From Maps to Action: Comprehensive Strategies for Pandemic Prevention and Response

7 th INTERNATIONAL CONFERENCE NOVA Health
Tackling Pandemics: Strategies for Prevention, Preparedness and Response

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Context

The Growing Challenge of Pandemics: The increasing frequency and impact of pandemics globally, highlights the need for proactive strategies.

Geospatial Analysis as a Key Tool: Mapping and spatial data have a key role in understanding and combating pandemics.

Case Studies: Dengue in Europe and respiratory diseases (Pneumonia and COVID-19) in Portugal—as examples of the relevance of such strategies.

Objective: Set the stage for exploring comprehensive strategies, linking data-driven insights to actionable outcomes.

DENGUE

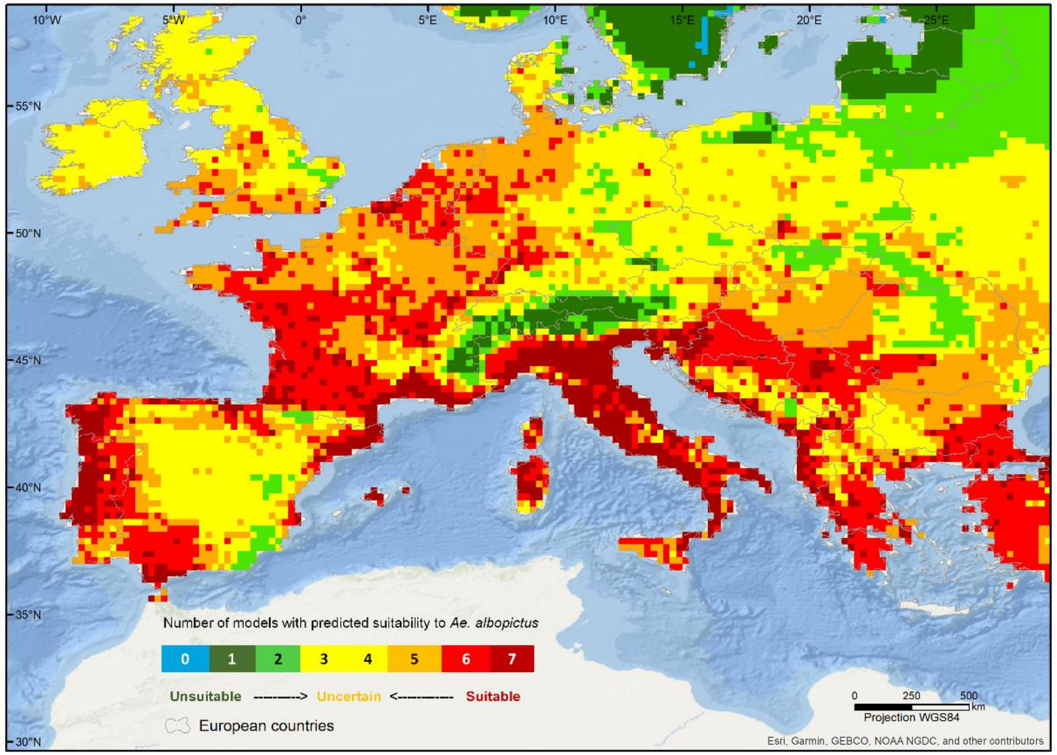
1. Environmental suitability in Europe

- Data from existing models in Europe (7 present, 5 future)
- Transform in binary scale (absence/presence)
- Harmonize spatial resolution (25 km)
- Identify common and divergent areas/patterns
- Classify consensus level and uncertainty
- Identify future trajectories (2 timeframes)

References models	Geog. coverage	Spatial resolution	Present-day period	Future period	Scenario	Modelling technique
Caminade et al. (2012[19])	Europe	0.25° ~25 km	1960–2009	2030–2050	SRES A1B	GIS-based (overwintering and seasonal activity); Multi-criteria decision analysis
Campbell et al. (2015)[8]	Global	0.16666° ~18 km	1950–2000	2041–2060	SRES B1	MaxEnt
Ding et al. (2018)[11]	Global	0.05° ~5 km	1970–2000			Support vector machine (SVM); Gradient boosting machine (GBM); random Forest (RF)
Kraemer et al. (2015[12], 2019[5])	Global	0.04166° ~5 km	1960–2014	2050	RCP 6.0	Boosted regression trees (BRT)
Proestos et al. (2015)[7]	Global	0.46875° ~50 km	2000–2009	2045–2054	SRES A2	Fuzzy-logic
Rogers (2015)[52]	Global	0.5° ~55 km	1961–1990	2080 (estimated for 2050 by linear interpolation)	SRES B1	K-means clustering; Nonlinear discriminant analysis
Santos and Meneses, (2017)[13]	Global	30 arc-sec ~1 km	1950–2000			MaxEnt

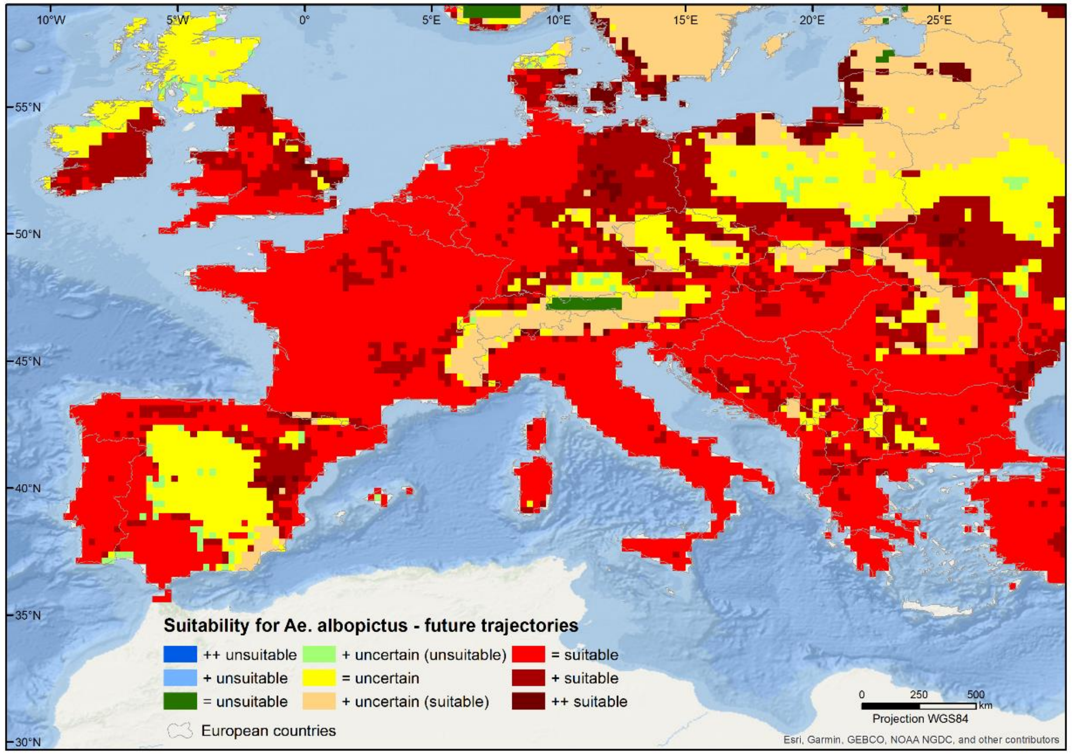
Categories	Present (7 models)	Future (5 models)
Unsuitable, low uncertainty	5 to 7 models agree unsuitable	4 to 5 models agree unsuitable
High uncertainty	Only 3 or 4 models agree	Only 2 or 3 models agree
Suitable, low uncertainty	5 to 7 models agree suitable	4 to 5 models agree suitable

1. Environmental suitability in Europe



Present conditions

Areas of high uncertainty (high disagreement between models) mainly in eastern Europe, northern Britain, Ireland and central Spain.

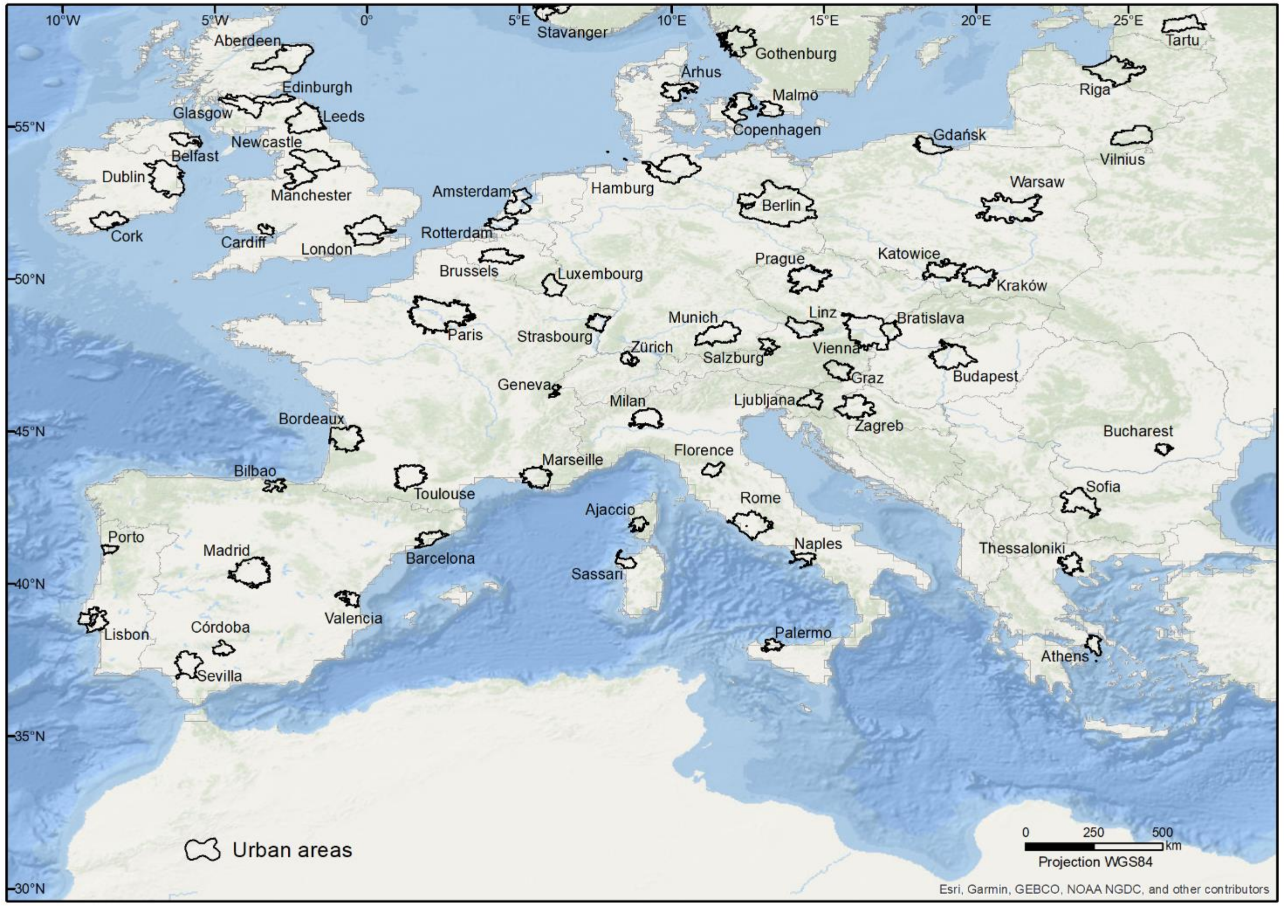


Future trajectories

Suitable regions will encompass 21% more area, adding to the 47% of the continent that is suitable nowadays.

2. Suitability in European urban areas

Functional urban area (FUA) - a city and its commuting zone. A densely inhabited city and a less densely populated commuting zone whose labor market is highly integrated with the city (*OECD, 2012*).



Urban Audit 2018, GISCO

62 metropolitan areas

- Large metropolitan (above 1.5 million people)
- Metropolitan (250.000 to 1.5 million people)

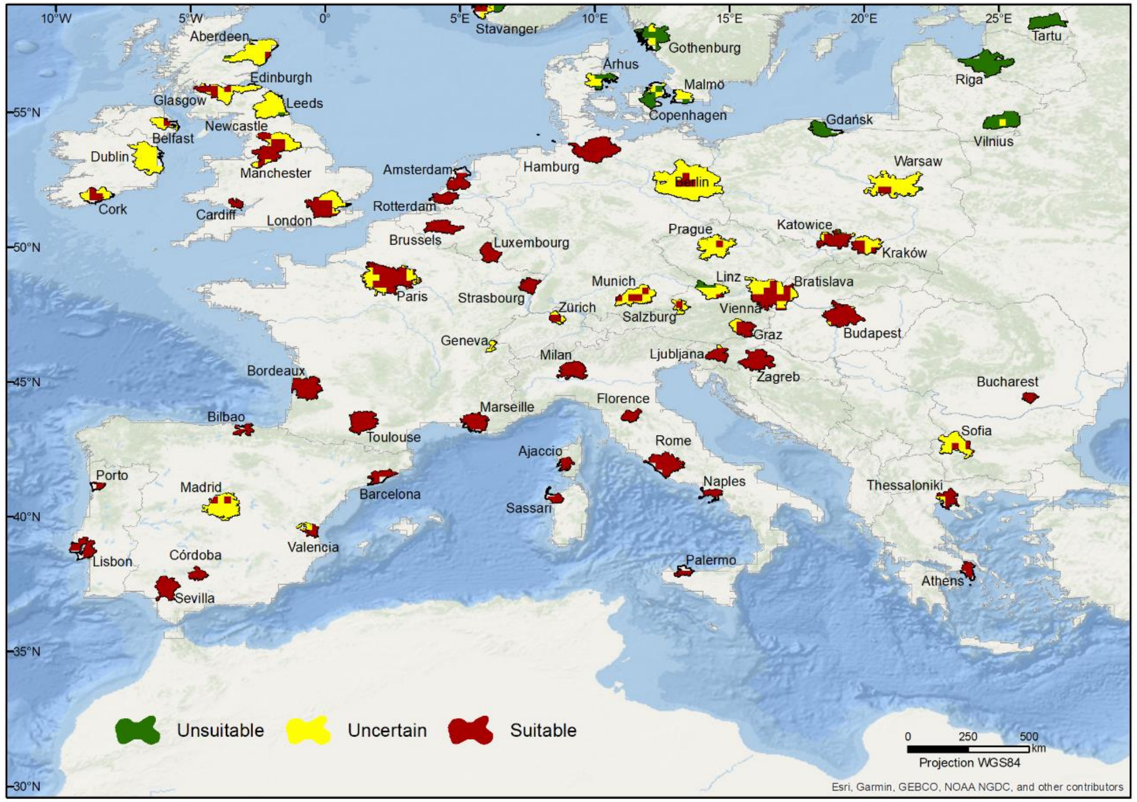
3 medium-size urban areas

- 3 medium areas (100.000 to 250.000 people), in Corsica, Sardinia and Estonia

- Predominant class within FUA boundaries
- *Future worst-case scenario* – 1/3 urban area covered by a more unfavorable variation than given by the baseline

2. Suitability in European urban areas

Present conditions

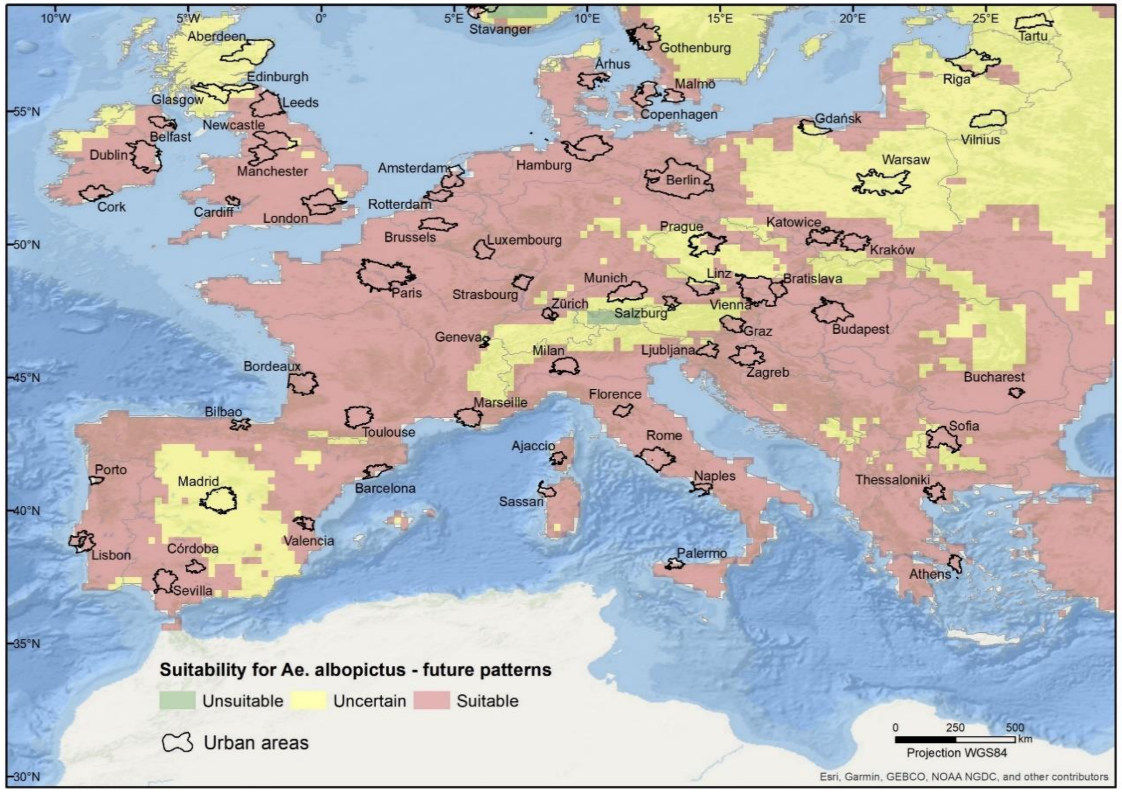


12% unsuitable

39% uncertain

49% suitable

Future conditions



0% unsuitable

17% uncertain

83% suitable

2. Suitability in European urban areas

Main city (country)	P	F
Aberdeen(UK)	Uncertain	Uncertain
Ajaccio (FR)	Suitable	Suitable
Amsterdam (NL)	Suitable	Suitable
Århus (DK)	Unsuitable	Suitable
Athens (EL)	Suitable	Suitable
Barcelona (ES)	Suitable	Suitable
Belfast (UK)	Uncertain	Suitable
Berlin (DE)	Uncertain	Suitable
Bilbao (ES)	Suitable	Suitable
Bordeaux (FR)	Suitable	Suitable
Bratislava (SK)	Uncertain	Suitable
Brussels (BE)	Suitable	Suitable
Bucharest (RO)	Suitable	Suitable
Budapest (HU)	Suitable	Suitable
Cardiff (UK)	Suitable	Suitable
Copenhagen	Unsuitable	Suitable
Cordoba (ES)	Suitable	Suitable
Cork (IE)	Uncertain	Suitable
Dublin (IE)	Uncertain	Suitable
Edinburgh (UK)	Uncertain	Uncertain
Florence (IT)	Suitable	Suitable
Gdansk (PL)	Unsuitable	Uncertain
Geneva (CH)	Uncertain	Suitable
Glasgow (UK)	Uncertain	Uncertain
Gothenburg (SE)	Unsuitable	Suitable
Graz (AT)	Suitable	Suitable
Hamburg (DE)	Suitable	Suitable
Katowice (PL)	Suitable	Suitable
Kraków (PL)	Uncertain	Suitable
Leeds (UK)	Uncertain	Suitable
Linz (AT)	Uncertain	Suitable
Lisbon (PT)	Suitable	Suitable
Ljubljana (SI)	Suitable	Suitable
London (UK)	Uncertain	Suitable
Luxembourg (LU)	Suitable	Suitable
Madrid (ES)	Uncertain	Uncertain
Malmö (SE)	Uncertain	Suitable
Manchester (UK)	Suitable	Suitable
Marseille (FR)	Suitable	Suitable
Milan (IT)	Suitable	Suitable
Munich (DE)	Uncertain	Uncertain
Naples (IT)	Suitable	Suitable
Newcastle	Uncertain	Suitable
Oporto (PT)	Suitable	Suitable
Palermo (IT)	Suitable	Suitable
Paris (FR)	Uncertain	Suitable
Prague (CZ)	Uncertain	Suitable
Riga (LV)	Unsuitable	Uncertain
Rome (IT)	Suitable	Suitable
Rotterdam (NL)	Suitable	Suitable
Salzburg (AT)	Uncertain	Suitable
Sassari (IT)	Suitable	Suitable
Sevilla (ES)	Suitable	Suitable
Sofia (BG)	Uncertain	Suitable
Stavanger (NO)	Unsuitable	Suitable
Strasbourg (FR)	Suitable	Suitable
Tartu (EE)	Unsuitable	Uncertain
Thessaloniki (EL)	Suitable	Suitable
Toulouse (FR)	Suitable	Suitable
Valencia (ES)	Uncertain	Suitable
Vienna (AT)	Uncertain	Suitable
Vilnius (LT)	Unsuitable	Uncertain
Warsaw (PL)	Uncertain	Uncertain
Zagreb (HR)	Suitable	Suitable
Zürich (CH)	Uncertain	Suitable

Unsuitable ● (green)
Uncertain ● (yellow)
Suitable ● (red)

- Cities located in northern Europe expected to undergo the most severe changes (from unsuitable to suitable)

Arhus, Copenhagen, Gothenburg, Stavanger

- Cities of central Europe, Great Britain and Ireland are expected to become suitable (from uncertain today)

Berlin, Dublin, Geneva, London, Prague, Vienna

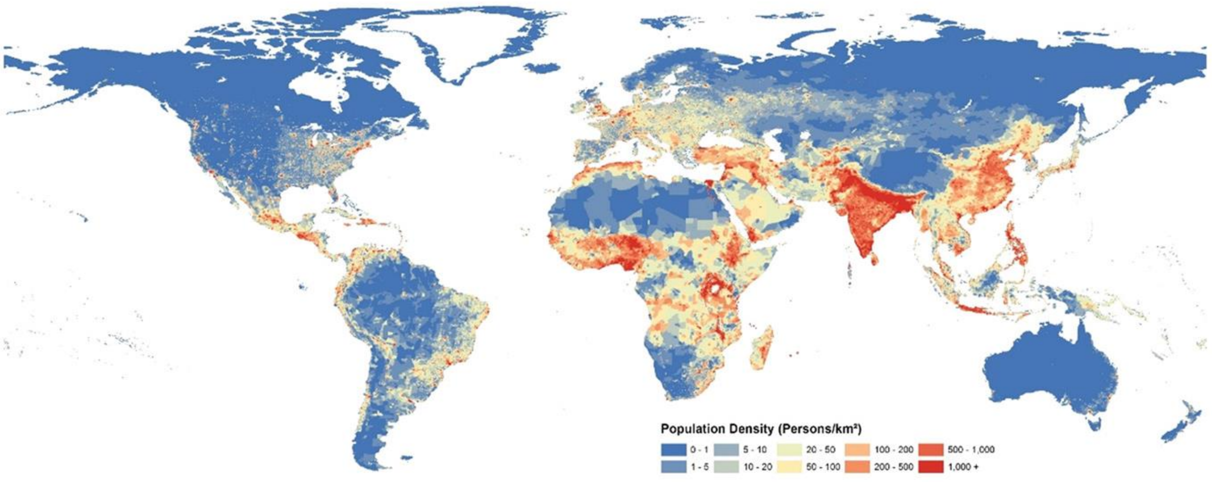
- Uncertainty remains in the future for cities such as:

Edinburgh, Madrid, Munich, Warsaw

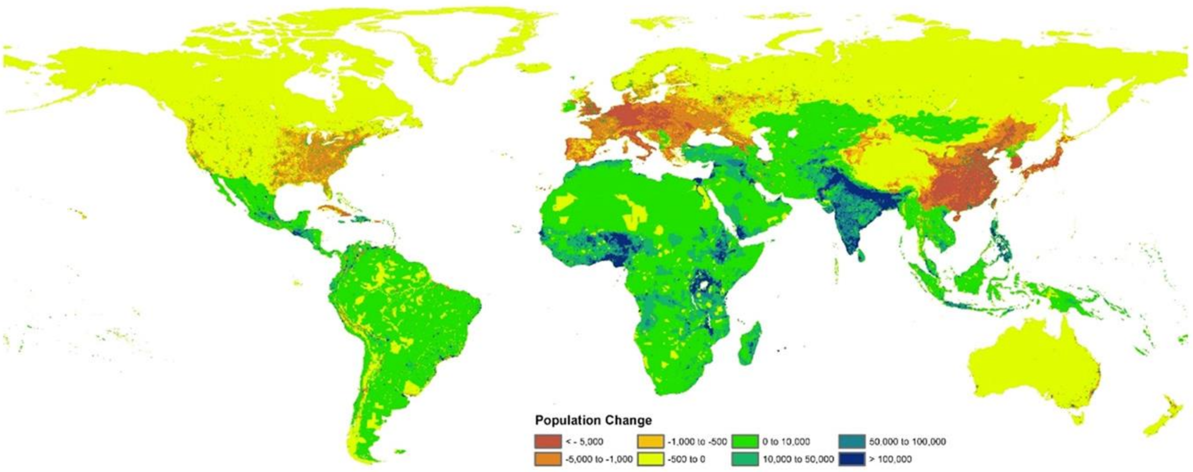
3. Urban population exposed in 2050

<u>Shared Socioeconomic Pathways</u> **(SSP) -** Future pathways of societal development

- **5 alternative outcomes** for trends in demographics, economics, technological development, lifestyles, governance…
- Provide **quantitative projections of key elements**, including national level population growth, educational composition, urbanization, and economic growth.



Population density

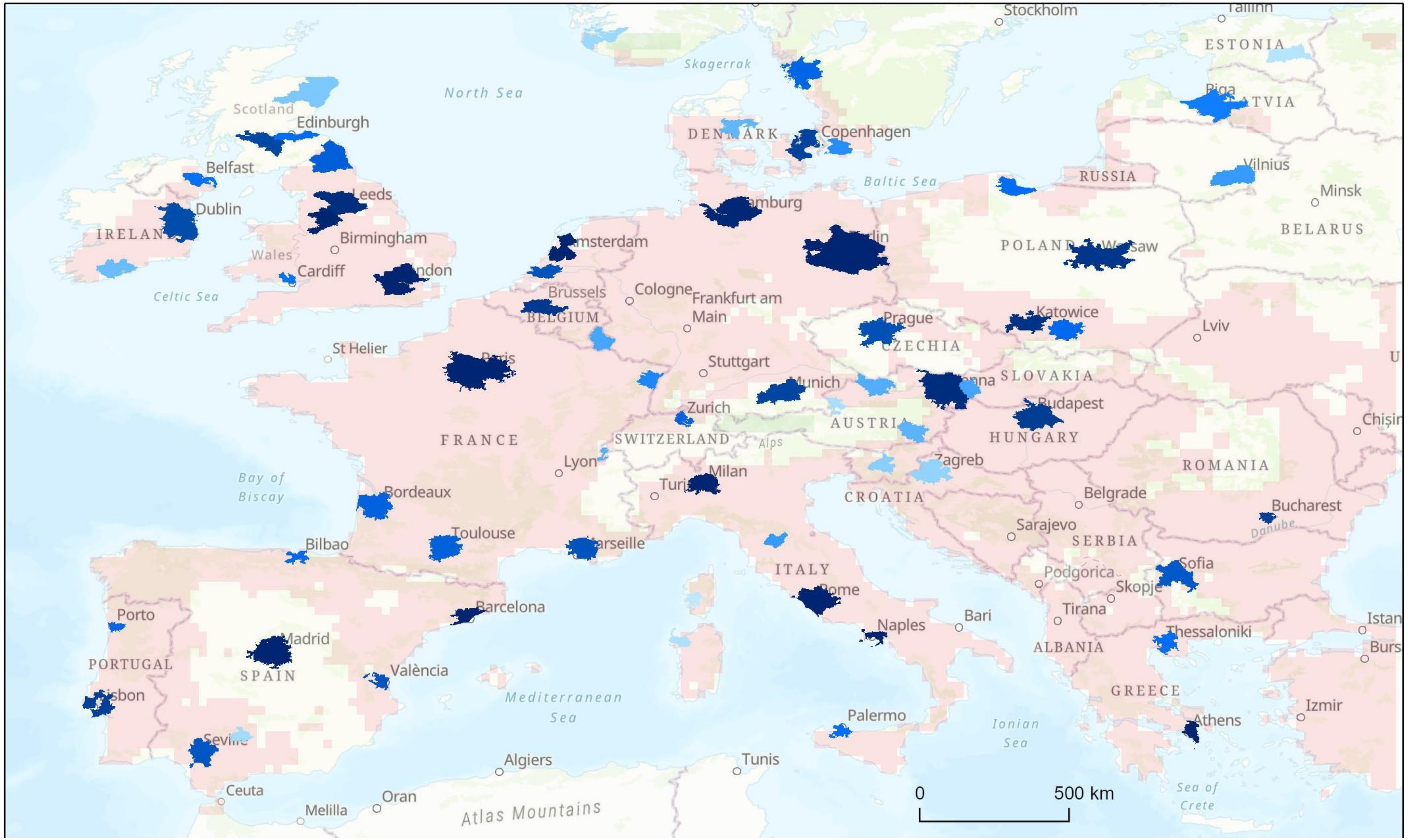


Population change

SSP3 - intermediate level of growth regarding demographics, economics, technology, governance (Gao, 2020; Jones & O'Neill, 2016).

Data from Global Population Grid (1 km) - *https://sedac.ciesin.columbia.edu/data/set/popdynamics-1-km-downscaled-pop-base-year-projection-ssp-2000-2100-rev01*

3. Urban population exposed in 2050



Suitable cities present
~60 million

Suitable cities future (2050)
~110 million

- Paris - 14 million
- London – 12 million
- Barcelona – 4.8 million
- Berlin – 4.7 million
- Milan – 4.6 million
- Valencia – 1.7 million
- Porto – 1.2 million

ITC

TRADE MAP

Trade statistics for international business development

Monthly, quarterly and yearly trade data. Import & export values, volumes, growth rates, market shares, etc.

Home & Search | Data Availability | Reference Material | Other ITC Tools | More

Product: ... 0602 - Live plants incl. their roots, cuttings and slips;

World / Country: Portugal — Country Group: None

Partner: All — Partner Group: None

other criteria: Imports | Yearly time series | by country | Direct data | Quantities | Primary unit

List of supplying markets for a product imported by Portugal

Product: 0602 Live plants incl. their roots, cuttings and slips; mushroom spawn (excluding bulbs, tubers, ...

Table | Graph | Map | Companies

Download:

Time Period (number of columns) : 5 per page — Rows per pag

Bilateral 4 digits	Exporters	2017	2018	2019	2020
		Imported quantity, Tons	Imported quantity, Tons	Imported quantity, Tons	Imported quantity, Tons
	World	38,358	33,952	35,750	33,343
⊞	Spain	23,289	18,589	19,813	18,695
⊞	Netherlands	9,392	10,429	11,757	10,672
⊞	Italy	2,277	2,628	2,170	1,588
⊞	United Kingdom	448	130	274	805
⊞	Poland	2	102	10	261
⊞	Germany	648	769	763	938
⊞	Belgium	133	190	251	149
⊞	China	29	22	17	58

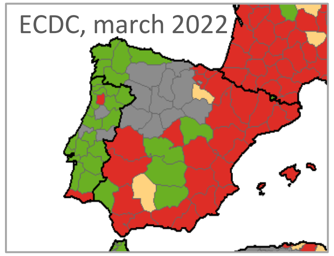
- ✓ *Monthly data (quantity)*
- ✓ *Imports by country*
- ✓ *Period: 2004 – 2019*
- ✓ *Specific products:*

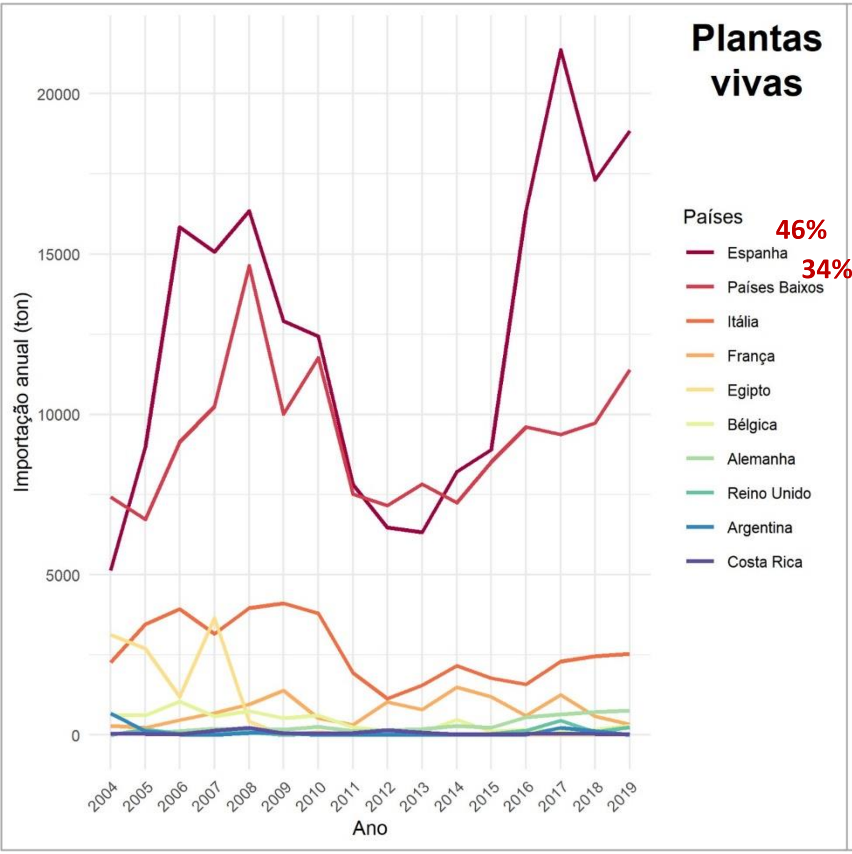
Live Plants

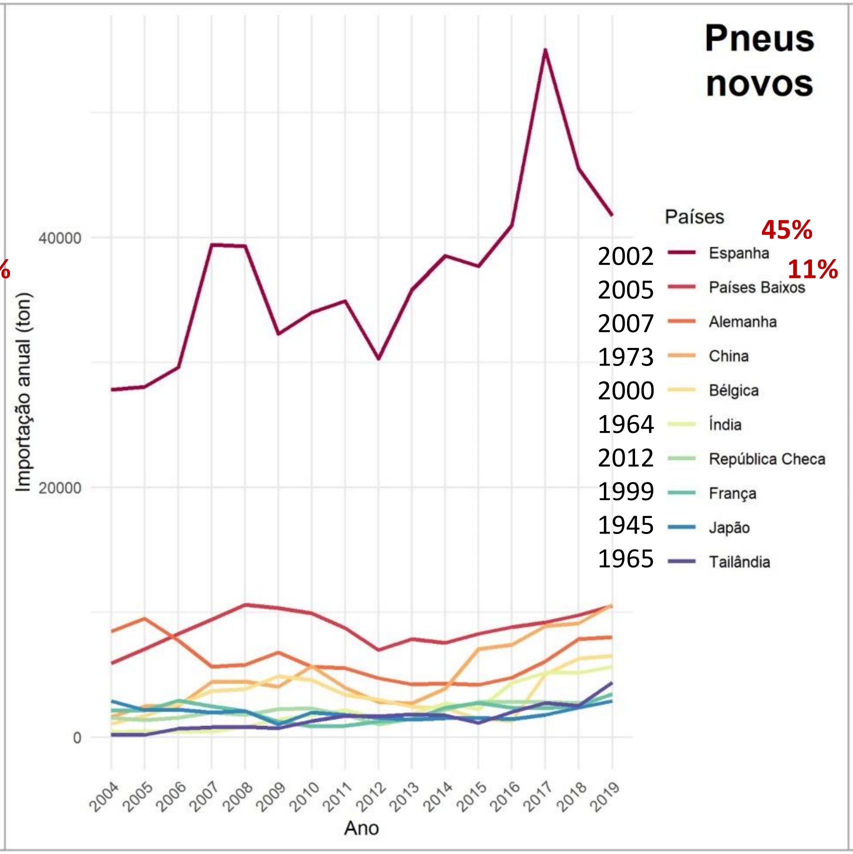
New Tires

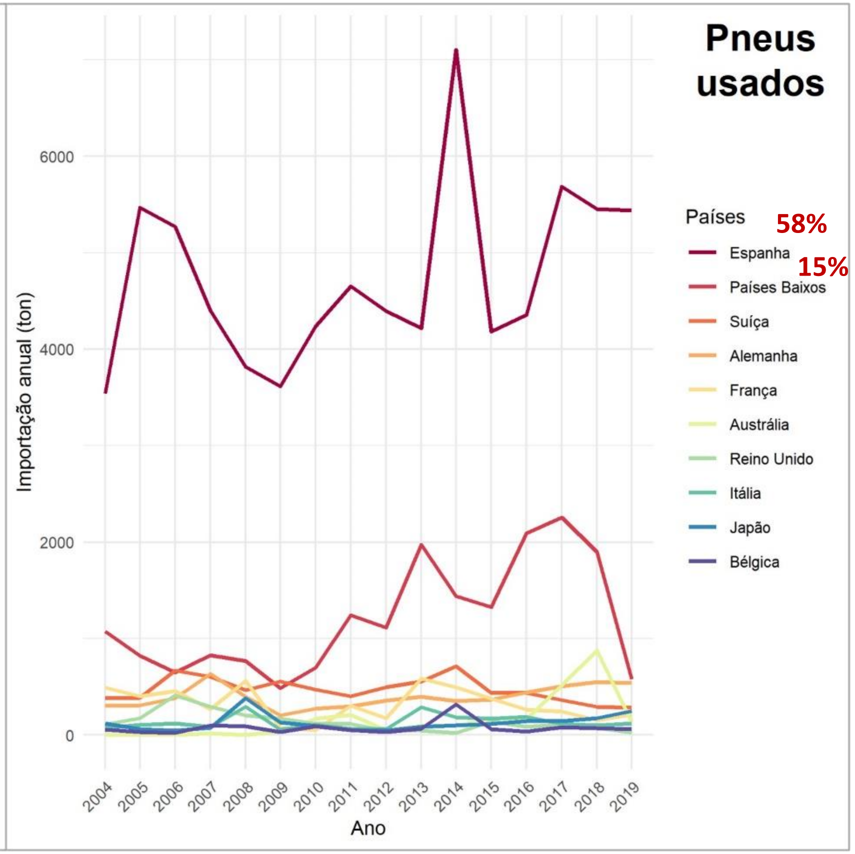
Used Tires

Portugal

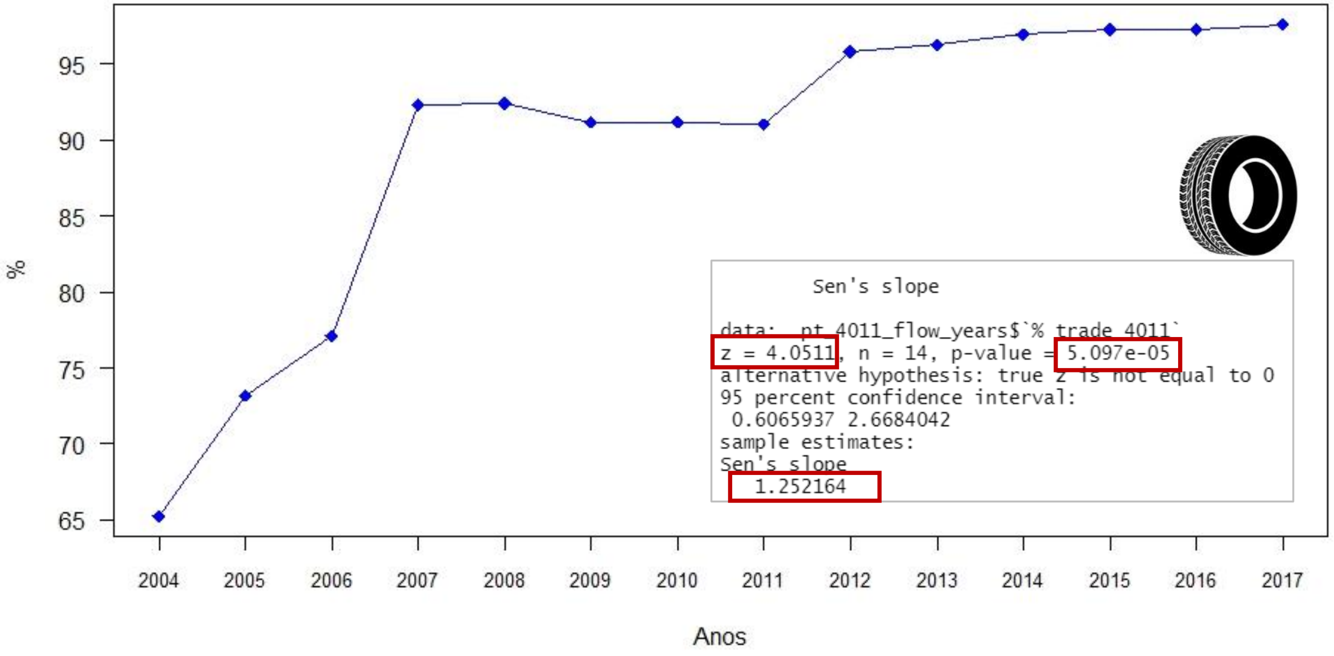

ECDC, march 2022

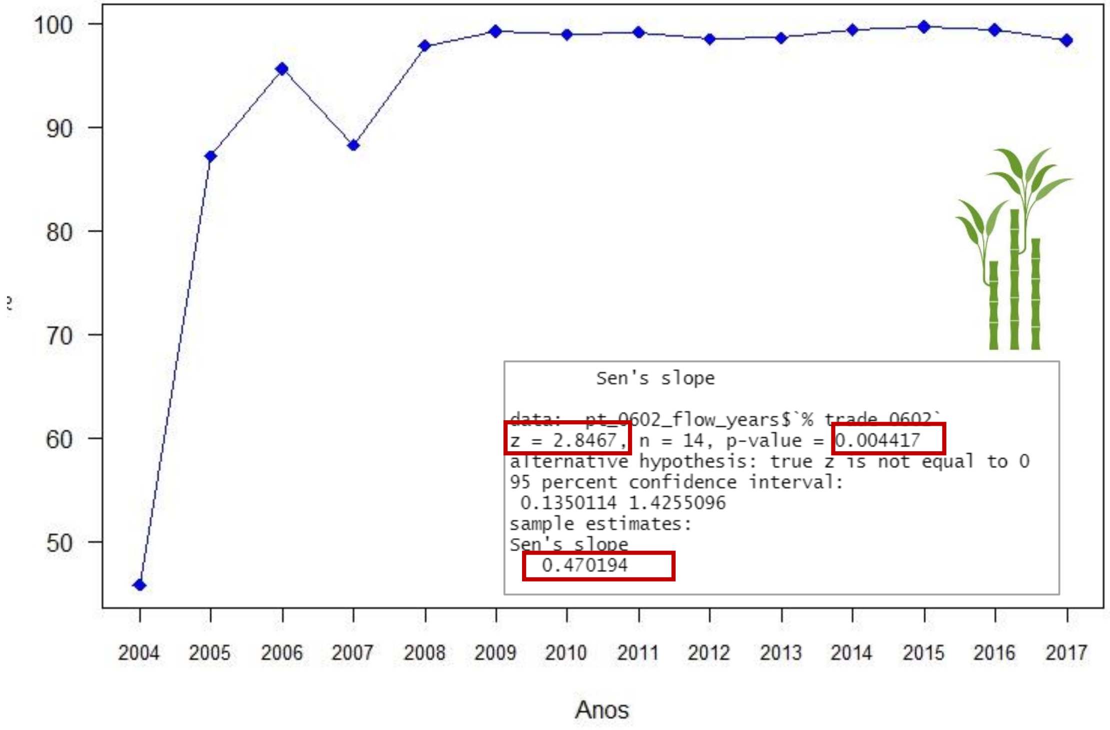

Plantas vivas
Países
Espanha 46%
Países Baixos 34%
Itália
França
Egipto
Bélgica
Alemanha
Reino Unido
Argentina
Costa Rica
Importação anual (ton)
Ano
0
5000
10000
15000
20000
2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019


Pneus novos
Países
2002 Espanha 45%
2005 Países Baixos 11%
2007 Alemanha
1973 China
2000 Bélgica
1964 Índia
2012 República Checa
1999 França
1945 Japão
1965 Tailândia
Importação anual (ton)
Ano
0
20000
40000
2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

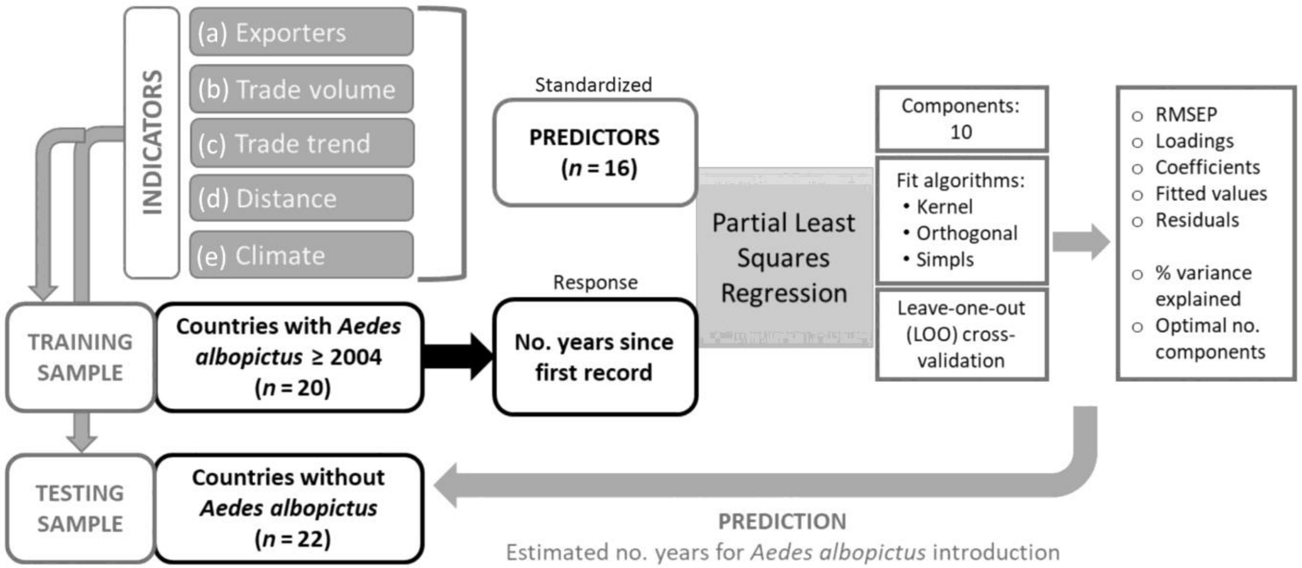

Pneus usados
Países
Espanha 58%
Países Baixos 15%
Suíça
Alemanha
França
Austrália
Reino Unido
Itália
Japão
Bélgica
Importação anual (ton)
Ano
0
2000
4000
6000
2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

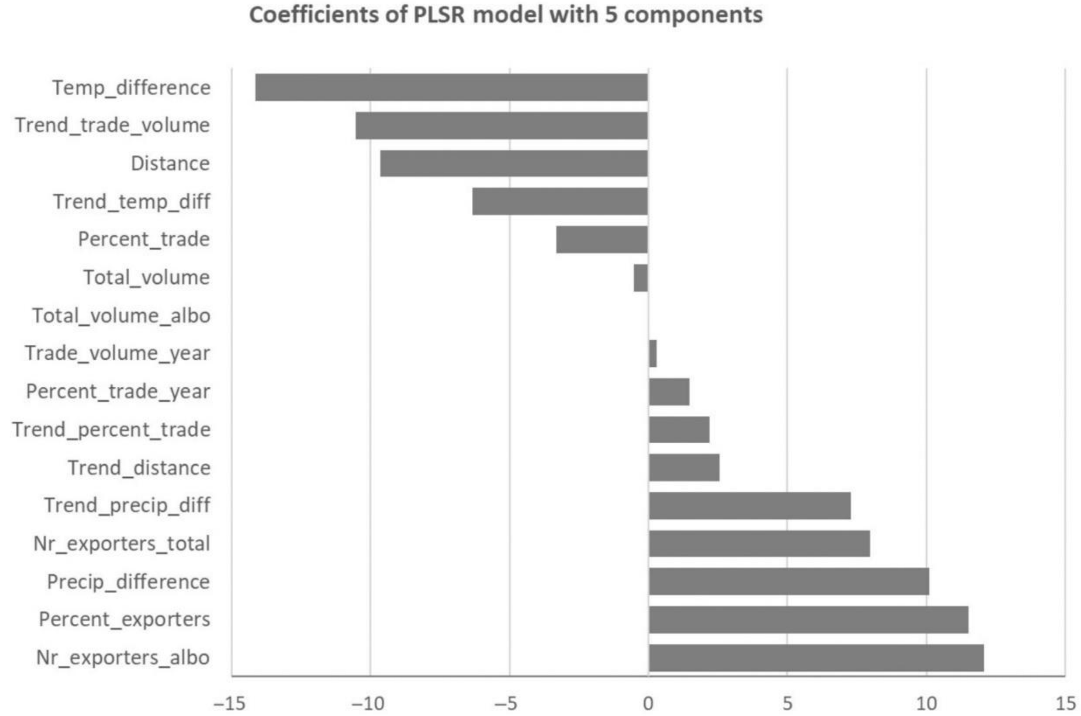
Portugal

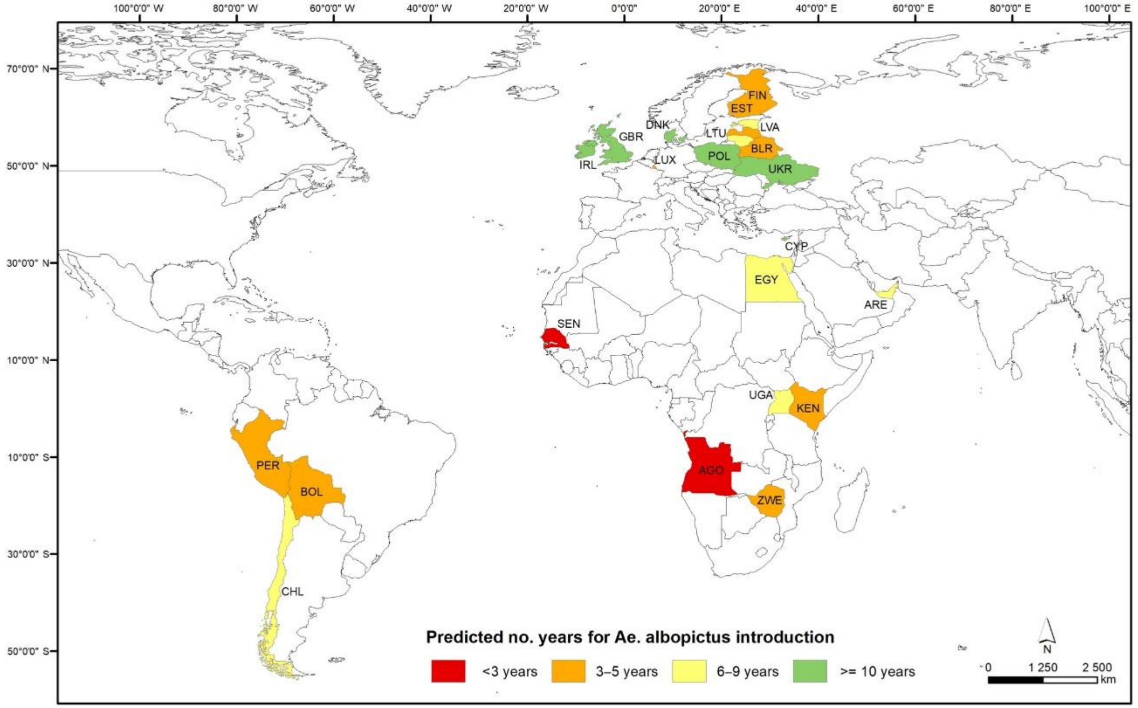


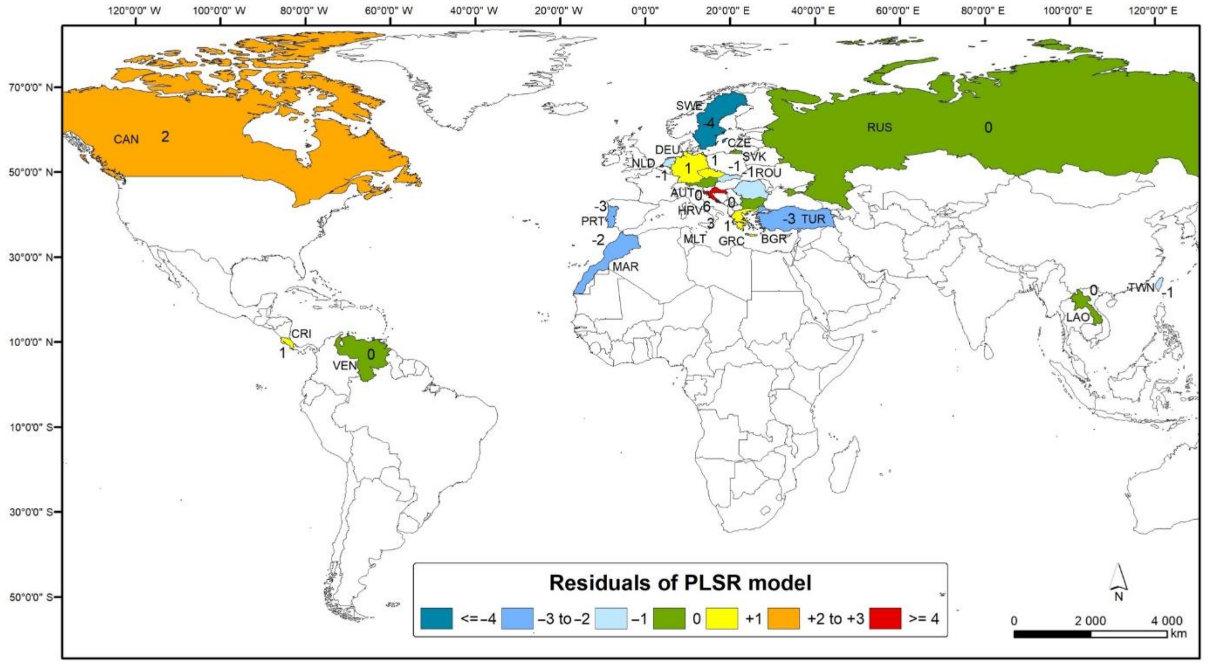


- Upward (positive) trend
- Statistically significant
- Magnitude > new tires (sen)

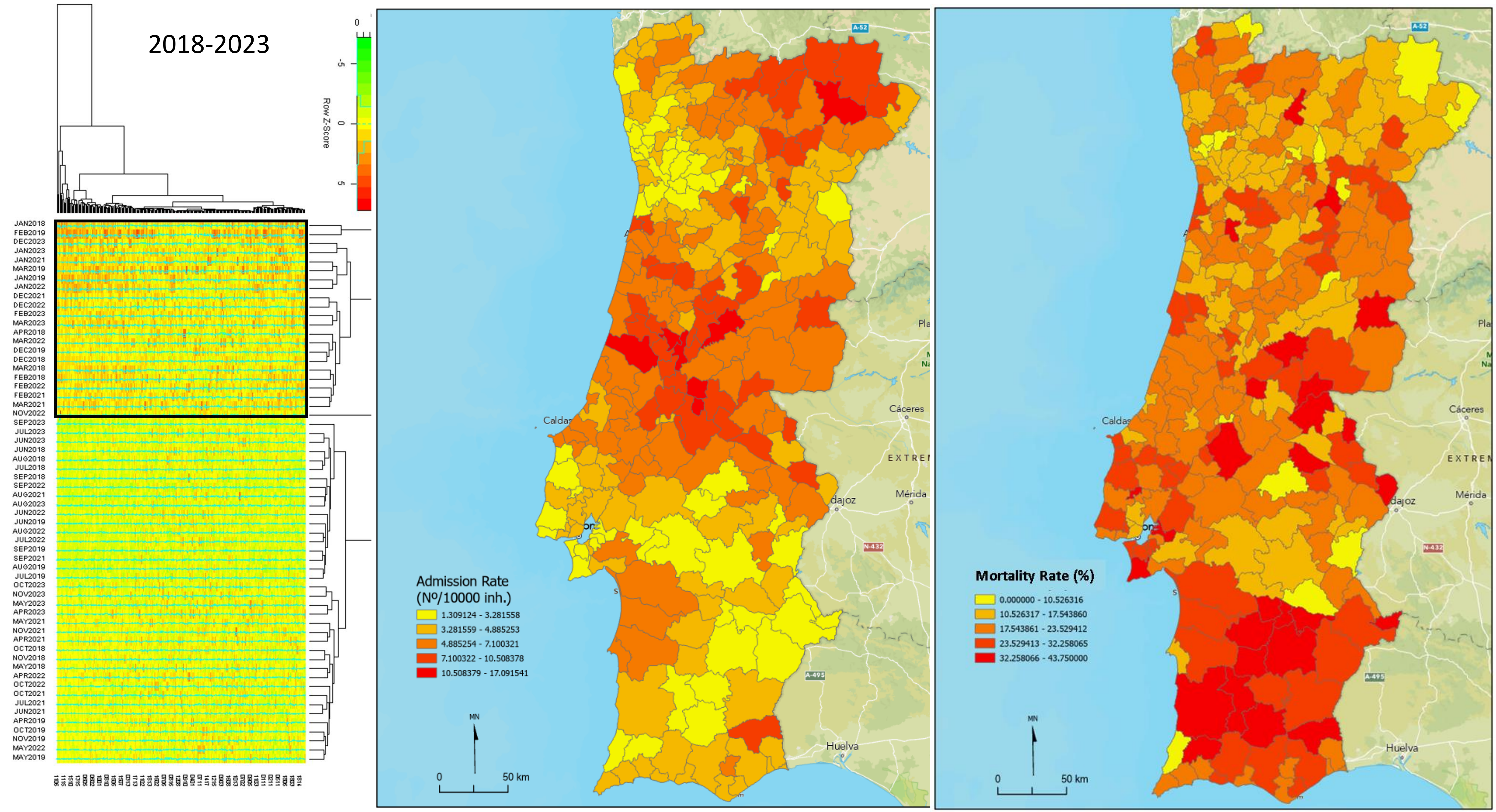

INDICATORS
(a) Exporters
(b) Trade volume
(c) Trade trend
(d) Distance
(e) Climate
Standardized
PREDICTORS
(n = 16)
Response
No. years since first record
Partial Least Squares Regression
Components: 10
Fit algorithms:
• Kernel
• Orthogonal
• Simpls
Leave-one-out (LOO) cross-validation
○ RMSEP
○ Loadings
○ Coefficients
○ Fitted values
○ Residuals
○ % variance explained
○ Optimal no. components
TRAINING SAMPLE
Countries with Aedes albopictus ≥ 2004 (n = 20)
TESTING SAMPLE
Countries without Aedes albopictus (n = 22)
PREDICTION
Estimated no. years for Aedes albopictus introduction


Coefficients of PLSR model with 5 components
Temp_difference
Trend_trade_volume
Distance
Trend_temp_diff
Percent_trade
Total_volume
Total_volume_albo
Trade_volume_year
Percent_trade_year
Trend_percent_trade
Trend_distance
Trend_precip_diff
Nr_exporters_total
Precip_difference
Percent_exporters
Nr_exporters_albo
–15
–10
–5
0
5
10
15


FIN
EST
LVA
DNK
GBR
LTU
BLR
IRL
LUX
POL
UKR
CYP
EGY
ARE
SEN
UGA
KEN
PER
BOL
AGO
ZWE
CHL
Predicted no. years for Ae. albopictus introduction
<3 years
3–5 years
6–9 years
>= 10 years
N
0 1 250 2 500 km


CAN 2
SWE
-4
RUS
0
CZE
DEU
SVK
NLD
ROU
AUT
HRV
PRT
TUR
MLT
GRC
BGR
MAR
TWN
LAO
CRI
VEN
Residuals of PLSR model
<=–4
–3 to –2
–1
0
+1
+2 to +3
>= 4
N
0 2 000 4 000 km

PNEUMONIA


2018-2023
Row Z-Score
JAN2018
FEB2019
DEC2023
JAN2023
JAN2021
MAR2019
JAN2019
JAN2022
DEC2021
DEC2022
FEB2023
MAR2023
APR2018
MAR2022
DEC2019
DEC2018
MAR2018
FEB2018
FEB2022
FEB2021
MAR2021
NOV2022
SEP2023
JUL2023
JUN2023
JUN2018
AUG2018
JUL2018
SEP2018
SEP2022
AUG2021
AUG2023
JUN2022
JUN2019
AUG2022
JUL2022
SEP2019
SEP2021
AUG2019
JUL2019
OCT2023
NOV2023
MAY2023
APR2023
MAY2021
NOV2021
APR2021
OCT2018
NOV2018
MAY2018
APR2022
OCT2022
OCT2021
JUL2021
JUN2021
APR2019
OCT2019
NOV2019
MAY2022
MAY2019
Admission Rate
(Nº/10000 inh.)
1.309124 - 3.281558
3.281559 - 4.885253
4.885254 - 7.100321
7.100322 - 10.508378
10.508379 - 17.091541
Mortality Rate (%)
0.000000 - 10.526316
10.526317 - 17.543860
17.543861 - 23.529412
23.529413 - 32.258065
32.258066 - 43.750000
MN
0
50 km
Cáceres
Mérida
Huelva
Caldas
EXTREM
A-52
N-432
A-495

Global Model-agnostic

V003 Isolated classical buildings

V005 Classical buildings in band

V007 Another type of classic building

V014 Buildings built before 1919

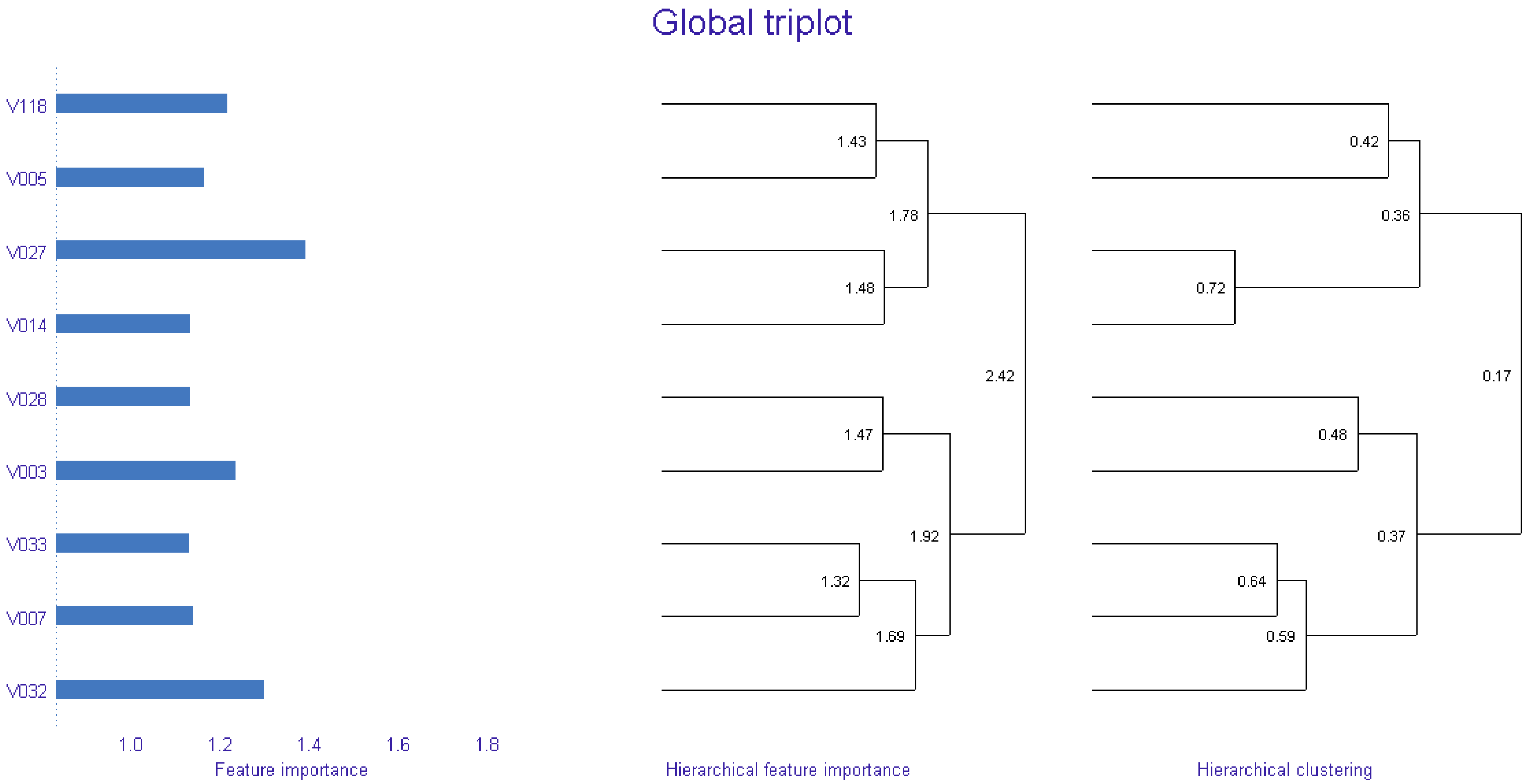
V027 Buildings with adobe wall structure or loose stone masonry

V028 Buildings with another type of structure

V032 Non-Classic Family Accommodations

V033 Collective accommodation

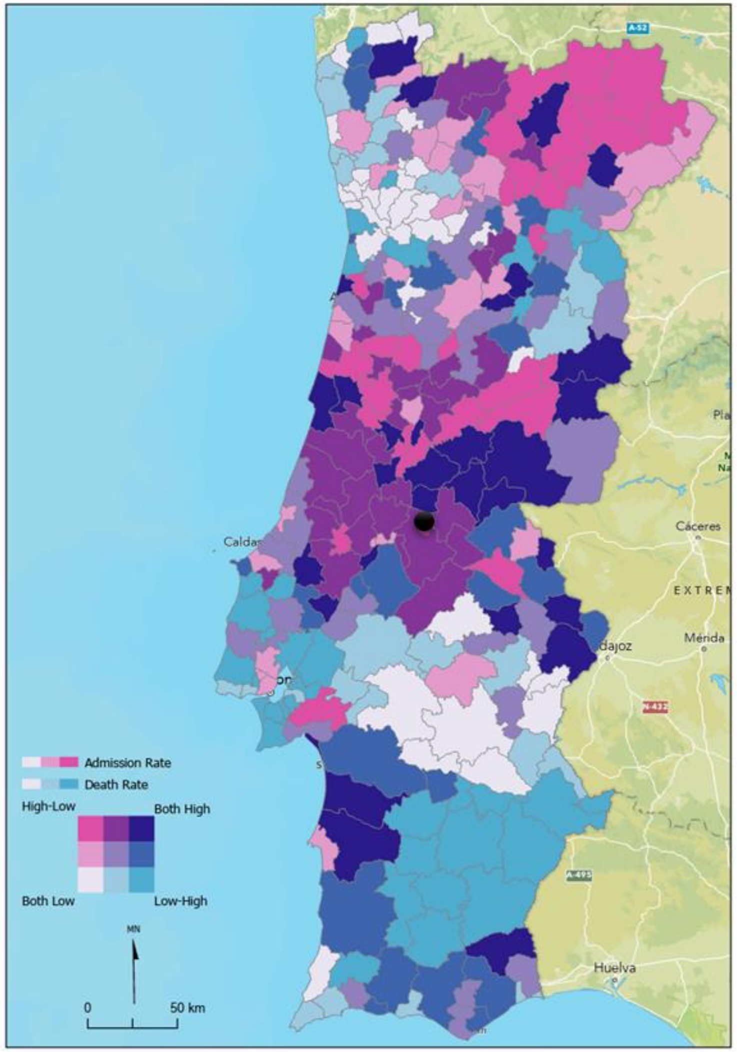
V118 Resident individuals employed in the primary sector

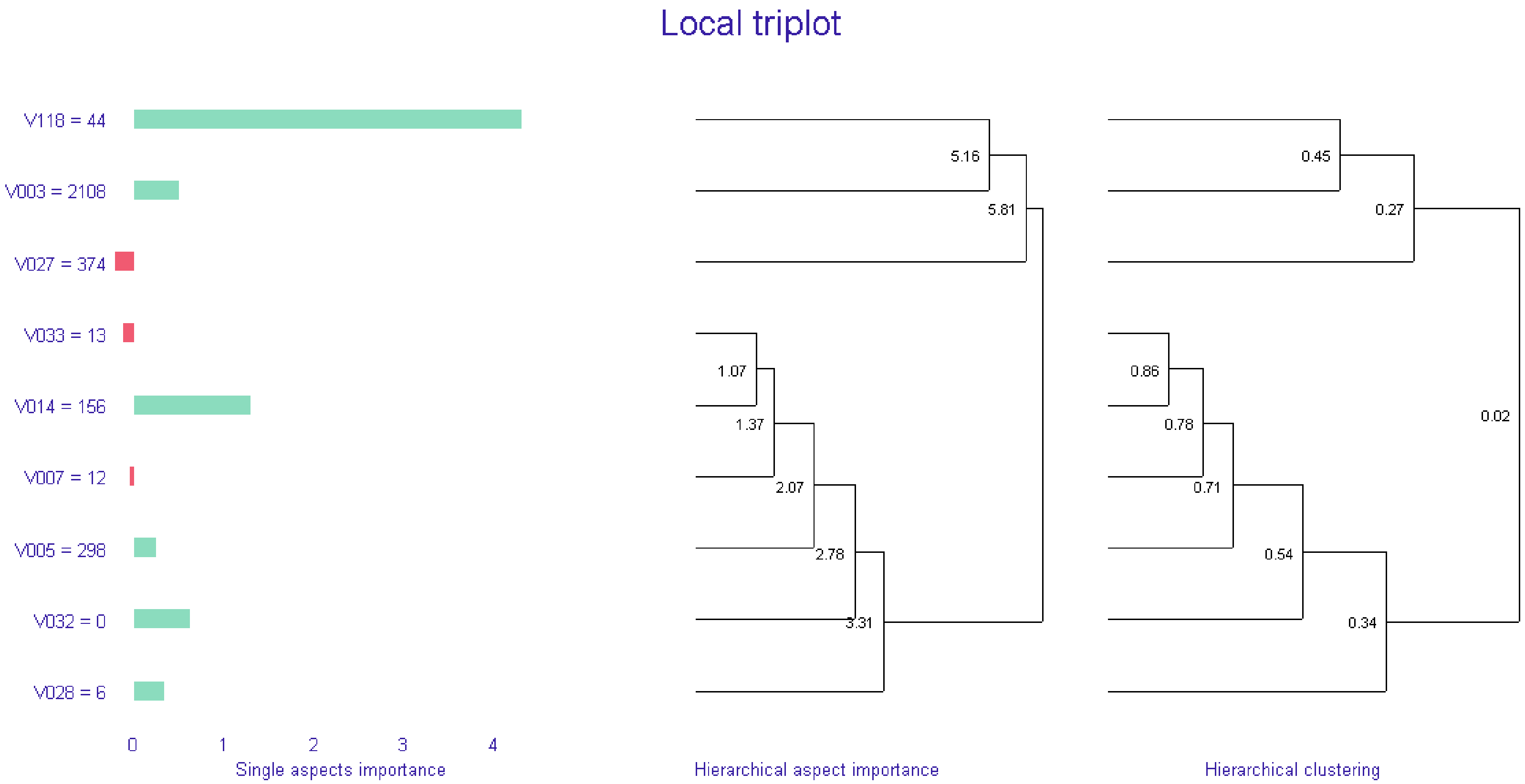


Random Forest

Vila de Rei

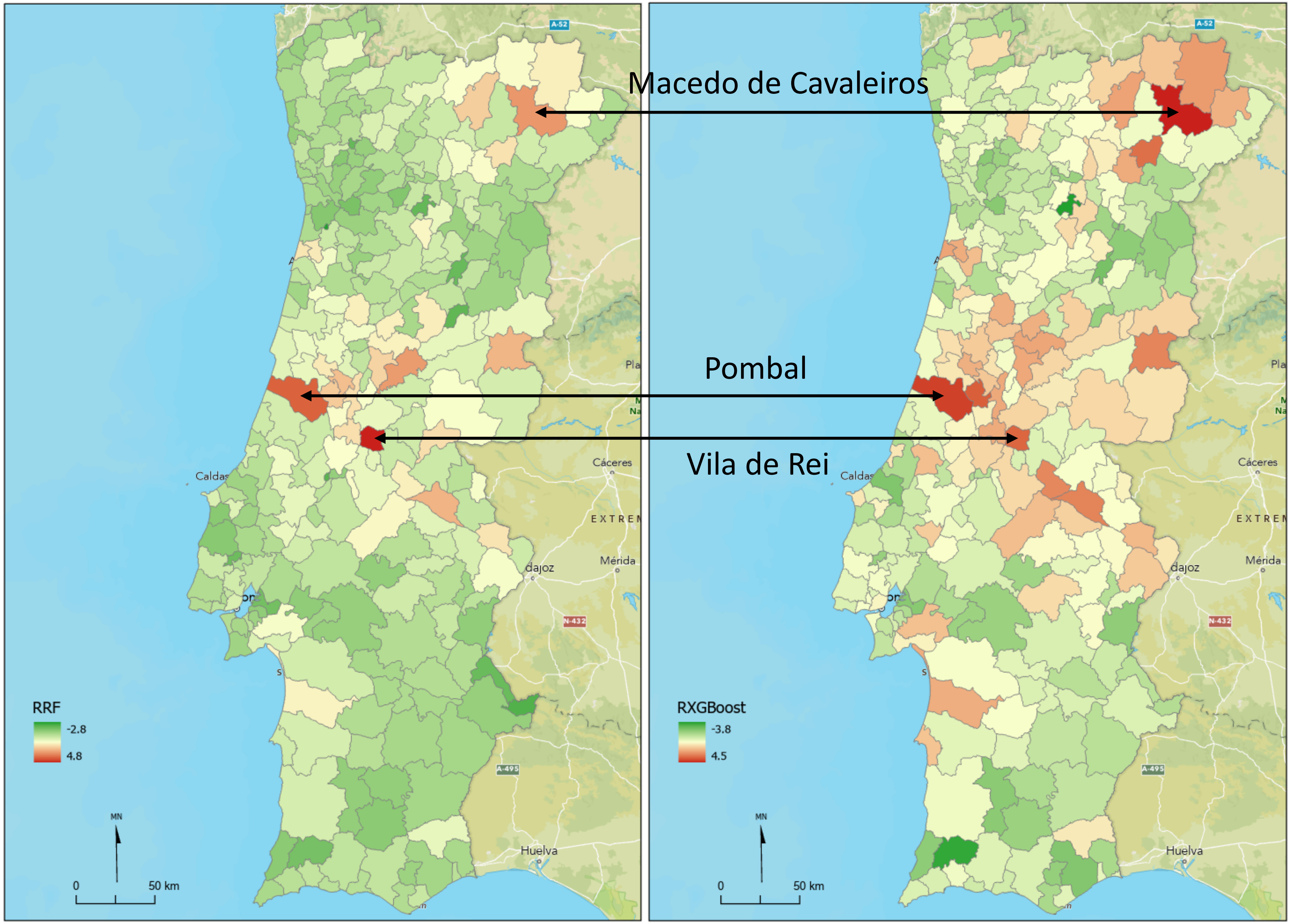
Local Model-agnostic



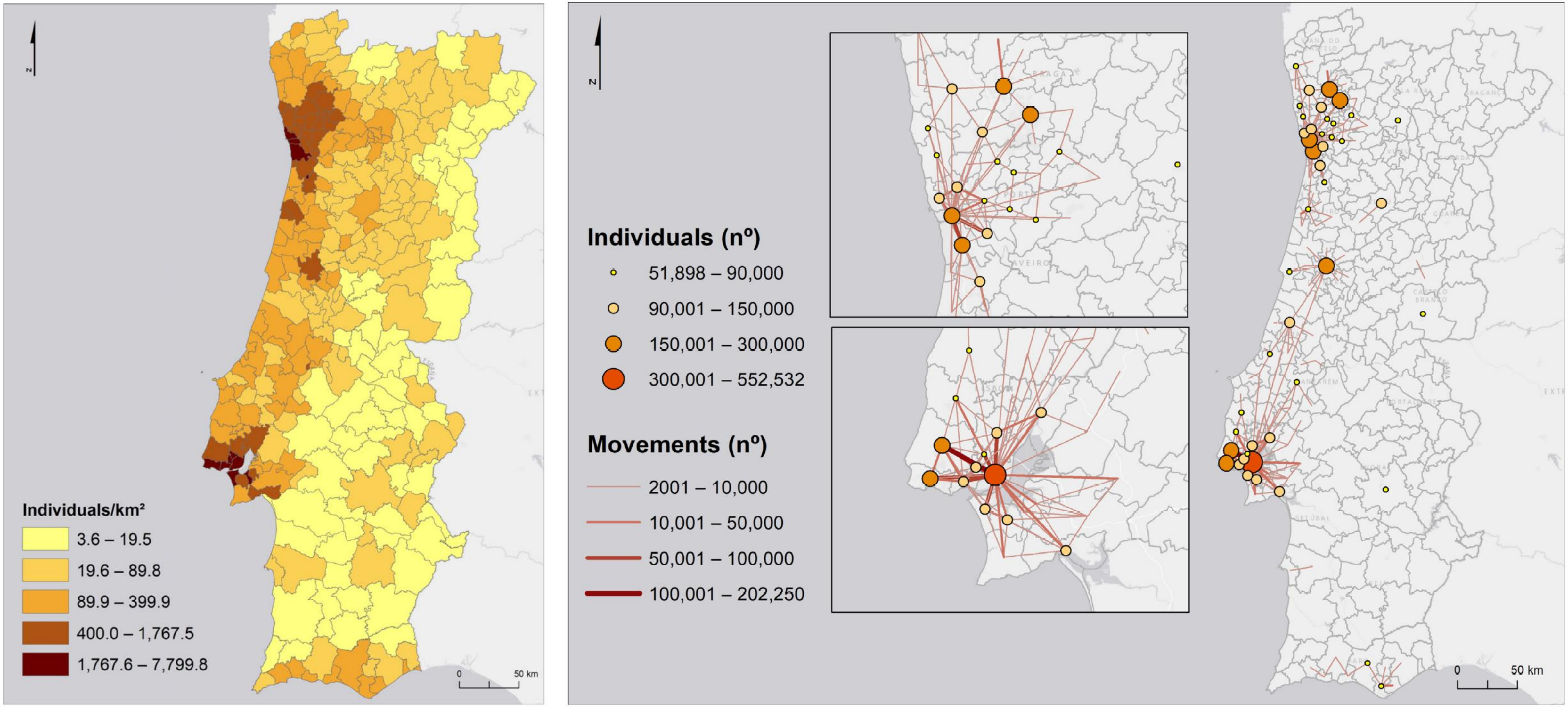


V003 Isolated classical buildings, **V005** Classical buildings in band, **V007** Another type of classic building, **V014** Buildings built before 1919, **V027** Buildings with adobe wall structure or loose stone masonry, **V028** Buildings with another type of structure, **V032** Non-Classic Family Accommodations, **V033** Collective accommodation, **V118** Resident individuals employed in the primary sector

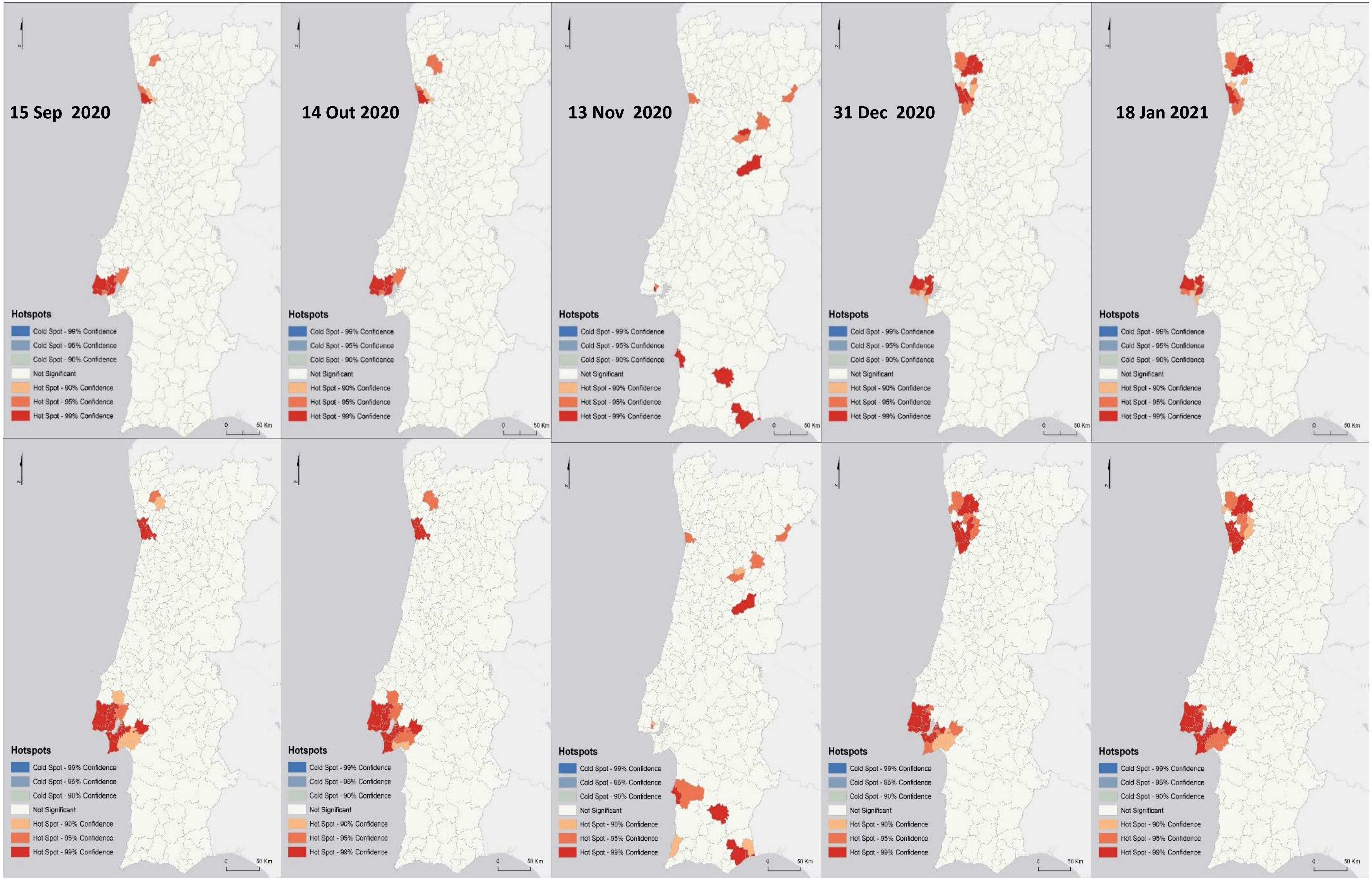
Model Residuals

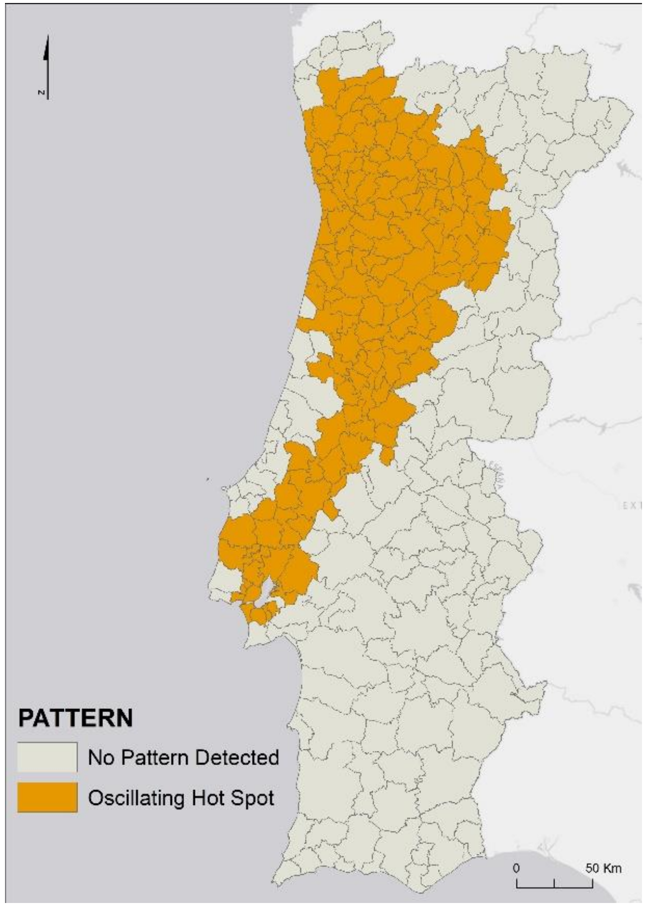


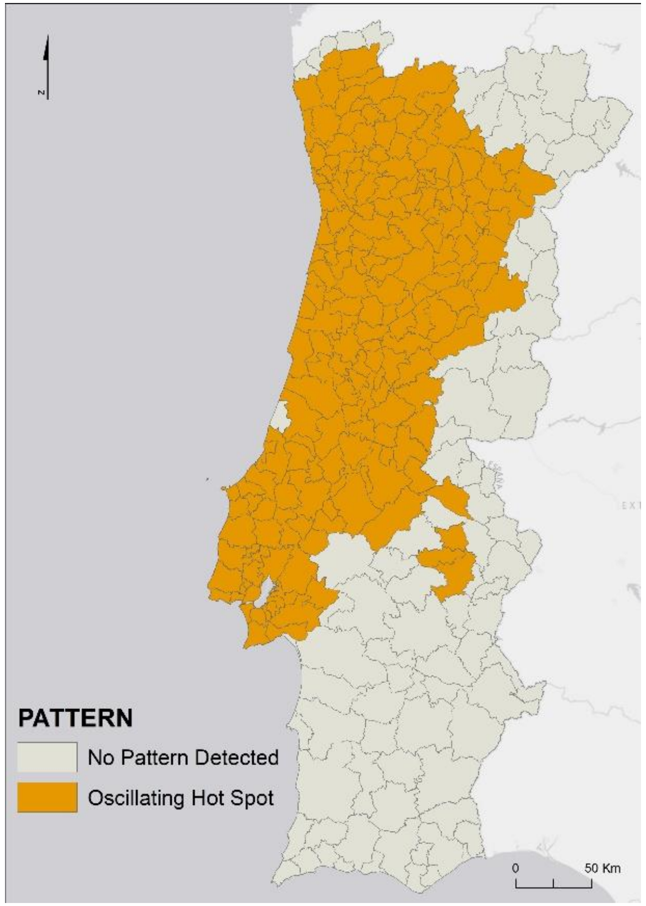
SARS-CoV-2

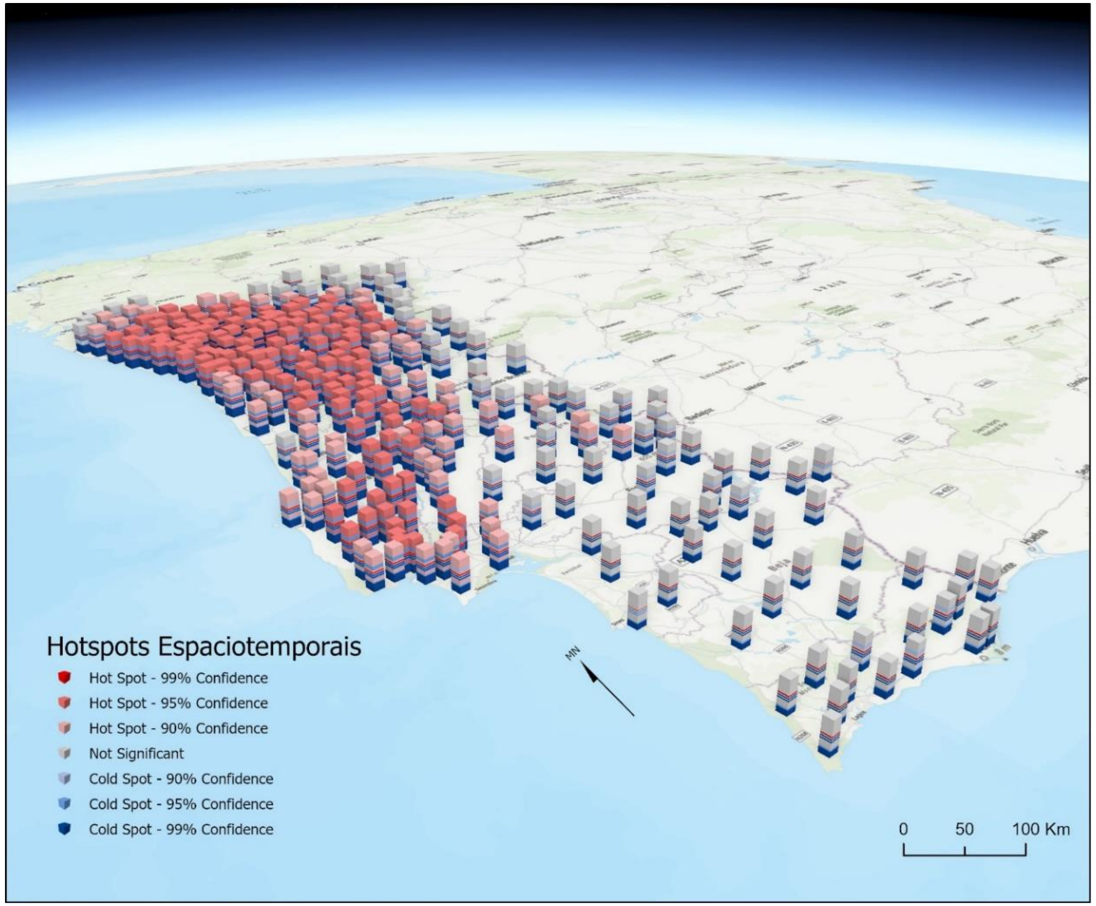


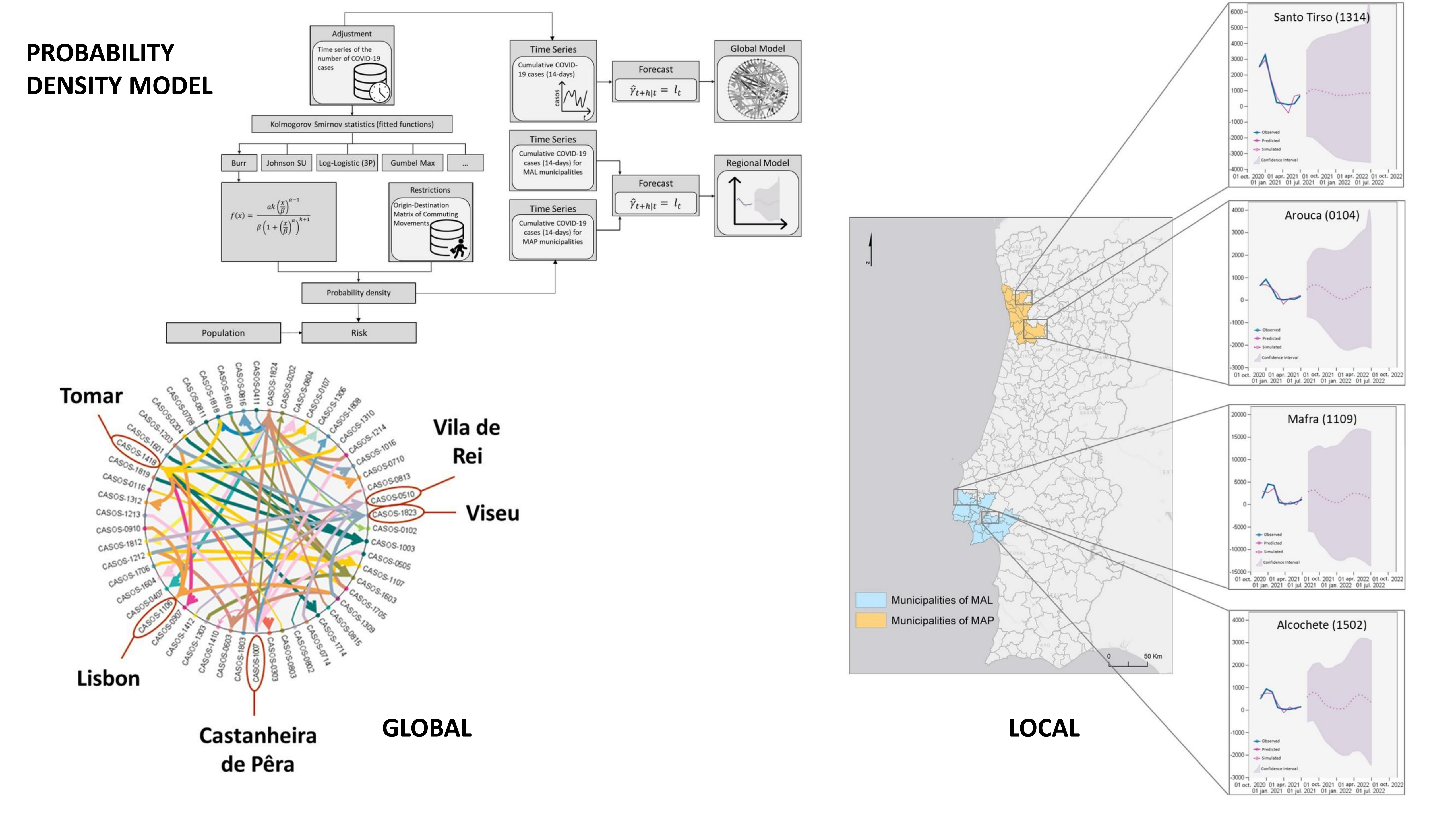
Individuals/km²
3.6 – 19.5
19.6 – 89.8
89.9 – 399.9
400.0 – 1,767.5
1,767.6 – 7,799.8
0
50 km
Individuals (nº)
51,898 – 90,000
90,001 – 150,000
150,001 – 300,000
300,001 – 552,532
Movements (nº)
2001 – 10,000
10,001 – 50,000
50,001 – 100,000
100,001 – 202,250
0
50 km


15 Sep 2020
14 Out 2020
13 Nov 2020
31 Dec 2020
18 Jan 2021
Hotspots
Cold Spot - 99% Confidence
Cold Spot - 95% Confidence
Cold Spot - 90% Confidence
Not Significant
Hot Spot - 90% Confidence
Hot Spot - 95% Confidence
Hot Spot - 99% Confidence
0
50 Km

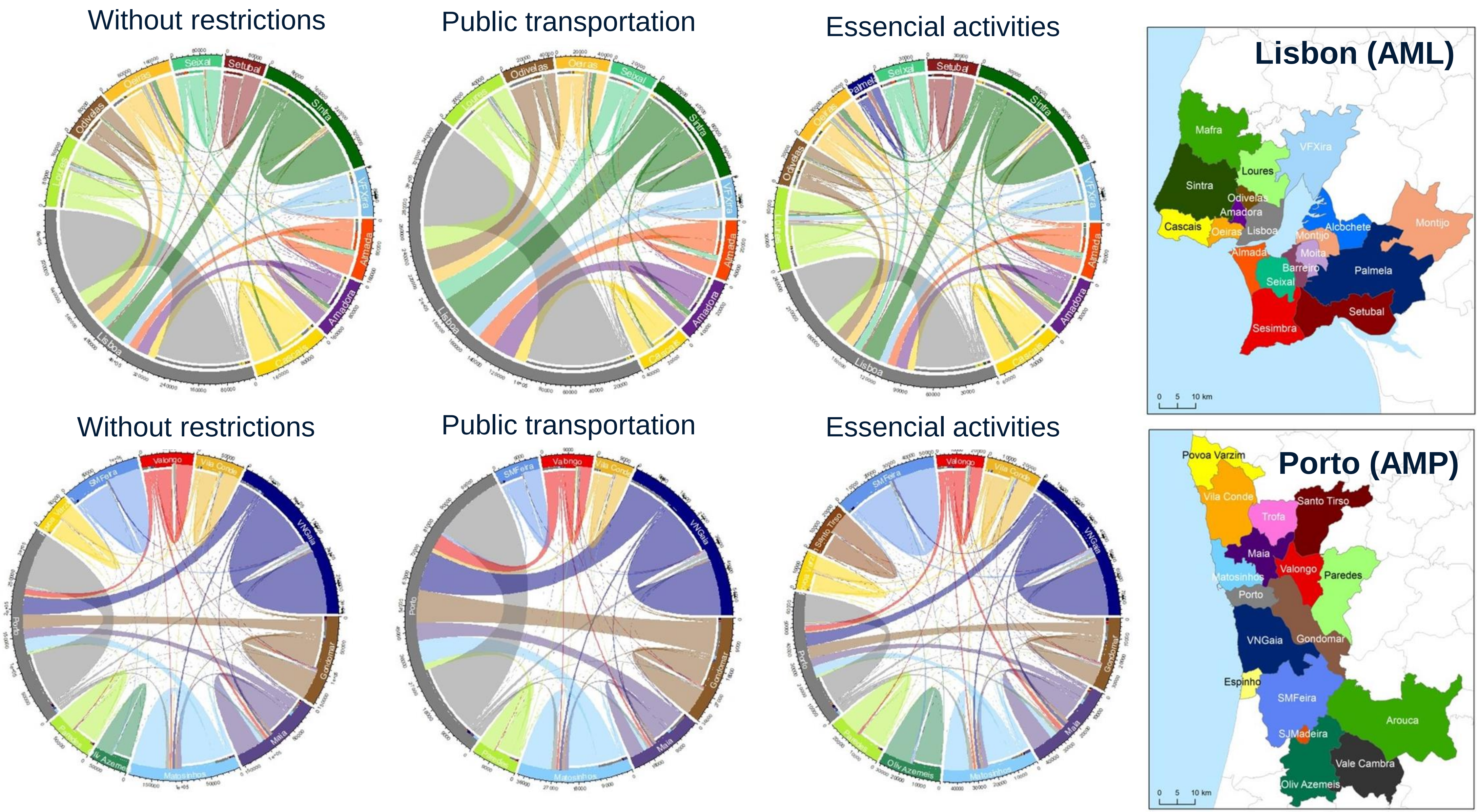

N
PATTERN
No Pattern Detected
Oscillating Hot Spot
0
50 Km

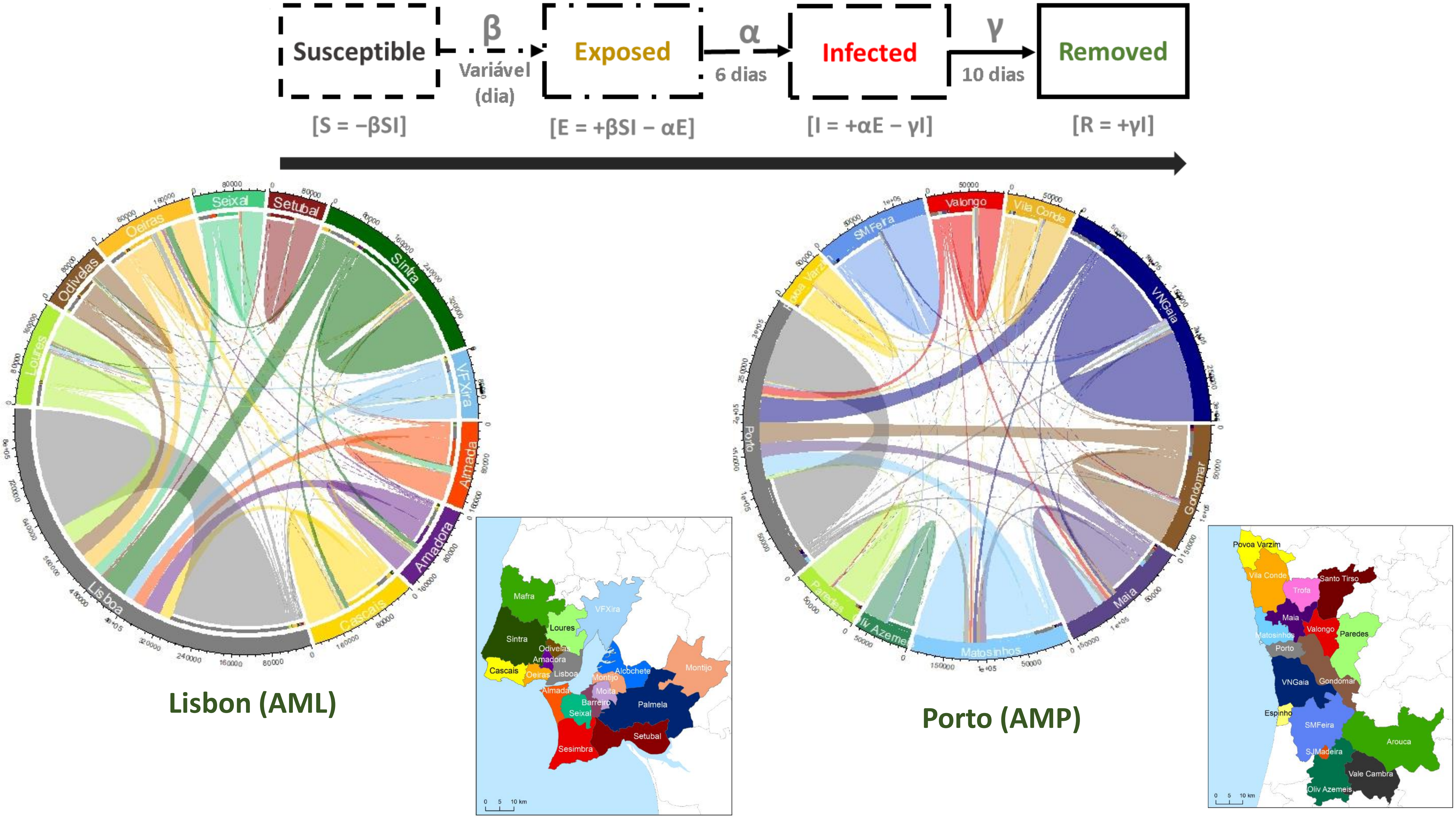

N
PATTERN
No Pattern Detected
Oscillating Hot Spot
0
50 Km


Hotspots Espaciotemporais
Hot Spot - 99% Confidence
Hot Spot - 95% Confidence
Hot Spot - 90% Confidence
Not Significant
Cold Spot - 90% Confidence
Cold Spot - 95% Confidence
Cold Spot - 99% Confidence
MN
0
50
100 Km



PROBABILITY DENSITY MODEL
Adjustment
Time series of the number of COVID-19 cases
Kolmogorov Smirnov statistics (fitted functions)
Burr
Johnson SU
Log-Logistic (3P)
Gumbel Max
...
$f(x) = \frac{\alpha k \left(\frac{x}{\beta}\right)^{\alpha-1}}{\beta\left(1+\left(\frac{x}{\beta}\right)^{\alpha}\right)^{k+1}}$
Restrictions
Origin-Destination Matrix of Commuting Movements
Probability density
Population
Risk
Time Series
Cumulative COVID-19 cases (14-days)
casos
Forecast
$\hat{Y}_{t+h|t} = l_t$
Global Model
Time Series
Cumulative COVID-19 cases (14-days) for MAL municipalities
Time Series
Cumulative COVID-19 cases (14-days) for MAP municipalities
Forecast
$\hat{Y}_{t+h|t} = l_t$
Regional Model
Tomar
Vila de Rei
Viseu
Lisbon
Castanheira de Pêra
GLOBAL
Santo Tirso (1314)
Arouca (0104)
Mafra (1109)
Alcochete (1502)
Observed
Predicted
Simulated
Confidence Interval
Municipalities of MAL
Municipalities of MAP
50 Km
LOCAL


Without restrictions
Public transportation
Essencial activities
Lisbon (AML)
Mafra
VFXira
Loures
Sintra
Odivelas
Amadora
Cascais
Oeiras
Lisboa
Alcochete
Montijo
Montijo
Moita
Almada
Barreiro
Seixal
Palmela
Setubal
Sesimbra
0 5 10 km
Without restrictions
Public transportation
Essencial activities
Porto (AMP)
Povoa Varzim
Vila Conde
Santo Tirso
Trofa
Maia
Valongo
Paredes
Matosinhos
Porto
VNGaia
Gondomar
Espinho
SMFeira
Arouca
SJMadeira
Vale Cambra
Oliv Azemeis
0 5 10 km


Susceptible
β
Variável
(dia)
Exposed
α
6 dias
Infected
γ
10 dias
Removed
[S = −βSI]
[E = +βSI − αE]
[I = +αE − γI]
[R = +γI]
Seixal
Setubal
Oeiras
Sintra
Odivelas
Loures
VFXira
Almada
Amadora
Cascais
Lisboa
Mafra
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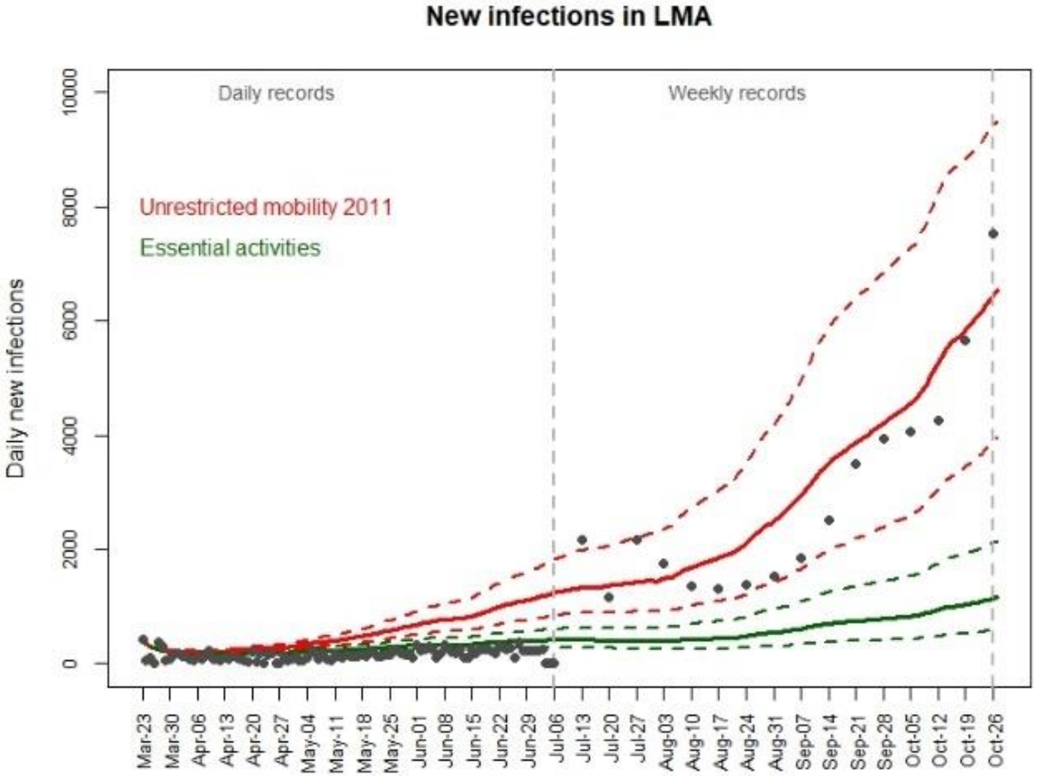
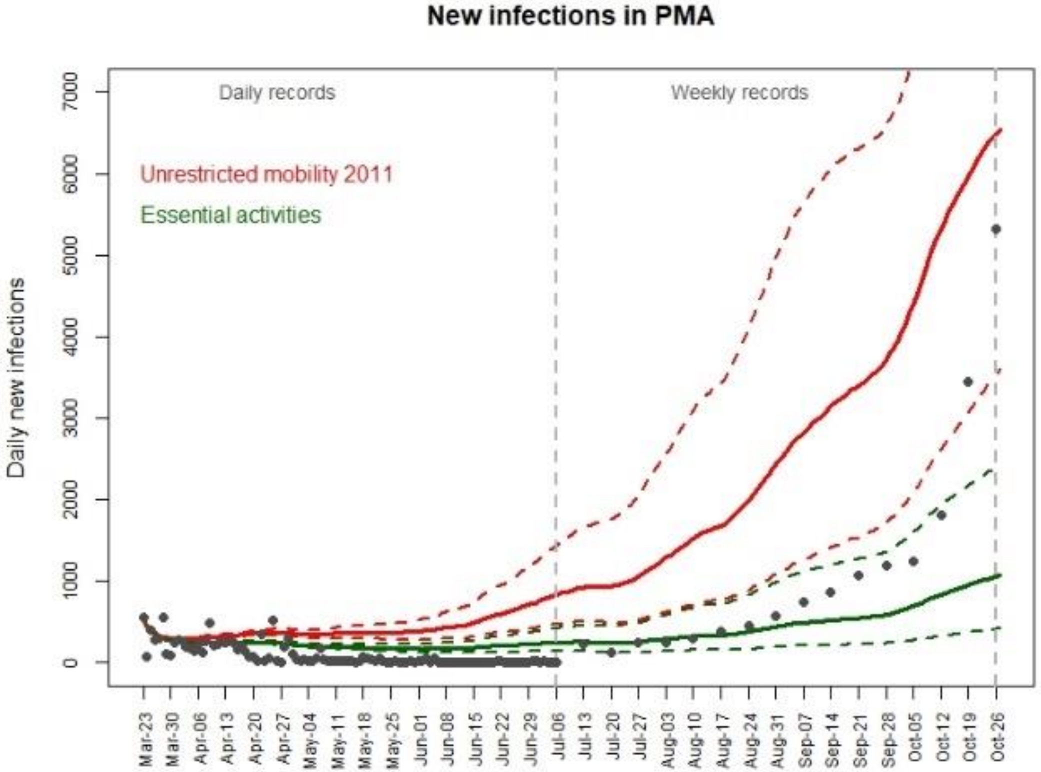
SJMadeira
Arouca
Vale Cambra
Oliv Azemeis
Porto (AMP)

- ✓ Daily new cases - Estimations *vs* oficial records (23 March 2020 to 26 October 2020)
- ✓ 2 scenarios: Unrestricted mobility & Restricted to Essential activities





Estimated values considering the upper and lower thresholds of the confidence interval (95%) of R_t (dashed lines).
Official recorded cases of new infections are represented as points, daily values until the 6th July, and cumulative weekly values afterwards.

Final Remarks

Key Insights: Lessons learned from the case studies emphasize the importance of early detection and intervention.

The Power of Integration: Value of combining geospatial data, public health policies, and community engagement.

Call to Action: Encourage stakeholders to adopt comprehensive approaches to pandemic prevention, grounded in data and collaboration.

Future Directions: Innovations like AI, real-time data integration, and predictive analytics to enhance pandemic preparedness.

Thank You
…and see you soon

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