

Modelling habitat selection across multiple spatial scales using varying coefficient regression

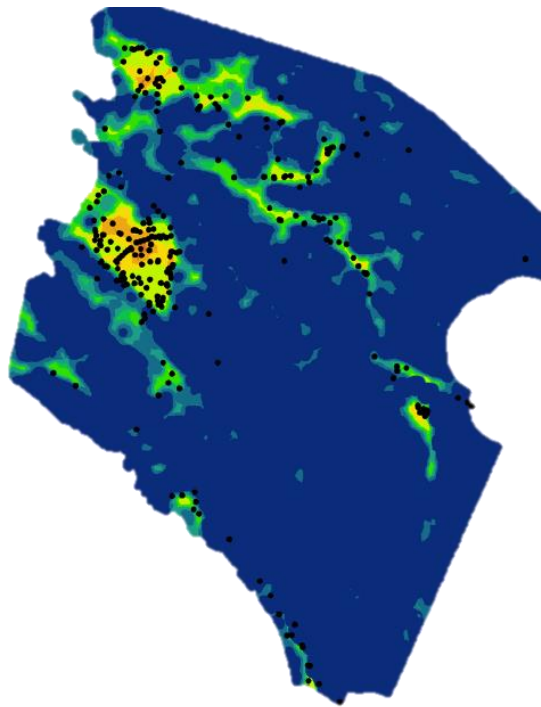
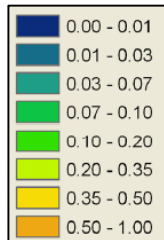
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Species-habitat relationship

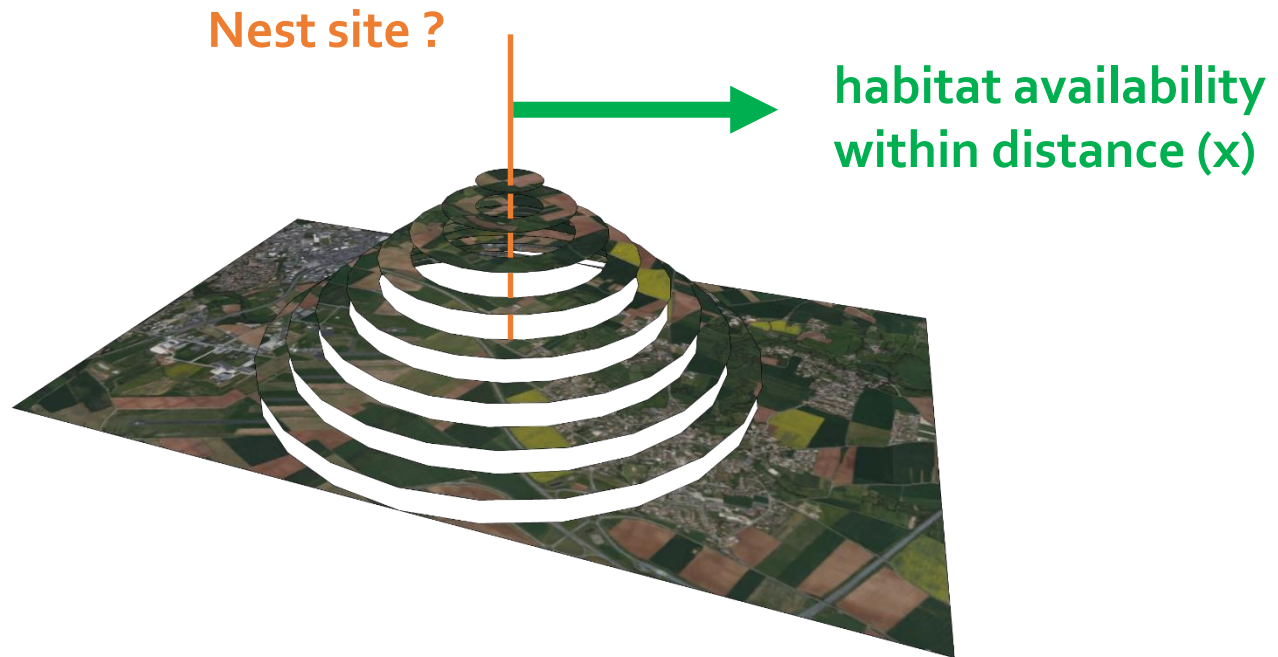
$$\text{Abundance} = f_1(\text{habitat}_1) + f_2(\text{habitat}_2) + \dots + \varepsilon$$



Predictor variables	Coefficient	SE
(Intercept)	-11.05	0.77
AgriPast	-0.71	0.97
AgriPast ²	0.43	0.30
WaterSurf	0.55	0.18
Log(AgriPerm)	-1.19	0.48
Aquatic	-0.28	0.07
Urban	-0.29	0.07
AgriIntens	-0.60	0.09
Stream	0.15	0.05
DistRoad	0.26	0.08
AgriHetero	-0.33	0.09

(Gadenne et al. 2014)

Scale-dependence

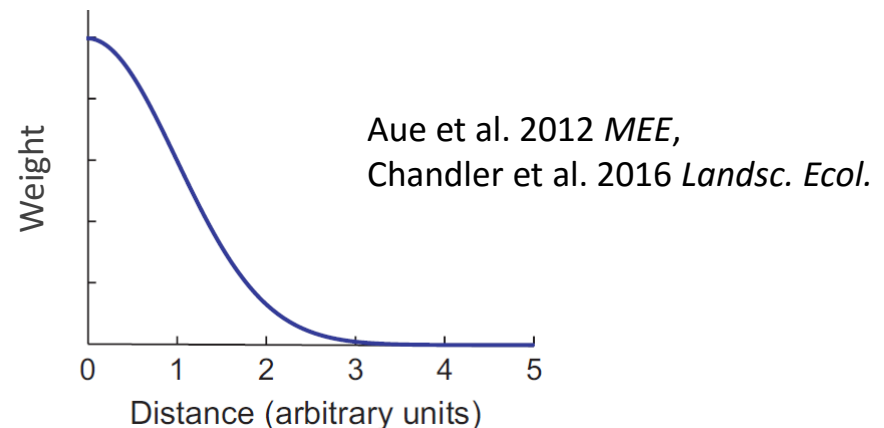
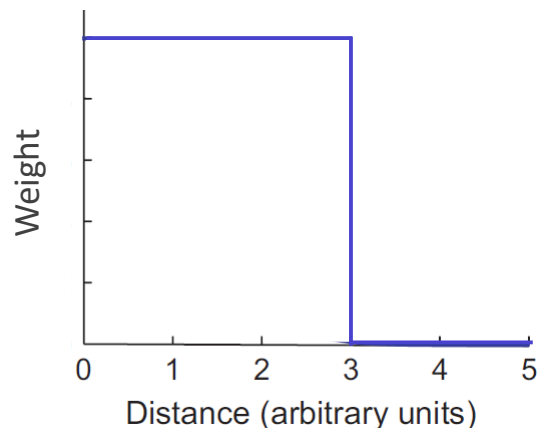


Statistical considerations (1)

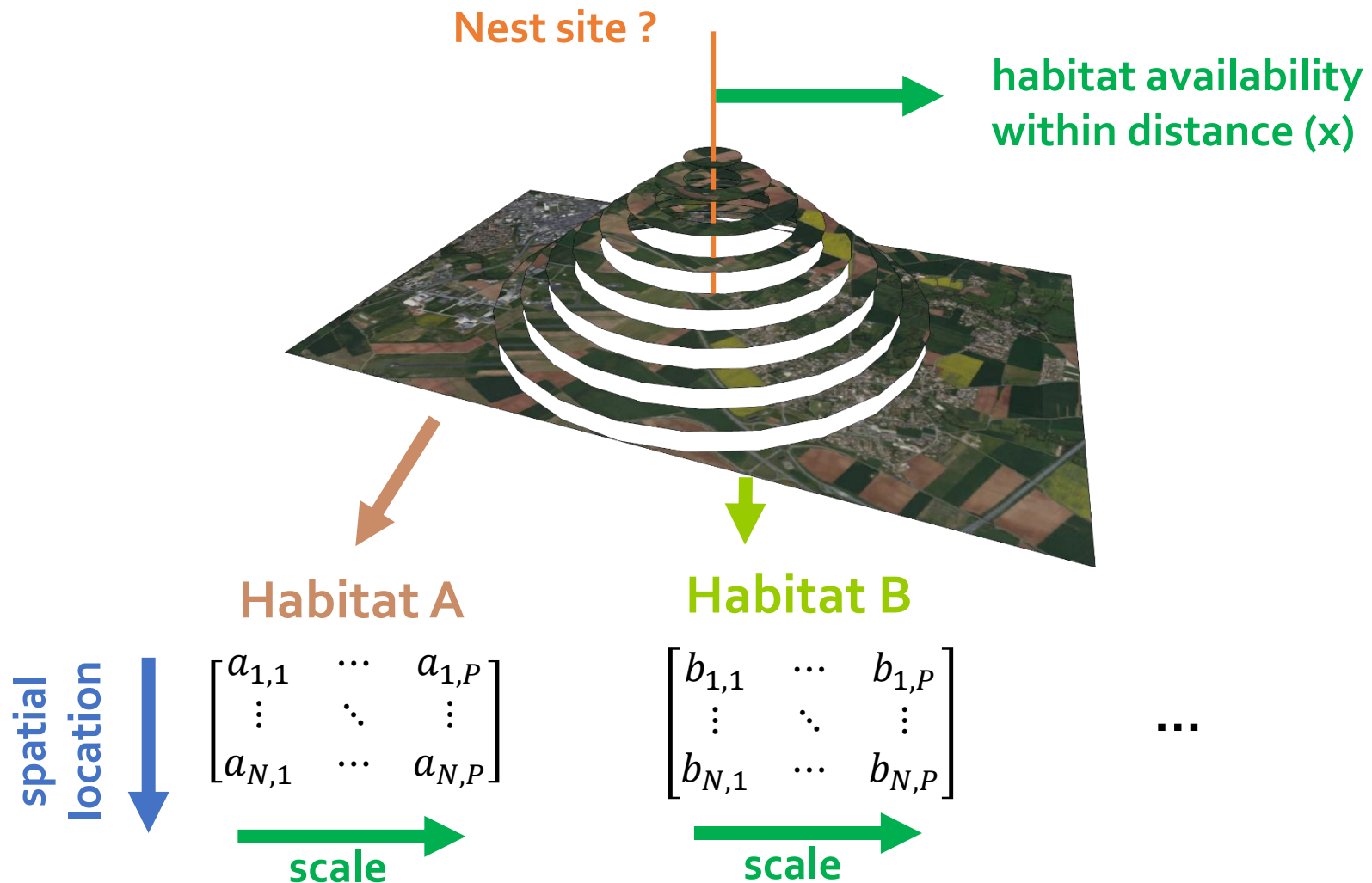
- Selecting optimal scale(s)
 - Model selection: likelihood profiling of fixed optimal scale?
 - Optimization / multiple testing
 - Control for effective # parameters / Overfitting?

Statistical considerations (1)

- Selecting optimal scale(s)
 - Model selection: likelihood profiling of fixed optimal scale?
 - Optimization / multiple testing
 - Control for effective # parameters / Overfitting?
- Selecting optimal shape: step function, gradual decay?



Scale-dependence



Statistical considerations (2)

- Combining effects at multiple scales
 - Multicollinearity
 - Multiple sets of coefficients equally plausible
 - -> ill-defined/unstable/overfitting models

Statistical considerations (2)

- Combining effects at multiple scales
 - Multicollinearity
 - Multiple sets of coefficients equally plausible
 - -> ill-defined/unstable/overfitting models
- Regularization:
 - Penalizing excessive variance in the coefficients by imposing a smoothness constraint

Insights from ecology

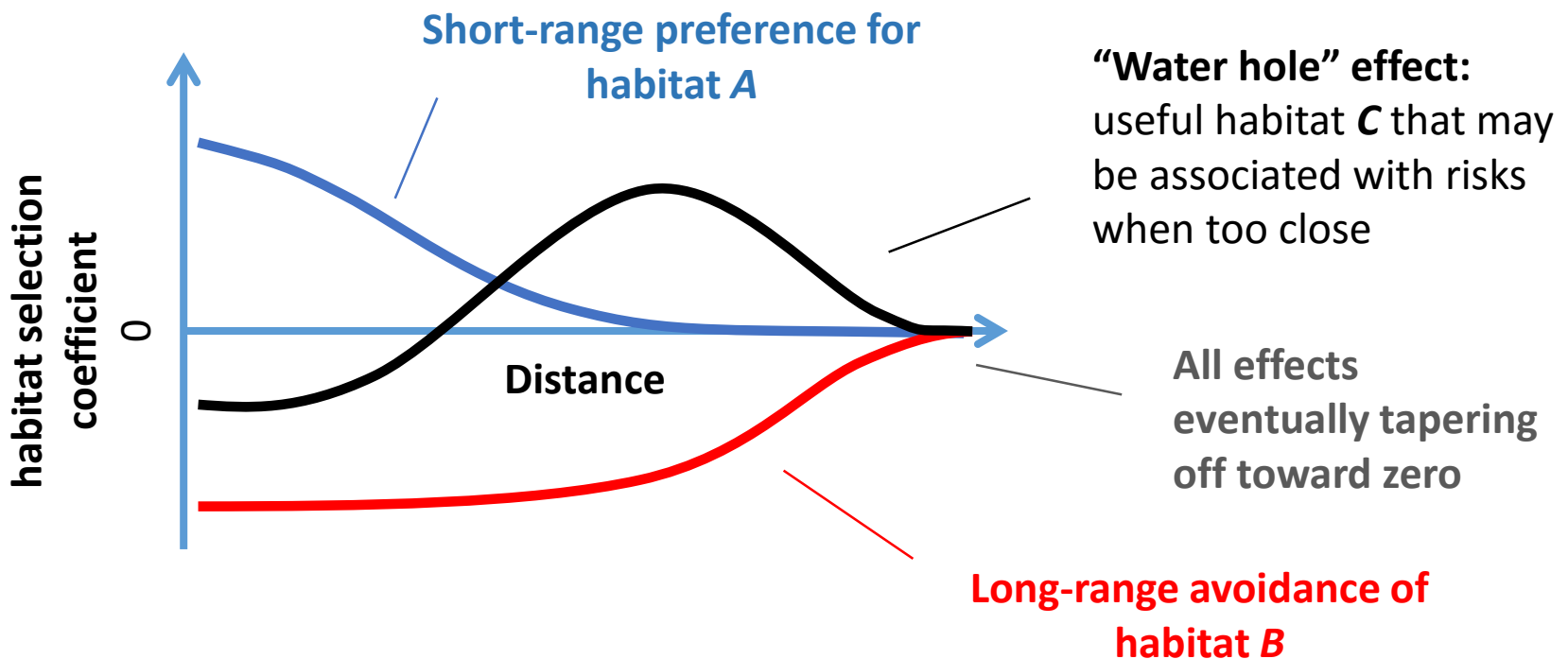
Scale of habitat effect
should depend on function

- Habitat for breeding
- Habitat for hiding
- Habitat for feeding
- ...



Insights from ecology

- Habitat selection strength varies with spatial scale.
- Shape and scale of selection habitat-specific.



We need

a practical approach to gain ecological insight about
the strength, shape and scale of habitat selection,
and able to deal with multicollinearity

Varying coefficient regression

See e.g. Hastie and Tibshirani (1993)

- Coefficients α_p for habitat A_p varying smoothly with distance p .

$$Y_i \sim \text{Poisson}(\lambda_i)$$

$$\log \begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_N \end{pmatrix} = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \gamma + \begin{bmatrix} a_{1,1} & \cdots & a_{1,P} \\ \vdots & \ddots & \vdots \\ a_{N,1} & \cdots & a_{N,P} \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_P \end{bmatrix}$$

$$\begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_P \end{bmatrix} = f \left(\begin{bmatrix} 1 \\ \vdots \\ P \end{bmatrix} \right)$$

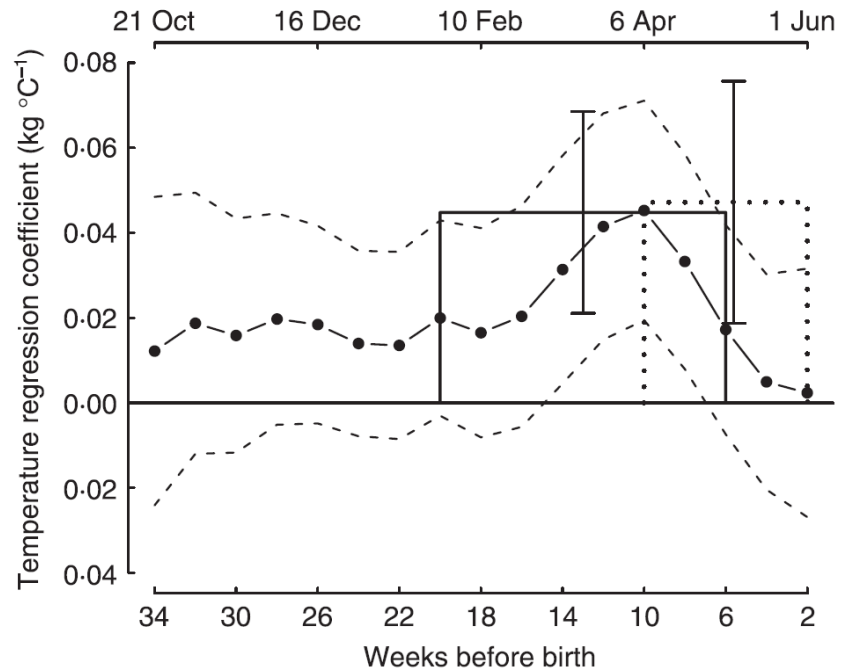
- f is some smooth function

Sims, Elston et al. (2007) Journal of Animal Ecology

- Red deer weight at birth ~ temperature prior to birth
- Coefficients for temperature varying smoothly with time lag.

• First-order random walk
“Difference Penalty Regression”

- Coded in R (about 60 lines)



Varying coefficient regression

- Coefficients α_p for habitat A_p varying smoothly with distance p .

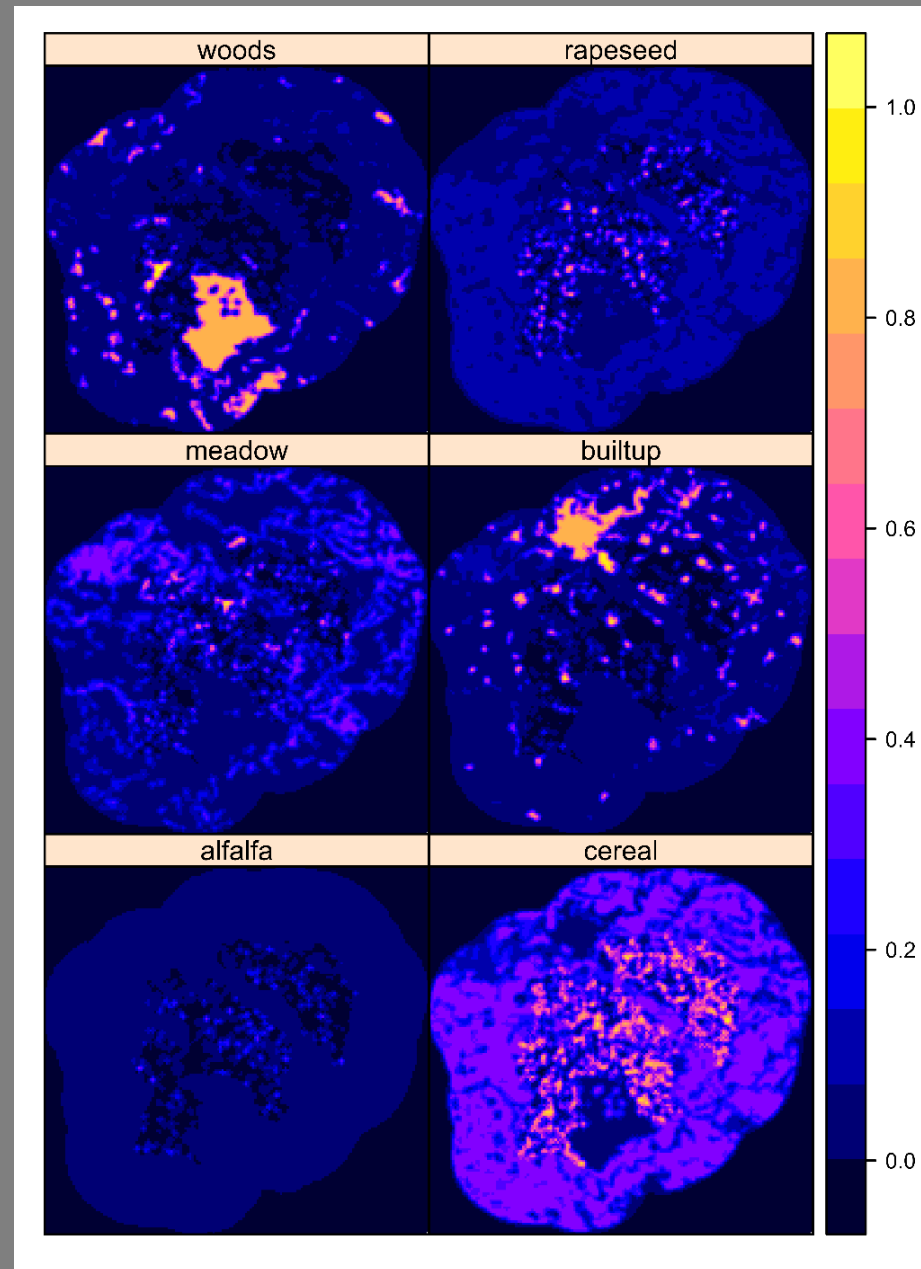
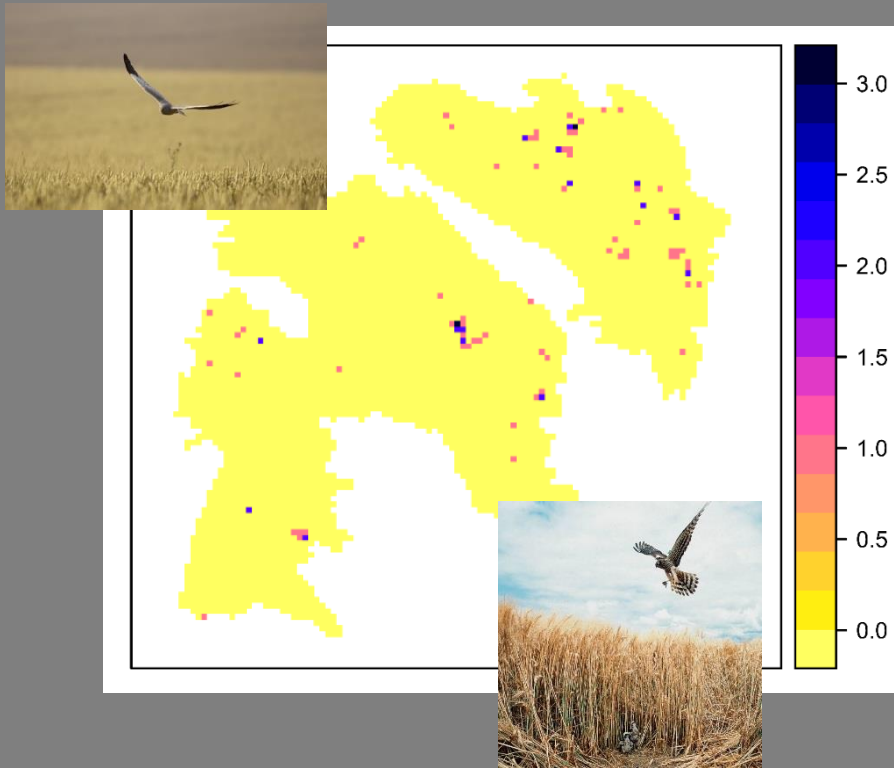
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- f is some smooth function (e.g. thin-plate spline).
- Estimated with `mgcv::gam` (Wood 2006) in R using GCV (1 line of R code)

Illustration

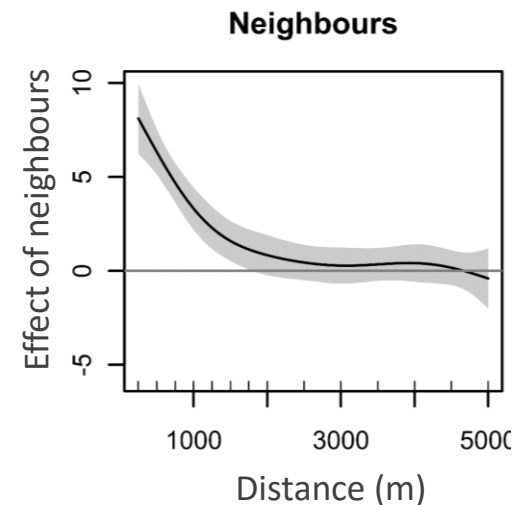
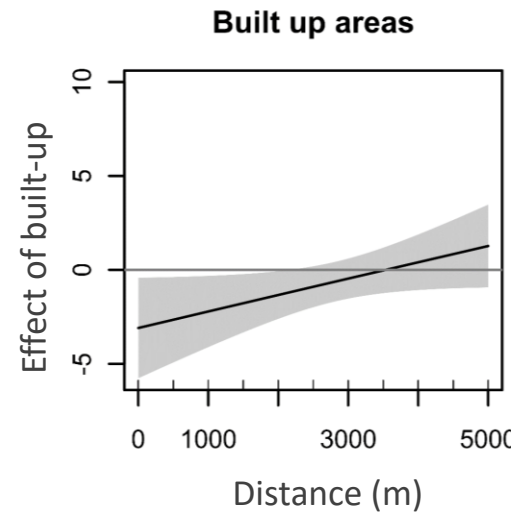
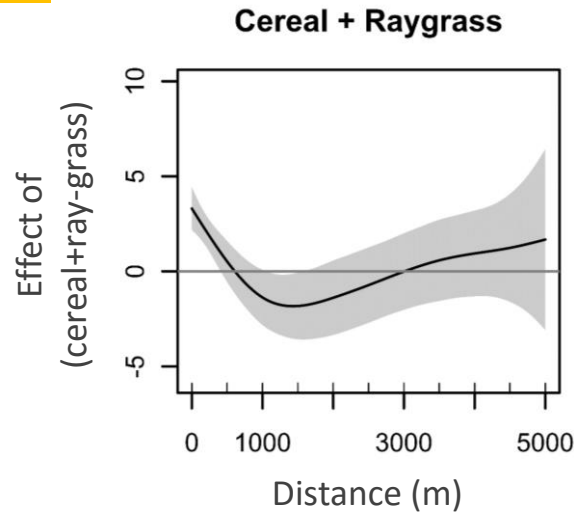
Nest site selection in Montagu's harrier (Semi-colonial raptor)



Illustration

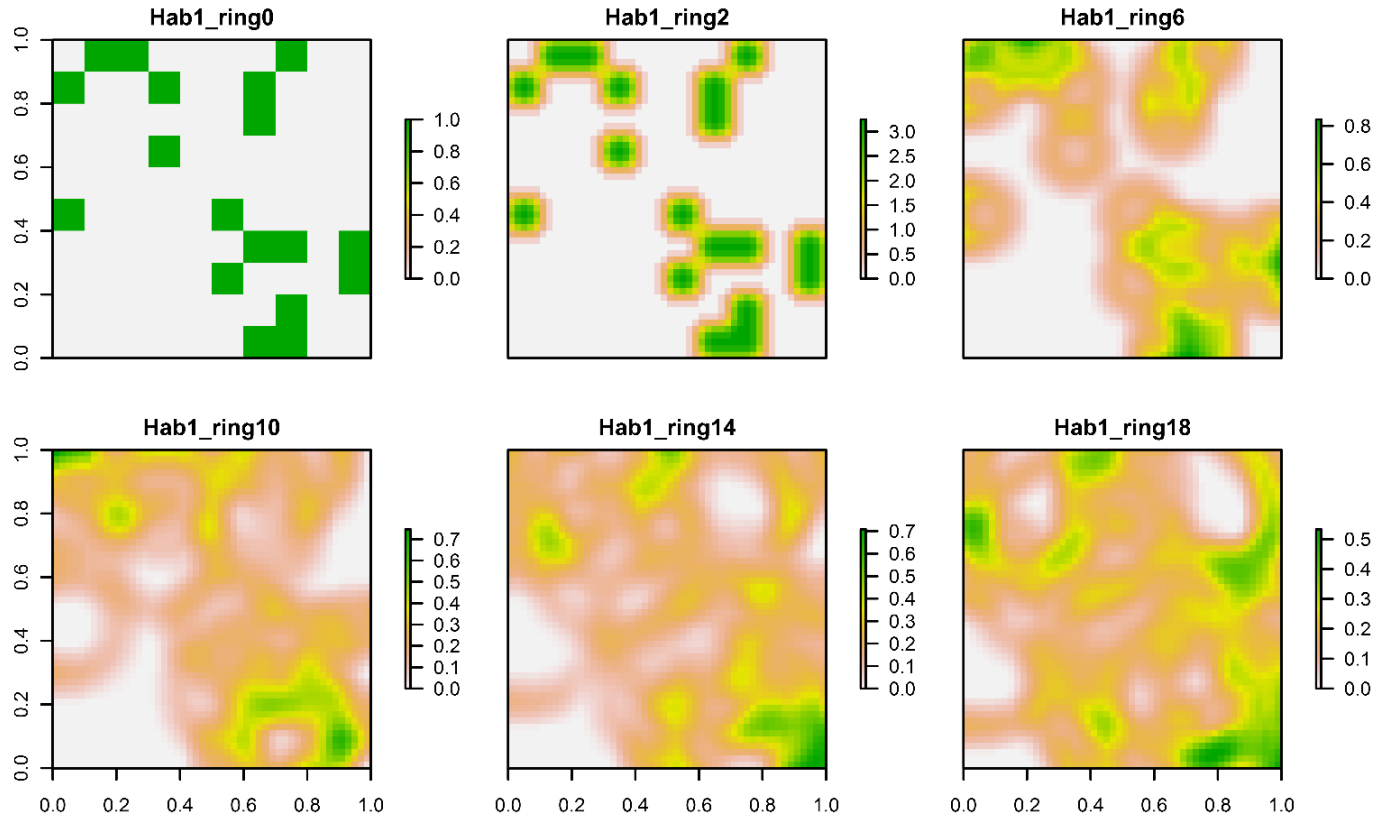


- Nesting and foraging habitats selected at short range (<1 km) with respect to foraging range (~5 Km).
- Built up areas avoided up to 2-3 Km.
- Seeks proximity to conspecifics within 1-1.5 Km.



Simulations

(1) Random landscapes: compute habitat availability within concentric rings (radius $x+\delta x$)



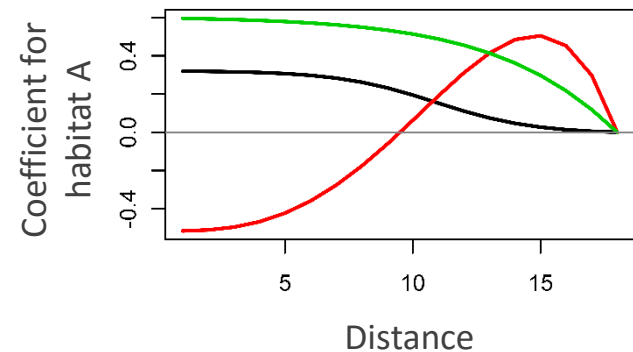
Simulations

(2) Random habitat selection functions $f(p)$

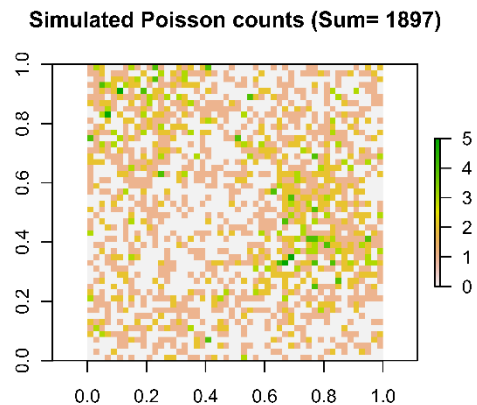
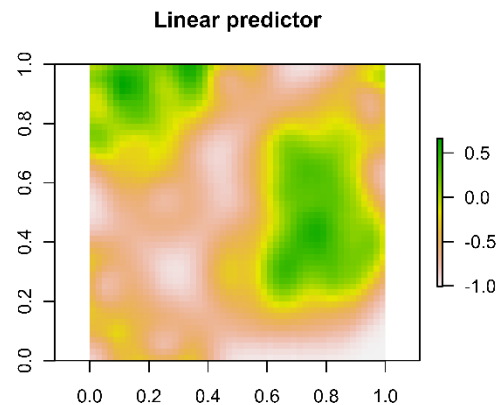
Either **Logistic** or **Beta**($U(0.5,10)$, $U(0.5,10)$)

Last coefficient always zero.

Direction \sim binomial(0.5)

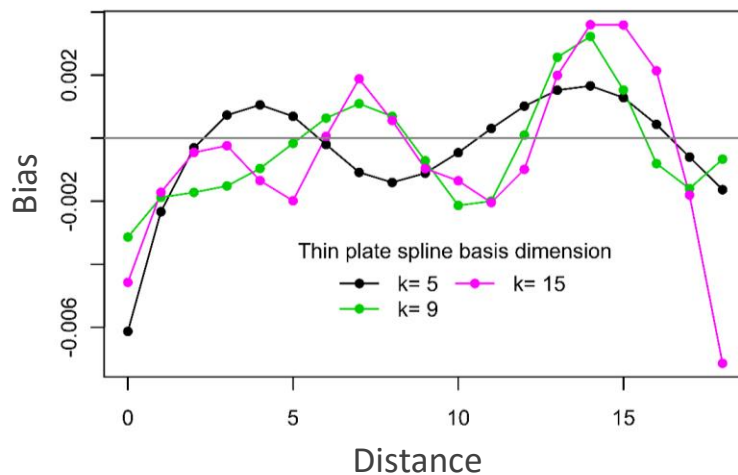
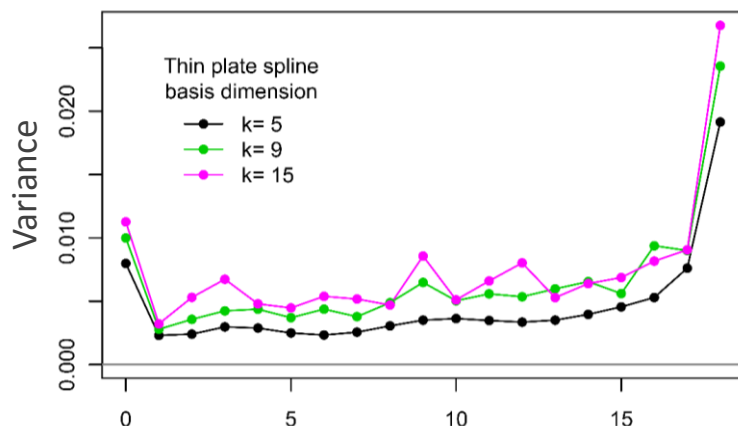


(3) Simulated species distributions

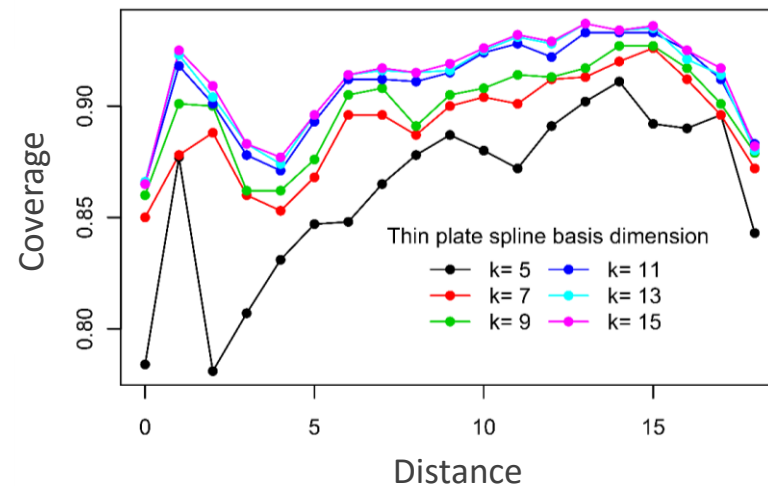


Model performance

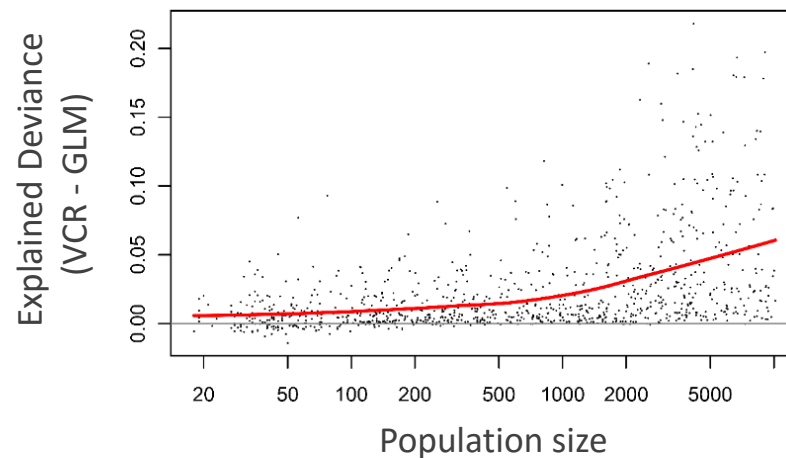
Point-wise variance and bias of coefficients α



Point-wise coverage for α



Explained Deviance



Conclusions

- **Multicollinearity** across spatial scales **taken care of** by smoothing function f .
- Great **simplification of model selection**:
1-stop estimation of **strength, shape and scale** of habitat selection.
- **Gains in stability and explanatory power** thanks to borrowing information across spatial scales.
- **Simple implementation** with standard software.
- **Ecologically meaningful**.

Future directions

- Investigate performance of different smoothing functions, e.g. difference penalty (Sims *et al.* 2007) or parametric smoothers?
- Control for scale-dependent collinearity between different resources in a multi-habitat regression setting.
- Impose explicit zero-effect constraint at large distances?