

Ciência espacial de dados para auxiliar na gestão da pandemia COVID-19

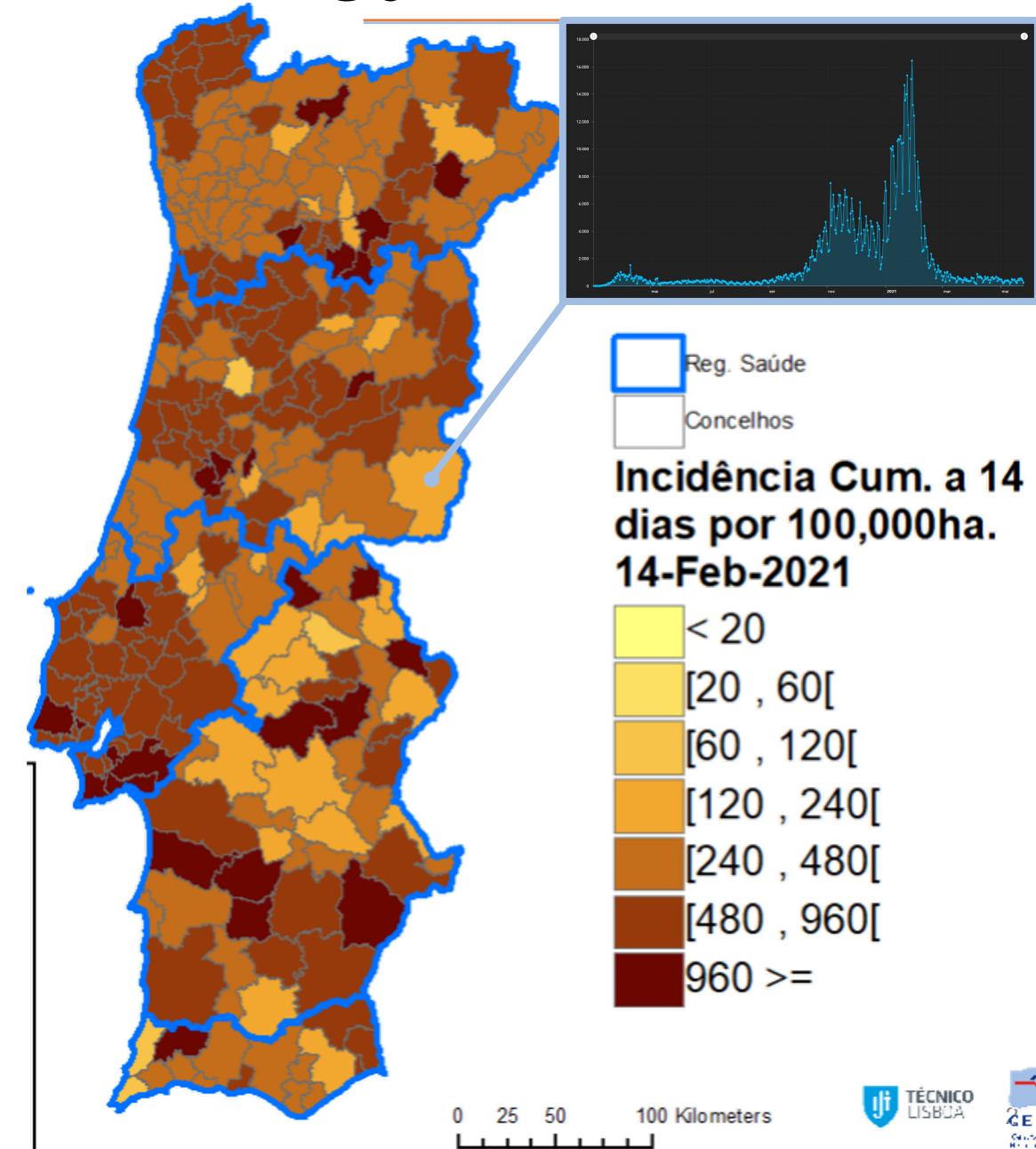
Maria João Pereira, Manuel Ribeiro, Amílcar Soares, Ana F. Duarte, Leonardo Azevedo

leonardo.azevedo@tecnico.ulisboa.pt

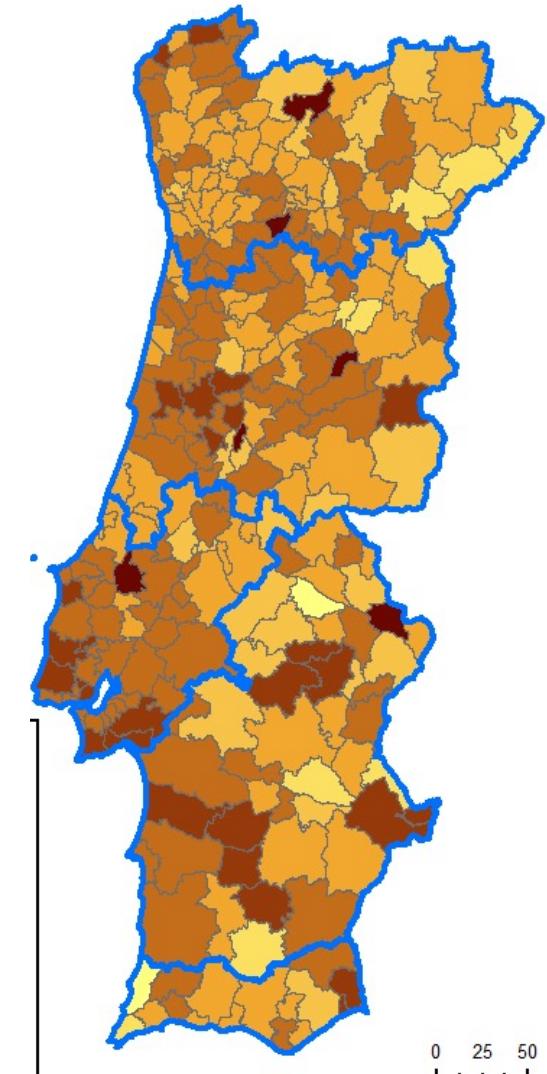


Data and risk maps in epidemiology

- Data viz tools to monitor and control disease spread, preventing and mitigation measures effectiveness and allocation of resources
- Most natural and anthropogenic phenomena are spatially structured;
- SARS-CoV-2 epidemic has simultaneous time and space dynamics;
- **Incidence** = the **rate of new cases** of a disease occurring in a **specific population** over a **given period of time**
- **Incidence** as a measure of **risk** presented in **discontinuous maps**



Risk is not discontinuous!



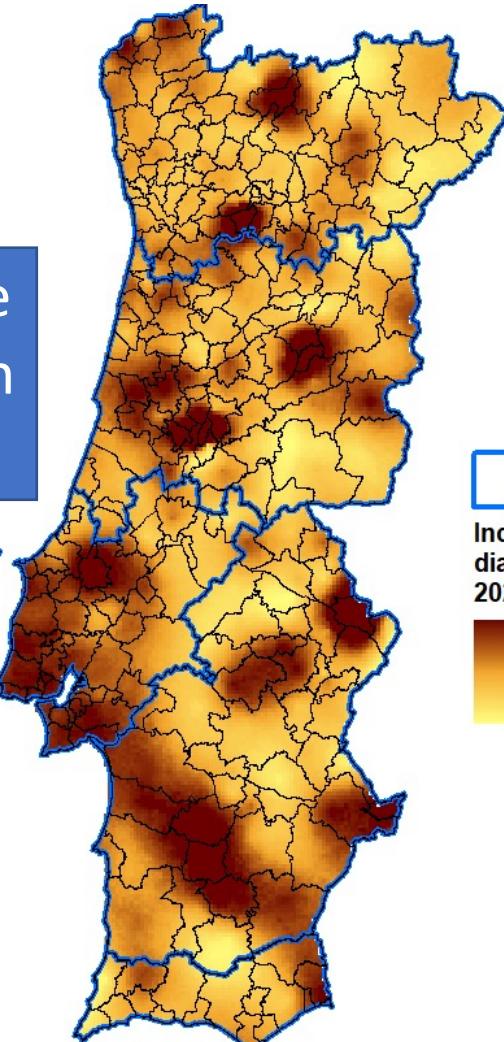
Reg. Saúde
Concelhos

Incidência Cum. a 14
dias por 100,000ha.
20-Feb-2021

< 20
[20 , 60[
[60 , 120[
[120 , 240[
[240 , 480[
[480 , 960[
960 >=

0 25 50 100 Kilometers

How to generate
a high-resolution
map?

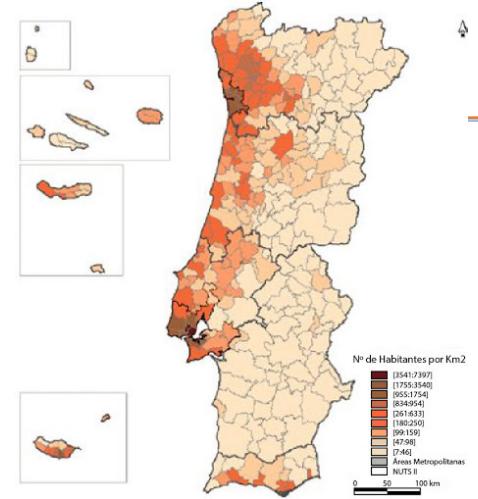
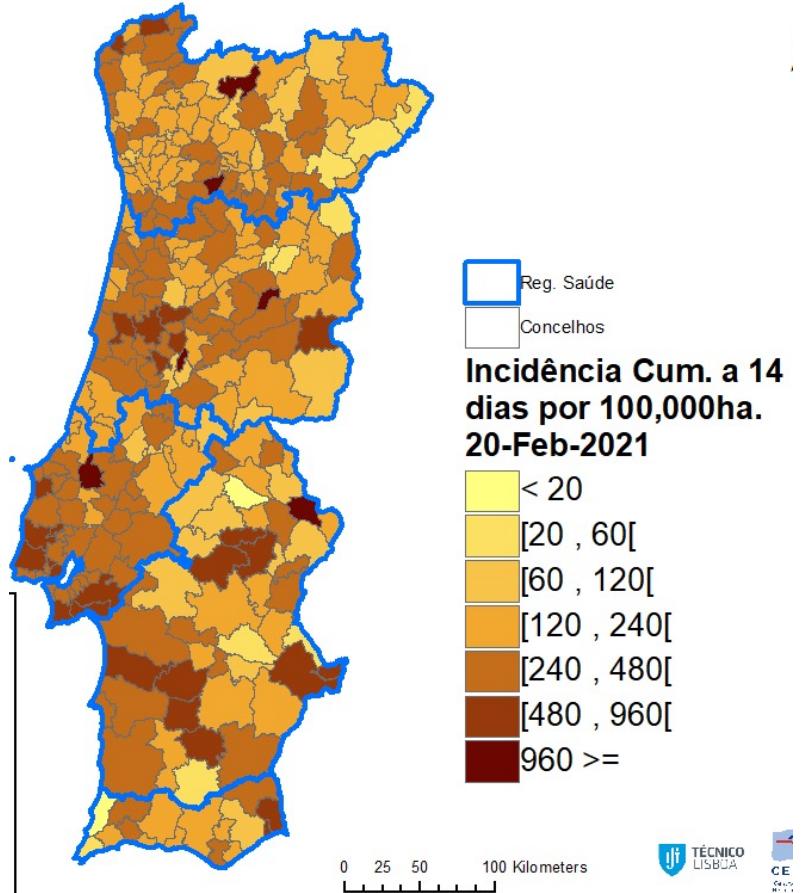


What is the
uncertainty of
estimates?

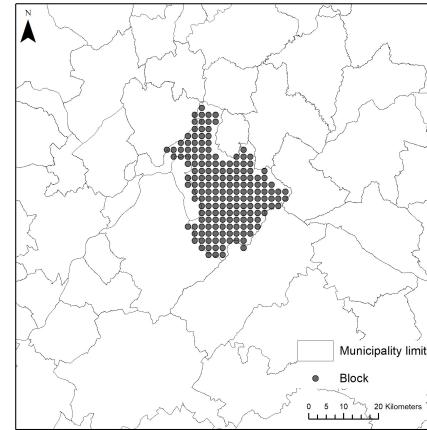
0 25 50 100 Kilometers

Challenges

$$\text{Incidence} = \frac{\text{new infections per municipality in 2 weeks period}}{\text{municipal resident population}}$$

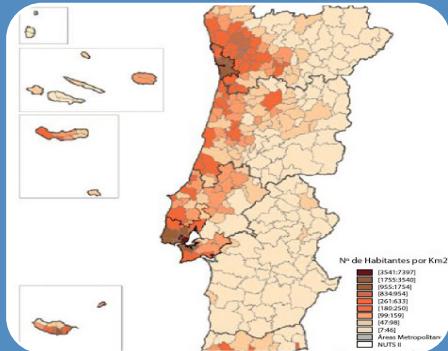


data uncertainty depends on the resident population of the municipality

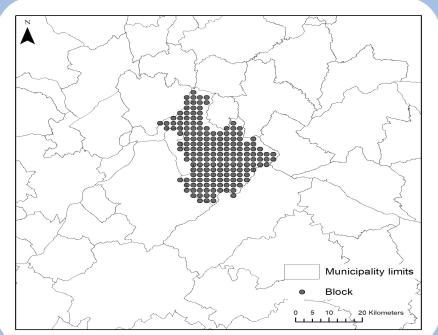


Each municipality data has a different support: "block" data or "areal" data

Methology



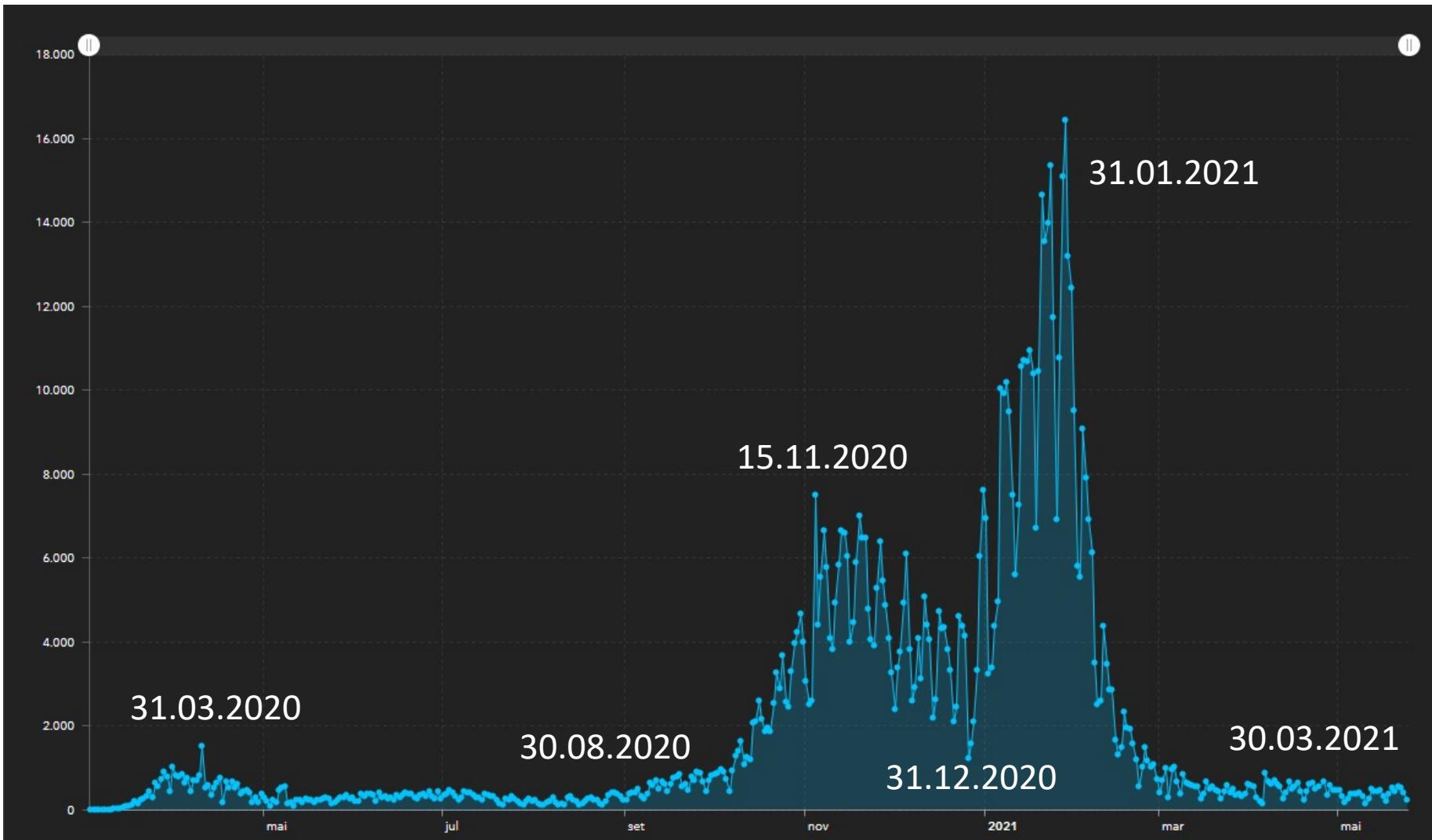
Poisson model for rare diseases proposed by Waller and Gotway [2004] and extended into a geostatistical framework by Goovaerts [2005] and Oliveira et al. [2013].



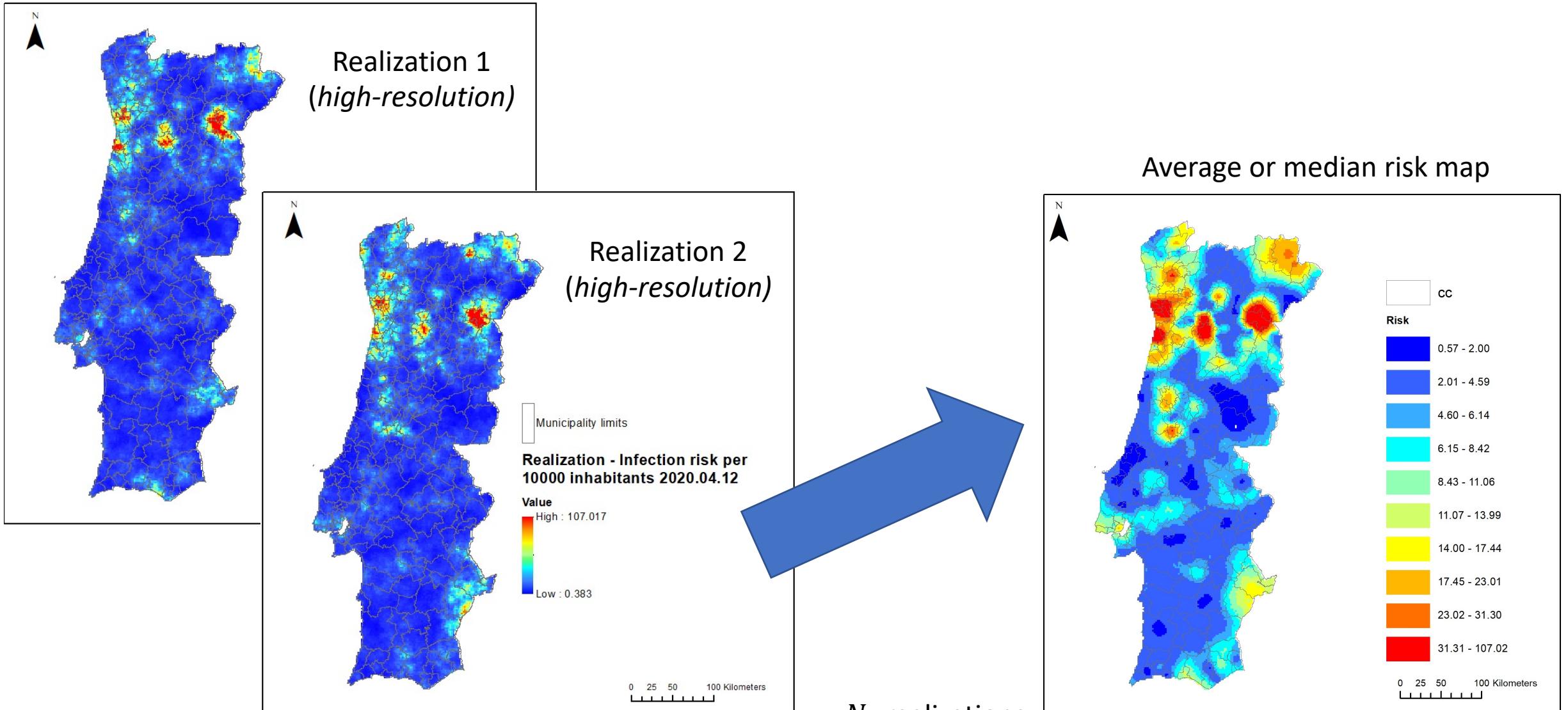
Direct block sequential simulation (block-DSS) by Liu and Journel [2009].

Azevedo, L., Pereira, M.J., Ribeiro, M.C. et al. Geostatistical COVID-19 infection risk maps for Portugal. *Int J Health Geogr* **19**, 25 (2020).
<https://doi.org/10.1186/s12942-020-00221-5>

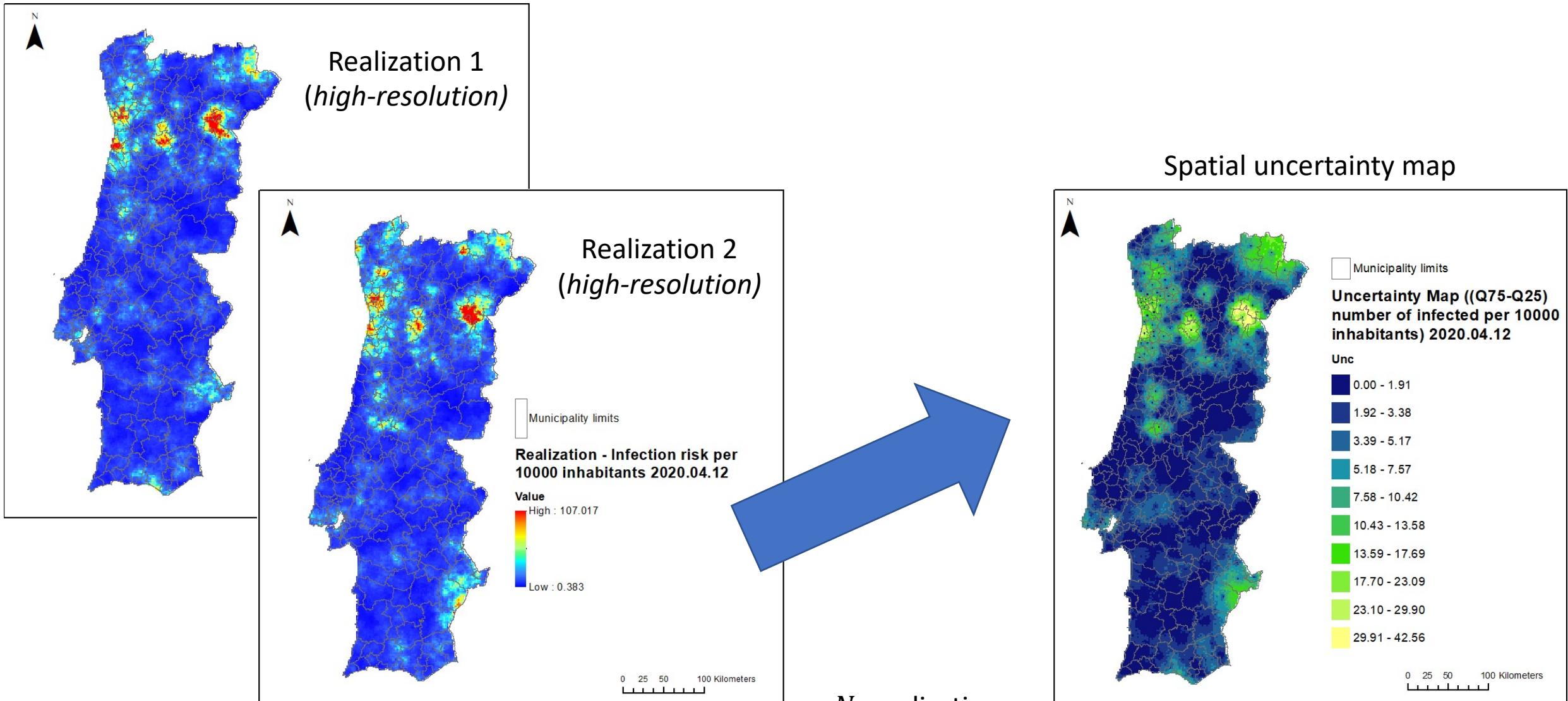
Daily number of new cases



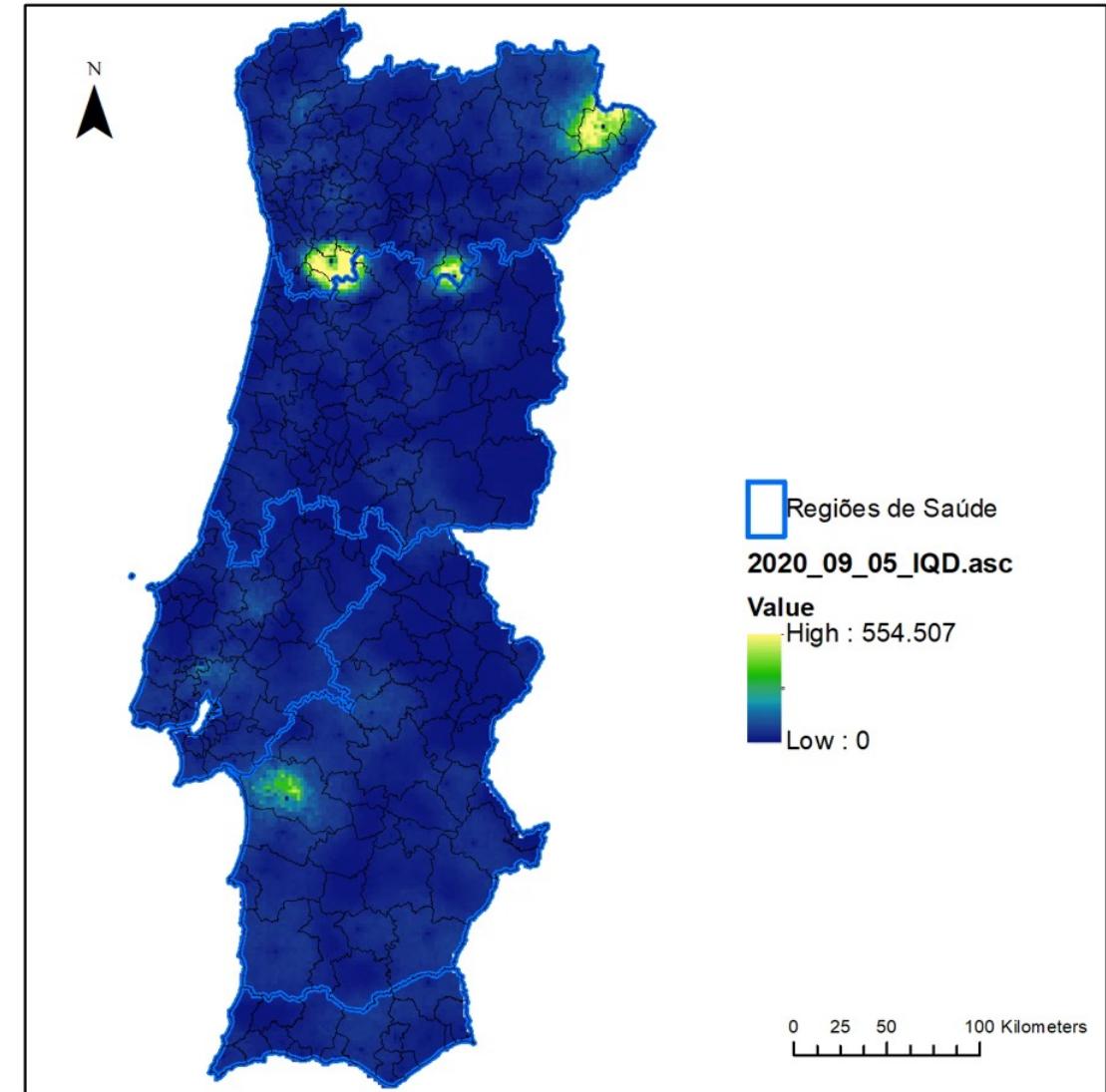
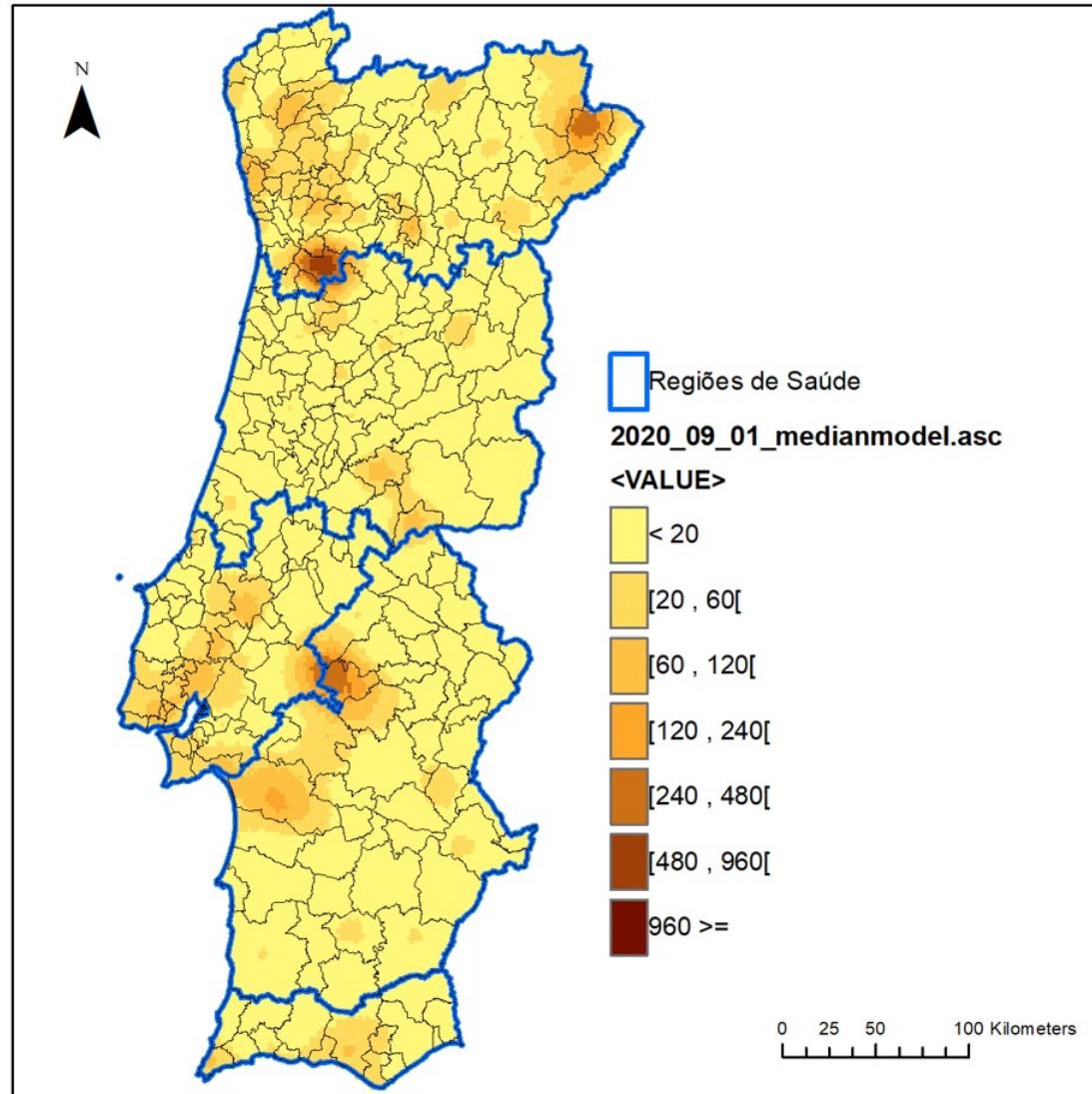
Daily updated Infection Risk Maps



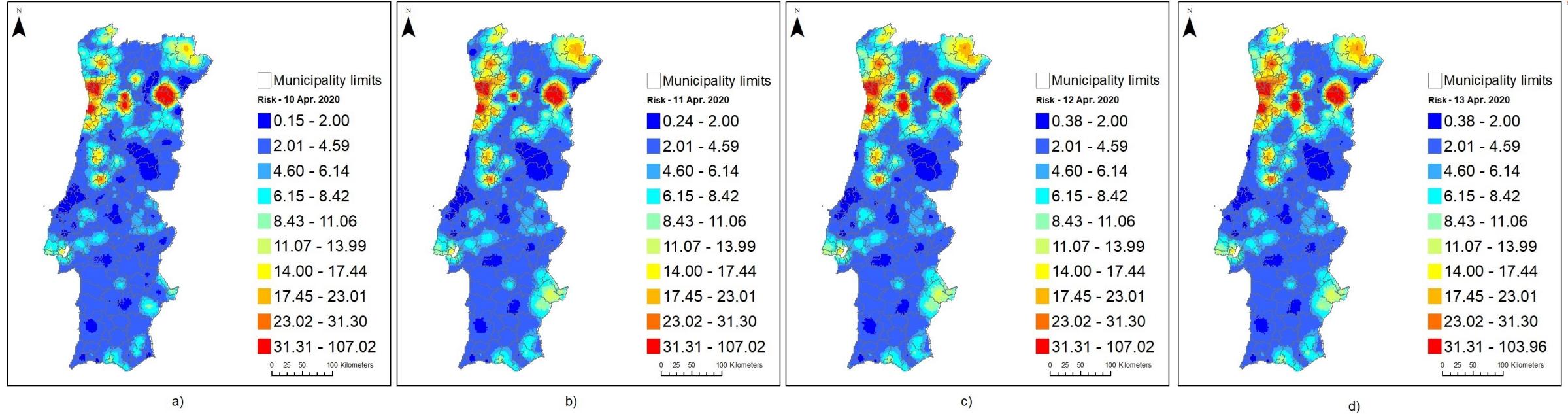
Daily updated Infection Risk Maps



Second and third epidemic wave



Temporal trend of COVID-19 infection risk

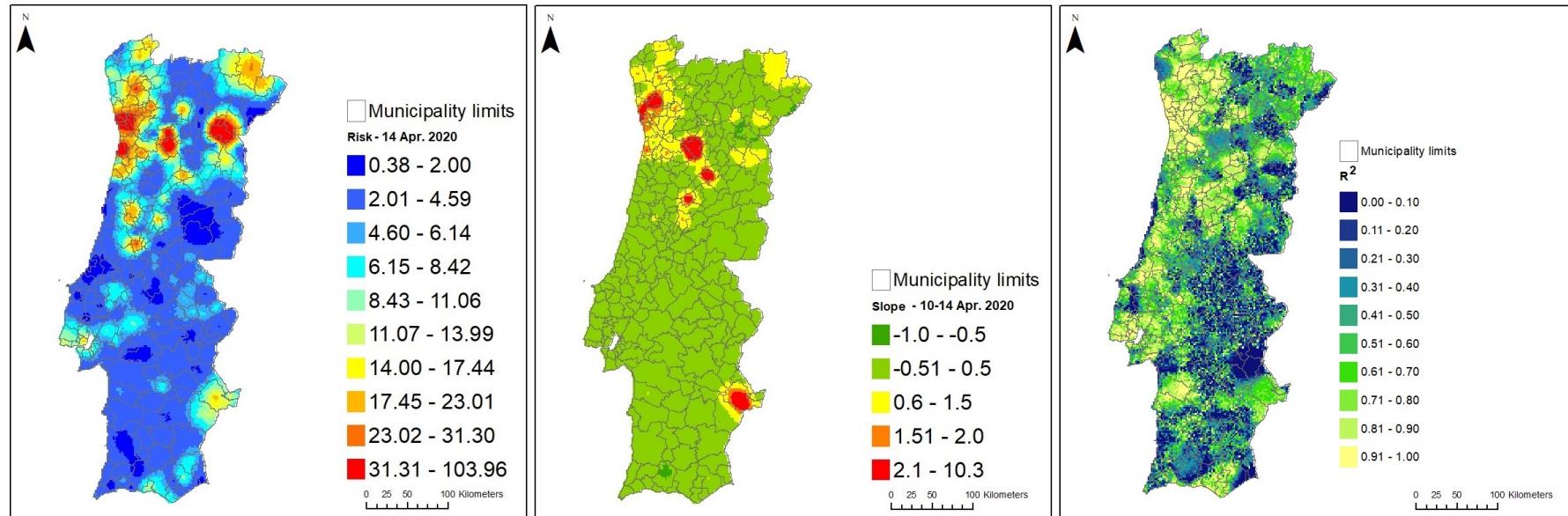


a)

b)

c)

d)

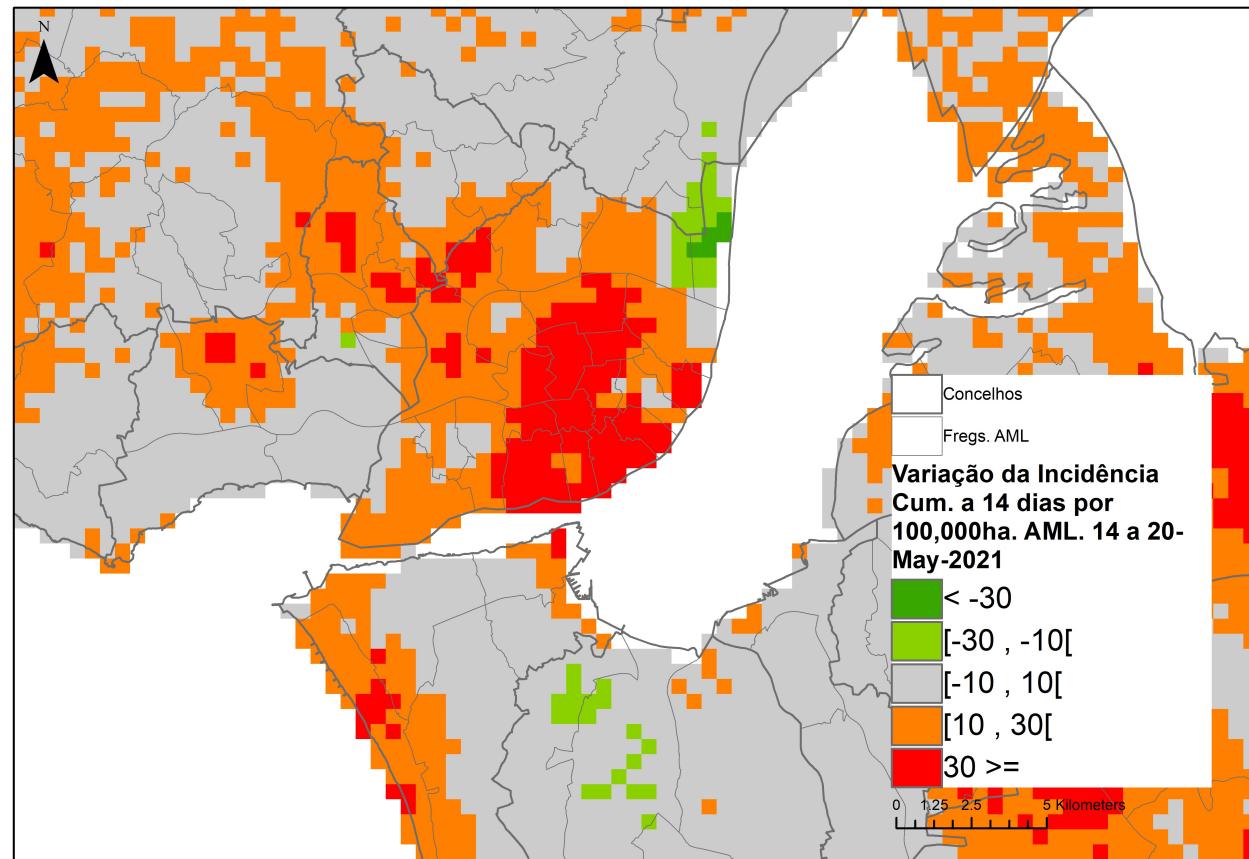
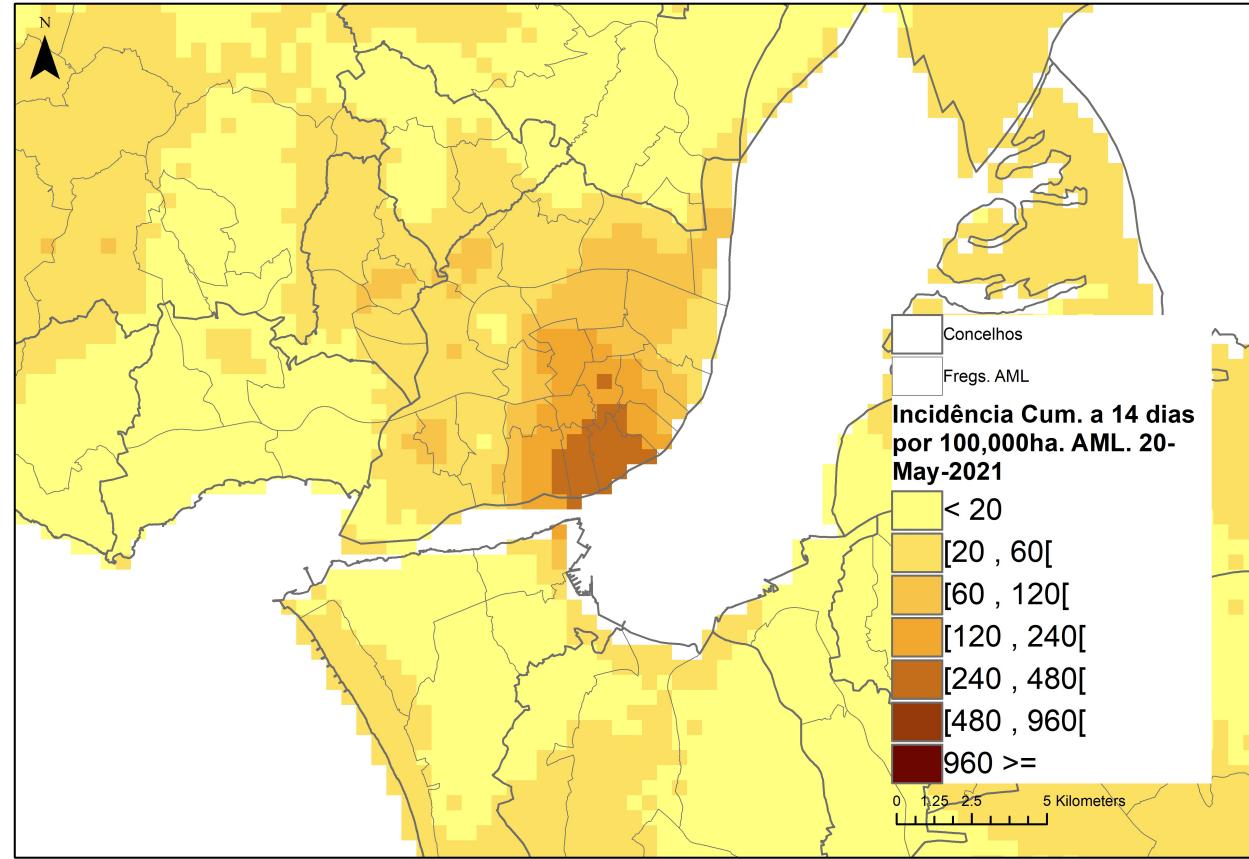


e)

f)

g)

Lisbon metropolitan area @ parish level



Ongoing projects

- **SMOCK-** Spatial Modelling for mapping COVID-19 risk
 - Funded by: Research4COVID, 6 months, started 01.07.2020
- **SCOPE-**Spatial Data Science Services for COVID-19 Pandemic
 - Funded by: AI4COVID - Data Science and Artificial Intelligence in the Public Administration to strengthen the fight against COVID-19 and future pandemics 3 years, started 01.03.2021

Partners



Ciéncia espacial de dados para auxiliar na gestâo da
pandemia COVID-19



Ciência espacial de dados para auxiliar na gestão da pandemia COVID-19

Maria João Pereira, Manuel Ribeiro, Amílcar Soares, Ana F. Duarte, Leonardo Azevedo

leonardo.azevedo@tecnico.ulisboa.pt



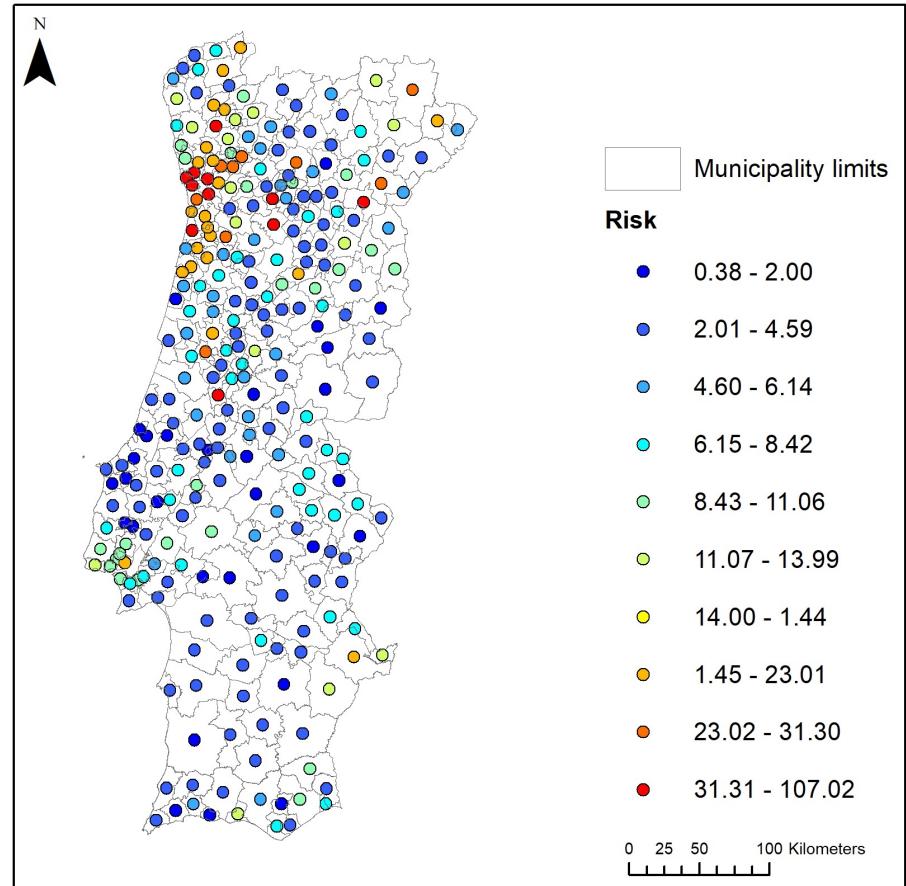
Incidence

$c(\mathbf{u}_\alpha)$ - the number of new infections recorded in each municipality on a period of consecutive 14 days, referenced by its geometric centroid \mathbf{u}_α

$n(\mathbf{u}_\alpha)$ - the size of the population at risk (i.e., resident population of a given municipality) at each location \mathbf{u}_α

$z(\mathbf{u}_\alpha)$ - incidence

$$z(\mathbf{u}_\alpha) = \frac{c(\mathbf{u}_\alpha)}{n(\mathbf{u}_\alpha)}$$



Poisson model

$c(\mathbf{u}_\alpha)$ is a realization of a Poisson random variable $C(\mathbf{u}_\alpha)$, with distribution parameter that is the “expected number of counts per unit of time”.

This parameter is the product of the population size, $n(\mathbf{u}_\alpha)$, and the local risk, $R(\mathbf{u}_\alpha)$, with expected mean m .

The expectation of risk at any location is equal to the expectation of the incidence

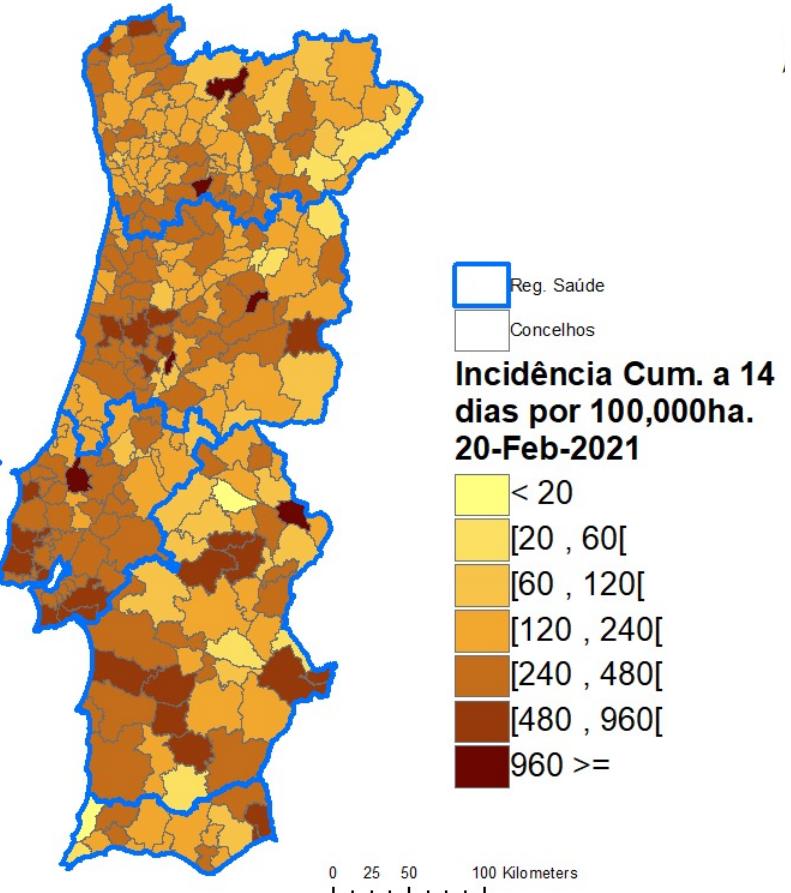
$$E[Z(\mathbf{u}_\alpha)] = E[R(\mathbf{u}_\alpha)] = m$$

and the risk variance is equal to the incidence variance plus an error term related to the size of the population,

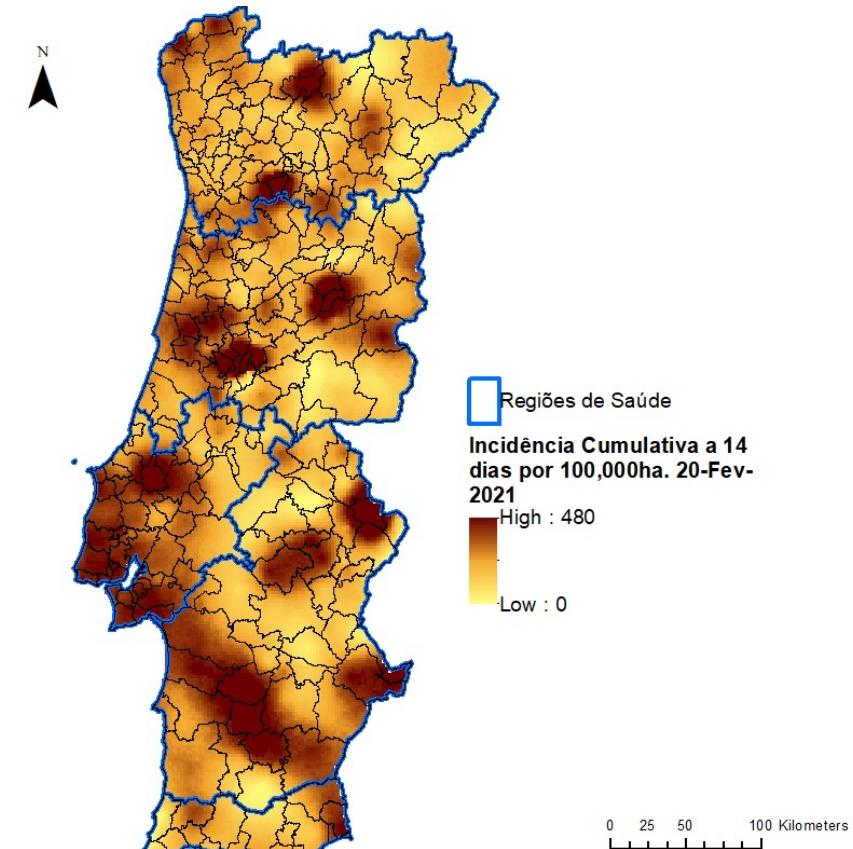
$$Var[Z(\mathbf{u}_\alpha)] = Var[R(\mathbf{u}_\alpha)] + E[R(\mathbf{u}_\alpha)/n(\mathbf{u}_\alpha)] = \sigma_R^2 + m/n(\mathbf{u}_\alpha)$$

Change of support

Block support



Point support



Direct Sequential Simulation (Soares, 2001)

Define a random path that visits each node, x , of the simulation grid;

For each node, x , search the conditioning data;

Calculate the local covariance values, build and solve kriging system to obtain the local mean and variance kriging estimate at location x ;

Draw a value from the global probability distribution function centered at the local mean and bounded by the local variance obtained in previous step;

Add the simulated value to the data set and repeat all steps until all grid nodes are simulated for one realization;

Repeat until a given pre-defined number of realizations are generated

Block-DSS (Liu and Journel, 2009)

Define a random path that visits each node, x , of the simulation grid;

For each node, x , search the conditioning data;

Calculate the local covariance values, build and solve kriging system to obtain the local mean and variance kriging estimate at location x ;

Draw a value from the global probability distribution function centered at the local mean and bounded by the local variance obtained in iii);

Add the simulated value to the data set and repeat all steps until all grid nodes are simulated for one realization;

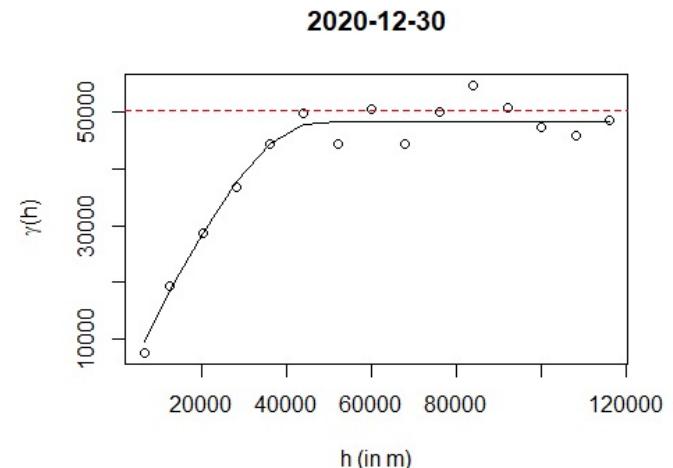
Repeat until a given pre-defined number of realizations are generated

Semivariogram of COVID-19 incidence

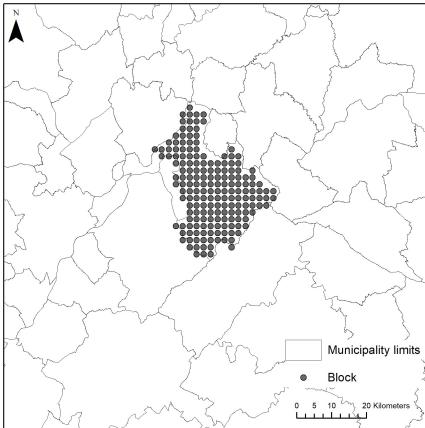
- Weighted experimental semivariogram

$$\gamma(\mathbf{h}) = \frac{1}{2 \sum_{\alpha=1}^{N(\mathbf{h})} w(\mathbf{h})} \sum_{\alpha=1}^{N(\mathbf{h})} \{w(\mathbf{h}) [z(\mathbf{v}_\alpha) - z(\mathbf{v}_\alpha + \mathbf{h})]^2\}$$

$$w(\mathbf{h}) = \frac{n(\mathbf{v}_\alpha) n(\mathbf{v}_\alpha + \mathbf{h})}{n(\mathbf{v}_\alpha) + n(\mathbf{v}_\alpha + \mathbf{h})}$$



Block kriging



block data, $B(\nu_\alpha)$, are defined as the spatial linear average of point values, $Z(x')$, within the block volume, ν_α :

$$B(\nu_\alpha) = \frac{1}{|\nu_\alpha|} \int_{\nu_\alpha} L_\alpha(Z(x')) dx' \quad \forall \alpha$$

$$Z_{SK}^*(x_u) - m = \sum_{\alpha} \lambda_{\alpha}(x_u) \cdot [z(x_{\alpha}) - m] + \sum_{\beta} \lambda_{\beta}(x_u) \cdot [B_{\nu}(x_{\beta}) - m]$$

Kriging system

$$\begin{bmatrix} \lambda_{\alpha} \\ \lambda_{\beta} \end{bmatrix} = \begin{bmatrix} C(., .), C(., v) \\ C(v, .), C(v, v) \end{bmatrix}^{-1} \cdot \begin{bmatrix} C(., xu) \\ C(v, xu) \end{bmatrix}$$

Integrating data uncertainty derived from population size

Assuming block errors, r , are homoscedastic and not cross-correlated, with zero mean and known variance, then the covariance between two errors located at ν_α and ν_β is:

$$C[r(\nu_\alpha), r(\nu_\beta)] = \begin{cases} \sigma_R^2(\nu_\alpha) & \text{if } \nu_\alpha = \nu_\beta \\ 0 & \text{if } \nu_\alpha \neq \nu_\beta \end{cases}$$

If errors are independent of the signal, uncorrelated and with known variance, then:

$$C(v, v) = \begin{cases} C(\nu_\alpha, \nu_\beta) + \sigma_R^2(\nu_\alpha) & \text{if } \nu_\alpha = \nu_\beta \\ C(\nu_\alpha, \nu_\beta) & \text{if } \nu_\alpha \neq \nu_\beta \end{cases}$$

Spatial Data Analysis

