Model Evaluation: Used Habitat Calibration (UHC) Plots

John Fieberg, Professor

Department of Fisheries, Wildlife and Conservation Biology

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

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This talk will focus on calibration methods.

Calibration plots: Logistic Regression

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

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3. Calibration plot:
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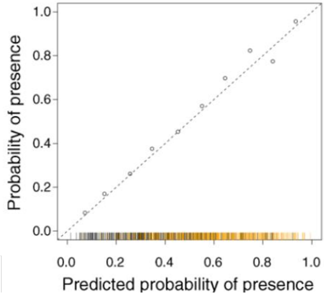
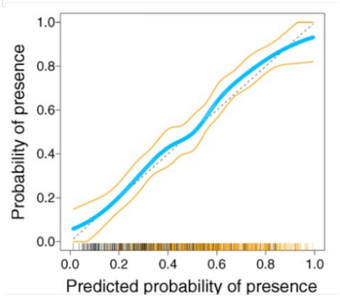
   - Option 3: Fit a more flexible, non-linear model: $logit(\pi_i^{test}) = f(x_i^{test}\hat{\beta^{train}})$

Calibration plots: Logistic Regression





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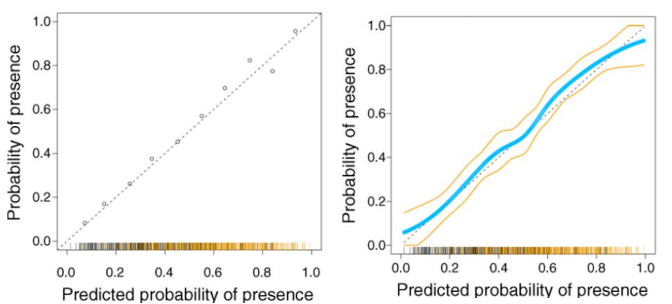
Calibration plots: Logistic Regression



Phillips, S. J., & Elith, J. (2010). POC plots: calibrating species distribution models with presence-only data. Ecology, 91(8), 2476-2484.

Adapted to presence-only data, transforming the y-axis since some of the 0's might actually be used.

The Boyce Cross-validation Method

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4. Calculate Spearman correlation (bin rank, number of observations in a bin)

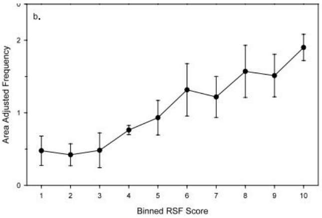

Fig. 4. Area-adjusted frequency of binned cross-validated use locations for fall (late-hyperphagia) RSF models in the Greater Yellowstone Ecosystem, USA. Frequency values for individual cross-validation sets ($n = 5$) are depicted with unique symbols (graph a). Mean ($\pm$S.D.) frequency values by bin are illustrated in graph b. A Spearman-rank correlation for mean frequency values by bins ($r_s = 0.972$, $P < 0.001$) indicates that the model predicted cross-validated use locations well.

Modified Boyce Method

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.

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Use $\pi_i^{test} = \frac{\exp(x_i^{train}\beta^{train})}{\sum_{j=1}^{n_{test}} \exp(x_j^{train}\beta^{train})}$ to estimate the expected number of observations within each bin.

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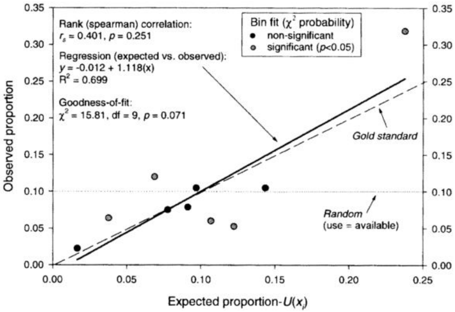

But what about?

- SSFs where availability changes with each used point?

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- SSFs where availability changes with each used point?
- 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

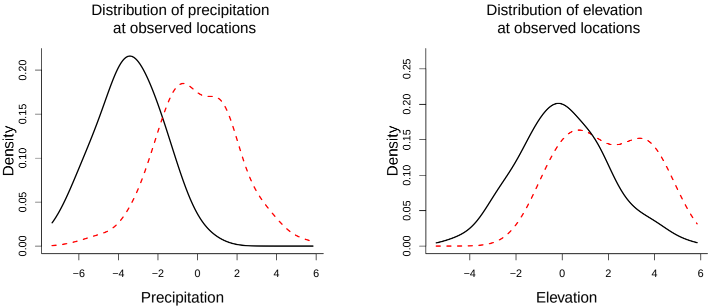
John R. Fieberg, James D. Forester, Garrett M. Street, Douglas H. Johnson, Althea A. ArchMiller and Jason Matthiopoulos

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.



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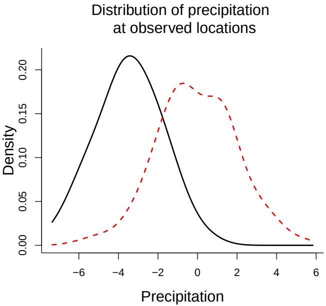

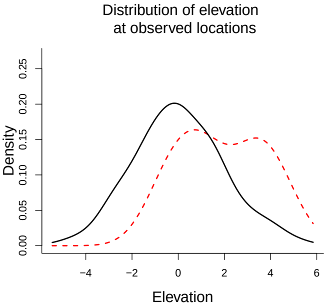

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Similar to a posterior predictive check to see if the model can produce data like those that were observed.

Producing an UHC Plot

Step 2: Fit a model to the training data set

- Logistic regression (for resource-selection functions)
- Conditional logistic regression (for step-selection functions)

Store $\hat{\beta}$ and its uncertainty ($\widehat{cov}(\hat{\beta})$).

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Can capture uncertainty using a bootstrap or posterior distribution.

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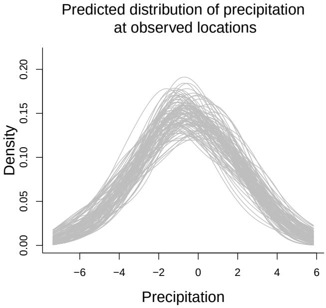
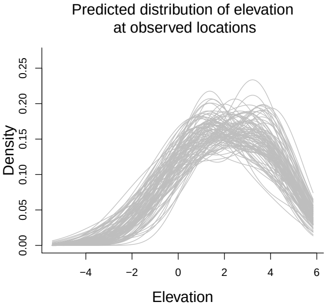
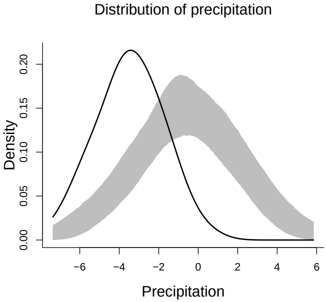
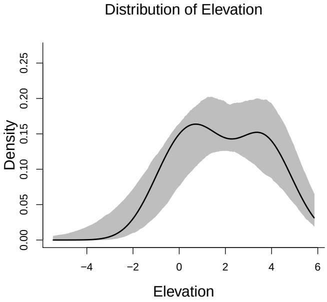




Producing an UHC Plot

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

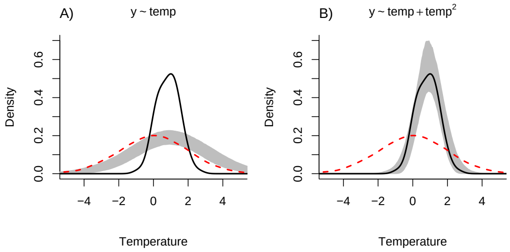




Simulation Example: Non-linear relationship

Species distribution driven by temperature (x_3)

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



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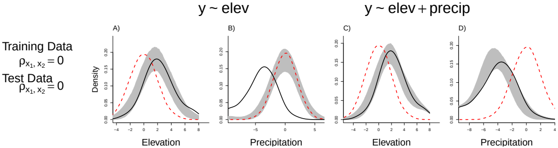
Simulation Example: Missing predictor

- 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)



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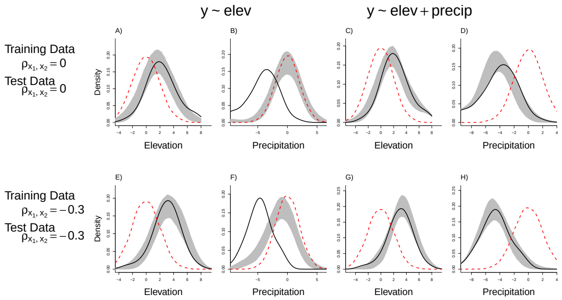

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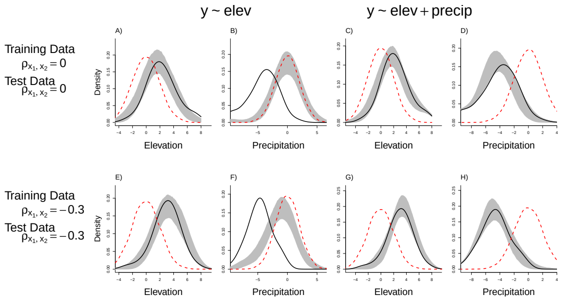

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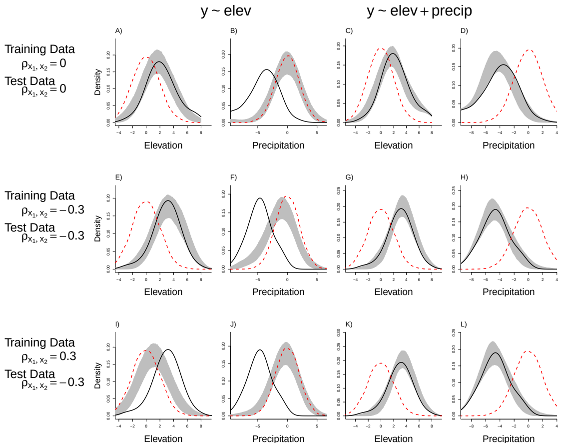

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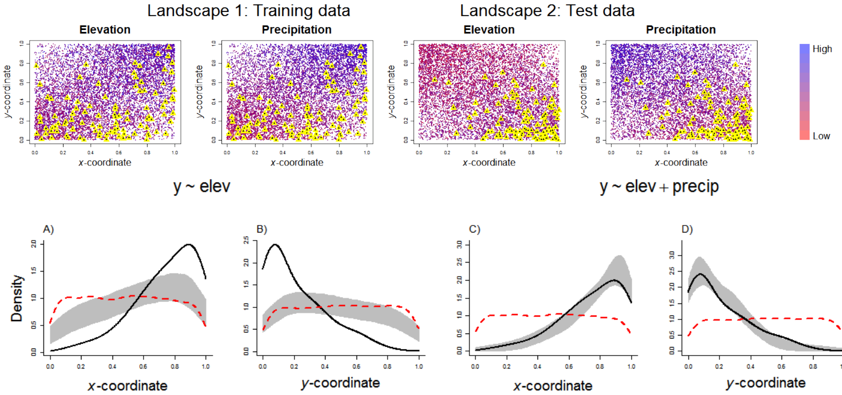
Simulation Example: Spatial Coordinates



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

Summary

Used-habitat calibration (UHC) plots are simple, graphical methods that 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

Brian will demonstrate how to calculate uhc plots using `amt`.