Lehrerfortbildung – Z_GIS, iDEAS:lab

Virtuelle und reale Räume

Verständnis unserer Welt mit Hilfe digitaler Geo-Technologien

Bernd Resch

20 April 2017

UNIVERSITÄT SALZBURG

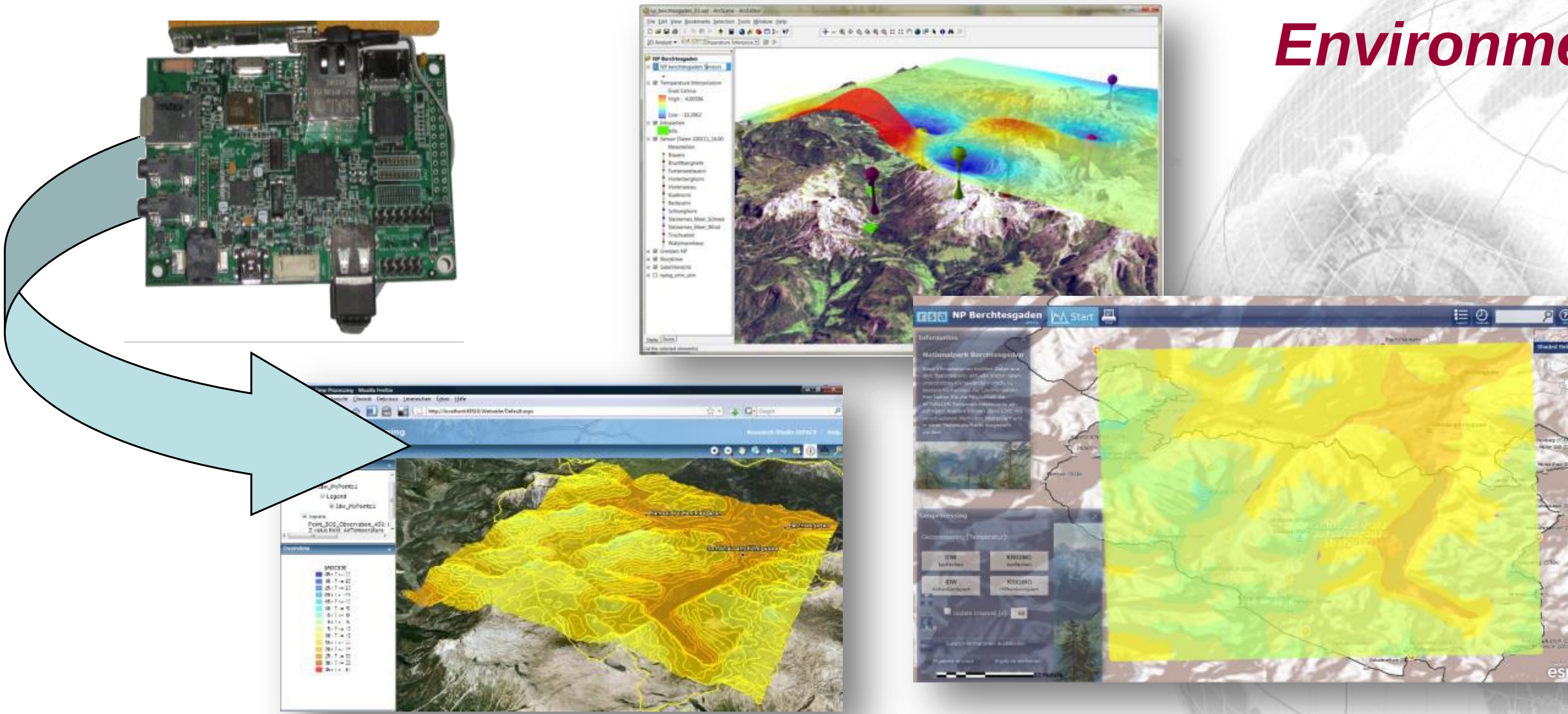
Z_GIS

Motivation ::: Geo-Sensors

Technical Geo-Sensors

Geo-Sensor Networks ::: Real-time GI

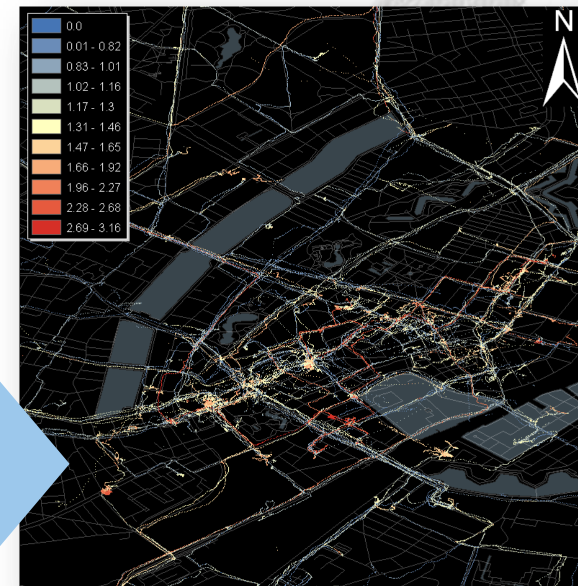
Environment



Geo-Sensor Networks ::: Real-time GI

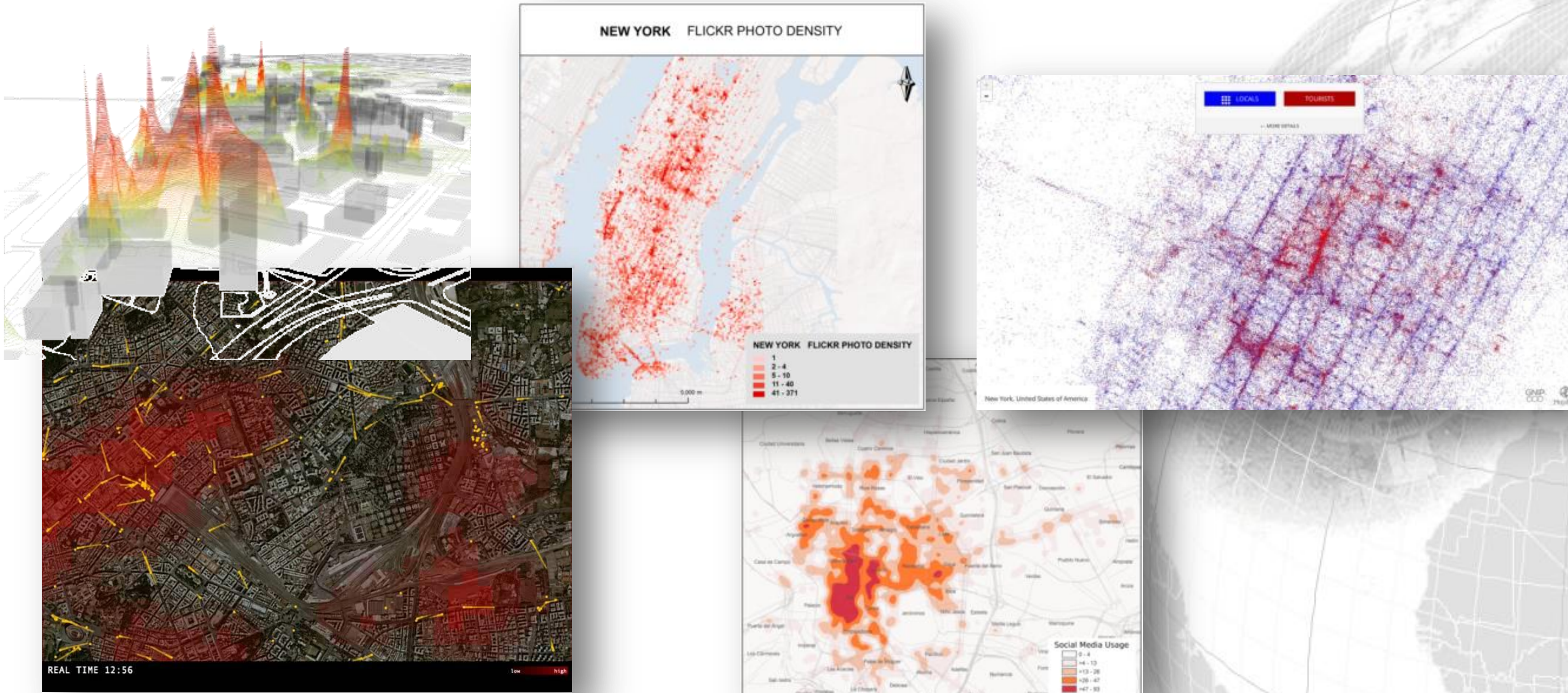
Air Quality

- Mobile sensor network
- City-wide air quality



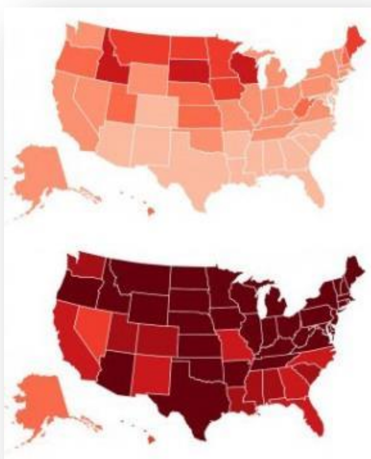
Human Sensors

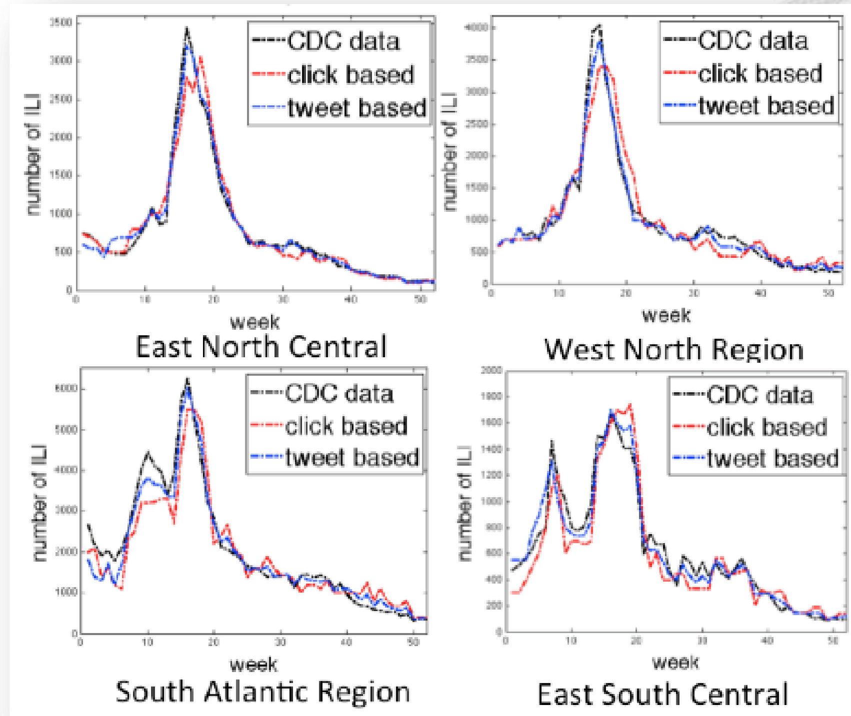
Motivation ::: Collective Sensing



Motivation ::: Collective Sensing

- …usage of Twitter data





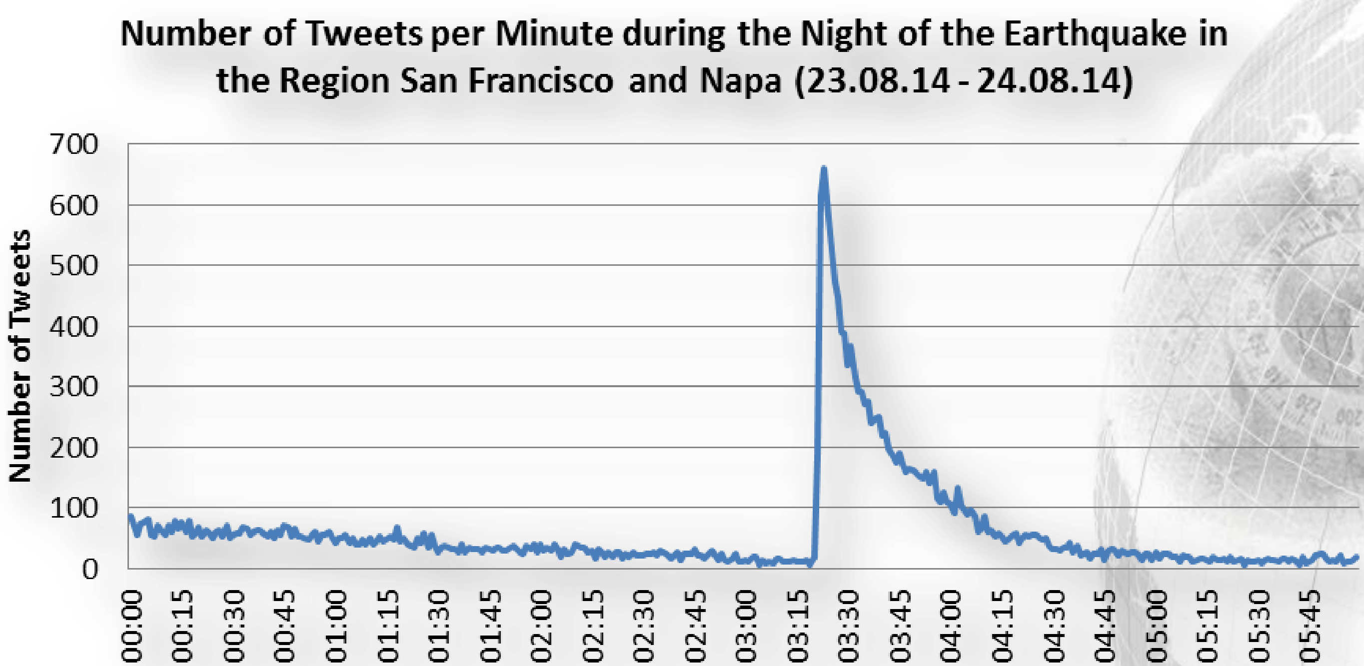
Source: http://www.mit.edu

Social Media in Crisis Management

Estimating Disaster and Damage Footprints

- Current approaches: temporal lag, limited resolution, lacking information for change detection
- Crowdsourced data: instant availability, in-situ information
- …but: uncertainty, unstructured and non-standardised information, diverse data types

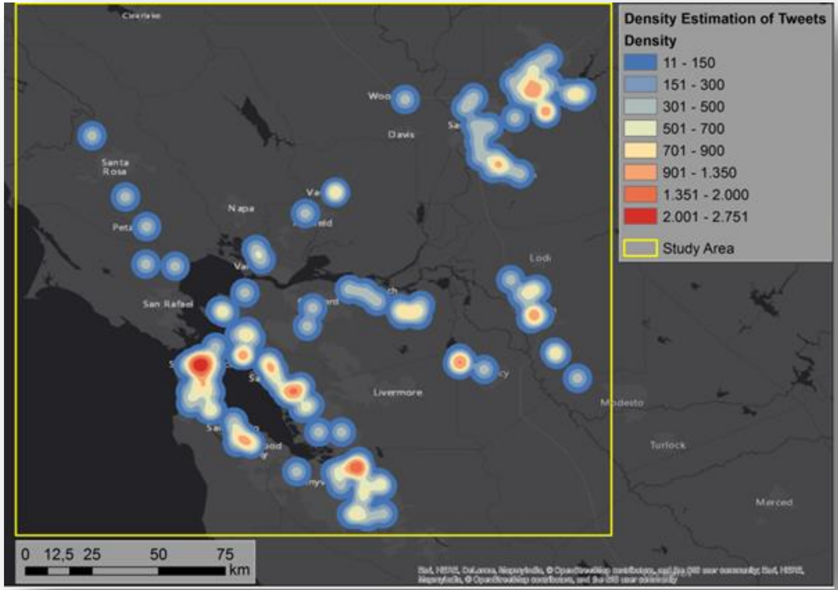
Estimating Disaster and Damage Footprints



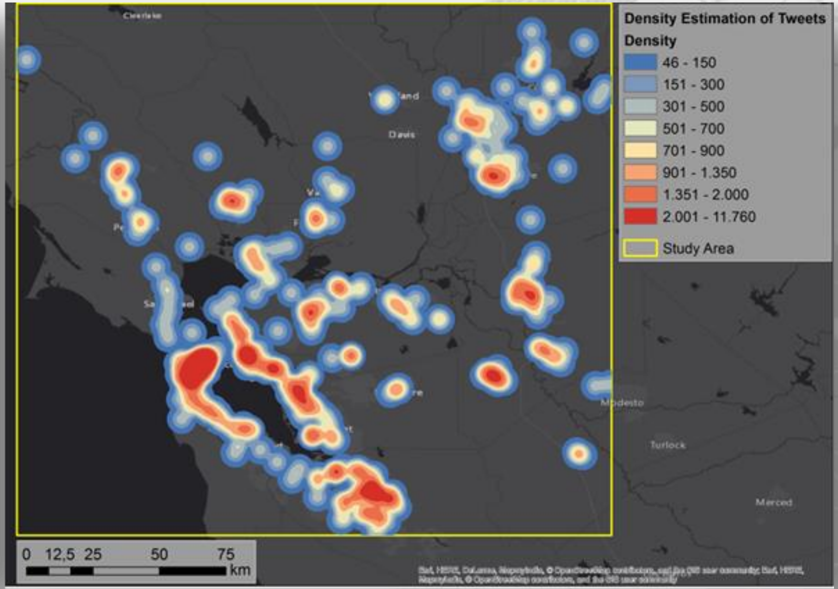
Source: Resch, B. and Usländer, F. (under review) Automated Damage Estimation after Natural Disasters through Semantic and Geospatial Analysis of Social Media Posts. Cartography and Geographic Information Science (CaGIS).

Estimating Disaster and Damage Footprints

- 17 August 2014



- 24 August 2014



Source: Resch, B. and Usländer, F. (under review) Automated Damage Estimation after Natural Disasters through Semantic and Geospatial Analysis of Social Media Posts. Cartography and Geographic Information Science (CaGIS).

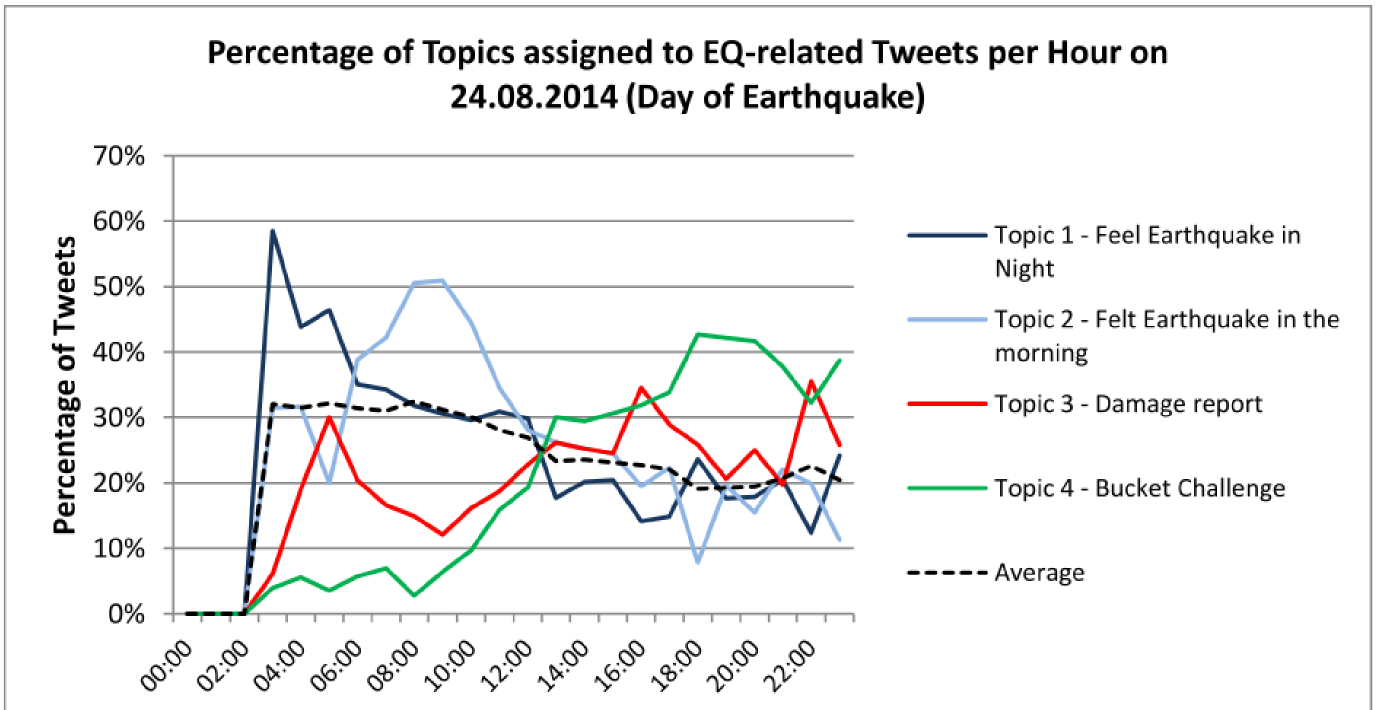
Estimating Disaster and Damage Footprints

- Cascading LDA
  - LDA earthquake topic: 43,3%

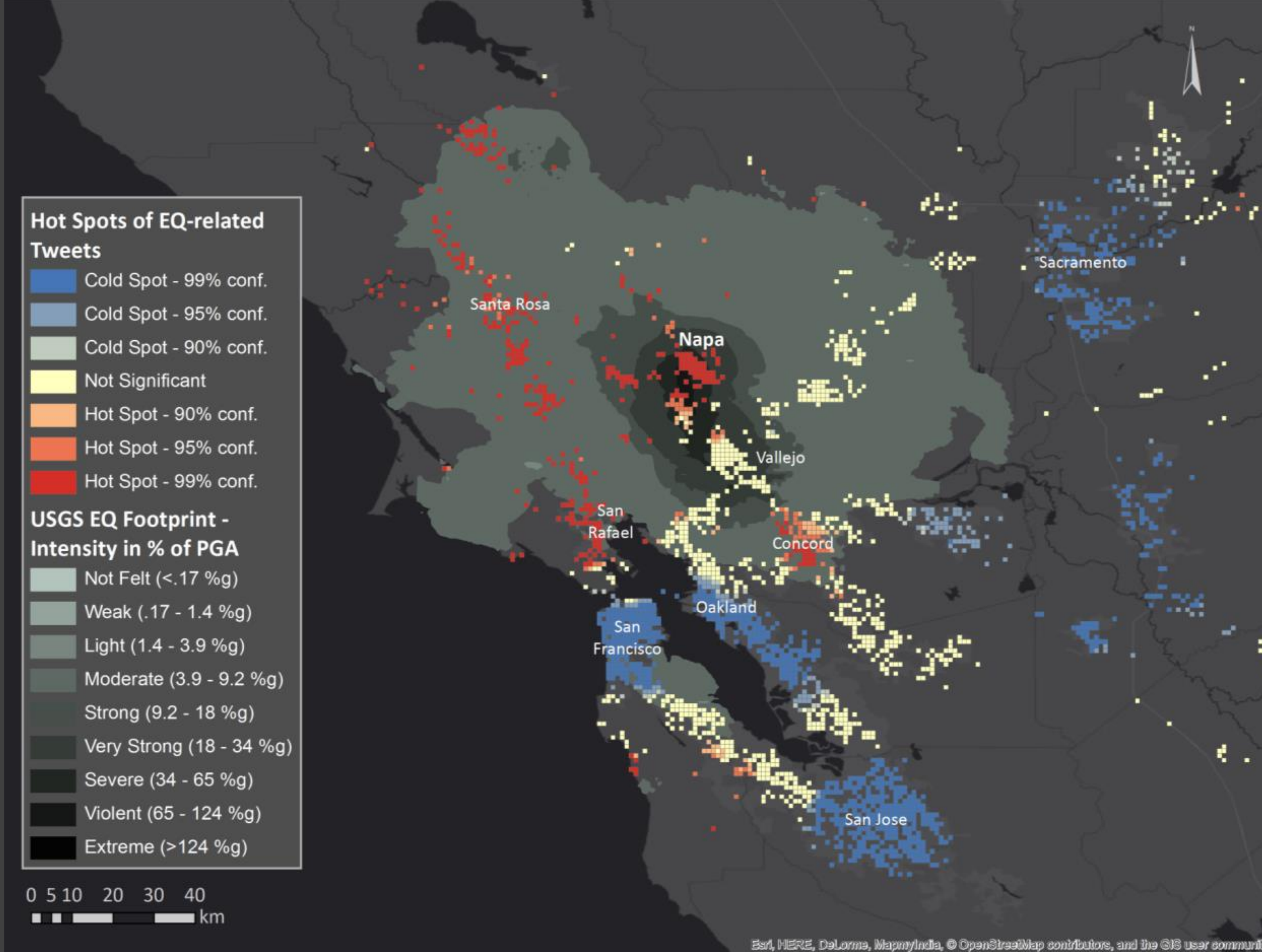
Topic Number	Interpretation of Topic	Word Distribution
1	Feel Earthquake in the night	*0.326*earthquak; 0.045*california; 0.032*wake; 0.024*feel; 0.019*report; 0.018*usg; 0.015*shit; 0.015*holi; 0.013*area; 0.012*sanfrancisco*
2	Report about Earthquake last night in the morning	*0.238*earthquak; 0.071*feel; 0.060*sleep; 0.026*wake; 0.020*last; 0.019*night; 0.012*morn; 0.012*right; 0.009*damn; 0.009*good*
3	Damage Report	*0.110*earthquak; 0.068*napa; 0.057*damag; 0.050*california; 0.020*northern; 0.016*colleg; 0.012*love; 0.010*magnitud; 0.009*north; 0.009*report*
4	Bucket Challenge	*0.071*earthquak; 0.046*challeng; 0.037*bucket; 0.030*napa; 0.028*near; 0.025*hit; 0.020*nomin; 0.020*white; 0.017*worri; 0.012*stand*

Source: Resch, B. and Usländer, F. (under review) Automated Damage Estimation after Natural Disasters through Semantic and Geospatial Analysis of Social Media Posts. Cartography and Geographic Information Science (CaGIS).

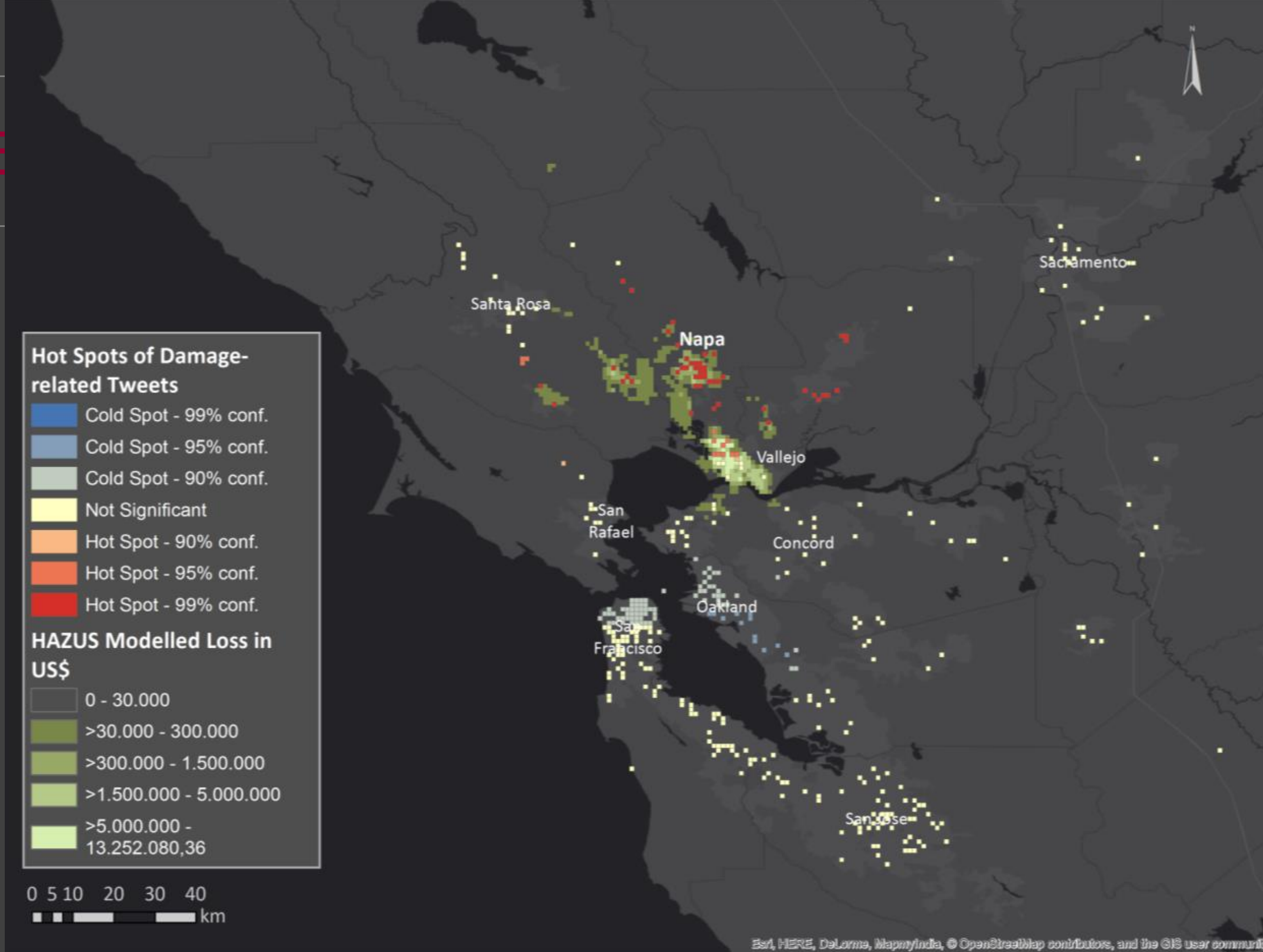
Estimating Disaster and Damage Footprints



Source: Resch, B. and Usländer, F. (under review) Automated Damage Estimation after Natural Disasters through Semantic and Geospatial Analysis of Social Media Posts. Cartography and Geographic Information Science (CaGIS).



Source: Resch, B. and Usländer, F. (under review) Automated Damage Estimation after Natural Disasters through Semantic and Geospatial Analysis of Social Media Posts. Cartography and Geographic Information Science (CaGIS).



Source: Resch, B. and Usländer, F. (under review) Automated Damage Estimation after Natural Disasters through Semantic and Geospatial Analysis of Social Media Posts. Cartography and Geographic Information Science (CaGIS).

Catchments from Mobile Networks

Catchment Areas from Mobile Networks

- Catchment areas of medical facilities
  - Essential for estimating the quality of a health-care system
  - Maximise the efficiency of health service provision
- Current approaches: far-reaching assumptions about a hospital’s patients by applying census data, travel times or gravity models

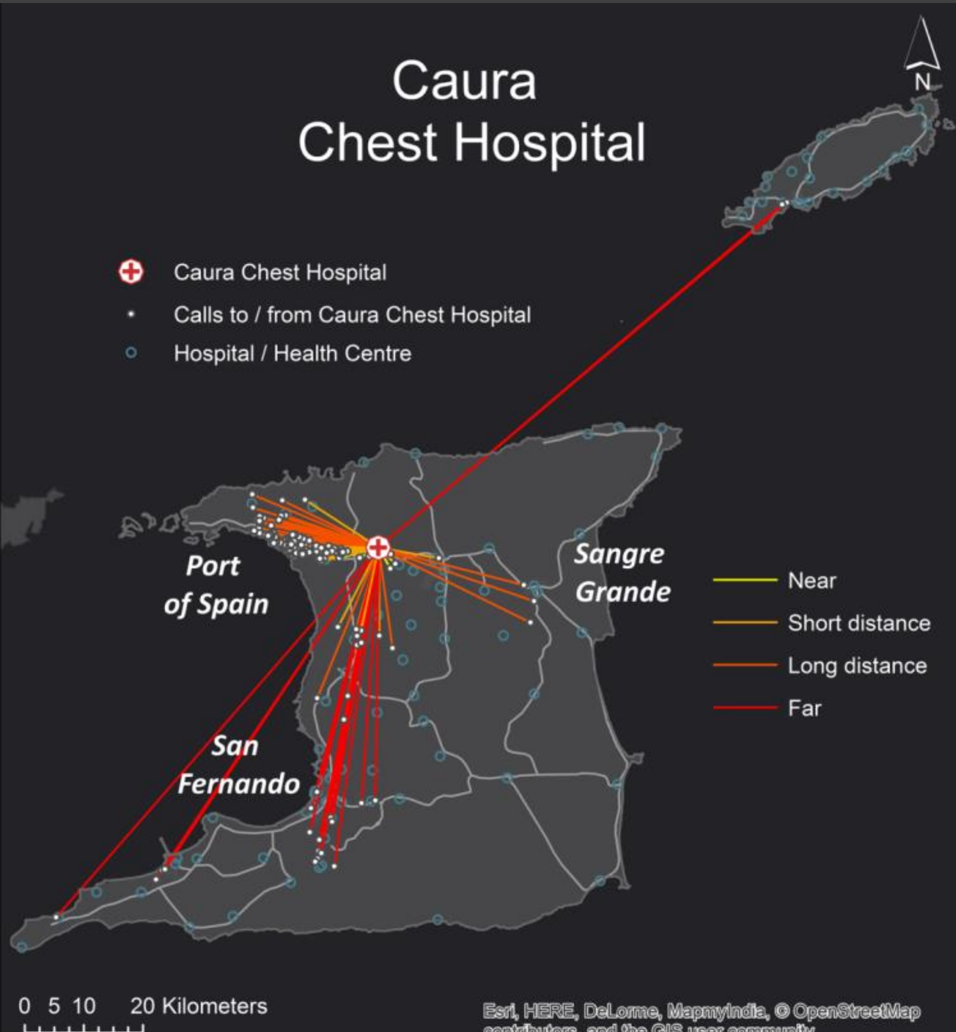
➔ Anonymised mobile and landline phone data
→ Identify areas, in which people use a hospital

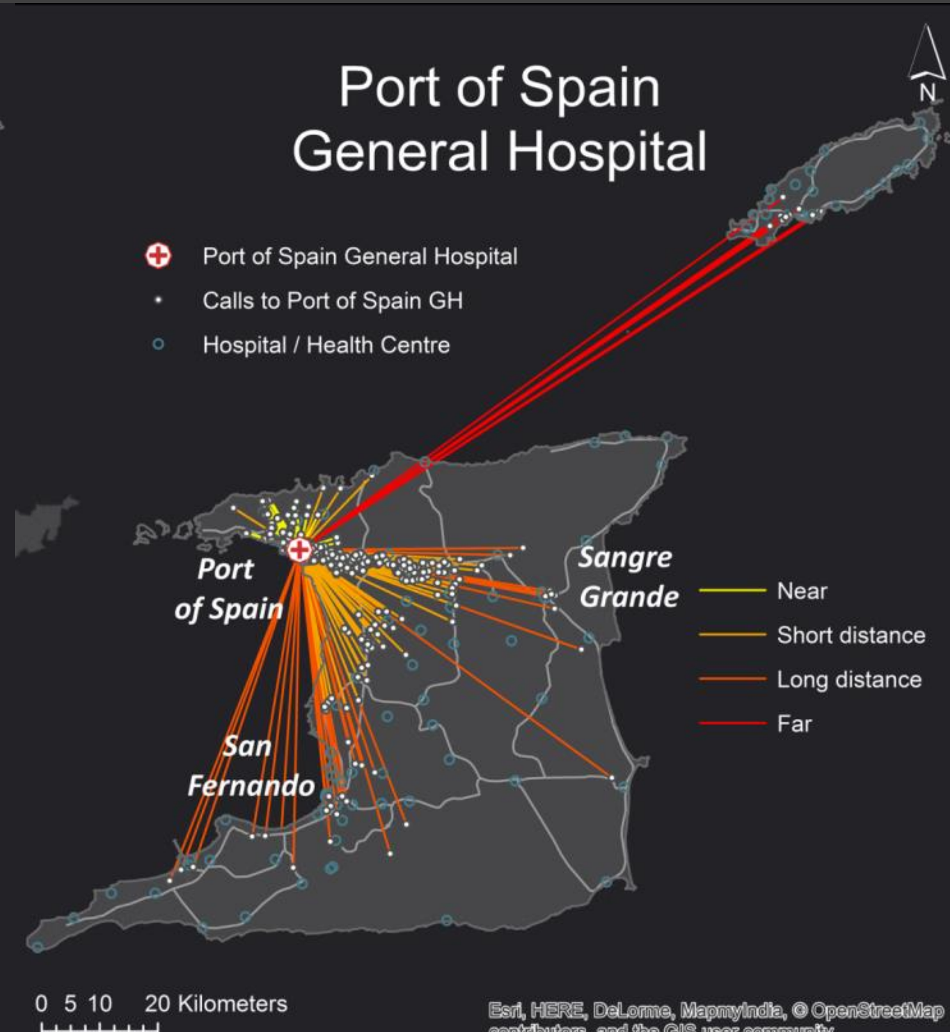
Resch, B., Arif, A., Krings, G., Vankeerberghen, G. and Buekenhout, M. (2016) Deriving Hospital Catchment Areas from Mobile Phone Data. GIScience 2016, Montreal, Canada.

Catchment Areas from Mobile Networks

- Data sources
  - 117 hospitals digitised
  - Call data records
    4,000 antennas 2.5 billion calls, 6 months
  - OpenCellID cells

Resch, B., Arif, A., Krings, G., Vankeerberghen, G. and Buekenhout, M. (2016) Deriving Hospital Catchment Areas from Mobile Phone Data. GIScience 2016, Montreal, Canada.

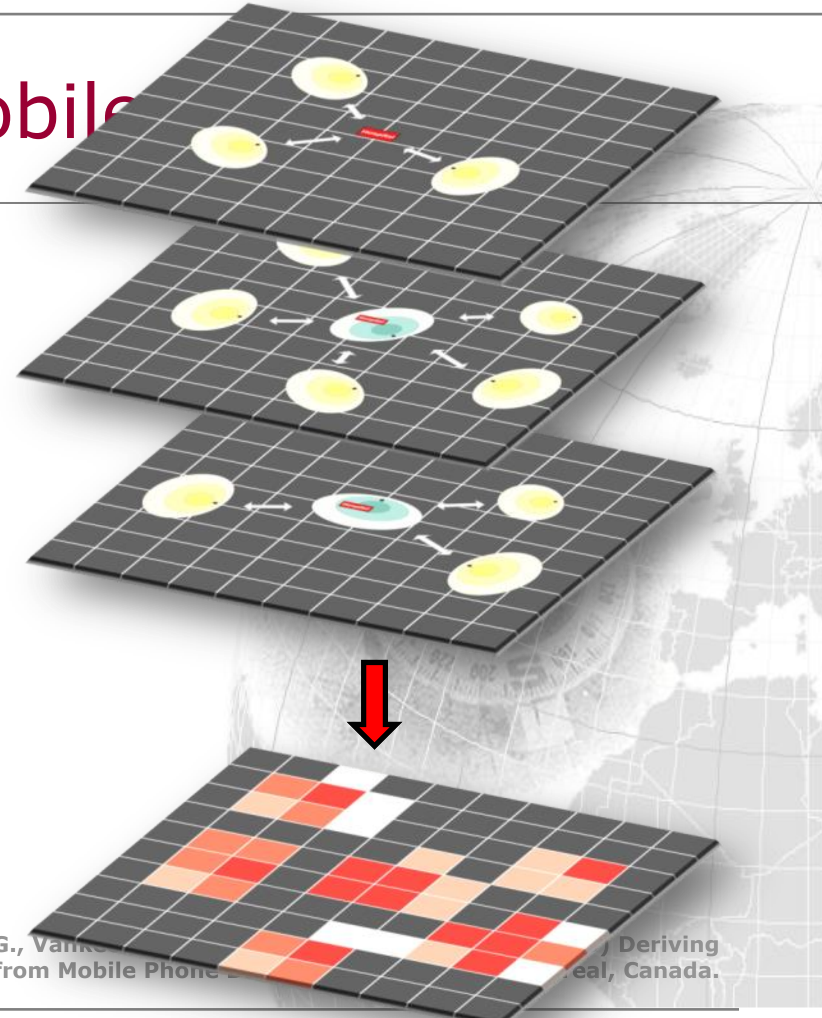




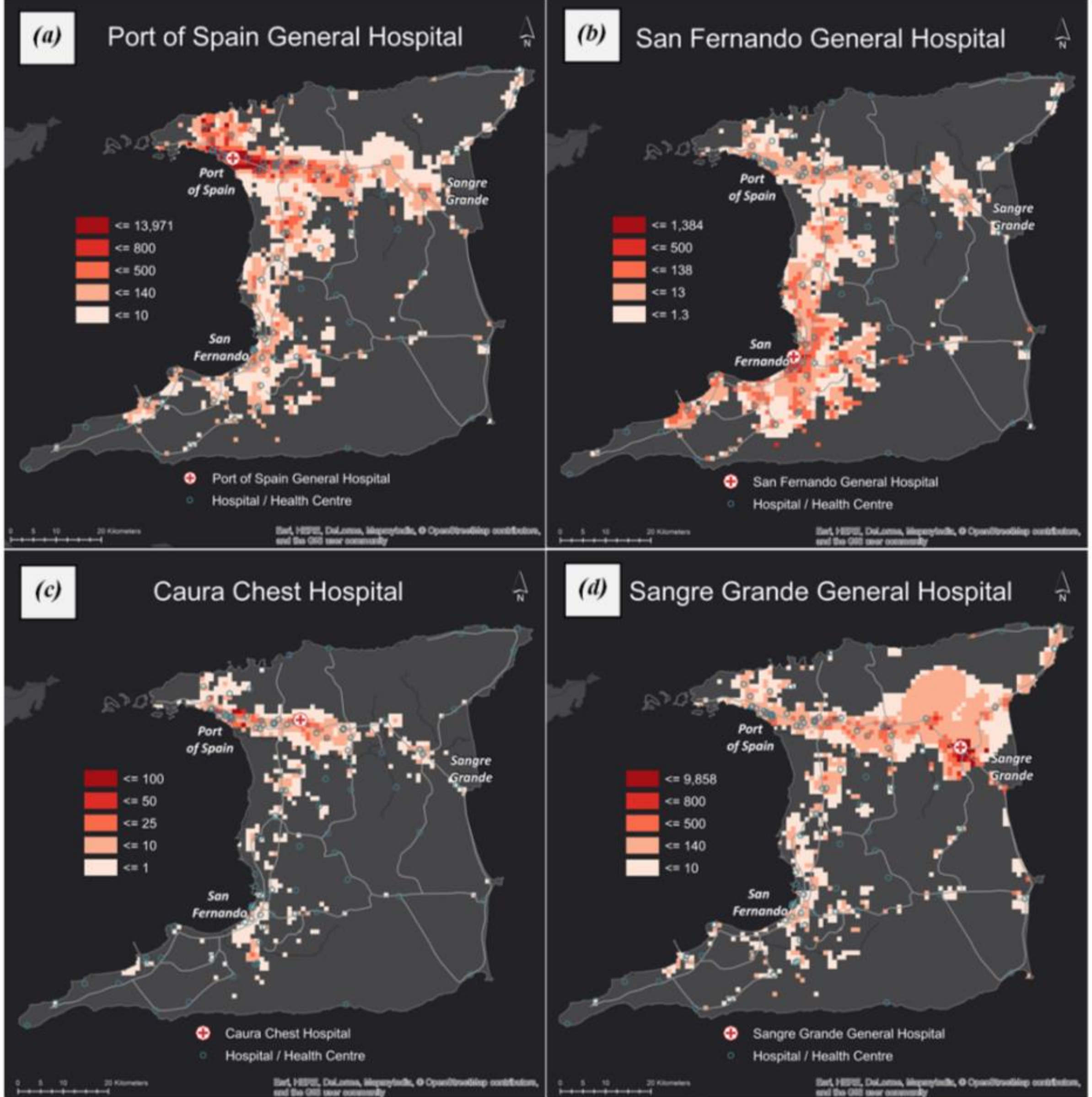
Resch, B., Arif, A., Krings, G., Vankeerberghen, G. and Buekenhout, M. (2016) Deriving Hospital Catchment Areas from Mobile Phone Data. GIScience 2016, Montreal, Canada.

Catchment Areas from Mobile

- Determining service areas for mobile cells
- Identifying calls to hospital landline numbers
- Identifying calls to and from cell phones located within a hospital
- Computing the catchment areas for each hospital



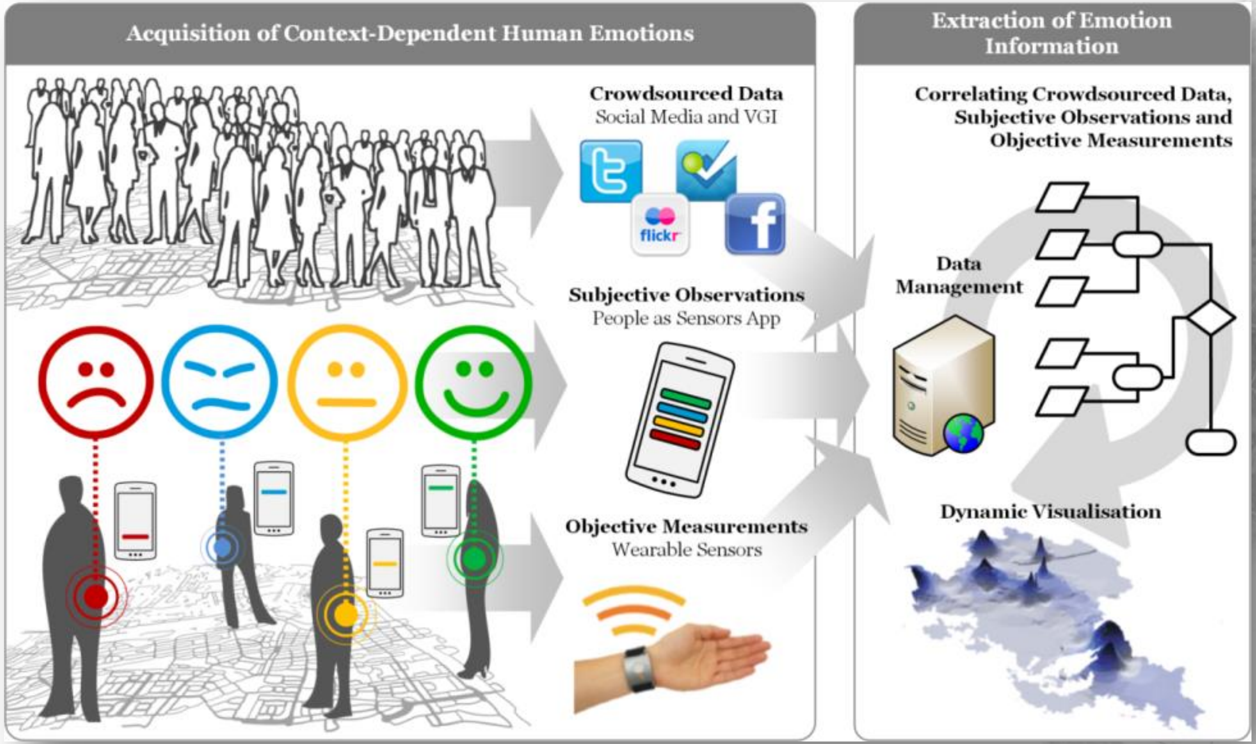
Resch, B., Arif, A., Krings, G., Vanke …) Deriving
Hospital Catchment Areas from Mobile Phone … eal, Canada.



(a)
Port of Spain General Hospital
Port of Spain
Sangre Grande
San Fernando
<= 13,971
<= 800
<= 500
<= 140
<= 10
Port of Spain General Hospital
Hospital / Health Centre
(b)
San Fernando General Hospital
Port of Spain
Sangre Grande
San Fernando
<= 1,384
<= 500
<= 138
<= 13
<= 1.3
San Fernando General Hospital
Hospital / Health Centre
(c)
Caura Chest Hospital
Port of Spain
Sangre Grande
San Fernando
<= 100
<= 50
<= 25
<= 10
<= 1
Caura Chest Hospital
Hospital / Health Centre
(d)
Sangre Grande General Hospital
Port of Spain
Sangre Grande
San Fernando
<= 9,858
<= 800
<= 500
<= 140
<= 10
Sangre Grande General Hospital
Hospital / Health Centre

Urban Emotions

Urban Emotions ::: Idea



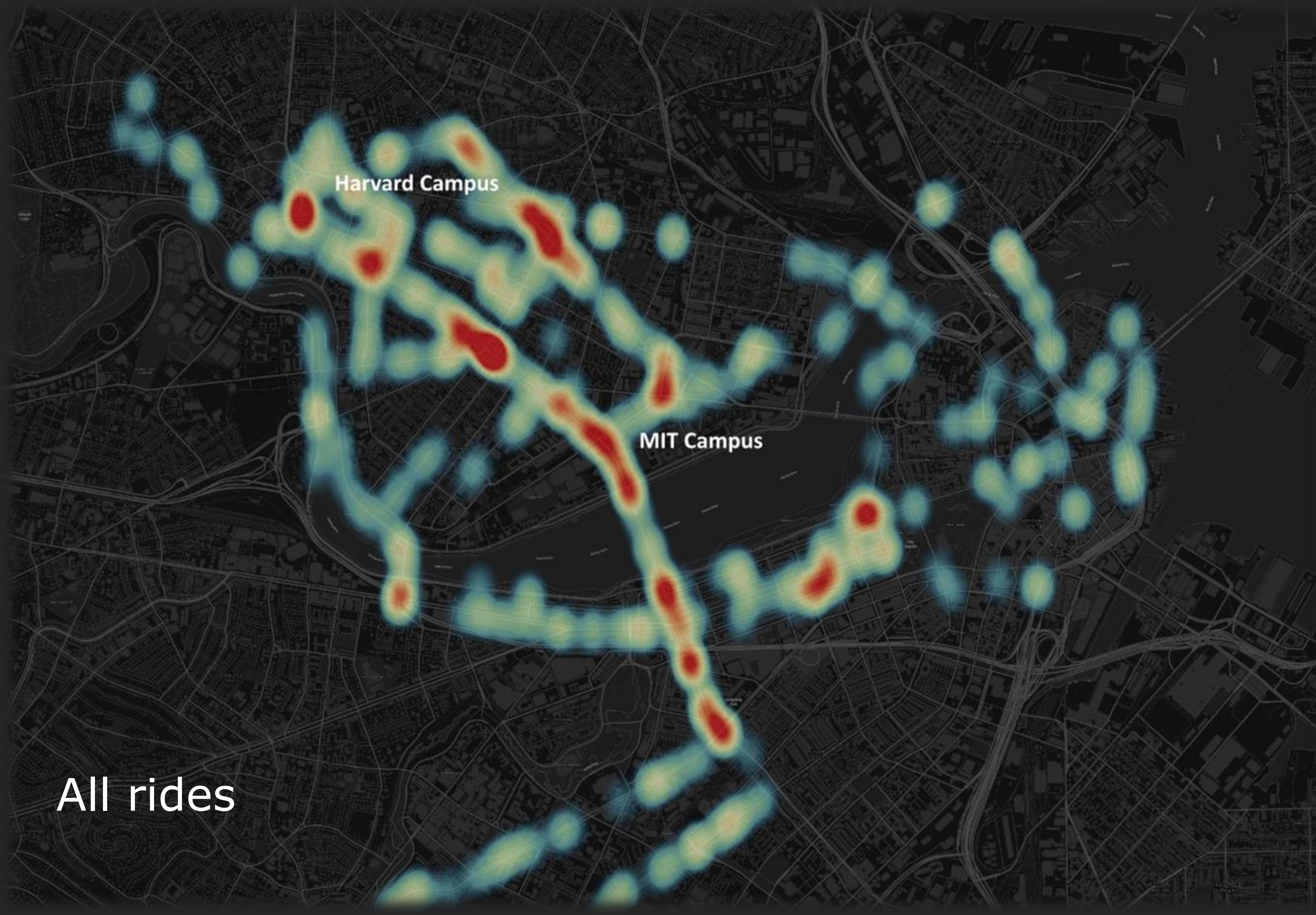


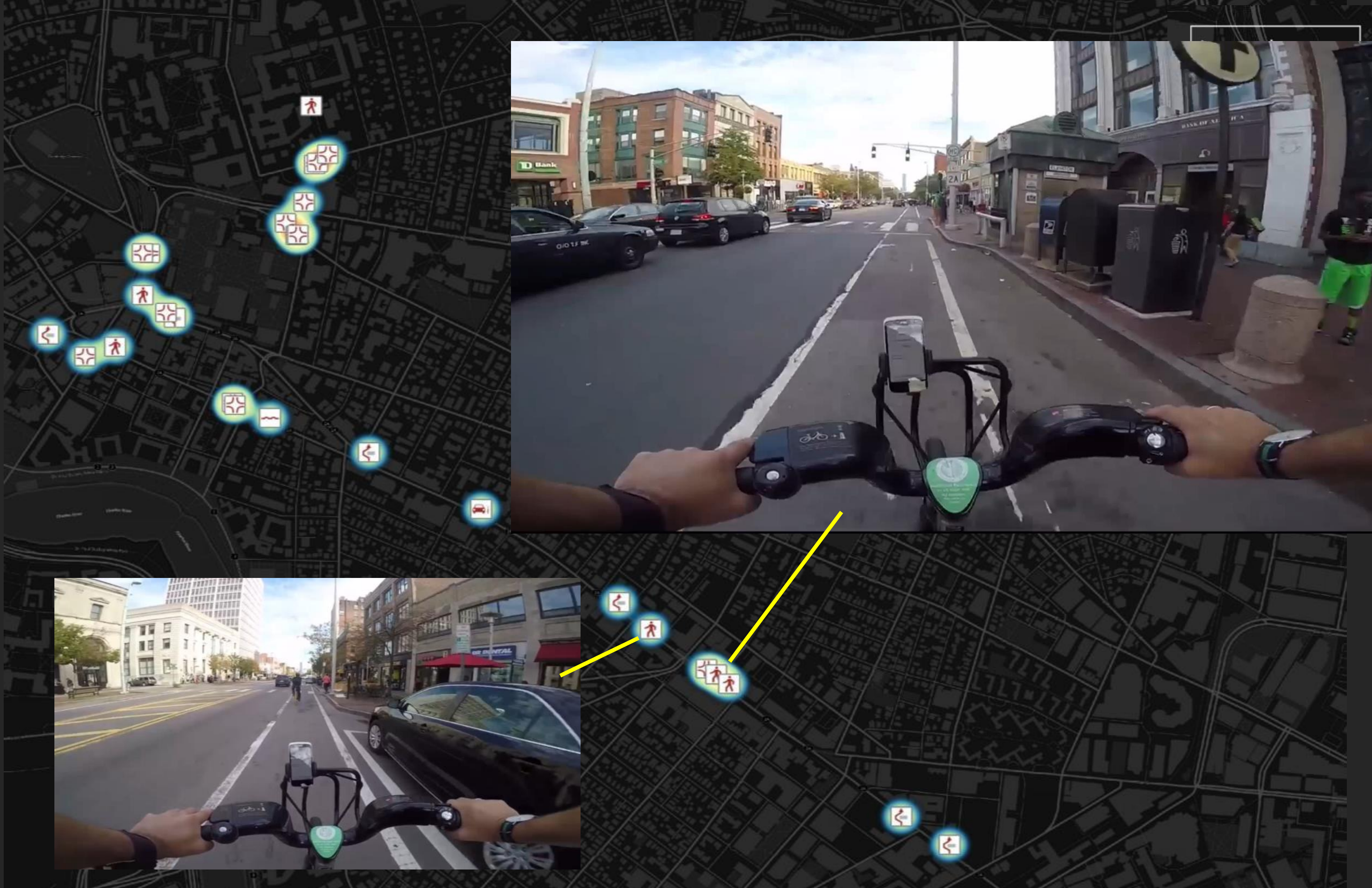
Gund Hall
project.
That's why we're doing it.
GROUNDED VISIONARIES



HARVARD-MIT DATA CENTER
CONCOURSE COMPUTER LAB
COMPUTER TRAINING ROOM
LAB HELP DESK
CGIS WINTER GARDEN

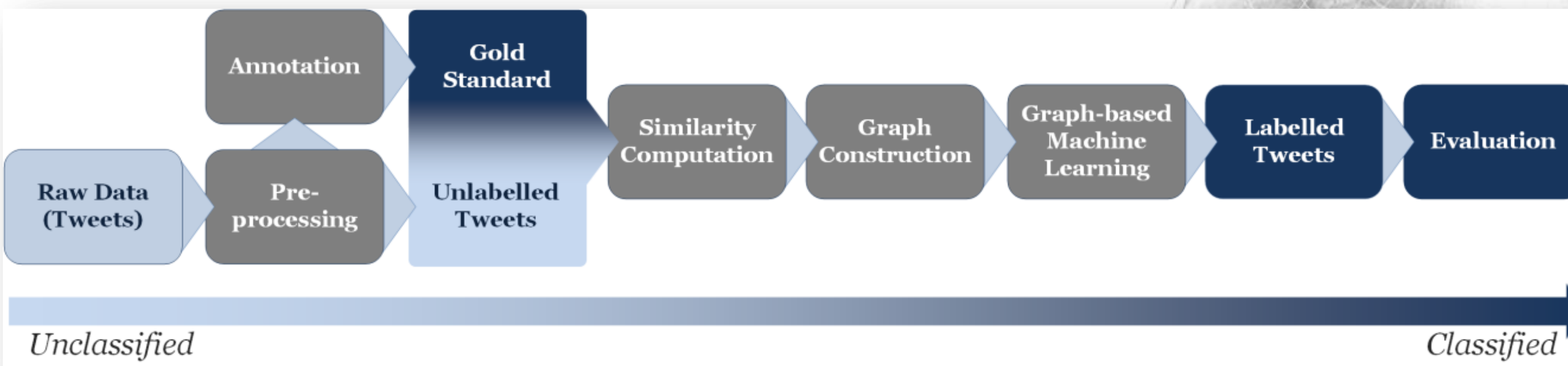
no small
project.
That's why we're doing it.
GROUNDED VISIONARIES



Harvard Campus
MIT Campus
All rides

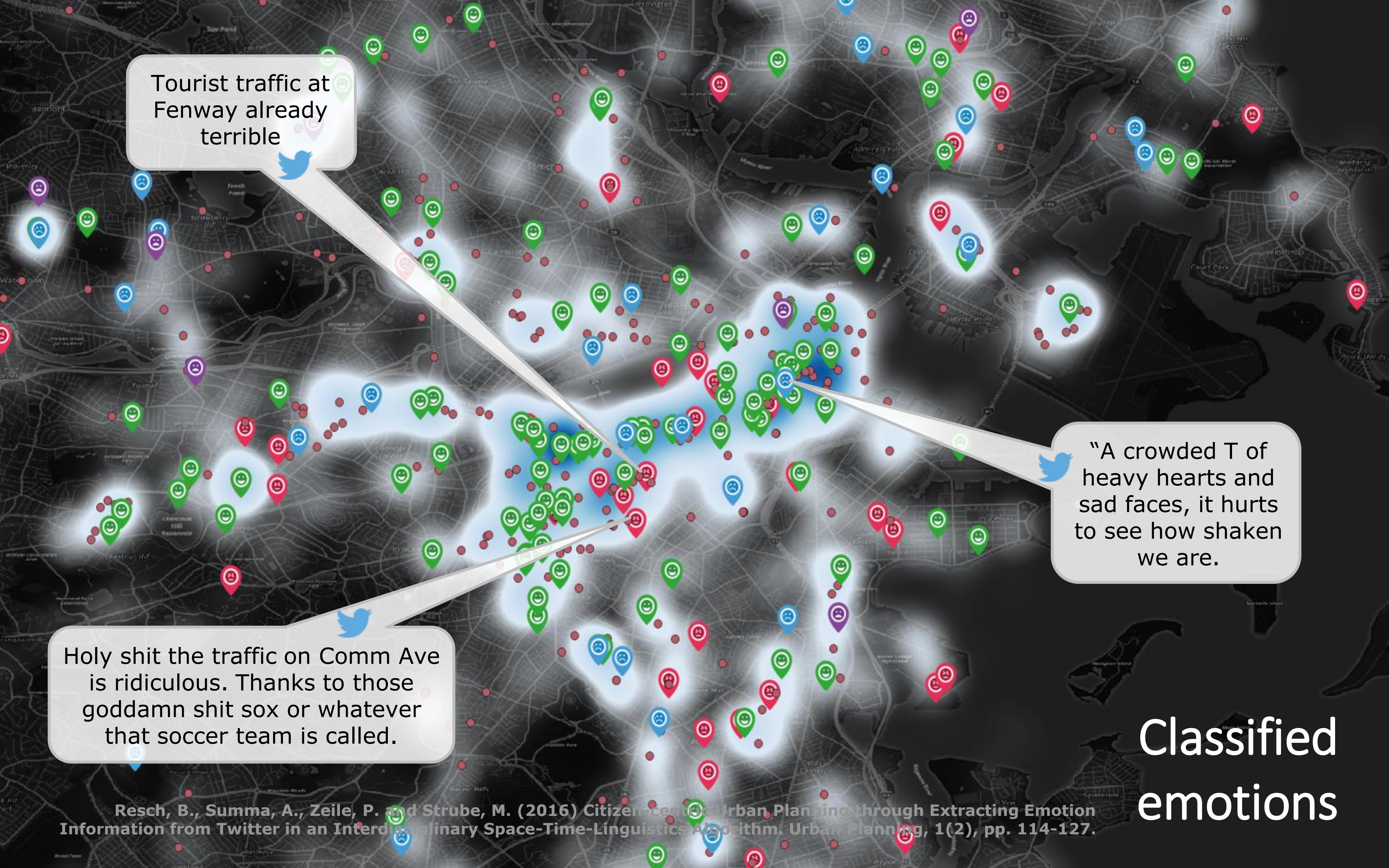

TD Bank

Urban Emotions ::: Twitter Emotions

- Extracting emotions from unedited text (social media)

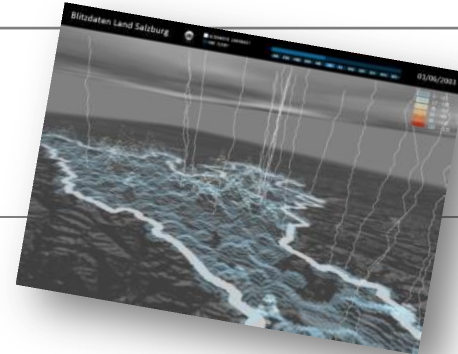


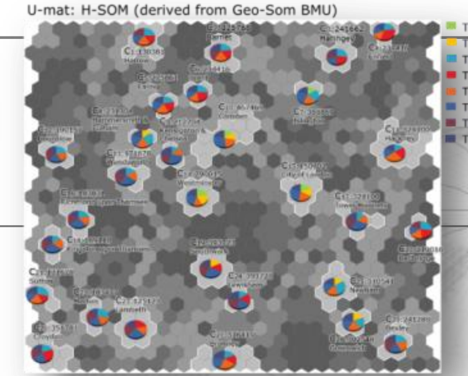
Resch, B., Summa, A., Zeile, P. and Strube, M. (2016) Citizen-centric Urban Planning through Extracting Emotion Information from Twitter in an Interdisciplinary Space-Time-Linguistics Algorithm. Urban Planning, 1(2), pp. 114-127.



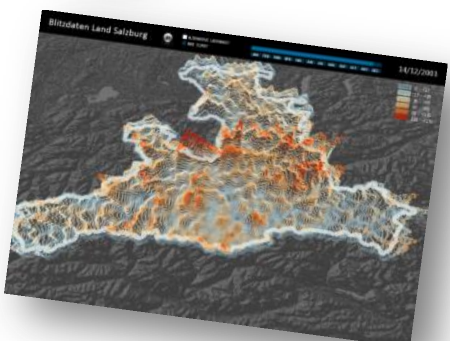
Tourist traffic at Fenway already terrible
"A crowded T of heavy hearts and sad faces, it hurts to see how shaken we are.
Holy shit the traffic on Comm Ave is ridiculous. Thanks to those goddamn shit sox or whatever that soccer team is called.
Classified emotions
Resch, B., Summa, A., Zeile, P. and Strube, M. (2016) Citizen-centric Urban Planning through Extracting Emotion Information from Twitter in an Interdisciplinary Space-Time-Linguistics Algorithm. Urban Planning, 1(2), pp. 114-127.

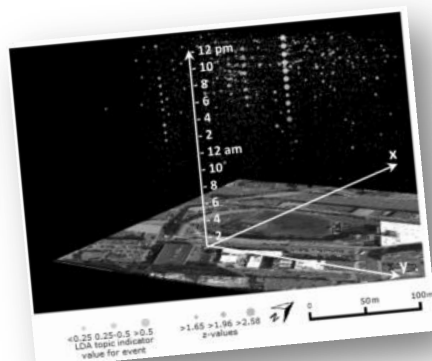
...and much more





- **bernd.resch@sbg.ac.at**





Acknowledgements

- Peter Zeile
- Günther Sagl
- René Westerholt
- Enrico Steiger
- Thomas Blaschke
- Anja Summa
- Andreas Petutschnig
- Stefan Zimmer
- Jan Kinne
- Max Bergmann
- Florian Usländer
- Azmat Arif
- Martin Sudmanns
- Veronika Priesner
- Clemens Havas
- Bernhard Reinel
- Alexander Zipf
- J.-P. Exner
- …

Lehrerfortbildung – Z_GIS, iDEAS:lab

Virtuelle und reale Räume

Verständnis unserer Welt mit Hilfe digitaler Geo-Technologien

Bernd Resch

20 April 2017

UNIVERSITÄT SALZBURG

Z_GIS