Past, Present, and Future of Evaluating the Impacts of Adaptive Management on Pollinators

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Middle Rio Grande Endangered Species Collaborative Program Science Symposium 2024

Western EcoSystems Technology, Inc.
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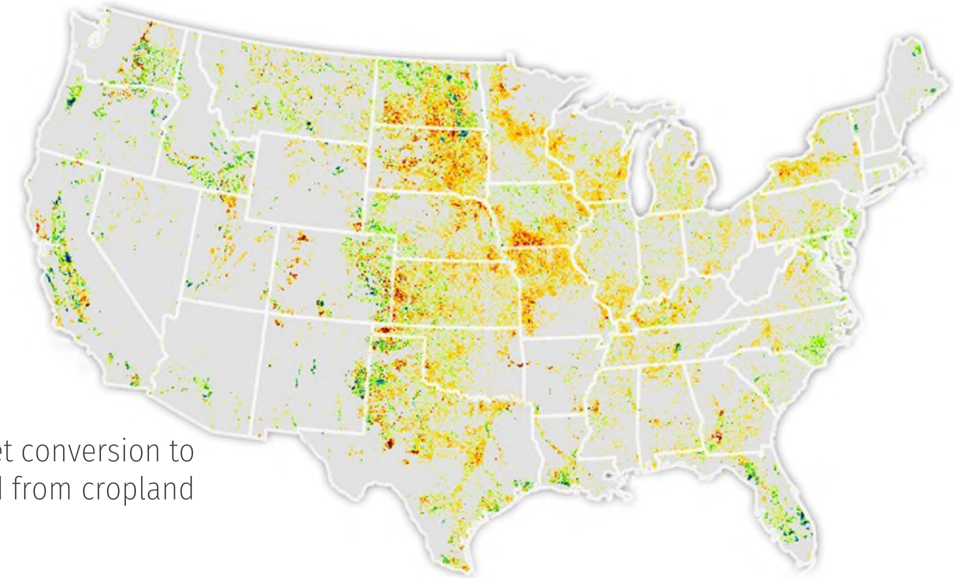
The Pollinator Conservation Challenge: Keeping track of 4,800+ species

Photos: Rodney Richardson

Pollinator Decline: A familiar story

- Habitat loss
- Climate change
- Parasites
- Pathogens
- Pesticides



Estimation of net conversion to and from cropland

Cropland expansion outpaces agricultural and biofuel policies in the United States. Lark et al. 2015, *Environ. Res. Lett.*

Well-Documented Examples of Decline

With many more uncertain examples

- Highly diverse groups
- Species are often small and obscure
- Taxonomic expertise required
- Adults often forage on specific plants

Federally Imperiled Pollinators of the Middle Rio Grande

- Sacramento Mountains Checkerspot Butterfly (Endangered)
- Monarch Butterfly (Candidate)
- Morrison Bumble Bee (Petitioned)
- Southern Plains Bumble Bee (Petitioned)
- Variable Cuckoo Bumble Bee (Petitioned)
- American Bumble Bee (Petitioned)
- Western Bumble Bee (Petitioned)
- Large Marble Butterfly (Petitioned)


Photo by Steve Cary; PEEC


Photo by Thomas Dunkerton; USFWS


Bombus morrisoni; Photo by Lisa H. Robinson

State Imperiled Pollinators of the Middle Rio Grande

Many uncertain examples of declining species

- **Yucca Giant Skipper, G5, unranked in NM**
- **Anasazi Crescent, G2, unranked in NM**
- ***Osmia watsoni*, G2, unranked in NM**
- **Obsolete Viceroy Butterfly**
  - *Limenitis archippus obsoleta*
  - T3; NV S1; NM SNR
  - Reliant on riparian areas, larval food plants are *Salix sp.*


Yucca Giant Skipper, Photo by Jonathan Batkin


Smithsonian


Anasazi Crescent, Photo by Larry de March


oto by Carol Davis

Passive Trapping Methods



Passive Trapping Methods

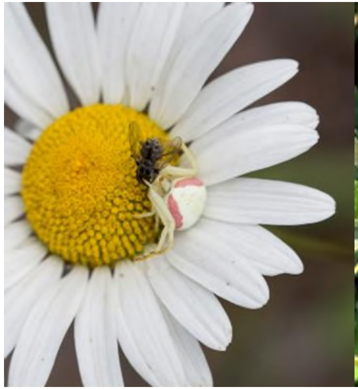
- Lethal to target species
- Catch rate is likely negatively related to floral availability
  - more flowers, fewer bees caught
- Pan traps tend to be biased toward small bees
  - *Lassioglossum*, difficult to ID
- It's not uncommon to kill 10 to 20 thousand bees
  - Up to 60K for relatively large-scales studies
- Creates considerable taxonomic bottleneck

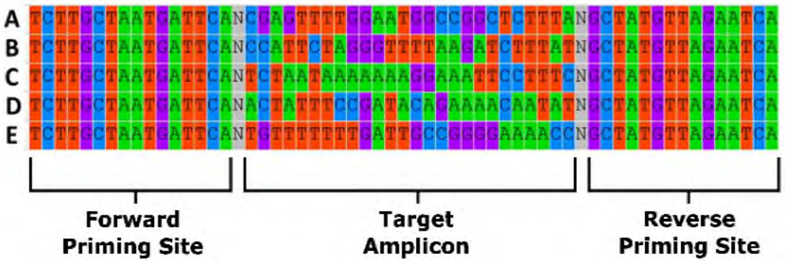
Active Sampling

Active Sampling

- **Requires experienced observer in the field for every survey**
  - Can't just set it and forget it
- **Every surveyor has unique bias**
- **Fewer bees are sampled per site relative to passive methods**
  - Leading to lower statistical power
- **Can only survey where humanly possible**
  - Sampling of bee-friendly trees is extremely difficult
  - Often restricted to certain times of year or day, weather events, etc.

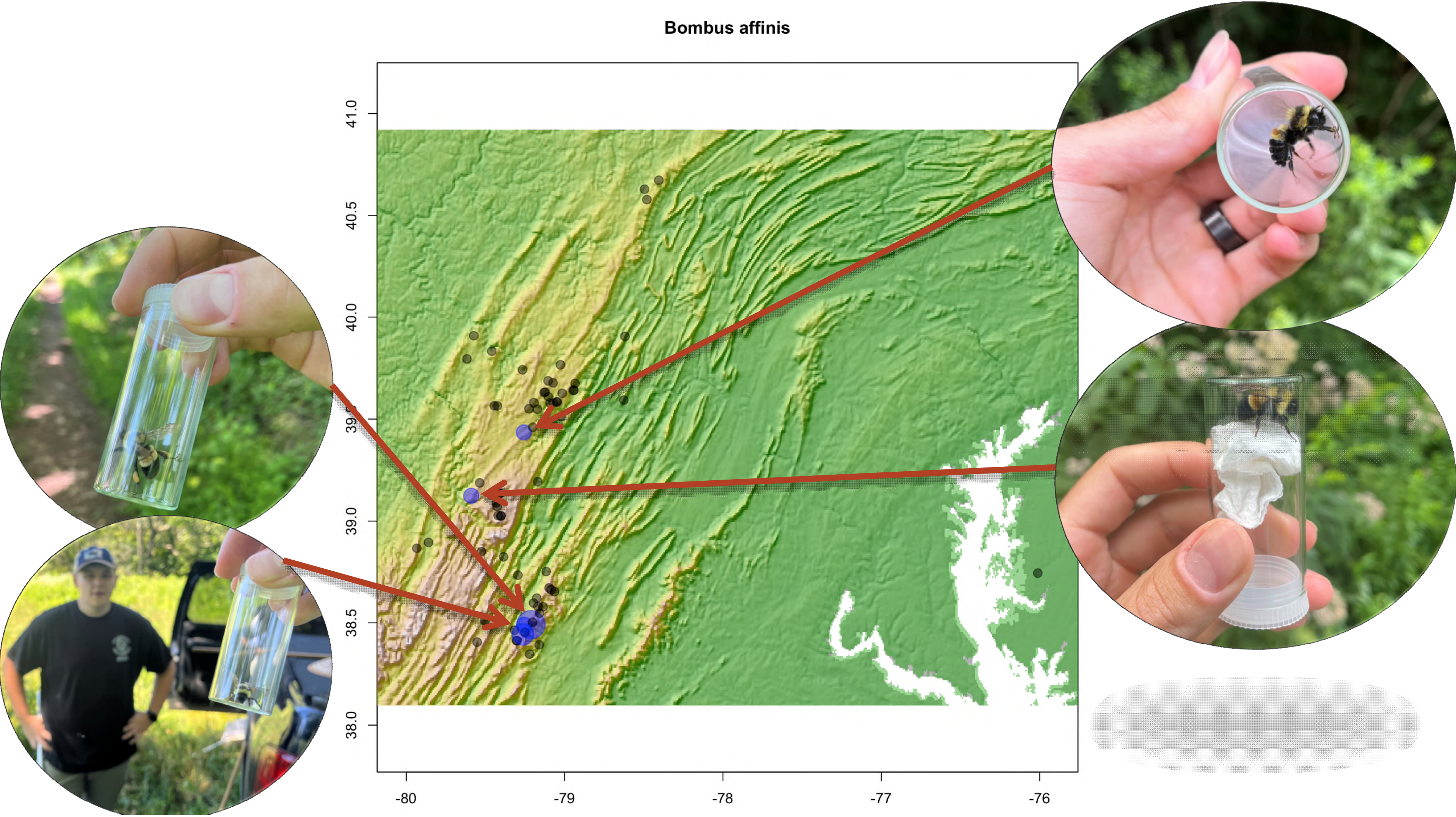
Pollinator Environmental DNA (eDNA)



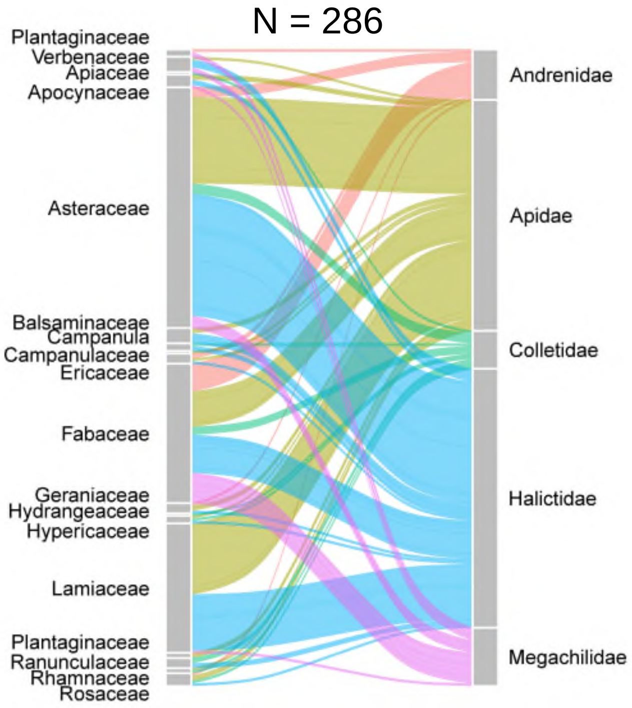



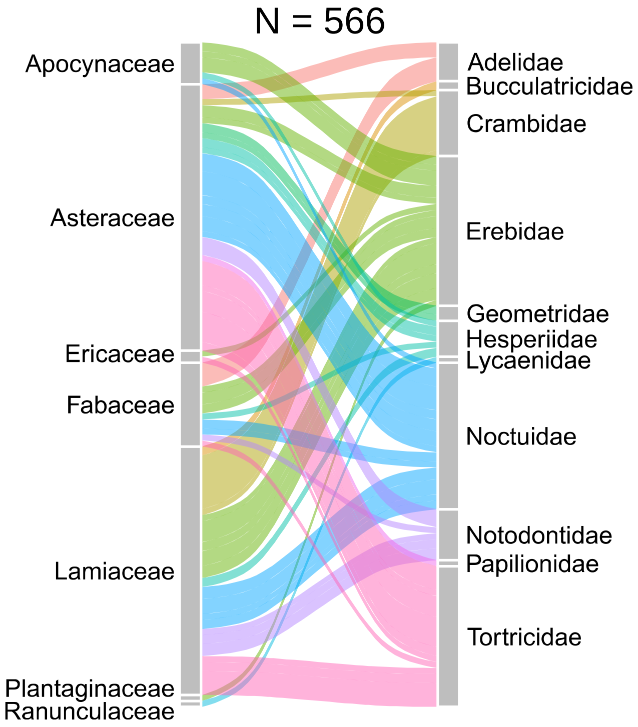
Paired eDNA and Net Surveys Across Central Appalachia

Replicated design to assess detectability

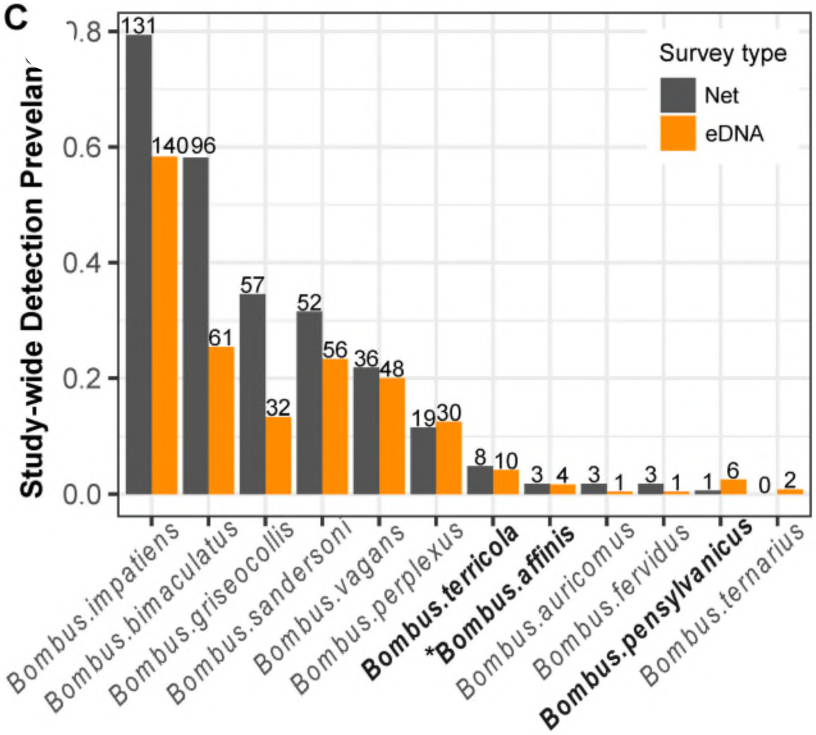

Bombus affinis
41.0
40.5
40.0
39.0
38.5
38.0
-80
-79
-78
-77
-76

eDNA case studies: 28S Bee-specific primers





eDNA Case Studies: Bumble bee-specific COI primers



Benefits and Challenges When Using eDNA Surveys In Adaptive Management

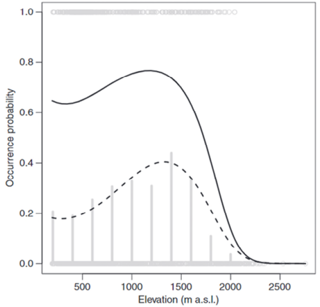
Benefits

- Ideal for sensitive ecosystems and threatened and endangered species sampling
- Good for data hungry modeling
    - Occupancy models

Challenges

- Limited set of study systems where it has been demonstrated beyond proof-of-concept
- May still be cost prohibitive for some organizations
- Does not capture reference organisms for future morphological study or health indicators

Kery et al., 2010, *J. Biogeography*



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Acknowledgements

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Thank You!

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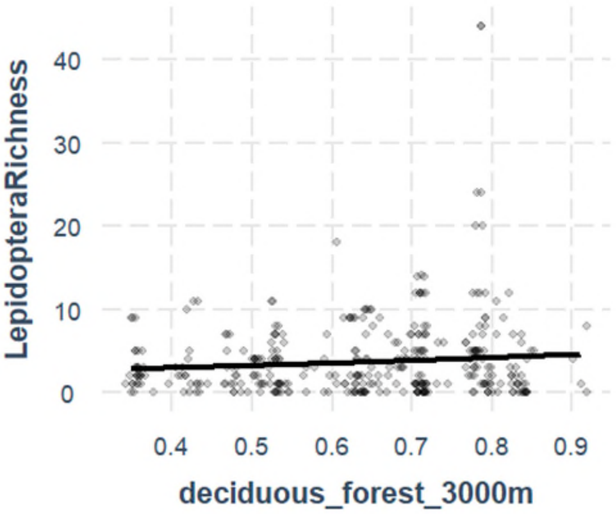
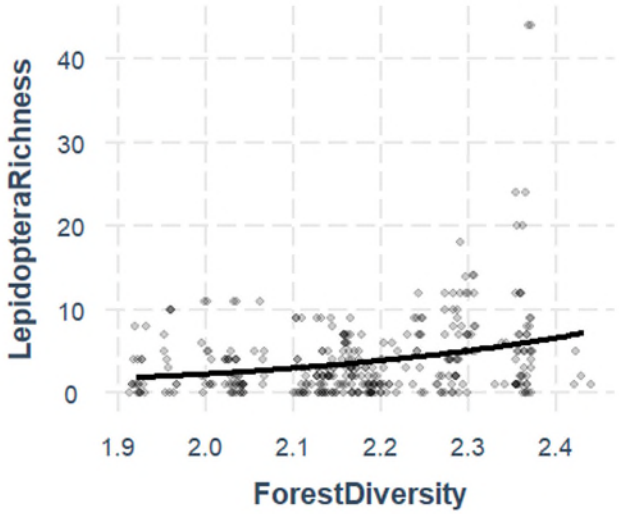
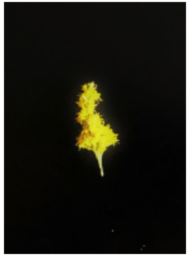
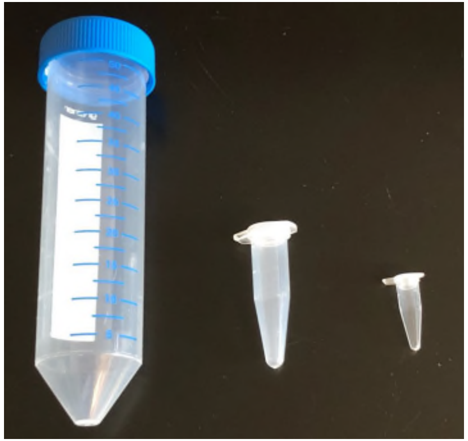
Can eDNA Provide Insight on Habitat Associations?









50 mL 1.5 mL 0.2 mL

Ecology, 83(8), 2002, pp. 2248–2255

ESTIMATING SITE OCCUPANCY RATES WHEN DETECTION PROBABILITIES ARE LESS THAN ONE

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Abstract. Nondetection of a species at a site does not imply that the species is absent unless the probability of detection is 1. We propose a model and likelihood-based method for estimating site occupancy rates when detection probabilities are <1. The model provides a flexible framework enabling covariate information to be included and allowing for missing observations. Via computer simulation, we found that the model provides good estimates of the occupancy rates, generally unbiased for moderate detection probabilities (>0.3). We estimated site occupancy rates for two anuran species at 32 wetland sites in Maryland, USA, from data collected during 2000 as part of an amphibian monitoring program, Frogwatch USA. Site occupancy rates were estimated as 0.49 for American toads (*Bufo americanus*), a 44% increase over the proportion of sites at which they were actually observed, and as 0.85 for spring peepers (*Pseudacris crucifer*), slightly above the observed proportion of 0.83.

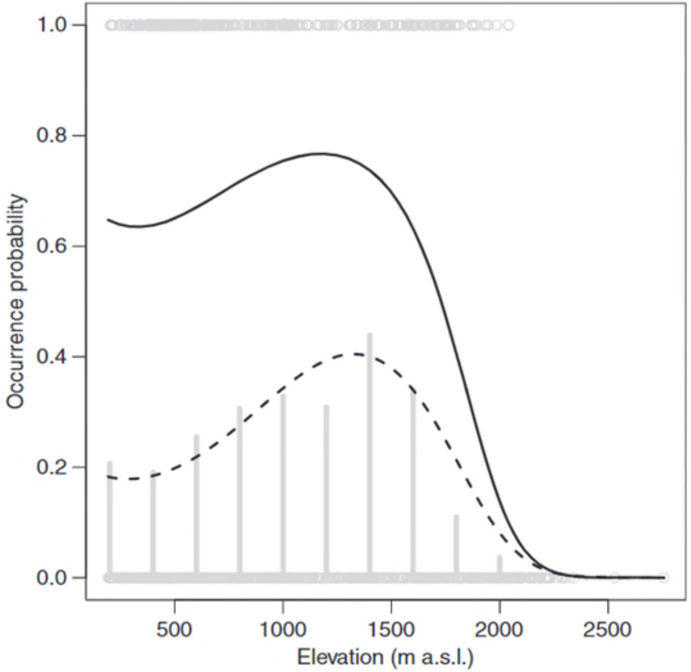
Adjusting for detection probability with occupancy models

Adjusting for detection probability with occupancy models

Generalized Linear Model	Occupancy Model
$z_i \sim \text{Bernoulli}(\psi)$	$z_i \sim \text{Bernoulli}(\psi)$
$y_i \mid z_i \sim \text{Bernoulli}(1 * z_i)$	$y_i \mid z_i \sim \text{Bernoulli}(p * z_i)$
$\text{logit}(\psi) = \beta 0 + \beta 1 * \text{covariate1}$	$\text{logit}(p) = \alpha 0 + \alpha 1 * \text{covariate1}$
	$\text{logit}(\psi) = \beta 0 + \beta 1 * \text{covariate1}$

GLMs capture a fraction of the true species extent

Kery et al., 2010, *J. Biogeography*



Tempering expectations around occupancy models

- Subject to all the same issues of any other regression technique
- Garbage in, garbage out
- Aimed at predicting spatial extent, NOT abundance
- Occupancy models don’t typically account for abundance