Hierarchical spatial modelling for applied population and community ecology

Jeffrey W. Doser, Marc Kéry, Gesa von Hirschheydt

24-27 June 2024

Multi-season spatial occupancy models

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- Assess occupancy trends over time
    - Detection-nondetection data are easier to collect than count data
    - Occupancy-abundance relationship
    - Exact interpretation of occupancy trends depends on how data are collected (see Steenweg et al. 2018 Ecology)

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  - Detection-nondetection data are easier to collect than count data
  - Occupancy-abundance relationship
  - Exact interpretation of occupancy trends depends on how data are collected (see Steenweg et al. 2018 Ecology)
- From a statistical perspective, having multiple seasons of data can improve our ability to estimate spatial random effects.

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- Seasons are sometimes referred to as **primary replicates** and repeat visits within a season as **secondary replicates**

Multi-season detection-nondetection data

- Recall the **closure assumption**.
- For multi-season models, we assume closure within a primary time period (i.e., season), but do not assume closure across primary time periods (i.e., across seasons)
- In other words, we assume the occupancy status does not change within a season, but that sites can change from occupied to unoccupied across seasons.

Multi-species detection-nondetection data

- Example: 6 sites, 2 seasons, 3 surveys within a season

Season 1

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

Season 2

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

Lots of interesting design questions in multi-season occupancy models

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"Mixed" occupancy designs: When do additional single-visit data improve the inferences from standard multi-visit models?

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"Fractional replication" in single-visit multi-season occupancy models: Impacts of spatiotemporal autocorrelation on identifiability

Jeffrey W. Doser, Sara Stoudt

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Terminology

Multi-season occupancy model

Dynamic occupancy model

Stacked occupancy model

Spatio-temporal occupancy model

Dynamic occupancy models

- MacKenzie et al. (2003)
- Explicitly estimates colonization and extinction (or survival)
- Arguably the most mechanistic form of multi-season occupancy model
- More data hungry and often harder to fit
- Can fit in `unmarked` (frequentist) and `ubms` (Bayesian)

Stacked occupancy models

- Fit a single-season occupancy model, but now your "sites" are really "site-seasons" (e.g., "site-years", combinations of site and year).
- Less mechanistic, but far less data hungry than dynamic models.
- Often a season trend is of interest and included in the model.
- Can account for pseudoreplication by including a random site effect.
- Can fit stacked models in `spOccupancy`

Spatio-temporal occupancy models

- A form of stacked occupancy model, but now includes explicit components to account for spatial and/or temporal autocorrelation.
- Less mechanistic than dynamic models.
- Better at predicting distributions (and changes) than basic stacked models
- Lots of different flavors.
- Some nice examples:
  - Rushing et al. (2019) Scientific Reports
  - Wright et al. (2021) Ecology and Evolution
  - Hepler et al. (2023) R Journal (the `multiocc` package)

Terminology

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- Dynamic occupancy model
- Stacked occupancy model
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Multi-season occupancy model

$j = 1, \dots, J$ (site)
$t = 1, \dots, T$ (season)
$k = 1, \dots, K_{j,t}$ (replicate)

Occupancy (ecological) sub-model

$$z_{j,t} \sim \text{Bernoulli}(\psi_{j,t})$$
$$\text{logit}(\psi_{j,t}) = \boldsymbol{x}_{j,t}\boldsymbol{\beta} + \text{w}_j + \eta_t$$

$z_{j,t}$ True occurrence of the species at site *j* in season *t*

$\psi_{j,t}$ Occurrence probability at site *j* in season *t*

$\boldsymbol{x}_{j,t}$ Site and/or season-varying covariates

w_j Site-level random effect

η_t Season-level (temporal) random effect

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Site-level random effects w_j

Two types:

1. **Unstructured** -> a typical random intercept with the form:

$$\mathrm{w}_j \sim \mathrm{Normal}(0, \sigma^2)$$

2. **Spatial NNGP** -> same as before. This is a "spatial multi-season occupancy model" or "spatio-temporal occupancy model".

Unstructured site-level random effects

- This is the standard approach in stacked occupancy models.
- Random site effect accounts for non-independence between occupancy probability at a site over the T seasons (i.e., pseudoreplication).
- Does not explicitly account for spatial autocorrelation
- Often reasonable when focus is on inference, but spatial effects are often much better for prediction.

$$\mathrm{w}_j \sim \mathrm{Normal}(0, \sigma^2)$$

Spatial NNGP site-level random effects

- Account for spatial autocorrelation in occupancy probability.
- Nothing new here from previous spatial models.

$$\mathbf{w} \sim \mathrm{Normal}(\mathbf{0}, \tilde{\boldsymbol{C}}(d, \phi, \sigma^2))$$

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  1. Unstructured -> a typical random intercept with the form:

$$\eta_t \sim \text{Normal}(0, \sigma_T^2)$$

  2. AR(1) -> random temporal effects follow an autoregressive structure. Covariance between two time points is:

$$\sigma_T^2 \rho^{|t-t'|}$$

Multi-season occupancy model

$$z_{j,t} \sim \text{Bernoulli}(\psi_{j,t})$$
$$\text{logit}(\psi_{j,t}) = \boldsymbol{x}_{j,t}\boldsymbol{\beta} + \boxed{\text{w}_j + \eta_t}$$

- In the statistics literature, this is known as a **separable** model, because the spatial random effects are independent from the temporal random effects.

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- Nonseparable models allow different types of interactions between the spatial and temporal effects.
  - Examples include Wright et al. (2021) and Hepler et al. (2021).

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- Nonseparable models allow different types of interactions between the spatial and temporal effects.
    - Examples include Wright et al. (2021) and Hepler et al. (2021).
- We will shortly discuss applications of spatially-varying coefficient models in `spOccupancy` for looking at spatial variation in occupancy trends over time.

Multi-season occupancy model

$j = 1, \dots, J$ (site)
$t = 1, \dots, T$ (season)
$k = 1, \dots, K_{j,t}$ (replicate)

Detection (observation) sub-model

$$y_{j,t,k} \sim \text{Bernoulli}(p_{j,t,k} \cdot z_{j,t})$$
$$\text{logit}(p_{j,t,k}) = \boldsymbol{v}_{j,t,k} \cdot \boldsymbol{\alpha}$$

$y_{j,t,k}$	Detection-nondetection data at site *j* during replicate *k and season t*
$p_{j,t,k}$	Detection probability at site *j* during replicate *k and season t*
$\boldsymbol{v}_{j,t,k}$	Covariates affecting detection at site j during replicate k and season t

Fitting multi-season occupancy models in `spOccupancy`

- `tPGOcc()`: non-spatial multi-season occupancy models (temporal Pólya-Gamma occupancy model)
- `stPGOcc()`: spatio-temporal Pólya-Gamma occupancy models
- All multi-season models require the use of an adaptive Metropolis-Hastings sampler, and so we specify the number of batches and batch length as with previous spatial models.
- `tMsPGOcc()` and `stMsPGOcc()` for multi-species models.

Fitting multi-season occupancy models in `spOccupancy`

Site Effect	Temporal Effect	`spOccupancy`
None	None	`tPGOcc()`
None	Unstructured	`tPGOcc()` with random time intercept
None	AR(1)	`tPGOcc()` with `ar1 = TRUE`
Unstructured	None	`tPGOcc()` with random site intercept
Unstructured	Unstructured	`tPGOcc()` with random time and site intercept
Unstructured	AR(1)	`tPGOcc()` with random site intercept and `ar1 = TRUE`
Spatial (NNGP)	None	`stPGOcc()`
Spatial (NNGP)	Unstructured	`stPGOcc()` with random time intercept
Spatial (NNGP)	AR(1)	`stPGOcc()` with `ar1 = TRUE`

Different ways to model the site-level and temporal random effects in multi-season occupancy models in `spOccupancy`.

Exercise: Estimating bat distributions in the Western USA

`08-bat-multi-season-occ.R`