Evaluating RSF and SSF Models

John Fieberg, Associate Professor

Department of Fisheries, Wildlife and Conservation Biology

Model Evaluation

Calibration: how well does the model describe the probability (or relative probability) of using different areas?

Model Evaluation

Calibration: how well does the model describe the probability (or relative probability) of using different areas?

- If the model predicts that 10% of forested sites will be occupied, are 10% of forested sites occupied?

Model Evaluation

Calibration: how well does the model describe the probability (or relative probability) of using different areas?

- If the model predicts that 10% of forested sites will be occupied, are 10% of forested sites occupied?
- If the model predicts sites within 1 km of water are twice as likely to be used as sites 10km from water, does this happen?

Model Evaluation

Calibration: how well does the model describe the probability (or relative probability) of using different areas?

- If the model predicts that 10% of forested sites will be occupied, are 10% of forested sites occupied?
- If the model predicts sites within 1 km of water are twice as likely to be used as sites 10km from water, does this happen?

Discrimination: how well does the model discriminate between ‘good’ and ‘bad’ habitat?

Model Evaluation

Calibration: how well does the model describe the probability (or relative probability) of using different areas?

- If the model predicts that 10% of forested sites will be occupied, are 10% of forested sites occupied?
- If the model predicts sites within 1 km of water are twice as likely to be used as sites 10km from water, does this happen?

Discrimination: how well does the model discriminate between ‘good’ and ‘bad’ habitat?

- Given two different locations, one close to water and one far from water, can the model identify which location is most likely to be used?

Model Evaluation

Calibration: how well does the model describe the probability (or relative probability) of using different areas?

- If the model predicts that 10% of forested sites will be occupied, are 10% of forested sites occupied?
- If the model predicts sites within 1 km of water are twice as likely to be used as sites 10km from water, does this happen?

Discrimination: how well does the model discriminate between ‘good’ and ‘bad’ habitat?

- Given two different locations, one close to water and one far from water, can the model identify which location is most likely to be used?

Often calibration and discrimination go hand-in-hand, but that need not be the case.

Model Evaluation

Methods largely borrowed from binary regression modeling literature

Model Evaluation

Methods largely borrowed from binary regression modeling literature

Discrimination: often measured using AUC (area under the receiver operating curve)

Model Evaluation

Methods largely borrowed from binary regression modeling literature

Discrimination: often measured using AUC (area under the receiver operating curve)

Calibration: usually explored with calibration plots

- Compare observed (y) and predicted ($\hat{y}$) response data
- Use data splitting, cross-validation, bootstrapping, or data from a different study site (i.e., out of sample data)

Model Evaluation

Methods largely borrowed from binary regression modeling literature

Discrimination: often measured using AUC (area under the receiver operating curve)

Calibration: usually explored with calibration plots

- Compare observed (y) and predicted ($\hat{y}$) response data
- Use data splitting, cross-validation, bootstrapping, or data from a different study site (i.e., out of sample data)

This talk will focus on calibration methods.

Calibration plots: Logistic Regression

1. Fit logistic regression model to *training* data $(x_i^{train}, y_i^{train})$:
   $logit(\pi_i^{train}) = x_i^{train}\beta^{train}$

Calibration plots: Logistic Regression

1. Fit logistic regression model to *training* data $(x_i^{train}, y_i^{train})$:
   $logit(\pi_i^{train}) = x_i^{train}\beta^{train}$
2. Form predictions for *test* data (x_i^{test}, y_i^{test}) using the fit from [1]:
   $\hat{\pi}_i^{test} = \frac{e^{x_i^{test}\hat{\beta}^{train}}}{1+e^{x_i^{test}\hat{\beta}^{train}}}$

Calibration plots: Logistic Regression

1. Fit logistic regression model to *training* data $(x_i^{train}, y_i^{train})$:
   $logit(\pi_i^{train}) = x_i^{train}\beta^{train}$
2. Form predictions for *test* data (x_i^{test}, y_i^{test}) using the fit from [1]:
   $\hat{\pi}_i^{test} = \frac{e^{x_i^{test}\hat{\beta}^{train}}}{1+e^{x_i^{test}\hat{\beta}^{train}}}$
3. Calibration plot:
   - Option 1: Bin data (e.g., based on quantiles of $\hat{\pi}_i$). Plot the proportion of values where $y_i^{test} = 1$ in each bin versus mean $\hat{\pi}_i^{train}$ in each bin.

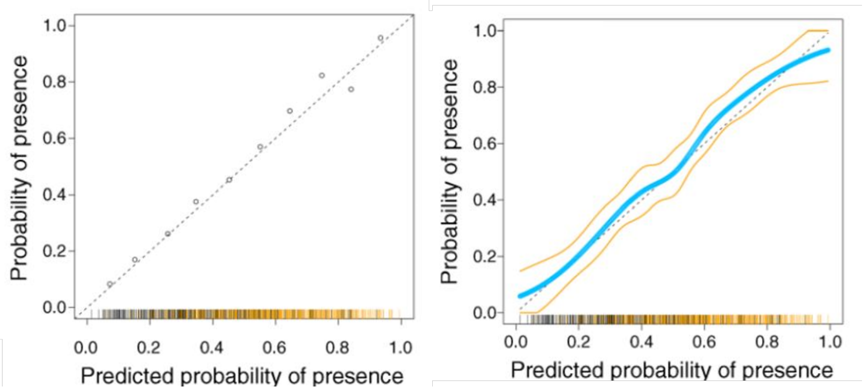
Calibration plots: Logistic Regression

1. Fit logistic regression model to *training* data $(x_i^{train}, y_i^{train})$:
   $logit(\pi_i^{train}) = x_i^{train}\beta^{train}$
2. Form predictions for *test* data (x_i^{test}, y_i^{test}) using the fit from [1]:
   $\hat{\pi}_i^{test} = \frac{e^{x_i^{test}\hat{\beta}^{train}}}{1+e^{x_i^{test}\hat{\beta}^{train}}}$
3. Calibration plot:
   - Option 1: Bin data (e.g., based on quantiles of $\hat{\pi}_i$). Plot the proportion of values where $y_i^{test} = 1$ in each bin versus mean $\hat{\pi}_i^{train}$ in each bin.
   - Option 2: Fit a new logistic regression model $logit(\pi_i^{test}) = b_0 + b_1(x_i^{test}\hat{\beta^{train}})$. $b_0 = 0, b_1 = 1$ indicates perfect calibration.

Calibration plots: Logistic Regression

1. Fit logistic regression model to *training* data $(x_i^{train}, y_i^{train})$:
   $logit(\pi_i^{train}) = x_i^{train}\beta^{train}$
2. Form predictions for *test* data (x_i^{test}, y_i^{test}) using the fit from [1]:
   $\hat{\pi}_i^{test} = \frac{e^{x_i^{test}\hat{\beta}^{train}}}{1+e^{x_i^{test}\hat{\beta}^{train}}}$
3. Calibration plot:
   - Option 1: Bin data (e.g., based on quantiles of $\hat{\pi}_i$). Plot the proportion of values where $y_i^{test} = 1$ in each bin versus mean $\hat{\pi}_i^{train}$ in each bin.
   - Option 2: Fit a new logistic regression model $logit(\pi_i^{test}) = b_0 + b_1(x_i^{test}\beta^{\hat{train}})$. $b_0 = 0, b_1 = 1$ indicates perfect calibration.
   - Option 3: Fit a more flexible, non-linear model: $logit(\pi_i^{test}) = f(x_i^{test}\beta^{\hat{train}})$

Calibration plots: Logistic Regression



Presence-only calibration plots

Ecology, 91(8), 2010, pp. 2476–2484
© 2010 by the Ecological Society of America

POC plots: calibrating species distribution models with presence-only data

Steven J. Phillips[1,3] and Jane Elith[2]

[1]*AT&T Labs–Research, 180 Park Avenue, Florham Park, New Jersey 07932 USA*
[2]*School of Botany, The University of Melbourne, Parkville 3010 Australia*

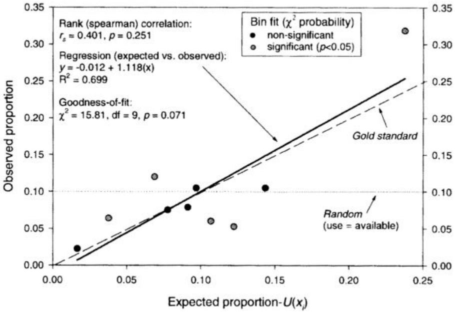
Abstract. Statistical models are widely used for predicting species' geographic distributions and for analyzing species' responses to climatic and other predictor variables. Their predictive performance can be characterized in two complementary ways: discrimination, the ability to distinguish between occupied and unoccupied sites, and calibration, the extent to which a model correctly predicts conditional probability of presence. The most common measures of model performance, such as the area under the receiver operating characteristic curve (AUC), measure only discrimination. In contrast, we introduce a new tool for measuring model calibration: the presence-only calibration plot, or POC plot. This tool relies on presence-only evaluation data, which are more widely available than presence–absence evaluation data, to determine whether predictions are proportional to conditional probability of presence. We generalize the predicted/expected curves of Hirzel et al. to produce a presence-only analogue of traditional (presence–absence) calibration curves. POC plots facilitate visual exploration of model calibration, and can be used to recalibrate badly calibrated models. We demonstrate their use by recalibrating models made by the DOMAIN modeling method on a comprehensive set of 226 species from six regions of the world, significantly improving DOMAIN's predictive performance.

Key words: background; calibration; discrimination; niche modeling; presence-only; pseudo-absence; species distribution modeling.

Transform y-axis to recognize that some of the 0's might actually be used (Phillips and Elith 2010)

Calibration: RSFs

Use $\pi_i^{test} = \frac{\exp(x_i^{train}\beta^{train})}{\sum_{j=1}^{n_{test}} \exp(x_j^{train}\beta^{train})}$ rather than $\pi_i^{test} = \frac{\exp(x_i\beta)}{1+\exp(x_i\beta)}$



Boyce, M.S., Vernier, P.R., Nielsen, S.E. & Schmiegelow, F.K. (2002). Evaluating resource selection functions. Ecol. Model., 157, 281–300.

Johnson, C.J., Nielsen, S.E., Merrill, E.H., McDonald, T.L. & Boyce, M.S. (2006). Resource selection functions based on use-availability data: Theoretical motivation and evaluation methods. J. Wildlife Manage., 70, 347–357.

Fieberg, J., J.D. Forester, G.M. Street, D.H. Johnson, A.A. ArchMiller, and J. Matthiopoulos. (2018). Used-habitat calibration plots: A new procedure for validating species distribution, resource selection, and step-selection models. Ecography 41:737-752.

But what about?

- SSFs where availability changes with each used piont?

But what about?

- SSFs where availability changes with each used piont?
- When models are not well-calibrated? How do we gain insights into *why*?

Used-habitat calibration plots (UHC plots)

ECOGRAPHY

Research

Used-habitat calibration plots: a new procedure for validating species distribution, resource selection, and step-selection models

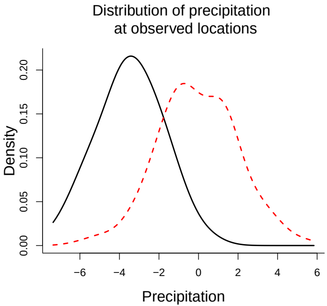
John R. Fieberg, James D. Forester, Garrett M. Street, Douglas H. Johnson, Althea A. ArchMiller and Jason Matthiopoulos

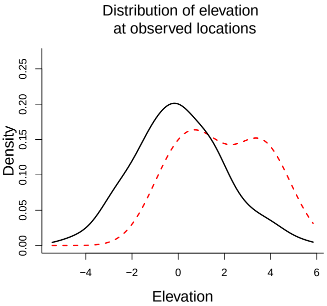
Focus on predicting the characteristics of the used locations in out-of-sample data

- Treats the environmental variables, x, as random (rather than the y's)
- Easily generalizes to step-selection functions
- Can compliment existing approaches for model evaluation

Producing an UHC Plot

Step 0: Split the data into test and training data sets.
Step 1: Summarize the distribution of the environmental variables at the available and **used** locations.





Red = available distribution   **Black** = used distribution

Producing an UHC Plot

Step 2: Fit a model to the training data set, storing $\hat{\beta}$ and its uncertainty ($\widehat{cov}(\hat{\beta})$).

- Logistic regression (for cross-sectional data)
- Conditional logistic regression (for step-selection models)

Step 3: Repeat Steps M Times

A. Draw random values of β (to represent our uncertainty), $\tilde{\beta}_i$

Step 3: Repeat Steps M Times

A. Draw random values of β (to represent our uncertainty), $\tilde{\beta}_i$
B. Estimate relative probability of selecting points in test data,
$\tilde{w}_i = \exp(x^{test}\tilde{\beta}_i)$

Step 3: Repeat Steps M Times

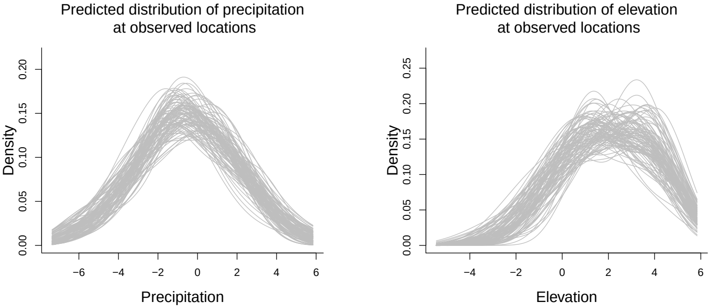
A. Draw random values of β (to represent our uncertainty), $\tilde{\beta}_i$
B. Estimate relative probability of selecting points in test data, $\tilde{w}_i = \exp(x^{test}\tilde{\beta}_i)$
C. Select n_u^{test} used locations from test data set with probability proportional to $\tilde{w}_i$

Step 3: Repeat Steps M Times

A. Draw random values of β (to represent our uncertainty), $\tilde{\beta}_i$
B. Estimate relative probability of selecting points in test data, $\tilde{w}_i = \exp(x^{test}\tilde{\beta}_i)$
C. Select n_u^{test} used locations from test data set with probability proportional to $\tilde{w}_i$
D. Summarize predicted distribution of x^{test} at chosen locations.

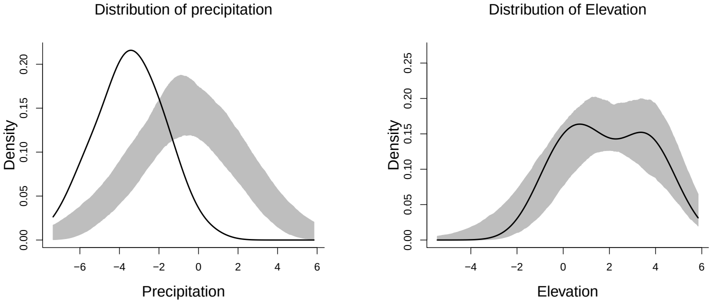
Step 3: Repeat Steps M Times

A. Draw random values of β (to represent our uncertainty), $\tilde{\beta}_i$
B. Estimate relative probability of selecting points in test data, $\tilde{w}_i = \exp(x^{test}\tilde{\beta}_i)$
C. Select n_u^{test} used locations from test data set with probability proportional to $\tilde{w}_i$
D. Summarize predicted distribution of x^{test} at chosen locations.



Producing an UHC Plot

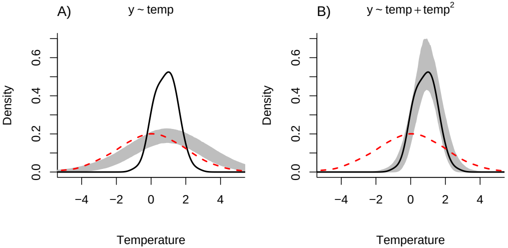
Step 4: Compare observed (black) and predicted (gray) distributions



Simulation Example: Non-linear relationship

Species distribution driven by temperature (x_3)

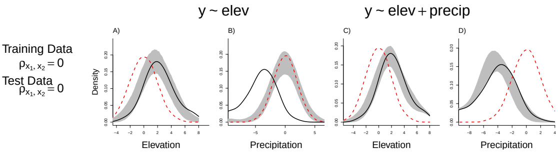
- Relative probability of use proportional to $\exp(2x_3 - x_3^2)$.
- Fit models: y$\sim$ temp (incorrect) and y$\sim$ temp + temp^2 (correct)



Red = available distribution **Black** = used distribution

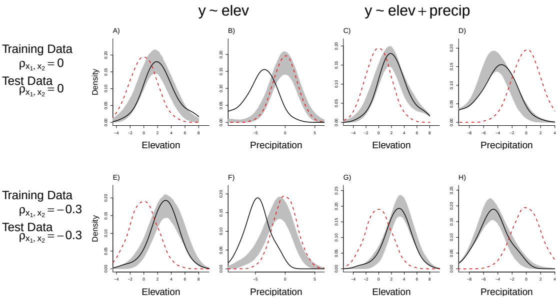
Simulation Example: Missing predictor

- Relative probability of use proportional to $\exp(0.5x_1 - x_2)$, with (x_1, x_2) = (elevation, precipitation).
- Fit models: $y \sim$ elev (left two columns) and $y \sim$ elev + precip (right two columns)



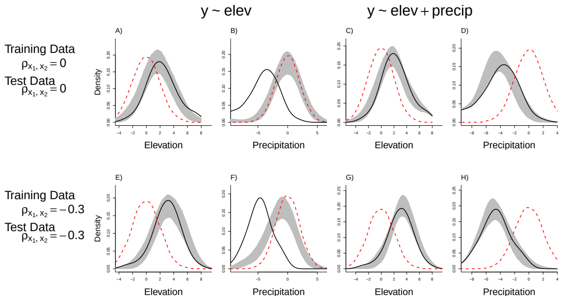
Simulation Example: Missing predictor

- Relative probability of use proportional to $\exp(0.5x_1 - x_2)$, with (x_1, x_2) = (elevation, precipitation).
- Fit models: $y \sim$ elev (left two columns) and $y \sim$ elev + precip (right two columns)



Simulation Example: Missing predictor

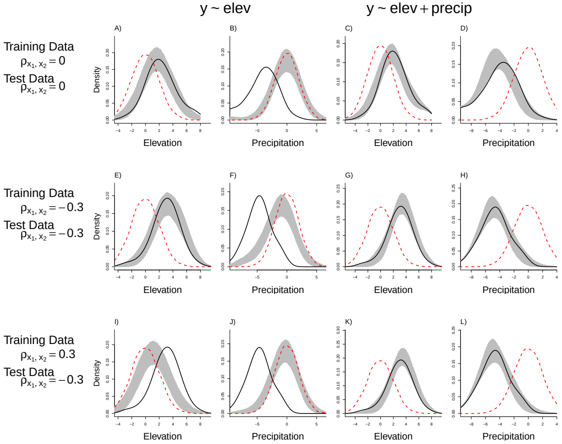
- Relative probability of use proportional to $\exp(0.5x_1 - x_2)$, with (x_1, x_2) = (elevation, precipitation).
- Fit models: $y \sim$ elev (left two columns) and $y \sim$ elev + precip (right two columns)



$\hat{\beta}_{x_1}$ = 0.8 (SE = 0.06)

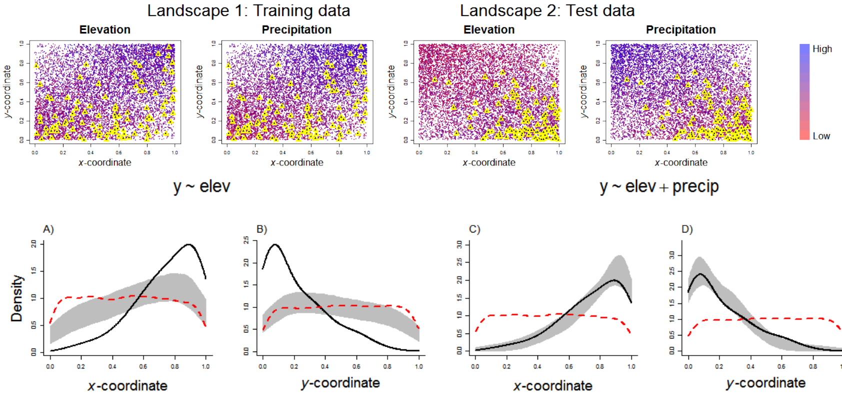
Simulation Example: Missing predictor

- Relative probability of use proportional to $\exp(0.5x_1 - x_2)$, with (x_1, x_2) = (elevation, precipitation).
- Fit models: $y \sim$ elev (left two columns) and $y \sim$ elev + precip (right two columns)



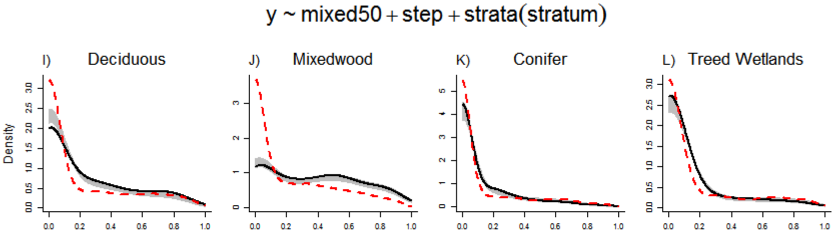
$\hat{\beta}_{x_1}$ = 0.8 (SE = 0.06)

Simulation Example: Spatial Coordinates



Can use this approach to explore accuracy of predictions in space.

Application to a Step-Selection Model for Moose



Compositional predictors (proportional within a 50m buffer of each location)

UHC plots

Use simple, graphical methods that are easy to interpret; compare distributions of resources at:

- available locations
- observed locations (training data)
- locations predicted to be used (test data)

Easily adapted to any model that can *rank* observations in terms of predicted probability of use

Questions

Code and package available via github:

https://github.com/aaarchmiller/uhcplots

Working to develop more general and robust code for future inclusion into `amt`