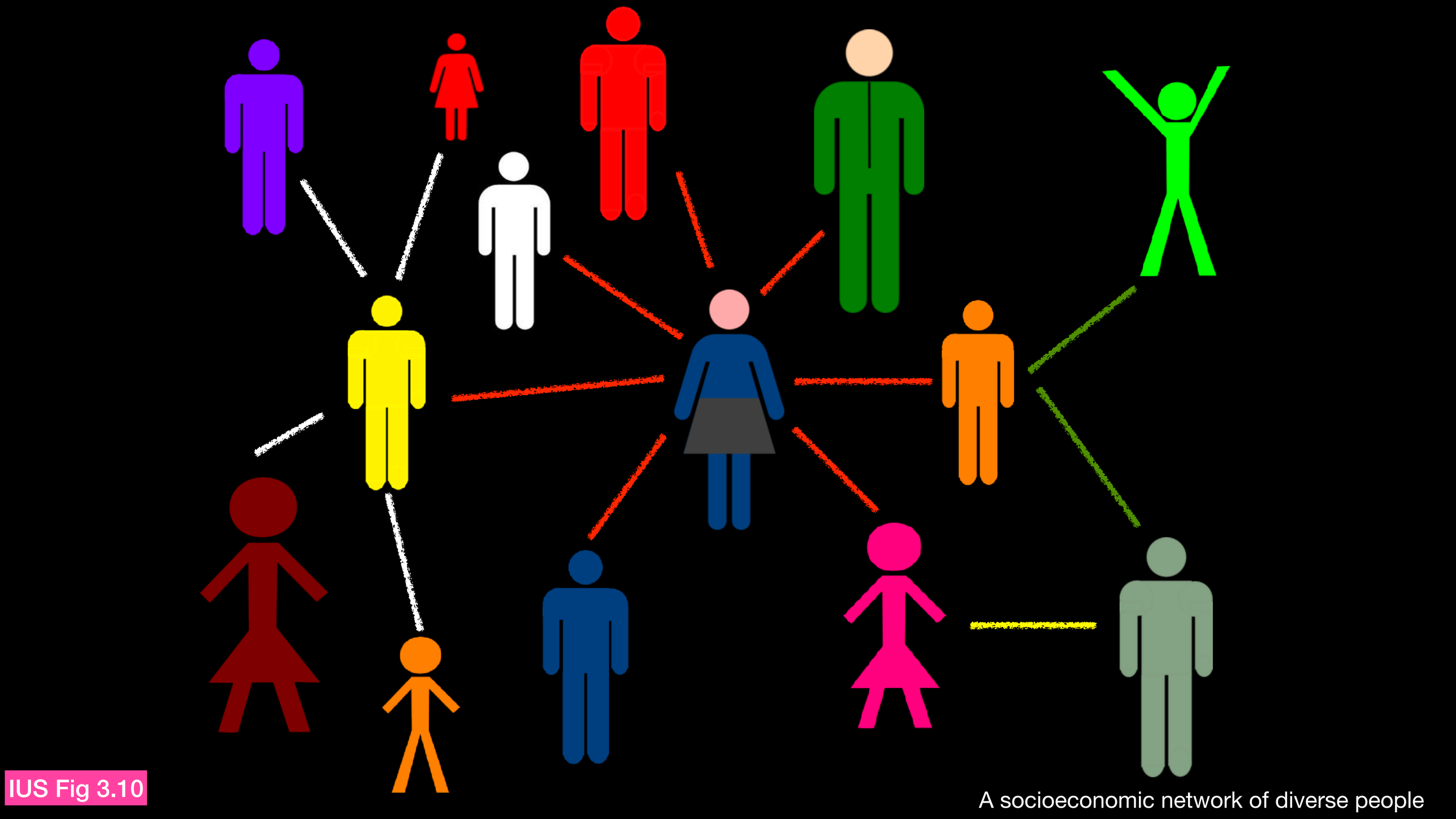
Lecture 8

Consequences of Network Models of Cities

8.1 Predictive Consequences of Urban Scaling

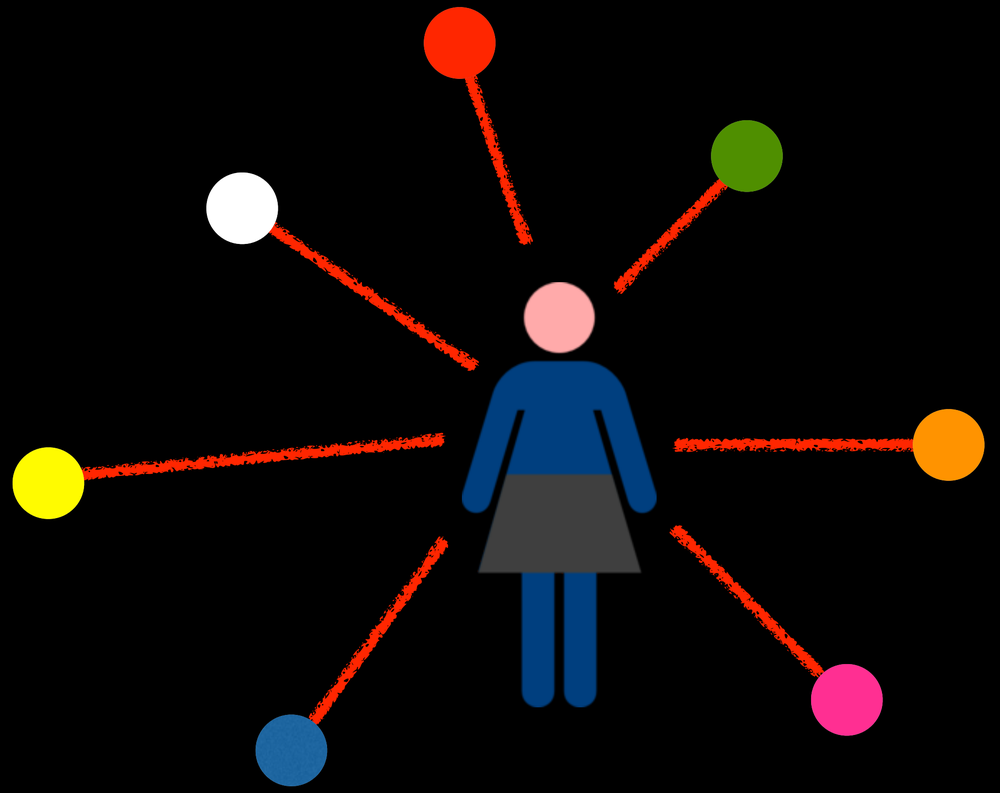
IUS 3.3

@BettencourtLuis bettencourt@uchicago.edu



IUS Fig 3.10

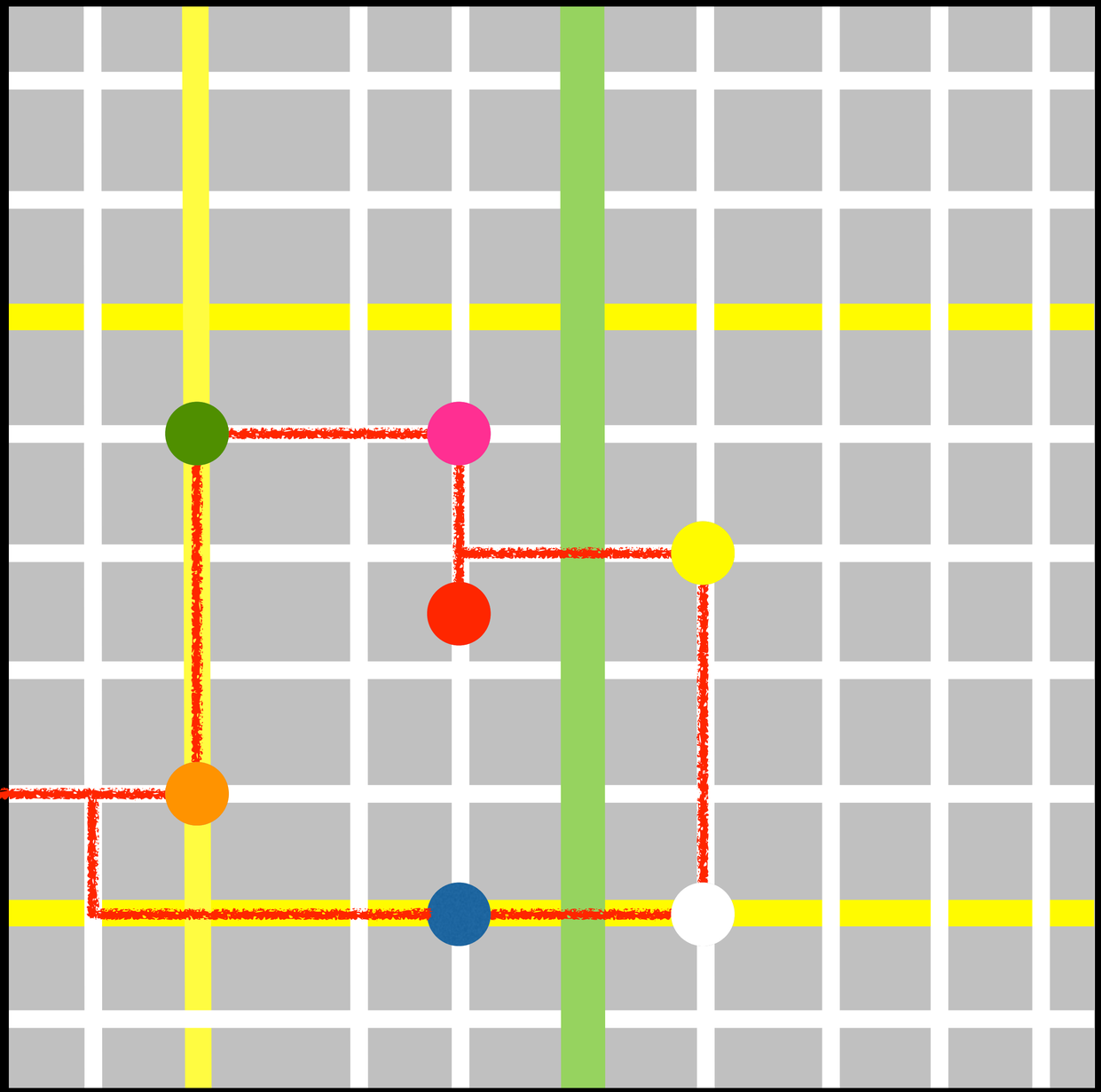
A socioeconomic network of diverse people

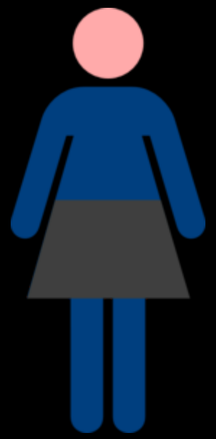


IUS Fig 3.10

…can be abstracted in terms of an “ego-network”

Health
Love
Money
Education
Fun
Food
Services
. . .

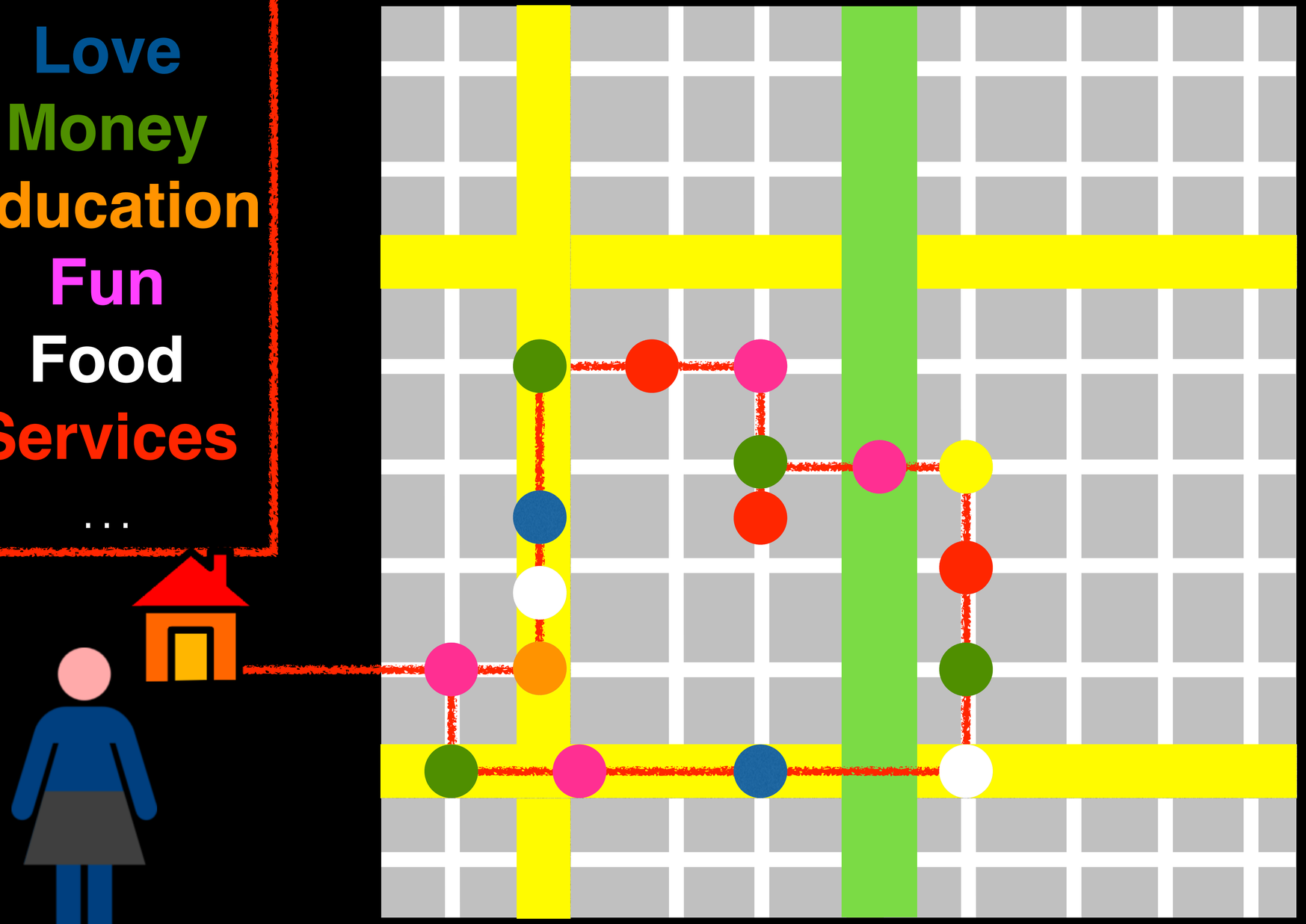




…which is embedded in spacetime via life paths (time geography)

IUS Fig 3.10

Health
Love
Money
Education
Fun
Food
Services
. . .



IUS Fig 3.10

…which is embedded in spacetime via life paths, which meet more events in larger, denser, more heterogeneous cities

Many quantitative predictions + general consequences

Urban scaling relation	Exponent prediction $D = 2, H_m = 1$	Exponent prediction General D, H_m
Land area $A = aN^{\alpha}$	$\alpha = 2/3$	$\alpha = \frac{D}{D + H_m}$
Network volume $A_n = A_0 N^{\nu}$	$\nu = 5/6$	$\nu = 1 - \delta$
Network Length $L_n = L_0 N^{\lambda}$	$\lambda = 2/3$	$\lambda = \alpha$
Interactions/capita $k = k_0 N^{\delta}$	$\delta = 1/6$	$\delta = \frac{H_m}{D(D + H_m)}$
Social outputs $Y = Y_0 N^{\beta}$	$\beta = 7/6$	$\beta = 1 + \delta$
Power dissipation $W = W_0 N^{\omega}$	$\omega = 7/6$	$\omega = 1 + \delta$
Land rents ($\$/m^2$) $P_L = P_0 N^{\beta_L}$	$\beta_L = 4/3$	$\beta_L = 1 + 2\,\delta$

cities in higher dimensions

Summary of Urban Scaling relations and exponent predictions for various important quantities. Note that agglomeration effects vanish when $H_m \to 0$ because then people remain spatially separated social networks fail to emerge (we will look at internet quantities later).

Besides predictions for scaling of all these quantities…

There are a number of very interesting combinations and ratios:

1. The ratio of built volume to total area of cities
2. The depth of social networks in cities vs the size of the entire population
3. The “price” of land (land rents): or the rate of money exchanged per land area

-

4. The ratio of land rents and incomes and building heights

-

Landscapes of Infrastructure

$$A_n/A \sim N^{\delta}$$

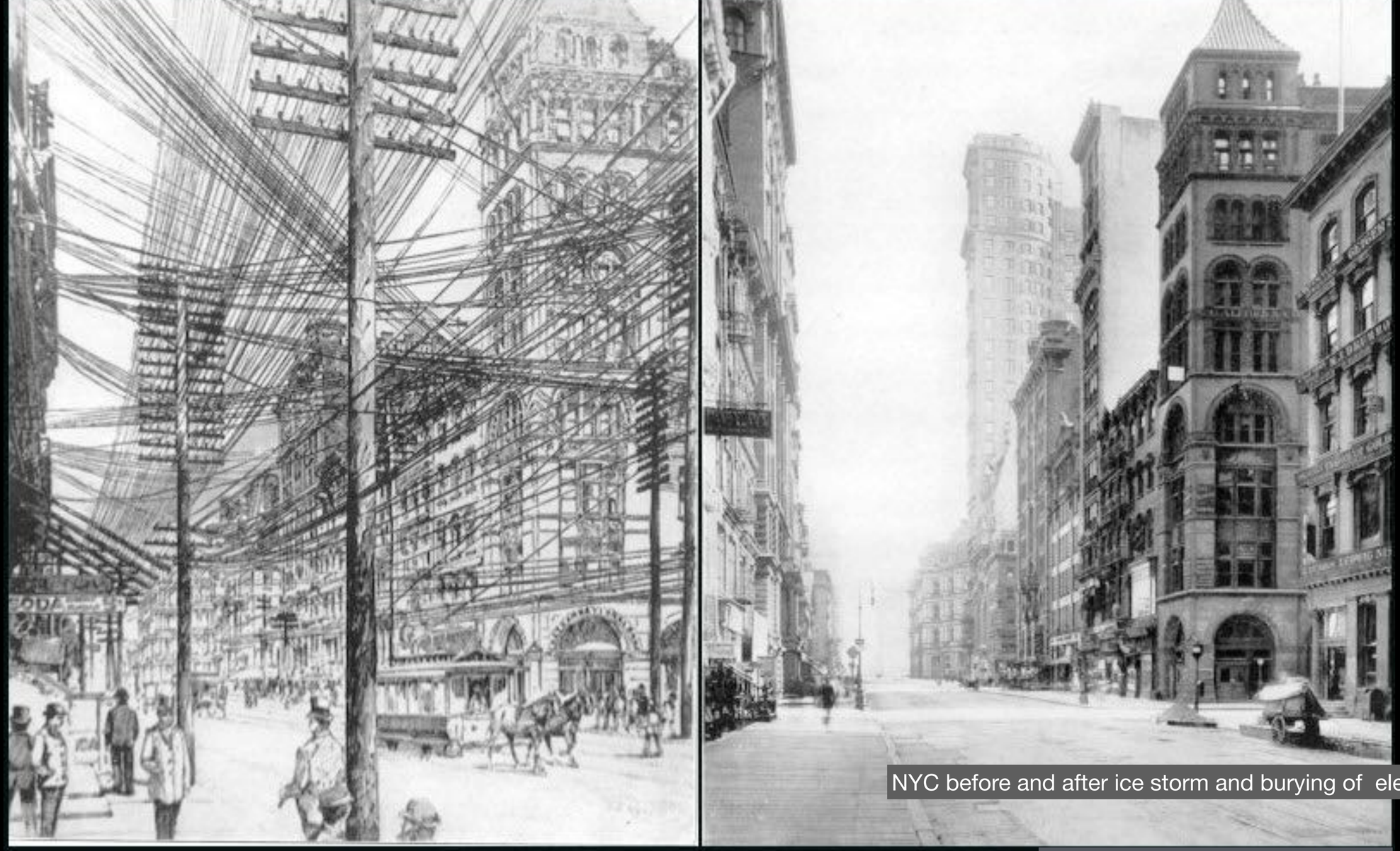
Greater infrastructure network volume per unit area with city size, especially in city centers

Master/Trunk infrastructure gets enormous

infrastructure networks must push
into the third dimension

credit: MacLean

credit: Robert Stone



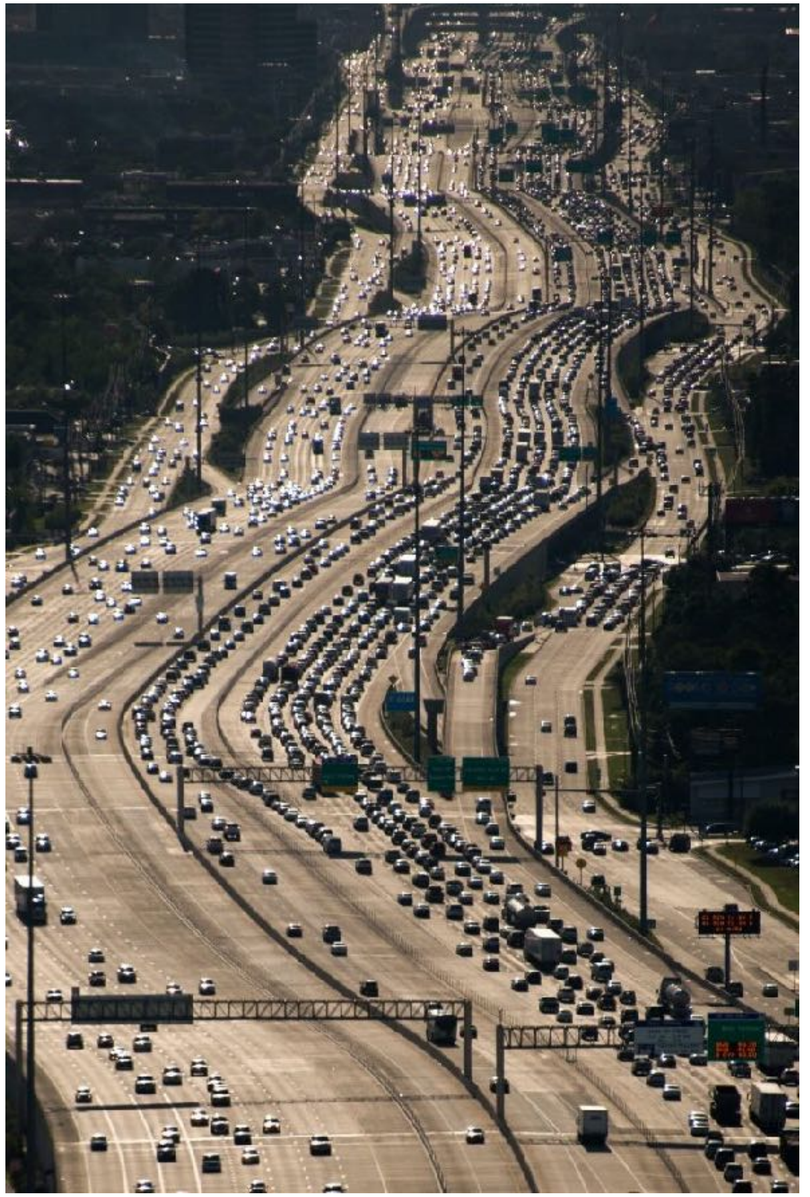
NYC before and after ice storm and burying of electrical cables

1890s New York City
credit: www.loper-os.org

And must go into the third dimension, above or below ground to leave space for people

World’s Widest Highways

G4 Beijing-Hong Kong-Macau Expressway (Image source: Reuters/China Daily)



IH-10 in Houston TX

what happens to width when speeds are lower?

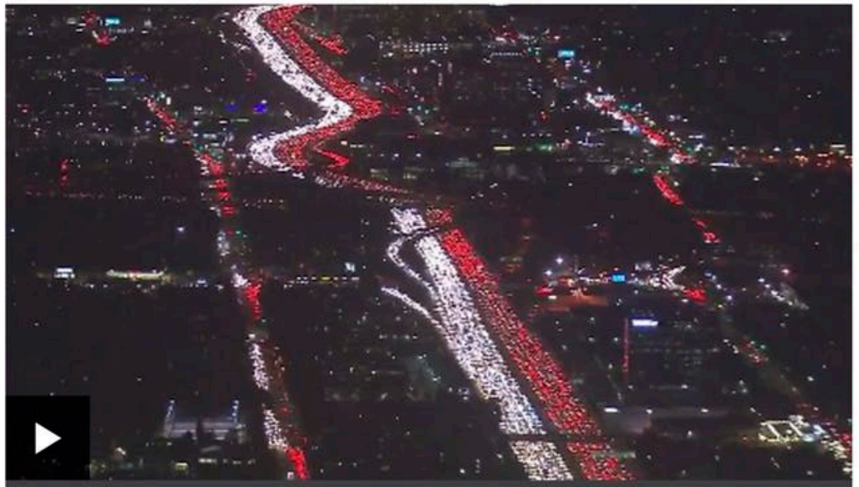
World’s Worst Traffic Jams

mostly in large developing cities

US & Canada

Thanksgiving traffic jam in Los Angeles is 'most epic'

23 November 2016



Thanksgiving traffic jam is 'most epic'

Aerial footage has gone viral of a massive traffic jam, captured during the great Thanksgiving getaway in southern California.

A news helicopter filmed the miles-long gridlock on the 405 motorway in the Los Angeles area on Tuesday.

BBC Sign in Home News Sport Reel Worklife Travel

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China traffic jam stretches 'nine days, 100km'

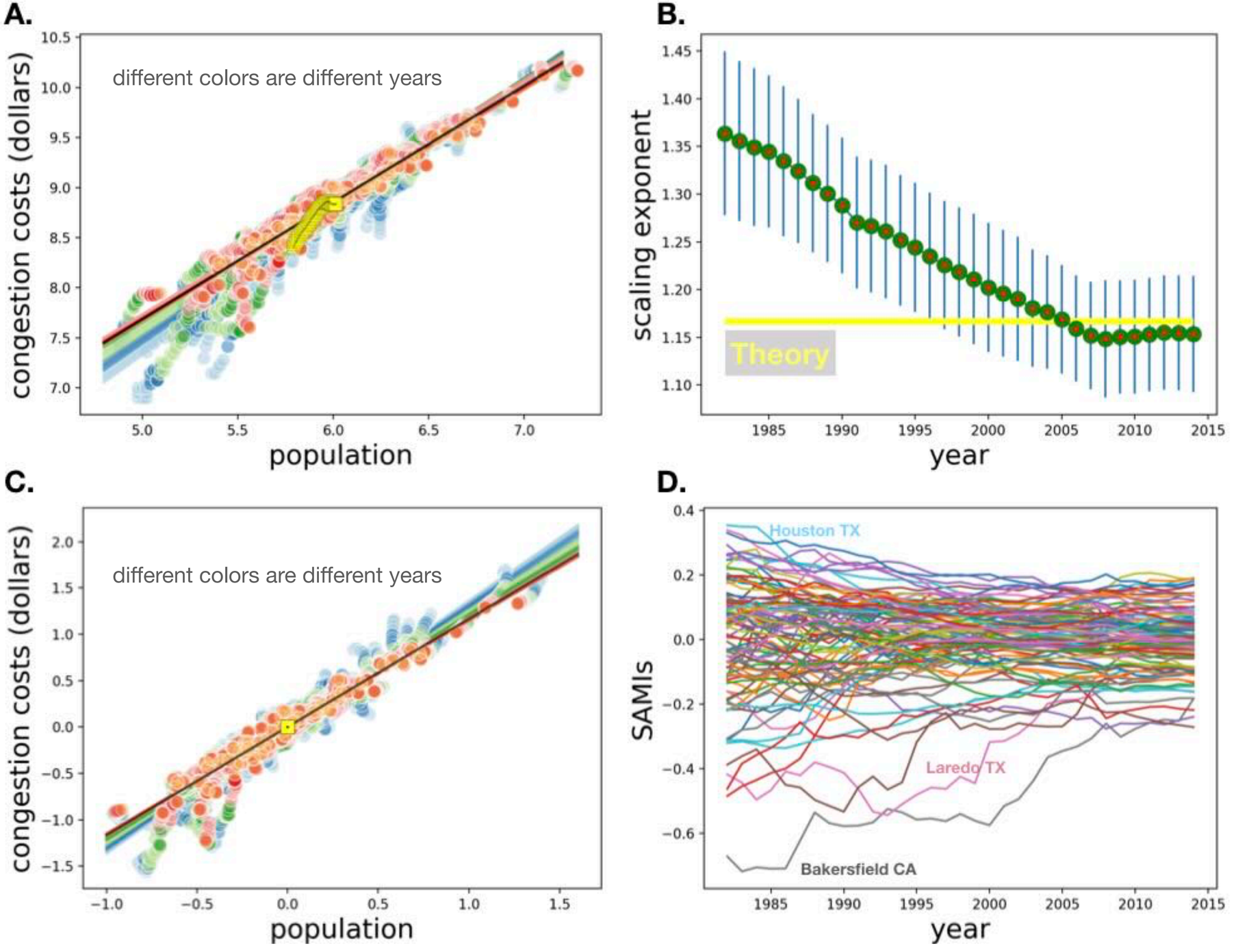
24 August 2010

A woman caught up in the jam describes her ordeal

A massive traffic jam in China has slowed vehicles to a crawl for nine days near Beijing, local media say.

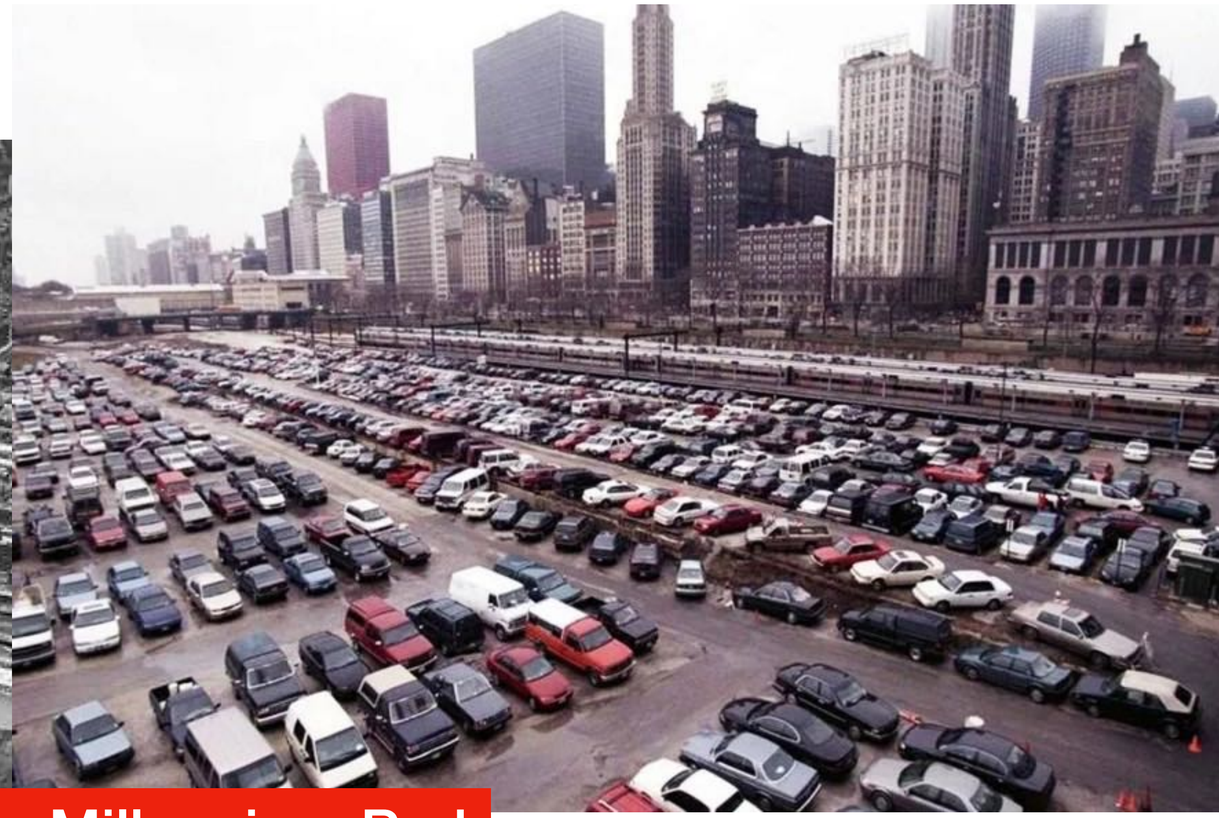
Vehicles, mostly lorries bound for Beijing, are in a queue for about 100km (62 miles) because of heavy traffic, road works and breakdowns.

The drivers have complained that locals were over-charging them for food and drink while they were stuck.



https://royalsocietypublishing.org/doi/pdf/10.1098/rsif.2019.0846

Frank Gehry: Jay Pritzker Pavillion



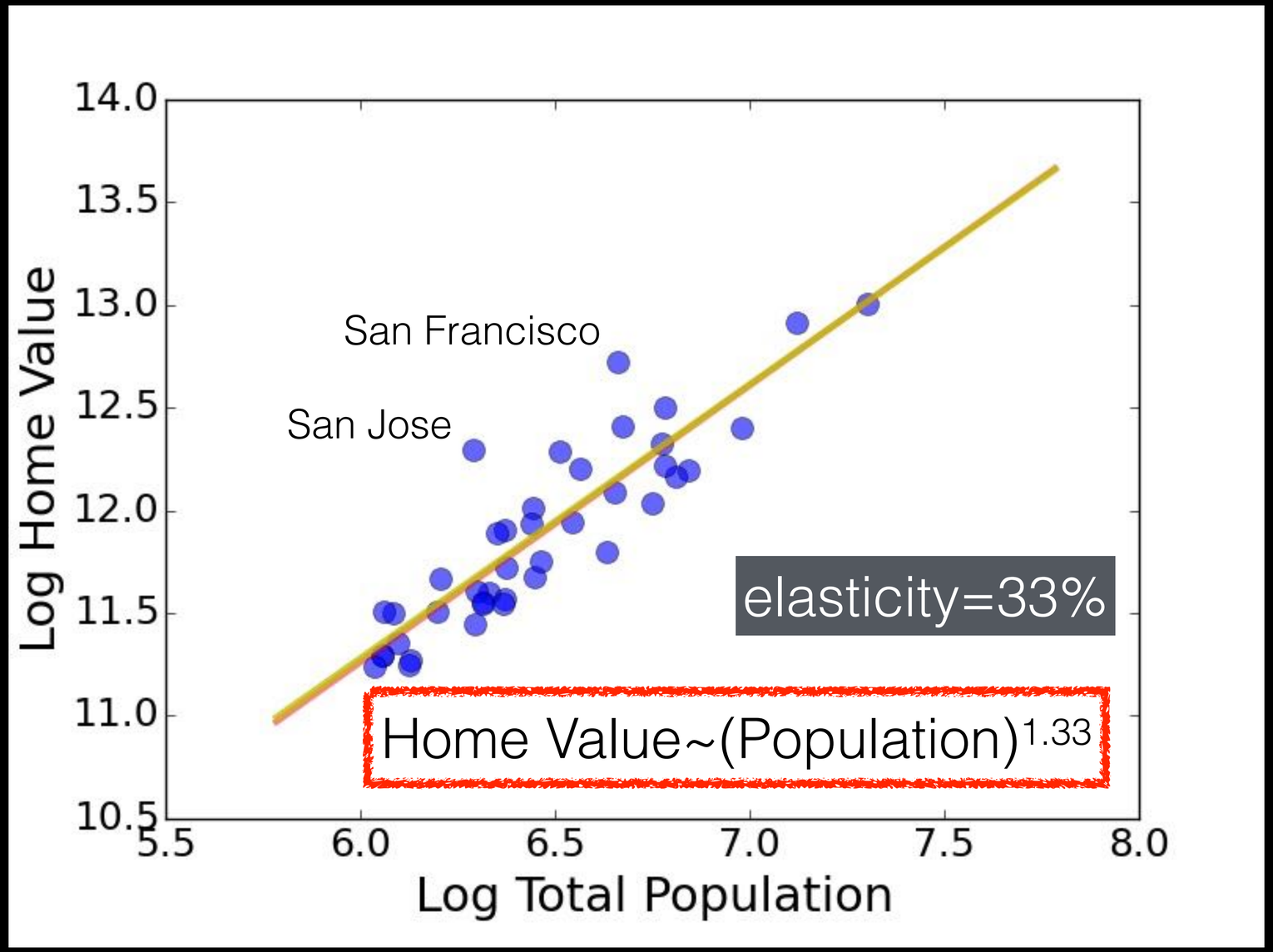
Before Millennium Park

building heights

$GDP_{pc}/a_n \sim N^{2\delta}$ Land rents increase faster than incomes!!

building heights $\sim N^{\delta}$ larger cities get rising skylines

Home Value US Metros

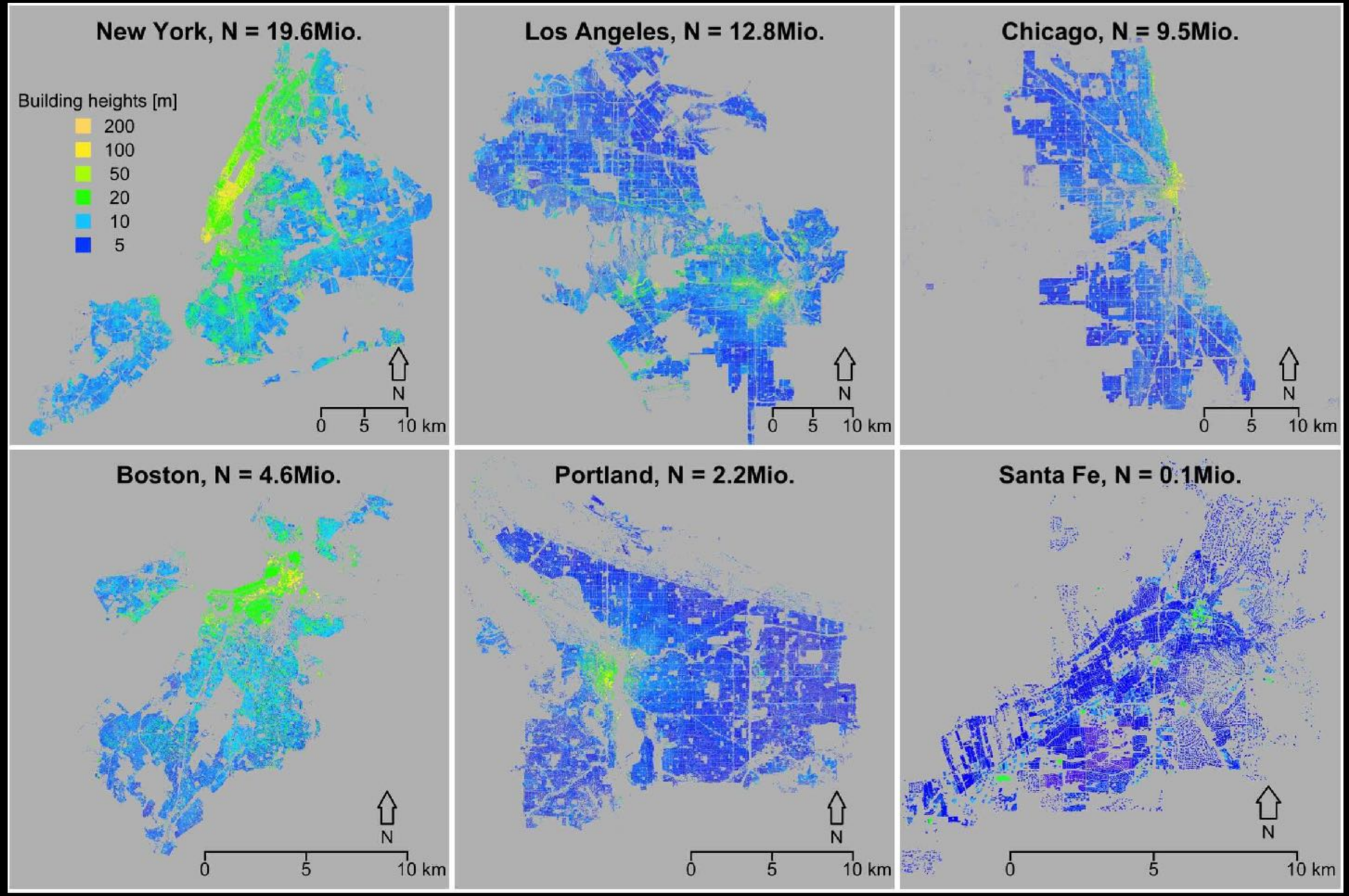


Housing is never affordable in large cities

why?

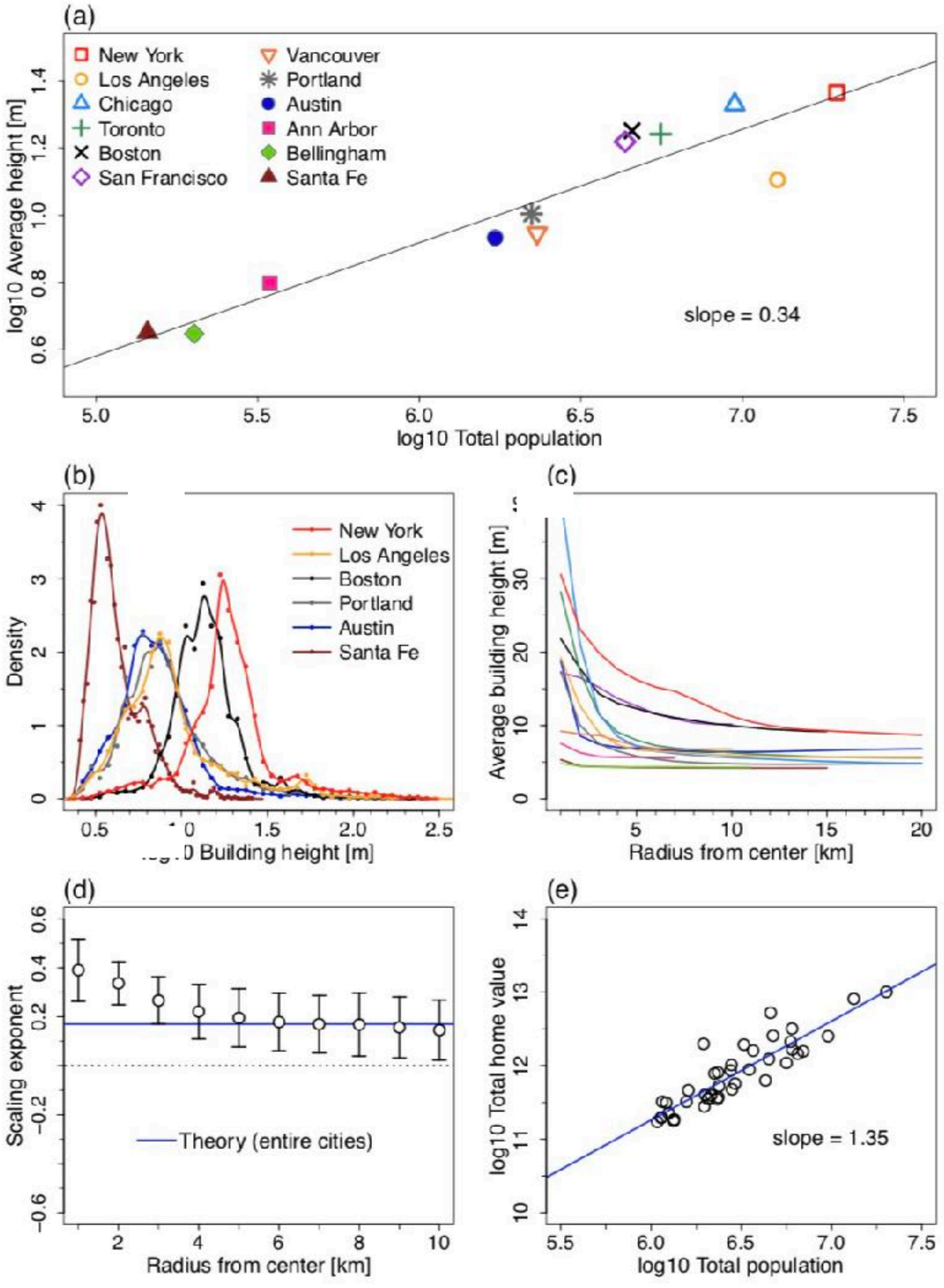
Hong Kong
credit:Guardian

credit: telegraph



data from LiDAR

Schlaepfer, Lee, Bettencourt (2016)
Urban Skylines: building heights and shapes as measures of city size


(a)
New York
Los Angeles
Chicago
Toronto
Boston
San Francisco
Vancouver
Portland
Austin
Ann Arbor
Bellingham
Santa Fe
slope = 0.34
log10 Average height [m]
log10 Total population
(b)
New York
Los Angeles
Boston
Portland
Austin
Santa Fe
Density
Building height [m]
(c)
Average building height [m]
Radius from center [km]
(d)
Scaling exponent
Theory (entire cities)
Radius from center [km]
(e)
log10 Total home value
slope = 1.35
log10 Total population

Characterizing (building) shapes

Simplest shape:

$$V_b = l_c^3$$

$$l_c = V_b^{1/3}$$

$$A_b = 6l_c^2$$

$$a_{A/V} = 6/l_c$$

cube

More general shape:

Cuboid: with height h_b and footprint l_b^2

$$V_b = l_n^2 h_b$$

$$A_b = 2l_b^2 + 4h_b l_b$$

$$a_{A/V} = \frac{6}{l_c}\left(\frac{x_b^{-2/3} + 2x_b^{1/3}}{3}\right)$$

$x_b = 1$ minimizes $a_{A/V}$

$$x_b = \frac{h_b}{l_b}$$

Skyscraper

Flat sheet (warehouse)

Energy Use (climate control)

$$\frac{\Delta E}{\Delta t} = \mu_b A_b \Delta T$$

temperature difference

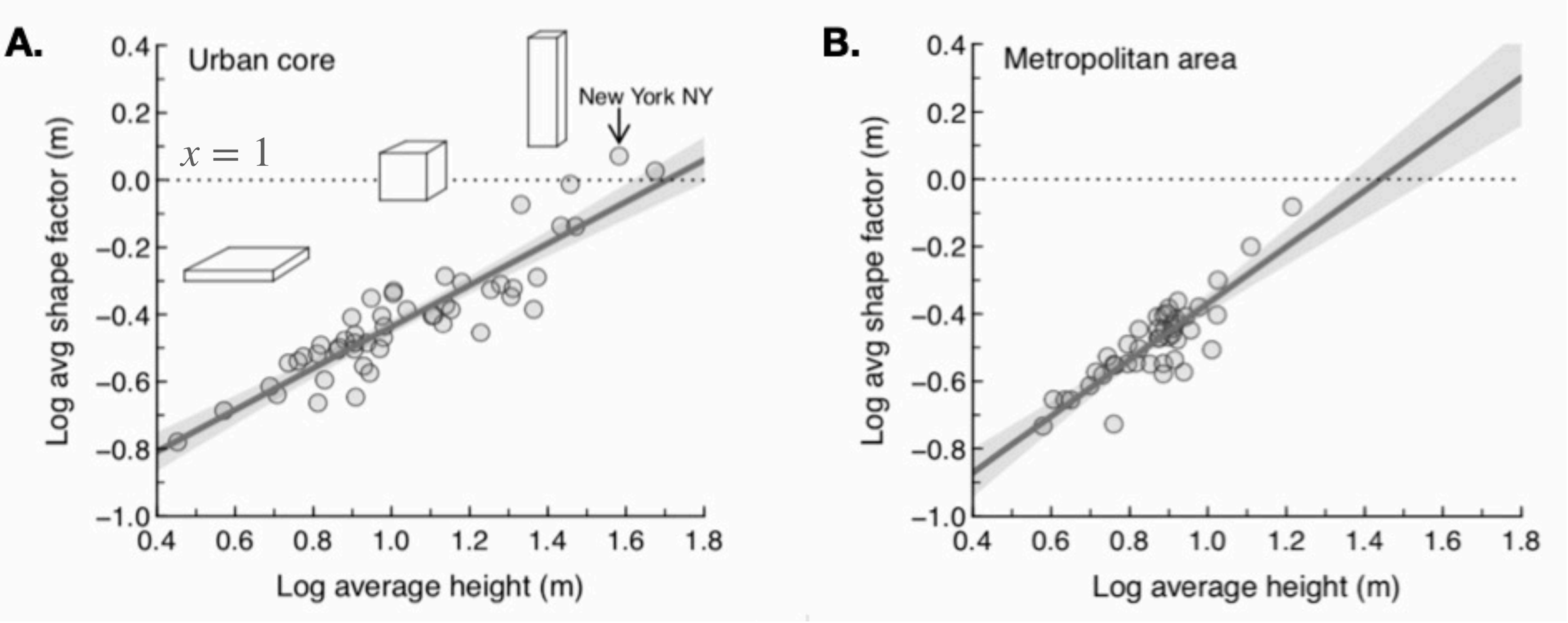
Power consumption

$$N_b = C(h_b)\frac{l_b^2}{a_f}\frac{h_b}{h_0} = \frac{V_b}{v_v}$$

Building max occupancy

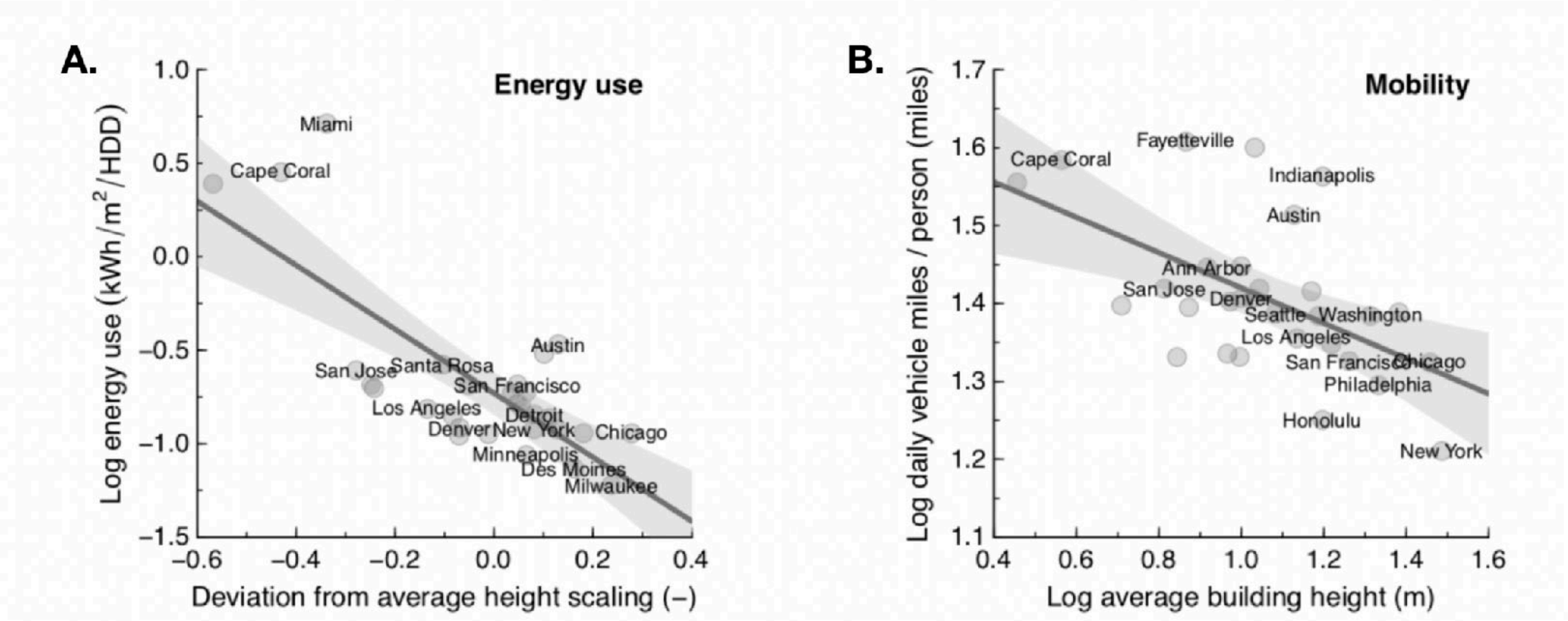
$$\frac{1}{N_b}\frac{\Delta E}{\Delta t} = a_{A/V}\mu_b v_b \Delta T$$

Energy use/capita (efficiency)



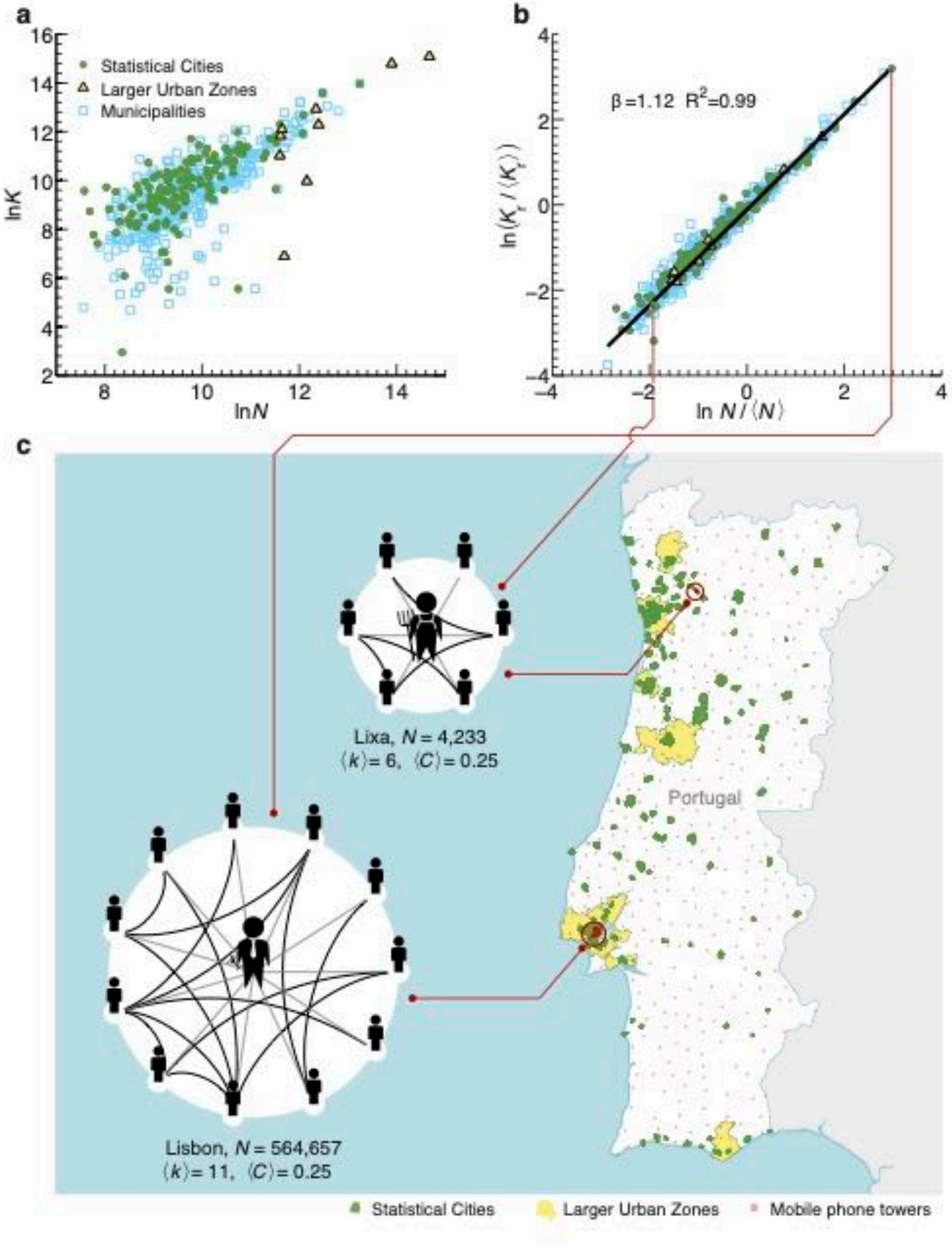
Heigh and footprint area are correlated

Higher buildings lead to savings in energy use and mobility



Social Networks get denser

average connectivity per capita: $\sim N^{\delta}$



Urban cellphone networks

$\beta = 1.12\text{-}1.19$

in agreement with theory.

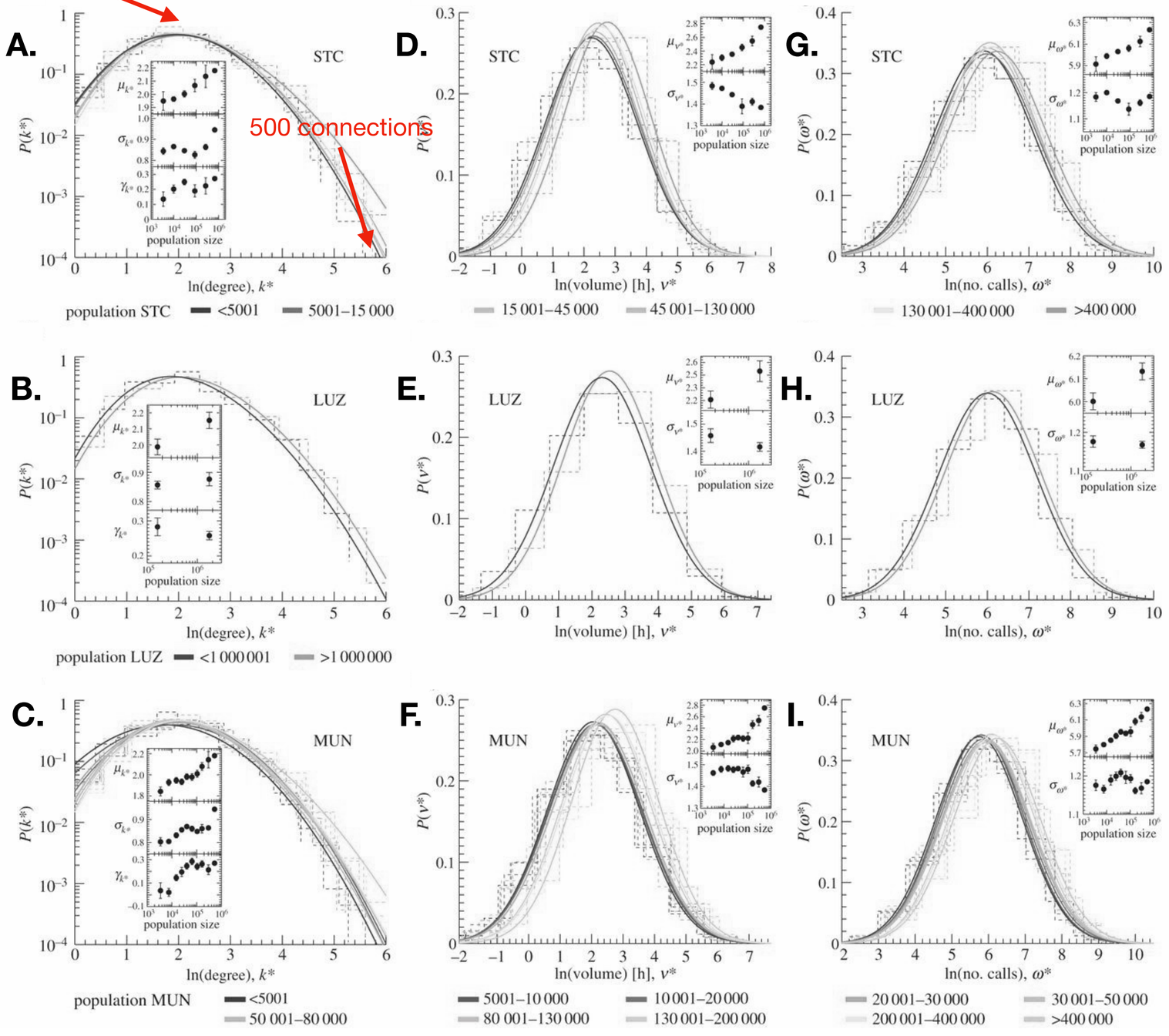
Network clustering is preserved:

same sense of community in town and country!

Schläpfer et al, 2014

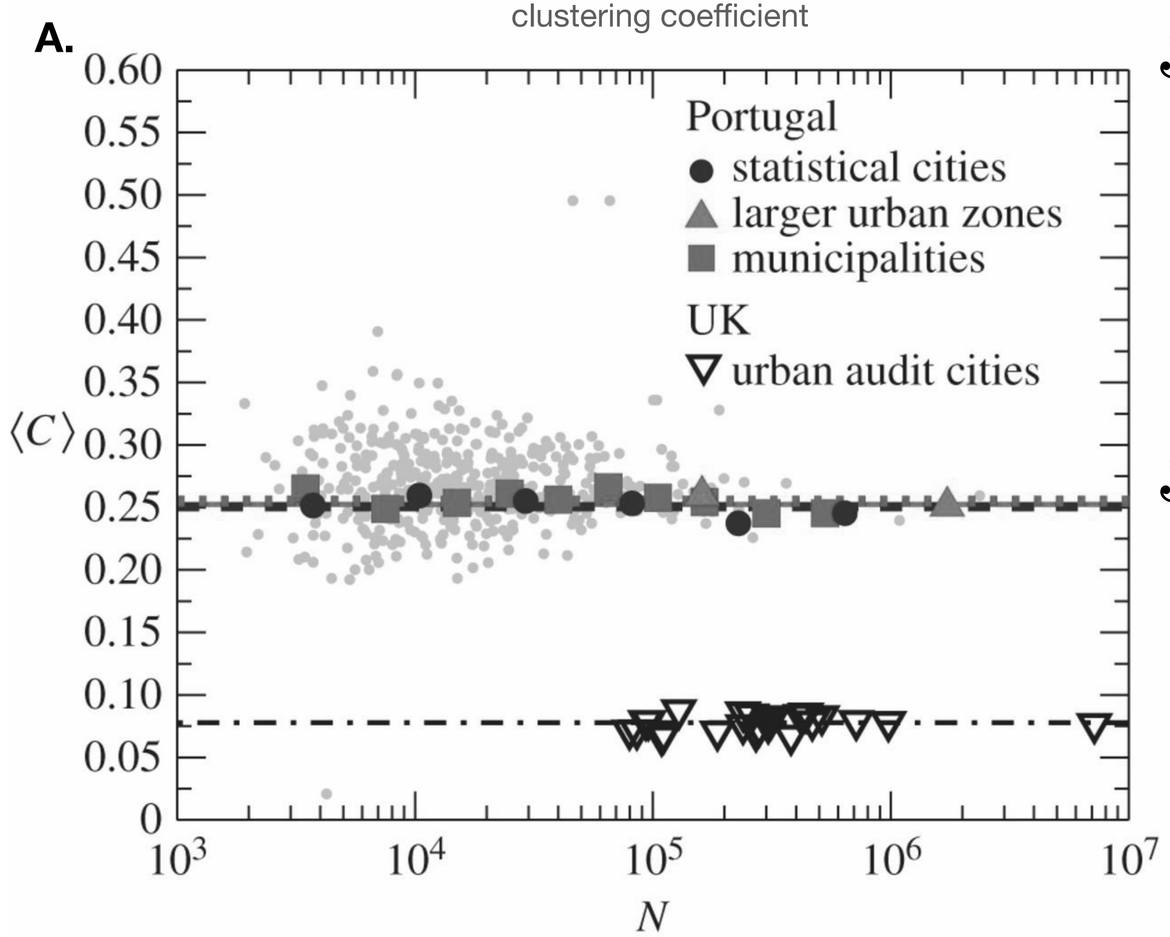
10 connections

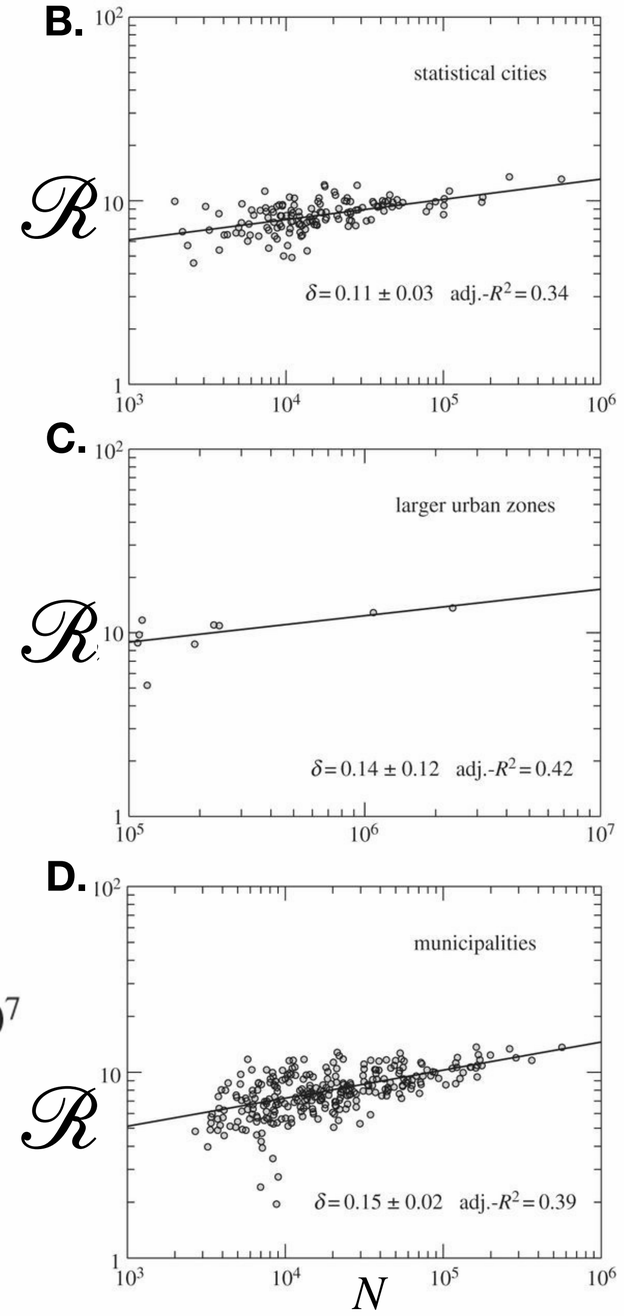
From cellphones" distribution of degree is very wide (lognormal)



How many of your friends are mutual friends ?

clustering coefficient





Contagion Dynamics

scales **superlinearly**

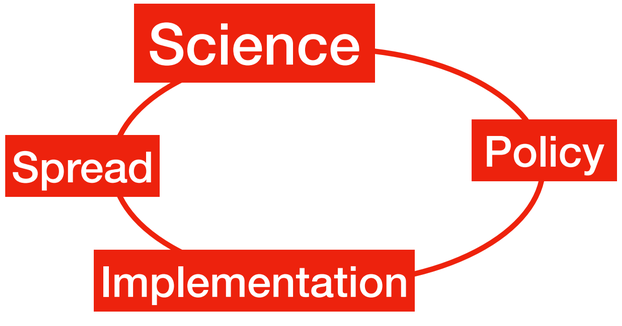
with population size

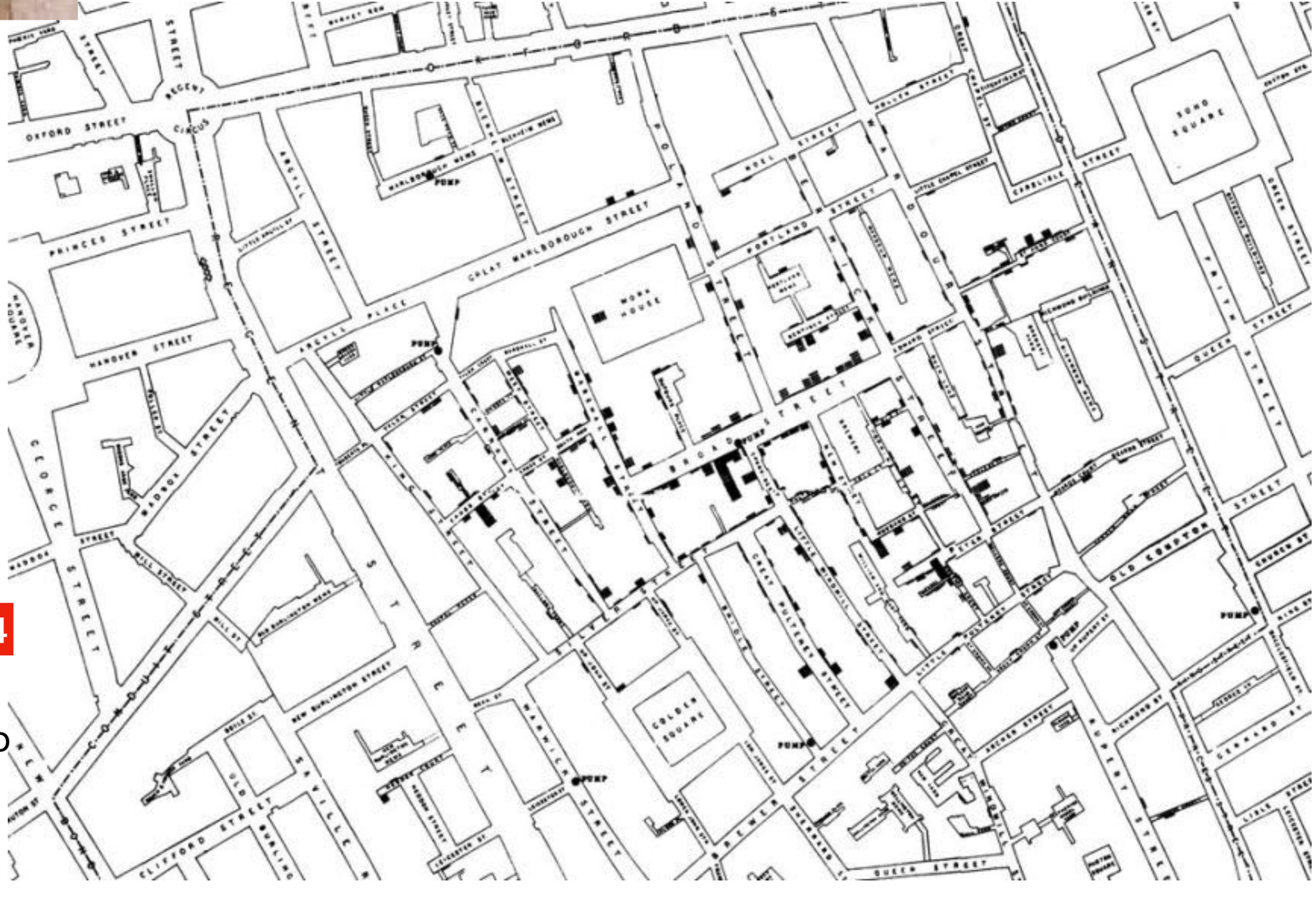
https://royalsocietypublishing.org/doi/full/10.1098/rsif.2013.0789

Contagious Diseases and Information spread faster in larger cities

average connectivity per capita: $k(N) \sim N^{\delta}$

beginning of modern medicine = beginning of modern urban planning





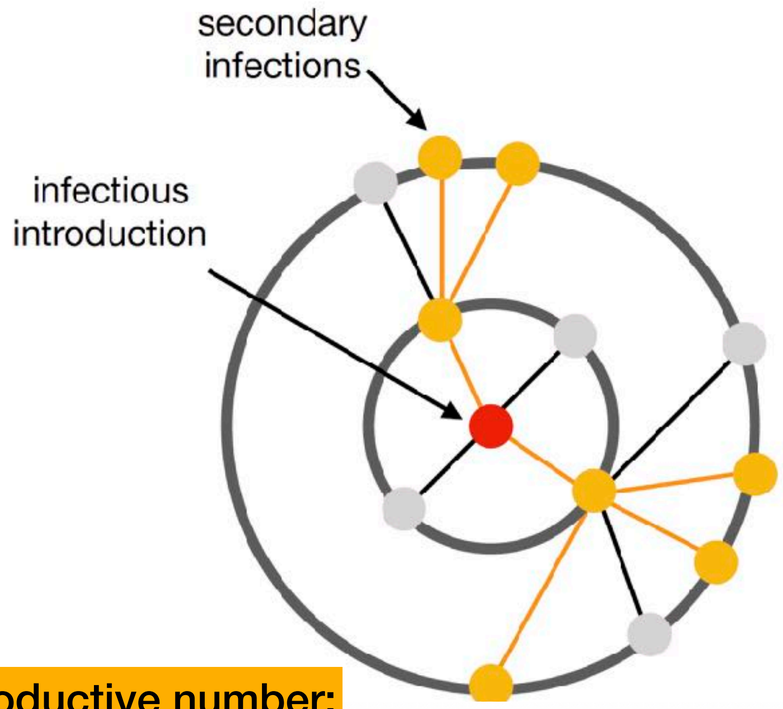
London 1854

Third cholera pandemic

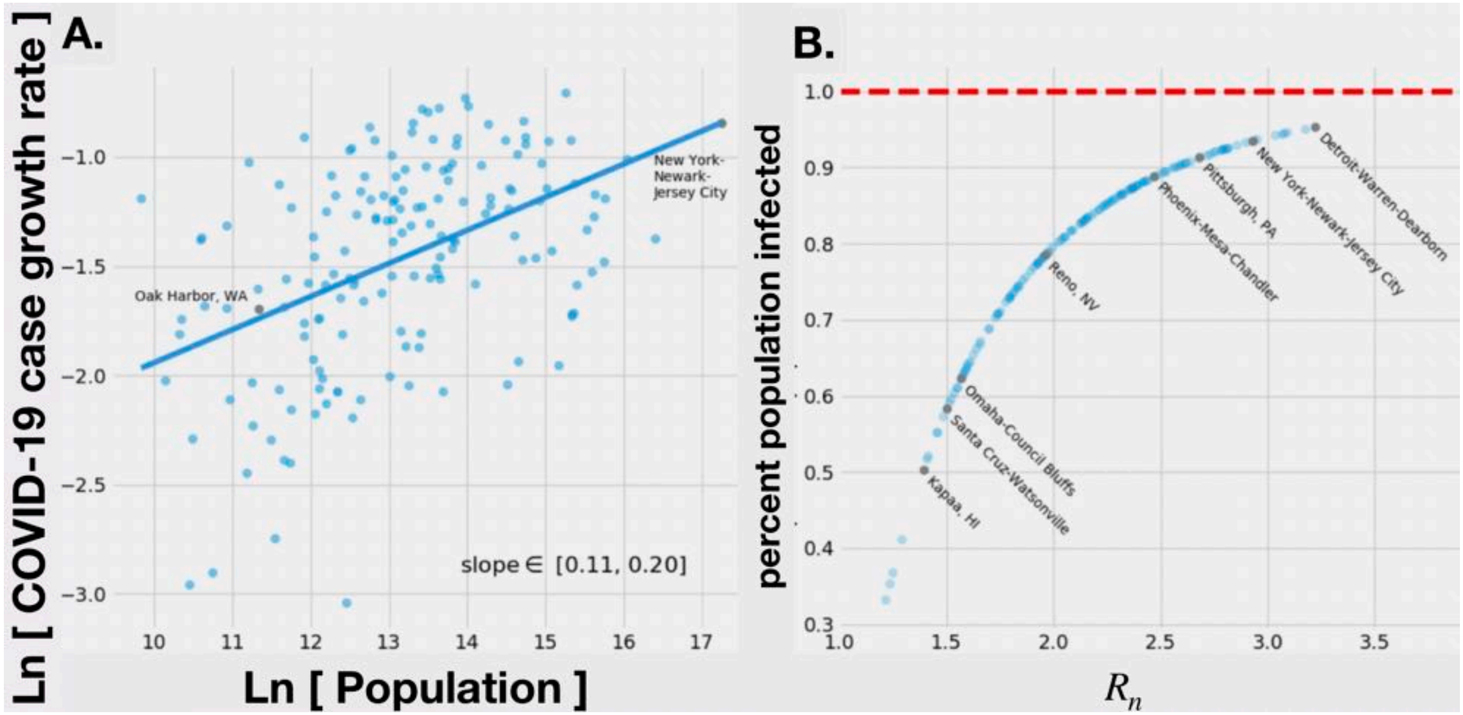
5.5% death rate in Chicago

https://www.nature.com/articles/s42949-021-00030-0

Contagious Processes on Networks



For COVID-19:



Reproductive number:

$$\mathcal{R} = P_I \frac{\langle k^2 \rangle}{\langle k \rangle} = P_I \langle k \rangle \left(1 + \frac{\sigma_k^2}{\langle k \rangle^2}\right)$$

$$k = \langle k \rangle = e^{\mu + \frac{\sigma^2}{2}}, \qquad \sigma_k^2 = \left(e^{\sigma^2} - 1\right) e^{2\mu + \sigma^2}$$

Lognormal

$$\mathcal{R}(N) = P_I \, e^{\sigma^2} \, k(N) \simeq P_I \, k_0 \, e^{\sigma^2} N^{\delta}$$

size of the outbreak $S_\infty = S_0 \, e^{-\mathcal{R}\left(1 - \frac{S_\infty}{N}\right)}$

vaccination rate: $P_v = 1 - 1/\mathcal{R}$

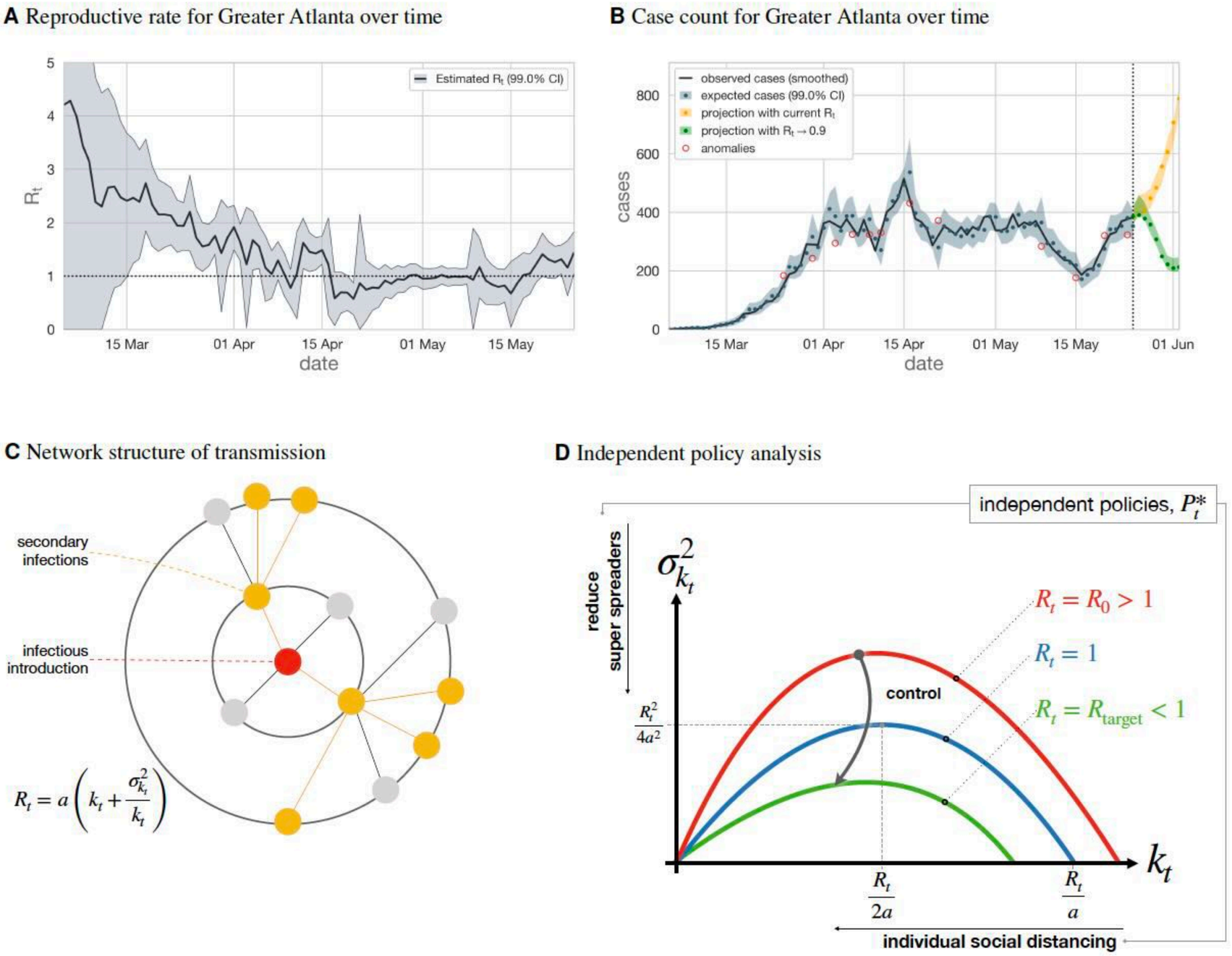
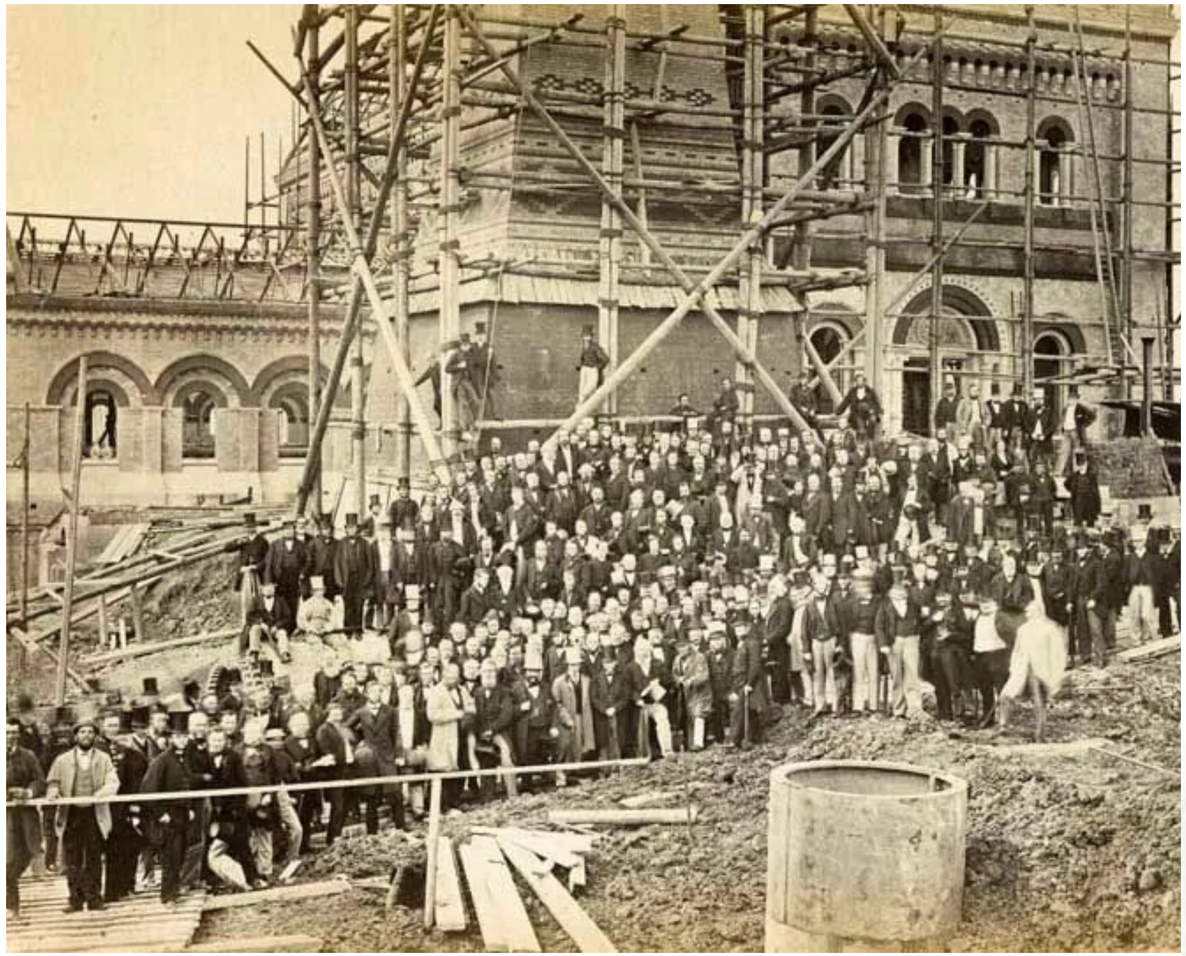


Figure 2. Real time estimation of transmissibility, forward case prediction and learning of least-disruptive effective epidemic controls. **A.** Real time Bayesian estimation of the effective reproductive number with quantified uncertainty based

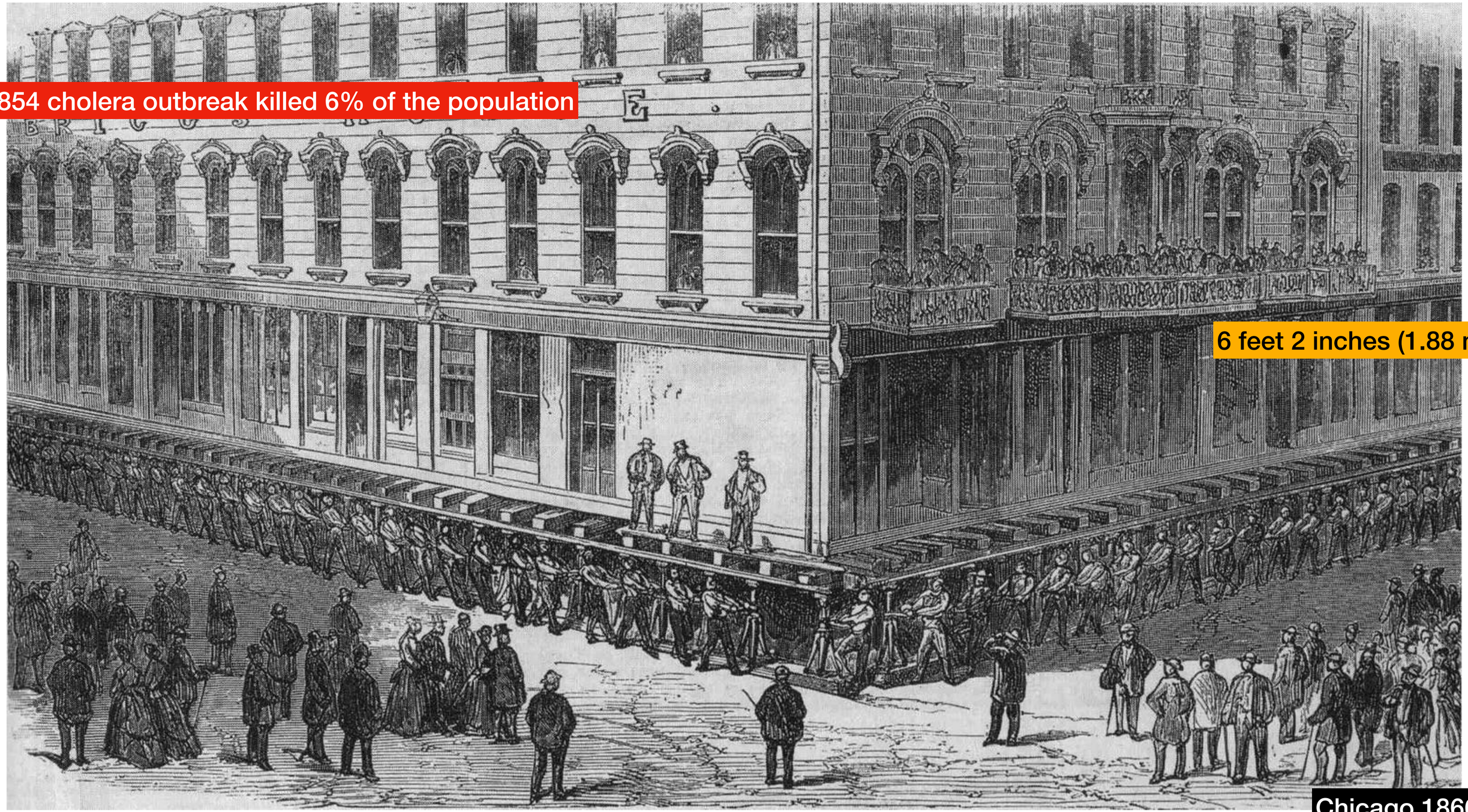
This led to major transformations of how we live in cities …



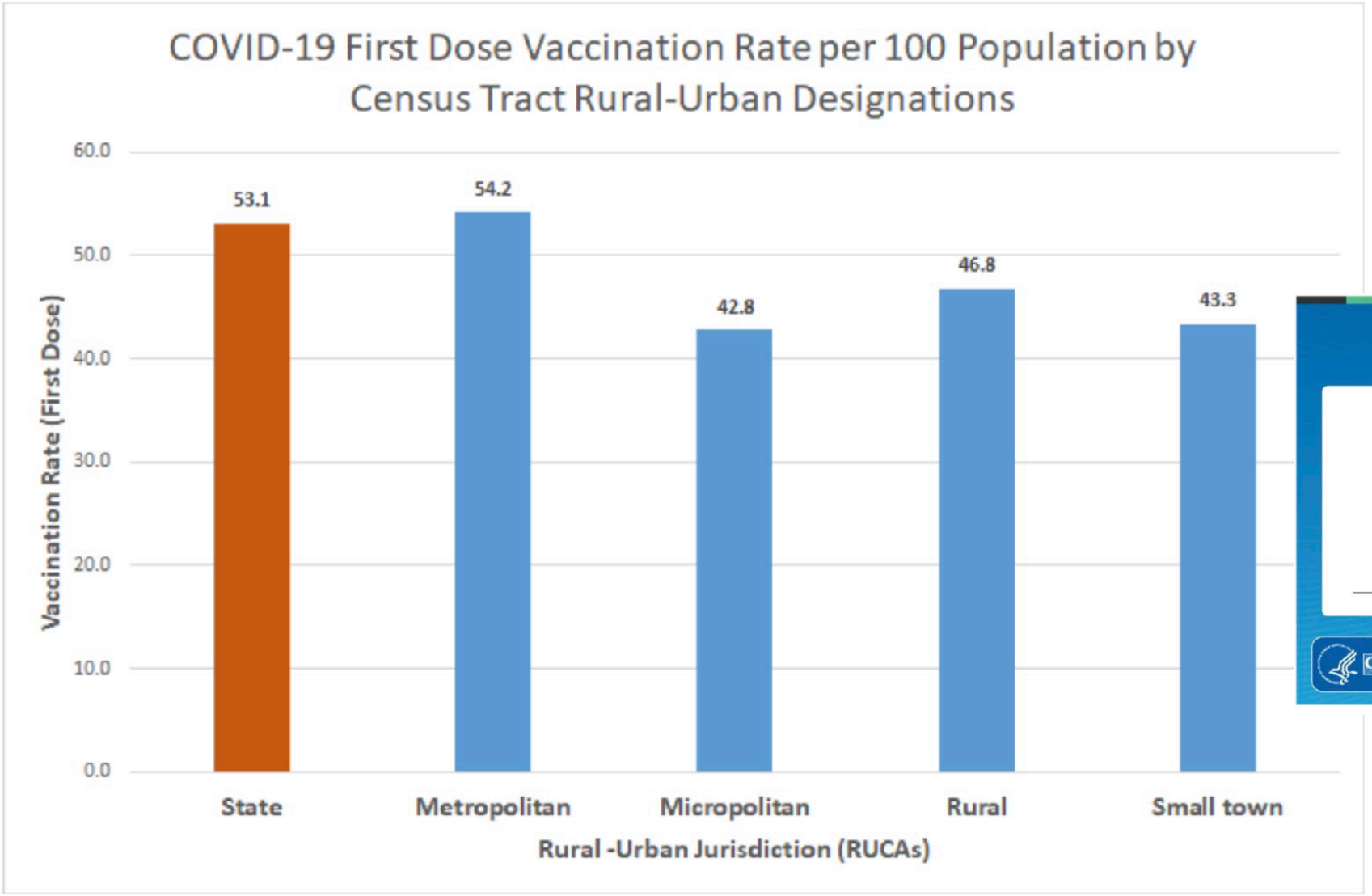
Sanitation works

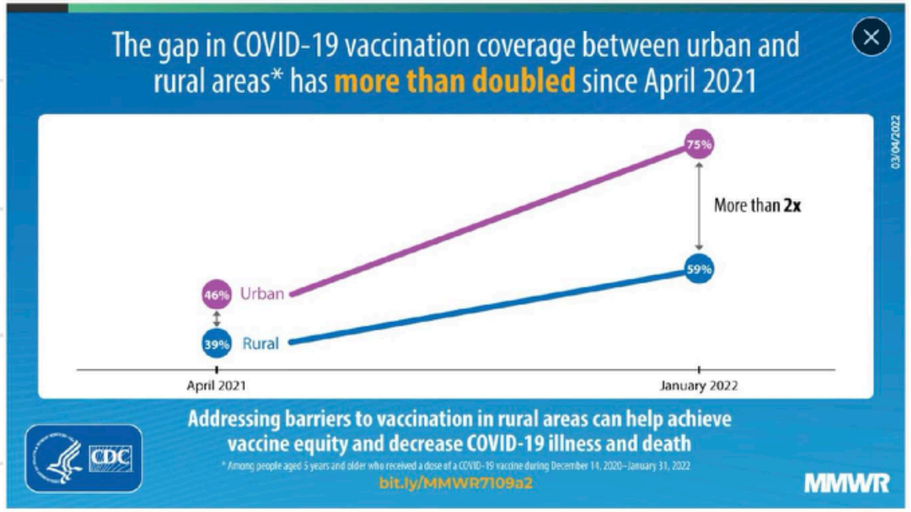
River clean up, hidden pipes

https://heritagecalling.com/2019/03/28/the-story-of-londons-sewer-system/

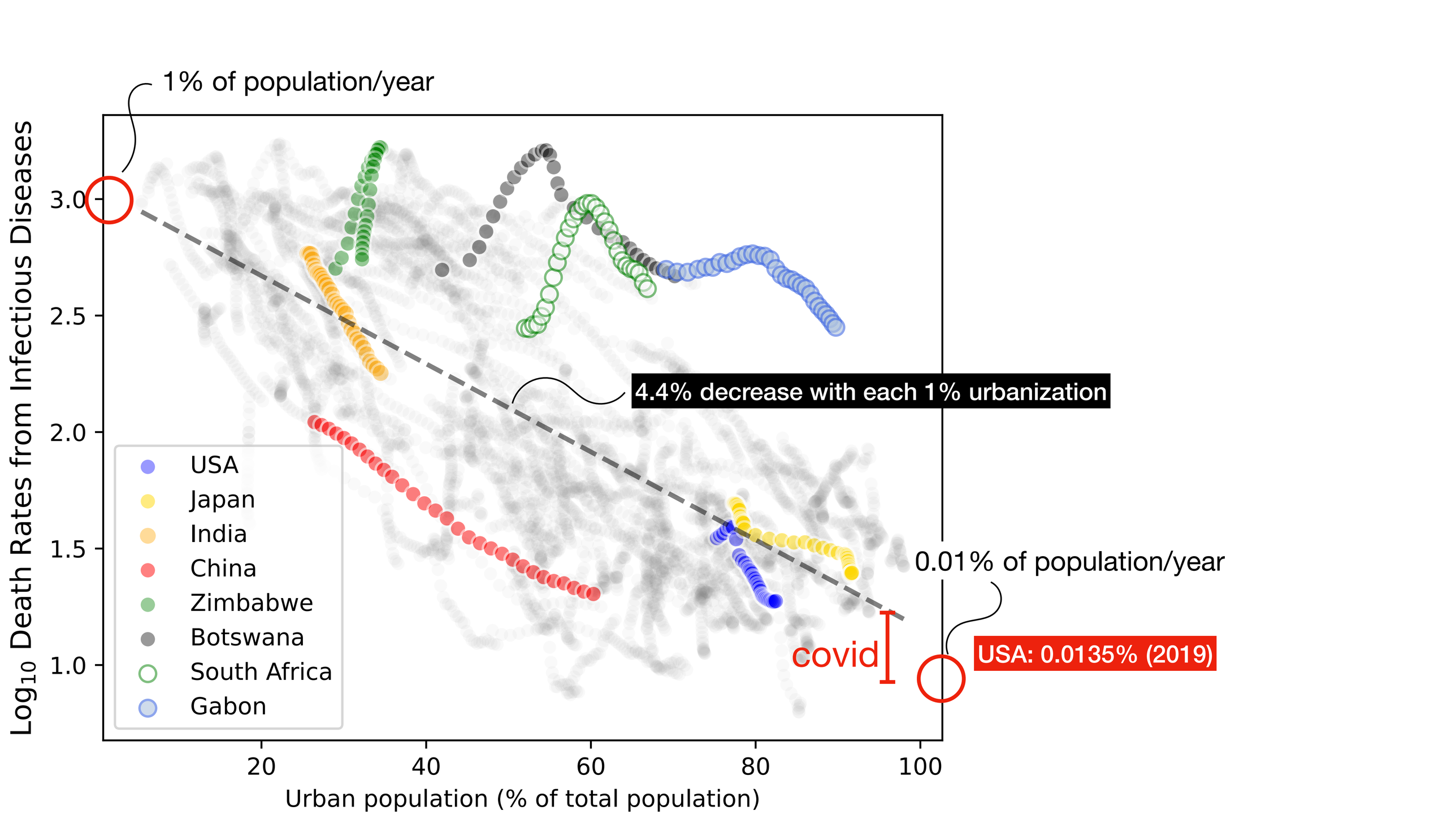


https://en.wikipedia.org/wiki/Raising_of_Chicago





https://www.vdh.virginia.gov/content/uploads/sites/182/2021/09/Rurality.png


1% of population/year
4.4% decrease with each 1% urbanization
0.01% of population/year
USA: 0.0135% (2019)
covid
USA
Japan
India
China
Zimbabwe
Botswana
South Africa
Gabon
Log10 Death Rates from Infectious Diseases
3.0
2.5
2.0
1.5
1.0
20
40
60
80
100
Urban population (% of total population)

Mental Health

Evidence and theory for lower rates of depression in larger US urban areas

Andrew J. Stier[a,1], Kathryn E. Schertz[a], Nak Won Rim[b], Carlos Cardenas-Iniguez[a], Benjamin B. Lahey[c], Luís M. A. Bettencourt[d,e], and Marc G. Berman[f,1]

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Edited by William A. V. Clark, University of California, Los Angeles, CA, and approved June 18, 2021 (received for review October 27, 2020)

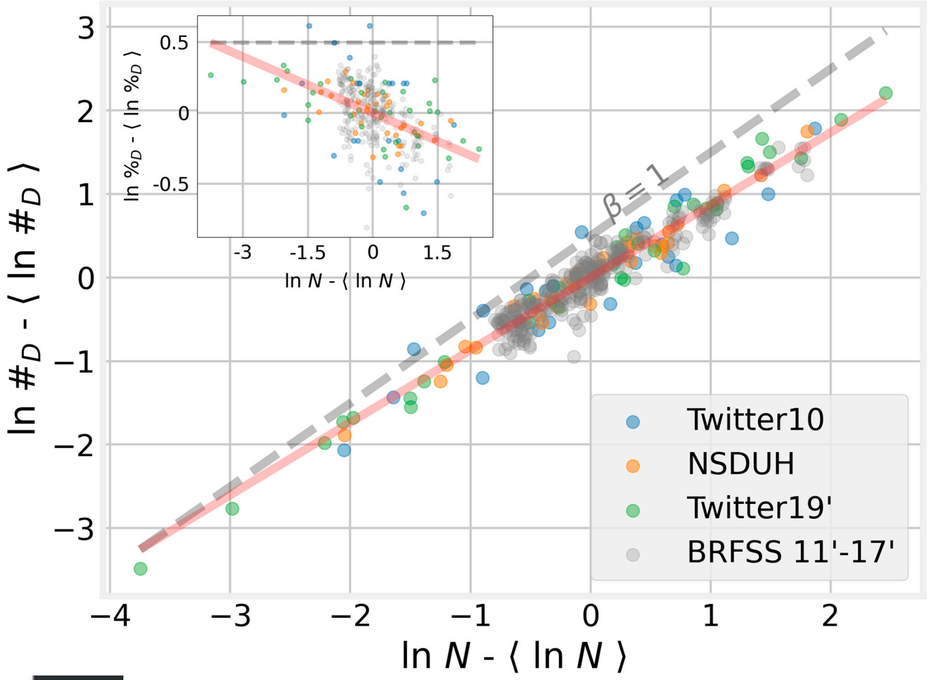
It is commonly assumed that cities are detrimental to mental health. However, the evidence remains inconsistent and at most, makes the case for differences between rural and urban environments as a whole. Here, we propose a model of depression driven by an individual's accumulated experience mediated by social networks. The connection between observed systematic variations in socioeconomic networks and built environments with city size provides a link between urbanization and mental health. Surprisingly, this model predicts lower depression rates in larger cities. We confirm this prediction for US cities using four independent datasets. These results are consistent with other behaviors associated with denser socioeconomic networks and suggest that larger cities provide a buffer against depression. This approach introduces a systematic framework for conceptualizing and modeling mental health in complex physical and social networks, producing testable predictions for environmental and social determinants of mental health also applicable to other psychopathologies.

cities | depression | social networks | built environment | complex systems

Living in cities changes the way we behave and think (1–3). Over a century ago, the social changes associated with mass-mental health in cities vs. rural areas (7, 8). However, this evidence and that linking SWB and cities (15–18) have remained mixed and often explicitly inconsistent (19, 20) due to differences in 1) reporting (e.g., surveys vs. medical records); 2) types of measurement (e.g., surveys vs. interviews); 3) definitions of what constitutes urban; and 4) the mental disorders studied (e.g., schizophrenia vs. depression).

For these reasons, it is desirable to create a systematic framework that organizes this diverse body of research and interrogates how varying levels of urbanization influence mental health across different sets of indicators. Here, we begin to build this framework for depression in US cities. We show that, surprisingly, the per capita prevalence of depression decreases systematically with city size.

Like earlier classic approaches, our strategy frames the effects of city size on mental health through the lens of the individual experience of urban physical and socioeconomic environments. Crucial to our purposes, many characteristics of cities have been recently found to vary predictably with city population size. These systematic variations in urban indicators are explained by denser built environments and their associated increases in the intensity of human interactions and resulting adaptive behaviors (21).



ECOLOGY

PSYCHOLOGICAL AND COGNITIVE SCIENCES

https://www.pnas.org/doi/10.1073/pnas.2022472118

The pace of life accelerates

average rates of production and exchange per capita: $y(N) \sim N^{\delta}$

speeds $[y] \sim 1/time$

times between events “shrink” : $\sim N^{-\delta}$

quantifies some measures of overload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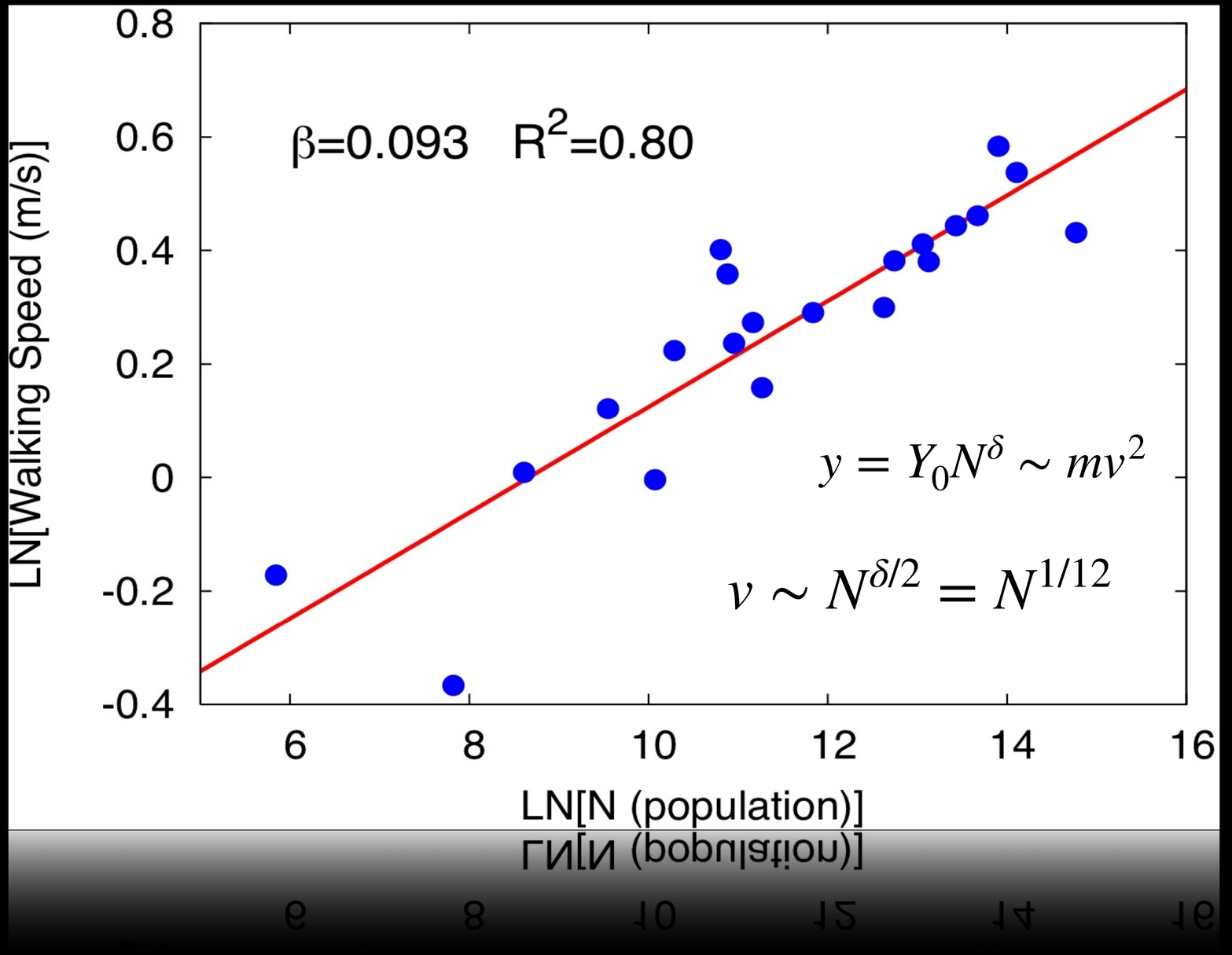
Walking Speed vs Population Size



NYC Tourists Are 'Like Walking Dead,' Anger Fast-Paced New Yorkers During Holiday Season

By JAKE PEARSON 12/12/13 01:07 PM ET EST AP

credit: Huffington Post

Fractal Dimension of Built Spaces

Shapes of built spaces of cities

1990s

Fractal Dimension

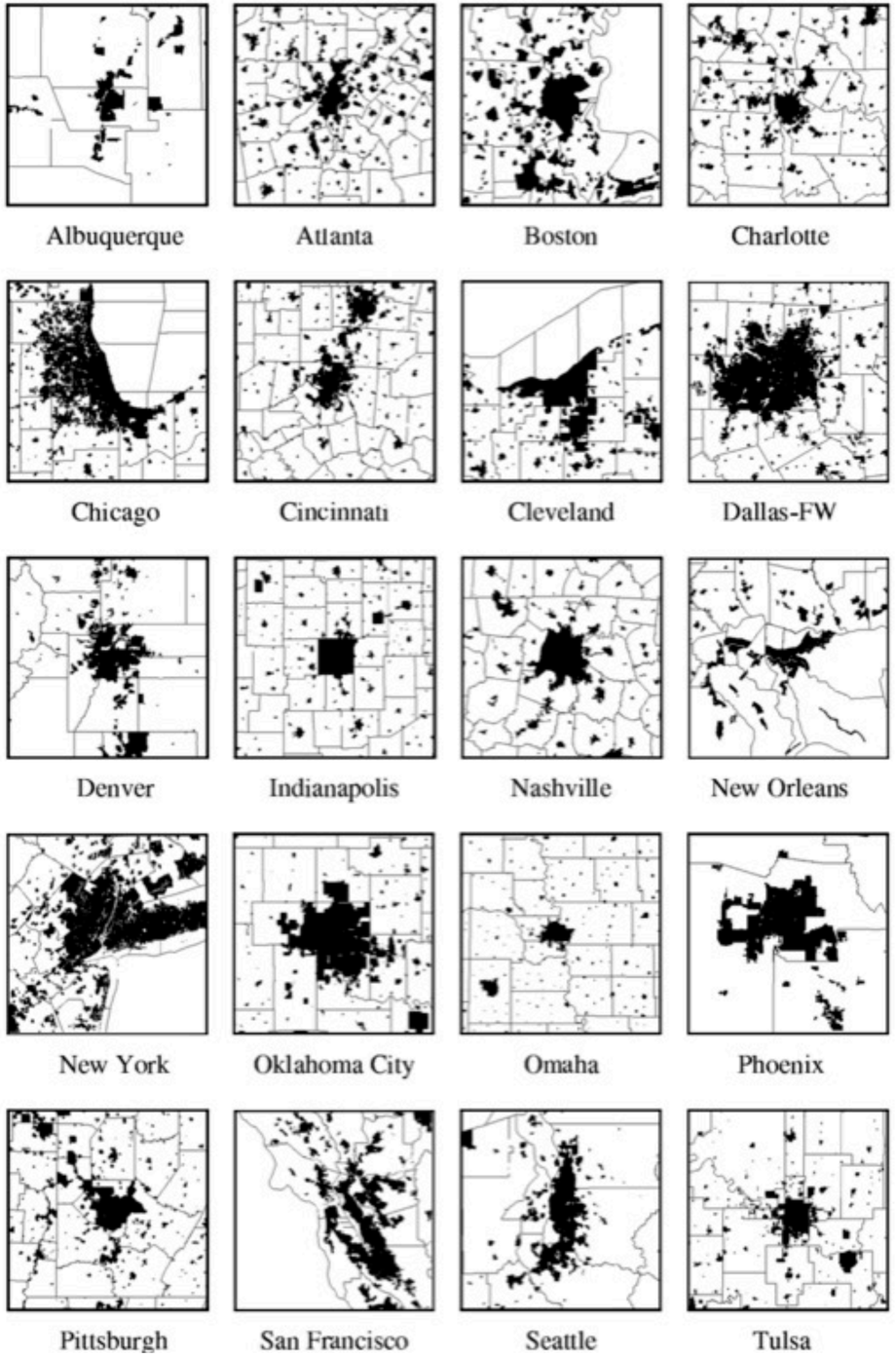
$$M(R) = M_0 R^{D_f} \qquad D_f = \frac{\log \frac{M(R)}{M_0}}{\log \frac{R}{R_m}}$$

Use it for built area and population

$$D_f{}^{N} = \frac{\log \frac{N}{N_0}}{\log \frac{R}{R_m}} \qquad D_f{}^{A_n} = \frac{\log \frac{A_n}{A_0}}{\log \frac{R}{R_m}}$$

$$\frac{D_f{}^{A_n}}{D_f{}^{N}} = \frac{\log A_n - \log A_0}{\log N - \log N_0} = \frac{\Delta \log A_n}{\Delta \log N} = \frac{5}{6}$$

another way to measure urban scaling exponents



Slums and Informal Settlements

Have incomplete infrastructure networks, can use these ideas to identify where and how much to do

Mapping Sub-Saharan Africa to Enable Life-saving Humanitarian Aid

As part of our commitment to using AI for good, we partnered with several humanitarian organizations to build the first comprehensive map of Sub-Saharan Africa.

https://www.ecopiatech.com/resources/case-study/mapping-sub-saharan-africa-to-enable-life-saving-humanitarian-aid

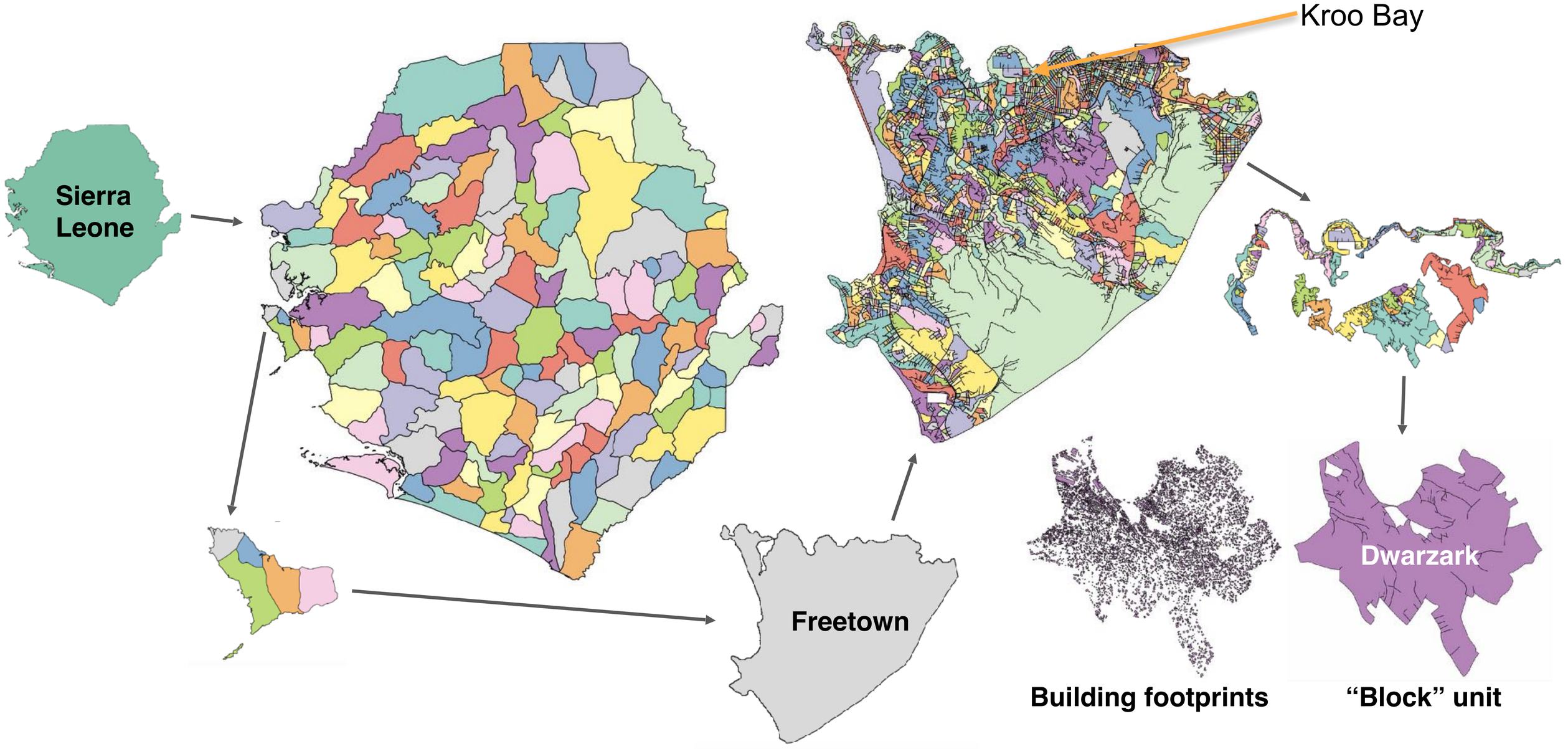
Summary Statistics of Population, Blocks, and Buildings

Urban level	Buildings number	Population (LandScan)	Blocks number	Building area m^2	Building density ha^{-1}	Building-block area ratio	Population per building	Block complexity
Urban	60,867,090	265,480,446	1,917,347	97.13	16.66	0.16183	4.36	3.70
Secondary Urban	11,414,328	45,242,998	306,272	106.78	13.04	0.13929	3.96	3.68
Peri-urban	71,107,546	197,061,072	1,643,668	63.64	0.58	0.00371	2.77	9.42
Rural	271,630,476	645,202,644	5,926,089	40.81	0.11	0.00045	2.38	9.65
Total	415,019,440	1,152,987,161	9,793,376	54.80	0.16	0.00088	2.78	8.01

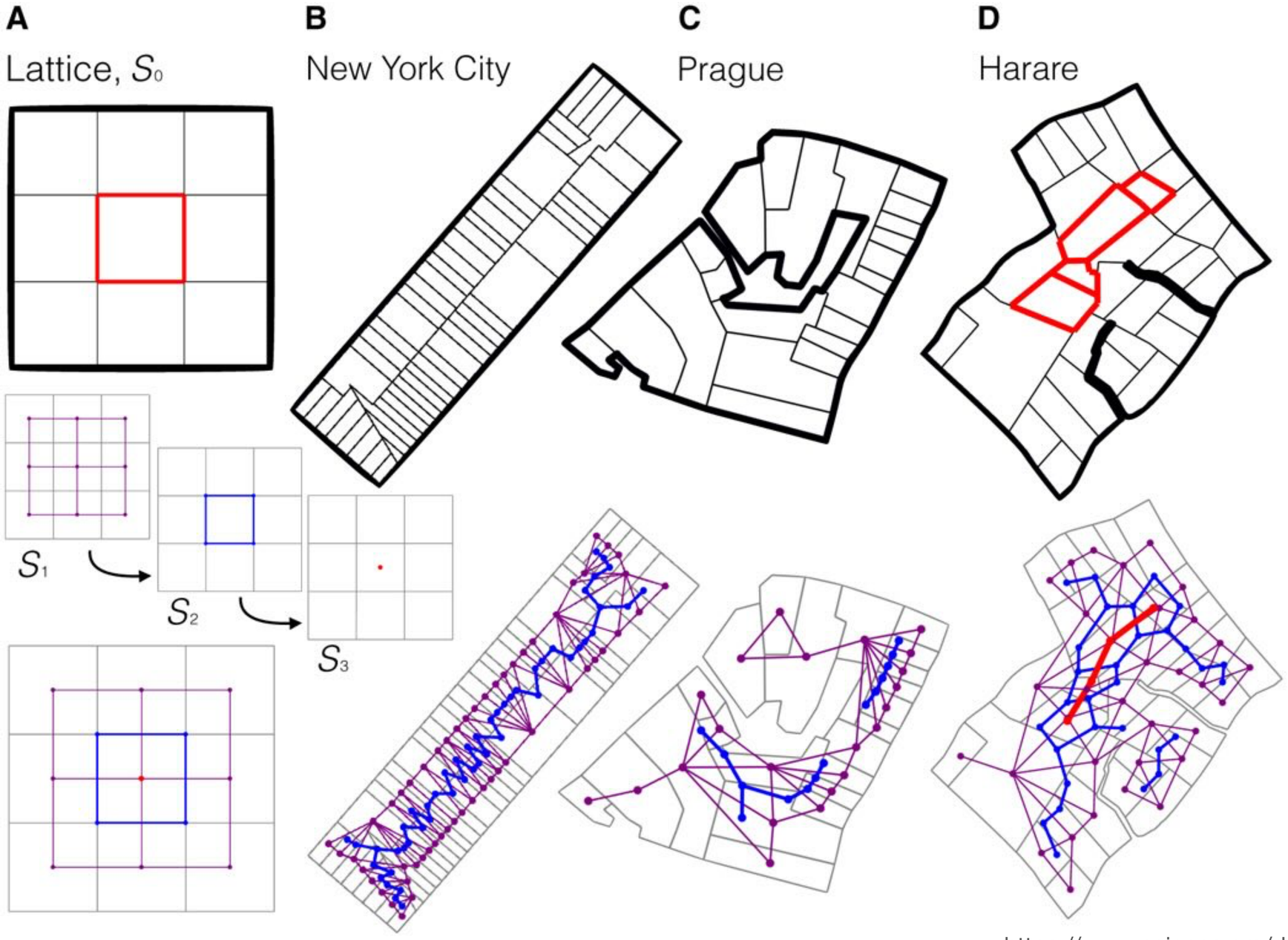
Summary statistics of buildings, population and street blocks by urban level. Note the changes in density from more to less urbanized areas and the opposite trend in service access expressed by rising block complexity. Note also the relative population weight and incipient infrastructure access in peri-urban areas.

Understanding settlements from global to local scales

a global map (of cities) neighborhood by neighborhood

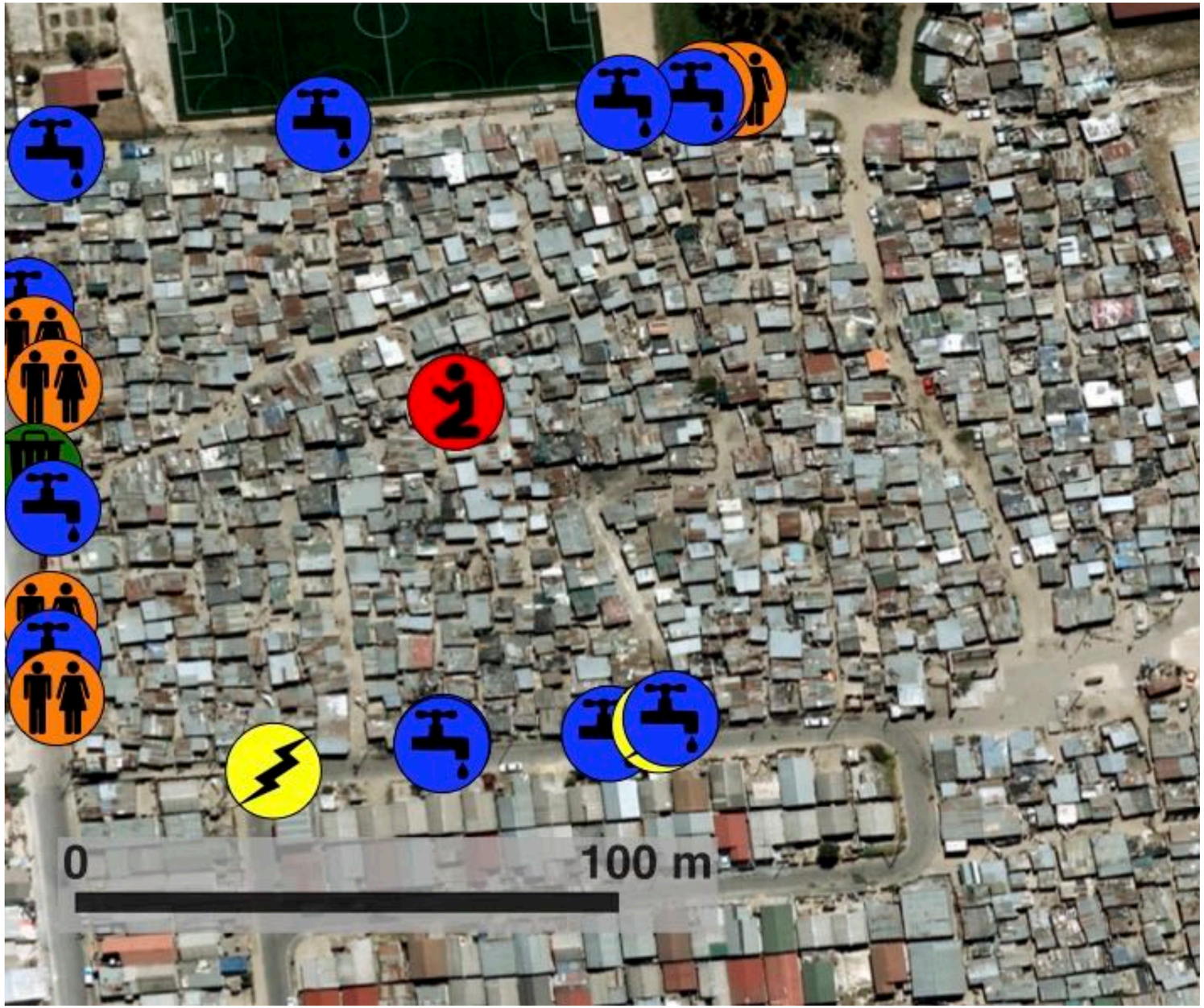


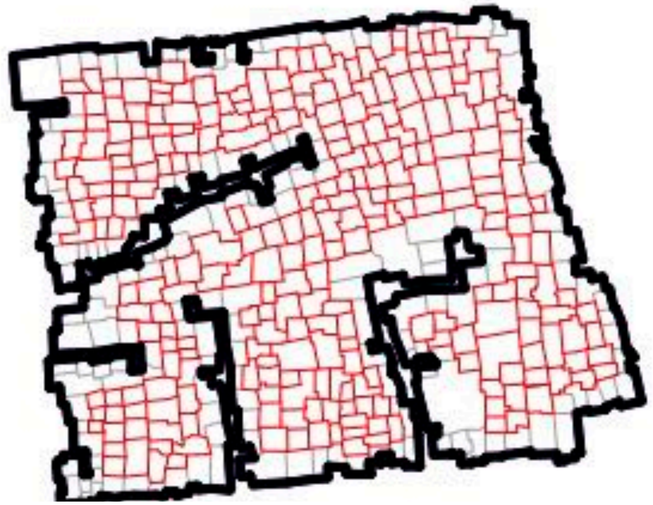
A network (graph theory) model to identify disconnected parcels and underserviced city blocks

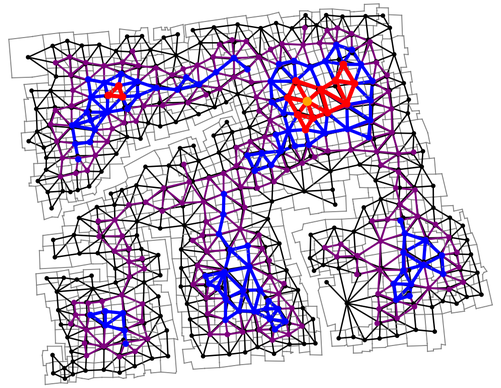


https://www.science.org/doi/10.1126/sciadv.aar4644

A disconnected block in a South African Township



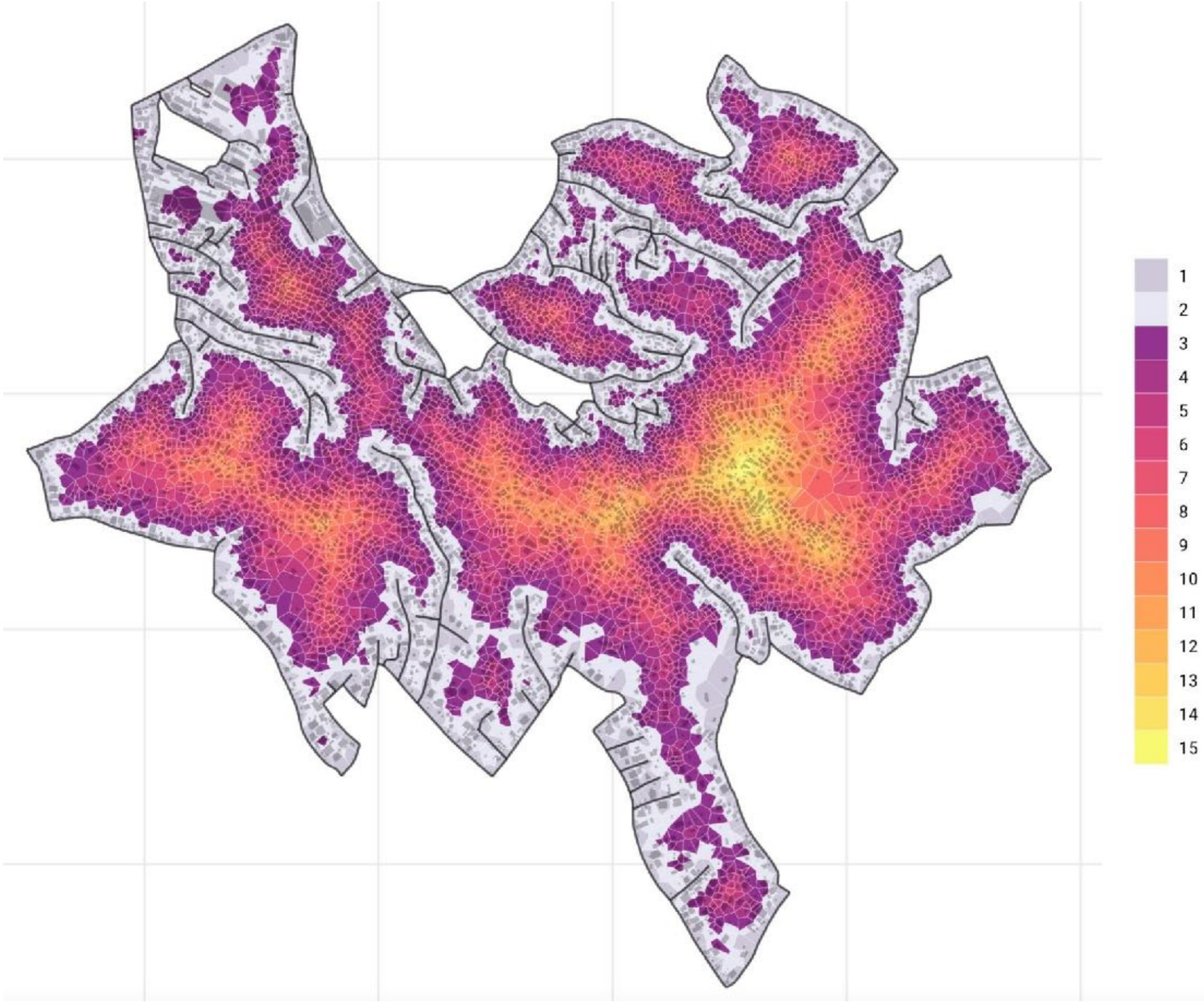




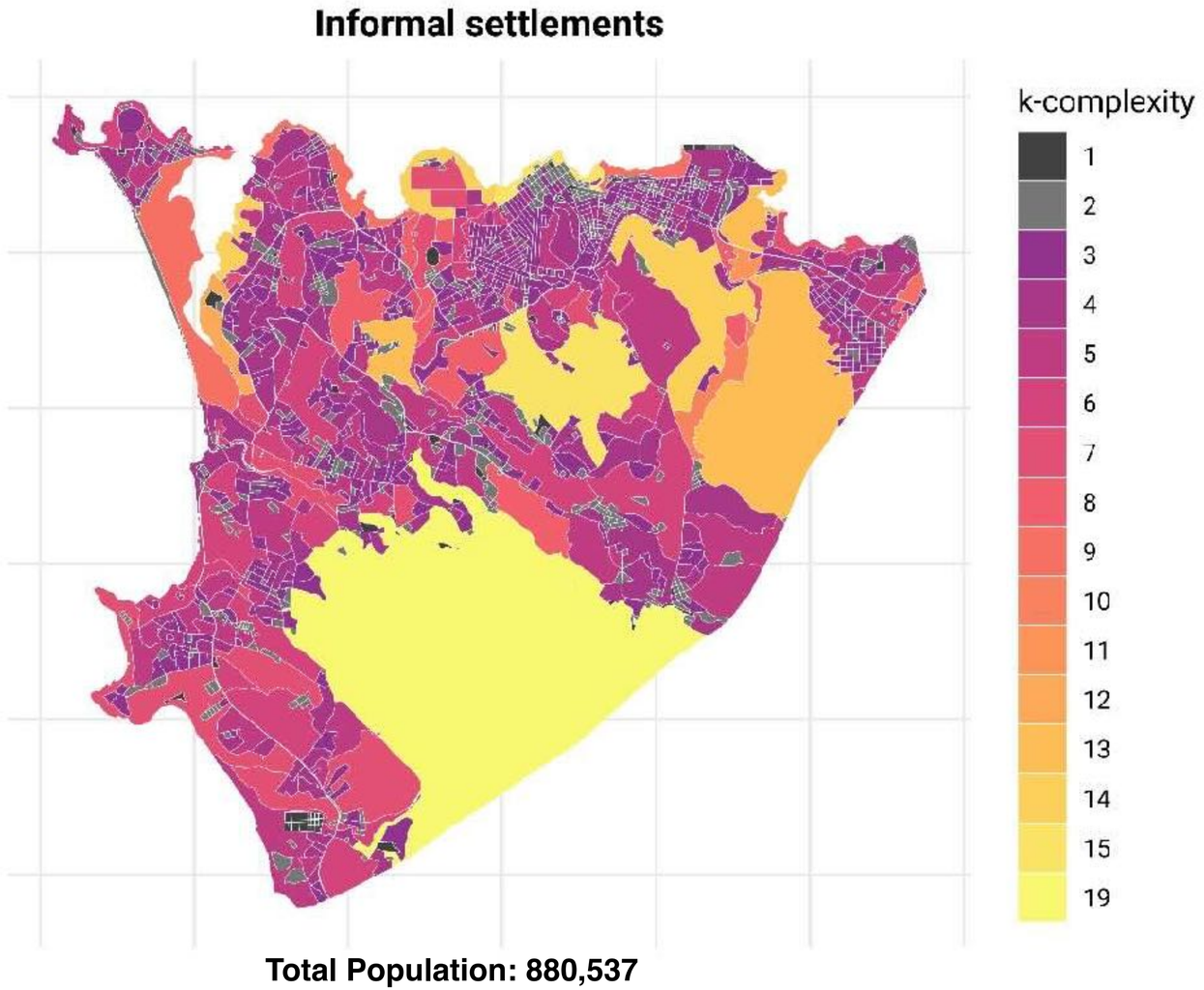
Detecting informality down to the street block

Building footprints

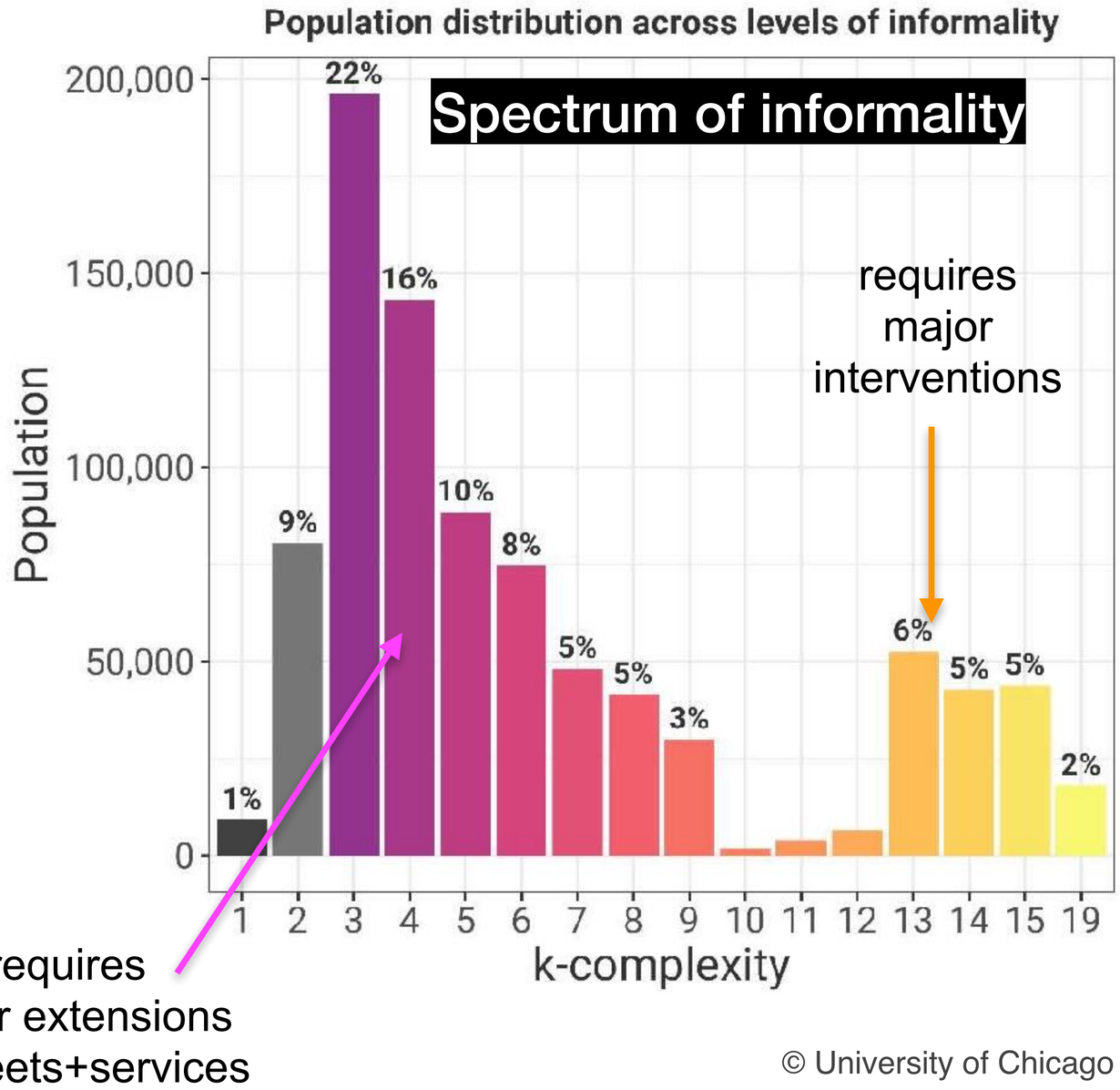
“Block” unit

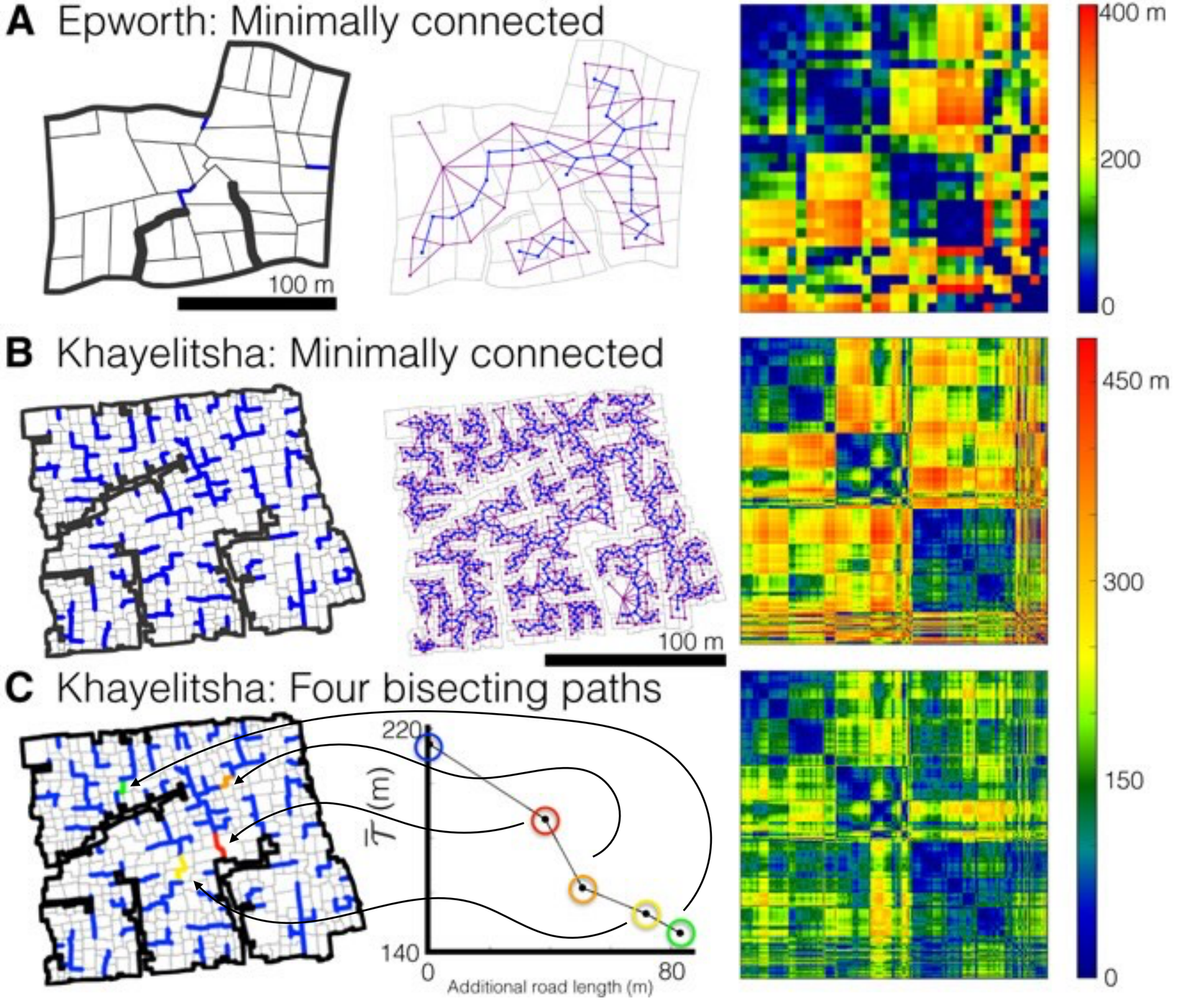


Mapping informality and population in Freetown

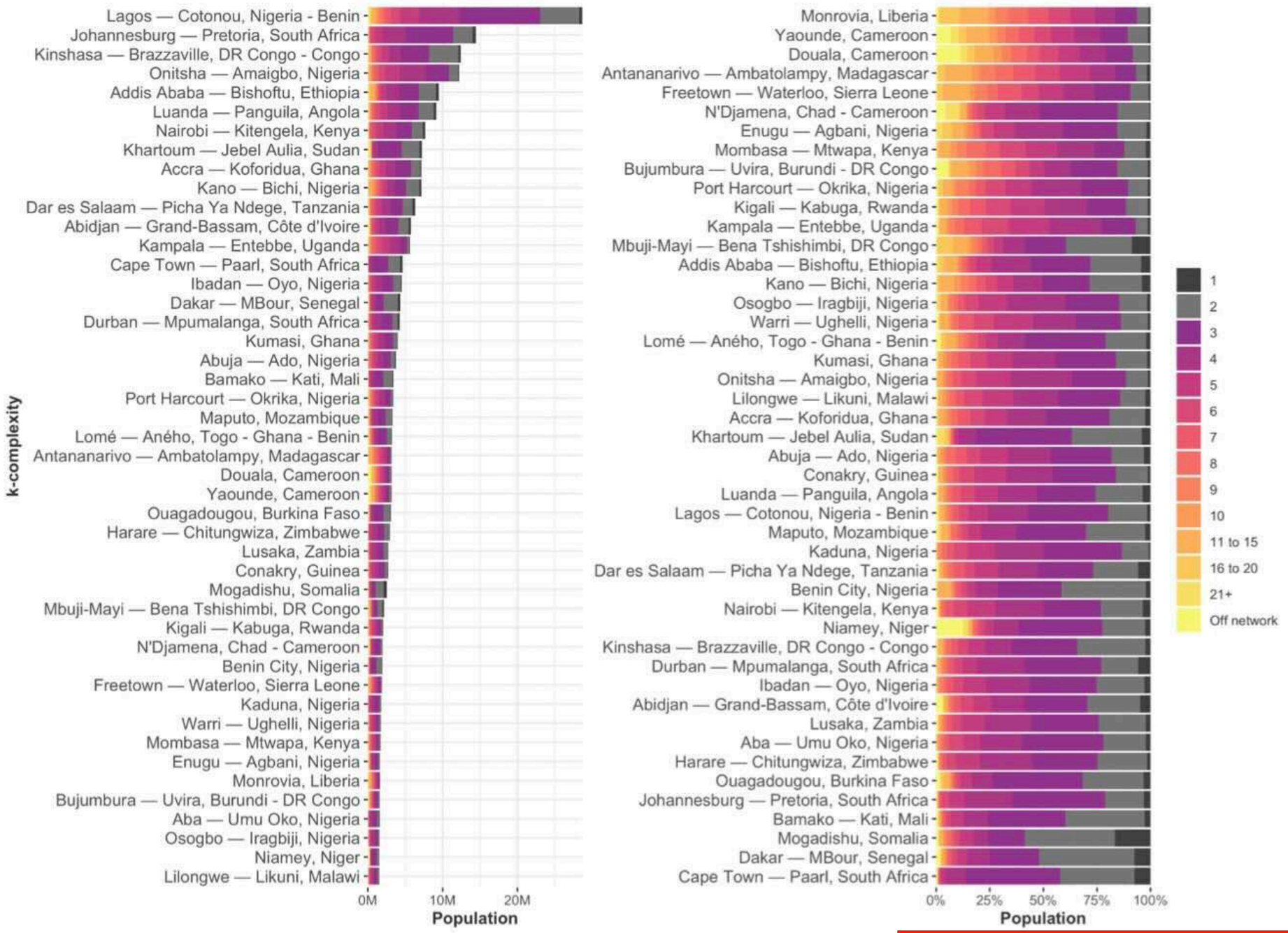


Total Population: 880,537




A Epworth: Minimally connected
100 m
400 m
200
0
B Khayelitsha: Minimally connected
100 m
450 m
300
150
0
C Khayelitsha: Four bisecting paths
220
140
0
80
$\bar{T}$ (m)
Additional road length (m)

About 150 km of new accesses are needed in Kibera.



Every city, town and hamlet: every block

New block level data worldwide

A large number of interconnected phenomena

From behavior and cognition

to infrastructure and services

to socioeconomic wellbeing and outcomes

are understood and predicted by a theory of cities as complex networks

This kind of theory will allow us to predict characteristics of cities throughout history and across diverse contexts

What about exceptions? Inequality? Growth? Information?