



Hierarchical spatial modelling for applied population and community ecology

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Spatial multi-species occupancy models

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Spatial autocorrelation in MSOMs

- Spatial autocorrelation may be more prevalent in MSOMs since different species are driven by different habitat requirements.
- Likely won't be able to include all covariates relevant to all species in the model.
- Can extend the MSOM just like we did with the SSOM to account for spatial autocorrelation in occupancy probability for each species.
- Two "flavors" of spatial MSOMs included in `spOccupancy`

Type 1: Spatial MSOMs

- Estimate a separate spatial random effect \mathbf{w} for each species
- Each \mathbf{w} is estimated with a NNGP as before
- Nothing new here, now just have N (the number of species) NNGP spatial random effects
- Would very rarely want to use a full GP instead of an NNGP, since we now need to estimate N spatial random intercepts
- `spMsPGOcc()` function

Type 1 Spatial MSOMs

$$z_{i,j} \sim \text{Bernoulli}(\psi_{i,j})$$

$$\text{logit}(\psi_{i,j}) = \beta_{1,i} + \beta_{2,i} \cdot X_{2,j} + \cdots + \beta_{r,i} \cdot X_{r,j} + \mathbf{w}_{i,j}$$

$$\beta_{r,i} \sim \text{Normal}(\mu_{\beta_r}, \tau_{\beta_r}^2)$$

$$\mathbf{w}_i \sim \text{Normal}(\mathbf{0}, \tilde{\mathbf{C}}(d, \phi_i, \sigma_i^2))$$

$$\mu_{\beta_r} \sim \text{Normal}(\mu_{0_r}, \sigma_{\beta_r}^2)$$

$$\tau_{\beta_r}^2 \sim \text{Inverse gamma}(a_{r,\beta}, b_{r,\beta})$$

$$\phi_i \sim \text{Uniform}(a_{\phi,i}, b_{\phi,i})$$

$$\sigma_i^2 \sim \text{Inverse gamma}(a_{\sigma,i}, b_{\sigma,i})$$

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The detection sub-model is exactly the same as the nonspatial MSOM

Problems with Type 1 spatial MSOMs

- Can become quite slow when the number of species in the community is greater than 10 or so
- Species-specific spatial random effects can be very difficult to estimate for rare species
- Most useful when working with a modest number of spatial locations (e.g. 100-500) and a modest number of species (e.g., <10) that are not extremely rare.

Type 2: Spatial factor MSOMs


- More powerful and efficient than the previously discussed spatial MSOMs
- A multi-species modeling approach that simultaneously accounts for:
 - Imperfect detection
 - Spatial autocorrelation
 - Species correlations

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

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Spatial factor MSOMs

- An extension of the latent factor MSOM we discussed previously
- Identical to the latent factor MSOM, but now the factors are estimated as spatial NNGPs!
- **Foundational concept:** spatial autocorrelation in the distributions of individual species may arise from a set of shared, common factors that have a spatial pattern
- Only difference from the previous spatial MSOM is in how the spatial random effects are modelled

Spatial factor MSOMs

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$$\text{logit}(\psi_{i,j}) = \beta_{1,i} + \beta_{2,i} \cdot X_{2,j} + \cdots + \beta_{r,i} \cdot X_{r,j} + w_{i,j}^*$$

Spatial factor MSOMs

Species-specific spatial
random effect



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Spatial factor MSOMs

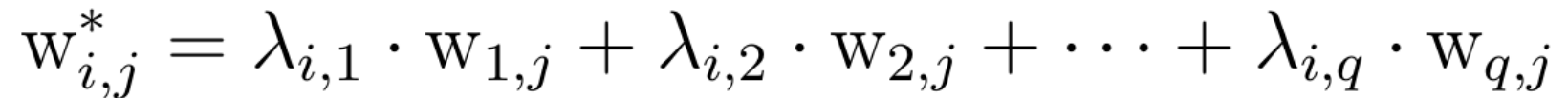
Species-specific spatial
random effect



A light blue rounded rectangle containing the text "Species-specific spatial random effect". An arrow points from this box to the $w_{i,j}^*$ term in the logit equation below.

$$z_{i,j} \sim \text{Bernoulli}(\psi_{i,j})$$

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$$w_{i,j}^* = \lambda_{i,1} \cdot w_{1,j} + \lambda_{i,2} \cdot w_{2,j} + \cdots + \lambda_{i,q} \cdot w_{q,j}$$


A light blue rounded rectangle containing the text "Species specific spatial effect is the sum of a set of q spatial factors and their species-specific coefficients (loadings)". An arrow points from this box to the $w_{i,j}^*$ term in the equation above.

Species specific spatial
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Spatial factor MSOMs

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"Missing covariates"
that account for
residual spatial
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Spatial factor MSOMs

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Species specific spatial
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Effects of the
missing covariates

"Missing covariates"
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Identical to latent factor MSOMs, except we now model each w with a NNGP instead of from a $\text{Normal}(0, 1)$.

Priors and identifiability considerations

- Same priors as we've seen before
- Normal priors on community-level means
- Inverse-gamma priors on community-level variances
- Uniform priors on spatial decay parameters
- Same restrictions on the factor loadings matrix as with latent factor models

Why use the spatial factor MSOM?

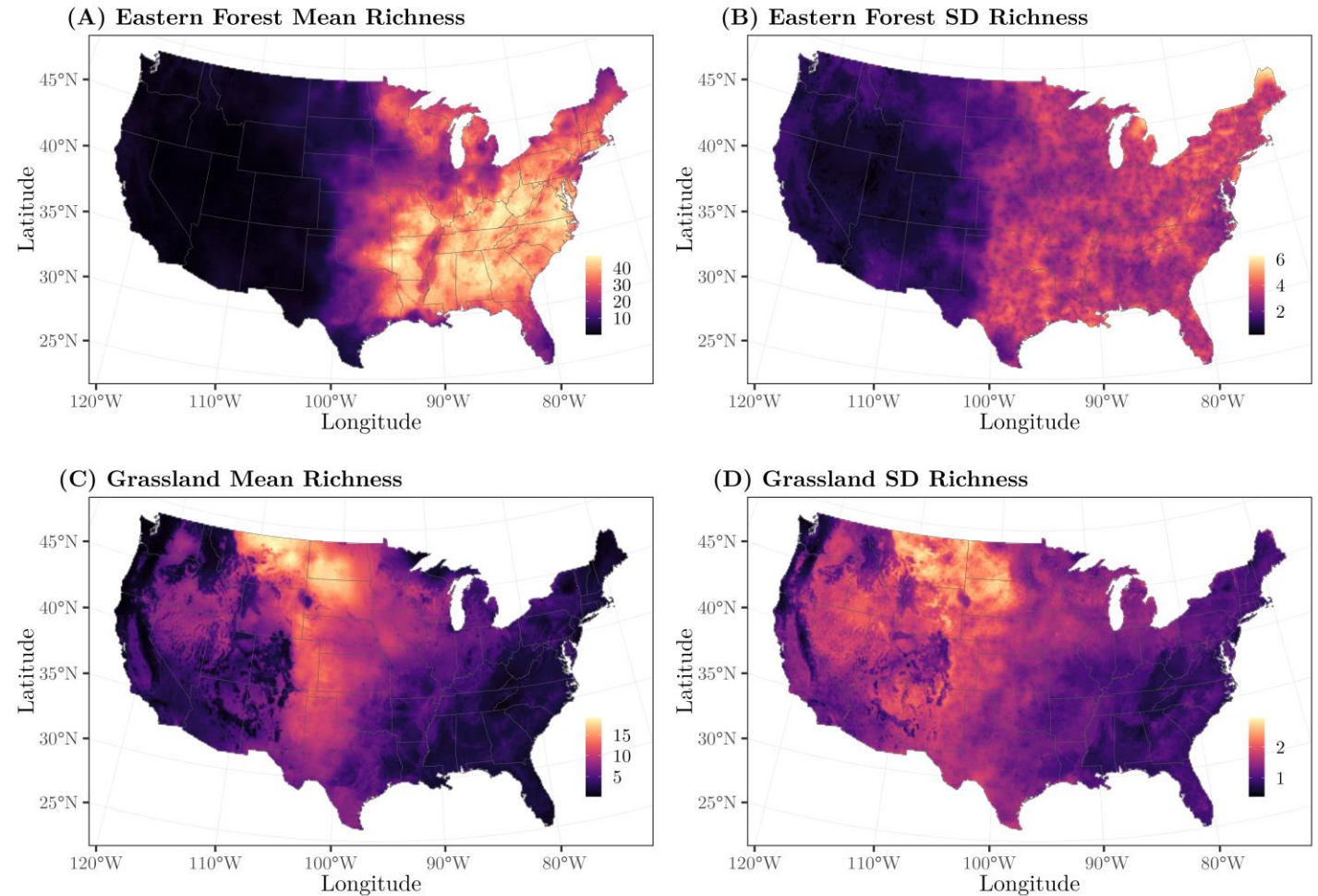
Performs well in a variety of scenarios while being more computationally efficient than alternative spatial MSOMs.

TABLE 2 Estimated coverage rates of simulated species-specific occurrence probabilities and covariate effects for six different simulation scenarios and six models of varying complexity, as well as average run time.

Parameter	Scenario	Model					
		lfJSDM	sfJSDM	msPGOcc	spMsPGOcc	lfMsPGOcc	sfMsPGOcc
$\psi_i(s_j)$	1	91.5	90.8	68.9	88.1	95.6	95.3
	2	91.6	91.0	69.1	89.1	95.5	95.4
	3	85.6	84.8	95.0	96.4	95.5	95.5
	4	77.5	76.4	80.2	93.1	95.7	95.5
	5	75.3	74.2	71.3	88.5	95.5	95.3
	6	76.0	75.0	72.2	89.6	95.3	95.2
β_i	1	88.7	88.2	82.0	91.1	95.2	95.1
	2	88.8	88.2	82.2	91.7	94.9	94.9
	3	73.8	73.1	95.1	94.4	90.4	90.8
	4	65.9	65.0	89.1	94.0	94.7	94.7
	5	64.2	63.6	83.6	91.7	95.2	95.0
	6	65.7	64.6	85.1	92.7	94.9	94.9

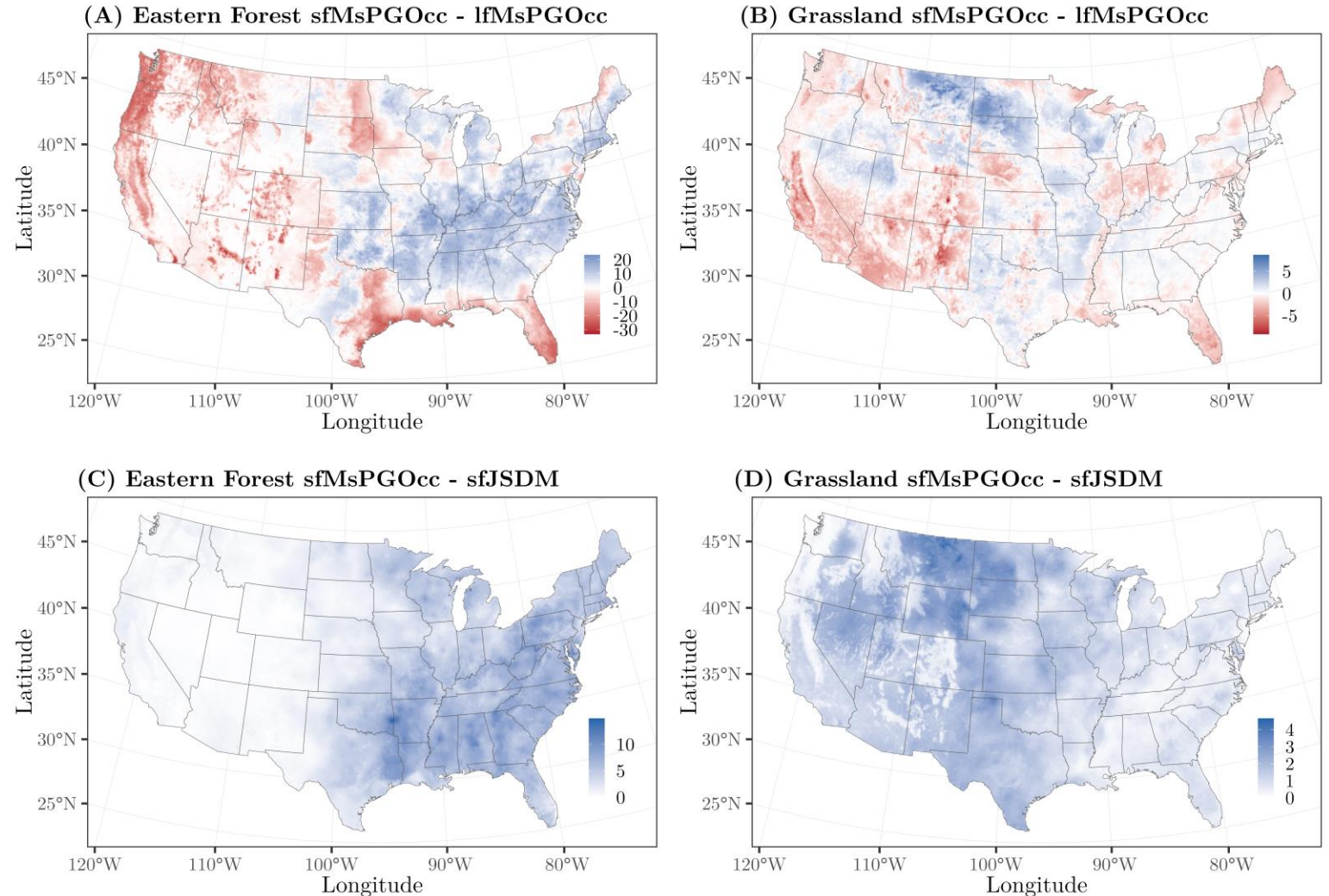
Why use the spatial factor MSOM?

Estimate distributions and biodiversity metrics with big multi-species data sets (ex: 2,619 sites and 98 species)



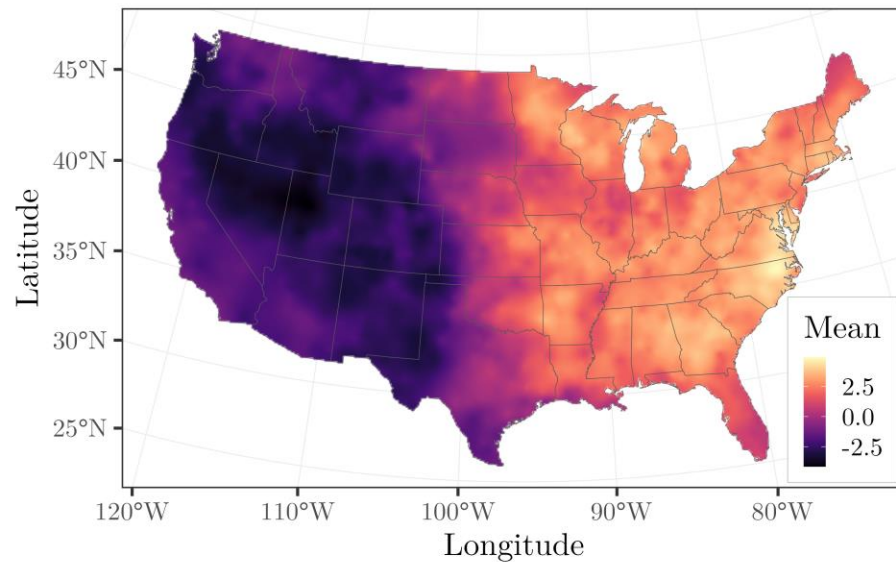
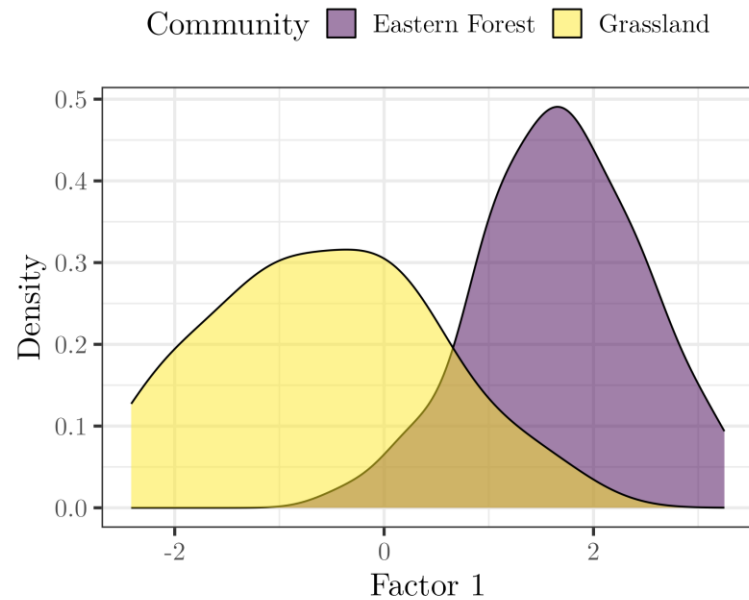
Why use the spatial factor MSOM?

Improved estimates
of biodiversity metrics



Why use the spatial factor MSOM?

Model-based ordination



Fitting spatial factor MSOMs in `spOccupancy`

- `sfMsPGOcc()`
- As with all spatial models, we break up the MCMC iterations into a set of batches, where each batch has a set number of iterations.
- Need to specify number of spatial factors to use



Multi-species, single-season models

spOccupancy function	Species correlations	Spatial autocorrelation	Imperfect detection
lfJSDM	✓		
sfJSDM	✓	✓	
msPGOcc			✓
spMsPGOcc		✓	✓
lfMsPGOcc	✓		✓
sfMsPGOcc	✓	✓	✓

Exercise: Niche partitioning in a simulated plant community

06-plant-spatial-multi-species-occ.R

