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perspectives for teaching and research

The Frontier of GIScience Research

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- **Peer reviewer for *Transactions in GIS* (TGIS)**

Outline

- Why spatial is special
- Urban Computing
- Geospatial Data Conflation
- GIS Trends
- Conclusions

Geographic information science

- The science behind the GISystems
- The fundamental issues raised by the technologies
- The principles implemented in the technologies

Michael F. Goodchild (1992)

Why Spatial is special?

* Location Uncertainty
* Spatial Dependence and Distance Decay (TFL)
* Spatial Heterogeneity (Geographically Weight Regression)
* Geographic World is Dynamic
* Geographic Information is Derivative (accuracy and precision)
* Scale

Anselin, L. (1989). What is special about spatial data?: Alternative perspectives on spatial data analysis.
Golledge, R. G. (2002). The nature of geographic knowledge.
Goodchild, M. F. (2001). A geographer looks at spatial information theory.

Any Laws in GIScience?

- Tobler's first law of geography: "Everything is related to everything else, but near things are more related than distant things".

  --Waldo Tobler (1970)

- First law of cognitive geography: "People believe closer things are more similar".

  -- Montello, Fabrikant, Ruocco, Middleton (2003)

- The Scaling Law

  --Batty, M. (2008). The size, scale, and shape of cities. *Science*, *319*(5864), 769-771.

  --Jiang, B., & Sui, D. (2013). A New Kind of Beauty Out of the Underlying Scaling of Geographic Space. *arXiv preprint arXiv:1303.7303*.

Outline

- Why spatial is special
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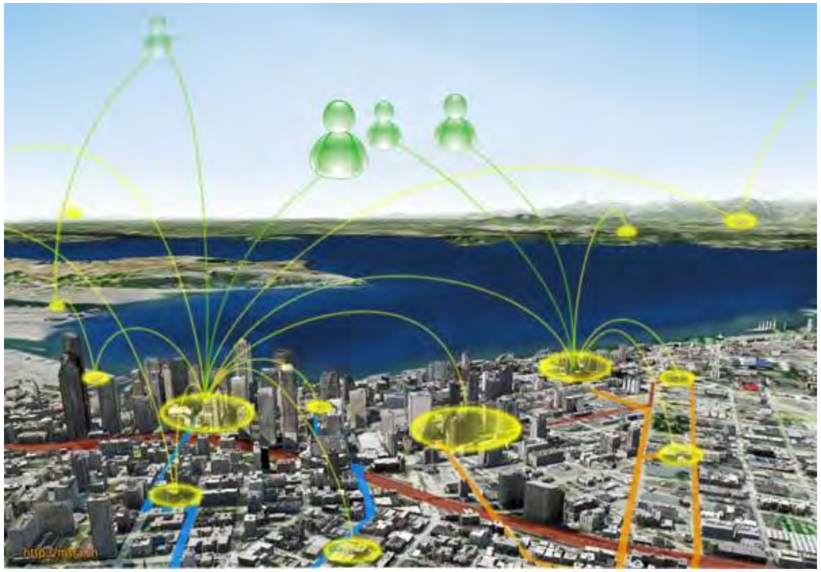
Urban Computing

It is emerging as a concept where sensor, device, person, vehicle, building, and street in the urban areas can be used as components to

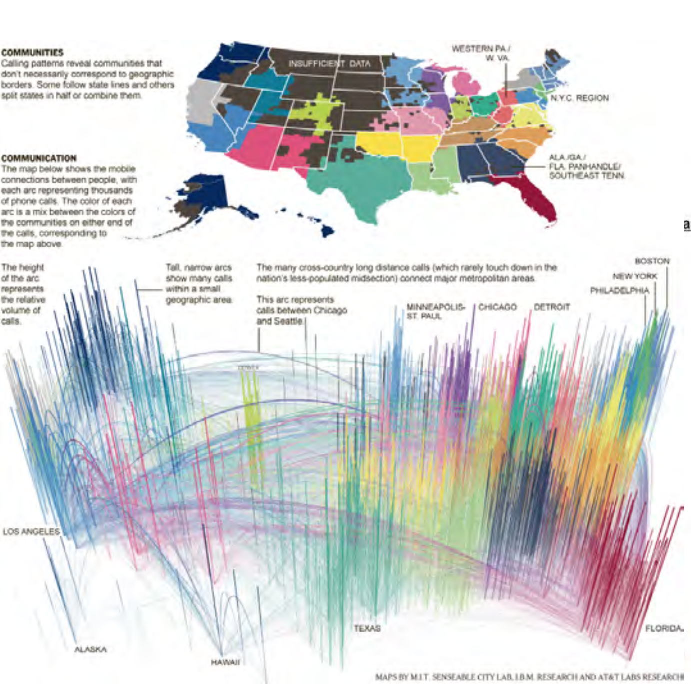


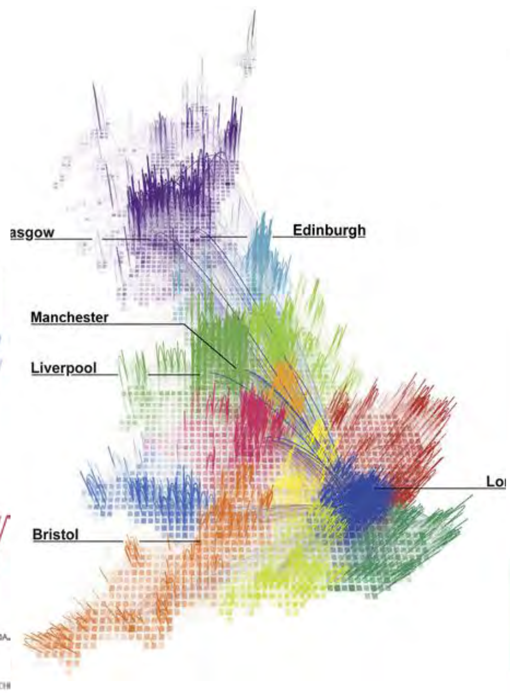
Yu Zheng (2012),
Microsoft Research Asia

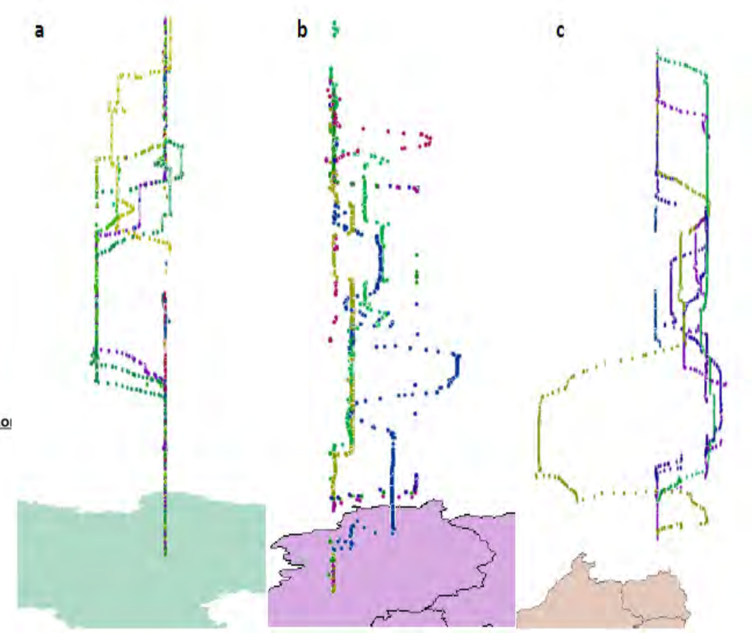
sense city dynamics to enable a city-wide computing as so to serve people and cities.

Background

- Location Awareness Devices（Mobile Phone、GPS)
- Large scale spatio-temporal datasets



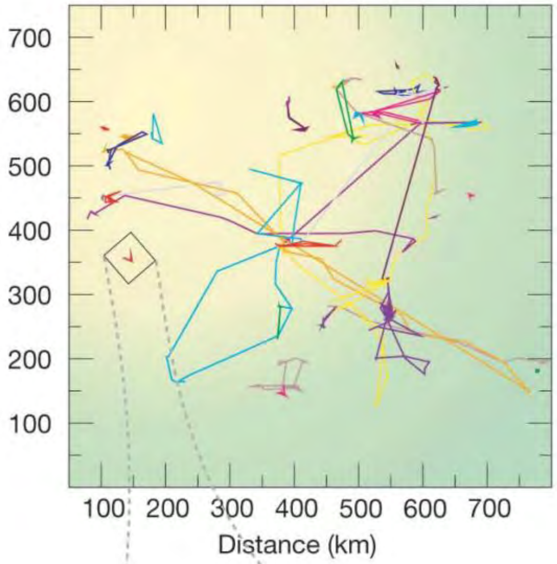


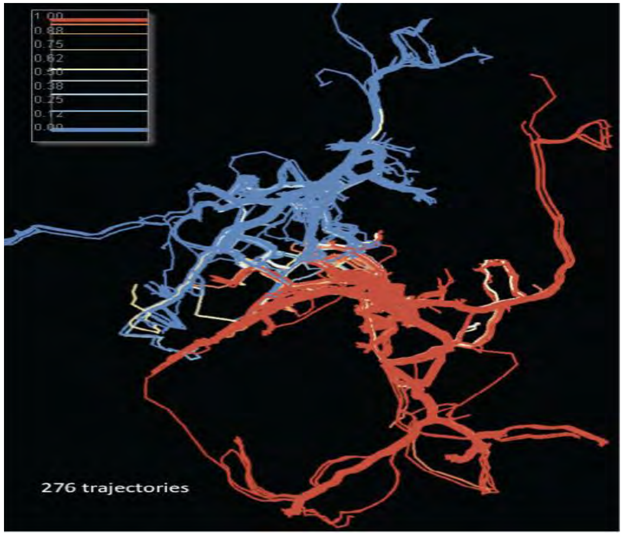


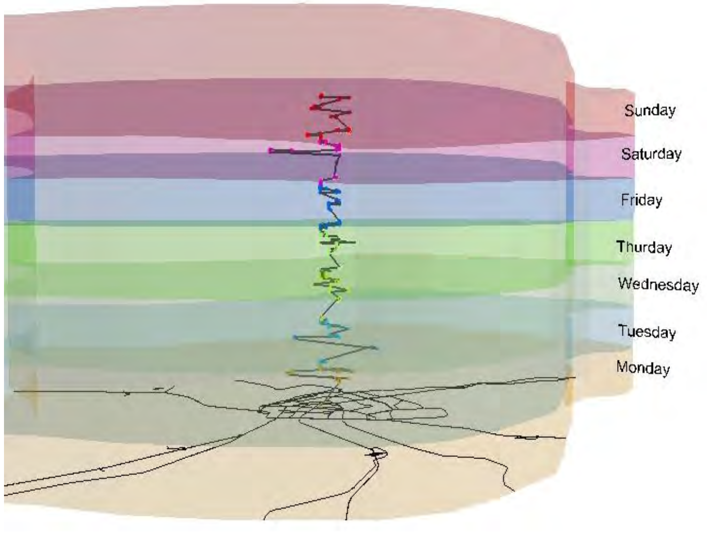
Background

Individual Level

- Human mobility (Nature, Science, PNAS)
- Trajectory data mining(ACM,IJGIS)
- Community Detection(Complex Networks)



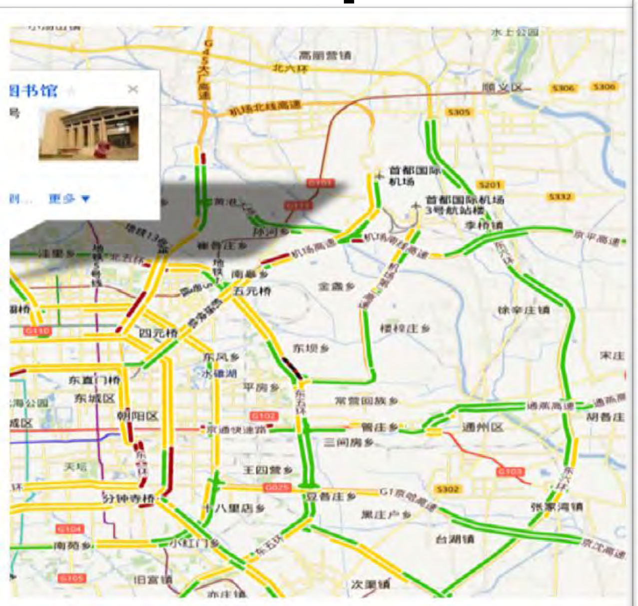


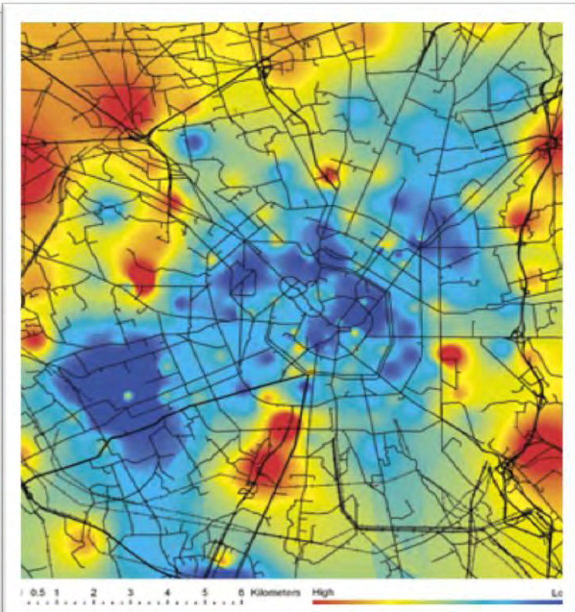


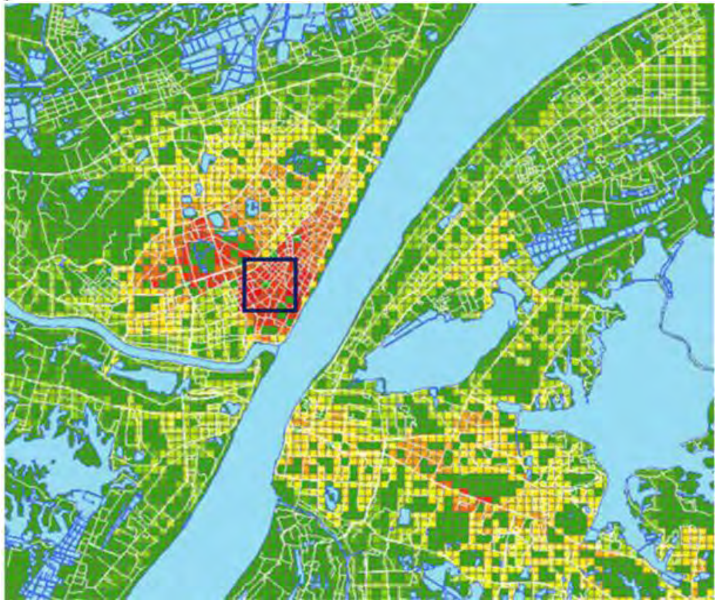
Background

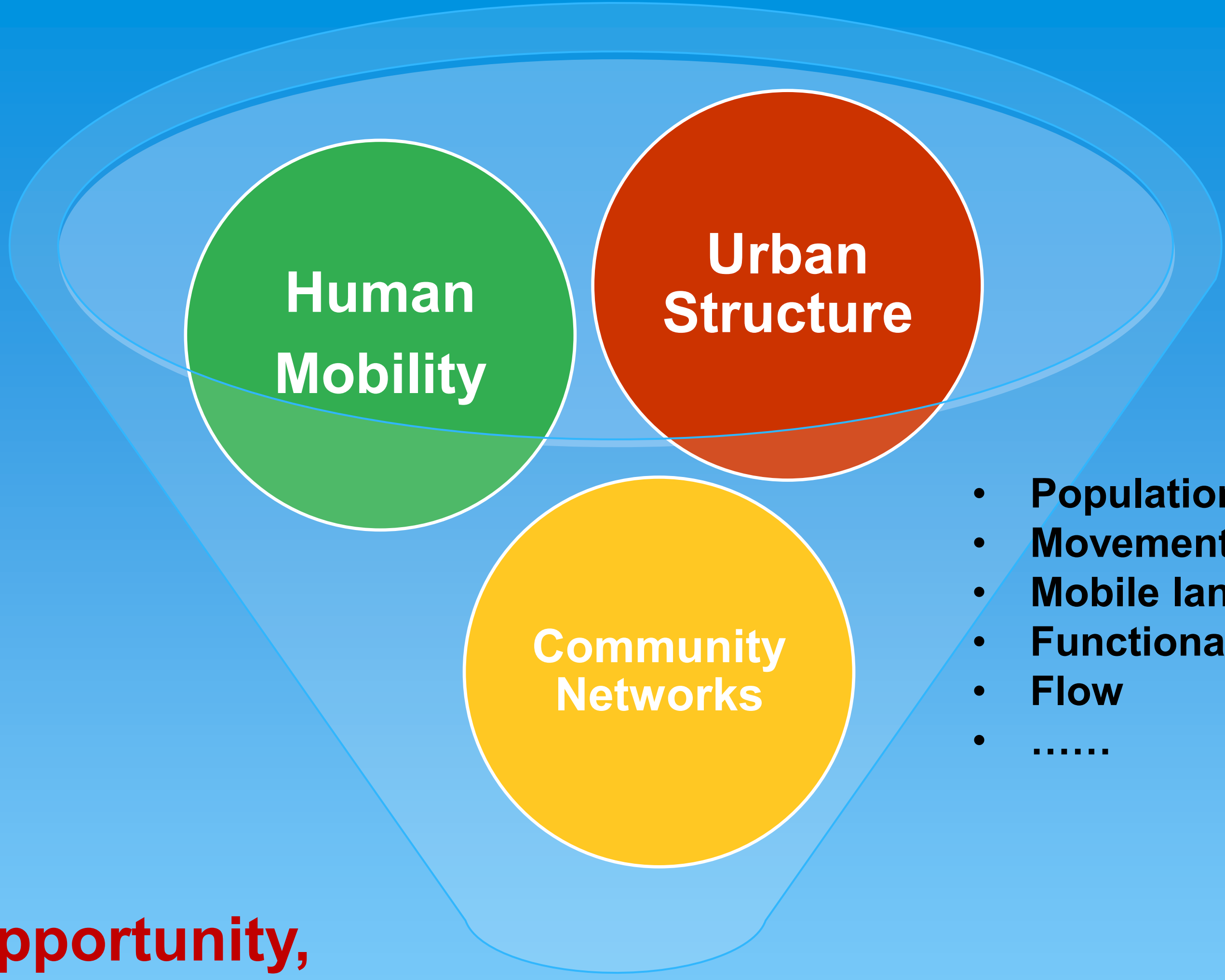
Aggregate (Regional Level)

* Dynamic urban landscape
* Spatial interactions between sub-regions
* Transportation demands estimation









- Population distribution
- Movements
- Mobile landscape
- Functional region
- Flow
- ……

Space is opportunity,
Place is understood reality.

Shorter time span

Information, Communication, Technology &
Space, Place & Social

Data

* **Smart Card Records (Bus, Subways)**
* **GPS-enabled Taxi Trajectories**
* **Mobile Phones**
* **Other sensors ……**

Human Mobility

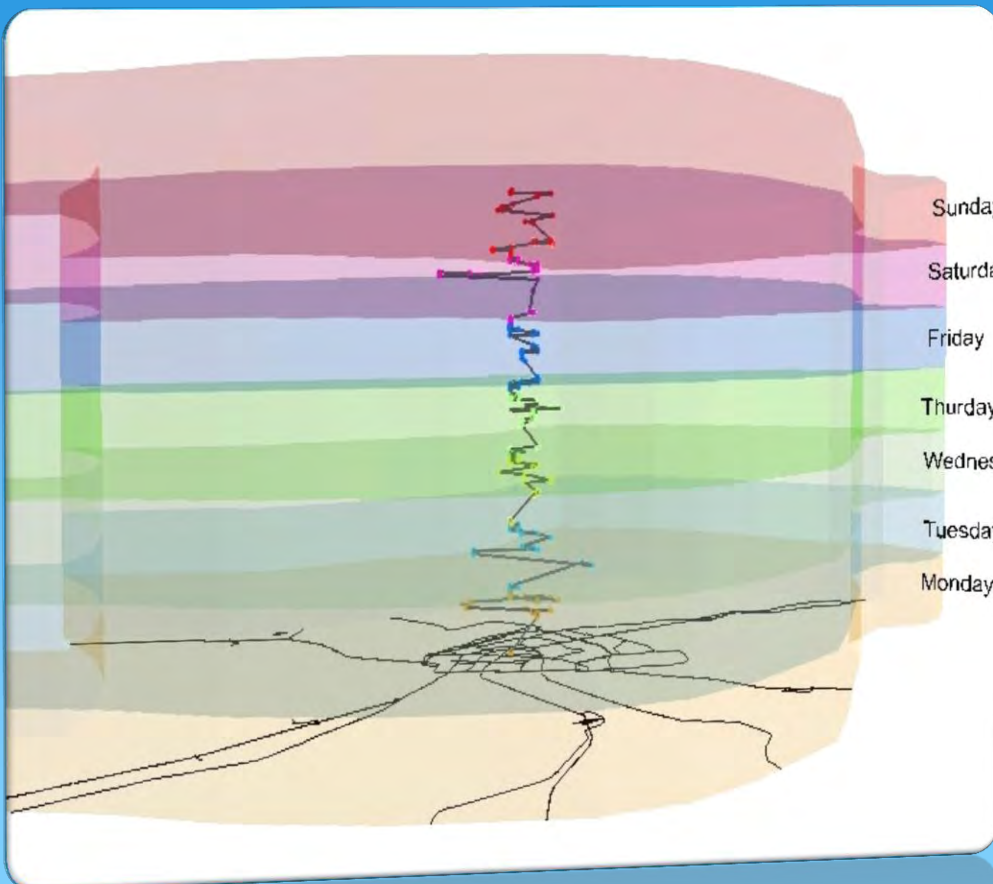
Human Mobility

- **Spatio-temporal patterns can be found with a large amount of trajectories (X,Y, T)**

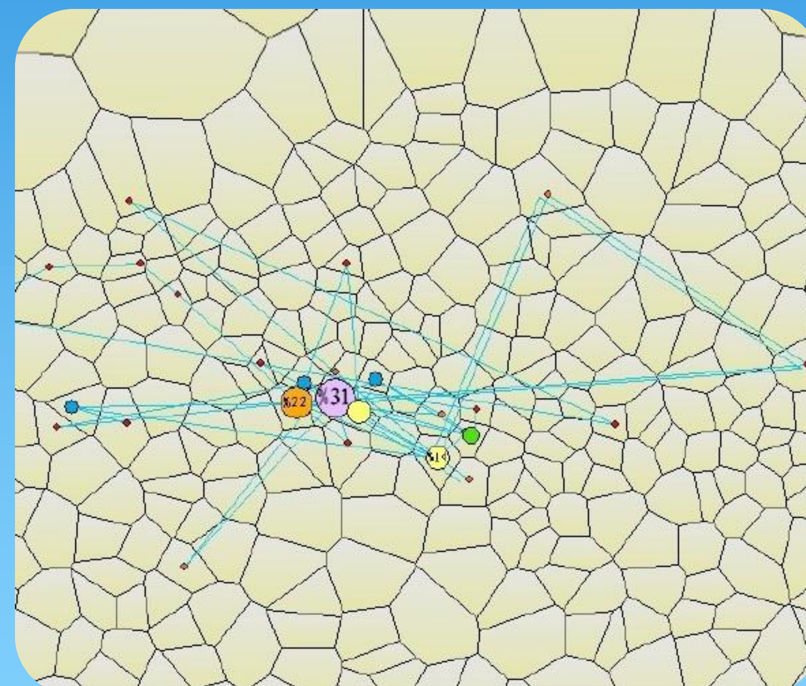
- **GIS visualization and analysis applied to represent and model individual dynamics**

Geo-visualizing

Kang C., Gao S. et al. Analyzing and Geo-visualizing Individual Human Mobility Patterns Using Mobile Call Records. 2010



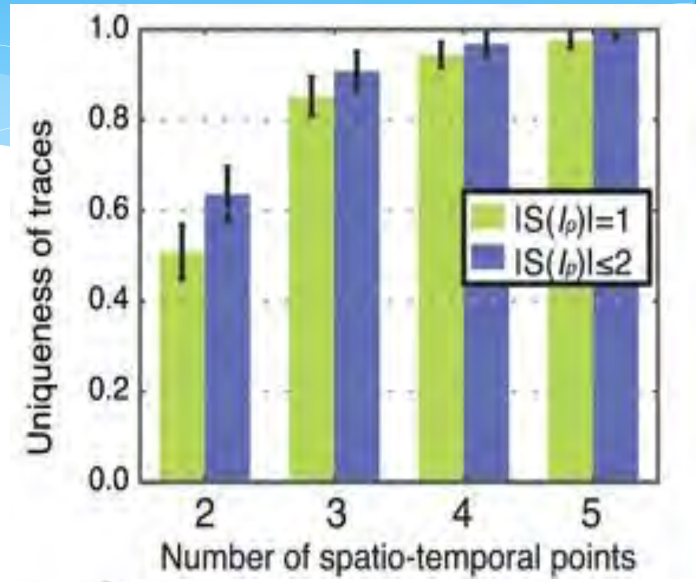
Space-time path

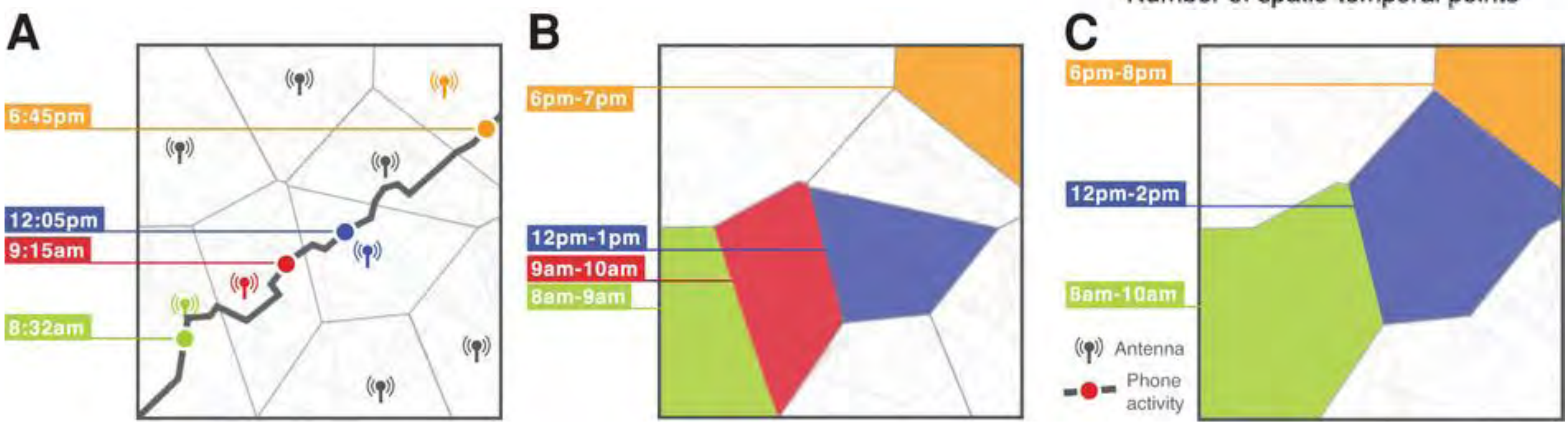


Frequency of occurrence

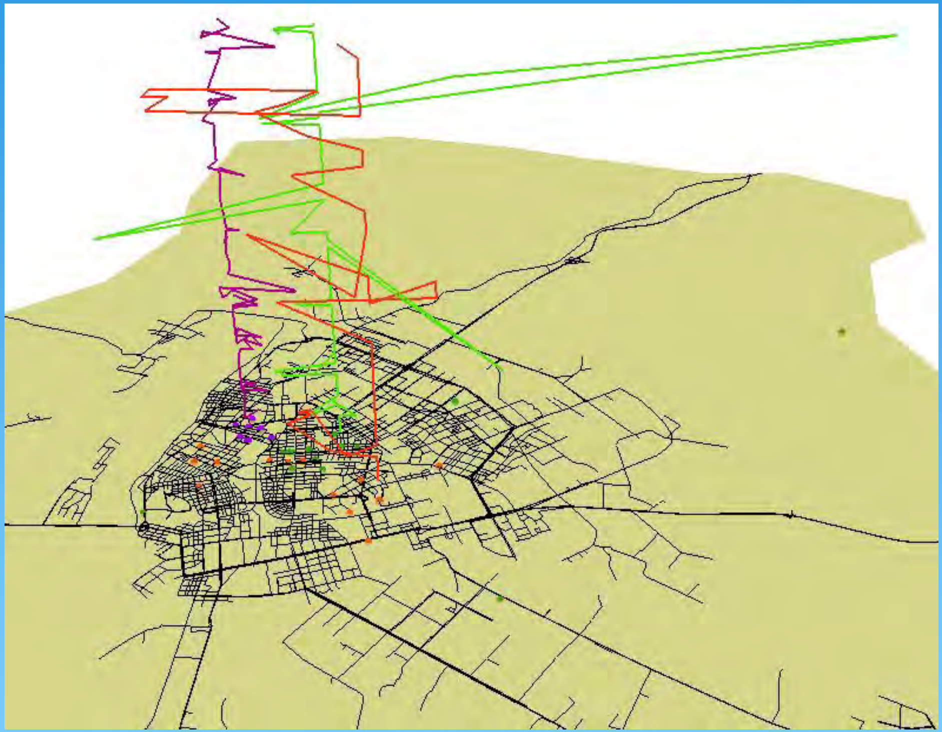
Unique in the Crowd: The privacy bounds of human mobility (Nature)

15 months of mobile phone data for **1.5 million** individuals , **four** spatio-temporal points are enough to uniquely identify **95%** of the individuals.

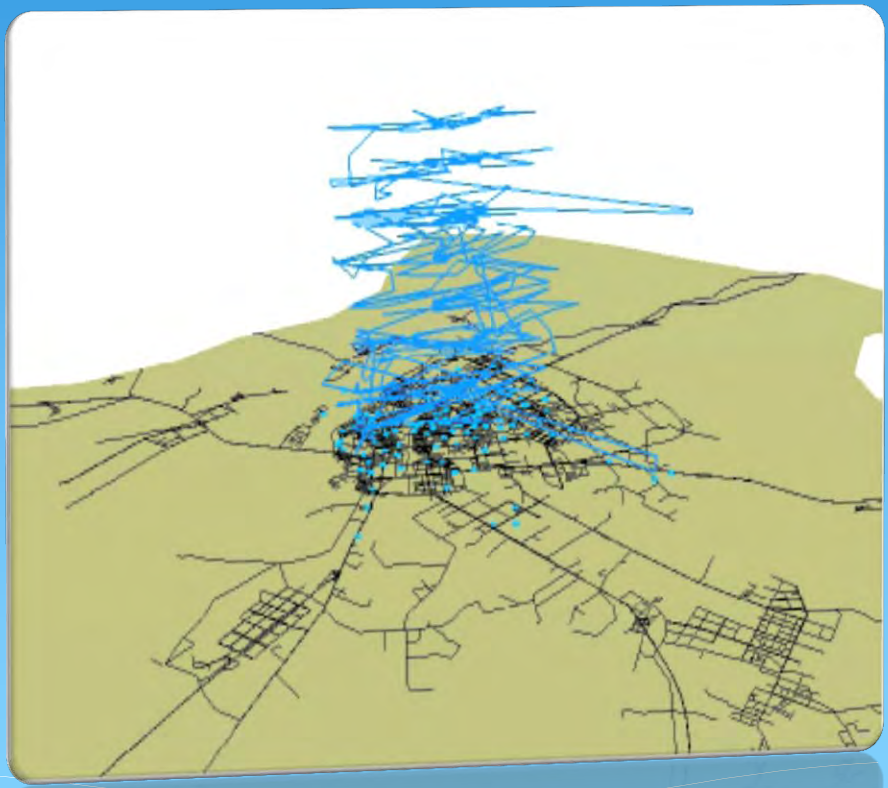




The variability *of mobility*



Regular



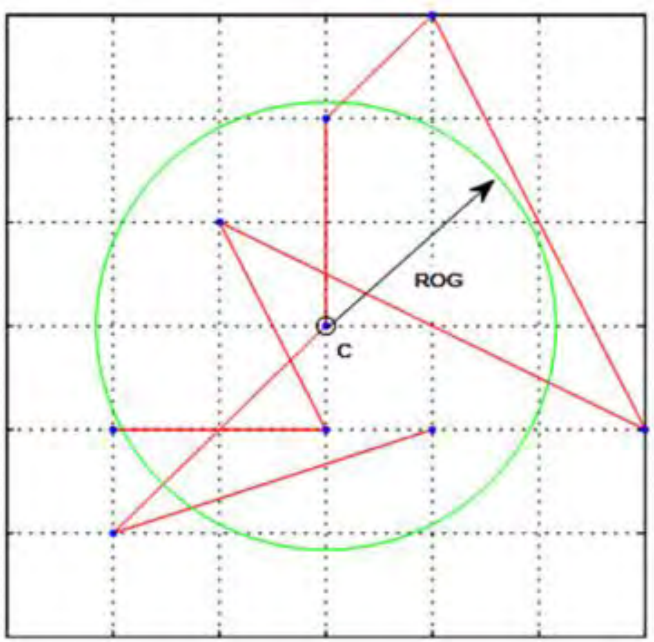
Irregular

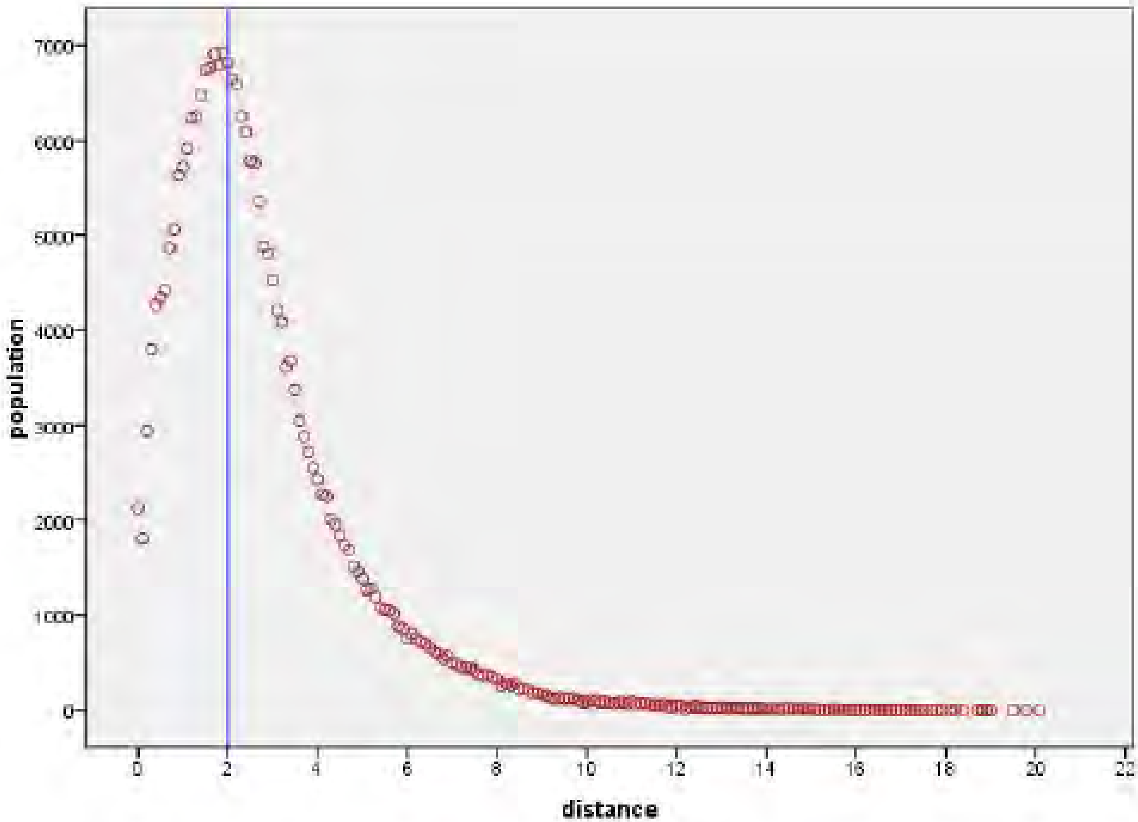
Song Gao, UCSB Geography, 2013

The distribution of the ROG covered with 869,992 mobile phone users.

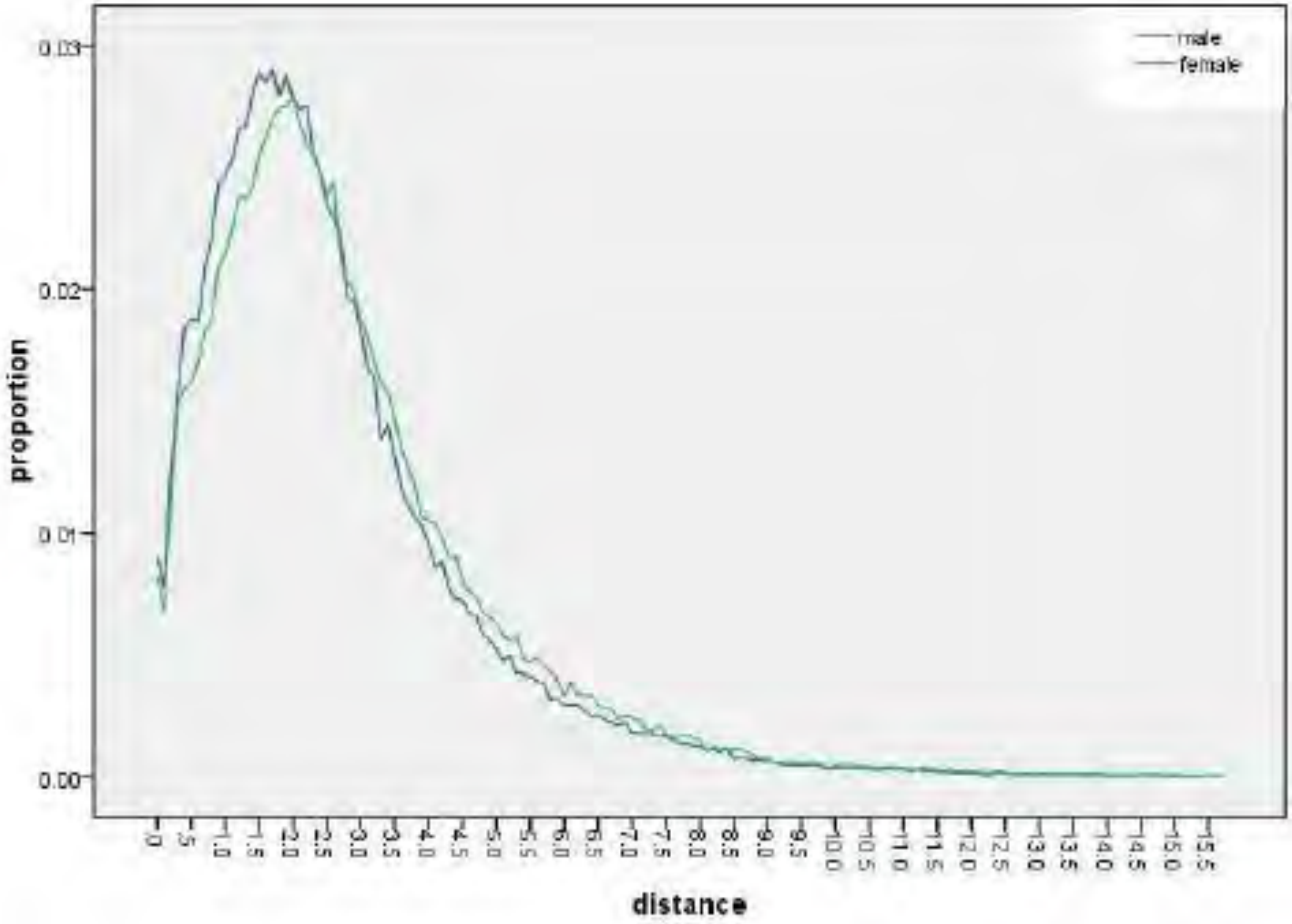
Radius of gyration

$$r_g^\alpha(t) = \sqrt{1/n_c^\alpha(t) \sum_{i=1}^{n_c^\alpha(t)} (x_i - x_c)^2 + (y_i - y_c)^2}$$



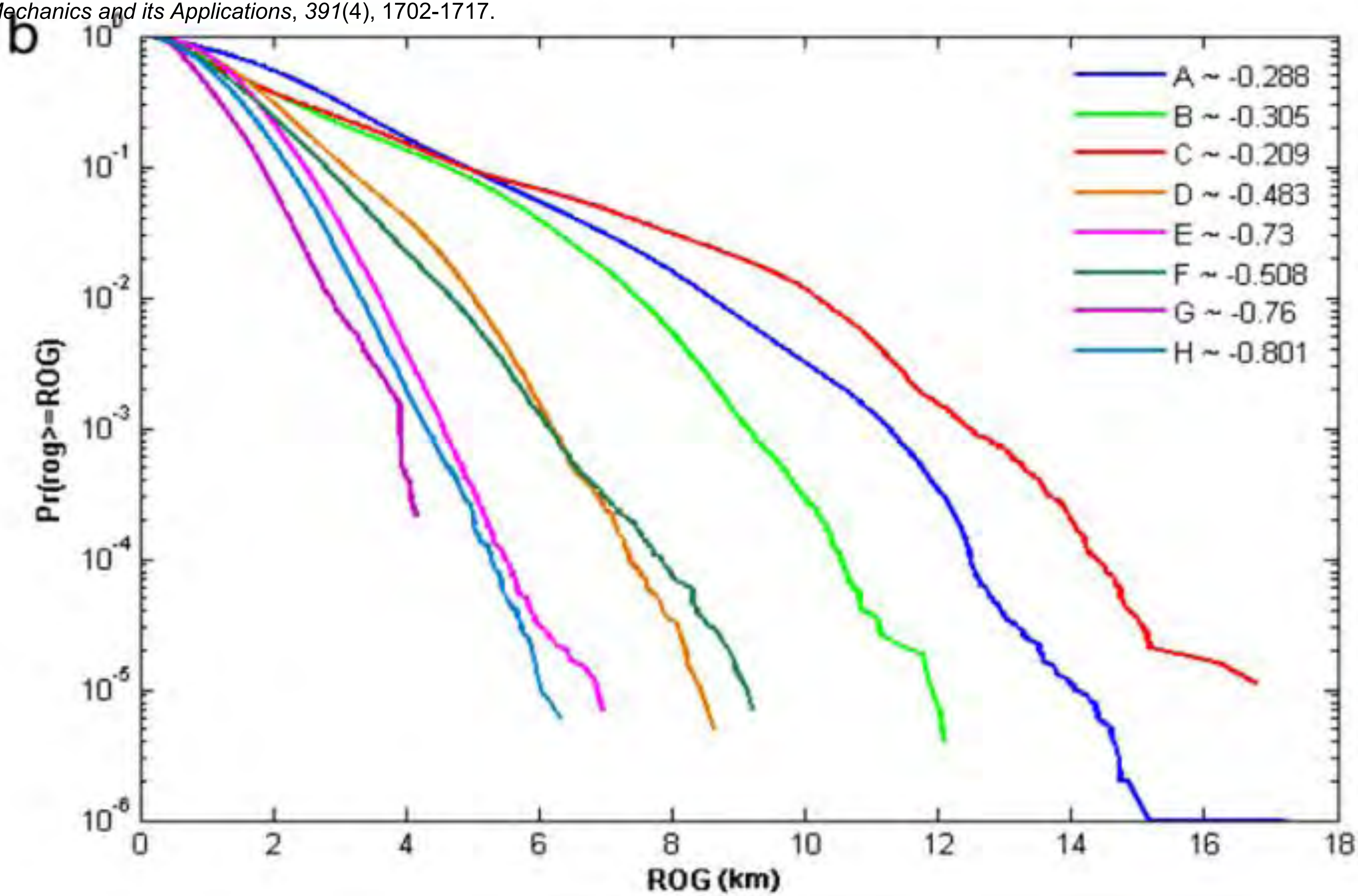


Gender



Distance Decay Effect in different cities

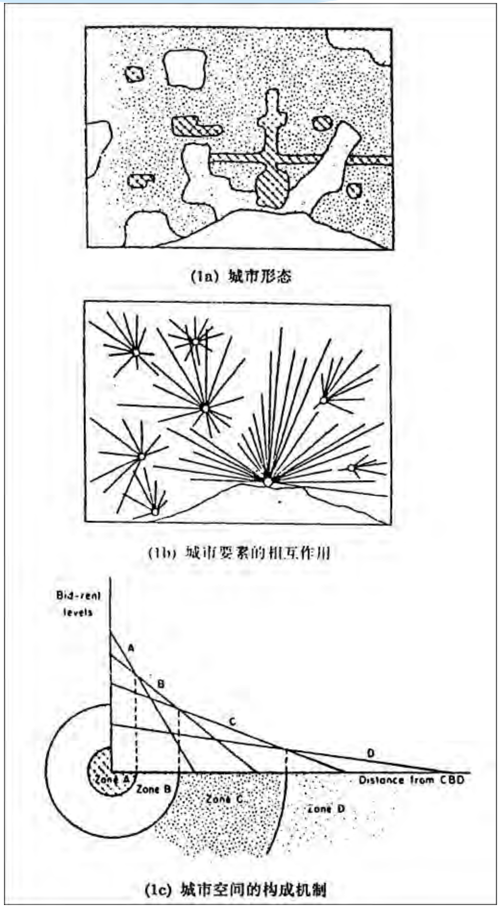
Kang, C., Ma, X., Tong, D., & Liu, Y. (2012). Intra-urban human mobility patterns: An urban morphology perspective. *Physica A: Statistical Mechanics and its Applications*, *391*(4), 1702-1717.



Urban Structure

Spatial Structure

1) **Land-use type**
2) **Population distribution**
3) **Transportation (accessibility)**
4) **Function division (POIs)**
5) **Intersections (flow, mobility)**



Urban Structure

- **Aggregate approach (Hourly)**

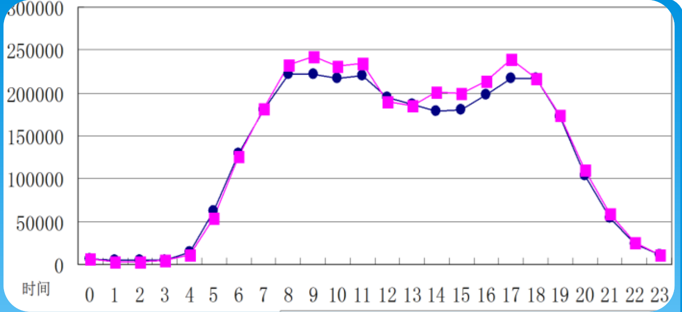
  --$Cell_i$ (volume00, volume01, volume02,…… volume23)

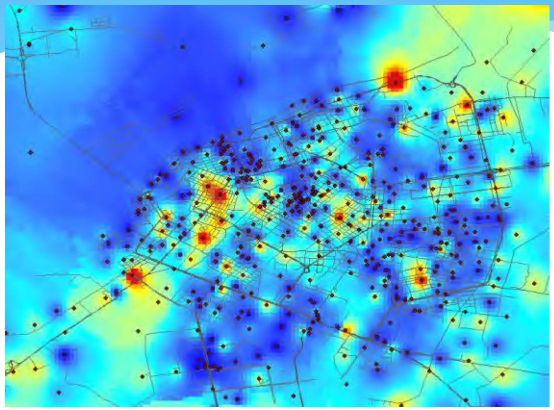
- **The scale of the urban area, may including the city and some inner suburbs, to highlight interesting metropolitan dynamics**

- **Calculate the kernel density**

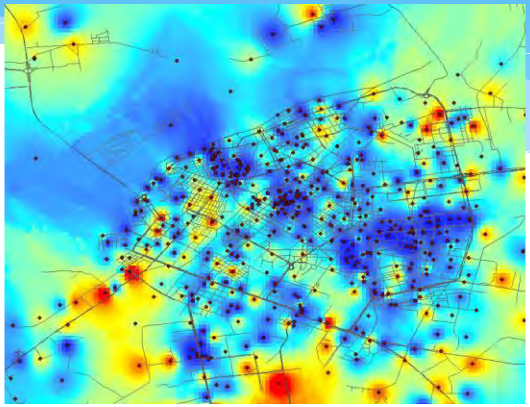
Spatio-temporal patterns

Mobile Landscape

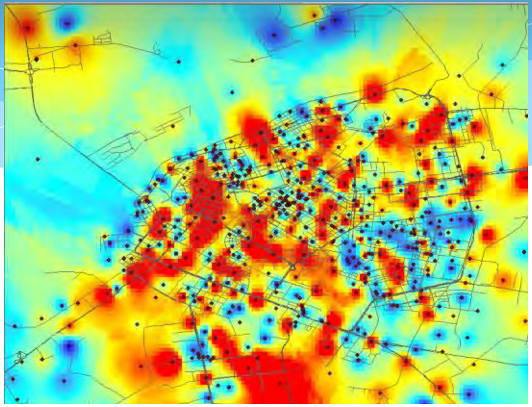




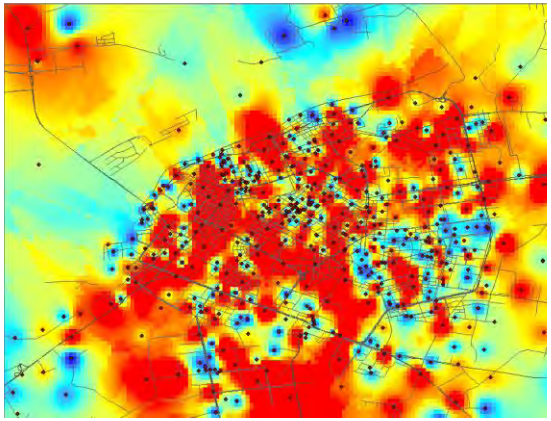
AM 03-04



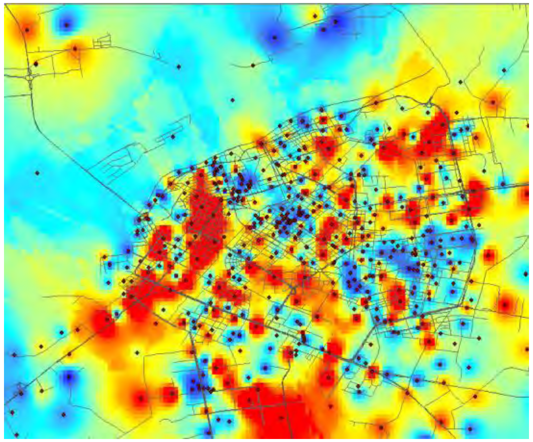
AM 06-07



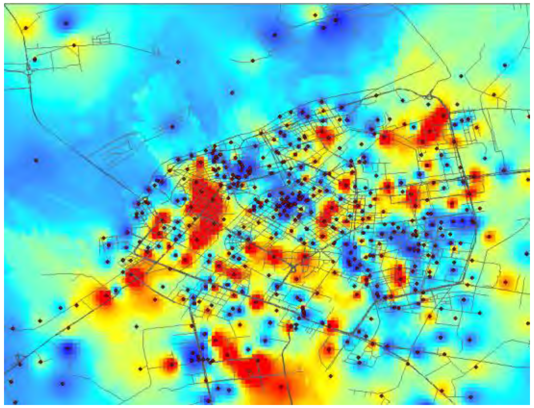
AM 09-10



PM 15-16



PM 18-19

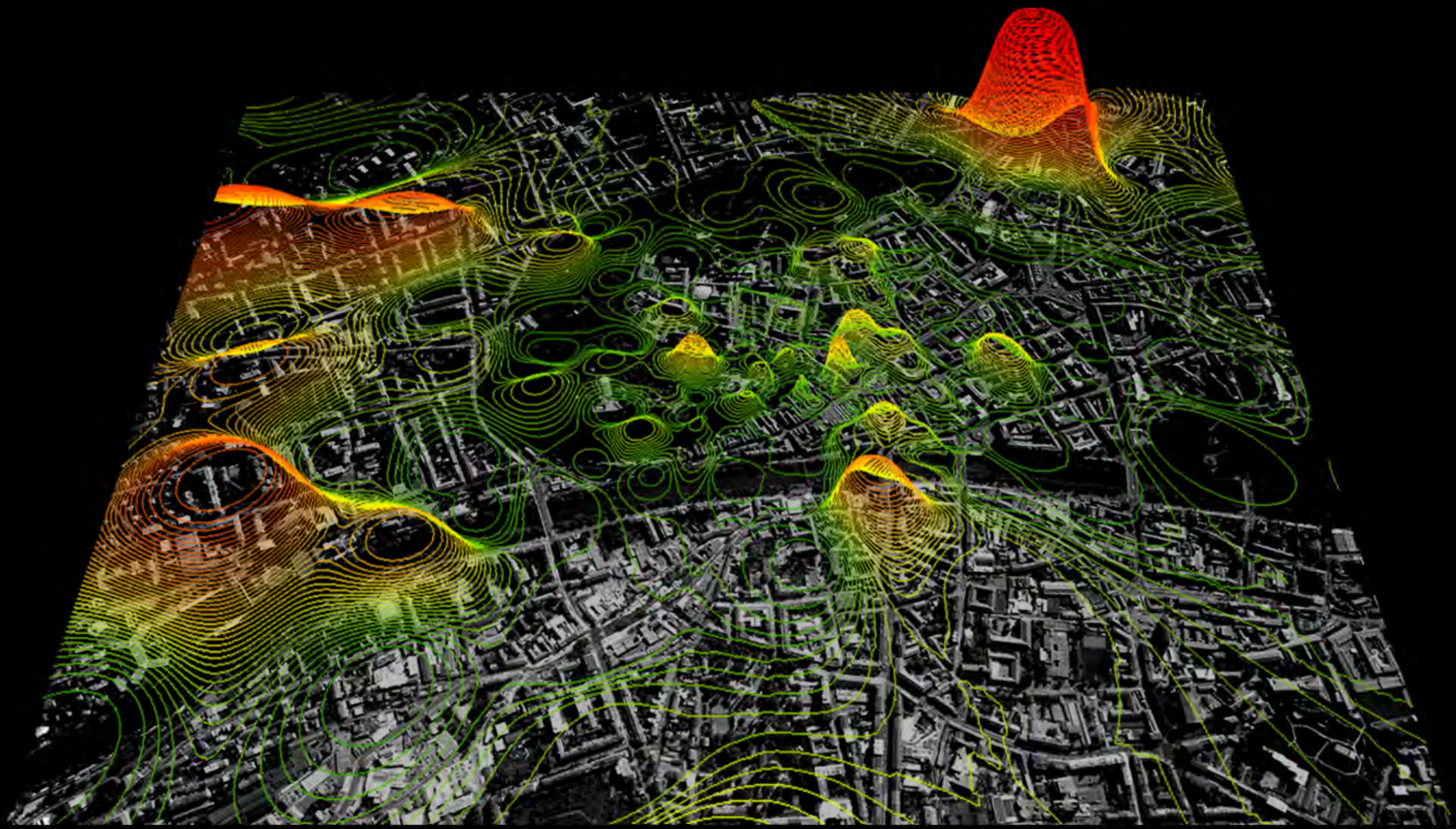


PM 21-22

Song Gao, UCSB Geography, 2013

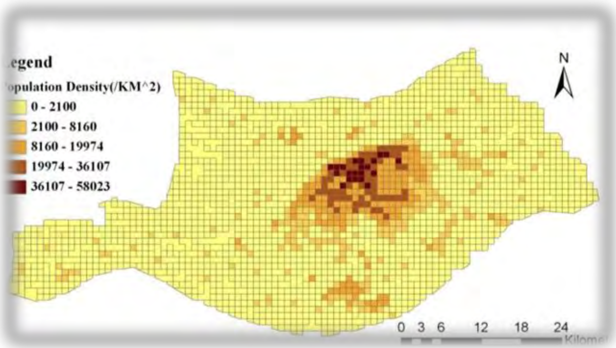
Mobile Landscape:

People of MIT SENSEable City Lab have developed a continuously changing real-time maps of cell phone usage in Graz, Austria.

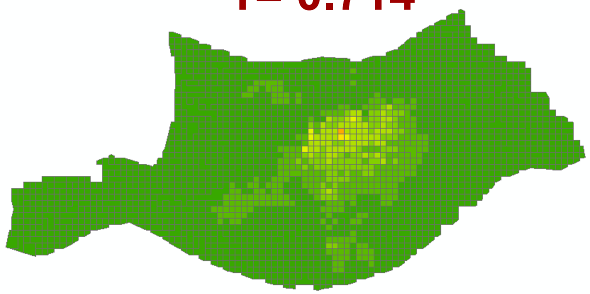


http://senseable.mit.edu/grazrealtime/

Correlation with population distribution

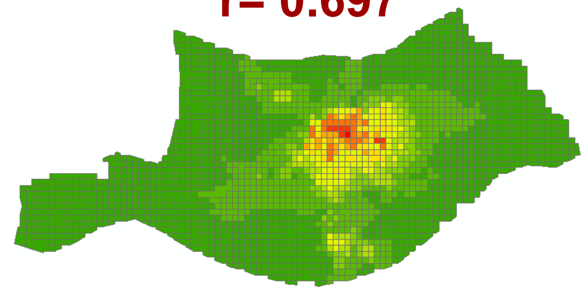


r= 0.714



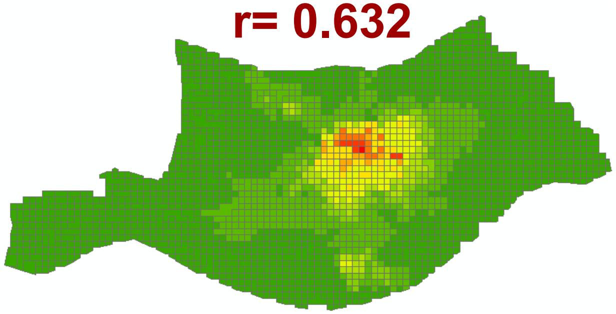
AM 06-07

r= 0.697



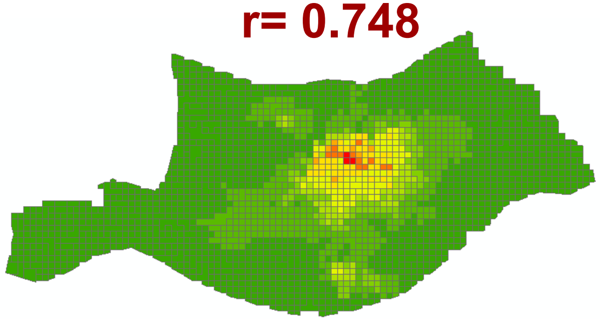
AM 09-10

r= 0.632



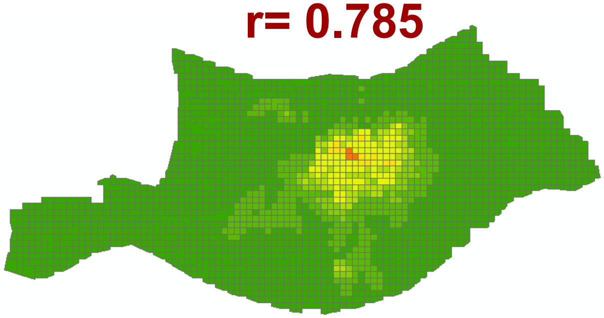
PM 15-16

r= 0.748



PM 18-19

r= 0.785

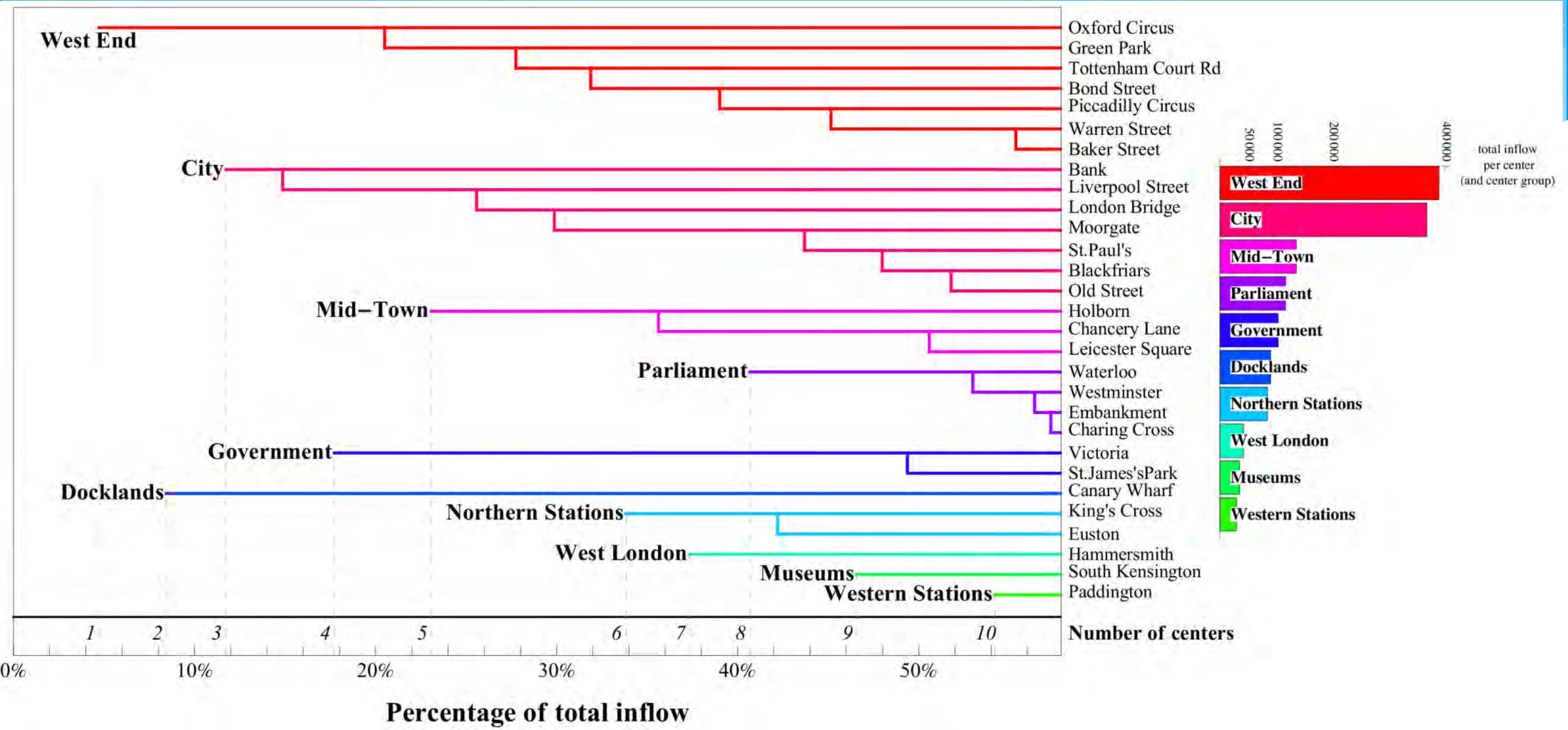


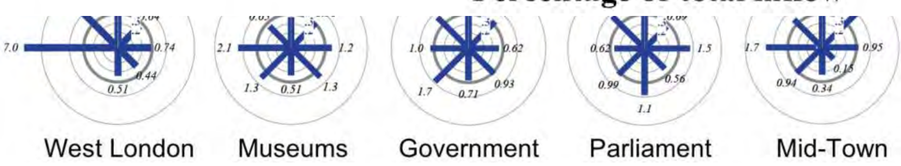
PM 21-22

Song Gao, UCSB Geography, 2013

Urban Transportation

Identifying the Structure of Urban Movements from Smart Card Data

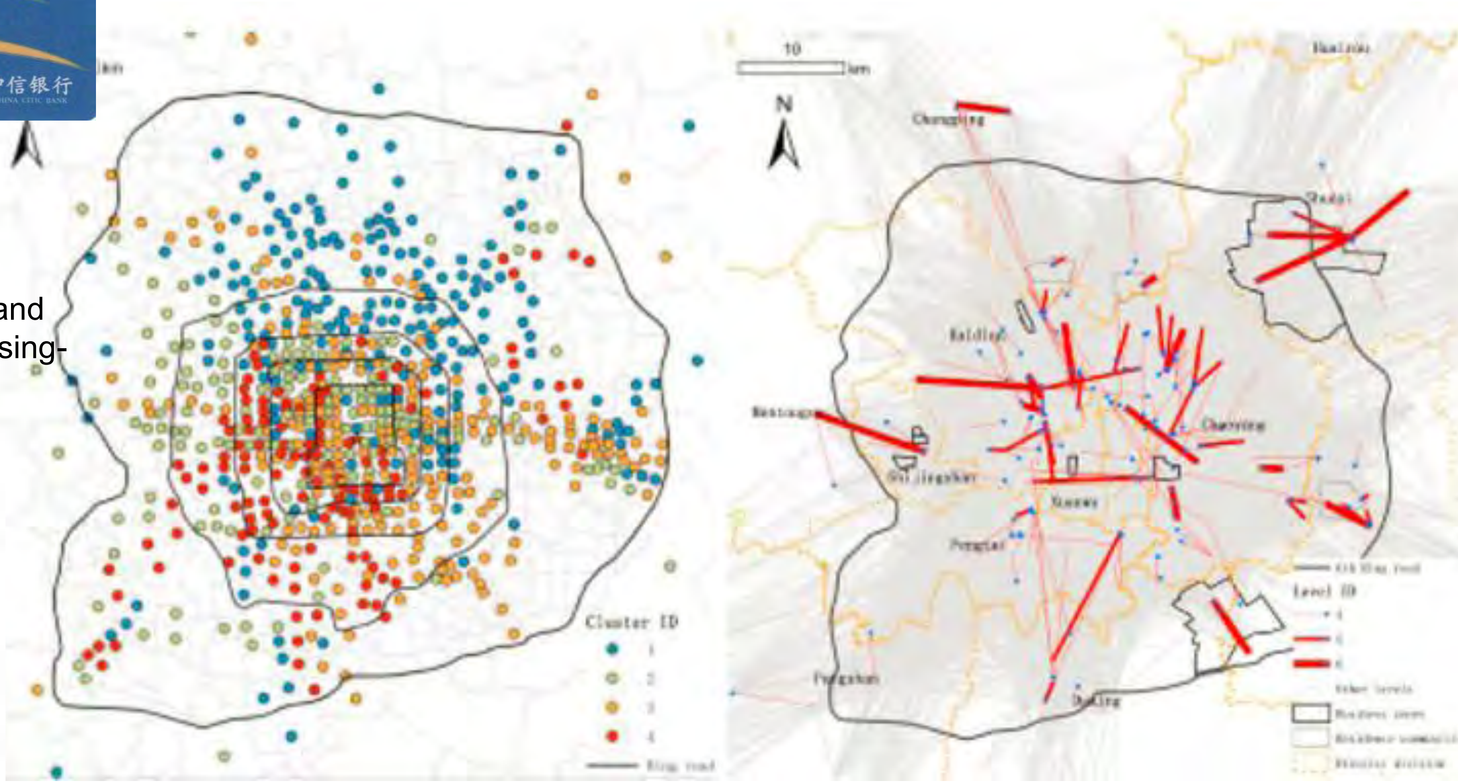




Roth, C., Kang, S. M., Batty, M., & Barthélemy, M. (2011). Structure of urban movements: polycentric activity and entangled hierarchical flows. *PLoS One*, *6*(1), e15923.

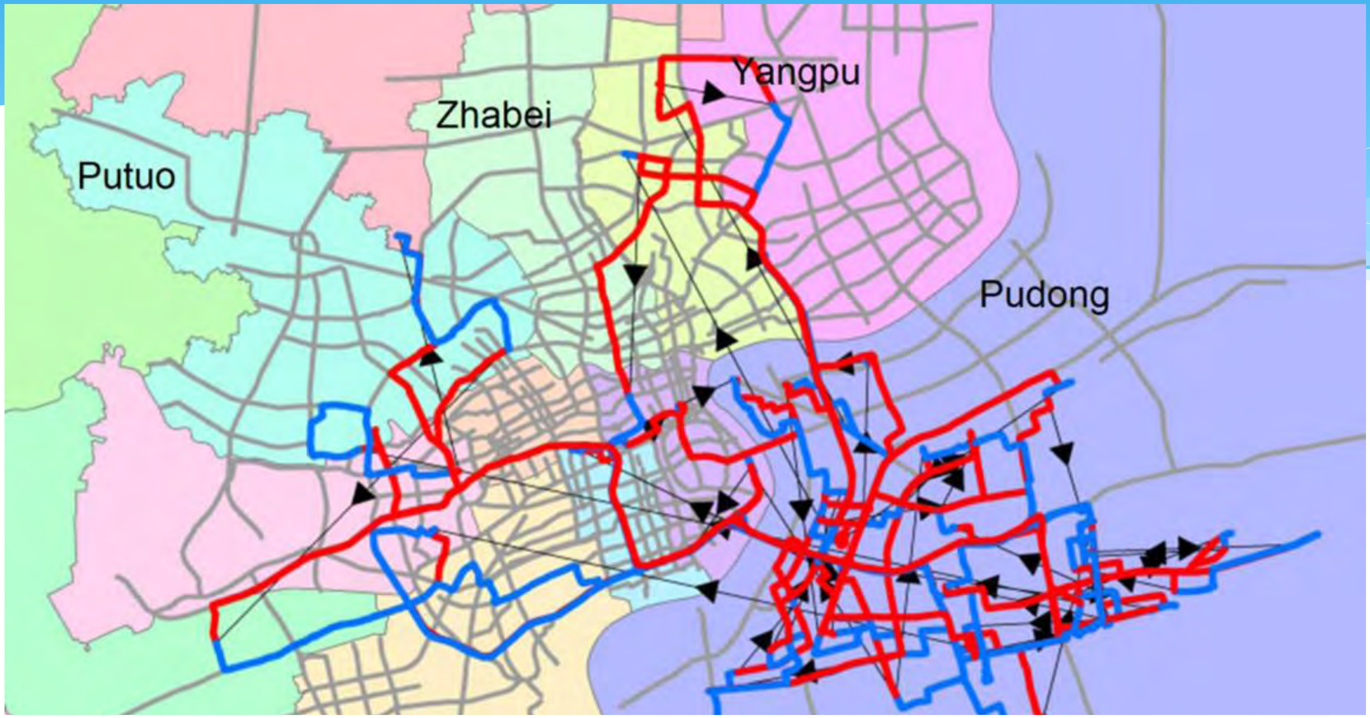
Analyzing jobs-housing relationships

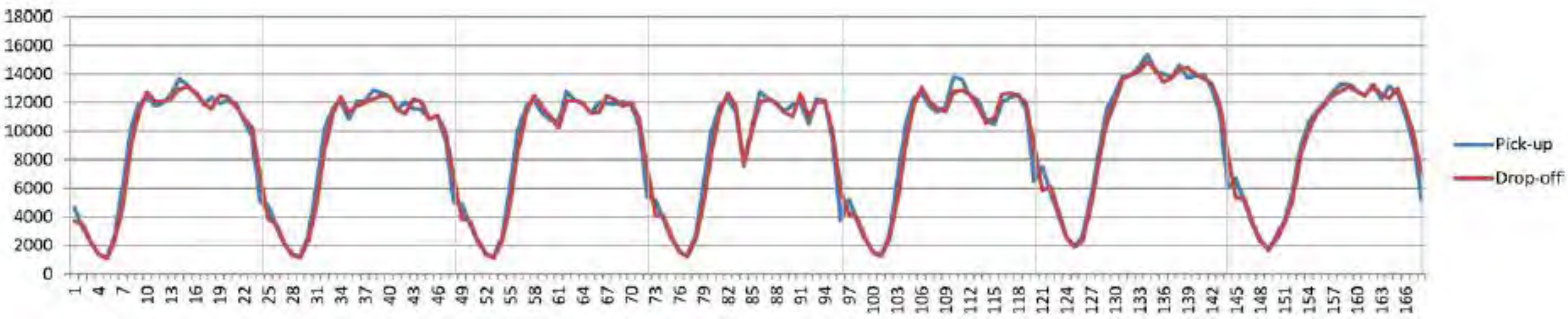
Long Y, Thill J-C, 2013, "Combining smart card data, household travel survey and land use pattern for identifying housing-jobs relationships in Beijing" Computers, Environment and Urban Systems.



Beijing City Lab

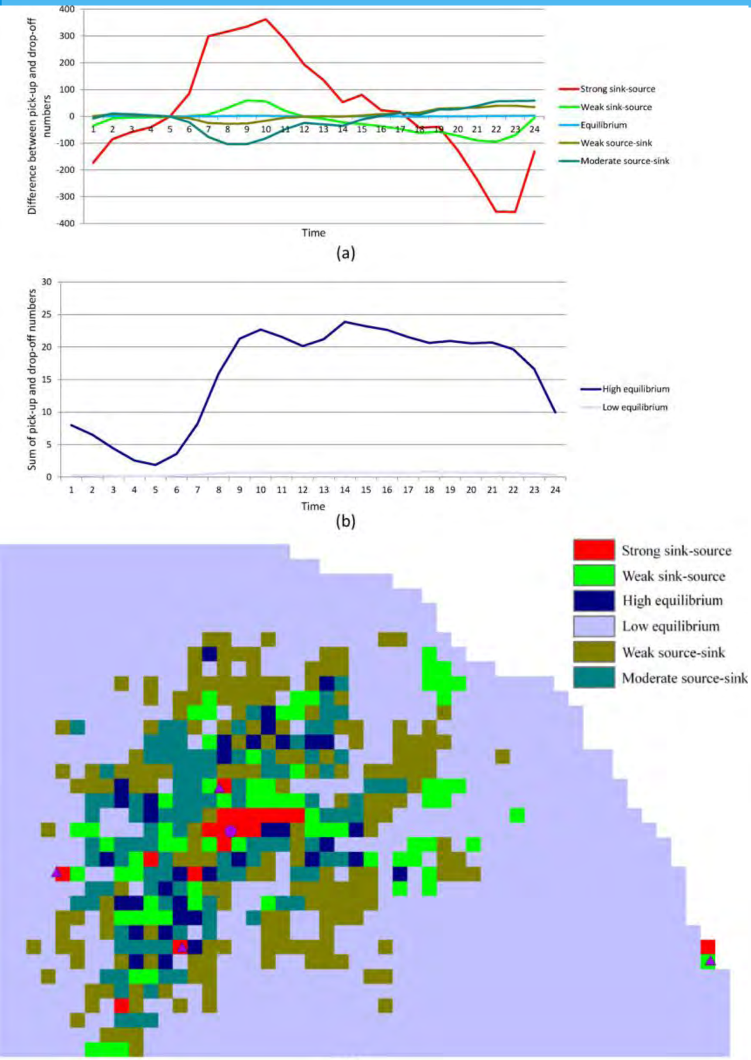
Exploring Urban Land Use from GPS-enabled Taxi Trajectory



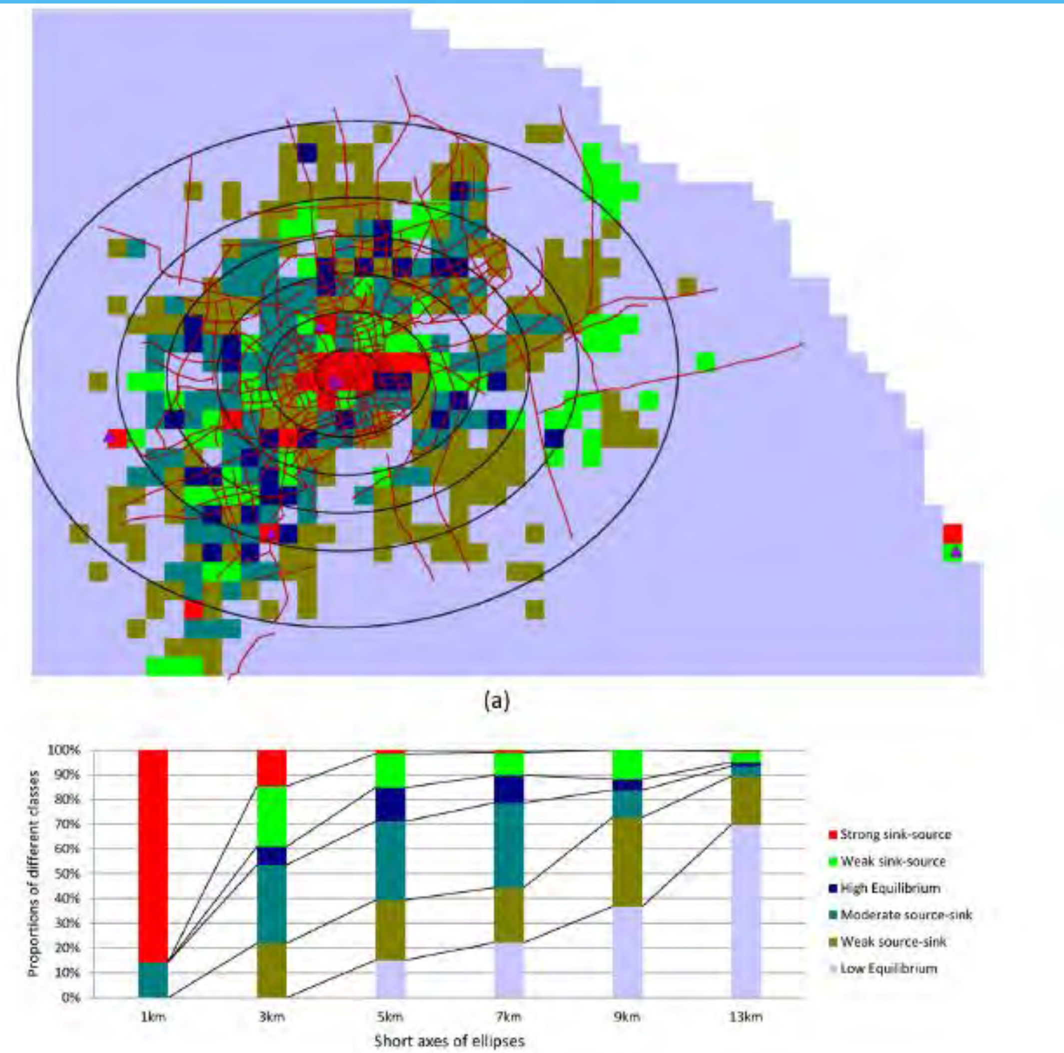


Liu, Y., Wang, F., Xiao, Y., & Gao, S. (2012). Urban land uses and traffic 'source-sink areas': Evidence from GPS-enabled taxi data in Shanghai. Landscape and Urban Planning, 106(1), 73-87.

Exploring Urban Land Use from GPS-enabled Taxi Trajectory



(c)

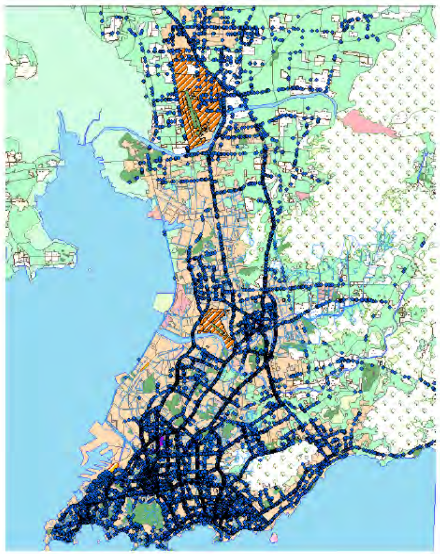


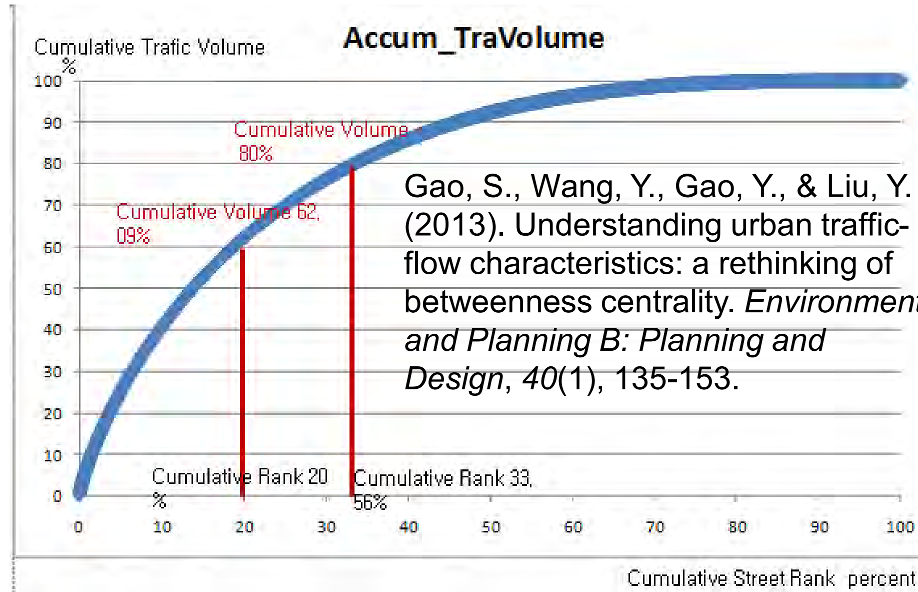
(b)

Liu, Y., Wang, F., Xiao, Y., & Gao, S. (2012). Urban land uses and traffic 'source-sink areas': Evidence from GPS-enabled taxi data in Shanghai. Landscape and Urban Planning, 106(1), 73-87.

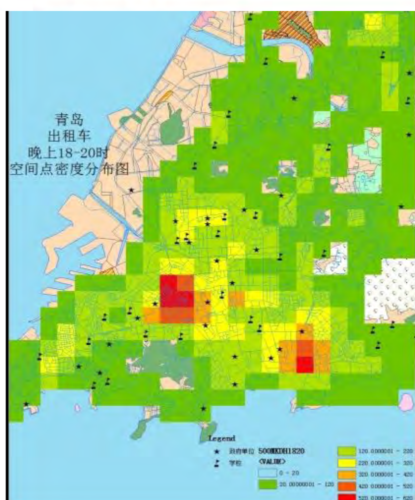
Understanding urban traffic flow characteristics and street centrality

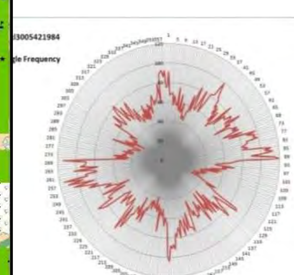
- 149 taxis in total.
- A taxi GPS file contains tracks points with the fields(FID,Date,Time,Latitude,Longitude, Velocity, Angle)
- time lasts more than a month(From March to April,2009),

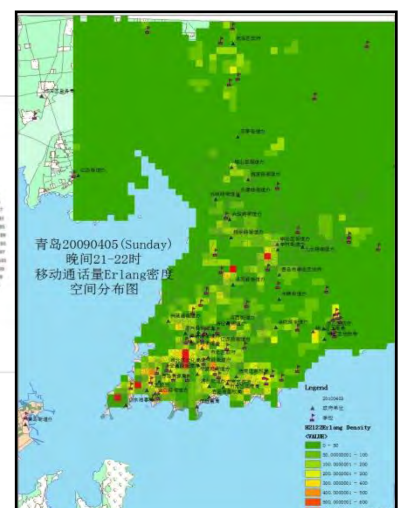


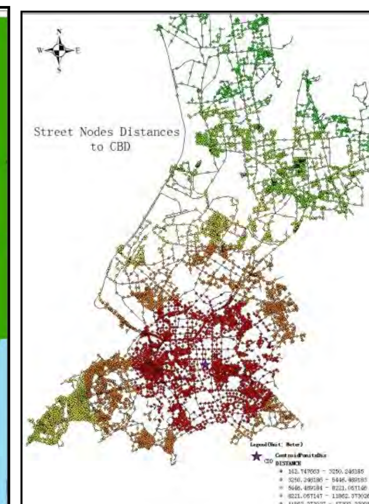


Gao, S., Wang, Y., Gao, Y., & Liu, Y. (2013). Understanding urban traffic-flow characteristics: a rethinking of betweenness centrality. *Environment and Planning B: Planning and Design*, *40*(1), 135-153.



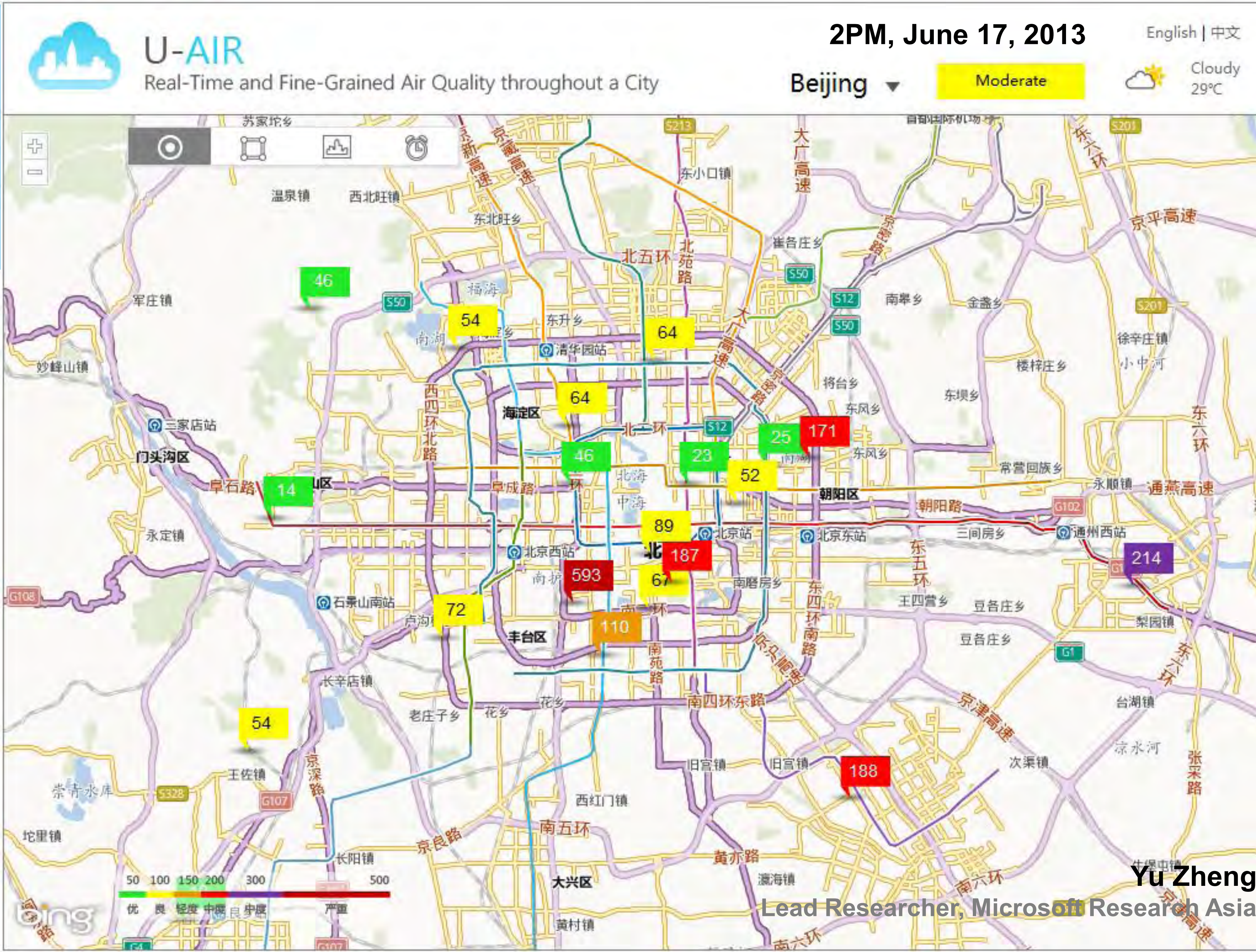






Urban Air Quality

2PM, June 17, 2013

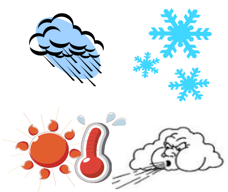


Yu Zheng

Lead Researcher, Microsoft Research Asia

Inferring **Real-Time** and **Fine-Grained** air quality throughout a city using **Big Data**

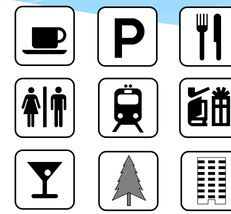
Yu Zheng
Lead Researcher, Microsoft Research Asia



Meteorology

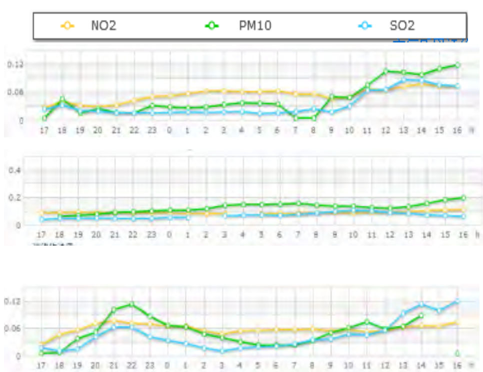
Traffic

Human Mobility

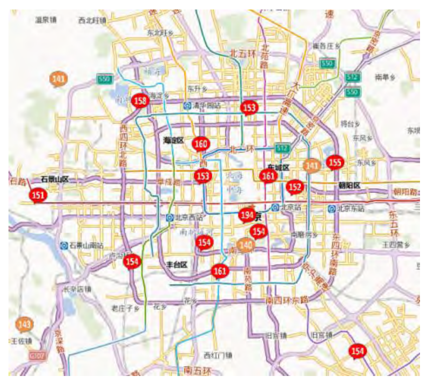


POIs

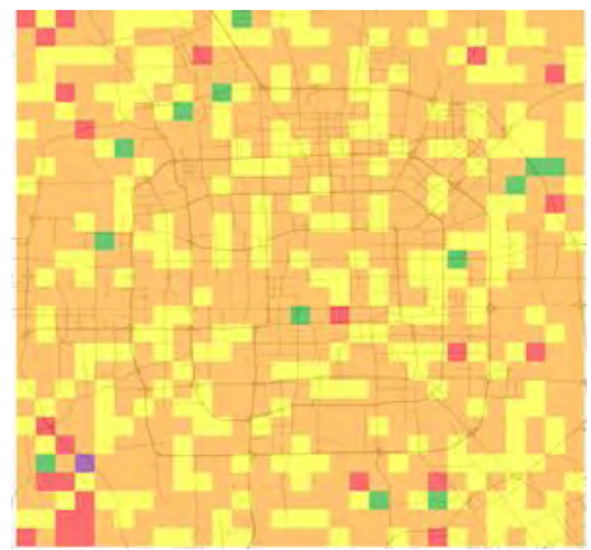
Road networks



Historical air quality data



Real-time air quality reports

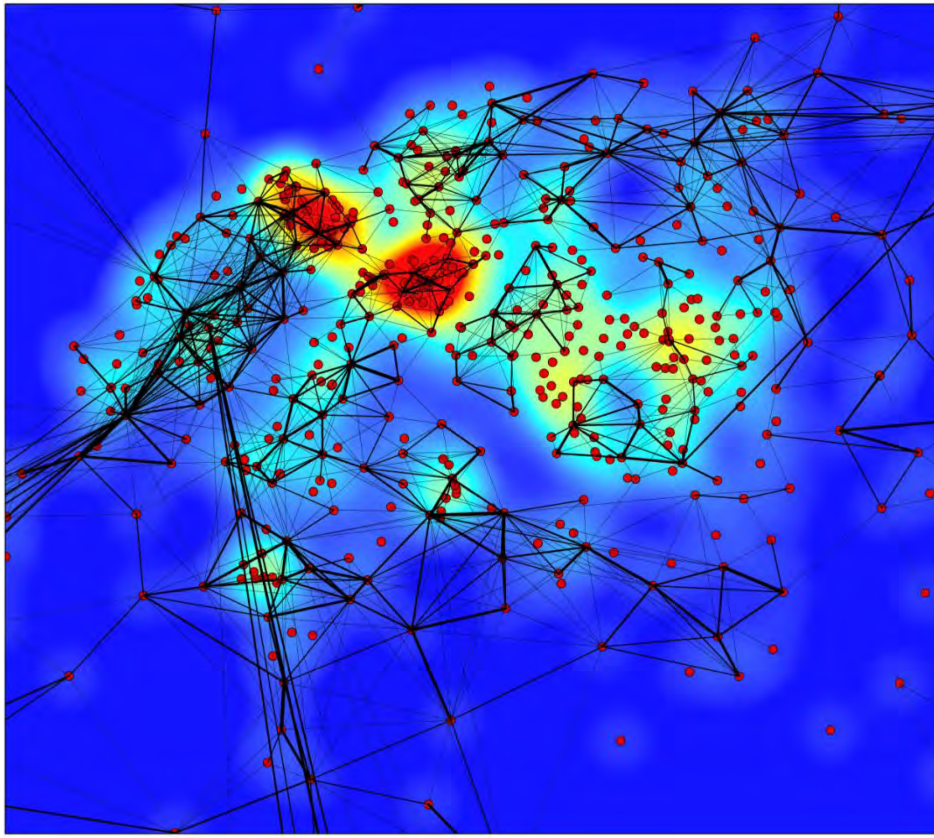


Spatial Interaction Network

Community in spatial networks

Spatial Networks describe the networks in which the nodes are embedded in a geographical space

Goal: to explore telecommunication flow in geographic space and to understand how the spatial context affect such interactions



Song Gao, UCSB Geography, 2013

Community in spatial networks

Spatial effects on networks

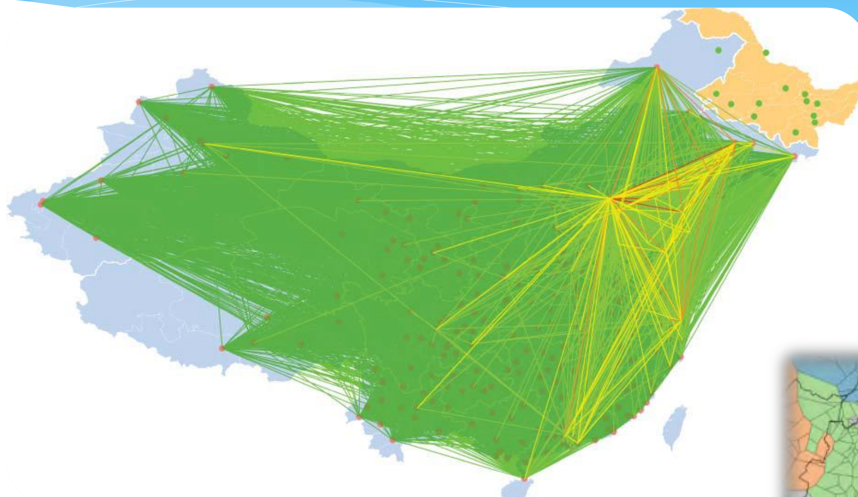
(1) Spatial constraints on the distribution of nodes embedded in geographical locations;

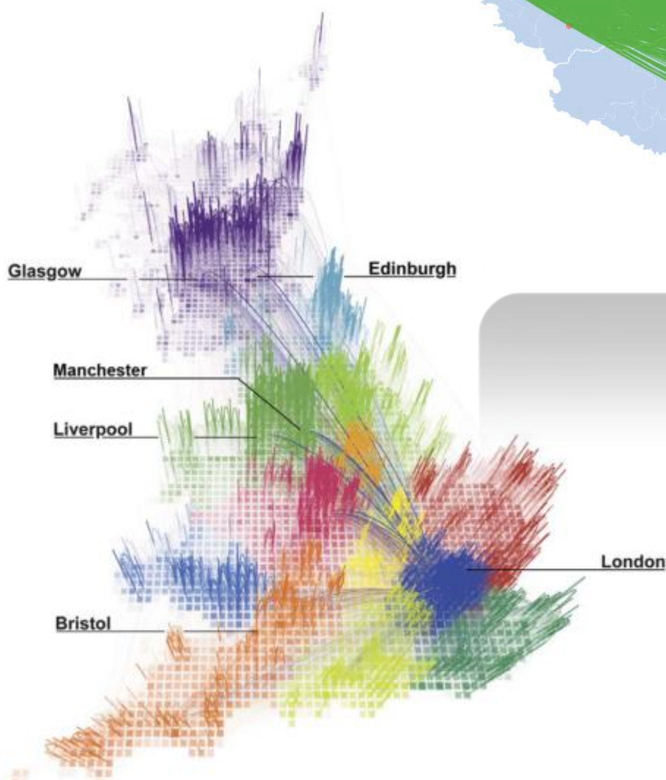
(2) Physical networks like roads and railways, which are affected by spatial topology;

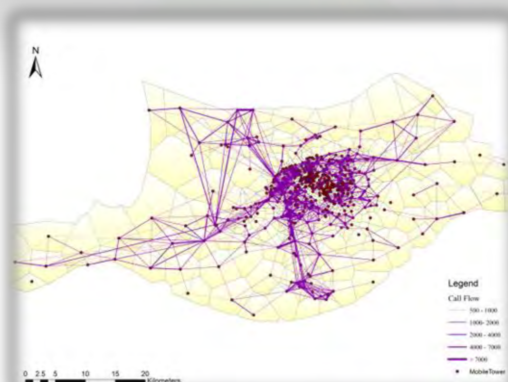
(3) Restrictions on long-distance links due to economic costs.

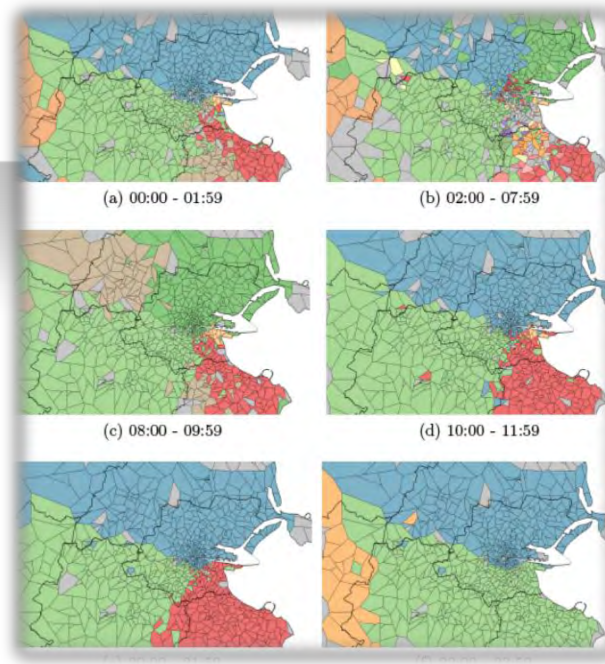
Motivation

Whether interaction structure, friendship likelihoods reveal political boundaries, physical barriers, or social divide

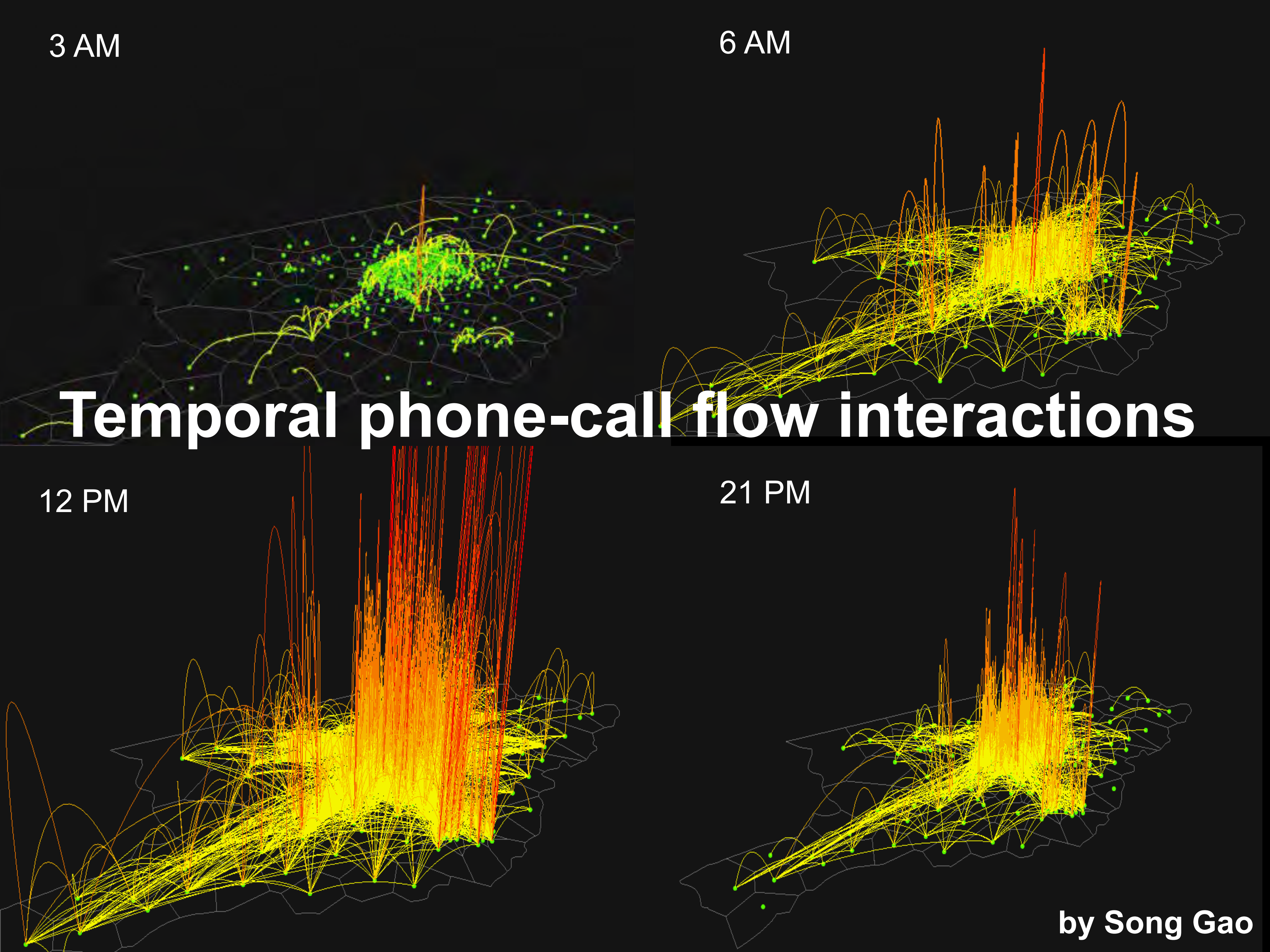








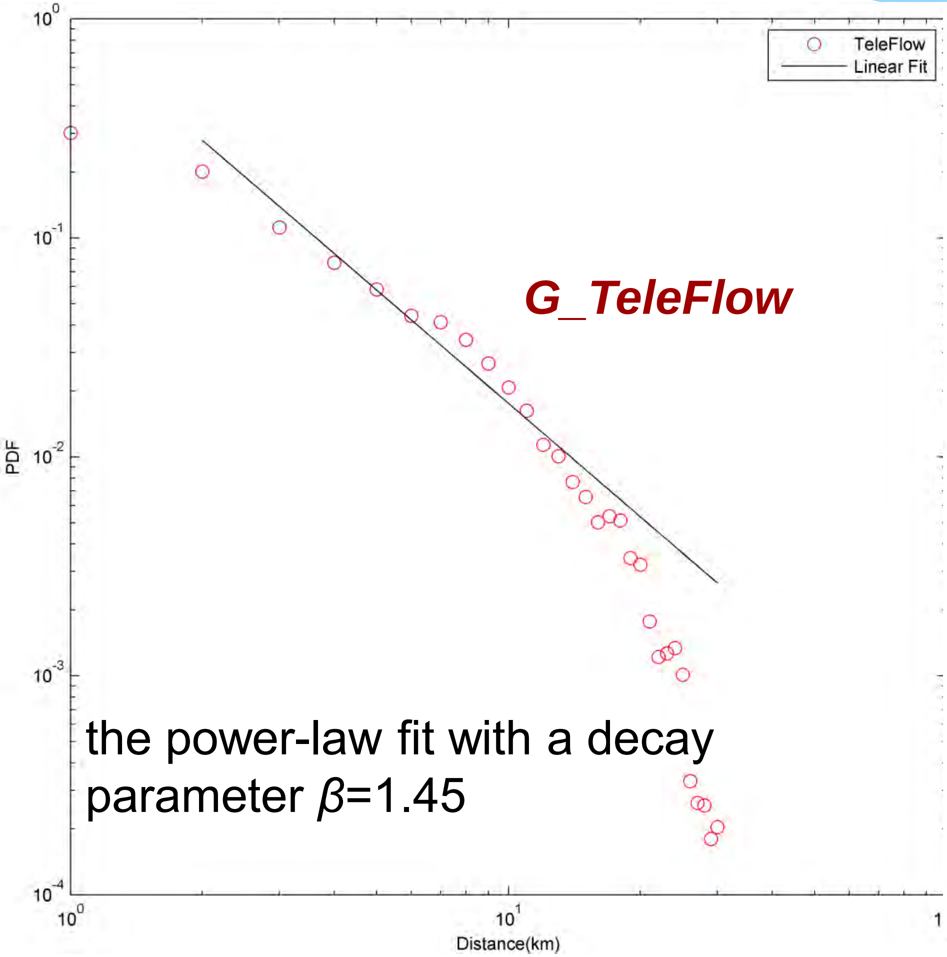
Temporal phone-call flow interactions



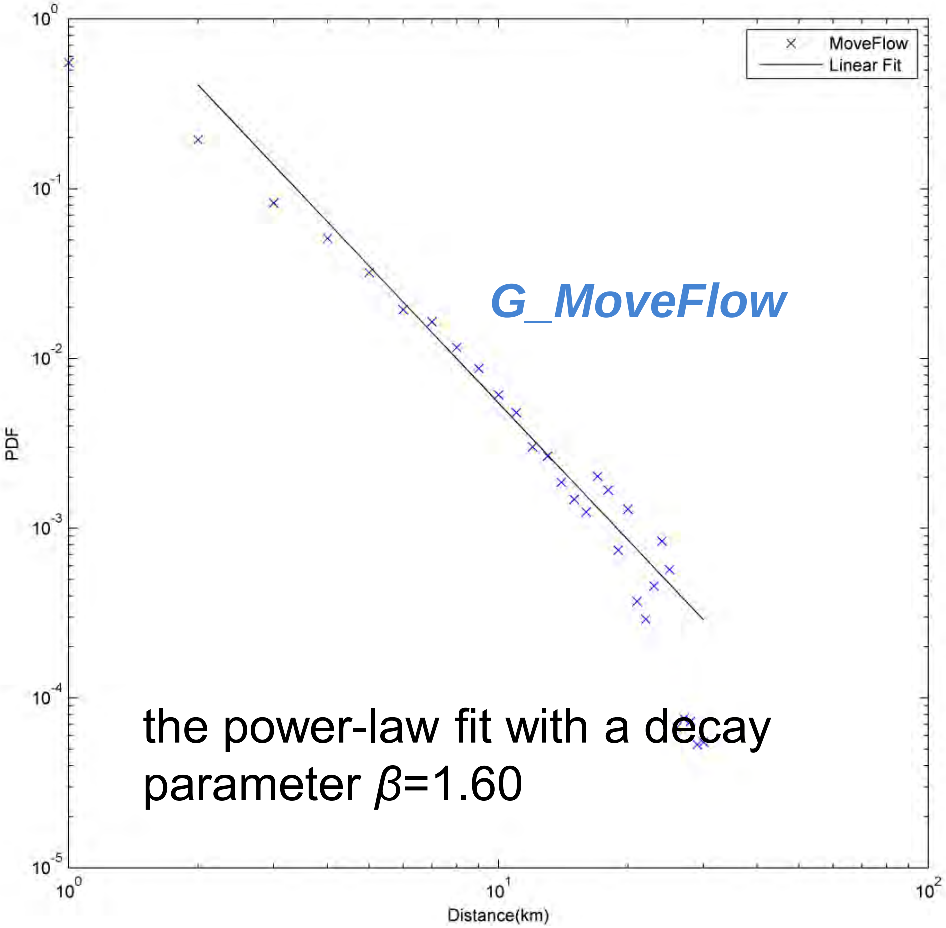
by Song Gao

Distance Decay of Spatial Interactions

$$P \propto d^{-\beta}$$



the power-law fit with a decay parameter β=1.45



the power-law fit with a decay parameter β=1.60

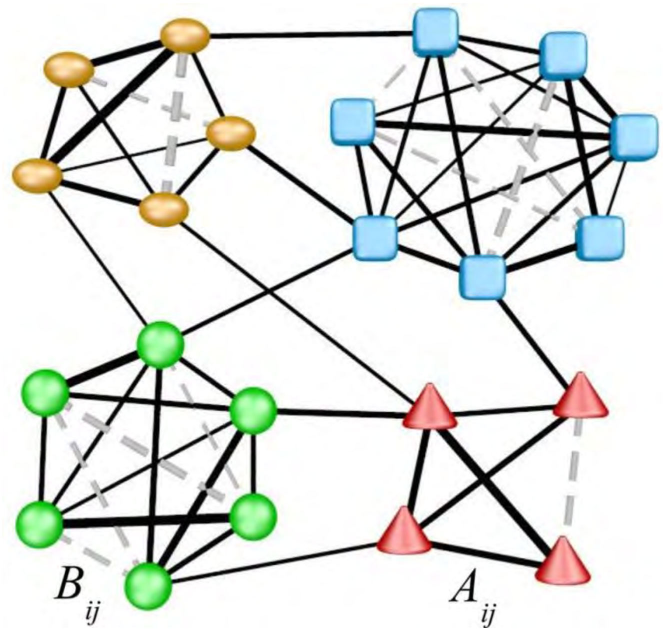
Gao, S., Liu, Y., Wang, Y., & Ma, X. (2013). Discovering Spatial Interaction Communities from Mobile Phone Data. *Transactions in GIS*.

Community Detection in Spatial Networks

The nodes of the network can be grouped into sets of nodes so that each community is densely connected internally.

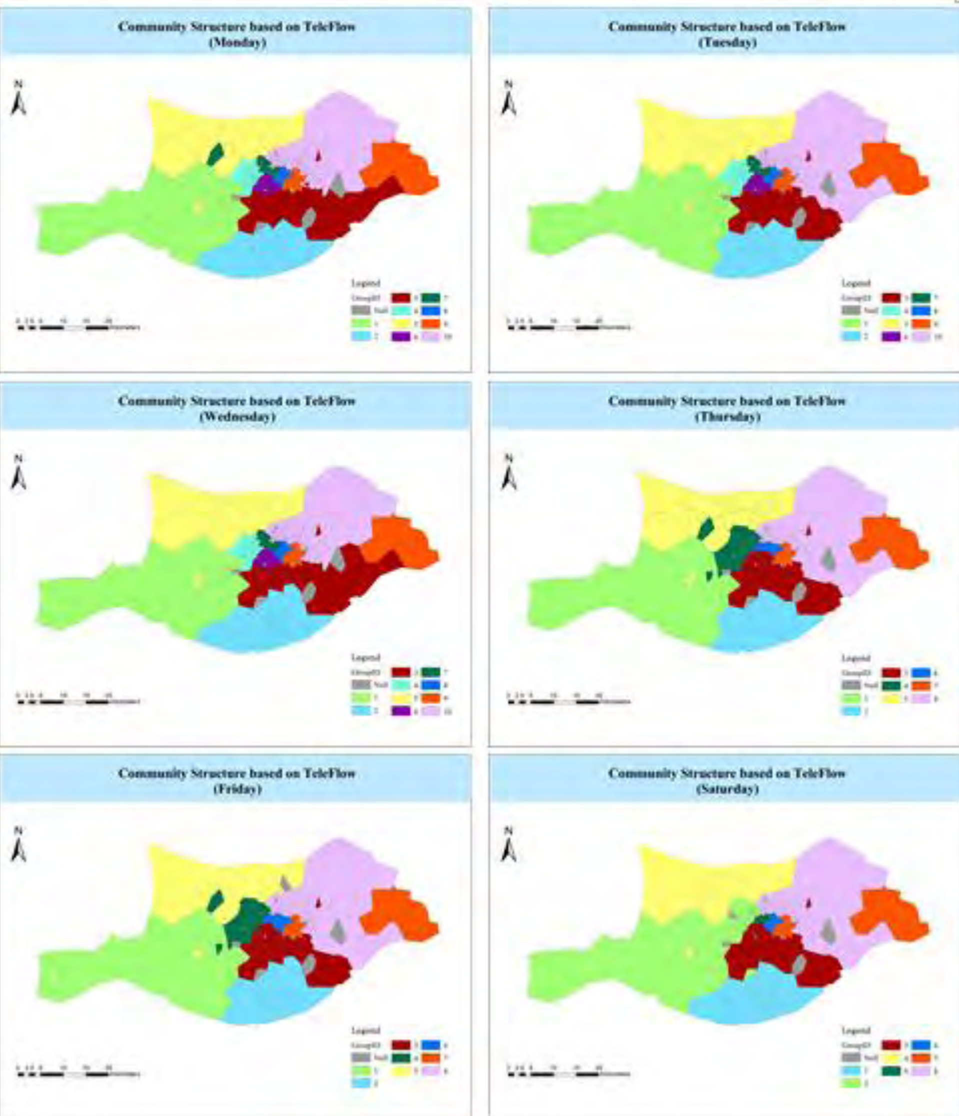
- **Modularity maximization**
- **Minimum-cut method**
- **Hierarchical clustering**
- **Girvan–Newman algorithm**
- **Clique based methods**

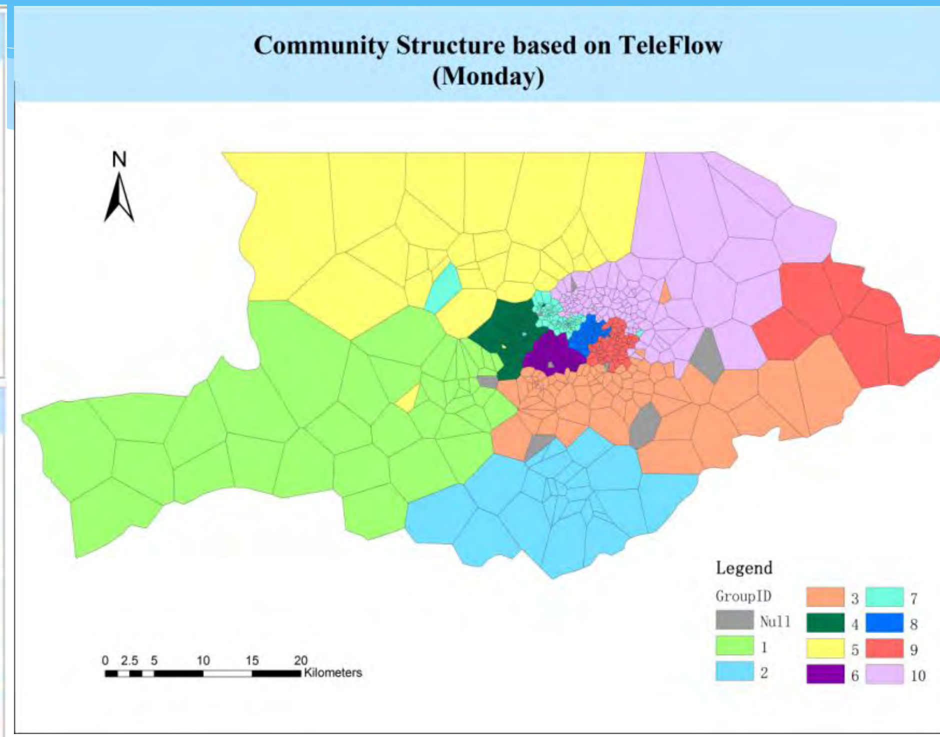
Modularity is defined as the sum of differences between the fraction of edges falling within communities and the expected value of the same quantity under the random null model.



Song Gao, UCSB Geography, 2013

Community detection results



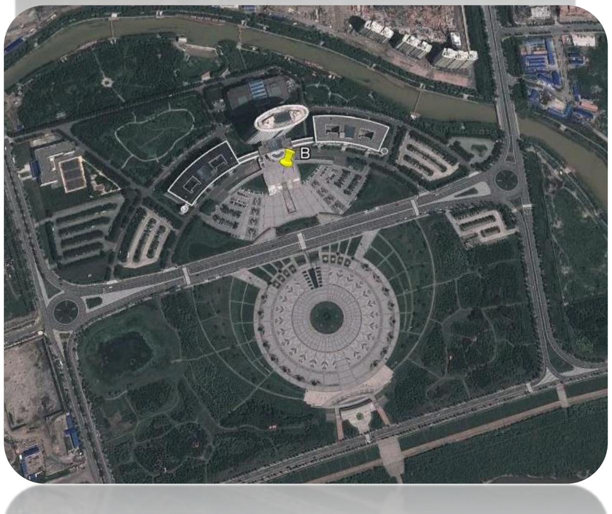


MAXID-----: 616
NUMNODES--: 609
NUMEDGES--: 41960
TOTALWT---: 934561
NUMGROUPS-: 10
MINSIZE---: 27
MEANSIZE--: 60.9
MAXSIZE---: 120
MAXQ------: 0.527837
STEP------: 599

Examples of differentiated geographical context of isolated regions in spatial communities

Cell A **locates in the overpass intersection of ring highway and the airport expressway which is near a large residential suburb area of this city, and a high volume of call interaction make it merged to the northern spatial community (yellow) of official cells.**

Examples of differentiated geographical context of isolated regions in spatial communities



Cell B has been grouped into the same distant community on Monday, Thursday and Friday, whereas it aggregates into nearby spatial adjacent community on weekends.

It corresponds to a set of governmental buildings which has strong connections with eastern cells (green) of central business district on weekdays.

Relation between Telecommunication and Movement

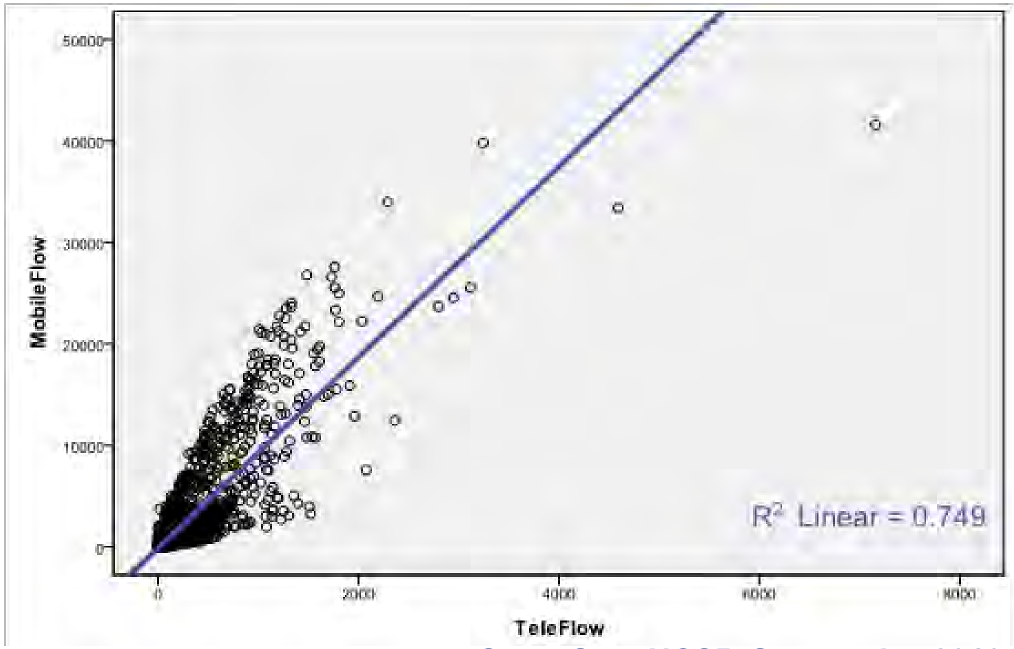
Correlation coefficients between phone call interaction and movements

	Mon	Tue	Wed	Thur	Fri	Sat	Sun
R^2	0.857	0.852	0.852	0.848	0.852	0.857	0.865

ICT & Mobility：

- -替代(Substitution)
- -增强(Stimulation)
- -缓和(Modificaiton)

a causal relationship?



Song Gao, UCSB Geography, 2013

Outline

- Why spatial is special
- Urban Computing
- Geospatial Data Conflation
- GIS Trends
- Conclusions

The Big-Data Age: more geospatial data

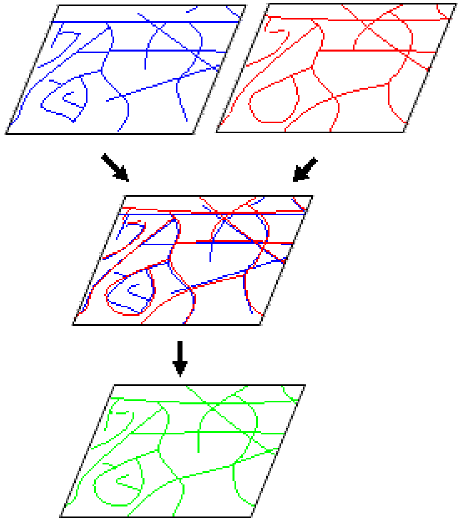
- Authoritative sources
  - US Census TIGER files
  - USGS
  - NGA
  - State and local governments
  - Geospatial data companies

- Assertive sources
  - VGI: OpenStreetMap, Wikimapia
  - Social Media: Twitter, Flickr, Foursquare

Geospatial Data conflation

* **Map conflation:** "a combining of two digital map files to produce a third map file which is 'better' than each of the component source maps" -- Lynch and Saalfeld, 1985

* **Geographic data conflation:** a process of combining information from two or more related geospatial datasets, and thus acquiring knowledge that cannot be obtained from any single data source alone.



* **Point of Interest (POIs) conflation:** enriching and updating business POIs

Feature matching framework

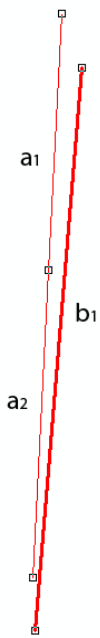
- Feature matching: integration of all possible characteristics
  - Geometry: Euclidean distance, Hausdorff distance, nearest neighbor pairing, shape (Saalfeld, 1988; Yuan and Tao, 1999； Filin and Doytsher, 2000; Chen, *et al*., 2006; Hastings, 2008)
  - Semantics: feature name, feature type, and other general information (Cohen *et al.* 2003; Hastings, 2008)
  - Topology: connectivity of lines (Saalfeld, 1988 ; Filin and Doytsher, 2000)

A generic model for linear feature matching

- **Two directed Hausdorff distances**

$$d_{i->j}^{DH} = \max_{x \in L_i} \{ d(x, L_j) \}$$

$$d_{j->i}^{DH} = \max_{x \in L_j} \{ d(x, L_i) \}$$

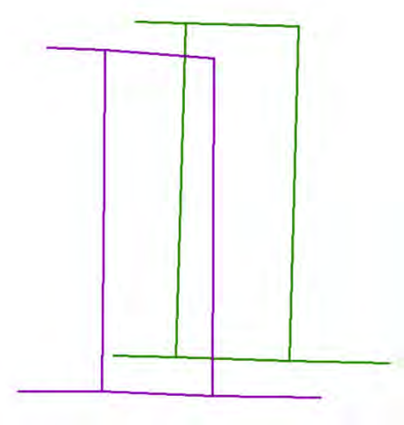


The shortest distance between a point x and a line L

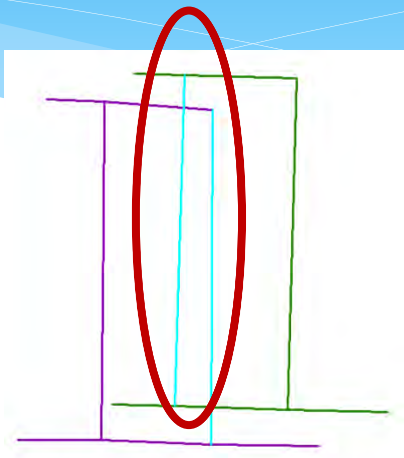
$$d(x, L) = \min \{ d(x, y) : y \in L \}$$

Greedy or Optimization in feature matching

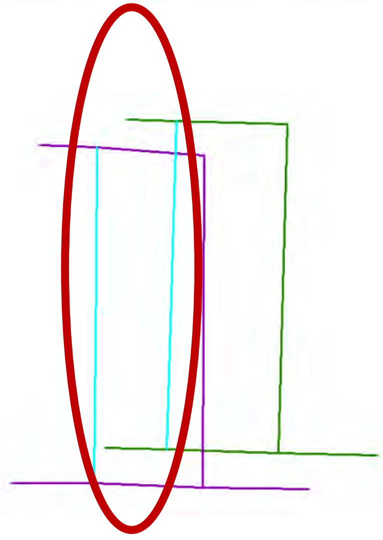
Input data



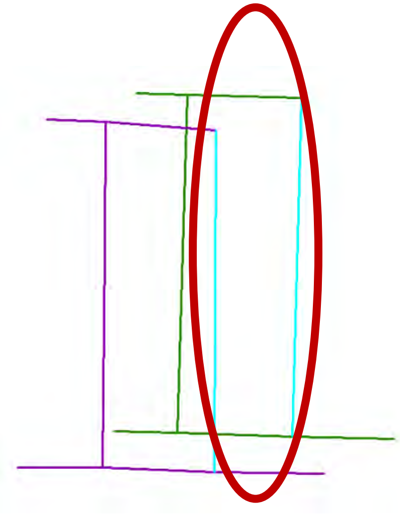
Greedy



Optimization



Optimization



Optimized linear feature matching in geographic data

Objective function: $$\textit{Maximize} \sum_{i=1}^{k}\sum_{j=1}^{l} s_{i->j} z_{i->j}$$

$$z_{i->j} = \begin{cases} 1, & \text{if a match is made from feature } i \text{ to } j \\ 0, & \text{otherwise} \end{cases}$$

Constraints: $$\sum_{j=1}^{l} z_{i->j} \le 1, \quad \forall i \qquad \sum_{i=1}^{k} z_{i->j} + \delta_j \ge 1, \quad \forall j$$

$$\delta_j = \begin{cases} 1, & \textit{if all similarities of feature } j \textit{ are less than a certain value} \\ 0, & \textit{otherwise} \end{cases}$$

$$\sum_{i=1}^{k} l_i * z_{i->j} \le k_j * \beta, \quad \forall j$$

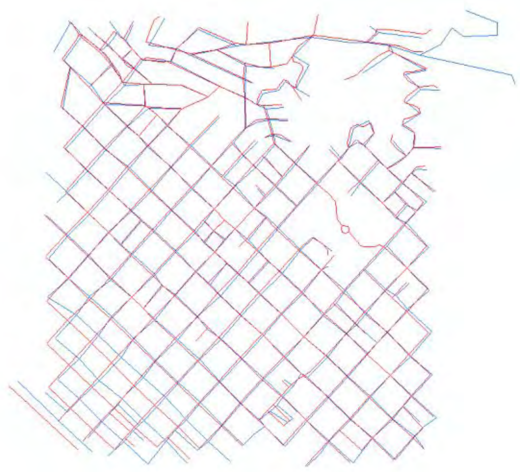
l_i the length of feature *i* in Dataset 1

k_j the length of feature *j* in Dataset 2

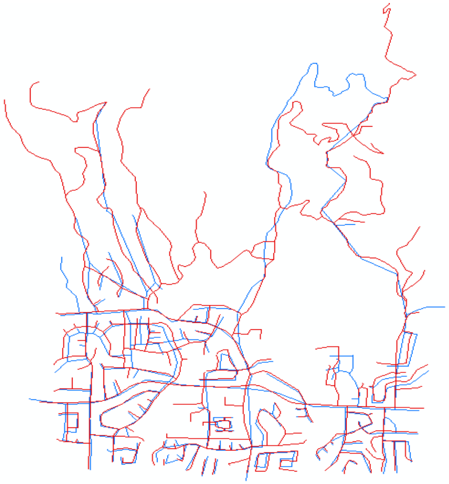
β a tolerance factor that takes into account uncertainty in feature length

Linna Li and Michael F. Goodchild. *An optimisation model for linear feature matching in geographical data conflation. International Journal of Image and Data Fusion 2(4): 309–328*

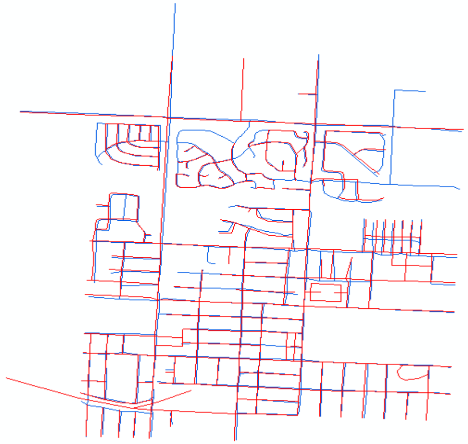
Test areas



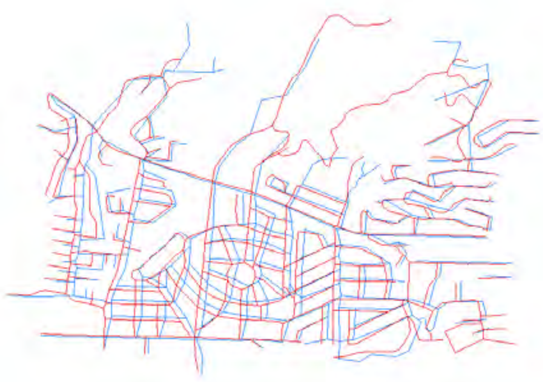
Test Area 1



Test Area 2



Test Area 3

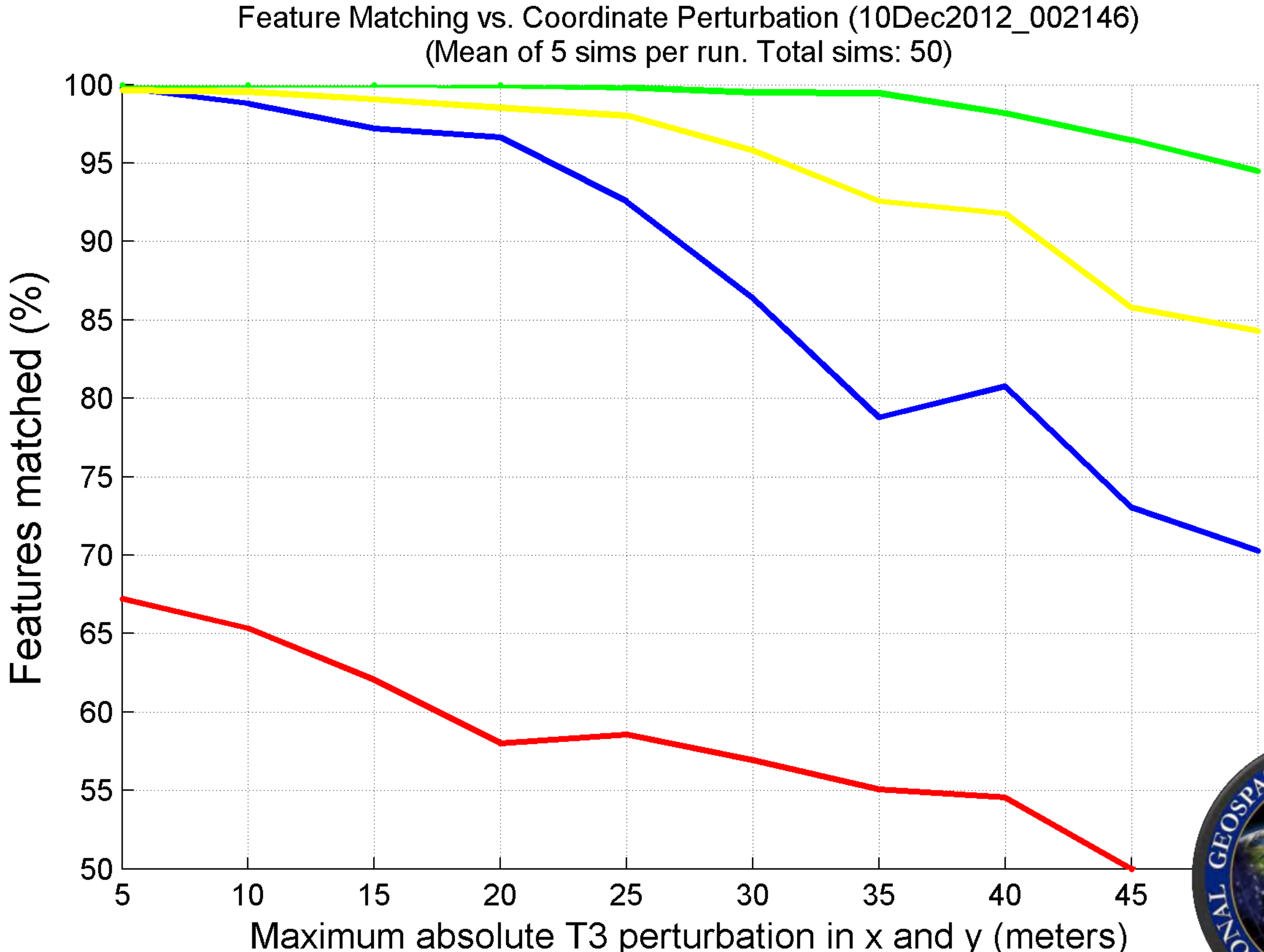


Test Area 4

Results of optimized feature matching

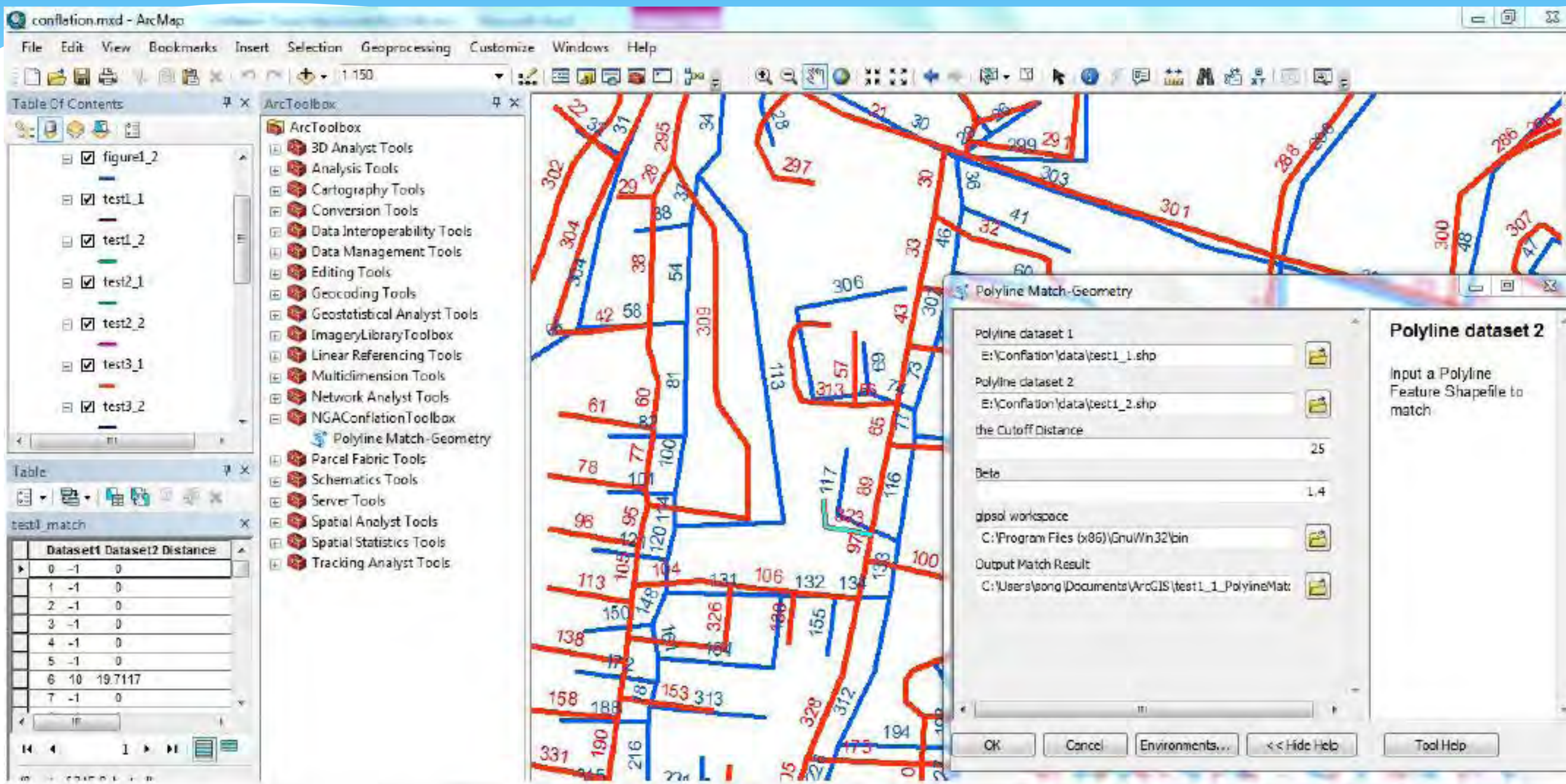
Test Area	Test Area 1	Test Area 2	Test Area 3	Test Area 4	Total
Number of features in Dataset 1	434	308	377	344	1463
Number of features in Dataset 2	423	264	374	322	1383
Number of corresponding pairs and singles	450	330	419	362	1561
Number of correct identifications	441	322	410	344	1517
Percentage of correct identifications	98.00%	97.58%	97.85%	95.03%	97.18%

Comparison between our conflation tool (green) and three other tools



Results provided by NGA

Feature Conflation Toolbox in ArcGIS



by Song Gao

The command line for batch processing

Windows Command Processor

```
*   3400: obj =   1.064287072e+005  infeas = 4.827e-016 (0)
*   3600: obj =   8.814061690e+004  infeas = 5.642e-017 (0)
*   3800: obj =   6.501038810e+004  infeas = 0.000e+000 (0)
*   4000: obj =   4.985349612e+004  infeas = 0.000e+000 (0)
*   4200: obj =   3.546004961e+004  infeas = 0.000e+000 (0)
*   4400: obj =   2.204840948e+004  infeas = 0.000e+000 (0)
*   4600: obj =   9.748313232e+003  infeas = 2.418e-017 (0)
*   4800: obj =   4.855035018e+003  infeas = 0.000e+000 (0)
*   5000: obj =   4.290270689e+003  infeas = 0.000e+000 (0)
*   5057: obj =   4.287068925e+003  infeas = 0.000e+000 (0)
OPTIMAL SOLUTION FOUND
Integer optimization begins...
+   5057: mip =     not found yet >=              -inf        (1; 0)
+   5057: >>>>>   4.287068925e+003 >=   4.287068925e+003   0.0% (1; 0)
+   5057: mip =   4.287068925e+003 >=     tree is empty   0.0% (0; 1)
INTEGER OPTIMAL SOLUTION FOUND
Time used:   23.5 secs
Memory used: 188.3 Mb (197446893 bytes)
Model has been successfully processed
Polyline matching successfully done! Check the result at E:\Conflation\matchnew.
out  Time used: 110.687439782

E:\Conflation>
```

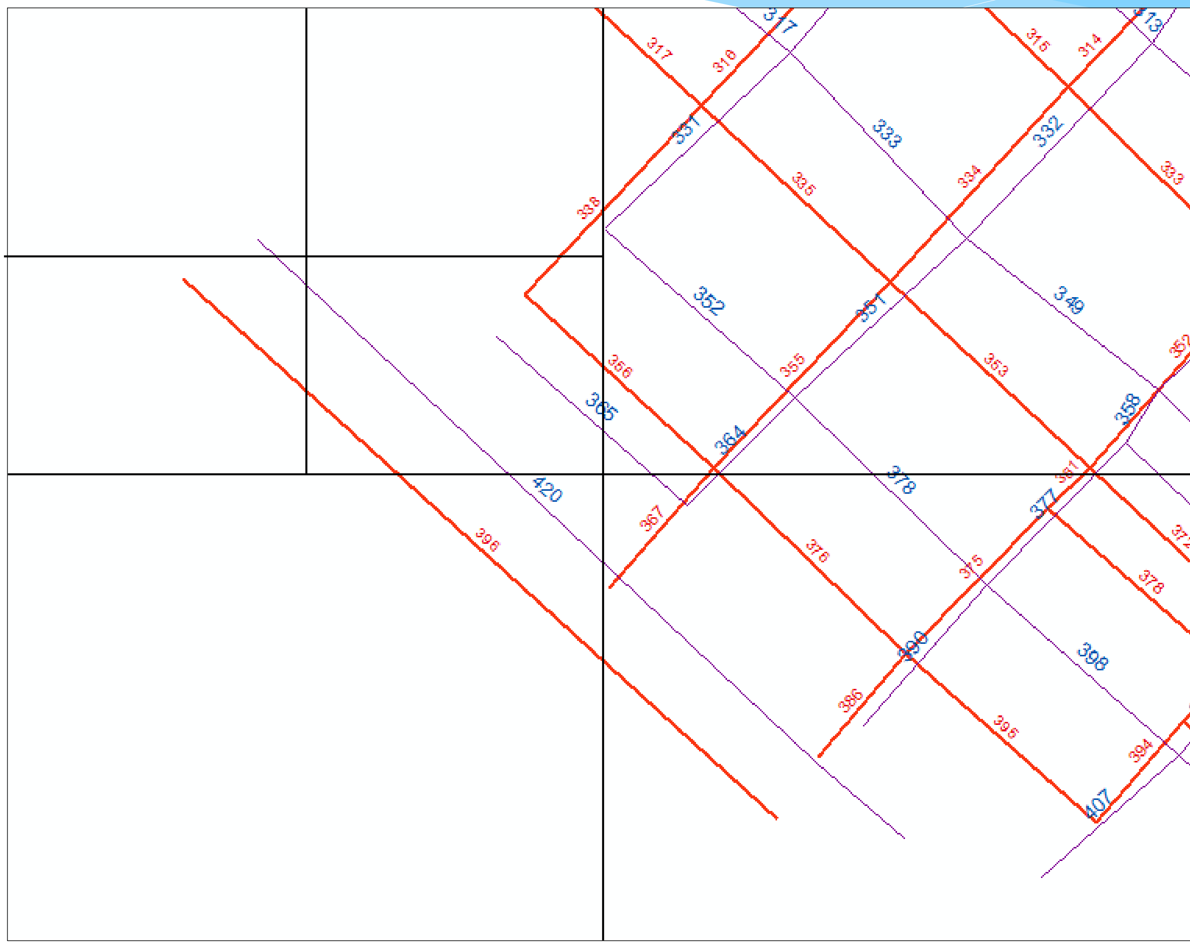
Speeding up the algorithm

- Time consuming: Calculation of Hausdorff distance matrix between linear features

- Divide-and-conquer
  - Divide the whole dataset into smaller sub-datasets
  - Parallel computing

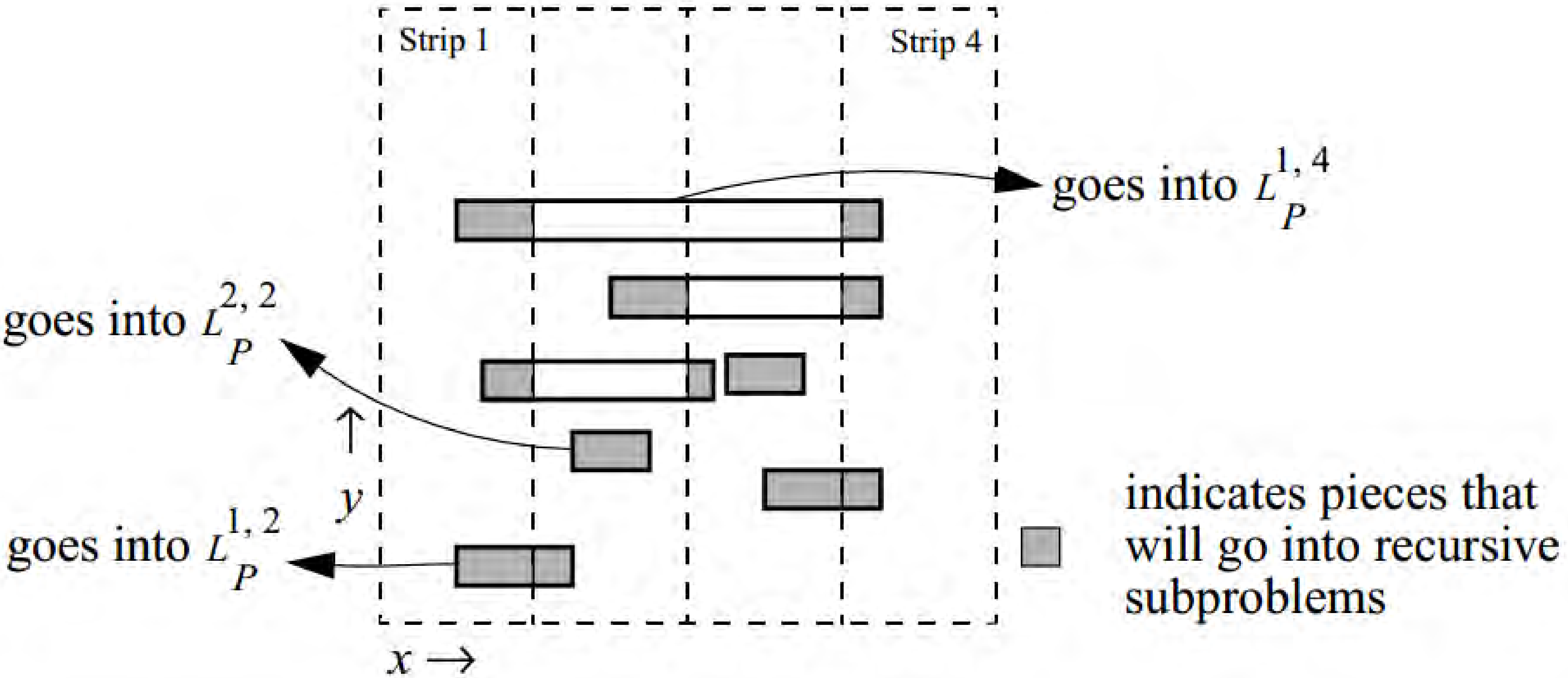
Partitioning for Parallel Computing

- (1) Quadtree-Based Approach



Partitioning for Parallel Computing

(2) Sweeping-Based Approach

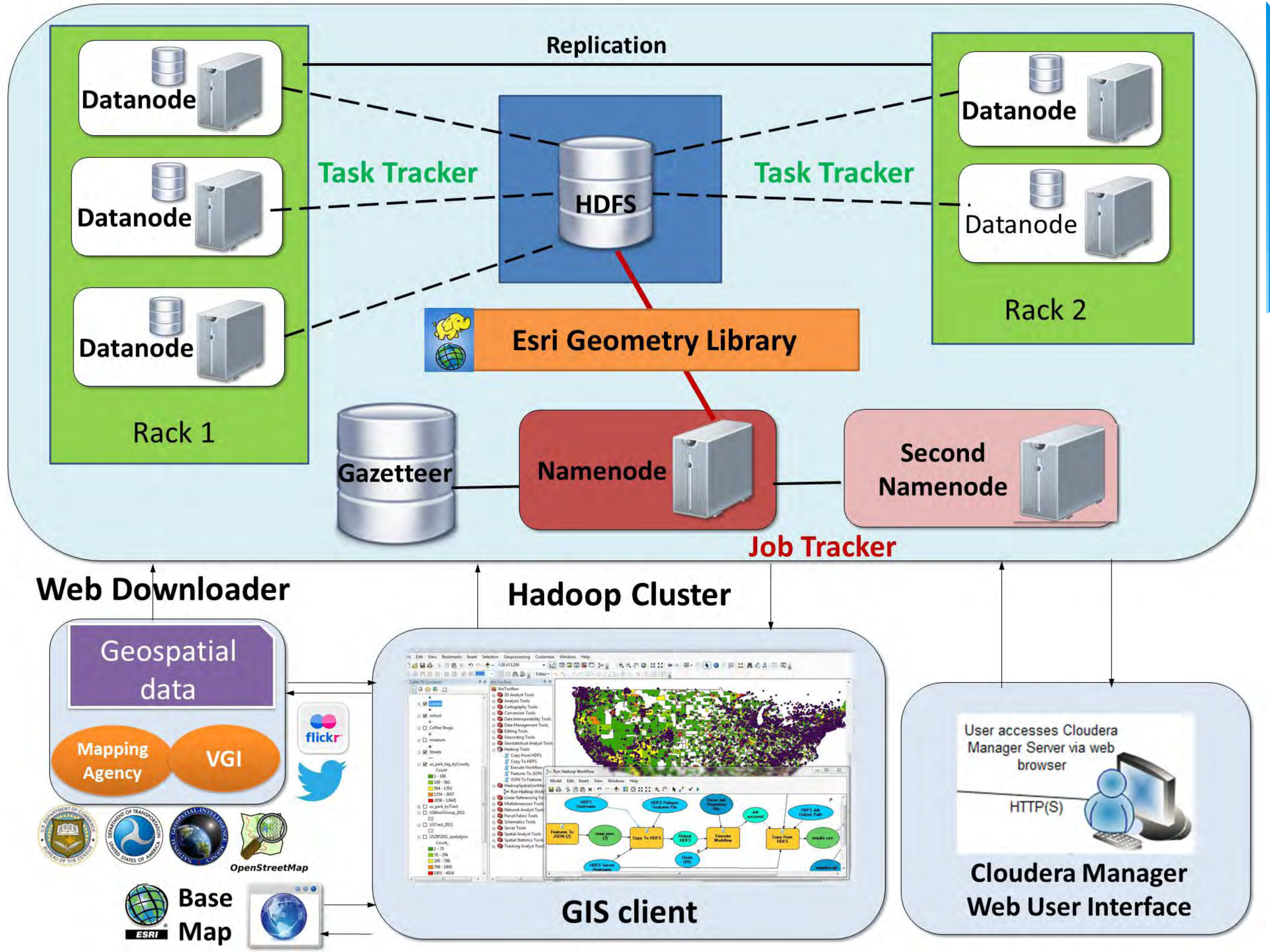


Partitioning for Parallel Computing

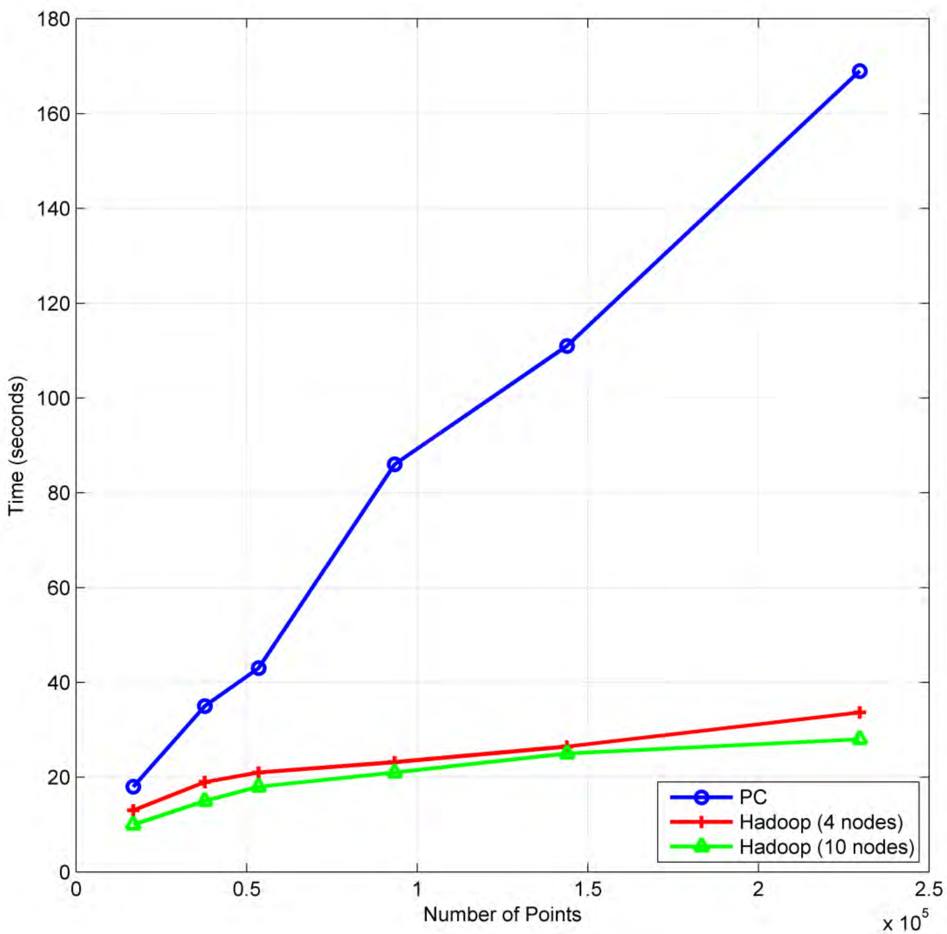
* (3) Object-Based Approach

Asymmetric Hausdorff Distance Matrix $O(n^2)$

	L1	L2	L3	L4	L5	L6	……
L1		d_{12}	d_{13}	d_{14}	d_{15}	d_{16}	……
L2	d_{21}		d_{23}	d_{24}	d_{25}	d_{26}	……
L3	d_{31}	d_{32}		d_{34}	d_{35}	d_{36}	……
L4	d_{41}	d_{42}	d_{43}		d_{45}	d_{46}	……
L5	d_{51}	d_{52}	d_{53}	d_{54}		d_{56}	……
L6	d_{61}	d_{62}	d_{63}	d_{64}	d_{65}		……
……	……	……	……	……	……	……	……


Replication
Datanode
Datanode
Datanode
Task Tracker
HDFS
Task Tracker
Datanode
Datanode
Rack 2
Esri Geometry Library
Rack 1
Gazetteer
Namenode
Second Namenode
Job Tracker
Web Downloader
Hadoop Cluster
Geospatial data
Mapping Agency
VGI
flickr
OpenStreetMap
Base Map
GIS client
User accesses Cloudera Manager Server via web browser
HTTP(S)
Cloudera Manager Web User Interface

Comparing the computation time between Hadoop-based spatial join and PC-based approach



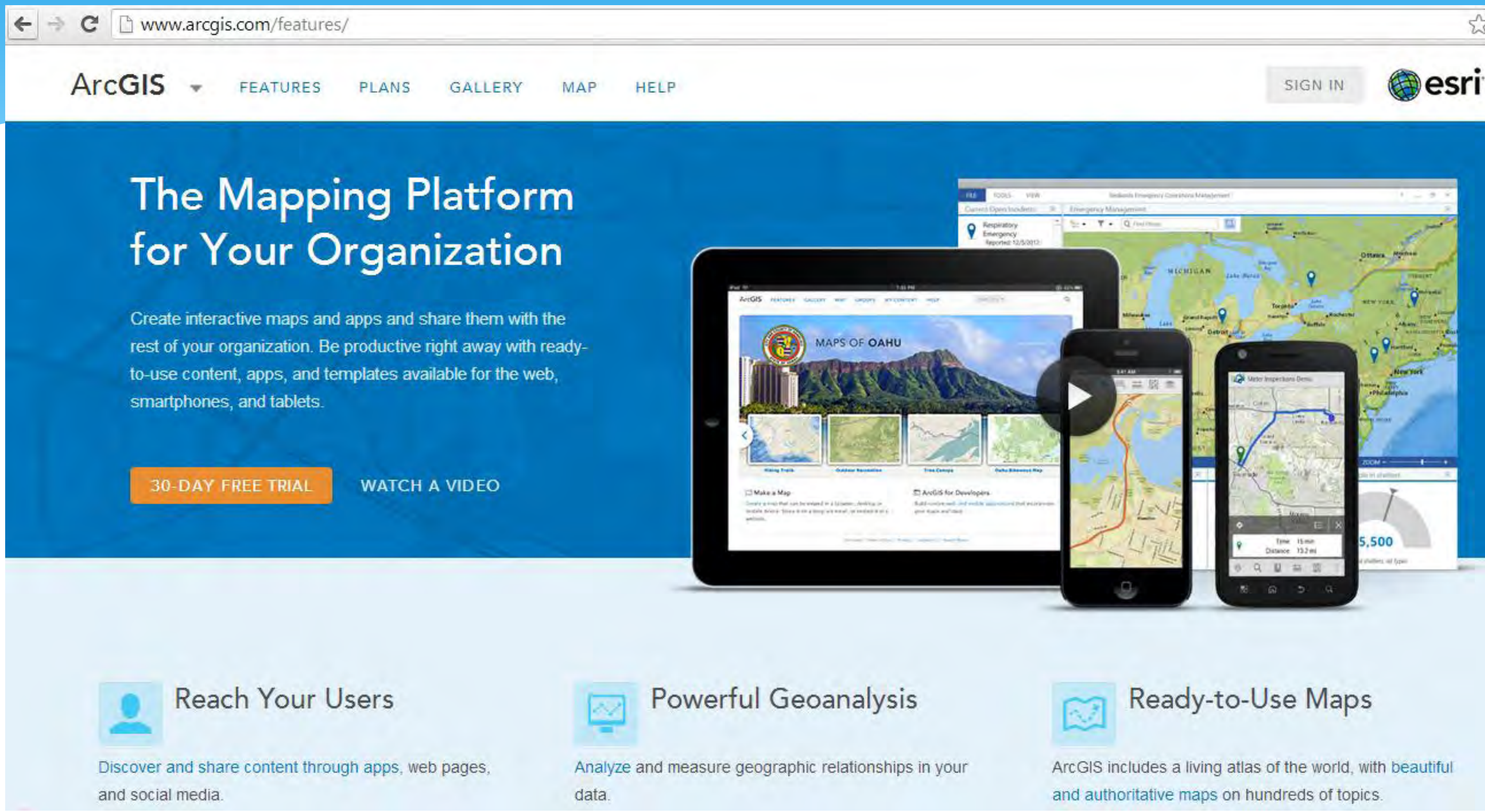
Gao. S., Li, L., & Goodchild, M. A Scalable Geoprocessing Workflow for Big Geo-Data Analysis and Optimized Geospatial Feature Conflation based on Hadoop. In *NSF CyberGIS AHM'13*, Sept. 15-17, 2013, Seattle, WA, USA.

Gao, S., Li, L., Li, W., Janowicz, K., & Zhang, Y. Constructing Gazetteers from Volunteered Geographic Information Based on Hadoop. (submitted to Computers, Environment and Urban Systems. 2014)

Outline

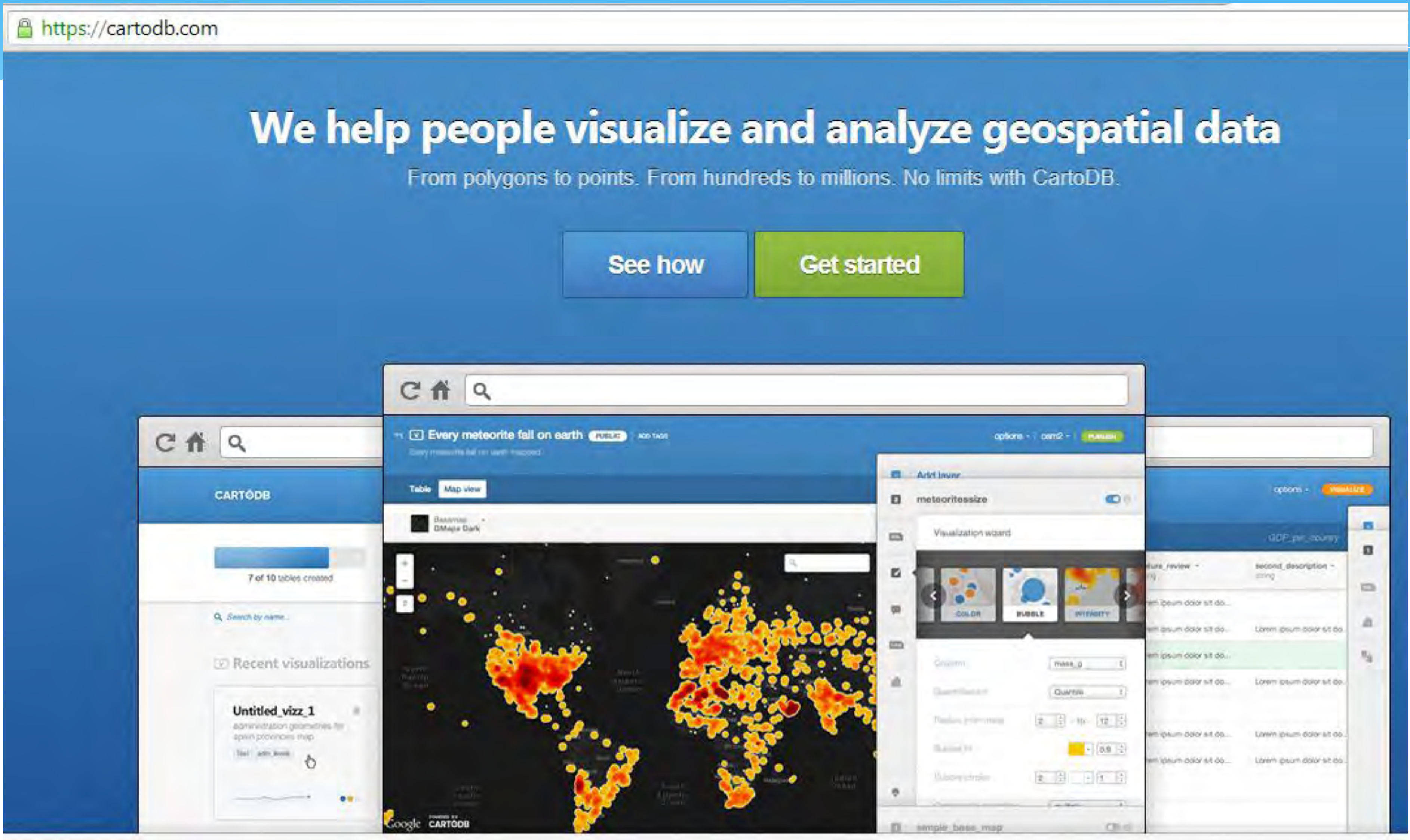
- Why spatial is special
- Urban Computing
- Geospatial Data Conflation
- GIS Trends
- Conclusions

Online (Cloud) GIS



Access GIS techniques without installing any software on your computers.

Online (Cloud) GIS

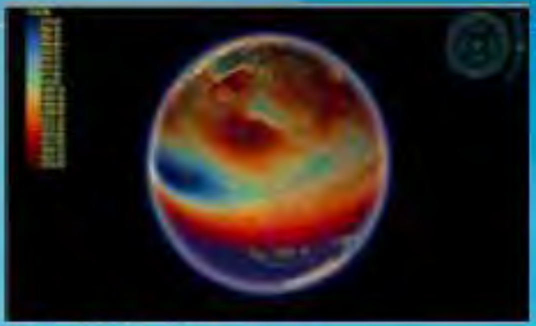


Web 3D Use Cases

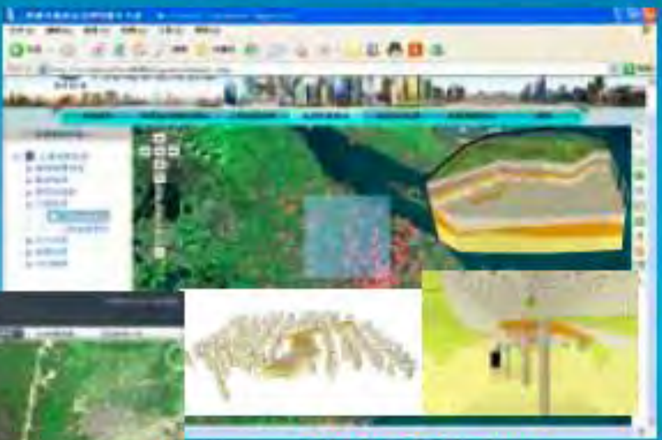
Digital City

Emergency Response

Urban Planning



Earth Science



Digital Mining

Digital Ocean

Digital Tourism

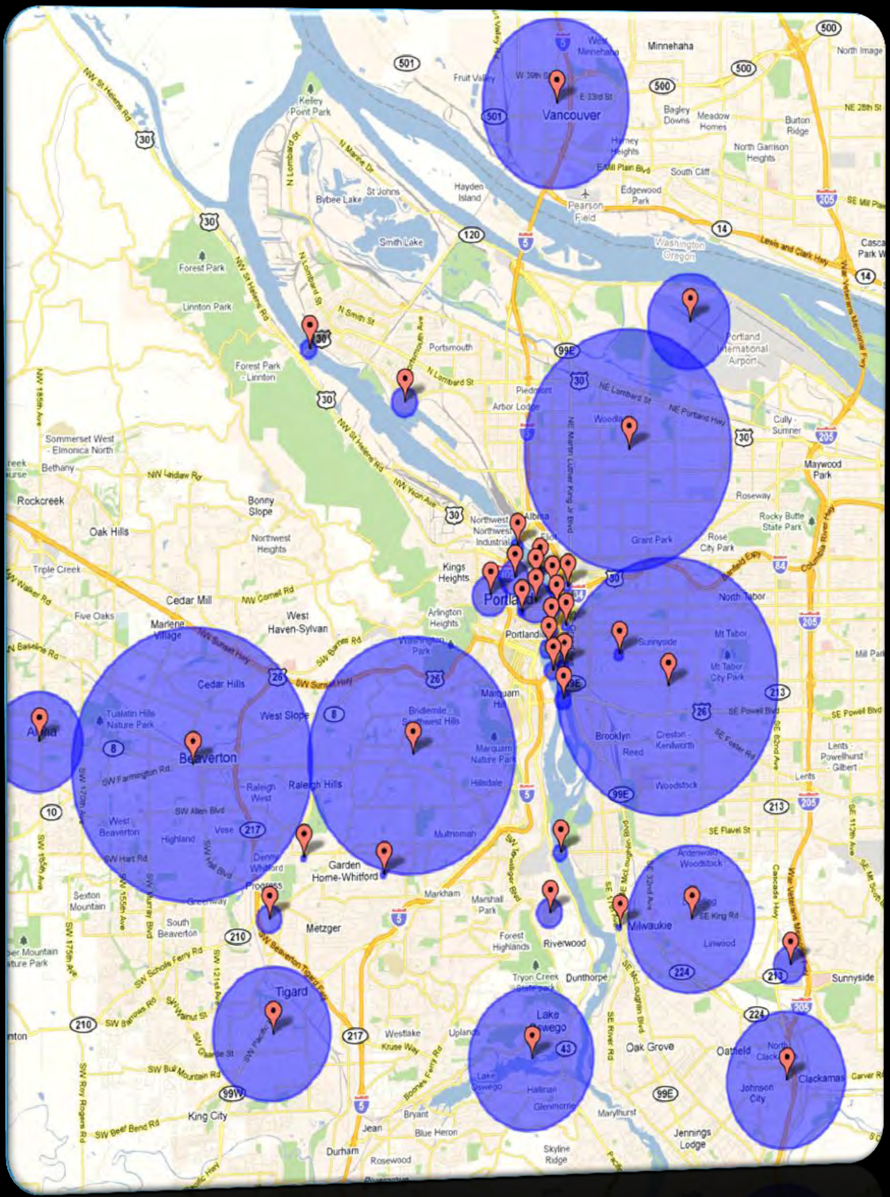
(Moxie Zhang at Esri Beijing Lab)

Web 3D Client Architecture

(Moxie Zhang at Esri Beijing Lab)

Mobile GIS

iPod
10:59 PM
Check In
geoloqi
ON
NE Sandy Blvd
Kerns
NE Glisan St
E Burnside St
E Burnside St
SE Stark St
SE Morrison St
SE Madison St
SE Grand Ave
SE 12th Ave
SE 11th Ave
Hosford - Abernethy
SE Division St
Richmond
SE 39th Ave
SE Powell Blvd
Brooklyn Action Corps
Brooklyn
Creston -
Google
Send Location
Map
Geonotes
Controls
Layers



Location-Based Events

Create actions based on **where** you are.

Esri Mobile API allows developers to build location-aware applications without having to write code from scratch. Developers can easily add automatic check-ins, user sign-ups, location-based messaging, event triggers, and real-time GPS maps to their existing applications.

Individual Geotrigger notifications are automatically pushed to mobile users upon crossing a Geofence

What about GIScience?

The National Center for Geographic Information and Analysis (NCGIA)

2013 Maine Meeting
UCSB, SUNY Buffalo, Maine

New kinds of data

* Big Geo-Data
* Closer to real-time
* Vastly increased volume
* Poor and diminishing quality control
  - from disparate sources
  - no lengthy synthesis by experts
  - no metadata or provenance
* Need to automate quality control and the production of metadata and provenance

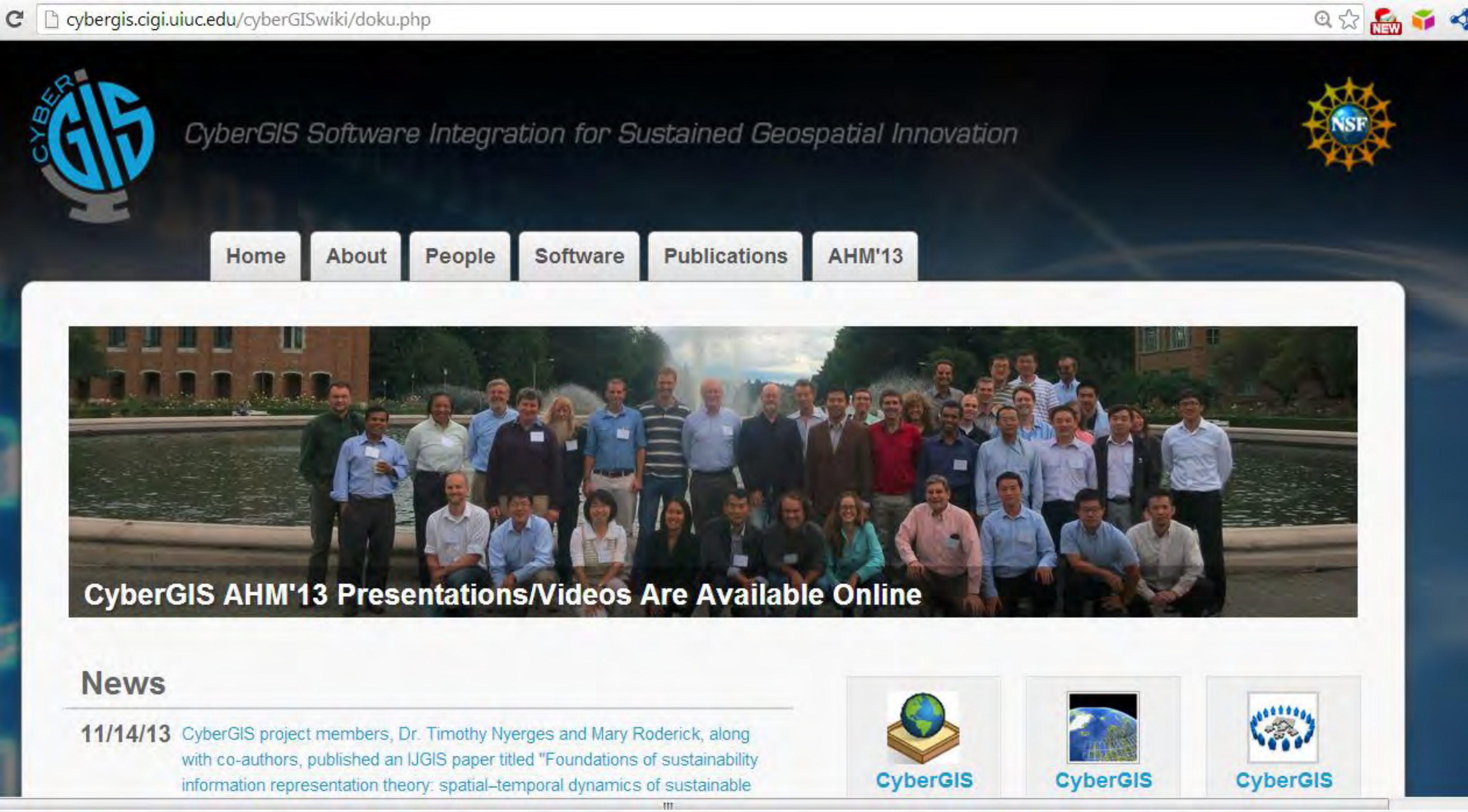
The Characteristics of Big Data

- Volume
  - tera-, peta-, exabyte scale
  - zetta (10^{21})
  - yotta (10^{24})
    - the mass of the Earth is 5,973.6 Yg
- Velocity
  - rapid change, speed of analysis
- Variety
  - many sources
  - varied quality

New kinds of analysis

- Of data with unknown or variable quality
- More suited to hypothesis generation than hypothesis testing
  - The softer end of science
  - Exploration, sampling design
  - Induction
  - Qualitative and Quantitative
- An increased role for machine learning and data mining

NSF Funding Project: CyberGIS



ASU esri NCSA OAK RIDGE SDSC SAN DIEGO SUPERCOMPUTER CENTER UCSD CIGI UCSB W USGS

CyberGIS

Volume 27, Issue 11, 2013 < Prev | Next >

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Special Issue: CyberGIS: blueprint for integrated and scalable geospatial software

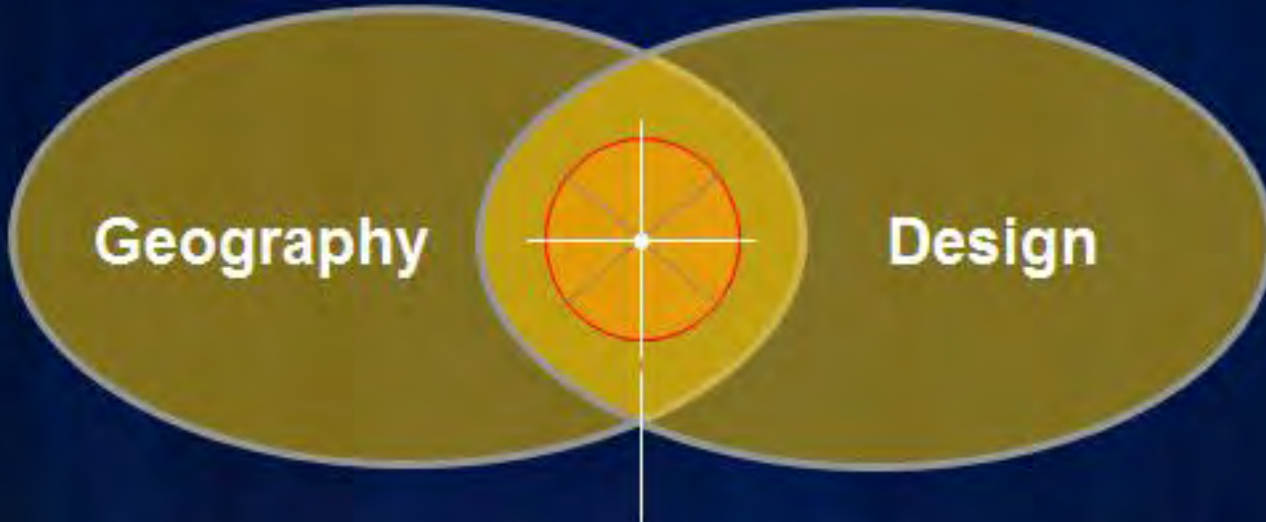
Editorial

CyberGIS: blueprint for integrated and scalable geospatial software ecosystems

Shaowen Wang

pages 2119-2121

GeoDesign

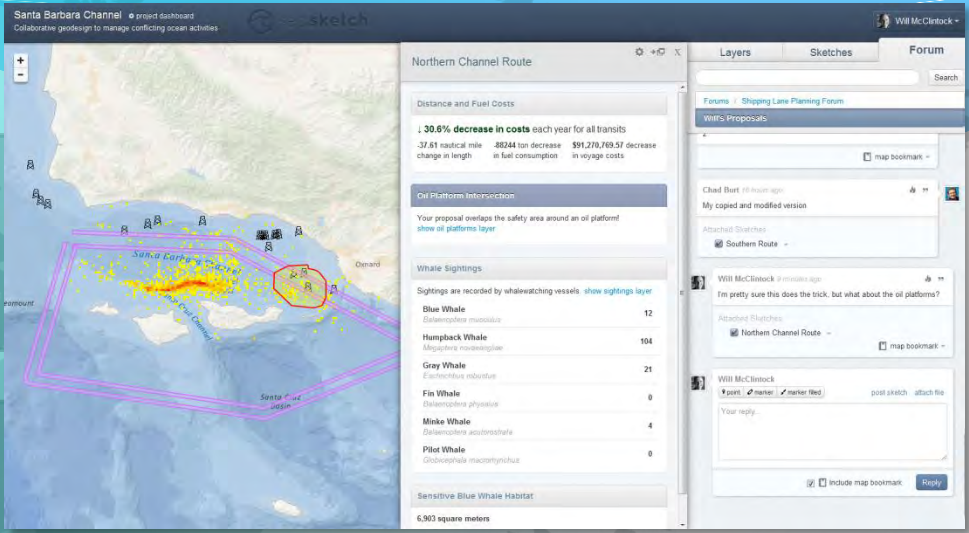


- GeoDesign is where geography meets design
- GeoDesign intervenes in the world
    - to achieve desirable objectives

GeoDesign

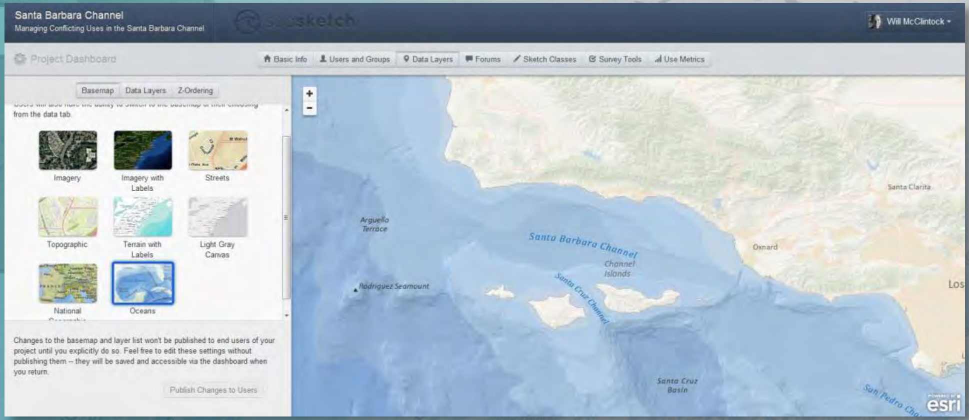
UCSB SeaSketch | GeoDesign for the Oceans

EXPRESS
Ideas and Opinions
In The Form of Sketches

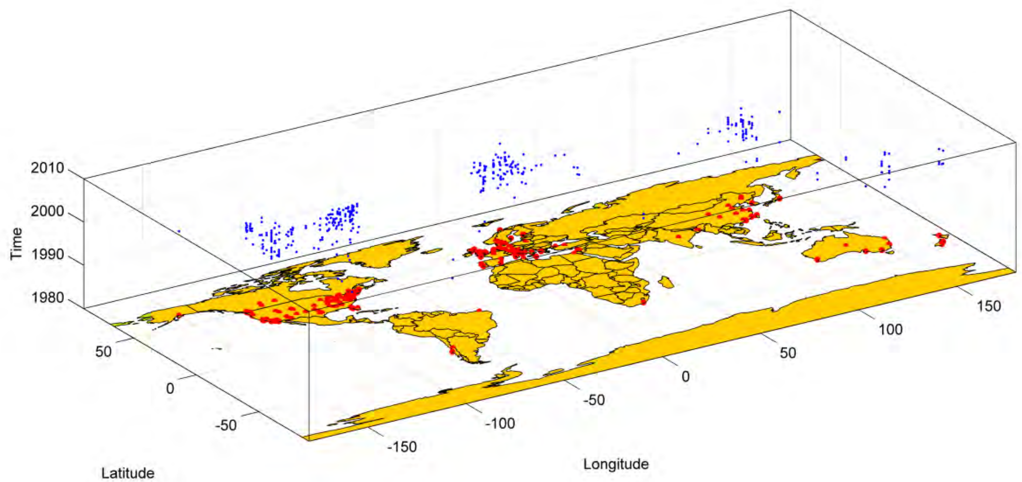


EVALUATE
Plans Based on Science

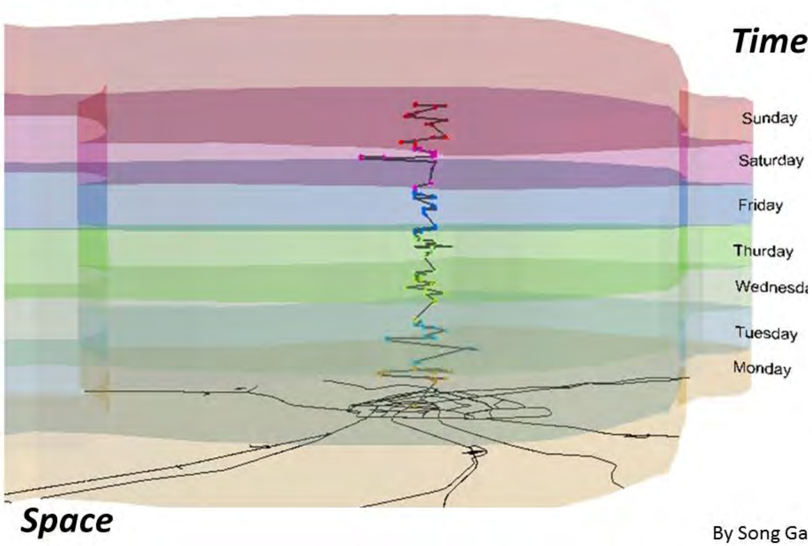
DISCUSS
The Merits of Design

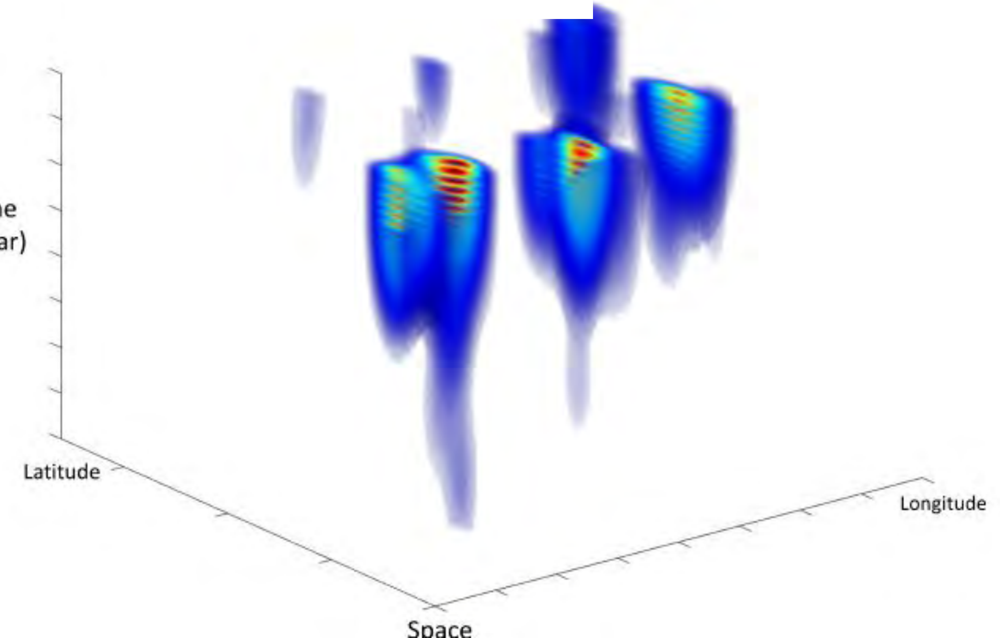


Space-Time GIS



A week-long individual mobility path in a city





Science 22 March 2013:
Vol. 339 no. 6126 pp. 1390-1392
DOI: 10.1126/science.1232257

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PERSPECTIVE

MEDICINE

Spatial Turn in Health Research

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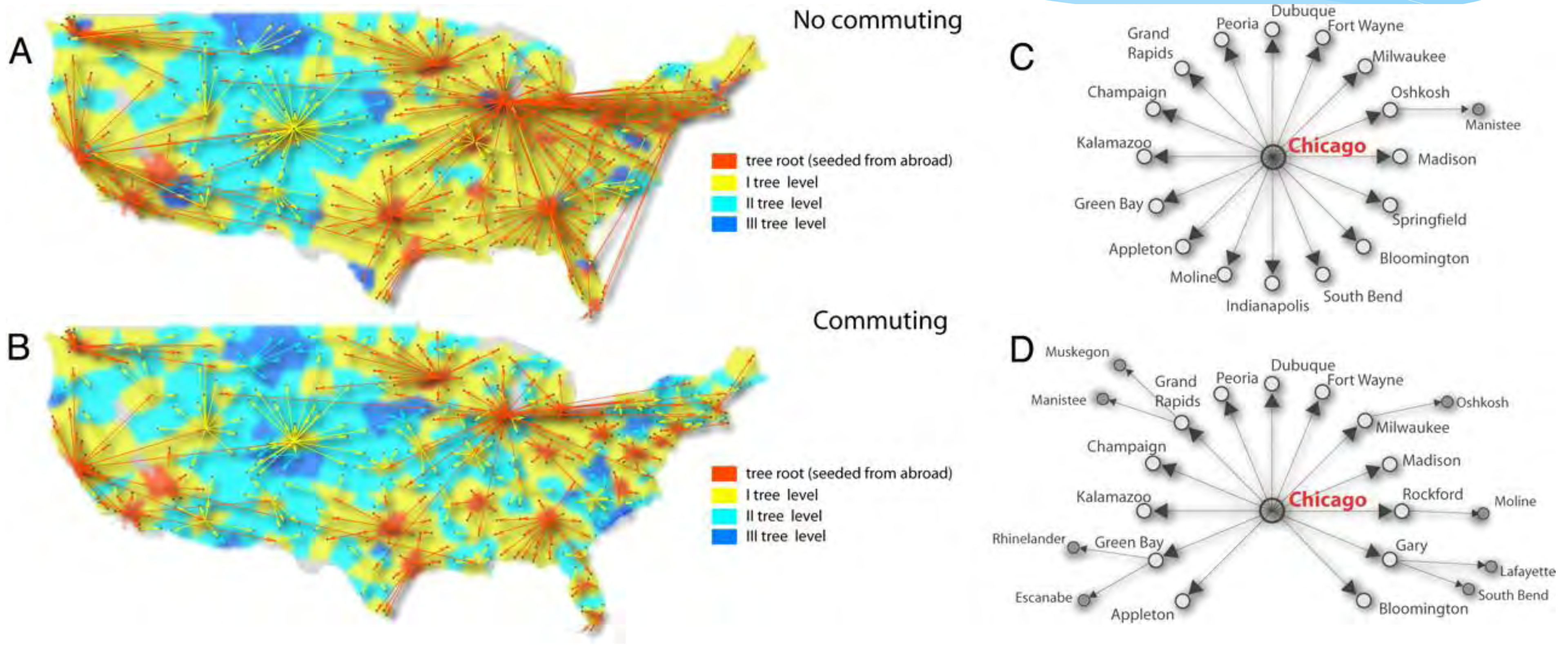
Spatial analysis using maps to associate geographic information with disease can be traced as far back as the 17th century. Today, recent developments and the widespread diffusion of geospatial data acquisition technologies are enabling creation of highly accurate spatial (and temporal) data relevant to health research. This has the potential to increase our understanding of the prevalence, etiology, transmission, and treatment of many diseases.

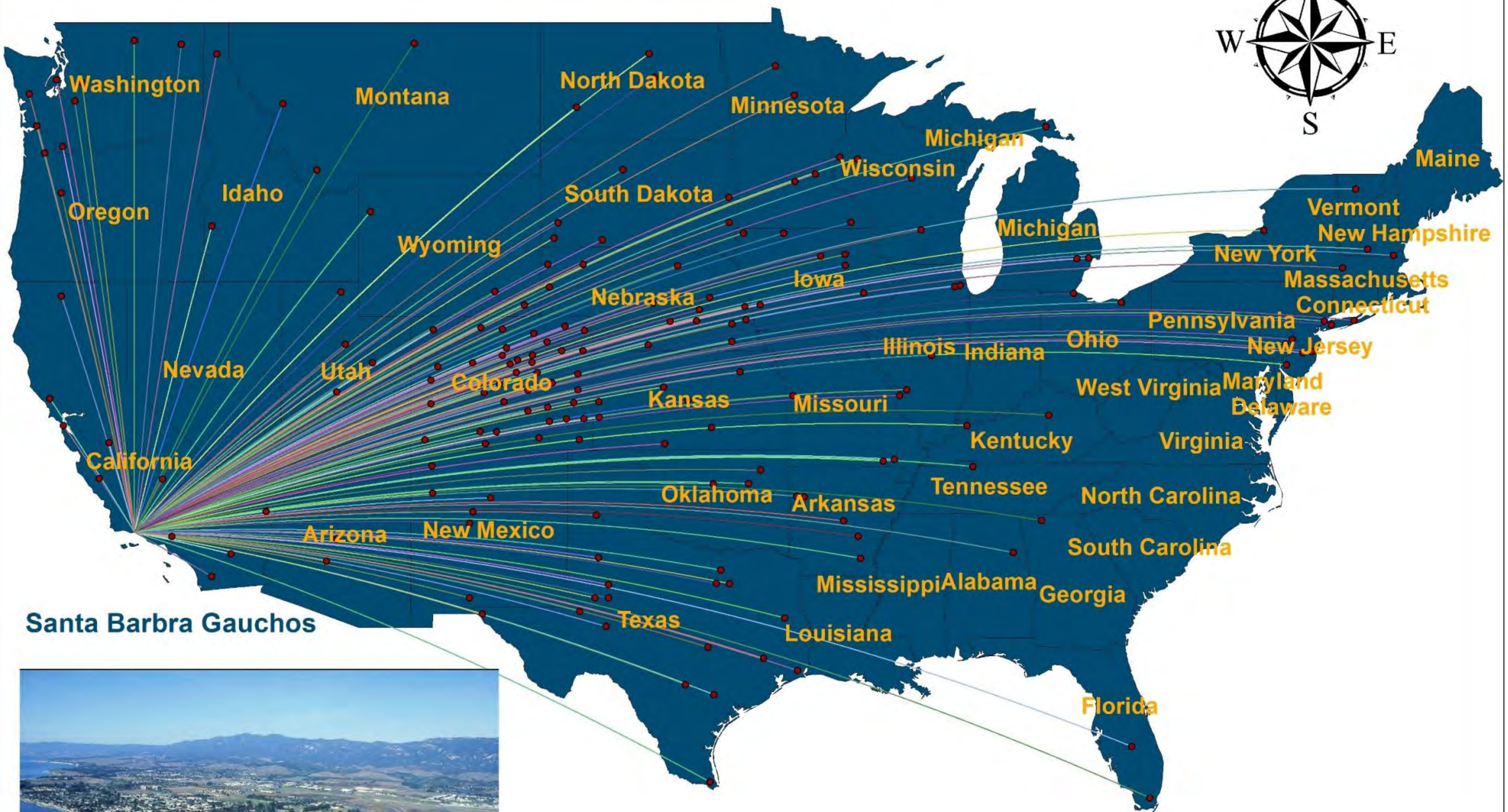
New approaches in geography and related fields, capitalizing on

Human Mobility and Diseases Spreading



Balcan, D., Colizza, V., Gonçalves, B., Hu, H., Ramasco, J. J., & Vespignani, A. (2009). Multiscale mobility networks and the spatial spreading of infectious diseases. *Proceedings of the National Academy of Sciences*, *106*(51), 21484-21489.

Flow to Santa Barbra



Santa Barbra Gauchos

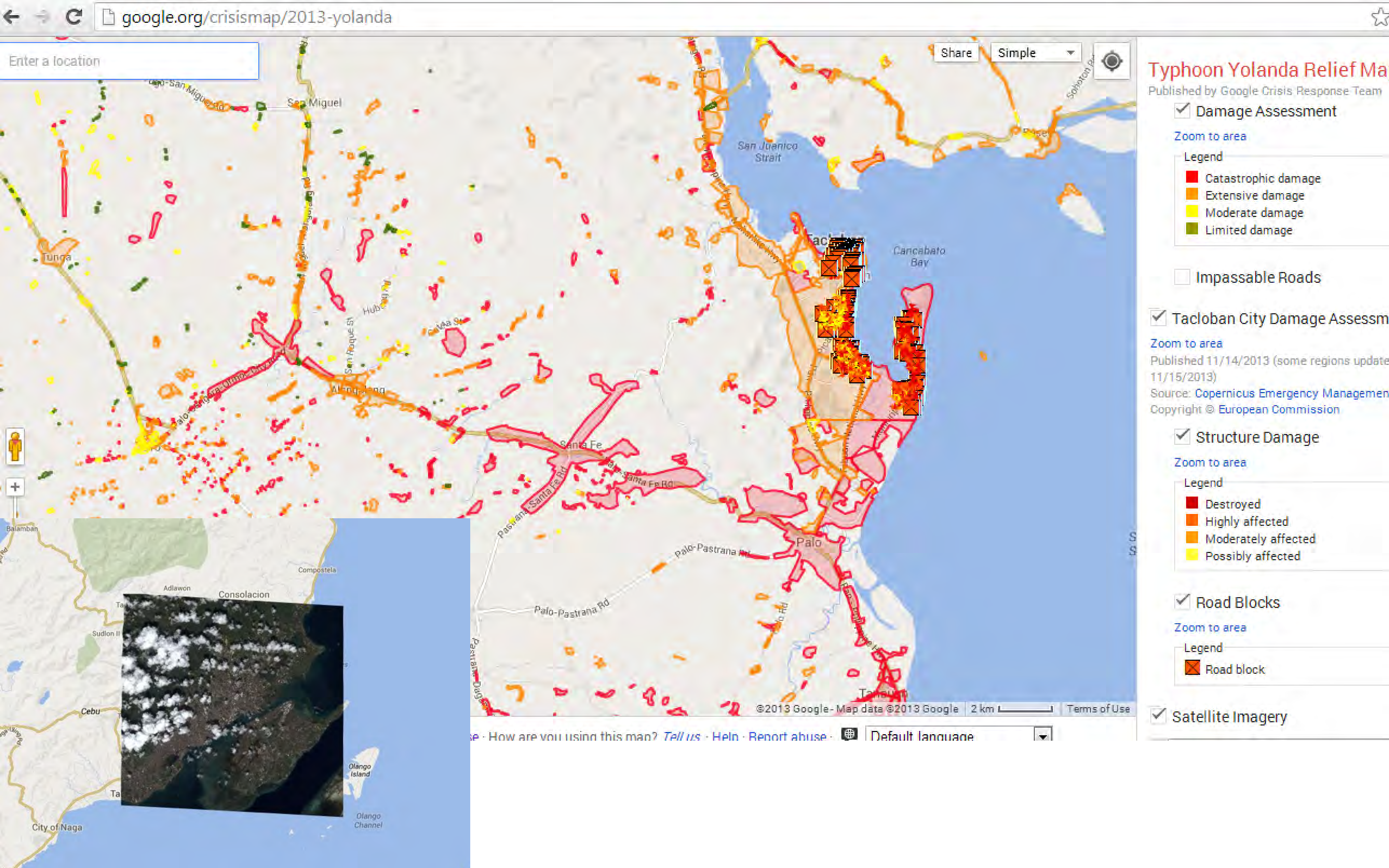
By GIS Song , Geography
Dec 14, 2012

Volunteered Geographic Information (VGI)

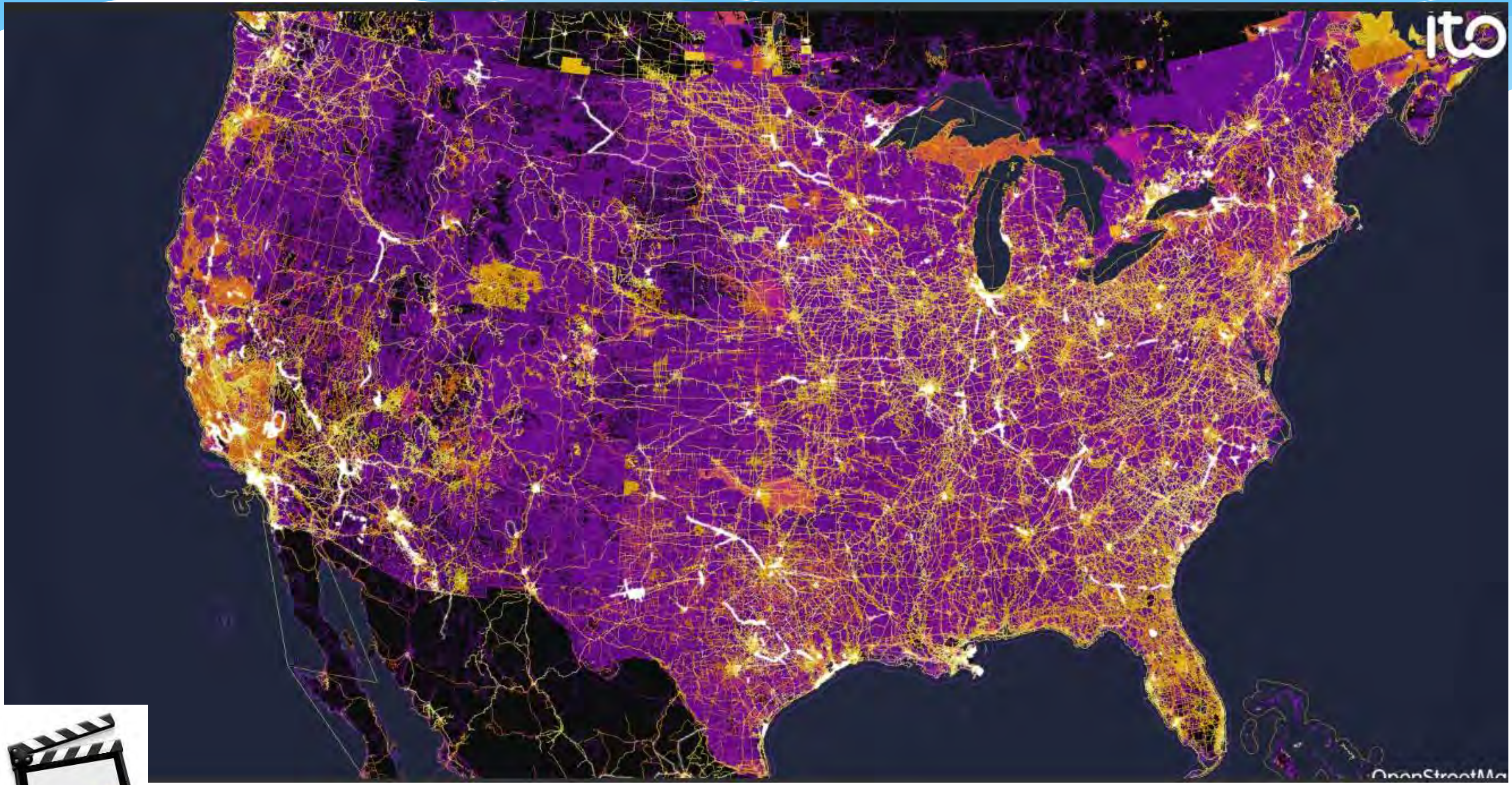
* Citizens as sensors: the world of volunteered geography – by Professor Michael F. Goodchild

www.wikimapia.org

Typhoon Haiyan/Yolanda GIS



OpenStreetMap Edits in US



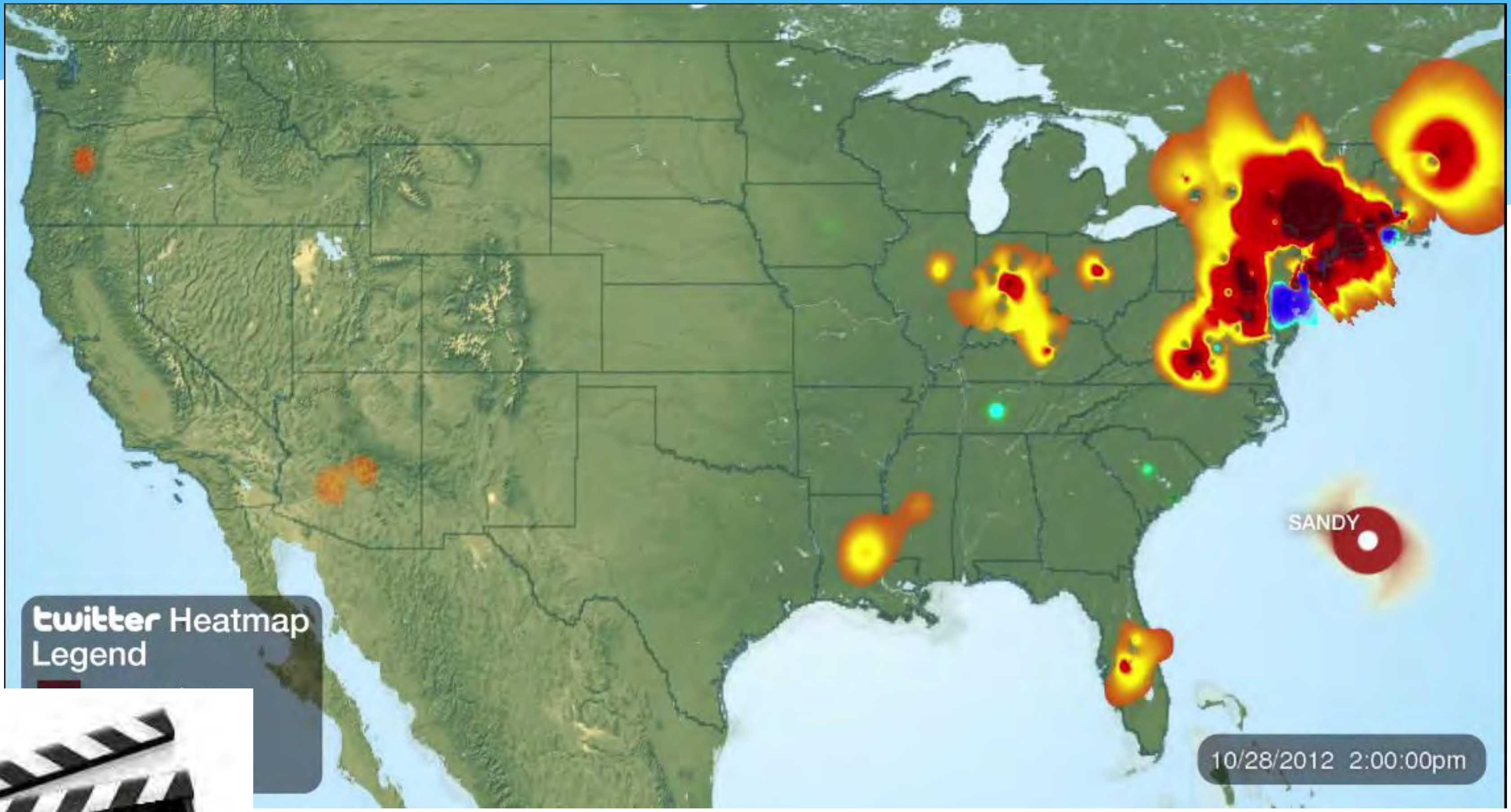
Created by ITO World

Mapping Social Media

by Paul Butler

https://www.facebook.com/notes/facebook-engineering/visualizing-

Hurricane Sandy Tweetbeat



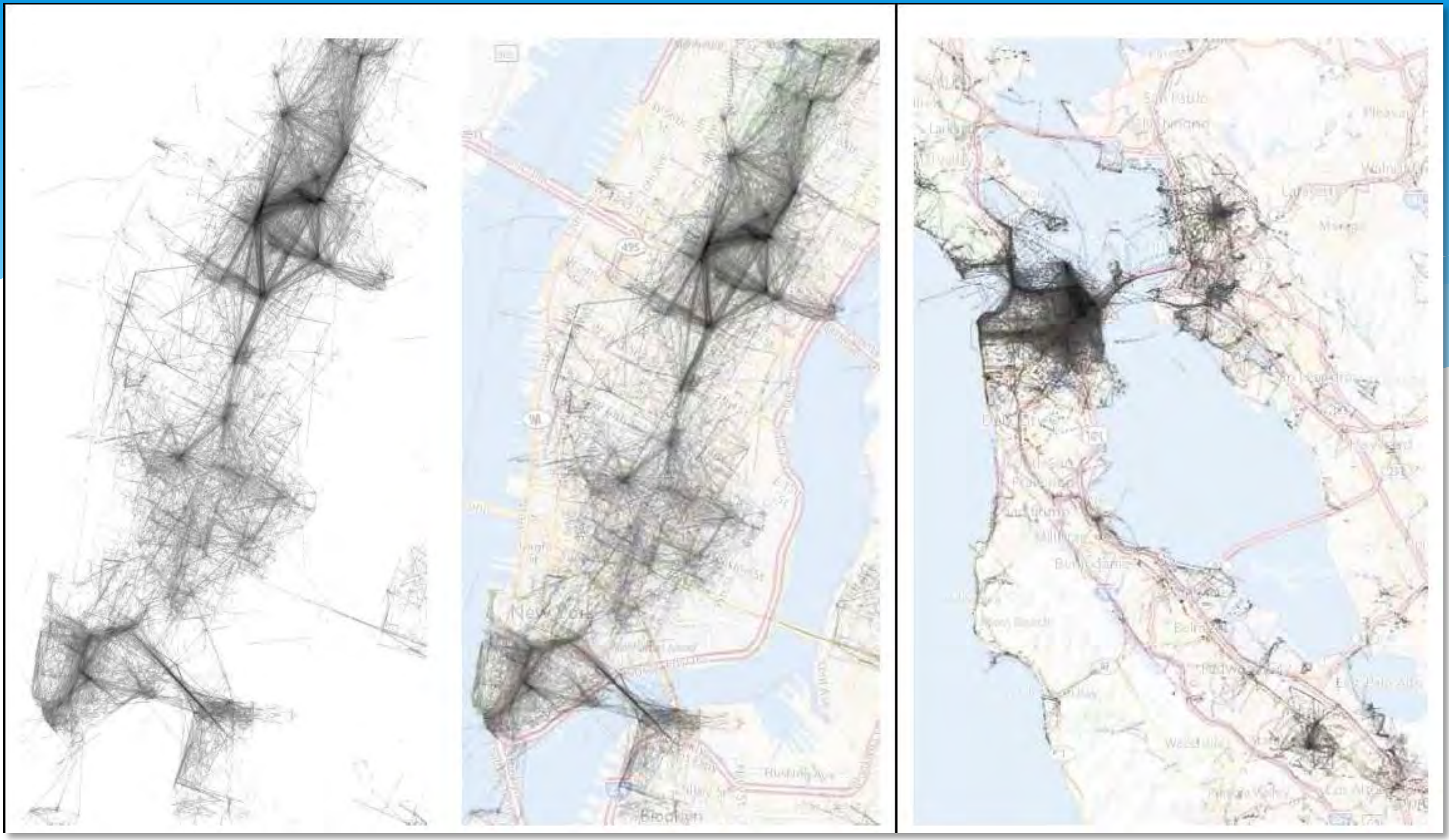
http://www.youtube.com/watch?v=g3AqdIDYG0c

SGI

Crandall *et al.* 2009. Mapping the world's photos.
http://www.cs.cornell.edu/~crandall/papers/mapping09www.pdf

Dots
Yellow: Photos
Blue: Tweets
White: Both

http://www.flickr.com/photos/walkingsf/sets/72157627140310742/



Tracks inferred from Flickr postings
(http://www.cs.cornell.edu/~crandall/papers/mapping09www.pdf)

See also
http://www.flickr.com/photos/walkingsf/sets/72157624209158632/

Outline

- Why spatial is special
- Urban Computing
- Geospatial Data Conflation
- GIS Trends
- Conclusions

Future prospects

- Knowing where everything is (at all times)
  - every mobile phone
  - every vehicle
  - every farm animal
  - every item in a store
  - every construction beam
  - every asset for emergency response
  - every victim of a disaster
- Representation of 3D structures
  - and positioning inside them
  - extending navigation to indoors

The role of the citizen

- Placenames, streets, social characteristics
- Early notification of change
- Early reports of damage from a disaster
- Both producer and consumer of geographic information
- The local expert

Spatial is special, To know the unknown!

Thanks for your attention!