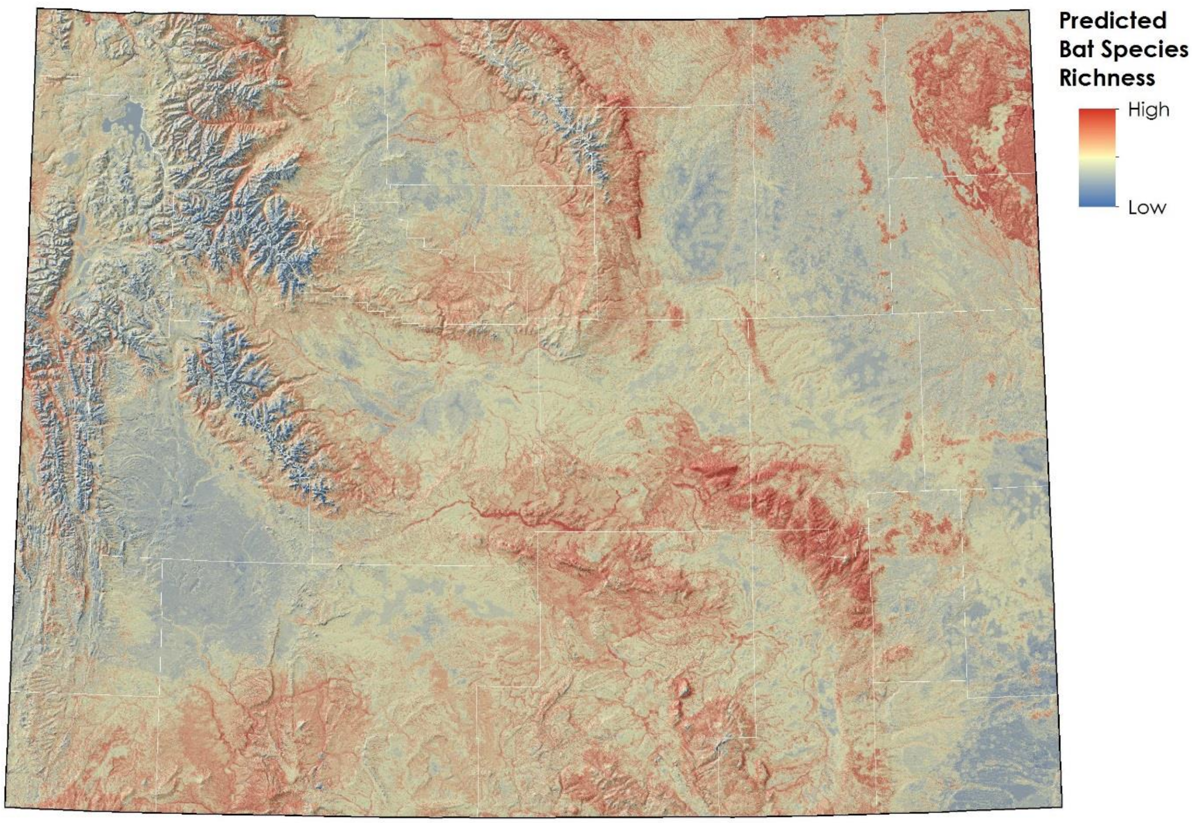
BATS OF WYOMING: MODELED DISTRIBUTION

2015

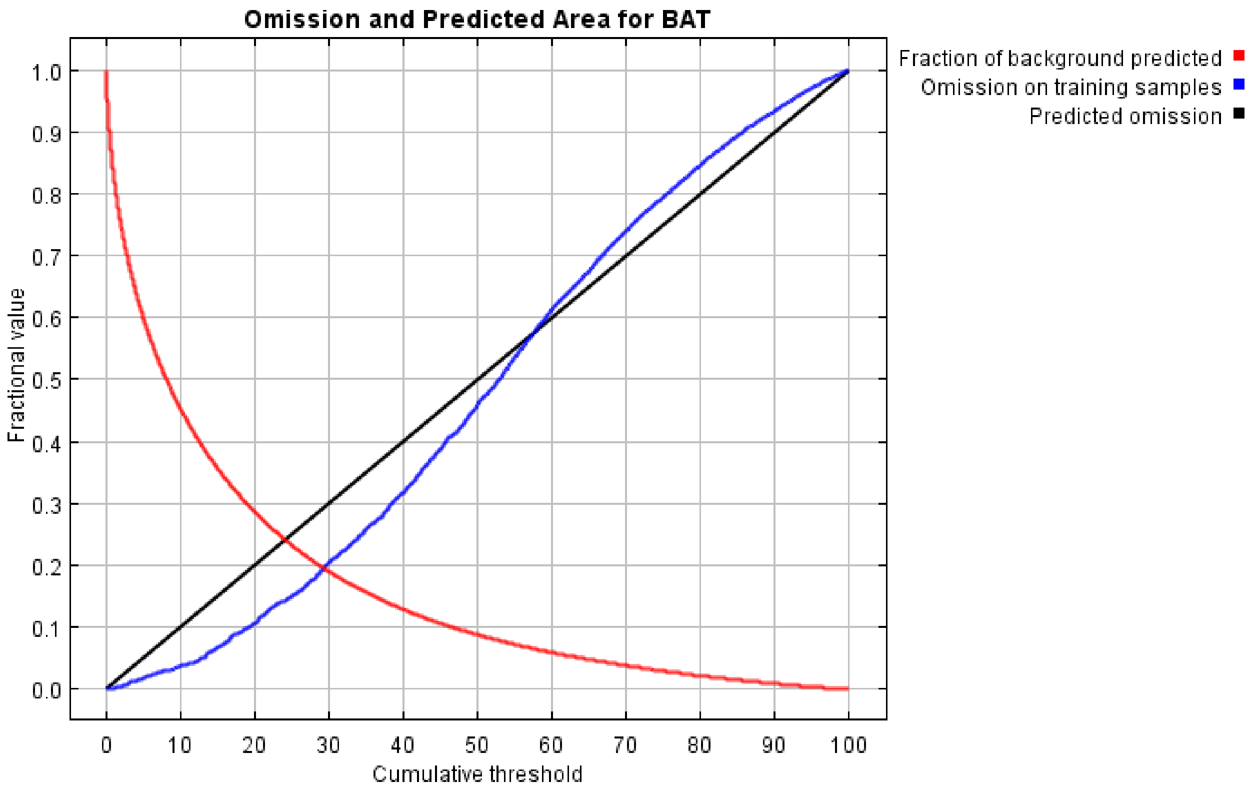
Appendix 3: Summer Distribution Model Output



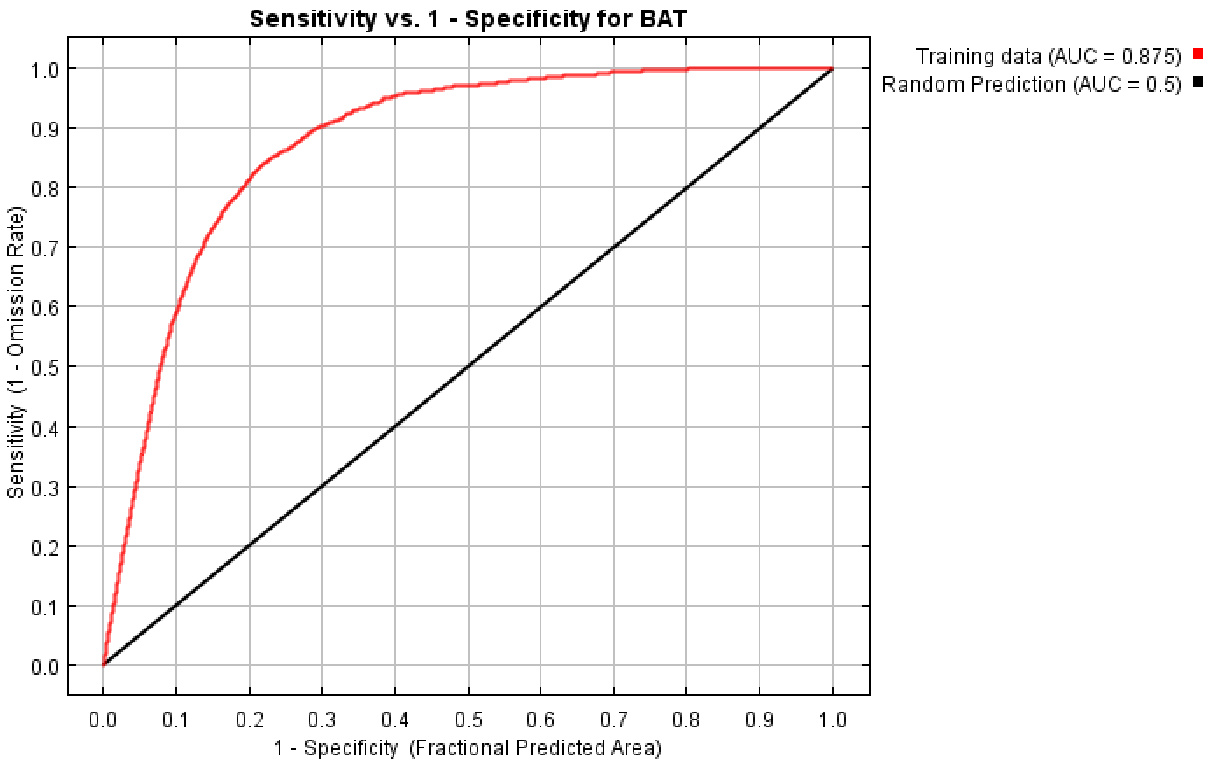
Contents

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 0.834 rather than 1; in practice the test AUC may exceed this bound.



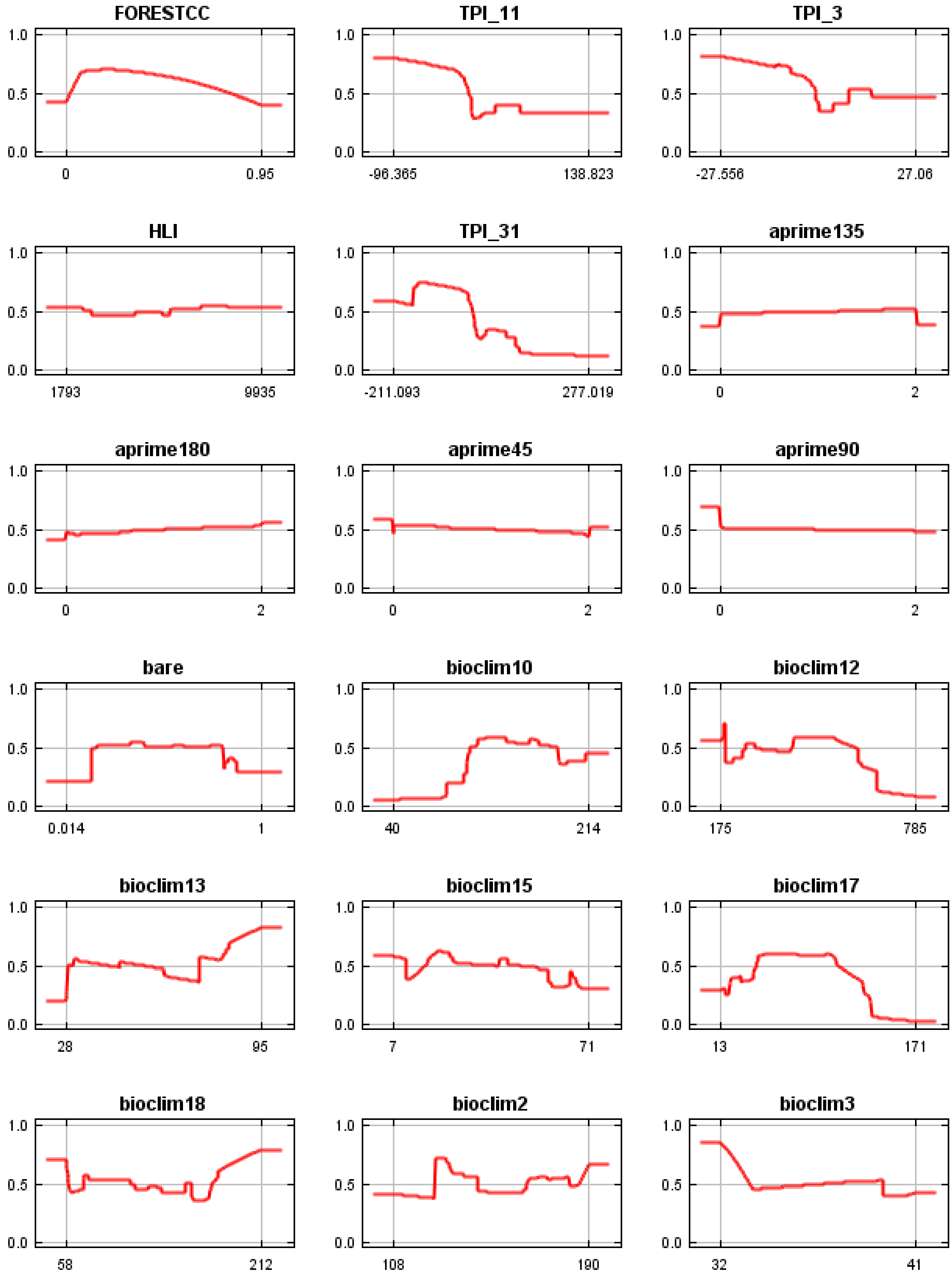
Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

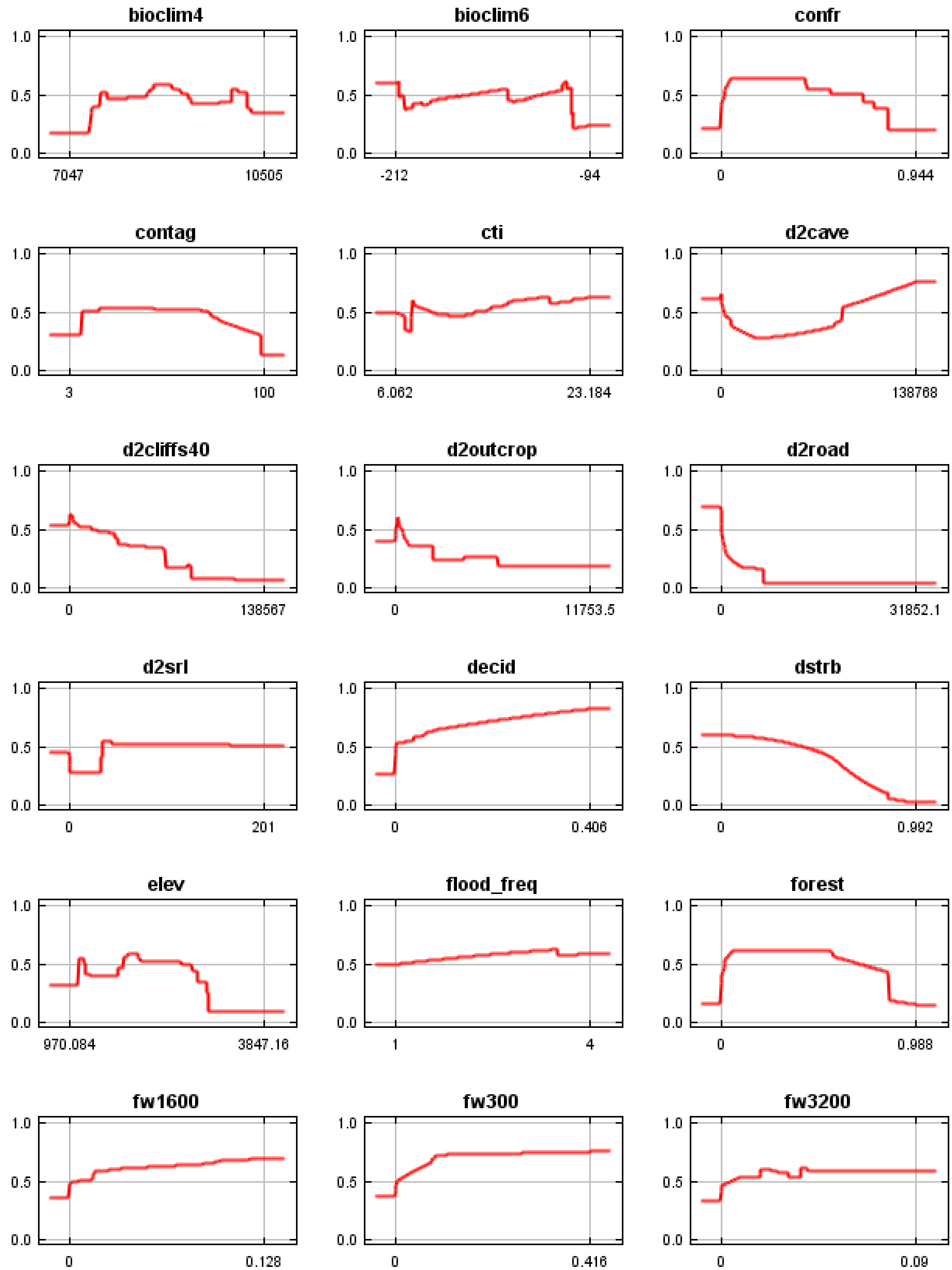
Cumulative threshold	**Logistic threshold**	**Description**	**Fractional predicted area**	**Training omission rate**
1.000	0.042	Fixed cumulative value 1	0.827	0.001
5.000	0.101	Fixed cumulative value 5	0.599	0.019
10.000	0.156	Fixed cumulative value 10	0.453	0.038
0.394	0.027	Minimum training presence	0.899	0.000
19.282	0.252	10 percentile training presence	0.295	0.100
29.297	0.353	Equal training sensitivity and specificity	0.195	0.195
26.469	0.323	Maximum training sensitivity plus specificity	0.219	0.161
4.707	0.097	Balance training omission, predicted area and threshold value	0.610	0.015
11.267	0.170	Equate entropy of thresholded and original distributions	0.425	0.042

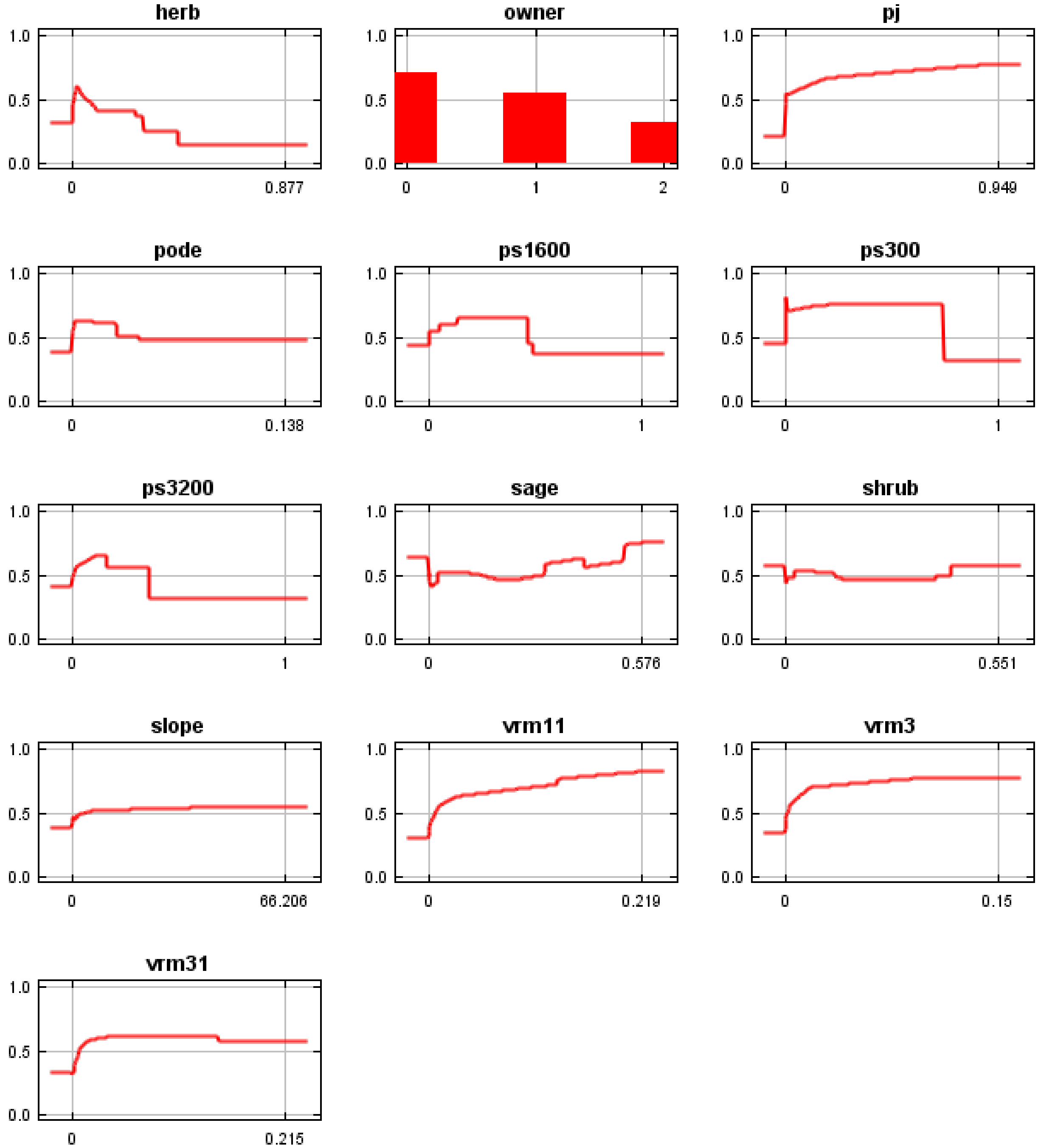
Response curves

These curves show how each environmental variable affects the Maxent prediction. 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.




bioclim4
1.0
0.5
0.0
7047
10505
bioclim6
-212
-94
confr
0
0.944
contag
3
100
cti
6.062
23.184
d2cave
0
138768
d2cliffs40
0
138567
d2outcrop
0
11753.5
d2road
0
31852.1
d2srl
0
201
decid
0
0.406
dstrb
0
0.992
elev
970.084
3847.16
flood_freq
1
4
forest
0
0.988
fw1600
0
0.128
fw300
0
0.416
fw3200
0
0.09



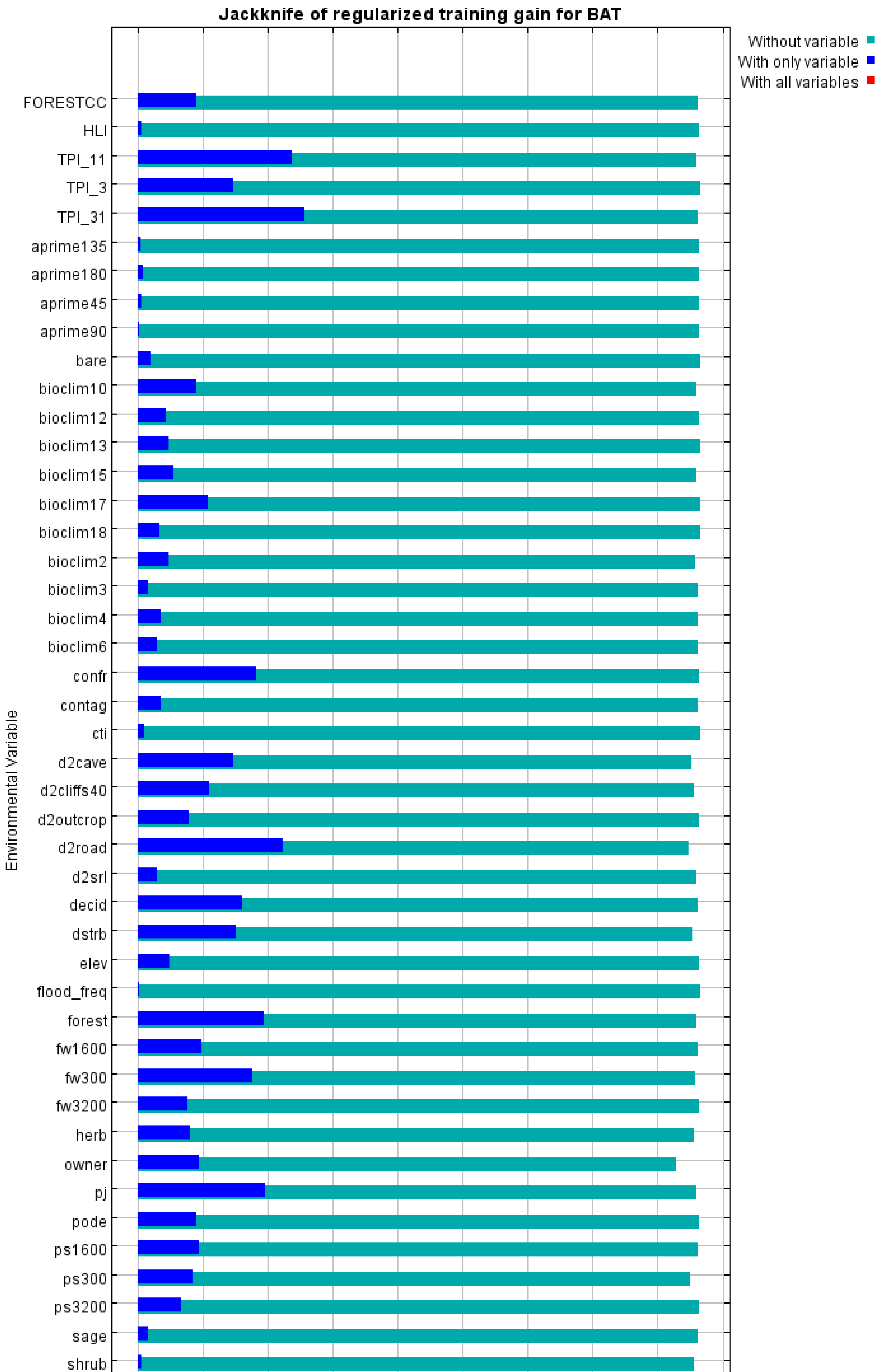
Analysis of variable contributions

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
d2road	14.9	11
TPI_31	11.8	1.1
pj	10	1.5
TPI_11	9.4	1.8
dstrb	9	8.3
forest	8.9	6
owner	7.9	11.2
fw300	3.9	1.6
ps300	3.8	2.5
d2cave	2	3.7
herb	1.3	4.6
shrub	1.2	6.4
bioclim2	1.1	1.7
bioclim3	1.1	0.5
elev	1	0.5
decid	1	0.2
d2cliffs40	1	5.6
bioclim15	1	0.9
d2srl	0.8	1.3
bioclim4	0.8	1.1
bioclim10	0.7	5.6
ps1600	0.7	1.7
bioclim12	0.7	1.5
vrm3	0.6	0.5
bioclim6	0.5	1.9
slope	0.5	2.6
bioclim13	0.5	0.4
FORESTCC	0.4	0.9
sage	0.4	1.4
aprime180	0.3	0.5
bare	0.3	2.2
vrm11	0.3	1.7
ps3200	0.3	0.8
vrm31	0.3	0.7
d2outcrop	0.3	1.1
bioclim17	0.2	0.6
bioclim18	0.2	1.1
cti	0.2	0
contag	0.2	0.8

TPI_3	0.1	0.3
fw1600	0.1	0.3
fw3200	0.1	0
aprime45	0.1	0.6
aprime135	0.1	0.1
pode	0.1	0.1
HLI	0.1	0.2
confr	0.1	0.3
aprime90	0	0.4
flood_freq	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 TPI_31, 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 owner, which therefore appears to have the most information that isn't present in the other variables. The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is TPI_31, 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 owner, which therefore appears to have the most information that isn't present in the other variables. he


Jackknife of regularized training gain for BAT
Without variable
With only variable
With all variables
Environmental Variable
FORESTCC
HLI
TPI_11
TPI_3
TPI_31
aprime135
aprime180
aprime45
aprime90
bare
bioclim10
bioclim12
bioclim13
bioclim15
bioclim17
bioclim18
bioclim2
bioclim3
bioclim4
bioclim6
confr
contag
cti
d2cave
d2cliffs40
d2outcrop
d2road
d2srl
decid
dstrb
elev
flood_freq
forest
fw1600
fw300
fw3200
herb
owner
pj
pode
ps1600
ps300
ps3200
sage
shrub

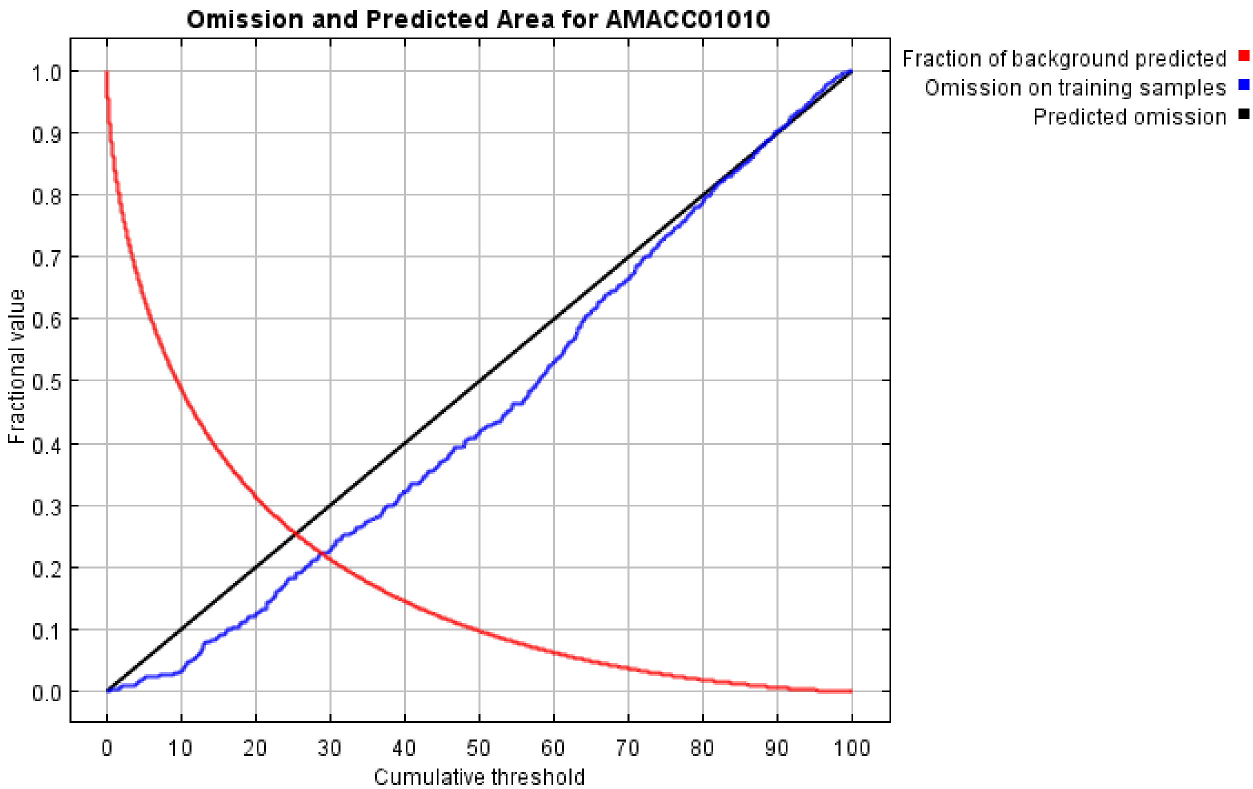
Raw data outputs and control parameters
Regularized training gain is 0.862, training AUC is 0.875, unregularized training gain is 1.028.
Algorithm terminated after 500 iterations (72 seconds).

The follow settings were used during the run:
1552 presence records used for training.
11158 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used: FORESTCC HLI TPI_11 TPI_3 TPI_31 aprime135 aprime180 aprime45 aprime90 bare bioclim10 bioclim12 bioclim13 bioclim15 bioclim17 bioclim18 bioclim2 bioclim3 bioclim4 bioclim6 confr contag cti d2cave d2cliffs40 d2outcrop d2road d2srl decid dstrb elev flood_freq forest fw1600 fw300 fw3200 herb owner(categorical) pj pode ps1600 ps300 ps3200 sage shrub slope vrm11 vrm3 vrm31
Regularization values: linear/quadratic/product: 0.050, categorical: 0.250, threshold: 1.000, hinge: 0.500
Feature types used: hinge product linear threshold quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\SAMPLING_EFFORT
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile: F:\MODELING\BATS_2015\MAXENT_IN\ALL_BATS.CSV
environmentallayers: F:\MODELING\BATS_2015\MAXENT_IN\RANDOM_BACKGROUND.CSV
writeclampgrid: false
writemess: false
writeplotdata: true
threads: 4
Command line used: dontwriteclampgrid

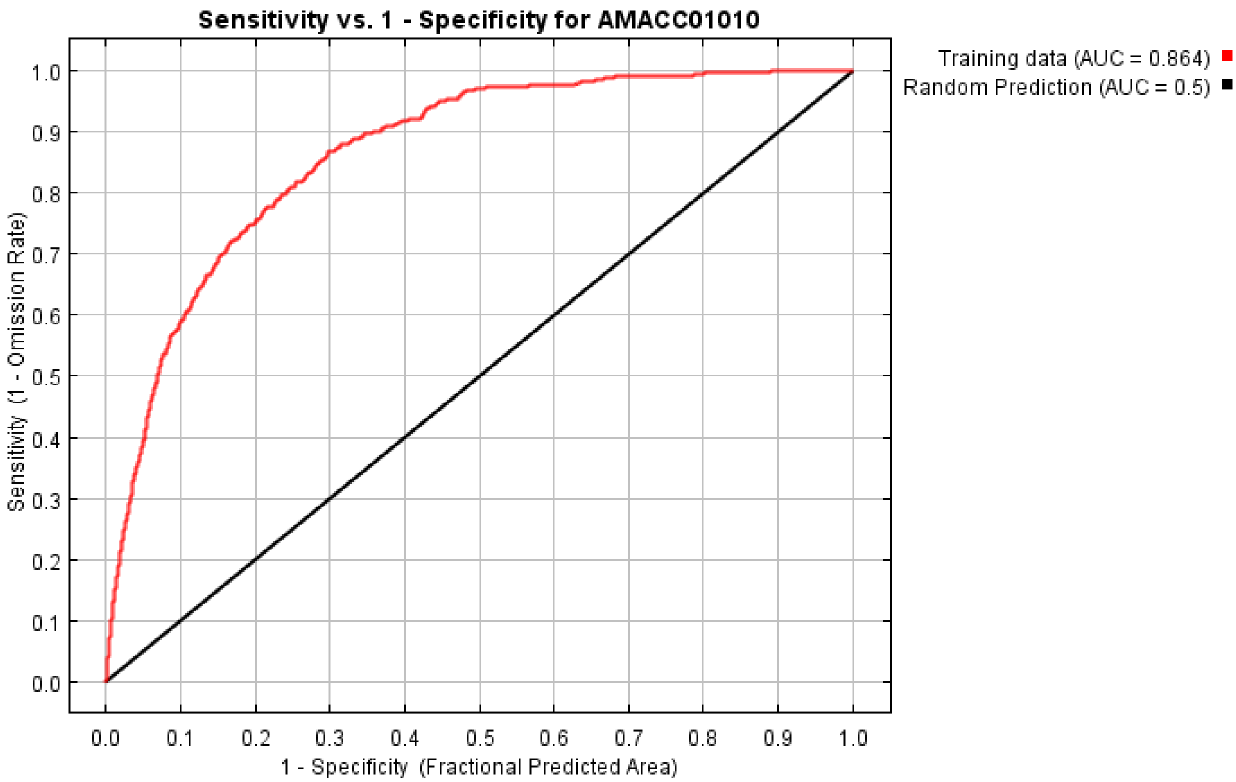
Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E BAT responsecurves nopictures jackknife outputfiletype=bil outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\SAMPLING_EFFORT projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=F:\MODELING\BATS_2015\MAXENT_IN\ALL_BATS.CSV environmentallayers=F:\MODELING\BATS_2015\MAXENT_IN\RANDOM_BACKGROUND.CSV nowriteclampgrid nowritemess writeplotdata threads=4 -N pipo -N rangepnorm -t owner

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 0.821 rather than 1; in practice the test AUC may exceed this bound.



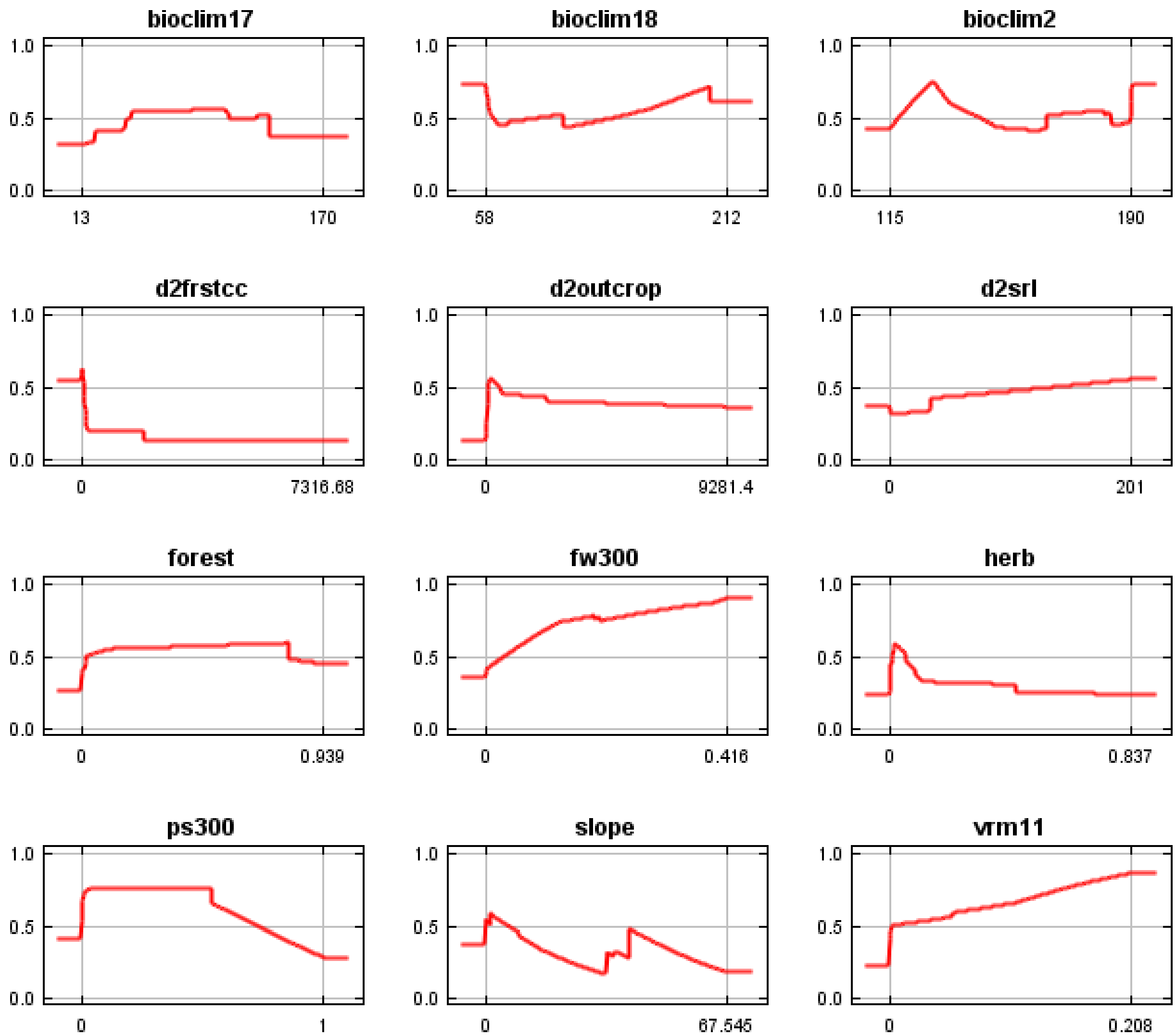
Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

Cumulative threshold	**Logistic threshold**	**Description**	**Fractional predicted area**	**Training omission rate**
1.000	0.049	Fixed cumulative value 1	0.847	0.005
5.000	0.106	Fixed cumulative value 5	0.634	0.020
10.000	0.160	Fixed cumulative value 10	0.486	0.034
0.480	0.036	Minimum training presence	0.899	0.000
16.603	0.225	10 percentile training presence	0.362	0.100
28.707	0.344	Equal training sensitivity and specificity	0.224	0.224
21.399	0.272	Maximum training sensitivity plus specificity	0.297	0.134
3.852	0.092	Balance training omission, predicted area and threshold value	0.680	0.011
11.928	0.179	Equate entropy of thresholded and original distributions	0.444	0.057

Response curves

These curves show how each environmental variable affects the Maxent prediction. Each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between

the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.



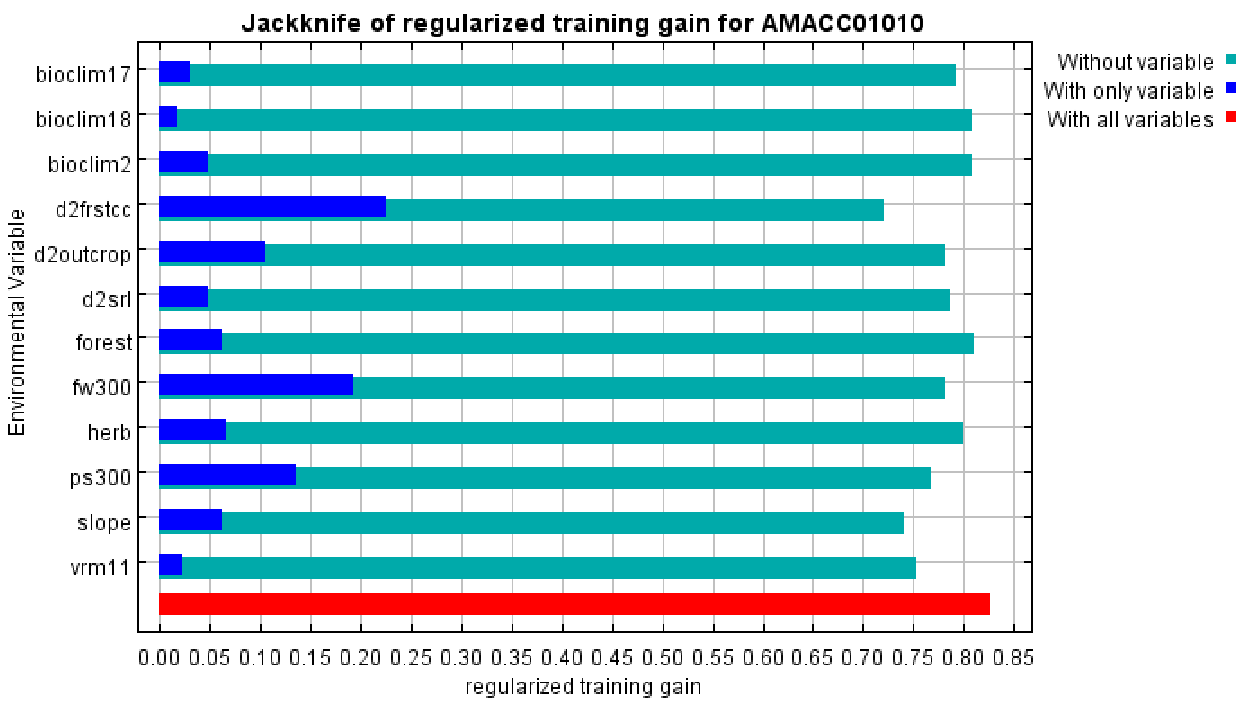
Analysis of variable contributions

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

Variable	Percent contribution	Permutation importance
d2frstcc	28.3	25.2
slope	12.9	15.1
fw300	12.9	4.4
ps300	11.6	4
d2outcrop	9.9	8.6
vrm11	6.6	19.5

herb	5.5	4.9
bioclim2	3	2.3
d2srl	2.8	4
bioclim17	2.8	2.9
forest	1.8	5.8
bioclim18	1.7	3.1

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is d2frstcc, 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 d2frstcc, 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 0.826, training AUC is 0.864, unregularized training gain is 1.015.
Algorithm terminated after 500 iterations (11 seconds).

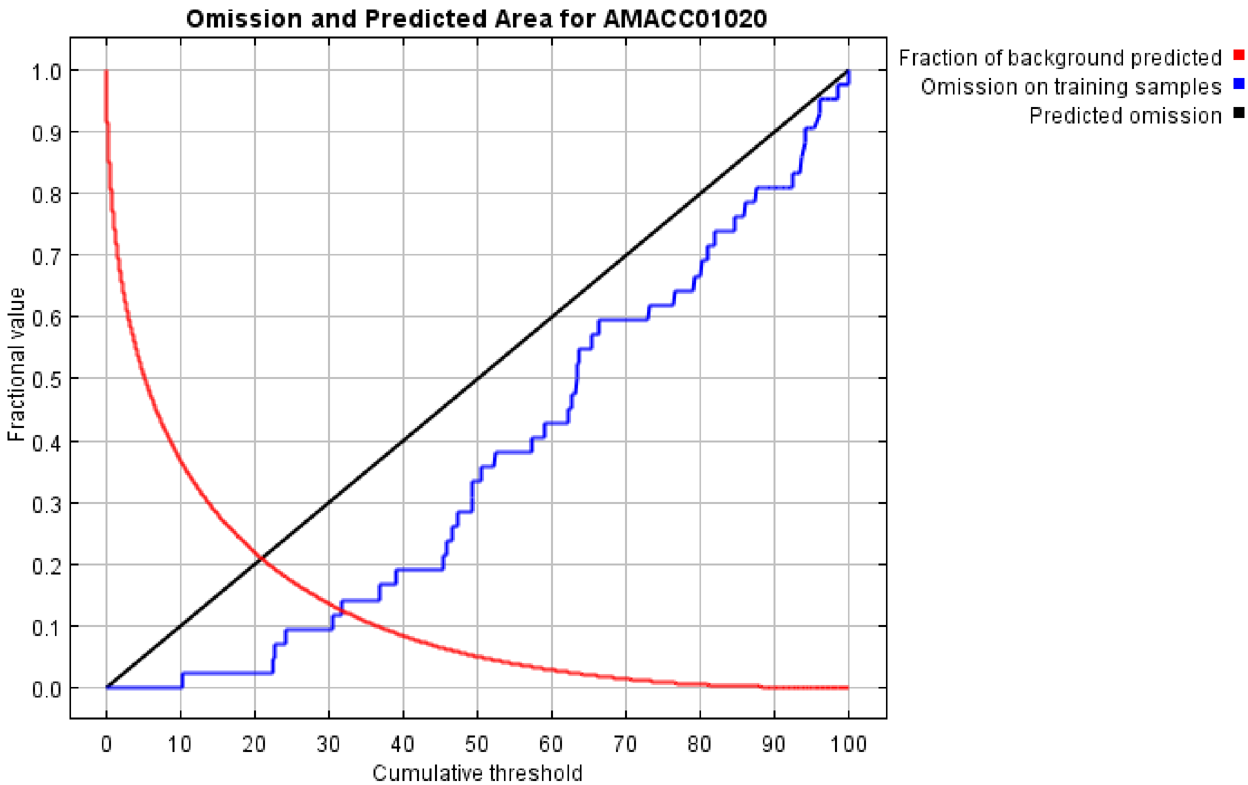
The follow settings were used during the run:
441 presence records used for training.
10441 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): bioclim17 bioclim18 bioclim2 d2frstcc d2outcrop d2srl forest fw300 herb ps300 slope vrm11
Regularization values: linear/quadratic/product: 0.050, categorical: 0.250, threshold: 1.000, hinge: 0.500
Feature types used: hinge product linear threshold quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01010
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC

samplesfile: C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV
environmentallayers: C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV
writeclampgrid: false
perspeciesresults: true
writeplotdata: true
threads: 4
Command line used: dontwriteclampgrid

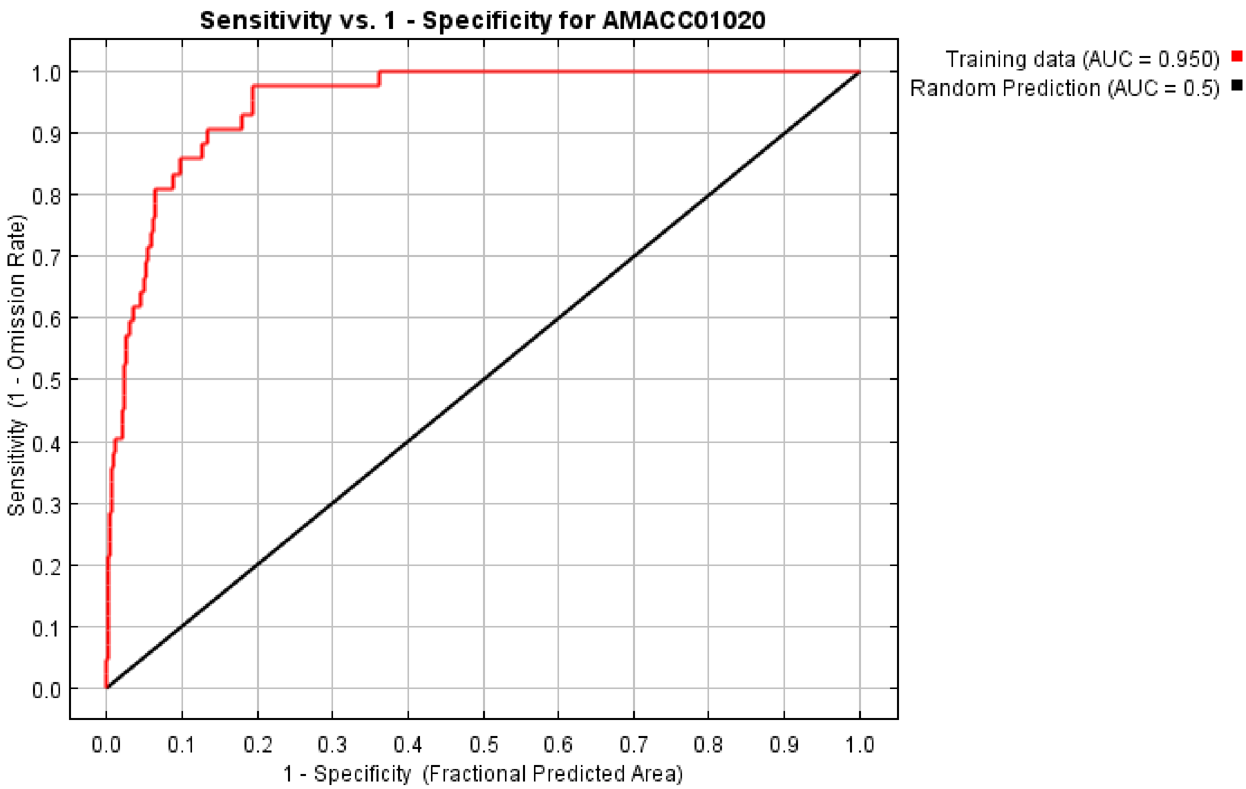
Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E AMACC01010 responsecurves nopictures jackknife outputfiletype=bil outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01010 projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV nowriteclampgrid perspeciesresults writeplotdata threads=4 -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N bare -N bioclim10 -N bioclim12 -N bioclim13 -N bioclim15 -N bioclim3 -N bioclim4 -N bioclim6 -N confr -N contag -N cti -N d2cave -N d2cliffs40 -N d2road -N decid -N dstrb -N elev -N flood_freq -N frestcc -N fw1600 -N fw3200 -N hli -N owner -N pj -N pode -N ps1600 -N ps3200 -N sage -N shrub -N tpi31 -N tpi_11 -N tpi_3 -N vrm3 -N vrm_31

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 0.871 rather than 1; in practice the test AUC may exceed this bound.



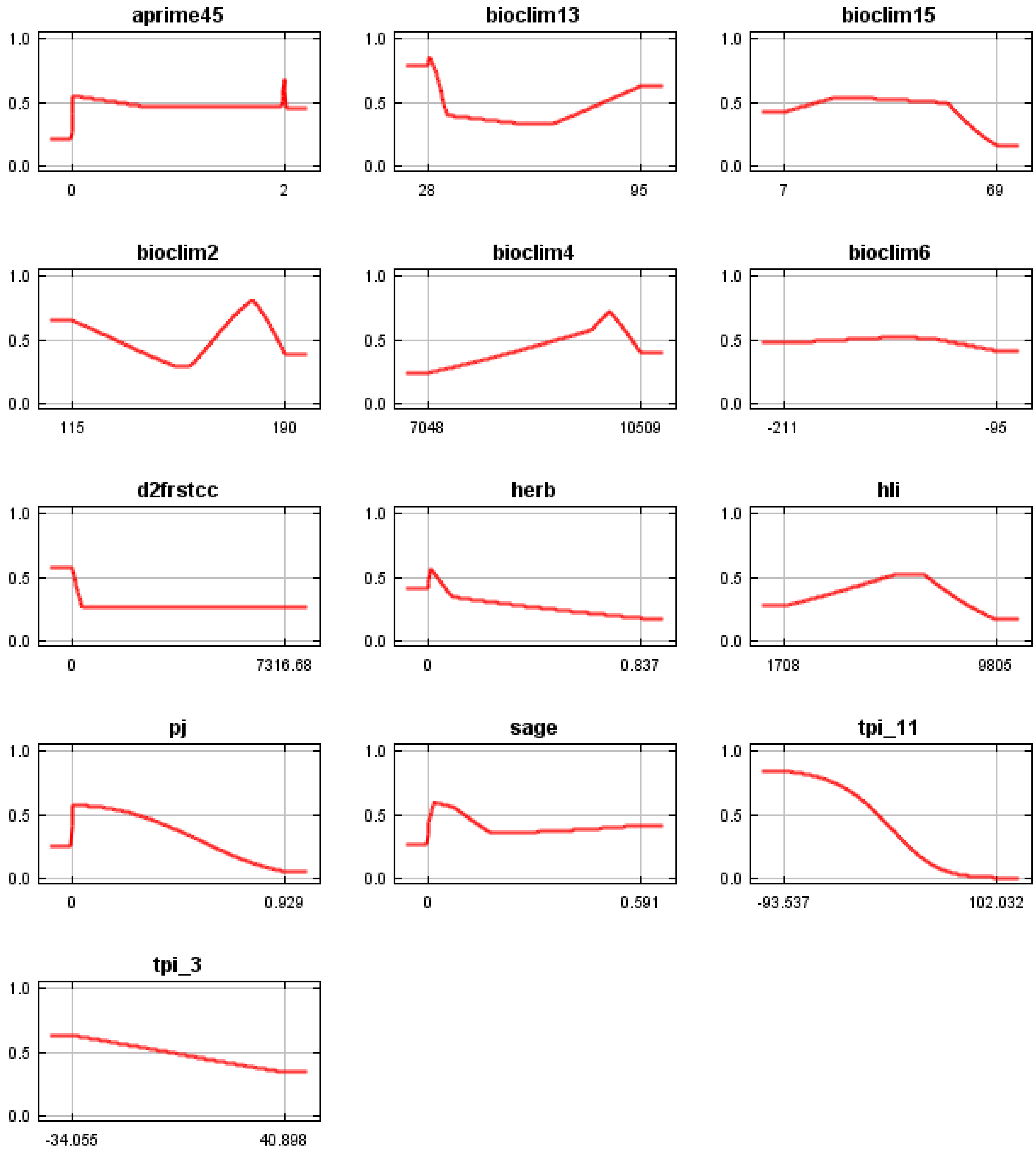
Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.023	Fixed cumulative value 1	0.753	0.000
5.000	0.065	Fixed cumulative value 5	0.508	0.000
10.000	0.113	Fixed cumulative value 10	0.368	0.000
10.265	0.115	Minimum training presence	0.362	0.000
30.443	0.296	10 percentile training presence	0.134	0.095
31.777	0.310	Equal training sensitivity and specificity	0.126	0.119
22.544	0.226	Maximum training sensitivity plus specificity	0.194	0.024
8.272	0.096	Balance training omission, predicted area and threshold value	0.407	0.000
16.047	0.165	Equate entropy of thresholded and original distributions	0.266	0.024

Response curves

These curves show how each environmental variable affects the Maxent prediction. Each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between

the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.

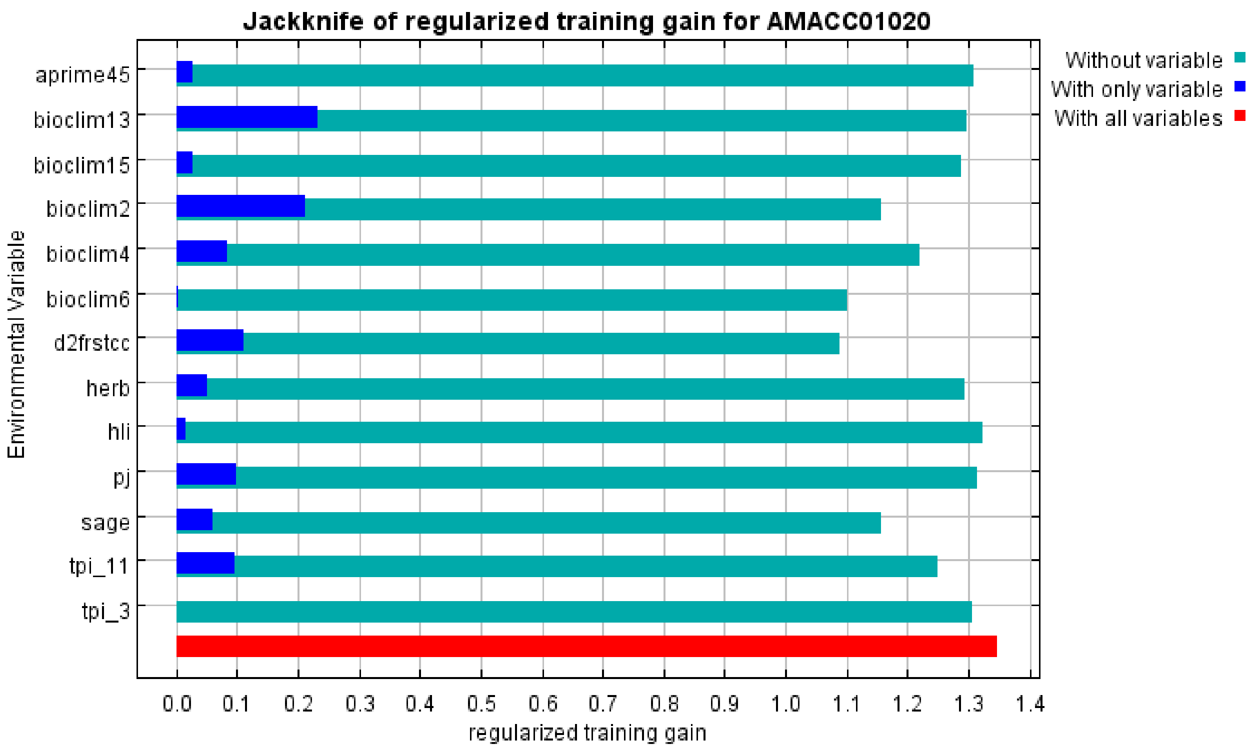


Analysis of variable contributions

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

Variable	**Percent contribution**	**Permutation importance**
bioclim13	22.1	2.3
d2frstcc	18.5	16.6
bioclim2	15.4	12.8
bioclim6	10.1	22.9
sage	9.8	8.3
bioclim4	6.2	15.9
pj	4.5	0.9
tpi_11	3.3	4.1
herb	3.2	3
aprime45	3.2	3
bioclim15	2	7.2
tpi_3	0.9	1.6
hli	0.7	1.4

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bioclim13, 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 d2frstcc, 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 1.347, training AUC is 0.950, unregularized training gain is 2.017.
Algorithm terminated after 500 iterations (11 seconds).

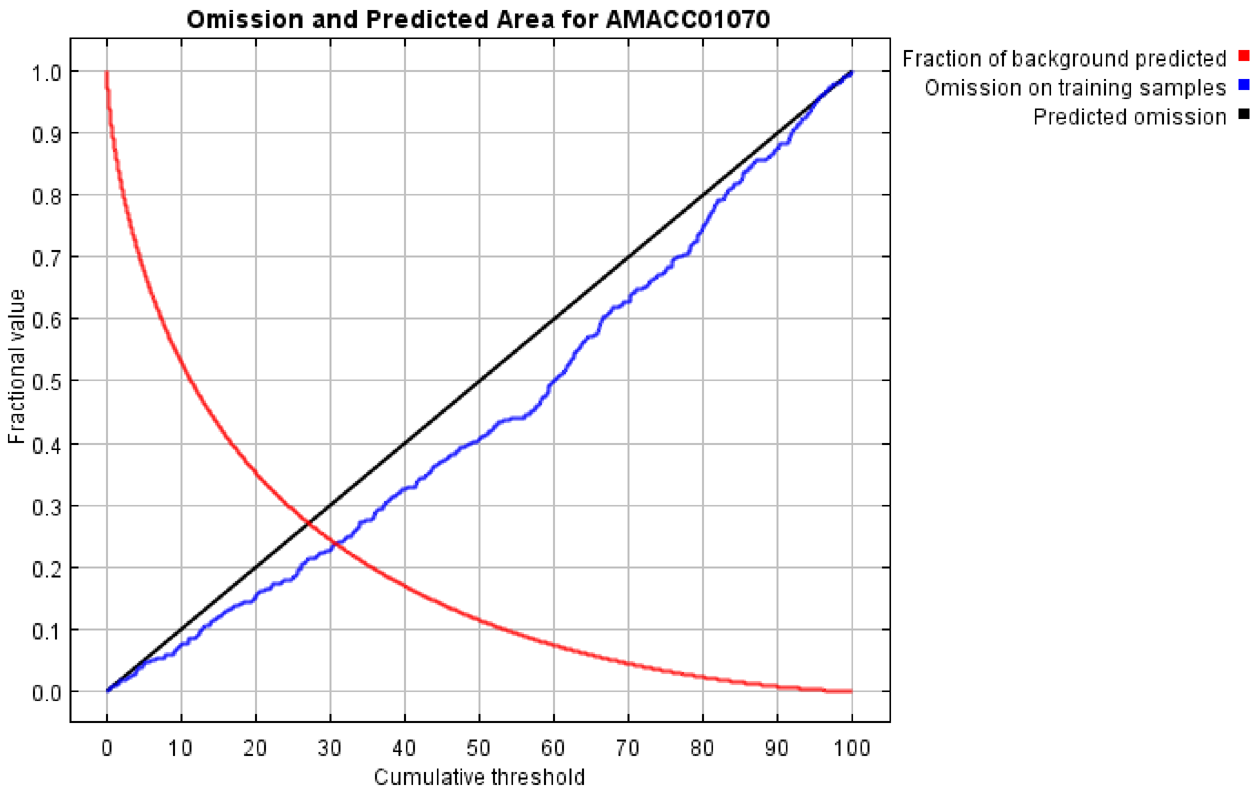
The follow settings were used during the run:
42 presence records used for training.

10042 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): aprime45 bioclim13 bioclim15 bioclim2 bioclim4 bioclim6 d2frstcc herb hli pj sage tpi_11 tpi_3
Regularization values: linear/quadratic/product: 0.216, categorical: 0.250, threshold: 1.580, hinge: 0.500
Feature types used: hinge linear quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01020
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile: C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV
environmentallayers: C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV
warnings: false
askoverwrite: false
writeclampgrid: false
writemess: false
writebackgroundpredictions: true
autorun: true
writeplotdata: true
visible: false
threads: 5
Command line used: -r -a nowarnings responsecurves novisible nopictures jackknife outputfiletype=bil projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions writeplotdata threads=5 -E -E AMACC01020 outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01020 -N -N aprime45 -N hli -N herb -N pj -N tpi_3 -N tpi_11 -N bioclim13 -N sage -N bioclim4 -N bioclim15 -N d2frstcc -N bioclim6 -N bioclim2

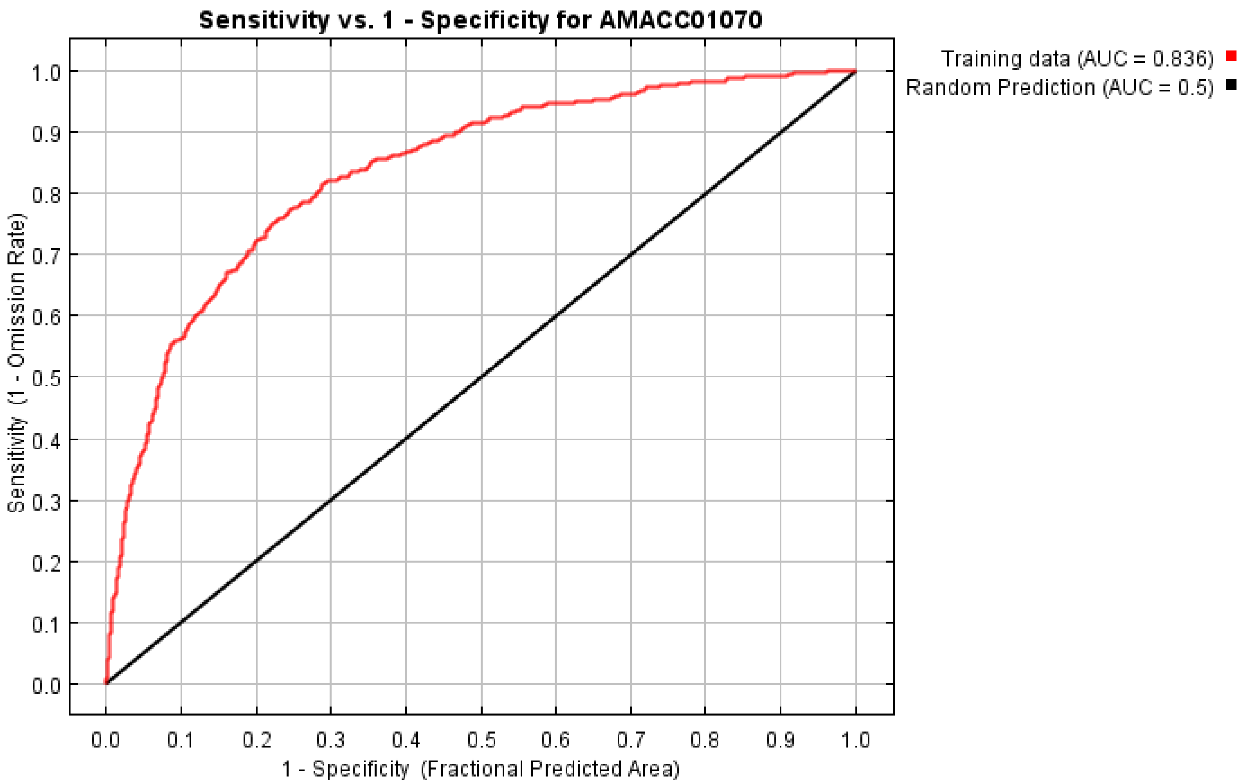
Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E AMACC01020 responsecurves nopictures jackknife outputfiletype=bil outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01020 projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV nowarnings noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions autorun writeplotdata novisible threads=5 -N aprime135 -N aprime180 -N aprime90 -N bare -N bioclim10 -N bioclim12 -N bioclim17 -N bioclim18 -N bioclim3 -N confr -N contag -N cti -N d2cave -N d2cliffs40 -N d2outcrop -N d2road -N d2srl -N decid -N dstrb -N elev -N flood_freq -N forest -N frestcc -N fw1600 -N fw300 -N fw3200 -N owner -N pode -N ps1600 -N ps300 -N ps3200 -N shrub -N slope -N tpi31 -N vrm11 -N vrm3 -N vrm_31

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 0.802 rather than 1; in practice the test AUC may exceed this bound.



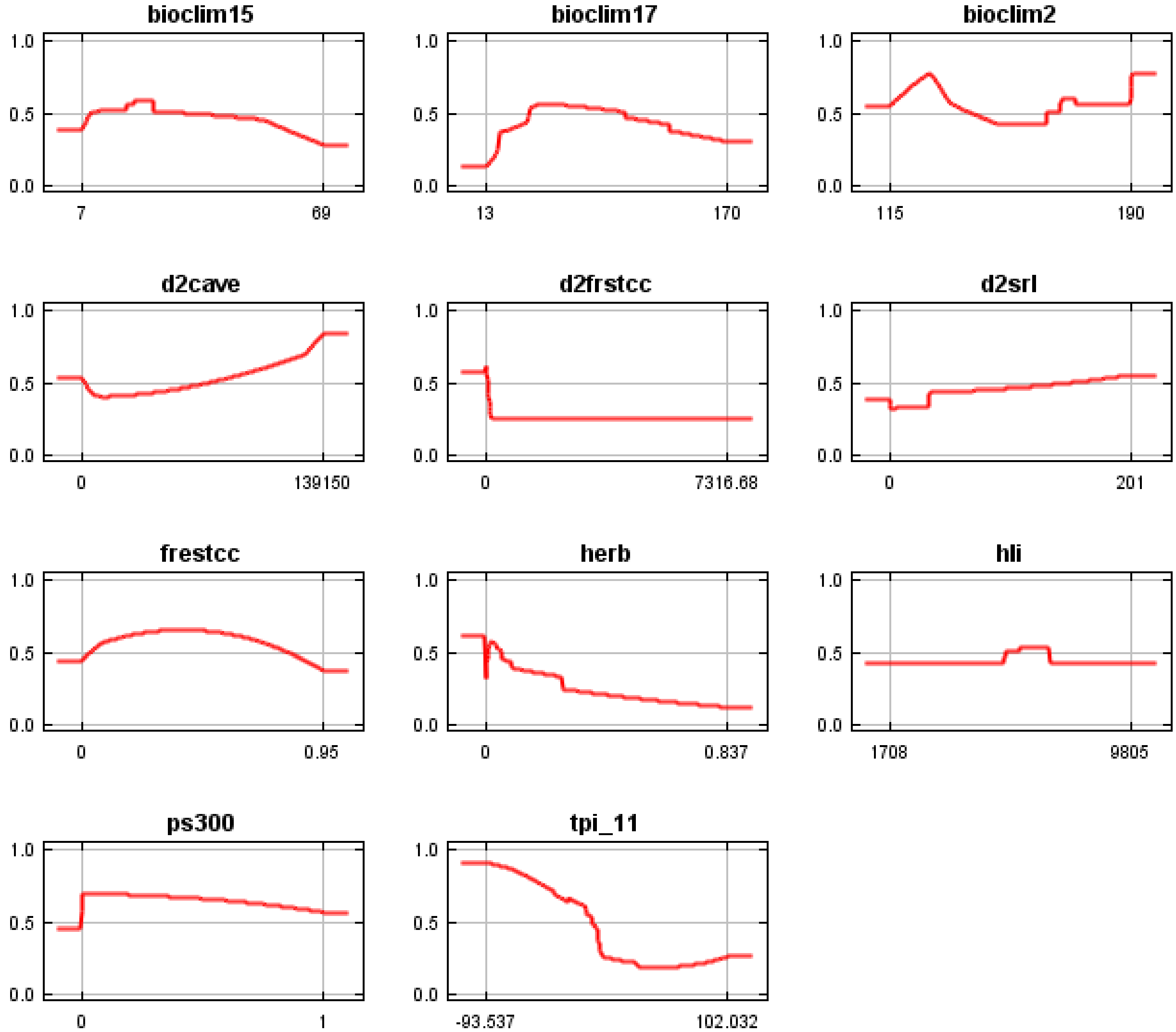
Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

Cumulative threshold	**Logistic threshold**	**Description**	**Fractional predicted area**	**Training omission rate**
1.000	0.061	Fixed cumulative value 1	0.879	0.009
5.000	0.119	Fixed cumulative value 5	0.677	0.046
10.000	0.175	Fixed cumulative value 10	0.530	0.077
0.160	0.031	Minimum training presence	0.963	0.000
13.021	0.205	10 percentile training presence	0.465	0.100
30.597	0.368	Equal training sensitivity and specificity	0.239	0.239
32.928	0.388	Maximum training sensitivity plus specificity	0.220	0.251
2.604	0.090	Balance training omission, predicted area and threshold value	0.780	0.020
11.271	0.187	Equate entropy of thresholded and original distributions	0.501	0.085

Response curves

These curves show how each environmental variable affects the Maxent prediction. Each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between

the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.



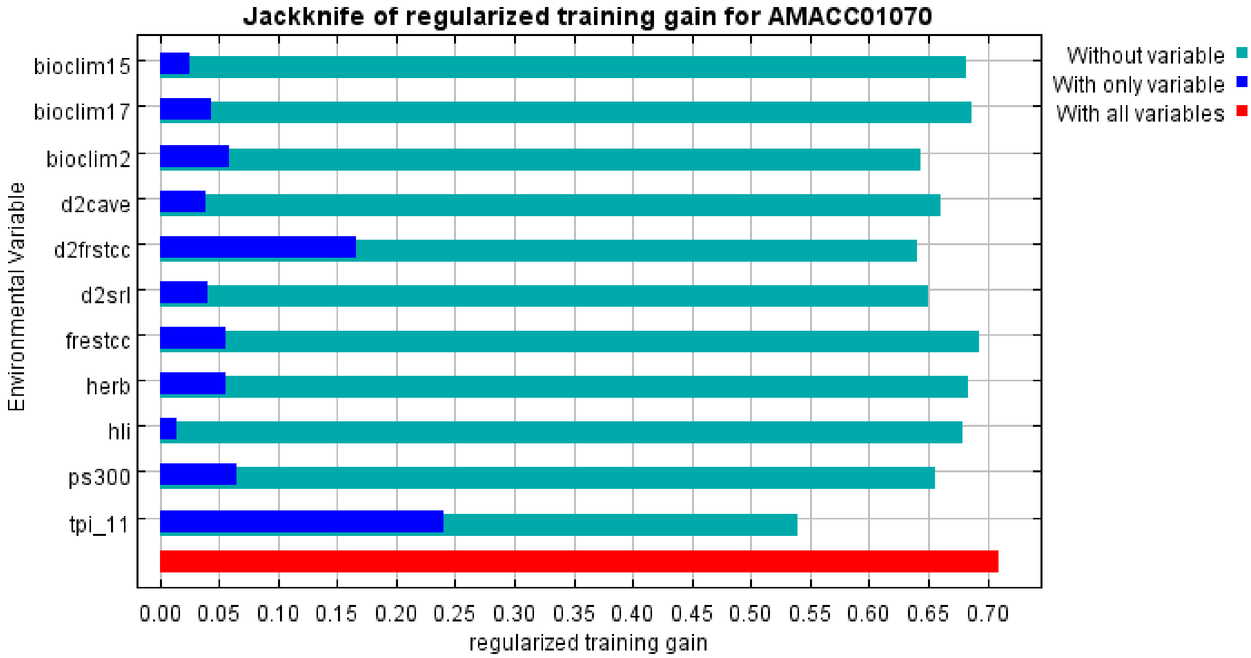
Analysis of variable contributions

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

Variable	Percent contribution	Permutation importance
tpi_11	32.6	23.3
d2frstcc	17.2	17.1
ps300	8.9	3.5
bioclim2	8.8	6.4
d2srl	6.9	7.6
d2cave	6.4	8.3
bioclim17	6.2	7.2

herb	4.8	8.6
hli	4.6	2.9
frestcc	1.9	2.5
bioclim15	1.8	12.7

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is tpi_11, 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 tpi_11, 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 0.710, training AUC is 0.836, unregularized training gain is 0.890.
Algorithm terminated after 500 iterations (9 seconds).

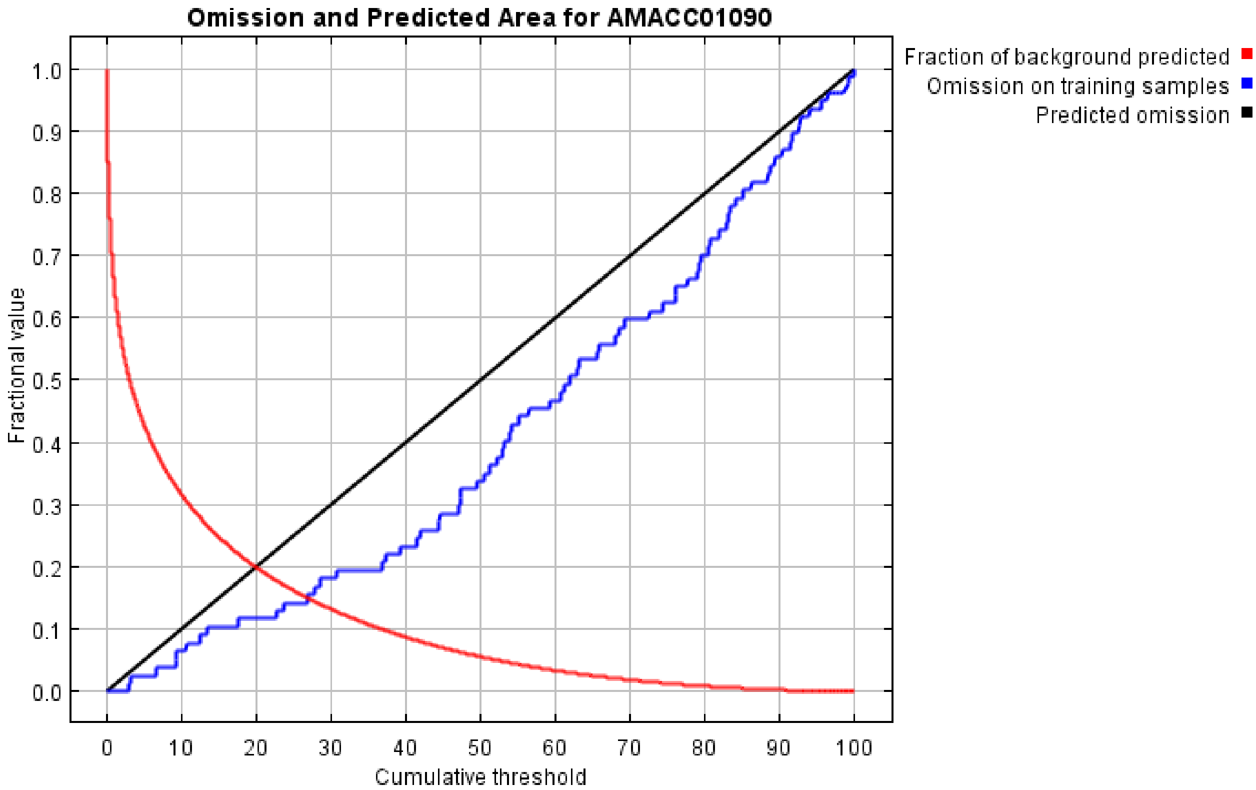
The follow settings were used during the run:
351 presence records used for training.
10351 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): bioclim15 bioclim17 bioclim2 d2cave d2frstcc d2srl frestcc herb hli ps300 tpi_11
Regularization values: linear/quadratic/product: 0.050, categorical: 0.250, threshold: 1.000, hinge: 0.500
Feature types used: hinge product linear threshold quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01070
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile: C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV
environmentallayers: C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV
warnings: false
askoverwrite: false
writeclampgrid: false

writemess: false
writebackgroundpredictions: true
autorun: true
writeplotdata: true
visible: false
threads: 5
Command line used: -r -a nowarnings responsecurves novisible nopictures jackknife outputfiletype=bil projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions writeplotdata threads=5 -E -E AMACC01070 outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01070 -N -N frestcc -N bioclim15 -N d2cave -N hli -N herb -N bioclim17 -N ps300 -N d2frstcc -N d2srl -N bioclim2 -N tpi_11 -N

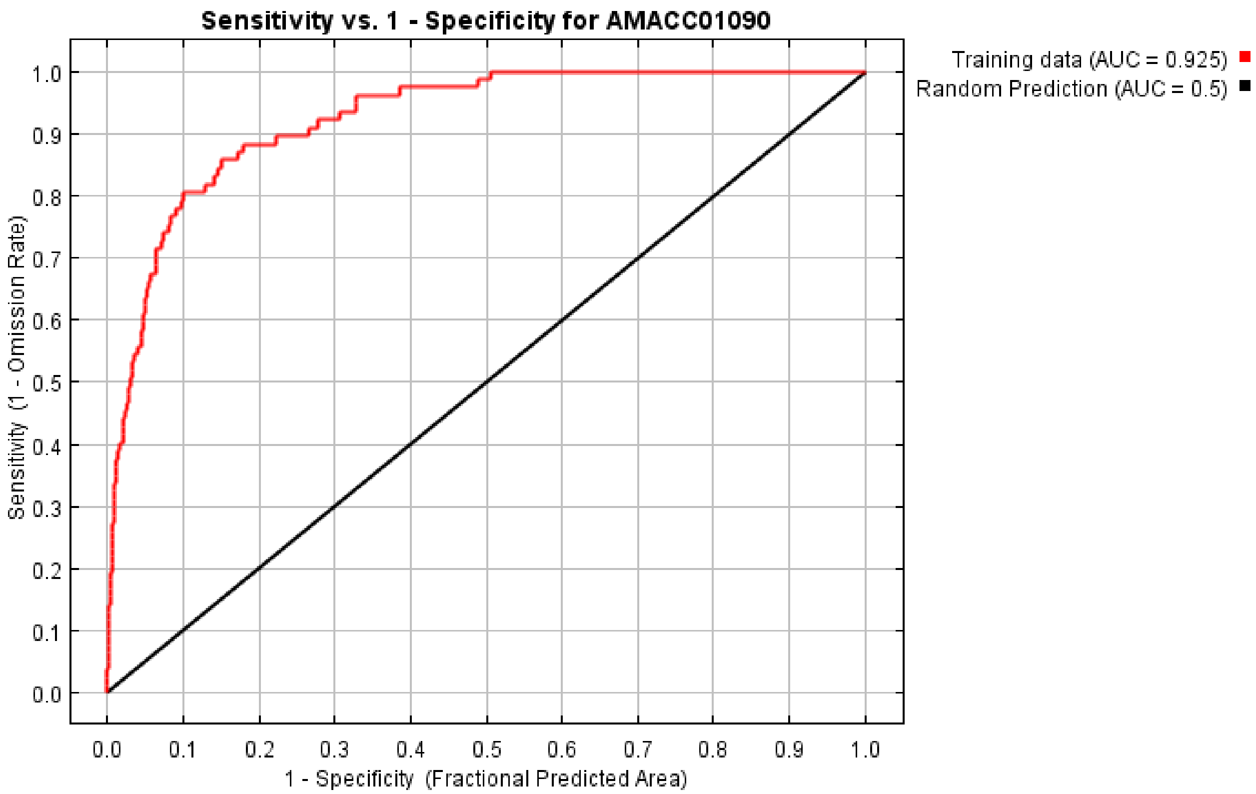
Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E AMACC01070 responsecurves nopictures jackknife outputfiletype=bil outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01070 projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV nowarnings noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions autorun writeplotdata novisible threads=5 -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N bare -N bioclim10 -N bioclim12 -N bioclim13 -N bioclim18 -N bioclim3 -N bioclim4 -N bioclim6 -N confr -N contag -N cti -N d2cliffs40 -N d2outcrop -N d2road -N decid -N dstrb -N elev -N flood_freq -N forest -N fw1600 -N fw300 -N fw3200 -N owner -N pj -N pode -N ps1600 -N ps3200 -N sage -N shrub -N slope -N tpi31 -N tpi_3 -N vrm11 -N vrm3 -N vrm_31

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 0.884 rather than 1; in practice the test AUC may exceed this bound.



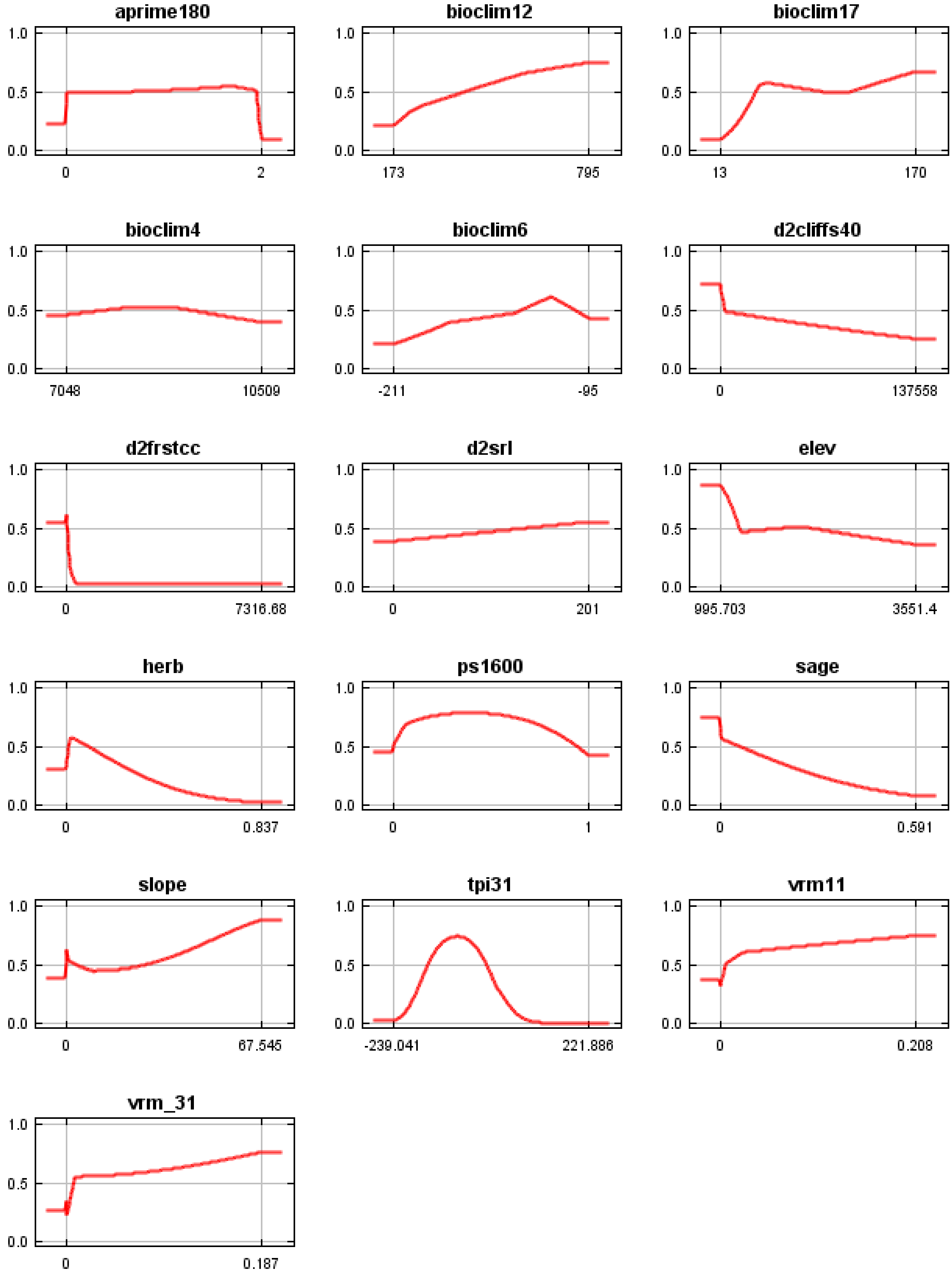
Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.022	Fixed cumulative value 1	0.646	0.000
5.000	0.082	Fixed cumulative value 5	0.427	0.026
10.000	0.140	Fixed cumulative value 10	0.316	0.065
2.878	0.053	Minimum training presence	0.507	0.000
13.528	0.179	10 percentile training presence	0.265	0.091
26.879	0.309	Equal training sensitivity and specificity	0.150	0.156
26.862	0.309	Maximum training sensitivity plus specificity	0.150	0.143
2.878	0.053	Balance training omission, predicted area and threshold value	0.507	0.000
13.049	0.174	Equate entropy of thresholded and original distributions	0.271	0.091

Response curves

These curves show how each environmental variable affects the Maxent prediction. Each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between

the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.

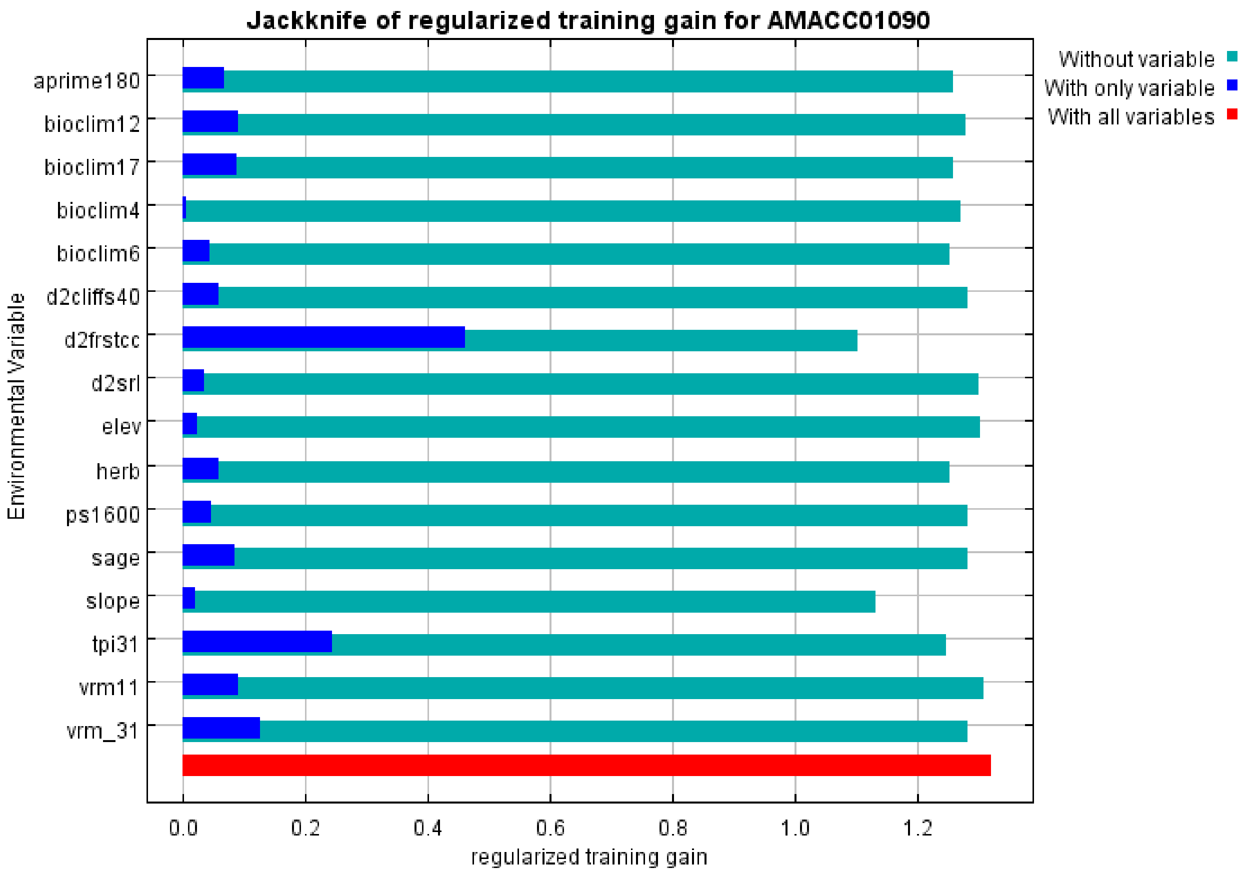


Analysis of variable contributions

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

Variable	Percent contribution	Permutation importance
d2frstcc	42.7	25.8
slope	10.2	11.4
vrm_31	6.4	1.8
bioclim6	5.4	11.5
aprime180	5.2	3
tpi31	4.2	4.1
elev	3.8	3
bioclim17	3.7	7.8
ps1600	3.5	1.3
herb	3.2	9.2
d2cliffs40	2.4	3
bioclim4	2.4	6.4
d2srl	2.3	0.4
sage	1.9	2.1
bioclim12	1.4	7.6
vrm11	1.3	1.5

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is d2frstcc, 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 d2frstcc, 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 1.322, training AUC is 0.925, unregularized training gain is 1.738.
Algorithm terminated after 500 iterations (17 seconds).

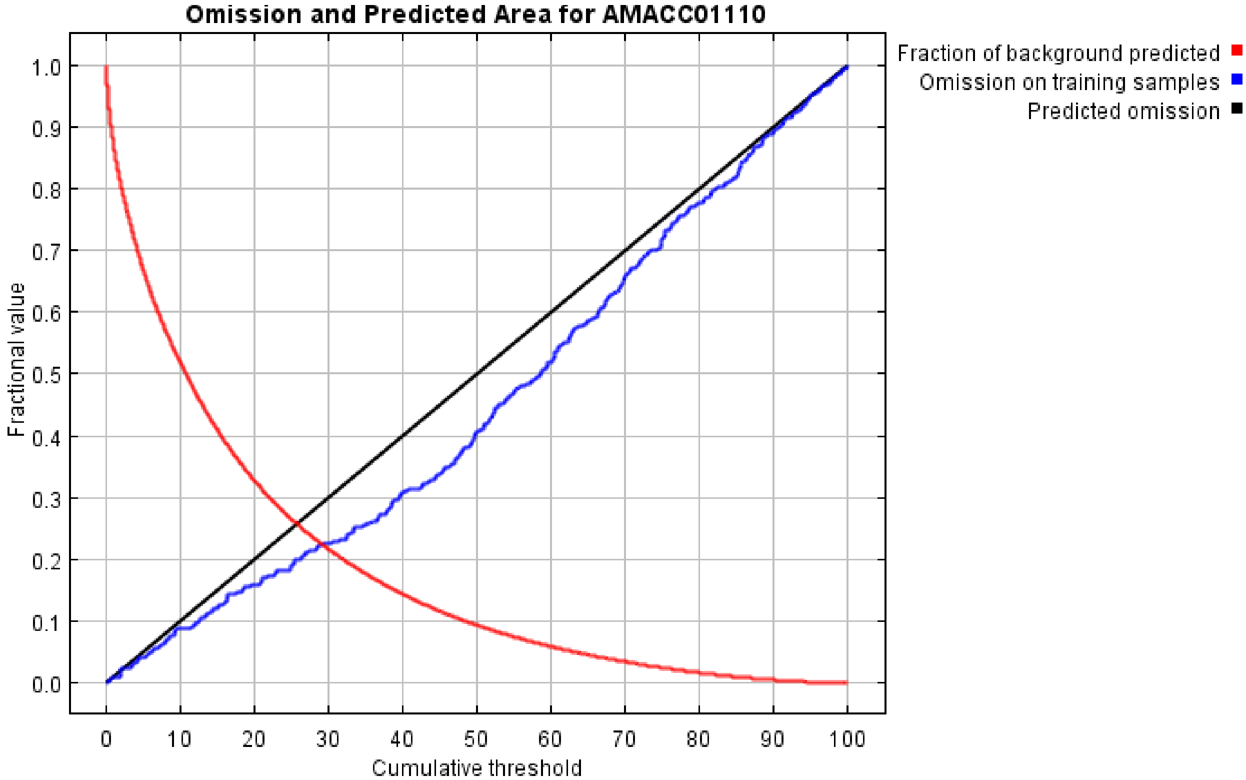
The follow settings were used during the run:
77 presence records used for training.
10077 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): aprime180 bioclim12 bioclim17 bioclim4 bioclim6 d2cliffs40 d2frstcc d2srl elev herb ps1600 sage slope tpi31 vrm11 vrm_31
Regularization values: linear/quadratic/product: 0.116, categorical: 0.250, threshold: 1.230, hinge: 0.500
Feature types used: hinge linear quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01090
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile: C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV
environmentallayers: C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV
warnings: false
askoverwrite: false
writeclampgrid: false
writemess: false
writebackgroundpredictions: true
autorun: true
writeplotdata: true

visible: false
threads: 5
Command line used: -r -a nowarnings responsecurves novisible nopictures jackknife outputfiletype=bil projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions writeplotdata threads=5 -E -E AMACC01090 outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01090 -N -N sage -N vrm11 -N aprime180 -N d2srl -N elev -N ps1600 -N d2cliffs40 -N bioclim12 -N tpi31 -N herb -N bioclim4 -N bioclim6 -N bioclim17 -N vrm_31 -N slope -N d2frstcc

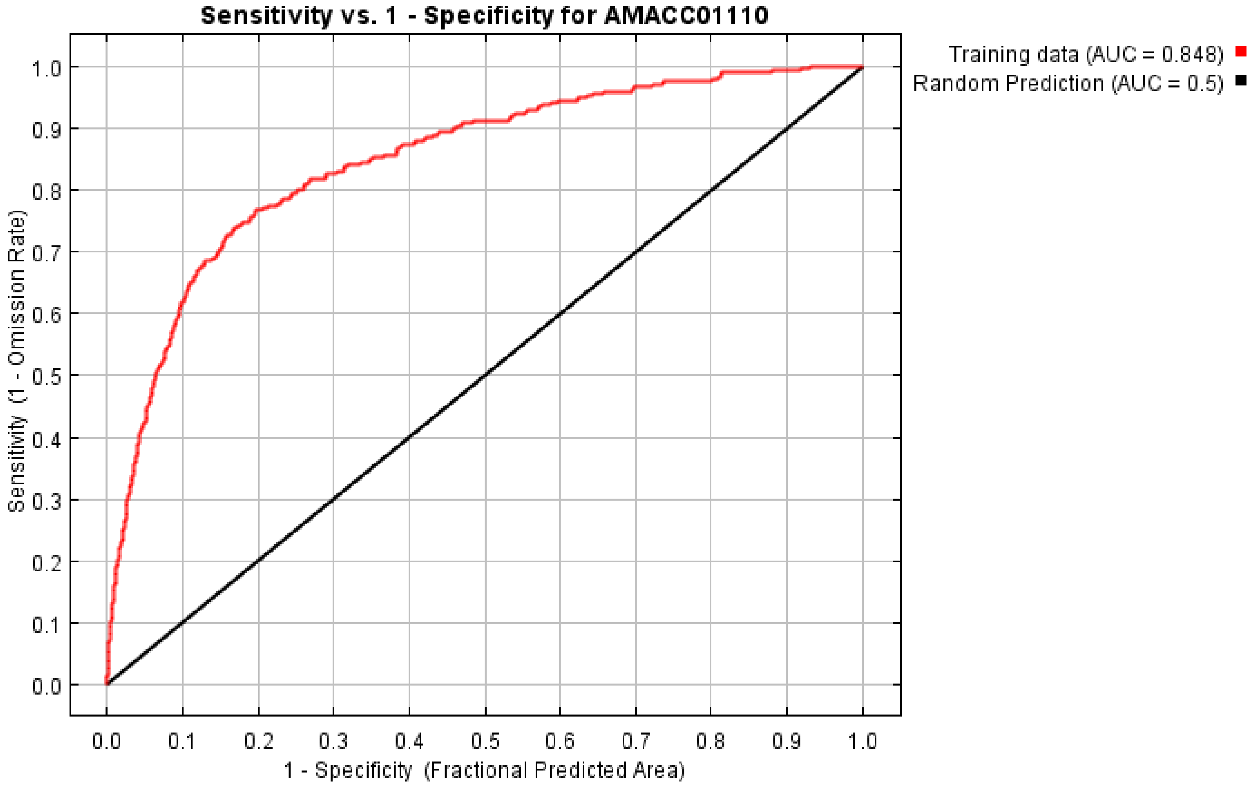
Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E AMACC01090 responsecurves nopictures jackknife outputfiletype=bil outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01090 projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV nowarnings noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions autorun writeplotdata novisible threads=5 -N aprime135 -N aprime45 -N aprime90 -N bare -N bioclim10 -N bioclim13 -N bioclim15 -N bioclim18 -N bioclim2 -N bioclim3 -N confr -N contag -N cti -N d2cave -N d2outcrop -N d2road -N decid -N dstrb -N flood_freq -N forest -N frestcc -N fw1600 -N fw300 -N fw3200 -N hli -N owner -N pj -N pode -N

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 0.816 rather than 1; in practice the test AUC may exceed this bound.



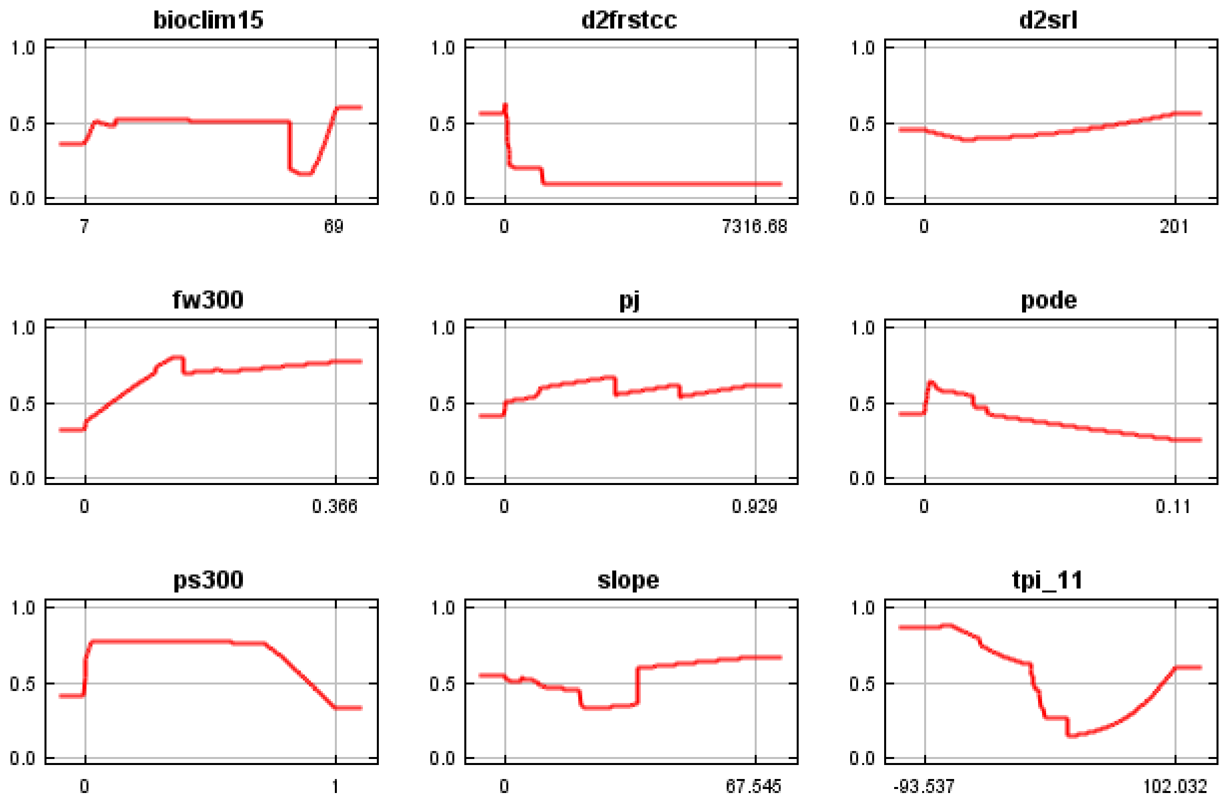
Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.053	Fixed cumulative value 1	0.869	0.011
5.000	0.102	Fixed cumulative value 5	0.669	0.041
10.000	0.152	Fixed cumulative value 10	0.518	0.089
0.355	0.034	Minimum training presence	0.931	0.000
12.612	0.169	10 percentile training presence	0.458	0.100
29.192	0.329	Equal training sensitivity and specificity	0.224	0.226
36.498	0.392	Maximum training sensitivity plus specificity	0.167	0.263
1.831	0.072	Balance training omission, predicted area and threshold value	0.815	0.011
13.349	0.175	Equate entropy of thresholded and original distributions	0.442	0.107

Response curves

These curves show how each environmental variable affects the Maxent prediction. Each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between

the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.

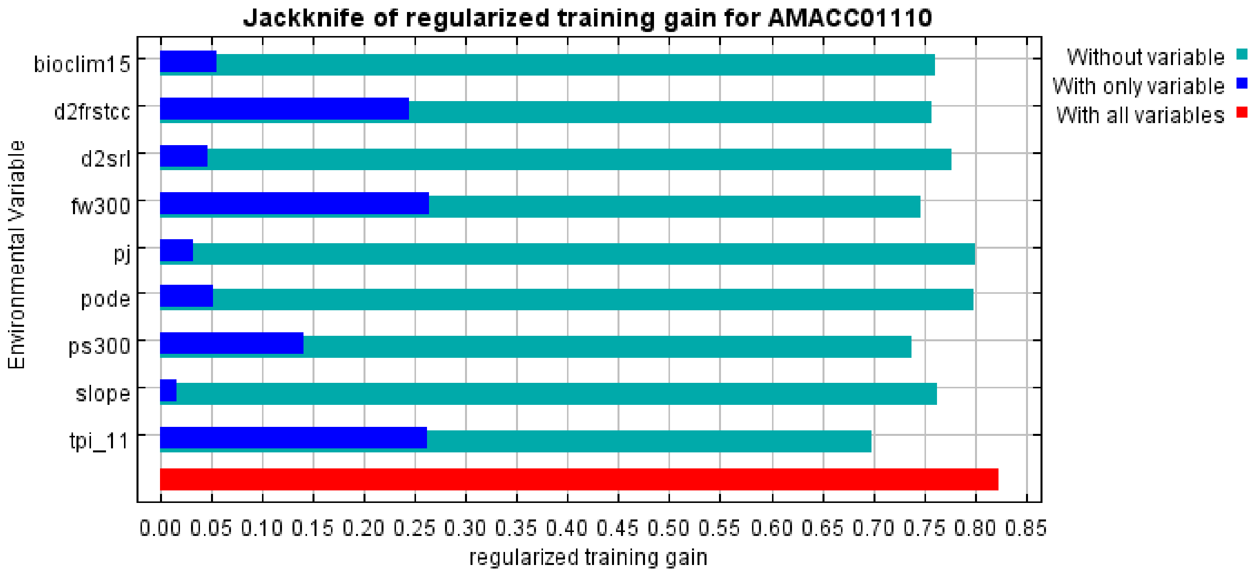


Analysis of variable contributions

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

Variable	Percent contribution	Permutation importance
tpi_11	22.3	18.7
fw300	19.8	8.4
d2frstcc	19.7	29.4
ps300	13.6	7.4
bioclim15	7.5	12.5
slope	6.6	9.8
pj	4	2.1
d2srl	4	5.7
pode	2.4	6

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is fw300, 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 tpi_11, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

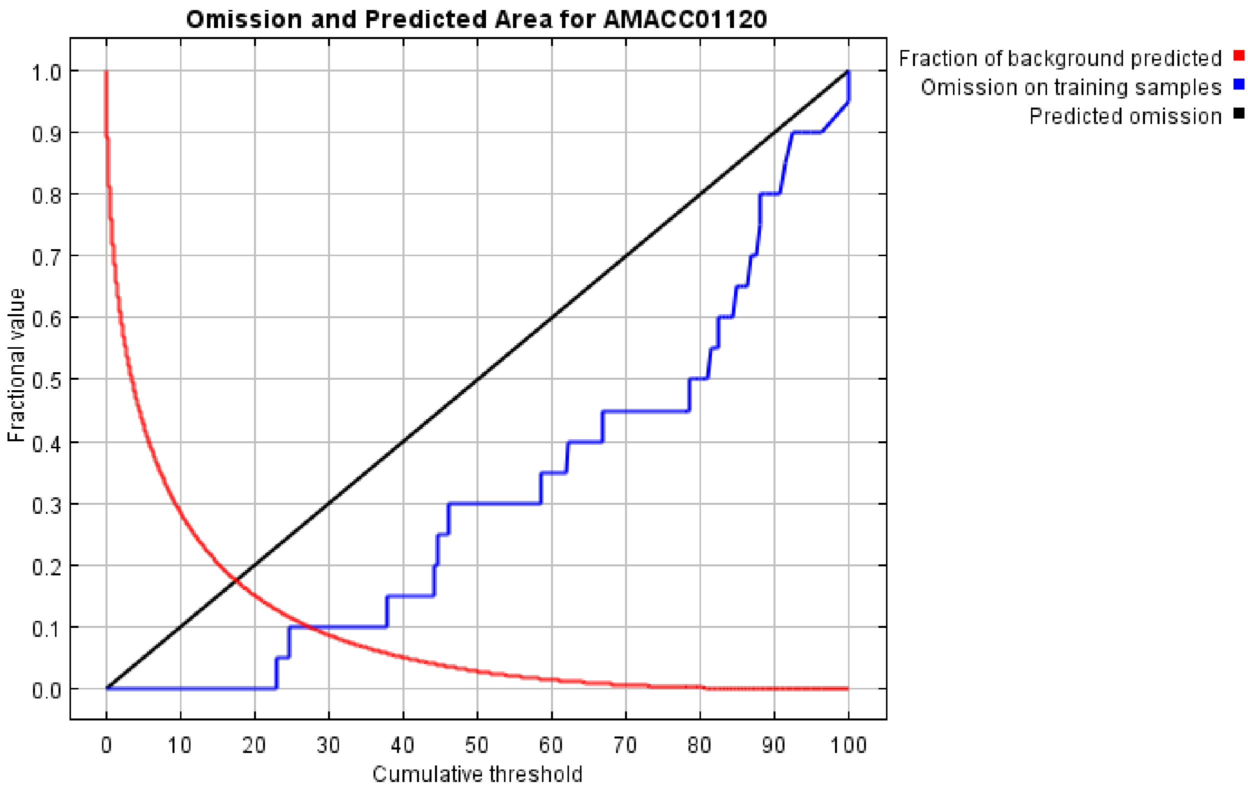
Regularized training gain is 0.823, training AUC is 0.848, unregularized training gain is 1.011.
Algorithm terminated after 500 iterations (9 seconds).

The follow settings were used during the run:
270 presence records used for training.
10270 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): bioclim15 d2frstcc d2srl fw300 pj pode ps300 slope tpi_11
Regularization values: linear/quadratic/product: 0.050, categorical: 0.250, threshold: 1.000, hinge: 0.500
Feature types used: hinge product linear threshold quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01110
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile: C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV
environmentallayers: C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV
writeclampgrid: false
perspeciesresults: true
writeplotdata: true
threads: 4
Command line used: dontwriteclampgrid

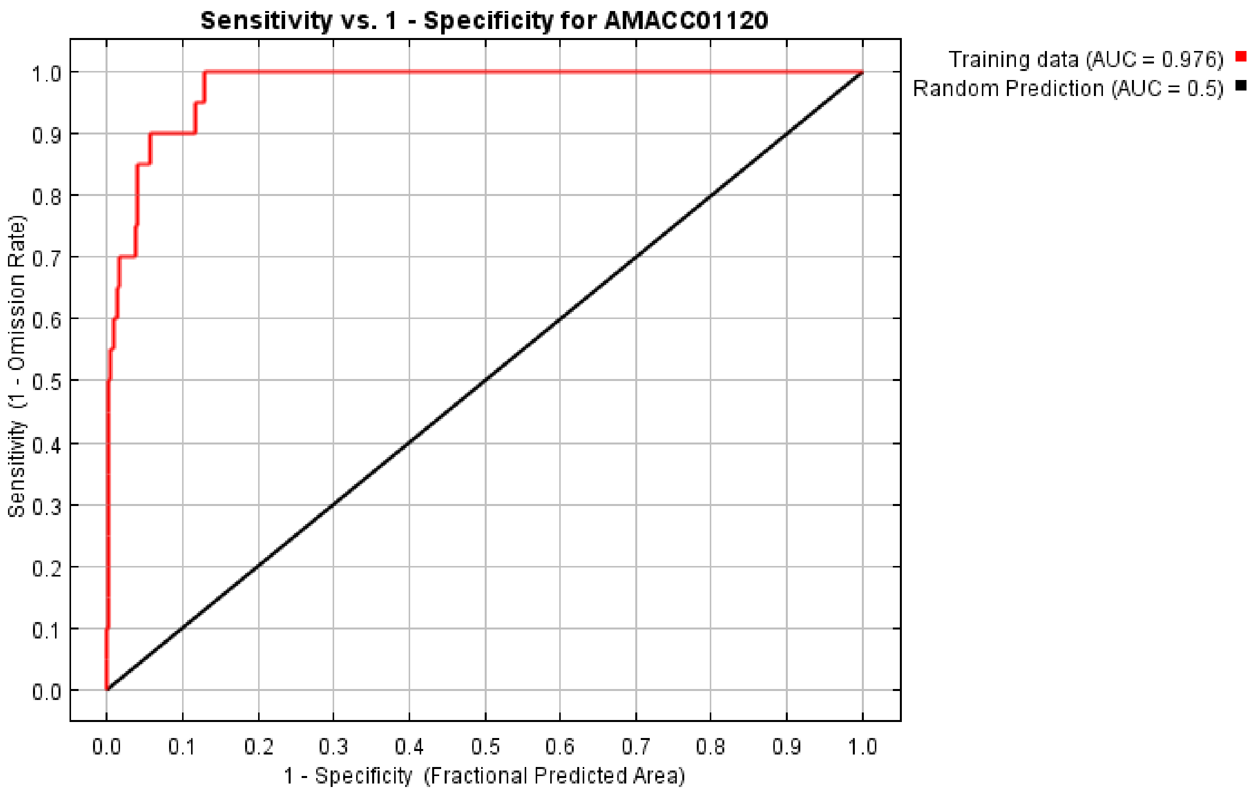
Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E AMACC01110 responsecurves nopictures jackknife outputfiletype=bil outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01110 projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV nowriteclampgrid perspeciesresults writeplotdata threads=4 -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N bare -N bioclim10 -N bioclim12 -N bioclim13 -N bioclim17 -N bioclim18 -N bioclim2 -N bioclim3 -N bioclim4 -N bioclim6 -N confr -N contag -N cti -N d2cave -N d2cliffs40 -N d2outcrop -N d2road -N decid -N dstrb -N elev -N flood_freq -N forest -N frestcc -N fw1600 -N fw3200 -N herb -N hli -N owner -N ps1600 -N ps3200 -N sage -N shrub -N tpi31 -N tpi_3 -N vrm11 -N vrm3 -N vrm_31

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 0.898 rather than 1; in practice the test AUC may exceed this bound.



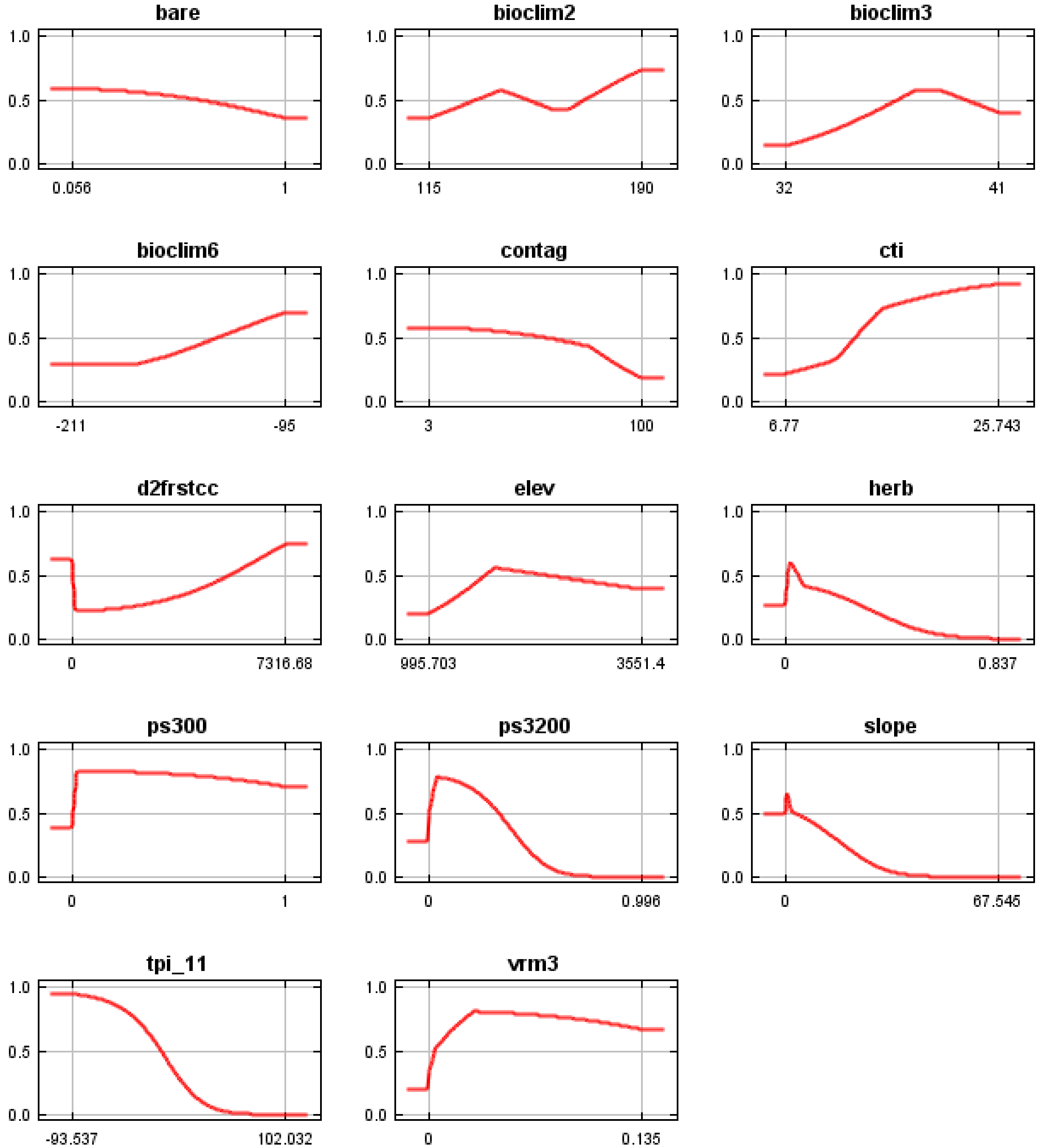
Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

Cumulative threshold	**Logistic threshold**	**Description**	**Fractional predicted area**	**Training omission rate**
1.000	0.012	Fixed cumulative value 1	0.699	0.000
5.000	0.040	Fixed cumulative value 5	0.427	0.000
10.000	0.075	Fixed cumulative value 10	0.285	0.000
22.935	0.189	Minimum training presence	0.128	0.000
37.893	0.351	10 percentile training presence	0.058	0.100
27.457	0.238	Equal training sensitivity and specificity	0.100	0.100
22.935	0.189	Maximum training sensitivity plus specificity	0.128	0.000
8.335	0.062	Balance training omission, predicted area and threshold value	0.323	0.000
18.345	0.145	Equate entropy of thresholded and original distributions	0.167	0.000

Response curves

These curves show how each environmental variable affects the Maxent prediction. Each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between

the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.

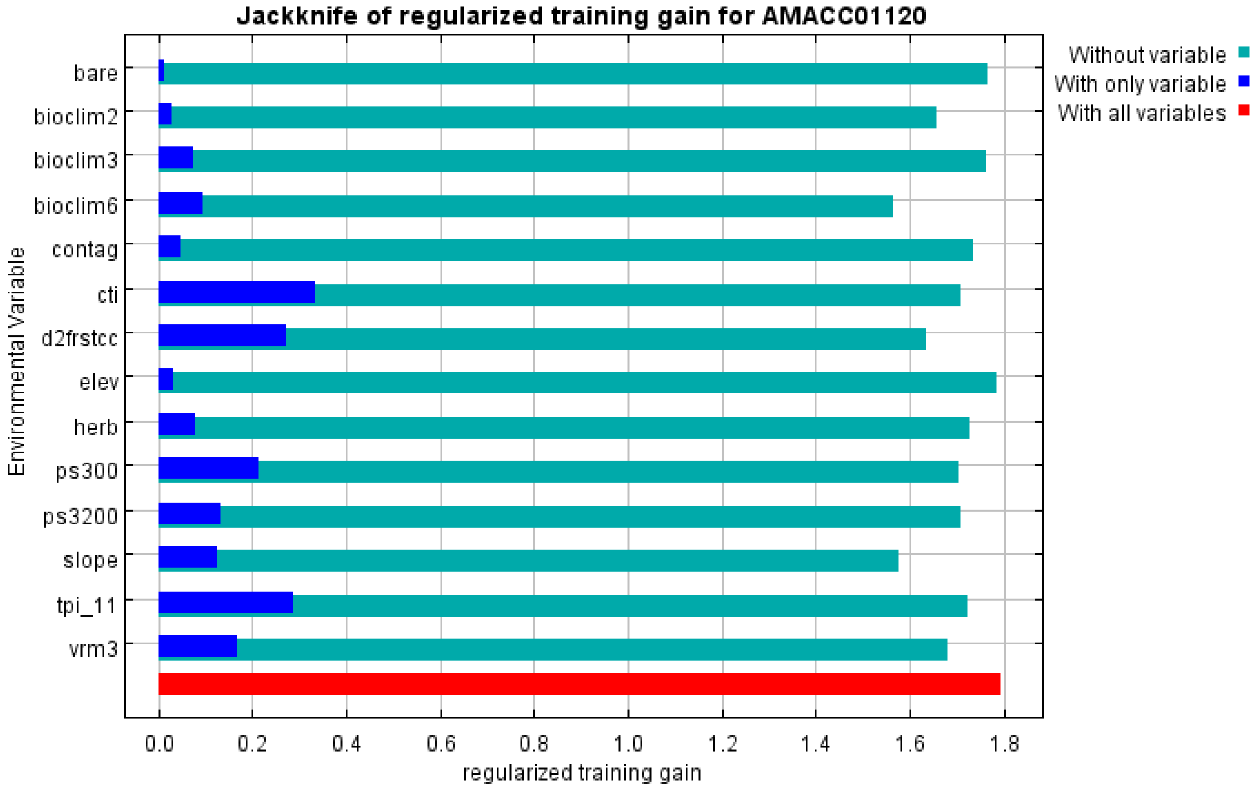


Analysis of variable contributions

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

Variable	Percent contribution	Permutation importance
d2frstcc	18.4	17.7
bioclim6	14.3	23.1
vrm3	13.6	10.3
cti	11.4	1.4
slope	10.4	12.5
ps300	10	0.1
herb	5.2	4.9
ps3200	5	5.2
bioclim3	4.1	1.7
bioclim2	3.2	13
tpi_11	2.1	2.8
contag	1.3	3.3
bare	0.7	1.9
elev	0.3	2.1

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is cti, 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 bioclim6, 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 1.791, training AUC is 0.976, unregularized training gain is 2.932.
Algorithm terminated after 500 iterations (13 seconds).

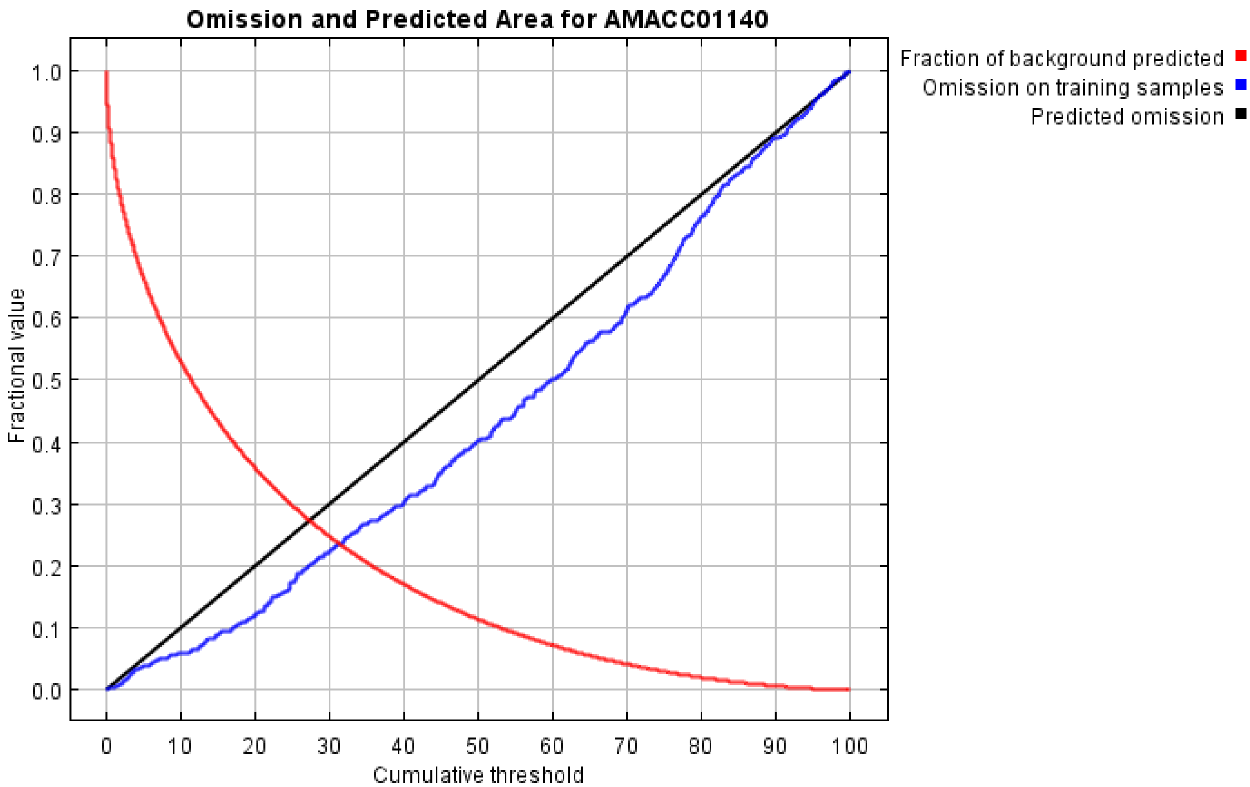
The follow settings were used during the run:
20 presence records used for training.
10020 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): bare bioclim2 bioclim3 bioclim6 contag cti d2frstcc elev herb ps300 ps3200 slope tpi_11 vrm3
Regularization values: linear/quadratic/product: 0.442, categorical: 0.250, threshold: 1.800, hinge: 0.500
Feature types used: hinge linear quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01120
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile: C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV
environmentallayers: C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV
warnings: false
askoverwrite: false
writeclampgrid: false
writemess: false
writebackgroundpredictions: true
autorun: true
writeplotdata: true
visible: false
threads: 5

Command line used: -r -a nowarnings responsecurves novisible nopictures jackknife outputfiletype=bil projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions writeplotdata threads=5 -E -E AMACC01120 outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01120 -N -N bioclim3 -N ps3200 -N vrm3 -N d2frstcc -N elev -N cti -N contag -N bare -N herb -N bioclim6 -N bioclim2 -N ps300 -N slope -N tpi_11

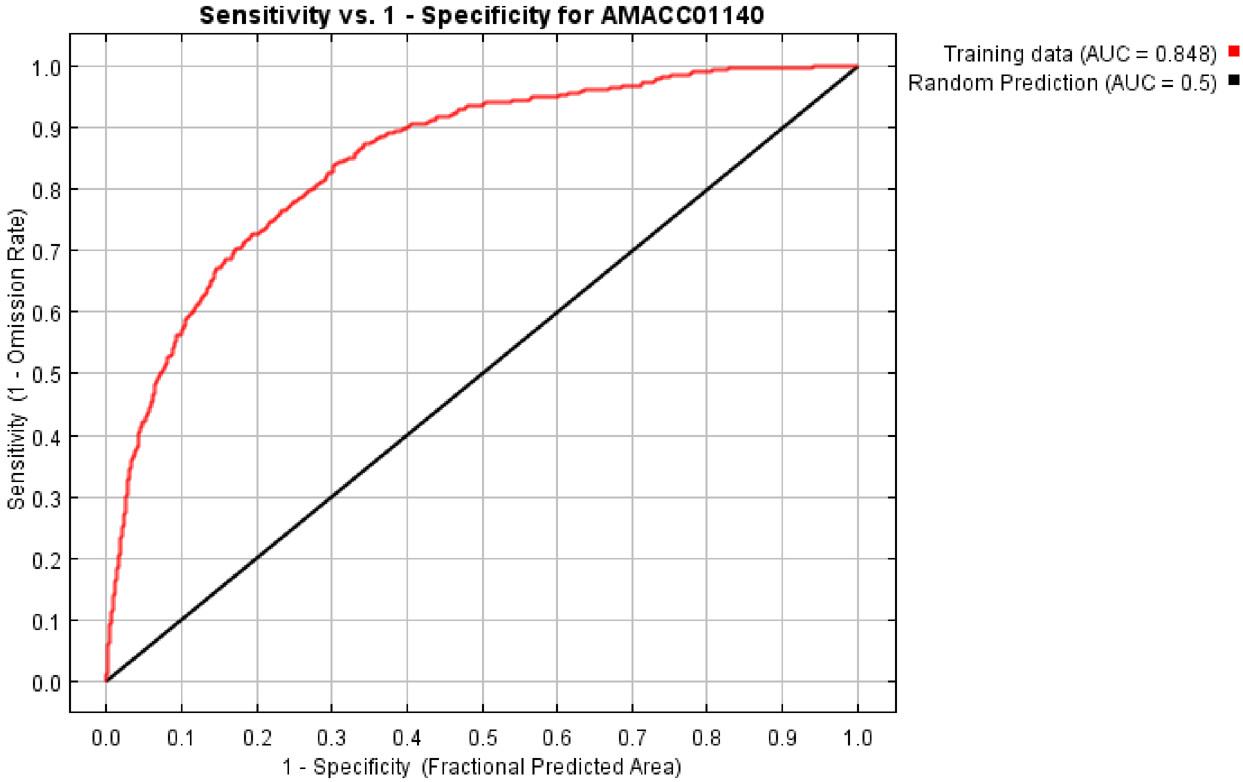
Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E AMACC01120 responsecurves nopictures jackknife outputfiletype=bil outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01120 projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV nowarnings noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions autorun writeplotdata novisible threads=5 -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N bioclim10 -N bioclim12 -N bioclim13 -N bioclim15 -N bioclim17 -N bioclim18 -N bioclim4 -N confr -N d2cave -N d2cliffs40 -N d2outcrop -N d2road -N d2srl -N decid -N dstrb -N flood_freq -N forest -N frestcc -N fw1600 -N fw300 -N fw3200 -N hli -N owner -N pj -N pode -N ps1600 -N sage -N shrub -N tpi31 -N tpi_3 -N vrm11 -N vrm_31

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 0.803 rather than 1; in practice the test AUC may exceed this bound.

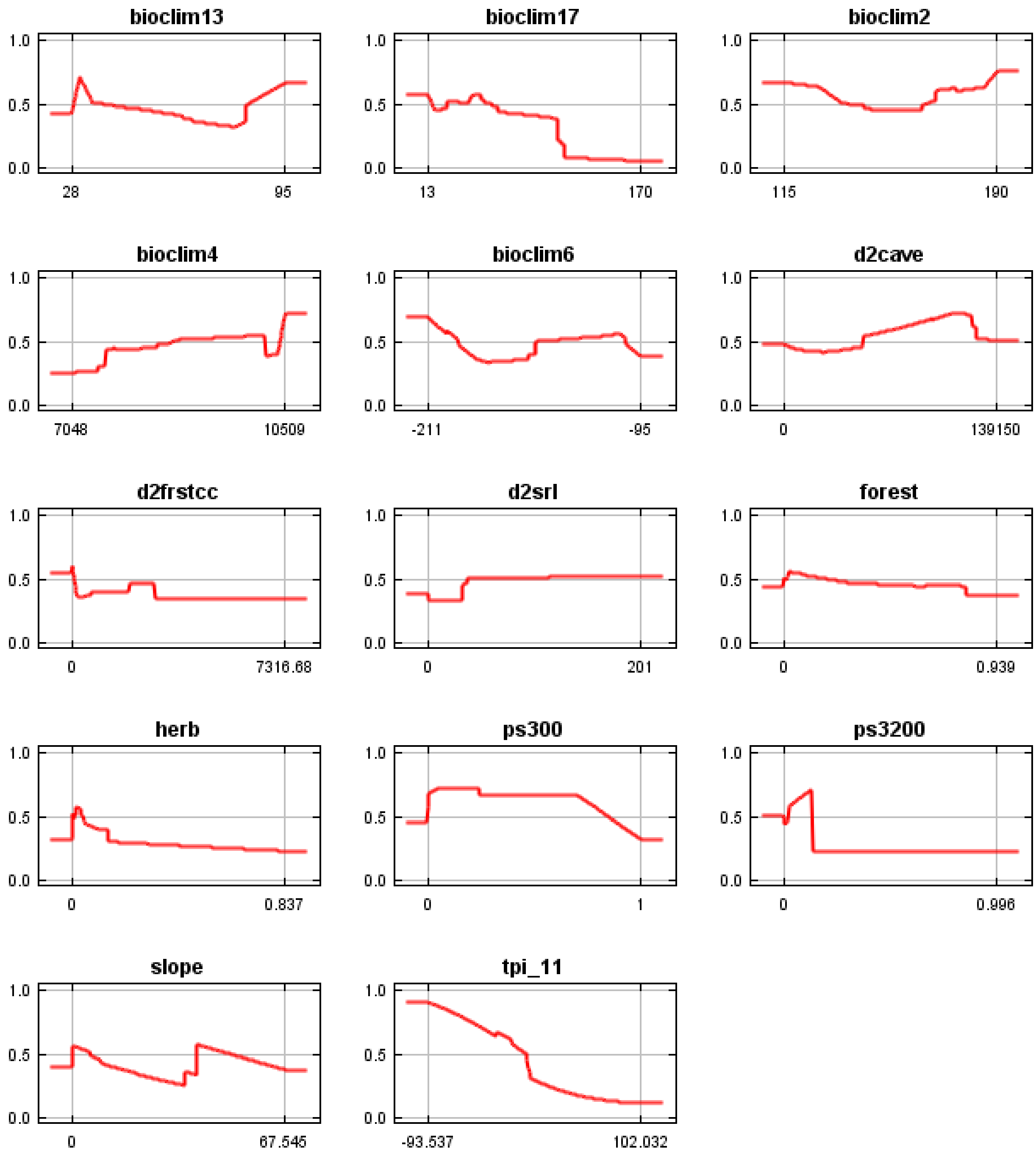


Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

Cumulative threshold	**Logistic threshold**	**Description**	**Fractional predicted area**	**Training omission rate**
1.000	0.061	Fixed cumulative value 1	0.848	0.005
5.000	0.128	Fixed cumulative value 5	0.664	0.039
10.000	0.180	Fixed cumulative value 10	0.529	0.059
0.059	0.014	Minimum training presence	0.960	0.000
16.808	0.238	10 percentile training presence	0.404	0.099
31.260	0.358	Equal training sensitivity and specificity	0.236	0.236
24.442	0.302	Maximum training sensitivity plus specificity	0.304	0.160
2.120	0.086	Balance training omission, predicted area and threshold value	0.780	0.010
12.167	0.199	Equate entropy of thresholded and original distributions	0.484	0.067

Response curves

These curves show how each environmental variable affects the Maxent prediction. 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.

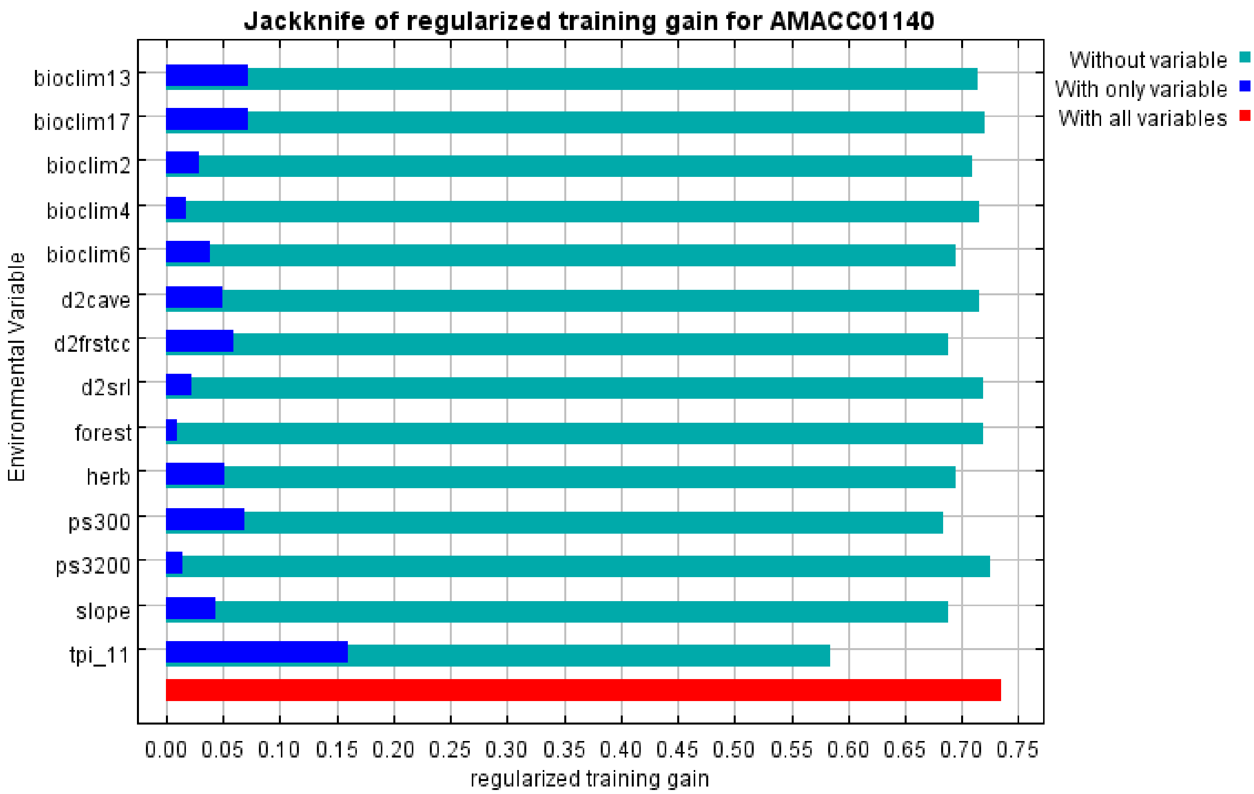

bioclim13
28
95
bioclim17
13
170
bioclim2
115
190
bioclim4
7048
10509
bioclim6
-211
-95
d2cave
0
139150
d2frstcc
0
7316.68
d2srl
0
201
forest
0
0.939
herb
0
0.837
ps300
0
1
ps3200
0
0.996
slope
0
67.545
tpi_11
-93.537
102.032
1.0
0.5
0.0

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**
tpi_11	26	18.2
bioclim17	13.4	7.2
ps300	10	3.3
d2frstcc	9	10.7
herb	8	8.8
slope	7.5	6.7
bioclim13	5.8	5.6
bioclim2	4.8	5.8
bioclim6	3.7	12.1
d2srl	3.6	2.4
ps3200	2.8	1.1
d2cave	2.4	3.8
forest	1.7	8.2
bioclim4	1.2	6

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is tpi_11, 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 tpi_11, 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 0.735, training AUC is 0.848, unregularized training gain is 0.959.
Algorithm terminated after 500 iterations (13 seconds).

The follow settings were used during the run:
406 presence records used for training.
10406 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): bioclim13 bioclim17 bioclim2 bioclim4 bioclim6 d2cave d2frstcc d2srl forest herb ps300 ps3200 slope tpi_11
Regularization values: linear/quadratic/product: 0.050, categorical: 0.250, threshold: 1.000, hinge: 0.500
Feature types used: hinge product linear threshold quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01140
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile: C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV
environmentallayers: C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV
warnings: false
askoverwrite: false
writemess: false
writebackgroundpredictions: true
autorun: true
writeplotdata: true
visible: false
threads: 5
Command line used: -r -a nowarnings responsecurves novisible nopictures jackknife outputfiletype=bil

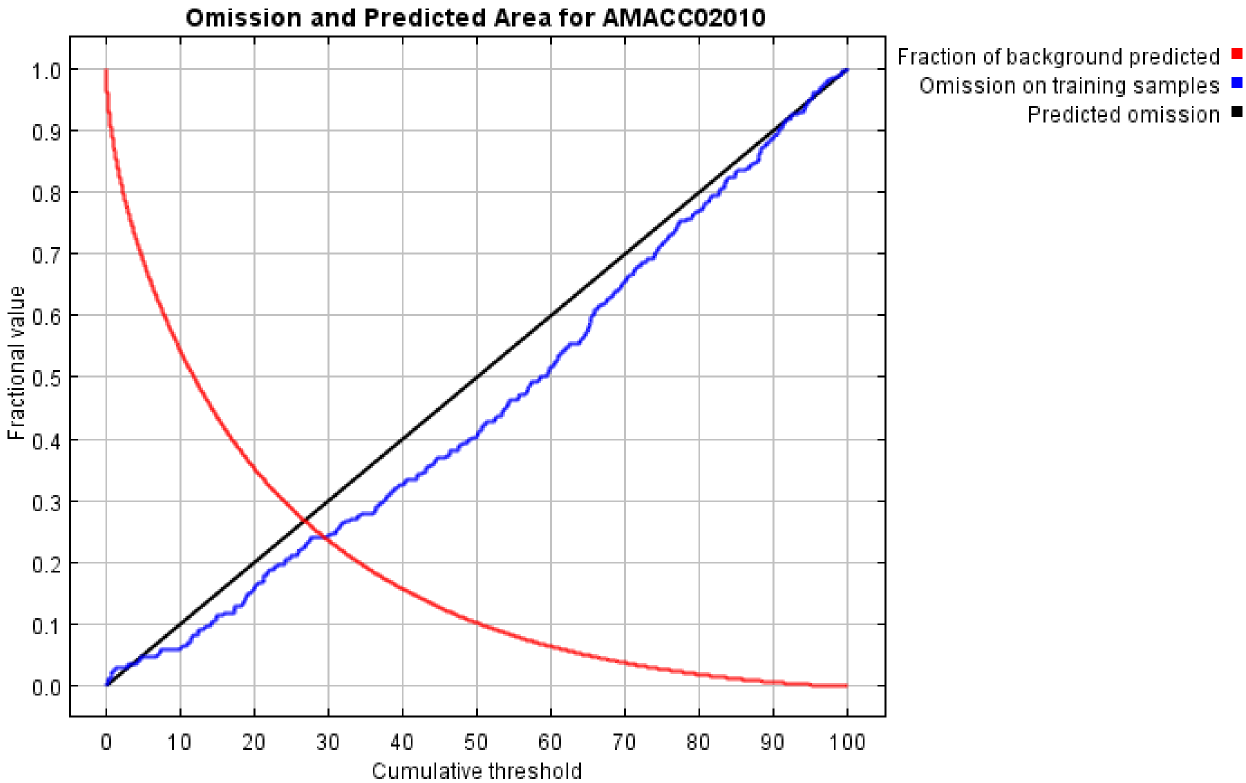
samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV noaskoverwrite projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC nowritemess writebackgroundpredictions writeplotdata threads=5 -E -E AMACC01140 outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01140 -N -N ps3200 -N bioclim17 -N d2srl -N d2cave -N forest -N slope -N herb -N bioclim4 -N bioclim2 -N d2frstcc -N bioclim6 -N ps300 -N bioclim13 -N tpi_11

Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E AMACC01140 responsecurves nopictures jackknife outputfiletype=bil outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01140 projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV nowarnings noaskoverwrite nowritemess writebackgroundpredictions autorun writeplotdata novisible threads=5 -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N bare -N bioclim10 -N bioclim12 -N bioclim15 -N bioclim18 -N bioclim3 -N confr -N contag -N cti -N d2cliffs40 -N d2outcrop -N d2road -N decid -N dstrb -N elev -N flood_freq -N frestcc -N fw1600 -N fw300 -N fw3200 -N hli -N owner -N pj -N pode -N ps1600 -N sage -N shrub -N tpi31 -N tpi_3 -N vrm11 -N vrm3 -N vrm_31

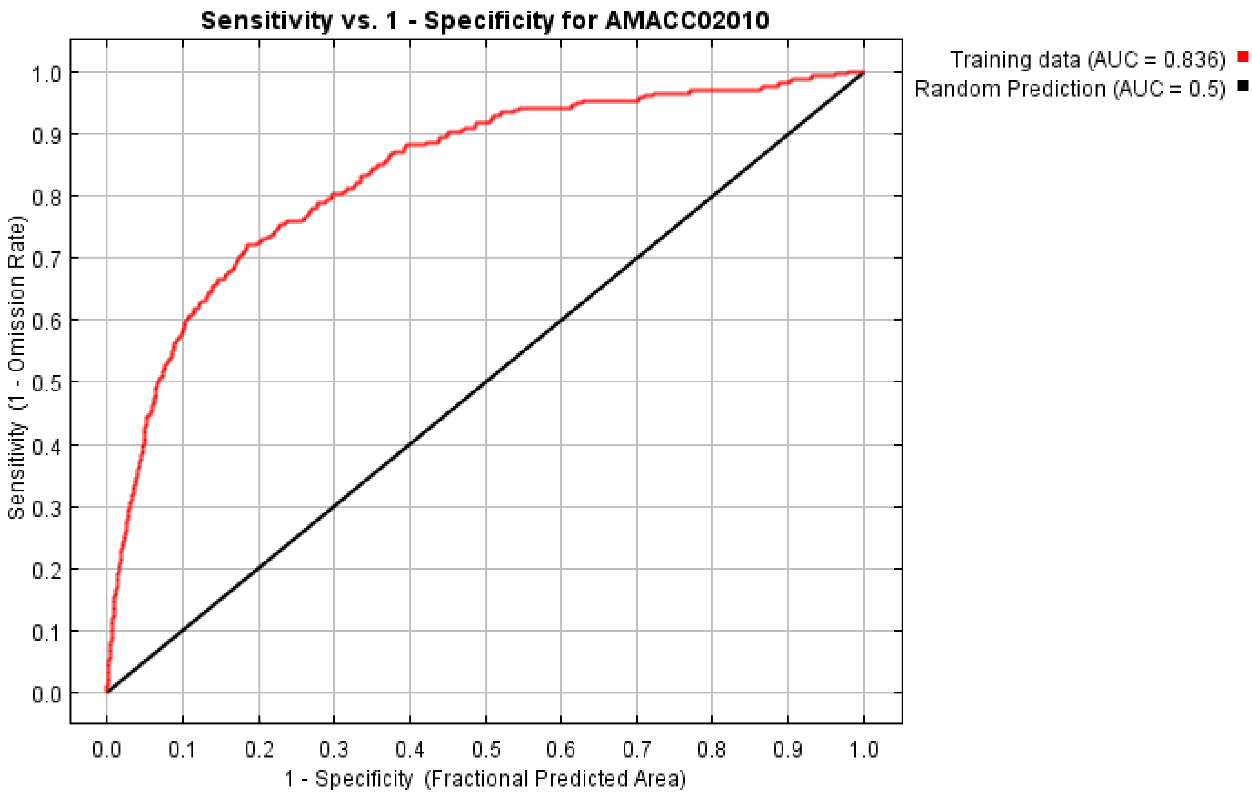
MODEL SUMMARY: SILVER-HAIRED BAT (LASIONYCTERIS NOCTIVAGANS)

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 0.805 rather than 1; in practice the test AUC may exceed this bound.



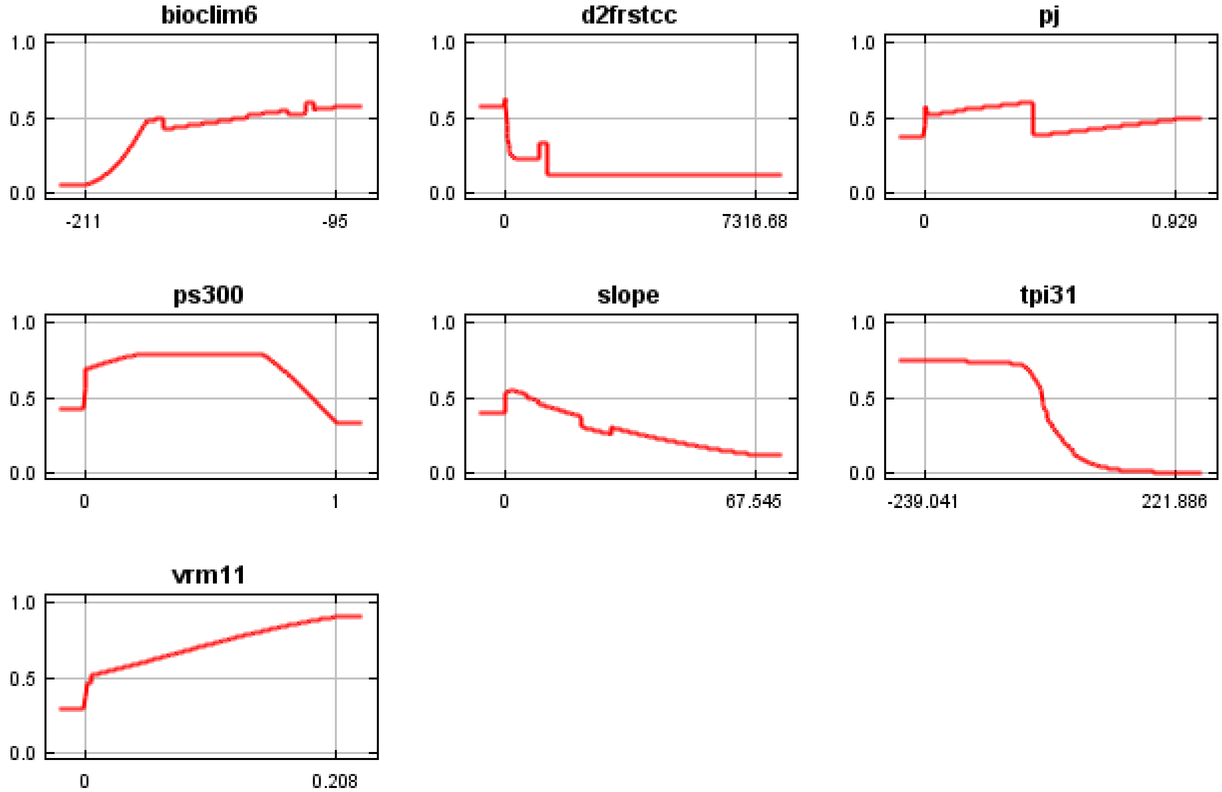
Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.062	Fixed cumulative value 1	0.875	0.024
5.000	0.119	Fixed cumulative value 5	0.688	0.047
10.000	0.161	Fixed cumulative value 10	0.543	0.063
0.043	0.017	Minimum training presence	0.979	0.000
14.176	0.193	10 percentile training presence	0.451	0.098
29.541	0.331	Equal training sensitivity and specificity	0.240	0.240
36.100	0.388	Maximum training sensitivity plus specificity	0.185	0.280
4.097	0.110	Balance training omission, predicted area and threshold value	0.721	0.035
13.177	0.185	Equate entropy of thresholded and original distributions	0.472	0.094

Response curves

These curves show how each environmental variable affects the Maxent prediction. Each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between

the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.

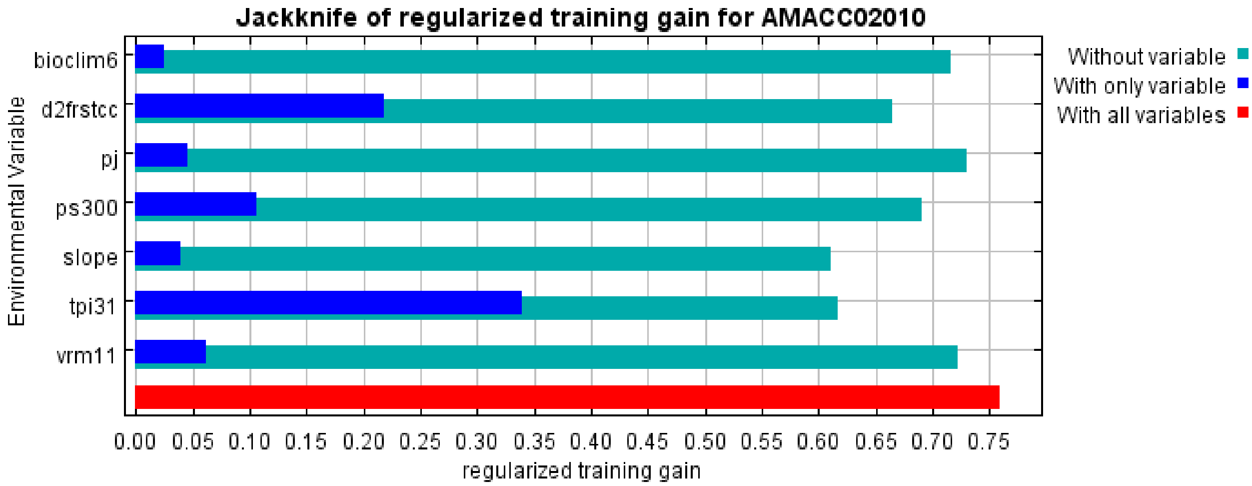


Analysis of variable contributions

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

Variable	Percent contribution	Permutation importance
tpi31	41.2	27.1
d2frstcc	19.5	24.1
slope	15.8	26
ps300	11.1	6
pj	5.2	3.7
bioclim6	4.6	6.6
vrm11	2.5	6.4

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is tpi31, 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 slope, which therefore appears to have the most information that isn't present in the other variables.



Raw data outputs and control parameters

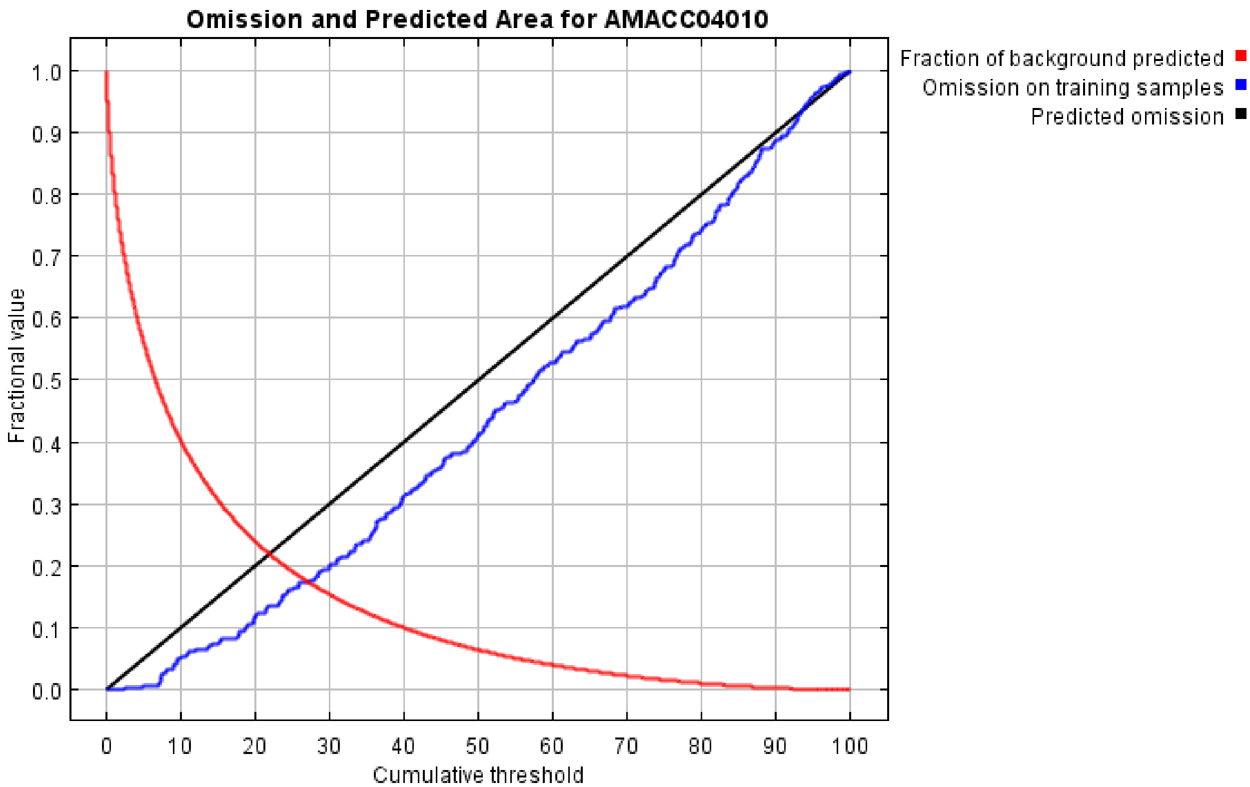
Regularized training gain is 0.758, training AUC is 0.836, unregularized training gain is 0.915.
Algorithm terminated after 500 iterations (10 seconds).

The follow settings were used during the run:
254 presence records used for training.
10254 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): bioclim6 d2frstcc pj ps300 slope tpi31 vrm11
Regularization values: linear/quadratic/product: 0.050, categorical: 0.250, threshold: 1.000, hinge: 0.500
Feature types used: hinge product linear threshold quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC02010_2
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile: C:\MODELING\2015_bats\MAXENT_IN\MIGRATORY_BAT_SAMPLES_DATA.CSV
environmentallayers: C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV
askoverwrite: false
writeclampgrid: false
writemess: false
writebackgroundpredictions: true
writeplotdata: true
threads: 5
Command line used: dontwriteclampgrid

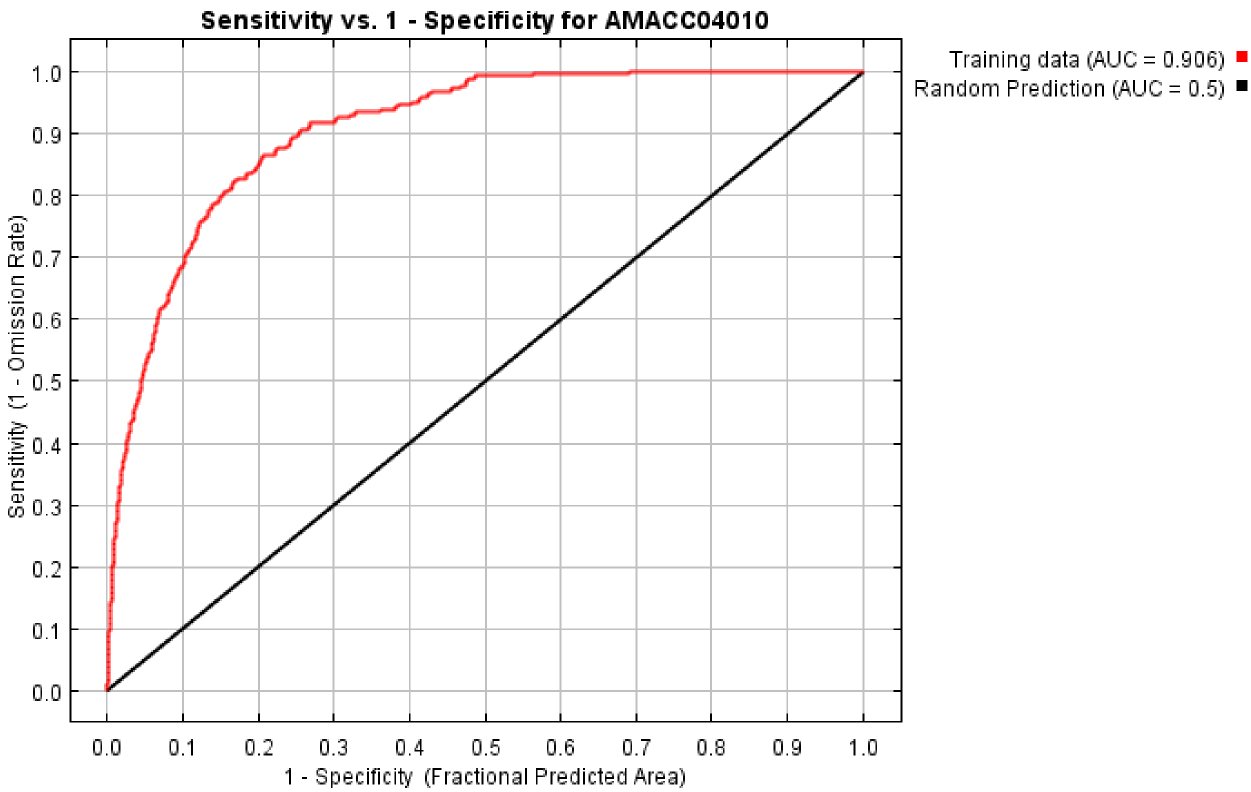
Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E AMACC02010 responsecurves nopictures jackknife outputfiletype=bil outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC02010_2 projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\MIGRATORY_BAT_SAMPLES_DATA.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions writeplotdata threads=5 -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N bare -N bioclim10 -N bioclim12 -N bioclim13 -N bioclim15 -N bioclim17 -N bioclim18 -N bioclim2 -N bioclim3 -N bioclim4 -N confr -N contag -N cti -N d2cave -N d2cliffs40 -N d2outcrop -N d2road -N d2srl -N decid -N dstrb -N elev -N flood_freq -N forest -N frestcc -N fw1600 -N fw300 -N fw3200 -N herb -N hli -N owner -N pode -N ps1600 -N ps3200 -N sage -N shrub -N tpi_11 -N tpi_3 -N vrm3 -N vrm_31

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 0.857 rather than 1; in practice the test AUC may exceed this bound.



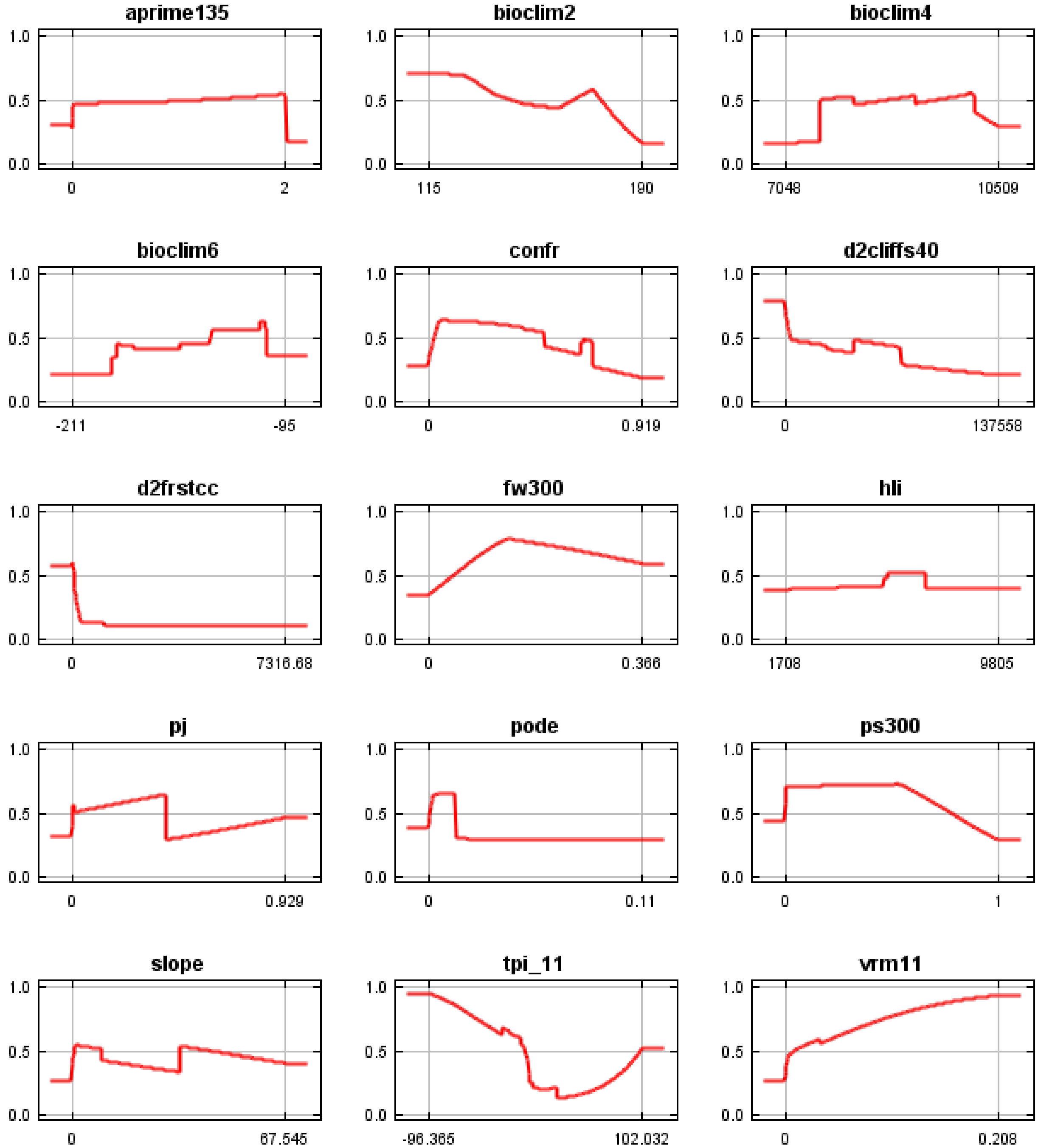
Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

Cumulative threshold	**Logistic threshold**	**Description**	**Fractional predicted area**	**Training omission rate**
1.000	0.030	Fixed cumulative value 1	0.814	0.000
5.000	0.072	Fixed cumulative value 5	0.560	0.008
10.000	0.123	Fixed cumulative value 10	0.402	0.054
2.488	0.048	Minimum training presence	0.692	0.000
18.714	0.213	10 percentile training presence	0.255	0.099
27.225	0.305	Equal training sensitivity and specificity	0.174	0.174
23.251	0.264	Maximum training sensitivity plus specificity	0.207	0.136
6.993	0.091	Balance training omission, predicted area and threshold value	0.486	0.008
13.528	0.158	Equate entropy of thresholded and original distributions	0.331	0.066

Response curves

These curves show how each environmental variable affects the Maxent prediction. Each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between

the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.

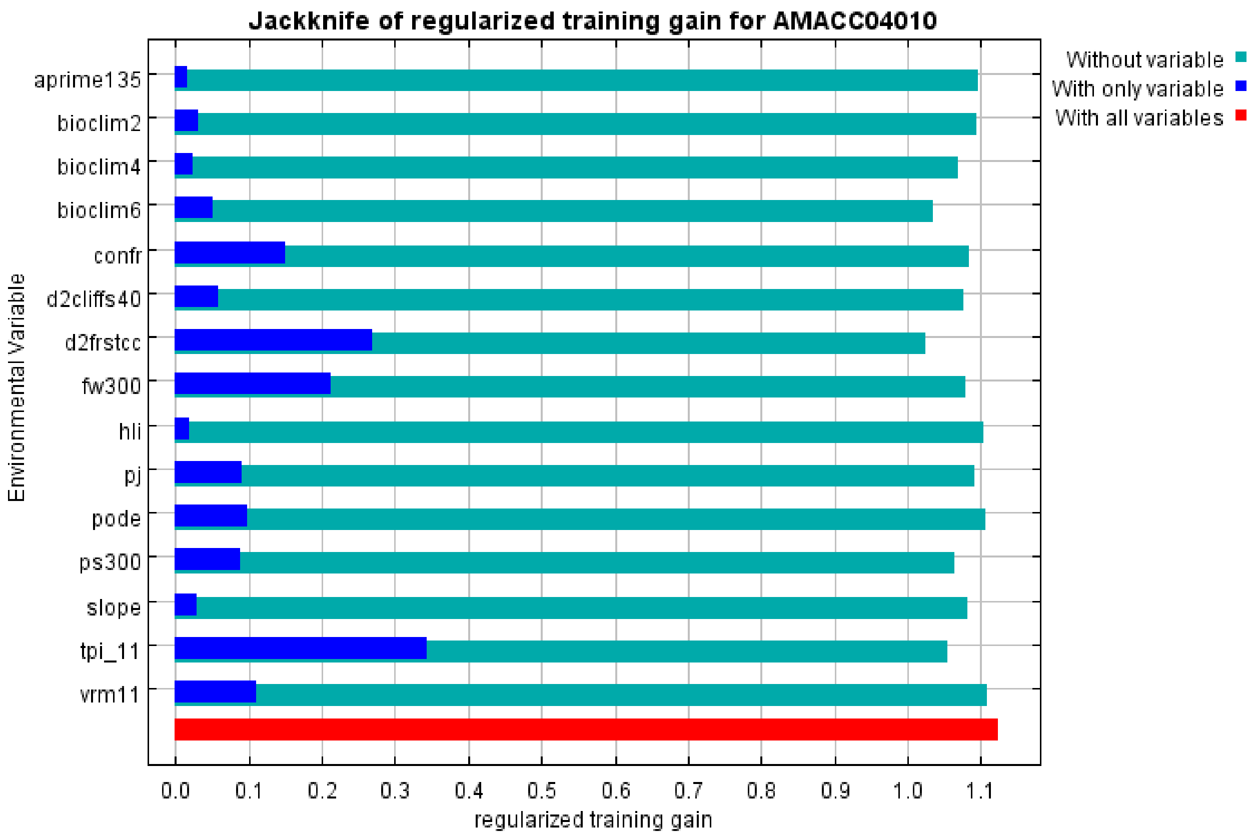


Analysis of variable contributions

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

Variable	Percent contribution	Permutation importance
tpi_11	24.5	8.4
d2frstcc	18.2	21.2
fw300	7.8	2.3
bioclim6	7.6	17.6
slope	7.4	7.6
bioclim4	6.2	7.1
ps300	6	2.4
pj	6	4
d2cliffs40	4	5.7
confr	3.4	12
pode	2.3	2.1
bioclim2	2.2	3.8
aprime135	1.7	2
hli	1.5	1.3
vrm11	1.2	2.6

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is tpi_11, 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 d2frstcc, 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 1.124, training AUC is 0.906, unregularized training gain is 1.439.
Algorithm terminated after 500 iterations (19 seconds).

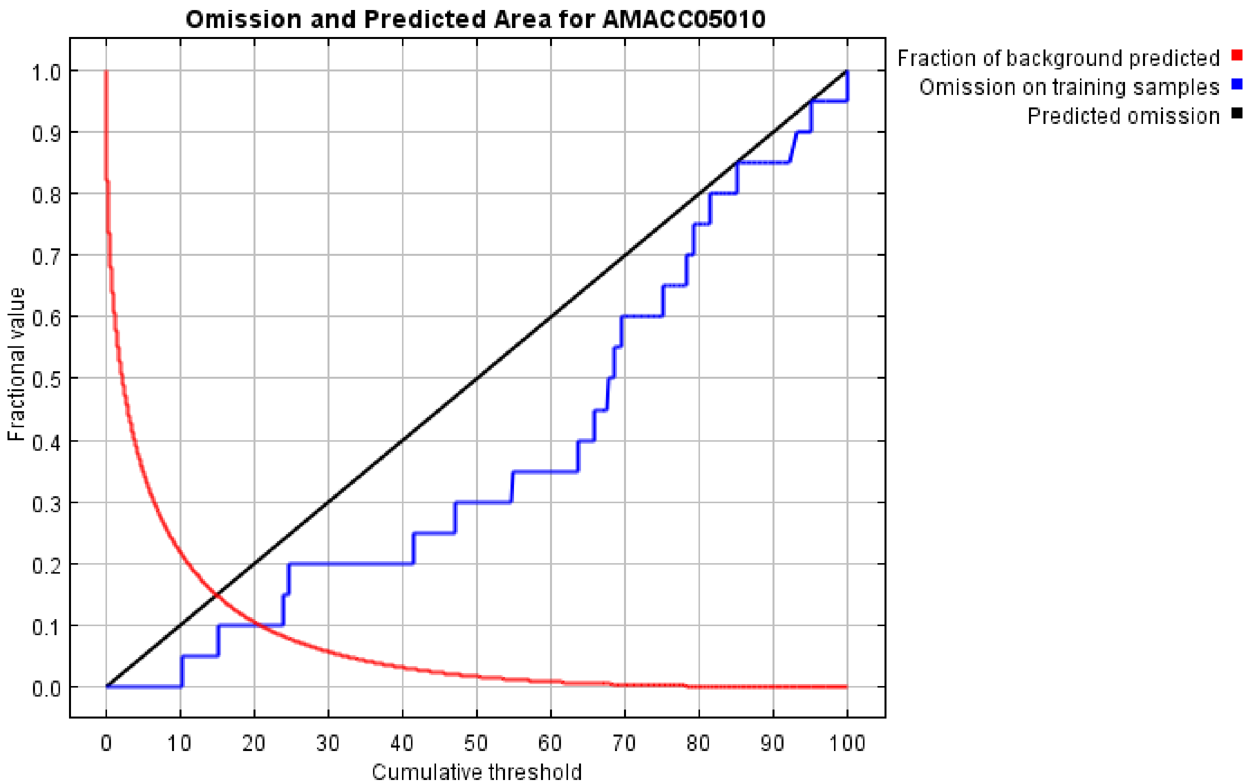
The follow settings were used during the run:
242 presence records used for training.
10242 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): aprime135 bioclim2 bioclim4 bioclim6 confr d2cliffs40 d2frstcc fw300 hli pj pode ps300 slope tpi_11 vrm11
Regularization values: linear/quadratic/product: 0.050, categorical: 0.250, threshold: 1.000, hinge: 0.500
Feature types used: hinge product linear threshold quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC04010_2
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile: C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV
environmentallayers: C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV
writeclampgrid: false
writemess: false
writebackgroundpredictions: true
writeplotdata: true
threads: 5

Command line used: dontwriteclampgrid

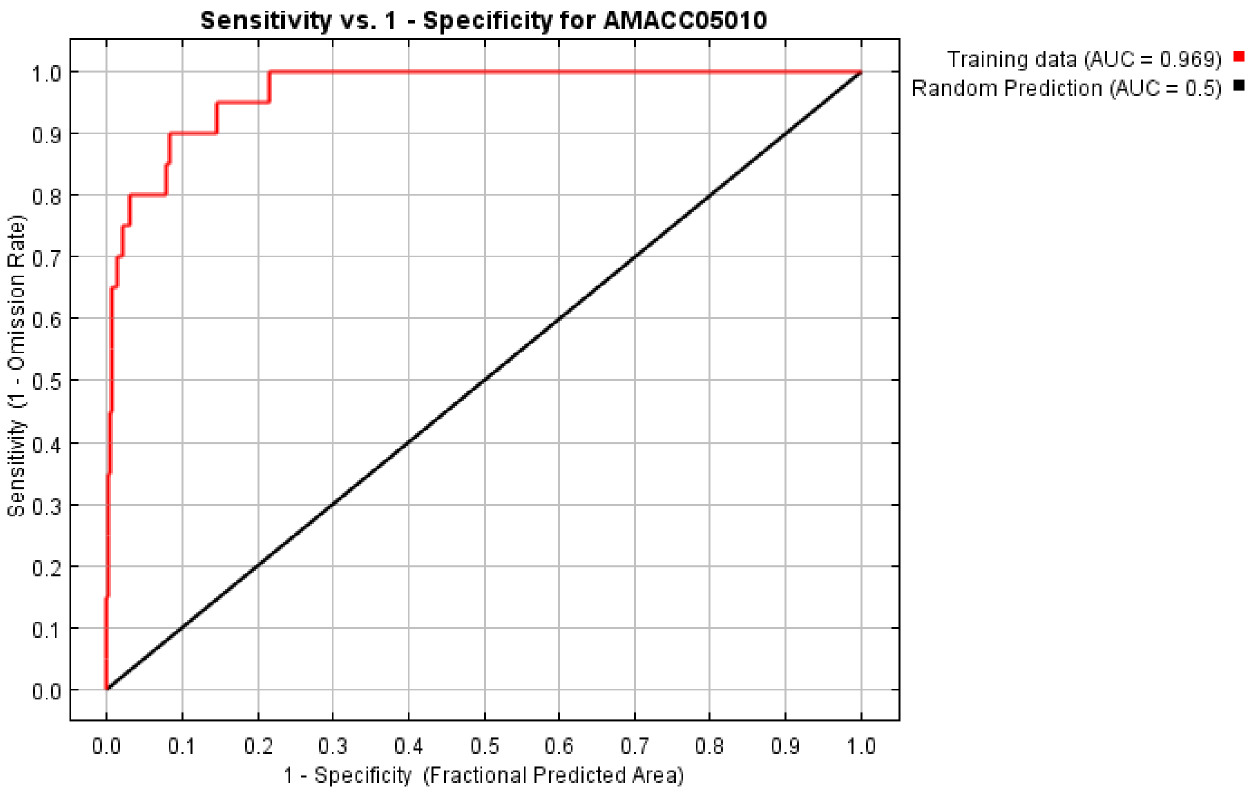
Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E AMACC04010 responsecurves nopictures jackknife outputfiletype=bil outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC04010_2 projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV nowriteclampgrid nowritemess writebackgroundpredictions writeplotdata threads=5 -N aprime180 -N aprime45 -N aprime90 -N bare -N bioclim10 -N bioclim12 -N bioclim13 -N bioclim15 -N bioclim17 -N bioclim18 -N bioclim3 -N contag -N cti -N d2cave -N d2outcrop -N d2road -N d2srl -N decid -N dstrb -N elev -N flood_freq -N forest -N frestcc -N fw1600 -N fw3200 -N herb -N owner -N ps1600 -N ps3200 -N sage -N shrub -N tpi31 -N tpi_3 -N vrm3 -N vrm_31

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 0.922 rather than 1; in practice the test AUC may exceed this bound.



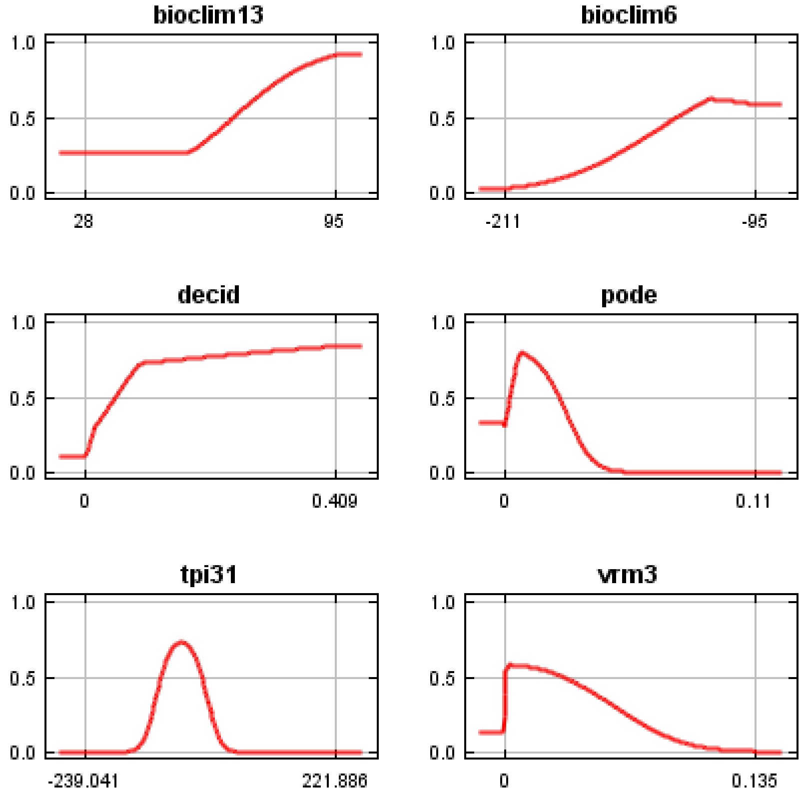
Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

Cumulative threshold	**Logistic threshold**	**Description**	**Fractional predicted area**	**Training omission rate**
1.000	0.009	Fixed cumulative value 1	0.618	0.000
5.000	0.031	Fixed cumulative value 5	0.349	0.000
10.000	0.063	Fixed cumulative value 10	0.219	0.000
10.217	0.065	Minimum training presence	0.215	0.000
23.942	0.193	10 percentile training presence	0.083	0.100
20.900	0.161	Equal training sensitivity and specificity	0.100	0.100
23.942	0.193	Maximum training sensitivity plus specificity	0.083	0.100
7.554	0.046	Balance training omission, predicted area and threshold value	0.271	0.000
17.888	0.130	Equate entropy of thresholded and original distributions	0.122	0.100

Response curves

These curves show how each environmental variable affects the Maxent prediction. Each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between

the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.

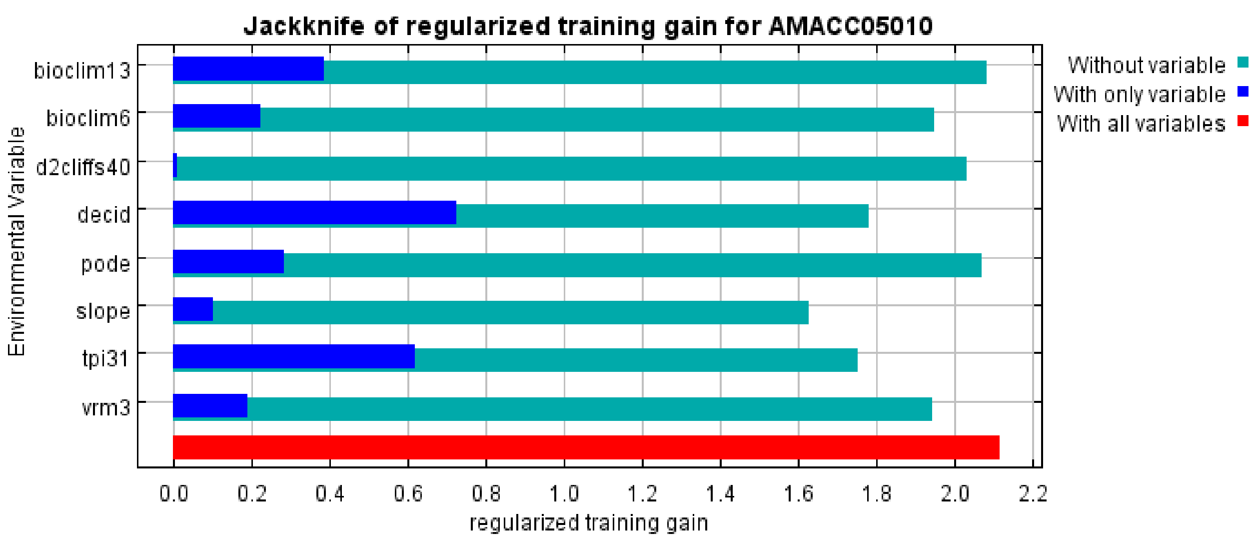


Analysis of variable contributions

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

Variable	Percent contribution	Permutation importance
decid	37.9	26.2
slope	17.5	27.5
tpi31	15.1	20.6
vrm3	12.6	5.6
bioclim6	7.6	6.3
pode	6	0.2
d2cliffs40	1.9	4.3
bioclim13	1.3	9.2

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is decid, 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 slope, 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 2.116, training AUC is 0.969, unregularized training gain is 2.904.
Algorithm terminated after 500 iterations (9 seconds).

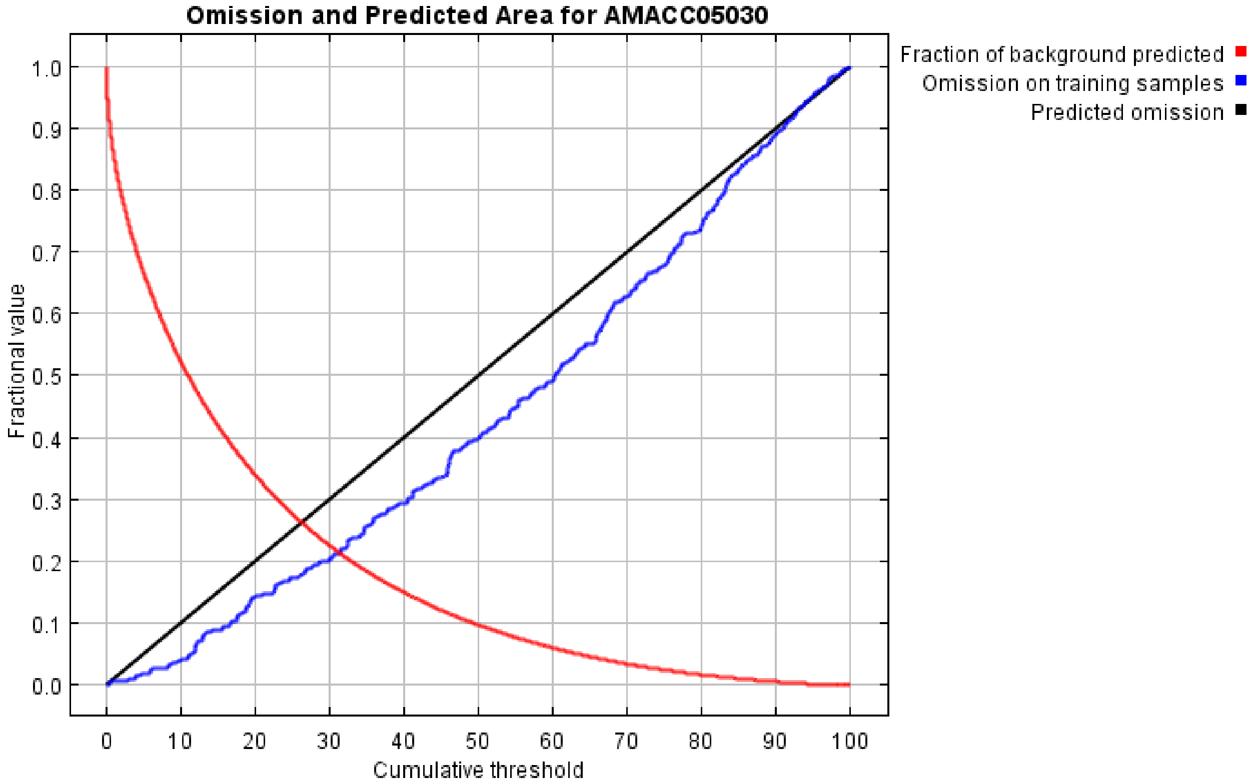
The follow settings were used during the run:
20 presence records used for training.
10020 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): bioclim13 bioclim6 d2cliffs40 decid pode slope tpi31 vrm3
Regularization values: linear/quadratic/product: 0.442, categorical: 0.250, threshold: 1.800, hinge: 0.500
Feature types used: hinge linear quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC05010
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile: C:\MODELING\2015_bats\MAXENT_IN\MIGRATORY_BAT_SAMPLES_DATA.CSV
environmentallayers: C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV
warnings: false
askoverwrite: false
writeclampgrid: false
writemess: false
writebackgroundpredictions: true
autorun: true
writeplotdata: true
visible: false
threads: 5
Command line used: -r -a nowarnings responsecurves novisible nopictures jackknife outputfiletype=bil projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\MIGRATORY_BAT_SAMPLES_DATA.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions writeplotdata threads=5 -E -E AMACC05010 outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC05010 -N -N bioclim13 -N d2cliffs40 -N bioclim6 -N pode -N vrm3 -N slope -N decid -N tpi31

Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E AMACC05010 responsecurves nopictures jackknife outputfiletype=bil outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC05010 projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\MIGRATORY_BAT_SAMPLES_DATA.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV nowarnings noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions autorun writeplotdata novisible threads=5 -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N bare -N bioclim10 -N bioclim12 -N bioclim15 -N bioclim17 -N bioclim18 -N bioclim2 -N bioclim3 -N bioclim4 -N confr -N contag -N cti -N d2cave -N d2frstcc -N d2outcrop -N d2road -N d2srl -N dstrb -N elev -N flood_freq -N forest -N frestcc -N fw1600 -N fw300 -N fw3200 -N herb -N hli -N owner -N pj -N ps1600 -N ps300 -N ps3200 -N sage -N shrub -N tpi_11 -N tpi_3 -N vrm11 -N vrm_31

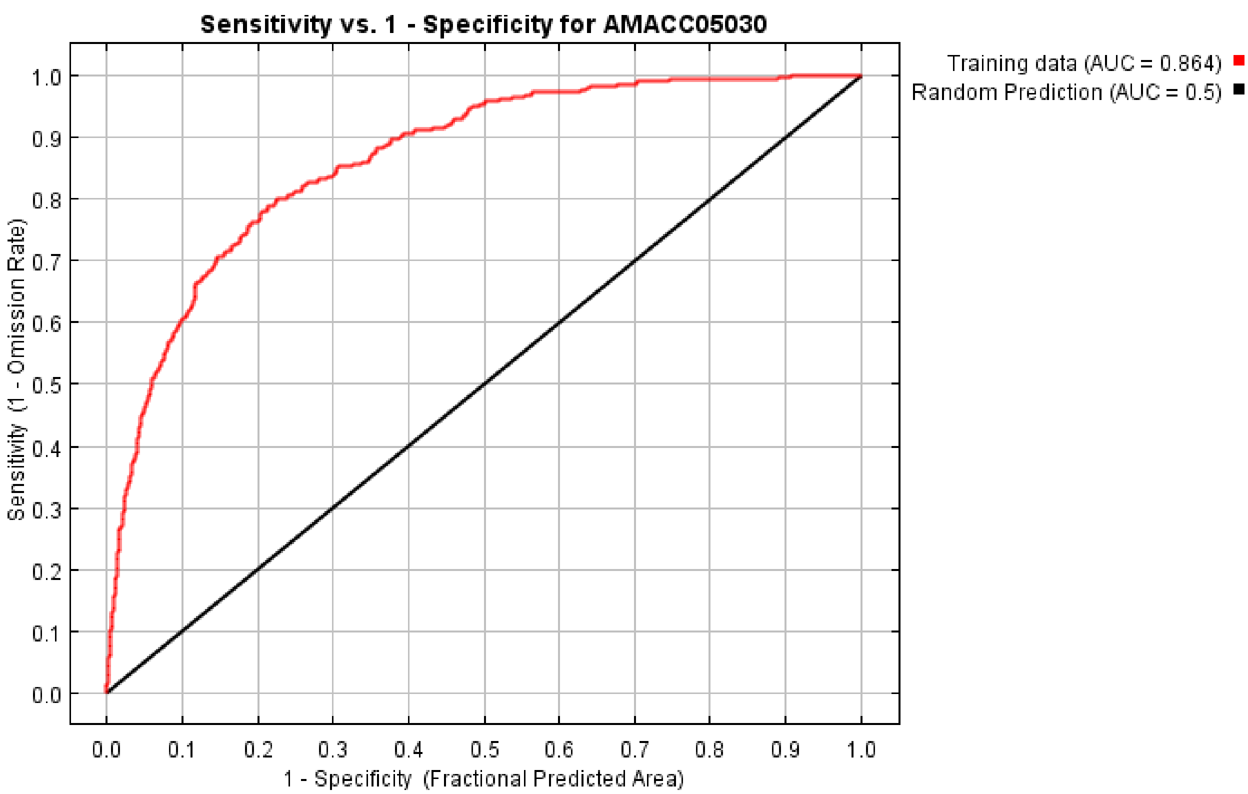
MODEL SUMMARY: HOARY BAT (LASIURUS CINEREUS)

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 0.813 rather than 1; in practice the test AUC may exceed this bound.

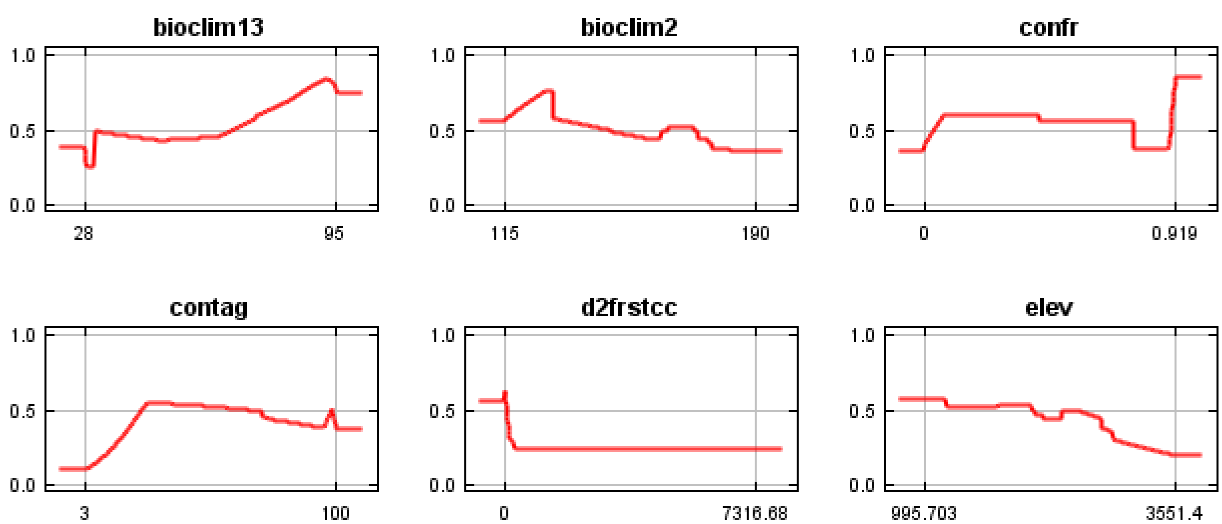


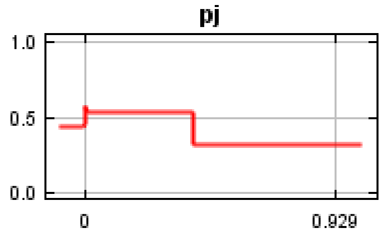
Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

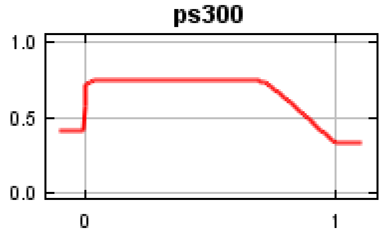
Cumulative threshold	**Logistic threshold**	**Description**	**Fractional predicted area**	**Training omission rate**
1.000	0.058	Fixed cumulative value 1	0.852	0.007
5.000	0.114	Fixed cumulative value 5	0.666	0.018
10.000	0.157	Fixed cumulative value 10	0.522	0.040
0.390	0.037	Minimum training presence	0.907	0.000
16.606	0.213	10 percentile training presence	0.391	0.097
31.406	0.338	Equal training sensitivity and specificity	0.213	0.212
31.406	0.338	Maximum training sensitivity plus specificity	0.213	0.212
4.002	0.104	Balance training omission, predicted area and threshold value	0.702	0.011
13.547	0.187	Equate entropy of thresholded and original distributions	0.446	0.086

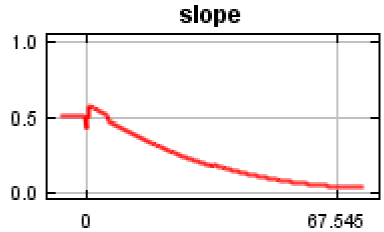
Response curves

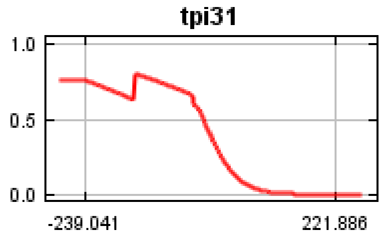
These curves show how each environmental variable affects the Maxent prediction. Each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and 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.

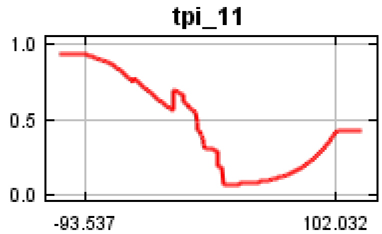



pj
1.0
0.5
0.0
0
0.929


ps300
1.0
0.5
0.0
0
1


slope
1.0
0.5
0.0
0
67.545


tpi31
1.0
0.5
0.0
-239.041
221.886

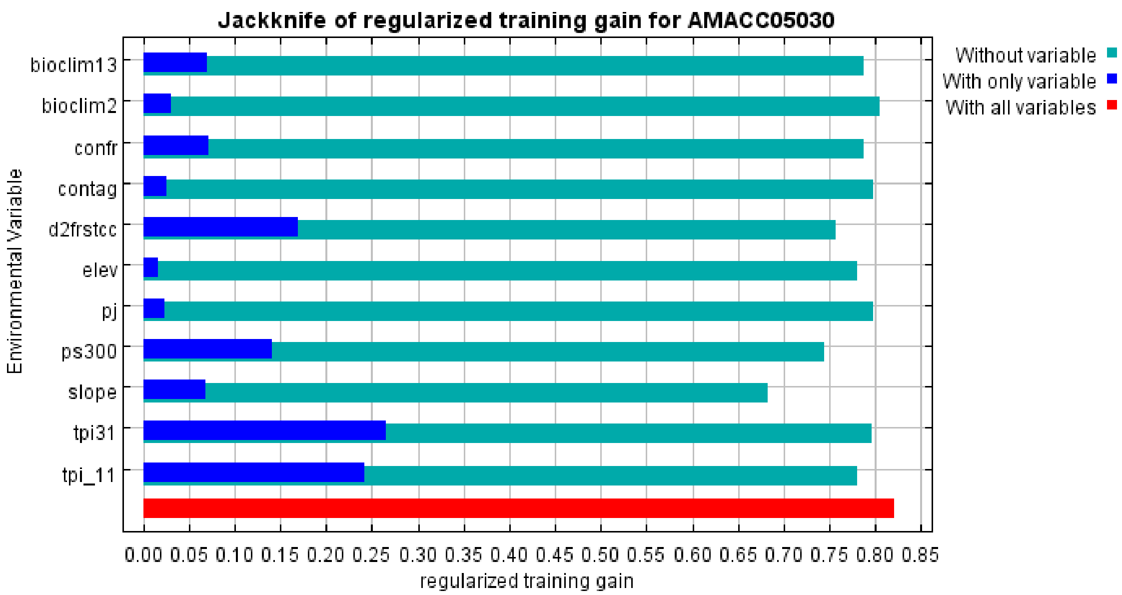

tpi_11
1.0
0.5
0.0
-93.537
102.032

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
tpi_11	18.8	9.9
slope	16	18.1
tpi31	15.8	4.3
d2frstcc	15	15.7
ps300	14.5	3.2
elev	5.6	14.8
bioclim13	5.6	7.1
pj	2.5	4.7
confr	2.2	15.6
bioclim2	2.1	4
contag	1.8	2.5

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is tpi31, 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 slope, 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 0.821, training AUC is 0.864, unregularized training gain is 1.077.
Algorithm terminated after 500 iterations (15 seconds).

The follow settings were used during the run:

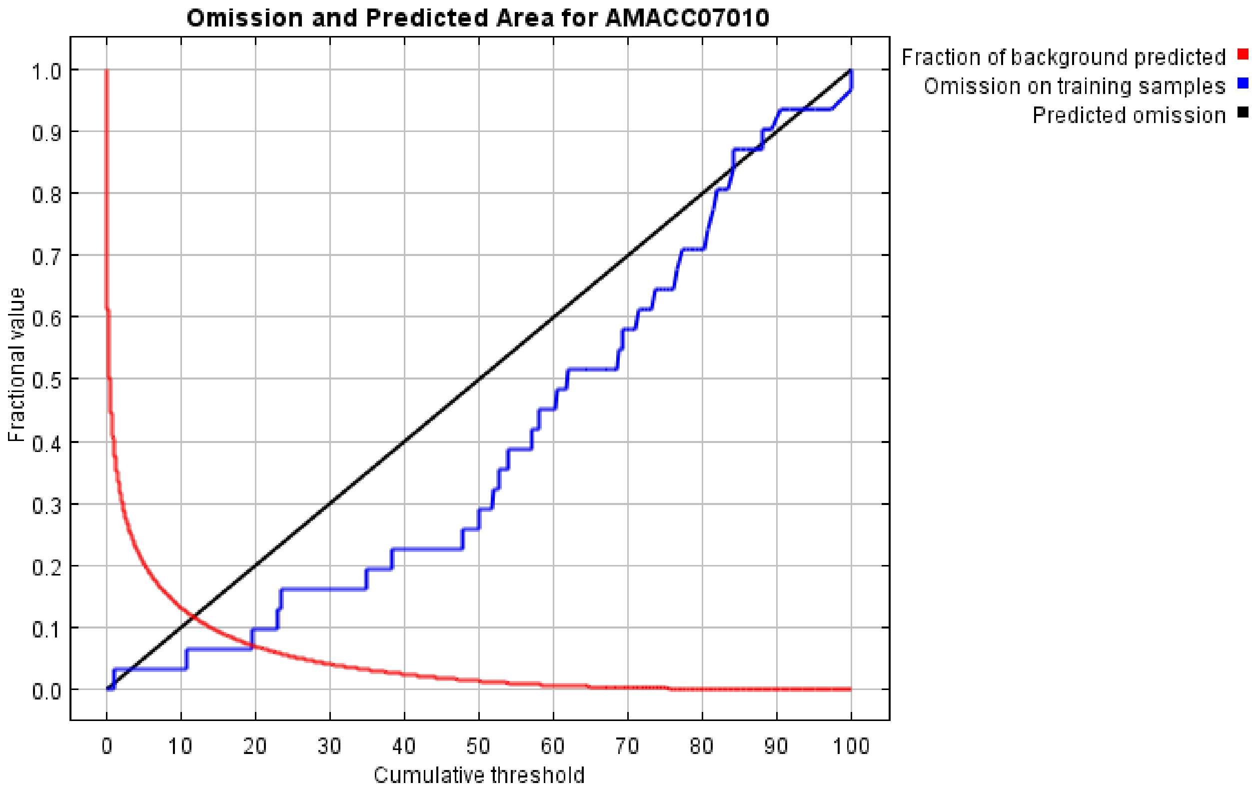
278 presence records used for training.
10278 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): bioclim13 bioclim2 confr contag d2frstcc elev pj ps300 slope tpi31 tpi_11
Regularization values: linear/quadratic/product: 0.050, categorical: 0.250, threshold: 1.000, hinge: 0.500
Feature types used: hinge product linear threshold quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC05030
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile: C:\MODELING\2015_bats\MAXENT_IN\MIGRATORY_BAT_SAMPLES_DATA.CSV
environmentallayers: C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV
warnings: false
askoverwrite: false
writeclampgrid: false
writemess: false
writebackgroundpredictions: true
autorun: true
writeplotdata: true
visible: false
threads: 5
Command line used: -r -a nowarnings responsecurves novisible nopictures jackknife outputfiletype=bil projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\MIGRATORY_BAT_SAMPLES_DATA.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions writeplotdata threads=5 -E -E AMACC05030 outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC05030 -N -N confr -N contag -N pj -N tpi_11 -N bioclim13 -N bioclim2 -N elev -N ps300 -N d2frstcc -N slope -N tpi31

Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E AMACC05030 responsecurves nopictures jackknife outputfiletype=bil outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC05030 projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\MIGRATORY_BAT_SAMPLES_DATA.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV nowarnings noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions autorun writeplotdata novisible threads=5 -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N bare -N bioclim10 -N bioclim12 -N bioclim15 -N bioclim17 -N bioclim18 -N bioclim3 -N bioclim4 -N bioclim6 -N cti -N d2cave -N d2cliffs40 -N d2outcrop -N d2road -N d2srl -N decid -N dstrb -N flood_freq -N forest -N frestcc -N fw1600 -N fw300 -N fw3200 -N herb -N hli -N owner -N pode -N ps1600 -N ps3200 -N sage -N shrub -N tpi_3 -N vrm11 -N vrm3 -N vrm

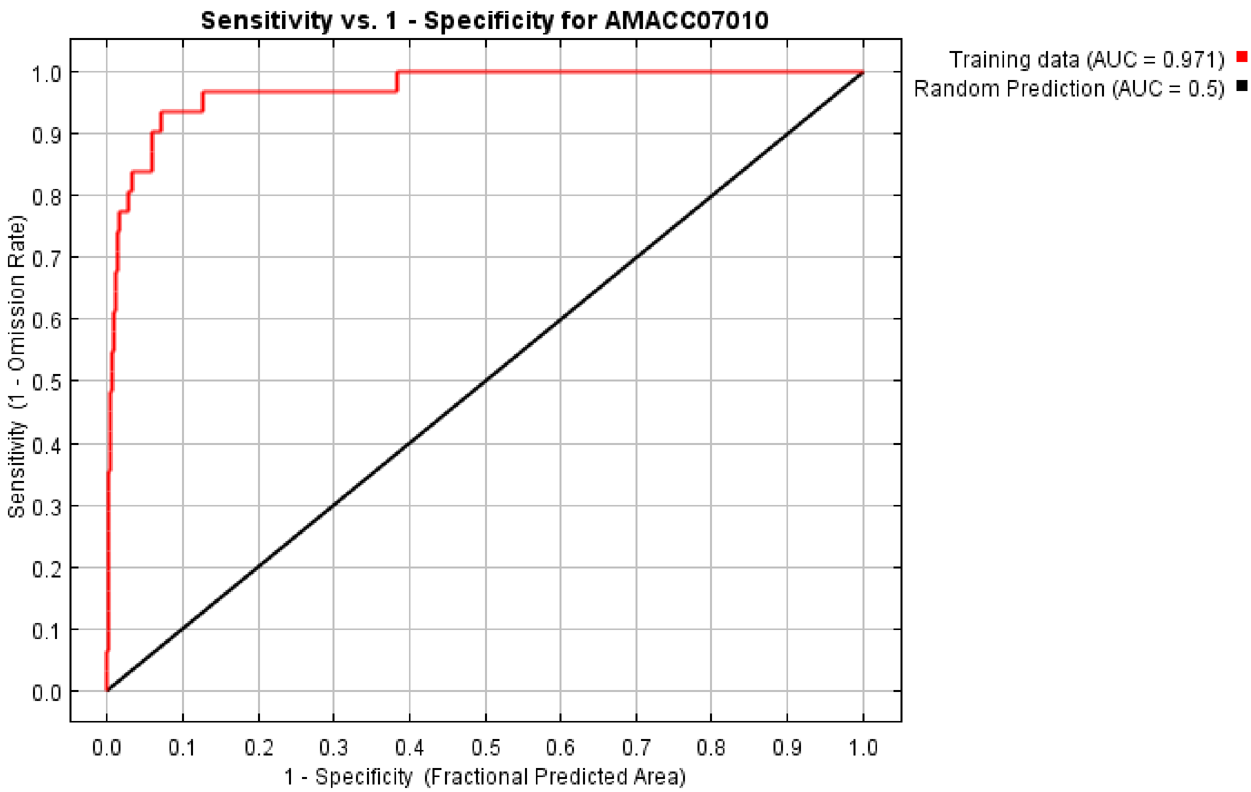
MODEL SUMMARY: SPOTTED BAT (EUDERMA MACULATUM)

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 0.949 rather than 1; in practice the test AUC may exceed this bound.



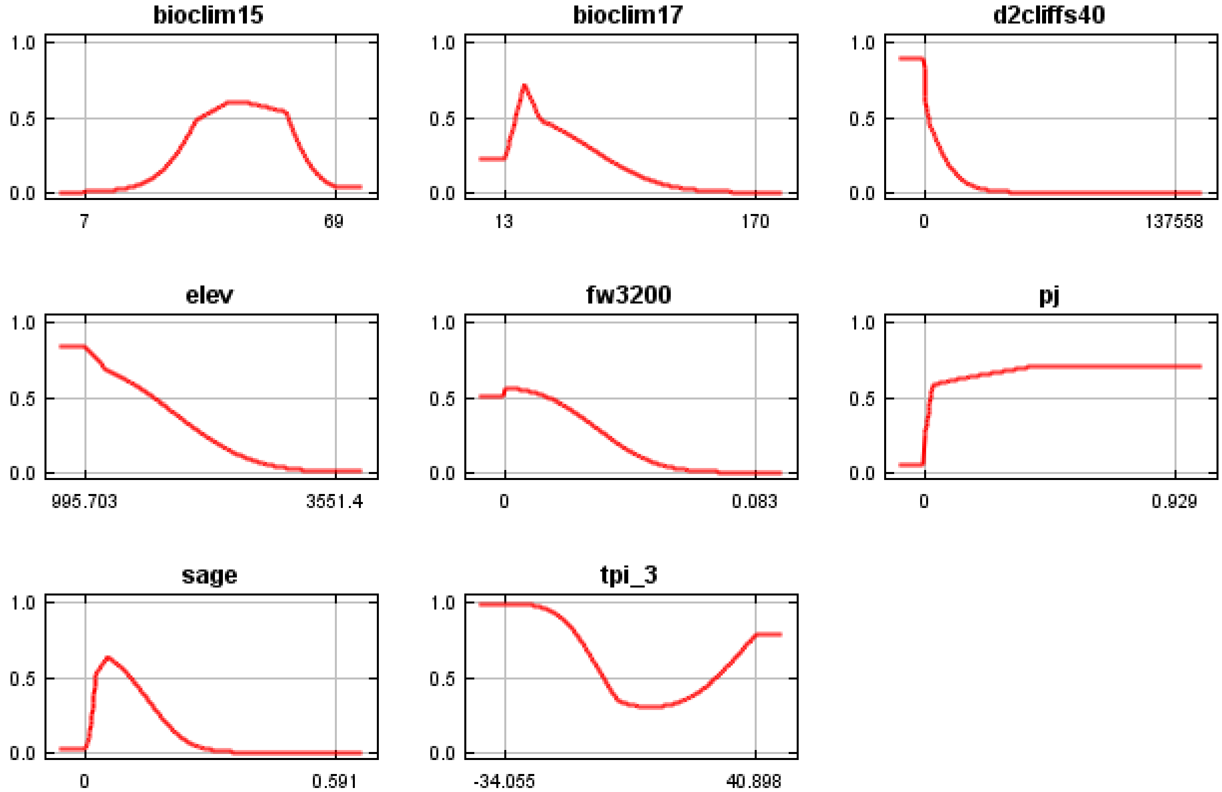
Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

Cumulative threshold	**Logistic threshold**	**Description**	**Fractional predicted area**	**Training omission rate**
1.000	0.007	Fixed cumulative value 1	0.388	0.000
5.000	0.039	Fixed cumulative value 5	0.204	0.032
10.000	0.081	Fixed cumulative value 10	0.132	0.032
1.040	0.008	Minimum training presence	0.383	0.000
22.929	0.212	10 percentile training presence	0.060	0.097
19.462	0.177	Equal training sensitivity and specificity	0.072	0.065
19.462	0.177	Maximum training sensitivity plus specificity	0.072	0.065
1.040	0.008	Balance training omission, predicted area and threshold value	0.383	0.000
16.283	0.141	Equate entropy of thresholded and original distributions	0.087	0.065

Response curves

These curves show how each environmental variable affects the Maxent prediction. Each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between

the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.

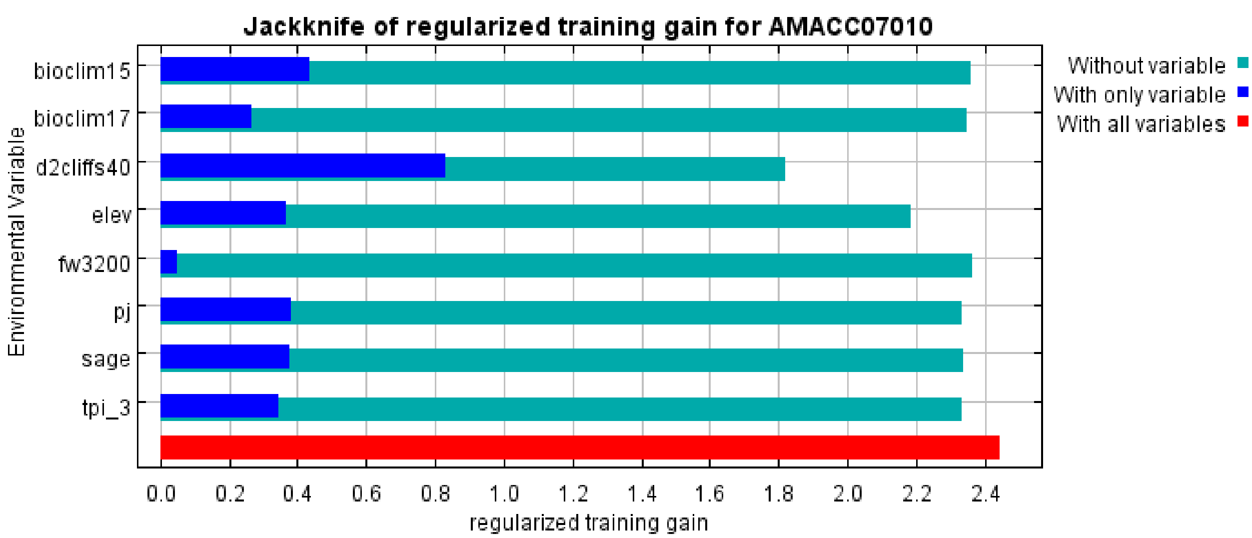


Analysis of variable contributions

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

Variable	Percent contribution	Permutation importance
d2cliffs40	38.3	63.8
elev	18.8	7.3
bioclim15	16.5	6.8
pj	8.5	3.8
sage	8.4	3.9
fw3200	3.8	1.5
bioclim17	3.4	11.5
tpi_3	2.3	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 d2cliffs40, 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 d2cliffs40, which therefore appears to have the most information that isn't present in the other variables.

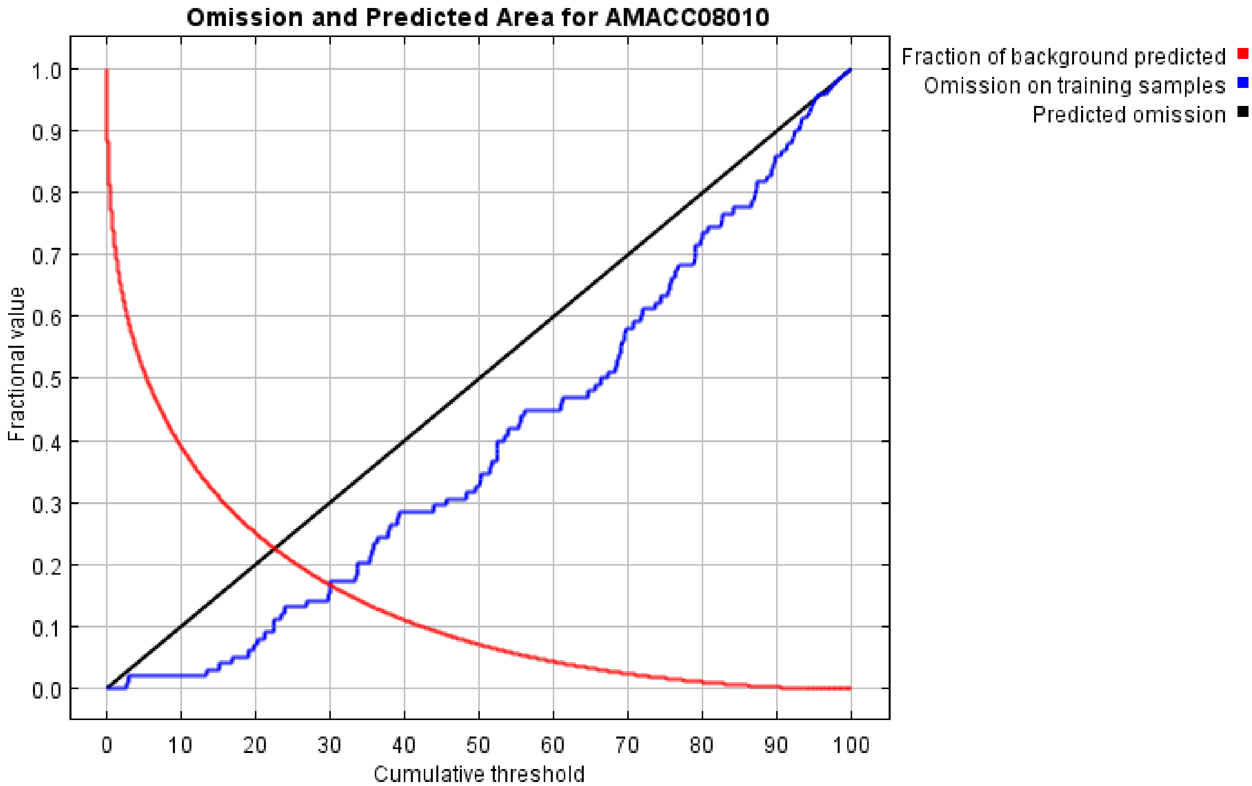


Raw data outputs and control parameters
Regularized training gain is 2.444, training AUC is 0.971, unregularized training gain is 2.951.
Algorithm terminated after 500 iterations (8 seconds).

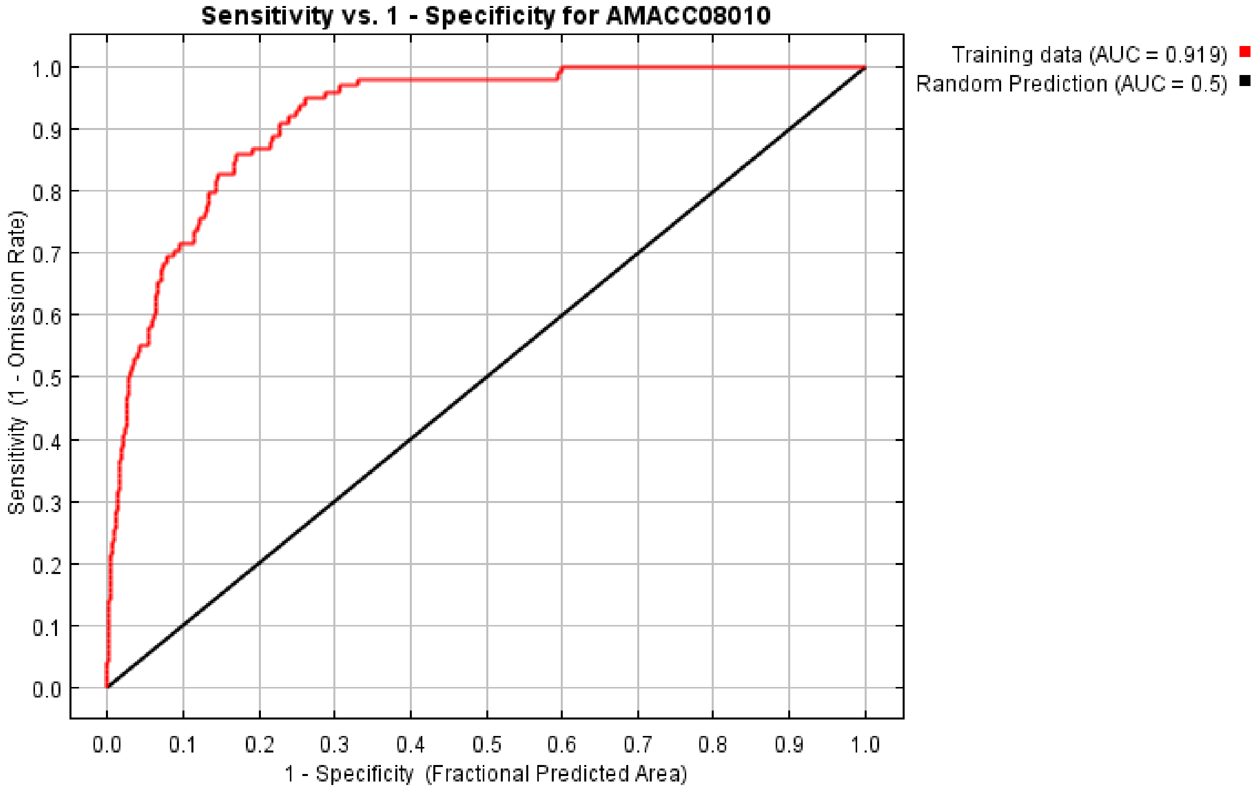
The follow settings were used during the run:
31 presence records used for training.
10031 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): bioclim15 bioclim17 d2cliffs40 elev fw3200 pj sage tpi_3
Regularization values: linear/quadratic/product: 0.247, categorical: 0.250, threshold: 1.690, hinge: 0.500
Feature types used: hinge linear quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC07010
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile: C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV
environmentallayers: C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV
askoverwrite: false
writeclampgrid: false
perspeciesresults: true
writeplotdata: true
threads: 4
Command line used: dontwriteclampgrid

Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E AMACC07010 responsecurves nopictures jackknife outputfiletype=bil outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC07010 projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV noaskoverwrite nowriteclampgrid perspeciesresults writeplotdata threads=4 -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N bare -N bioclim10 -N bioclim12 -N bioclim13 -N bioclim18 -N bioclim2 -N bioclim3 -N bioclim4 -N bioclim6 -N confr -N contag -N cti -N d2cave -N d2frstcc -N d2outcrop -N d2road -N d2srl -N decid -N dstrb -N flood_freq -N forest -N frestcc -N fw1600 -N fw300 -N herb -N hli -N owner -N pode -N ps1600 -N ps300 -N ps3200 -N shrub -N slope -N tpi31 -N tpi_11 -N vrm11 -N vrm3 -N vrm_31

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 0.857 rather than 1; in practice the test AUC may exceed this bound.

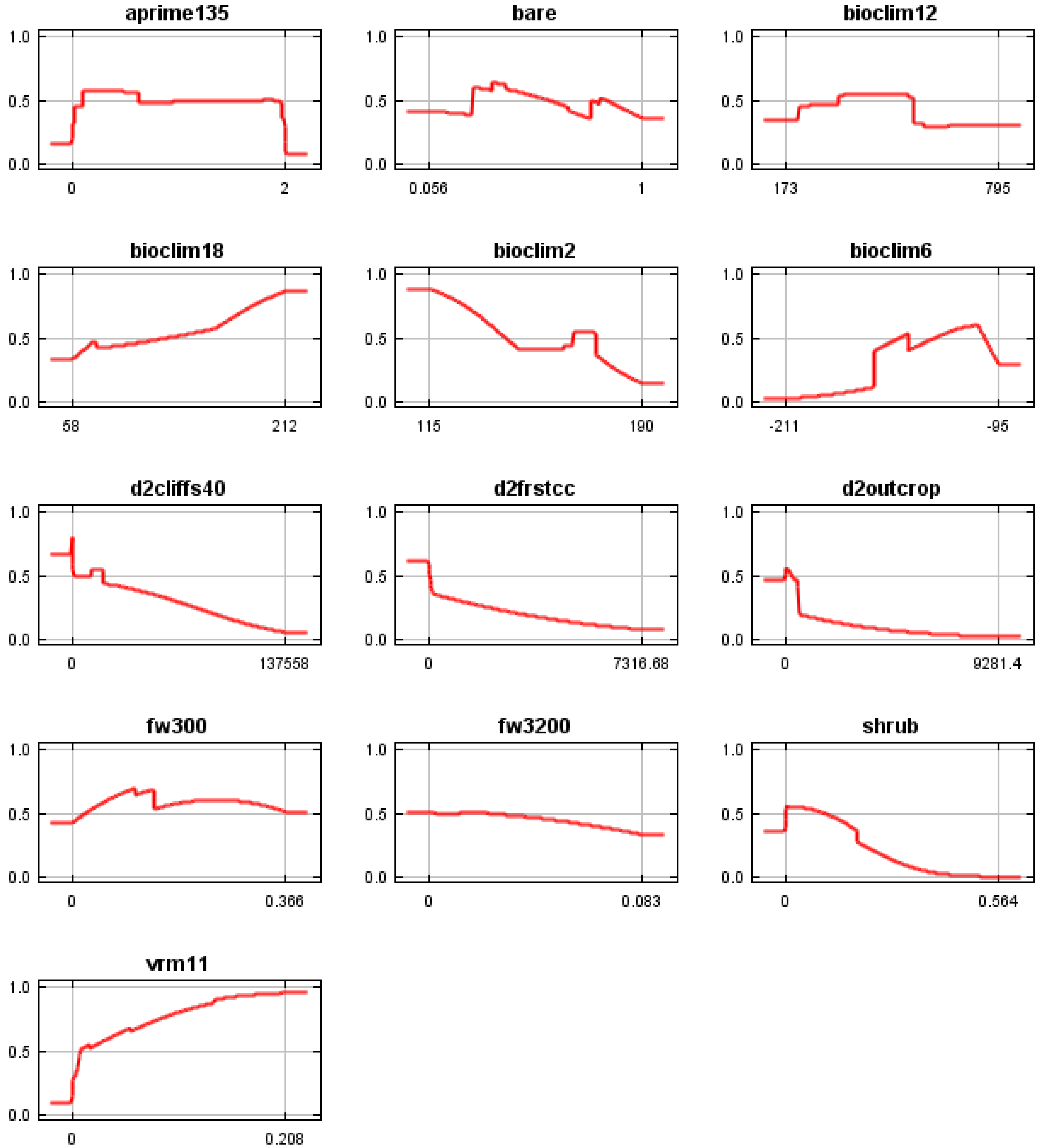


Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate
1.000	0.031	Fixed cumulative value 1	0.723	0.000
5.000	0.092	Fixed cumulative value 5	0.512	0.020
10.000	0.147	Fixed cumulative value 10	0.390	0.020
2.803	0.061	Minimum training presence	0.599	0.000
22.340	0.261	10 percentile training presence	0.228	0.092
30.077	0.325	Equal training sensitivity and specificity	0.167	0.163
19.058	0.232	Maximum training sensitivity plus specificity	0.261	0.051
2.803	0.061	Balance training omission, predicted area and threshold value	0.599	0.000
13.828	0.183	Equate entropy of thresholded and original distributions	0.327	0.031

Response curves
These curves show how each environmental variable affects the Maxent prediction. Each of the following curves represents a different model, namely, a Maxent model created using only the corresponding variable. These plots reflect

the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between the selected variable and other variables. They may be easier to interpret if there are strong correlations between variables.

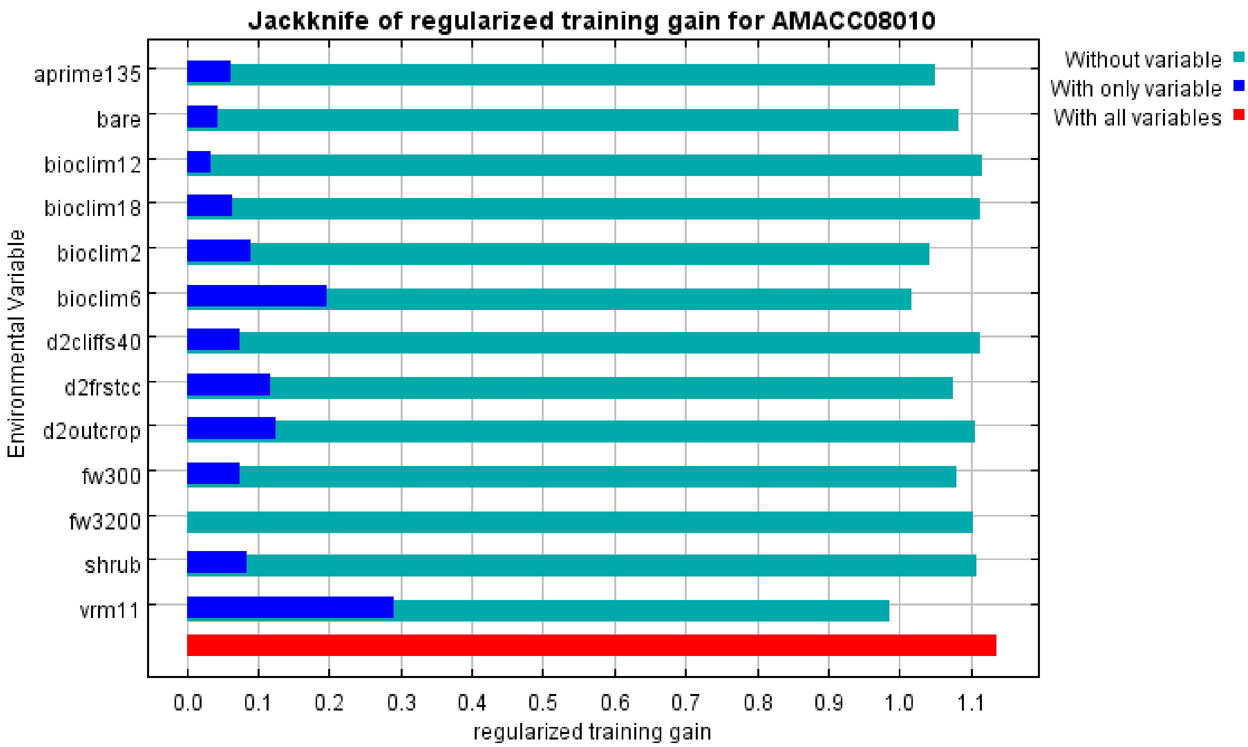


Analysis of variable contributions

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

Variable	Percent contribution	Permutation importance
vrm11	24.7	19.8
bioclim6	21.3	23.4
fw300	9.5	4
bioclim2	8	7.2
aprime135	7.3	7.1
d2frstcc	6.7	6.9
d2outcrop	6.2	3.2
shrub	4.5	3.3
bare	3.6	5.8
fw3200	3.5	2.5
d2cliffs40	1.7	3.4
bioclim12	1.6	9.9
bioclim18	1.4	3.5

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is vrm11, 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 vrm11, 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 1.136, training AUC is 0.919, unregularized training gain is 1.594.
Algorithm terminated after 500 iterations (14 seconds).

The follow settings were used during the run:
98 presence records used for training.
10098 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): aprime135 bare bioclim12 bioclim18 bioclim2 bioclim6 d2cliffs40 d2frstcc d2outcrop fw300 fw3200 shrub vrm11
Regularization values: linear/quadratic/product: 0.064, categorical: 0.250, threshold: 1.020, hinge: 0.500
Feature types used: hinge product linear threshold quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC08010
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile: C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV
environmentallayers: C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV
warnings: false
askoverwrite: false
writeclampgrid: false
writemess: false
writebackgroundpredictions: true
autorun: true
writeplotdata: true

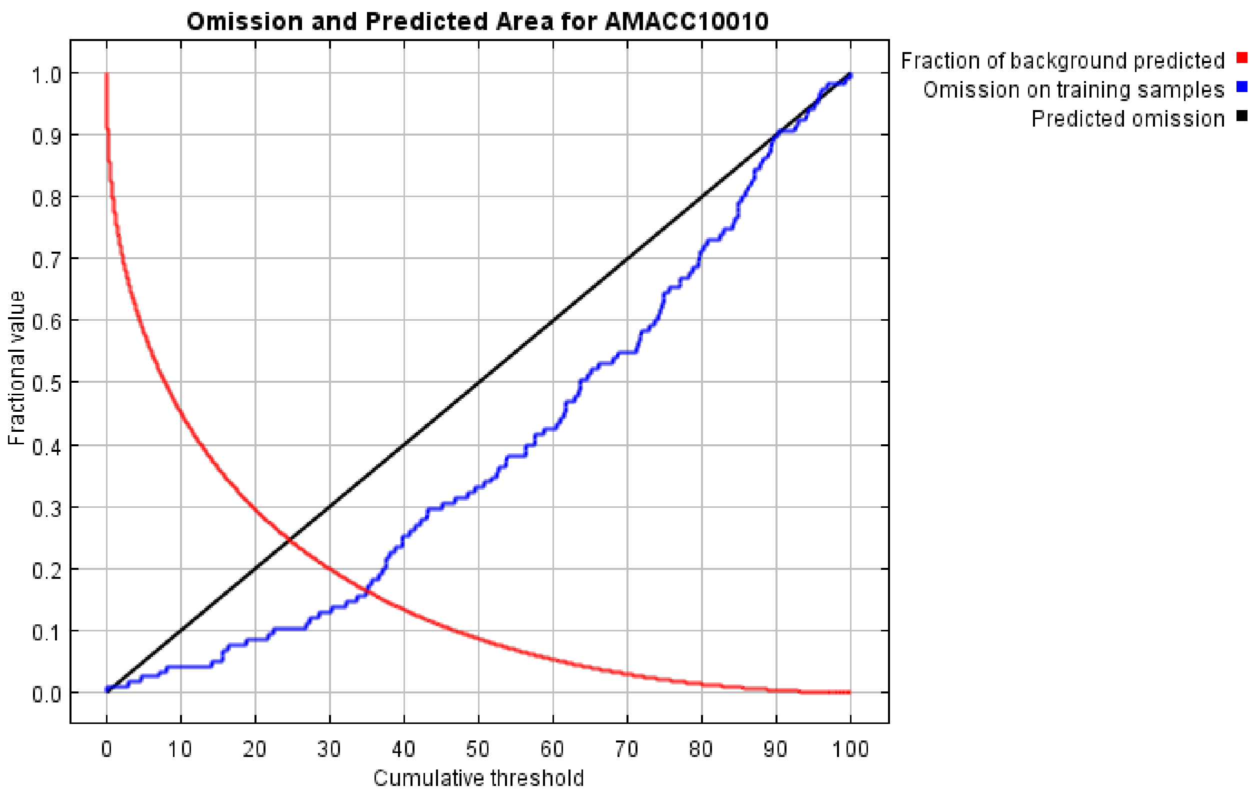
visible: false
threads: 5
Command line used: -r -a nowarnings responsecurves novisible nopictures jackknife outputfiletype=bil projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions writeplotdata threads=5 -E -E AMACC08010 outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC08010 -N -N d2outcrop -N fw3200 -N d2cliffs40 -N aprime135 -N shrub -N bioclim12 -N bioclim18 -N fw300 -N bare -N d2frstcc -N bioclim2 -N bioclim6 -N vrm11

Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E AMACC08010 responsecurves nopictures jackknife outputfiletype=bil outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC08010 projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV nowarnings noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions autorun writeplotdata novisible threads=5 -N aprime180 -N aprime45 -N aprime90 -N bioclim10 -N bioclim13 -N bioclim15 -N bioclim17 -N bioclim3 -N bioclim4 -N confr -N contag -N cti -N d2cave -N d2road -N d2srl -N decid -N dstrb -N elev -N flood_freq -N forest -N frestcc -N fw1600 -N herb -N hli -N owner -N pj -N pode -N ps1600 -N ps300 -N ps3200 -N sage -N slope -N tpi31 -N tpi_11 -N tpi_3 -N vrm3 -N vrm_31

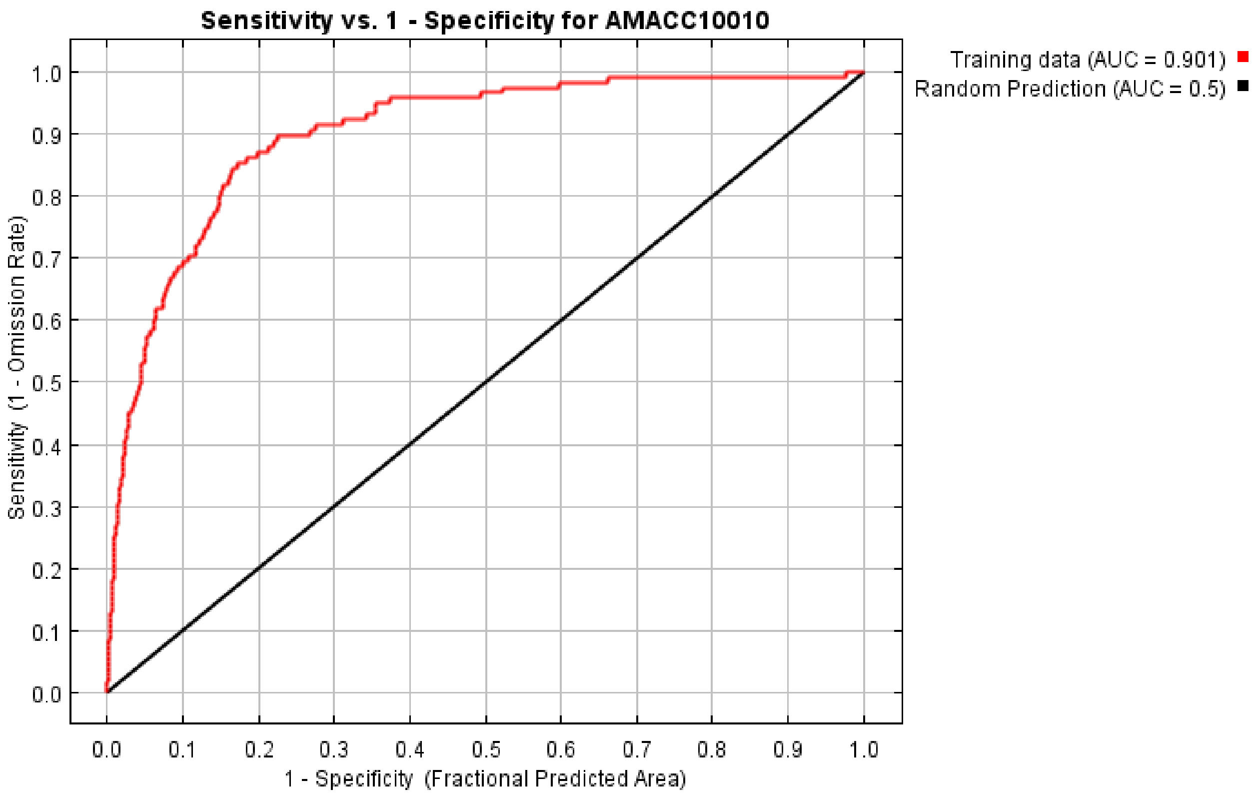
MODEL SUMMARY: PALLID BAT (ANTROZOUS PALLIDUS)

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 0.835 rather than 1; in practice the test AUC may exceed this bound.



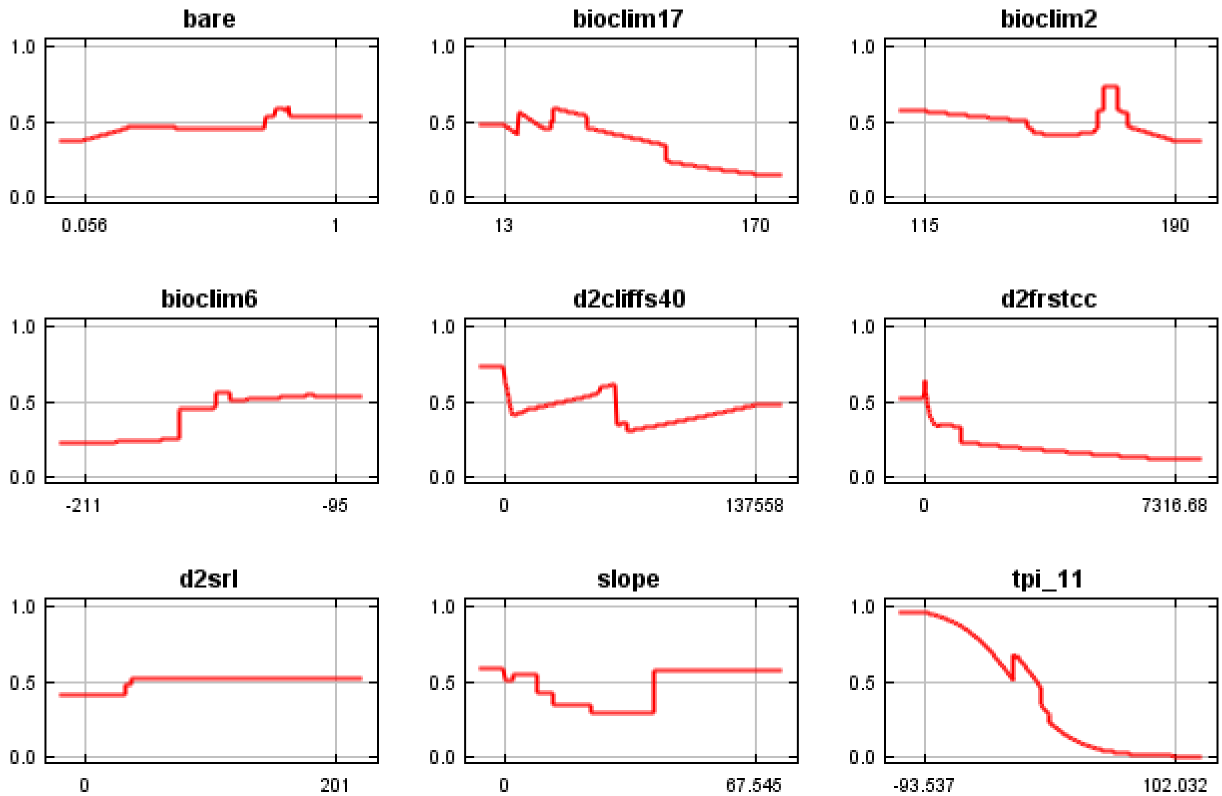
Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

Cumulative threshold	**Logistic threshold**	**Description**	**Fractional predicted area**	**Training omission rate**
1.000	0.042	Fixed cumulative value 1	0.782	0.009
5.000	0.105	Fixed cumulative value 5	0.582	0.026
10.000	0.158	Fixed cumulative value 10	0.451	0.043
0.004	0.002	Minimum training presence	0.977	0.000
22.362	0.269	10 percentile training presence	0.269	0.096
34.875	0.374	Equal training sensitivity and specificity	0.165	0.165
33.659	0.365	Maximum training sensitivity plus specificity	0.173	0.148

2.925	0.078	Balance training omission, predicted area and threshold value	0.662	0.009
13.145	0.188	Equate entropy of thresholded and original distributions	0.392	0.043

Response curves

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

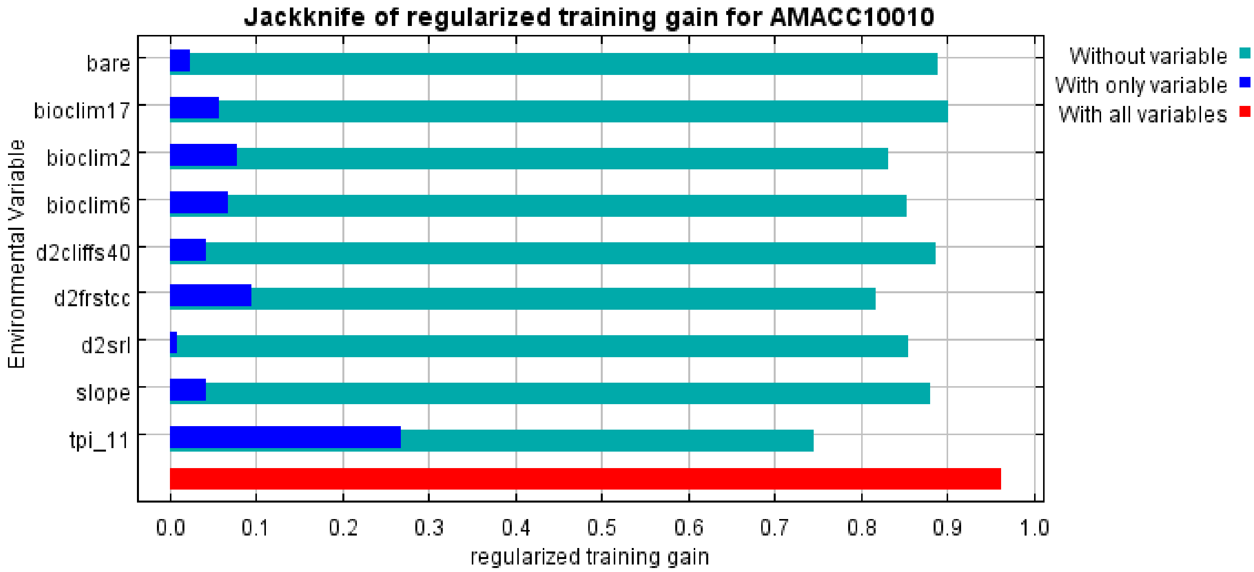


Analysis of variable contributions

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

Variable	Percent contribution	Permutation importance
tpi_11	28.4	15.9
bioclim6	15.7	19.4
d2frstcc	13.8	14.6
bioclim2	12.6	11.4
slope	8.5	14.9
bare	7.4	8.3
d2cliffs40	5.2	5.5
d2srl	4.7	6.3
bioclim17	3.7	3.7

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is tpi_11, 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 tpi_11, 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 0.963, training AUC is 0.901, unregularized training gain is 1.364.
Algorithm terminated after 500 iterations (10 seconds).

The follow settings were used during the run:
115 presence records used for training.
10115 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): bare bioclim17 bioclim2 bioclim6 d2cliffs40 d2frstcc d2srl slope tpi_11
Regularization values: linear/quadratic/product: 0.050, categorical: 0.250, threshold: 1.000, hinge: 0.500
Feature types used: hinge product linear threshold quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil
outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC10010
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile: C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV
environmentallayers: C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV
warnings: false
askoverwrite: false
writeclampgrid: false
writemess: false
writebackgroundpredictions: true
autorun: true
writeplotdata: true
visible: false
threads: 5
Command line used: -r -a nowarnings responsecurves novisible nopictures jackknife outputfiletype=bil

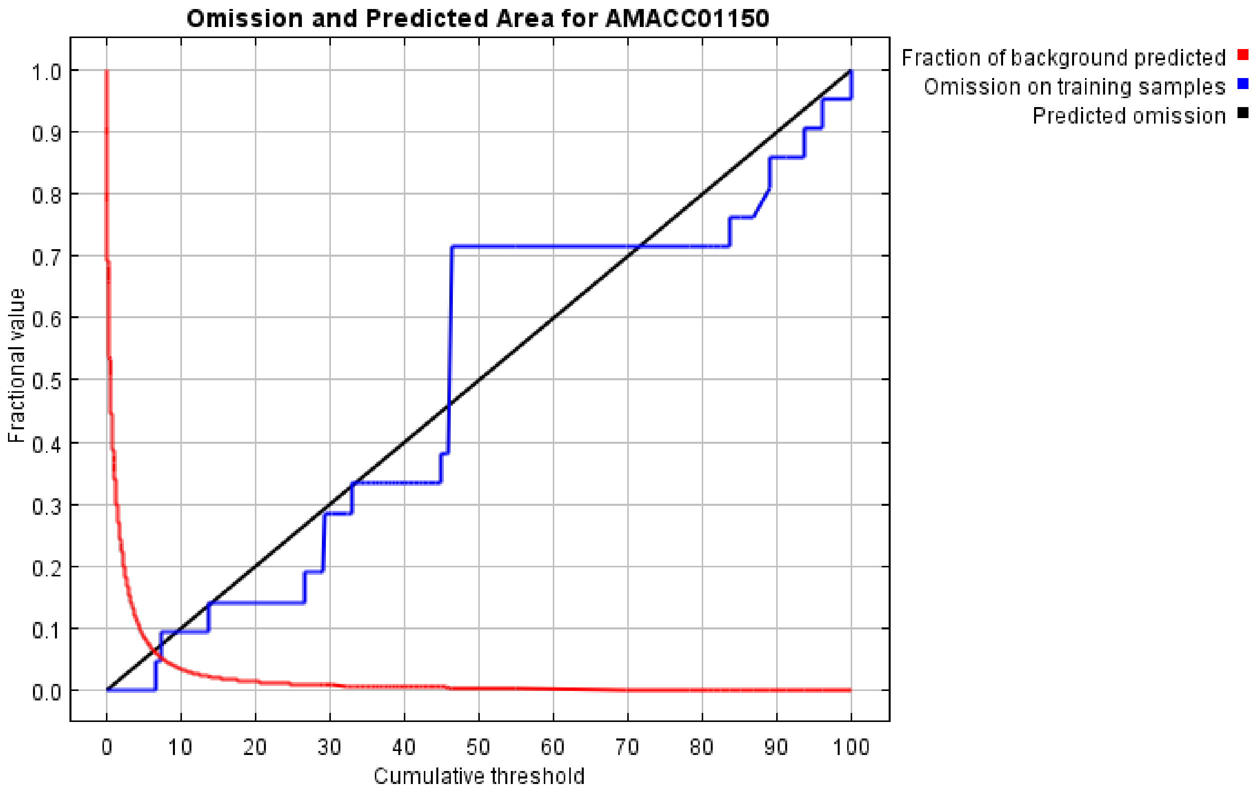
projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV
environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions writeplotdata threads=5 -E -E AMACC10010 outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC10010 -N -N d2cliffs40 -N d2srl -N tpi_11 -N bioclim17 -N slope -N VRM3 -N bare -N d2frstcc -N bioclim2 -N bioclim6 -N FW300

Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E AMACC10010 responsecurves nopictures jackknife outputfiletype=bil
outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC10010
projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV
environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV nowarnings noaskoverwrite nowriteclampgrid nowritemess writebackgroundpredictions autorun writeplotdata novisible threads=5 -N aprime135 -N aprime180 -N aprime45 -N aprime90 -N bioclim10 -N bioclim12 -N bioclim13 -N bioclim15 -N bioclim18 -N bioclim3 -N bioclim4 -N confr -N contag -N cti -N d2cave -N d2outcrop -N d2road -N decid -N dstrb -N elev -N flood_freq -N forest -N frestcc -N fw1600 -N fw300 -N fw3200 -N herb -N hli -N owner -N pj -N pode -N ps1600 -N ps300 -N ps3200 -N sage -N shrub -N tpi31 -N tpi_3 -N vrm11 -N vrm3 -N vrm_31

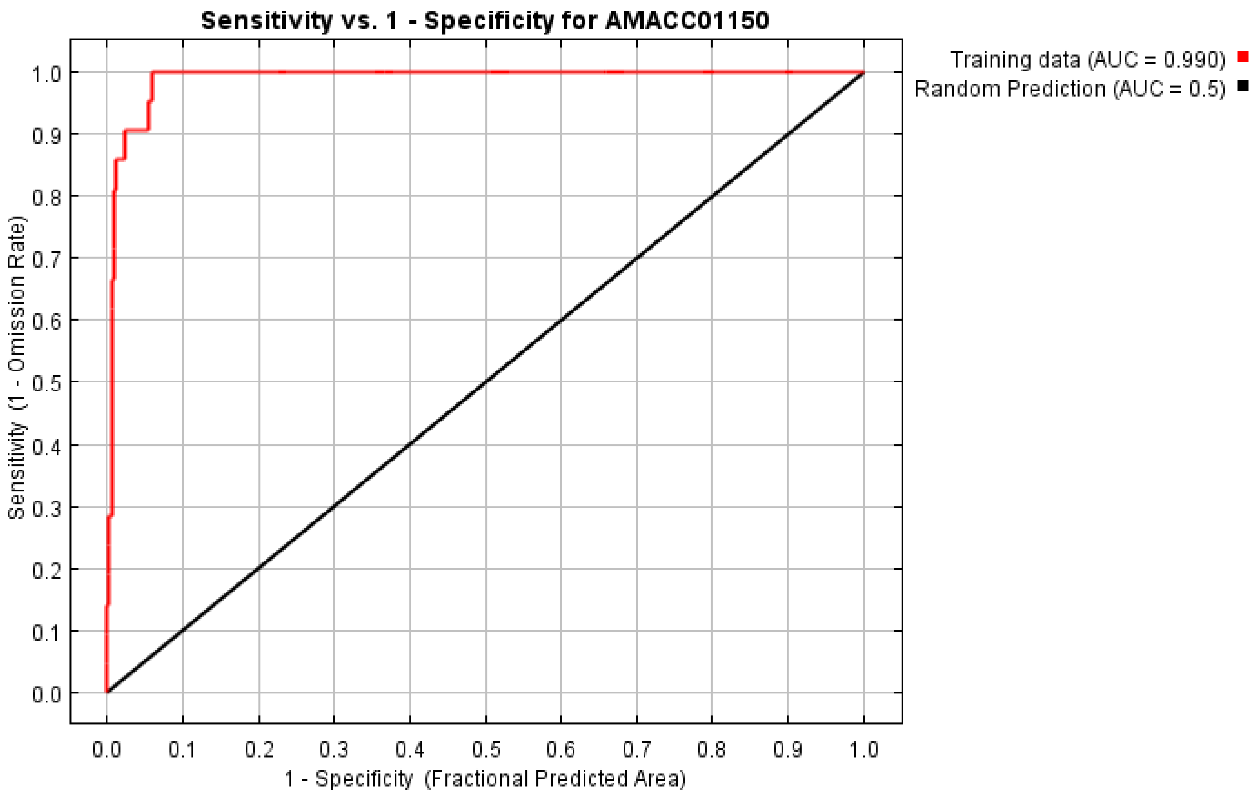
MODEL SUMMARY: NORTHERN LONG-EARED MYOTIS (MYOTIS SEPTENTRIONALIS)

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 0.974 rather than 1; in practice the test AUC may exceed this bound.



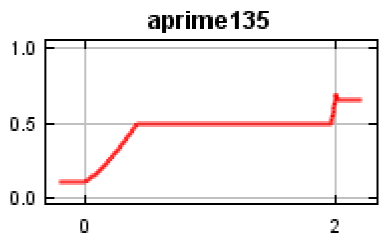
Some common thresholds and corresponding omission rates are as follows. If test data are available, binomial probabilities are calculated exactly if the number of test samples is at most 25, otherwise using a normal approximation to the binomial. These are 1-sided p-values for the null hypothesis that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

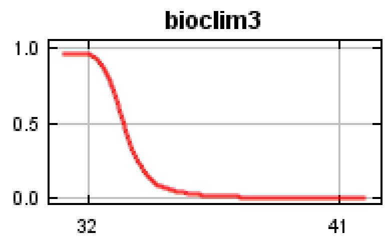
Cumulative threshold	**Logistic threshold**	**Description**	**Fractional predicted area**	**Training omission rate**
1.000	0.002	Fixed cumulative value 1	0.353	0.000
5.000	0.013	Fixed cumulative value 5	0.087	0.000
10.000	0.058	Fixed cumulative value 10	0.035	0.095
6.664	0.025	Minimum training presence	0.060	0.000
13.776	0.125	10 percentile training presence	0.023	0.095
7.233	0.029	Equal training sensitivity and specificity	0.054	0.048
6.664	0.025	Maximum training sensitivity plus specificity	0.060	0.000

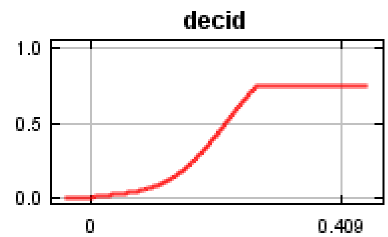
4.602	0.012	Balance training omission, predicted area and threshold value	0.097	0.000
11.428	0.078	Equate entropy of thresholded and original distributions	0.029	0.095

Response curves

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





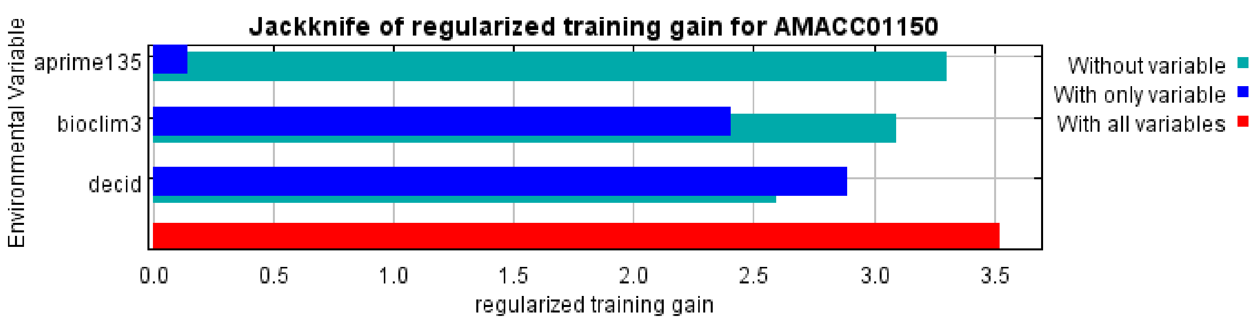


Analysis of variable contributions

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

Variable	Percent contribution	Permutation importance
decid	76.3	38
bioclim3	18	43.3
aprime135	5.7	18.7

The following picture shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is decid, 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 decid, 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 3.527, training AUC is 0.990, unregularized training gain is 3.850.
Algorithm converged after 420 iterations (3 seconds).

The follow settings were used during the run:
21 presence records used for training.
10021 points used to determine the Maxent distribution (background points and presence points).
Environmental layers used (all continuous): aprime135 bioclim3 decid
Regularization values: linear/quadratic/product: 0.423, categorical: 0.250, threshold: 1.790, hinge: 0.500
Feature types used: hinge linear quadratic
responsecurves: true
pictures: false
jackknife: true
outputfiletype: bil

outputdirectory: F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01150
projectionlayers: F:\MODELING\MAXENT_IN\LOGISTIC
samplesfile: C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV
environmentallayers: C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV
warnings: false
askoverwrite: false
writemess: false
writebackgroundpredictions: true
autorun: true
writeplotdata: true
visible: false
threads: 5
Command line used: -r -a nowarnings responsecurves novisible nopictures jackknife outputfiletype=bil samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV noaskoverwrite projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC nowritemess writebackgroundpredictions writeplotdata threads=5 -E -E AMACC01150 outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01150 -N -N aprime135 -N bioclim3 -N decid

Command line to repeat this species model: java density.MaxEnt nowarnings noprefixes -E "" -E AMACC01150 responsecurves nopictures jackknife outputfiletype=bil outputdirectory=F:\MODELING\BATS_2015\MAXENT_OUT\FINAL_W_SPATIAL_OUTPUT\AMACC01150 projectionlayers=F:\MODELING\MAXENT_IN\LOGISTIC samplesfile=C:\MODELING\2015_bats\MAXENT_IN\NON_MIGRATORY_BAT_SAMPLES_DATA2.CSV environmentallayers=C:\MODELING\2015_bats\MAXENT_IN\BIASED_BACKGROUND2.CSV nowarnings noaskoverwrite nowritemess writebackgroundpredictions autorun writeplotdata novisible threads=5 -N aprime180 -N aprime45 -N aprime90 -N bare -N bioclim10 -N bioclim12 -N bioclim13 -N bioclim15 -N bioclim17 -N bioclim18 -N bioclim2 -N bioclim4 -N bioclim6 -N confr -N contag -N cti -N d2cave -N d2cliffs40 -N d2frstcc -N d2outcrop -N d2road -N d2srl -N dstrb -N elev -N flood_freq -N forest -N frestcc -N fw1600 -N fw300 -N fw3200 -N herb -N hli -N owner -N pj -N pode -N ps1600 -N ps300 -N ps3200 -N sage -N shrub -N slope -N tpi31 -N tpi_11 -N tpi_3 -N vrm11 -N vrm3 -N vrm_31