

# **Some spacetime models for areal data**

Elias Teixeira Krainski<sup>1</sup>

<sup>1</sup>King Abdullah University of Science and Technology (KAUST)

May 2024

# Outline

The pre spacetime work

Spacetime models

Continuous domain attempts

## **The pre spacetime work**

# A graph from the map (Scotland)

Scotland map



Neighborhood graph



## Besag: random walk over areas, Besag (1974)

$$\pi(x_i | \mathbf{x}_{-i}, \tau) \sim N\left(\frac{1}{n_i} \sum_{j \sim i} x_j, \frac{1}{n_i \tau}\right)$$

where  $j \sim i$  means  $j$  neighbour of  $i$ . This gives:

## Besag: random walk over areas, Besag (1974)

$$\pi(x_i | \mathbf{x}_{-i}, \tau) \sim N\left(\frac{1}{n_i} \sum_{j \sim i} x_j, \frac{1}{n_i \tau}\right)$$

where  $j \sim i$  means  $j$  neighbour of  $i$ . This gives:

$$\pi(\mathbf{x} | \tau) \propto \tau^{\frac{n-1}{2}} \exp\left(-\frac{\tau}{2} \sum_i^n \left(x_i - \frac{1}{n_i} \sum_{j \sim i} x_j\right)^2\right)$$

# Besag: random walk over areas, Besag (1974)

$$\pi(x_i | \mathbf{x}_{-i}, \tau) \sim N\left(\frac{1}{n_i} \sum_{j \sim i} x_j, \frac{1}{n_i \tau}\right)$$

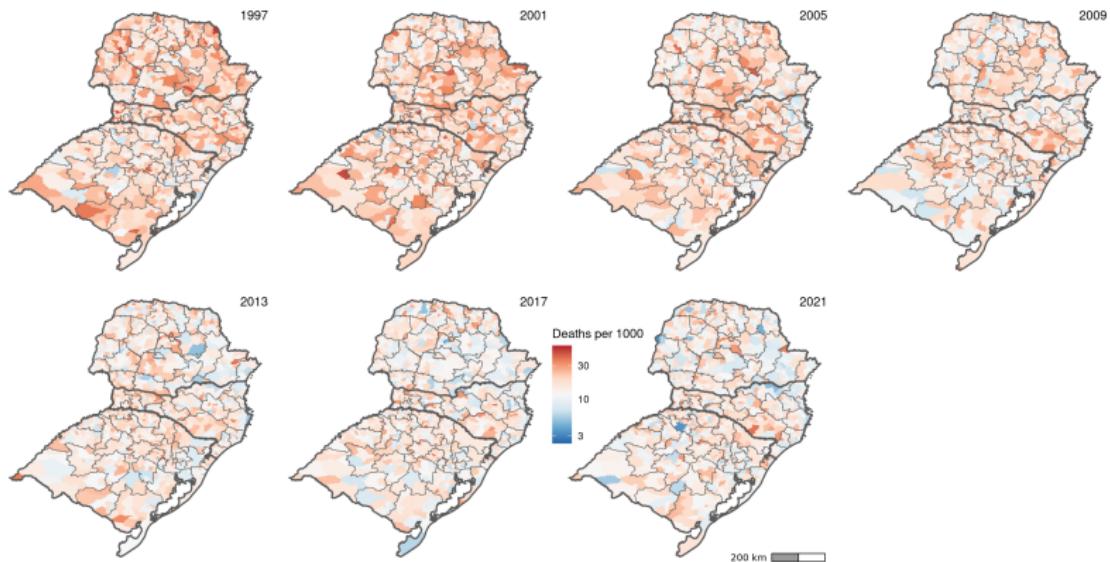
where  $j \sim i$  means  $j$  neighbour of  $i$ . This gives:

$$\begin{aligned}\pi(\mathbf{x} | \tau) &\propto \tau^{\frac{n-1}{2}} \exp\left(-\frac{\tau}{2} \sum_i^n \left(x_i - \frac{1}{n_i} \sum_{j \sim i} x_j\right)^2\right) \\ &= \tau^{\frac{n-1}{2}} \exp\left(-\frac{\tau}{2} \sum_{j \sim i}^n (x_i - x_j)^2\right) = \tau^{\frac{n-1}{2}} \exp\left(-\frac{\tau}{2} \mathbf{x}^T \mathbf{R} \mathbf{x}\right)\end{aligned}$$

$$\mathbf{R}_{ij} = \begin{cases} n_i & \text{if } i = j \\ -1 & \text{if } j \sim i \\ 0 & \text{otherwise} \end{cases}.$$

# The spacetime discrete domain case

$$\mathbf{u} = \{u_{11}, \dots, u_{n1}, u_{12}, \dots, u_{n2}, \dots, u_{1T}, \dots, u_{nT}\}$$



## Spatially structured trends

- ▶ Combine models for variation over space with models for variation over time

## Spatially structured trends

- ▶ Combine models for variation over space with models for variation over time
- ▶ Interaction between fixed and random terms
  - ▶ linear trend for each area, Bernardinelli et al. (1995)
  - ▶ quadratic trend for each area, Assunção, Reis, and Oliveira (2001)
  - ▶ B-splines over time with spatially structured coefficients, MacNab and Dean (2001) and MacNab and Dean (2002)

# Spatially structured trends

- ▶ Combine models for variation over space with models for variation over time
- ▶ Interaction between fixed and random terms
  - ▶ linear trend for each area, Bernardinelli et al. (1995)
  - ▶ quadratic trend for each area, Assunção, Reis, and Oliveira (2001)
  - ▶ B-splines over time with spatially structured coefficients, MacNab and Dean (2001) and MacNab and Dean (2002)
- ▶ Interaction between spatial and temporal random effects, Clayton (1996)

## **Spacetime models**

# Kronecker product models

- ▶ Consider the random vector indexed as follows

$$\mathbf{x} = \{x_{11}, \dots, x_{n1}, x_{12}, \dots, x_{nT}\}$$

# Kronecker product models

- ▶ Consider the random vector indexed as follows  
 $\mathbf{x} = \{x_{11}, \dots, x_{n1}, x_{12}, \dots, x_{nT}\}$
- ▶ Assume

$$\pi(\mathbf{x}) \propto (|\mathbf{Q1} \otimes \mathbf{Q2}|^{-1})^{1/2} \exp\left(-\frac{1}{2}\mathbf{x}^T \{\mathbf{Q1} \otimes \mathbf{Q2}\} \mathbf{x}\right)$$

where

- ▶ **Q1** has dimension equals  $T$  (from a model over time)
- ▶ **Q2** has dimension equals  $n$  (from a model over space)

# Kronecker product models

- ▶ Consider the random vector indexed as follows  
 $\mathbf{x} = \{x_{11}, \dots, x_{n1}, x_{12}, \dots, x_{nT}\}$
- ▶ Assume

$$\pi(\mathbf{x}) \propto (|\mathbf{Q1} \otimes \mathbf{Q2}|^{-1})^{1/2} \exp\left(-\frac{1}{2}\mathbf{x}^T \{\mathbf{Q1} \otimes \mathbf{Q2}\} \mathbf{x}\right)$$

where

- ▶ **Q1** has dimension equals  $T$  (from a model over time)
- ▶ **Q2** has dimension equals  $n$  (from a model over space)
- ▶ The Kronecker product models follows the Clayton's rule
- ▶ Combine **Q1** (time) and **Q2** (space) available

## Some examples on spacetime interactions

- ▶  $\text{Precision}(\mathbf{u}) = \tau \mathbf{H} \otimes \mathbf{R}$ , Knorr-Held (2000)
  - ▶  $\mathbf{H}$ : precision structure matrix over the temporal domain
  - ▶  $\mathbf{R}$ : precision structure matrix over the spatial domain
  - ▶ This defines a precision/covariance separable model for  $\mathbf{u}$

## Some examples on spacetime interactions

- ▶  $\text{Precision}(\mathbf{u}) = \tau \mathbf{H} \otimes \mathbf{R}$ , Knorr-Held (2000)
  - ▶  $\mathbf{H}$ : precision structure matrix over the temporal domain
  - ▶  $\mathbf{R}$ : precision structure matrix over the spatial domain
  - ▶ This defines a precision/covariance separable model for  $\mathbf{u}$
- ▶ **care** when main effects are in the model
- ▶ **super care** when **Q1** and/or **Q2** have rank deficiency
  - ▶ e.g. `rw1`, `rw2` and `besag` models
  - ▶ if both Q1 and Q2 are intrinsic, Knorr-Held (2000):
    - ▶ see `inla.knmodels()`

# Some examples on spacetime interactions

- ▶  $\text{Precision}(\mathbf{u}) = \tau \mathbf{H} \otimes \mathbf{R}$ , Knorr-Held (2000)
  - ▶  $\mathbf{H}$ : precision structure matrix over the temporal domain
  - ▶  $\mathbf{R}$ : precision structure matrix over the spatial domain
  - ▶ This defines a precision/covariance separable model for  $\mathbf{u}$
- ▶ **care** when main effects are in the model
- ▶ **super care** when  $\mathbf{Q1}$  and/or  $\mathbf{Q2}$  have rank deficiency
  - ▶ e.g. `rw1`, `rw2` and `besag` models
  - ▶ if both  $\mathbf{Q1}$  and  $\mathbf{Q2}$  are intrinsic, Knorr-Held (2000):
    - ▶ see `inla.knmodels()`
- ▶ Proper in time, Martínez-Beneito, López-Quilez, and Botella-Rocamora (2008)
  - ▶ example in INLA:

```
f(spatial, model='besag', ...,
group=time, control.group=list(model='ar1'))
```
  - ▶ NOTE: Here the constraints are only set for the main model, and not for the group model!

## The Knorr-Held (2000) models

- ▶ Linear predictor is modeled as

$$\eta_{it} = \text{other effects} + v_t + s_i + d_{it}$$

- ▶  $v_t$  is a temporal effect common for all areas,
- ▶  $s_i$  is a spatial effect common for all times and
- ▶  $d_{it}$  is the space-time effect.

# The Knorr-Held (2000) models

- ▶ Linear predictor is modeled as

$$\eta_{it} = \text{other effects} + v_t + s_i + d_{it}$$

- ▶  $v_t$  is a temporal effect common for all areas,
  - ▶  $s_i$  is a spatial effect common for all times and
  - ▶  $d_{it}$  is the space-time effect.
- 
- ▶ Decompose:  $v_t = \gamma_t + \alpha_t$  and  $s_i = \phi_i + \theta_i$ 
    - ▶ zero mean Gaussian distributions, with precision  $\tau_\gamma \mathbf{I}$ ,  $\tau_\alpha \mathbf{K}$ ,  $\tau_\phi \mathbf{I}$  and  $\tau_\theta \mathbf{R}$ , for  $\gamma$ ,  $\alpha$ ,  $\phi$  and  $\theta$ , respectively.
    - ▶  $\mathbf{I}$ : identity matrix with required dimension
    - ▶  $\mathbf{K}$  and  $\mathbf{R}$ : temporal and spatial precision structure matrices, from the neighborhood structure

## The Knorr-Held (2000) models (cont.)

- ▶ Let  $\mathbf{R} = \tilde{\mathbf{G}} - \mathbf{G}$ , where
  - ▶  $\mathbf{G}$  is the spatial neighborhood structure

$$\mathbf{G}_{i,j} = \begin{cases} 1 & \text{if } j \sim i \\ 0 & \text{otherwise,} \end{cases}$$

- ▶  $j \sim i$  means “ $j$  neighbor to  $i$ ”
- ▶  $\tilde{\mathbf{G}}$  is a diagonal matrix, having its diagonal as the row sum of  $\mathbf{G}$ .

## The Knorr-Held (2000) models (cont.)

- ▶ Let  $\mathbf{R} = \tilde{\mathbf{G}} - \mathbf{G}$ , where
  - ▶  $\mathbf{G}$  is the spatial neighborhood structure

$$\mathbf{G}_{i,j} = \begin{cases} 1 & \text{if } j \sim i \\ 0 & \text{otherwise,} \end{cases}$$

- ▶  $j \sim i$  means “ $j$  neighbor to  $i$ ”
- ▶  $\tilde{\mathbf{G}}$  is a diagonal matrix, having its diagonal as the row sum of  $\mathbf{G}$ .
- ▶ Considering the type IV interaction:

$$\begin{aligned}\tau_d \mathbf{K} \otimes \mathbf{R} &= \tau_d (\tilde{\mathbf{H}} - \mathbf{H}) \otimes (\tilde{\mathbf{G}} - \mathbf{G}) \\ &= \tau_d (\tilde{\mathbf{H}} \otimes \tilde{\mathbf{G}} - \tilde{\mathbf{H}} \otimes \mathbf{G} - \mathbf{H} \otimes \tilde{\mathbf{G}} + \mathbf{H} \otimes \mathbf{G})\end{aligned}$$

## **Continuous domain attempts**

## Areal count data

- ▶ Relative risk model:  $r_i = \exp(f_i + u_i = \eta_i)$ 
  - ▶  $y_i$  cases at area  $i$  given the expected number of cases  $E_i$ 
$$y_i \sim \text{Poisson}(E_i r_i)$$
  - ▶  $f_i$  is the fixed effects and  $u_i$  is the spatial random effect

## Areal count data

- ▶ Relative risk model:  $r_i = \exp(f_i + u_i) = \eta_i$ 
  - ▶  $y_i$  cases at area  $i$  given the expected number of cases  $E_i$ 
$$y_i \sim \text{Poisson}(E_i r_i)$$
  - ▶  $f_i$  is the fixed effects and  $u_i$  is the spatial random effect
- ▶ Attempt 1: Continuous domain model at the centroids,  $\mathbf{s}_i$

$$u_i = u(\mathbf{s}_i)$$

# Areal count data

- ▶ Relative risk model:  $r_i = \exp(f_i + u_i) = \eta_i$ 
  - ▶  $y_i$  cases at area  $i$  given the expected number of cases  $E_i$ 
$$y_i \sim \text{Poisson}(E_i r_i)$$
  - ▶  $f_i$  is the fixed effects and  $u_i$  is the spatial random effect
- ▶ Attempt 1: Continuous domain model at the centroids,  $\mathbf{s}_i$

$$u_i = u(\mathbf{s}_i)$$

- ▶ Attempt 2: work in the linear predictor level

$$u_i = \int_{\mathbb{A}_i} u(\mathbf{s}) \partial \mathbf{s} \approx \tilde{u}_i$$

# Areal count data

- ▶ Relative risk model:  $r_i = \exp(f_i + u_i) = \eta_i$ 
  - ▶  $y_i$  cases at area  $i$  given the expected number of cases  $E_i$ 
$$y_i \sim \text{Poisson}(E_i r_i)$$
  - ▶  $f_i$  is the fixed effects and  $u_i$  is the spatial random effect
- ▶ Attempt 1: Continuous domain model at the centroids,  $\mathbf{s}_i$

$$u_i = u(\mathbf{s}_i)$$

- ▶ Attempt 2: work in the linear predictor level

$$u_i = \int_{\mathbb{A}_i} u(\mathbf{s}) \partial \mathbf{s} \approx \tilde{u}_i$$

Jensen's inequality:  $\exp\left(\tilde{u}_i = \frac{\sum_j a_j u_j}{\sum_j a_j}\right) \leq \frac{\sum_j a_j \exp(u_j)}{\sum a_j} = \hat{u}_i$

# Areal count data

- ▶ Relative risk model:  $r_i = \exp(f_i + u_i) = \eta_i$ 
  - ▶  $y_i$  cases at area  $i$  given the expected number of cases  $E_i$ 
$$y_i \sim \text{Poisson}(E_i r_i)$$
  - ▶  $f_i$  is the fixed effects and  $u_i$  is the spatial random effect
- ▶ Attempt 1: Continuous domain model at the centroids,  $\mathbf{s}_i$

$$u_i = u(\mathbf{s}_i)$$

- ▶ Attempt 2: work in the linear predictor level

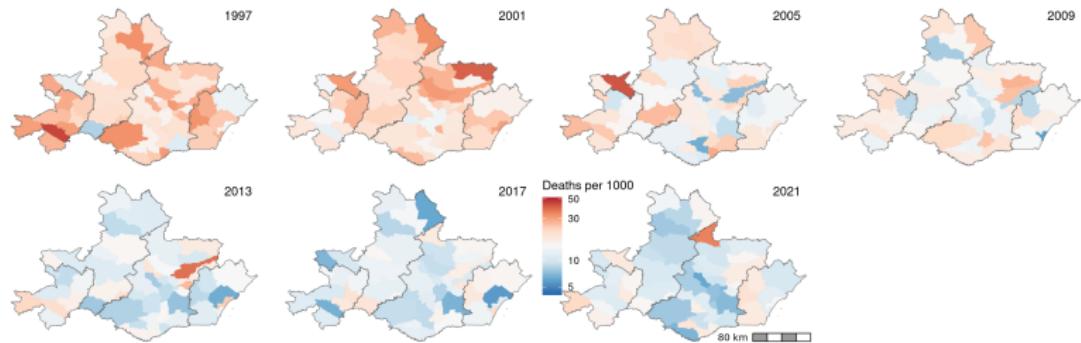
$$u_i = \int_{\mathbb{A}_i} u(\mathbf{s}) \partial \mathbf{s} \approx \tilde{u}_i$$

Jensen's inequality:  $\exp\left(\tilde{u}_i = \frac{\sum_j a_j u_j}{\sum_j a_j}\right) \leq \frac{\sum_j a_j \exp(u_j)}{\sum a_j} = \hat{u}_i$

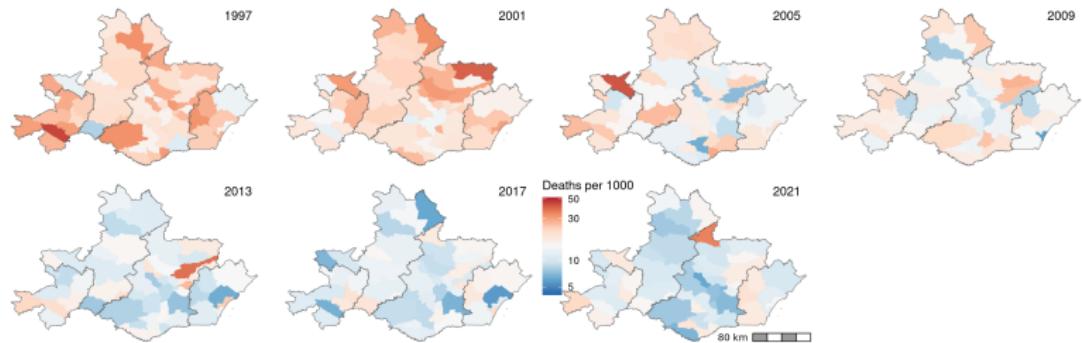
The right thing to do: Integral in the risk scale

$$u_i = \int_{\mathbb{A}_i} \exp(u(\mathbf{s})) \partial \mathbf{s} \approx \hat{u}_i$$

# Application (work in progress.)



# Application (work in progress.)



$$y_{it} \sim \text{Poisson}(n_{it}\lambda_{it}), \quad \log(\lambda_{it}) = \eta_{it}, \quad i \in \{1, \dots, n\}, \quad t \in \{1, \dots, T\}$$

# Models considered

- ▶  $M0$ , a model without spatio-temporal effect
  - ▶  $\eta_{ij} = \alpha + v_t + r_i$
- ▶ Add a spatio-temporal areal effect
  - ▶ considering the Knorr-Held's type 1, 2, 3 and 4
  - ▶ a proper spatio-temporal interaction
- ▶ Proper models for  $v$  and  $r$  plus spatio-temporal continuous domain models: MA (102), MB (121), MC (202) and MD (220)

# Models considered

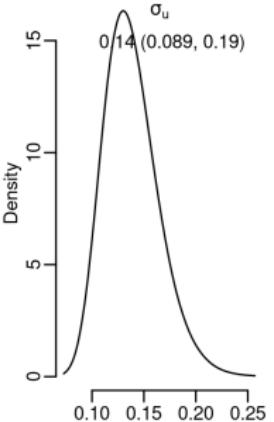
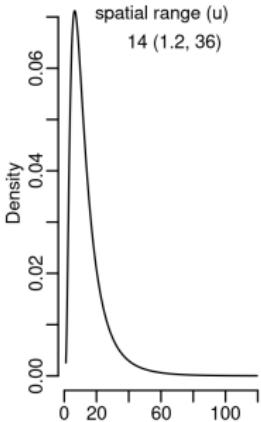
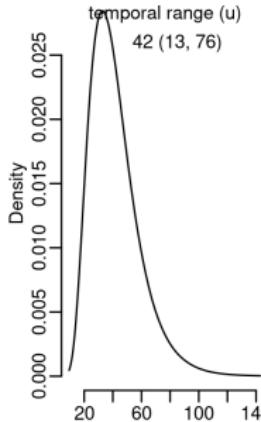
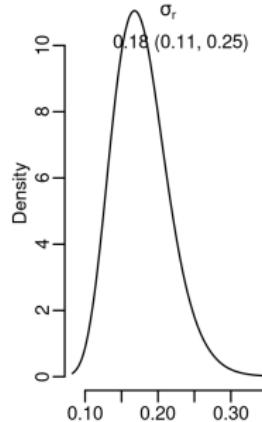
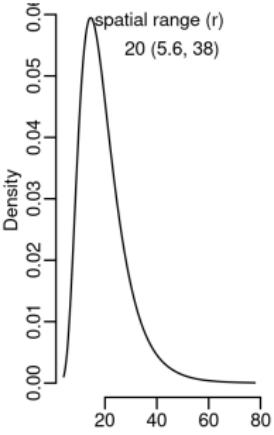
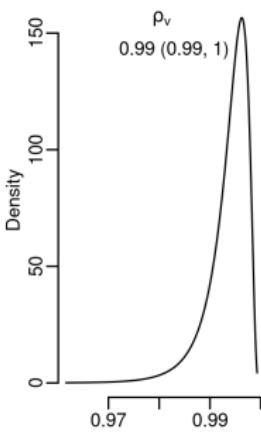
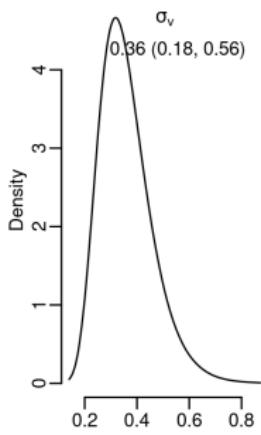
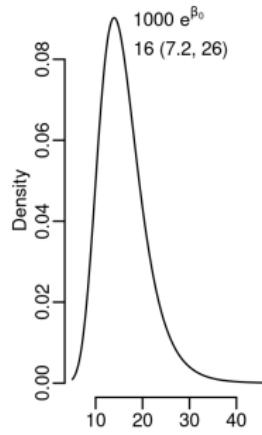
- ▶  $M_0$ , a model without spatio-temporal effect
  - ▶  $\eta_{ij} = \alpha + v_t + r_i$
- ▶ Add a spatio-temporal areal effect
  - ▶ considering the Knorr-Held's type 1, 2, 3 and 4
  - ▶ a proper spatio-temporal interaction
- ▶ Proper models for  $v$  and  $r$  plus spatio-temporal continuous domain models: MA (102), MB (121), MC (202) and MD (220)

DIC, WAIC, minus the sum of the log score (LPO) and its cross-validated version (LCPO)

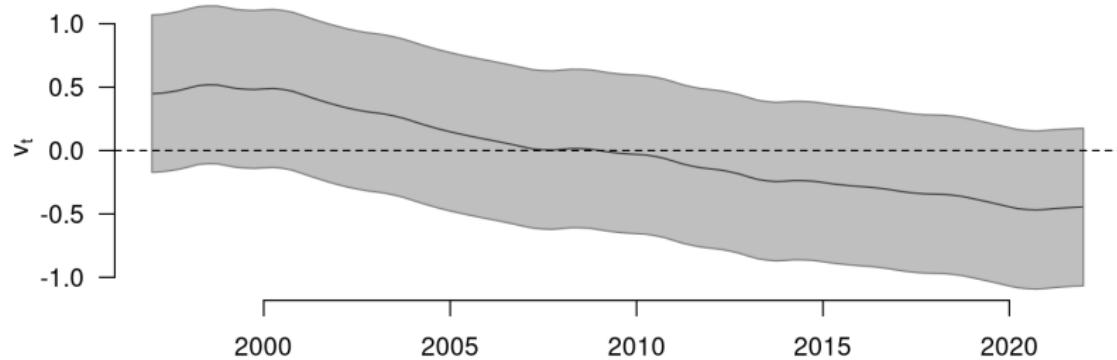
	M0	T1	T2	T3	T4	T4p	M102	M121	M202	M220
DIC	62.7	14.6	11.9	23.6	11.2	0.0	9.1	9.6	11.4	12.3
WAIC	66.9	8.6	17.6	28.7	17.0	0.0	12.5	12.6	15.7	16.4
LCPO	26.6	15.1	4.6	16.3	3.7	0.0	1.5	1.8	2.8	3.1
LPO	143.4	0.0	63.8	23.3	63.4	16.2	68.7	67.8	72.2	74.1

\* differences with respect to the lowest

# Posterior for the model parameters with MD

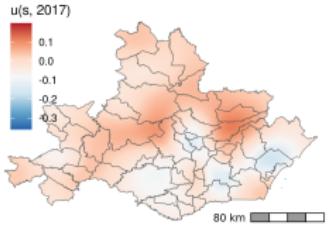
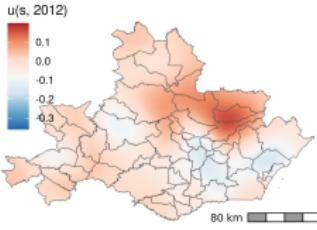
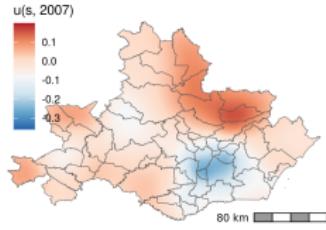
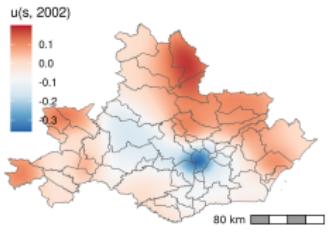
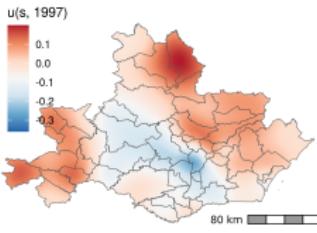
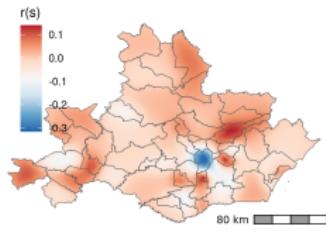


# Time effect

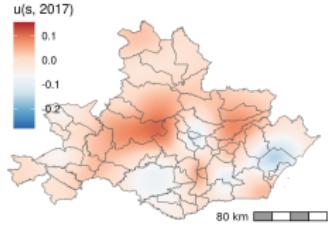
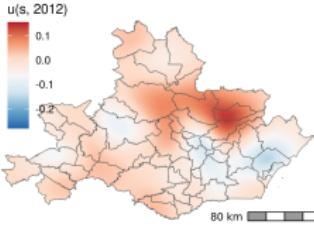
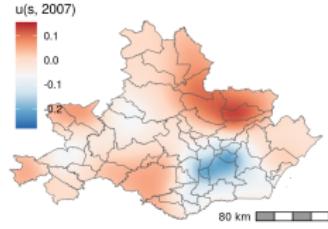
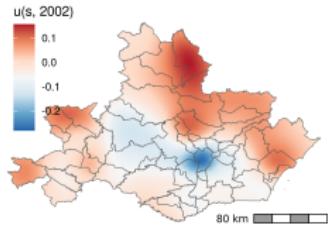
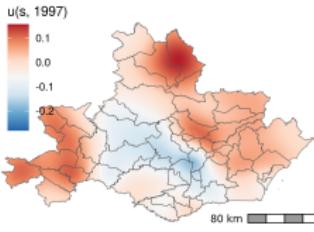
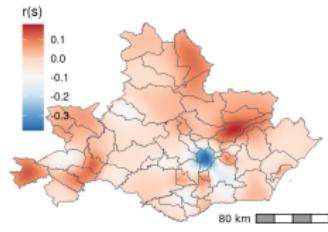


- ▶  $v$  could be replaced by a linear trend in this case

# Spatial and spatio-temporal (with MB)



# Spatial and spatio-temporal (with MD)



# References

- Assunção, R. M., I. A. Reis, and C. Di L. Oliveira. 2001. "Diffusion and Prediction of Leishmaniasis in a Large Metropolitan Area in Brazil with a Bayesian Spacetime Model." *Statistics in Medicine* 20 (15): 2319–35.
- Bernardinelli, L., D. G. Clayton, C. Pascutto, C. Montomoli, M. Ghislandi, and M. Songini. 1995. "Bayesian Analysis of Space-Time Variation in Disease Risk." *Statistics in Medicine* 21–22 (14): 2433–43.
- Besag, J. 1974. "Spatial Interaction and the Statistical Analysis of Lattice Systems." *JRSS-B* 36 (2): 192–236.
- Clayton, D. G. 1996. "Markov Chain Monte Carlo in Practice." In, edited by W. R. Gilks, S. Richardson, and D. J. Spiegelhalter, 275–301. Chapman & Hall.
- Knorr-Held, L. 2000. "Bayesian Modelling of Inseparable Space-Time Variation in Disease Risk." *Statistics in Medicine* 19: 2555–67.
- MacNab, Y. C., and C. B. Dean. 2001. "Autoregressive Spatial Smoothing and Temporal Spline Smoothing for Mapping Rates." *Biometrics* 57 (3): 949–56.
- . 2002. "Spatio-Temporal Modelling of Rates for the Construction of Disease Maps." *Statistics in Medicine* 21 (3): 347–58.
- Martínez-Beneito, M. A., A. López-Quilez, and P. Botella-Rocamora. 2008. "An Autoregressive Approach to Spatio-Temporal Disease Mapping." *Statistics in Medicine* 27 (10): 2874–89.