ASSESSING MODEL ACCURACY DAVID ORME

OVERVIEW

- The confusion matrix
- Measures of model accuracy
- Thresholds for continuous predictions
- Application to Species Distribution Models

MODIS LAND COVER CLASSIFICATION

| Site | Class | | | | | CI | assi | ficat | ion | Outc | ome | | | | | | |
|-------|-----------------------------|------|------|-----|-----|------|------|-------|-----|------|------|-----|------|------|------|------|-------|
| Class | Name | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 14 | 15 | 16 | Total |
| 1 | Evergreen Needleleaf | 1460 | 42 | 18 | 11 | 266 | 7 | 9 | 17 | 23 | 10 | 15 | 21 | 2 | 0 | 0 | 1901 |
| 2 | Evergreen Broadleaf | 31 | 4889 | 0 | 14 | 14 | 11 | 18 | 79 | 23 | 17 | 4 | 38 | 10 | 0 | 1 | 5149 |
| 3 | Deciduous Needleleaf | 87 | 0 | 104 | 25 | 118 | 0 | 0 | 4 | 0 | 0 | 0 | 10 | 0 | 0 | 0 | 348 |
| 4 | Deciduous Broadleaf | 22 | 56 | 16 | 384 | 278 | 0 | 3 | 11 | 1 | 3 | 0 | 47 | 8 2 | 0 | 0 | 903 |
| 5 | Mixed Forest | 405 | 63 | 9 4 | 148 | 1355 | 3 | 1 | 27 | 7 | 8 | 40 | 41 | 17 | 0 | 0 | 2209 |
| 6 | Closed Shrubland | 34 | 35 | 2 | 12 | 5 | 140 | 124 | 29 | 15 | 30 | 2 | 158 | 19 | 0 | 8 | 613 |
| 7 | Open Shrubland | 10 | 12 | 3 | 9 | 1 | 41 | 1002 | 33 | 4 5 | 203 | 0 | 210 | 6 | 0 | 213 | 1788 |
| 8 | Woody Savanna | 62 | 133 | 0 | 16 | 110 | 11 | 104 | 577 | 141 | 71 | 0 | 221 | 22 | 0 | 3 | 1471 |
| 9 | Savanna | 10 | 53 | 1 | 0 | 21 | 18 | 48 | 93 | 440 | 43 | 1 | 252 | 79 | 0 | 16 | 1075 |
| 10 | Grasslands | 2 | 16 | 0 | 2 | 20 | 4 | 179 | 6 | 101 | 632 | 0 | 249 | 13 | 0 | 363 | 1587 |
| 11 | Pmnt Wtlnd | 63 | 24 | 0 | 5 | 28 | 23 | 1 | 2 | 36 | 2 | 89 | 1 | 7 | 0 | 0 | 281 |
| 12 | Cropland | 6 | 75 | 2 | 7 | 16 | 8 | 61 | 42 | 132 | 133 | 2 | 5168 | 183 | 0 | 18 | 5853 |
| 14 | Cropland/Natural Vegn | 2 | 133 | 0 | 48 | 28 | 2 | 8 | 16 | 66 | 8 | 1 | 320 | 832 | 0 | 7 | 1471 |
| 15 | Snow+ice | 1 | 0 | 0 | 0 | 0 | 1 | 2 | 0 | 0 | 0 | 5 | 1 | 0 | 1297 | 5 | 1312 |
| 16 | Barren | 0 | 2 | 1 | 0 | 0 | 1 | 162 | 4 | 5 | 126 | 3 | 56 | 5 | 14 | 3537 | 3916 |
| | Total | 2195 | 5533 | 241 | 681 | 2260 | 270 | 1722 | 940 | 1035 | 1286 | 162 | 6793 | 1277 | 1311 | 4171 | 29877 |

Accuracy = 21906 / 29877 = 73.3%

A SIMPLER CONFUSION MATRIX

Zoom in on just two of those categories:

| Site | Class | | |
|-------|----------------------------|------|------|
| Class | Name | 1 | 2 |
| 1 | Evergreen Needleleaf | 1460 | 42 |
| 2 | Evergreen Broadleaf | 3 1 | 4889 |

Model predicts: Is this evergreen forest needleleaf or broadleaf

Easy to calculate accuracy:

| | Pred. Needle | Pred. Broad | Sum | | |
|-------------|-----------------|----------------|--------|--|--|
| Obs. Needle | 1460 | 42 | 1502 | | |
| Obs. Broad | 31 | 4889 | 4920 | | |
| Sum | 1491 | 4931 | 6422 | | |
| \$\$A = 14 | 460 + 4889}{146 | 50 + 4889 + 42 | 2+31}= | | |
| 98.9%\$\$ | | | | | |

But random models have ~50% accuracy!

| | Pred. Needle | Pred. Broad | Sum | | |
|---|--------------|-------------|------|--|--|
| Obs. Needle | 737 | 765 | 1502 | | |
| Obs. Broad | 2520 | 2400 | 4920 | | |
| Sum | 3257 | 3165 | 6422 | | |
| $$A = \frac{737 + 2400}{6422} = 48.8\%$ | | | | | |

Bad models: everything is a broadleaf

| | Pred. Needle | Pred. Broad | Sum | | |
|---------------------------------------|--------------|-------------|------|--|--|
| Obs. Needle | 0 | 1502 | 1502 | | |
| Obs. Broad | 0 | 4920 | 4920 | | |
| Sum | 0 | 6422 | 6422 | | |
| $$A = \frac{0 + 4920}{6422} = 76.6\%$ | | | | | |

PREVALENCE

Proportion of the observed positive outcomes

| | Pred. Pos | Pred. Neg | Sum |
|----------|-----------|-----------|------|
| Obs. Pos | 1460 | 42 | 1502 |
| Obs. Neg | 31 | 4889 | 4920 |
| Sum | 1491 | 4931 | 6422 |

 $\protect\$ = \frac{1502}{6422} = 0.234\$\$

And accuracy is affected by prevalence

| | Pred. Pos | Pred. Neg | Sum | |
|---------------------------------------|-----------|-----------|------|--|
| Obs. Pos | 0 | 35 | 35 | |
| Obs. Neg | 0 | 6407 | 6407 | |
| Sum | 0 | 6442 | 6442 | |
| $$A = \frac{0 + 6407}{6422} = 99.5\%$ | | | | |

PREDICTION OUTCOMES

Giving some simple names to the four outcomes:

| | Pred. Pos | Pred. Neg |
|----------|-----------|-----------|
| Obs. Pos | True | False |
| | Positive | Negative |
| Obs. Neg | False | True |
| Obs. Neg | Positive | Negative |

PREDICTION OUTCOMES

Other more confusing names do get used:

| | Pred. Pos | Pred. Neg |
|----------|------------------|------------------|
| Obs. Pos | True Positive | Type II Error |
| Obs. Neg | Type I Error | True Negative |

RATES OF OUTCOMES

Divide the four outcomes by the **observed** positive and negative counts to give **rates**:

| | Pred. Pos | Pred. Neg |
|----------|-----------|-----------|
| | True | False |
| Obs. Pos | Positive | Negative |
| | Rate | Rate |
| | False | True |
| Obs. Neg | Positive | Negative |
| | Rate | Rate |

RATES OF OUTCOMES

Calculate those values:

| | Pred. Pos | Pred. Neg | Sum |
|------|------------------|------------------|------|
| Obs. | \$\$\frac{1460} | \$\$\frac{42} | 1502 |
| Pos | {1502}=97.2%\$\$ | {1502}=2.8%\$\$ | |
| Obs. | \$\$\frac{31} | \$\$\frac{4889} | 4920 |
| Neg | {4920}=0.6%\$\$ | {4920}=99.4%\$\$ | |

SENSITIVITY AND SPECIFICITY

Sensitivity

- Another name for the True Positive Rate
- The proportion of correctly predicted positive observations

Specificity

- Another name for the True Negative Rate
- The proportion of correctly predicted negative observations

SENSITIVITY AND SPECIFICITY

| | Pred. Pos | Pred. Neg | Sum |
|----------|-----------|-----------|------|
| Obs. Pos | 1460 | 42 | 1502 |
| Obs. Neg | 2010 | 2910 | 4920 |
| Sum | 3470 | 2952 | 6422 |

| | Pred. Pos | Pred. Neg |
|----------|-----------|-----------|
| Obs. Pos | 97.2% | 2.8% |
| Obs. Neg | 40.9% | 59.1% |

COHEN'S KAPPA

Cohen's kappa (\$\kappa\$) is a measure of agreement that rescales accuracy (\$A\$) to account for chance agreement (\$P_e\$):

\$\$\kappa = \frac{A - P_e}{1 - P_e}\$\$

It can take values from \$-\infty\$ to 1, where 1 is perfect prediction and anything below zero is worse than chance.

COHEN'S KAPPA

Multiply proportions of observed and predicted to get probability of each outcome

| | Pred. Pos | Pred. Neg | Sum |
|----------|-----------|-----------|------|
| Obs. Pos | 1460 | 42 | 1502 |
| Obs. Neg | 31 | 4889 | 4920 |
| Sum | 1491 | 4931 | 6422 |

 $P_{YY} = \frac{1491}{6422} \times \frac{1502}{6422} = 0.054$

COHEN'S KAPPA

| | | Pred. Pos | Pred. Neg | р | |
|-------|----------|----------------|-------------|--------------|------|
| С | bs. Pos | 0.054 | 0.180 | 0.234 | |
| С | bs. Neg | 0.178 | 0.588 | 0.766 | |
| р | | 0.232 | 0.768 | 1.000 | |
| P_e = | P_{YY} + | $P_{NN} = 0.0$ | 054 + 0.588 | = 0.642 \$\$ | \$\$ |
| \kapp | a = | 0.989 - 0.64 | 2}{1-0.642} | = 0.969 \$\$ | |

TRUE SKILL STATISTIC

Journal of Applied Ecology





Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS)

OMRI ALLOUCHE, ASAF TSOAR, RONEN KADMON

First published: 12 September 2006 | https://doi.org/10.1111/j.1365-2664.2006.01214.x

Citations: 1,633

TRUE SKILL STATISTIC

An alternative measure is TSS:

```
 \$ \mbox{TSS} = \mbox{Sensitivity} + \\ \mbox{Specificity} - 1 \$\$ \$ \mbox{TSS} = [0, 1] + [0, 1] - \\ 1 \$\$
```

- TSS = 1 (perfect)
- TSS = 0 (random)
- TSS = -1 (always wrong)
- Unaffected by prevalence.

WAIT, NO. NOT TSS!

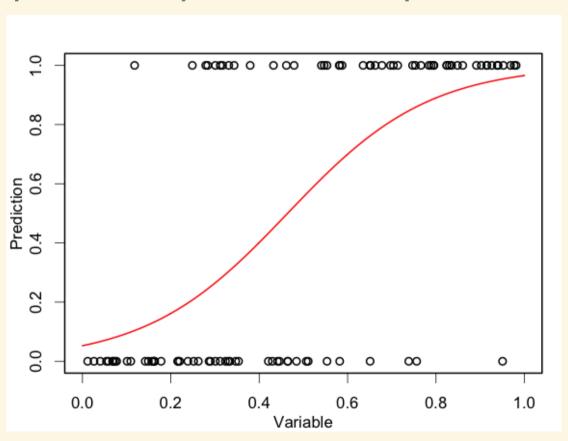


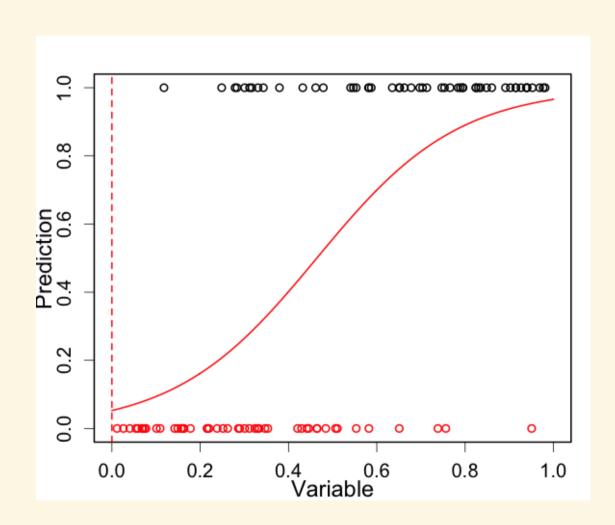
Two alternative evaluation metrics to replace the true skill statistic in the assessment of species distribution models

Rainer Ferdinand Wunderlich, Yu-Pin Lin, Johnathen Anthony, Joy R. Petway

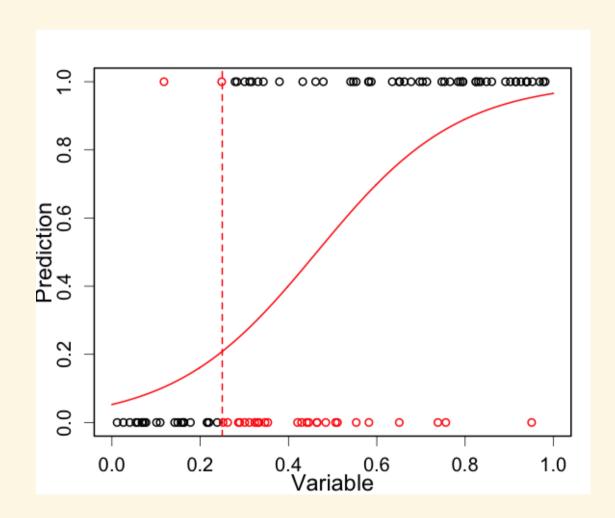
PROBABILISTIC CLASSIFICATION

A model predicting the probability of success / presence

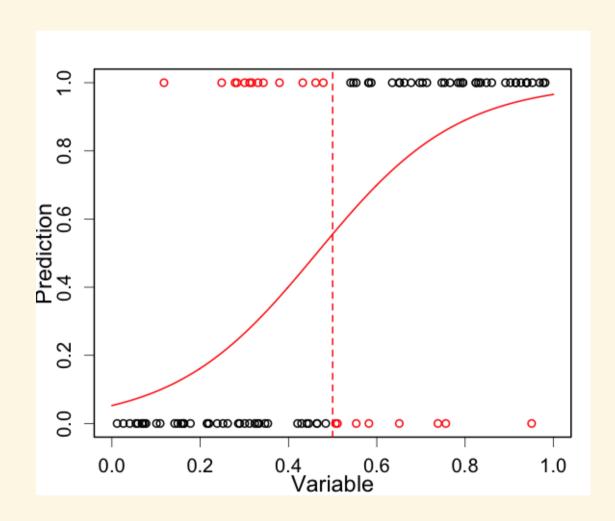




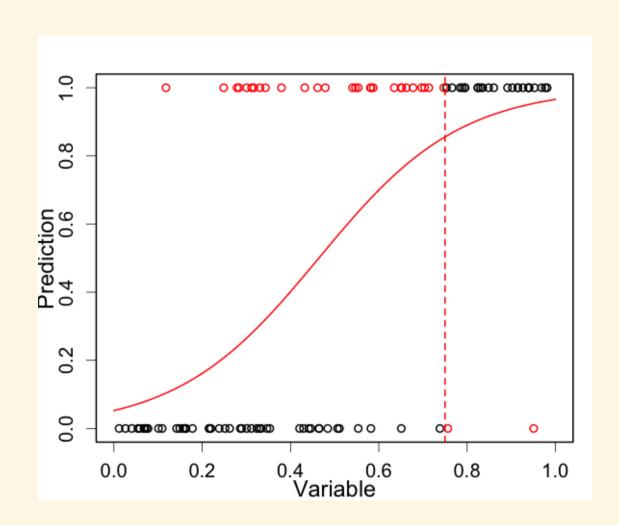
| | 0 | 1 |
|-----|---|-------|
| 1 | 0 | 52 |
| 0 | 0 | 48 |
| | • | value |
| Sen | S | 1 |
| Spe | С | 0 |
| TSS | | 0 |



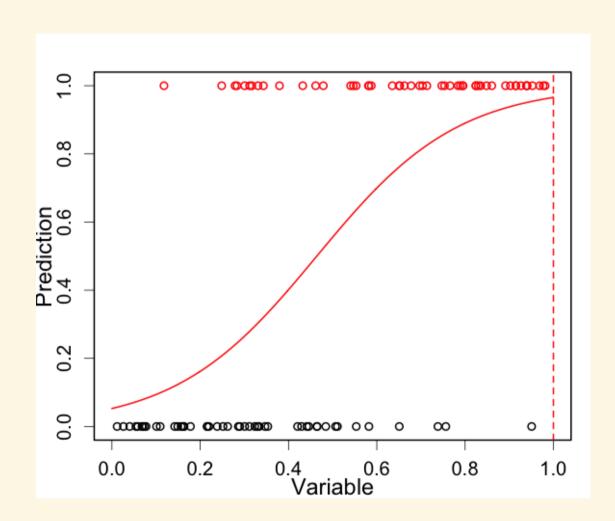
| | 0 | 1 |
|-----|------|------|
| 1 | 2 | 50 |
| 0 | 22 | 26 |
| | V | alue |
| Sen | s 0 | .962 |
| Spe | ec 0 | .458 |
| TSS | 0 | .420 |



| | 0 | 1 |
|-----|------|------|
| 1 | 13 | 39 |
| 0 | 40 | 8 |
| | V | alue |
| Ser | ns O | .750 |
| Spe | ec O | .833 |
| TSS | 5 0 | .583 |

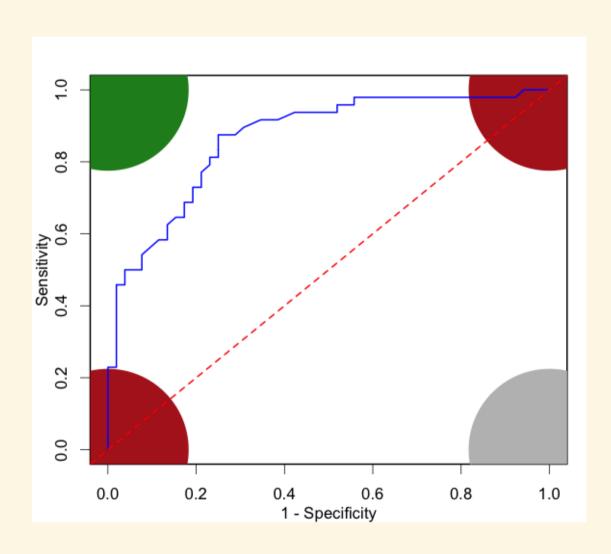


| | 0 | 1 |
|-----|------|------|
| 1 | 28 | 24 |
| 0 | 46 | 2 |
| | V | alue |
| Ser | ns O | .462 |
| Spe | ec O | .958 |
| TSS | 6 0 | .420 |



| | 0 | 1 |
|-----|------|------|
| 1 | 52 | 0 |
| 0 | 48 | 0 |
| | Vä | alue |
| Sen | IS | 0 |
| Spe | eC . | 1 |
| TSS | | 0 |

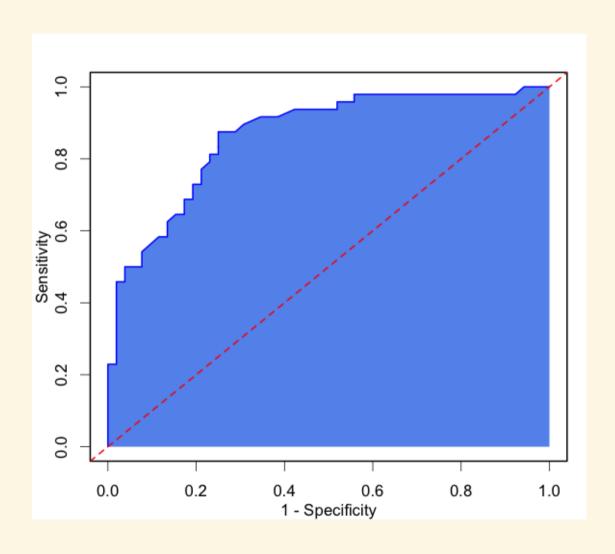
ROC CURVE



- Receiver

 operating
 characteristic
 (ROC)
- A random model gives the red line

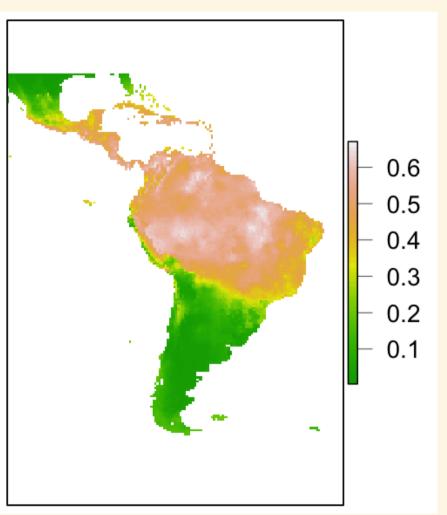
AREA UNDER ROC CURVE (AUC)



- AUC varies between 0 and 1.
- AUC = 0.5 is random.
- Overall model performance

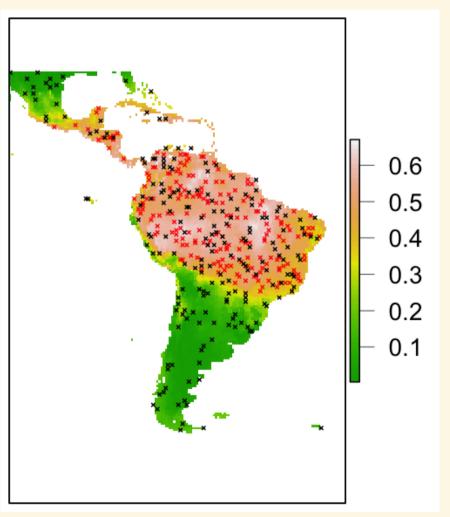


Kinkajou (Potos flavus)



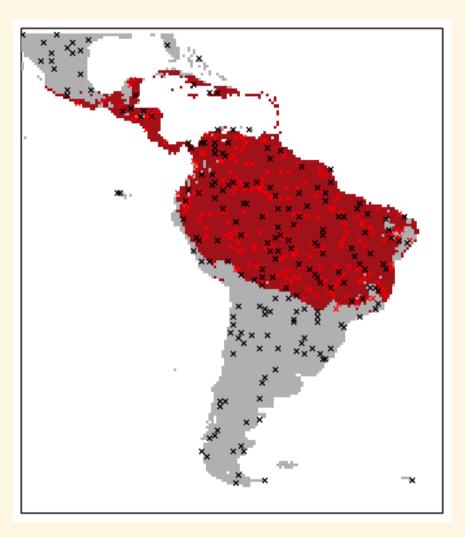


- Observed (red)
- Background (black)

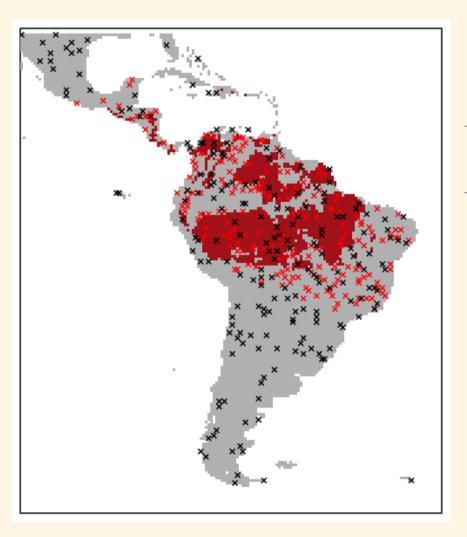




| Threshold = 0.1 | | | | |
|-----------------|-------|-----|----|------|
| | Prese | ent | Ab | sent |
| Obs | 2 | 00 | | 0 |
| Back | 1 | 162 | | 38 |
| | value | | | |
| | Sens | 0. | 19 | |
| | Spec | 1. | 00 | |
| | TSS | 0. | 19 | |



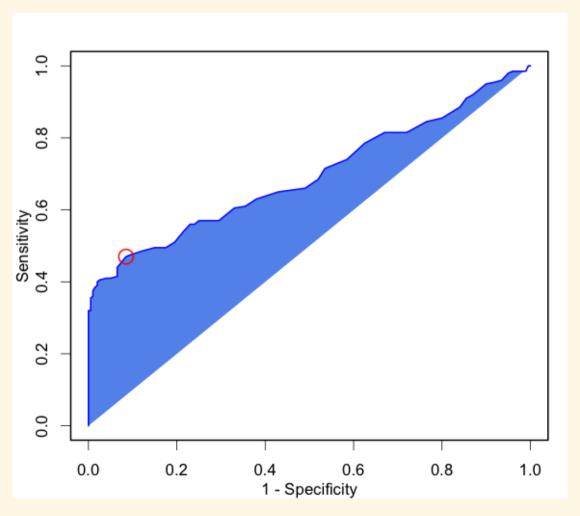
| Threshold = 0.4 | | | | |
|-----------------|------|-----|----|------|
| | Pres | ent | Ab | sent |
| Obs | - | 187 | | 13 |
| Back | - | 111 | | 89 |
| | | val | ue | |
| | Sens | 0.4 | 45 | |
| | Spec | 0.9 | 35 | |
| | TSS | 0.3 | 80 | |

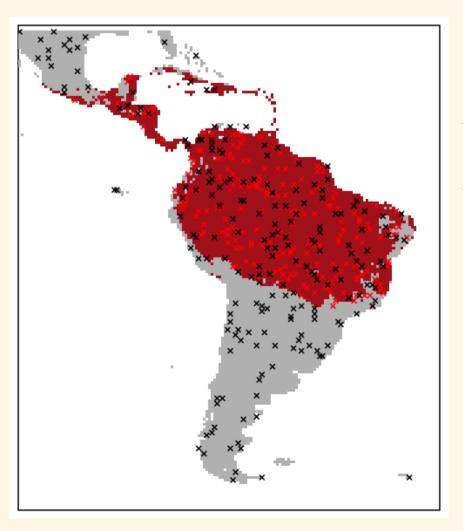


| Threshold = 0.55 | | | | |
|------------------|------|-----|----|------|
| | Pres | ent | Ab | sent |
| Obs | | 67 | | 133 |
| Back | | 37 | | 163 |
| _ | | val | ue | |
| | Sens | 0.8 | 15 | |
| | Spec | 0.3 | 35 | |
| | TSS | 0.1 | 50 | |

AUC FOR THE KINKAJOU

Maximum sensitivity + specificity shown in red.





| Threshold = 0.411 | | | | | |
|-------------------|------|-------|----|------|--|
| | Pres | ent | Ab | sent | |
| Obs | - | 183 | | 17 | |
| Back | - | 106 | | | |
| | | value | | | |
| | Sens | 0.4 | 70 | | |
| | Spec | 0.9 | 15 | | |
| | TSS | 0.3 | 85 | | |

THRESHOLD CHOICES

| Method | Definition |
|--|--|
| Fixed value | An arbitrary fixed value (e.g. probability = 0.5) |
| Lowest predicted value | The lowest predicted value corresponding with an observed occurrence record |
| Sensitivity-specificity equality | The threshold at which sensitivity and specificity are equal |
| Sensitivity-specificity sum maximization | The sum of sensitivity and specificity is maximized |
| Maximize Kappa | The threshold at which Cohen's Kappa statistic is maximized |
| Equal prevalence | Propn of presences relative to the number of sites is equal in prediction and calibration data |