AppliBUGS – Montpellier – November, 28th 2014

Hierarchical Bayesian species distribution models with the **hSDM** R Package

Ghislain Vieilledent[⋆,1] Cory Merow[2] Jérôme Guélat[3]
Andrew M. Latimer[4] Marc Kéry[3]
Alan E. Gelfand[5] Adam M. Wilson[6] Frédéric Mortier[1]
and John A. Silander Jr.[2]

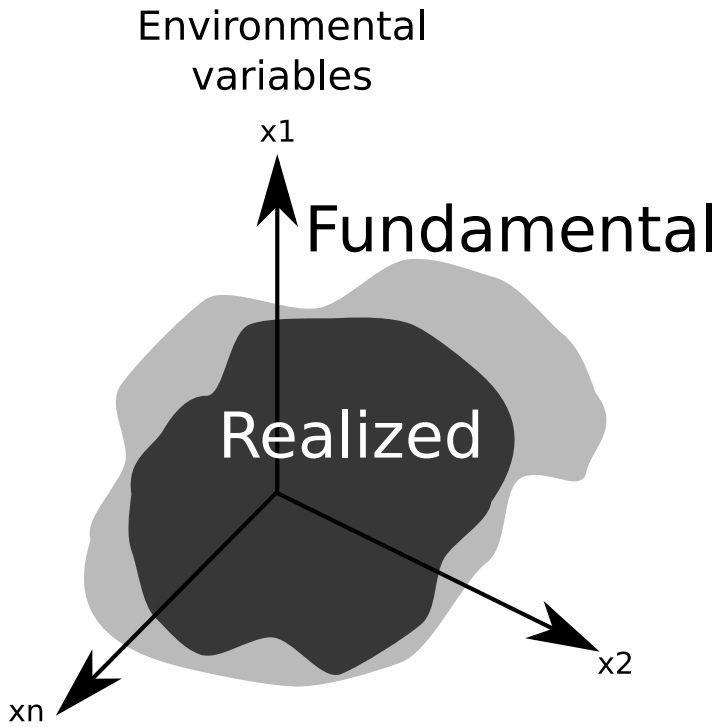
[1] **Cirad** France, [2] **University of Connecticut** USA, [3] **Swiss Ornithological Institute** Switzerland, [4] **University of California** USA, [5] **Duke University** USA, [6] **Yale University** USA

1. Introduction
   - Species distribution models
   - Issues : imperfect detection and spatial correlation
   - Available softwares
2. hSDM R package
   - Package main characteristics
   - Parameter inference
3. Examples
   - N-mixture iCAR model
   - Binomial iCAR model with large data-set
4. Recommendations
   - “statistical machismo” ?
   - hSDM and applied research in ecology

SDM definition

Objectives

- Identifying the suitable habitat for species persistence
- Reference : species niche (Hutchinson 1957)
- Representing this habitat spatially (maps)
- Applications : conservation biology

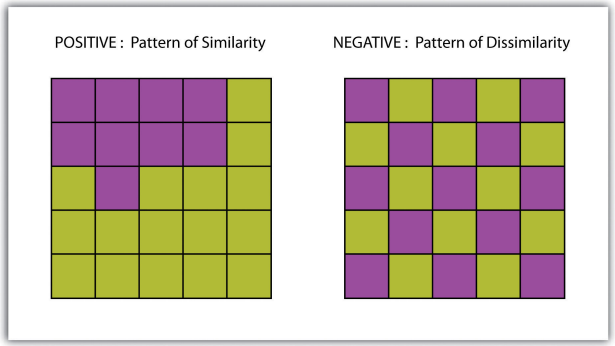


Imperfect detection

- Species is not observed perfectly ("Now you see me, now you don't")
- Detection probability < 1
- Treating observations as the "true" species distribution might lead to completely wrong habitat models
- See **Lahoz-Monfort et al.** 2014 *Global Ecology and Biogeography*

Spatial autocorrelation

- Most species present geographical patchiness
- Positive spatial correlation
- Causes :
  - Exogeneous environmental factors (climate, soil)
  - Endogeneous biotic processes (dispersal, migration)
- Ignoring spatial correlation may lead to biased conclusions about ecological relationships
- See **Lichstein et al.** 2002 *Ecological Monographs*



Site-occupancy and N-mixture models

Site-occupancy model (occurrence data)

Ecological process :

$Z_i \sim \mathcal{B}ernoulli(\theta_i)$

$\text{logit}(\theta_i) = X_i\beta$

Observation process :

$y_{it} \sim \mathcal{B}ernoulli(\delta_{it} \times Z_i)$

$\text{logit}(\delta_{it}) = W_{it}\gamma$

N-mixture model (count data)

Ecological process :

$N_i \sim \mathcal{P}oisson(\lambda_i)$

$\log(\lambda_i) = X_i\beta$

Observation process :

$y_{it} \sim \mathcal{B}inomial(N_i, \delta_{it})$

$\text{logit}(\delta_{it}) = W_{it}\gamma$

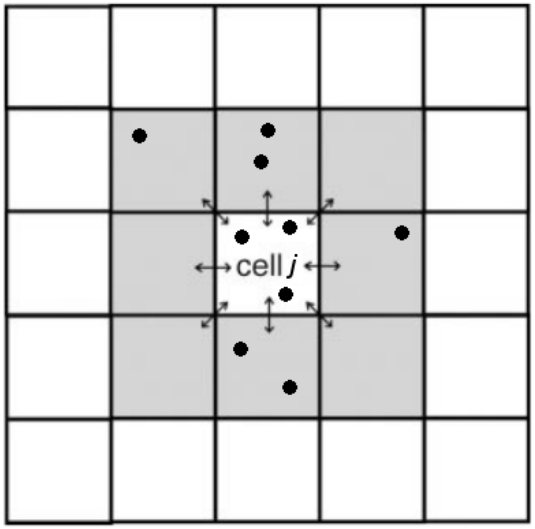
Repeated observations at particular sites (multiple visits)

CAR process

intrinsic CAR

$$p(\rho_j|\rho_{j'}) \sim \mathcal{N}ormal(\mu_j, V_\rho/n_j)$$

μ_j : mean of $\rho_{j'}$ in the neighborhood of j.
V_ρ : variance of the spatial random effects.
n_j : number of neighbors for cell j.



CAR process

Site-occupancy model (occurrence data)

Ecological process :

$Z_i \sim \mathcal{B}ernoulli(\theta_i)$

$\text{logit}(\theta_i) = X_i\beta + \rho_{j(i)}$

Observation process :

$y_{it} \sim \mathcal{B}ernoulli(\delta_{it} \times Z_i)$

$\text{logit}(\delta_{it}) = W_{it}\gamma$

N-mixture model (count data)

Ecological process :

$N_i \sim \mathcal{P}oisson(\lambda_i)$

$\log(\lambda_i) = X_i\beta + \rho_{j(i)}$

Observation process :

$y_{it} \sim \mathcal{B}inomial(N_i, \delta_{it})$

$\text{logit}(\delta_{it}) = W_{it}\gamma$

Available softwares

Softwares for mixture models

PRESENCE, **MARK**, **E-SURGE**, **unmarked**, **stocc**, **JAGS**, **stan**, **WinBUGS**, **OpenBUGS**

Softwares for spatial autocorrelation

OpenBUGS, **WinBUGS**, **BayesX**, **stocc**, **CARBayes**, **R-INLA**, **spatcounts**, **OpenBUGS**, **spdep**, **CARramps**, **spBayes**

Mixture models + spatial autocorrelation

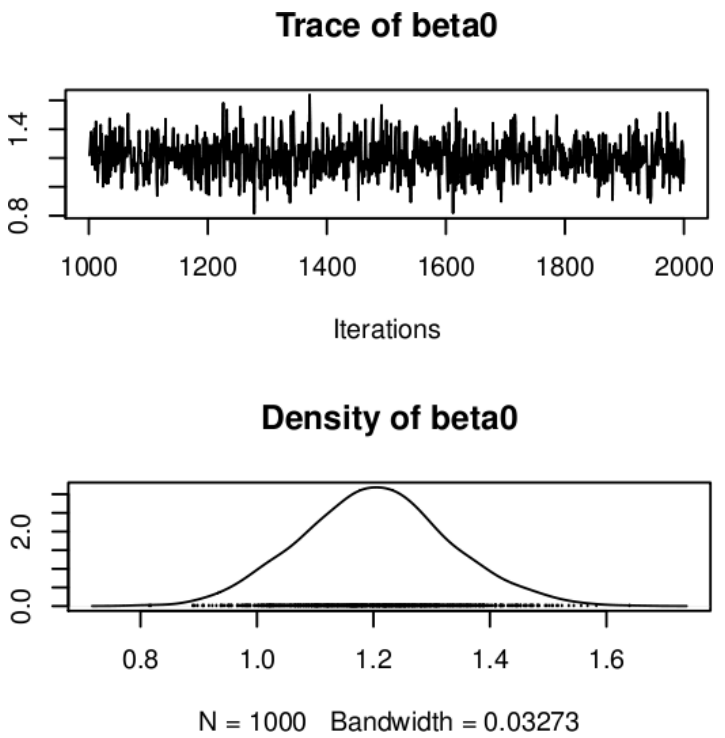
Very few softwares available and limitations : **OpenBUGS**, **WinBUGS** (might be slow), **stocc** (probit and binary data only).

Package main characteristics

- **hSDM** : R "user-friendly" package
- Mixture models : **site-occupancy**, **N-mixture**, but also **ZIB** and **ZIP** models
- Including a spatial autocorrelation process (**iCAR**)
- Web-site : `http://hSDM.sf.net`
- Vignette with several examples on simulated and real data-sets

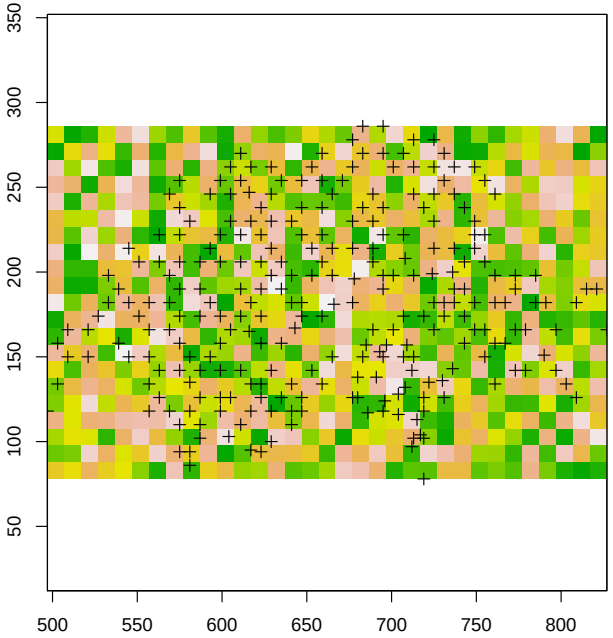
Parameter inference

- hierarchical Bayesian models
- MCMC methods (no approximation of the posterior)
- adaptive Metropolis within Gibbs (**"efficient"**)
- written in pure **C** code (**"fast"**)
- source code available through `git` on Sourceforge



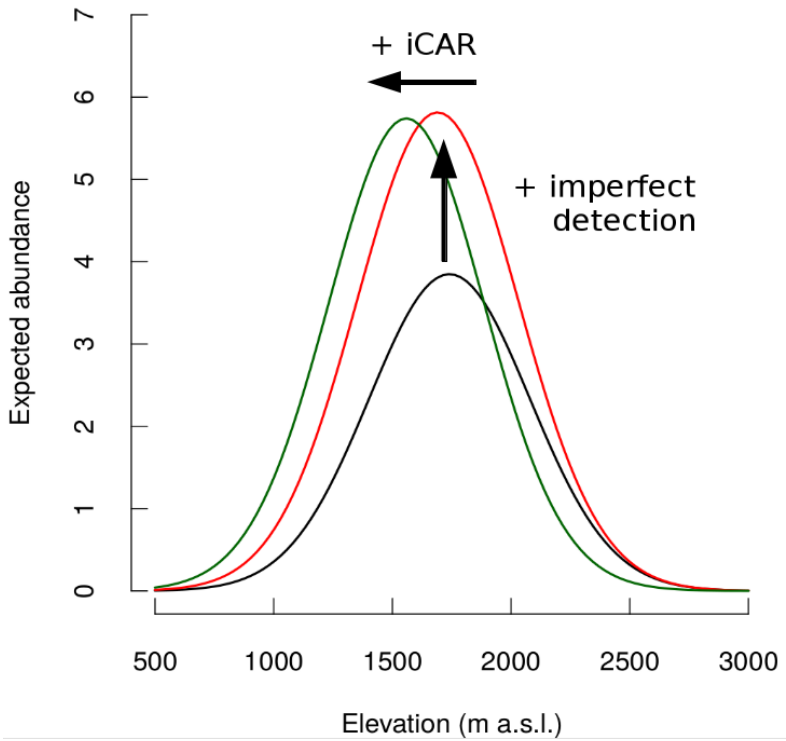
N-mixture iCAR model

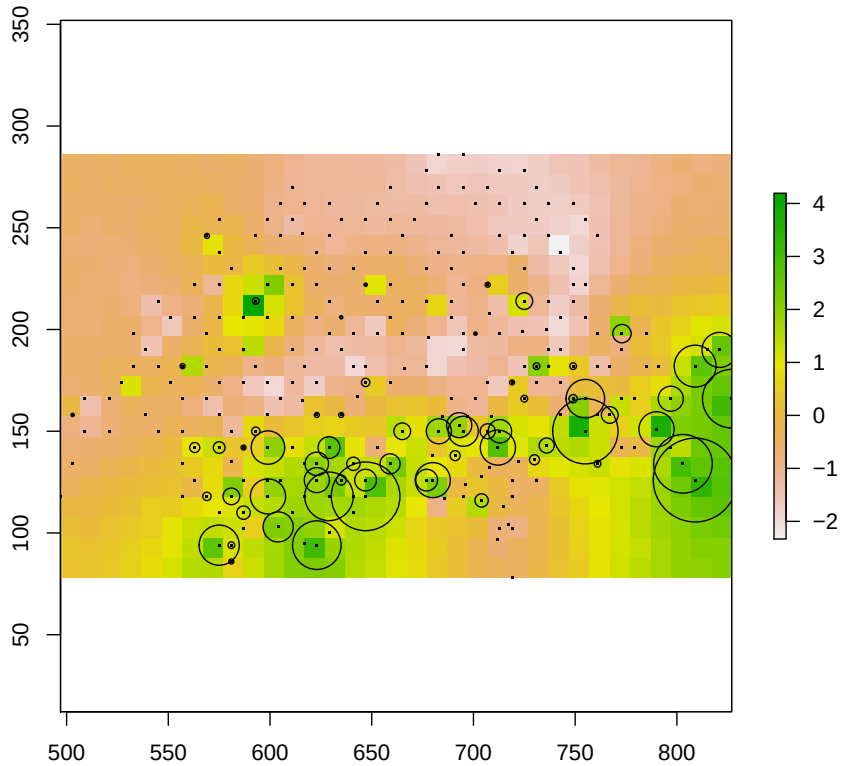
- **Kéry & Royle** 2010, *Journal of Animal Ecology*
- Abundance of the Willow tit (*Poecile montanus*)
- Switzerland
- 264 sites with 2 or 3 visits
- 10×10 km cells



N-mixture iCAR model

- Models of increasing complexity
- (1) Poisson, (2) N-mixture and (3) N-mixture + iCAR

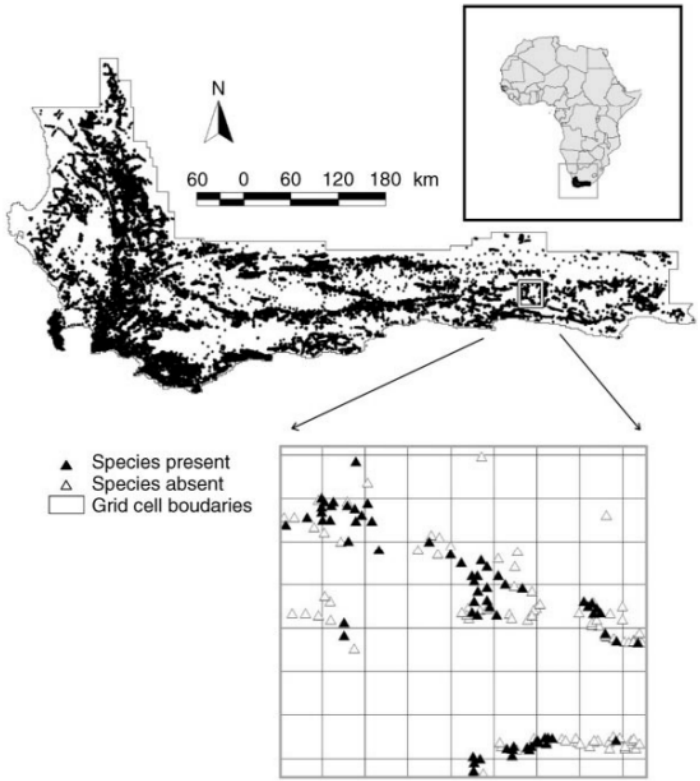




Spatial random effects (raster) and observed abundance (circles)

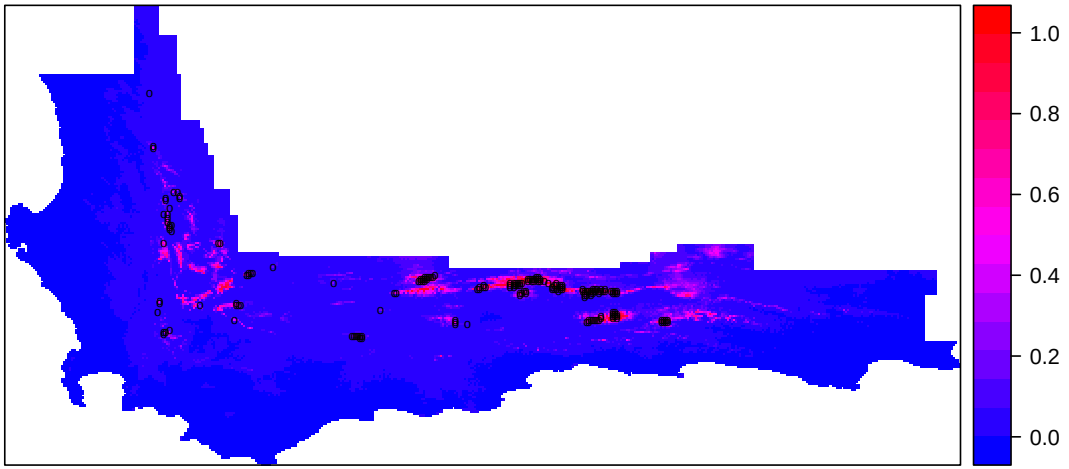
Binomial iCAR model with large data-set

- **Latimer et al.** 2006, *Ecological Applications*
- Occurrence of *Protea punctata*
- Cap Floristic Region (South Africa)
- 36909 1'×1' grid cells
- Too many data to use ⋆**BUGS** programs

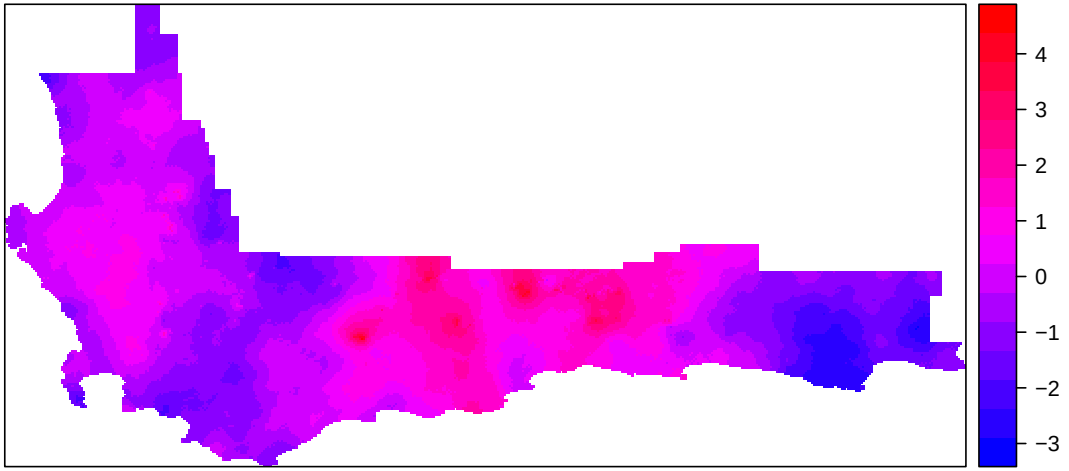


Binomial iCAR model with large data-set

Probability of presence



Spatial random effects



“statistical machismo” ?

Following **Brian McGill**’s post

- Bonferroni corrections
- Phylogenetic corrections
- Spatial regression
- Detection error
- Bayesian methods

“statistical machismo” ?

Following **Brian McGill**’s post

- Bonferroni corrections
- Phylogenetic corrections
- Spatial regression
- Detection error
- Bayesian methods

Can we be accused of “statistical machismo” ?

hSDM and applied research in ecology

Some recommendations

- Complex models need **appropriate data** (quantity + structure).
- Beware of over-parametrization and identifiability problems.

Complex models and applied research

- It is true that in some cases, complex models do not significantly improve our ecological knowledge of the species.
- Conservation planning : we need to identify the level of **model complexity** we need to reach in order to take good decisions.

When complex models are necessary ?

hSDM : tool to investigate the situations (species, place) where imperfect detection and spatial correlation lead to significant different results that impact decisions.

hSDM and applied research in ecology

Global Change Biology (2014) **20**, 3591–3592, doi: 10.1111/gcb.12728

EDITORIAL COMMENTARY

Editorial commentary on 'BIOMOD – optimizing predictions of species distributions and projecting potential future shifts under global change'

WILFRIED THUILLER[1,2]

[1]*Laboratoire d'Écologie Alpine (LECA), University of Grenoble Alpes, Grenoble F-38000, France,* [2]*Laboratoire d'Écologie Alpine (LECA), CNRS, Grenoble F-38000, France*

hSDM R package is mentioned alongside MAXENT, biomod2 and ppmlasso


. . . Thank you for attention . . .