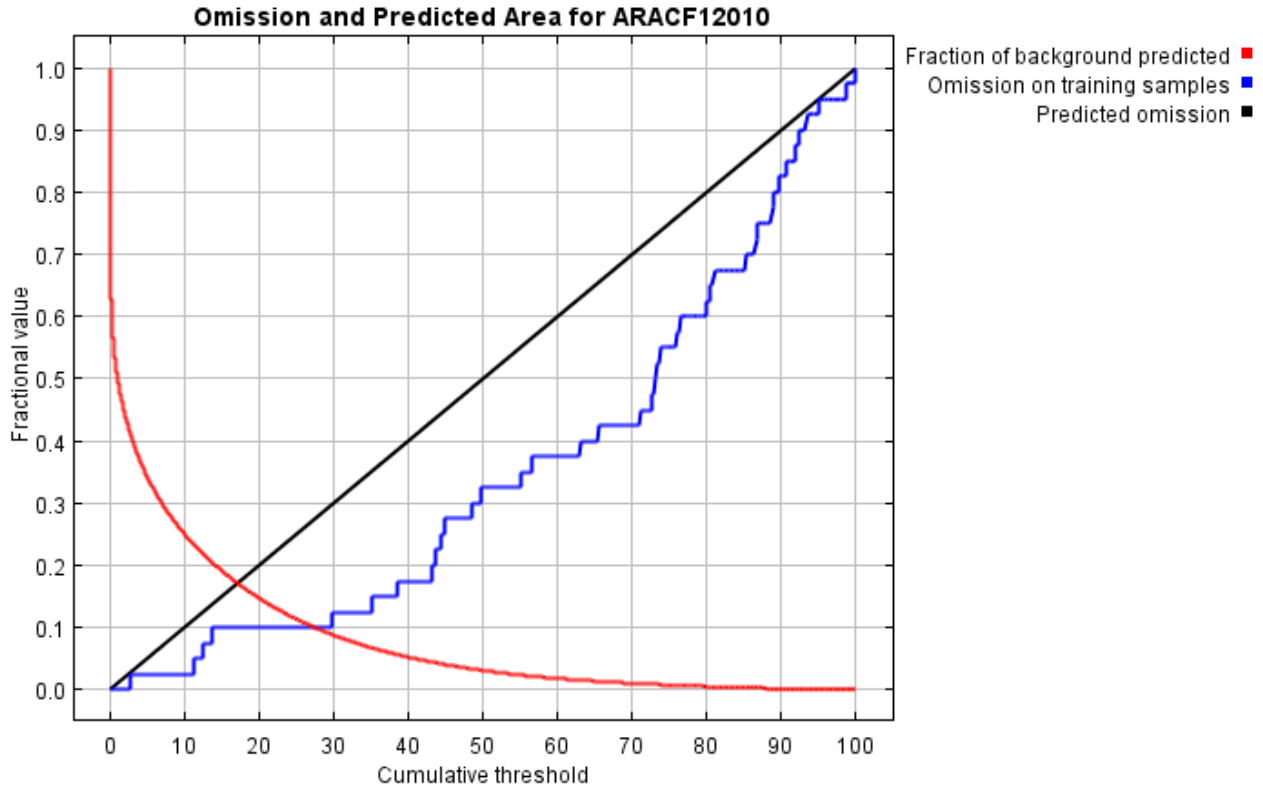
Maxent version: 3.3.3k





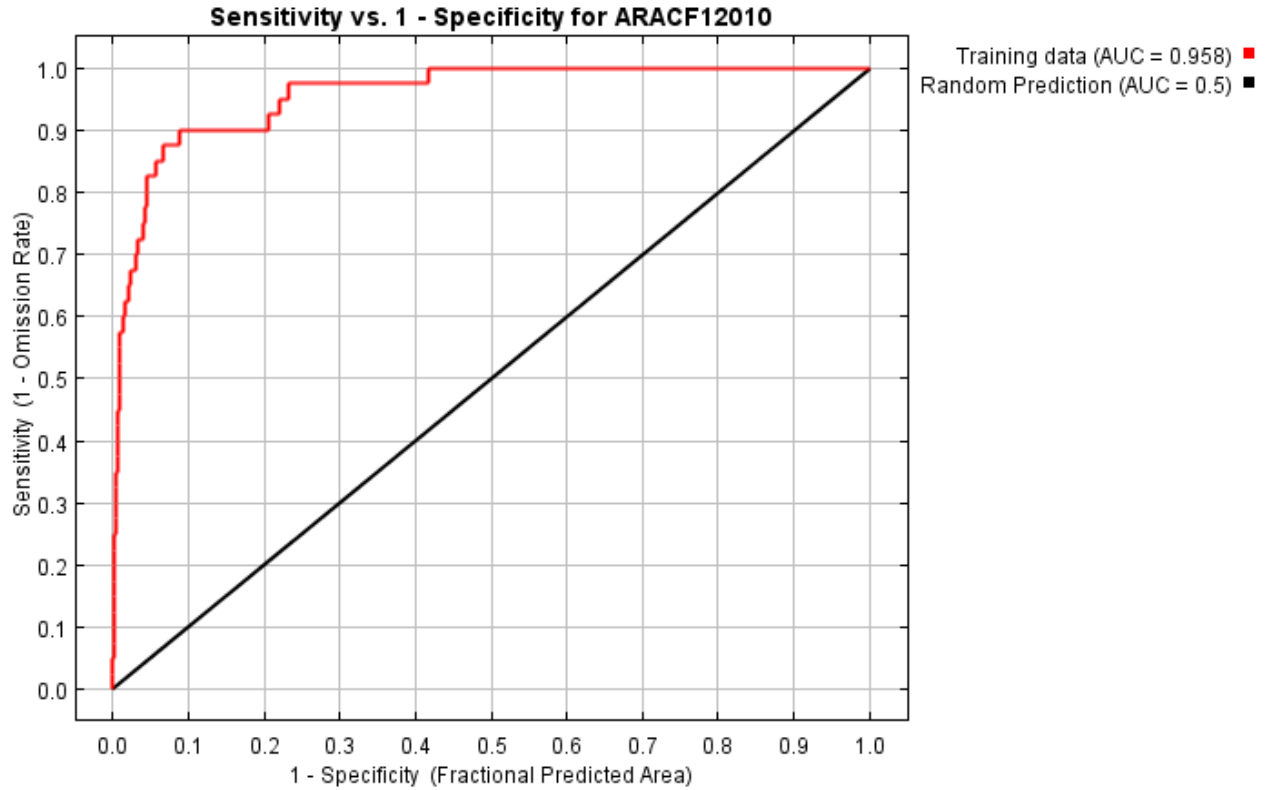
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.915 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

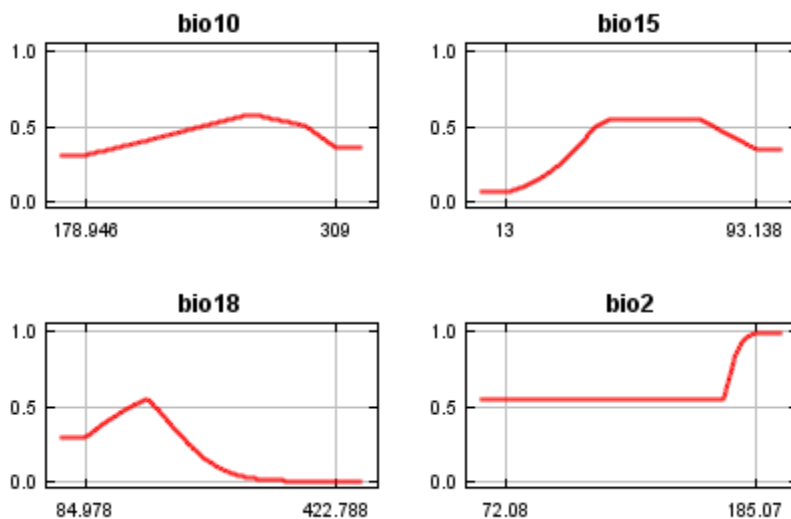
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.024	Fixed cumulative value 1	0.499	0.000
5.000	0.070	Fixed cumulative value 5	0.341	0.025
10.000	0.114	Fixed cumulative value 10	0.250	0.025
2.570	0.045	Minimum training presence	0.417	0.000
29.721	0.285	10 percentile training presence	0.089	0.100

Appendix 2 – Model Reports

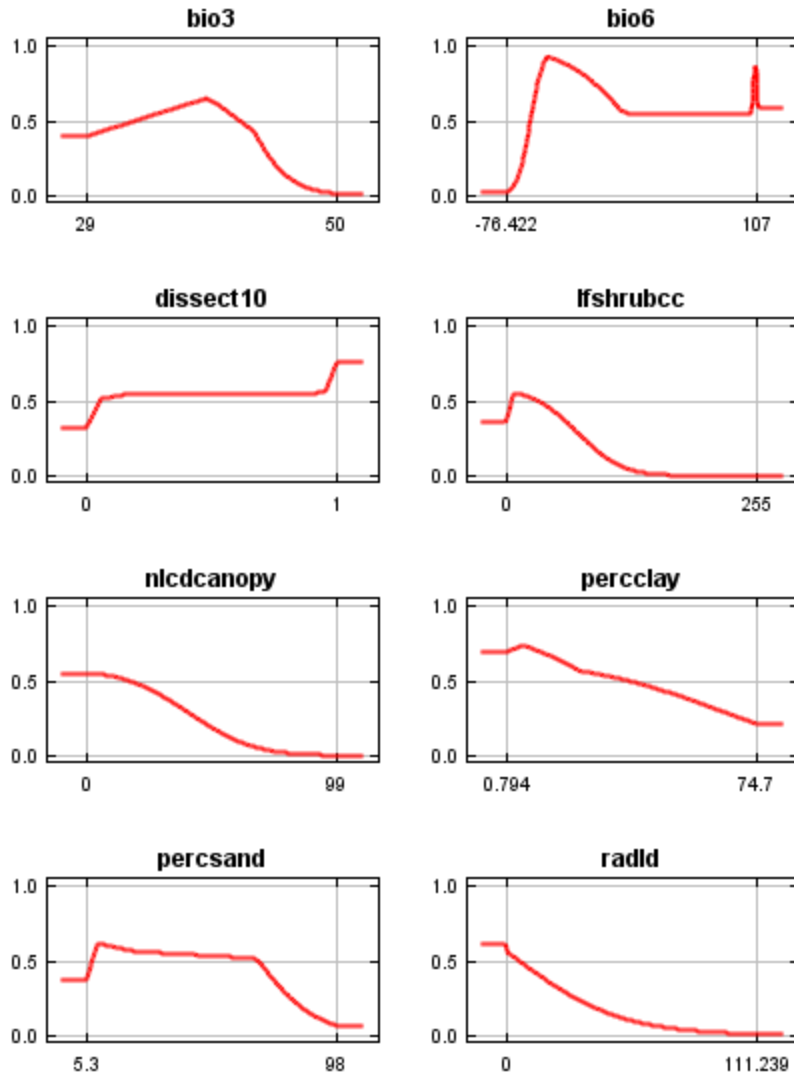
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
27.478	0.260	Equal training sensitivity and specificity	0.100	0.100
29.721	0.285	Maximum training sensitivity plus specificity	0.089	0.100
2.570	0.045	Balance training omission, predicted area and threshold value	0.417	0.000
15.865	0.161	Equate entropy of thresholded and original distributions	0.183	0.100

Response curves

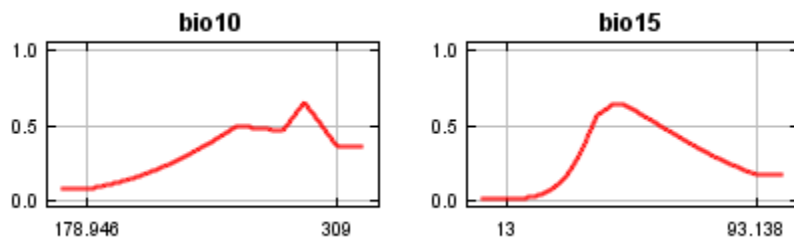
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



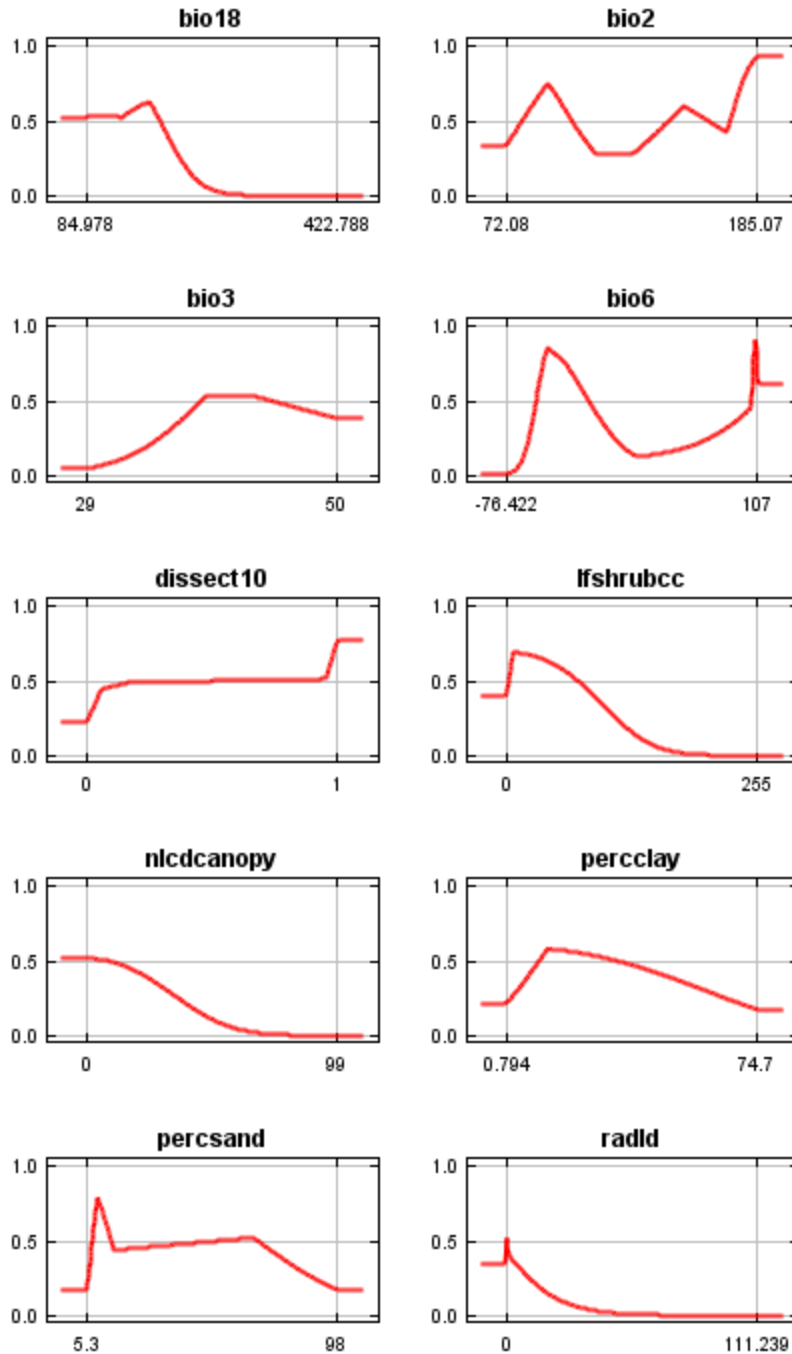
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



Analysis of variable contributions

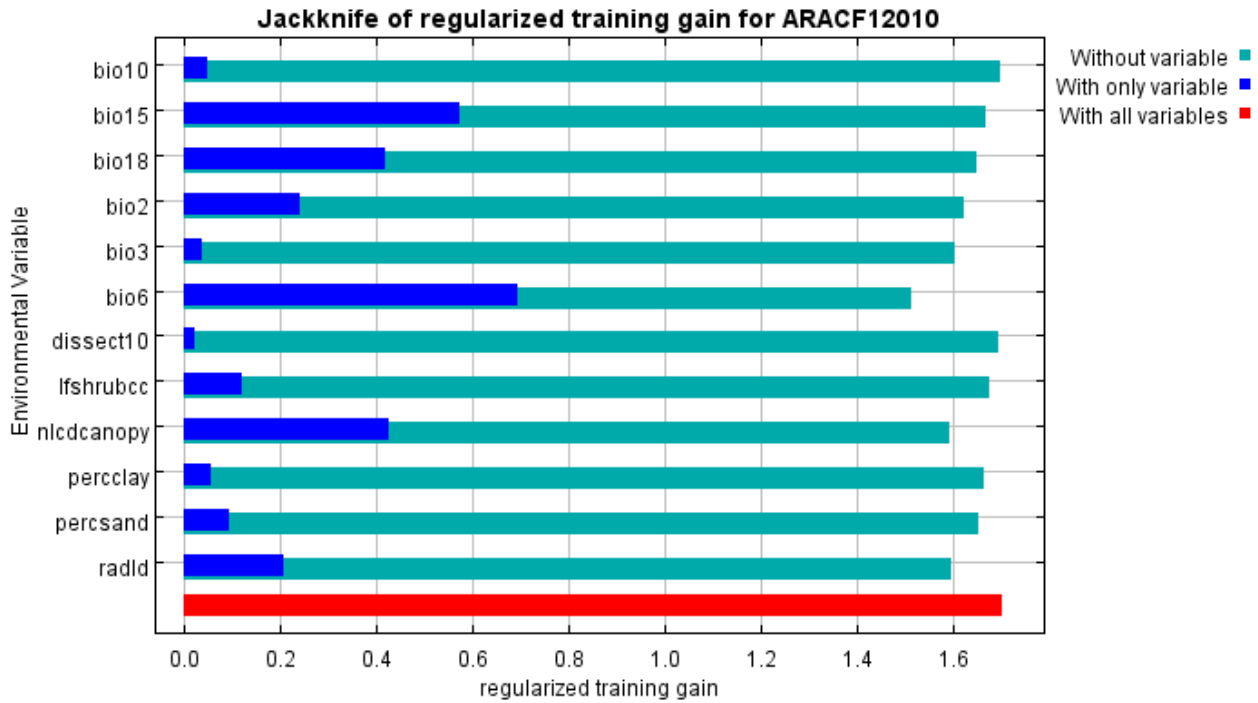
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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

Appendix 2 – Model Reports

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
bio6	29.5	5.9
nlcdcanopy	20.5	34.5
bio15	18.2	7.4
bio3	8.7	16.9
radld	6.1	3.3
bio2	3.9	1.9
bio18	2.9	24.2
percsand	2.7	4.2
lfshrubcc	2.3	0
percclay	2.1	1.1
bio10	2.1	0
dissect10	0.8	0.5

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio6, 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 bio6, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 1.702, training AUC is 0.958, unregularized training gain is 2.392. Algorithm terminated after 500 iterations (31 seconds).

The follow settings were used during the run:

40 presence records used for training.
 7378 points used to determine the Maxent distribution (background points and presence points).
 Environmental layers used (all continuous): bio10 bio15 bio18 bio2 bio3 bio6 dissect10 lfshrubcc
 nlcdcanopy percclay percsand radld
 Regularization values: linear/quadratic/product: 0.221, categorical: 0.250, threshold: 1.600, hinge:
 0.500
 Feature types used: linear quadratic hinge
 responsecurves: true
 pictures: false
 jackknife: true
 outputfiletype: bil
 outputdirectory: F:\MAXENT_OUT\ARACF12010\RUN_3
 projectionlayers: F:\MAXENT_IN\PROB
 samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
 environmentalayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV
 writeclampgrid: false
 writemess: false
 writebackgroundpredictions: true
 writeplotdata: true

Appendix 2 – Model Reports

Command line used: dontwriteclampgrid

Command line to repeat this species model:

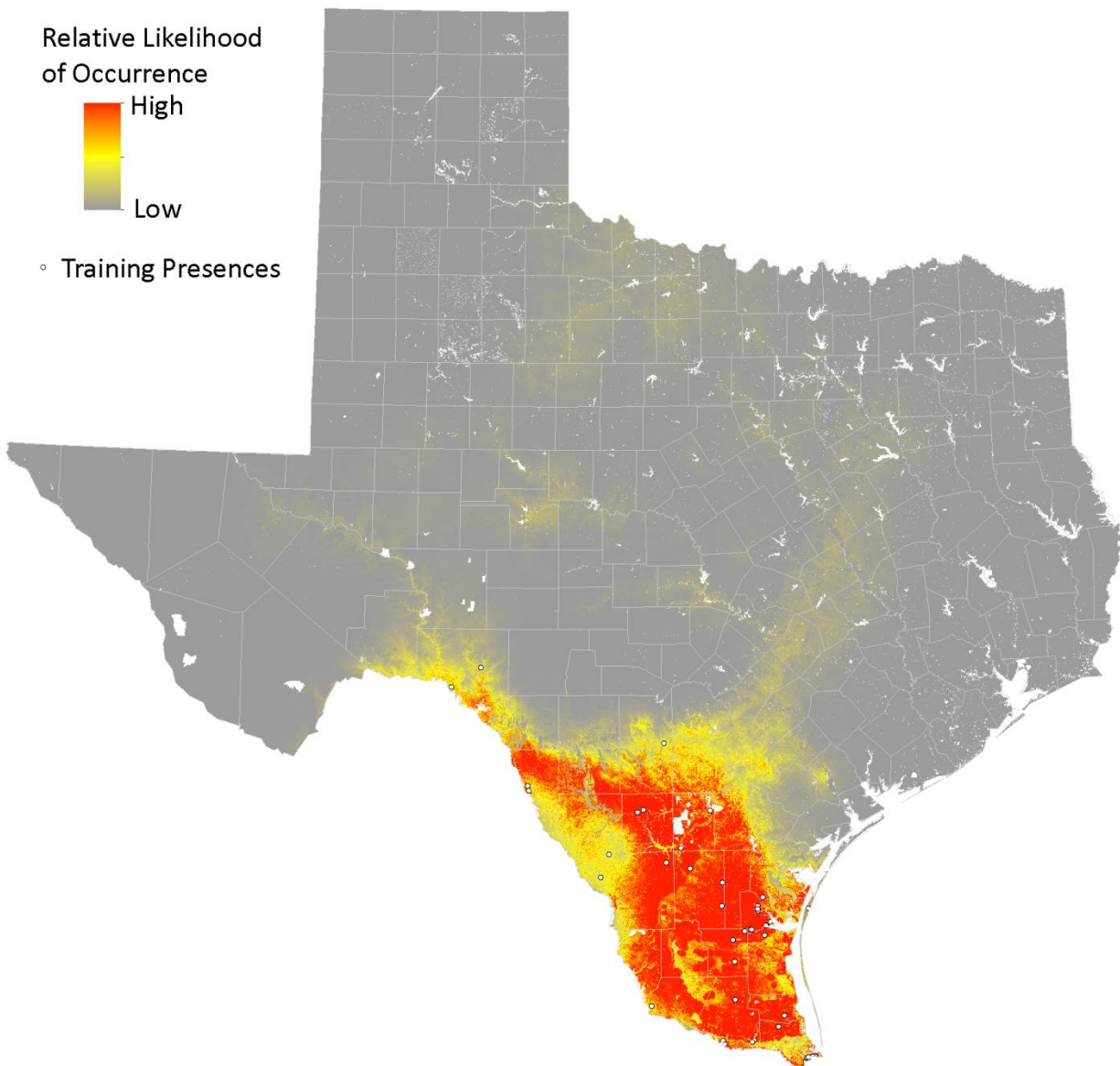
```
java density.MaxEnt nowarnings noprefixes -E "" -E ARACF12010 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\ARACF12010\RUN_3  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -N aglands -N allwatdist -N  
aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N avoid12800 -N avoid1600 -N  
avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio19 -  
N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N d2wsl -N  
dissect5 -N drainclass -N hydgroup -N ksats -N lf_evh -N lf_forstcc -N lfherbcc -N ned -N percsilt -N  
slope -N soilec -N soilph -N vrm10 -N vrm5 -N water1600 -N water300 -N water3200
```

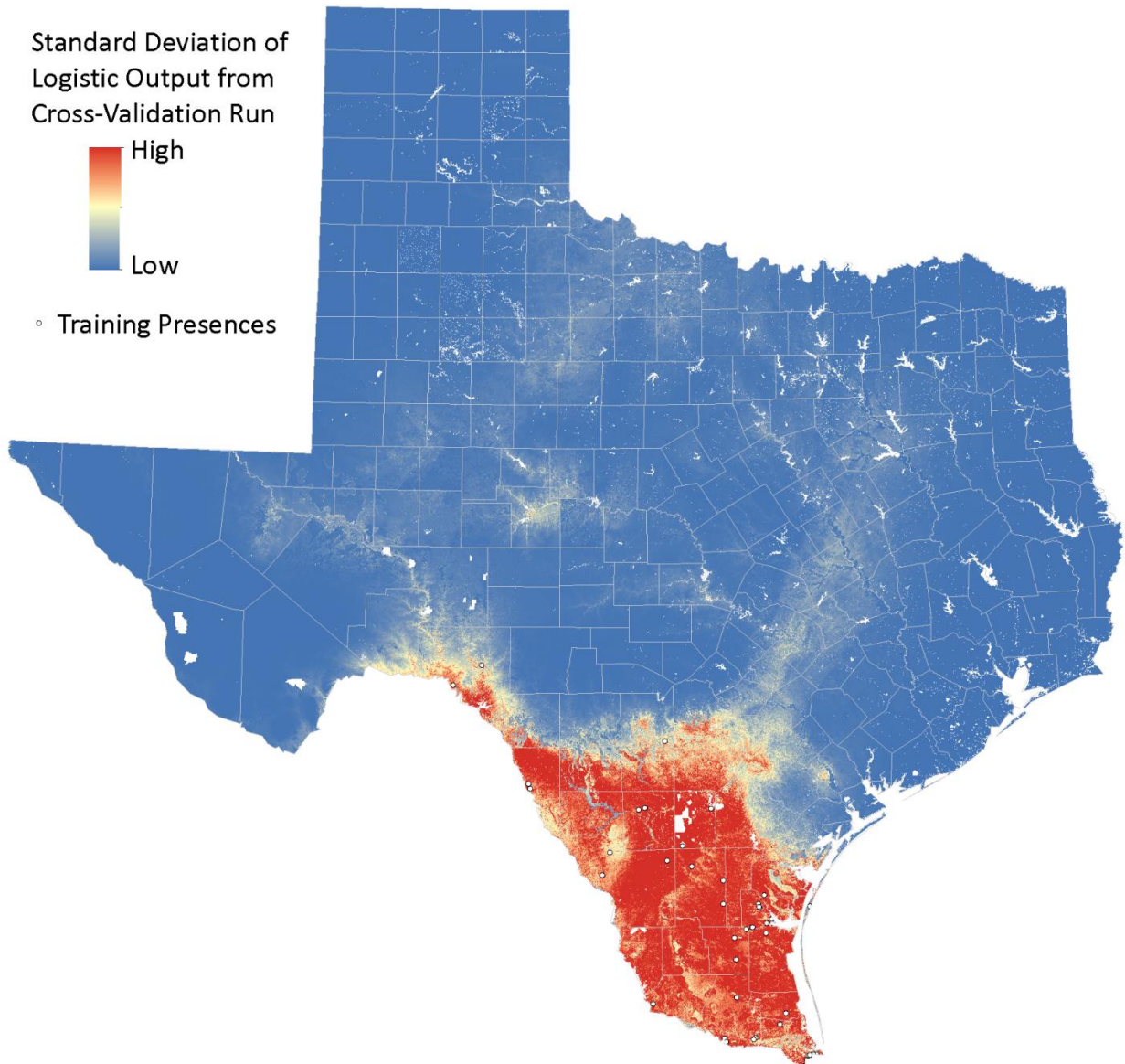
Texas Indigo Snake (*Drymarchon melanurus erebennus*)

ELCODE: ARARDB11010

Date: August 15, 2013

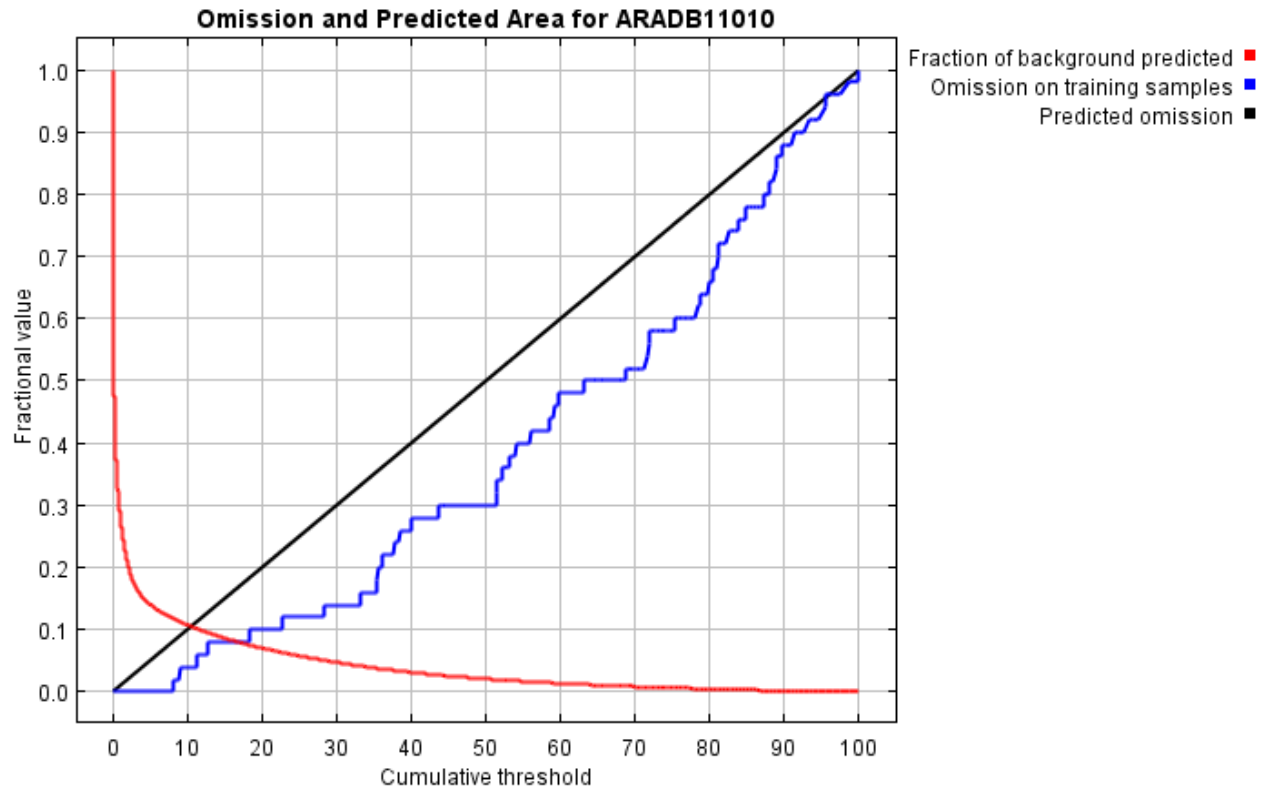
Maxent version: 3.3.3k





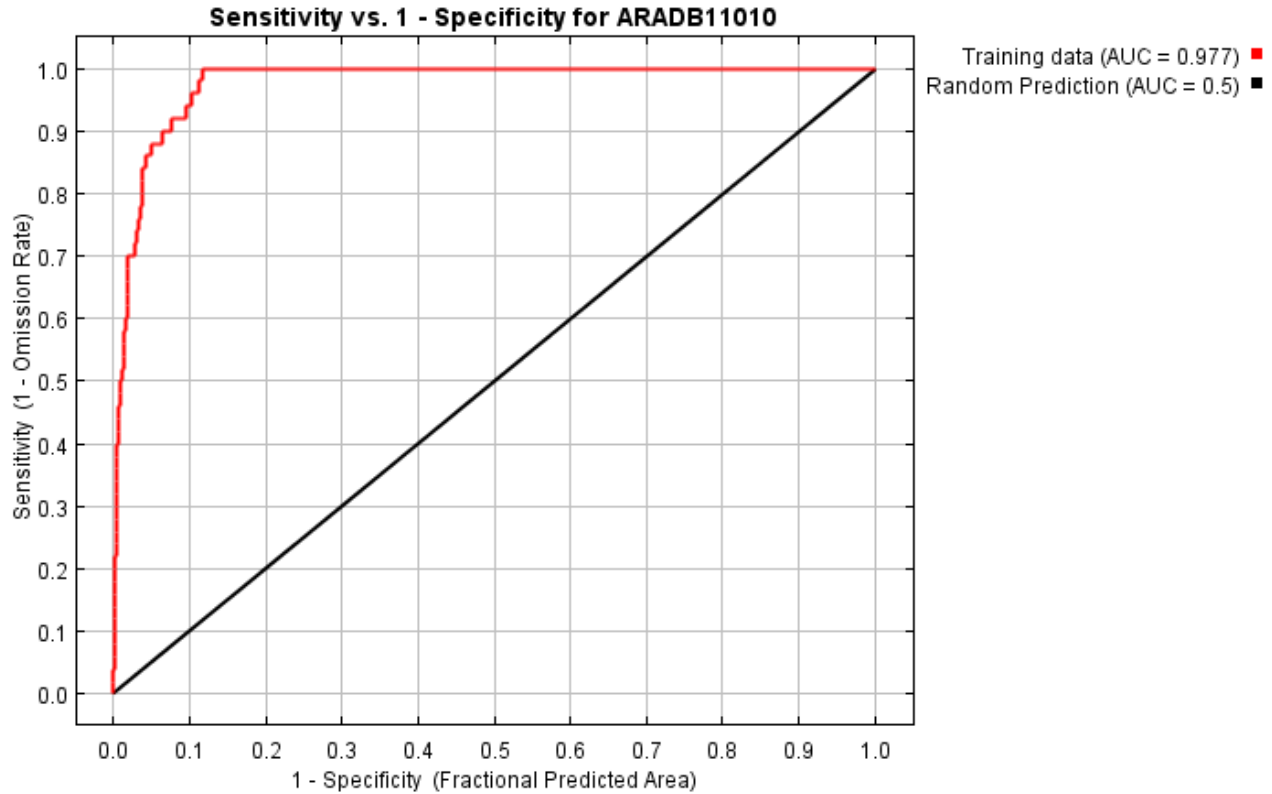
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.957 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

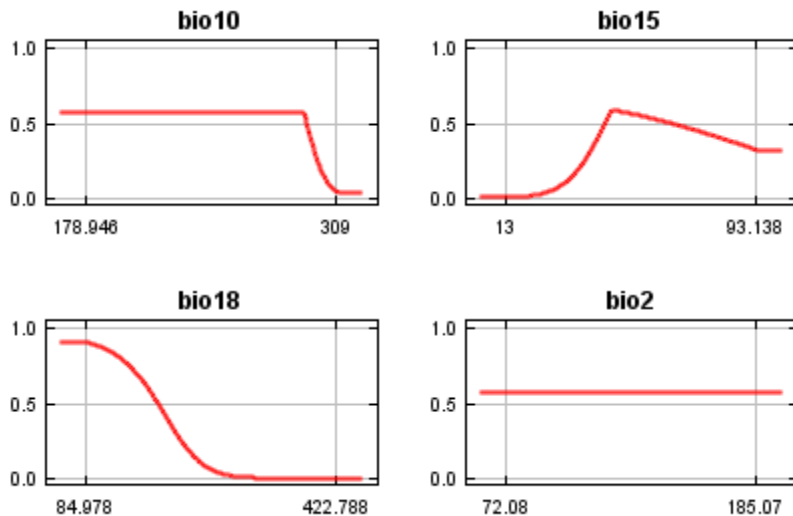
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.010	Fixed cumulative value 1	0.274	0.000
5.000	0.097	Fixed cumulative value 5	0.140	0.000
10.000	0.172	Fixed cumulative value 10	0.107	0.040
7.970	0.151	Minimum training presence	0.118	0.000
22.637	0.296	10 percentile training presence	0.063	0.100

Appendix 2 – Model Reports

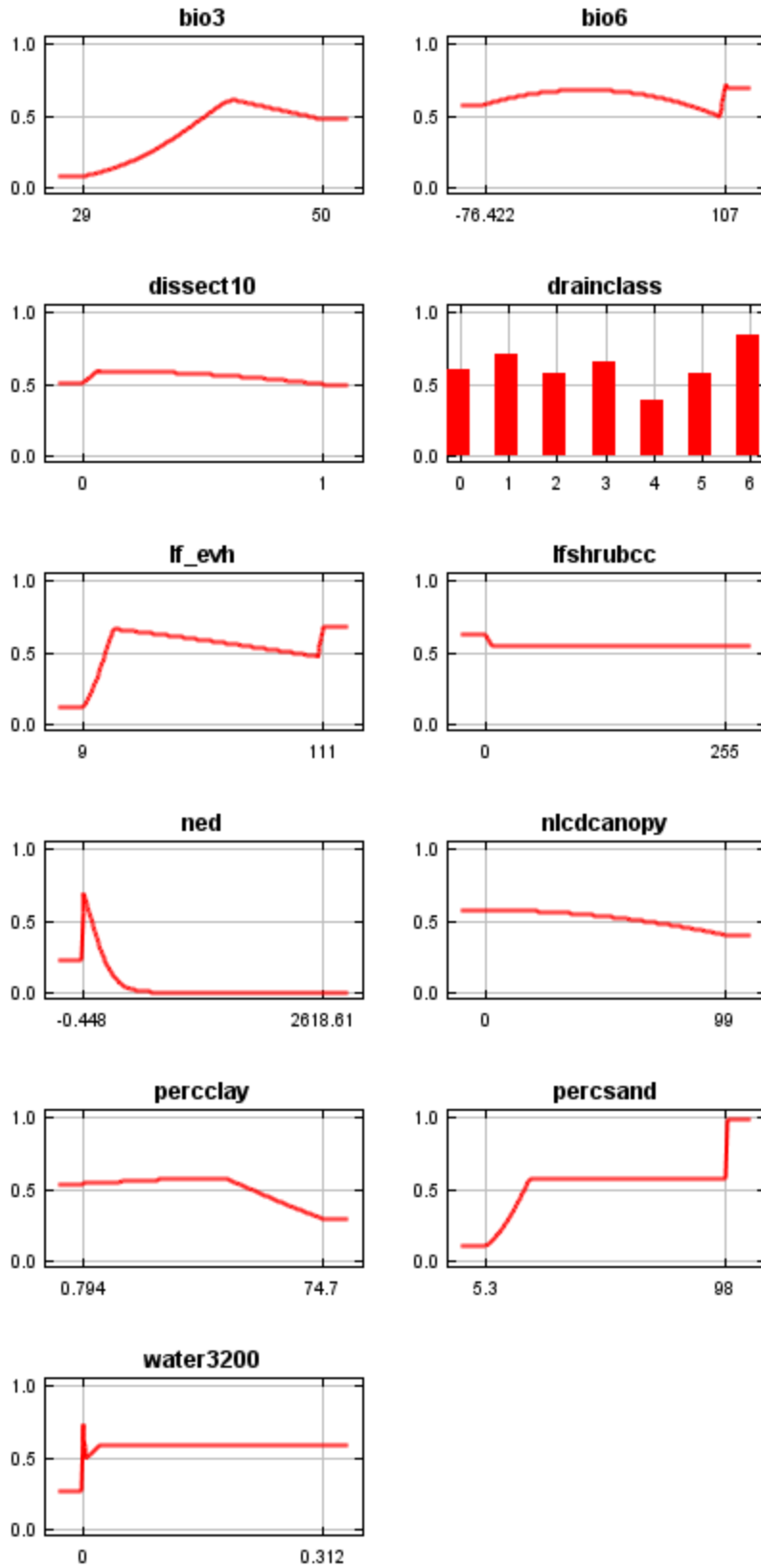
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
16.787	0.241	Equal training sensitivity and specificity	0.080	0.080
7.970	0.151	Maximum training sensitivity plus specificity	0.118	0.000
2.830	0.040	Balance training omission, predicted area and threshold value	0.173	0.000
10.755	0.178	Equate entropy of thresholded and original distributions	0.104	0.040

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. See Appendix 1 for detailed explanations of all environmental predictor layers.



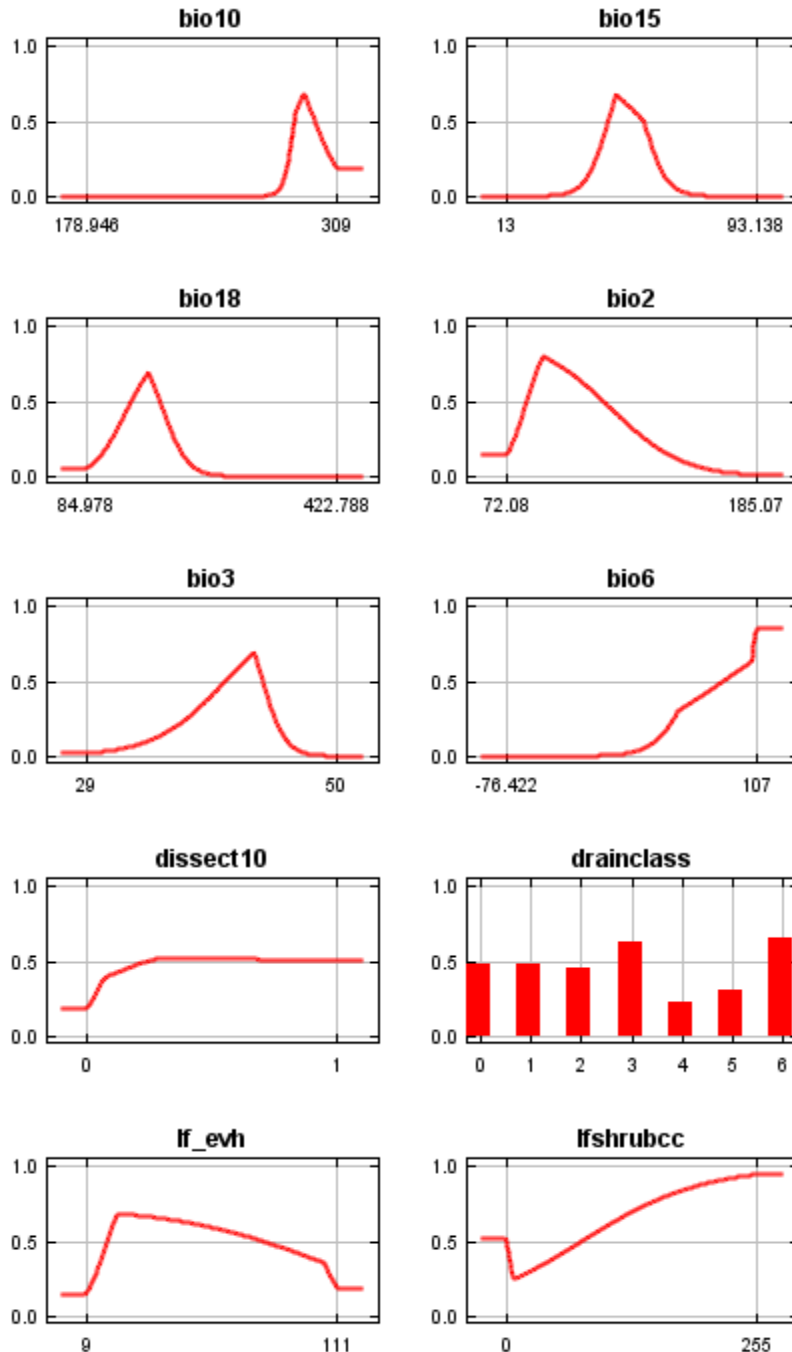
Appendix 2 – Model Reports



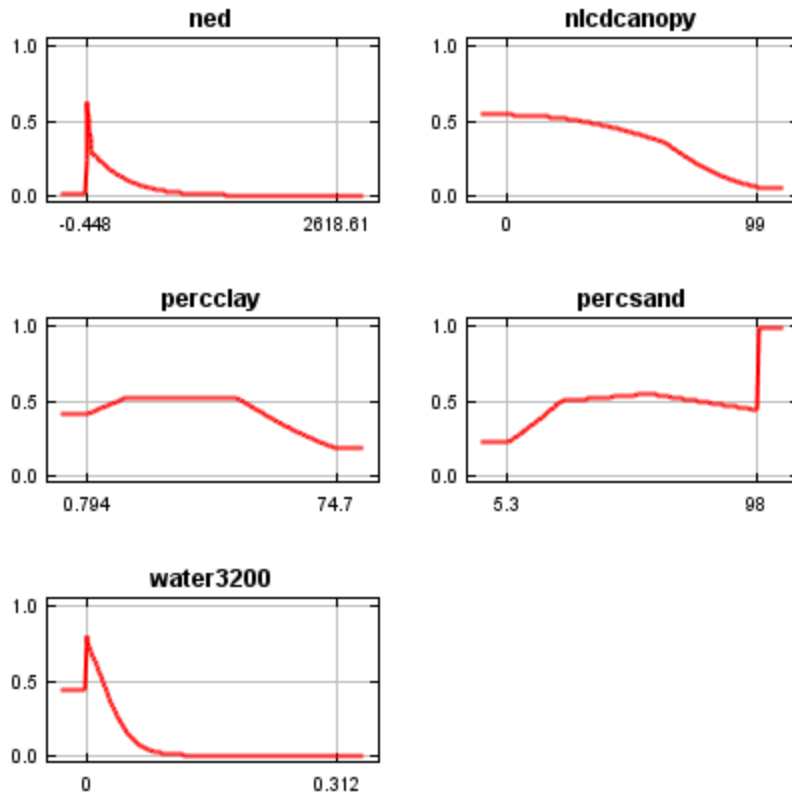
In contrast to the above marginal response curves, each of the following curves represents a

Appendix 2 – Model Reports

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.



Appendix 2 – Model Reports



Analysis of variable contributions

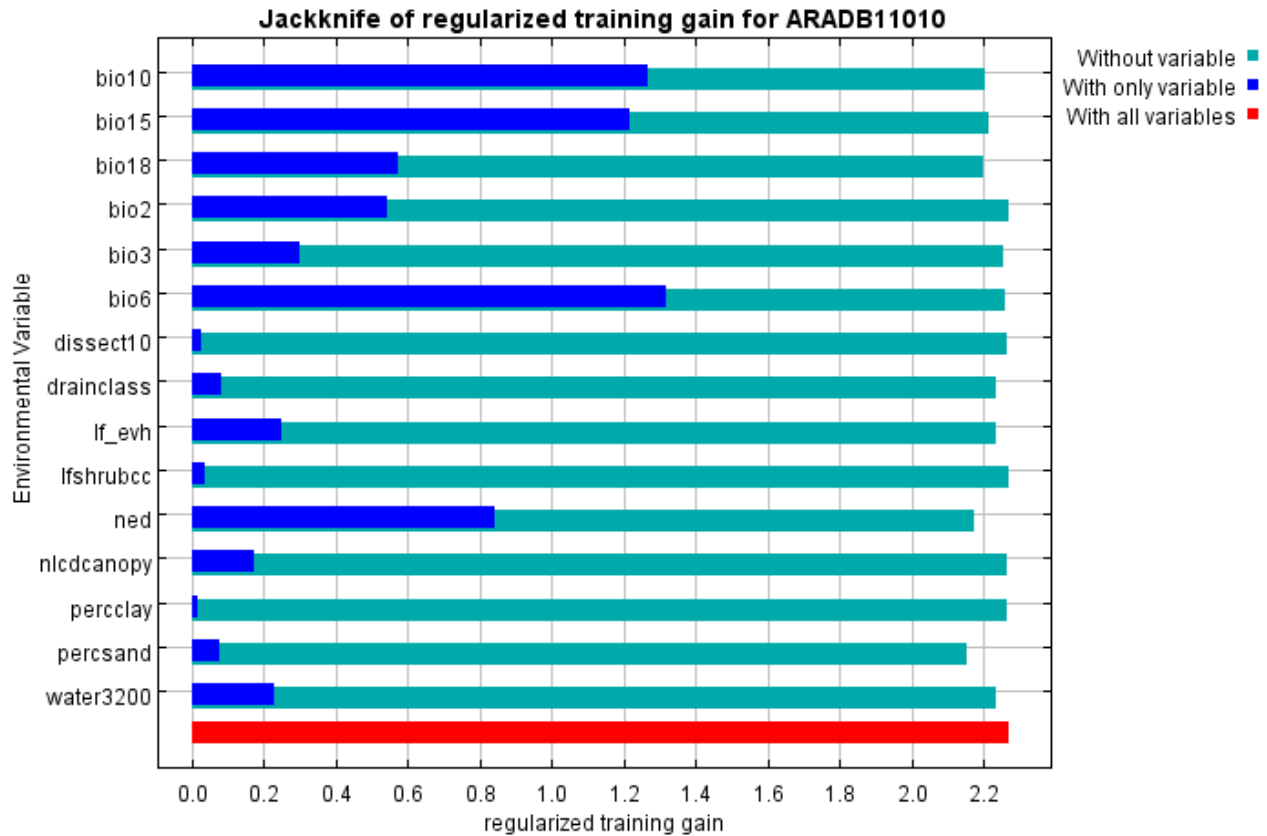
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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
bio6	37.7	0.6
bio15	26.2	21.9
ned	16	55
percsand	7.3	3.1

Appendix 2 – Model Reports

Variable	Percent contribution	Permutation importance
lf_evh	2.9	0.8
drainclass	2.6	0.1
bio18	2.2	14.8
water3200	1.8	0.5
bio10	1	1.7
bio3	0.7	1
percclay	0.6	0.2
dissect10	0.4	0.1
bio2	0.3	0
lfshrubcc	0.2	0
nlcdcanopy	0.1	0.1

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio6, 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 percsand, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 2.271, training AUC is 0.977, unregularized training gain is 2.775. Algorithm terminated after 500 iterations (34 seconds).

The follow settings were used during the run:

50 presence records used for training.
 7340 points used to determine the Maxent distribution (background points and presence points).
 Environmental layers used: bio10 bio15 bio18 bio2 bio3 bio6 dissect10 drainclass(categorical) lf_evh lfshrubcc ned nlcdcanopy percclay percсанд water3200
 Regularization values: linear/quadratic/product: 0.193, categorical: 0.250, threshold: 1.500, hinge: 0.500
 Feature types used: linear quadratic hinge
 responsecurves: true
 pictures: false
 jackknife: true
 outputfiletype: bil
 outputdirectory: F:\MAXENT_OUT\ARADB11010\RUN_3
 projectionlayers: F:\MAXENT_IN\PROB
 samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
 environmentalayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV
 writeclampgrid: false

Appendix 2 – Model Reports

writemess: false
writebackgroundpredictions: true
writeplotdata: true
Command line used: dontwriteclampgrid

Command line to repeat this species model:

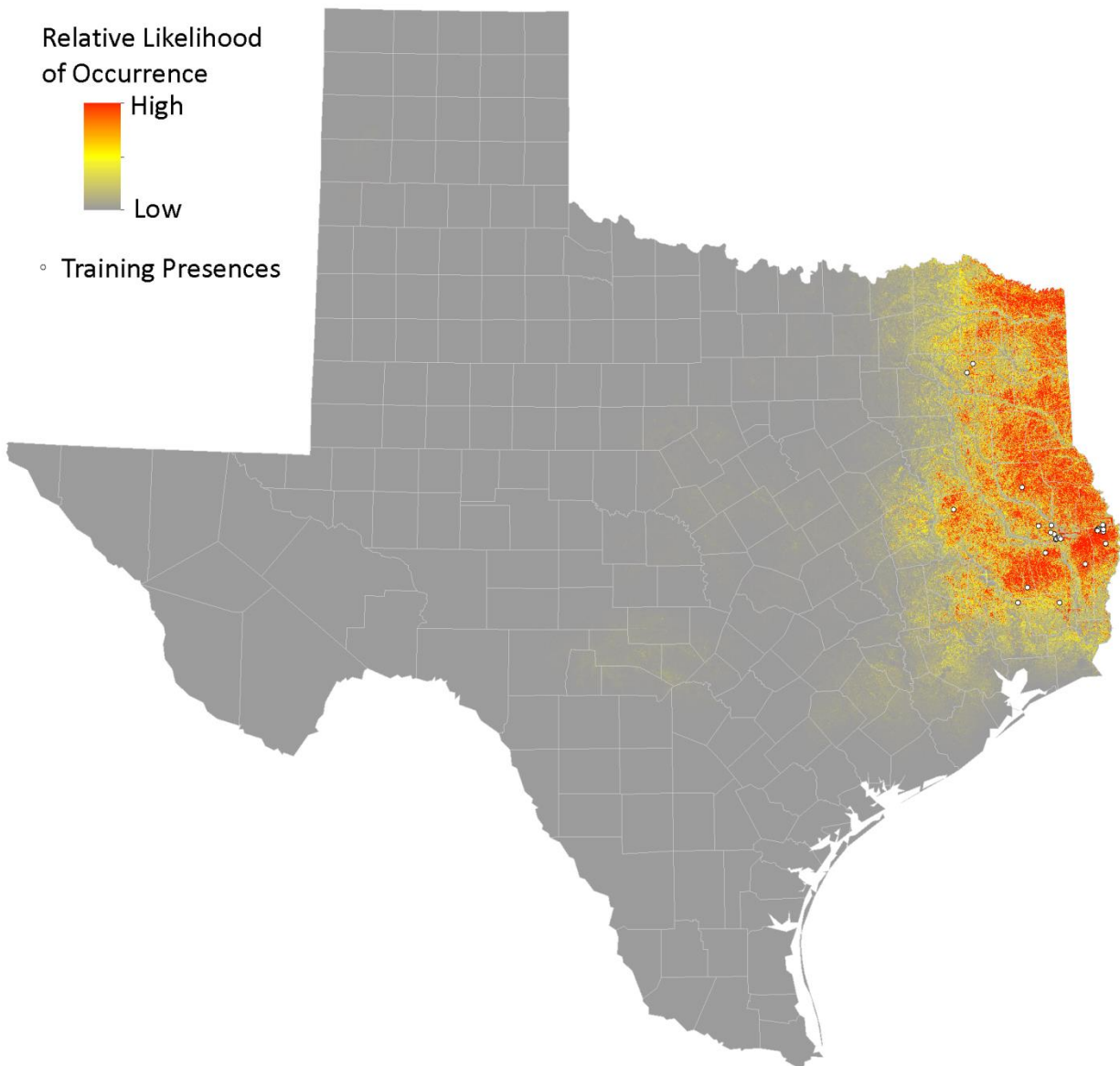
```
java density.MaxEnt nowarnings noprefixes -E "" -E ARADB11010 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\ARADB11010\RUN_3  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -N aglands -N allwatdist -N  
aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N avoid12800 -N avoid1600 -N  
avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio19 -  
N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N d2wsl -N  
dissect5 -N hydgroup -N ksats -N lf_forstcc -N lfherbcc -N percstilt -N radld -N slope -N soilec -N  
soilph -N vrm10 -N vrm5 -N water1600 -N water300 -t drainclass
```

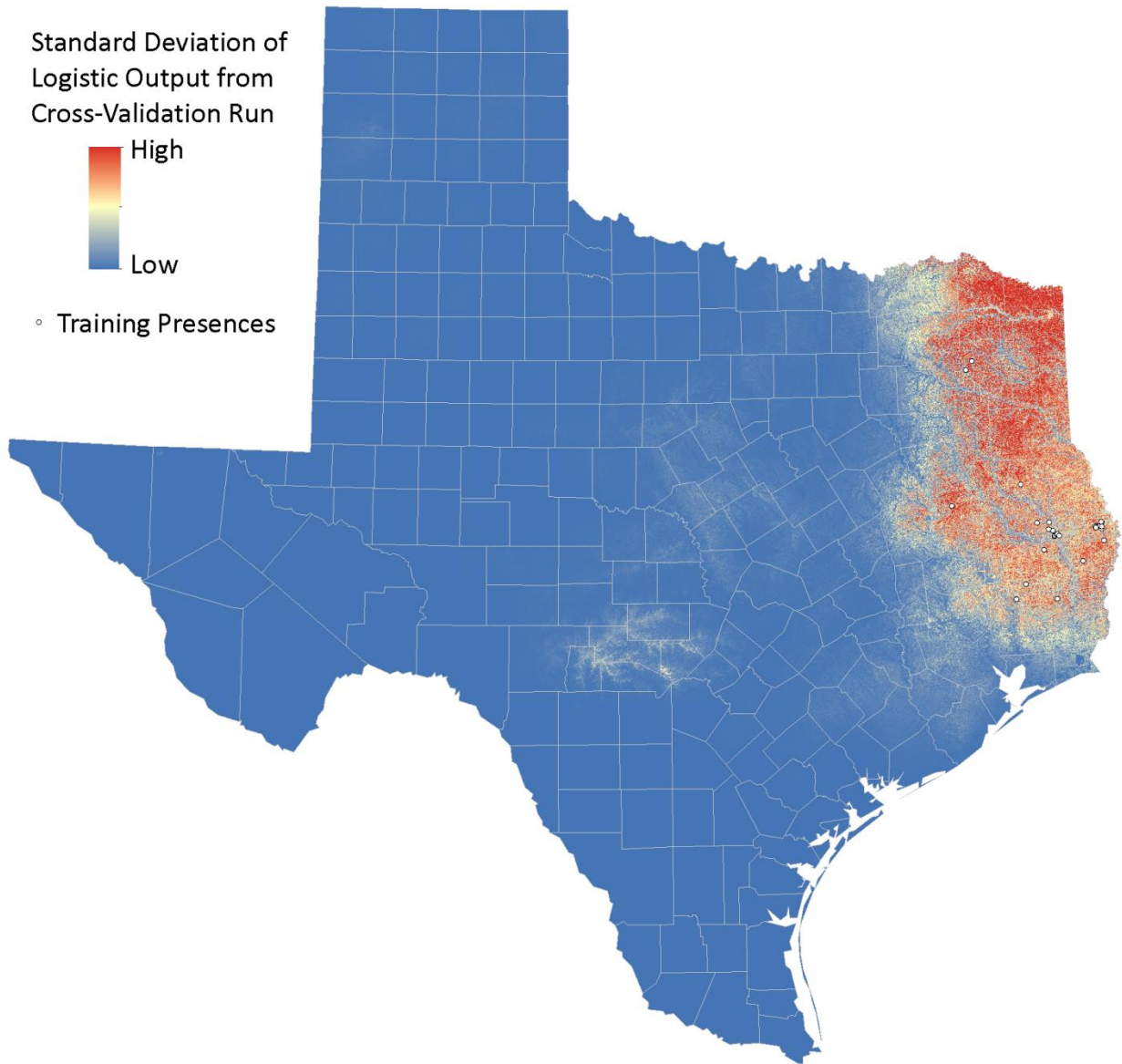
Louisiana Pine Snake (*Pituophis ruthveni*)

ELCODE: ARADB26030

Date: August 15, 2013

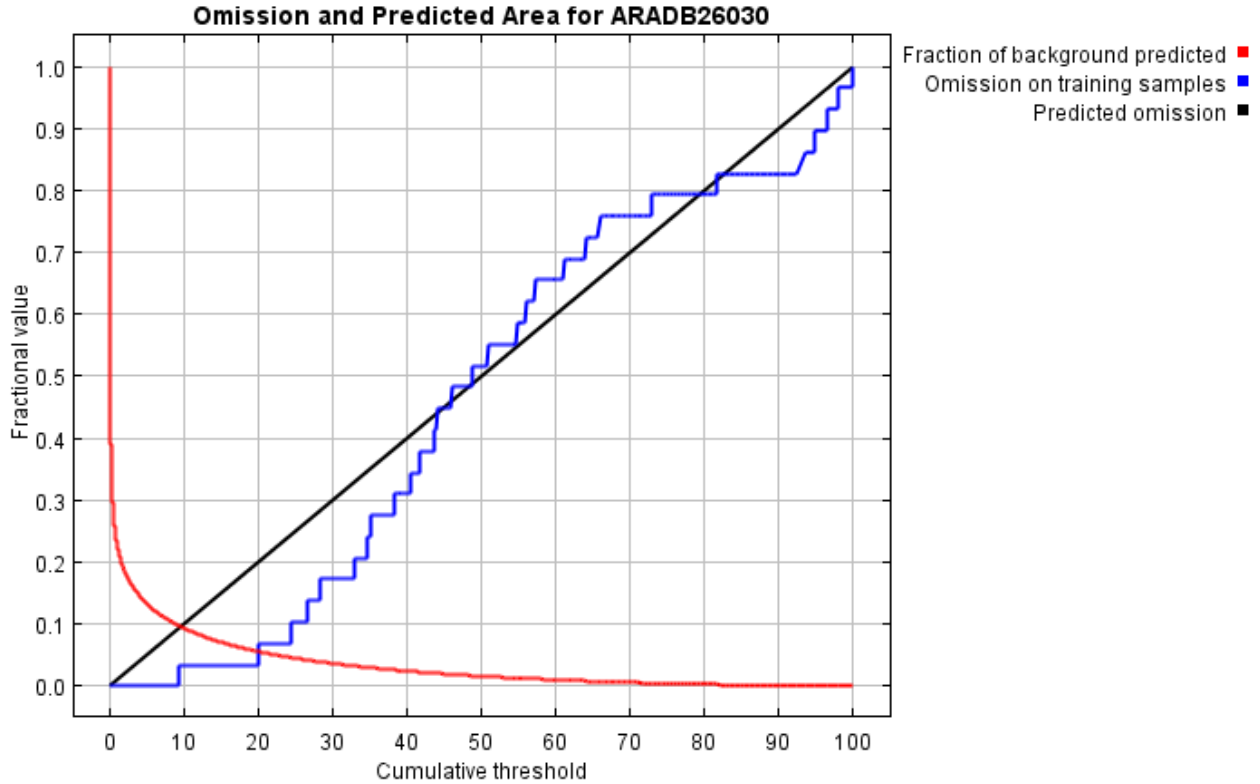
Maxent version: 3.3.3k





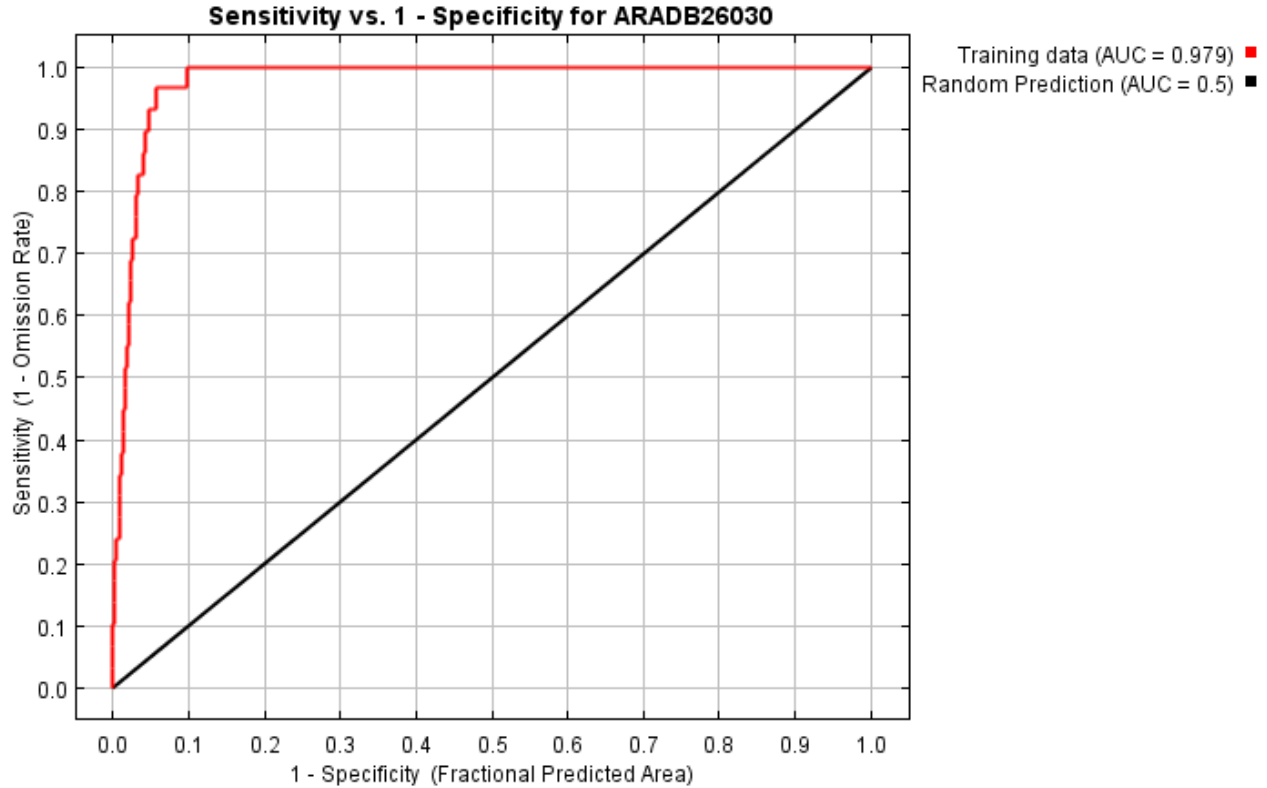
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.963 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

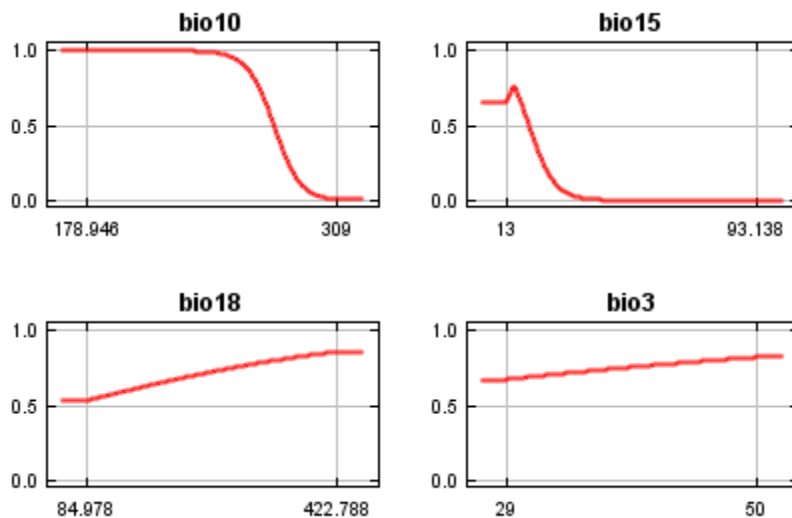
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.013	Fixed cumulative value 1	0.226	0.000
5.000	0.065	Fixed cumulative value 5	0.133	0.000
10.000	0.129	Fixed cumulative value 10	0.093	0.034
9.320	0.121	Minimum training presence	0.097	0.000
24.420	0.297	10 percentile training presence	0.046	0.069

Appendix 2 – Model Reports

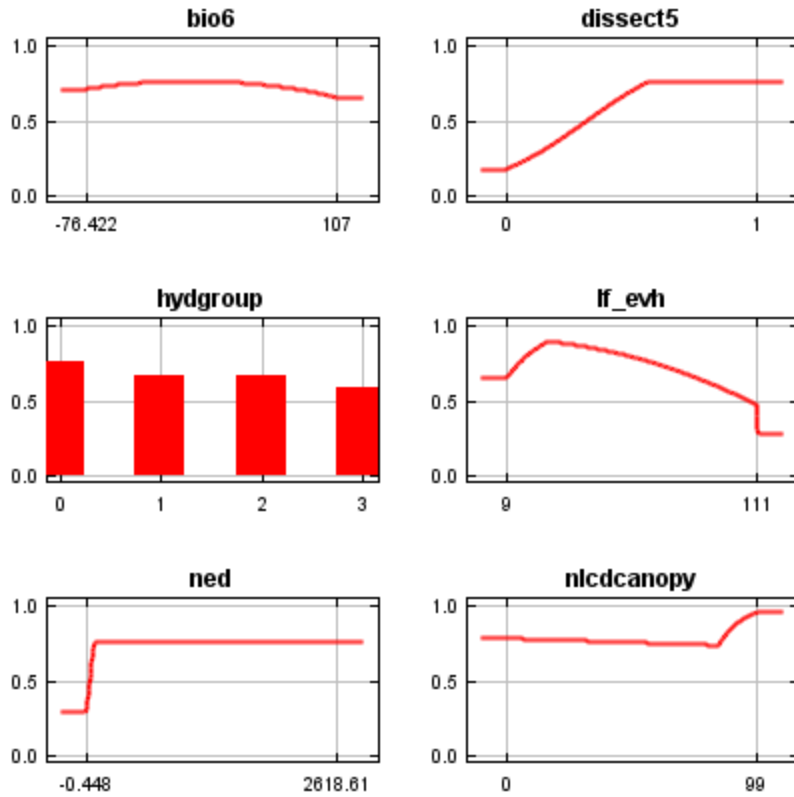
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
20.055	0.251	Equal training sensitivity and specificity	0.056	0.069
20.055	0.251	Maximum training sensitivity plus specificity	0.056	0.034
2.201	0.032	Balance training omission, predicted area and threshold value	0.179	0.000
12.078	0.149	Equate entropy of thresholded and original distributions	0.083	0.034

Response curves

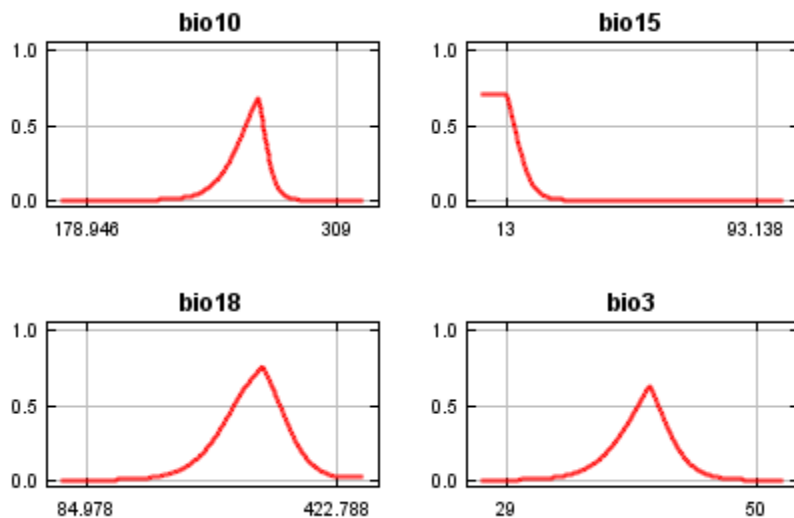
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



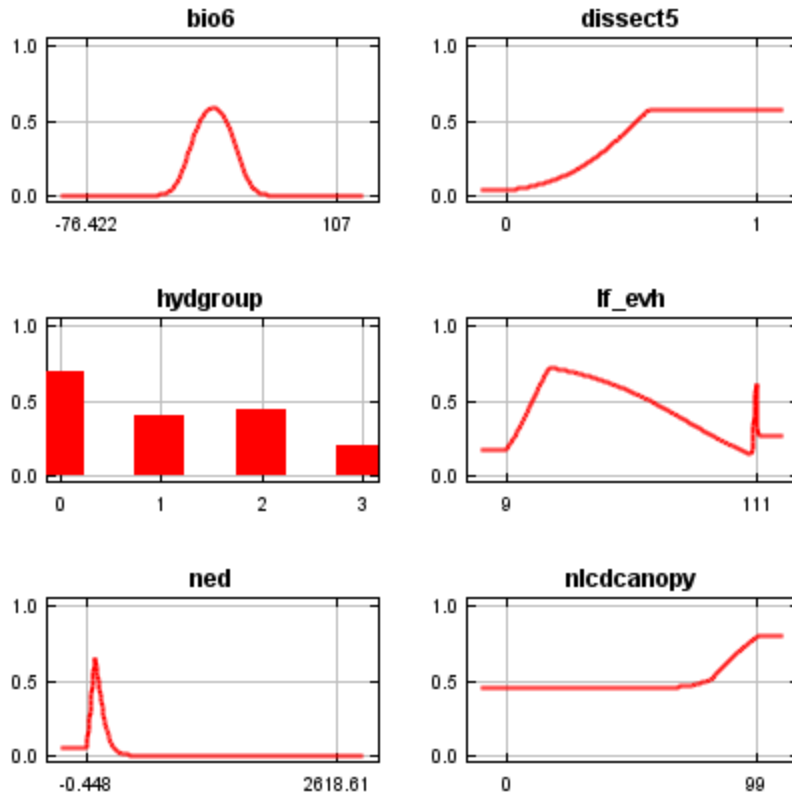
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



Analysis of variable contributions

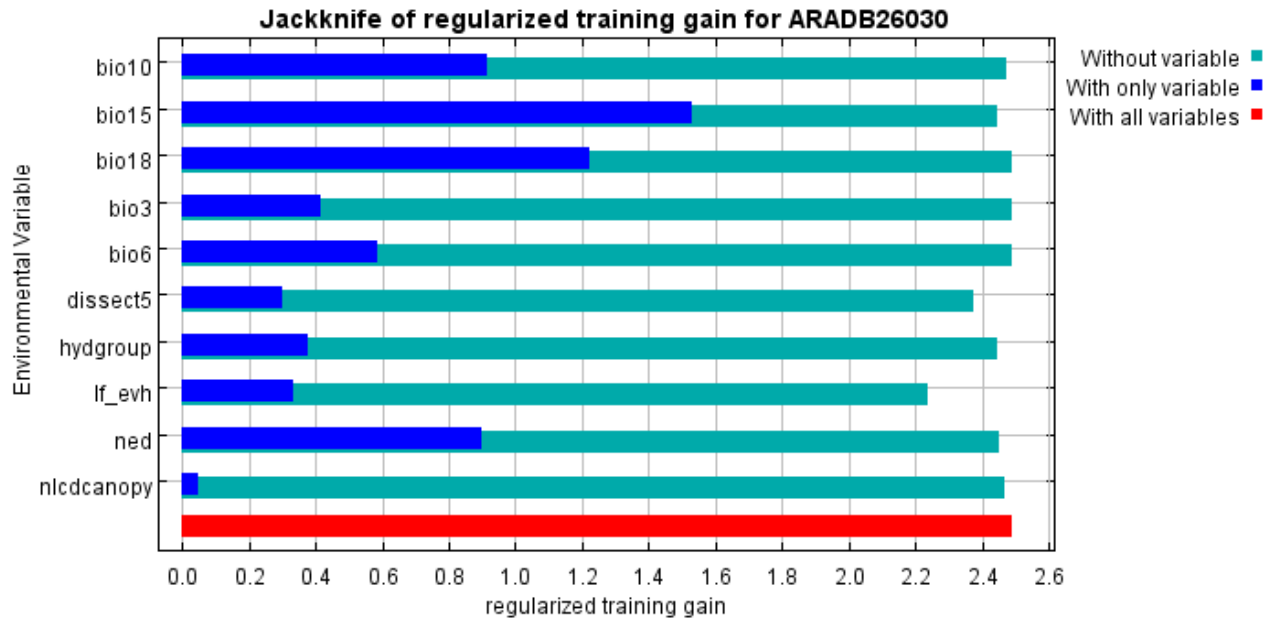
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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
bio15	63.3	73
lf_evh	11.6	4.5
dissect5	8.8	2.9
hydgroup	7.4	0.6

Appendix 2 – Model Reports

Variable	Percent contribution	Permutation importance
ned	5	1.7
bio18	2.1	0.7
nlcdcanopy	1	0.5
bio10	0.4	16.2
bio6	0.4	0
bio3	0	0

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio15, 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 lf_evh, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 2.491, training AUC is 0.979, unregularized training gain is 2.803. Algorithm terminated after 500 iterations (26 seconds).

Appendix 2 – Model Reports

The follow settings were used during the run:

29 presence records used for training.
7405 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used: bio10 bio15 bio18 bio3 bio6 dissect5 hydgroup(categorical) lf_evh ned
nlcdcanopy
Regularization values: linear/quadratic/product: 0.269, categorical: 0.250, threshold: 1.710, hinge:
0.500
Feature types used: linear quadratic hinge
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MAXENT_OUT\ARADB26030\RUN_4
projectionlayers: F:\MAXENT_IN\PROB
samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
environmentallayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV
writeclampgrid: false
writemess: false
writebackgroundpredictions: true
writeplotdata: true
Command line used: dontwriteclampgrid

Command line to repeat this species model:

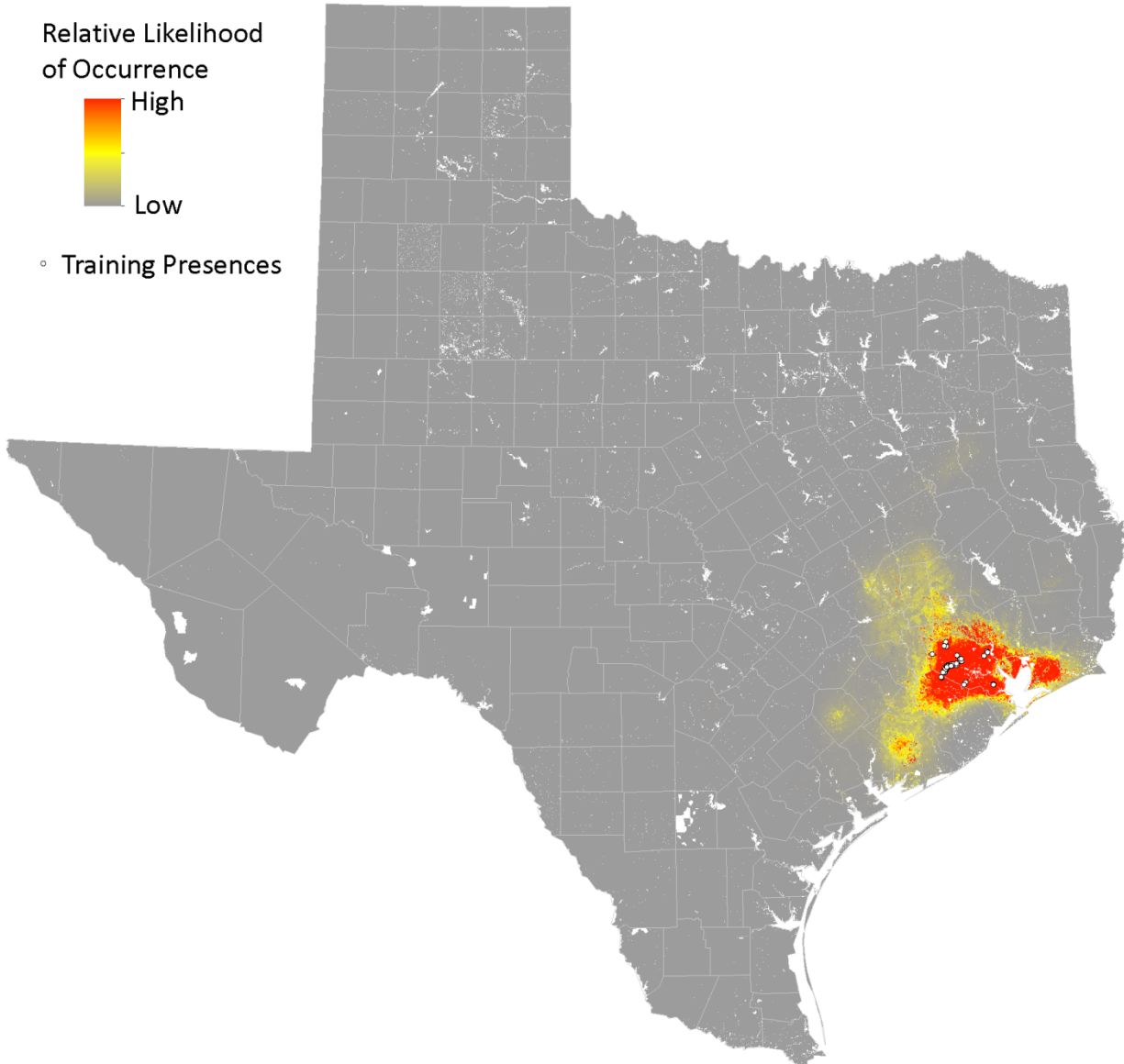
```
java density.MaxEnt nowarnings noprefixes -E "" -E ARADB26030 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\ARADB26030\RUN_4  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -N aglands -N allwatdist -N  
aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N avoid12800 -N avoid1600 -N  
avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio19 -  
N bio2 -N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N d2wsl -  
N dissect10 -N drainclass -N ksats -N lf_forstcc -N lfherbcc -N lfshrubcc -N percclay -N percsand -N  
percsilt -N radld -N slope -N soilec -N soilph -N vrm10 -N vrm5 -N water1600 -N water300 -N  
water3200 -t hydgroup
```

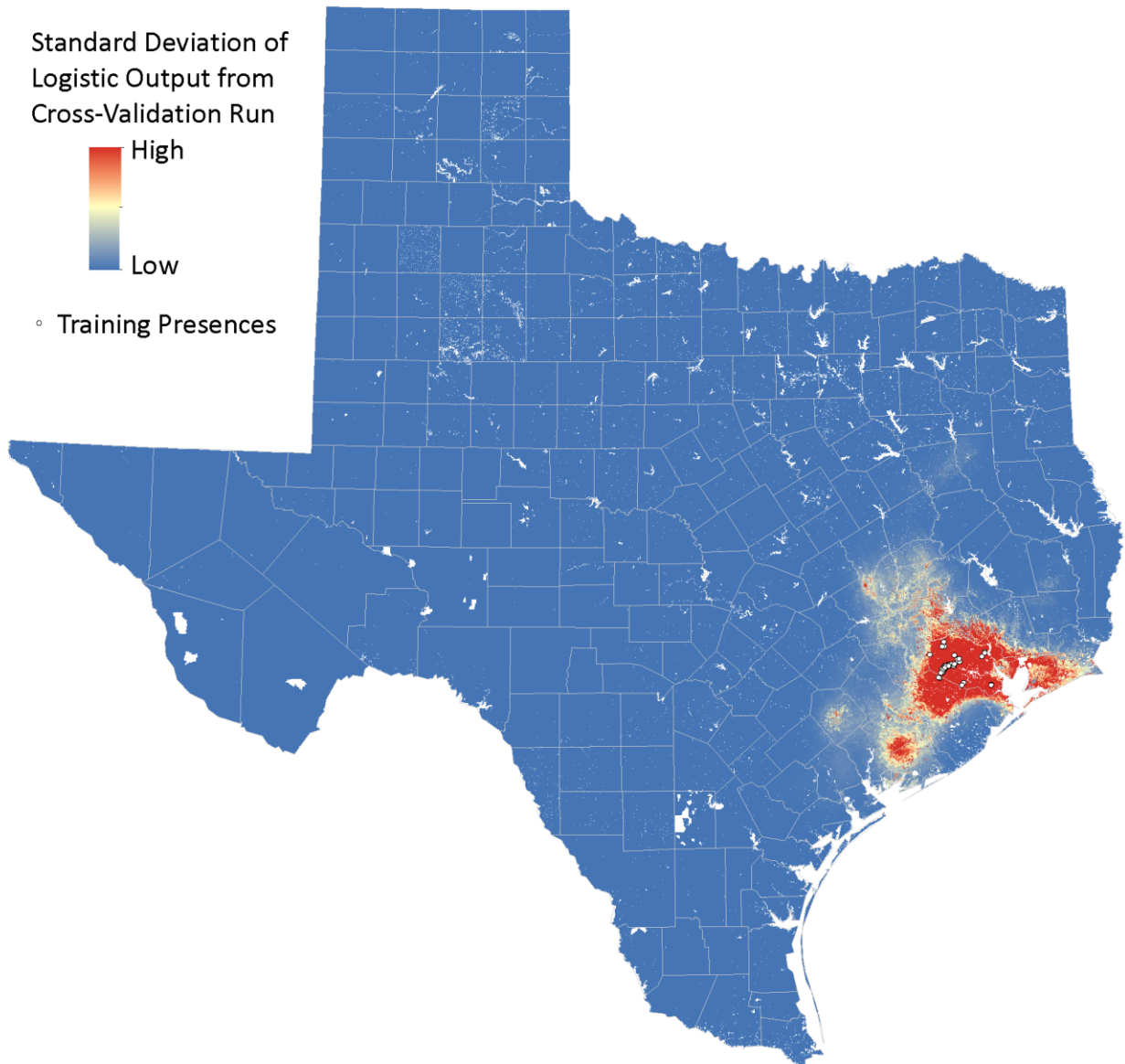
Texas Prairie Dawn (*Hymenoxys texana*)

ELCODE: PDAST53010

Date: August 13, 2013

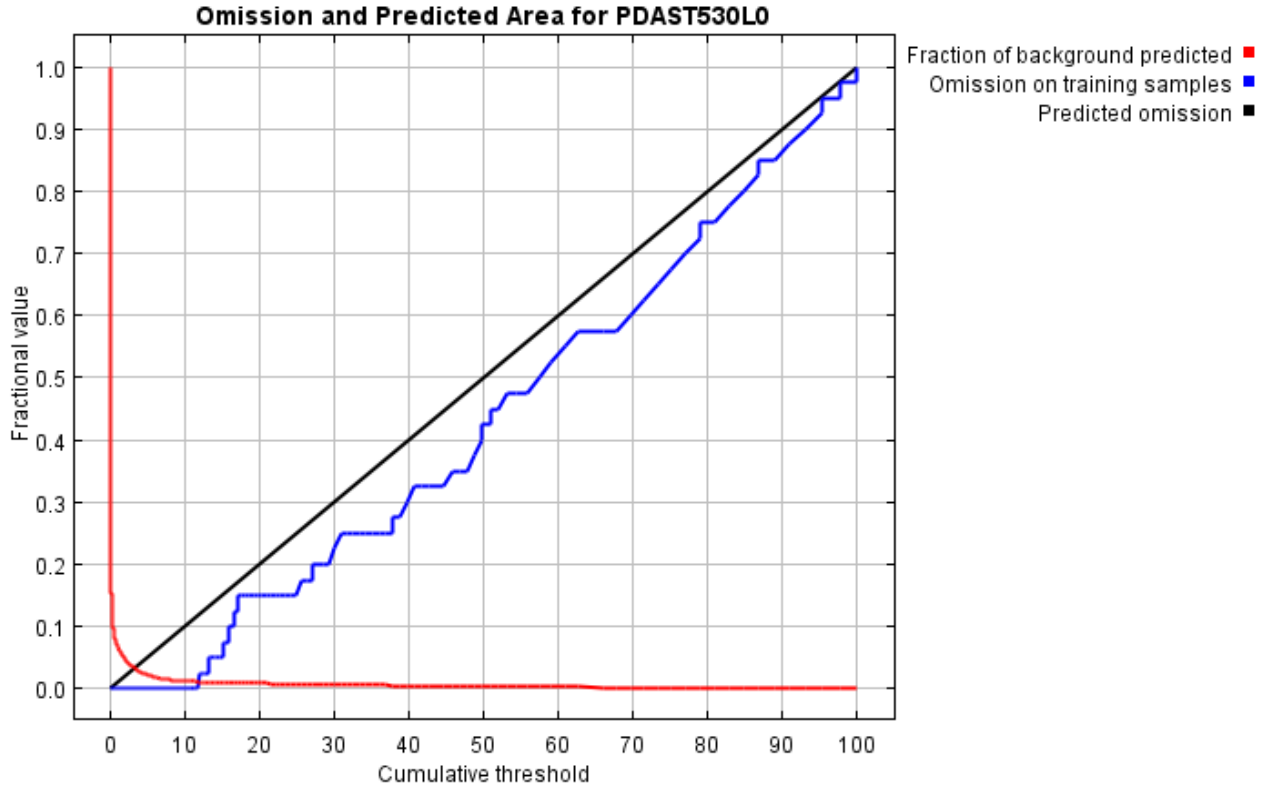
Maxent version: 3.3.3k



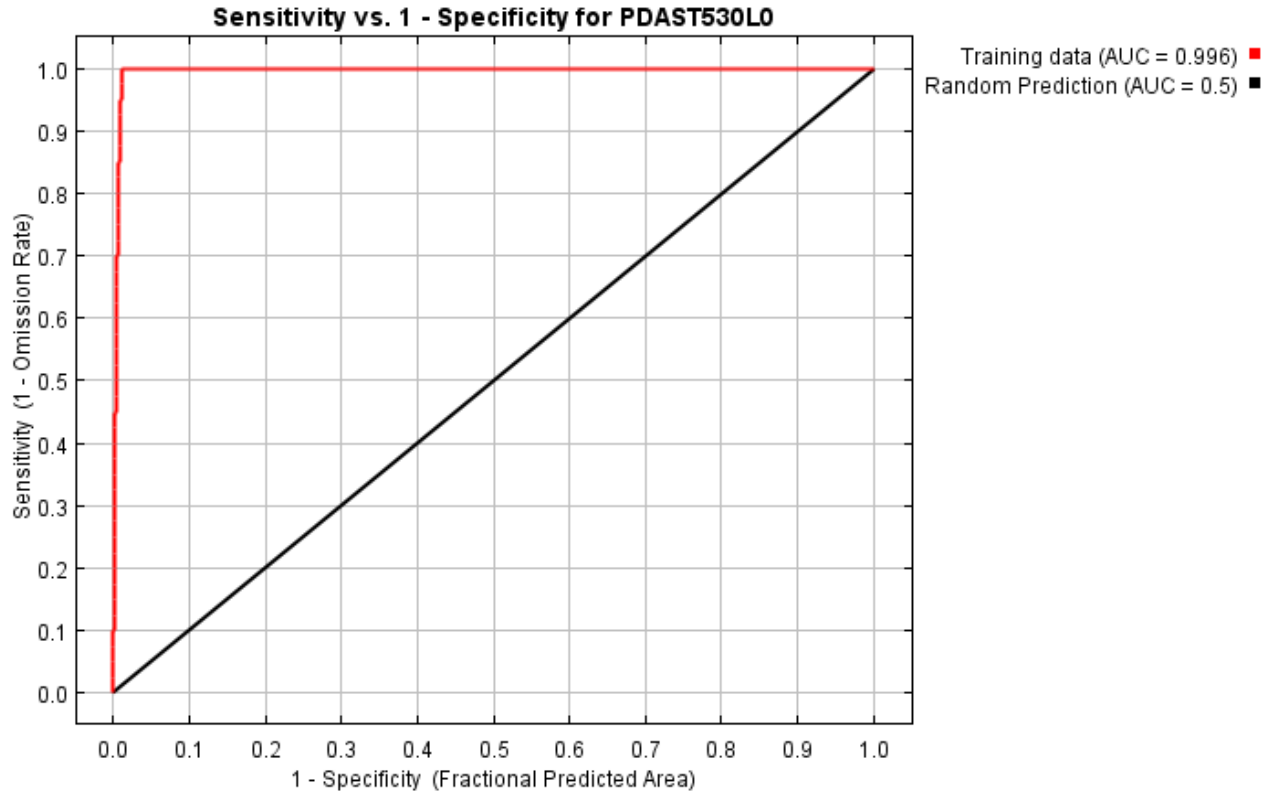


Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.991 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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

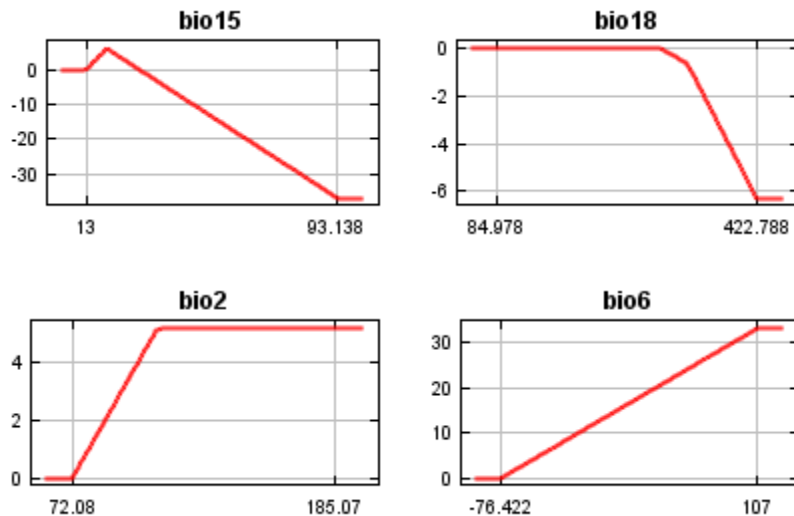
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.006	Fixed cumulative value 1	0.067	0.000
5.000	0.038	Fixed cumulative value 5	0.022	0.000
10.000	0.192	Fixed cumulative value 10	0.012	0.000
11.644	0.219	Minimum training presence	0.011	0.000
16.476	0.388	10 percentile training presence	0.010	0.100

Appendix 2 – Model Reports

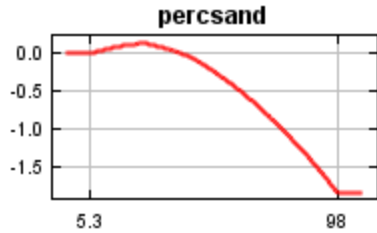
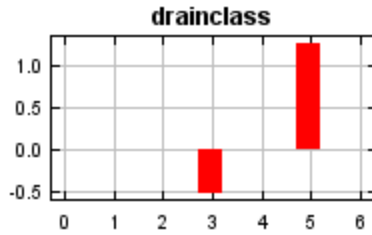
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
11.644	0.219	Equal training sensitivity and specificity	0.011	0.000
11.644	0.219	Maximum training sensitivity plus specificity	0.011	0.000
1.143	0.007	Balance training omission, predicted area and threshold value	0.063	0.000
6.801	0.070	Equate entropy of thresholded and original distributions	0.017	0.000

Response curves

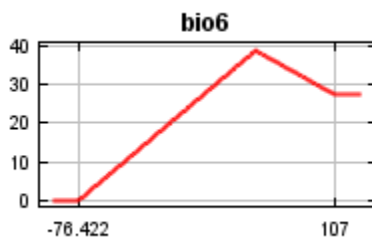
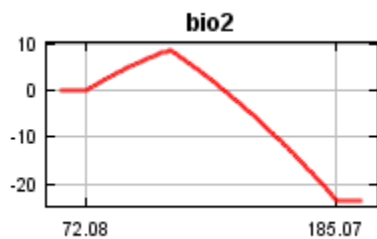
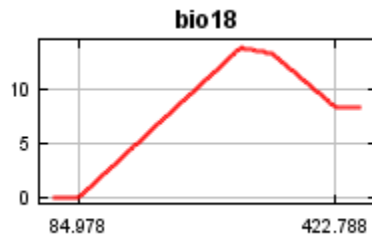
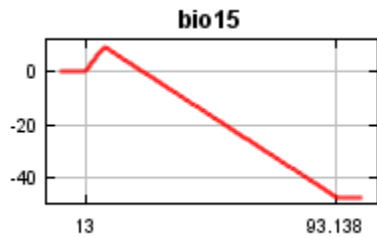
These curves show how each environmental variable affects the Maxent prediction. The (raw) Maxent model has the form $\exp(\dots)/\text{constant}$, and the curves show how the exponent changes as each environmental variable is varied, keeping all other environmental variables at their average sample 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



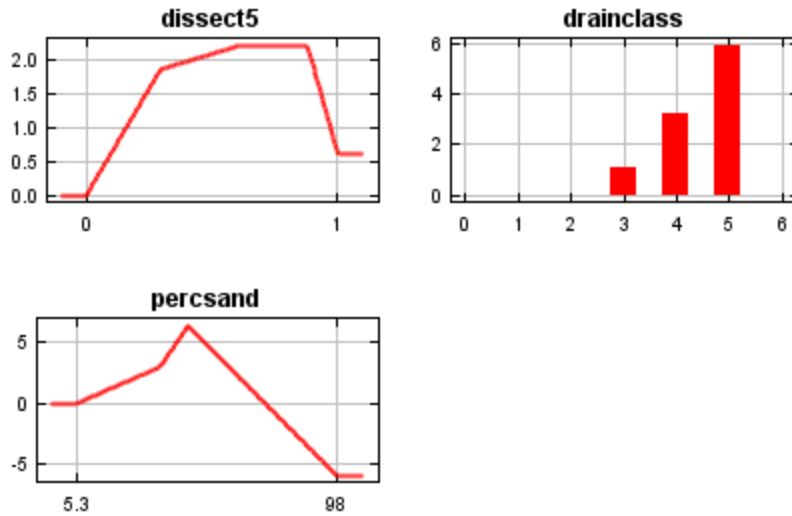
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



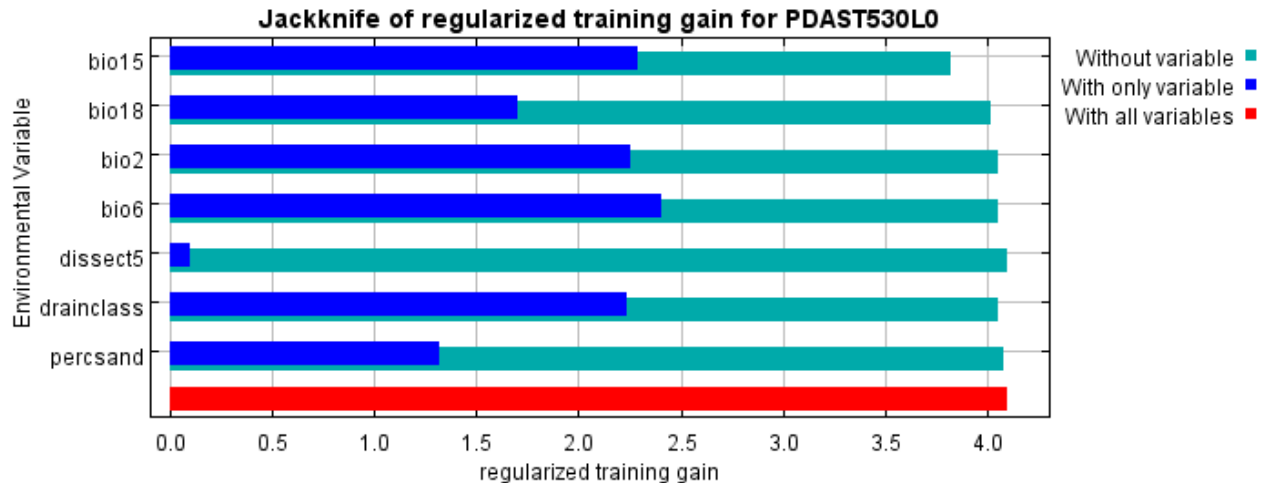
Analysis of variable contributions

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
drainclass	49	0.2
bio15	21.3	74.8
bio18	17.2	0.4
percsand	6.6	0
bio2	4.5	0.5
bio6	1.1	23.9
dissect5	0.3	0

Appendix 2 – Model Reports

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio6, 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 bio15, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 4.097, training AUC is 0.996, unregularized training gain is 4.468. Algorithm terminated after 500 iterations (20 seconds).

The follow settings were used during the run:

40 presence records used for training.

7368 points used to determine the Maxent distribution (background points and presence points).

Environmental layers used: bio15 bio18 bio2 bio6 dissect5 drainclass(categorical) persand

Regularization values: linear/quadratic/product: 0.221, categorical: 0.250, threshold: 1.600, hinge: 0.500

Feature types used: linear quadratic hinge

responsecurves: true

pictures: false

jackknife: true

outputfiletype: bil

outputdirectory: F:\MAXENT_OUT\PDAST530L0\RUN_5

projectionlayers: F:\MAXENT_IN\PROB

samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV

environmentallayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV

writeclampgrid: false

writemess: false

writebackgroundpredictions: true

responsecurvesexponent: true

writeplotdata: true

Command line used: dontwriteclampgrid

Command line to repeat this species model:

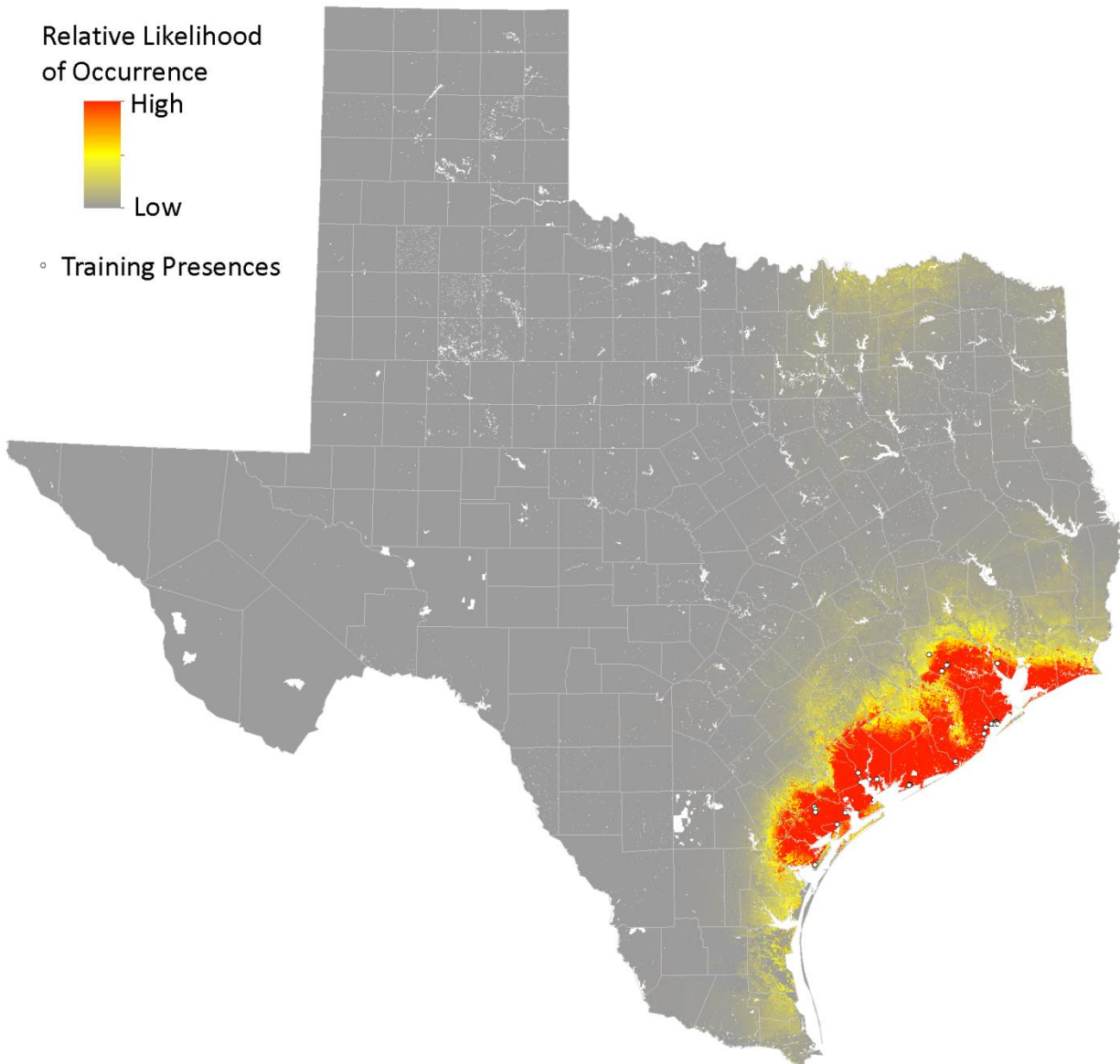
```
java density.MaxEnt nowarnings noprefixes -E "" -E PDAST530L0 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\PDAST530L0\RUN_5  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
nowritemess writebackgroundpredictions responsecurvesexponent writeplotdata -N UNIQUE_ID -  
N aglands -N allwatdist -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N  
avoid12800 -N avoid1600 -N avoid3200 -N avoid6400 -N bio1 -N bio10 -N bio11 -N bio12 -N bio13  
-N bio14 -N bio16 -N bio17 -N bio19 -N bio3 -N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N  
curve10 -N curve5 -N d2foredge -N d2wsls -N dissect10 -N hydgroup -N ksats -N lf_evh -N lf_forstcc -  
N lfherbcc -N lfshrubcc -N ned -N nlcdcanopy -N percclay -N percsls -N radld -N slope -N soilec -N  
soilph -N vrm10 -N vrm5 -N water1600 -N water300 -N water3200 -t drainclass
```

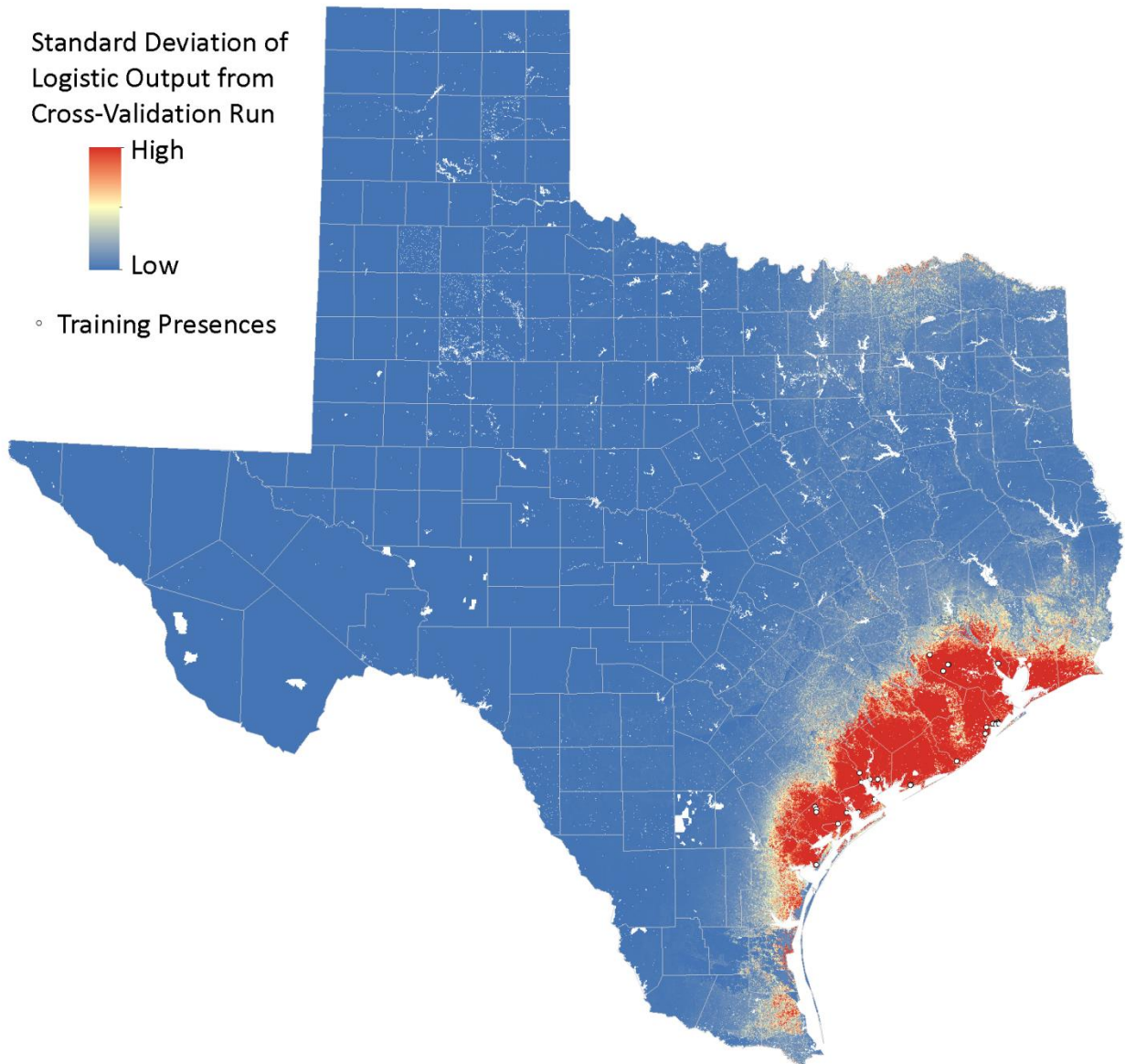

Threeflower Broomweed (*Thurovia triflora*)

ELCODE: PDASTCZ010

Date: August 13, 2013

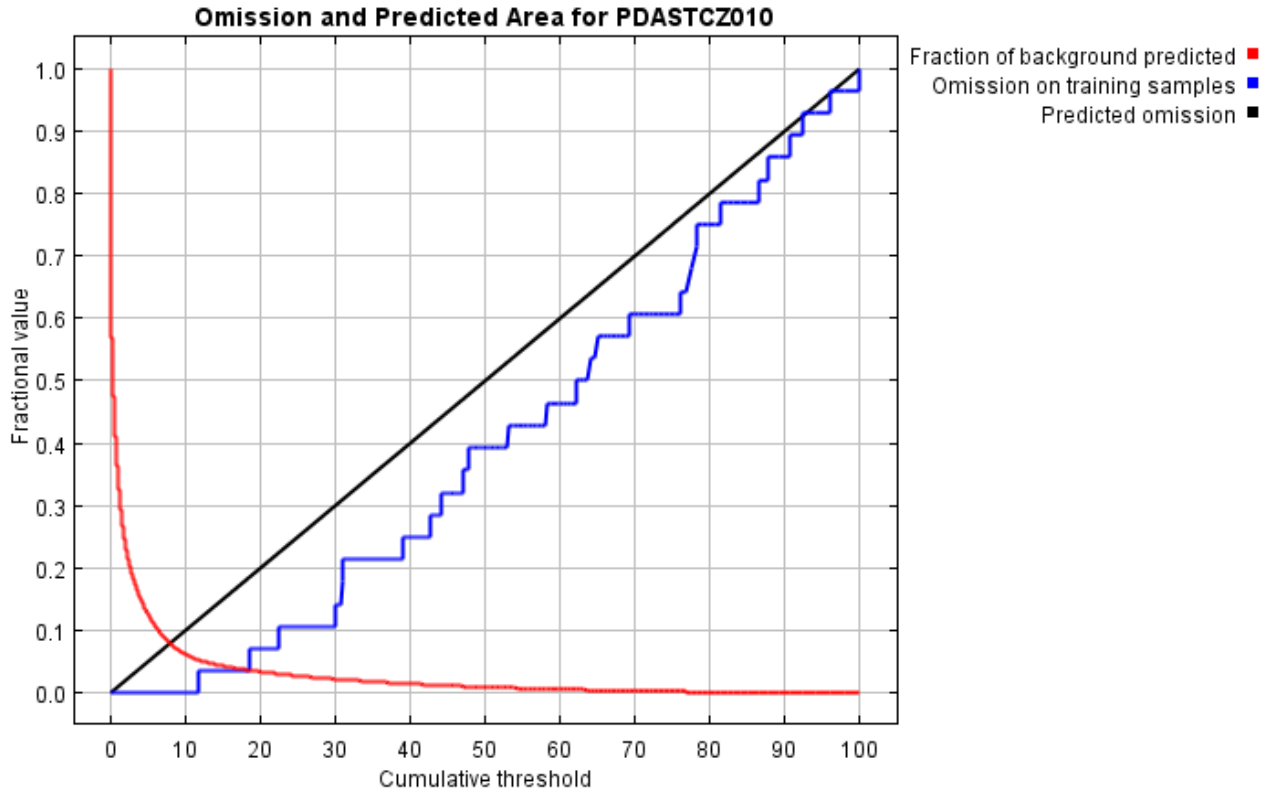
Maxent version: 3.3.3k





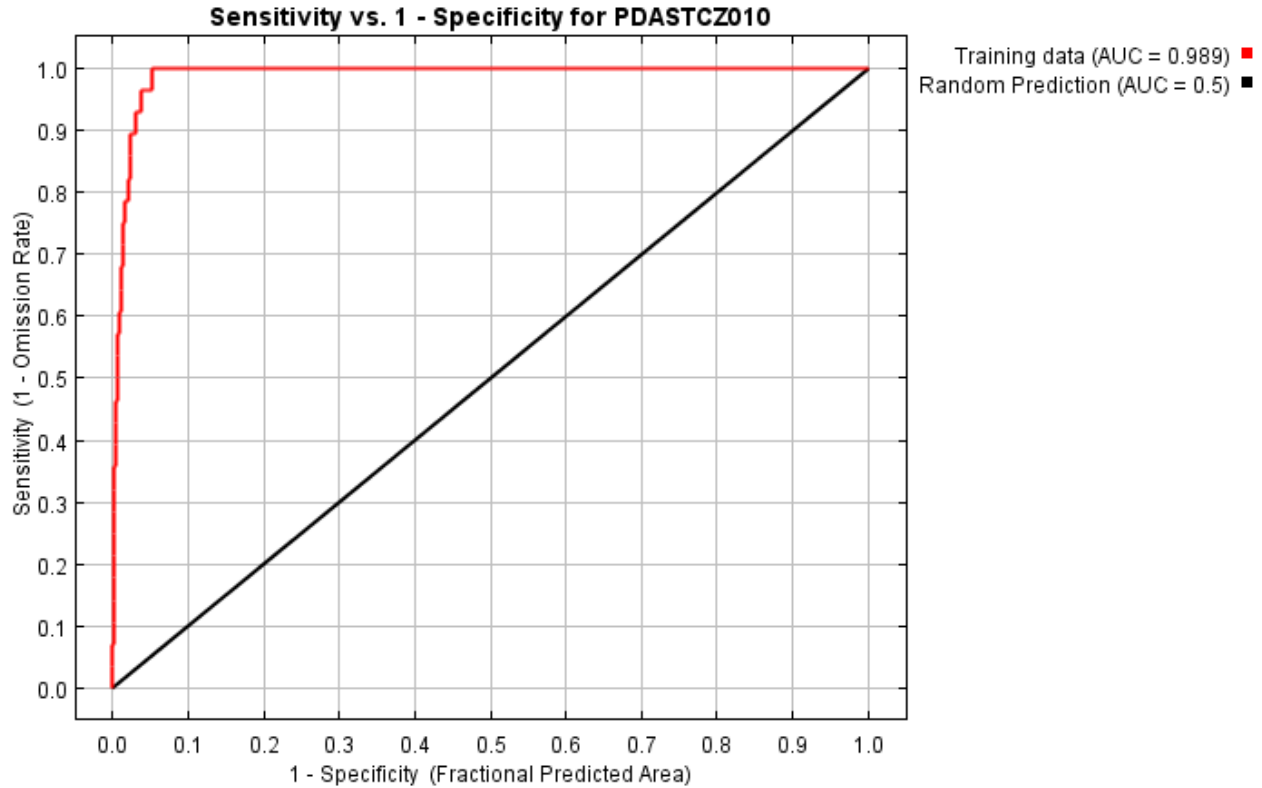
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.968 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

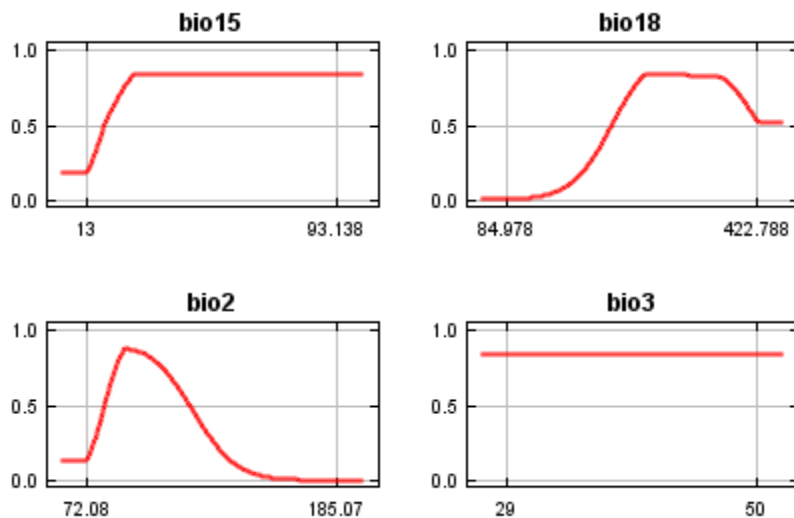
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.004	Fixed cumulative value 1	0.339	0.000
5.000	0.027	Fixed cumulative value 5	0.126	0.000
10.000	0.083	Fixed cumulative value 10	0.062	0.000
11.746	0.136	Minimum training presence	0.053	0.000
22.420	0.311	10 percentile training presence	0.031	0.071

Appendix 2 – Model Reports

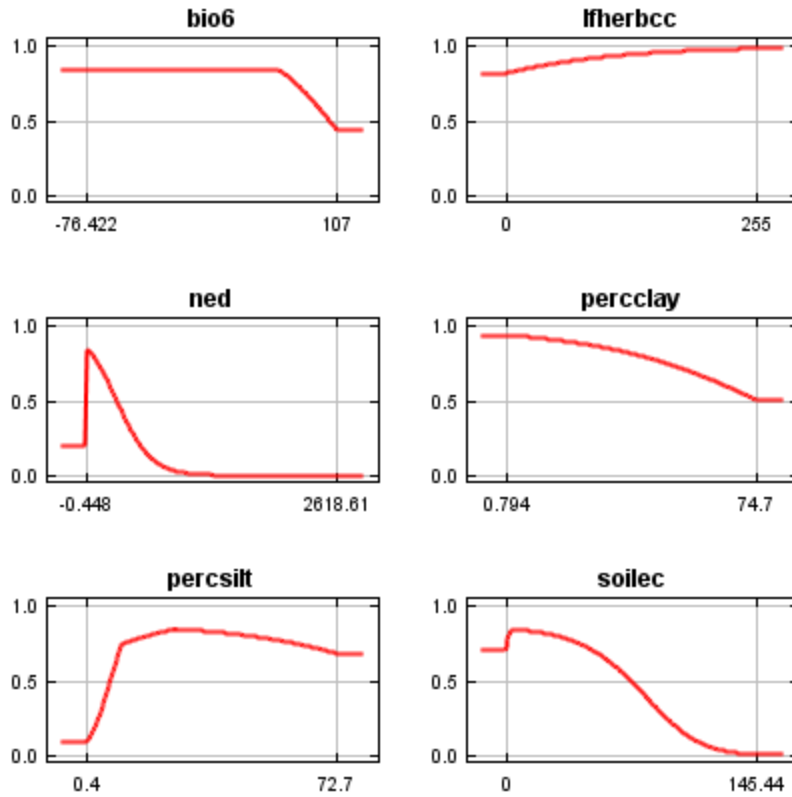
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
18.448	0.260	Equal training sensitivity and specificity	0.037	0.036
11.746	0.136	Maximum training sensitivity plus specificity	0.053	0.000
4.473	0.023	Balance training omission, predicted area and threshold value	0.138	0.000
10.555	0.092	Equate entropy of thresholded and original distributions	0.059	0.000

Response curves

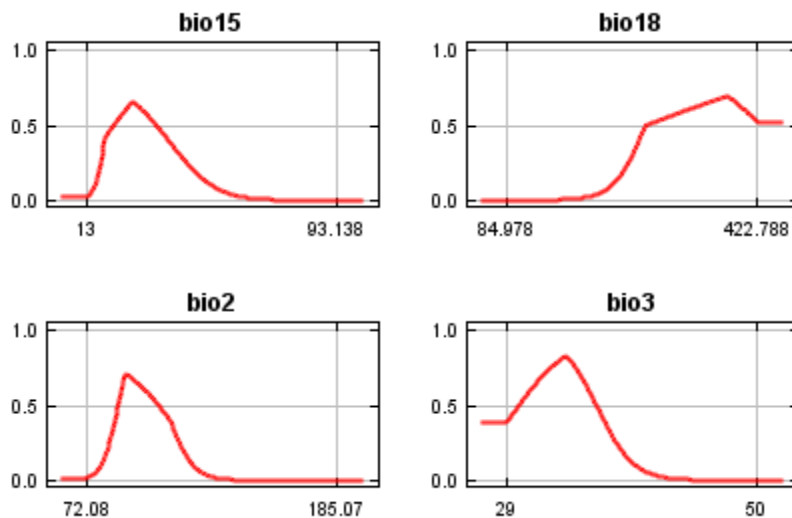
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



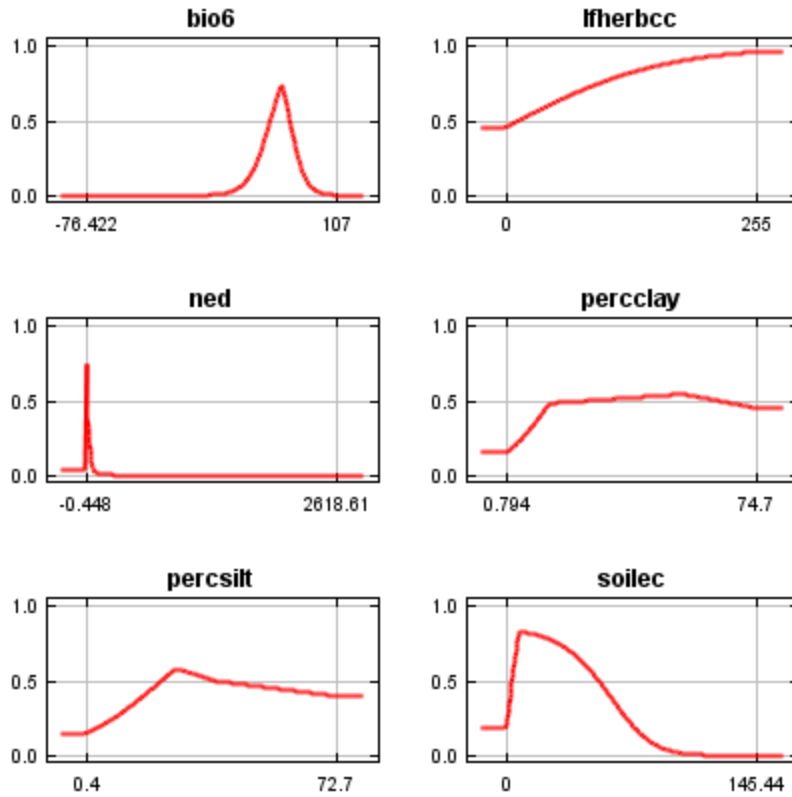
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



Analysis of variable contributions

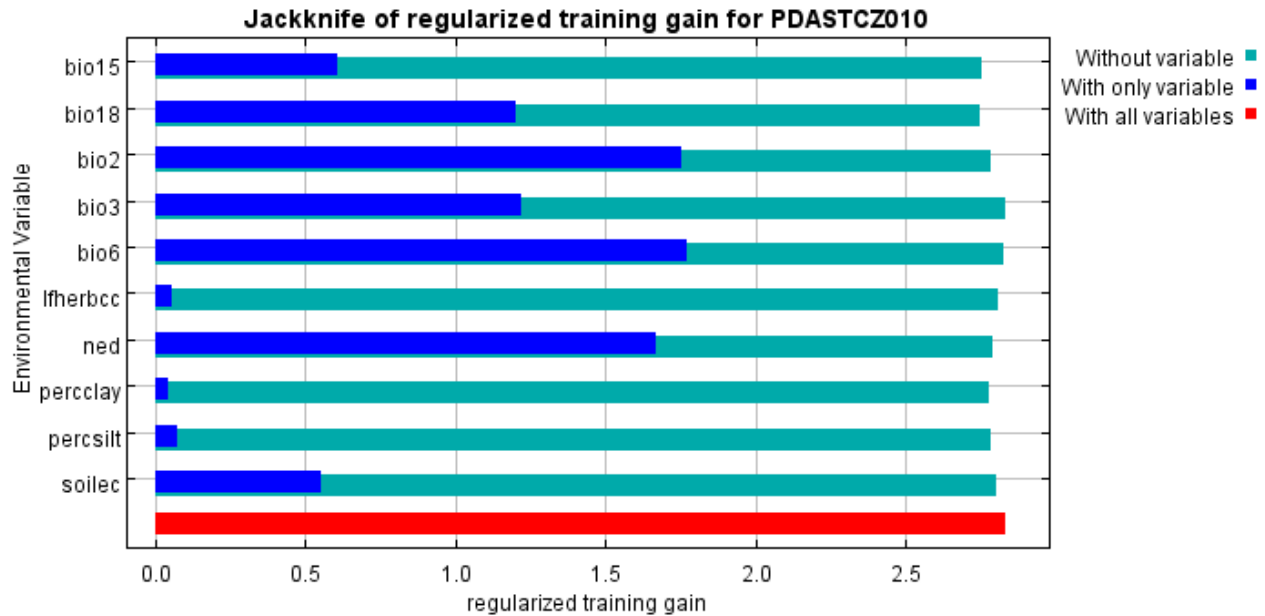
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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
ned	50.3	32.5
bio18	28.1	12.6
bio15	10.1	8.3
percsilt	4.6	1.8

Appendix 2 – Model Reports

Variable	Percent contribution	Permutation importance
bio2	2.2	41.4
lfherbcc	2	0
soilec	1.3	0.6
percclay	1.3	1.9
bio3	0.1	0
bio6	0.1	1

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio6, 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 bio18, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 2.835, training AUC is 0.989, unregularized training gain is 3.361. Algorithm terminated after 500 iterations (23 seconds).

The follow settings were used during the run:

Appendix 2 – Model Reports

28 presence records used for training.

7350 points used to determine the Maxent distribution (background points and presence points).

Environmental layers used (all continuous): bio15 bio18 bio2 bio3 bio6 lfherbcc ned percclay
percsilt soilec

Regularization values: linear/quadratic/product: 0.288, categorical: 0.250, threshold: 1.720, hinge:
0.500

Feature types used: linear quadratic hinge

responsecurves: true

pictures: false

jackknife: true

outputfiletype: bil

outputdirectory: F:\MAXENT_OUT\PDASTC010\RUN_3

projectionlayers: F:\MAXENT_IN\PROB

samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV

environmentallayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV

writeclampgrid: false

writemess: false

writebackgroundpredictions: true

writeplotdata: true

Command line used: dontwriteclampgrid

Command line to repeat this species model:

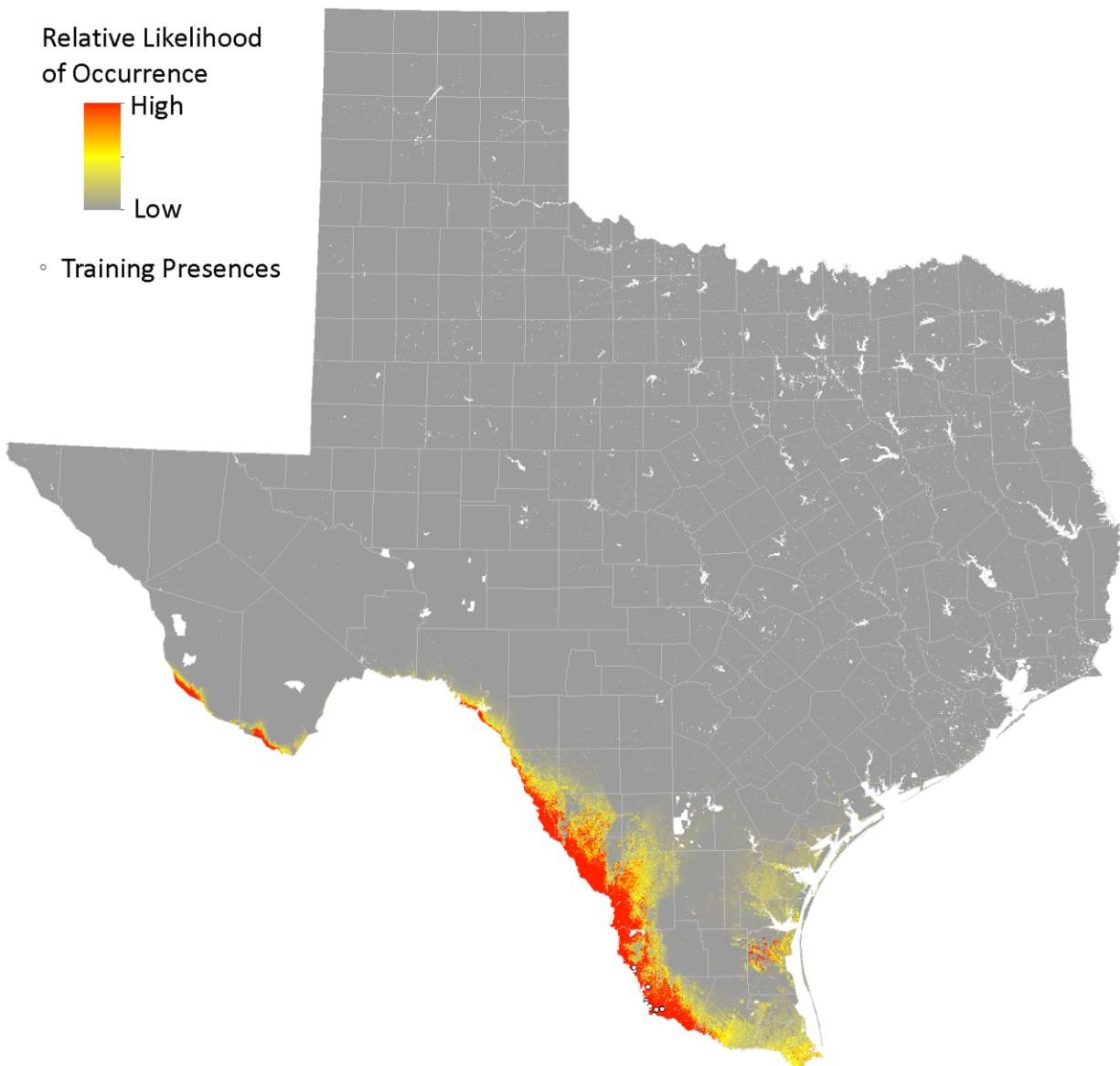
```
java density.MaxEnt nowarnings noprefixes -E "" -E PDASTCZ010 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\PDASTC010\RUN_3  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -N aglands -N allwatdist -N  
aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N avoid12800 -N avoid1600 -N  
avoid3200 -N avoid6400 -N bio1 -N bio10 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -  
N bio19 -N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N d2wsl  
-N dissect10 -N dissect5 -N drainclass -N hydgroup -N ksats -N lf_evh -N lf_forstcc -N lfshrubcc -N  
nlcdcanopy -N percsand -N radld -N slope -N soilph -N vrm10 -N vrm5 -N water1600 -N water300 -  
N water3200
```

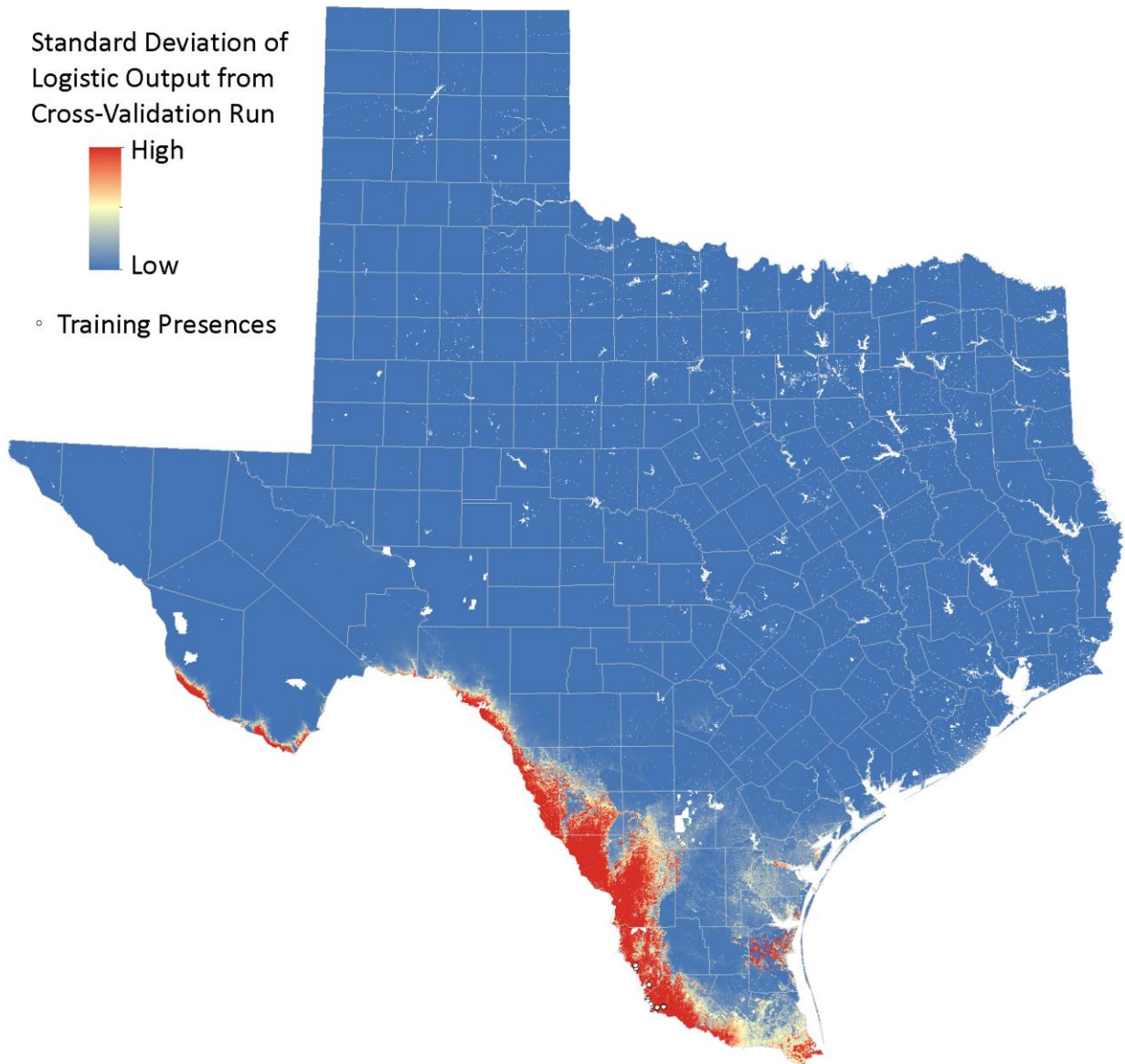
Zapata Bladderpod (*Physaria thamnophila*)

ELCODE: PDBRA1NM0

Date: August 13, 2013

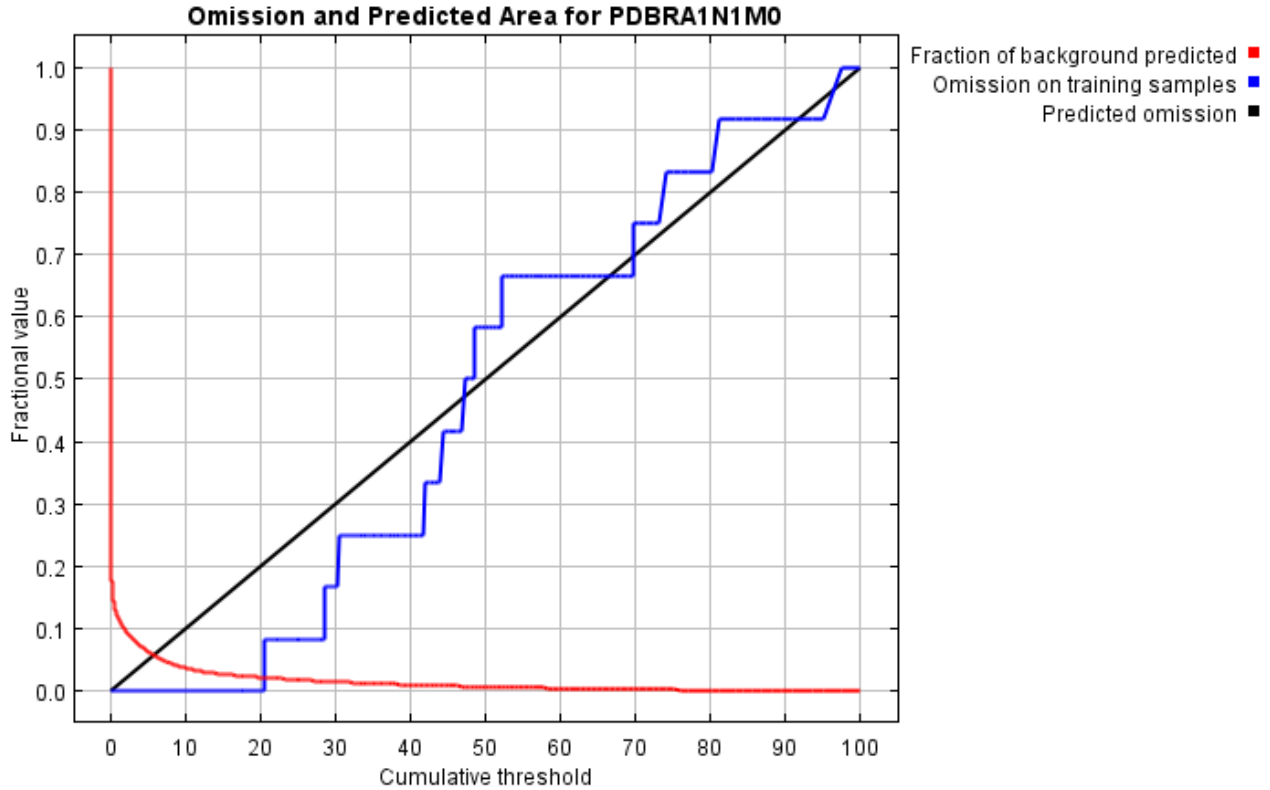
Maxent version: 3.3.3k





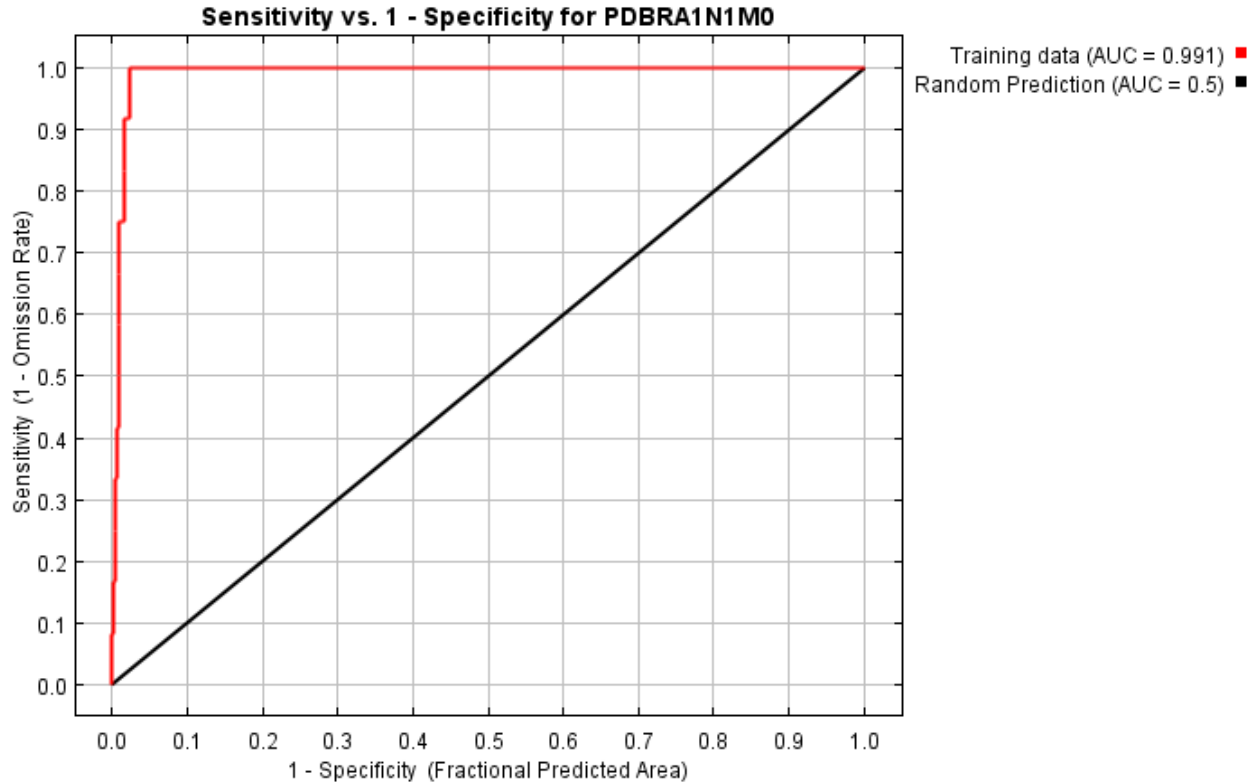
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.983 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

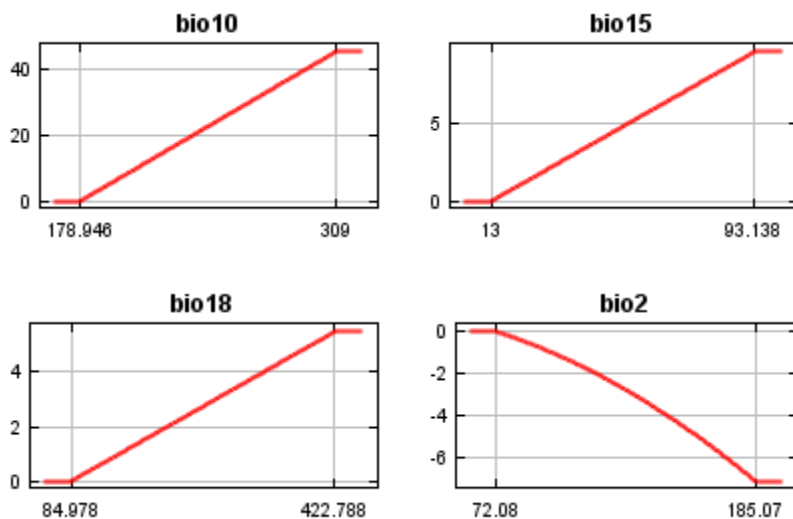
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.014	Fixed cumulative value 1	0.117	0.000
5.000	0.046	Fixed cumulative value 5	0.064	0.000
10.000	0.110	Fixed cumulative value 10	0.037	0.000
20.552	0.309	Minimum training presence	0.022	0.000
28.509	0.381	10 percentile training presence	0.016	0.083
20.552	0.309	Equal training sensitivity and specificity	0.022	0.000

Appendix 2 – Model Reports

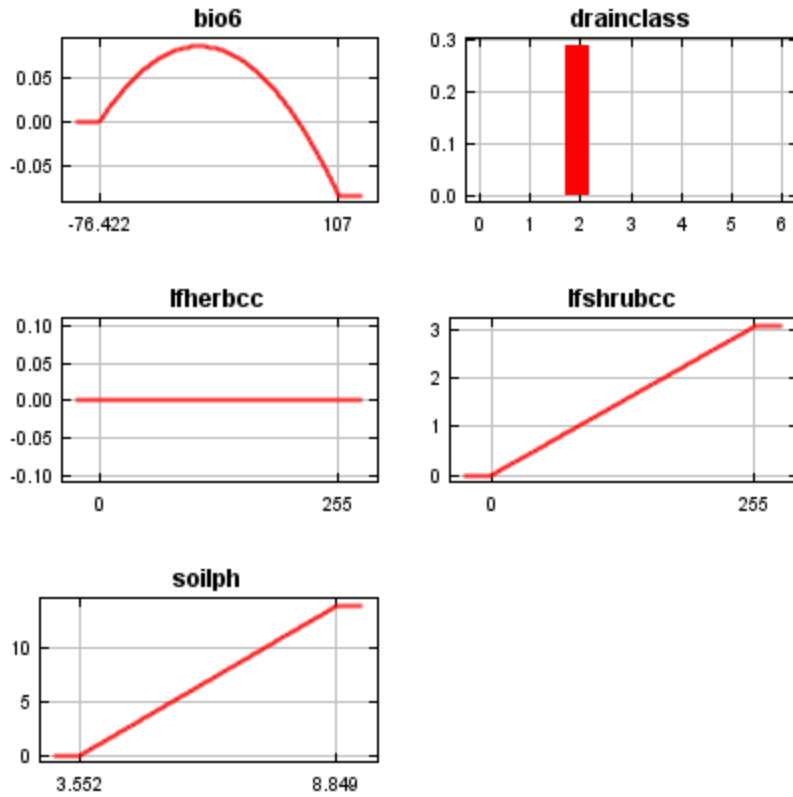
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
20.552	0.309	Maximum training sensitivity plus specificity	0.022	0.000
1.093	0.015	Balance training omission, predicted area and threshold value	0.115	0.000
9.771	0.105	Equate entropy of thresholded and original distributions	0.038	0.000

Response curves

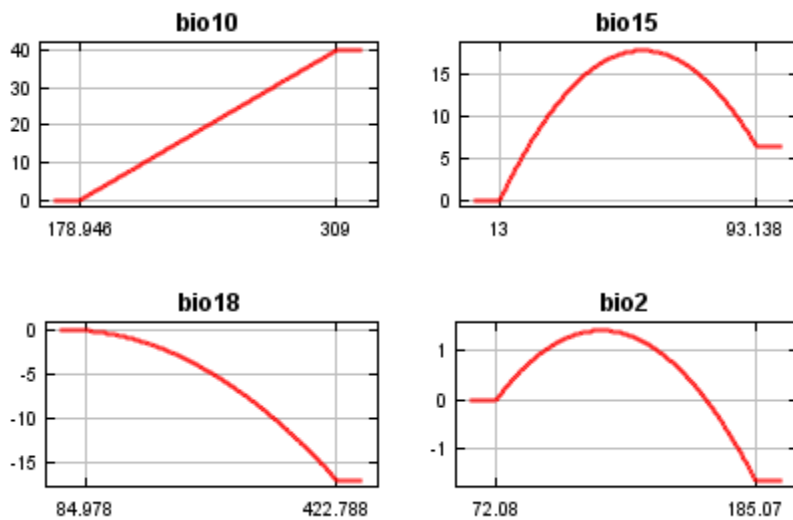
These curves show how each environmental variable affects the Maxent prediction. The (raw) Maxent model has the form $\exp(\dots)/\text{constant}$, and the curves show how the exponent changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



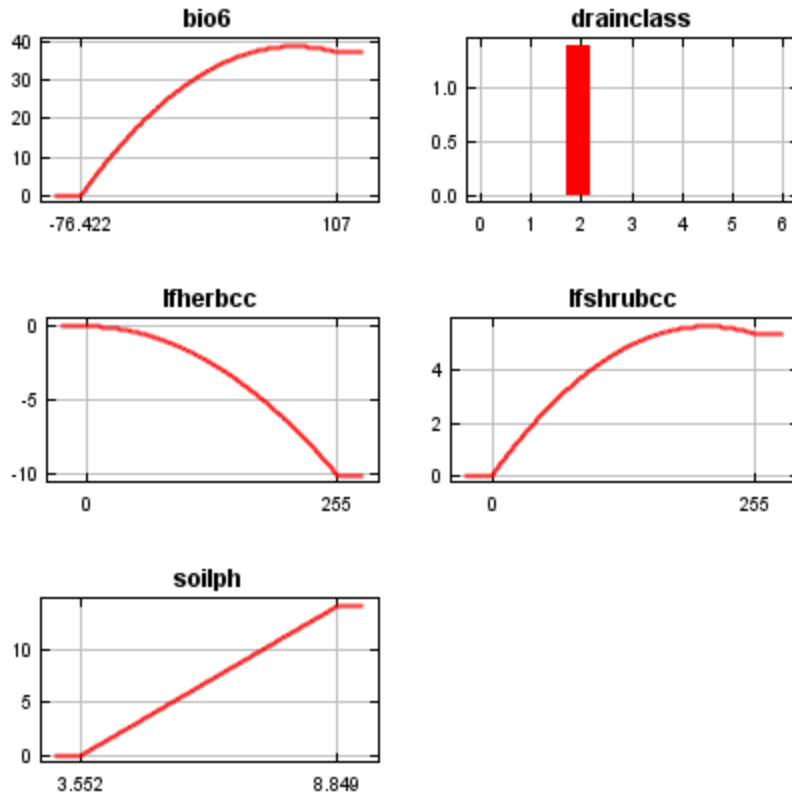
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



Analysis of variable contributions

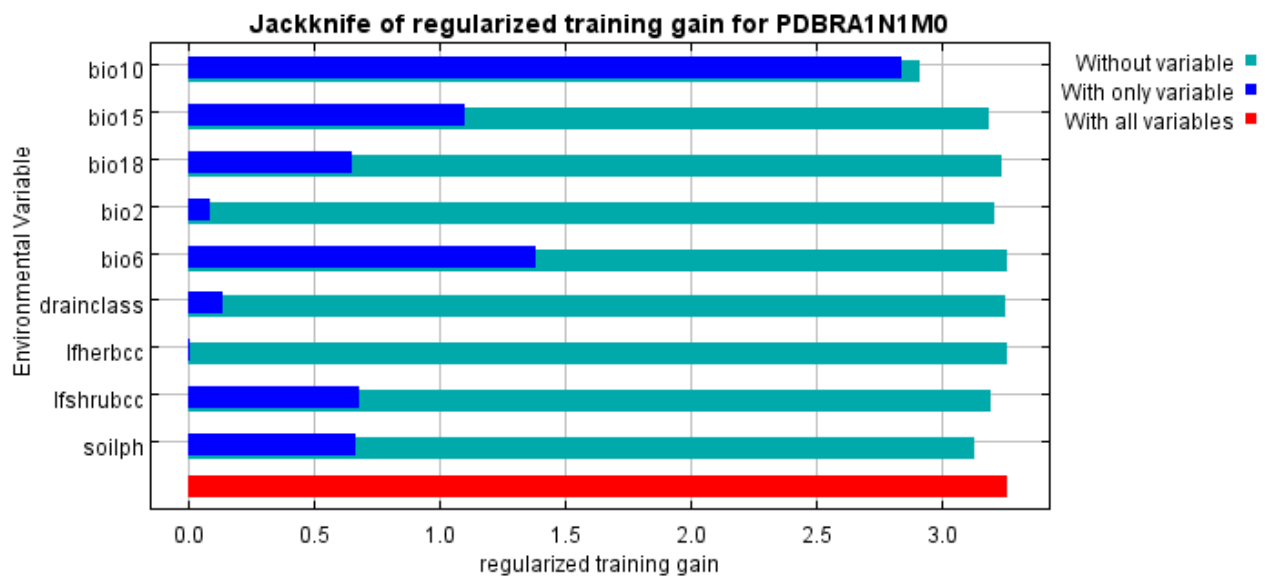
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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
bio10	70.5	70.3
bio6	10.3	0
lfshrubcc	7.3	0.3
soilph	5	15.4

Appendix 2 – Model Reports

Variable	Percent contribution	Permutation importance
drainclass	3.7	0.2
bio2	1.5	3.6
bio15	1.2	8.5
bio18	0.3	1.6
lfherbcc	0.2	0

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio10, 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 bio10, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 3.262, training AUC is 0.991, unregularized training gain is 3.575. Algorithm converged after 280 iterations (2 seconds).

The follow settings were used during the run:

12 presence records used for training.

7370 points used to determine the Maxent distribution (background points and presence points).

Environmental layers used: bio10 bio15 bio18 bio2 bio6 drainclass(categorical) lfherbcc lfshrubcc

Appendix 2 – Model Reports

soilph

Regularization values: linear/quadratic/product: 0.714, categorical: 0.429, threshold: 1.880, hinge: 0.500

Feature types used: linear quadratic

responsecurves: true

pictures: false

jackknife: true

outputfiletype: bil

outputdirectory: F:\MAXENT_OUT\PDBRA1N1MO\RUN_5

projectionlayers: F:\MAXENT_IN\PROB

samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV

environmentallayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV

writeclampgrid: false

writemess: false

writebackgroundpredictions: true

responsecurvesexponent: true

writeplotdata: true

Command line used: dontwriteclampgrid

Command line to repeat this species model:

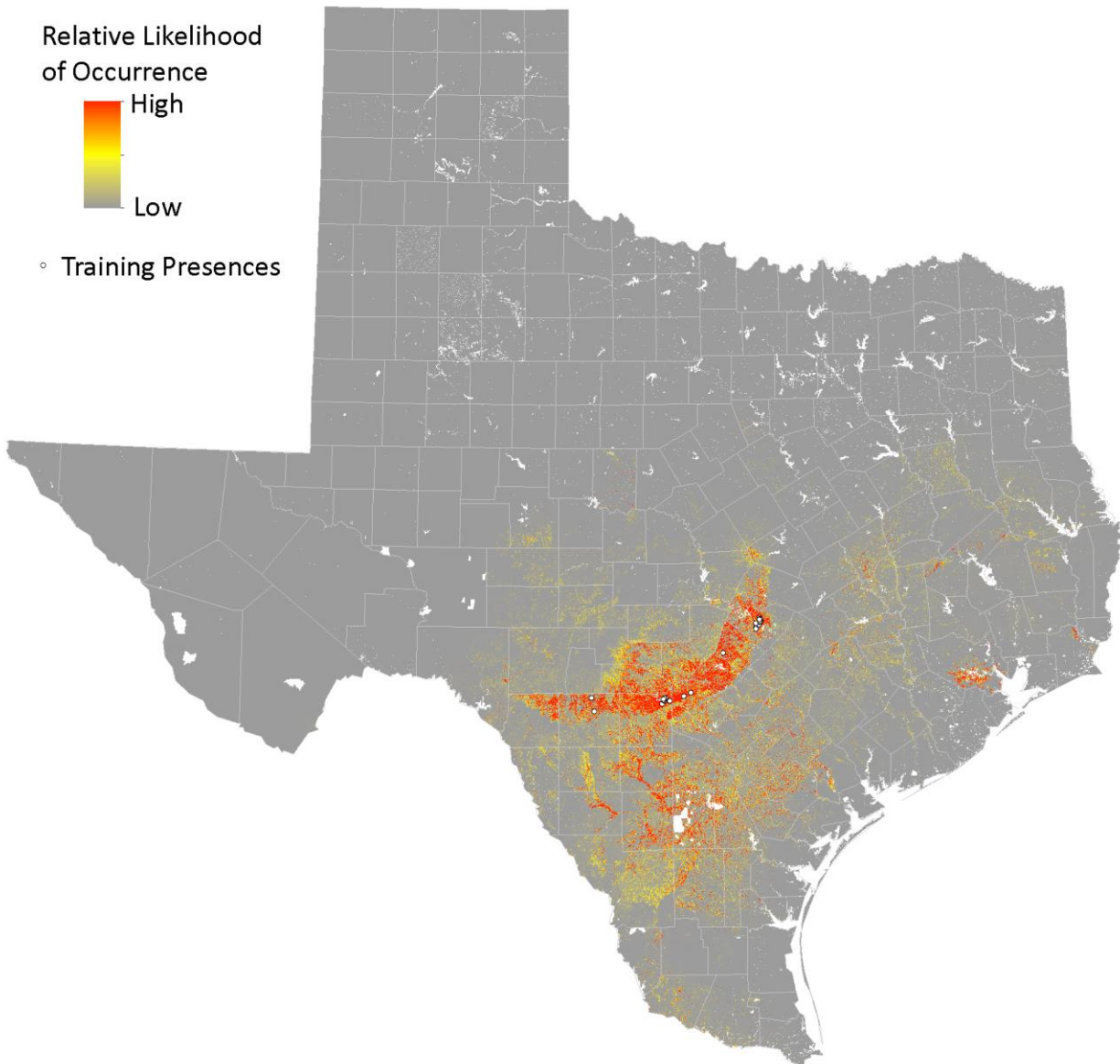
```
java density.MaxEnt nowarnings noprefixes -E "" -E PDBRA1N1M0 responsecurves nopictures
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\PDBRA1N1MO\RUN_5
projectionlayers=F:\MAXENT_IN\PROB
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid
nowritemess writebackgroundpredictions responsecurvesexponent writeplotdata -N UNIQUE_ID -
N aglands -N allwatdist -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N
avoid12800 -N avoid1600 -N avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14
-N bio16 -N bio17 -N bio19 -N bio3 -N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N
curve5 -N d2foredge -N d2wsl -N dissect10 -N dissect5 -N hydgroup -N ksats -N lf_evh -N lf_forstcc -
N ned -N nlcdcanopy -N percclay -N percsand -N percsilt -N radld -N slope -N soilec -N vrm10 -N
vrm5 -N water1600 -N water300 -N water3200 -t drainclass
```

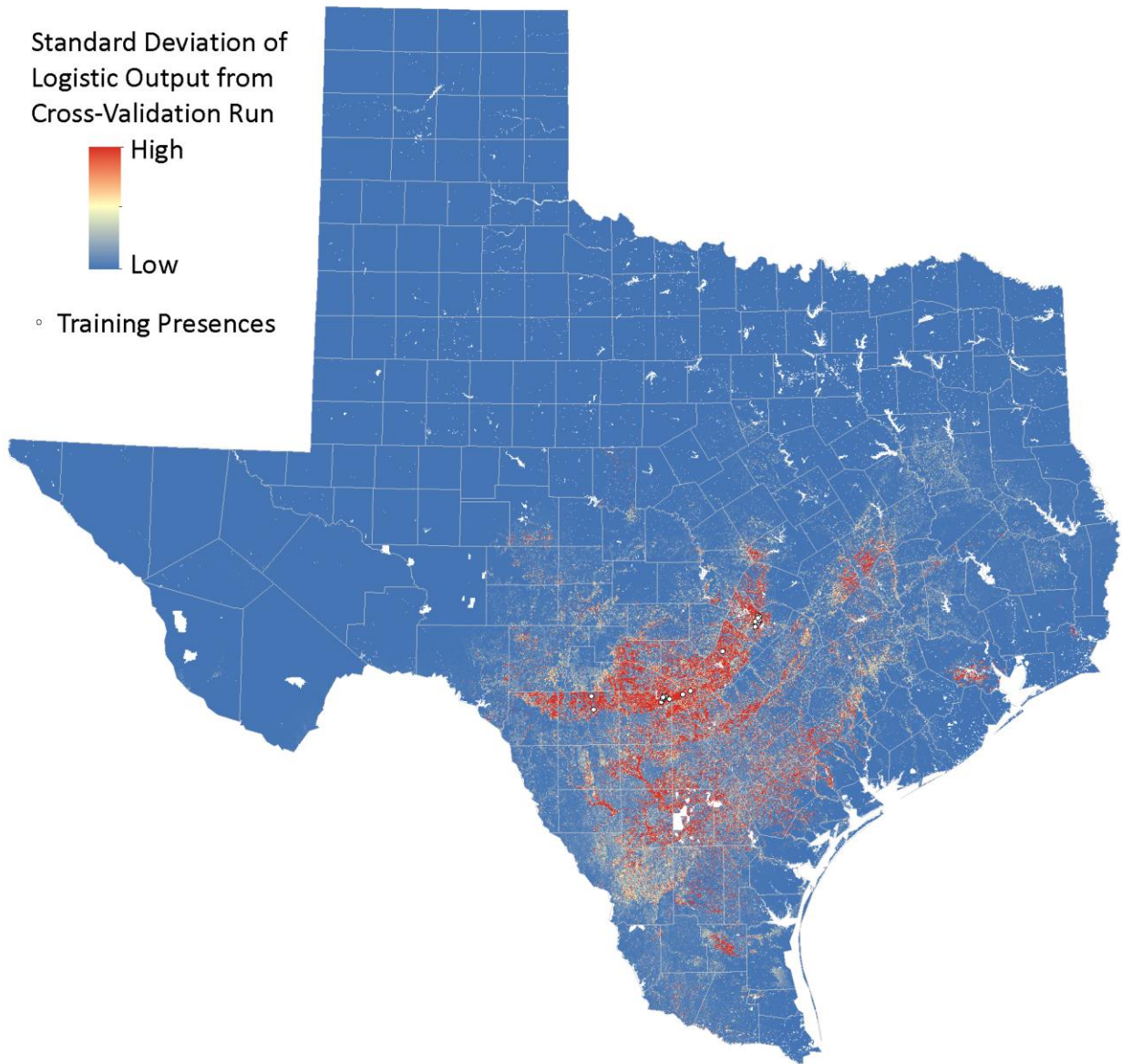
Bracted Twistflower (*Streptanthus bracteatus*)

ELCODE: PDBRA2G080

Date: August 13, 2013

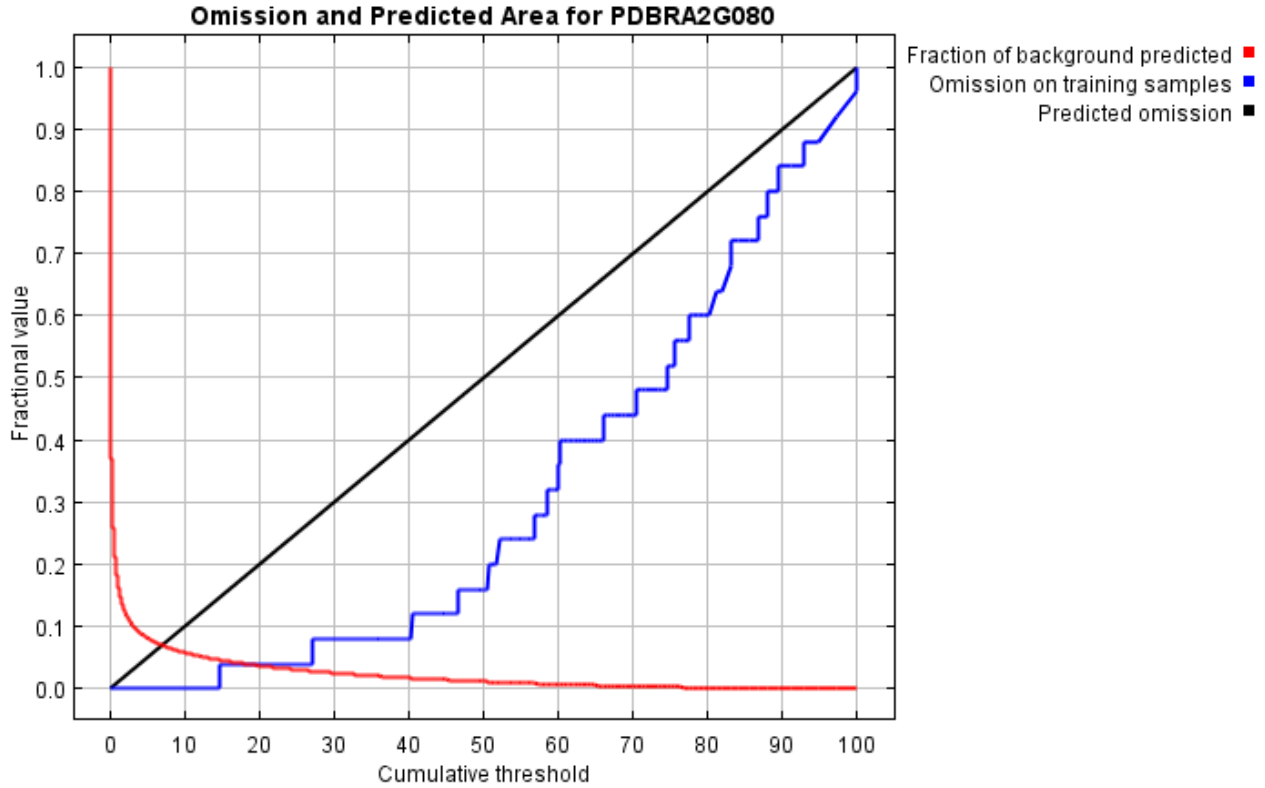
Maxent version: 3.3.3k





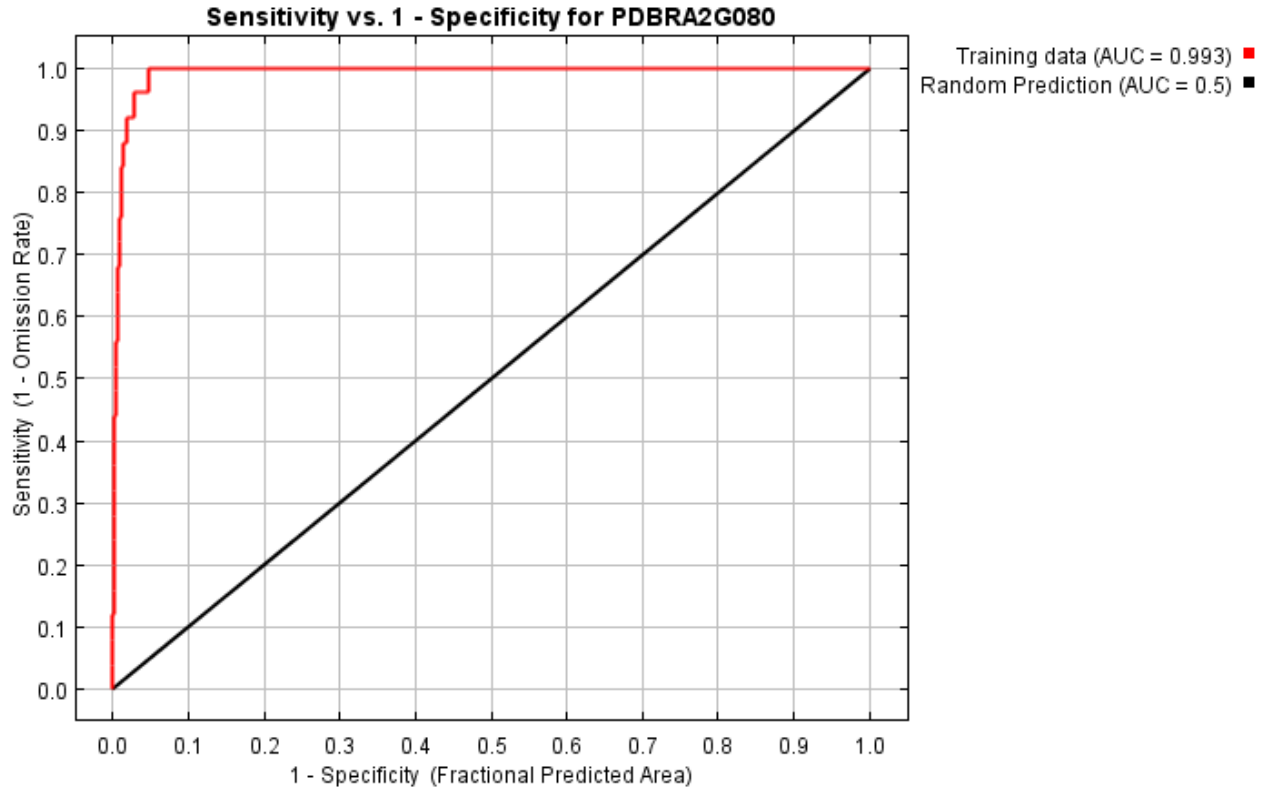
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.973 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

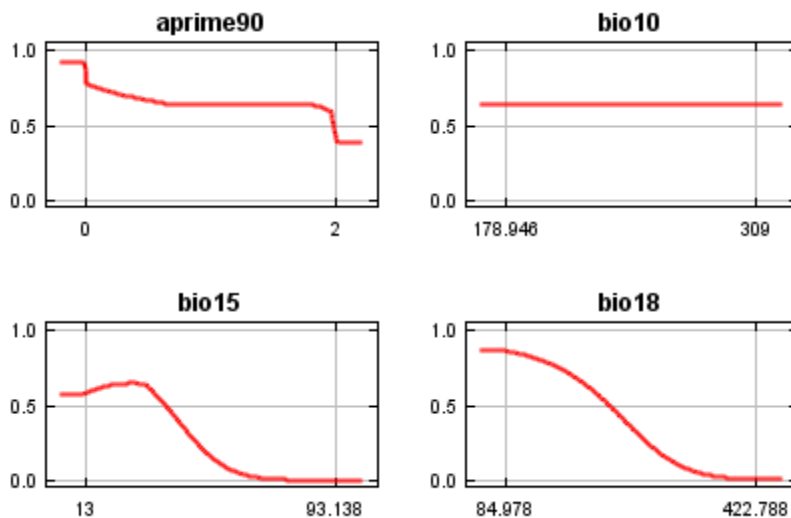
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.007	Fixed cumulative value 1	0.169	0.000
5.000	0.071	Fixed cumulative value 5	0.082	0.000
10.000	0.152	Fixed cumulative value 10	0.058	0.000
14.597	0.210	Minimum training presence	0.046	0.000
40.173	0.458	10 percentile training presence	0.017	0.080

Appendix 2 – Model Reports

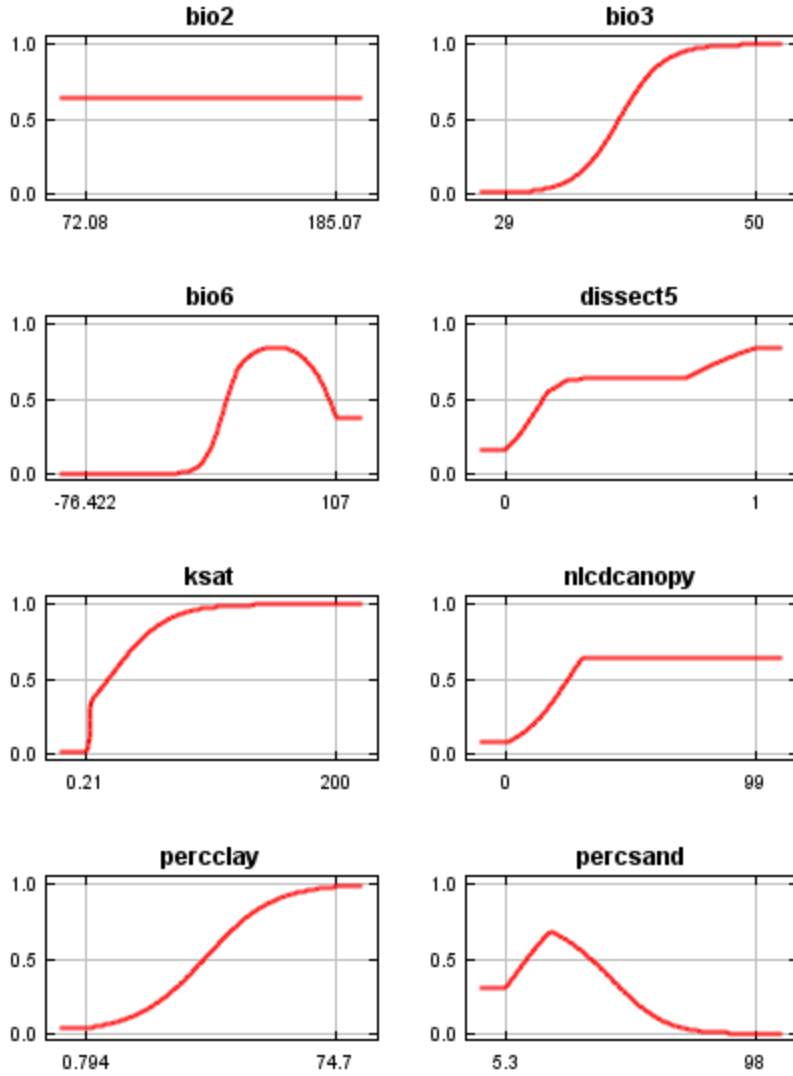
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
18.296	0.256	Equal training sensitivity and specificity	0.040	0.040
14.597	0.210	Maximum training sensitivity plus specificity	0.046	0.000
2.055	0.022	Balance training omission, predicted area and threshold value	0.120	0.000
10.890	0.160	Equate entropy of thresholded and original distributions	0.056	0.000

Response curves

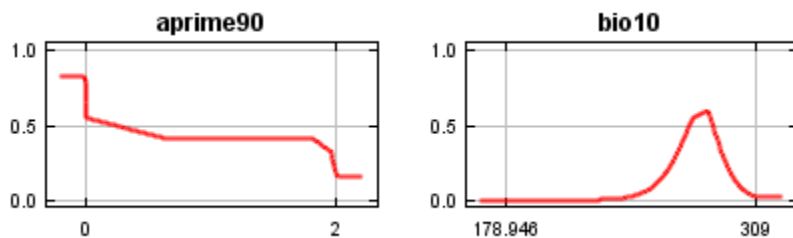
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



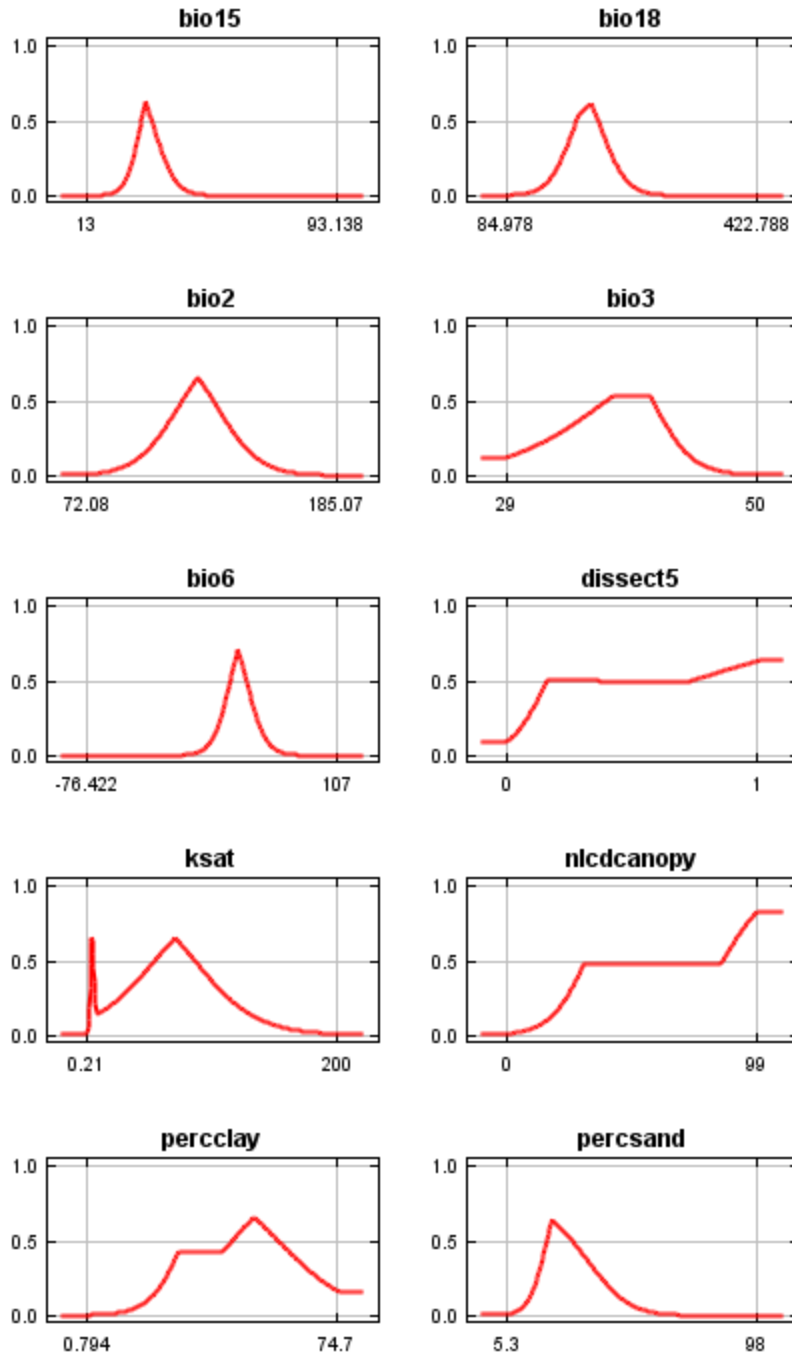
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



Analysis of variable contributions

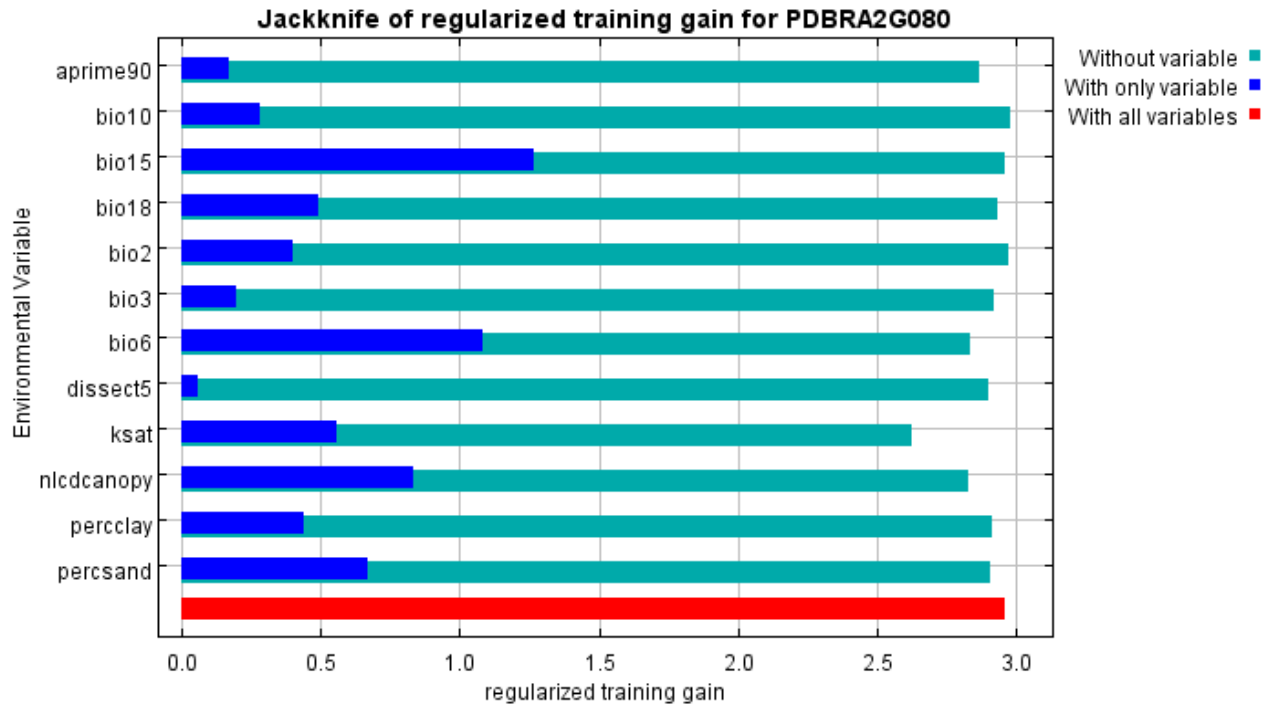
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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

Appendix 2 – Model Reports

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
nlcdcanopy	30.1	5
bio6	16.9	33.2
bio15	14.5	9.1
percclay	12.7	3.9
ksat	11.9	24.5
percsand	4.6	13.4
dissect5	3.7	1.7
bio3	2.8	5.3
aprime90	2.5	0.7
bio18	0.4	3
bio2	0	0
bio10	0	0

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio15, 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 ksat, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 2.959, training AUC is 0.993, unregularized training gain is 3.644. Algorithm terminated after 500 iterations (31 seconds).

The follow settings were used during the run:

25 presence records used for training.
 7362 points used to determine the Maxent distribution (background points and presence points).
 Environmental layers used (all continuous): aprime90 bio10 bio15 bio18 bio2 bio3 bio6 dissect5 ksat nlcdcanopy perclay persand
 Regularization values: linear/quadratic/product: 0.346, categorical: 0.250, threshold: 1.750, hinge: 0.500
 Feature types used: linear quadratic hinge
 responsecurves: true
 pictures: false
 jackknife: true
 outputfiletype: bil
 outputdirectory: F:\MAXENT_OUT\PDBRA2G080\RUN_4
 projectionlayers: F:\MAXENT_IN\PROB
 samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
 environmentalayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV
 writeclampgrid: false
 writemess: false
 writebackgroundpredictions: true
 writeplotdata: true

Appendix 2 – Model Reports

Command line used: dontwriteclampgrid

Command line to repeat this species model:

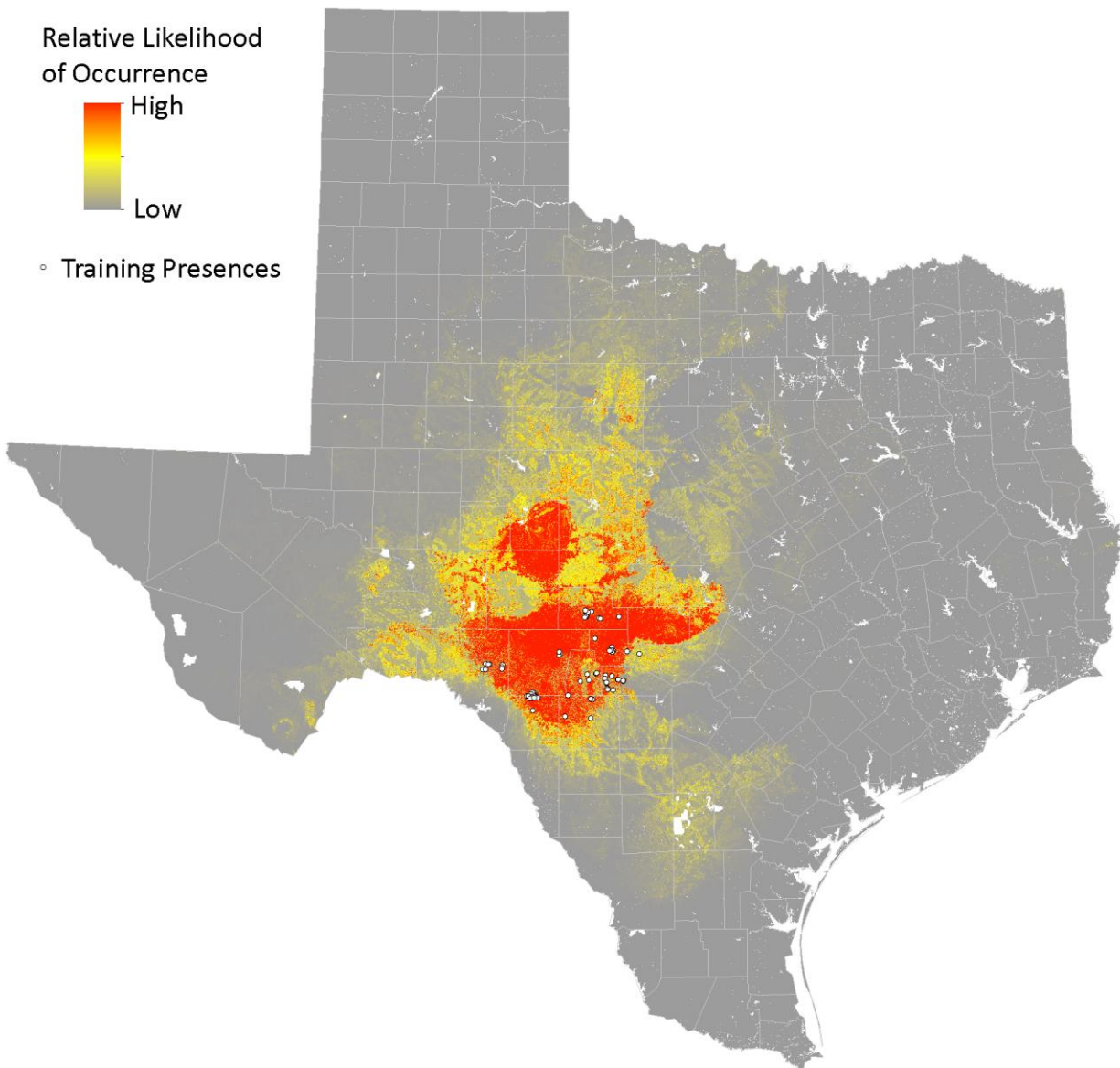
```
java density.MaxEnt nowarnings noprefixes -E "" -E PDBRA2G080 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\PDBRA2G080\RUN_4  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -N aglands -N allwatdist -N  
aprime135 -N aprime180 -N aprime45 -N avoid -N avoid12800 -N avoid1600 -N avoid3200 -N  
avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio19 -N bio4 -N bio5  
-N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N d2wsl -N dissect10 -N  
drainclass -N hydgroup -N lf_evh -N lf_forstcc -N lfherbcc -N lfshrubcc -N ned -N percstilt -N radld -N  
slope -N soilec -N soilph -N vrm10 -N vrm5 -N water1600 -N water300 -N water3200
```

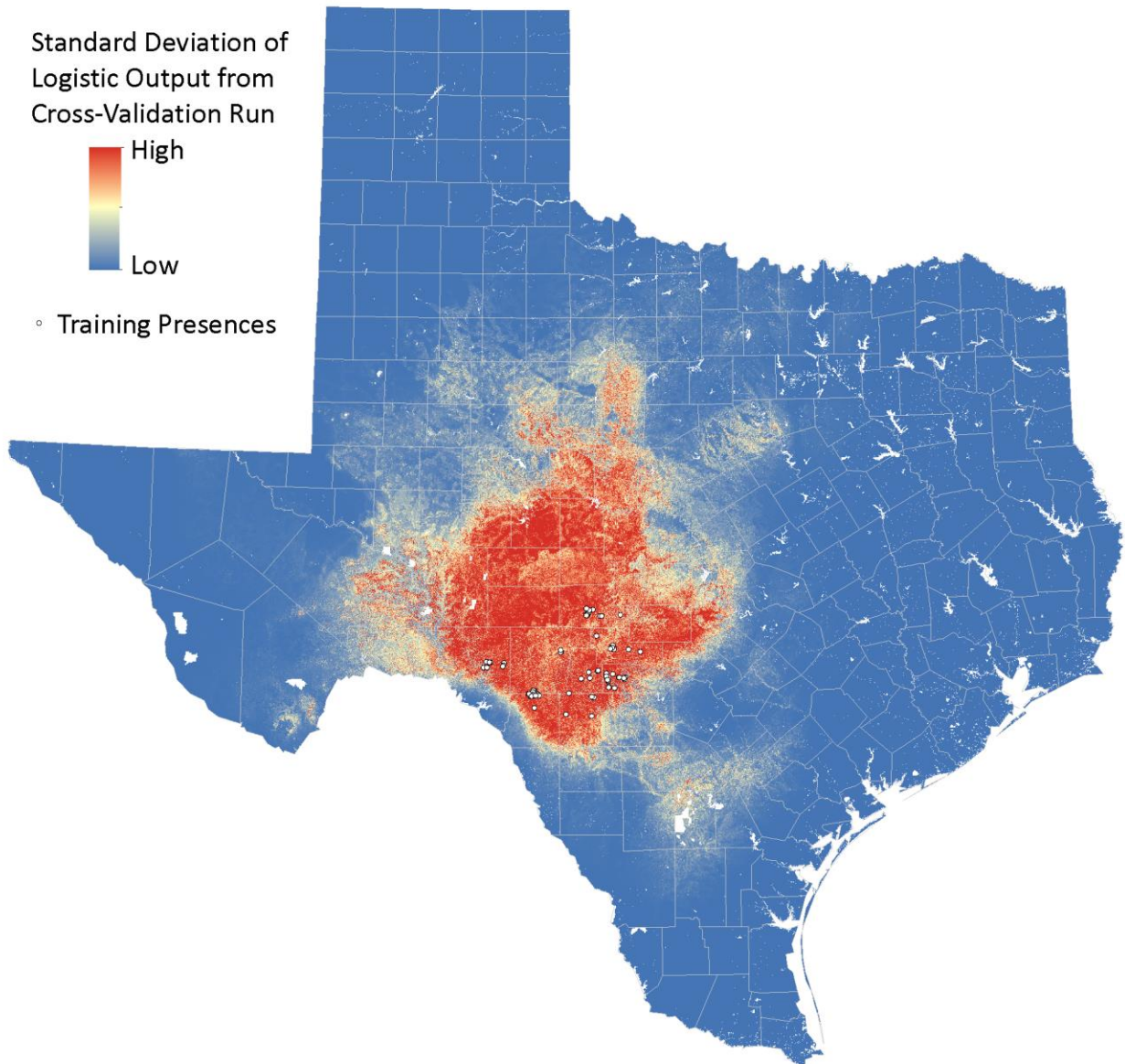
Tobusch Fishhook Cactus (*Sclerocactus brevihamatus* ssp. *tobuschii*)

ELCODE: PDCAC0J0S1

Date: August 15, 2013

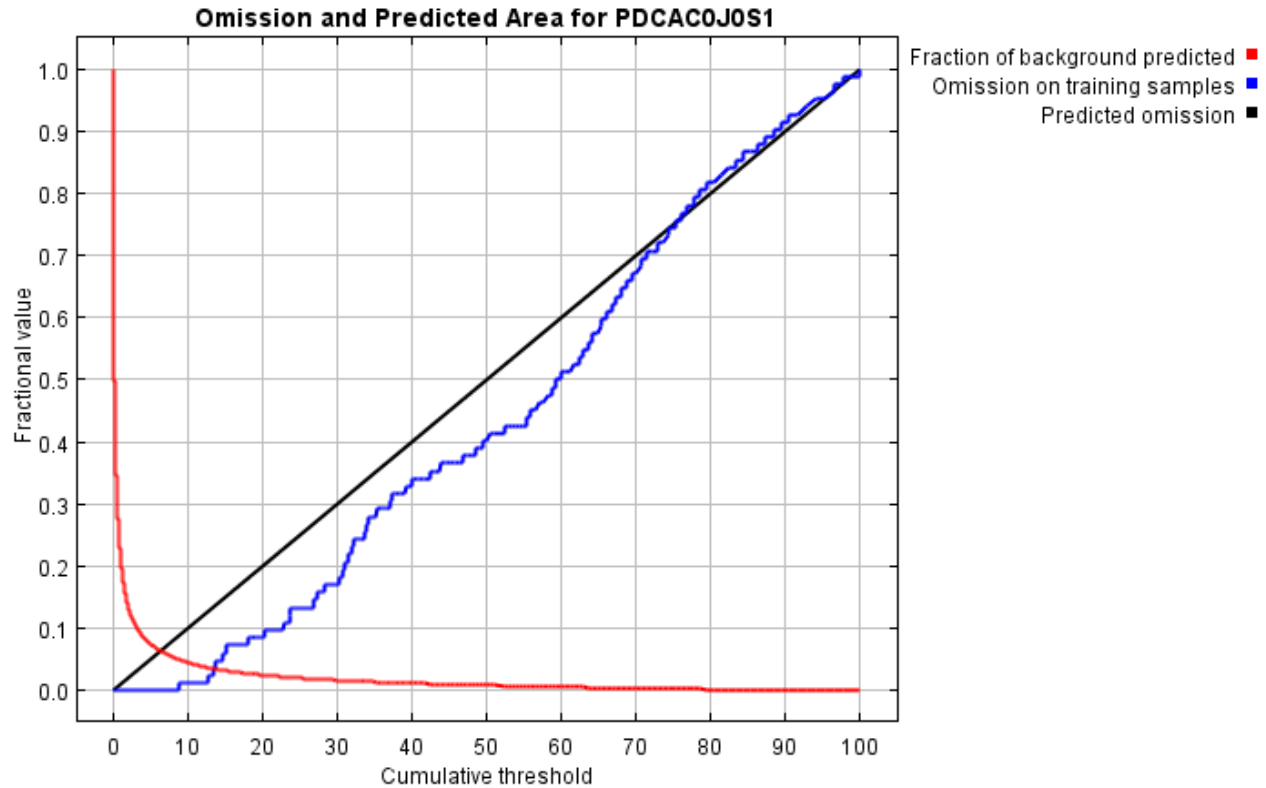
Maxent version: 3.3.3k





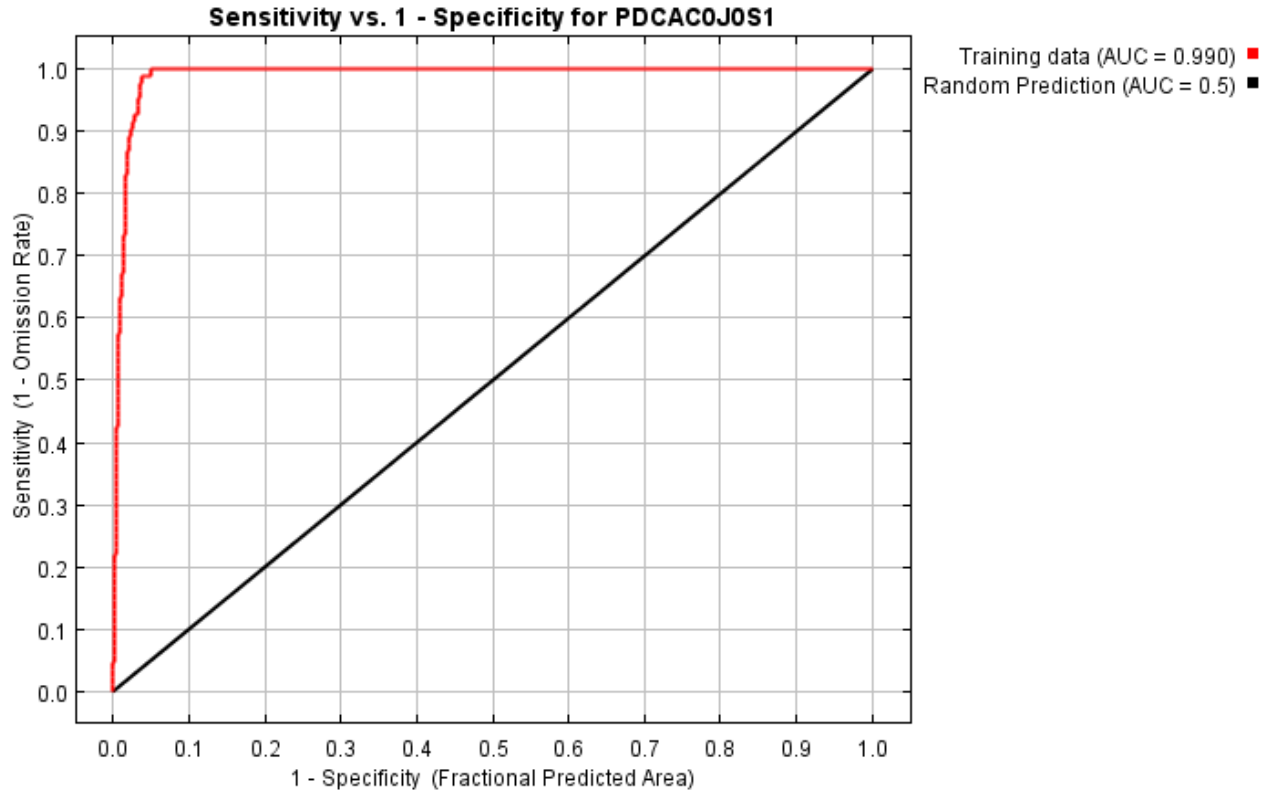
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.976 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

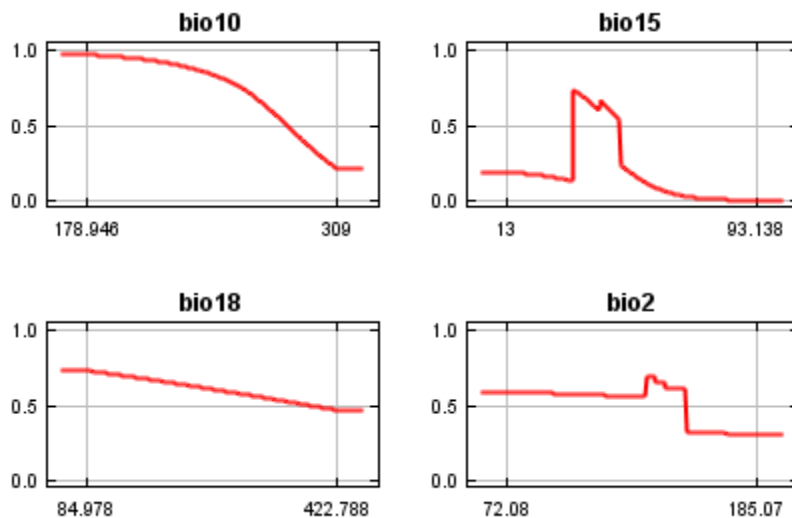
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.004	Fixed cumulative value 1	0.209	0.000
5.000	0.045	Fixed cumulative value 5	0.075	0.000
10.000	0.114	Fixed cumulative value 10	0.045	0.012
8.836	0.091	Minimum training presence	0.050	0.000
22.773	0.316	10 percentile training presence	0.022	0.098

Appendix 2 – Model Reports

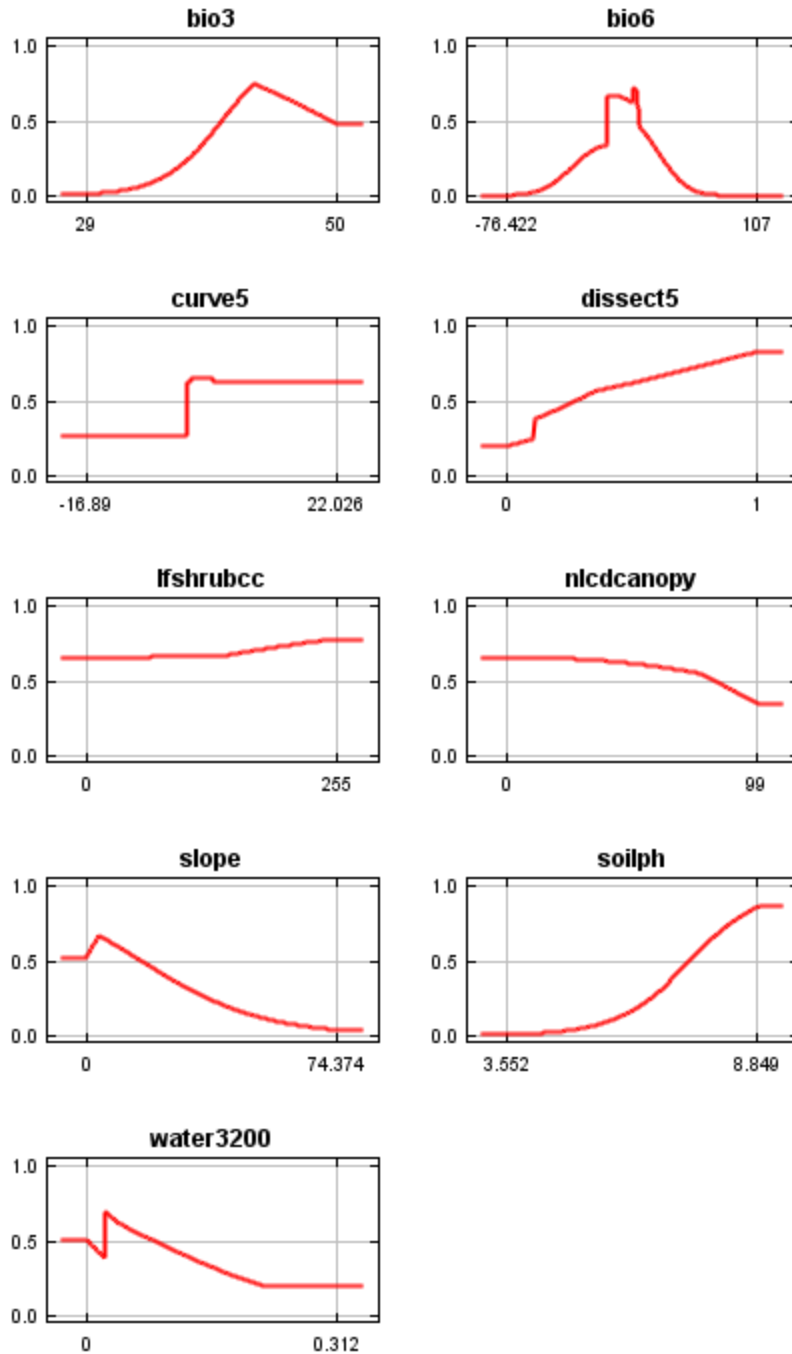
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
13.354	0.174	Equal training sensitivity and specificity	0.036	0.037
12.770	0.162	Maximum training sensitivity plus specificity	0.037	0.012
2.768	0.018	Balance training omission, predicted area and threshold value	0.109	0.000
9.709	0.108	Equate entropy of thresholded and original distributions	0.046	0.012

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. 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. See Appendix 1 for detailed explanations of all environmental predictor layers.

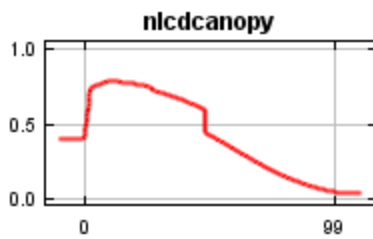
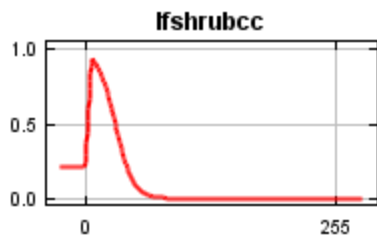
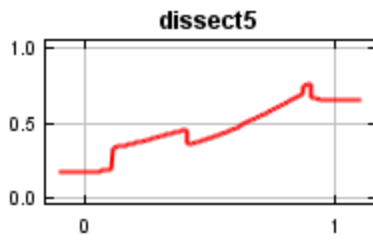
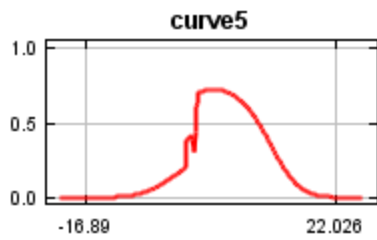
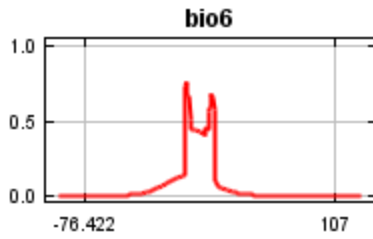
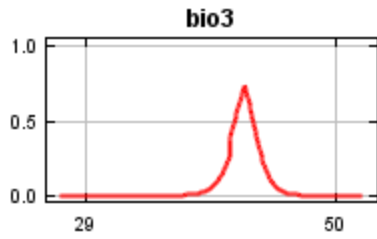
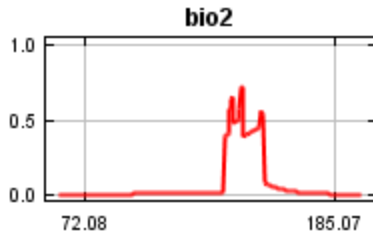
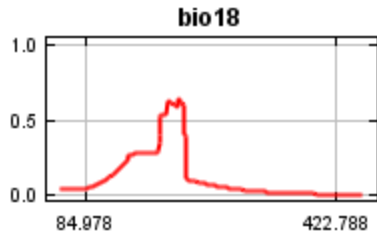
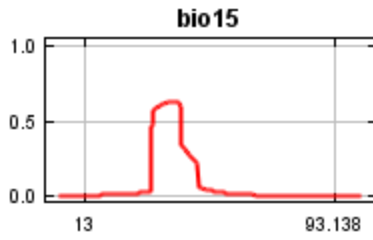
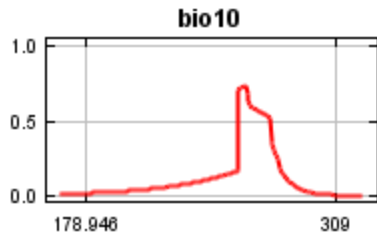


Appendix 2 – Model Reports

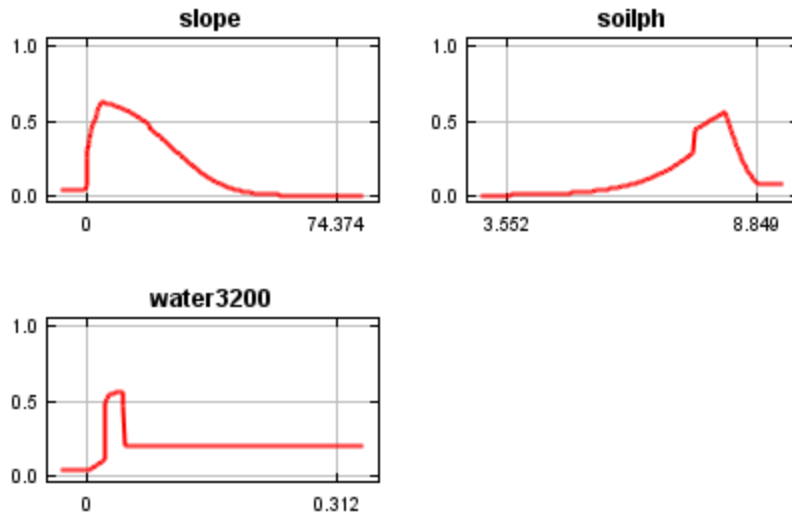


In contrast to the above marginal response curves, each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by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

Appendix 2 – Model Reports



Appendix 2 – Model Reports



Analysis of variable contributions

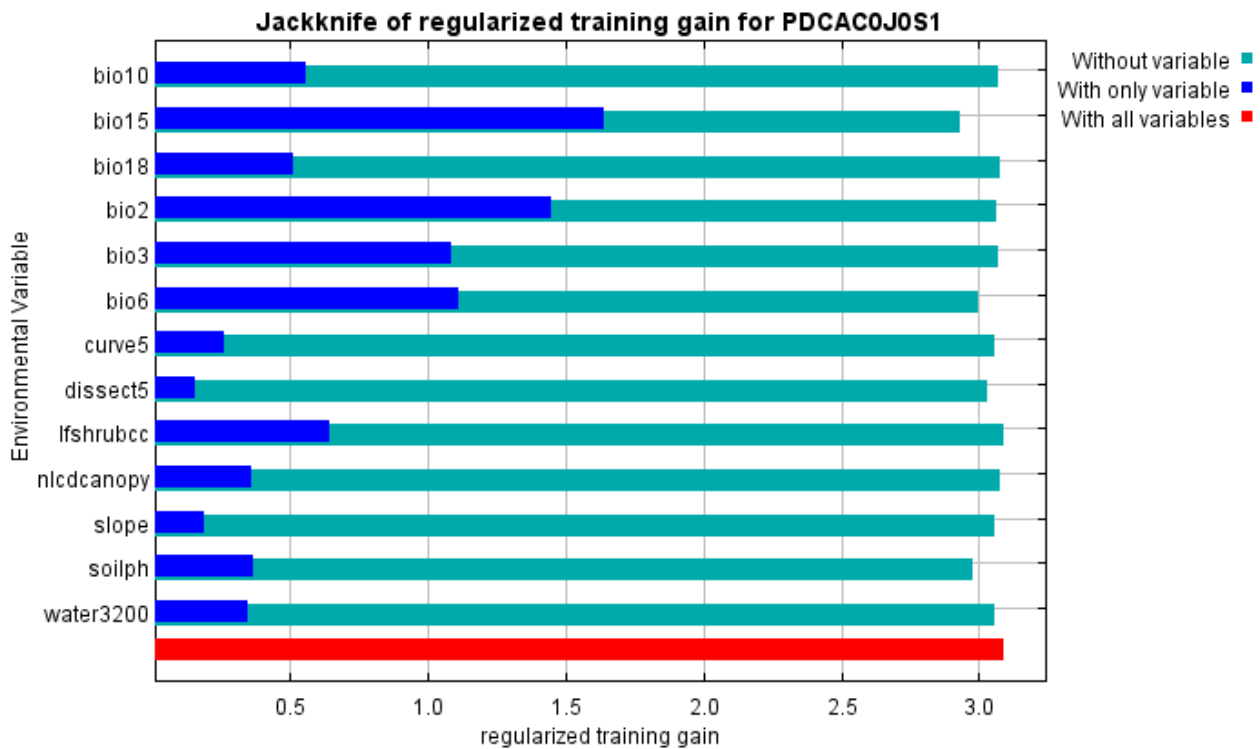
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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
bio15	39.4	22.3
bio2	21.4	1.8
bio6	11.9	47.5
curve5	7.5	1.1
water3200	6	1.3
soilph	5.6	14.2
dissect5	3.5	4.7
bio10	2.3	2

Appendix 2 – Model Reports

Variable	Percent contribution	Permutation importance
nlcdcanopy	1.3	0.5
slope	0.7	1
bio3	0.3	2.8
bio18	0.1	0.7
lfshrubcc	0	0.1

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio15, 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 bio15, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 3.091, training AUC is 0.990, unregularized training gain is 3.462. Algorithm terminated after 500 iterations (41 seconds).

Appendix 2 – Model Reports

The follow settings were used during the run:

82 presence records used for training.

7445 points used to determine the Maxent distribution (background points and presence points).

Environmental layers used (all continuous): bio10 bio15 bio18 bio2 bio3 bio6 curve5 dissect5

lfshrubcc nlcdcanopy slope soilph water3200

Regularization values: linear/quadratic/product: 0.179, categorical: 0.250, threshold: 1.180, hinge: 0.500

Feature types used: product linear quadratic hinge threshold

responsecurves: true

pictures: false

jackknife: true

outputfiletype: bil

outputdirectory: F:\MAXENT_OUT\PDCAC0J0S1\RUN_5

projectionlayers: F:\MAXENT_IN\PROB

samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV

environmentallayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV

writeclampgrid: false

Command line used: dontwriteclampgrid

Command line to repeat this species model:

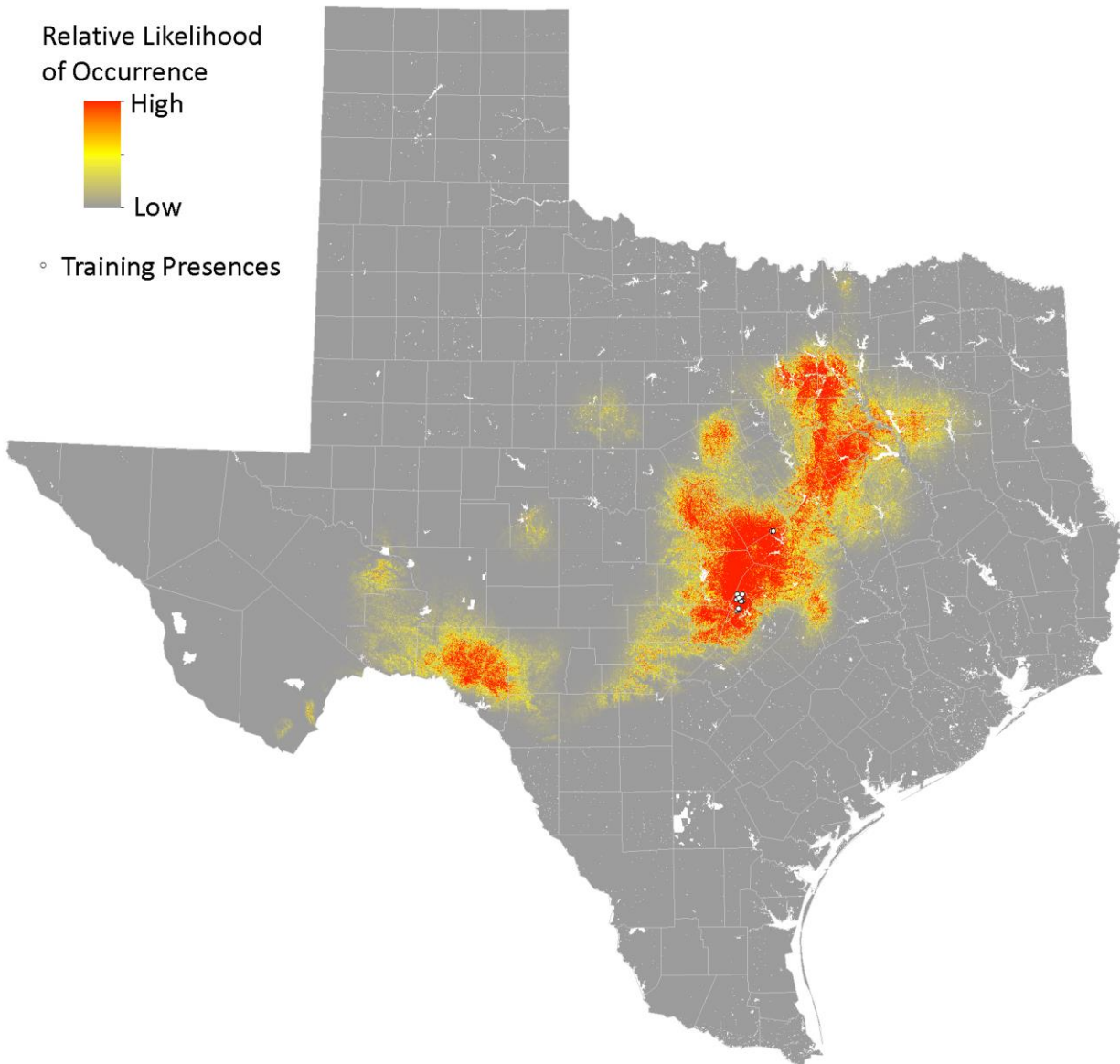
```
java density.MaxEnt nowarnings noprefixes -E "" -E PDCAC0J0S1 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\PDCAC0J0S1\RUN_5  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
-N UNIQUE_ID -N aglands -N allwatdist -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N  
avoid -N avoid12800 -N avoid1600 -N avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13  
-N bio14 -N bio16 -N bio17 -N bio19 -N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N  
d2foredge -N d2wsl -N dissect10 -N drainclass -N hydgroup -N ksats -N lf_evh -N lf_forstcc -N  
lfherbcc -N ned -N percclay -N percсанд -N percсilt -N radld -N soilec -N vrm10 -N vrm5 -N  
water1600 -N water300
```

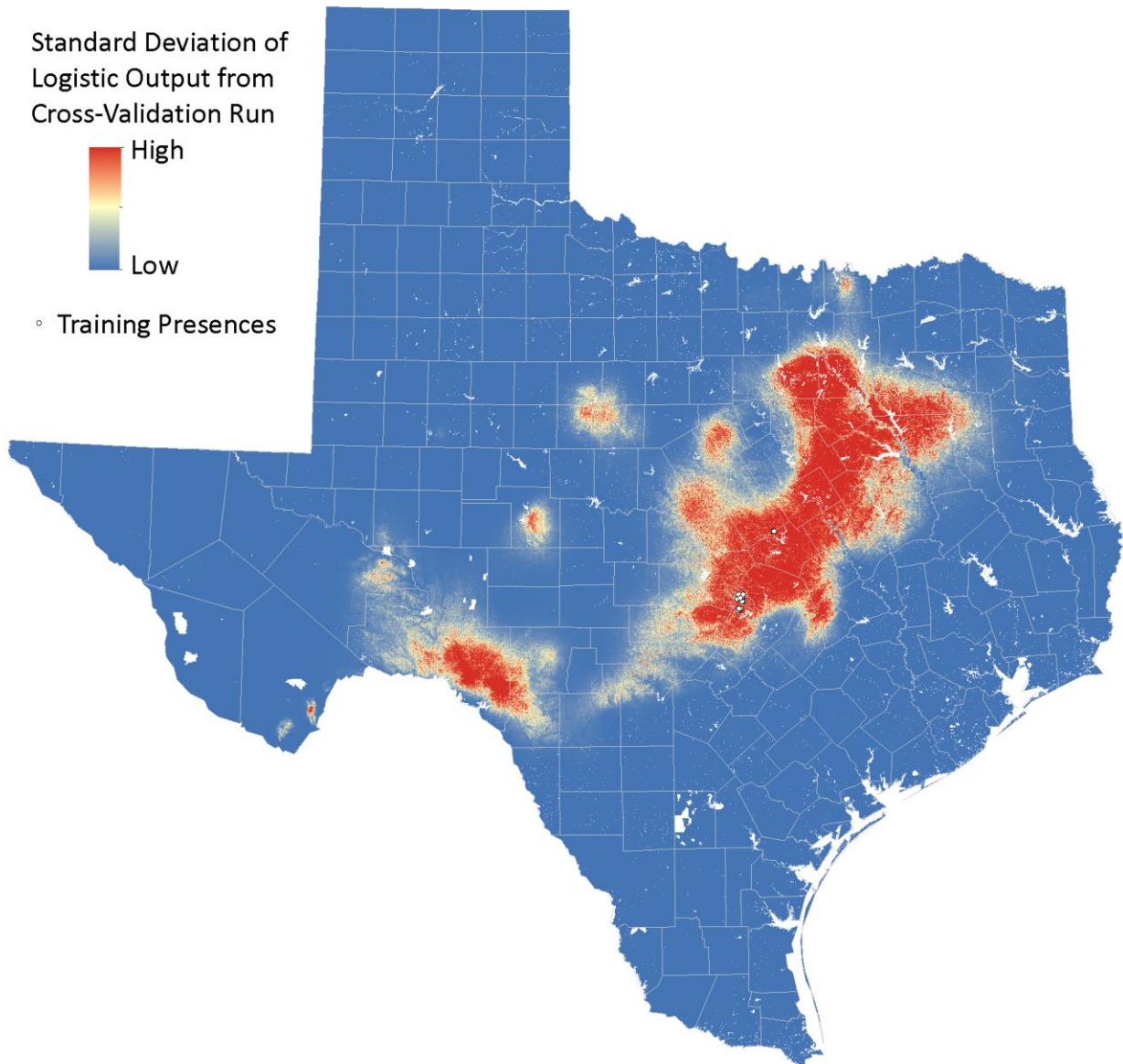
Texabama Croton (*Croton alabamensis* var. *texensis*)

ELCODE: PDEUP0H011

Date: August 13, 2013

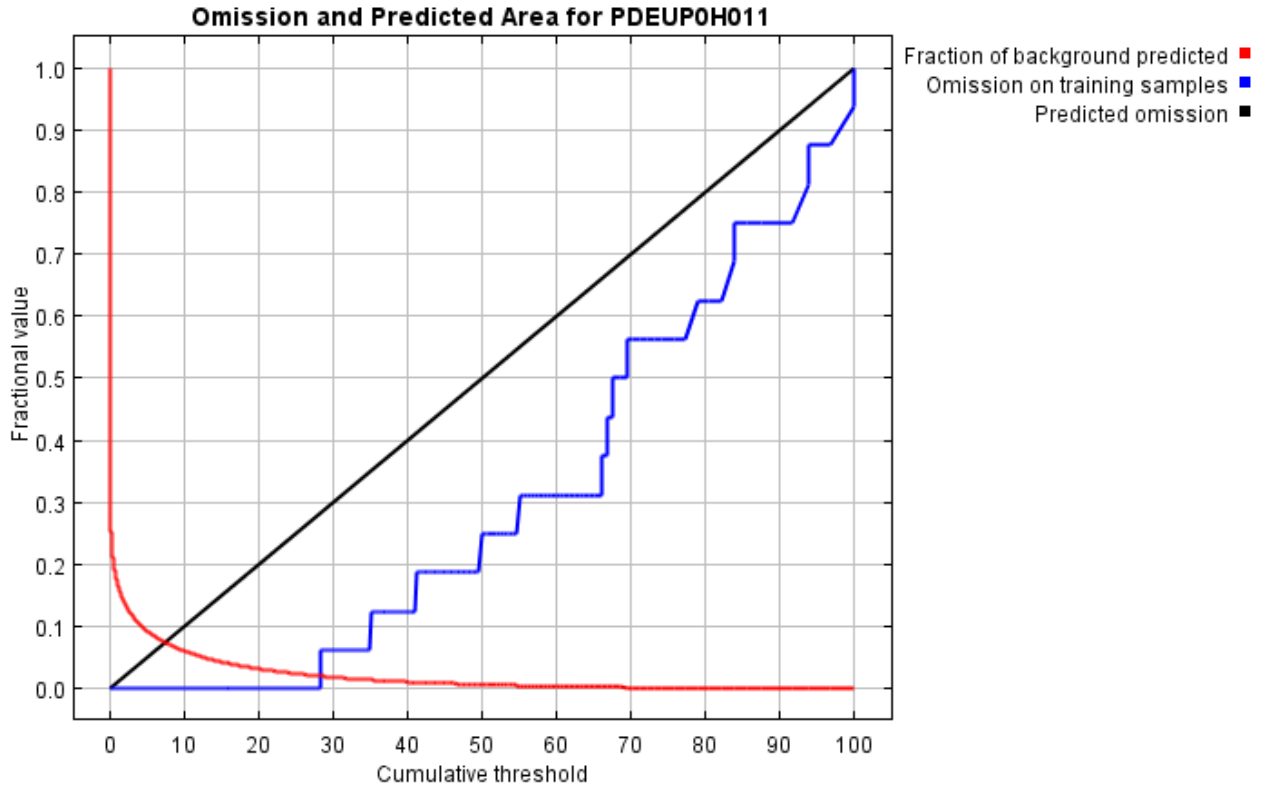
Maxent version: 3.3.3k





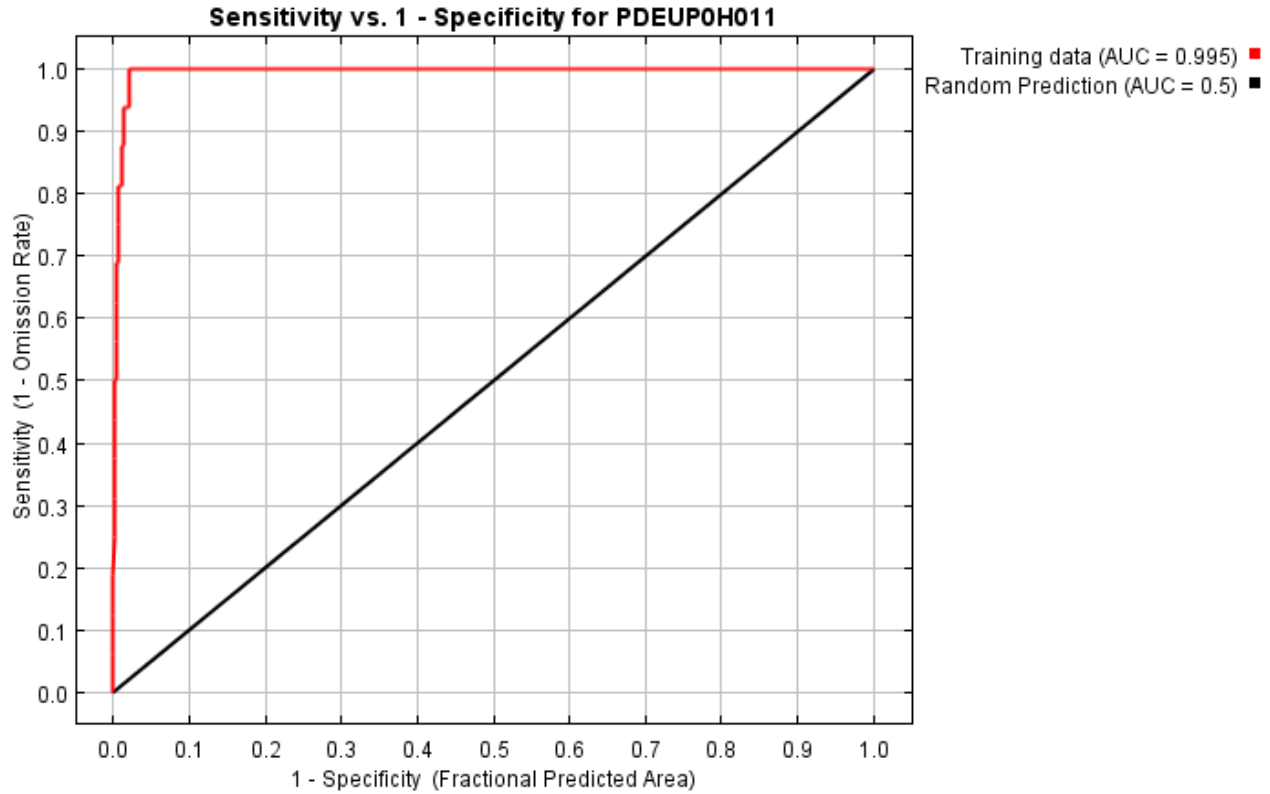
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.976 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

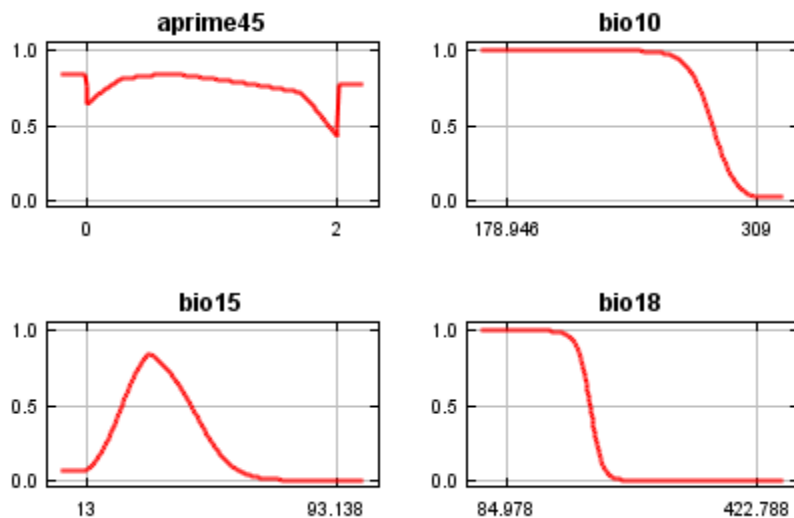
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.010	Fixed cumulative value 1	0.169	0.000
5.000	0.044	Fixed cumulative value 5	0.093	0.000
10.000	0.089	Fixed cumulative value 10	0.061	0.000
28.258	0.281	Minimum training presence	0.021	0.000
34.909	0.376	10 percentile training presence	0.015	0.062

Appendix 2 – Model Reports

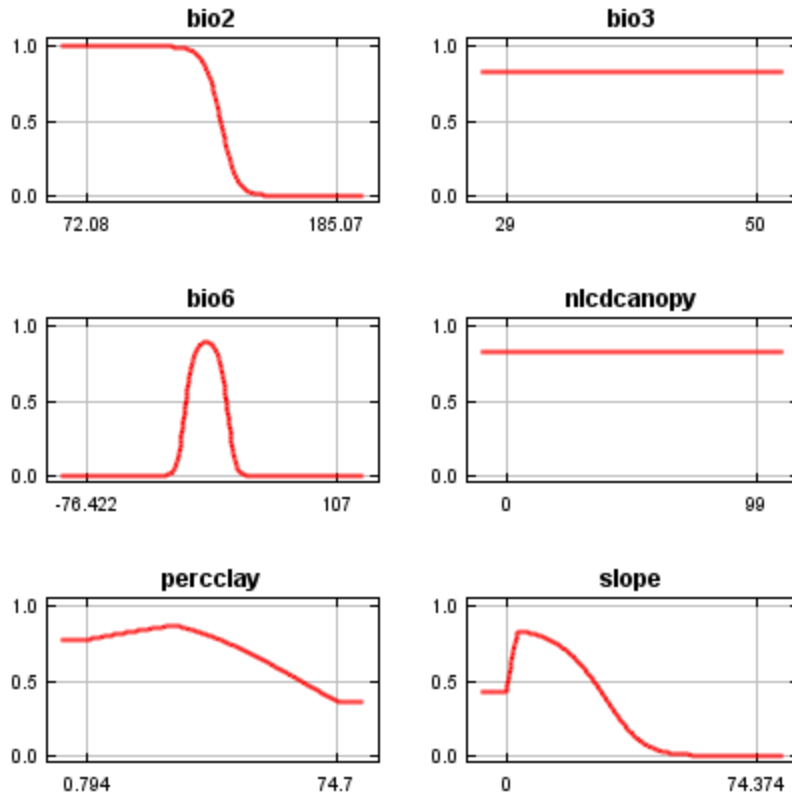
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
28.258	0.281	Equal training sensitivity and specificity	0.021	0.000
28.258	0.281	Maximum training sensitivity plus specificity	0.021	0.000
1.866	0.017	Balance training omission, predicted area and threshold value	0.141	0.000
14.655	0.135	Equate entropy of thresholded and original distributions	0.044	0.000

Response curves

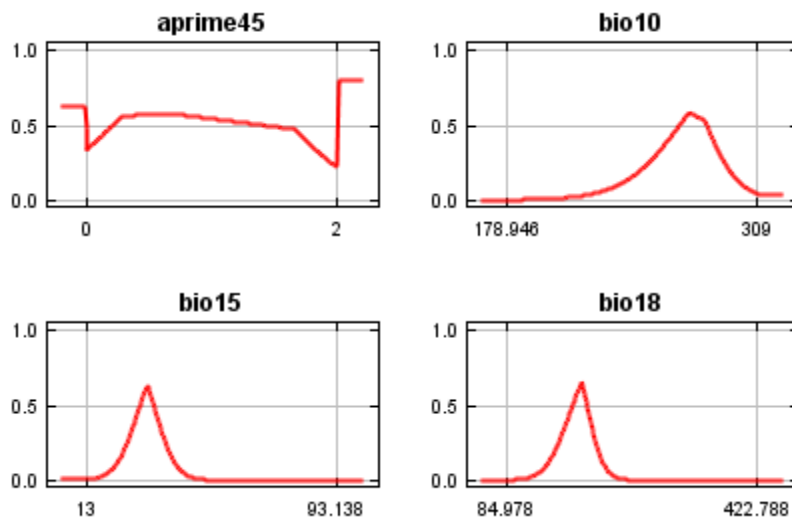
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



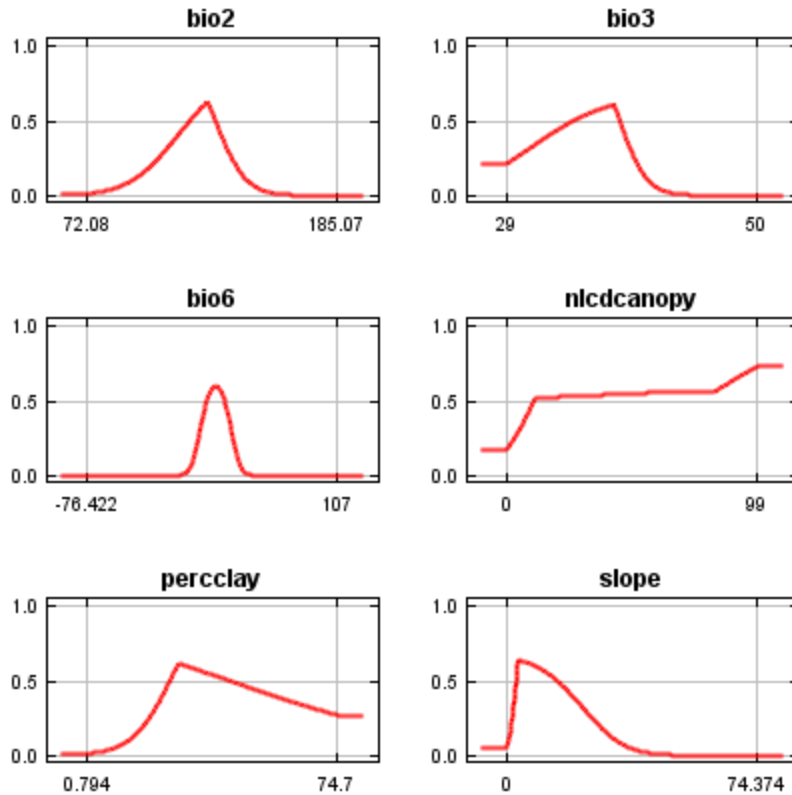
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



Analysis of variable contributions

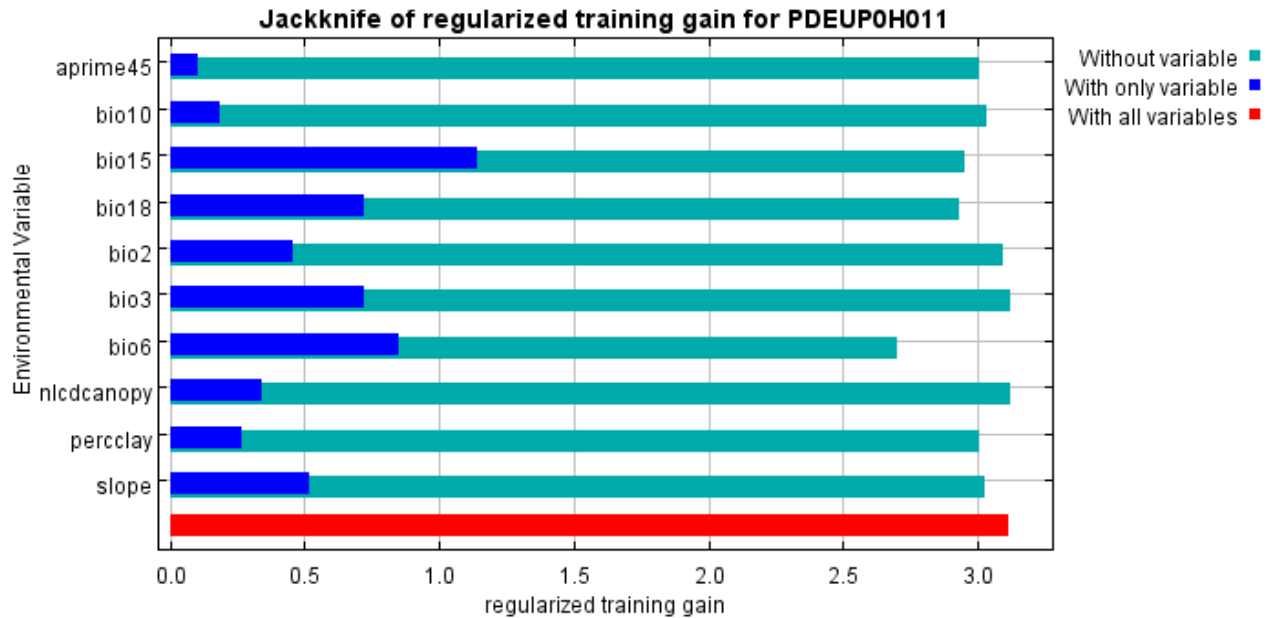
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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
bio3	24.6	0
bio6	22.3	44.2
slope	15.8	0.6
bio15	12.1	4.9

Appendix 2 – Model Reports

Variable	Percent contribution	Permutation importance
nlcdcanopy	6.6	0
bio2	5.4	18.3
bio18	4.9	27.3
aprime45	3.6	0.5
percclay	3.2	0.2
bio10	1.5	4

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio15, 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 bio6, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 3.114, training AUC is 0.995, unregularized training gain is 4.147. Algorithm terminated after 500 iterations (28 seconds).

Appendix 2 – Model Reports

The follow settings were used during the run:

16 presence records used for training.
7371 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): aprime45 bio10 bio15 bio18 bio2 bio3 bio6
nlcdcanopy percclay slope
Regularization values: linear/quadratic/product: 0.543, categorical: 0.286, threshold: 1.840, hinge:
0.500
Feature types used: linear quadratic hinge
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MAXENT_OUT\PDEUP0H011\RUN_3
projectionlayers: F:\MAXENT_IN\PROB
samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
environmentallayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV
writeclampgrid: false
writemess: false
writebackgroundpredictions: true
writeplotdata: true
Command line used: dontwriteclampgrid

Command line to repeat this species model:

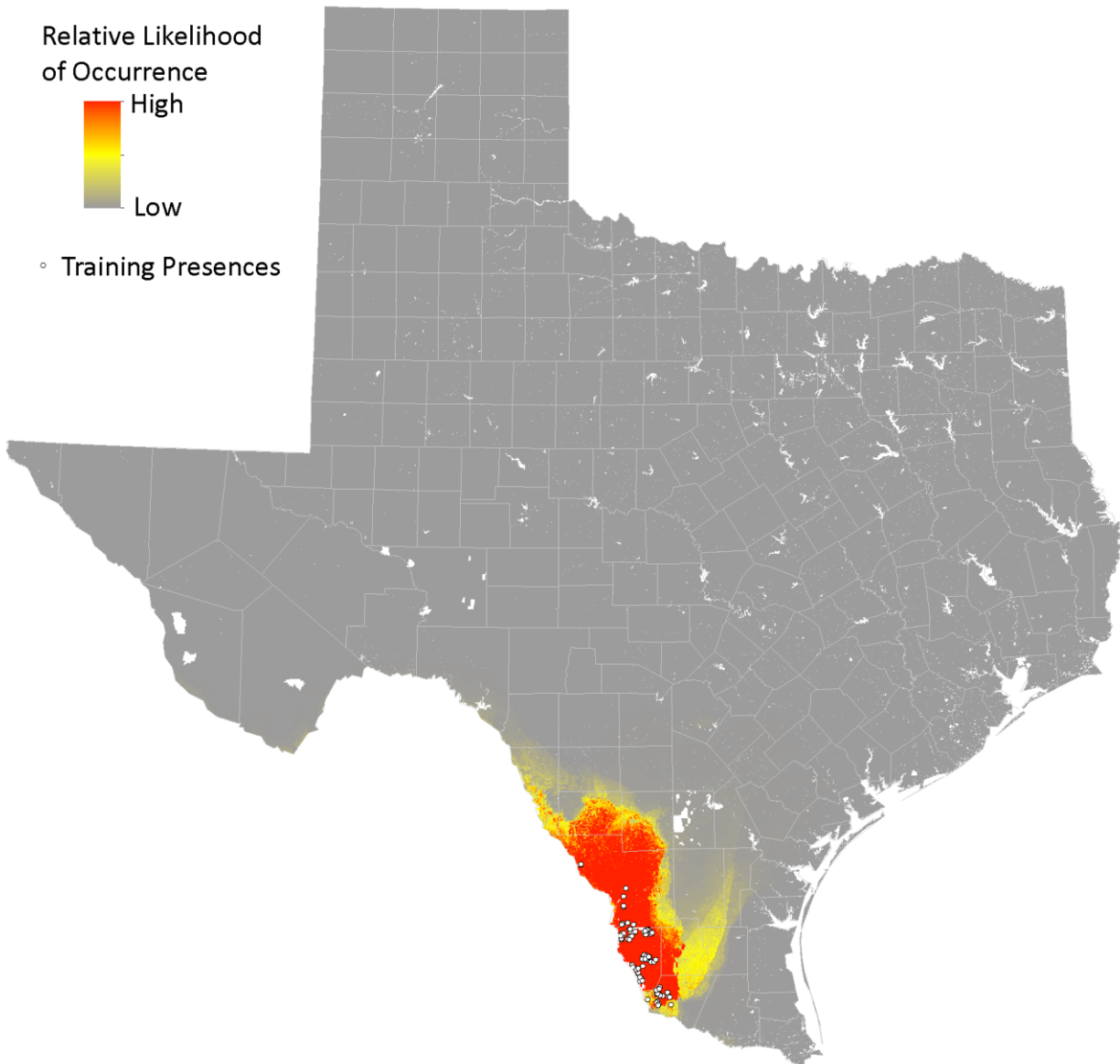
```
java density.MaxEnt nowarnings noprefixes -E "" -E PDEUP0H011 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\PDEUP0H011\RUN_3  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -N aglands -N allwatdist -N  
aprime135 -N aprime180 -N aprime90 -N avoid -N avoid12800 -N avoid1600 -N avoid3200 -N  
avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio19 -N bio4 -N bio5  
-N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N d2wsl -N dissect10 -N dissect5  
-N drainclass -N hydgroup -N ksats -N lf_evh -N lf_forstcc -N lfherbcc -N lfshrubcc -N ned -N percsand  
-N percstilt -N radld -N soilec -N soilph -N vrm10 -N vrm5 -N water1600 -N water300 -N water3200
```

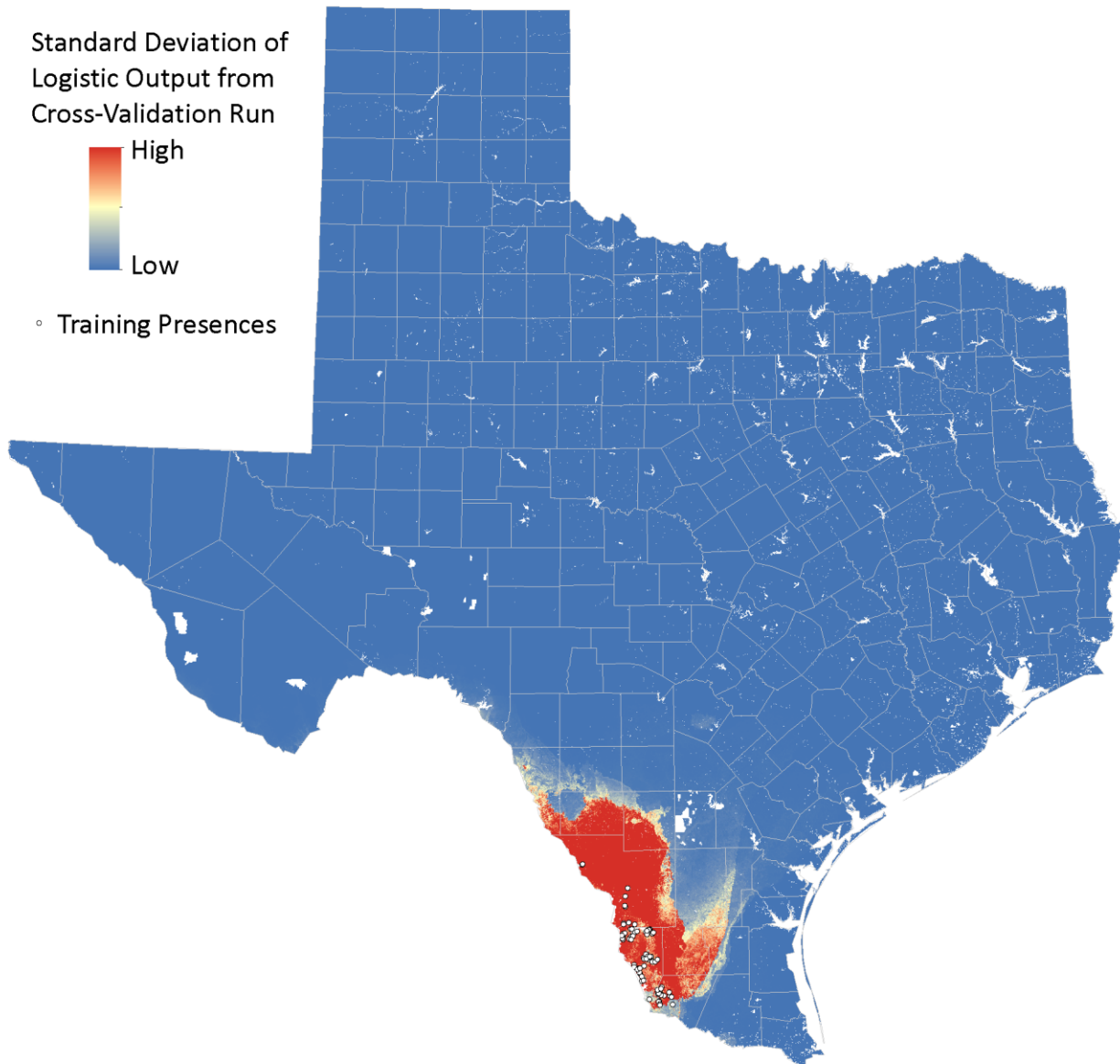
Johnston's Frankenia (*Frankenia johnstonii*)

ELCODE: PDFRA01030

Date: August 13, 2013

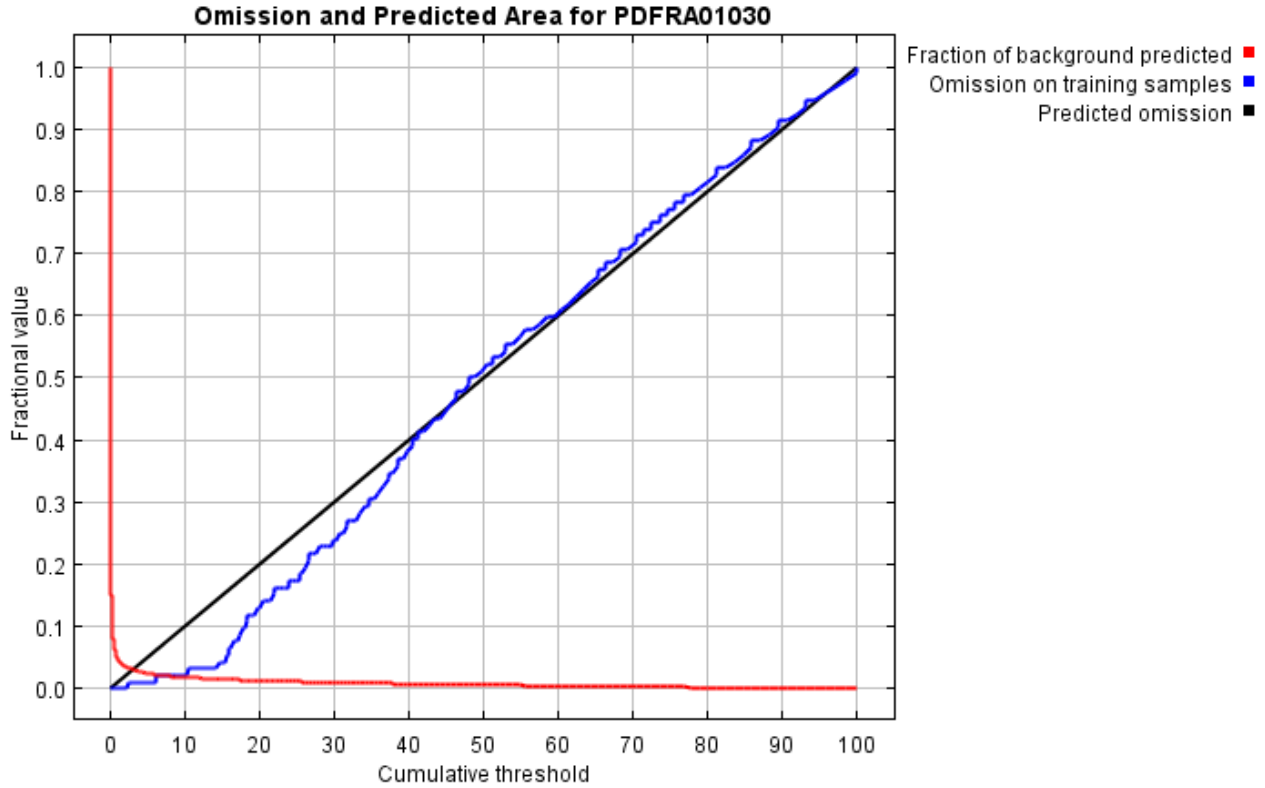
Maxent version: 3.3.3k





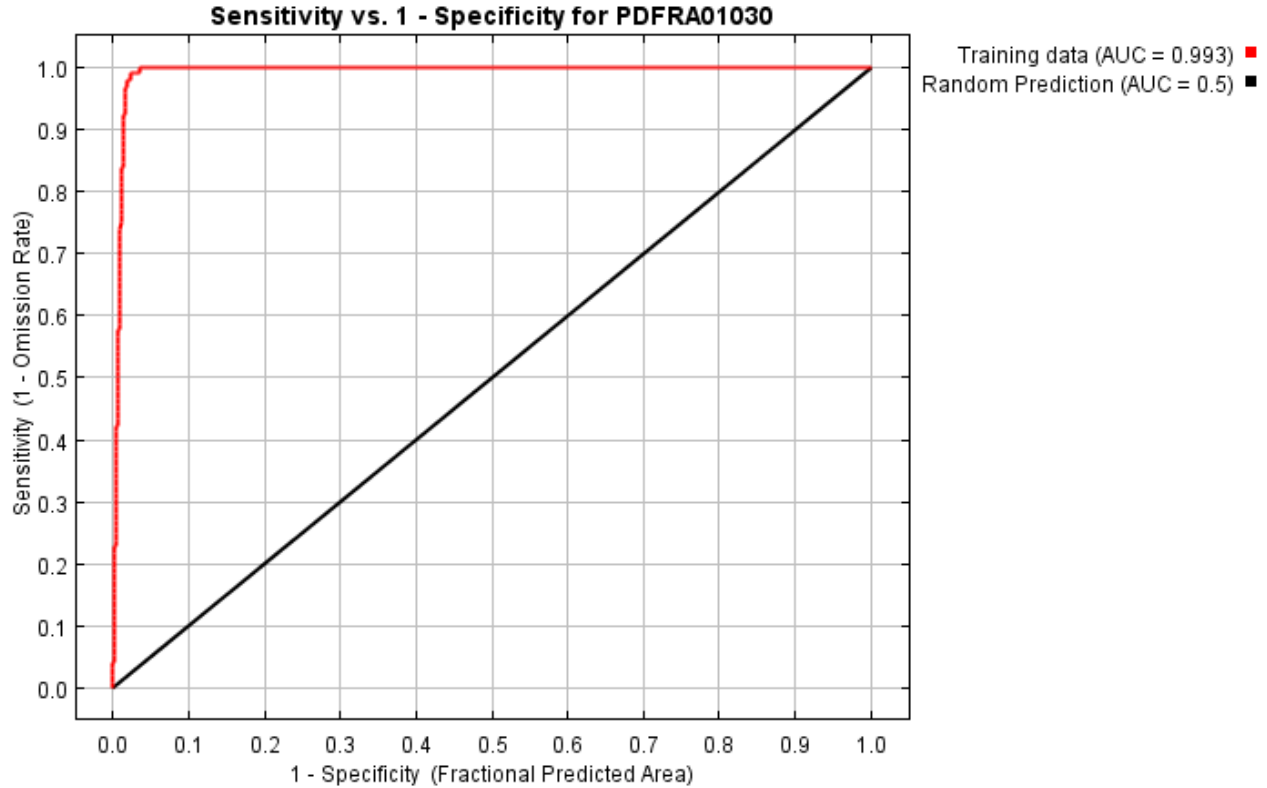
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.990 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

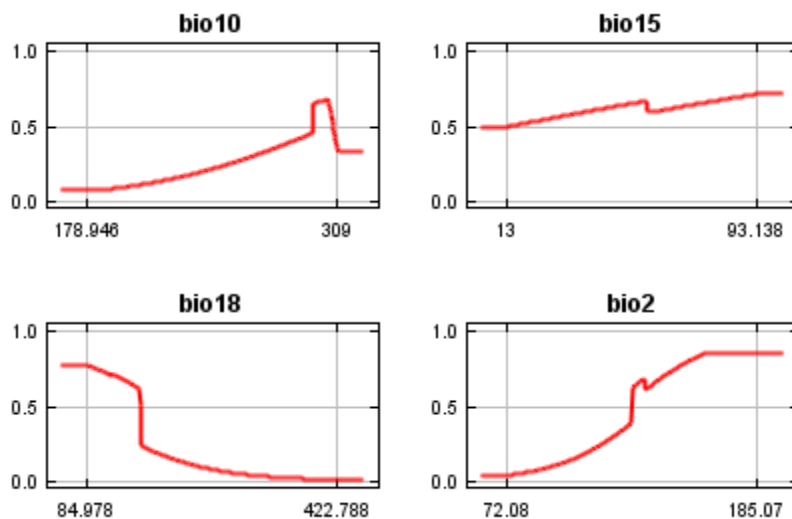
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.010	Fixed cumulative value 1	0.048	0.000
5.000	0.096	Fixed cumulative value 5	0.025	0.011
10.000	0.254	Fixed cumulative value 10	0.018	0.022
2.303	0.041	Minimum training presence	0.034	0.000
18.036	0.365	10 percentile training presence	0.014	0.098

Appendix 2 – Model Reports

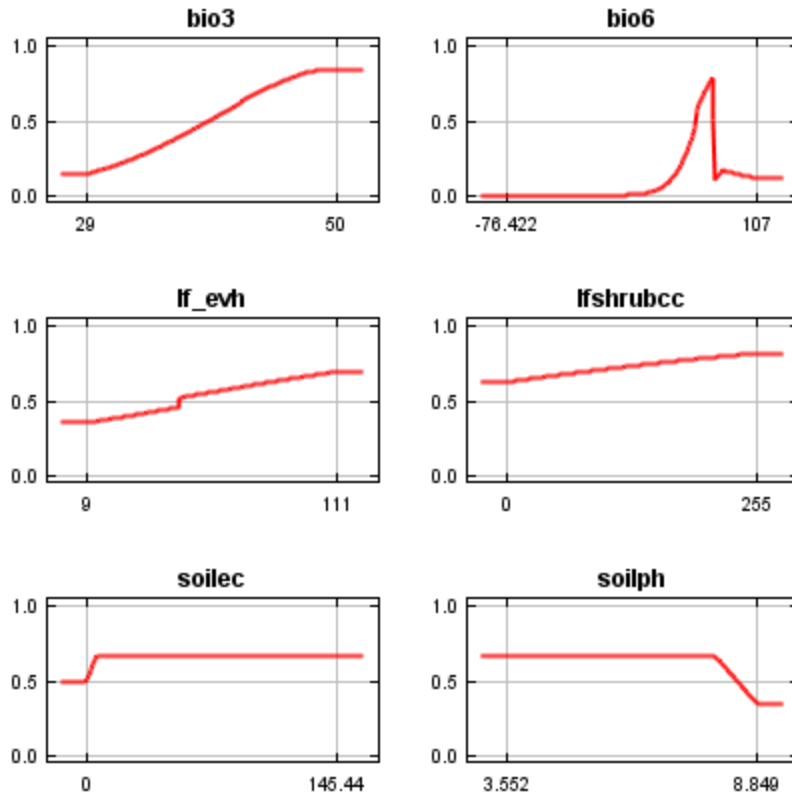
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
6.718	0.146	Equal training sensitivity and specificity	0.022	0.022
6.201	0.116	Maximum training sensitivity plus specificity	0.023	0.011
0.959	0.009	Balance training omission, predicted area and threshold value	0.049	0.000
5.619	0.106	Equate entropy of thresholded and original distributions	0.024	0.011

Response curves

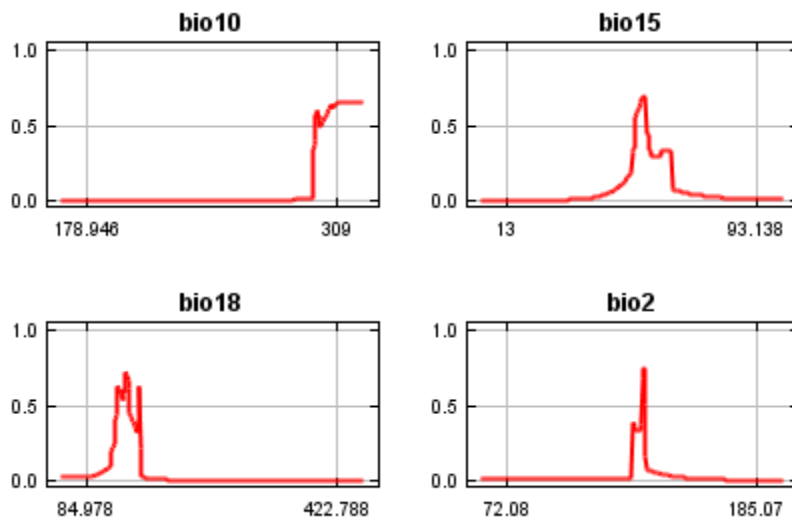
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if you 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



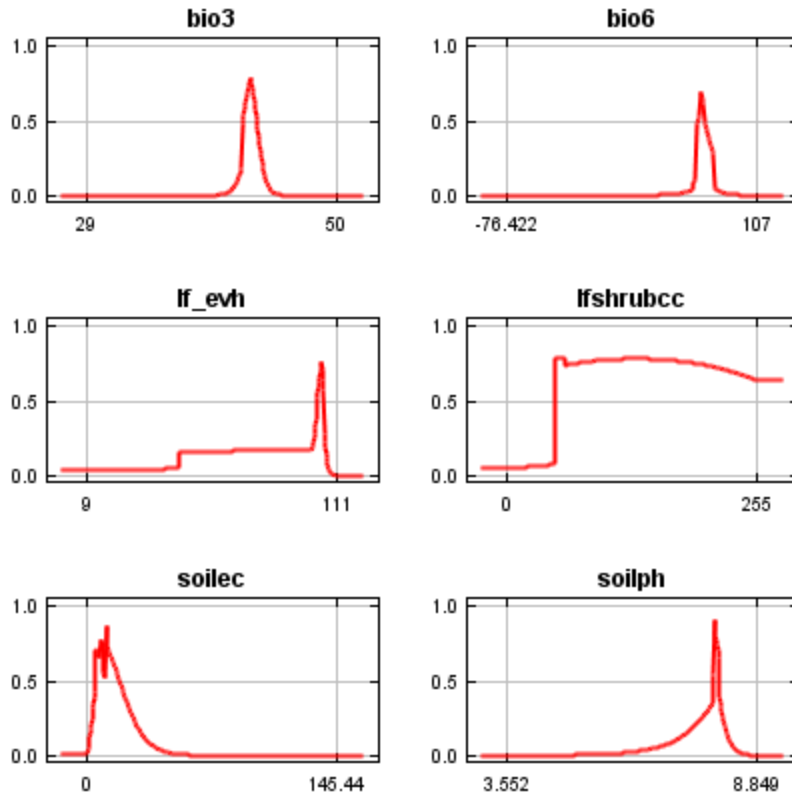
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



Analysis of variable contributions

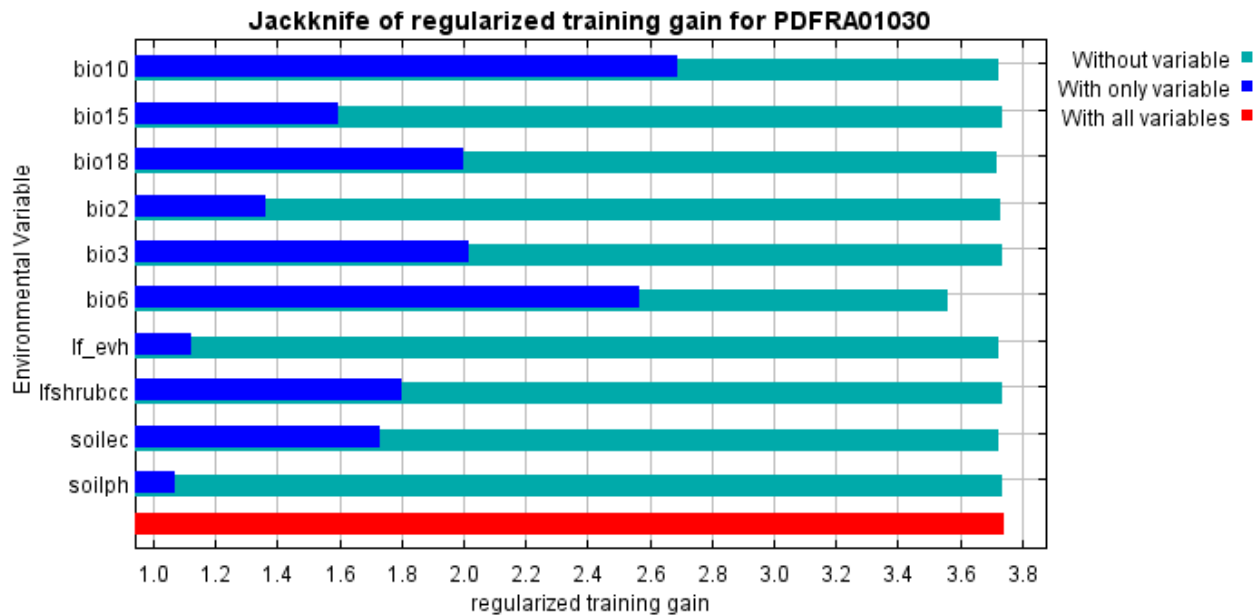
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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
bio10	52.1	0.7
bio6	22.9	93.6
bio18	14.3	2.9
soilec	4.7	0.2

Appendix 2 – Model Reports

Variable	Percent contribution	Permutation importance
bio2	2.4	1.1
lfshrubcc	2.2	0
lf_evh	0.7	0.7
bio3	0.3	0.4
soilph	0.1	0.1
bio15	0.1	0.2

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio10, 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 bio6, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 3.741, training AUC is 0.993, unregularized training gain is 3.936. Algorithm terminated after 500 iterations (21 seconds).

Appendix 2 – Model Reports

The follow settings were used during the run:

92 presence records used for training.
7453 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): bio10 bio15 bio18 bio2 bio3 bio6 lf_evh lfshrubcc
soilec soilph
Regularization values: linear/quadratic/product: 0.107, categorical: 0.250, threshold: 1.080, hinge:
0.500
Feature types used: product linear quadratic hinge threshold
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MAXENT_OUT\PDFRA01030\RUN_3
projectionlayers: F:\MAXENT_IN\PROB
samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
environmentallayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV
writeclampgrid: false
writemess: false
writebackgroundpredictions: true
writeplotdata: true
Command line used: dontwriteclampgrid

Command line to repeat this species model:

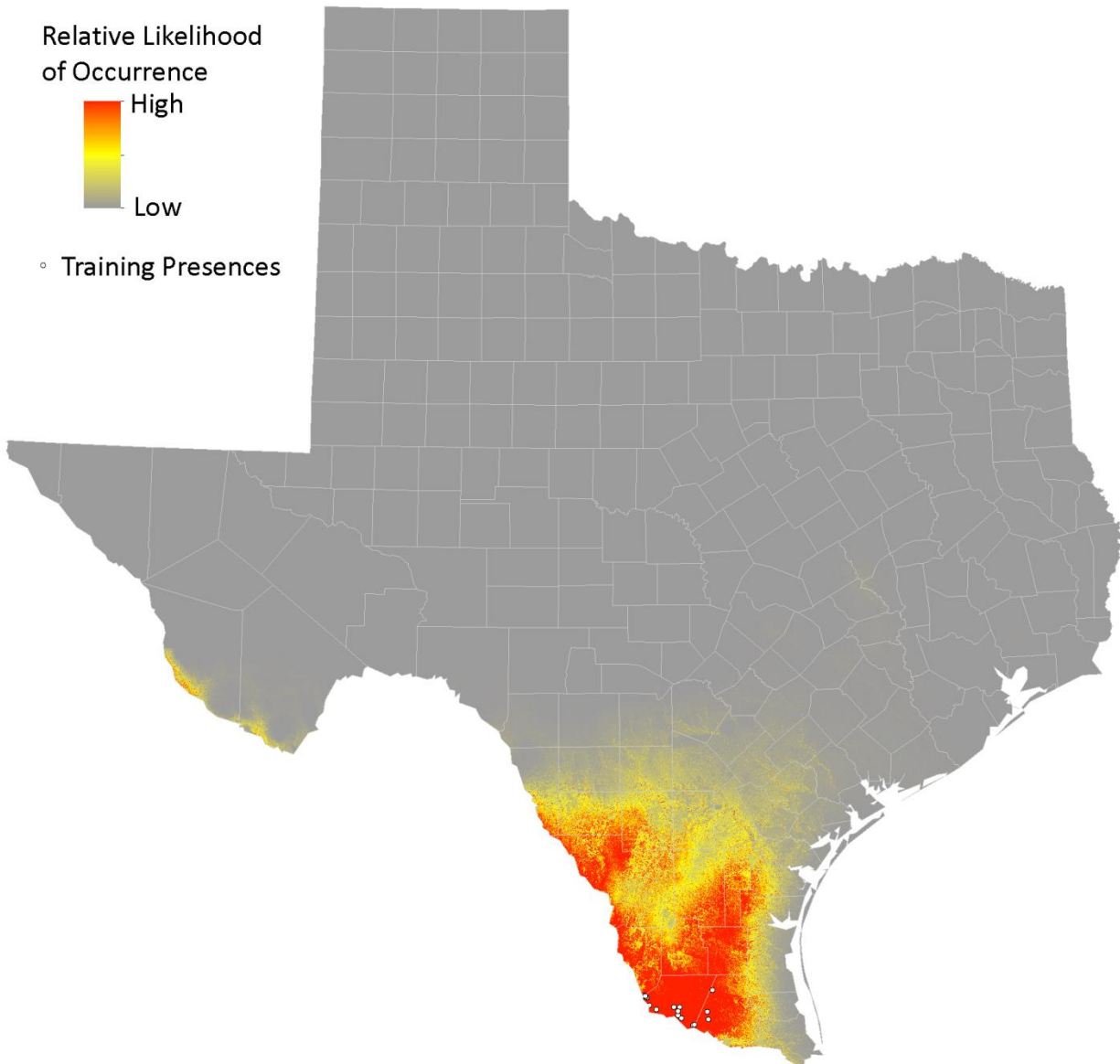
```
java density.MaxEnt nowarnings noprefixes -E "" -E PDFRA01030 responsecurves nopictures  
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\PDFRA01030\RUN_3  
projectionlayers=F:\MAXENT_IN\PROB  
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV  
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid  
nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -N aglands -N allwatdist -N  
aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N avoid12800 -N avoid1600 -N  
avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio19 -  
N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N d2wsl -N  
dissect10 -N dissect5 -N drainclass -N hydgroup -N ksat -N lf_forstcc -N lfherbcc -N ned -N  
nlcdcanopy -N percclay -N percsand -N percsilt -N radld -N slope -N vrm10 -N vrm5 -N water1600 -  
N water300 -N water3200
```

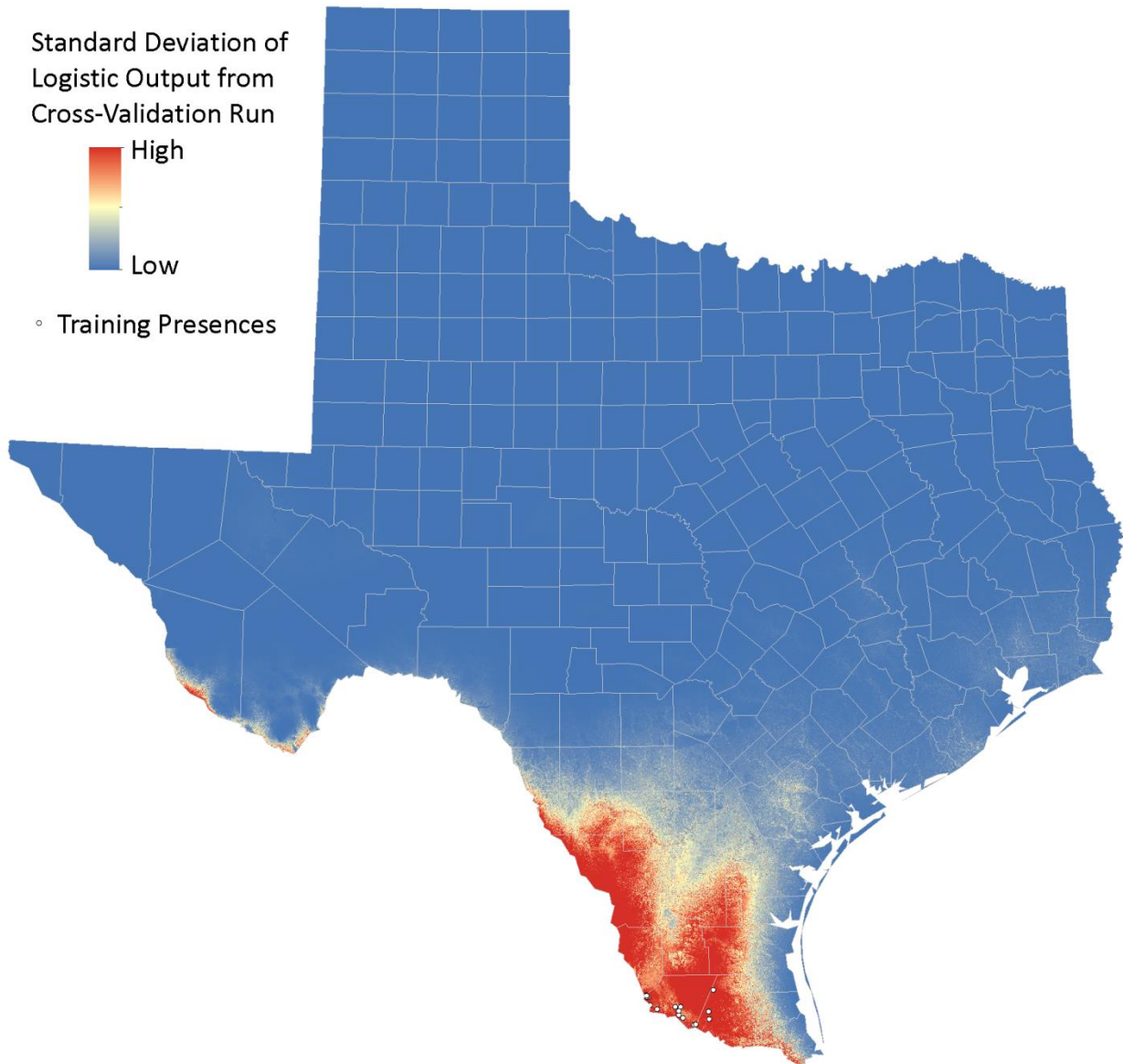

Chihuahua Balloon-vine (*Cardiospermum dissectum*)

ELCODE: PDSPN03020

Date: August 13, 2013

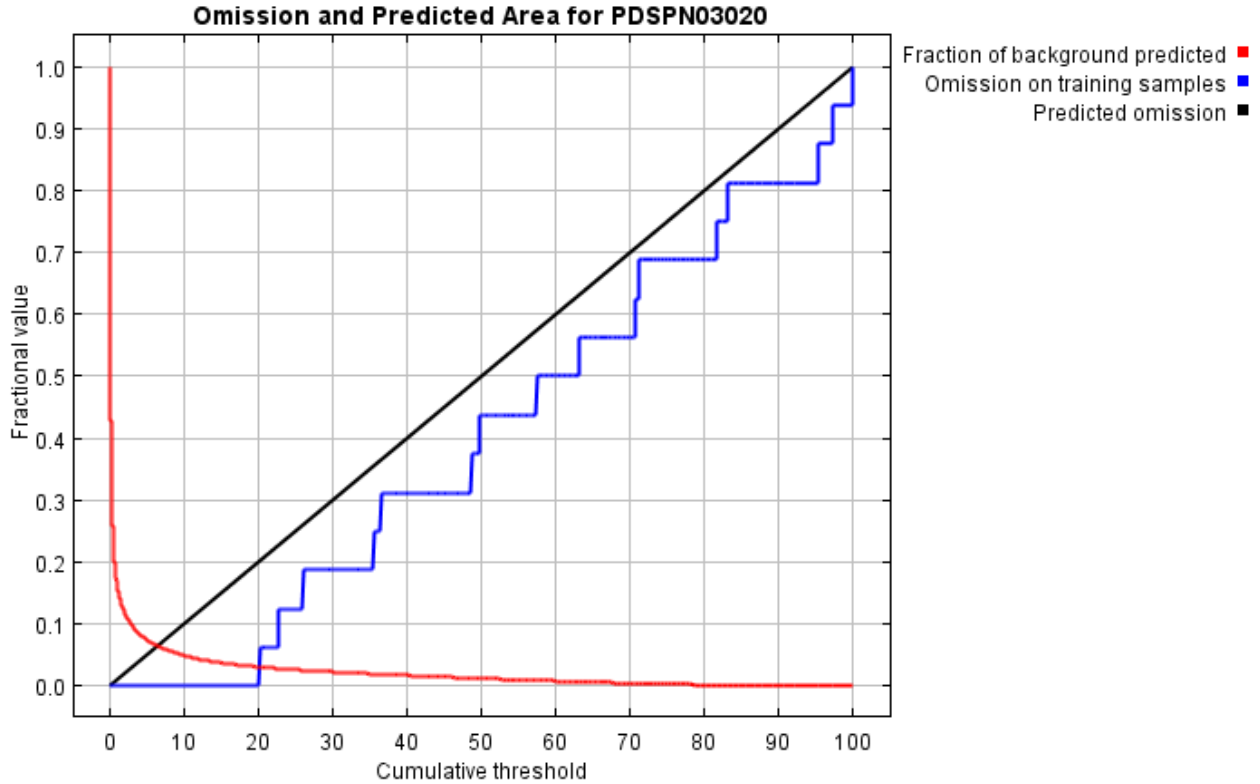
Maxent version: 3.3.3k





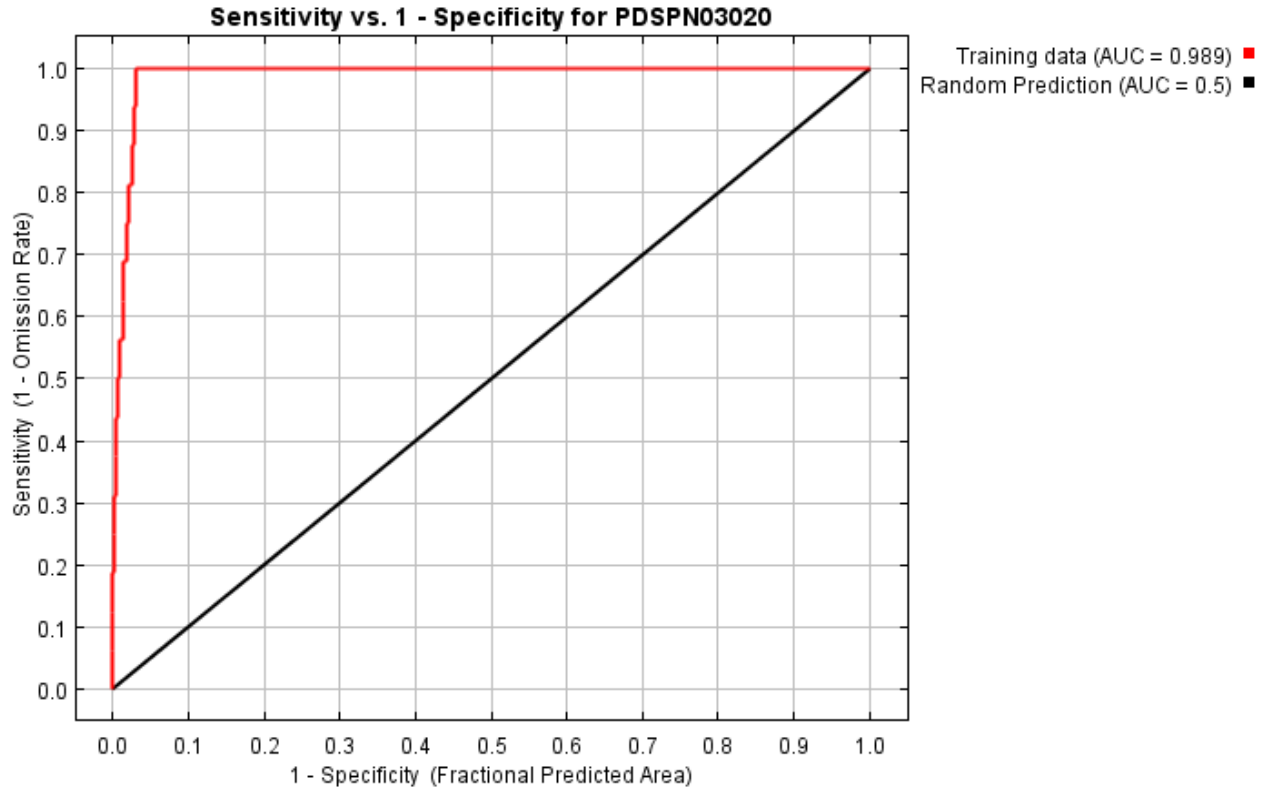
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.975 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

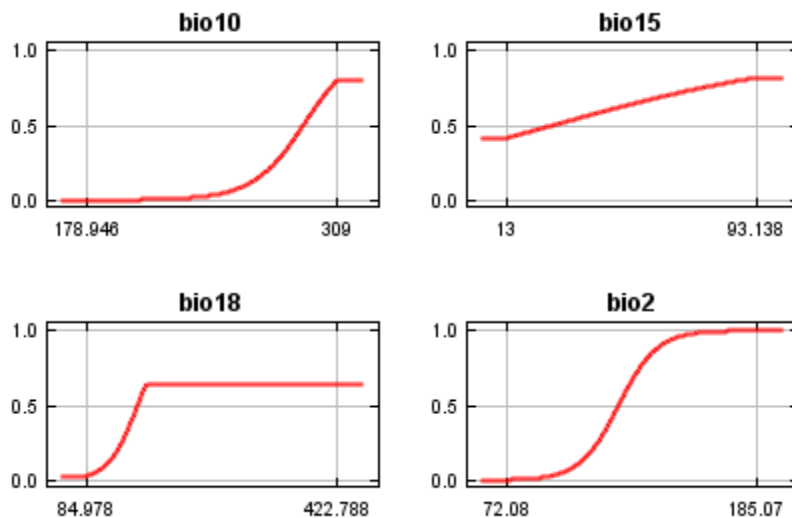
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.008	Fixed cumulative value 1	0.161	0.000
5.000	0.061	Fixed cumulative value 5	0.074	0.000
10.000	0.134	Fixed cumulative value 10	0.050	0.000
20.052	0.325	Minimum training presence	0.031	0.000
22.720	0.371	10 percentile training presence	0.028	0.062

Appendix 2 – Model Reports

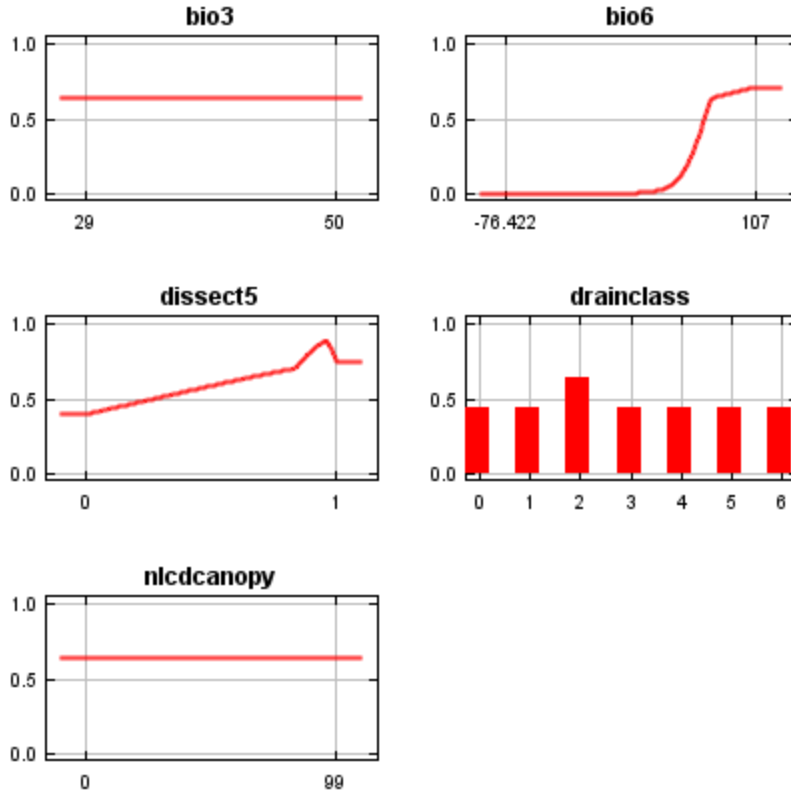
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
20.052	0.325	Equal training sensitivity and specificity	0.031	0.000
20.052	0.325	Maximum training sensitivity plus specificity	0.031	0.000
2.119	0.021	Balance training omission, predicted area and threshold value	0.115	0.000
9.064	0.125	Equate entropy of thresholded and original distributions	0.053	0.000

Response curves

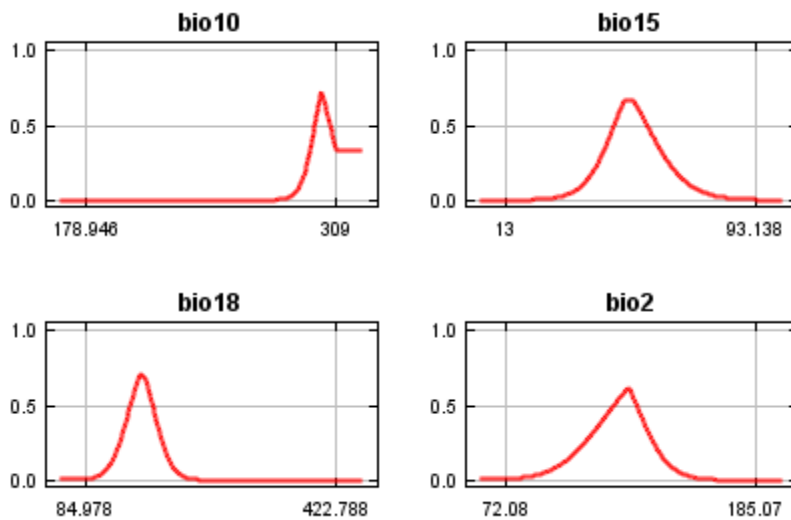
These curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Click on a response curve to see a larger version. Note 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. See Appendix 1 for detailed explanations of all environmental predictor layers.



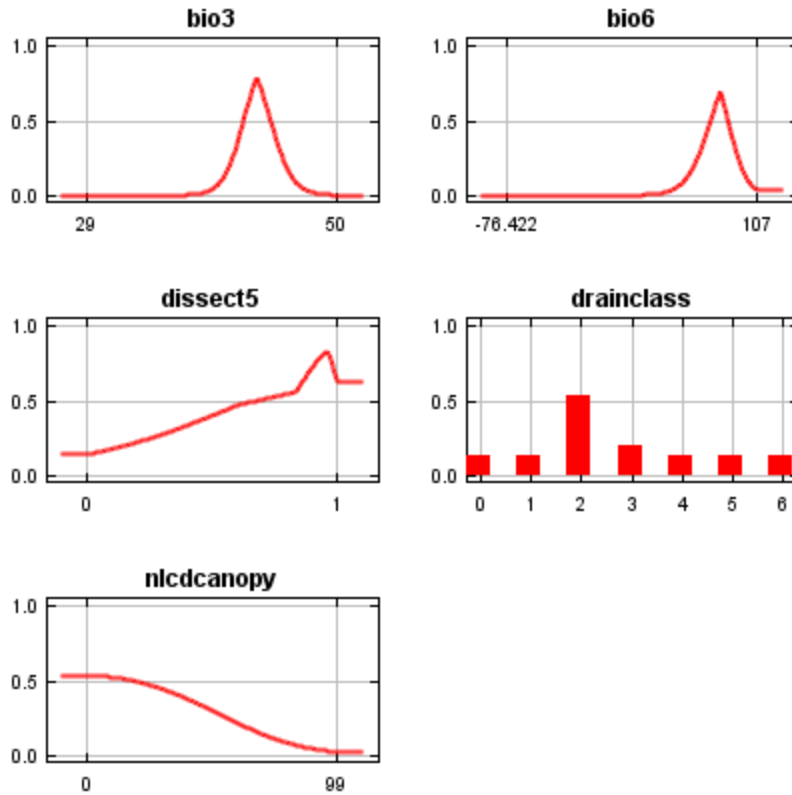
Appendix 2 – Model Reports



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.



Appendix 2 – Model Reports



Analysis of variable contributions

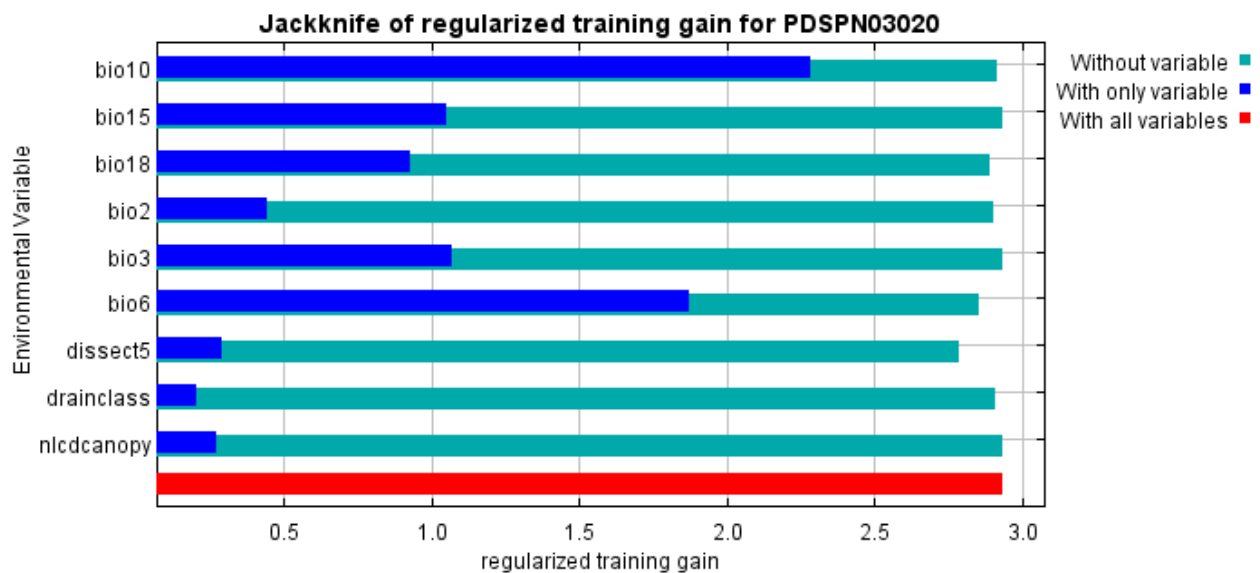
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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
bio10	62.5	3.1
bio6	18.4	75.2
dissect5	6.7	1.7
drainclass	4.3	0.8

Appendix 2 – Model Reports

Variable	Percent contribution	Permutation importance
bio18	3.7	0.8
bio2	2.5	17.7
bio15	1.2	0.8
nlcdcanopy	0.7	0
bio3	0	0

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio10, 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 dissect5, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Regularized training gain is 2.935, training AUC is 0.989, unregularized training gain is 3.454. Algorithm terminated after 500 iterations (28 seconds).

The follow settings were used during the run:

16 presence records used for training.

7379 points used to determine the Maxent distribution (background points and presence points).

Environmental layers used: bio10 bio15 bio18 bio2 bio3 bio6 dissect5 drainclass(categorical)

nlcdcanopy

Appendix 2 – Model Reports

Regularization values: linear/quadratic/product: 0.543, categorical: 0.286, threshold: 1.840, hinge: 0.500

Feature types used: linear quadratic hinge

responsecurves: true

pictures: false

jackknife: true

outputfiletype: bil

outputdirectory: F:\MAXENT_OUT\PDSPN03020\RUN_3

projectionlayers: F:\MAXENT_IN\PROB

samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV

environmentallayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV

writeclampgrid: false

writemess: false

writebackgroundpredictions: true

writeplotdata: true

Command line used: dontwriteclampgrid

Command line to repeat this species model:

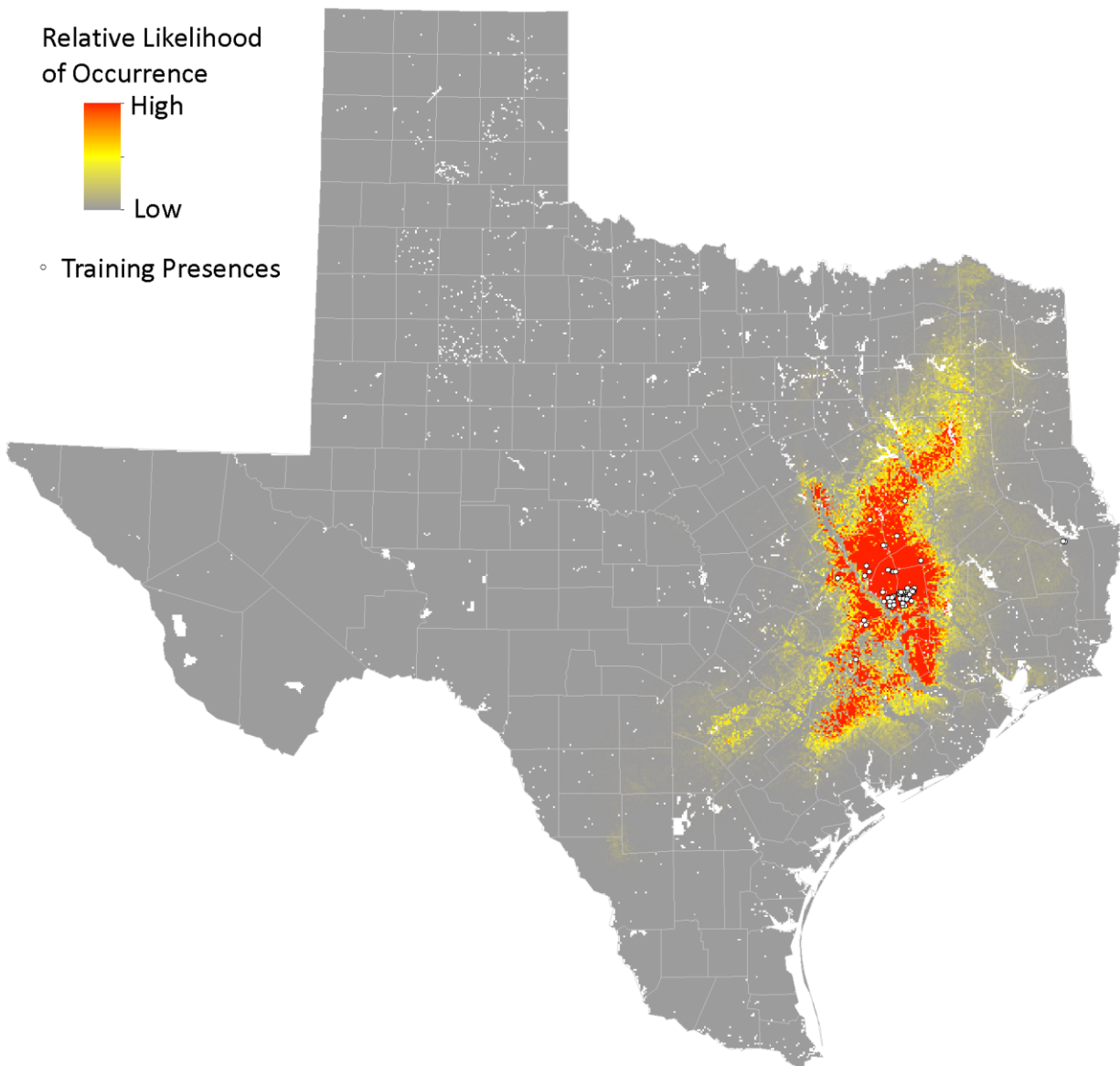
```
java density.MaxEnt nowarnings noprefixes -E "" -E PDSPN03020 responsecurves nopictures
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\PDSPN03020\RUN_3
projectionlayers=F:\MAXENT_IN\PROB
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid
nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -N aglands -N allwatdist -N
aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N avoid12800 -N avoid1600 -N
avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio19 -
N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N d2wsl -N
dissect10 -N hydgroup -N ksats -N lf_evh -N lf_forstcc -N lfherbcc -N lfshrubcc -N ned -N percclay -N
percsand -N percsilt -N radld -N slope -N soilec -N soilph -N vrm10 -N vrm5 -N water1600 -N
water300 -N water3200 -t drainclass
```

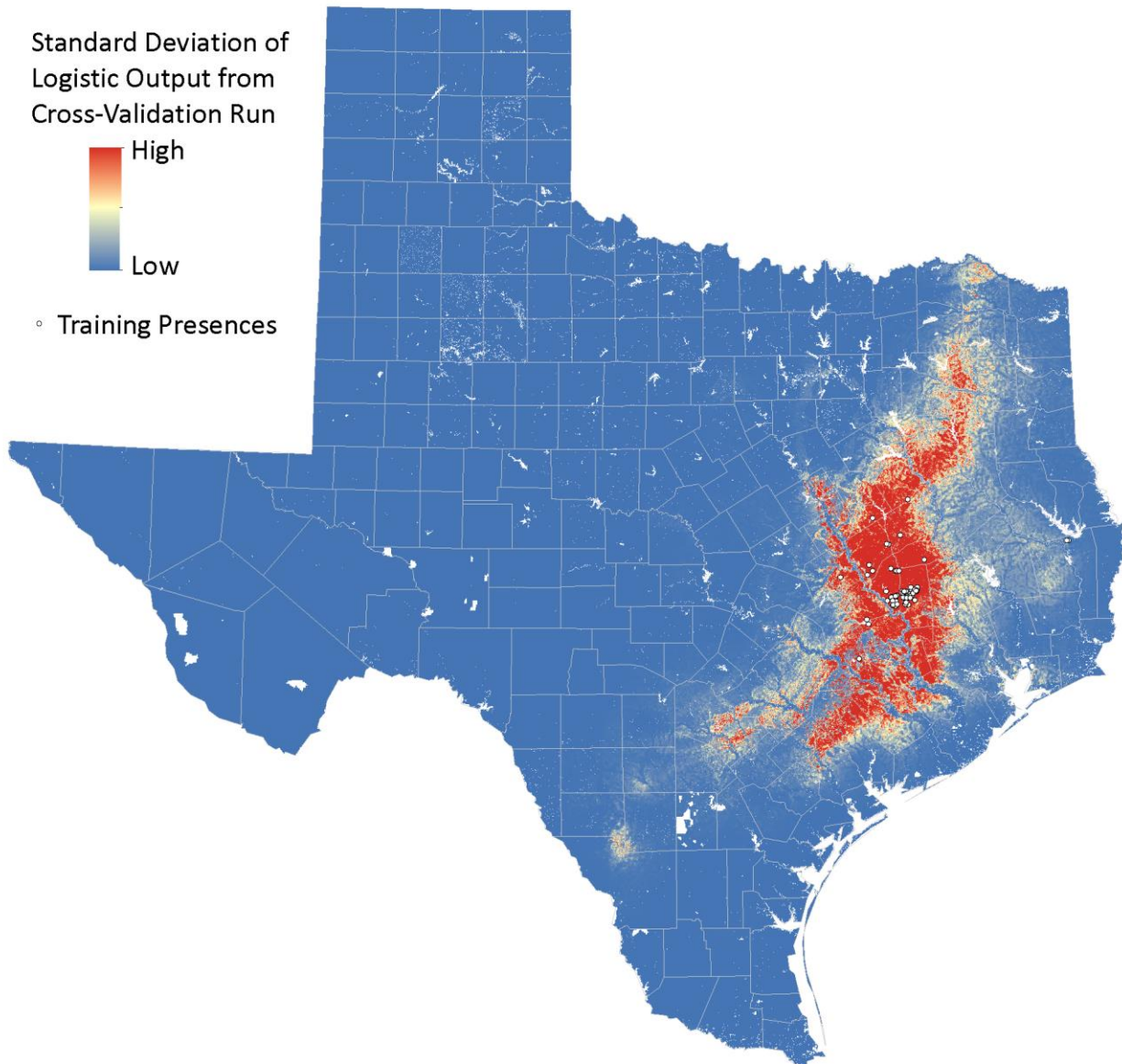
Navasota Ladies'-tresses (*Spiranthes parksii*)

ELCODE: PMORC2B0R0

Date: August 13, 2013

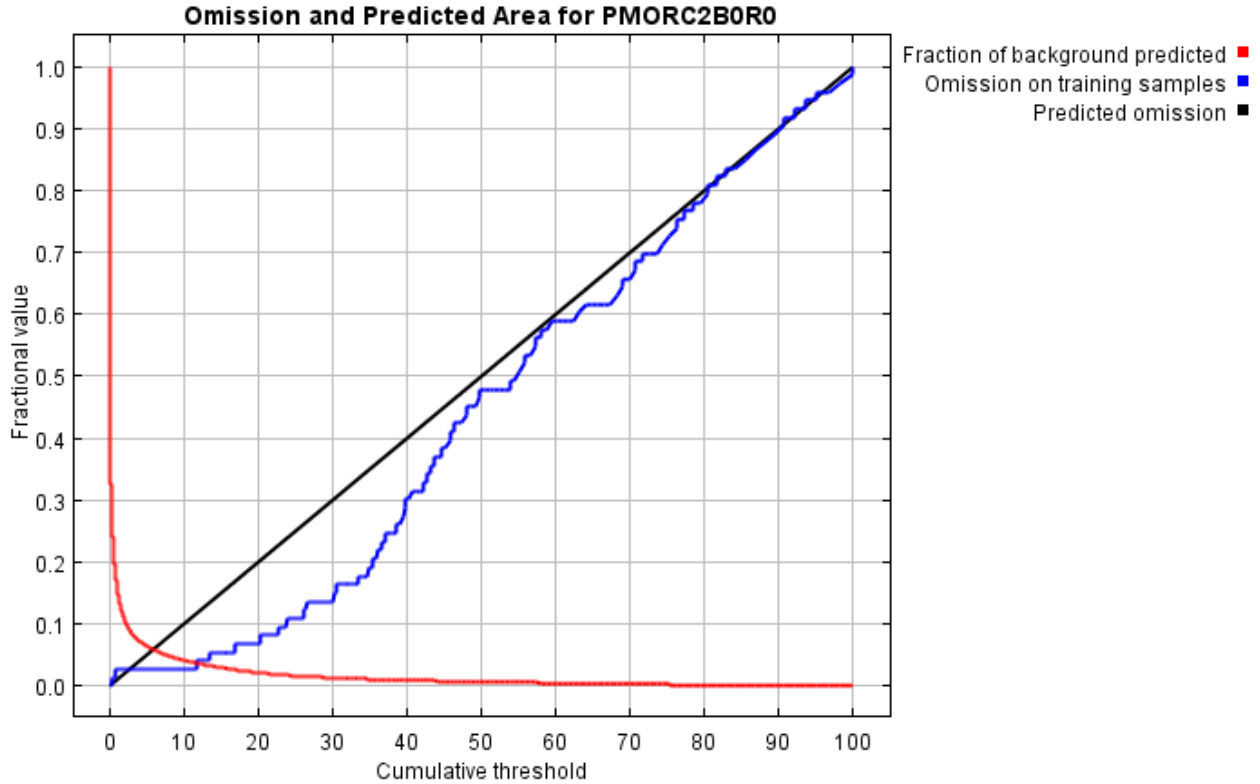
Maxent version: 3.3.3k





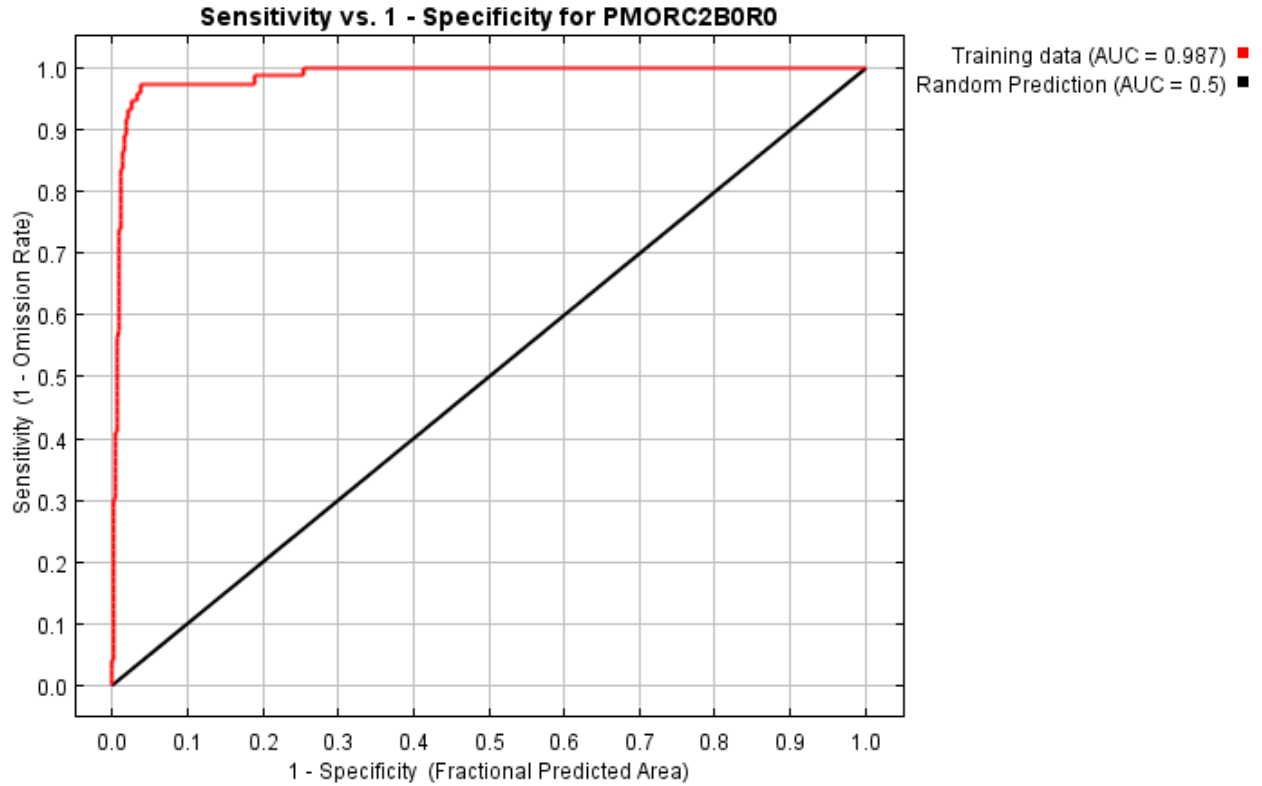
Analysis of omission/commission

The following picture shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is 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 0.981 rather than 1; in practice the test AUC may exceed this bound.

Appendix 2 – Model Reports



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 $6 * \text{training omission rate} + .04 * \text{cumulative threshold} + 1.6 * \text{fractional predicted area}$.

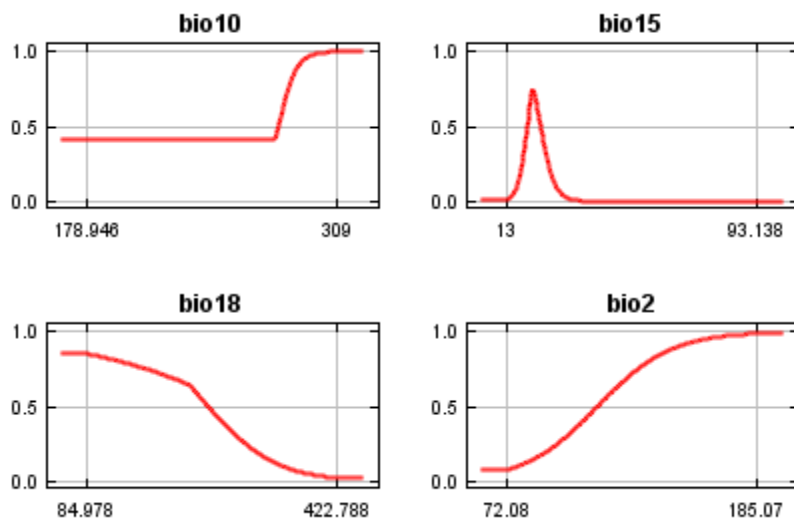
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.005	Fixed cumulative value 1	0.156	0.027
5.000	0.051	Fixed cumulative value 5	0.065	0.027
10.000	0.113	Fixed cumulative value 10	0.042	0.027
0.309	0.001	Minimum training presence	0.253	0.000
23.736	0.307	10 percentile training presence	0.018	0.096

Appendix 2 – Model Reports

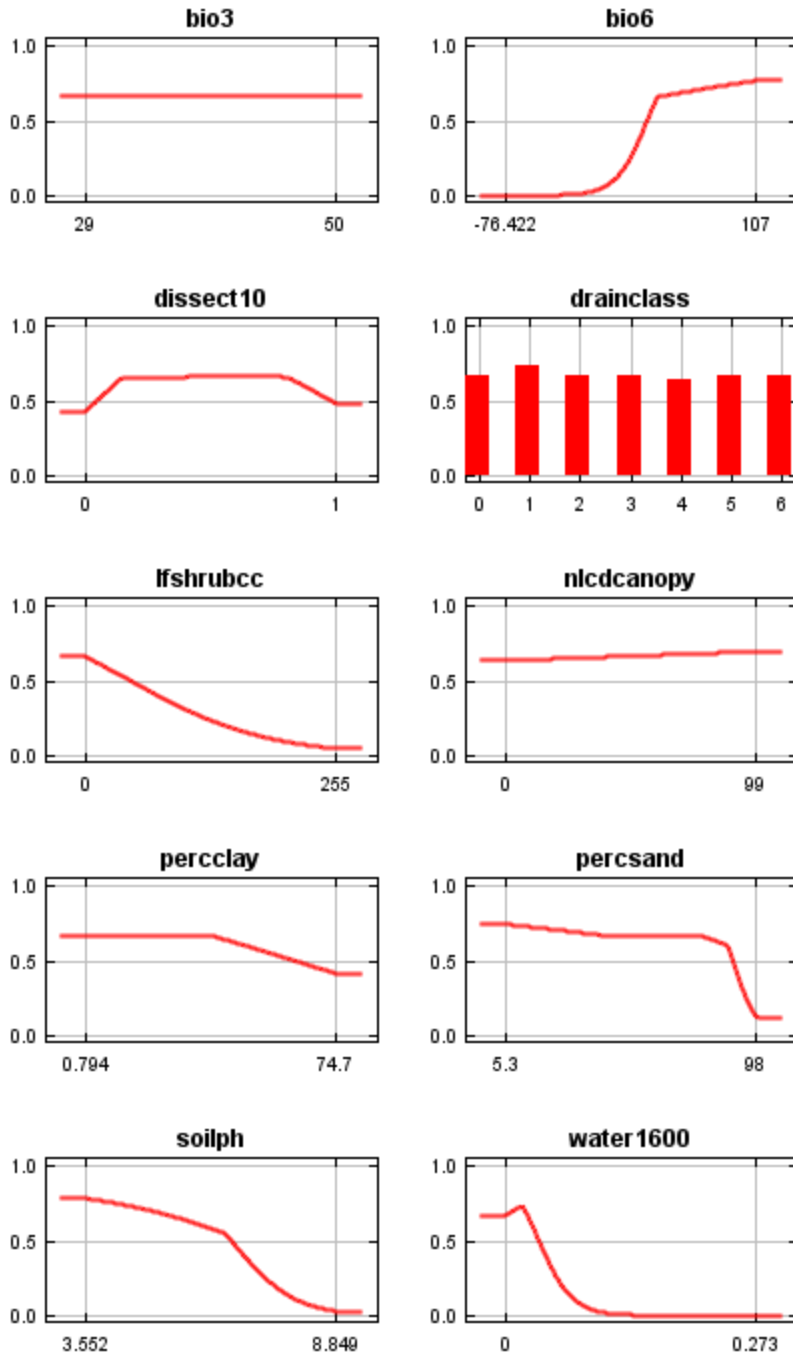
Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
11.735	0.135	Equal training sensitivity and specificity	0.037	0.041
11.680	0.134	Maximum training sensitivity plus specificity	0.037	0.027
0.668	0.003	Balance training omission, predicted area and threshold value	0.189	0.014
11.147	0.128	Equate entropy of thresholded and original distributions	0.039	0.027

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. 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. See Appendix 1 for detailed explanations of all environmental predictor layers.

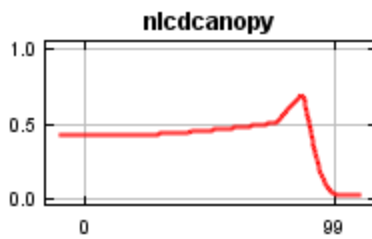
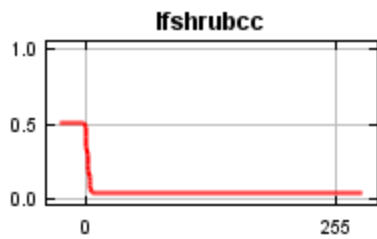
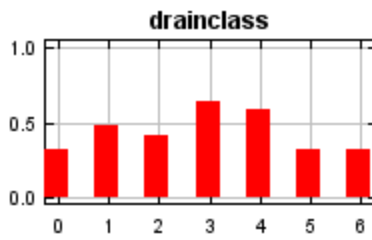
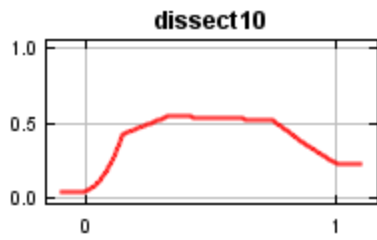
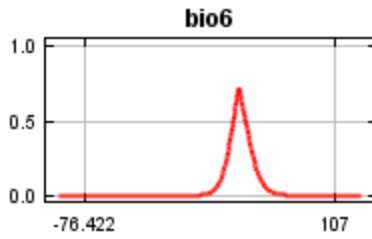
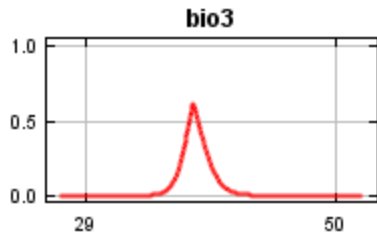
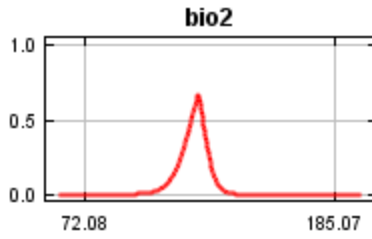
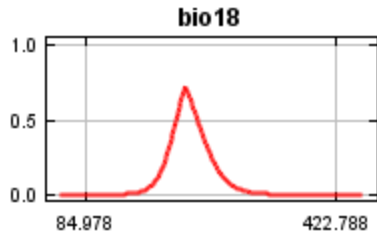
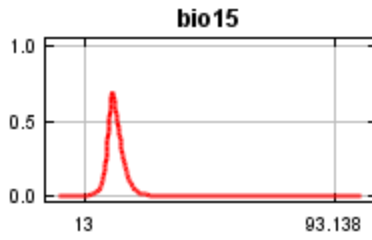
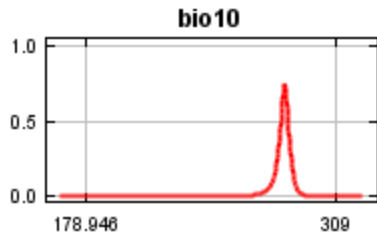


Appendix 2 – Model Reports

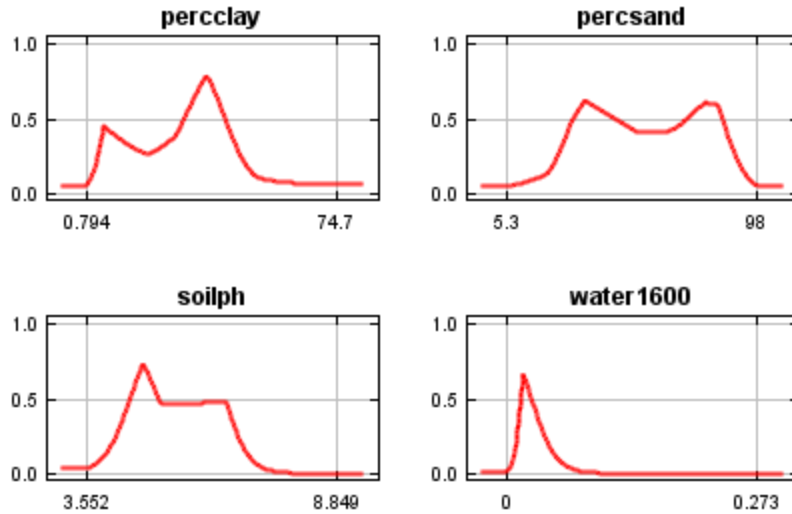


In contrast to the above marginal response curves, each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by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

Appendix 2 – Model Reports



Appendix 2 – Model Reports



Analysis of variable contributions

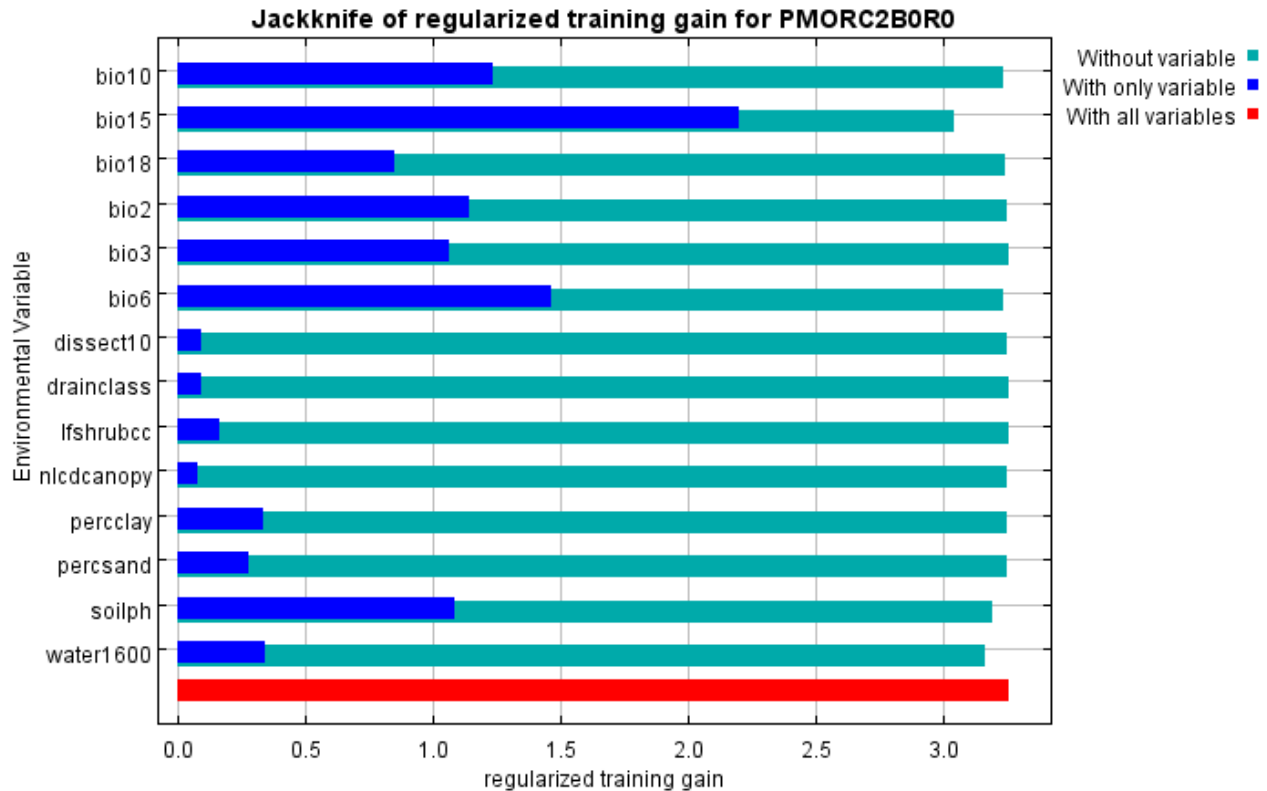
The following table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from 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
soilph	39.6	3.4
bio15	26.4	81.8
bio6	14.2	7.5
bio18	6.1	1
bio3	4.8	0
water1600	2.8	1
percclay	2.3	0.1
percsand	1.3	0.3

Appendix 2 – Model Reports

Variable	Percent contribution	Permutation importance
lfshrubcc	0.9	0
drainclass	0.6	0
dissect10	0.3	0
bio10	0.3	3.3
nlcdcanopy	0.2	0
bio2	0.1	1.7

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio15, 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 bio15, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

Appendix 2 – Model Reports

Regularized training gain is 3.254, training AUC is 0.987, unregularized training gain is 3.583. Algorithm terminated after 500 iterations (29 seconds).

The follow settings were used during the run:

73 presence records used for training.

7407 points used to determine the Maxent distribution (background points and presence points).

Environmental layers used: bio10 bio15 bio18 bio2 bio3 bio6 dissect10 drainclass(categorical)

lfshrubcc nlcdcanopy percclay percsand soilph water1600

Regularization values: linear/quadratic/product: 0.127, categorical: 0.250, threshold: 1.270, hinge: 0.500

Feature types used: linear quadratic hinge

responsecurves: true

pictures: false

jackknife: true

outputfiletype: bil

outputdirectory: F:\MAXENT_OUT\PMORC2B0R0\RUN_3

projectionlayers: F:\MAXENT_IN\PROB

samplesfile: C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV

environmentallayers: C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV

writeclampgrid: false

writemess: false

writebackgroundpredictions: true

writeplotdata: true

Command line used: dontwriteclampgrid

Command line to repeat this species model:

```
java density.MaxEnt nowarnings noprefixes -E "" -E PMORC2B0R0 responsecurves nopictures
jackknife outputfiletype=bil outputdirectory=F:\MAXENT_OUT\PMORC2B0R0\RUN_3
projectionlayers=F:\MAXENT_IN\PROB
samplesfile=C:\MAXENT_IN\OCCURRENCE_DATA\TRAINING.CSV
environmentallayers=C:\MAXENT_IN\OCCURRENCE_DATA\BACKGROUND.CSV nowriteclampgrid
nowritemess writebackgroundpredictions writeplotdata -N UNIQUE_ID -N aglands -N allwatdist -N
aprime135 -N aprime180 -N aprime45 -N aprime90 -N avoid -N avoid12800 -N avoid1600 -N
avoid3200 -N avoid6400 -N bio1 -N bio11 -N bio12 -N bio13 -N bio14 -N bio16 -N bio17 -N bio19 -
N bio4 -N bio5 -N bio7 -N bio8 -N bio9 -N cti -N curve10 -N curve5 -N d2foredge -N d2wsl -N
dissect5 -N hydgroup -N ksat -N lf_evh -N lf_forstcc -N lfherbcc -N ned -N percstilt -N radld -N slope -
N soilec -N vrm10 -N vrm5 -N water300 -N water3200 -t drainclass
```