Unravelling hierarchies through percolation

Elsa Arcaute

CASA0002: Urban Simulation

Week 10: 18th March 2024

Any hope for universality?

- Cities are very different
- Historical paths are all very different
- Societies and their cultures are very different
- Subjected to different environmental stresses

Looking for universal patterns, that regardless of all the geographical constraints, historical, socio-political trajectories, these can be identified all over the world.

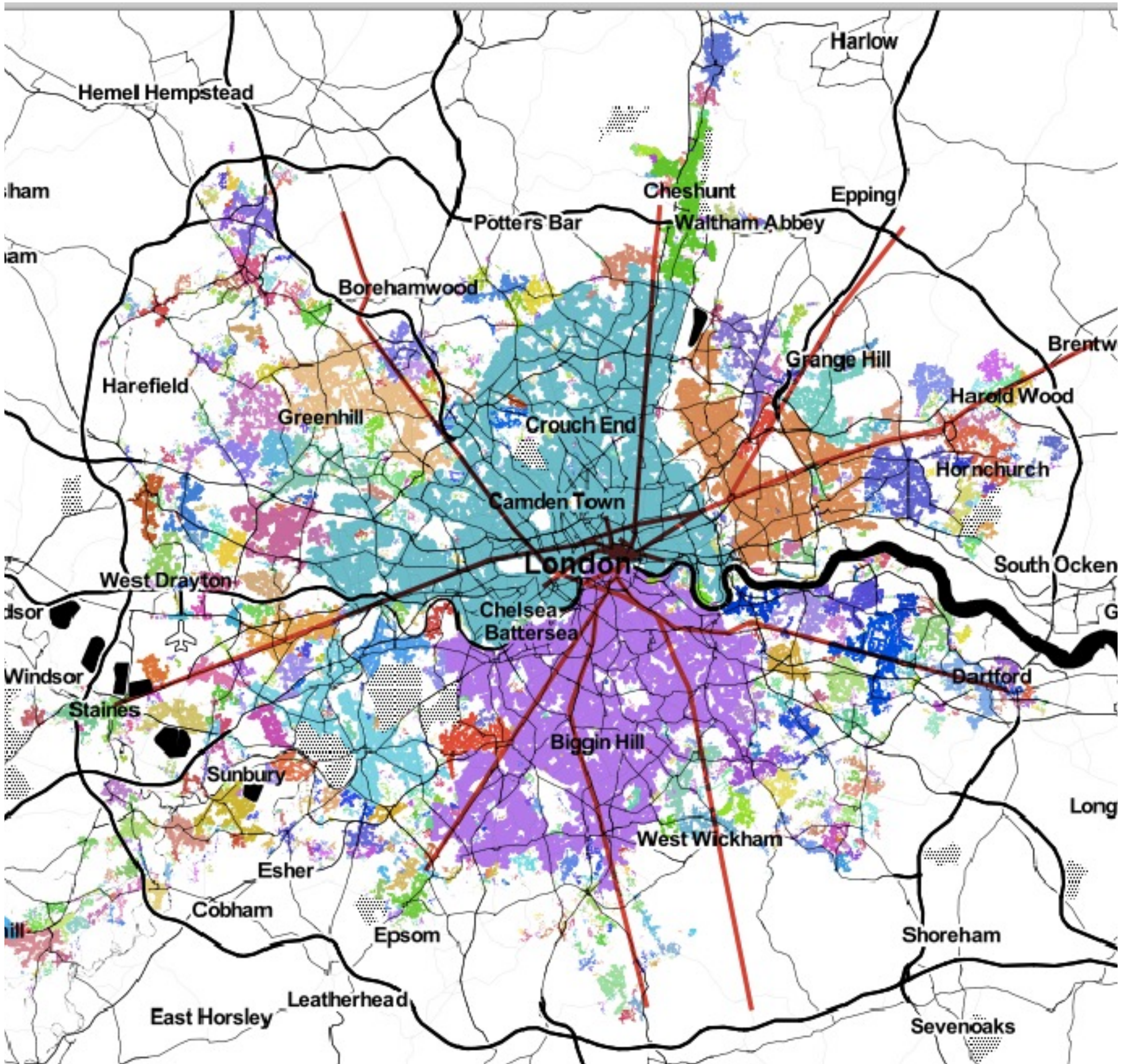
Morphology

Cities are places for interactions, and cities need to be connected

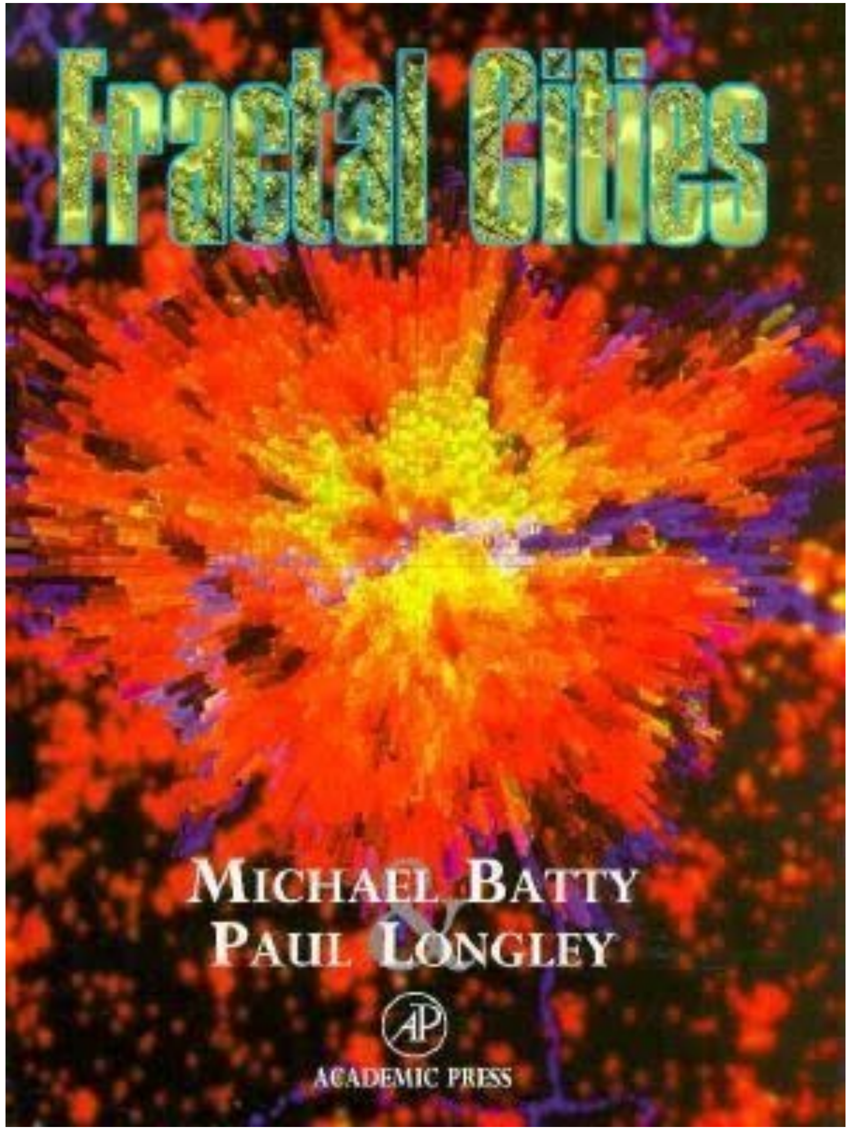
Roads: that we observe nowadays are the outcome of the reinforcement of relevant connectivity between 2 places

Roman roads that remain nowadays are important roads where retail is concentrated

Connectivity is fractal!

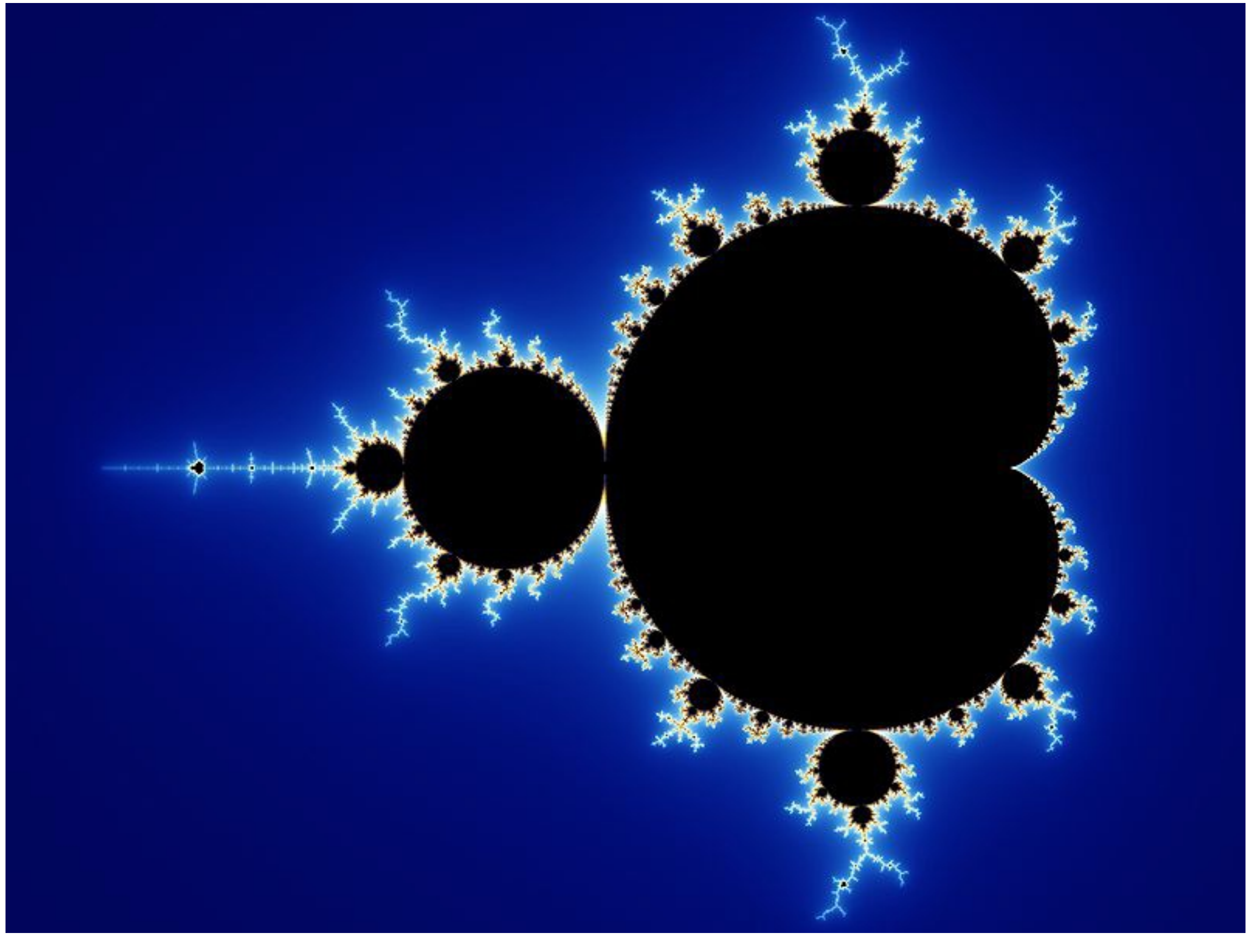


Fractal Cities



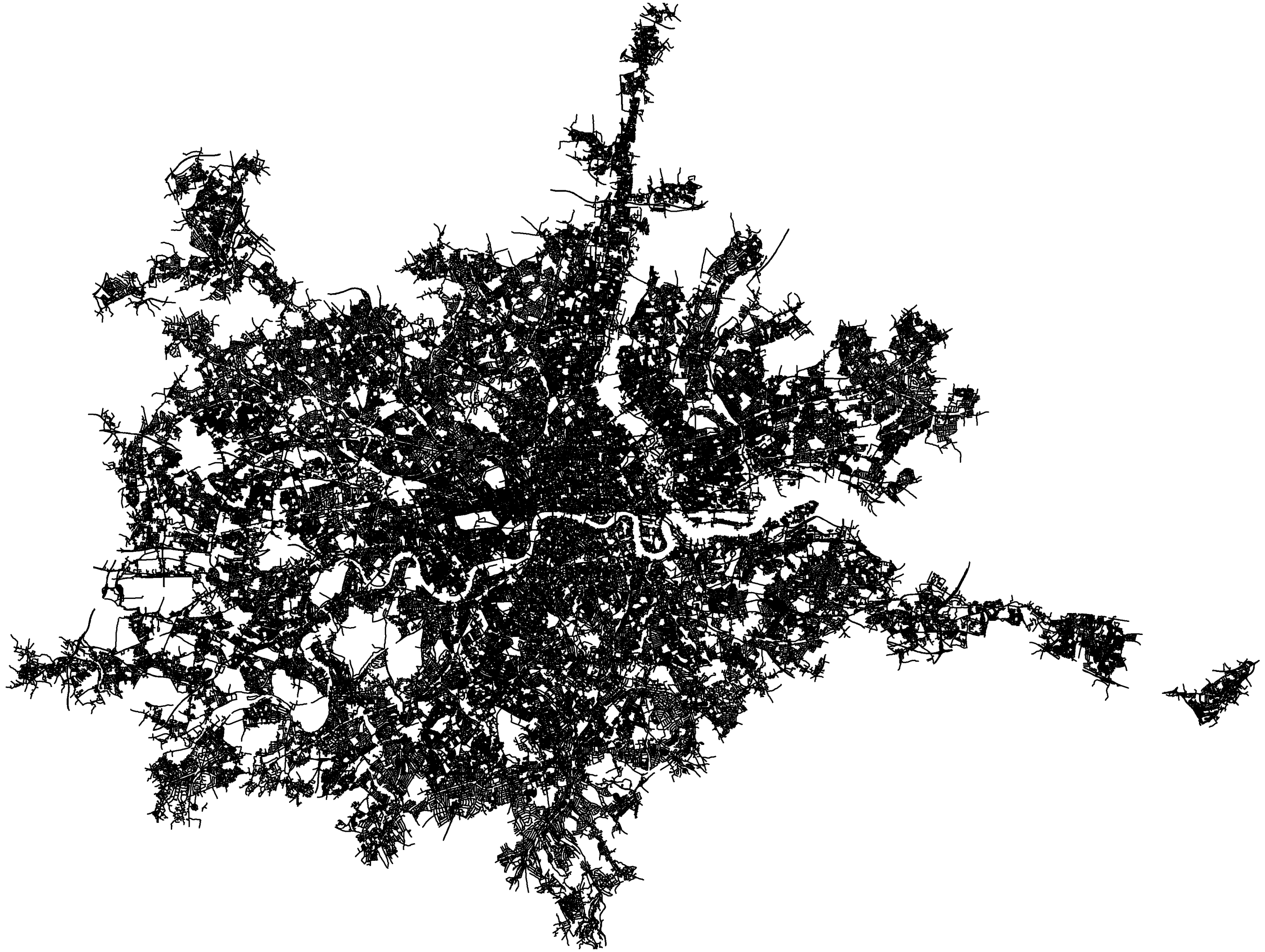
Michael Batty is one of the original proposers of considering cities as fractals! The other person is Frank Frankhauser. Both in 1994.

Regular vs random fractals



The Mandelbrot set

London street network



Fractals

Volcanic landscape

Tenerife

Zoom: volcanic rock, also fractal

Forest

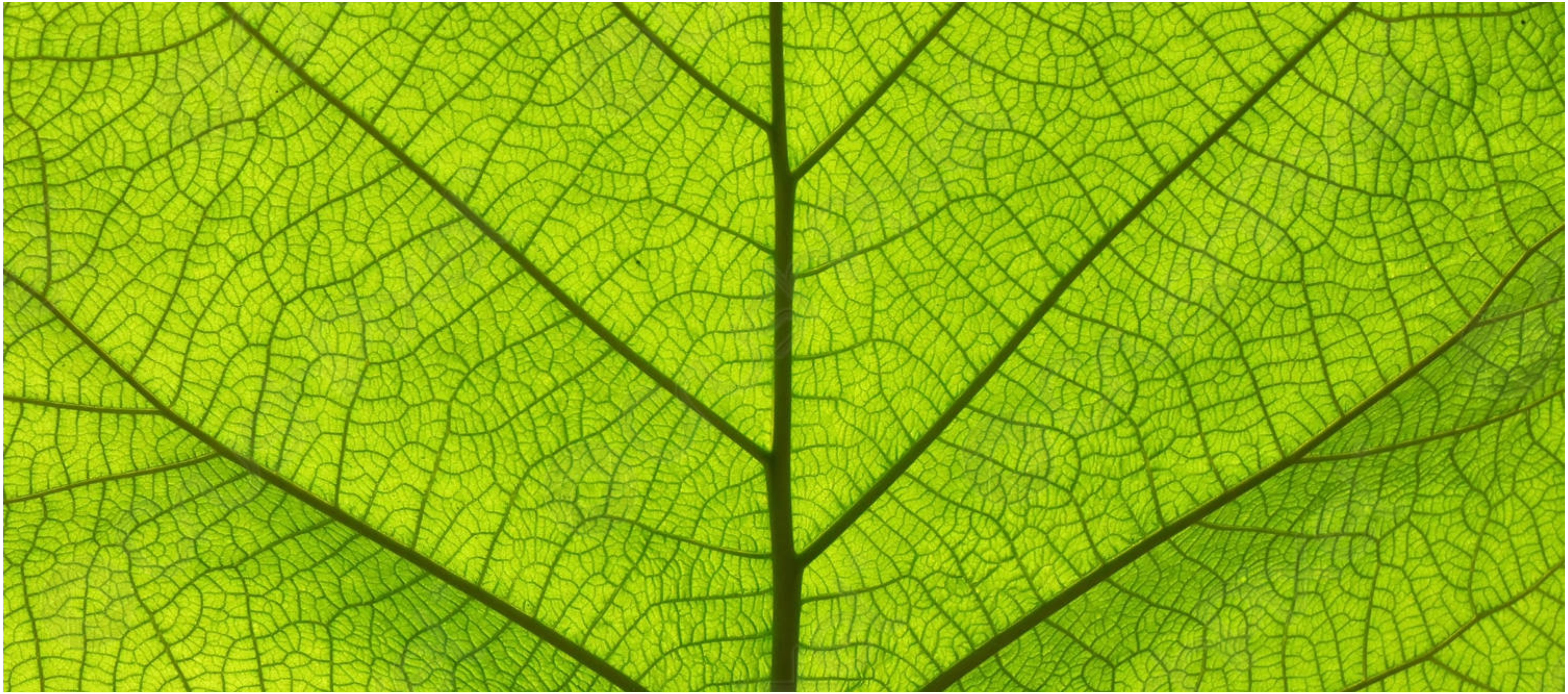
Crown shyness: fractal pattern

Hemis, Alamy

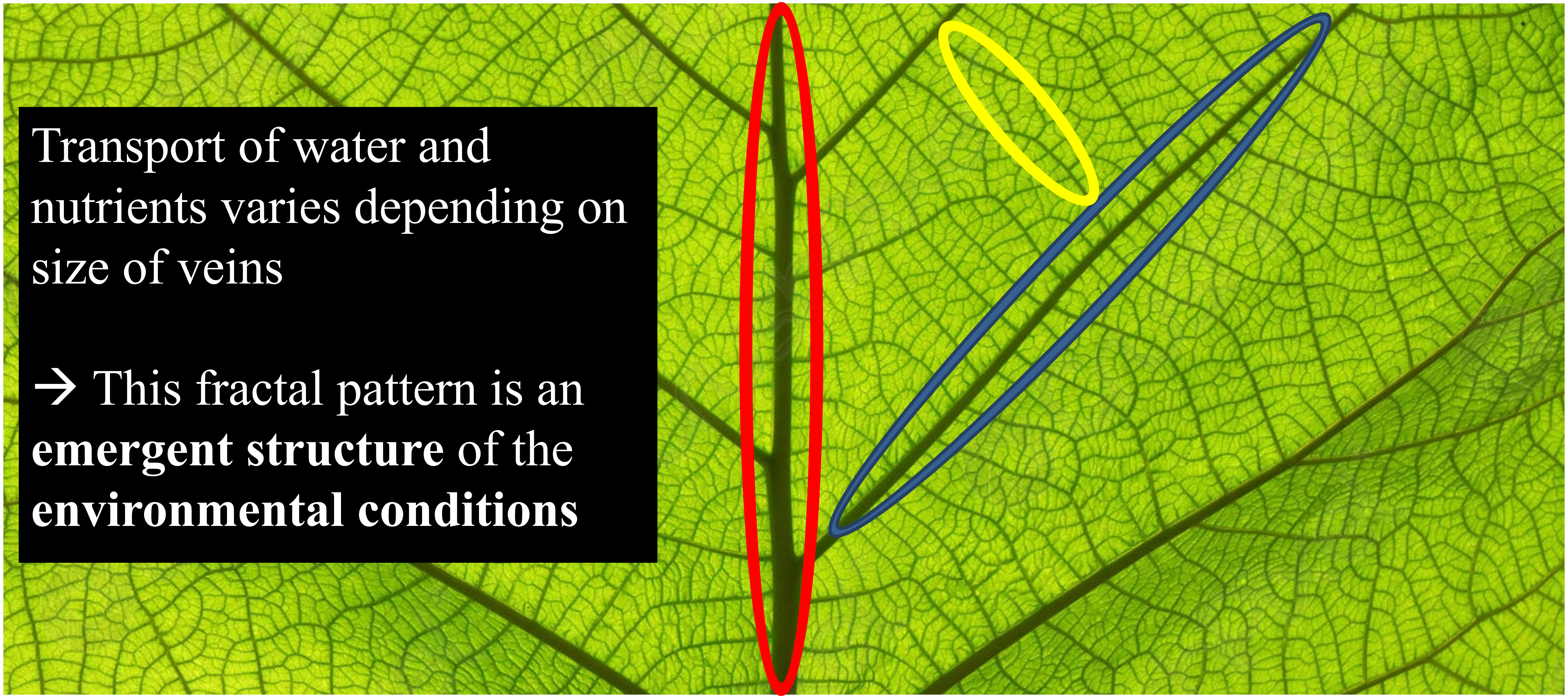
Zoom: tree

Catherine MacBride, Getty Images

Zoom: leaf



Hierarchical organisation



Hierarchical organisation of the street network

Emergent hierarchies

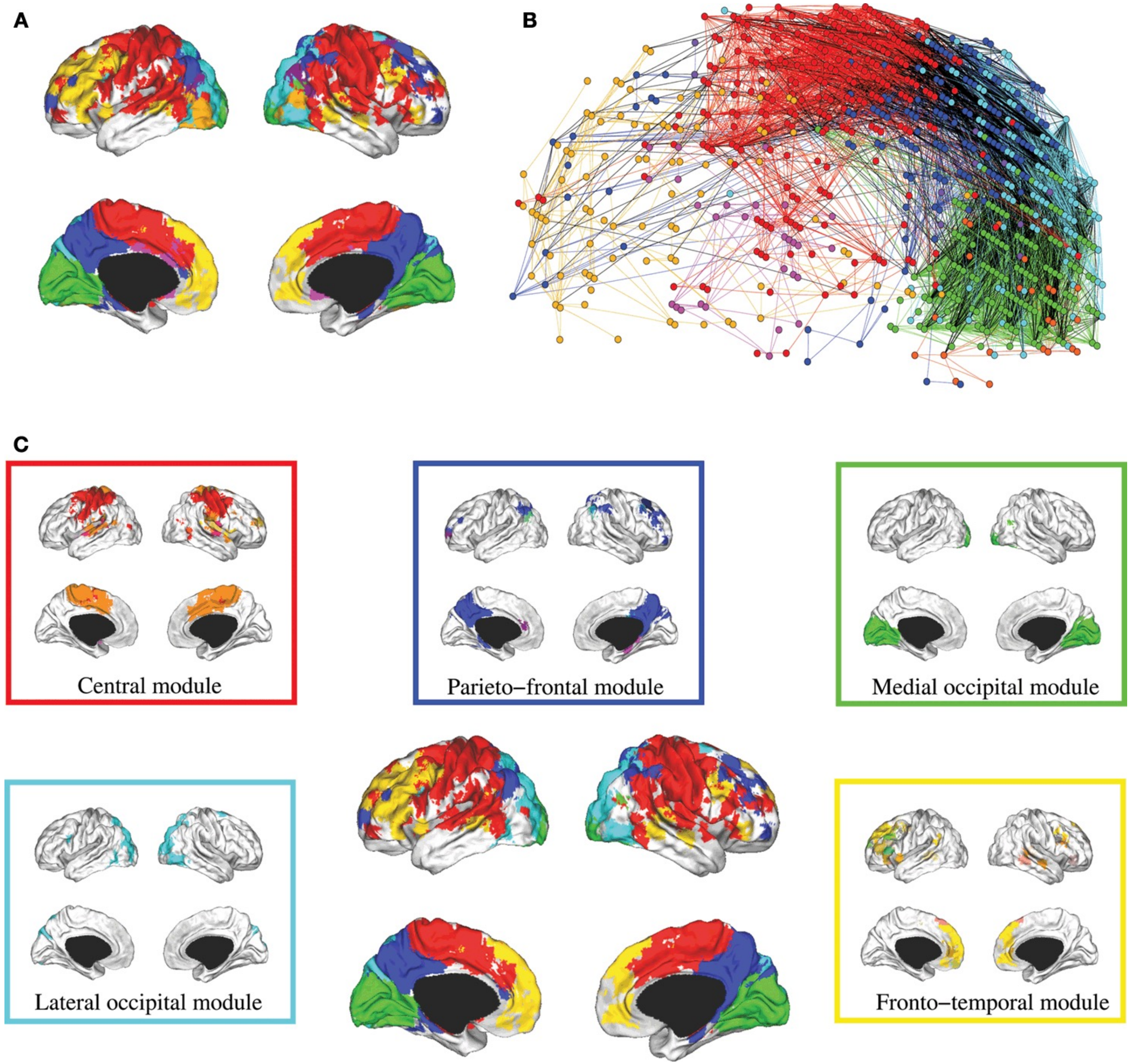
The brain

Front. Neuroinform., 30 October 2009
Volume 3 - 2009 | https://doi.org/10.3389/neuro.11.037.2009

Hierarchy and dynamics in neural networks
View all 9 Articles

Hierarchical modularity in human brain functional networks

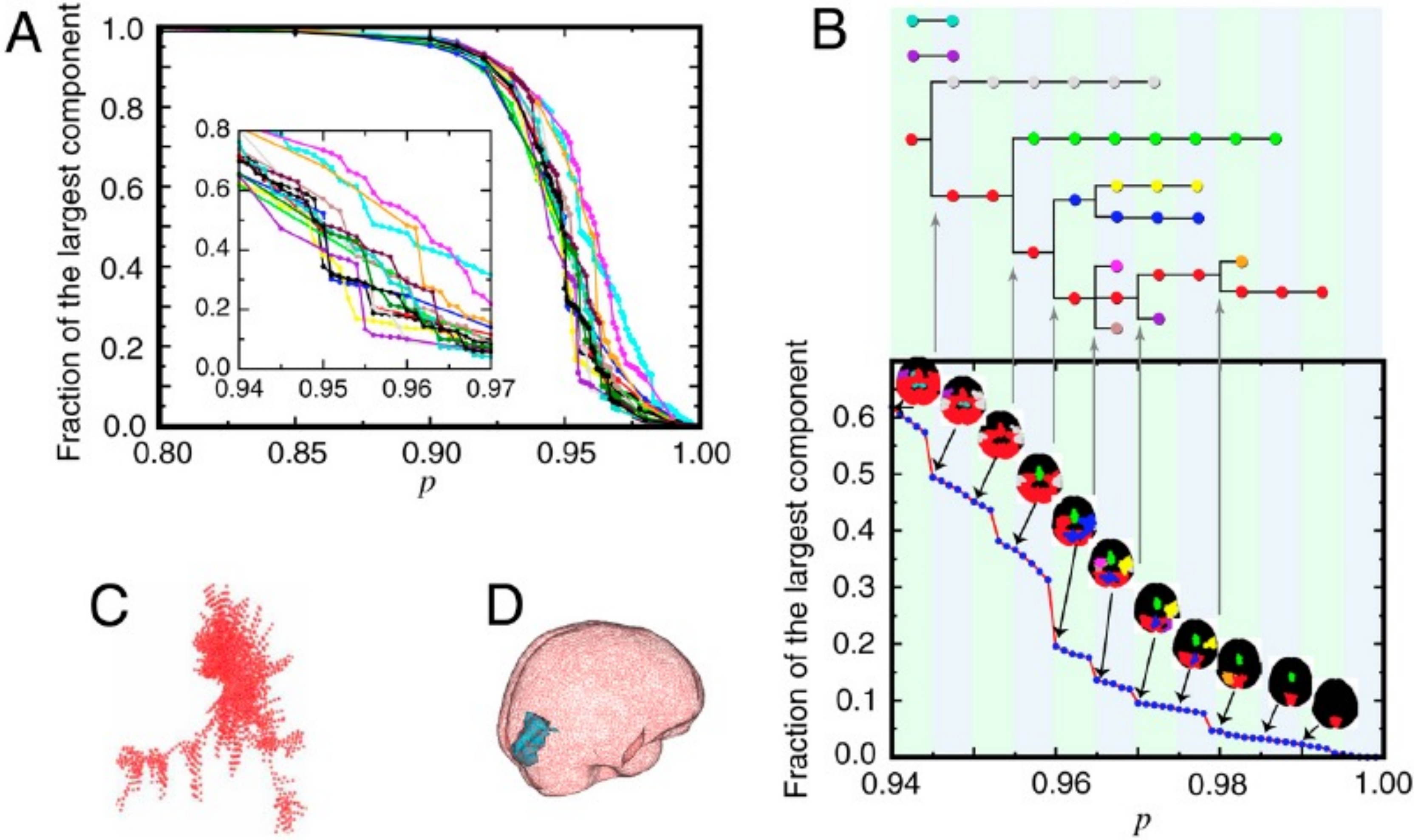
David Meunier[1,2] Renaud Lambiotte[3] Alex Fornito[1,2,4] Karen D. Ersche[1,2] Edward T. Bullmore[1,2,5]*



Extracting the hierarchical structure of the brain

A small world of weak ties provides optimal global integration of self-similar modules in functional brain networks

Lazaros K. Gallos[a], Hernán A. Makse[a,b,1], and Mariano Sigman[b]



Percolation: fire propagation

Mathl Comput. Modelling Vol. 13, No. 11, pp. 77–96, 1990
0895-7177/90 $3.00 + 0.00

FIRE SPREAD AND PERCOLATION MODELLING

Tom Beer
National Bushfire Research Unit, CSIRO
Private Bag No. 1, Mordialloc, Vic. 3195 Australia
I. G. Enting
Division of Atmospheric Research, CSIRO
Private Bag No. 1, Mordialloc, Vic. 3195 Australia

(Received April 1990)

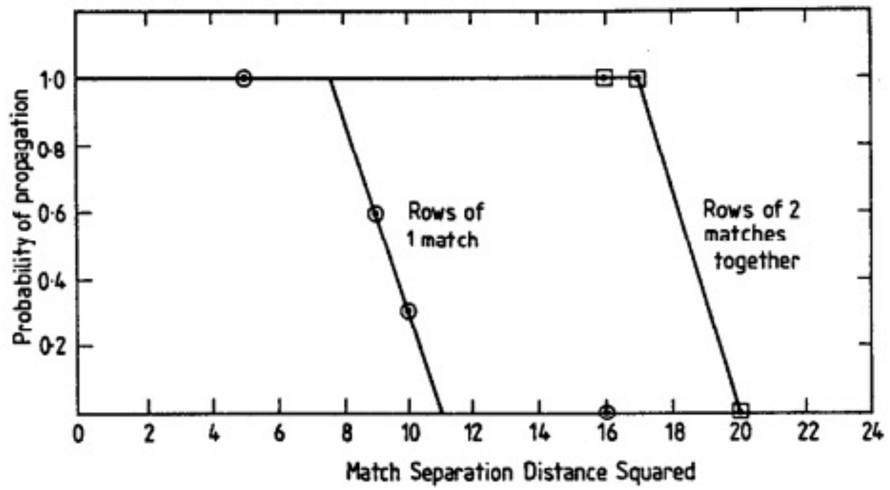


Figure 1: Propagation probabilities for lines of matches as a function of spacing squared (in units of mesh size squared).

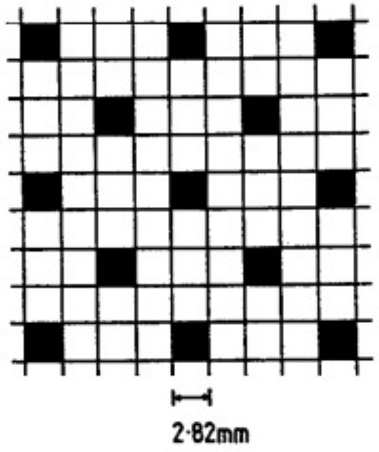
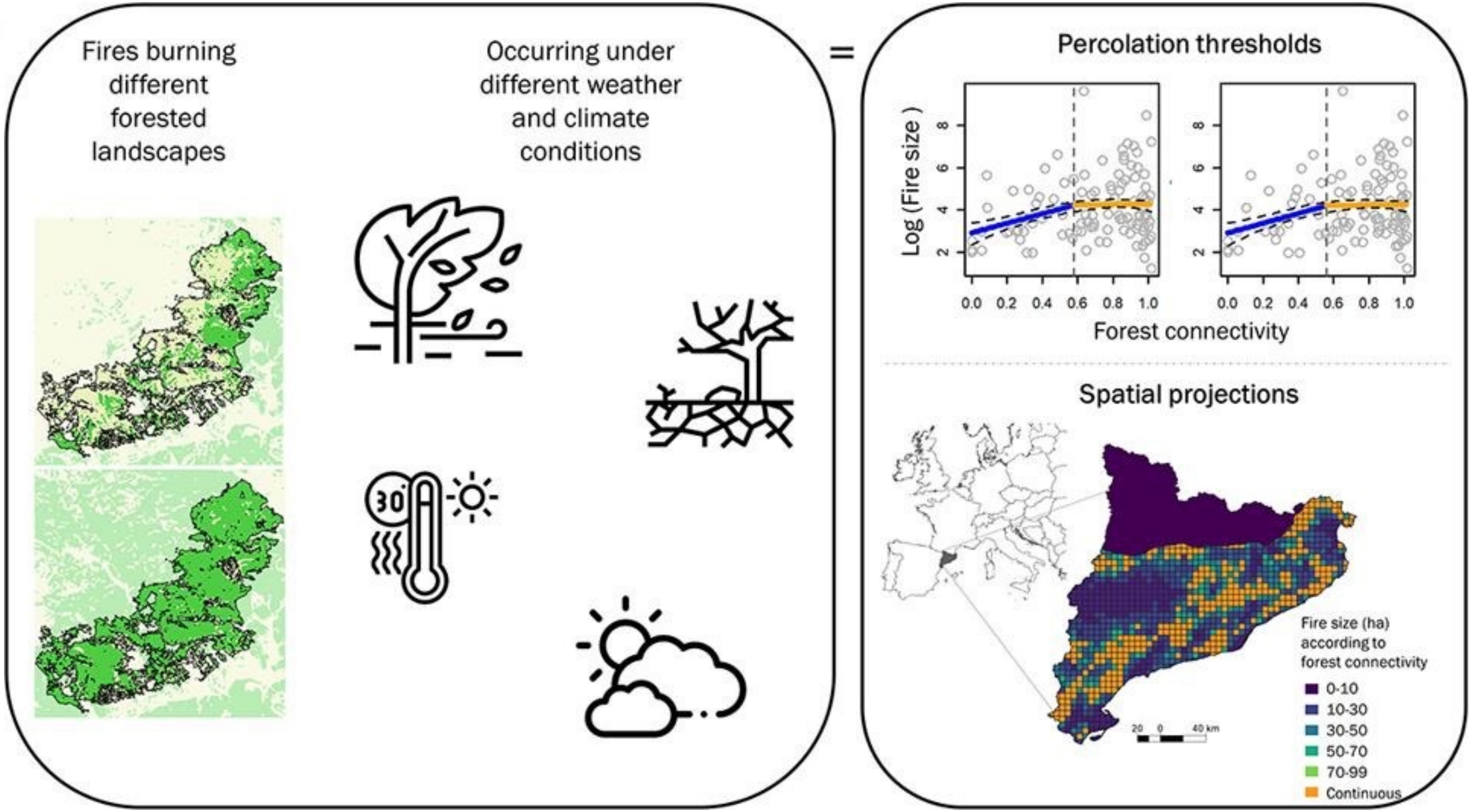


Figure 2: Spacing of matchsites (to be occupied randomly) relative to supporting mesh.

Forest Ecology and Management
Volume 498, 15 October 2021, 119558

Forest connectivity percolation thresholds for fire spread under different weather conditions

Andrea Duane [a], Marcelo D. Miranda [b, c], Lluís Brotons [a]



The city

Cities are not isolated entities.

Distance modulates the probability of interaction between different parts of the city.

→ Distance is also modulated by transport!!!

- **The probability of encounters is not the same everywhere in the city.**
- **The probability of flows between cities is not the same for all cities.**

→ In principle cities belonging to the same region should interact more, have larger flows, etc. Is it the case?

Cities belong to regions: can we extract the *hierarchy* emerging from the interactions?

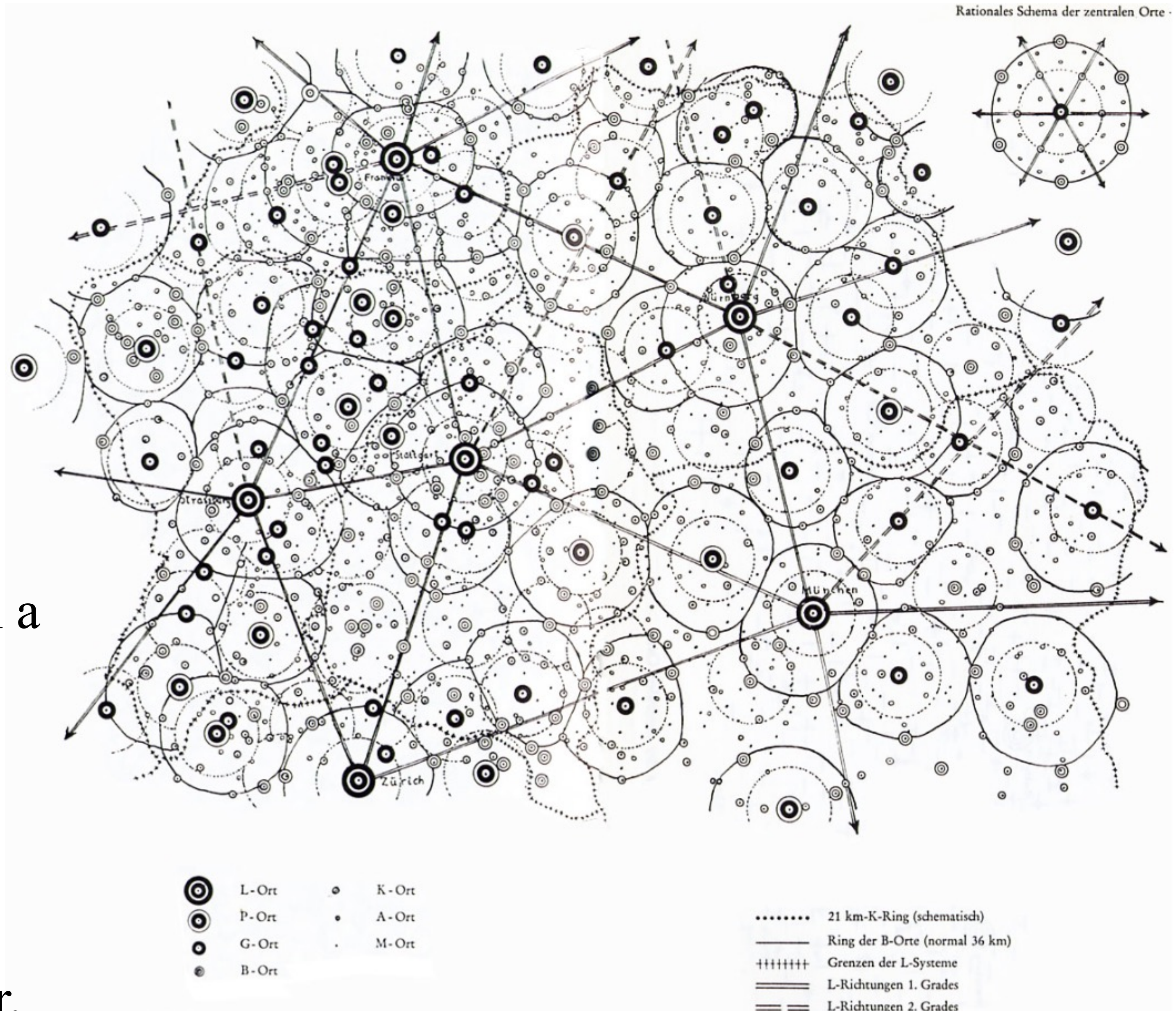
Christaller’s Central Place Theory 1933

Central places provide goods and services to surrounding areas

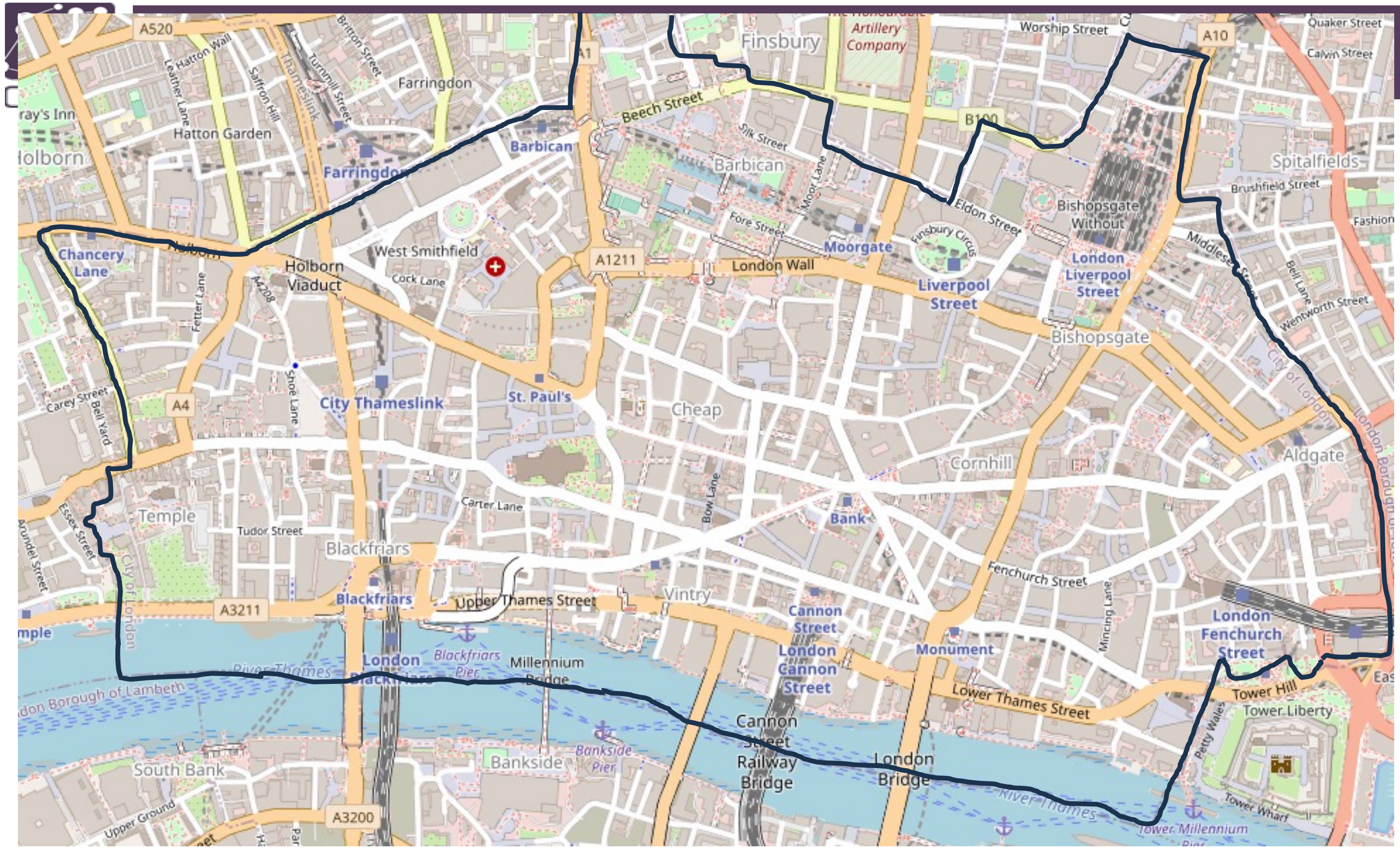
Hierarchical organisation of urban centres

Assumptions:

- Evenly distributed population
- All settlements are equidistant and exist in a triangular lattice
- Evenly distributed resources
- Perfect competition
- Consumers visit the nearest place minimising travel
- Everybody has the same purchasing power, etc.

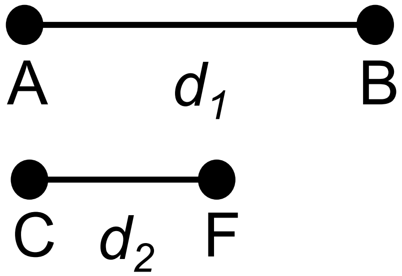


Karte 4
Das System der zentralen Orte in Süddeutschland



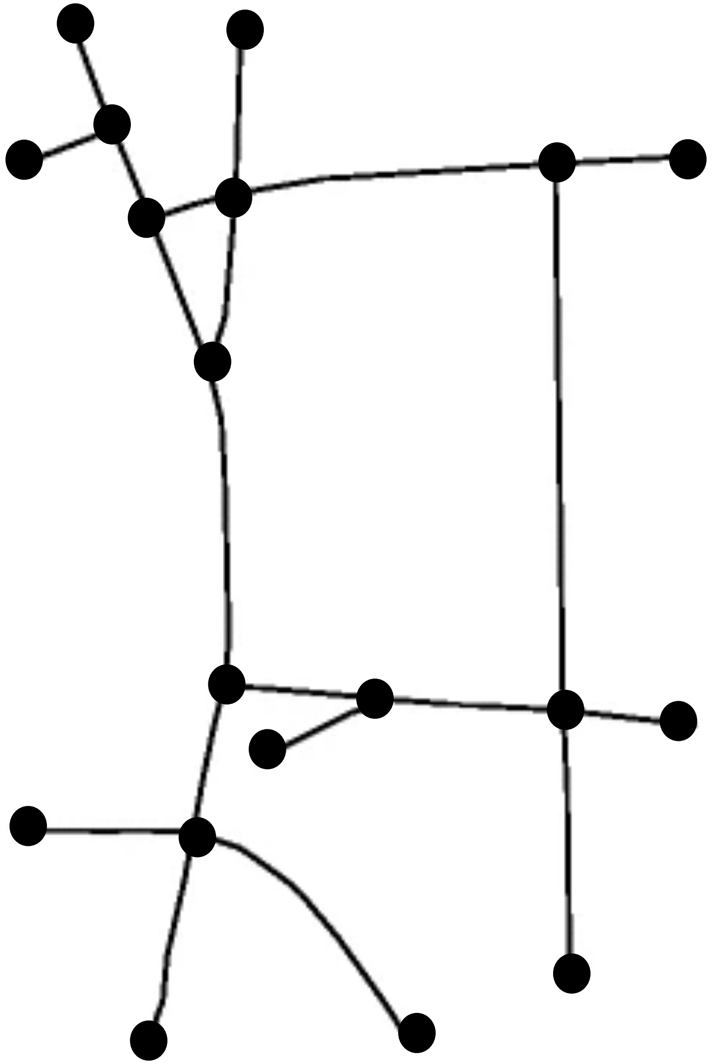
Get the street network and transform it into a network.

Proxy for interaction → distance



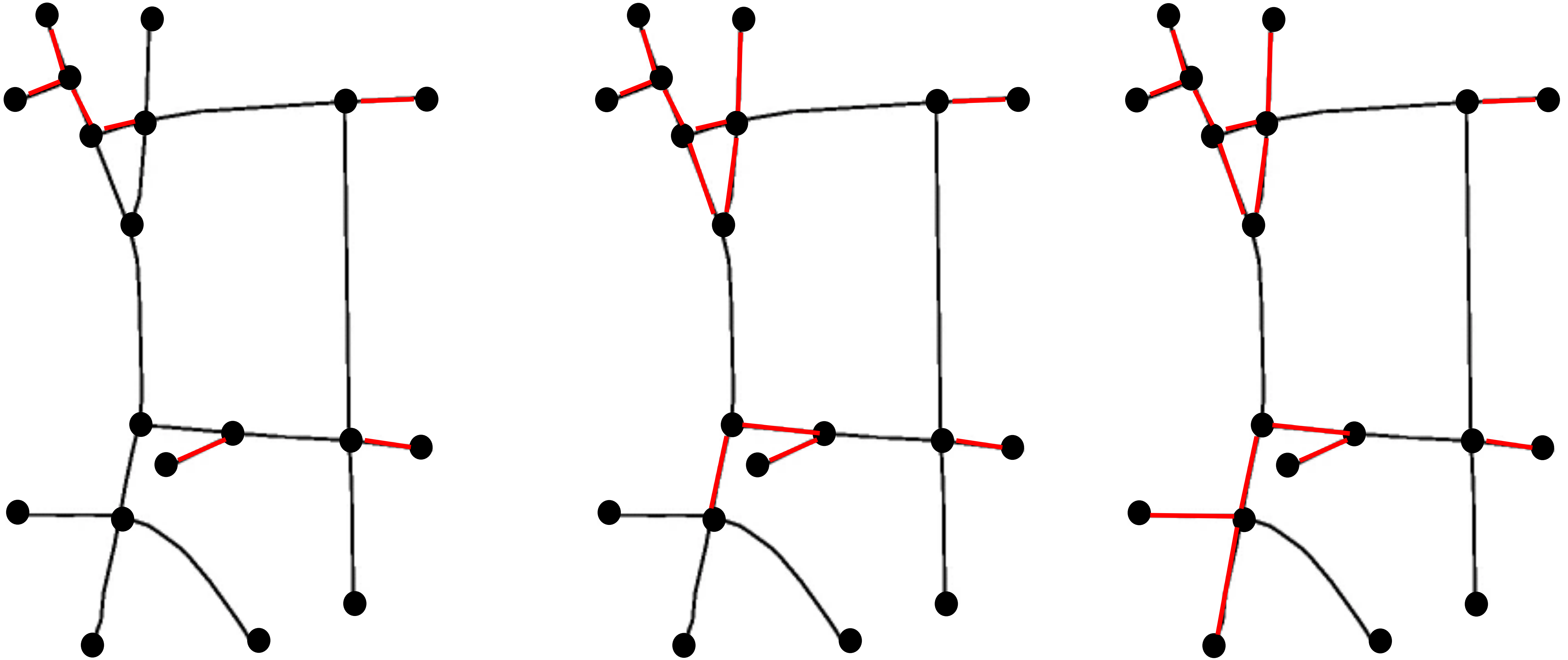
Higher probability of interaction between C and F

Recover communities in urban systems in the same way as modules in the brain



Marshall, et al. Netw Spat Econ 18, 735–749 (2018).

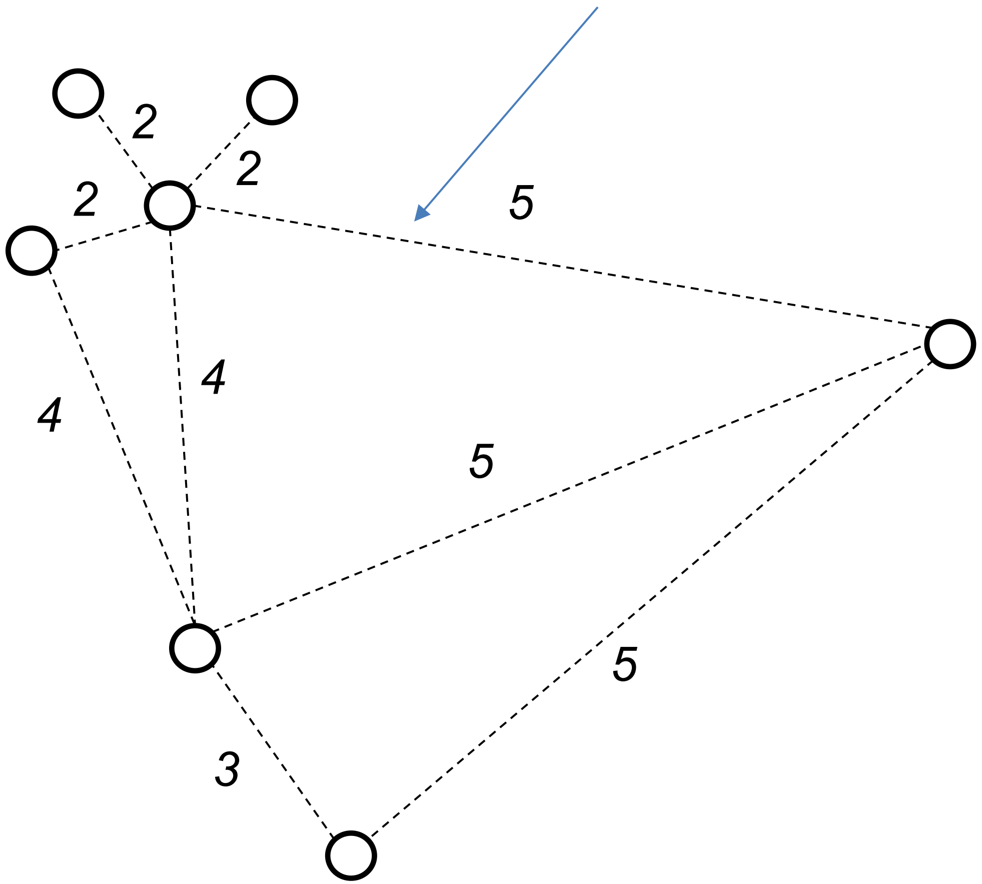
Recover communities in urban systems in the same way as modules in the brain: proximity modulates connectivity



Stimulus in the brain ~ distance in the network

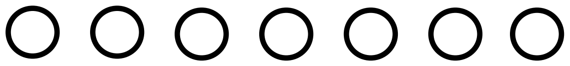
Network at d = 1

Distance between intersections



At the shortest distance, no nodes are connected

→ Visualise them as the leaves in a tree

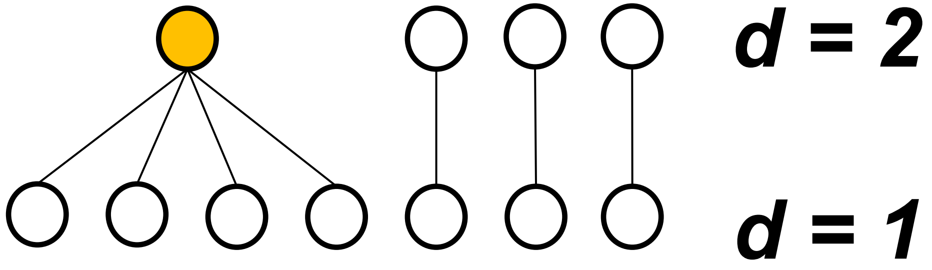


***d* = 1**

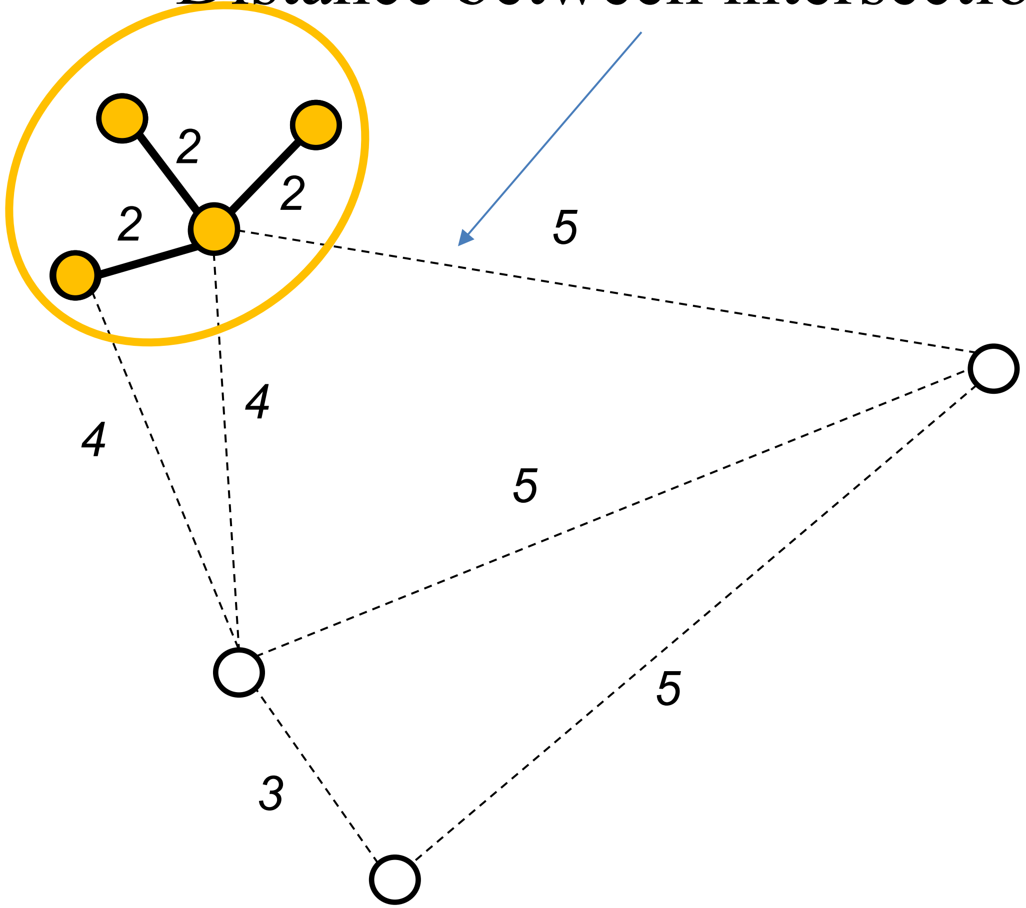
Stimulus in the brain ~ distance in the network

Network at d = 2

→ Tree starts to form

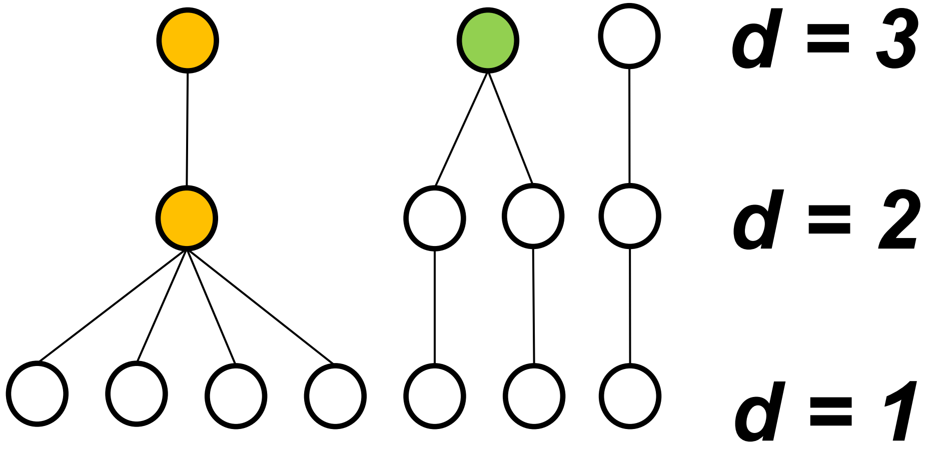


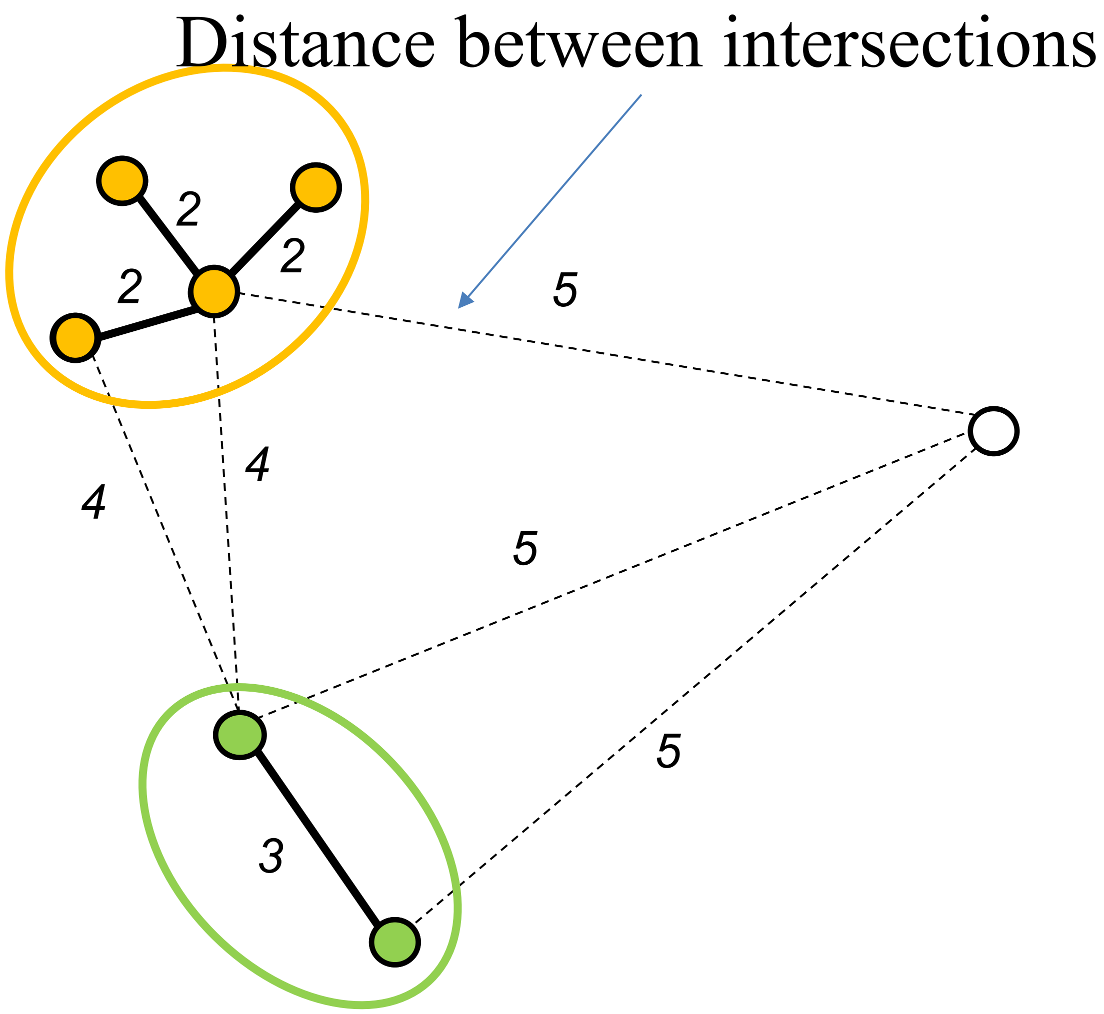
Distance between intersections



Stimulus in the brain ~ distance in the network

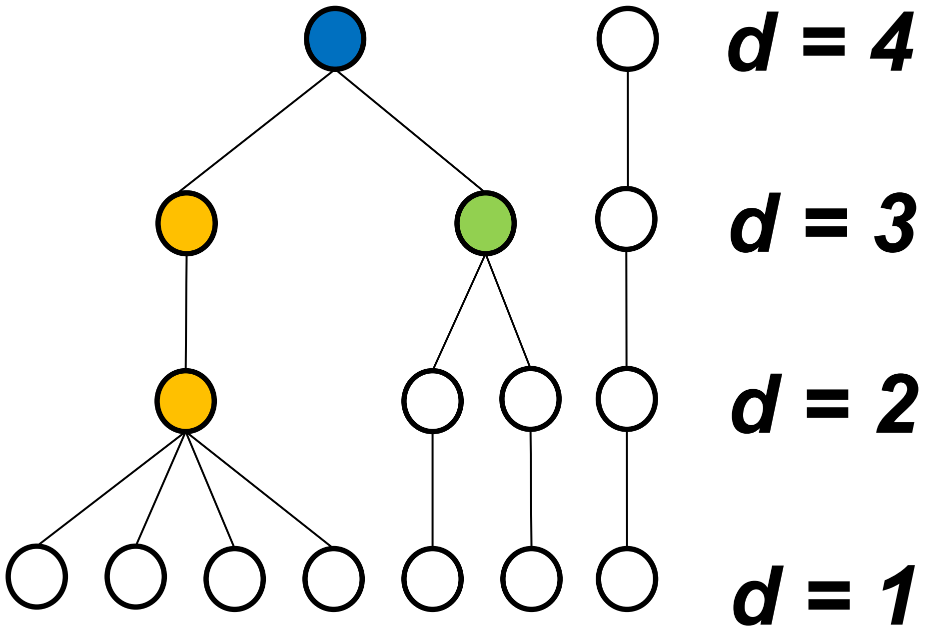
Network at d = 3



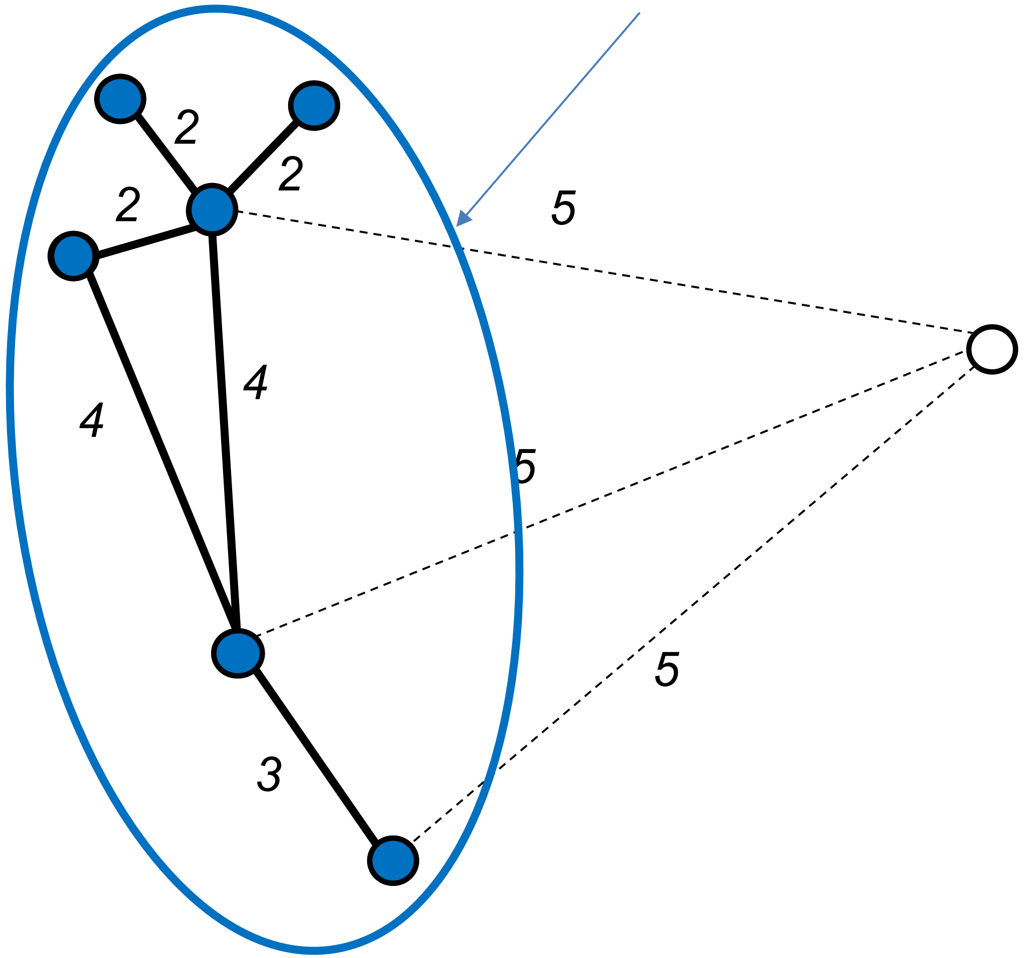


Stimulus in the brain ~ distance in the network

Network at d = 4

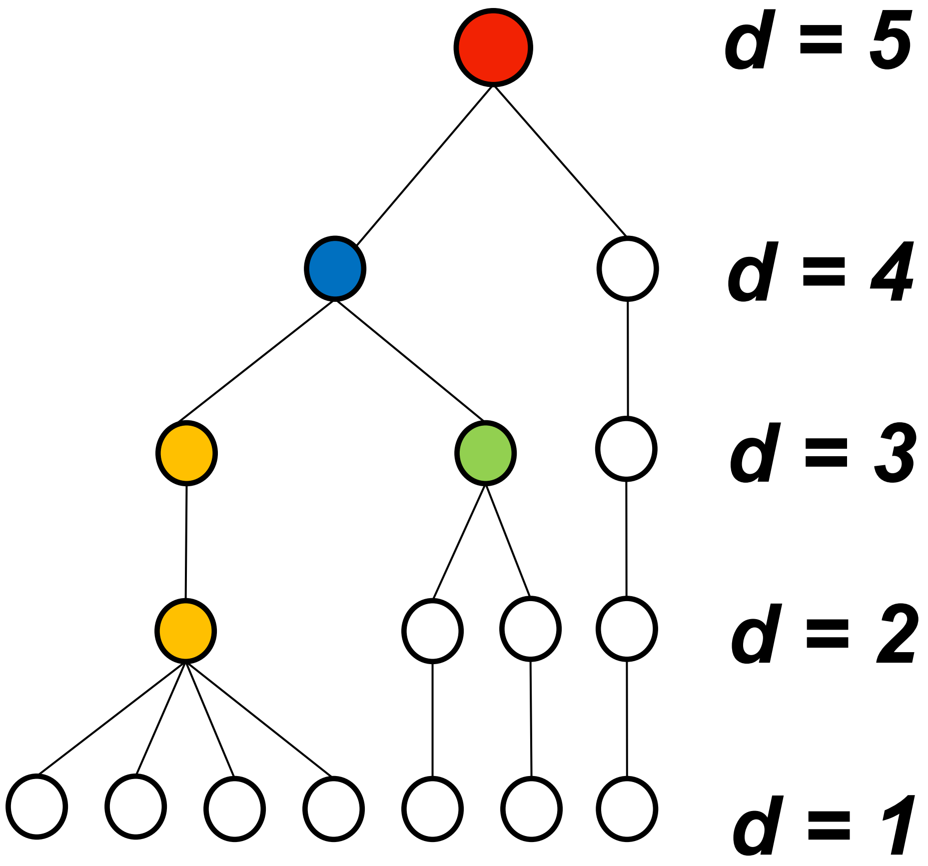


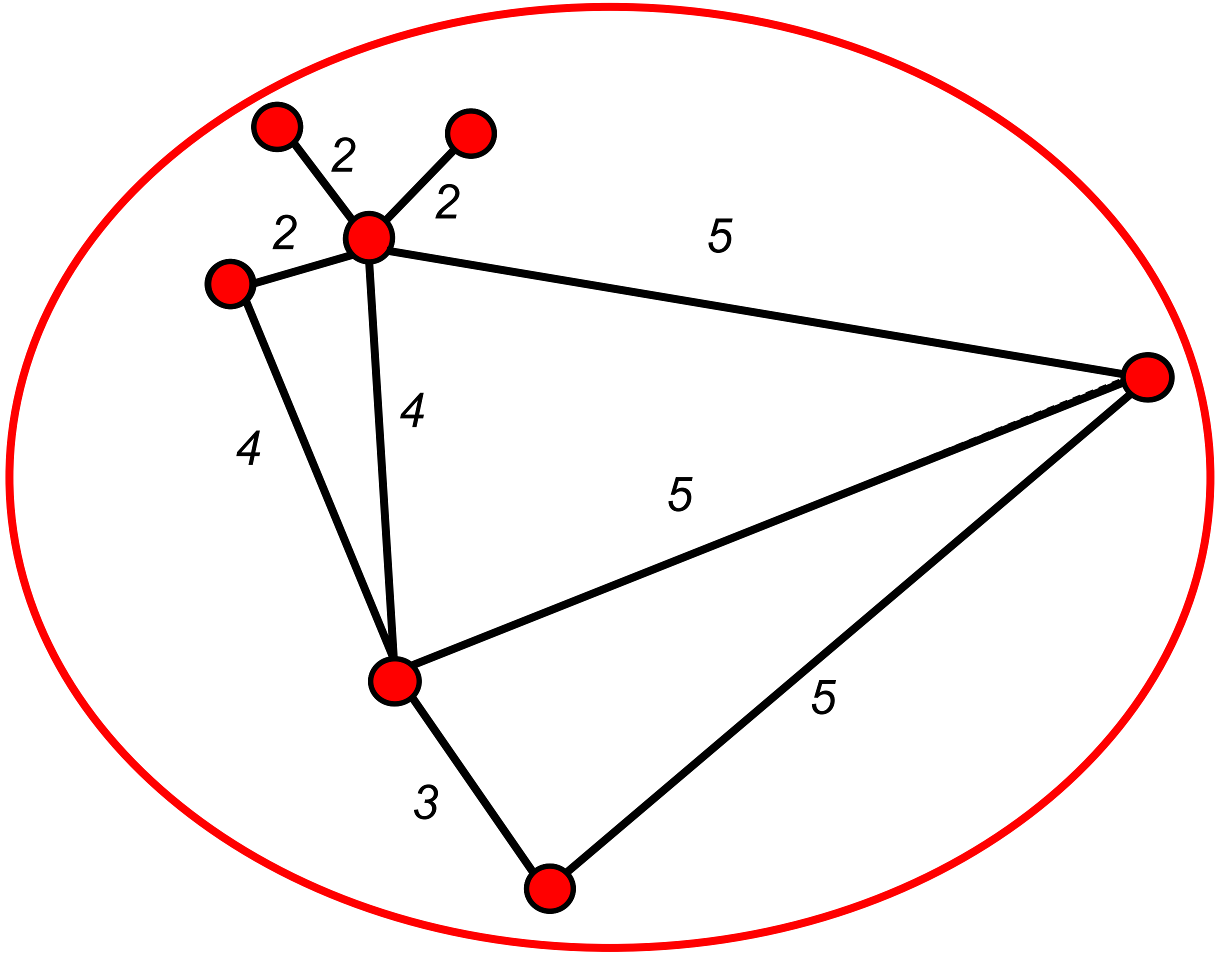
Distance between intersections



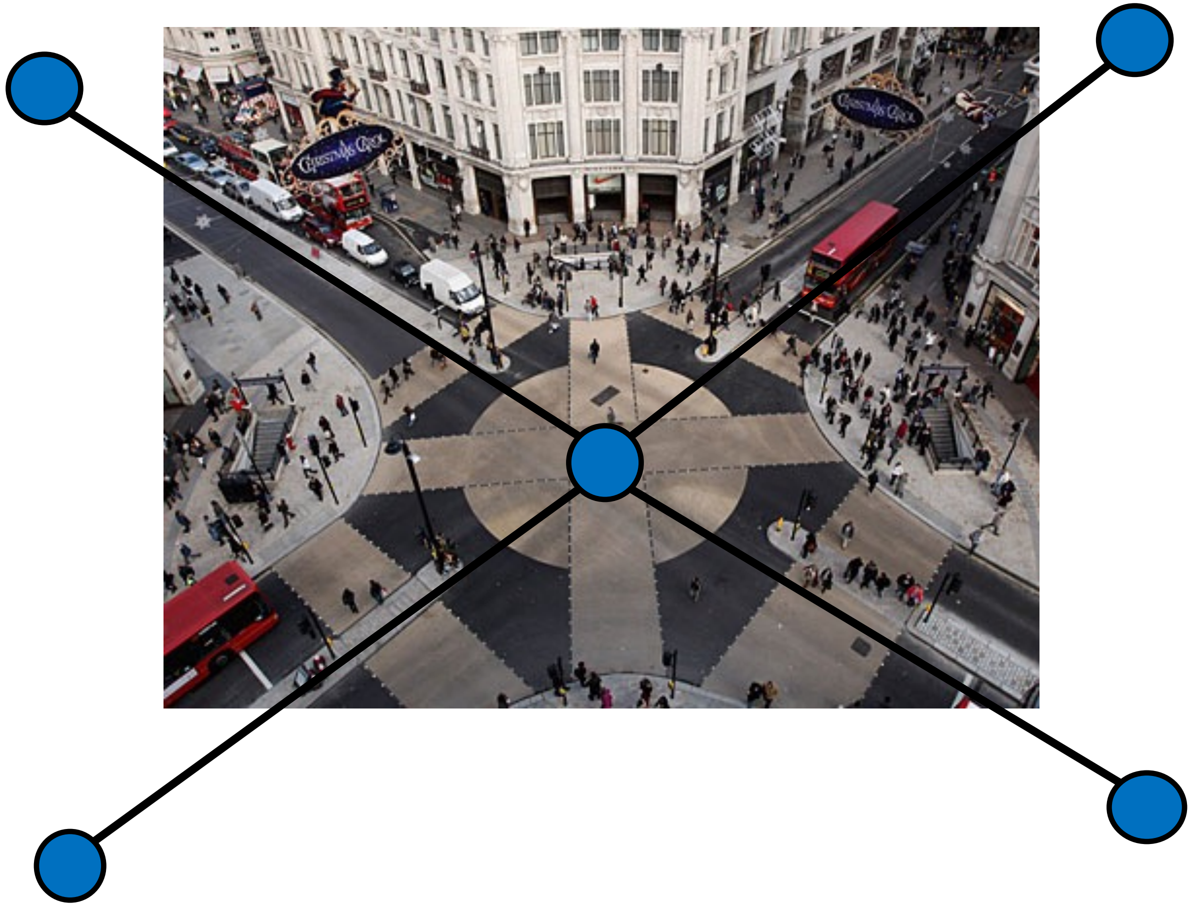
Stimulus in the brain ~ distance in the network

Network at d = 5





Percolation: imagine a message spreading in a city as fire in a forest



- Street network: interconnectivity between settlements

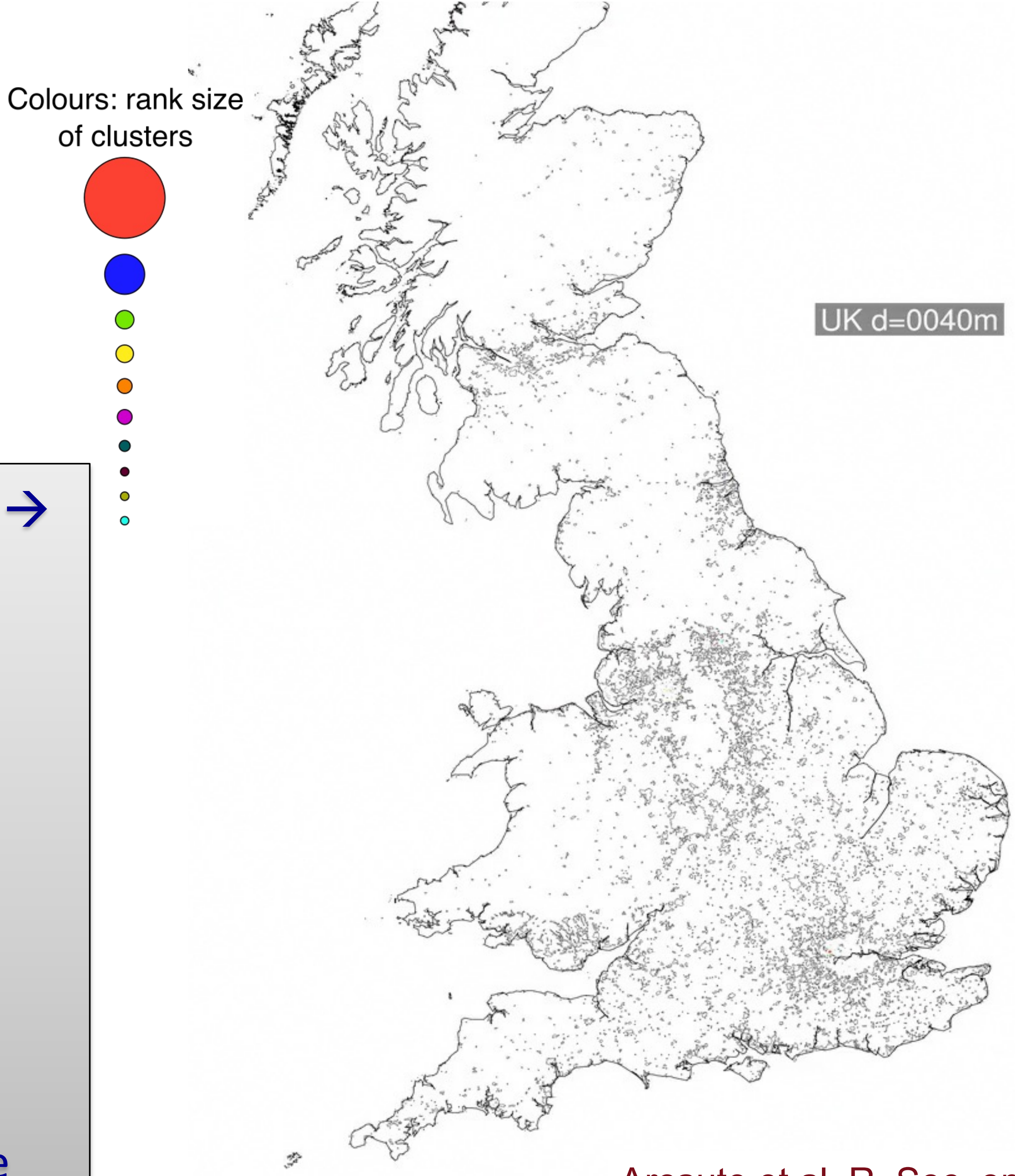
⇓

interactions!

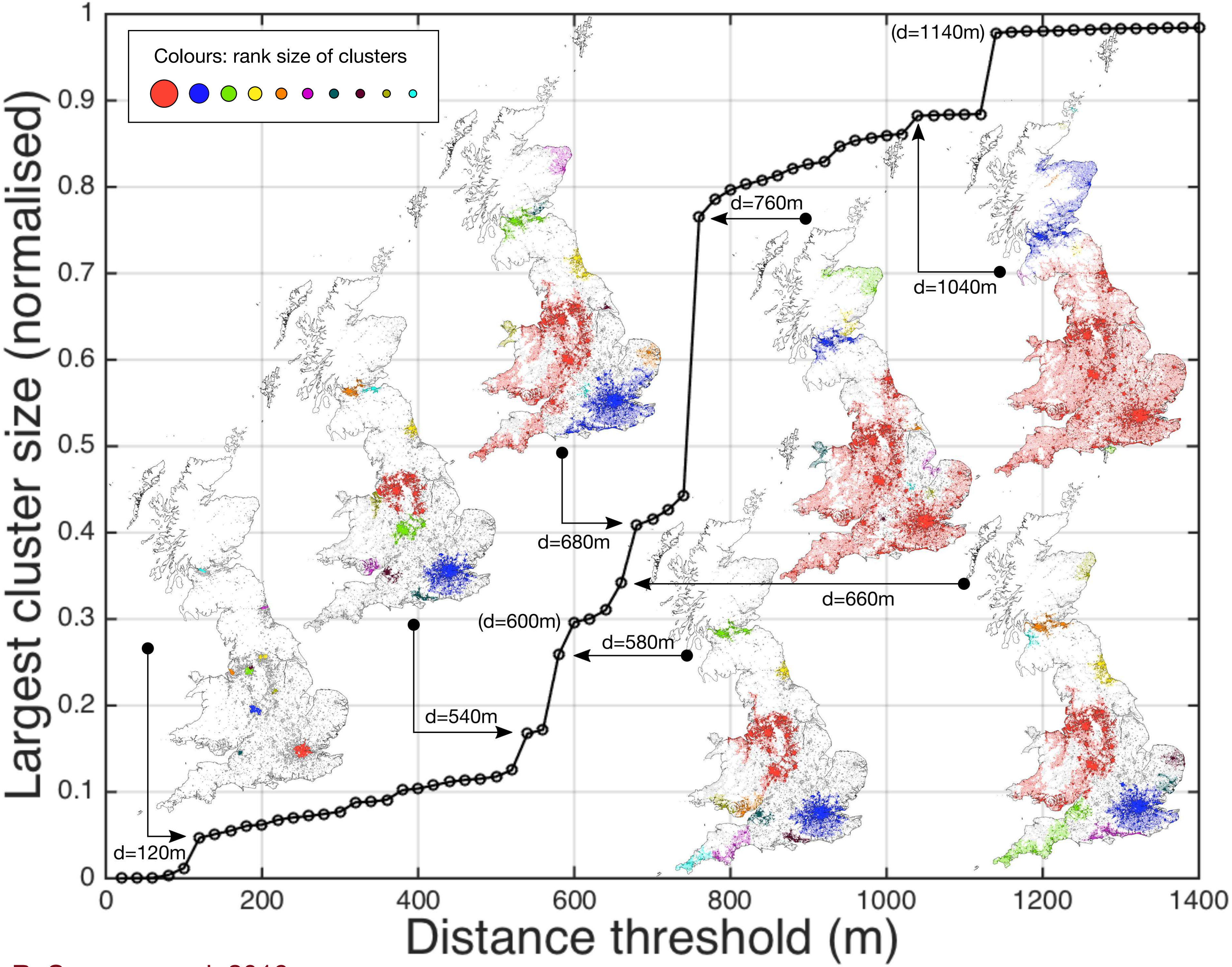
- Communities/cities/regions → outcome of interactions
- Model connectivity as a percolation process on the road network
- Multiple transitions

⇓

- Obtain hierarchical structure

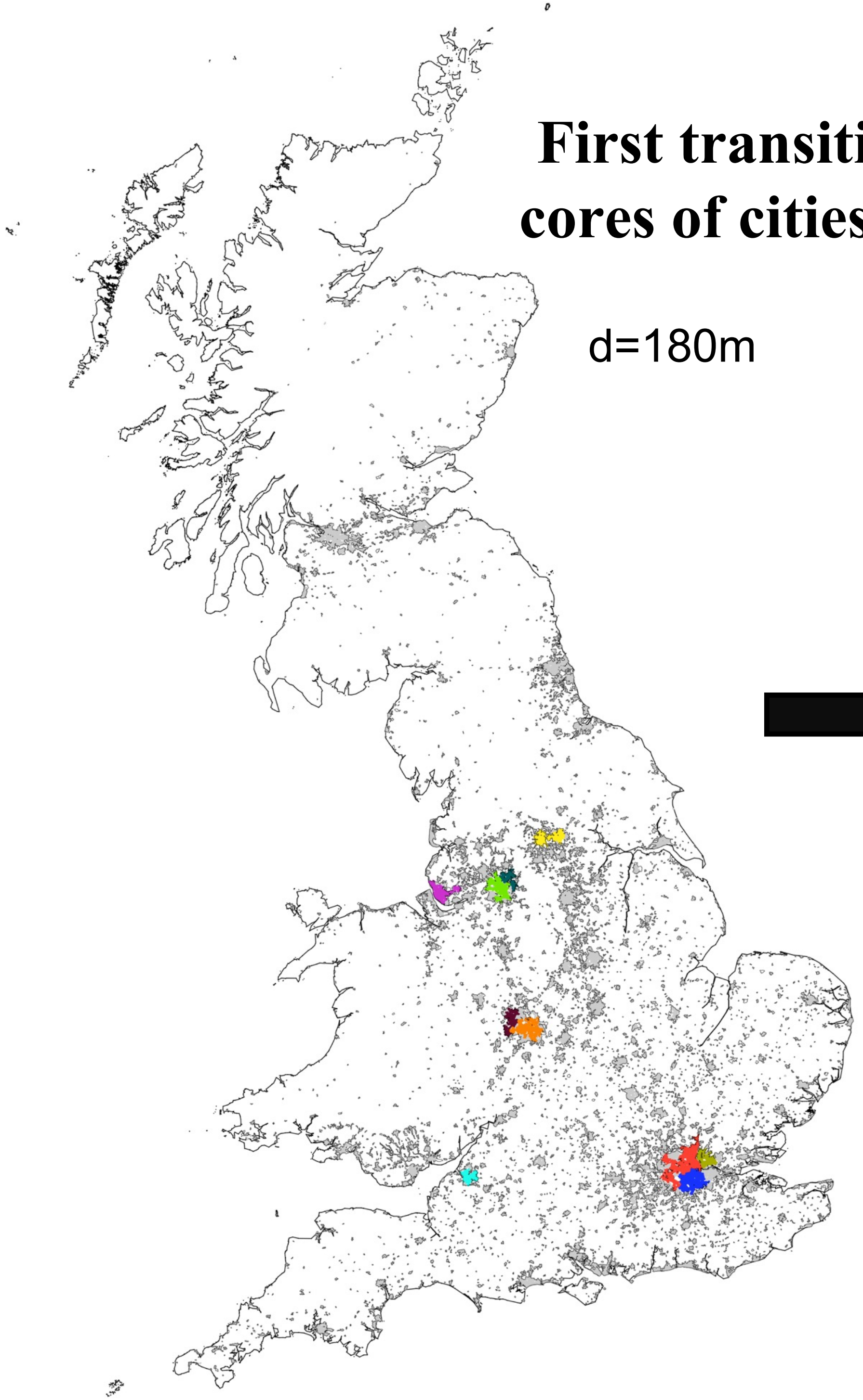


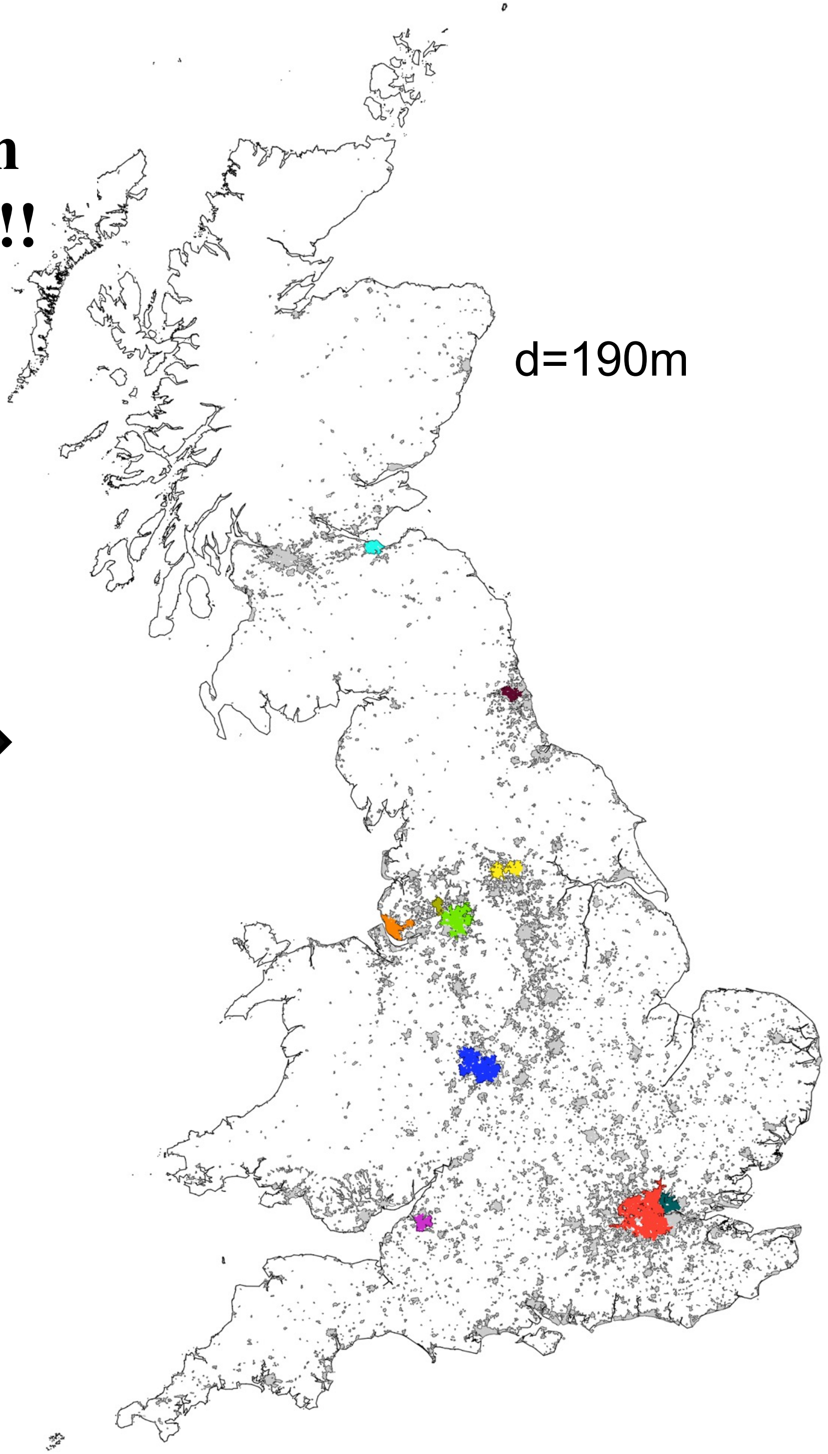
Arcaute et al, R. Soc. open sci. 2016



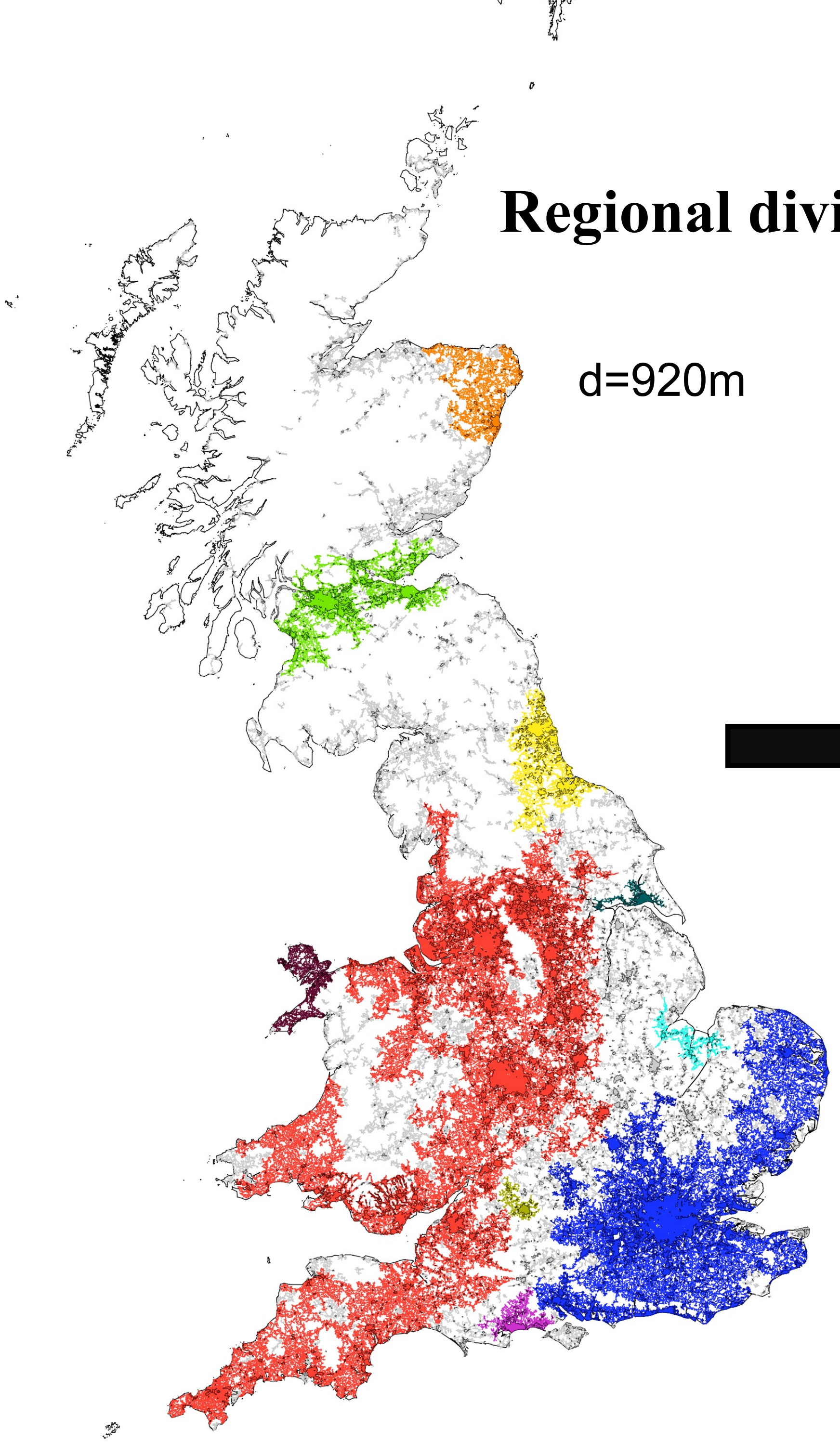
Arcaute et al, R. Soc. open sci. 2016

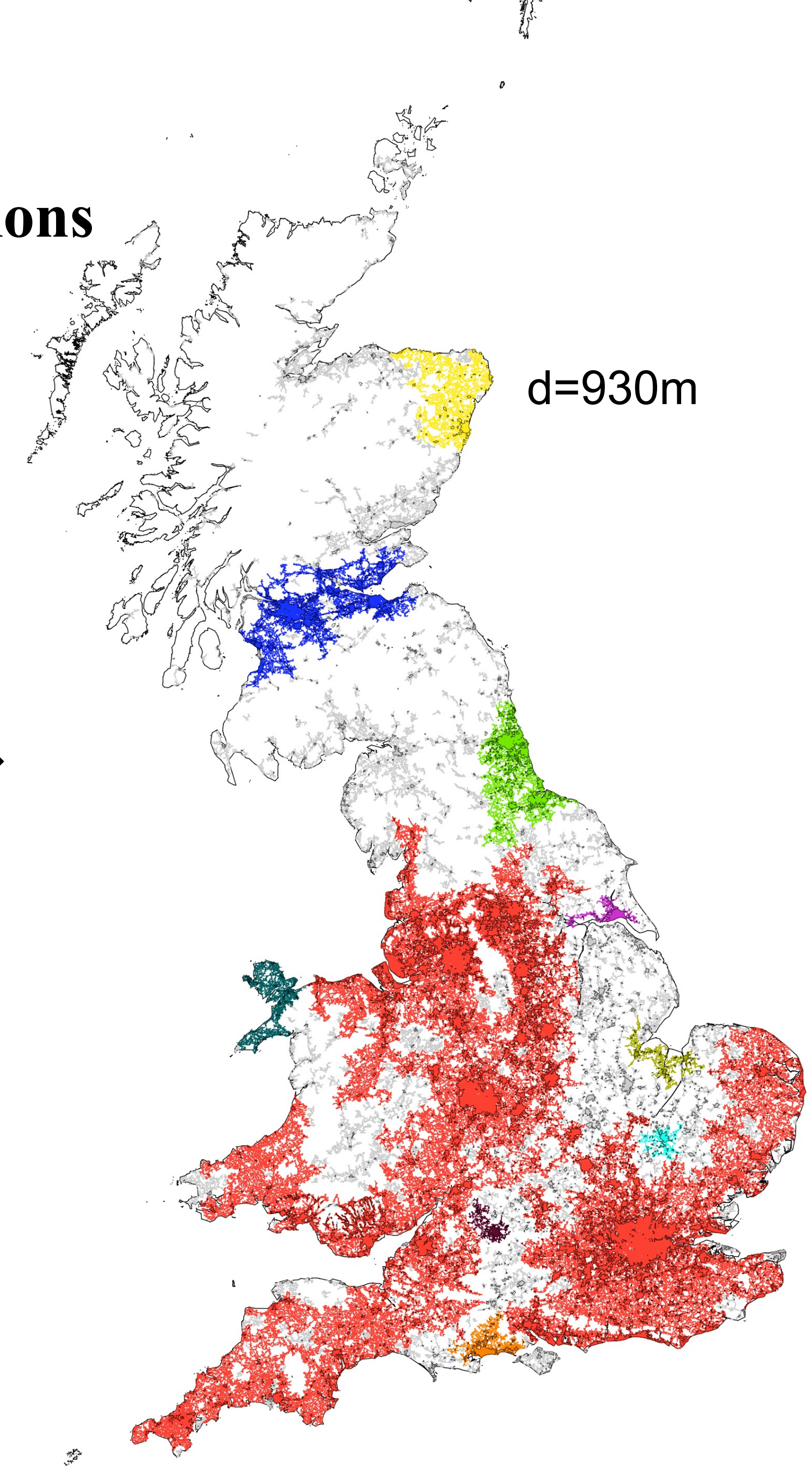
First transition
cores of cities!!!!



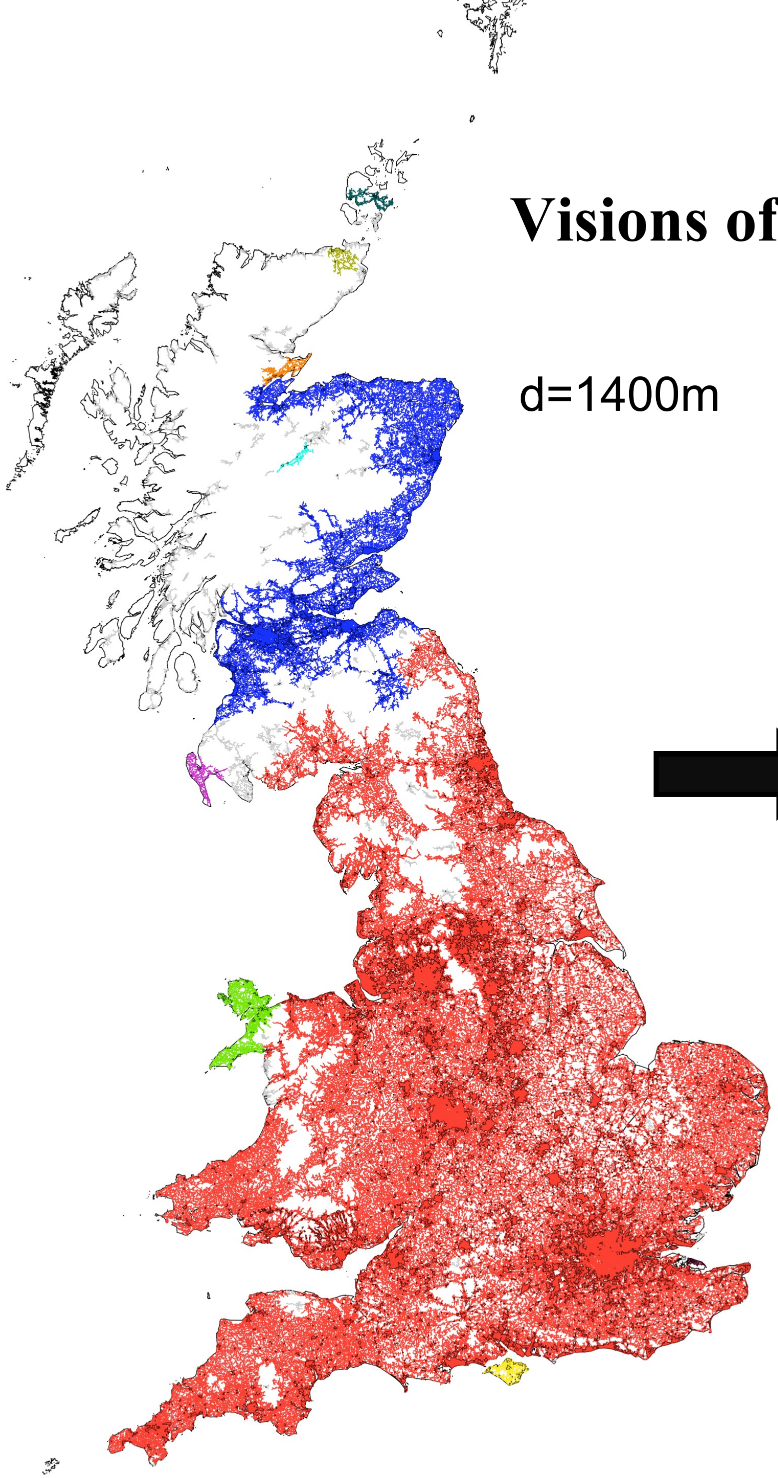


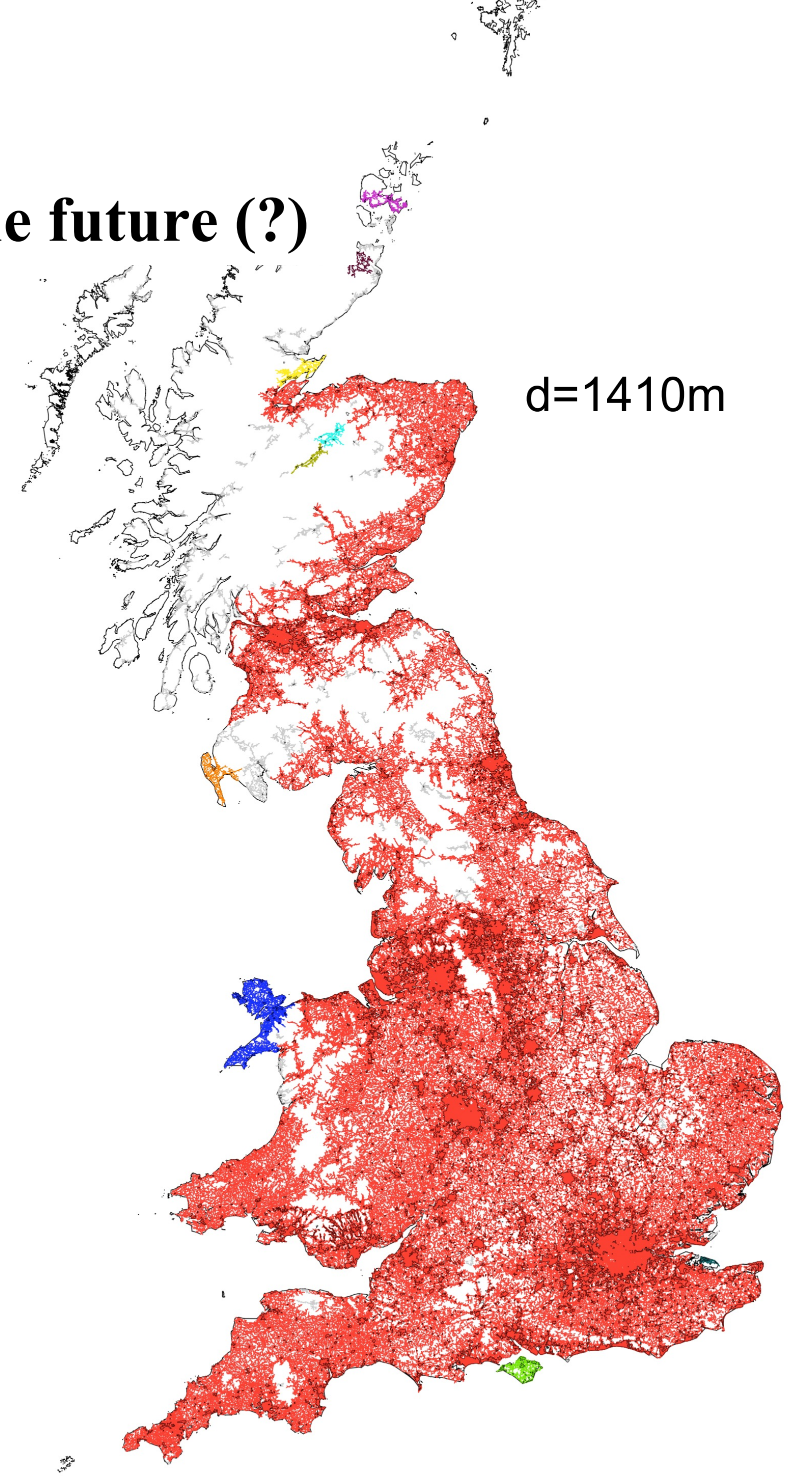
Regional divisions



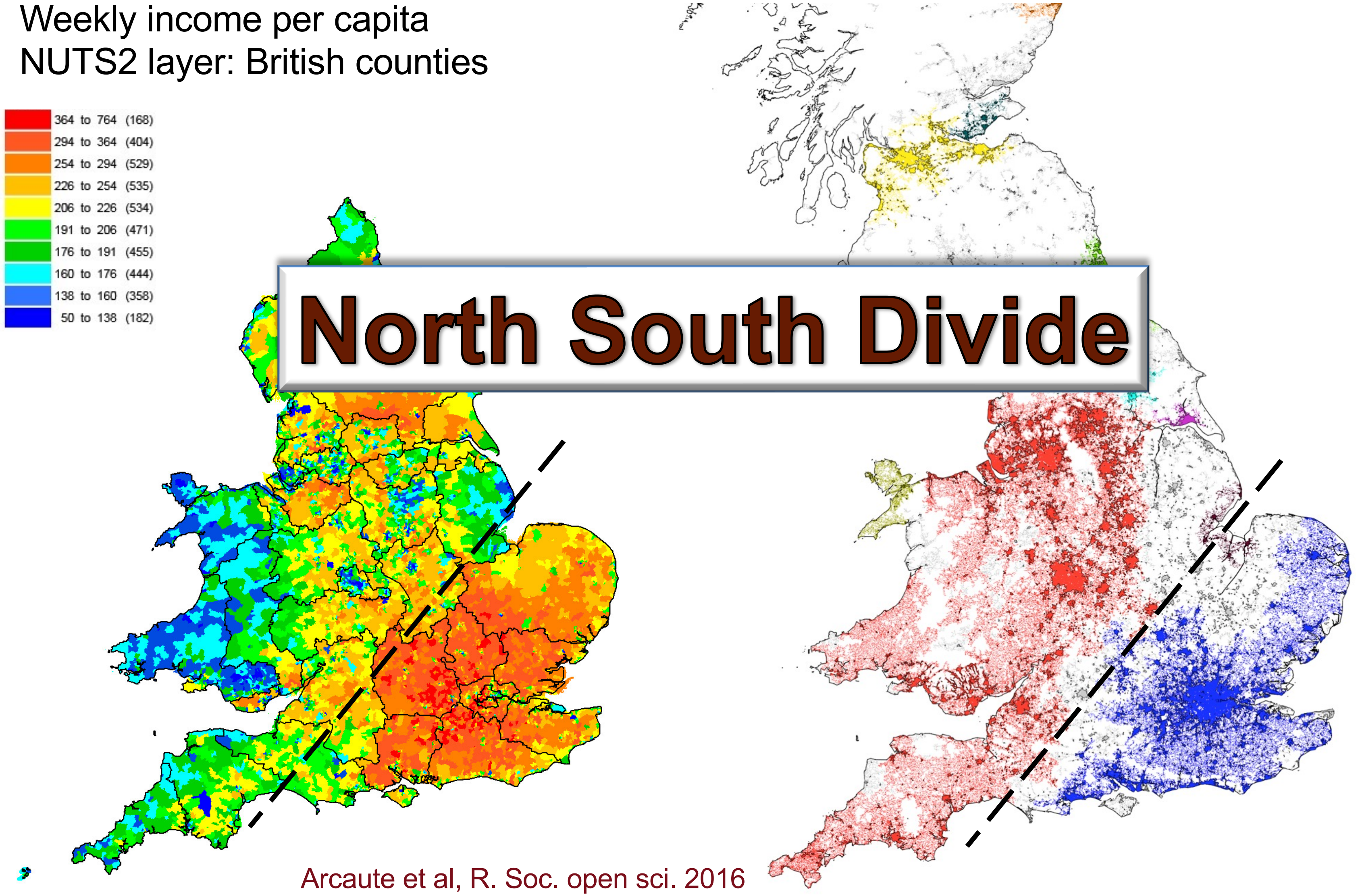


Visions of the future (?)



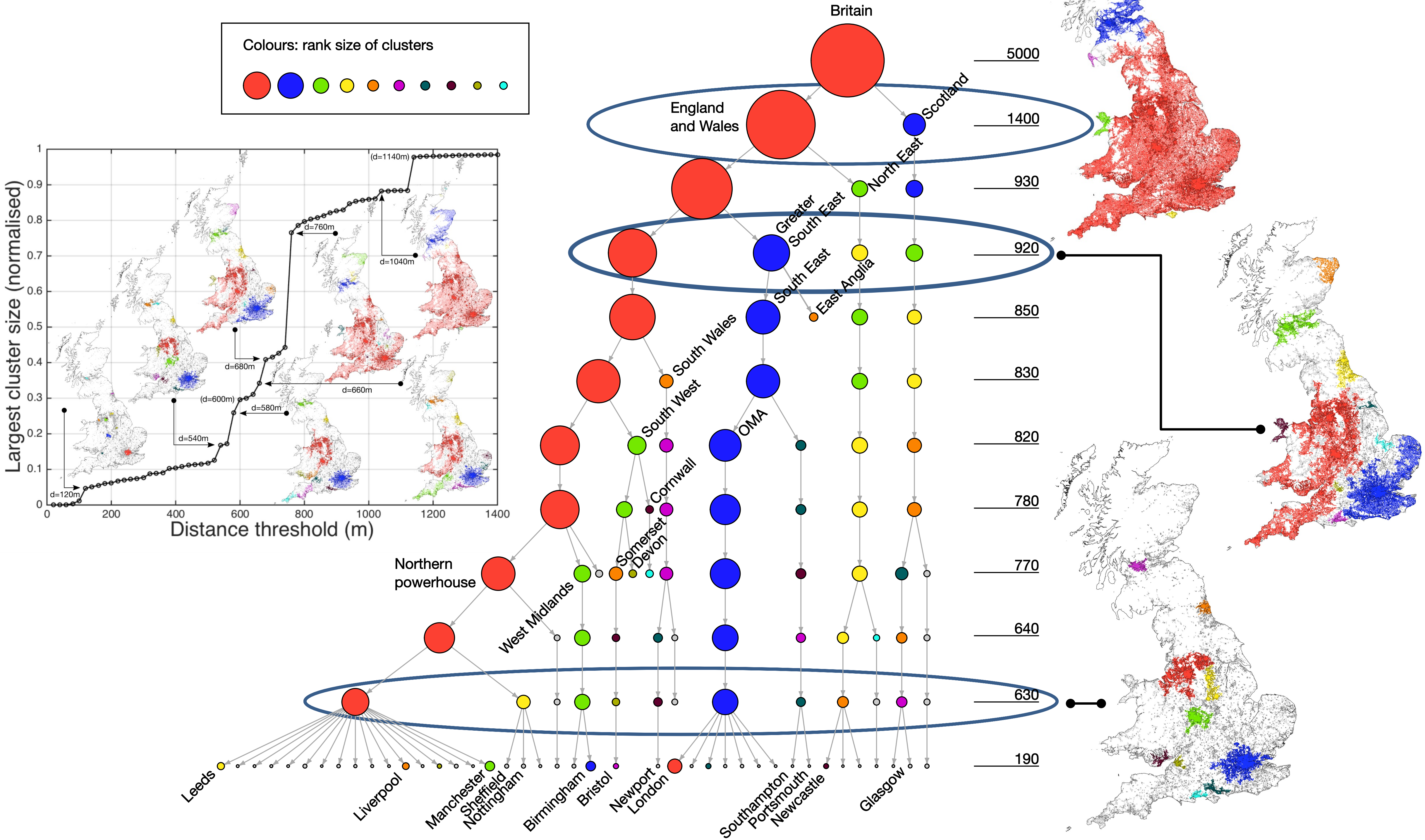


Weekly income per capita
NUTS2 layer: British counties



Arcaute et al, R. Soc. open sci. 2016

Hierarchical structure



Defining cities

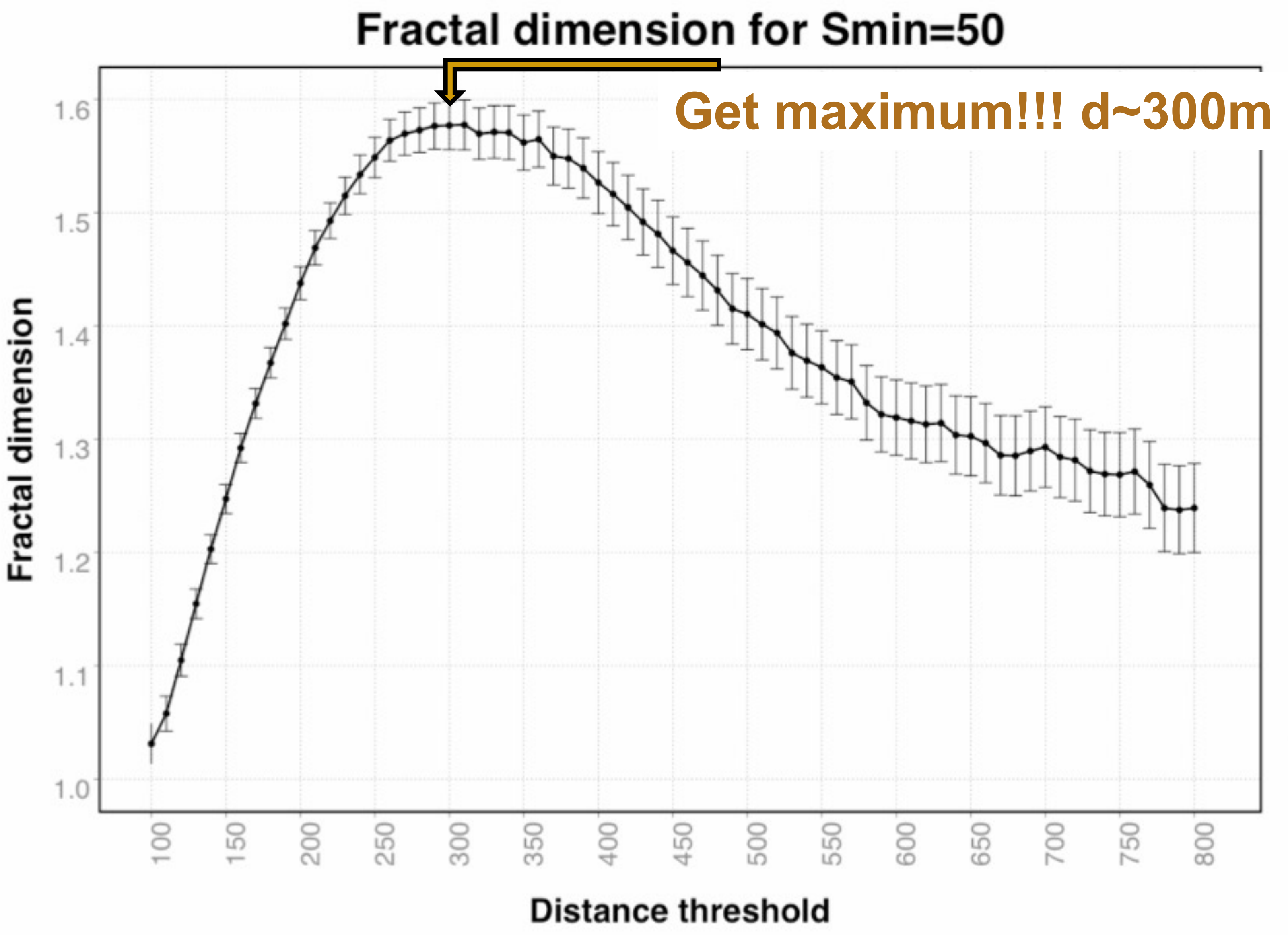
Fractal dimension of networks

- At each threshold compute the size of each network, given by the number of nodes N, and its diameter r_{max}.

- Using the following relation, extract the exponent, which corresponds to the fractal dimension of the system

$$N \sim r_{\max}^{\alpha}$$

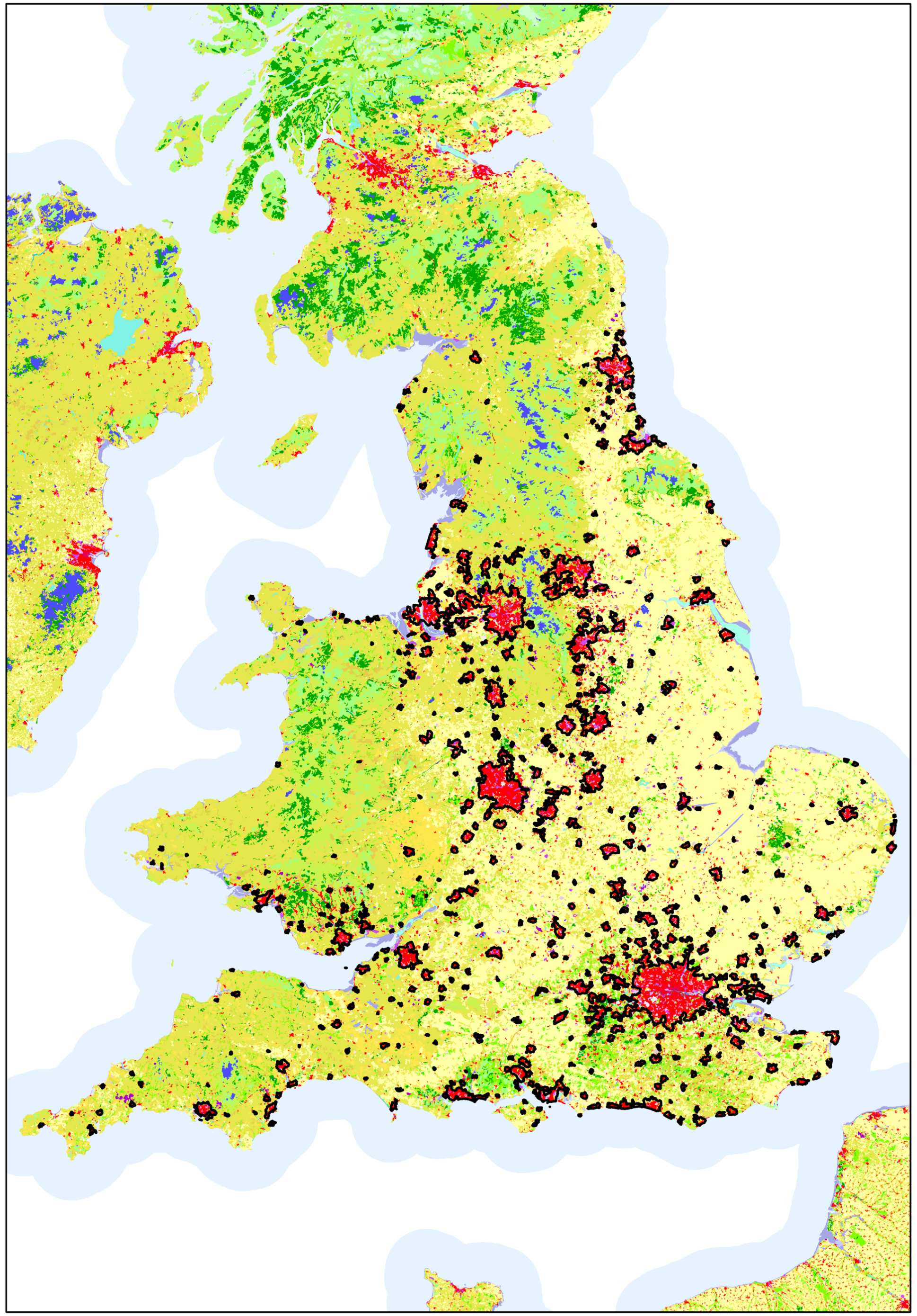
Fractal dimension of clusters at each distance threshold

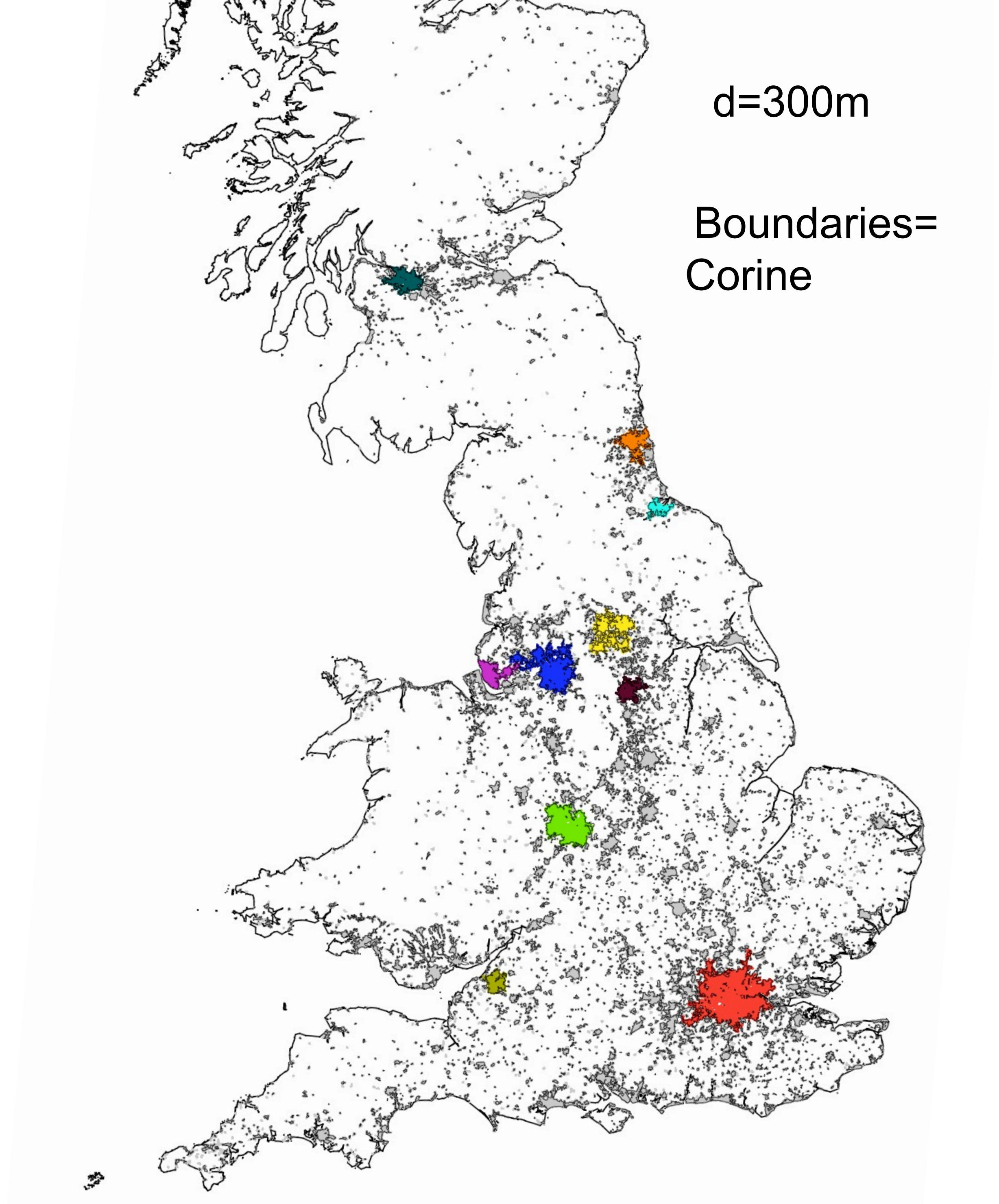


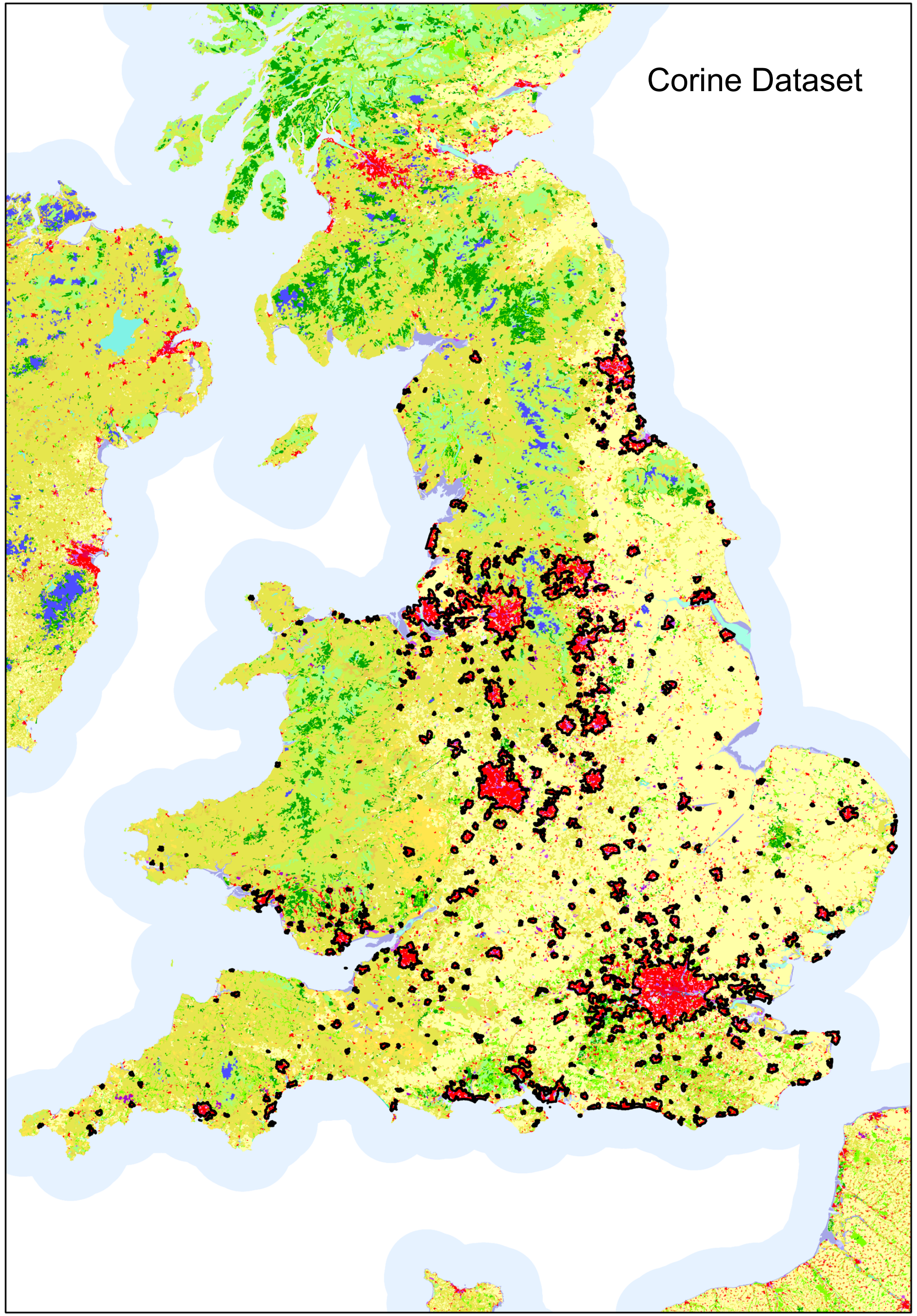
Arcaute et al, R. Soc. open Sci. 2016

Validation of results using satellite maps

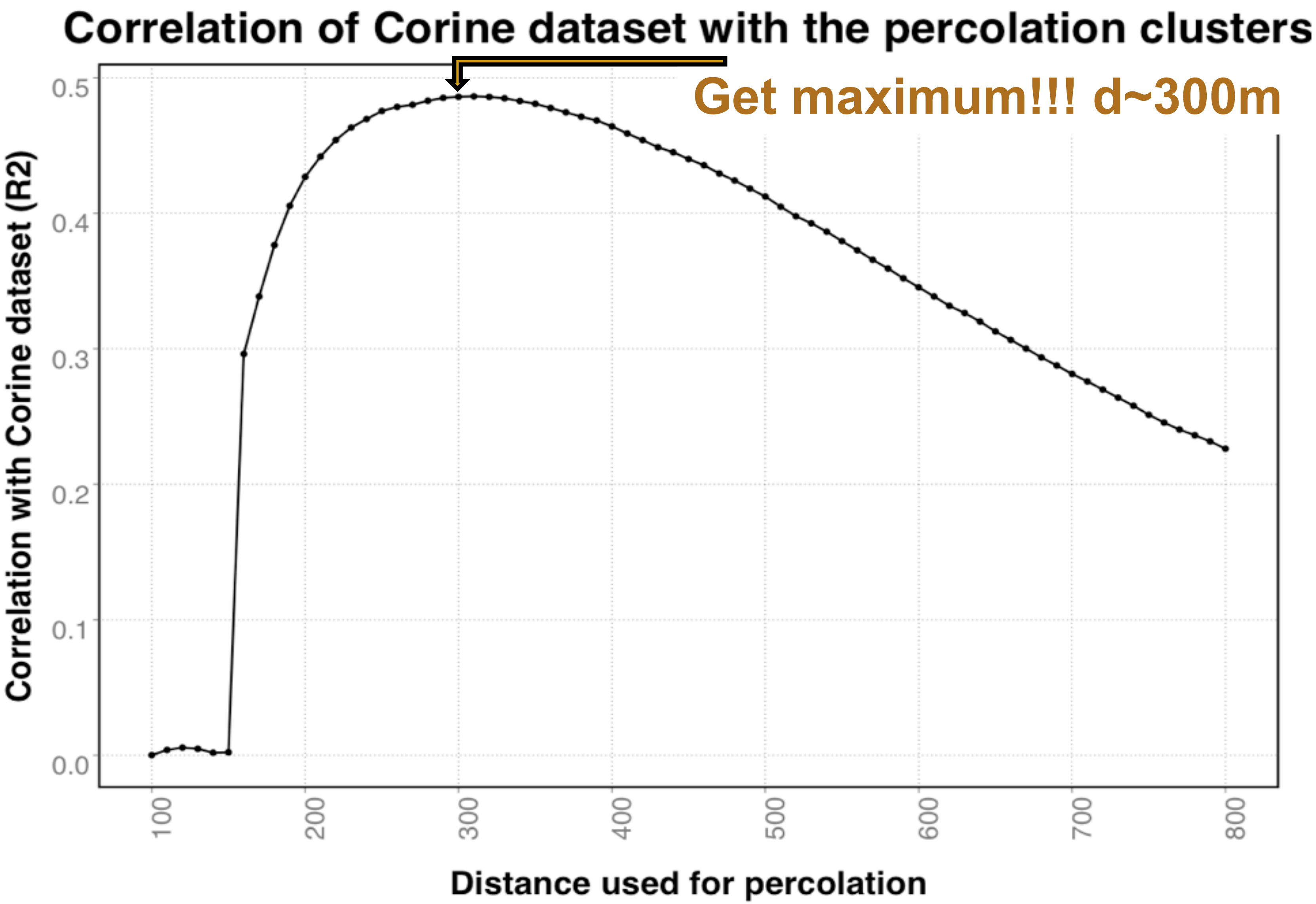
- Corine dataset from Lansat satellite.
- Pink colour corresponds to built-up area
- Black boundaries are added as proxies for the delimitation of cities







Arcaute et al, R. Soc. open Sci. 2016



Arcaute et al, R. Soc. open Sci. 2016

Universal fractal dimension for cities?

No!!!

→ Computing the exponent is no simple matter…. Different methods might might lead to slightly different results.

Also, it turns out that cities are not fractals, they are multifractals!!!

→ Probability of growth is not the same everywhere

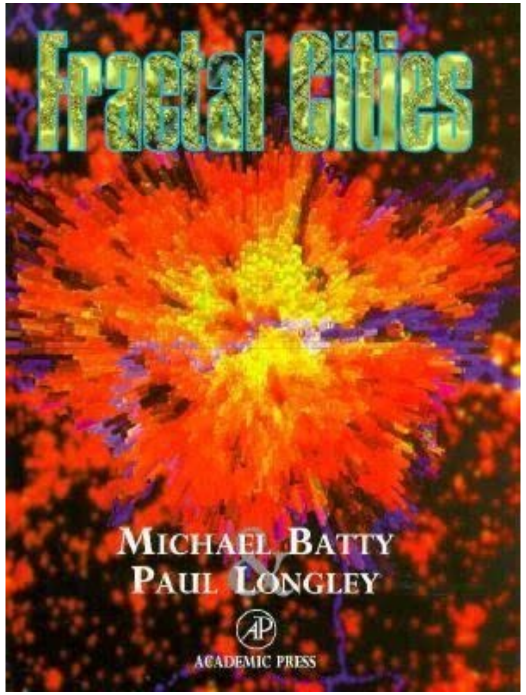
Multifractal measures

→ Fractal objects reduce their density as they grow

→ Usually, obtain a unique global fractal dimension: **monofractal**

→ Density distribution is assumed uniform:

→ growth probability uniform



Michael Batty & Paul Longley (1994)
Fractal Cities: A Geometry of Form and Function
(Academic Press, San Diego, CA and London)

→ What if this is not uniform any longer, and different regions present different growth probabilities?

→ E.g. DLA: different growth probabilities at the tips than deep into the structure

→ Observe local fractal dimensions that differ among regions

→ Would need an infinite amount of these to fully characterise the system

Multifractal

Cities as fractals in time

London's evolution

Dataset: Kiril Stanilov
Paolo Masucci

AP. Masucci, K. Stanilov, and M. Batty. London's street network dynamics since the 18th century. *PLoS ONE*, 8:e69469, 2013.

Multifractal analysis:
Roberto Murcio, A. Paolo Masucci, Elsa Arcaute and Michael Batty
Phys. Rev. E 92, 062130 (2015)

→ Compute 3 special fractal dimensions from whole spectrum

i) D_0 ⟺ box counting
ii) D_1 ⟺ information dimension
iii) D_2 ⟺ correlation

NATURE VOL. 335 29 SEPTEMBER 1988 REVIEW ARTICLE 405

Multifractal phenomena in physics and chemistry

H. Eugene Stanley* & Paul Meakin†

* Center for Polymer Studies and Department of Physics, Boston University, Boston, Massachusetts 02215, USA
† Central Research and Development Department, E. I. du Pont de Nemours and Company, Experimental Station, Wilmington, Delaware 19898, USA

Stanley and Meakin, Nature vol. 335, 29, 1988

$$D_q = \frac{\tau(q)}{(q-1)}$$

For monofractals: $D_0 \sim D_1 \sim D_2$

A. Analogies of multifractals with thermodynamics and multifractal scaling

Consider the sum in equation (1) in the form

$$Z(q) = \sum_p e^{F(p)} \tag{A1}$$

where

$$F(p) = \log n(p) + q \log p \tag{A2}$$

The sum in (A1) is dominated by some value $p = p^*$, where p^* is the value of p that maximizes $F(p)$. Thus

$$Z(q) \sim e^{F(p^*)} = n(p^*)(p^*)^q \tag{A3}$$

For fixed q, p^* and $(n(p^*)$ both depend on the system size L, leading one to define the new q-dependent exponents α and f by

$$p^* \sim L^{-\alpha}; \qquad n(p^*) \sim L^f \tag{A4}$$

Substituting (A4) into (A3) gives

$$Z(q) \sim L^{f - \alpha q} \tag{A5}$$

Comparing (A5) with equation (2), we find the desired result

$$\tau(q) = q\alpha(q) - f(q). \tag{A6}$$

From (A2) it follows that

$$\frac{d}{dq}\tau(q) = \alpha(q). \tag{A7}$$

Hence we can interpret $f(\alpha)$ as the negative of the Legendre transform of the function $\tau(q)$

$$f(\alpha) = -(\tau(q) - q\alpha) \tag{A8}$$

where $\alpha \equiv d\tau/dq$. The function $Z(q)$ is formally analogous to the partition function $Z(\beta)$ in thermodynamics, so that $\tau(\beta)$ is like the free energy. The Legendre transform $f(\alpha)$ is thus the analogue of the entropy, with α being the analogue of the energy E. Indeed, the characteristic shape of plots of $f(\alpha)$ against α (compare Fig. 3) are reminiscent of plots of the dependence on E of the entropy for a thermodynamic system.

Cities as fractals in time

London's evolution

Dataset: Kiril Stanilov

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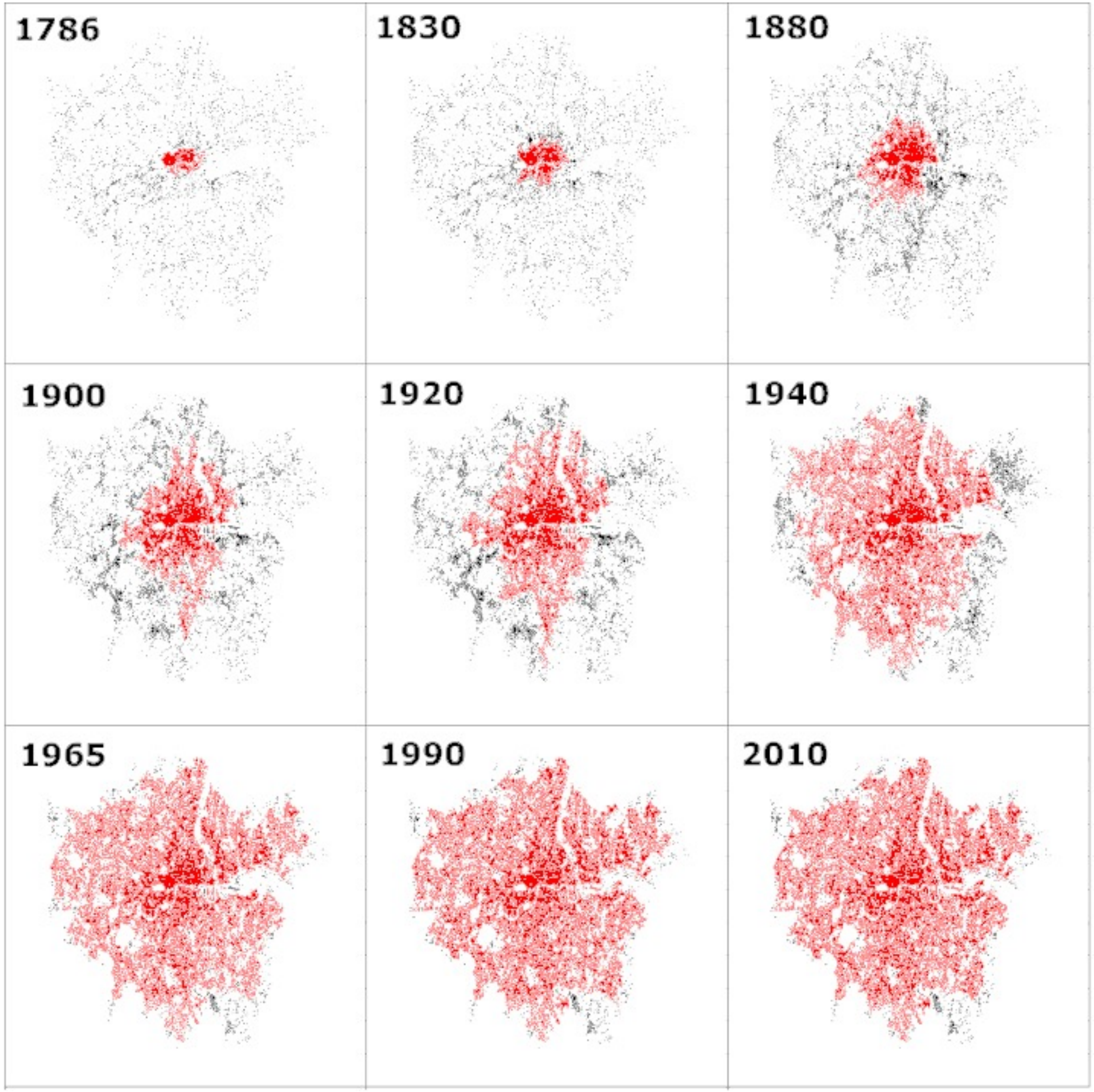
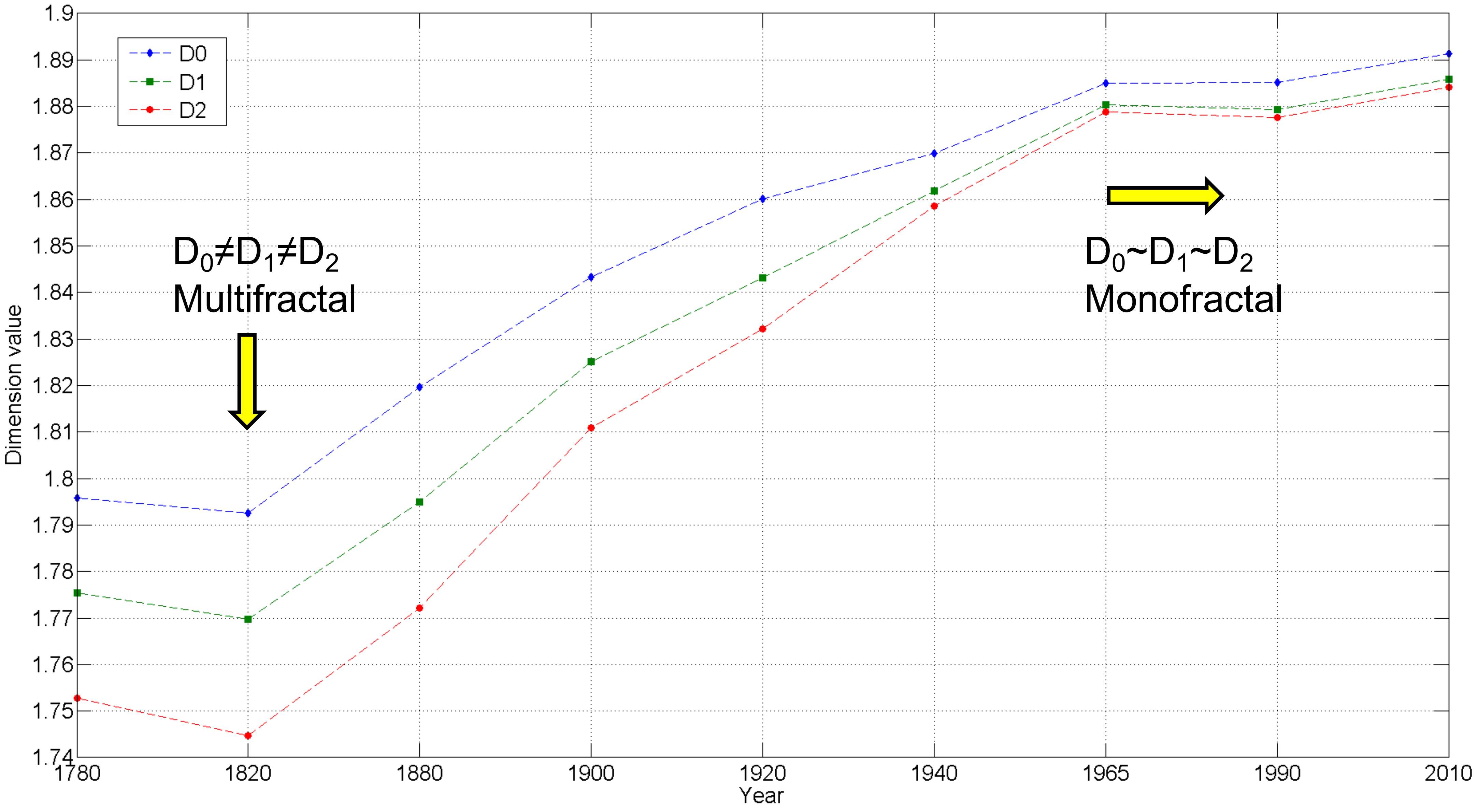
AP. Masucci, K. Stanilov, and M. Batty. London's street network dynamics since the 18th century. *PLoS ONE*, 8:e69469, 2013.



Multifractal analysis:
Murcio et al, PRE, 2015



Murcio et al, PRE, 2015

London is evolving from multifractality to monofractality!!

→ greenbelt is constraining growth, the space is getting filled
→ policy changes the morphology of the streets

For review of different methodologies to compute the multifractal spectrum

Physica A 473 (2017) 467–487

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Minireview

Multifractal methodology

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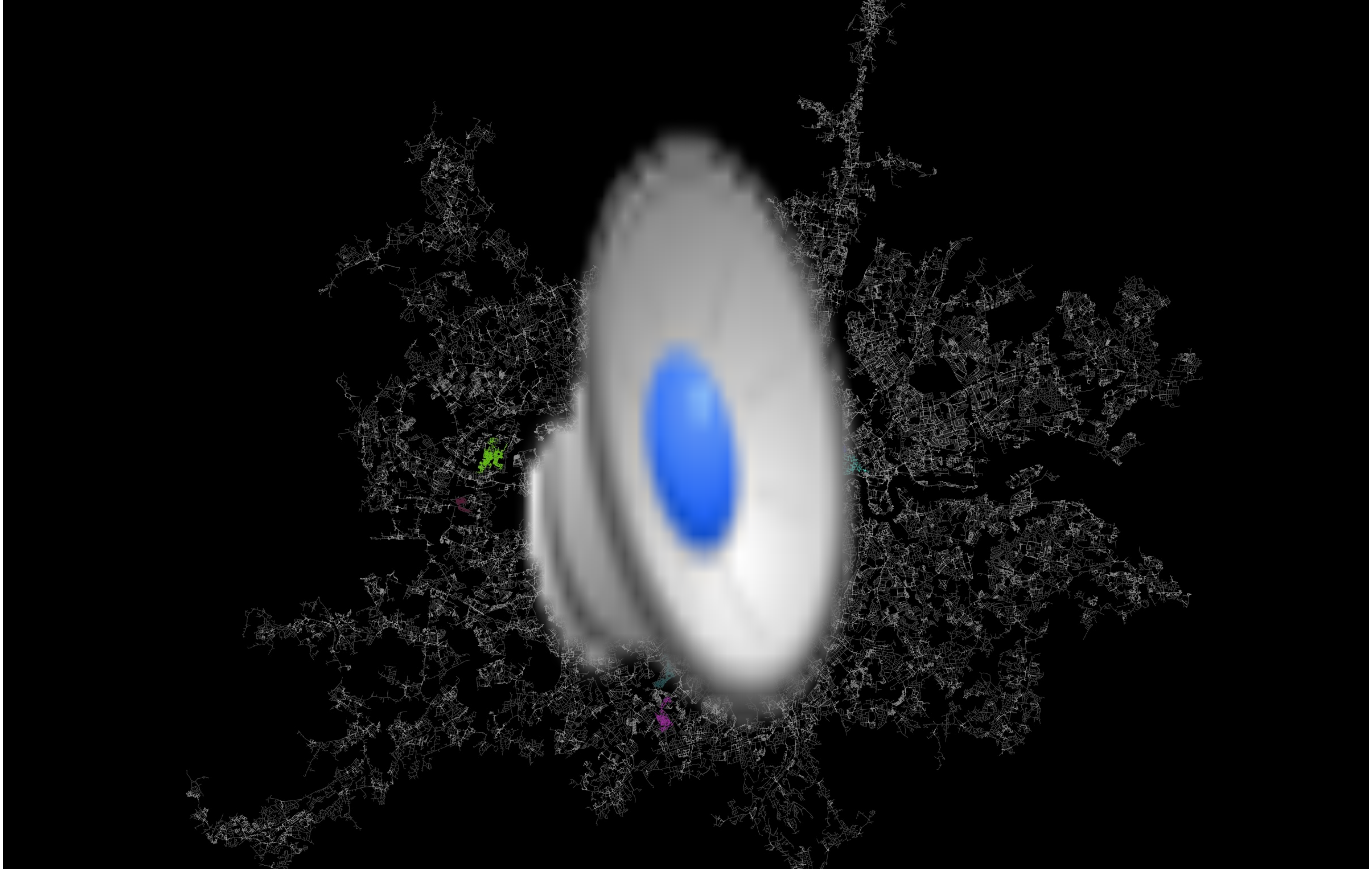
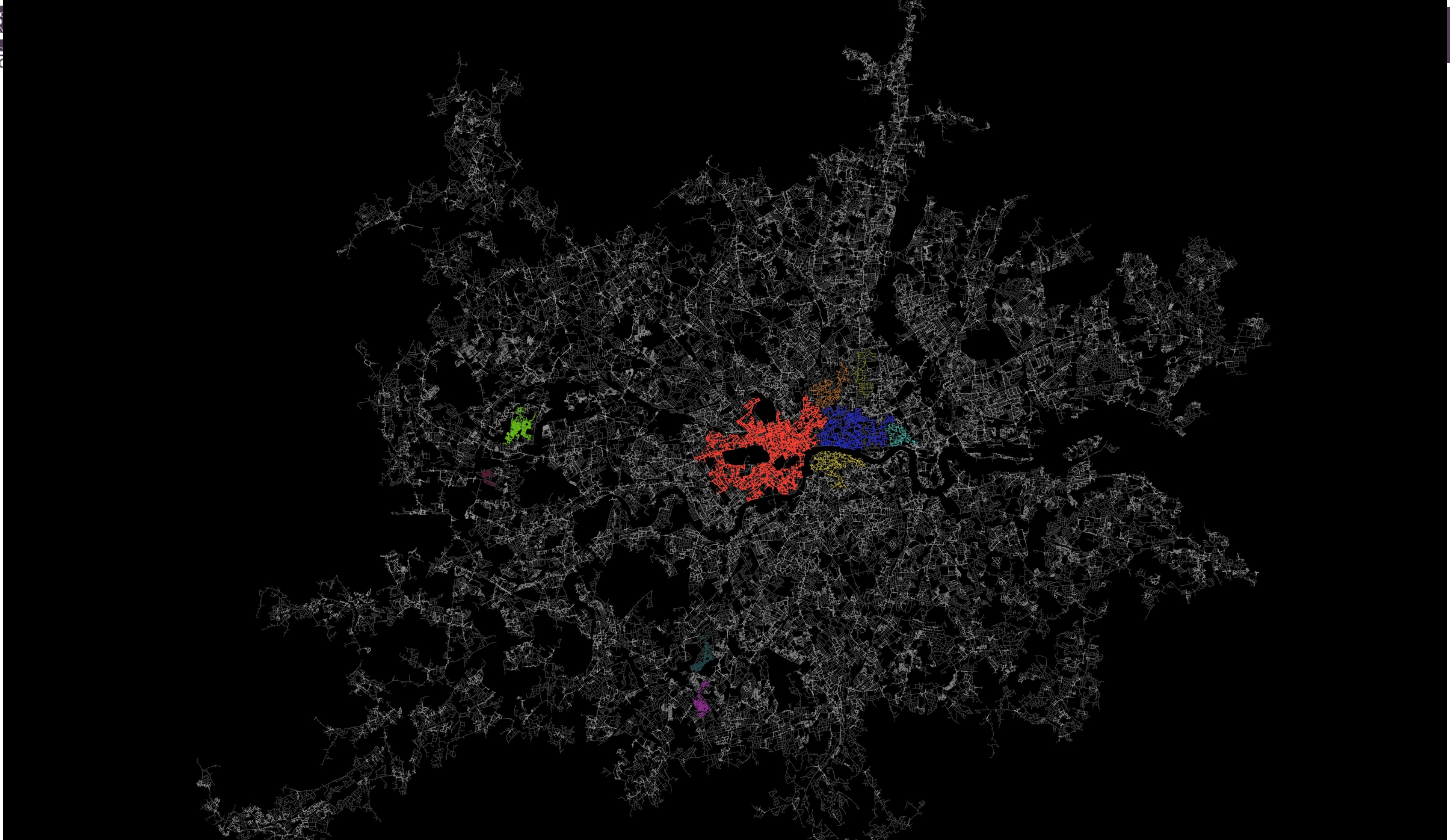
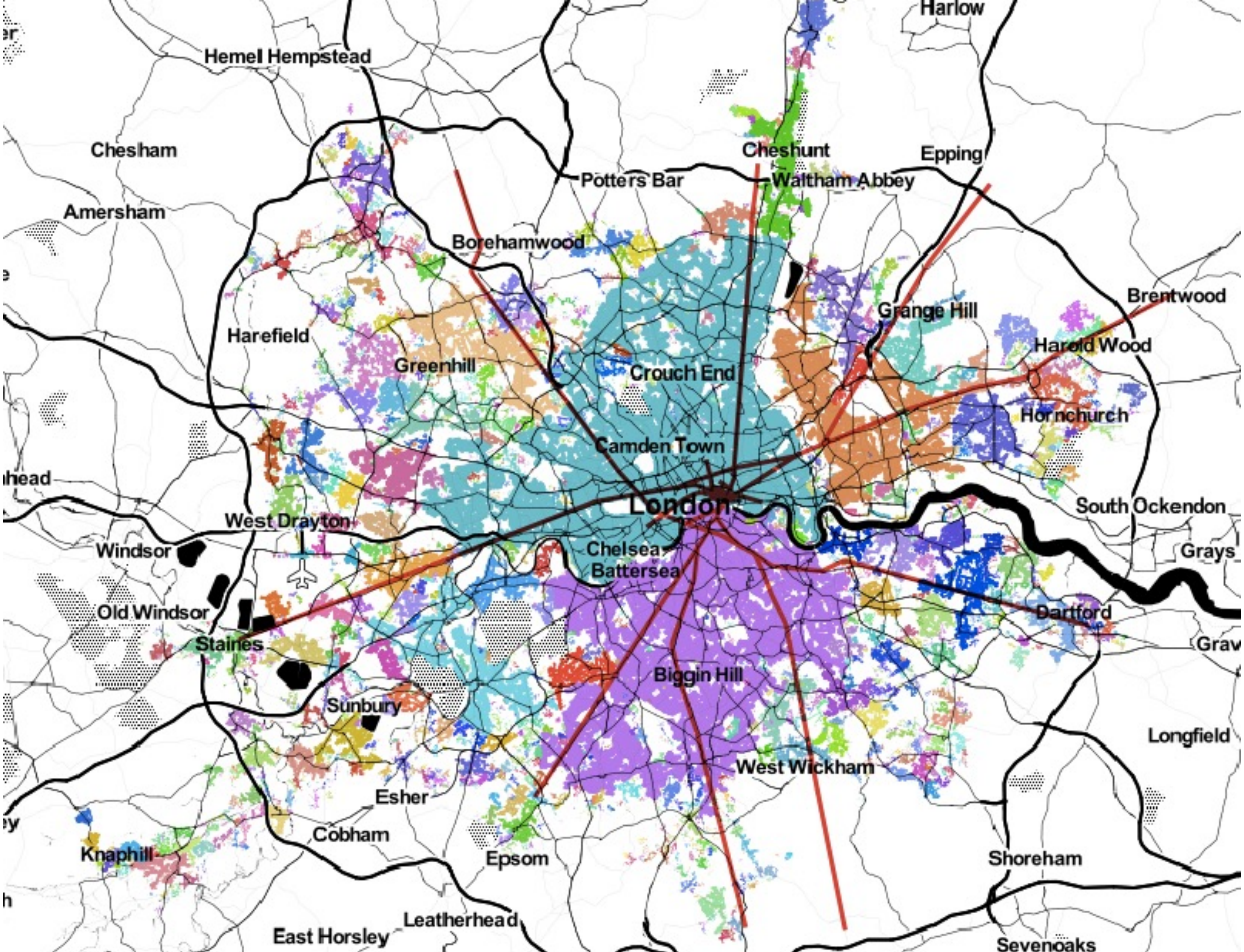
Hadrien Salat
Mathematician
Alan Turing Institute






Harlow
Hemel Hempstead
Chesham
Cheshunt
Epping
Potters Bar
Waltham Abbey
Amersham
Borehamwood
Brentwood
Grange Hill
Harold Wood
Harefield
Greenhill
Crouch End
Hornchurch
Camden Town
London
South Ockendon
West Drayton
Windsor
Chelsea
Battersea
Grays
Old Windsor
Dartford
Staines
Biggin Hill
Sunbury
Longfield
West Wickham
Esher
Cobham
Knaphill
Epsom
Shoreham
Leatherhead
East Horsley
Sevenoaks

What about other countries?

Let us look at Europe: Open Street Map

- ✧ Work by master student Tom Russell

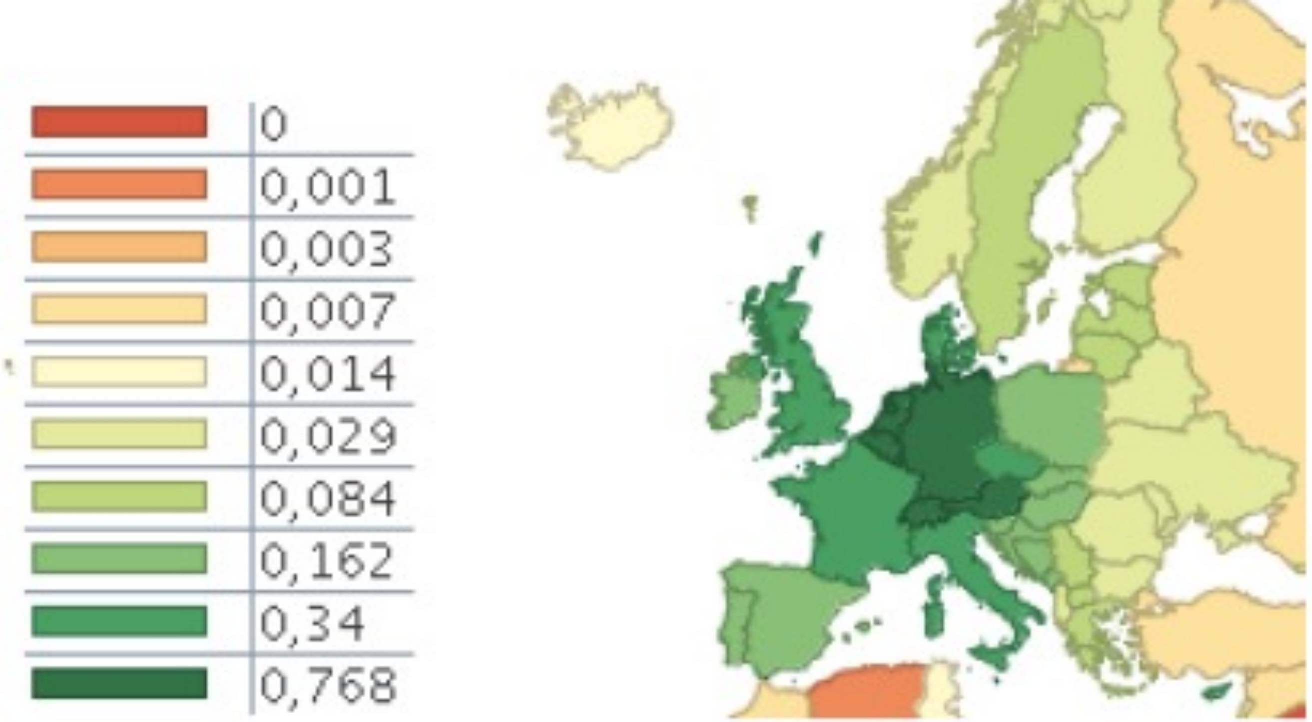


Figure 2: OSM users/day/1,000km², from Neis (2012)

Figure 3: Population density in 2000, from Hyde 3.1

Higher population density → more potential contributors to the dataset

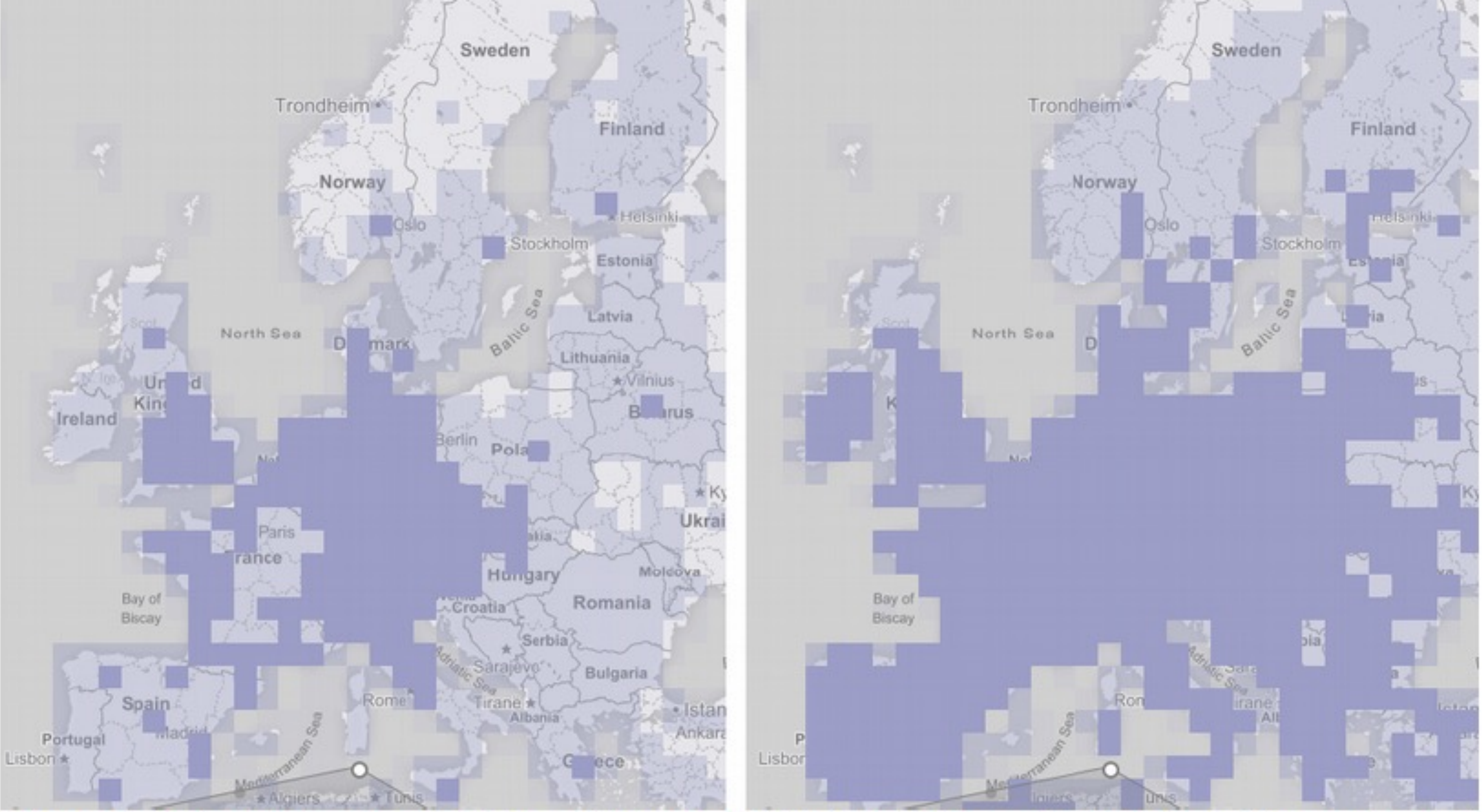
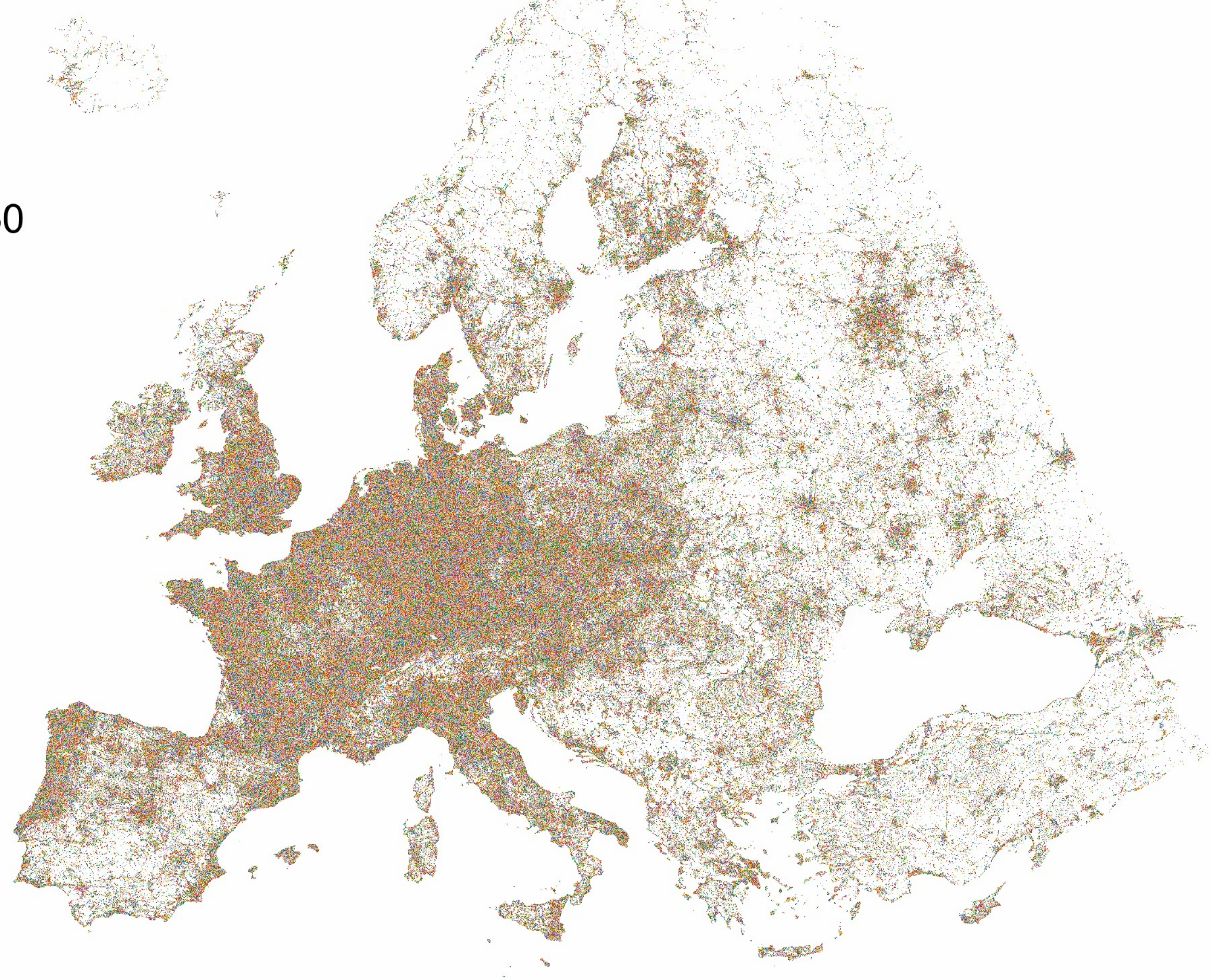
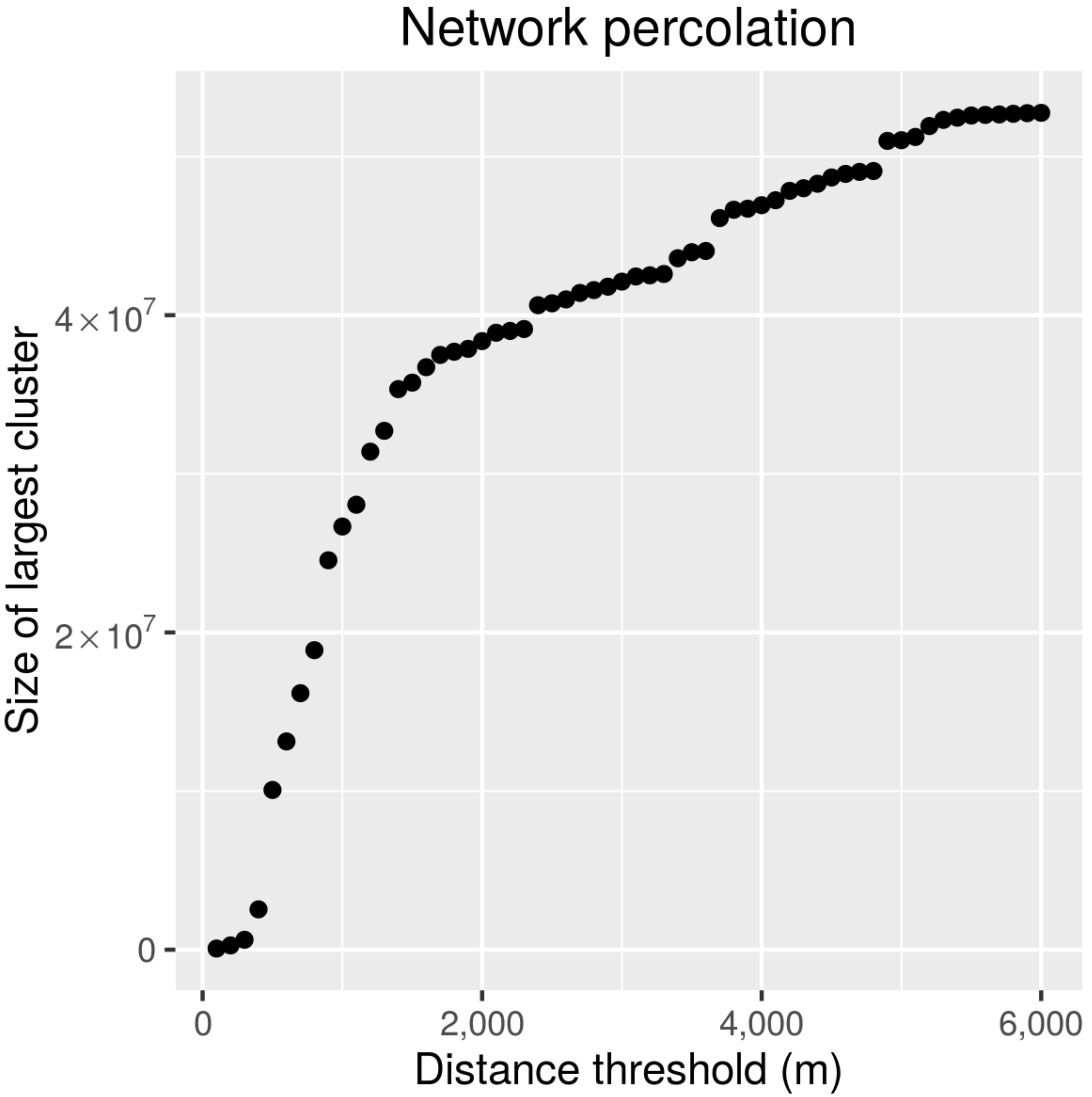


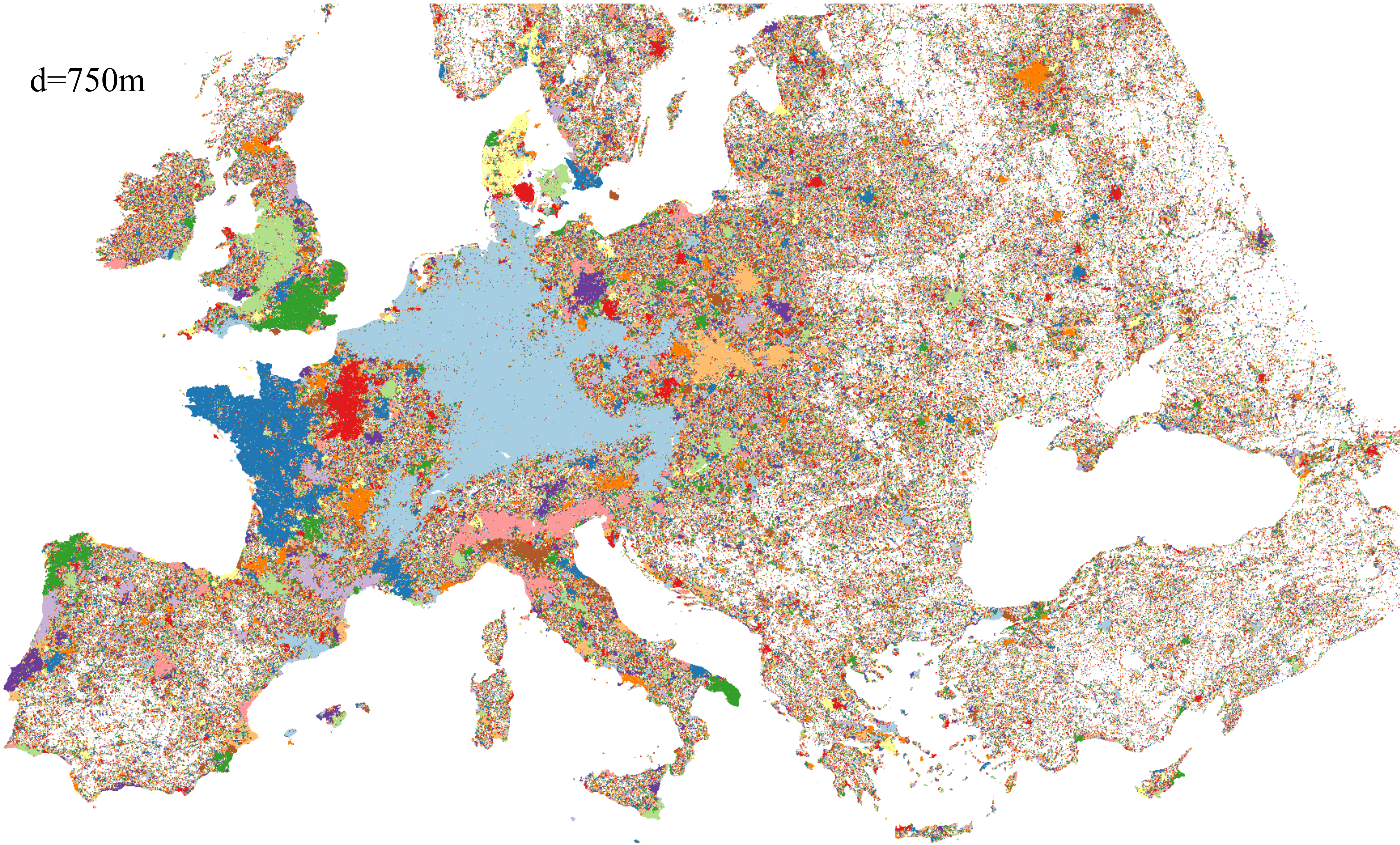
Figure 4: Relative density of OSM roads last modified in 2011 and 2016, from Humanitarian OpenStreetMap Team (2016)

50

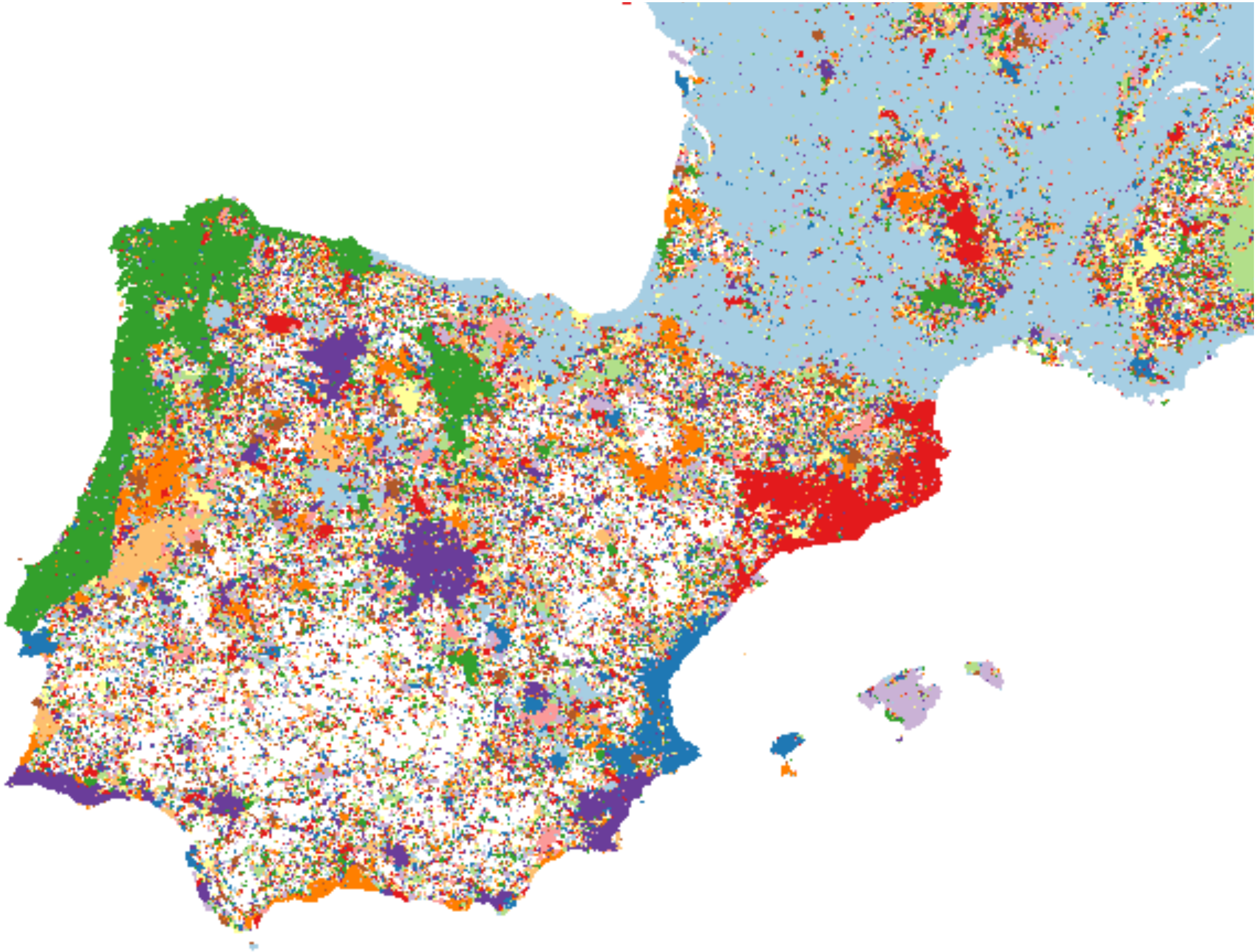


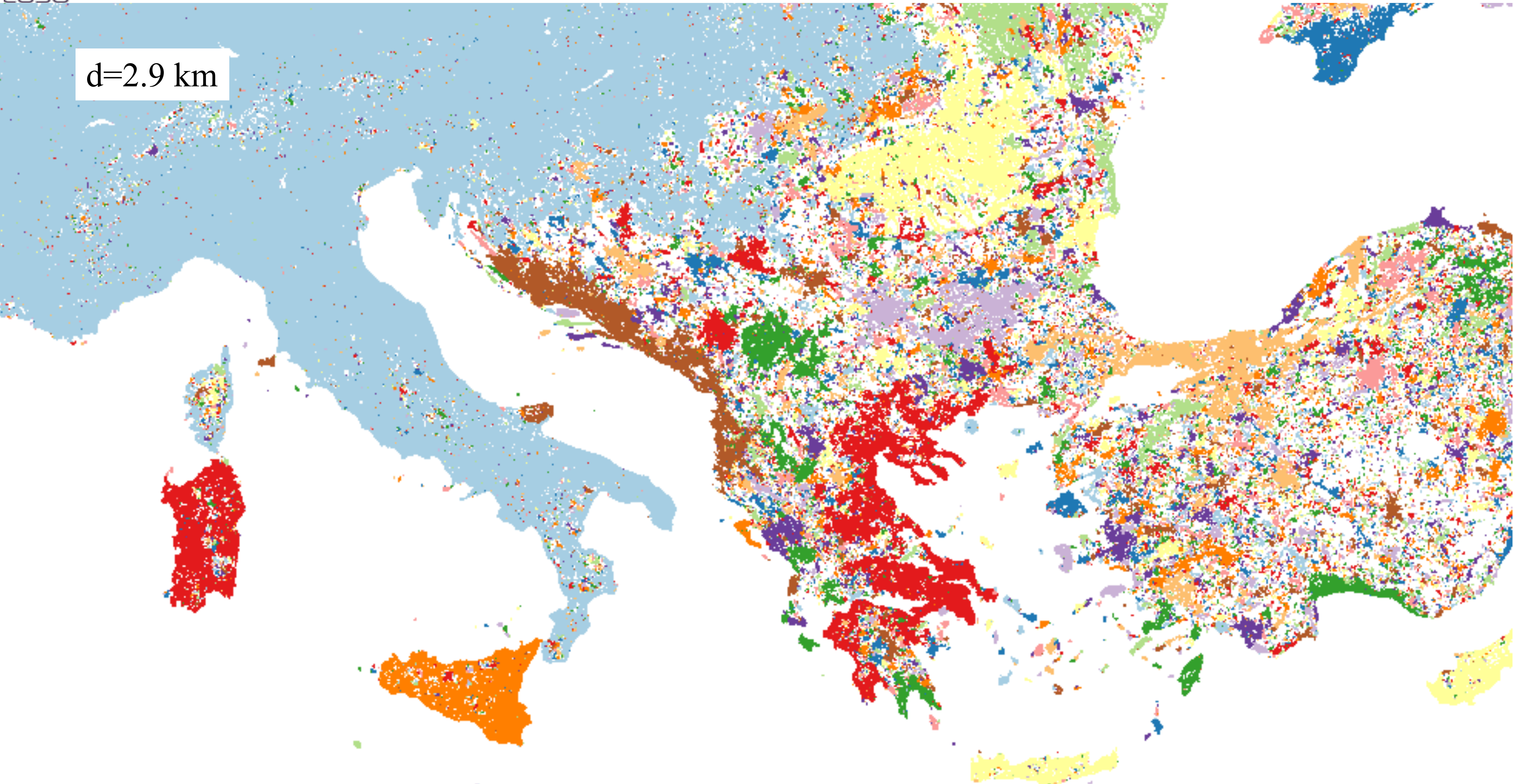
Are the transitions representative of any expected divisions?



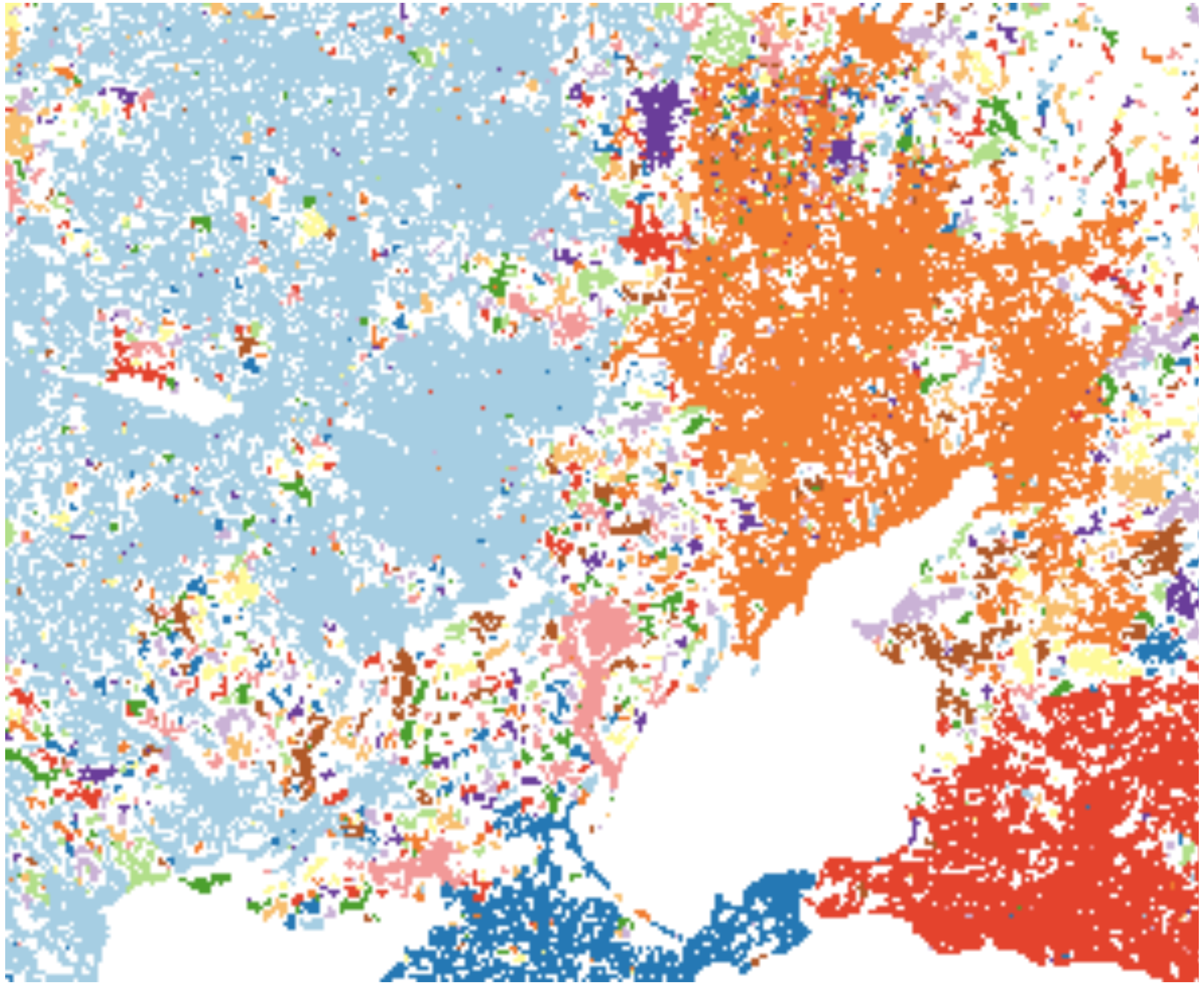

d=750m

d=1 km




d=2.9 km

Donbass region




Kiev
UKRAINE
LUHANSK
Stanytsia
Luhanska
Mayorsk
DONETSK
Marinka
UKRAINE
Novotroitske
RUSSIA
Hnutove
Crossing points
Russian-backed
separatist-controlled area

BBC

Multiscalarity and dependencies

Local perspective of system misses bigger picture

FINANCIAL TIMES

Richard Milne and Peter Spiegel FEBRUARY 25 2016

Multiscalar approach: system of cities

- Construct scales according to interactions between cities → **FLOWS**
- Commuting flows in particular → **dependencies**

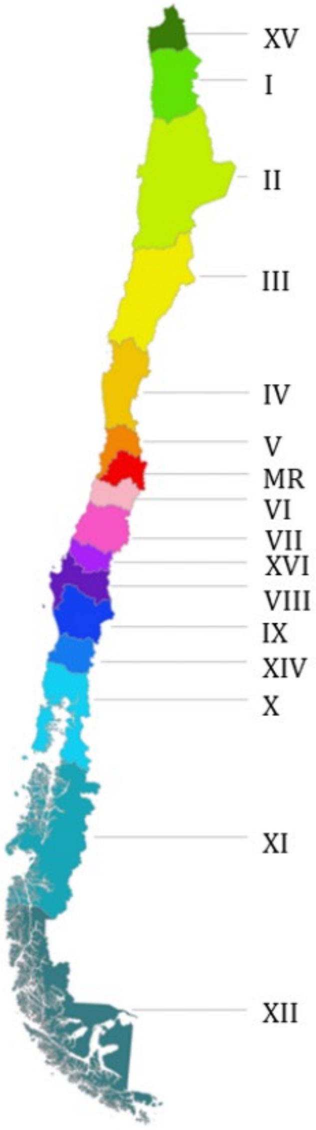
Total flows not enough, need to understand **DIVERSITY**

Spatial diversity

Workers-skills diversity

- Gain insights into level of **adaptability** to external shocks
- Gain insights into **polycentricity** and **monocentricity** of system
- Gain insights into potential for **knowledge spillovers** between a wide range of workers-skills

Case study: Chile



The following framework was derived by Dr Valentina Marin during her PhD, awarded a few months ago.

Dr Valentina Marin

Modelling the multi-scalar effect of commuting on exposure to diversity

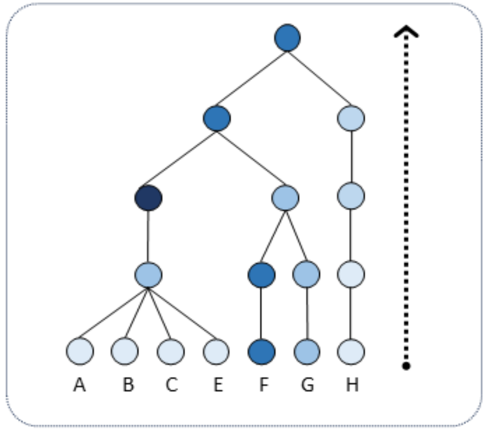
Valentina Marin[1,*], Carlos Molinero[1], and Elsa Arcaute[1]

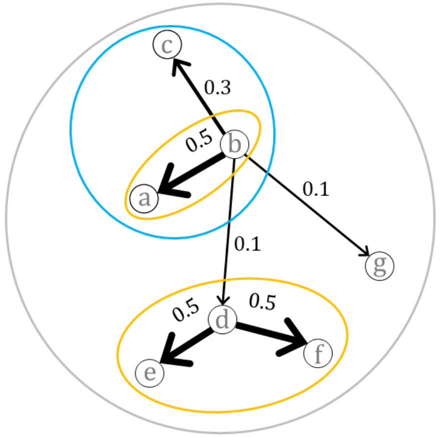
[1]Centre for Advanced Spatial Analysis (CASA) University College London, UK
[*]corresponding author: v.marin@ucl.ac.uk

https://doi.org/10.48550/arXiv.2306.00213

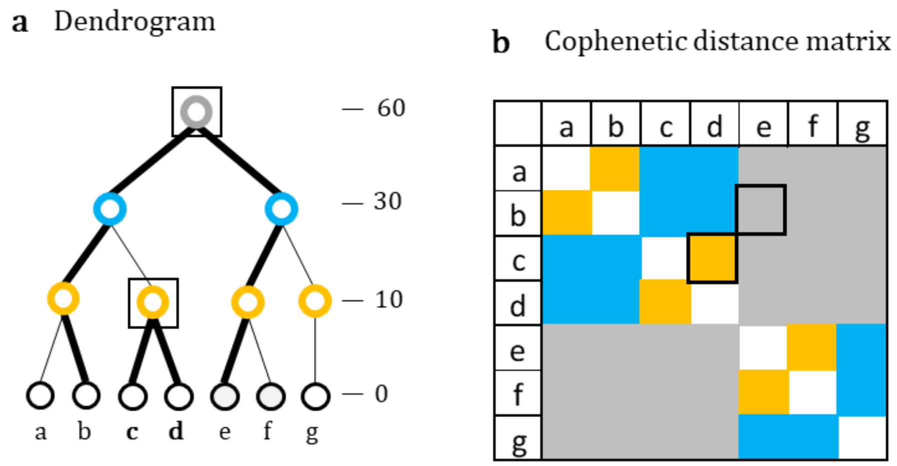
Framework

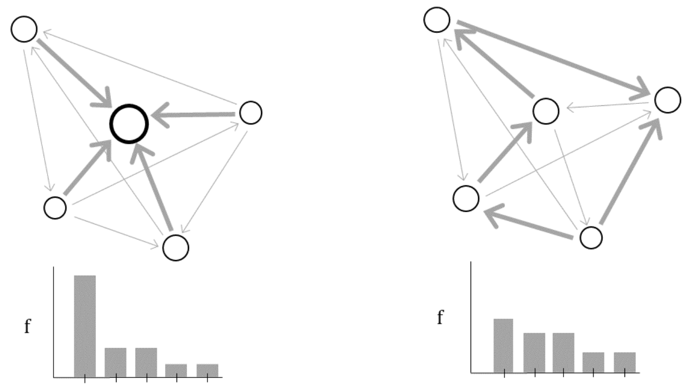
1.- Retrieve the hierarchical organisation of the commuting patterns given by the heterogeneity of the interactions





2.- Retrieve the distance in the tree between the different elements and their diversity (entropy-based metrics)

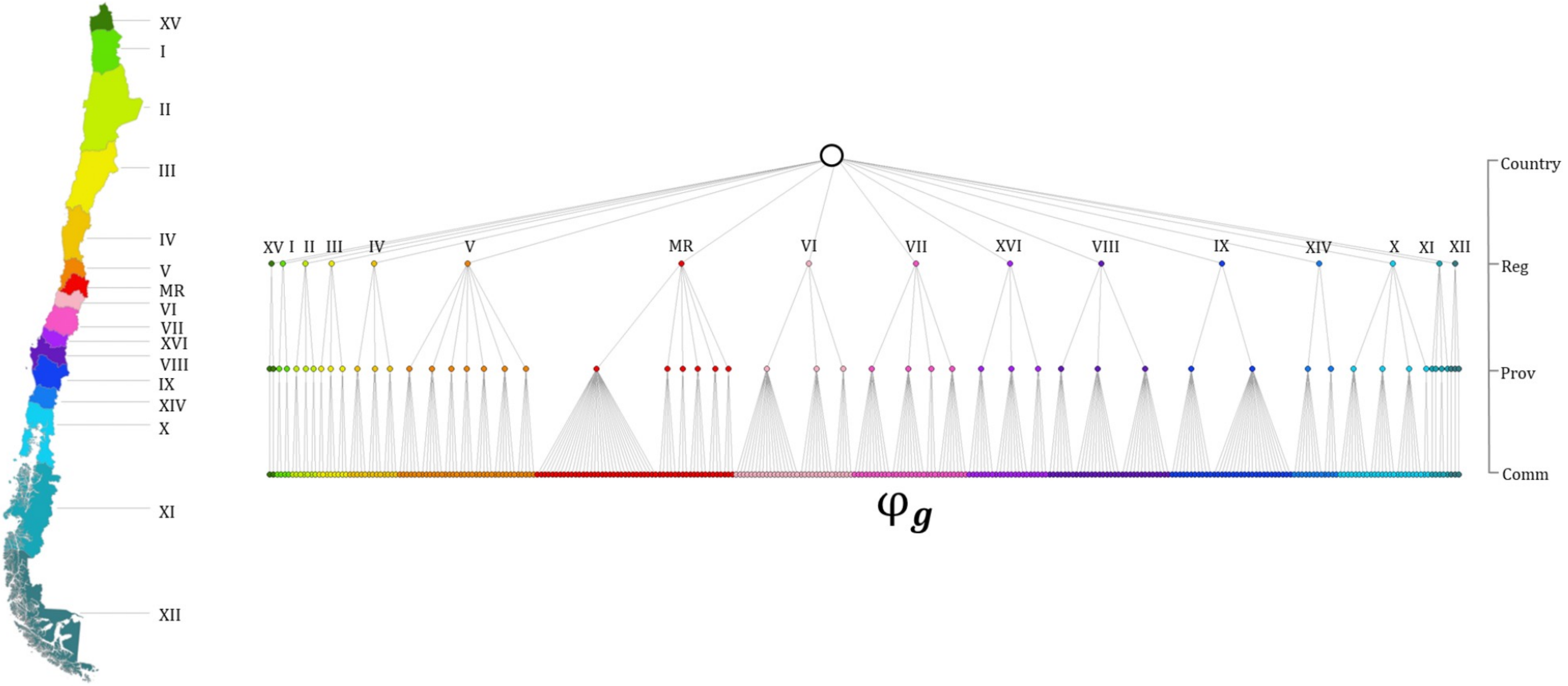




3.- Identify categories of systems of cities based on multi-scalar accessibility to diversity

1. Hierarchical organisation

Structure of governance

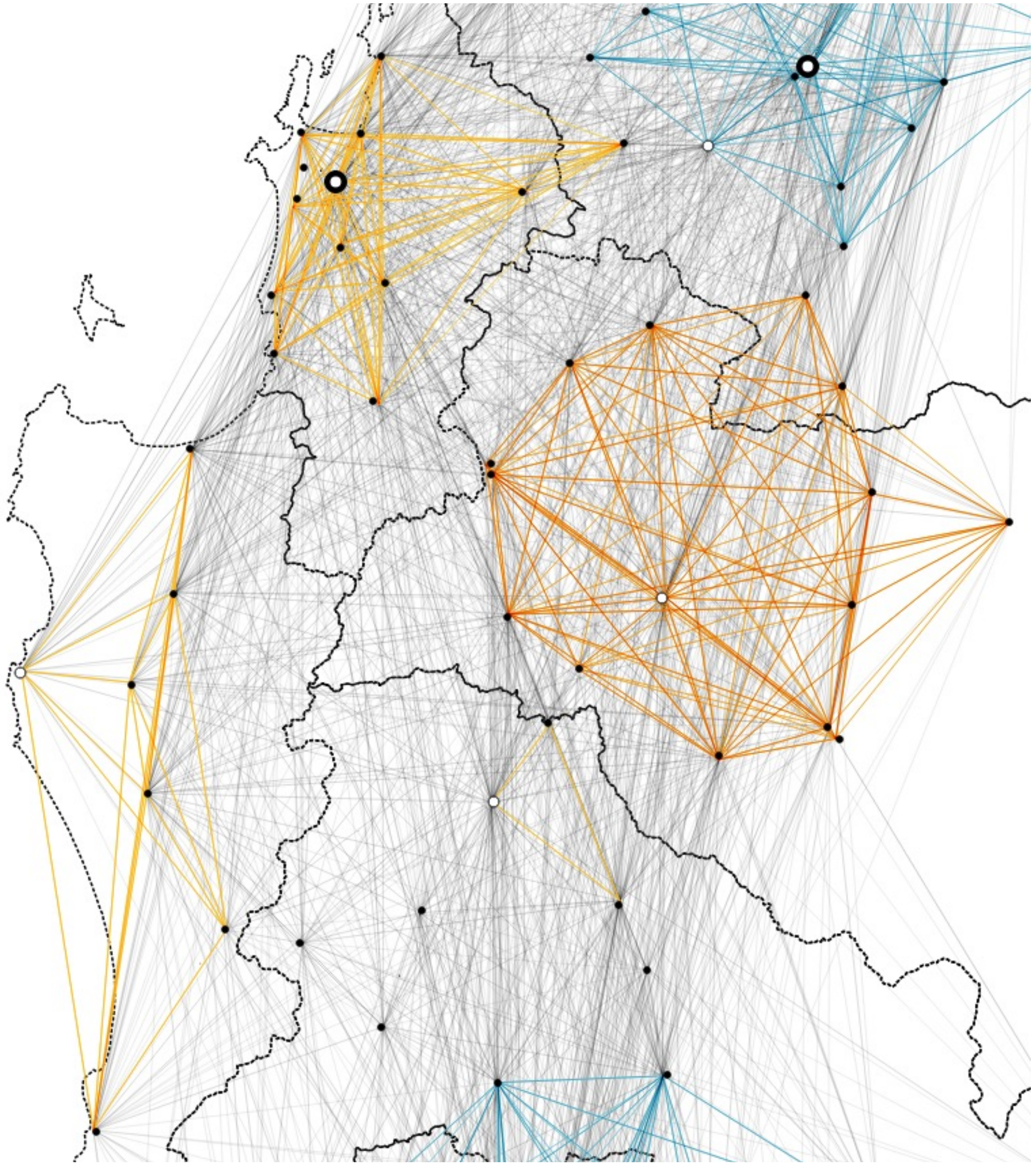


Commuting Networks: Data

- **Census 2002**
- Data aggregated from commune to **City level**
- Weighted directed network where cities are nodes and the weight indicates **dependency**
- **3 hours** is the max travel time (shortest path driving)
- The international Standard Classification of Occupations (ISCO)

The International Standard Classification of Occupations (ISCO)

ISCO-08 Major groups	Skill
1- Managers	4
2- Professionals	4
3- Technicians and associate professionals	3
4- Clerical support workers 5- Service and sales workers 6- Skilled agricultural, forestry and fishery workers 7- Craft related trades workers 8- Plant and machine operators, and assemblers	2
9- Elementary occupations	1
10- Armed forces occupations	

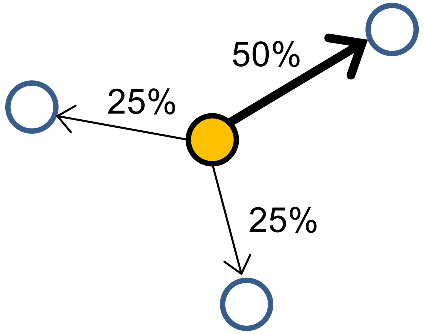


PERCOLATION-BASED HIERARCHICAL CLUSTERING

- **Commuting as a network**
  - cities as <u>nodes</u>
  - flows of commuters as <u>links</u>

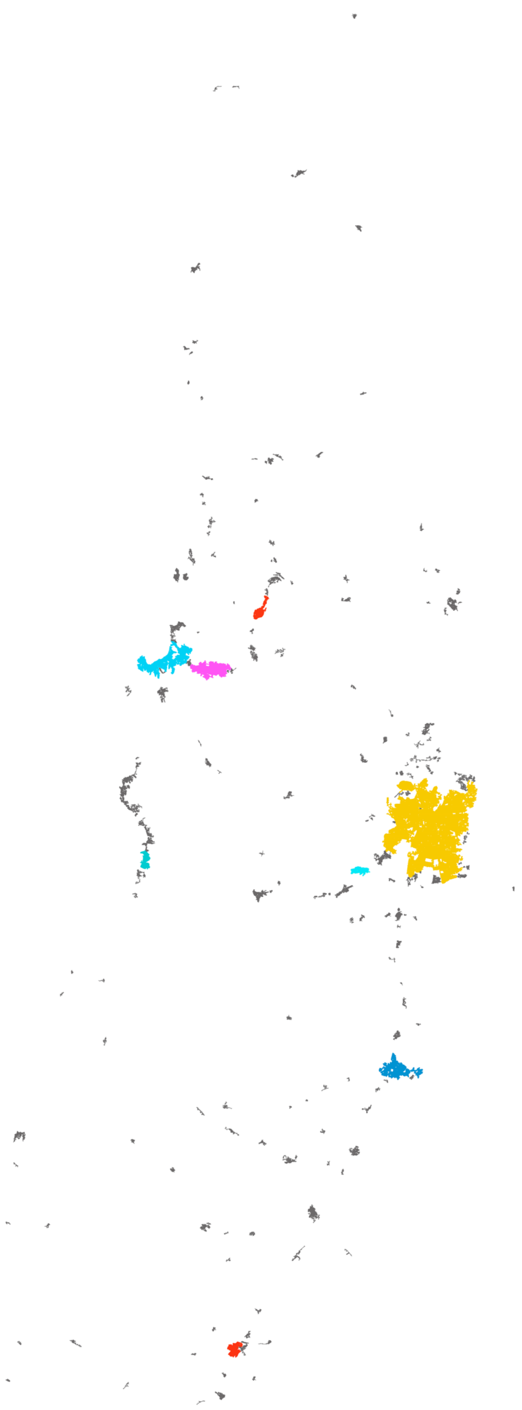
- **Links weighted by share of flows**

Dependence weight $w_{ij} = \frac{T_{ij}}{\sum_j T_{ij}}$



- **Extracting nodes of connected links when $w_{ij} > \tau$**

Clusters are induced by the intensity given by the number of commuters, and the relative dependencies.



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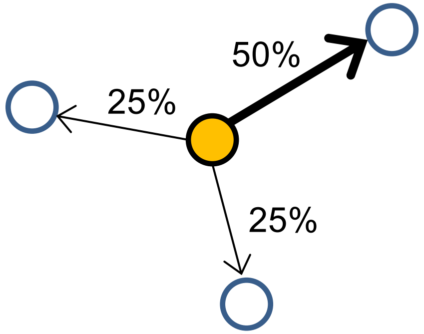

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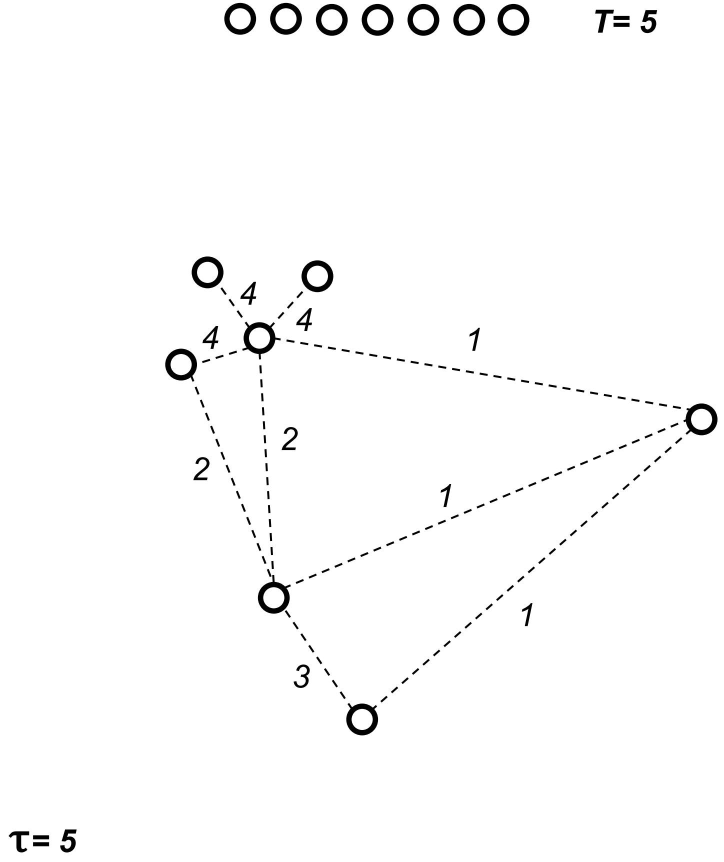

PERCOLATION-BASED HIERARCHICAL CLUSTERING

- **Commuting as a network**
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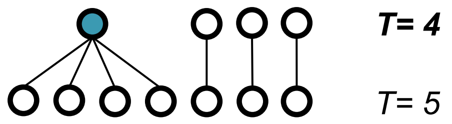
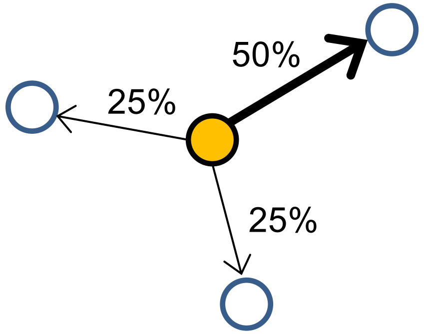
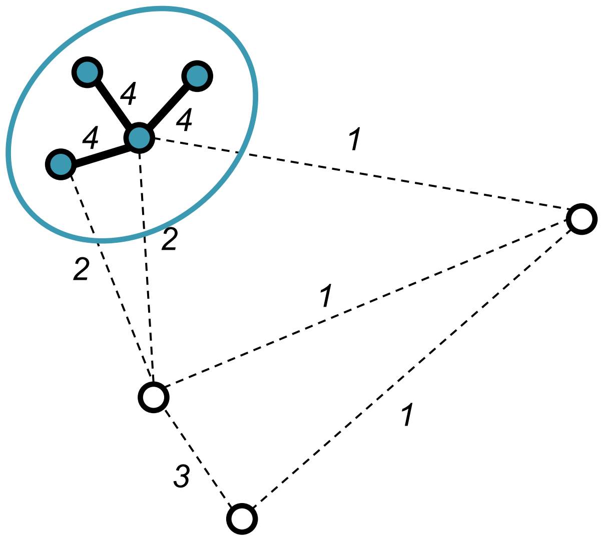
  - flows of commuters as <u>links</u>



- **Links weighted by share of flows**

Dependence weight $w_{ij} = \frac{T_{ij}}{\sum_j T_{ij}}$





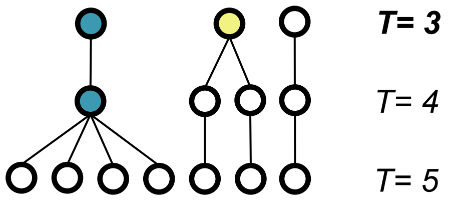
- **Extracting nodes of connected links when $w_{ij} > \tau$**

Clusters are induced by the intensity given by the number of commuters, and the relative dependencies.

τ= 4

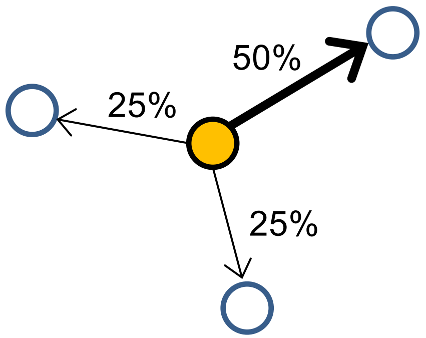
PERCOLATION-BASED HIERARCHICAL CLUSTERING

- **Commuting as a network**
  - cities as nodes
  - flows of commuters as links

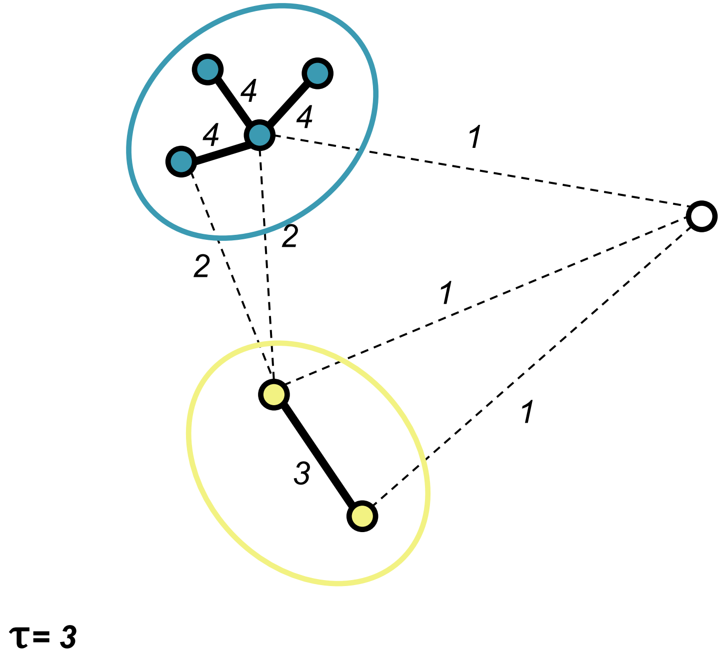


- **Links weighted by share of flows**

Dependence weight $w_{ij} = \frac{T_{ij}}{\sum_j T_{ij}}$



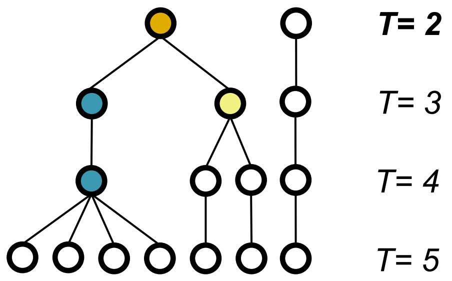
- **Extracting nodes of connected links when w_{ij} > τ**



Clusters are induced by the intensity given by the number of commuters, and the relative dependencies.

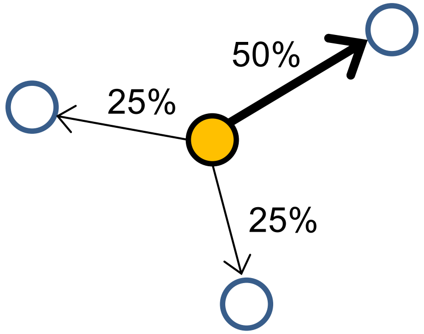
PERCOLATION-BASED HIERARCHICAL CLUSTERING

- **Commuting as a network**
  - cities as nodes
  - flows of commuters as links



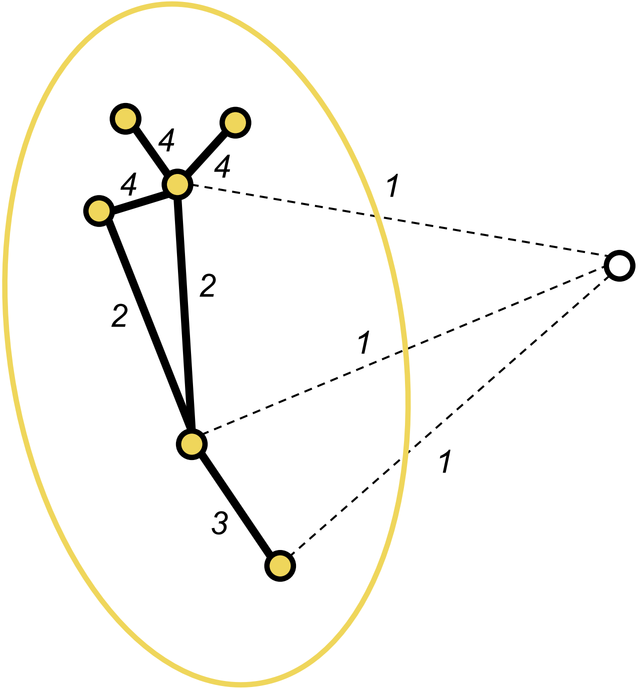
- **Links weighted by share of flows**

Dependence weight $w_{ij} = \frac{T_{ij}}{\sum_j T_{ij}}$



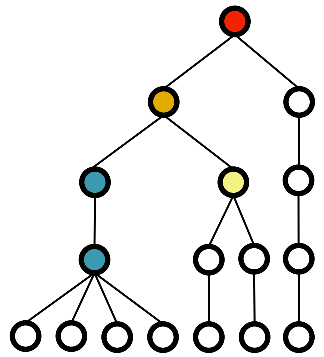
- **Extracting nodes of connected links when $w_{ij} > \tau$**

Clusters are induced by the intensity given by the number of commuters, and the relative dependencies.



τ= 2

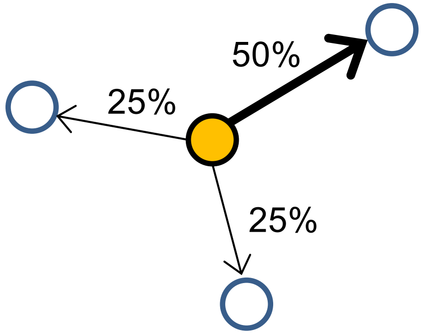
PERCOLATION-BASED HIERARCHICAL CLUSTERING



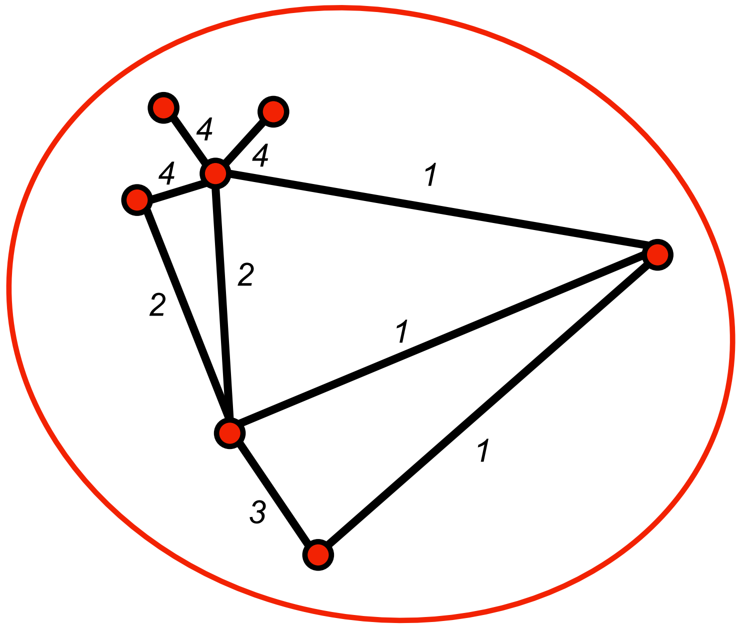
- **Commuting as a network**
  - cities as nodes
  - flows of commuters as links

- **Links weighted by share of flows**

Dependence weight $w_{ij} = \frac{T_{ij}}{\sum_j T_{ij}}$



- **Extracting nodes of connected links when w_{ij} > τ**



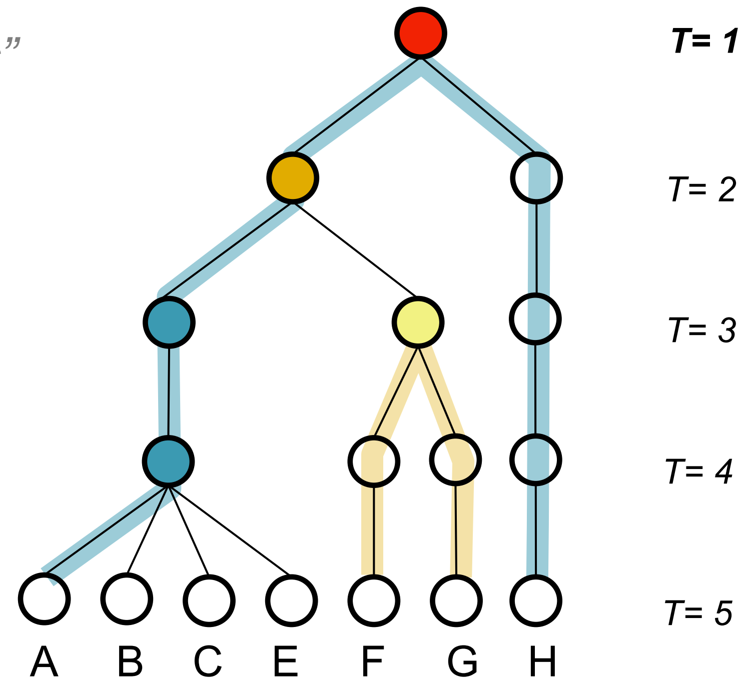
τ= 1

Clusters are induced by the intensity given by the number of commuters, and the relative dependencies.

SCALAR DISTANCE

- **Reconstruct hierarchy by ordering percolation clusters**

"Everything is connected, but some things are more connected than others" (Simon, 1977)



- **Clusters are organised according to the intensity of connectivity**

Horizontally: *Stronger intra-cluster connectivity*
Weaker inter-cluster connectivity

Vertically: *Cross-scalar relationships*

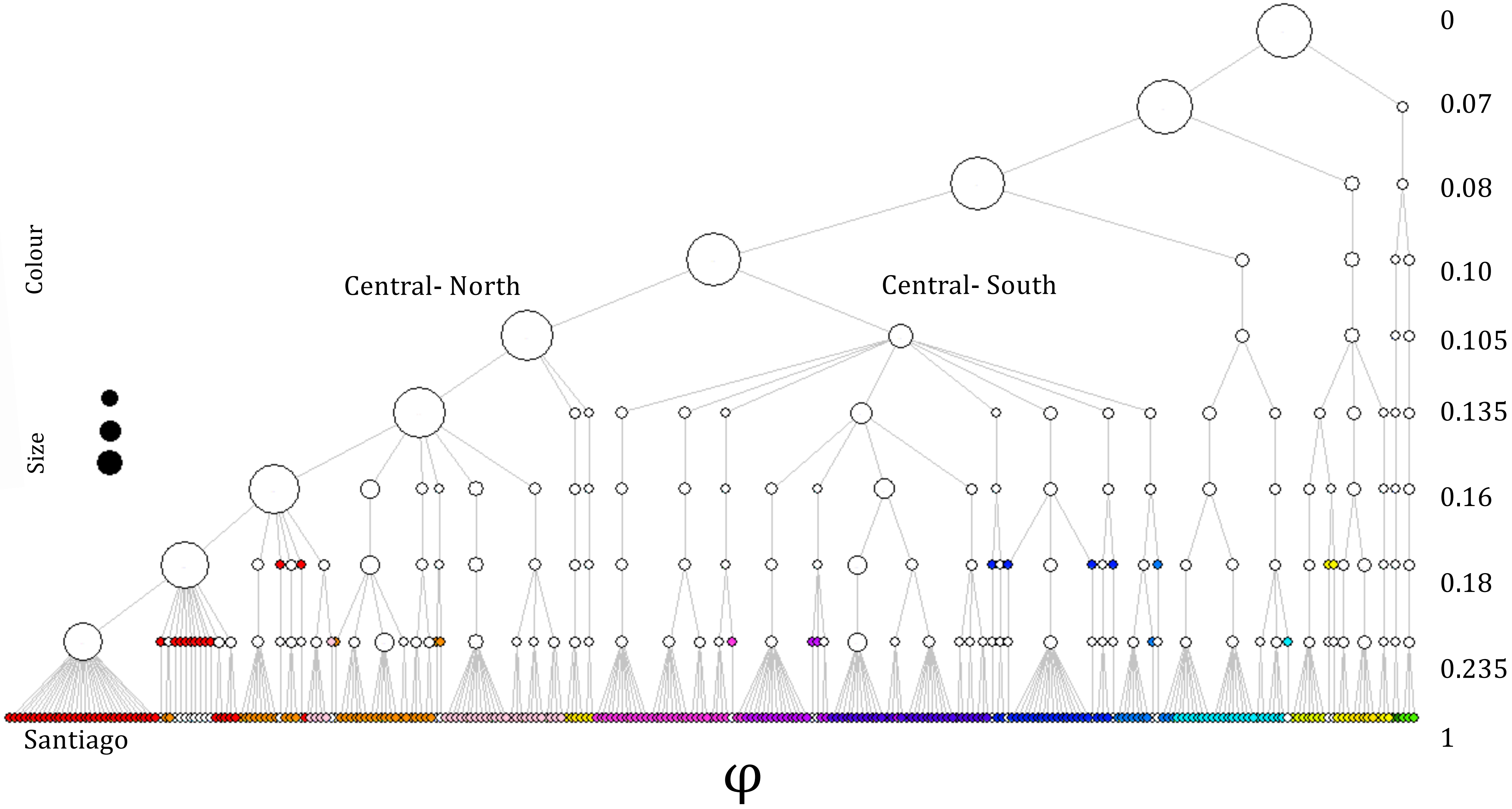
- **Scalar distance between two points (Cophenetic Distance)**

Distance is the height of the node at which two points are first joined together

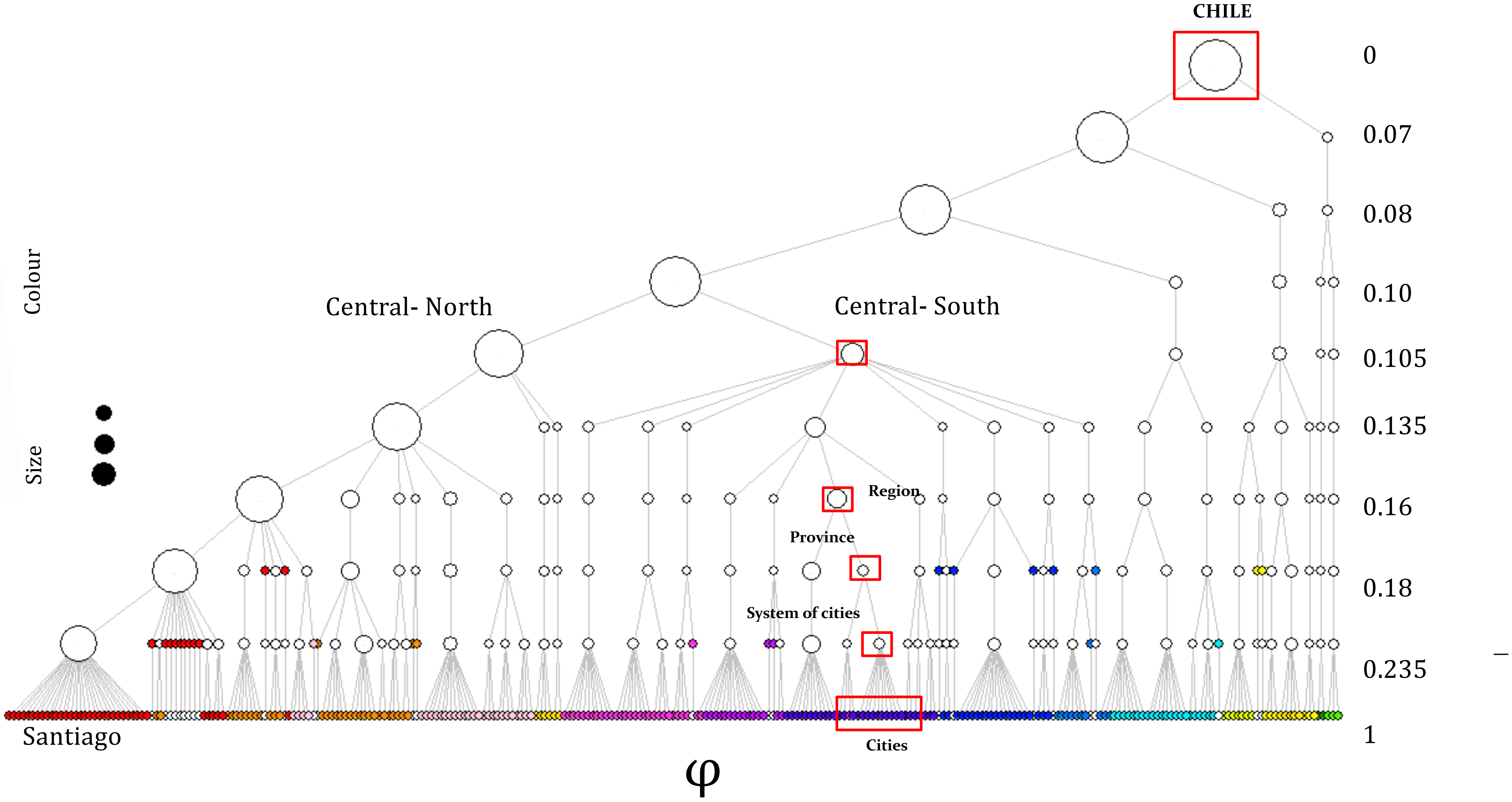
$D(F,G) = 2$

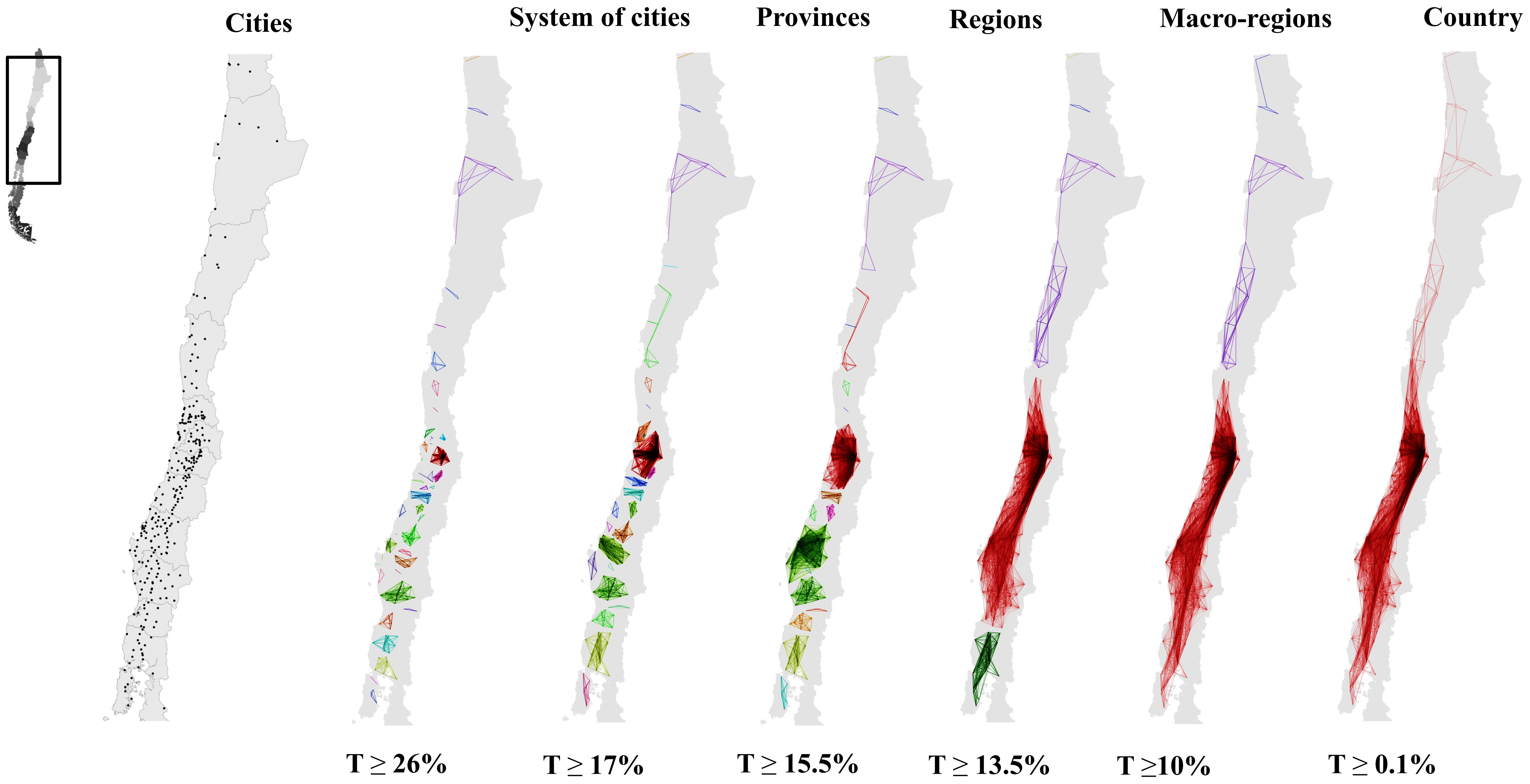
$D(A,H) = 4$

PERCOLATION-BASED HIERARCHICAL CLUSTERING

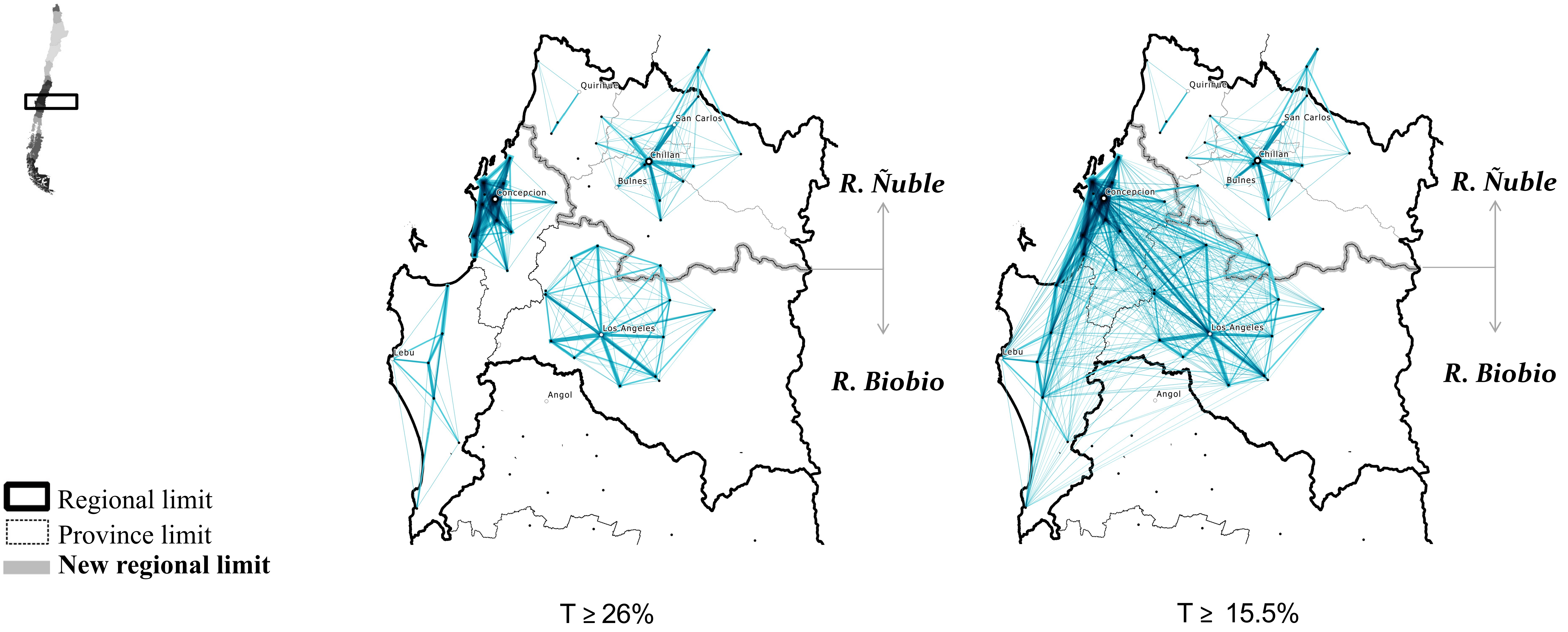


PERCOLATION-BASED HIERARCHICAL CLUSTERING



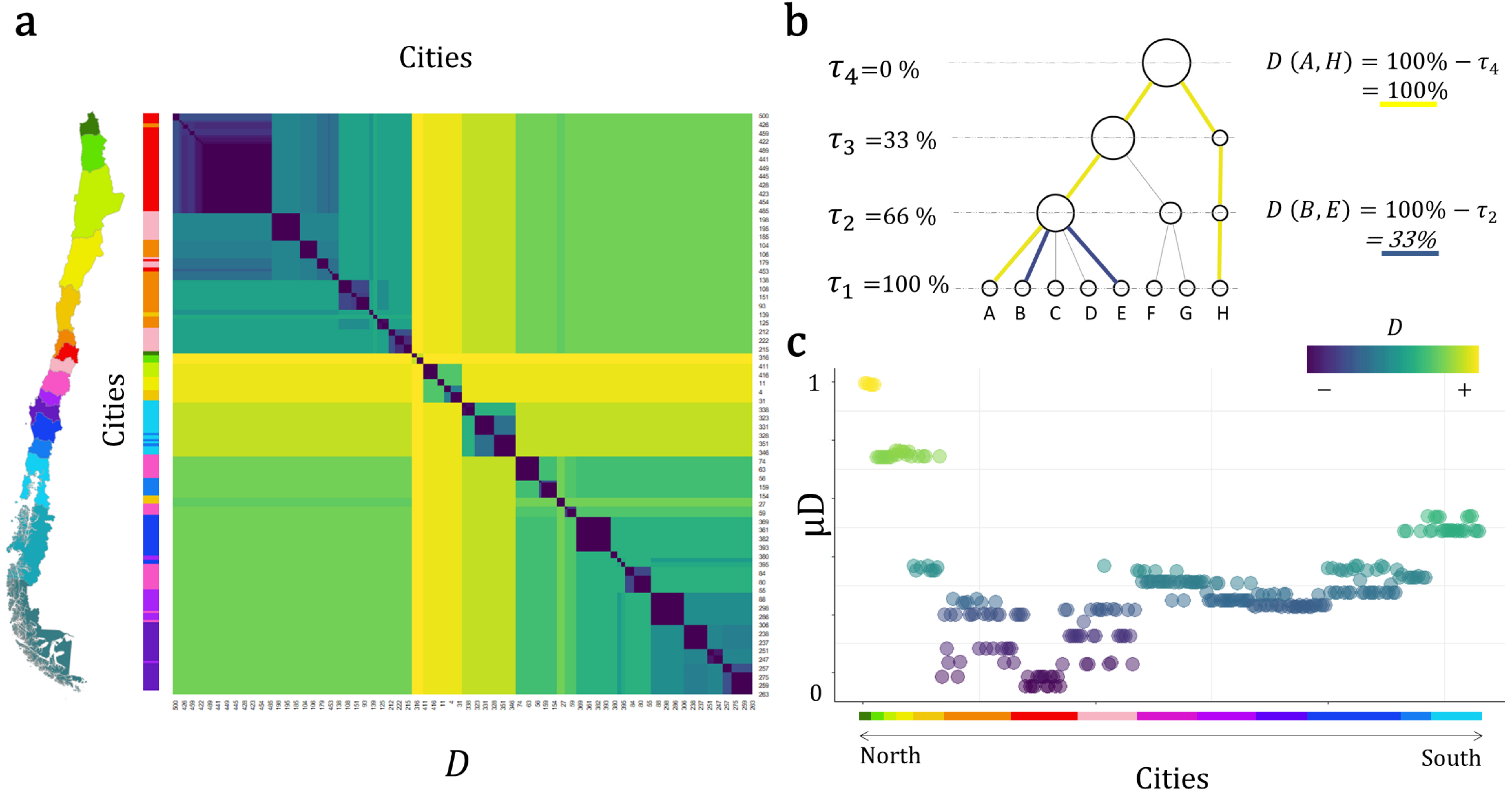

Cities
System of cities
Provinces
Regions
Macro-regions
Country
T ≥ 26%
T ≥ 17%
T ≥ 15.5%
T ≥ 13.5%
T ≥10%
T ≥ 0.1%

PERCOLATION-BASED HIERARCHICAL CLUSTERING



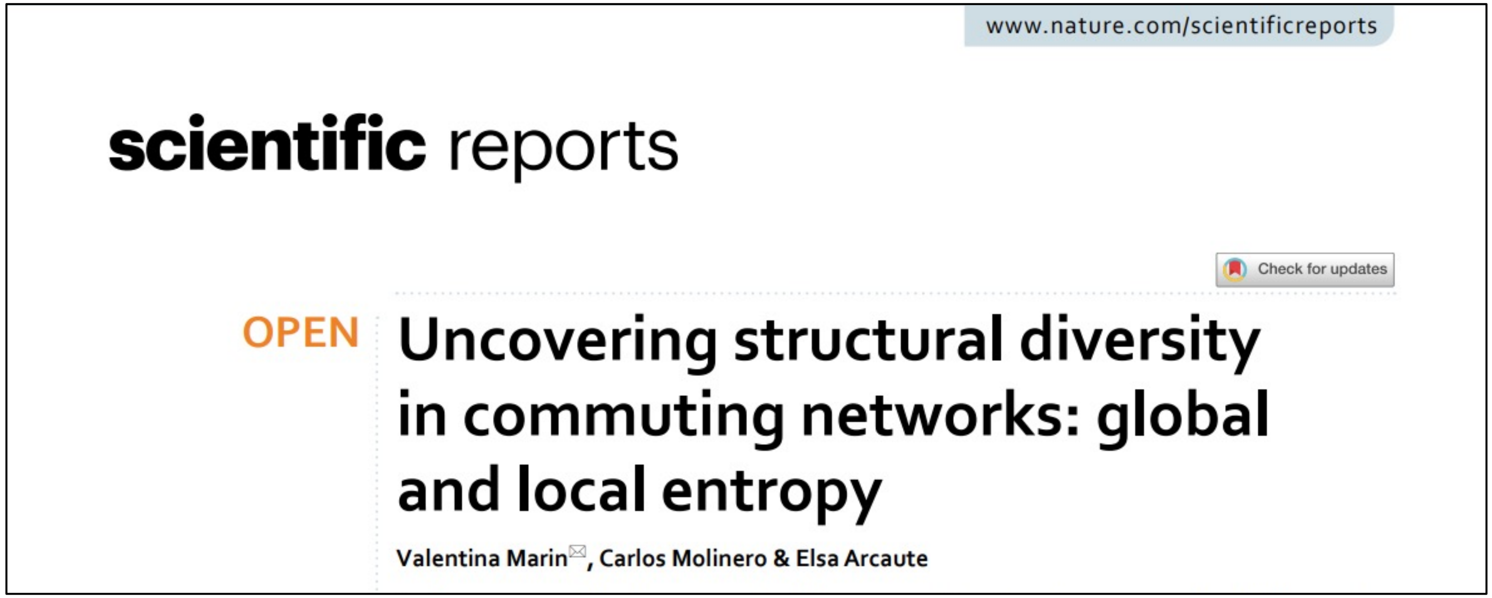
2. Distance and diversity

SCALAR DISTANCE



STRUCTURAL DIVERSITY

Network entropy



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scientific reports

Check for updates

OPEN **Uncovering structural diversity in commuting networks: global and local entropy**

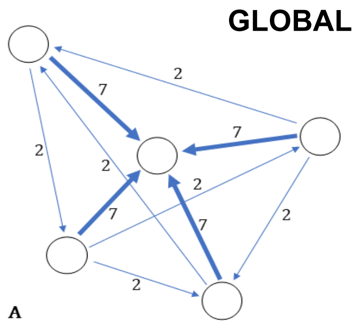
Valentina Marin, Carlos Molinero & Elsa Arcaute

- **Structural diversity of commuting networks**

  Structure of concentration and dispersion of flows

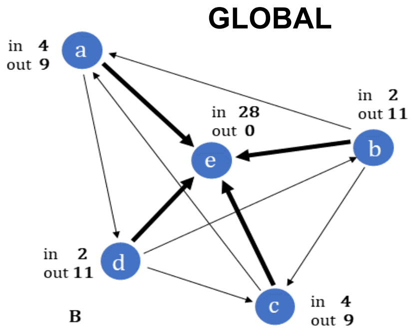
- **Global and local entropy measures**

  Not affected by scalar and size change



Links Global Entropy

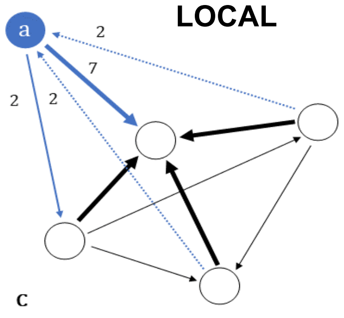
$$H_{GL} = -\sum_{\forall i}\sum_{\forall j} p_{ij}\log p_{ij}$$



Node Global Entropy

$$H^{in}_{GN} = -\sum_{\forall j}\left(\sum_{\forall i} p_{ij}\right)\log\left(\sum_{\forall i} p_{ij}\right)$$

$$H^{out}_{GN} = -\sum_{\forall i}\left(\sum_{\forall j} p_{ij}\right)\log\left(\sum_{\forall j} p_{ij}\right)$$



Node Local Entropy

$$H^{in}_{L} = -\sum_{\forall i} p_{(i|j)}\log p_{i|j} = -\sum_{\forall i}\frac{p_{ij}}{p_j}\log\frac{p_{ij}}{p_j}$$

$$H^{out}_{L} = -\sum_{\forall j} p_{j|i}\log p_{j|i} = -\sum_{\forall j}\frac{p_{ij}}{p_i}\log\frac{p_{ij}}{p_i}$$

STRUCTURAL DIVERSITY

Network entropy

- GLOBAL IN-NODE ENTROPY

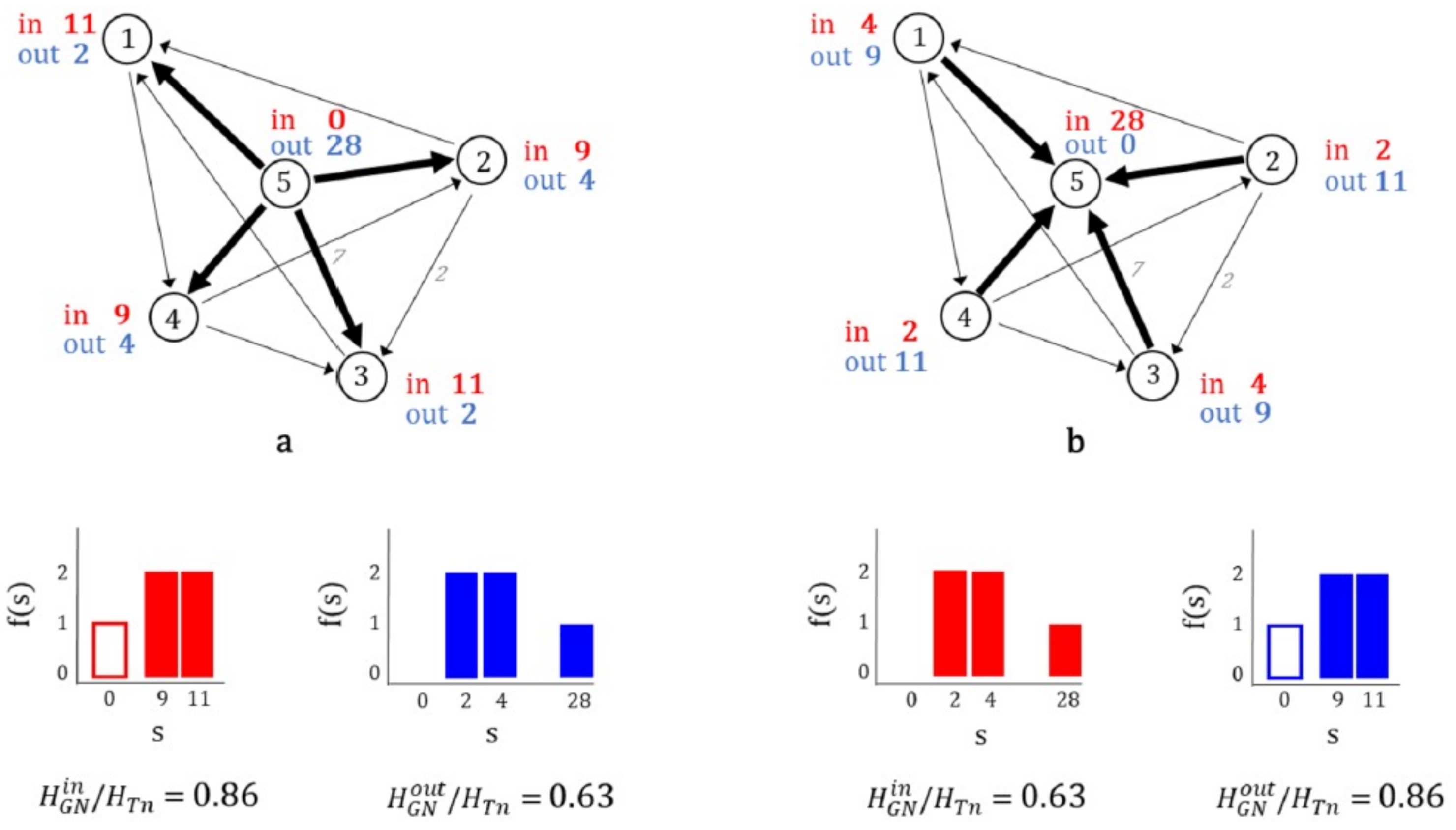
  Concentration or dispersion of in- commuting flows among urban centres.

- Spatial distribution of labour supply and demand

  Explore whether the flows in a system tend to be concentrated in dominant areas, or evenly dispersed from many origins to many destinations.

  Identifying monocentricity or polycentricity

  Possible functional dependencies due to disproportionate flow concentration

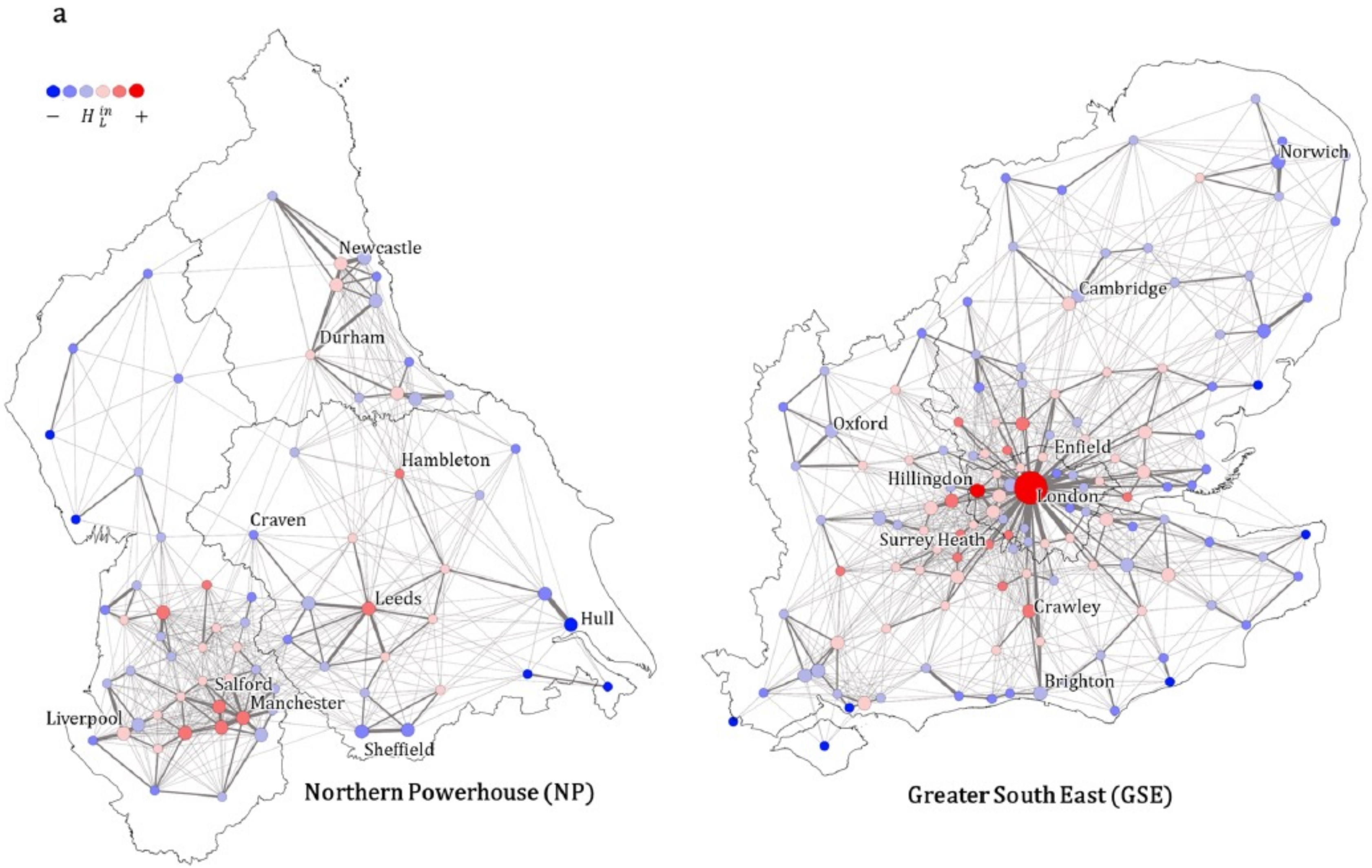


STRUCTURAL DIVERSITY

Network entropy

- **GLOBAL IN-NODE ENTROPY**

$$H_{GN}^{in} = -\sum_{\forall j}\left(\sum_{\forall i} p_{ij}\right)\log\left(\sum_{\forall i} p_{ij}\right)$$



H_{Global}^{in} = 0.910

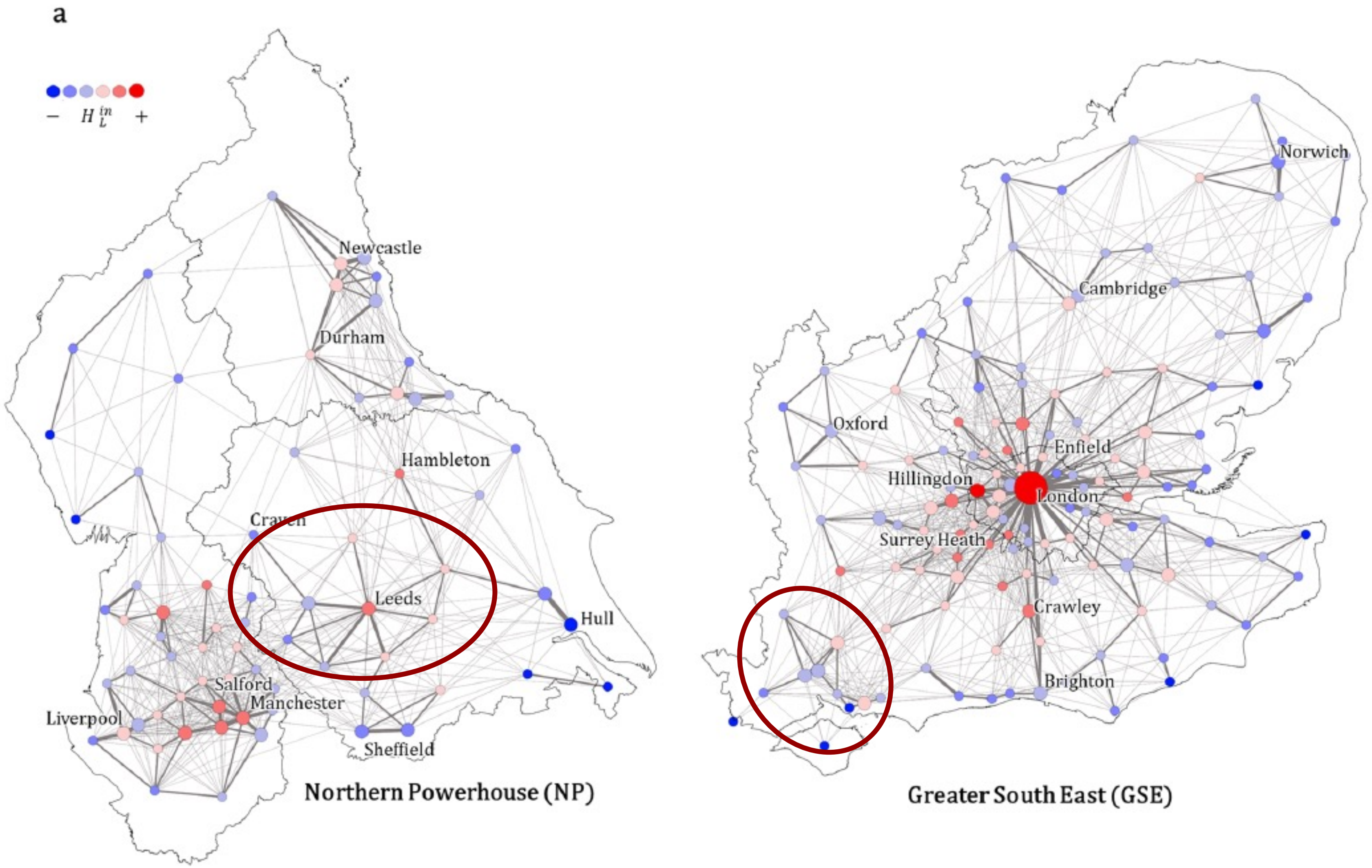
H_{Global}^{in} = 0.798

STRUCTURAL DIVERSITY

Network entropy

- **GLOBAL IN-NODE ENTROPY**

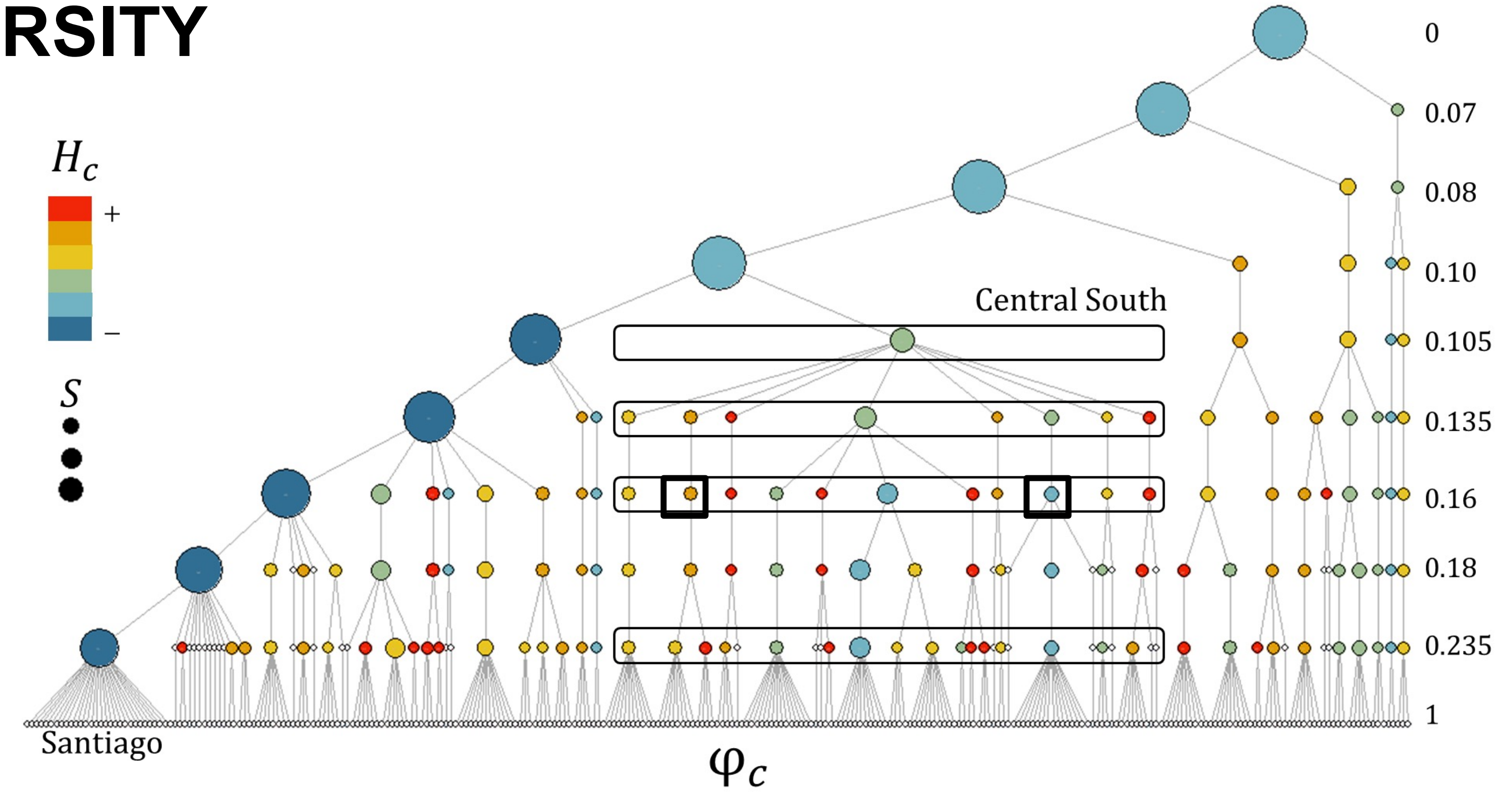
$$H^{in}_{GN} = -\sum_{\forall j}\left(\sum_{\forall i} p_{ij}\right)\log\left(\sum_{\forall i} p_{ij}\right)$$

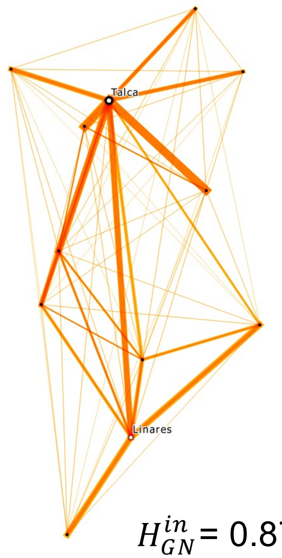


H^{in}_{Global} = 0.910

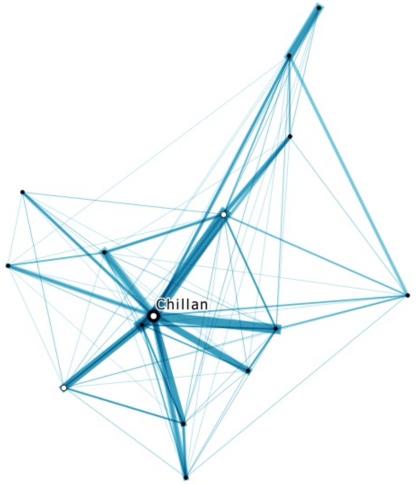
H^{in}_{Global} = 0.798

STRUCTURAL DIVERSITY



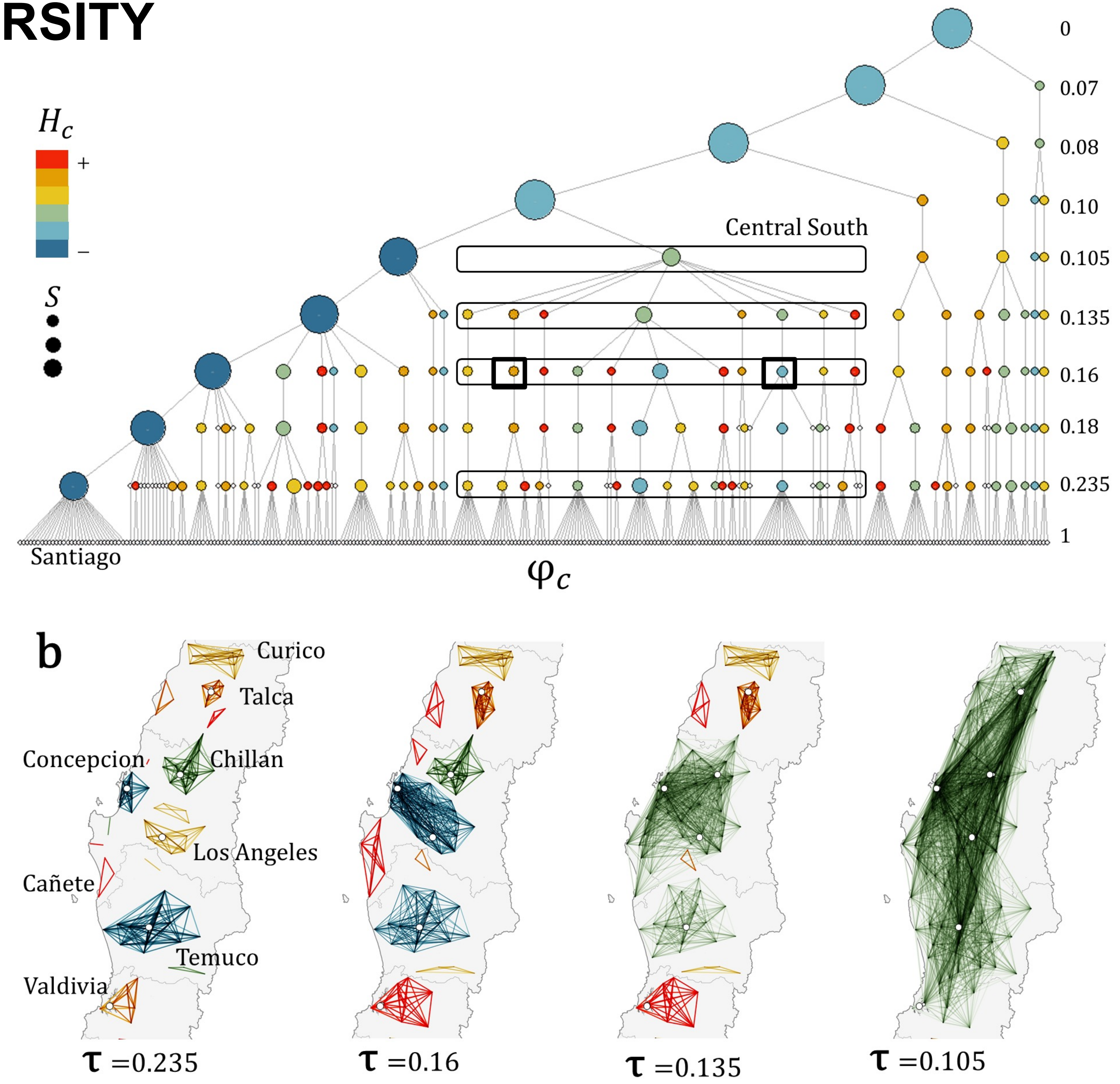


$H_{GN}^{in} = 0.8759$

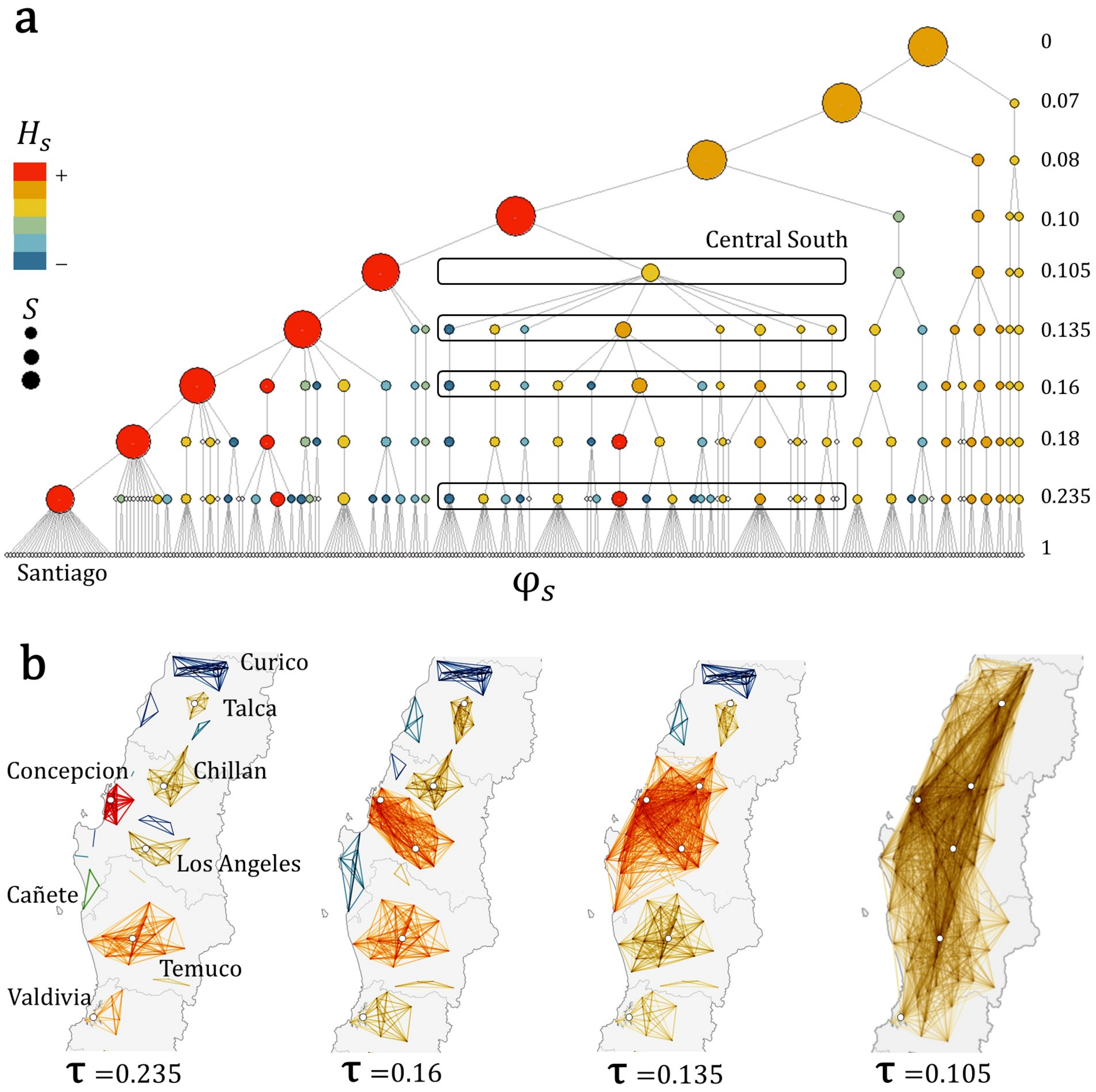


$H_{GN}^{in} = 0.6876$

STRUCTURAL DIVERSITY



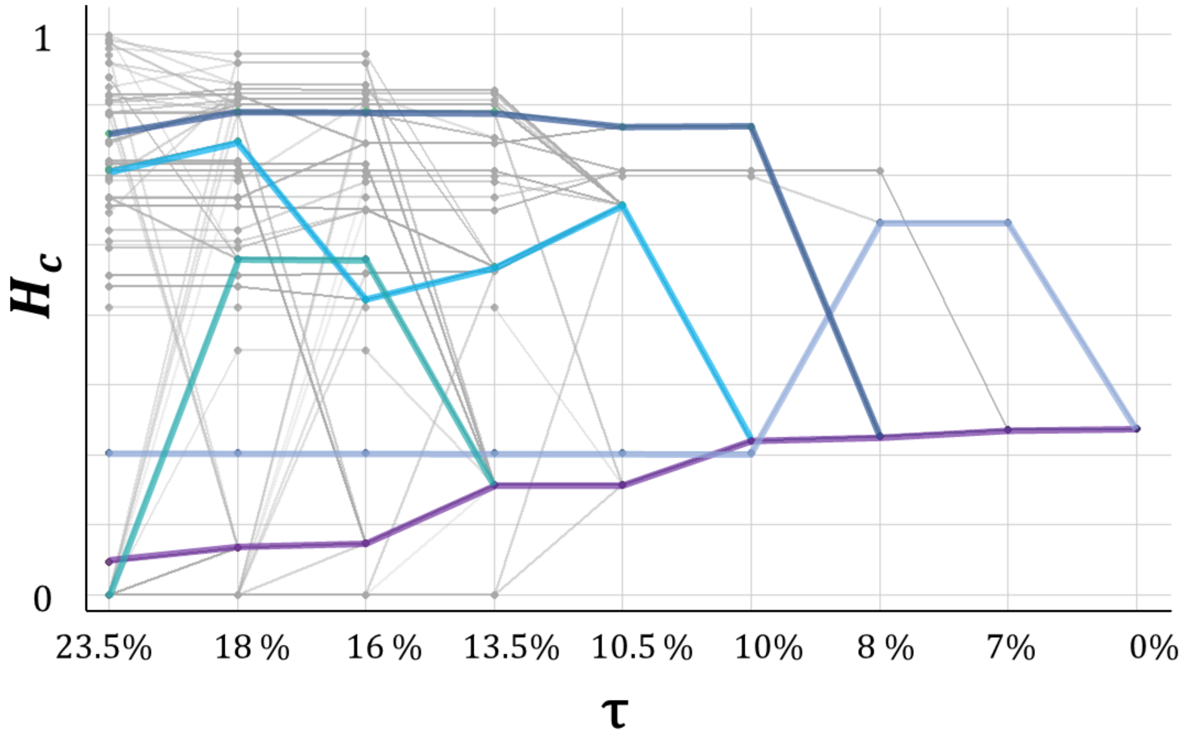
SKILLS DIVERSITY



SCALAR VARIATION

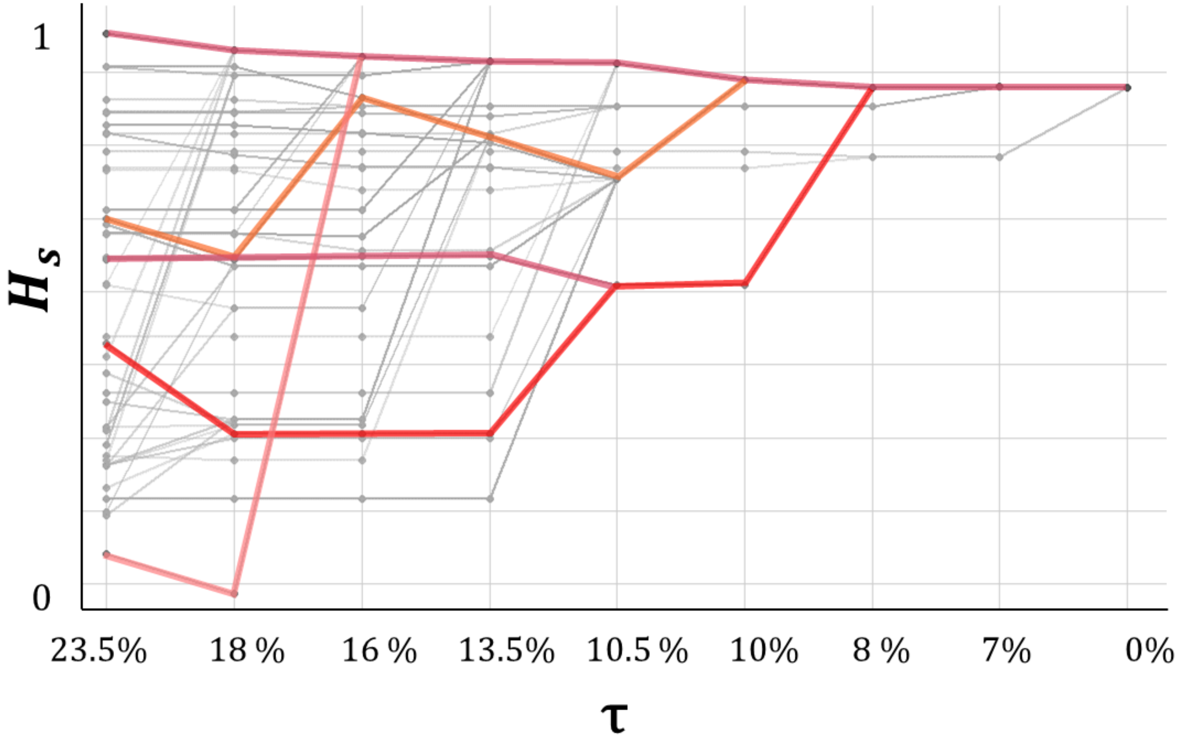
Structural diversity

a



Skills diversity

b



3. Classification of cities

MULTIDIMENSIONAL ANALYSIS

- **Structural diversity**

  Global Node In-commuting entropy across scales

- **Commuters' diversity**

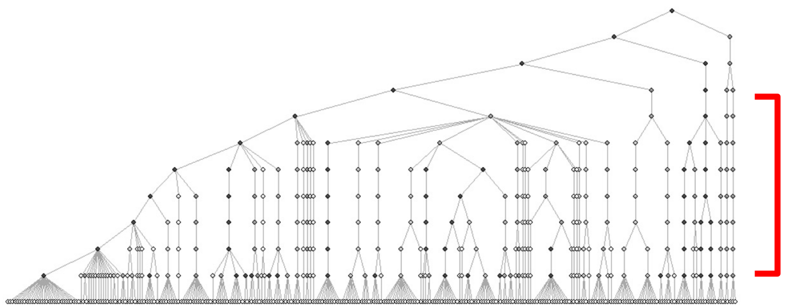
  Skill Levels diversity across scales

PCA across scales

→2 principal components account for 67% of total variance

K-means clustering of PCA results

→Obtain 5 city clusters



T 26% - 14.5%

MULTIDIMENSIONAL ANALYSIS

- **Structural diversity**

Global Node In-commuting entropy across scales

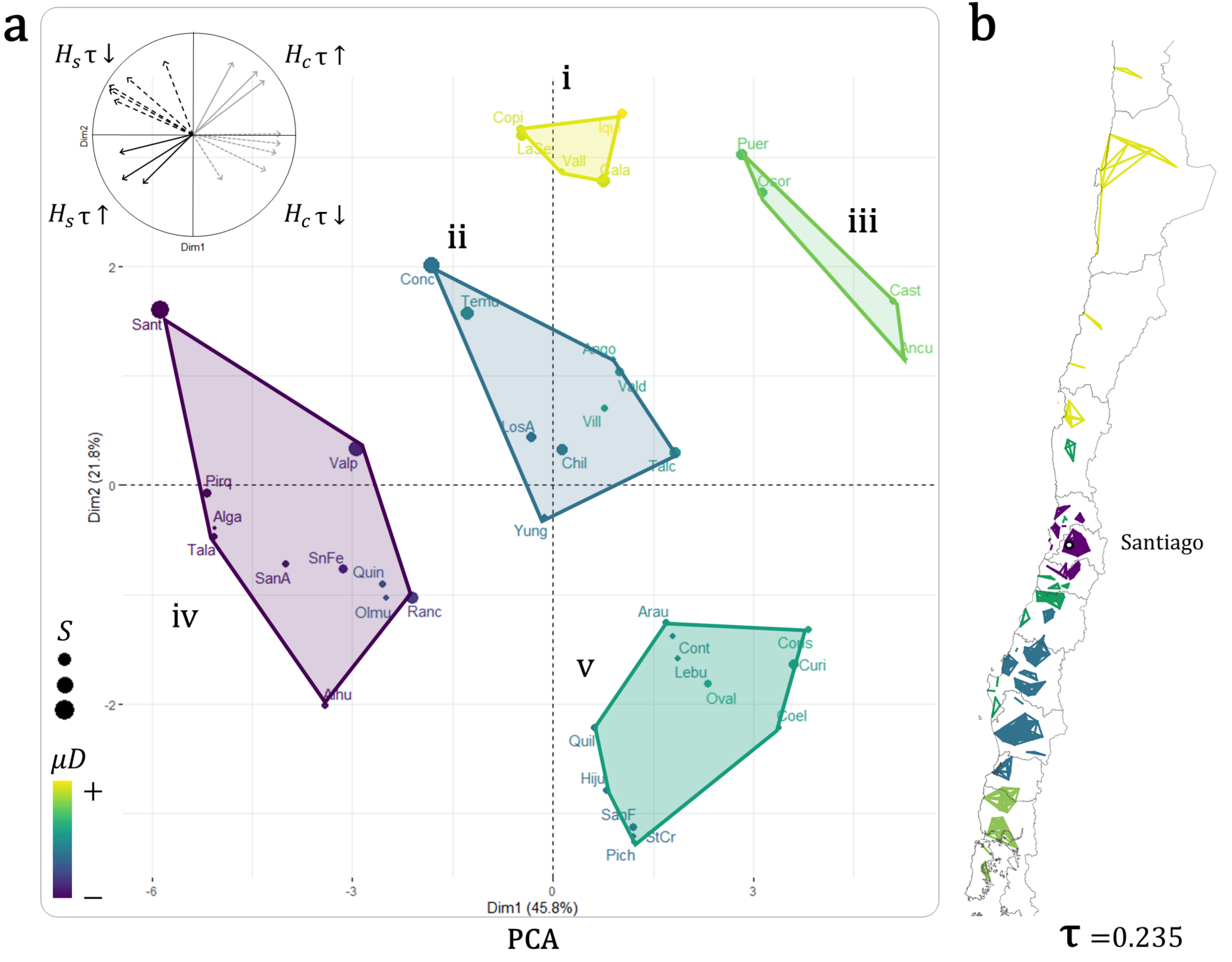
- **Commuters' diversity**

Skill Levels diversity across scales

Results:

→ local and global scales of commuting diversity tend to be negatively correlated with local and global scales of skills diversity.

→ cities with high commuting diversity tend to have lower levels of skills diversity, and vice versa.



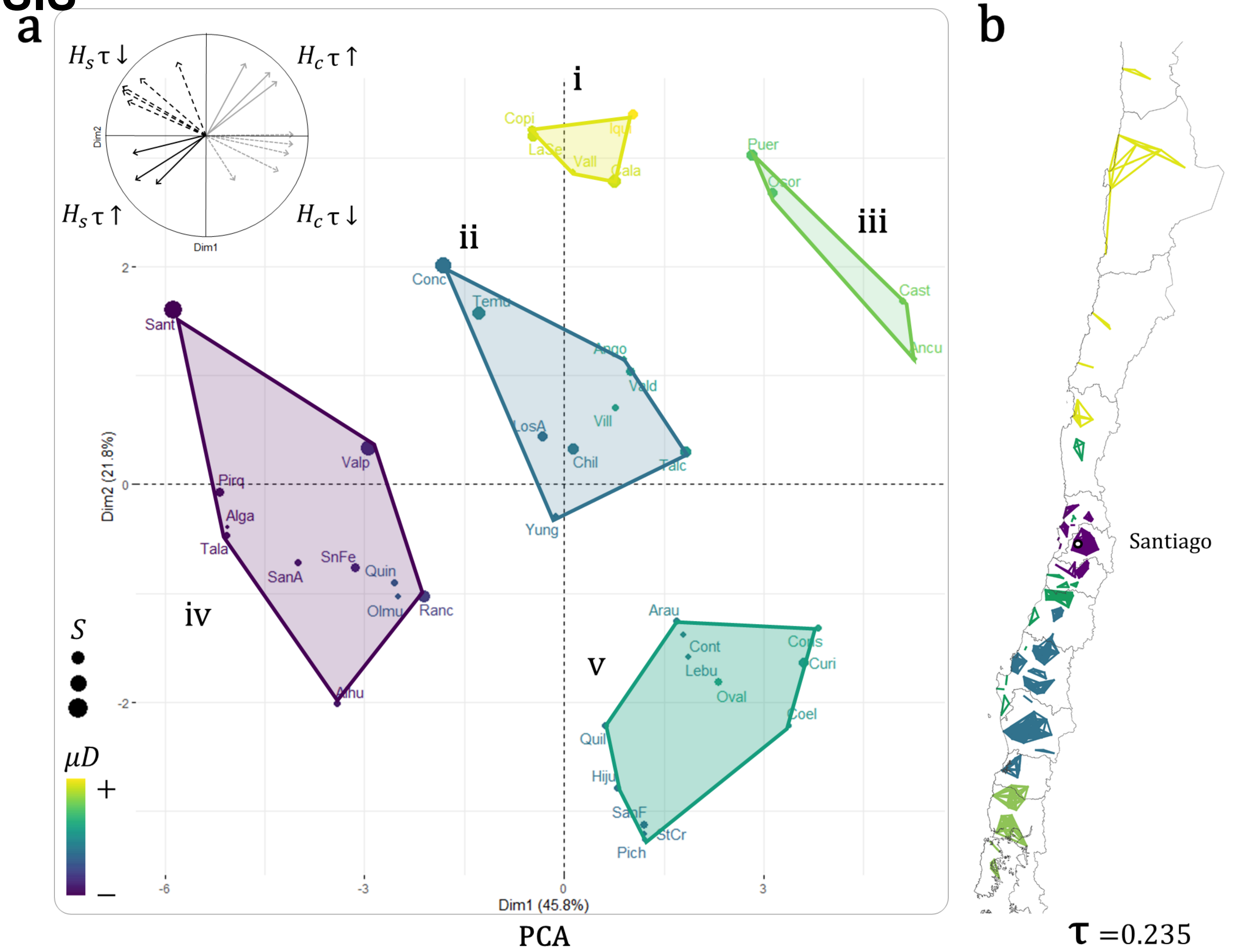
MULTIDIMENSIONAL ANALYSIS

iii "Southern specialised centres":

- Polycentric city systems
- low skill diversity across scales
- small to medium-sized cities characterised by highly specialised economies
- active local exchange, but limited interdependence with larger systems as shown by high hierarchical distances at the national level.

iv "Metropolitan urban systems":

- Highly monocentric structures that persist at larger scales due to the dominance of Santiago and Valparaiso throughout the country.
- smaller cities in the system have limited local skill diversity, they gain exposure to greater diversity as they merge with larger cities at the first thresholds.



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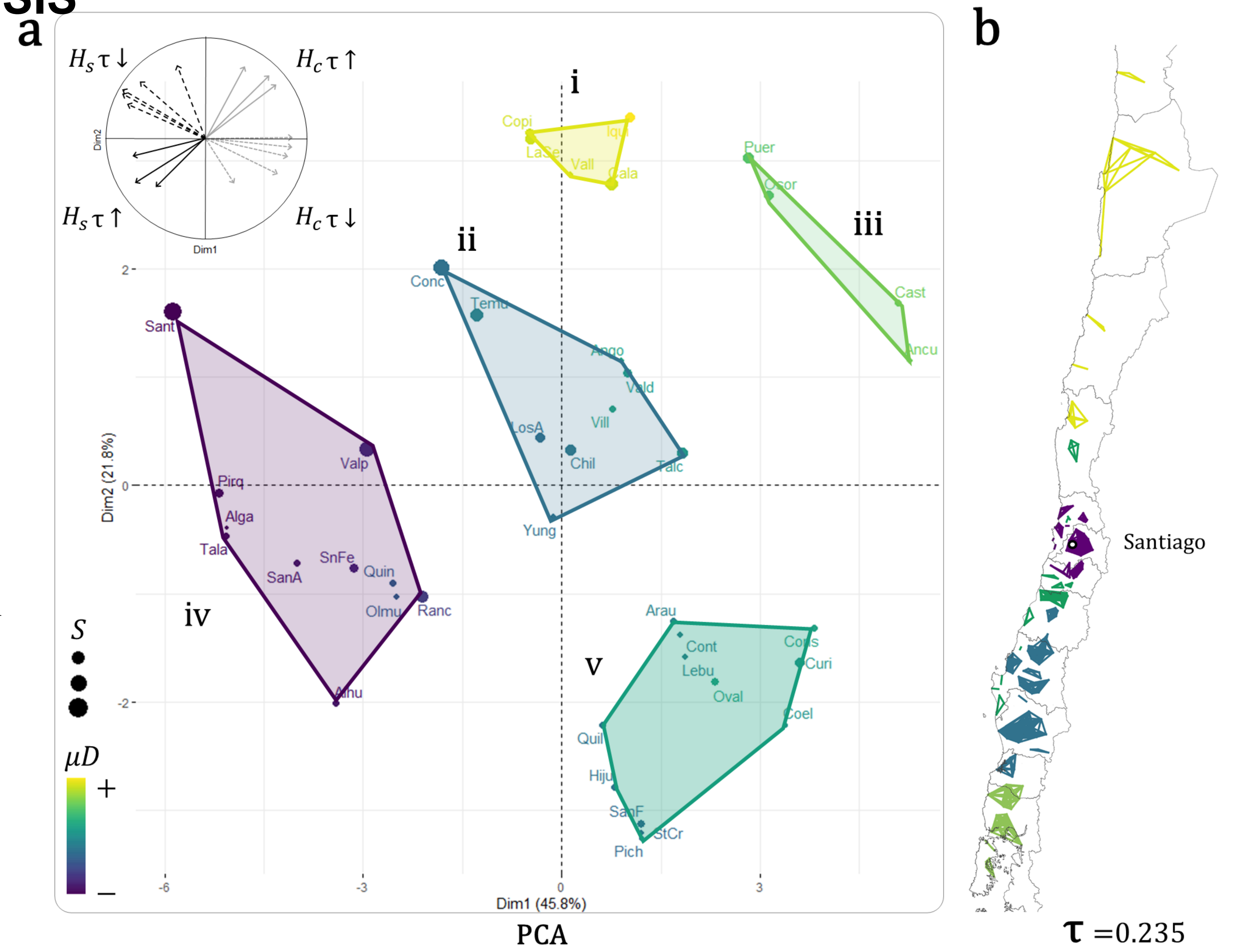
MULTIDIMENSIONAL ANALYSIS

i "Northern urban hubs": Cities of medium to large size, exhibit monocentric structures and high skill diversity at a local scale. At larger scales, they form more polycentric regions with limited intercity exchange.

ii "Regional cities": Cities with structures that tend to be monocentric at smaller scales but more polycentric at larger scales.

v "In-between cities": Exhibit limited skill diversity at the local level and are dominated by a single economic sector. Despite being part of a local polycentric system, they are also part of larger monocentric regions, with dominant urban centres, which means they have exposure to a broader range of skills beyond their local area.



Conclusions

- Cities are complex systems that have non-linear relationships, feedback loops, and path dependencies.
- Connectivity between individuals and settlements leave footprints in the form of spatial patterns that can be traced back. All interactions are heterogeneous.
- Heterogeneity gives rise to a hierarchical organisation of the urban system.
- The street network is an excellent proxy for urbanisation.
- Dependencies can also be recovered from the flows of the system.
- Understanding the relationship between different scales is essential for interventions, that need to be introduced at the right scale for effectiveness

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Thank you!