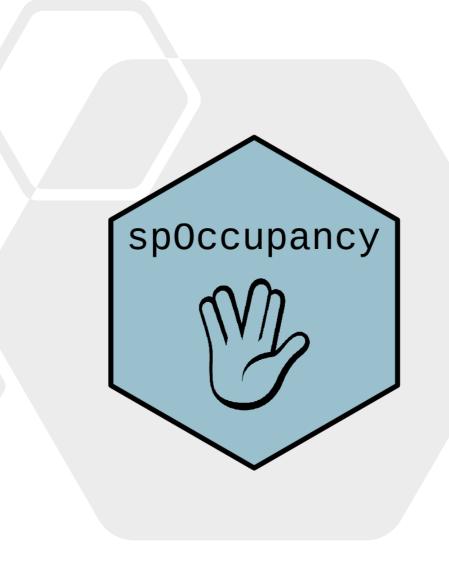
Bayesian occupancy modeling with acoustic data in spOccupancy

Jeff Doser Michigan State University Cornell Acoustic Methods Working Group July 19, 2022

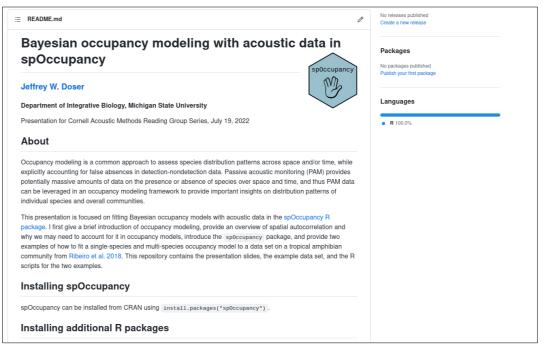




Overview

Overview

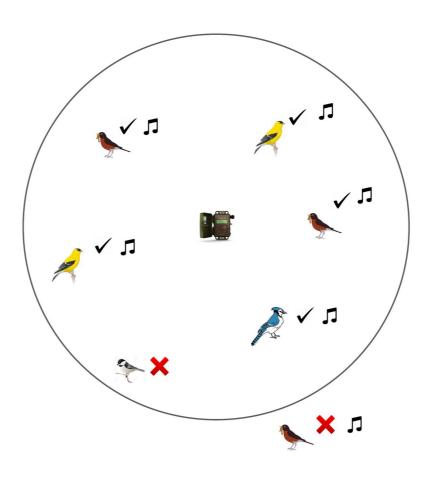
- Occupancy modeling in passive acoustics
- Overview of spatial autocorrelation
- spOccupancy syntax and example
 - Single-species modeling
 - · Multi-species modeling



https://github.com/doserjef/acoustic-spOccupancy-22

Motivation

- Goal: understand occupancy patterns/dynamics across space and/or time of one (or more) species
 - More broadly: where do species occur in both space and how does this change over time?
 - Relevant for ecological theory, conservation, management, etc.
- Two important complexities:
 - 1. Imperfect detection
 - 2. Spatial autocorrelation



Data for occupancy modeling

Detection-nondetection matrix

Site	Survey 1	Survey 2	Survey 3	Survey 4
1	1	0	0	1
2	0	0	0	0
3	1	1	0	NA
4	1	NA	0	NA
5	0	1	1	1
6	0	0	0	1

- Basic idea: obtain repeated surveys at a given site to account for imperfect detection
- ARUs -> easy to obtain replicate surveys (i.e., multiple recordings per site)
- Assume no false positives

Occupancy model

Occupancy (ecological) sub-model

$$z_j \sim \text{Bernoulli}(\psi_j)$$

 $\text{logit}(\psi_j) = \beta_1 + \beta_2 \cdot X_{2,j} + \dots + \beta_r \cdot X_{r,j}$

Detection (observation) sub-model

$$y_{j,k} \sim \text{Bernoulli}(p_{j,k} \cdot z_j)$$

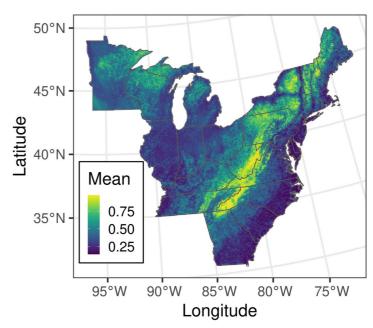
 $\text{logit}(p_{j,k}) = \alpha_1 + \alpha_2 \cdot V_{2,j,k} + \dots + \alpha_r \cdot V_{r,j,k}$

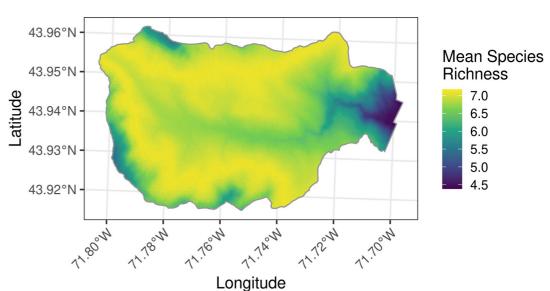
What if we're interested in multiple species?

- First approach: fit separate single-species occupancy models
 - Easy to do
 - Models are fast
 - Requires adequate sample size, often won't work for rare species
 - Does not directly estimate community-level parameters
- Alternative approach: Multi-species (community) occupancy model
 - Dorazio et al. (2005), Zipkin et al. (2009)
 - Estimates occupancy for multiple species simultaneously
 - Treats species as random effects -> more precise estimates
 - Allows occupancy estimation for rare species as a result of "borrowing strength"
 - Longer model run times

Spatial autocorrelation

- Things closer together in space tend to be more similar than things farther apart
- What leads to spatial autocorrelation in species distributions?
 - Shared use of environmental space
 - Underlying environmental drivers (e.g., elevation, climate) are spatially correlated
 - Dispersal
 - Conspecific attraction





How to account for spatial autocorrelation?

- Spatial covariates
 - Often sufficient, but may not always be available
- Residual spatial autocorrelation: spatial correlation in data after including spatial covariates
 - Missing covariates
 - Biotic factors (e.g., dispersal, conspecific attraction)
 - Use spatial random effects

Single-season spatial occupancy model

Occupancy (ecological) sub-model

$$z_j \sim \text{Bernoulli}(\psi_j)$$

 $\text{logit}(\psi_j) = \beta_1 + \beta_2 \cdot X_{2,j} + \dots + \beta_r \cdot X_{r,j} + w_j$
 $w_j \sim \text{Normal}(0, \Sigma)$

Detection (observation) sub-model

$$y_{k,j} \sim \text{Bernoulli}(p_{j,k} \cdot z_j)$$

 $\text{logit}(p_{j,k}) = \alpha_1 + \alpha_2 \cdot V_{2,j,k} + \dots + \beta_r \cdot V_{r,j,k}$

sp0ccupancy

spOccupancy

- Designed to fit Bayesian single-species and multispecies occupancy models
- Options to accommodate spatial autocorrelation (efficiently!)
- Workflow completely in R (no Bayesian programming languages necessary)
- Additional functionality:
 - Data integration
 - Species correlations
 - Multi-season (spatio-temporal) models (hot off the press!)

Benefits of Bayesian analysis

- 1. Interpretation
- 2. More flexible to accommodate spatial autocorrelation
- 3. Easy to extend to multi-species frameworks/integrate multiple data sources
- 4. Uncertainty
- 5. Ideal for complex data (e.g., highly correlated, multivariate)
- 6. Readily accommodate false positives from automated algorithms
 - Chambert et al. 2018, Doser et al. 2021, Rhinehart et al. 2022

Example data set: tropical amphibians

Ecological Applications, 28(6), 2018, pp. 1554–1564 © 2018 by the Ecological Society of America

- Data from Ribeiro Jr. Et al (2018)
 Eco Apps
- 50 sites along a gradient of landscape characteristics
- 3 ARU recordings at each site (repeat surveys/visits)
- 36 amphibian species analyzed
- Focus on Crossodactylus caramaschii



Effects of agriculture and topography on tropical amphibian species and communities

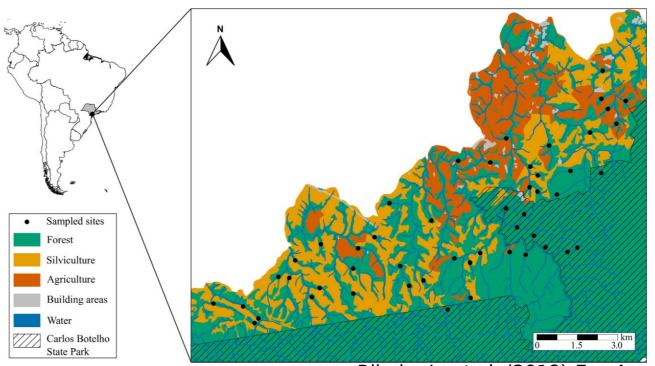
José Wagner Ribeiro, Jr., 1,2,4 Tadeu Siqueira, Gabriel Lourenço Brejão, And Elise F. Zipkin²

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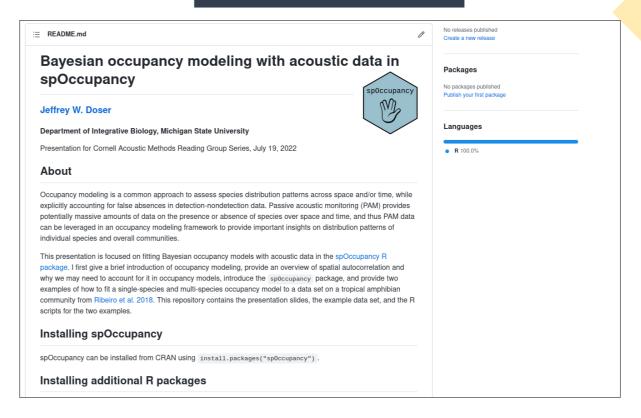


Ribeiro Jr. et al. (2018) Eco Apps

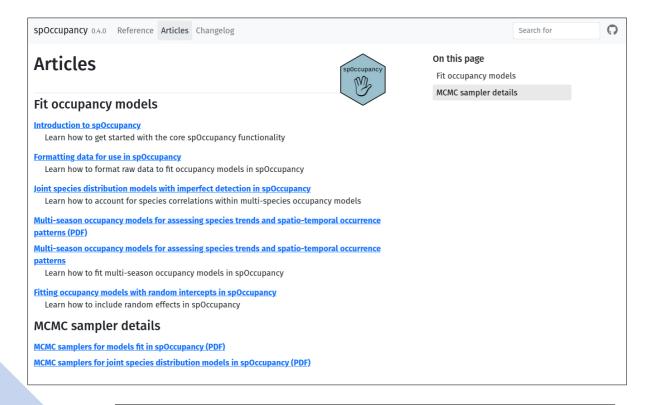
spOccupancy workflow

- 1. Data simulation/prep
- 2. Model fitting
- 3. Model validation
- 4. Model comparison
- 5. Posterior summaries
- 6. Prediction

Switch to RStudio



Overview



- Package Website
- GitHub development page
- MEE intro paper
- arXiv preprint
- 🗾 @jeffdoser18
- Email: doserjef@msu.edu



Joint species distribution models with imperfect detection for high-dimensional spatial data

Jeffrey W. Doser^{1, 2}, Andrew O. Finley^{2, 3}, Sudipto Banerjee⁴

Acknowledgments



Andy Finley



Elise Zipkin



Marc Kéry



Sudipto Banerjee

Data: José Wagner Ribeiro Jr.





Thank you!