Hierarchical spatial modelling for applied population and community ecology

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Single-species spatial occupancy models

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Recall the basic occupancy model

Occupancy (ecological) sub-model

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

Detection (observation) sub-model

$$y_{j,k} \sim \text{Bernoulli}(p_{j,k} \cdot z_j)$$
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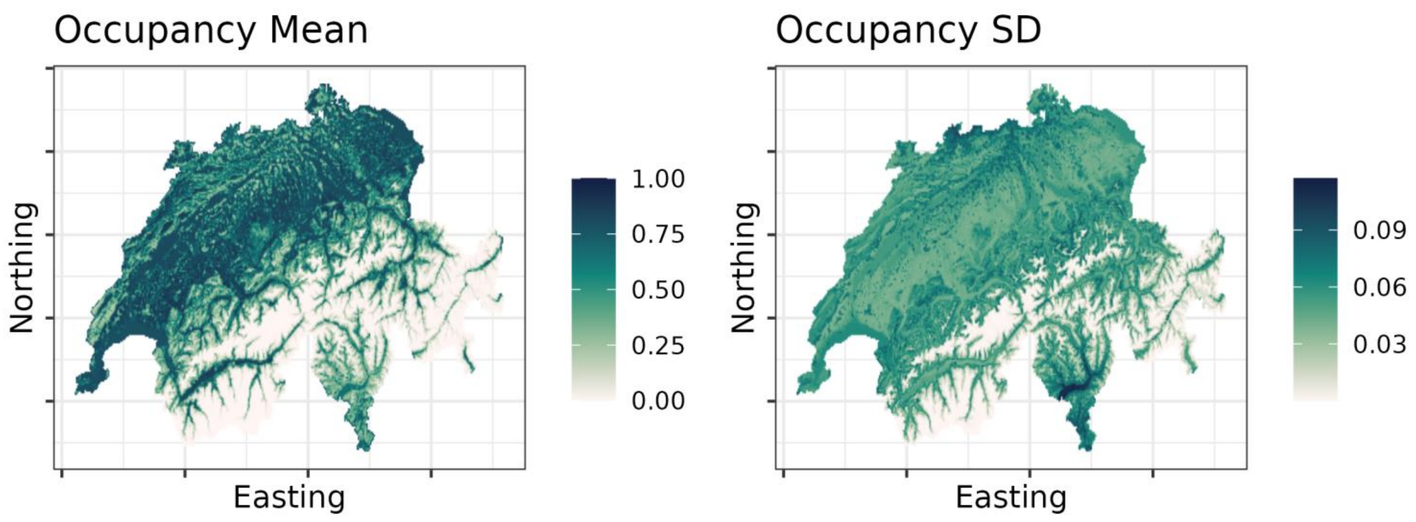
$j = 1, \ldots, J$ (site)
$k = 1, \ldots, K_j$ (replicate)

European Goldfinch example

```
out.full <- PGOcc(occ.formula = ~ scale(elevation) + I(scale(elevation)^2) + scale(forest),
                  det.formula = ~ scale(date) + I(scale(date^2)) + scale(dur),
                  data = data.goldfinch,
                  n.samples = 5000,
                  inits = inits.list,
                  priors = prior.list,
                  n.thin = 4,
                  n.burn = 3000,
                  n.chains = 3,
                  n.report = 500)
```



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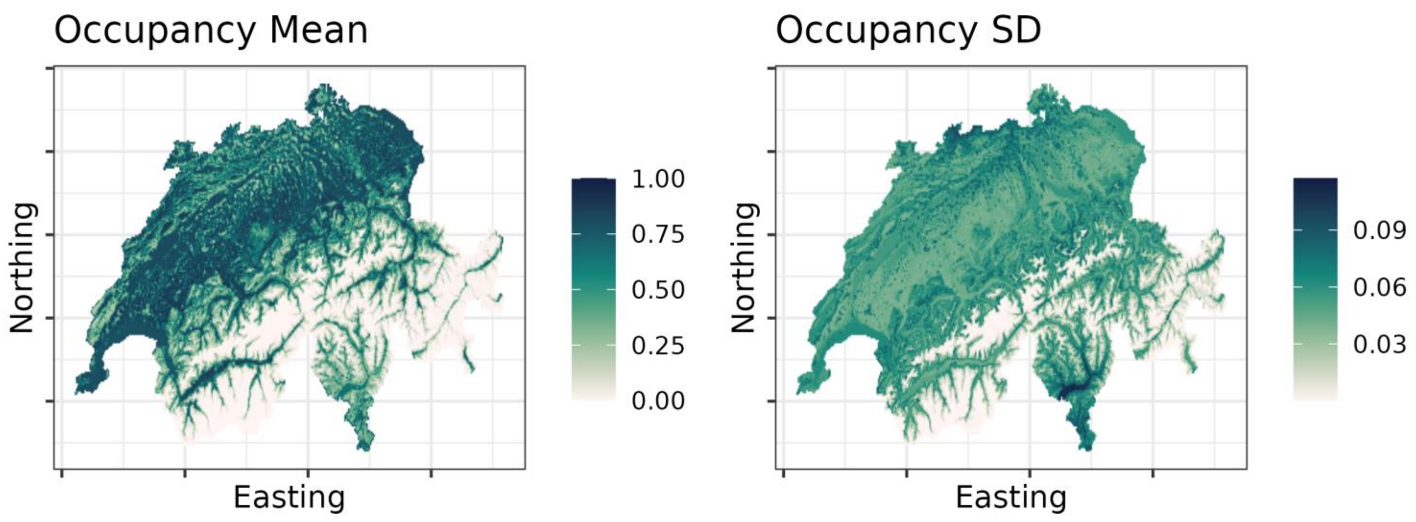

Does accounting for spatial autocorrelation improve our model and resulting species distribution map?

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- Accounting for spatial autocorrelation can often improve predictions.
- Maps of the predicted spatial effects can give insights on the underlying drivers.

Spatial occupancy model

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$$\text{logit}(\psi_j) = \beta_1 + \beta_2 \cdot X_{2,j} + \cdots + \beta_r \cdot X_{r,j} + \text{w}_j$$
$$\mathbf{w} \sim \text{Multivariate Normal}(\mathbf{0}, \boldsymbol{C}(d, \phi, \sigma^2))$$

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Spatial NNGP occupancy model

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Prior distributions (and `spOccupancy` defaults)

$$\beta_r \sim \text{Normal}(0, 2.72)$$

$$\alpha_r \sim \text{Normal}(0, 2.72)$$

$$\sigma^2 \sim \text{Inverse-gamma}(2, 1)$$

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See "2-intro-to-spatial-models.pdf" lecture

Prior distributions (and `spOccupancy` defaults)

Where does the 2.72 come from?

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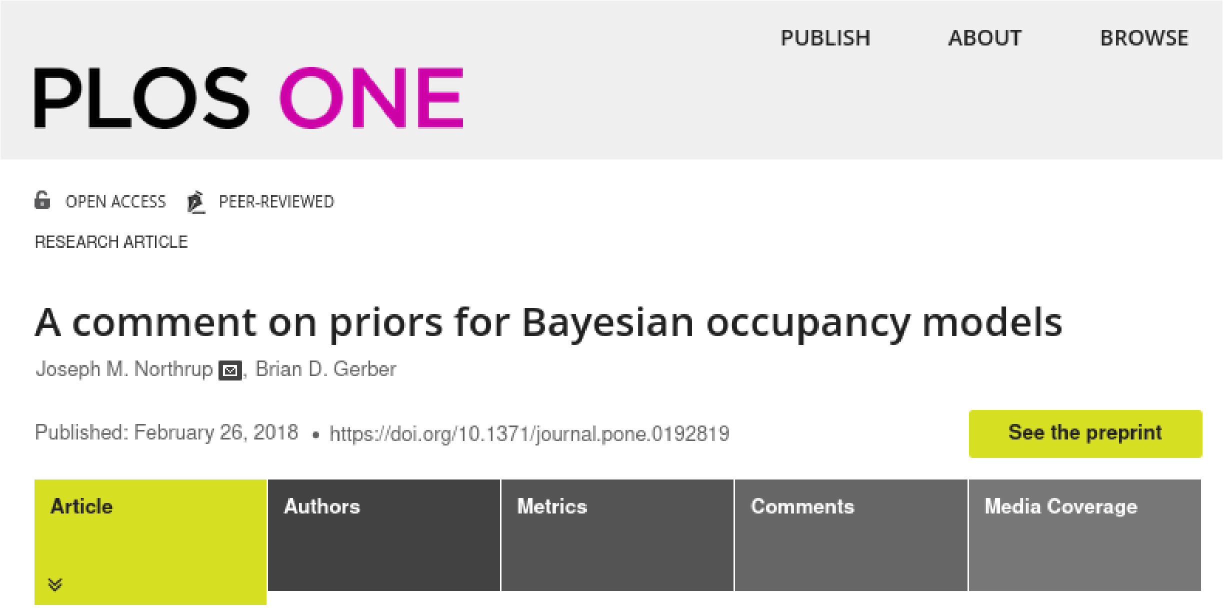
Priors on regression coefficients in occupancy models

- A standard prior in regression models for the intercept and coefficients is a Normal prior with mean 0 and a very big variance (e.g., 1000).
- However, this actually becomes a very informative prior in occupancy models (and any type of binomial GLM)!!
- This is because the regression coefficients are on the logit scale.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RESEARCH ARTICLE

A comment on priors for Bayesian occupancy models

Joseph M. Northrup, Brian D. Gerber

Published: February 26, 2018 • https://doi.org/10.1371/journal.pone.0192819

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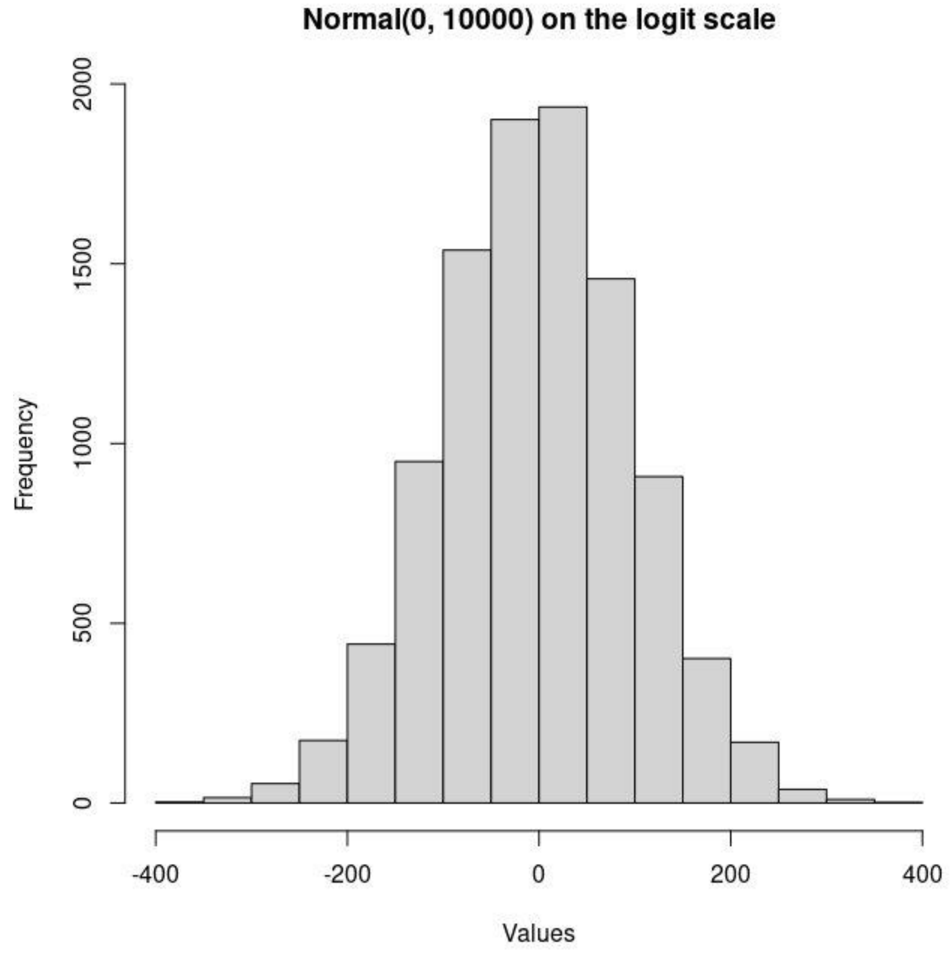
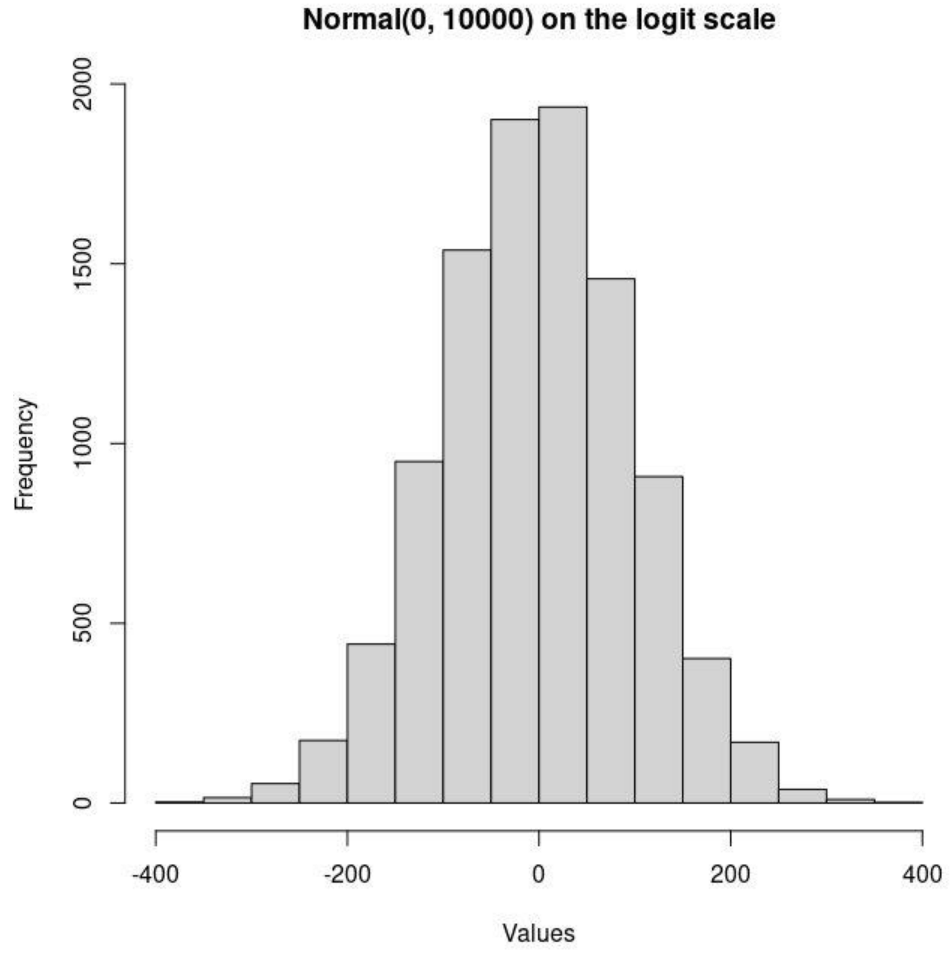
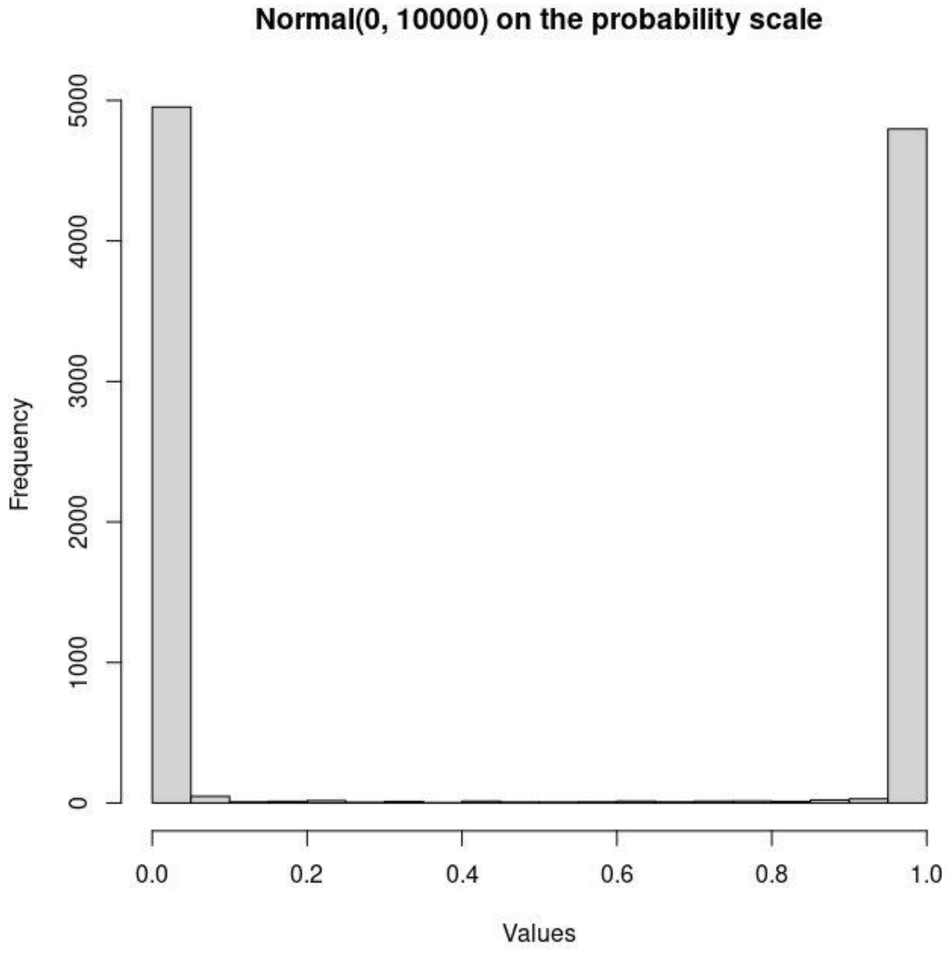
Priors on regression coefficients in occupancy models



Priors on regression coefficients in occupancy models





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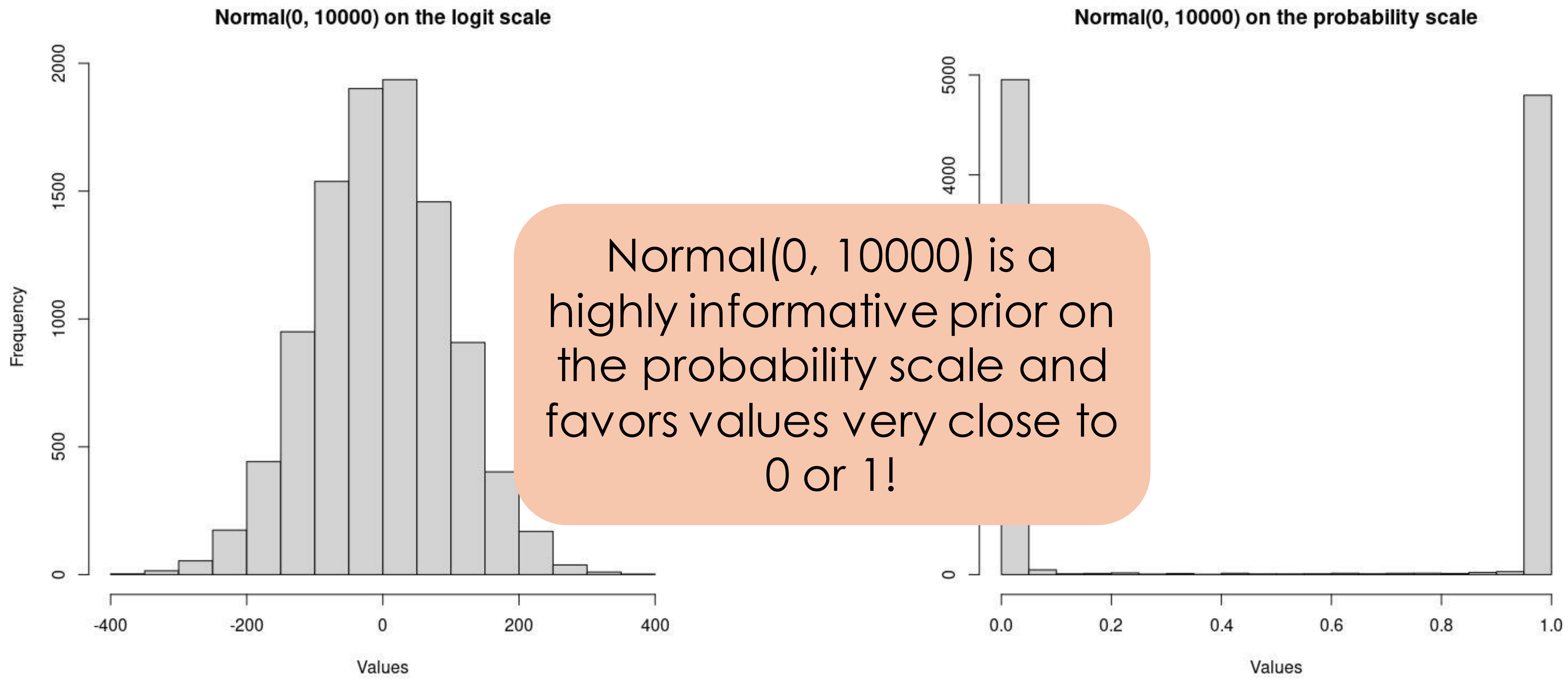
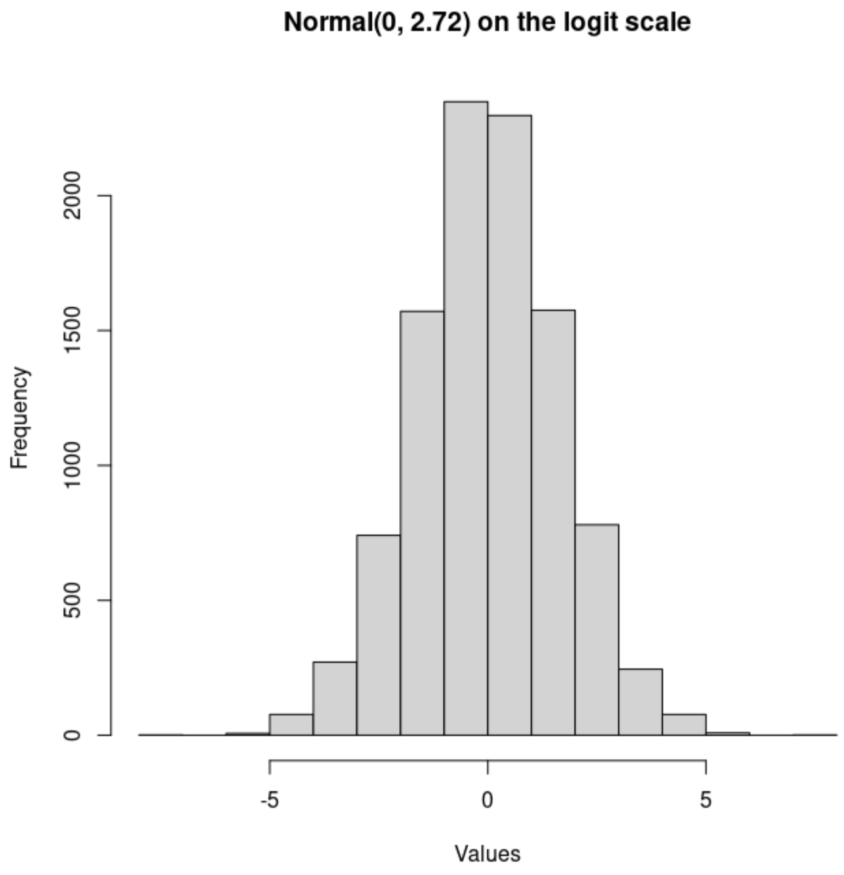


Normal(0, 10000) is a highly informative prior on the probability scale and favors values very close to 0 or 1!

Priors on regression coefficients in occupancy models

- Instead, a good prior is Normal(0, 2.72)



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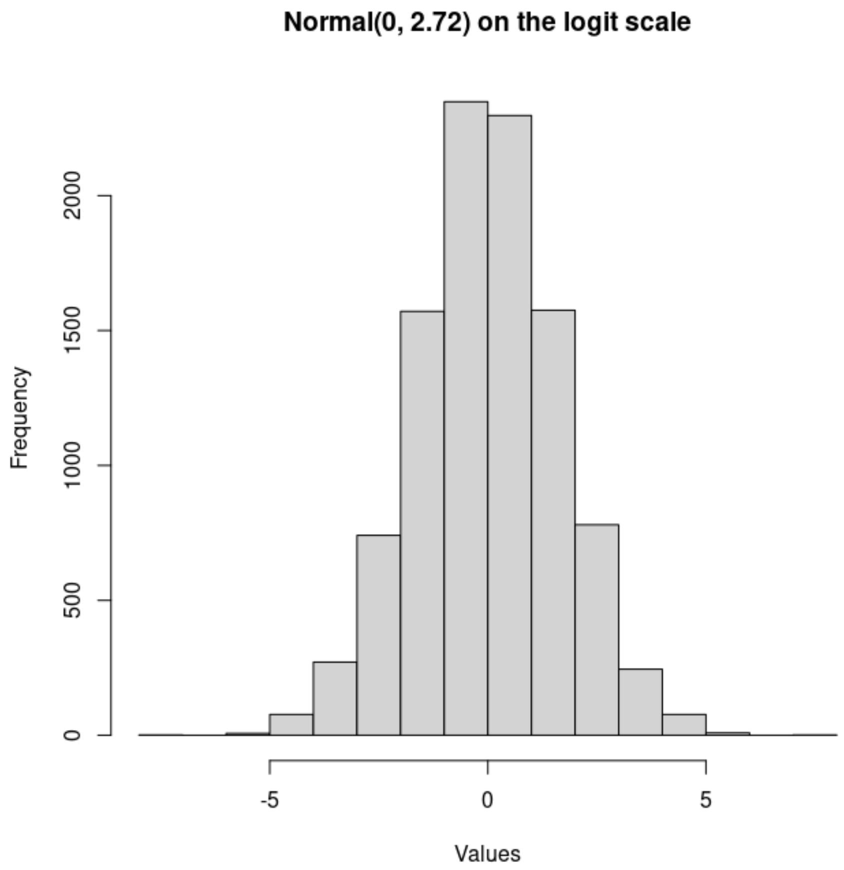

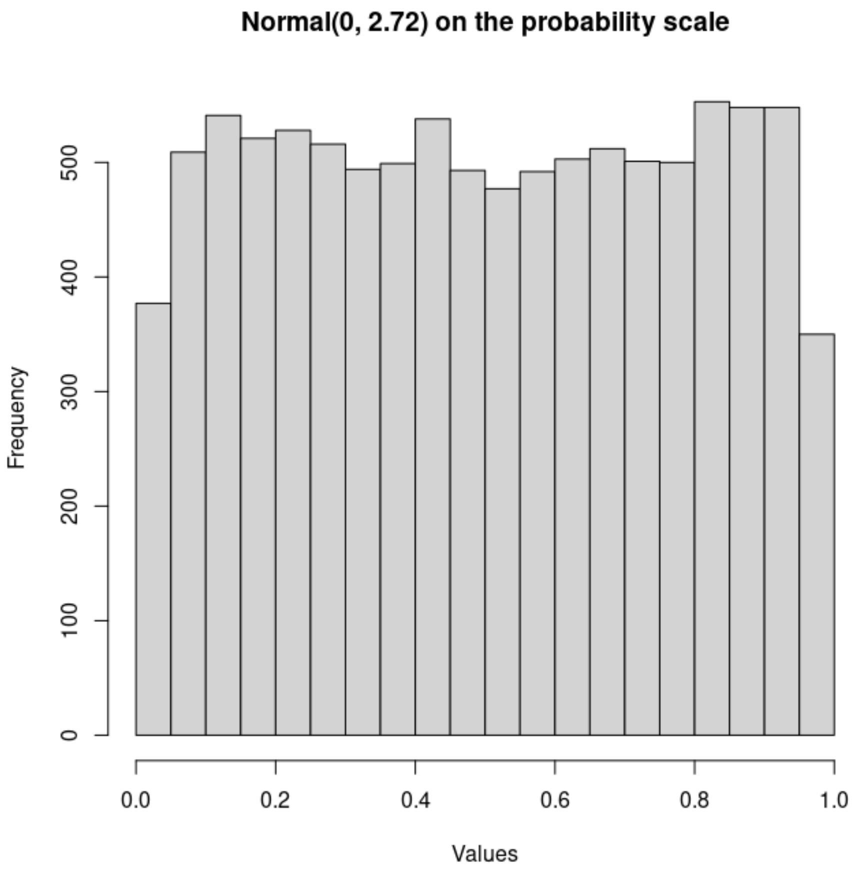

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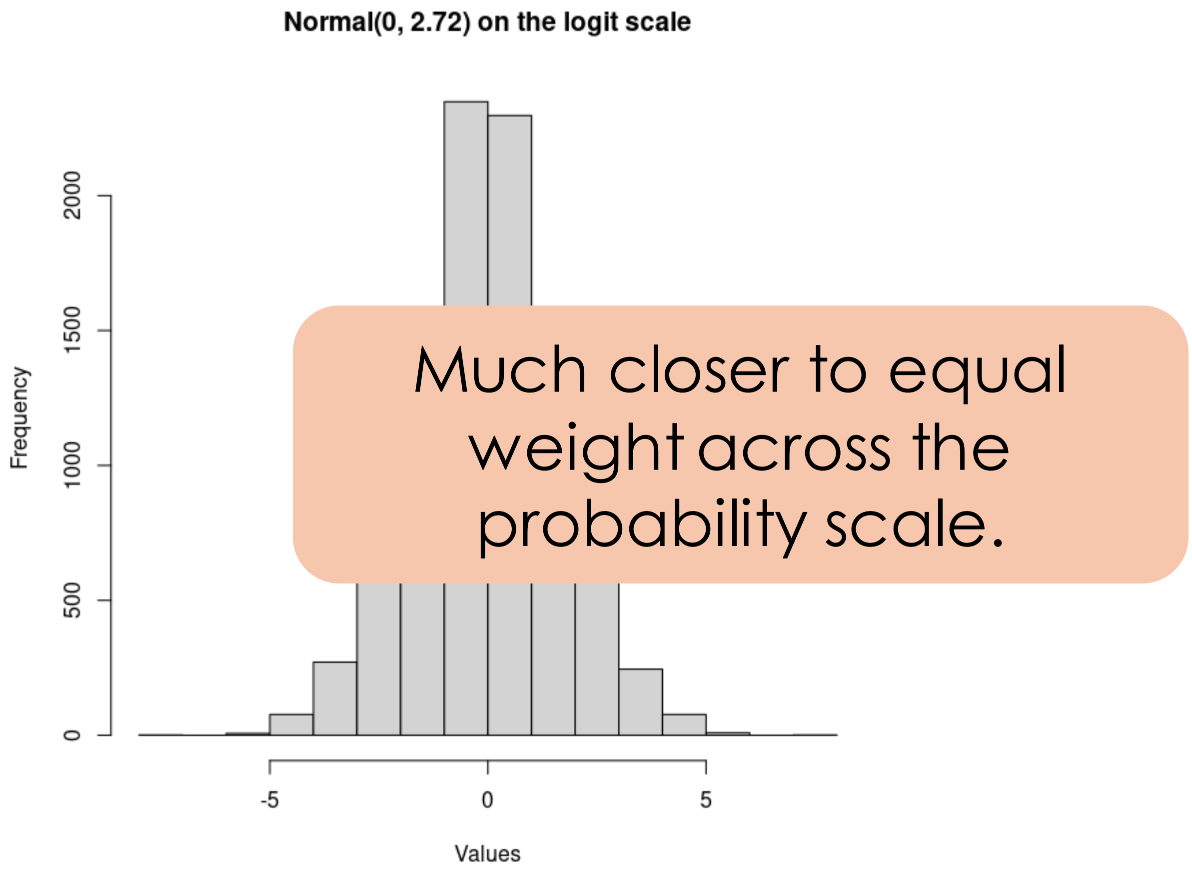

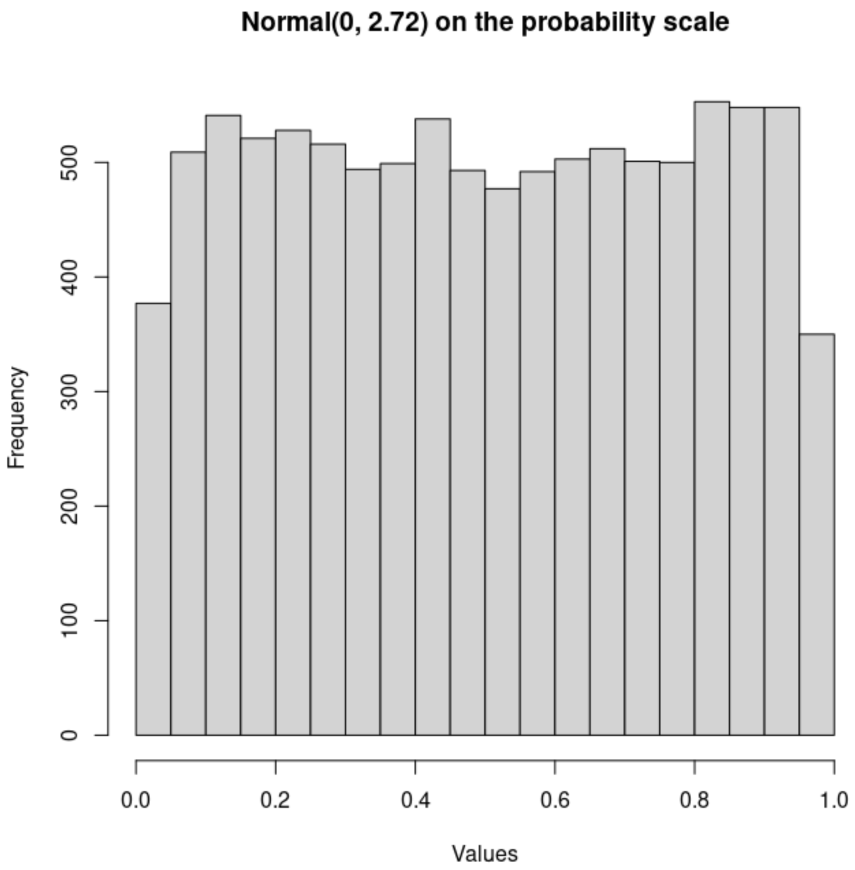

Fitting spatial occupancy models in `spOccupancy`

- Function: `spPGOcc` (spatial Pólya-gamma occupancy model)
- Supports both full GP and NNGP models.
- The model is implemented using an algorithm called an Adaptive Metropolis sampler, which requires special considerations.

```
spPGOcc(occ.formula, det.formula, data, inits, priors,
        tuning, cov.model = "exponential", NNGP = TRUE,
        n.neighbors = 15, search.type = "cb", n.batch,
        batch.length, accept.rate = 0.43,
        n.omp.threads = 1, verbose = TRUE, n.report = 100,
        n.burn = round(.10 * n.batch * batch.length),
        n.thin = 1, n.chains = 1, k.fold, k.fold.threads = 1,
        k.fold.seed = 100, k.fold.only = FALSE, ...)
```

A quick overview of the adaptive Metropolis algorithm

- Estimating the spatial decay parameter ϕ is difficult.
- At each step of the MCMC algorithm, we propose a new value for ϕ.
- The proposed value comes from a Normal distribution:
  - Mean: the current value of ϕ
  - Variance: the ***Tuning Variance***
- We use an algorithm to determine if we should keep the previous value, or accept the new one.
- Ideally, we want to accept the proposed value around 43% of the time.

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- An adaptive Metropolis algorithm changes the tuning variance throughout the MCMC sampler to get closer to the target acceptance rate.
- To do this, the MCMC samples are split into a set of ***batches***
- Each batch has a pre-specifed set of MCMC samples (e.g., 25)
- After each batch, the tuning variance is adjusted to get closer to an acceptance rate of 0.43.

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- To do this, the MCMC samples are split into a set of ***batches***
- Each batch has a pre-specifed set of MCMC samples (e.g., 25)
- After each batch, the tuning variance is adjusted to get closer to an acceptance rate of 0.43.
- **This approach can greatly speed up the time to convergence for difficult to estimate parameters like ϕ.**

What do you need to specify in `spOccupancy`?

1. The initial tuning variance (`tuning`).
2. The acceptance rate (`accept.rate`).
3. The number of MCMC batches to run (`n.batch`).
4. The number of MCMC samples in each batch (`batch.length`).

The total number of MCMC samples is n.batch * batch.length

Exercise: Spatial modelling of the European goldfinch

`04-spatial-european-goldfinch.R`