Digital health and computational epidemiology

Lesson 11

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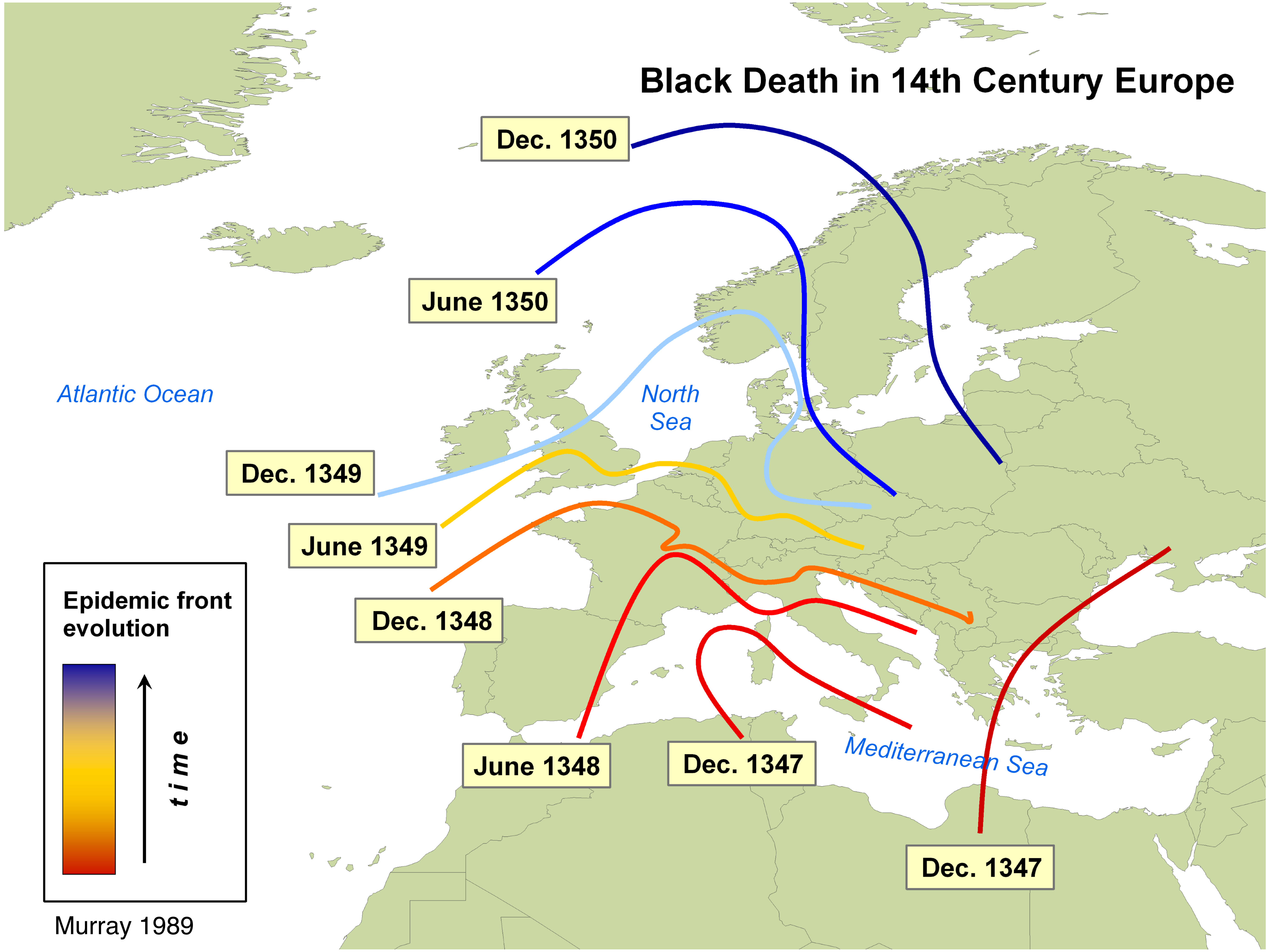
C2S2 Center for Computational Social Science and Human Dynamics

Human mobility and epidemics

Human mobility drives the spread of infectious diseases

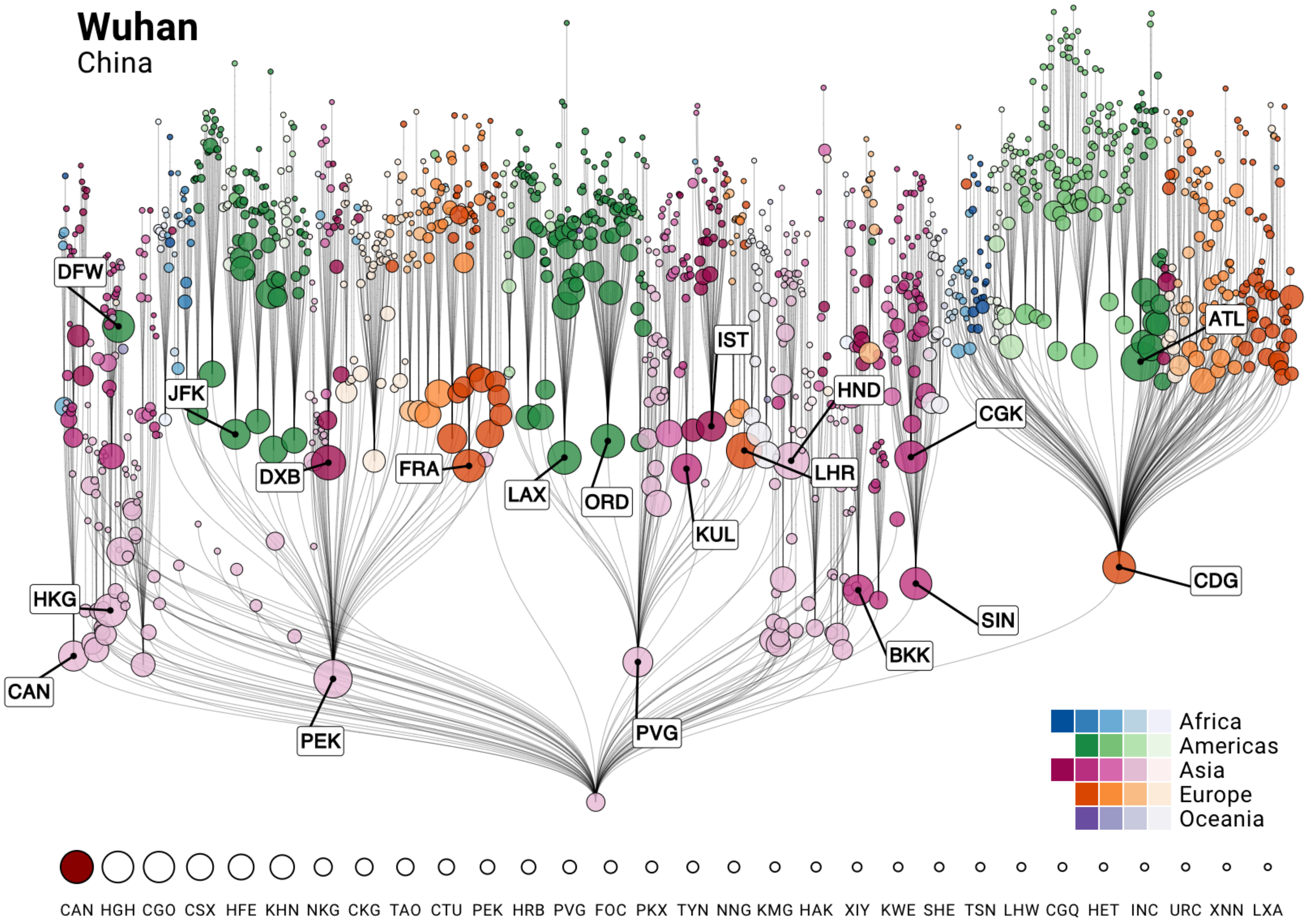


Murray 1989

The black death in the XIV century

a continuous diffusion wave process

Human mobility drives the spread of infectious diseases



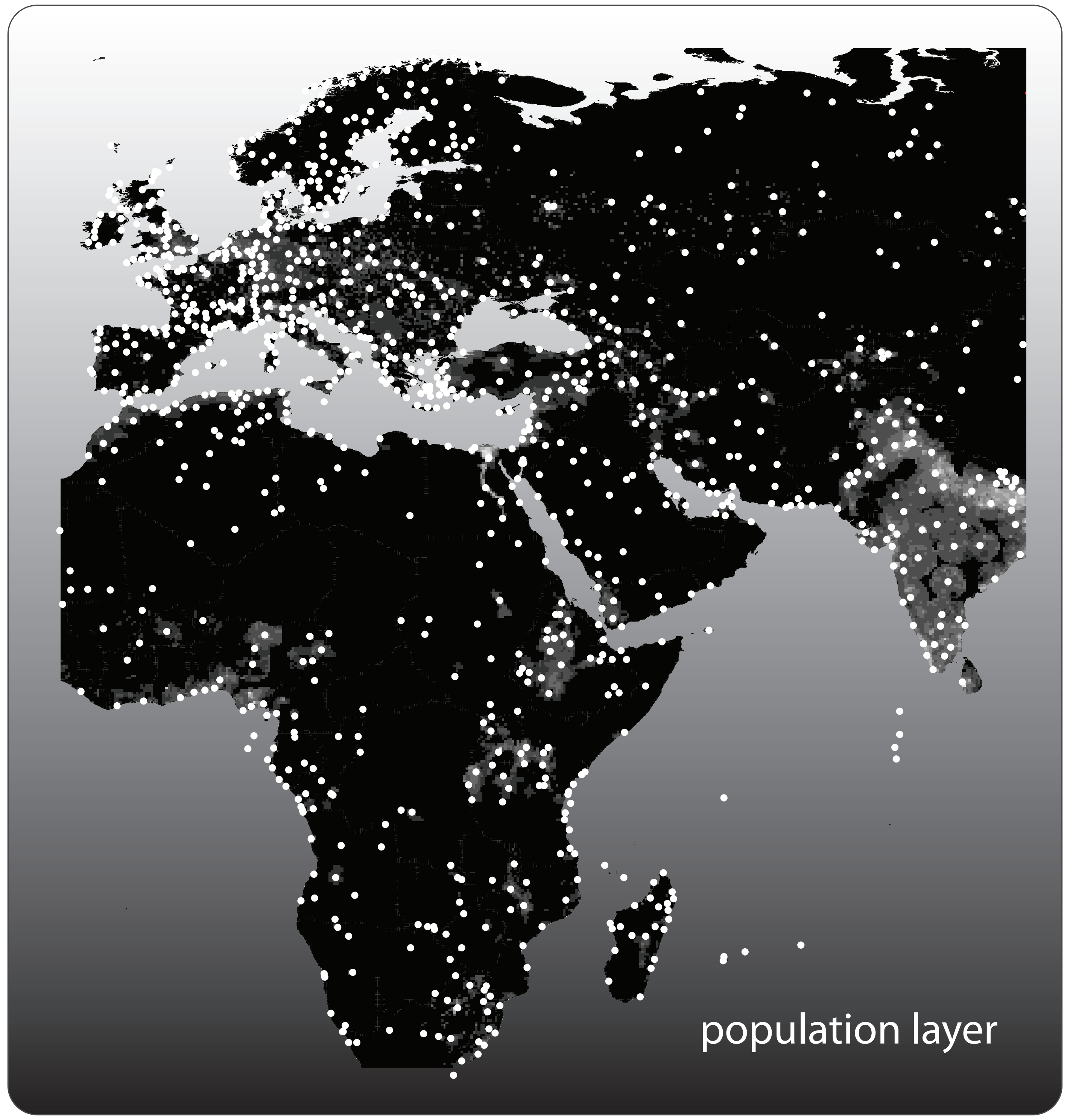
SARS-CoV-2 in the XXI century

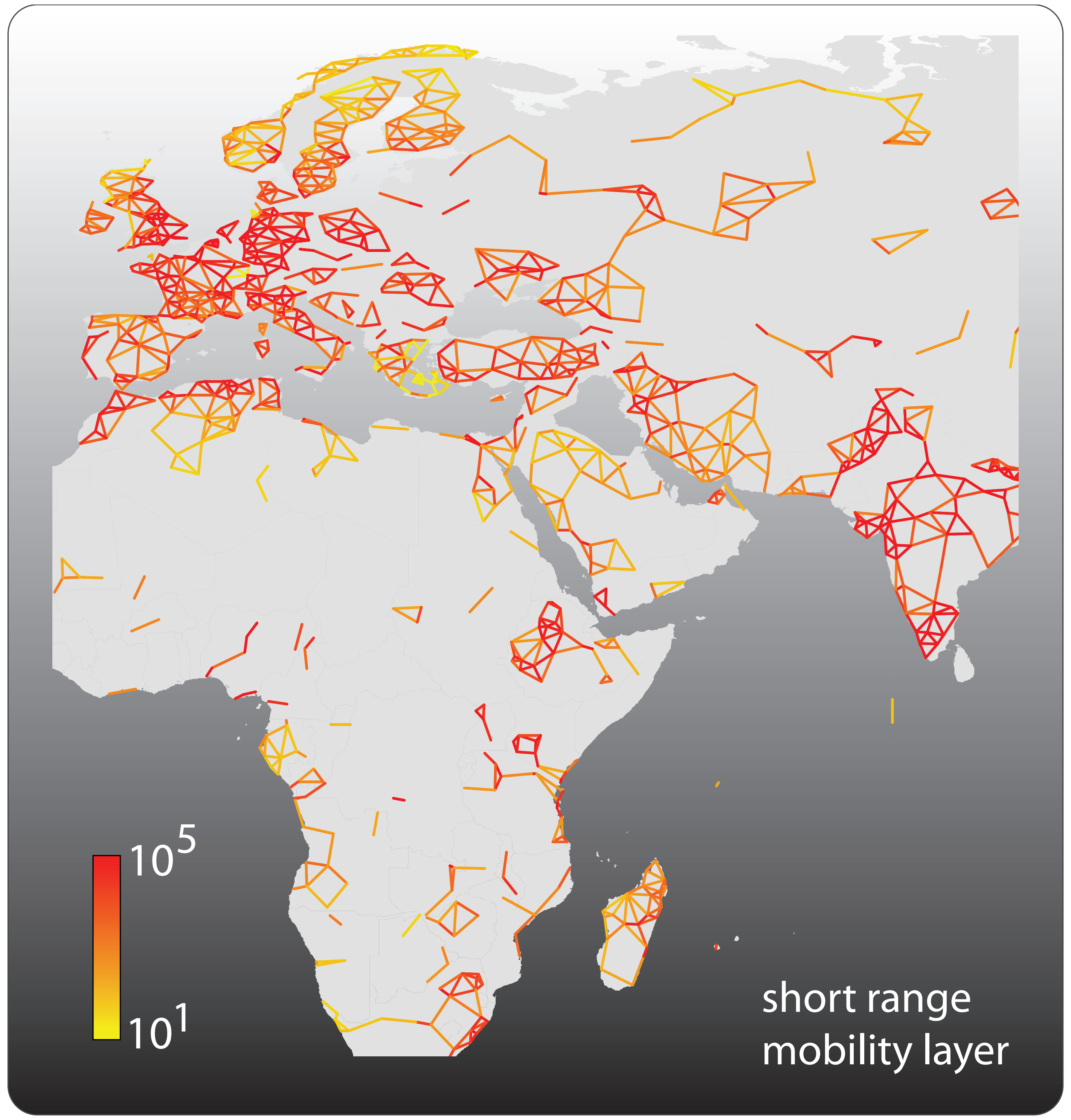
a network driven diffusion process

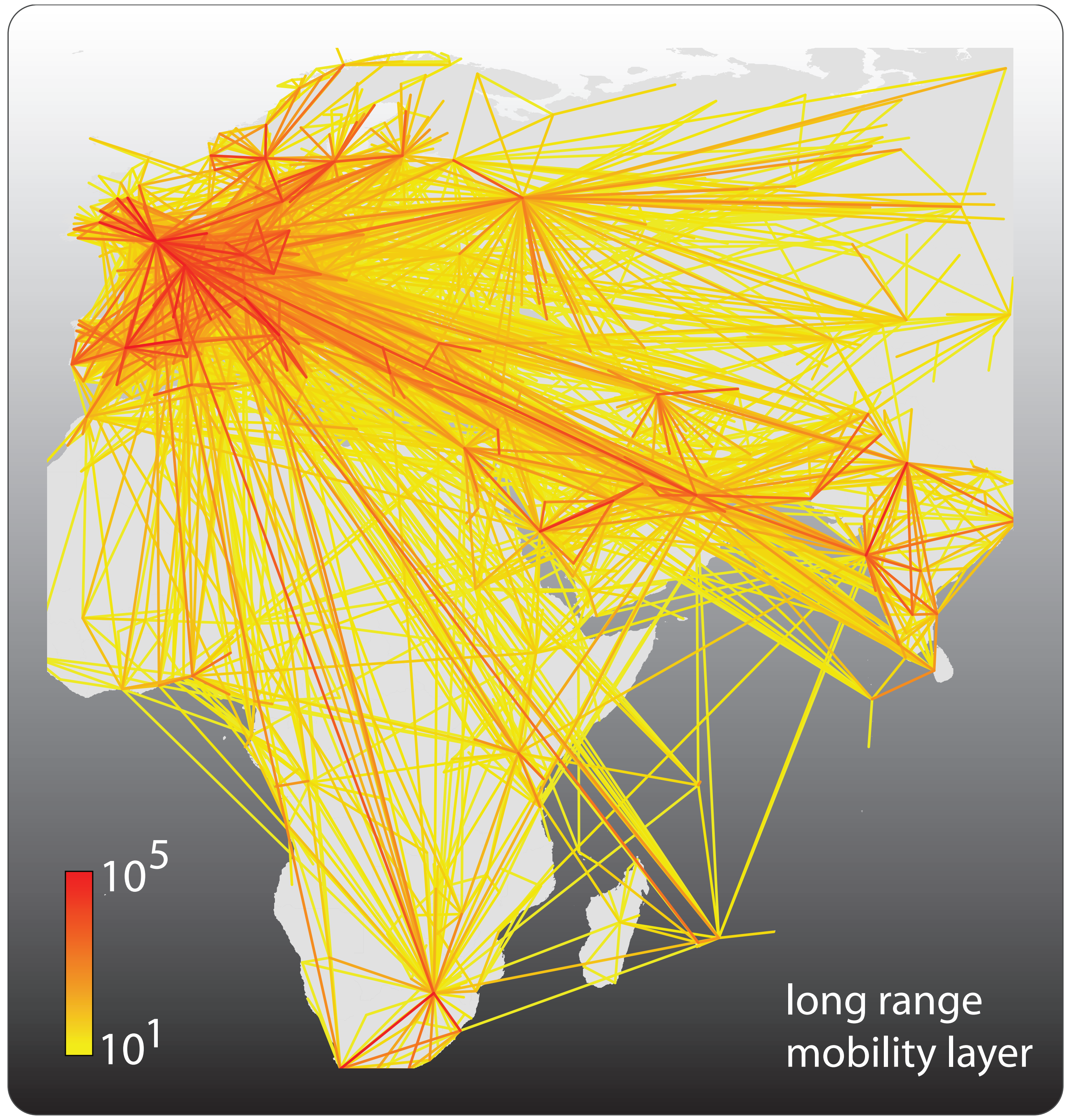
Robert Koch Institute

GLEAM: a data-driven metapopulation model

Data-driven







Worldwide population distribution

Short range mobility (commuting)

Air travel

Balcan et al. *PNAS* 2009

Epi-pop

Human mobility models

Modeling human mobility

ELSEVIER

Physics Reports

Volume 734, 6 March 2018, Pages 1-74

Human mobility: Models and applications

Hugo Barbosa [a], Marc Barthelemy [b c], Gourab Ghoshal [a], Charlotte R. James [d], Maxime Lenormand [e], Thomas Louail [g], Ronaldo Menezes [h], José J. Ramasco [f], Filippo Simini [d], Marcello Tomasini [h]

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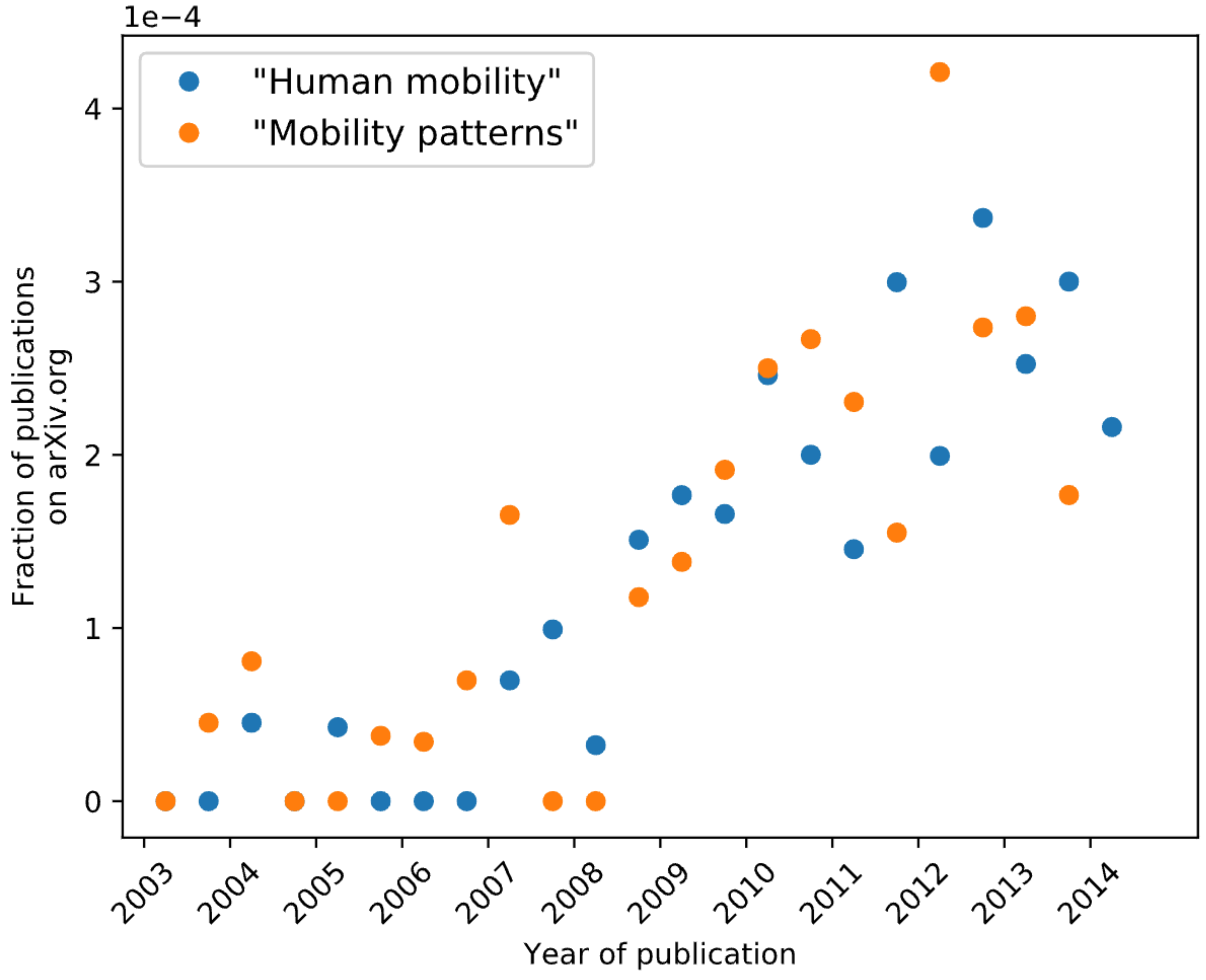

Modeling human mobility

- **Individual mobility**: modeling the movements of a single person
- **Population mobility**: modeling the aggregated flows of population displacements

- **Individual mobility:**
  - Brownian motion (random walk)
  - Lévy flights
  - *Many others…*

- **Population mobility:**
  - Gravity model
  - Radiaton model

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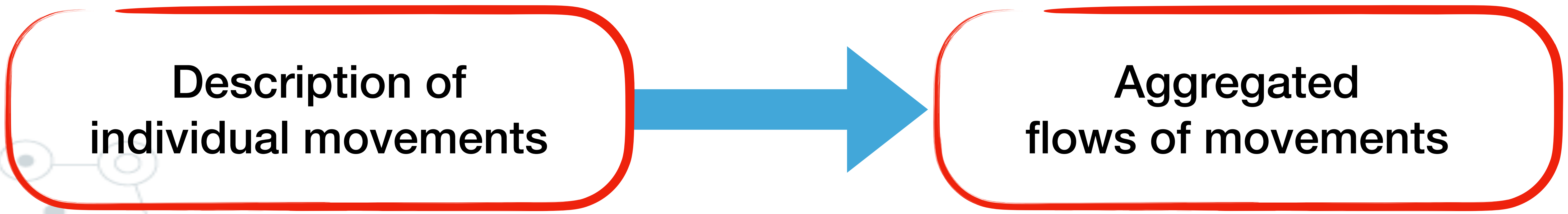


Individual mobility

- A random walk is mathematically defined as a path formed by successive discrete random steps.
- each displacement ΔX_i is a random variable extracted from a probability distribution $f(\Delta X)$, and draws are assumed to be statistically independent. The total distance walked by the walker after N steps is $X(t_N) = \sum_i^N \Delta X_i$
- The mean square displacement (MSD) is $\langle X^2(t) \rangle = \langle (X(t) - X(t_0))^2 \rangle$
- The MSD is a measure of dispersal, indicating how far the walker drifts away from the origin and its scaling with time characterises the type of diffusion

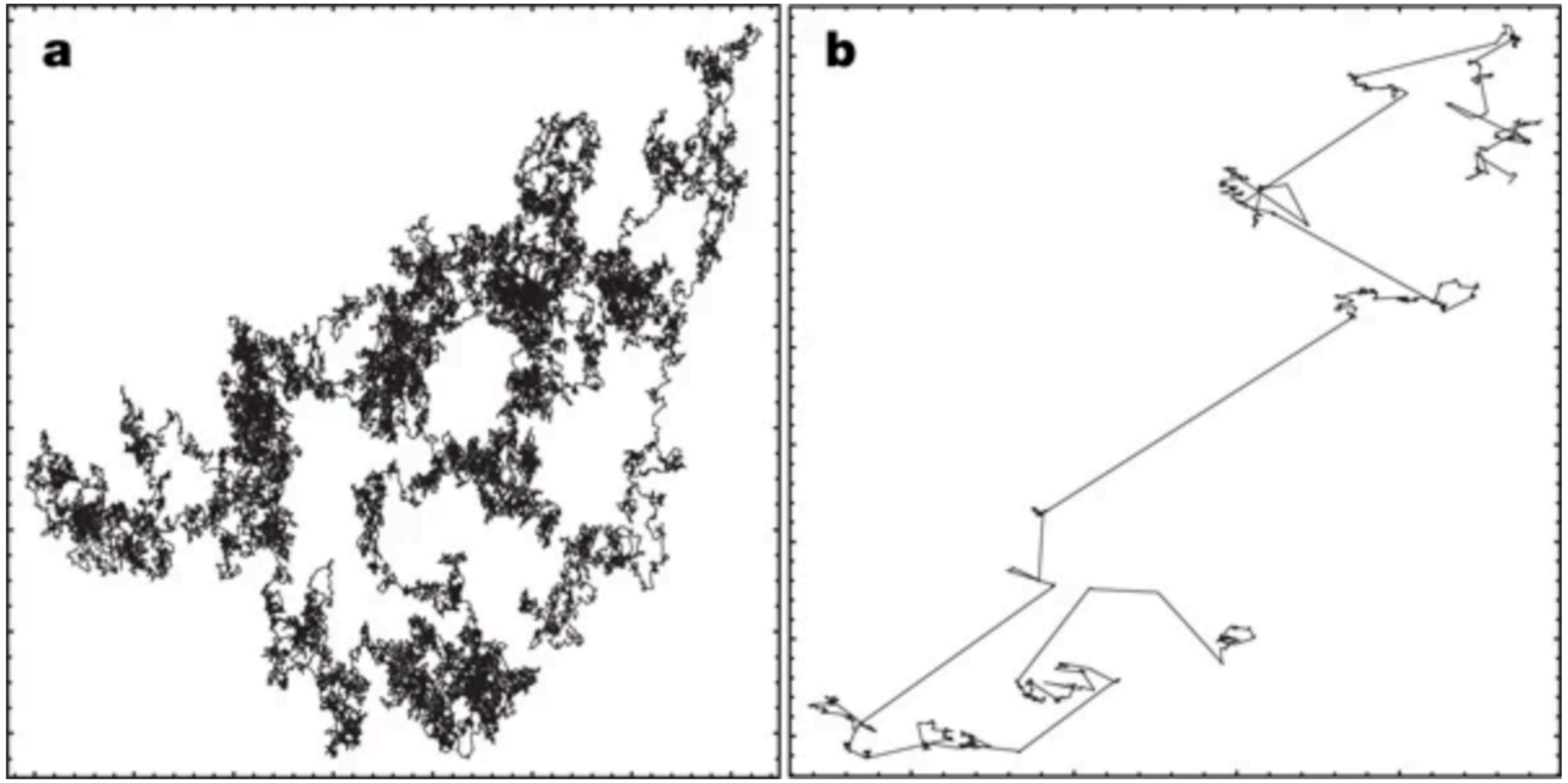
Brownian motion

- Brownian motion is a class of random walk originally developed to describe the motion of a particle suspended in a fluid (liquid or gas)
- 1-dimensional Brownian motion is a random walk in the space of real numbers R with **independent and normally distributed increments** where the probability to observe a displacement of magnitude X from the origin location after a time t is Gaussian distributed with mean zero and variance proportional to t.
- $\langle X(t) \rangle = 0 \quad \langle X^2(t) \rangle = t$
- Root mean square displacement: RMSD = $\sqrt{\langle X^2 \rangle} \sim t^{1/2}$

Lévy flight

- A Lévy Flight is composed of a series of small displacements, interspersed occasionally by a very large displacement
- It is the sum of independent identically distributed random variables whose PDF for a single jump has a divergent second moment due to a long-tailed distribution of the form: $f(\Delta x) \sim \dfrac{1}{\Delta x^{1+\beta}}$ with $0 < \beta < 2$.

Realistic individual movements?



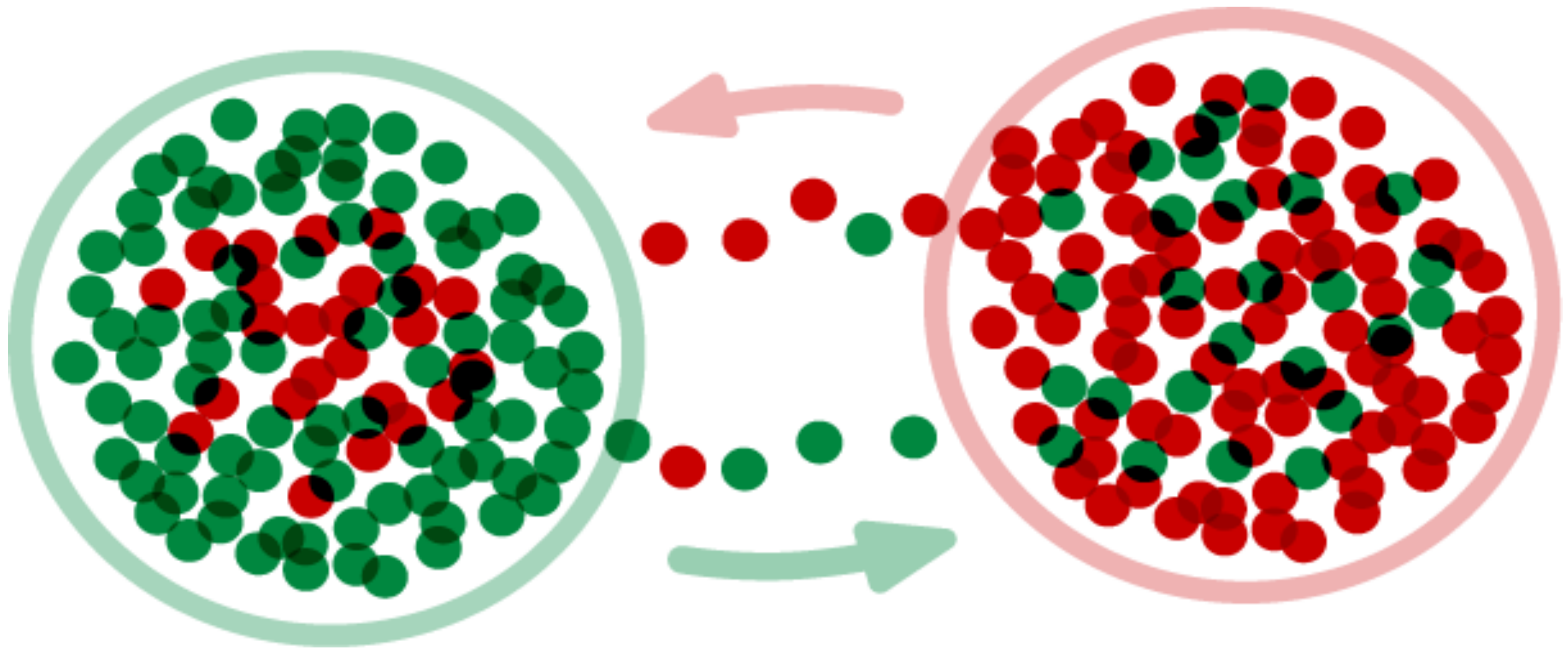
Brownian motion

Diffusive process
Explores the whole space
Each displacement has constant size

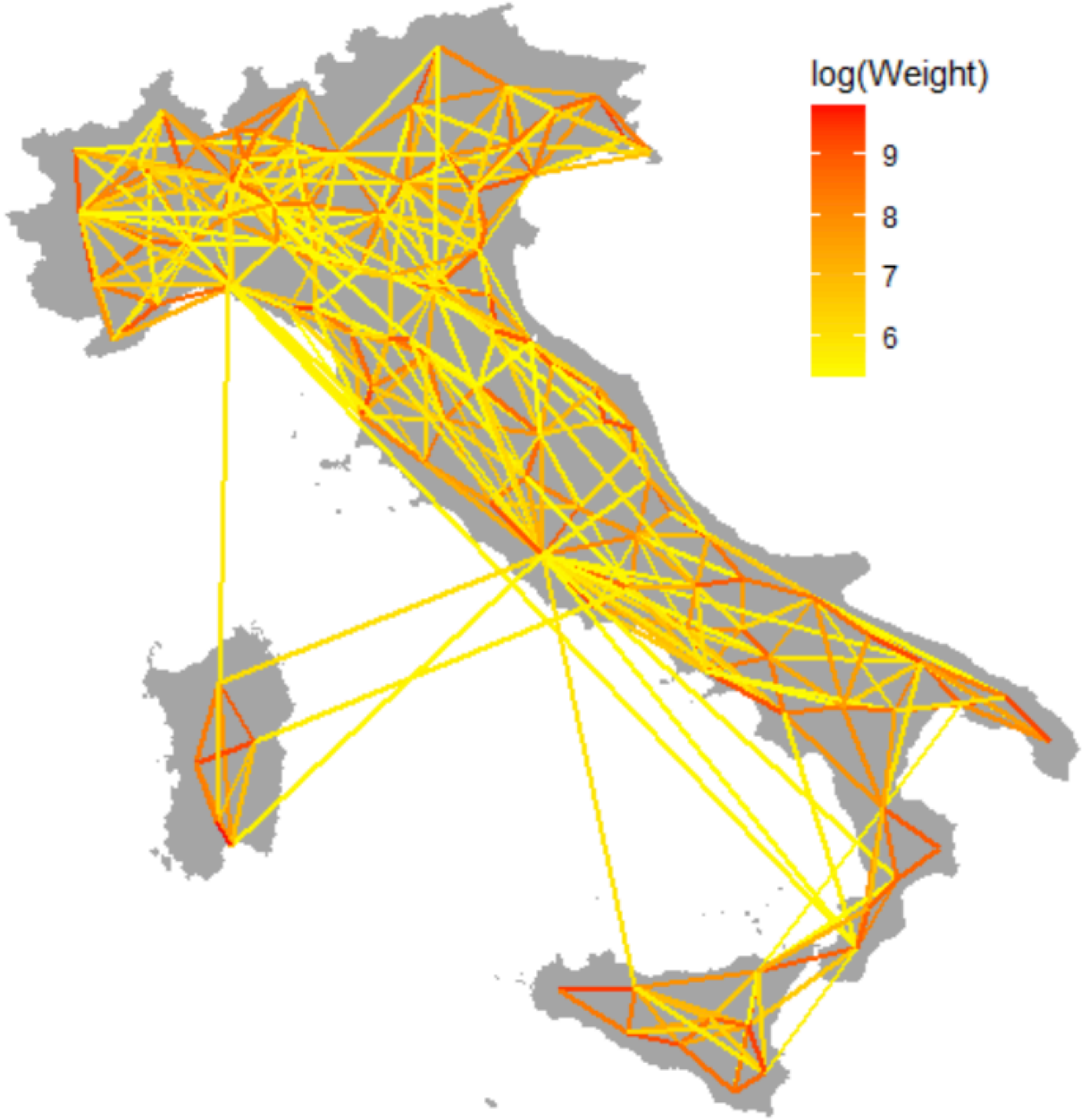
Lévy flight

Super-diffusive process
Explores the whole space
Power-law size of displacements

Population mobility

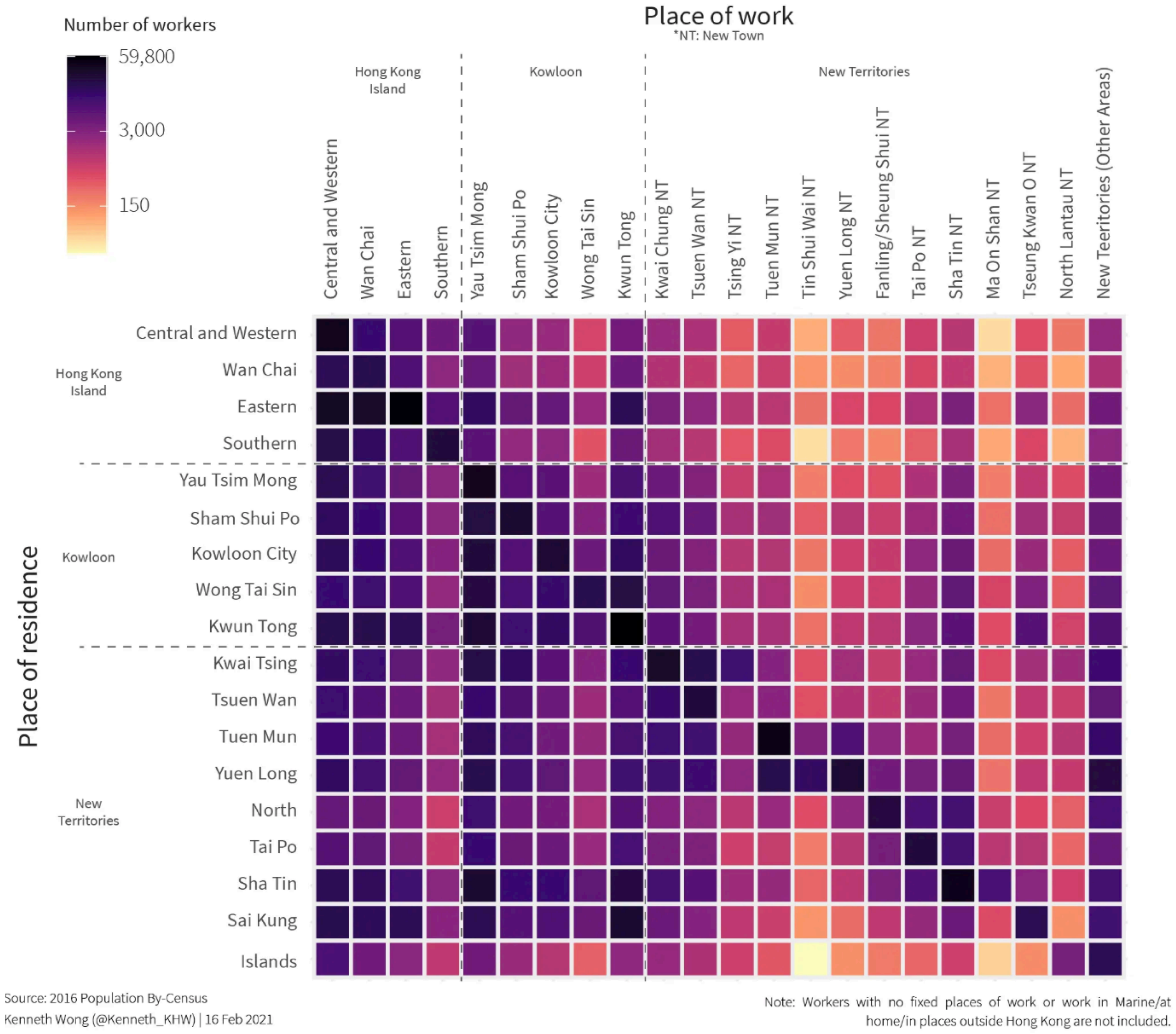


w_{ij} = number of individuals traveling between i and j



Origin-destination matrix

- Common representation in urban and transportation studies
- It corresponds to the weighted adjacency matrix of the mobility network
- Constraints on the system can be thought as constraints on the matrix properties (e.g. total sums of rows and columns)



Main approaches

- **Distance-based.** Assume that the number of trips between two locations is a decreasing function of their distance, giving rise to the so-called **gravity models**

- **Intervening opportunities.** The number of intervening opportunities, defined as the number of potential destinations between two locations, determines the mobility flow between them.

Gravity model

- Originally proposed by G. K. Zipf in 1946
- A gravity model states that mobility flows between any two locations *i* and *j* are described by a Newton-like formula:

$$w_{ij} \propto \frac{P_i \, P_j}{d_{ij}}$$

- Where P stands for population and d is the Euclidean distance between the two locations.

Gravity model

- The formula has been generalised to different settings, and spatial scales, by considering more general forms of the functions of populations and distance

$$w_{ij} \propto K_i P_i^{\alpha} \; P_j^{\beta} f(d_{ij})$$

- Where the parameters α and β allow non-linear dependencies on population sizes
- The function $f(d_{ij})$ can be a power law ($d_{ij}^{-\gamma}$) or an exponential ($e^{-d_{ij}}$) or a combination of the two
- The K_i is a generic constant to correctly normalise the OD matrix

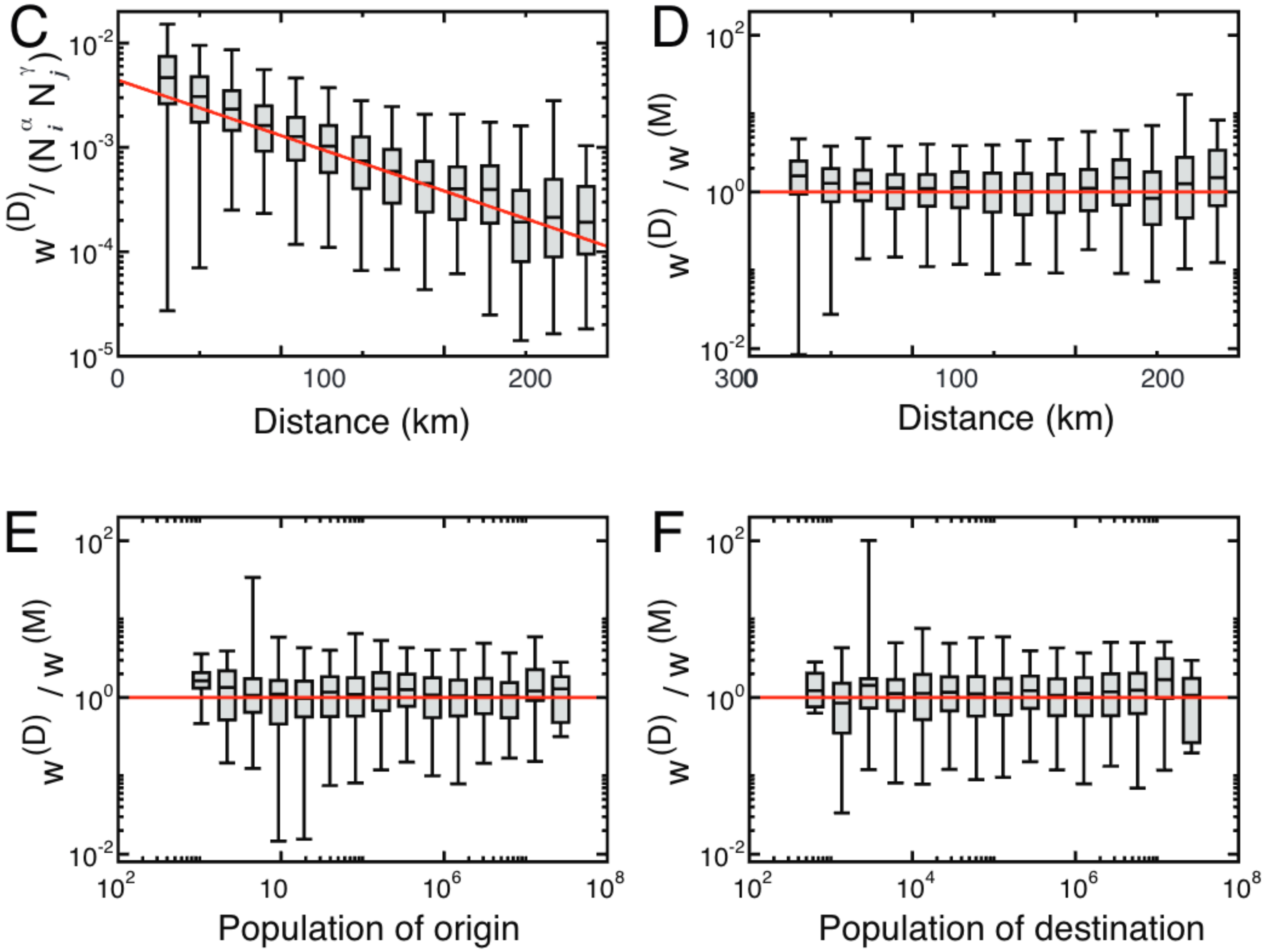
Gravity model: an example

Multiscale mobility networks and the spatial spreading of infectious diseases

Duygu Balcan[a,b], Vittoria Colizza[c], Bruno Gonçalves[a,b], Hao Hu[d], José J. Ramasco[b], and Alessandro Vespignani[a,b,c,1]

[a]Center for Complex Networks and Systems Research, School of Informatics and Computing, Indiana University, Bloomington, IN 47408; [b]Pervasive Technology Institute, Indiana University, Bloomington, IN 47404; [c]Computational Epidemiology Laboratory, Institute for Scientific Interchange Foundation, 10133 Torino, Italy; and [d]Department of Physics, Indiana University, Bloomington, IN 47406

Edited by H. Eugene Stanley, Boston University, Boston, MA, and approved October 13, 2009 (received for review June 19, 2009)

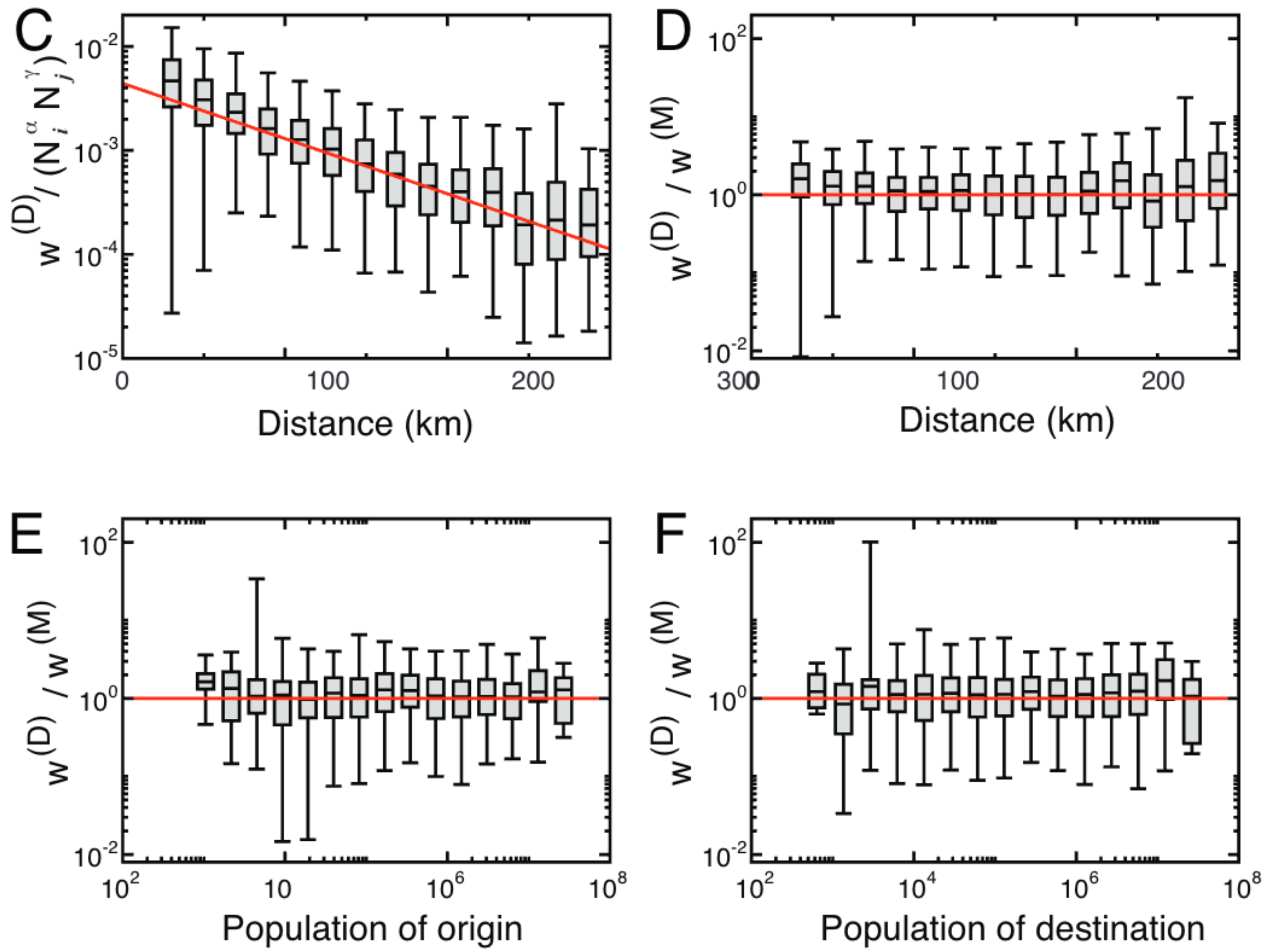


Gravity model: an example

- Generic formula to fit **commuting flows** between subpopulations in all countries worldwide

- $$w_{ij} = C\frac{P_i^{\alpha} P_j^{\beta}}{e^{d_{ij}/r}}$$

- The fit is done on real commuting data for 20 countries and then used to generate flows in the remaining 140 countries.



Pros and cons

- Very flexible approach which can be tuned to represent mobility flows at different spatial granularities
- Other variables can be used instead of populations: GDP, density of POIs, etc.

BUT

- Need a sample of mobility data to fit the model.
- Many parameters to fit, sometimes too many.
- Hard to generalize across settings. Very domain-specific.

Law of intervening opportunities

- Originally proposed by Samuel Stouffer in 1940

the number of people going a given distance
is directly proportional to the **number of opportunities at that distance**
and inversely proportional to the **number of intervening opportunities.**

Law of intervening opportunities

- Assumption: the decision to make a trip is not explicitly related to the distance between origin and destination, but to the relative accessibility of opportunities.
- An **opportunity** is a destination that a trip-maker considers as a possible termination point for their journey.
- An **intervening opportunity** is a location that is closer to the trip maker than the final destination but is **rejected** by the trip maker.
- Distance is hidden in the distribution of opportunities over space.
- The model can be interpreted as a gravity model with the function $f(r_{ij})$ replaced by a function of the total number of opportunities between i and j: $f(V_{ij})$

Radiation model

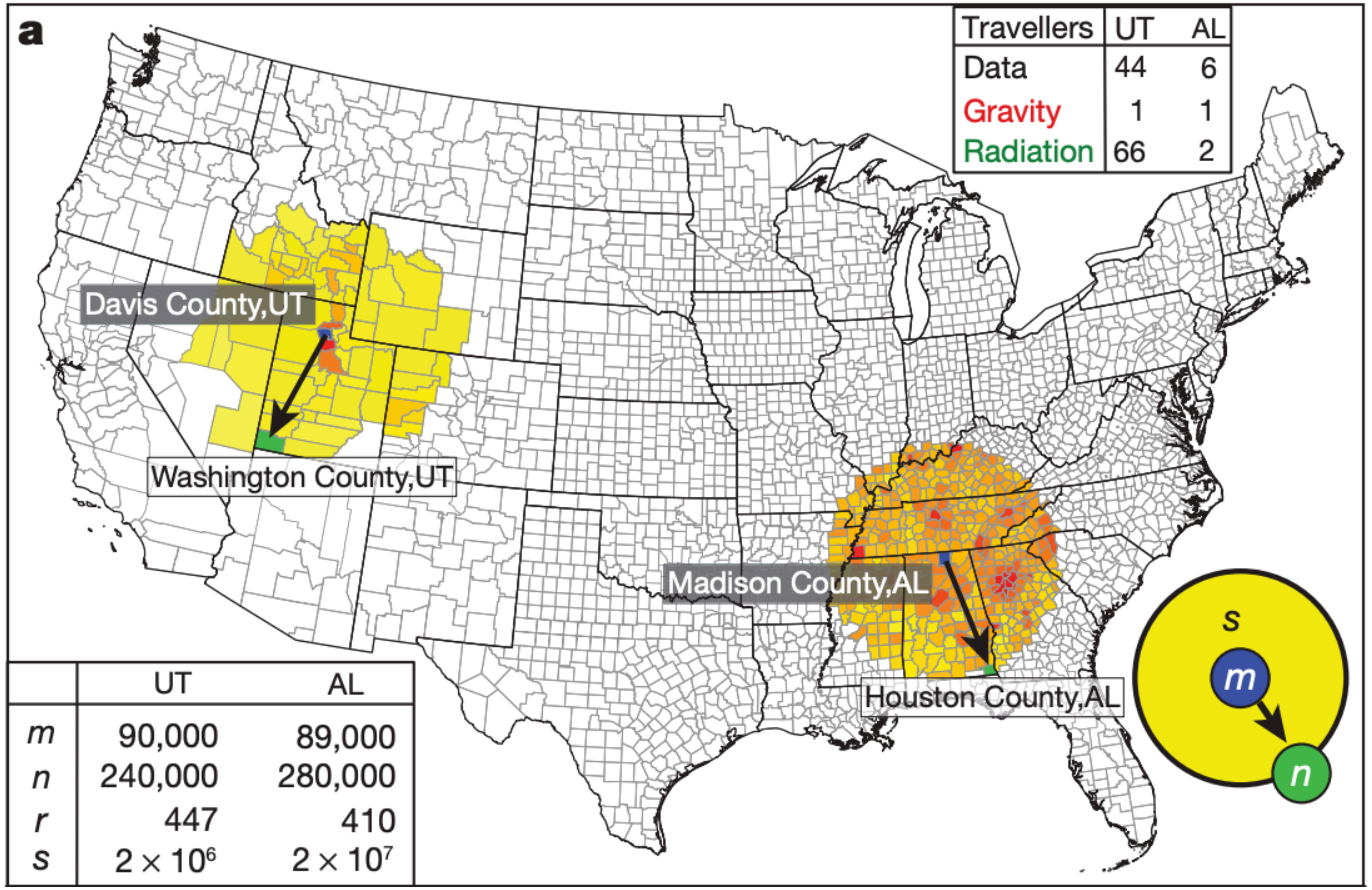
LETTER

doi:10.1038/nature10856

A universal model for mobility and migration patterns

Filippo Simini[1,2,3], Marta C. González[4], Amos Maritan[2] & Albert-László Barabási[1,5,6]

The gravity model does not perform well across heterogeneous mobility landscapes

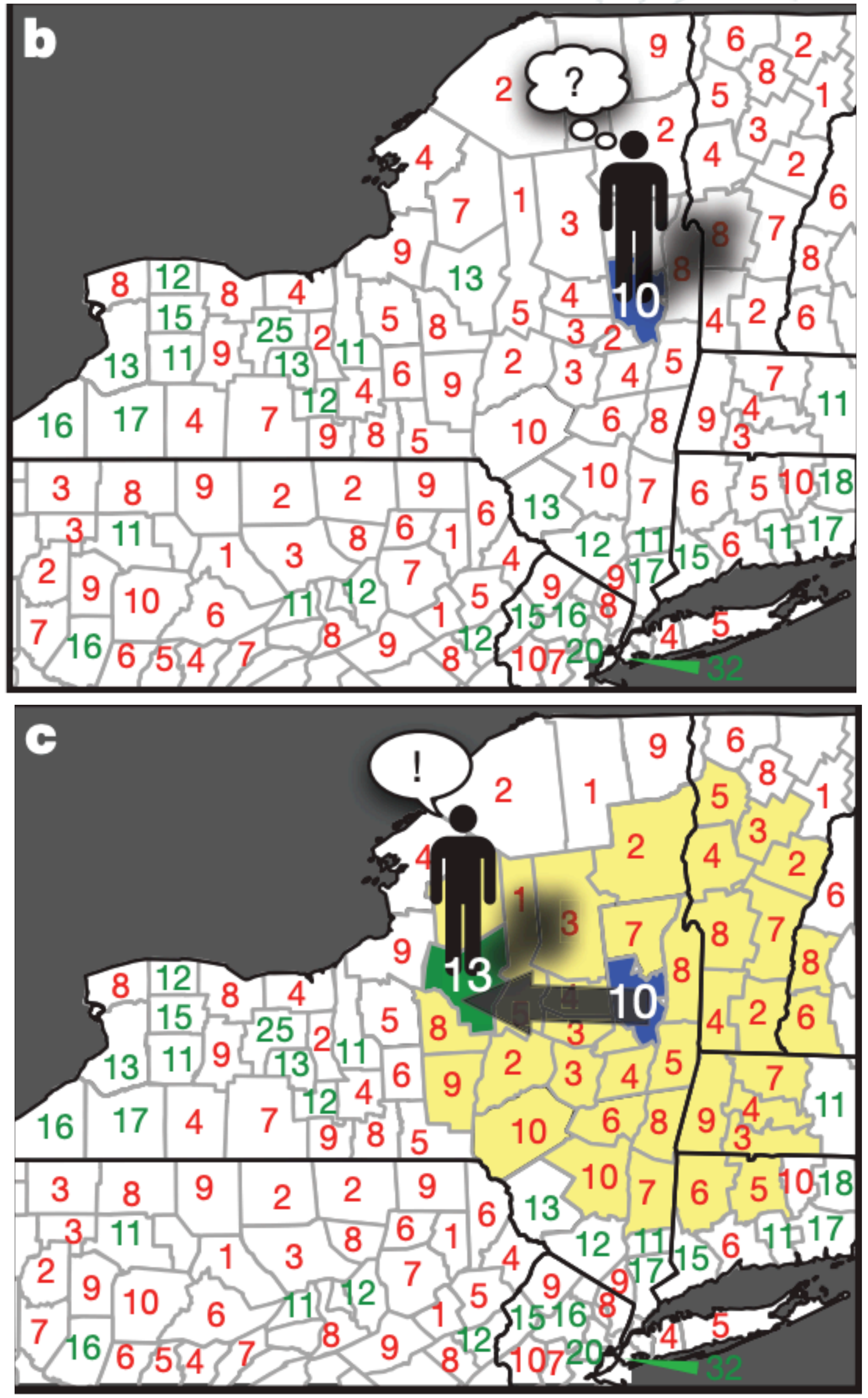


Travellers	UT	AL
Data	44	6
Gravity	1	1
Radiation	66	2

	UT	AL
m	90,000	89,000
n	240,000	280,000
r	447	410
s	2×10^6	2×10^7

Radiation model

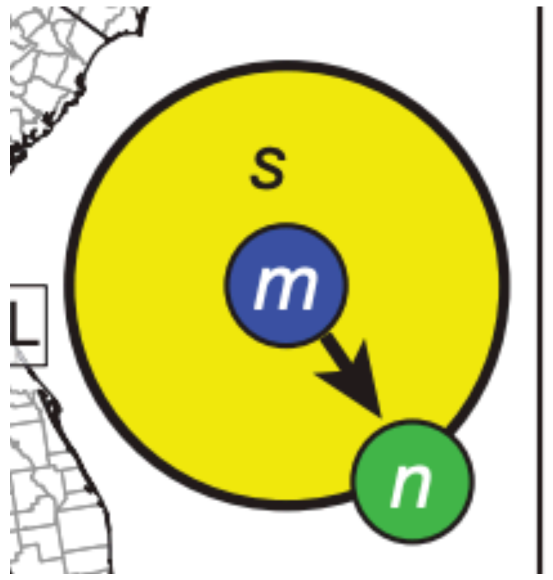
- A commuter leaves the county of population n and looks for a job in all counties around home.
- The number of job opportunities is chosen to be proportional to the resident population.
- Each **offer's attractiveness (benefit)** is represented by a random variable with distribution $p(z)$
- Each county is marked in green (red) if its best offer is better (lower) than the best offer in the home county (z=10),
- An individual accepts the closest job that offers better benefits than his home county,



Radiation model

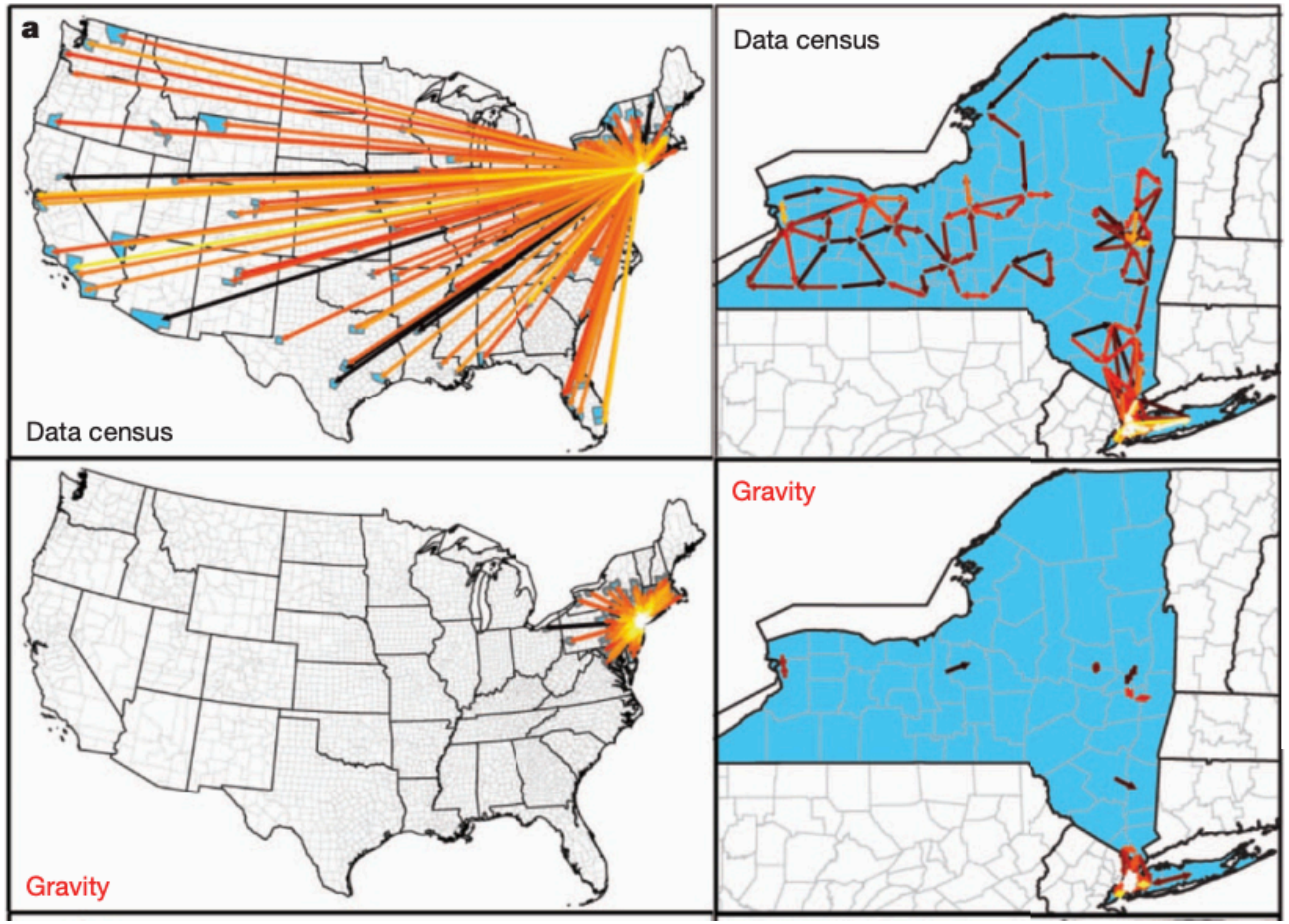
- It can be shown that the model is **parameter-free**, that is the average mobility flow between two locations (i,j) does not depend on $p(z)$ and the number of jobs.

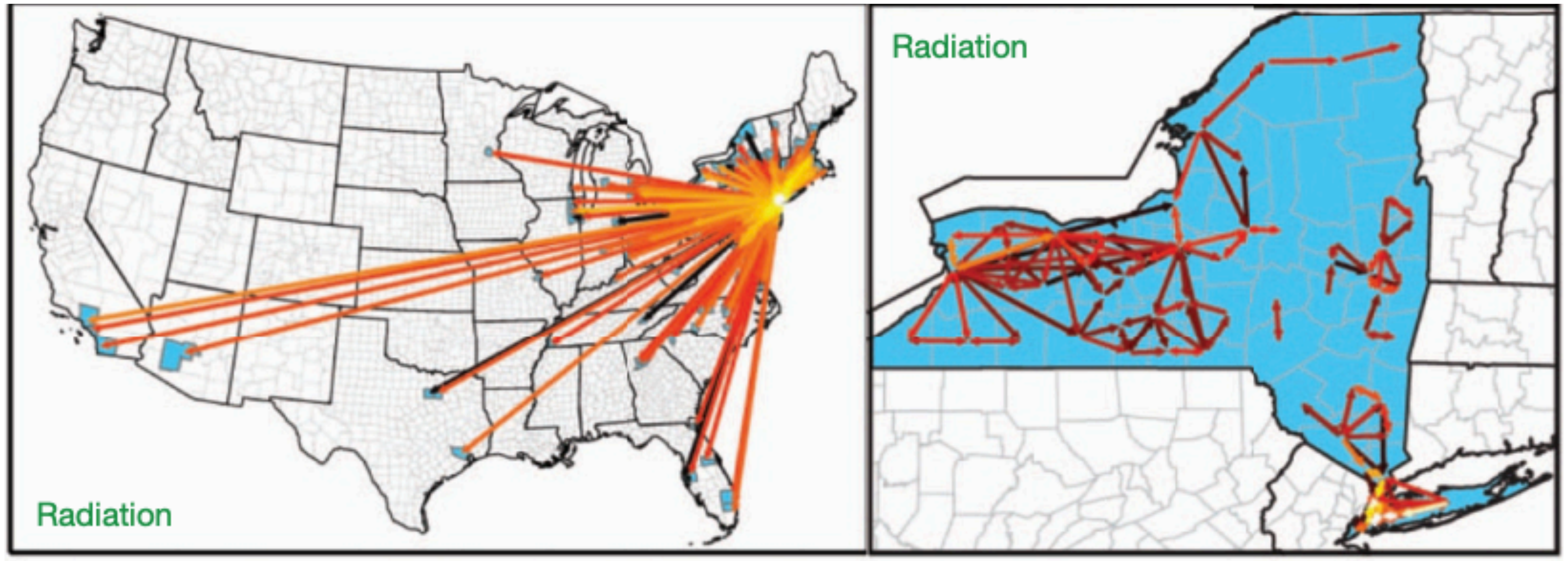
$$\langle T_{ij} \rangle = T_i \frac{m_i n_j}{(m_i + s_{ij})(m_i + n_j + s_{ij})}$$



- Given the population distribution and the total number of commuters leaving each node, we can generate the full commuting network from scratch.

Radiation model





Pros and cons

- (Almost) parameter-free.
- Grounded into a theoretical framework of individual mobility.
- Generates highly realistic mobility flows.

BUT

- Works well for commuting but not for all types of movements.
- Does not work well at all spatial granularities: issues arises within urban areas.

Human mobility data

Bills movements

nature > letters > article

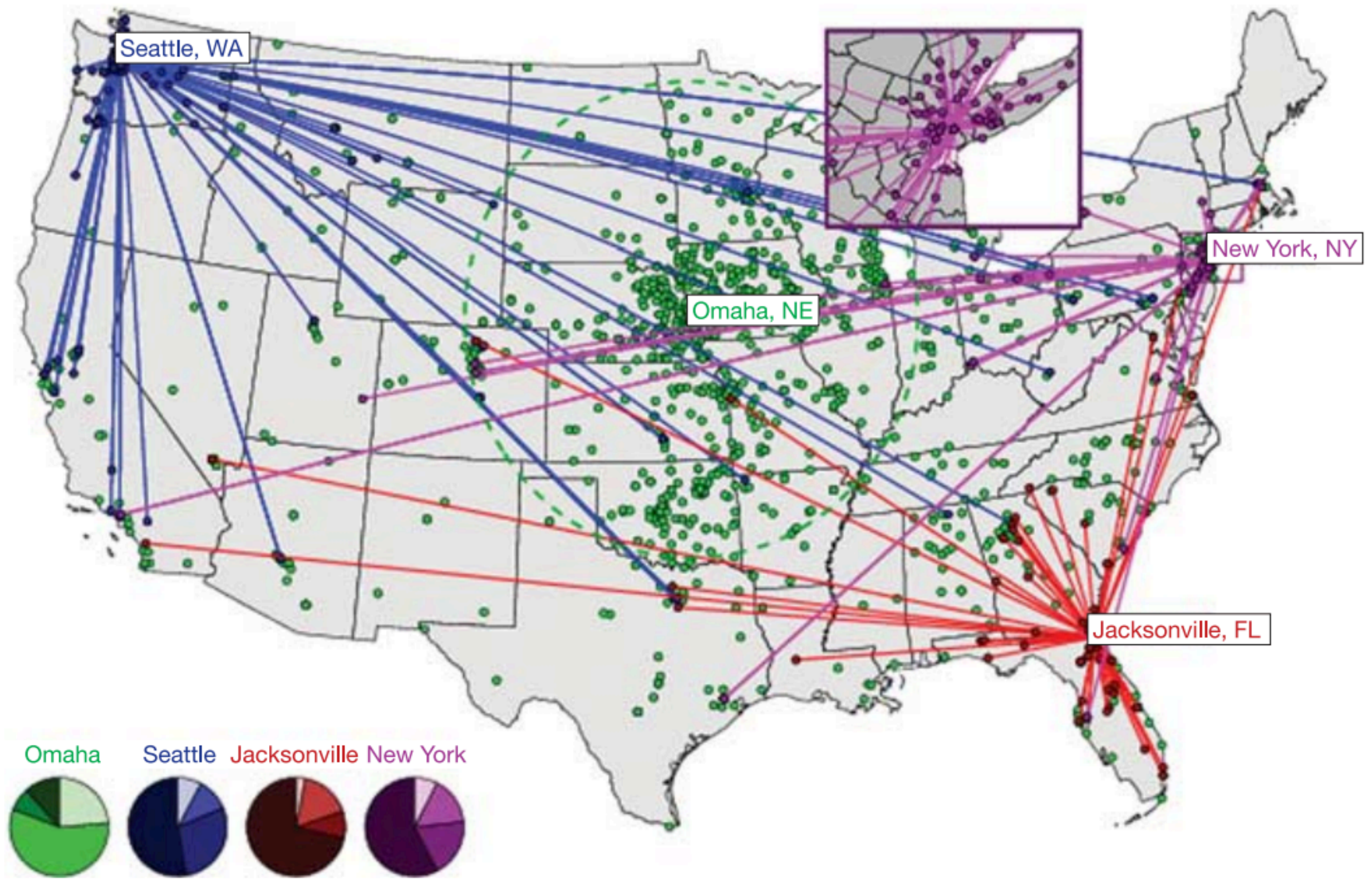
Published: 26 January 2006

The scaling laws of human travel

D. Brockmann, L. Hufnagel & T. Geisel

Nature **439**, 462–465 (2006) | Cite this article

15k Accesses | **1504** Citations | **342** Altmetric | Metrics



wheresgeorge.com

Individual movements
inferred from bank notes
can be described as Lévy flights

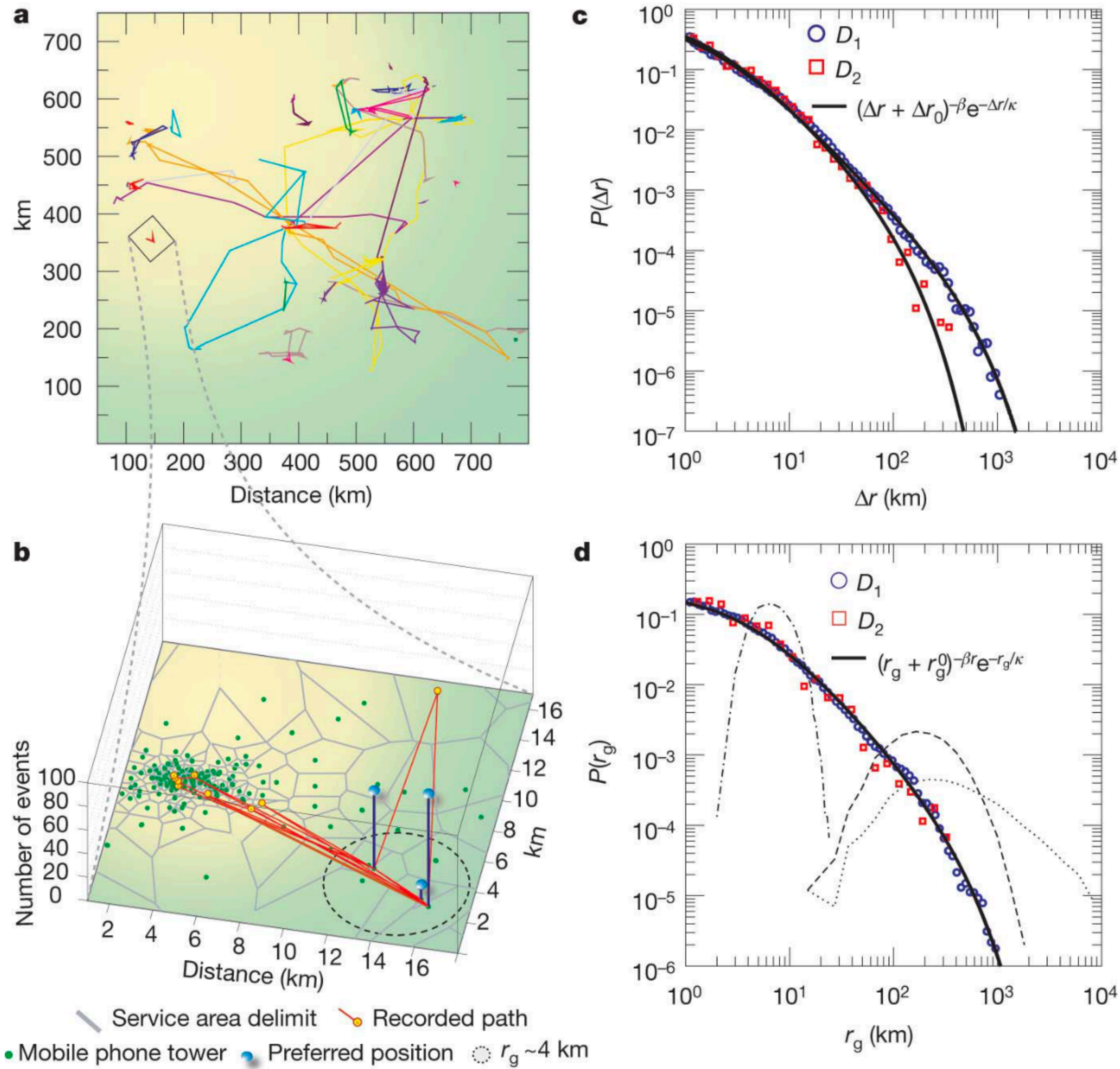
Mobile phone data

LETTERS

Understanding individual human mobility patterns

Marta C. González[1], César A. Hidalgo[1,2] & Albert-László Barabási[1,2,3]

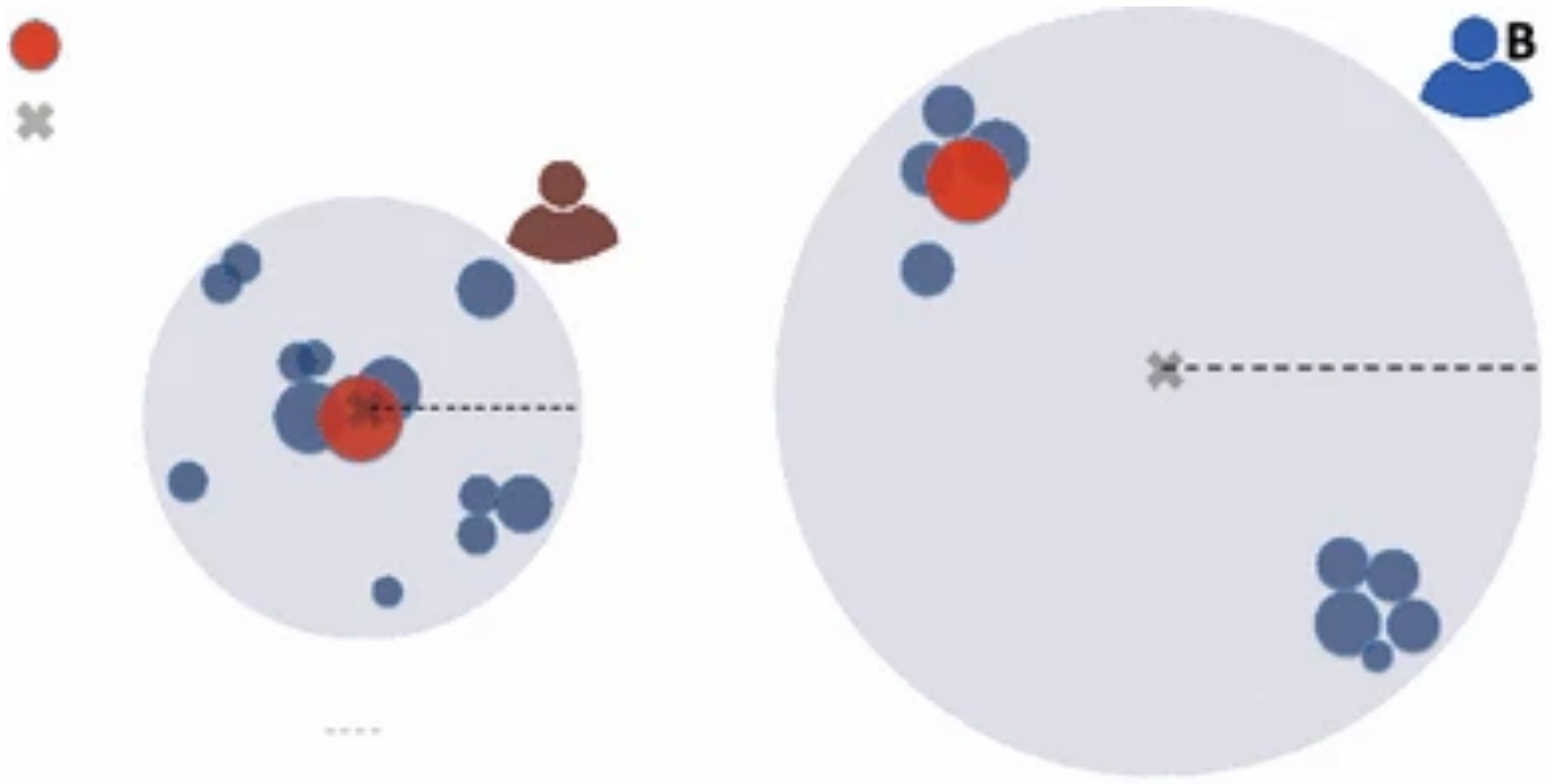
- Individual human movements are highly recurrent and not random.
- Movement distances follow a truncated power-law.
- Individuals do not explore new places as walkers but instead they tend to keep a constant **radius of gyration**



Radius of gyration

- The radius of gyration is a physical inspired measure of individual mobility.
- It measures the extent of the average distance a user explores around his center of mass.
- For mobile phone users the RoG **increases logarithmically** with time, a much slower increase than predicted by random walks.

$$r_g^{(u)} = \sqrt{\frac{1}{N} \sum_{i \in L} (\vec{r}_i - \vec{r}_{\text{cm}})^2}$$



(a) (b)

Mobile phone data

Pros

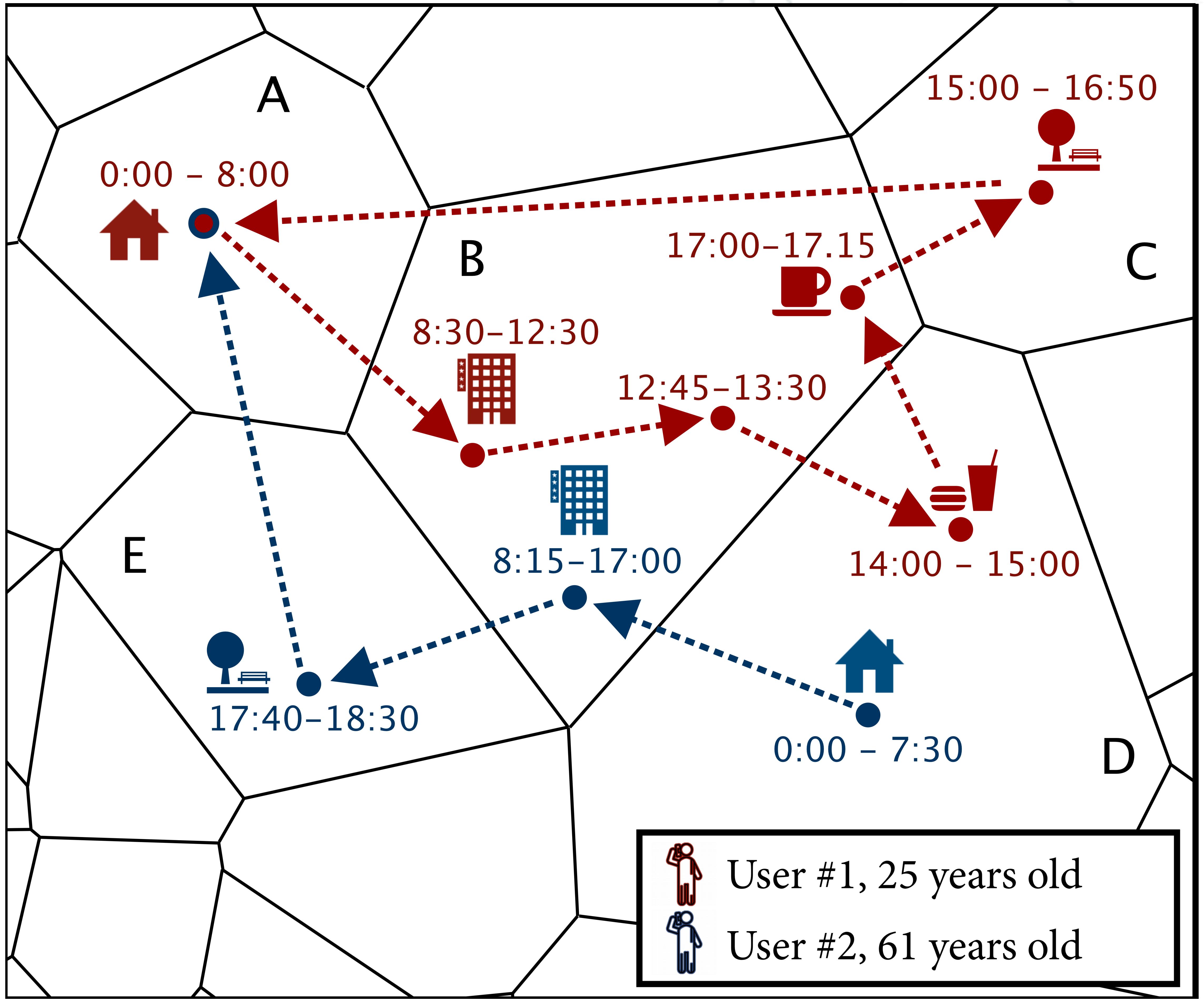
- Unprecedented temporal and spatial scales
- High volumes
- Much less costly with respect to surveys
- Updated frequently
- Sometime metadata (age, demographics) also available

Cons

- Privacy risks due to re-identification
- Users sample not representative
- Trajectories are reconstructed from users' activity which is biased (calling times, app usage)

Mobile phone data

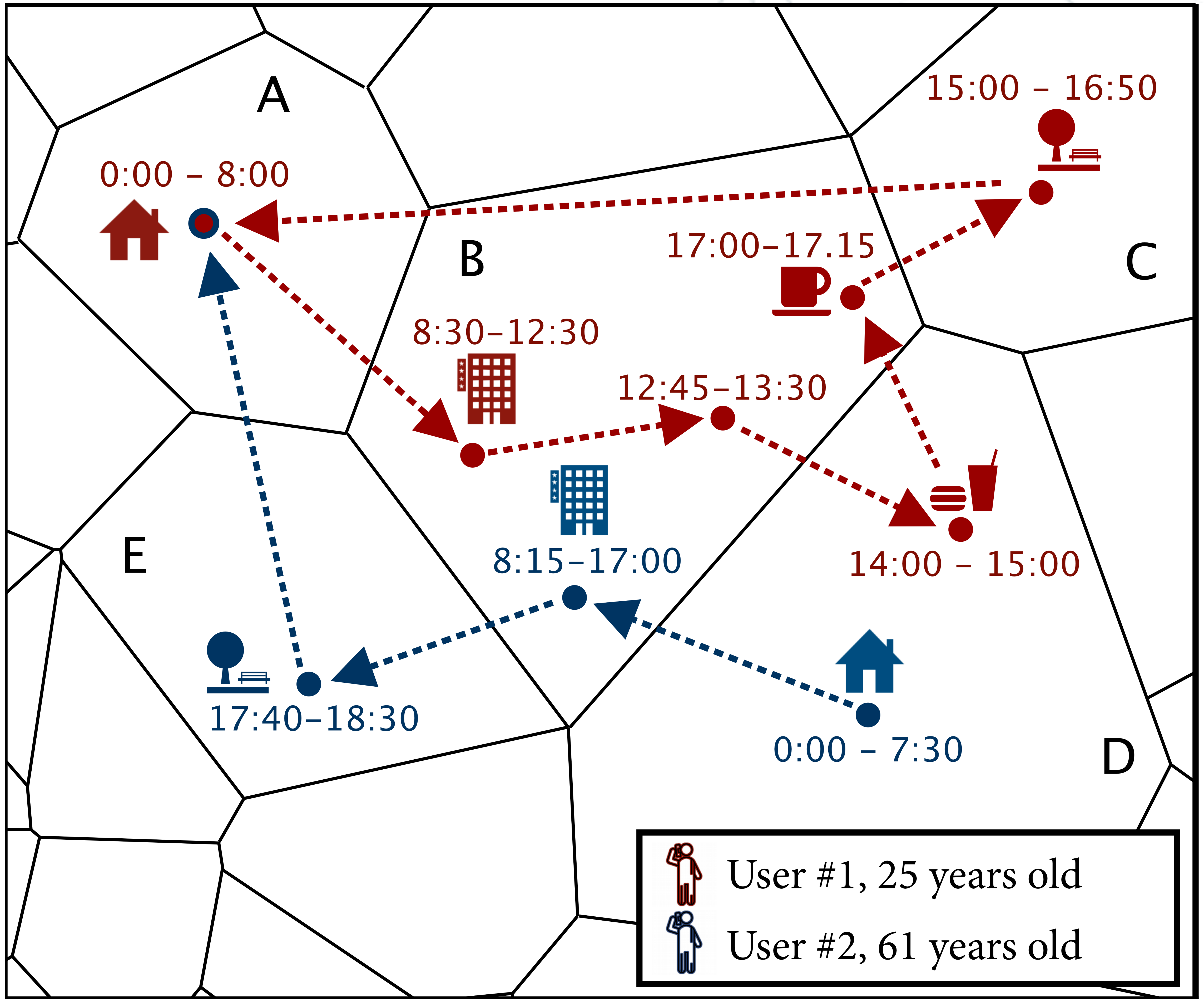
- Call Detail Records (CDRs)
  - calling activity (outgoing, incoming)
  - mobility + social network
  - lower resolution



Oliver et al. Sci Adv 2020

Mobile phone data

- Call Detail Records (CDRs)
    - calling activity (outgoing, incoming)
    - mobility + social network
    - lower resolution
- xData Records (XDR) and GPS
    - mobility only
    - higher accuracy / higher sampling rate



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2020: 300 million devices

nature human behaviour

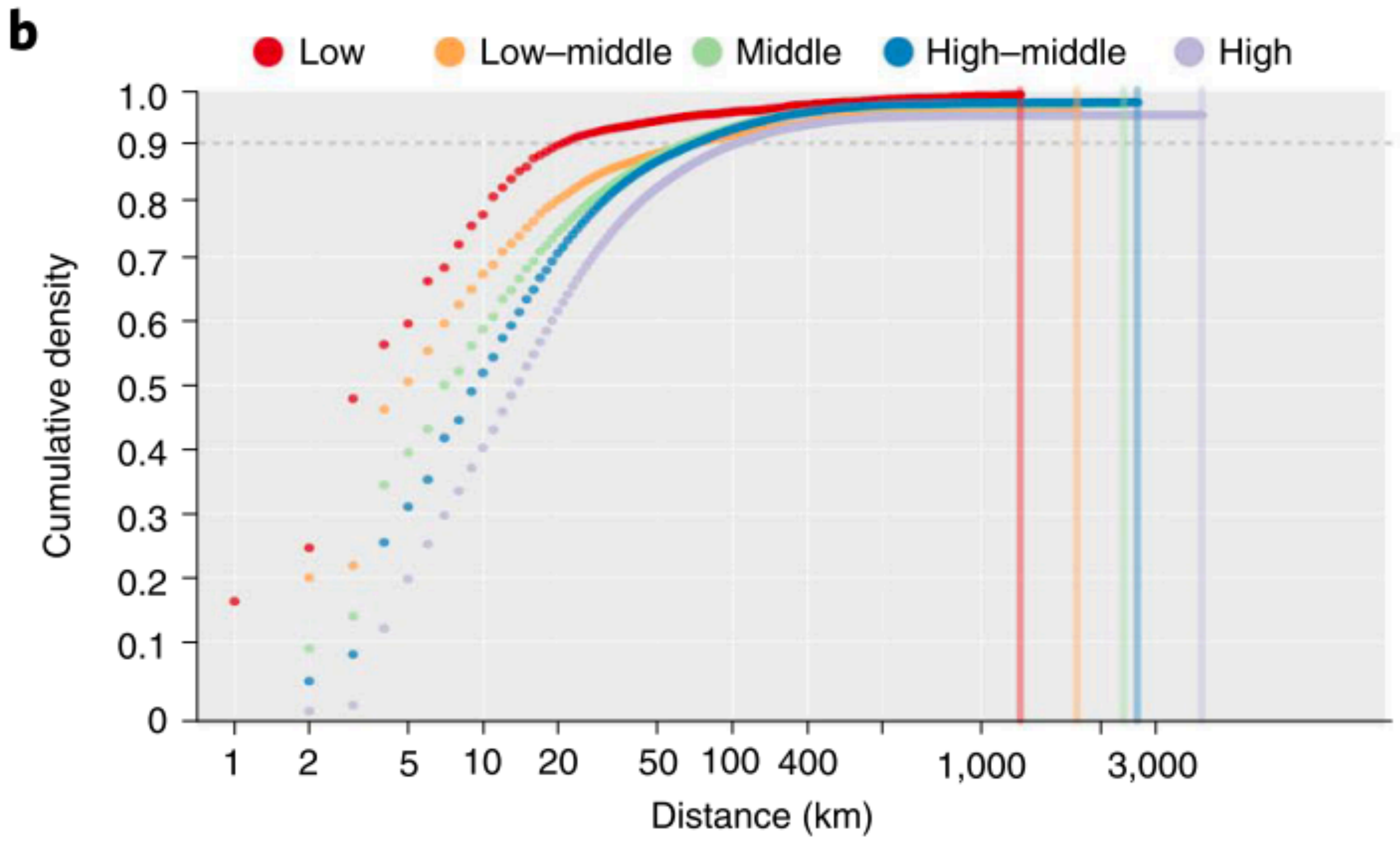
ARTICLES

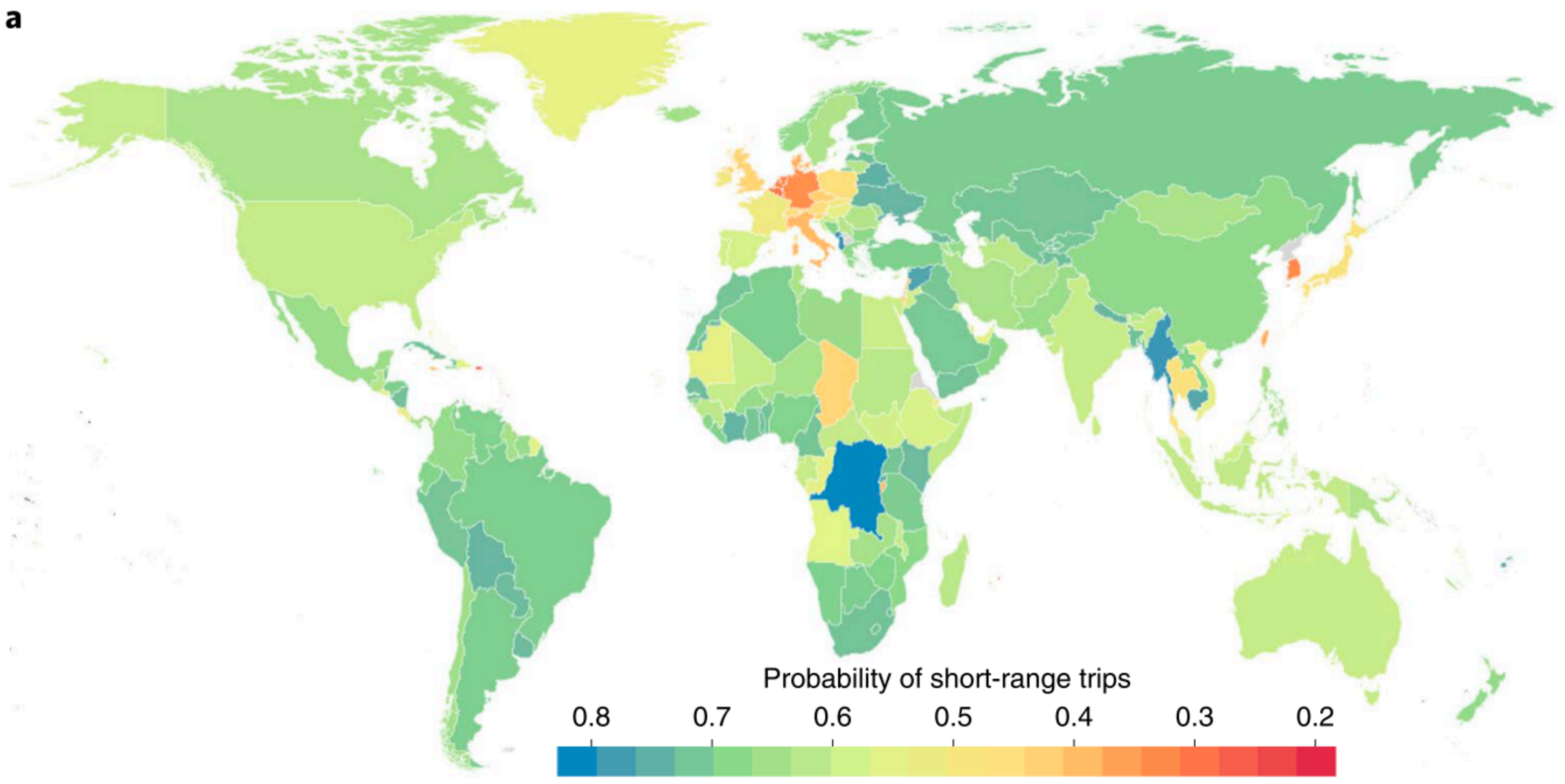
https://doi.org/10.1038/s41562-020-0875-0

Check for updates

Mapping global variation in human mobility

Moritz U. G. Kraemer[1,2,3,10,11] ✉, Adam Sadilek[4,10], Qian Zhang[5,10], Nahema A. Marchal[6], Gaurav Tuli[2], Emily L. Cohn[2], Yulin Hswen[2,7], T. Alex Perkins[8], David L. Smith[5,9], Robert C. Reiner Jr[5,9,11] ✉ and John S. Brownstein[1,2,11] ✉





More and more studies

Article

The scales of human mobility

https://doi.org/10.1038/s41586-020-2909-1

Received: 3 February 2020

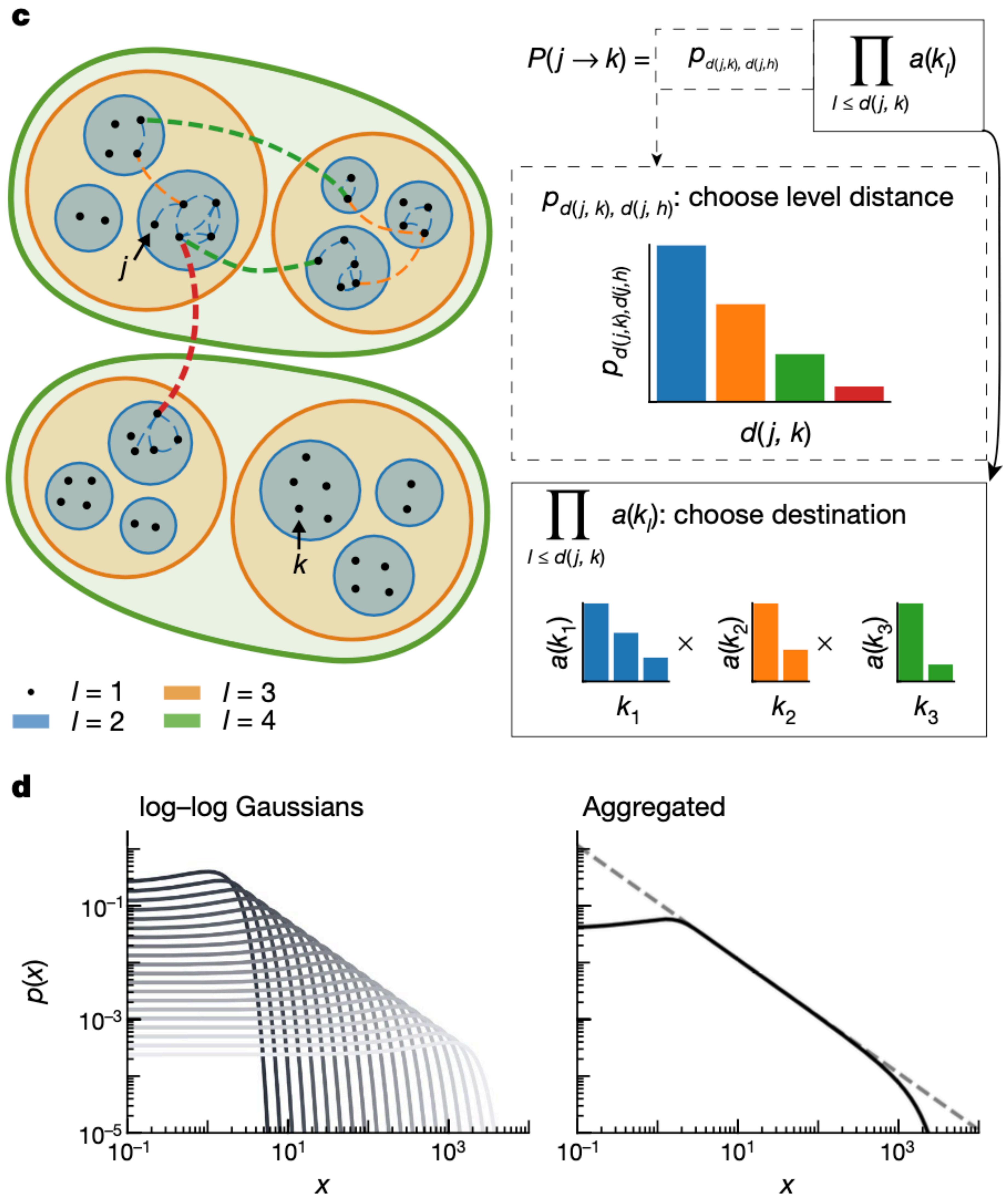
Accepted: 25 September 2020

Published online: 18 November 2020

Check for updates

Laura Alessandretti[1,2,3], Ulf Aslak[1,2,3] & Sune Lehmann[1,2]✉

There is a contradiction at the heart of our current understanding of individual and collective mobility patterns. On the one hand, a highly influential body of literature on human mobility driven by analyses of massive empirical datasets finds that human movements show no evidence of characteristic spatial scales. There, human mobility is described as scale free[1–3]. On the other hand, geographically, the concept of scale—referring to meaningful levels of description from individual buildings to neighbourhoods, cities, regions and countries—is central for the description of various aspects of human behaviour, such as socioeconomic interactions, or political and cultural dynamics[4,5]. Here we resolve this apparent paradox by showing that day-to-day human mobility does indeed contain meaningful scales, corresponding to spatial 'containers' that restrict mobility behaviour. The scale-free results arise from aggregating displacements across containers. We present a simple model—which given a person's trajectory—infers their neighbourhood, city and so on, as well as the sizes of these geographical containers. We find that the containers—characterizing the trajectories of more than 700,000 individuals—do indeed have typical sizes. We show that our model is also able to generate highly realistic trajectories and provides a way to understand the differences in mobility behaviour across countries, gender groups and urban–rural areas.



More and more studies

Article

The universal visitation law of human mobility

https://doi.org/10.1038/s41586-021-03480-9

Received: 30 May 2017

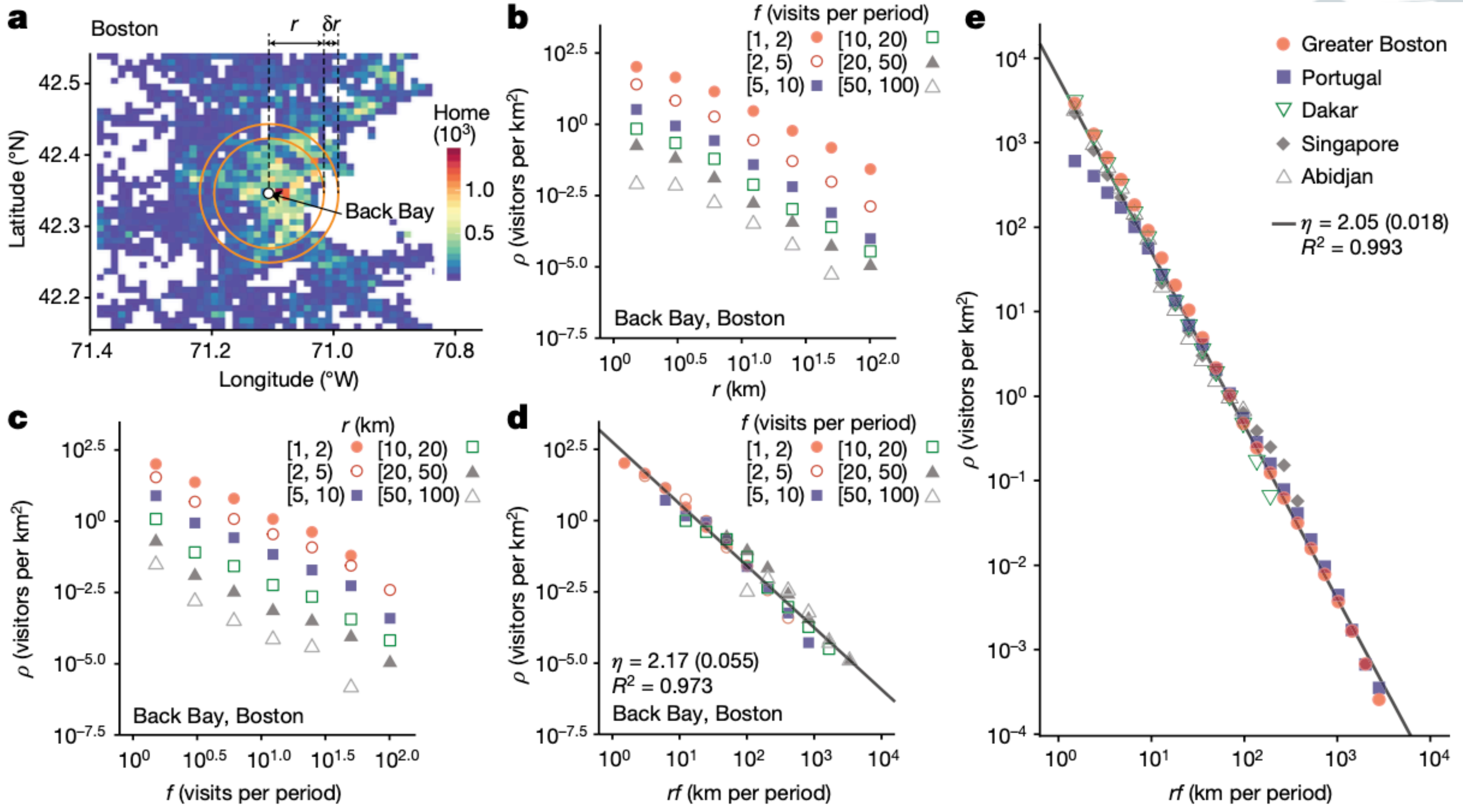
Accepted: 22 March 2021

Published online: 26 May 2021

Check for updates

Markus Schläpfer[1,2,3,9], Lei Dong[1,4,9]✉, Kevin O'Keeffe[1,9], Paolo Santi[1,5], Michael Szell[1,6,7], Hadrien Salat[3,8], Samuel Anklesaria[1], Mohammad Vazifeh[1], Carlo Ratti[1,10] & Geoffrey B. West[2,10]

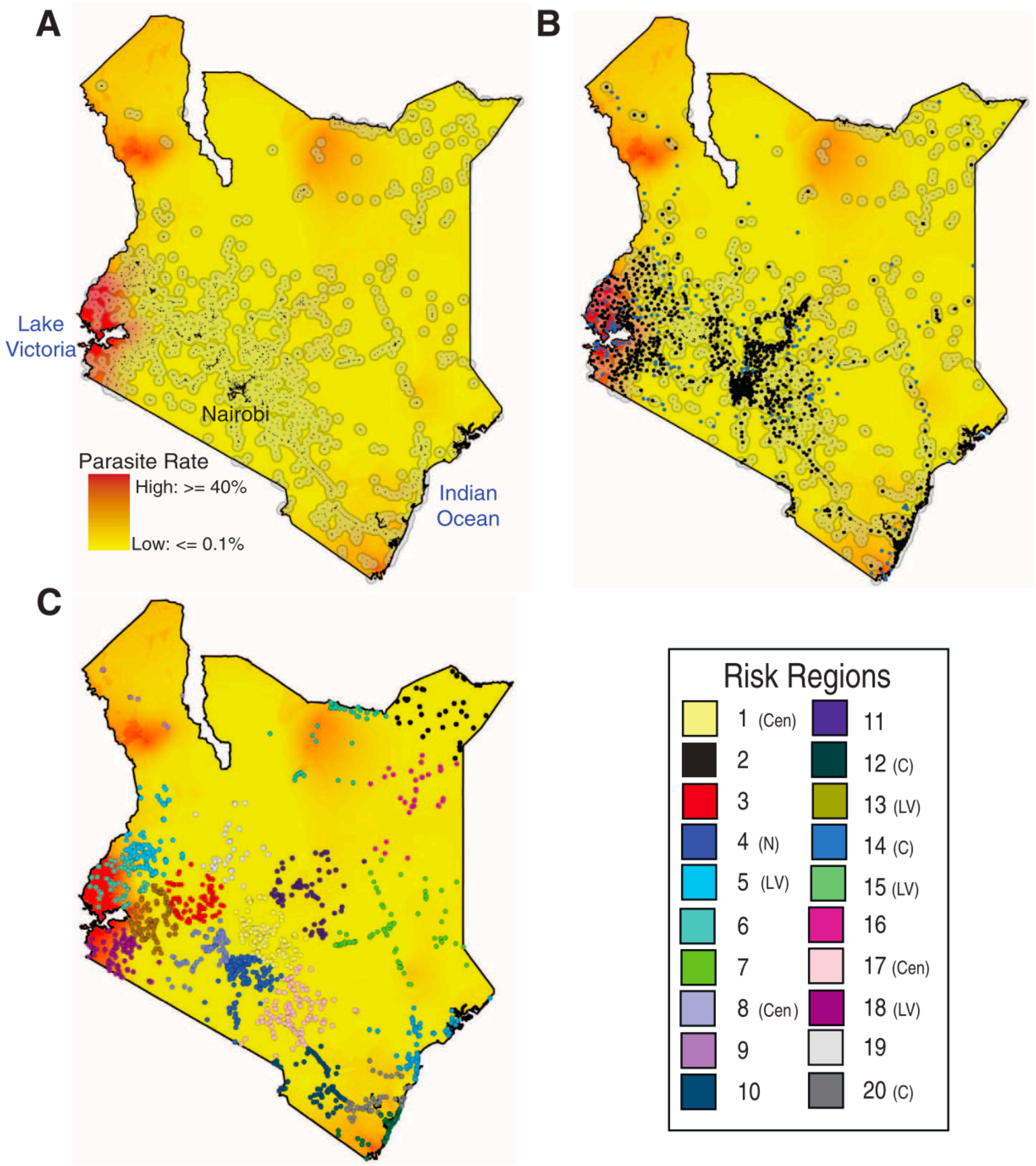
Human mobility impacts many aspects of a city, from its spatial structure[1–3] to its response to an epidemic[4–7]. It is also ultimately key to social interactions[8], innovation[9,10] and productivity[11]. However, our quantitative understanding of the aggregate movements of individuals remains incomplete. Existing models—such as the gravity law[12,13] or the radiation model[14]—concentrate on the purely spatial dependence of mobility flows and do not capture the varying frequencies of recurrent visits to the same locations. Here we reveal a simple and robust scaling law that captures the temporal and spatial spectrum of population movement on the basis of large-scale mobility data from diverse cities around the globe. According to this law, the number of visitors to any location decreases as the inverse square of the product of their visiting frequency and travel distance. We further show that the spatio-temporal flows to different locations give rise to prominent spatial clusters with an area distribution that follows Zipf's law[15]. Finally, we build an individual mobility model based on exploration and preferential return to provide a mechanistic explanation for the discovered scaling law and the emerging spatial structure. Our findings corroborate long-standing conjectures in human geography (such as central place theory[16] and Weber's theory of emergent optimality[10]) and allow for predictions of recurrent flows, providing a basis for applications in urban planning, traffic engineering and the mitigation of epidemic diseases.



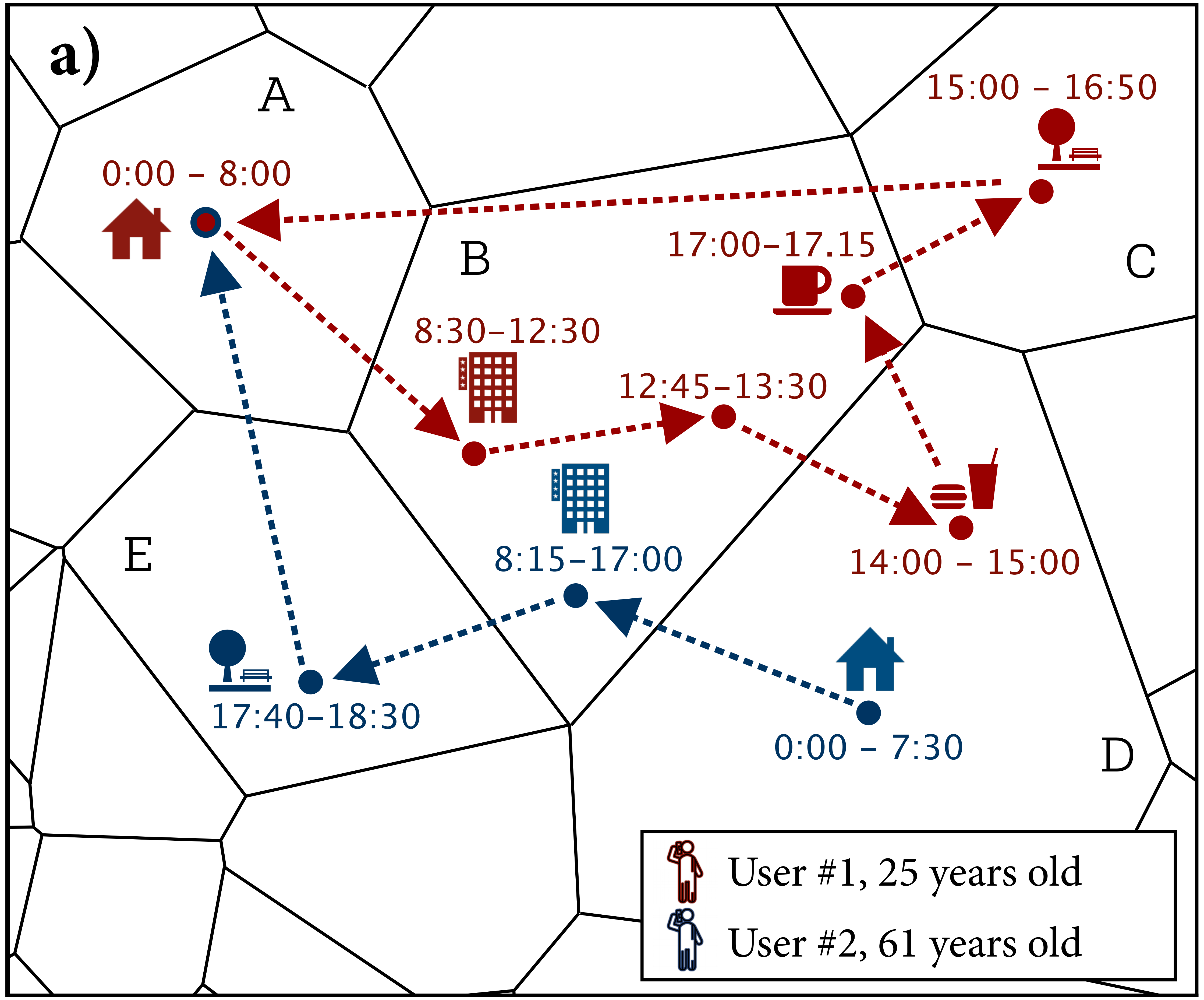
Applications to epidemic modelling

Mobile phone data and disease spread

- Malaria (Wesolowski et al. Science 2012)
- Cholera (Bengtsson et al. Sci Rep 2015)
- Dengue (Wesolowski et al. PNAS 2015)
- Comparisons between census data, surveys, and mobile phone data (Tizzoni et al. PLOS Comp Bio 2014)
- COVID-19 —tens of studies…



Mobile phone data and disease spread



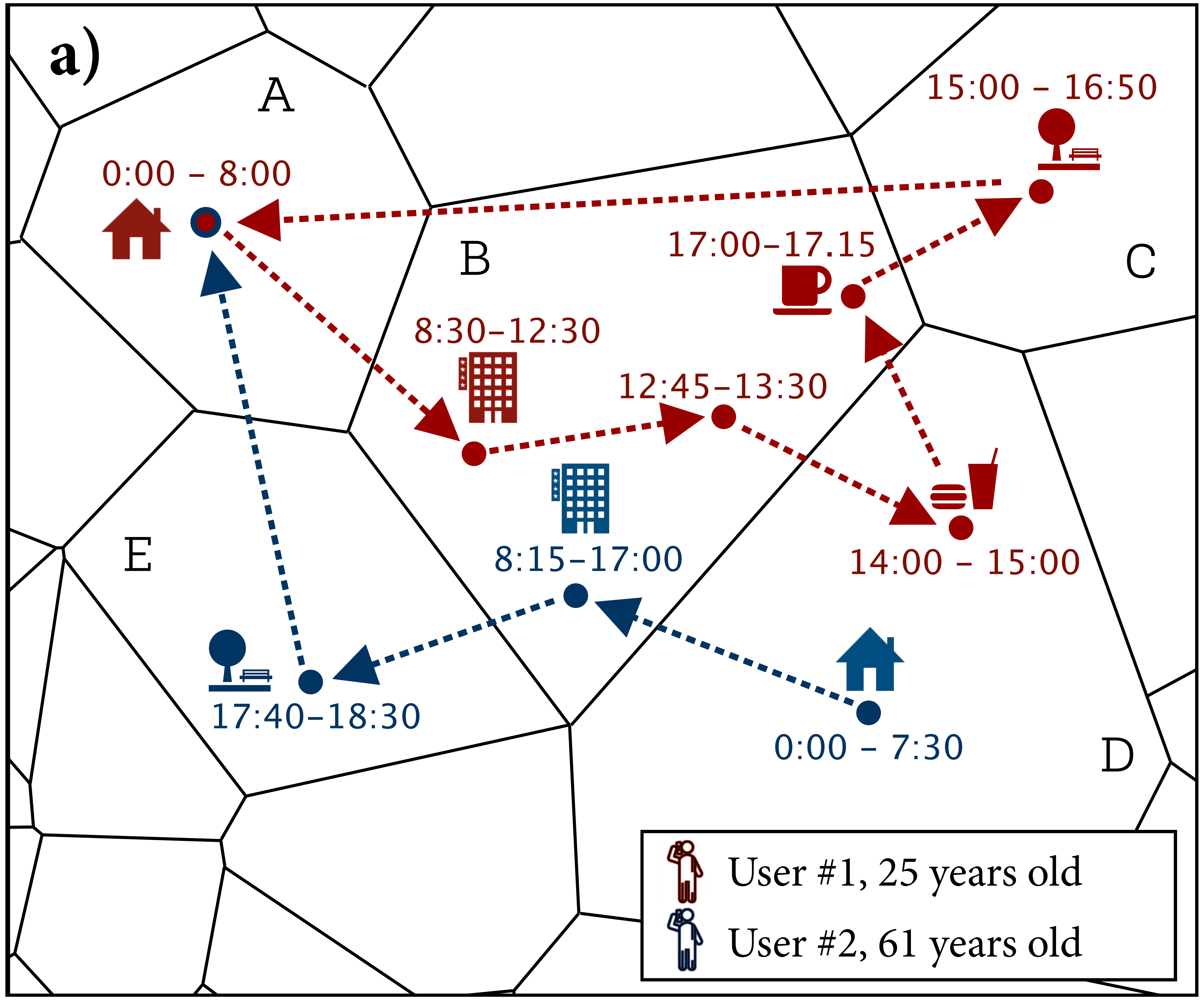
b)

	A	B	C	D	E
A	0	1	0	0	0
B	0	1	1	1	1
C	1	0	0	0	0
D	0	2	0	0	0
E	1	0	0	0	0

Origin-Destination matrices

Oliver et al. Sci Adv 2020

Mobile phone data and disease spread



b)

	A	B	C	D	E
A	0	1	0	0	0
B	0	1	1	1	1
C	1	0	0	0	0
D	0	2	0	0	0
E	1	0	0	0	0

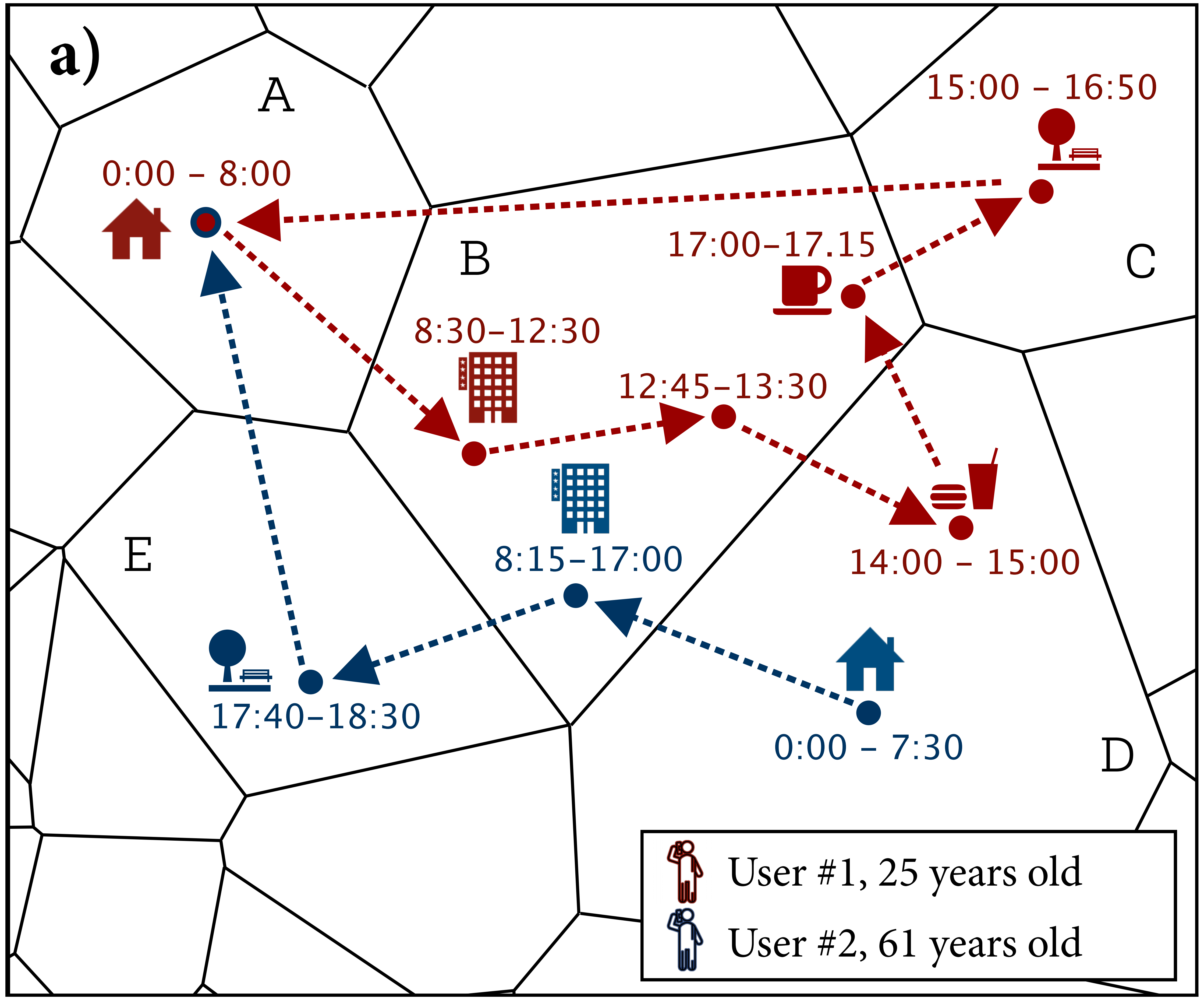
c)

	<20	20-29	30-59	60-79	80+
<20	0	0	0	0	0
20-29	0	0	0	1	0
30-59	0	0	0	0	0
60-79	0	1	0	0	0
80+	0	0	0	0	0

Contact matrices

Oliver et al. Sci Adv 2020

Mobile phone data and disease spread

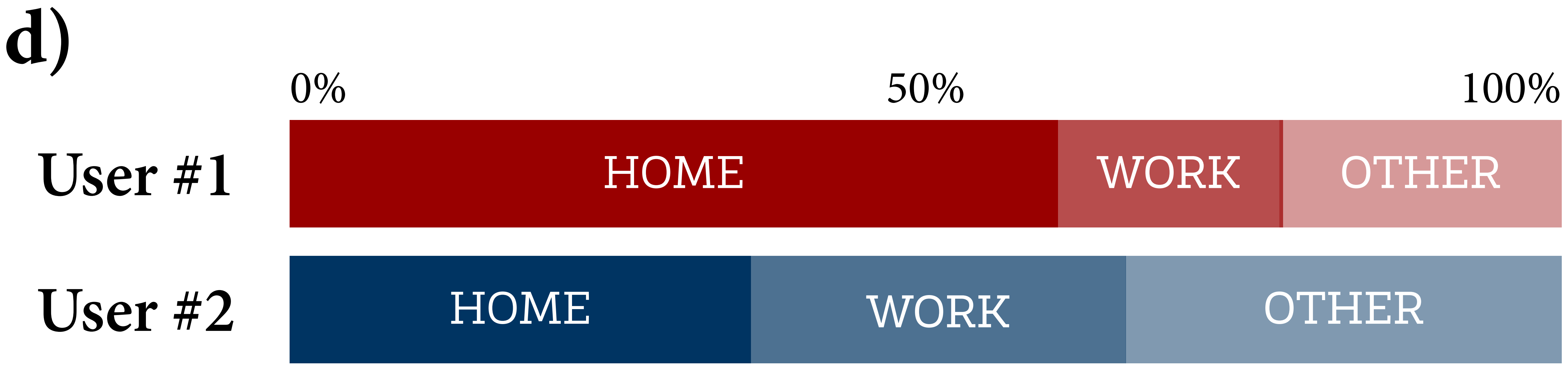


b)

	A	B	C	D	E
A	0	1	0	0	0
B	0	1	1	1	1
C	1	0	0	0	0
D	0	2	0	0	0
E	1	0	0	0	0

c)

	<20	20-29	30-59	60-79	80+
<20	0	0	0	0	0
20-29	0	0	0	1	0
30-59	0	0	0	0	0
60-79	0	1	0	0	0
80+	0	0	0	0	0



Time use data

Oliver et al. Sci Adv 2020

Mobile phone data and behavior

- Real-time analysis of changes in movements across regions and within a region
- Quantitative measure of social-distancing and physical proximity
- Changes in mobility patterns depending on the location, the time of the day, the day of the week, and socio-demographic factors

Date: 2020-03-04

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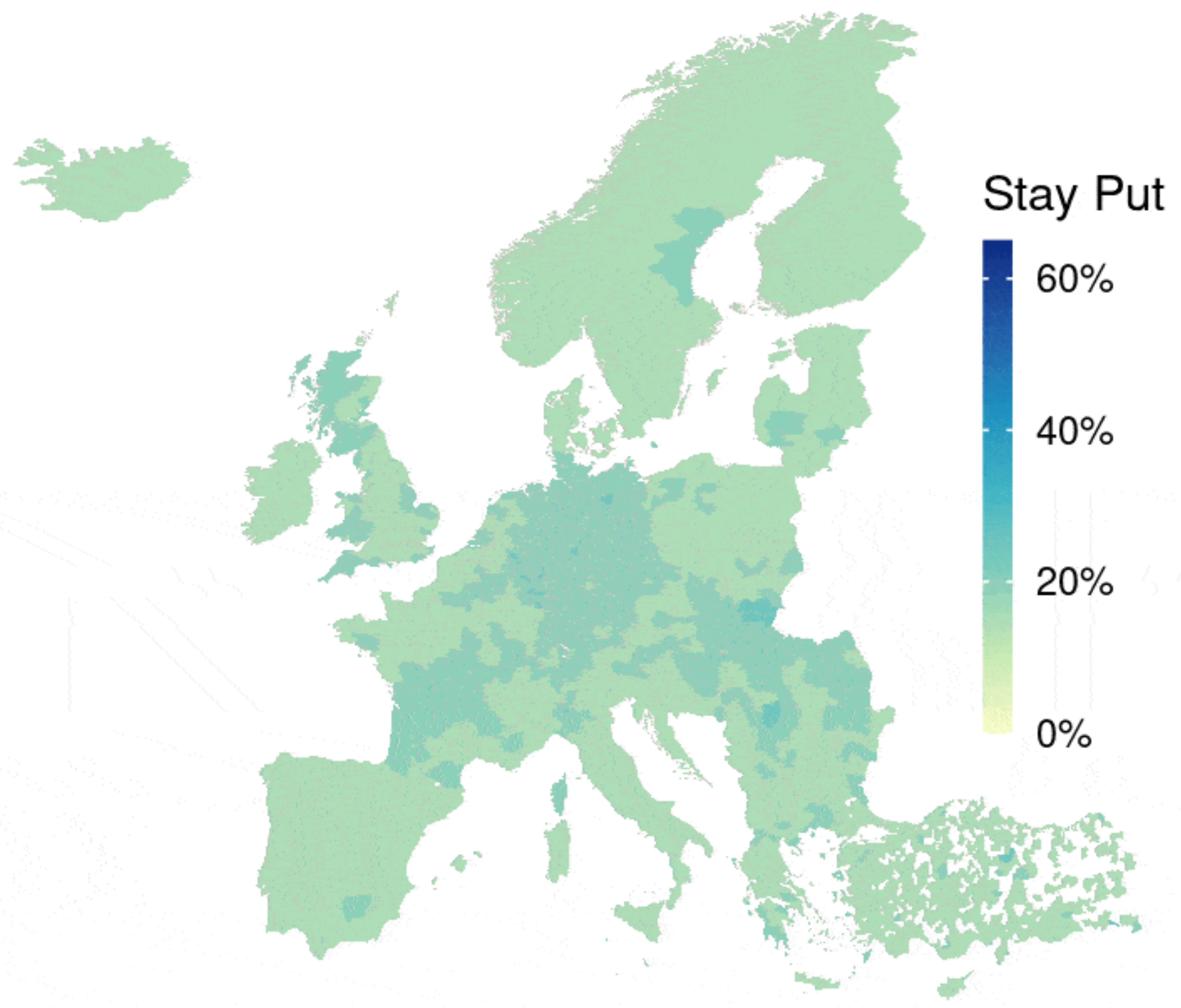


FACEBOOK Data for Good

https://research.fb.com/blog/2020/06/protecting-privacy-in-facebook-mobility-data-during-the-covid-19-response/

Mobile phone data and behavior

See how your community is moving around differently due to COVID-19

As global communities respond to COVID-19, we've heard from public health officials that the same type of aggregated, anonymized insights we use in products such as Google Maps could be helpful as they make critical decisions to combat COVID-19.

These Community Mobility Reports aim to provide insights into what has changed in response to policies aimed at combating COVID-19. The reports chart movement trends over time by geography, across different categories of places such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential.

Maps

Mobility Trends Reports

Learn about COVID-19 mobility trends. Reports are published daily and reflect requests for directions in Apple Maps. Privacy is one of our core values, so Maps doesn't associate your data with your Apple ID, and Apple doesn't keep a history of where you've been.

Mobile phone data and behavior

Retail & recreation

-35%

compared to baseline

Mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.

Grocery & pharmacy

-11%

compared to baseline

Mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies.

Parks

-6%

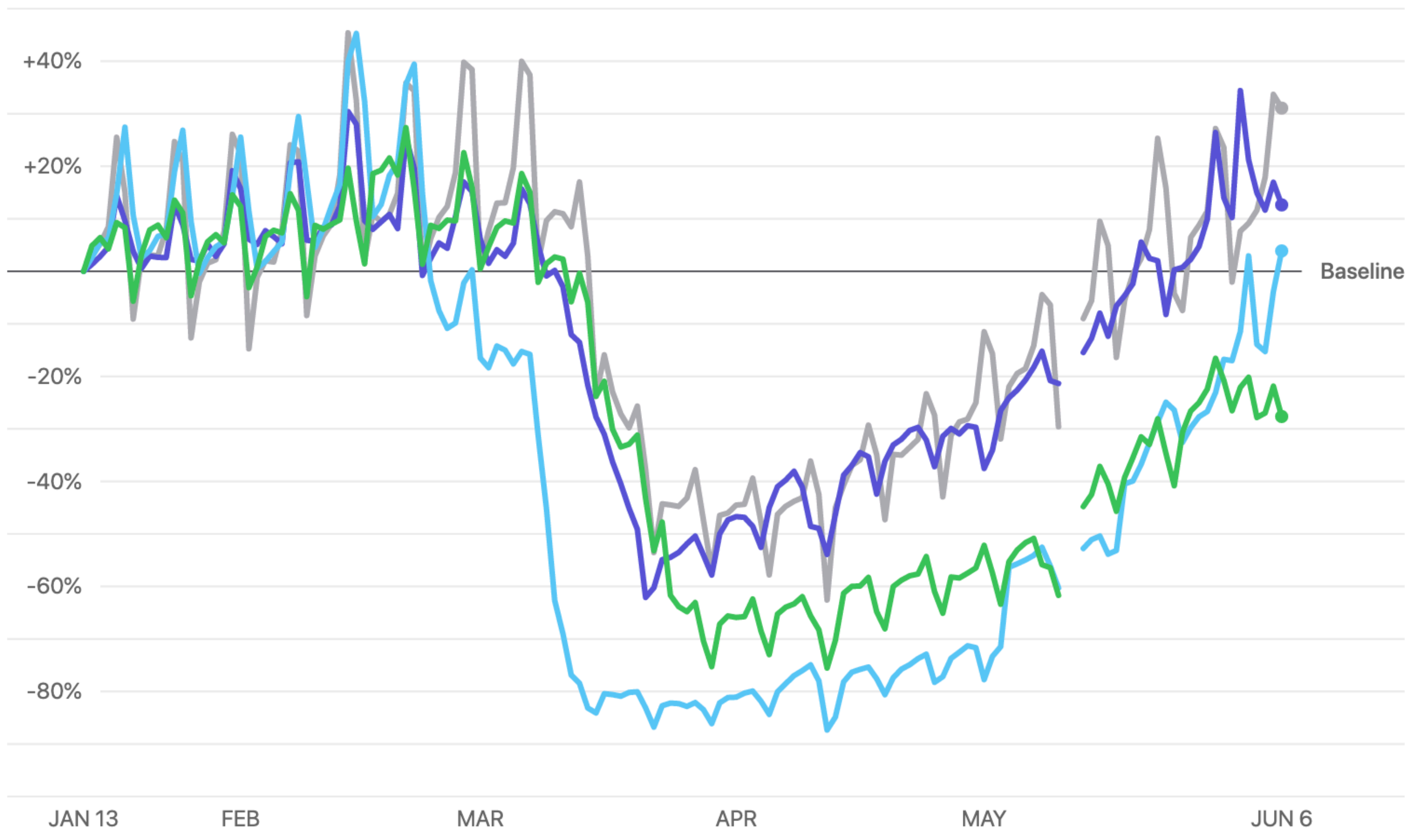
compared to baseline

Mobility trends for places like national parks, public beaches, marinas, dog parks, plazas, and public gardens.

Mobility Trends

Change in routing requests since January 13, 2020

Search (for example Italy, California, or New York City)



United States +31%
Germany +13%
Italy +4%
United Kingdom -28%

Mobile phone data and the COVID-19 pandemic

date	country	dtype	paper	tags
13/03/2020	Italy	gps	paper	mobility
22/03/2020	US (BOS)	gps	paper	mobility
24/03/2020	China	gps	paper	mobility
25/03/2020	Italy	gps	paper	mobility;social mixing
29/03/2020	US (NYC)	gps	paper	mobility
31/03/2020	US	gps	paper	mobility
03/04/2020	Ghana	unclear	paper	mobility
05/04/2020	Chile (SCL)	xdr	paper	mobility
05/04/2020	Germany	xdr	paper	mobility
09/04/2020	UK	gps	paper	mobility
09/04/2020	US	gps	paper	mobility
11/04/2020	Estonia	xdr	paper	mobility
11/04/2020	Argentina	madid	paper	mobility
11/04/2020	Uruguay	madid	paper	mobility
11/04/2020	Mexico	madid	paper	mobility
11/04/2020	Spain	xdr/cdr	paper	mobility
13/04/2020	India (Kerala)	cdr	paper	moobility
15/04/2020	US	gps	paper	politics
17/04/2020	LACRO	gps	paper	mobility
23/04/2020	US	gps	paper	social distancing
27/04/2020	Italy	cdr/xdr	paper	mobility

Beyond Google, tens of studies have used mobile phone data to study mobility changes during the COVID-19 pandemic

https://leoferres.info/blog/2020/04/10/covid19-mobility-reports/

Italy

- Emanuele Pepe
- Paolo Bajardi
- Laetitia Gauvin
- Ciro Cattuto
- Michele Tizzoni

INSTITUTE
FOR SCIENTIFIC INTERCHANGE
FOUNDATION

- Brennan Lake
- Filippo Privitera

cuebiq

Pepe, Emanuele, et al. "COVID-19 outbreak response: a first assessment of mobility changes in Italy following national lockdown." https://doi.org/10.1101/2020.03.22.20039933

Objectives

Measuring in near real-time the impact of COVID-19 non-pharmaceutical intervention (NPIs) in Italy on:

- long-range mobility
- short-range mobility
- spatial proximity

through the analysis of **de-identified location data.**

COVID-19 Mobility Monitoring project

a research project on human mobility and COVID-19

https://covid19mm.github.io

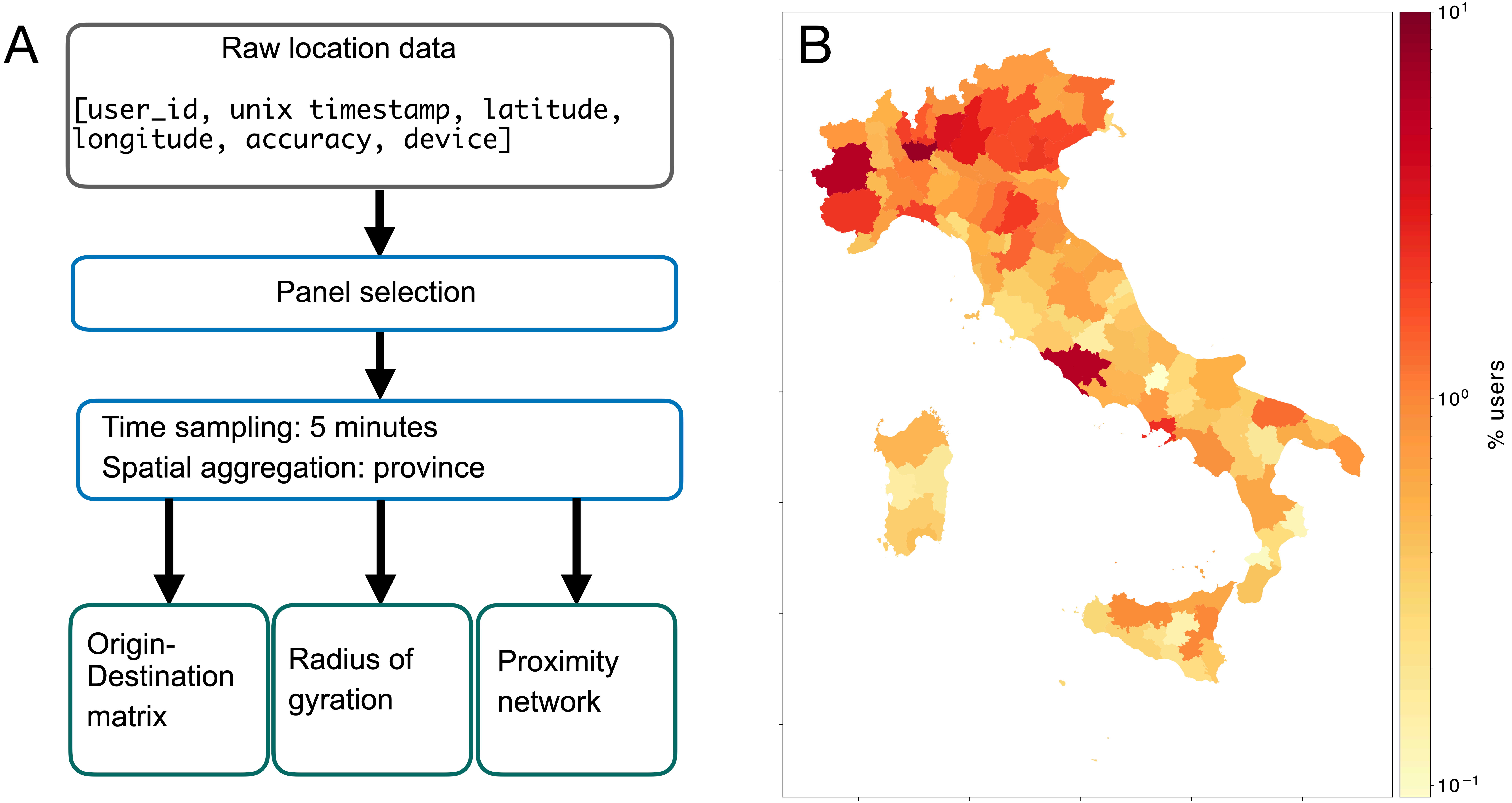
Dataset

- *stops* of about 167,000 de-identified users in Italy
- starting January 18, 2020
- `[anonymous hashed user id, time, latitude, longitude]`
- 200 million data points
- accuracy in the range of 10-100 meters

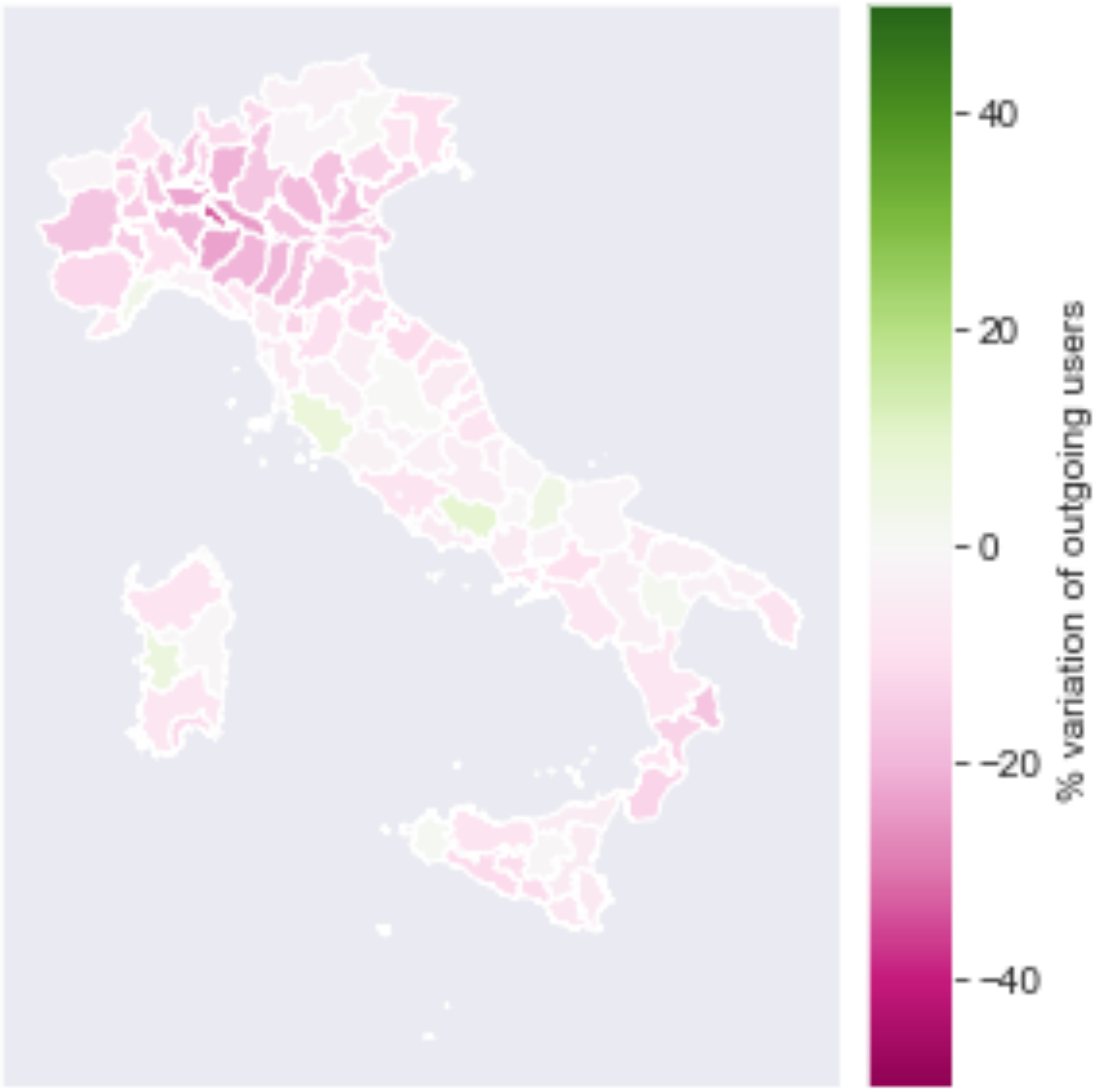
Data protection

- anonymized users who have opted-in to provide access to their location data anonymously, through a GDPR-compliant framework
- users can opt-out at any time
- never singled out identifiable individuals / no link to 3rd party
- no demographic information available
- no health information available

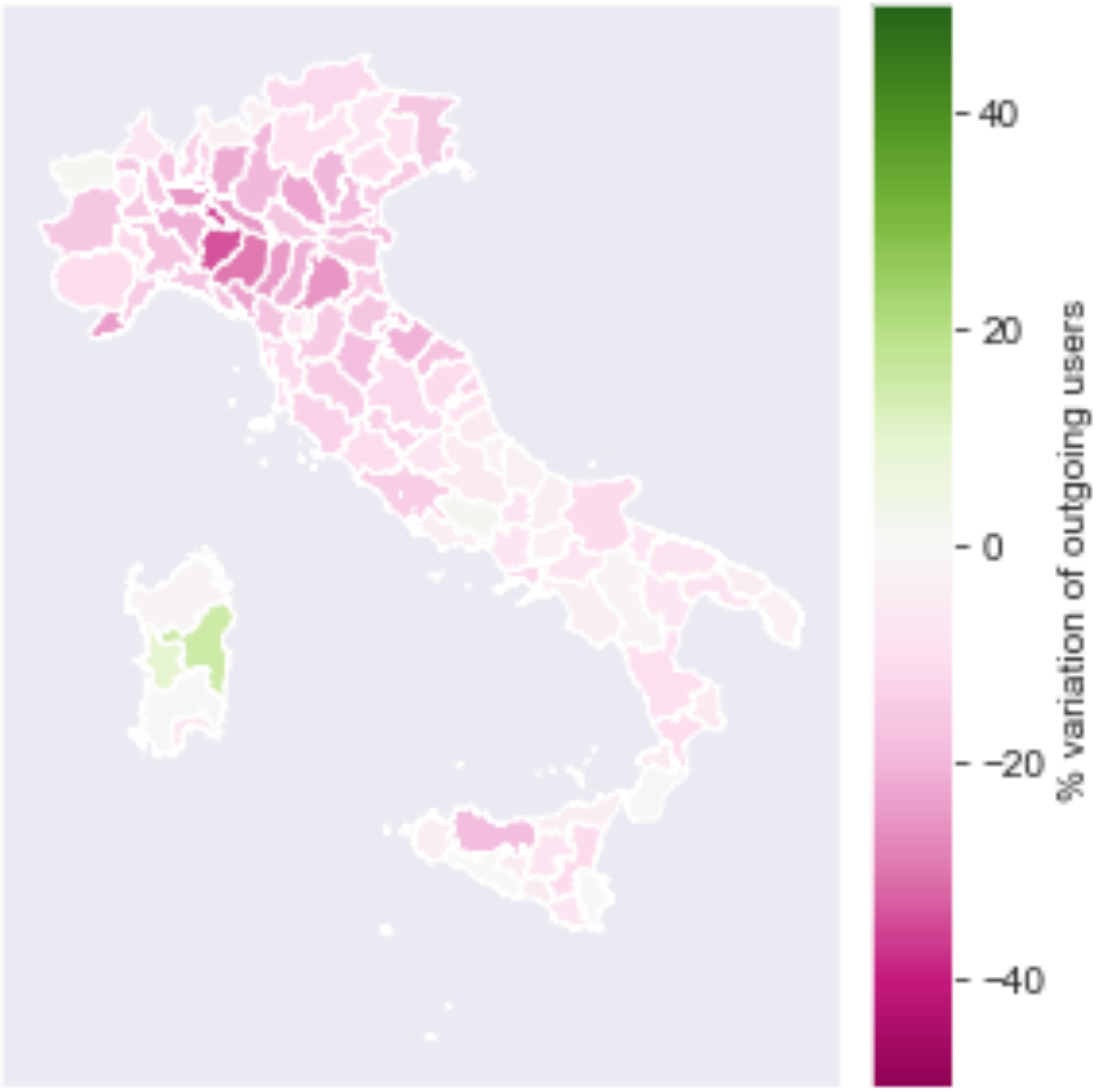
Workflow


A
Raw location data
[user_id, unix timestamp, latitude, longitude, accuracy, device]
Panel selection
Time sampling: 5 minutes
Spatial aggregation: province
Origin-Destination matrix
Radius of gyration
Proximity network
B
10^1
10^0
10^{-1}
% users

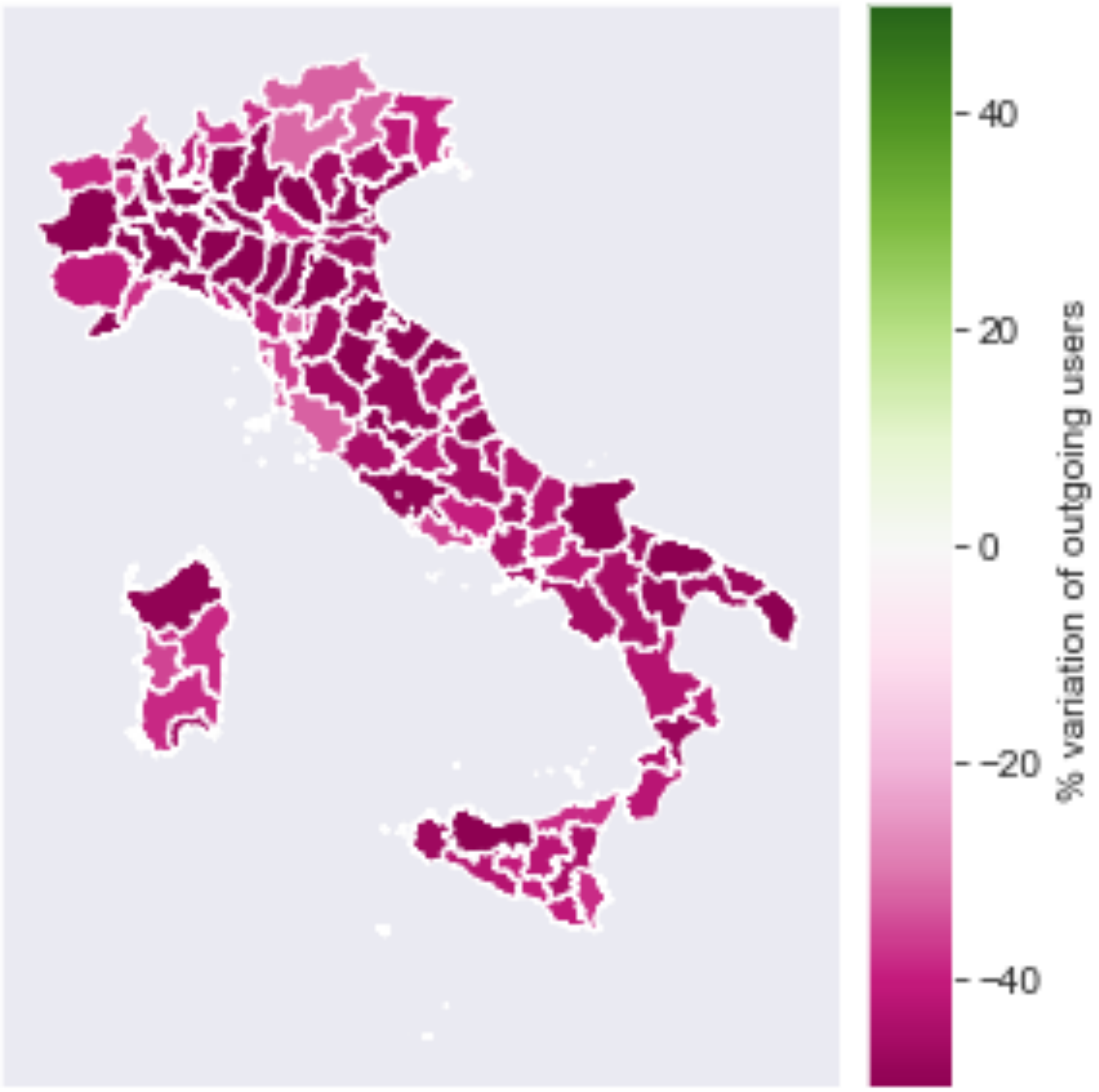
Outgoing traffic



February 21-28

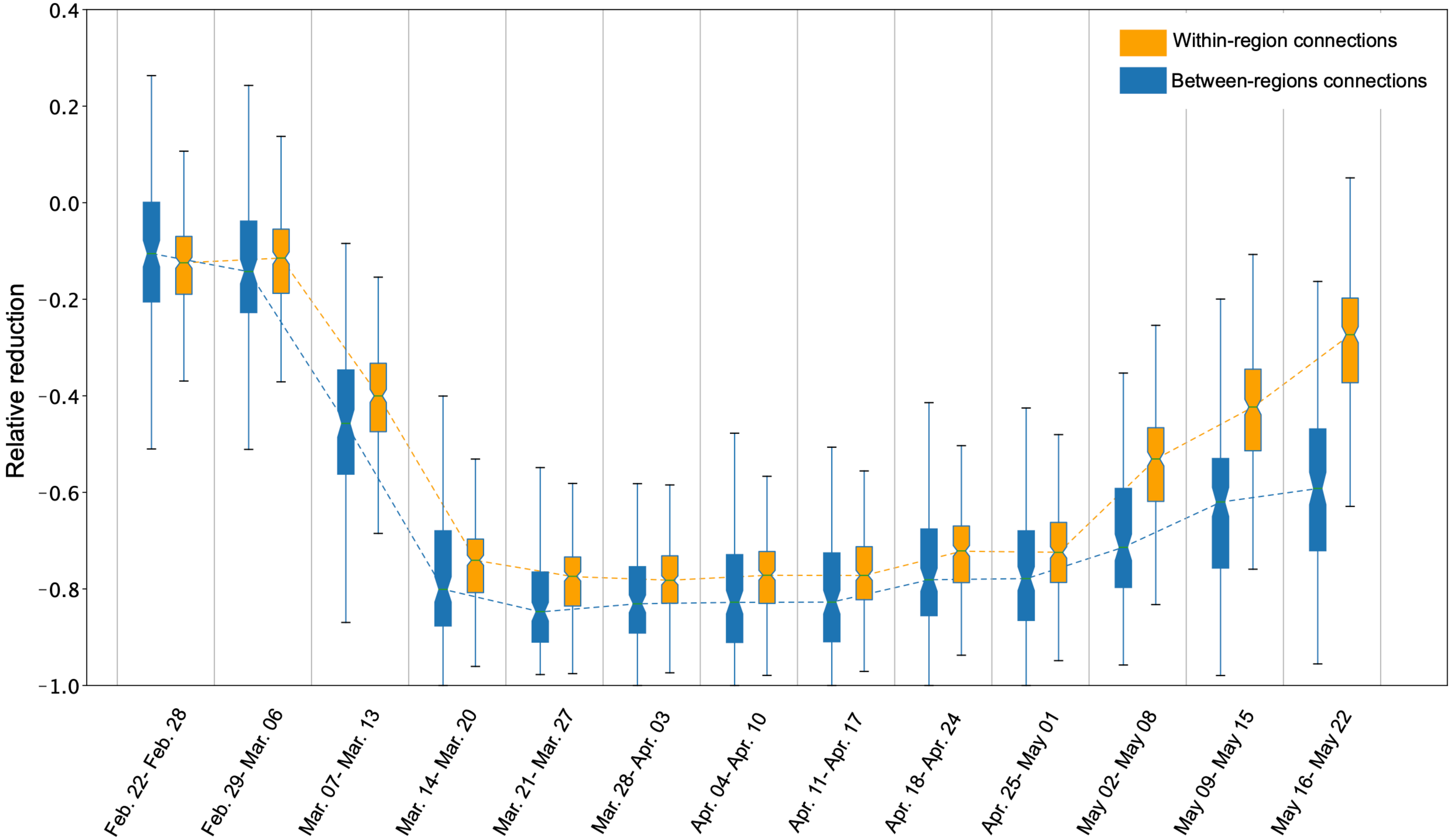


February 29 - March 6



March 7 - 13

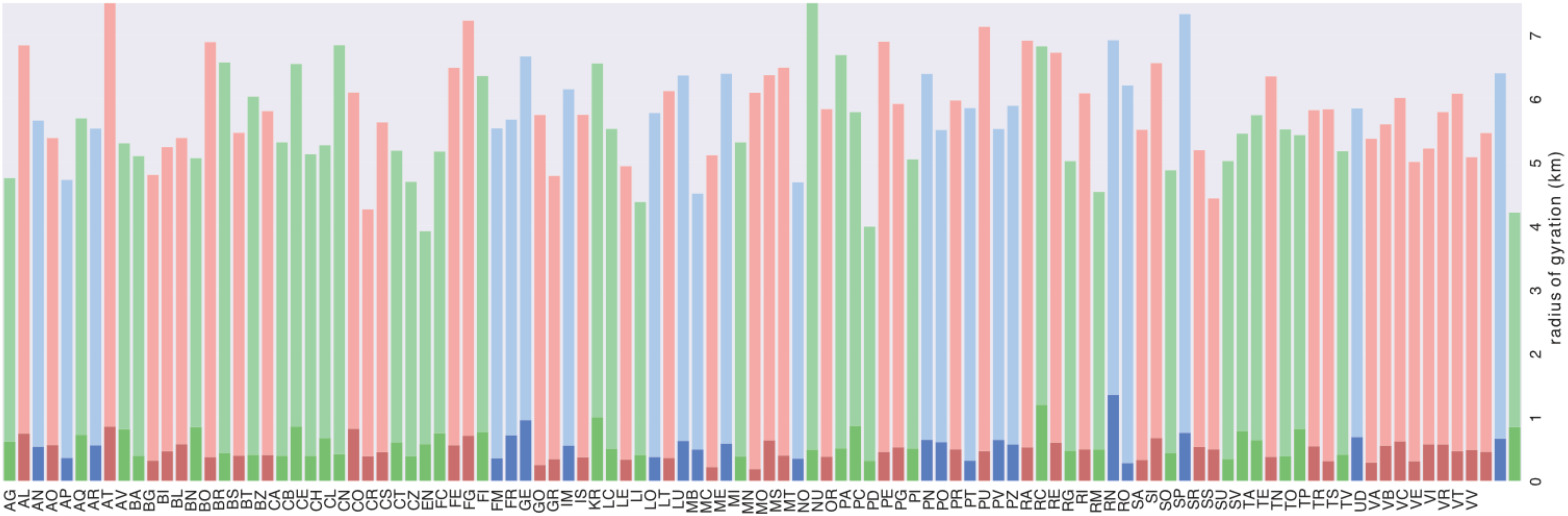
Lifting the lockdown



Short-range mobility

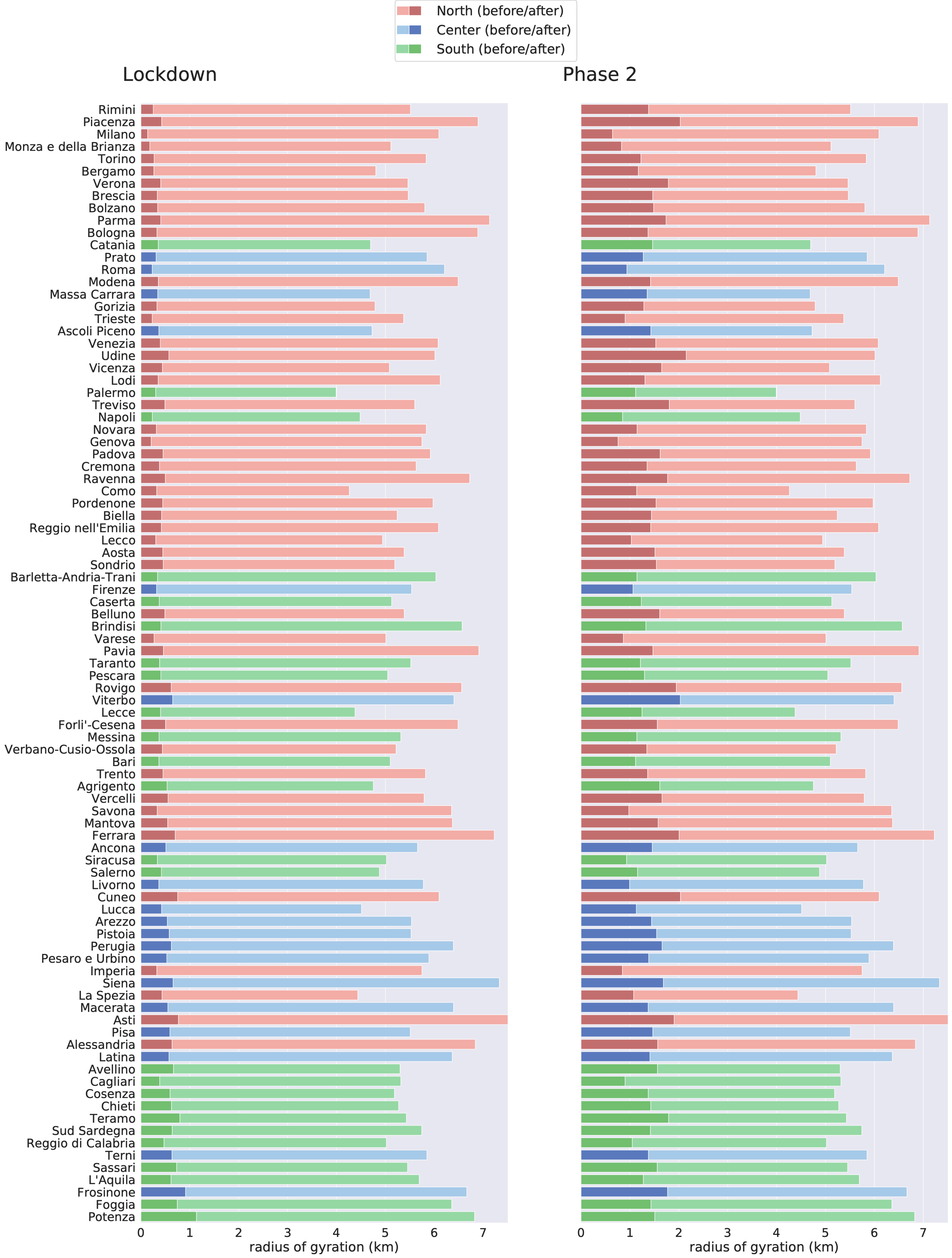
During the week of March 21 -28, the median RoG has declined to <1 km almost everywhere in Italy.

The median RoG before the lockdown was about 6 kms.

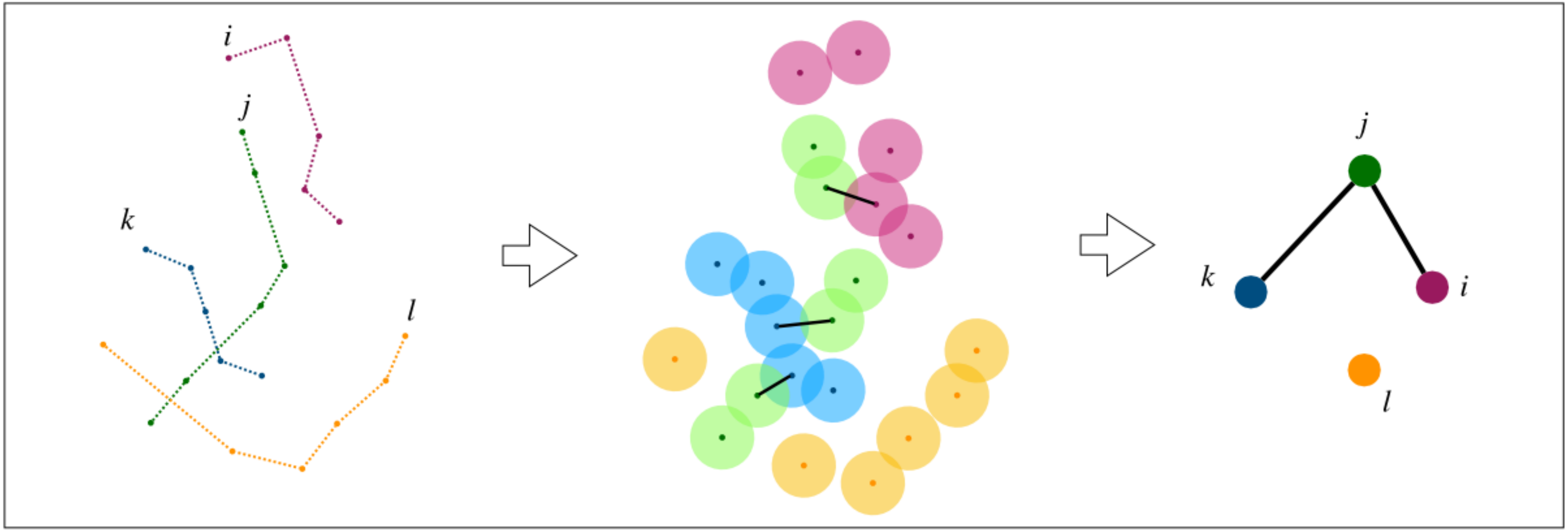


Lifting the lockdown

The radius of gyration increased after the lift of the restrictions, but it has not reached pre-outbreak levels yet
(as of May 22, 2020)

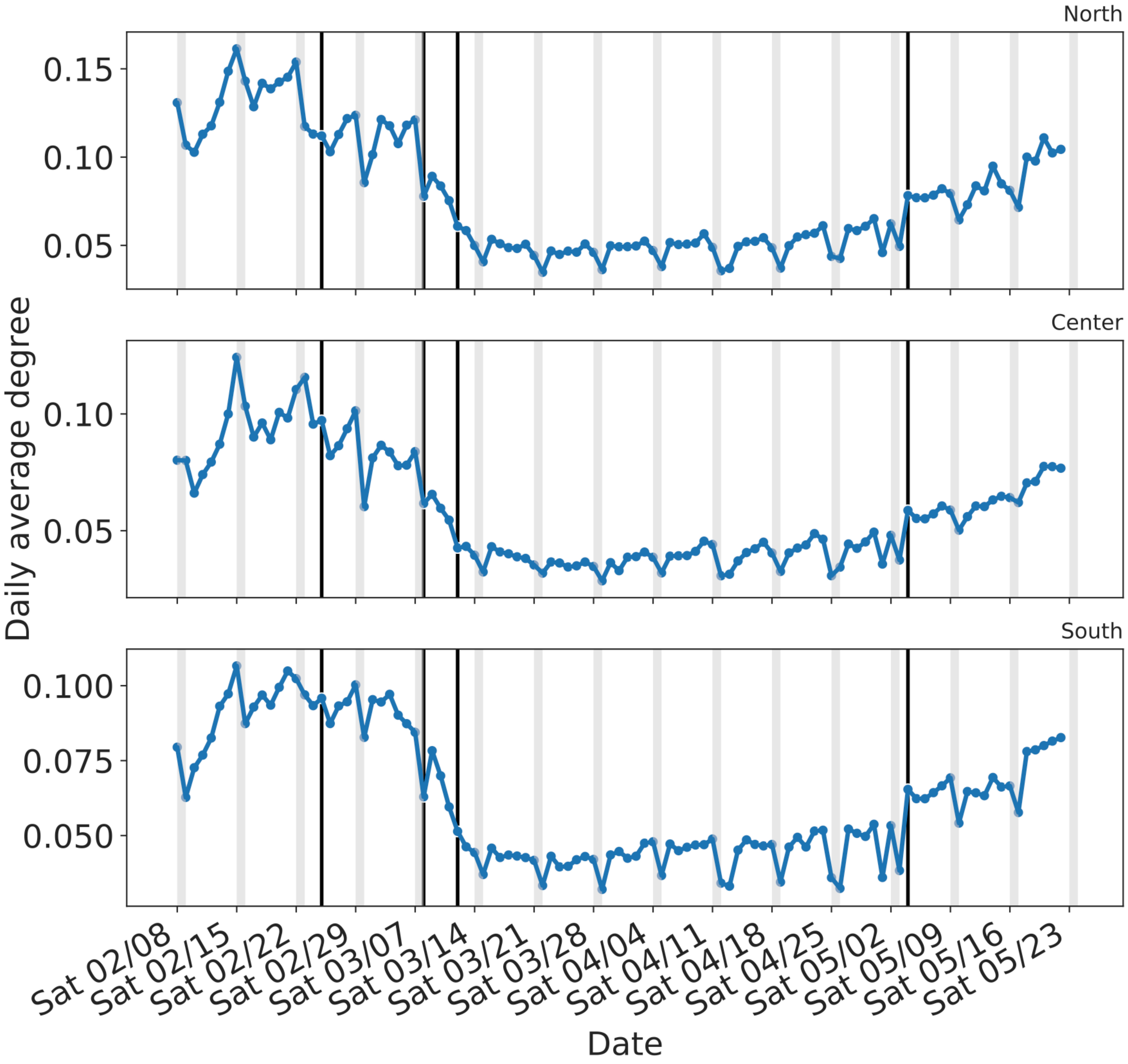


Spatial proximity



radius = 50 m
time interval = 1 h

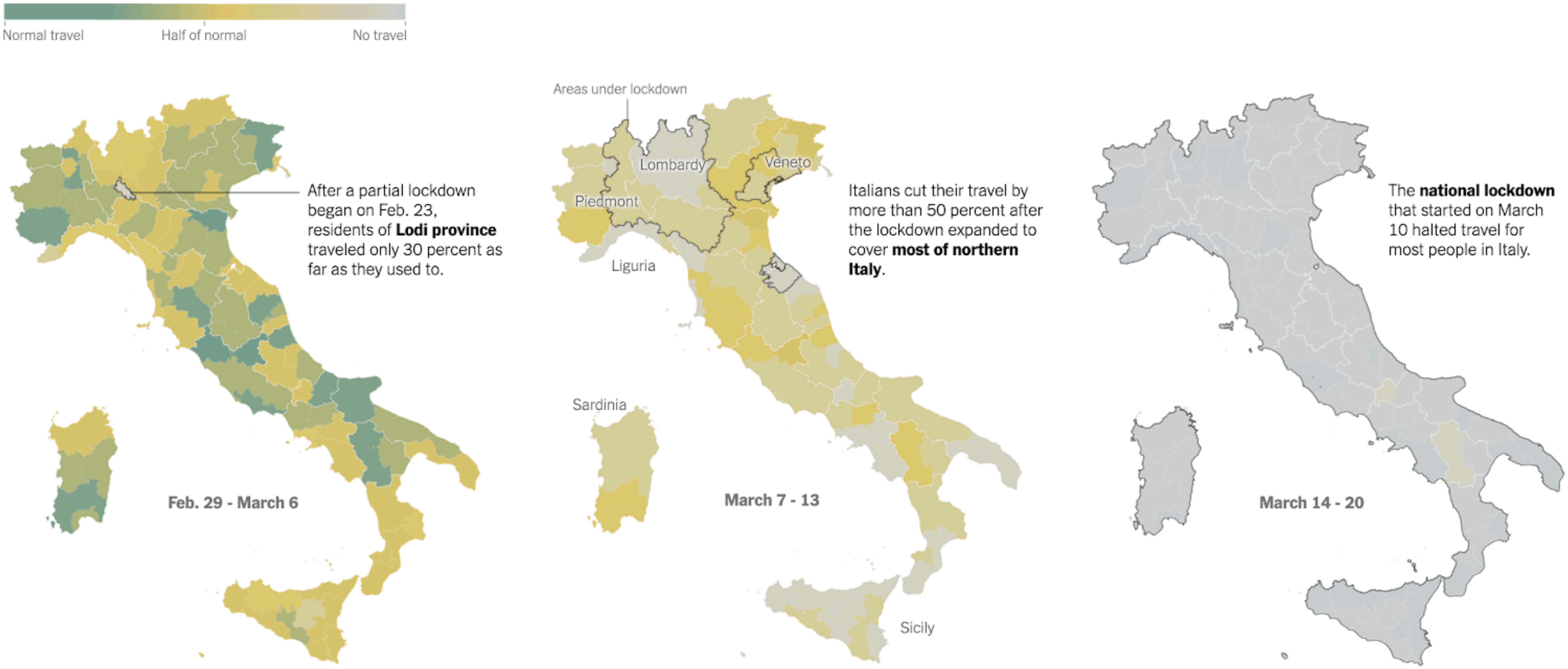
$$\langle k \rangle = 2E/N$$



- Reduction of about 80% during the lockdown, similar to Wuhan
- Weekly patterns with strong reductions during weekends
- After the ease of the restrictions (May 4), the increase of proximity is gradual
- In phase 2, the reduction of proximity during weekends is less marked

Media coverage

The lockdowns reduced **how far people traveled** compared with travel before the outbreak.



Note: To calculate reductions in travel, researchers drew a circle around all the points individuals visited in each period. Reductions in each province reflect the change in the median per-person distance traveled. ▪ Source: Data compiled for The New York Times based on a paper by Pepe et al.

Santiago de Chile

COVID-19 in Santiago

3 March 2020

Patient Zero

SARS-CoV-2 is first detected in Chile

16 March 2020

First Restrictions

Schools closing, banning of public gatherings, isolation of passengers from high-risk countries

15 May 2020

Full Lockdown

After case increase, a full lockdown is extended to the whole Metropolitan Region of Santiago

1 Sept 2020

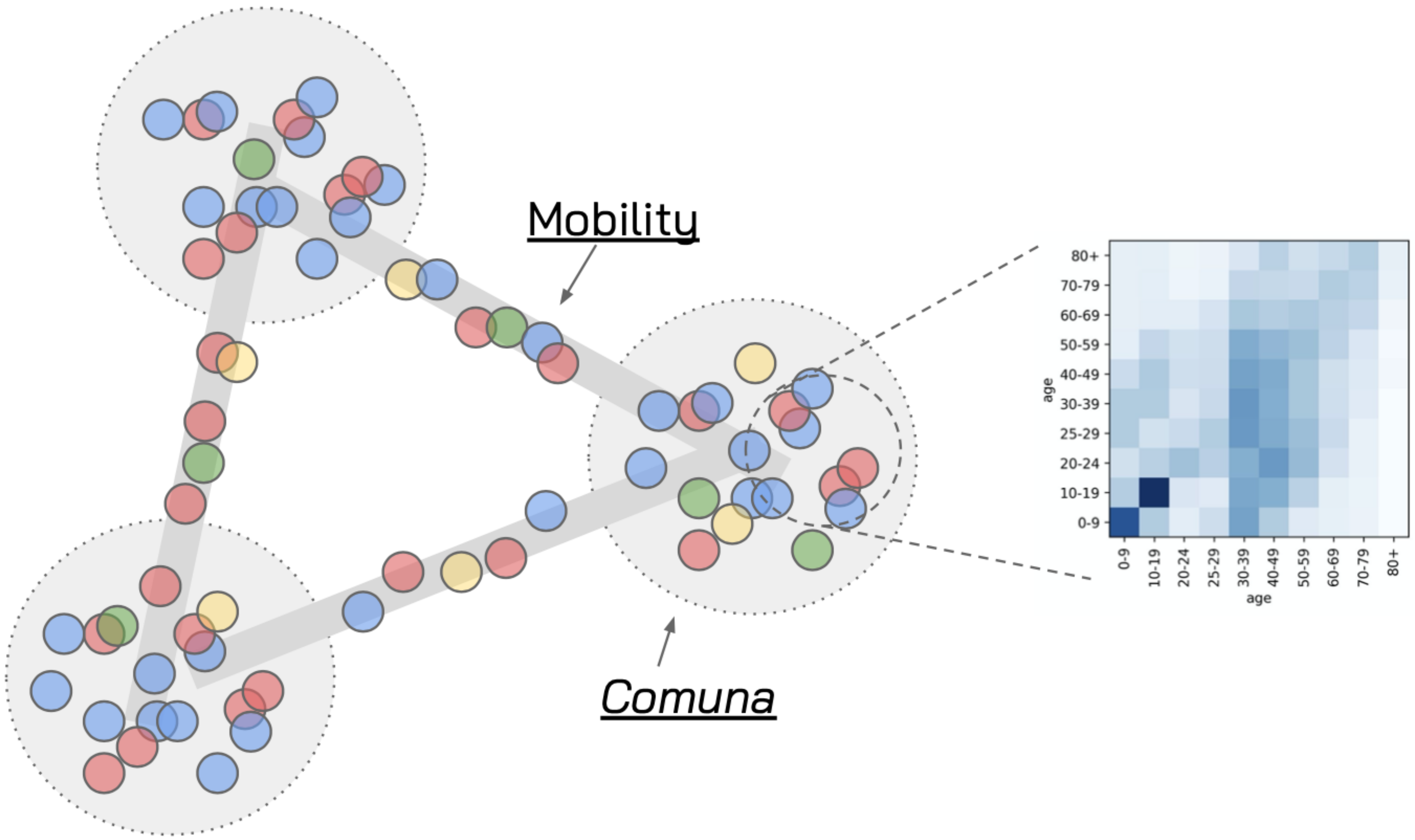
274,145 Total Cases
8,559 Total Deaths

As comparison, at the same date Italy reported 270,189 cases

Mobile phone data and modeling

We use data from Telefonica Movistar: 1.4M individuals (22% population of Santiago)

Build an epidemic model that includes mobility patterns between *comunas* inferred from mobile phone data



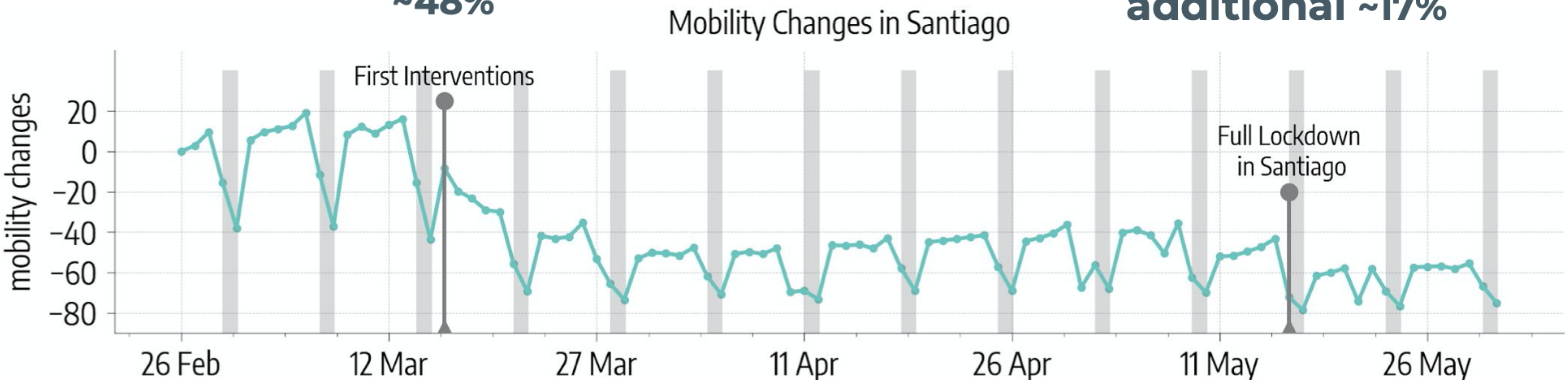
Mobility and restrictions

Drop after first interventions:

~48%

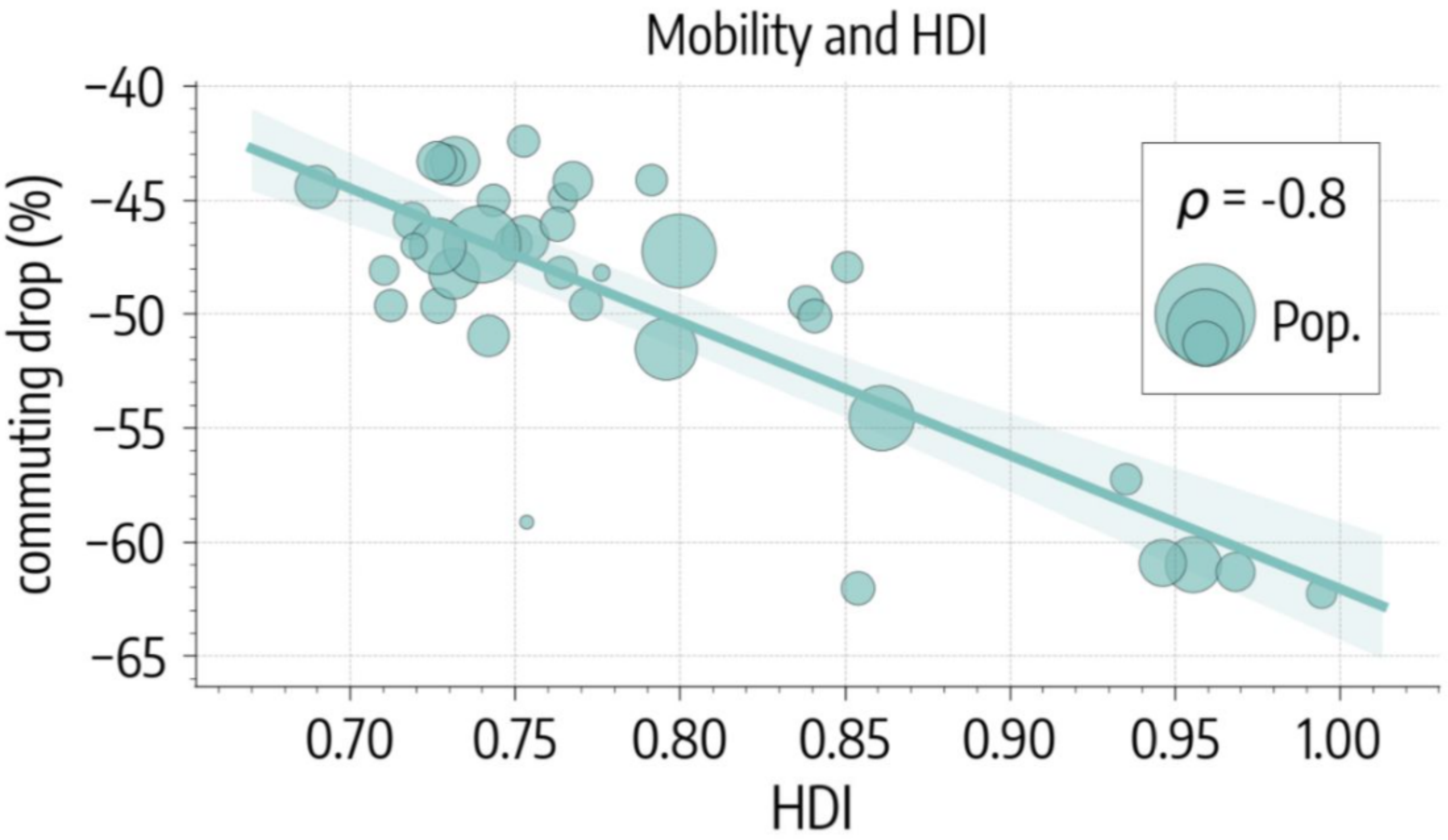
Drop after full lockdown:

additional ~17%



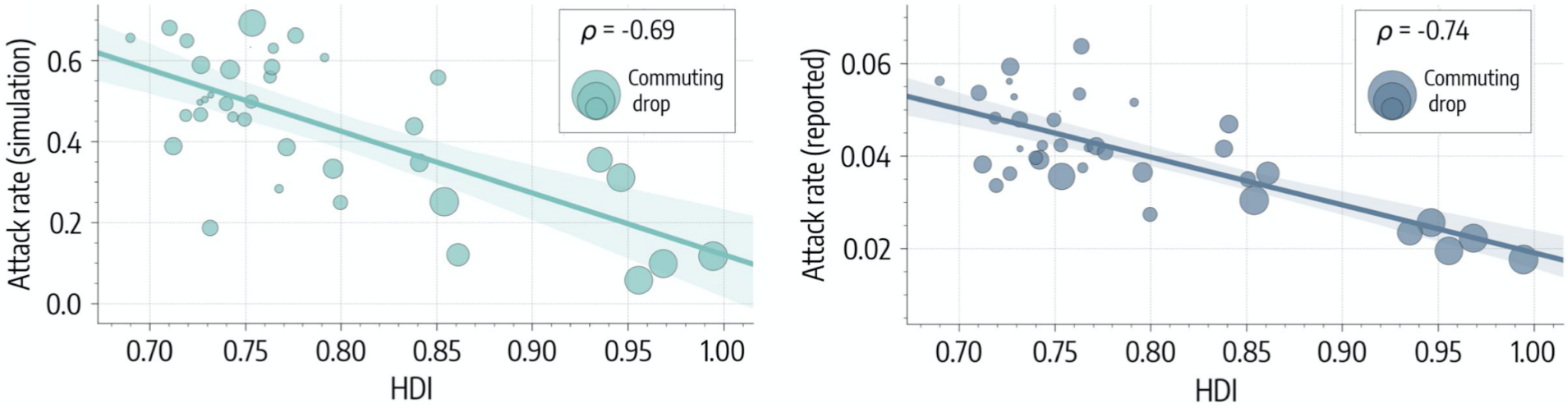
Socioeconomic effects on mobility

- Unequal distribution of mobility changes
- Wealthier *comunas* afforded larger reductions in mobility



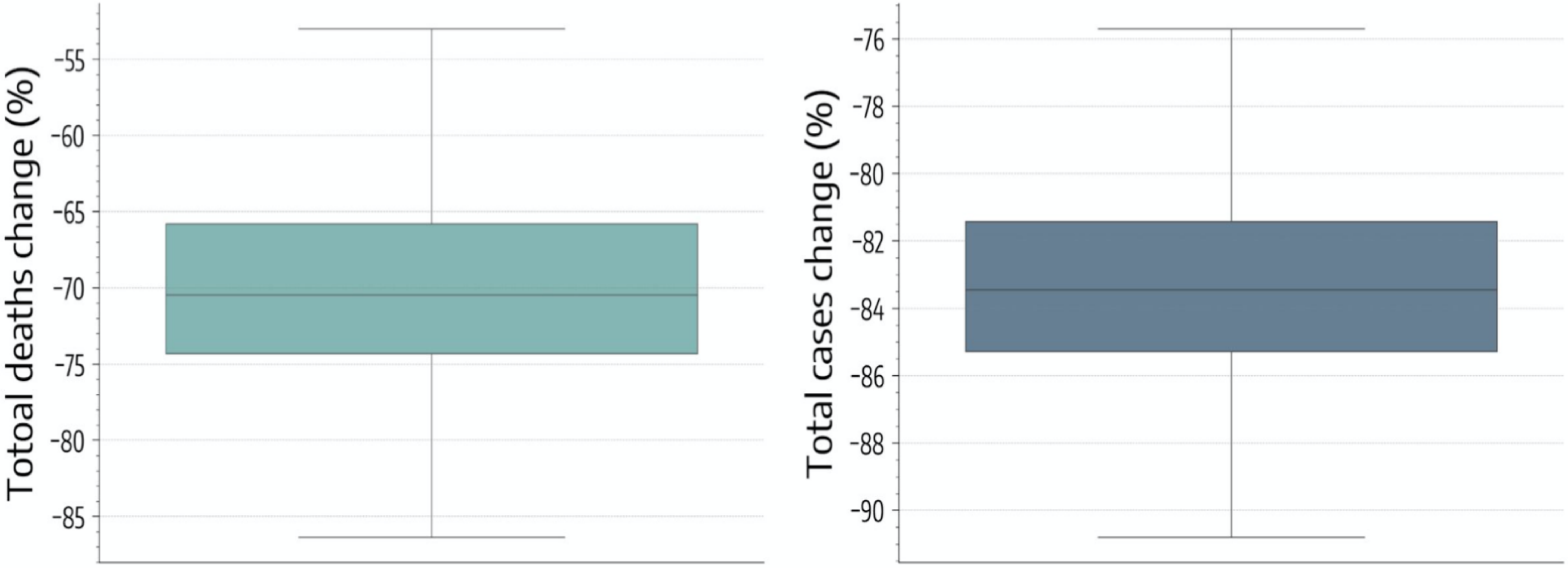
HDI = Human Development Index

Epidemic consequences



Wealthier *comunas* experienced significantly smaller outbreaks

Counterfactual



If every *comunas* could afford the same mobility reduction of the 25% wealthiest ones, 70% of deaths could have been averted.

Next… temporal networks