Habitat Selection and Species Distribution Models

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Outline

1. Introduce Resource Selection Functions (RSFs) and Species Distribution Models (SDMs)

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2. Illustrate a simple method for fitting models (logistic regression)

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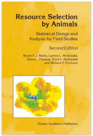
2. Illustrate a simple method for fitting models (logistic regression)
3. Discuss parameter interpretation

Habitat Selection versus Species Distribution Models



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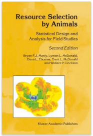

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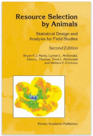

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'ISI's Essential Science Indicators identifies species distribution modeling as the top ranked research front in ecology and the environmental sciences.' (Renner and Warton 2013)

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- Link species occurrence (or abundance) to *resources*, *risks*, and *environmental conditions*

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- Remotely sensed environmental covariates, weather (temp, precip data), habitat, etc

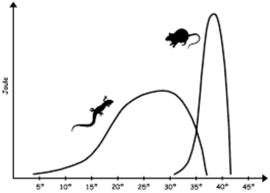
Objectives:

- Link species occurrence (or abundance) to *resources*, *risks*, and *environmental conditions*
- Predict distributions in novel environments
  - Areas not previously sampled
  - In response to climate change or habitat manipulations

RSFs and SDMS

Lots of modeling approaches (and jargon)

We are modeling the spatial distribution of locations as a function of spatial covariates....



Resources (more is better), risks (less is better), and conditions (not too much or too little)

Use-availability, presence-background

Models typically compare locations where animals are found to…

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- A set of ‘available’, ‘control’, ‘background’, or ‘pseudo-absence’ locations.
- Many ways to select points (depending on scale of inference)

‘Preference’ = used/availability depends critically on what the researcher deems is available!

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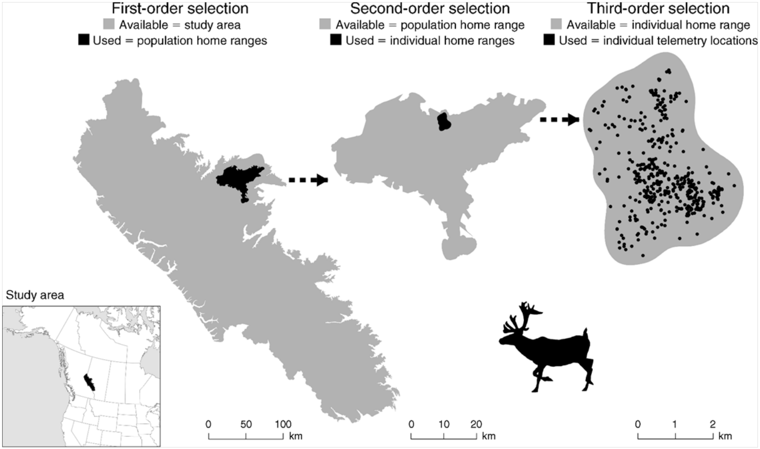
Johnson, D. 1980. The comparison of usage and availability measurements for evaluating resource preference. Ecology 61:65-71.

Google Scholar: 4091 citations as of September 25, 2019!



Fourth order: local selection (e.g., within a feeding site)

DeCesare, et al. 2012. Transcending scale dependence in identifying habitat with resource selection functions. Ecological Applications 22(4):1068- 1083.

Logistic Regression

Consider a prospective study:

- involving n sites with camera traps
- species detections $y_i = 1$ if detected (0 otherwise)
- spatial predictors $(x_{i1}, \ldots, x_{ip})$

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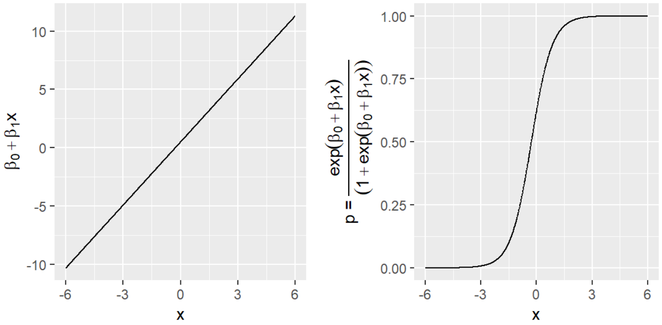
Model for probability of detecting a species:

$$y_i \sim \text{Bernoulli}(p_i)$$

$$\text{logit}(p_i) = \log\left(\frac{p_i}{(1-p_i)}\right) = \beta_0 + \beta_1 x_{i1} + \ldots \beta_p x_{ip}$$

Probability(site used)

$$p_i = \frac{\exp(\beta_0 + \beta_1 x_{i1} + \ldots \beta_p x_{ip})}{1 + \exp(\beta_0 + \beta_1 x_{i1} + \ldots \beta_p x_{ip})}$$



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Lots of Historical Debate ...

- Manly et al. (2002) OK if... availability points sampled without replacement, prior to used points being collected, no overlap between used and available points.
- Keating and Cherry (2004) argued strongly against
- Johnson et al. (2006), Lele and Keim (2006)...generally OK
- Warton & Shepherd (2010), Aarts et al. (2012), Fithian and Hastie (2013) made connections to a point process model.

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- Probability of using a site depends on the size of the site and how long individuals are monitored.
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Notes on probability of use

Traditionally, **resource-selection functions** were described as measuring "relative probabilities of use."

- Probability of using a site depends on the size of the site and how long individuals are monitored.
- Probability of using a point in space = 0 (to ensure integration over space = 1 for continuous probability distributions).
- Better to think of modeling hazards (rates of use), which can be integrated over time or space to estimate utilization distributions.

Logistic Regression

For use availability designs, we focus on:

$$w(x, \beta) = exp(x_1\beta_1 + x_2\beta_2 + \ldots x_p\beta_p)$$

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Frameworks for Interpreting Resource Selection Functions:

- Weighted Distribution Theory
- Inhomogeneous Poisson Process Models

Traditional ‘Use-Availability’ likelihood

Lele and Keim (2006), weighted distribution theory:

$$f^u(x) = \frac{w(x,\beta)f^a(x)}{\int_{z\in E} w(z,\beta)f^a(z)dz}$$

- $f^u(x)$ = distribution of used habitat
- $f^a(x)$ = distribution of available habitat

Formulated in *Environmental Space*: $w(x,\beta)$ is a function that takes us from “available” to “used” habitat.

Weighted Distributions in Geographic Space

$$f^u(s) = \frac{w(x(s), \beta)f^a(s)}{\int_{z \in A} w(x(z), \beta)f^a(z)dz}$$

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We are modeling the spatial distribution of 'used' locations, as a function of covariates (through $w(x(s), \beta)$), while accounting for what is 'available'!

Likelihood

If we:

- let $w(x, \beta) = exp(x(s)\beta)$
- assume all habitat in the availability domain A is equally available ($f^a(s) = 1$)

$$L(\beta; x_i) = \frac{\exp(x_i\beta)}{\int_{s\in A} \exp(x(s)\beta)ds}$$

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"Available points" are used to numerically evaluate the integral (Warton & Shepherd 2010, Aarts et al. 2012).

IPP Model; The Grand Unifier

- **Maxent** (Aarts et al. 2012, Renner and Warton 2013, Fithian and Hastie 2013)
- **Logistic regression** (Warton & Shepherd 2010, Fithian and Hastie 2013)
  - If model is correctly specified.
  - If available points are given *arbitrarily large* weights.
- **Poisson regression** applied to grid cells (Aarts et al. 2012)
- **Weighted distribution theory** with exponential model (Lele and Keim 2006, Aarts et al. 2011)
- **Resource utilization functions** ($log(UD_{KDE}) \sim$ covariates) (Hooten et al. 2013)

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  $N \sim \text{Poisson}(\lambda|A|)$

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- If λ is constant in A, then this is equivalent to a Poisson random variable with mean that depends on the area of A: $N \sim \text{Poisson}(\lambda|A|)$
- The number of events in disjoint areas are independent.

Logistic regression and IPP model

- Logistic regression provides unbiased estimates of β in the IPP model if n_a is "large enough" (Warton and Shepherd 2010)[1]

[1] Warton, D.I. and Shepherd, L.C., 2010. Poisson point process models solve the "pseudo-absence problem" for presence-only data in ecology. The Annals of Applied Statistics, 4(3), pp.1383-1402.

[2] Fithian, W. and T. Hastie (2013). Finite-sample equivalence in statistical models for presence-only data. Annals of Applied Statistics 7, 1917-1939.

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- Fithian and Hastie (2013)[2] showed logistic regression results in biased estimators of β in finite samples, unless available points are given large weights.
  - In practice, assign W = 1000 to available points, 1 to used points.

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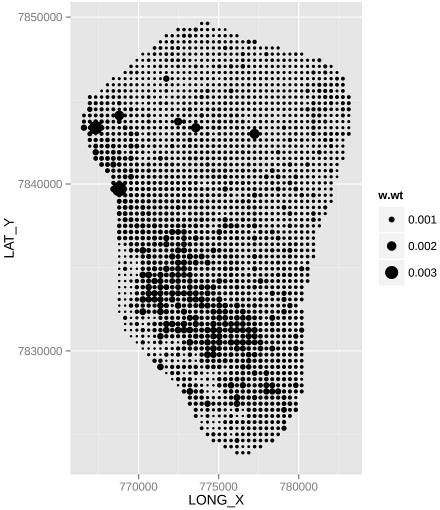
5. Increase the number of available points until slope parameters are stable.

How to Create a Map

Approximate $f^u(x) = \frac{\exp(x_i\beta)}{\int_{s\in A}\exp(x(s)\beta)ds}$ with $f^u(x) = \frac{\exp(x_i\beta)}{\sum_{i=1}^{n_a}\exp(x_i\beta)}$



Modeling Leroy's Habitat Use

3

Leroy is a Fisher from Upstate New York, tracked as part of a larger telemetry study designed to quantify the use and importance of habitat corridors (LaPoint et al. 2013).

- Used Env-Data to merge on data layers representing population density, elevation, landcover

[3] Photo of a fisher by ForestWander Nature Photography (ForestWander.com)

```r
FisherLeroy$w<-ifelse(FisherLeroy$case_==1,
                      1, 5000)
RSF.Leroy<-glm(case_ ~ elev + popD + landC,
               data = FisherLeroy,
               weight=w,
               family = binomial)
```

Parameter Interpretation

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-5.782	0.526	-10.985	0.000
elev	7.707	0.707	10.902	0.000
popD	0.284	0.039	7.288	0.000
landCgrass	-1.503	0.355	-4.237	0.000
landCother	1.087	0.140	7.759	0.000
landCshrub	-1.394	0.707	-1.971	0.049
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- we would expect the animal to select the 2nd observation with higher elevation.

Quantitative interpretation

Consider two locations, s_1 and s_2, both equally accessible, in the same habitat category (lets say “wet”), that have the same population density, and. . .

- elevation at s_2 is 1 unit higher than at s_1 (it is important to know the units of elevation)

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Claim: Leroy is $\exp(\beta_{elev}) = \exp(7.707)$ times more likely to use s_2 than s_1.

We can calculate the *relative risk* of an animal using s_2 relative to s_1 as:

$$\frac{f^u(x_{s_2})}{f^u(x_{s_1})} = \frac{w(x_{s_2}\beta)f^a(x_{s_2})}{w(x_{s_1}\beta)f^a(x_{s_1})}$$

where we have dropped $\int_{s\in A} w(x,\beta)f^a(x)ds$ since it appears in both numerator and denominator.

Quantitative interpretation

$$\frac{f^u(x_{s_2})}{f^u(x_{s_1})} = \frac{\exp(elev_2\beta_{elev} + popD_2\beta_{popD} + \beta_{wet})f^a(x_{s_2})}{\exp(elev_1\beta_{elev} + popD_1\beta_{popD} + \beta_{wet})f^a(x_{s_1})} \tag{1}$$

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Setting:

- $elev_2 = elev_1 + 1$
- $popD_2 = popD_1$
- $f^a(x_{s_1}) = f^a(x_{s_2})$ (assuming both locations are equally available)

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$$\implies \frac{f^u(s_1)}{f^u(s_2)} = \frac{\exp([elev_1 + 1]\beta_{elev})}{\exp([elev_1]\beta_{elev})} = \exp(\beta_{elev})$$

For continuous variables, β gives the change in log-relative risk associated with increasing *x* by 1 unit, while:

- holding everything else constant
- and assuming equal availability

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Given equal availability of all landcover classes, and *holding elevation and population density constant*

- this fisher would "select" locations in the "wet" class over grass, shrub, and…

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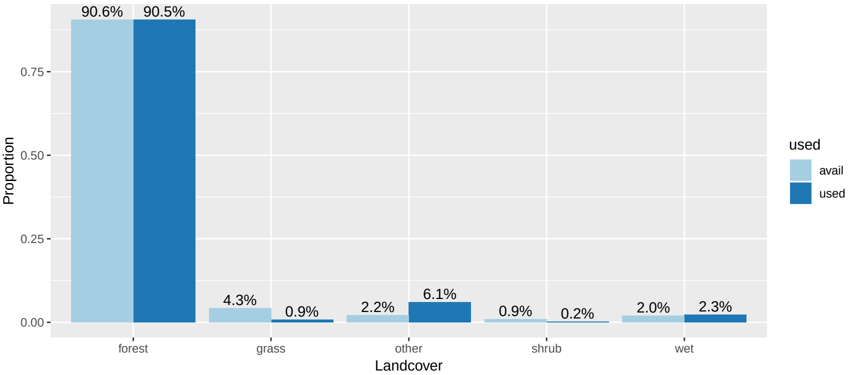
*But...availability is **not** equal!*



- *selection* (use/available) is strongest for `other`, but *use* is highest for `forest`!
- the positive coefficient for `wet` reflects a larger use/available ratio relative to the reference category, `forest`.

What if we use a different reference class?

```
FisherLeroy <- within(FisherLeroy ,
                landC <- relevel(landC, ref = "other"))
RSF.Leroy2<-glm(case_ ~ elev+popD+landC,
                data = FisherLeroy,
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landCforest	-1.087	0.140	-7.759	0.000
landCgrass	-2.589	0.378	-6.853	0.000
landCshrub	-2.480	0.719	-3.449	0.001
landCwet	-0.819	0.258	-3.174	0.002

- coefficients for *elev* and *popD* do not change

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  - becuase the ratio of used to available points is greater for the reference class (`other`) than for `wet`.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-4.695	0.561	-8.370	0.000
elev	7.707	0.707	10.902	0.000
popD	0.284	0.039	7.288	0.000
landCforest	-1.087	0.140	-7.759	0.000
landCgrass	-2.589	0.378	-6.853	0.000
landCshrub	-2.480	0.719	-3.449	0.001
landCwet	-0.819	0.258	-3.174	0.002

- Note the coefficient for `forest` is also negative despite Leroy spending more than 90% of his time in the forest!

Summary

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For categorical predictors:

- the β's describe the log-relative risk of selecting different levels of the variable relative to a reference level, while *holding all other predictor variables constant and assuming equal availability of the different levels of the categorical predictor*.

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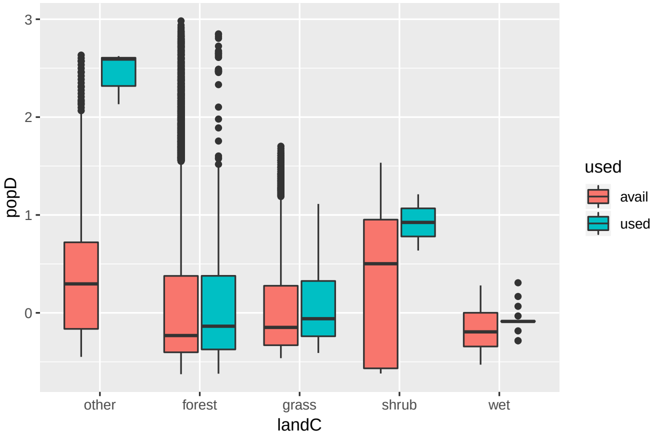
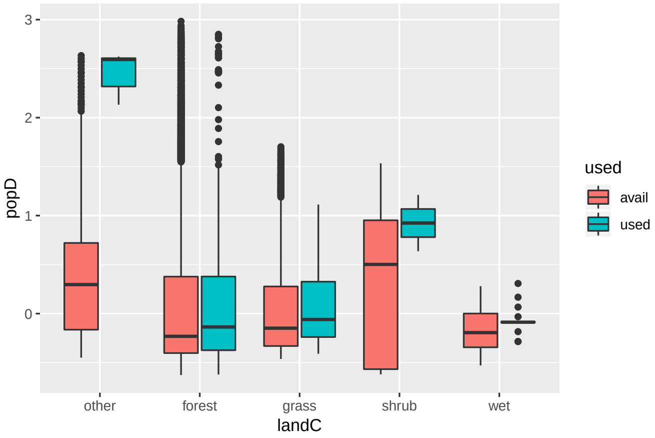
$\implies$ β may change as we change habitat availability (*functional responses in habitat selection*)

Lets consider population density and landcover:



If we compare locations in `other` and `forest`, population density is not likely to be held constant.



The importance of population density seems much more pronounced in the `other` and shrub categories. This effect could be modeled by including an interaction between population density and landcover class.