Urban Complexity

—

From hidden universalities to predictive models

Markus Schläpfer

Future Cities Laboratory, Singapore-ETH Centre
School of Computer Science and Engineering, NTU

Guest Lecture

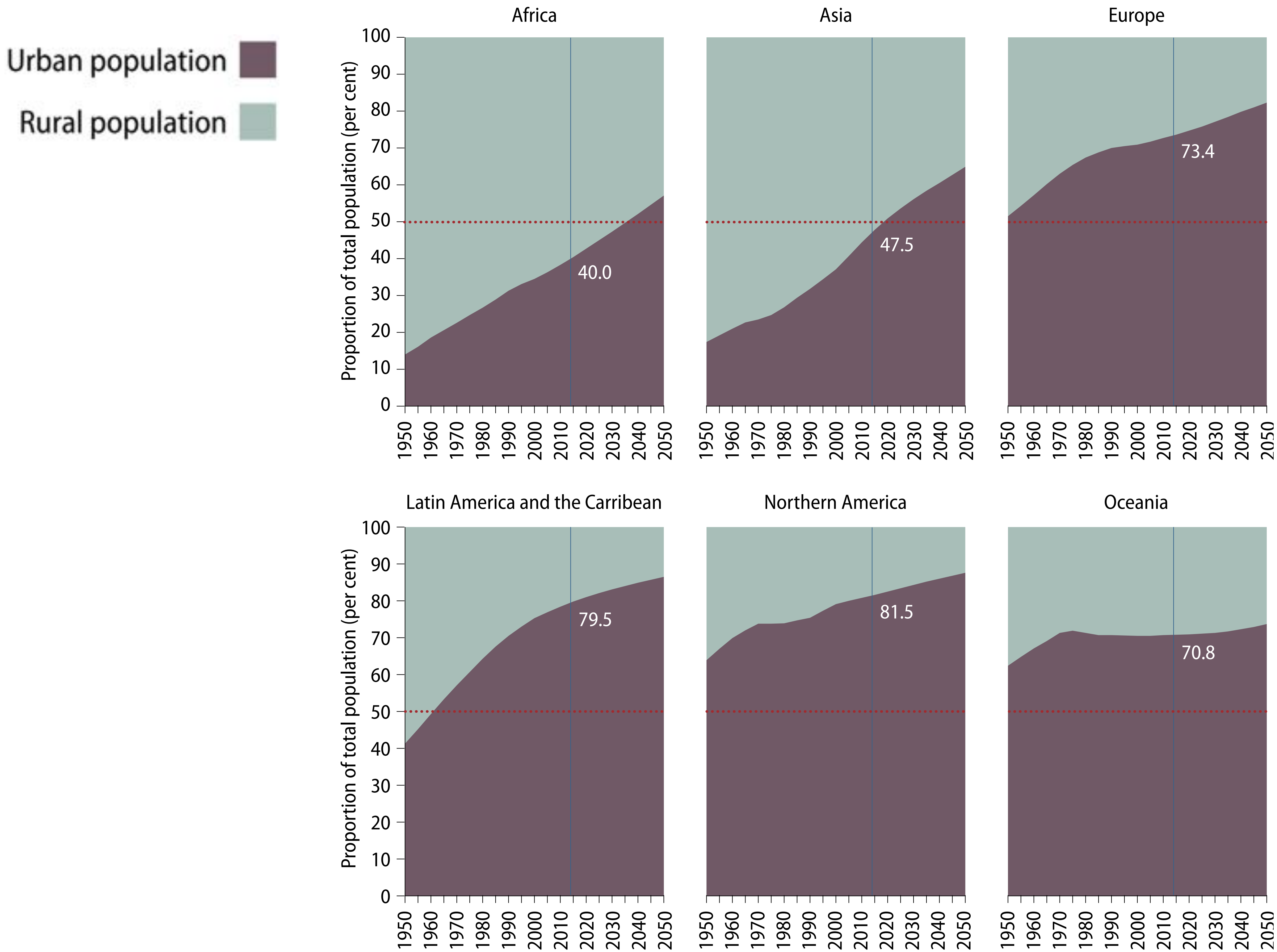
Chair of Information Architecture, ETH Zurich

April 3, 2017

Mortula / shutterstock.com

Ever-increasing complexity of cities

A. Population growth and mass urbanization



UN Population Division, 2015

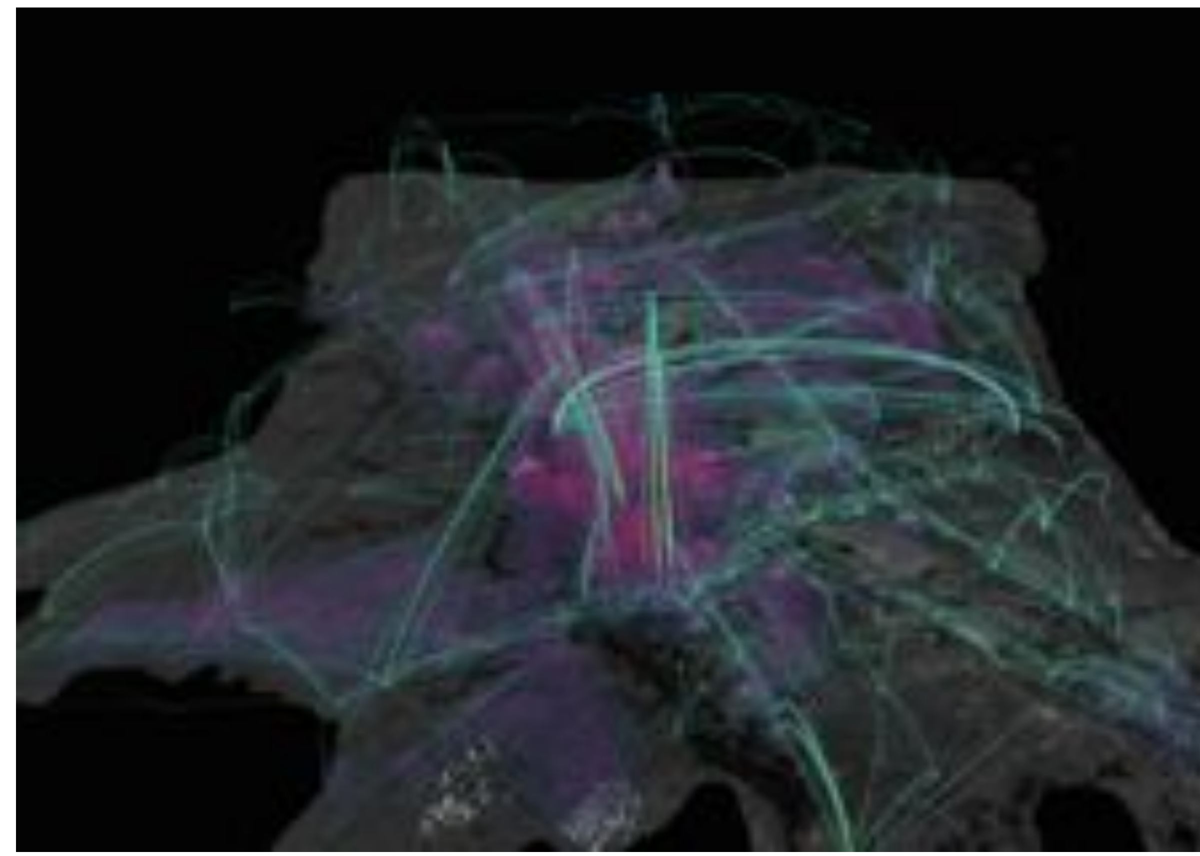
Ever-increasing complexity of cities

B. New forms of urban organization

Monocentricity

Univ. Munster

Polycentricity



MIT/Senseable City Lab, Kael Greco

Increasing uncertainties in urban planning and design

- Urban mobility
- Infrastructure design
- Social sustainability
  (social segregation, job accessibility)
- …

Urgent need for a quantitative *understanding* of cities

Content

1. Complexity science in a nutshell
2. Urban scaling laws
3. Urban mobility
4. Application: infrastructure design

Content

1. **Complexity science in a nutshell**
2. Urban scaling laws
3. Urban mobility
4. Application: infrastructure design

What are Complex Systems?

Examples in biology

daraka / shutterstock.com

(see MOOC on Smart Cities)

What are Complex Systems?

Examples in biology

daraka / shutterstock.com

vitstudio / shutterstock.com

What are Complex Systems?

Properties

1. Many (relatively simple) components

Adapted from:
Complexity Explorer - „Introduction to Complexity“
Santa Fe Institute, 2016 (www.complexityexplorer.org)

What are Complex Systems?

Properties

1. Many (relatively simple) components
2. Nonlinear interactions (including feedback loops)

Adapted from:
Complexity Explorer - „Introduction to Complexity“
Santa Fe Institute, 2016 (www.complexityexplorer.org)

What are Complex Systems?

Properties

1. Many (relatively simple) components
2. Nonlinear interactions (including feedback loops)
3. No centralized control

Adapted from:
Complexity Explorer - „Introduction to Complexity“
Santa Fe Institute, 2016 (www.complexityexplorer.org)

What are Complex Systems?

Properties

1. Many (relatively simple) components
2. Nonlinear interactions (including feedback loops)
3. No centralized control
4. Emergent behavior
5. Evolution and adaptation

Adapted from:
Complexity Explorer - „Introduction to Complexity“
Santa Fe Institute, 2016 (www.complexityexplorer.org)

What is Complexity Science?

Goals and Approach

Goals:

- To reveal **regularities** in the overall behavior of complex systems
- To derive **simple (mathematical) rules** that are able to explain and predict these regularities

Approach:

- System-level approach („big picture view“)
- Methods: Scaling, network theory, agent-based modeling, non-equilibrium dynamics, …
- Learning from different scientific disciplines

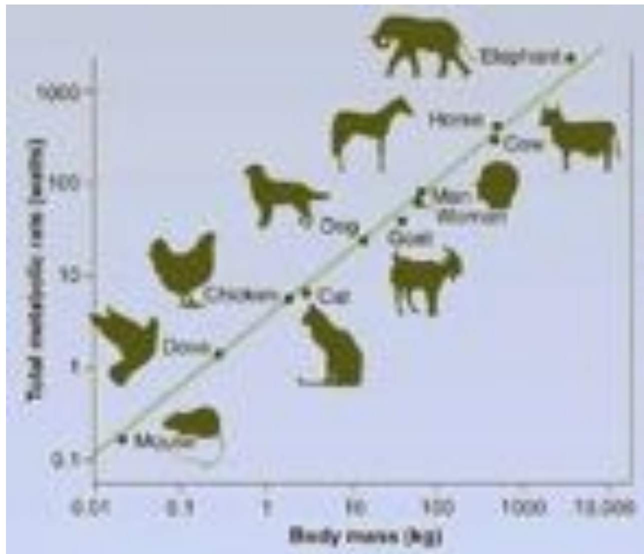
Growing availability of human activity data

- Mobile phone data
- Smart card data from public transportation
- GPS traces from vehicular devices
- Location-based social networks

  (Foursquare, Twitter, Flickr, Running Apps, etc.)
- User-generated mapping projects (OpenStreetMap)
- Open data provided by city governments
- ….

Content

The scaling of socio-economic quantities with city size



Luís M.A. Bettencourt

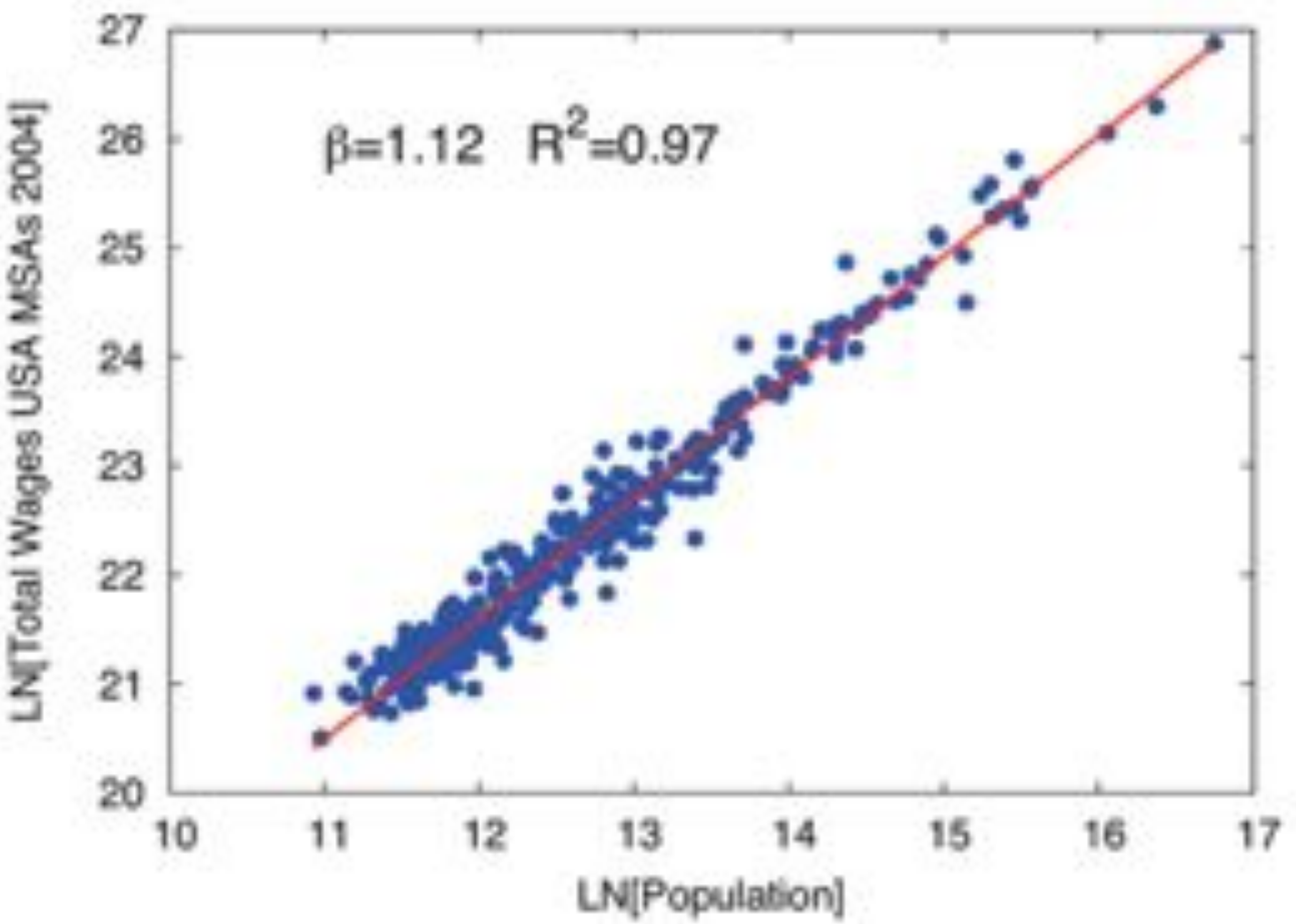
Geoffrey B. West

$$Y \propto N^{\beta}$$

Exponent

City population size

Socio-economic quantity
(wages, patents, crime,
AIDS cases etc.)



$$\beta \approx 1.15 > 1$$

L.M.A. Bettencourt et al.
Proc. Natl. Acad. Sci. USA (2007)

Greater population —
„faster life and greater dividends“

Y	β	95% CI	Adj-R^2	Observations	Country–year
New patents	1.27	[1.25,1.29]	0.72	331	U.S. 2001
Inventors	1.25	[1.22,1.27]	0.76	331	U.S. 2001
Private R&D employment	1.34	[1.29,1.39]	0.92	266	U.S. 2002
″Supercreative″ employment	1.15	[1.11,1.18]	0.89	287	U.S. 2003
R&D establishments	1.19	[1.14,1.22]	0.77	287	U.S. 1997
R&D employment	1.26	[1.18,1.43]	0.93	295	China 2002
Total wages	1.12	[1.09,1.13]	0.96	361	U.S. 2002
Total bank deposits	1.08	[1.03,1.11]	0.91	267	U.S. 1996
GDP	1.15	[1.06,1.23]	0.96	295	China 2002
GDP	1.26	[1.09,1.46]	0.64	196	EU 1999–2003
GDP	1.13	[1.03,1.23]	0.94	37	Germany 2003
Total electrical consumption	1.07	[1.03,1.11]	0.88	392	Germany 2002
New AIDS cases	1.23	[1.18,1.29]	0.76	93	U.S. 2002–2003
Serious crimes	1.16	[1.11, 1.18]	0.89	287	U.S. 2003

≈15% per capita increase in wages, GDP, patents etc.
for each doubling of city size

L.M.A. Bettencourt et al.
Proc. Natl. Acad. Sci. USA (2007)

Network of human interactions as a unifying mechanism?

Growing availability of human activity data

- Mobile phone data

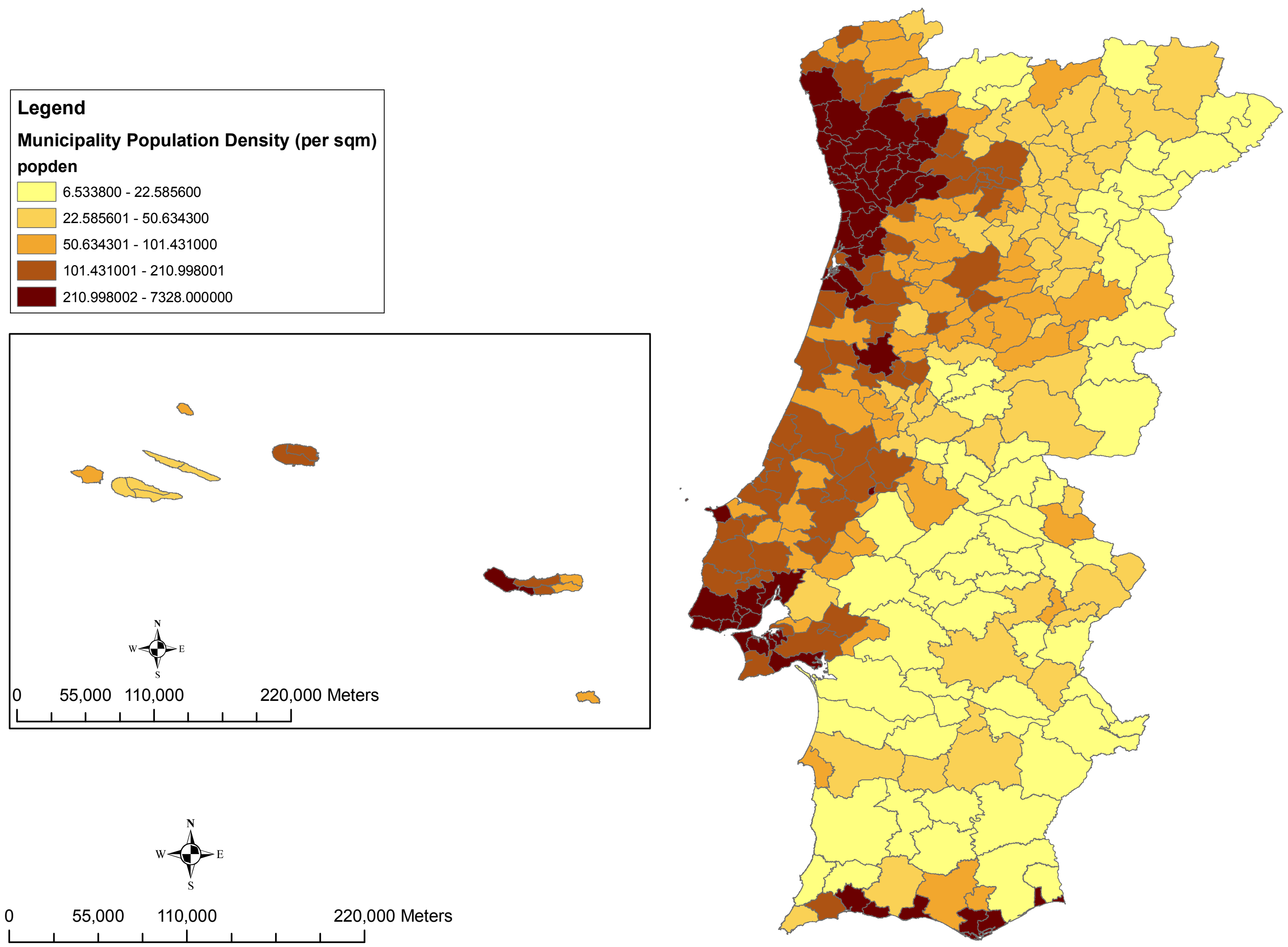
Mobile phone data - exemplary data sources

- Open data
  - *Italy* - Telecom Italia Open BigData Initiative
    http://theodi.fbk.eu/openbigdata

- Big data research competitions
  - *Ivory Coast* - Orange D4D Challenge 2013
    http://www.d4d.orange.com/en/Accueil
  - *Senegal* - Orange D4D Challenge 2015
    http://www.d4d.orange.com/en/Accueil
  - *Italy* - Telecom Italia BigData Challenge 2015
    http://www.telecomitalia.com/tit/en/bigdatachallenge.html

- (Telco providers and data analytics companies)

Lets look into the data!



Several millions of anonymized call detail records (CDRs) from Portugal for a period of ≈15 months

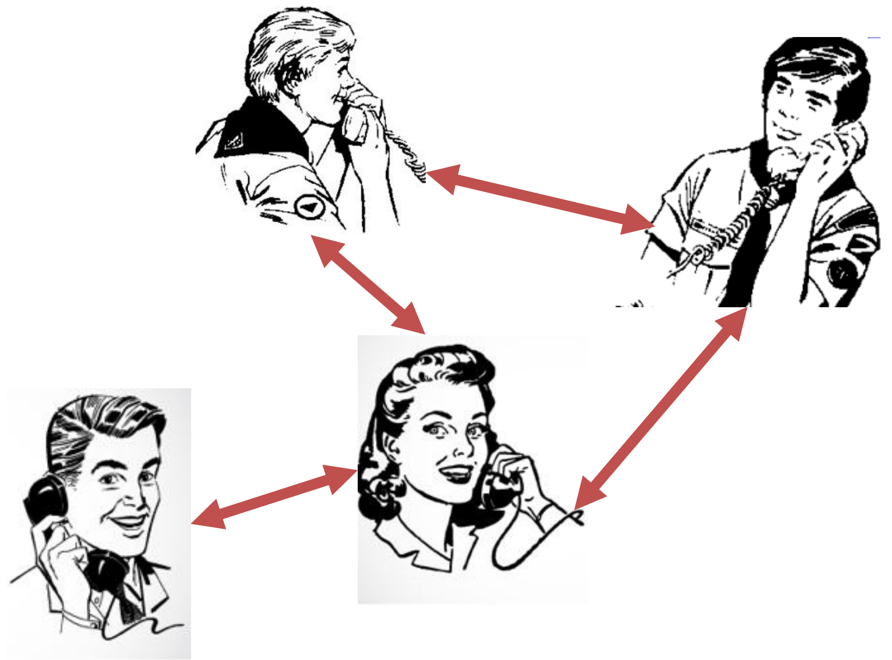
Call detail records (CDRs)

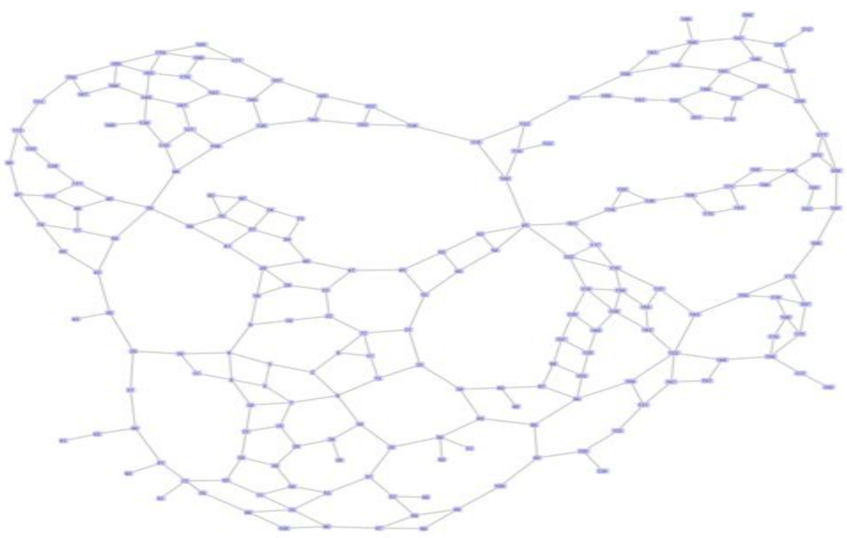
- Anonymized ID (surrogate number) of the caller
- Anonymized ID of the callee
- Start time of the call
- Duration of the call
- The locations of the antennas routing the call

Inferring the interaction network

Mobile phone user → Node

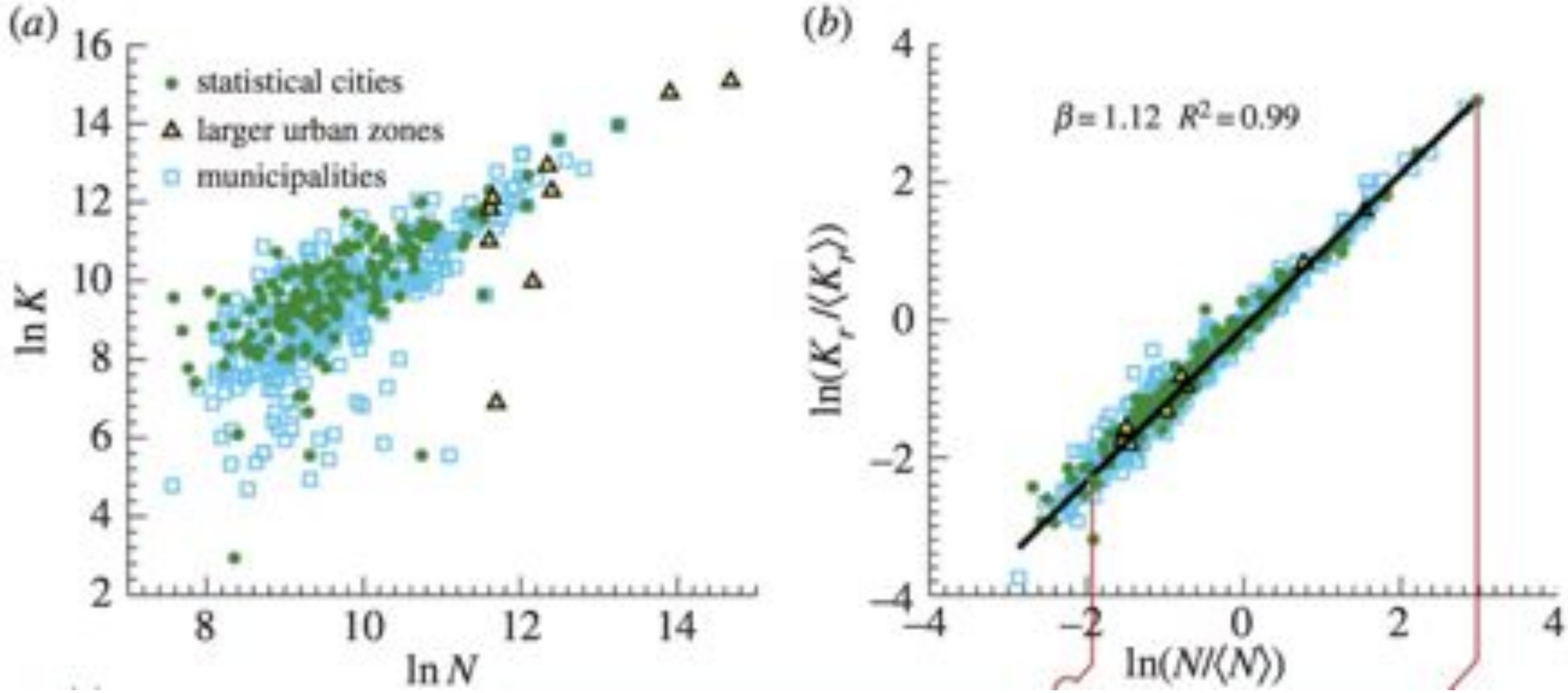
Reciprocal call between two users → Link



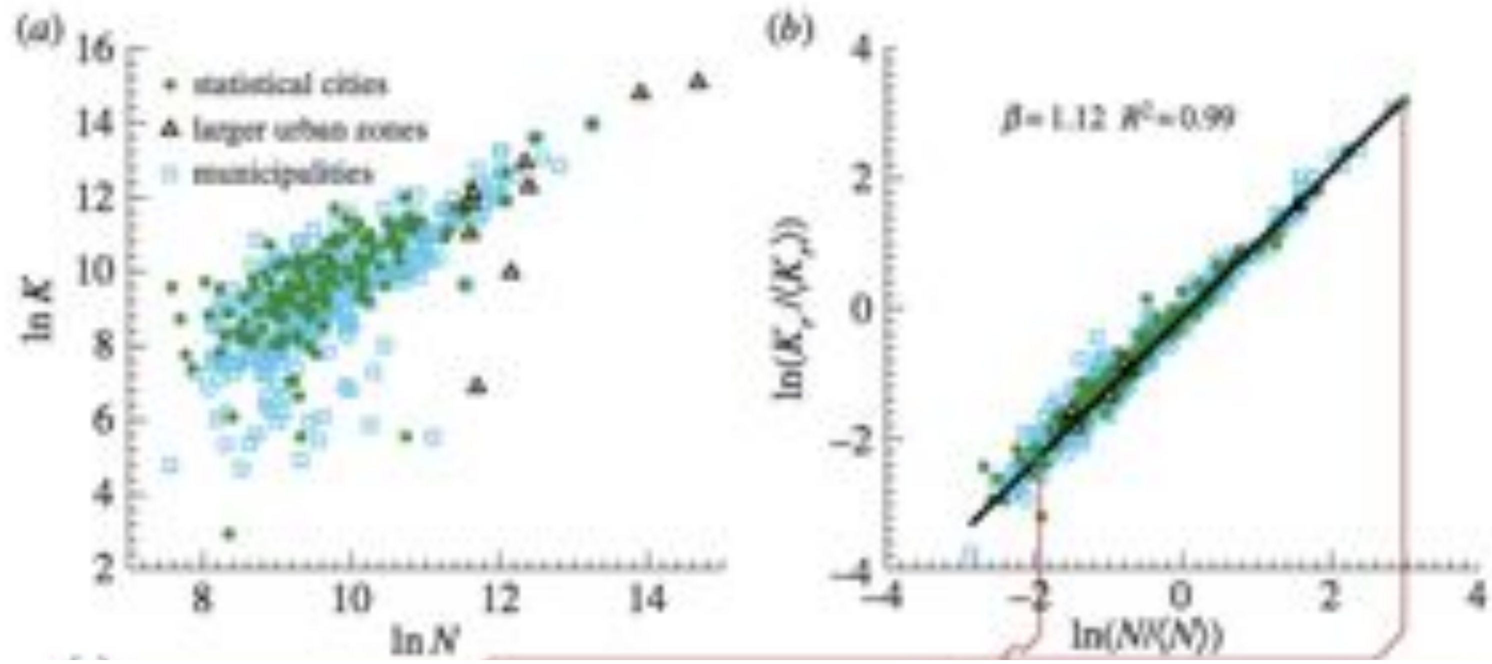


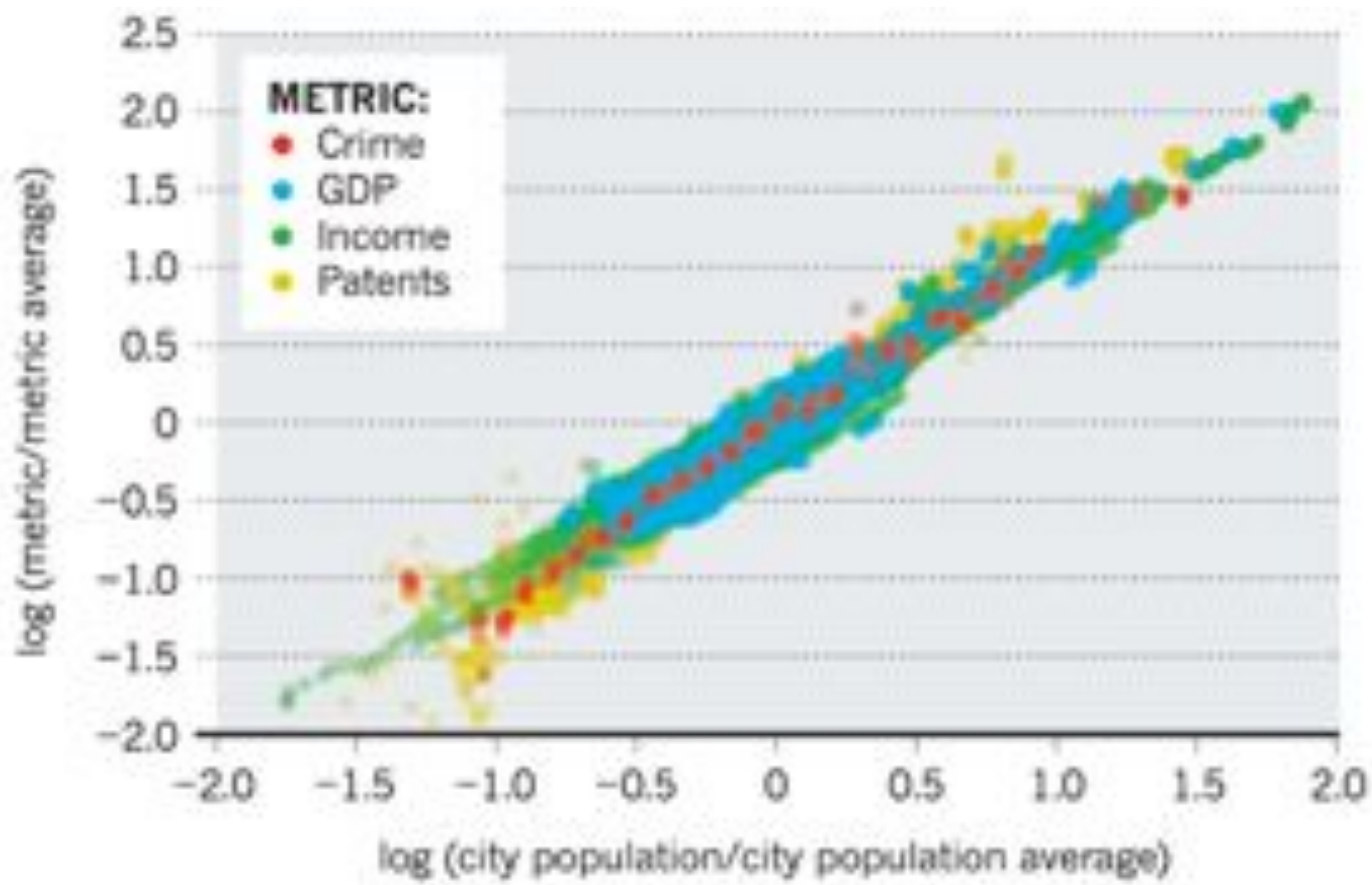
Portugal data:
1.6 Mio nodes
6.8 Mio links

$$K_r = K/s_{/}$$



(a)
statistical cities
larger urban zones
municipalities
ln K
ln N
(b)
β = 1.12 R² = 0.99
ln(K_r/⟨K_r⟩)
ln(N/⟨N⟩)


(a)
statistical cities
larger urban zones
municipalities
ln K
ln N
(b)
β = 1.12 R² = 0.99
ln(K_r/⟨K_r⟩)
ln(N/⟨N⟩)

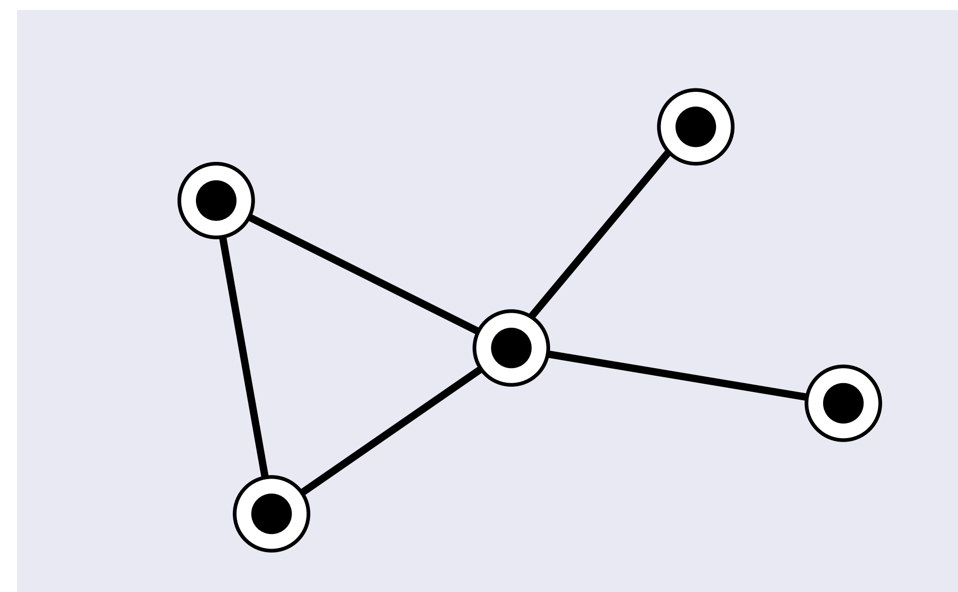

METRIC:
Crime
GDP
Income
Patents
log (metric/metric average)
log (city population/city population average)

Nodal clustering

Clustering coefficient:
Probability that one‘s contacts are also connected with each other.

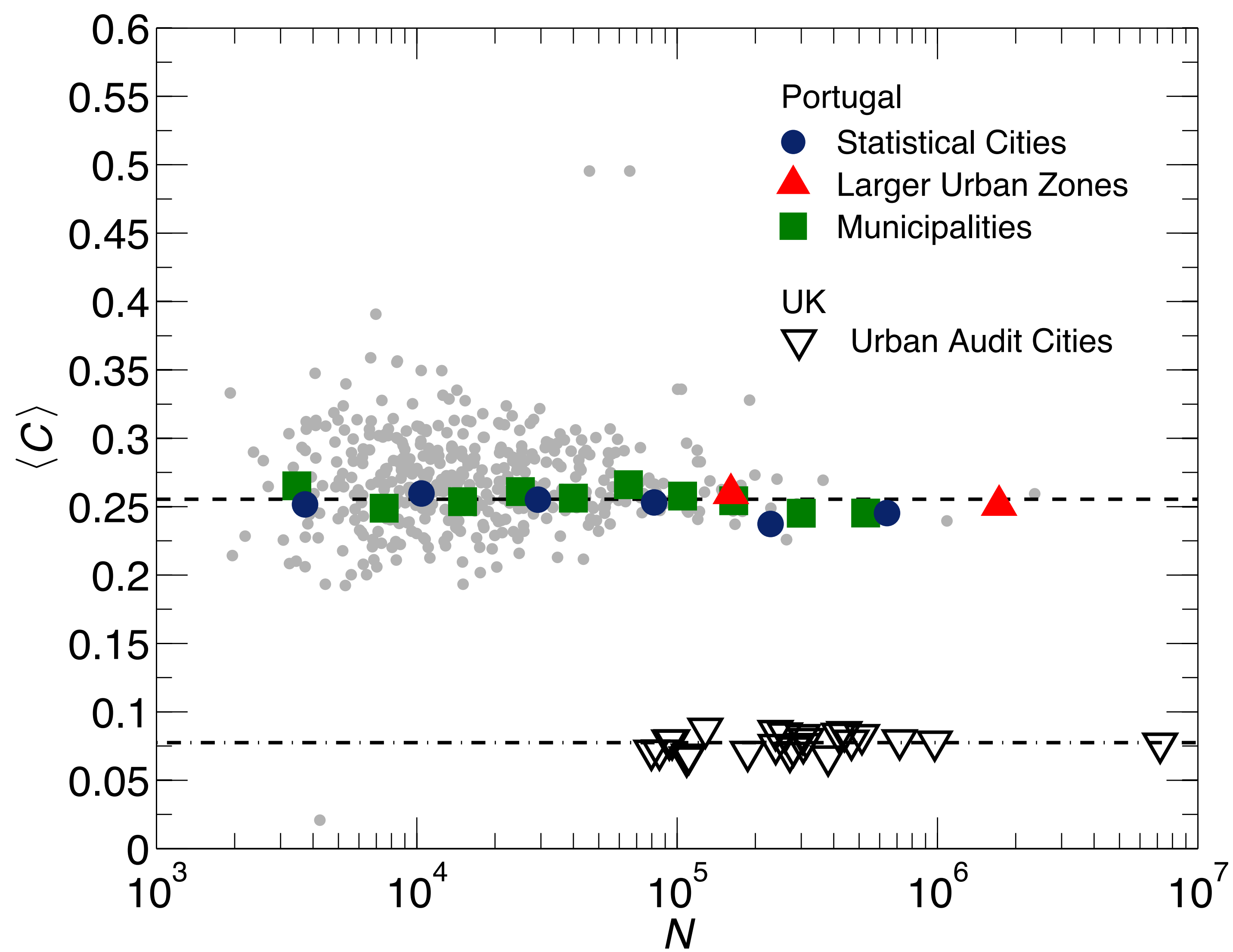
$$C_i \equiv 2z_i/[k_i(k_i-1)]$$

z_i Number of links between the k_i neighbours
k_i Degree of node i



As larger cities provide a larger pool of people, the clustering coefficient should decrease if contacts were established at random.

Nodal clustering



- Average clustering is an invariant of city size.
- Even in large cities we live in groups that are as tightly knit as those in small towns or 'villages'.

Schläpfer M. et al., J Royal Soc Interface, 11(98):20130789, 2014

Human interactions

Potential ‚hidden' biases

Important to test on many different data sets

- UK, mobile phones and landlines (Schläpfer et al. 2014)
- Ivory Coast, mobile phones (Andris and Bettencourt, 2014)
- France and Portugal (Deville, 2014)
- „Unnamed" European Country, mobile phones (Llorente, 2015)
- US and Europe, Twitter data (Tizzoni, 2015)
- Switzerland, mobile phones (Büchel and von Ehrlich, 2016)

Building Heights and Shapes

PERSPECTIVE

Building functional cities

J. Vernon Henderson,[1*] Anthony J. Venables,[1,2] Tanner Regan,[1] Ilia Samsonov[1]

The literature views many African cities as dysfunctional with a hodgepodge of land uses and poor "connectivity." One driver of inefficient land uses is construction decisions for highly durable buildings made under weak institutions. In a novel approach, we model the dynamics of urban land use with both formal and slum dwellings and ongoing urban redevelopment to higher building heights in the formal sector as a city grows. We analyze the evolution of Nairobi using a unique high–spatial resolution data set. The analysis suggests insufficient building volume through most of the city and large slum areas with low housing volumes near the center, where corrupted institutions deter conversion to formal sector usage.

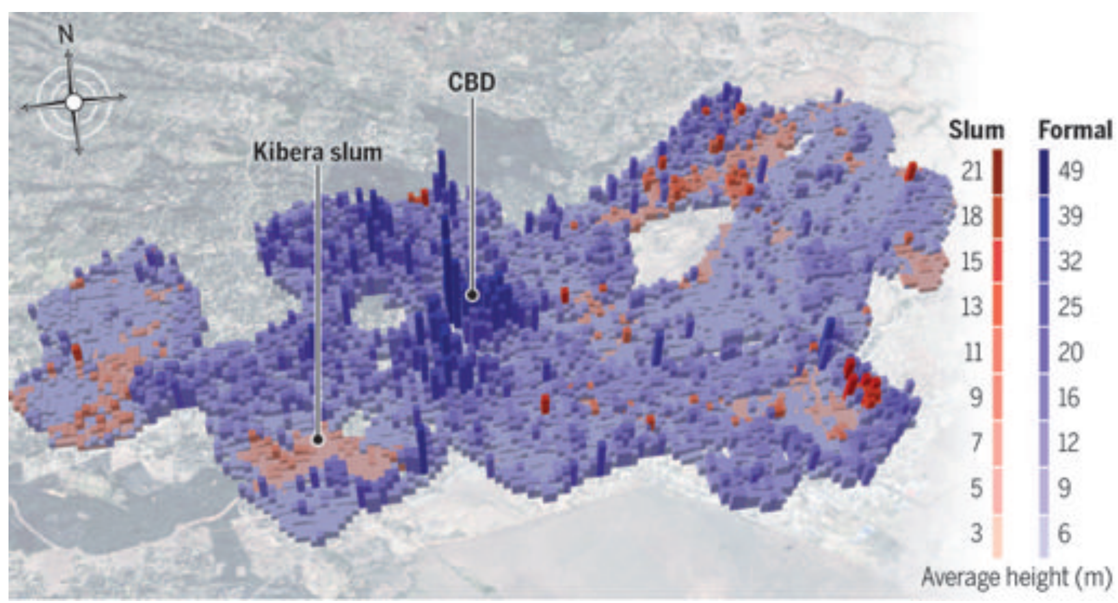
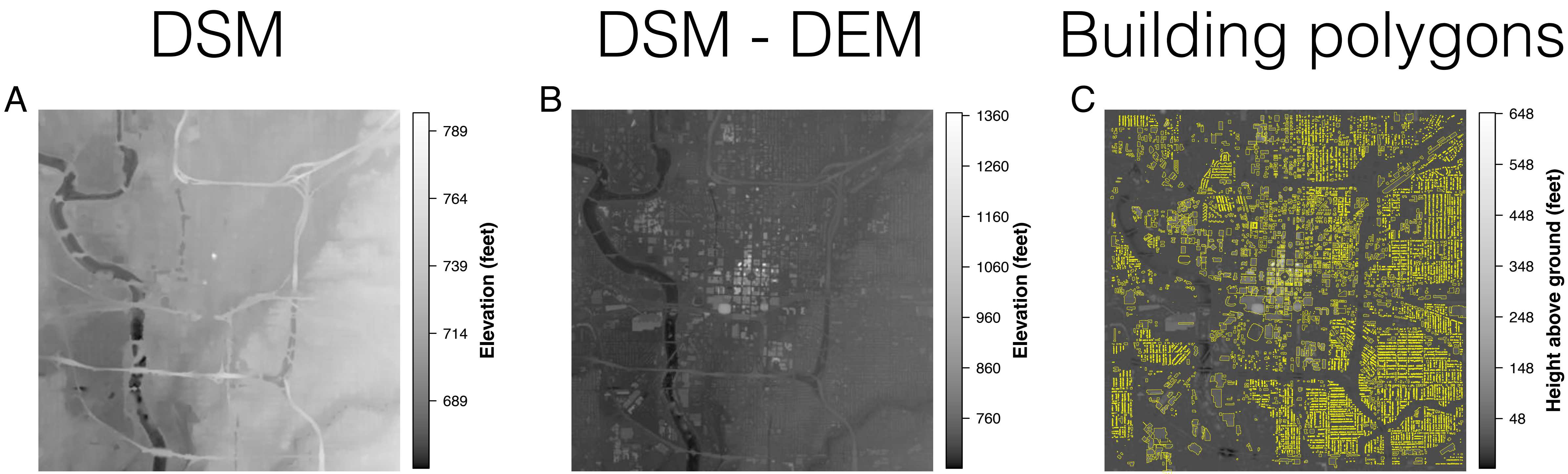


Fig. 1. City of Nairobi building height and distribution. Nairobi shows average built height in 2015 as 150-m by 150-m cells split across the formal and slum sectors. The compass (top left) points north. The location of the Kibera slum and the CBD are marked. The boundary of the city spans about 22 km east to west and 11 km north to south; the map tilt may distort the appearance of distances. Modified from HRV. [Background imagery Airbus Defense and Space 2016, taken from the SPOT5 satellite 20 September 2004].

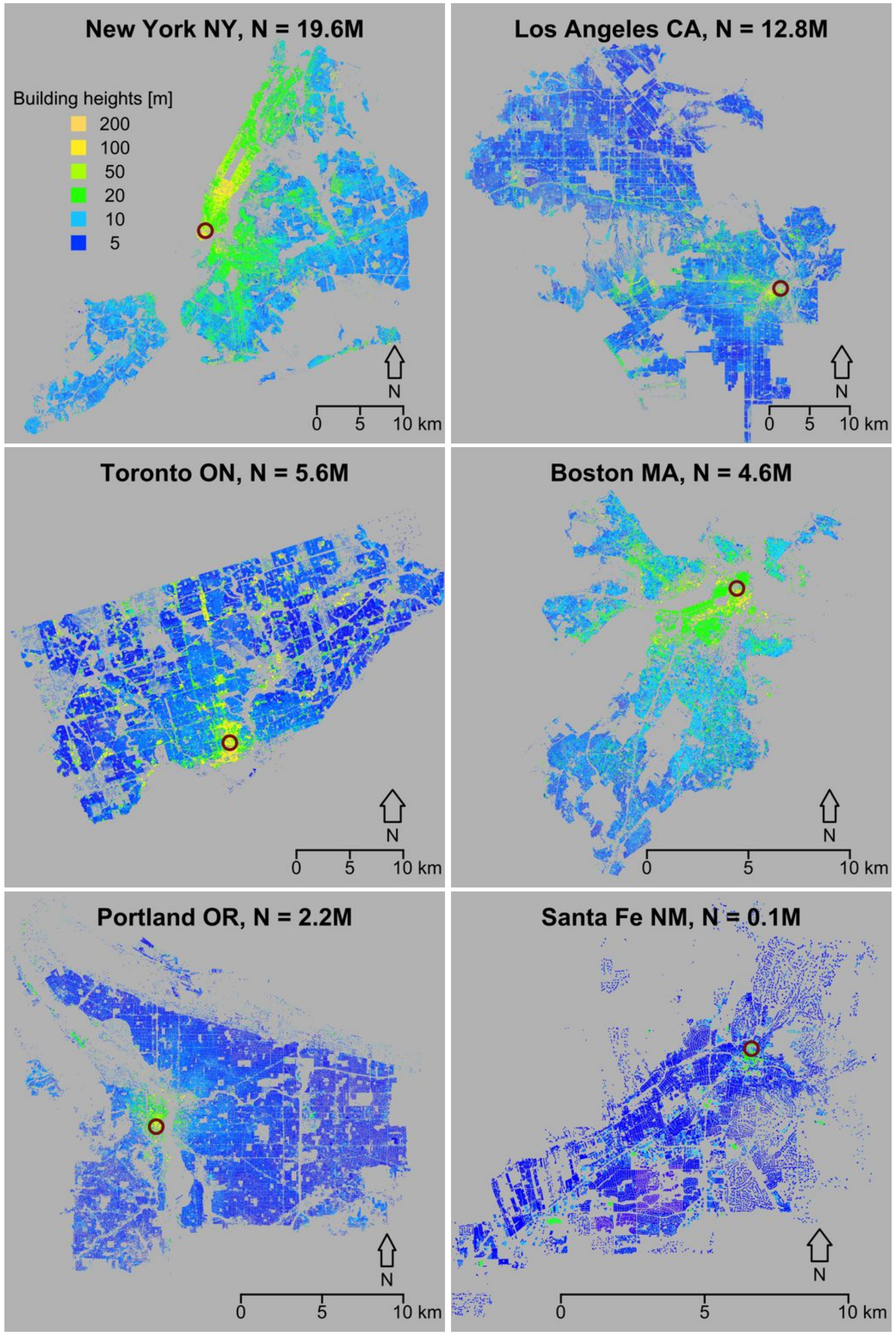
Generating simple 3D city models



DSM: Digital surface model
DEM: Digital elevation model

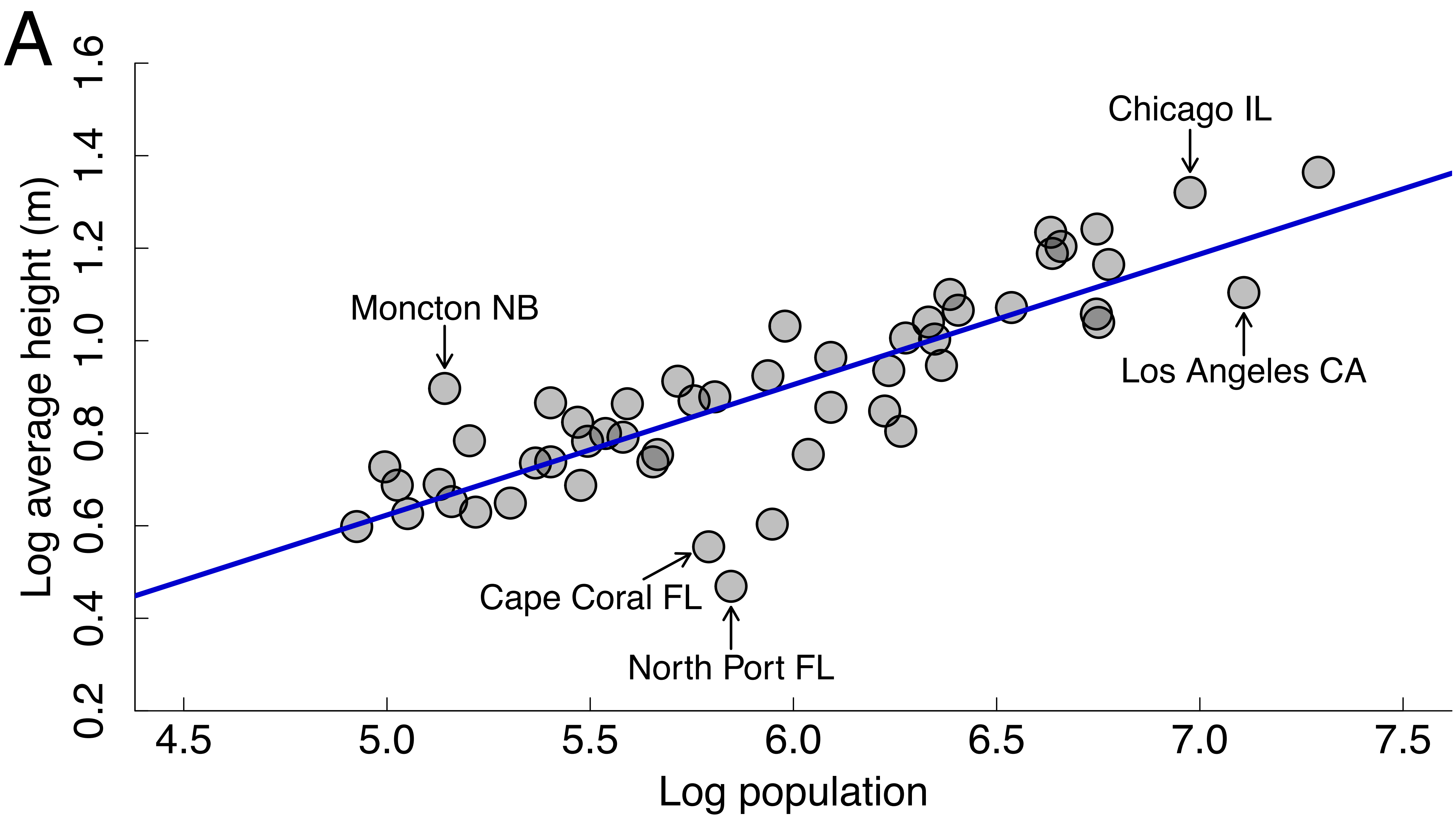
Schläpfer, Lee, Bettencourt, arXiv:1512.00946, 2015

Building heights



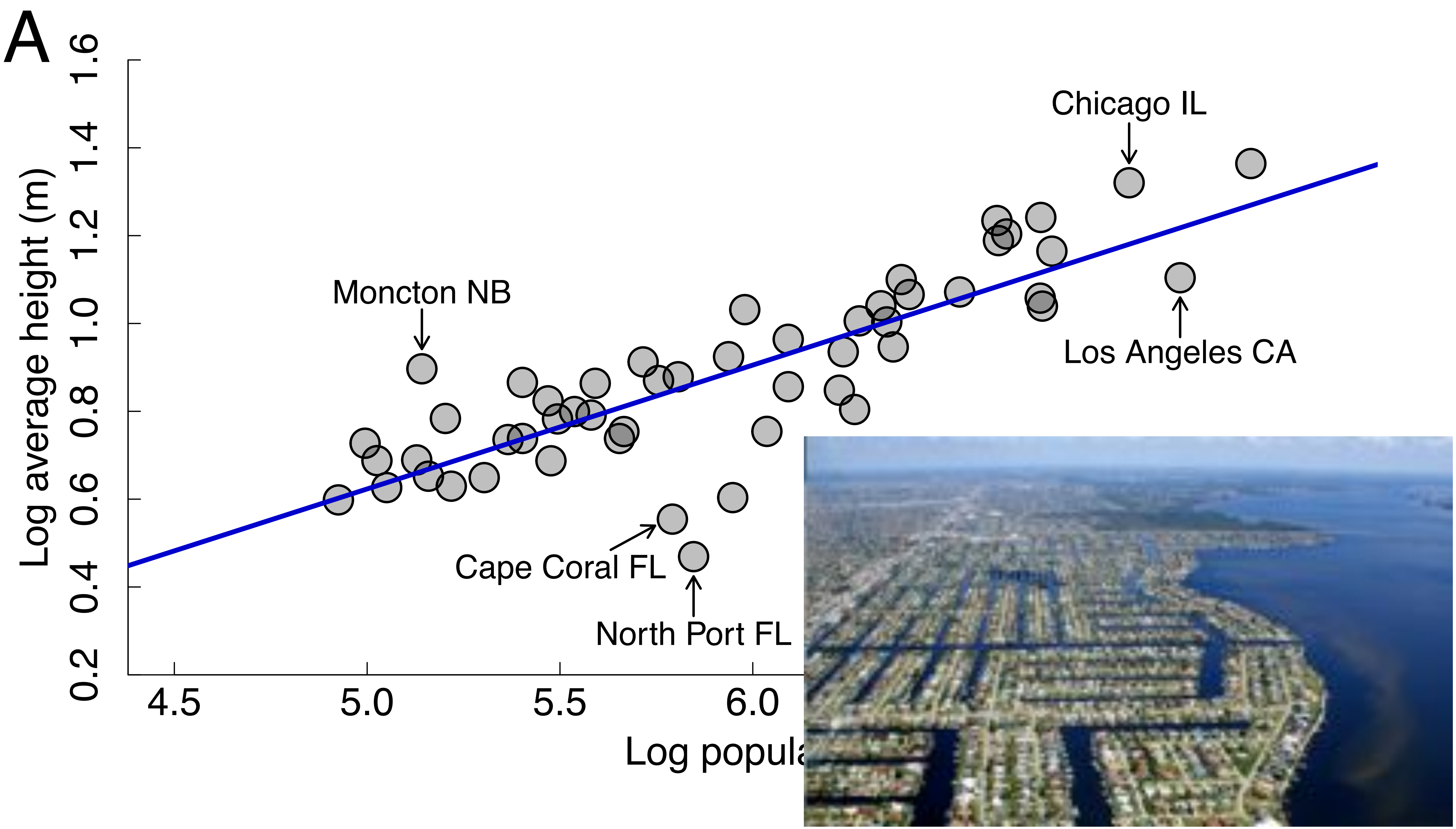
Schläpfer, Lee, Bettencourt, arXiv:1512.00946, 2015

Building heights



Schläpfer, Lee, Bettencourt, arXiv:1512.00946, 2015

Building heights



Schläpfer, Lee, Bettencourt, arXiv:1512.00946, 2015

Height prediction from urban scaling theory

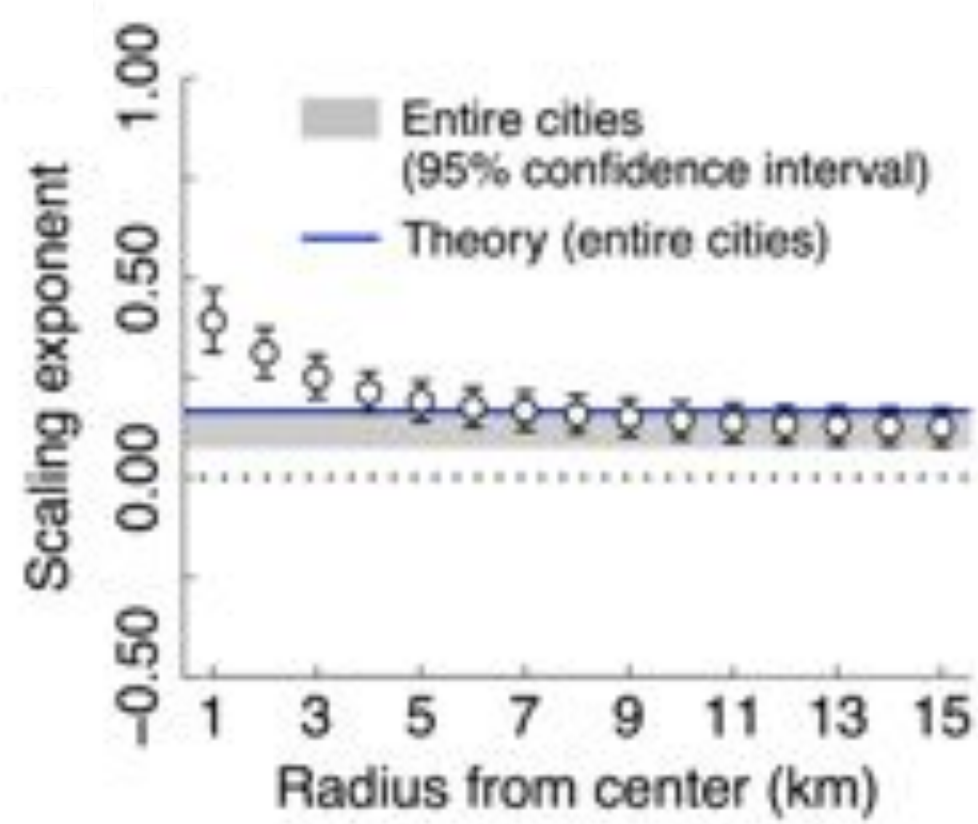
For cities to be **functional:**

$$\boxed{h \propto N^{1/6}}$$

Building height

Population size

Scaling exponent



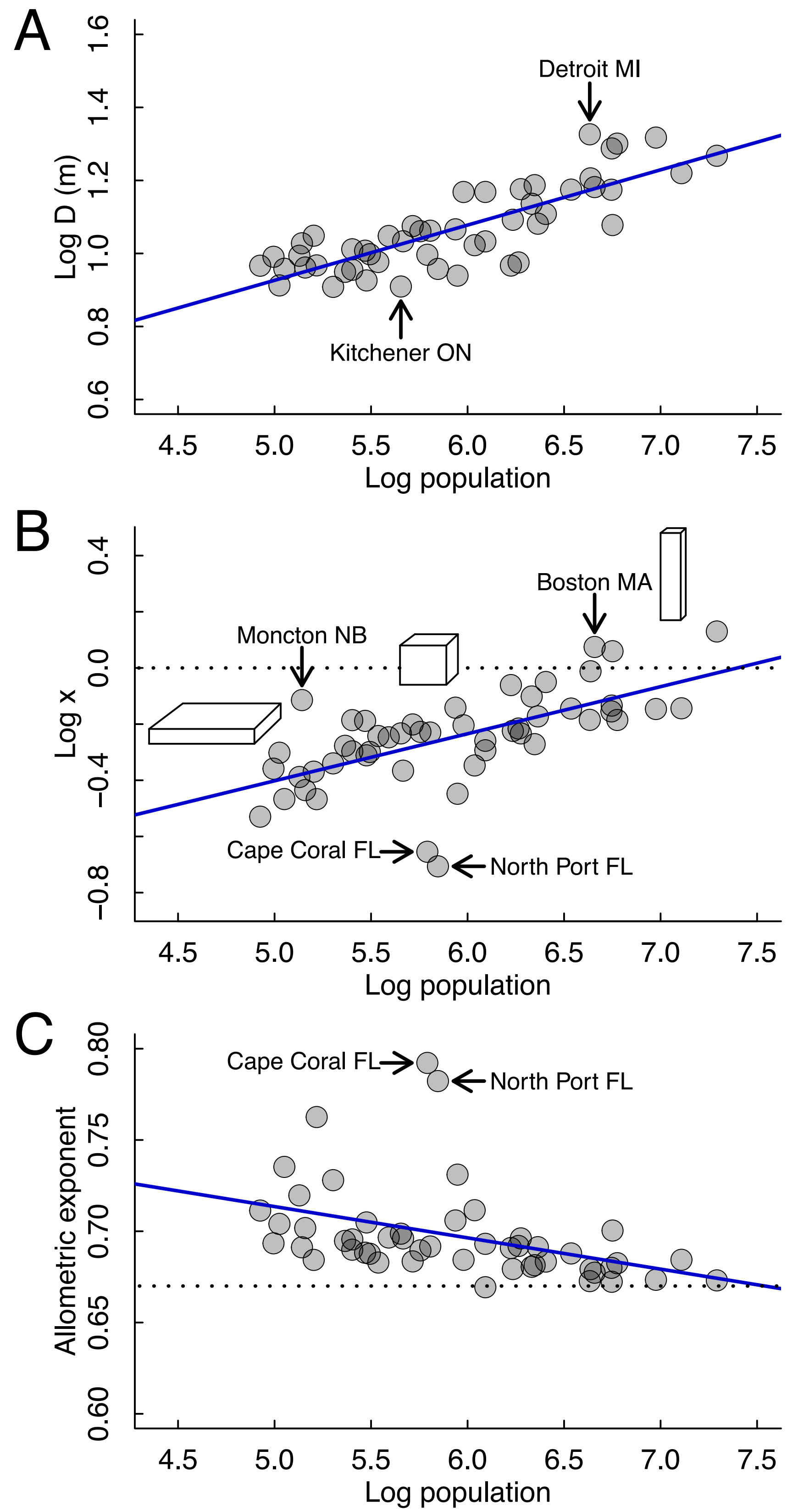
Schläpfer, Lee, Bettencourt, arXiv:1512.00946, 2015

Building shapes

Building volume

Building shape

Allometric scaling



Schläpfer, Lee, Bettencourt, arXiv:1512.00946, 2015

Content

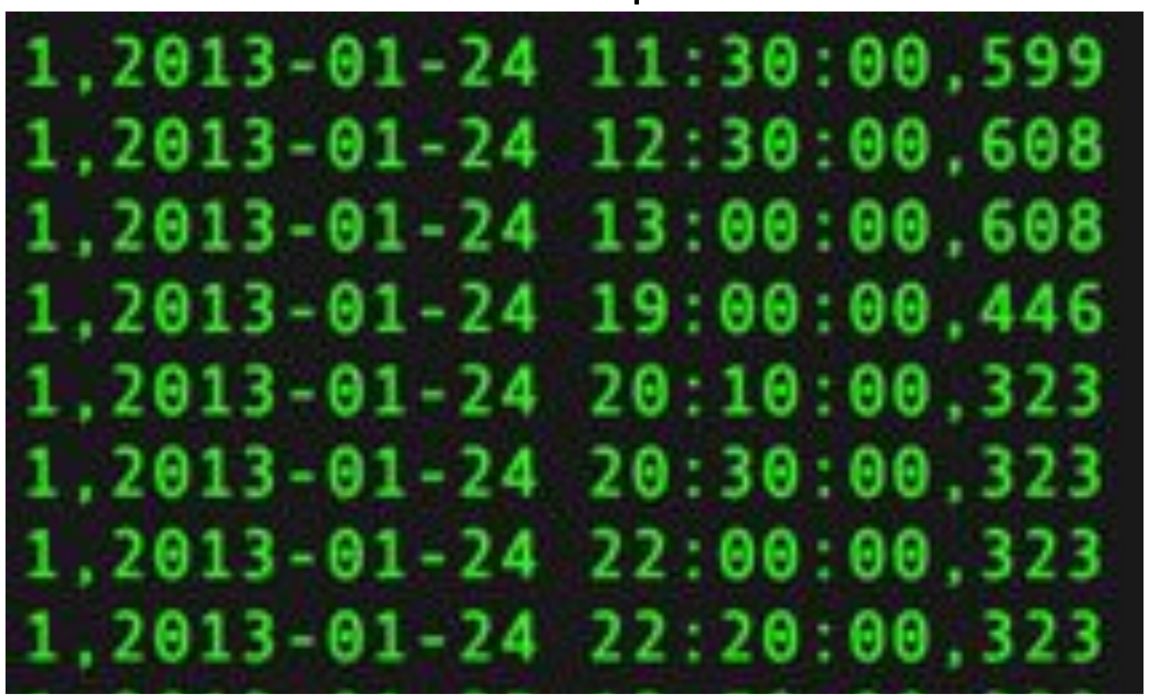
1. Complexity science in a nutshell
2. Urban scaling laws
3. **Urban mobility**
4. Application: infrastructure design

‚Collective' movements in cities

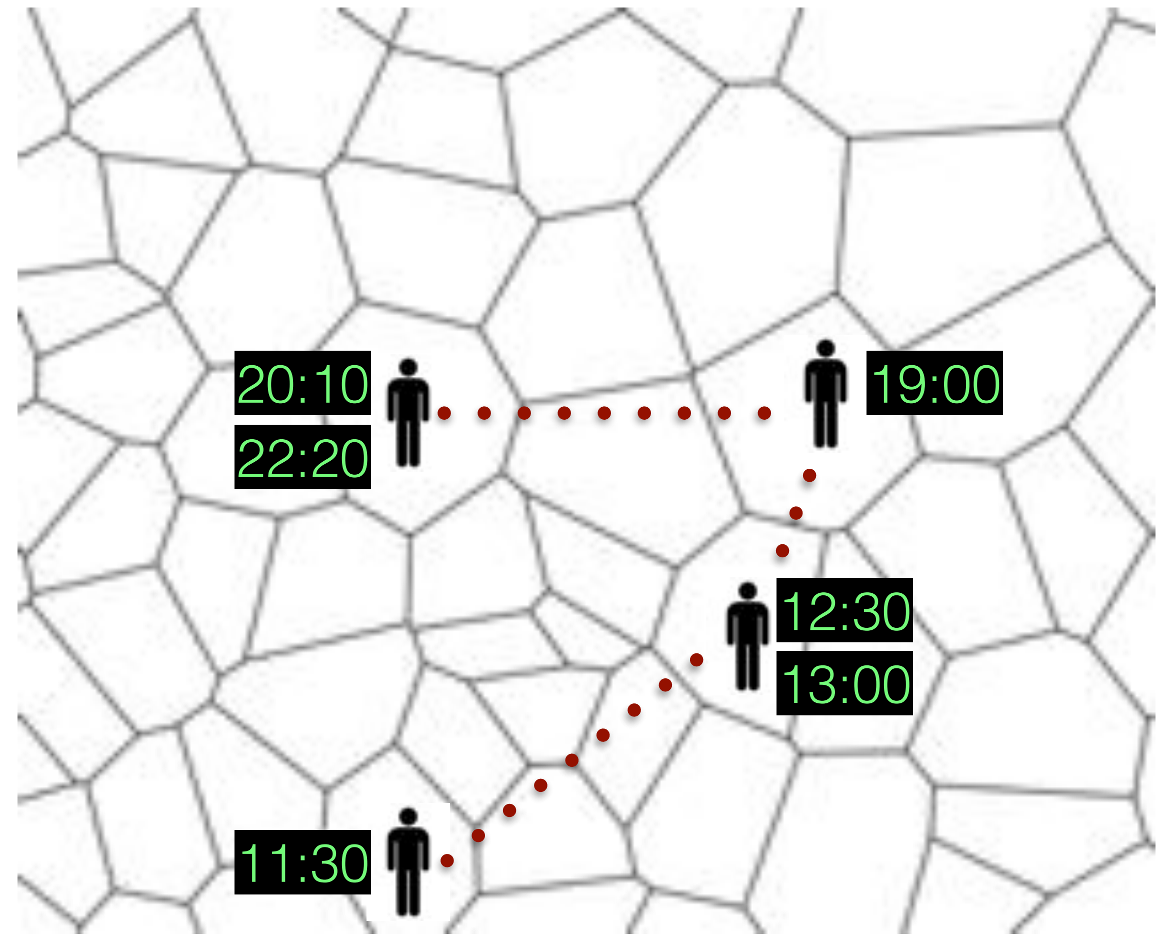
Source: New York Time Lapse by Dimid Vazhnik, 2015

Individual trajectories from mobile phone data

User ID, Timestamp, Cell tower ID



```
1,2013-01-24 11:30:00,599
1,2013-01-24 12:30:00,608
1,2013-01-24 13:00:00,608
1,2013-01-24 19:00:00,446
1,2013-01-24 20:10:00,323
1,2013-01-24 20:30:00,323
1,2013-01-24 22:00:00,323
1,2013-01-24 22:20:00,323
```



1. ***How many*** people visit a given location?
2. From ***how far*** do they come?
3. ***How often*** do they visit?

Spatial networks: strength of nodal interaction

Gravity law: $$T_{ij} = K \frac{P_i P_j}{d_{ij}^{\sigma}}$$

Batty, 2013
Barthelemy, 2011

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

Simini et al., 2012

… …

→ no explicit consideration of visiting frequencies!

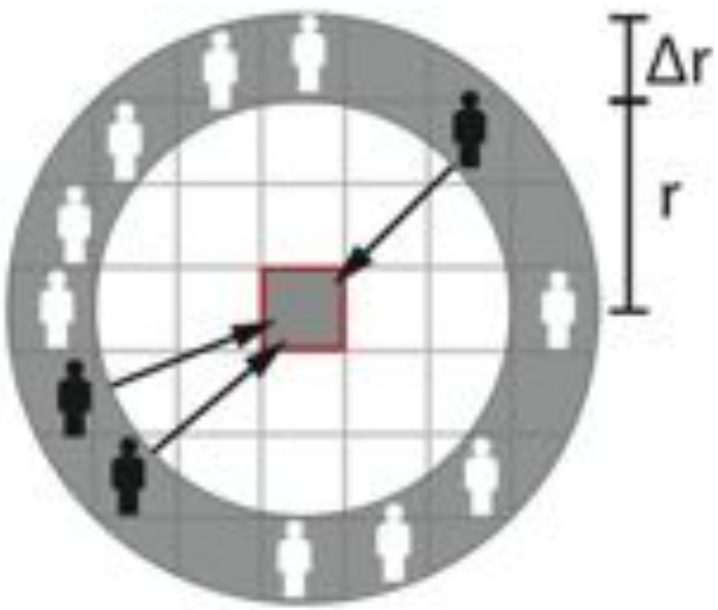
Marc Barthelemy, *Spatial networks*, Physics Reports, 2010

Lets look into the data!

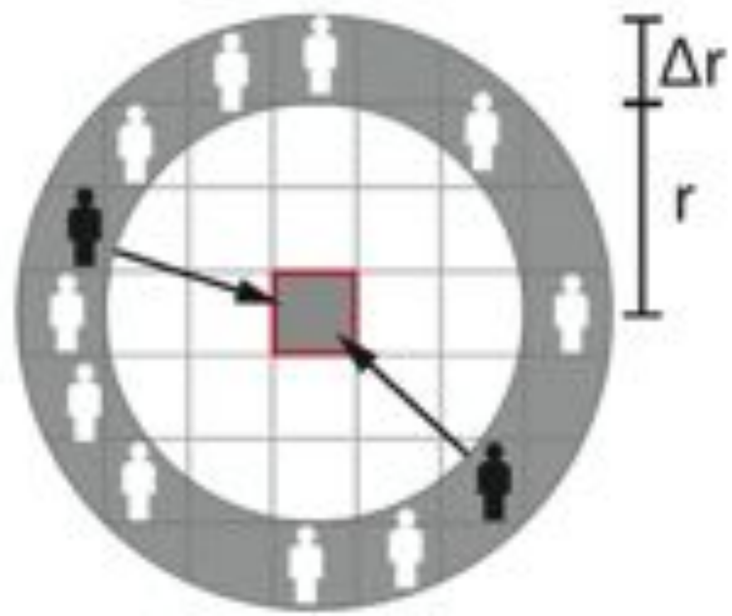
- Greater Boston area
- $\approx$2 Mio. mobile phone users over 4 months
- $\approx 10^9$ location based records per month (triangulation)
- 46,210 locations (500m x 500m grid cells)

Quantifying the attractiveness of locations

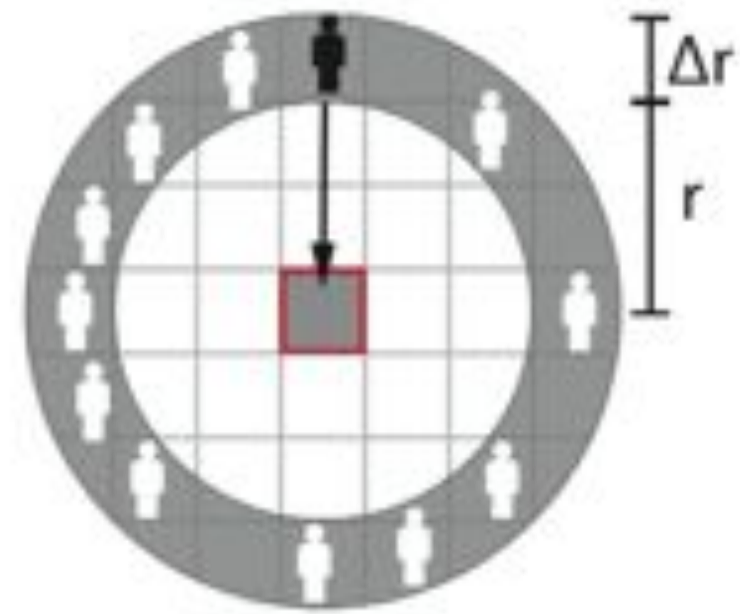
1 visit per month



2 visits per month

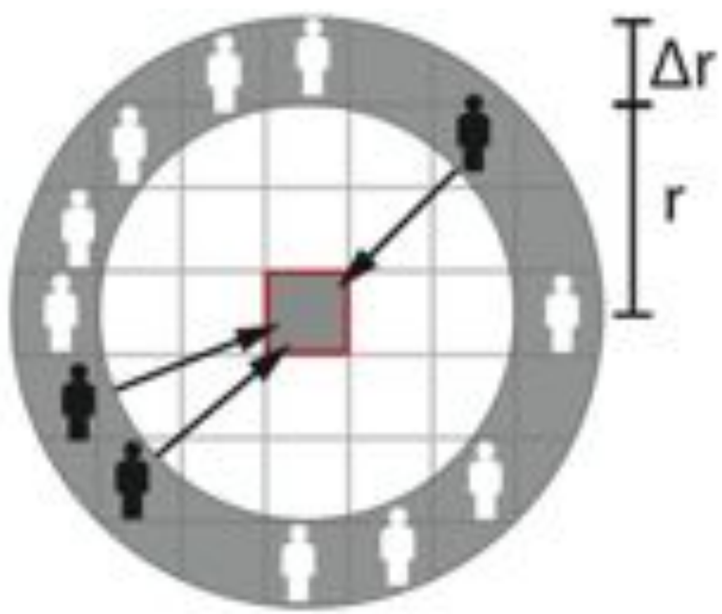


3 visits per month

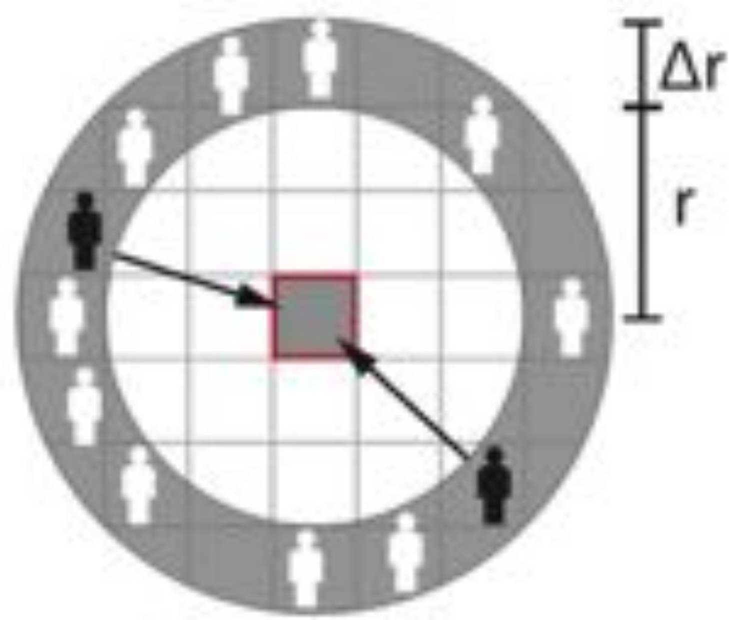


Quantifying the attractiveness of locations

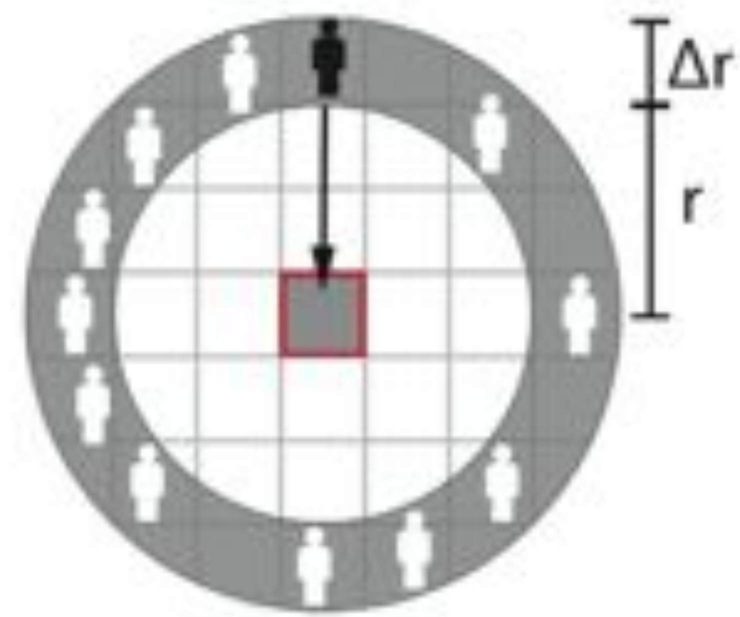
1 visit per month



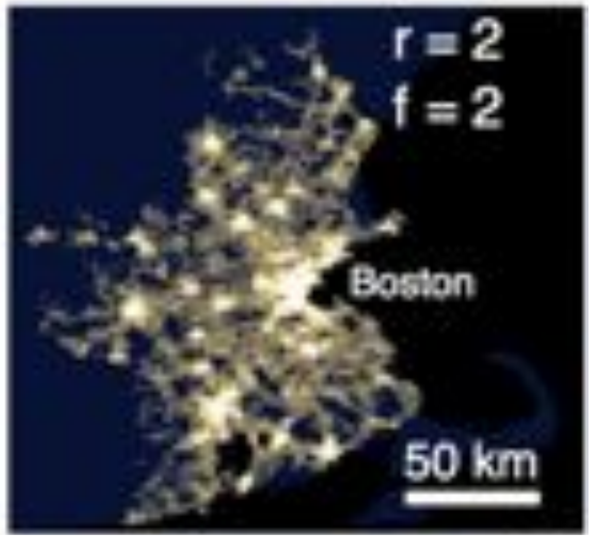
2 visits per month



3 visits per month



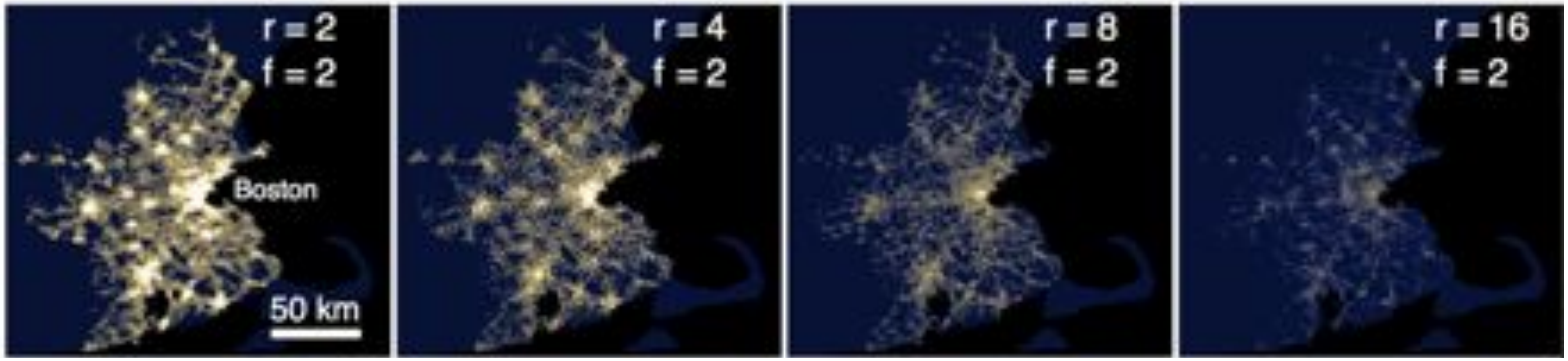
(Weighted, directed network)



r visiting distance (km)
f visiting frequency (visits per month)

Brightness of pixel: number of visitors, $\boldsymbol{q(r,f)}$

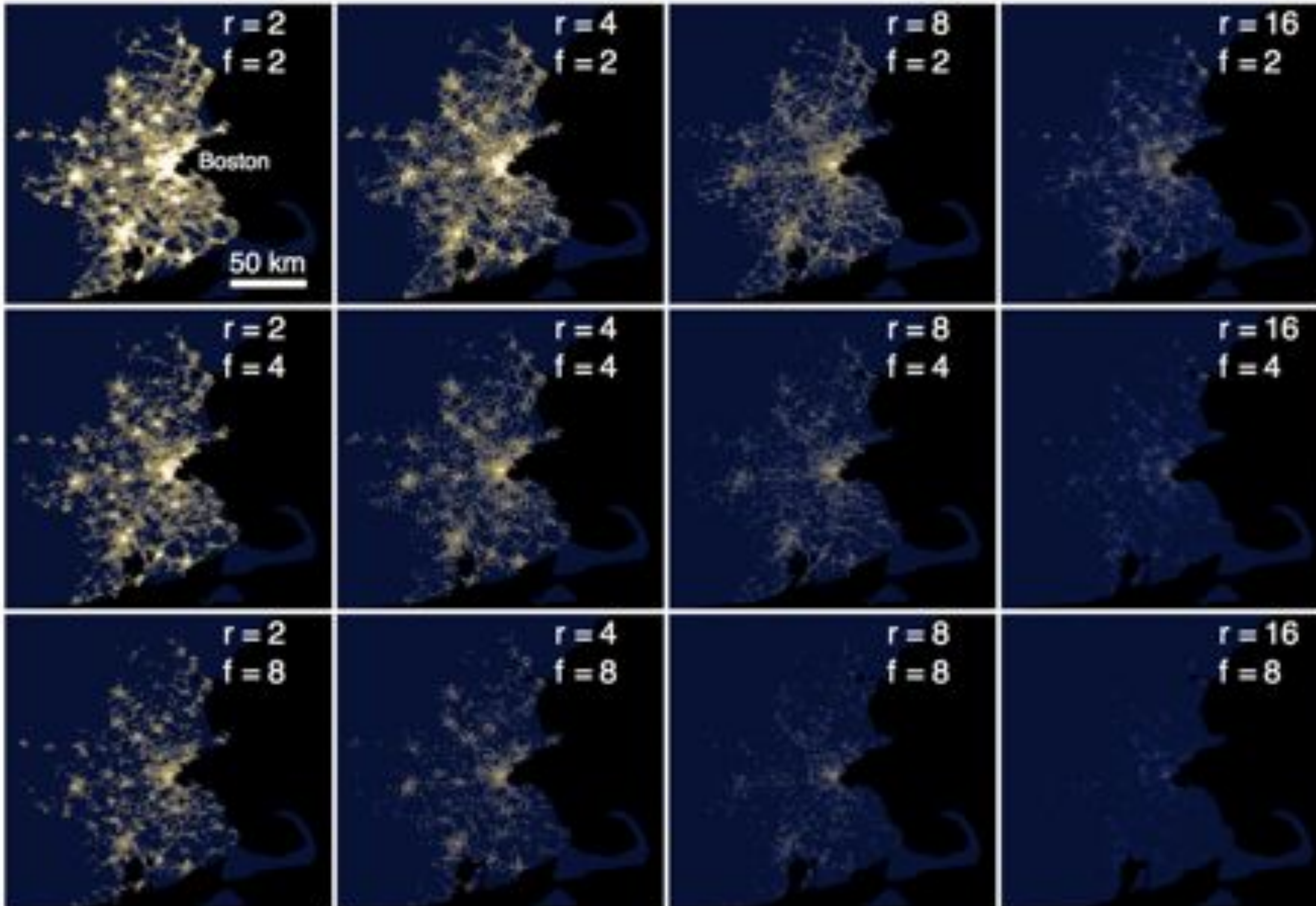
Increasing visiting distance



Increasing visiting frequency

Increasing visiting distance

Increasing visiting frequency



Dimensional analysis

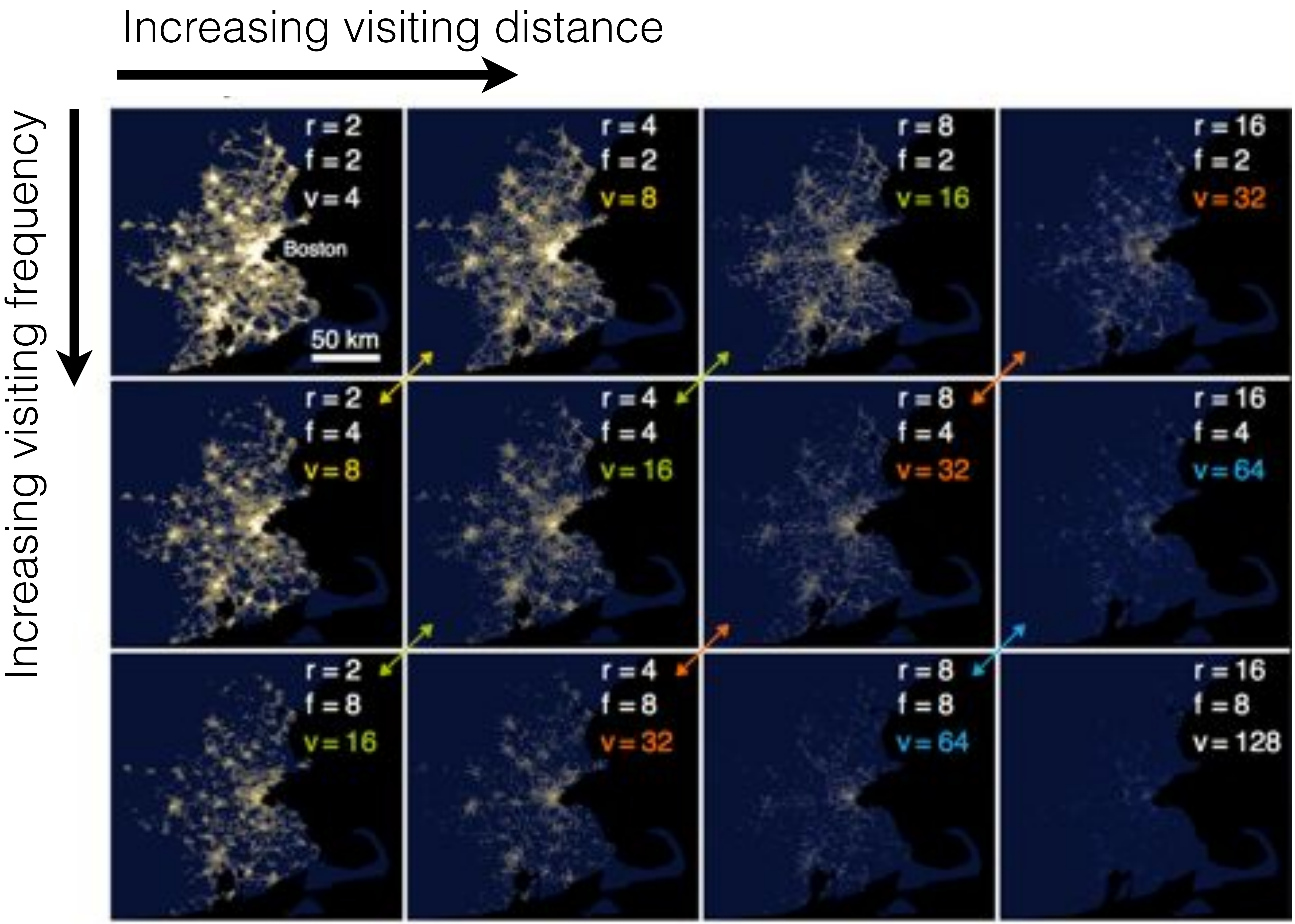
$$q = q\Big[r, f, u, Y(N)\Big]$$

Travel speed

Socioeconomic features

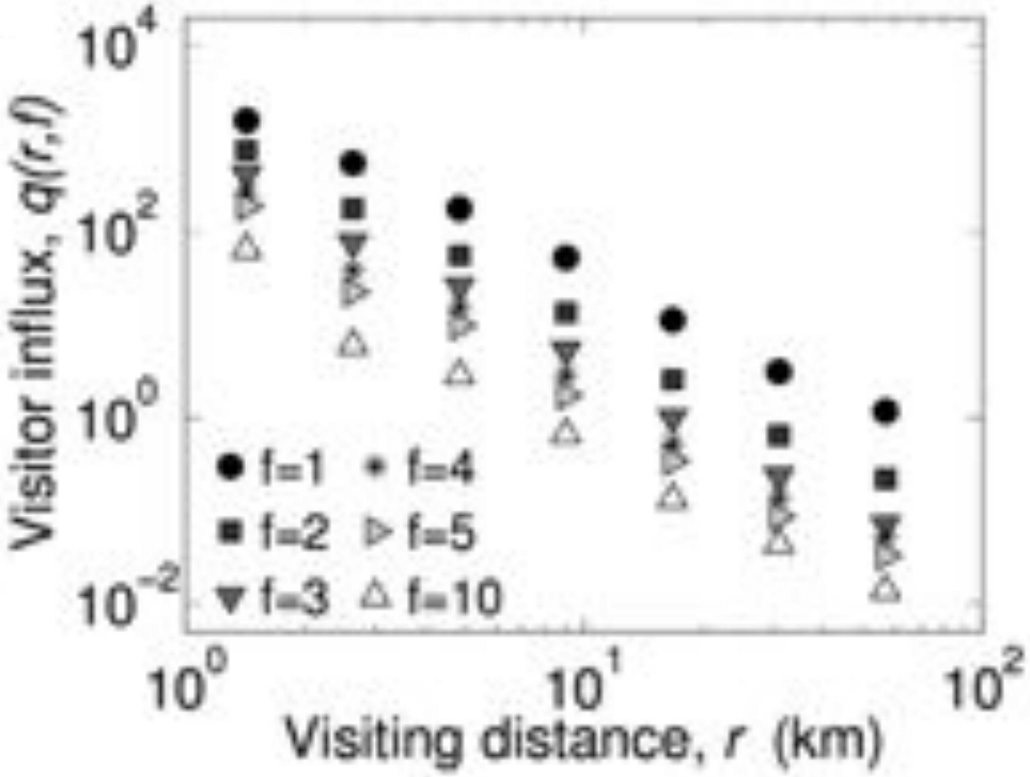
$$\Rightarrow q(r, f) = G\left(\frac{rf}{u}\right) = F(rf)$$

Sonin, *Dimensional Analysis*, Lecture Notes MIT.

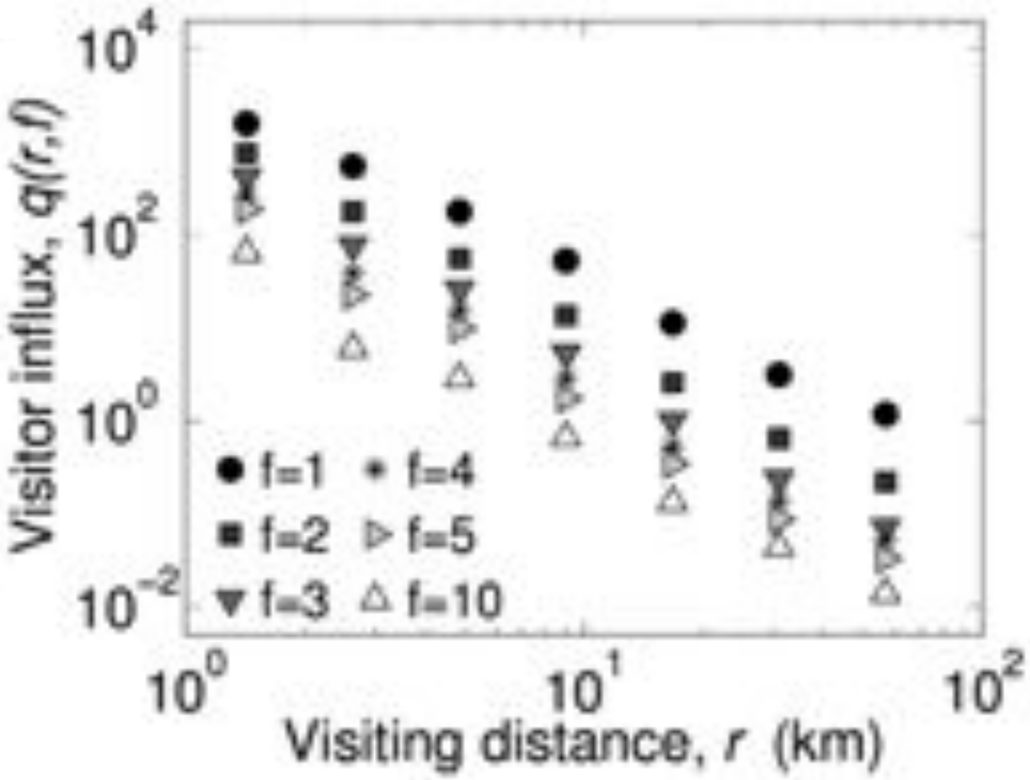


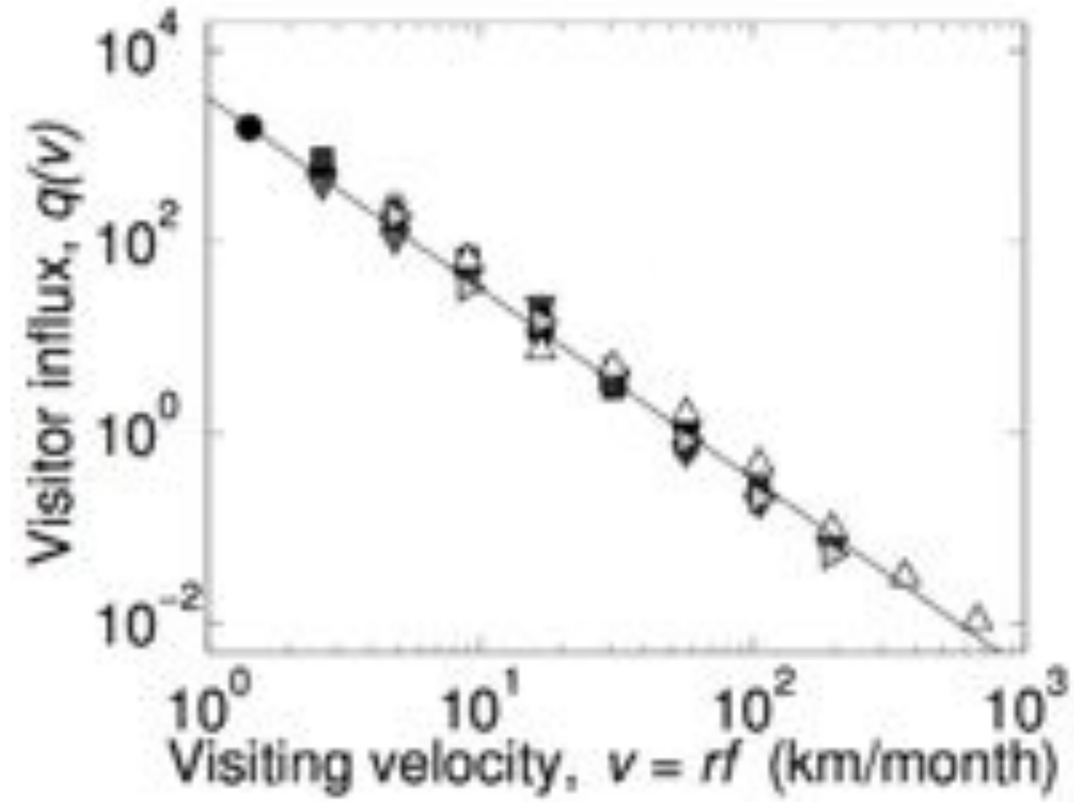
Increasing visiting distance
Increasing visiting frequency
r = 2
f = 2
v = 4
Boston
50 km
r = 4
f = 2
v = 8
r = 8
f = 2
v = 16
r = 16
f = 2
v = 32
r = 2
f = 4
v = 8
r = 4
f = 4
v = 16
r = 8
f = 4
v = 32
r = 16
f = 4
v = 64
r = 2
f = 8
v = 16
r = 4
f = 8
v = 32
r = 8
f = 8
v = 64
r = 16
f = 8
v = 128

Newbury Street, Boston



Newbury Street, Boston





Example (v = 20km/month):

number of visitors coming from 5 km and 4 times a month

=

number of visitors coming from 10 km and 2 times a month

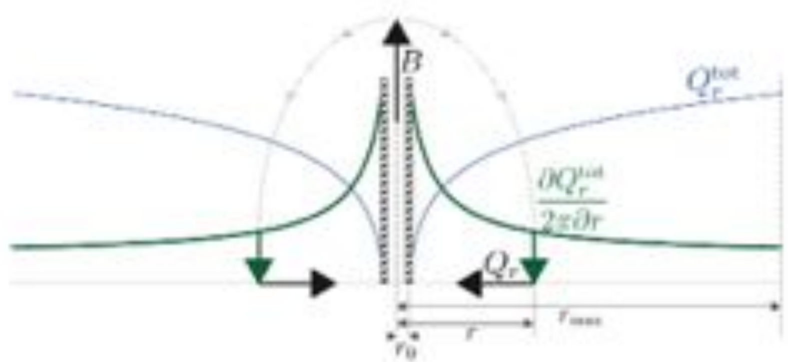
=

number of visitors coming from 20 km and once a month

What is the **functional relation** between:

- number of visitors,
- their travel distance from home,
- their visiting frequency?

Fluid dynamic model



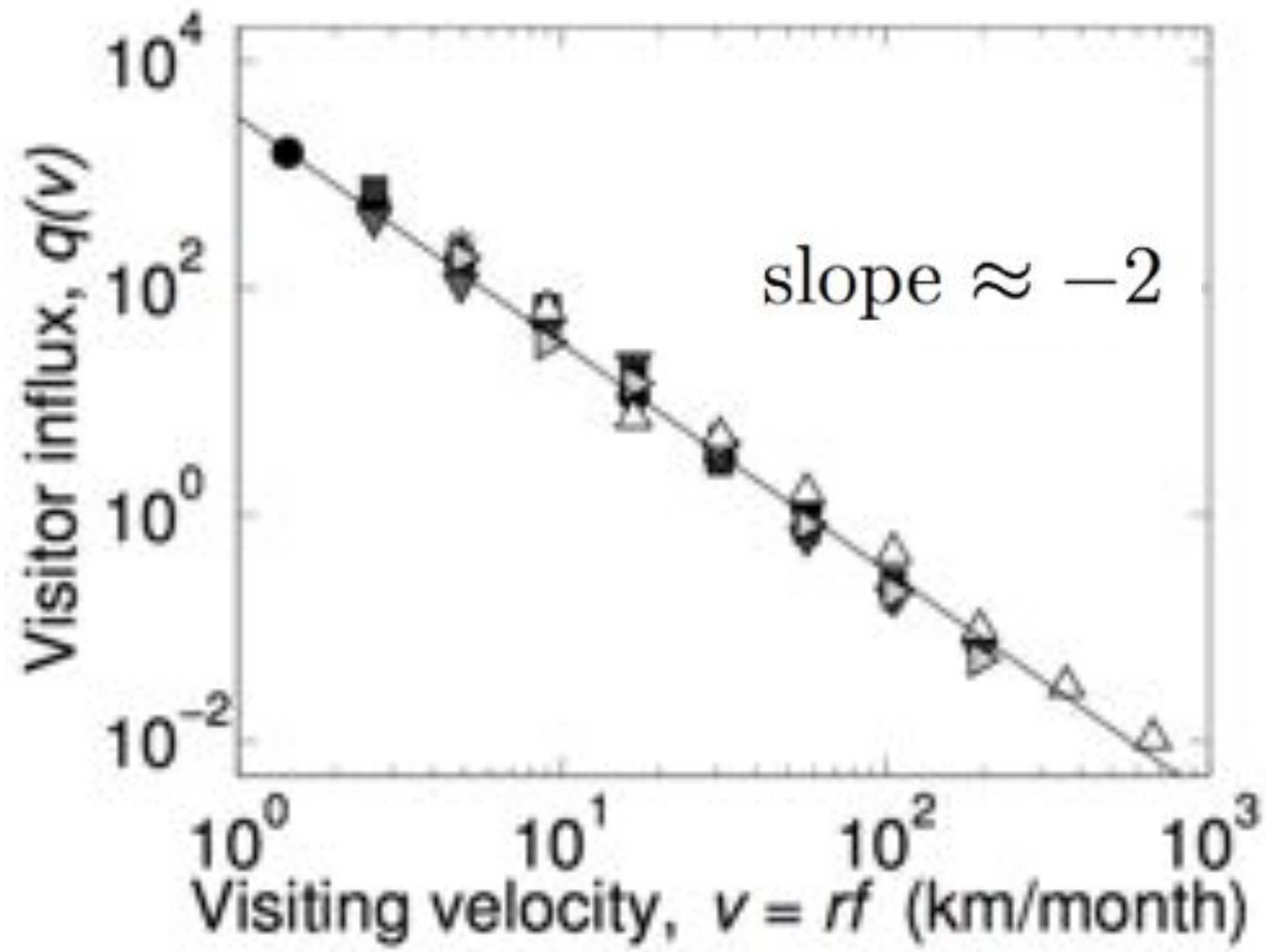
Dimensional argument

$$\Rightarrow q(r,f) = G\left(\frac{rf}{u}\right) = F(rf)$$

Theoretical expectation

Number of visitors
$\propto$
[travel distance x visiting frequency]$^{-2}$

Number of visitors
$\propto$
[travel distance x visiting frequency]$^{-2}$



Schläpfer, Szell, Ratti, West (in preparation)

1. ***How many*** people visit a given location?
2. From ***how far*** do they come?
3. ***How often*** do they visit?

1. ***How many***
2. From
3. ***How often***

1. ***How many*** people visit a given location?

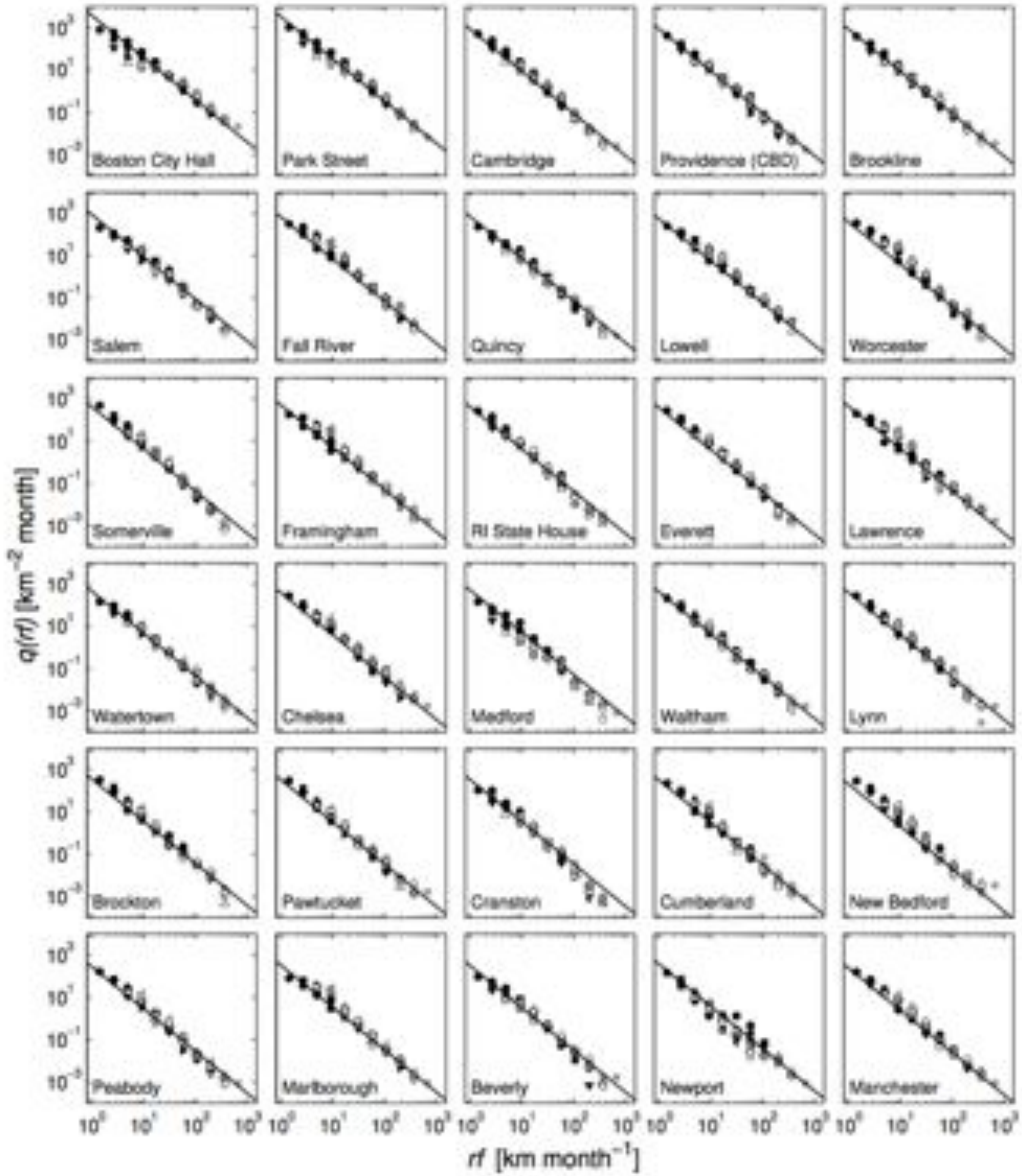
predicts

predicts

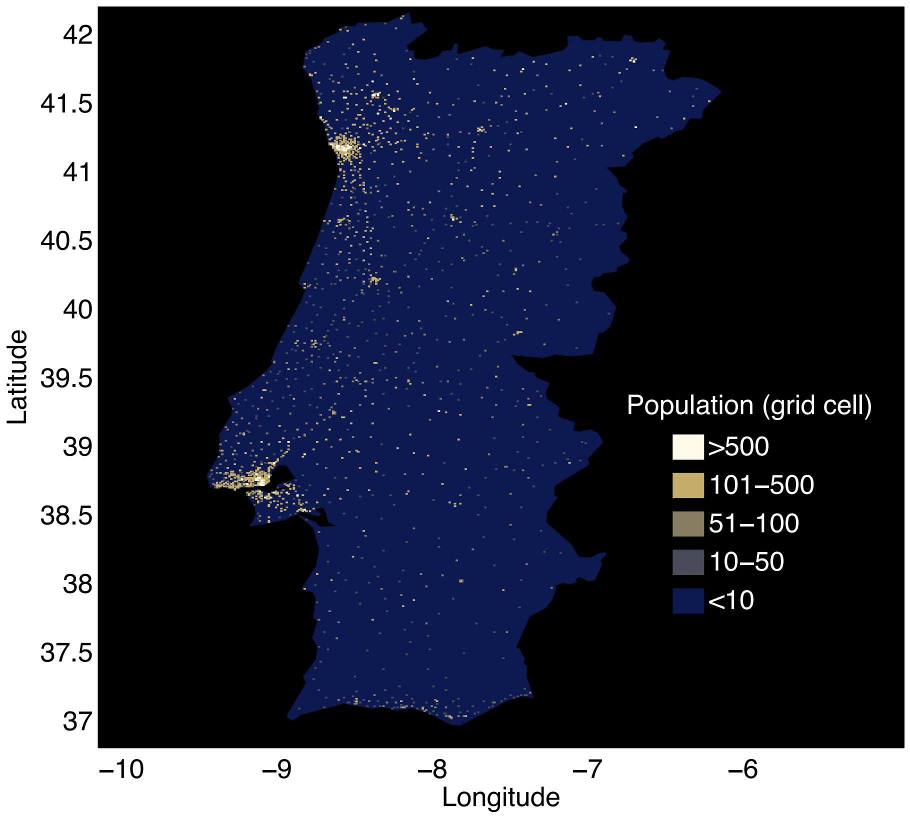
From ***how far*** do they come.

How often do they visit.

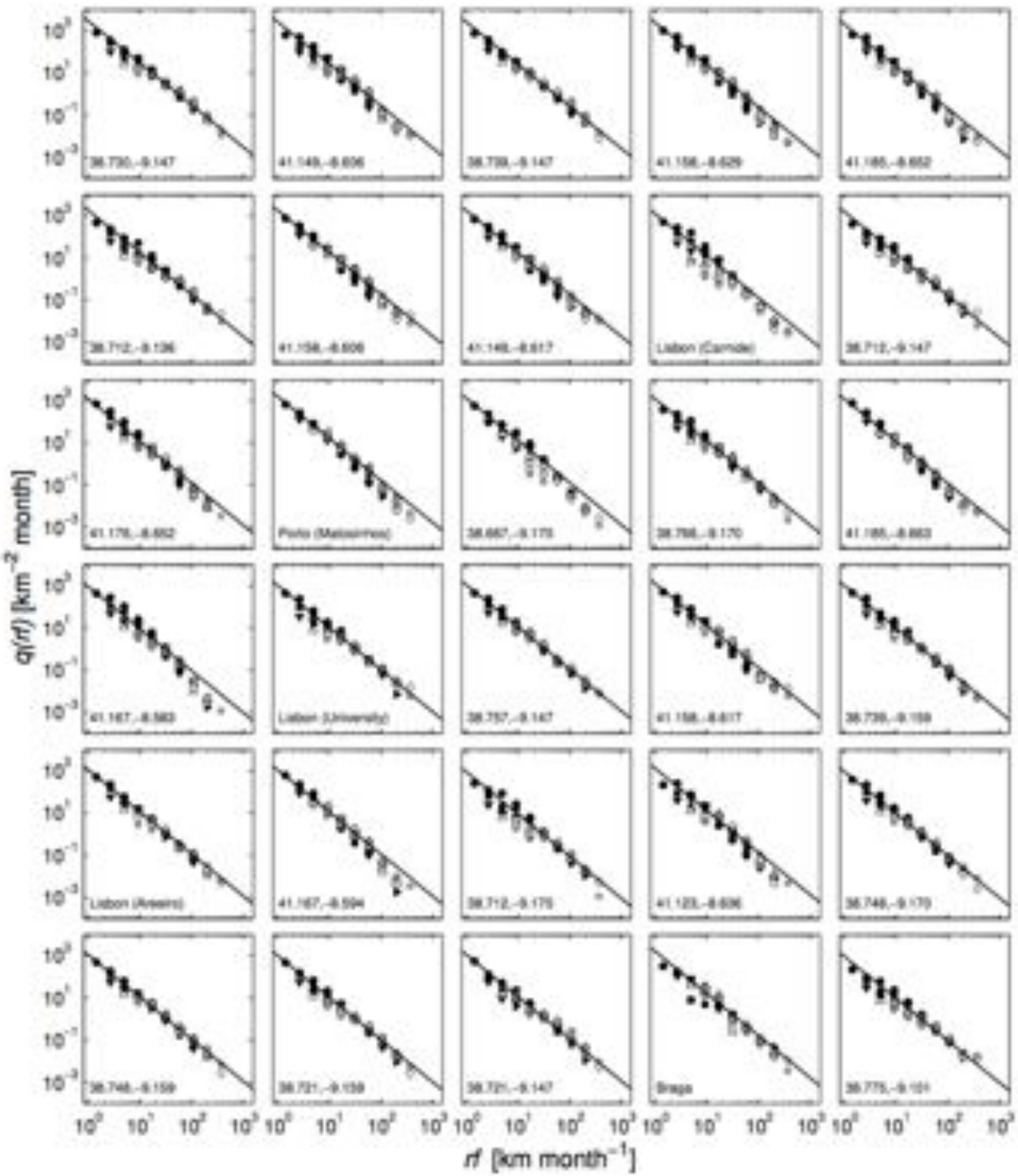
Greater Boston



Portugal

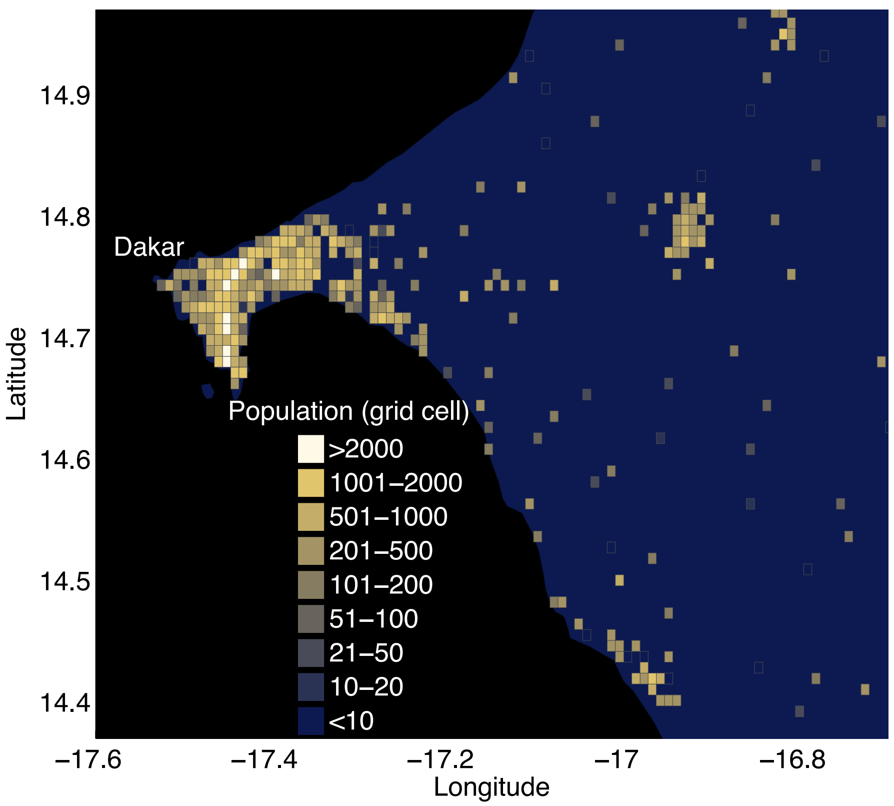


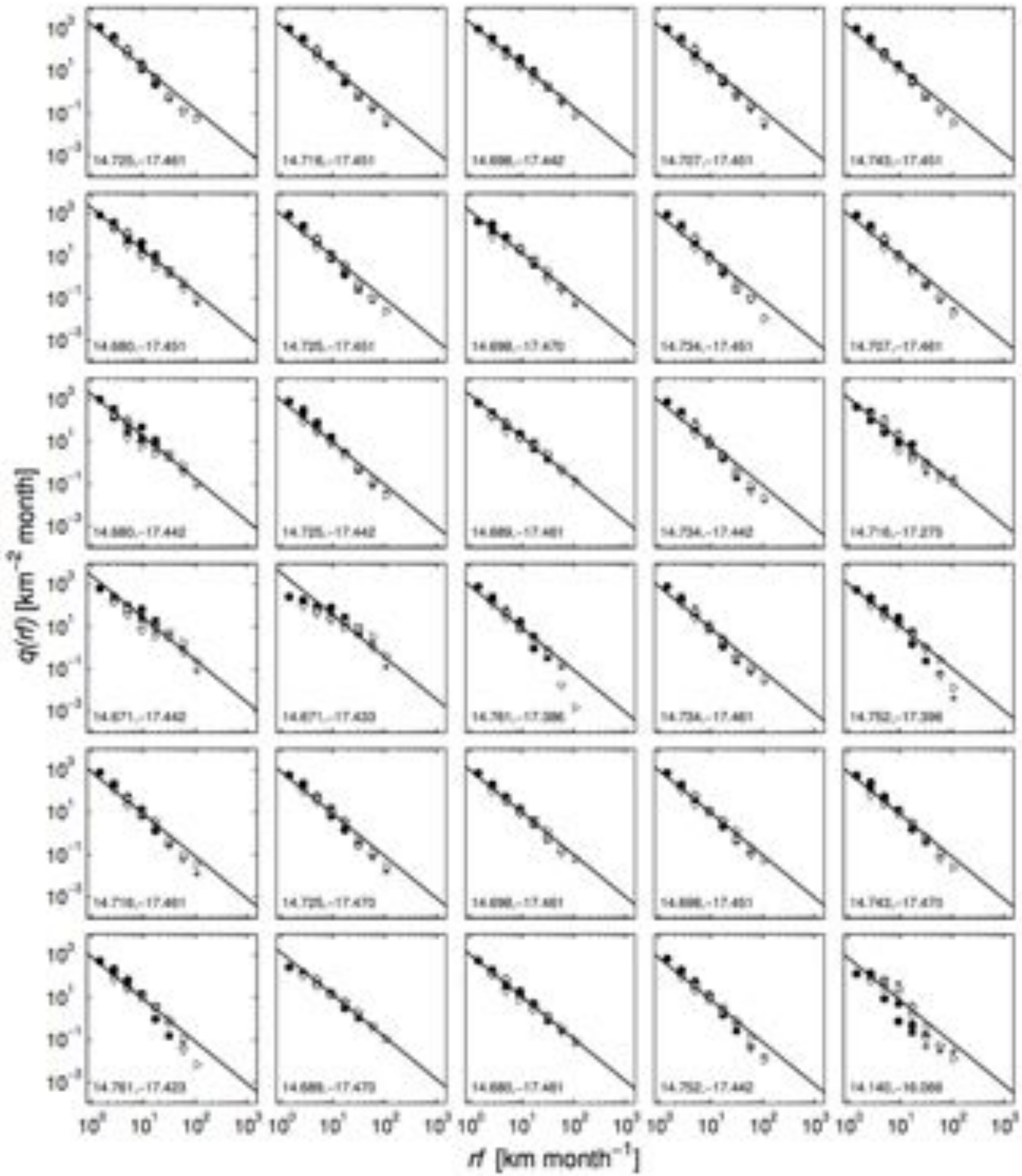
Latitude
Longitude
Population (grid cell)
>500
101–500
51–100
10–50
<10



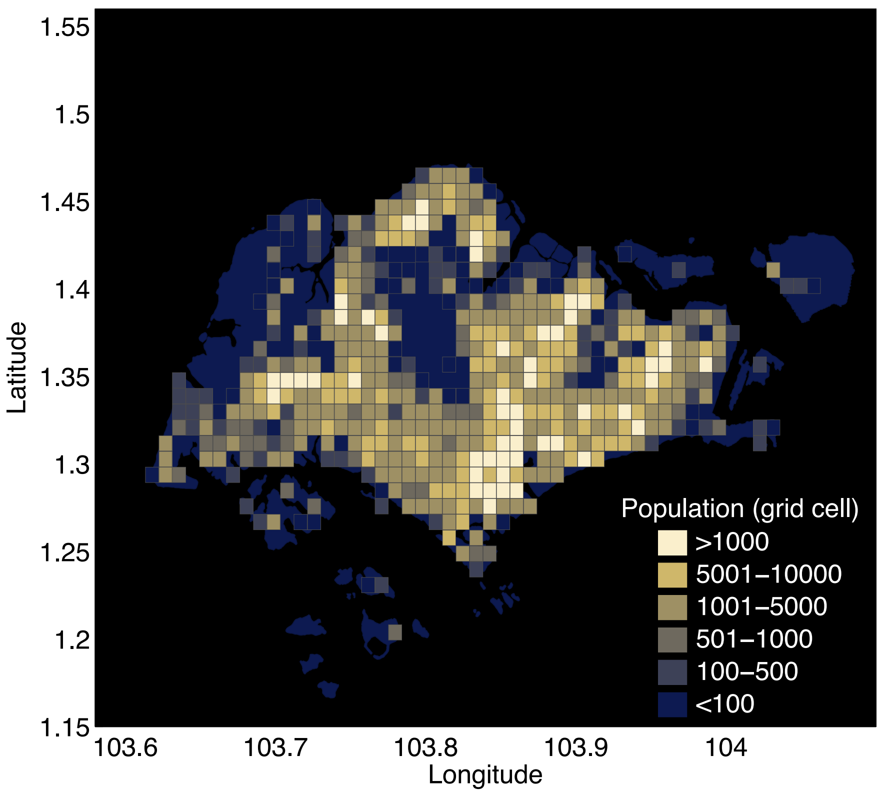
q(rf) [km^-2 month]
rf [km month^-1]

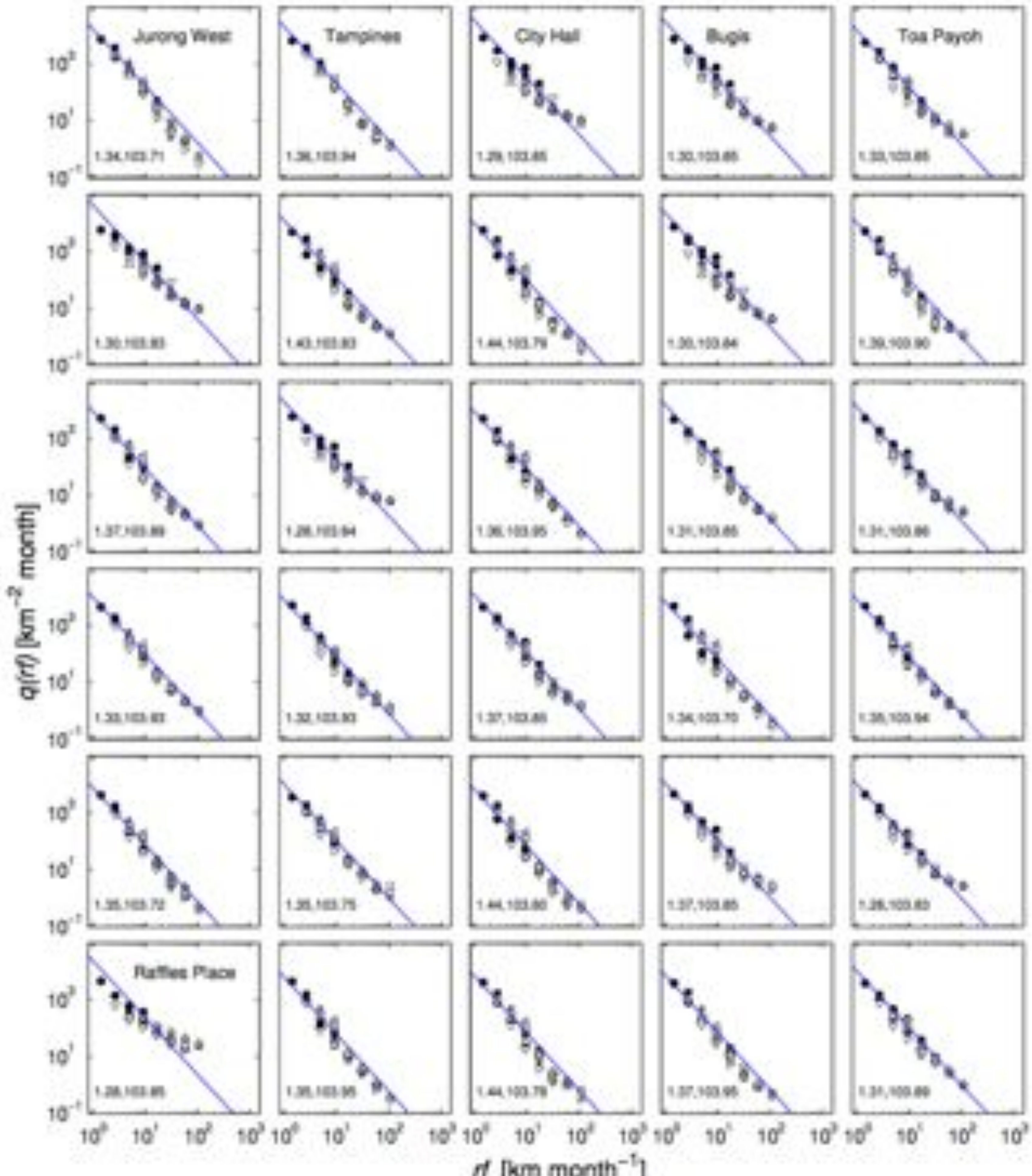
Senegal


Dakar
Population (grid cell)
>2000
1001–2000
501–1000
201–500
101–200
51–100
21–50
10–20
<10
Latitude
Longitude

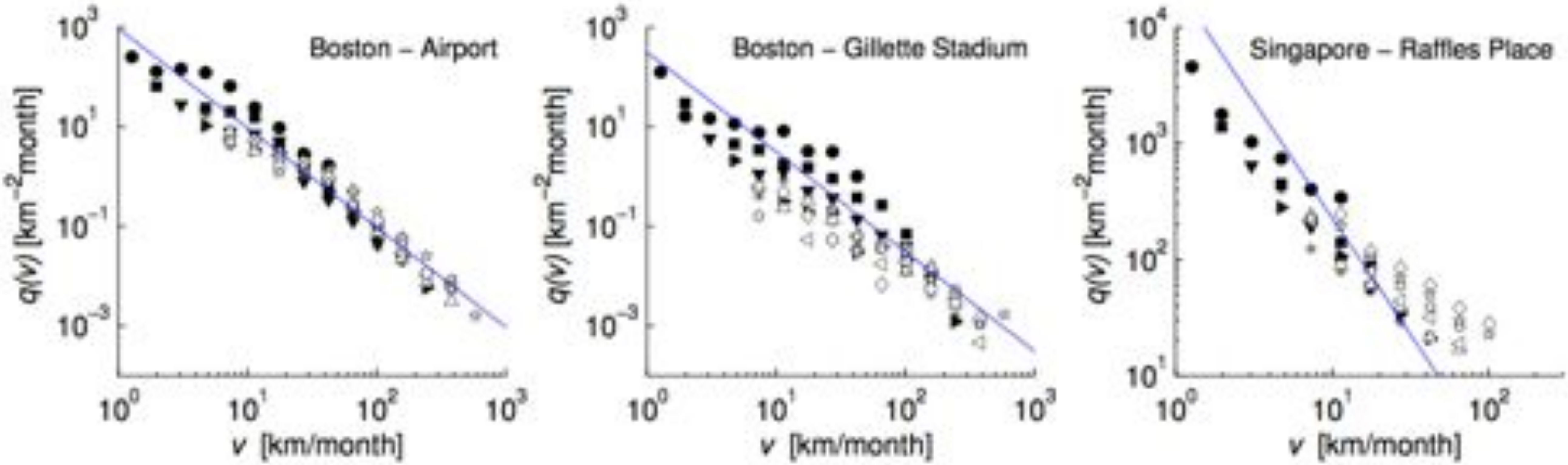

$q(rf)$ [km^{-2} month]
rf [km month^{-1}]

Singapore

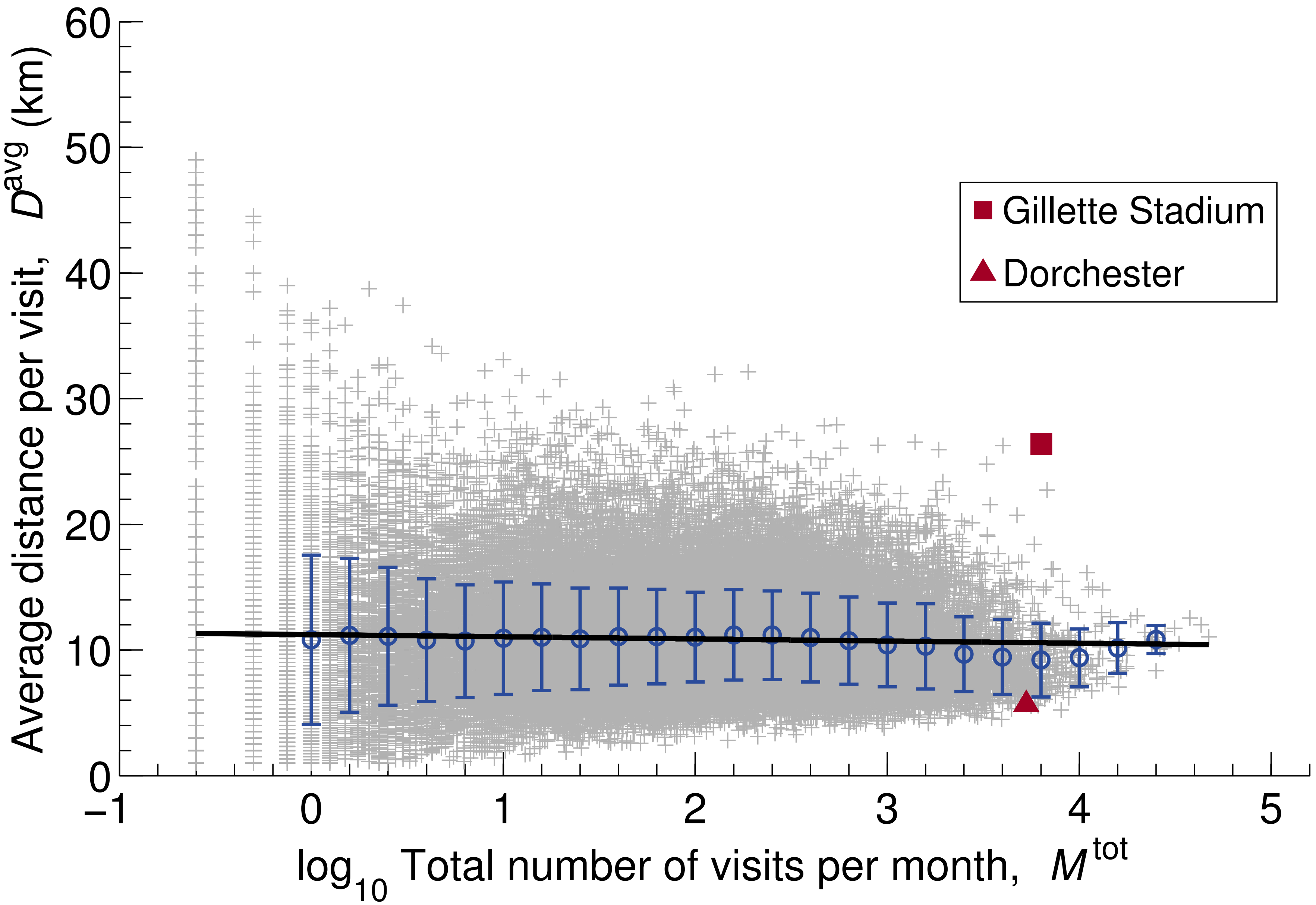

Latitude
Longitude
Population (grid cell)
>1000
5001–10000
1001–5000
501–1000
100–500
<100
1.55
1.5
1.45
1.4
1.35
1.3
1.25
1.2
1.15
103.6
103.7
103.8
103.9
104


Jurong West
Tampines
City Hall
Bugis
Toa Payoh
Raffles Place
$q(rf)$ [km^{-2} month]
rf [km month^{-1}]

Locations with ‚anomalous‘ behavior



Average travel distance is independent of specific location!



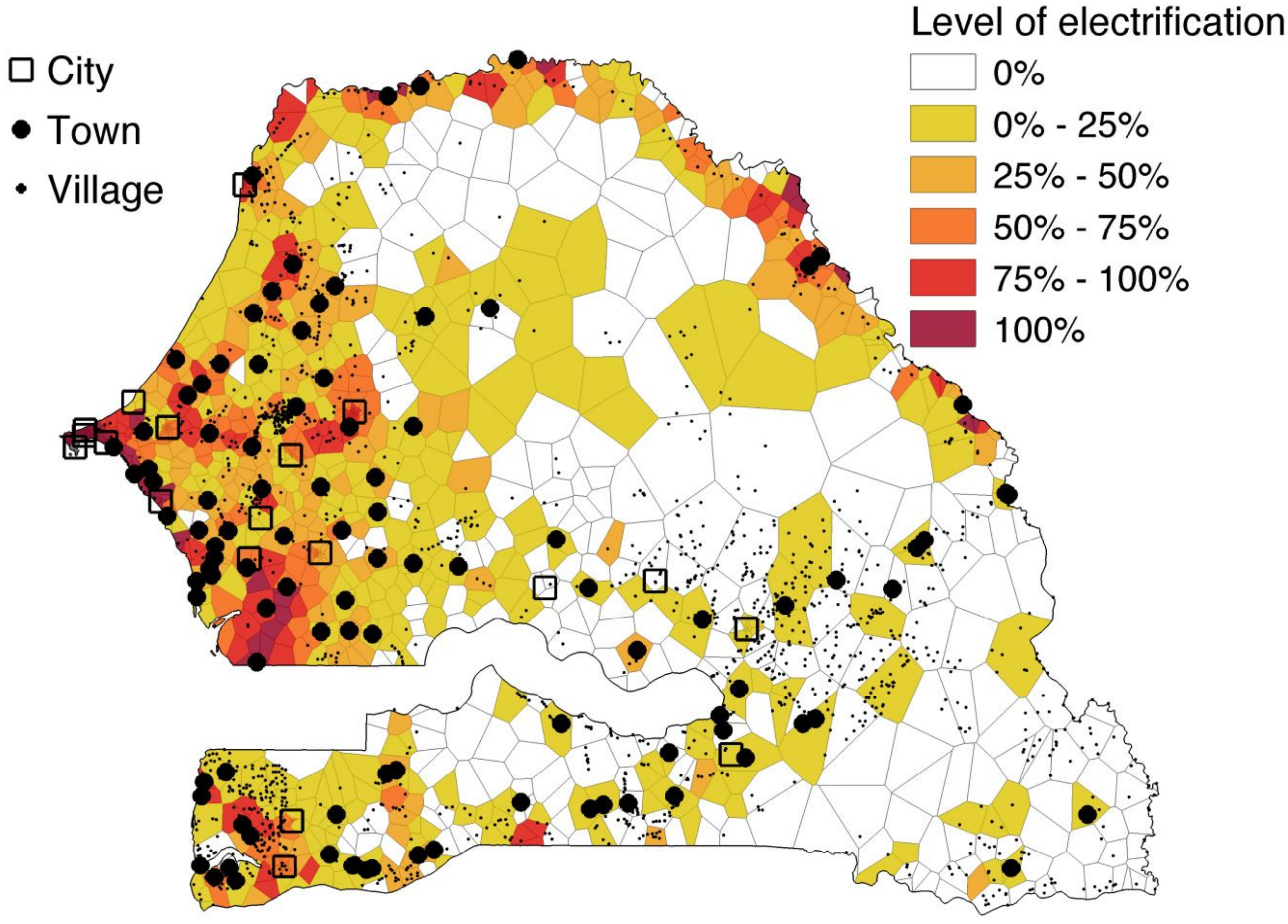
Content

1. Complexity science in a nutshell
2. Urban scaling laws
3. Urban mobility
4. **Application: infrastructure design**

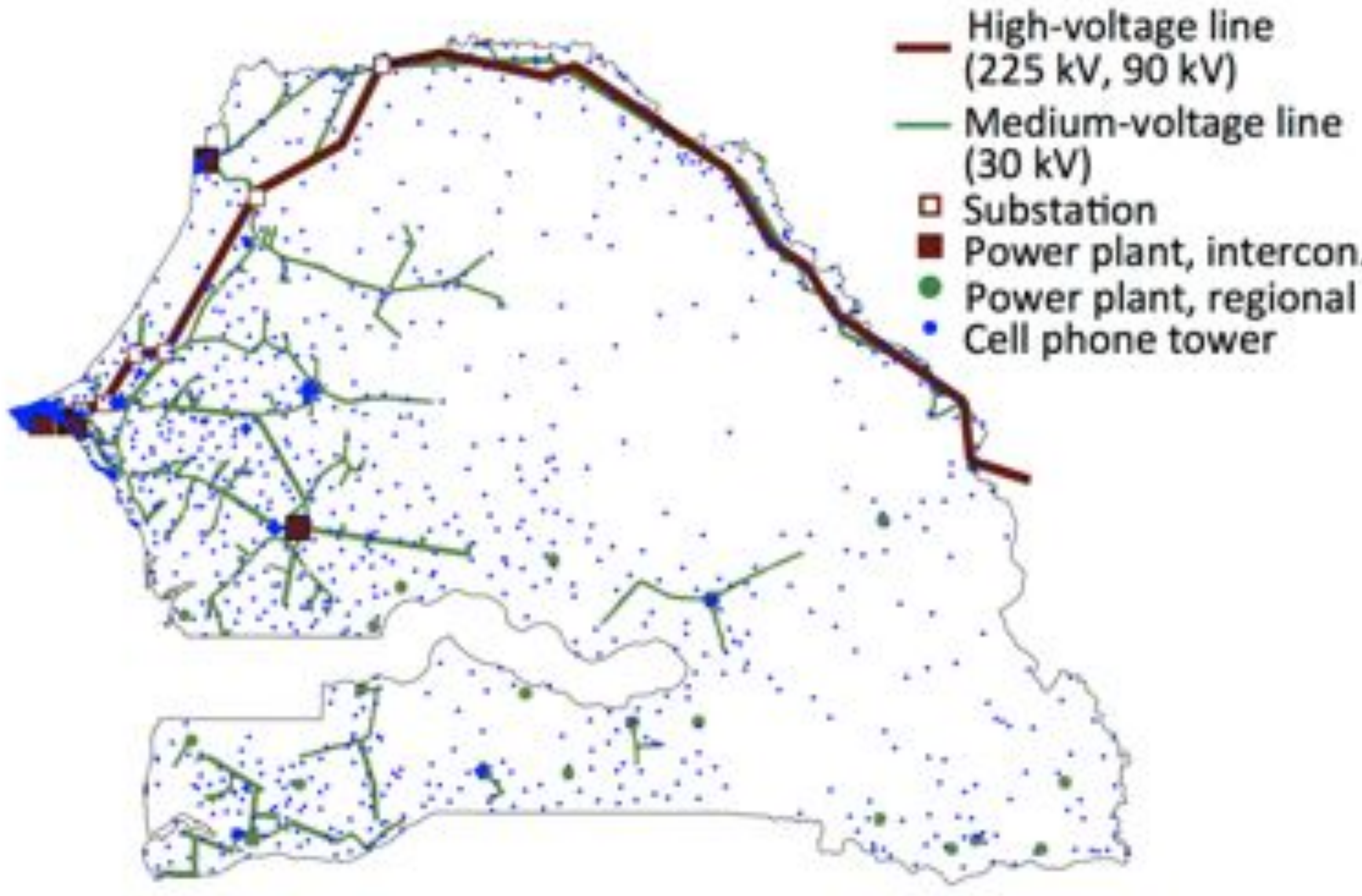
Electrification planning in developing countries

D4D challenge

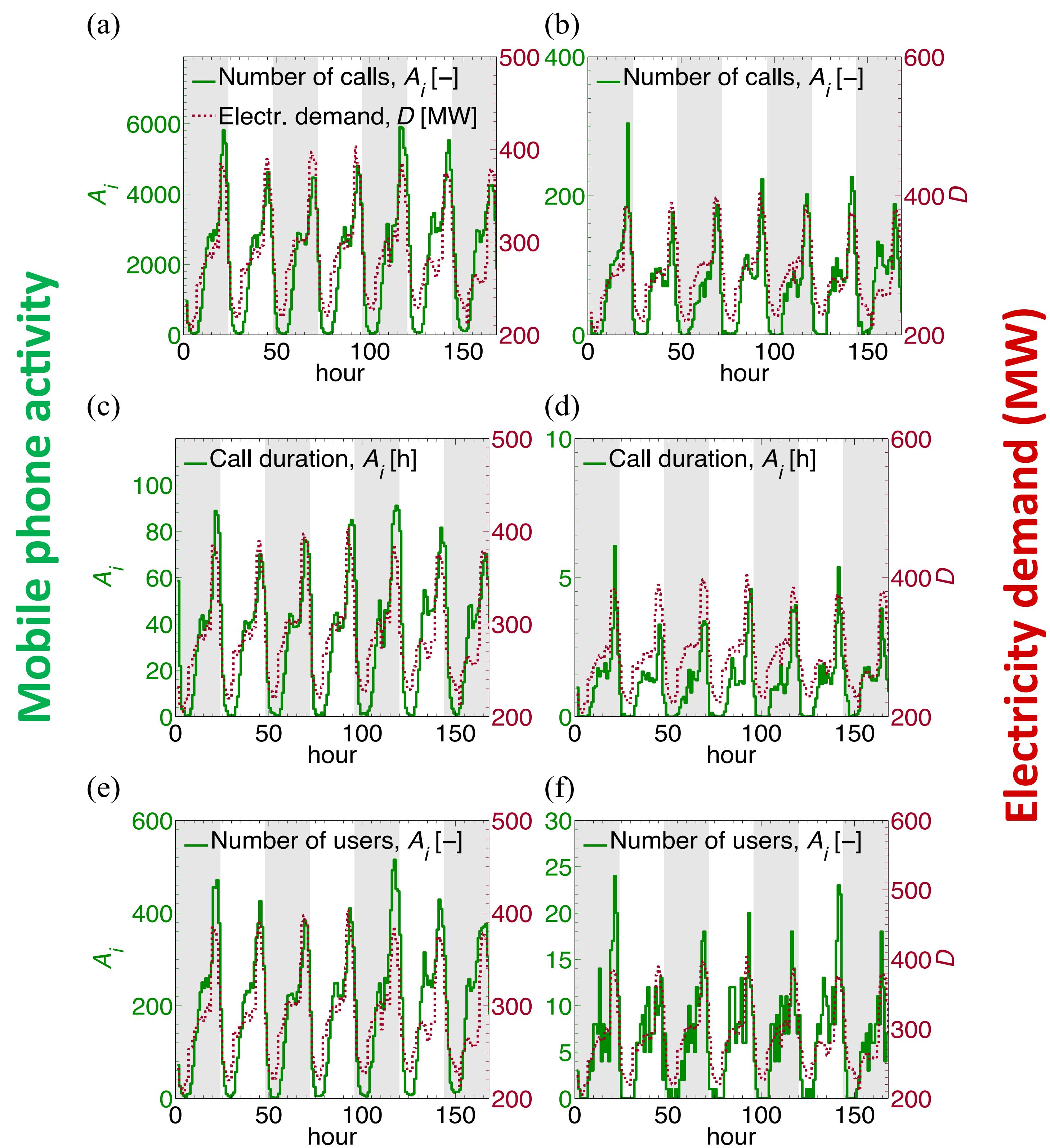
Electrification rates in Senegal



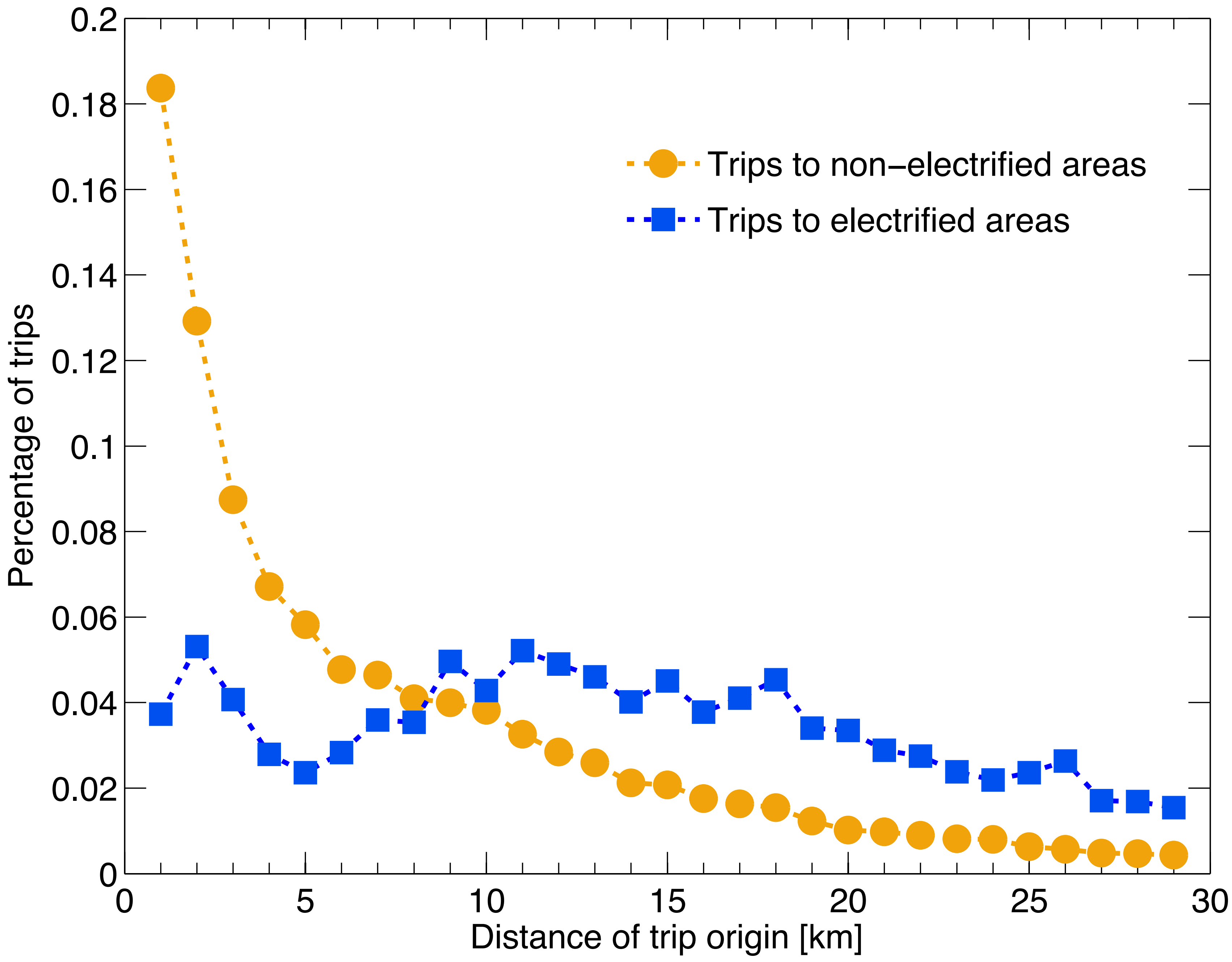
Using information from mobile phone infrastructure to facilitate electrification



Mobile phone data as a proxy for electricity demand



But not only…



Trips to non−electrified areas
Trips to electrified areas
Percentage of trips
Distance of trip origin [km]
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
0
5
10
15
20
25
30

Electrification technology optioneering: techno-economic analysis

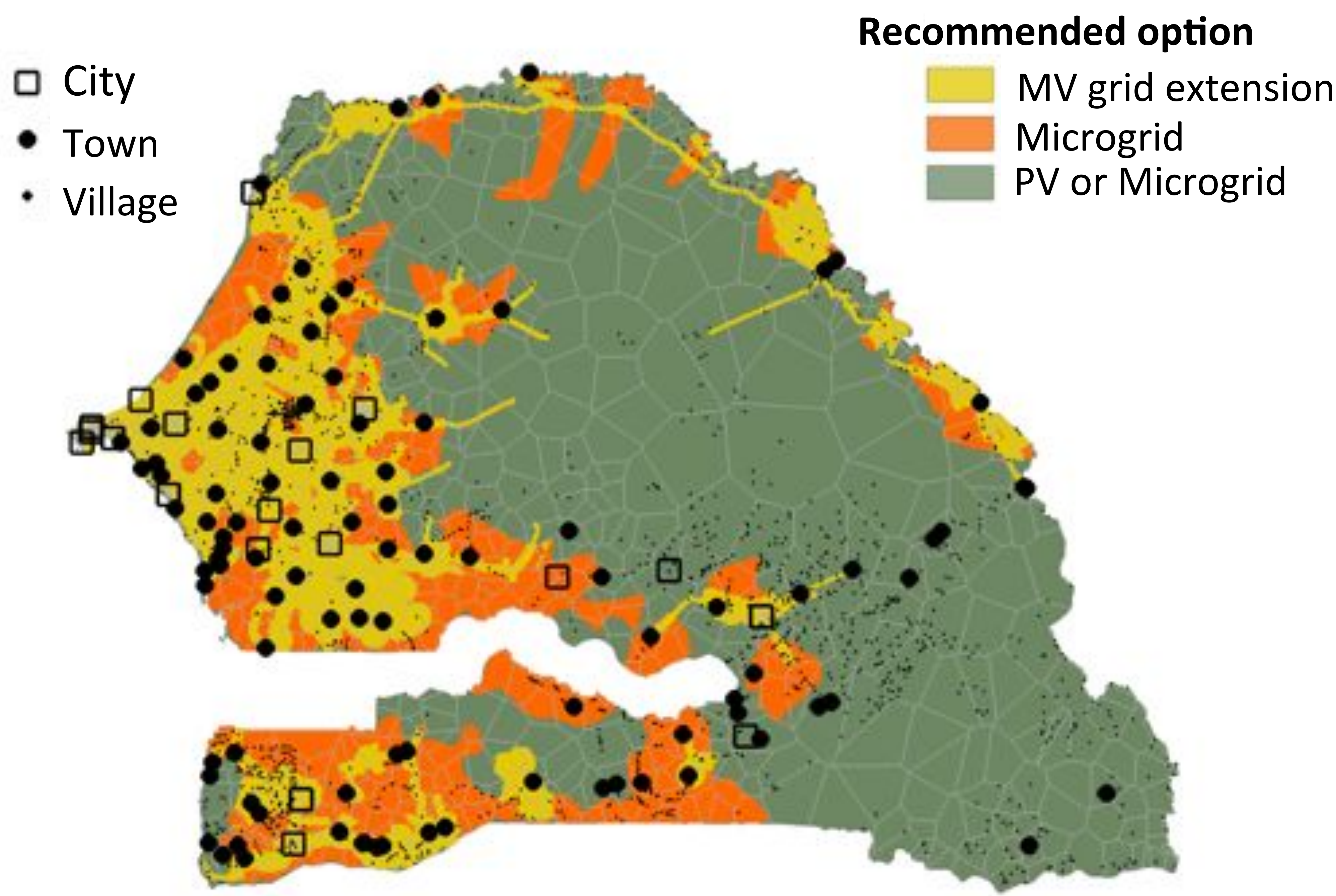
- Medium voltage electricity grid extension

- Diesel-based microgrid installation

- Traditional and minimalistic solar photovoltaic system

The model and equations are in the paper ;)

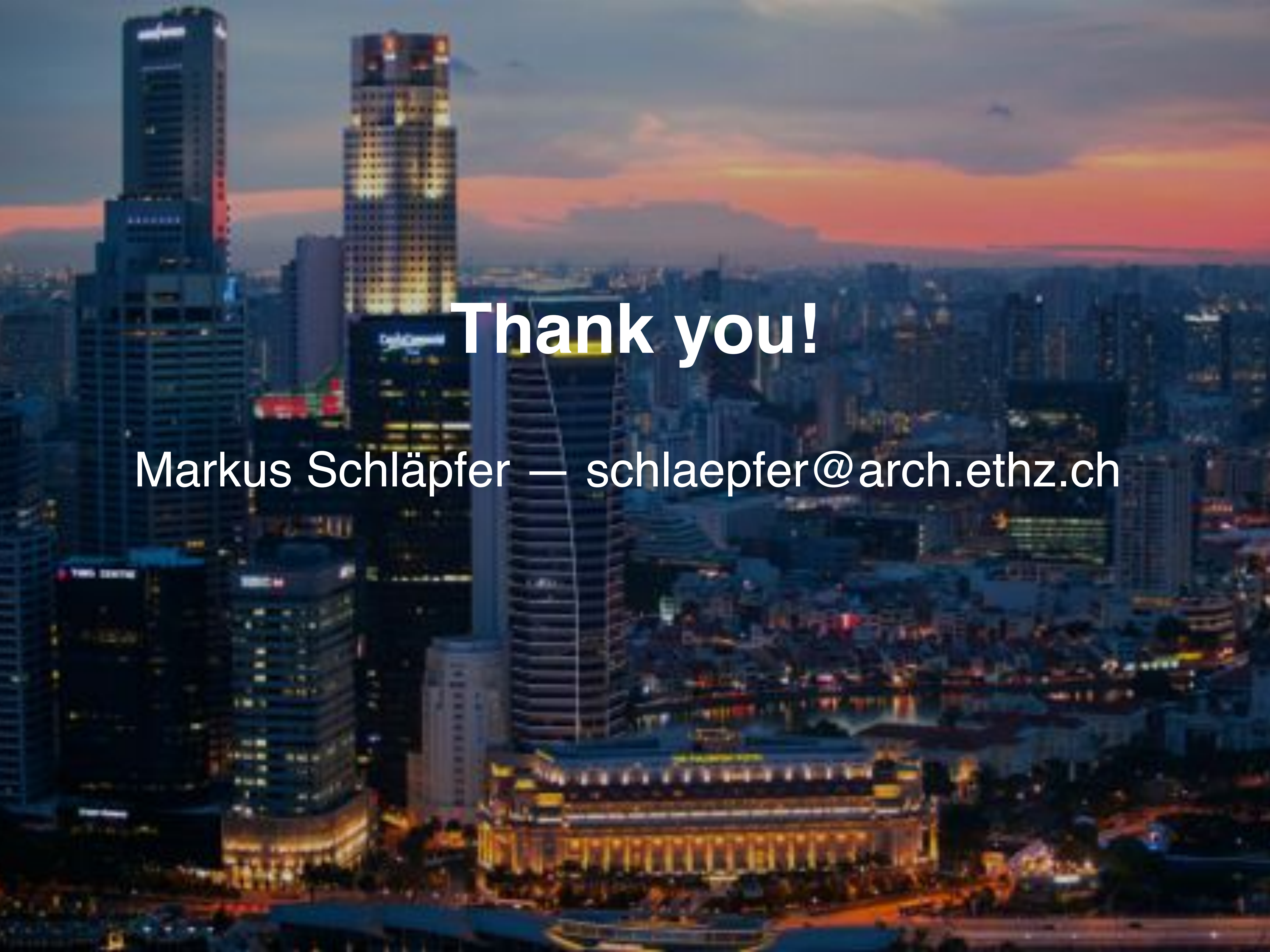
Electrification recommendations



Martinez-Cesena, Mancarella, Ndiaye, Schläpfer
D4D Challenge 2015, First Prize (best overall) and Energy Prize

Recommended readings

- Marc Barthelemy, *Spatial networks*, Physics Reports, 2010
- Michael Batty, *The new science of cities*, MIT Press, 2013
- Santa Fe Institute, *Project on Cities, Scaling and Sustainability*, www.santafe.edu



Thank you!

Markus Schläpfer — schlaepfer@arch.ethz.ch