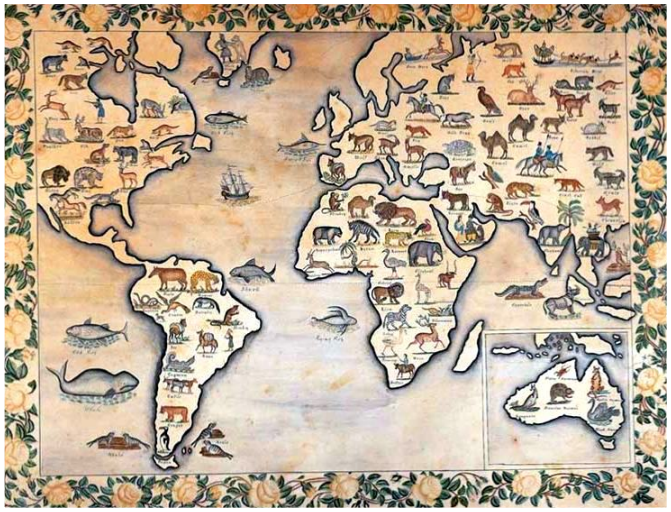
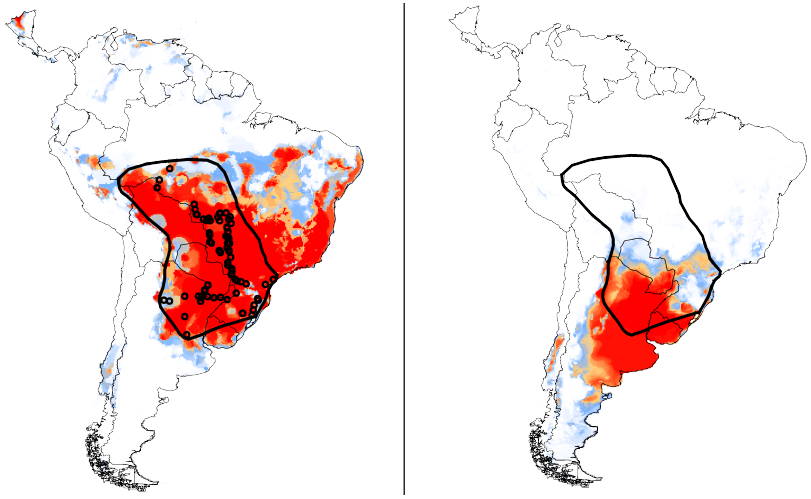


Evaluating SDMs

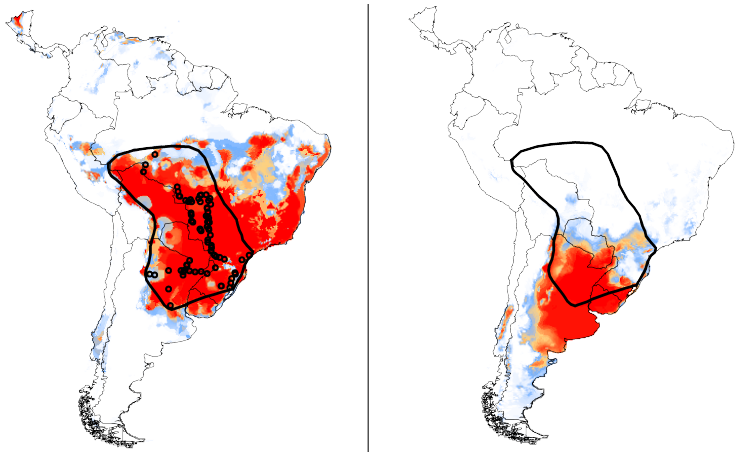
Model evaluation

- Not the same as model selection
  - Based on information criterion (e.g., AIC, BIC)
- Most evaluations focus on predictive accuracy
- Other considerations
  - Realism
  - Spatial pattern of error
    - Ecologically interesting?
    - Over- vs. under-prediction



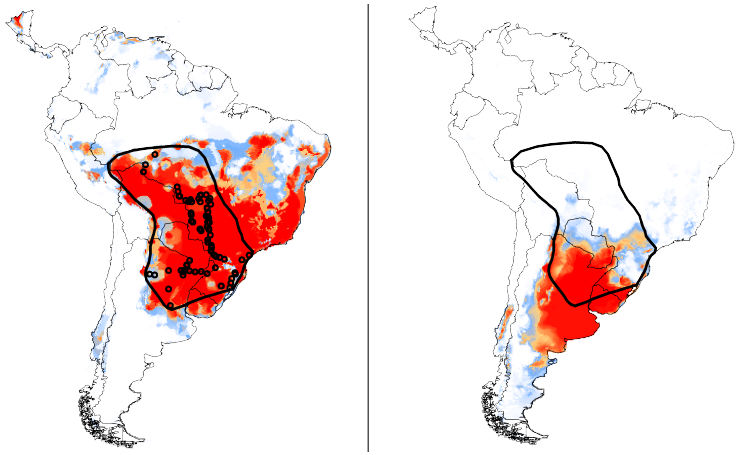
Model evaluation

- Should check both:
  - **Discrimination**
  - **Calibration**



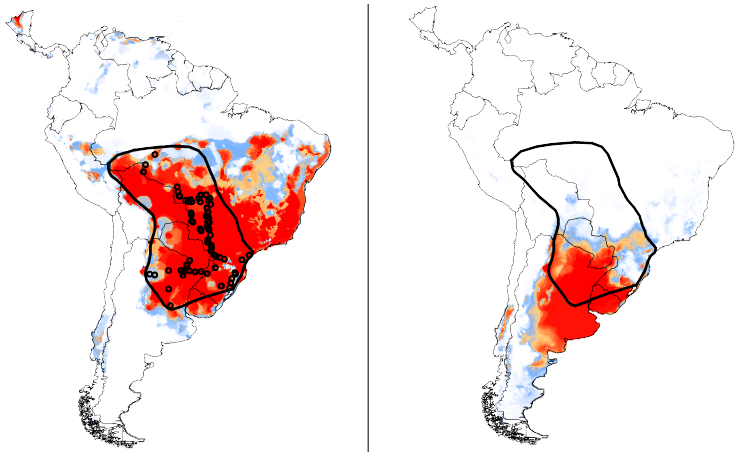
Model evaluation

- Should check both:
  - **Discrimination**
    - the ability of the model to correctly distinguish between occupied and unoccupied sites
    - Most studies measure and report only discrimination ability
    - Two kinds
      - Threshold dependent
      - Threshold independent



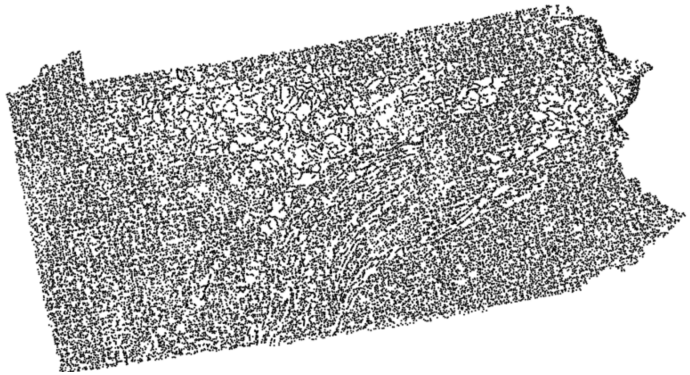
Model evaluation

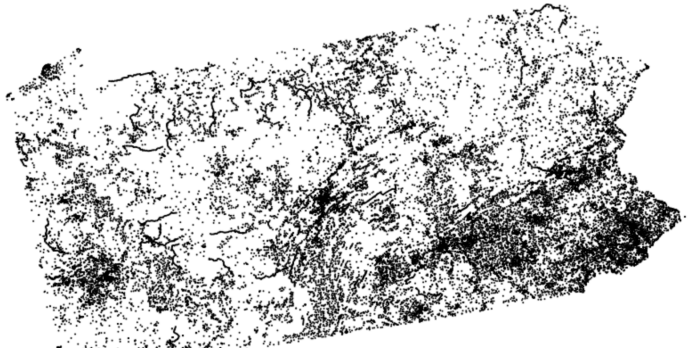
- Should check both:
  - **Calibration** (Reliability)
  - Also important
    - Do predictions of 0.6 have a 60% chance of being occupied and are these twice as likely (or twice as suitable) as predictions of 0.3?
    - Brier Score
      - equivalent to mean squared error
      - applicable when comparing continuous probabilities to presence / absence
      - Ranges from 0 to 1
        - 0 = complete agreement between observed and predicted
        - 1 indicates complete disagreement.

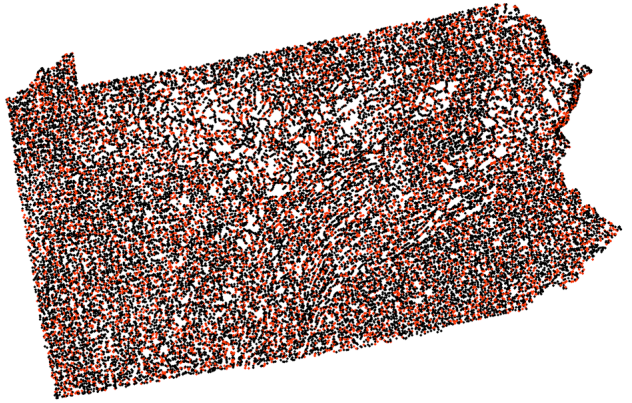


Data for model evaluation

- New / independent data are best, but usually not available
  - Model performance over estimated when using the same data for training & evaluation
- Partition data into training / testing sets
  - i.e. 75 training / 25% testing
  - Testing proportion = 1/(1+sqrt(p-1)) where p is the number of predictors
    - 50% for 2 predictors
    - 33% for 5 predictors



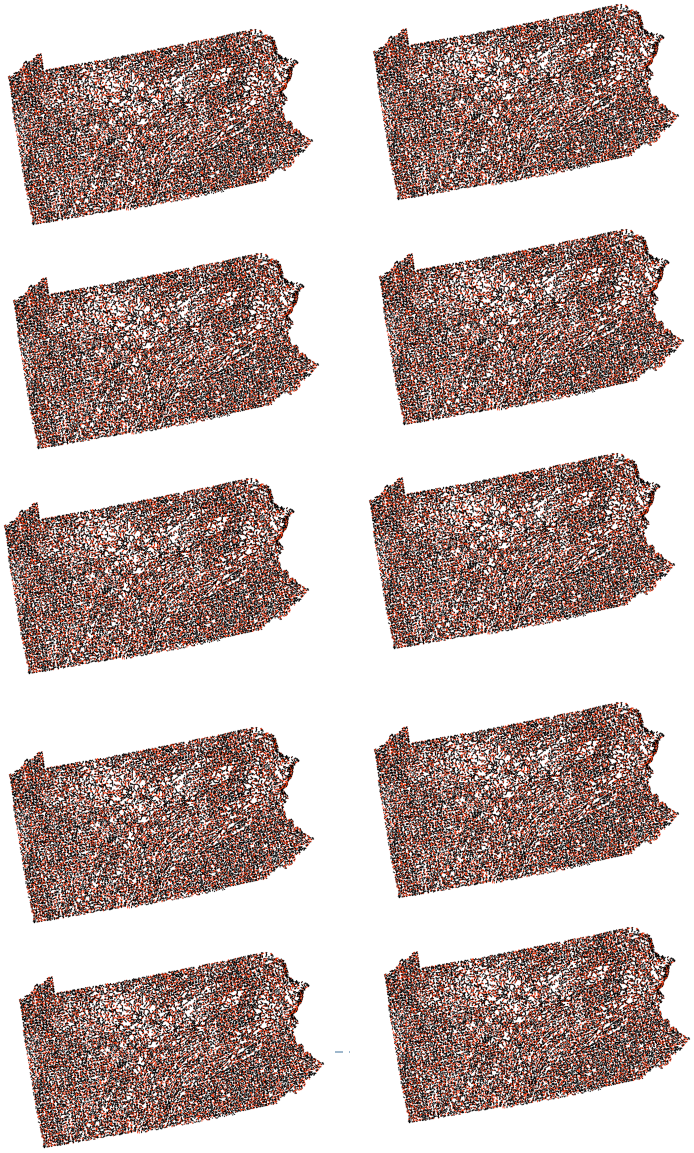




Data for model evaluation

K = 10

- Partition data into training / testing sets
  - K-fold cross validation
    - Partition data k times at random
    - Fit models to each resulting set
  - For small sample sizes
    - Bootstrap sampling with replacement
    - Jackknife
    - Use all data to fit final model



Model evaluation

- K-fold cross validation using spatial blocks

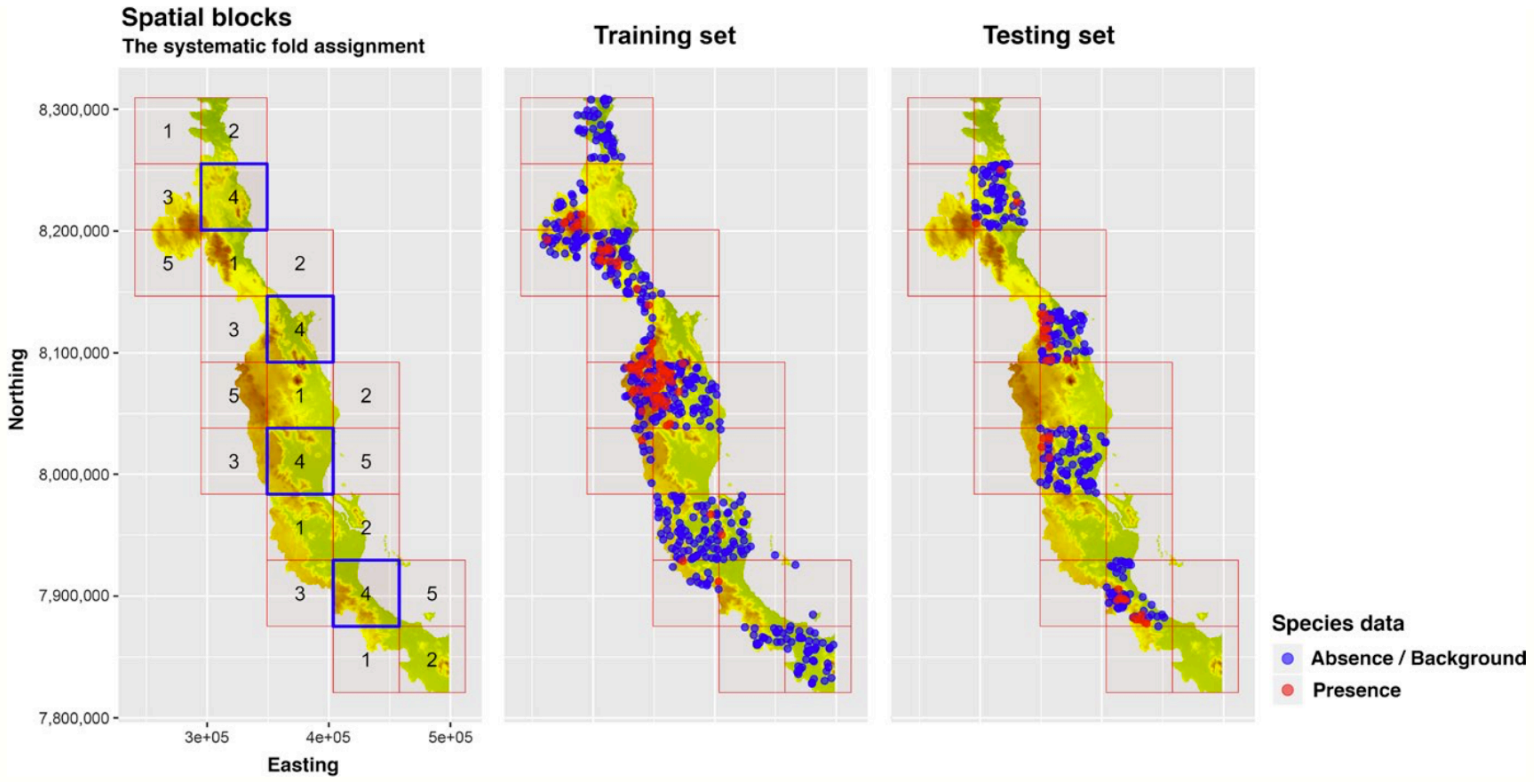
Received: 19 January 2018 | Accepted: 5 October 2018
DOI: 10.1111/2041-210X.13107

APPLICATION

Methods in Ecology and Evolution

blockCV: An r package for generating spatially or environmentally separated folds for *k*-fold cross-validation of species distribution models

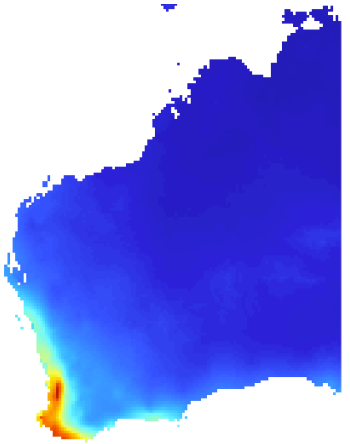
Roozbeh Valavi | Jane Elith | José J. Lahoz-Monfort | Gurutzeta Guillera-Arroita



Discrimination metrics - threshold dependent

- Use threshold to convert continuous prediction to presence (1) and absence (0)
- Construct “confusion matrix”

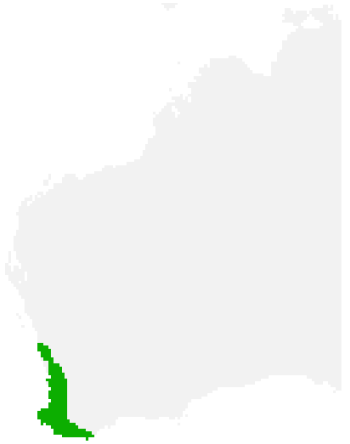
		Observed: True	Observed: False
Predicted	True	correct	error
Predicted	False	error	correct



Discrimination metrics - threshold dependent

- Use threshold to convert continuous prediction to presence (1) and absence (0)
- Construct “confusion matrix”

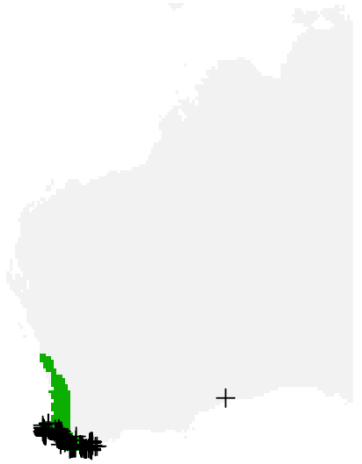
		Observed	
		True	False
Predicted	True		
	False		



Discrimination metrics - threshold dependent

- Use threshold to convert continuous prediction to presence (1) and absence (0)
- Construct “confusion matrix”

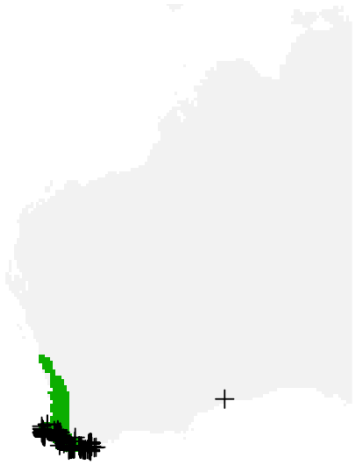
		Observed	
		True	False
Predicted	True		
	False		



Discrimination metrics - threshold dependent

- Use threshold to convert continuous prediction to presence (1) and absence (0)
- Construct “confusion matrix”
- Compare / assess error rates for presences and absences

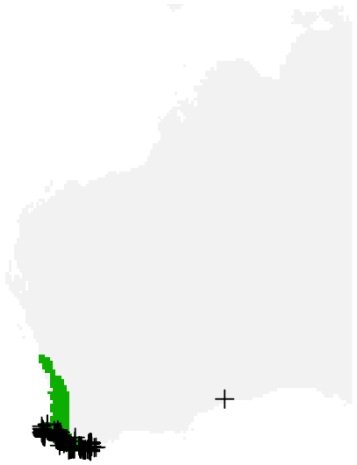
		Observed: True	Observed: False
Predicted	True	**639**	**87**
Predicted	False	**138**	**391**



Discrimination metrics - threshold dependent

- **Sensitivity**
  - True positive rate
    - TP / (TP+FN)
  - Proportion of correctly predicted presences
  - Omission error = predicting species absent where it is present
    - Want to minimize when predicting invasions

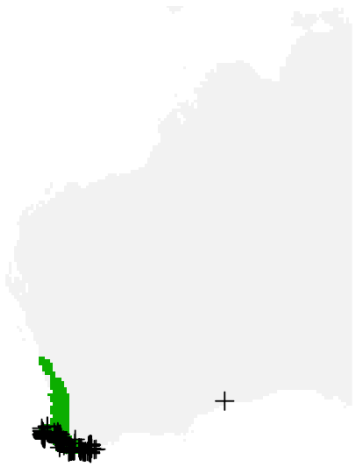
		Observed: True	Observed: False
Predicted	True	639	87
Predicted	False	138	391



Discrimination metrics - threshold dependent

- **Specificity**
  - True negative rate
    - TN/(TN+FP)
  - Proportion of correctly predicted absences
  - Commission "errors" = predicting species present where it is "absent"
    - Want to minimize when design reserves / protecting habitat

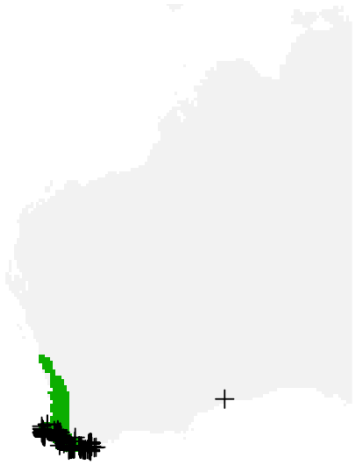
		Observed: True	Observed: False
Predicted	True	639	87
Predicted	False	138	391



Discrimination metrics - threshold dependent

- **Kappa**
  - Takes the proportion of correct predictions expected by chance into account
  - Sensitive to prevalence
- **True Skill Statistic (TSS)**
  - 1 - max(Sensitivity + Specificity)
  - -1 to +1
    - +1 = perfect agreement
    - 0 = no better than random
  - Less sensitive to prevalence
  - Equal to kappa when the number of presences and absences in the validation set are equal (prevalence=0.5)

		Observed: True	Observed: False
Predicted	True	**639**	**87**
Predicted	False	**138**	**391**

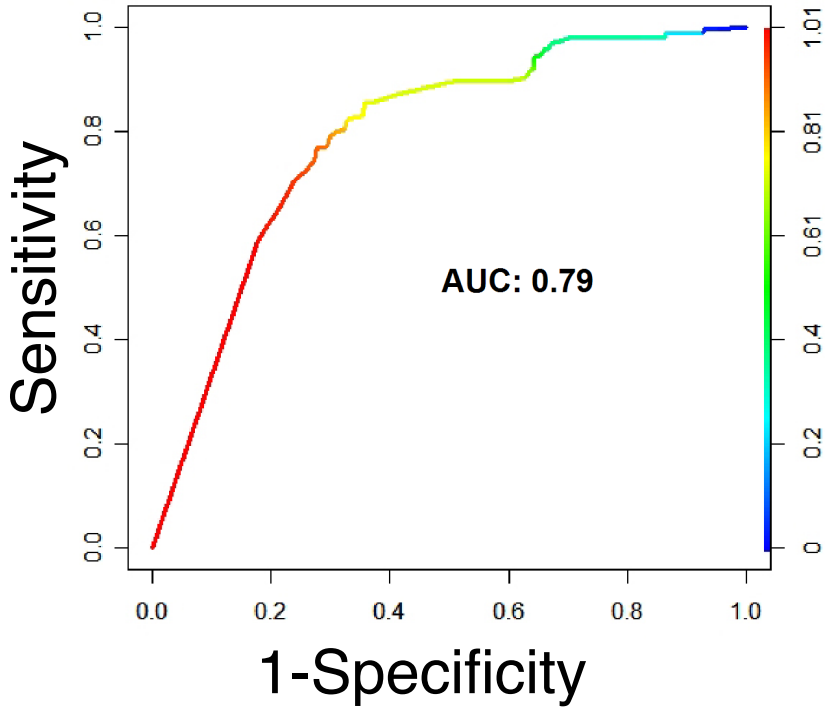


Discrimination metrics - threshold independent

positive is presence and negative is absence

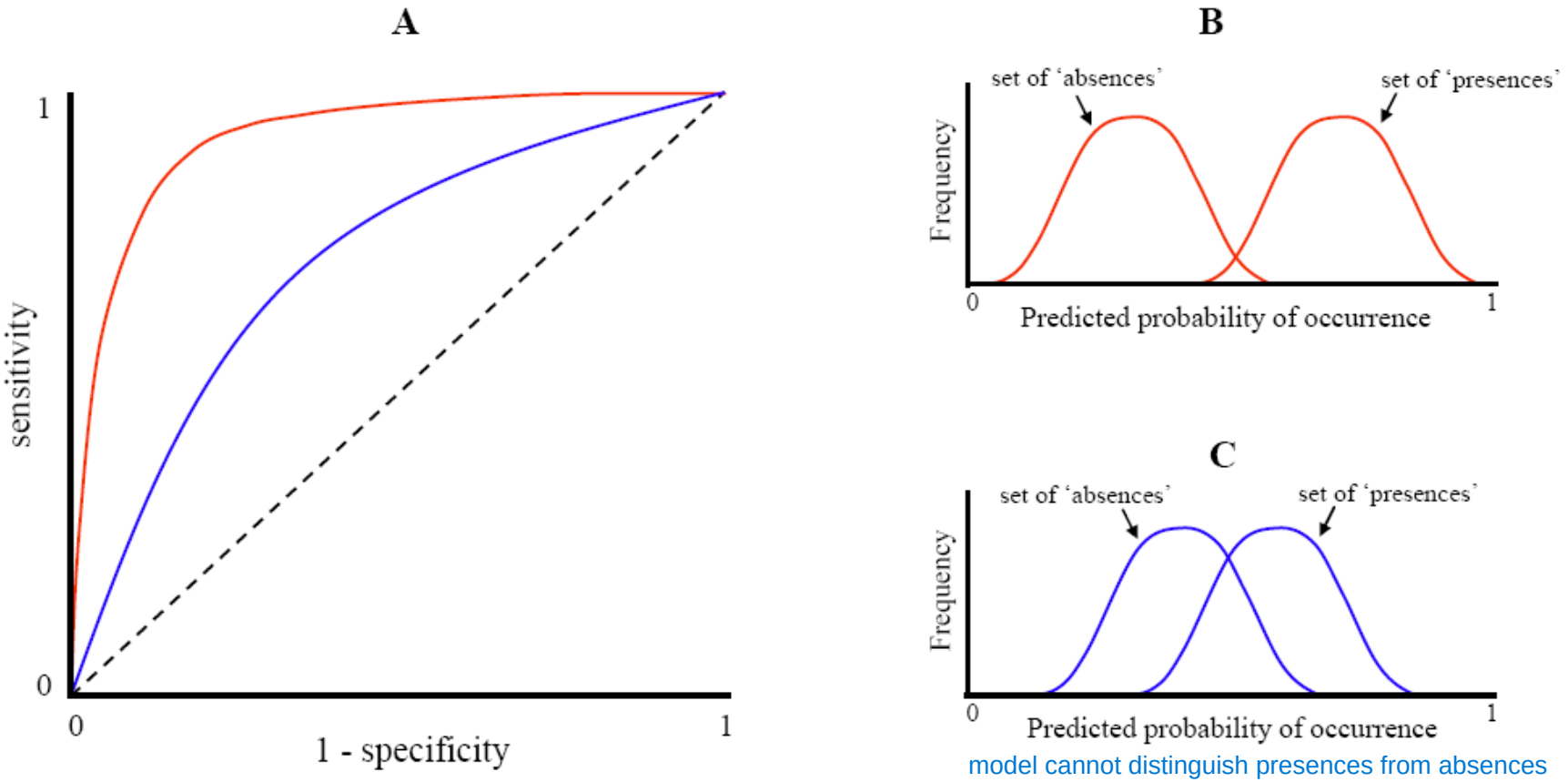
AUC-ROC

- Area Under the Curve of the Receiver-Operating characteristic (ROC) plot
- The proportion of random selections from the positive group that will score higher than random selections from the negative group
- 0-1
  - AUC = 0.5 = no better than random
- Calculated across all probability values predicted by the model

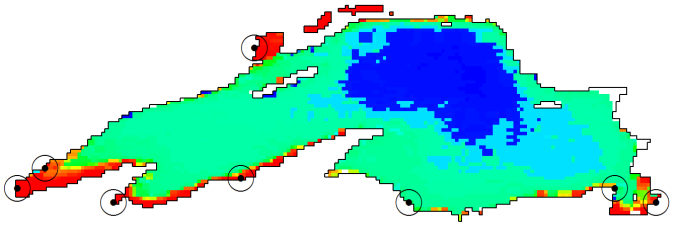


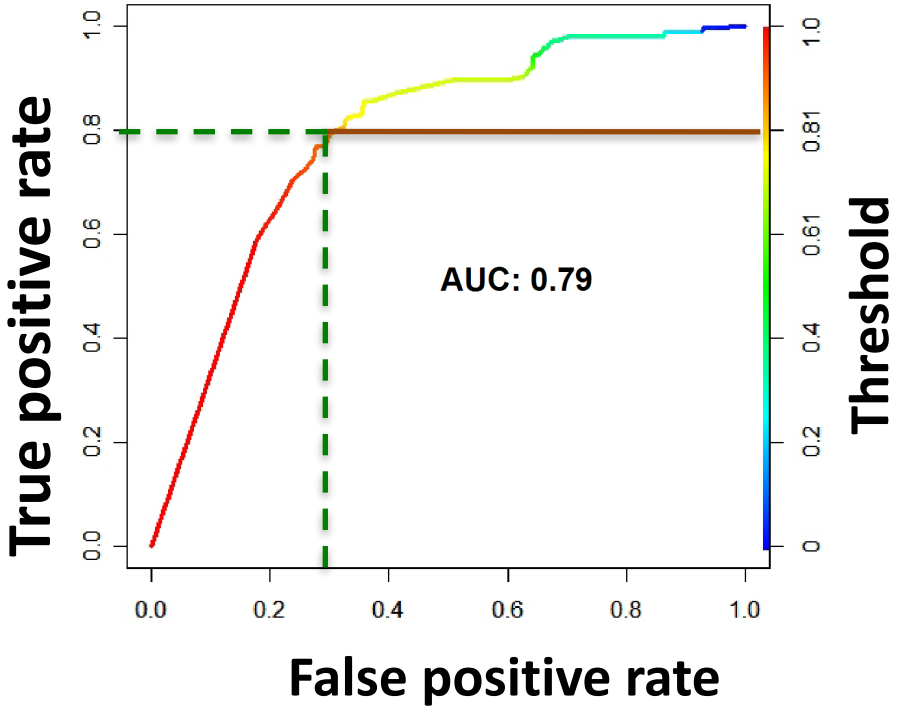
Discrimination metrics - threshold independent

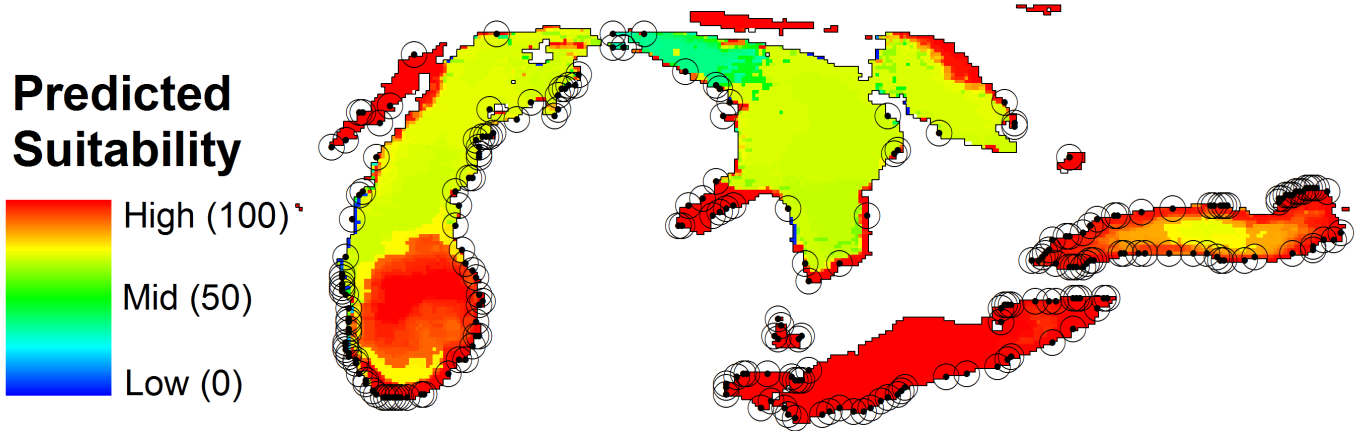
AUC



model cannot distinguish presences from absences




True positive rate
False positive rate
Threshold
AUC: 0.79
0.0
0.2
0.4
0.6
0.8
1.0
0
0.2
0.4
0.61
0.81
1.0


Predicted Suitability
High (100)
Mid (50)
Low (0)

Discrimination metrics - Presence Only

- Presence-only data present a problem for model evaluation
- All discrimination metrics can be applied to presence-background, but interpretation changes
  - AUC=the probability a model scores a random presence site higher than a random background site

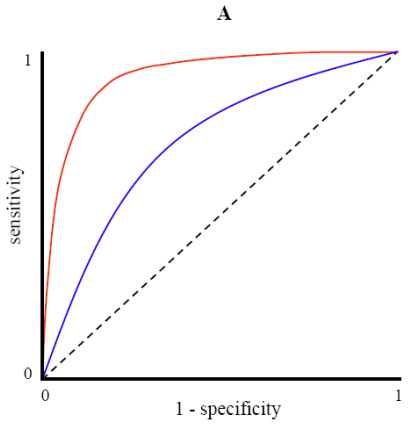
^presence (if presence only)

overprediction and underprediction are not equally penalized in the case of presence only

Observed

sometimes still used for only presences:

Predicted	True	False
True	**639**	**87**
False	**138**	**391**



Discrimination metrics - AUC-PR

- AUC-PR (Area Under the Precision-Recall Curve)

Received: 22 May 2018 | Accepted: 25 November 2018

DOI: 10.1111/2041-210X.13140

RESEARCH ARTICLE

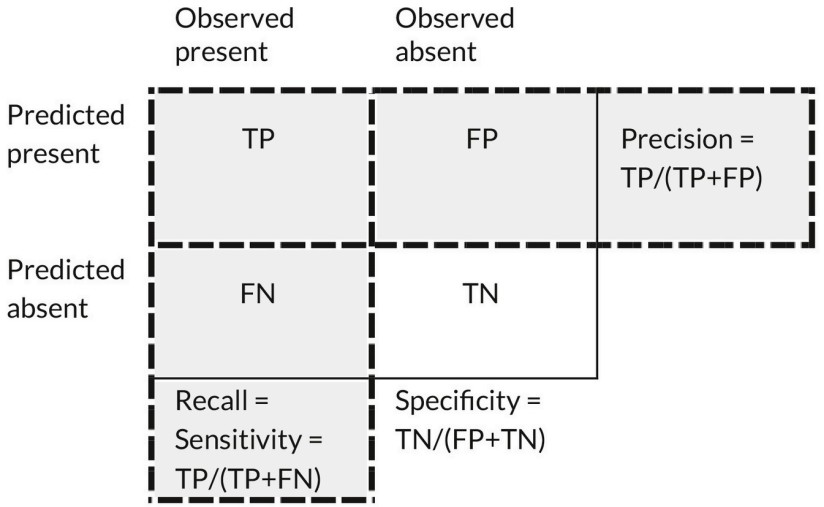
Methods in Ecology and Evolution BRITISH ECOLOGICAL SOCIETY

The area under the precision-recall curve as a performance metric for rare binary events

Helen R. Sofaer[1] | Jennifer A. Hoeting[2] | Catherine S. Jarnevich[1]

Discrimination metrics - AUC-PR

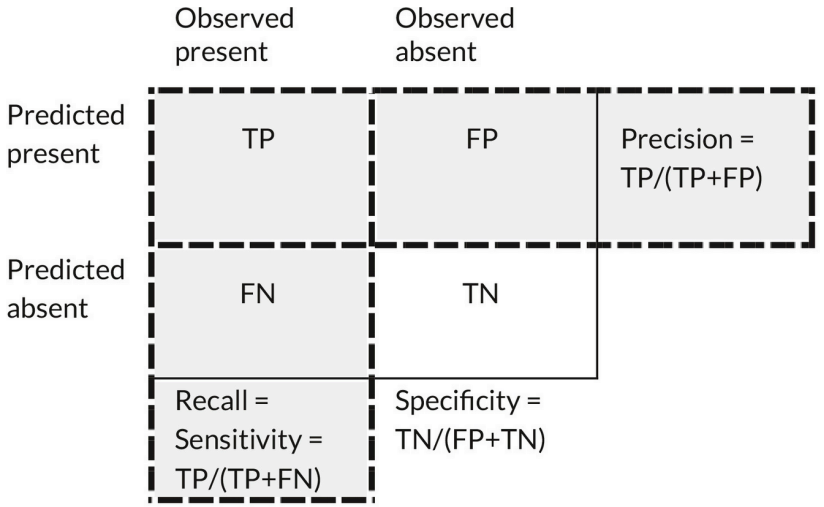
- Precision = probability that a species is present given a predicted presence
- Recall (more commonly called sensitivity) = probability the model predicts presence in locations where the species has been observed. doesn't include absences



AUC-ROC is the area under the curve of the plot of sensitivity (recall) versus 1-specificity across thresholds. Sensitivity is based on all observed presences (left column), while specificity is based on all observed (or inferred) absences (right column). Thus, AUC-ROC incorporates all quadrants of the confusion matrix. AUC-PR is the area under the curve of the plot of precision versus recall (sensitivity) across thresholds. Precision is based on all predicted presences (top row). Thus, AUC-PR does not incorporate the number of true negatives (TN); cells used in calculating AUC-PR are shaded grey and outlined in dashes.
TP, True positive; FP, False positive; FN, False negative; TN, True negative.

Discrimination metrics - AUC-PR

- AUC-PR does not incorporate correctly predicted absences and is therefore less prone to exaggerate model performance for unbalanced datasets.

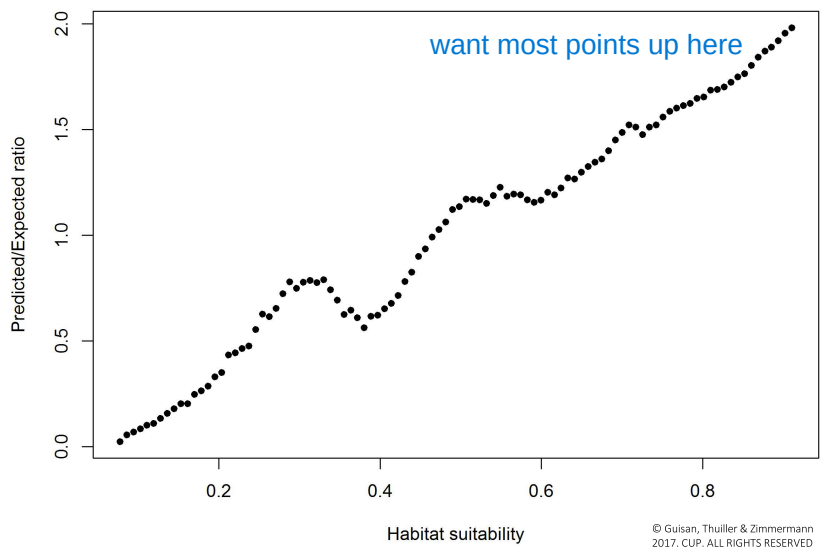


AUC-ROC is the area under the curve of the plot of sensitivity (recall) versus 1-specificity across thresholds. Sensitivity is based on all observed presences (left column), while specificity is based on all observed (or inferred) absences (right column). Thus, AUC-ROC incorporates all quadrants of the confusion matrix. AUC-PR is the area under the curve of the plot of precision versus recall (sensitivity) across thresholds. Precision is based on all predicted presences (top row). Thus, AUC-PR does not incorporate the number of true negatives (TN); cells used in calculating AUC-PR are shaded grey and outlined in dashes.
TP, True positive; FP, False positive; FN, False negative; TN, True negative.

Discrimination metrics - Presence Only

- Boyce Index — true presence only metric
  - Split model predictions into *b* regular bins
  - Assess the proportion of presences in each bin and compare to the expected proportion if the presences were randomly distributed
  - **A good model will predict a large proportion of presences in the high value bins**

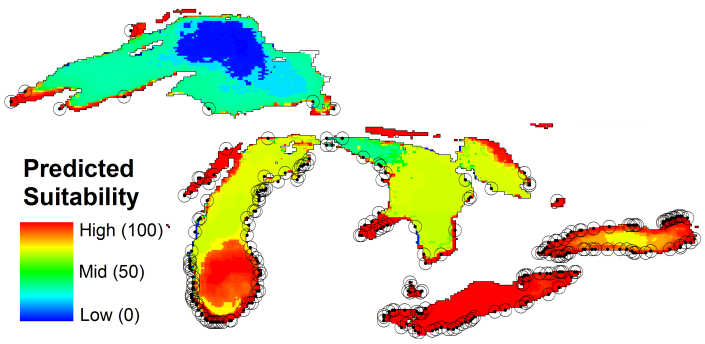
metric ends up being the correlation between the predicted expected ratio and habitat suitability



put 100 points down at random. The 0-0.1 bin holds 20%. How many points do you expect to fall into that bin? 20 points.
If a really good model, you would expect the most presences to be in the high value bins.

Discrimination metrics - Presence Only

- Minimum predicted area (MPA)
  - Proportion of the study area predicted as present using a threshold required to predict as present a user-defined proportion of the test data (e.g., 95%)
  - Smaller = better



if 100 points, user says wants 95% of points to be present. Convert the 0-1 map and a better model will predict a smaller area than a bad model.

not great for a single model, better for multiple or area

Questions?